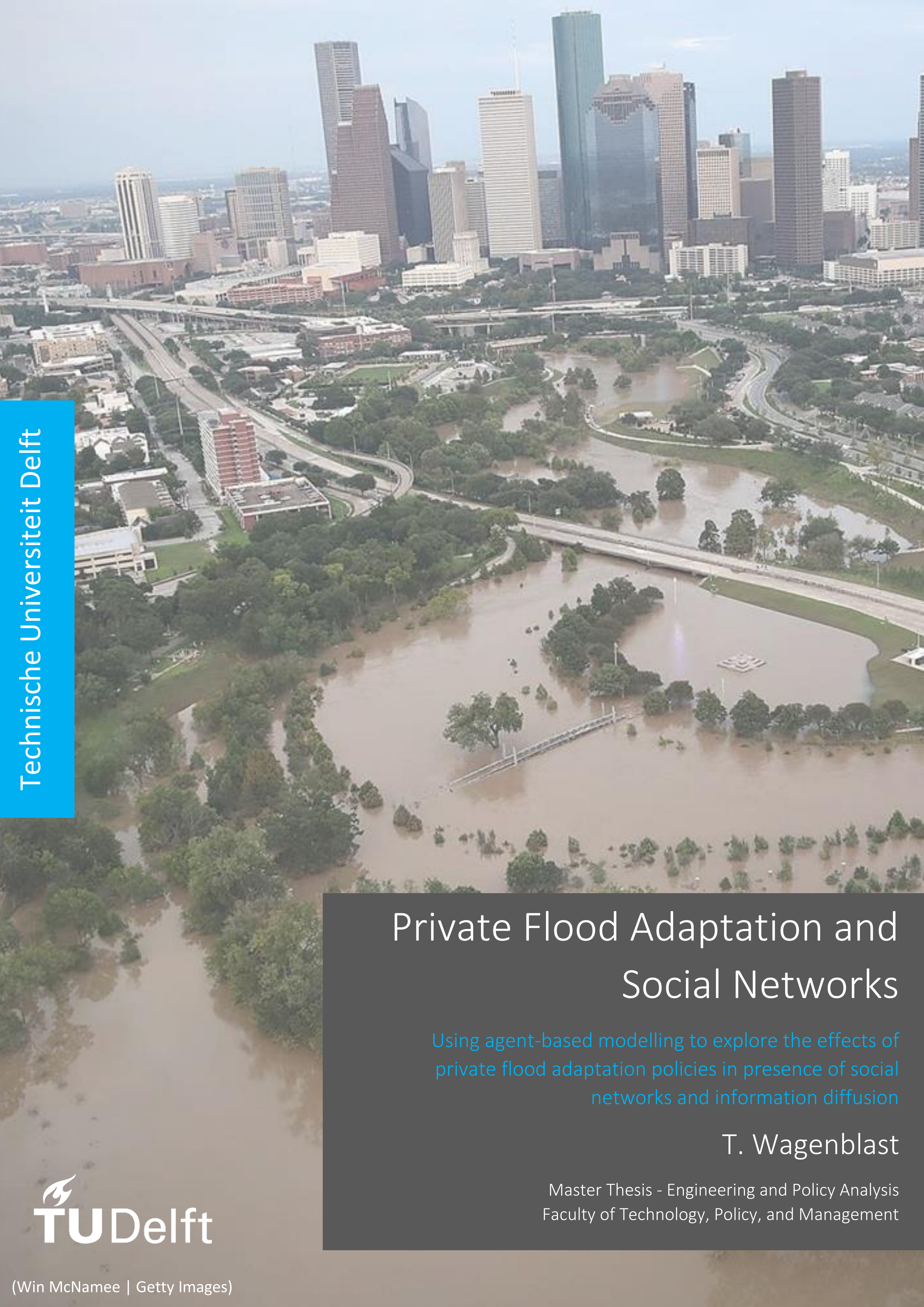

Technische Universiteit Delft

Private Flood Adaptation and Social Networks

Using agent-based modelling to explore the effects of private flood adaptation policies in presence of social networks and information diffusion

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Master Thesis - Engineering and Policy Analysis
Faculty of Technology, Policy, and Management

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TU Delft

Preface

After working on this thesis for the last five months, I am proud to present my graduation thesis on the role of networks in the effectiveness of cross-scale adaptation to climate change. This work would not have been possible without the help of many others.

First of all, I would like to thank my thesis committee. It was a pleasure working with them, learning form them and receiving insightful comments and feedback throughout the process. I would specifically like to thank Tatiana Filatova for the regular meetings, the time and resources she put into this – you allowed me to explore the topic according to my interest and guided me with useful ideas. Furthermore, I am grateful for the feedback by Nihit Goyal – even though we did not meet as regularly, the insights especially in the policy side were very valuable. Furthermore, I am grateful for the help by Brayton Noll and Alessandro Taberna for sharing their experiences and knowledge regarding the survey data and modelling. Next, I would like to thank Antonia Sebastian and Lauren Grimley for their provision of data and observations regarding flooding in Houston.

On a more personal note, I would like to thank my thesis circle and friends – having people to celebrate with and complain to made this entire experience much more bearable and fun. Finally, a big thank you to my family for their encouragement and support throughout the entire time.

Thorid Wagenblast
The Hague, August 2022

Abstract

Climate is changing. It is widely accepted that irrespective of the emission reductions efforts, adaptation to the already committed climate change is a must in the coming decades. Flooding is one of the most devastating climate-induced hazards, calling for adaptation across scales: from government-led adaptation (e.g. dikes), to personal household-led adaptation. There are numerous private adaptation measures, both structural and non-structural, that households can autonomously take to reduce damages and speed up own recovery, in case of the adverse event does occur. Worldwide household surveys provide the empirical evidence suggesting that the appraisal of fear, perceptions of own coping abilities and social influences affect individual decision to adapt. Especially the latter appear as a strong determinant of household-led adaptation. Yet, the role of social networks has not been studied systematically, let alone the exploration of the interplay between private households' adaptation and public policies in the presence of social influences. To increase the understanding of social networks' impact on private flood adaptation under various public policies, an empirical agent-based model is built. In addition to empirical flood maps, I employ Protection Motivation Theory and households' survey data from Houston (Texas, USA) to capture the household's adaptation decisions, which are subject to social influence. To represent a range of social networks, I explore the effect of three random networks – Erdős-Rényi random network, Barabasi-Albert scale-free network, Watts-Strogatz small-world network – on the diffusion of flood preparedness. These three networks could serve as a proxy of diverse types of social relationships that vary across cultures, with some being hierarchical and others egalitarian. Furthermore, I test how the diffusion of private adaptation among households evolves under four generic public policy strategies: protection by publicly-funded infrastructure, market-based policy such as subsidy, information policy and regulatory policy. The thesis findings reveal that the type of social networks influence success of private adaptation decisions significantly. Notably, the effect of social norms depends on the network configuration, where more homogeneous networks lead to higher private adaptation uptake. Furthermore, the thesis quantifies the interaction effects between social networks and policies designed to support private climate change adaptation, for example communication campaigns affecting individual risk perceptions that in turn drive household-led adaptation. Therefore, information policies can be very effective in steering public opinions and, hence, the uptake of households' adaptation measures. Moreover, I find that in the presence of social networks, public adaptation policies interact with each other: a combination of subsidies with communication exhibit synergistic effects on the flood damage reduction from private adaptation. Policies that do not interact with households' perceptions, like infrastructure projects or laws, can be considered more robust – less sensitive to social networks. To conclude, networks can shape the success of climate change adaptation policies and should be accounted for in their design. Further research should focus on the endogenous evolution of social networks and the model behavior under changing flooding conditions and what this complex adaptive system's dynamics means for future cross-scale adaptation efforts.

Contents

1

Introduction

For decades it has been known that humans change the climate on earth. With the latest IPCC'2022 report (IPCC, 2022a), it has become more obvious, how significant this influence is. The world is heating up and the measures to reduce emissions can only lessen the severity but not stop the changes that are already happening.

All around the globe more extreme weather events can be observed: Recurring droughts in the Horn of Africa region (Humanitarian Aid, 2022), weeks of temperatures above 40 degrees in India (Pratt, 2022), the frequency and magnitudes of flooding in Australia (Whiteman, 2022), water shortage in Italy (Orlandi & Jewell, 2022) and so on – just in the past half year. Weather extremes are increasing in magnitude and frequency; the results from human-induced climate change are experienced by an increasing number of people. The current way of living cannot deal with these changes adequately in most places across the globe. Hence, adaptation is key to ensure that society is prepared for unknown and more extreme climate-related events in order to reduce and prevent damage and human loss (IPCC, 2022b).

Due to the global changes in the climate, extreme floods become more likely resulting from more intense precipitation events, rising sea-levels and closer recurrence of these events (Hagelberg, 2020). Flooding is one of the most occurring and most expensive natural hazards and damages are expected to increase in the future (Yin et al., 2021). Next to the government-led adaptation, such as large-scale infrastructure projects like dikes, adaptation actions across a variety of stakeholders operating at various scales is important (Neil Adger et al., 2005). Notably, there are numerous ways in which households can prepare and take precautionary measures (Koerth et al., 2013). This includes taking precautions both on a non-structural (e.g., storing emergency supplies) and on structural level (e.g., reinforcing property walls). These measures can complement the public risk management and reduce flood damage by 80% (Grothmann & Reusswig, 2006).

Individual adaptation measures are known but not taken up widely yet. A number of studies have been carried out to increase the understanding of factors that influence the decision of taking private flood adaptation (PFA) measures (e.g., Bubeck et al. (2012); Grothmann & Reusswig (2006); Porter et al. (2014)). PFA is commonly studied theoretically and empirically through the lens of Protection Motivation Theory (PMT) that showed that the threat appraisal but also the ability to cope with adversity is decisive (Grothmann & Reusswig (2006); Koerth et al. (2013); Bubeck et al. (2012) among others). Additionally, the influence from social environment and social norms like friends and relatives is very important (Porter et al., 2014; Wilson et al., 2020; Bubeck et al., 2018). The fact that the social network influences and shapes the perceptions of households that are the basis for the decision to take protective action define the need for its consideration (Bubeck et al., 2018). Yet, little research has been carried out investigating the influence these social networks have on the diffusion of private adaptation and its interplay with various public adaptation policies. So far, no study was done to systematically test how PFA diffuses through different types of social networks and what influence this has on the uptake of PFA measures. Furthermore, it is unclear, how various public adaptation policies interplay with private adaptation in the presence of such networks. This thesis aims to increase the understanding of household adaptation dynamics, which is influenced by diverse social environments, and the interplay of this behaviorally-rich PFA with various public policies. To this end, this thesis aims to answer the following research question:

What role do social networks play in effectiveness of cross-scale adaptation to climate change?

To address this question, the interplay of "effectiveness" and "networks" will be viewed from different angles resulting in the following three subquestions:

1. How does information diffusing through different networks affect private adaptation?
2. What impact does households' adaptation have on flood damage under various policies and their interactions?
3. How does the presence of networks influence the impact of policies on households' adaptation?

Chapter 2 provides an overview of the literature regarding the state of the art of research on PFA, specifically the relations between social environment, policies and a household's decision making, as well as the use of agent-based modelling (ABM) in that field. Chapter 3 outlines the methods used. This is followed by the analysis of results in Chapter 4, and a discussion and conclusion (see Chapter 5).

2
State of the Art

To gain a better understanding of PFA and the factors that influence it, in Section 2.1 several studies are reviewed regarding the factors influencing households in taking private measures against flood damage (more details on the potential measure, their efficiency and costs are found in the Table A.7 in Appendix A). Following in section 2.2, the commonly used decision-making theory in PFA, PMT, is examined. As the focus of this research is set on the interplay between policies and networks, studies on policies (Section 2.3) and social networks (Section 2.4) in the context of PFA are reviewed. In closing, the research gap in this topic is identified in Section 2.5.

2.1. Studies on Private Flood Adaptation

An overview of the literature studied and which factors they find to be important in PFA can be found in Table 2.1.

Risk perception is a factor mentioned multiple times and plays an important role when it comes to people's intention to adapt (Van Valkengoed & Steg, 2019; Koerth et al., 2017; Bubeck et al., 2012; Han & Peng, 2019). Other factors like knowledge, trust, attachment to a place or past experiences are not as important, according to Van Valkengoed & Steg (2019). This is in contrast to findings by Porter et al. (2014), Koerth et al. (2013), Koerth et al. (2017) and Grothmann & Reusswig (2006): they all reach the conclusion that past experiences with floods or extreme weather events in general are key drivers for households to take adaptive measures.

However, as Porter et al. (2014) point out, this can also lead to anxiety avoidance and hence reduce the uptake of adaptation measures. This is further supported by Bubeck et al. (2012), who find that coping appraisal is important for actually taking mitigation measures. Noll, Filatova, & Need (2022) specifically highlight the importance of intending or having taken a measure and that this can also reduce the influence of fear on an adaptation decision. Furthermore, the social surroundings like the pressure of social acceptability (Porter et al., 2014) or personal history (Koerth et al., 2013) were found to play an important role. Koerth et al. (2017) also observe that socio-economic factors have a strong impact on flood adaptation behaviour. In contrast, Grothmann & Reusswig (2006) do not see this and identify perceptual factors better at predicting the implementation of PFA measures.

It is also interesting, that four of the seven studies refer to Protection Motivation Theory (PMT) or extended PMT (Grothmann & Reusswig, 2006; Koerth et al., 2013; Bubeck et al., 2012; Noll, Filatova, & Need, 2022). A more detailed look into PMT is given in section 2.2. Furthermore, various authors emphasise the need for a risk communication that also includes possible adaptation behaviours (Koerth et al., 2013, 2017; Grothmann & Reusswig, 2006; Bubeck et al., 2012), highlighting the importance of coping appraisal in the uptake of PFA measures.

2.2. Protection Motivation Theory and Households' Adaptation to Floods

Coping appraisal and risk perception are one of the key influential factors in PFA uptake and explain, why many studies use PMT to explain PFA decision making (e.g., Grothmann & Reusswig (2006); Koerth et al. (2013); Bubeck et al. (2012); Erdlenbruch & Bonté (2018); Haer et al. (2016); Aerts et al. (2018); Han et al. (2021); Noll, Filatova, & Need (2022)) and highlight the potential of PMT to provide important insights (Bubeck et

Table 2.1: Literature about factors influencing household adaptation

Citation	**Point of focus**	**Factor(s) found important**	**Factor(s) found not as important**
Bubeck et al. (2012)	literature review on relationship between flood risk perceptions and mitigation behaviour	coping appraisal, perceived responsibility	risk perception alone
Grothmann & Reusswig (2006)	socio-psychological model based on PMT validated with surveys	past experiences, perceptual factors (e.g., perceived risk, coping capabilities)	socio-economic factors
Koerth et al. (2013)	understand motivation of coastal households to adapt proactively against sea-level rise and flooding through questionnaire based on PMT	past experiences, personal history and background	age, property location
Koerth et al. (2017)	meta-analysis of empirical studies about coastal household adaptation to floods	past experiences, socio-economic factors, perceived risk and responsibility	
Noll, Filatova, & Need (2022)	analysis of influence of the past and intended adaptation using survey data	adaptive capacities (self-efficacy, already undergone and intended measures)	
Porter et al. (2014)	meta-analysis of factors that influence household climate adaptation in the UK	past experiences, social acceptability, long-term financial rewards	
Van Valkengoed & Steg (2019)	meta-analysis of factors that drive climate adaptation	descriptive norms, perceived self-efficacy, effectiveness of adaptation measures, risk perception	knowledge, trust, attachment to a place, past experiences

al., 2012). The concept of PMT was originally developed in the field of psychological research about health behaviour and health threats in particular (Rogers, 1983; Rogers & Prentice-Dunn, 1997): fears and any information regarding these start a process of threat and coping appraisal, where the threat appraisal evaluates the results of "bad" adaptation, while the coping appraisal considers adaptation responses. This theory can also be applied in a different context e.g., for analysing natural disasters and hence, PFA. Grothmann & Reusswig (2006) find that perception factors, that is factors outside of the typical socio-economic model, are better predictors of PFA uptake and allow to apply this concept to the context of flood hazards. Figure 2.1 shows a conceptual overview of using PMt for flood hazards and PFA.

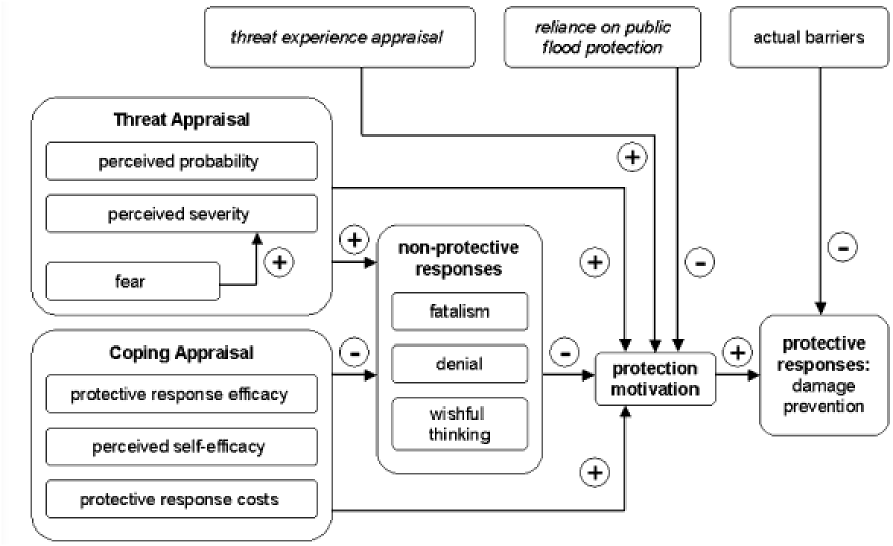


Figure 2.1: Conceptual model of PMT regarding flood risk. Source: Grothmann & Reusswig (2006) (*Figure 2, p.105*).

2.3. Interplay between Public and Private Adaptation in Models

The literature about PFA reviewed in the previous Section 2.1 mentions the importance of public adaptation policies repeatedly. Some studies using ABM to explore PFA also study public policy interventions and their effects on flood protection (e.g., Erdlenbruch & Bonté (2018); Haer et al. (2020); Tonn et al. (2020); Abebe et al. (2020)). These include both interventions aimed at reducing flood risk on a communal and on a private level. Tonn et al. (2020) find that the severity of the flooding determines which action is needed: less severe flood events can be mitigated by PFA, while more serious flooding calls for public community measures.

Public adaptation policies that focus on communicating risk and coping possibilities perform best in terms of supporting individual adaptation efforts (Erdlenbruch & Bonté, 2018; Haer et al., 2016; Tonn et al., 2020). In addition, Erdlenbruch & Bonté (2018) point out, that information policies in general seem to have a significant impact on adaptation uptakes. Haer et al. (2016) specify, that communication tailored for and centred towards people is more effective than general top-down governmental communication even though this people-centred approach might reach less households. Furthermore, policies that steer households to a rational behaviour so that they neither over- nor underestimate the floor risk, provide a measure to counter the "levee-effect". This effect occurs when governmental flood protection like publicly-funded infrastructure projects lower the yearly flood risk on average but also reduce the individuals' stimulus to implement PFA measures, leading to more severe damages in case of extreme flood events. It is also known as the "safe development paradox" (Haer et al., 2020). While Haer et al. (2020) stress the importance of communicating flood risk, Bubeck et al. (2012) sees the potential of information policies in stimulating the coping appraisal, when the risk information is paired by practical guidance on implementation of PFA measures. Information policies may also result in more public participation, which is of importance in local risk mitigation (Han & Peng, 2019).

In contrast, Haer et al. (2017) set the focus on economic models and reach the conclusion that market-based policies can have a large impact on nudging households to implement PFA measures. This is supported by Abebe et al. (2020) and Hanger et al. (2018) who find that subsidies in particular but also insurance can increase the number of adapting households in the long run. However, others reach the conclusion that public risk mitigation (e.g., government-funded infrastructure projects) and the enforcement of adaptation rules (regulatory policies) have more impact than financial incentives (Han et al., 2021). However, as mentioned, Haer et al. (2020) indicate that this might not always be a good choice considering the levee effect (Haer et al., 2020). A review of market-based instruments for flood risk management is provided by Filatova (2014). These instruments include preferential taxes, insurance, development rights, among others. Filatova (2014) conclude that in particular the combination of market-based policies with other flood risk management policies are effective.

2.4. Social Networks in Private Flood Adaptation

The influence and criticality of considering social surroundings in PFA is highlighted in numerous studies (e.g., Porter et al. (2014); Wilson et al. (2020); Bubeck et al. (2018)). Wilson et al. (2020) reviews theoretical and empirical work on behavioural adaptation and concludes that social interactions play a critical role. Even though this is being increasingly recognised, there is still a need to further investigate the role of interpersonal relations, social dynamics and feedback (Wilson et al., 2020). Observation and learning form the social environment like friends, neighbours or family, seem to influence flood-coping appraisal in a positive manner, highlighting the role of social norms and networks when it comes to taking preparatory decisions for flood events (Bubeck et al., 2018). Especially when it comes to information policies, social networks are an important driver for the adoption of measures. Often, information spreads to others that were not directly targeted by the policy. This provides possibilities for policies to exploit those effects (Haer et al., 2016). Furthermore, households are generally more influenced by their close friends, family and neighbours and tend to take their opinions and experiences more seriously than governmental top-down communication (Haynes et al., 2008; Brenkert-Smith et al., 2013). The research of Haer et al. (2016) is one of the few looking into this specifically: they evaluate and compare communication strategies about flood risk through ABM and look at information propagation through the social network.

2.5. Research Gap

As outlined in Section 2.1, there is already a good understanding of the factors that influence the uptake of PFA measures and how these factors influence household decision making through PMT (see Section 2.2). Furthermore, there is knowledge on which policies can be effective in increasing the flood adaptation effort of households (see Section 2.3) and the importance of social networks, as highlighted in section 2.4. However, a comprehensive approach to understand the interplay between households' motivation to adapt, the influence of social environment on their perceptions, and effects on policies is not studied, yet.

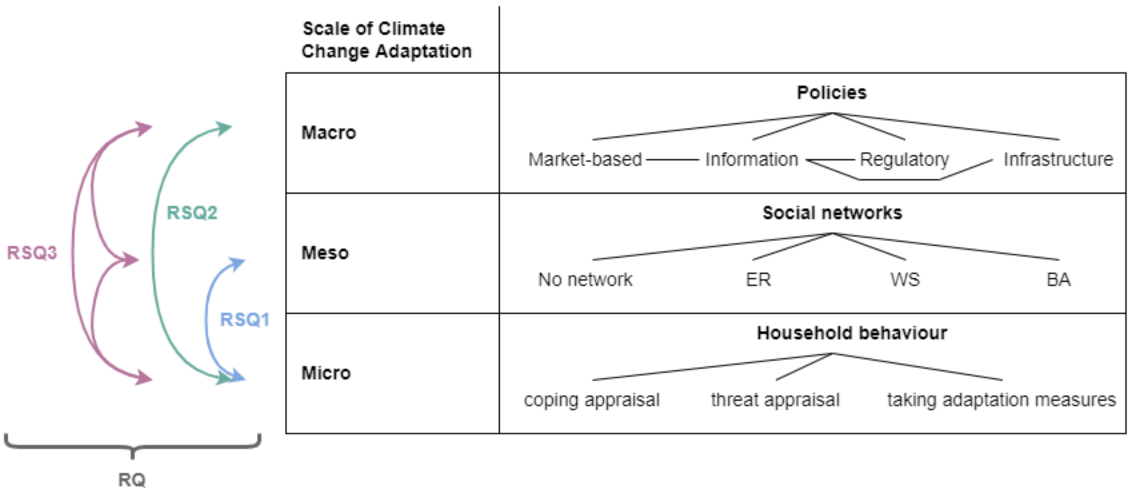


Figure 2.2: Research design to answer the research question (RQ) and the three research subquestions (SRQ1, SRQ2, SRQ3) as posed in chapter 1. Source: own research design.

In Figure 2.2 the research design is shown, including the relation of the research questions posed in Chapter 1 to it. The following Chapter 3 will explain the policies, social networks and household behaviour selected for this thesis in more detail. This thesis aims to bridge the research gap with a systematic testing of a number of generic policies, their interactions and their performance over multiple proxies of social network setups.

3 Methods

3.1. Agent-based Modelling

Many of the factors influencing households in implementing measures for private flood protection are a result of human interaction and are different for every household. Therefore, the understanding of the interplay of households with their different characteristics and experiences is important (Wilson et al., 2020). Increasing this knowledge can be done through the use of ABM, as this technique allows to model the interaction of agents (e.g., humans or households) and observe the patterns that emerge from it (Macal, 2016; Will et al., 2020). In the ABM model designed as part of this thesis, the households are represented as the agents.

In the fields of private flood and climate change adaptation ABM is commonly used, but the focus of the studies varies. Erdlenbruch & Bonté (2018) and Haer et al. (2016) concentrate on communication, Haer et al. (2017) set economics at heart and investigate household investments into loss-reducing measures with different economic models. Han et al. (2021) base their model similarly on the households willingness to spend money on insurance and connect this with the risk appraisal of agents. Haer et al. (2020) examine governmental action and Tonn et al. (2020) individual versus community adaptation, whereas Abebe et al. (2020) put risk management policies at their focus. There are multiple ways to model the PFA decision-making of agents: Erdlenbruch & Bonté (2018); Haer et al. (2016); Aerts et al. (2018) and Han et al. (2021) use the psychological PMT, which also will be used in this study in extended form. Others look into bounded rational behaviour and prospect theory (Aerts et al., 2018; Han & Peng, 2019).

In this study, it is sought to capture the effectiveness of public adaptation policies and diffusion of opinion under the influence of different social network setups. Therefore, an agent-based model was developed in Python using the *mesa* library (Project Mesa Team, 2016). The model allows to prescribe a social network that defines the interaction between agents (Will et al., 2020). Within the network, the household agents exchange opinions with their connections. The model simulates how and under which circumstances households take a predefined set of adaptation measures (five structural and five non-structural, see Appendix A.1.2) and evaluates the influence of the different network types and policies on this.

Figure 3.1 provides an overview of the processes in the model: Household agents have parameters on their perceptions regarding threat and coping appraisal, their flood situation and the measures taken. Each step, based on these parameters and PMT, a probability to take a measures is calculated. Depending on this probability and the agent's savings (agents save a certain percentage of the income every months that is used to "pay" for the measures), the household agent takes a measure. Taking a measure will increase the household agent's preparedness for a flood. This means, the flood damage of the household is reduced to a certain extend (see Appendix A.3.1). The household agents' decision making process is also displayed in Figure 3.2 in more detail.

Furthermore, each step agents are influenced in their perceptions regarding worry and coping appraisal by their network and adapt the perceptions based on this influence. Since these perceptions are fed into PMT and with this build the basis for the PFA uptake decision, the information exchange is considered especially important for the progression of the simulation. Lastly, external changes e.g., policies or changing flood risk can be introduced into the model and make an observation of the households' reactions and their interaction effect possible.

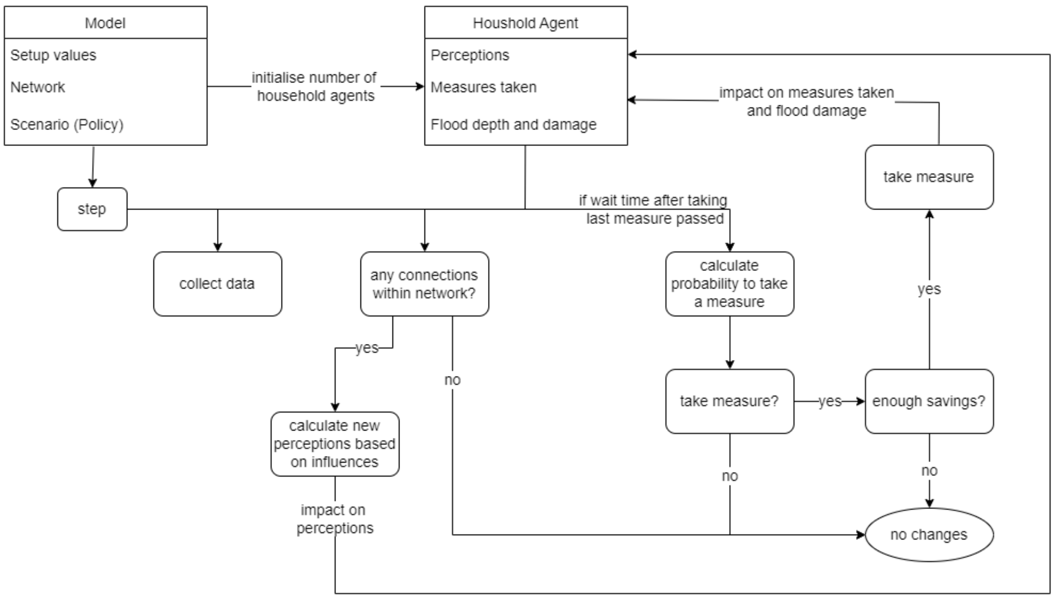


Figure 3.1: General overview of processes in the model. Source: own model design.

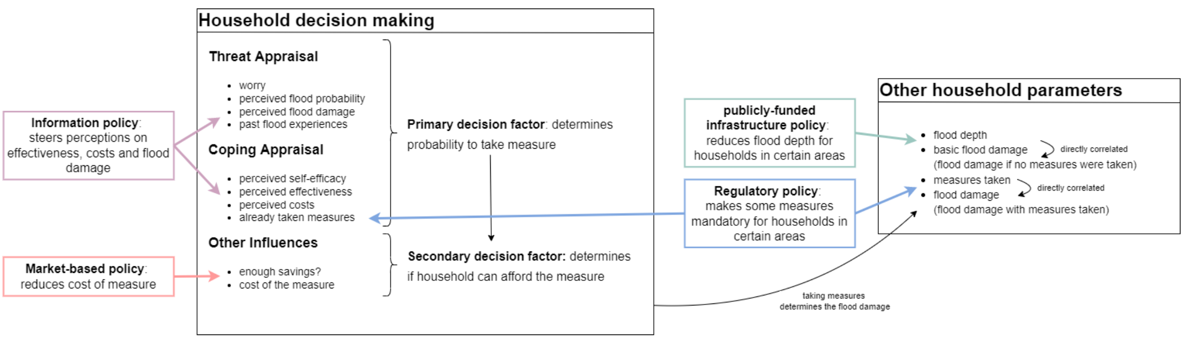


Figure 3.2: Decision making of household agents regarding the uptake of protective measures. The interference of the policies in the decision process is shown as well as their influence on other household parameters. Source: own model design.

A detailed description of the model is given in Appendix A following the ODD (Overview, Design concepts, Details) protocol as proposed by Grimm et al. (2006, 2010).

3.1.1. Networks

As explained, social networks play an important role in PFA. Integrating social network analysis in ABM is commonly done and valuable as it provides insight into a wide range of interactions (Will et al., 2020). To capture and investigate this effect, the model is explored under the presence of different network setups. Random graphs are frequently used to investigate properties of "typical" networks (Peach et al., 2022). To capture a wide range of potential social networks, three different, random network configurations are selected: Erdős-Rényi random network (ER), Barabasi-Albert scale-free network (BA), and Watts-Strogatz small-world network (WS) (Peach et al., 2022; Rifki & Ono, 2021).An exemplary visualisation of these network types can be found in Figure 3.3.

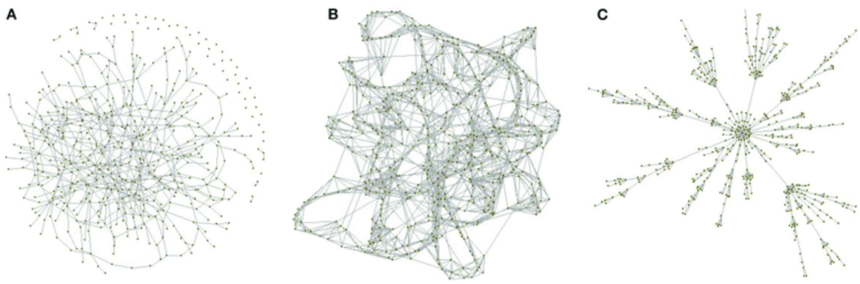


Figure 3.3: Three classical network structures employed in this thesis. Panel (A): Erdős-Rényi random network; Panel (B): Barabasi-Albert scale-free network; Panel (C): Watts-Strogatz small-world network. Source: Koutrouli et al. (2020) (*Figure 5, p.7*)

These three networks could serve as a proxy of diverse types of social relationships that vary across cultures and contexts, with some capturing hierarchical and others egalitarian relationships. ER is a network where each connection (edge) is included with a certain probability independent from any other edges (Erdős & Rényi, 1959). This should lead to the most homogeneous structure of all networks considered here as most nodes have a very similar degree (Trpevski et al., 2010) making it the most egalitarian of the networks considered here. WS was the first small-world model, meaning that the network generally contains small-world properties like a short average path length and a high clustering coefficient (Watts & Strogatz, 1998). With this properties, WS is considered to be the network closest structurally to many real-world social networks (Labs, 2012). Lastly, BA is considered for the representation of a scale free network - a network where the degree distribution at least asymptotically follows power law (Barabási & Albert, 1999). This means that there are nodes with very high degree in comparison to the other nodes, so called "hubs". This hierarchy is a characteristic of many global social networks[1] (Held et al., 2015).

Peach et al. (2022) systematically generated and compared the three networks of the aforementioned types. They found, that especially the standard deviation and skewness of edges distinguishes the different networks: BA setups generally have a larger standard deviation and dissymmetry resulting from the varying degree distribution. ER and WS are much more similar. The main difference here is that ER graphs show a smaller standard deviation compared to WS following from a more uniform degree distribution.

It is assumed that households are influenced most by close connections in their social network and that these connections do not vary within the time frame considered here. Therefore, the network for all cases is imposed endogenously and does not change throughout the simulation. The three aforementioned network type BA, WS and ER are used. They are calibrated to confirm with the literature. This finds that on average, the number of close contacts is somewhere between three and five in western cultures (Hill & Dunbar, 2003). This results in a distribution of number of connections as shown in figure 3.4. Similar to the findings from Peach et al. (2022), Figure 3.4 shows that with the BA setup, the number of contacts is the most skewed with a majority between two and six, but also agents that are connected to up to 135 others. This shows the formation of hubs and smaller clusters. ER and WS are more similar and have a significantly lower dissymmetry compared to BA.

As already mentioned, the household agents exchange opinions only with their connecting nodes, i.e. households they have established contact with. This information exchange is based on the DeGrootian opin-

[1] Social networks here as in online social networks (e.g., Twitter, Facebook)

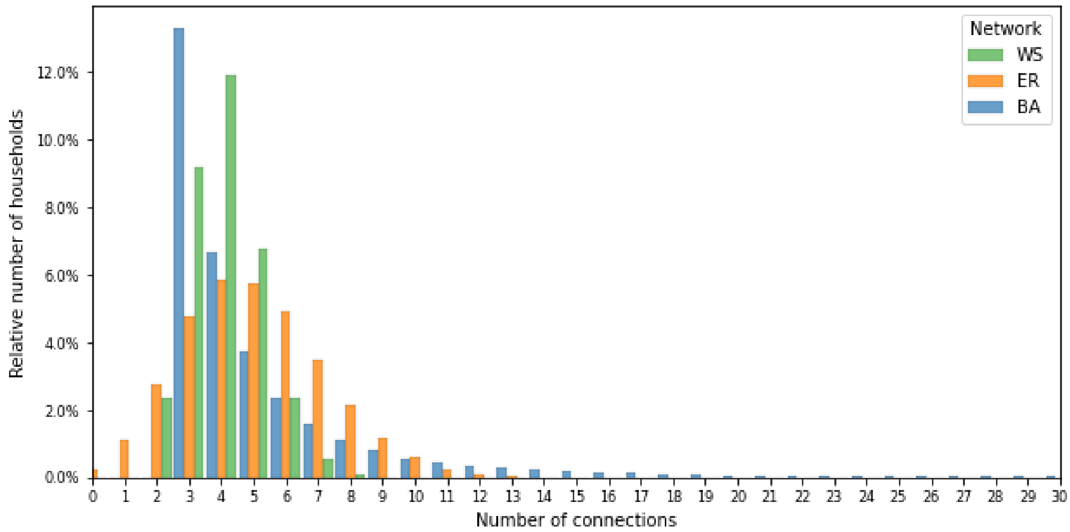


Figure 3.4: Histogram showing the distribution of network connections for the network parameters used in the simulations. Here ER denotes the Erdős-Rényi random network, BA – the Barabasi-Albert scale-free network, WS – the Watts-Strogatz small-world network. The visualisation was cut at 30 connections; for the BA network there are few cases of up to 135 connections. Source: own calculations.

ion dynamics model (Degroot, 1974), meaning that households put a weight to their own and their connections' opinions and adapt their views based on that (see also Appendix A.2). This should lead to changes in the perceptions of the household agents throughout the course of the simulation. Since these opinions are at the basis of PMT decision making, the networks and the thereby accompanied information diffusion are expected to change the course of the simulation.

3.1.2. Policies

Policies play a key role in climate adaptation. In flood mitigation and adaptation, public adaptation policies are aimed at preparing the society for natural flood risk events and mitigating damage. This includes encouraging households to take PFA measures but can result in different outcomes, as explained in section 2.3.

Therefore, if the role of public adaptation policies and its facilitation (or not) of PFA should be considered. Various policies and their performance under different assumptions of social networks need to be tested. In order to allow for a comprehensive examination of policies in PFA, inspiration is taken from frameworks that classify policies. There are numerous classification attempts: Vedung et al. (1998) uses *sticks* (for regulations, sanctioned rules), *carrots* (economic means that dis- or incentivise certain behaviour), and *sermons* (information tools), while Olejniczak et al. (2020) categorises using six policy tools (*Equip, Ban, Dis-/ incentivise, Inform, Boost, or Nudge*). Hood (1983) identifies four different governmental resources in his typology: *nodality* (information), *authority* (legal power), *treasure* (financial means), and *organisation* (infrastructure and human capacity).

For PFA policies the classification proposed by Hood (1983) is chosen: It is more comprehensive than that of Vedung et al. (1998), the resources needed to promote each policy type are clear and it appears to fit most policies in the PFA field. An overview of this classification and the implementation in this study is given in Table 3.1.

An explanation of how the policies interact with the household agents and influence their decision making is also found in Figure 3.2. The organisational (hereafter: publicly-funded infrastructure or infrastructure policy) and the authoritative policy (hereafter: regulatory policy) influence the initial state of the household agents: the infrastructure policy changes the flood depths found at households located inside a certain area while the regulatory policy makes certain structural measures mandatory for some households. The treasure policy (hereafter: market-based policy) decreases the costs of the measures by a certain percentage. None of these policies influence the perceptions of the household agents. In contrast, the information policy directly

Table 3.1: Policy types according to Hood (1983) and examples for these in the PFA context.

Policy type (Hood, 1983)	**Examples**	**Example in this study**
exchangeable assets (*treasure*)	insurance, subsidies, ...	subsidies on all structural measures i.e., reducing the cost of structural measures by a percentage
information (*nodality*)	information sessions, communication (social media, media, ...), workshops and training, ...	communication of flood-related facts to all households
legal power (*authority*)	laws and regulations	mandatory PFA measures in some areas
human resources and infrastructure (*organisation*)	dams, bayous, basins, dikes, ...	flood reduction because of basin (re-)construction in some areas

targets and influences the household agent's perceptions. Since the decision to take action is based on advanced PMT and hence mainly on the views of the agents, this policy is expected to alter the course of the simulation most.

3.1.3. Experimental Design

The model is run for 90 time ticks. Since the flood situation and the policy introduction are static, it is thought to represent short- to mid-term developments. The ABM model simulates the PFA decision making and uptake of measures of 1000 households.

Even though the model is mainly based on empirical data, there are some input parameters that are based on assumptions. As a result, there are several uncertainties in the input space of this model, as well as the outputs it generates. In order to determine how the uncertainty in the model's outputs can be distributed over the various sources of uncertainty in the model input, it was decided to conduct a sensitivity analysis (Saltelli, 2002). The results from verification and sensitivity analysis can be found in Appendix B.

The experimentation involved combining the four network setups (no network, BA, ER, WS) with the five policy cases (base case (no policies active), infrastructure, communication, regulation, subsidies). This results in 20 different policy-network combinations. Because the communication policy is deemed to lead to the most interesting results, the other policies are combined with it (communication and infrastructure, communication and regulation, communication and subsidies). Special focus here is set on whether the combination of policies only has additive effects or whether it has a counter-productive or synergistic effect on the flood damage (Maor & Howlett, 2021). In total, this results in 32 different model setups that are simulated.

To answer the first subquestion on information diffusion, data on the perceptions of agents is collected and especially the impact of the communication policy is examined. For subquestion two, the flood damage and the influence of the policies on it is assessed in detail. Lastly, the networks' impact is examined through the flood damage and the information diffusion.

3.2. Case Study and Data

In this work, a case study approach is used. This means, that data from a certain case is used to feed the agent-based model.

The City of Houston (TX, USA) is situated at the coast of the Gulf of Mexico, an area where tropical storms and cyclones are no rarity. In the past five years, Hurricane Harvey (2017), Tropical Storm Imelda (2019) or Tropical Storm Beta (2020) have caused severe flooding and damage (National Centers for Environmental Information, 2022). The occurrence and magnitude of such storms is not expected to decrease with the changing climate (Dart, 2017). Data availability for this area is good: flood data from the Super-Fast INundation of CoastS (SNFICS) model depicts the impacts of an devastating flood event like hurricane Harvey (Sebastian et al., 2021). Furthermore, detailed and representative data on opinion towards climate change, demographic background, perceptions towards PFA measures and their uptake is available for Houston through an ERC SCALAR survey (Noll, Filatova, Need, & Taberna, 2022).

3.2.1. Survey Data

The model is tested using the behavioural and flooding data from Houston (TX, USA). As indicated, the behavioural data is based on a ERC SCALAR survey data Noll, Filatova, Need, & Taberna (2022), that is aligned with PMT and considered representative (Noll, Filatova, & Need, 2022). For this model, the survey results from the first wave of the survey conducted in the first quarter of 2020 are used. This contains answers from 849 Houston households. The data is cleaned to only contain the needed information on perceptions around flood damage and probability, measures taken as well as the measures' costs, the household's view on taking this measure and its effectiveness. Furthermore, data on financial background and social expectations is kept. The distribution of these values determines the initial state of the model. This means e.g., the initial percentage of agent population considering the potential flood damage as very severe is the same as in the survey population. Furthermore, the measures considered in the model are the five most popular structural and non-structural measures. This means that ten measures are included, slightly fewer compared to the survey data.

Additionally, the decision to take a measure is based on the survey data from the ERC SCALAR project (Noll, Filatova, Need, & Taberna, 2022). Following PMT, I ran a logistic regression to estimate how households intention to take structural flood adaptation measures is driven by behavioral, economic and social factors (for more information on the various factors and how they were measured, see Appendix A.3.2). This means, the intercept and beta factors for the logistic regression function are determined through the empirical data. Through this, based on their views on floods in general and the measures in particular, as well as their already demonstrated coping abilities (taking other measures), a probability to take a certain measure is assigned to each household.

3.2.2. Flood Maps

Flood maps from the SNFICS model are used, more specifically from the hindcast of tropical storm Harvey (Sebastian et al., 2021). The map is shown in Figure 3.5. The flood map entails the different flood depths across the city in meters that could be found during hurricane Harvey. Households are assigned a location and based on this map, each household agent's basic flood depth without any measures taken is determined. Based on the flood depth-damage function as given by Moel et al. (2017), the flood depth can directly be related to a damage factor. This damage factor is also used to determine the impact of household adaptation, policies and the networks on the flood damage.

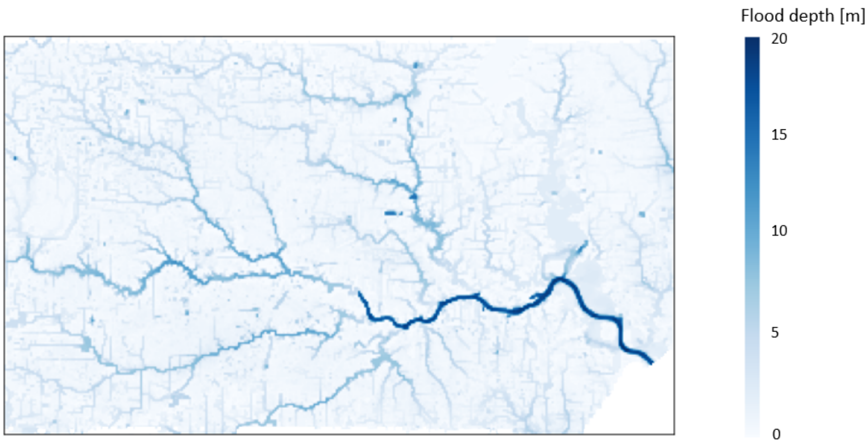


Figure 3.5: Flood depth in the inner Houston area during hurricane Harvey (2017) as determined by the hindcast through the SFINCS mode (Sebastian et al., 2021). Source: own visualisation based on data from the SFINCS model (Sebastian et al., 2021).

4
Results

4.1. Analysis of Survey Data

The survey results from the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022) is evaluated regarding the measures considered in this thesis as well as the dependent variables used. The measures considered are selected based on their uptake documented in the survey data. Details can be found in Table A.3 in Appendix A.1.2. Furthermore, the dependent variables used in this thesis are analysed. An overview of these is shown in Appendix C.

4.1.1. Survey Responses and Flood Map

In Figure 4.1 the number of responses to the survey by Noll, Filatova, Need, & Taberna (2022) are shown based on the stated zip code. Furthermore, the extend of the available flood map (Sebastian et al., 2021) is depicted. The area of the flood map does not cover the entire area from which survey responses are received. Hence, it determines the study area used in the model. Survey responses do not differ significantly from neighbourhood to neighbourhood. Thus, the entire survey data set is used. Further information and details on the data used can be found in Appendix A.3.1.

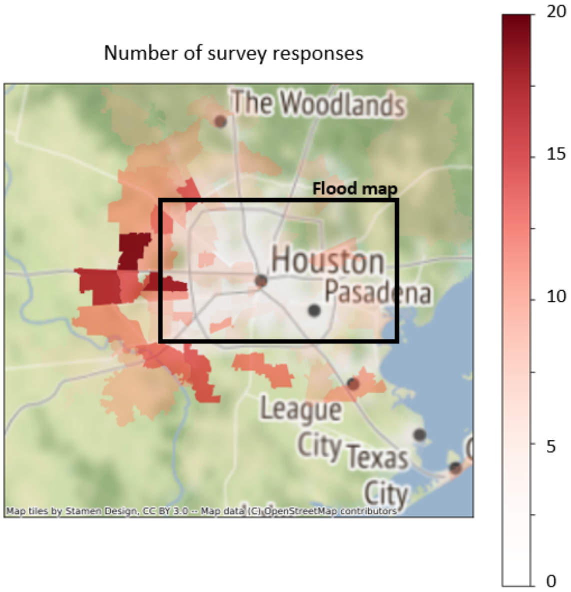


Figure 4.1: Geographical location of the survey respondents in Houston according to their zip-code and the overlap with the flood-map available for Hurricane Harvey. Source: own visualization based on ERC SCALAR survey dataset (Noll, Filatova, Need, & Taberna, 2022) and SFINCS model area (Sebastian et al., 2021).

4.1.2. Survey Data for PMT

The survey results from the Houston area are examined specifically regarding the factors that have an impact in the PMT-base decision making of the household agents. The influence of the threat appraisal (e.g., worry about flooding, perceived flood damage, perceived flood probability, past flood experience) and coping appraisal (e.g., perceived self-efficacy, perceived responsibility to act, experience with taking other measures) on the intention to take a measure in the next six months is examined. If a household decides to take a measure in the next six months it is considered very likely to do so.

Figure 4.2 shows the correlation between different variables and the intention to take a measure exemplary for the first structural measure (S1, elevating the ground floor above the most likely flood level). Correlations for the uptake of the other considered measures are very similar to the one shown in Figure 4.2 and can be examined Appendix D.2.1. Therefore, looking at the first structural measure: The perception about costs and self-efficacy but also flood damage have the largest influence. Furthermore, taking non-structural measures in general influences the decision to take a measure more than other variables. Less influential are the perceived responsibility to act, taking structural measures and the perceived effectiveness of the measure.

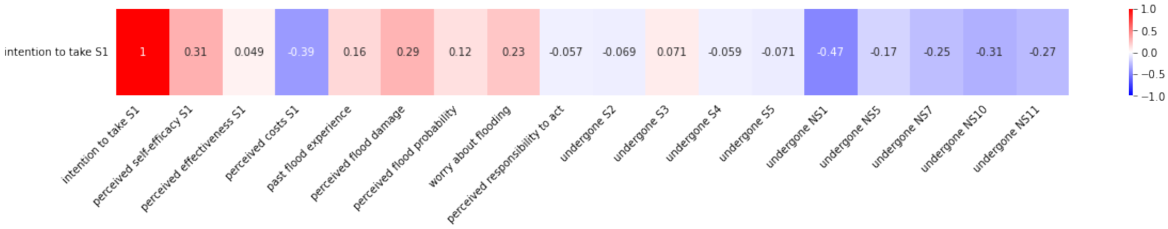


Figure 4.2: Exemplary plot to show the correlation between uptake of measures and PMT variables: intention to take structural measure 1 (S1, elevation of house above expected flood level) in the very near future (next 6 months) and the threat and coping appraisal from the survey data. The variables *undergone S2, undergone S3*, etc. reflect the coping appraisal through the uptake of other measures, where *S* refers to structural, and *NS* to non-structural measures. To see which measure this refers to, please consult appendix A.1.2. Source: own calculations based on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022).

These correlations determine how much weight is assigned to the perceptions of people in their decision to take a PFA measure. The likeliness to take a measure is based on logistic regression. The regression parameters used can be found in Table 4.1 (more details in Appendix A.3.2). Changes in perceptions about costs, self-efficacy, flood damage or worry should influence this likeliness more than others (e.g., perceptions about flood probability, responsibility). These findings are used to determine the factors which the communication policy targets. As some of the mentioned are purely subjective, like worry or self-efficacy, the influence is limited to the factors that can be communicated objectively like the effectiveness and cost of a measure, as well as the potential flood damage at the household's location.

4.2. Analysis of the ABM Simulations

Using ABM involves abstracting from reality. Opinions, interactions between people and the influence of policies cannot always be quantified and are based on assumptions. These assumptions are stated in Appendix A. For this reason, only qualitative conclusions can be drawn from the simulation. Due to the probabilistic nature of ABM, the results are not deterministic.

4.2.1. Influence of Networks

Flood Damage and Networks

The three different network assumptions are compared to the runs without a network. In Figure 4.3 the development of the flood damage throughout the simulation is visualised for both the different networks and policies.

First, a closer look is taken at the networks in the base case. With the no-network setup, there are no changes observed between the start and end of the simulation. This is because there is no network, so household agents are not influenced by any connections. This influence from the contacts in the network is the driver for change in views surrounding PFA. Since the probability and, hence, the decision to take a measure, that in turn would reduce flood damage, depend on the perceptions, no flood-damage reducing measures are taken throughout the simulation (non-structural measures might be taken but do not reduce flood damage). As a result the flood damage factor does not change. The difference of the BA, ER or WS to the no-network is

Table 4.1: Logistic regression parameters for determining the probability to take a measure (left column: all beta-values apart from intercept). Further information on the parameters used and the measures can be found in Appendix A. Source: own calculations based on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022).

	S_1	S_2	S_3	S_4	S_5	NS_1	NS_5	NS_7	NS_10	NS_11
Intercept	-0.930	-2.946	-1.894	-2.790	-3.797	-1.466	-2.250	-2.418	-0.757	-2.258
fl_dam	0.830	2.675	1.784	1.374	1.724	2.782	1.374	2.577	2.041	2.270
fl_prob	0.038	0.069	0.064	0.071	0.040	0.003	0.032	0.081	0.014	-0.004
worry	0.040	1.836	1.086	1.067	2.237	2.531	3.755	3.855	2.504	4.432
fl_dam:worry	1.184	-2.680	-1.008	-1.007	-1.316	-3.545	-3.920	-4.906	-2.386	-3.834
RE	1.333	1.828	1.564	1.561	1.481	0.176	0.226	0.234	0.393	0.745
SE	2.019	1.993	1.662	1.521	2.233	-2.364	0.906	0.208	-0.786	0.295
Cost	-3.146	-2.108	-2.536	-0.697	-0.504	2.586	1.293	0.728	0.215	0.493
fl_exp	1.221	0.863	0.565	0.507	0.411	-0.039	-0.171	-0.076	-0.215	-0.073
S_UG1		0.657	0.570	0.460	1.004	-1.040	0.263	-1.110	0.983	0.760
S_UG2	-2.012		-1.145	-1.804	-1.796	0.053	-0.146	-1.089	-0.241	0.090
S_UG3	0.793	-0.018		1.110	0.764	-0.239	0.204	0.731	0.325	-0.026
S_UG4	0.448	0.094	0.758		0.282	0.282	-0.084	0.606	-0.222	-0.605
S_UG5	-1.174	-0.998	0.184	-0.645		-0.158	-0.145	0.352	-0.153	-0.321
NS_UG1	-1.887	-1.055	-1.818	-1.677	-1.569		-0.743	-0.728	-0.609	-0.353
NS_UG5	0.025	0.190	0.225	0.043	-0.145	-0.887		-0.344	-0.064	-0.471
NS_UG7	-0.139	-0.289	0.215	-0.254	0.057	-0.520	-0.181		-0.253	-1.298
NS_UG10	-0.744	-0.901	-0.411	-0.696	-0.378	-0.680	-0.315	-0.564		-1.194
NS_UG11	-0.238	-0.748	-0.482	-0.347	-0.292	-0.892	-0.474	-1.997	-1.627	

mainly, that the household exchange perceptions. Therefore, there is a change in probability and thus decision to take a measure. This leads to a change in the flood damage factor over time (compared to a constant development in the base case without any network), especially towards the end of the simulation. The effect is greatest in the ER and WS setup: These network considerations reduce the flood damage slightly. Note that both WS and ER evolve in a similar manner, leading to the same evolution of flood damage over time. For BA, this change is not as developed – the overall flood damage is not reduced compared to the no-network setup. The only exception here is the information policy. This is unexpected because, as mentioned before, the information exchange should influence the decision to take measures. An explanation might lie in this information exchange and is viewed in more detail later.

Now considering the influence of the networks with the different policy setups: It is noted that the overall flood damage in the regulatory and infrastructure policy has a lower initial flood damage. Otherwise, they evolve in parallel to the base case for all network setups. The relative reduction of flood damage in the WS and ER setup is larger though, due to the lower starting damage. For the market-based and especially the information policy, this is different. The flood damage with the market-based policy setup is reduced more significantly for WS and ER. In addition, the deviation between BA or no-network and WS or ER network runs starts already halfway through the model. The information policy has the most significant impact on the evolution of the flood damage factor. Furthermore, in contrast to the other policies, the no-network setup leads to the highest flood damage reduction. Again, WS and ER develop very similarly and BA has the least effect on the flood damage. Since the information policy is so influential, a closer look at the role of networks in this policy setup is taken in Section 4.2.3.

Looking at the overall development of the flood damage factor, there seem to be certain points in time (around step 35 or 72 for the communication policy; step 75 for base case, regulation, infrastructure and subsidies policies; step 40 for WS and ER with subsidies policies; etc.) where changes happen across all networks. In the first 30-40 time steps, no changes are observed within the flood damage for any network or policy setups. This can most likely be attributed to the manner in which the agents take measures and how they change their perceptions. Following, these two mechanisms will be explained in detail.

First, looking at how the household agents take measures: Households always take the measure with the highest probability first. However, the costs of the measure are only considered in a next step. This means, that if a household agent's measure with the highest probability to be taken is an expensive measure, the household agent can only take it if there are enough savings. Therefore, it can take some time until the agent

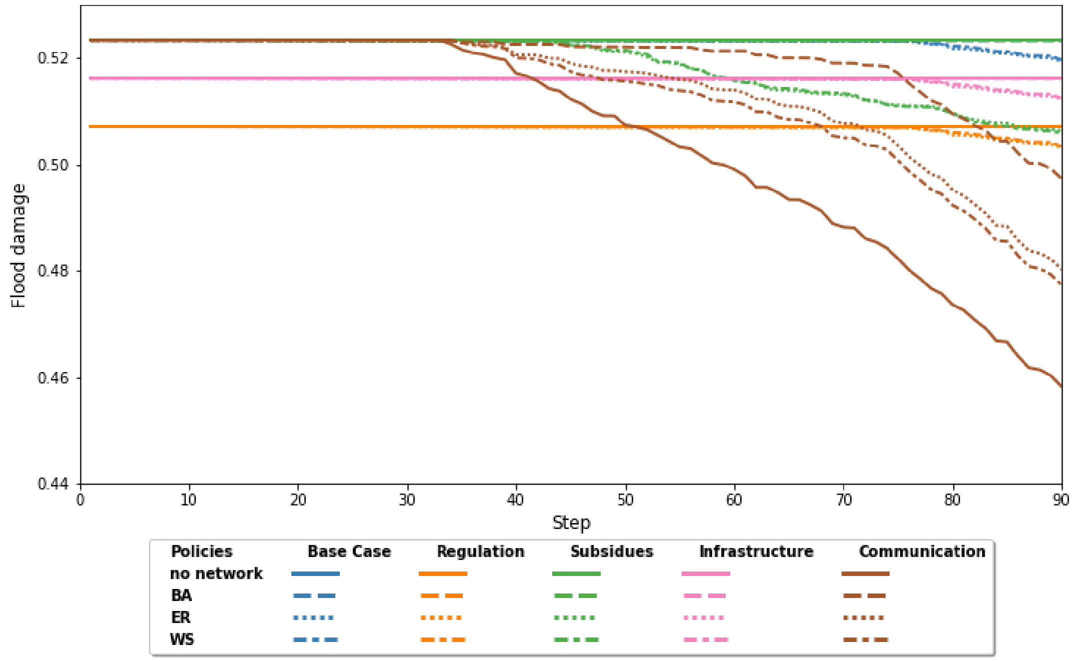


Figure 4.3: Dynamics of flood damage factor as introduced by Moel et al. (2017) under different policies and network combinations. The curves are the means of 50 Monte Carlo runs. Here ER denotes the Erdős-Rényi random network, BA – the Barabasi-Albert scale-free network, WS – the Watts-Strogatz small-world network. Furthermore, Base Case is used for the run without any policies active, Regulation for the regulatory policy, Subsidies for the market-based policy, Infrastructure for government-funded infrastructure policy and Communication for information policy. The presence of the networks does not always have an impact and therefore in certain cases is overlain by other lines (e.g., base case overlain by subsidies). Source: own analysis.

has enough savings to take the measure. Especially the structural measures are expensive, but those also reduce the damage most significantly. Non-structural measure on the other hand are cheap in comparison, but have little to no effect on the damage reduction. This effect is further influenced by the fact that after taking a measure, household agents do not attempt to take the next one for the following two time steps. This is done to reflect that people do not adapt in one go, but save and take time to adapt to the changes. This leads to not many effective measures taken at the start of the simulation. The damage only starts to reduce after a certain time when a critical mass of households reduces their flood damage so that it shows in the average flood damage over all households.

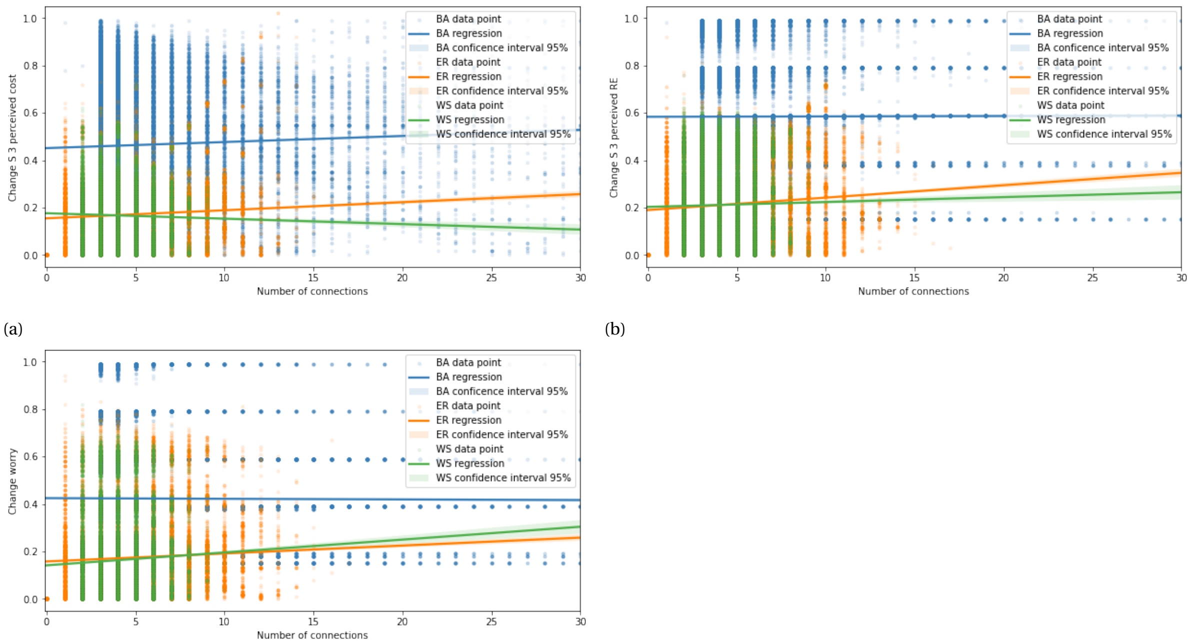
Second, looking at the influence of perception exchange: Households exchange perceptions based on the DeGrootian opinion dynamics model, so assign weights to their own and their connections opinions (Degroot (1974), see Section 3.1.1). These perceptions determine the agent's probability to take a measure, the uptake of measures and hence the reduction in flood damage. However, households are not considered to change their perceptions significantly in a short time. The own opinion is always weighted highest, so change in opinion happens gradually. Therefore, it takes some time until the networks influence the perceptions in a way that will lead to changed probabilities to take a measure and hence decrease the overall flood damage factor.

Overall, the sheer consideration of WS and ER networks leads to a lower flood damage at the end of the simulation. For BA, this is only true for the information policy. It will be examined in more detail in the following and reflected on in Section 5.1.1.

Information Diffusion and Perceptions

In order to gain a better understanding of the household agents' interactions within different networks, a closer look is taken at the perceptions since these are influenced by the connected household agents and are the basis for the decision to take measures.

The impact of the connections, the relationship between the number of connections and the change in a certain perception (absolute difference between value at beginning and end of simulation) is investigated. Exemplary in Figure 4.4, the perception variables *worry, perceived cost of structural measure 3* and *perceived response efficacy (effectiveness) of structural measure 3* are chosen (for results of other variables see Appendix



(a) (b) (c)

Figure 4.4: Influence of the number of social ties on the extent and speed of change in households' perceptions regarding (a) costs and (b) response efficacy of the three structural measures (Reconstructing / Reinforcing walls / Reinforcing ground floor with water-resistant materials), as well as (c) individual risk perception measured as worry. All perception values vary between 0 and 1 in this heterogeneous population of agents. The change depicts the absolute change in perceptions of a household between the first and the last step of the simulation. All figures are based on the 50 Monte Carlo runs. Here ER denotes the Erdős-Rényi random network, BA – the Barabasi-Albert scale-free network, WS – the Watts-Strogatz small-world network. Source: own analysis.

D.2.5). Interesting to note is, that in the BA setup, the number of connections does not seem to influence the change in perception noticeably: the slope is close to zero for most perceptions. For ER and WS the number of connections does have a greater impact on the changes in perceptions that occur.

For these two network setups (WS and ER) the higher the number of connections, the more change in perception is expected to occur throughout the simulation (apart from perceived costs for WS - see Figure 4.4a). This is counter-intuitive to the thinking that more connections mean a wider representation of perspectives in the network and hence a more balanced effect on the perception, i.e. presumably less change. It has to be kept in mind though, that there are only few households with more than ten connections in the ER and WS setup (see Section 3.1.1, Figure 3.4). The extrapolation has to be handled carefully and the trend might not be true for more than 15 connections.

Furthermore, the changes in perceptions within the BA setup are generally higher than in WS or ER settings. Considering that all perception values are set to be between 0 and 1, average changes of more than 0.4 for most perceptions suggest drastic shifts in opinions in the BA setup. For WS and ER the average difference in perception from start to end is around 0.2, so significantly lower than in the BA setup.

4.2.2. Influence of Policies

Individual Policies

As indicated, the tested policies have a differing impact on the flood damage (see Figure 4.3). Comparing the flood damage factor with the policies active to the base case, with no policies in place, all policies (apart from the market-based policy in the no-network or BA setup) have some effect on reducing the flood damage, either through different starting conditions or over the course of the simulation.

The infrastructure and regulatory policy reduce the flood damage factor from the start. This is, because how the policies are designed in the model, they decrease the flood damage for a number of household agents that are located in an area affected by an government-funded infrastructure project or where certain structural measure become mandatory (see also Section 3.1.2). This means that a number of households benefit from the changed initial conditions, i.e. less flood depth at their house or the flood damage reduction through the measures taken. Therefore, the flood damage is reduced adequately. These two policies are in effect from the start but do not affect any perceptions. Consequently, the development over the steps stays the same as in the base case, only at a different level.

For the market-based policy, the starting conditions are the same as in the base case where no policies are active. Similar to the infrastructure and regulatory policies, the market-based policy does not influence the perceptions of the household agents. Only the costs of the measures are reduced, while the probability for taking a measure does not change. Hence, as the costs are only the secondary condition to taking a measure, the effect of the market-based policy does not take effect in the no-network setup. However, especially with the WS and ER networks an effect can be observed, resulting in a more significant decrease in flood damage compared to the base case. This is due to the reduced costs, so households that change their opinion about taking a measure have enough savings earlier in the simulation to implement it.

The information policy is an exception in the evolution of flood damage: the influence on the flood damage is significant and the development differs notably from the other policies and the base case. It leads to the biggest changes throughout the simulation for all network configurations, including the no-network setup. The no-network setup leads to the greatest changes, whereas BA results in the lowest reduction of flood damage for this policy. ER and WS again evolve very similarly. This is due to the way in which the household agents are influenced: the more connections, the less weight is attributed to the “objective” information passed through the communication policy. A closer look into this is taken in Section 4.2.3.

Combination of Policies

Various policy strategies are rarely introduced in isolation. As they are used in combination of policy mixes, some can create synergies or hinder each others effect. Here I test the model with different policy combinations runs, specifically focusing on the information policy and its interactions with one of the other policies (Communication & Infrastructure (CI), Communication & Subsidies (CS), Communication & Regulation (CR)). Figure 4.5 presents the results on the flood damages factor.

The starting conditions for each of the combinations are the sum of the two combined policies. This is, because the information policy does not have an effect on the flood damage from the start of the simulation but only influences the dynamics later. In combination with an infrastructure project or the regulatory policy (CR or CI), the flood damage at step 0 is reduced by the influence of this policy, with communication policy adding no value in boosting households’ adaptation at this point. Consequently, CR and CI evolve in parallel for all the different network setups and the dynamics can be attributed entirely to the information policy. The no-network case yields the most significant changes, BA the least. This is similar to the observations made for the case where the communication policy is in place exclusively and is further discussed in the following Section 4.2.3.

With CS, an unexpected development of the flood damage is observed. The flood damage diverges from the initial state significantly earlier in the simulation compared to any other policy-network combination of the individual policies (see Figure 4.3). Furthermore, the overall impact on the flood damage factor is higher, reducing it significantly compared to just the impact of the information or market-based policy individually or the addition of those two individual policies.

The differences between CR / CI on the one hand, and CS on the other lie in the influence of the policies on the decision to take a measure. All policy combinations comprise the information policy and are hence influenced on the first decision criteria – the probability to take a measure (see Figure 3.2). For CR and CI it stops there and only the starting conditions are changed. CS, in contrast, also influences the second criterion – the affordability of the measure to be taken. This means that through the “objective” information spread, more households change their perceptions and are more likely to take a measure. Additionally, if the household agent wants to take a measure, it is more likely to be able to have enough savings to then actually implement such measure.

4.2.3. Communication Policy and Networks

As already pointed out, the information policy proved especially effective when it comes to influencing the uptake of flood adaptation measures by households, and consequently the flood damages (see Section 4.2.2). It is particularly interesting as the information policy directly impacts households’ perceptions which in turn determine the PFA uptake. The information policy is defined as an extra connection with an “objective” perception within each household’s network. This means that household agents with less or no connections experience a larger influence by the objective value from the policy because the “fact” is not diluted by the opinion of other connections. Figure 4.6 provides more detail on this. The perceptions on flood damage, costs and effectiveness of structural measure 3 (reconstruction or reinforcement of walls and/or ground floor

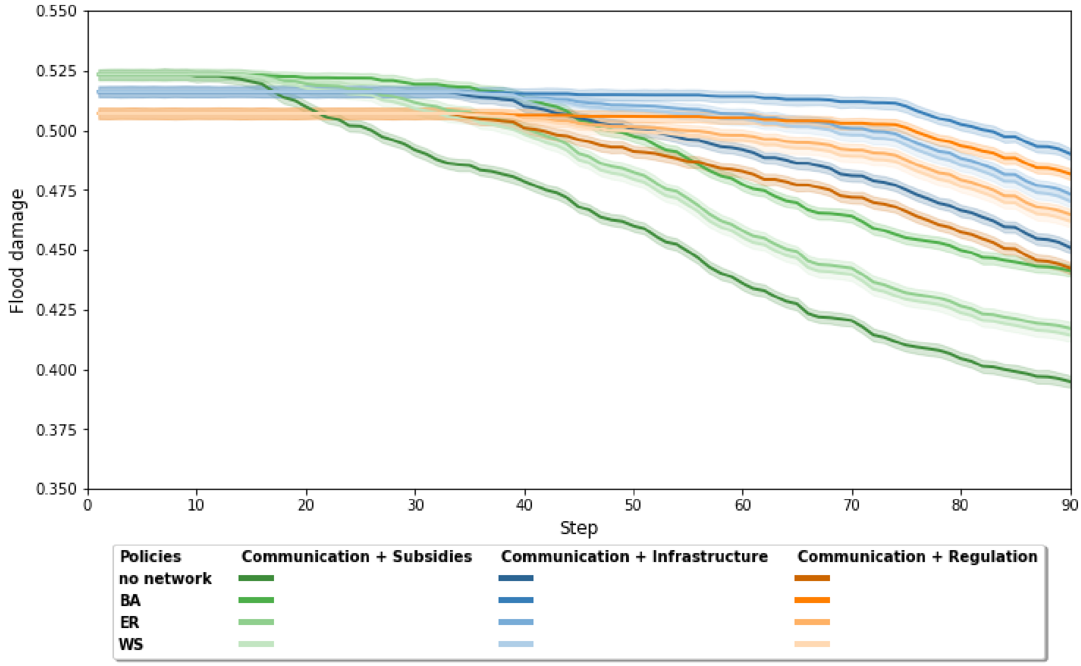
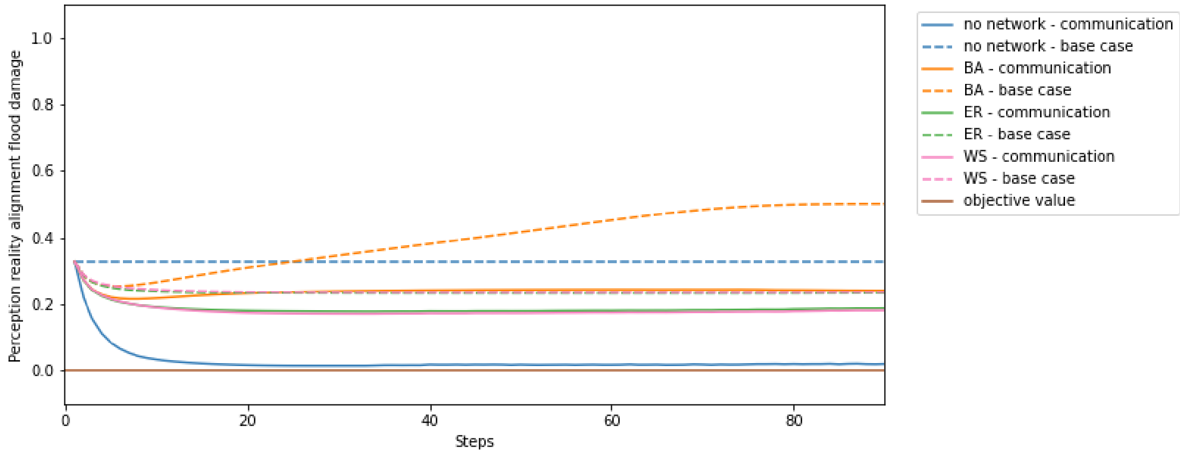


Figure 4.5: Dynamics of flood damage factor as introduced by Moel et al. (2017) for different policy combinations and different network setups with a 95% confidence interval. The communication (information) policy is combined with the three other policies (Subsidies – market-based policy, Infrastructure – government-funded infrastructure policy, Regulation – regulatory policy). Here ER denotes the Erdős-Rényi random network, BA – the Barabasi-Albert scale-free network, WS – the Watts-Strogatz small-world network. The curves are based on the 50 Monte Carlo runs. Source: own analysis.

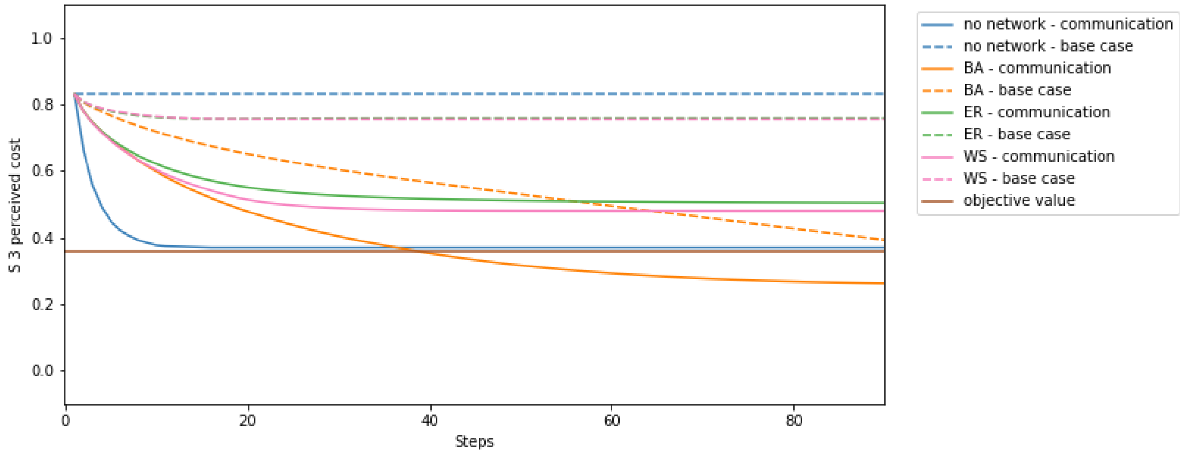
with water-resistant materials) are exemplary for the evolution of other perceptions. More information on the development of the other influenced opinions can be found in Appendix D.2.3.

It can be seen that in the base case, so without any policy active, the perceptions of the household agents change. This is not true for the case where there is no network, as household agents simply do not have any connections that could influence their perceptions. For all other network types, there is some change in overall perceptions though. Supporting what was already observed in before in Figure 4.4, the changes in perception are greatest for the BA setup. In some cases, the overall network influences the opinions in a beneficial way, steering towards the objective value (e.g., the perceived costs of structural measure 3 in Figure 4.6b). In others, the network does not influence the overall opinion positively and results in an overall opinion further away from reality (see Figure 4.6c or BA in Figure 4.6a). These findings demonstrate, that swarm intelligence can shift opinions and perceptions away from reality.

With the information policy in place, the change in perception evolves differently. As indicated before, the communication's effect is closely linked to the number of connections (see Section 4.2.2). The perceptions of the runs without a network, that is the household agents have no connection to other households, align the fastest with the objective value. In the cases where on of the network types was employed, this alignment is not as rapid and the influence of the objective value not as significant. In all cases however, the information policy influences the perceptions in a positive way i.e., reducing the gap between perception and reality.



(a)



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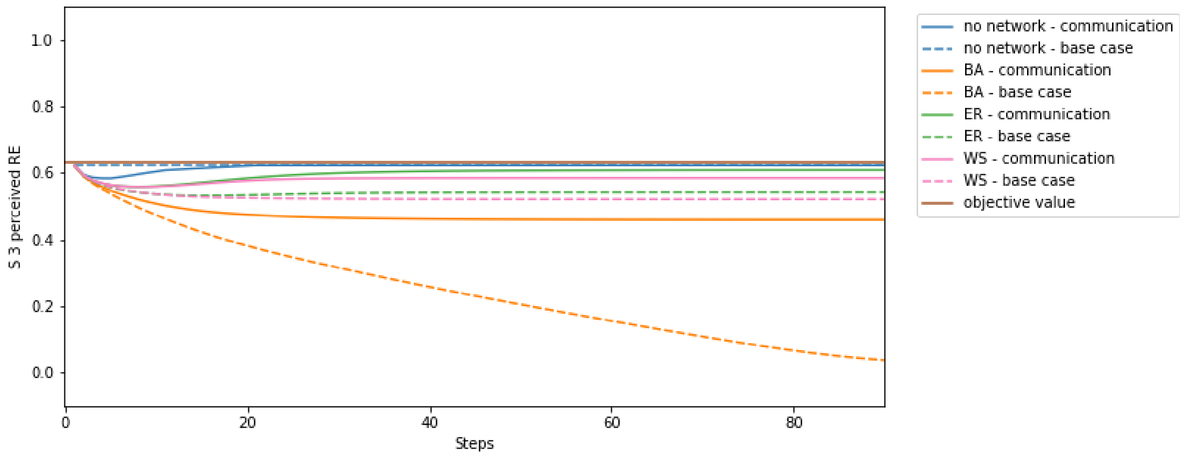

(c)

Figure 4.6: Evolution of perceptions overall for the base case and the communication policy. Exemplary here the development for perceptions on (a) flood damage, (b) costs and (c) response efficacy (effectiveness) of structural measure 3 (reconstruction / reinforcement of walls / ground floor with water-resistant materials). All figures are based on the 50 Monte Carlo runs. Here ER denotes the Erdős-Rényi random network, BA – the Barabasi-Albert scale-free network, WS – the Watts-Strogatz small-world network. Source: own analysis.

5

Discussion and Conclusions

5.1. Reflection on Results

In Chapter 4, the simulation results are examined. The main findings are:

1. The existence of a network has an impact on how and if households adapt to and prepare for flood events.
2. The BA network type differs significantly from the ER or WS network results. In the BA network, the influence on the development of flood damage throughout the simulation is significantly less compared to WS or ER setups even though individual household's opinions change most in BA setup.
3. WS and ER network setups lead to very similar results.
4. Policies that influence the opinion and perception of people, such as the information policy, are most helpful and can steer opinions closer towards the objective value i.e., reality. The magnitude of the effect is influenced by the presence and type of social network.
5. Individually, regulatory or infrastructure policies can reduce flood damage. The impact, however, is limited to those directly affected by those policies.
6. Subsidies alone only influence measure uptake if households are already likely to take a measure.
7. Pairing market-based instruments with information policies has a synergistic effect on reducing the flood damage.
8. The combination of infrastructure or regulatory policy with information only leads to an additive effect.

5.1.1. Implications from the Network Findings

As Haer et al. (2016); Wilson et al. (2020); Bubeck et al. (2018); Rifki & Ono (2021) forbode, the results show that consideration of networks plays a crucial role in PFA (point 1). All networks lead to changes in perceptions and influence the overall flood damage, ER and WS more than BA (point 2). Considering that the uptake of PFA measures is so closely linked to PMT and therefore perceptions about reality, it was expected that an exchange of perceptions within networks would lead to different results in comparison to not modelling interactions between households. The results proof, that is is crucial to include the influence of household interactions in PFA uptake modelling. Even though the networks were generated randomly, considering them as a proxy for real-life social interaction proofed to be a valid approach.

First, the existence of networks generally facilitates PFA uptake. This is related to the perception change as explained. Especially the positive effect in the WS or ER networks could also stem from the fact that the household parameters are distributed randomly across the study area. This means, that clusters of similar, extreme opinions are unlikely. Therefore, the existence of "echo chambers" is unlikely and extreme opinions are equalised within their network, resulting in tempered opinions for every household. This finding is in line with Lazer et al. (2010) that reports that people conform in their views to those of their contacts. In contrast, in the no-network or BA scenario, more extreme opinions do not adjust. Perceptions change the likeliness to take measures and hence reduce the overall flood damage through PFA.

Second, the BA setup leads to less change throughout the simulation compared to ER and WS, even though it leads to the greatest changes in perception. This could mean that in the ER and WS scenarios, the opinions are getting more moderate, while with BA they are more likely to shift from one extreme to the other. Furthermore, it indicates that the perceptions of the overall population then do not adjust, but that potentially one agent's starting perceptions become the other's final opinion and vice versa. Looking at these drastic changes in perception, the question arises how realistic they are. Especially, when the changes only happen through the influence of the social network and not through other developments in the environment like extreme weather events, political shifts or similar. Furthermore, it is debatable whether it is realistic that households with such diverging perceptions would even be connected and influenced by each other – homophily, the principle that similar people are more likely to be in contact compared to people with diverging interests and opinions, is commonly found in social networks (McPherson et al., 2001).

Third, a striking similarity between the WS and ER scenarios can be found (point 3). This is also found by Peach et al. (2022). A reason might lie in the setup of those networks as outlined in Section 3.1.1: Most household agents in an WS and ER network have between two and seven connections and the maximum number of connections is below 20. As the distribution of parameter values across the study area is balanced, the overall influence of household agents on each other should be comparable.

In comparison to WS and ER, BA represents low-degree nodes forming dense sub-graphs connected through high-degree node hubs and follows power law for the number of connections at least asymptotically (Barabási & Albert, 1999). This could indicate that especially the degree distribution of a network is an important characteristic for the transfer of information, the moderation of opinion and, hence, the reduction of flood damage. This is in line with the findings They find, that information is transferred more easily in networks where the distribution of number of connection throughout the population is less skewed. Due to the information exchange in the model is set up, hub nodes are not expected to be influenced significantly by one opinion or the communication policy. This is because they have too many connections that reduce the influence of the "objective" information. However, high-degree nodes are thought to have a considerable influence on their connections with lower degree.

With these findings, the first research subquestion can be answered clearly. The results show that the network assumptions influence how information diffuses through the agent population. Social networks that are more homogeneous in terms of the number of contacts support the formation of more tempered opinions compared to more skewed networks. Targeting communication at the network participants can steer their opinion into certain directions. However, the magnitude of the impact is depending on the social network configuration.

It is unclear, which of the network setups matches reality best. Most likely, real-world networks exhibit properties of all networks considered here in parts. Thus, especially when trying to find policy solutions that might work in different communities or societies with a changing structure, it is important to consider policies that are robust over different assumptions of social linkage.

5.1.2. Implications from the Policy Findings

Individual Policies

The results have shown that all policies are reducing the overall flood damage. The information policy is most effective across all networks (point 4). This supports the findings by Erdlenbruch & Bonté (2018); Haer et al. (2016); Tonn et al. (2020); Haer et al. (2020); Bubeck et al. (2012) on the importance of communicating risks (actual flood damage at a household's location) and coping appraisal (costs and efficiency of measures). The policy has shown to be most effective though in a completely isolated world, where households are not subject to any outside influences. In reality, the effect of such an information policy will most likely not be as great as in the simulation. Usually, communication does not reach all households and households do not trust public information without further questioning (Mabillard & Pasquier, 2016). More realistically, only a fraction of the population would be reached and the extend to which the population takes in the information might vary significantly. Therefore, it would be interesting to test what effects a communication targeted at and tailored for specific households would have or how information could be spread most efficiently through the social network.

For the other three policies considered, the effect was limited. This can also be attributed to how the policies are represented and included in the simulation or their near indifference towards social developments. Looking at their representation in the model, infrastructure and regulatory policies mostly affect the flood depth at the place (point 5). However, the impact of such measures on perceptions like worry, perceived responsibility to act or perceived flood probability are not considered. This might also be the reason why the levee effect mentioned by Haer et al. (2020) cannot be observed.

The market-based policy's impact was also limited as it did not have any influence on the probability to take a measure (point 6). This assumes that households do not know about the subsidies until they already decided to take a measure. Combining the subsidence of costs with an effective communication should result in greater success: the perceived costs would be influenced and consequently the likeliness to take the measure would change. This interaction is examined in the following.

Policy Interaction

Interesting results were obtained with the combination of the different policies. Maor & Howlett (2021) introduce the terms *synergistic, counter-productive*, and *additive* to describe the effects of policy interactions. While for the CI and CR combination only additive effects were observed, simultaneous consideration of the information and the market-based policy had synergistic effects on the flood damage (point 7 and 8). Especially the CS combination addresses the issue found when only the individual market-based policy is considered. Instead of only knowing of the subsidies when it comes to paying for a measure, households are already changing their perceptions through the information policy. In this simulation, the communication was not adapted to pair the other policy. This adaption could be that with the market-based policy the cost factor communicated is lowered, with infrastructure policy the communication mainly focuses on flood depth, or similar. Adapting the communication to the policy it is paired with would be interesting to explore and is subject to further research.

Answering the second research subquestion, it is found that most policies have an impact on the flood damage. This magnitude of the impact is closely linked to the social network present. Generally, communication policies that influence the perceptions of people are most effective in increasing the preparedness among the population. More static policies like regulations or infrastructure projects are limited to those directly affected by it. Combining the policies strategically, like market-based instruments with information, synergies can lead to significant reductions of flood damage compared to individual policies or other combinations.

5.1.3. Further Implications

This research has shown that networks have a significant effect in PFA and influence the decisions of households taking measures in a positive way. To answer the third research subquestion: The presence of networks can enhance the effect of policies, both for individually considered policies or their combinations. Policies that rely on reducing flood damage through influencing the populations' perceptions (i.e., information policies) are the more effective, the less the population is influenced in other ways. Policies are not designed to influence the perceptions of people are more robust to the different network setups and perform similarly over all of them.

Looking at the overarching research question posed and drawing from the answers of the research subquestions: Networks play an important role in effectiveness of policies for adaptation. More specifically, they are the key drivers behind information transfer and have a significant impact on how the policies play out. Furthermore, policies that take the network into account can be very effective in reducing flood damage, whereas policies that reduce flood damage more directly and do not influence the perceptions of people are limited in their impact, but are also more robust over the different network types.

5.2. Academic Reflection

This study aimed to increase the understanding of cross-scale climate change adaptation, more specifically PFA, and how to increase preparedness of households. To do so, ABM was combined with empirical data from Houston (TX, USA) and tested systematically over different proxies of social networks and policy.

Improvements

The model was kept simple regarding the representation of households, the network structures and the policy design. To gain more detailed insights into how more households can be convinced to take PFA measures, refining the model with respect to these aspects might be beneficial.

This could include adding interdependence between the the household agents' attributes which could be found in the existing survey data or by considering other measures. Especially the effect of insurance would be interesting to explore, as this is very common and mandatory in some parts of Texas, USA (Federal

Emergency Management Agency, 2022). Also, reducing the effectiveness of measures over time or adding a maintenance cost could result in interesting effects on the flood damage. Households then could not only improve their situation, but also take decisions influencing their situation negatively.

Regarding the design of policies, the infrastructure, regulatory or market-based policy do not influence the perceptions of households directly. Acknowledging that an infrastructure project in the neighbourhood or the obligation to take certain measures most likely also impact perceptions about threat, responsibility and potential damage, would increase representation of policies' impacts. This could significantly influence the results from the model.

Next to that, the model should be tested for different case studies. Here, the comparison of results for different cases would be especially compelling considering the further generalisation of findings. In addition, different flooding scenarios occurring throughout the simulation could be considered. This could provide insights into how the household network reacts to environmental changes.

Broader Context

In this study, the different network types and policies used are representatives of real-world societies and the approaches to steer these in the context of climate change adaptation, more specifically PFA.

In a fast changing world, solutions that are robust are often sought for. In the context of policies, this would mean that policy designs that perform well in different contexts are preferred. Considering the networks, this means that infrastructure and regulation policies are a safe bet: No matter the social context, these approaches will reduce harm. However, as Haer et al. (2020) point out, especially with infrastructure policies this could be a pitfall. This policy does not facilitate PFA and could even hinder its uptake, leading to potentially catastrophic in case weather extremes behave different than expected.

The findings on the policies can further be viewed in greater context. Next to the absolute benefit, the cost-benefit ratio is often a key factor when it comes to decisions regarding governmental actions (Hood & Margetts, 2007). Infrastructure projects are often expensive and only a fraction of the population benefits from these. Market-based policies like subsidies are often limited and cost-intensive. Laws and regulations need to be enforced in order to not loose their effect. This all requires an ample amount of either financial, administrative or human resources that may not always be available (Margetts & Hood, 2016). Information campaigns in comparison are considered resource-efficient. A smart combination and comparison of the trade-off among policies and their combination is needed to allow for most successful and efficient management.

A homogeneous social network regarding their distribution of connections in general leads to a larger damage reduction in most policies. This suggests, that societies that are more egalitarian (characteristics close to ER or WS) can count more on the positive influence of the information diffusion. This is not a given for more hierarchical societies (characteristics closer to BA). Whether these results also hold for targeted communication like using highly influential households to spread information is debatable. It might lead to different results and should be examined in more detail.

Furthermore, communication is more effective, the less the population is influenced elsewise, so when individuals trust the communicated information and it is not diluted through other influences. This suggests, that societies where information diversity is limited are more successful in steering the population to the desired behaviour. However, receiving clear information does not mean, that they are automatically trusted (Cologna & Siegrist, 2020). Considering the trust into government and policies could lead to interesting results, especially when considering that trust in government can differ greatly over in different countries (Ceron & Memoli, 2015). Challenging assumptions about behaviour of policies and social networks needs to happen case- and context-specific.

Considering that the administrative power is not static, but policies are modified and readjusted on a rolling basis, understanding and observing how this interplay develops could provide further insights. Using ABM to not only consider the households but also policies as active agents, reacting to changes within the environment would allow to explore future scenarios and adaptive policies (see dynamic adaptive policy pathways (DAPP), Haasnoot et al. (2013)).

Drawing from these findings and the reflection on them, policy makers in the PFA field, but also other areas of climate adaptation are advised to consider the social prerequisites in their policy design. Policies are not just placed in a vacuum, but interact with the present structures. Knowing how people interact and opinions form within the population, can be crucial for a strategy's success. Using this knowledge, policies can be introduced and combined smartly to prepare and protect their subjects from damage and loss.

5.3. Conclusion

As the climate is changing, weather extremes like flooding become more frequent and adaptation is needed on all levels. This research aimed to increase the understanding of how social networks influence cross-scale climate adaptation, more specifically the decision to take PFA and what policies might be successful in that context. There is already a good understanding and agreement within the research community that perceptions, especially on threat and coping ability influence this decision decisively and that extended PMT is useful in this context. Furthermore, the influence of the social environment like friends and relatives should not be underestimated.

To gain more insights into the influence of the social network of households on their decision to take adaptive measures against flooding, an ABM simulation was carried out using empirical data from Houston (TX, USA). With this, the effects of considering connections within three random networks (Barabasi-Albert scale-free network, Erdős-Rényi random network, Watts-Strogatz small-world network) compared to no network were examined using five different, general policy scenarios (no policies, information, government-funded infrastructure, regulatory, market-based) and their combinations. It could be shown that the consideration of networks influences the uptake of adaptation measures through the exchange of opinions. While policies influencing the initial conditions like infrastructure projects or regulations perform most robust over all considerations of networks, communicating facts about costs and effectiveness of measures but also the potential flood damage have shown to be most effective in reducing flood damage. This indicates that aligning households perceptions with reality can be very powerful when trying to increase private flood preparedness.

This study only provides a starting point for further research on the influence of networks on policies and in climate change adaptation. Overall, the social networks, policies and environment are static in this model. Research on the endogenous development of the social network, the policies and the flooding conditions could provide valuable insights into the dynamics of this complex system and its adaptive powers for future cross-scale climate adaptation efforts. This should allow for best decisions in the transformation to a world that is prepared for climate extremes.

A

ODD Description of the Model

A.1. Overview

A.1.1. Purpose

This model should provide insights that help reduce vulnerability of households when it comes to flooding. More specifically, this model is build to explore which policies motivate households to take private flood adaptation measures and how they perform across different assumptions of network configurations between the households.

A.1.2. State Variables and Scales

Time

The simulation is aimed to represent a short to medium time frame. The processes in the model mostly are not quantified. Therefore, only qualitative judgements can be made on the evolution and the time span. The shortest process determines is determined by the time of the influence of a household's perception and the reevaluation of the personal situation regarding the uptake of another adaptation measure. Perceptions of people do not change from week to week and until a person is influenced enough by their connections some time passes. This process was considered to happen on average every one to three months. The model is run for 90 ticks which in total would correspond to seven to twenty years.

Model and Agent Variables

Next to the time setting, there are numerous other variables that get specified for the model run. These model variables are outlined and explained in Table A.1. Some of these are defined by the user (see Section A.2.1), while others evolve from the model setup and development.

Table A.1: Model variables

Name	Explanation	Type	Values
Variables as passed from the initialisation: number_of_households seed network probability_of_network_connection number_of_edges number_of_nearest_neighbours scenario	for more info see Section A.2.1		
Continued on next page			

Table A.1 – continued from previous page

Name	Explanation	Type	Values
G	graph generated with the network parameters	NetworkX graph	
grid	mesa network grid as given by the graph G	Mesa NetworkGrid	
schedule	schedule for the activation of the household agents	Mesa RandomActivation	
flood_map	flood map generated from flood map path as passed from initialisation		
band_flood_img, bound_left, bound_right, bound_top, bound_bottom	variables for the description of the flood map	float	>0, range depending on flood map passed
policies	basic dictionary for the policies - different values in dictionary changes depending on policy scenario considered	dictionary	{'subsidies': 0, infrastructure': 0, 'regulation': 0, 'communication': 0}
cost_reduction	cost reduction from the subsidies policy (percentage_cost_reduction as passed from initialisation) or no cost reduction	int	0-100
percentage_S_1_taken, percentage_S_2_taken, ...	percentage of the different measures taken over all households	float	0-100
datacollector	datacollector for the collection of agent and model data	Mesa DataCollector	

Next to the model variables, there are variables of the household agents. An overview of these can be found in Table A.2. Some of these are set through the input data as described in Section A.3.2, while others evolve from the processes within the model.

Table A.2: Agent variables

Name	Explanation	Type	Values
unique_id	ID set by Mesa to identify each household agent	int	
seed	seed of each agent (model seed as passed from model initialisation + unique_id if not none)	None or int	
time parameters			
tick	counter of the steps	int	≥ 0
tick_time	what one tick corresponds to as passed from model initialisation	string	quarter', 'months'
month_multiplier	how many months the tick_time corresponds to - used to calculate savings from monthly income	int	1, 3
tick_last_measure_taken	step at which the last measure was taken	int	≥ 0

Continued on next page

Table A.2 – continued from previous page

Name	Explanation	Type	Values
pause_after_last_measure	how many steps no further measure is taken after taking one, passed from model initialisation	int	≥ 0
flood depth and location			
loc_x, loc_y, row, col	position of agent on the flood map and corresponding row / column for getting the flood depth at that location	int	>0, range depending on flood map passed
flood_d	flood depth depending on the location on the flood map used	float	≥ 0
min_flood_depth	minimum flood depth in the model area as passed from model initialisation	float	≥ 0
flood_depth	flood depth either flood_d or min_flood_depth (in case right at the corner of the flood map)	float	$\geq$ min_flood_depth
basic_flood_damage	flood damage solely based on flood depth at the location without considering any measures taken	float	0-1
flood_damage	flood damage taking the measures taken into account	float	0-1
policy related			
flood_reduction	flood depth reduction if household in area of and hence affected by the infrastructure policy	float	≥ 0
in_regulation_area	whether an agent is within the regulation area (True) or outside of it (False)	boolean	True, False
mandatory_measures	mandatory measures household agents located in regulation area have to take as passed from model initialisation	list	['measure', 'measure', . . .]
cost_reduction	factor by which the costs for measures are reduced with the subsidies policy, else 0	float	0-1
mandatory_measures_to_take	list of mandatory measures the agent hast to take in order to take the measure		
perceptions and setup parameters	deducted from survey data, details see section A.3.1		
flood_experience	whether household agents have experienced a flood before	int	0, 1
perceived_flood_probability	how likely the household agent thinks a flooding at their location is	float	0-1
worry	how worried the household agent is about flooding	float	0-1

Continued on next page

Table A.2 – continued from previous page

Name	Explanation	Type	Values
perceived_flood_damage	how great the household agents thinks the damage for their home would be	float	0-1
social_expectation	how much the household agent is influenced by their social surroundings	float	0-1
income_category	in which income category the household is placed	float	0-1
savings_category	in which savings category the household agent is placed	int	1-7
months_savings	how many months of savings the household agent has	float	0-12
money related variables			
total_income	depending on income category, a random number within the range is chosen as the yearly total income	int	100 - 1000000
monthly_income	total_income divided by 12	float	
savings	total savings calculated through multiplying the monthly_income and the months_savings	float	
savings_rate	monthly savings rate as passed from the model initialisation	float	0-1
monthly_savings	how much the household agent saves each month - multiplying savings_rate with monthly_income		
network related			
basic_own_trust	how much household agents always trust themselves as passed from model initialisation	float	0-1
trust_in_others	how much households value other opinions based on the social_expectation and the basic_own_trust	float	0-1
trust_in_oneself	how much household agents value their own perceptions (1 - trust_in_others)	float	0-1
connecting_nodes	which other household agents the agent is connected to	list	['unique_id_agent_1, 'unique_id_agent_2', ...]
number_of_connections	how many other household agents the agent is connected to	int	>= 0
perceived_cost_of_measures_of_me	list of household agent's perceptions about costs of measures in specific order	list	
perceived_response_efficacy_of_measures_of_me	list of household agent's perceptions about response efficacy of measures in specific order	list	

Continued on next page

Table A.2 – continued from previous page

Name	Explanation	Type	Values
future_worry	stores the worry perception after calculating the influence of the connections	float	0-1
future_perceived_flood_damage	stores the flood damage perception after calculating the influence of the connections	float	0-1
future_perceived_cost_of_measures_list	stores the perceptions about costs of measures after calculating the influence of the connections	list	
future_perceived_response_efficacy_of_measures_list	stores the perceptions about response efficacy of measures after calculating the influence of the connections	list	
households_measures_df	dataframe containing the households information on the measures as outlined in the following subsection	pandas dataframe	
actions_to_take_df	dataframe containing only the information of the measures the household still can take, so a subset of the households_measures_df	pandas dataframe	
measure_to_take	if household decided to take a measure, this variable will indicate which measure it is	string	measure' or 'no_measure_to_take'
parameters_updated	variable indicating whether there have been any changes in the perceptions since the last step	boolean	False, True

Measures

The measures to be considered in the model are selected based on implementation numbers as stated in the survey. The top-5 implemented structural measures, top-5 implemented non-structural measures are selected to be considered in the model. An overview of these can be found in Table A.3, including the percentage of households that have taken adaptation measures and those that intend to do so.

In the following, the numbering of the measures follows the numbering from the survey and the survey results. This list of measures included can be adapted to any measures considered in the survey data. To do so, the input data used would need to be expanded regarding the new measures. With the list of measures and the according to the input data, each household agent then stores their perceptions and uptake of measure in a dataframe as shown in Table A.4.

The values for *undergone* are either 0 (not taken) or 1 (taken). *Perceived cost, perceived self-efficacy* and *perceived response efficacy* are all between 0 and 1. For *perceived cost* 0 corresponds to “very cheap” and 1 to “very expensive”. For *perceived self-efficacy* 0 means the household thinks they are unable to perform this measure, while 1 corresponds to being “very able” to take the measure. And lastly, for *perceived response efficacy* 0 corresponds to thinking the measures is “extremely ineffective”, while 1 means “extremely effective”. All values between 0 and 1 denote opinions that range between those extremes.

The *probability to take measure* is determined using logistic regression and shows how likely a household is to take a certain measure. More info on the decision making process can be found in Section A.3.2.

Table A.3: The structural and non-structural PFA measures considered in this thesis and the uptake and intention to implement them for the 849 survey respondents from the area of Houston (TX, USA). Source: own calculations based on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022).

Label	**Explanation**	**Percentage undergone**	**Percentage intention**
NS1	Keeping a working flashlight and/or a battery-operated radio and/or emergency kit in a convenient location	74.41	17.69
NS5	Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do	27.71	35.97
NS7	Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage	59.32	25.24
NS10	Storing emergency food and water supplies	49.88	33.96
NS11	Moving/ storing valuable assets on higher floors or elevated areas	43.75	32.90
S1	Raising the level of the ground floor above the most likely flood level	9.43	16.27
S2	Strengthen the housing foundations to withstand water pressures	6.96	19.46
S3	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	7.55	18.99
S4	Raising the electricity meter above the most likely flood level or on an upper floor	11.91	19.22
S5	Installing anti-backflow valves on pipes	7.43	22.88

Table A.4: Exemplary table each household has that stores the opinions and actions regarding each measure. The numbers inserted here are selected at random.

Measure	**Undergone**	**Perceived cost**	**Perceived self-efficacy**	**Perceived response efficacy**	**Probability to take measure**	**Cost**
S_1	0	0.2	0.2	0.2	0.12	35 000
S_2	0	0.4	0.8	1.0	0.83	12 000
S_3	0	0.6	0.4	0.4	0.07	2200
S_4	1	0.8	0.2	0.6	already_-taken	3500
S_5	0	0.4	0.6	0.6	0.47	1900
NS_1	1	0.2	0.6	1.0	already_-taken	12
NS_5	0	0.4	0.4	0.3	0.15	0
NS_7	0	0.6	0.8	0.4	0.72	0
NS_10	1	1.0	0.2	0.4	already_-taken	183
NS_11	0	0.2	1.0	0.8	0.31	0

A.1.3. Process Overview and Scheduling

An overview of the processes within the model can be found in Figure 3.1 in the main text. Further details on how these processes influence on household agent level are depicted in Figure A.1. This graph also highlights how the policies that are explained in detail in Section A.3.3 interact with the household agents.

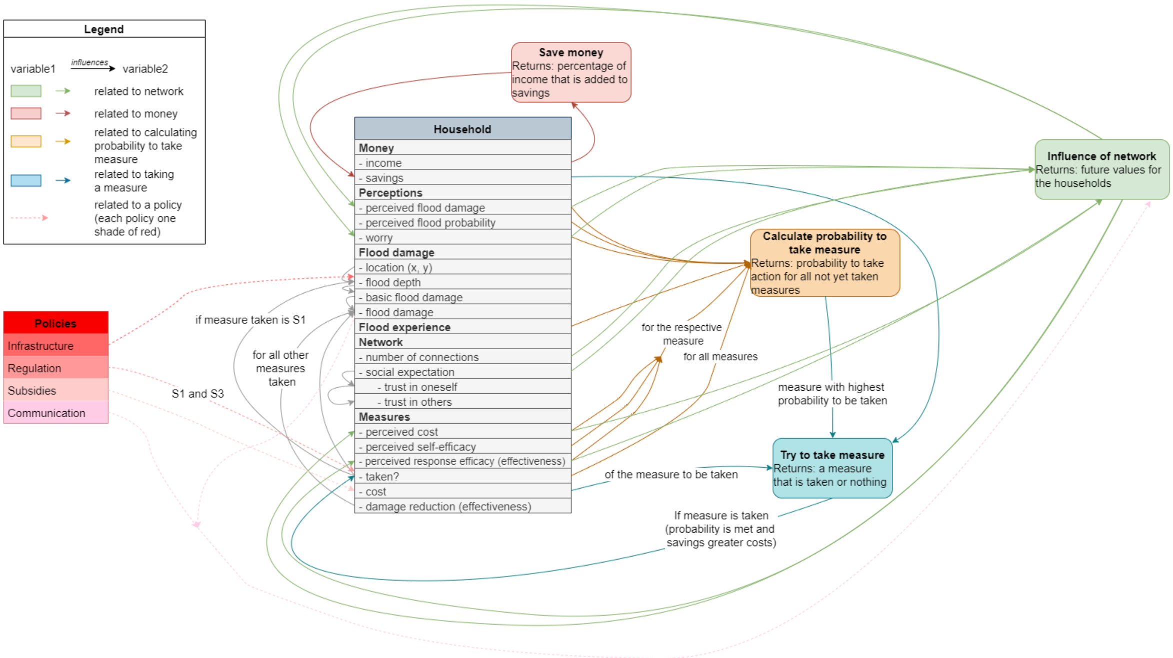

Figure A.1: Interaction of household agent variables within the model. Source: own model design

A.2. Design Concepts

Adaptation

Households adapt their own opinions based on the opinions of the other households they are connected with. To specify the influence, the opinion formation model of Degroot (1974) is used, which calculates opinion formation based on own and surrounding opinions, each with a weight to them. It can be summarised through

$$F_{i1} = \sum_{j=1}^{k} p_{ij} F_j \tag{A.1}$$

where F_{i1} is the new opinion of a household based on their own opinion and those of others F_j. Each opinion (the own and that of others) has a weight p_{ij} assigned to it denoting the importance given to the own opinion and those from connections in the network. k denotes the number of households the household is connected to.

The opinions that can be influenced are the following factors:

- response efficacy of each measure
- cost of each measure
- perceived flood damage
- worry

Households put a weight to their opinion and those of others. This is determined by the *basic own trust*, which is can be set and should be a value between 0 and 1, and the *social expectation*, as specified in the survey data. In total, the influence of others' opinions is specified through *social expectation* × *(1 - basic own trust)*. The rest of the new opinion is the households old opinion. To provide an example:

> The goal is to calculate the new *worry* of household 1. Currently, household 1's *worry* is 0.6. Household 1 is connected with households 3, 4, 9 and 11. Their corresponding *worry* values are 0.2, 0.2, 0.8 and 0.6. It is assumed that the *basic own trust = 0.5* and the *social expectation* of household 1 is 0.4. This means that household 1 in total values others' opinions with 0.4 × (1 − 0.5) = 20% and therefore their own opinion with 80 %. Therefore, the new *worry* of household 1 is calculated through the following:

$$\begin{aligned}\text{new worry} = 80\% \times \text{old worry} + \frac{20\%}{4} \times (&\text{worry household 3} + \text{worry household 4}\\ &+ \text{worry household 9} + \text{worry household 11})\\ &= 0.8 \times 0.6 + 0.05 \times (0.2 + 0.2 + 0.8 + 0.6)\\ &= 0.57\end{aligned} \tag{A.2}$$

Learning

As described above, household agents exchange perceptions and through this "learn" from each other. When communication policy is examined (for more details see section A.3.3), this effect is enhanced through the introduction of "objective" perception values - values that put the different perceptions on measures into perspective. Through this, the household agents learn and are expected to align their perceptions with reality.

Interaction

The household agents are connected within a network. Each household agent represents a node within that network. The mesa package *NetworkX* is used for the generation of the networks. Four different setups are considered:

- **No network:** The nodes are not connected, so no information exchange happens between the households. No further parameters need to be specified.
- **Erdős-Rényi random network:** The graph is constructed randomly where each edge is included with a probability independent from any other edge (Erdős & Rényi, 1959). The following parameters are specified:

- n = number of households i.e., number of nodes.
- p = probability of network connection. Default: p = number of nearest neighbours / number of households = 5 / number of households

- **Barabasi-Albert scale-free network:** A network whose degree distribution (asymptotically) follows power law so nodes with high degree attract more connections (Barabási & Albert, 1999). The following parameters are specified:
  - n = number of households i.e., number of nodes.
  - m = number of edges for each node. Default: m = 3
- **Watts-Strogatz small world network:** random graph generation model producing graph with small-world properties, so a short average path length and high clustering (Watts & Strogatz, 1998). The following parameters are specified:
  - n = number of households i.e., number of nodes.
  - k = number of nearest neighbors. Default: k = 5
  - p = probability of network connection. Default: p = 0.4

As already explained above, the household agents exchange views and opinions based on their connections.

Stochasticity

The input parameters are drawn from the survey data from (Noll, Filatova, Need, & Taberna, 2022). For each used parameter the percentage of a certain value occurring is calculated. Based on this percentage, the starting values are assigned in the model. Table A.5 provides an example of this for the parameter *worry*: The values from the survey are converted to values between 0 and 1 for the model. Then the occurrence of each answer is given through a percentage. This is assumed to reflect more or less the distribution of worry across the city. This percentage is then used to assign the *worry* value to the household agent in the model. This means, the model population should have the same distribution of worry as the real population. Based on this concept, initial values of parameters specified in Section A.1.2 are assigned to the households.

Table A.5: Exemplary distribution of input value *worry*

Value in survey	Value in model	Meaning	Percentage
1	0.2	not at all worried	28.98
2	0.4	a little worried	31.80
3	0.6	somewhat worried	25.68
4	0.8	quite worried	8.83
5	1	very worried	4.71

Observation

Data is collected on agent, as well as on model level:

- Household agents (collected at beginning since parameters do not change):
  - location (x and y)
  - number of connections
- Household agents (collected at each step, changing parameters):
  - flood damage
  - perceived flood damage
  - worry
  - perceived cost of each measure
  - perceived response efficacy of each measure
- Model parameter (collected at each step):
  - percentage taken of each measure

A.2.1. Initialisation

The model is initialised setting the variables as outlined in Table A.6. Through changing these variables, experimentation and sensitivity analysis can be run.

Table A.6: Cost and effectiveness of household measures

Name	Explanation	Type	Possible values	Default values
seed	to set seed	int or None	None, >0	None
nr_households	specifies the number of households modelled	int	> 0	1000
basic_own_trust	how much households always keep their own opinion. Important when it comes to determining the influence of connections in the network	float	0-1	0.5
tick_time	specifies if tick roughly represents one or three months	string	'quarter' or 'month'	'quarter'
pause_after_last_measure	specifies how many ticks households do not take a measure after taking one	int	≥ 0	2
savings_rate	how much of their income households save each months (rate, not percentage)	float	≥ 0	0.05
scenario	which scenario / policy is run	string	'base_case', 'infrastructure', 'subsidies', 'regulation', 'communication', 'communication_infrastructure', 'communication_subsidies' or 'communication_regulation'	'base_case'
percentage_cost_reduction	how much the costs of structural measures are reduced when the subsidies policy is active	int	0-100, give min and max	30, 75
infrastructure_effect_area	where the infrastructure policy reduces the flood risk if it is active	dictionary	{'x_min': , 'x_max': , 'y_min': , 'y_max': }	{'x_min':265000, 'x_max':283590, 'y_min':3302443, 'y_max':3308500}
flood_depth_reduction_in_infrastructure_effect_area	how much the flood depth is reduced in meter in the area where the infrastructure would be active	int	≥ 0, give min and max	0.5, 3
households_in_infrastructure_area_in_percent	how many households in the infrastructure area would profit from the policy in percent	int	0-100	50

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Table A.6 – continued from previous page

Name	Explanation	Type	Possible values	Default values
regulation area	where the regulation policy is active	dictionary	{'x_min': , 'x_max': , 'y_min': , 'y_max': }	{'x_min':260200, 'x_max':269495, 'y_min':3289800, 'y_max':3297857 }
mandatory_measures	which measures are mandatory in the regulation area, if the regulation policy is active	list of strings	["measure", "measure"]	['S_1', 'S_3']
network	what network is active	string	'no_network', 'barabasi_albert', 'watts_strogatz', 'erdos_renyi'	"base_case"
probability_of_network_connection	probability of network connection in the Watts-Strogatz network setup	float	0-1	0.4
number_of_edges	number of edges for the Barabasi-Albert network setup	int	≥ 0	3
number_ of_ nearest_ neighbours	number of nearest neighbours for the Watts-Strogatz network setup, also used for the Erdős-Rényi setup	int	≥ 0	5
flood_map_path	path to file of flood map in .tiff format	string		r"../input_data/hmax.tiff"
min_flood_depth	minimum flood depth in meters as specified in the flood map	float	≥ 0	0.05

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A.3. Details

A.3.1. Input Data

Survey

Survey data for the area of Houston was used to set the initial state of the model (Noll, Filatova, Need, & Taberna, 2022). This survey includes extensive data on peoples household composition, economic and social situation, opinions regarding climate change and intention to take certain adaptive measures. The survey questions are aligned with PMT, meaning that data for the factors for decision making based on PMT can be drawn from the survey. For the Houston area there are 849 responses documented.

Flood Maps

Flood maps for the Houston area from the SFINCS model were provided (Sebastian et al., 2021). An example of such a map can be seen in Figure A.2. The data is provided in *.tiff* format with the flood depth in meters. In the model, each household agent is assigned a random location within the model domain. Depending on this location, the flood depth is drawn. The minimum flood depth at every location is 0.05 m.

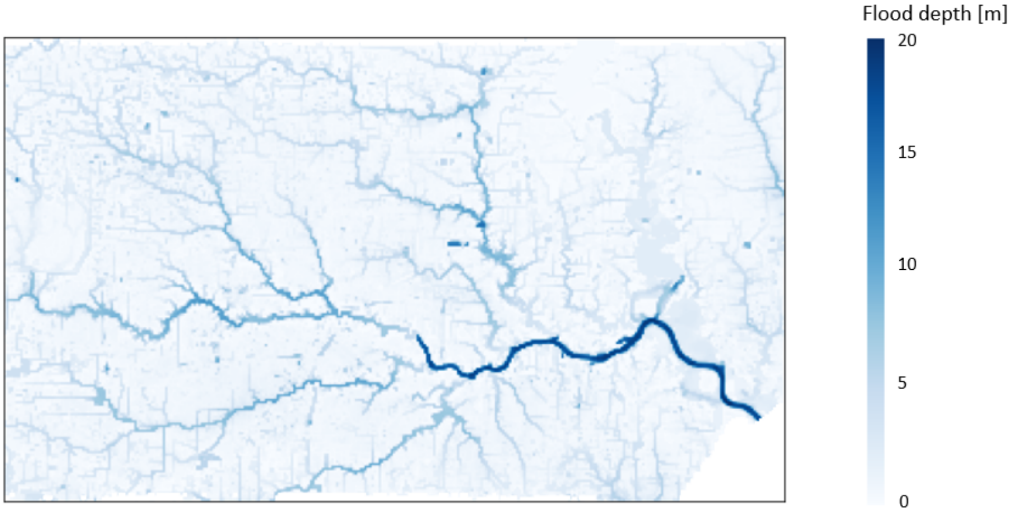

Figure A.2: Exemplary flood depth map generated from *.tiff* file from the hindcast of hurricane Harvey. Source: own visualisations based on SFINCS model data (Sebastian et al., 2021).

Flood Depth - Damage Function

Based on the just previously mentioned flood-depth map, depending on a households location in the model, a damage value is assigned. Moel et al. (2017) provide data for the relation between damage and flood depth for different regions of the world. The data for North America is used and a logarithmic line fitted over the data points resulting in the following:

$$d = \begin{cases} 1 & d_w >= 6\text{m} \\ 0.1746 \times \log(d_w) + 0.6483 & d_w < 6\text{m} \end{cases} \tag{A.3}$$

where d is damage and d_w the depth of water. The damage factor corresponds to the damage at a location only considering the flood height, so without any measures in place.

Cost and Damage Reduction of Measures

To quantify the costs and effects of the household measures, Table A.7 is used. In the table, for each measure mentioned in the survey, cost and damage reduction are assigned. The damage reduction for non-structural measures (apart from NS_2 - sandbags) is set to 0% as these measures do not prevent damage at the building.

Damage reduction and costs are given by a range to represent that households take the measures under different circumstances and, hence, the cost and the effectiveness will vary. When a household takes a measure, the cost is deducted from their savings and their flood damage reduced by the percentage with $d_{new} = d_{old} \times (1 - d_{reduction})$, where d_{new} is the new damage value, d_{old} the value before taking the measure and $d_{reduction}$ the percentage of damage reduction as defined in the table. The measure S_1 is an exception: The damage reduction is 0 since in the model the damage is indirectly reduced through changing the flood depth when taking the measure. When S_1 is taken, the flood depth of the household is set to the minimum flood depth of the model and the damage recalculated on the damage function as explained above.

The objective cost and efficacy of the measures is obtained by the fraction of the value of the measure and the highest value of all measures. These are used for an "objective" opinion when the communication policy is tested. In this format (between 0 and 1), the values are directly comparable to the perceptions of the household agents and can be inserted in the DeGroot opinion dynamics model (see Section A.2).

Table A.7: Cost and effectiveness of household measures

Measure	**Explanation**	**Damage reduction range (%)**	**Cost range ($)**	**Objective cost**	**Objective efficacy**	**Comment**	**Source**
NS_1	Keeping a working flashlight and/or a battery-operated radio and/or emergency kit in a convenient location	0	10-30	0	0	guess	
NS_2	Purchasing sandbags, or other water barriers	30 - 60	50 - 250	0.003	0.947	3-6$ per bag, total amount dependent on bags needed (10/20 - 40/80 bags)	Kreibich et al. (2015)
NS_3	Buying a spare power generator to power your home	0	500 - 800	0.012	0	googled cost private power generator	
NS_4	Being an active member in a community group aimed at making the community safer	0	5 - 15	0	0	guess	
NS_5	Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do	0	0	0	0	guess	

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Table A.7 – continued from previous page

Measure	Explanation	Damage reduction range (%)	Cost range ($)	Objective cost	Objective efficacy	Comment	Source
NS_6	Installing a refuge zone, or an opening in the roof of your home or apartment	0	800 - 1500	0.022	0		LB Supplies (2019)
NS_7	Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage	0	0	0	0	guess	
NS_8	Asking someone (local government, Civil Defense, etc.) for information about what to do in case of emergency	0	0	0	0	guess	
NS_9	Asking/ petitioning government representative to increase the public protection measures	0	0	0	0	guess	
NS_10	Storing emergency food and water supplies	0	100-200	0.003	0	guess, one time investment for the extra food –> no recurring costs since old food exchanged with new food	
NS_11	Moving/ storing valuable assets on higher floors or elevated areas	0	0	0	0		

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Table A.7 – continued from previous page

Measure	Explanation	Damage reduction range (%)	Cost range ($)	Objective cost	Objective efficacy	Comment	Source
S_1	Raising the level of the ground floor above the most likely flood level	0	30.000 - 60.000	0.857	1	elevating, raise floor level, damage reduction 0 since it changes the flood depth for the house and with this already covers the damage reduction since the basic flood damage is different	Kreibich et al. (2015)
S_2	Strengthen the housing foundations to withstand water pressures	30 - 50	8.000 - 15.000	0.821	0.842	dry proofing 60-180 cm from lit, damage reduction guess with lit	Kreibich et al. (2015)
S_3	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	15 - 45	2.000 - 8.000	0.357	0.632	wet-proofing	Kreibich et al. (2015)
S_4	Raising the electricity meter above the most likely flood level or on an upper floor	30 - 40	2.000 - 4.000	0.214	0.737	resilient kitchen taken as reference with some band	Kreibich et al. (2015)
S_5	Installing anti-backflow valves on pipes	15 - 35	1.800 - 2.200	0.143	0.526	1900 € –> calculated to $, damage reduction guessed	Kreibich et al. (2015)
S_6	Installing a pump and/or one or more system(s) to drain flood water	10 - 30	1.000 - 8.000	0.321	0.421	googled pump costs (average french drain cost), damage reduction guessed	Liaison Ventures (2022)

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Table A.7 – continued from previous page

Measure	Explanation	Damage reduction range (%)	Cost range ($)	Objective cost	Objective efficacy	Comment	Source
S_7	Fixing water barriers" (e.g., water-proof basement windows)	10 - 85	8.000 - 20.000	1	1		Kreibich et al. (2015)

A.3.2. Submodels

Decision Making of Households

Households take new measures based on PMT and financial ability.

The probability of a household to take a measure is rooted in logistic regression. The values are drawn from the survey results for the intention to take a certain measure in the following months and can be found in Table 4.1. Based on the parameters and the household agent's perceptions, a probability is calculated that reflects the likeliness to take each measure. The household agent will always take the measure with the highest probability first. Each step it draws a random number, compares this with the probability and based on that tries (or not) to take the measure.

Before the measure is taken for sure, the household agent needs to check, whether it can afford to take the measure it wants to take. As specified in Table A.7 measures have a different monetary value assigned to them. The cost of the measure for the household lies somewhere between the minimum and maximum cost and is determined randomly. This is done to reflect that measures' costs vary for households depending on circumstances like size, age, and location of the house. If a household is able to take the measure financially (so its savings are greater than the costs of the measure that is to be taken), it takes the measure. The cost of the measure is then deducted from the agent's savings.

Interaction

As already explained in Section A.2, households interact and exchange views based on the DeGroot model.

A.3.3. Policies

The policies are specified through the input parameters of the model. Turning policies on and off is done through modification of a simple dictionary:

$$\text{policies} = \{\text{'subsidies'}: 0,\ \text{'infrastructure'}: 0,\ \text{'regulation'}: 0,\ \text{'communication'}: 0\} \tag{A.4}$$

where policies can be switched on (1) and off (0) by changing the corresponding value in the dictionary. This is done automatically within the model. The user has to insert the correct scenario as explained in Table A.6 in Section A.3.1.

The further input for the policies is specified in Table A.8 and explained in the following subsections. Each policy is active from the beginning and throughout the entire model run.

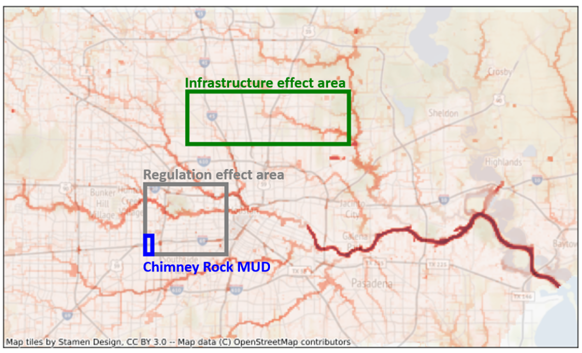
For the coordinate system, EPSG 26915 is used as this is the format the flood maps are displayed in.

Infrastructure

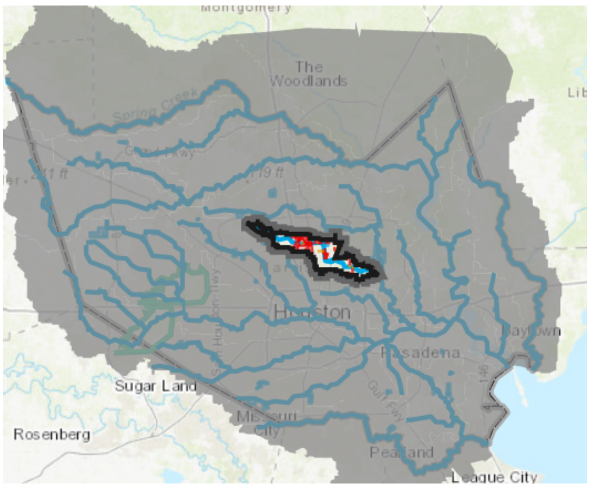
The *infrastructure policy* represents large infrastructure projects, that reduce the flood risk in an area, e.g., the construction of a dam, bayou, or other flood protection. In Houston, there is a wide range of projects running (Harris County, 2022a, 2020). As an exemplary project for the model, the Halls Bayou is selected (see Figure A.3b, Harris County (2022b)). The input parameters for this are specified in table A.8 and are also visualised in figure A.3a. For simplification, a rectangular area is used as the area where the infrastructure project has an effect and 50% of the households within the area will be affected by the infrastructure project. Since not all households would benefit from the project in the same way, the flood depth reduction is set to vary between 0.5 and 3 m for the households in the area, as specified in Table A.8.

Table A.8: Policy input parameters

Policy	Variable in model	Type	Default values
Infrastructure	infrastructure_effect_-area	dictionary with location (x_{min}, x_{max}, y_{min}, y_{max})	{'x_min': 265000, 'x_-max': 283590, 'y_min': 3302443, 'y_max': 3308500}
	flood_ depth_reduction_in _infrastructure_effect_ area	list with minimum and maximum value in meters	[0.5, 3]
	households_in_infrastructure_area_in_ percent	integer between 0 and 100	50
Communication	objective cost and efficacy as specified in table A.7	value between 0 and 1 for each measure	see table A.7
Regulation	regulation_area	dictionary with location (x_{min}, x_{max}, y_{min}, y_{max})	{'x_min': 260200, 'x_-max': 269495, 'y_min': 3289800, 'y_max': 3297857 }
	mandatory_measures	list with measure names	['S_1', 'S_2']
Subsidies	percentage_ cost_reduction	integer between 0 and 100	30



(a)



(b)

Figure A.3: Areas where regulation and infrastructure policy are in effect: (a) Areas as used for the simulation. Source: own visualisation based on own model design. (b) Location of Halls Bayou watershed projects within the Houston area – this was used as inspiration for the infrastructure effect area. Source: (Harris County, 2022b).

Communication

As briefly pointed out in Section A.3.1, with the *communication policy* a “objective” actor is added to the network and connected with every household. This means, that the household is not only influenced by other households, but also by the “objective” perception of the policy through the DeGrootian model (see Section A.2). The policy influences the households in their

- perceived response efficacy of each measure, where the policy’s influences is as specified in table A.3.1 (Objective efficacy),
- perceived cost of each measure, where the policy’s influences is as specified in table A.3.1 (Objective cost),
- perceived flood damage, where the policy’s influence is as given by the flood depth and taken measures of the household at that moment.

Regulation

Similar to the *infrastructure policy*, the *regulation policy* is present in a certain area of the city, as specified in the Table A.8. It represents a policy where it is mandatory to have certain structural adaptation measures present at the house e.g., if a household is located in a high-risk area, it needs to have anti-backflow valves installed (measure S_5). For the mandatory measures considered, see Table A.8. The selection has been based on the private measures mentioned in the National Flood Insurance Program of the Federal Emergency Management Agency (FEMA) (Federal Emergency Management Agency, 2021), that names elevation and dry proofing as the measures to reduce insurance costs. The FEMA mentions a number of municipal utility units (MUDs) within the City of Houston that participate in the National Flood Program (Federal Emergency Management Agency, 2022). The Chimney Rock MUD is taken as an orientation for the regulation area mentioned in Table A.8 (also see figure A.3a). However, since there are multiple of such participating MUDs in Houston, the area is expanded slightly in order to see an effect on the overall performance in the model, as can be seen in Figure A.3a.

Subsidies

The *subsidies policy* represents a policy that would subsidies and hence reduce the costs of taking a measure for the households. For NFIP flood insurance holders, up to 100% of elevation costs can be claimed (McCulloch & Federal Emergency Management Agency, 2018). Since not all households are considered to have flood insurance and are equally eligible for subsidies, for a start, this cost reduction is set at 30-75%. It reduces the cost of all structural measures by this factor and is applied to all households within the model.

B

Model Verification

B.1. Reproducibility and Variability

To ensure reproducibility of the results, the seed can be fixed. The agent variation was run with 100 household agents in five replications with the same seed to show reproducibility and varying seed to show variability. The results can be see in Figure B.1.

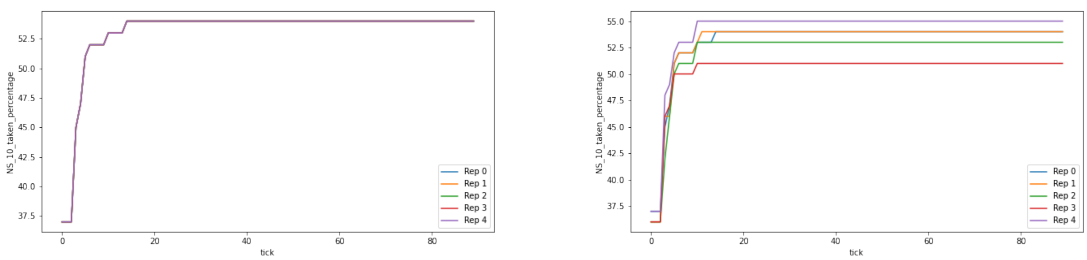
Figure B.1 shows that the results from runs with the same seeds do not vary (see Figure B.1a), while runs with different seeds yield different results (see Figure B.1b). This demonstrates, that reproducibility and variability can be guaranteed.

B.2. Sensitivity Analysis

In order to test the selected variable values, a sensitivity analysis is performed. This means that a certain parameter range around a selected default parameter is observed in the simulation, so that it can be insured that the model behaves as expected in the selected parameter space.

The parameters for the policies and network setup are not tested for sensitivity as the setup of these is purely qualitative and cannot be quantified. The parameters tested are specified in Table B.1 including the parameter range tested and the default value. The sensitivity analysis is performed for the base case (no policies active) with no network present and the three network setups ER, WS, and BA.

The results from the sensitivity analysis are found in Figure B.2. How much weight households assign to their own opinion and hence to the ones of others influences the development of the flood damage factor in case of networks (see Figure B.2a). Considering the overall scale, the differences between the different sensitivity values are relatively small and the dynamics are similar in all the cases. The obligatory pause between taking measures does not impact the dynamics of the flood damage factor significantly (see Figure B.2b). Of the three variables evaluated for sensitivity here, the flood damage factor is most sensitive to the savings rate (see Figure B.2c). This was expected as the uptake of measures depends on the financial abilities of the household agent (see Figure 3.2 for more details).



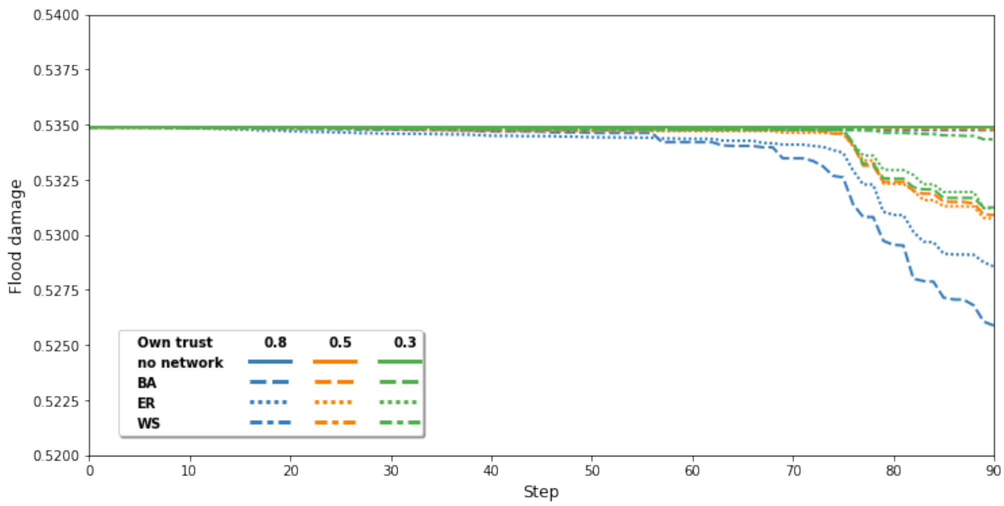
(a) (b)

Figure B.1: Results of agent variation regarding the percentage of non-structural measure (NS_10) being taken - (a) reproducibility i.e., same seed, (b) variability i.e., varying seed.

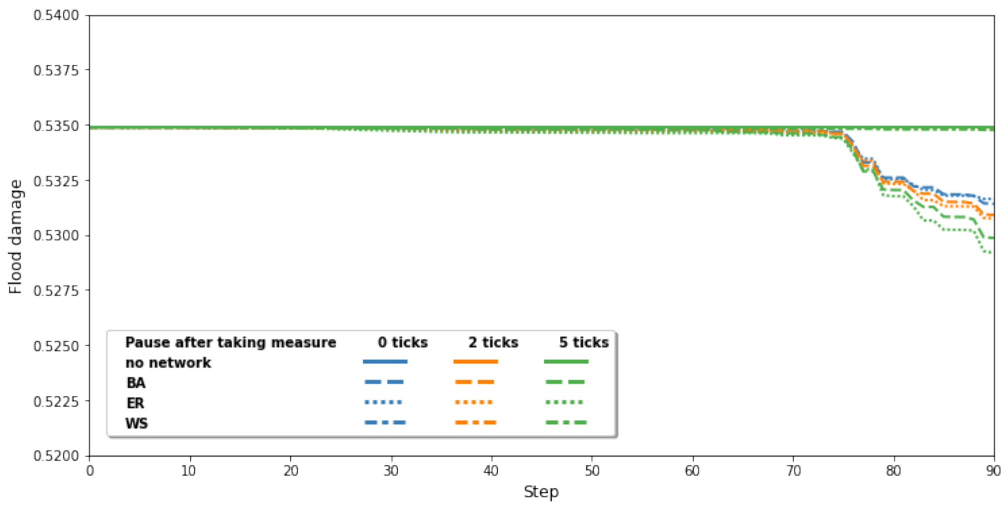
Table B.1: Overview of the uncertainty ranges for each parameter.

Parameter	Explanation	Values for sensitivity analysis	Default value
pause_after_last_measure	how many ticks a household refrains from taking another measure after taking one	0, 2, 5	2
savings_rate	how much of their income households save each months	0.01, 0.05, 0.1	0.05
basic_own_trust	how much households always keep their opinion	0.3, 0.5, 0.8	0.5

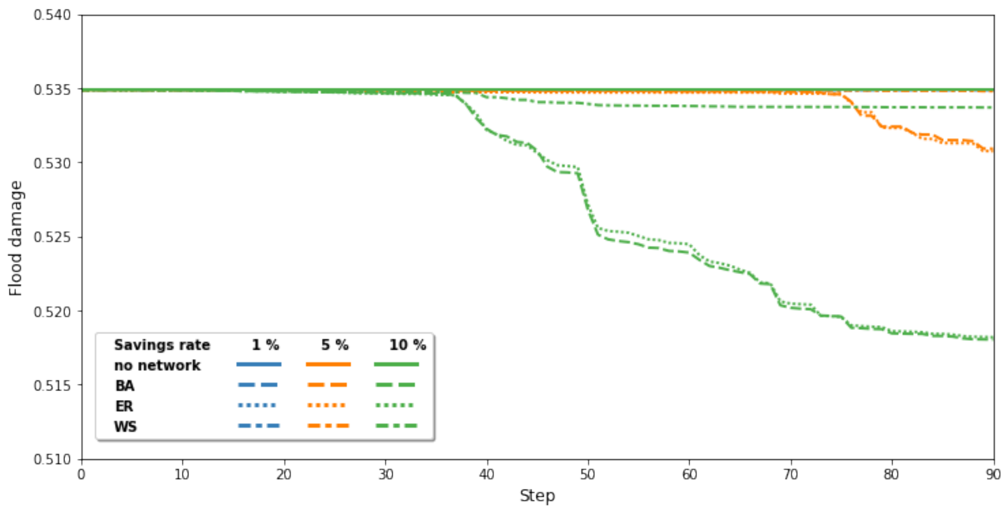
Overall, the different values for the pause between taking measures impacts the flood damage factor the least, while changing the savings rate has the highest impact.



(a)



(b)



(c)

Figure B.2: Flood damage factor for the different sensitivity runs over different network types for (a) basic trust households have in their opinion, (b) the pause between taking two measures, and (c) monthly savings rate. Mean results over 50 Monte Carlo runs. Source: own analysis.

C

Analysis of Survey Data

This appendix provides some more details on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022) used in this thesis. In Chapter 3 and Appendix A, the data has already been introduced, including the measures considered and how it is prepared for the model input. In Table C.1, more details on the dependent variables of the model can be found.

Table C.1: Dependent variables used in the model and the analysis from the survey responses for the area of Houston (TX, USA). Source: own calculations based on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022).

Variable	Question from survey	Response options	Mean	Standard deviation
perceived responsibility	In your opinion, whose responsibility is it to deal with natural hazards and floods?	Five-point scale. (1) it is completely the government's responsibility to protect its citizens from floods and natural hazards - (5) it is completely an individual's / household's responsibility to protect themselves from floods and natural hazards	2.966	0.912
flood experience	18. Have you ever personally experienced a flood of any kind?	(0) no – (1) yes	0.552	0.498

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Table C.1 – continued from previous page

Variable	Question from survey	Response options	Mean	Standard deviation
perceived flood probability	How often do you think a flood occurs on the property on which you live (e.g. due to rivers or heavy rain, storms and cyclones)? Which category is the most appropriate?	Nine-point scale. (1) My house is completely safe 0.0% chance annually, (2) Less often than 1 in 500 years or 0.1% chance annually, (3) Once in 500 years or a 0.2% chance annually, (4) Once in 200 years or a .5% chance annually (5) Once in 100 years or 1% chance annually, (6) Once in 50 years or a 2% chance annually, (7) Once in 10 years or 10% chance annually, (8) Annually or 100% chance annually, (9) More frequent than once per year	4.139	2.621
perceived flood damage	In the event of a future major food in your area on a similar scale to the flooding from Hurricane Harvey in Houston in 2017 how severe (or not) do you think the physical damage to your house would be?	Five-point scale. (1) not at all severe – (5) very severe	2.663	1.231
worry	How worried or not are you about the potential impact of flooding on your home?	Five-point scale. (1) not at all worried – (5) very worried	2.285	1.115
social expectations	Do your family, friends and/or social network expect you to prepare your household for flooding?	Five-point scale. (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	3.212	1.255
income	What was your total family income from all sources last year in 2019?	Five-point scale. (1) less than 25730 $ annually, (2) $ 25731-49200 annually, (3) $ 49201-80995 annually, (4) $ 80996-132490 annually, (5) more than $ 132490 annually	2.986	1.331

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Table C.1 – continued from previous page

Variable	Question from survey	Response options	Mean	Standard deviation
savings	With regards to your household's savings, what statement most closely reflects your current household situation?	Seven-point scale. (1) My household has little to no savings – we use practically all of the money we earn each month, (2) My household has roughly half a month's wages in savings, (3) My household has roughly 1 month's wages in savings, (4) My household has roughly 1.5 month's wages in savings, (5) My household has roughly 2 month's wages in savings, (6) My household has roughly 3 month's wages in savings, (7) My household has 4 or more month's wages in savings.	3.996	2.473
perceived self-efficacy of structural measures[1]	Do you have the ability to undertake this structural measure either yourself or paying a professional to do so?	Five-point scale. (1) I am unable – (5) I am very able	2.267	1.415
perceived effectiveness of structural measures[1]	How effective do you believe that implementing this structural measure would be in reducing the risk of flood damage to your home and possessions?	Five-point scale. (1) Extremely ineffective – (5) Extremely effective	3.245	1.299
perceived costs of structural measures[1]	When you think in terms of your income and your other expenses, do you believe that implementing (or paying someone to implement) this structural measure, would be cheap or expensive?	Five-point scale. (1) Very cheap – (5) Very expensive	4.014	1.126
perceived self-efficacy of non-structural measures[2]	Do you have the ability to undertake this Non-structural measure either yourself or paying a professional to do so?	Five-point scale. (1) I am unable – (5) I am very able	4.089	1.258

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[1] Combination of variable for all structural measures considered in this study as defined in Appendix A.1.2. Mean and standard deviation are hence obtained over all values of this variable for the five structural measures considered.

[2] Combination of variable for all non-structural measures considered in this study as defined in Appendix A.1.2. Mean and standard deviation are hence obtained over all values of this variable for the five non-structural measures considered.

Table C.1 – continued from previous page

Variable	Question from survey	Response options	Mean	Standard deviation
perceived effectiveness of non-structural measures[2]	How effective do you believe that implementing this Non-structural measure would be in reducing the risk of flood damage to your home and possessions?	Five-point scale. (1) Extremely ineffective – (5) Extremely effective	3.897	1.254
perceived costs of non-structural measures[2]	When you think in terms of your income and your other expenses, do you believe that implementing (or paying someone to implement) this non-structural measure, would be cheap or expensive?	Five-point scale. (1) Very cheap – (5) Very expensive	2.165	1.284

D

Experimentation and Results

D.1. Experimentation Setup

The experimentation setup is a combination of policies and networks as specified in the model description in Appendix A. This results in the experimentation matrix shown in Tables D.1 and D.2 for the individual and combined policies. For each combination of network and policy, 50 Monte Carlo replications are run with a pre-defined seed to ensure variety and also reproducibility of the results. The number of households was set to 1000.

The experiments were run using the *batch_run* function within the mesa package (Project Mesa Team, 2016) and executed on the DelftBlue Supercomputer (Delft High Performance Computing Centre (DHPC), 2022).

Table D.1: Experimentation matrix - isolated policies

	No policies	**Subsidies**	**Infrastructure**	**Regulation**	**Communication**
No network	base_case_no_nw	sub_no_nw	infra_no_nw	reg_no_nw	comm_no_nw
Barabasi-Albert	base_case_ba	sub_ba	infra_ba	reg_ba	comm_ba
Watts-Strogatz	base_case_ws	sub_ws	infra_ws	reg_ws	comm_ws
Erdős-Rényi	base_case_er	sub_er	infra_er	reg_er	comm_er

Table D.2: Experimentation matrix - interacting policies

	Communication & Subsidies (CS)	**Communication & Infrastructure (CI)**	**Communication & Regulation (CR**
No network	CS_no_nw	CI_no_nw	CR_no_nw
Barabasi-Albert	CS_case_ba	CI_ba	CR_ba
Watts-Strogatz	CS_case_ws	CI_ws	CR_ws
Erdős-Rényi	CS_case_er	CI_er	CR_er

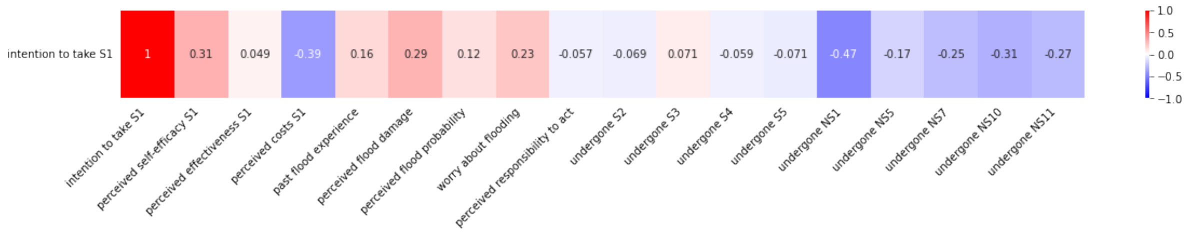
D.2. Results

D.2.1. PMT Correlations

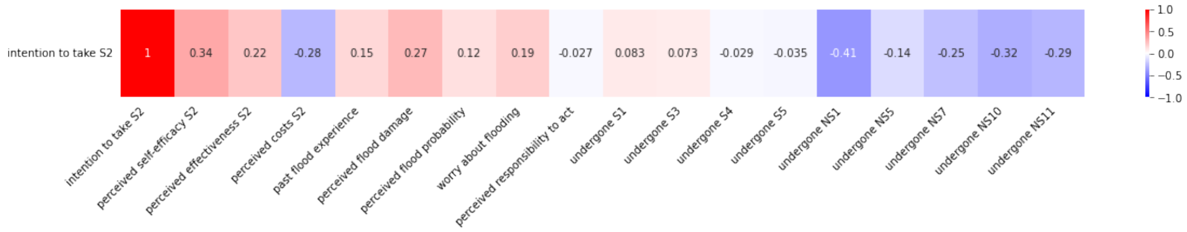
Figure D.1 shows the correlation between PMT values and the intention to take a measure for the five considered structural measures, Figure D.2 for the considered non-structural measures.

D.2.2. Regulation and Infrastructure Policy

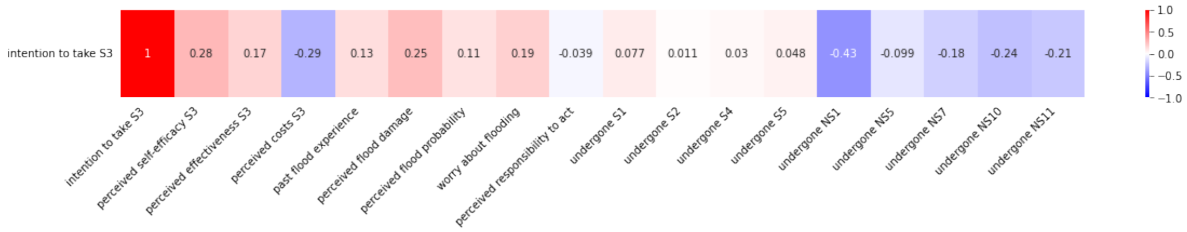
The regulation and infrastructure policy do not influence the evolvement of the simulation but only the conditions at initialisation differ. Therefore, the household agents affected by the policy are compared to those that are not. Figure D.3 shows that the household agents affected by the policy develop in parallel to those that are not affected, only have a lower damage value through the policy.



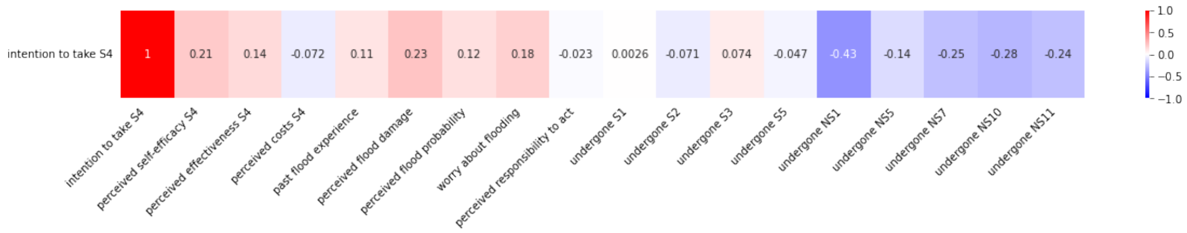
(a)



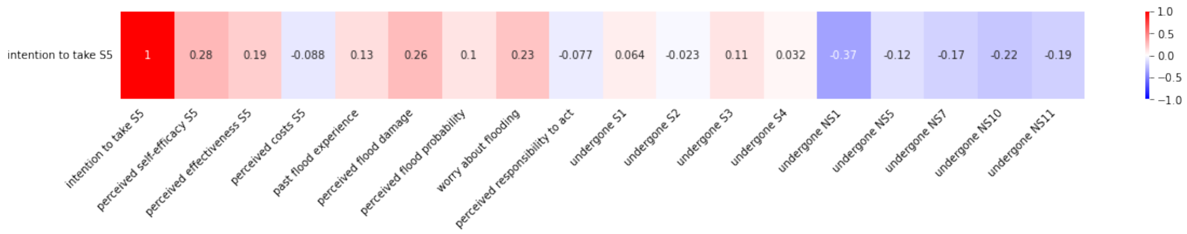
(b)



(c)

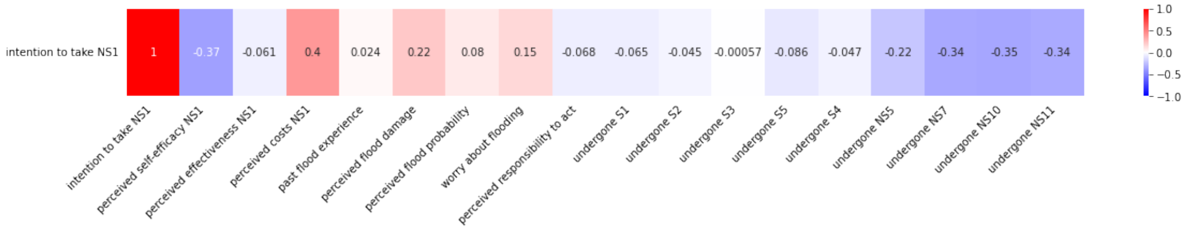


(d)

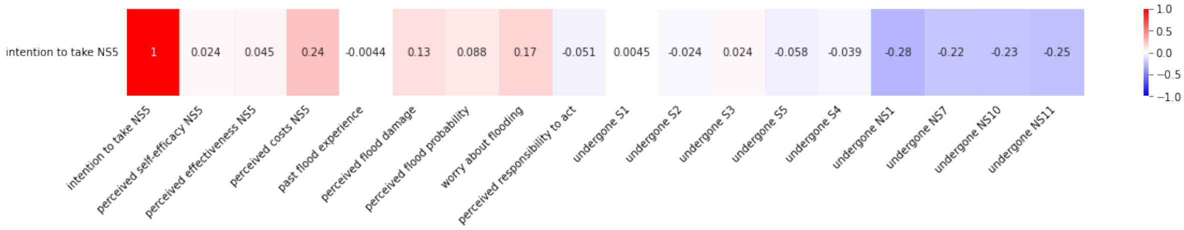


(e)

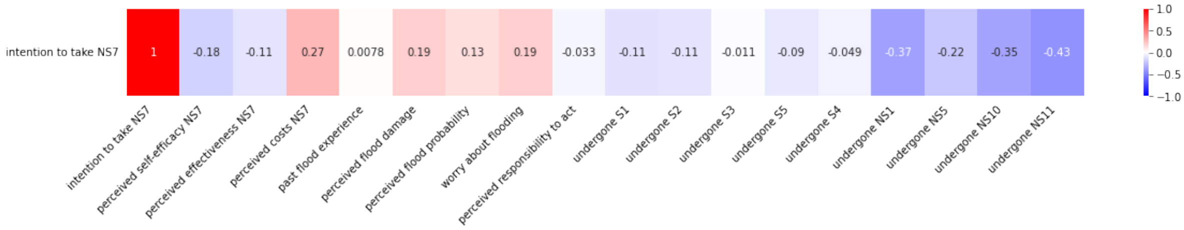
Figure D.1: The correlation between the intention to take a measure in the near future and the variables considered for the decision making of the household agents for structural measure 1 (a), 2 (b), 3 (c), 4 (d), 5 (e). Source: own calculations based on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022).



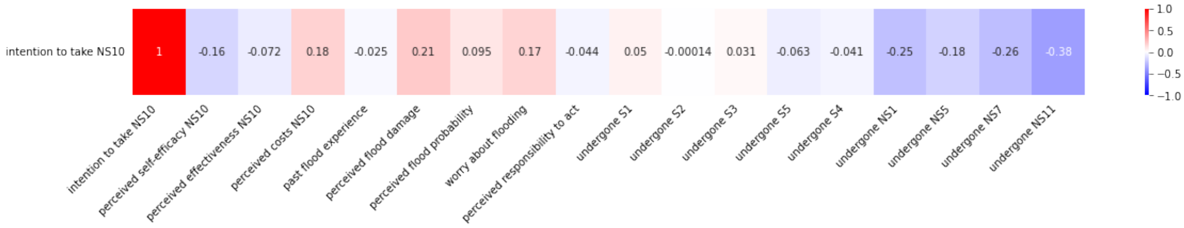
(a)



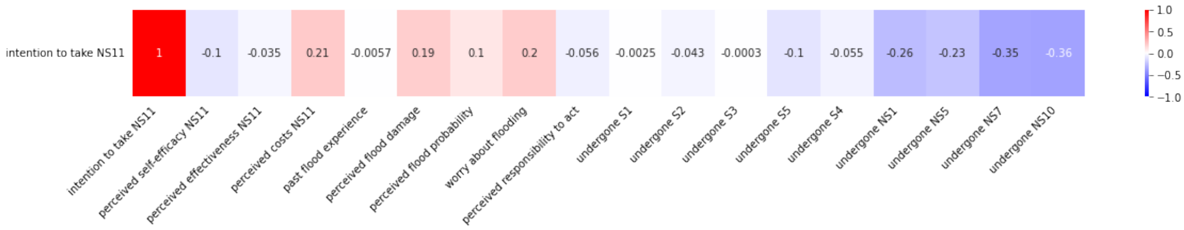
(b)



(c)

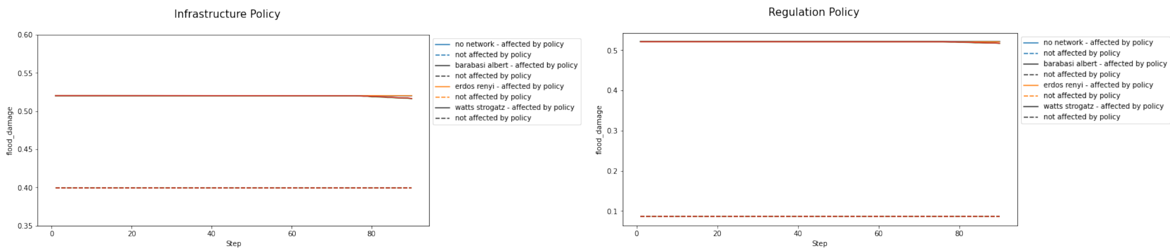


(d)



(e)

Figure D.2: The correlation between the intention to take a measure in the near future and the variables considered for the decision making of the household agents for non-structural measures 1 (a), 5 (b), 7 (c), 10 (d), 11 (f). Source: own calculations based on the ERC SCALAR dataset (Noll, Filatova, Need, & Taberna, 2022).



(a) (b)

Figure D.3: Damage factor over the different networks for the infrastructure policy (a) and the regulation policy (b) differentiating between households affected by the policy and those that are not. Source: own analysis

D.2.3. Communication Policy

In the following Figures D.4, D.5 and D.6 show the influence of the communication policy on the perception factors of the household agents is depicted.

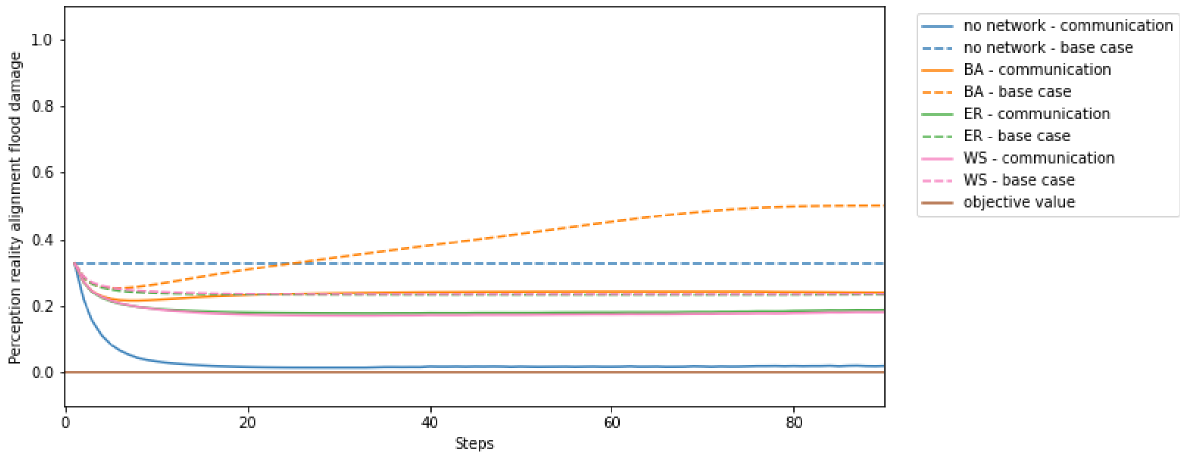


Figure D.4: (a) Alignment of perceived flood damage with actual flood damage (absolute value of difference between the two) for base case and communication policy for the different networks. Source: own analysis.

D.2.4. Subsidies Policy

The effect of the subsidies policy on the uptake of structural measures (only structural measures are subsidised) is visualised in Figure D.7.

D.2.5. Influence Connections on Perceptions

Through the network setup, the connections influence the perceptions of a household agent. Figures D.8, D.10, and D.9 show the impact of the connections on a change of perceptions. It cannot generally be set, that more connections lead to a higher or lower change. What can be said though is that the number of connections with BA does not have an impact on the magnitude of change.

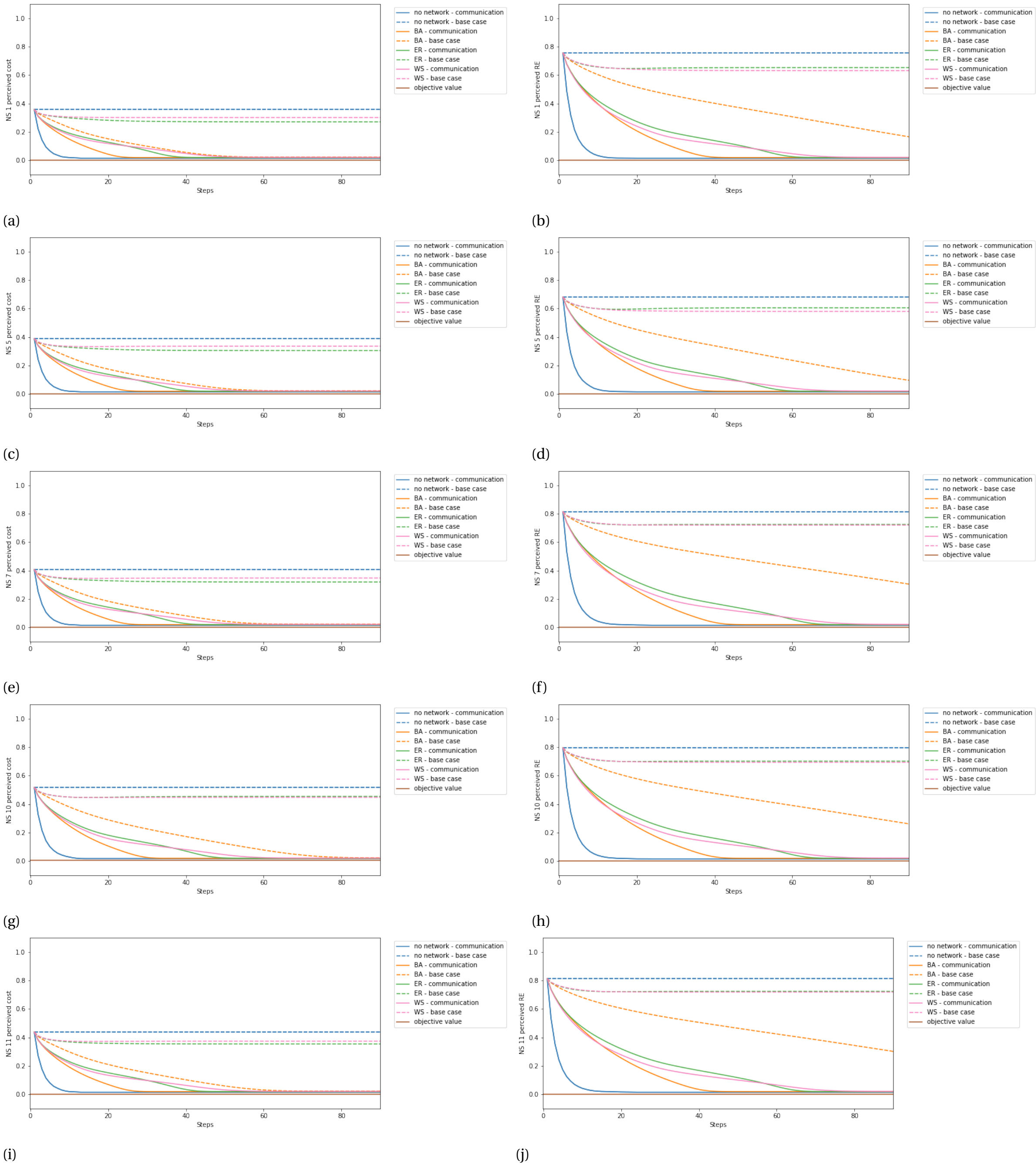


Figure D.5: Overall perception regarding the non-structural measures. (a), (c), (e), (g), (i) for perceived cost; (b), (d), (f), (h), (j) for perceived response efficacy (effectiveness) of considered non-structural measures. Source: own analysis.

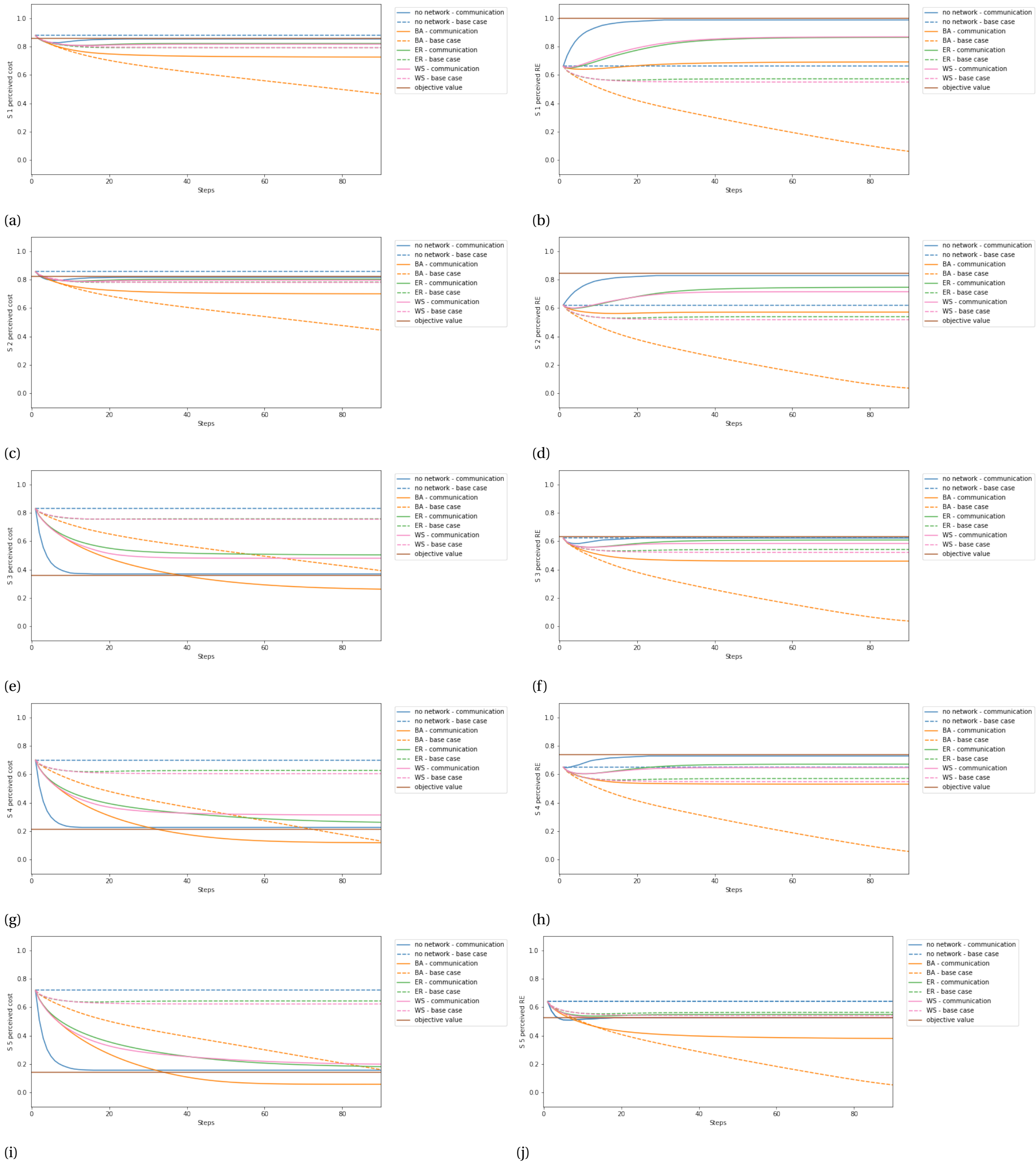
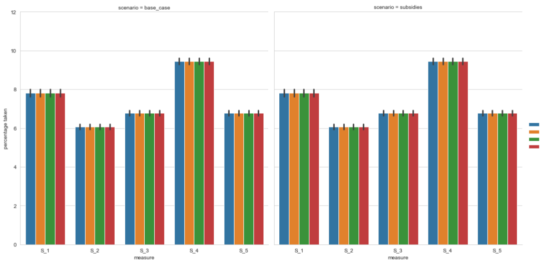
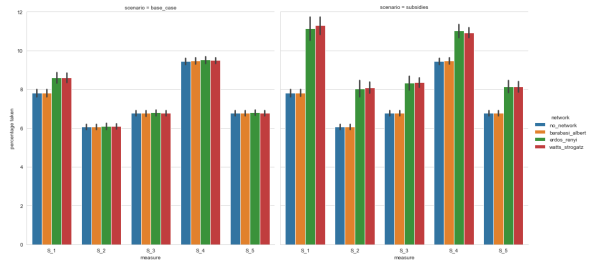


Figure D.6: Overall perception regarding the structural measures. (a), (c), (e), (g), (i) for perceived cost; (b), (d), (f), (h), (j) for perceived response efficacy (effectiveness) of considered structural measures. Source: own analysis.



(a)



(b)

Figure D.7: The distribution of the percentage of structural measures taken with and without the subsidies policy for the different networks at (a) step 1 - initialisation; (b) step 90 - end of the simulation. Source: own analysis.

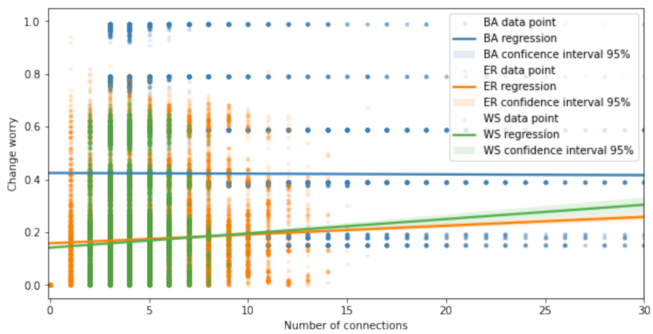


Figure D.8: Relation between change in worry (absolute difference worry at start and end of simulation) and number of connections for the different network setups. Source: own analysis.

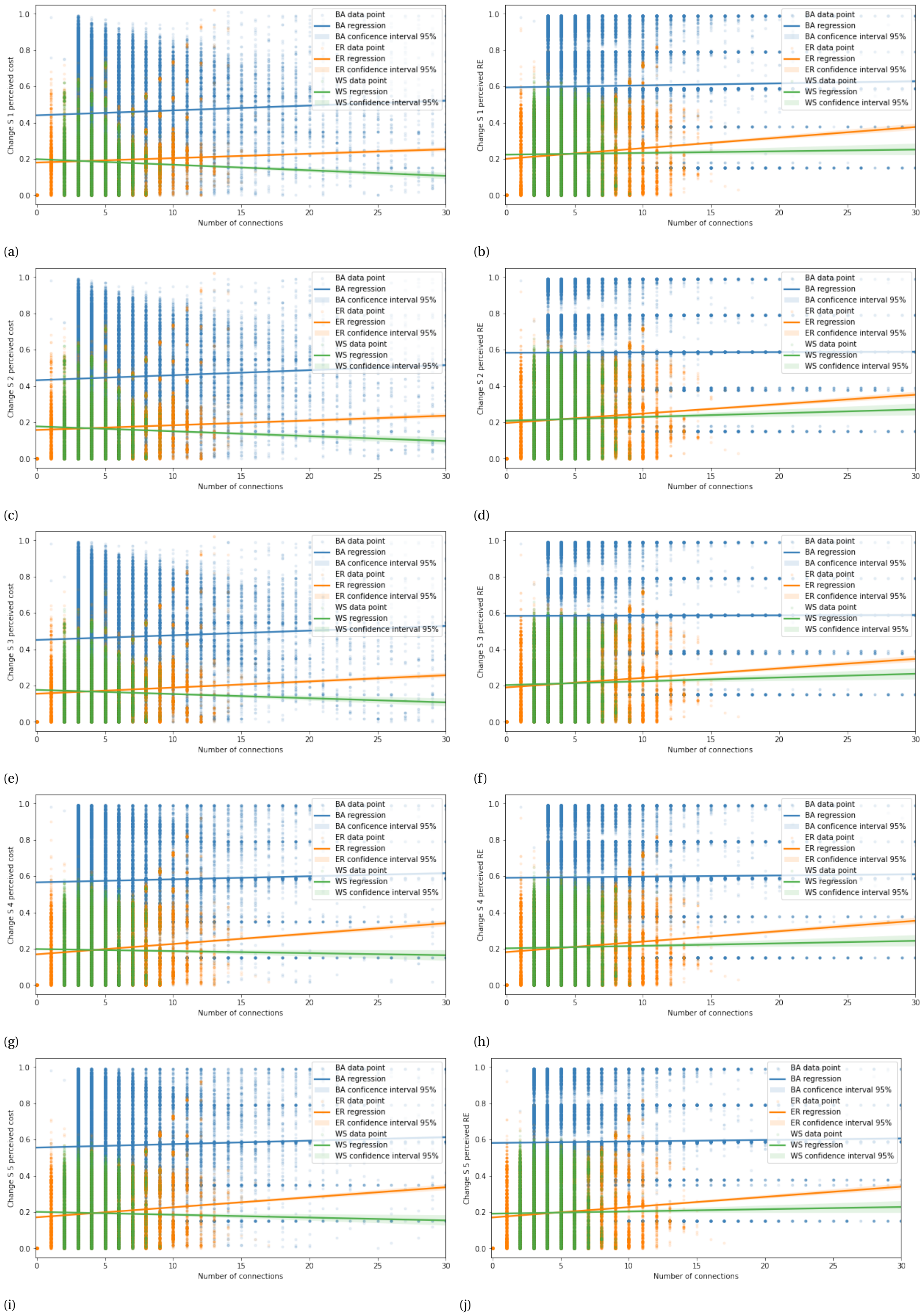


Figure D.9: Perception change (absolute difference between start and end of simulation) in comparison to number of connections regarding the structural measures. (a), (c), (e), (g), (i) for perceived cost; (b), (d), (f), (h), (j) for perceived response efficacy (effectiveness) of considered structural measures – see Section A.1.2 for considered measures. Source: own analysis.

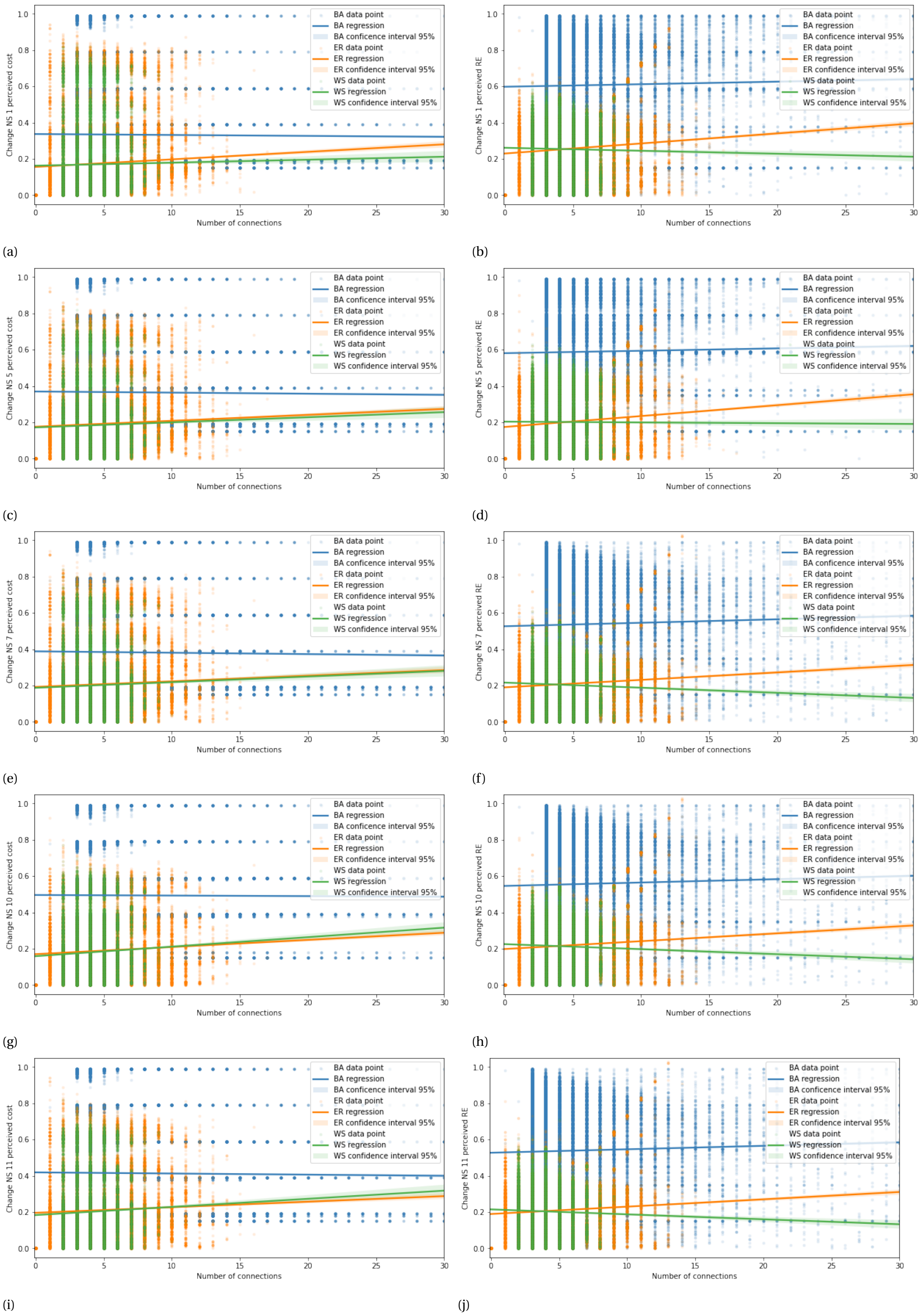


Figure D.10: Perception change (absolute difference between start and end of simulation) in comparison to number of connections regarding the non-structural measures. (a), (c), (e), (g), (i) for perceived cost; (b), (d), (f), (h), (j) for perceived response efficacy (effectiveness) of considered non-structural measures – see Section A.1.2 for considered measures. Source: own analysis.

E

EPA Program Requirements

The relation of the main Engineering and Policy Analysis master thesis requirements to this thesis are explained in Table E.1.

Table E.1: Requirements for an EPA thesis and how this thesis fits into them

Criterion	**Explanation**
Relation to Grand Challenge	This thesis focuses dealing with the consequences of climate change. The focus is on climate change adaptation, more specifically on private adaptation to flooding.
Application of analytical techniques for problem analysis and exploration	The problem was analysed to identify the concepts that are needed to conceptualise the problem. Using empirical data from Houston (TX, USA) an agent-based model was constructed that simulates the uptake of private adaptation measures by households.
Exhibits systems and multi-actor perspective	The system was analysed and destructed in order to allow for the conceptualisation and construction of the agent-based model. A multi-actor perspective is present through the interaction between households and policies.
Advice for decision makers and relevance for (public) policy domain	Different policies were tested. Examining their performance over different assumptions of social networks provided insights into the performance of policies. Based on this, recommendations for policy makers could be made.

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