From Attachment to Action: Exploring the Role of Place Attachment in Households’ Flood Adaptation

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From Attachment to Action: Exploring the Role of Place Attachment in Households' Flood Adaptation

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Student Number: 5721482

in partial fulfilment of the requirements for the degree of

Master of Science

in Engineering and Policy Analysis

at the Delft University of Technology,

to be defended publicly on Friday August 30, 2024 at 11.00 AM.

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This thesis was made possible by the survey data provided through the European Research Council's SCALAR project (grant agreement no. 758014), funded by the European Union's Horizon 2020 Research and Innovation.

Acknowledgements

I would like to begin by expressing my deepest gratitude to Prof. Dr. T. Filatova for her unwavering support throughout this long and challenging journey. Her invaluable guidance has played a pivotal role in bringing my ideas together and shaping this thesis into its current form. I am also deeply thankful to Dr. A. Ghorbani, whose insights and feedback during our meetings have contributed significantly to the development of my work. A special note of thanks goes to Thorid; her contributions and encouragement have been a tremendous help along the way.

My deepest thanks go to my family, whose support has been a source of strength throughout this process. Even in moments when I doubted myself, they never stopped believing in me. I am deeply thankful to my dear mother, who has always been there for me, providing her unstinting support every step of the way. I would also like to thank my brother, Serhan Tezgeç, for always listening to my concerns and offering motivation when I needed it most. I also sincerely thank my father for his support throughout this journey. To my beloved partner, Emanuele: your patience and constant support have been my rock. You inspire me to be my best self, and I am deeply grateful for your presence in my life.

Lastly, I would like to thank all my friends who have been there for me from the very beginning of this journey, offering their time, encouragement, and support right up to the final defense. Whether you are close by or halfway around the world, your support has meant everything to me.

C. Tezgec
Delft, August 2024

Executive Summary

Climate change has significantly increased the frequency and intensity of flooding, leading to widespread destruction and substantial economic losses. While government-led adaptations are crucial, they are insufficient on their own, highlighting the necessity for household-level adaptations. However, household decisions are not purely rational; rather, they are influenced by many psychological and social factors. Considering the crucial role of households in reducing flood risk, policymakers need to understand their decision mechanisms in order to create tailored policies that help increase household-level adaptation.

Given the growing interest in this area, many studies have been conducted to understand what motivates households to undertake adaptation measures. It has been found that several factors contribute to this decision-making process, such as risk perception, coping appraisal, and personal experience. However, among these factors, **place attachment** has not been fully explored and analyzed. Although existing literature examines the relationship between place attachment and flood adaptation, it often neglects the dynamic nature of place attachment. Place attachment not only influences adaptation decisions but is also shaped and changed by various factors, including the adaptations themselves. This thesis, therefore, approaches place attachment as a **dynamic concept**, exploring how it evolves over time and interacts with household-level adaptations to provide a more comprehensive understanding of its impact on flood damage reduction.

To capture the interplay between place attachment and household adaptation decisions, an agent-based model (ABM) was utilized, supported by statistical analysis, data analysis, and a literature review. We adopted a case study approach in the Houston (Texas) region, a coastal urban area prone to flooding, employing previously collected survey data from the U.S. to calibrate the models and provide an empirical foundation for the research. The survey data included seven different questions directly targeting place attachment. To conceptualize place attachment based on these questions, we employed Exploratory Factor Analysis. Our analysis revealed two different dimensions of place attachment. While the first dimension involved active participation in the community, the second reflected a more passive characteristic, supporting the conceptualization of place attachment into 'active' and 'traditional' dimensions as discussed in the literature. To conceptualize households' flood adaptation behavior, we relied on the Protection Motivation Theory (PMT), which was extended to include active and traditional place attachments. The structural adaptation measures available in the survey data were categorized into elevation, dry-proofing, and wet-proofing. For each measure, we ran a logistic regression to quantify how the PMT variables would affect households' adaptation intention. After identifying the factors that drive changes in active and traditional place attachment based on the literature and their characteristics, we also ran two linear regressions to quantify the relationships between these factors and the respective dimensions of place attachment. Three adaptation measures, namely elevation, wet-proofing, and dry-proofing, were also included in the linear regression for active place attachment. Then, we incorporated these regression results into the ABM to explore how dynamic place attachment, along with PMT variables, shapes adaptation decisions over time.

We created two main experiments alongside our sensitivity analysis on initial place attachment levels: introducing a flood event and constructing a large-scale public protection measure. We found that both active and traditional place attachments play a role in influencing households' flood adaptation decisions and their subsequent impact on damage reduction, where active place attachment has a more

prominent effect. A key finding was the synergistic relationship between these two types of attachment. When households have both strong active and traditional place attachments, the combined effect drives higher adaptation rates and more reductions in flood damage. We also found that the impact of flood experiences on household adaptation was profoundly influenced by place attachment. If a flood weakened place attachments, the increase in adaptation decreased, becoming almost identical to the baseline where no flooding occurred. We also observed that public protection measures can significantly reduce flood risk; however, if they damage place attachment, they reduce household-level adaptations. If these public measures fail, the lack of household-level adaptation can put people in greater danger. Our results also highlighted the nuanced relationship between adaptation measures and active place attachment. While elevation and dry-proofing weakened active place attachment, wet-proofing strengthened it based on the survey data. We concluded that the interplay between place attachment and household-level climate adaptation formed a complex relationship. While place attachment increases flood adaptation, the adaptation measures can, in turn, either strengthen or weaken place attachment depending on the nature of the changes, resulting in mixed outcomes for flood resilience.

This thesis contributes significantly to the literature by focusing on the dynamic nature of place attachment, a critical aspect primarily overlooked in previous research. By integrating place attachment into the PMT as a multi-dimensional and dynamic concept, this study offers a more comprehensive understanding of how place attachment evolves over time and interacts with household adaptation decisions. We also examine the relationship between structural adaptation measures and different dimensions of place attachment, underscoring the importance of considering both the adaptations and place attachment dimensions separately to thoroughly understand their impact on flood resilience.

From a policy perspective, the findings of this research underscore the importance of leveraging place attachment in policies aimed at motivating household-level flood adaptation. Since both active and traditional place attachments increase the probability of households implementing adaptation measures, policymakers should consider strategies that foster these attachments.

While this research has provided valuable insights by studying place attachment as a dynamic concept, there are several areas for improvement. These include a small sample size in later survey waves, reliance on limited literature for modeling dynamic place attachment, and the absence of panel or before-and-after data to capture how adaptations impact place attachment over time. Future studies should include more targeted survey questions on place attachment to a larger, balanced population. Conducting surveys in specific neighborhoods rather than over a large area could offer more detailed insights for policymakers. Furthermore, collecting panel data could help better understand the factors influencing place attachment over time. These improvements would contribute to a more comprehensive understanding of the dynamics of place attachment and help policymakers use it more effectively to promote household adaptation to reduce looming damages.

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1
Introduction

Climate change is exacerbating severe weather events worldwide, causing widespread destruction and increased losses (IPCC, 2023). Events in 2023 alone clearly illustrate this worrying trend: a record-breaking heatwave in July, intense wildfires in places such as Hawaii, Canada, and Europe, and significant flooding events in Libya, Greece, and New Zealand (WMO, 2023). Of all these extreme events, floods stand out as the most prevalent and destructive. Floods were responsible for almost half of all climate-related disasters between 2000 and 2019, affecting 1.6 billion people and causing 651 billion dollars of damage (UNDRR, 2020). When the ongoing impacts of climate change are combined with socio-economic trends, this devastating impact is expected to increase in the forthcoming years (IPCC, 2023; Jongman et al., 2012). All of this further increases the urgency for flood adaptation measures across all societal levels.

Government-led flood adaptation measures, particularly the implementation of large-scale infrastructure projects, play a crucial role in addressing climate change. However, these alone are inadequate in the face of heightening risks (Driessen et al., 2018; Takao et al., 2004). Hence, it is necessary to take complementary adaptation measures at the household level, as they can substantially reduce the impacts of floods (Bubeck et al., 2012; Poussin et al., 2015; Takao et al., 2004). Many adaptation measures are available to households, varying in the continuum of effort required and effectiveness in reducing damage (Duijndam et al., 2023; Noll et al., 2022). Elevating houses and reinforcing walls can exemplify high-effort measures (i.e., structural), whereas measures like purchasing sandbags and storing valuable assets in high places fall under low-effort measures (i.e., non-structural) available to households (Noll et al., 2022). Despite facing substantial risks and having numerous options to reduce damage, many households have yet to adopt flood adaptation measures. Considering the key role of households in reducing flood risk, policymakers need to understand the underlying mechanisms of households' adaptation decisions to create tailored policies that help increase household-level adaptation. However, this task is challenging because household decisions are shaped by various psychological and social factors rather than being purely rational (van Valkengoed & Steg, 2019).

Given the key role of households in implementing adaptation measures, numerous studies have been conducted to explore the behavioral and social drivers that motivate households to undertake such actions (e.g., Bubeck et al., 2018; Duijndam et al., 2023; Noll et al., 2022; van Valkengoed and Steg, 2019). These studies have provided valuable insights into factors, such as risk perception, coping appraisal, and personal experiences, that influence household decisions. However, the role of place attachment in these decisions remains understudied despite its importance for adaptation

(Devine-Wright, 2009). This gap likely exists because place attachment involves a wide range of personal and contextual factors, making it more difficult to capture and quantify compared to other subjective attributes like risk perception. This difficulty also manifests itself in the existence of different conceptualizations of place attachment, in which multi-dimensional place attachment is measured in various ways (e.g., Lewicka, 2011a; Raymond et al., 2010; Scannell and Gifford, 2010). Although challenging, studying place attachment is crucial as it can reveal how emotional connections to a place motivate households to take adaptive actions or hinder them from doing so (Amundsen, 2015; Devine-Wright & Quinn, 2020; Fresque-Baxter & Armitage, 2012). Some studies have examined the relationship between place attachment and flood adaptation (e.g., De Dominicis et al., 2015; Domingues et al., 2021; Parreira and Mouro, 2023), yet they did not look into the complex interplay between place attachment and other factors and the dynamic nature of place attachment in shaping household adaptation decisions. This thesis aims to bridge these gaps by exploring the comprehensive, dynamic relationships between place attachment and household adaptation decisions on flooding. To address the knowledge gap, this research employs statistical and data analysis techniques, and computational social science simulations. This research makes its scientific contribution by deepening our understanding of the role of various dimensions of place attachment in driving household adaptation behavior by quantifying how both evolve over time. Its societal relevance lies in enabling better-designed and more effective flood adaptation strategies by providing comprehensive insights into the role of place attachment in household adaptation decisions.

The structure of this thesis is as follows. Chapter 2 reviews the current research on the factors that shape household adaptation decisions and then examines studies that particularly focus on the relationship between place attachment and flood adaptation decisions. This is followed by identifying research gaps and formulating research questions. Chapter 3 provides the main research approach of the thesis and a detailed explanation of the methods and data sources. Chapter 4 gives place attachment index creation, exploratory data analysis, and regression results. In light of these findings, Chapter 5 explains the model and experiments. Finally, Chapter 6 provides the model results, followed by the discussion and conclusion in Chapter 7, where all findings come together to answer the research questions.

2

State of the Art

In this chapter, relevant studies are reviewed. Initially, Section 2.1 provides a general understanding of factors influencing households' decision to take flood adaptation measures. Following this, in Section 2.2, the leading behavioral theory in flood adaptation studies is introduced. In Section 2.3, the focus shifts to place attachment, which is determined as a more specific factor influencing households' decision-making. Section 2.3.1 first provides an overview of the place attachment concept and the field's current state. Following this, studies exploring the relationship between place attachment and flood adaptation are discussed in Section 2.3.2. Then, in Section 2.3.3, how changes in a place affect place attachment is examined. Upon reviewing these two bodies of literature, the research gap and questions are presented in Section 2.4.

2.1. Factors Influencing Household Flood Adaptation

A growing body of literature has examined the underlying factors influencing households' decisions to take flood adaptation measures. Most of the research has emphasized that households do not make purely rational decisions, as social and psychological factors significantly influence their decision-making (Bubeck et al., 2018; Duijndam et al., 2023; Grothmann & Reusswig, 2006; Noll et al., 2022; van Valkengoed & Steg, 2019). Risk perception stands out as a significant factor; households with a higher perceived risk of flooding tend to adapt more as they recognize the necessity of adaptation measures (Bubeck et al., 2018; Duijndam et al., 2023; Grothmann & Reusswig, 2006; van Valkengoed & Steg, 2019). Noll et al. (2022) confirmed that universally across countries, worry influences adaptation decisions more than perceived flood damage and perceived flood probability, with this heuristic component having a positive role in contrast with a near zero influence of the two rational components of risk perception. Past flood experience has also been found to be a motivator for undertaking flood adaptation measures (Duijndam et al., 2023; Grothmann & Reusswig, 2006). According to Duijndam et al. (2023), flood experience may also indirectly influence adaptation behavior by increasing worry, perceived risk, and perceived damage. Besides, access to information plays a crucial role in shaping adaptation decisions since it helps close the gap between actual and perceived risk (Bubeck et al., 2018). In contrast, van Valkengoed and Steg (2019) found the effect of knowledge and experience on adaptation to be minimal. Self-efficacy and response effectiveness are other crucial factors influencing adaptation behavior, as discovered by (Grothmann & Reusswig, 2006; Noll et al., 2022; van Valkengoed & Steg, 2019). People who believe they can implement adaptation measures and that these measures effectively protect against flooding tend to adapt more. Conversely, the perceived cost of measures has a negative impact on adaptation uptake (Grothmann & Reusswig, 2006; Noll et al., 2022). Additionally, households' adaptation decisions are significantly influenced by social networks (Bubeck et al., 2018; Noll et al., 2022; van Valkengoed & Steg, 2019). Observing the actions of others in their social network positively affects an individual's coping appraisals, increasing their motivation to take protective measures. Noll et al. (2022) also emphasize the importance of expectations within an individual's social network. Interestingly, although place attachment is a factor at the intersection of social and psychological factors, it has not been considered in this group of literature, except for the study by van Valkengoed and Steg (2019). They discovered a statistically significant, albeit small, positive relationship between place attachment and adaptation.

2.2. Protection Motivation Theory

In Section 2.1, we discussed various factors influencing household decisions to adapt to flood risks, many of which are directly related to the core concepts of Protection Motivation Theory (PMT), which are threat and coping appraisal. This makes PMT a particularly prominent theory for representing the adaptation behavior of households to climate change (van Valkengoed & Steg, 2019).

PMT is a psychological theory explaining how fear appeals can lead to attitude changes, particularly in behaviors related to health (Floyd et al., 2000; Rogers, 1983). PMT mainly relies on two mental procedures: 'threat appraisal' and 'coping appraisal' (Floyd et al., 2000). Initially, individuals evaluate how serious a threat is and their likelihood of being affected. In the next step, known as coping appraisal, individuals assess whether they can cope with the threat based on their beliefs about the adaptation measure's effectiveness, their confidence in their abilities, and the expected cost of the measure. These two processes shape individuals' intention to start, continue, or stop the adaptation measure (Floyd et al., 2000). However, it is important to note that intention does not always turn into action, mainly due to the limitations in money and time (Floyd et al., 2000; Grothmann & Reusswig, 2006).

The application of PMT to flood risk studies was pioneered by Grothmann and Reusswig (2006), as illustrated in Figure 2.1. Since then, it has been widely used in flood adaptation studies to explain households' adaptation decisions and has been extended to include additional factors (e.g., Duijndam et al., 2023; Holley et al., 2022; Noll et al., 2022; Poussin et al., 2014). Common extensions to the framework often include factors such as already implemented adaptation measures, past flood experience, trust in government, sociodemographic variables like age and education, and social influence (Bubeck et al., 2018; Duijndam et al., 2023; Noll et al., 2022; Poussin et al., 2014). However, to our knowledge, place attachment has only been included in an extended PMT in a study conducted by Holley et al. (2022), where it was treated as a uni-dimensional concept. However, due to space limitations in the survey, they only measured participants' self-efficacy as part of the coping appraisal and thus applied a limited version of the PMT.

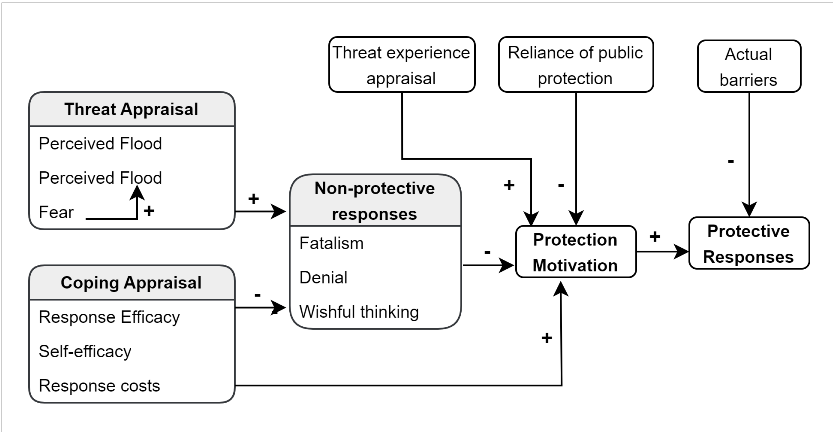


Figure 2.1: Application of PMT to households' flood adaptation behavior. *Source:* Adjusted from "People at Risk of Flooding: Why Some Residents Take Precautionary Action While Others do not," by Grothmann and Reusswig, 2006, *Natural Hazards*, *38*, p.105.

2.3. Place Attachment in the Context of Flood Adaptation

2.3.1. Understanding Place Attachment

Place is not limited to physical features; it represents a complex concept that incorporates social and psychological aspects. People see a place not just as a space but as a "meaningful location" shaped by their experiences and emotions (Lewicka, 2011b, p.213). Similarly, Tuan (1977) argues that space transforms into a place when individuals become familiar with it and attach meanings to it. This evolving relationship forms the foundation for place attachment, which is traditionally defined as the cognitive and emotional bonds people develop with their communities and places over time (Brown & Perkins, 1992).

People can develop attachments to their places for different reasons. Their attachment can arise from social factors, such as close relationships with neighbors, or from physical characteristics, like the environment's attractiveness (Hidalgo & Hernandez, 2001; Lewicka, 2011b). These attachments are shaped by personal interactions, community ties, and environmental features, highlighting the multifaceted nature of place attachment. Besides, the strength of these bonds can vary significantly between individuals and over a person's life. These changes could be attributed to various factors, including personal experiences, age, education, and environmental changes (Lewicka, 2011b).

The complexity of place attachment has led researchers to propose various conceptual frameworks. While some scholars conceptualize place attachment as uni-dimensional, others acknowledge its multifaceted nature and propose a multi-dimensional approach (Hernández et al., 2020). For instance, Lewicka (2011a) proposes a conceptualization that consists of two types of attachment: active and traditional. Active attachment is built on dynamic interactions with the community and place, whereas traditional attachment is based on a more passive and inherited connection. Additionally, Lewicka (2011a) identifies three types of non-attachment, which can be seen in Figure 2.2a. Lewicka (2011a) highlights the necessity of using multi-dimensional place attachment based on her findings that have demonstrated people can develop different types of attachment to their places. Another example of the multi-dimensional place attachment concept is created by Raymond et al. (2010), which consists of five dimensions that capture personal, social, and environmental elements (see Figure 2.2b). This variation in the conceptualization has been highlighted by many researchers, including Giuliani and Feldman, 1993; Hernández et al., 2020; Hidalgo and Hernandez, 2001; Lewicka, 2011b. They argue that the dissensus on the conceptualization of place attachment results in ambiguous findings and decelerates progress in the field.

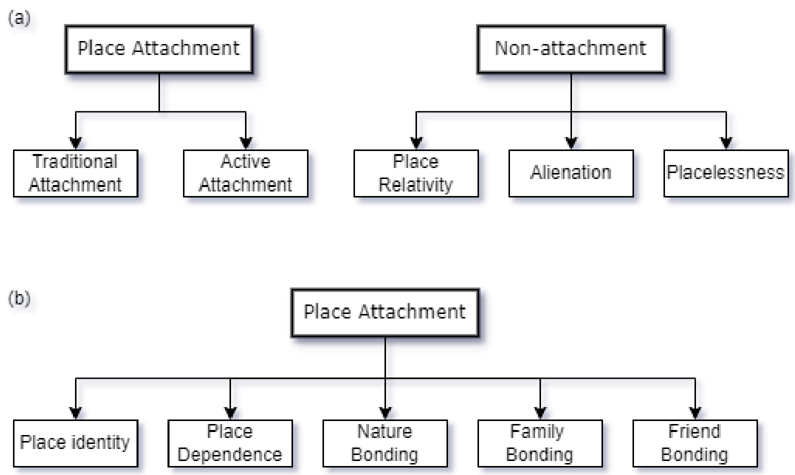


Figure 2.2: Multi-dimensional place attachment conceptualizations by (a) Lewicka (2011a) and (b) Raymond et al. (2010). Source: Figure created by the author.

2.3.2. Place Attachment and Flood Adaptation

Many researchers have investigated the effect of place attachment on flood adaptation, including De Dominicis et al., 2015; Domingues et al., 2021; Holley et al., 2022; Lie et al., 2023; Mishra et al., 2010; Parreira and Mouro, 2023. However, as discussed in Section 2.3.1, the findings, as well as the conceptualization of place attachment, vary across studies. Place attachment is conceptualized in both uni-dimensional (see De Dominicis et al., 2015; Domingues et al., 2021; Holley et al., 2022) and multi-dimensional (see Lie et al., 2023; Mishra et al., 2010; Parreira and Mouro, 2023) frameworks. Table 2.1 provides an overview of these studies.

De Dominicis et al. (2015) discovered that place attachment negatively moderated the relation between adaptation intention and risk perception, particularly in a place with a high level of flood risk. This finding indicates that even when individuals' risk perception is high, their strong place attachment can decrease the intention to implement flood adaptation measures. Likewise, Holley et al.) (2022) showed that place attachment lessens the effects of coping and threat appraisal on disruptive adaptation intentions such as relocation. Conversely, place attachment was found to be a motivator for intention to take non-disruptive measures like supporting flood-related policies (Holley et al., 2022). In the same vein, Lie et al. (2023) reported that although people know the risk, their stronger place attachment led them to underestimate it, thereby being reluctant to relocate but willing to implement measures in situ, enabling them to stay. This mixed finding suggests that place attachment may work both as a mediator and moderator between adaptation and risk perception. In contrast to earlier findings (see Section 2.1), a study conducted by Domingues et al. (2021) discovered a negative relationship between risk perception and flood preparedness. People with stronger place attachments were associated with a lower risk perception; however, they still underwent some adaptation measures despite having a low-risk perception (Domingues et al., 2021). Parreira and Mouro (2023) deployed the framework created by Lewicka (2011a) to study relationships between active (place discovered) and traditional place attachment (place inherited) and active (e.g., problem-solving and expressing emotions) and passive adaptation measures (e.g., seeking relaxation, self-protection, and maintaining routine). They found that risk perception is only a mediator between active place attachment and active measures, not for the traditional pair. This implies that active adaptation measures are predicted positively by risk perception, while active place attachment positively influences risk perception. Another study employed a different multi-dimensional place attachment concept, consisting of economic, ancestry, and religious aspects (Mishra et al., 2010). While people with the first two dimensions were found to be prepared for floods, religion was not a significant factor.

Table 2.1: Summary of the main findings from studies on place attachment and adaptation. Note: + and - represent positive and negative relations, respectively.

Study	Methodology	Place Attachment Conceptualization	Adaptation Measures	Main Findings
De Dominicis et al. (2015)	Regression Analysis	Uni-dimensional	- Seek flood-related information - Avoid risky behaviors - Store essential items	- Place Attachment - Adaptation (−) - Place attachment negatively moderates the relationship between risk perception and adaptation, especially in high-risk contexts.
Domingues et al. (2021)	Structural Equation Modeling	Uni-dimensional	- Preparedness for disasters - Have a contingency plan	- Place attachment - Risk perception (−) - Risk perception - Adaptation (−)
Holley et al. (2022)	Regression Analysis	Uni-dimensional	- Relocate within or outside the state - Implement elevation or floodproofing - Support flood risk reduction initiatives - Pay extra taxes - Support climate change regulation	- Place attachment - Disruptive adaptation (-) - Place attachment - Non-disruptive adaptation (+)
Lie et al. (2023)	Qualitative Analysis	Multi-dimensional	Not mentioned explicitly	- Place attachment - Risk perception (mixed) - Place attachment - Adaptation (mixed) - Place attachment works both as a moderator and mediator between adaptation and risk perception.
Mishra et al. (2010)	Regression Analysis	Multi-dimensional	- Maintain fully operational radios - Keep flashlights and candles on hand - Locate nearby emergency shelters	- Place attachment - Risk perception (+) - Place attachment - Adaptation (+) - Economic and family connections positively influence flood preparedness. - Religious attachment does not.
Parreira and Mouro (2023)	Mediation Analysis	Multi-dimensional	- Active: problem-solving and expressing emotions - Passive: seeking relaxation, self-protection (staying inside when the risk is high), and maintaining routine	- Place attachment - RP (+ for active) - Place attachment - Adaptation (+ for active) - Risk perception is a mediator between active attachment and coping. - Traditional attachment does not significantly influence risk perception or coping.

2.3.3. Changing Places and Place Attachment

Most studies in this field explore how place attachment shapes people's risk perceptions and, consequently, flood adaptation behavior (see Section 2.3.2). However, human or environmentally-induced changes, such as adaptation measures or natural disasters, have an impact on attachment in return. This opposite direction has been investigated only by a limited number of researchers (namely, Brown and Perkins, 1992; Clarke et al., 2018; Devine-Wright, 2009; Quinn et al., 2018, 2023; Wirth et al., 2016). Brown and Perkins (1992) examine disruptions in people's place attachments resulting from changes in their sociophysical environment due to voluntary displacement and disasters. They emphasize that the impact of these disruptions depends on the strength of pre-disruption place attachments and on the characteristics of the disruption itself, such as its predictability or severity. For instance, planned relocation allows people to gradually detach from their old places and prepares them for new places, whereas disasters such as flooding cause more sudden and unexpected impacts on people's lives, further weakening their attachment. After the disruption, they argue, forming new attachments is possible, but careful strategies are required, especially to (re)create a space that closely resembles its previous version (Brown & Perkins, 1992). Anton and Lawrence (2016) and Devine-Wright (2009) have conducted studies whose results support Brown and Perkins (1992)'s statement on the significance of the level of pre-disruption place attachment. Both papers argue that individuals with a strong initial attachment are more inclined to perceive changes as unfavorable and threatening for their place and thus for their place attachment.

On the one hand, changes in the place can improve people's place attachment if carefully designed and implemented. Wirth et al. (2016) studies the positive impacts that a change can have on place attachment. They demonstrate that urban changes that are perceived as improvements or maintain a certain level of familiarity with the place influence place attachment positively. On the other hand, changes can be perceived negatively by residents, leading to a reduction in their place attachment. For example, Clarke et al. (2018) found that although survey participants in Dublin acknowledged the necessity of flood defenses, they were not supportive of them. This lack of support was caused by the participants' place attachments being rooted in aesthetic values, leading them to view the alterations as disruptive to their place. This situation illustrates how beneficial transformations can negatively be viewed if they conflict with the existing reasons for place attachment. Furthermore, Quinn et al. (2018) extended the dynamic relationship between place attachment, risk perception, and adaptation to include mobility, as shown in Figure 2.3 created by the authors. They evaluated this conceptual model by comparing two towns with similar flood risks: one that constructs hard protection measures and another that continues to live with the flood. The hard protection measures, such as dikes, while aimed at decreasing flood risk, also alter the landscape (Quinn et al., 2018). Besides physical changes, it changes the socioeconomic characteristics of the area, which in turn increases mobility and drives further changes (Quinn et al., 2018). Consequently, it redefines what the place means to people and results in various types and levels of place attachment.

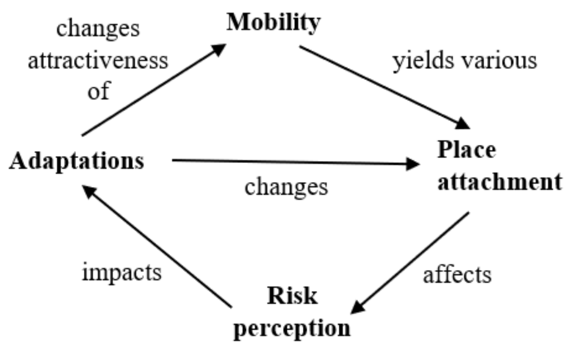


Figure 2.3: Conceptual model showing how place attachment, risk perception, adaptation, and mobility are interconnected. *Source:* Adjusted from "The dynamic relationship between sense of place and risk perception in landscapes of mobility," by Quinn et al., 2018, *Ecology and Society*, *23*(2), p.39.

Quinn et al. (2018) tested their conceptual model with large-scale flood adaptation, given that the main focus of their study was mobility. However, during the development of the model, they also mentioned the impact of household-level adaptation on place attachment without providing further detail. Harries (2008) found in his study conducted in the United Kingdom that people often chose to "feel secure" over to "be secure," leading them not to adapt. In other words, they avoided making changes to their homes, such as flood-proofing, because these modifications would serve as constant reminders of the threat, making them feel less secure in their houses. This relates to the concept of ontological security, where maintaining a sense of stability and continuity in one's environment is crucial (Giddens, 1984). Considering its close relation to place attachment (Lewicka, 2011a), it can be inferred that household-level adaptation influences place attachment. However, the impact of household-level adaptation on place attachment has been limited in research. Previous studies have primarily focused on large, disruptive changes, as discussed above, since their impact is bigger and easier to observe than that of small-scale changes. As the effects of climate change continue to intensify, more adaptation measures are expected to be taken in the near future across all scales; however, the effects of these measures on place attachment remain unclear (Quinn et al., 2023).

2.4. Research Gap and Questions

Following an extensive literature review, it has become apparent that place attachment is a significant factor in shaping the flood adaptation decisions of households. However, previous studies have often examined the relationship between solely place attachment and flood adaptation, overlooking the complex interplay between place attachment and other factors in shaping household adaptation decisions. Furthermore, these studies have not adequately addressed the dynamic nature of place attachment, which is influenced by changes in the surrounding environment, sociodemographic factors, and social interactions. By neglecting this dynamic aspect, studies overlook how shifts in place attachment over time influence adaptation decisions and how adaptations may not only be influenced by place attachment but could also feed back into it, changing households' future adaptation decisions. Therefore, this thesis aims to address these gaps by exploring the comprehensive, dynamic interplay between place attachment and household adaptation decisions, providing novel insights that can drive more effective flood adaptation strategies.

The main research question of this thesis can be articulated as follows:

? Main Research Question

Given the feedback between multi-dimensional place attachment and household-level climate change adaptation, how does their complex interplay over time influence damage reduction from climate-induced floods?

The following sub-questions (SQ) are formulated to address the main research question:

1. What are the different dimensions of place attachment for households, and how can they be operationalized?

Given the many conceptualizations available, the first SQ aims to explore which types are relevant to the study and how they can be operationalized. Defining and quantifying place attachment is a necessary initial step to study its role in household-level adaptation to flood risk.

2. What are the behavioral, socioeconomic, and physical factors that influence place attachment dimensions, and to what extent do these factors affect them?

The second SQ seeks to understand the various factors that drive changes in place attachment so that we can integrate the dynamic nature of place attachment into our study.

3. How do multi-dimensional place attachments, along with other socio-psychological factors, affect households' flood adaptation intentions?

The third sub-question aims to quantify the impact of place attachment and other socio-psychological factors on households' adaptation intentions so that households' adaptation dynamics can be incorporated into our research.

4. How does multi-dimensional place attachment impact households' adaptation level and flood damage reduction over time?

After defining place attachment, understanding the factors that drive its changes, and examining how they impact adaptation decisions together with other factors, the fourth SQ investigates how multi-dimensional place attachment impacts households' adaptation levels and, thus, flood damage reduction over time.

3
Research Design

This chapter starts by providing the necessary theoretical background in Section 3.1. Section 3.2 discusses the main research approach of this thesis. Following this, in Section 3.3, a detailed explanation of all the methods and data sources used in this research is provided.

3.1. Theoretical Framework

In order to answer the main research question, first, flood risk and households' adaptation behavior need to be defined. Section 3.1.1 outlines how flood risk is assessed in our study. The theoretical framework representing households' adaptation behavior is then detailed in Section 3.1.2.

3.1.1. Flood Risk

Flood risk is mostly defined as a function of three components: hazard, exposure, and vulnerability (IPCC, 2012; Kron, 2005). As climate change and urbanization exacerbate the frequency and severity of floods, the 'hazard' element of the risk is correspondingly increasing; however, the extent to which these extreme events will affect society depends primarily on the 'exposure' and 'vulnerability' levels (IPCC, 2012; Kron, 2005). Each of these components is defined as follows:

- Hazard: "the possible, future occurrence of natural or human-induced physical events that may have adverse effects on vulnerable and exposed elements" (IPCC, 2012, p. 69).
- Exposure: "the inventory of elements in an area in which hazard events may occur" (IPCC, 2012, p. 69).
- Vulnerability: "the propensity of exposed elements such as human beings, their livelihoods, and assets to suffer adverse effects when impacted by hazard events" (IPCC, 2012, p. 69).

In our study, households' flood risk is calculated by considering all of these three components. Households can reduce their flood risk through adaptation measures, which they decide to implement based on the extended PMT.

3.1.2. Extended Protection Motivation Theory

The extended PMT framework, which is used to represent households' adaptation behavior in our research, is illustrated in Figure 3.1. The original PMT is extended to include place attachment, flood experience, and previously implemented measures in line with the aim of our study. While flood experience and past adaptations are commonly included in extended PMT models in other studies (e.g., Duijndam et al., 2023; Noll et al., 2022; Wagenblast, 2022), this is not the case for place attachment as detailed in Section 2.2. To our knowledge, this study is the first to incorporate place attachment as a multi-dimensional concept into the PMT.

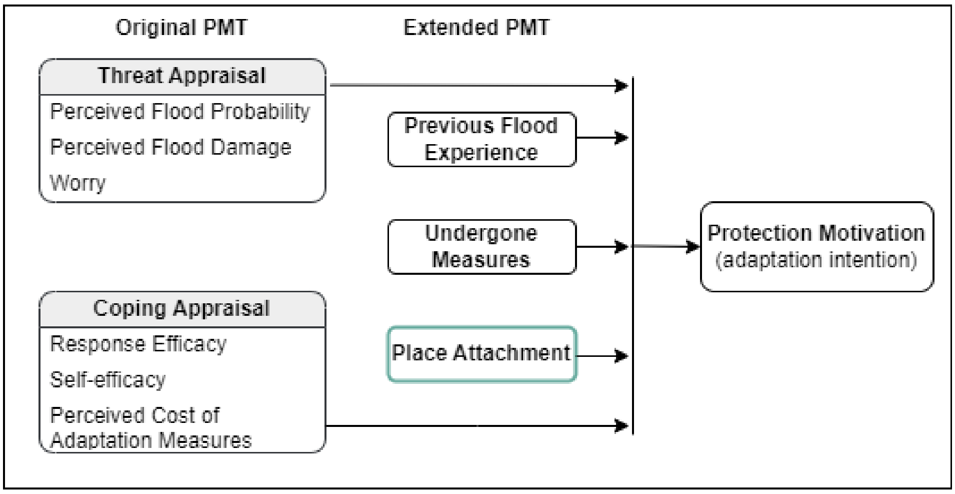


Figure 3.1: An expanded version of Protection Motivation Theory. Source: Adapted from Grothmann and Reusswig (2006) and Poussin et al. (2014), with modifications by the author.

3.2. Research Approach

The system we are investigating is a complex adaptive system consisting of households with a different place attachment, socioeconomic backgrounds, and socio-behavioral factors. These households interact with each other and their environment, learn from each other, and adapt to the changing flood risk environment, generating complex and emergent behavior patterns (Carmichael & Hadžikadić, 2019). Their place attachment levels can also change over time depending on interactions with the surrounding environment and people, as well as shifts in socioeconomic characteristics. Analyzing the system at the household level is insufficient to understand the system-level properties; a more holistic approach is needed to comprehend the bigger picture (Carmichael & Hadžikadić, 2019). In other words, emergent and complex patterns arising from household interactions cannot be fully understood by examining individual households in isolation. Similarly, statistical models, frequently used to explore the impact of place attachment on households' adaptation, only explain the relationships between variables collected at a specific moment (Gilbert & Troitzsch, 2005), failing to capture complex interactions and evolving behavioral patterns that develop over time. Given the primary goal of our research—to investigate how the interplay between household adaptations and place attachment affects flood damage reduction over time— and the characteristics under study, a simulation approach, in particular, **agent-based modeling (ABM)**, has been adopted.

Despite the numerous benefits, certain aspects, particularly the calibration and validation of models, require attention while developing the ABM. Aerts (2020) proposes using survey data or expert knowledge to realistically calibrate parameter values to ensure the empirical validity of the results. In line with the recommended solution, this study adopts a **case study**. However, it is important to acknowledge that while the case study improves the empirical validity of the model, it may pose challenges in the generalization of the results (Cartwright et al., 2022). Particularly considering that place attachment is context-dependent (Daryanto & Song, 2021), one should approach the findings with caution.

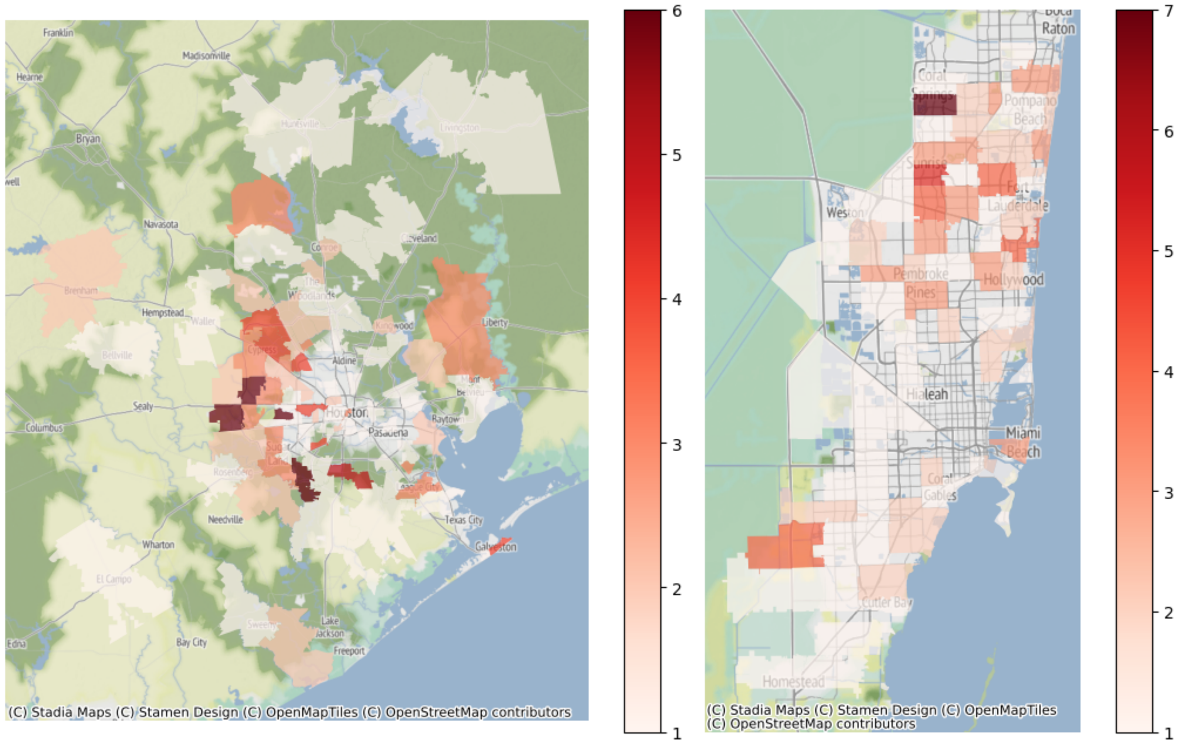
3.3. Methods

Section 3.3.1 explains how the case study is selected. Next, Section 3.3.2 details the place attachment index creation. Following this, Sections 3.3.3 and 3.3.4 describe the linear and logistic regressions utilized in this thesis. Finally, the agent-based model and the additional data sources are presented in Section 3.3.5. After explaining each method used, the research flowchart of this thesis is provided at the end of the section in Figure 3.6. This flowchart outlines the key steps of the study, illustrating how these steps are related, showing the input and output relationships, identifying the research questions they address, and specifying the chapters where each part of the research is presented.

3.3.1. Case Study

For this thesis, access to the ERC SCALAR survey data (Filatova et al., 2022; Noll, 2023; Noll et al., 2022) has been granted. This data served as the primary source for our research, used to extract place attachment dimensions and represent household adaptation behavior in our analysis. The use of real-world data strengthened the empirical validity of our results. These survey data were collected from households in coastal urban areas prone to flooding across several countries: the United States (U.S.), the Netherlands, China, and Indonesia (Filatova et al., 2022). The aim of these surveys was to collect comprehensive data at the household level, including socioeconomic variables, PMT variables, and place attachment, among others, to understand flood adaptation behaviors. The surveys began in March 2020, with follow-up waves every six months for a total of five waves. In each wave, the same participants were asked a series of questions, with the majority being different in each wave. As common to longitudinal studies, attrition was occurring across the waves, with some participants dropping out over the course of nearly 3 years of study. Since place attachment questions exist only in the fourth wave, which has the lowest participation, data availability has become a primary criterion for our case selection. Consequently, the author performed the following calculations based on the obtained data (Filatova et al., 2022). First, the Netherlands (N=65) and China (N=231) were eliminated since the number of participants left was insufficient to produce valid results. The final decision between Indonesia (N=731) and the U.S. (N=680) was made based on the completeness of the data. It was observed that the data collected in Indonesia had more missing values and inconclusive answers, which is why **the United States** was chosen as a case study. After the decision, the U.S. data was cleaned and prepared for the upcoming steps (see Appendix A.1).

The U.S. data contains the greater areas of Miami, Houston, and New Orleans (Noll, 2023). Hereafter, references to Miami, Houston, and New Orleans imply their respective greater areas. Considering the necessity of distinct flood maps for each region in the ABM and time constraints, it would have been unfeasible to study all regions. In the processed data, most respondents were located in Houston (N=205) and Miami (N=204) (see Figure 3.2), while only a few remained in New Orleans (N=48). Based on the availability of both survey and flood map data, Houston was selected as a case study for this research. Afterward, similarities between the Houston and Miami data were identified (see Appendix A.1.1), and two datasets were merged, recognizing the benefits of a larger dataset. Consequently, in this thesis, all participants, including those from Miami, have been treated as if they were located in **Houston**. In the upcoming steps, any reference to survey data pertains to this merged dataset.



(a) Houston Greater Area (N=205) (b) Miami Greater Area (N=146)

Figure 3.2: Number of Respondents by ZIP Code in (a) Houston Greater Area and (b) Miami Greater Area. Note: For visualization purposes, only 146 data points are used in Miami. Source: Maps are created by the author based on data from (Filatova et al., 2022).

3.3.2. Exploratory Factor Analysis

Place attachment cannot be measured directly; instead, it is defined through a set of questions about an individual's neighborhood, social environment, participation in activities in the neighborhood, and other related aspects. In the fourth wave of the ERC SCALAR survey, seven specific questions were designed to understand participants' place attachment (Filatova et al., 2022). However, as already discussed in Section 2.3, place attachment consists of multiple dimensions with no consensus on its dimensions, let alone which variables constitute these dimensions. To overcome this problem, Exploratory Factor Analysis (EFA) was employed to construct the place attachment index. EFA is a statistical method that allows us to uncover the latent variable(s) that can explain the relationships between the observed variables (Fabrigar & Wegener, 2011). It is highly suitable for this thesis as it explores the place attachment dimensions without requiring any pre-assumption.

The following procedure was adopted to answer our first research question. First, the correlation among place attachment variables in the survey data was calculated. It is a crucial step since having at least ± 0.3 correlation between some variables is necessary to perform EFA according to Hair et al. (1995). However, it is important to check for multicollinearity while having sufficient correlation. To ensure no multicollinearity, the determinant of the correlation matrix was calculated (Shrestha, 2021). Then, Bartlett's test of sphericity was conducted to determine if the variables have adequate interrelations (Shrestha, 2021). The Kaiser-Meyer-Olkin (KMO) test was also performed to decide whether the sample was adequate for EFA or not (Shrestha, 2021). After these criteria were satisfied, the number of factors was determined based on the Kaiser criterion, which keeps factors with eigenvalues greater than one (Joint Research Centre, 2008). This rule ensures that each remained factor explains a significant amount of variance (Joint Research Centre, 2008). Next, varimax rotation was applied to simplify the factors and make them easier to interpret (Hair et al., 1995; Joint Research Centre, 2008). Upon obtaining the factor loadings, Cronbach's Alpha was calculated to ensure their reliability, with 0.7 as the acceptable threshold (Shrestha, 2021). Finally, place attachment indices (or index) can be created. For this step, only loadings that are bigger than 0.4 are kept (Guadagnoli & Velicer, 1988). These loadings were then squared to give more weight to the most strongly related variables. Finally, the squared loadings were normalized to ensure scale alignment with the survey questions. These weights were used in the following equation to create place attachment indices for each survey respondent in the dataset:

$$\text{Place Attachment}_j = w_{1,j}x_{1,j} + w_{2,j}x_{2,j} + \cdots + w_{n,j}x_{n,j} \tag{3.1}$$

where:

- $w_{k,j}$: normalized squared loading for variable k on factor j
- $x_{k,j}$: survey data variable k for factor j
- n: number of variables retained in the factor
- j: factor index, i.e., the number of place attachment types

3.3.3. Linear Regression

In order to integrate the dynamic nature of place attachment into our model, we initially needed to understand which factors drive changes in place attachment and to what extent. Linear regression stood as an apt choice for assessing the extent of the selected factors. It is a simple yet effective tool for quantifying the relationships between dependent and independent variables, making it ideal for our analysis. Separate linear regression models were built on the survey data for each place attachment dimension/type determined through EFA, as each dimension was expected to be influenced by different factors. To determine the independent variables of these regressions, data-driven selection methods, such as backward and forward elimination, were considered to be employed. However, data-driven methods produced complex regression models that had many interaction variables, making the interpretation difficult - if not impossible. Since we wanted to keep the theoretical ground in our study, the independent variables of these regressions were selected based on previous literature and personal judgment, following exploratory data analysis conducted on the survey data. The results of these models helped us to answer the second research question. The linear regression coefficients were then integrated into the ABM to calculate the changes in place attachment.

It is important to note that place attachment is a complex psychological concept that can be shaped by many factors, some of which we may not even be aware of. This might be a problem when introducing a limited number of variables in our regressions, as we could suffer from omitted variable biases. Given that our model is not complete, we cannot claim causality in our inferences; however, we are still able to claim that our coefficients depict a somewhat accurate representation of the relationships between variables based on the alignment with the existing literature.

3.3.4. Logistic Regression

Logistic regression is a statistical method that explains the relationship between a binary outcome and independent variables (Field, 2005). This method effectively estimates the probability of one of two possible outcomes occurring. After the regression model is fitted, the coefficients are used to calculate the logit, which can then be converted into a probability indicating a specific outcome's probability. Logistic regression was a suitable choice for our study since it enabled us to understand how socio-psychological factors influence households' adaptation intentions, which were later employed in our simulation model to calculate adaptation probabilities.

This thesis performed logistic regression using survey data, with the extended PMT factors (see Figure 3.1) as independent variables and adaptation intention as the dependent variable. Separate logistic regressions were conducted for each flood adaptation measure households could implement. Before running the regressions, the variance inflation factor (VIF) was checked to ensure no multicollinearity among the predictor variables (Senaviratna & A Cooray, 2019). According to Midi et al. (2010), one should be careful with VIF values higher than 2.5 in logistic regression models.

3.3.5. Agent-Based Modeling

The main objective of our research is to explore how the complex interplay between household adaptations and place attachment influences flood damage reduction over time. We needed a method that could capture these emergent and complex patterns. ABM was selected because it simulates heterogeneous agents (households) and their dynamic, complex interactions within the system and, thus, inherently provides a way to capture bottom-up emergence (Bonabeau, 2002). Most importantly, in the absence of panel data, ABM enabled us to integrate the dynamic nature of place attachment into our study and explore its interplay with household adaptation decisions over time, answering our fourth research question.

The simulation model of this thesis has been built upon the ABM created by Wagenblast (2022) in Python 3.11 using the *mesa* library. The original model was developed to explore the impact of different social networks on households' flood adaptation in the presence of various policies. Households in her model were created based on the first wave of ERC scalar survey data in Houston (Filatova et al., 2022), whereas their behavioral rules, i.e. adaptation decisions, were represented by the extended PMT. For more information about the original model, please refer to the related publications by Wagenblast (2022) and Wagenblast et al. (2024). While the backbone of our work was similar, we made significant changes in the model to integrate dynamic place attachment. Figure 3.3 illustrates the conceptualization of our model. The two primary modifications were extending the PMT framework to include multi-dimensional place attachment, allowing it to influence households' decisions, and utilizing linear regression coefficients to update place attachment dimensions at each step. These modifications, along with others, and the experimental design are further discussed in Chapter 5.

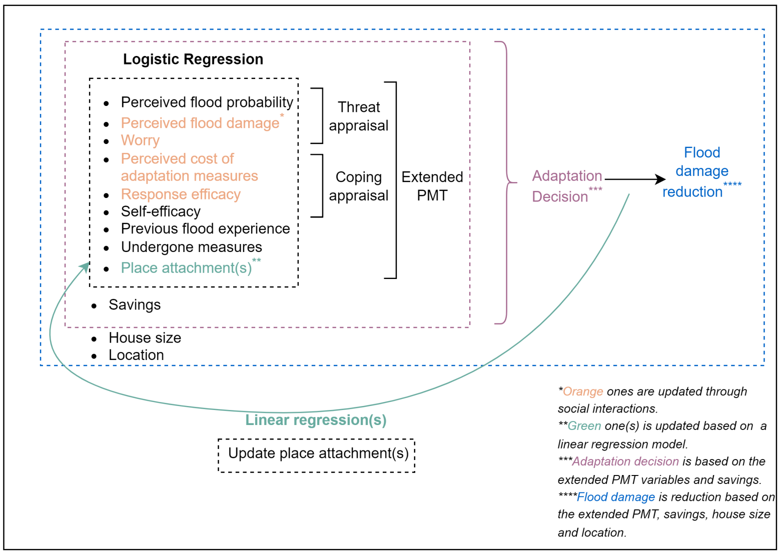


Figure 3.3: Conceptualization of the agent-based model based on the previous findings.

3.3.6. Data Sources for Agent-Based Model

The parameters of our model were primarily derived from the survey data, as detailed in previous sections. The model agents were also created using this survey data (see Section 3.3.6) and placed on the Houston map. Besides the survey data, three other datasets were required for this model: flood risk, flood adaptation measures, and macro data to create a synthetic population from the survey data.

Flood Risk Data

The flood risk data sources and their combination to calculate households' flood risk are shown in Figure 3.4. Based on the flood risk framework described in Section 3.1.1, it was necessary to obtain data specifically for Houston for each risk component: hazard, exposure, and vulnerability (Kron, 2005). Since the original model also used Houston as a case study (Wagenblast, 2022), the necessary datasets for hazard and vulnerability were obtained through its sources. Hazard data, i.e., Houston flood maps, was obtained using the Super-Fast INundation of CoastS (SFINCS) model (Leijnse et al., 2021). Using the SFINCS, Grimley et al. (2023) generated different flood maps showing the extent and depth of a 100-year flood, a 500-year flood, and Hurricane Harvey, which happened in Houston, Texas, in 2017. After getting these flood maps from Wagenblast et al. (2024), we needed to place households on the map to get their corresponding flood depth. In the original model (Wagenblast, 2022), the location of the households was randomly assigned, but this could result in households being located in places that are not residential areas. To make households' exposure more realistic, residential buildings in Houston were obtained from OpenStreetMap (OSM, 2024), and households were randomly assigned to one of them (see Appendix C.3.1). Upon obtaining the flood depth, the flood depth-damage equations, which were obtained by Wagenblast et al. (2024) using the flood depth-damage curve data from Moel et al. (2017), were used to obtain households' damage factor. The damage factors were converted to monetary values (flood damage) using the house size and the average maximum damage per square meter. The average maximum damage per square meter, 1216.65 $\$/m^2$, was obtained from Moel et al. (2017) and was adjusted by Wagenblast et al. (2024) for 2020 inflation to align it with the survey data collection date. It should be noted that this value includes both content and structural damage (Moel et al., 2017).

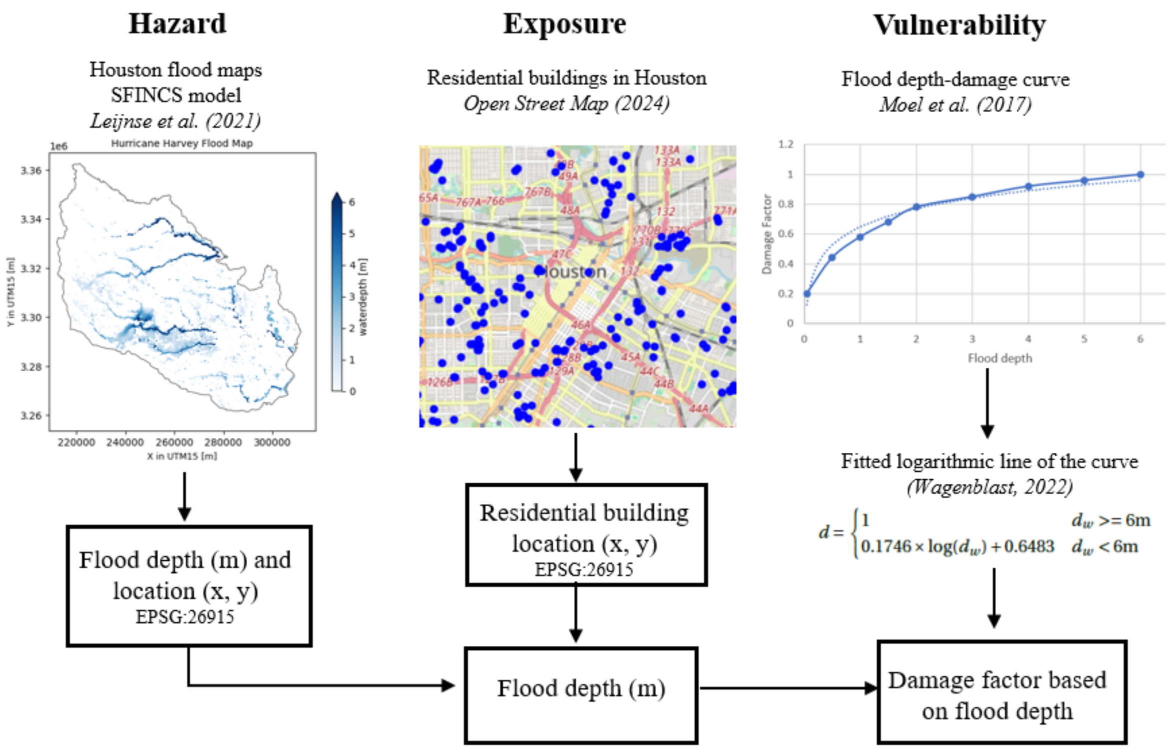


Figure 3.4: Data sources for measuring flood risk. Source: The figure, including the sub-figures, is created by the author based on the data obtained from Leijnse et al., 2021; Moel et al., 2017; OSM, 2024; Wagenblast, 2022; Wagenblast et al., 2024, using the design idea of Lechner (2022).

Adaptation Measures

The adaptation measures that households could take in our model were selected based on the ERC SCALAR survey data, which has seven structural and eleven non-structural adaptation measures (Filatova et al., 2022). We decided to exclude non-structural measures from our study due to their lower and non-permanent effects (Noll et al., 2022). Following this decision, the structural measures in the survey were grouped into three main categories: dry-proofing, wet-proofing, and elevation (Aerts, 2018; Taberna et al., 2023). The categorization of each flood adaptation measure can be found in Table 3.1. The working principles of these three categories can be explained simply: dry-proofing prevents water from entering the house, wet-proofing allows water to enter but minimizes the damage it causes, and elevation raises the ground floor of the house above potential flood levels (Aerts, 2018; FEMA, 2016). Their cost and effectiveness in damage reduction vary significantly in the literature. That's why we decided to take the average of them based on the reviews conducted by Aerts (2018) and Kreibich et al. (2015). Table 3.1 demonstrates these average values for each adaptation category. Elevation changes the flood depth and, thus, flood damage, whereas dry and wet-proofing directly reduces the flood damage, as in the model created by Wagenblast (2022). The elevation was decided to be one foot (~0.3 meters) above the 100-year flood map in line with the current regulations (Houston Public Works, 2018).

Table 3.1: Cost and effectiveness of structural flood adaptation measures.

Category	Structural Measure	Damage Reduction (%)	Cost ($)
Elevation	- Raising the level of the ground floor above the most likely flood level	It changes the flood depth	38,000
Dry-proofing	- Installing anti-backflow valves on pipes - Installing a pump and/or one or more system(s) to drain flood water - Fixing water barriers (e.g. water-proof basement windows)	50	8,000
Wet-proofing	- Strengthen the housing foundations to withstand water pressures - Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials - Raising the electricity meter above the most likely flood level or on an upper floor	40	6,000

Note: Damage reduction and cost values were obtained by averaging the values in Kreibich et al. (2015) and Aerts (2018). The cost values were adjusted for 2020 inflation.

Neighborhood Level Data

The limited number of survey respondents and the fact that they come from two different states necessitate careful consideration when creating a synthetic population for the model. To create a more realistic population in Houston, it is decided to utilize neighborhood-level data, which can guide us while constructing the population from our micro-level survey data. This neighborhood-level data, obtained from Planning and Development Department (2020), includes information on 88 'Super Neighborhoods' of Houston. These Super Neighborhoods are adjacent areas that have similar characteristics (Department of Neighborhoods, 2024), providing more manageable and meaningful macro-level data for our study compared to single zip codes. Although macro-level data representing the place attachment level of neighborhoods would be a game-changer, it was not available. As a close approximation for general neighborhood configuration and, to some extent, for place attachment, we utilized the income distribution of these neighborhoods. Due to time and computational limitations, only ten neighborhoods were integrated into our study. The idea behind a synthetic population creation is summarized in Figure 3.5.

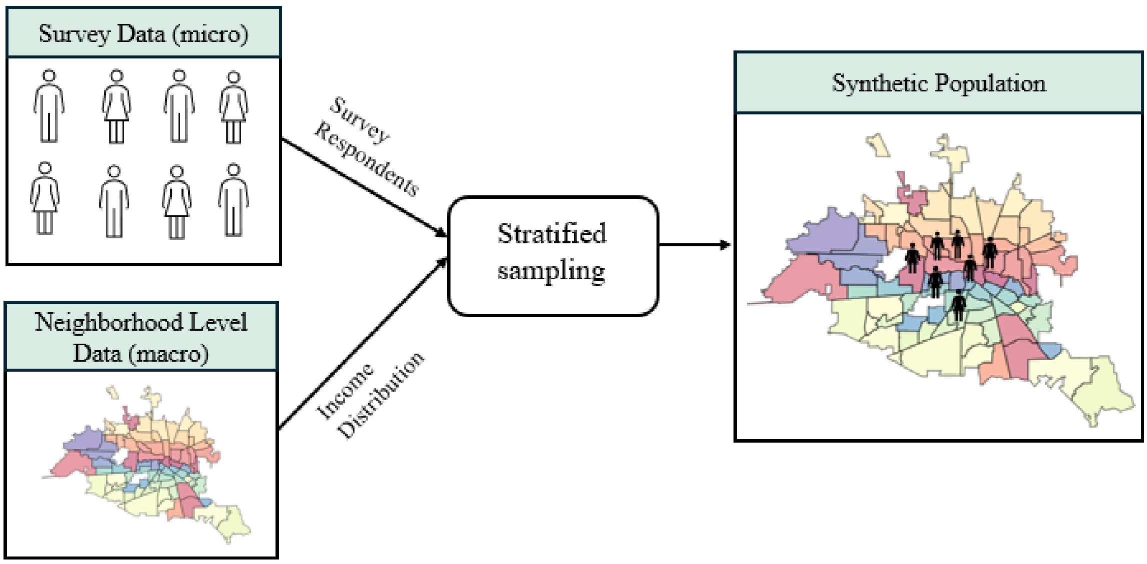


Figure 3.5: Synthetic population creation. Source: The figure is inspired by the work of Crooks et al., 2018.

The ten neighborhoods were selected based on their average flood depths from the Harvey flood map and the availability of the OSM residential building data. Based on the income distribution of the selected neighborhoods, we sampled individuals from the survey data with replacement. First, the respondents in the survey data were grouped according to their income categories (see Table A.3 for the categories). Next, the total number of households in the simulation and its distribution across neighborhoods were decided, enabling us to obtain the neighborhoods' population. The required number of individuals per income category was determined using the neighborhood's income distribution and population. These individuals were then sampled from the survey data with replacement, ensuring that the neighborhood's income distribution was accurately represented. Households were later randomly placed on one of the residential buildings in their neighborhood. Sampling households as a whole prevented the creation of individuals with unrealistic attribute combinations, such as having the minimum level of worry but the highest perceived damage. Besides, placing individuals in specific neighborhoods aligns better with our study's goals since place attachment is context-specific. It would be inappropriate to have our agents spread randomly across the city. The selection process of the neighborhoods and further details of the synthetic population creation can be found in Appendix C.3.1.

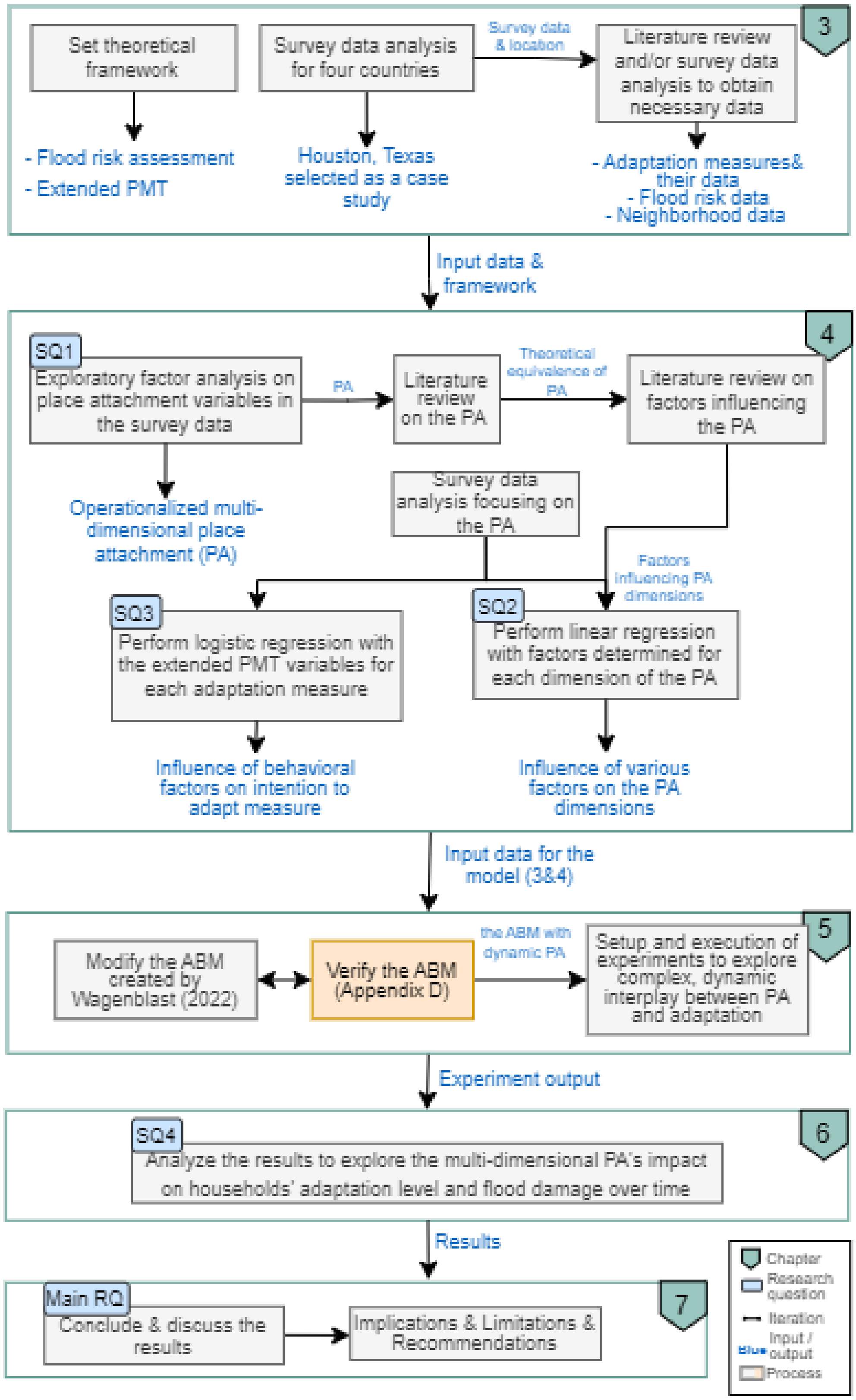


Figure 3.6: Research flowchart illustrating the steps, methods, and input/output relationships.

4

Statistical Analysis Results

This chapter presents the results of statistical analysis conducted prior to the ABM. First, in Section 4.1, the place attachment index is created. Next, Section 4.2 provides the exploratory data analysis results. Following this, Section 4.3 and 4.4 discuss linear and logistic regression results, respectively.

4.1. Construction of Place Attachment

This section starts with constructing place attachment indices in Section 4.1.1. After creating, these indices are connected to a theoretical framework in Section 4.1.2. Lastly, past studies are reviewed in Section 4.1.3 to determine factors influencing place attachment.

4.1.1. Exploration and Operationalization of Place Attachment

The fourth wave of the ERC SCALAR survey (Filatova et al., 2022) had seven targeted questions to assess households' place attachment. These questions ranged from satisfaction with one's neighborhood to actions taken for the neighborhood's benefit, as detailed in Table 4.1. Interestingly, civic engagement and creation variables had lower means than the other place attachment variables, such as trust, community, and pleasure.

Table 4.1: Descriptive statistics of variables used in the place attachment (N=409). Source: Calculations performed by the author based on data from Filatova et al. (2022).

Variable Name	Question	Response Options	Mean (Std. Error)
Neighborhood Trust	I believe that residents in my neighborhood can be trusted	5-point scale (1) Strongly disagree (5) Strongly agree	3.68 (0.94)
Neighborhood Community	I feel that I am a member of my neighborhood community	5-point scale (1) Strongly disagree (5) Strongly agree	3.45 (1.13)
Neighborhood Pleasure	Being in this neighborhood gives me a lot of pleasure	5-point scale (1) Strongly disagree (5) Strongly agree	3.56 (1.10)
Neighborhood Favorite	My neighborhood is my favorite place to be	5-point scale (1) Strongly disagree (5) Strongly agree	3.35 (1.13)
Neighborhood Identity	My neighborhood reflects the type of person I am	5-point scale (1) Strongly disagree (5) Strongly agree	3.24 (1.17)
Civic Creator	I engage with local/civic arts and entertainment either as an observer or as a creator	5-point scale (1) Strongly disagree (5) Strongly agree	2.33 (1.28)
Civic Engagement	I am involved in civic engagement: either through volunteering, participation in politics, local groups, protests, etc.	5-point scale (1) Strongly disagree (5) Strongly agree	2.55 (1.36)

After exploring these variables, the requirements for conducting the EFA were checked (see Section 3.3.2 for the criteria). The results indicated that the data met the necessary requirements; for details, see Table A.5 in Appendix A.3. Following the tests, the number of factors was determined to be two based on the Kaiser criterion, with eigenvalues of 3.84 and 1.32. The factor loadings were then obtained using varimax rotation. In the order presented in Table 4.1, the first five variables loaded into the first factor, while the remaining two loaded into the second factor. The Cronbach's alpha values for both factors were satisfactory, though the second factor's value was precisely at the threshold. Two place attachment indices were derived after completing the remaining steps as explained in Section 3.3.2. since the place attachment indices were calculated based on a weighted average of 5-point scale variables, they can also take non-integer values within the range of 1 to 5. Figure 4.1 illustrates the final weights obtained to construct each place attachment dimension/index. Details of the factor loadings and weights are presented in Table A.6 Appendix A.3.

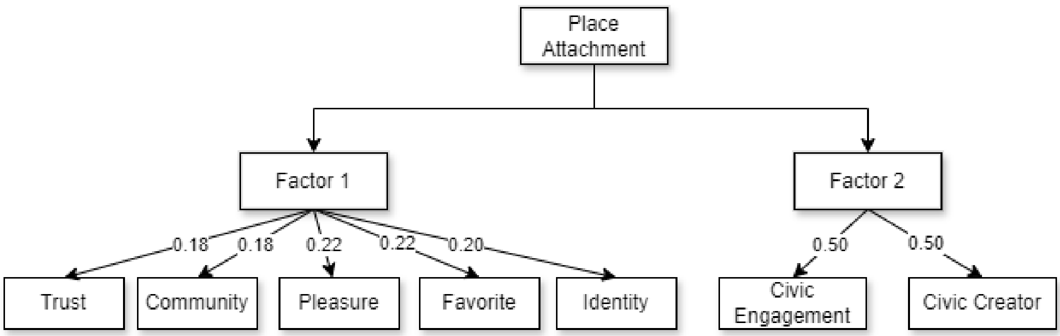


Figure 4.1: Place attachment variables and their weights in each factor. Source: Figure created by the author based on the EFA results.

4.1.2. Linking with a Theoretical Framework

Hummon (1992) identified two types of place attachment, which were afterward confirmed in a case study conducted by Lewicka (2011a). These two types, called 'everyday' and 'ideological rootedness' by Hummon (1992), have been renamed 'traditional' and 'active' place attachment by Lewicka

(2011a). Active place attachment is rooted in personal exploration and active involvement in a place (Lewicka, 2011a). This type represents a self-discovered connection, emerging from experiences and deliberate efforts to engage with the environment or community. Actively attached people tend to be involved in local affairs and aware of changes within their neighborhood (Parreira & Mouro, 2023). In contrast, traditional place attachment is a bond passed down through generations or formed by long-term residency (Lewicka, 2011a). Thus, it involves no active engagement and is often considered 'taken for granted' (Hummon, 1992). Traditionally attached people enjoy living in their neighborhood and prefer to stay there, yet they do not actively participate in efforts to improve or protect it.

Upon reviewing these studies, it is determined that **Factor 1 and Factor 2** (see Figure 4.1) align with traditional and active place attachments, respectively. These factors will hereafter be referred to as **traditional and active place attachments**. However, it is important to note that these two attachment types are not mutually exclusive (Lewicka, 2011a). They simply represent different reasons for forming attachments to the place, which can coexist. So, one can exhibit both high traditional and active place attachment or any combination thereof.

4.1.3. Factors Influencing Place Attachment

This section aims to understand which factors shape active and traditional place attachments by discussing relevant literature. These findings help build regression models that are theoretically grounded. However, there is limited research particularly addressing the factors influencing active and traditional place attachment due to many different conceptualizations. Although we expect the underlying factors for traditional and active place attachment to vary significantly, existing literature mainly focuses on the impacts of a few sociodemographic factors on both types of place attachment, leaving many potential factors unaddressed. Table 4.2 summarizes the relationships found in the literature.

Active place attachment is positively related to education level, while traditional place attachment has a negative relationship with education (Lewicka, 2011a). Furthermore, age and residency length exhibits a positive relation with traditional place attachment. Differently, the relationship between age and active place attachment is concave, indicating that people of medium age have the highest. Residency length either has a negative relationship with active place attachment or does not have a relationship at all (Lewicka, 2020). Besides, Jaśkiewicz (2018) demonstrates that social interactions are a positive predictor of active place attachment. Hence, the more interactions in the neighborhood, the more actively attached to the place.

Table 4.2: Variables impacting active and traditional place attachments. Source: Table is created by the author based on the information from Lewicka (2011a) and Jaśkiewicz (2018).

Variable	Relationship	
	Active	Traditional
Age	$\frown$	+
Education	+	-
Residency length	- or 0	+
Social interactions	+	

Note: + and - represent positive and negative relationships, respectively. 0 indicates no correlation/relationship. $\frown$ represents a concave relation.

4.2. Exploratory Analysis

The survey data introduced in Section 3.3.1 is explained further in detail in Table A.3 in Appendix A.2. The variables described in this table do not include the entire survey data; they only include potential independent variables that might be used in at least one of the two regressions. The dependent variables of these regressions, on the other hand, are explored in this section. Figure 4.2 (right-hand side) shows the dependent variables for our logistic regression models. These binary variables represent households' intention to implement the respective measure within a year (1) or do not intend to implement it (0). Figure 4.2 reveals that many people have not adapted (left-hand side), and a significant portion still has no intention to do so.

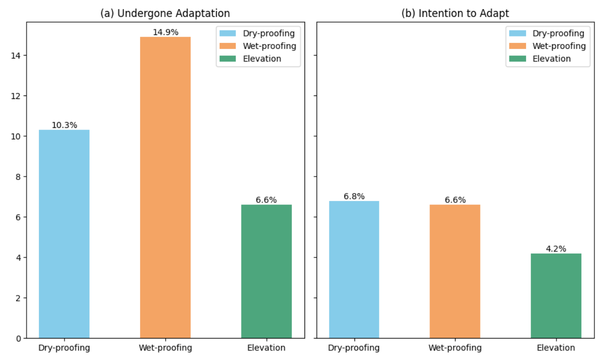


Figure 4.2: Percentage of people already adapted (a) and intending to adapt within one year (b). Note: In graph (a), the full sample (N=409) is used. In graph (b), individuals who have already adapted the respective measure are excluded, resulting in samples of 367 for dry-proofing, 348 for wet-proofing, and 382 for elevation.

Next, the dependent variables used in our linear regression models are explored. Figure 4.3 demonstrates the distribution of these two variables. They are the two indices that we created in Section 4.1: traditional and active place attachment. Traditional place attachment levels are generally higher among respondents. In contrast, active place attachment levels are concentrated at the lower end of the scale. However, this result is not surprising since active place attachment consists of two variables (civic engagement and creator), which have lower means than the ones creating the traditional attachment (see Table 4.1).

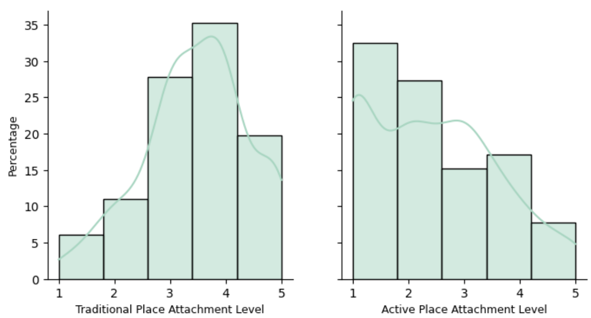


Figure 4.3: Distributions of the traditional (a) and active (b) place attachment levels of the respondents (N=409). Note: The number of bins is set to five for visual purposes. However, since these two indices are created taking the weighted average, they can take non-integer values between 1 and 5.

Given the purpose of our study, it is significant to understand the background of the survey participants. Figure A.4 in Appendix A.2 presents the percentage of the participants according to their gender, age, education, and other factors. Their background can be simply explained as follows: there is a balanced gender distribution, they are generally older, highly educated, and mostly homeowners and live in independent houses. To understand the relationships of these variables with place attachment levels, we utilize stacked bar charts showing the distribution of place attachment in each category. Figures 4.4 and 4.5 are made for traditional and active place attachment, respectively. It is important to note that these figures do not imply any causal relationships. Hence, the upcoming explanations only describe associations.

Traditional place attachment is clearly the highest among individuals with the least education. From high school to post-graduate education, we observe a slight decrease in the share of the highest level of place attachment. Although there are some exceptions, traditional place attachment generally increases with age. Interestingly, the youngest group has no one in the lowest attachment level. It may be related to the fact that most are still high school students. Females exhibit higher traditional attachment than males, but the difference is minor. Traditional place attachment also increases with income, although the fourth highest income group slightly exceeds the highest income group. Being a house owner is another factor that increases the traditional attachment.

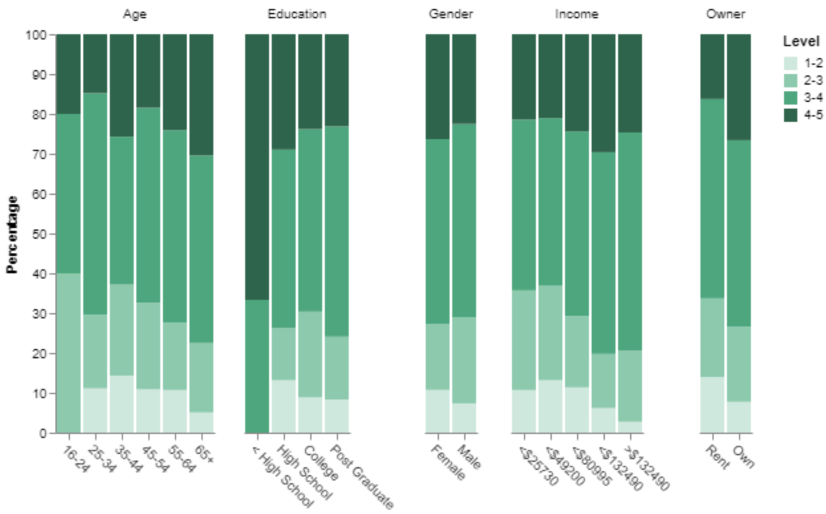


Figure 4.4: Stacked bar chart of traditional place attachment level in each sociodemographic category. Note: Level 1-2 corresponds to [1, 2), Level 2-3 to [2, 3), Level 3-4 to [3, 4), and Level 4-5 to [4, 5].

Active place attachment, unlike traditional attachment, increases with education. This trend is evident in the top three education groups. However, people with the lowest education level do not follow it. Homeownership is also another indicator of higher active attachment. Although the impact of age seems unclear, we can observe a convex trend in the lowest attachment group. This indicates that middle-aged individuals have a higher share in the top three attachment levels. Similar to traditional attachment, females exhibit slightly higher place attachment than males. Higher income is also associated with higher active attachment, although the fourth highest income group surpasses the highest income group.

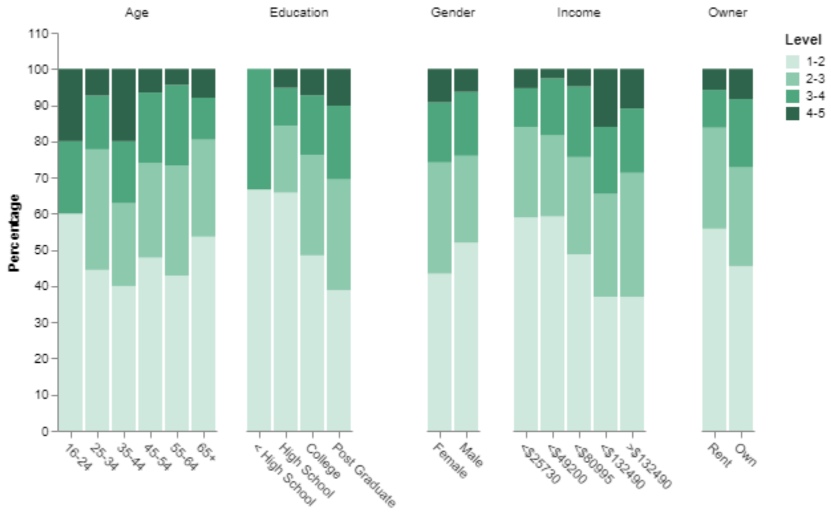


Figure 4.5: Stacked bar chart of active place attachment level in each sociodemographic category. Note: Level 1-2 corresponds to [1, 2), Level 2-3 to [2, 3), Level 3-4 to [3, 4), and Level 4-5 to [4, 5].

4.3. Linear Regression

Following the literature review (Section 4.1.3) and data exploration (Section 4.2), different linear regression models are constructed for each type of place attachment. A key consideration in building the models is ensuring clear distinctions between them, as they represent two different types. This distinction is important for observing their dynamic aspects in our simulation model. Without these distinctions, the variables would change similarly, and their unique characteristics could not be captured. Furthermore, considering which variables are or can be updated at each step of our simulation model is crucial for making the place attachment dynamic. The variables updated through the social network and flood adaptation decision in the original model, which can be helpful for our linear regression models, are perceived flood damage, worry, and undergone structural adaptation measures. For the purpose of our thesis, three more variables, namely, age, income, and community are made dynamic. The details of how these variables are made dynamic are given in Chapter 5. Lastly, the existing literature does not clearly explain how and which threat appraisal, experience, and adaptation status changes influence active and traditional place attachments. Thus, we used our understanding of these two attachment types to select the variables for our regression models. Figure 4.6 illustrates the selected variables, with previously dynamic variables shown in orange and the newly dynamic variables introduced in this study highlighted in purple. Their correlation with the dependent variable can be seen in Figures B.1 and B.2 in Appendix B.2 for traditional and active place attachment, respectively.

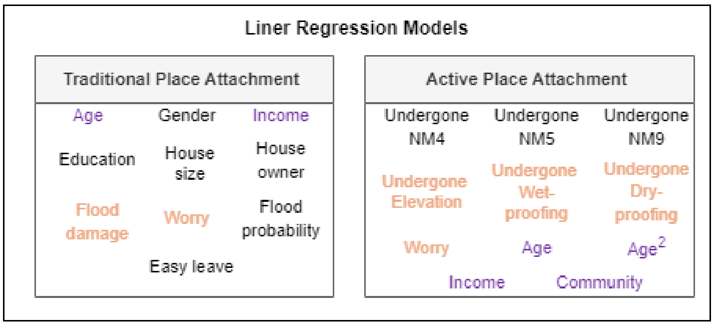


Figure 4.6: Variables selected for (a) Traditional place attachment and (b) Active place attachment linear regressions. Note: The orange-colored icon represents the dynamic variables in the original model, whereas the purple icon represents the variables made dynamic by the author. 'NM' stands for non-structural measures. Further details of all variables can be found in A.3 in Appendix A.2.

For the traditional place attachment model, sociodemographic factors are primarily selected, following the existing literature. In contrast, the residency length, which corresponds to the year the survey respondents moved in, is not included in our model due to its small coefficients and lack of added value to the results. Since the distribution of the residency length is right-skewed (see Figure B.3 in Appendix B.2), a logarithmic transformation was tried; however, it did not improve the model metrics (Akaike Information Criterion (AIC) and adjusted R-squared). This issue might be due to insufficient variance in the independent variable, as many respondents have recently moved in. Gender and income are also included as additional sociodemographic factors. The rest of the variables are chosen based on our interpretation of traditional attachment due to the limited literature. For the active place attachment model, both age and age-squared are included due to the concave relationship identified by Lewicka (2011a). Social interactions are tried to be captured through community and non-structural measures; however, only the community variable is made dynamic in this study. Additionally, we assume that taking adaptation measures only impacts active place attachment because active attachment arises from ongoing interaction with the environment. Implementing measures such as dry-proofing shows active engagement, which can, in return, influence active place attachment. In contrast, traditional place attachment is rooted in long-term and inherited factors. Thus, it is not expected to change rapidly with recent flood adaptation measures.

Following the selection, two linear regressions are performed, and the results are presented in Figure 4.7 with 95% confidence intervals. The linear regression results for traditional place attachment show that age, income, house size, and ease of leaving the place are both statistically and economically significant. Age and income have a positive and significant effect, indicating that as age or income increases, traditional place attachment increases. Conversely, larger house size and a stronger perception that leaving would be easy are associated with lower traditional place attachment. The coefficients for gender and education indicate that females may have slightly higher place attachment, and those with less education may also experience stronger attachment. However, these effects are not strong. Similarly, threat appraisal variables have a slight influence on the traditional place attachment level of households.

The active place attachment regression results reveal that being active in community organizations, such as a book club or religious association, positively influences active place attachment. Similarly, participation in local affairs focused on flood safety (NM4) also has a positive effect. The other two non-structural measures (NM5 and NM9) increase active place attachment slightly, but they are not statistically significant like the previous one. In contrast, elevating houses is negatively associated with active place attachment and is the only significant structural measure in the results. Unlike in traditional place attachment, age is not statistically significant here, but it still has a considerable impact. Income shows a similar positive influence as in the previous regression. Worrying about flooding also contributes to increasing active place attachment. Further details of the regression results can be found in Tables B.4 and B.5 in Appendix B.2.

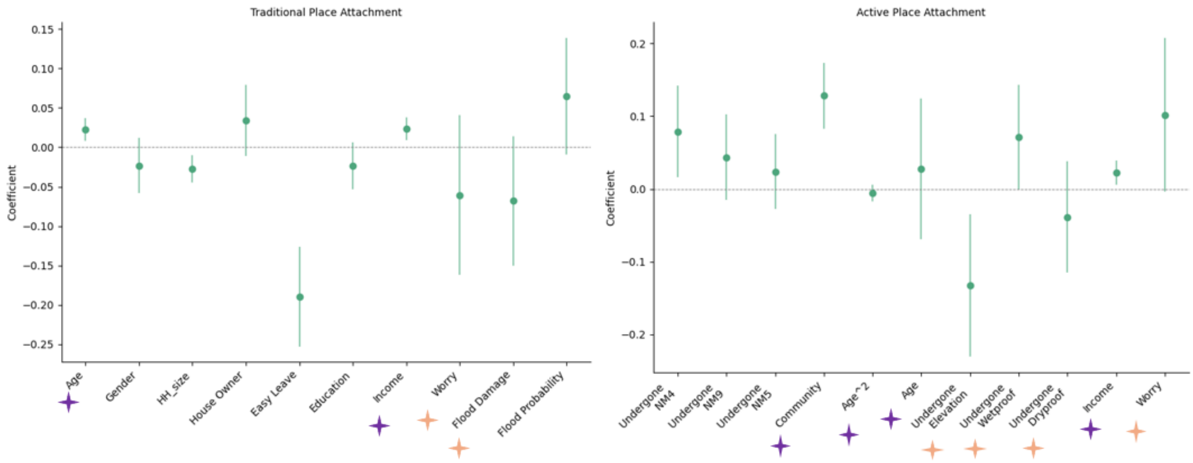


Figure 4.7: Linear regression results: (a) Traditional place attachment and (b) Active place attachment. Note: The orange-colored icon represents the dynamic variables in the original model, whereas the purple icon represents the variables made dynamic by the author. 'NM' stands for non-structural measures. Further details of all variables can be found in A.3 in Appendix A.2.

4.4. Logistic Regression

Logistic regression is conducted to determine how the variables in our extended PMT framework (see Figure 3.1) influence households' intentions to take an adaptation measure, namely elevation, wet-proofing, and dry-proofing. As explained in Section 4.2, the dependent variable of each model is binary, representing whether a household intends to implement the respective measure within a year. Following the results of Section 4.1, place attachment is represented by its two dimensions: active and traditional. Consequently, each model includes 11 independent variables. Prior to the regression, it is ensured that no multicollinearity exists between the independent variables of each model: the VIF for all variables is below the 2.5 threshold. For further details, please refer to Table B.1 in Appendix B.1.1.

Figure 4.8 illustrates the results of our three logistic regression models. The figure demonstrates the 'log-odds ratios' of coefficients with their 95% confidence intervals. Note that all variables are normalized according to their respective point scale. Further details, such as their standard errors and 'odds ratios', are provided in Table B.2 in Appendix B.1.2. Since the results are easier to understand when examined based on a specific increase, Table B.3 in Appendix B.1.2 is created. In this section, only the results of place attachment variables are discussed. An increase of 0.2 is selected for illustrative purposes, as it is equivalent to an increase of 1 on a 5-point scale.

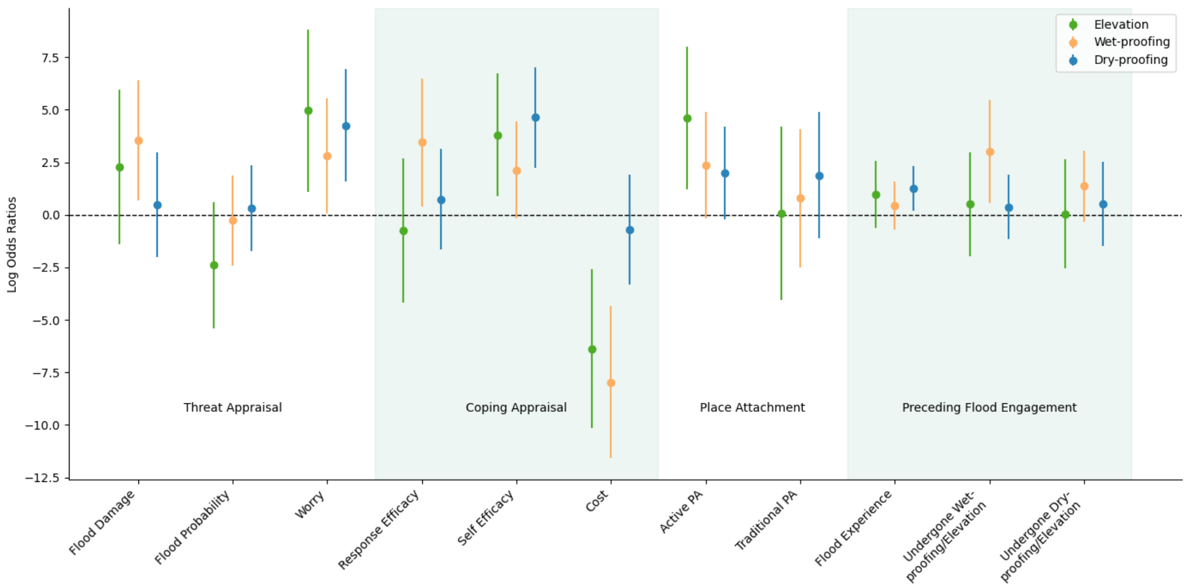


Figure 4.8: Log odds ratios for structural measures with their 95% confidence intervals. Source: Graph adapted from Noll et al. (2022), with calculations performed by the author.

On the one hand, increasing active place attachment by 0.2 significantly increases the odds of intention to take flood adaptation measures. Notably, it raises the odds of elevation intention by 2.51 times, the highest impact observed across all measures and attachment types. It also substantially increases the odds of intention to adopt dry-proofing and wet-proofing by 1.49 and 1.6 times, respectively. On the other hand, increasing traditional place attachment by 0.2 has a lower impact than active attachment, as expected. In particular, it shows almost no effect on the odds of intention to elevate, raising it by just 1%. The odds for wet-proofing intentions increase modestly by 17% (1.17 times). However, it does increase the odds of intention to dry-proof by 1.45 times, almost the same effect as the active place attachment.

5

Agent-Based Model

In this chapter, we detail the new version of the model after carrying out modifications to the model created by Wagenblast (2022). The model has been adapted to serve our purpose of exploring the dynamic and complex relationship between two types of place attachments and household behavior, providing deeper insights into the role of place attachments in their adaptation decision-making processes. The further model details can be found in the ODD protocol in Appendix C, in which the focus is given to the adjustments made by the author. For more information on the original model, please refer to the publications by Wagenblast (2022) and Wagenblast et al. (2024). Following the model description, the details of the experimental setup are provided in Section 5.3.

5.1. Household Agents

In this model, households are represented as agents. Each agent is created based on survey data collected from the household representative (Noll et al., 2022). These households are then placed in single-family houses within one of the ten selected neighborhoods in Houston (see Figure 5.1). They do not relocate or perish throughout the simulation. Their locations, represented by the centers of their houses, help us assess the flood risk to which they are exposed, as detailed in Section 3.1.1. Each household has multiple attributes, which can be mainly categorized under threat appraisal, coping appraisal, place attachment, adaptation status, and socioeconomic factors. These attributes are detailed in Table C.2 in Appendix C. For more details on the synthetic population creation, including neighborhood selection and assignment of attributes and location, refer to Appendix C.3.1.

These households live and interact within the environment defined by the boundaries of the selected neighborhoods. The parameters of the environment, i.e., model, are detailed in Tables C.1 and C.3 in Appendix C. Households interact within their social networks, influence each other, and respond to the passage of time and environmental changes, such as flood events and the implementation of large-scale flood adaptations (see Section 5.3 for the latter). These interactions shape household attributes and their decisions, resulting in the emergence of flood adaptation behaviors. In each step, the environment activates households in a random order. Households update some of their attributes based on the influence of their network and their active and traditional place attachment using the coefficients from the linear regression models (see Section 4.3). If an adaptation measure (elevation, wet-proofing, or dry-proofing) is still available to them, they decide whether to implement it based on their extended PMT attributes (refer to Figure 3.1). When households want to take the measure, actual barriers like time and money are considered. If no barriers exist, households implement the adaptation measure and update the relevant attributes. Following this, they update their savings, age, and, occasionally, their income and move to the next step. Figure 5.2 illustrates the general flow of the model. The key model dynamics are explained further in the following section.

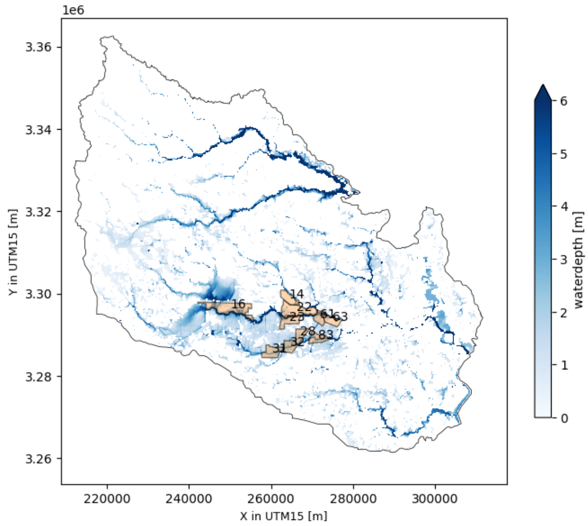


Figure 5.1: Ten selected neighborhoods. Source: The figure is created by the author using the Harvey flood map obtained from Grimley et al., 2023; Leijnse et al., 2021 and neighborhood shapefiles downloaded from City of Houston GIS, 2024.

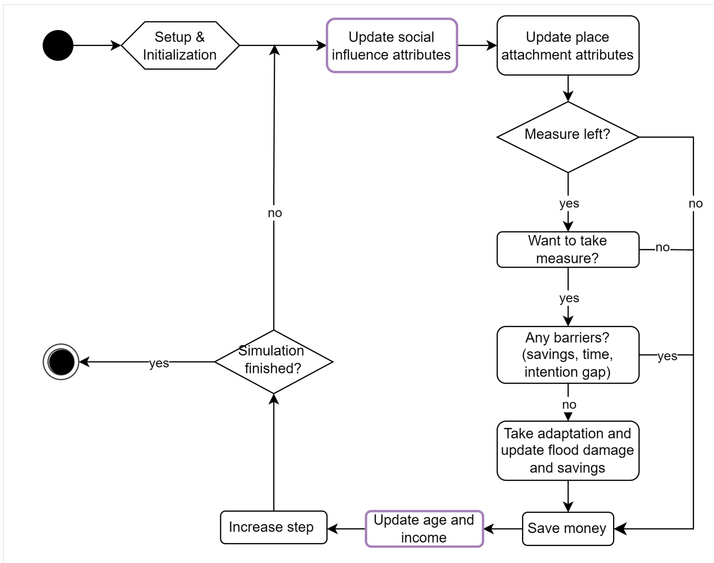


Figure 5.2: General overview of the model. Note: Purple steps become active only after the first step.

5.2. Household Rules and Actions

Each household follows certain rules and actions that shape their adaptation behaviors (Dam et al., 2012). These rules determine how households update their attributes, interact with their social connections, and respond to environmental changes. The following subsections describe these rules and actions.

5.2.1. Flood Adaptation Decision

Households make their adaptation decisions based on the Protection Motivation Theory, which is extended to include place attachment, flood experience, and adaptation measures implemented, as illustrated in Figure 3.1. There are three adaptation measures that households can take: elevation, wet-proofing, and dry-proofing. Section 3.3.6 provides detailed information about these measures. Three separate logistics regressions are conducted to determine how the extended PMT variables impact households' intentions to implement an adaptation measure within a year (refer to Section 3.3.4 for the details). The complex decision-making process of households for which we utilize these regression coefficients is as follows.

In each step, households calculate their intention to implement each available adaptation measure by inserting their updated attributes into the corresponding logistic regression coefficients. These calculations provide the odds ratios, which are then converted to probabilities. Afterward, households select the measure with the highest probability. This probability is then used in a Bernoulli trial: households decide to take the measure if the probability is higher than a random number generated; otherwise, they do not. If the result is a success, households check for any barriers that might prevent adaptation. If their savings sufficiently cover the cost and enough time has passed since the previous measure, they take the adaptation measure. The adaptation status of that measure immediately becomes 'adapted,' and their savings, flood damage, and flood depth (if it is elevation) are changed accordingly. Once implemented, the adaptation measure remains valid for the rest of the simulation. The corresponding pseudocodes can be found in Appendix C.3.3.

5.2.2. Place Attachment Dynamics

One of the most significant modifications made to the model created by Wagenblast (2022) is the integration of dynamic place attachment. The initial values for active and traditional place attachment are obtained by taking the weighted average of place attachment-related variables existing in the ERC SCALAR survey data (Filatova et al., 2022). Details on how these place attachment indices are created are already discussed in Section 4.1. Following their construction, two separate linear regression models are developed to determine how changes in certain variables influence active and traditional place attachments (see Section 4.3). The coefficients of these regressions form the basis of the dynamic place attachment in our model.

Households' initial active and traditional place attachment values are set during the creation of the synthetic population. Since we sample individuals as a whole from the survey data, their place attachment values are automatically assigned (refer to Appendices C.3.1 and C.3.1). In every subsequent step, households calculate new regression values using their updated attributes and the static linear regression coefficients. The difference between the new and previous regression values represents the change in place attachment. This change is then added to the current place attachment value. This process is repeated at each time step for both active and traditional place attachment values. In brief, active and traditional place attachment values are initialized from the survey data, and each change calculated by the regressions accumulates on these initial values without going out of the bounds of 0.2 to 1. Further details are provided in Appendix C.3.3.

5.2.3. Social Interactions

Households are situated in a social network resembling the Watts-Strogatz (WS) model. The WS model creates small-world networks with high clustering and short path lengths, i.e., local and global connections. (Watts & Strogatz, 1998). In our model, the WS model is modified to incorporate homophily— the tendency for individuals to connect with others who share similar attributes (McPherson et al., 2001). We focus on two main attributes: neighborhood and income. People in the same neighborhood experience similar flood risks and are more likely to discuss and influence each other about these risks. Besides, place attachment is a concept closely related to neighborhoods.

Income homophily is also common in real networks and can indicate similar place attachment values, as income is often linked to place attachment (Williams et al., 1992). Therefore, these attributes are selected to create homophily in the network and better represent social interactions. This modified network, referred to as 'neighborhood,' is created following the steps outlined by Tur et al. (2024). These steps are elucidated in Appendix C.2.4.

In each step, households communicate with their connections in the 'neighborhood' network, exchanging worry, perceived flood damage, perceived costs, and self-efficacy of adaptation measures like in the original model (Wagenblast, 2022; Wagenblast et al., 2024). They adjust these attributes by averaging their opinions with those of their network using trust-based weights, following the DeGroot opinion dynamics model (DeGroot, 1974; Wagenblast, 2022; Wagenblast et al., 2024). In addition to these PMT attributes, in our model, households exchange their community attribute, which demonstrates whether they are an active member of a community organization or not (see Table A.3 in Appendix A). However, instead of a trust-based structure, the community attribute is updated based on the proportion of connections in community organizations. If this proportion exceeds the predetermined threshold, the household also becomes a community member. Details of social influence are presented in Appendix C.3.3. These social interactions between households are the main drivers of both place attachment and adaptation decision dynamics in our model.

5.2.4. Age and Income Dynamics

Age is one of the factors found to be related to both active and traditional place attachment (Lewicka, 2011a). To incorporate its impact on place attachment levels, age is included in our model as a dynamic variable. Since people's incomes tend to change with age, typically rising until retirement and then slightly declining (Ozhamaratli et al., 2022), income is also included as a dynamic variable.

Similar to the place attachment attributes, age and income categories are set with household initialization. Then, age and income values are randomly assigned within the boundaries of their respective categories. In each step, households get older, and if they are not already in the last age category, they switch to the next age category after a while. When they move to the next category, their income is also updated. Households' rules and actions for updating age are shown in Figure 5.3.

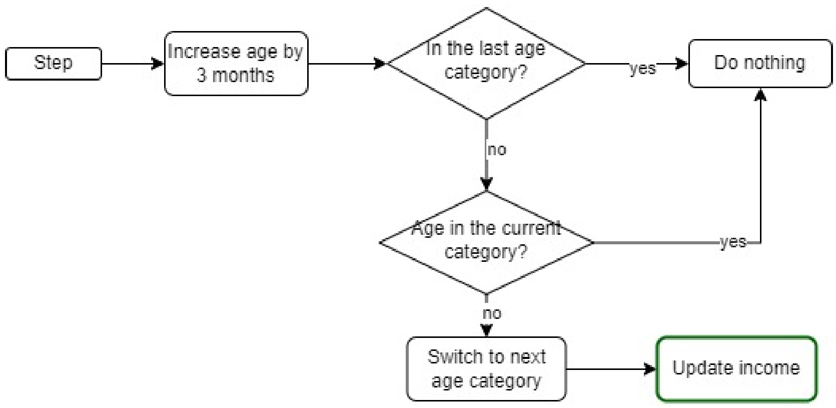


Figure 5.3: Age update. Note: The green color represents another method, which is detailed in Figure 5.4.

There is no clear direction of change between age and income groups. It is a stochastic process varying from person to person. Therefore, to represent this stochasticity, income transition probabilities are derived from the survey data (Filatova et al., 2022), as explained in Appendix C.3.2. When households change their age category, they refer to the new age category row in the transition table C.7. They take the probabilities for their current income category, one level below and one level above. This restriction is set because jumping many income groups at once is considered uncommon. Then, the probabilities of possible income categories are normalized. Based on these normalized probabilities, one of the income categories is randomly selected. This process is illustrated in Figure 5.4 and further explained in Appendix C.3.3.

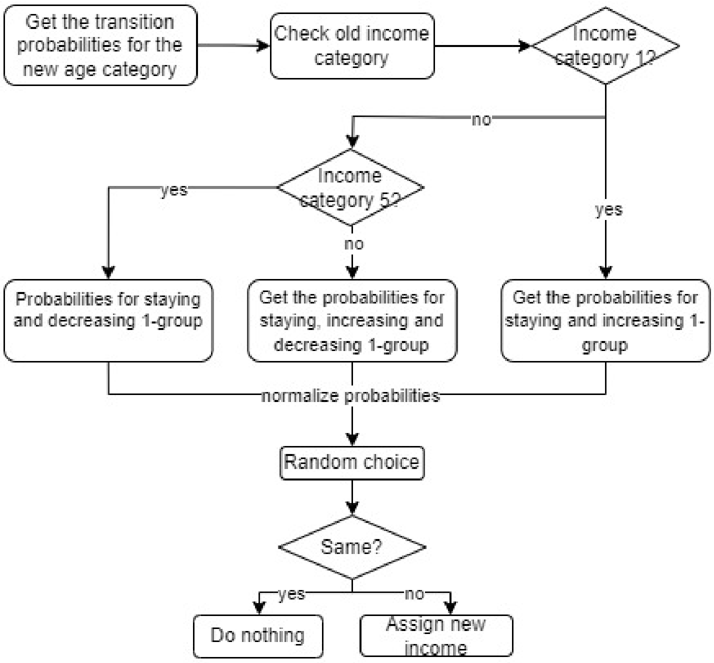


Figure 5.4: Income update.

5.3. Experiment Design

The purpose of the experiments is to examine how external shocks that alter place attachment affect household-level flood adaptation and flood damage reduction over time. The dynamic nature of place attachment is already incorporated into our model through linear regression models that account for implemented measures, social interactions, past decisions, and temporal effects like aging and income changes. Through these experiments, we aim to introduce another significant factor impacting place attachment: human or environmentally-induced changes in the places (see Section 2.3.3). Two different experiments are designed: a flood event and large-scale public flood protection. Each experiment is performed separately for active and traditional place attachments. Therefore, in each experiment, only one type of place attachment is influenced. The setup for these experiments is detailed in Table 5.1. These experiments enable us to explore further the complex and dynamic interplay between place attachment and household-level flood adaptations.

Table 5.1: Experimental setup. Note: Neighborhoods can be seen in Figure 5.1.

Experiment	Type of place attachment influenced	Place attachment impact	Time	Area influenced
Flood event	Active or traditional place attachment	-50%, 0, +50% (0.5, 1, 1.5)	20 or 40	Global
Public Protection	Active or traditional place attachment	-50%, 0, +50% (0.5, 1, 1.5)	0 or 20	Neighborhood 61, 63, 22, 23,14

The first experiment introduces a flood event into the model. Flooding causes a sudden impact on people's lives. After such a disruption, people may feel more attached to their places, having faced the reality of potentially losing their homes, friends, and communities (Anton & Lawrence, 2016). Conversely, the damage to the environment, loss of familiar landscapes, and relocation of neighbors (out of the model scope) may lead to decreased place attachment (Brown & Perkins, 1992). To explore how flood experience and its impact on place attachment influence households' adaptation behavior, we schedule a flood event in our model using the Harvey flood map (Grimley et al., 2023; Leijnse et al., 2021), which is based on a recent, actual event in the Houston area. This map is likely more up-to-date and accurate than older flood maps, considering the region's rapid urbanization and changing climate patterns (Blackburn & Borski, 2023). When the flood occurs, each household's flood risk is determined from the map after taking into account the effect of any existing adaptation measures on the flood depth or damage. The remaining financial damage is then deducted from their savings, and a flood experience between 0 and 1 is assigned based on their flood damage factor, as explained in Table 5.2. Noll (2023) found that flood experience does not change the threat appraisal variables of the households. Following his findings, we also keep these variables unchanged after the flooding. In this experiment, we analyze three potential effects on place attachment: a decrease, no change, or an increase. In addition, savings are stopped for one year, considering the recovery time for households.

Table 5.2: Flood experience level based on flood damage factor.

Damage Factor	Flood Experience
0	0
(0, 0.2)	0.2
[0.2, 0.4)	0.4
[0.4, 0.6)	0.6
[0.6, 0.8)	0.8
[0.8, 1]	1

The second experiment involves the implementation of government-level flood protection. The increasing flood risk level drives governments to implement large-scale adaptation measures, such as dikes or nature-based solutions (Jongman, 2018). However, the effects of these measures on place attachment are often overlooked in planning and implementation. If people in the area perceive these measures as disruptive to their places, it can decrease their place attachment (Clarke et al., 2018) and, consequently, reduce the implementation of household-level adaptation measures. Also, these protections may attract more people to move in due to the increasing safety, further changing the environment and decreasing place attachment (Quinn et al., 2018). This phenomenon is known as the "safe-development paradox," where people adapt less because they feel safer, and exposure to risk increases as more people move into those protected areas (out of the model scope) (Haer et al., 2020). The decline in place attachment level worsens this paradox, causing lower adaptation levels. Conversely, if people see these changes as an improvement or if the changes maintain a sense of familiarity, their place attachment can increase (Wirth et al., 2016), and thus adaptations at the household level.

To understand these dynamics better, we introduce a government-level flood adaptation to our model. This measure reduces the flood depth by 3 meters for inhabitants in the project area. These inhabitants' perceived flood damage levels are adjusted to incorporate the safe-development paradox. However, since not everyone responds the same way, their risk aversion levels are used to determine changes in the perceived damage (see Table 5.3). It is assumed that the implementation of a large-scale measure in the neighborhood will constantly remind the threat to a risk-averse person, thereby increasing their perceived flood damage. In contrast, a risk-seeking person may feel more secure and perceive less flood damage. Similar to the first experiment, three potential effects on place attachment are studied, as described in Table 5.1.

Table 5.3: Effect of dike construction on perceived flood damage across different levels of risk aversion. Note: (1) Risk averse- (5) Risk seeking.

Risk Aversion	Perceived Flood Damage
1	+0.2
2	+0.1
3	No change
4	-0.1
5	-0.2

Each experiment is simulated with 2000 households distributed equally across 10 selected neighborhoods. The simulations run for 80 steps, which is equivalent to 20 years. Each experiment is replicated 50 times to control stochasticity, and the results are aggregated over the seeds. All simulations are performed on the DelftBlue Supercomputer (Delft High Performance Computing Centre, 2024).

Before conducting experiments, our modified model is verified to ensure it is built correctly (Dam et al., 2012). Although the model primarily relies on the survey data, some parameters are assumption-based. To understand their influence on the results, we conducted a sensitivity analysis. Both the verification process and sensitivity analysis can be found in Appendix D.

6

Agent-Based Model Results

6.1. Baseline Scenario: No Environmental Changes

Figure 6.1 shows the results for the baseline scenario where there is no external shock, such as flooding or the implementation of public protection measures. The results represent the average of experiments conducted with fifty different seeds. The uncertainty intervals for the results are presented in Figure E.1 in Appendix E. The initial observation is the difference in the starting levels of adaptation across the three measures. This can be explained by the survey data on which the population is created: wet-proofing is the most commonly adopted measure, followed by dry-proofing and then elevation (refer to Table C.6). There is no change in adaptation levels for any of the measures at the beginning. Starting from step 4, households begin adapting. This delay may be attributed to social influence, place attachment dynamics, and/or savings accumulation. While the first two influence the adaptation probability, the latter addresses the actual barrier. We observe a faster adaptation rate for wet-proofing and dry-proofing compared to elevation, which is the most expensive measure. However, these two measures reach saturation earlier. In other words, households who intend to implement wet-proofing or dry-proofing take the measure quickly, after which the adaptation almost stops. Conversely, elevation requires more time to stabilize, likely because it is an expensive measure, and more time is necessary to save that amount.

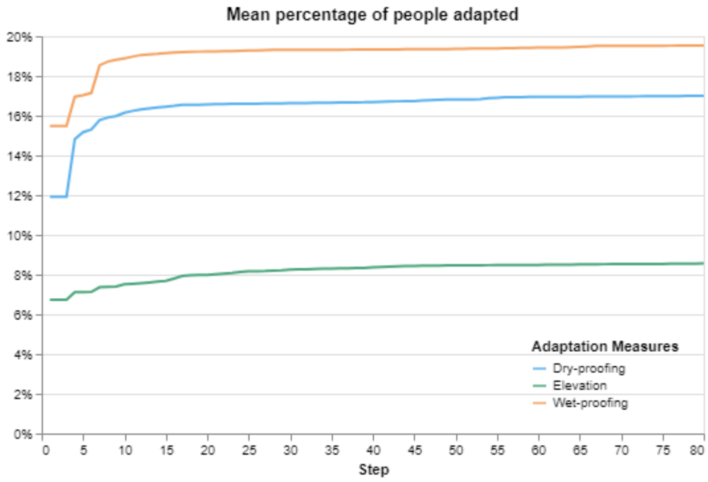
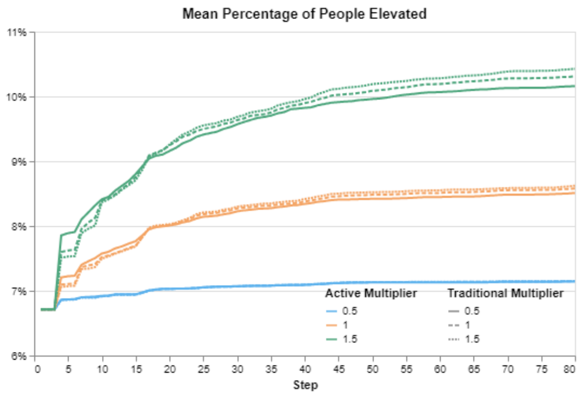


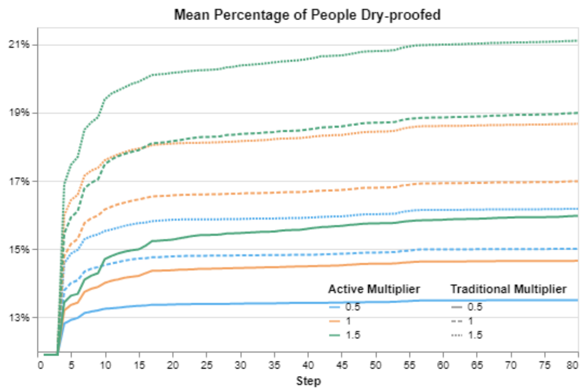
Figure 6.1: Household adaptation levels over time.

Following the baseline, the initial place attachment levels are adjusted to see how they shape households' adaptation decisions. Initial active and traditional place attachment levels of households are reduced by 50%, left unchanged, or increased by 50%. By exploring the sensitivity to these initial conditions, we aim to gain insights into the role of these two attachment types in households' adaptation uptake and flood damage reduction. The results for each adaptation measure are presented in Figure 6.2.

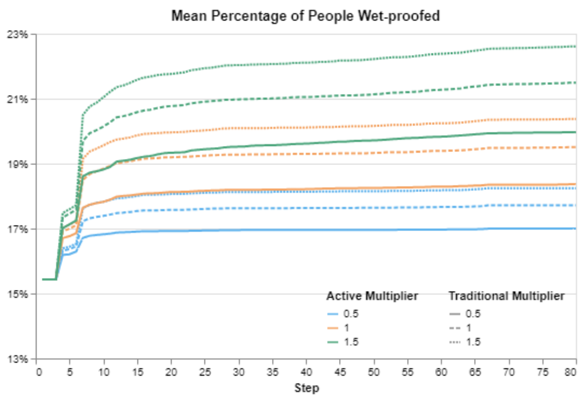
First, we observe that compared to active place attachment, traditional place attachment has almost no impact on households' decision to elevate their houses (Figure 6.2a). Interestingly, as active place attachment increases, the impact of traditional place attachment also grows, albeit to a lesser extent. In the blue lines, there is almost no distinction; however, in the orange, and especially in the green lines, the influence of traditional attachment becomes more visible. Dry-proofing presents a different pattern than elevation (Figure 6.2b). The impact of active (dashed lines) and traditional place attachment (orange lines) on the adaptation of dry-proofing are pretty similar. The third and final adaptation, wet-proofing, is influenced by the active place attachment more than traditional place attachment: the lines are mostly separated by color; the higher the active place attachment, the higher the adaptation. However, unlike elevation, traditional place attachment increases wet-proofing uptake, as can be seen by the differences in the same colored but different style lines.



(a)



(b)



(c)

Figure 6.2: Mean percentage of people implemented (a) elevation, (b) dry-proofing, and (c) wet-proofing based on different initial place attachments. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

Figure 6.3 shows the percentage reduction in flood damage at the end of the simulation compared to the beginning for each possible combination of the three scenarios. First, we observe that changing only active place attachment (medium shade bars, where traditional is stable) has a greater impact on the reduction than changing only traditional attachment (orange bars). Although there are exceptions, the reduction in flood damage increases from left to right on the graph, i.e. with increasing active place attachment, indicating that active place attachment is the main driver in flood damage reduction. However, the highest (lowest) reduction is observed when both active and traditional place attachments are increased (decreased) by 50%. This demonstrates a synergic effect between the two types of place attachment, significantly improving (reducing) flood damage reduction.

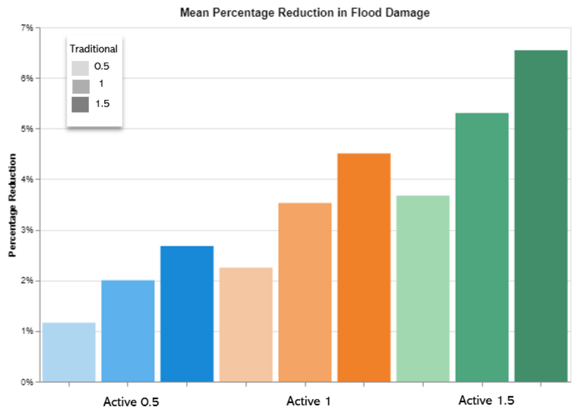


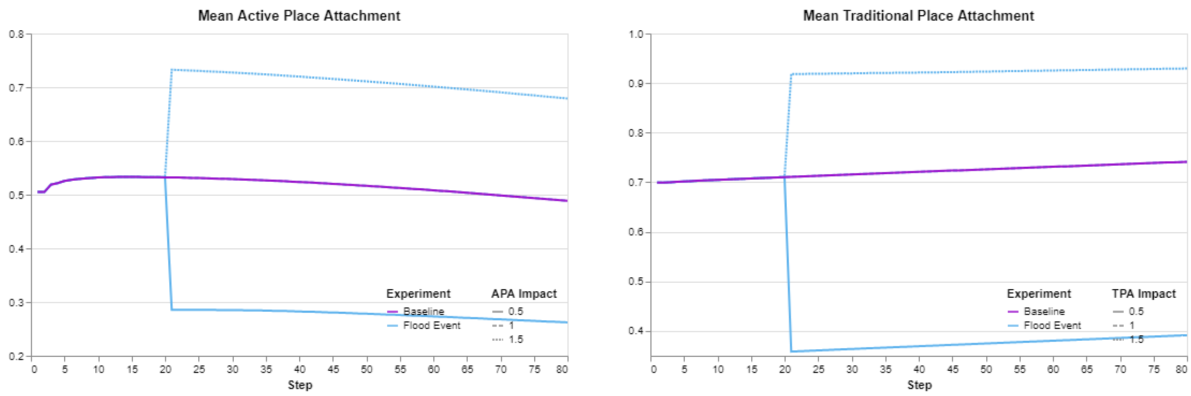
Figure 6.3: Mean percentage reduction in flood damage based on different initial place attachments. The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively. Note: Blue, orange, and green colors represent a 50% decrease, no change, and a 50% increase, respectively.

6.2. Impact of the Flood Event on Household Adaptation and Damage Reduction

As discussed in Section 5.3, a flood event is introduced into our model as an external shock, where every household is flooded, and their either active or traditional place attachment levels are changed. The resulting dynamics of the flood event scheduled at step 20 are analyzed in this section, whereas the results of the flooding at time step 40 are provided in comparison in Appendix E. Our primary focus is on observing the dynamics that emerge after perturbing the levels of active and traditional place attachment, with attention to both household adaptation levels and flood damage reduction. First, we discuss the place attachment dynamics observed throughout the simulation. Then, we examine elevation, wet-proofing, and dry-proofing separately due to their distinct relationships with active and traditional place attachments (see Section 4.4), followed by a discussion on flood damage reduction.

Figure 6.4 shows the average active and traditional place attachment levels throughout the flood experiment, compared to the baseline scenario. We see that active place attachment slightly increases and then subsequently decreases, as illustrated in the baseline in Figure 6.4a. Social influence can explain the initial increase as households adjust their opinions based on their networks. Particularly, participating in community organizations significantly impacts active place attachment. This increase might be partially attributed to the rapid implementation of wet-proofing in the initial steps (Figure 6.1). This statement is also valid for elevation and dry-proofing, but they have a negative influence on the attachment, unlike wet-proofing. Following this trend, active place attachment decreases after a certain point, which can primarily be attributed to the aging population. In our model, the population is static (no death or migration), resulting in a higher average age and, consequently, a lower average level of active place attachment. Conversely, the average traditional place attachment increases when the population gets older (Figure 6.4b). Thus, we can say that increasing age dominates both active and traditional place attachment levels, but in opposite directions.

Following the sudden changes in place attachment caused by the flooding, both active and traditional place attachment follow a similar pattern in a higher or lower level. Yet, the upper blue line in Figure 6.4a shows a bigger decrease. This might be explained by the increasing adaptation of elevation. Higher active place attachment motivates people to elevate their homes; however, elevating a house reduces active place attachment in return (see Figure 4.7). In addition, since place attachment levels are constrained between 0.2 and 1, the average levels may not increase or decrease exactly by 50%. This limitation may also explain why the upper blue line in Figure 6.4b and the lower blue line in Figure 6.4a have a smaller slope.



(a) (b)

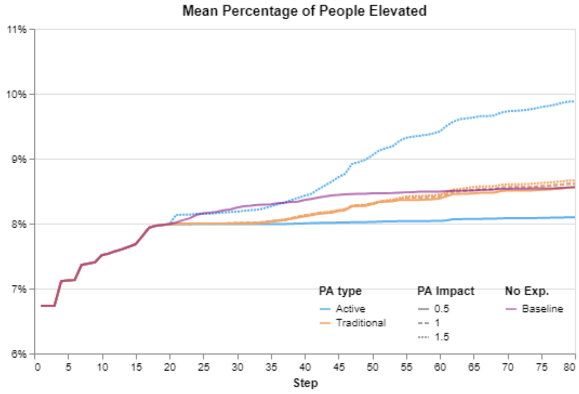
Figure 6.4: Mean changes in (a) active (b) traditional place attachment throughout the flood experiment (t=20). Note: The purple line is the baseline scenario (no experiment).

First, it is observed that after the flooding event, in every combination of place attachment types and impacts —except for active 1.5— people elevate their houses less frequently than the baseline, which can be seen in Figure 6.5a. This decrease can primarily be explained by the financial damage caused by the flood; households lose a portion, or sometimes all, of their savings and stop saving for one year to recover. Another reason is that traditional and active place attachments have the lowest and highest impacts on elevation, respectively. Since households first take the measure with the highest probability, others might get ahead of the elevation, extending the no adaptation period. Afterward, households start to elevate again. Approximately ten years later, the experiments targeting traditional place attachment catch the baseline, with traditional 1 and 1.5 slightly surpassing it. Put another way, flood experience and traditional place attachment increase people's probability of adapting, and when they have enough money and no other option with a higher probability, they elevate their houses. However, we observe that traditional place attachment does not significantly impact elevation, as the results of the three experiments remain close and converge at a similar level (Figure 6.5a orange colored lines). Note that the active 1 and traditional 1 experiments give the same results since the only changes arise from the flood experience and savings, which are identical in both experiments.

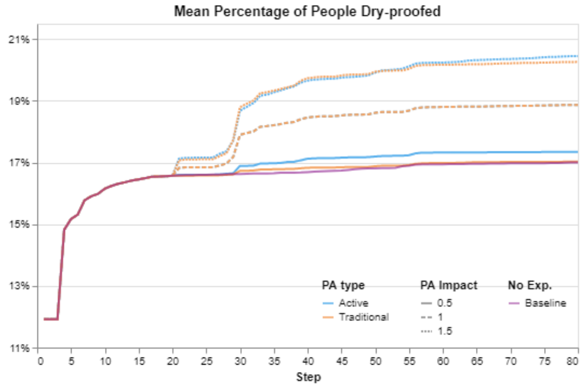
Conversely, unlike its traditional counterpart, active place attachment appears to have a substantial impact (see Figure 6.5a). When households' active place attachment increases by 50% (active 1.5), we see an immediate albeit small increase. This change in active attachment increases people's probability of elevating considerably, and those with sufficient savings quickly elevate their homes. As before, the decrease in savings slows down the adaptation uptake for a period, but once households have enough money, they continue to elevate their houses rapidly, resulting in a higher level of adaptation. Interestingly, when flooding decreases households' active attachment levels, even after recovering, almost none of the households elevate their homes. Additionally, these low levels of active attachment cannot find an opportunity to bounce back because of the aging population. As the population gets older, age dominates the regular active place attachment updates.

Second, the adaptation patterns for dry-proofing differ from those for elevation, showing similar results for both the active and traditional experiments and higher level adaptations compared to the baseline (see Figure 6.5b). We observe that financial damage and recovery time do not cause a significant delay in the adaptation in any of the experiments, which can be attributed to the lower cost of dry-proofing compared to elevation. In experiments where only flood experience alters the probability of adaptation (active 1 and traditional 1), the percentage of people dry-proofed increases approximately 2%, more than what we observed in the other measures (Figures 6.5a and 6.5c). When we increase either active or traditional place attachment by 50%, the outcomes of these experiments are almost the same, driving many people to dry-proof their homes. Conversely, if active or traditional place attachment decreases by 50%, the adaptation levels stay similar to the baseline. We can say that the negative impact of reduced place attachment offsets the expected positive effect of the flood experience. One of the interesting observations is that active 0.5 experiment shows a bit higher adaptation rates than the traditional 0.5, although active place attachment has slightly more impact on dry-proofing on average (Table B.2). This can be explained by the fact that households select the adaptation measure with the highest probability, and among the three measures, dry-proofing is the least influenced by active (which increases its chance of being selected) and most influenced by traditional attachment (which decreases its chance).

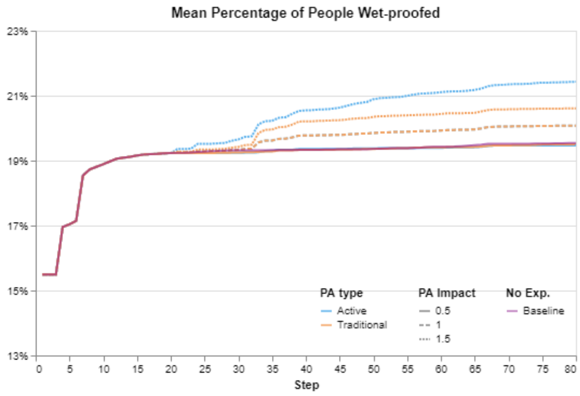
The third and final adaptation measure is wet-proofing, whose results are quite similar to dry-proofing, except that traditional and active attachment results are not as close (refer to Figure 6.5c). Like dry-proofing, wet-proofing also experiences a shorter delay than elevation, most likely due to its lower costs. We see that both active and traditional place attachments positively impact wet-proofing uptake; however, active attachment has a more noticeable influence. Conversely, when place attachment is reduced 50% (active 0.5 or traditional 0.5), the adaptation level of wet-proofing closely follows the same pattern as the baseline. A similar argument might apply to wet-proofing as in dry-proofing: the negative impact of reduced place attachment is somewhat balanced by the positive influence of flood experience. Yet, wet-proofing has a different situation: it is neither the one least affected by active attachment (dry-proofing) nor by traditional attachment (elevation), leaving it mostly as a second choice. So, it might be the reason why we do not see a difference between active 0.5 and traditional 0.5 like in dry-proofing.



(a) Elevation



(b) Dry-proofing



(c) Wet-proofing

Figure 6.5: Mean percentage of people implemented (a) elevation (b) dry-proofing (c) wet-proofing after the flood event scheduled at time step 20, i.e., fifth year. Note: The purple line is the baseline scenario (no experiment). Each time step represents 3 months. The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

Lastly, we examine the impact of all adaptation measures on flood damage reduction by analyzing the change in flood damage between the initial and final steps. The results demonstrate that flood experience itself is a powerful driver for household adaptation uptake, as evidenced by the medium-shade blue and orange bars surpassing the baseline. On the one hand, when coupled with increasing place attachment (darker blue or darker orange), the reduction in flood damage improves even further, with active place attachment being more effective than traditional. On the other hand, if either active or traditional place attachment decreases (lighter blue or orange bars), the flood damage stabilizes near the base level. In the base case, people do not take an adaptation measure significantly after a certain point (Figure 6.5). Even after the flooding, a reduction in place attachment discourages households from adaptation efforts, leading to stabilization near the base scenario.

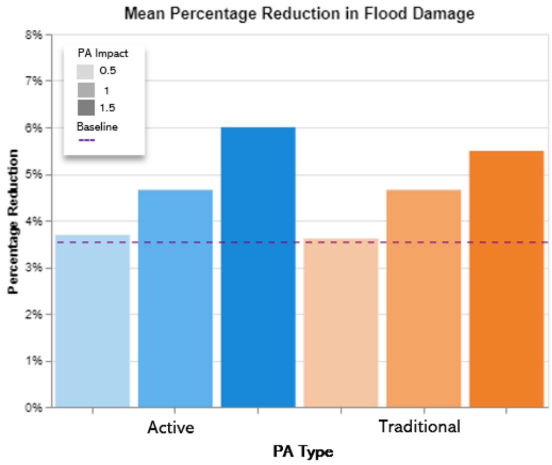
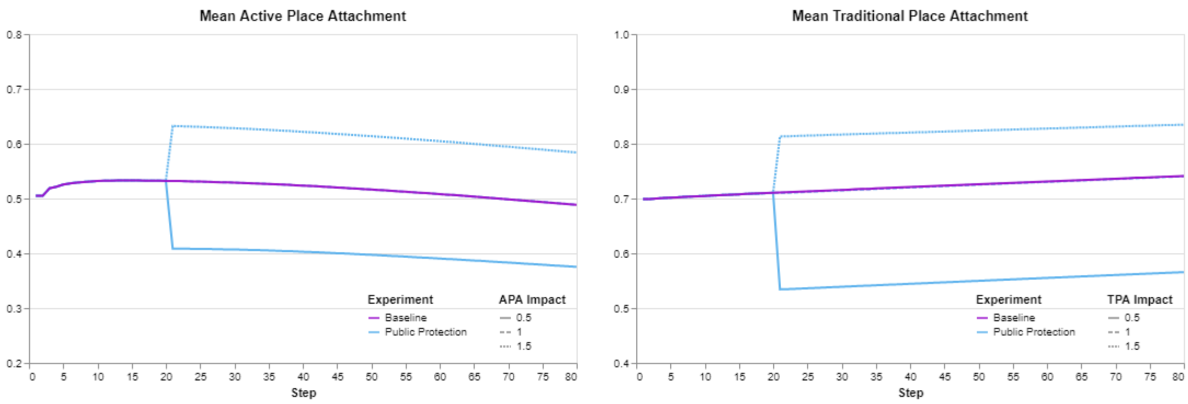


Figure 6.6: Mean percentage reduction in flood damage reduction during the experiment, where a flood is introduced at step 20. Note: The purple dashed line is the baseline scenario (no experiment). Blue and orange colors represent experiments targeting active and traditional place attachments, respectively.

6.3. Impact of the Public Protection Measure on Household Adaptation and Damage Reduction

This section examines the impact of a large public protection measure that affects specific neighborhoods (see Section 5.3). The results for implementation at step 20 are presented here, while those for implementation at step 0 are provided in comparison in Appendix E. Similar to the previous experiment, we aim to explore the dynamics following the implementation of public protection and place attachment change, focusing on both household adaptation levels and the reduction in flood damage.

Figure 6.7 demonstrates the average active and place attachment levels throughout the experiment, compared to the baseline scenario. Place attachment dynamics observed in the second experiment are similar to the previous experiment (refer Figure 6.5). The main difference is that since not everyone is affected, the average increase and decrease are smaller, as seen in both active (6.7a) and traditional (6.7b) place attachment.



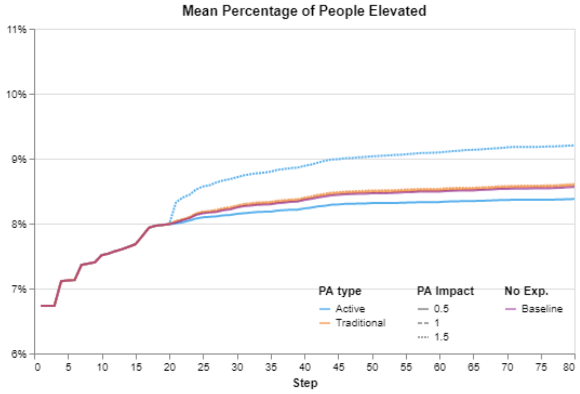
(a) (b)

Figure 6.7: Mean changes in (a) active (b) traditional place attachment during the public protection experiment (t=20).

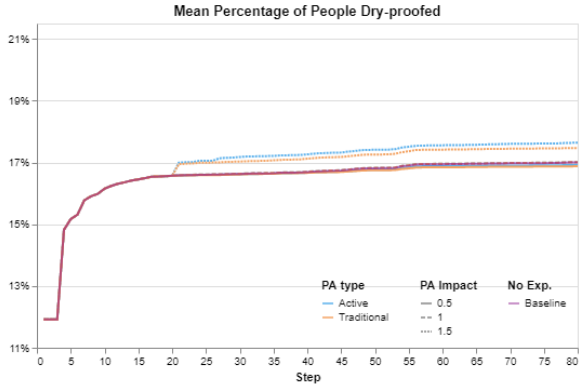
Figure 6.8 shows the changes in household adaptation levels for each measure, namely elevation, dry-proofing, and wet-proofing, after the implementation of the large-scale public protection measure. Unlike in the flood experiment, there are no delays in the adaptation levels for any of these measures since there is no financial burden on households caused by public protection. Aligning with the findings in Section 6.2, active place attachment substantially impacts elevation uptake (Figure 6.8a). When households' active place attachment increases by 50% (active 1.5), the percentage of people elevating their houses rises by more than 0.5%. Considering the generally low implementation levels for elevation, this represents a significant increase. Conversely, a reduction in active place attachment by the same amount (active 0.5) slows down the adaptation process, resulting in levels below the baseline. However, the percentage of people elevating their houses still increases, as the public protection measure is not global; those unaffected by the changes continue their adaptations as in the base case. In line with the previous results, traditional place attachment has almost no impact on elevation uptake, and all experiments (0.5, 1, and 1.5) converge toward almost the same level. Traditional experiments show slightly higher levels than the baseline, likely due to a minor change in perceived flood damage. Please refer to Figure E.6 in the appendix to see the perceived flood damage of households over time.

For dry-proofing, a similar pattern is observed for both traditional and active place attachment (Figure 6.8b), with active place attachment slightly surpassing when raised by 50% (active 1.5). The increase is smaller than the flood experiment (Figure 6.5b) because only half of the population is impacted, and the positive influence of flood experience is absent. Perceived flood damage hardly changes the odds of intention to implement dry-proofing (see Section 4.4); therefore, it does not have the same positive impact as the flood experience. Besides, the perceived flood damage does not change as much as the flood experience (see Tables 5.2 and 5.3), limiting its effect. This limitation applies not only to dry-proofing but also to elevation and wet-proofing, as clearly observed in the experiments with no change in place attachment (Figures 6.8a and 6.8c). Furthermore, as seen in the baseline, the percentage of people dry-proofed saturates pretty early, around step 20. This suggests that even without the negative shock (0.5 and 0.5), there is little intention to continue adopting this measure. As a result, their already low motivation to implement dry-proofing decreases even further, resulting in a level nearly identical to the baseline. Yet, if the public measure had been implemented before reaching saturation, it would have led to lower levels of adaptation than the baseline. This is supported by the experiment conducted at time zero; see Appendix E for details. As a side note, we do not observe the slightly higher levels seen in the 0.5 experiment that is present in the previous experiment (Figure 6.5b). The lack of flood experience can likely explain this situation, which otherwise helps increase the intention to implement measures.

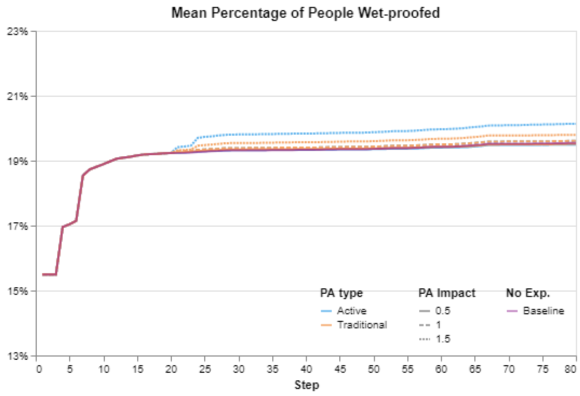
As in the previous experiment, wet-proofing shows similar results to dry-proofing (Figure 6.8c). Active place attachment (1.5) motivates people to implement wet-proofing more than traditional place attachment (1.5), consistent with the findings in Section 6.2. We observe a plateau in the baseline again around the same time step, and a 50% decrease in active or traditional place attachment produces results similar to those in dry-proofing (Figure 6.8b). The only difference is that, in the case of no change in place attachment, the results slightly exceed the baseline, indicating that perceived flood damage has a greater impact on the adoption of wet-proofing compared to the other two measures.



(a) Elevation



(b) Dry-proofing



(c) Wet-proofing

Figure 6.8: Mean percentage of people implemented (a) Elevation (b) Dry-proofing (c) Wet-proofing when there is a large public protection measure (t=20). Note: The purple line is the baseline scenario (no experiment). Each time step represents 3 months. The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

Finally, the impact of household-level adaptations on flood damage reduction is investigated in the presence of large-scale public adaptation. Figure 6.9 shows the percentage flood damage reduction resulting from only household-level adaptations. On top of household adaptations, the implementation of the public protection measure reduces the flood depth for inhabitants in the project area by 3 meters, leading to a drastic reduction in flood damage by approximately 30% (not included in Figure 6.9). Varying levels of decrease in flood damage are observed across different experiments (different place attachment types and their different impacts), yet the difference is tiny. Increasing either active or traditional place attachment by 50% reduces the flood damage factor slightly more than the others. However, in each case, the flood damage reduction resulting from household adaptations is smaller than the baseline and what we observed in the flooding experiment (Figure 6.6). This is likely because the large-scale public adaptation completely eliminates flood damage for some households, leaving no damage to reduce further.

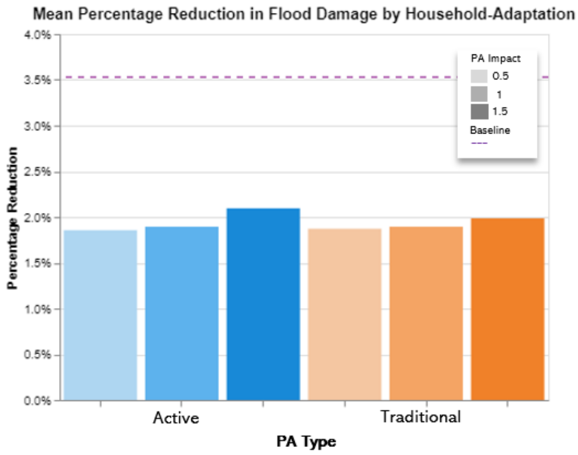


Figure 6.9: Flood damage reduction during the experiment, where a public measure is introduced at the beginning of step 20. Note: The reduction in flood damage resulting from the public protection measure is not included in the graph. The purple dashed line is the baseline scenario (no experiment). Blue and orange colors represent experiments targeting active and traditional place attachments, respectively.

7
Discussion and Conclusion

7.1. Addressing Research Questions

Climate change heightens the frequency and intensity of flooding, creating an urgent need for climate change adaptation at the household level to complement government measures. Understanding why households do or do not adapt to floods is crucial for designing effective flood adaptation strategies. One significant but understudied factor influencing households' adaptation decisions is place attachment, individuals' emotional bond with their places. While place attachment influences adaptation decisions, it is also shaped and altered by various factors, including the adaptations themselves. This dynamic interplay makes place attachment particularly complex and requires a careful, comprehensive approach to fully understand its role in adaptation behavior. This thesis examined place attachment as a dynamic concept, exploring how it evolves over time and interacts with household-level adaptation, intending to understand the impact on flood damage reduction. Thus, the main research question of this thesis was:

"Given the feedback between multi-dimensional place attachment and household-level climate change adaptation, how does their complex interplay over time influence damage reduction from climate-induced floods?"

To understand the interplay between place attachment and household adaptation decisions, an agent-based model, alongside statistical analysis, data analysis techniques, and a literature review, was utilized. The findings are discussed below to answer each sub-question, and then they are synthesized to address the main research question of this thesis.

SQ1. What are the different dimensions of place attachment for households, and how can they be operationalized?
To identify and operationalize the dimensions of place attachment, we conducted an Exploratory Factor Analysis (EFA) on the secondary survey data collected from households in Houston and Miami greater areas (Filatova et al., 2022). Our analysis revealed two different dimensions of place attachment. The first dimension involved active participation in the community, whereas the second reflected more passive characteristics, such as a sense of identity with the place and the enjoyment of simply being there. These findings supported the conceptualization of place attachment into 'active' and 'traditional' dimensions, as proposed by (Lewicka, 2011a). Active place attachment is characterized by personal exploration and active involvement in a place (Lewicka, 2011a; Parreira & Mouro, 2023). In contrast, traditional place attachment is characterized by passive enjoyment of the neighborhood, typically passed down through generations or associated with long-term residency or age (Lewicka, 2011a). This theoretical connection enabled us to use existing literature to understand

the factors influencing active and traditional place attachment, providing a solid foundation for addressing our second research question.

SQ2. What are the behavioral, socioeconomic, and physical factors that influence place attachment dimensions, and to what extent do these factors affect it?
To integrate the dynamic nature of place attachment into our research, we needed to understand the factors that drive changes in place attachment and the extent of their influence. Given the different characteristics of active and traditional place attachments—two dimensions identified in our study—we built two separate linear regression models guided by the insights from past studies and our exploratory data analysis. The model for traditional place attachment primarily included sociodemographic factors, while the model for active place attachment focused on factors reflecting its 'active and social' nature.

Our results for traditional place attachment showed that age, ease of leaving the place, and income were significant predictors. These findings are consistent with the existing literature, which emphasizes the role of continuity and stability as factors fostering traditional place attachment (Hummon, 1992; Lewicka, 2005, 2011a). However, gender was not found to be a significant predictor in our study, unlike a study conducted by Lewicka (2011a) that suggested being female increases traditional place attachment. Similarly, while education decreased traditional place attachment in our study, it was not as significant as in their findings. These differences might be related to contextual differences as Lewicka (2011a) conducted the survey in Poland. Contrary to expectations that an increase in house size would strengthen place attachment through increased residential satisfaction (Bellet, 2019), our findings indicated a significant negative impact. A possible explanation is that larger homes may create a sense of independence or isolation from the surrounding neighborhood. House ownership has generally been recognized as a significant factor in place attachment according to the literature review conducted by Lewicka (2011b). However, in our study, it showed only a slight positive impact. This may be because 80% of our respondents were homeowners, leaving little variance to capture its effect in the regression analysis. Interestingly, worry and perceived flood damage had a negative relationship with traditional place attachment, likely due to increased fear and insecurity. Flood probability had the opposite relation, which can be attributed to the fact that the possibility of losing their place of attachment may strengthen their attachment.

The regression results for active place attachment are in line with Jaśkiewicz (2018), who also found that social interactions positively predict active place attachment. Active involvement in community organizations, such as book clubs or religious associations, was found to be a significant predictor of active place attachment. Similarly, participation in local initiatives focused on flood safety emerged as an important factor. However, these findings also present a causality dilemma: it is unclear whether individuals participated in these activities because they were already actively engaged in the community or if their participation increased their active place attachment. In our pursuit to understand the dynamic interplay between place attachment and adaptation measures, we included adaptation strategies, i.e., elevation, dry-proofing, and wet-proofing, in our regression model. Interestingly, our analysis revealed that increased active place attachment motivates households to elevate their houses (see SQ4); elevation, in return, has a significant negative influence on active place attachment. Dry-proofing had a slight negative impact, whereas wet-proofing was positively associated with active place attachment. We initially expected these adaptation strategies to be positively related to active place attachment. However, these findings challenge that assumption, suggesting that certain adaptation strategies may introduce changes that weaken active place attachment. Due to limitations in the existing literature, we could not further interpret the differences in the coefficients for these adaptation measures. Besides these active elements, we included age, income, and worry like the previous model. Income was also a significant predictor of active place attachment. Age supported the concave relationship discovered by Lewicka (2011a). Interestingly, worry emerged as a positive predictor of active place attachment. This may be because individuals who are more worried about potential risks in their environment tend to engage more actively in their community to address those concerns. Having explored how place attachment can be dynamic for each dimension in our study, the next step was understanding how households make decisions to adapt to floods.

SQ3. How do multi-dimensional place attachments, along with other socio-psychological factors, affect households' flood adaptation intentions?
We decided to ground households' decision-making in Protection Motivation Theory (PMT), a leading behavioral theory in flood risk studies. The original PMT, which consists of threat and coping appraisal variables, is extended to include previous flood experience, implemented flood adaptation measures, and active and traditional place attachments. We then performed logistic regression analyses for each adaptation measure (elevation, wet-proofing, and dry-proofing) to determine how these factors influence household intentions to take adaptation measures.

The results showed that both active and traditional place attachments were positive predictors of households' adaptation intention for each measure to different degrees, with active place attachment having a more prominent effect. In contrast to the study by Parreira and Mouro (2023) that distinguished between passive (maintaining routine) and active adaptation strategies (problem solving) according to the type of place attachment, we found that both active and traditional place attachment are positive predictors of the uptake of structural adaptation measures, i.e., active strategies.

The significant influence of active place attachment across all three adaptation measures, especially elevation, demonstrates that households actively engaged in their community intend to undertake effective protection measures. Traditional place attachment also played an important role, particularly regarding wet-proofing and dry-proofing. This supports the findings of Holley et al. (2022), who suggested that households with higher place attachment (conceptually similar to our traditional dimension) tend to implement adaptation measures to continue living in their current places. However, traditional place attachment did not influence the intention to elevate homes, likely because elevation is a more disruptive measure that may conflict with the desire to maintain the status quo (Hummon, 1992; Lewicka, 2011a). Due to the different relations discovered, these findings underscore the importance of studying place attachment in a disaggregated manner.

SQ4. How does multi-dimensional place attachment impact households' adaptation level and flood damage reduction over time?
After laying the foundation of our study with the first three questions, we moved on to the final sub-question to explore the impact of active and traditional place attachments on households' adaptation levels and flood damage reduction over time. To address this question, first, we identified the effectiveness of adaptation measures in reducing flood damage through a literature review to relate adaptation to damage reduction. We found that the effectiveness of these three measures in reducing flood damage varies. Elevation, while the most expensive option, is highly effective in reducing flood damage by changing the flood depth to which households are exposed. Wet-proofing and dry-proofing are more affordable alternatives; however, their effectiveness is limited compared to elevation, though they still provide a significant degree of protection. Then, we modified the ABM created by Wagenblast (2022), taking into account how place attachment itself evolves in response to various factors, including but not limited to adaptation. We then conducted a series of experiments to examine the dynamic interplay between place attachment and adaptation decisions on damage reduction over

time.

Our experimental results underscored the significant role that both active and traditional place attachments play in influencing households' flood adaptation decisions and their subsequent impact on damage reduction. A key finding was the **synergistic relationship** between these two types of attachment. When households have both strong active and traditional attachments, the combined effect drives higher adaptation rates and more substantial reductions in flood damage. In all experiments, active place attachment was particularly influential in motivating the adoption of elevation, which led to the most significant decreases in flood damage. It also significantly increased the implementation of wet proofing and dry proofing, further strengthening flood protection. While traditional place attachment was less effective in encouraging significant structural changes like elevation; however, it significantly contributed to the adoption of dry-proofing and moderately influenced wet-proofing. This suggests that traditional attachment may be more in line with measures that preserve the character of a place while still offering protection.

The experiments also demonstrated that the impact of flood experiences on household adaptation was profoundly influenced by place attachment. It was not only the flood event that drove adaptation; it was how that event affected the emotional bonds within the community. When flood experiences strengthened place attachment—particularly active attachment—households implemented more adaptation measures. However, when a flood weakened these attachments, the increase in adaptation diminished, becoming almost identical to the baseline where no flooding occurred. This finding exposed a vulnerability: the decrease in place attachment could undermine flood resilience even when the risk was evident.

Besides the external shock introduced, place attachment variables vary over time based on the linear regression coefficients (SQ2). Active and traditional place attachment showed different trends over time. While active place attachment decreased after a slight increase, traditional place attachment finished higher than its initial level. Therefore, traditional had a constant positive impact on adaptation, whereas active had a mixed impact throughout the simulation. Their difference can be attributed to the influence of age, which has a positive relationship with traditional place attachment and a concave relationship with active place attachment. In our model, age is updated at each step, resulting in a total age increase of 20 years by the end of the simulation. As a result, the effect of age becomes the dominant factor shaping place attachment dynamics, as other independent variables, being either binary or categorical, do not change significantly over time.

Main Research Question
Place attachment → Adaptation
We found that place attachment does play a significant role in reducing flood damage; however, its effects are complex and multi-faceted. Place attachment cannot be generalized into a single concept but must be addressed in its dimensions, which we identified as "active" and "traditional." Active place attachment drives all structural measures (elevation, wet-proofing, and dry-proofing), while traditional place attachment, favoring less disruptive measures, primarily motivates dry-proofing and wet-proofing. These findings confirmed the necessity, as suggested by Lewicka (2011a), of distinguishing place attachment dimensions to comprehensively understand their roles in adaptation. However, our results also demonstrated that when both active and traditional place attachments are strong, they can create a synergistic effect, resulting in the highest levels of adaptation. Thus, their synergistic effect should not be overlooked, although studying place attachment dimensions in a disaggregated manner allows for a finer-grained analysis.
Adaptation → Place Attachment

We observed that both dimensions positively drive adaptation. However, the adaptations themselves can have complex effects on place attachment, sometimes diminishing it, especially when the adaptations disrupt the community or environment. In our study, we assumed that adaptation measures would directly influence active place attachment, with traditional place attachment being influenced by other factors but not by adaptation measures. Our study highlighted the nuanced relationship between adaptation measures and active place attachment. While elevation and dry-proofing weakened active place attachment, wet-proofing strengthened it based on the survey data.

Adaptation ↔ Place Attachment
We conclude that the interplay between place attachment and household-level climate adaptation formed a complex relationship. While place attachment increases flood adaptation, the adaptation measures can, in turn, either strengthen or weaken place attachment depending on the nature of the changes, resulting in mixed outcomes for flood resilience. When adaptation measures positively impact place attachment, they increase households' motivation to adapt further and thus provide greater protection against future floods. Conversely, when these measures disrupt place attachment, the long-term effectiveness of adaptation may be damaged as the motivation to continue adapting decreases.

7.2. Scientific Relevance

The present study makes several noteworthy contributions to household-level flood adaptation and place attachment studies. Many studies extend the PMT to include additional factors. However, only a study by Holley et al. (2022) integrates place attachment into the PMT framework, treating it as a uni-dimensional concept. In our research, we extend PMT to include place attachment with its two dimensions: active and traditional. To our knowledge, this is the first attempt to integrate place attachment into the PMT as a multi-dimensional concept. Next, most studies examining the relationship between place attachment and flood adaptation behavior of households analyze non-structural adaptation measures such as keeping flashlights and seeking flood-related information (De Dominicis et al., 2015; Domingues et al., 2021; Mishra et al., 2010; Parreira & Mouro, 2023). Holley et al. (2022) investigate "implement elevation or floodproofing" as one group alongside non-structural measures and relocation. However, structural adaptation measures have not been studied in detail in the existing literature. These measures are the most effective options, significantly supporting government-level adaptations and allowing households to continue staying in their current places. We contribute to the field by exploring separately the relationship between structural adaptation measures, namely elevation, wet-proofing, and dry-proofing, and the two dimensions of place attachment. Our results reveal that the relationship between place attachment dimensions and adaptation measures varies both between the different dimensions of place attachment and among the adaptation measures themselves. We confirm the necessity of studying the dimensions of place attachment separately, as urged by Lewicka (2011a).

The final and most important contribution of this research is the incorporation of the dynamic nature of place attachment into flood adaptation studies. The existing literature mainly offers a snapshot of the relationship between place attachment and adaptation behavior, without considering how place attachment evolves over time and interacts with other factors, including the adaptation itself. Our study builds on the pioneering work of Lewicka (2020), who was among the first to examine place attachment as a dynamic concept. By integrating this dynamic perspective, our research offers a more comprehensive understanding of how place attachment influences and is influenced by ongoing household-level adaptations. This study is also one of the first attempts to integrate place attachment into a simulation model, extending our contribution beyond the flood adaptation studies.

7.3. Policy Recommendation

Household-level adaptation is becoming increasingly important. However, their adaptation levels are far below what is necessary to prevent the adverse effects of climate change. To increase adaptation to the desired levels, it is crucial to understand the factors that motivate or hinder these decisions. Our research has demonstrated that place attachment can be one of the effective tools that policymakers can leverage to promote household-level adaptations. Both active and traditional place attachment increases the chances of adapting, and together, they have an even stronger effect. Policymakers can improve active place attachment by organizing community events and facilitating more interaction within the community. However, traditional place attachment is usually associated with inter-generational transmission, age, or long-term residency (Lewicka, 2011a). If limited by these factors, it may not be possible to change it by external intervention. Further research is needed to understand the factors that shape traditional place attachment and how they can be influenced. On the other hand, older residents tend to have higher traditional attachments but lower active place attachments. If policymakers can find a way to increase their active attachment, they would benefit from a positive interaction effect in terms of adaptation.

Another key consideration is that place attachment influences different measures in different magnitudes. This should be considered when designing policies, as different measures have different cost efficiencies; implementing a policy based on place attachment might lead to less cumulative societal benefit if people avoid measures that are more low-hanging fruits. Moreover, we observed that flood experience, when coupled with strong place attachment, motivates households to implement more adaptation measures. For policymakers, this translates into considering the population's place attachment levels when developing flood policies in previously flooded areas. For instance, populations with higher attachments can be granted subsidies to accelerate their adaptation process, whereas different policies should be formulated to stimulate populations with low-place attachments that have no intention to implement adaptation measures after a flood.

Finally, the impact of adaptation measures, both public and household level, on place attachment should be considered while designing policies to ensure long-term flood resilience. For public adaptation measures, it is essential to involve residents in the planning process to respect and enhance the existing bonds people have with their place. If these measures decrease place attachment, households might implement fewer adaptation measures, limiting overall adaptive capacity. Therefore, maintaining or enhancing place attachment should be a key focus for policymakers.

7.4. Limitations and Future Recommendations

Several significant limitations of this thesis need to be considered. The first limitation concerns the data. The number of participants remaining in the fourth wave of the survey was low. To overcome this, we combined data from the Greater Houston and Miami areas. Although these datasets were similar, this approach may pose a limitation, particularly for a place attachment study, which is context-specific. While the first wave had a more balanced demographic, the fourth wave mainly consisted of older individuals. This resulted in a population with high traditional but low active place attachment. Besides, except for place attachment variables, every variable was taken from wave 1. There might be inconsistencies since there is a time difference between the waves. Most importantly, the questions targeting the place attachment were limited. Therefore, claiming that they fully represent active and traditional place attachment would be reductive.

To integrate the dynamic nature of place attachment into our model, we needed to understand which variables influence active and traditional place attachments. If we had panel data and used it to identify factors, we could make causal inferences from our linear regression results. However, there was no panel data, and we relied on limited literature and our personal judgment to determine the factors affecting them. Thus, our linear regression models have major limitations. Another limitation is that not every variable in our linear regression models is dynamic in the ABM; only some variables change during the simulation. This further limits our ability to capture how place attachment changes over time. While our model incorporates a feedback mechanism between place attachment and adaptation decisions through linear regression, we did not explicitly measure the contribution of this feedback. This presents a limitation in our ability to quantify the exact impact of the dynamic interplay we sought to examine.

Furthermore, having before and after data or interviewing people who live in a flooded area or nearby public measures could have enhanced our experimental design. Particularly for the second experiment, our ability to represent the "safe-development paradox" and changes in households' risk perception was limited. Since our population was designed to be static, we did not consider population growth due to increased safety in the area. The model did not account for hydraulic dynamics, so we simplified the impact of the measure and did not consider its effects on the surrounding area. We also did not consider the potential financial costs of public measures on households, such as additional taxes. Moreover, in each experiment, we changed place attachment immediately after the external shock, but in reality, place attachment may not change so quickly. All of these points significantly constrained our experiments.

For future research, the data collection should target a larger and more balanced sample of participants. However, instead of collecting data from a wider area, focusing on specific neighborhoods would be more beneficial. This approach can better capture social interactions and reactions to local changes. Besides, with neighborhood-specific data, community-level adaptation measures can be studied, which can provide interesting insights into place attachment. Collecting data from neighborhoods with varying levels of place attachment can further enhance our understanding. Surveys should include more questions that target place attachment and assess how adaptation measures impact it. Panel data is ideal for capturing its dynamic nature, but interviews with before-and-after questions can also be useful. Furthermore, migration should be considered in addition to adaptation measures, as low levels of place attachment may encourage individuals to relocate rather than adapt. Moreover, future research should include a comparative analysis, where each experiment is performed with and without the feedback mechanism, to better understand its contribution to the outcomes observed. Lastly, the stochastic nature of the population creation in our model resulted in a high standard deviation in the results. Due to time and computational constraints, we conducted only 50 replications. Future experiments should aim for a higher number of replications to improve the robustness of the results.

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A

Survey Data

A.1. Data Preparation and Cleaning

In Table A.1, the number of data points for Wave 1 and Wave 4, the respondents who remained in the same house between these waves, and those who did not answer “I do not know” to perceived damage and flood probability are presented. Organizing this data is challenging because we do not know precisely when the participants changed houses. The main problem is the uncertainty of whether their responses are for their old or new houses, potentially misleading our data. Therefore, these people were eliminated from our analysis. In addition, the participants responding “I do not know” to perceived damage and flood probability were removed from the datasets. This decision was made based on the findings of Noll (2023), who concluded that these individuals genuinely do not know the specific risk. Hence, imputation would not be an appropriate solution. As explained in Section 3.3.1 in the main text, we decided to continue with the U.S. data.

Table A.1: Number of data points in each country. Source: The analysis is conducted by the author using the survey data obtained from Filatova et al., 2022. Note: For the Netherlands, after observing only 65 people responded to Wave 4, the next steps of the analysis were not conducted.

# of participants / **Country**	Wave 1 (Mar. 2020)	Wave 4 (Nov. 2022)	Same House	Risk Perception without “I don’t know”
the U.S.	1993	680	597	458
Indonesia	2061	731	622	385
China	1174	231	188	145
the Netherlands	1251	65	-	-

After deciding on the U.S. data, as a first step, two waves are merged, with only the necessary columns. The process can be seen in Figure A.1. Later, we excluded “New Orleans” from our data and continued with the greater areas of Houston and Miami (see Section 3.3.1 and Appendix A.1.1).

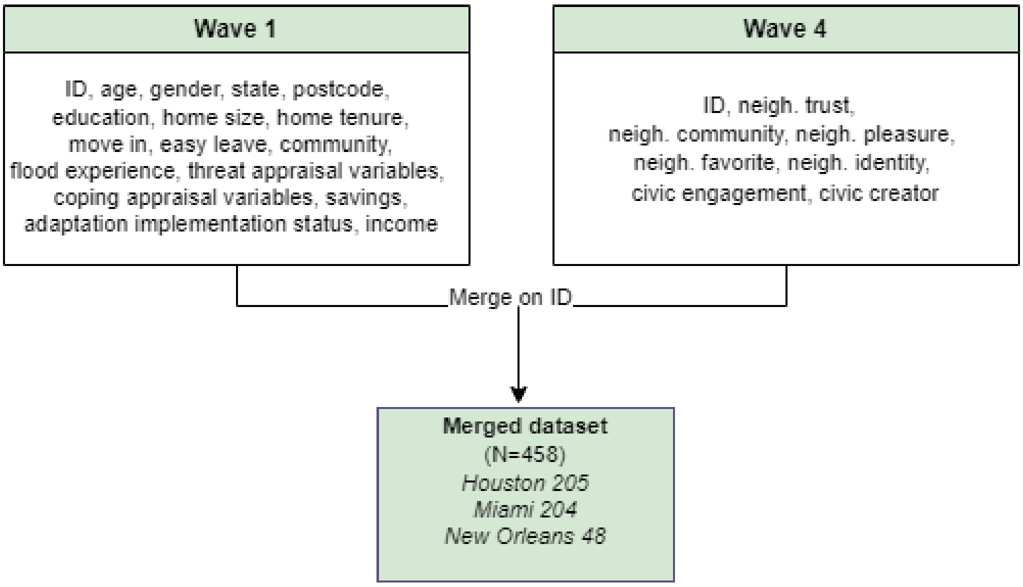


Figure A.1: Merge process of Wave 1 and Wave 4.

After finalizing our data (N = 409), we made several modifications to variables and addressed null values:

- Home tenure variable originally has 3 options: rent, own, and other. We created a dummy variable called house owner, where the owner is (1), and rent & other (0).
- Gender has two options Male (1) and Female (2). We converted it to a 0-1 dummy as Male (1) and Female (0).
- Education has 6 options. Following Noll (2023), we converted it into 4 groups: < high-school, high-school graduate, college graduate (including some college, 2-year, and 4-year), and post-grad.
- Home size has an "I do not know" option. We replaced it with the mode of home size in our data, which is 3.
- Since we already had a small amount of data, we could not drop people without savings and income answers. Therefore, we applied expectation maximization imputation using a Python package called "impyute". After the imputation, float values were obtained. Then, we rounded them to the closest integer. If they were out of the range after the rounding, they were converted into the smallest or highest value within the range.
- Finally, structural measure (SM) 1 was renamed elevation. SM2, SM3, and SM4 were combined into a single variable called wet-proofing, while SM5, SM6, and SM7 were grouped together under the name dry-proofing. Each group's self-efficacy, response efficacy, and perceived cost values were averaged. If a person implemented any of the measures in a group, their "adaptation status" was recorded as 1 (otherwise 0). Additionally, **"intention to adapt" was restricted to within a year**, meaning if someone planned to adapt within a year, their intention was recorded as 1 (otherwise 0).

A.1.1. City Selection

As already explained in Section 3.3.1, Houston and Miami respondents are combined and, later in our ABM, placed in a residential building in Houston. The following figures (Figure A.3 and A.2) are created to demonstrate that these two areas are not significantly different.

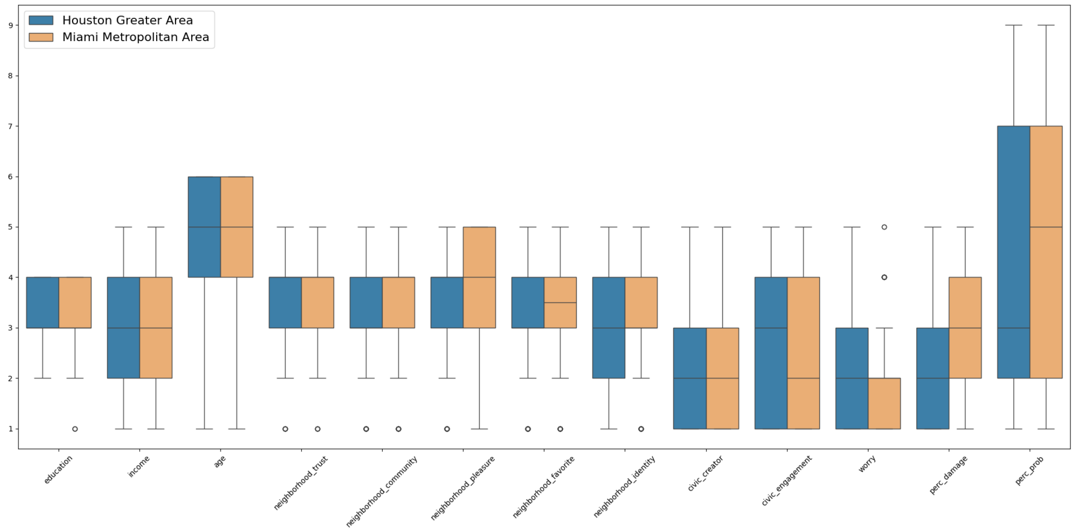


Figure A.2: Boxplots of key variables of Houston and Miami Greater data.

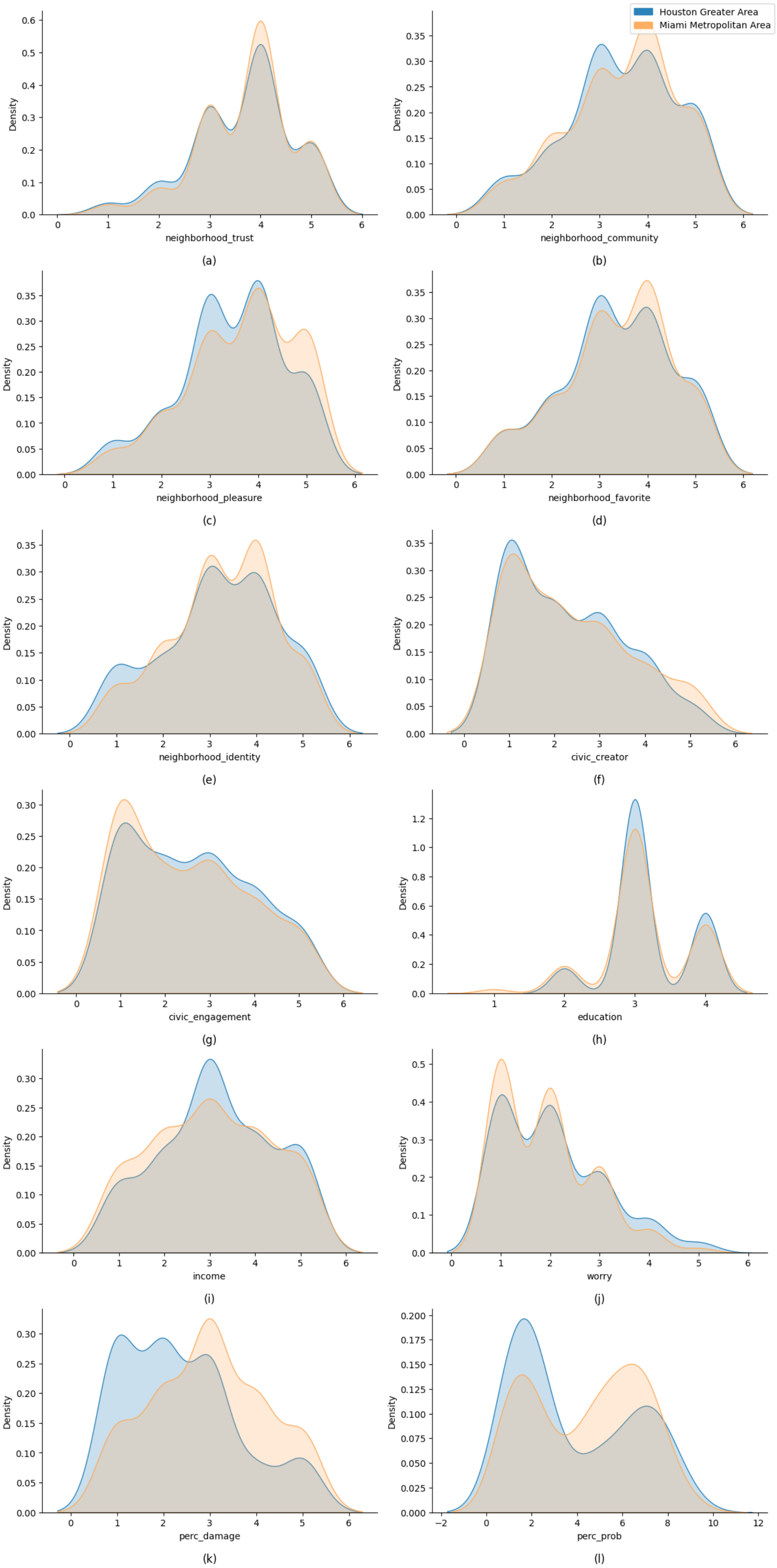


Figure A.3: Comparison of the distribution of key variables in Houston and Miami Greater Areas. Place attachment variables (a-g), demographics (h-i), and threat appraisal (k-l).

A.2. Data Description

Table A.3: Descriptive statistics and explanation of survey variables. Source: Explanations are directly taken from Noll et al., 2022. Calculations performed by the author based on data from Filatova et al., 2022.

Variable Name	Question	Response Options	Mean (Std. error)
Flood Damage (fl_dam)	In the event of a major flood such as the flooding from Hurricane Harvey, how severe (or not) do you think the physical damage to your house would be?	*5 point scale* (1) Not at all severe - (5) Very severe	2.68 (1.27)
Flood Probability (fl_prob)	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?	*9 point scale* (1) My house is completely safe (2) Less often than 1 in 500 years (3) Once in 500 years or a 0.2% chance annually (4) Once in 200 years or a 0.5% 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 (9) More frequent than once per year	4.13 (2.54)
Worry (worry)	How worried or not are you about the potential impact of flooding on your home?	*5 point scale* (1) Not at all worried - (5) Very worried	1.97 (0.99)
Response Efficacy (RE)	How effective do you believe that implementing this measure would be in reducing the risk of flood damage to your home and possessions?	*5 point scale* (1) Extremely ineffective - (5) Extremely effective *(from top to bottom: elevation, wet-proof, dry-proof)*	3.19 (1.47) 3.01 (1.23) 2.89 (1.22)
Self Efficacy (SE)	Do you have the ability to undertake the measure either yourself or by paying a professional to do so?	*5 point scale* (1) I am unable - (5) I am very able *(from top to bottom: elevation, wet-proof, dry-proof)*	1.72 (1.25) 2.11 (1.22) 2.22 (1.24)
Perceived Cost (PC)	When you think in terms of your income and your other expenses, do you believe that implementing or paying someone to implement this measure would be cheap or expensive?	*5 point scale* (1) Very cheap - (5) Very expensive *(from top to bottom: elevation, wet-proof, dry-proof)*	4.63 (0.85) 4.15 (0.84) 3.80 (1.04)
Flood Experience (fl_exp)	Have you ever personally experienced a flood of any kind?	(1) Yes or (0) No	0.39 (0.49)
Undergone Measures (UG)	I have already implemented this structural measure	(1) Yes or (0) No for each measure (If Household has implemented 1 measure, measure(s) in a category the dummy variable = 1) *(from top to bottom: elevation, wet-proof, dry-proof)*	0.07 (0.25) 0.15 (0.36) 0.10 (0.30)
Non-structural Undergone Measures (UG)	I have already implemented this non-structural measure	(1) Yes or (0) No for each measure (from top to bottom: Being an active member in a community group aimed at making the community safer (UG_NM4), Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do (UG_NM5), Asking/ petitioning government representative to increase the public protection measures (UG_NM9))	0.23 (0.42) 0.35 (0.48) 0.20 (0.40)
Community	Are you an active member of one or more community organizations such as a religious organization, civil group, book club, cooking club, neighborhood organization etc.?	(1) Yes or (0) No	0.39 (0.49)
Risk Aversion	Are you generally ready to take risks in your life or do you avoid risks?	*5 point scale* (1) Not willing to take - (5) Very willing to take	2.82 (1.08)

Variable Name	**Question**	**Response Options**	**Mean (Std. error)**
Social Expectation (soc_exp)	Do your family, friends and/or social network expect you to prepare your household for flooding?	*5 point scale* (1) They do NOT expect me to prepare for flooding - (5) They expect me to prepare for flooding	3.08 (1.33)
Income (inc)	What was your total family income from all sources last year in 2019?	*5 point scale* (1) Less than $25730 (2) Between $25731 and $49200 (3) Between $49201 and $80995 (4) Between $80996 and $132490 (5) More than $132490	3.10 (1.28)
Savings (savings)	With regards to your household's savings, what statement most closely reflects your current household situation?	*7 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	4.61 (2.43)
Years Lived (years_lived)	How many years have you been living in this accommodation?	Open answer	16.73 (13.21)
House Size (house_size)	How many square feet is your accommodation? If you don't know for sure, please provide your best estimation.	*6 point scale* (1) Less than 150 square feet (2) Between 151 and 225 square feet (3) Between 226 and 300 square feet (4) Between 301 and 375 square feet (5) Between 376 and 450 square feet (6) More than 451 square feet	5.60 (1.03)
Easy leave (easy_leave)	How easy or difficult would it be to leave the place you currently live?	*5 point scale* (1) It would be difficult to leave this area - (5) I could leave this area very easily	2.74 (1.36)
Age (age)	Age	(1) 16-24 (2) 25-34 (3) 35-44 (4) 45-54 (5) 55-64 (6) 65+	4.69 (1.27)
Education (education)	What is the highest level of education you have completed?	(1) High School (2) High School (3) College Degree (4) Post Graduate	3.16 (0.60)
Gender (gender)	What gender do you identify with?	(1) Male or (0) Female	0.5 (0.5)

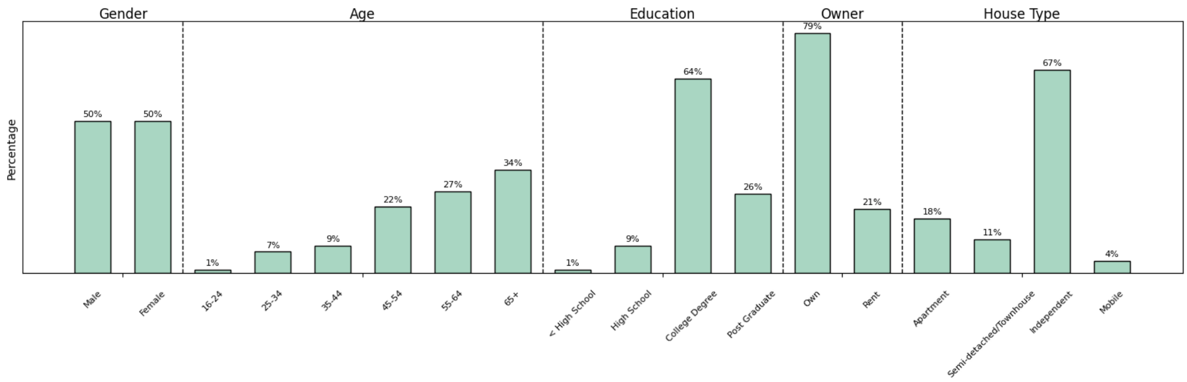


Figure A.4: Profile of survey respondents (N=409). Source: The figure is created by the author based on data from Filatova et al., 2022)

A.3. Place Attachment Analysis

Table A.4: Correlation matrix for place attachment variables. Source: Analysis performed by the author based on data from Filatova et al., 2022.

	Trust	Community	Pleasure	Favorite	Identity	Civic Creator	Civic Engagement
Trust	1.00	0.63	0.60	0.58	0.57	0.15	0.20
Community	-	1.00	0.65	0.62	0.60	0.25	0.31
Pleasure	-	-	1.00	0.80	0.72	0.23	0.23
Favorite	-	-	-	1.00	0.74	0.21	0.21
Identity	-	-	-	-	1.00	0.24	0.24
Civic Creator	-	-	-	-	-	1.00	0.53
Civic Engagement	-	-	-	-	-	-	1.00

Table A.5: Statistical tests for evaluating data requirements for EFA.

Test	Value	Criteria	Satisfied
Correlation Determinant	0.025	|corr.| > 0.00001 (Shrestha, 2021)	+
Bartlett's Test	1.37e-12	p-value < 0.05 (Shrestha, 2021)	+
KMO Test	0.85	KMO value > 0.8 (Shrestha, 2021)	+

Table A.6: Factor loadings for place attachment variables.

Variables	**Factor loadings**		**Squared factor loadings (normalized)**	
	Factor 1	Factor 2	Factor 1	Factor 2
Neighborhood Trust	**0.78**	0.08	0.18	-
Neighborhood Community	**0.79**	0.24	0.18	-
Neighborhood Pleasure	**0.89**	0.13	0.22	-
Neighborhood Favorite	**0.88**	0.10	0.22	-
Neighborhood Identity	**0.84**	0.15	0.20	-
Civic Creator	0.11	**0.87**	-	0.50
Civic Engagement	0.14	**0.86**	-	0.50
Variance explained (%)	51	23		
Cronbach's Alpha	0.90	0.69		

B

Regression

B.1. Logistic Regression

B.1.1. Multicollinearity Check

Table B.1: Variance Inflation Factor results for each logistic regression.

	Variance Inflation Factor (VIF)		
	Elevation	**Wet-proofing**	**Dry-proofing**
Flood Damage (fl_dam)	1.49	1.50	1.53
Flood Probability (fl_prob)	1.56	1.52	1.55
Worry	1.47	1.47	1.48
Response Efficacy (RE)	1.11	1.15	1.20
Self Efficacy (SE)	1.19	1.30	1.31
Perceived Cost (PC)	1.12	1.21	1.19
Flood Experience (fl_exp)	1.12	1.12	1.11
Active Place Attachment (active_pa)	1.15	1.19	1.20
Traditional Place Attachment (traditional_pa)	1.17	1.18	1.15
Undergone Wetproof (UG_wetproof)	1.30	-	1.52
Undergone Dryproof (UG_dryproof)	1.29	1.16	-
Undergone Elevation (UG_elevation)	-	1.16	1.44

B.1.2. Results

People who have already implemented a measure are excluded from that specific measure's logistic regression since they no longer intend to adopt it and might deceive the results. The sample sizes are 382 for elevation, 348 for wet-proofing, and 367 for dry-proofing.

Table B.2: Logistic regression results for structural measures. Significance level: * 0.05, ** 0.01, *** 0.001.

	Elevation			**Wet-proofing**			**Dry-proofing**		
	B	Std. Error	exp(B)	B	Std. Error	exp(B)	B	Std. Error	exp(B)
Constant	-5.28	2.40	0.01	-5.72	2.09	0	-10.65	2.05	0
Flood Damage (fl_dam)	2.26	1.88	9.61	3.54*	1.47	34.54	0.47	1.27	1.59
Flood Probability (fl_prob)	-2.40	1.53	0.09	-0.27	1.09	0.76	0.31	1.05	1.37
Worry	4.96**	1.97	142.21	2.81*	1.40	16.61	4.25**	1.37	70.29
Response Efficacy (RE)	-0.76	1.75	0.47	3.44*	1.55	31.24	0.73	1.22	2.08
Self Efficacy (SE)	3.79**	1.49	44.24	2.13	1.18	8.44	4.63***	1.21	102.40
Perceived Cost (Cost)	-6.39***	1.93	0	-7.97***	1.84	0	-0.69	1.34	0.5
Active Place Attachment (active_pa)	4.60**	1.73	99.08	2.34	1.29	10.36	2.00	1.13	7.39
Traditional Place Attachment (traditional_pa)	0.06	2.10	1.06	0.80	1.68	2.22	1.87	1.53	6.51
Flood experience (fl_exp)	0.97	0.81	2.63	0.42	0.58	1.52	1.26*	0.54	3.53
Undergone Wetproof (UG_wetproof)	0.51	1.26	1.67	-	-	-	0.37	0.78	1.45
Undergone Dryproof (UG_dryproof)	0.05	1.33	1.05	1.37	0.87	3.93	-	-	-
Undergone Elevation (UG_elevation)	-	-	-	3.00*	1.25	20.16	0.52	1.03	1.67

Table B.3: The effect of an increase in independent variables on the odds ratios. Note: It demonstrates how many times the odds ratio changes when one of the variables changes by *x*.

	Elevation	**Wet-proofing**	**Dry-proofing**
Flood Damage (fl_dam)	1.57	2.03	1.1
Worry	2.7	1.75	2.34
Response Efficacy (RE)	0.86	1.99	1.16
Self Efficacy (SE)	2.13	1.53	2.52
Perceived Cost (Cost)	0.28	0.2	0.87
Active Place Attachment (active_pa)	2.51	1.6	1.49
Traditional Place Attachment (traditional_pa)	1.01	1.17	1.45
Flood Probability (fl_prob)*	0.77	0.97	1.04
Flood experience (fl_exp)**	2.63	1.52	3.53
Undergone Wetproof (UG_wetproof)**	1.67	-	1.45
Undergone Dryproof (UG_dryproof)**	1.05	3.93	-
Undergone Elevation (UG_elevation)**	-	20.16	1.67

Note: The reference point is the odds ratio before the increase. Variables with one asterisk increase by 1/9. Variables with two asterisks represent binary variables. The rest is calculated based on a 1/5 increase.

Table B.3 can be interpreted as follows: if one's worry increases by 0.2, the odds of intending to elevate increases by 2.7 times (calculated as exp(4.96 * 0.2)). Similarly, if one's perceived cost increases by 0.2, the odds of intending to elevate decrease by 72%, calculated as 1 - exp(-6.39 * 0.2).

B.2. Linear Regression

B.2.1. Variables

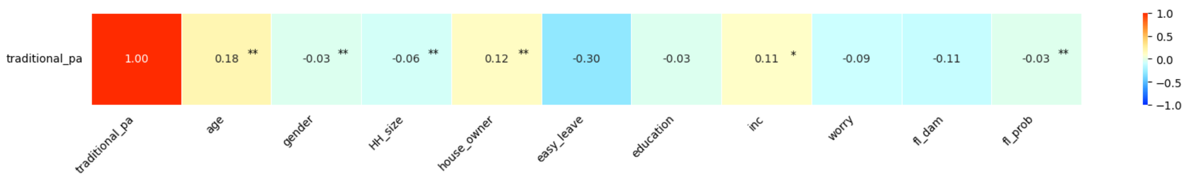


Figure B.1: Correlation of the variables with traditional place attachment. Note: One asterisk and two asterisk stand for p-value 0.05 and p-value 0.01, respectively.

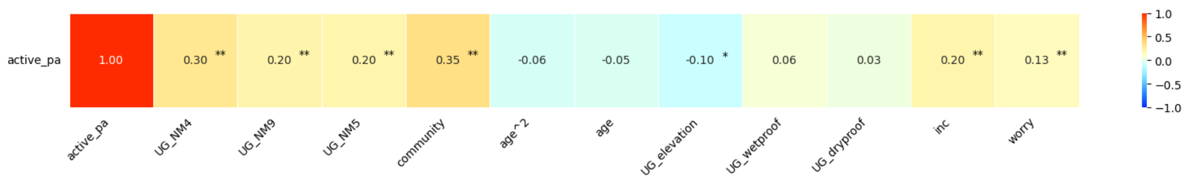


Figure B.2: Correlations of the variables with active place attachment. Note: One asterisk and two asterisk stand for p-value 0.05 and p-value 0.01, respectively.

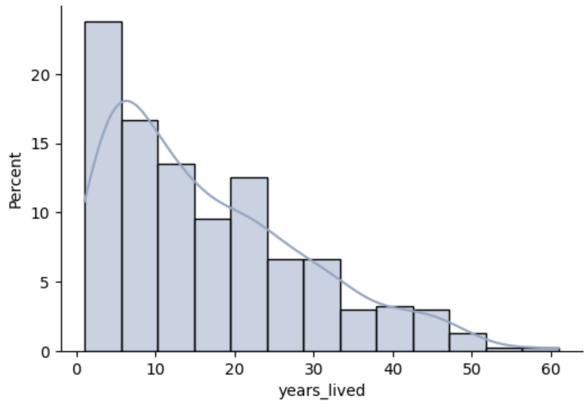


Figure B.3: Distribution of years lived by survey respondents. Source: Calculated and visualized by the author, using the variable called move_in in the survey data collected by Filatova et al., 2022.

B.2.2. Results

In the following linear regression models, undergone adaptation measures, community, gender, and house owner are binary variables. All variables except age, house size, education, and income are normalized. These four are kept at their original scale to integrate into our model easily. That's why their coefficients tend to be smaller due to their different scaling.

Table B.4: Linear regression results for traditional place attachment.

Variable	Coefficient	Significance	95% CI [0.025	0.975]
constant	0.8576	0.000	0.712	1.003
age	0.0225	0.002	0.008	0.037
gender	-0.0232	0.190	-0.058	0.012
HH_size	-0.0275	0.002	-0.045	-0.010
house_owner	0.0343	0.134	-0.011	0.079
easy_leave	-0.1896	0.000	-0.253	-0.126
education	-0.0232	0.125	-0.053	0.006
inc	0.0235	0.002	0.009	0.038
worry	-0.0606	0.243	-0.162	0.041
fl_dam	-0.0676	0.106	-0.150	0.014
fl_prob	0.0651	0.085	-0.009	0.139

Table B.5: Linear regression results for active place attachment.

Variable	**Coefficient**	**Significance**	**95% CI**	
			[0.025	**0.975]**
constant	0.2906	0.005	0.087	0.495
UG_NM4	0.0787	0.014	0.016	0.142
UG_NM9	0.0432	0.148	-0.015	0.102
UG_NM5	0.0235	0.374	-0.028	0.075
community	0.1280	0.000	0.083	0.173
age^2	-0.0053	0.364	-0.017	0.006
age	0.0276	0.574	-0.069	0.124
UG_elevation	-0.1324	0.008	-0.230	-0.035
UG_wetproof	0.0711	0.053	-0.001	0.143
UG_dryproof	-0.0388	0.319	-0.115	0.038
inc	0.0223	0.008	0.006	0.039
worry	0.1011	0.060	-0.004	0.207

C

Model Overview, Design Concepts, and Details (ODD)

This chapter explains the model using the ODD protocol designed by (Grimm et al., 2020). The primary focus is on the adjustments made to the original model created by Wagenblast (2022).

C.1. Overview

C.1.1. Purpose

The purpose of this model is to **explore** the complex and dynamic interplay between place attachment and households' adaptation behavior. Place attachment is studied as two types: active and traditional. Through different experiments and the base model, we aim to understand how changes in these types of place attachments impact households' adaptation levels and flood damage reduction over time. We expect active place attachment to have more impact on household adaptation uptake than traditional place attachment.

C.1.2. Entities, State Variables, and Scales

Entities

This model consists of two main entities: the environment and households. These entities are explained below. Table C.1 and C.2 present the model parameters and agent attributes.

- **Households**:
  Households represent the (synthetic) residents of Houston and are created using survey and neighborhood data (see Section 3.3.6). They live in single-family houses in their neighborhoods, and their location is static. Households are located at the centers of their houses' polygons. Their coordinates help us to assess their flood risk using the Harvey flood map (see Section 3.3.6). Each household has a social network in which they have an influence on each other. They make decisions on implementing one of three measures (elevation, wet-proofing, or dry-proofing) based on their extended PMT attributes (see Figure 3.1).
- **Environment**:
  In this model, the environment contains flood event, dike, and time. The environment can have a scheduled flood event using available flood maps and may include a dike when activated.

Scale

- **Time:** Each time step represents 3 months. Although the original model has a monthly option, the quarterly option is utilized due to computational constraints. Besides, people's attachment and risk perceptions do not change significantly in a short period. Therefore, the quarterly step fits our purpose. The model is run for 80 steps, equivalent to 20 years.
- **Spatial:** Households' locations (x, y) (represented by the centers of their houses' polygons) provide the spatial dimension for our ABM. The boundaries of the flood map and the selected neighborhoods define the spatial boundaries of our model.

Table C.1: Model parameters. Note: This table is not inclusive. Table C.3 presents the parameters utilized in the population creation. Source: Some variables are taken from Wagenblast (2022).

	Parameter	Description	Type	Value
Time	data_collection_period	data is collected every how many steps	int	Default: 1
	tick_time	how much time each step represents	str	Default: quarter Options: quarter or monthly
	pause_after_last_measure	time required between two adaptation measures	int	Default: 2 Options: non-negative
Social Influence	basic_own_trust	weight given to own opinion	float	Default: 0.5 Options: [0, 1]
	exchange_what	which variables are exchanged in the social network	list	Default: ['worry', 'effectiveness_measures', 'costs_measures', 'flood_damage', 'community']
	community_threshold	the minimum proportion of people in one's social network who belong to the community for someone to be included in the community	float	Default: 0.6 Options: [0, 1]
Adaptation Measures	measure_eff	effectiveness of adaptation measures (elevation, wet- and dry-proofing)	dict	Default: 0, 40, 50
	measure_costs	costs of adaptation measures ($) (elevation, wet- and dry-proofing)	dict	Default: 38k, 6k, 8k
Financial	savings_rate	how much each household saves of their monthly income	float	Default: 8.5% (the U.S. average personal savings rate obtained from U.S. Bureau of Economic Analysis, 2024)
Experiment	active_multiplier traditional_multiplier	multipliers that adjust households' initial place attachment values	float	Default: 1 Options: non-negative
	which_pa	which place attachment is affected from the experiment	str	Default: 'active' Options: active or traditional
	flood_experiment	whether a flood event is scheduled or not	bool	Default: 0
	flood_time	when the flood event takes a place	int	Default: 20 Options: non-negative
	flood_pa_impact	how much the flood impacts place attachment	float	Default: 0.5, i.e., 50% decrease Options: non-negative
	pause_savings_after_flood	number of steps that agents cannot save money after flooding (recovering time)	int	Default: 4 Options: non-negative
	dike_experiment	whether a dike is constructed or not	bool	Default: 0
	dike_time	when the public measure is constructed	int	Default: 20 Options: non-negative
	neighborhoods_in_dike_option	which neighborhoods are inside the dike	int	Default: 1
	flood_depth_reduction_in_dike_effect_area	how many meters the flood depth is decreased	float	Default: 3 Options: non-negative
	dike_pa_impact	how much the dike impacts place attachment	float	Default: 0.5, i.e., 50% decrease Options: non-negative
Flood Map	flood_map_path	path to the flood map used	str	Default: Harvey_depth_meters.tif
	elevation_level_map_path	path to the flood map which is used to calculate households' flood depth after elevation	str	Default: 100yr_storm_depth_meters.tif
	min_flood_depth	the minimum flood depth possible (in meters)	float	Default: 0.05
	max_damage_dol_per_sqm	parameter to convert damage factor into a monetary damage	float	Default: 1216.65

Table C.2: Agent attributes. Source: Some variables are taken from Wagenblast (2022).

	Attribute	Description	Type	Value
Stochasticity	seed	starting point for random number generation (model.seed + unique_id)	int	Default: None Options: non-negative
Identifier	unique_id	unique identifier	int	Options: non-negative
	neighborhood_id	the neighborhood's id where the agent lives	int	Options: [1, 88]
Threat appraisal	fl_dam	perceived flood damage	float	Options: [0.2, 1]
	fl_prob	perceived flood probability	float	Options: [0.11, 1]
	worry	worry	float	Options: [0.2, 1]
Coping appraisal	RE_m	separate response efficacy for each measure (elevation, wet-proofing, and dry proofing)	float	Options: [0.2, 1]
	SE_m	separate self efficacy for each measure (elevation, wet-proofing, and dry proofing)	float	Options: [0.2, 1]
	PC_m	separate perceived cost for each measure (elevation, wet-proofing, and dry proofing)	float	Options: [0.2, 1]
Flood Experience	fl_exp	past flood experience	float	Options: 0, 0.2, 0.4, 0.6, 0.8, 1, based on the flood damage.
Undergone adaptation	UG_m	whether an adaptation measure is implemented or not (elevation, wet-proofing, and dey-proofing)	bool	Options: {0,1}
Place Attachment	active_pa	active place attachment level	float	Options: [0.2, 1]
	traditional_pa	traditional place attachment level	float	Options: [0.2, 1]
	active_regr	regression value for active place attachment	float	
	trad_regr	regression value for traditional place attachment	float	
	location	the center point of an agent's house	Point	Options: Point(x, y) where x and y are in the neighborhood boundaries
Sociodemohraphics	house_size_cat	house size category	int	Options: [1, 6]
	house_size	random integer assigned for the house size based on the category	int	Options: [30, 180]
	age_category	age category	int	Options: [1, 6]
	age	random integer assigned for the age based on the category	int	Options: [16, 94]
	income_category	income category	int	Options: [1, 5]
	total_income	random integer assigned for the total income based on the category	int	Options: [100, 1000000]
	monthly_income	total_income / 12	float	
	savings_category	savings category	int	Options: [1, 7]
	months_savings	how many months of income is saved (assigned based on savings_category)	int	Options: [0, 12]
	savings	savings (months_savings * monthly_income)	float	Options: non-negative
Flood related	flood_depth	flood depth	float	Options: $\geq$ min_flood_depth
	flood_damage	flood damage factor	float	Options: [0, 1]
	financial_damage	monetary flood damage (flod_damage_factor * house_size * model.max_damage_per_sq_meter)	float	Options: non-negative
Network	neighbors	IDs of the connections in an agent's social network	list	
	connecting_nodes	agent instances in an agent's social network (agents instances are retrived using the 'neighbors' list)	list	
	community	whether an agent is a member of a community organization or not	bool	Options: {0, 1}
	risk_aversion	risk aversion level of an agent	int	Options: [1, 5]

C.1.3. Process Overview and Scheduling

In each step, the environment activates households in a random order. Each household follows a set of actions, as explained below. Note that items with lavender color are taken from the model created by Wagenblast (2022). Among the colored items, we only made a small change to the "social influence."

1. **Social attributes update:** Households update some of their attributes based on the influence of their network.
2. **Place attachment update:** Households update their active and traditional place attachments using the coefficients from linear regression models (see Figure 4.7).
3. **Adaptation measure evaluation:**
   - If households still have an available adaptation measure (elevation, wet-proofing, or dry-proofing), they recalculate the probability of taking each adaptation measure using specific logistic regression coefficients.
   - If a household decides to take an adaptation measure and at least two steps have passed since their previous adaptation, they check if they have sufficient funds to implement it.
4. **Implementation:** If a household has enough money, they implement the adaptation measure and reduce their savings.
5. **Damage reduction:** The decrease in their flood damage is calculated.
6. **Social Influence:** Households communicate with their networks and save the impact for the next step.
7. **Savings, age, and income update:** They save a portion of their quarterly income and get three months older. Their income is also updated if they fall into the next age group.
8. **Initial step:** Since no social influence comes from the previous step, updating parameters and place attachments are skipped in the first step (t=1).

C.2. Design Concepts

C.2.1. Basic Principles

In this model, households make their adaptation decisions based on the Protection Motivation Theory (PMT) as detailed in Section 3.1.2. Furthermore, place attachment, another psychological factor influencing household decisions, is integrated into the PMT framework. Place attachment is incorporated as two dimensions: active and traditional, following the frameworks created by Hummon (1992) and Lewicka (2011a).

C.2.2. Emergence

Household-level flood adaptation, thereby flood damage reduction, emerges from households' adaptation decisions. These decisions are dynamically shaped by households' social interactions, previous adaptation choices, and changes in place attachment levels. These changing place attachment levels also emerge from social interactions, past decisions, and the effects of time.

C.2.3. Adaptation

Households decide to take an adaptation measure from the available measures that have not been implemented yet if the probability is above the random threshold. Besides, households decide to participate in community activities if the percentage of people joining community activities in their network exceeds the threshold set. Households also adjust their worry, perceived damage, RE, and PC based on a trust structure, where they give weight to their own views and the views of their network. This approach is based on the DeGroot model (DeGroot, 1974). Please refer to Wagenblast (2022)'s model for further explanation about the opinion dynamics.

C.2.4. Interaction

In this model, we utilize a modified version of the Watts-Strogatz model (Watts & Strogatz, 1998), which incorporates homophily. The attributes considered are neighborhood and income. This choice is driven by two reasons:

- Neighbors share similar flood risks and are more likely to discuss and influence each other about these risks.
- Income homophily is common in real networks, thereby improving our network's realism. Besides, it may indicate similar place attachment levels, as some income groups show higher/lower attachments on average.

To create the modified network, which we named as 'neighborhood,' we follow the 4 steps described in Tur et al. (2024, p. 15):

1. Create a "regular lattice" where nodes represent agents with specific attributes. Each node is connected to its nearest neighbors (not physically).
2. Sort nodes based on neighborhood and income to place nodes with "similar preferences" next to each other, creating "perfect homophily."
3. "Swap each node randomly, with probability $1-\rho$" to reduce homophily.
4. Rewire each edge with a "probability of μ" to introduce "small-world" properties.

C.2.5. Prediction

This model has two types of prediction:

- Three logistic regression models are used to predict households' probability to adapt (see Section 3.3.4 and 4.4 for further details).
- Two linear regression models are utilized to estimate the change in households' active and traditional place attachments (see Section 3.3.3 and 4.3).

C.2.6. Sensing

In addition to their attributes, such as coping appraisal, threat appraisal, and place attachment, and their houses' coordinates, households are assumed to know each possible adaptation measure: elevation, dry-proofing, and wet-proofing. They also know their network connections' level of worry, perceived flood damage, the perceived cost of adaptation measures, response efficacy for each adaptation measure, and their involvement in community activities.

C.2.7. Stochasticity

This model incorporates stochasticity in different aspects:

- **Population creation:** Based on the income distribution obtained from the neighborhood data, households are divided into strata based on their income groups. Then, they are randomly sampled.

- **Location:** The residential buildings in the selected neighborhoods are obtained from OSM. Each household created in the previous step is assigned to a random house in their neighborhood.
- **Homophily:** The initial network starts with perfect homophily. To adjust the homophily level, nodes are swapped when a random number exceeds a predetermined threshold. Then, akin to the Wattz-Strogatz model (Watts & Strogatz, 1998), the rewiring method is applied when a random number is smaller than another predetermined threshold. These processes introduce randomness to create a more realistic network. See Appendix C.2.4 for further details.
- **Adaptation decision:** Households first calculate their probability of taking an adaptation measure. Then, they only implement it if it is higher than a random number generated.
- **Sociodemographic:** The population is created with categories for age, income, savings, and house size. A random value within the category's boundaries is assigned to each household for each category. Moreover, when a household becomes old enough to change its age category, its income category is also updated by a random choice.

C.2.8. Observation

Following Wagenblast et al. (2024), the outputs are collected at the agent level. The agent data collector she created is adjusted to include place attachment and place attachment-related variables. In each step, the extended PMT and sociodemographic variables, the number of people adapted (separately for each measure and cumulatively), and the reduction in flood damage are collected. These results are stored in data frames and extracted as CSV files.

C.3. Details

C.3.1. Initialization

The model is initialized by creating 2000 households using the neighborhood and survey data. Their locations are then assigned based on their assigned neighborhood and OSM data. Subsequently, their social network, called 'neighborhood,' is created. Finally, these households, with their attributes, locations, and networks, are transformed into agents in our model and added to the schedule. In the agent class, these households then initialize their attributes using the *setattr()* method. The steps followed are summarized in Figure C.1, and Table C.3 presents the parameters utilized in the model initialization. These steps are explained further in the following subsections. Note that each seed generates a different synthetic population with a different location and network.

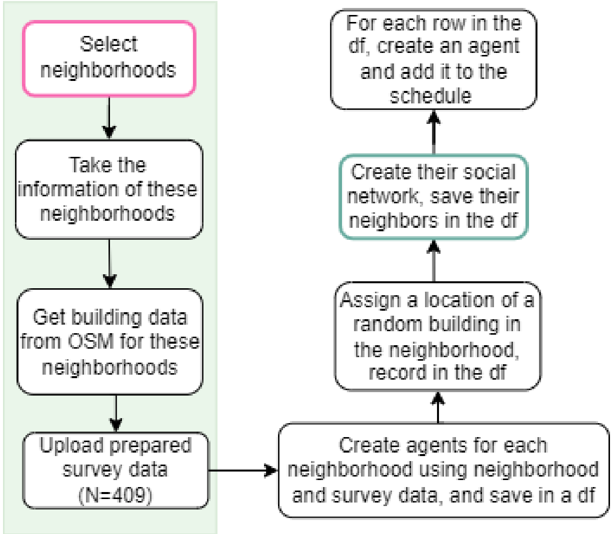


Figure C.1: Initialization of the model. Note: The green parts are completed outside of the model and uploaded as input.

Table C.3: Model initialization parameters.

	Parameter	Description	Type	Value
Stochasticity	seed	starting point for random number generation	int	Default: None Options: non-negative
Population Creation	number_of_households	number of agents to create	int	Default:2000 Options: integers that are divisible by len(snb_demog)
	snb_demog_path	path to data of selected neighborhoods' income distributions	str	'input_data/population_creation/data_for_population.csv'
	buildings_path	path to buildings data in selected neighborhoods	str	'input_data/population_creation/house_buildings.csv'
	survey_data_path	path to cleaned and prepared survey data	str	'input_data/population_creation/survey_data.csv'
	neighborhood_boundaries_path	path to neighborhoods boundary data	str	'input_data/population_creation/neighborhood_boundaries.csv'
Social Network	number_of_nearest_neighbours	number of nearest neighbors each node is initially connected	int	Default: 6 Options: non-negative even
	rho	swapping probability (1-rho) to arrange homophily level	float	Default: 0.7 Options: [0, 1]
	mu	rewiring probability to introduce small world properties	float	Default: 0.4 Options: [0, 1]

Neighborhood Selection

Due to limited computational power, 10 neighborhoods are selected out of 88 based on their average flood depth and the availability of OSM building data. To calculate the average flood depth, the Harvey flood map is masked with the neighborhood geometries, and the flood depth values are extracted and averaged for each neighborhood. Next, the OSM data of these neighborhoods are collected. It is observed that most people only used the tag “building=yes” without specifying whether it is residential or commercial. To provide more realistic locations, only buildings tagged as “house, detached, residential, terraced, and semi-detached houses” are kept. Although a “residential” building can be an apartment with multiple residents, for the purposes of this model, we assume that residential buildings are single-family homes. To assign 2000 households equally to 10 neighborhoods, more than 200 residential buildings per neighborhood are needed. Only 29 neighborhoods have more than 200 residential buildings. Among these 29 neighborhoods, the top 10 neighborhoods with the highest average flood depth are selected. These neighborhoods’ income distributions are given in Table C.4.

Table C.4: Income distribution of selected neighborhoods. Source: Planning and Development Department, 2020. Note: Survey data has 5 income categories, whereas neighborhood data has 4. Based on the thresholds, it is converted to 5 categories. That is why the sum of the percentages might not add up to 1.

Neighborhood Name	ID	Income 1	Income 2	Income 3	Income 4	Income 5
Downtown	61	0.15	0.07	0.16	0.39	0.24
Macgregor	83	0.27	0.20	0.12	0.26	0.14
Washington Avenue	22	0.07	0.07	0.12	0.43	0.30
Braeswood	32	0.15	0.12	0.14	0.36	0.23
Memorial	16	0.10	0.13	0.14	0.38	0.24
Afton Oaks	23	0.07	0.10	0.10	0.42	0.32
Second Ward	63	0.35	0.22	0.13	0.22	0.08
Meyerland Area	31	0.14	0.18	0.11	0.34	0.23
Lazybrook/Timbergrove	14	0.18	0.26	0.10	0.28	0.18
University Place	28	0.13	0.07	0.10	0.40	0.30

OSM Building Data

The subset of OSM building data is taken according to the tags and the selected neighborhoods (see section C.3.1). These houses with their IDs, neighborhoods, and centroid coordinates (Point (x,y)) are saved into a CSV file.

Table C.5: Number of houses after subsetting with the tags.

Neighborhood Name	ID	# of houses
Downtown	61	279
Macgregor	83	351
Washington Avenue	22	1208
Braeswood	32	890
Memorial	16	479
Afton Oaks	23	217
Second Ward	63	210
Meyerland Area	31	638
Lazybrook/Timbergrove	14	342
University Place	28	1492

Population Creation

In this model, a total of 2000 households are generated. Since the total number of households is relatively small, creating populations proportionally to their actual population would result in some neighborhoods having only a few agents. Therefore, households are distributed equally across 10 neighborhoods.

For each neighborhood, agents are sampled from the survey data using stratified sampling based on income. Agents are grouped into income strata, and the number of agents in each income group is calculated proportionally to the neighborhood's income distribution. According to these proportions, agents are then sampled with replacements from the survey data. The neighborhood ID is added to each agent for future reference. Then, all sampled agents are combined into a single data frame. Figure C.6 shows the mean values of some attributes for both synthetic households and survey data. Notably, despite the use of macro-level neighborhood data in generating the synthetic population, the results are close to the survey data means.

Table C.6: Comparison of means between survey data and synthetic population. Note: Synthetic population is an average of 50 seeds (range (12345, 12395).

Variable	Survey Mean	Synthetic Population Mean
age	4.69	4.65
gender	0.50	0.52
education	3.16	3.20
savings	4.61	4.82
income	3.10	3.33
house_size	5.60	5.59
fl_exp	0.39	0.39
fl_prob	0.46	0.45
fl_dam	0.54	0.54
worry	0.39	0.39
active_pa	0.49	0.51
traditional_pa	0.69	0.70
SE_elevation	0.34	0.34
SE_wetproof	0.42	0.44
SE_dryproof	0.44	0.46
RE_elevation	0.64	0.64
RE_wetproof	0.60	0.60
RE_dryproof	0.58	0.58
PC_elevation	0.93	0.92
PC_wetproof	0.83	0.82
PC_dryproof	0.76	0.75
UG_elevation	0.07	0.07
UG_dryproof	0.10	0.12
UG_wetproof	0.15	0.15
easy_leave	0.55	0.54
community	0.39	0.40

After creating the population, the OSM buildings data is employed to **assign a location** to each household created according to their neighborhood. Each building is given to only one household. The x and y coordinates of the assigned houses are then added to the agents' data frame. Next, as explained in Appendix C.2.4, a **social network** called "neighborhood" is created. Finally, the model's agents are created by looping through each node in the social network. Each node's attributes are taken from the population data, and the "Household" agents are created using the node ID and attributes. Note that each seed produces a different population due to stochastic processes.

C.3.2. Input Data

Adaptation Measures

The model uses parameters related to the effectiveness and costs of different flood adaptation measures as input data (see Section 3.3.6 in the main text). These parameters are provided as two separate dictionaries: one for effectiveness and one for cost, in which elevation, wet-proofing, and dry-proofing are the keys.

Probability to Adapt

The coefficients of the three logistic regression models are combined into one CSV file and used as input data. Please refer to Section 3.3.4 and Appendix B.1.2 for the coefficients.

Place Attachment Change

The coefficients of the two linear regression models are used in separate methods of our model to calculate changes in active and traditional place attachments. Details are provided in Section 4.3 and Appendix B.2.

Flood Map

The Harvey flood map shows a recent, actual event in the Houston area. This map is likely more up-to-date and accurate than older flood maps, considering the rapid urbanization and changing climate patterns in the region (Blackburn & Borski, 2023). Therefore, in this thesis, 100-year and 500-year flood maps are not studied. Only the Harvey flood map is used and provided in tiff format. Figure C.2 illustrates the flood map of Houston during Hurricane Harvey. Also, the details of how to use a flood map to assign a flood risk are explained in Section 3.3.6 in the main text.

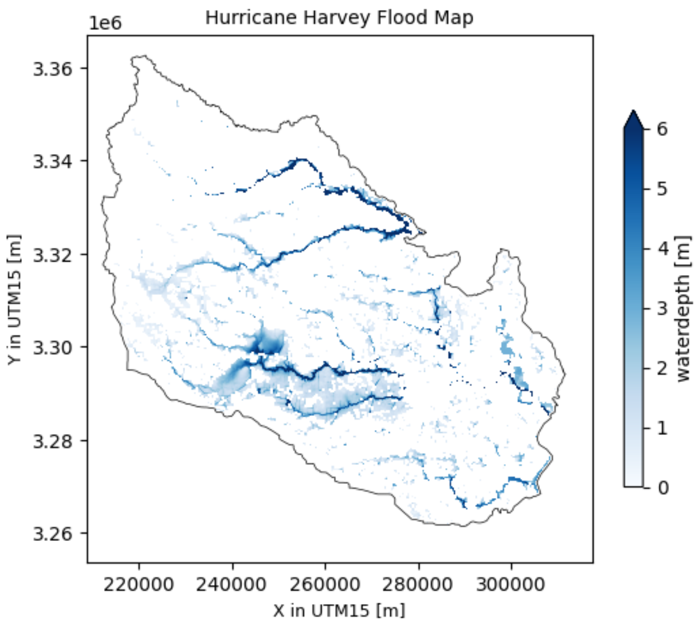


Figure C.2: Hurricane Harvey flood map that shows flood depth across the city. Source: Created by the author using the flood map obtained from Grimley et al., 2023; Leijnse et al., 2021; Wagenblast et al., 2024.

Income Transition Probabilities

In our model, households get older and move into different age categories unless they are already in the last group. Typically, people's incomes rise with age, peak near retirement, and then slightly decline (Ozhamaratli et al., 2022). To incorporate these age and income dynamics into our model, we use the survey data (Filatova et al., 2022).

First, we analyze the survey data to count the number of individuals within each age and income category. We then normalize these counts to convert them into percentages, representing the proportion of each income category within each age group (see Table C.7). In the model, as households age and transition into new age categories, their incomes are updated based on these percentages.

Table C.7: Income transition probabilities based on age groups. Source: Calculations made by the author using the survey data obtained from Filatova et al., 2022.

Age	Income 1	Income 2	Income 3	Income 4	Income 5
1	0.20	0.20	0.20	0.20	0.20
2	0.19	0.22	0.26	0.22	0.11
3	0.06	0.14	0.23	0.37	0.20
4	0.16	0.16	0.28	0.16	0.23
5	0.13	0.18	0.32	0.16	0.21
6	0.13	0.21	0.33	0.20	0.13

C.3.3. Submodels

Agent Initialization

In the model, households are created with their attributes and then added to the schedule. When a household is created, its attributes are passed as a dictionary. During initialization, the household uses the *setattr()* method to assign these attributes. So, for every key in the dictionary, an attribute with the same name is created on the agent and set to the corresponding value. These two are explained in the following two pseudocodes, C.3 and C.4.

```
For each node in the network:
    Retrieve the attributes for the household from
        the population data.
    Create a household instance with the unique ID
        and attributes.
    Add the household to the simulation schedule.
    Place the household on the grid at the node's
        location.
EndFor
```

Figure C.3: Pseudocode 1- Creation of households at the model initialization.

```
Require unique_id, model, attributes
Initialize household with unique_id and model.
For each key-value pair in the attributes dictionary:
    Assign the attribute using setattr(self, key,
        value).
EndFor
```

Figure C.4: Pseudocode 2- Agent initialization.

These dictionaries include various attributes such as the extended PMT, sociodemographic information, and location. After setting these attributes, house size, age, income, and savings are randomly selected within the boundaries of their respective categorical attributes. Next, the households' flood depth and damage are calculated based on the coordinates and house size as explained in Section 3.3.6 in the main text. If any adaptations have already been implemented, the flood depth and damage are updated at step 0 based on the effectiveness of the measures.

Social Influence

At each step, households communicate with their network, exchanging worry, perceived flood damage, PC, and SE of adaptation measures (Wagenblast, 2022). They adjust these attributes by averaging their views with those of their network, using weights based on trust. In the next step, they update these attributes based on the values from the previous step (Wagenblast, 2022).

In addition to the original model, the **community** attribute of the households is also exchanged in the social network. However, since we want to keep this variable as a binary variable, a different method is used. The community attribute is updated based on the proportion of connections who are members of community organizations. This proportion is calculated as:

$$\text{Proportion} = \frac{\text{Number of community members within the network}}{\text{Total number of connections}} \tag{C.1}$$

If this proportion exceeds a certain threshold, the household will also become a member of the organization in the following step. It is explained in Figure C.5.

```
If current community status is 0:
    If proportion of neighbors in the community >=
       community threshold:
        Set future community status to 1
    Else:
        Set future community status to 0
Else:
    Set future community status to current community
       status
EndIf
```

Figure C.5: Pseudocode 3- Updating community status.

Place Attachment Update

Two separate methods are created for active and traditional place attachment. The only differences between them are the linear regression coefficients and attribute names (see Appendix B.2 for the coefficients). Since the same logic applies, we explain these methods together here.

Both active and traditional place attachments are updated at each time step (t>1) using a linear regression model. The initial place attachment values (PA^{t0}) are derived from the survey data during the household initialization (see Section 4.1 for the creation of the place attachment). The regression model used to calculate the place attachment at any step t is given by:

$$PA^t_{\text{reg}} = \beta_0 + \beta_1 x^t_1 + \ldots + \beta_n x^t_n \tag{C.2}$$

where β values are the fixed coefficients obtained from the regression analysis, and x values are the attributes updated in the ABM, such as age and risk perception. Please refer to Figure 4.7 for all dynamic variables.

In each step, the change in place attachment is calculated as the difference between the new regression value and the previous regression value:

$$\Delta PA_{\text{reg}}^{t-1,t} = PA_{\text{reg}}^{t} - PA_{\text{reg}}^{t-1} \tag{C.3}$$

This change is then added to the current place attachment value to obtain the updated place attachment:

$$PA^{t1} = PA^{t0} + \Delta PA_{\text{reg}}^{01} \tag{C.4}$$

$$PA^{t2} = PA^{t1} + \Delta PA_{\text{reg}}^{12} \tag{C.5}$$

This process is repeated at each time step to update the place attachment value based on the new regression calculations from the updated attributes. The pseudocode of the method can be seen in Figure C.6.

```
Method calculate_place_attachment:
    Calculate new regression value using linear
       regression coefficients

    If step count > 1:
        Calculate change in place attachment (delta)
           between old and new regression values

        If delta != 0:
            Update place attachment value, ensuring
               it stays within bounds [0.2, 1]

    Save new regression value for the next step
EndMethod
```

Figure C.6: Pseudocode 4- Updating place attachment.

Calculate Probability to Adapt and Try

These methods were created by Wagenblast (2022). Only the logistic regression variables and their coefficients have been modified. These methods are explained here shortly, as they are the keystone of our model.

Based on logistic regression coefficients, households calculate their probability of implementing each available adaptation measure (see Figure C.7 below). They then select the measure with the highest probability and compare this probability to a random number. Suppose the probability is higher than the random number. In that case, the households check their savings and the last time they implemented a measure. If their savings sufficiently cover the cost and enough time has passed, they implement the measure and update their related attributes: savings, flood damage, and flood depth (only for elevation). The steps following the probability calculation are described in Figure C.8.

```
Method calculate_probability_to_take_measure:
    For each measure:
        If measure is already taken:
            Continue
        Else:
            Calculate y_hat using logistic regression
                coefficients and extended PMT
                parameters
            Apply inverse logit function to y_hat to
                get probability to take measure
            Round the probability to two decimal
                places
            Add the probability to the household
                measures dataframe
    EndFor
EndMethod
```

Figure C.7: Pseudocode 5- Calculation of probability to take an adaptation measure.

```
Method try_to_take_measure:
    Generate random value for probability
    Sort measures by probability to take measures in
        descending order

    If there are measures available to take:
        If the random value is less than the highest
            probability:
            If savings are sufficient to cover the
                cost:
                Set a measure to take to the one with
                    the highest probability
            Else:
                Set measure to take to '
                    no_measure_to_take'
        Else:
            Set measure to take to '
                no_measure_to_take'

        If there is a measure to take:
            Mark measure as taken in the data frame
            Deduct the cost from savings
            If the measure is 'S_elevation':
                Update flood depth and damage
            Else:
                Update flood damage based on the
                    effectiveness of the measure

EndMethod
```

Figure C.8: Pseudocode 6- Taking an adaptation measure.

Update Age and Income

In our model, households get older and move into different age categories unless they are already in the last group. Their age increases every step; however, changing the age category takes more time. This process is further illustrated in Figure C.9.

```
Method update_age:
    Increase age by age increment
    Set age_category_updated to False
    If the current age category is not the last
       category:
        Get current_category_range and next_category
        If age is within the current range:
            Keep current age category
        Elif age is within the next range:
            Move to the next age category
            Set age_category_updated to True
    EndIf
    If age_category_updated:
        Update income
    EndIf
EndMethod
```

Figure C.9: Pseudocode 7- Age update.

If the age category is updated, the income update is called. Figure C.10 explains this method in detail. Simply, the income group can decrease by one level, stay the same, or increase by one level.

```
Method update_income:
    If age category is in transition probabilities:
        Get probabilities for the new age category
        Define possible transitions:
            current income group,
            1 decrease (if not the minimum),
            1 increase (if not the maximum)
        Normalize the filtered probabilities
        Store the old income category

        Choose a new income category based on
           transition probabilities using random
           choice

        If income category has changed:
            Assign new total income based on the new
               income category
            Update monthly income and savings
    EndIf
EndMethod
```

Figure C.10: Pseudocode 8- Income update.

C.3.4. Model Assumptions

Adaptation

- The efficacy of measures is stable.
- The costs of measures are also stable, using averaged values.
- Adaptation measures do not expire and have no implementation time.
- Households can only adapt one measure in one step if they can afford it.
- They need to wait two steps to take another measure after implementing one.
- Elevation is set to 100-year flood level + 1 ft.

- Everyone is assumed to live in a single-family house, which can be elevated. It is assumed that they all live on the base floor or have a base floor in their house.

Location

- All residential buildings obtained from the OSM are assumed to house only one household.

Social Network and Influence

- Income and neighborhood bias exist in the social network.
- Households share only five variables within their social network.
- Place attachment is updated via calculations, not directly through the social network, although variables affected by the social network may be included in the calculation function.
- Once households become community members, they remain members.

Age and Income

- Households do not die or migrate.
- The maximum initial age assigned is 74, so households age up to 94 in the model (a reasonable lifespan).
- When households reach age group 6, their age category and income become stable, although their age continues to increase.
- Age and income categories/ values are updated, but education is not. We do not update education in the model because it typically remains stable once individuals reach a certain level of education. Additionally, education is a more subjective choice and more challenging to capture in the model.
- Income level can decrease by one level, stay the same, or increase by one level depending on the age group and current income category. Households can only jump one income group at a time.

Financial Aspects

- Savings cannot be negative, meaning households can only spend if they have the money and cannot borrow from the future. Following the same logic, if the flood experiment is active, the maximum damage caused is limited to their savings level.
- If a flood occurs, households do not save money for a while as they focus on recovering from the damage caused by the event.
- The savings rate is the same for everyone, based on the U.S. average, although it varies in reality.
- Monetary damage is calculated based on the average maximum damage per square meter without separating it into content and building. Although damage varies for everyone in real life, it is assumed to be the same in this model.

Experiments

- The model does not include a separate hydraulic model, so the impact of dikes is neglected in adjacent areas. It is assumed that it decreases only the flood depth of the people in the area it is implemented.
- Only one flood is scheduled in 20 years if the flood experiment is active. However, Houston might experience more frequent floods, even multiple floods in a year.
- When households experience a flood, they do not forget.

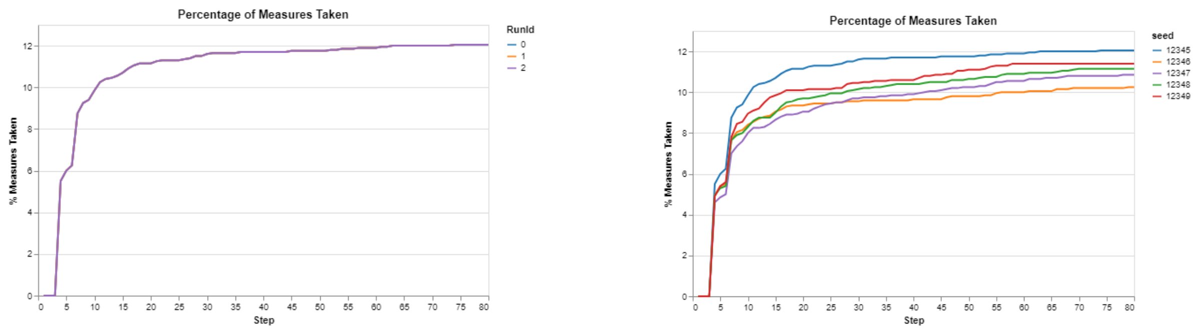
D

Model Verification

The main goal of verification is to ensure the model is built correctly and free of errors (Dam et al., 2012). The following sections explain the verification techniques that are applied to our model.

D.1. Reproducability

First, we verify that the model gives identical results when the same seed is used to ensure the seed is set correctly for each stochastic process (Figure D.1a). Then, we check that different seeds produce different results, confirming the model's stochastic nature (Figure D.1b).



(a) Same seed

(b) Five seeds

Figure D.1: The model results with the same seed (a) and five different seeds (b).

D.2. Unit Testing

Unit testing checks the behavior of individual components, i.e., single agent, in the model (Dam et al., 2012). We test some parts of the code by setting expected outputs. An automatic error message arises if the code does not give a result as expected.

- **Income Update:** If the difference in income update is not -1, 0, or 1, the model should give an error. This ensures that income changes are correctly restricted.
- **Savings:** If an agent's savings are negative, the model should give an error.
- **Social interaction:** If an agent has no worry values from their connections, the model should flag an error for that agent. The same check applies to perceived flood damage, perceived costs,

and response efficacy of measures. This ensures that agents are properly receiving information from their connections.

- **Community dynamics:** If the proportion of the connections in the community exceeds the threshold, the future community of an agent should be set to 1. If it does not, an error message should arise.
- **Network creation:** If the number of connections or the IDs of connected agents for any given agent does not match the ones in the data frame recorded right after network creation, the model should flag an inconsistency. This ensures that the agent's network connections are accurately transferred.

D.3. Sensitivity Analysis

To explore how variations in the parameters based on our assumptions influence the outcomes, we conducted a One-Factor-At-a-Time (OFAT) sensitivity analysis. Simply, we change one parameter at a time while keeping the others fixed to see its direct effect (Ten Broeke et al., 2016). Due to time and computational limitations, the sensitivity analyses are limited to three values for each parameter: one smaller than the base value, the base value, and one larger than the base value, as presented in Table D.1.

Table D.1: Sensitivity analysis parameters and ranges.

Parameter	Description	Base Value	Sensitivity Analysis
basic_own_trust	weight given to own opinion	0.5	0.2, 0.8
savings_rate	how much each household saves of their monthly income	0.085	0.05, 0.1
community_threshold	the minimum proportion of people in one's social network who belong to the community for someone to be included in the community	0.6	0.4, 0.8
pause_savings_after_flood	number of steps that agents cannot save money after flooding (recovering time)	4 (1 year)	0, 8

Figure D.2 and D.3 show the sensitivity analysis graphs, where the y-axis represents the percentage of structural measures taken—calculated as the sum of elevation, wet-proofing, and dry-proofing—and percentage reduction in flood damage compared to the initial level. The analysis shows that opinion trust and community threshold have a modest impact on the adoption of structural adaptation measures, with higher trust in personal judgment and lower threshold to be part of the community slightly increasing adaptation rates. The monthly savings rate also has a moderate impact, with higher savings rates leading to a small increase in adaptation. The savings pause sensitivity, examined separately for active and traditional place attachment, demonstrates that longer pauses after flooding delay the adaptation further, resulting in a slightly lower adaptation level at the end of the simulation. In summary, our results show that the impacts of opinion trust, community threshold, monthly savings rate, and savings pause on adaptation and flood damage reduction are not significant.

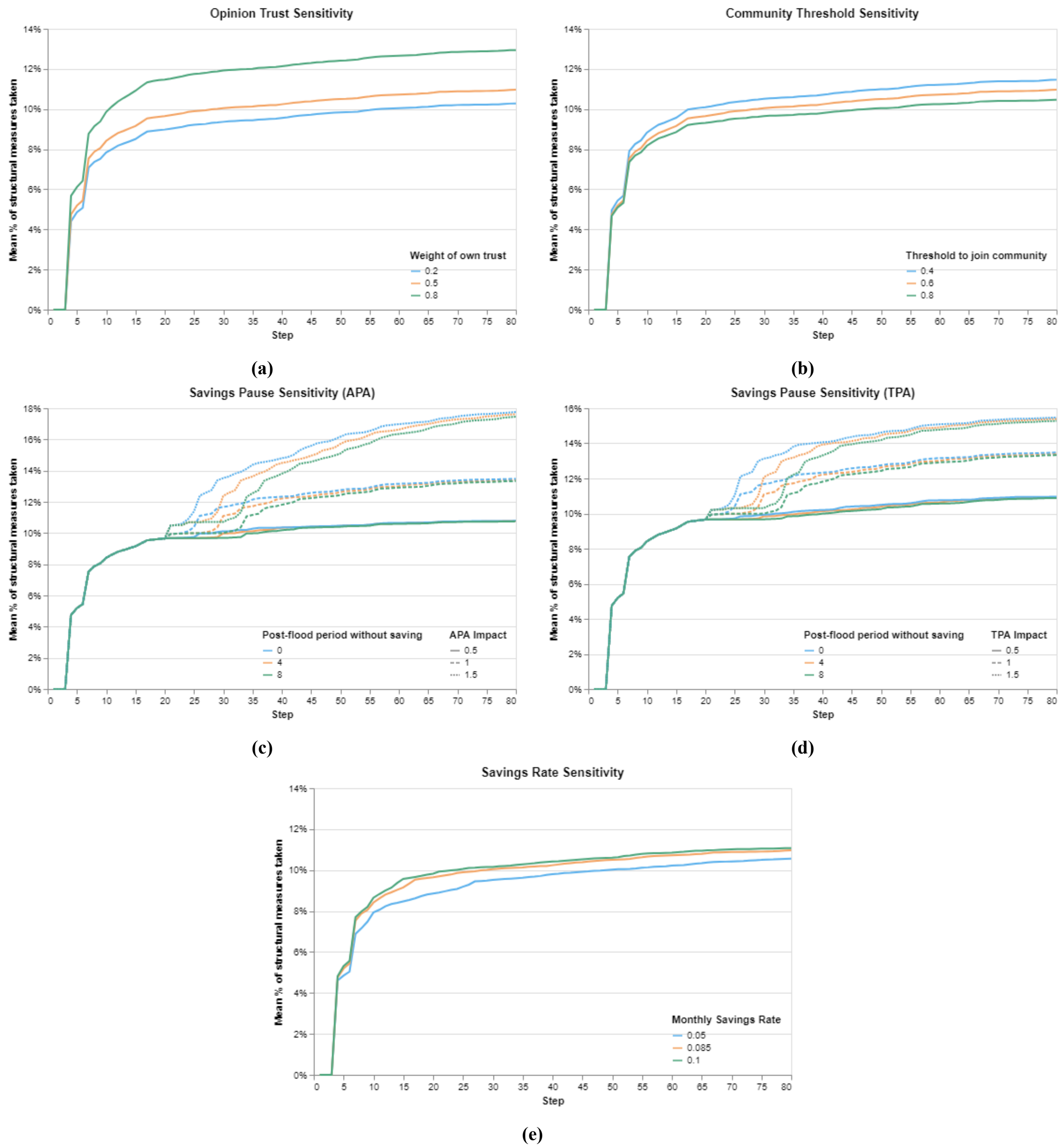
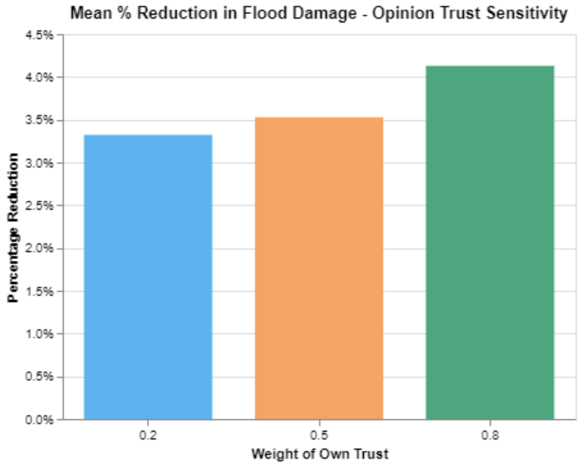
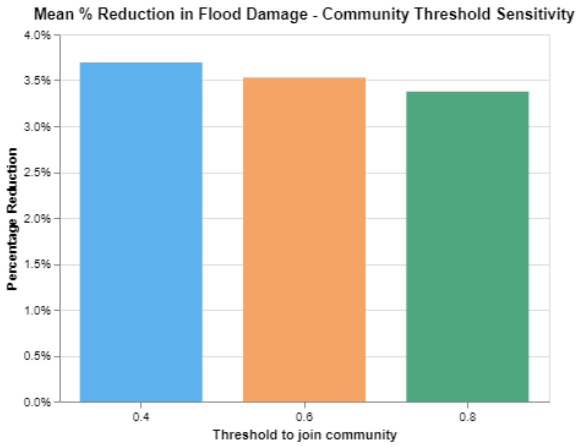


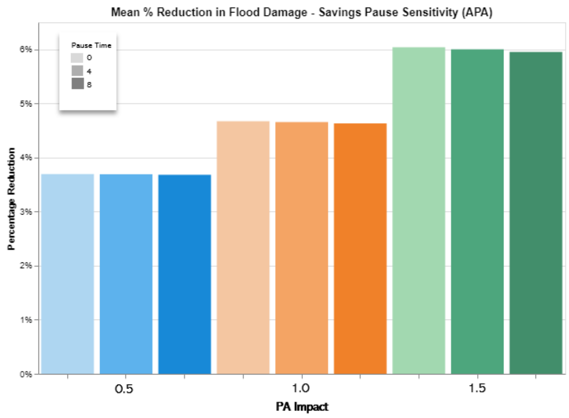
Figure D.2: Sensitivity analysis of the (a) opinion trust, (b) community threshold, (c) savings pause (active), (d) savings pause (traditional), and (e) monthly savings rate on the percentage of structural measures adopted. Note: The results are averaged for 50 replications.



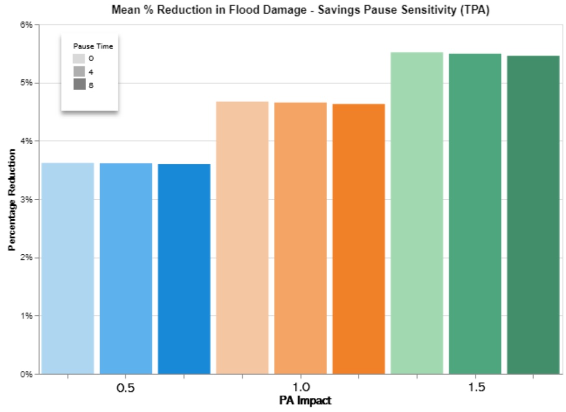
(a)



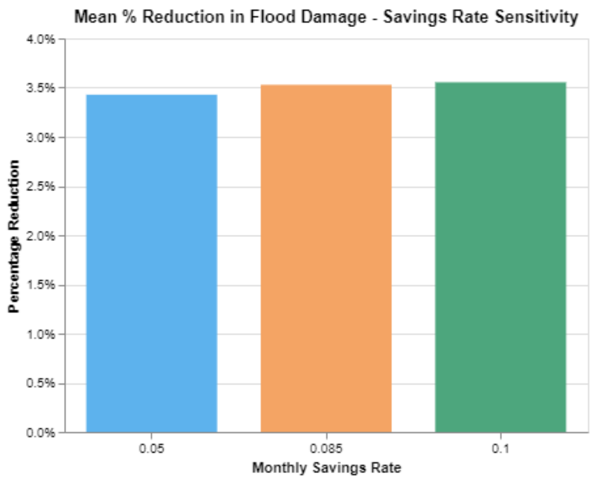
(b)



(c)



(d)



(e)

Figure D.3: Sensitivity analysis of the (a) opinion trust, (b) community threshold, (c) savings pause (active), (d) savings pause (traditional), and (e) monthly savings rate on flood damage reduction. Note: The results are averaged for 50 replications.

E

Model Results

E.1. Baseline - No Experiment

The high uncertainty intervals observed in the results are due to the different populations generated with each random seed. To better account for this stochasticity, more replications would be ideal. However, due to computational and time limitations, we could only conduct a limited number of replications in this study.

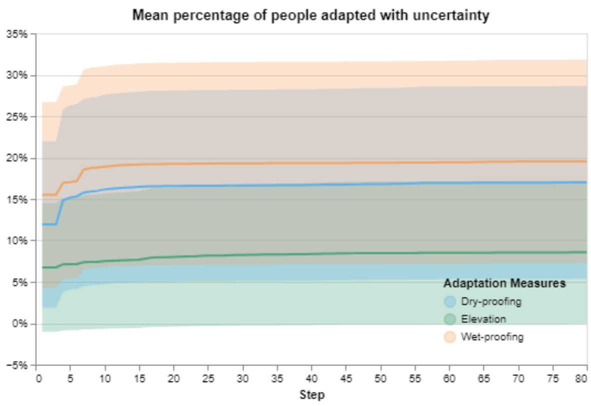
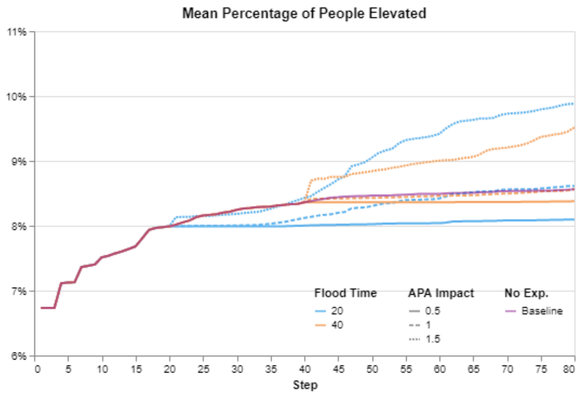
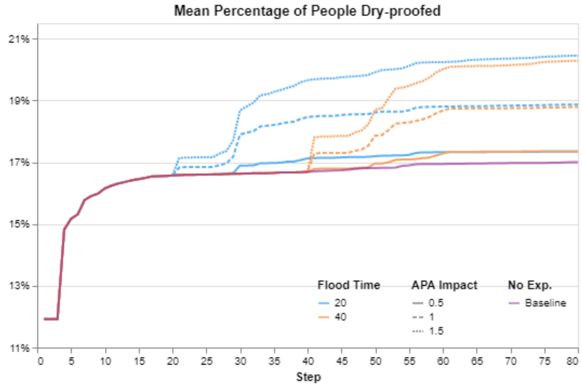


Figure E.1: Uncertainty intervals for mean percentage of people adapted resulting from 50 different seeds.

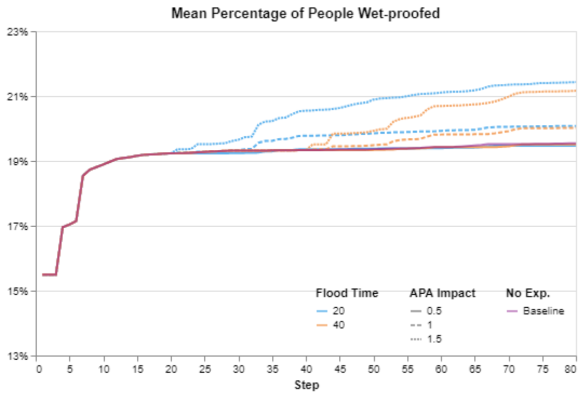
E.2. Flood Events at Steps 20 and 40



(a) Elevation



(b) Dry-proofing



(c) Wet-proofing

Figure E.2: Mean percentage of people implemented (a) elevation, (b) dry-proofing, and (c) wet-proofing in flood experiment targeting active place attachment, comparing time steps 20 and 40. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

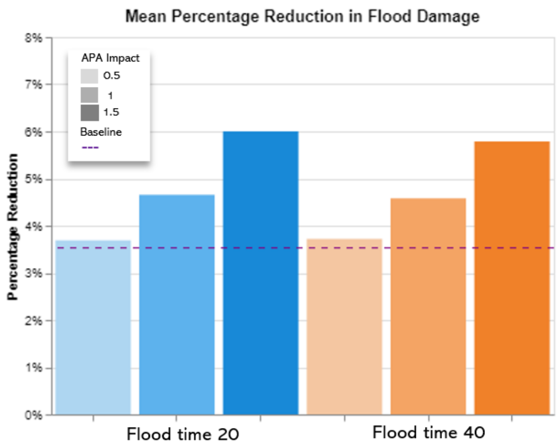
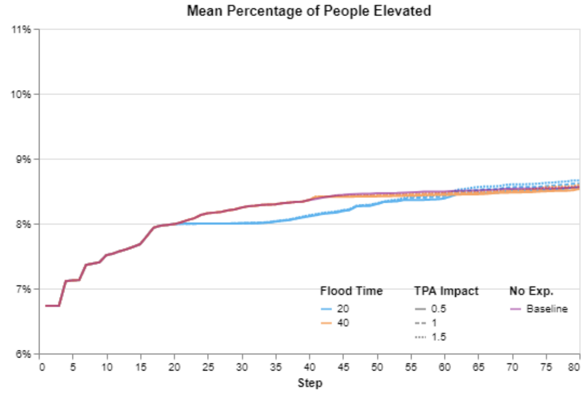
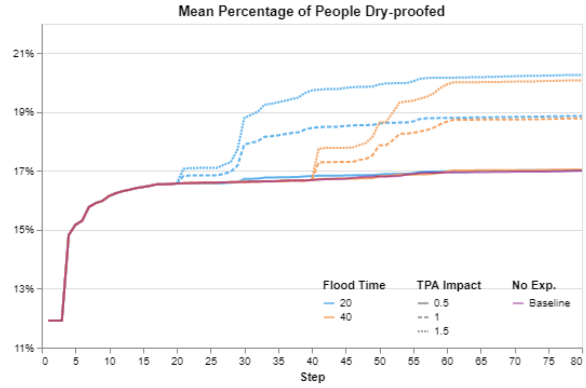


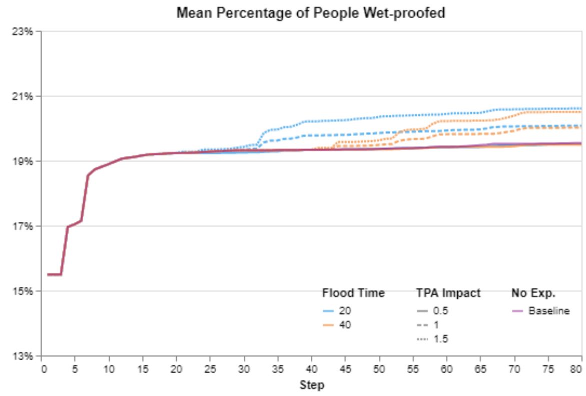
Figure E.3: Mean percentage reduction in flood damage in flood experiment targeting active place attachment, comparing time steps 20 and 40. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.



(a) Elevation



(b) Dry-proofing



(c) Wet-proofing

Figure E.4: Mean percentage of people implemented (a) elevation, (b) dry-proofing, and (c) wet-proofing in flood experiment targeting traditional place attachment, comparing time steps 20 and 40. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

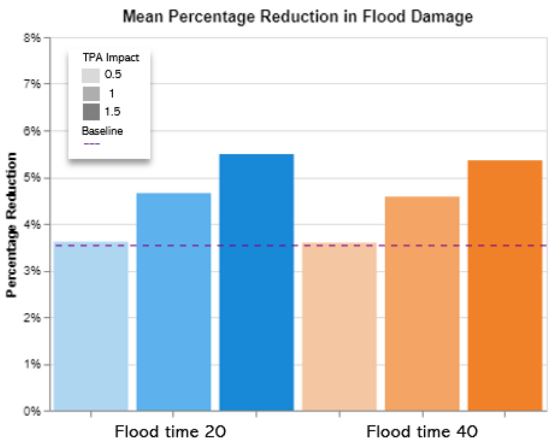


Figure E.5: Mean percentage reduction in flood damage in flood experiment targeting traditional place attachment, comparing time steps 20 and 40. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

E.3. Public Protection Measure

E.3.1. Details of the Public Protection at Step 20

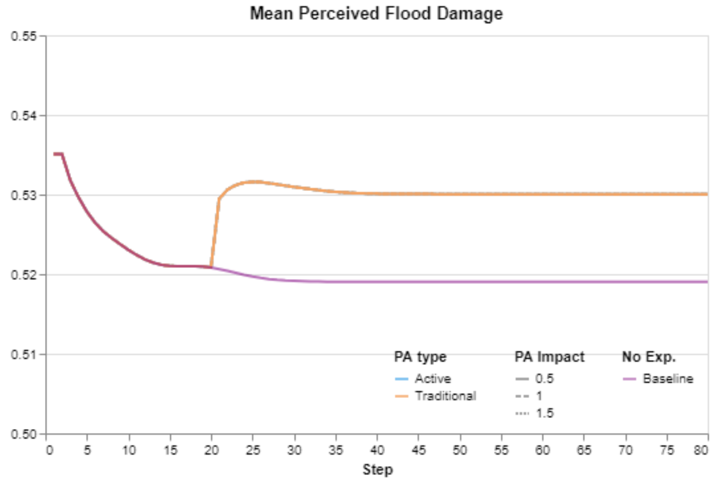
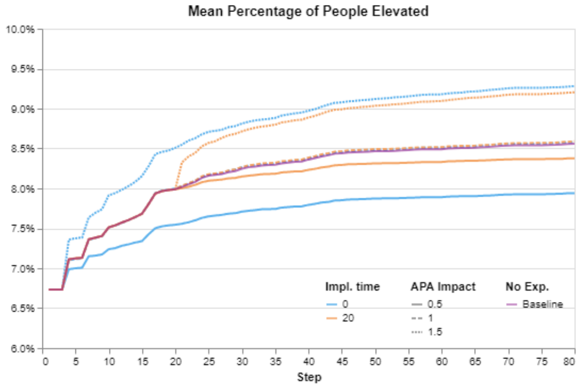
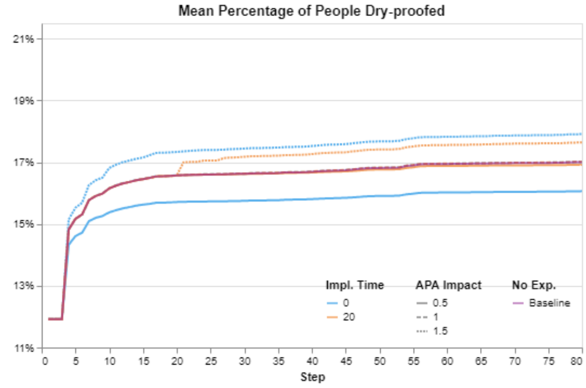


Figure E.6: Change in perceived flood damage of households when the public adaptation measure is introduced at step 20.

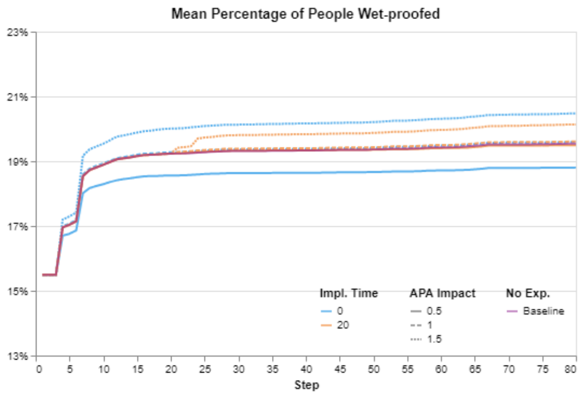
E.3.2. Public Protection at Steps 0 and 20



(a) Elevation



(b) Dry-proofing



(c) Wet-proofing

Figure E.7: Mean percentage of people implemented (a) elevation, (b) dry-proofing, and (c) wet-proofing in public adaptation experiment targeting active place attachment, comparing time steps 0 and 20. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

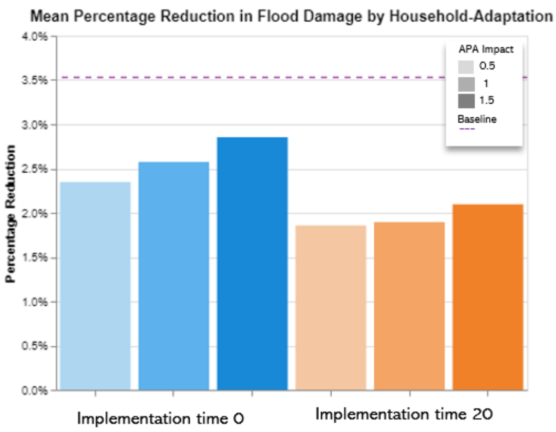
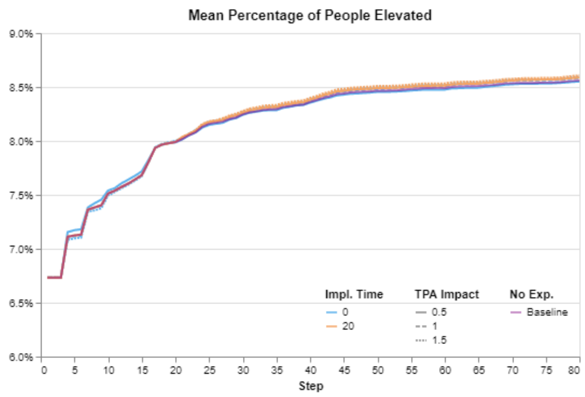
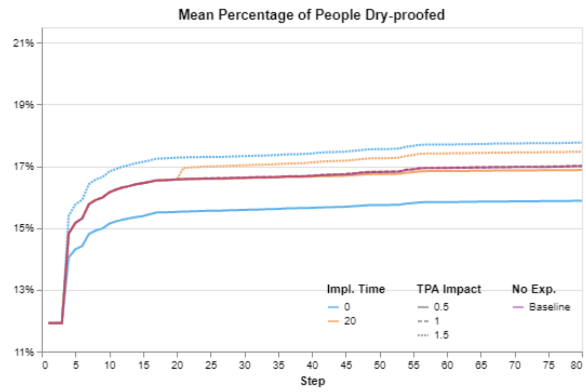


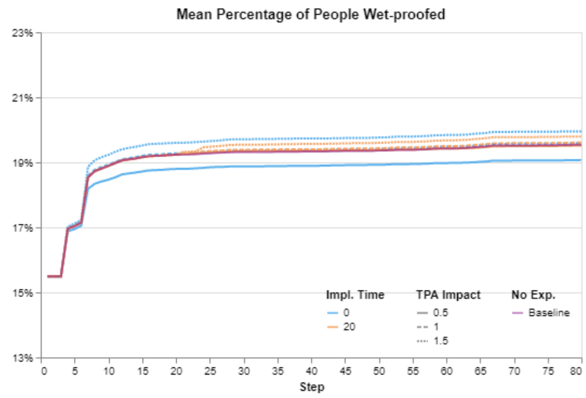
Figure E.8: Mean percentage reduction in flood damage through only household-level adaptations in public adaptation experiment targeting active place attachment, comparing time steps 0 and 20. Note: On top of this reduction, the public protection measure reduces the flood damage by approximately 30%. The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.



(a) Elevation



(b) Dry-proofing



(c) Wet-proofing

Figure E.9: Mean percentage of people implemented (a) elevation, (b) dry-proofing, and (c) wet-proofing in public adaptation experiment targeting traditional place attachment, comparing time steps 0 and 20. Note: The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.

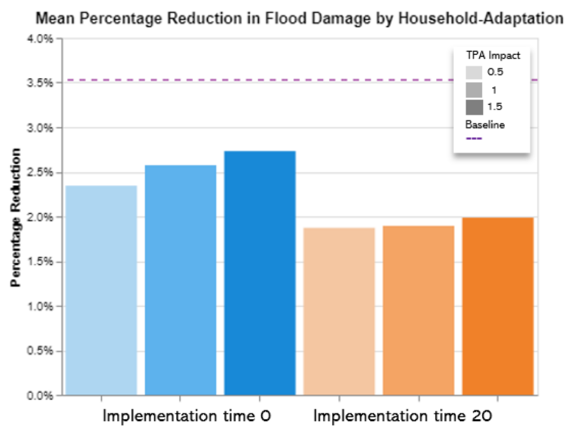


Figure E.10: Mean percentage reduction in flood damage through only household-level adaptations in public adaptation experiment targeting traditional place attachment, comparing time steps 0 and 20. Note: On top of this reduction, the public protection measure reduces the flood damage by approximately 30%. The values 0.5, 1, and 1.5 correspond to a 50% decrease, no change, and a 50% increase, respectively.