Role of household climate change adaptation in reducing coastal flood risk: the case of Shanghai

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Executive summary

Climate change intensifies the **frequency and severity of floods** - the most devastating and costly climate-induced hazard. Since most flood damage occurs in urban areas, where population and infrastructure are concentrated, adaptation to climate-related flooding is particularly necessary for **coastal flooding in cities**. Government adaptations such as dikes or beach nourishments are important, yet insufficient in the face of worsening hazards. They reduce the hazard probability, but the local actions at the **household level** determine the extent of damages and inequalities in its distributional impacts on various societal groups. To design effective policies and risk reduction strategies it is critical to understand the factors that motivate household adaptation intentions. How and why households adapt to climate-induced hazards is increasingly studied – especially for flooding. What remains a challenge is to **quantify the speed and scope** of the system-level adaptation uptake and the resulting damage prevention. This is especially the case for distributional impacts, which are often neglected. Quantifying both aggregate and distributional impacts of household climate change adaptation (CCA) on flood risk fosters the design of tailored flood risk management (FRM) policies which allocate resources to the societal groups that need them most.

This thesis presents a **state-of-the-art agent-based flood model** (flood-ABM) in **downtown Shanghai, China** to understand the role of household CCA in reducing coastal flood risk both in its aggregate and distributional impacts. To model the households' exposure to climate-induced floods we overlayed the geolocations of **18.039 residential buildings** with **21 inundation maps** that depict dike failures and dike overtopping under different climate-change scenarios. We further parameterized households using **context-specific micro-level survey data** from Shanghai and depicted households' adaptation decisions using an extended version of the **Protection Motivation Theory** which takes into consideration both internal and external factors.

We conclude that autonomous household adaptation (adaptation without government policy) to climate change plays an **essential role in reducing flood damage** (up to 50%) in downtown Shanghai. However, despite the considerable adaptation uptake, the residual damages increase over time due to the effects of sea level rise and land subsidence. This shows that **autonomous household adaptation alone is not sufficient to keep pace with the increasing severity of climate-related flooding**, as it is constrained by barriers in the form of measure costs and regulations. Therefore, **external incentives are needed** to overcome these barriers. When designing such policies, it is necessary to take into consideration the differences in the adaptation uptake and damage prevention between societal household groups. Our results indicate that households with **lower worry, self-efficacy, and income adapt measurably slower** to climate-induced floods. For example, the average proportion of high-income households adopting wet-proofing increases by 30% in absolute terms over the simulation period, compared to less than 10% for low-income households. The slower adaptation makes these household groups **significantly more vulnerable**. For example, high-income households prevent on average of 59%, while low-income households prevent only 27% of flood damage for a 1000-year flood in 2040 under the Representative Concentration Pathway (RCP) 8.5. Hence, households with lower income, worry, and self-efficacy levels are more vulnerable to flood events, which can further reduce their adaptive capacity and lead to a vicious cycle.

The **methodological contributions** of this thesis to the state-of-the-art in flood-ABMs are as follows: First, we populate households in our flood-ABM with context-specific micro-level survey data. Second, we base the households' adaptation behaviour on an extended version of the Protection Motivation Theory. Lastly, we link households' adaptation decisions to climate-induced floods using inundation maps that integrate climate dynamics. Thus, our ABM enables more realistic modelling of household CCA to coastal flooding. Next to these methodological contributions, our results provide **new insights for the FRM debate**. On the one hand, we provide context-specific insights on the aggregate impact of behavioural household CCA on flood risk in China, which are scarce in flood risk literature. On the other hand, our results show the distributional impacts of household CCA, which can help design tailored FRM policies that allocate resources to the societal groups that need them the most. Hence, our work is an important contribution at the interface of behavioural household CCA and social vulnerability research.

The **societal relevance** of this thesis can be expressed in terms of *social*, *cultural*, *environmental*, and *economic* impacts. Our model can inform the public debate and FRM policies on the social inequality of climate change by quantifying the differences in flood damage prevention between various socio-economic household groups (**social** impact). Moreover, our model is one of the first flood-ABMs that integrate behavioural theories for agent decision-making in the Global South (**cultural** impact). In addition, the results of this thesis could inform FRM policy in Shanghai and therefore contribute to reducing the adversities of climate change (**environmental** impact). Lastly, the flood-ABM can contribute to determining the cost-effectiveness of government policies and household adaptation actions (**economic** impact).

Our results have **implications for local FRM policies** in Shanghai. Based on the distributional effects, we suggest **subsidies** for lower-income classes, **awareness campaigns** for households with lower worry levels, and **information campaigns** for lower self-efficacy groups. In addition, we suggest the idea of a "**build back better fund**" to ensure that the households' adaptive capacity remains intact after severe flood events.

The model results and our analysis are subject to **limitations**. The model could be improved by including additional adaptive actions (e.g., insurance), comparing the adaptation gap between different behavioural theories (e.g., with the Prospect Theory), refining human-flood interactions (e.g., coupling the ABM with flood models) and extending social interactions (e.g., to family and friends). Furthermore, we recommend including company adaptation and indirect damages in the model.

Our flood-ABM can be used for a multitude of **additional experiments**. We suggest analysing the impact of policies e.g., subsidies on the adaptation behaviour. Next, we suggest comparing the benefit and costs of household adaptive actions for different socio-economic groups. Additionally, the model can be used to compare the adaptation behaviour of a set of 'personas' that combine multiple attribute levels e.g., low income and low self-efficacy. Lastly, we recommend applying the model to two or more countries and comparing the household adaptation under different environmental, institutional, and cultural contexts.

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List of abbreviations and acronyms

ABM	Agent-based model
ANOVA	Analysis of variance
Bil.	Billion (10^9)
CAS	Complex adaptive system
CCA	Climate change adaptation
CoSEM	Complex Systems Engineering and Management
DEFRA	Department for Environment, Food and Rural Affairs
EU	Expected Utility Theory
Flood-ABM	ABM that focuses on individual flood adaptation
FRM	Flood risk management
ICPR	International Commission for the Protection of the Rhin
IPCC	Intergovernmental Panel on Climate Change
Mil.	Million (10^6)
ODD	Overview, design concepts, and details
OECD	Organization for Economic Cooperation and Development
OFAT	One-factor-at-a-time
OSM	OpenStreetMap
PMT	Protection Motivation Theory
PT	Prospect Theory
QGIS	Quantum Geographic Information System
RCP	Representative Concentration Pathways
SD	Standard deviation
SQ	Sub-question
SMSB	Shanghai Municipal Statistics Bureau
UN	United Nations
VV&T	Validation, Verification, and Testing

1. Introduction

1.1. Research problem

Climate change intensifies the frequency and severity of natural hazards such as floods, heatwaves, and droughts (IPCC, 2014a). This leads to large economic damage (Stern, 2007) and the loss of numerous lives (Patz et al., 2005). Flooding, in particular, is considered one of the most devastating and costly climate-related hazards (Aerts et al., 2014; Hoegh-Guldberg et al., 2018). By 2080, the population at risk of **coastal storm surge flooding** is expected to grow from 75 to 200 million considering a medium climate change scenario which projects a 40 cm rise in sea level (McCarthy et al., 2001). As most flood damage occurs in urban areas where population and infrastructure are concentrated (Jha et al., 2011), an adaptation to climate-induced coastal floods is especially necessary for **coastal cities**.

Research has shown that traditional public adaptation measures such as dams, reservoirs, or beach nourishments are **important but insufficient** in the face of worsening hazards (Fankhauser et al., 1999; Mendelsohn, 2000; Stern, 2007; Takao et al., 2004). If these top-down measures fail to mitigate the damage of climate-induced floods, individuals are left vulnerable (Takao et al., 2004). Consequently, additional adaptation at the individual and household levels is necessary (Adger et al., 2005; de Wit et al., 2008; Takao et al., 2004; van Valkengoed & Steg, 2019). Such household-level adaptation measures include for instance elevating the building, strengthening the housing foundations to withstand water pressures, or moving valuable assets to higher floors (Noll, Filatova, Need, et al., 2022).

Recognizing the pivotal role of households in successfully adapting to climate change, governments are seeking effective approaches to encourage household adaptation (Kievik & Gutteling, 2011; Vulturius et al., 2018). To develop such flood risk management (FRM) policies it is essential to apprehend the **households' motivating factors** for climate change adaptation (CCA) (Noll, Filatova, & Need, 2022; van Valkengoed & Steg, 2019). These factors are increasingly being studied - in particular for flood hazards (Berrang-Ford et al., 2021; van Valkengoed & Steg, 2019). Research recognizes that the drivers and barriers of household CCA to floods can differ among cultural, social, environmental and institutional contexts (Noll et al., 2020; Noll, Filatova, Need, et al., 2022). Additionally, it is acknowledged that these factors can differ for adaptation types which vary in effort and cost (Noll, Filatova, Need, et al., 2022). Moreover, there is an increasing understanding of the effect of prior and additionally intended adaptation on a household's intention to adapt to climate-induced floods (Noll, Filatova, & Need, 2022).

To inform FRM policies, it is not only necessary to determine how and why households adapt, but also to **quantify the impacts of household CCA on flood risk**. Contemporary flood risk models which integrate household CCA predominantly focus on **aggregate impacts** of household CCA – see for instance Abebe et al. (2020), Y. Han et al. (2021) and Michaelis et al. (2020). Quantifying the aggregate impacts of household CCA is important as it provides insights into the cumulative speed and scale of behavioural household adaptation, which helps policy makers to prioritize the most effective CCA strategies at the municipal, provincial, and national levels. However, such aggregate impacts alone do not suffice to inform FRM policies as the differences in the adaptation diffusion and damage prevention amongst various societal household groups are neglected. Quantifying the **distributional impacts** of household CCA on flood risk is therefore of high relevance, as these insights can help design tailored FRM policies that allocate resources to the societal groups that need them most (Bubeck et al., 2020).

This thesis aims to address this research gap and quantify both the aggregate and distributional impacts of household CCA to provide FRM policies with insights on the role of household CCA in reducing coastal flood risk.

1.2. Research questions

Based on the research gap explained in the previous sub-chapter we derive the main research question of this thesis. By answering this research question, we aim to provide new insights for FRM policies:

"What role does household climate change adaptation play in reducing coastal flood risk?"

To answer this main research question, we formulate the following sub questions (SQs). The first SQ aims at determining the **flood risk** of households:

SQ1: "How can we determine the coastal flood risk of households for different climate-induced flood scenarios?"

The second SQ aims at understanding **how** households adapt to flooding i.e., which adaptation measures they can take and how these measures differ in reducing flood risk.

SQ2: "What are the households' main climate change adaptation measures and how do they reduce coastal flood risk?"

Now that we know how households adapt, it is necessary to understand **why** they adapt. Hence, we need to understand the **behavioural factors** that influence household adaptation intentions, resulting in the third SQ:

SQ3: "What are the behavioural factors that motivate household flood-adaptation intentions?"

While these first three SQs build the foundation for quantifying the risk reduction by household adaptation the following two SQs aim to quantify the aggregate and distributional effects. For the **aggregate impacts**, we are interested in the households' cumulative adaptation uptake and flood damage reduction under different climate-induced flood scenarios, resulting in the fourth SQ:

SQ4: "What are the aggregate impacts of household adaptation to climate-induced coastal floods in terms of adaptation uptake and damage prevention?"

Lastly, we want to understand the **distributional impacts** of the adaptation uptake and how this is translated into flood damage prevention for different socio-economic and socio-behavioural household groups for different food scenarios. This leads to the last SQ:

SQ5: "What are the distributional impacts of household adaptation to climate-induced coastal floods in terms of adaptation uptake and damage prevention?"

As explained in chapter *1.1*, the insights in both the aggregate (SQ4) and the distributional impacts (SQ5) can be applied to better understand the role of household CCA in reducing coastal flood risks and thus answer the main research question.

1.3. Systems perspective and link to CoSEM program

Integrating human dynamics into flood risk assessment to inform FRM policy requires a multidisciplinary approach (Aerts et al., 2018), which takes into account the interaction between the human and physical subsystems (Schanze, 2006). The **human** subsystem, which comprises household decision-making, is embedded in and interacts with the **physical** subsystem, which includes dikes and flood events (Abebe et al., 2019). Interactions between the two subsystems across different organizational, temporal and spatial scales in combination with the learnings from previous flood events characterize this human-flood system as a **complex adaptive system** (CAS) (Abebe et al., 2019). Hence, complex system properties such as emergence, path dependence, or instability may need to be taken into consideration (Nikolic, 2009). Thus, this thesis topic fits nicely into the **Complex Systems Engineering and Management** (CoSEM) study program as it addresses the impact of socio-behavioural household adaptation on the complex adaptive human-flood system.

1.4. Research approach

As shown in Figure 1, there are several ways to study the role of household CCA in the human-flood system (Law & Kelton, 1991): Experimentations with the real human-flood system over time e.g., in the form of longitudinal surveys – see for instance Bubeck et al. (2020), and Noll, Filatova, & Need (2022) are cost and effort intensive and do not allow studying the system under different flood scenarios ('what if'). Thus, we select a **modelling** approach. A physical model can capture efficacy, as shown by Yorkshire Flood Resilience (2021), but is insufficient to investigate the system interactions between the flood events and household actions. Therefore, we chose a **mathematical model**. As the human-flood system interactions appear too complex to be evaluated analytically, we take a **simulation modelling** approach.

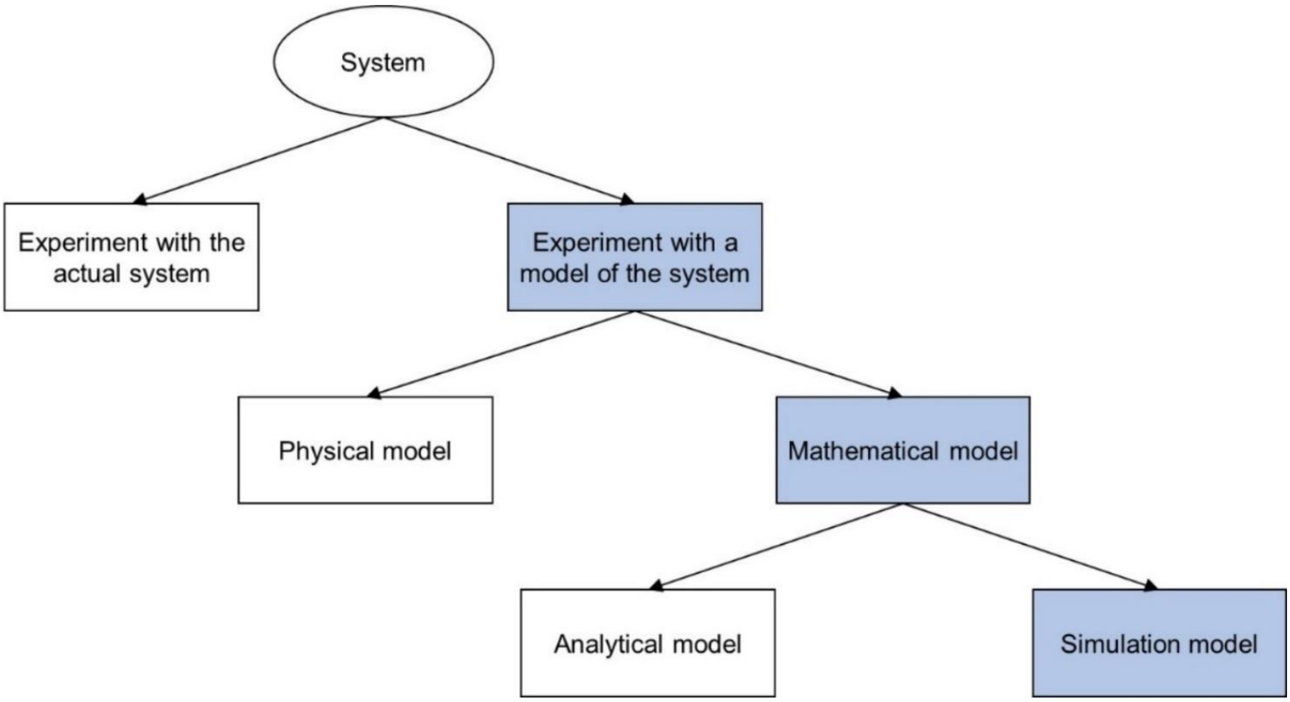


Figure 1: Ways to study a system (Source: adapted from Law & Kelton (1991), blue colour highlight our scoping decisions)

To study the complex adaptive human-flood system we require a simulation modelling approach that is multidisciplinary, generative, and adaptive (Nikolic & Kasmire, 2013). **Agent-based modelling (ABM)**, a bottom-up simulation method where heterogeneous actors interact with each other and with the environment (Macal & North, 2010) fulfils these requirements (Nikolic & Kasmire, 2013). Moreover, ABM is well suited to quantify the aggregate impacts of household climate adaptation for flood risk assessment as it takes into account interactions in social networks, the effect of behavioural biases, as well as feedback across different organizational, temporal and spatial scales which can exacerbate flood risks (Taberna et al., 2020). Furthermore, ABM enables to capture the heterogeneity of household adaptation behaviour (Aerts, 2020), which is especially important for studying the distributional impacts of household adaptation.

Due to the data specificity which is essential for quantifying household CCA to coastal floods (see chapter *4*), it is difficult to create a generic ABM. Hence, we choose a **case study approach** instead. As the complicated model structure of behaviourally rich ABMs can lead to severe modelling challenges such as high data collection, model construction, testing, validation, and computing efforts (Z. Sun et al., 2016) we solely conduct one case study.

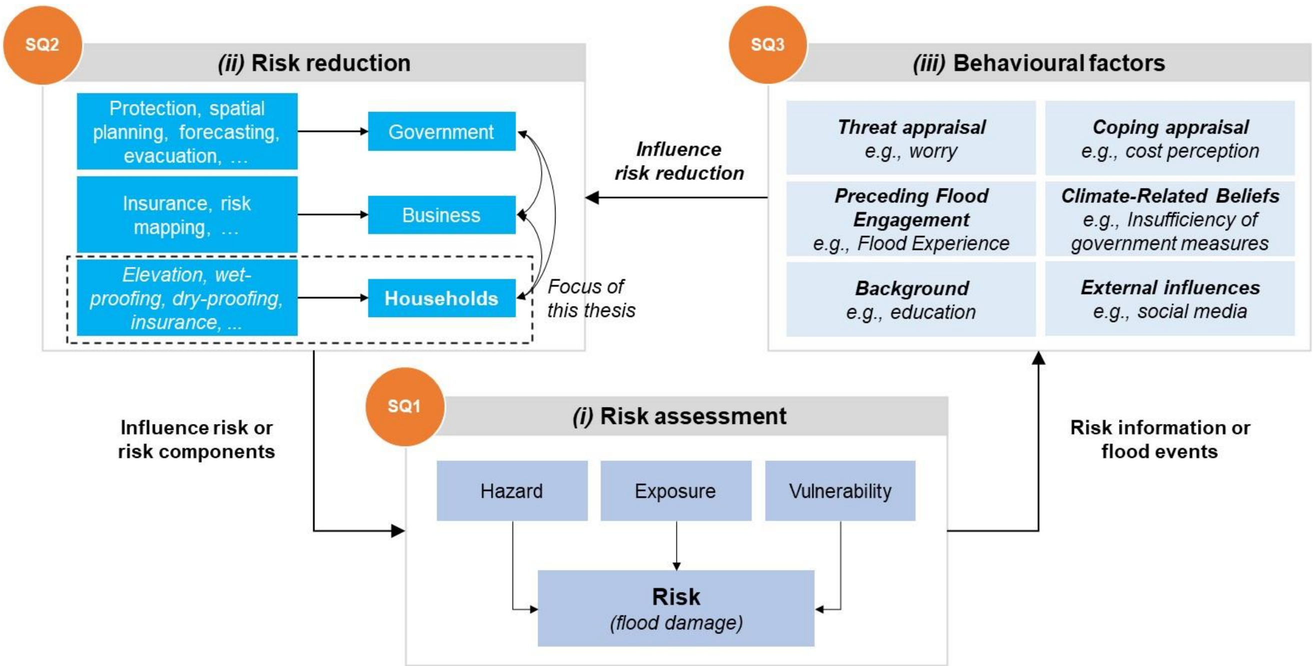
1.5. Outline

This thesis is structured as follows: Chapter 2 describes the theoretical frameworks and concepts which are necessary to understand the research methods. Chapter 3 details the research methods and presents the research framework that guides our research. Chapter 4 shows the data for integrating household behavioural dynamics into flood risk assessment. Chapter 5 presents the ABM on behavioural household CCA, the model evaluation, and the experimental setup. Chapter 6 shows the results of the experiments with the flood-ABM. The concluding Chapter 7 discusses the results and the relevance of this thesis to science, society, and policy as well as the limitations and future research. The appendices report on further details.

2. Theoretical foundations

2.1. Integrating household CCA behaviour into flood risk assessment

Before we can detail the research methods, we need to define the theoretical frameworks and core concepts our methods build upon. In general, understanding the role of household CCA adaptation in reducing flood risk is an interdisciplinary endeavour that involves methods from both the natural and social sciences (Aerts et al., 2018). To structure this large research field we apply a multidisciplinary framework that integrates the human behaviour dynamics into flood risk assessment: the **extended risk assessment framework** of Aerts et al. (2018) shown in Figure 2. It consists of three parts: **(i) risk assessment, (ii) risk reduction,** and **(iii) behavioural factors**[1], which align with our first three SQs. In essence, it shows that food risk and flood events can influence the behavioural factors of stakeholders based on which they make adaptation decisions which in turn can influence their flood risk. We further detail the three parts and the underlying concepts in the following.



Although the fundamental components of the framework are identical to Aerts (2018) we adjusted some of the text (marked in *italic*) as described in the following. First, we changed the **numbering** to (i) risk assessment, (ii) risk reduction, and (iii) behavioural factors, as it better suits the structure of this thesis. Second, we added a **description for the link** between (ii) and (iii). Third, we changed **the examples for the behavioural factors** by aligning them with the ones used in the behavioural theory shown in chapter 2.2. Fourth, we changed the **examples for the risk reduction factors** of households to better align them with our thesis. Fifth, we **highlighted our stakeholder scoping** using the dashed line in (ii). Sixth, we determine risk in terms of total **flood damage** instead of expected annual flood damage. Lastly, we linked the framework parts to our **sub questions** (SQs).

Figure 2: Extended risk assessment framework including SQs (Source: adapted from Aerts et al. (2018) as described in the note below the figure)[2]

Risk assessment (i): This part of the framework constitutes the traditional flood risk assessment (Aerts et al., 2018) where flood risk can be seen as a function of **hazard**, **exposure**, and **vulnerability** (see Box 1 for the detailed definition of flood risks and its components). This part of the framework links to **SQ1**.

[1] Aerts et al. (2018) use the terminology *disaster risk reduction*. For simplicity reasons, we refer to it as *risk reduction*.
[2] It is important to note that the framework extends the traditional risk assessment framework shown in (i) and is therefore labelled as *extended* by Aerts et al. (2018). We do not extend the framework of Aerts et al. (2018), but solely align the text in the framework with our thesis.

Box 1: Definitions of key terms and concepts for this thesis (Sources: Idea of the box with definitions is adapted from Abebe (2020); individual sources for definitions are listed inside the box)

Adaptation: "The process of adjustment to actual or expected climate and its effects. In human systems, adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects" (IPCC, 2014a, p.1758)

Flood: "The overflowing of the normal confines of a stream or other body of water, or the accumulation of water over areas not normally submerged." (IPCC, 2014a, p.1765)

- **Coastal flood:** "Coastal flooding is caused by a combination of high tides, storm surges and wave conditions." (Horsburgh et al., 2017, p.219)

Flood risk: "Risk is often represented as probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur. Risk results from the interaction of vulnerability, exposure, and hazard." (IPCC, 2014a, p.1772)

- **Hazard:** "The potential occurrence of a natural or human-induced physical event or trend or physical impact that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources." (IPCC, 2014a, p.1766)
- **Exposure:** "The presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected." (IPCC, 2014a, p.1765)
- **Vulnerability:** "The propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt." (IPCC, 2014a, p.1775)

Flood risk assessment: "The qualitative and quantitative scientific estimation of *flood* risks." (IPCC, 2014a, p.1772)*

Flood risk management: "Processes for designing, implementing, and evaluating strategies, policies, and measures to improve the understanding of *flood* risk, foster *flood* risk reduction and transfer, and promote continuous improvement in *flood* preparedness, response, and recovery practices, with the explicit purpose of increasing human security, well-being, quality of life, and sustainable development." (IPCC, 2014a, p.1763)*

Risk reduction (ii): The second part of the framework aligns with **SQ2** and focusses on risk reduction. Stakeholders can react to the threat posed by flooding and adapt (see Box 1 for the detailed definition of adaptation). Flood adaptation can be distinguished based on multiple dimensions. First, there is a differentiation between **administrative** adaptation e.g., by the government and **private** adaptation e.g., by households (Grothmann & Reusswig, 2006). While we specifically focus on household adaptation, we take the effects of administrative adaptation such as dikes on flood risk into account. Next, there is a difference between **autonomous** and **planned** adaptation (Fankhauser et al., 1999). While autonomous adaptation entails "natural or spontaneous adjustments in the face of a changing climate" (Carter et al., 1994, p.32), planned adaptation require conscious interventions. Fankhauser et al. (1999) note that this distinction depends on the stakeholder perspective e.g., a household adapting to floods is autonomous from the government's perspective but planned from the household's perspective. Within this thesis we apply the 'government's perspective', defining household adaptation as planned if it results from policy interventions and as autonomous otherwise.[4]

* The definition for *disaster risk* of the IPCC was adjusted to *flood risk* – see italic text.

[4] It is to be noted that our definition of autonomous household adaptation can differ to other studies or reports e.g., IPCC (2014b).

Furthermore, one can distinguish between **pre-event** adaptation before a flood to prepare for flood events and **post-event** adaptation after a flood such as a flood recovery or emergency response (Abebe, 2020). We are interested in studying the effects of mid-, to long-term adaptation, and hence we exclude short-term post-event emergency response from the scope. Moreover, adaptation actions can be **permanent** or **non-permanent** (Abebe et al., 2020; Erdlenbruch & Bonté, 2018). Measures are considered non-permanent if they expire, fail, are forgotten or are abandoned. We consider both permanent and non-permanent measures.

Behavioural factors (iii): The last part of the framework includes the behavioural factors that motivate households' adaptation intentions (Aerts et al., 2018). This part links to **SQ3**. Flood experience, flood risk perception, self-efficacy, response-efficacy, trust in measures, trust in government, responsibility, and negative affect are motivational factors which are often observed in studies focusing on flood adaptation (van Valkengoed & Steg, 2019). To determine such motivational factors, **behavioural theories** can be applied (Noll, Filatova, & Need, 2022). We explain such a theory in more detail in the subsequent chapter *2.2*.

2.2. Theoretical foundations of behavioural household CCA

Villamor et al. (2022) provide a structured overview of behavioural theories which can be applied to CCA. One of the most commonly used theories to explain households' intentions to adapt to floods is the **Protection Motivation Theory (PMT)** (Babcicky & Seebauer, 2017).

The PMT consists of two major processes: **Threat appraisal** and **coping appraisal**. While threat appraisal describes "how a person assesses a threat's probability and damage potential to things he or she values, assuming no change in his or her own behavior", coping appraisal includes the ability of a person "to cope with and avert being harmed by the threat, along with the costs of coping" (Grothmann & Reusswig, 2006, p.104). Noll, Filatova, Need, et al. (2022) extend the base PMT to account for **preceding flood engagement**, **external influences** by media and peers, **climate-related beliefs**, and the demographic **background** (Figure 3). This extension takes both internal (also referred to as "interpersonal") and external (also known as "intrapersonal") factors into consideration which are considered relevant for behavioural adaptation (Noll, Filatova, Need, et al., 2022; Wilson et al., 2020).

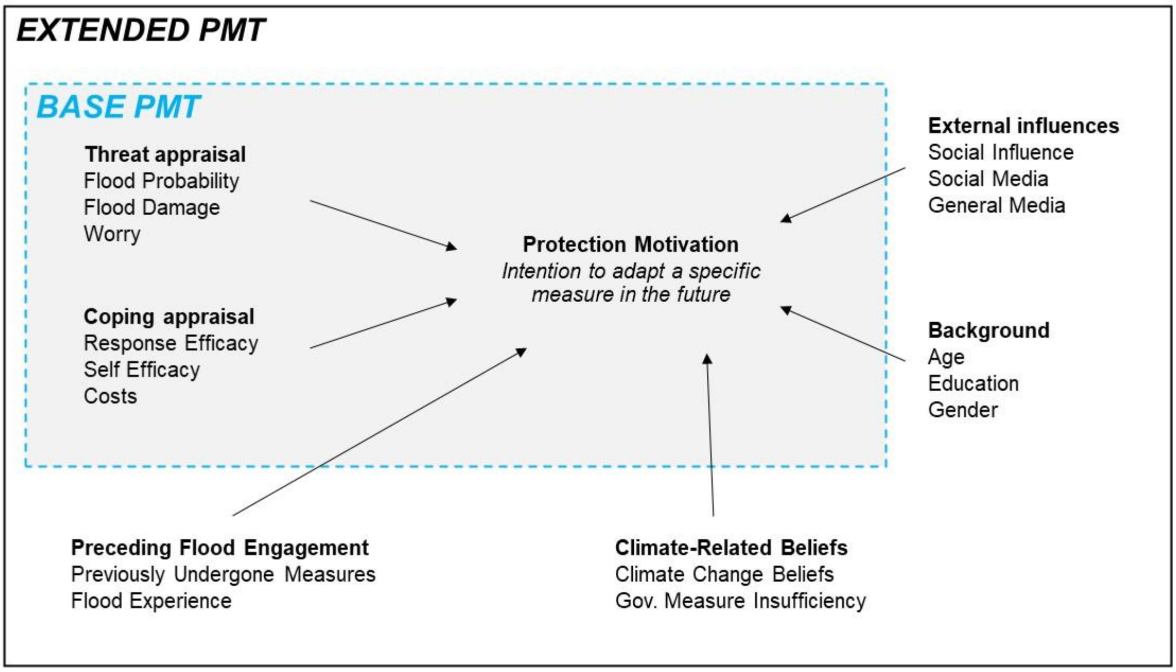


Figure 3: Extended Protection Motivation Theory including the 16 socio-behavioural factors (Source: created based on Noll, Filatova, Need, et al. (2022))

3. Research methods

3.1. Research gaps in flood-ABMs

To determine the research gaps in ABMs that focus on individual flood adaptation (flood-ABMs), we conduct a structured literature review according to the guidelines of Kable et al. (2012). Due to the considerable number of flood-ABMs, we **review the literature** in two rounds. A first round on identifying existing reviews on flood-ABMs and then a second round to scope down on research gaps identified in the first round. Further details on our structured literature review methodology are shown in Appendix A *Literature review*.

In the **first round**, we identified three recent reviews by Aerts (2020), Taberna et al. (2020) and Zhuo & Han (2020) that highlight **three major research gaps** in flood-ABMs. First, empirical data for decision-making often stems from expert knowledge or secondary literature (Aerts, 2020; Taberna et al., 2020). The minority of flood-ABMs base the agent behaviour on **case-related micro-level data** e.g., from surveys (Aerts, 2020; Taberna et al., 2020). Not only does this lack of empirical data make the validation and benchmarking of these ABMs difficult (Aerts, 2020), but the use of aggregate data for critical behaviour parameters can be misleading policy (Erdlenbruch & Bonté, 2018). Second, the decision-making in the majority of the flood-ABMs relies on ad-hoc assumptions instead of behavioural theories (Aerts, 2020; Taberna et al., 2020; Zhuo & Han, 2020). The **theoretical foundation of decision-making** has several advantages such as enabling the testing of alternative theories in case of data scarcity, fostering interdisciplinary communication, facilitating model improvements, and ensuring faster and more sustainable scientific progress (Bell et al., 2015; Groeneveld et al., 2017; Klabunde & Willekens, 2016). Moreover, “using more robust theories to manifest agents would allow a more in-depth analysis of the interactions” (Taberna et al., 2020, p.17). Lastly, Aerts (2020) and Taberna et al. (2020) highlight the importance of **integrating ABMs with numerical flood models** as flood events and flood damage influence household adaptation decisions. According to Abebe et al. (2020), this is often neglected in flood-ABMs. A two-way feedback between the human and the physical subsystem is recommended to show the effects of adaptation actions on future floods (Aerts, 2020; Taberna et al., 2020) – see for instance Abebe et al. (2019). Taberna et al. (2020) further highlight that flood events which are integrated into the ABM should reflect the evolvement of flood hazards with climate change.

In the **second round**, we conduct a structured literature review on the application of behavioural theories in flood-ABMs – one of the previously mentioned methodological research gaps.[5] Within our second round, we identify 13 articles that describe flood-ABMs which integrate behavioural theories (see Table 4 in Appendix *A.2*). We notice that these ABMs are only applied in Europe and the United States. Flood-ABMs incorporating behavioural theories appear to be **underrepresented in the Global South**. This might be explained by the fact that most empirical work on factors motivating individual CCA is conducted in Europe and North America (Hopkins, 2015; van Valkengoed & Steg, 2019). According to Noll et al. (2020), empirical work on private adaptation in the Global South is lacking despite floods being common in all parts of the world (EM-Dat, 2019). As empirical data enables integrating behavioural theories into flood risk assessment (Aerts et al., 2018) the lack of empirical data may hinder the development of flood-ABMs with behavioural theories in these nations. As a result, there is not only a lack of knowledge about what drives household adaptation in the Global South (Noll et al., 2020), but also a lack of understanding about the speed and extent of household CCA in these countries. "Institutional transplantation" (De Jong et al., 2002) of policy measures from a country in the Global North to a country in the Global South might be flawed due to potential differences in adaptation drivers and barriers (Noll et al., 2020). This makes it more difficult to inform FRM policies and puts the Global South, which is disproportionally impacted by climate-induced hazards (IPCC, 2014b) at greater risk (Noll et al., 2020). To overcome this gap, we focus our ABM on a coastal city in the Global South.

In summary, we create a state-of-the-art flood-ABM that approaches all three methodological research gaps identified in the first literature review round: We integrate **case-specific survey data** with the **extended version of the PMT** described in chapter 2.2 and apply **inundation maps under different climate change scenarios** as one-way inputs to depict the influence of climate-induced floods on the adaptation behaviour. Moreover, to overcome the gap in behavioural flood adaptation studies in the **Global South** we focus our ABM on a coastal city in Asia, which we further detail in subsequent subchapter *3.2.*

[5] This second round review offers the following benefits. On the one hand, additional databases and search strings are researched, and hence more papers can be identified. On the other hand, it enables a new and more detailed perspective of the flood-ABMs and their features

3.2. Case study scope

For our case study, we choose **Shanghai** as a coastal city of the Global South for the following reasons.

First, Shanghai has been affected by flooding for a long time and is considered **one of the most flood-exposed cities in the world** (Hanson et al., 2011; Nicholls et al., 2008). This is partly due to the low average elevation of 4 m (K. Xu et al., 2021), which means that about 85% of the area is at risk of high water levels and frequent storm surges (Du et al., 2020). Between 1949 and 2005, more than 1800 flood-related deaths were counted (Wen & Xu, 2006). Shanghai is most susceptible to flooding from typhoon-induced storm surges (S. Xu & Huang, 2011). For instance, in 1997 Typhoon Winnie led to a rise of the Huangpu River to 5.99 m (Du et al., 2015) causing seven deaths and a direct economic loss of 80 million USD (K. Xu et al., 2021). Sea level rise, land subsidence, and socioeconomic development are likely to increase the severity and frequency of flooding in the future (Ke, 2014; J. Wang et al., 2012; K. Xu et al., 2021; J. Yin et al., 2020).

Second, Shanghai with its 25 million inhabitants (National Bureau of Statistics of China, 2021) is an **economic powerhouse** of the Chinese mainland (Ke, 2014). Due to its dense population, rapid growth and economic importance, the flood impact is far-reaching (Ke et al., 2016). Hence, FRM is a high priority in Shanghai (Ke, 2014).

Next, Shanghai currently relies **mainly on top-down structural flood-adaptation measures** such as dikes or floodwalls (Du et al., 2015). Due to its structural flood defence system, which is designed to withstand 1000-year floods, Shanghai is seen as one of the most well-protected cities against flooding in China (Du et al., 2020). However, sea-level rise and land subsidence increase the likelihood of dike overtopping and failure by storm surges in Shanghai (Ke et al., 2021; J. Yin et al., 2020). The publicly-funded flood defences successfully reduce the probability of flooding towards a predefined safety norm, e.g., a 100-year or 1000-year return period usually based on historical records, not always accounting for the new normal due to climate change. Moreover, public flood defence infrastructure creates unintended consequences, like the ‘safe development paradox’ (Burby, 2006) also known as the ‘dike paradox’ (Hartmann & Spit, 2016) or ‘levee effect’ (Tobin, 1995). These defences attract more people and capital to the newly protected locations and eventually increase risks – see also Haer et al. (2020). Yet should an adverse event occur, private adaptation actions determine how much damage a hazard will impose, and how quickly individuals and communities will recover. Therefore, studying the effect of household adaptation is necessary to improve the flood resilience of any coastal city, even as centrally protected as Shanghai.

Lastly, **micro-level survey data** and **climate-induced inundation maps** are available for Shanghai. On the one hand, we have access to the results of a survey conducted in Shanghai in April 2020 as part of the ERC project ‘SCALAR’. This survey examines the adaptation intentions of 933 households for 18 different household-level actions – see Noll, Filatova, & Need (2022) and Noll, Filatova, Need, et al. (2022). On the other hand, we have access to inundation maps of Du et al. (2020) and J. Yin et al. (2020) which depict the flood depth for storm surge floods under different climate change scenarios and return periods in Shanghai. This data is essential for overcoming the aforementioned methodological research gaps.

3.3. Research framework for studying household CCA in Shanghai

Figure 4 summarizes the entire research framework for studying household CCA in Shanghai. It guides the research in this thesis and hence depicts the relationship between the sub questions, the main research steps, simulation process phases, and the key in/outputs of these phases e.g., data and the thesis chapters. More specifically, we create the ABM following the simulation process steps by Nikolic et al. (2013). While Nikolic et al. (2013) define verification and validation as individual process steps, Balci (1994) highlights that validation, verification, and testing (VV&T) should be seen as a continuous activity throughout the entire simulation lifecycle. As a result, we modify the lifecycle of Nikolic et al. (2013) by integrating VV&T into the most important process steps (Figure 4). To keep this thesis concise, we use the appendix for documenting details. Specifically, we use the ODD protocol (Grimm et al., 2020) to describe the ABM. We explain the research framework in the following based on the simulation process steps of Nikolic et al. (2013):

Problem Identification: To identify our problem and to determine the research scope we conduct a literature review on flood-ABMs. The results of this review were already presented in this chapter. The review methodology can be found in Appendix A *Literature review*. Moreover, we exchange with two flood modelling researchers at the beginning of the process, one who specifically focuses on flood risk in Shanghai, and use this feedback to improve the scoping.

System Identification and Decomposition: Within this process phase we decompose the human-flood system and determine the input data for our ABM. This is described in Chapter 4 *Data for integrating human dynamics into flood risk assessment* and in Appendix B.6 *Input Data*. Specifically, we apply the extended risk assessment framework of Aerts et al. (2018) shown in chapter *2.1* to decompose the system into three parts **(i) risk assessment**, **(ii) risk reduction**, and **(iii) behavioural factors** and to answer the first three SQs. In terms of **risk assessment (i)**, we determine the exposure of households to flood hazards by overlaying the inundation maps with geospatial residential building data from our study area in QGIS. Moreover, we review existing flood studies to determine the exposed asset values and the depth-damage curves to assess the households' vulnerability. This provides the data for all the three risk components (hazard, exposure, and vulnerability) which is needed to determine the flood risk of households and to answer the first SQ. For the **risk reduction (ii)**, we analyse micro-level survey data in our study area and review existing flood studies to cluster the individual measures into measure categories and to determine the characteristics of these measure categories. This answers the second SQ. In terms of **behavioural factors (iii)**, we create logistic regression models for each measure category in SPSS based on context-specific micro-level survey data to determine the effect of socio-behavioural factors on the intention of households to adapt the measures of the respective measure category. We use the resulting regression coefficients in combination with the extended Protection Motivation Theory to model the households' CCA decisions. This helps us answer SQ3. We also apply additional linear regression models to model the social household interactions and to depict the number of households that intend but do not realize their adaptation. To verify the system decomposition and data we apply the tests outlined by Balci (1994) in Appendix E.1 *System and Objectives Definition VV&T* and Appendix E.2 *Data VV&T*.

Concept and Model Formulization: Based on the decomposed system inventory, a conceptual model is created. This conceptual model is highlighted among others with flow-charts. We validate our conceptual model with three different flood-ABM experts in Appendix E.3 *Conceptual Model VV&T* and use their feedback for model improvements. We transform the conceptual model into a formal model, which is described in the form of pseudo code and a model narrative (Nikolic et al., 2013). We describe the conceptual model in chapter 5.1 *Conceptual model* and provide all the details on the conceptual and formal models in the ODD protocol in Appendix B *Model description – ODD*.

Computational model: Based on the formal model, we code a computational model using Netlogo 6.2.2 (Wilensky, 1999). We describe the requirements of this computational model as well as the applied programming practises in Appendix C *Software Implementation*. We verify this computational model using steps outlined by Balci (1994) and Wilensky & Rand (2015) in Appendix E.4 *Computational Model VV&T*.

Experimentation: We conduct experiments using the computational model. The experiments are set up to answer SQ4 and SQ5. We summarize the experimental setup in Chapter 5.3 *Experimental setup* and provide the details e.g., on the number of replications required in Appendix D *Experimentation*. We then run these experiments on our 'Shanghai-Flood-ABM' server of the TU Delft Faculty of Technology, Policy, and Management. Moreover, we conduct a sensitivity analysis of the programmed model, which we detail in Appendix E.5 *Sensitivity Analysis*. This provides further insights on model improvements and helps us with the analysis in the next step.

Data Analysis: In chapter 6 *Results* we describe and analyse the results of our experiments. On the one hand, we analyse the aggregate impacts of household adaptation to answer SQ4. On the other hand, we analyse the distributional impacts to answer SQ5. We use Appendix F *Data analysis* to document data analysis details.

Model Use: In chapter 7 *Conclusions and discussion* we use the insights on the aggregate and distributional effects of household adaptation to answer our main research question and to discuss the potential impacts of our findings on flood risk management policies.

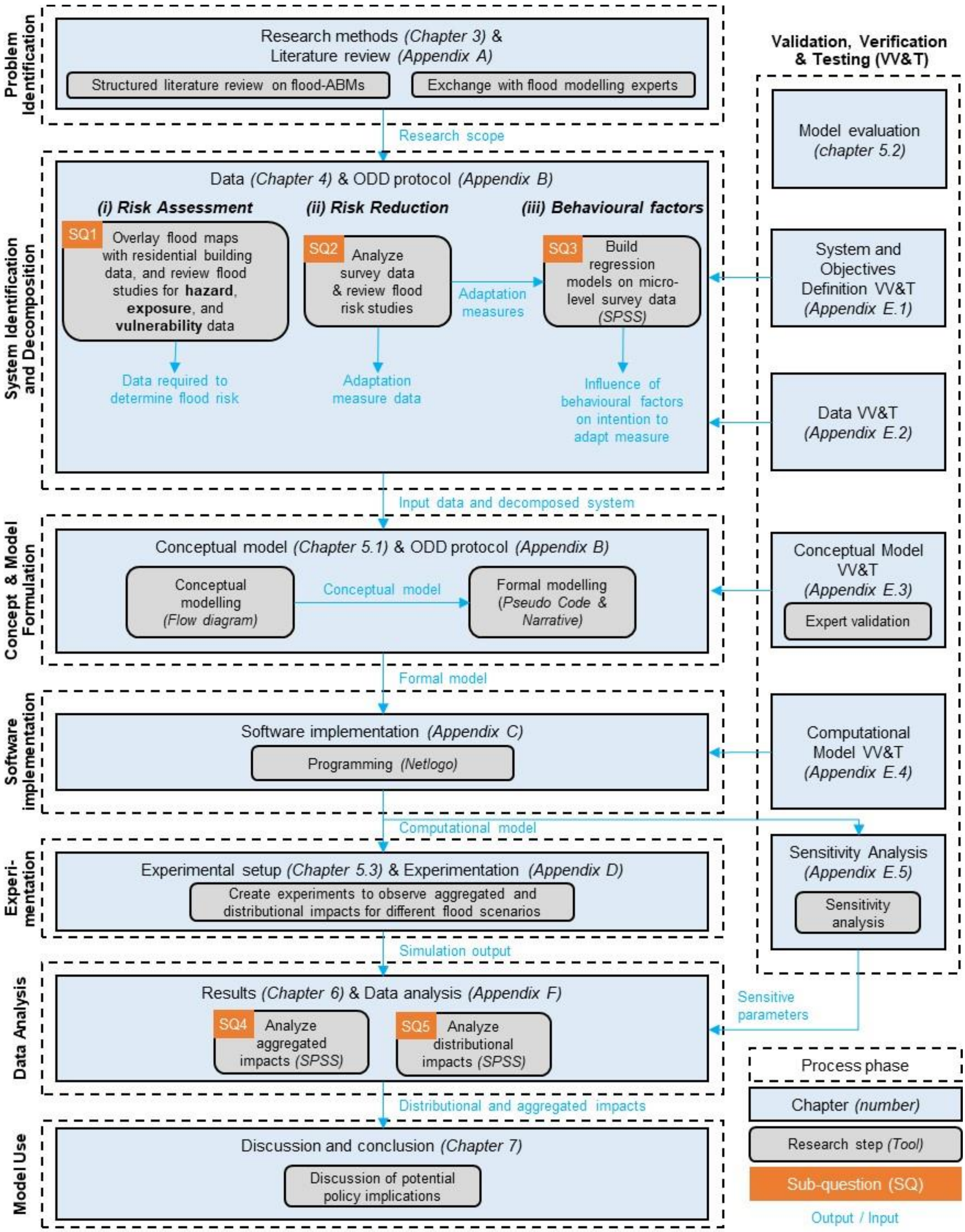


Figure 4: Research framework linking research questions to research steps, thesis chapters, simulation process phases, and in/outputs (Source: simulation process phases adapted from Nikolic et al. (2013), risk assessment framework adapted from Aerts et al. (2018), validation, verification and testing adapted from Balci (1994))

4. Data for integrating human dynamics into flood risk assessment in Shanghai

4.1. Data on hazard, exposure, and vulnerability

To determine the potential flood damage in our ABM we combine hazard, exposure, and vulnerability data (Figure 5). Specifically, we use inundation maps which depict the probability, depth and location of climate-induced floods and overlay them with geospatial residential building data to determine the inundation depth of residential buildings for the different flood scenarios. In combination with asset values of building and contents and depth-damage curves, we can evaluate the direct and tangible flood damage to residential buildings in our ABM.

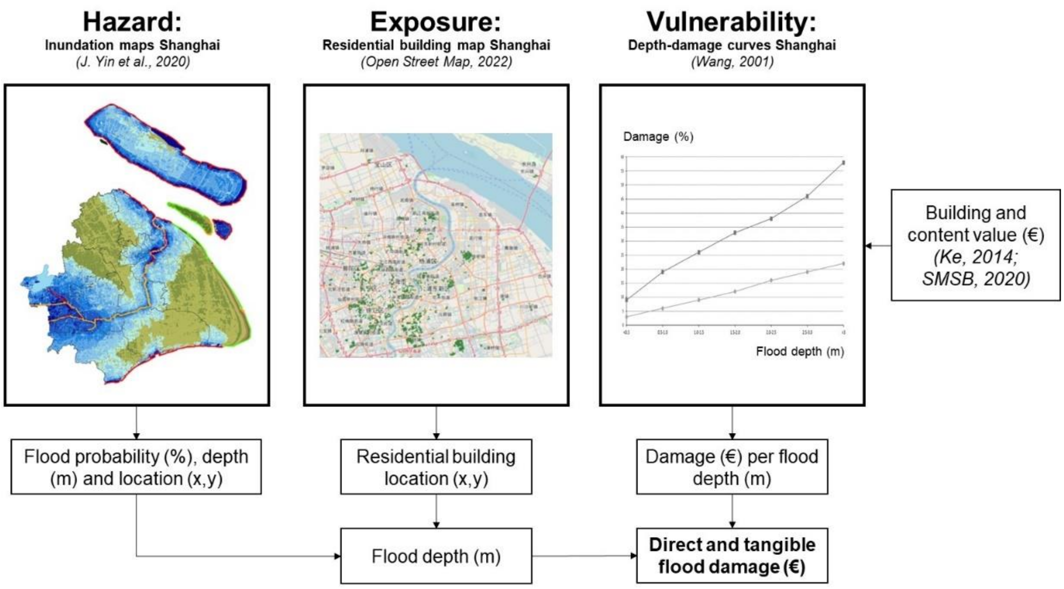


Figure 5: Data for flood risk assessment (Source: hazard picture from J. Yin et al. (2020), exposure picture from OpenStreetMap (2022))

4.1.1. Determining the severity of climate-induced storm surge floods

In Shanghai, extreme water levels at the coast and Huangpu river are mainly caused by storm surges, high tides, heavy rainfall, and upstream flooding (J. Yin et al., 2020). This thesis focusses on storm surges combined with high tides, which cause one of the greatest flood risks in Shanghai (S. Xu & Huang, 2011; J. Yin et al., 2013). We assess the damage based on the flood depth, as it is the most frequently utilized metric for determining flood severity (Apel et al., 2009; Merz et al., 2007), and as it appears to be one of the most influential parameters on flood damage (Penning et al., 1995; Wind et al., 1999). To represent the flood scenarios in the model we use 21 **inundation maps** drawn by J. Yin et al. (2020), which depict dike overtopping and breaching for storm surges in Shanghai under the effect of sea-level rise and land subsidence. These inundation maps show the flood location and depth in the years 2010, 2030, 2050 and 2100 for ten, one-hundred, and one-thousand-year floods and for different Representative Concentration Pathways (RPC) in Shanghai (J. Yin et al., 2020).

4.1.2. Determining households' exposure to climate-induced floods

As the scope of this thesis is household adaptation, we focus on residential buildings, which are an essential part of the flood risk assessment in Shanghai (Shan et al., 2019; Wu et al., 2019; Z. Yin et al., 2011). Government-provided residential building data appears scarce. Instead, the location of residential buildings in Shanghai can be retrieved from **OpenStreetMap** (2022) (OSM). By overlapping the location of the residential buildings with the inundation maps, we determine the inundation levels of the residential buildings for each flood scenario (details in the ODD protocol, Appendix *B.6.1*).

Within Shanghai, we specifically focus on 18.039 residential buildings in the seven city centre districts Huangpu, Changning, Putuo, Yangpu, Xuhui, Jing 'an, and Hongkou (Figure 6) for the following reasons. First, our analysis highlights that the residential buildings in the city centre are most exposed to floods, accounting for 55-100% of the inundated residential buildings depending on the flood map of J. Yin et al. (2020). Shan et al. (2019) also demonstrate that residential buildings in Shanghai's city centre districts are among the most exposed to extreme flooding (5000-year flood). Second, our comparison with official statistics from the Shanghai Municipal Statistics Bureau (2020) shows that the city centre districts have by far the highest mapping accuracy (90%) in terms of the number of buildings in OSM. Finally, according to our analyses, the majority (66%) of survey respondents in Shanghai with a recognisable zip code live in the city centre districts. (Details in the ODD protocol, Appendix *B.6.1*).

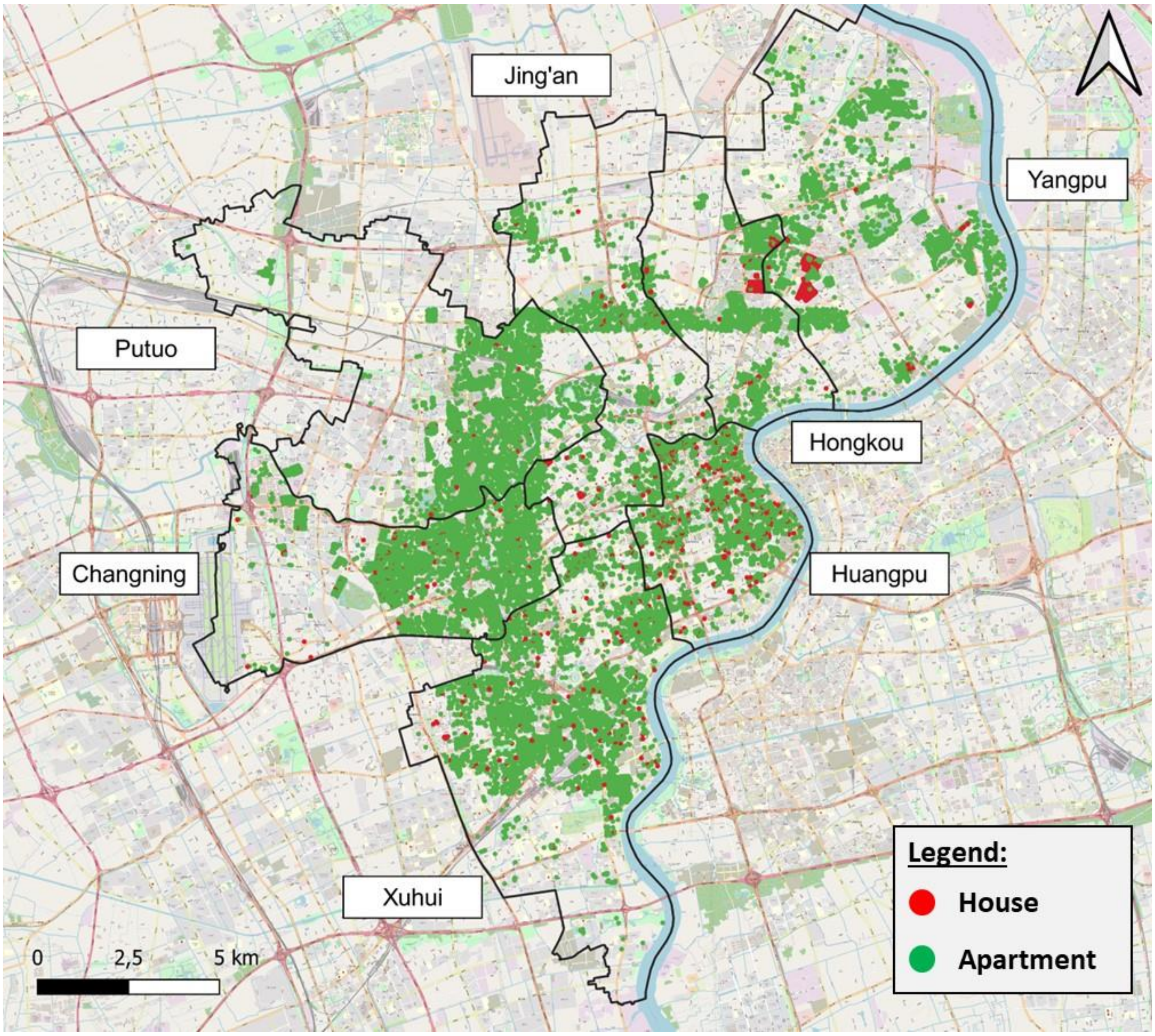


Figure 6: Residential buildings in Shanghai city centre districts (n = 18.039) (Source: data adjusted from OpenStreetMap (2022))

Figure 7 depicts the number of inundated residential buildings in the city centre districts for different flood scenarios. When comparing the 10-, 100- and 1000-year flood events, we notice that a 10-year flood in 2100 under the RCP 8.5 scenario affects more residential buildings than a 100-year flood in 2050 and a 1000-year flood in 2010. This highlights the significant effects of sea-level rise and land subsidence on the exposure of households in the Shanghai city centre and underlines the need for promoting household adaptations complementary to the government-led adaptation to cope with the adversities of climate change. The details of this analysis together with a comparison with another risk study in Shanghai can be found in the ODD protocol in Appendix *B.6.1*.

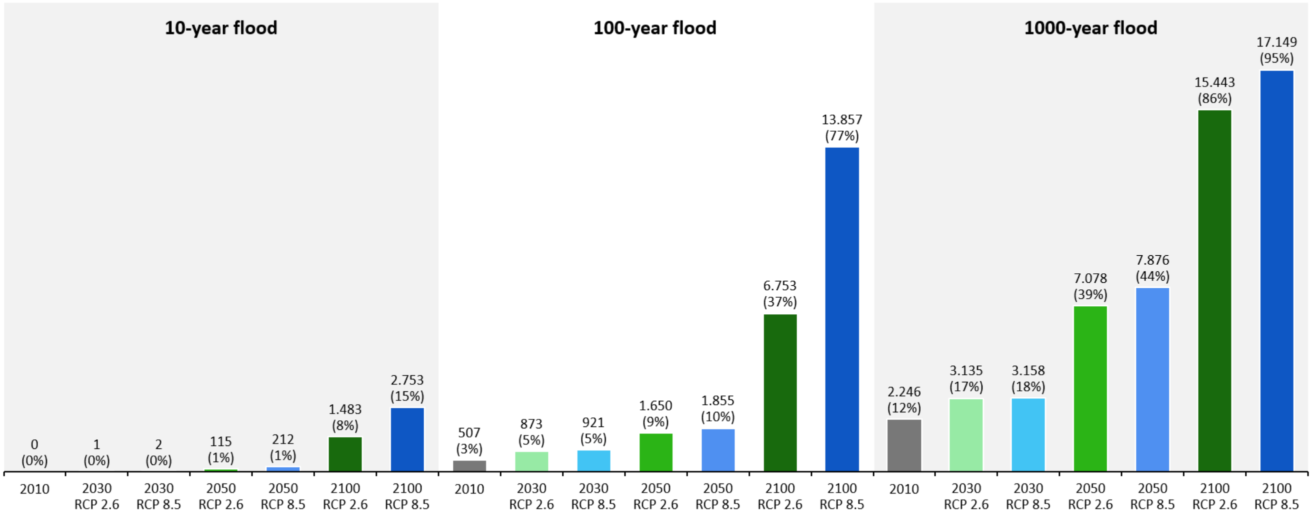


Figure 7: Number of inundated residential buildings for different flood scenarios in the Shanghai city centre – building considered inundated if inundation level is larger than foundation height of 0.1 meter (Source: based on data from J. Yin et al. (2020), OpenStreetMap (2022), and Shanghai Municipal Statistics Bureau (2020))

To determine the exposed residential asset values, we use additional data on the residential building and content values in Shanghai. For the **building value**, we follow Wu et al. (2019) and determine the construction cost per square meter (861 €/sqm) using official data from the Shanghai Municipal Statistics Bureau (2020). For the **content value**, we use the data of Ke (2014) to determine the value of popular household items which are fragile to inundation for a small building. With the assumption that the content value increases with the household size, we determine the content value per square meter (209 €/sqm). Using the heterogeneous building size data from the survey we can determine the total building and content value for each household in the ABM. Details on the asset values and comparison with values used in other risk assessments are shown in the ODD protocol in Appendix *B.6.1.4*.

4.1.3. Measuring households' vulnerability to climate-induced floods

Within this study, we focus on direct tangible damage (Merz et al., 2010) in the form of building and content damage. The direct and tangible flood damage is determined using **depth-damage curves** (Merz et al., 2010), which depict the relationship between hazard characteristics (e.g., water depth) and damage extent (Hu et al., 2019). We chose the depth-damage curves of Wang (2001) (Figure 8), as they focus on building and content damage of residential buildings in Shanghai and have been applied in other risk assessments (Ke, 2014; Shan et al., 2019). A more detailed overview and comparison with other depth-damage functions in Shanghai are shown in the ODD protocol in Appendix *B.6.2*.

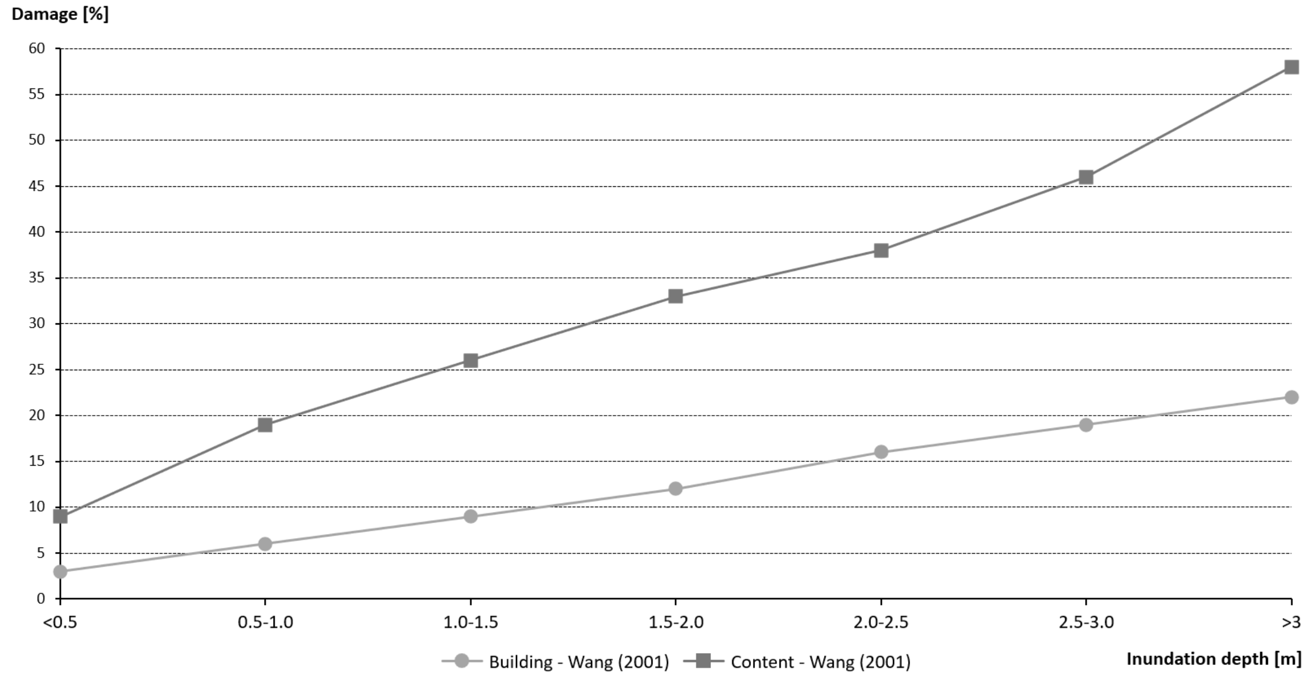


Figure 8: Depth-damage functions (Source: based on data from Wang (2001))

4.2. Data on households' CCA measures

For this thesis, we have employed unique micro-level data from the aforementioned survey about factors motivating households' adaptation intentions. The survey examines 18 different household-level actions in Shanghai. As empirical evidence shows that households' CCA intentions to floods in Shanghai can differ depending on the measure type (Noll, Filatova, Need, et al., 2022), we categorize 10 of the 18 measures into three groups - elevation, wet-proofing, and dry-proofing[6]: **Elevation** entails raising the building ground level above the most-likely flood level (Lasage et al., 2014). **Wet-proofing** means that floodwater can enter the building while the damage is limited by adjusting the interior or building structure (Du et al., 2020) e.g., by strengthening the housing foundations to withstand water pressures. **Dry-proofing** assures that floodwater is kept from entering the building (Du et al., 2020) e.g., in the form of sandbags.

The three categories differ in terms of their effectiveness in reducing flood damage, their cost, their lifetime, and implementation time (Table 1). While elevation is very effective in reducing flood damage below the elevation level, it is also costly and requires the longest implementation time. Wet-proofing is less effective but can reduce damages at high flood depths. In addition, wet-proofing has a similar cost to elevation but has a shorter implementation time. Dry-proofing has greater effectiveness than wet-proofing but reduces flood damage only at lower flood depths. In addition, dry-proofing has the lowest cost and a similar implementation time to wet-proofing. We assume that dry-proofing is the only non-permanent measure. Further details are provided in the ODD protocol in Appendix *B.6.3.*

Table 1: Household climate change adaptation measures and characteristics

Measure category	Individual adaptation measure*	Average cost [€]*	Effectiveness in reducing damage	Lifetime [years]	Implementation time [years]
Elevation	Raising the level of the ground floor 30 cm above the level of a 100-year flood in 2030 under the RCP8.5 scenario	4040	**100%** below elevation level (Du et al., 2020)	Permanent	**3** (assumption)
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 Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage Moving/ storing valuable assets on higher floors or elevated areas	4027	**40%** (ICPR, 2002; DEFRA, 2008; Kreibich et al., 2005) below **3 meters** (Lasage et al., 2014; de Moel et al., 2013)	Permanent	**2** (assumption)
Dry-proofing	Purchasing sandbags, or other water barriers 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)	1706	**85%** (ICPR, 2002; DEFRA, 2008) below **1 meter** (Bubeck & de Moel, 2010; de Moel et al., 2013; Lasage et al., 2014)	**N(20,2)** (mean from Du et al., 2020)	**2** (Du et al., 2020)

* From micro-level survey data in Shanghai (Noll, Filatova, & Need, 2022; Noll, Filatova, Need, et al., 2022).

[6] This categorization appears to be common for flood risk assessment (de Moel et al., 2013; Du et al., 2020; Lasage et al., 2014).

4.3. Empirical micro-foundations of behavioural household CCA

4.3.1. Regression models to determine factors influencing households' CCA intentions

To determine the behavioural factors that influence households' CCA intentions, we estimate **logistic regression models** for each adaptation measure category (elevation, wet-proofing, dry-proofing – see chapter *4.2*) based on the survey data. A binary dependent variable indicates for each measure category whether a survey respondent intends to adapt at least one of the measures in the respective category. The 16 socio-behavioural variables of the extended PMT are the independent variables (see the ODD protocol, Appendix *B.6.4.1*).

Following Bubeck et al. (2013), we apply a backward stepwise regression. This means that for each adaptation measure category we start with the so-called 'full models' that include all 16 independent variables (see the ODD protocol, Appendix *B.6.4.2*). Next, for each adaptation measure category, the non-significant independent variables are removed step-by-step from the model, resulting in the 'best-fitting' models that only include significant independent variables ($p<.05$) (see the ODD protocol, Appendix *B.6.4.3*). As we aim to quantify the distributional impacts, we need to be able to compare the influence of the socio-behavioural variables between the different adaptation measure categories. Moreover, the behaviour should be based on at least all the base PMT variables. Therefore, we create three 'final models' for each adaptation measure category which include all the base PMT variables as well as the PMT extension variables which show a significant effect in at least one of the best-fitting models (see the ODD protocol, Appendix *B.6.4.4*). As a result, the variables 'Gender', 'Government Measure Insufficiency', and 'General Media' are not included in our final models.[7]

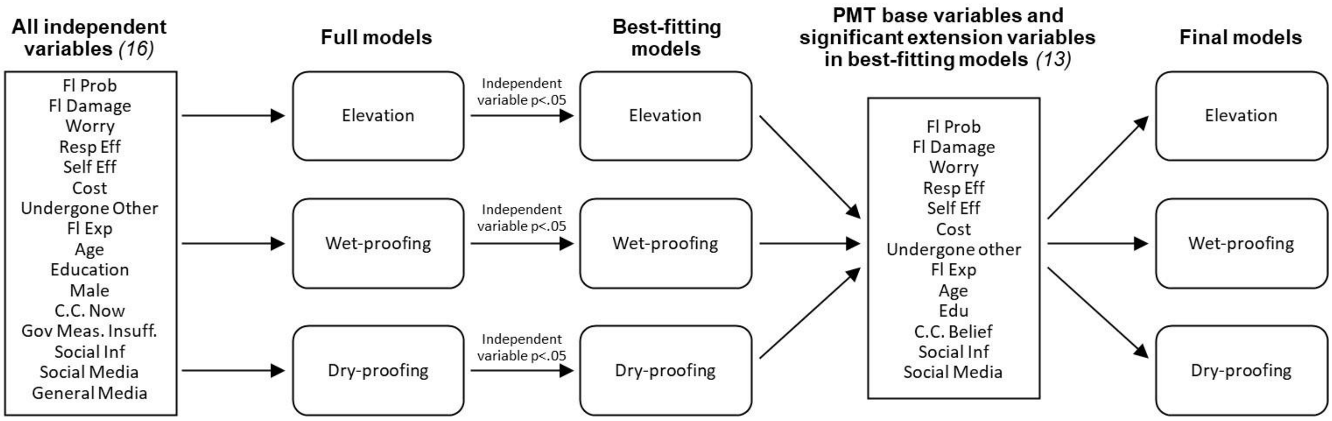


Figure 9: Flow chart of the binary logistics regressions for the intention to adapt elevation, wet-proofing, and dry-proofing measures (Source: adjusted from Bubeck et al. (2013))

The final models of elevation, wet-proofing, and dry-proofing explain 54%, 29%, and 47% of the variance in intending to implement measures of the respective category. This corresponds to a good to very good explanatory power for psychological studies (Bubeck et al., 2013).

[7] In comparison, Bubeck et al. (2013) only include independent variables in the final models which were found significant in at least one of the best-fitting models. However, this would lead to the exclusion of core PMT variables such as Perceived Flood Damage and Response Efficacy in our final models. Hence, the approach is altered as explained.

4.3.2. Effect of socio-behavioural factors on households' CCA intentions

Figure 10 shows the resulting **odds ratios** with the 95% confidence intervals of the final models for elevation, wet-proofing, and dry-proofing. Odds ratios depict the change in the odds of the dependent variable (intention to adapt) when the independent variable (e.g., worry) changes by one unit (Sperandei, 2014). When the odds ratio is larger than 1, the likelihood of the dependent variable increases and vice versa (Bubeck et al., 2013). In the following, we discuss the role of socio-behavioural attributes on the intention of Shanghai households to adapt to floods. For an overview of the significance of the factors, we refer to the ODD protocol in Appendix *B.6.4*.

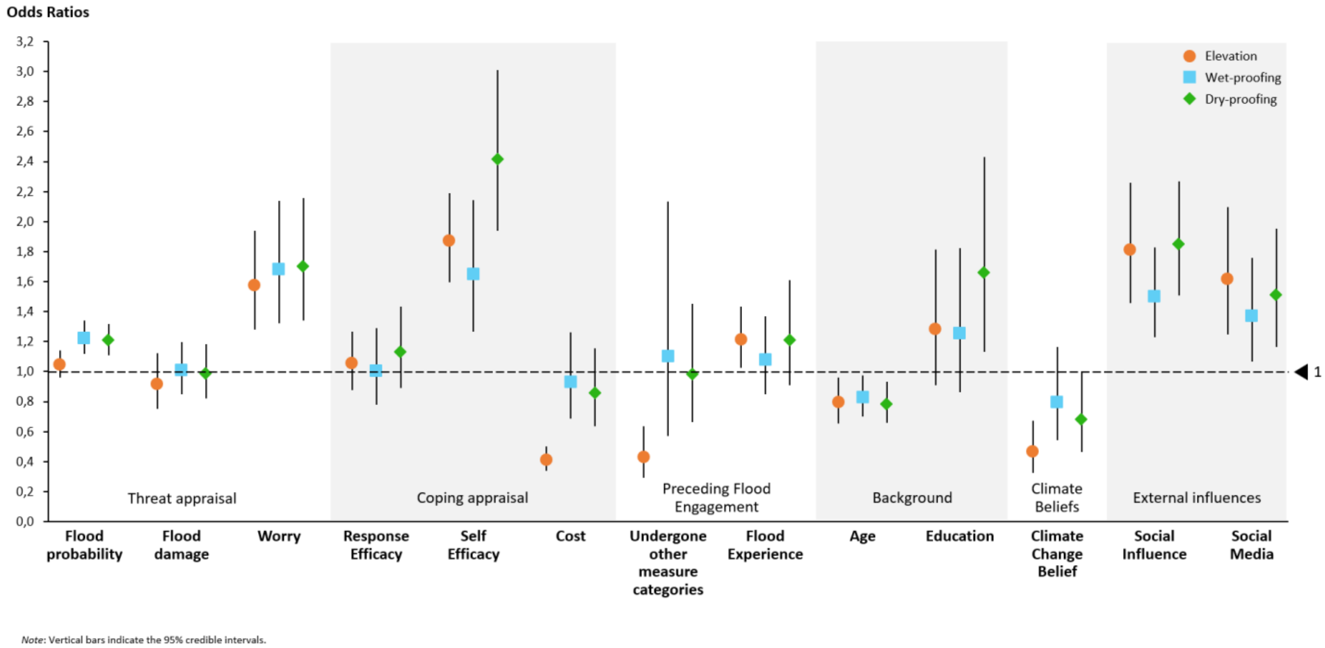


Figure 10: Comparison of odds ratios for final models of elevation, wet-proofing, and dry-proofing for the subset of the 2020 Shanghai survey data (n=933) (Source: adjusted from Noll, Filatova, Need, et al. (2022)[8])

Regarding **threat appraisal**, perceived flood probability and damage appear to have a low positive effect on the adaptation intention. Worry on the other hand provides significant and positive explanatory power for all measures: With each 1-point increase in worry, the odds that a household intends to adapt are 1.6 times higher.

For **coping appraisal**, the effect of self-efficacy and costs is noticeable. Self-efficacy has a significant and consistently positive impact on households' adaptation intentions. Especially for dry-proofing, the positive effect of self-efficacy is very high. For each 1-point increase in self-efficacy, the likelihood that a household intends to dry-proof is 2.4 times higher. The included dry-proofing measures (e.g., fixing water barriers, installing a pump, or anti-backflow valves) appear more technically challenging than wet-proofing measures (e.g., moving/storing valuable assets on higher floors), which might explain the higher effect of self-efficacy for dry-proofing. Looking at cost, elevation appears to have a considerable negative impact on adaptation intention. For each 1-point increase in cost, the odds that a household intends to elevate are 0.6 times lower. Additionally, the confidence interval for elevation is considerably smaller than for wet- or dry-proofing. Elevating a house appears to be considered more cost- and time-intensive than dry- and water-proofing measures.

[8] Although Noll, Filatova, Need, et al. (2022) use the same survey data for their cross-national comparison, the results in the effects of the socio-behavioural variables can differ due to differences in the regression technique (logistic vs Bayesian beta regression), the number of respondents included (933 vs 842), the adaptation measure categories (elevation, wet-proofing, dry-proofing vs structural, non-structural), and the number and types of independent variables included (13 vs 16).

Overall, these observations seem in line with past research which shows that threat and coping appraisal appear important predictors of household adaptation (Bubeck et al., 2013; Grothmann & Reusswig, 2006; Noll, Filatova, Need, et al., 2022; Zaalberg et al., 2009).

Regarding **preceding flood engagement**, the effects observed from dry- and wet-proofing are mixed and generally weak due to large confidence intervals. However, prior undergone adaptation in other measure categories has a strong negative effect on the intention to elevate the building. When a household has already adapted one other dry-or wet-proofing measure, the likelihood that a household intends to elevate is 60% lower. This observation contradicts the empirical results of Noll et al. (2022), who identified a positive impact of prior adaptations on the adaptation of structural measures. A logical explanation for this type of behaviour would be that once households implement wet, or dry-proofing measures, they no longer deem it necessary to apply further adaptation measures, as the vulnerability of the building structure and content are reduced. 19% of the survey respondents have previous experience with floods. However, flood experience appears a weak predictor for all categories. This overlaps with the findings of van Valkengoed & Steg (2019) who highlight in their review on factors motivating climate-change adaptation that experience is relatively weakly related to adaptation. Other empirical evidence suggests a strong influence of flood experience on household adaptation intentions – see for instance Bubeck et al. (2013).

Regarding the **background**, the effect of age is consistently small and negative for all three measure categories. The effect of education is not consistent and rather uncertain. Overall, the effect of the two background variables is small and inconsistent, which appears in line with previous research (Bubeck et al., 2012, 2013; Grothmann & Reusswig, 2006; Noll, Filatova, Need, et al., 2022; Zaalberg et al., 2009).

59% of the respondents **believe in climate change**. The belief in climate change negatively affects adaptation intention, which is explained in more detail by Noll, Filatova, Need, et al. (2022).

Regarding the **external influences**, the effects of family and friends' expectations on a household's adaptation intentions are positive and consistent for all measure categories. With an increase in social influence by 1, the likelihood of adaptation intention increases between ~50% for wet-proofing and ~80% for elevation and dry-proofing. These findings appear consistent with previous research which shows the relevance of interactions in social networks on individual CCA (Bubeck et al., 2013; Figueiredo et al., 2009; Haer et al., 2016; H. Kunreuther et al., 2013; Lara et al., 2010; Lo, 2013; Noll, Filatova, Need, et al., 2022; van der Linden, 2015). The influence of social media is consistently positive. A cross-national comparison shows however that the effect is small compared to other countries, which may be explained by the restriction of the Chinese internet (Noll, Filatova, Need, et al., 2022).

The effects of the socio-behavioural factors for elevation, wet-proofing, and dry-proofing are applied in the ABM to model households' CCA decisions. In addition to the binary logistics regression models, we also estimate two linear regression models for the intention-behaviour gap (see the ODD protocol, Appendix *B.6.4.5*) and the social network interactions (see the ODD protocol, Appendix *B.4.6*).

4.4. Integrating the case data in the ABM

As the household attributes influence household behaviour, we require a **synthetic household population** with attribute values that represent the real Shanghai population as closely as possible (Chapuis et al., 2022; L. Sun & Erath, 2015). Hence, we create a population of 18.039 households via direct sampling from the micro-level survey data (933 households) with as many households living in apartments/houses as indicated by the macro-level residential building data (18.039 buildings). Appendix *B.5.1* in the ODD protocol provides further details on the approach as well as the descriptive statistics of the synthetic household population attributes.

Figure 11 highlights how the case data from the extended risk assessment framework components is integrated into the ABM. Data on the asset values (see chapter *4.1.2*), the depth-damage curves (see chapter *4.1.3*), the adaptation measures (effectiveness, cost, life-and implementation time – see chapter *4.2*), and the odds ratios of the 13 behavioural factors for elevation, wet- and dry-proofing (see chapter *4.3*) are captured by the global parameters. The synthetic population data is used for the parameters of the heterogeneous households, which are the agents in our ABM. At the start of a simulation run each household from the synthetic population is randomly assigned to a residential building with a corresponding building type (apartment/house) (details see the ODD protocol, Appendix *B.5.1*).

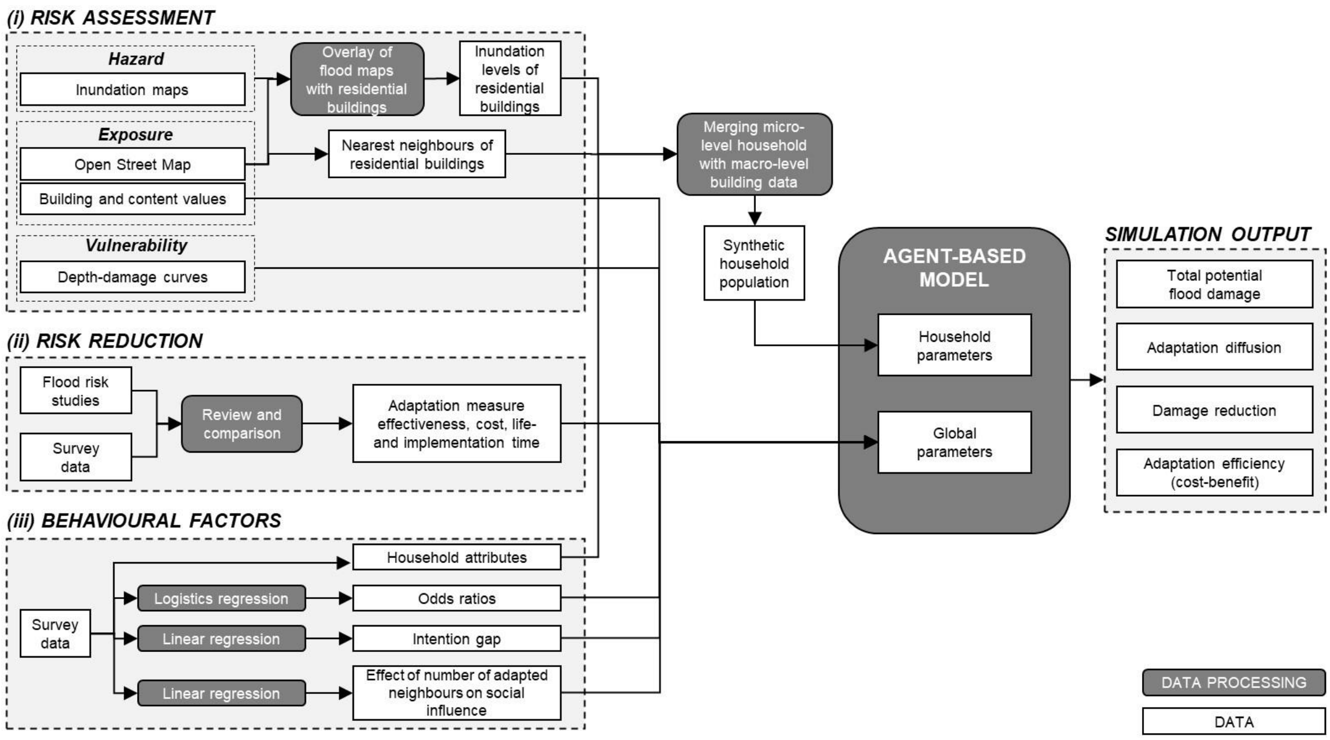


Figure 11: Integration of risk assessment, risk reduction, and behavioural factor data in the ABM (Source: risk assessment framework components from Aerts et al. (2018))

5. An ABM of adaptation behaviour to climate-induced flooding

5.1. Conceptual model

In this chapter, we describe our spatially explicit flood-ABM that integrates case-specific survey data with the PMT and applies inundation maps as one-way inputs to depict the influence of climate-induced flood events on the adaptation behaviour. Specifically, we describe our conceptual model using the main ABM building blocks which are the agent parameters and states (chapter *5.1.1*), rules and actions (chapter *5.1.2*), as well as interactions with other agents and with the environment (chapter *5.1.3*) (Macal & North, 2010; Nikolic & Kasmire, 2013). We describe the model details in the ODD protocol in Appendix *B*, which also includes a summary of all the model assumptions in Appendix *B.8* as well as a model narrative in Appendix *B.9*.

5.1.1. Agents, parameters, and states

Households are the agents in our ABM. Households are therefore non-mobile and are represented by the residential buildings in which they live. In the case of multi-story buildings, we assume that households live on the ground floor. Households have two state variables: **Adaptation state** and **flooded**. For each of the three measures elevation, wet-proofing, and dry-proofing, households can have different **adaptation states**: ***Do nothing*** means that the household has not started implementing the measure yet. When the household decided to start implementing the measure, but the implementation is not yet finished, the adaptation status is ***implementing***. In this case, we assume that the adaptation measure does not reduce any flood damage. When the household finished the implementation of the measure, the measure can reduce flood damage, and the status is ***adapted***. We assume that a household can adapt multiple measures (e.g., elevation and wet-proofing) at the same time. The second state variable **flooded** depicts if a household is flooded[9]. Table 2 provides a detailed description of all the model parameters and the agent states, including their data types, value ranges and sources.

[9] Following Abebe et al. (2020) we assume a household to be flooded if the inundation depth is 0.1 meters higher than the ground level of the building.

Table 2: Model parameters

			Parameter*	Description	Type	Value range / Base value**	Source type***
Household	PMT	Threat Appraisal	$Fl\_prob\_percpt_h$	Perceived flood probability	Integer	(1) Completely safe - (9) More frequent than once per year	Survey
			$Fl\_dam\_percpt_h$	Perceived flood damage	Integer	(1) Not at all severe – (5) Very severe	Survey
			$Worry_h$	Worry	Integer	(1) Not at all worried– (5) Very worried	Survey
		Coping Appraisal	$RE_{h,m}$	Perceived response efficacy of measure	Integer	(1) Extremely ineffective – (5) Extremely effective	Survey
			$SE_{h,m}$	Perceived self efficacy of measure	Integer	(1) I am unable – (5) I am very able	Survey
			$Cost\_percpt_{h,m}$	Perceived cost of measure	Integer	(1) Very cheap – (5) Very expensive	Survey
		Preceding Flood Engagement	$UG_{h,m}$	Previously undertaken measure	Binary	(1) >=1 measures implemented in the category (0) No measures implemented in the category	Survey
			$UG\_other_{h,m}$	Previously undertaken measures within the other categories	Binary	(1) >=1 measure implemented in other categories (0) No measures implemented in other categories	Survey
			Fl_exp_h	Personal financial losses of last flood in €	Integer	(0) 0, (1) <1270, (2) <2540, (3) <3810, (4) <5080, (5) >=5080	Survey
		Social Background	Age_h	Age	Integer	(1) [16-24], (2) [25-34], (3) [35-44], (4) [45-54], (5) [55-64], (6) [65+]	Survey
			Edu_h	Education level	Integer	(1) < High School, (2) High School, (3) College, (4) Post Graduate	Survey
		Climate Beliefs	CC_belief_h	Personal beliefs on effects of climate change	Binary	(0) Else, (1) Climate change is happening	Survey
		External Influences	Soc_inf_h	Effect of social network on household adaptation	Integer	(1) They do NOT expect me to prepare for flooding - (5) They strongly expect me to prepare for flooding	Survey
			Soc_media_h	Effect of social media on household adaptation	Double	(1) Very unfrequently & no trust - (9) Very frequently & trust completely	Survey
		Decision-Making	$Odds_{h,m}$	Odds of adaptation intention for measure	Double	[0; inf.)	Computation
			$Prob\_implement_{h,m}$	Yearly probability of adaptation implementation	Double	[0;1]	Computation
			$Implement\_threshold_{h,m}$	Yearly implementation threshold	Double	[0;1]	Computation
	Non-PMT	Economic background	$Income_h$	Income quintile	Integer	(1) 1^{st}, (2) 2^{nd}, (3) 3^{rd}, (4) 4^{th}, (5) 5^{th}	Survey
			$Savings_{h,t}$	Savings of household in year t in €	Double	(-inf.;inf)	Survey
			$Change\_Savings_h$	Yearly change in savings in €	Double	[0; inf)	Survey
		Accommo-dation	HH_status_h	Accommodation status of household	Integer	(0) Own, (1) Rent, (2) Other	Survey
			$Build\_type_h$	Building type	Integer	(0) House, (1) Apartment	Survey & OSM
			$Build\_size_h$	Size of the building in square meters	Integer	(40), (63), (88), (113), (138), (181)	Survey
			$Value_{h,d}$	Building/Content value in €	Double	[0; inf)	Computation
			$District_h$	District of the residential building	String	Huangpu, Changning, Putuo, Yangpu, Xuhui, Jing 'an, Hongkou	OSM
			$Inund_{h,s}$	Inundation level of household in meter for flood scenario	Double	[0;inf)	Inundation maps
		Social Network	ID_h	ID of residential building to identify nearest neighbours	Integer	[0; inf.)	OSM
			Soc_net_h	The size of the social network of each household	Integer	[0, 1 , 2, 3, ... 15]	Survey
			$NN\_adapt_{h,t}$	Number of neighbours that adapted at least one measure	Integer	[0; Soc_net_h)	Computation
			$Direct\_NN\_IDs_h$	IDs of the direct nearest neighbours of a household: The households which I consider a neighbour	Integer	[0; Soc_net_h]	OSM
			$Indirect\_NN\_Ids_h$	IDs of the indirect nearest neighbours of a household: The households which consider myself their neighbour	Integer	[0; inf.)	OSM
		KPIs	$Fl\_dam_{h,d,t}$	Total building/content flood damage in € without adaptation	Double	[0; inf.)	Computation
			$B_{h,t,m}$	Benefit of adaptation measure (avoided annual damage)	Double	[0; inf.)	Computation
			$C_{h,t,m}$	Cost of adaptation measure	Double	[0; inf.)	Computation
		Time	$Implement\_start_{h,m}$	Starting time in ticks of measure implementation	Integer	[0; Time_horizon]	Computation
			$Implement\_end_{h,m}$	Finish time in ticks of measure implementation	Integer	[0; Time_horizon]	Computation
	Agent States		$Adapt\_status_{h,t,m}$	Adaptation status for measure	Integer	(0) Do nothing, (1) Implementing, (2) Adapted	Computation
			$Flooded_h$	Residential building is flooded (not taking into account effect of elevation measure)	Binary	(0) Building is not flooded (1) Building is flooded	Computation
Global	Risk Assessment		$Depth\_dam_d$	Stepwise depth-damage function for building / content	Double	Wang (2001)	Literature
			Sqm_value_d	Building and content value in € per square meter	Double	Building: 861, Content: 209	Literature
			$Flood\_scenario_t$	Flood scenarios which takes place in a year	String	See ODD protocol	Inundation maps
			$Foundation\_height$	Height of the building foundation in meter	Double	0.1	Literature
	Behavioural Factors		$OR_{i,m}$	Odds ratios for the independent PMT variables	Double	See ODD protocol	Survey
			$Constant_m$	Odds ratio intercept	Double		Survey
			$Intention\_gap$	Percentage of households that turn adaptation intention into action	Double	0.278	Survey
			$Beta\_soc\_inf$	Regression coefficient that shows the effect of one more adapted neighbour on the social influence attribute.	Double	0.263	Survey
	Risk Reduction		$Effectiv_m$	Effectiveness in reducing flood damage of adaptation measure	Double	Elevation: 1.0, Wet-proofing: 0.4, Dry-proofing: 0.85	Literature
			$Effectiv\_lvl_m$	Inundation level in meter below which measure is effective	Double	Elevation: 0.3, Wet-proofing: 3.0, Dry-proofing: 1.0	Literature
			$Cost_m$	Implementation cost in € of the adaptation measure	Double	Elevation: 4040.0, Wet-proofing: 4027.0, Dry-proofing: 1706.0	Literature
			$Life\_time_m$	Lifetime in years of the adaptation measure	Integer	Elevation: inf., Wet-proofing: inf., Dry-proofing: N(20,2)	Literature
			$Implement\_time_m$	Implementation time in years of the adaptation measure	Integer	Elevation: 3, Wet-proofing: 2, Dry-proofing: 2	Assumption
	Time		$Time\_horizon$	Simulation time in years	Integer	30	Literature

* Indices: t = tick; i = PMT attribute (e.g., worry); h = household; m = measure (e.g., elevation); d = damage category (e.g., content); s = flood scenario (e.g., 10-year flood in 2030 under RCP 8.5 scenario); n = neighbour).
** For the descriptive statistics of the base values of the household parameters we refer to Appendix *B.5.1.3* in the ODD protocol.
*** As we often combine multiple sources, we cannot list the individual sources in the table due to space constraints. Therefore, we refer to the respective sections in the input data chapter of the ODD protocol in Appendix *B.6* for a detailed listing of the sources.

5.1.2. Household climate change adaptation rules and actions

We apply the three final logistics regression models for elevation, wet-proofing, and dry-proofing (see chapter *4.3.2*) in combination with the synthetic population data (see chapter *4.4*) in our ABM to determine the households' adaptation actions. In each year (one time-step) each household determines the adaptation action in a randomized order for each of the three adaptation measures based on the respective adaptation status $Adapt\_status_{h,t,m}$. This is shown in Figure 12 and explained in the following.

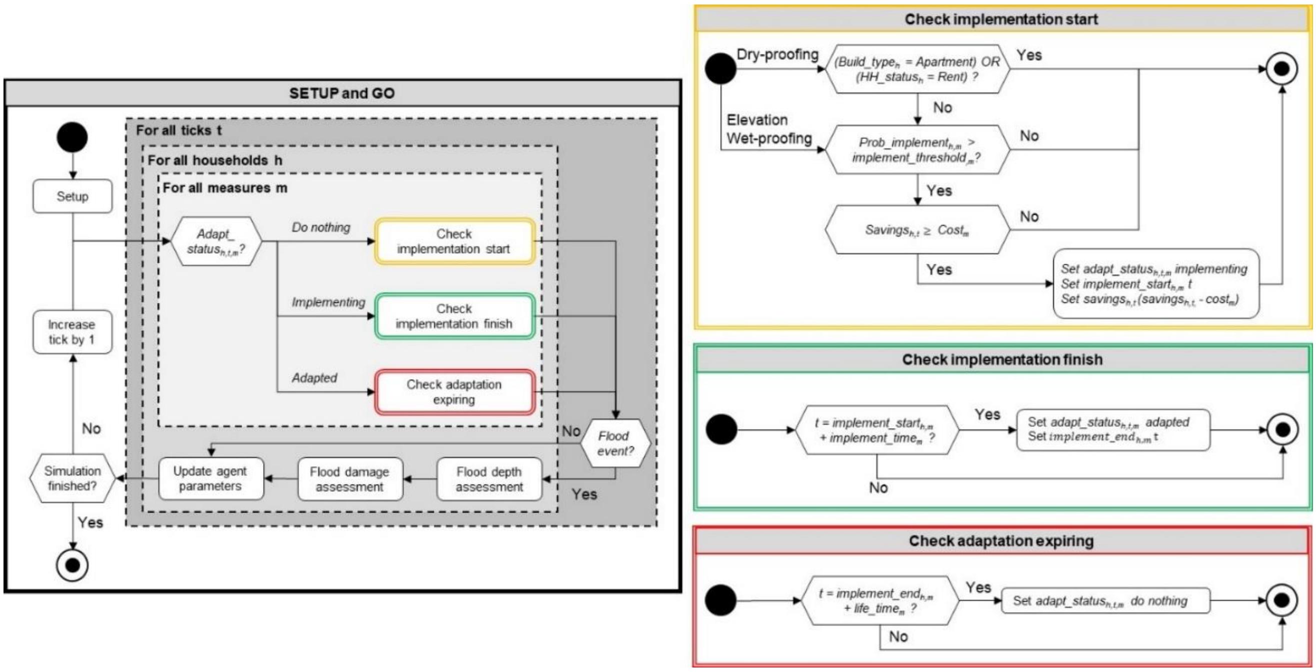


Figure 12: Conceptual model – household adaptation actions and rules

If a household has not yet taken an action (adaptation status is ***do nothing*** – see the **yellow box** in Figure 12) a household checks whether the specific measure should be implemented based on the empirically-derived and theory-based probability of implementation from the survey data and additional adaptation rules.

$$Odds_{h,m} = Constant_m \times \prod_{i=1}^{I} OR_{i,m}{}^{a_{i,\,h,m}} \tag{1}$$

Equation 1 determines the odds $Odds_{h,m}$ of a household h to **intend** to implement measure m, where $OR_{i,m}$ is the odds ratio of PMT attribute i for measure m (see Figure 10), $a_{i,h,m}$ is the heterogeneous attribute level of the PMT attribute i of household h for measure m (see Table 2)[11], and $Constant_m$ is the intercept (Haer et al., 2016). The odds express the likelihood that the household intents to adapt divided by the likelihood that it will not (Erdlenbruch & Bonté, 2018). Based on the odds we can determine the yearly probability of a household h to **intend** the implementation of a measure m, by dividing $Odds_{h,m}$ with $(1 + Odds_{h,m})$ (Haer et al., 2016). However, households who intend to adapt, do not necessarily follow through with their adaptation intention (Grothmann & Patt, 2005) due to barriers in the form of time, knowledge, money, or social support (Grothmann & Reusswig, 2006). Hence, we introduce an intention gap parameter *Intention_Gap* - also referred to as 'intention-behaviour gap' (Noll, Filatova, Need, et al., 2022) - which is derived from the ERC project's longitudinal survey data in Shanghai. It captures the average percentage of households that put their adaptation intention into action within approximately one year (details in the ODD protocol, Appendix *B.6.4.5*).

[11] As the PMT variables *Response Efficacy*, *Self Efficacy*, *Cost*, and *Undergone Other* depend on the adaptation measure, a household can have different attribute levels for the same variable.

By multiplying the *Intention_Gap* parameter with the probability of a household *h* to **intend** the adaptation of measure *m*, we can determine the yearly probability $Prob\_Implement_{h,m}$ of household *h* to **implement** measure *m* (see equation 2).

$$Prob\_Implement_{h,m} = \left(\frac{Odds_{h,m}}{1 + Odds_{h,m}}\right) \times Intention\_Gap \quad (2)$$

To determine if a household starts the implementation of the measure, we compare $Prob\_Implement_{h,m}$ to a threshold $Implement\_Threshold_{h,m}$ in the form of a random number between 0 and 1 which is generated yearly for each measure *m* of a household *h*. If the probability is higher than the threshold the adaptation status is set to ***implementing***, on the condition that the following two adaptation rules are adhered to, which take into consideration additional regulative and financial barriers. First, we assume that elevation measures cannot be implemented by tenants (HH_status_h = *Rent)* and households that live in apartment buildings ($Build\_Type_h$ = *Apartment*). Second, households can only implement a measure if it is affordable, hence if their savings ($Savings_h$) exceed the measure cost ($Cost_m$). We mark the year when household *h* starts the implementation of the measure *m* ($Implement\_start_{h,m}$).

Furthermore, our model explicitly treats the process of implementation of adaptation measures and their lifetime. If at the start of a time step a household is in the process of implementing a certain measure (adaptation status is ***implementing*** – see the **green box** in Figure 12), the model determines based on the starting time of the implementation $Implement\_start_{h,m}$, the current tick, and the implementation time $Implement\_time_m$ of the respective measure *m* if the measure implementation is finished. If the measure is implemented, the adaptation status is changed to ***adapted*** and the time is marked when household *h* ended the implementation of the measure *m* ($Implement\_end_{h,m}$). At model initialization, the implementation finish time of households that start the simulation with an adapted measure is set to a period of 0-9 years before the simulation start following a uniform distribution.

If a household has already implemented a measure (adaptation status is ***adapted*** – see the **red box** in Figure 12) the model determines for household *h* if the measure *m* expires based on the ending time of the implementation $Implement\_end_{h,m}$, the current tick, and the lifetime $Life\_time_m$. We assume that elevation and wet-proofing measures are permanent, while dry-proofing measures are non-permanent and can expire after their lifetime $Life\_time_m$ (see chapter *4.2*). If a measure expires, the adaptation status is set back to ***do nothing***.

5.1.3. Household interactions and adaptation dynamics

In our model households interact with other agents, with the environment and with themselves (Figure 13). These interactions can influence both a household's socio-behavioural attributes and therefore its probability to implement a measure (see the **green colour** in Figure 13) and a household's savings (see the **blue colour** in Figure 13), which influence the ability to finance adaptation. We explain these interactions and the emerging adaptation dynamics in the following.

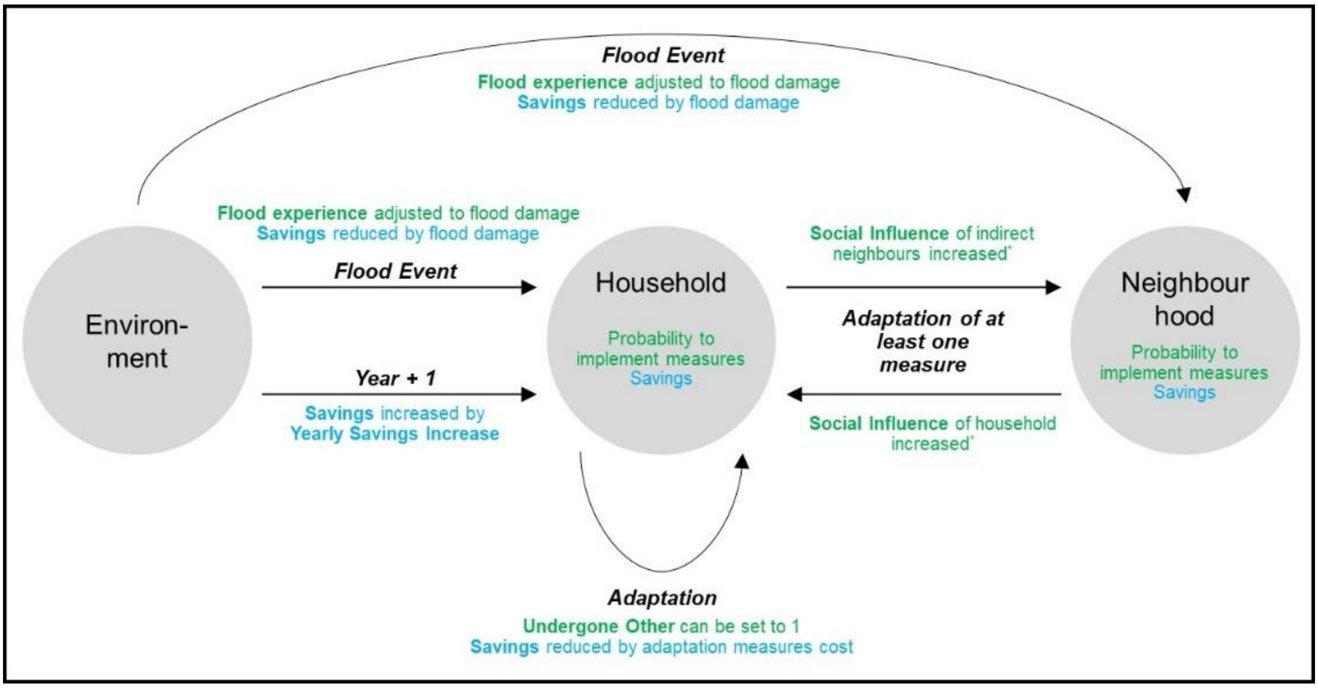


Figure 13: Household interactions: The green colour indicates the influence on a household's probability to adapt (socio-behavioural model) while the blue colour depicts the impact on a household's savings (economic model)[12]

5.1.3.1. *Interaction of households within their social network*

Scientific literature highlights the relevance of interactions in social networks (Bubeck et al., 2013; Figueiredo et al., 2009; Haer et al., 2016; H. Kunreuther et al., 2013; Lara et al., 2010; Lo, 2013; Noll, Filatova, Need, et al., 2022; van der Linden, 2015), and more specifically in an individual's neighbourhood on climate-adaptation decisions (H. C. Kunreuther & Erwann, 2009). Following the findings of Noll, Filatova, Need, et al. (2022) our regression results for Shanghai specifically also show a significant and consistently positive effect of Social Influence on the intention to adapt. Hence, we create a social network, where households adjust their **Social Influence** attribute level based on the adaptation behaviour of their direct nearest neighbours, which positively influences the probability of a household implementing a measure.

For each residential building, we determine the IDs of the nearest other residential buildings in QGIS. Based on the survey data on the number of adapted households in a household's social network, and the aggregated percentage of the households that adapted at least one measure, we estimate the heterogeneous social network size for each household. By combining the IDs of the nearest neighbours with the social network size we can determine the social network for each household. Using a linear regression, we determine the effect of the number of neighbouring households that adapted at least one measure (independent variable) on the Social Influence attribute (dependent variable). The social interactions are in more detail described in the ODD protocol in Appendix *B.4.6*.

* As we build the social network on proximity, we differentiate a direct neighbourhood which is influenced by a household's decisions (which are closest to the household) and an indirect neighbourhood, which influences the household's social influence parameter but do not necessarily need to be direct neighbours of the household (details see ODD protocol, Appendix *B.4.6*)

In reality, the social network of family and friends might reach beyond the neighbourhood. For instance, the adaptation decision of one's parents who live in a different city might still influence one's adaptation decision. This is neglected within this model.

5.1.3.2. Interaction of households with the environment and the flood hazards

In our model, time and flood hazards are part of the environment. Every year, a household's savings change heterogeneously as indicated by the respondents in the survey. Hence, with the increase in ticks, the financial ability of households to afford adaptation measures can increase.

In terms of flood hazards, we assume a household to be flooded if the inundation depth is larger than the building foundation – see also Abebe et al. (2020). For each inundated household, we determine the potential direct and tangible flood damage based on the respective building and content values and depth damage curves as well as the predefined inundation depth of the occurring flood scenario (Figure 5). If the household has implemented at least one adaptation measure the flood damage reduction is determined using the effectiveness of the adapted measure(s)[13]. By deducting the damage reduction from the potential damage, the residual damage is determined. The occurrence and the severity of floods influence the adaptation behaviour in two ways.

On the one hand, floods impact the **savings of households**. We assume that households pay for the flood damage out of their savings: While households that own their building pay for both the building and the content damage, households that are tenants only pay for the content damage. This means that household adaptation decisions can reduce the impact of future floods on their savings and hence their ability to afford other adaptation measures (see Chapter *5.1.3.3*).

On the other hand, we assume that flood events impact the PMT attribute **Flood Experience**. Within the survey, households indicate the monetary damage extent of their last experienced flood. In case of no previous experience, the *Flood Experience* is zero. When a household is impacted by a flood in the model, we update the *Flood Experience* to the residual flood damage. This change in the attribute level can positively influence the probability to intend a measure due to the small but positive odds ratios of *Flood Experience* for all measures (see chapter *4.3*). Consequently, adaptation decisions of households which reduce the flood damage also reduce the influence of the *Flood Experience* on the adaptation behaviour. As each flood affects each household and their behaviour differently, we randomly vary the odds ratio of *Flood Experience* for each household in the range of one standard deviation from the mean effect of flood experience on the adaptation intention.

In reality, the adaptation behaviour can also influence the environmental processes e.g., placing sandbags in the street can change the flood hydraulics. This is not considered since we use existing flood maps and do not couple the ABM with numerical flood models as suggested by Abebe et al. (2019).

[13] In case multiple measures are adopted at the same time, we first determine the impact of the elevation, then of the dry-proofing and lastly of the wet-proofing measure (details see ODD protocol, Appendix *B.7.9*).

5.1.3.3. Interaction of households with themselves

According to the empirical evidence (Noll, Filatova, & Need, 2022) the action of a household to implement a measure of a certain category (e.g., wet-proofing) influences the household's own likelihood and ability to implement measures in the remaining categories (e.g., elevation and dry-proofing). We integrate these findings in our ABM as follows.

On the one hand, we assume that, when a household implements a measure of a certain category (e.g., wet-proofing), the **Undergone Other** attribute is set to 1 for the remaining adaptation measure categories (e.g., elevation and dry-proofing). The change in the attribute level influences the probability of intending the measure of the respective categories in the subsequent ticks. For instance, the likelihood that a household intends to adapt an elevation measure is 60% lower, when a wet-, or dry-proofing measure was already undergone (see chapter *4.3*). When a measure expires, the *Undergone Other* attribute can also be reset to 0 (details in the ODD protocol, Appendix *B.7.6*).

On the other hand, the implementation decisions impact current and future **savings**. The savings are reduced by the measure cost when a household starts the measure implementation. This immediately reduces the households' ability to finance and hence implement other measures. At the same time, households reduce their vulnerability to future flooding with the adaptation and thus reduce the impact of flood damage on their future savings.

Following this conceptual model, we coded a computational model using Netlogo 6.2.2 (Wilensky, 1999), which is openly accessible via *https://github.com/jlechn01/Shanghai-Flood-ABM*. Details regarding the software implementation are shown in Appendix *C*.

5.2. Model evaluation

ABMs are valid if they fulfil their purpose (Edmonds et al., 2019). Our flood-ABM aims to understand the aggregate and distributional impacts of household adaptation. Hence, we are not interested in building a predictive model that can forecast the future effectiveness of household adaptation in Shanghai. Instead, we aim for an explanatory model, which allows us to study the causal chain between household-level adaptation behaviour and system-level adaptation diffusion and damage prevention. According to Edmonds et al. (2019, p.6) "for explanatory purposes, the structure of the model is important, because that limits what the explanation consists of." Therefore, we validated our conceptual model with three different flood-ABM experts. To further underline the credibility of our flood-ABM, we conducted a series of verification and validation tests for the different process phases of the simulation as suggested by Balci (1994). One of these tests is a one-factor-at-a-time (OFAT) sensitivity analysis, which enables insights into the formation of emergent patterns in our ABM and into the robustness of these patterns (ten Broeke et al., 2016). Details on the model validation, verification and testing are provided in Appendix *E*.

5.3. Experimental setup

We select **2020 as the starting point** for our experiments, as the survey and inundation data are from this year. Furthermore, we choose a **30-year time horizon** as this allows us to observe the medium- to long-term effects of behavioural adaptation while containing the uncertainties of future developments such as technological advances that are associated with longer time horizons (Taberna et al., 2020). Moreover, we simulate our experiments with all **18.039 households** in the Shanghai city centre. Each experiment is replicated **100 times**. Details on how we determine the number of replications are provided in Appendix *D.2*.

To understand the impacts of household adaptation to climate induced-floods we run our model under **seven different predetermined flood scenarios** (Figure 14). These scenarios vary in the number of floods occurring (no flood vs. one flood vs. two floods), the year of the flood events (early flood in 2021 vs. late flood in 2040), the flood probabilities (100-year flood vs. 1000-year flood), as well as the Representative Concentration Pathways (RCP 8.5 vs. RCP 2.6). The seven flood scenarios *No flood*, *2021_100_RCP8*.5, 2021*_1000_RCP8.5*, *2040_100_RCP8.5*, *2040_1000_RCP8.5*, *2040_1000_RCP2.6*, and *2020_100_RCP8.5* + *2040_1000_RCP8.5* are shown in Figure 14.[14] Further details on the selection of the flood scenarios can be found in Appendix *D.1*. For all other global model parameters, we apply the base values as shown in Table 2.

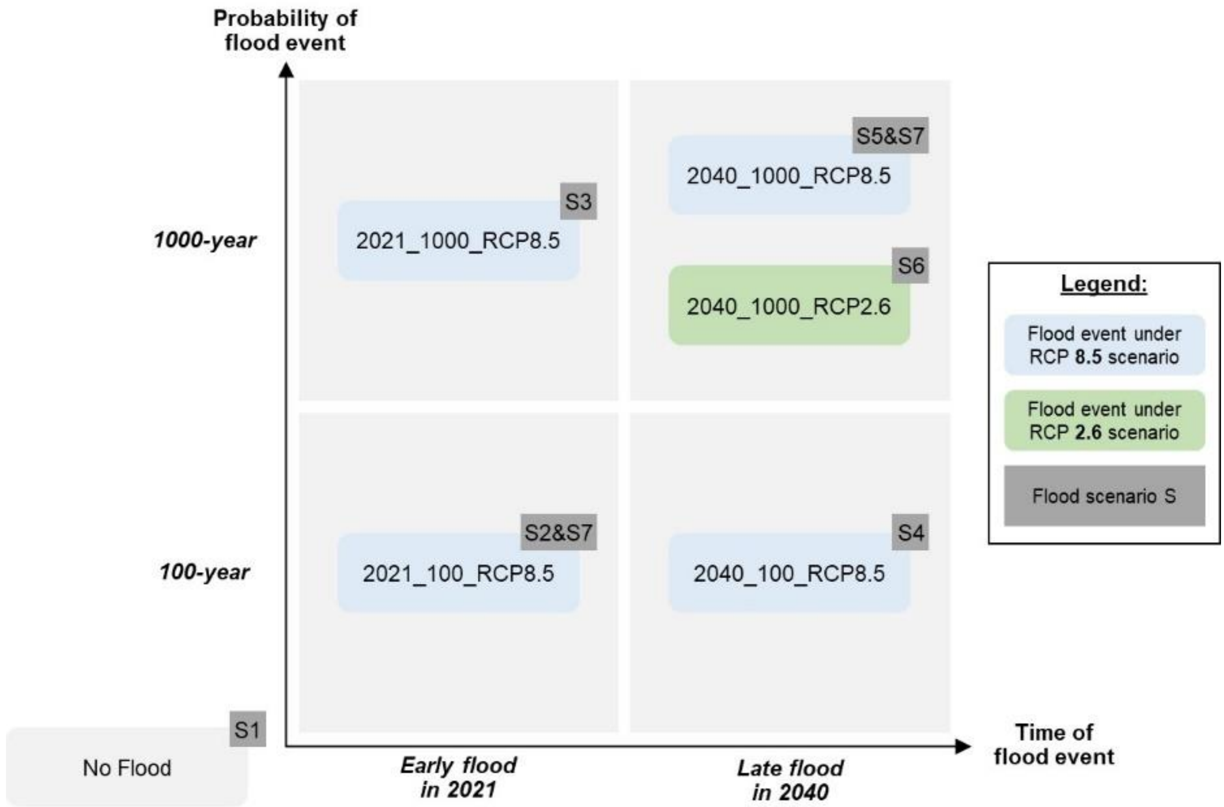


Figure 14: Overview of the seven flood scenarios. A flood scenario can be composed of multiple flood events. Scenario S1 consists of no flood event, scenarios S2 to S6 have one flood event and scenario S7 consists of an early 100-year and a late 1000-year flood event

[14] We do not need to compose additional scenarios that compare the impacts of adaptation with no adaptation, as this is automatically determined by the simulation model.

For each experiment, we observe both the aggregate and the distributional impacts of household CCA. In terms of aggregate effects (SQ4), we observe the cumulative adaptation behaviour and damage prevention. In terms of distributional impacts (SQ5), we observe the adaptation uptake and the damage prevention of different household groups in our heterogeneous population of agents. Therefore, we differentiate among agents with various socio-behavioural attributes: **worry**, **self-efficacy**, **social network size**, and **income**. Worry and self-efficacy are selected as the PMT core attributes because both have a consistently positive and significant effect on the intention to adapt. Social network size is included because it affects a household's level of social influence, which also has a consistently positive and significant impact on the intention to adapt. All three constitute a set of socially-constructed limits to adaptation. Finally, we select income as a traditional suspect for inequality because it is an important indicator of a household's savings, which constrain its ability to adapt. For comparability of the results, we transform the four attributes into 3-point scales (low, medium, and high, see Appendix *D.3*).

It is to be noted that while we focus on **household adaptation**, the effects of administrative adaptation on flood risk e.g., in the form of dikes are indirectly considered via the inundation maps. Moreover, within our experiments, we only consider **autonomous household adaptation**, hence adaptation without additional external policies e.g., subsidies (see chapter *2.1* for our definitions).

6. Results

6.1. Aggregate impacts of household adaptation

To answer SQ4 we analyse the aggregate impacts of household adaptation both in terms of the general adaptation behaviour and the effects of the flood scenarios.

6.1.1. General aggregate household adaptation behaviour

Figure 15-A shows the adaptation diffusion of the three measure categories averaged for all flood scenarios. We observe multiple patterns.

First, we observe that the three measures start with different penetration rates at the beginning of the simulation. While 33% of the households adapted wet-proofing in 2020 (**blue** graph in Figure 15-A), 9% adapted dry-proofing (**green** graph in Figure 15-A) and 2% of the population adapted elevation measures (**orange** graph in Figure 15-A). These differences can be explained by the number of survey respondents that already adapted elevation, wet-proofing, or dry-proofing (see the ODD protocol, Appendix *B.5.1.3*). For our analysis this means that we need to take into consideration the starting points when comparing the adaptation diffusion of measures.

Second, we identify plateaus in the adaptation uptake until 2022 for wet- and dry-proofing (**blue** and **green** graph in Figure 15-A) and until 2023 for elevation (**orange** graph in Figure 15-A). These plateaus can be explained by the different measure implementation times. This implies the delay between the adaptation decision and the measure adaptation that needs to be considered when drawing conclusions about the adaptation uptake.

Lastly, we observe a decline in the adaptation of wet-proofing starting from 2040 until 2048 (**green** graph in Figure 15-A). This pattern can be explained by the expiration of wet-proofing measures and their subsequent re-implementation. In practical terms, this means that if a flood occurs during this period, households with expired wet-proofing measures are vulnerable.

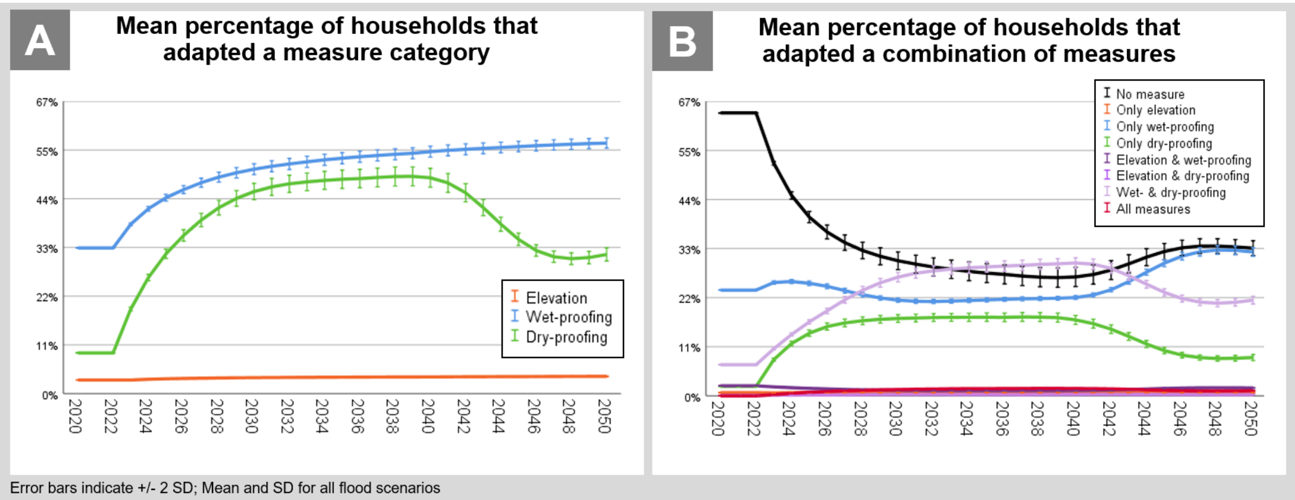


Figure 15: Diffusion of household adaptation over time: (A) shows the three measure categories, (B) shows all possible combinations of the three measure categories elevation, wet-proofing, and dry-proofing

Regarding the uptake in adaptation, dry-proofing is most popular, followed by wet-proofing and lastly elevation. For instance, while the mean percentage of households that adapted dry-proofing increases from 9% in 2020 to 49% in 2040 (**green** graph in Figure 15-A), wet-proofing grows from 33% to 55% (**blue** graph in Figure 15-A) and elevation from 2% to 3% (**orange** graph in Figure 15-A) in the same period. The low adoption of the elevation measure results primarily from the rule that only house owners can elevate. Since 94% of households live in apartments and 16% are tenants (see Appendix *B.5.1.3*), a large fraction of the population is not able to implement elevation measures, despite possible adaptation intentions. This highlights the significant impact of this additional adaptation rule which mimics regulative barriers on the adaptation diffusion. The faster adaptation of dry-proofing compared to wet-proofing is mainly a result of their cost difference (1706 € vs. 4027 €). Households which are not able to finance wet-proofing might still afford dry-proofing. When the measure cost is not considered for decision-making, wet-proofing is adapted at a similar rate as dry-proofing as shown in the sensitivity analysis in Appendix *E.5.2.1*. This underlines the importance of savings on the households' ability to realize adaptation intentions. Moreover, a considerable share of households adapts both wet- and dry-proofing measures (see **light purple** graph in Figure 15-B). Households that adapt multiple measures are better protected from the adversities of climate-induced floods.

6.1.2. Impact of climate-induced floods on aggregate household adaptation behaviour

As explained in chapter *5.1.3.2*, flood events impact both the savings, which influence a household's adaptive capacity and the flood experience, which effects a household's adaptation intention. To determine the aggregate impacts on climate-induced flood risk, we need to understand the impact of the flood scenarios on the households' flood experience and ability to finance measures. Figure 16-A depicts the percentage of households which have personally experienced a flood[15]. It shows the increase in flood experience depending on the severity and year of the flood event. Even when no flood occurs, 16% of households have flood experience which is derived from the survey data (see the ODD protocol, Appendix *B.5.1.3*). Figure 16-B shows the number of households who want to adapt but do not have the savings to do so. It highlights that from the first tick where households can decide whether they want to adapt, the share of households which are not able to do so is approximately 17%. With the occurrence of 1000-year flood events (e.g., **dark green** graph in Figure 16-B), we notice an increase in the inability to finance adaptation intentions as the savings are reduced by the flood damages. In theory, the effects of flood experience and savings on the adaptation diffusion are opposing as flood experience increases the probability to adapt due to the small but positive odds ratios while lower savings limit a household's ability to finance a measure. We discuss their impacts on the **adaptation diffusion** and **prevented flood damages** in the following.

The effect of the seven flood scenarios on the **adaptation diffusion** is shown in Figure 16-C. When comparing the trajectories of the flood scenarios, the 1000-year flood in 2021 (**dark green** graph in Figure 16-C) stands out as the adaptation uptake increases at a lower rate. This can be explained by the fact that the severe flood damage at the beginning of the simulation significantly decreases the savings of the exposed households which reduces their ability to finance subsequent adaptation. This can also be seen by the incline in the number of households who cannot afford the measure implementation in comparison to the other scenarios (**dark green** graph in Figure 16-B). The increase in flood experience (**dark green** graph in Figure 16-C) and the subsequent increase in the probability of implementing a measure, do not appear to compensate for the significant decrease in savings. Starting from the year 2045, a similar pattern appears to occur for the other 1000-year flood events (**yellow** and **baby blue** graphs in Figure 16-C), where the adaptation trajectories continue declining while the remaining scenarios appear to increase again.

[15] To compare the scenarios, we show the binary flood experience. In our model, the flood experience is a 6-point variable that captures the flood damage of the last experienced flood – see chapter *5.1.1*.

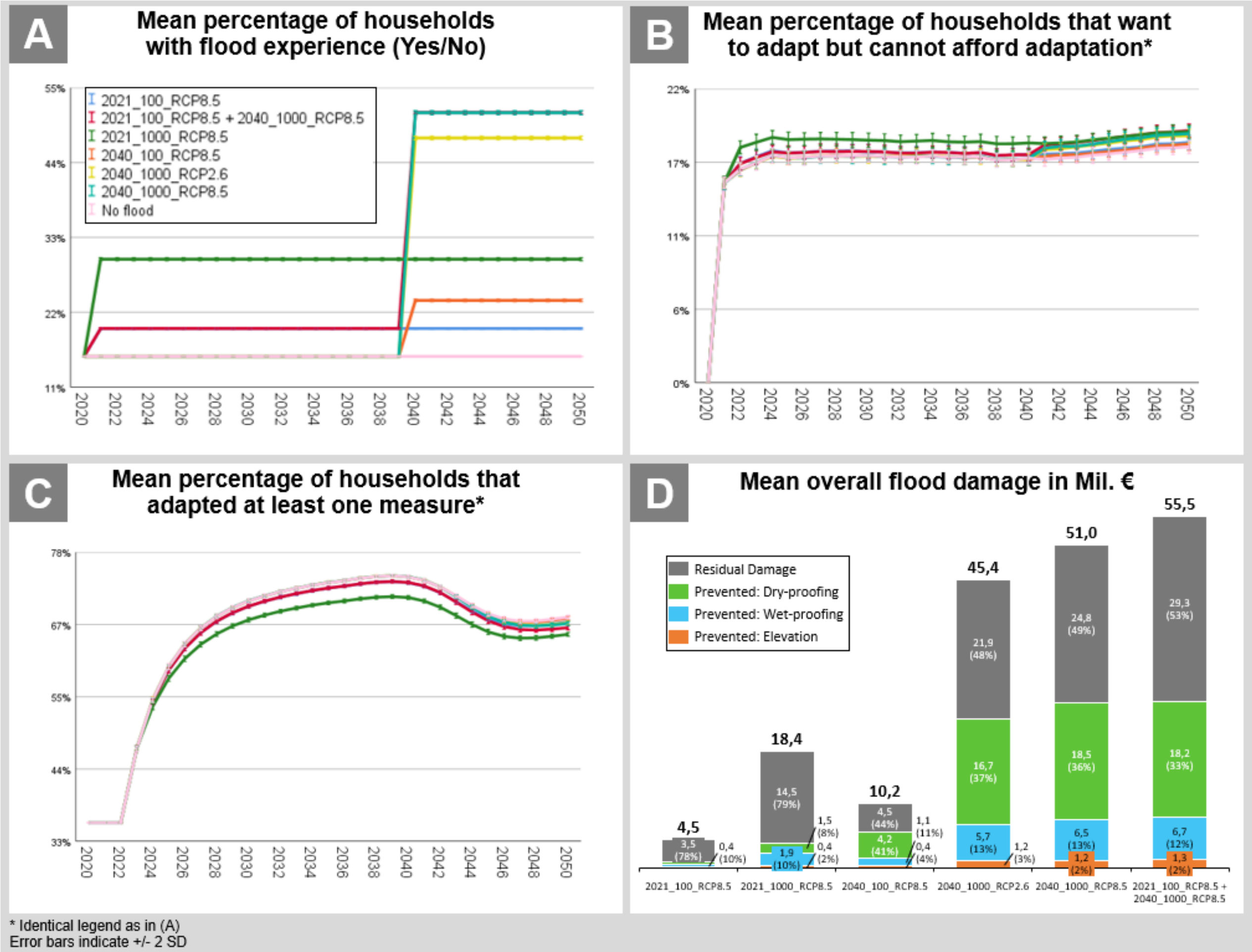


Figure 16: Influence of flood scenarios on the flood experience of households (A), the percentage of households that would like to adapt but cannot afford adaptation (B), the household adaptation diffusion (C), and the overall flood damage and damage reduction (D)[16]

Figure 16-D shows for the flood scenarios the **total prevented flood damages** in the Shanghai city centre due to individual adaptation as well as the residual flood damages. For the 2021 single flood scenarios, on average 21% of the Shanghai residential flood damage is prevented due to autonomous household adaptation (see Figure 16-D) as 36% of households adapted at least one measure at the time of the flood event (see Figure 16-C). For the 2040 flood scenarios, the total potential flood damage increases significantly due to sea-level rise and land subsidence. Moreover, we observe a measurable difference of 5.6 Mil. € in total potential flood damage between the RCP 2.6 and the RCP 8.5 scenario (see Figure 16-D) which highlights the increase in flood risk for Shanghai households for more severe climate change scenarios. With an increase in the average share of adapted households to approximately 74% in 2040 (see Figure 16-C), the mean flood damage prevention also rises to between 51% and 56% depending on the flood scenario (see Figure 16-D). Hence, for the 2040 flood scenarios, the relative prevented flood damage is more than twice as large as for the 2021 flood scenarios. In essence, this means that with an increase in severity and frequency of climate-induced flood hazards over time, households also considerably uptake their adaptation efforts, which can make them less vulnerable in relative terms. Nevertheless, the absolute residual flood damage of flood scenarios in 2040 is still larger than in 2021. For instance, the residual damage for a 1000-year flood under the RCP 8.5 scenario is 14.5 Mil. € in 2021 compared to 24.8 Mil. € in 2040 (see grey bars in Figure 16-D). This implies that autonomous household CCA is important but insufficient to cope with the increasing severity of climate-induced floods, necessitating additional policies that further motivate household adaptation.

[16] See the Appendix *F.1* for standard deviations of flood damage.

The differences in the total damage prevention between the adaptation measures can be explained by their effectiveness in reducing damage and their diffusion at the time of the flood event (Figure 15-A). This is in more detail explained in Appendix *F.1*.

In practical terms this analysis of the aggregate impacts underlines the importance of a household's savings on the adaptation behaviour: On the one hand, the results show that large floods reduce the household's savings in such a way that they limit the household's future adaptive capacity which makes them more vulnerable for future floods. On the other hand, households tend to opt for more inexpensive adaptation measures due to financial constraints despite other initial adaptation intentions.

6.2. Distributional impacts of household adaptation

To answer SQ5, we analyse the distributional effects of the adaptation uptake and how this translates into damage prevention in our heterogeneous population of agents.

6.2.1. Adaptation uptake for different household groups

Figure 17 shows for each level (low, medium, high) of **worry**, **self-efficacy**, **social network size**, and **income** the percentage of households within the household group that adapted an elevation (**orange**), wet-proofing (**blue**), or dry-proofing (**green**) measure.

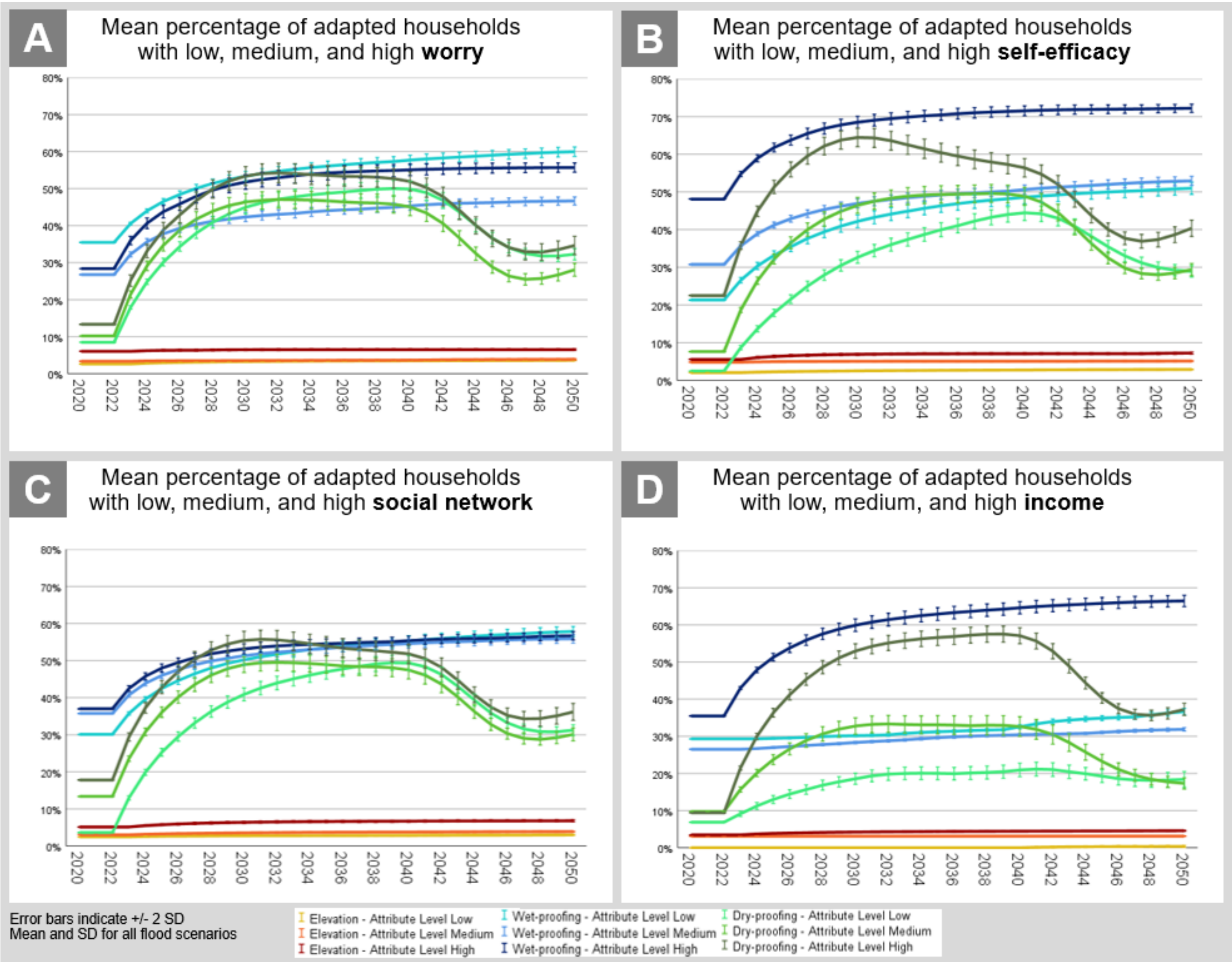


Figure 17: Impact of (A) worry, (B) self-efficacy, (C) social network, and (D) income levels (low, medium, high) on the adaptation of elevation, wet-, and dry-proofing measures over time

Figure 17-A highlights that households with high **worry** levels adapt on average faster. For instance, in the year 2030 on average 10% more households with high worry levels adapt wet-, and dry-proofing measures (dark blue and green colour in Figure 17-A) than medium-worry households (medium blue and green colour in Figure 17-A) despite a relatively similar starting point. This is a result of the high and positive odds ratios of worry for all adaptation measures. Consequently, these household groups are more prepared if a flood occurs which reduces the impact of flood events on their savings which in turn benefits their financial capability to adapt further measures in the future.

A similar pattern can be seen for **self-efficacy** in Figure 17-B. Especially for dry-proofing, the difference in the speed of the adaptation between household groups with high and low self-efficacy is prominent. For example, while the percentage of households that adapted wet-proofing with high self-efficacy grows from 23% in 2020 to 64% in 2030 (dark green colour in Figure 17-B), the percentage of low self-efficacy levels only increases from 3% to 31% in the same period (light green colour in Figure 17-B). This can be explained by the exceptionally high and positive odds ratio of self-efficacy for dry-proofing intentions. This implies that household groups which have the knowledge and the physical ability to undertake measures themselves or the financial backing to pay professionals to do so will be more prepared if a flood occurs.

The differences in the adaptation uptake for households with different **social network sizes** appear less prominent than for the other socio-behavioural factors (Figure 17-C). On the one hand, this might be explained by the rather small increase of the social influence attribute (0.263) when one more direct neighbour adapts at least one measure (see the ODD protocol, Appendix *B.4.6*). On the other hand, the diffusion through the social network takes time. When a direct neighbour of a household adapts at least one measure, the household's social influence attribute level increases which increases the probability to implement a measure. If this probability surpasses the adaptation threshold, the implementation time needs to be exceeded before the measure is adapted and other potential neighbours are influenced.

We observe the most dominant effect in terms of adaptation speed and scope for **income** (Figure 17-D). Especially for the more expensive elevation and wet-proofing measures, low- to middle-income households adapt very little. For instance, the mean proportion of high-income households that adapt wet-proofing measures increases from 35% to 65% over the simulation lifetime (dark blue graph in Figure 17-D), while the low to medium income levels grow less than 10% in absolute terms (lighter blue graphs in Figure 17-D). This can be explained by the fact that a household's savings are dependent on income. Hence, high-income households have more financial capacity to adapt which makes them less vulnerable to future floods. Low and medium-level households lack the financial backing to put into practice their adaptation measures. This means that in the event of a flood their savings and hence their future adaptive capacity are further reduced making them more and more vulnerable to the increasing threat of climate-induced flooding over time.

For dry-proofing, a faster adaptation also means that the measures will expire earlier which explains that for certain time intervals households with lower attribute levels have a higher adaptation diffusion. For instance, in the year 2048, households with low self-efficacy (light green in Figure 17-B) adapt more than households with medium self-efficacy (medium green in Figure 17-B). This highlights the importance of renewing non-permanent adaptation measures in time as otherwise, household groups with attribute levels that favour the flood adaptation uptake can become even more vulnerable than less adaptive groups.

6.2.2. Damage prevention for different household groups

With the knowledge on the differences in the adaptation uptake, we analyse the prevented damage within the respective household groups for **worry**, **self-efficacy**, **social network size**, and **income** for the flood scenarios (Figure 18). To enable better comparability of the results, we analyse the relative damage prevention[17].

Both **self-efficacy** (Figure 18–B) and **income** (Figure 18-D) show a considerable difference in damage reduction between high, medium, and low attribute levels for all flood scenarios[18]. For instance, households with low self-efficacy reduce damage by 48%, medium self-efficacy households by 51% and high self-efficacy households by 60% for a 1000-year flood in 2040 (Figure 18-B). For the same flood scenario, low-income households prevent on average 27%, medium-income households 34% and high-income households 59% of flood damage within their group (Figure 18-D). These differences between the household groups can be explained by the differences in the adaptation diffusion in the group at the time of the flood event (see previous subchapter *6.2.1*). The difference between high- and medium-**worry** level households in the adaptation uptake is also recognizable in the prevented damage (Figure 18–A). Similarly, our previous findings on the lower effect of the **social network** on the adaptation diffusion are reflected in the similarities in damage reduction between the groups (Figure 18–C).

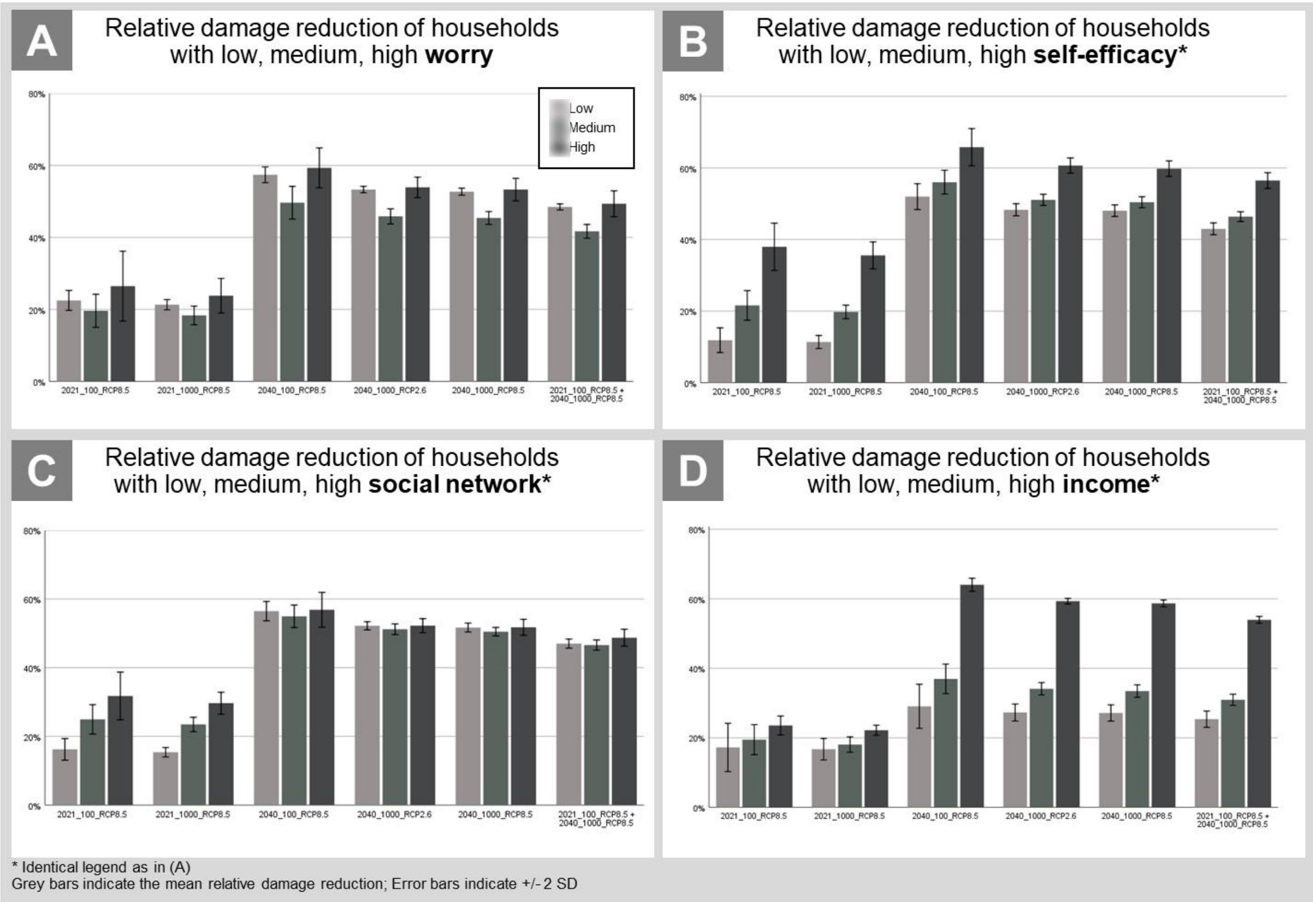


Figure 18: Impact of (A) worry, (B) self-efficacy, (C) social network, and (D) income levels on the relative damage reduction for six different flood scenarios

[17] The building and content values of households from different societal groups e.g., different income classes, can differ, leading to differences in absolute flood damage and hence also absolute damage prevention between the groups. Thus, we use the relative damage reduction (prevented damage divided by the total potential flood damage) as a metric to compare the groups.

[18] In Appendix *F.2* we apply the Welch's ANOVA (W-test) and the Brown-Forsythe test (F*-test) which show that there are significant differences of the mean damage reduction between the groups for each socio-behavioural factor (worry, self-efficacy, social network size, and income).

Overall, it needs to be mentioned that our results are very dependent on the timing of the flood events. For flood events in 2021, the adaptation uptake within a household group depends on the number of households within the group that adapted a measure in the survey. It does not yet take into consideration the adaptation uptake during the simulation. For flood events in 2040, the adaptation of measures is heavily impacted by the expiration of the wet-proofing measures – the most adapted measure category during the simulation runs. Hence, the flood scenarios are by accident constructed in such a way that other model mechanisms such as the measure expiration and the measure implementation time appear to overshadow the differences in the adaptation uptake between the attribute levels. Different flood scenarios, e.g., with flood events in 2030 may lead to different patterns in the damage reduction.

The practical takeaway from the distributional results is that household groups with lower worry, self-efficacy, and income adapt measurably slower to climate-induced floods, which makes them more vulnerable to climate-induced floods. Therefore, policies need to be designed that specifically target these disadvantaged household groups.

7. Conclusions and discussion

7.1. Answering the main research question

This thesis presented an agent-based model (ABM) to understand the role of household climate change (CCA) adaptation in reducing coastal flood risk in downtown Shanghai, China. In the following, we answer each sub-question (SQ), which in combination with each other provides a holistic perspective that helps answer the main research question.

SQ1: "How can we determine the coastal flood risk of households for different climate-induced flood scenarios?"

To determine the flood risk, we combined context-specific hazard, exposure, and vulnerability data. To model the households' exposure to climate-induced floods we overlayed the **geolocations** of 18.039 **residential buildings** in the Shanghai city centre districts from OpenStreetMap with 21 **inundation maps** for storm surges that depict dike failure, dike overtopping, sea level rise and land subsidence under different climate-change scenarios in Shanghai. The results indicate that a 10-year flood in 2100 under the RCP 8.5 scenario leads to a higher exposure of residential buildings than a 100-year flood in 2050 and a 1000-year flood in 2010 (Figure 7). This underlines the nonlinear impacts of sea-level rise and land subsidence on the households' exposure in the Shanghai city centre. Furthermore, it emphasizes the need to promote household adaptations that complement government-level measures to address the adversities of climate change. In combination with context-specific **depth-damage curves** and **asset values** for residential buildings and contents, we determined the direct and tangible flood damages of each household in our ABM. In SQ2, we show how households can adapt to reduce their flood risk.

SQ2: "What are the households' main climate change adaptation measures and how do they reduce coastal flood risk?"

We applied unique micro-level survey data on factors motivating household's adaptation intentions in Shanghai (n=933) and categorized ten of the individual measures into three household-level measure categories: **Elevation**, **wet-proofing**, and **dry-proofing**. We further analysed the context-specific survey data to determine the average cost of the adaptation categories and compared these costs with other risk studies. Furthermore, we reviewed risk studies to determine the measures' effectiveness in reducing flood damage, as well as their life- and implementation times.

We concluded that the three adaptation actions differ in terms of damage reduction effectiveness, cost, lifetime, and implementation time. While elevation is very effective in reducing flood damage below the elevation level, it is also costly and requires the longest implementation time. Wet-proofing is less effective but can reduce damage at high flood depths. In addition, wet-proofing has a similar cost to elevation but has a shorter implementation time. Dry-proofing has greater effectiveness than wet-proofing but reduces flood damage only at lower flood depths. In addition, dry-proofing has the lowest cost and a similar implementation time to wet-proofing. We assume that dry-proofing is the only non-permanent measure. Now that we know how households adapt, it is necessary to understand why they adapt.

SQ3: "What are the behavioural factors that motivate household flood-adaptation intentions?"

To specify households' adaptation behaviour, we relied on the most prominent theory used to examine climate change adaptation (CCA): the **Protection Motivation Theory (PMT).** We use an extension of the base PMT, which next to threat and coping appraisal also accounts for preceding flood engagement, external influences by media and peers, climate-change beliefs as well as the demographic background (Noll, Filatova, Need, et al., 2022). This extension allowed us to consider not only internal but also external factors which are considered relevant for behavioural adaptation (Noll, Filatova, Need, et al., 2022; Wilson et al., 2020).

To determine the impact of these factors on the household's adaptation intentions, we created logistic regression models based on the micro-level survey data for each adaptation measure category (elevation, wet-proofing and dry-proofing). Our results show for the **base PMT variables**, that worry, and self-efficacy provide high positive explanatory power for all adaptation actions. Overall, these observations appear in line with past research which shows that threat and coping appraisal are an important predictor of household adaptation (Bubeck et al., 2013; Grothmann & Reusswig, 2006; Noll, Filatova, Need, et al., 2022; Zaalberg et al., 2009). The results for the **extended PMT** variables show a consistent and positive effect on the adaptation intention of the external influence parameters, which include the expectation of family and friends as well as social media. These findings appear consistent with previous research which show the relevance of interactions in social networks on individual CCA (Bubeck et al., 2013; Figueiredo et al., 2009; Haer et al., 2016; H. Kunreuther et al., 2013; Lara et al., 2010; Lo, 2013; Noll, Filatova, Need, et al., 2022; van der Linden, 2015). It is to note that adaptation intentions do not necessarily lead to adaptation actions (Grothmann & Patt, 2005). Hence, we included adaptation barriers in the form of a household's savings and adaptation regulations in our model and included an intention-behaviour gap parameter.

The answers to the first three SQs provide the data for our flood-ABM which we use for experiments to answer SQ4 and SQ5.

SQ4: "What are the aggregate impacts of household adaptation to climate-induced coastal floods in terms of adaptation uptake and damage prevention?"

In terms of aggregate impacts, our results show that a **household's savings** appear to be a relevant adaptation barrier. On average, about one-fifth of households are hindered by a lack of savings from acting upon their adaptation intentions. Therefore, households tend to opt for more inexpensive adaptation measures such as wet-proofing. This explains why from 2020 until 2040 on average 40% of the household population adapts dry-proofing compared to 12% who uptake wet-proofing.

Due to the increase in adaptation uptake the damage prevention rises from on average 21% for the single 2021 flood scenarios to approximately 50% for the 2040 single flood scenarios. Nevertheless, the **residual damages increase** due to the effects of climate change. For instance, the residual damage for a 1000-year flood under the RCP 8.5 scenario rises from 14.5 Mil. € in 2021 to 24.8 Mil. € in 2040. This highlights that autonomous household CCA is very important to prevent flood damages when dikes break or are overtopped, but insufficient to keep up with the increasing severity of climate-induced flooding. Hence, households should be encouraged by FRM policies to further uptake adaptation.

Our findings also indicate that the damages caused by 1000-year floods negatively impact the exposed households' savings, reducing their ability to finance subsequent adaptations. This results in a measurable decrease in the aggregated adaptation uptake, increasing the households' vulnerability to future floods. With the understanding of the aggregated behaviour, we take a closer look in the next SQ at how different household groups behave and what this means for their damage prevention.

SQ5: "What are the distributional impacts of household adaptation to climate-induced coastal floods in terms of adaptation uptake and damage prevention?"

To observe distributional impacts, we differentiated households with various socio-behavioural attributes: **worry**, **self-efficacy**, **social network size**, and **income**. As shown in SQ3, worry, self-efficacy, and social network size (which impacts social influence) pose a set of socially-constructed adaptation limits as they significantly and positively influence a household's probability to adapt. On the other hand, income is an important indicator of a household's savings, constraining the household's adaptive capacity.

Our results show that household groups with lower worry, self-efficacy, and income adapt measurably slower to climate-induced floods. The most dominant effect can be observed for income, followed by self-efficacy. For instance, the mean proportion of high-income households that adapt wet-proofing measures increases in absolute terms by 30% over the simulation lifetime, compared to less than 10% for the lower-income households. The slower adaptation uptake makes these household groups considerably more vulnerable. For instance, for a 1000-year flood in 2040 under the RCP 8.5 scenario, high-income households prevent on average 59% of the flood damage, while low-income households only prevent 27%. Combined with the results of SQ4, this implies that low-income households and their savings are more affected by flood events, which reduces their future adaptive capacity, leading to a vicious cycle as described by the United Nations (2017). These results are in line with other research findings which suggest that the adversities of climate change will have a disproportionate impact on already disadvantaged societal groups e.g., low-income, thus further increasing social inequality of climate change (Gourevitch et al., 2022; Hsiang et al., 2017; Ringquist, 2005; United Nations, 2017).

Main research question:

"What role does household climate change adaptation play in reducing coastal flood risk?"

In summary, climate change increases the likelihood that the publicly-funded flood defences in Shanghai such as dikes are breached or overtopped, increasing households' flood risk. At the same time, the public flood defence infrastructure entails unintended consequences e.g., attracting more people and capital to the newly protected areas and ultimately increasing the risks ('self-development paradox'). If these top-down measures fail due to the effects of climate change, the **private adaptation** actions determine the extent of the damage and the resilience of communities.

We conclude that **autonomous household CCA plays an essential role** in reducing coastal flood risk when public flood defence infrastructures fail, even in well-protected coastal cities such as Shanghai. However, **autonomous household CCA is not sufficient to keep pace with the increasing severity of climate-induced flooding**, as it is limited by **adaptation barriers** in the form of measure costs and regulations. Therefore, **additional policies are required** to overcome these barriers and increase the adaptation uptake. These policies should take into account differences in adaptation behaviour and damage prevention among **socio-economic household groups** to avoid amplifying social inequalities of climate change.

7.2. Policy implications

This thesis aims at understanding the role of household CCA in reducing coastal flood risk in Shanghai to gain new insights for policymakers. In the following, we discuss the potential implications of our results for flood risk management (FRM) policies.

In terms of **aggregate** effects, the key takeaways for flood policies are as follows. First, our results indicate that autonomous household CCA can play a significant role in reducing residential flood damage in the Shanghai city centre (up to 50%) when dikes fail or are overtopped. However, due to the increase in the severity of climate-induced floods, the absolute residual damage increases despite the autonomous adaptation of households, necessitating government policies that further motivate household adaptation. This is in line with Fankhauser et al. (1999, p.74) who suggest that "…the main role for government will be to provide the right legal, regulatory and socio-economic environment to support autonomous adaptation." Shanghai authorities should therefore reinforce their centralized FRM early on with **greater involvement of individuals such as households**, as also suggested by Du et al. (2020). Second, our results show that high measure costs appear a relevant barrier to household adaptation. About one-fifth of households are hindered by their financial situation from acting upon their adaptation intentions. Therefore, **subsidization of the measure costs** could be helpful. Alternatively, **information campaigns** could be beneficial to emphasize the use of low-cost measures such as storing expensive possessions on higher levels. Next, our findings show that households require external help to cover their flood damages after severe flood events. This would help households in financing subsequent adaptation intentions that result from the increased flood experience. Authorities could provide such relief in the form of a **"build back better"** fund. Lastly, our findings indicate that adaptation regulations – in our case the artificial rule that only households who own a house can implement elevation measures – can have a considerable impact on the adaptation uptake and hence damage reduction. For Shanghai policy makers this means that a change in **local flood adaptation regulations** could alter private adaptation uptake and the aggregated residential flood damage prevention.

In terms of **distributional** effects, we analysed the influence of four socio-behavioural attributes - worry, self-efficacy, social network, and income - on the adaptation uptake and risk reduction. Our results show that household groups with lower worry, self-efficacy, and income levels adapt on average slower. This can make them vulnerable to climate-induced flooding, which in turn can result in a higher proportion of unmitigated flood losses, thus reducing households' savings and their future adaptive capacity, resulting in a vicious cycle similar to the one described by the United Nations (2017). Especially income plays a dominant role on the speed and scope of household adaptation and damage prevention. Shanghai authorities should therefore specifically **subsidize flood adaptation measures for the first- and second-income quintiles of households** ('low-income') to allocate monetary resources to the societal groups that need them the most. In addition, **awareness campaigns** that educate lower worry households about the magnitude of the threat posed by climate-induced flooding could be beneficial. To increase the awareness of the threat of climate-induced floods, additional **policies could be designed that foster climate change education** – see for instance Q. Han (2015). Furthermore, **information campaigns** could be helpful to increase the ability of lower self-efficacy households to undertake measures themselves. Our results also underline that fast-adapting household groups can become vulnerable if flood events occur at the time when their non-permanent adaptation measures have expired. Shanghai authorities should therefore regularly **encourage households to renew their non-permanent measures** in time.

7.3. Scientific relevance

7.3.1. Methodological research contributions

The main **methodological** research contributions of this thesis are as follows.

First, we populate households in our flood-ABM with **context-specific micro-level survey data**. On the one hand, this leads to more realistic agent behaviour and model results (Chapuis et al., 2022) which increases the suitability of our flood-ABM to inform policies (L. Sun & Erath, 2015). On the one hand, the empirical micro-foundation of household behaviour simplifies the validation and benchmarking of our flood-ABM (Aerts, 2020).

Next, we base the households' adaptation behaviour on an extended version of the most prominent theory used to examine CCA: the **Protection Motivation Theory (PMT)**. The extended PMT takes not only internal but also external factors into consideration which are considered relevant for behavioural adaptation (Noll, Filatova, Need, et al., 2022; Wilson et al., 2020). Furthermore, the theoretical foundation of behavioural household CCA is beneficial for sustainable and fast scientific progress, interdisciplinary communication, testing of alternative theories and the in-depth analysis of agent interactions (Bell et al., 2015; Groeneveld et al., 2017; Klabunde & Willekens, 2016; Taberna et al., 2020).

Lastly, we apply inundation maps in our flood-ABM which depict the effects of sea level rise and land subsidence for different Representative Concentration Pathways on dike breaking and overtopping. We then link the households' adaptive decisions to these **climate-induced floods**. An integration of such climate dynamics is especially important since private adaptation determines the damage extent when public flood defence infrastructures fail, which is becoming more likely due to climate change (J. Yin et al., 2020).

In summary, we conclude that our ABM enables more realistic modelling of household CCA to coastal flooding. This increases the credibility of our flood risk assessment and its suitability for FRM policies.

7.3.2. Insights for flood risk management debate

Our results also provide **new insights for FRM research**.

On the one hand, we quantify the impacts of behavioural household CCA in **Shanghai, China**. Currently, most work on behavioural household adaptation focuses on Europe and North America (see chapter *2.2*). As cultural, social, environmental and institutional contexts matter for behavioural CCA of households, transplantation of FRM policies from Europe and North America to Asia is not recommended (Noll et al., 2020; Noll, Filatova, Need, et al., 2022). We provide context-specific insights on the cumulative scope and extent of behavioural household CCA in China, which could be applied to inform local FRM policies. Hence, the results of this thesis are an important addition to the scarce adaptation evaluations in China (Du et al., 2019, 2020).

On the other hand, in contrast to most contemporary flood risk models which integrate household CCA, we not only quantify the aggregate but also the **distributional impacts** of household CCA on flood risk. Aggregate impacts alone do not suffice to inform FRM policies as the differences in the adaptation diffusion and damage prevention amongst various societal household groups are neglected Consequently, it is essential to also quantify the distributional impacts of household CCA. Our results can provide policymakers with insights into the adaptation behaviour and risk reduction of different societal groups, e.g., low-income, or low self-efficacy households. These insights can help design tailored FRM policies which allocate resources to the societal groups that need them the most. Therefore, this work is an important contribution at the novel interface between behavioural household CCA and social vulnerability research - see Aerts et al. (2018).

7.4. Societal relevance

The societal impact of research is becoming more and more important in academia (Bornmann, 2013). According to Bornmann (2013, p.218), this entails the "(a) social, (b) cultural, (c) environmental, and (d) economic returns (impact and effects) from results (research output) or products (research outcome)…"[19]. We will apply these four dimensions to discuss the potential societal impacts of this thesis. In our case, the 'results' are the research findings, while the 'product' is the flood-ABM.

7.4.1. Social impact

Social benefits refer to research contributions to a nation's **social capital** for instance for approaching social issues, policymaking or public debate (Bornmann, 2013). A pressing social issue of climate change is the inequality between those who cause the problem and those who suffer from the consequences (Roberts, 2001). The inequality exists both between different nations ('inter-country') and within nations themselves ('within-country inequalities') (United Nations, 2017). According to the United Nations (2017) especially 'within-country' inequality, which they refer to as **'social inequality'**, has received little attention. Our thesis helps contribute to the debate on social inequality of climate change by studying the distributional impacts of household CCA on flood risk. Our results **quantify the extent of the social inequality** of climate change in terms of flood damage prevention between different socio-economic household groups. For instance, we show that high-income households (5th income quintile) prevent on average of 59%, while low-income households (1st and 2nd income quintile) prevent only 27% of flood damage for a 1000-year flood in 2040 under the RCP 8.5 scenario. Between 2002 and 2012 the top 40% of the high-income population in China was responsible for more than 58% of the indirect carbon emissions (Liu et al., 2019). Thus, the portion of the population that appears to be less responsible for climate change and the resulting increase in the severity and frequency of flood hazards also appears to be less able to adapt. This comparison is not only relevant for the public debate, but it also can be very helpful in designing tailored FRM policies that allocate resources to the societal groups that need them most, thus addressing the social inequalities of climate change (see Chapter 7.2).

7.4.2. Cultural impact

Cultural benefits entail research contributions to a nation's **cultural capital** e.g., in the terms of cultural preservation (Bornmann, 2013). Cultural contexts play an important role in individual CCA motivations (Noll et al., 2020). Yet, most empirical work on factors motivating individual CCA is conducted in Europe and North America (Hopkins, 2015; van Valkengoed & Steg, 2019). Household-level survey data on adaptation intentions to climate-induced floods are underrepresented for nations in the Global South (Noll et al., 2020). As argued in chapter *1.3*, this scarcity of micro-level survey data may restrict the development of flood-ABMs that integrate behavioural theories. Our structured literature review underlines that flood-ABMs which integrate behavioural theories and focus on bottom-up precautionary flood adaptation are only applied in Europe and North America (see chapter *1.3*). Hence, the Global South not only lacks an understanding of how and why households adapt to climate-induced floods (Noll et al., 2020) but also lacks knowledge of the speed and scope of household adaptation and subsequent damage prevention, which can be generated from the aforementioned flood-ABMs. Due to the potential differences in the drivers and barriers across cultures, it might be misleading to apply flood risk mitigation strategies from a country in the Global North to a country in the Global South (Noll et al., 2020). Ultimately, this makes it more difficult to inform FRM policies and puts the Global South, which is disproportionally impacted by climate-induced hazards (IPCC, 2014b) at greater risk (Noll et al., 2020).

[19] It should be noted that these dimensions are not mutually exclusive (Bornmann, 2013).

Within this thesis, we developed to our knowledge one of the **first flood-ABMs in the Global South** that bases the agent behaviour on behavioural theories. The results take into consideration the local contexts of Shanghai households e.g., how they perceive floods or their relationship towards social media. Hence, we argue that this thesis contributes to Shanghai's cultural capital. This can also be seen as a contribution toward 'inter-country' inequality, which we mentioned previously under the social impact in Chapter *7.4.1*.

7.4.3. Environmental impact

Environmental benefits include the research contributions to a nation's **natural capital** (Bornmann, 2013) e.g., combatting the effects of climate change. The *Special Report on the Ocean and Cryosphere in a Changing Climate* by the IPCC (2019) discovered that sea level rise is happening more quickly than previously thought, necessitating faster climate-change adaptation of coastal cities. Our results provide further understanding of the speed and scope of household adaptation that is necessary for flood risk management policies. Hence, the results of this thesis could contribute to a better protection of households against the adversities of climate change and therefore have a positive environmental impact. Consequently, this thesis contributes to **Sustainable Development Goal 13** which focuses on taking "urgent action to combat climate change and its impacts" (United Nations, 2022).

7.4.4. Economic impact

Economic benefits entail the research contributions to a nation's **economic capital** (Bornmann, 2013) e.g., improving public spending. Our flood-ABM could have a positive economic impact both on the government- and on the household-level, as explained in the following. On the **government level**, our flood-ABM can be used to understand the impact of policies such as subsidies on the household adaptation uptake and the cumulative prevention of direct and tangible residential flood damage under different climate change scenarios. These benefits could be compared with the respective costs of the policy measure e.g., from other countries, to generate new insights into the efficiency of policies for stimulating private CCA to flooding. This could help policymakers prioritize the most efficient policies and potentially allow a comparison with the efficiency of government-level adaptation measures such as dikes. Hence, it could make the government's risk mitigation strategies more cost-effective and therefore contribute to the economic capital of Shanghai. On the **household level**, the flood-ABM can provide insights into the benefits and costs of different household adaptation actions (elevation, wet-, and dry-proofing) for different flood scenarios. This information could be used by households to make more efficient adaptation decisions and therefore positively contribute to the households' economic capital.

However, limitations of assessing the adaptation effectiveness and efficiency need to be carefully considered (Adger et al., 2005): Limitations when assessing the **effectiveness** of CCA in reducing damage include 1) the uncertainty about the effect of adaptation measures, 2) the dependence on actions by others (e.g., response to flood-warning), 3) the uncertainty of the future system states (e.g., change of hazard characteristics due to climate change, socio-economic developments, technological innovations), and 4) the unintended impacts of adaptation on other parts of the human-flood system (e.g., higher downstream damage due to upstream adaptation). Limitations of assessing the adaptation **efficiency** i.e., a comparison of the costs and benefits of adaptation are 1) the distribution of benefits and costs (e.g., between private and public actors), 2) the consideration of non-market goods (e.g., aesthetic impacts), and 3) the timing of the adaptation action (long-term vs. short-term). In addition, it needs to be mentioned that the purpose of our model is of explanatory and not predictive nature. Hence, a model adjustment is required if the model purpose is altered to make financial predictions (Edmonds et al., 2019).

7.5. Limitations and recommendations for future research

The model results and our analysis are subject to limitations. Our one-factor-at-a-time **sensitivity analysis** shows that the **adaptation measure cost** and the **intention-behaviour gap** have a measurable impact on the households' adaptation behaviour. Moreover, the **foundation height**, and specifically the **depth-damage curve** as well as the **asset value** significantly influence the total flood damage. Hence, these parameters should be further researched to improve the credibility of the results. Specifically, longitudinal surveys would be helpful in better understanding the intention-behaviour gap (Noll et al., 2020; Noll, Filatova, & Need, 2022; Noll, Filatova, Need, et al., 2022). On the one hand, such surveys could be useful in further understanding the extent to which adaptation intentions lead to actions (Noll, Filatova, & Need, 2022; Noll, Filatova, Need, et al., 2022). On the other hand, longitudinal surveys could help determine the socio-behavioural and environmental factors that influence the implementation of the previously intended (Noll, Filatova, & Need, 2022) and unintended adaptation actions. However, our sensitivity analysis also shows several limitations – see Appendix *E.5.3*. For instance, the one-factor-at-a-time sensitivity analysis does not allow for the exploration of interaction effects, which is why we recommend an **additional global sensitivity analysis** (ten Broeke et al., 2016).

In terms of the households' **adaptation behaviour**, our model focuses only on elevation, wet-proofing, and dry-proofing measures. To make the model more realistic **further adaptation actions** such as flood insurance (Haer et al., 2016, 2017; Y. Han & Peng, 2019), or the movement of households from high-risk areas (de Koning & Filatova, 2020; Haer et al., 2016) could be included. In terms of decision-making, the model behaviour is sensitive to the adaptation rules e.g., that only households that own a house can elevate. Hence, we recommend supporting these assumptions with **further research on formal and informal adaptation rules** in Shanghai and suggest a structured approach for integrating these rules in the flood-ABM – see Abebe et al. (2019). Additionally, research has shown that behavioural theories influence the adaptation behaviour in flood-ABMs (Haer et al., 2017). The difference in the adaptation behaviour between different behavioural theories is also known as the 'adaptation gap'. Hence, we suggest evaluating the **adaptation gap** in our flood-ABM for different behavioural theories such as the Prospect Theory, or the Expected Utility Theory. Alternatively, intelligent decision-making models in the form of **machine learning** methods could be integrated to make the household behaviour even more realistic (Zhuo & Han, 2020). In terms of agents, we currently only focus on households. To provide a more holistic perspective on the impact of private adaptation to climate-induced floods, the model could include **company adaptation** (Taberna et al., 2020).

The model would also benefit from refining **human-flood interactions**. This includes **coupling the ABM with numerical flood models** to account for influences of the adaptation behaviour on the flood hydraulics – see Abebe et al. (2019). Moreover, we recommend **extending the influence of flood events** to other household attributes such as worry, or perceived flood probability and damage (Lechowska, 2018), which would increase a flood's impact on the probability to adapt. In addition, we suggest modelling households with a **flood memory** – see Bhattacharya-Mis & Lamond (2014) and de Guttry & Ratter (2022).

We also recommend further extending the **social interactions**. This includes making the social network **dynamic**, as in real life social connections can change over time. Moreover, we suggest extending the impact of household actions in the social network to **additional parameters.** For instance, Bubeck et al. (2013) argue that actions in the neighbourhood could influence the cost perception of a measure. In our model, a household's social network is represented via its closest neighbours. In reality, the social connections might reach beyond the neighbourhood e.g., family or friends. Hence, we recommend taking such **additional social ties** into consideration.

The experiments performed in this thesis represent only a fraction of the ABM's potential use cases. In the following, we describe **additional experiments** that can be conducted. Our flood-ABM allows us to further analyse the **impact of policies** such as subsidies, or information campaigns – which are discussed in Chapter *7.2* – on the adaptation uptake and damage reduction. The external effect of such policies could be simulated by altering the attribute levels of households e.g., cost perception in case of subsidies. By comparing the cost of such policies with the prevented damage, insights on the policy efficiency could be generated (see the economic impact in Chapter *7.4.4*). Moreover, experiments can be designed to compare the **benefits and costs** of household adaptation. Especially with regards to distributional effects, this could be very insightful e.g., *'does private adaptation yield a better benefit-cost ratio for high-income or low-income households?'* Furthermore, our model allows observing the adaptation behaviour of **household subgroups that combine multiple attribute levels** e.g., low income and low worry. On the one hand such household subgroups or 'personas' could be determined in a participatory manner for instance using interviews with policy makers – see Adler (2005) and Aquino & Filgueiras (2005). The participatory development would also enhance the suitability of the ABM for the analysis of flood risk management (FRM) policies (Ghorbani et al., 2014). On the other hand, data-driven classification methods such as the Latent Class Analysis could be applied to determine the different subgroups of households and to gain more insights into the heterogeneity of flood adaptation – see Bubeck et al. (2020). Comparing the adaptation diffusion and risk reduction for a set of household subgroups in our flood-ABM could therefore provide more detailed insights for FRM policies. While we only apply the inundation maps of J. Yin et al. (2020) in the experiments of this thesis, the ABM also includes data from the inundation maps of Du et al. (2020). Hence, we recommend comparing the **effect of the flood maps** which differ in hazard characteristics on the household climate change adaptation behaviour. Although our model focuses on Shanghai it can be applied to **other case locations** by updating the input data. Hence, it could be used to compare household adaptation diffusion in two different countries with different environmental, institutional, and cultural contexts to generate further insights into cross-contextual transplantation of policies.

A. Literature review

To identify research gaps in the application of flood-ABMs, we conduct a literature review according to the guidelines of Kable et al. (2012) on the use of ABMs for individual adaptation to floods. We review the literature in two rounds: A first-round on finding existing reviews on flood-ABMs and then a second round to detail research challenges identified in the first round. In this appendix we show our methodology and provide the results. We discuss the results in chapter *1*. Please note that this literature review has been conducted as part of the 'Master Thesis Preparation Course' (SEN2321).

A.1. Round 1 literature review

Due to a large number of ABM applications in flood adaptation research, we specifically search for existing literature reviews on flood-ABMs. As shown in Figure 19, the search string for the first round is composed of keywords from three domains: ABM, flood, and literature review.

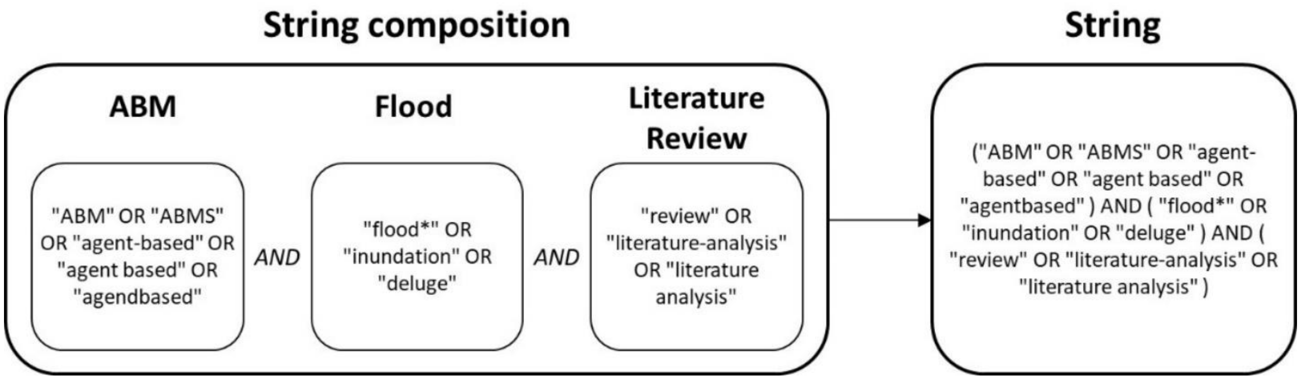


Figure 19: Round 1 search string composition

The bibliography search engines Scopus and Web-of-Science are used. Entries in the titles, keywords, and abstracts are searched for. In addition, only English-language articles and articles published in the final stage are included on Scopus.

The first-round review was conducted on the 23rd of November 2021 and resulted in 10 hits in Scopus and 2 hits in Web-of-Science. The results are further filtered in two stages, as shown in Figure 20. First, articles which are not literature reviews are removed. Second, articles are excluded which focus exclusively on hydrological modelling or short-term operational response such as emergency management. After accounting for duplicates one additional article is identified via backward snowballing and hence three records are included.

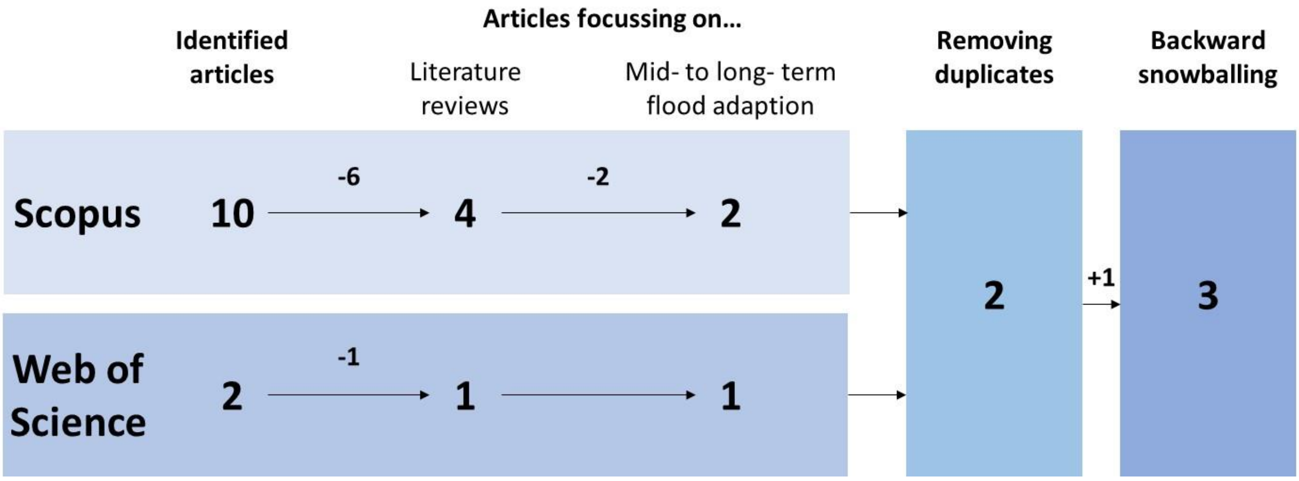


Figure 20: Round 1 search scheme depicting the number of articles

Table 3: Round 1 results overview

Reference	Scope of reviewed articles	Number of reviewed articles	Year range of reviewed articles
Aerts (2020)	Flood adaptation effectiveness in decreasing flood risk, economic loss, and optimizing the efficiency of evacuations	18	2016-2020
Taberna et al. (2020)	Socioeconomic impacts and responses to urban floods, specifically the mid-and long-term adaptive behaviour and resilience to climate-induced flooding.	28	2017-2020
Zhuo & Han (2020)	Flood risk management perspective on the link between human/institutional decisions and behaviour to flood risk.	61	2009-2020

As shown in Table 3, we can identify three suitable literature reviews with slightly different but overlapping research scopes. Consequently, they provide a broad perspective on our research field. One important feature explored in these reviews is the modelling accuracy of the agent decision-making. All three reviews point to two gaps which we discuss in chapter 1.

A.2. Round 2 literature review

The research string – see Figure 21 – combines keywords from three research fields: ABM, flooding, and (behavioural) theory. The bibliography search engines Scopus and Web-of-Science are used. Entries in the titles, keywords, and abstracts are searched for. In addition, only English-language articles are included. Moreover, only articles published in the final stage, as well as journal articles, are included on Scopus.

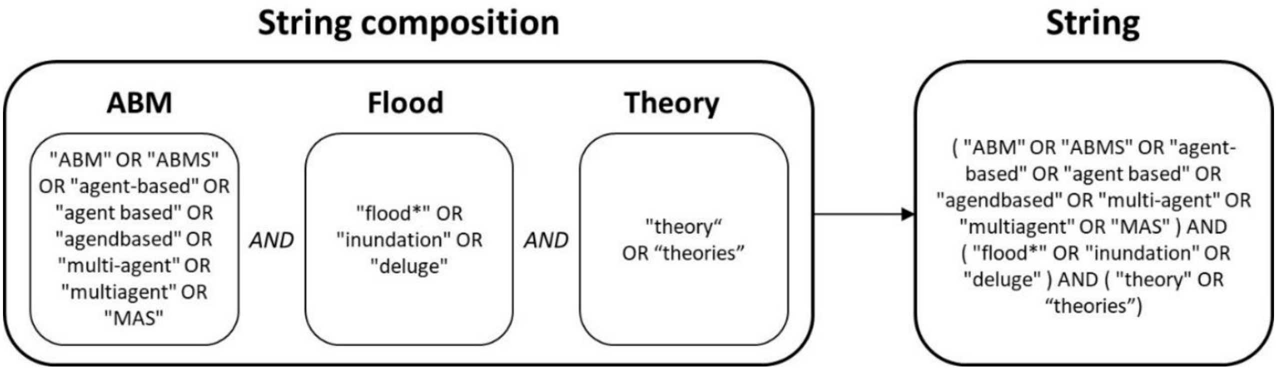


Figure 21: Round 2 search string composition

The review was conducted on the 25th of November 2021 and resulted in 36 hits in Scopus and 19 hits in Web-of-Science. A multi-stage screening is applied to the results as shown in Figure 22. Articles without bottom-up precautionary flood-adaptation ABMs incorporating behavioural theories are excluded. Moreover, as the results are retrieved from two databases, duplicates are removed, resulting in six articles. In addition, six articles are identified via backward snowballing and hence twelve articles are included.

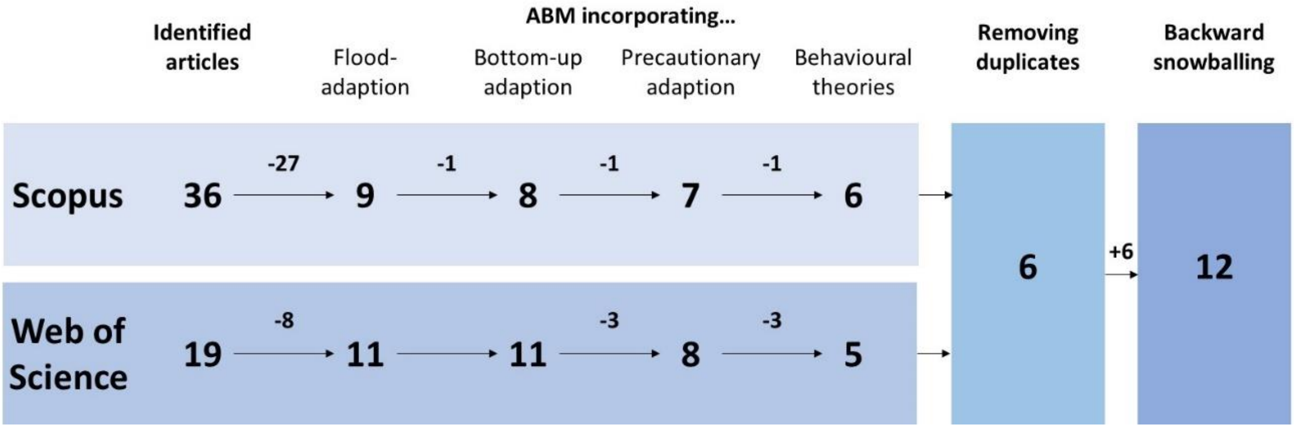


Figure 22: Round 2 search scheme depicting the number of articles

As shown Table 4, we depict which behavioural theories are used in the ABMs. Moreover, we show the geographical scope to understand in which areas knowledge has already been generated with the help of flood-ABMs with behavioural theories. Three different behavioural theories can be identified: the Expected Utility Theory (EU), the Protection Motivation Theory (PMT), and the Prospect Theory (PT). Their characteristics and differences for the application in a flood risk context are discussed in the three existing literature reviews of Aerts (2020), Taberna et al. (2020), and Zhuo & Han (2020). Moreover, their advantages and disadvantages in the context of climate change adaptation are summarized by Villamor et al. (2022). Hence, we refer to these papers and will not further compare them in this thesis. Regarding the geographical scope, we notice that the ABMs are only applied in Europe and the United States. We discuss these results further in chapter *1*.

Table 4: Round 2 results overview

Reference	Behavioural theories			Geographical scope
	EU	PMT	PT	
Abebe et al. (2020)		X		Hamburg (GER)
De Koning & Filatova (2020)	X		X	Greenville & Beaufort (US)
De Koning et al. (2017)	X		X	Greenville (US)
Erdlenbruch & Bonté (2018)		X		Aude & Var (FR)
Filatova (2015)	X			Beaufort (US)
Filatova et al. (2011)	X			Coast region (NL)
Haer et al. (2016)		X		Rotterdam-Rijnmond (NL)
Haer et al. (2017)	X		X	Heijplaat (NL)
Han & Peng (2019)			X	Miami-Dade County (US)
Han et al. (2021)		X		Miami-Dade County (US)
Magliocca & Walls (2018)	X		X	Different regions (US)
Michaelis et al. (2020)		X		Floodplain of the river Po (IT)

B. Model description – ODD

In this chapter we describe the model using the ODD protocol (Grimm et al., 2020), which is extended by a summary of the model assumptions and a model narrative. With regards to the process steps of Nikolic et al. (2013), it details the system identification and decomposition, the concept formulization and the model formulization.

B.1. Purpose and Patterns

The higher-level purpose of this model is to *understand* the role of household climate change adaptation to coastal floods in Shanghai. We are not interested in building a predictive model that can forecast how many households adapt in a certain year. Instead, we aim for an *explanatory* model - see Edmonds et al., (2019) - which allows us to study the “causal chain” between the agent’s adaptation behaviour and system-level impact on the flood risk.

More specifically, we build the model to understand both the aggregate and distributional effects of household climate change adaptation. In terms of aggregate effects, we want to build a model that helps us understand how households’ adaptation decisions influence the overall mitigated flood damage. In terms of distributional impacts, the model should help in understanding how household groups with different socio-behavioural attribute levels adapt differently and what this means for the flood risk of the group.

On the one hand, the model could be used by scientists to understand the impact of different policy measures e.g., subsidies or information campaigns on the adaptation behaviour of households. On the other hand, the model could be used by policymakers to generate insights into the adaptation behaviour and risk exposure of different social groups. This could foster the design of multi-actor cross-scale flood adaptation strategies that address “within-country inequalities” of climate change (United Nations, 2017).

B.2. Entities, State Variables, and Scales

B.2.1. Entities

Two entities are considered in this model: Households and the environment.

Households: We only consider households as agents in this model as we focus on household adaptation to climate induced floods. Households are static and are represented by the residential buildings in which they live which means that each household lives in one residential building and vice versa. In the case of multi-story buildings, it is assumed that households live on the ground floor.

Environment: The environment includes the flood events and the time. To represent flood events, we apply inundation maps. The flood depth, location, and probability depend on the respective flood scenario.

Other entities such as companies, or the government were not included as they are not within our research scope.

B.2.2. State Variables

Households have two state variables: Adaptation status and flooded. Table 2 in the main text summarizes the agent states together with the model parameters, the variable type, value range, and source.

B.2.2.1. Adaptation status

Within our model, for each of the three measure categories elevation, wet-proofing, and dry-proofing, households can have different adaptation states:

- ***Do nothing*** (adaptation status = 0): The household either has not started implementing yet, or the measure has expired.
- ***Implementing*** (adaptation status = 1): The household decided to start implementing the measure, but the implementation is not yet finished. If this is the case, we assume that the adaptation measure is not "active" yet and does not reduce any flood damage that occurs while the implementation is ongoing.
- ***Adapted*** (adaptation status = 2): The household finished the implementation of the measure, and the measure is now able to reduce flood damage.

We assume that a household can adapt multiple measures at the same time. E.g., a household can elevate and dry-proof at the same time.

B.2.2.2. Flooded

This state determines whether a household is flooded or not. We assume a household to be flooded if the residential building in which the household lives has an inundation depth which is larger than the elevation of the building foundation. This assumption also is considered in other flood ABMs – see Abebe et al. (2020). The building flood depth is extracted at the location of the centroid of the building polygon. The flood depth of a residential building is determined by overlaying the inundation map with the residential building map.

B.2.3. Scales

B.2.3.1. Temporal scales

The selection of an appropriate temporal scale is highly relevant for flood-ABMS (Taberna et al., 2020, p.8):

"Risk propagates through time. Moreover, resilience encompasses the risk framework and the system's ability to cope with a shock considering its capacity to learn, adapt, recover and self-organize. Therefore, the temporal dimension is crucial to capture critical transitions happening in such systems."

Three factors determine the temporal scale: The **time step**, the **starting point**, and the **time horizon**.

- **Time step**: In our model, one year reflects one time step. This appears to be the standard in socio-hydrology flood-ABMs – see Taberna et al. (2020).
- **Starting point**: We choose 2020 as the starting point for our model, as the majority of the input data (survey & inundation maps) is from this year. Hence, the monetary data (e.g., measure cost) is transformed into 2020 values.
- **Time horizon**: The main goal is to study the impact of socio-behavioural factors motivating household adaptation over time and not to study short-term post-event flood responses or recovery. Hence, we are interested in studying the effect of household adaptation in the mid-to long term. A time horizon of 30 years appears a good trade-off for studying both social dynamics and environmental processes. A similar time horizon is chosen by Erdlenbruch & Bonté (2018) and Han & Peng (2019). Longer time horizons would better capture the impact of sea-level rise and land subsidence on the flood risk – see J. Yin et al. (2020). However, long-term horizons (50-100 years) pose the issue of increasing uncertainty in socioeconomic projections such as technological innovations (Taberna et al., 2020) and therefore 30 years appear more suitable.

B.2.3.2. Spatial Scale

The ABM does not have a direct spatial component itself. Instead, the spatial model components are determined in QGIS and loaded into the ABM in the form of data tables to improve the simulation time.

- **Inundation maps:** The inundation maps are overlayed with the residential building data to determine the inundation depth of each residential building.
- **Nearest neighbours:** Instead of determining the nearest neighbours within the simulation model, the N nearest neighbours of each residential building are determined in QGIS via the distance matrix. Hence, each household knows the IDs of the N closest residential buildings which are used in the simulation model to call the respective household and exchange information.

Geographically, the ABM focusses on the city centre districts of Shanghai. [20] To improve the simulation time, the model is designed in such a way that Shanghai city centre districts can be easily added to or removed from the experiment via switches in the user interface without requiring further adjustments in the program or data (see software implementation, Appendix *C.1*). Technically, the spatial area can be increased to all Shanghai districts. This would however limit the speed of the simulation and it would require higher data quality of residential buildings in the non-city centre districts (see ODD protocol, Appendix *B.6.1.2*).

[20] See chapter *3.2* for scoping decisions on Shanghai and in particular the city centre districts.

B.3. Process Overview and Scheduling

After declaring and initializing the parameters in the setup function, the process for every tick goes as shown in Figure 23 and as described in the following:

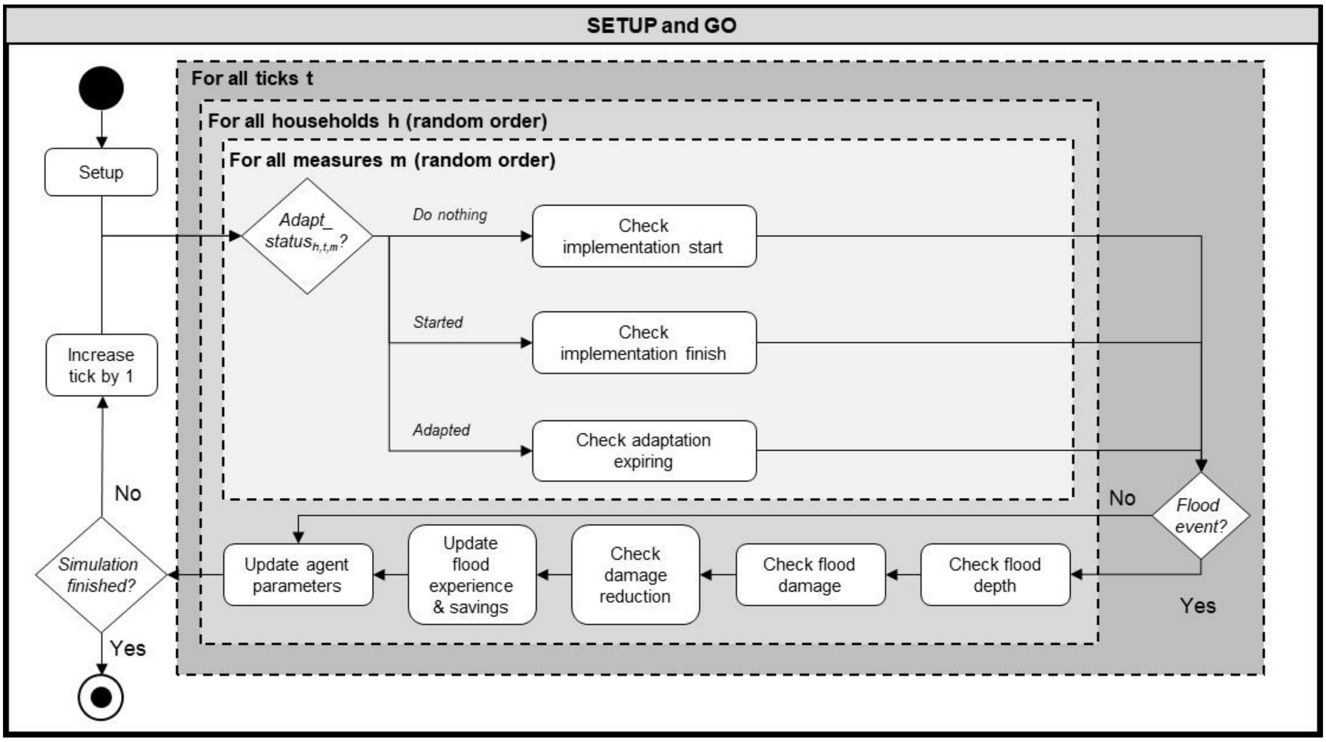


Figure 23: Process overview and scheduling

B.3.1. Determining household action based on the adaptation status

Each household determines for each of the adaptation measures elevation, wet- and dry-proofing the action based on the respective adaptation status.

Households can already start the simulation with implemented adaptation measures, depending on whether or not the respective survey respondent that is assigned to the household indicated that previous measures in the respective measure category were already undertaken. Therefore, all adaptation states need to be checked to start from the first tick.

If the adaptation status is *do nothing* (0) the sub model *Check Implementation Start* (Appendix *B.7.4*) is called. Based on the attribute levels of households and the odds ratios from the regression analysis as well as additional rules for the regulative and economic barriers, it is determined whether or not the household starts the implementation of the measure. In this case, the adaptation status is changed to *implementing* (1). Else, the status stays at *do nothing* (0). If the implementation time of the measure is set to 0 and the measure implementation is started, the sub model *Check Implementation Finish* (Appendix *B.7.5*) is entered, as in this case, the measure would be implemented in the tick in which the decision is made to implement.

If the adaptation status is *implementing* (1) the sub model *Check Implementation Finish* (Appendix *B.7.5*) is called. Based on the starting time of the implementation, the current tick, and the implementation time of the respective measure it is determined if the measure implementation is finished. If so, the adaptation status is changed to *adapted* (2), otherwise, it stays at *implementing* (1). It is important to note that every household which starts the implementation also finishes it after the implementation time is passed. If a household adapts at least one measure, the indirect neighbours increase their count of the number of neighbours who adapted at least one measure by one.

If the lifetime of the respective measure is set to 0 and the measure is adapted, then the sub model *Check Adaptation Expiration* (Appendix *B.7.6*) is called immediately, as the measure would expire in the tick in which it is implemented.

If the adaptation status is *adapted* (2) the sub model *Check Adaptation Expiration* (Appendix *B.7.6*) is called. Based on the finish time of the implementation, the current tick, and the lifetime of the respective adaptation measure, it is determined if the measure expires. Some measures are assumed permanent (elevation and wet-proofing) and hence have an "infinite" lifetime, while others are assumed non-permanent (dry-proofing) and can expire (see the Appendix *B.6.3.2*). If a measure expires, the adaptation status is set back to *do nothing* (0), otherwise, it stays *adapted* (2). If a household transitions from adapting at least one measure to zero measures, the adaptation count of the indirect neighbours is decreased by one.

B.3.2. Determining flood damage (reduction) based on the flood status

After checking and updating the adaptation status the model determines the influence of potential flood events. In other words, this means we assume that floods occur at the "end" of a year. Based on the inputs in the user interface it is determined which flood scenario occurs in which tick.

In case of a flood event, the flood depth is determined for each household by looking at the respective inundation depth which was pre-determined in QGIS (see sub model *Check Flood Depth* in Appendix *B.7.7*). If a household is flooded the flood damage is assessed for the building structure and content using the respective value and depth-damage-curve (see sub model *Check Flood Damage* in Appendix *B.7.8*). If a household is flooded and the household has implemented at least one adaptation measure the flood damage reduction of the measure is determined using the respective effectiveness level and damage reduction effectiveness (see sub model *Check Flood Damage Reduction* in Appendix *B.7.9*). Based on the flood damage, the savings and flood experience are adjusted (see sub model *Update Flood Experience and Savings* in Appendix *B.7.10)*. In case there is no flood event, these steps are skipped.

B.3.3. Updating the agent parameters and checking simulation end

This process step updates agent parameters based on the actions and interactions in this tick.

First, the agent state flooded is reset for the next tick. Second, based on the adaptation of the direct neighbours of a household in this tick, the social influence variable is adjusted. This must be done before the probability is recalculated. Third, for each adaptation measure the probability to implement the measure is calculated together with the implementation threshold. Afterwards, the model checks if the time horizon is passed, and ends the simulation run. Otherwise, the process starts from step i again and the tick counter is increased by one. More details can be found in the sub-model *Update agent parameters* in Appendix *B.7.2.*

B.4. Design Concepts

B.4.1. Basic Principles

The adaptation decisions in our model are based on the Protection Motivation Theory, on the most prominent theory used to examine climate change adaptation to floods (Babcicky & Seebauer, 2017). A description of the PMT which we use in this model can be found in the Chapter *4.3* in the main text and in the input data chapter of the ODD protocol in Appendix *B.6*.

B.4.2. Emergence

In our model, households make adaptation decisions based on their heterogeneous parameters and states. These decisions can influence the household's own future adaptive actions as well as the adaptation decisions of the household's neighbours. Moreover, flood events effect the households' adaptation decisions (details see *Interaction*). Hence, the cumulative adaptation behaviour and the flood mitigation is a result from the interactions of multiple heterogeneous households with each other in a social network and with the environment. It is therefore more than the sum of individual household actions and can potentially lead to emergent system-level behaviour.

B.4.3. Adaptation

The adaptation of households is in detail described in the Chapter *5.1.2* in the main text.

B.4.4. Prediction

One could argue that within the model, three predictions based on regression analysis take place:

First, the calculation of the probability to intend to adapt a measure is based on the results of a binary logistics regression (see the Appendix *B.6.4*). Hence, one could say that we try to predict a household's probability to intend to adapt in each time step based on its attribute values.

Second, the change in the social influence parameter based on the amount of adapted direct neighbours is calculated using the beta factor of a linear regression model (see the Appendix *B.4.6*). One could say that we try to predict by how much the social influence parameter changes if one more direct neighbour adapts at least one measure.

Lastly, the intention gap, which results from the average slopes of three linear regressions (see the Appendix *B.6.4*) is used to "predict" the number of households which put their adaptation intention into action.

B.4.5. Sensing

Household agents are assumed to know when their direct neighbours adapt to flooding. Moreover, households realize when their non-permanent measure expires.

B.4.6. Interaction

In summary, agents interact within their static social network and adjust their social influence attribute level based on the adaptation behaviour of the households within their direct neighbourhood, which positively influences the probability of a household implementing a measure. In the following, we further detail our decisions.

Why do we include a social network?
On the one hand, previous research shows the relevance of interactions in social networks on individual climate change adaptation (Bubeck et al., 2013; Figueiredo et al., 2009; Haer et al., 2016; H. Kunreuther et al., 2013; Lara et al., 2010; Lo, 2013; Noll, Filatova, Need, et al., 2022; van der Linden, 2015). On the other hand, our binary logistics regression results (see input data – behavioural factors) show that the influence of a household's social network is one of the strongest predictors on the adaptation intention for all measures.

Which households are included in the social network?
Following Erdlenbruch & Bonté (2018) we decide to represent a household's social network via its neighbours. We assume that a household can see the process of installing the adaptation measures of its neighbours. Research also suggests that the likelihood of an individual's adaptation increases if the majority of residents in a neighbourhood adapt to floods (H. C. Kunreuther & Erwann, 2009).

We determine the neighbours based on proximity as in our opinion proximity matters in flooding following the logic: *"If households who are physically close to me adapt, then I am likely more influenced by their actions compared to households which are further away and have other physical conditions (e.g., live on a hill)."*

Instead of determining the nearest neighbours within the ABM itself, which would increase the computational effort, the 15 nearest neighbours of each residential building are determined in QGIS via the distance matrix. We choose 15 neighbours as this appears a reasonable maximum network size of a household's neighbours. Hence, each household knows the IDs of the 15 closest residential buildings which are used in the simulation model to call the respective household and exchange information. There are however two caveats to this approach:

First, we need to make sure that in case of spatial down- or upscaling of the model (e.g., selecting only one city centre district), a household still has access to the information of its neighbours. Therefore, we assume that each household can only consider the households within the same district as a neighbour. Hence, adding or removing districts does not impact the neighbourhood of households. However, this means that there are no connections across districts, which means that adaptation diffusion through the social network is limited to the district.

Second, as the nearest neighbours for each household are based on proximity, this means that the neighbourhoods are one-directional: If household A is neighbour to household B, household B does not necessarily need to be a neighbour of household A, as B might have other neighbours which are closer than A. As a result, we need to distinguish between a direct and an indirect neighbourhood: ***Direct neighbours*** are the households which are closest to me and hence which influence me with their actions. In other words, these are the households that I consider neighbours. ***Indirect neighbours*** on the other hand are the households which consider me a direct neighbour and hence, which I influence with my actions.

How many households are included in the social network?
We assume the social network size Soc_net_h of a household h to be heterogeneous. We use the number of adapted households $NN\_adapt_{h,t}$ in a household's social network (data from survey) and the percentage of the households which adapted at least one measure (data from survey) to estimate the size of the household's social network Soc_net_h, as explained in the following.

For each household we know from the survey data the number of households in the social network which have taken some adaptive action towards flooding $Adapted\_soc\_net_h$. From the survey data (933 households) we know the proportion of households in Shanghai which adapted at least one measure (64%), and which did not (36%). By combining these two data points we can estimate that the social network size is approximately 3 times the size of the adapted social network for each household as shown in Equation 3:

$$Soc\_net_h = Adapted\_soc\_net_h \times 3 \tag{3}$$

What actions of households within a social network are influential?
Following Haer et al. (2016) and Erdlenbruch & Bonté (2018), we assume that a household is influenced by the adaptation actions of the household's (direct) neighbourhood. We do not distinguish between the different types of adaptation measures a neighbour is taking. Also, we assume that the number of measures a direct neighbour adapts is not influential, but whether they adapt at least one measure or not.

How are these actions influencing a household?
For the household interaction, we use the social influence parameter Soc_inf_h that captures how much the social network expects a household to prepare for flooding. As the odds ratio of this social influence parameter is a strong indicator for adaptation intention (see the Appendix *B.6.4.4*), the change within the social network can lead to behaviour change of the household.

We model that a household feels more influenced to intend an adaptation measure by its social network (Soc_inf_h) when the number of households in the social network which have undergone at least one measure $NN\_adapt_{h,t}$ increases as there is a moderate correlation of 0.479 between Soc_inf_h and $Adapted\_soc\_net_h$ in the survey data. By applying a linear regression, we determine that when $Adapted\_soc\_net_h$ increases by 1 point (one more household in the social network adapts at least one measure), then Soc_inf_h increases by 0.263 (see Table 5).

Table 5: Linear regression model for social influence (Source: input data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the B	
				Lower	Upper
Adapted Soc Net	0.263	0.018	0.000	0.227	0.300
Constant	2.385	0.048	0.000	2.291	2.479

R square of 0.229 | Dependent variable: Soc inf

From tick 1 when the number of direct neighbours which implement at least one adaptation measure increases by 1, the social influence variable increases by 0.263 (beta of the linear regression). If later at a later point in time the adaptation measure of a neighbouring household expires and it no longer has any adaptation measure installed, the social influence parameter Soc_inf_h of the influenced neighbours decreases by 0.263 considering the following conditions:

First, Soc_inf_h is an attribute with a value range from minimum (1) "They do NOT expect me to prepare for flooding" to maximum (5) "They strongly expect me to prepare for flooding" (see the Appendix *B.6.4.1*). These minimum and maximum values cannot be exceeded.

Second, the decrease in the number of direct neighbours with at least one adaptation measure $NN\_adapt_{h,t}$ does not necessarily mean that Soc_inf_h changes. For instance, if a household has a very high social influence (Soc_inf_h = 5) and a large number of neighbours that adapted a measure ($NN\_adapt_{h,t}$ = 15) which now decreases by 1 as the adaptation measure expires for one neighbour, this does not necessarily mean that Soc_inf_h decreases automatically. To determine below which threshold of adapted neighbours ($NN\_adapt_{h,t}$) Soc_inf_h starts to decrease, we use the parameters of the linear regression (see Table 5) according to the equation 4:

$$Soc\_inf_h = 2.385 + 0.263 \times NN\_adapt_{h,t} \quad (4)$$

Hence, we implement that if $NN\_adapt_{h,t}$ falls below 10, then Soc_inf_h decreases below 5.

For the interaction of agents with the environment and with themselves we refer to Chapter *5.1.3.3* in the main text .

B.4.7. Stochasticity

Stochasticity is included both in *setup* (Appendix *B.7.1*) and in the *go* function (Appendix *B.7.3*).

Matching of households to residential buildings in *Setup*: Each residential building (either apartment or house) has a different location, which determines the inundation depth for the different flood scenarios. The synthetic population data shows us which household lives in an apartment or a house. However, we do not know which households live in which building. Hence, for each run ,we need to match the synthetic population of households from the survey data to the residential buildings from OpenStreetMap based on the building type they live in. We decide to re-match households with residential buildings randomly within each simulation run as relying on one random matching might be highly influential on the simulation results. For instance, households with attribute levels that favour adaptation (.e.g., high worry) might be randomly matched to houses that are highly exposed to floods, which might influence the flood risk. For more details see the Appendix *B.5.1*.

Determining the threshold for the adaptation probability: For each run we need to determine both the probability of a household to implement an adaptation measure and the threshold to which this probability is compared. If the probability of implementation is higher or equal to the threshold, the implementation starts under the condition that the other adaptation rules are met. While the probability of implementation is determined based on the Protection Motivation Theory, the threshold is randomly generated as a number between 0 and 1 for each tick. This random number is generated for each household for each measure. For instance, a household A might have a threshold of 0.3 for elevation, 0.5 for wet-proofing, and 0.9 for dry-proofing, while household B might have different thresholds. The reason why we choose an individual instead of a unified threshold is that there would be jumps in the adaptation diffusion, as everybody has the same threshold in a specific time step e.g., very low or very high, which seems unrealistic. For more details see the Appendix *B.4.3*.

Order in which households determine the adaptation of the measures*:* The order in which households assess the adaptation status of the three adaptation measures influences the decision-making, as no savings might be left for the implementation of other measures. As a result, we randomly vary for every agent and every tick the order in which households assess the adaptation status of the adaptation measures.

Implementation finish time of measures which have been implemented before the simulation start: If a household indicated in the survey that they already adapted a measure, then we need to set the implementation end time of the measure. As measures have a lifetime, they expire based on when the implementation was started. Hence, the adaptation diffusion of households needs to generate a realistic expiration pattern. Thus, we assume that households that implemented a measure before, did so in the 10 previous years following a uniform distribution.

Lifetime of dry-proofing measure: We assume a normally distributed lifetime of adaptation measures with a mean of 20 years and a standard deviation of 2 years to create a more realistic adaptation curve.

Odds ratio of Flood Experience: As each flood affects each household and their behaviour differently, we randomly vary the Odds Ratio of Flood Experience for each household in the range of one standard deviation from the mean effect of flood experience on the adaptation intention.

B.4.8. Collectives

Within our model, agents interact within their social network. These social networks can be considered explicit collectives in which adaptation actions can influence other households (details see the Appendix *B.4.6*).

B.4.9. Observation

Per time step the simulation model can track for each household the adaptation status of each measure, the flood experience, the number of adapted direct neighbours, the flood damage to building structure and content, the household savings and the benefit and the cost of each adaptation measure. Based on these parameters the following aggregated information can be retrieved for each time-step: the number of flooded households (if the flood damage is larger than 0, there is a flood), the number of adapted households, the potential flood risk in terms, the total avoided annual building and content damage by each adaptation measure, the residual damage, and cost by each adaptation measure. In summary, the model can be used to observe the adaptation diffusion, the adaptation effectiveness, and the adaptation efficiency. In addition, these KPIs be observed for different household groups based on their attribute levels e.g., low-worry households that adapt elevation measures.

For our experiments, we observed both the aggregate and the distributional impact of household adaptation. In terms of aggregate effects, we observed for each tick the number of households that adapted no measure, only elevation, only wet-proofing, only dry-proofing, both elevation and wet-proofing, both elevation and dry-proofing, both wet- and dry-proofing, all measures, and at least one measure. Moreover, we observed per tick the total building and content damage for all households. Additionally, we let the model output in each tick the total mitigated flood damage by each adaptation measure. Furthermore, we observed in each tick the total household savings, the total number of households that want to adapt but cannot afford an adaptation, and the total number of households with flood experience.

For the distributional effects, we observed for worry ($Worry_h$), self-efficacy (SE_h), social network size (Soc_net_h), and income ($income_h$) for each attribute level low, medium, and high (see experimentation appendix):

- The relative number of households within the group (with the same attribute level) which adapted an elevation measure, a wet-proofing measure, and a dry-proofing measure,
- the total flood damage within the group, and the
- the total mitigated damage by elevation, wet-proofing, and dry-proofing within the group.

B.5. Initialization

B.5.1. Initialization of synthetic population

B.5.1.1. General Overview

We require a population of households with attribute levels which represent the real Shanghai population as good as possible. Such a "simplified microscopic representation of the real target population" is referred to as a synthetic population (Chapuis et al., 2022, p.1). "The goal of population synthesis is to effectively and efficiently utilize the available microsamples — together with the complementary aggregated/marginal information on each attribute of interest—to create a realization of population that could satisfy the underlying population structure as much as possible" (Sun & Erath, 2015, p.50):

- **Micro-level data**: On the one hand, we have micro-level survey data of 933 households in Shanghai. It specifies for each household the building type, the household status, the building size, as well as the 13 socio-behavioural factors motivating flood adaptation. Of the 933 households, 92.1% live in apartments, while 7.9% live in houses.
- **Macro-level data**: On the other hand, we have macro-level residential building data from Open Street Map and the inundation maps of J. Yin et al. (2020) for the Shanghai city centre. It captures the 18039 residential buildings in the Shanghai city centre districts and their attributes (building type, district, and inundation depth for each flood scenario). Of the 18039 residential buildings, 94% are apartments and 6% are residential buildings. This macro-level data is included in the 'Macrolevel_data.csv' file.

B.5.1.2. Creation of synthetic population

To create our synthetic population, we first need to create 18039 households and in a second step match these households to the residential buildings.

Creation of households:

Our goal is to create 18039 households where exactly 94% (16949) live in an apartment and 6% (1090) live in a house. At the same time, the underlying population structure of the households should be changed as little as possible (e.g., the correlation of the attributes should stay similar to the survey). To create these 18039 households, we select individual household data via direct sampling from the survey data. The answer of each of the 933 survey respondents is used to populate the attributes of 14 households. After that, 4977 households remain to be populated, of which 4923 need to be apartments and 54 houses to match the overall building type distribution. These remaining households are directly and randomly populated from the survey data until the number of apartments and houses required is reached. The resulting synthetic population of households is captured in the 'Microlevel_data.csv' file.

This method produces a synthetic population which is similar to the sample data for instance in terms of the correlations between the variables – see Table 6. However, using probability distributions would enable a more diverse set of agent properties and variations between the properties. For each simulation run a new synthetic population could be created, which would allow "the model to consider and produce alternative and potentially more realistic populations" (Harland et al., 2012, p.3). Alternatively, we could choose one synthetic population for all simulation runs. This would enable us to better quantify the impact of changing other parameters on the simulation results which according to (Harland et al., 2012, p.3) "can be very important for policy evaluation". As our model purpose is to understand the aggregate and distributional impacts of household climate change adaptation to draw new insights for flood risk management policies we choose one fixed synthetic population for all simulation runs.

Table 6: Correlation coefficient comparison between survey data and synthetic population

	Mean survey	Mean synthetic population	Mean difference
fl_prob	0.08921	0.08764	0.00156
fl_dam	0.05526	0.05906	-0.00380
worry	0.08211	0.08236	-0.00025
elev_RE_avg	0.11922	0.11865	0.00057
wet_RE_avg	0.16311	0.16272	0.00039
dry_RE_avg	0.15308	0.15271	0.00037
elev_SE_avg	0.09298	0.09569	-0.00271
wet_SE_avg	0.16788	0.16825	-0.00037
dry_SE_avg	0.15972	0.15993	-0.00021
elev_cost_avg	0.04228	0.04128	0.00100
wet_cost_avg	0.05515	0.05562	-0.00047
dry_cost_avg	0.05205	0.05112	0.00093
elev_UG	0.00511	0.00614	-0.00104
wet_UG	0.05855	0.05895	-0.00040
dry_UG	0.08912	0.09184	-0.00272
fl_exp	0.07316	0.07637	-0.00321
age	-0.02677	-0.02720	0.00042
edu	0.05764	0.06069	-0.00305
CC_belief_new	0.03489	0.03426	0.00063
soc_exp	0.10174	0.10148	0.00026
s_media_avg	0.12856	0.12735	0.00122
HH_size_new	0.04347	0.04577	-0.00230
HH_status_new	-0.06091	-0.06097	0.00006
Build_type	-0.00394	-0.00250	-0.00143

Matching of households to residential buildings:

Each residential building (either apartment or house) has a different location, which determines the inundation depth for the different flood scenarios. The synthetic population data shows us which household lives in an apartment or a house. However, we do not know which households lives in which building. Hence, for each run we match the synthetic population of households from the survey data to the residential buildings from Open Street Map based on the building type they live in. We decide to re-match households with residential buildings randomly within each simulation run as relying on one random matching might be highly influential on the simulation results. For instance, household with attribute levels that favour adaptation (.e.g., high trust and frequency of social media) might be randomly matched to houses that are highly exposed to floods, which might influence the drastically impact on the flood risk.

In case the geographical scope is reduced to a subset of city centre districts, only the respective residential buildings will be matched with households from the synthetic population.

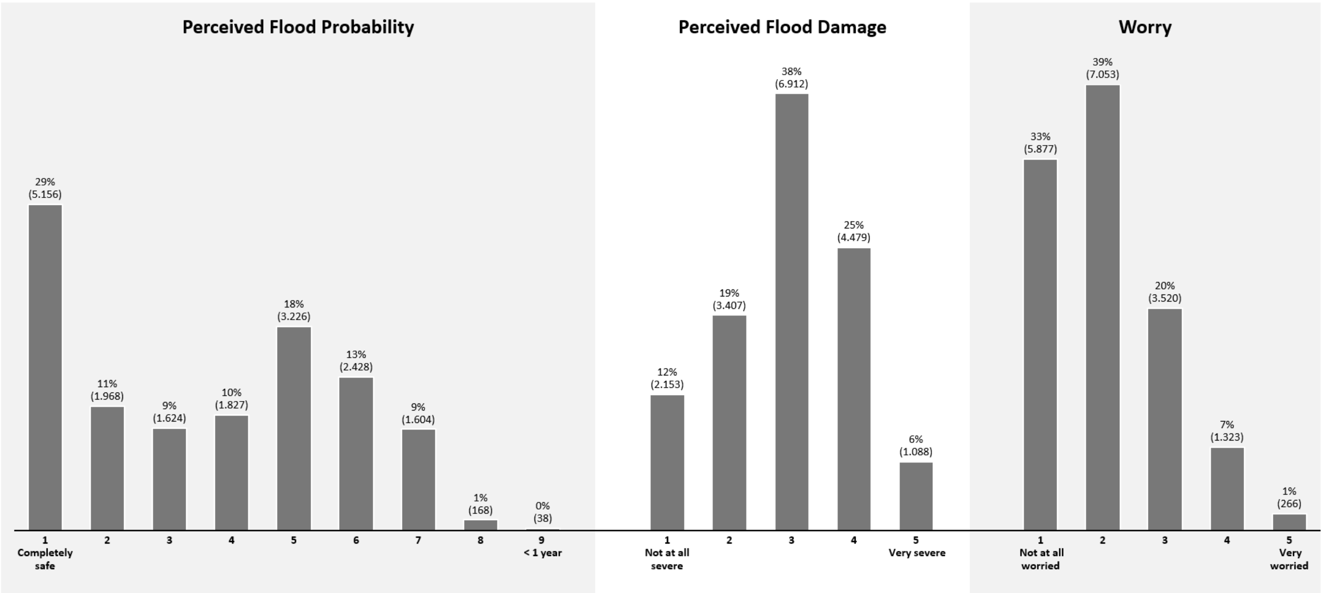
B.5.1.3. Attribute values of synthetic household population

Table 7 summarizes the descriptive statistics of both the PMT and non-PMT attributes of the synthetic household population. The frequency distributions of these attributes are further shown in more detail in the histograms in this subchapter.

Table 7: Descriptive statistics of synthetic household population attributes (n=18039) (Source: Adjusted from Noll, Filatova, Need, et al. (2022))

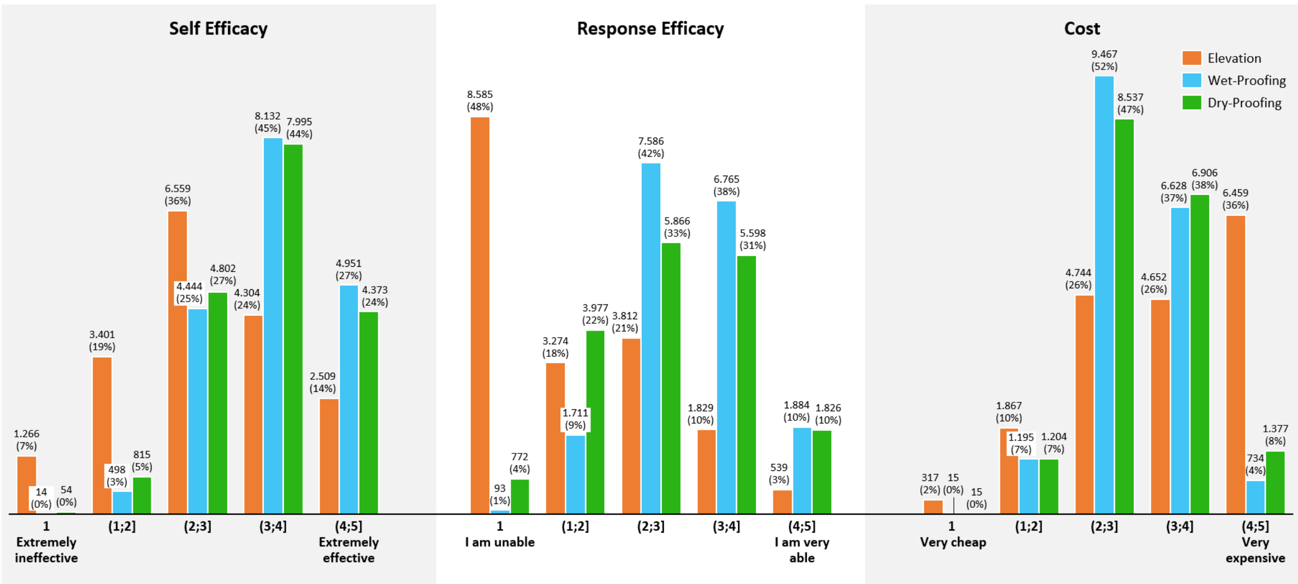
	Construct (Abbreviation)	**Questions**	**Response Options**	**Descriptive statistics** μ	*s.d.*
PMT	Flood Probability (Fl Prob)	How often do you think a flood occurs on the property on which you live (e.g., due to rivers or heavy rain, storms and cyclones)? Which category is the most appropriate?	*9-point scale* • My house is completely safe • Less often than 1 in 500 years, • Once in 500 years or a 0.2% chance annually, • Once in 200 years or a .5% chance annually, • Once in 100 years or 1% chance annually, • Once in 50 years or a 2% chance annually, • Once in 10 years or 10% chance annually, • Annually ~ 100% chance annually, • More frequent than once per year	3.60	2.16
	Flood Damage (Fl Dam)	In the event of a future major food in your area on a similar scale to [Name of flood depending on country[1]] 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	2.94	1.07
	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	2.06	0.97
	Response Efficacy (Resp Eff)	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** *(Averaged for all measures in the same category)* *(Order: Elevation, Wet-proofing, Dry-proofing)* (1) Extremely ineffective – (5) Extremely effective	3.19 3.61 3.53	1.11 0.76 0.79
	Self Efficacy (Self Eff)	Do you have the ability to undertake this measure either yourself or paying a professional to do so?	*5-point scale** *(Averaged for all measures in the same category)* *(Order: Elevation, Wet-proofing, Dry-proofing)* (1) I am unable – (5) I am very able	2.03 3.10 2.88	1.17 0.79 0.98
	Perceived Cost (Cost)	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** *(Averaged for all measures in the same category)* *(Order: Elevation, Wet-proofing, Dry-proofing)* (1) Very cheap – (5) Very expensive	3.84 2.99 3.13	1.08 0.62 0.68
	Previously undertaken measure(s) (Undergone)	I have already implemented this measure.	Yes (1) or No (0) for each measure *(If Household has implemented ≥ 1 measure in a category, the dummy variable = 1)* *(Order: Elevation, Wet-proofing, Dry-proofing)*	0.03 0.33 0.09	0.17 0.47 0.29
	Flood Experience (Fl Exp)	Have you ever personally experienced a flood of any kind? Please provide an approximation of the financial losses that the last flood or inundation caused to your personal property.	6-point scale (0) None – (6) Very High	0.40	1.12
	Age (Age)	YouGov collected this information prior to the survey	1: [16-24], 2: [25-34], 3: [35-44], 4: [45-54], 5: [55-64], 6: [65+]	2.27	0.99
	Education (Edu)	YouGov collected this information prior to the survey	1: < High School, 2: High School, 3: College Degree, 4: Post Graduate	3.24	0.51
	Beliefs on effects of climate change (C.C. Belief)	There is a lot of discussion about global climate change and its connection to extreme weather events. Which of the following statements do you most agree with?	*Bold response a dummy (0,1)*** • **Global climate change is already happening** • Global climate change isn't yet happening, but we will experience the consequence in the coming decades • Global climate change won't be felt in the coming decades, but the next generation will experience its consequences • Other	0.60	0.49
	Social Influence (Social Inf)	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 strongly expect me to prepare for flooding	2.83	0.99
	Effect of social media on household adaptation (Social Media)	How frequently do you read information about flooding and other hazards from social media? To what extent, if at all, do you trust information about flooding and other hazards on social media?	*5-point scale**** (1) Very infrequently – (5) Very frequently (1) Do not trust at all – (5) Trust completely	3.09	0.78
Non-PMT	Household Size (HH Size)	How many square meters is your accommodation? If you don't know for sure, please provide your best estimation	• Less than 50 sqm (44) • Between 50 and 75 sqm (63) • Between 76 and 100 sqm (88) • Between 101 and 125 sqm (113) • Between 125 and 150 sqm (138) • More than 151 sqm (181)	100.21 sqm	34.88 sqm
	Household Status (HH Status)	Do you rent or own your accommodation?	0: Rent, 1: Own	0.16	0.37
	Building Type (Build Type)	What category best describes your current home or accommodation?	0: House, 1:Apartment	0.94	0.24
	Social Network Size (Social Net)	Thinking about your friends, families, and neighbours, how many households have taken some adaptive action towards flooding?	0: None of them, 1: One, 2: Two, 3: Three, 4: Four, 5: Greater than or equal to five	1.64	1.70
	Income (Income)	What was your total family income after taxes from all sources last year in 2019?	*(Transformed into € values in 2020)* • Less than 14325 Yuan (1863 €) • Between 14326 and 25625 Yuan (3225 €) • Between 25626 and 35260 Yuan (3959 €) • Between 35261 and 47140 (5359 €) • Between 47141 and 80475 (8299 €) • More than 80475 (10467 €)	8394€	2854€
	Savings (Savings)	With regards to your household's savings, what statement most closely reflects your current household situation?	*(Transformed into € values in 2020)***** • My household has little to no savings. We use practically all of the money we earn each month. • My household has roughly half a month's wages in savings • My household has roughly 1 month's wages in savings • My household has roughly 1.5 month's wages in savings • My household has roughly 2 month's wages in savings • My household has roughly 3 month's wages in savings • My household has 4 or more month's wages in savings	2930€	2080€
	Yearly Change in Savings (Change Savings)	How does your current TOTAL household savings compare to what you expect to have saved in 2 years? By how much do you expect your savings change? If you are not exactly sure please provide your best estimation	Free Text Field*****	72€	655€

[*] Following Noll, Filatova, Need, et al. (2022) we average the response scores of the individual measures included in each measure category.
** Following Noll, Filatova, Need, et al. (2022) we model the belief variable C.C. Belief as a dummy variable instead of using scales.
*** Following Noll, Filatova, Need, et al. (2022) we average probability (media frequency) and affect (media trust).
**** The response options are applied together with the yearly earnings to determine the savings of a household.
***** The response options are applied together with the savings to determine the yearly change in savings.



Total number of households: 18039
Due to rounding percentages may not sum exactly to 100.

Figure 24: Histogram - threat appraisal



Total number of households: 18039
Due to rounding percentages may not sum exactly to 100.
Following Noll et al. (2021) we average the response scores of the individual measures included in each measure category.

Figure 25: Histogram - coping appraisal

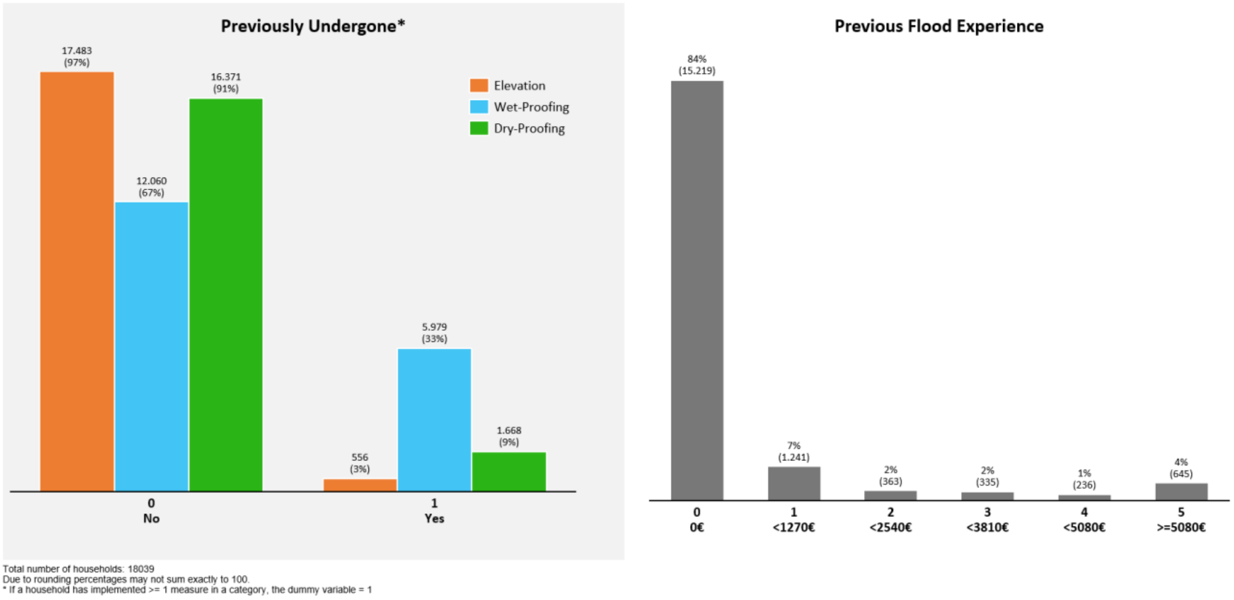


Figure 26: Histogram - preceding flood engagement

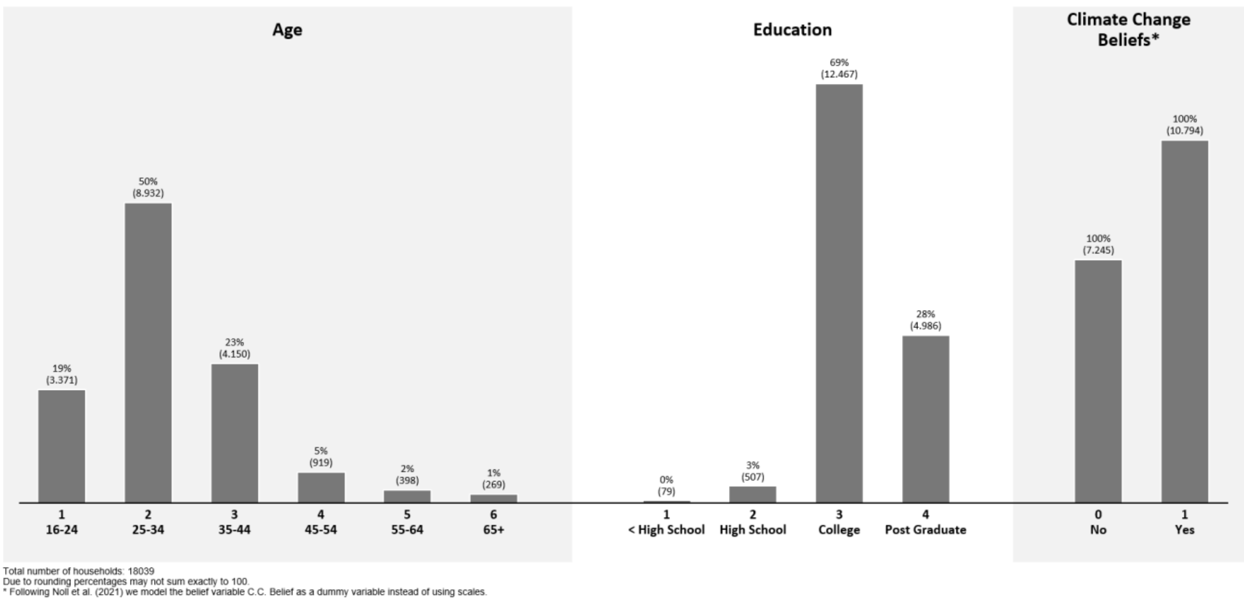
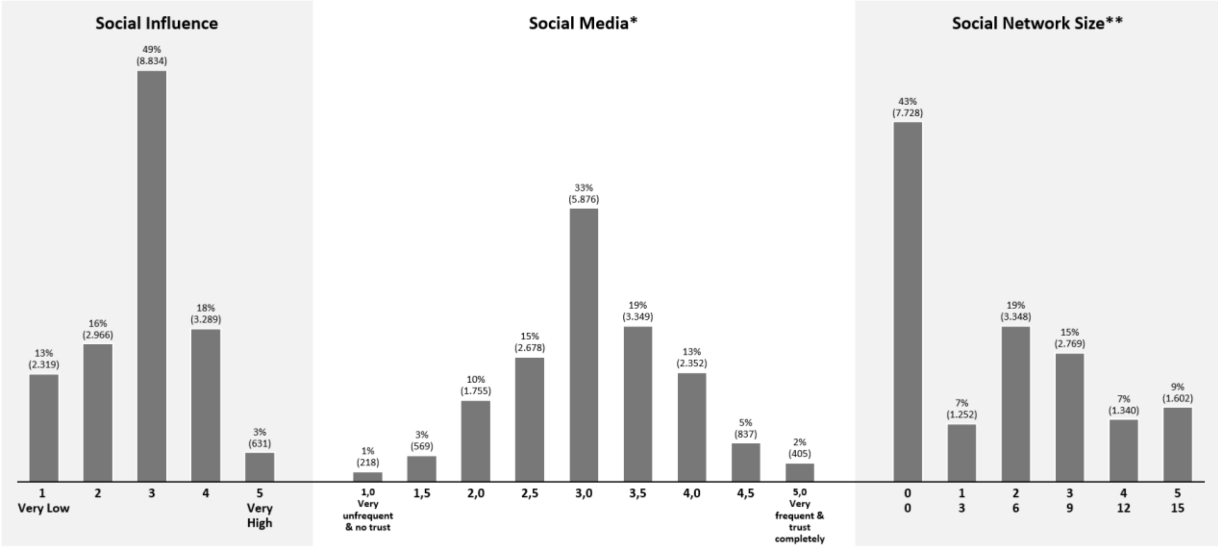
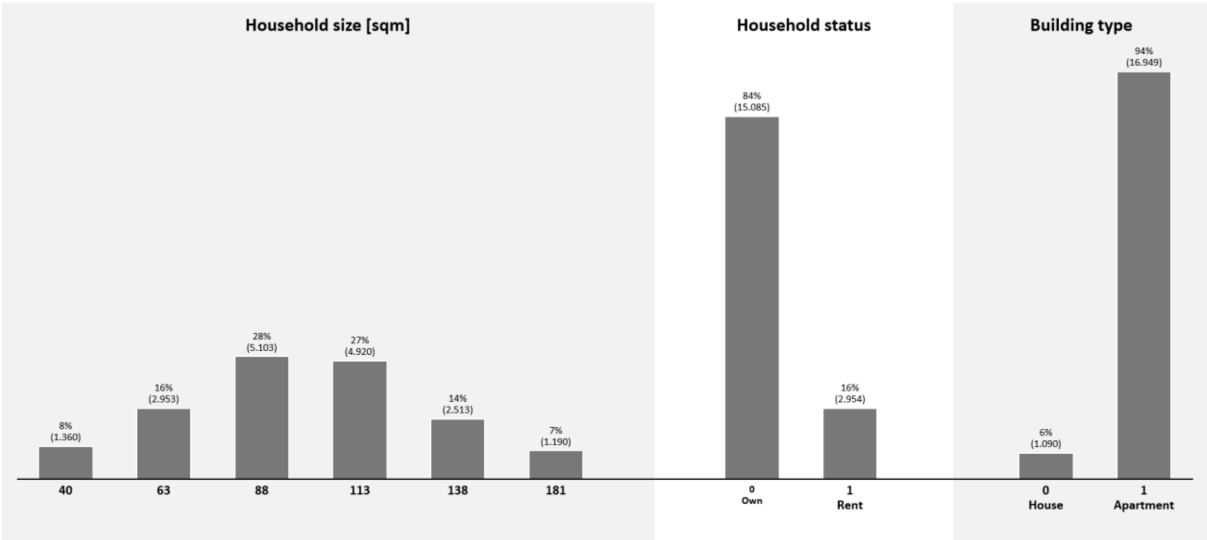


Figure 27: Histogram - social backgrounds and climate beliefs



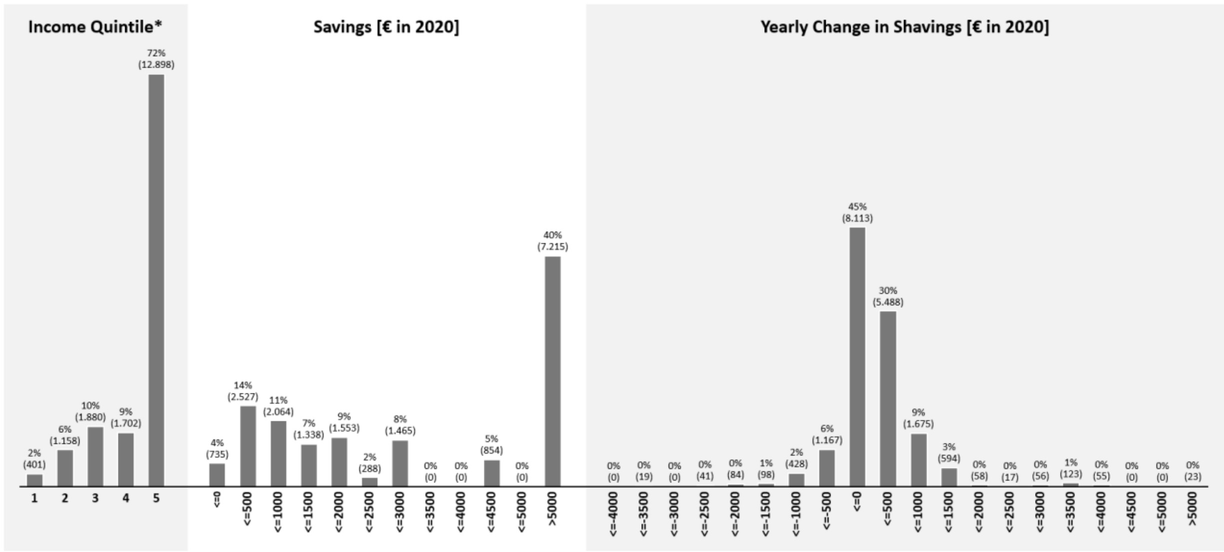
Total number of households: 18039
Due to rounding percentages may not sum exactly to 100.
* Following Noll et al. (2021) we average probability (media frequency) and affect (media trust).
** For each household we know from the survey data the number of households in the social network which have taken some adaptive action towards flooding. From the survey data (933 households) we know the proportion of households in Shanghai which adapted at least one measure (64%), and which did not (36%). By combining these two data points we can estimate the size of the social network for each household. Hence, we assume that the social network size is 3 times the size of the adapted social network

Figure 28: Histogram – external influence



Total number of households: 18039
Due to rounding percentages may not sum exactly to 100.

Figure 29: Histogram – accommodation



Total number of households: 18039
Due to rounding percentages may not sum exactly to 100.
*First Quintile (14325 Yuan), Second Quintile (24793 Yuan), Third Quintile (30443 Yuan), Forth Quintile (41201 Yuan), Fifth Quintile (>=63808 Yuan)

Figure 30: Histogram – economic background

B.5.2. Initialization of other parameters

At model initialization, the implementation finish time of households that start the simulation with an adapted measure is set to a period of 0-9 years before the simulation start following a uniform distribution. Parameters which are not set with values from the input data are set to 0 and changed in the model during the ticks.

B.6. Input Data

The purpose of this subchapter is to create verifiability and replicability for the generation and transformation of the input data. We structure the following subchapters based on the extended risk assessment framework of Aerts et al. (2018): (Disaster) Risk assessment, (Disaster) risk reduction, and behavioural factors (and perception).

B.6.1. Risk assessment: Exposure data

B.6.1.1. Location data from the survey

The goal of this analysis is to determine in which districts the survey respondents live. This information can help in the scoping decision on certain districts.

We use the zip codes in the survey data to determine the city districts in which the survey respondents live. 933 households are included in the survey data of which 657 have a zip code. Shanghai zip codes have six digits are in the format of 20xxxx (Shanghaimap360.com, 2022). Based on this information we can determine that 525 of the 627 responses with zip codes are located in a Shanghai district. Of these 525 respondents, we can assign 447 directly to one of the Shanghai districts. The zip code of the other 74 responses appear unidentifiable.

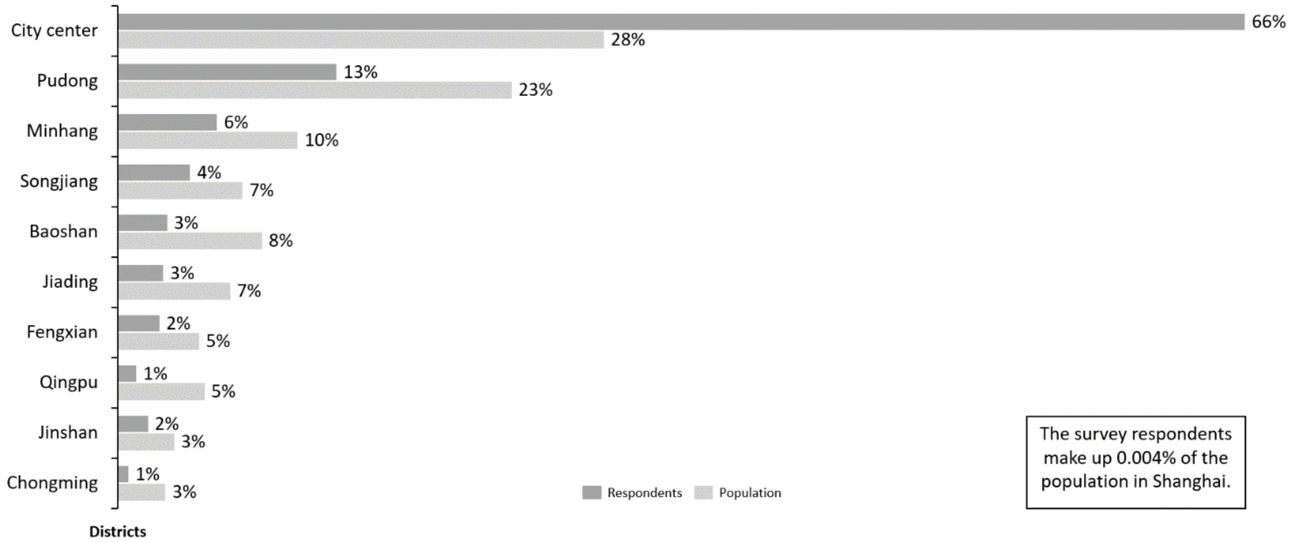


Figure 31: Comparison of the distribution of survey respondents and population in Shanghai (Source: respondents data from Noll, Filatova, Need, et al. (2022), population data form Shanghai Municipal Statistics Bureau (2020))

The results are shown in Figure 31 and compared to the distribution of the Shanghai population which is based on official data from the Shanghai Municipal Statistics Bureau (2020). The results show that two-thirds of the survey respondents are located within the Shanghai City Centre districts, also referred to as Downtown Shanghai. A considerable portion, 23%, lives in Pudong. The comparison with the real-life distribution shows that the share of respondents who reside in the city centre districts is considerably more than the share of Shanghai inhabitants living in the city centre. This insight supports the decision to scope down on the city centre districts, as their behaviour is best captured in the survey data.

However, this analysis is limited in multiple aspects. First, the survey respondents only make up a fraction (0.004%) of the population in Shanghai. Second, the location of 36% of the survey respondents is unknown.

B.6.1.2. OSM building data

As we focus on household adaptation, the scope of this thesis is residential buildings, which are an essential part of the flood risk assessment in Shanghai (Wu et al., 2019; Z. Yin et al., 2011). Government-provided residential building data appears scarce. Instead, the location of residential buildings in Shanghai can be retrieved from Open Stream Map (OSM). OSM is a free digital map of the world, where the data is collected by volunteers (Openstreetmapwiki, 2022). We downloaded the OSM data in March 2022.

However, the OSM data shows some deficits concerning the labelling of the buildings:

- **Residential vs Non-residential**: 53 % of the buildings in entire Shanghai are not labelled regarding their building use (residential/non-residential) in OSM. Hence, we use official statistics of the Shanghai Municipal Statistics Bureau (2020) to label the unlabelled buildings in such a way that the distribution of residential/non-residential buildings in OSM matches the real-life data.
- **Apartment vs House**: 56% of the buildings we consider residential are not labelled regarding their building type (house/apartment). Again, we use official statistics of the Shanghai Municipal Statistics Bureau (2020) to label the unlabelled buildings in such a way that the distribution of house/apartment residential buildings in OSM matches the real-life data.

These two data transformation steps are described in detail in the following subchapters.

B.6.1.2.1. Residential vs. Non-Residential Buildings

In Shanghai, OSM depicts 69.539 buildings of which 27.008 are labelled as residential buildings and 5.799 as non-residential buildings. The remaining 53% of the buildings are not labelled in terms of their building use (residential/non-residential) – see Figure 32.

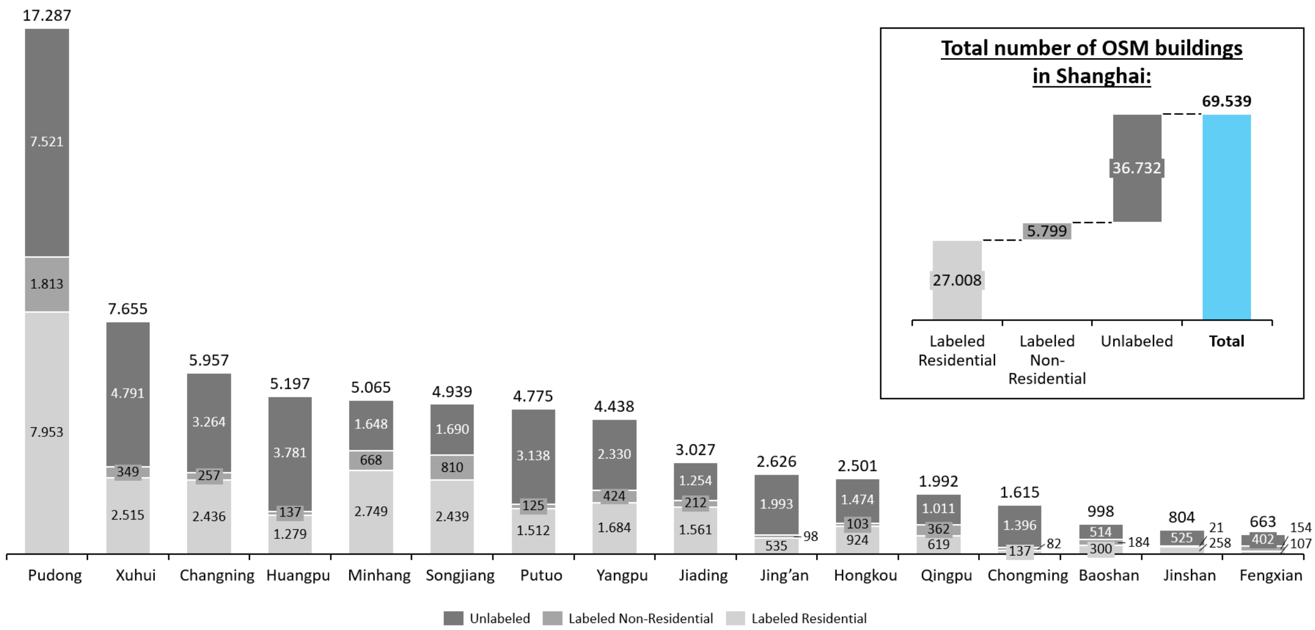


Figure 32: Pre-adjusted distribution of OSM buildings in Shanghai districts (Source: data from OpenStreetMap (2022))

Hence, for each district, we label the unlabelled OSM buildings using the real-life frequency distributions of residential and non-residential buildings from the Shanghai Municipal Statistics Bureau (2020) (see Figure 33).

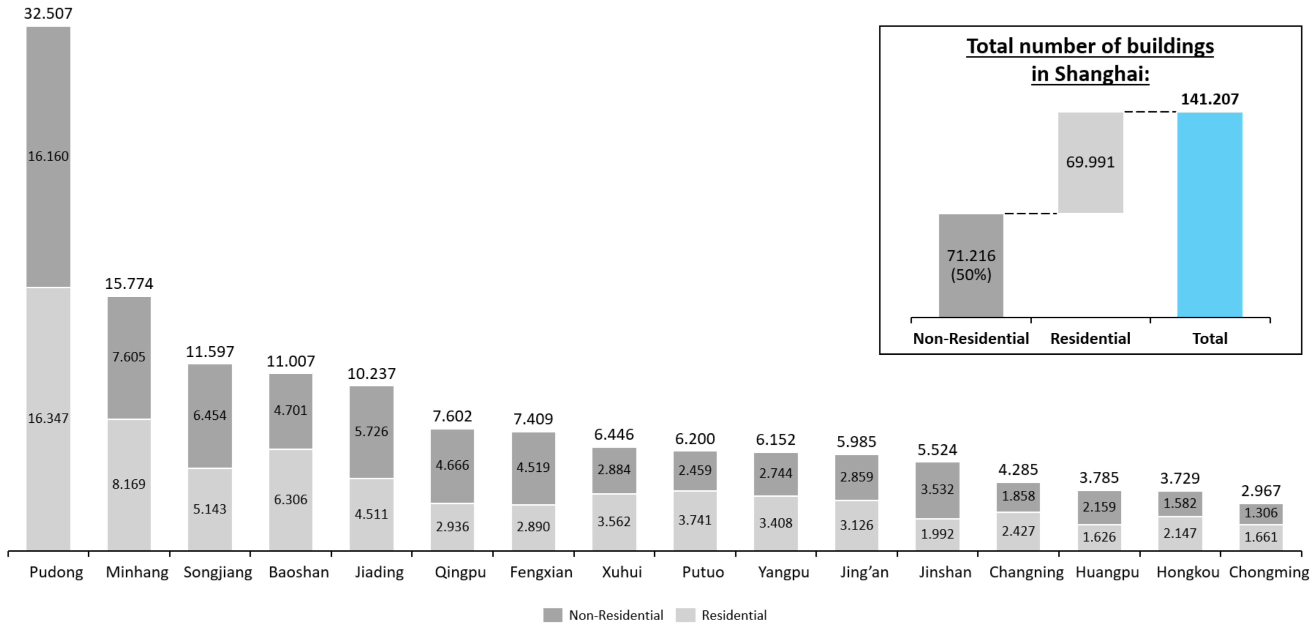


Figure 33: Real distribution of buildings in Shanghai districts (Source: data from Shanghai Municipal Statistics Bureau (2020))

Figure 34 shows the resulting distribution of the OSM buildings after the additional labelling of the building type.

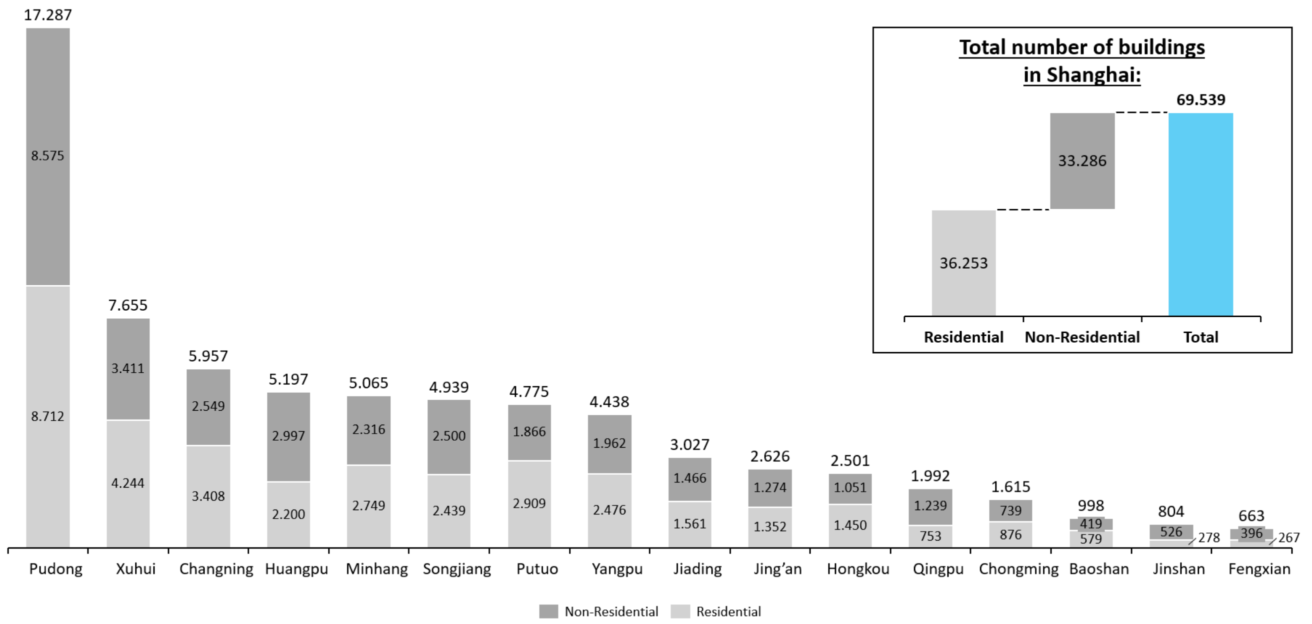


Figure 34: Adjusted distribution of OSM buildings in Shanghai districts (Source: data adjusted from OpenStreetMap (2022))

The comparison of the adjusted OSM data with the official government statistics (see Figure 35) reveals the accuracy of the OSM residential building data. Overall, 48% of the residential buildings are depicted in OSM in terms of the number of buildings. Figure 35 shows that the mapping accuracy differs greatly for the different districts. While the city centre districts (Huangpu, Changning, Putuo, Yangpu, Xuhui, Jing 'an, and Hongkou) show an accuracy of 90%, districts such as Boashan or Fengxian have a 9% accuracy.

The low overall mapping accuracy of residential buildings might be linked back to the Surveying and Mapping Law of the People's Republic of China, which prohibits private surveying and mapping activities (National People's Congress, 2022). We can overcome this problem by scoping down on the districts with high mapping accuracy.

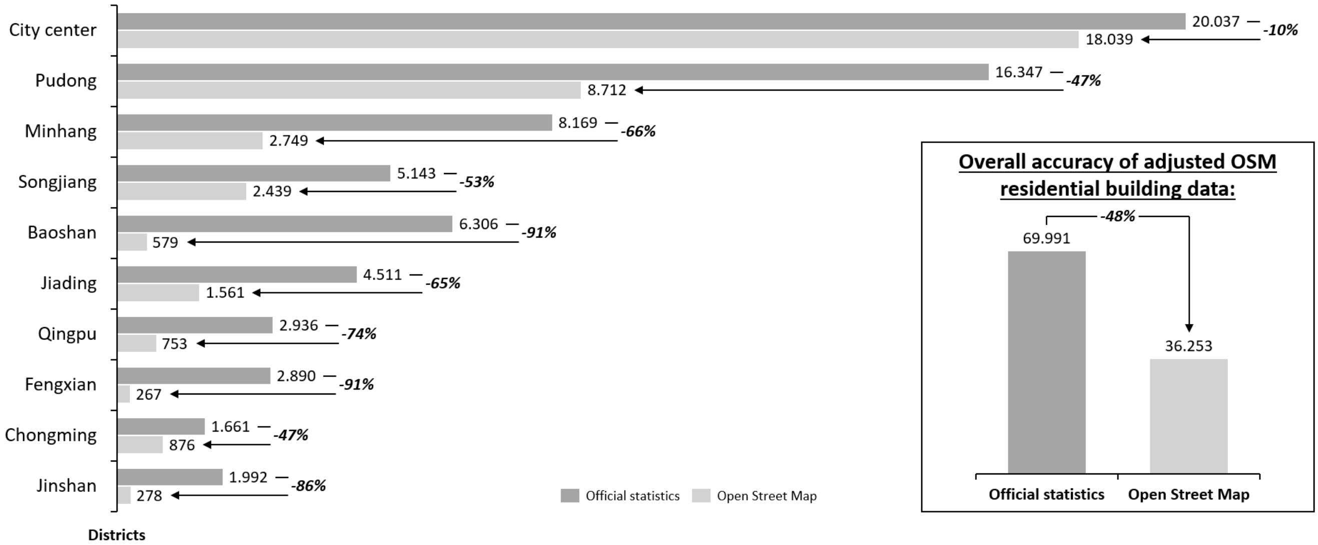


Figure 35: Comparison of adjusted residential building data with government statistics (Source: building data adjusted from OpenStreetMap (2022), official statistics from Shanghai Municipal Statistics Bureau (2020))

B.6.1.2.2. Apartment vs. House

The survey data of Noll, Filatova, Need, et al. (2022) which is used to depict the behaviour of the household distinguishes the type of residential building (house/apartment) the households live in. Hence, we also want to distinguish the residential buildings in OSM into houses and apartments. OSM also allows distinguishing different residential building types via the 'building' key (Openstreetmapwiki, 2022). As depicted in Table 8, we use the description Openstreetmapwiki (2022) to assign the different building key values to three building categories: House, Apartment, and Unidentified.

Table 8: Differentiation between houses and apartments using building key in OSM (Source: values and descriptions from Openstreetmapwiki (2022))

Value	Description (Openstreetmap Wiki, 2022)	Assigned category
Apartments	"A building arranged into individual dwellings, often on separate floors. May also have retail outlets on the ground floor."	Apartment
Bungalow	"A single-storey detached small house, Dacha."	House
Cabin	"A cabin is a small, roughly built house usually with a wood exterior and typically found in rural areas."	House
Detached	"A detached house, a free-standing residential building usually housing a single family."	House
Dormitory	"A shared building intended for college/university students"	Apartment
Farm	"A residential building on a farm (farmhouse)."	House
Ger	"A permanent or seasonal round yurt or ger."	House
House	"A dwelling unit inhabited by a single household (a family or small group sharing facilities such as a kitchen)."	House
Residential	"A general tag for a building used primarily for residential purposes. "	Unidentified
Semidetached_house	"A residential house that shares a common wall with another on one side. Typically called a "duplex" in American English"	House
Static_caravan	"A mobile home (semi)permanently left on a single site"	House
Terrace	"A single way used to define the outline of a linear row of residential dwellings, each of which normally has its own entrance, which form a terrace ("row-house" or "townhouse" in North American English). "	House
Yes	"Use this value where it is not possible to determine a more specific value"	Unidentified

Figure 36 shows the resulting distribution of the residential building types in Shanghai. From the 36.253 residential buildings, 10.858 are labelled as apartment buildings and 5.040 as houses according to our definition. The remaining 20.355 residential buildings are unlabelled, as they either have the key Building=Residential OR Building=Yes, which does not provide information on the type of the residential building.

Hence, we apply the same approach as before with the residential/non-residential building data transformation. For each district, we label the unlabelled OSM residential buildings using the real-life frequency distributions of houses and apartment buildings from the Shanghai Municipal Statistics Bureau (2020) (Figure 37). In reality, 93% of the residential buildings are apartments and 7% are houses.

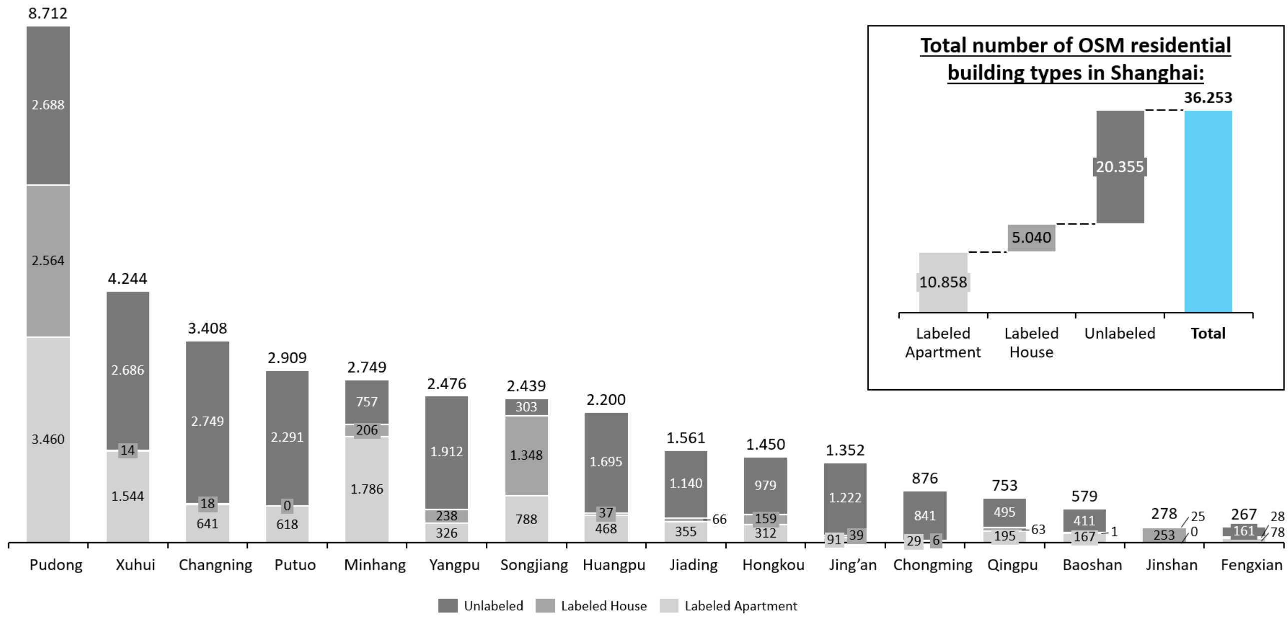


Figure 36: Pre-adjusted distribution of residential building types in Shanghai districts (Source: data from OpenStreetMap (2022))

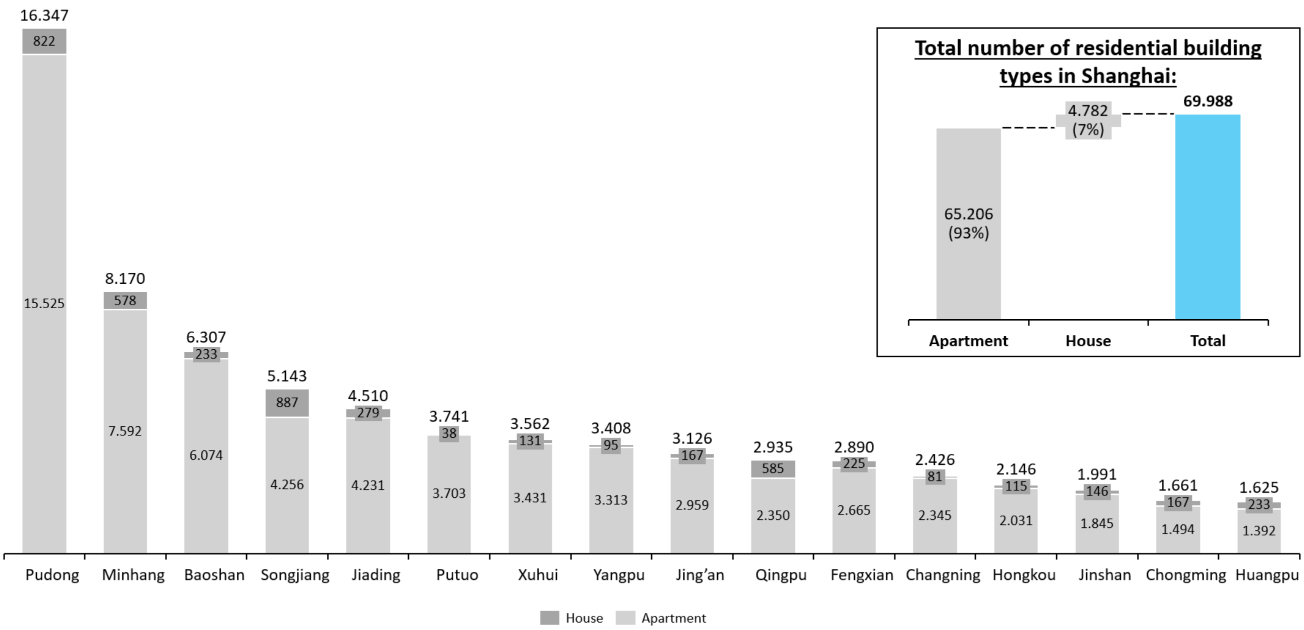


Figure 37: Real distribution of residential building types in Shanghai districts (Source: data from Shanghai Municipal Statistics Bureau (2020))

The resulting distribution of apartments and houses for the different Shanghai districts is shown in Figure 38. Here, 84% of the residential buildings are apartments and 16% are houses. This means that the share of houses in our transformed data is about twice as large as in reality. This can be explained by the fact that the share of labelled houses in OSM is very high (5040 ~ 14%) – see Figure 36.

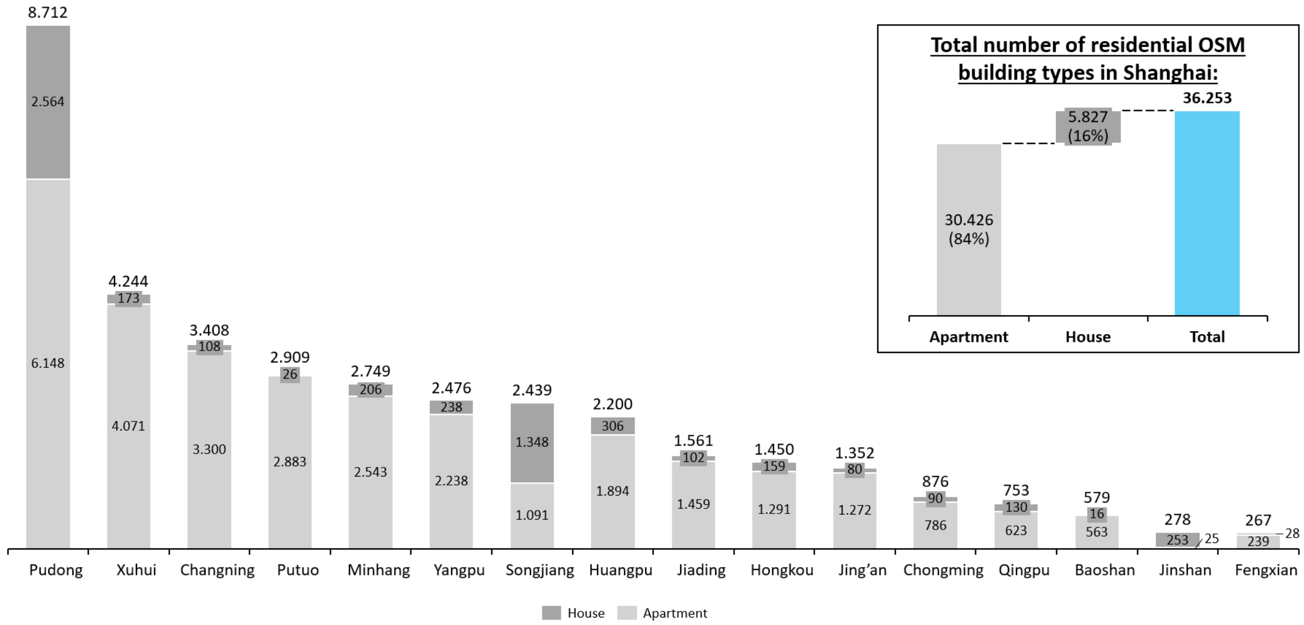


Figure 38: Adjusted distribution of OSM residential building types in Shanghai districts (Source: data adjusted from OpenStreetMap (2022))

To verify the accuracy of our transformed data, we compare the number of apartments and houses in each district with the official data from the Shanghai Municipal Statistics Bureau (2020) – see Figure 39 and Figure 40.

Regarding the apartments, our comparison shows that across all the Shanghai districts we only map 47% of the apartment buildings in terms of the number of buildings (see Figure 39). The city centre districts such as Xuhui, Putuo, Yangpu, Hongkou, and Huangpu show the lowest deviations.

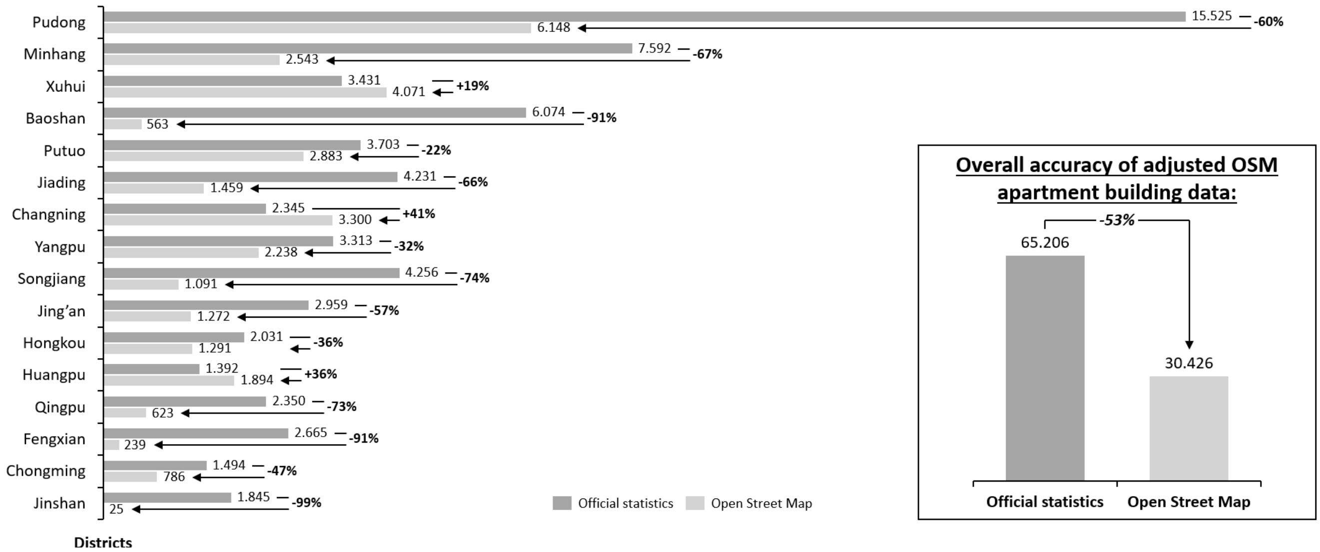


Figure 39: Comparison of adjusted distribution of residential apartment buildings from OpenStreetMap (2022) with government statistics from Shanghai Municipal Statistics Bureau (2020).

The comparison of the distribution of residential houses in OSM with official government statistics highlights that proportionally more houses (22%) are included in our model than in real-life (Figure 40). For the ABM results, this would mean that the effectiveness of the elevation measure, which is assumed not possible for apartments, might be overestimated.

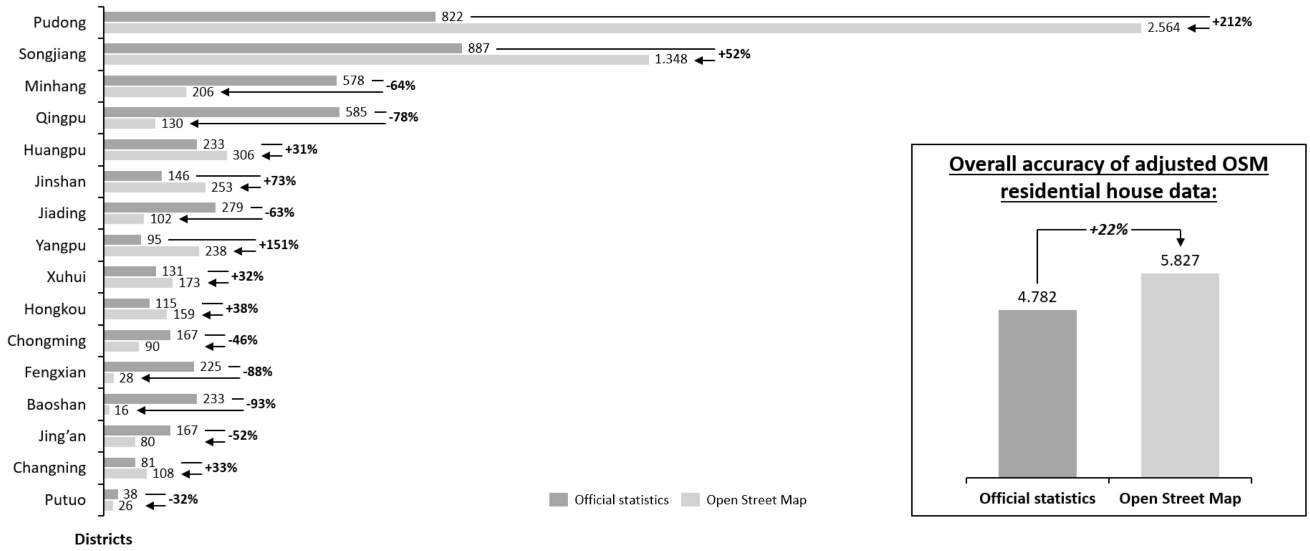


Figure 40: Comparison of the adjusted distribution of residential houses from OpenStreetMap (2022) with government statistics from Shanghai Municipal Statistics Bureau (2020).

To summarize, Figure 41 shows the categorized OSM buildings in the Shanghai districts.

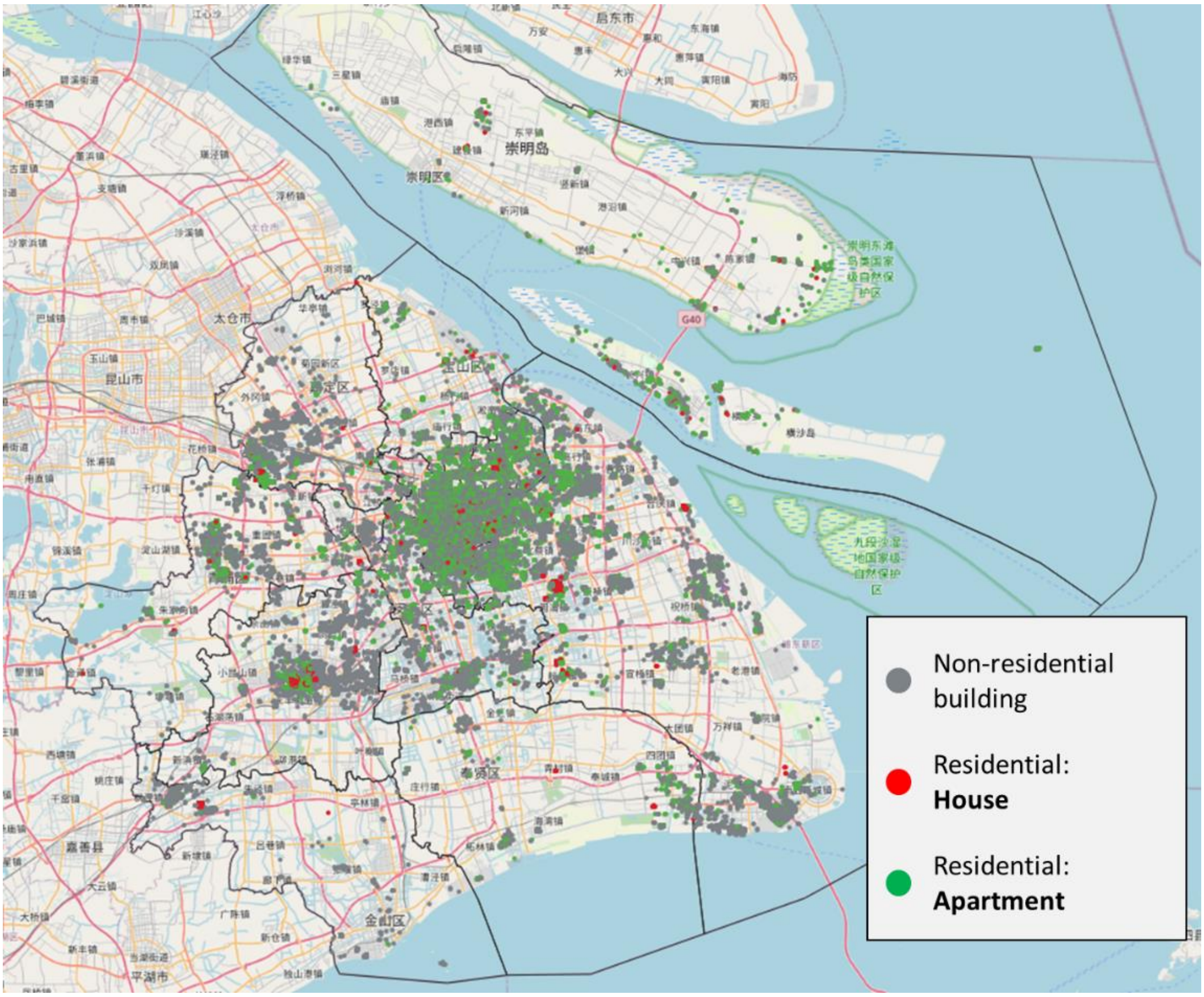


Figure 41: Adjusted OSM building types in Shanghai districts illustrated in QGIS (Source: data adjusted from OpenStreetMap (2022))

B.6.1.3. Exposure of residential buildings of Shanghai districts

By overlaying the location of the residential buildings of OSM with the inundation maps of Yin et al. (2020) in QGIS, we determine the inundation levels of each residential building in Shanghai for each of the 21 flood scenarios. It is important to note that we consider households flooded if the inundation level is larger than 10 cm, which we assume to be the building foundation height.

We analyse the inundation depths of the residential buildings under the different flood scenarios as this provides important information for the experimental setup. On the one hand, we are interested in the difference in the number of inundated households between the Shanghai districts. On the other hand, we are interested in how the type of the different flood scenarios which are defined by the probability of the flood (10-year, 100-year, 1000-year), the year in which the flood occurs (2010, 2030, 2050, 2100), and the Representative Concentration Pathway (RCP 8.5, RCP 2.6) influence the inundation depths of the residential buildings in Shanghai.

B.6.1.3.1. Exposure of residential buildings in Shanghai

The Shanghai districts are exposed differently to the flood scenarios. According to Yin et al. (2020, p.10) "the most susceptible areas to the magnified flood hazard are Chongming island and the Huangpu River floodplain including the city centre, where the inundation distance exceeds 10–20 km inland". We are interested in what this means for the difference in the number of inundated residential buildings in the districts. Figure 42 and Figure 43 depict the distribution of the number of inundated buildings for the RCP 8.5 and the RCP 2.6 scenario respectively.

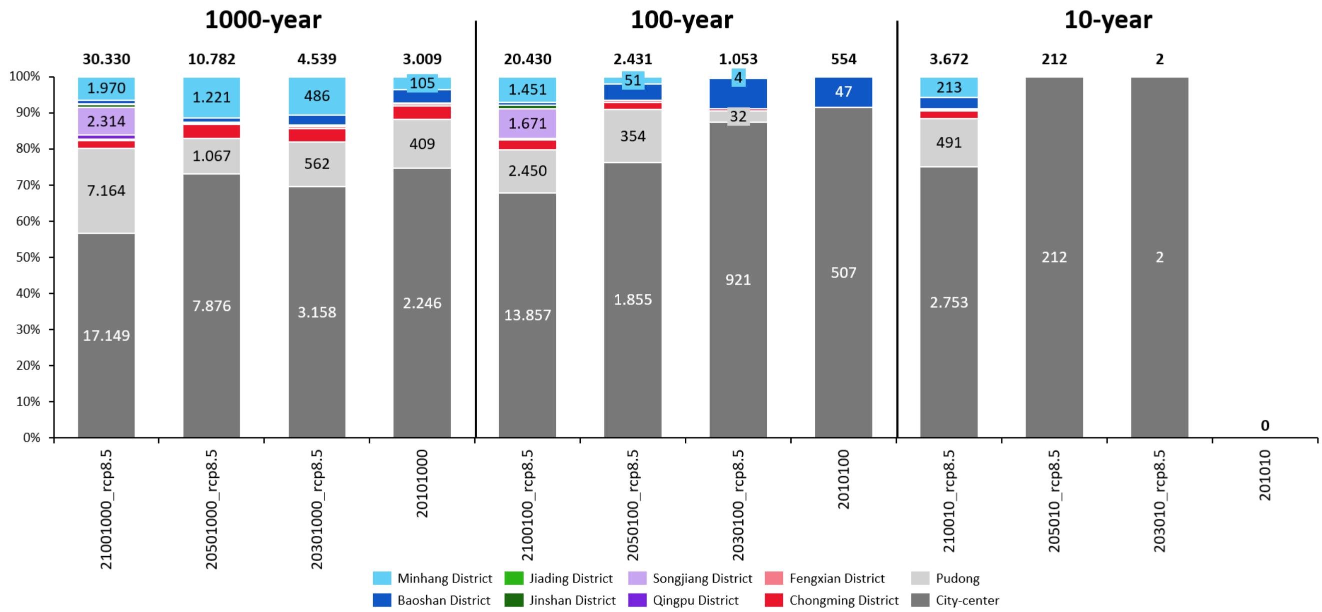


Figure 42: Proportional and absolute distribution of inundated residential buildings (RCP 8.5) (Source: inundation data adjusted from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

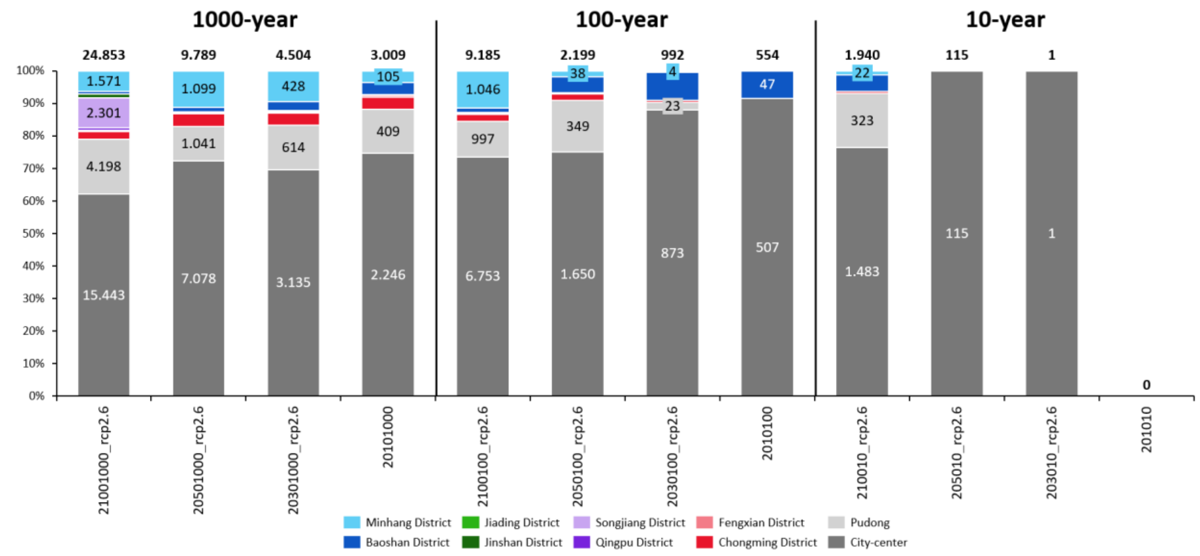


Figure 43: Proportional and absolute distribution of inundated residential buildings (RCP 2.6) (Source: inundation data adjusted from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

The results show that the distribution only changes slightly between the RCP 8.5 and the RCP 2.6 scenarios. Regarding the distribution between the districts our analysis highlights that the residential buildings in the city centre (grey colour) are most exposed to the floods, accounting for 55-100% of the inundated residential buildings depending on the flood scenario. On the one hand, this can be explained by the fact that the city centre districts make up 48.7% of the residential buildings in our data (see the previous subchapter). On the other hand, the city centre districts are among the most exposed to the flood scenarios according to Yin et al. (2020).

The distribution of the number of flooded households in the city centre districts is depicted in Figure 44. The Xuhui District (dark blue colour) is most prominent for 2010, 2030 and 2050 scenarios. In the 2100 scenario, also other districts such as Changning, Putuo, or Yangpu are impacted. Huangpu (light blue colour) also has a considerable portion (~10-30% depending on the scenario) of inundated residential buildings. The prominence of Xuhui and Huangpu can be explained by the fact that they are located directly next to the Huangpu river and are therefore directly affected during floods - see also Figure 3 of Yin et al. (2020).

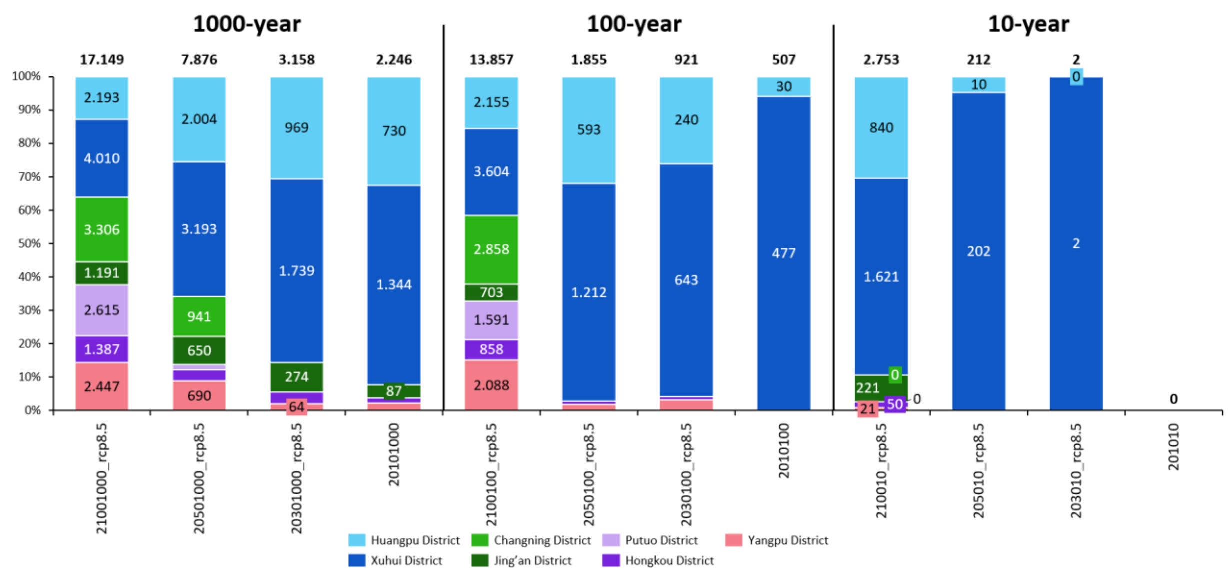


Figure 44: Inundated residential buildings for city centre districts (RCP 8.5) (Source: inundation data adjusted from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

As we want to understand the influence of floods on household adaptation, we need to select a set of districts which have exposure to floods. As a result, we choose the city centre districts as the geographical scope within Shanghai. To design a reasonable experimentation plan we analyse the inundation depths of the residential buildings in the Shanghai city centre in more detail in the following subchapter.

B.6.1.3.2. Exposure of residential buildings in the Shanghai city centre

Figure 45 shows the impact of a 1000-year flood under the RCP8.5 and RCP2.6 scenarios in 2010, 2030, 2050, and 2100. The 1000-year flood already has a considerable impact in 2010 with ~12% of 18.039 residential buildings inundated. With an increase in years, the effects of sea-level rise and land subsidence lead to more severe floods - see Yin et al. (2020) – and hence to an increase in the number of inundated residential buildings. Moreover, with an increase in years, the differences between the RCP scenarios in terms of number of inundated residential buildings and the depth of inundation itself become larger. In 2100, 95% of residential buildings are flooded under the RCP 8.5 scenario, and 86% under the RCP 2.6 scenario.

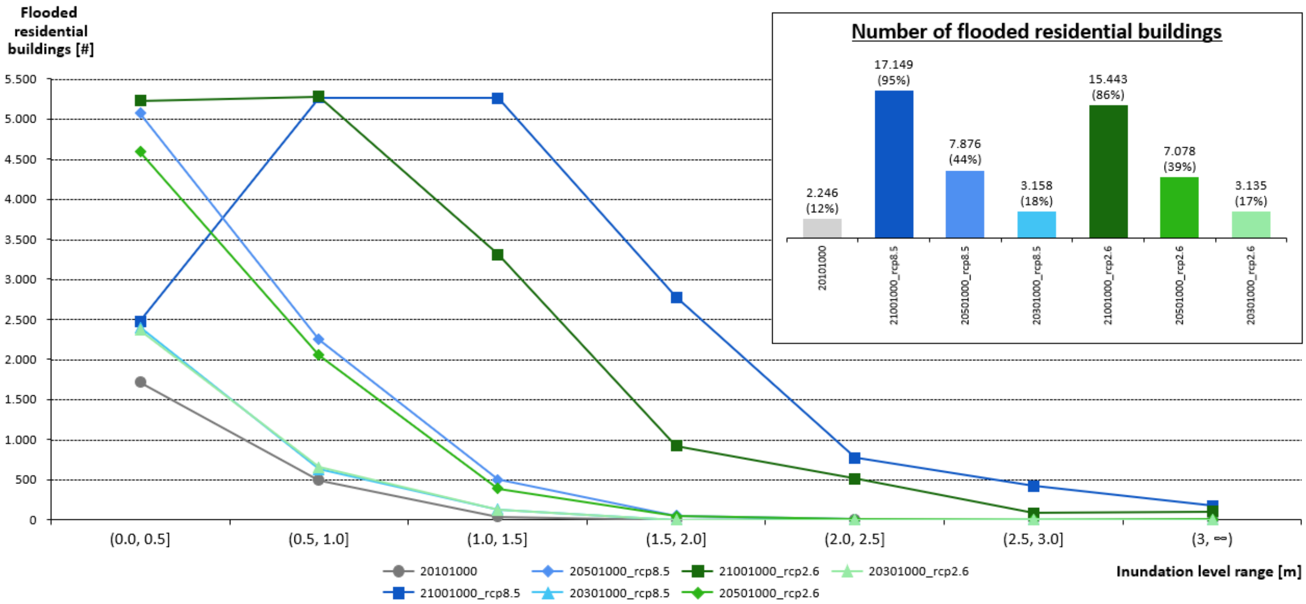


Figure 45: Comparison of RCP 8.5 with RCP 2.6 scenario for 1000-year floods (Source: inundation data adjusted from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

In Figure 46 the impact of a 100-year flood is shown. While the flood barely has any impact in 2010, and a measurable but rather small impact of less than 10% in 2030 and 2050, the number of inundated households increases sharply to 77% in 2100 for the RCP 8.5 and 37% for the RCP 2.6 scenario because of sea-level rise and land subsidence.

The exposure of residential buildings under the 10-year flood is depicted in Figure 47. The influence of this flood on the residential buildings in Shanghai in the years 2010, 2030, and 2050 is very small as less than 1% of the residential buildings are flooded. In 2100, 15% of residential buildings are flooded under the RCP 8.5 and 10% under the RCP 2.6 scenario.

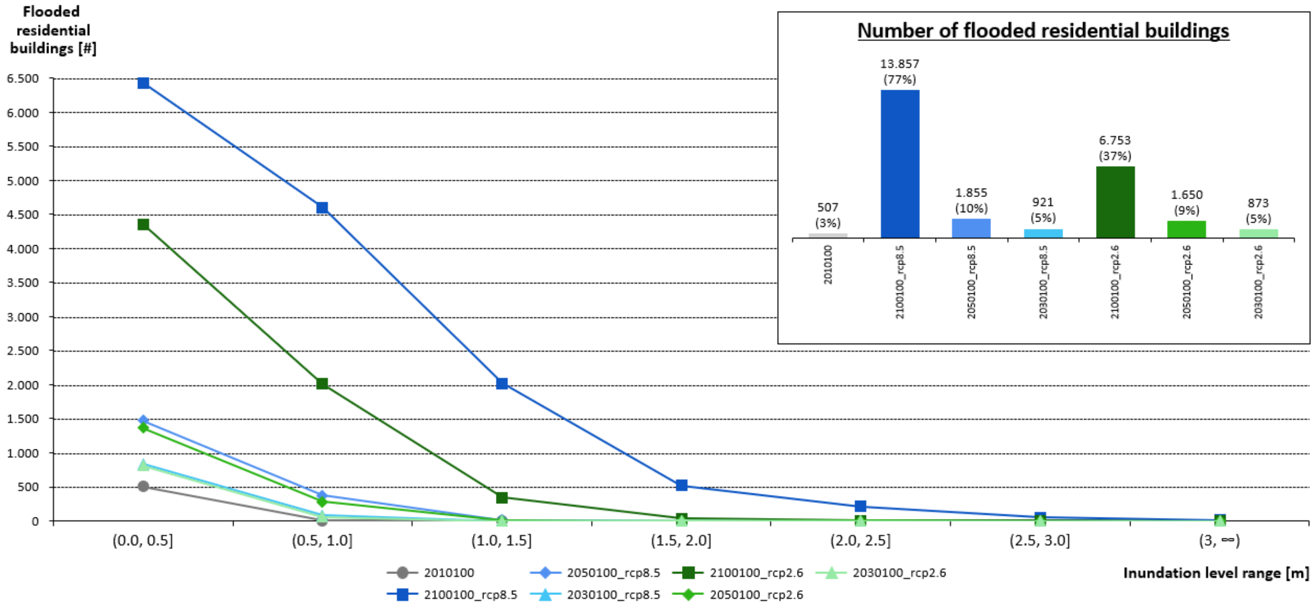


Figure 46: Comparison of RCP 8.5 with RCP 2.6 scenario for 100-year floods (Source: inundation adjusted data from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

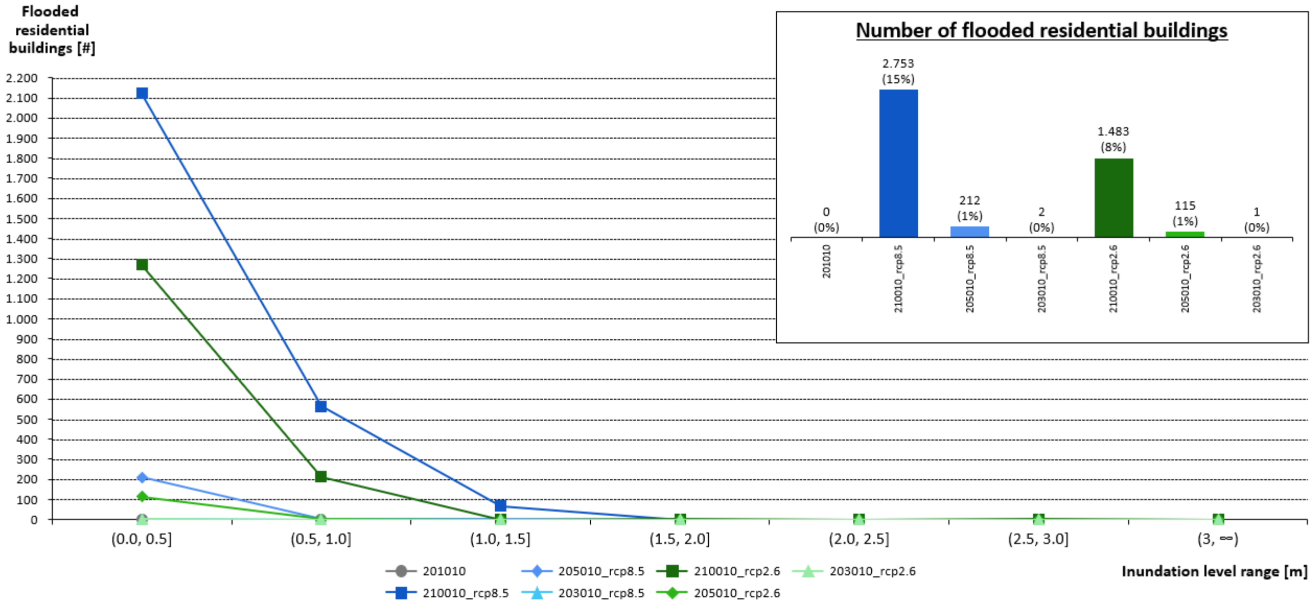


Figure 47: Comparison of RCP 8.5 with RCP 2.6 scenario for 10-year floods (Source: inundation data adjusted from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

When comparing the 10-, 100- and 1000-year flood events, we notice that a 10-year flood in 2100 under the RCP 8.5 scenario floods more residential buildings than a 100-year flood in 2050 or a 1000-year flood in 2010. This highlights again the large effects of climate change in the form of sea-level rise and land subsidence on the exposure of households in Shanghai and underlines the need for further household adaptation in the Shanghai city centre.

B.6.1.4. Asset Values

Within our model we differentiate building and content values.

B.6.1.4.1. Building Value

We assume households would rebuild their residential building if their building were damaged. Therefore, construction costs are of interest to determine the replacement value. This is in line with the suggestions of with Huizinga et al. (2017). To determine the construction costs we follow Wu et al. (2019) and determine the construction cost per square meter using official data from the Shanghai Municipal Statistics Bureau (2020). Specifically, we divide the value of the buildings completed by the floor area completed (see Table 9).

Table 9: Calculation of construction costs based on data for residential buildings (Source: in table)

Floor Area Completed (10 000 sqm) 2019	Value of Building Completed (100 million yuan) 2019	Construction cost [yuan/sqm] 2019	Construction cost [eur/sqm] 2020
1453.28	965.31	6642	861

Note: Approach similar to Wu et al. (2019); average exchange rate 2019 from European Central Bank; Data from SMSB (2020); Data for residential buildings used

Our calculation for previous years shows that the construction costs increased by 72% between 2010 and 2019 and by 20% between 2015 and 2019. This highlights the importance to use a contemporary value.

To verify our construction costs, we compare them with values used in other flood risk assessment studies in Shanghai – see Table 13 and Figure 48. The comparison shows that our construction costs are approximately 30% larger than the ones used in other flood risk assessments in Shanghai. This might be traced back to the increase in construction costs over the last years.

A limitation of using the construction value per sqm of floor area for our case study is that a majority of the buildings in Shanghai are multi-story apartment blocks (Shanghai Municipal Statistics Bureau, 2020). The construction cost per sqm of the multi-story apartment might not reflect the cost per sqm of the first building floor. The building values might therefore be overestimated.

Table 10: Comparison of construction costs with values from the literature (Source: in table)

Source	Construction cost [eur/sqm] 2020
SMSB (2020)	861
Ke (2014)	645
Z. Yin et al. (2011)	683

Note: Values adjusted to inflation and multiplied with respective average yearly exchange rate

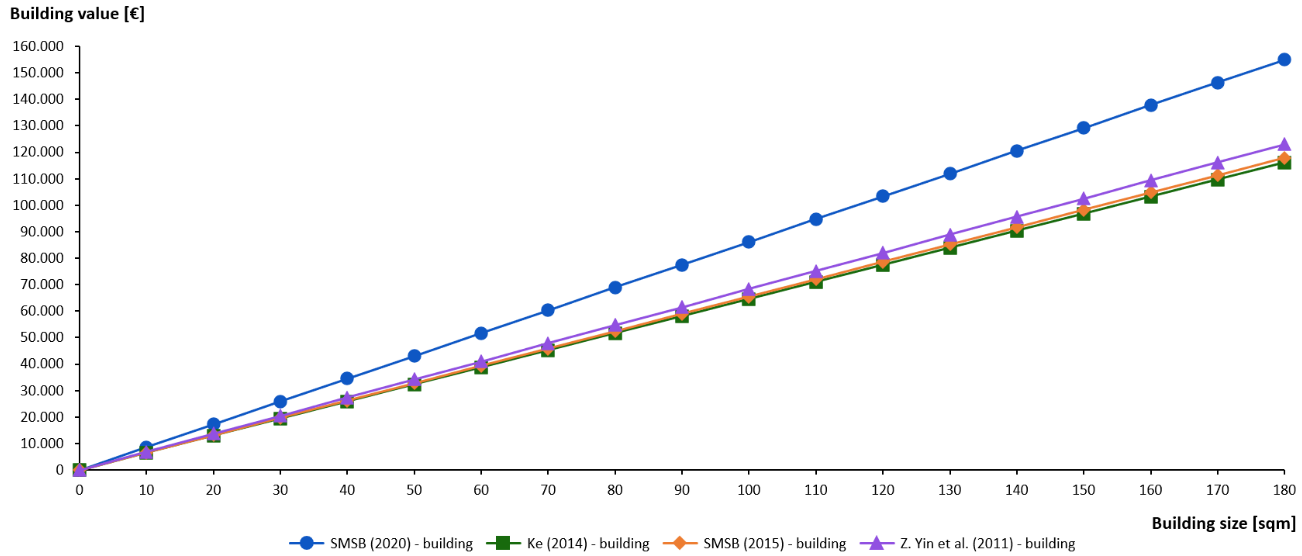


Figure 48: Comparison of building values (Source: Data adjusted from Ke (2014), Shanghai Municipal Statistics Bureau (2020), and Z. Yin et al. (2011))

To determine the total value of a residential building, we require the building size. Within the survey, households can indicate the size of their accommodation. The respective frequency distribution is shown in Figure 49. The average building size of the survey participants is 98.9 sqm/household. According to China's National Bureau of Statistics (2016), the per capita residential building area in Chinese cities (urban areas) is 36.6 in 2016 (China Banking News, 2017). With ~2.69 people per household in Shanghai in 2017 (Shanghai Municipal Statistics Bureau, 2020), this leads to 98,45 sqm/household, which is almost identical to the mean of our distribution. This validates the use of the distribution of our survey for the household size. We apply this data to generate the building values of the households.

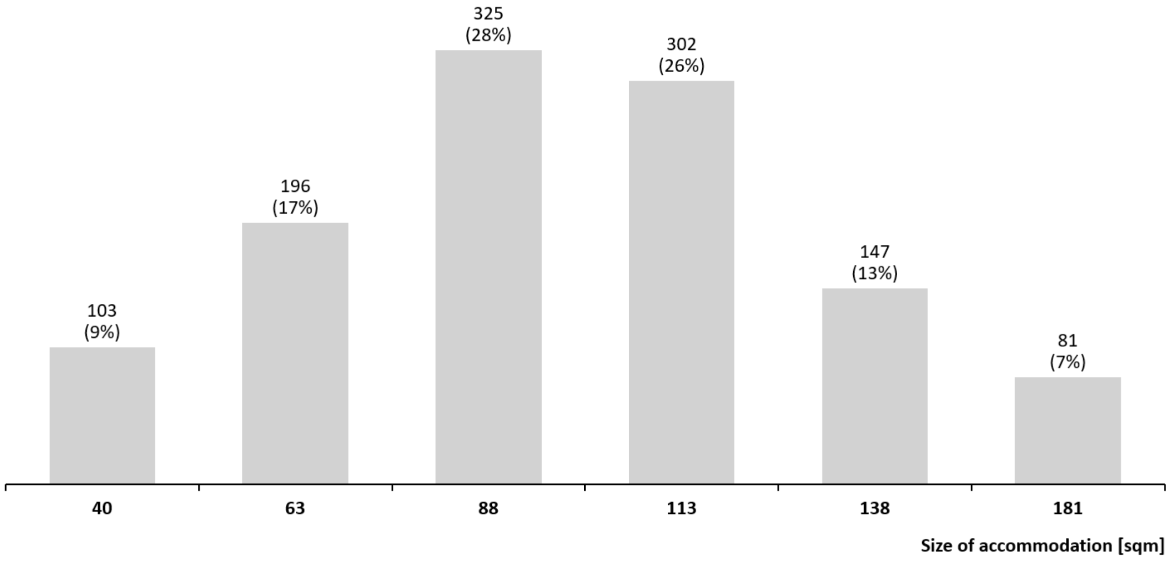


Figure 49: Distribution of accommodation size of survey participants (Source: survey data adjusted from Noll, Filatova, Need, et al., 2022)

B.6.1.4.2. Content Value

Ke (2014) uses popular household items which are fragile to inundation to determine the household content value by multiplying the items in the inventory from official survey results with price estimations. As the content values gathered by Ke (2014) are based on popular household items such as refrigerators, washing machines, TVs, etc. we assume that these items are possessed by the smallest building class of 44 sqm. Moreover, we assume that with an increase in household size the value of the building content increases. Hence, we calculate the ratio between the building value for the 40 sqm building and the overall content cost. This leads to a content value of 209 EUR/sqm or 24% of the building value. We can then use this ratio to calculate the content values for the remaining building classes.

The difference between the fixed content value of Ke (2014) and our approach is illustrated in Figure 50. Especially with higher building sizes, the content value is considerably different. It is to be noted that we adjusted the values of Ke (2014) to inflation and change in currency.

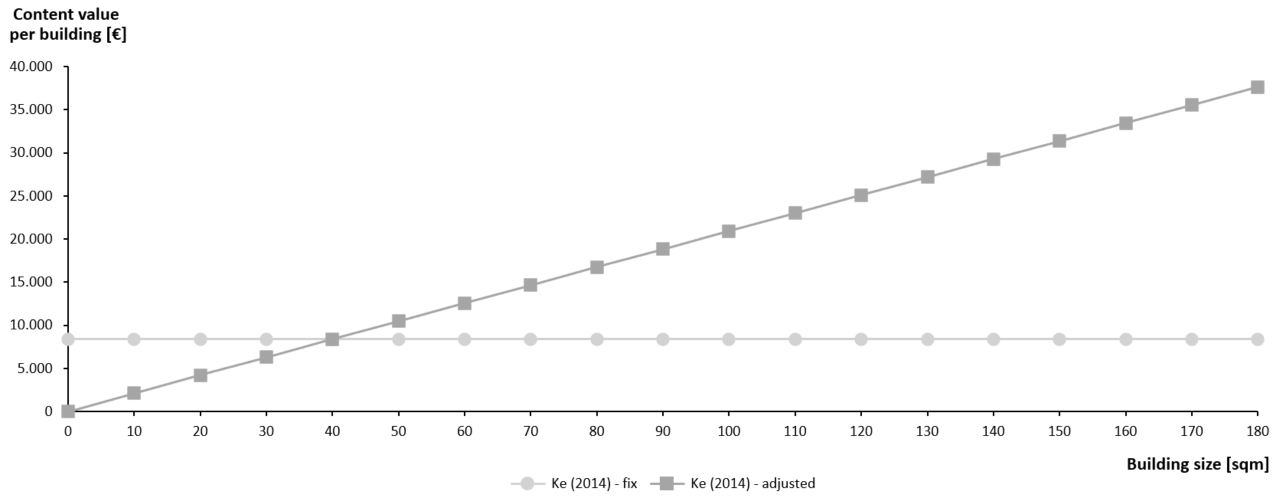


Figure 50: Comparison of content values (Source: data adjusted from Ke (2014))

B.6.1.5. Validation of residential building exposure

Based on the number of inundated buildings (see the Appendix B.6.1.3.2) and the asset values[22] (see the Appendix *B.6.1.4*) we determine the exposed assets in the Shanghai city centre in monetary terms for validation purposes – see Figure 51. The results show a total exposure of residential buildings of up to 1.8 Bil. Euros (10^9) under a 1000-year flood in the RCP 8.5 scenario in 2100.

[22] Calculation is based on an average building size of 98.9 sqm: Average building value of 85153 EUR and content value of 20670 EUR.

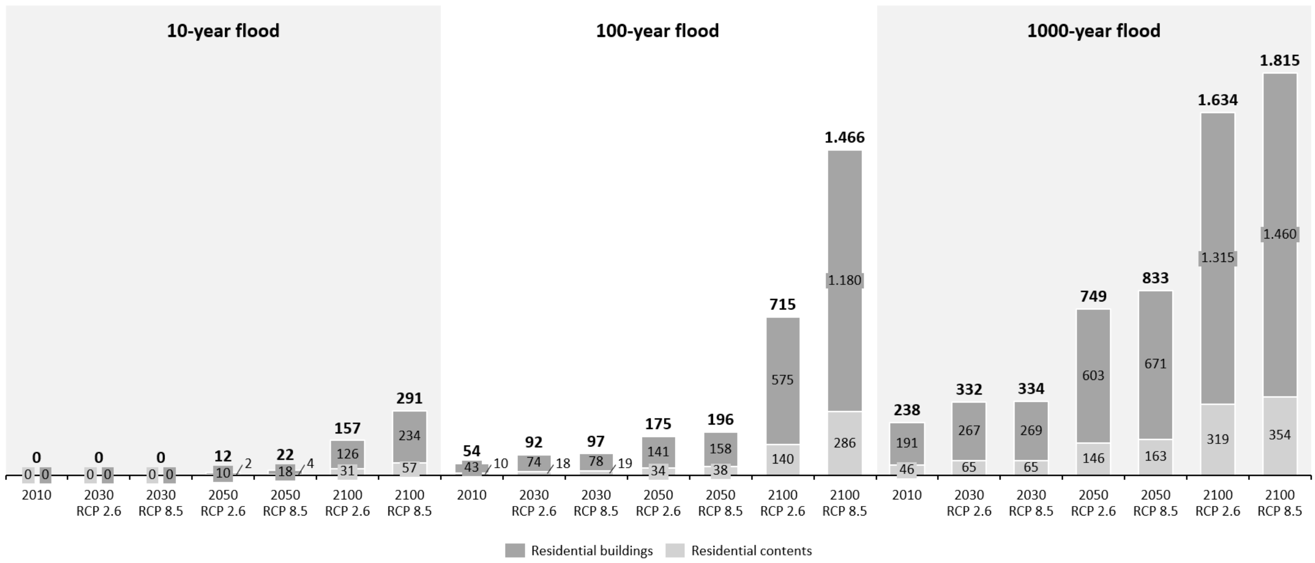


Figure 51: Exposure of residential assets in Mil. € in Shanghai city centre districts (Source: inundation data adjusted from J. Yin et al. (2020), building data adjusted from OpenStreetMap (2022))

To validate our results we compare them with studies of similar scope in Shanghai. Shan et al. (2019) estimate the flood damage of residential buildings and household properties in Shanghai based on extreme storm flood scenarios of 1/200, 1/500, 1/1000 and 1/5000-year. A comparison of the asset exposure in the city centre districts with Shan et al., (2019) for a 1000-year flood shows that our estimated exposure is ~1% in comparison to Shan et al., (2019). This large difference can be explained by three factors: The asset price, the footprint area of the residential buildings, and the flood maps.

First, Shan et al. (2019) apply an average residential building price of 6.764 €/sqm[23] which is ~8 times higher than our value of 861 €/sqm which is derived from the average construction cost[24]. Second, the footprint area of residential buildings (in the Shanghai city centre) which is used by Shan et al. (2019) to determine the asset value is ~200 km². In comparison, the total footprint area of the households' residential buildings taken into consideration in this study is ~1.8 km². This difference results from our assumption that one building is occupied by one household. Lastly, the difference in the flood maps themselves might explain the differences in exposure.

Table 11: Validation of residential asset exposure for city centre districts

Exposed Assets [Bil. € *(10^9)*]	**1000-year (Shan et al., 2019)[25]**	**1000-year in 2100 (RCP 8.5)**
Residential buildings	149.54	1.46
Household properties	7.01	0.35
Total	**156.55**	**1.81**

In summary, this divergence appears acceptable in the light of the different study scopes. While Shan et al. (2019) aim to determine the risk exposure of all residential assets in Shanghai, we focus on the asset values of 18.039 households in Shanghai.

[23] Value is inflation- and currency-adjusted.

[24] To determine the impact of this value on our ABM, we include the value of Shan et al. (2019) in our sensitivity analysis (see verification and validation appendix).

[25] Adapted from CNY to EUR; Applying share of city centre district of 41.4%

B.6.2. Risk assessment: Vulnerability data – Depth-Damage Functions

Wang (2001), Yu et al. (2012), J. Yin et al. (2011), Z. Yin et al. (2011) and Shi (2010) provide depth-damage curves in Shanghai.

- **Wang (2001):** This function is based on historical flood events. It is applied in the flood risk assessment models of Ke (2014) and Shan et al. (2019).
- **Yu et al. (2012):** The underlying data steam from survey data and insurance records after a flood event. According to Ke (2014), it underestimates the flood damage as other cities are included in the data.
- **J. Yin et al. (2012):** It differentiates depth-damage functions for multi-story houses, high-rise houses, and villas. However, there is no differentiation between structure and content damage. Hence, it does not apply to our study.
- **Z. Yin et al. (2011):** This function focuses on the Jing'an district. The data for the content-damage function stems from survey data, interviews, and local content prices in shops. The data for the building damage is retrieved from building construction costs.
- **Shi (2010, cited by Shan et al., 2019):** This function is applied by Wu et al. (2019). As the depth-damage curve only focuses on content damage, it is not applicable for our study.

The functions of Wang (2001), Yu et al. (2012), and Z. Yin et al. (2011) are shown in Figure 52. To enable better comparability between the different damage functions, the continuous functions of Z. Yin et al. (2011) are transformed into discrete functions.

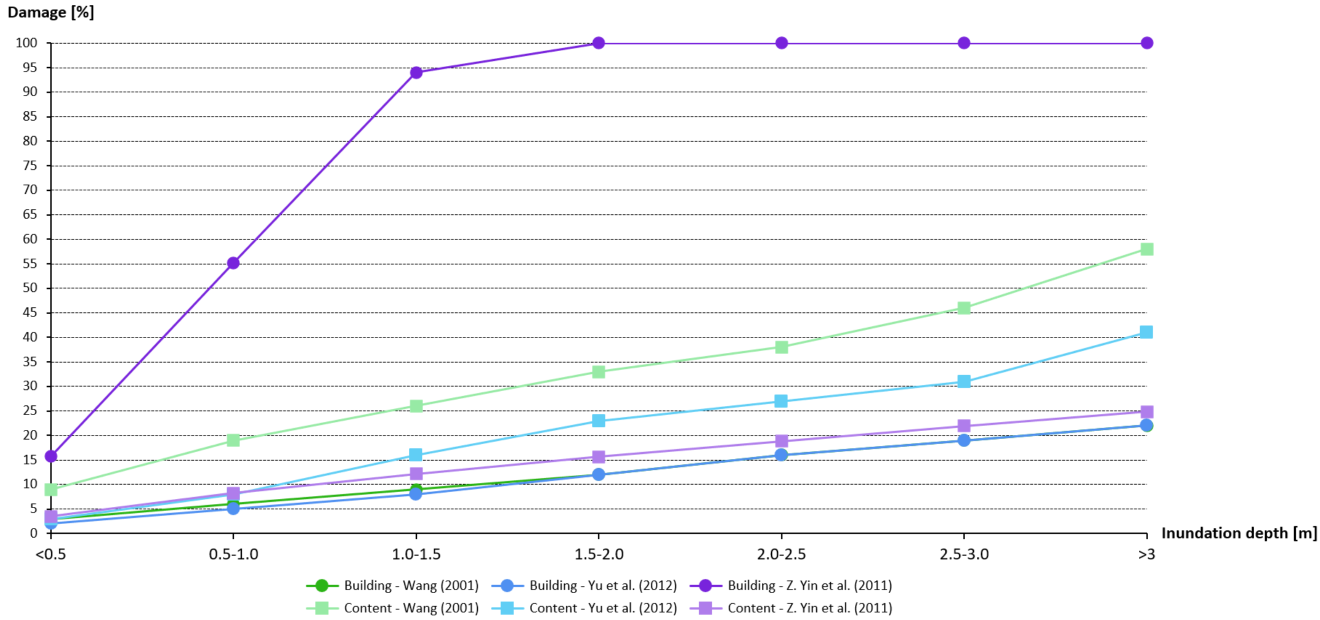


Figure 52: Comparison of depth-damage functions for residential buildings and content damage in Shanghai (Source: data from Wang (2001), Z. Yin et al. (2011), and Yu et al. (2012))

While the differences between the functions of Wang (2001) (dark green colour) and Yu et al. (2012) (dark blue colour) are minor for the content damage the building damage is between 5%5 and 15% higher for Wang (2011) (light green colour). The content-damage curve of Z. Yin et al. (2011) (light purple colour) is similar to Wang (2001) and Yu et al. (2012) in terms of the slope of the curve. However, the damage is between 5% and 15% lower than indicated by Yu et al. (2012). See also Ke (2014) for a more detailed discussion of the depth-damage curves.

The depth-damage function for building damage of Z. Yin et al. (2011) (dark purple colour) differs greatly from the ones of Wang (2001) and Yu et al. (2012). While Wang (2001) and Yu et al. (2012) depict building damage of approximately 12% between 1.5 and 2 meters, Z. Yin et al. (2011) show a damage of 100%. This deviation might be traced back to different definitions of maximum damage.

We select the depth-damage curves of Wang (2001), as they appears most suitable for urban Shanghai and they are is applied in other risk assessment studies – see Ke (2014) and Shan et al. (2019).

B.6.3. Risk reduction: Data on adaptation measures

B.6.3.1. Adaptation measure categories

The survey examines 18 different structural and non-structural household-level actions (Table 12). We categorize ten of these adaptation measures from the survey into elevation, wet-proofing, and dry-proofing measures – see Table 13.

Table 12: Overview of all household level-actions in survey (Source: measures from survey data of Noll, Filatova, Need, et al. (2022))

Type	Measure
Structural (high-effort)	Raising the level of the ground floor above the most likely flood level
	Strengthen the housing foundations to withstand water pressures
	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials
	Raising the electricity meter above the most likely flood level or on an upper floor
	Installing anti-backflow valves on pipes
	Installing a pump and/or one or more system(s) to drain flood water
	Fixing water barriers" (e.g., water-proof basement windows)
Non-structural (low-effort)	Keeping a working flashlight and/or a battery-operated radio and/or emergency kit in a convenient location
	Purchasing sandbags, or other water barriers
	Buying a spare power generator to power your home
	Being an active member in a community group aimed at making the community safer
	Coordinating with the neighbors in case you are not home when a flood occurs, they would know what to do
	Installing a refuge zone, or an opening in the roof of your home or apartment
	Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage
	Asking someone (local government, Civil Defense, etc.) for information about what to do in case of emergency
	Asking/ petitioning government representative to increase the public protection measures
	Storing emergency food and water supplies
	Moving/ storing valuable assets on higher floors or elevated areas

Table 13: Categorization of adaptation measures (Source: measures from survey data of Noll, Filatova, Need, et al. (2022))

Category	Adaptation Measure
Elevation	Raising the level of the ground floor above the most likely flood level
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
	Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage
	Moving/ storing valuable assets on higher floors or elevated areas
Dry-proofing	Purchasing sandbags, or other water barriers
	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)

B.6.3.2. *Adaptation measure effectiveness*

The effectiveness of adaptation measures is described by two factors which we will refer to as the **effectiveness** which is the influence of the adaptation measure on the building and content damage reduction and the **effectiveness level**, which is the inundation level until which the measure is effective in reducing the damage. In the following we describe the values selected for elevation, wet-proofing and dry-proofing.

Elevation: Within the survey data elevation is defined as "raising the level of the ground floor above the most likely flood level". Therefore, we assume that the elevation measure increases the buildings' ground floor (which is assumed to be 10-cm above the ground) by 30-cm above the 100-year flood level. This is in line with Du et al. (2020). We choose the flood level from the 2030 scenario, as this can be considered a "current" flood-level from a 2020 perspective. Moreover, we choose the RCP8.5 scenario. However, we only have the inundation levels of the buildings for different flood scenarios and not the actual elevation level. Hence, we assume that if a household's inundation level for a 100-year flood in 2030 under the RCP 8.5 scenario is zero, then the ground floor will be elevated by only 30cm.

Wet-Proofing: We apply a 40% effectiveness in reducing building and content damage, as this is line with values outlined by ICPR (2002), DEFRA (2008) and Kreibich et al. (2005). For the effectiveness level, we follow Lasage et al. (2014) and de Moel et al. (2013) who assume that households place their valuable goods on the second floor, which is estimated to be 3 meters high.

Dry-Proofing: Similar to de Moel et al. (2013) we choose an effectiveness value of 85% in line with ICPR (2002) and DEFRA (2008). For the effectiveness level we follow Bubeck & de Moel (2010), de Moel et al. (2013) and Lasage et al. (2014) with 1 meter. According to de Moel et al. (2013, p.901) "dry proofing walls above a certain level is not useful, as the pressure difference between water outside and lack of water inside the building would make it structurally unstable and could result in failure of the outside walls."

The use of this data is limited by the fact that the effectiveness of the measures depends heavily on the local flood conditions (Kreibich et al., 2015). The values which we selected stem mainly from studies that were conducted in Europe and North America. The local conditions of the building and content value, and the damage caused by the flood might differ substantially from our context in the Shanghai city centre.

B.6.3.3. Adaptation measure cost

For the costs of the adaptation measures, two different sources are available. On the one hand, households which indicated in the survey that they adapted a measure in the past can indicate the cost of the measure. We first determine the average individual measure costs (e.g., installing a pump) and then we sum the individual measure costs for each measure category (see Table 14). This leads to average costs of 4040 € for elevation, 4027 € for wet-proofing and 1706 € for dry-proofing.

Table 14: Adaptation measure cost data from survey (Source: survey data adjusted from Noll, Filatova, Need, et al. (2022))

Category	Individual measure	Individual measure Cost [€]	Cost for measure category [€]
Elevation	Raising the level of the ground floor above the most likely flood level	4040	4040
Wet-proofing	Strengthen the housing foundations to withstand water pressures	1572	4027
	Reconstructing or reinforcing the walls and/or the ground floor with water-resistant materials	1203	
	Raising the electricity meter above the most likely flood level or on an upper floor	485	
	Storing or placing important possessions (such as documents or expensive furniture) in such a manner to avoid flood damage	317	
	Moving/ storing valuable assets on higher floors or elevated areas	450	
Dry-proofing	Purchasing sandbags, or other water barriers	393	1706
	Installing anti-backflow valves on pipes	240	
	Installing a pump and/or one or more system(s) to drain flood water	443	
	Fixing water barriers" (e.g., water-proof basement windows)	630	

On the other hand, we can use cost data which is applied in other risk assessment studies, such as Du et al. (2020) who provide the implementation cost for elevation, wet- and dry-proofing in Shanghai – see Table 15.

Table 15: Adaptation measure cost data from literature (Source: data adjusted from Du et al. (2020))

Cost [EUR]	Installation *(one-time)*
Elevation	**153.2** per m^3 of concrete (price of concrete plus construction)
Wet-proofing	**15.323** (relocate facilities from basement to above 1000-year flood levels)
Dry-proofing	**33.2** per m^2 of floor surface (sum variable cost) • 25.5 per m^2 (windows) • 7.7 per m^2 (walls) **1036** (sum fixed cost) • 383 (plumbing check valve) • 192 (sump and sump pump) • 462 (waterproof door)

Source: Du et al. (2020) | Adjusted to inflation and exchange rate

Figure 53 shows a comparison of the cost data from the two different sources for different building sizes: While elevation is cheaper using the data of Du et al. (2020) below a building size of ~90sqm, wet-proofing and dry-proofing costs are always more expensive (as our minimum building size is 44 sqm). For this study, we select the cost data from the survey, as it is directly linked to the adaptation measures which are included in our categories: elevation, wet-, and dry-proofing. Moreover, it appears in a range which is more compatible with the income of the households. The cost data from Du et al. (2020) is however used for the sensitivity analysis (see the Appendix *E.5.1*).

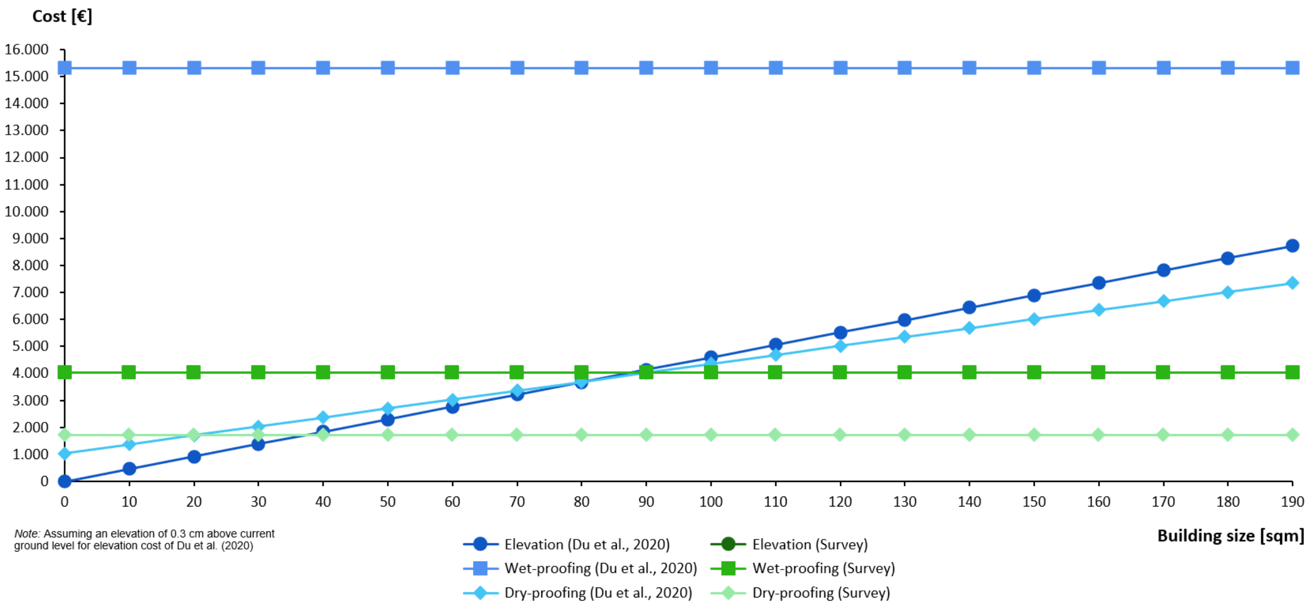


Figure 53: Comparison of adaptation measure cost sources (Source: data adjusted from Du et al. (2020) and from Noll, Filatova, Need, et al. (2022))

B.6.3.4. Adaptation measure lifetime and implementation time

Following Du et al. (2020) we assume that the elevation and wet-proofing measures are permanent and hence have an “infinite” lifetime, while dry-proofing measures are assumed non-permanent and can expire. The mean lifetime for dry-proofing is set to 20 years – following Du et al. (2020). However, we assume the lifetime to be normally distributed with a standard deviation of 2 years.

Du et al. (2020) indicate the implementation time of dry-proofing measures to be 2 years. As the measures included in the wet-proofing category appear to require a similar sort of effort and time to implement, we assume wet-proofing measures to also have an implementation time of 2 years. For elevation measures, we assume 3 years of implementation as the effort to elevate the building appears larger than the effort to dry-proof or wet-proof buildings. The times are summarized in Table 16.

Table 16: Life- and implementation time of measures (Source: dry-proofing data adjusted form Du et al. (2020))

Measure	**Implementation time [years]**	**Lifetime [years]**
Elevation	3 (Assumption)	Inf.
Wet-Proofing	2 (Assumption)	Inf.
Dry-Proofing	2 (Du et al., 2020)	N(20,2)

B.6.4. Behavioural factors

For a description of the approach, we refer to *4.3* chapter in the main text.

B.6.4.1. Dependent and independent variables

The 16 socio-behavioural variables of the extended PMT are the independent variables. Dependent and independent variables are further shown in Table 17. Figure 54 further highlights the socio-economic background variables of the survey respondents.

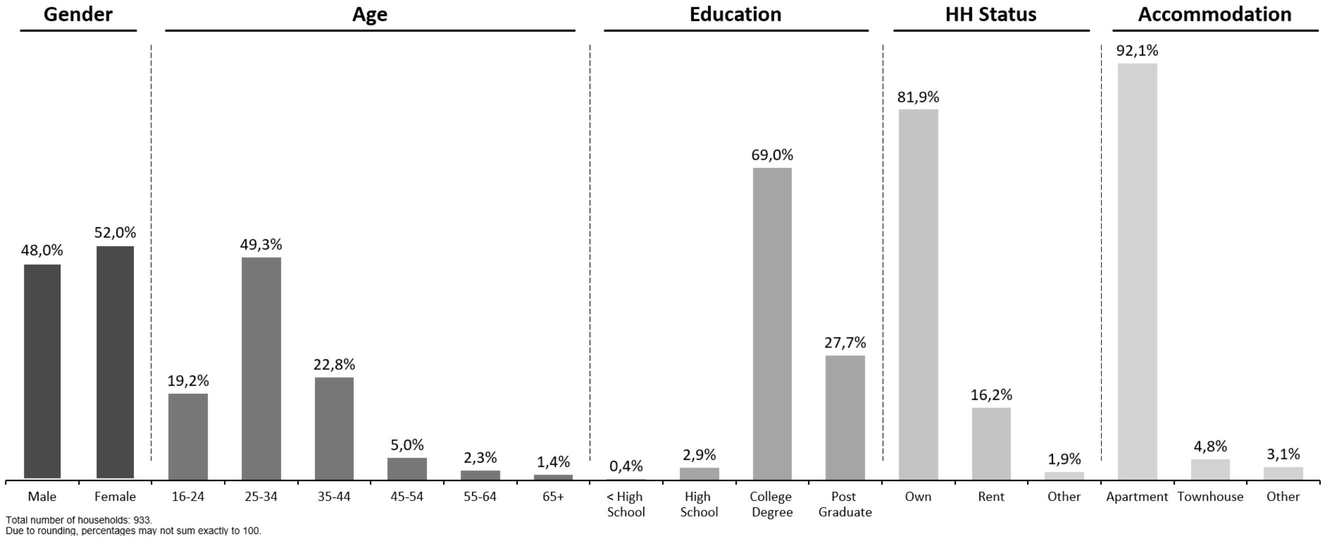


Figure 54: Background of respondents[26] (Source: survey data from Noll, Filatova, Need, et al. (2022))

[26] Gender, age, and education are selected as independent variables for the regression analysis

Table 17: Overview of dependent and independent variables (n=933) (Source: adjusted from Noll, Filatova, Need, et al. (2022))

Variable	Construct (Abbreviation)	Questions	Response Options	Descriptive statistics μ	s.d.
Independent	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* • My house is completely safe • Less often than 1 in 500 years, • Once in 500 years or a 0.2% chance annually, • Once in 200 years or a .5% chance annually, • Once in 100 years or 1% chance annually, • Once in 50 years or a 2% chance annually, • Once in 10 years or 10% chance annually, • Annually ~ 100% chance annually, • More frequent than once per year	3.60	2.16
	Flood Damage (Fl Dam)	In the event of a future major food in your area on a similar scale to [Name of flood depending on country[1]] 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	2.95	1.08
	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	2.06	0.97
	Response Efficacy (Resp Eff)	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** *(Averaged for all measures in the same category)* *(Order: Elevation, Wet-proofing, Dry-proofing)* (1) Extremely ineffective – (5) Extremely effective	3.18 3.60 3.52	1.12 0.76 0.80
	Self Efficacy (Self Eff)	Do you have the ability to undertake this measure either yourself or paying a professional to do so?	*5-point scale** *(Averaged for all measures in the same category)* *(Order: Elevation, Wet-proofing, Dry-proofing)* (1) I am unable – (5) I am very able	2.03 3.10 2.87	1.17 0.80 0.98
	Perceived Cost (Cost)	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** *(Averaged for all measures in the same category)* *(Order: Elevation, Wet-proofing, Dry-proofing)* (1) Very cheap – (5) Very expensive	3.82 2.99 3.13	1.08 0.62 0.68
	Previously undertaken measure(s) (Undergone)	I have already implemented this measure.	Yes (1) or No (0) for each measure *(If Household has implemented ≥ 1 measure in a category, the dummy variable = 1)* *(Order: Elevation, Wet-proofing, Dry-proofing)*	0.03 0.33 0.09	*0.17* *0.47* *0.29*
	Flood Experience (Fl Exp)	Have you ever personally experienced a flood of any kind? Please provide an approximation of the financial losses that the last flood or inundation caused to your personal property.	6-point scale (0) None – (6) Very High	0.39	*1.11*
	Age (Age)	YouGov collected this information prior to the survey	1: [16-24], 2: [25-34], 3: [35-44], 4: [45-54], 5: [55-64], 6: [65+]	See Background Table	
	Education (Edu)	YouGov collected this information prior to the survey	1: < High School, 2: High School, 3: College Degree, 4: Post Graduate		
	Gender (Male)	YouGov collected this information prior to the survey	Male (1) and Female (0)		
	Beliefs on effects of climate change (C.C. Belief)	There is a lot of discussion about global climate change and its connection to extreme weather events. Which of the following statements do you most agree with?	*Bold response a dummy (0,1)*** • **Global climate change is already happening** • Global climate change isn't yet happening, but we will experience the consequence in the coming decades • Global climate change won't be felt in the coming decades, but the next generation will experience its consequences • Other	0.59	*0.49*
	Perception of Government Measures (Gov Meas Insuff)	Do you think the current measures that the municipal government have implemented are sufficient to stop the risk of floods and heavy rain?	*Bold response a dummy (0,1)*** • Yes – they are sufficient and will last for the foreseeable future (30+ years) • Yes – but they will need to be updated within the next decade • **No – they are not currently sufficient**	0.21	*0.41*
	Social Influence (Social Inf)	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 strongly expect me to prepare for flooding	2.84	0.99
	Effect of social media on household adaptation (Social Media)	How frequently do you read information about flooding and other hazards from social media? To what extent, if at all, do you trust information about flooding and other hazards on social media?	*5-point scale**** (1) Very infrequently – (5) Very frequently (1) Do not trust at all – (5) Trust completely	3.10	0.79
	Effect of general media on household adaptation (General Media)	How frequently do you read information about flooding and other hazards on general media? To what extent, if at all, do you trust information about flooding and other hazards from social media?	*5-point scale**** (1) Very infrequently – (5) Very frequently (1) Do not trust at all – (5) Trust completely	3.17	0.77
Dependent	Intention to adapt measure (Int)	I intend to implement this measure in the future.	Yes (1) or No (0) for each measure *(If Household intends ≥ 1 measure in a category, the dummy variable = 1)* *(Order: Elevation, Wet-proofing, Dry-proofing)*	0.40 0.78 0.72	*0.49* *0.41* *0.45*

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* Following Noll, Filatova, Need, et al. (2022) we average the scores of the individual measures included in each measure category .
** Following Noll, Filatova, Need, et al. (2022) we model C.C. Belief and Gov. Meas. Insuff. as dummy variables instead of scales.
*** Following Noll, Filatova, Need, et al. (2022) we average probability (media frequency) and affect (media trust).

B.6.4.2. Full Models

We check the correlation matrixes of all full models for the presence of high correlations to avoid multicollinearity issues. The correlations for the full models of elevation, wet-proofing and dry-proofing are shown in Table 18, Table 19, Table 20. For the full models, the correlations are smaller than |0.67|. According to Field (2009) correlations with coefficients higher than 0.8 cause multicollinearity issues.

Table 18: Full Model – Elevation – Correlations between independent variables (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 FL Prob	-															
2 FL Dam	-0.05	-														
3 Worry	-0.18	-0.34	-													
4 Resp Eff	0.08	0.07	-0.05	-												
5 Self Eff	-0.06	0.01	0.00	-0.18	-											
6 Cost	-0.11	0.01	-0.10	-0.30	0.09	-										
7 Undergone Other	-0.07	0.05	-0.07	-0.06	-0.04	0.06	-									
8 Fl Exp	-0.11	-0.08	-0.08	-0.01	0.01	-0.06	-0.05	-								
9 Age	-0.04	0.06	0.00	0.00	-0.05	0.11	0.04	-0.03	-							
10 Education	-0.03	-0.02	0.10	-0.06	-0.10	-0.12	-0.05	-0.06	0.04	-						
11 Male	-0.10	-0.01	0.06	-0.04	-0.02	0.06	0.00	-0.06	-0.07	0.02	-					
12 C.C. Belief	-0.08	0.06	0.08	-0.08	-0.01	-0.06	-0.09	-0.04	-0.01	0.03	0.08	-				
13 Gov Meas Insuff	-0.14	-0.02	-0.15	-0.08	0.15	0.03	0.12	0.06	0.03	0.03	0.05	-0.07	-			
14 Social Inf	-0.07	-0.05	0.01	0.00	0.04	-0.07	-0.10	-0.06	-0.05	-0.04	-0.03	-0.01	0.06	-		
15 Social Media	0.05	-0.09	-0.10	0.01	0.05	-0.06	-0.03	0.05	-0.01	0.00	0.00	-0.08	0.00	-0.09	-	
16 General Media	-0.04	-0.03	0.03	-0.09	-0.04	-0.05	-0.05	-0.08	-0.08	0.02	0.02	-0.03	0.03	-0.09	***-0.67***	-

Note: Largest correlation coefficient: Social Media (15) – General Media (16) with |0.67|. Coefficients larger than |0.8| cause problems with multicollinearity (Field, 2009)

Table 19: Full Model – Wet-Proofing – Correlations between independent variables (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 FL Prob	-															
2 FL Dam	-0.09	-														
3 Worry	-0.18	-0.31	-													
4 Resp Eff	0.04	0.00	-0.01	-												
5 Self Eff	-0.05	-0.01	0.04	-0.34	-											
6 Cost	0.01	-0.04	-0.03	-0.06	0.19	-										
7 Undergone Other	-0.01	0.02	-0.03	-0.02	-0.10	0.05	-									
8 Fl Exp	-0.08	-0.03	-0.07	0.02	-0.05	-0.04	-0.09	-								
9 Age	0.00	0.14	0.00	0.09	0.00	-0.03	0.06	0.00	-							
10 Education	-0.03	0.00	0.07	-0.03	-0.09	-0.02	-0.07	-0.09	0.08	-						
11 Male	-0.12	0.05	0.06	0.01	-0.01	-0.02	-0.08	-0.04	-0.12	0.01	-					
12 C.C. Belief	-0.04	0.01	0.11	-0.21	0.04	0.01	-0.05	-0.01	-0.05	0.03	0.09	-				
13 Gov Meas Insuff	-0.03	-0.07	-0.10	-0.04	0.06	0.01	0.02	0.06	0.06	0.06	-0.02	-0.03	-			
14 Social Inf	-0.03	0.04	-0.04	0.10	-0.12	-0.11	-0.05	-0.05	-0.02	-0.05	0.02	0.10	0.10	-		
15 Social Media	0.00	-0.06	-0.11	-0.02	-0.01	-0.08	0.02	0.03	0.04	0.00	0.02	-0.01	0.01	-0.16	-	
16 General Media	0.00	0.01	0.00	-0.06	-0.03	0.04	-0.01	-0.06	-0.11	0.03	-0.04	-0.07	0.04	-0.02	***-0.68***	-

Note: Largest correlation coefficient: Social Media (15) – General Media (16) with |0.68|. Coefficients larger than |0.8| cause problems with multicollinearity (Field, 2009)

Table 20: Full Model – Dry-Proofing – Correlations between independent variables (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 FL Prob	-															
2 FL Dam	-0.08	-														
3 Worry	-0.17	-0.34	-													
4 Resp Eff	0.06	-0.04	0.02	-												
5 Self Eff	-0.02	0.00	0.09	-0.17	-											
6 Cost	-0.05	0.01	-0.04	-0.21	0.19	-										
7 Undergone Other	-0.04	0.00	0.03	-0.12	-0.01	0.04	-									
8 Fl Exp	-0.06	-0.02	-0.05	-0.01	-0.07	-0.01	0.02	-								
9 Age	-0.03	0.13	-0.01	0.09	0.00	0.04	-0.01	0.00	-							
10 Education	-0.01	0.00	0.09	0.00	-0.11	-0.01	-0.02	-0.07	0.02	-						
11 Male	-0.10	0.04	0.05	0.05	-0.05	0.04	0.02	-0.05	-0.10	0.00	-					
12 C.C. Belief	-0.05	0.01	0.08	-0.15	0.00	0.00	-0.15	0.01	-0.04	0.02	0.06	-				
13 Gov Meas Insuff	-0.03	-0.06	-0.11	-0.01	0.05	0.01	0.02	0.06	0.03	0.06	-0.03	-0.02	-			
14 Social Inf	0.02	0.02	0.01	0.01	-0.03	-0.03	0.03	-0.04	-0.07	0.00	0.04	0.09	0.08	-		
15 Social Media	0.00	-0.06	-0.11	-0.03	0.00	-0.09	-0.01	0.02	0.01	0.03	0.03	-0.02	0.00	-0.15	-	
16 General Media	0.02	-0.01	0.01	-0.01	-0.04	0.01	-0.07	-0.04	-0.11	0.02	-0.05	-0.05	0.04	0.00	***-0.68***	-

Note: Largest correlation coefficient: Social Media (15) – General Media (16) with |0.68|. Coefficients larger than |0.8| cause problems with multicollinearity (Field, 2009)

The Full Models for elevation, wet-proofing, and dry-proofing are shown in Table 21, Table 22, and Table 23. Figure 55 compares the odds ratios of these models.

Table 21: Full Model – Elevation (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the Odds ratio		
				Lower	Odds ratio (Exp (B))	Upper
Fl Prob	0.053	0.045	0.237	0.966	1.055	1.152
Fl Dam	-0.084	0.103	0.418	0.751	0.920	1.126
Worry	0.473	0.108	0.000	1.298	1.605	1.985
Resp Eff	0.061	0.094	0.519	0.884	1.062	1.277
Self Eff	0.609	0.082	0.000	1.567	1.839	2.158
Cost	-0.893	0.099	0.000	0.337	0.409	0.498
Undergone other	-0.871	0.201	0.000	0.282	0.419	0.621
Fl Exp	0.186	0.086	0.031	1.017	1.204	1.425
Age	-0.236	0.098	0.016	0.652	0.790	0.957
Education	0.242	0.176	0.169	0.902	1.273	1.797
Male	-0.019	0.182	0.918	0.687	0.981	1.403
C.C. Belief	-0.746	0.188	0.000	0.328	0.474	0.685
Gov Meas Insuff	-0.292	0.236	0.217	0.470	0.747	1.187
Social Inf	0.584	0.113	0.000	1.437	1.793	2.236
Social Media	0.462	0.181	0.010	1.114	1.588	2.263
General Media	0.018	0.184	0.920	0.711	1.019	1.459
Constant	-2.386	0.817	0.003		0.092	

Note: Nagelkerke R^2 = .54

Table 22: Full Model – Wet-Proofing (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the Odds ratio		
				Lower	Odds ratio (Exp (B))	Upper
Fl Prob	0.206	0.046	0.000	1.122	1.229	1.345
Fl Dam	0.003	0.088	0.974	0.844	1.003	1.191
Worry	0.510	0.123	0.000	1.309	1.666	2.120
Resp Eff	0.002	0.128	0.985	0.780	1.002	1.288
Self Eff	0.501	0.134	0.000	1.268	1.650	2.147
Cost	-0.071	0.156	0.652	0.686	0.932	1.266
Undergone other	0.120	0.339	0.723	0.580	1.128	2.192
Fl Exp	0.081	0.123	0.511	0.852	1.084	1.380
Age	-0.179	0.086	0.037	0.707	0.836	0.989
Education	0.225	0.191	0.238	0.861	1.253	1.822
Male	-0.169	0.184	0.360	0.588	0.845	1.212
C.C. Belief	-0.242	0.195	0.215	0.535	0.785	1.151
Gov Meas Insuff	0.027	0.229	0.905	0.657	1.028	1.608
Social Inf	0.404	0.101	0.000	1.228	1.498	1.826
Social Media	0.328	0.175	0.061	0.986	1.388	1.956
General Media	-0.018	0.170	0.917	0.704	0.982	1.371
Constant	-3.710	0.996	0.000		0.024	

Note: Nagelkerke R^2 = .29

Table 23: Full Model – Dry-Proofing (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the Odds ratio		
				Lower	Odds ratio (Exp (B))	Upper
Fl Prob	0.188	0.045	0.000	1.105	1.206	1.317
Fl Dam	-0.012	0.093	0.897	0.823	0.988	1.186
Worry	0.532	0.122	0.000	1.340	1.703	2.164
Resp Eff	0.123	0.122	0.316	0.889	1.131	1.437
Self Eff	0.877	0.113	0.000	1.926	2.403	2.998
Cost	-0.152	0.152	0.316	0.638	0.859	1.157
Undergone other	-0.025	0.200	0.902	0.659	0.976	1.445
Fl Exp	0.184	0.146	0.208	0.902	1.202	1.602
Age	-0.254	0.090	0.005	0.651	0.776	0.925
Education	0.508	0.195	0.009	1.135	1.663	2.437
Male	0.062	0.189	0.741	0.735	1.064	1.541
C.C. Belief	-0.386	0.198	0.051	0.461	0.680	1.001
Gov Meas Insuff	0.009	0.229	0.968	0.645	1.009	1.580
Social Inf	0.616	0.105	0.000	1.506	1.851	2.275
Social Media	0.344	0.181	0.057	0.990	1.411	2.011
General Media	0.096	0.180	0.592	0.774	1.101	1.566
Constant	-6.772	1.023	0.000		0.001	

Note: Nagelkerke R^2 = .47

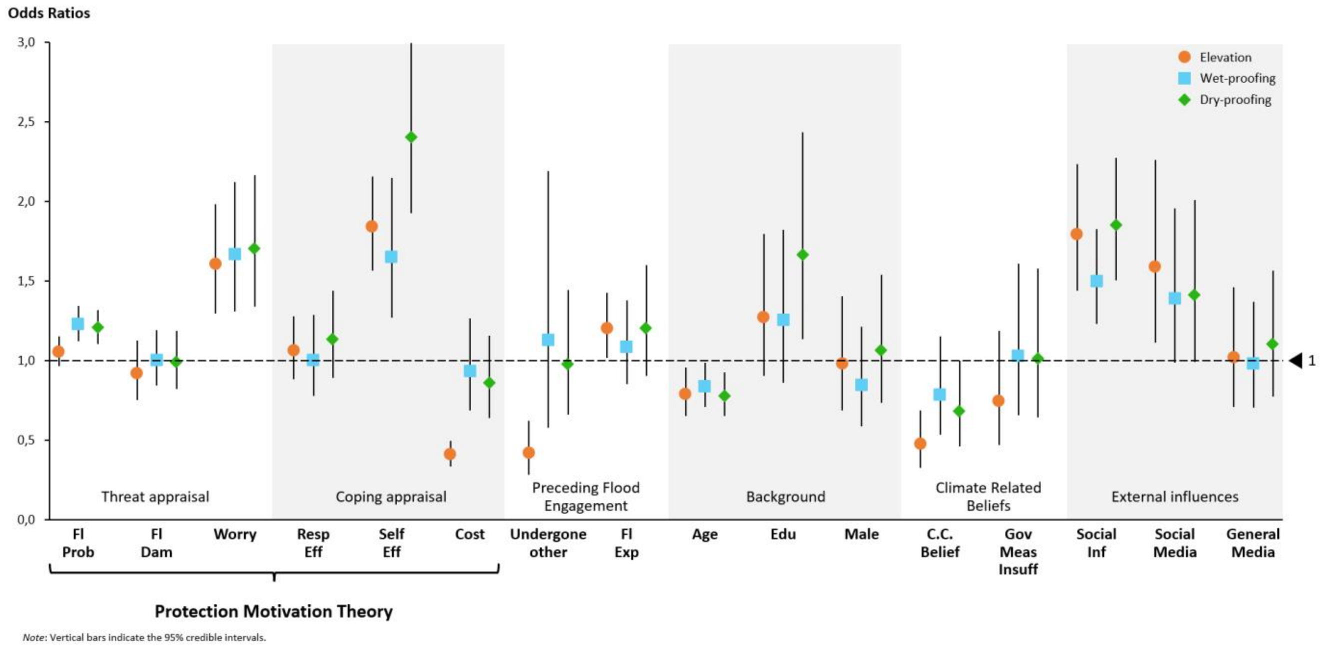

Figure 55: Comparison of odds ratios for full models (Source: adjusted from Noll, Filatova, Need, et al. (2022))

B.6.4.3. Best-Fitting Models

Table 24 shows the significant variables for each of the three best-fitting models. Worry, Self Efficacy, Age, Social Influence, and Social Media are significant independent variables in for all three best-fitting models. Elevation has the most (9) and wet-proofing the least (6) significant independent variables. Cost, Undergone Other, as well as Flood Experience only play a significant role for the elevation model. The variables Gender, Government Measure Insufficiency, and General Media are insignificant for all measure categories and are hence not included in the final models

Table 24: Overview of significant variables and p-values of the three best-fitting models for the three different categories of adaptation actions (Source: adjusted from Bubeck et al. (2013))

Independent variables	Elevation	Wet-proofing	Dry-proofing
Fl Prob		0.000	0.000
Worry	0.000	0.000	0.000
Self Eff	0.000	0.000	0.000
Cost	0.000		
Undergone other	0.000		
Fl Exp	0.015		
Age	0.018	0.012	0.004
Edu			0.006
C.C. Belief	0.000		0.060
Soc Inf	0.000	0.000	0.000
Soc Media	0.000	0.019	0.002

B.6.4.4. Final Models

We also check the correlation matrixes of all final models for the presence of high correlations to avoid multicollinearity issues. The correlations for the final models of elevation, wet-proofing and dry-proofing are shown in Table 25, Table 26, and Table 27 . For the final models, the correlations are smaller than |0.24|, which is under the threshold outlined by Field (2009).

Table 25: Final Model – Elevation – Correlations between independent variables (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Fl Prob	-												
2 Fl Dam	-0.06	-											
3 Worry	-0.20	-0.34	-										
4 Resp Eff	0.06	0.07	-0.05	-									
5 Self Eff	-0.04	0.01	0.02	-0.19	-								
6 Cost	-0.11	0.00	-0.10	-0.30	0.08	-							
7 Undergone other	-0.04	0.05	-0.05	-0.06	-0.06	0.05	-						
8 Fl Exp	-0.12	-0.08	-0.07	-0.01	0.00	-0.07	-0.06	-					
9 Age	-0.05	0.06	0.01	-0.01	-0.06	0.10	0.03	-0.05	-				
10 Edu	-0.02	-0.02	0.10	-0.05	-0.11	-0.12	-0.05	-0.06	0.05	-			
11 C.C. Belief	-0.08	0.06	0.06	-0.09	0.00	-0.07	-0.09	-0.03	0.00	0.03	-		
12 Social Inf	-0.08	-0.05	0.02	-0.01	0.03	-0.09	-0.12	-0.07	-0.06	-0.04	-0.01	-	
13 Social Media	0.03	-0.16	-0.10	-0.07	0.02	-0.12	-0.09	-0.02	-0.09	0.01	-0.13	***-0.21***	-

Note: Largest correlation coefficient: Social Media (13) – Social Inf (12) with |0.21|. Coefficients larger than |0.8| cause problems with multicollinearity (Field, 2009)

Table 26: Final Model – Wet-Proofing – Correlations between independent variables (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Fl Prob	-												
2 Fl Dam	-0.09	-											
3 Worry	-0.18	-0.32	-										
4 Resp Eff	0.04	-0.01	-0.01	-									
5 Self Eff	-0.06	0.00	0.05	-0.34	-								
6 Cost	0.00	-0.04	-0.03	-0.05	0.18	-							
7 Undergone other	-0.02	0.02	-0.02	-0.02	-0.11	0.04	-						
8 Fl Exp	-0.08	-0.03	-0.06	0.02	-0.06	-0.04	-0.09	-					
9 Age	-0.02	0.15	0.01	0.09	-0.01	-0.03	0.05	-0.01	-				
10 Edu	-0.03	0.00	0.07	-0.02	-0.10	-0.03	-0.08	-0.09	0.08	-			
11 C.C. Belief	-0.04	0.01	0.11	-0.21	0.05	0.02	-0.05	-0.01	-0.04	0.03	-		
12 Social Inf	-0.02	0.05	-0.04	0.10	-0.13	-0.11	-0.05	-0.06	-0.03	-0.06	0.09	-	
13 Social Media	0.00	-0.07	-0.15	-0.08	-0.05	-0.08	0.02	-0.02	-0.05	0.02	-0.07	***-0.24***	-

Note: Largest correlation coefficient: Social Media (13) – Social Inf (12) with |0.24|. Coefficients larger than |0.8| cause problems with multicollinearity (Field, 2009)

Table 27: Final Model – Dry-Proofing – Correlations between independent variables (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022)

Correlations	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Fl Prob	-												
2 Fl Dam	-0.07	-											
3 Worry	-0.17	-0.36	-										
4 Resp Eff	0.06	-0.04	0.02	-									
5 Self Eff	-0.02	0.00	0.09	-0.18	-								
6 Cost	-0.05	0.01	-0.05	-0.21	0.19	-							
7 Undergone other	-0.04	0.00	0.04	-0.12	-0.01	0.04	-						
8 Fl Exp	-0.07	-0.01	-0.05	0.00	-0.07	0.00	0.01	-					
9 Age	-0.04	0.14	0.00	0.09	-0.02	0.04	-0.02	-0.01	-				
10 Edu	-0.01	0.01	0.09	0.00	-0.12	-0.01	-0.02	-0.08	0.02	-			
11 C.C. Belief	-0.04	0.01	0.07	-0.15	0.00	0.00	-0.15	0.01	-0.04	0.01	-		
12 Social Inf	0.03	0.03	0.01	0.01	-0.03	-0.03	0.02	-0.05	-0.07	-0.01	0.09	-	
13 Social Media	0.02	-0.08	-0.13	-0.05	-0.03	-0.12	-0.07	-0.01	-0.09	0.05	-0.07	***-0.20***	-

Note: Largest correlation coefficient: Social Media (13) – Social Inf (12) with |0.20|. Coefficients larger than |0.8| cause problems with multicollinearity (Field, 2009)

Table 28, Table 29, and Table 30 show the final models for elevation, wet-proofing, and dry-proofing. The odds ratios of the final models for elevation, wet-proofing, and dry-proofing are compared and discussed in the main text in chapter *4.3.2*.

Table 28: Final Model – Elevation (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the Odds ratio		
				Lower	Odds ratio (Exp (B))	Upper
Fl Prob	0.045	0.044	0.305	0.960	1.046	1.141
Fl Dam	-0.086	0.103	0.405	0.750	0.918	1.123
Worry	0.454	0.107	0.000	1.278	1.575	1.940
Resp Eff	0.052	0.093	0.578	0.878	1.053	1.264
Self Eff	0.626	0.081	0.000	1.598	1.871	2.191
Cost	-0.890	0.099	0.000	0.338	0.411	0.499
Undergone other	-0.842	0.199	0.000	0.292	0.431	0.637
Fl exp	0.193	0.085	0.023	1.027	1.213	1.434
Age	-0.231	0.097	0.017	0.656	0.794	0.960
Education	0.250	0.176	0.155	0.910	1.284	1.812
C.C. Belief	-0.762	0.187	0.000	0.324	0.467	0.673
Social Inf	0.595	0.112	0.000	1.456	1.813	2.257
Social Media	0.480	0.133	0.000	1.246	1.616	2.098
Constant	-2.470	0.802	0.002		0.085	

Note: Nagelkerke R^2 = .54

Table 29: Final Model – Wet-Proofing (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the Odds ratio		
				Lower	Odds ratio (Exp (B))	Upper
Fl Prob	0.201	0.046	0.000	1.118	1.223	1.338
Fl Dam	0.007	0.088	0.932	0.848	1.007	1.196
Worry	0.519	0.122	0.000	1.322	1.680	2.136
Resp Eff	0.003	0.128	0.979	0.781	1.003	1.288
Self Eff	0.499	0.134	0.000	1.267	1.647	2.141
Cost	-0.072	0.156	0.643	0.685	0.930	1.263
Undergone other	0.096	0.337	0.776	0.568	1.100	2.131
Fl exp	0.075	0.122	0.542	0.848	1.078	1.370
Age	-0.190	0.084	0.024	0.701	0.827	0.975
Education	0.226	0.190	0.234	0.863	1.254	1.821
C.C. Belief	-0.227	0.194	0.241	0.545	0.797	1.165
Social Inf	0.405	0.101	0.000	1.231	1.500	1.827
Social Media	0.314	0.128	0.014	1.066	1.369	1.758
Constant	-3.790	0.978	0.000		0.023	

Note: Nagelkerke $R^2 = .29$

Table 30: Final Model – Dry-Proofing (n = 933) (Source: survey data from Noll, Filatova, Need, et al. (2022))

Independent variable	Coefficient (B)	Standard error (S.E.)	Significance	95% confidence interval for the Odds ratio		
				Lower	Odds ratio (Exp (B))	Upper
Fl Prob	0.189	0.045	0.000	1.107	1.208	1.319
Fl Dam	-0.013	0.093	0.890	0.823	0.987	1.185
Worry	0.530	0.122	0.000	1.338	1.698	2.155
Resp Eff	0.122	0.122	0.320	0.889	1.129	1.435
Self Eff	0.882	0.112	0.000	1.937	2.415	3.010
Cost	-0.155	0.152	0.307	0.637	0.857	1.153
Undergone other	-0.019	0.200	0.924	0.663	0.981	1.451
Fl exp	0.190	0.145	0.192	0.909	1.209	1.607
Age	-0.246	0.089	0.006	0.658	0.782	0.931
Education	0.506	0.195	0.009	1.132	1.659	2.430
C.C. Belief	-0.385	0.197	0.050	0.462	0.680	1.001
Social Inf	0.614	0.105	0.000	1.506	1.848	2.269
Social Media	0.411	0.132	0.002	1.164	1.508	1.953
Constant	-6.653	1.000	0.000		0.001	

Note: Nagelkerke $R^2 = .47$

B.6.4.5. *Intention Gap*

To determine the proportion of households that realize their intention, we look at the slopes of three linear regression models (independent variable: #HHs that intended measure, dependent variable: #HHs that implemented measure) between the survey waves 1 to 2, 2 to 3, and 3 to 4 in Shanghai. From wave 1 to 2 64.8%, from wave 2 to 3 15.6% and from wave 3 to 4 3% of the households who intended to adapt actually adapted – see Figure 56. The intention gap is the average slope, hence 27.8%. The longitudinal survey data shows that households also adapt if they did not intend to do so before. This behaviour is neglected in this model.

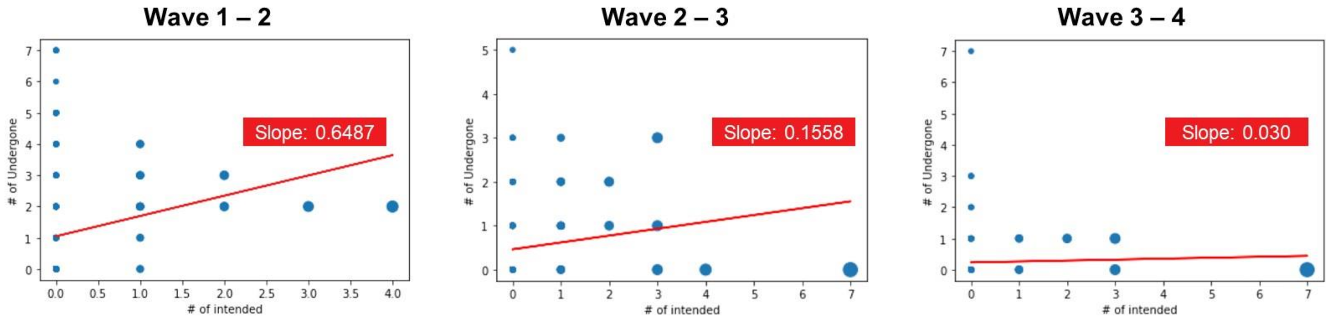

Figure 56: Slopes for the ratios on adaptation intention to action between the different survey waves (Source: survey data from Noll, Filatova, Need, et al. (2022))

B.7. Sub-models

This subchapter further explains the sub-models, which are also shown in Figure 23 in the process overview. We detail these sub models using pseudo code, as suggested by Nikolic et al. (2013).

B.7.1. Setup

B.7.1.1. Setup Global Parameters

All global parameters are either initialized via the user interface or directly in the code

Interface:

- ***Districts***: Via on/off switches users can include/exclude city centre districts form the simulation
- ***Damage***: User can select the source of the depth damage function.
- ***Time***: User can select the time horizon and the starting year of the simulation.
- ***Economic Model***: User can decide if the economic processes should be taken into consideration.
- ***Cost-Source***: User can decide the source of the cost data.
- ***Intention Gap***: User can indicate the percentage of people who intend to adapt and follow through with the adaptation.
- ***Asset Value***: User can indicate the building cost per sqm. Based on the building cost the content cost per sqm are calculated (24.2%).
- ***Effectiveness***: Users can select the adaptation effectiveness ratios for building and content damage and the effectiveness levels.
- ***Foundation Height***: Users can indicate the foundation hight.
- ***Flood***: User can select the representative concentration pathway of floods which occur after 2020, the number of floods (up to three), and for each flood separately the year of the flood event as well as the probability of the flood (10, 100, 1000-year flood).
- ***Policy Impact***: The user can simulate the effect of a hypothetical policy measure on a set of 9 socio-behavioural factors motivating household adaptation which might be influenced by policies. For each of these 9 factors, they can increase or decrease the attribute levels of all households by a x-point value up to the maximum or down to the minimum.

Code:

- ***Binary Logistics Regression***: the odds ratios for all the 13 socio-behavioural factors for elevation, wet-proofing and dry-proofing, the intention gap parameter are initialized.
- ***Linear Regression***: The beta and intercept are initialized.
- ***Cost***: The cost for the three types of adaptation measures are initialized.
- ***Time***: The lifetime and implementation time are initialized.
- ***Building***: The selected depth-damage are initialized.
- ***Flood***: Based on the inputs of the user interface, for each tick the respective name of the flood scenario is captured (see sub-subfunction *initiate floods*).
- ***Districts***: Based on the switches in the user interface the name of the selected districts are added to a list.

Initiate floods:

This sub-sub-function determines which flood map is used in which tick based on the inputs of the user in the user interface.

- ***Probability***: Based on the input either a 10-, 100-, or 1000-year flood map is selected.
- ***Year***: We have flood maps for the years 2010, 2030, 2050 and 2100. Hence, we divide the time into intervals of years where a certain flood map year is selected. Before 2020 the 2010 flood maps are chosen. From 2020 until 2039 the 2030 flood maps are selected. From 2040 until 2074, the 2050 flood maps are selected. From 2075 on the 2100 flood maps are chosen.
- ***RCP***: Depending on the RCP (2.6. or 8.5) the respective flood maps are chosen. This is only relevant for "future" flood maps, hence flood maps starting from the year 2030.

The name of each flood map is then put in a list at the item of the tick in which the flood occurs. It is important to note that only one flood can occur in one year. If two floods are selected for one year, the model asks the user to change the calibration respectively.

B.7.1.2. Setup Household Parameters

Macro-level data:

First the macro-level data is loaded: The CSV file "Macrolevel_data.csv" is read row by row, where each row represents one residential building. Depending on whether or not the residential building is part of the set of districts which is selected for this simulation run, a new turtle is created, and the values from the CSV file (ID, building type, district, inundation levels, and ids of the 15 nearest neighbours) are loaded in the respective turtle parameters. When the file is finished, a verification of the loading is executed.

Micro-level data:

Then the households are loaded from the synthetic population and matched randomly to the buildings: The CSV file "Microlevel_data.csv" is read row by row, where each row represents one household. If the household is living in an apartment, it is randomly matched with one of the apartment turtles which have not been matched yet with a household and the turtle is populated with the parameters from the household: Survey ID, 13 socio-behavioural factors motivating flood-adaptation, building size, household status, number of households in the social network which have adapted at least one measure, income, savings, and yearly change of savings. Then, the social network size is immediately determined by multiplying the number of households in the social network which adapted at least one measure with the factor to determine the entire social network size of each household (see the Appendix *B.4.6*). Depending on which policy applies, the respective attribute values of the impacted socio-behavioural factors are immediately changed. The same procedure applies for houses. Hence, if no more unassigned residential buildings are left, then the remaining rows in the Microlevel CSV file are skipped. In the end we verify that no unmatched building remain.

To setup households the model iterates trough two loops.

In a **first** loop, for each household first, the value of both the building structure and content is determined by multiplying the building size in sqm with the building/content value per sqm. Second, the undergone other parameter (*UG_other*$_{h}$) is determined for each adaptation measure depending on which measure is already undergone. Third, the direct neighbourhood is initiated: Currently each household has 15 nearest neighbours in the list *Direct_NN_IDs*$_{h}$ (which is the maximum size of the social network). However, not every HH has a network size of 15. Instead, the households have heterogeneous social network sizes which is included in the *Soc_net*$_{h}$ parameter. Therefore, we need to reduce the list *Direct_NN_IDs*$_{h}$ so that its length matches the individual network size variable *Soc_net*$_{h}$. When doing so it is important the most remote nearest neighbours are removed from the list. This can be done by reducing the list form the right, as the list *Direct_NN_IDs*$_{h}$ is sorted by increasing distance. Lastly, the household checks whether their direct neighbours have adapted at least one measure and adjust the counter for the number of adapted direct neighbours (*NN_adapt*$_{h,t}$) accordingly, as shown in Figure 57.

Initiate adapted neighbours

```
For all households h ∈ H
    For all neighbours n ∈ Direct_NN_IDs_h
        If (UG_n,elevation + UG_n,wet-proofing + UG_n,dry-proofing) ≥ 1
            Set NN_adapt_h (NN_adapt_h +1)
```

Figure 57: Pseudo code – Initiate adapted neighbours

In a **second** loop we aim to initiate the indirect neighbours. A second loop through all turtles is required, because in order to determine the indirect neighbours, the direct neighbours of all turtles need to be already defined. First, the indirect neighbourhood is initiated. Each household adds the turtles to the list of indirect nearest neighbours where the household itself is included in the list of direct nearest neighbours. Next, the remaining household parameters are determined in the same loop to save computational time. The adaptation status parameter is adjusted in tick 0 depending on whether or not a measure has already been implemented. The remaining household parameters are set to 0. Lastly, the direct neighbourhood, the indirect neighbourhood, the cost calculation, and the agent state are verified with sanity checks.

Update agent parameters:

The setup finishes by updating the agent parameters. At a first glance it seems counter-intuitive to already update parameters in tick 0. However, in order to start the *Go* function in tick 1, we need to determine the probability of implementing a measure, as well as the implementation threshold. This is something that needs to be done every tick. To save unnecessary functions, we therefore already call the *Update agent parameters* function in tick 0.

B.7.2. Update agent parameters

This function is executed for each household in a random order. After setting flooded to 0, as in the next tick all households are no longer flooded, two major subfunctions are executed. The first concerns the social interaction. The second concerns the calculation of the probability to implement and the respective implementation threshold. The pseudo code for this function is shown in Figure 58.

Social interaction: This subfunction cannot be executed in the setup (tick 0), as the social influence parameter in tick 0 already reflects the number of adapted direct neighbours. First, we determine the change in number of adapted direct neighbours ($NN\_adapt_{h,t}$) from the last tick to the current tick. If the number of direct adapted neighbours increased, we adjust the social influence value of the household by adding the size of the change multiplied with the factor which determines by how much the social influence changes if the number of neighbours that adapted in the social network changes by 1 (*Beta_soc_inf*). The maximum value of the social influence parameter (5) can however not be exceeded. If the number of neighbours which adapted decreased e.g., due to expiration of measures, we only decrease the social influence variable if the number of adapted neighbours is less than 10. 10 is the threshold below which the number of adapted neighbours needs to be for the social influence value to be below 5 (see Design Concepts - Interaction). If the value is below 10, we change the social influence parameter as explained. The minimum value of the social influence parameter (1) can however not be exceeded. Further details on the social interaction can be found in Design Concepts - Interaction.

Probability to implement: This subfunction calculates the probability of implementation for each measure and hence is executed for each measure (elevation, wet-, and dry-proofing). First, the implementation threshold is set as a random number between 0 and 1. After that we adjust the odds ratio for the flood experience for each household. As each flood affects each household and their behaviour differently, we randomly vary the odds ratio of flood experience for each household in the range of one standard deviation from the mean effect of flood experience on the adaptation intention. Next, the odds are calculated based on intercept, odds ratios, and attribute levels. Based on the odds, the probability of "intending" to implement a measure is calculated. By multiplying the probability to intent, a measure implementation with the intention gap parameter we get the probability to "implement". The intention gap parameter is generated from the survey data (see the Appendix *B.6.4.5*). This is also in detail described in the Design Concepts (Appendix B.4.3). Lastly, we verify that the value range of the probability is correct (between 0 and 1).

Update agent parameters

For all households $h \in H$
  Set flooded$_h$ 0
  if $t > 0$
    Define new local variable *change_NN_adapt* and set it to ($NN\_adapt_{h,t}$ - $NN\_adapt_{h,t-1}$)
    If $change\_NN\_adapt > 0$
      Set Soc_inf_h $Minimum(5; Soc\_inf_h + change\_NN\_adapt \times Beta\_soc\_inf)$
    If $change\_NN\_adapt < 0$
      if $NN\_adapt_{h,t} < 10$
        Set Soc_inf_h $Maximum(1; Soc\_inf_h + change\_NN\_adapt \times Beta\_soc\_inf)$
  For all measures $m \in M$
    Set $implement\_threshold_{h,m}$ *random number between 0 and 1*
    Set $OR_{Fl\_exp,m}$ random float between the odds ratio for flood experience +/- its standard deviation
    Set $Odds_{h,m}$ $(Constant_m \times (OR_{Fl\_prob,m}{}^{Fl\_prob\_percpt_h} \times OR_{Fl\_dam,m}{}^{Fl\_dam\_percpt_h} \times OR_{Worry,m}{}^{Worry_h}$
    $\times\ OR_{RE,m}{}^{RE_{h,m}} \times OR_{SE,m}{}^{SE_{h,m}} \times OR_{Cost,m}{}^{Cost\_percpt_{h,m}} \times OR_{UG\_other,m}{}^{UG\_other_{h,m}}$
    $\times\ OR_{Fl\_exp,m}{}^{Fl\_exp_h} \times OR_{Age,m}{}^{Age_h} \times OR_{Edu,m}{}^{Edu_h} \times OR_{CC\_belief,m}{}^{CC\_belief_h}$
    $\times\ OR_{Soc\_inf,m}{}^{Soc\_inf_h} \times OR_{Soc\_media,m}{}^{Soc\_media_h}))$
    Set $prob\_implement_{h,m}$ $(Odds_{h,m} / (1 + Odds_{h,m})) \times Intention\_gap$

Figure 58: Pseudo code – Update agent parameters

B.7.3. Go

The pseudo code for the Go function is shown in Figure 59. After updating the savings of household based on the yearly savings increase[28] and the number of adapted neighbours, the function checks in a random order the adaptation status of the adaptation measures at the beginning of the tick and executes the respective subfunctions:

- If the adaptation status is do nothing (0) the function ***Check Implementation Start*** (Appendix *B.7.4*) is called for the respective measure.
- If the adaptation status is started (1) the function ***Check Implementation Finish*** (Appendix *B.7.5*) is called for the respective measure.
- If the adaptation status is finished (2) the function ***Check Adaptation Expiration*** (Appendix *B.7.6*) is called for the respective measure.

If a flood occurs in this tick, all households are asked to check the flood depth (function ***Check Flood Depth***). At the end of the go function, the agent parameters are updated by calling the respective function ***Update Agent Parameters*** (Appendix *B.7.2*). If the tick exceeds the time horizon, the simulation is stopped.

Go

```
t+1
For all households h ∈ H
        Set Savings_h,t (Savings_h,t-1 + Change_savings_h)
        Set NN_adapt_h,t (NN_adapt_h,t-1)
For all households h ∈ H in a random order
        For all measures m ∈ M in a random order
                Ifelse
                        adapt_status_h,t,m = 0
                                Execute function "check implementation start"
                        adapt_status_h,t,m = 1
                                Execute function "check implementation finish"
                        adapt_status_h,t,m = 2
                                Execute function "check adaptation expiring"
If NOT (flood_scenario_t = "No flood")
        For all households h ∈ H
                Execute function "check flood depth"
Execute function "update agent parameters"
if (t ≥ time_horizon)
        Stop simulation
```

Figure 59: Pseudo code – Go

[28] We assume the change in yearly savings cannot be negative (see overview assumptions)

B.7.4. Check implementation start

The pseudo code for this function is shown in Figure 60. This function is called in GO for each household and is only entered with $adapt\_status_{h,t,m}$ = 0 (do nothing). Also, this function is called in Go separately for each measure type (elevation, wet-proofing, dry-proofing).

If the probability to implement the measure is larger than the implementation threshold, the adaptation status is set to 1 (started). Also, the tick when the implementation of the measure was started is marked in order to be able to determine later when the implementation is finished. In addition, if the implementation time of the measure is zero, we need to check if the implementation is finished, and hence enter the function ***Check Implementation Finish*** (Appendix *B.7.5*).

For the elevation measure, there are two additional conditions that a household needs to fulfil in order to be able to implement an elevation measure. First, a household must not implement elevation measures if they **rent**: Only 3% of survey respondents who rent indicated that they elevated their house. This appears reasonable as an elevation of the house requires a substantial interference with the house foundation, which we assume a tenant does not have the rights for. Second, a household must not implement elevation measures if they live in an **apartment**: We assume that the foundation of a residential apartment building is collective property of all households within the respective apartment building. Therefore, an individual household cannot drive the decision to elevate the entire apartment building itself. We assume the same is the case in Shanghai. As a result, we assume that a household living in an apartment cannot implement an elevation measure.

Moreover, households can only start the adaptation if their savings are larger than the cost of the intended adaptation measure. When a household has enough savings to implement the measure, these savings are immediately reduced by the measure cost, so that the household does not go into debt by adapting further measures in the same tick. This is also explained in the conceptual model in the Chapter *5.1* in the main text.

Check implementation start

```
If measure m ∈ {wet-proofing, dry-proofing}
        If prob_implement_{h,m} > implement_threshold_{h,m}
                If savings_{h,t} ≥ Cost_m
                        Set adapt_status_{h,t,m} 1
                        Set implement_start_{h,m} t
                        Set savings_{h,t} (savings_{h,t} – Cost_m)
                        If implement_time_m = 0
                                Execute function "check implementation finish"
If measure m ∈ {elevation}
        If NOT(hh_status_h = 1)
                If NOT(build_type_h = "Apartment")
                        If prob_implement_{h,m} ≥ implement_threshold_{h,m}
                                If savings_{h,t} ≥ Cost_m
                                        Set adapt_status_{h,t,m} 1
                                        Set implement_start_{h,m} t
                                        Set savings_{h,t} (savings_{h,t} – Cost_m)
                                        If implement_time_m = 0
                                                Execute function "check implementation finish"
```

Figure 60: Pseudo code – Check implementation start

B.7.5. Check implementation finish

This function is called for each household and is only entered with $adapt\_status_{h,t,m}$ = 1 (started). Also, this function is called in Go separately for each measure type (elevation, wet-proofing, dry-proofing).

Based on the starting time of the implementation, the current tick, and the implementation time of the respective measure it is determined if the measure implementation is finished. When the implementation time is at the end, the adaptation status of measure at current tick is set to "adapted" (2), Undergone (UG_h) is set to 1 and the tick when the implementation of the measure is finished is marked to later be able to determine when the lifetime is expired. In addition, the undergone other parameter is adjusted for the other measures. When the household adapts his first measure ($UG\_other_{h,m} = 0$), the adaptation counts of all the household's indirect neighbours is increased by one. If the lifetime of the respective measure is set to 0 and the measure is adapted, then the function ***Check adaptation expiring*** (Appendix *B.7.6*) is called immediately, as the measure would expire in the tick in which it is implemented. The pseudo code for this function is shown in Figure 61.

Check implementation finish

```
If t = implement_start_{h,m} + implement_time_m
        Set adapt_status_{h,t,m} 2
        Set implement_end_{h,m} t
        Set UG_{h,m} 1
        If m = elevation
                Set UG_other_{h,wet-proofing} 1
                Set UG_other_{h,dry-proofing} 1
        If m = wet-proofing
                Set UG_other_{h,elevation} 1
                Set UG_other_{h,dry-proofing} 1
        If m = dry-proofing
                Set UG_other_{h,elevation} 1
                Set UG_other_{h,wet-proofing} 1
        If UG_other_{h,m} = 0
                For all neighbours n ∈ Indirect_NN_Ids_h
                        set NN_adapt_{n,t} (NN_adapt_{n,t} + 1)
        If Life_time_m = 0
                Execute function "check adaptation expiring"
```

Figure 61: Pseudo code – Check implementation finish

B.7.6. Check adaptation expiring

This function is called for each household and is only entered with *adapt_status*$_{h,t,m}$ = 2 (adapted). Also, this function is called in Go separately for each measure type (elevation, wet-proofing, dry-proofing).

Based on the finish time of the implementation, the current tick, and the lifetime of the respective adaptation measure, it is determined if the measure expires. When the lifetime of the measure is at the end, set adaptation status of measure at current tick back to “do nothing” (0) and set undergone (UG_h) to 0. Also, if applicable, adjust the undergone other parameter. When the only adaptation measure of the household expires ($UG\_other_{h,m} = 0$), the adaptation count for the indirect neighbours is reduced by one. The pseudo code for this function is shown in Figure 62.

Check adaptation expiring

```
If t = implement_end_{h,m} + life_time_m
    Set adapt_status_{h,t,m} 0
    Set UG_{h,m} 0
    If m = dry-proofing
        If UG_{h,elevation} = 0
            Set UG_other_{h,wet-proofing} 0
        If UG_{h,wet-proofing} = 0
            Set UG_other_{h,elevation} 0
    If m = wet-proofing
        If UG_{h,elevation} = 0
            Set UG_other_{h,dry-proofing} 0
        If UG_{h,dry-proofing} = 0
            Set UG_other_{h,elevation} 0
    If m = elevation
        If UG_{h,wet-proofing} = 0
            Set UG_other_{h,dry-proofing} 0
        If UG_{h,dry-proofing} = 0
            Set UG_other_{h,wet-proofing} 0
    If UG_other_{h, m} = 0
        For all neighbours n ∈ Indirect_NN_Ids_h
            set NN_adapt_{n,t} (NN_adapt_{n,t} - 1)
```

Figure 62: Pseudo code – Check adaptation expiring

B.7.7. Check flood depth

This function is called for each household in GO. We can then determine if a household is flooded by calling the inundation level of a household for the current flood scenario. This data is predetermined by overlapping the inundation maps with the location of the residential building in which the household is living (see the Appendix *B.6.1.3*). If the inundation is higher than the foundation-level, then we consider the household flooded.

When a household is flooded, we set $flooded_h$ to 1, and we need to check the flood damage. Hence, ***Check Flood Damage*** (Appendix *B.7.8*) is called for this household. After that we update the flood experience and household savings by calling the function ***Update Flood Experience and Savings*** (as the flood experience takes into consideration the flood damage and damage reduction, this function needs to be called after updating the flood damage, see the Appendix *B.7.10*). The pseudo code for this function is shown in Figure 63.

Check flood depth
If $(Inund_{h,flood\_scenario} - foundation\_height) > 0$
set $flooded_h$ 1
Execute function “check flood damage”
Execute function “update food experience and saving”

Figure 63: Pseudo code – Check flood depth

B.7.8. Check flood damage

The pseudo code of this function is shown in Figure 64. This function is called by each household that is considered flooded. Within this function, we determine the total potential building and content damage (prevented damage + residual damage) and update the respective parameters. In our model we do this by using two sub functions called ***Check Building Damage*** and ***Check Content Damage***. The damage for both building and content can be determined by multiplying the value of building/content with the proportional damage to the building/content for the current inundation depth of the building. The proportional damage is retrieved from the selected depth-damage function. The depth-damage functions used in this model are discrete (often also called 'step damage function'), which explains the different inundation intervals. It is important to note that we need to take into consideration the foundation height when determining the building/content damage.

We further verify the flood damage calculation by making sure that the damage to building/content is not larger than the value of building/content. Now that the potential total flood damage is assessed we are interested in understanding by how much the damage is reduced via the active adaptation measures of the household. Hence, the function ***Check Flood Damage Reduction*** (Appendix *B.7.9*) is called.

Check flood damage

Set $Fl\_dam_{h,building,t}$ (check_building_damage[$Inund_{h,flood\_scenario}$ - *foundation_height*]) **//Calling function building damage with input in []**
Set $Fl\_dam_{h,content,t}$ (check_content_damage[$Inund_{h,flood\_scenario}$ - *foundation_height*]) **//Calling function content damage with input in []**
Execute function "check flood damage reduction"

Check building damage

Set up function with input *inundation_depth*
Ifelse
(*inundation_depth*) ≤ 0
Return 0
(*inundation_depth*) < 0.5
Return $depth\_dam_{building}[0] \times value_{h,building}$
(*inundation_depth*) < 1.0
Return $depth\_dam_{building}[1] \times value_{h,building}$
(*inundation_depth*) < 1.5
Return $depth\_dam_{building}[2] \times value_{h,building}$
(*inundation_depth*) < 2.0
Return $depth\_dam_{building}[3] \times value_{h,building}$
(*inundation_depth*) < 2.5
Return $depth\_dam_{building}[4] \times value_{h,building}$
(*inundation_depth*) < 3.0
Return $depth\_dam_{building}[5] \times value_{h,building}$
Else
Return $depth\_dam_{building}[6] \times value_{h,building}$

Check content damage

Set up function with input *inundation_depth*
Ifelse
(*inundation_depth*) ≤ 0
Return 0
(*inundation_depth*) < 0.5
Return $depth\_dam_{content}[0] \times value_{h,content}$
(*inundation_depth*) < 1.0
Return $depth\_dam_{content}[1] \times value_{h,content}$
(*inundation_depth*) < 1.5
Return $depth\_dam_{content}[2] \times value_{h,content}$
(*inundation_depth*) < 2.0
Return $depth\_dam_{content}[3] \times value_{h,content}$
(*inundation_depth*) < 2.5
Return $depth\_dam_{content}[4] \times value_{h,content}$
(*inundation_depth*) < 3.0
Return $depth\_dam_{content}[5] \times value_{h,content}$
Else
Return $depth\_dam_{content}[6] \times value_{h,content}$

Figure 64: Pseudo code – Check flood damage

B.7.9. Check flood damage reduction

This function is called by each household that is considered flooded. It is only executed if at least one measure is undergone ($UG_{h,m}$). The pseudo code for this function is shown in Figure 66. An important assumption for this function is that there is an order in which the measures reduce damage: First elevation, then dry-proofing, then wet-proofing:

If implemented, the elevation measure reduces the damage first. This is logical, if the building is elevated above the flood level, then all the damage is reduced by the elevation measure, even if the other measures are implemented. If the water reaches the building despite the elevation, then dry-proofing (if implemented) reduces the remaining damage which is not reduced by the elevation measure. This is also logical. If dry proofing, does its job right, water does not enter the building and hence the damage that can be reduced via wet-proofing is smaller. If damage remains after applying elevation and dry-proofing measures, then the wet-proofing measures (if implemented) decreases the remaining damage.

Following the order of the damage reduction, which is explained above, we start with the elevation measure. If the elevation measure is implemented, we want to determine the benefit of the elevation measure, which is the mitigated damage. The mitigated damage is the difference between the total damage without the elevation measure minus the remaining damage after applying the elevation measure for both content and building.[29] We call the respective functions *check building damage* and *check content damage* for this (see the Appendix *B.7.8*). If the elevation level is higher than the flood level, the benefit of the measure equals the entire avoided damage. There is however one caveat of using a discrete ('step') depth-damage function compared to a continuous depth-damage function: When the inundation depth after the elevation measure is in the same inundation class (e.g. < 0.5, 0.5-1 etc.), the benefit of applying the elevation measure is 0, as the damage before applying the elevation measure is the same as the damage after applying the elevation measure due to the use of the stage depth damage function. This is a limitation of this model. If the elevation measure is not implemented, the benefit of the measure is 0. However, we do not need to change anything as the benefit of the elevation measure is initiated with zero in the setup and does not need to be changed.

Moreover, we define a local variable for the building elevation which equals the foundation height if no elevation measure is implemented. If the building is elevated, the building elevation is set to 30cm above the inundation level in case of a 100-year flood in 2030 under the RCP 8.5 scenario including the building foundation.

Now we need to determine the damage reductions of the dry-proofing and wet-proofing measures. Here, we need to take into consideration that each measure type has a different effectiveness level, and that each measure type has a different effectiveness factor in reducing flood damage. Taking this into consideration, we can distinguish four flood level intervals, see also Figure 65:

1. If the inundation level is smaller than the building elevation: There is no damage remaining which can be reduced by dry-proofing or wet-proofing (if implemented). The benefit is 0.
2. If the inundation level is higher than the building elevation and smaller than both the dry- and wet-proofing effectiveness levels: Both dry-proofing and wet-proofing can reduce the remaining damage. Both measures have a benefit if they are both implemented.
3. If the inundation depth is higher than the building elevation and within one of the dry- or wet-proofing effectiveness levels: Only the one measure which is still within its effectiveness level has a benefit if it is implemented.

[29] As the depth-damage curves are not linear, we cannot determine the mitigated damage by using the damage percentage value of the building elevation from the depth-damage curve. Instead, we need to determine the mitigated damage by calculating damage without elevation and subtracting the damage with elevation.

4. If the inundation depth it is out of both the dry- and wet-proofing effectiveness levels: Both dry- and wet-proofing are not effective within this inundation range and hence, we assume the benefit is 0.

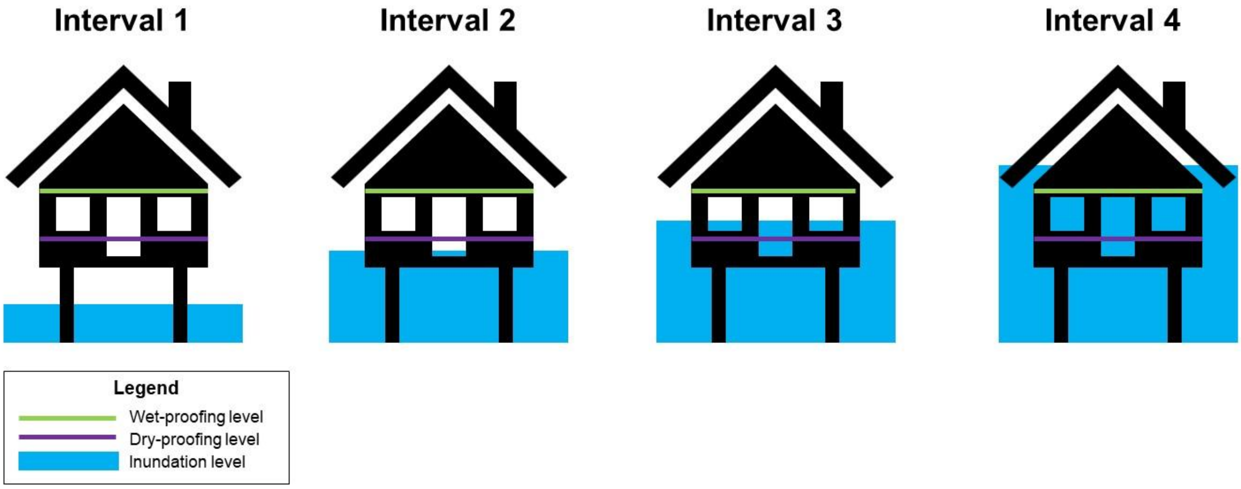

Figure 65: Visualization of different intervals of inundation levels

Hence, we need to determine the benefit only if the inundation level is in the interval 2 or 3.

If the inundation level is within both the dry- and wet-proofing effectiveness levels (interval 2), we need to determine if the measures are undergone. If dry-proofing is undergone, we set the benefit of dry-proofing in this tick to the damage which remains after the building elevation multiplied with the effectiveness of the dry-proofing measure. If wet-proofing is undergone, we set the benefit of wet-proofing in this tick to the damage which remains after the building elevation and the dry-proofing multiplied with the effectiveness of the wet-proofing measure.

If the inundation level is in a range where only wet- or dry-proofing is still active (interval 3) we wet the benefit of the measure which is still active to the damage which remains after the building elevation multiplied with the effectiveness of the respective measure.

We verify the damage reduction by making sure that the sum of the flood damage reductions of the different measures cannot be larger than the flood damage itself, and that a benefit (damage reduction) can only occur if the measures is active.

Check flood damage reduction

```
If ((UG_h,elevation = 1) OR (UG_h,wet-proofing = 1) OR (UG_h,dry-proofing = 1))
        Define new local double variable build_elev
        If UG_h,elevation = 1
                Set build_elev(Inund_h, 2030_100_rcp8.5 + foundation_height + effectiv_lvl_elevation)
                Set B_h,t,elevation ((Fl_dam_h,building,t + Fl_dam_h,content,t) – (check_building_damage[Inund_h,flood_scenario - build_elev] + check_content_damage[Inund_h,flood_scenario - build_elev]))
        Else
                Set build_elev foundation_height
        Ifelse
                (Inund_h, flood_scenario > build_elev) AND (Inund_h, flood_scenario ≤ (build_elev + MINIMUM(effectiv_lvl_wet-proofing ; effectiv_lvl_dry-proofing))) //Interval 2
                        Set B_h,t,dry-proofing ((check_building_damage[Inund_h,flood_scenario - build_elev]) × effectiv_dry-proofing + (check_ content_damage[Inund_h,flood_scenario - build_elev]) × effectiv_dry-proofing) × UG_h,dry-proofing
                        Set B_h,t,wet-proofing ((check_ building_damage[Inund_h,flood_scenario - build_elev]) × (1-effectiv_dry-proofing × UG_h,dry-proofing) × effectiv_wet-proofing
                        + (check_ content_damage[Inund_h,flood_scenario - build_elev]) × (1-effectiv_dry-proofing × UG_h,dry-proofing) × effectiv_wet-proofing ) × UG_h,wet-proofing
                (Inund_h, flood_scenario > (build_elev + MINIMUM(effectiv_lvl_wet-proofing ; effectiv_lvl_dry-proofing))) AND (Inund_h, flood_scenario ≤ (build_elev + MAXIMUM(effectiv_lvl_wet-proofing ; effectiv_lvl_dry-proofing))) // interval 3
                        If MAXIMUM(effectiv_lvl_wet-proofing ; effectiv_lvl_dry-proofing) = effectiv_lvl_wet-proofing
                                Set B_h,t,wet-proofing ((building_damage[Inund_h,flood_scenario - build_elev]) × effectiv_wet-proofing + (content_damage[Inund_h,flood_scenario - build_elev]) × effectiv_wet-proofing) × UG_h,wet-proofing)
                        Else
                                Set B_h,t,dry-proofing ((building_damage[Inund_h,flood_scenario - build_elev]) × effectiv_dry-proofing + (content_damage[Inund_h,flood_scenario - build_elev]) × effectiv_dry-proofing) × UG_h,dry-proofing)
```

Figure 66: Pseudo code – Check flood damage reduction

B.7.10. Update Flood Experience and Savings

When a household is impacted by a flood in the simulation, we update the Flood Experience attribute Fl_exp_h to the new flood damage value after taking into consideration the damage mitigation by the adaptation measures. The flood experience is a parameter with a 6-point scale, as shown in Table 31.

Table 31: Updating flood experience based on the flood damage range

Flood damage range [EUR]	Flood Experience
[0]	0
(0;1270)	1
[1270;2540)	2
[2540;3810)	3
[3810;5080)	4
[5080; inf.)	5

Moreover, the savings needs to be adjusted. We assume that households pay for the flood damage out of their savings: While households that own their building have to pay for both the building and the contents damage, households that are tenants only have to pay for the contents damage. Hence, we reduce the savings for building owners by the full building and content damage, and the savings of tenants by the content damage (after taking into consideration the impact of the adaptation measures on the respective damage category). The pseudo code for the function is shown in Figure 67.

Update flood experience and savings

```
Define new local variable remaining_fl_dam_cont which captures the unmitigated content damage
Define new local variable remaining_fl_dam which captures the unmitigated building and content damage
Ifelse
        (remaining_fl_dam = 0€)
                Set fl_exp_h 0
        (remaining_fl_dam < 1270€)
                Set fl_exp_h 1
        (remaining_fl_dam < 2540 €)
                Set fl_exp_h 2
        (remaining_fl_dam < 3810 €)
                Set fl_exp_h 3
        (remaining_fl_dam < 5080 €)
                Set fl_exp_h 4
        (remaining_fl_dam >= 5080 €)
                Set fl_exp_h 5
if (hh_status_h = 0)
        set savings_h,t (savings_h,t - remaining_fl_dam)
if (hh_status_h = 1)
        set savings_h,t (savings_h,t - remaining_fl_dam_cont)
```

Figure 67: Pseudo code – Update flood experience and savings

B.8. Model assumptions

Table 32: Summary model assumptions 1

	Assumption	Reasoning for assumption	Potential impact on results
Hazard	We focus on storm surges with high tides.	Storm surges combined with high tides cause one of the greatest flood risks in Shanghai (S. Xu & Huang, 2011; J. Yin et al., 2013).	Rainstorm-induced floods, which make up a large portion of the floods in Shanghai (Quan, 2014) are not taken into consideration. Hence, flood risk and the impact of household adaptation might be underestimated.
	We measure flood intensity with flood depth.	Flood depth is the most commonly used parameter to measure the flood intensity (Apel et al., 2009; Merz et al., 2007), one of the most influential parameters on flood damage (Wind et al., 1999), and the most commonly available flood parameter (Poussin et al., 2011).	Other variables such as flood duration, flow velocity, and sediment or contamination load (Poussin et al., 2011; Putra et al., 2015) are not taken into consideration and hence the flood risk and the impact of household adaptation might be underestimated.
	Each year (step) only flood can occur.	On the one hand, this aligns with our inundation maps that indicate the yearly probability of a flood occurrence. On the other hand this is applied in other flood-ABMs – see Abebe et al. (2020).	In reality, multiple foods can occur in the same year. As we apply predetermined flood scenarios, this assumption does not appear to influence our simulation output.
	We ignore the impact of the agent behaviour on the flood hydraulics.	Creating and linking a numerical flood-model of Shanghai to our ABM exceeds the scope of this thesis.	The influence of the adaptation actions e.g., placing sandbags in front of the house on the flood hydraulics are not considered. “With a two-way linkage, hazards affect human actions, but social activities have consequences on future floods.” (Taberna et al., 2020, p.7). This is neglected and hence the human-flood system dynamics cannot be fully depicted.
Exposure	We only consider households as agents.	Including multiple agent types in our model and studying their impact on the adaptation effectiveness exceeds the scope this thesis.	The adaptation behaviour of other actors such as companies are neglected. As a result, “the backbone of regional resilience and recovery – the role of firms that provide households with jobs and income – is entirely overlooked.” (Taberna et al., 2020, p.16).
	Households are static	Movement of households is not included in the survey as an adaptation measure and hence this is not modelled.	The movement of households e.g., out of high-risk areas is not taken into consideration– see Haer et al. (2016). The lack in mobility might overestimated the flood risk and hence the effectiveness of the remaining mitigation measures.
	Each household lives in one residential building and vice versa.	On the one hand, this appears to be a common assumption in flood-ABMs – see for instance Abebe et al. (2020). On the other hand, data on the number of living-accommodations within each residential building appears scarce in Shanghai.	The majority of citizens in Shanghai live in apartments (Shanghai Municipal Statistics Bureau, 2020). A residential building in OSM can consist of multiple apartments. This means that the number of households is drastically underestimated which might leads to an underestimation of the flood risk and the cumulative adaptation effectiveness.
	In case of multi-story buildings, it is assumed that households live on the ground floor.	On the one hand, this appears to be a common assumption in flood-ABMs – see for instance Abebe et al. (2020). On the other hand, the data on the number of stories within each residential building appears poor.	Households which live on the ground floor have a higher exposure to flooding. Therefore, our hypothesis is that they would be more willing to adapt than people living in higher floors which are less exposed to floods. The majority of survey participants (82%) does not use the ground floor. This means that within our model the behaviour of households living mainly on the first floor or higher is used to model the behaviour of households living on the ground floor. As a result, the probability to intend adaptation measures and consequently the adaptation effectiveness might be impacted.
	The building flood depth is extracted at the location of the centroid of the building polygon.	This information can be extracted from QGIS.	In reality, damage would occur when water reaches the building structure (the edges of the polygon), which would thus be the relevant flood inundation. The flood depth of the building might thus slightly differ to reality.
	We assume that residential buildings have a floor elevation of 0.1 meter.	In our experience buildings tend to have a small floor elevation. This assumption also is considered in other flood ABMs – see Abebe et al. (2020).	This means that we consider a building inundated if the flood depth is 0.1 meter higher than the ground level of the building. In reality, not all buildings might have such an elevation and might be flooded already at a lower inundation level. Furthermore, in reality, buildings may have basements, which are neglected with this assumption. Thus, the exposure and therefore the flood risk of households might be underestimated.
	Households do not forget floods.	Although literature suggests that flood experience can decrease over time (- see for instance Bhattacharya-Mis & Lamond (2014), and de Guttry & Ratter (2022)), we do not assume this to be the case in our model. This assumption is in line with other flood ABMs e.g., Abebe et al. (2020)	Our regression results show that flood experience has a positive impact on the adaptation intention. Hence, as we assume a perfect memory of flood experience, the probability to adapt will be higher compared to an imperfect memory. As a result, the adaptation rate might be overestimated. As the Odds Ratios for Flood experience are however small, the impact of this assumption is likely small.
Vulnerability	We only focus on direct tangible damages.	Including indirect and intangible damages in Shanghai exceeds the scope for this thesis.	Indirect damages e.g., business interruptions or intangible damages e.g., death are neglected. The impact of mostly non-structural adaptation behaviour e.g., storing emergency kits can therefore not be studied. Moreover, this leads to an underestimation of the potential flood risk and hence also damage reduction.
	For the assessment of building damages, we consider the construction cost.	On the one hand, we have contemporary and official information available from the Shanghai Statics Bureau. On the other hand, this approach appears to be common in flood risk research – see Huizinga et al. (2017), and Wu et al. (2019)	Building damages consider the cost of reconstruction, i.e., the cost it would take a household to hire a construction company to repair the flood damage to the building structure. This means that we don’t consider the “market price” of a new home in case the building is damaged to such an extent that it is no longer habitable. As shown by Shan et al. (2019) this can lead to a drastic underestimation on the flood risk.
	We apply damage reduction values for dry- and wet-proofing from sources from the Global North (Europe or United States).	The Shanghai values provided by Du et al. (2020) for the damage reduction effect of wet-, and dry-proofing are assumed 100%, which does not appear reasonable when comparing it with other values from studies from the Global North. Hence, we apply the values from the Global North for the damage reduction effect of wet- and dry-proofing.	As explained by Kreibich et al. (2015, p.977) damage reduction effects of measures from different studies have a large spread “since the effectiveness depends on the specific local conditions during a flood.” The local conditions in Europe and the US might differ drastically from those in Shanghai e.g., flood type, flood intensity, flood duration, building quality, materials used, urban vs rural environment,… – see Huizinga et al. (2017). The damage assessment therefore contains considerable uncertainty.

Table 33: Summary model assumptions 2

	Assumption	Reasoning for assumption	Potential impact on results
Flood Adaptation	Adaptation measures are split into elevation, wet-proofing and dry-proofing.	First, the measure effectiveness (and cost) appear to differ measurably between the categories. Second, this categorization provides a suitable trade-off between modelling effort and details. Lastly, this categorization appears to be common in flood risk assessment (de Moel et al., 2013; Du et al., 2020; Lasage et al., 2014)	The effectiveness of the individual measures within the different categories can differ measurably – see Kreibich et al. (2015). By categorizing the measures, we need to apply an overall effectiveness of the measure category. This might lead to uncertainty in the outcome.
	Survey respondents intend to elevate, dry-or wet-proof, if they intend at least one individual measure within the respective category.	To create a binary logistics regression model, we require binary values for the intention to elevate, wet-proof and dry-proof. Therefore, we set these values to 1 if at least one adaptation measure within the respective category is intended.	The difference between households which intend one vs all adaptation measure within an adaptation category (elevation, wet-proofing, dry-proofing) is neglected. This impacts the resulting odds ratios and hence the probability to intend to adapt, which influences the adaptation rate and hence the adaptation effectiveness.
	Elevation and wet-proofing measures are assumed permanent, dry-proofing non-permanent.	Following Du et al. (2020) we assume that the elevation and wet-proofing measures are permanent and hence have an "infinite" lifetime, while dry-proofing measures are assumed non-permanent and can expire. After the lifetime is expired, households will no longer have dry-proofing implemented and benefit from the respective damage reduction.	Over time, less households will have adapted the dry-proofing measure than without this assumption. Hence, this assumption influences the adaptation diffusion, measure effectiveness, and flood risk.
	Dry-proofing measures have a normally distributed lifetime.	We assume a normally distributed lifetime of adaptation measures with a mean of 20 years and a standard deviation of 2 years to create a more realistic adaptation curve.	This assumption directly influences the adaptation diffusion of dry-proofing measures, measure effectiveness, and flood risk.
	We assume an intention gap between households who intend to adapt and households who actually adapt.	Households who intend to adapt do not necessary follow through with their adaptation intention (Grothmann & Patt, 2005) due to barriers in the form of time, knowledge, money, or social support (Grothmann & Reusswig, 2006). Hence, we introduce an intention gap parameter Intention_Gap which is derived from our longitudinal survey data in Shanghai. It captures the average percentage of household that put their adaptation intention into action within approximately one year	This parameter has a direct influence on the number of households who undertake adaptation measures. Therefore, it directly influences the adaptation diffusion and the adaptation effectiveness. Variations in this parameter may thus have a significant result on the model outcome.
	A household can adapt multiple measures at the same time.	The adaptation measures (elevation, wet-proofing, dry-proofing) pursue different mitigation. Therefore, it makes sense that households are able to use these different strategies at the same time to protect them from flood damage.	Households with attributes that favour adaptation intention as well as with high savings likely adapt multiple measures, which has a positive effect on the adaptation diffusion and the flood risk.
	A household must not implement elevation measure if they rent.	Only 3% of survey respondents who rent indicated that they elevated their house. This appears reasonable as an elevation of the house requires a substantial interference with the house foundation, which we assume a tenant does not have the rights for.	Tenants who intend to adapt an elevation measure are hindered to do so by this rule. Hence, the adaptation diffusion decrease and the risk increases. The effect of this assumption might be small due to the small number of tenants in the survey (16.2%).
	A household must not implement elevation measure if they live in an apartment.	We assume that the foundation of a residential apartment building is collective property of all households within the respective apartment building. Therefore, and individual household cannot drive the decision to elevate the entire apartment building itself. As a result, we assume that a household living in an apartment cannot implement an elevation measure.	Households living in apartments which intend to adapt elevation measures are hindered to do so by this rule (less adapted households, more risk). This institution is likely to have a large impact on the simulation results, as the majority of households live in apartment buildings.
	Household can only implement a measure if they can afford the cost.	We think it is important to include the financial capability of a household to adapt, as this is an important adaptation barrier (Grothmann & Reusswig, 2006). Hence, households can only implement a measure if their savings exceed the measure cost.	This means that households which would like to intend to adapt but cannot afford it do not implement the measure. Hence, the adaptation diffusion will be lower and the flood risk higher as households are more vulnerable.
	Households cannot take loans.	Loan-taking of households exceeds the scope of this thesis.	With loan-taking, households that do not have the savings could still finance and hence implement adaptation measures. Hence, our assumption likely leads to an underestimation of the adaptation uptake and thus of the damage prevention.
	The elevation measure increases the floor elevation to a level which is 30 cm higher than a current 100-year flood-level.	Within the survey data of Noll, Filatova, Need, et al. (2022) elevation is defined as "raising the level of the ground floor above the most likely flood level". Therefore, we assume that the elevation measure increases the buildings ground floor (which is assumed to be 10-cm above the ground) by 30-cm above the 100-year flood level. This is in line with Du et al. (2020). We choose the flood level from the 2030 scenario, as this can be considered a "current" flood-level from a 2020 perspective. Moreover, we choose the RCP8.5 scenario. However, we only have the inundation levels of the buildings for different flood scenarios and not the actual elevation level. Hence, we assume that if a household's inundation level for a 100-year flood in 2030 under the RCP 8.5 scenario is zero, then the ground floor will be elevated by 30cm.	This assumption directly influences the elevation level and hence the damage reduction.
	The adaptation measure reduces damage after the implementation time is passed.	We assume that the measure is only active and able to reduce damage after the implementation time is passed. If a flood happens during the implementation of a measure, the damage reduction by that measure will not take place.	In reality, even if an adaptation measure is only partially implemented e.g., only half the house structure is wet-proofed, the damage would be reduced in case of a flood. This is neglected in our model. Hence, this may have a negative effect on the damage reduction and hence flood risk
	Households receive an early warning to put up non-structural measures such as placing sandbags, which are included in the measure categories.	Implementing the effect of warning systems in our model is out of scope for this master's thesis. Therefore, we assume that all households receive an early warning and take the warning seriously	By assuming that all households receive a flood-warning in time, we might overestimate the effectiveness of the adaptation measure and hence underestimate the flood risk.

Table 34: Summary model assumptions 3

	Assumption	Reasoning for assumption	Potential impact on results
Flood Adaptation	We assume that households that implemented a measure before, did so in the 10 previous years (uniform distribution).	The median age group in the survey is 25-34 years old (~30). Hence, we assume that households that indicated in the survey that they already adapted a measure, did so in previous 10 years based on a uniform distribution for every simulation run.	This assumption influences when the non-permanent measure expires and hence directly influences the adaptation diffusion.
	Households can only adapt if they intend to do so before.	With the PMT, we determine the probability of a household to intend to adapt. As we based the agent behaviour on the PMT, we assume that a household can only start implementing an adaptation measure, if this is intended before.	The survey data shows that households also adapt which did not intend to do so before. This behaviour will hence be neglected in our model. As a result of our assumption, the total amount of households which adapt might be underestimated, which might lead to an overestimation of the flood risk.
	For the damage reduction assessment of a flood, we first determine the impact of the elevation, then of the dry-proofing and lastly of the wet-proofing measure.	The adaptation categories differ with regards to their damage reductio approaches. If the flood level is below the elevation level, the elevation measure contributes to 100% decrease in the flood damage. Although other measures also might have been implemented, they were not responsible for the decrease in damage and hence will not be accredited for it. If the flood level is above the elevation level, then the damage which is not avoided by the elevation measure can be decreased by the dry-proofing measure, which tries to avoid water from reaching or entering the building. Only if water enters or reaches the building, wet-proofing measures can reduce damage. Therefore, wet proofing measures can only reduce the damage which is not reduced by elevation and dry-proofing measures.	As a result of this logic, the dry-, and wet-proofing measure might be less effective when multiple measures are combined.
	The yearly change in savings cannot be negative.	Although a considerable portion of households indicate that their future savings will decrease, we assume that this is not possible. The main reason is that the majority of our households are from the 5th income percentile and hence we assume that households can only have a yearly change of savings which is large than or equal to 0.	As a result of this assumption, the average savings of a household will be higher and hence more households are able to afford the adaptation measure cost.
	We randomly vary the odds ratio for Flood experience for every household between the mean and the standard deviation.	As each flood affects each household and their behaviour differently, we randomly vary the odds ratio of flood experience for each household in the range of one standard deviation from the mean effect of flood experience on the adaptation intention.	This assumption introduces more stochasticity into how the flood experience of households influences their probability to intend an adaptation measure and hence makes the adaptation diffusion more diverse.
Household Interaction	The social network of the household is represented via its closest neighbours.	On the one hand, previous research shows the relevance of interactions in social networks on individual climate change adaptation (Bubeck et al., 2013; Figueiredo et al., 2009; Haer et al., 2016; H. Kunreuther et al., 2013; Lara et al., 2010; Lo, 2013; Noll, Filatova, Need, et al., 2022; van der Linden, 2015). On the other hand, our binary logistics regression results show that the influence of a household's social network is one of the strongest predictors on the adaptation intention for all measures.	In reality, the social network (in particular family and friends) might reach beyond neighbourhood. For instance, the adaptation decision of one's parents which live in a different city might still influence one's adaptation decision. This is neglected within this model.
	Each household can only consider the households within the same district as a neighbour.	We need to make sure that in case of spatial down- or upscaling of the model (e.g., selecting only one city centre district), a household still has access to the information of its neighbours. Therefore, we assume that each household can only consider the households within the same district as a neighbour. Hence, adding or removing districts does not impact the neighbourhood of households.	As a result of this assumption there are no social ties across districts. Hence, adaptation diffusion through the social network is limited to the district. In reality, households can be influenced by the behaviour of households in other districts. This is neglected in the model.
	The neighbourhood behaviour influences the social influence parameter of a household.	We assume the agent interaction influences the social influence parameter of a household as the odds ratio of the social influence parameter is a strong indicator for adaptation intention. .	The adaptation behaviour could also influence other agent parameters e.g., cost perception. According to Bubeck et al. (2013, p.1336) "the observation that the majority of the neighbours have implemented a certain flood mitigation measure (or not), can be regarded as a good indication that the respective measure is cost-effective (or not)". Including the influence of social network on other household parameters might increase the effect of the social network on the adaptation diffusion.

Assumptions are an important part of the conceptual model which according to Balci (1994, p.157) "should be explicitly specified." Hence, we list our assumptions together with the reasoning behind each assumption as well as the potential impact of the assumption on the model results in Table 32, Table 33, and Table 34.

B.9. Model narrative

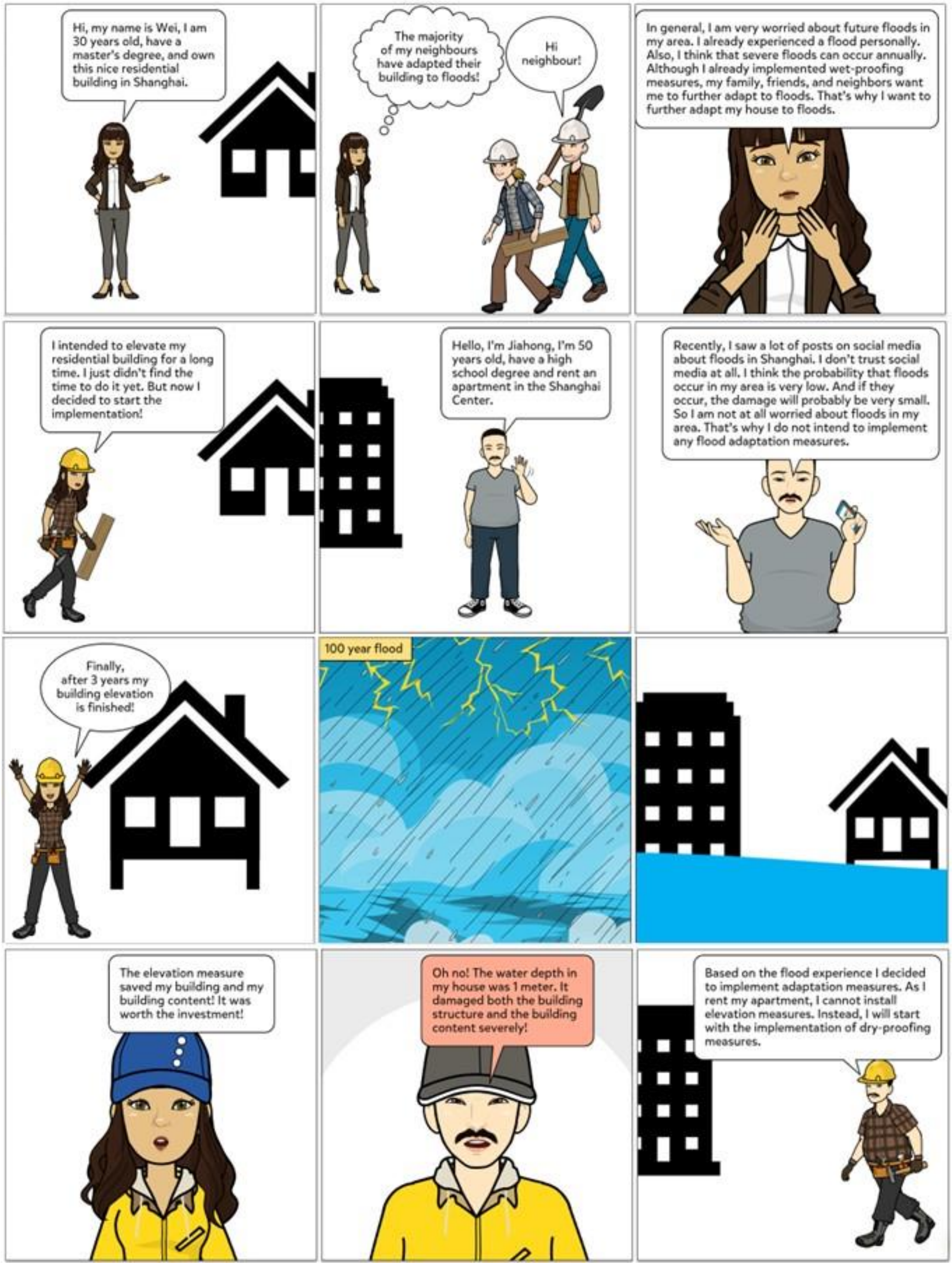

Figure 68: Model narrative (Source: created with Pixton (2022))

For the model formulization Nikolic et al. (2013, p.88) recommend a model narrative, which is "an informal description of the generative theory of the system under study, leading to emergent patterns we are interested in exploring". For our model, we explain the narrative with the help of a comic – see Figure 68. Within the narrative we distinguish two hypothetical household agents: The first household represented by *Wei* has PMT attribute levels which favour adaptation intention such as high perceived flood probability, high perceived flood damage, high worry, flood experience, a young age, high education, and high social influence. The second household represented by *Jiahong* has PMT attribute levels which do not favour adaptation intention e.g., low trust in social media, high age, low education, low flood probability perception, low flood damage perception, and low worry.

In addition, the following concepts are shown within the narrative: interaction with other households and the environment, the intention gap, the adaptation states (Do nothing, Implementing, Adapted), and the different adaptation measures. Due to the model size not every possible flood scenario, agent attribute combination and concept can be depicted. However, the narrative gives a good code-independent understanding of "which agent does what and with whom" (Nikolic et al., 2013, p.88).

C. Software Implementation

This appendix chapter details the software implementation of the model.

C.1. Program requirements

Following Robinson (2008) we define the requirements for our model:

- **Run-speed**: It is important that the model experiments can be conducted in reasonable time. This is one of the high-priority requirements of the model and will be prioritized over other design criteria, such as visual display.
- **Visual display**: Is not an important requirement for our model. In our model, there is not movement of the households. However, some form of graphical representation of the ABM processes are desirable.
- **Ease-of-use**: The model should be intuitive to calibrate and initiate. User should be able to change the agent parameters e.g., the socio-behavioural factors of the households via the GUI. Moreover, users should be able to change the environment over the GUI e.g., different flood scenarios, or different damage curves.
- **Flexibility and model/component reuse**: A model should be created which can be easily adapted to other geographic locations. This means that the model should be created in a manner, that changes in geographic context only influence the model data and not the main parts of the model structure.

We implement the model in Netlogo Version 6.2.2., as it is an easy-to-use ABM software with lots of documentation available, simple syntax, and an extensive online community (Nikolic et al., 2013). Moreover, as run-speed is one of the most important requirements, we improve the simulation time in the model as follows:

Outsourcing computation: We outsourced computational steps within the ABM to the input and output data. Regarding the input data we designed the model in such a way that all spatial model components are determined in QGIS and loaded into the ABM as simple data tables. On the one hand, we overlay the inundations maps with the residential building data to determine the inundation depth of each building. Hence, the inundation does not need to be determined by the ABM itself. On the other hand, instead of determining the nearest neighbours within the simulation model, the 15 nearest neighbours of each residential building are determined in QGIS via the distance matrix. Hence, each household knows the IDs of the 15 closest residential buildings which are used in the simulation model to call the respective household and exchange information. We outsourced computation to the output data analysis by letting the ABM only track the fundamental parameters (adapted HHs, flood damage, benefit and cost) which are required to determine the final reporting KPIs e.g., the NPV. These calculations itself are done post-simulation in our data analysis program e.g., SPSS.

Enabling easy spatial up- and downscaling of the model: The model is designed in such a way that Shanghai city centre districts can be easily added to or removed from the model via switches in the user interface without requiring further adjustments in the program or data. No adjustments in the program are needed, as the program only loads the buildings from the macrolevel csv-file which are included in the setup. Moreover, the data does not need to be adjusted as each household can only consider the households within the same district as a neighbour. Hence, adding or removing districts does not impact the neighbourhood of households. As the number of households has a big influence on the simulation time, this function enables the program to also work on computers with less computational power by simply reducing the number of districts included in the simulation.

Avoiding unnecessary calculation steps: During the setup, only the data which is required for the simulation is loaded into the model e.g., households which are not part of the scope are skipped while reading the csv files. During the execution**,** functions are only entered when it is necessary e.g., when there is no flood, a flood depth assessment is not necessary. Moreover, unnecessary loops are avoided e.g., instead of first letting all households determine their flood depth, then letting all households determine their flood damage, and finally letting all household determine their flood damage reduction (3 loops through all households), we use one loop and let first the first household determine its flood depth, flood damage, and flood damage reduction and then the second one and so on.

C.2. Applied programming practises

In line with Nikolic et al. (2013) we apply the following programming practices:

- **Version Control:** We regularly create a new model version.
- **Code documentation:** Besides the conceptual and formal model, we document within the code itself via extensive comments.
- **Naming conventions**: We adhere to the naming conventions established in the conceptual model.
- **Bug Tracking:** As Netlogo does not offer a debugging function, we develop a simple debugging function ourselves which gives out the micro-level information of important functions. This allows for bottom-up testing, execution monitoring, and execution tracing.

D. Experimentation

This appendix chapter provides supplementary information on the experimental setup of the ABM.

D.1. Design of flood scenarios

The ABM enables a selection of the RCP and up to three floods for each of which the time of occurrence and the flood probability can be selected. Based on this selection, the corresponding floods maps of J. Yin et al. (2020) with different Representative Concentration Pathways (RCP2.6 vs RCP8.5), different years (2010, 2030, 2050, 2100) and different flood probabilities (10-, 100-, 1000-year flood) are applied. This leads to a multitude of potential flood scenarios. Due a restriction in time and computation power, not all these scenarios can be examined. Therefore, a selection of the most relevant scenarios is conducted.

We select the flood scenarios based on the time of the flood events, the flood probabilities, the Representative Concentration Pathways, as well as the number of floods occurring,

Time of flood event: Our simulation span reaches from 2020 (tick 0) until 2050. Hence, until the year 2039, the 2030 flood maps will be selected and from 2040 onwards the 2050 flood maps are chosen by the model. Therefore, we distinguish between an early flood based on the 2030 flood maps and a late flood based on the 2050 flood maps. For the early flood we choose the year 2021 (first tick) as this allows us to best observe how flood events shortly after the simulation start impact the adaptation behaviour in the long-term. For the late flood event we choose the year 2040, as the simulation runs end in the year 2050 and it might take some years until patterns of change become visible. Within our scenarios we assume floods to occur 10 years earlier than indicated by the flood-maps (we use 2030 in 2021 and the 2050 in 2040). This means that we might overestimate the effect of sea-level rise and land subsidence in our scenarios. However, the *Special Report on the Ocean and Cryosphere in a Changing Climate* by the IPCC (2019) discovered that sea level rise is happening more quickly than previously thought. This justifies in our opinion the earlier application of the inundation maps.

Probability of floods: Based on the flood maps and the location of the residential buildings the inundation depth of each household are determined (see ODD protocol, Appendix *B.6*). For the city centre districts our analysis of the input data shows that in the event of a 10-year flood 0% of households are flooded in 2030 and 1% of households in 2050 for both RCP scenarios. Hence, the 10-year flood event is very close to the no flood event and therefore we only investigate the 100- and 1000-year probabilities.

Representative Concentration Pathway: The RCP impacts the effect of sea-level rise and hence the severity of the floods. Our analysis results show that with increase in years (2010, 2030, 2050, 2100) the difference between the RCP 2.6 and RCP 8.5 in terms of the number of flooded residential buildings increases (see ODD protocol, Appendix *B.6.1.3.2*). For the 100-year flood, the difference between the RCP 2.6 and RCP 8.5 scenario both for a flood in 2030 and 2050 in terms of flooded households is negligible (< 1%). For the 1000-year flood, the difference between the RCP 2.6 and the RCP 8.5 scenario is negligible in 2030 (~1%). In 2050 the difference between the RCP scenarios accounts for ~800 households (~5%). Hence, we only compare the RCP scenarios in this case. For the years and probabilities where the difference between the RCP scenarios is negligible, the RCP8.5 scenario is chosen.

Number of floods: Regarding the number of floods, we decide on scenarios with zero, one, and two floods occurring per simulation run. A scenario without a flood enables us to determine how households adapt in the absence of floods. The other scenarios allow us to examine the adaptation behaviour in the presence of one or two floods. For the scenario with two floods, we want to determine the combined effect of a 100-year flood in an earlier period where the effects of sea-level rise and land subsidence are small (low severity) to a 1000-year flood in a later period with larger effects of sea-level rise and land subsidence (high severity). Similar to Taberna et al. (2021), this scenario mimics a climate tipping point, where the severity of the flood increases.

As a result of these decisions, the following seven flood scenarios emerge: *No flood*, *2021_100_RCP8.5*, *2021_1000_RCP8.5*, *2040_100_RCP8.5*, *2040_1000_RCP8.5*, *2040_1000_RCP2.6*, and *2020_100_RCP8.5 + 2040_1000_RCP8.5*.

D.2. Number of replications per experiment

We follow the approach outlined by Lorscheid et al. (2012) to determine the number of replications per experiment. Hence, we estimate the coefficient of variation for different response variables with increasing number of simulation runs. As response variables we choose the percentage of households at the end of the simulation time (tick 30) which have adapted an elevation, a wet-proofing, and a dry-proofing measure. We measure the response variable in each run in the last tick. Moreover, as suggested by Lorscheid et al. (2012) we apply two different scenarios. A “normal” flood scenario with no flood occurring and an “extreme” flood scenario with a 100-year flood occurring in 2021 and a 1000-year flood occurring in 2040.

Table 35: Error variance matrices (Source: Adapted from Lorscheid et al. (2012))

Flood scenario "No flood"

Number of runs		10	20	50	100	200	400	600	800	1000	1200
Adpated elevation measures*	MEAN	3.95%	3.95%	3.95%	3.94%	3.94%	3.94%	3.94%	3.94%	3.94%	3.94%
	VARIANCECOEFF	0.011	0.010	0.011	0.011	0.012	0.011	0.011	0.011	0.011	0.011
Adapted wet-proofing measures*	MEAN	57.55%	57.54%	57.55%	57.55%	57.53%	57.53%	57.53%	57.53%	57.54%	57.54%
	VARIANCECOEFF	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Adapted dry-proofing measures*	MEAN	32.78%	32.78%	32.71%	32.69%	32.71%	32.71%	32.72%	32.71%	32.71%	32.71%
	VARIANCECOEFF	0.010	0.009	0.009	0.008	0.008	0.008	0.008	0.008	0.008	0.008

**At tick 30*

Flood scenario "2021_100_RCP8.5 + 2040_1000_RCP8.5"

Number of runs		10	20	50	100	200	400	600	800	1000	1200
Adpated elevation measures*	MEAN	3.92%	3.92%	3.91%	3.90%	3.91%	3.90%	3.90%	3.90%	3.90%	3.90%
	VARIANCECOEFF	0.010	0.011	0.012	0.012	0.011	0.011	0.011	0.011	0.011	0.011
Adapted wet-proofing measures*	MEAN	56.45%	56.47%	56.47%	56.49%	56.51%	56.51%	56.51%	56.51%	56.52%	56.52%
	VARIANCECOEFF	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Adapted dry-proofing measures*	MEAN	30.26%	30.28%	30.27%	30.25%	30.28%	30.26%	30.26%	30.27%	30.26%	30.26%
	VARIANCECOEFF	0.010	0.011	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.009

**At tick 30*

The error variance matrices in Table 35 suggests that the coefficient of variation for the three response variables are stable with 100 replications (see green marking) in terms of a difference criterion of 0.001. Therefore, we select 100 replications per experiment.

D.3. Experimentation output

Table 36: Attribute levels for simulation output (n=18039)

Attribute	New attribute levels			Old attribute levels		
	Level	Frequency	Percent	Level	Frequency	Percent
Worry (Worry)	Low	12930	72%	1	5877	32.6%
				2	7053	39.1%
	Medium	3520	20%	3	3520	19.5%
	High	1589	9%	4	1323	7.3%
				5	266	1.5%
Self Efficacy Elevation (Self Eff)	Low	11859	66%	1	8585	47.6%
				2	3274	18.1%
	Medium	3812	21%	3	3812	21.1%
	High	2368	13%	4	1829	10.1%
				5	539	3.0%
Self Efficacy Wet-Proofing (Self Eff)	Low	2991	17%	1,0	93	0.5%
				1,2	35	0.2%
				1,4	219	1.2%
				1,6	104	0.6%
				1,8	803	4.5%
				2,0	550	3.0%
				2,2	1187	6.6%
	Medium	10933	61%	2,4	952	5.3%
				2,6	1968	10.9%
				2,8	1437	8.0%
				3,0	2042	11.3%
				3,2	1419	7.9%
				3,4	1757	9.7%
				3,6	1358	7.5%
	High	4115	23%	3,8	1257	7.0%
				4,0	974	5.4%
				4,2	591	3.3%
				4,4	506	2.8%
				4,6	294	1.6%
				4,8	245	1.4%
				5,0	248	1.4%
Self Efficacy Dry-Proofing (Self Eff)	Low	5801	32%	1,00	772	4.3%
				1,25	520	2.9%
				1,50	875	4.9%
				1,75	1124	6.2%
				2,00	1458	8.1%
				2,25	1052	5.8%
	Medium	8259	46%	2,50	1105	6.1%
				2,75	1365	7.6%
				3,00	2344	13.0%
				3,25	1446	8.0%
				3,50	1999	11.1%
	High	3979	22%	3,75	1020	5.7%
				4,00	1133	6.3%
				4,25	718	4.0%
				4,50	486	2.7%
				4,75	285	1.6%
				5,00	337	1.9%
Social Network Size (Soc Net)	Small	8980	50%	0	7728	42.8%
				3	1252	6.9%
	Medium	6117	34%	6	3348	18.6%
				9	2769	15.4%
	Large	2942	16%	12	1340	7.4%
				15	1602	8.9%
Income Quintile (Income)	Low (1st and 2nd)	1559	9%	1863	401	2.2%
				3225	1158	6.4%
	Medium (3th and 4th)	3582	20%	3939	1880	10.4%
				5359	1702	9.4%
	High (5th)	12898	72%	8299	2135	11.8%
				10467	10763	59.7%

To make the results more significant and to better compare the variables of interest for each socio-behavioural attribute, we convert the socio-behavioural attributes of the synthetic population of households into 3-point scales for the output of our experiments as shown in Table 36.

E. Verification and Validation

Model validation and verification are arguably two of the most critical steps in the simulation lifecycle. Whereas "model validation deals with building the right model", "model verification deals with building the model right" (Balci, 1994, p.165). Tests are applied to perform the validation and verification of simulation models (Balci, 1994; Rabe & Spiekermann, 2008). Validation, verification, and testing (VV&T) can help to avoid errors of type 1, 2, and 3 in the simulation model – see Balci & Nance (1985). While Nikolic et al. (2013) define verification and validation as separate steps in the life-cycle, Balci (1994) highlight that VV&T should be seen as a continuous activity throughout the lifecycle. As a result, we modify the lifecycle of Nikolic et al. (2013) by integrating VV&T into the most important process steps. Since models are abstractions of the real-world system, our tests do not provide formal proof of the absolute correctness of a model, but merely confirm the credibility of our model (Balci, 1989; Rabe & Spiekermann, 2008).

E.1. System and Objectives Definition VV&T

System and Objectives Definition Verification and Validation is used to check the credibility of the system definition. The system identification should be examined especially with regards to changes over time, environment, counterintuitive behaviour, tendency to low performance and dependency relationships. Errors in the system definition can otherwise lead to type 2 and type 3 errors. (Balci, 1994).

- **Changes over time:** While the system structure consisting of household as actors, residential buildings as objects, and floods as the environment will likely stay similar over the simulation time horizon (30 years), the values of the system parameters likely change over time. The dynamics of climate change over time are integrated via the flood maps. Socio-economic developments e.g., the amount of households and buildings in Shanghai due to population growth, the building and content values, or the effectiveness of adaptation measures due to technological advances are assumed static in our model. To limit the effect of the neglecting changes over time for the aforementioned parameters, we choose a time horizon of 30 years (see ODD protocol, Appendix *B.2.3.1*).
- **Environment:** The identification of the system boundary has been validated via conversations with ABM as well as flood modelling experts.
- **Counterintuitive behaviour:** One counterintuitive behaviour which is included in this model is the negative influence of belief in climate change on the adaptation intention, as highlighted by Noll, Filatova, Need, et al. (2022).
- **Drift to low performance:** Drift to low performance describes the performance decrease of system components over time, such as the wear and tear of machinery (Balci, 1994). In our case, the effectiveness of adaptation measures might decrease over time. Therefore, we have introduced the expiration for dry-proofing measures.
- **Dependencies:** "In a complex stochastic system, many activities or events take place simultaneously and influence each other. The system complexity can be overcome by way of decomposing the system into subsystems and subsystems into other subsystems." (Balci, 1994, p.156) We follow this advice and decompose the system based on the extended risk assessment framework of Aerts et al. (2018).

E.2. Data VV&T

For the validation and verification of the data, further *Consistency Checking* and *Face Validation* tests proposed by Balci (1994) are performed. In addition to the tests for data validation, indicators for the quality of data preparation are provided in the form of questions (Balci, 1994) which we answer in the following.

On the one hand, the question is raised whether the identified and processed input parameters accurately represent the real-world system (Balci, 1994). To represent the household behaviour, we apply survey data from 933 survey respondents of Shanghai, of which 66% of the survey respondents located in Shanghai city centre. To model the residential buildings, we use OSM data with 18039 residential buildings in the city centre with an accuracy of 90% to the real-world data in terms of the number of mapped buildings. To model the floods, we apply inundation maps from local Shanghai experts which include dike breaking and overtopping, the effect of sea level rise and land subsidence. Hence, we conclude that the input parameters appear to represent the real-world system in an adequate manner.

Furthermore, the reliability of the data collection tools needs to be evaluated (Balci, 1994). This also includes the quality of the data sources. Data for the hazard, vulnerability, risk reduction and behaviour factors stems from peer-reviewed academic models or papers (details see ODD protocol, Appendix *B.6*). As government-provided residential building data appears scarce, the location of residential buildings in Shanghai is retrieved from OSM, a licence-free digital map of the world, where the data is collected by volunteers. These volunteers act independently of each other and are usually not experts in data collection and preparation, leading to data quality concerns (Haklay, 2010). However, an analysis by Zheng & Zheng (2014, p.187) shows “that the OSM data in Beijing and Shanghai is mostly complete, with high positional accuracy.” Therefore, OSM appears a suitable source for open-source data in Shanghai. In terms of residential buildings, we compare the accuracy of the building data ourselves and focus on the districts in Shanghai with the highest mapping accuracy of residential buildings.

Balci (1994) also raises the question of whether the data transformations are completed correctly. For residential building data, the application of the correct OSM filter tag is of great importance. The correctness of the filter tag is verified, for example, by searching for the filtered elements after applying the filter tag. Regarding the inundation data, merging the 21 inundation maps with the residential buildings has a great error potential. Hence, we check that the inundation at the building location is mapped correctly and verify that the maximum inundation levels of households are within reasonable ranges.

Lastly, Balci (1994) asks about the actuality of the data. The residential building data stems from 2022, the inundations maps from 2020, the survey data from 2020 and the adaptation measure data is from >2010. Hence, we can conclude that the data appears up to date. However, it should be noted that some data in the real-world system changes during the modelling process. For example, new residential buildings might be added by mappers in OSM, which are consequently not represented in the simulation model.

It is to be noted that next to the Data VV&T mentioned in this subchapter, we perform additional data verification and validation within the input data subsection of the ODD protocol (Appendix *B.6*). For instance, we compare the residential building data to government statistics (Appendix *B.6.1.2*), or validate the risk exposure with other risk assessment studies in Appendix (*B.6.1.5*). Further verification and validation tests can be found in the individual input data subchapters.

E.3. Conceptual Model VV&T

To be able to verify and validate the complicated model structure, Balci (1994) suggests to follow a structured approach for the conceptualization. Hence, we apply the extended risk assessment framework of Aerts et al. (2018) as a foundation for our conceptual model. We verify this conceptual model using *Consistency Checking* tests. More specifically we check the model for contradictions, and adhere to naming conventions (Balci, 1994).

To validate the conceptual model, we apply *Face Validation* tests (Balci, 1994) with flood-ABM experts. Expert Interviews can provide an indication if the model appears reasonable, which according to Nikolic et al. (2013, p.129) is an "appropriate way to address the validation of agent-based models". During the interviews the conceptual model structure and assumptions are discussed with the expert in order to determine if the model has a "face value". However, there are several challenges related to expert validation (Nikolic et al., 2013): First, experts assess the validity of the ABM with their own internal model which is shaped by their world views and might contain inexplicit biases. Therefore, we provide a detailed list of the model assumptions to the experts prior to the interview to avoid misunderstandings. Second, especially for behaviourally-rich models, experts might assume how the model functions instead of understanding it, resulting in potentially misleading conclusions. Hence, we conduct the face validation with three flood-ABM experts who have different academic backgrounds.

E.4. Computational Model VV&T

To verify the computational model we apply tests, which are described in the following

Unit testing: Unit testing checks that individual units work correctly (Wilensky & Rand, 2015). According to (Wilensky & Rand, 2015, p.317) these tests make sure that "future changes to our code do not disrupt previous code". We apply a multitude of such unit-testing functions (listed in the following). If these unit tests detect an error, a user-message appears that informs the user about the error and helps them better identify the problem.

- **Verify-flood-calibrations**: Makes sure that only one flood can occur per year.
- **Verify-direct-neighbourhood**: Verifies that the number of direct neighbours which have been assigned to a household match the network size of the respective household.
- **Verify-indirect-neighbourhood**: Checks that the number of households which consider a household a direct neighbour is calculated correctly.
- **Verify-cost-calculation**: Verifies that each household which starts the simulation with an implemented adaptation measure also pays for the measure.
- **Verify-agent-state**: Checks that when a measure is marked as undergone (UG = 1) that the adaptation state for this measure needs to be 2 (adapted).
- **Verify-position-flood-scenario**: Makes sure that the flood scenario which is selected is included in the csv file.
- **Verify-adapt-change**: Verifies that when a household adapts it correctly asks its direct neighbours to increase their adaptation count of the indirect neighbours.
- **Verify-flood-damage**: Checks that the damage is lower than the value of the content/building.
- **Verify-flood-damage-reduction**: Checks that the damage reduction is lower than the damage to the content/building.

Bottom-up testing: In bottom-up testing, first the functions of the sub models and then the functions of the higher-level model are tested (Balci, 1994). For instance, we first test whether the flood damage is calculated correctly and then test whether the flood damage reduction is executed accordingly.

Execution monitoring: According to Balci (1994, p.139) "execution monitoring is used to reveal errors by examining low-level information about activities and events which take place during model execution." For instance, for our model we monitored the updating of the count of nearest neighbours of a household that adapted a measure.

Execution tracing: In execution tracing, the execution of the simulation is monitored step by step for the household (Balci, 1994). For our case, all the calculation steps to determine the benefit of an adaptation measure in a tick are checked manually step by step using a self-built debug function.

E.5. Sensitivity Analysis

To gain insights in the generation of emergent patterns in our ABM and to examine the robustness of these patterns we apply a local one-factor-at-a-time (OFAT) sensitivity analysis, where starting from a base case, we change one parameter[30] or assumption at a time, while keeping the remaining parameter values constant (ten Broeke et al., 2016). Next to the ability of OFAT to examine emergent patterns and model robustness, OFAT has the advantage of requiring less computational effort than other sensitivity methods (ten Broeke et al., 2016).

E.5.1. Parameter selection and parameter variation

Due to runtime constraints, not all parameters can be included in the sensitivity analysis. Moreover, not all parameter values can be assessed. Hence, we approach the sensitivity analysis in two steps: First, we preselect the most relevant parameters based on literature insights and exchange with flood-ABM experts. Second, for each of the selected parameters we determine a set of values that we derive from literature and the survey data. The selected parameters, the base case and their variation is shown in Table 37 and explained in the following:

Table 37: Sensitivity scenarios (Source: see explanation in main text)

Sensitive parameter *(model notation)*	Base case	Parameter variation
Intention gap *(Intention_gap)*	27.8%	13.9%, 41.7%, 100%
Effectiveness in damage reduction *(Effectiv$_m$)*	Wet: 40% Dry: 85%	Wet: 60%, 20% Dry: 100%, 50%
Effectiveness level *(Effectiv_lvl$_m$)*	Elev: 0.3 m Wet: 3.0 m Dry: 1.0 m	Elev: 0.0 m Wet: 1.8 m Dry: 0.5 m
Foundation height *(Foundation_height)*	0.1 m	0 m, 0.2 m
Measure cost *(Cost$_m$)*	Elev: 4040 € Wet: 4027 € Dry: 1706 €	Elev: 153.2 €/m^3, 0 € Wet: 15323 €, 0 € Dry: 33.2 €/m^2 + 1036 €, 0 €
Asset cost *(Sqm_value$_d$)*	Building: 861 €/m^2 Content: 209 €/m^2	Building: 6764 €/m^2 Content: 1642 €/m^2
Depth damage function *(Depth_dam$_d$)*	Wang (2001)	Yu et al. (2012), Z. Yin et al. (2011)

[30] As we categorize adaptation measures into elevation, wet-, and dry-proofing measures, the parameters that refer to the adaptation measures are lists which contain three values, one for each of the three measure categories. Within the sensitivity analysis, we vary the parameter values for all three measures at the same time.

Intention gap: The intention gap parameter is multiplied by the probability of intention to determine the probability to implement. Hence, the larger the intention gap the higher the probability to implement and hence the number of adapted households. Moreover, the flood-ABM experts suggested examining the influence of this parameter. Hence, we include it in our sensitivity analysis. The intention gap for our base case is 27.8% (see ODD protocol, Appendix *B.6.4.5*). For the parameter variation we choose 50% and 150% of the base case as these values appear realistic (see intention gap values between different survey waves). Moreover, we are interested in the model behaviour without the intention gap (=100%).

Effectiveness in damage reduction: The effectiveness parameter has a direct influence on the avoided flood damage. Research shows a high variability for this parameter – see Kreibich et al. (2015). Hence, we include this parameter in the sensitivity analysis. For ***wet-proofing***, we apply a 40% reduction of content and building damage for our base case (see ODD protocol, Appendix *B.6.3.2*). For the sensitivity analysis we set this value to 20% and 60% in line with values shown by Kreibich et al. (2015) for wet-proofing. For ***dry-proofing*** we assume an 85% damage reduction for building and content damage for our base case (see ODD protocol, Appendix *B.6.3.2*). We choose to vary this parameter to a 50% in line with values outlined by Kreibich et al. (2015) and 100%. Varying the effectiveness of the ***elevation*** measure is in our opinion not necessary as we assume it to be at 100%[31]. This leads to two sensitivity scenarios for the adaptation measures: *Measure effectiveness low* and *Measure effectiveness high*.

Effectiveness level: The effectiveness level determines below which inundation level the measures can reduce damage. This parameter has a direct influence on the avoided flood damage and is hence included in our sensitivity analysis. For ***wet-proofing***, we follow de Moel et al. (2013) and apply a level of 3 meters in our base case (see ODD protocol, Appendix *B.6.3.2*). Other sources such as Du et al. (2020) apply a value of 1.8 meters. Hence, we choose 1.8 meter for the varied wet-proofing effectiveness level to test the sensitivity. For ***dry-proofing*** we follow Bubeck & de Moel (2010), de Moel et al. (2013), and Lasage et al. (2014) with an effectiveness level of 1 meter in our base case (see ODD protocol, Appendix *B.6.3.2*).. For the parameter variation, we are interested in how the model behaviour changes if we reduce the parameter by 50%. Overall, we combine the parameter variations into one sensitivity scenario: *Effectiveness level low*.

Foundation height: The foundation height has a direct influence exposure of households and hence the flood damage as well as the flood experience and is therefore included in the sensitivity analysis. For our base case, we follow Abebe et al. (2020) and apply a foundation height of 0.1 meters. For the sensitivity analysis, we choose 0 meters and 0.2 meters.

Adaptation Measure Cost: Households only adapt if they can afford to pay for the adaptation measure costs. Therefore, the measure costs have a direct influence on the adaptation diffusion and flood risk and appears relevant to study in our sensitivity analysis. For our base case, we select the cost data from the survey, as it is directly linked to the adaptation measures which are included in our categories (see ODD protocol, Appendix *B.6.3.3*). For the sensitivity analysis, we compare two scenarios. In a first scenario we use the cost data of Du et al. (2020) for elevation, wet-proofing, and dry-proofing in Shanghai. Compared to our survey-based cost data, their measure costs stem from local engineering experts. Moreover, while we assume fixed cost for all measure categories, Du et al. (2020) apply cost values per m^2 for dry-proofing measures and per m^3 for elevation measures. In a second scenario, we assume that the measure costs are fully subsidized by the government, which means that households no longer need to pay for the measure from their own savings[32].

[31] Either the building is elevated above the inundation level, or it is not. If it is above the level, there is no flood damage (neglecting the potential damage to the elevated building foundation). If it is below, flood damage occurs according to the depth-damage function.

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Asset Cost: The building and content value have a direct influence on the flood damage and hence the flood experience as well as household savings and might therefore be very influential for the model outcomes. For our base case, we base the building value on the construction costs and the content values based on the house items which are susceptible to flooding (details see ODD protocol, Appendix *B.6.1.4*). For the parameter variation, we base the building value on the average building price following Shan et al. (2019) while applying the same building to content value ratio (24%) as in the base case (details see ODD protocol, Appendix *B.6.1.4*).

Depth-Damage Function: Our review shows that the depth-damage functions in Shanghai can differ substantially (details see ODD protocol, Appendix *B.6.2*) and therefore they are included in the sensitivity analysis. For our base case, we select the depth-damage curve of Wang (2001) – the reasons for the selection of this function are explained in the ODD protocol in the Appendix *B.6.2*. For the parameter variation, we apply the functios of Yu et al. (2012) and Z. Yin et al. (2011)[33] to our model.

E.5.2. Sensitivity results

Similar to our main experiments we run the sensitivity experiments from 2020 until 2050. However, due to runtime constrains, we limited our replications per experiment to 50. For the flood scenario, we select the climate tipping point scenario (100-year flood in 2021 and a 1000-year flood in 2040 under the RCP 8.5 scenario). We examine the influence of the parameter variations on the adaptation diffusion, and the total potential flood damage

E.5.2.1. Adaptation diffusion

Figure 69, Figure 70, and Figure 71 depict the effects of the parameter variations on the adaptation diffusion, the number of households who cannot afford adaptation, and the average household savings. In the following we analyse the effect of the parameter variation on the adaptation diffusion.

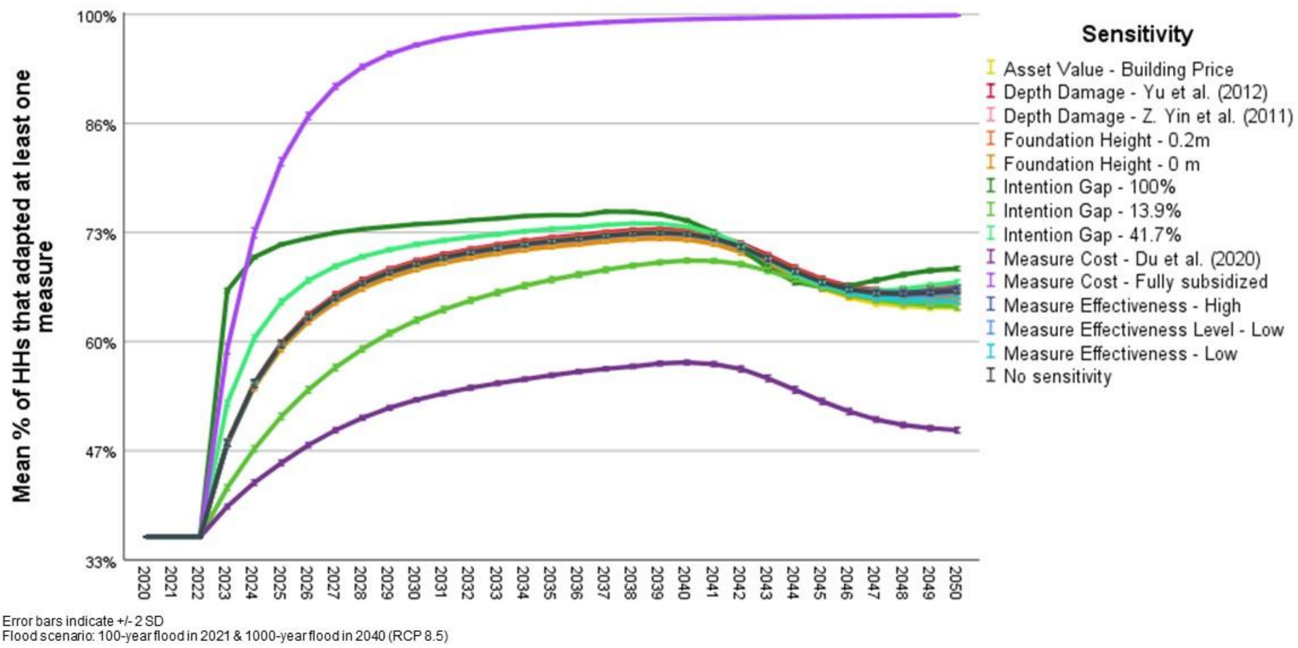

Figure 69: Sensitivity - Adaptation diffusion

[33] As shown in the ODD protocol Appendix *B.6.2*, we transfer the continuous depth-damage function of Z. Yin et al. (2011) into a discrete function.

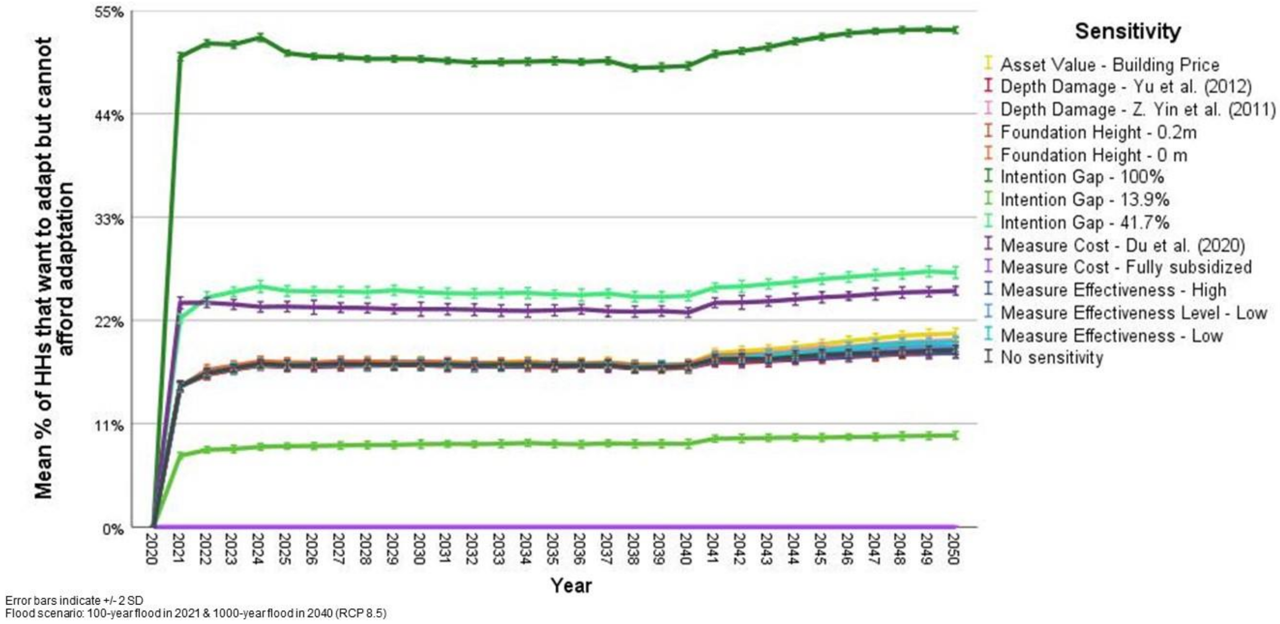

Figure 70: Sensitivity - Percentage of households that cannot afford adaptation

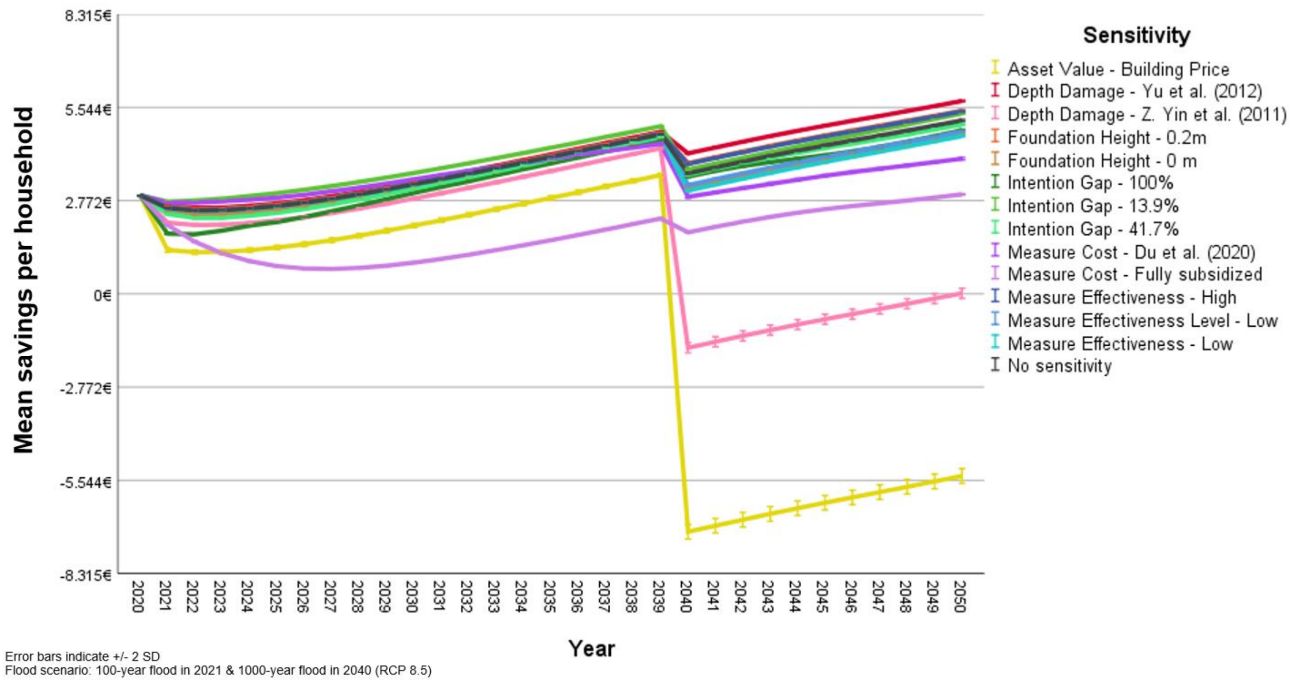

Figure 71: Sensitivity - Mean savings per household

Depth damage function: In the model, the depth damage function influences the flood damage. On the one hand, this effects a household's flood experience attribute level which influences the probability of a household to adapt. The higher the flood damage and hence the flood experience, the higher the probability to adapt. On the other hand, the flood damage impact the savings and hence a household's financial capability to adapt. The higher the flood damage, the lower the savings, and the lower the capability to adapt. Hence, the effects on the adaptation diffusion are in theory opposing. Our sensitivity results show that the different depth damage functions do not appear to have a large impact on the adaptation behaviour (see red graphs in Figure 69). This might be explained by multiple factors. First, the aforementioned opposing effect of adaptation probability and financial capacity. Second, it appears that independent of the depth-damage function, the damages caused by the flood are so large that the households are not able to afford adaptation in the following ticks. This is supported by the fact that the depth-damage function has a considerable effect on the average household savings (see red graphs in Figure 71), but the average number of household who cannot afford the adaptation (see red graphs in Figure 70) remains similar to the base case.

Measure effectiveness and effectiveness levels: The measure effectiveness influences the impact of flood events on the flood experience and savings of adapted households. In theory, the higher the effectiveness the smaller the change in adaptation probability and the smaller the reduction of the household's savings due to the lower flood damage (and vice versa). Our results in Figure 69 (blue graphs) indicate that the change in effectiveness and effectiveness level do not appear influential on the adaptation diffusion of households, which can be explained by multiple factors. First, the opposing effect of adaptation probability and financial capacity. Second, it seems although the change in effectiveness impacts the influence of the flood on the household savings (see blue graphs in Figure 71), it does not appear relevant as the savings appear already low previous to the flood event. This is supported by the fact that the average number of households who cannot afford the adaptation (see blue graphs in Figure 70) remains similar to the base case

Foundation height. In our model, the decrease in foundation height leads to an increase in the exposure of households. The decrease in the foundation height means that on the one hand, more households will be flooded and on the other hand that the inundation depths of households which have been flooded before increases even further, which in theory should lead to an increase in flood damage. As explained before, with the increase in flood damage, the flood experience increases and hence the probability to adapt while the savings decrease and hence the capability of households to undertake action. The results in Figure 69 (orange graphs) shows that a change in the foundation height leads to a small but not significant change in the adaptation diffusion which can be explained as follows: Households that already have been flooded before are even less capable to adapt, as their flood damage either stays the same or decreases even further having a negative effect on the savings (see orange graphs in Figure 71) and hence their adaptation capabilities. Households which are now considered flooded have less savings and hence less capability to finance the adaptation which results in a decrease in the adaptation diffusion.

Intention gap: In theory, the larger the intention gap (more households that intend to adapt also take action) the higher the probability to adapt and hence also the higher the number of adapted households. Our results overlap with this theory. With no intention gap (all households that intend also take action), ~35% of the household population adapt at least one measure between 2022 and 2023, which is a considerable faster increase in the adaptation diffusion than in the base case (see dark green graph in Figure 69). Moreover, the intention gap influences the time of the measure expiration. The larger the intention gap parameter, the faster households adapt and hence the dry-proofing measures will expire at an earlier point in time. Depending on the time of the flood event this can either be beneficial or detrimental. Similarly, with a lower intention gap parameter, it takes longer for the diffusion of adaptation measures in the population.

If a flood occurs right at the beginning of the simulation, the slower adaptation rate might have a significant effect on the flood risk. Overall, we conclude that the intention gap has a significant influence on adaptation diffusion of households.

Measure cost: In our model the measure costs directly influence the ability of households to afford the measure and hence they directly influence the adaptation diffusion. Our results indicate the drastic effect of this parameter. In case households do not have to pay for their adaptation measures (fully subsidized), almost 100% of households adapt at least one measure by 2040 (see light purple graph in Figure 69). The majority of households even adapt multiple measures - especially wet- and dry-proofing (see purple graphs in Figure 72). This shows the restrictive effect of the savings on the adaptation diffusion. When the cost data of Du et al. (2020) is applied, where wet-proofing and dry-proofing are more expensive than in the base case with the survey data, a sharp drop in the adaptation diffusion over time can be noticed (see dark purple graph in Figure 69). Households either no longer can afford to adapt or if they manage to have enough savings to adapt, savings decrease by the high measure cost, which hinders subsequent adaptation actions – which is reflected in the significant change in savings (see dark purple graph in Figure 70) and number of households that cannot afford adaptation (see dark purple graph in Figure 71).

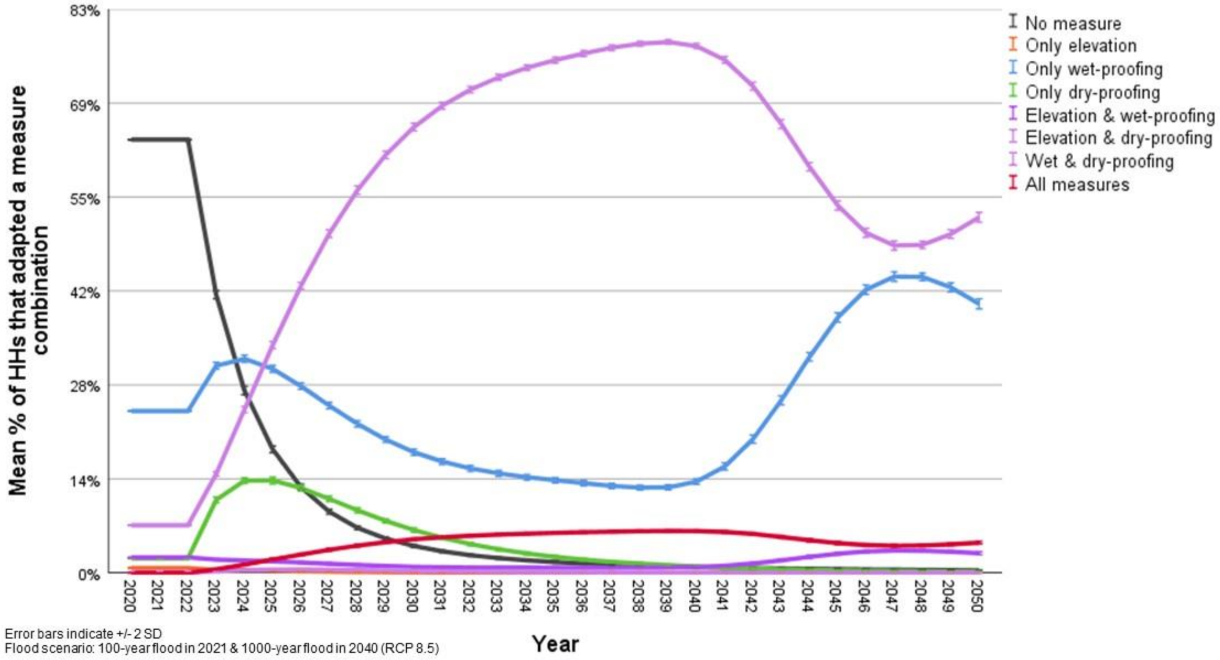

Figure 72: Sensitivity - Fully subsidized measure cost - Diffusion of adaptation measure combinations within the household population[34]

Asset value: Similar to the change in the depth-damage curve, the change in the asset value influences the impact of flood events on the household's behaviour (flood experience, savings). As with the depth-damage curves, also the asset value does not appear to have lots of impact on the adaptation diffusion (see yellow graph in Figure 69).

[34] It is important to note that we do not change the cost perception attribute levels of households as we want to determine the impact of the savings constraint on the model behaviour.

E.5.2.2. Total potential flood damage

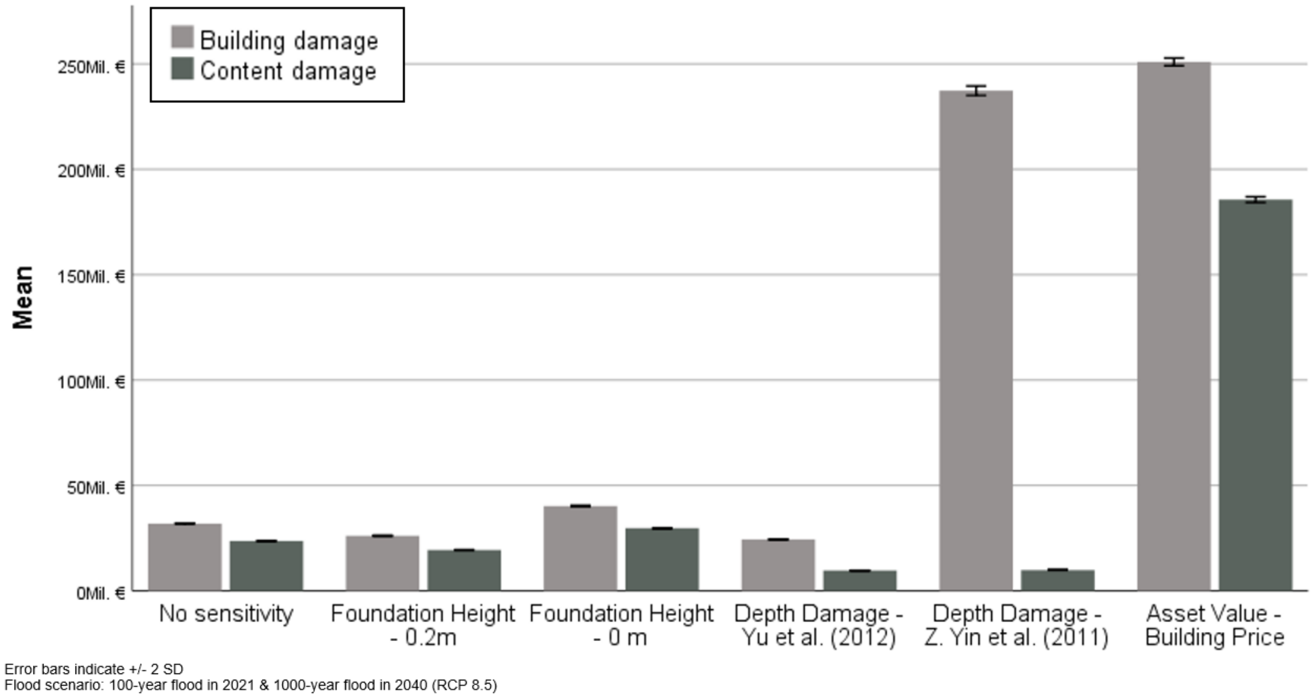

Figure 73: Sensitivity - Total flood damage (2020-2050) without adaptation for different sensitivity scenarios

Figure 73 shows the total flood damage over the entire simulation without household adaptation for the sensitivity scenarios which have an influence on the flood damage. For the base case we determine a total flood damage of 55 Mil. € with 57% building (light grey) and 43% content damage (dark grey). This value changes significantly especially when changing the asset value and the depth damage function, as explained in the following.

Foundation height: The foundation height influences the household exposure and hence the total potential flood damage. While the total damage decreases to 45 Mil. € with 0.2 m in foundation height, the total damage increases to 70 Mil. € without including any foundation height. The ratio between building and content damage stays similar to the base case.

Depth Damage: The depth damage function also has a considerable effect on the flood damage. Using the depth-damage function on Yu et al. (2012) the total flood damage is 39% lower than in the base case. We also notice a change in the distribution of building (72%) and content damage (28%). Using the depth-damage function of Yin et al., the damage increases to 247 Mil. €, with 96% building and 4% content damage. This drastic jump can be explained by the high proportional building damage at low inundation levels (100% damage below 2 meters), which might result from a different definition of maximum building damage (see ODD protocol, Appendix *B.6.2*).

Asset Value: By using the actual housing price instead of the construction price, the flood damage increases drastically to 436 Mil. €. This sharp incline in flood damage overlaps with the observations of Shan et al. (2019), who compare their building-price based results to the construction-price based results of Wu et al. (2019).

E.5.2.3. Flood damage prevention

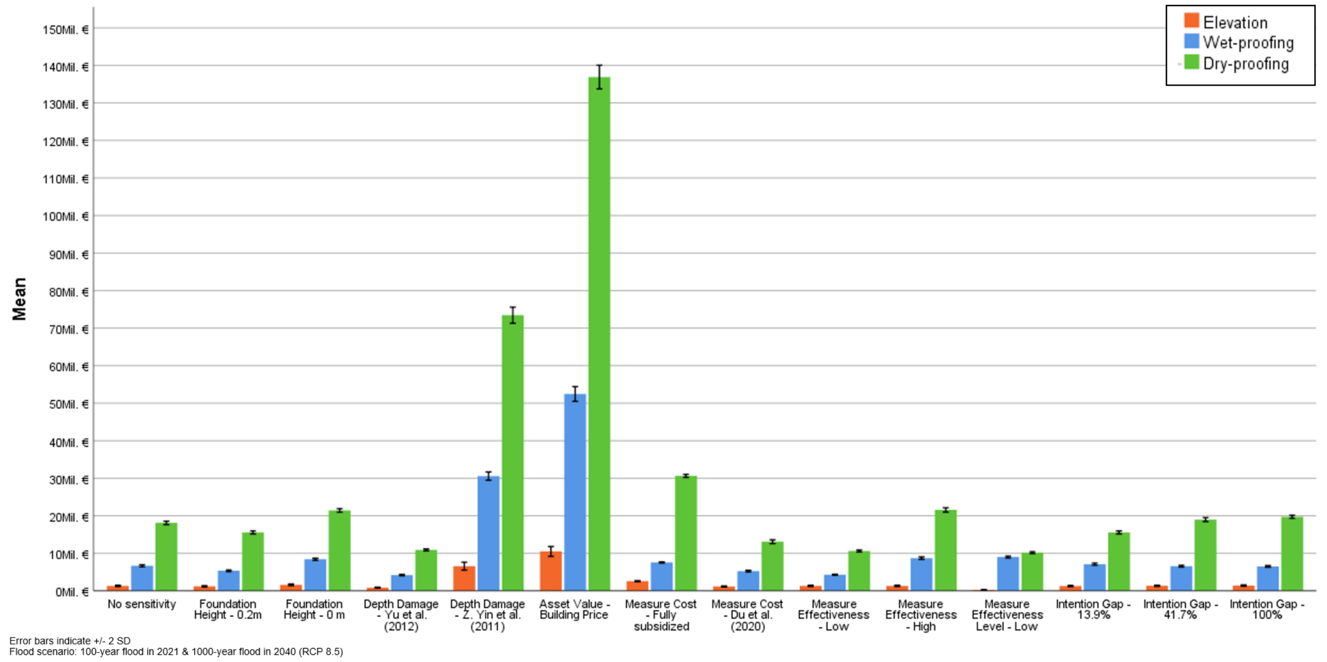

Figure 74: Sensitivity - Total flood damage mitigation (2020-2050) for different sensitivity scenarios

Figure 74 depicts the changes in the prevention of flood damage for the different sensitivity scenarios. In the base case, on average 26.1 Mil. € in flood damage is prevented by household adaptation, which can be broken down into 1.3 Mil. € damage by elevation, 6.7 Mil. € by wet-proofing and 18.1 Mil. € by dry-proofing. The change in the flood damage reduction for the different scenarios can be explained by the change in the adaptation diffusion, the flood damage (see previous subchapters) and the measure effectiveness. This is explained in the following.

Change in adaptation diffusion: The measure cost and the intention gap significantly influence the adaptation diffusion (see chapter *E.5.2.1*). The change in measure cost leads to a significant change in the flood damage reduction. In case of full subsidization of measure cost the average mitigated damage increases to 41 Mil. € and with the cost data of Du et al. (2020) it decreases to 20 Mil. €. In comparison the effect of the intention gap is lower, with a total mitigated damage of 24 Mil. € for a 13.9% intention gap, 27 Mil. € for the 41.7% intention gap, and 28 Mil. € for the 100% intention gap. This can be explained by the timing of the flood event. The majority of the flood damage is caused by the 2100 flood in 2040. A glance at the adaptation diffusion (see green graphs in Figure 69) shows that despite their varying trajectories, the differences between the intention gap scenarios are rather small at year 2040, which explains the small differences in the reduced flood damage. Hence, we conclude that the effect of the intention gap parameter on the flood damage reduction depends on the timing of large flood events. We therefore recommend additional flood scenarios for future experiments.

Change in flood damage: The foundation height, depth damage function and asset value have a significant influence on the flood damage which is reflected in the flood damage reduction (see Figure 74). Specifically, the depth-damage function of Z. Yin et al. (2011) which leads to a flood damage reduction of 111 Mil. € and the building-price based asset values with a flood damage reduction of 200 Mil. € have a high influence on the flood damage reduction.

Change in the measure effectiveness: The measure effectiveness and the effectiveness level directly influence the flood damage reduction (see Figure 74). The low effectiveness scenario leads to a reduced damage of 16 Mil. €, while the high effectiveness scenario results in a reduced damage of 32 Mil. €. Reducing the effectiveness level results in a reduced flood damage of 19 Mil. €.

E.5.2.4. Summary of sensitivity results

Table 38 summarizes the influence of the sensitivity scenarios on the adaptation diffusion, the total flood damage, and the flood damage mitigation. Our OFAT sensitivity analysis shows that the adaptation measure cost and the intention gap have a measurable impact on the adaptation behaviour of households. Moreover, the foundation height, and specifically the depth-damage curve as well as the asset value significantly influence the total flood damage. Hence, these parameters should be further researched to improve the credibility of the results.

Table 38: Summary of sensitivity results

Sensitivity scenario	Mean % of HHs that adapted >= 1 measure	Mean total flood damage in Mil. €	Mean total mitigated flood damage in Mil. €
No sensitivity (Base Case)	65%	56	26
Foundation Height - 0.2m	65%	45	22
Foundation Height - 0 m	64%	70	31
Depth Damage - Yu et al. (2012)	65%	34	16
Depth Damage - Z. Yin et al. (2011)	64%	247	111
Asset Value - Building Price	64%	437	200
Measure Cost - Fully subsidized	89%	55	41
Measure Cost - Du et al. (2020)	51%	56	20
Measure Effectiveness - Low	64%	55	16
Measure Effectiveness - High	65%	56	32
Measure Effectiveness Level - Low	65%	56	19
Intention Gap - 13.9%	61%	56	24
Intention Gap - 41.7%	66%	56	27
Intention Gap - 100%	68%	55	28

E.5.3. Limitations of sensitivity analysis

Our sensitivity analysis shows several limitations.

First, due to the model complexity as well as computational restrictions we perform a local sensitivity analysis where we only vary one input parameter at a time. However, since we do not know whether the model is linear, we cannot make any statements about the effects of changing two or more parameters at the same time (Saltelli et al., 2008) which limits the significance of our sensitivity results.

Second, due to computational constraints not all parameters and assumptions can be included in the sensitivity analysis which limits our understanding of the formation of emergent patterns as well as the robustness of these patterns. Neglected parameters and assumptions include for instance the household population size, the confidence intervals of the Odds Ratios, the measure lifetime, the measure implementation time, the time horizon, the inundation maps, as well as the assumption of non-negative yearly change in savings.

Third, our variation of the parameters is limited. On the one hand, the number of parameter variations is relatively small due to the large impact on the computational time. This makes it difficult to understand the model linearity as well as model tipping points (ten Broeke et al., 2016). On the other hand, we do not change parameters at equal intervals, as we base our parameter variation mostly on values applied in other risk assessment studies. This makes the comparability of the model sensitivity between the parameters more difficult.

Further limitations are the reduced number of replications per experiment, which are set at 50 due to computational limits instead of the 100 repetitions for the main experiments. Additionally, the sensitivity observations are only valid for the selected flood scenario. With change in flood scenario the patterns might change e.g., if a large flood occurs at an earlier point in time e.g., in 2025, the intention gap might have a larger influence on the damage reduction.

F. Data analysis

This subchapter provides supplementary information to the results described in Chapter *6*.

F.1. Details on aggregate impacts of household adaptation

In addition to the results shown in the main text (see Chapter *6*), Figure 75 and Figure 76 give a more detailed insight into the stochasticity of the flood damage and flood damage prevention. The standard deviations of the building and content damage are relatively small. As we use predetermined flood maps for the flood scenarios, the only variation between the simulation runs stems from the random matching of the households to the residential buildings. As the building and content values of each households differs, the aggregated flood damage varies to some extend between the simulation runs of a flood scenario.

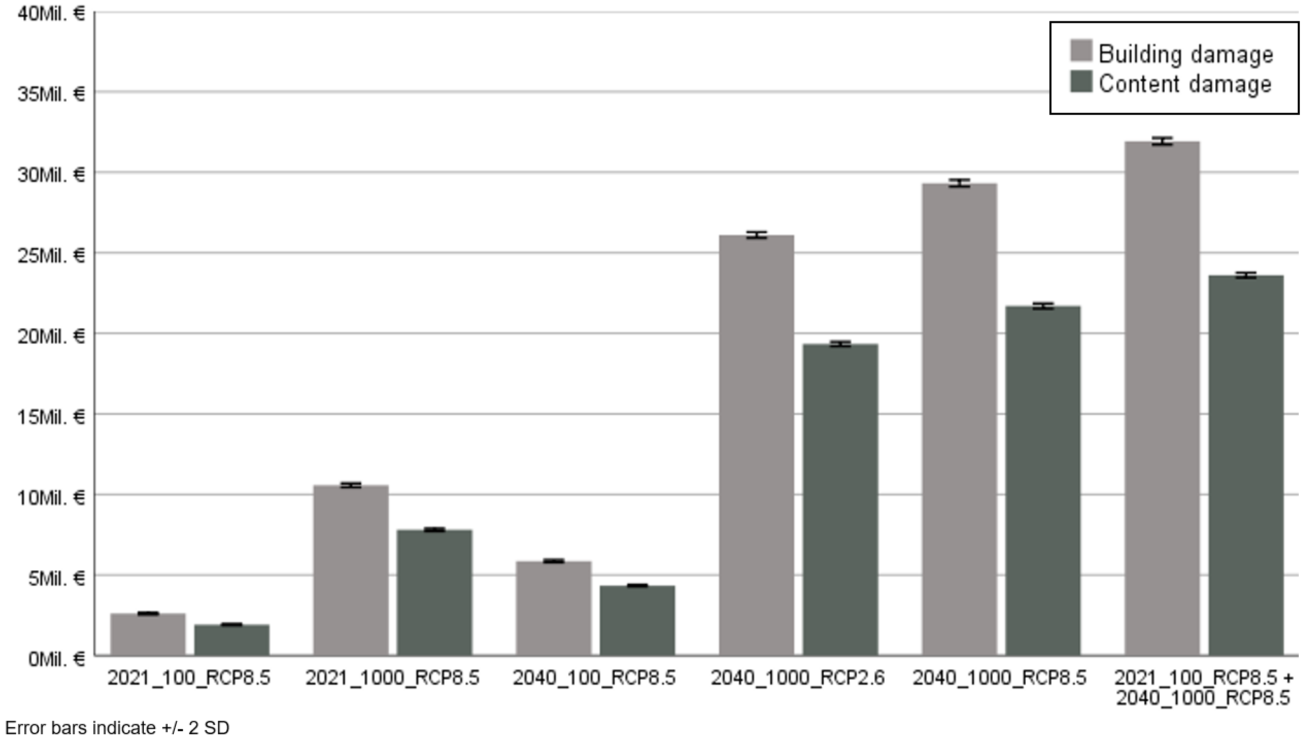

Figure 75: Mean total flood damage (2020-2050) for different flood scenarios without household adaptation

The standard deviations of the mitigated flood damage by the different adaptation measures are more noticeable (see Figure 75). They can be explained by two factors. On the one hand, the flood damage itself varies for each simulation run as explained above and hence the damage prevention varies. On the other hand, within each run households make different adaptation decisions, leading to the differences in the prevented flood damage.

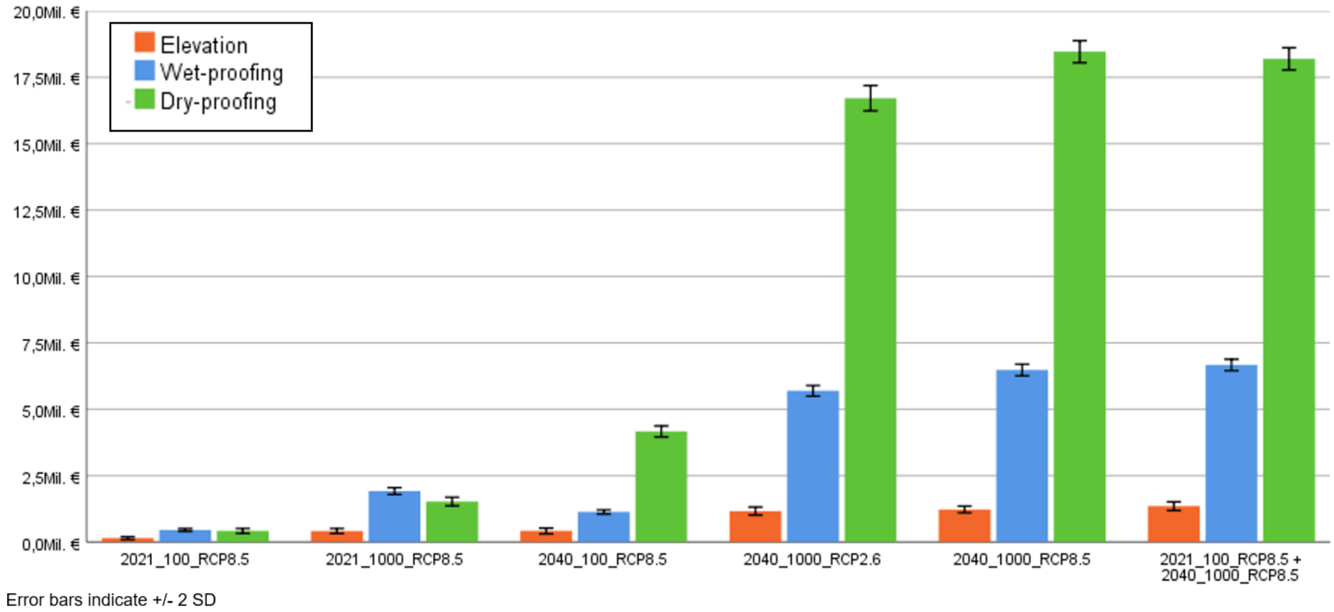

Figure 76: Total prevented flood damage (2020-2050) by household adaptation

The differences in the total damage mitigation between the adaptation measures (Figure 76Figure 75) can be explained by their effectiveness and their diffusion at the time of the flood event. While elevation (orange colour) has a relatively high effectiveness with a 100% damage reduction below 0.3 meter above the 100-year flood level in 2030, wet-proofing (blue colour) reduces damage by 40% below 3.0 meter and dry-proofing (green colour) by 85% below 1 meter (details see ODD protocol, Appendix *B.6.3.2*). For the 2021 flood, on average 3% adapted elevation, 33% wet-proofing and 9% dry-proofing measures (see Chapter *6.1.1*). Hence, the most damage is mitigated by wet-proofing in 2021 due to the medium penetration rate and medium effectiveness, followed by dry-proofing with a low penetration rate and high effectiveness and followed by elevation with a very low penetration rate and very high effectiveness. For the 2040 flood the situation changes. On average 4% adapted elevation, 55% wet-proofing and 49% dry-proofing measures(see Chapter *6.1.1*). As dry-proofing has a high penetration rate and high effectiveness it now mitigates the most damage, followed by wet-proofing with a high penetration rate and medium effectiveness and followed by elevation with a very low penetration rate and very high effectiveness.

F.2. Differences in damage prevention between household groups

In the main text in chapter *6.2.2* we showed the differences in damage prevention of household groups with different worry, self-efficacy, social network, and income levels. The question arises if the differences in relative damage prevention between the groups (of the same socio-behavioural factor) are statistically significant. Hence, we apply a one-way analysis of variance (ANOVA) for worry, self-efficacy, social network size, and income. For each ANOVA analysis, the dependent variable is the relative flood damage prevention, while the independent variables are the three groups (low, medium, and high)[35] for the respective socio-economic factor worry, self-efficacy, social network, and income (see chapter *5.3* and Appendix *D.3*). The main assumptions underlying an ANOVA are a normal distribution of the dependent variables as well as a homogeneity of variances (Delacre et al., 2019; Stahle & Wold, 1989). We test these assumptions in the following.[36]

F.2.1. Testing normality assumption of ANOVA

For each flood scenario and for each household group we test the damage prevention of the different levels within the group for normality by calculating the z-scores of each item with regards to the skewness and kurtosis. To determine the z-scores, we divide the skewness and kurtosis values by the respective standard deviations as shown in Table 39 (Mishra et al., 2019). As we replicate each experiment 100 times (see Appendix *D.2*), our sample sizes are 100 for each flood scenario. Therefore, we apply the cut-off value for the z-scores of +-3.29 (Kim, 2013). All z-scores are within the aforementioned range. Next to this numerical method of detecting normality, we also conducted a visual method (Mishra et al., 2019), by looking at the histograms of the results. Based on the results of both the numerical and visual method we conclude the distributions to be normal. Thus, the first assumption for ANOVA is satisfied.

[35] As a household can only be part of one group (low, medium, high) for each socio-behavioural factor, we conclude that the groups are independent of each other.
[36] In addition to the normality and homogeneity of variances we also tested the dependent variable on outliers based on an inter-quartile range multiplier of 3. No such outlier has been identified.

Table 39: Kurtosis and Skewness z-scores for household groups (n=100 for each flood scenario)

Flood scenario	Descriptive	Worry			Self Efficacy			Social Network			Income		
		Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
2021_100_RCP8.5	Mean	0.225	0.196	0.265	0.119	0.216	0.380	0.162	0.249	0.318	0.172	0.195	0.235
	Std. Deviation	0.014	0.023	0.048	0.017	0.021	0.033	0.016	0.021	0.035	0.035	0.022	0.014
	Skewness	0.219	-0.020	0.326	-0.042	-0.119	-0.082	0.100	0.496	0.345	0.426	0.104	-0.091
	Std. Error of Skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
	Skewness z score	***0.907***	***-0.084***	***1.351***	***-0.175***	***-0.494***	***-0.340***	***0.415***	***2.054***	***1.429***	***1.764***	***0.432***	***-0.377***
	Kurtosis	0.608	-0.236	-0.432	-0.194	-0.313	-0.336	-0.430	-0.299	-0.007	0.131	0.405	-0.388
	Std. Error of Kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
	Kurtosis z score	***1.270***	***-0.494***	***-0.902***	***-0.405***	***-0.654***	***-0.702***	***-0.900***	***-0.624***	***-0.014***	***0.273***	***0.847***	***-0.812***
2021_100_RCP8.5 + 2040_1000_RCP8.5	Mean	0.485	0.417	0.493	0.430	0.464	0.565	0.470	0.466	0.487	0.254	0.309	0.539
	Std. Deviation	0.004	0.010	0.018	0.008	0.007	0.011	0.007	0.007	0.012	0.012	0.008	0.005
	Skewness	0.108	-0.078	0.200	0.099	0.106	0.111	0.304	0.391	0.521	0.173	0.075	-0.074
	Std. Error of Skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
	Skewness z score	***0.446***	***-0.322***	***0.827***	***0.409***	***0.440***	***0.459***	***1.258***	***1.621***	***2.158***	***0.716***	***0.312***	***-0.307***
	Kurtosis	-0.322	-0.510	-0.691	-0.281	-0.164	0.036	0.111	0.453	0.368	0.508	-0.786	-0.063
	Std. Error of Kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
	Kurtosis z score	***-0.672***	***-1.067***	***-1.444***	***-0.587***	***-0.343***	***0.076***	***0.233***	***0.947***	***0.770***	***1.062***	***-1.643***	***-0.132***
2021_1000_RCP8.5	Mean	0.213	0.183	0.238	0.114	0.198	0.356	0.154	0.235	0.297	0.167	0.181	0.222
	Std. Deviation	0.007	0.013	0.024	0.009	0.009	0.019	0.007	0.011	0.016	0.015	0.011	0.007
	Skewness	-0.372	0.023	0.024	0.083	-0.258	0.368	-0.144	-0.205	-0.071	0.351	-0.169	0.088
	Std. Error of Skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
	Skewness z score	***-1.540***	***0.094***	***0.100***	***0.344***	***-1.068***	***1.525***	***-0.596***	***-0.848***	***-0.295***	***1.455***	***-0.702***	***0.366***
	Kurtosis	1.017	0.101	-0.319	0.711	0.141	0.234	0.190	-0.165	-0.043	0.567	0.487	0.449
	Std. Error of Kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
	Kurtosis z score	***2.126***	***0.212***	***-0.666***	***1.487***	***0.294***	***0.490***	***0.396***	***-0.344***	***-0.089***	***1.186***	***1.019***	***0.939***
2040_100_RCP8.5	Mean	0.574	0.496	0.593	0.520	0.560	0.658	0.565	0.550	0.569	0.291	0.370	0.640
	Std. Deviation	0.011	0.023	0.028	0.018	0.017	0.026	0.014	0.016	0.025	0.032	0.021	0.009
	Skewness	0.089	-0.265	0.247	0.004	0.112	0.362	-0.056	0.073	0.096	0.337	0.238	-0.360
	Std. Error of Skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
	Skewness z score	***0.370***	***-1.098***	***1.021***	***0.018***	***0.464***	***1.498***	***-0.234***	***0.301***	***0.396***	***1.394***	***0.986***	***-1.491***
	Kurtosis	0.111	0.716	-0.096	-0.254	0.635	0.612	0.458	-0.066	-0.484	0.040	-0.189	1.542
	Std. Error of Kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
	Kurtosis z score	***0.232***	***1.497***	***-0.200***	***-0.532***	***1.327***	***1.279***	***0.958***	***-0.139***	***-1.013***	***0.084***	***-0.395***	***3.224***
2040_1000_RCP2.6	Mean	0.533	0.458	0.539	0.483	0.511	0.607	0.522	0.512	0.523	0.273	0.341	0.593
	Std. Deviation	0.005	0.010	0.014	0.008	0.008	0.011	0.006	0.008	0.010	0.012	0.009	0.004
	Skewness	-0.212	-0.229	0.036	-0.308	-0.282	-0.242	0.041	-0.017	-0.130	-0.032	0.058	-0.230
	Std. Error of Skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
	Skewness z score	***-0.880***	***-0.951***	***0.149***	***-1.275***	***-1.167***	***-1.002***	***0.169***	***-0.072***	***-0.540***	***-0.133***	***0.240***	***-0.953***
	Kurtosis	-0.028	-0.468	-0.409	0.186	-0.292	-0.153	0.186	-0.282	-0.281	0.365	0.539	-0.028
	Std. Error of Kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
	Kurtosis z score	***-0.058***	***-0.978***	***-0.856***	***0.389***	***-0.609***	***-0.320***	***0.389***	***-0.590***	***-0.588***	***0.764***	***1.127***	***-0.058***
2040_1000_RCP8.5	Mean	0.527	0.454	0.533	0.481	0.504	0.598	0.517	0.505	0.518	0.272	0.335	0.587
	Std. Deviation	0.005	0.009	0.016	0.008	0.008	0.011	0.006	0.006	0.012	0.012	0.009	0.005
	Skewness	-0.135	0.423	0.264	0.130	0.094	0.169	0.313	0.219	-0.419	-0.258	-0.432	0.078
	Std. Error of Skewness	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241	0.241
	Skewness z score	***-0.561***	***1.751***	***1.095***	***0.540***	***0.388***	***0.701***	***1.298***	***0.906***	***-1.735***	***-1.071***	***-1.788***	***0.322***
	Kurtosis	0.080	-0.237	-0.429	-0.310	-0.032	0.165	-0.293	-0.459	0.259	0.070	-0.140	0.240
	Std. Error of Kurtosis	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478	0.478
	Kurtosis z score	***0.167***	***-0.496***	***-0.896***	***-0.648***	***-0.067***	***0.344***	***-0.613***	***-0.960***	***0.542***	***0.146***	***-0.292***	***0.503***

F.2.2. Testing homogeneity of variances

To test the homogeneity of variances we apply Levene's test (Glass, 1966) as shown in Table 40. The results show a significant value (p<.05) for all flood scenarios and for all household groups. Hence, we reject the assumption of equal variances within the household groups. This means that the assumption of homogeneity of variances is violated and hence an ANOVA cannot be applied. Although numerous investigations suggest a robustness of the hypothesis of homogeneity of variances for equal sample sizes (which is the case in our data) for the ANOVA F-test, Rogan & Keselman (1977) argue that this is not always the case. Hence, we apply alternative tests that appear more robust against heterogeneous variances in the subsequent subchapter *F.2.3*.

Table 40: Levene's test for homogeneity of variances for relative damage reduction based on mean

Behavioural factor	Flood scenario	Levene Statistic	df1	df2	Sig.
Worry	2021_100_RCP8.5	62.259	2	297	0.000
	2021_100_RCP8.5 + 2040_1000_RCP8.5	72.227	2	297	0.000
	2021_1000_RCP8.5	53.627	2	297	0.000
	2040_100_RCP8.5	33.265	2	297	0.000
	2040_1000_RCP2.6	48.641	2	297	0.000
	2040_1000_RCP8.5	50.378	2	297	0.000
Self Efficacy	2021_100_RCP8.5	20.286	2	297	0.000
	2021_100_RCP8.5 + 2040_1000_RCP8.5	9.671	2	297	0.000
	2021_1000_RCP8.5	23.744	2	297	0.000
	2040_100_RCP8.5	7.674	2	297	0.001
	2040_1000_RCP2.6	5.160	2	297	0.006
	2040_1000_RCP8.5	6.390	2	297	0.002
Social Network	2021_100_RCP8.5	25.050	2	297	0.000
	2021_100_RCP8.5 + 2040_1000_RCP8.5	19.626	2	297	0.000
	2021_1000_RCP8.5	27.511	2	297	0.000
	2040_100_RCP8.5	23.497	2	297	0.000
	2040_1000_RCP2.6	13.250	2	297	0.000
	2040_1000_RCP8.5	18.204	2	297	0.000
Income	2021_100_RCP8.5	23.930	2	297	0.000
	2021_100_RCP8.5 + 2040_1000_RCP8.5	23.122	2	297	0.000
	2021_1000_RCP8.5	18.518	2	297	0.000
	2040_100_RCP8.5	38.872	2	297	0.000
	2040_1000_RCP2.6	30.119	2	297	0.000
	2040_1000_RCP8.5	26.042	2	297	0.000

F.2.3. Robust Tests

We apply tests which are more robust against heterogeneous variances, namely Welch's ANOVA (W-test) and the Brown-Forsythe test (F*-test) (Delacre et al., 2019; Roth, 1983) as shown in Table 41. Both the W-test and the F*-test show significant results (p<.05) for all household groups for all flood scenarios. Hence, we can reject the null hypothesis of equal means of damage reduction between the household groups

Table 41: Robust Tests – Welch and Brown-Forsythe

Behavioural factor	Flood scenario	Test	Statistic[a]	df1	df2	Sig.
Worry	2021_100_RCP8.5	Welch	101.569	2	170.781	***.000***
		Brown-Forsythe	115.053	2	159.600	***.000***
	2021_100_RCP8.5 + 2040_1000_RCP8.5	Welch	2154.857	2	158.276	***.000***
		Brown-Forsythe	1214.607	2	163.424	***.000***
	2021_1000_RCP8.5	Welch	284.070	2	167.974	***.000***
		Brown-Forsythe	283.882	2	172.246	***.000***
	2040_100_RCP8.5	Welch	535.724	2	169.203	***.000***
		Brown-Forsythe	560.236	2	224.166	***.000***
	2040_1000_RCP2.6	Welch	2197.684	2	161.760	***.000***
		Brown-Forsythe	1820.437	2	205.044	***.000***
	2040_1000_RCP8.5	Welch	2675.379	2	169.118	***.000***
		Brown-Forsythe	1663.831	2	179.310	***.000***
Self Efficacy	2021_100_RCP8.5	Welch	2569.614	2	188.342	***.000***
		Brown-Forsythe	2872.991	2	223.454	***.000***
	2021_100_RCP8.5 + 2040_1000_RCP8.5	Welch	4939.406	2	191.721	***.000***
		Brown-Forsythe	6279.249	2	257.961	***.000***
	2021_1000_RCP8.5	Welch	7077.554	2	187.303	***.000***
		Brown-Forsythe	8543.562	2	195.910	***.000***
	2040_100_RCP8.5	Welch	950.460	2	192.698	***.000***
		Brown-Forsythe	1182.446	2	253.364	***.000***
	2040_1000_RCP2.6	Welch	4323.983	2	195.241	***.000***
		Brown-Forsythe	5136.510	2	276.199	***.000***
	2040_1000_RCP8.5	Welch	3893.989	2	194.455	***.000***
		Brown-Forsythe	4753.697	2	268.487	***.000***
Social Network Size	2021_100_RCP8.5	Welch	1107.215	2	183.610	***.000***
		Brown-Forsythe	953.770	2	209.633	***.000***
	2021_100_RCP8.5 + 2040_1000_RCP8.5	Welch	111.223	2	189.299	***.000***
		Brown-Forsythe	152.777	2	222.553	***.000***
	2021_1000_RCP8.5	Welch	4506.549	2	179.473	***.000***
		Brown-Forsythe	3723.411	2	211.360	***.000***
	2040_100_RCP8.5	Welch	31.740	2	189.707	***.000***
		Brown-Forsythe	27.697	2	232.887	***.000***
	2040_1000_RCP2.6	Welch	58.467	2	189.725	***.000***
		Brown-Forsythe	52.673	2	252.740	***.000***
	2040_1000_RCP8.5	Welch	105.894	2	189.023	***.000***
		Brown-Forsythe	72.077	2	213.796	***.000***
Income	2021_100_RCP8.5	Welch	224.254	2	177.417	***.000***
		Brown-Forsythe	165.041	2	200.733	***.000***
	2021_100_RCP8.5 + 2040_1000_RCP8.5	Welch	45572.276	2	177.350	***.000***
		Brown-Forsythe	30391.307	2	214.890	***.000***
	2021_1000_RCP8.5	Welch	807.191	2	181.704	***.000***
		Brown-Forsythe	587.171	2	226.658	***.000***
	2040_100_RCP8.5	Welch	11046.935	2	161.814	***.000***
		Brown-Forsythe	6528.157	2	193.294	***.000***
	2040_1000_RCP2.6	Welch	56172.108	2	164.814	***.000***
		Brown-Forsythe	34773.724	2	206.434	***.000***
	2040_1000_RCP8.5	Welch	52176.982	2	173.693	***.000***
		Brown-Forsythe	34846.176	2	222.753	***.000***

The aggregate statistics above show that not all group means are equal. However, we don't know which discrepancies between group means are statistically significant. A multiple comparisons post-hoc test can be applied to find significant differences between particular groups (Toothaker, 1993). In cases of heterogeneous variances, like in ours, the Games-Howell test can for instance be applied (Lee & Lee, 2018). Due to time constraints of this thesis, we do not perform such a post-hoc test, and conclude for our analysis that for each socio-behavioural variable, there is at least one significant difference between the three groups.

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