Household adaptation decision making in response to extreme flooding

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Preface

This report is prepared as part of the SEN1211 - Agent-Based Modelling course. As a component of this course, we engaged in a group project tasked with modeling flood adaptation decision making for households under various parameters. We utilized the Python programming language with the Mesa package for the modeling.

We extend our sincere appreciation to Dr. Ir. Igor Nikolic and Dr. Natalie van der Wal for their invaluable contributions to this project. Their guidance and expertise greatly enriched our understanding and implementation of agent-based modeling principles in addressing complex real-world scenarios.

1. Introduction

In an era marked by intensifying climate challenges, the imperative to adapt to extreme weather events, especially floods, has grown more pressing (Wilby, & Keenan, 2012). Harris County, Texas serves as a focal point, emblematic of this urgent need for adaptation measures due to its susceptibility to severe flooding induced by hurricanes and heavy rainfall leading to high damages (e.g., hurricane Harvey in 2017). As climate change continues to disrupt weather patterns, a critical examination of barriers hindering flood adaptation at the household level in this region becomes paramount.

Financial constraints emerge as a dominant barrier, underscoring the pivotal role of subsidies in facilitating flood adaptation among households. Insufficient funds often impede the implementation of effective strategies, amplifying the overall impact of floods. For example, Aerts (2018) investigated the cost of individual flood adaptation measures and found out that a Periphery wall and a flood resistant door can cost up to € 5,000 and € 3,000 respectively.

Additionally, the spread of information about flood risk and adaptation measures through social networks emerges as a significant influencer in household decision-making. Merill et al. (2018) showed that visualizations and data on local economic damage and return on investment of potential adaptation options increased willingness to invest in adaptations. The role of social networks in disseminating critical knowledge and shaping perceptions about flood risks and adaptation strategies becomes an integral part of understanding and implementing effective adaptation measures at the grassroots level.

Information campaigns are commonly employed to boost flood adaptation rates among households. However, research suggests that large-scale flood risk awareness campaigns, as currently implemented in many countries, have limited effectiveness in enhancing actual flood protection or insurance behavior among households (Osberghaus & Hinrichs, 2021). Haer et al. (2016) concluded that information campaigns are effective primarily when they not only provide information about flood risk but also communicate strategies for protecting against floods. This approach proves more effective than the traditional strategy of solely focusing on flood risk communication.

Agent-based modeling (ABM) stands out as a robust approach to gaining insights in this context. It offers a compelling methodology to simulate how system behavior emerges from the interactions of multiple actors and physical elements within ABM systems (Van Dam, Nikolic & Lukszo, 2012)

. Thus, it provides a means to model the effect of flood adaptation costs and the spread of information within social networks on individual decisions regarding flood adaptation measures taken and subsequent damages as a consequence of flooding events. Unsurprisingly, various studies have taken an ABM approach for modeling individual actor decisions in relation to flood adaptation under various parameterizations (Haer et al., 2017; Han et al., 2020).

This leads to the following research question:

1) *How do subsidies and information campaigns influence the decision-making process regarding adaptation to flooding among households?*

1.1 Prospect theory

When we model households as agents it becomes possible to understand their behavior. Households are agents in the context of an ABM. They are encapsulated and situated in a particular environment. An agent is capable of performing actions in anticipation. They are autonomous and are designed to meet objectives. They interact with other agents, mutually modifying each other's states allowing us to gain insights in emergent behavior.

An agent decides to adapt or not adapt based on their environment and objectives influenced by bounded rationality. Agents will evaluate whether it is beneficial for them or not to invest in adaptation based on various factors like the cost of adaptation, the perceived likelihood of a flooding happening and perceived damages. Humans also have bounded rationality meaning, their decision making is not perfectly rational.

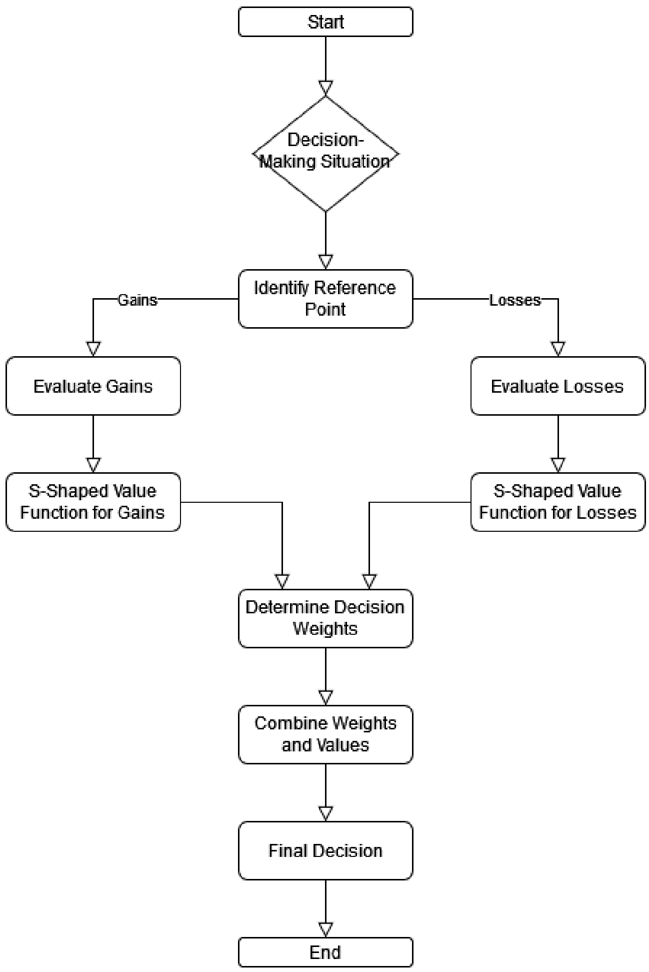

Figure 1: prospect theory flow diagram

Prospect theory attempts to account for bounded rationality in individual processing of probabilities. The flow chart from figure 1 depicts the decision-making process based on Prospect Theory, a psychological framework for understanding how individuals navigate choices under uncertainty. At the outset, individuals face a decision input involving potential gains or losses. The establishment of a reference point serves as a baseline against which subsequent evaluations unfold. The flow then diverges into pathways for gains and losses, reflecting the central tenet of Prospect Theory that individuals don't assess these outcomes symmetrically (Tversky & Kahnerman, 1992). Losses typically have a disproportionately stronger impact on decision-making than equivalent gains (Tversky & Kahnerman, 1992). The value function associated with losses tends to be steeper, indicating that individuals feel losses more acutely than gains of the same magnitude (Tversky & Kahnerman, 1992).

As the decision-making process unfolds, subjective probabilities known as decision weights come into play. Individuals subjectively assign probabilities to different outcomes, acknowledging the influence of cognitive and emotional biases on risk perception. Prospect theory proposes that people tend to overweight low-probability events and underweight high-probability events (Tversky & Kahnerman, 1992). The final decision integrates these subjective probabilities and perceived values, leading to an assessment of potential outcomes.

1.2 Hypothesis

The following hypotheses have been developed based on the research question:

Hypothesis 1: Higher savings levels positively influence the likelihood of households making adaptation decisions.

Hypothesis 2: Subsidies positively impact the adoption of flood adaptation measures by households which leads to a decrease in damage related to flooding.

Hypothesis 3: Information campaigns positively influence households to adopt flood adaptation measures which leads to a decrease in damage related to flooding.

Hypothesis 4: Subsidies are more effective than information campaigns in encouraging households to adopt flood adaptation measures from a government investment perspective.

Hypothesis 5: Combining subsidies and information campaigns leads to a greater increase in households' adoption of flood adaptation and to a greater decrease in damage related to flooding compared to either measure alone.

2. Conceptualization

This chapter offers an overview of the model on a conceptual level, detailing its system boundaries, the model description including policies, agents, concepts/features, processes, and their interactions with agents, KPIs coupled to the hypotheses, a visual representation of the conceptual model and assumptions and model reductions. The conceptual model serves as the foundation for constructing a formal model, which is discussed in Chapter 3. Nevertheless, there have been iterative processes among the formal model, the implemented model, and the conceptual model.

2.1 System Boundaries

Geographic boundaries

As stated in the introduction, the geographic area of interest is Harris County. Houston, the most populous city of Texas is part of this county. Figure 2 shows the geographics and possible flood heights at different coordinates.

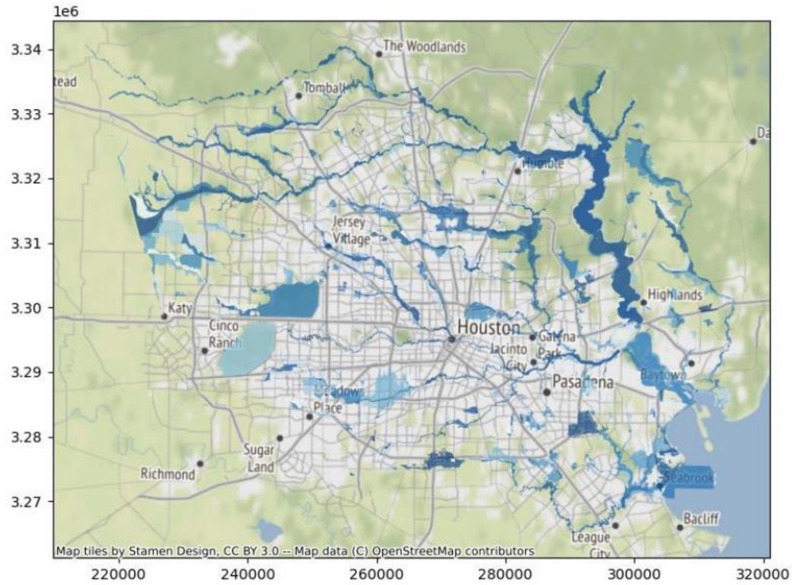

Figure 2: Map of Houston representing the geographic boundary of this study

Temporal boundaries

Temporal boundaries are crucial for simulation runs. The model operates across 80 ticks, each representing a quarter of a year. Within a single tick, households engage in various actions critical to flood adaptation: saving money, communication with other households, updating perceptions, reconsidering adaptation decisions, and implementing measures.

2.2 Description

Harvey County consists of various households distributed over the nodes. At tick 70, a simulated flood event occurs in the form of three possible and different flood level severity. The floods are referred to as 'harvey', '100yr' and '500yr. Each household can get their property damaged based on several factors such as flood type, their location and whether they have taken adaptation measures.

For the model, one adaptation measure is considered. This is the elevation of existing houses. Aerts (2018) found out that elevating a house in the United States by 6 feet (approx. 1.3m) costs between $35,000–90,0000/building. For the model, we assumed a single price of 35,000 USD. Elevating the building shifts the flood height at which the building gets damaged by 6 foot. The damage curve is based on the flood height.

Households are part of a social network where their connectedness is represented by connected neighbouring nodes. These connections are based on social networks using a Watt Strogatz network model, with the probability of a network connection being 0.4, number of edges 3 and number of nearest neighbours 5.

2.2.1 Policies

Two policies can be introduced during model runs. For the policy analysis, occurring flood ‘100yr’ is used as a base scenario with the flood happening at tick 70.

Firstly, information campaigns organized by the government which proactively disseminates information to households, enhancing awareness of flood risks and available adaptation measures. This measure is implemented during the initialization of the model and continues throughout each tick, consistently influencing households' perception of risk and severity regarding flooding. The information campaign leads to the media portraying the risk of a flood higher as it objectively is.

Secondly, a subsidy of 5,000 USD is implemented during the initialization of the model. This subsidy reduces the cost of adaptation measures, making them more appealing, all else being equal. Moreover, it enables individuals with insufficient savings to invest in adaptation measures, broadening access to flood adaptation measures.

2.3 Conceptual Model

2.3.1 Agents

There are two agent classes in this model. The first agent class are households. Households will be subjected to a flood during each model run. The model initializes 100 households randomly placed on the geographic environment, Harris County. The households' geographies influence their flood risk and their expected flood damage. The cost of the adaptation measure and the flood damage influence their utility perception of investing in a measure or not. Additionally, they have to be in the financial situation to be able to afford the measure. For each tick they can decide to invest in the adaptation measure or not. The goal of the agent is to maximize their utility by choosing between investing or not investing in the adaptation measure.

Agents perform the following actions at each tick:

- Households save and spend money.
- Households communicate with other households.
- Households update their risk perceptions.
- Households reconsider their adaptation decision.
- Households take adaptation measures.

The risk perception of a flooding of the individual household depends on the risk perception of their social contacts, on their own risk perception prior to the current tick and on a influence of media/public information about the flood risk. At each tick, the households can reconsider their decision to adapt and adapt if the utility of action has become bigger than that of inaction, assuming that they have enough savings.

By having a closer look at the prospect theory equations, it shows what the objectives of the agent are and how it can be modeled. If the household has sufficient savings, they need to evaluate whether it aligns with their objectives. For this, prospect theory equations have been used as outlined by Haer et al., (2017). In short, the utility for taking action at a given time must be larger than to take no action, for an agent to be compelled to take action and invest in adaptation measures (equation 1). Elements that determine the utility are C, the cost of adaptation, R the residual loss after adaptation, and the subsidies, which are multiplied by the subjective probability the flooding event will happen (π). The utility of not taking action is determined by L, the damage incurred when not adapting times the subjective probability of the event happening. "i" presents the different possible magnitudes of floods that can occur. This means the actor is informed about and sums the information about all flood events occurring with a specific objective probability. The subjective probability of the flooding event happening is influenced by the objective risk and the risk perception (RPt), which in turn gets influenced by previous experience (RPt-1), social connections and media (equation 2 & 3). In our model the values for social connections are determined by the neighboring nodes that have invested in adaptation measures (I is the average RPt of all social connections at time t), the media value is binary based on the information campaign policy similarly to experience which refers to having experienced previous flooding events. For more details on the equations, access the paper from Haer et al., (2017).

Equation 1

$$\mathrm{PT}\,(\text{action}) = \sum_{i=1}^{I} \pi_i U\,(-C - R_i + D)$$

$$\mathrm{PT}\,(\text{no action}) = \sum_{i=1}^{I} \pi_i U\,(-L_i)$$

Equation 2

$$RP_t = \frac{aRP_{t-1} + bI_{\text{experience}} + cI_{\text{social}} + dI_{\text{media}}}{a+b+c+d}$$

Equation 3

$$\pi_i = \frac{\left(10^{2RP_t-1}\ p_i\right)^{\delta}}{\left(\left(10^{2RP_t-1}\ p_i\right)^{\delta} + \left(1-\left(10^{2RP_t-1}\ p_i\right)\right)^{\delta}\right)^{1/\delta}}$$

The second agent is the government. The government can enact the policies. For the information campaign the government will incur fixed costs for each tick. The information campaign reaches all households. The information campaigns affect the agents by influencing their risk perception and are activated from tick 0 whereas subsidies are introduced at tick (x) and increase the utility of action.

For subsidies, which are introduced at the initialization, each time a household decides to invest in the adaptation measure the government pays the subsidy and incurs those costs.

2.3.2 KPIs

To test the hypotheses developed, it is necessary to identify the metrics (outputs of the model), that are needed per hypothesis. Table 1 gives an overview of the metrics needed to answer each hypothesis. In short, we need to know the **government spendings**, **Accumulated flood damage, Accumulated number of adapted households** and the **savings category** (low, medium, high) the agents belong to. Table 1 provides an overview of what KPIs are needed to validate the hypotheses.

Table 1: Metric outputs to answer hypotheses

Hypotheses	Relevant KPIs
Hypothesis 1: Higher savings levels positively influence the likelihood of households making adaptation decisions.	Savings category of households, Accumulated number of adapted households
Hypothesis 2: Subsidies positively impact the adoption of flood adaptation measures	Accumulated flood damage & Accumulated number of adapted households (base case compared to subsidies scenario).

by households which leads to a decrease in damage related to flooding.	
Hypothesis 3: Information campaigns positively influence households to adopt flood adaptation measures which leads to a decrease in damage related to flooding.	Accumulated flood damage & Accumulated number of adapted households (base case compared to information campaign scenario).
Hypothesis 4: Subsidies are more effective than information campaigns in encouraging households to adopt flood adaptation measures from a government investment perspective.	Accumulated flood damage & Accumulated number of adapted households (information campaign compared to subsidies scenario). Government spendings (information campaign compared to subsidies scenario).
Hypothesis 5: Combining subsidies and information campaigns leads to a greater increase in households' adoption of flood adaptation and to a greater decrease in damage related to flooding compared to either measure alone.	Accumulated flood damage & Accumulated number of adapted households (combined subsidies and compared to information campaign scenario).

2.4 Visual representation

We have now gathered all the building blocks to assemble the conceptual model which is depicted as Figure 3. A full list of model parameters can be accessed in Appendix A. The figure shows which parameters and processes influence each other and need to be formalized and modeled in line with these relationships. One critical decision is modeled, which is whether households adapt or not. This is indicated as a diamond. Policies are highlighted in green. In orange the KPIs are highlighted.

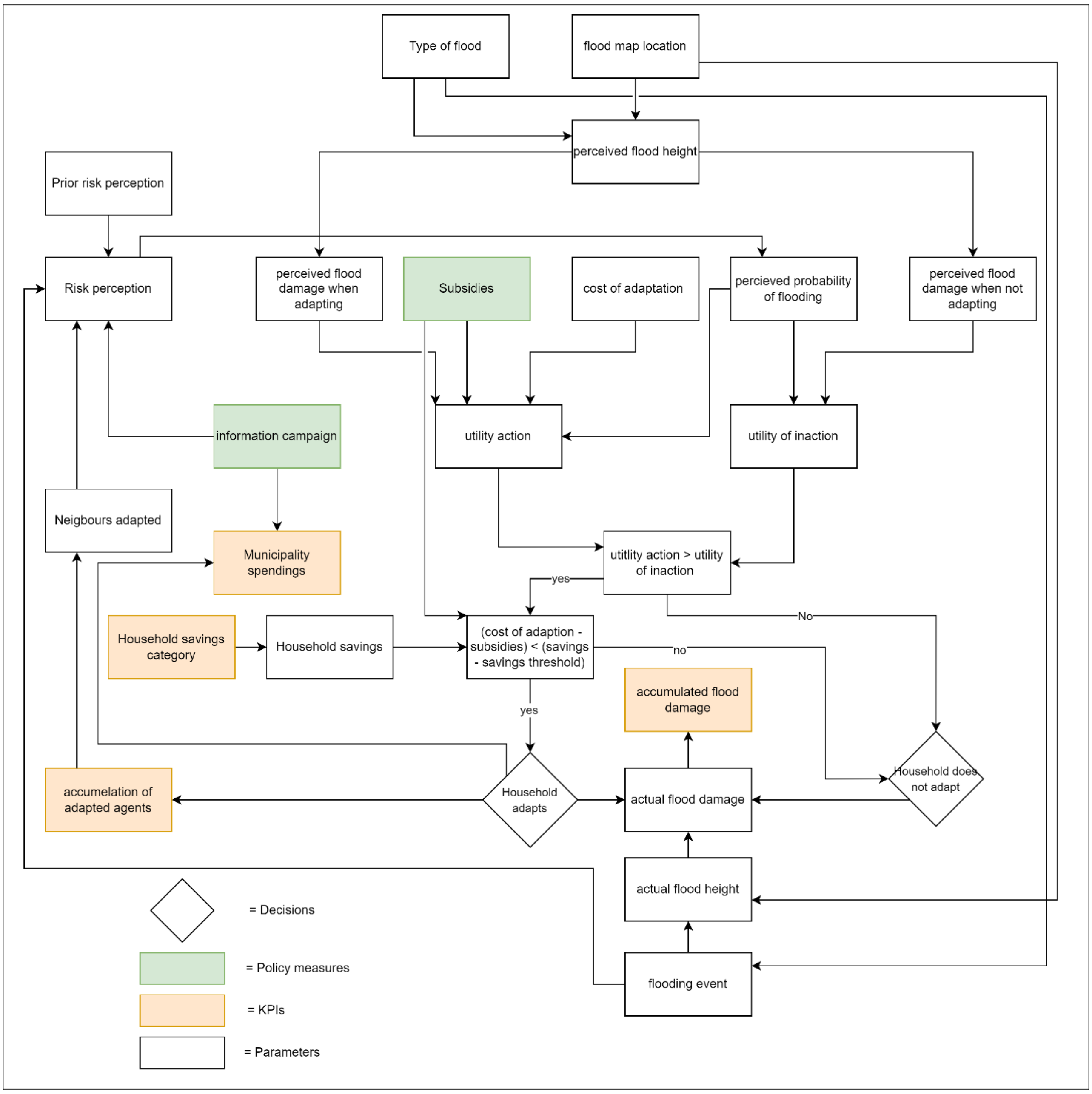

Figure 3: Visual representation conceptual model

3. Formalization

This chapter introduces the formalization of the conceptual model. For a comprehensive overview of all variables, refer to Appendix A. The model is implemented in Python, utilizing various libraries and packages, with mesa and networkx being among the most notable ones.

3.1 Initialization Model

In the model, the networkx library in python was used to visualize the map with a graph of links and nodes based on the watts strogatz network. Each node on the map represents a household agent and each node is automatically linked to its neighboring (social contact) nodes. Every household agent is assigned a random location on the map creating a random dispersion of households on the map. The map represents a flood map of Houston, where each location has a different pre-determined estimated flood depth. Therefore, each household has a specific initial estimated flood depth depending on its location on the map. As the aim of the model is to observe how many households choose to adapt, it is important to mention that initially all households (nodes) are represented as not adapted.

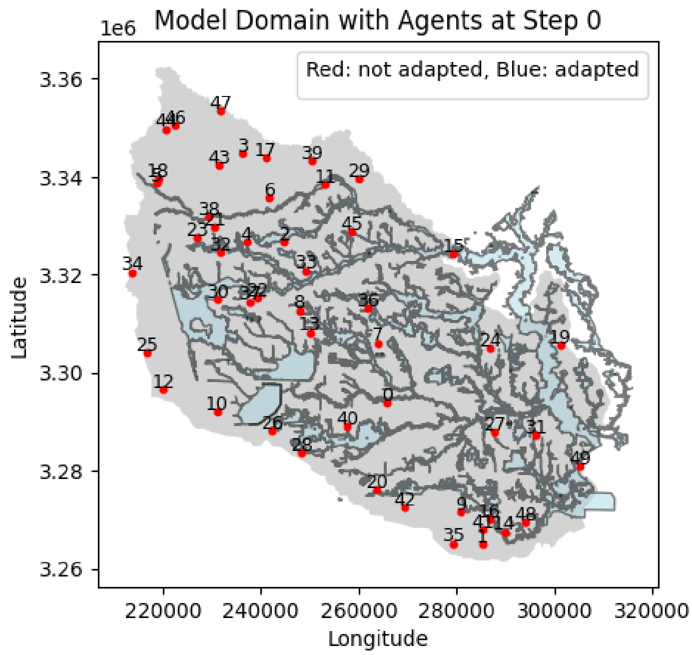

Figure 4: Initialization model: dispersion of households on flood map

In addition, various attributes of both household and government agents are initialized. Table 2 provides a detailed overview of the agents' initialization. After this initialization, the model runs per step and the processes of the agents are conducted as described in section 3.2.

Table 2: Formalization of agents: attributes and functions

Household
Attributes
ID
Savings range
Savings threshold
Floodplain check
Estimated flood depth
Estimated flood damage
Perceived flood risk
Cost of adaptation measure
Actual flood depth
Actual flood damage
Risk perception
Expected utility
Functions
Count friends (social network)
Update risk perception
Calculate expected utility for adaptation
Calculate expected utility for no adaptation

Government
Attributes
ID
Subsidy level
Information bias
Spending
Already adapted household count
Functions
Pay information campaign: per ¼ year
Pay subsidies per adapted agent

3.2 Processes

3.2.1 Processes during Initialization

Household savings range and threshold

When generated, household agents are assigned a savings amount based on the income group they are in. They are assigned into either a low, medium, or high-income group. The distribution of income groups in the model is based on secondary data on Houston's income distribution (Time, 2023). Every income group has an upper bound savings value associated to it where a household in a specific income group is randomly assigned a savings value within the limits of the pre-defined upper bound. The range of pre-defined savings values are also based on secondary data on Houston's income to savings values (Time, 2023)

In addition, a savings threshold is defined in the model at 5,000 USD. This value represents the amount of savings deemed necessary to have on standby for every household just in case of emergencies. This means that the savings value cannot go under this value. Everything above this value, the household is willing to spend on adaptation measures.

Estimated flood depth and estimated flood damage

The estimated flood depth is a pre-defined value for each household agent depending on its respective location on the flood map. The estimated flood depth is used to calculate the estimated flood damage. The estimated flood damage without adaptation is defined by the following: if flood depth is >= 6 meters then the damage equates to 1 within a range of damage between 0 and 1. This is converted to monetary damage per household by multiplying the damage by 100,000.

Risk perception

Every household is randomly assigned a risk perception value between 0 and 1 from a normal distribution during the initialization of the model. The normal distribution has a mean and standard deviation of 0,5. This is to ensure a heterogeneous distribution of initial risk perception values among households, reflecting the diversity of attitudes and perceptions within the modelled population.

Expected Utility

During the initialization, the expected utility function based on the prospect theory is initialized and set to 0 for all household agents. It is set to 0 because, at the beginning of the simulation, agents have not yet experienced any outcomes, and initializing the expected utility function at 0 provides a neutral starting point before incorporating the influence of subsequent events and decisions.

Subsidy level, information bias, and cost of adaptation measure.

The cost of the adaptation measure and the value of the subsidy are fixed values defined in the initialization of the model. The information bias, a product of the information campaign by the government agent is a value between 0 and 1. This value is added to the information attribute that is initially at a value of 0.5, which represents objective information. This is explained in greater detail in Hear at al. (2016).

3.2.2 Processes during Model Run

Updating social network

During every step, for each household agent, the number of linked nodes are counted. The social influence on the household agent equates to the average risk perception of the linked nodes. It is assumed that the more blue nodes that are linked (the more neighbours that are adapted) the higher the average risk perception of all the linked nodes.

Updating risk perception

The household agents risk perception is updated in every time step from the previous risk perception value. The risk perception is influenced by the social network mentioned previously, the information campaign (information bias) of the government agent, and the experience of a flood taking place (if a the flood took place in previous steps).

The full mechanism can be interfered from Haer et al. (2017) referring to the Prospect Theory after the Bayesian model.

Calculating expected utility of adapting and not adapting

The expected utility of adapting and not adapting (based on prospect theory) is updated in every step for every household agent. It is based on the risk of flood, the perceived flood damage, the risk perception, cost of adaptation measure, and value of subsidies.

If the expected utility of adapting is greater than the expected utility of not adapting + (if the savings are greater than the cost of the measure – (the subsidies + the subsidy threshold) then the household agent will adapt otherwise they won't adapt.

Information campaign and subsidy cost

In every time step, the cost of implementing the policies is calculated for the government agent. This is cumulative, so the total cost throughout all steps is added up. Subsidies are accounted as a cost if agents adapt in that time step. Information campaigns are accounted as a cost every tick they are employed at a fixed rate of 2,000 USD.

Update actual flood damage

Once the flood hits, the actual flood depth and damage are calculated. The damage factor is between 0 and 1. If a household is not adapted, a flood depth equal to or greater than 6 equals to a damage of 1. If a household is adapted, this increases by 1.3m.

For a pseudo representation of the code for both the initialization and running of the model refer to appendix B1 and B2 respectively.

4. Assumptions & Model Reductions

Table 3 provides a list of assumptions and model reductions that enabled us to make a working model that still captures the insights we need to answer the research question and hypotheses. The model represents a stark simplification of reality, which comes with a lot of reality to model simplifications. Table 3 represents the most important simplifications that are relevant and should be kept in mind, when analyzing model outcomes.

Table 3: Assumptions and model reductions

Assumption/Model reduction	Explanation
Only social no geographical network connections	It is assumed that households are influenced by the perception of their friends (social network) and not by their neighbors (geographical network)
One adaptation measure	The agents can only consider one or no adaptation measure. The adaptation measure costs 35,000 USD and equals an elevation of the house of 1.3m based on Aerts et al. (2018). The cost of the adaption measure doesn't vary per agent (i.e. housing size not considered).
Static subsidy level	Subsidy levels are directly connected to the purchase of the adaptation measure. When a household adapts it always makes use of the subsidy.
Static information campaign	The cost for an information campaign that leads to a overestimate of the flood risk by the media, which influences the households risk perception, costs 2,000 USD per ¼ year. The information campaign reaches all household agents in the same manner and impact.
Simplified damage function	The flood damage calculation do not consider housing sizes or other environmental factors (e.g., capital goods in house) that might influence these
Simplified influence on agents' flood risk perception	Agents update their individual risk perception based on their prior risk perception, social connections, and influence through the media
Savings per timestep	Agents only in- or decrease their savings by 5% per period (representing spendings and savings per period)
Arbitrary residual savings	Households, no matter their income level do not invest into the adaption measure when this would reduce their savings to <5,000 USD

5. Verification & Validation Model

5.1 Verification of Model

In the verification phase, we evaluate how well the empirical model matches the conceptual model. This includes ensuring that the events and processes described in the model conceptualization are correctly implemented and are working as intended. To verify this the main decision step in an agent behaviour (the decision to take a flood adaptation or not) was examined. Two single agents tests were performed both aimed at verification of a single agent's behaviour.

The first test considered the calculation of the utility of taking the measure or not. The utility is based on the Bayesian Prospect Theory (Hear at al., 2016) and uses parameters drawn from a distribution, to calculate an agent's perceived utility. Nevertheless, the utility should never be greater than zero as only losses an agent can experience are considered. Furthermore, if the decision is run multiple times under the fixed parameter of risk perception (RPt) and estimated flood damage (flood_damage_estimated) of an agent the utility of taking no measure should be higher than taking the measure. The expected results have been confirmed in a single agent test running the decision 1E6 times (figure 5).

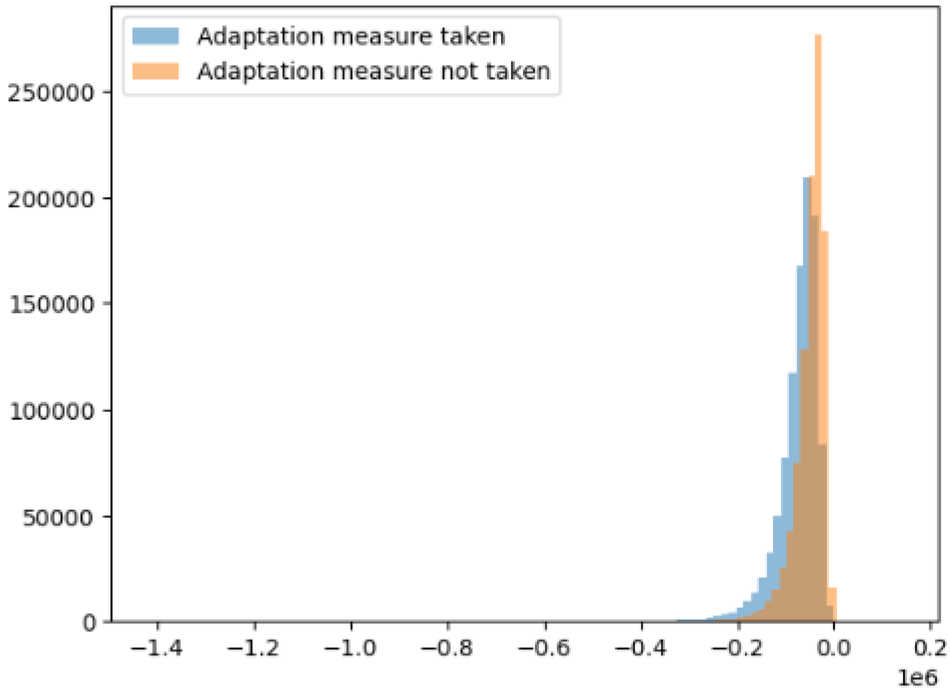

Figure 5: Comparison of expected utility of a single agent with a fixed risk perception and expected flood damage, for taking the adaptation measure and not taking it. 1E6 model runs.

The second single-agent test included examining the decision process of taking the adaptation measure or not. This is based on the expected utility (as presented above) and the individual savings of the household. The following logic was tested in the single agent verification: An agent only adapts if it has enough savings to cover the cost of the measure plus the 5,000 USD savings threshold. An agent only adapts if the expected utility of taking the measure is greater than not taking it. Table 4 represents the outcomes of the test based on selected test input parameters.

Table 4: Outcomes of the adaptation decision process of a single actor based on different fixed parameters

	Parameters			*Outcome*
	Expected utility with measure	**Expected utility w/o measure**	**Savings (initial)**	**Adaption taken (yes/no)**
Alternative 1	-200,000	-100,000	40,000	No
Alternative 2	-100,000	-200,000	40,000	Yes
Alternative 3	-100,000	-200,000	0	No

Both of the single agent tests verify the models function, specifically the adaptation decision process of the individual actor.

5.2 Validation of Model

The validation tests aim to assess the alignment of the model-derived behaviour with real-world behaviour. The aim of this research is to test the implications of various policies on flood adaptation levels and flood damage levels in Houston. The policies tested are government subsidies and government information campaigns promoting adaptation. A central assumption of this research is not to create a hyper realistic flood simulation but rather to build a model and interpret its results. Therefore, the validation test will be based on whether the impact of the chosen policies have a similar effect on adaptation rates in the real-world.

As per Valkengoed and Werff (2022), subsidies primarily function as incentives for undertaking adaptation measures but may not necessarily alleviate the financial obstacles linked to implementing such measures. The literature on the efficacy of information campaigns in influencing human behavior demonstrates a positive correlation, indicating that higher levels of information campaigns are associated with increased adaptation levels (Khatibi et al., 2021). Nevertheless, despite extensive information, economic and social barriers, such as a lack of institutional support, can still hinder the levels of adaptation. Our findings similarly suggest a positive correlation between implemented policies and levels of adaptation.

6. Results

6.1 Flood scenarios

Three flood types have been analyzed to see how they affect the actual damages and adaptation. Figure 6 shows the average accumulated damage in USD and total adapted households at step 80 for the three flood maps. Overall, the results are very similar. Ranges for the actual flood damage fall within a few percent. There was more relative difference for the total number of adapted households which ranged from 13.9 to 14.4 approximately. This shows the model variation for a total of 25 model runs, as households adaptation does not depend on the model flood map choice, as risk perceptions of floods are calculated for an average over each possible flooding event.

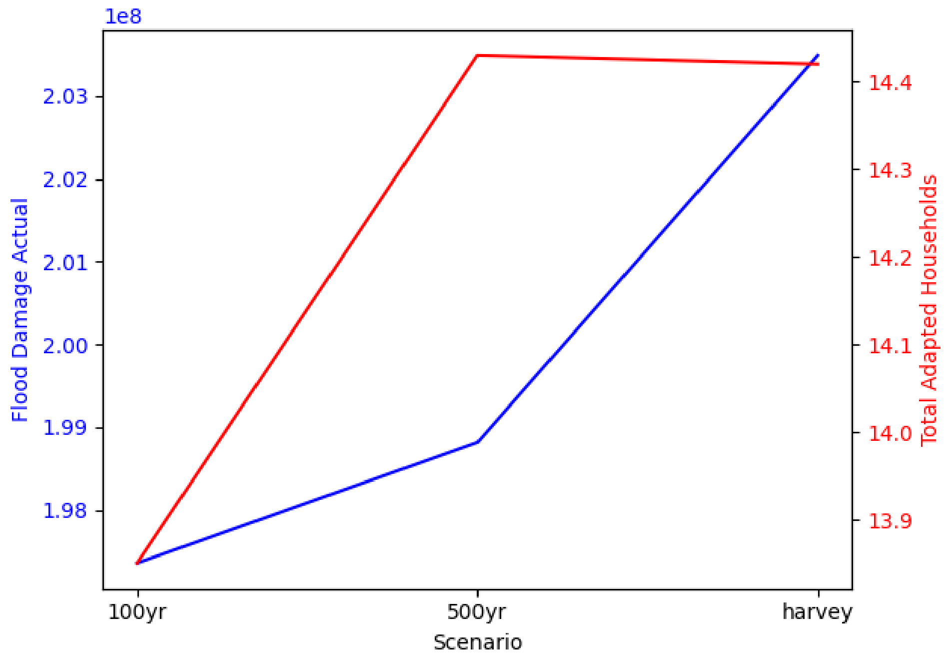

Figure 6: Average accumulated damage in USD and total adapted households at step 80 for 3 flood map types.

This shows that no definite conclusion can be drawn for stating that one scenario is more severe than other scenarios. This led to the arbitrary choice of the flood event 100yr flooding for all further analysis.

A deep dive into '100yr' shows the inequality of opportunity to invest into adaptation measures due to limited savings. Table 5 provides an overview of the share of people adapted and to what savings category they belong. 100 agents are randomized from a distribution and put in either low, medium, or high savings category according to the distribution displayed. After 25 runs, the average number of high, medium and low-income households adapted was 8.68, 4.88 and 0 respectively. When accounting for the distribution between the groups it becomes clear that high savings households are more than double as likely to adapt compared to medium savings households. Low savings households are unable to adapt given the current parameters. This shows that hypothesis 1 is correct.

Hypothesis 1: Higher savings levels positively influence the likelihood of households making adaptation decisions.

Table 5: Adaptation measure adopted by income group

Average number of households adapted	Income group	Distribution	Adapted scaled to distribution
8.68	High	0.37	3.2116
0.00	Low	0.34	0
4.88	Medium	0.29	1.415

For the policy analysis it was decided to go with flood map '100yr'.

6.2 Policy analysis

Four policy scenarios were analyzed: one with only an information campaign active, one with only subsidies, one with both policy measures, and finally one without any policy. Table 6 provides an overview of the models and their parameterization. Each policy scenario underwent 25 runs, and the average results are visually presented in Figure 7 per step.

From both Table 6 and figure 7, it's evident that the absence of measures leads to the lowest adaptation rate. The information campaign performs slightly better, while subsidies alone outperform the information campaign alone. Notably, the combination of subsidies and information campaigns yields the highest adaptation rate. It's intriguing to observe that information campaigns, when combined with subsidies, exhibit a greater benefit than when employed alone. Adaption rate increases from 16 to 17 when combined with subsidies, compared to an increase from 13.56 to 14 when introduced without. This highlights a synergistic relationship between the two measures.

Moreover, the actual damages show an inverted pattern, where high adaptation rates correlate with lower actual flood damage. An exception to this pattern is observed in scenarios without any policy measures, where actual damage surpasses that of information campaigns, albeit by a marginal difference of only 136 USD. This variance is attributed to inherent fluctuations of the random nature of parameter selection. Consequently, Hypotheses 2 and 5 are accepted based on these findings. Hypothesis 3 is partly confirmed with regard to the increase in adaptation rate, but not that it leads to a decrease in accumulated damage.

Hypotheses:

Hypothesis 2: Subsidies positively impact the adoption of flood adaptation measures by households which leads to a decrease in damage related to flooding.

Hypothesis 3: Information campaigns positively influence households to adopt flood adaptation measures which leads to a decrease in damage related to flooding.

Hypothesis 5: Combining subsidies and information campaigns leads to a greater increase in households' adoption of flood adaptation and to a greater decrease in damage related to flooding compared to either measure alone.

Figure 7 illustrates the evolution of adaptation decisions over time. The data reveals a notable trend: the majority of adaptation decisions occur during the initial time step. Subsequent steps witness a gradual decline in the number of households opting to adapt, eventually dwindling to nearly zero new adapted households between steps 10 and 20, continuing until step 80.

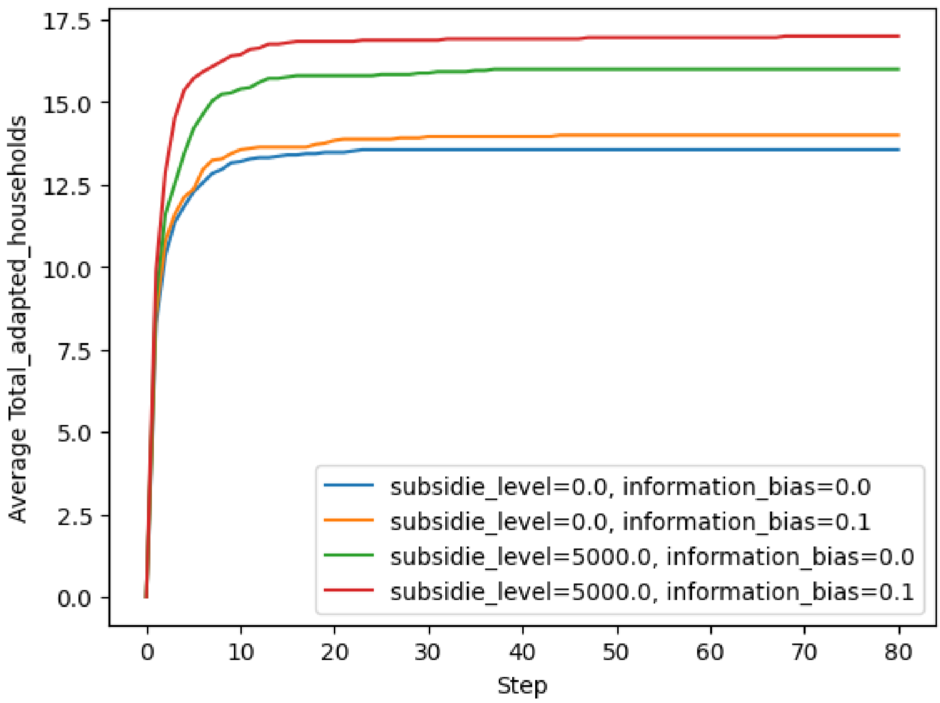

Figure 7: Average total adapted households per policy scenario

Table 6: Policy scenario results

Measure(s)	Subsidy level	Information bias	Number of adapted households	Government spending	Flood damage actual USD
No policy measures	0	0	13.56	0	20144
Information campaign	0	0.1	14.00	162000	20280
Subsidies	5000 USD	0	16.00	80000	19359
Subsidies and information campaign	5000 USD	0.1	17.00	247000	18334

Upon closer examination of government spending and adaptation rates, subsidies emerge as not only better in absolute terms but also in relative terms compared to information campaigns. Table 7 underscores the amount of money spent by the government to increase adaptation rates per household, highlighting the relative effectiveness of each scenario. Subsidies demonstrate the highest relative effectiveness, contradicting the previous observation where the combination scored highest in absolute terms. Thus, Hypothesis 5 is also accepted:

Hypothesis 4: Subsidies are more effective than information campaigns in encouraging households to adopt flood adaptation measures from a government investment perspective.

Table 7: Municipality spendings per adapted household.

measure	Number of households adapted	Government spending	Improvement from no measures in terms of adapted households	Spendings per household additional adapted household. (USD)
No policy measures	13.56	0	x	x
Information campaign	14	162000	0.44	368182
Subsidies	16	80000	2.44	32787
Subsidies and information campaign	17	247000	3.44	71802

As outlined in table 7, considering that the cost of adaptation is 35000 USD, government spending per additional adapted household is higher for all scenarios except for subsidies (32787 USD). This puts into question the cost effectiveness of the information campaign and shows that under these modelling parameters the municipality is better off gifting the adaptation to people who cannot afford it than undertaking an information campaign.

6.3 Sensitivity Analysis

For the base scenario of a "100yr" flood event and the four different policy implementations, a global sensitivity analysis was conducted, employing the EMA-Workbench. The analysis explores the sensitivity of the whole parameter space over 25 runs for each scenario. The results allow for an interpretation of which parameter influences the model results total adapted households and government spendings. The global sensitivity considered the following model parameters:

- Number of households
- Number of nearest neighbors
- Number of edges
- Probability of network connection
- Time of flooding
- Different policies (measures)

The analysis showed that the number of adapted households is only influenced by the different policy measures but is also highly dependent on the other parameter selection. The government spendings as expected showed sensitivity to the different policies, as those majorly influence the spendings. Only minor sensitivity and influence on the outcomes of government spendings is present for the other parameters.

This analysis, although only giving an indication of what to make of the results, shows that the interpretation of the total adapted households per policy measure can only hold true for this models' specified parameters. A variation of those might lead to different results and should always be considered during analysis.

A detailed description of the analysis is shown in appendix C.

7. Conclusion, Recommendation & Limitations

7.1 Conclusion & Recommendations

The central aim of this research was to investigate how subsidies and information campaigns influence households' decisions regarding flood adaptation. It shows that subsidies positively impact adaptation rates, with information campaigns also contributing, albeit to a lesser extent. Moreover, combining both measures proved more effective than implementing them individually.

An analysis of government spendings highlighted the cost-effectiveness of these measures. Information campaigns showed low cost-effectiveness per additional household adapted, while subsidies, although relatively costly, remained within the realm of cost-effectiveness.

Further analysis showed that the results are sensitive to input parameters which makes the model useful for exploring certain scenarios under abstractions of the real world. The sensitivity should always be considered when analysing the results.

Based on these findings, it is recommended to prioritize investments in subsidies over information campaigns when considering cost-effectiveness. However, if cost-effectiveness is not a primary concern, the combination of information campaigns and subsidies is preferred, as it offers a comprehensive approach to flood adaptation. Other recommendations are to precisely target information campaigns or have certain periods of time where campaigns are pushed instead of conducting them for a extended period of time. The exploration of such option was not feasible with our model, therefore it should be part of future research.

The analysis of the base scenario highlights a stark inequality in the opportunity to adapt, primarily driven by disparities in household savings. Notably, none of the low-income households made investments in adaptation, while high-income households were twice as likely to do so. This disparity underscores the need for a strategic approach to subsidy implementation.

Currently, there is a risk associated with the existing subsidy policy, as it predominantly benefits households that would have invested in adaptation regardless. To address this issue, it is recommended to implement a differentiated subsidy scheme based on income, serving as a proxy for savings. Under this scheme, low-income households would receive higher subsidies, while high-income households would receive lower or no subsidies.

By adopting such a differentiated subsidy approach, it becomes possible to achieve a more equitable distribution of subsidies and compel a greater number of households, particularly those with limited savings, to invest in adaptation measures. This targeted strategy ensures that subsidies are effectively utilized to maximize their impact and address the underlying inequalities in adaptation opportunities.

7.2 Limitations

Several limitations were encountered during the course of this study, which must be acknowledged to provide a comprehensive understanding of the research outcomes.

Firstly, the input parameters on the cost per capita of information campaigns were unreliable. The uncertainty and inaccuracies in these parameters have contributed to unreliable results in terms of the cost-effectiveness of the information campaign.

Second, only one adaptation measure was investigated which happened to also be one of the more costly ones (relative to other common adaptation measures). This singular focus on an expensive adaptation measure raises the barrier to implementation, limiting the generalizability of the findings.

Moreover, only one subsidy value was analyzed. Often, various subsidy schemes exist depending on one's income level. Considering that savings and income were incorporated in the model as household attributes, disregarding various subsidy values reduces the validity of the model.

The model represents a stark simplification of reality, making it feasible to explore where future research efforts should be focused towards to, considering model assumptions and limitations.

7.3 Future Work

In acknowledging the limitations of our study, there are significant opportunities for future research to enhance the depth and breadth of our understanding. Firstly, an exploration of a broader range of subsidies and an assessment of the effects of these differentiated subsidy levels are imperative. Given that subsidies emerged as pivotal policies leading to the highest adaptation rates, a nuanced examination of various subsidy levels becomes crucial in identifying optimal policy configurations.

Secondly, not all households necessitate raising their homes, as their locations vary within or outside the floodplain. Hence, it is worthwhile for future research to investigate the effects of different, potentially more cost-effective, adaptation measures. This exploration will shed light on strategies that cater to a wider range of households, offering a more inclusive and adaptable approach to addressing the challenges posed by the studied phenomena.

To gain a more comprehensive indication of the effectiveness of varying strategies among diverse income and geographical demographics, future research should consider the combined impact of varying subsidy levels and diverse adaptation measures. By synthesizing these elements, researchers can uncover synergies and trade-offs within the proposed strategies, contributing to a more nuanced understanding of adaptive behaviours.

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9. Appendices

9.1 Appendix A: List of all variables and their ranges

Table A1: List of all variables and their ranges

Entity	Variables	Range	Unit	Other Comments
Households				
	Income_category	Low, medium, high	Dollars	Based on Houston income distribution. 34% households are in low income category; 29% are in medium income category; 37% are in high income category (Time, 2023)
	Savings_low	0-20000	Dollars	Based on income to savings (Time, 2023)
	Savings_medium	20000-70000	Dollars	Based on income to savings (Time, 2023)
	Savings_high	70000-250000	Dollars	Based on income to savings (Time, 2023)
	Flood_depth_estimated	0-infinity	meters	
	Flood_damage_estimated	0-1	X	
	Flood_depth_actual	0-infinity	meters	
	Flood_damage_actual	0-1	Dollars	Flood damage of 0-1 is multiplied by 100000 to monetize the damage and turn it into a cost. The damage factor is between 0 and 1. If a household is not adapted, a flood depth equal to or greater than 6 equals to a damage of 1. If a household is adapted, this increases by 1.3m.
	Risk_perception	0-1	X	
	Expected_utility_measure	0-1	X	
	Expected_utility_nomeasure	0-1	X	
	Influence_social	0-1	X	
	Influence_media	0-1	X	
	Perceived flood damage?		X	

Government				
	Spendings	0-inifity	Dollars	
	Previous_adapted_households	0-infinity	X	Depends on number of households chosen in model

Table A2: List of all experimental variables and their ranges

Agent	Experimental variables	Range	Unit	Other comments
Household				
	Initial_perceived_flood_risk	0.05, 0.15, 0.3, 0.5	X	
	Cost_of_measure	0-infinity	Dollar	Currently set at 35000
	Savings_threshold	0-infinity	Dollars	Currently set at 5000
Government				
	Subsidies	0-infinity	Dollars	Currently set at 5000
	Information_bias	0-1	X	
Model				
	Number_of_households	0-infinity	X	Currently set at 25
	Flood_map_choice	Harvey, 100yr, 200yr		
	Network	Erdos renyi, barabasi albert, watts strogatz, no network	X	Currently chosen watts strogatz
	Probability_of_network_connection	0-1?	X	
	Number_of_edges	?		
	Number_of_nearest_neighbours	?		
	Time_of_flooding	0-80		

9.2 Appendix B: Pseudo code for model setup and model run

Pseudo code model setup

Model class

Attributes

- Choose number of households
- Choose flood map type (Harvey, 100yr, 500yr)
- Choose network type ('erdos_renyi', 'barabasi_albert', 'watts_strogtaz', 'no_network')
- Choose probability of network connection (likeliness of edge being created between two nodes)

- Choose number of edges if 'barabasi_albert' network chosen
- Choose number of nearest neighbours if 'watts_strogtaz' network chosen
- Choose what time step flood will take place
- Set Government related parameters (subsidy level and information bias)
- Set the three savings range (low, medium, high)

Initialisation Household

- Allocate households randomly to various locations (nodes) on the map and collect their unique ID (ensure equal distribution throughout map with no cluttering and no two housholds in the same location)
- For each household
    - Initiate savings attribute and set savings value
    - Initiate risk perception attribute and set initial risk perception
    - Initialize expected utility attribute and set to 0 for first iteration
    - Initiate estimated flood depth
    - Initiate estimated flood damage
    - Initate actual flood depth (calculated when flood occurs)
    - Initate actual flood damage (calculated when flood occurs)

Initialisation Government

- Initiate spendings attribute (keep track of government spendings)
- Set subsidy value
- Initiate information attribute

<u>Pseudo Code Model Run</u>

Update Household

- Update friends count (average risk perception of all linked nodes)
- Update information bias
- Update risk perception
- Update savings
- Update expected utility of adapting
- Update expected utility of not adapting

if utility action > utility no action then

Adapt

Else

Do nothing

Update Government

- Update value on amount government is spending on policies

9.3 Appendix C: Global Sensitivity Analysis

Table C.1: Model parameters spaces that are used for the global sensitvity analysis

Model parameters	**Base model/scenario**	**Parameter space of global sensitivity analysis**
Number of households	100	50 – 100
Flood map choice	100yr	100yr
Network	Watts Strogatz	Watts Strogatz
Propability of network connection	0.4	0.3 – 0.5
Number of edges	3	2 – 4
Number of nearest neighbours	5	4 – 6
Time of flooding	70	40 – 80
Subsidie levels	0	0, 5000
Information bias	0	0.0, 0.1

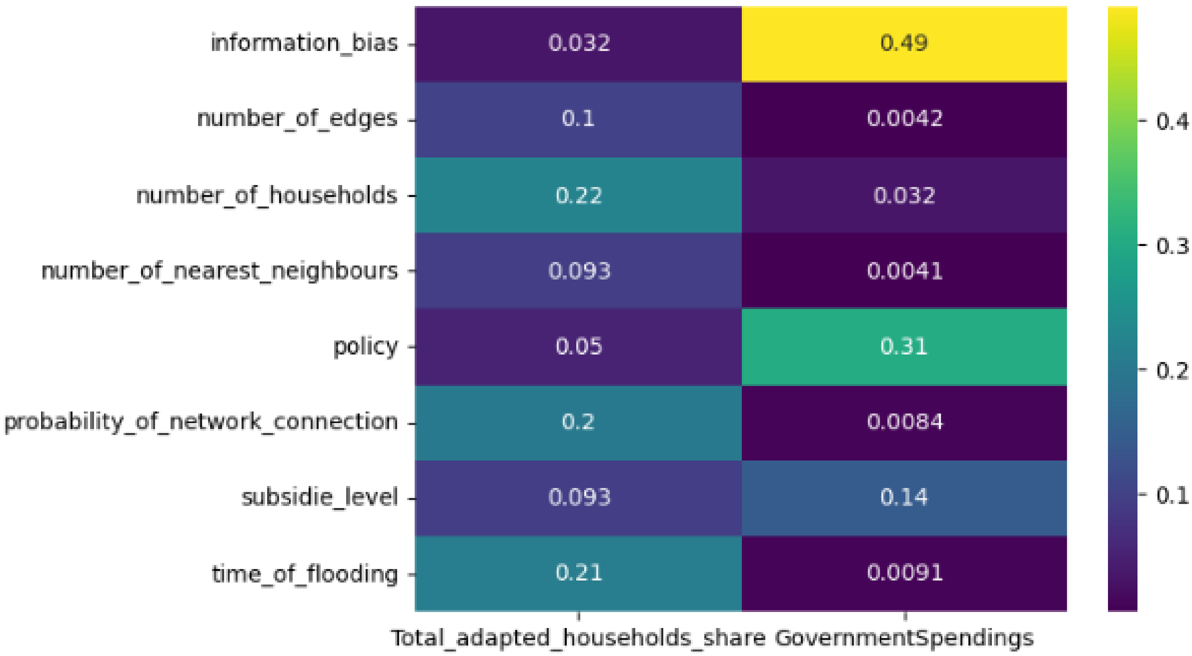

Figure C.1: Heatmap showing the model paramters (y-axis) influence on the model outcomes (x-axis) using a global sensitivity analysis. Higher numbers represent a higher influence.