Income inequality and flood damage:

Exploring the effectiveness of income-based subsidies on flood adaptation of different household income groups.

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SEN1211 – Agent-based Modelling

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1 Executive Summary

The report was prepared in broad alignment with the main steps for creating and using an agent-based model (ABM) of a socio-technical system outlined by (Dam et al., 2013). The research seeks to assess the effectiveness of income-based subsidies on households taking flood adaptation measures across various income groups. The area assessed is Harris County, Texas. Rising global income inequality and the vulnerability of lower-income households to floods highlight the need for exploring the effectiveness of potential policies.

Using agent-based modelling, this report seeks to answer the following research question:

What is the effect of subsidies on flood adaptation under flooding conditions as measured by the total number of households that decide to take the adaptation measures?

The hypothesis is that income inequality hinders household flood adaptation, and the report aims to validate this by modelling the decision to adapt of households and in turn assess the efficacy of income-based subsidies.

Two main theories have been used within the modelling decisions, namely the PMT and individual risk, the latter of which was included as the Reusable Building Block. One key performance indicator was tracked to answer the research question, namely the total number of households that decide to take adaptation measures. Validation of the model was used to test outcomes under different parameters, and verification of the model was used to explore the behaviour of individual agents. Thereafter, experimentation was used to test different policy variations: the base case had no subsidy, policy 1 would only consider individual risk in tiering of subsidy height, and policy 2 would consider both individual risk and the income group to tier the subsidy height. The results and limitations of this research are then discussed.

The results indicate that overall policy 1 sees more adaptation across the entire 80 ticks. However, when looking more closely at the distributional effects across income groups we can see that high income groups adapt more in policy 1 to drive this KPI up for the overall adaptation. In contrast, policy 2 has less overall adapted households over the entire timeframe, but has more medium and low income groups that adapt. The report calls on policymakers to consider not only the overall effectiveness of households that decide to adapt, but also the distributional effects across income groups when designing flood risk management policies.

2 Introduction

2.1 Background

Human induced climate change is believed to modify weather patterns on the regional scale causing more extreme weather events. These include hurricanes, tropical cyclones, heavy rain, and floods that can cause severe damage to life and property (Colbert, 2022; Hashim & Hashim, 2014) Flooding is one of the most central concerns when a hurricane hits and climate change is expected to worsen the damage.

However, both exposure and vulnerability depend on socio-economic factors. Exposure is defined as the presence of people, their livelihoods, assets, and infrastructure that all form part of a socio-technical system (Cappelli, 2023). Vulnerability is the tendency of an exposed system and its components to experience various levels of impact caused by extreme events. Different parts of the population can be adversely affected due to their inability to adjust to potential damage and prepare to cope with it. Consequently, while public adaptation measures can mitigate the damage of climate-induced floods to some extent, their failure can leave individuals vulnerable (Colbert, 2022). Therefore, household-level adaptation measures such as elevating the building, strengthening the housing foundations, moving valuable assets to higher floors or other measures that allow minimizing flood damage are crucial in flood affected areas. Understanding the factors that influence the ability and willingness of households to implement flood adaptation measures is essential to finding policy measures for flood risk management (FRM) that can motivate households to adapt. It requires considering human dynamics and the interaction between different subsystems within the socio-technical system. The social and technical subsystems consist of various components such as social actors with their behaviors, interactions and developments, and different objects with their physical properties, technical intricacies, and developments (Dam et al., 2013). Understanding how these systems interact is central to policy making.

2.2 Problem formulation

The ability of individual households to adapt is largely affected by their income (Tonn & Guikema, 2018a). Global income inequality between the average income of the top 10% and the average income of the bottom 50% more than doubled between 1820 and 1910, and has since stabilised at a high level (Piketty et al., 2022). The share of global income allocated to the top 10% highest incomes on a global level has been between 50% to 60% as a share of the total world income between the years 1820 and 2020, meanwhile the share allocated to the bottom 50% has been either below or around 10% (Piketty et al., 2022). See Figure 1 for a visual representation.

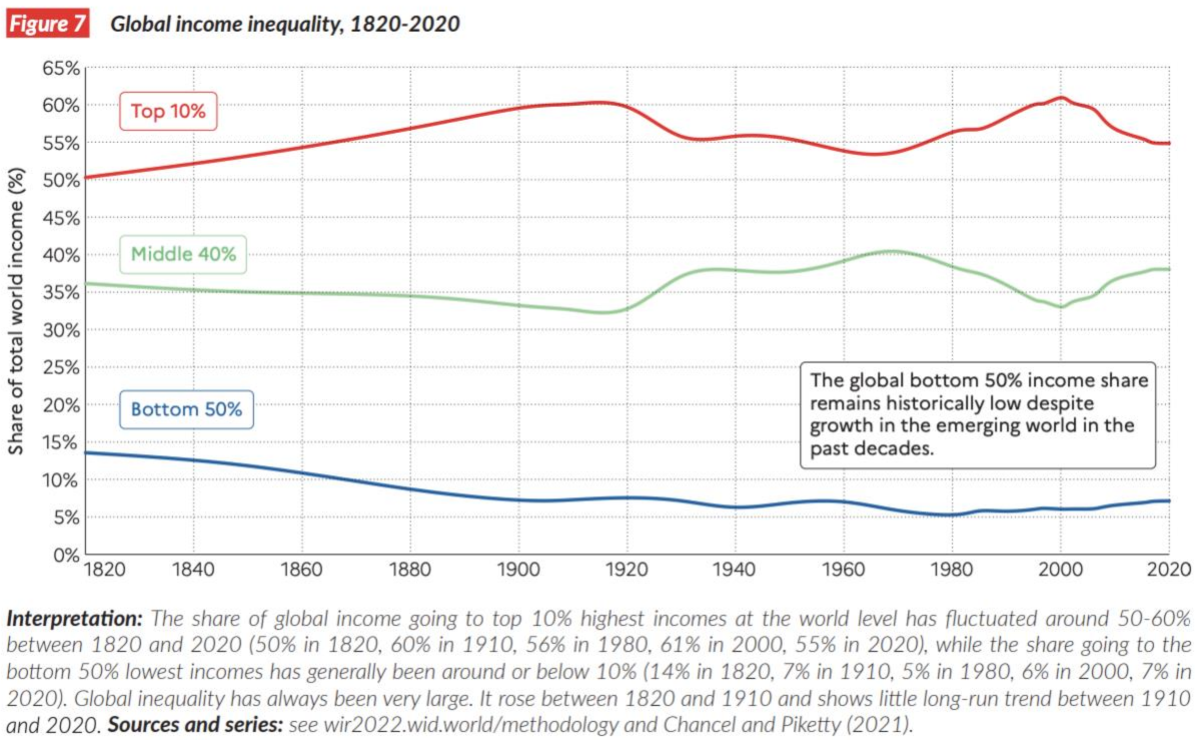

Figure 1: Global income inequality from 1820 through 2020 across the bottom 50%, middle 40%, and top 10% as a share of total world income in % (Piketty et al., 2022).

Households in Harris County the United States also have similar patterns of unequal income distribution, similar to the state and national levels in the United States. In 2021, the top 10% of households in Harris County received 54% of the income, while the bottom 20% received only 3% of the income (Pager & Shepherd, 2008). Furthermore, Harris County is an area that experiences relatively frequent floods and more than one third of the county's land falls within the Federal Emergency Management Agency (FEMA) designated flood plain with the figure expected to increase (Lloyd et al., 2023). Consequently, there is a potential risk that households with lower income will be unequally affected in the future.

Considering the unequal income distribution that contributes to differentiated vulnerability, the social and technical components that can affect adaptation behaviour and the frequent flooding in the area, finding the right policy measures to motivate implementation of flood adaptation measures is essential to minimise losses and prepare for future events. Therefore, the main lack of insight addressed in the following report is the limited understanding of how income inequality impacts decisions of households from taking flood adaptation measures in a flood affected are in Harris County in the United States.

2.3 Research approach

The behaviour of different actors will be studied using Agent-based modelling (ABM). For this case the actors considered are households and the government. However, in the base model, government is passive whereas each household is represented as an agent. A comprehensive literature review discovered that adaptation behaviours are strongly related to income Click or tap here to enter text.. Additionally, flood adaptation behaviour is frequently explained using protection motivation theory (PMT) that consists of two major processes: threat appraisal and coping appraisal (Babcicky & Seebauer, 2019). Agent-based models can deal with complexity, addressing not only technological aspects but also social dimensions attempting to capture the behavior of diverse actors (Dam et al., 2013). It attempts to replicate certain aspects that are proposed to exist in the real-world such as actions, relations or underlying mechanisms. Therefore, PMT and income can be implemented in the decision rules of households using ABM. The model can be then used to improve the process of decision-making.

2.4 Research question and hypothesis

The goal of the ABM is to model the adaptation behaviour of household agents and to understand the role of government subsidies in increasing the implementation of flood adaptation measures in the Harrison County. Therefore, the research question is formulated as follows and is primarily covered in the experimentation section of the research:

What is the effect of subsidies on flood adaptation under flooding conditions as measured by the total number of households that decide to take the adaptation measures?

The initial hypothesis that the ABM developed for the following report seeks to validate is that income inequality prevents people from taking flooding adaptation measures. This is done by modelling the behaviour of household agents and their ability to implement adaptation measures. Subsequently it is done by evaluating the effectiveness of income-based subsidies on influencing different household income groups in deciding whether to implement flooding adaptation measures.

3 Conceptualisation

3.1 System boundaries

The system boundaries that were decided upon reflect the goal to understand the behaviour of households and the role of government subsidies in implementing flood adaptation measures in Harrison County, Texas. The area is based on the map of Harris County in Texas, US including the City of Houston. It is located on the coast of the Gulf of Mexico. The actors considered in the model are households located within the area of Harrison County and the government. However, the government decisions such as the implementation of subsidies are modeled as environmental factors affecting decisions of agents within the system. The adaptation measure that the households have an option to implement depending on their state is elevation of the house. However, companies producing or selling these technologies and materials are not considered within the system boundaries. Figure 2 shows a visual representation of the model domain with agents and the social network state at step 0.

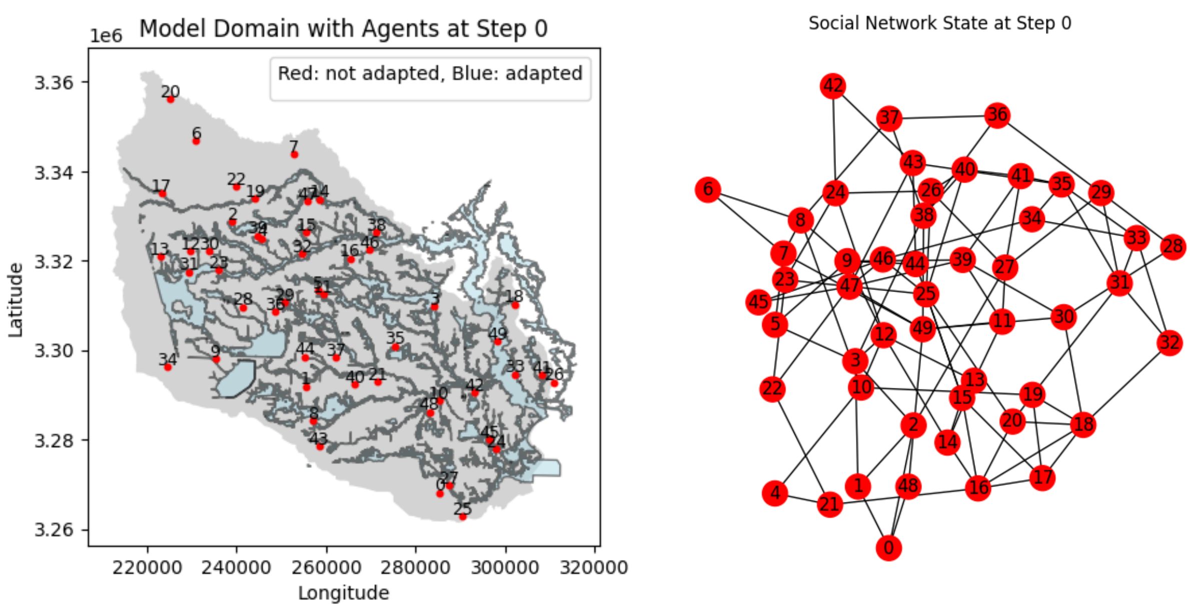

Figure 2: Graphical representation of the system under observation. The red dots represent the agents that are spread throughout the map (left side) and each agent has an individual set of social connections (right side).

3.2 Agents, processes, actions, and interactions

The following section aims to discern the physical and social entities that the system entails. Furthermore, it aims to identify agents, their properties, actions, and interactions and describe the environment.

Actors: households and the government.

Interactions: households interact with the environment, in this model households don't interact with other households, but they are connected in a social network.

Agents are households and they:

- Make certain amount of money depending on their income group.
- Save money depending on their income group.
- Own a property and assets.
- Have coping appraisal and threat appraisal.
- Have a social network.
- Decide on taking Climate Change Adaptation (CCA) measures based on their savings, coping- and threat appraisal.
- Are eligible for subsidies based on their IR and income.
- Have household specifications, which are the location of their property.
- Have current adaptation measures (or not) in place.
- Have previous flood experiences.
- Can be flooded at a given timestep which changes their damage.

Environment:

- Sells the service for implementing the adaptation measure.
- Receives the adaptation measure costs.
- Randomly distributes the income groups.
- Provides income.
- Creates the social network that connects households.
- Provides subsidies based on individual risk theory.
- Has an elevation profile based on the flood map.
- Gives flood events and their severity based on a flood map.

3.3 Parameters

For running the model there are many parameters that need to be set for it to run. This includes basic parameters such as the number of households and flood map choice, but also parameters regarding the PMT such as thresholds and weighing factors, and ones that shape the policy package (Table 1). For relevant parameters it was tried to base them on real values, such as for the cost of the measure, but simplifications were made such as that the cost is the same for all houses despite their differences in sizes. In other cases, well-educated guesses were made due to time constraints. For an actual model these should be based on literature and survey data to better capture the variations in the real-world. Please note that throughout the report, 'time steps' is used interchangeably with 'ticks'.

Table 1: Parameters used in the model with description, unit, and the chosen value for the base runs. Some of the sources have additional details regarding how we used the data, which can be found underneath the table and are also referenced in the 'Source' column.

	Parameter	Description	Unit	Value	Source
General	Seed	Random seed for reproducibility	Any value	None	N/A
	Number of households	Number of households in the model	Number	100	N/A
	Network	Type of network used for household connections	String	watts_strogatz	Base model
	Flood map choice	Choice of flood map	String	harvey	Base model
	Time since last flood	Time since the last flood event	Quarter of a year	10	N/A
	Flood probability	Probability of a flood event occurring	Probability	0.02	(Emanuel, 2017) [1]
Policy & Measure	Mitigation effectiveness	Effectiveness of flood mitigation measures in meters of elevation	Meters	2.4	(Hurley, 2017) [2]
	Cost of measure	Cost of implementing a flood mitigation measure	$	150000	(Hurley, 2017) [3]
	Policy	Flag indicating whether a policy is implemented	Boolean	FALSE	Own policy package
	Low risk subsidy height	Height of subsidy for low-risk households	$	0	
	Medium risk subsidy height	Height of subsidy for medium-risk households	$	75000	
	High risk subsidy height	Height of subsidy for high-risk households	$	150000	
	Low income subsidy factor	Subsidy factor for low-income households	Multiplier	1	
	Medium income subsidy factor	Subsidy factor for medium-income households	Multiplier	0.5	
	High income subsidy factor	Subsidy factor for high-income households	Multiplier	0	
	Low risk threshold	Threshold for low-risk classification	Probability	4.845E-12	(Risk Factor, n.d.) [4]

	Medium risk threshold	Threshold for medium-risk classification	Probability	1E-10	(Risk Factor, n.d.) [4]
Income & Savings	Income distribution	Distribution of household incomes	String	uniform	N/A **[5]**
	Income min	Minimum income value per quarter	$	4000	(Statista, 2023)
	Income max	Maximum income value per quarter	$	80000	
	Low income threshold	Threshold for low-income classification	$	25000	N/A
	Medium income threshold	Threshold for medium-income classification	$	60000	N/A
	Savings share low income	Savings share for low-income households	Percentage	0.001	(Batdorf, 2023) [6]
	Savings share medium income	Savings share for medium-income households	Percentage	0.04	
	Savings share high income	Savings share for high-income households	Percentage	0.2	
PMT	Flood probability percept	Perceived flood probability based on time since last flood	Number (0-1)	0.98201379	N/A
	Flood probability percept weight	Weight for flood probability perception	Weight (0-1)	0.5	N/A
	Flood damage percept weight	Weight for flood damage perception	Weight (0-1)	0.5	N/A
	Savings weight	Weight for savings in decision-making	Weight (0-1)	0.5	N/A
	Income weight	Weight for income in decision-making	Weight (0-1)	0.2	N/A
	Social network weight	Weight for social network in decision-making	Weight (0-1)	0.3	N/A
	Self efficacy weight	Weight for self-efficacy in decision-making	Weight (0-1)	0.7	N/A
	Coping (response) efficacy weight	Weight for coping efficacy in decision-making	Weight (0-1)	0.3	N/A
	Threat threshold	Threshold for perceiving flood as a threat	Number (0-1)	0.6	(Tonn & Guikema, 2018b)
	Coping threshold	Threshold for perceiving coping as effective	Number (0-1)	0.3	(Tonn & Guikema, 2018b)

[1] Flood probability: Source says that for 1981 – 2000 there was a 1 in 100 likelihood for a flood like Harvey to occur in that time period. For 2081 – 2100 the likelihood is expected to be 1 in 5 years. Therefore, we assumed an average probability of 1 in 50 years.

[2] Mitigation effectiveness: Eight-foot-elevated homes (~2.4m) are now required in parts of Harris County.

[3] Cost of measure: The source says that the piling method is $180,000 to $200,000 for typical 2,500-square-foot house. We just adapted it to $150,000.

[4] Low risk threshold and medium risk threshold: Both have no concrete source but we adjusted the values so that they match the reference where the percentage of households that are likely to be severely affected by flooding in Houston is 64%.

[5] Income distribution: Set to be uniform to better observe the impacts on the different income groups without skewed results due to income distribution.

[6] Savings share (low income, medium income, and high income): U.S. personal savings rate (personal savings as a percentage of disposable personal income) in April 2023 was 4.1%.

An interesting example of how the model functions can be seen by how the flood probability perception was implemented. This function calculates the flood probability based on the time since the last flood. It uses the logistics (sigmoid) function, which is defined as 1 divided by 1 plus the exponential of the product of the steepness and the difference between the time since the last flood and the midpoint. The resulting value represents the probability of a flood occurring. In this case the used steepness = 0.1 and the midpoint = 50. Maximum flood probability perception is 1 and is when a flood just occurred. Over time, the flood probability perception decreases towards 0.

$$\boldsymbol{flood\_probability\_percept} = \mathbf{1} \,/\, (\mathbf{1} + \boldsymbol{exp}(\boldsymbol{steepness} * (\boldsymbol{time\_since\_last\_flood} - \boldsymbol{midpoint}))$$

3.4 Explanation of relevant concepts

As previously mentioned, flood adaptation behaviour is frequently explained using the PMT that consists of two major processes: threat appraisal and coping appraisal which are outlined below.

3.4.1 Threat appraisal

Threat appraisal generally captures how threatened a person feels by a certain risk. It consists of two subcomponents; the first one is a cognitive subcomponent of risk perception and the second is an affective one relating to threat related feelings. Risk perception can be defined as the perceived probability of a prospective flood event, the expected exposure to it and anticipated damage. The cognitive subcomponent accounts for the effect that emotions have on flood risk behaviour relating to feelings such as fears or worries about flooding.

3.4.2 Coping appraisal

Coping appraisal is linked to cognitive processes that are used to evaluate possible responses that may reduce the perceived threat. It consists of three subcomponents response efficacy, self-efficacy and response costs. Response efficacy refers to the perceived effectiveness of a protective action in reducing the expected damage from a specific threat. Self-efficacy is linked to the feeling of being capable of carrying out this protective action. Response costs are the financial resources, time and effort necessary for its implementation.

3.4.3 Individual risk

An **individual risk function** has been included as the Reusable Building Block (RBB) based on the individual risk (IR) measure used by the Dutch Ministry of Housing, Spatial Planning, and Environment (VROM), which is defined as the probability of death due to an accident for an average unprotected person permanently placed at the location point (Jonkman, 2002). The formula is below.

$$\boldsymbol{IR = Pf * Pd|f}$$

$\boldsymbol{Pf}$ = probability of failure.

$\boldsymbol{Pd|f}$ = probability of dying of the individual in the case of failure, with the assumption of the permanent unprotected presence of the individual.

The selected **risk threshold** in our ABM model is generally based on the (Jonkman, 2002) paper. The acceptable annual IR per year is $IR < 10^{-6}$ *(yr^{-1})*, in accordance with the VROM standard for populated areas. See Figure 3 for the visualisation of individual risk and the different risk contours. However even then, risks that are lower that 10^{-6} per year should always be reduced to a level as low as reasonably achievable (Jonkman, 2002). Future research should conduct sensitivity analysis on using the TAW standard which adds a policy factor ß based on the degree of voluntariness of the activity and accounting for perceived benefit, with a range from 10 being full freedom of choice and 0.01 being imposed risk without specific perceived direct benefits (Jonkman, 2002). The formula is $IR < \beta * 10^{-4}$ *(yr^{-1})*. Although it would be useful to analyse how realistic this adjustment would be on impacting outcomes, such as probability of dying, this is outside of the scope of the research.

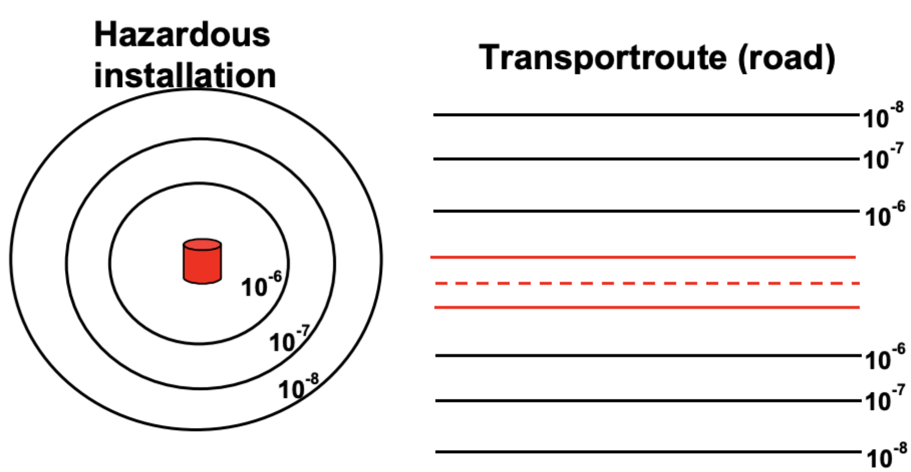

Figure 3: Visualisation of the Individual Risk and the different risk contours (distances from the hazardous object). Different risk countours are corresponding to different risk thresholds that are to be defined and correspond to which risks are tolerable and which require mitigation measures (Jonkman, 2002).

The **RBB** has been implemented within the ABM in the *functions.py* file. It consists of two functions: *calculate_probability_of_dying* and *calculate_individual_risk*. The model's P_f is a global value that is the same for all agents and depends on the selected flood map and is calculated by P_f *= 1 / (years in flood map)*. For example, if the flood map is based on a 100 year flood, then the P_f is 1/100. The model's $P_{d|f}$ depends on the estimated flood depth at the agent's location, considering their adaptation status, and uses a mortality function based on Boyd & Levitan, 2005 to estimate the fatality.

$$\boldsymbol{Pd|f} = \mathbf{0.34} / (\mathbf{1} + \boldsymbol{exp}\,(\mathbf{20.37} - \mathbf{6.18} * \boldsymbol{depth}))$$

Whereas the fixed values are constants from the (Boyd & Levitan, 2005) **mortality function**. The exp() function calculates the exponential value. While there are newer iterations of this function, those typically also include parameters such as evacuation time which were not part of this model. Therefore, the original version of this function was implemented. The function returns a risk group (low, medium, or high) based on the set thresholds for the IR in the model parameters.

The individual risk group is then used in the *calculate_subsidy_height* function to determine the actual **subsidy height** of the agent. It includes also other factors such as income group, the subsidy heights for the different risk categories, and a factor that that is multiplied with the subsidy height depending on the income group.

Thus, this RBB ideally can be integrated into a larger agent-based model on urban flood adaptation. It can also be re-used in other circumstances by replacing the mortality function with the appropriate one and by adjusting the risk thresholds.

3.5 Assumptions and model reductions

The model is built using several assumptions and reductions while aiming to maintain aspects that are relevant for the purpose of the model. The model is designed to focus on household adaptation measures and does not consider public adaptation measures and their impact on e.g. threat appraisal and decision to adapt. The model does not distinguish between different adaptation measures, their costs and efficiency. It considers elevation of the house as the only possible measure that is recognized to be most effective in reducing damage by elevating the house about 2.4 meters. Additionally, the time for implementation is not considered. Instead, when a certain level of threat appraisal coupled with coping appraisal is reached and enough money is saved the state of the agent changes to be adapted. Furthermore, households are residential single-family homes owned by the agents that all have the same size and value. Therefore, they can decide to adapt and experience flood damage. The agents do not pay for repairs losing money from their savings but rather the damage is accumulating over time. Regarding income of the households, it is assumed that there is equal number of households in each income category to better assess the impacts on the different income groups. When aiming for more realistic results the distribution of households to income groups should be made based on statistics. Savings increase with every tick by a certain amount depending on the income level and the associated average share of money going to savings. Finally, even though households are connected in a social network, they do not exchange knowledge and the influence of friends and neighbours is not considered in their adaptation measures. However, the number of connections is considered for coping appraisal, as an agent with a larger extended social network might feel more secure to adapt.

Regarding the threat appraisal it is determined using only one subcomponent, which is risk perception. The affective subcomponent referring to threat related feelings such as fear and worry are not considered. Additionally, according to PMT, coping appraisal consists of three subcomponents - response efficacy, self-efficacy, and response costs. However, response costs are not considered as a separate category but as a part of self-efficacy and only in monetary terms. When government subsidies are introduced, their height depends on either individual risk or individual risk and income group. No other aspects are considered. Furthermore, all agents are considered as possible recipients of subsidies, regardless of whether they are informed about them and applied to receive the subsidies. See Table 2 for a full list of model assumptions and reductions.

Table 2: Assumptions and reductions of the model.

Element	Assumptions and reductions
Public adaptation measures	• Not considered
Private adaptation measures	• Elevation of the house • Other types not considered • Uniform pricing that does not change per household or over time • Maximum effectiveness by elevating the house ~2.4m • No implementation time
Households	• Single family units • Apartments and other types not considered • All have the same size and value • Are not able to move out of their houses • Building owners with freedom to implement adaptation measures
Flood damage	• Repair costs are not taken from savings • Damage accumulates
Income	• Equal number of households in each income category
Savings	• Increase with every tick based on income level and associated average share savings from income
Social network	• No knowledge exchanges • Have social links that are counted
Threat appraisal	• Based on risk perception • Threat related feelings not considered
Coping appraisal	• Based on response efficacy and coping efficacy • Response costs only considered in monetary terms and included in self-efficacy
Government subsidies	• Based on individual risk and/or income group • Everyone is informed and applies to subsidies

4 Formalisation

The household agent is at the core of the model: it makes the decision to adapt or not. A simulation tick represents 1 quarter of a year, and it entails all households that perform a sequence of actions. A household agent receives income and saves a certain amount of money that is added to its savings. If a certain threshold of threat appraisal and coping appraisal are met, and the savings are high enough, the household implements flood adaptation measures. If flood adaptation measures have not been implemented at the time of the flood, depending on the flood depth households experience flood damage. A flood shock takes place at a predetermined point in the simulation (time step 5), and it affects all households in the model. The actual flood depth at each household is calculated, deviating from the initial estimates that are based on pre-loaded flood maps that represent potential flood scenarios. This estimated flood damage is used to inform the adaptation decisions of households whose perception is updated in each tick.

4.1 Initialisation and steps

4.1.1 During initialisation

During the initialisation of the **model** all parameters from the main.ipynb notebook are loaded. Then a network for the agents is initialised, a random activation scheduler gets activated and households with their unique ID's are generated and placed on the map. Also, the necessary model and agent metrics are set-up to collect the data during the model runs.

During the initialisation of the **agents** there are many parameters, such as their adaptation status, income, initial savings, share of income going to savings, their location, an estimated flood depth and -damage based on their location, as well as parameters regarding their PMT, IR and subsidy height.

4.1.2 During each step

During a timestep of the **model**, the following actions are performed:

1. The time since the last flood is incremented by 1 quarter.
2. The flood probability perception is calculated based on the time since the last flood.
3. At timestep 5, a global flooding event occurs.
4. For each agent in the model:
5. The actual flood depth is calculated as a random number between 0.5 and 1.2 times the estimated flood depth.
6. The actual flood damage is calculated based on the actual flood depth and the agent's adaptation status.
7. The total damage and total damage per income group are accumulated.
8. The time since the last flood is reset to 0.

9. Data is collected for analysis.
10. The model advances by one step.

During each timestep for the **agent**, the following actions are performed:

1. **Update Friends Count:**
    - The count of friends within a network radius of 3 is updated.
2. **Increase Savings:**
    - The agent's savings are increased based on its income and the specified savings share.
3. **Update Threat and Coping Appraisal**:
    - Threat appraisal is updated based on the calculated flood probability perception and estimated flood damage.
    - Coping appraisal is updated based on coping efficacy and self-efficacy, considering savings, income, and social network contributions.
4. **Adapt to Flooding**:
    - If the agent has not already adapted and meets certain conditions:
    - The agent adapts to flooding, setting the adaptation status to True.
    - The subsidy amount used is deducted from the total subsidies spent.
    - The agent's savings are adjusted by subtracting the cost of the adaptation measure and adding the actual subsidy height.

The friend's count is used in the coping appraisal but was intended to reflect the number of friends that have adapted to integrate social influence in the model. Due to modelling challenges, it was not achieved and instead the number of friends in the extended social network was used as proxy for simulating a social safety net, influencing the agent's confidence in undertaking a costly adaptation measure.

In Figure 4 the model flowchart for what happens at each timestep is outlined.

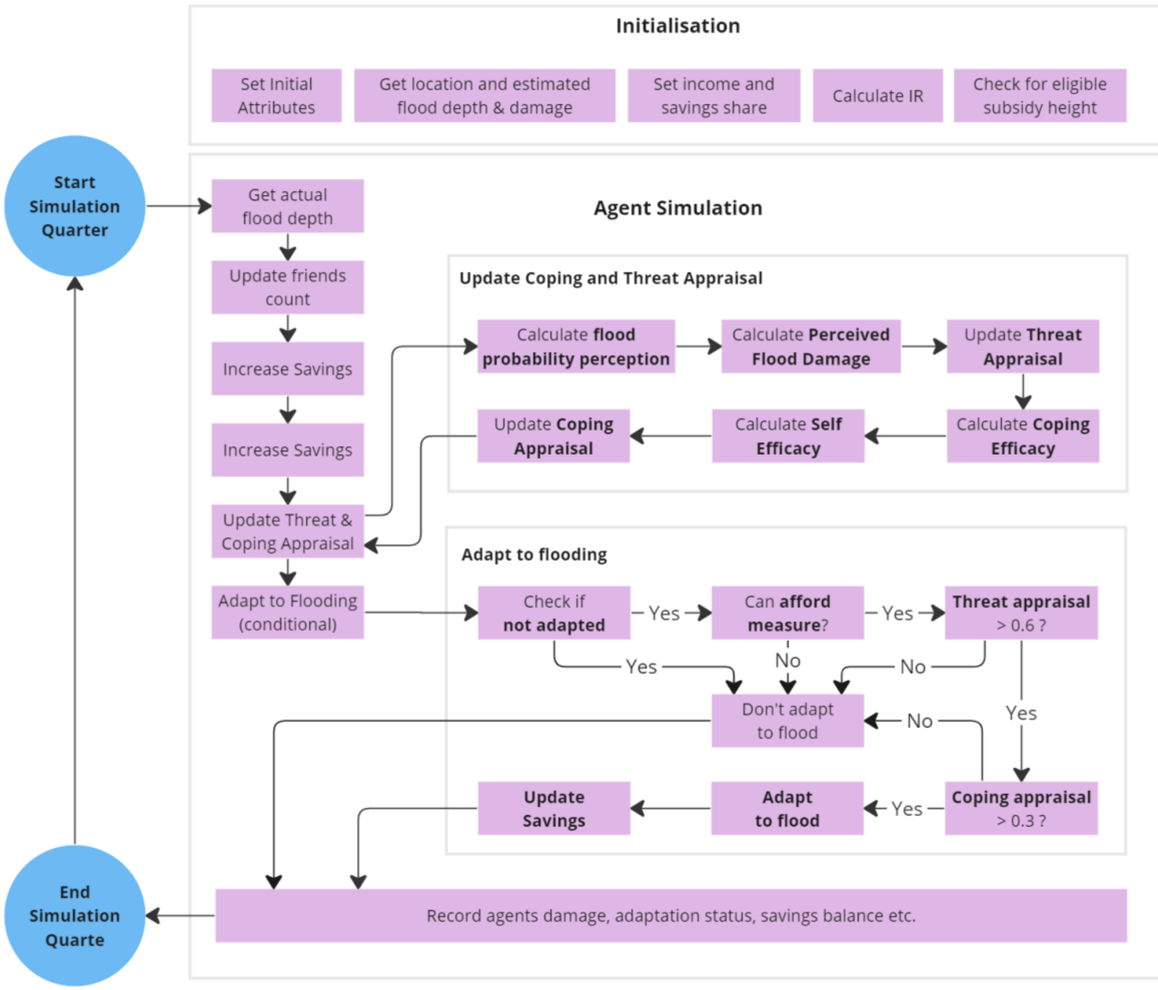

Figure 4: Flowchart of agents initialisation and what happens each time step during the simulation.

4.2 Key Performance Indicators

Although many Key Performance Indicators (KPIs) can be collected from the model, one main output of interest was selected to answer the research question and address the project requirements (Table 3).

The KPI selected is the total number of households that decide to take adaptation measures. These data points were collected for the following three income groups to have more specificity in the analysis by having both income grouping and individual risk groupings. In future research, it would also be useful to have IR levels for each of the income groups. This would allow for more specificity. For example, then it can be analysed if low individual risk households with low incomes have (1) more or fewer damaged households and (2) more or fewer households which decide to adapt than low individual risk households with high incomes.

Table 3: Three sub-groups analysed for each KPI across three income levels.

Group Number	Income Level	Share of Adapted	Total Damage
1	Low income	$Share\ adapted_{\,in\ group} = \frac{Households_{adapted\ in\ group}}{Households_{total\ in\ group}}$	$Total$
2	Medium income		
3	High income		

This metric answer the main RQ since the total number of households that decide to take the adaptation measures is directly part of the RQ, and is most relevant to understanding if flood damage disproportionately impacts different income groups. In terms of the project requirements, as the ticks progress the diffusion of adaptation over time also becomes visible.

5 Validation and verification

5.1 Model validation

Model validation seeks to test the model outcomes under different parameterisations prior to experimentation. In essence, a sensitivity analysis is conducted to check if the behaviour that is derived from the model is comparable to real-life behaviour. Since the main function of the model is to analyse income groups, the selected input parameters which were chosen were all related to adjusting the ability of households to pay for adaptation measures.

5.1.1 Savings share

The first test is run on adjusting the savings share parameters. Table 4 shows the cases for a base case, test with -25%, and test with +25% for three income groups. The model was run for three iterations on each parameter combination (27), resulting in a total of 81 model runs. Ideally it would ideally be run more times as done in experimentation, but the possible iterations were restricted due to time constraints.

Table 4: Input parameters for the batch parameter sweep (100 agents, 80 time steps, 27 parameter combinations, 3 iterations each).

Savings share level	Base	-25% *base – (base * 0.25)*	+25% *base + (base * 0.25)*
savings_share_low_income	0.001	0.0008	0.00125
savings_share_medium_income	0.04	0.03	0.05
savings_share_high_income	0.20	0.15	0.25

The results in Figure 5 shows the average amount of households that adapt over time using the different parameter combinations with a 95% confidence interval.

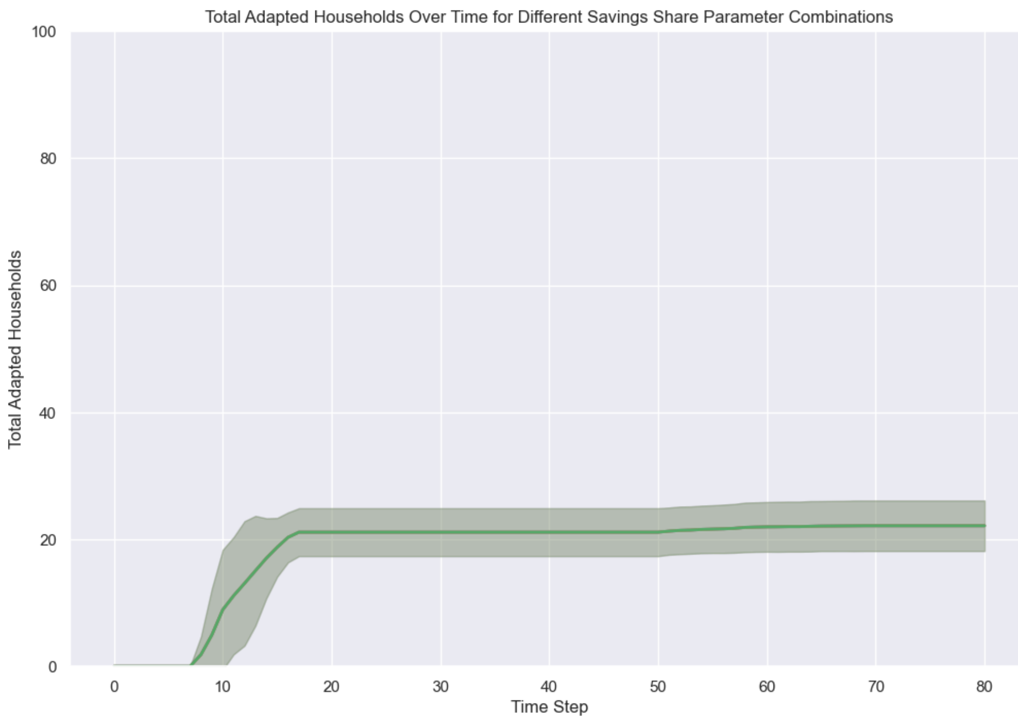

Figure 5: Total adapted households over time with 95% condidence intervals for the saving parameter combination sweep (100 agents, 80 time steps, 27 parameter combinations, 3 iterations each).

5.1.2 Income distribution

A second validation test was also run three times on the type of distribution used for the income distribution parameter. However, due to time constraints graphs and a detailed discussion of results could not be shown. In future research, it would be useful to include this second test. The reasoning is that in the base model, uniform distribution was applied to income distribution in order to effectively see the impact on each group. However, in reality high income groups would not have more people than in medium or low income groups. Therefore, three additional cases of distribution were explored which can be seen in Table 5, namely normal (case A), normal with low-peak (case B), and normal with medium-peak (case C).

Table 5: Input parameters for income distribution validation.

Variable	Base	Case A	Case B	Case C
income_distribution	Uniform	Normal	Normal (medium-peak)	Normal (low-peak)

5.1.3 Future research

If this project had a larger scope, it would be interesting to assess how changing all the input parameters by for example +25%, +50%, -25%, and -50% would impact the selected KPIs over several runs. Then a range of the datapoints over all the runs for each of the sensitivity levels could be compiled. This would allow for a test on which parameters are the most sensitive on the selected KPIs. Given time constraints, here the aforementioned two input parameters to adjust were qualitatively selected based on our research question. Additionally, data inputs for savings share levels was quite limited since distribution of savings across income groups was not readily available.

5.2 Model verification

5.2.1 Single agent testing

Exploring the behaviour of several individual agents was conducted through theoretical prediction and sanity checks. Pseudo-code created before was compared with the actual code to identify any potential logical errors throughout as well. In future research, it would be useful to conduct additional tests such as breaking the agent with feeding the household agent very large or small inputs. Throughout the modeling process we observed the impacts on the agent data within the generated data frames from the data collector, and in turn plotted the change of different variables over time in order to test agent memory. For example, savings for individual agents were plotted over time (Figure 6) to assess this change. In Figure 6, we see that the savings of agents in the high-income groups increase significantly faster and makes it possible for them to adapt early in the process. For agents with high savings that did not adapt around timestep 10, their risk at their location was not high enough or the other thresholds in threat and coping were not reached. Low-income agents have a lower share of savings given their lower income, and thus we never see a dip in their savings as they are never able to afford the measure.

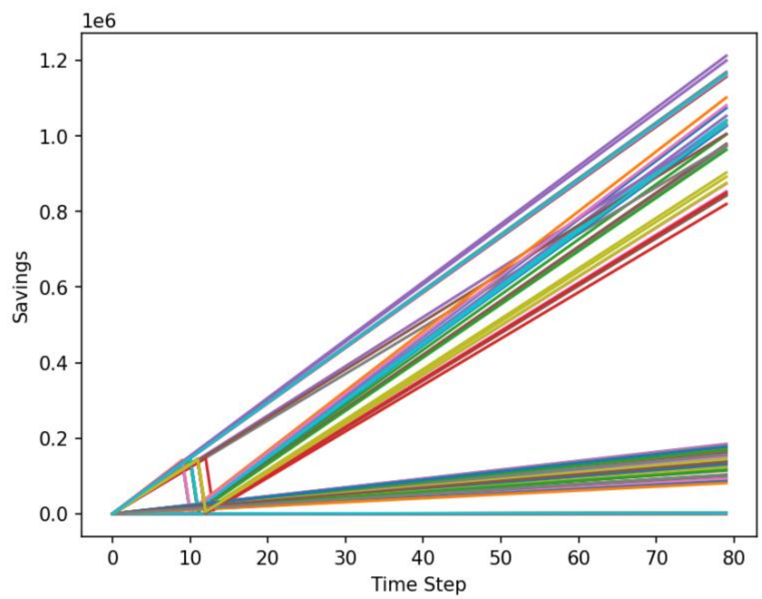

Figure 6: Tracking of individual agents for their savings over time (100 agents, 80 time steps, 1 parameter combination, 1 iteration).

A test on how the PMT is attributed to different individual agents was also conducted with print functions while coding and also plotting the graphs in Figure 7, which show the PMT parameters. In plotting the PMT parameters for coping appraisal and threat appraisal, we can see more clearly how the perception of agents on the flood and their ability to cope with it changes over time. We can observe that the probability perception is the same for all agents since it is based on the time since the last flood and decreases over time based on a logistics function, in which it is represented that the flood is very present in the minds of all agents right after the flood. The flood damage perception is evidently dependent on the elevation of household agents, which influences their beliefs on whether they will receive any damage. In combination with the weighting factors, these elements shape households' threat appraisal and is evident visually in the graphs.

The coping appraisal also in Figure 7, is slightly more complicated as it consists of more parameters. The coping efficacy (response efficiency in literature) remains constant for each individual agent as the potential on how much the measure is actually able to reduce the flood risk is based on its effectiveness. The self efficacy is based on the savings of agents, income group, and the size of the social network. Appendix A provides deeper insights into self-efficacy, revealing that some agents constantly have low self efficacy. This is because they may have low to no savings and have low income, making them believe that they lack the means to adapt. The sharp drop for agents with high self efficacy could be explained by them adapting, and thus reducing their savings.

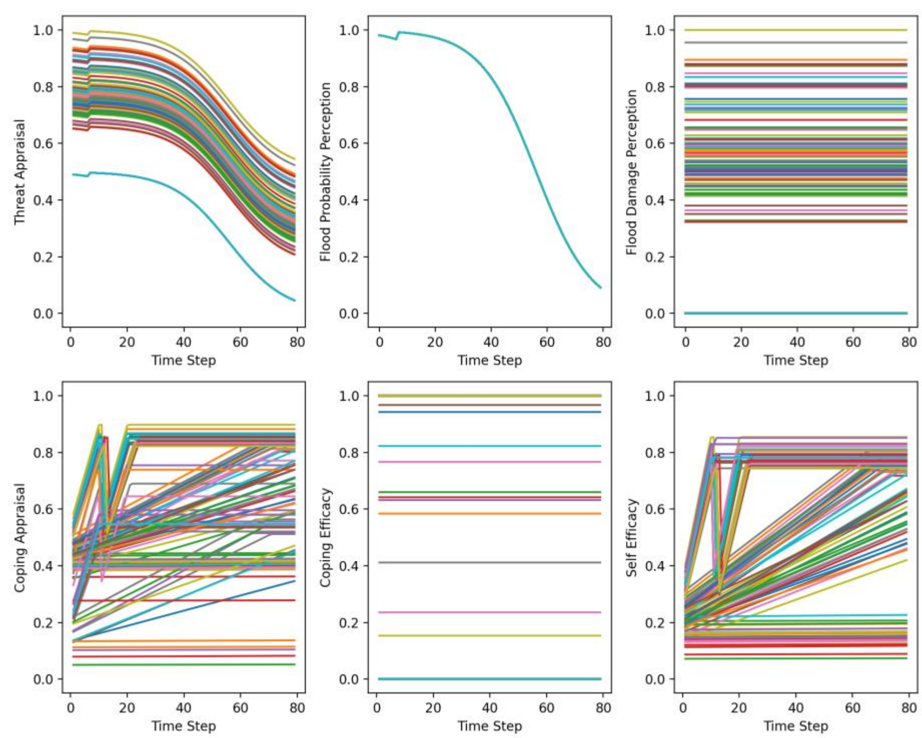

Figure 7: Tracking of individual agents for PMT parameters over time (100 agents, 80 time steps, 1 parameter combination, 1 iteration).

6 Experimentation

6.1 Experimental design

Once the model has been created and verified, experiments are to be performed which provide insights to answer the main research question and test the hypothesis. Each experiment had multiple repetitions since one single run of an ABM should not be trusted considering that just one run could potentially be an outlier. A random seed was fixed in order to produce the exact same sequence of pseudo-random numbers (although there is no true randomness in these numbers) in order to replicate results. Each of the base case, policy 1, and policy 2 had 100 agents, 80 time steps, 9 parameter combinations, and 5 iterations. The KPI 'total number of households that decide to take adaptation measures' was checked for across the three groups mentioned in the KPIs section.

There were two main subsidy policies that were tested in addition to the base case with no subsidy policy. Both policies have a difference in the way to determine the level of subsidy given to different groups of households. Policy 1 only considers IR, while policy 2 considers both IR and income group. Ultimately, policy 2 is more inclusive in also considering income level and not just IR. Analysing the results from this experiment can help to see what type of policy would be most effective on seeing which groups of households actually implement the flooding mitigation measures and how many households are damaged across both income groups and individual risk groups. The parameters can be seen in Table 6.

Table 6: Parameters for the different policy sets used in the policy experimentation batchrun.

Parameter	**Base case:** *No subsidy*	**Policy 1:** Only IR considered	**Policy 2:** Both IR & income group considered
		No IR based tiering of subsidy height, no accounting for income (only risk focused)	*Combined subsidy height and subsidy factor (both risk and income focused)*
policy	False	True	True
low_risk_subsidy_height	0	0	0
medium_risk_subsidy_height	0	\$25,000; \$50,000; \$75,000	\$25,000; \$50,000; \$75,000
high_risk_subsidy_height	0	\$100,000; \$125,000; \$150,000	\$100,000; \$125,000; \$150,000
low_income_subsidy_factor	0	1	1
medium_income_subsidy_factor	0	1	0.5
high_income_subsidy_factor	0	1	0

In future research, it would be useful to run descriptive statistics over the total set of runs, but due to time limitations this was not possible. Moreover, additional experiments would be useful to run such as Monte Carlo to find a reasonable subset of the scenario space that we would want to test.

6.2 Experimentation results

As seen in Figure 8 below, policy 1 with only accounting for individual risk on average over all the timesteps (ticks) had the largest number of households adapt. In the figure, the solid lines show the results of taking all the possible different combinations of subsidy heights, and then averaging the deviation of these. The dotted lines show the impact on total adapted households that would occur if the subsidy height was to be placed at the highest level. Then, a subset of the batch run was used where the subsidy was at the maximum height and run several times. The means are then illustrated within the charts with confidence intervals for the non-maximum subsidy scenarios.

Although policy 2 which also accounts for the income levels has slightly fewer households adapt, there may be more households which are low income that might benefit from this measure even though the average across all income groups may appear lower. This is important to consider when governments are thinking of policies that may appear to on average help the most households when only considering individual risk factors, but that might not account for which populations are disproportionately most impacted. There is also a significantly larger jump in the policy 1 and policy 2 experiments which use the policy parameter combinations with the highest subsidy values. This implies that especially for policy 1 since the increase is very large and quick, trying to maximise the amount of the policy could have a significant impact on the amount of households which adapt.

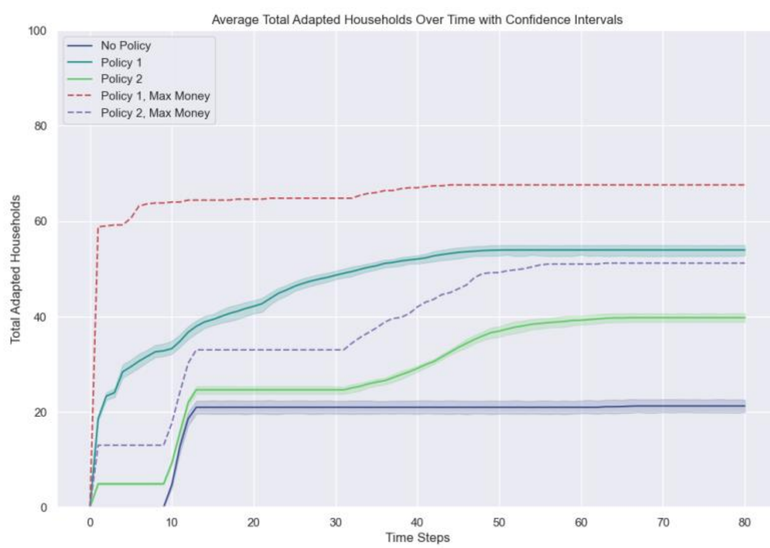

Figure 8: Average number of total adapted households over time across the no policy case, policy 1, policy 2 with 95% confidence intervals. Additionally the means for the policy parameter combinations with the highest subsidy values (75,000 and 150,000) have been added. (100 agents, 80 time steps, 9 parameter combinations, 5 iterations).

In Figure 9 below, the number of adapted households across different income groups for each of the scenarios are shown. In the no policy scenario, high income households adapt disproportionately more than the medium income group and the low income group cannot adapt at all. The policies are visibly more effective to help influence medium and low income households to adapt. The high income households remain relatively stable, with a very marginal decrease in policy 2 that does not give high income households a share of the subsidy. This suggests that the high income group is less sensitive to subsidies due to their higher incomes and savings, but in future research should be run with more statistical tests to evaluate the implications further. In contrast, having any of the two subsidies already significantly increase the amount of adapted households, suggesting increased sensitivity to input parameter changes for medium and low income groups. These results also imply that the medium income group is slightly more likely to adapt than the low income group, and that policy 2 has just a bit more adaptation than for policy 1. An interesting finding is that when comparing Figure 8 and Figure 9, overall policy 1 has more adaptation across the entire 80 ticks. However, when looking at the distributional effects across income groups we can see that high income groups adapt more in policy 1 to drive this KPI up. In contrast, policy 2 has less overall adapted households over the entire timeframe, but has more medium and low income groups that adapt. With more computing power, more runs should be conducted with additional parameters to assess if this agent behaviour would remain.

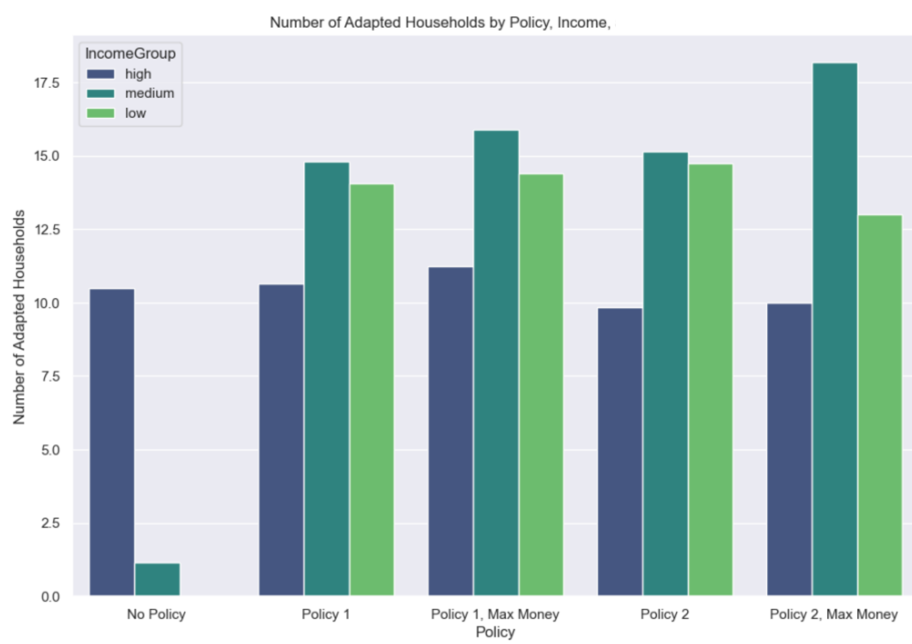

Figure 9: Average number of total adapted households across the no policy case, policy 1, policy 1 using parameter combinations with subsidy height at maximum values, policy 2, and policy 2 using parameter combinations with subsidy height at maximum values. (100 agents, 80 time steps, 9 parameter combinations, 5 iterations).

7 Discussions

7.1 Limitations and future research

While modelling, it is important to comprehend the limits of prediction by not saying what will happen, but rather saying with relative certainty what will not happen (Dam et al., 2013)

The model is able to offer a general understanding of the behavior of households in Harrison County regarding their adaptation behavior, how it is affected by their income, and the role of government subsidies in increasing the number of households that implement adaptation measures and in reducing flood damage. However, in comparison to a real-life scenario, mainly due to the extensive list of assumptions and reductions, the model lacks detail and to some extent can be considered too optimistic. These include:

- The government budget is not linked to any real budget, it does not consider its relationship with higher level budgets and how much money would be available to support the implementation of flood adaptation measures.
- When a subsidy is available all households that have reached certain thresholds receive them. However, not all households might be aware of the subsidies and apply to receive money.
- No public adaptation measures such as dykes are not considered. However, they can influence the sense of security which can also attract more people to a place.
- The households are all house owners whereas some of them might be renting their homes and therefore not be able to make direct decisions on adaptation measures. People also do not move away even when they might feel unsafe and have the option to move.
- Households are not able to implement other adaptation measures that cost less and can protect and reduce flood damage such as sandbags, flood barriers, waterproof doors, strengthening housing foundations or moving valuable assets to higher floors.
- No insurance is considered in either how agents perceive the need to adapt or in regard to flood damage.
- The social network is used only to count the links between agents. However, there is no knowledge exchange or coordination between neighbors happening that might influence the adaptation behavior.
- Negative savings are not accounted for in the model, however in reality some households are in debt.
- The deterministic nature of the base model stems from fixed input parameters which were originally used to ensure its proper function. However, future research could benefit from randomising more input parameters.
- Uniform distribution is used across income groups to better understand the model, however in reality income tends to be unevenly distributed. If we had more time, expanding upon the preliminary part of the income distribution within ‘model validation’ to be normal around low and middle income groups could be interesting to analyse.

In future research, wealth would be useful to analyse since there tend to be data gaps, as for Harris County this could not be evaluated due to data limitations. Also looking at income or wealth inequalities between ethnic groups, educational backgrounds, and across gender could facilitate more precise research on the particular backgrounds of people within the households who are most negatively impacted by inability to pay for flooding adaptation measures. This type of research is especially needed since Black, Latino, low-income, and immigrant communities are relatively more vulnerable to impacts caused by natural disasters (Understanding Houston, n.d.). More data gaps tend to exist for wealth levels, which is the case for Houston area (Pager & Shepherd, 2008). However, this issue is pressing to analyse as on a national scale the distribution of wealth in the United States has become more unequal from 1963 to 2019, with households in the top 1% of earners having seen wealth multiplied by 8 times over this time period while families in the bottom 1% are 15 times more in debt than in 1963 (Pager & Shepherd, 2008).

Moreover, since the experimentation stage tests the effects of policies it would be useful to conduct statistical tests. For example, T-tests could be useful to conduct when assuming normal distribution. Due to time limitations, these were outside of the scope of the research but we understand it limits the current applicability of actually recommending these policies.

7.2 Conclusion

This research aimed to answer the research question: *What is the effect of subsidies on flood adaptation under flooding conditions as measured by the total number of households that decide to take the adaptation measures?*

Attention is drawn to the limitations to ensure we do not try to make clear policy recommendations as the underlying data is largely based on assumptions rather than survey data, and there has been limited statistical testing. With acknowledgement of the limitations of the model, the parameters as they are set, and the underlying assumptions made, the following conclusions can be drawn. In the absence of a policy, high income households disproportionately adapt while low and medium income groups are less likely to. This is perhaps the most clear answer to our initial hypothesis that income inequality hinders household flood adaptation, which is that our hypothesis was correct given the constraints of the model. Additional insights can also be drawn, such as that high income households are less sensitive to subsidies due to their higher incomes and savings, while medium and low income groups exhibited increased sensitivity to policy changes. Even though over the entire 80 ticks Policy 1 overall had more households adapt than Policy 1, this does not account for distributional adaptation across income groups. In doing so, Policy 2 was marginally more effective than policy 1 in having low and medium households adapt, as income levels were also considered and not just individual risk. Overall, policymakers should consider not only the overall effectiveness of households that decide to adapt, but also the distributional effects across income groups when designing flood risk management policies.

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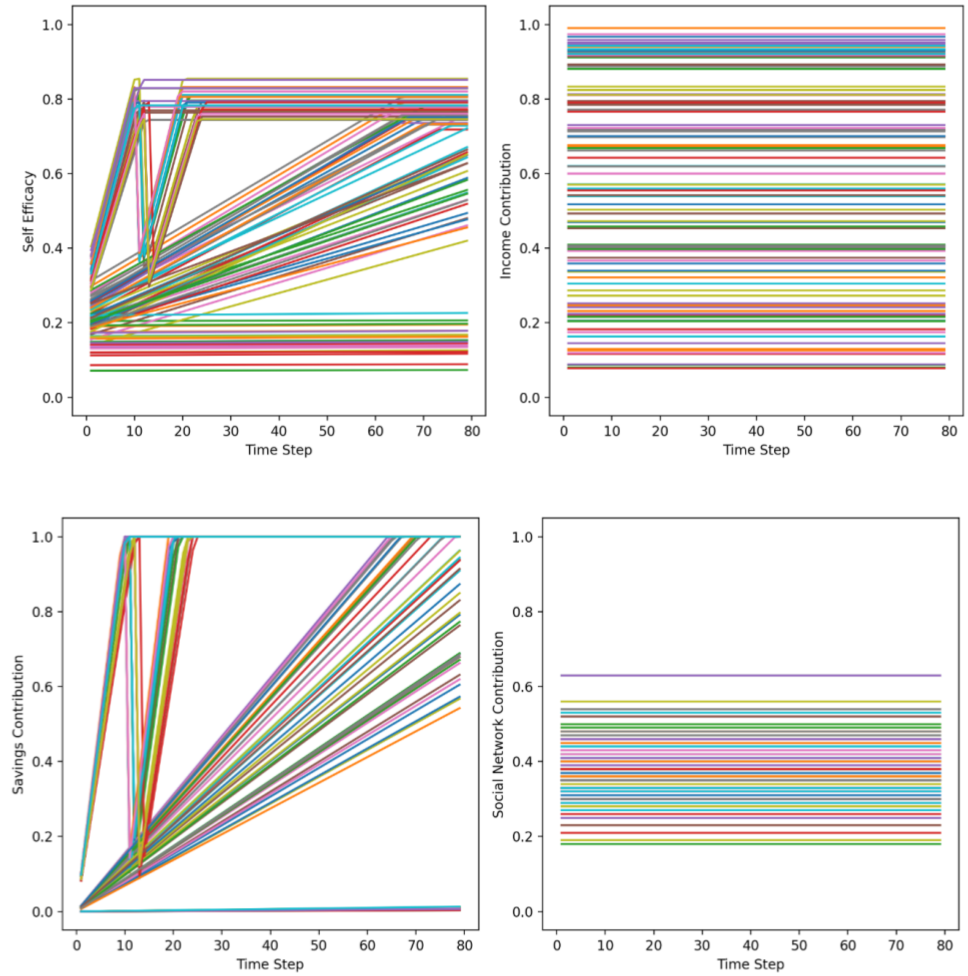
9 Appendices

9.1 Appendix A



Appendix A: More in-depth tracking of individual agents for self efficacy parameters over time (100 agents, 80 time steps, 1 parameter combination, 1 iteration).