Project report

On a mission to turn the tides:

A simulation study on the impact of government subsidies on household adaptation in Harris County using Agent-Based Modeling

SEN1211 Agent-based Modelling 23/24

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Preface

This report has been written as a part of the course SEN1211 Agent Based Modelling at the faculty of Technology, Policy and Management of the TU Delft.

As we did not have much experience with modeling in Python, from time to time we had to limit our thinking and expectations within this project, which was quite a confronting challenge in itself. However, the project did give us valuable insights into complex systems thinking and Agent-Based Modelling principles.

We would like to thank Dr. Ir. Igor Nikolic and the TAs for their support during the practicals.

1. Introduction

Increased flood risk is considered a major problem under climate change (Dittrich et al., 2018). Under current circumstances, both the frequency and the intensity of floodings will increase in the future (Berke et al., 2015).

Costs resulting from flooding disasters are high. For instance, the general global weather related disasters in the US led to a total cost of 300 billion dollars in 2017 (Jongman, 2018). Such impacts can be reduced through all kinds of climate change adaptive measures.

In order to manage flooding risks, a proper understanding is required into the way individuals perceive and respond to risk, as peoples' risk reducing behavior, willingness to relocate, and access to information play a key role in the actual level of risk (Jongman, 2018).

The adaptation measures undertaken by households play a large factor in the total amount of damage experienced. However, it has been found that income has a serious influence on the ability to afford these kinds of property adaptation measures. This ability to afford property-level adaptation measures is linked to broader socioeconomic inequalities (Kaufmann, Priest, & Leroy, 2018). This is because it could lead to inequality in the exposure of flood impacts for whom an adaptation strategy is unaffordable, since they will probably face higher flood damage costs, resulting in new patterns of inequality. This unequal distribution of burden is an important concern and increases mandates to act (Hudson, 2020).

As the income influences the ability to adapt to flooding, requiring a mandate to prevent flood damage inequality, it is worthwhile to investigate the effects of a potential mandate by the government on the ability to adapt and on the damage experienced by households. In this research, the aim is to take a look at the decision-making process for flood adaptation measures by households influenced by the provision of different types of subsidies as a government mandate.

One of the areas seriously affected by these risks, is the Texas Gulf Coast in the United States (Zhu et al., 2015). Therefore, this research will focus on the floodings in Harris County (Texas) as an example case.

With the use of Agent Based Modelling in Python (Mesa), the interactions of different actors (government actions, households as well as their perceptions and efforts to assess the preparedness against flooding events in the region) can be evaluated. This all can be summarized into the following main research question:

What is the effect of various government subsidy policies on household flood adaptation measures, under different flooding conditions, on the damage experienced compared to income and inequality between various household income classes in Harris County?

Hypothesis

Within this research, experiments will be conducted with three types of government subsidies on household adaptation measures. These subsidy constructions include:

1) Standardized subsidy amount for all households and all types of adaptation measures provided.
2) Varying subsidy amounts depending on the income class of households, where lower incomes receive relatively larger amounts of subsidies on adaptation measures.
3) Varying subsidy amounts based on the location with regard to flood risk. Households facing higher flood risks receive higher subsidies.

The hypothesis is as follows:

It is expected that subsidy alternative (3) will lead to less flood damage inequality within the different income classes, since the ability for lower income classes to adapt will increase (coping capacity), reducing relative differences in flood damage of all individual households.*

It is assumed that alternative (3) will be most effective, since it considers the vulnerability of households and is not purely based on income, like subsidy alternative (2). This way, damage can be targeted and reduced more specifically to those households who rely the heaviest on affordable adaptation measures.

Moreover, it is assumed that every policy option leads to better performance with regard to the key performance indicators (more on that in paragraph 2.6) than not introducing any policy.

**measured as reduced difference of damage/income ratio between income classes.*

2. Conceptualization

In this section, a conceptual model is constructed in order to define the boundaries of the system which will be modeled. Moreover, the actors involved, which will be referred to as agents, their properties and interactions are clarified.

2.1. System boundaries

Harris County

The area is based on Harris County, USA. We will model the adaptation of households against flooding. The system boundary is therefore Harris County, including the households that live there. Each of these households have a location within Harris County, that is related to a specific flood depth, representing a base for their potential flood risks. Households are connected through a social network, each household representing a node. Some actors have not (directly) been included and provide behavior, such as insurance companies or the local government.

Flood conditions

Three types of flooding occurrences have been considered. Which can be named respectively representing the impacts of hurricane Harvey, the impacts of a flooding of which this has a probability to occur once every 100 years and one that could potentially occur every 500 years, therefore having a larger impact than the other two types of flooding.

Time

Within the model a tick represents ¼ of a year. Meaning that four times per year within this model, a household has the opportunity to take adaptation measures. Flooding occurs according to a random distribution and the model will stop after this happens. Thus, only the model behavior before the occurrence of a flooding is analyzed. The model can run for a maximum of 80 ticks, therefore considering a maximum period of 20 years to analyze the behavior of household agents.

2.2. Actors

There are two types of agents included in the conceptualization of the model.

1. **Households**

   First, we make a distinction between household agents. These actors are directly affected by potential flooding. Moreover, these are the actual agents that can take flood adaptation measures on an *individual level* to reduce flood damages.

2. **Government**

   The local government of the flooding area is also included for experimental purposes, to investigate the influence of different types of subsidy policies on the behaviors of households and the impact on flood damages.

2.3. Processes and interactions

The **households** can differ based on a range of variables which correspond with their characteristics. They can differ in their income class, total income per year, house size and initial perception towards flooding. Moreover, they have an initial flood danger opinion which is influenced by their neighbors and friends (to which they are connected in a ‘friend network’). This does not necessarily represent their individual risk, but relates to their general risk attitude, concern or sentiment towards flooding events. It is considered that households save to enable implementation of specific adaptation measures. The height of these savings per year are based on their income, and also on their willingness to save for an adaptation measure, which is influenced by their flood perception.

The decision to adapt is based on an individual flood risk (of which the components will be explained shortly) and the flood perception they have (as influenced through their social network). As it has been found that the social network influences the decision to adapt strongly (Poussin et al., 2014).

According to literature, (individual) flood risk consists of exposure, vulnerability and coping capacity, of which the last component refers to the ability to undertake measures (Osberg, 2021). This shows resemblance to the Protection Motivation Theory as depicted in Figure 1 (Oakly et al., 2020). Exposure and vulnerability are in correspondence with ‘threat appraisal’ as stated in the PMT, and similarly coping capacity with the ‘coping appraisal’.

A household's vulnerability in this model is determined by their location, also referred to as their ‘estimated flood depth’ and changes by means of their coping capacity when an adaptation measure is taken. This estimated flood depth is based on the flood-depth curves for North America by Huizinga et al. (2017).

Their exposure, which refers to the value of intangible assets such as home size (Osberg, 2021) is also included in this individual risk. In relation to vulnerability and exposure, we take the estimated flood damage (which is a function of home size and flood depth) as a proxy for this individual flood risk based on vulnerability and exposure (Osberg, 2021).

Coping capacity is also included in taking the decision to adapt, by incorporating the costs of the adaptation measure as well as the efficacy of that measure based on the house size of this household (Oakly et al., 2020). For modeling purposes, the self efficacy (the ability an individual household thinks having) and response efficacy (the efficacy of the chosen adaptation measure) have not been included, as it has been found that costs are the highest contributors in the decision to adapt or not (Poussin et al., 2014).

This individual flood risk, consisting of an estimated flood depth (vulnerability) and home size (exposure), together with the opinion influenced through the social network functions, results as an incentive to either adapt or not. The costs of a measure then function as a final determinant for adaptation, if it is reasonable within a household's savings. There are multiple adaptation measures to choose from, for which an increased effectiveness (which means a decrease in the estimated flood depth) also comes with a higher price to adapt.

The estimated flood depth determines the flood damages experienced, which serves as a key output per income class within this research.

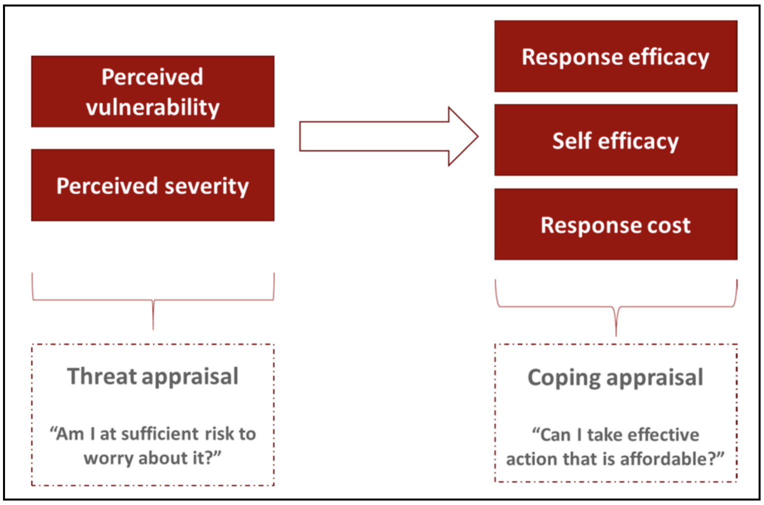

Figure 1. Key elements of the Protection Motivation Theory (PMT) by Oakly et al. (2020).

Government policies

The local government can decide on implementing different kinds of policies. These can be structural (for example the construction of dikes), financial (such as subsidies), but also informative in order to influence the risk perceptions of household agents. In this research, we only focus on the effects of different kinds of subsidy policies.

The following policy types are considered within this research:

1. Standardized subsidy amount for all households and all types of adaptation measures provided.
2. Varying subsidy amounts depending on the income class of households, where lower incomes receive relatively larger amounts of subsidies on adaptation measures.
3. Varying subsidy amounts based on the location with regard to flood risk. Households facing higher flood risks receive higher subsidies.

The government only becomes relevant with regard to the experiments and is modeled as an external agent, having no further interactions with household agents. The actions of and interactions between household agents and the government can be summarized in the conceptual model of section 2.5.

2.4. Nominal opinion scale - Reusable Building Block (RBB)

The decision of a household to make adaptation measures is - amongst other variables - influenced by the social network of the household. This social network consists of other households, all with their own opinions on flood danger. Every household has an initial opinion on flood danger, that, throughout time can be influenced by the opinions of their friends. The category of the household's flood perception determines the willingness to adapt, as it represents their general risk attitude and sentiments towards flooding occurrences. The higher this category is, the more willing a household is to adapt.

As the opinion on flood danger influences the choice on whether a household will implement adaptation measures, it is interesting to take a closer look at this opinion on flood danger.

Several formal theories assume that the opinion scale within a model is nominal (Flache, et al., 2017). This means that the opinion on flood danger can consist of different nominal ‘options’, or ‘perspectives’. In the model we have implemented this by creating three opinion stages: (1) no danger is acknowledged, (2) danger is acknowledged, no need for adaptation and (3) ready for adaptation.

Every household gets a random nominal option as initial flood danger opinion. Then, during every timestep the household will reconsider its flood danger opinion by checking its own opinion within its network of friends. Only when within this network another opinion seems to be in the majority, the household will adjust its flood warning opinion to the commonly shared opinion. If there is no majority, the household will not change its opinion.

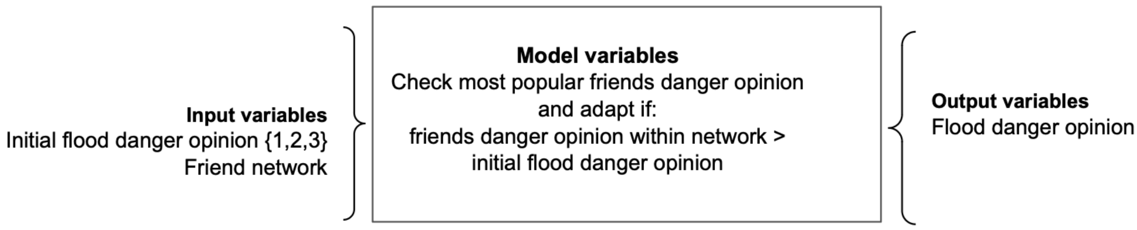

Figure 2. Input, output and model variables of the Reusable Building Block (RBB).

2.5. Conceptual model

The conceptualization can be summarized in Figures 3 and 4 below. These figures show the processes an agent runs through each tick, as well as the conditions for certain processes to occur. It should be noted that the conceptualizations do not follow the specific syntax of a process diagram.

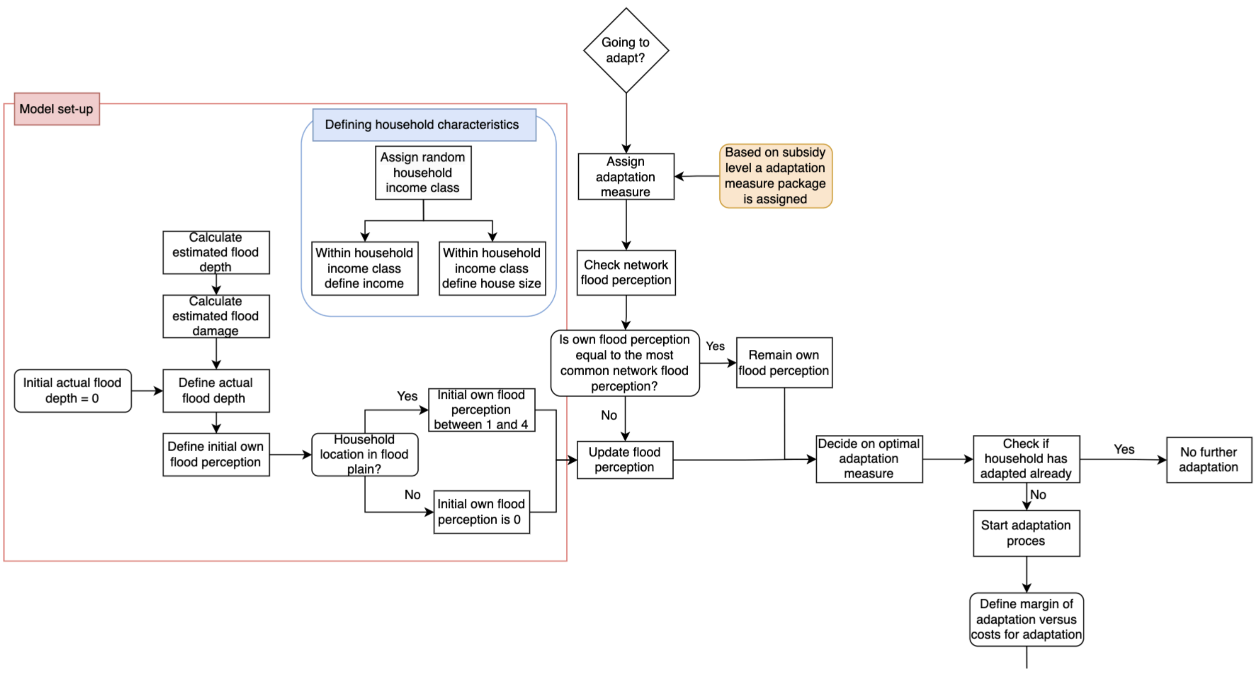

Figure 3. Conceptual model (part 1).

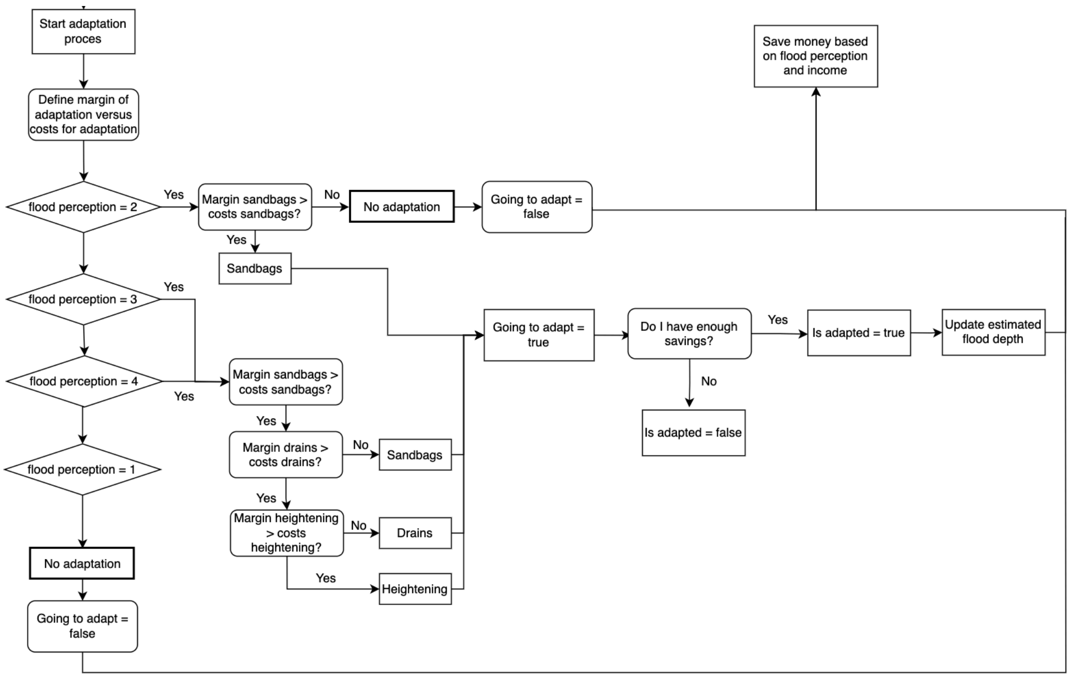

Figure 4. Conceptual model (part 2).

2.6. Key performance indicators (KPI)

The research question focuses on understanding the impact of different subsidy packages on the total damage experienced within Harris County, as well as comparing this to the different income classes in trying to investigate if lower incomes are affected relatively more severely than higher incomes.

- Average actual flood damage per household (relative to income)
- Relative differences between average actual flood damage/income for each income class.
- Total subsidy costs.

Total subsidy costs are considered to be relevant if two policy types show the same effectiveness with regard to the other KPIs. Then, the trade-off for a preferred policy can be made based on the costs an alternative would include.

2.7. Assumptions and model reductions

Specific assumptions and model reductions have been made to simplify the model, and to be able to formalize the model. These simplifications were made due to limited time and modeling skills.

3.2.1. Households

Household savings

- A household saves money in each tick in order to afford possible adaptation measures. The money saved is considered dependent on income and their flood perception at that moment. It is assumed that a higher flood perception, thus a

greater fearful sentiment towards flooding leads to a higher amount of saved money per tick.
- A household starts saving when it has chosen a most optimal adaptation measure.

Decision for adaptation measure
- It is assumed that household agents do not have the ability to make choices based on saving for the most optimal adaptation *in the long term*. They always pick the first possible adaptation measure based on their current state (flood perception, depth and savings at that moment).
- It is assumed agents make only **one decision for a specific adaptation measure**. Once an adaptation is chosen, no other adaptation measure is taken during the proceeding of the model time period. However, in reality it can be possible that a household opts for a combination of adaptation measures.
- **No delay is assumed in the implementation of an adaptation measure**. This means that the estimated flood depth is changed immediately and therefore, it does not take time to implement the chosen measure.

Available adaptation measures
- The model assumes three possible adaptation measures: **sandbags, drains and heightening of the house.** It is assumed that the three options increase in their effectiveness. That is, the estimated flood depth is further reduced depending on the measure. However, it is assumed that an implemented adaptation measure imposes the **same effectiveness for every household**, which, however in reality, can be questioned.
- The costs for the adaptation are assumed to be dependent on the house size of that household.

3.2.3. Social network interactions assumptions (RBB)

Network interactions
- It has been neglected that people are in contact with other households living nearby or through other means of social interaction. **The relationships to exchange discrete opinions only happens through the non-spatial network already created.**
- Moreover, it is assumed that the connections between nodes do not change within the model timeline, therefore the **network does not change throughout a run**. However, in reality it could be possible that connections do not last, or people create new connections.
- A radius of one has been applied to determine the network perception. Households can only copy one of the opinions of their direct neighbors.

3.3. Parameter set-up

Household income
- The income of household agents is classified into three types of income classes. These classes are defined as (1) poor, (2) middle-class and (3) rich. The income classes are assigned to the agents which is based on the distribution for household

incomes as mentioned by Houston State of Health (2023). More information about the income distribution can be found in Appendix A.
- Within the three income classes an income range with a maximum income and a minimum income is defined. Within these ranges an agent gets a randomly defined income, that is within its income class.The income range per income class can be found in Appendix A.

House size
- According to the American Home Shield, the average house size in Texas in 2022 was 2170 square feet, which is 201,6 squared meters (AHS, 2022). This is what we have used as the average household size for the middle classes. For the poor and the rich we have made our own assumption. For the household sizes we have created a similar construction as with the income for every household. This means that every household gets a random house size which is defined within the range of its income class. The range of the house sizes for households in the poor, middle class or rich income classes can be found in Appendix A.

Household savings
- It is assumed that households save 10% of their income per tick. However, this 10% is multiplied with a factor dependent on their flood perception.

Flood perception
- It is assumed that household agents have an **initial flood perception**, partially based on their estimated flood depth and location in the floodplain. Therefore, it is not assumed that there is a relationship between households facing higher risks of flooding and having a higher fearful sentiment towards flooding, leading to higher initial incentives to possibly adapt.
- There are four categories within the model initialization. In this model, the perceptions can rather be considered of an ordinal scale, implying that the higher the network perception, the more ‘fearful’ or ‘risk-averse’ the perception is towards flooding.
- Even though earlier flooding experience does have a significant role in taking adaptation measures (Poussin et al., 2014), it has not been included in the model.

3. Formalization

In this section, the implementation of the conceptual model is discussed. The model is developed in Python, with use of the Mesa library.

3.1. Variables

3.1.1. Model variables

Variable	***Description***	***Unit***	***Variable name in Python***
Number of households	Indicates the number of households included within Harris County	#household	number_of_households
Number of steps	Decides the maximum time span of the model, the flood occurs randomly between 0 and this variable	#steps	number_of_steps
Subsidies package	Indicates which subsidies package is active in the model	[0,1,2,3]	subsidies_package
Income distribution	Gives the distribution of income amongst the three income classes for households to determine their income by	{‘Poor’: [mean, std_dv, ‘Middle-Class’: [mean, std_dv], ‘Rich’:[mean, std_dv]’}	income_distribution
Average household surfaces	Indicates the distribution by which household agents determine their housesize based on their income label	{‘Poor’: [mean, std_dv, ‘Middle-Class’: [mean, std_dv], ‘Rich’:[mean, std_dv]’}	average_household_surfaces
Probability of network connection	Likeliness of edge being created between two nodes	float	probability_of_network_connection
Number of edges	Number of edges for BA network	#edges	number_of_edges
Number of nearest neighbors	Number of nearest neighbors for WS social network	#neighbors	number_of_nearest_neighbors
Network type	Structure of the social network used.	[Watts-strogatz, Erdos Renyi, Barabasi Albert, no-network]	network
Flooding scenario	Includes the flooding scenario	[Harvey, 100yr,	flood_map_choice

	for different types of storms as explained in Chapter 2	500yr]	

Table 1. Model variables.

3.1.2. Agent variables

Household agents

Variable	*Description*	*Desired value*	*Unit*	*Variable name in Python*
Household income class	Indicates which income class the household falls into.	A higher income label is a determinant for a higher household income.	[Poor/Middle-Class/Rich]	income_label
Household income	The income of the household per tick (quarter of a year).	Higher incomes are able to more easily afford adaptation measures.	€	income
Household size	The size of the household property.	Higher value will also result in a higher (estimated flood) damage.	m2	housesize
Household savings	Represents the amount of money a household has saved in order to buy potential adaptation measures.	High, so that household agents are able to buy adaptation measures.	€	savings
Flood perception	Represents the individual nominal opinion category towards flooding and can be altered based on a differing network perception.	A higher flood perception refers to a greater sentiment of 'danger' towards flooding and a higher incentive to adapt.	[1,...,4]	own_flood_perception
Network perception	Indicates the majority category within the flood perception of an agent's network connections and can potentially alter the flood perception.	A high network perception means the same as a high flood perception. Higher network perception, if copied, will lead to a greater incentive to adapt.	[1,...4]	network_flood_perception
Estimated flood depth	The estimated flood depth and therefore vulnerability towards flooding.	A lower estimated flood depth will lead to less vulnerability and estimated damage.	meters	

Adaptation depth	The reduced flood depth that follows from the chosen adaptation measure of a household.	A higher adaptation depth refers to a higher effectivity of the 'optimal adaptation measure' chosen.	meters	adaptation_depth
Incentive to adaptation	If there is an incentive to adapt, based on flood perception and estimated flood damage.	True	True/False	going_to_adapt
Optimal individual adaptation measure	Refers to the most optimal adaptation measure a household could choose, based on its flood perception, flood depth and savings.	Heightening with regard to reducing the estimated flood depth - sandbags with regard to costs.	[Sandbags, Drains, Heightening, None]	optimal_measure
Cost of adaptation	Costs of the chosen adaptation measure.	*Agent dependent.*	€	cost_of_adaptation
Adapted?	Indicates whether an agent has adapted or not.	Yes.	True/False	is_adapted
Flood damage	Shows the damage experienced by a specific household in case a flooding occurs. Can also be estimated or actual.	Low value, meaning less costs follow from the flooding.	€	household_damage

Table 2. Household agent variables.

4. Verification and validation

In this section, the model will be verified and validated, to determine if the 'right model has been built in the right way'. The validation has been conducted according to the parametrizations in Table 3.

Initial flood perception distribution [1,2,3,4]	Income labels distribution [Poor, Middle, Rich]	Subsidies	Households	Flood map
[0.15, 0.25, 0.30, 0.30]	[25.68%, 63.76%, 10.55%]	None	1000	100yr

Table 3. Parametrizations for verification.

4.1. Verification

In order to verify the model, this subsection will try to determine whether the model has been built according to the conceptualisation. Throughout the formalization and model construction, small tests have been conducted, such as following a specific agent throughout the model ticks to see if the agent produces expected behavior.

This verification section includes single-agent testing (which we have combined with step 1 of van Dam et al. (2013), where agent variables are logged for internal processes) and interaction testing between agents for a minimal model, according to verification steps for ABM-models as described by van Dam et al. (2013).

According to van Dam et al. (2013) this single-agent testing consists of two tests. First of all, a single agent will be followed, input and output of that agent will be checked based on theoretical predictions and sanity checks. An extreme value test with a simple set-up has also been performed, to see if the model breaks.

Single agent-testing

First, a single agent will be tracked. For a household agent with ID 2, we show the results of its attributes for 10 steps. The results are shown below in Figure 5. This agent lives in an area that has an estimated flood depth of 0, also resulting in an estimated flood damage of 0. The flood has not taken place during one of the ticks.

Because the household the estimated flood damage is 0, according to the conceptualisation, the agent will have no incentive to consider adaptation measures. This is also in line with Figure 5.

Step	AgentID	FloodDepthEstimated	FloodDamageEstimated	HouseSize		FloodDepthAct	FloodDamageActu	OptimalMeasure		GoingToAdapt	IsAdapted
0	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
1	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
2	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
3	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
4	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
5	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
6	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
7	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
8	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
9	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False
10	2	0.0	0.0	310	…	0.0	0.0	None	…	False	False

Figure 5. Screenshot of an agent's attributes for 10 model steps.

Because the agent does not have any incentive to adapt, it will also not save any money in order to afford the adaptation measure it would desire. Figure 6 below confirms that this is in line with the conceptualisation of the model.

CostOfAdaptation	IncomeLabel	Income	Savings	OwnFloodPerception	NetworkPerception
0	Rich	79592	0.0	2	0
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3
0	Rich	79592	0.0	3	3

Figure 6. Screenshot of an agent's attributes (ID 2) for 10 model steps - 2nd part.

To verify this for another agent with different initialized attributes, the combined Figure 7 shows the tracking of Agent ID 8. Within the verification & validation tab in the model file, a few more agents with different characteristics have been checked in order to see if the outcomes of each step correspond to the conceptualisation and functions work properly.

Step	AgentID	FloodDepthEstimated	FloodDamageEstimated	HouseSize		FloodDepthActual	FloodDamage	Optima	AdaptationMeasures
0	8	0.156406	60321.520358	236	…	0.0	0.0	None	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
1	8	0.156406	60321.520358	236	…	0.0	0.0	Drains	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
2	8	0.156406	60321.520358	236	…	0.0	0.0	Drains	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
3	8	0.156406	60321.520358	236	…	0.0	0.0	Drains	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
4	8	0.156406	60321.520358	236	…	0.0	0.0	Drains	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
5	8	0.000000	0.000000	236	…	0.0	0.0	Drains_4	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
6	8	0.000000	0.000000	236	…	0.0	0.0	Drains_4	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
7	8	0.000000	0.000000	236	…	0.0	0.0	Drains_4	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
8	8	0.000000	0.000000	236	…	0.0	0.0	Drains_4	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
9	8	0.000000	0.000000	236	…	0.0	0.0	Drains_4	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30
10	8	0.000000	0.000000	236	…	0.0	0.0	Drains_4	{'Sandbags': [0.2, 5], 'Drains': [0.7, 30

GoingToAdapt	IsAdapted	CostOfAdaptation	IncomeLabel	Income	Savings	OwnFloodPerception	NetworkPerception
False	False	0	Middle-Class	22379	0.000	3	0
True	False	0	Middle-Class	22379	1678.425	3	3
True	False	0	Middle-Class	22379	3356.850	3	3
True	False	0	Middle-Class	22379	5035.275	3	3
True	False	0	Middle-Class	22379	6713.700	3	3
False	True	7080	Middle-Class	22379	1312.125	3	3
False	True	7080	Middle-Class	22379	1312.125	3	3
False	True	7080	Middle-Class	22379	1312.125	3	3
False	True	7080	Middle-Class	22379	1312.125	3	3
False	True	7080	Middle-Class	22379	1312.125	3	3

Figure 7. Screenshots for another agent's attributes (ID 8) for 10 model steps.

This agent has a Middle-Class income label and due to its initial relatively high flood perception (3), as well as an estimated flood depth that would lead to damages, it decides that it has an incentive to adapt towards drains (its most optimal adaptation measure) as seen in the first table. At tick 6, it has saved enough money (1678.425 per tick as its perception does not change), leading to left over savings of 6713.700 + 1678.425 - 7030 = 1312.125).

The cost of adaptation have also been computed correctly, as the house size of the household is 236 square meters, and this has to be multiplied by the costs of drains per square meter (236*30 = 7030).

The decision to adapt leads to a reduction in estimated flood depth to 0. This can be explained due to the fact that the effectiveness of drains (0.7 meters) is quite high.

Therefore, the estimated flood depth becomes 0, as 0.7 meters is deducted from 0.156486 (estimated flood depth before adaptation) and negative values are not possible.

Figures 5, 6 and 7 point out that for single-agent testing the model can be verified according to the conceptualisation and assumptions made.

Interaction testing

For the interaction testing, we examine the interaction between two household agents in the social network. Within the established model, there is limited interaction between agents. Agents only check each other's states when determining their own network perception. Figure 8 below, shows this process, again for Agent ID 2. During the initialization, the friends of the household have not yet been determined yet and it has an initial flood perception og 2. After, we see that Agent ID 2 has 4 friends, of which three have perception 3. Since this is the majority, it decides to adapt its own flood perception towards 3 as well.

IncomeLabel	Income	Savings	OwnFloodPerception	NetworkPerception	Friends
Rich	79592	0.0	2	0	{}
Rich	79592	0.0	3	3	{0: 2, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}
Rich	79592	0.0	3	3	{0: 3, 4: 3, 18: 3, 10: 3}

Figure 8. Screenshot that shows change in flood perceptions (ID 2).

A third verification test is known as multi-agent testing (van Dam et al., 2013). Due to conceptual decisions and a single agent within the model, the model has limited interactions. Therefore, multi-agent testing is not as useful to conduct for this model and thus has not been performed.

Extreme Values

The model is run once with the income distribution set to almost zero for all the income labels. Running it with 0 would make the model initialization run endless because of while statement that was built to give every household at least some income and to make negative incomes impossible. The model runs and shows that the income of the agents is too low to acquire enough savings over time to adapt. This is shown by counting the values in the column ‘IsAdapted’, where no True value appears.

4.2. Sensitivity analysis

This subsection reports the sensitivity analysis to check the sensitivity of the output from our model on the input and assumptions made. Some input parameters are constructed under heavy assumptions or preferences. The first input parameter is the income distribution that determines the mean income of every income class. Households take this mean and standard deviation and determine their income per step from it. Although the initial distribution is based on some facts and numbers, there were some generalizations regarding Harris County, Texas and the US. Therefore, income distribution is tested for sensitivity on output parameters. Another input parameter that is presumed to be of heavy influence on the decision making is the network-type. This determines the social-network graph that Households form and retrieve their friends from. Their own flood perception can change depending on the flood perception most common in this network. Their own flood perception determines if they decide to adapt for flooding or not. Therefore, the network-type is presumed to be of influence on the decision-making process of Households.

Both of the input parameters introduce randomness as a one-time initialization factor which then stays constant throughout simulations. Other methods, like Monte Carlo simulations, are used for randomness factors that differ throughout the steps of the model or did not suit the characteristics of these input parameters in another way. Therefore, The method used for conducting this sensitivity analysis is “One-at-a-Time” (OAT) sensitivity analysis.

4.2.1. Sensitivity on income distribution

For this sensitivity test, the income distribution has been varied with both +/- 10% and +/- 30% for each income class. Within this section, only the results for the poor income class are discussed. Results of middle-class and rich income class are not discussed within this section but shown in Appendix B, as the poor income class showed to be most sensitive to the different parameters settings. Especially for rich households, the model proves that this class is capable enough of reducing their estimated damages by themselves, without policies needed to be implemented.

Figure 9 shows the graph that depicts the average damage experienced compared to income over time.

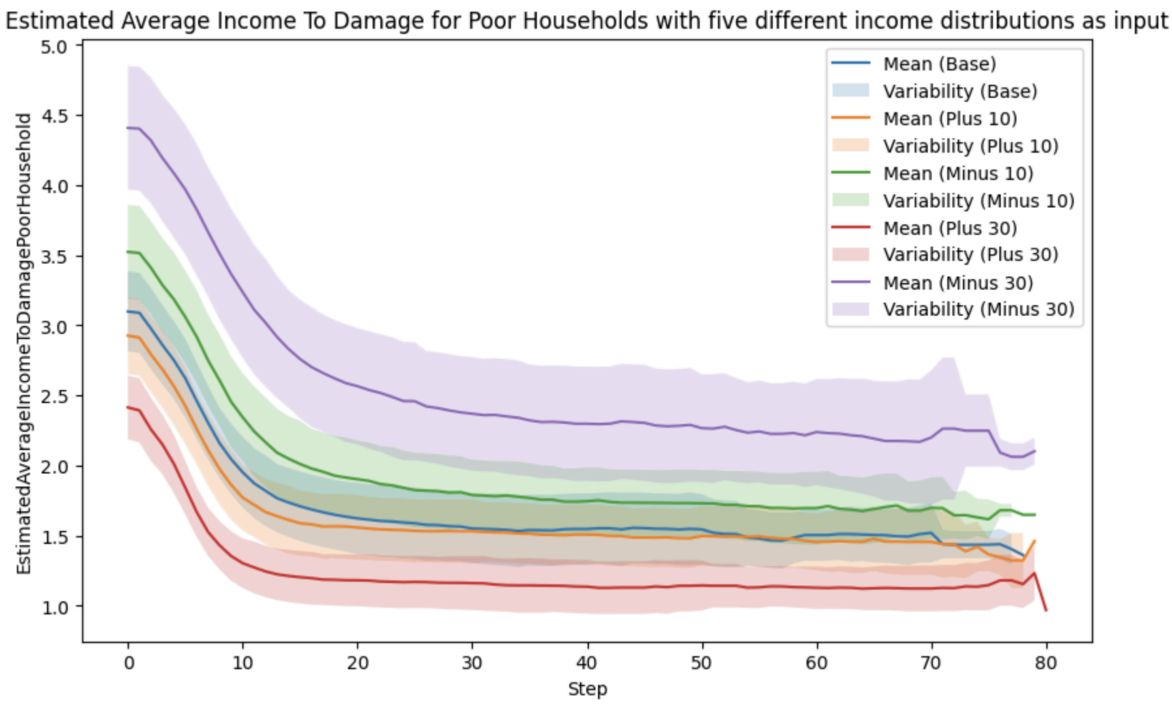

Figure 9. Estimated average damage to income for poor households with five different income distributions as input.

When looking at Figure 9, the average income to damage ratio however, is proven to be sensitive. This is because a higher income not only leads to more financial possibilities for adaptation measures, but since this KPI includes a division by the income, a +30% variety on initialized average income for poor people will result in a reduction of this ratio.

Additionally, from Figure 9 it can be derived that a decrease (-30%) affects the damage to income ratio more severely than the same increase (+30%). It can be concluded that smaller income differences logically contribute to higher levels of experienced damage equality. Lower incomes compared to the base case for poor households relatively further increase inequality.

4.2.2. Sensitivity on network-type

In the model parameters, there are four choices for network-type: "watts_strogatz", "erdos_renyi", "barabasi_albert", "no_network". Each of these network types construct the network-graph of household agents differently.

As in the previous subsection, only the Poor Households produced interesting results. As seen from the graphs in Appendix B, the network shows to have effect on both the damage-to-income-ratio and the average damage of poor households. No-network shows to produce the highest on both those output parameters. This shows that having friends that influence the households' perception on floods could result in less damage under the assumptions in the model. The other network-types show different values for both output parameters, indicating that the assumption of how the network is formed could be influential.

The main influence of the network-type is on the total adapted households in the model. This is shown in Figure 10 below

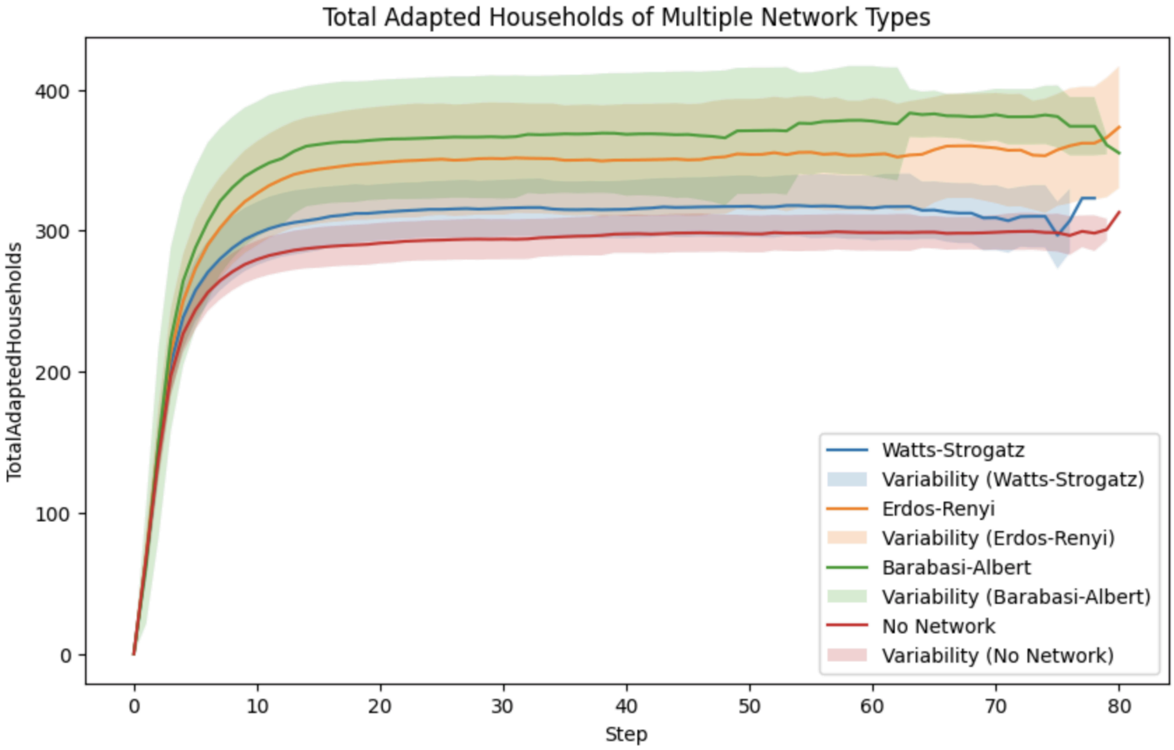

Figure 10. Total adapted households for multiple network types over time.

In this graph, the number of total adapted households is on the y-axis. First, the “Barabasi-Albert” network-type on average results in the most adapted households. However, the green variability edges of the line show great randomness for maximum and minimum values. This is much less at “no-network” which shows the lowest mean of total adapted households more consistently. Looking at the line at 10 steps in the model, the “Barabasi-Albert” network-type produces on average 50 to 60 more adapted households than “no-network” network-type. Therefore, this graph shows that the assumption on how the network is formed can influence the model outcome. A One-Way ANOVA test is conducted to test for significance between the different outcomes. The p-value from this test is 2.870e-18, which proves the alternative hypothesis that there are significant differences between at least two network-type means. As for the Total Adapted Households in the model, the network-type matters.

A metric that is highly influenced by the total adapted households in the model is the total actual damage when the flood happens. The calculation of the actual damage is dependent on more decision making processes, factors and a more complex calculation. Therefore, it is interesting to see what the effect is of choosing a different network-type on this metric. For this, another One-way ANOVA test is conducted. The p-value for this test is 9.738e-11, which again proves the alternative hypothesis that there are significant differences between at least two network-type means. Therefore, the choice for a network-type is crucial for the outcome of the model, even for a more complex variable.

4.3. Validation

In order to see if the behavior as observed from the model compares to real-life, validation is performed. In this case, the Harvey flood map has been used. For the validation of the model, only the total amount of damage experienced within the base case has been evaluated by comparing this to real world data. By doing so, an attempt has been made to empirically validate the model.

However, it should be noted that the validation will always show outcomes that are not directly comparable to a real-life situation, especially within this model due to severe simplification of processes and interactions in our model, as well as chosen parameters. Moreover, it is hard to obtain real world data for all output variables. Since the base case includes 1000 households, this is for example not comparable to the 1,726 million households in Harris County (Houston State of Health, 2023).

After hurricane Harvey, the estimated damage to homes could be upwards 15 billion dollars (Helman, 2017). After 100 model runs, the base case model reports an average total actual damage of 16,5 million euros. Compared to the number of households applied, these numbers fall within the same order of magnitude and are therefore considered a plausible outcome.

Due to extreme model simplification, it could even be argued empirical validation is not possible in the slightest. Another form of validity consists of face validity. It is a subjective measure to indicate whether the model and its outcomes seem relevant and reasonable.

Model runs of the base case with multiple replications show that poor incomes need a longer period of time to adapt. This would, based on face validity, correspond with micro behavior of households as observed in real-life.

However, when validating the model on a macro level, based on Flache et al. (2017) the model strongly depends on the network of friends, which becomes stable over a period of time. This results in regions that share opinions, which determine the level of adaptation. Even though Poussin et al. (2014) concluded that social influence strongly determines the incentive to adapt or not, this would lead to stagnating model results (dynamics become less or none when the network of friends becomes stable). It can be questioned if behavior completely stagnates in real-life.

Concluding, validating our model proves challenging due to its simplified processes, limited real-world data, and disparities in scale. The extreme simplification raises doubts about achieving empirical validation. Despite the subjective insights from face validity, the complexities of real-world dynamics add difficulty to the validation process.

5. Model results from policy alternatives

This section includes the results from the base case as well as the results of the experiments with different policy alternatives. For each experiment, 100 runs were conducted. The experiments aim to answer the main research question:

What is the effect of various government subsidy policies on household flood adaptation measures, under different flooding conditions, on the damage experienced compared to income and inequality between various household income classes in Harris County?

5.1. Results for base case

This section discusses the results of the base case (Table 4), where no subsidies are provided by the (local) government of (Harris County) Texas.

Initial flood perception distribution [1,2,3,4]	Income labels distribution [Poor, Middle, Rich]	Subsidies	Households	Flood map
[0.15, 0.25, 0.30, 0.30]	[25.68%, 63.76%, 10.55%]	None	1000	‘100 years’

Table 4. Base case parameter initialization.

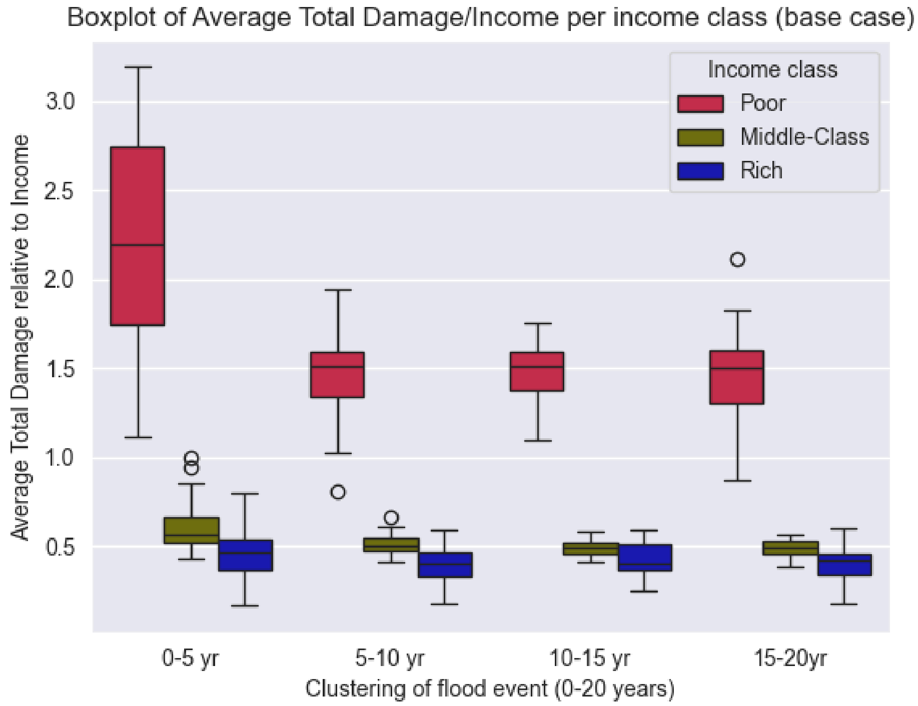

Figure 11. Base case: box plot average total damage/income per income class.

The x-axis of Figure 11 shows the influence of the timing of a flood event. Meaning that the 0-5 cluster indicates the relative damage experienced considering a flood occurring in the next 5 years, or between 5 to 10 years for the next cluster. This way, the results can be analyzed by taking into account the time households still have to implement adaptation measures.

To investigate the influence of the random occurrence of a flood between 0 and 20 years, a box plot has been created to enable comparison. From these results depicted in Figure 11, it can be derived that poor income classes have a significantly higher total damage relative to their income compared to the other two income classes. Poor households also need a longer period of time in order to implement flood adaptation measures to reduce their total damage.

The results of the base case (all model limitations aside) show that from a perspective that strives towards equality in damage experienced, policy alternatives that focus on poor households can be considered necessary.

5.2. Policy alternatives

Table X below shows the experiments that have been conducted to analyze the proposed policy alternatives of section 2.3. These subsidy policies presented in section 2.3 were:

1. Standardized subsidy amount for all households and all types of adaptation measures provided.

2. Varying subsidy amounts depending on the income class of households, where lower incomes receive relatively larger amounts of subsidies on adaptation measures.
3. Varying subsidy amounts based on the location with regard to flood risk. Households facing higher flood risks receive higher subsidies.

Table 5 shows a summary of all experiments conducted.

Experiment name	**0 (Base Case)**	**Package 1**	**Package 2**	**Package 3**
Policy type	No subsidy	Equal subsidy	Subsidy based on income label	Subsidy based on location
Input parameters	Base case	Base case	Base case	Base Case

Table 5. Overview of conducted experiments.

The results have been analyzed first within each of the income classes, to determine which policies suit which income label most properly. Thereafter, the relative differences for each income label per policy is shown, to see which subsidy policy makes the experienced damage over all income labels more 'equal', i.e. which subsidy policy levels for each income label the factor of average damage compared to income.

Again, The x-axis of the figures show the influence of the timing of a flood event. Meaning that the 0-5 cluster indicates the relative damage experienced considering a flood occurring in the next 5 years, or between 5 to 10 years for the next cluster. This way, the results can be analyzed by taking into account the time households still have to implement adaptation measures.

5.2.1. Policy effects per income class

The results for the first comparative analysis are depicted in Figures 12, 13 and 14 and elaboration is provided.

For all figures, the effect of when the flooding occurs has been addressed, by clustering the results based on if the flood occurs in the next 5, 10, 15 or 20 years. The longer the wait for flooding to occur, the more time households have to potentially adapt.

Income class: Poor

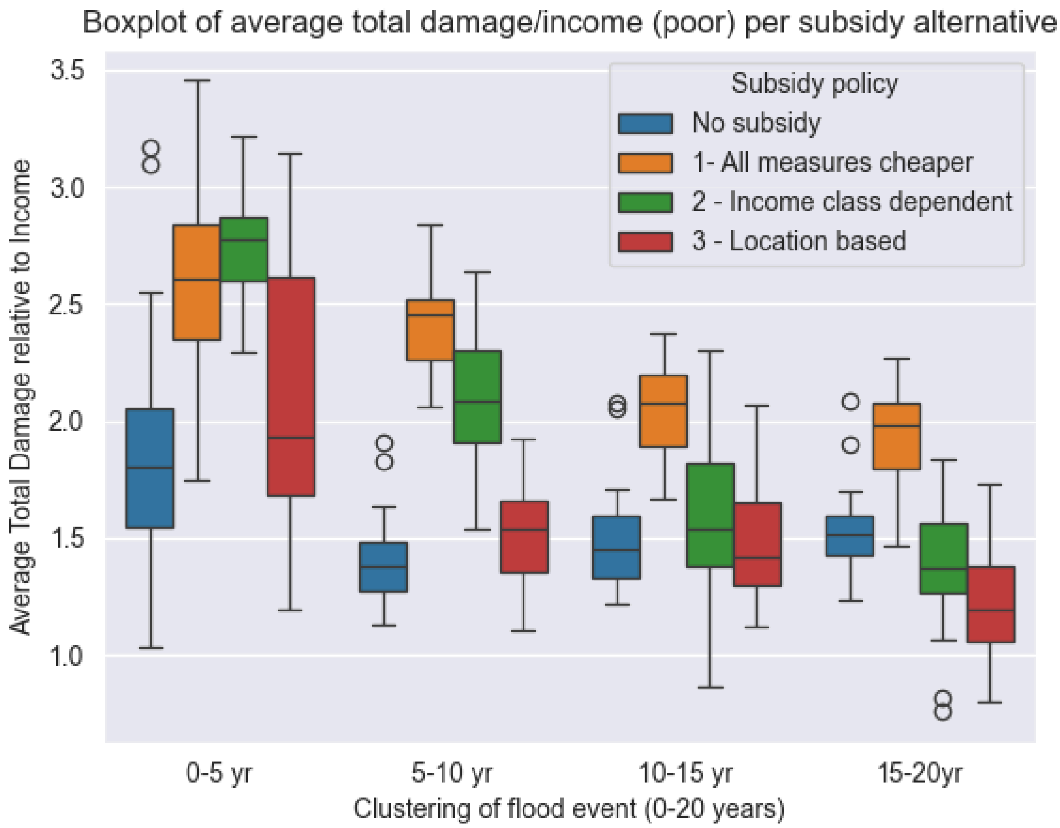

Figure 12. Poor: box plot including average experienced damage to income ratio depending on flood occurrence.

Figure 12 shows logically that the moment a flood occurs within the 20 year timespan, has an important influence on the damage experienced, as it strongly reduces the average factor of experienced actual damage compared to income. For every boxplot color (thus every policy type) we can observe that the interquartiles have a decreasing gradient.

Furthermore, the differences between poor households in their experienced damage become smaller, as the interquartiles of the box plots become smaller, as well as the minimum and maximum values.

According to the hypothesis, it would be expected that all subsidy types would result in less experienced damage compared to income. However, it shows that especially for the first 5-10 years this is not the case. This can be explained since households choose their most suitable adaptation measure based on a margin of the expected damage versus the cost of that adaptation measure. When enabling any type of subsidy policy, poor households can have a most suitable adaptation measure that requires a bit more time to save money for. However, if a flooding occurs before enough money has been saved to implement the policy, the actual damage experienced is higher than when no subsidy policy is implemented. That is why, especially for the first 10 years a no subsidy policy still performs very well.

In the long term however, we see the quartiles of the boxplots becoming smaller, indicating less variety in relative damage experienced between poor households. Moreover, a location based policy performs well and provides a damage to income ratio that can even reach a value below 1. A very desirable outcome that can indicate high resilience for poor households, as the damage experienced is lower than the income earned per quarter of a year.

Income class: Middle-Class

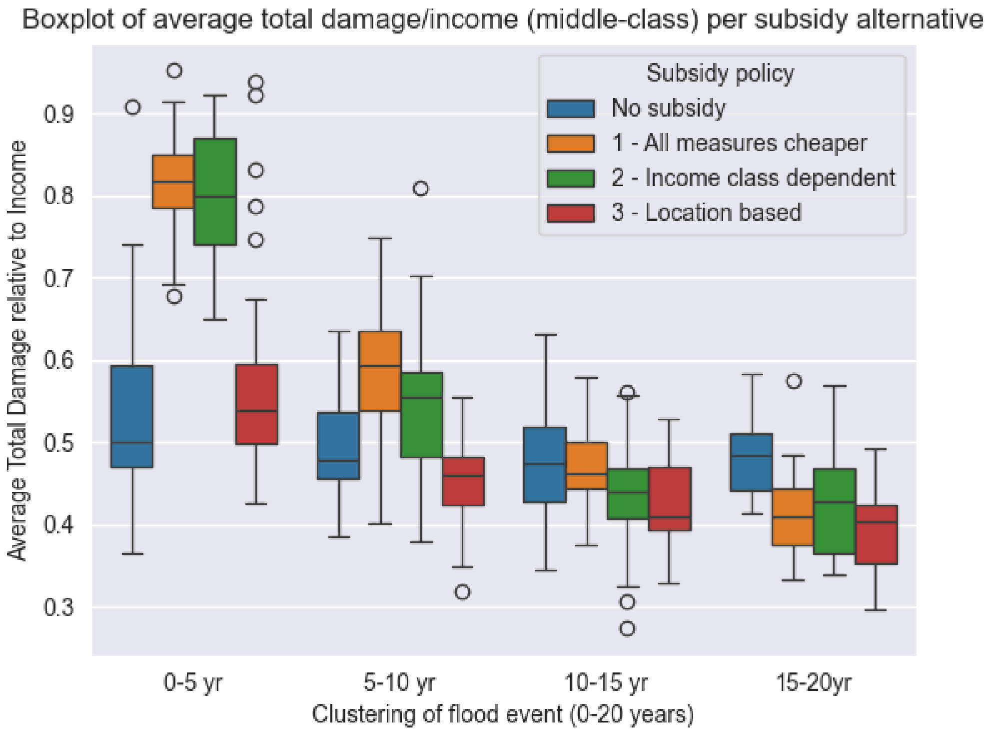

Figure 13. Middle-Class: box plot including average experienced damage to income ratio depending on flood occurrence.

Following the elaboration on the outcomes for poor labeled households, middle-class incomes seem to benefit quickly from location based policies in Figure 13. In the long-run however, especially in the last 10 years, the reduction of the average damage compared to the damage experienced if the flooding happened in the 5 years before, is little.

When there is uncertainty about when a flooding is to occur, either no subsidy or a location based policy can be preferred for this income class.

Income class: Rich

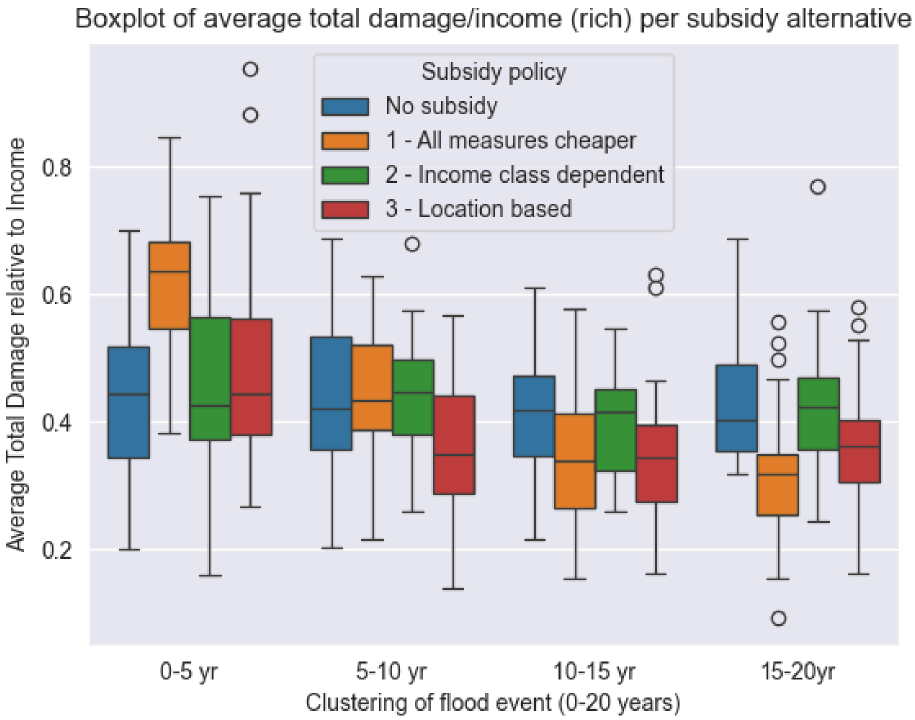

Figure 14. Rich: box plot including average experienced damage to income ratio depending on flood occurrence.

For the rich income class, a decreasing gradient in the experienced damage compared to income does not appear over the timing of a flood occurrence. This shows that policies mostly target the poor incomes in the way over a longer period of time (meaning it takes a long time for the next flooding to occur).

5.2.2. Comparison between income classes per policy type

As this research has an interest in finding out what the influence is on the inequality experienced by different income classes, it is relevant to investigate the effects of each policy type on this inequality. The results are shown in Figures 15, 16, and 17 respectively for the three subsidy packages. The results of no policy package represent the outcomes of the base case of section 5.1.

Within this research, a policy is considered to increase equality when the average total damage to income ratio becomes more even between the three income classes.

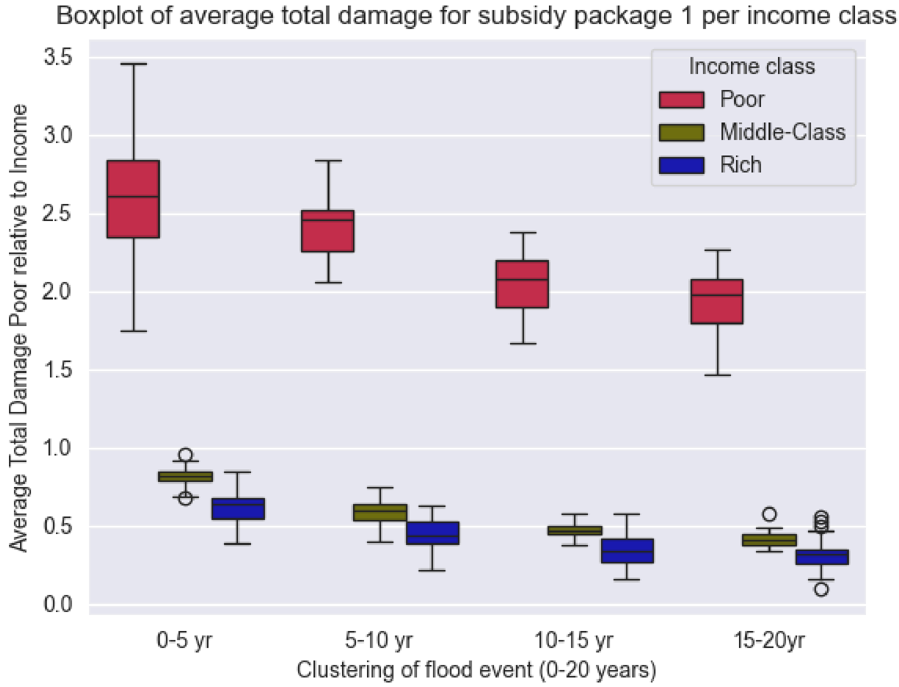

Figure 15. Effects of equal subsidy for each adaptation measure (package 1) on the average total damage/income ratio of the income classes.

Resulting from Figure 15, it can be stated that subsidy package 1 on average does not lead to smaller differences between income classes with regard to the damage/income ratio. Relatively, especially middle-class and rich households benefit from this policy alternative.

When examining these results from a viewpoint of fairness, it can be derived that this alternative does not suit the aims of the proposed policies.

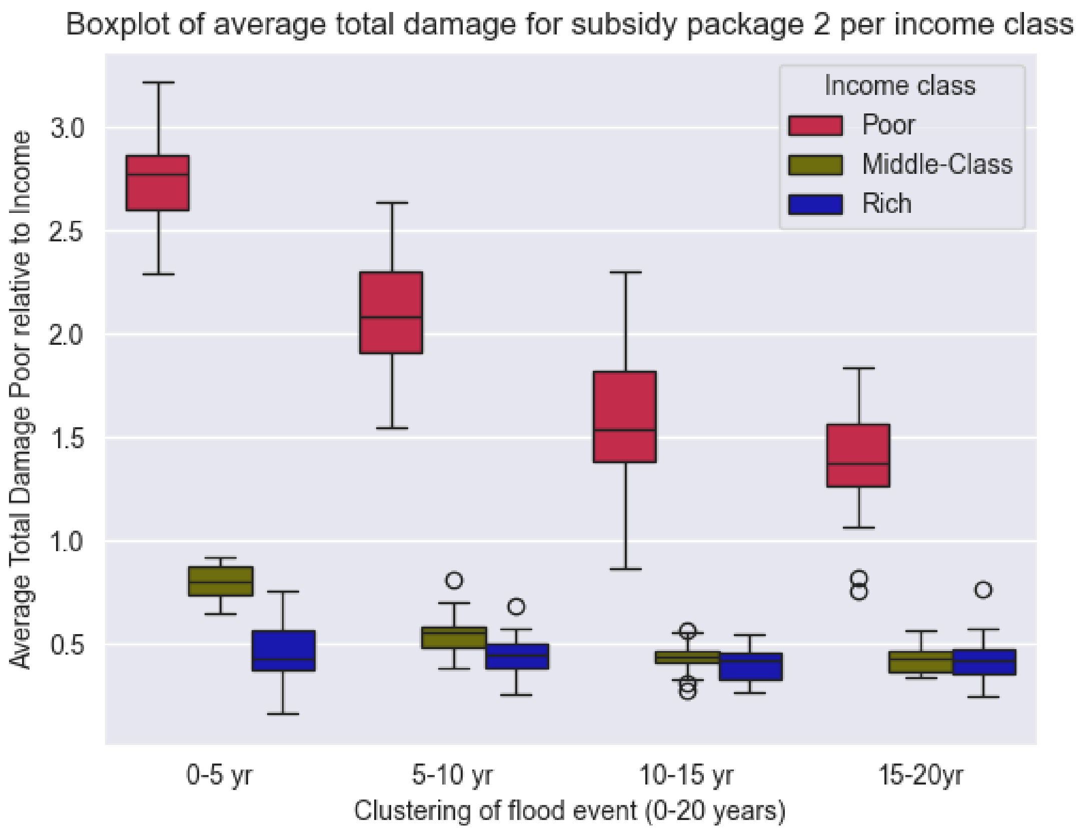

Figure 16. Effects of income-based varying subsidy for adaptation measures (package 2) on the average total damage/income ratio of the income classes.

Compared to package 1, subsidy package 2 shows an apparent increase in equality. The vertical distances between the box plots of the three income classes become smaller with an increased waiting time for the next flood. This indicates the policy enables a higher level of equality (when a flood is still distant in prospect). This difference compared to policy alternative 1 can be explained by the fact that within this subsidy alternative, lower income classes receive a higher amount of subsidy per adaptation measure, enabling them to adapt to more effective measures.

However, it can be observed again that to reach these desired effects, there should be sufficient time to make these adjustments before a flood occurs. Highlighting the importance of accurate flooding predictions and early prediction.

Additionally, but foremost important is that these results do not create significant benefits compared to the base case, where no subsidies are applied. The reason for this is that the most optimal measure for households based on their calculated margins of flood damage costs compared to costs of adaptation changes towards a more extensive adaptation measure, which takes a longer time to save for but does not reduce the total damage as much.

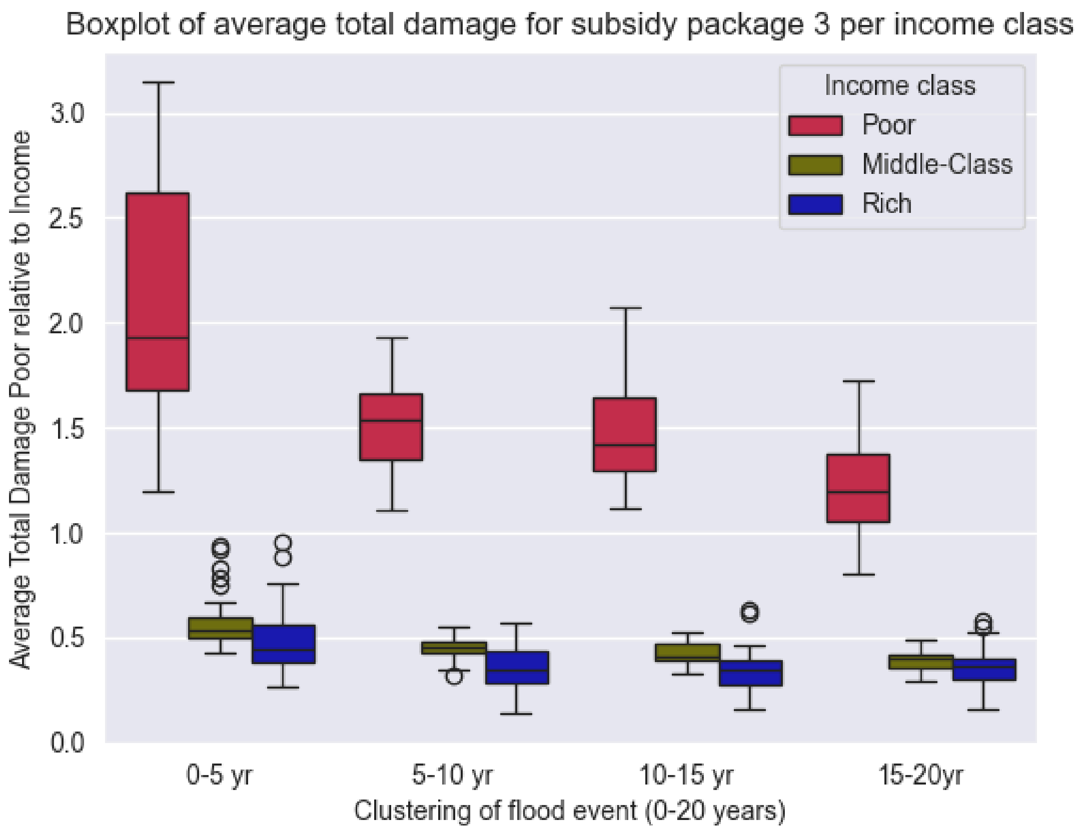

Figure 17. Effects of varying subsidy based on location (vulnerability) (package 3) on the average total damage/income ratio of the income classes.

Lastly, policy package 3 is examined. Compared to package 2, this policy alternative reaches not only a higher level of equality, but also *sooner*. Within 5-10 years the average damage for poor households is strongly reduced and moves towards the level of the middle-class and rich income classes. This means that the desired effects of lower damages and increased equality become apparent earlier, resulting in more robustness for potential early flooding.

The interquartiles of the average damage to income ratios are lower for each cluster of a flood occurrence. Overall, with this analysis it can be concluded that policy alternative 3, where subsidy measures are based on the location of households, referring to their estimated flood depth and thus vulnerability to flooding, provides the most beneficial outcomes with regard to lower experienced damages *compared to income*, as well as with regard to the defined level of equality.

Policy package 3 increases equality, but not as much as what would have been expected compared to not offering subsidies. This is in contradiction with the hypothesis, where it was assumed that every policy would be more effective than no policy, with the aspect of saving money based on a predetermined most suitable flood adaptation measure as a cause.

5. Conclusion and discussion

The main research question of this report was as follows:

What is the effect of various government subsidy policies on household flood adaptation measures, under different flooding conditions, on the damage experienced compared to income and inequality between various household income classes in Harris County?

This section aims to answer that question, as well as providing recommendations for subsidy policies in order to reduce flood damages experienced and increase equality in damage experienced by households.

6.1. Conclusion & recommendations

In conclusion the model proved to be sensitive towards network type and the average income levels assigned to income classes (especially for poor households). Additionally, the implementation of an assimilative model of social influence with nominal opinion categories, creates stable regions over time sharing similar opinions and therefore saturation in adaptation. These results, next to the limitations described in the subsequent section, should be taken into account when interpreting the results of the different subsidy policies.

When examining the results of the different subsidy alternatives, with regard to the research question, policy package 3, where subsidy is based on location and therefore vulnerability to flooding, shows the most promising effects on relative damage experienced as well as increased inequality compared to the other policy packages.

However, this research has demonstrated that these promising effects are only acquired when a flooding is still distant in time. This leads to a more interesting result that, given an uncertainty about the timing of a flood, governments should take into account when designing subsidy policies that it can take more time for households to implement the (more effective) adaptation measure. This is because of the fact that within this model, subsidies create new trade-offs to be made between expected damage costs of households, compared to the costs it takes them to implement the measure. But the increase in effectiveness does not have to match the level of this trade-off. Households have to save longer, but the average damage experienced does not decrease as much.

All in all, this leads to the conclusion that even though policy package 3 shows the most promising effects, these effects do not differ significantly compared to offering no subsidies, especially when a flood happens early (between 0 to 10 years). This is an interesting outcome of this research compared to the hypothesis, in which it was expected that every policy alternative would perform better than implementing no policy.
However, floods are extremely hard to predict, due to the chaoticness of the weather (Thielen et al., 2009).

Therefore, it can be concluded that 1) an increased effectiveness (i.e., reduction of vulnerability) of flood adaptation would be necessary (based on the estimated effectiveness of measures within this specific research) for the subsidy policies to work as desired. Therefore, based on this model and the chosen conceptualisation, not providing any subsidy policy is advised until this is reached.

Moreover, 2) this research shows that accurate and early predictions of possible floodings would prove to be beneficial for designing fitting policies, as often sufficient time is needed for policies to become effective. However, as mentioned earlier it is virtually impossible to achieve this.

6.2. Reflection and limitations

Within this section, limitations of the model are pointed out, which should be taken into account. Additionally, reflection on the modeling process is provided.

6.2.1. Model limitations

First of all, it should be noted that within this research, we were unable to fully validate the model that has been built. Therefore, the practical relevance should be considered with care. Moreover, due to simplification of agent behavior, some key considerations could have been left out that are of high relevance when determining the effects of different types of subsidy policies.

Foremost we want to point out that this research focuses heavily on modeling behavior of households with regard to flooding, as well as behavior within a social network. As many theories for behavior exist, for example with regard to social networks (Flache et al., 2017), simplifications or specific modeling decisions can therefore have large influences. The proper understanding of this behavior, as well as translating this accordingly within the conceptualization is key for creating a valid and useful model. Within the timeframe of this research project and limited modeling experience, this becomes difficult to achieve.

In line with this, the following most important limitations compared to a real-life setting should be taken into account:

- Dynamics between agents that are spatially close are not considered, only the ‘friends’ they have by means of the existing network structure. Moreover, they are only influenced by means of a nominal ‘perception’, not depending on other factors of influence, such as what kind of measures their connections have taken. Which in reality, would be presumable. As well as the fact that this network does not change over time.
- The model starts with no initial adapted households. However, in a current real-life setting, most households have already implemented some measures.
- Following from our social influence network, there are limited opinion categories as well as the possibility to shift. In real life, more nuances are expected and thus more opinion categories should be considered. This would lead to less quick convergence of stable regions sharing the same opinion.
- The model does not include previous experiences with flooding in the behavior of agents, which does play an important role in real life settings (Markanday & Galarraga, 2021).

- Insurances are a prominent way to deal with expected flood damages in a real-life setting (Jongman, 2018), but have not been incorporated within this model. This does not reflect a real-life setting as well as it also influences the agent's behavior when deciding on whether or not and which type of adaptation measure to choose - meaning this could lead to completely different model behavior when this element was incorporated.
- The influence of the presence of other governmental policy measures on the behavior of actors, like governments building structural measures such as dikes.
- The model includes three types of household adaptation measures, where in real life, households can opt for more measures. As well as governmental measures as mentioned in the previous bullet point.

6.2.2 Reflection on modeling process

As we had limited modeling experience, some modeling decisions led to a relative static model. This can be explained due to the strong influence of the network perceptions on the behavior in our model. The RBB implemented will always lead to reaching stable situations, where network perceptions are not altered anymore. Moreover, the bottom up approach of ABM's, where interactions between agents and their environment are simulated, is used to analyze patterns on a macro-level. Our model has not implemented sufficient interactions between agents and their environment, to become interesting enough to analyze. It could be stated that our model contains too little feedback-loops to unlock new, perhaps unexpected behaviors on a macro-level. This will definitely be taken into consideration for the development of an improved model version.

6.3. Further research

Further research could compare different conceptualizations of household behavior to determine the influence on change in measured effectiveness. Another suggestion for further research is further expanding the decision-making process of the households. It is now only based on their network/own flood perception and the marginal profit. However, in real life, there are more factors that lead to choice of a certain adaptation measure. For instance, this model has restricted itself to only flood. However, what happens when households experience a flood an take this state as an event into the decision making. This might influence their decision to take adaptation measures more heavily than perception and profit.

Another suggestion for further research is a more complicated process of flooding and the warning signals households receive. This model has scoped the flooding as a random event to which households receive no warning. However, in real life, predictions of rising water levels could give households more information on sufficient adaptation measures on the short term.

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8. Appendices

Appendix A: Income distribution Harris County

Household by income per year	Number of households	Percentage of households	
Under $15,000	156,44	9,06%	
$15,000 - $24,999	138,61	8,03%	
$25,000 - $34,999	148,18	8,59%	
$35,000 - $49,999	212,1	12,29%	
$50,000 - $74,999	296,92	17,20%	
$75,000 - $99,999	207,88	12,04%	
$100,000 - $124,999	152,95	8,86%	
$125,000 - $149,999	108,31	6,28%	
$150,000 - $199,999	122,33	7,09%	
$200,000 - $249,999	60,981	3,53%	
$250,000 - $499,999	77,042	4,46%	
$500,000+	44,268	2,56%	

Table 6. Income distribution in Harris County (Houston State of Health, 2023).

Household classes		**Poor**	**Middle class**	**High**
Income [€/ quarter year]	Lowest income	€3.125	€19.063	€68.750
	Highest income	€6.875	€39.687	€106.250
House size [m^2]	Smallest house size	70	151,6	300
	Largest house size	130	251,6	700

*Average income = minimal income + ((maximum income - minimum income)/2)

Table 7. Household classes and their estimated income (base case).

Appendix B: Sensitivity Analysis

Income distribution sensitivity

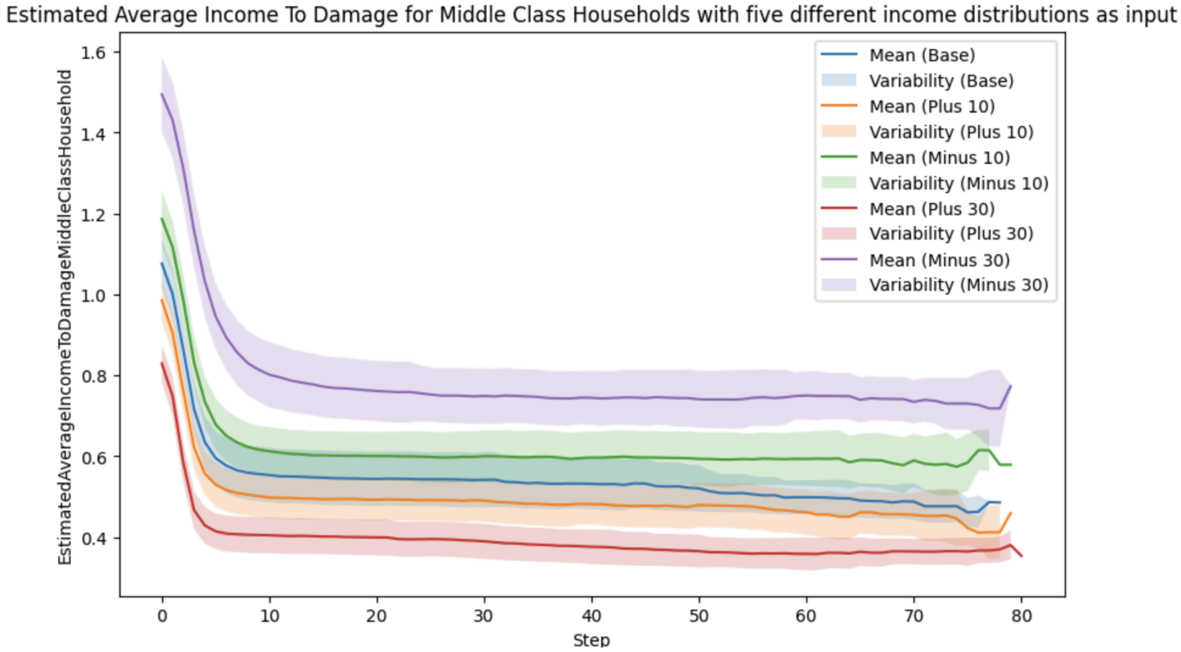

Figure 18. Estimated average damage to income for middle-class households with five different income distributions as input.

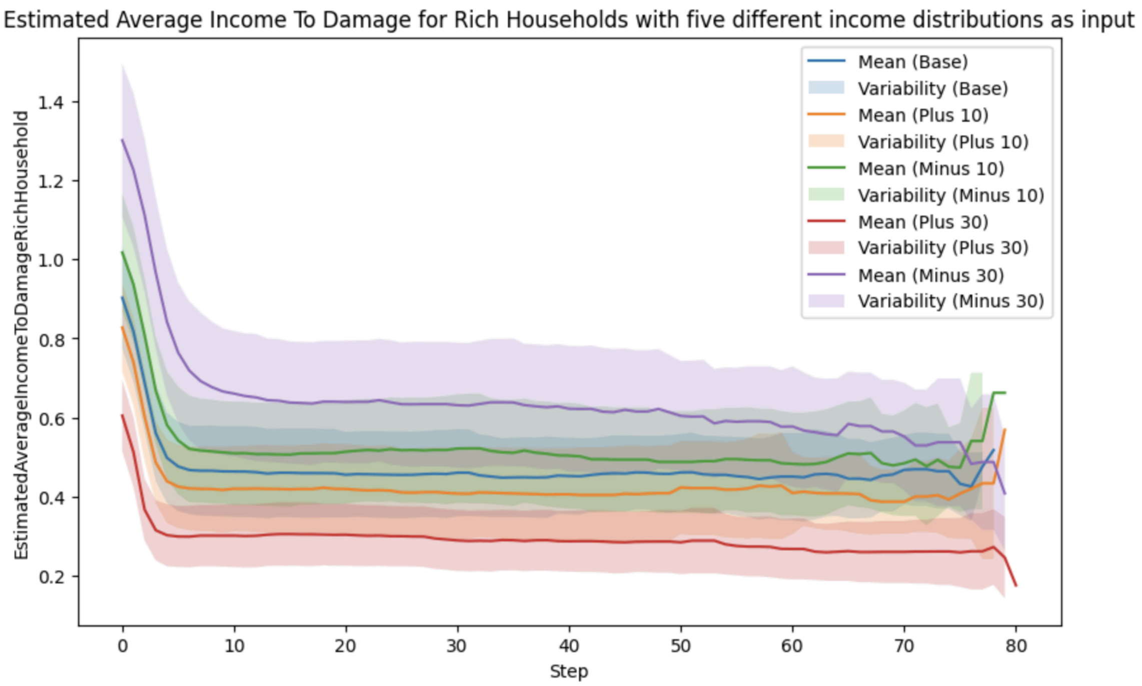

Figure 19. Estimated average damage to income for rich households with five different income distributions as input.

Network type sensitivity

Graphs in Section 4.2.2. Sensitivity Analysis for network-type

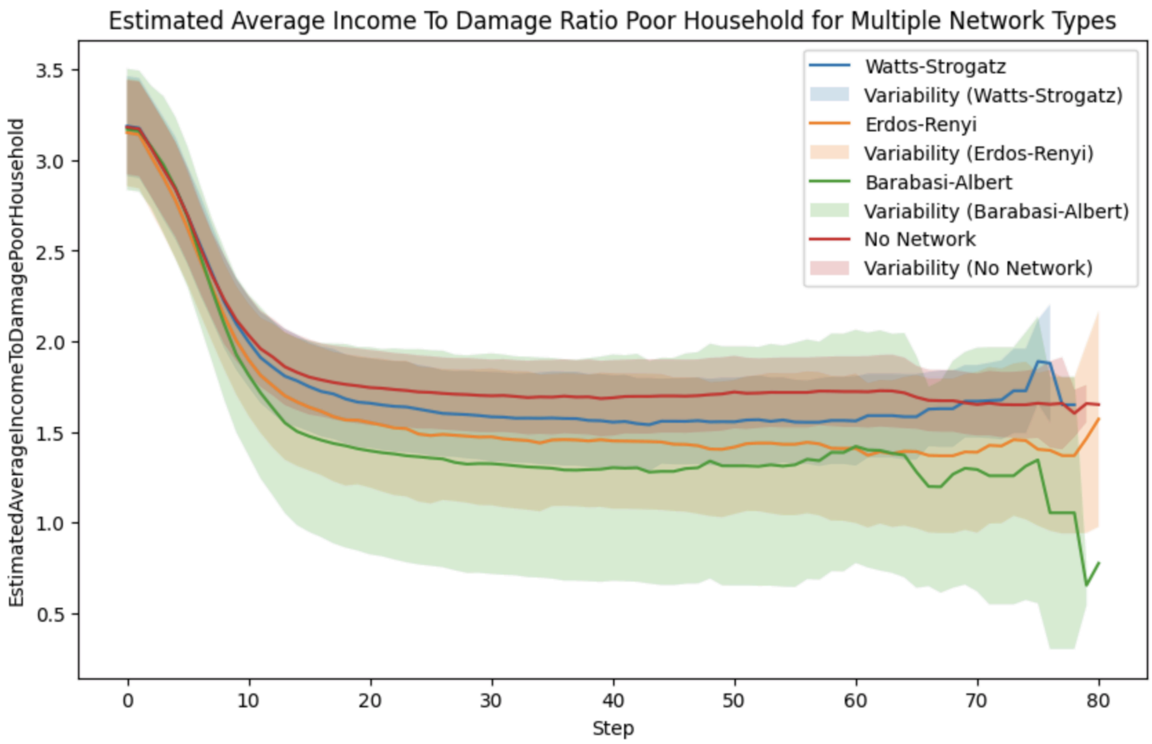

Figure 20. Estimated average income to damage ratio poor household for multiple network types.

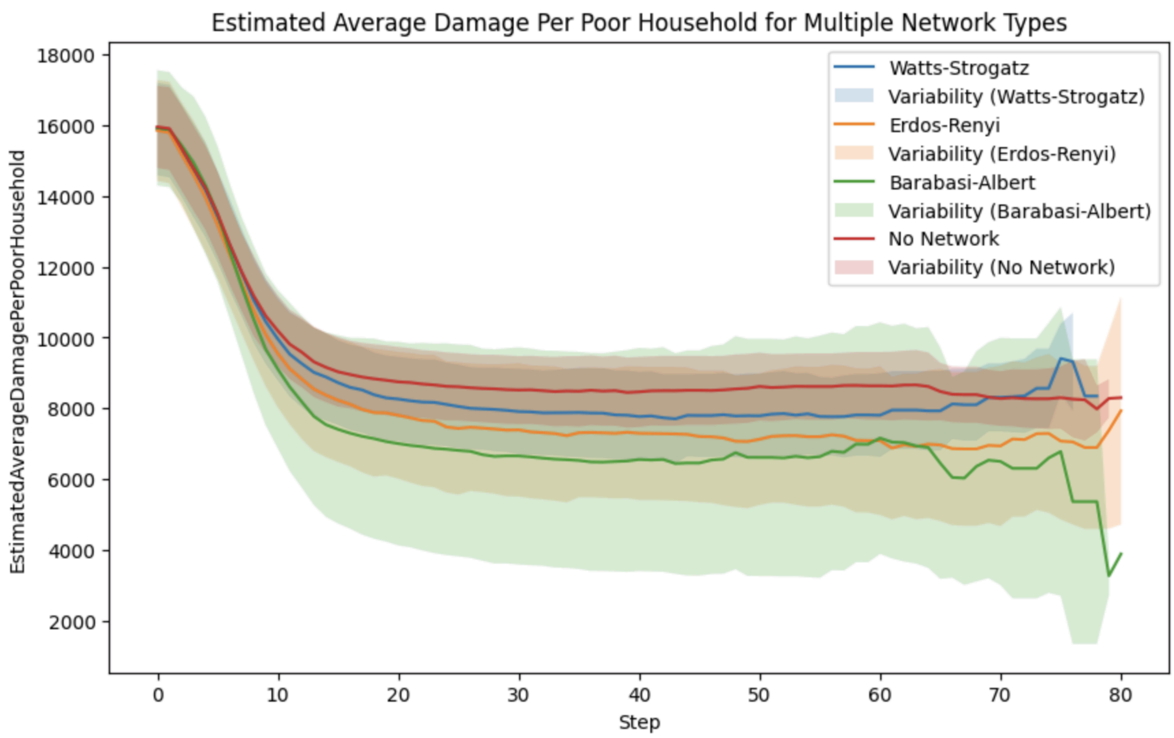

Figure 21. Estimated average income to damage ratio poor household for multiple network types.