Flood adaptation

Using an agent-based model to analyse flood adaptation by households and flood damaging

Group 14
Authors: Elize Bruintjes (6088074), Anne van Ekert (5974089) and Finn van Kolmeschate (4876113)
Supervisor:
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Preface

This report was written for the course SEN1211 - Agent-Based Modelling. This report concerns a flood adaptation model in which the decision-making process of household agents to adapt to urban flooding in Texas, the United States, is simulated. Python is used as a modelling software with the installed package Mesa. Prior to the assignment, two of the three group members had some very basic experience with Python, although none had thorough experience with agent-based modelling.

1. Introduction

1.1 Context

The effects of global climate change are imminent and give rise to major environmental problems, both impacting ecosystems and the well-being of human populations (WHO, 2023). Climate change tends to exacerbate geo-disasters, therefore it is clear that adaptation to climate change has rapidly become one of the most important and urgent issues for the future existence of human beings on Earth (Yasuhara et al., 2012).

In recent years, the frequency and intensity of flooding events as a result of climate change have increased globally, posing significant threats to communities and their infrastructures (Swain et al., 2020).
As urbanisation continues to expand, cities such as Austin, Texas, are faced with escalating challenges associated with flood management (Ekeanyanwu et al., 2020).
In 2017 hurricane Harvey occurred in Texas, which sparked extreme flooding, causing $125 billion dollars in damage (Lamar University, 2019).

To adapt to these challenges and in order to prevent such high damages as with the Harvey flooding, flood risk management has been an important approach adapted by governments to provide protection to residents and their properties. In flood risk management, the focus lies on reducing human vulnerabilities to flood risks instead of preventing floods to occur (Bergsma, 2019). The implementation of flood adaptation measures at the household level significantly contributes to diminishing the vulnerability of communities (Abayneh Abebe et al., 2020). Therefore, it is interesting to evaluate the decision making process regarding the flood adaptation and how the measures taken by households in an urban area impact the consequences of flooding.

In this report, flooding adaptation, as part of climate change adaptation, will be modelled in an urban context using agent-based modelling. As a case study, the city of Austin, Texas, will be modelled. This will be done using Python as a modelling software with installed package Mesa, to create an agent-based model. The aim of the study is to understand the decision-making process of households in the context of urban floods and explore the consequences of the selected decisions for damage assessments after a flooding. The states and behaviour of households and the government agents, will be studied and the interactions between the two to assess the overall adaptation against flooding event. In the model, the main focus is the residual damage, the remaining damages after adaptation is taken, and how this can be reduced. Additionally, the distribution of damages across household agents with different attributes will be modelled as well as the diffusion of adaptation over time.

1.2 Research questions

The main research question addressed is as follows:

1. *How can the decision-making processes of a household agent engaged in urban flooding adaptation be simulated in an agent-based model, with the intention to decrease the residual damages after a flooding?*

The following sub questions are also answered using the model:

2. *What are the model outcomes under various parameterizations?*
   2.1 How does a social network of household agents relate to the perceived flood probability and amount of residual damages after flooding in the model?
   2.2 How do individual characteristics such as different perceived flood probabilities of household agents relate to the amount of residual damages after flooding in the model?
   2.3 How does the cost of measures influence flood adaptation and the residual damages following from this?

3. *What is the influence of implementing policy intervention on the awareness and preparedness of household agents against urban flooding?*
   3.1 In the form of certifications (fines)
   3.2 In the form of government flood warnings

Question 3.1 will be answered using the Reusable Building Block (RBB) that we have built, which represents the concept of government authority in enforcing regulations and policies for flood risk management. A RBB is a submodel that represents a particular mechanism or process that is relevant across many agent-based models in an application domain (Railsback & Grimm, 2023). The complete building block can be found online on agentblocks.org.

In order to answer these questions, first a conceptualisation will be made in Chapter 2. In this conceptualisation the agents, processes, interaction and parameters will be explained. This chapter will also include the KPI and the theories and assumptions that are used in the model. Following, Chapter 3 will include the formalisation, where the implementation of the model will be discussed. In Chapter 4 the results will be discussed, with a model verification and validation, as well as the running of experiments and a sensitivity analysis. Chapter 5 includes a conclusion, recommendation & limitations description.

1.3 Hypothesis

It is anticipated that a higher level of flood adaptation by households will lead to a decrease in remaining damage following a flood. The greater the flood depth, the higher the damages without adaptation are expected to be.

The desire to adapt is expected to be positively affected by high values of perceived flood probability and the perceived effectiveness of measures. The higher the cumulative weight of these values, the more likely a household is to desire the adaptation of measures.

Whether a household actually adapts its house, if desired, is influenced by its income and savings. Higher savings make a household more likely to fully elevate its house and reduce residual damage to zero.
Furthermore, it is expected that government interventions will encourage the adaptation of flood measures. Both a higher parametrization of flood warnings from the government and fines are anticipated to have a positive effect on the perceived flood probability, consequently decreasing total residual damages.

Neighbouring agents can either stimulate or discourage adaptation based on their own perceptions. If neighbours are highly concerned about the occurrence of flooding, they are likely to convey this concern to their neighbours as well. A higher parametrization of the trustworthiness of a neighbour is expected to increase the influence she has on the perceived flood probability of her neighbour. More extreme parametrization of trustworthiness is expected to create smaller heterogeneity in the residual flood damage among different households.

Perceived flood probability is expected to decrease every year by a certain percentage because households will remember previous flooding less each year. A higher parametrization of the discount rate has a negative effect on perceived flood probability, thereby increasing residual damages.

Lastly, the costs of adaptation measures are expected to influence the financial implications of adaptation measures. With a higher parametrization of elevation costs per square meter, the costs of adaptation measures increase, thereby reducing effectiveness and affordability. An increase in this parameter is expected to lead to an increase in residual damages.

1.4 Modelling technique

In the project, an Agent-Based Model (ABM) is built. Agent-Based Modelling is a modelling technique to build explanations of social processes, based on ideas about the emergence of complex behaviour from simple activities (Salgado & Gilbert, 2013). As adaptations cover a lot of independent decision making based on individual reasoning, Agent Based Modeling is a prima candidate to investigate the behaviour and emergent model in this system, The model consists of multiple agents, individual entities that act in the model, belonging to a certain class. Using ABM, the local interactions among independent components which lead to emergent behaviour can be studied. The model is made in Python, a programming language, in which the Mesa package is used. Mesa is an open-source Python library for agent-based modelling, ideal for simulating complex systems and exploring emergent behaviours (GitHub, n.d.).

2. Conceptualisation

This chapter provides a description of the model. The system boundaries, description, KPI's, parameters, conceptual model and assumptions of the model will be elaborated on. The conceptual model is used to build a formal model, further explained in Chapter 3.

2.1 System boundaries

2.1.1 Geographic boundaries

The model of urban flooding is based on the area Harris County in Texas, US. This includes the City of Houston and has a population of about 4.8 million. It is located on the coast of the Gulf of Mexico and has to deal with flooding due to storm surges which can come in combination with very heavy rainfalls when hurricanes hit the city (e.g., hurricane Harvey in 2017) (PennState University, n.d.).The system boundary is therefore the area Harris County with its households, which each have a house, the government and their interactions/processes. The number of households in the model is fixed, being 25. All other buildings beside houses belonging to households are not included in the model.

Figure 1: *Aerial view of Harris County*

2.1.2 Time and shock event

The model simulates 20 years in total. The model runs in ticks, in which each tick represents a quarter of a year, so in total the model runs for 80 ticks. The flood shock occurs at a specific time, after tick 60. This shock represents an actual flooding event, affecting all households in the model. Following this event, the actual flood depth at each household location is calculated. This actual flood depth and the level of adaptation measures taken is then used to compute the residual flood damage, the remaining damages after adaptation is taken.

2.2 Description

In figure 2 the logic to take flood adaptation measures and the resulting residual damage is visually illustrated. The rectangles represent variables that are changed throughout time as a result of actions and interactions in the model. The variables in circles are values that are more or less predetermined. Variables in italics are influenced by the government, underlined variables are influenced by neighbours.

<u>Cost effectiveness of measures</u>
In the city, some houses are more prone to flooding than others. The flooding occurs in the entire area but has a different impact depending on the location of a household on the map. Households use the estimated flood damage derived from flood maps, to calculate their estimated flood damage costs. The household flood damage is based on the flood depth-damage curves for North America by Huizinga et al. (2017) where the actual flood depth is translated into a damage factor, ranging from 0 (no damage) to 1 (maximum damage). Households receive a fine if they do not meet the minimal amount of required adaptation measures specific for their location. By taking into account the estimated flood damage costs, the cost of measures and the fine for not being certified the household agents are able to make a prediction about the cost effectiveness of adapting flood measures.

<u>Perceived flood probability</u>
Perceived flood probability is both influenced by neighbours and the government. The worry and trustworthiness of the social network influences the households. The government also influences this variable, by giving flood warnings. Perceived flood probability also decreases over time because the longer a flooding does not occur the less worried households are.

<u>Adaptation measures taken</u>
Based on a combination of the perceived flood probability and the effectiveness of measures a household either desires or not desires to take adaptation measures. If the household indeed takes measures and to what degree is then influenced by how much money the household is able to spend on flood adaptation.

<u>Damage in Euros</u>
The location of the household on the map and therefore the flood depth influences the damage factor. Thereafter the damage factor is adjusted for the various adaptation measures that households may have implemented. Depending on the adaptation measures the household has taken, the factor is reduced by a percentage. Together with the house size, this can be transferred to monetary damage.

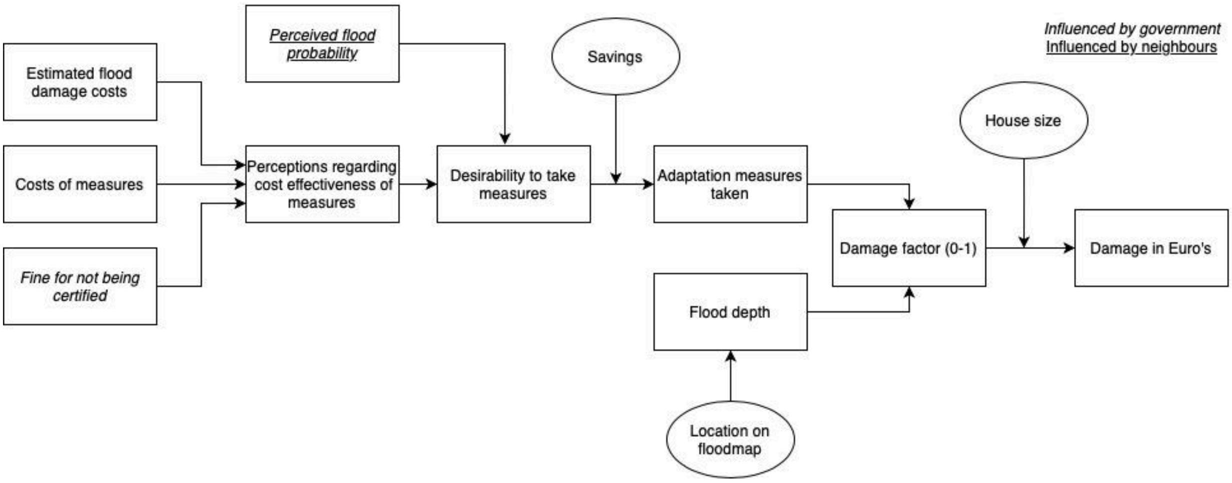


Figure 2: *logic for residual flood damage*

2.3 Conceptual model

2.3.1 Agents, Processes and interaction

In total there are 2 agent classes containing household agents and a government agent. Household agents are placed on a visual map as nodes and are connected to their neighbours through nodes, so that they can interact with one and another. The government is also placed in the model and is through nodes connected to all existing household agents, so that it can communicate and interact with all these agents. There is 1 other object, the flooding. In figure 3 a mind map of the system is given, containing the properties (states and behaviour) of the agents, the objects, KPI's and external factors. In the table below the processes caused by interactions between agents are provided.

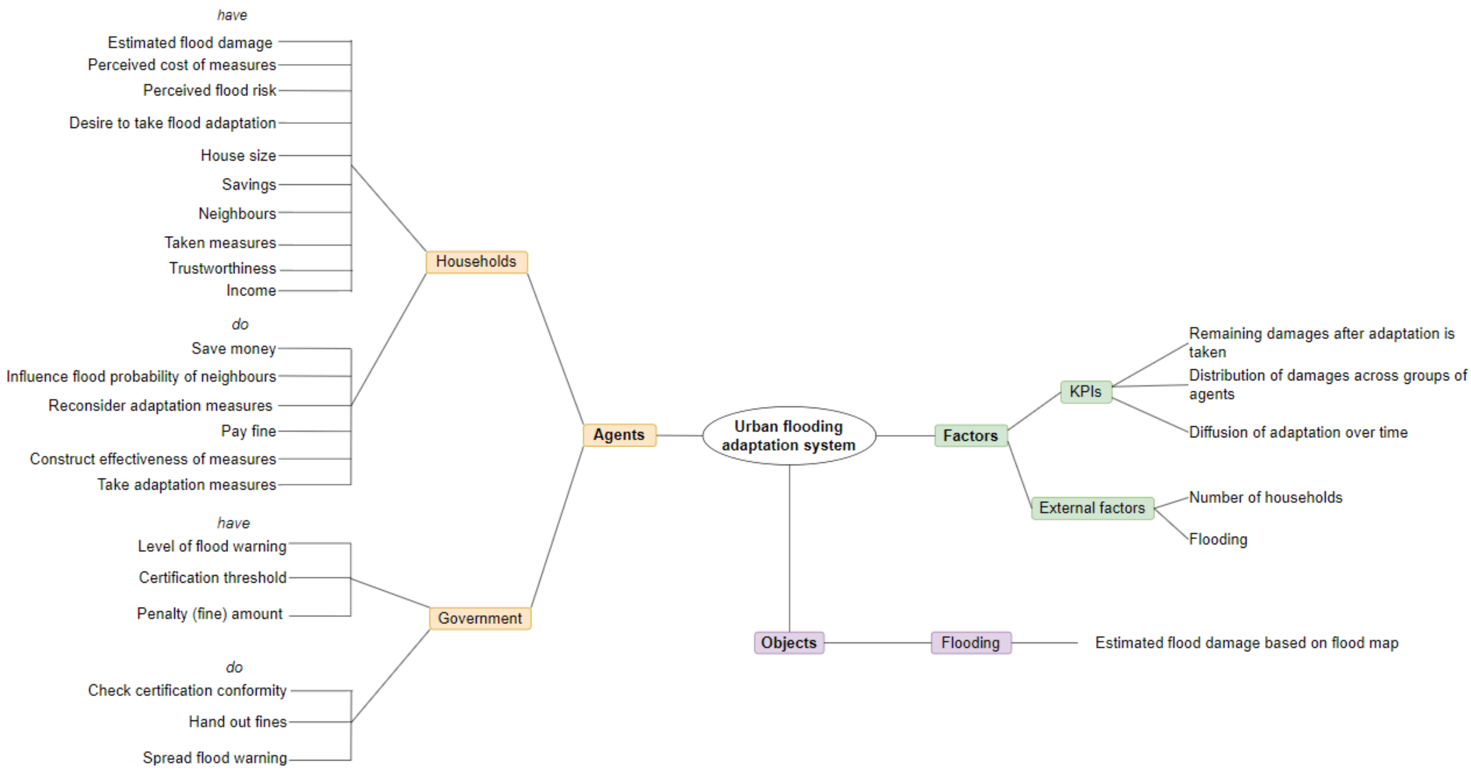


Figure 3: *Mindmap of the Urban Flooding Adaptation System*

Table 1: *Processes in model caused by interactions between agents (and object)*

Processes	**Interaction**
Perceived flood probability is influenced by neighbours	Household and household
Government influences perceived flood probability	Household and government
Government warns households about flooding which influences perceived flood probability	Households and government
Government introduces certification and imposes fine on households	Households and government
Houses get damaged	Household and flooding

2.3.2 Parameters

The model consists of both variable and fixed parameters. Fixed parameters remain the same throughout the model. The variable parameters will be varied during the experimentation and the results following from this can be used to answer the research questions. The experimental parameters with their base value are shown in the table below.

Table 2: *Experimental parameters in model*

Experimental parameters	**Unit**
Government flood warning	-
Trustworthiness of neighbours	%
Government fine	€
Costs of flood adaptation	€/m^2
Discount factor	%

2.4 KPI's

The research question aims to answer how the residual damage after flooding can be decreased by simulating the decision making process for Climate Change Adaptation (CAA). KPI's (key performance indicators) for understanding the decrease of residual damage include:

- Dynamics of regional residual damages (i.e., remaining damages after adaptation is taken)
- Distribution of damages across the groups of actors and across agents within the same group (e.g. households with different risk perceptions)

- Diffusion of adaptation over time

2.5 Theory, assumptions and model reductions

To simplify the model, certain assumptions and model reductions have been made. This simplification has been done mainly due to time limitations and lack of previous experience with modelling. First theory and assumptions are discussed, afterwards model reductions.

Theory

- **Trustworthiness of neighbours**: According to Seebauer & Babcicky (2018), neighbours exert a great influence on its peers regarding flood mitigation. They state that a high trust in neighbours makes households more likely to implement adaptation measures, rely on social support and indulge in wishful thinking. For this reason the trustworthiness of a neighbour is integrated in the model repeatedly during the decision making process of a household to adapt.
- **Discount rate:** Risk perception of residents declines over time when memories of flood events disappear (Rufat & Botzen, 2022). Therefore a discount rate has been integrated into the model and at each time step.
- **Flood warning by government:** Rufat & Botzen (2022), stress the importance of risk communication strategies implemented by the government and its influence on risk perceptions. For this reason the perceived flood probability in the model is not only influenced by an initial value and by other households, but also by a government agent who gives flood warnings.
- **Effectiveness of measures:** Household agents reason about the effectiveness of flood adaptation measures by comparing the costs of taking measures with the decrease in expected flood damage (Jonkman et al., 2004). If the benefits are higher than the costs, the measures are expected to generate an increase in welfare and are considered attractive. Therefore, this logic is used in the decision making process of an agent in the model to adapt to flooding .
- **Preference for full elevation:** Despite the much higher costs of elevation, the share of households that is willing to invest in complete elevation is not significantly smaller than the share that desires to invest in cheaper (and less protective) forms of adaptation measures (Botzen et al., 2012). From this it has been reasoned that if a household has the desire to undertake flood adaptation and if there is enough money available they will elevate their house.
- **Protection with elevation:** According to the Federal Emergency Management Agency (n.d.), in case of proper elevation, the living area will be above all but the most severe floods (such as the 500-year flood). From this it has been derived that if a house is fully elevated it has zero residual damage costs, which is implemented in the model as well.

Assumptions about variables:

- **Income:** In the model households are assumed to have an income per time step ranging between €13.000 and €20.000 euros. These values are based on the average earnings and distribution of earnings in the USA (Federal Reserve Bank Of St. Louis, 2023).

- **Initial savings:** from extensive research, based on the Federal Reserve, we came to the conclusion that average savings of households are more or less equal to 1.8 times the quarterly salary, for this reason the initial savings is the income multiplied by 1.8.
- **Housesizes**: In reality the size of houses varies and we wanted to account for this in the model as well. The average house size in Harris County is 1,713 feet, which translates to 159.14 square metres (Property Shark, 2016). To be able to take differing house sizes into account in the model it is assumed that house sizes range between 120 m2 and 200 m2.
- **Savings**: In the model agents have an income and are able to save money. To decide how much money is saved by the agents the 50-30-20 rule is considered. This rule recommends putting 50% of someone's income toward needs, 30% towards wants and 20% toward savings (UNFCU, n.d.). Because agents do not want to spend all their savings on flood adaption it is assumed that 5% of the income is put aside for flood adaptation measures
- **Influence of fine:** The fine is incorporated in the calculation for the effectiveness of measures. The fine is added up to the avoided flood damage costs, because it is assumed that the fine does not need to be paid when sufficient measures have been taken.
- **Costs of elevation:** The elevation of a house ranges between $10 and $35 per square foot (Forbes, 2023). From this an average cost of € 270 per m2 elevation has been derived.
- **Flood adaptation measures/full protection:** For the purpose of simplification solely the quantitative implications of adaptation are modelled, by constructing a measure of protection between 0 and 1 (0 = no protection, 1 = full protection). Therefore it is not specified in the model whether a household either instals flood barriers or fully elevates its house, because it is not relevant for the eventual results. As discussed earlier, housing elevation is the preferred option for households and entails full protection resulting in 0 residual damage in the case of flooding. As it would be too complicated (and not useful for the model) to specify individual lower cost structural measures a fraction of protection can be bought, from which the costs are completely relative to complete elevation. In this manner lower income households are also able to eventually have a house which is fully protected against flooding costs.
- **Adaptation measures taken and damage factor:** in the model it is assumed that the damage factor decreases linearly with the adaptation of flood measures
- **Flood damage costs:** flood damage costs are calculated by multiplying the damage factor with the maximum damage costs per square metre (€788) and the size of the house.

<u>Model reductions</u>

- The number of households is fixed, always being 25
- Households are placed randomly on the map
- Each household has one house which is exposed to flooding
- House sizes differ from each other
- The estimated flood depth for each household is derived from pre-loaded flood maps
- No other buildings than houses of households are considered

- Household agents can form social networks, which represents social connections
- The amount of residents per household is not considered
- Per household there is only one provider/someone with an income
- A household has the same trustworthiness for all its neighbours
- All households have the same amount of trust towards the government

2.6 Requirements

Certain requirements for the model to run have been formulated and are adhered to in the model. These are the following:

- A single tick/step represents 1 quarter of a year
- The model runs for 80 ticks/steps

In 1 tick/step:

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

2.7 Reusable Building Block

In addition, a reusable building block (RBB) is created which is used in the model. This RBB focuses on the use of certifications by the government specifically, as part of policy tools for flood risk management. In this RBB, the decision-making process of the government agent is modelled with as output the decision to give households a fine (yes/no) if they do not comply with a certain certification baseline based on their flood depth and adaptation measures taken. If the household does not comply with the certification it needs to pay the penalty, which is in this case extracted from their savings. The fine stimulates households, who may not perceive the flood risk high , to take adaptation measures to prevent monetary loss by fines.

3. Formalisation

3.1 Map and visualisation

The map of Houston (the model domain) and flood maps have been imported into the agent based model. All household agents are initialised by generating a random location on the flood map (x- and y-value).
Based on this location, the estimated flood depth can be determined. A choice from different flood maps can be made, but in our model the ‘Harvey’ flooding map is used (Figure 4). This is done to keep results consistent and Harvey will therefore be considered our reference flood. In the model itself, the flood height will be varied with a random factor.
With the occurrence of a flooding the actual flood depth is calculated. The actual depth deviates from the estimated depth with a certain factor to mimic the uncertainty which a flooding entails.

All households are also initialised in a social network (making use of random activation), for which a graph with nodes is created (amount of nodes is based on the number of households assigned to the model). On each node of the social network graph a household is initiated, and links are created between households (Figure 5). With the placement of a household to the grid, the household is also added to the ‘household schedule’ list. The characteristics of the model are dependent on the social network structure that is chosen, in this model a ‘Watts Strogatz’ structure is used. The households that are connected with each other by links can communicate and interact with one and another. The government is linked with all
Households, so that policy interventions can interact with all households.

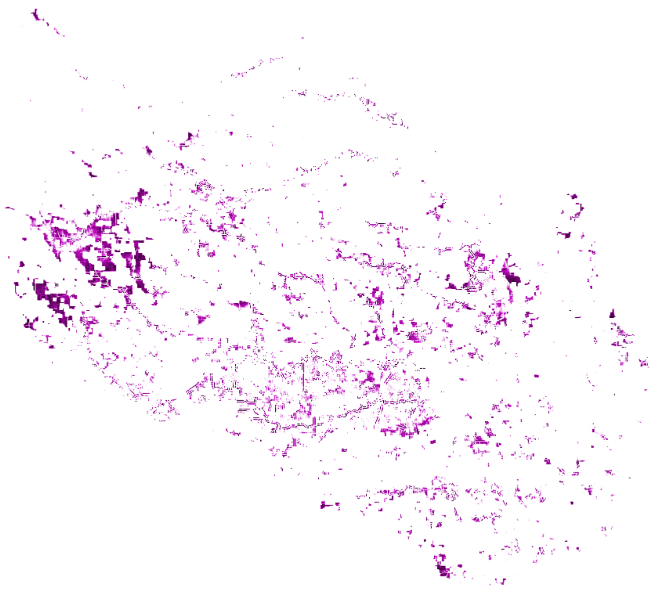


Figure 4: *Harvey flood map*

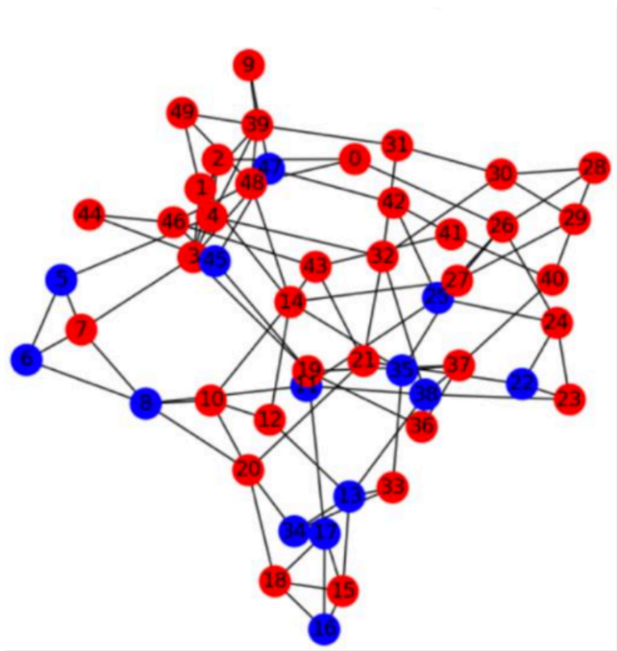


Figure 5: *agents illustrated as nodes, with links between agents*

3.2 Variables

In table 3 the variables and properties per entity are given.

Table 3: *variables per entity*

Entity	**Variable**	**Range**	**Unit**	**Other**
Household	income	13000-22000	€	Random value from range is taken
	money_saved	0 - infinity	€	Dependent on income and money spent on adaptation measures
	size_of_house	120-200	m2	Random value from range is taken
	trust_factor	0-1	x	Random value from range is taken. Influences to what extent a neighbour influences another agent. The higher the factor, the more an agent is able to influence its neighbour
	taken_measures	0-1	x	The inital value is randomized, after which flood adaptation by households increases this value. The higher the value the better adapted to flooding a household is.
	perceived_flood_probability	0 - 1	x	Initial value is randomized, consequently influenced by neighbours and the government. A value of 0 means that a household estimates the change of a flooding as nihil. If the variable is equal to 1, they are 100% sure that a flooding will occur next timestep.
	perceived_costs_of_measures	0 - infinity	€	Value is determined by multiplying the size of the house by the elevation costs per m2. Constant throughout model.
	perceived_flood_damage	0 - infinity	€	Value is determined by multiplying the size of the house, the estimated flood damage factor and the maximum damage per m2. Constant throughout model.
	perceived_effectiveness_of_measures	0- infinity	x	Determined by 'perceived_costs_of_measures', 'perceived_flood_damage' and 'fine'. The higher this value is the more effective the adaptation of measures are deemed.
	desire_to_take_measures	False, True	x	Initial status = false. The status will be adapted to true for sufficient values of perceived_effectiveness_of_measures and perceived_flood_probability
	is_adapted	False, true	x	Initial status = false. Is modified to true if taken_measures is above a threshold of 0.8
Government	flood_warning	0-1	x	The amount of flood probability that may be added to households
	regulations	0-1	x	The maximum degree of damage that a household may incur from a flood according to perceived flood damage.
	fine	0-infinity	€	A monetary punishment that households may incur when not fulfilling the regulations.

3.3 Functions

In table 4 the functions per agent are given. Afterwich the code in the model will also be shown. This way the formalisation of the conceptual model in the agent based model will be clear.

Table 4: functions per agent

<table>
<tr><th>Agent</th><th>Function</th><th>In model</th></tr>
<tr><td>Household</td><td>save_money()</td><td><pre>self.money_saved += self.income * 0.05</pre></td></tr>
<tr><td></td><td>construct_perceived_flood_probability()</td><td><pre>neighbors = self.model.grid.get_neighbors(self.pos,
include_center=False)
self.perceived_flood_probability = self.discount_rate *
self.perceived_flood_probability
for neighbor in neighbors:
    if isinstance(neighbor, Households):
        self.perceived_flood_probability = (
            self.perceived_flood_probability * (1 -
neighbor.trust_factor) +
            neighbor.trust_factor *
neighbor.perceived_flood_probability)</pre></td></tr>
<tr><td></td><td>construct_perceived_flood_damage()</td><td><pre>self.perceived_flood_damage = self.size_of_house *
self.max_damage_dol_per_sqm * self.flood_damage_estimated</pre></td></tr>
<tr><td></td><td>Construct_perceived_effectiveness_off
_measures()</td><td><pre>self.perceived_effectiveness_of_measures =
((self.perceived_flood_damage + self.fine*5) /
self.perceived_costs_of_measures)</pre></td></tr>
<tr><td></td><td>reconsider_adaptation_measures()</td><td><pre>if self.perceived_effectiveness_of_measures > 4 and
self.perceived_flood_probability > 0.2:
    self.desire_to_take_measures = True
elif self.perceived_effectiveness_of_measures > 3 and
self.perceived_flood_probability > 0.4:
    self.desire_to_take_measures = True
elif self.perceived_effectiveness_of_measures > 2 and
self.perceived_flood_probability > 0.6:
    self.desire_to_take_measures = True
elif self.perceived_effectiveness_of_measures > 1.5
and self.perceived_flood_probability > 0.8:
    self.desire_to_take_measures = True</pre></td></tr>
<tr><td></td><td>take_adaptation_measures()</td><td><pre>if self.taken_measures < 1 and self.desire_to_take_measures ==
True:
    money_to_spend_on_measures = self.money_saved
    elevation_costs = self.size_of_house *
self.elevation_costs_per_square_metre
    if money_to_spend_on_measures >= elevation_costs:
        self.taken_measures = 1
        self.money_saved -= elevation_costs
    elif 1.000 < money_to_spend_on_measures < elevation_costs:
        self.taken_measures += (money_to_spend_on_measures /
elevation_costs)
    else:
        return
else:
    return</pre></td></tr>
<tr><td>Government</td><td>warn_households(schedule_of_housholds)</td><td><pre>for agent in schedule_of_households:
    if isinstance(agent, Households):
        agent.perceived_flood_probability = (
            agent.perceived_flood_probability * (1 -
self.flood_warning) +
            self.flood_warning)</pre></td></tr>
<tr><td></td><td>check_all_households()</td><td><pre>for household in self.household_list:
    if isinstance(household, Households):
        self.check_certification(household)</pre></td></tr>
</table>

	check_certification(household)	`if not self.complies_with_certification(household):` `    self.fine_household(household)`

	complies_with_certification()	`if calculate_basic_flood_damage(flood_depth=`
		`household.flood_depth_Harvey) - household.taken_measures <=`
		`self.regulations:`
		`    return True`
		`else:`
		`    return False`

	fine_household(household)	`household.money_saved -= self.fine`
		`self.fined_household_list.append(household)`
		`self.fined_total += self.fine`

4. Results

In this section results from model runs and experiments will be presented. First, a verification and validation of the model will be presented to test whether the model performs as expected. Next, a sensitivity analysis will be presented, in which experimentations of the parameters are conducted.

4.1 Verification

A verification has been conducted to check whether the model was implemented correctly according to the conceptualisation. It is important to conduct this verification because in this manner it can be demonstrated that the model does what it is intended to do.
To make sure everything is initialised well, we have analysed the model and agent metrics that are reported when running the model, and the values follow our expectations from the model.

During the coding constantly small checks were performed in order to assess whether the code was performing as it intended to. This was done by implementing a ‘print’ function through which functions could be checked. Also, as can be seen in the sensitivity section, extreme values for parameters have been run next to general parameter variation to check whether the model still produces logical results, even if there is a significant amount of unexpected behaviour. In the sensitivity section there will be elaborated on the extreme values test. In these tests there was no different behaviour shown than expected.

4.2 Model validation

In the validation step it is analysed whether the model performs as expected.
The model can be validated by comparing the outputs to real-world data. In this manner it can be verified that the model replicates observed patterns and behaviours accurately.

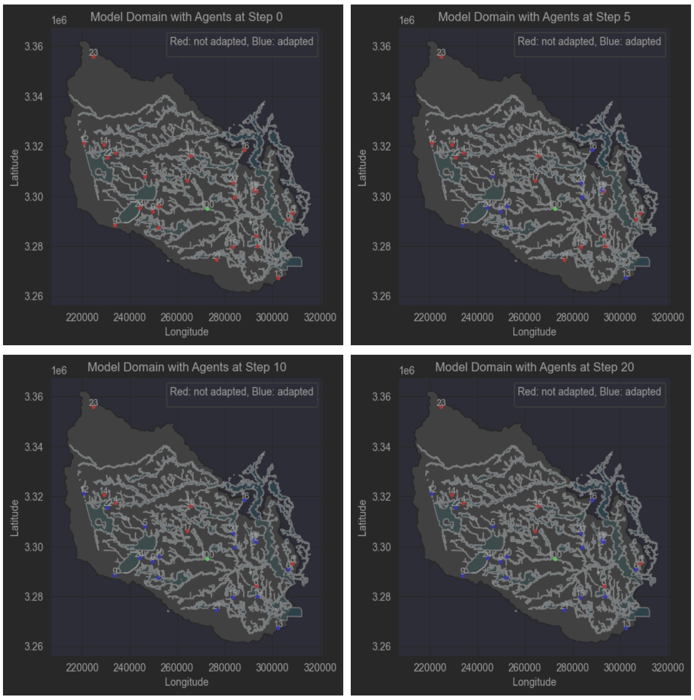


Figure 6: *households becoming adapted over time.*

In figure 6 it is visualised how households become adapted over time. The red dots are the households that are not adapted and the blue agents are the households that are adapted. The green dot is the government agent in the model. This follows our expectation of the model behaviour. First households did not adapt yet, but will start to adapt. According to Ngo et al. (2019) adaptation is less likely if the perceived flood probability is low and/ or the household is not vulnerable to flooding. This is the reason for the delayed adaptation as they still are getting influenced by their neighbours and the government to adapt and some people that lag behind and become adapted later. It is however visible in the model that most of the adaptation is done at the start of the model, but this is how the model is intended to function.

It is also clear that the adaptation does prevent damage. In the figure below you can see that in the what-if scenario (orange) where no adaptation would be in place, there would be a lot more damage than in the scenario where they have actually implemented adaptation measures (red).

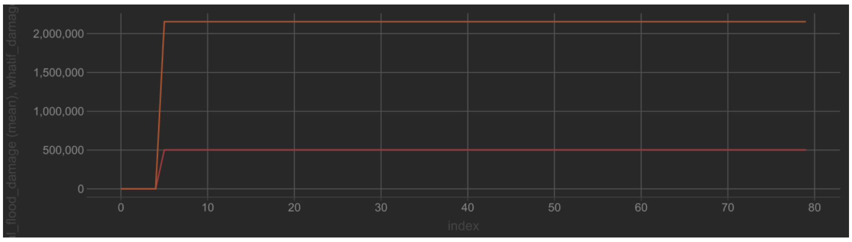


Figure 7: *Differences between damages without adaptation and with adaptation.*

A sensitivity analysis has also been done as part of our validation and experimentation, as can be seen in paragraph 4.3.2.

4.3 Experimentation

In this section, the experimentation of the results is elaborated on, by first presenting the base case and then the sensitivity analysis. The base case was run 15 times, a sufficient number of runs is required because the initialization of the model has a high degree of randomness. More runs would of course always be more reliable, but also very time consuming. From these runs every time the average variable values were taken and noted down in tables.

4.3.1. Base case

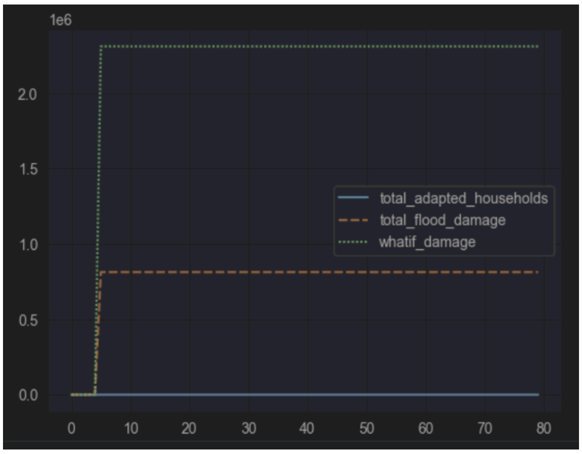
The agent-based model was set up in such a way to yield results that align with logical comparisons and emulate typical decision-making processes.
As mentioned in paragraph 2.3.2. fixed parameters remain the same for all runs, experimental parameters are varied. The base case is modelled in such a way that it would reflect reality best. However No model is able to capture reality perfectly, likewise for this model. However insights from varying the parameters and comparing this to the base case can give interesting insights. The base case values for the experimental parameters are as follows:

- government_warning: 0.15
- elevation_costs_per_square_metre: 290
- discount_rate: 0.99
- fine: 1000
- trust_factor: random.uniform (0, 0.1)

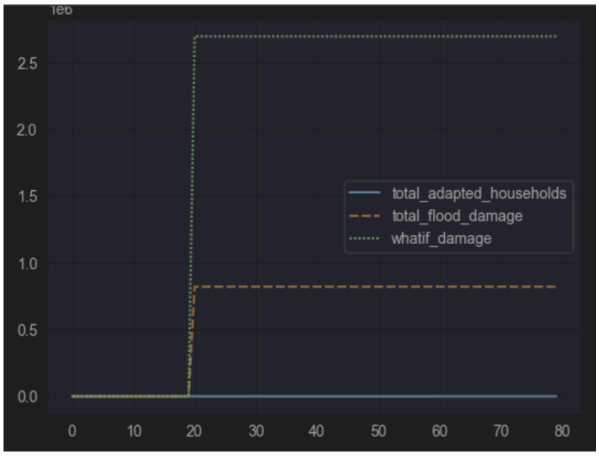
Table 5: *results base case*

Number of adapted households at last timestep	**Residual damage**	**Average perceived flood probability at last timestep**	**Average measures taken at last time step**
17	207,605	0.602	0.867

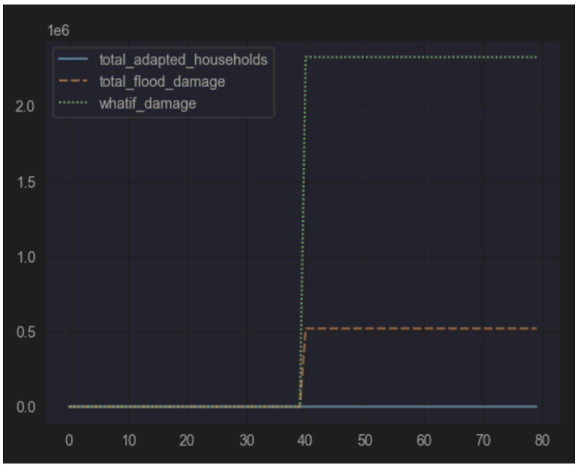
<u>What if damage and residual damage</u>
The shock can be introduced at different moments (steps) in time, which is illustrated in the 4 graphs below. Through these graphs the damage if no flood adaptation measures at all would have been taken (green) can be compared with the actual flood damage (orange). The model has been run multiple times and the graphs below are representative for the general values following from this. What can be seen is that the later a flooding occurs the lower the residual damages are. This can be explained by the variable ‘measures_taken’, which increases throughout the model.



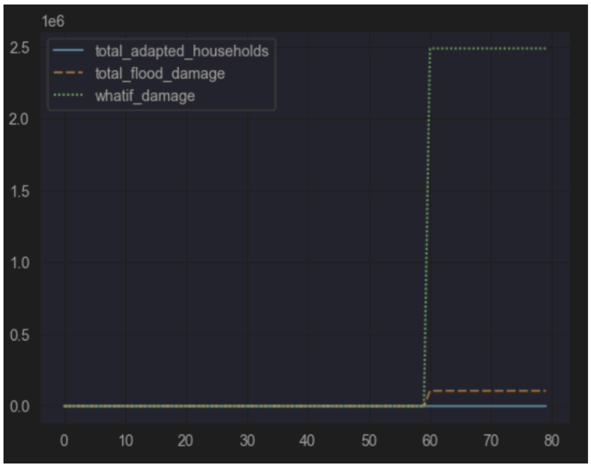
Flooding at t=5



Flooding at t = 20



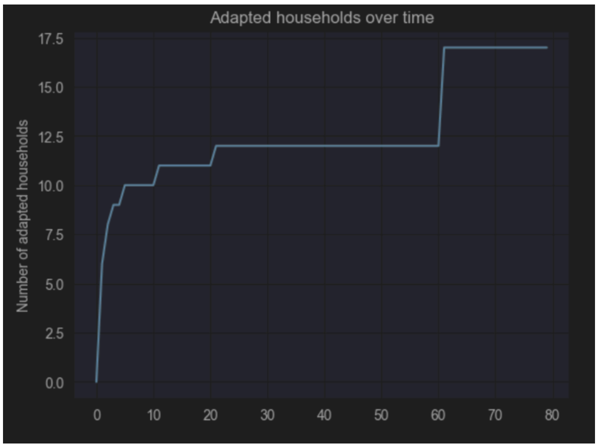
Flooding at t = 40

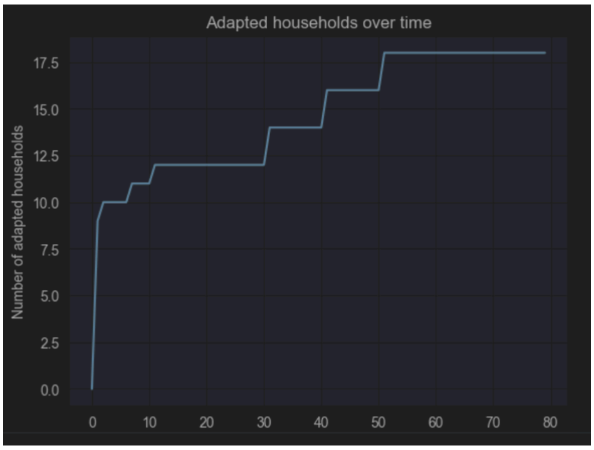


Flooding at t=60

<u>Adaptation of households over time</u>

Below two examples of the progression of adapted households over time are shown (representative of multiple runs). Which can be seen is that after the first step, the number of adopted households immediately increases with around 10. This is the case because all households in the model start unadapted. Immediately after the first step a lot of households will have a combined ‘perceived probability’ and ‘perceived effectiveness of measures’ which makes them desire to take measures. Further increases in the amount of adapted households are caused by an increased perceived flood probability or money saved over time.





4.3.2. Sensitivity analysis

In this section the results of the sensitivity analysis are presented. The parameters government warning, discount rate, fine, cost of measures, and the trust factor are varied. Each of the parameter variations was run 5 times, while all the other non-varied parameters were kept the same as in the base case. 5 was chosen as more would take too long to run and the data would become too large. From these runs every time the average variable values were taken and noted down in tables. The sensitivity analysis is performed to see how these influence the KPI's.

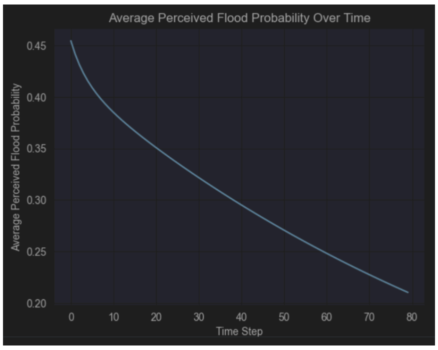
Variation of government warning

All other variable parameters are kept the same as the base case and the government warning is varied. Also an extreme value is tested. From 5 runs the average value is taken for every indicator. The results of these runs can be seen in the table and figures below.

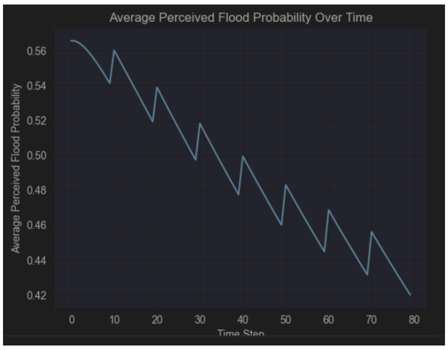
Table 6: *results variation of government warning*

value	**Residual damage**	**Average perceived flood probability at last timestep**	**Number of adapted households at last timestep**
0	489,771	0.331	8
0.05	443,486	0.392	9
0.1	382,412	0.495	11
0.15 (Base case)	207,605	0.602	17
0.2	139,626	0.653	18
0.25	58,106	0.706	19
0.8 (Extreme input)	0	0.916	21

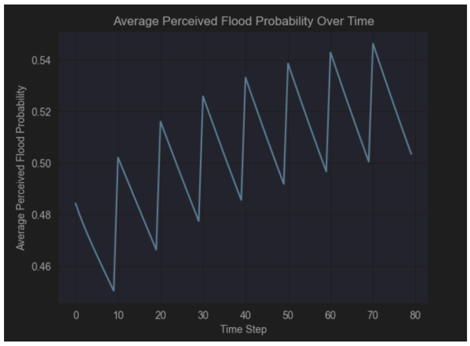
What can be observed is that the number of adapted households at the last timestep is increasing when the government warning value is increasing. Furthermore, the residual damage is decreasing as the government warning is increasing, this is a logical result as households adapt their protection measures based on the government warning. Also, as visualised in the figures below, when the government warning value is low, the perceived flood probability declines. Also, with higher government warning values, the average perceived flood probability over time is higher. Especially in the extreme case, the perceived flood probability increases to a very high value already at time step 10 and stays high. This is a logical result. From this we can learn that government warning leading to an increase in perceived flood probability can greatly reduce the damage caused by a future flood.



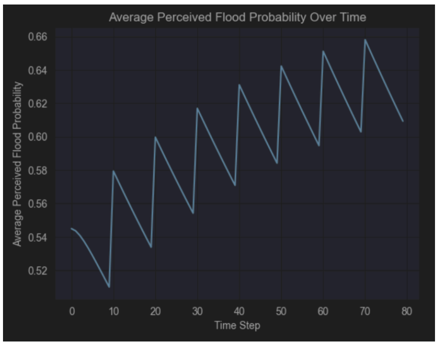
Government warning = 0



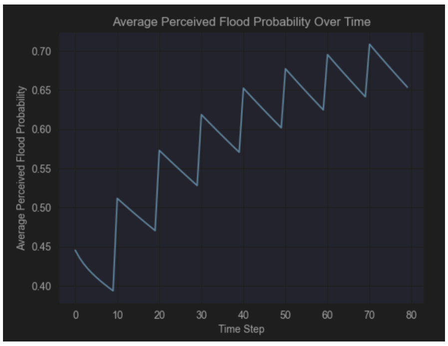
Government warning = 0.05



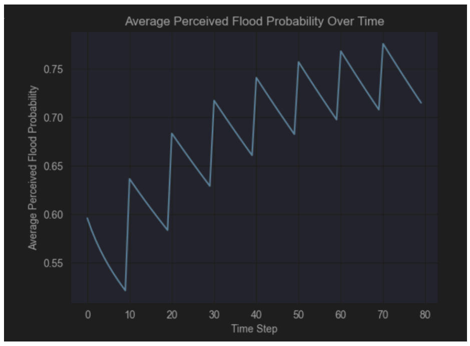
Government warning = 0.1



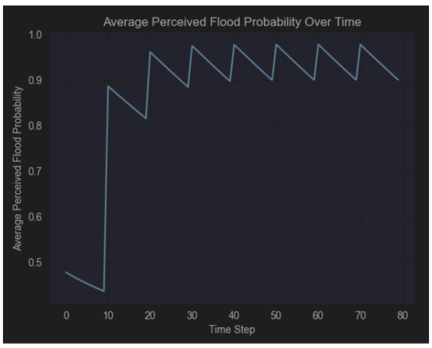
Government warning = 0.15



Government warning = 0.2



Government warning = 0.25



Extreme case (Government warning = 0.8)

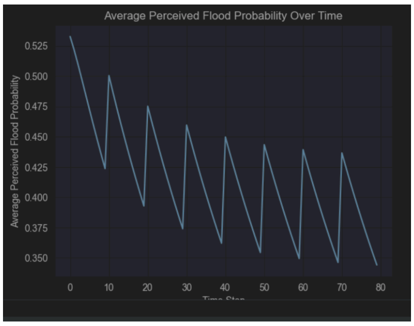
Varying of discount rate

All other variable parameters are kept the same as the base case and the discount rate is varied. Also an extreme value is tested. From 5 runs the average value is taken for every indicator. The results of these runs can be seen in the table and figures below.

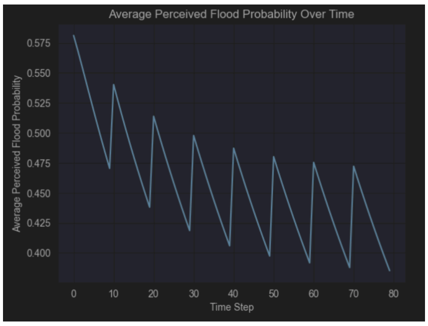
Table 7: *results of varying discount rate*

value	**Residual damage**	**Average perceived flood probability at last timestep**	**Number of adapted households at last timestep**
0.9 (Extreme input)	462,848	0.09	7
0.97	391,741	0.326	9
0.975	347,215	0.382	11
0.98	307,215	0.444	12
0.985	276,249	0.506	13
0.99 (Base case)	207,605	0.572	17
0.995	78,909	0.672	18

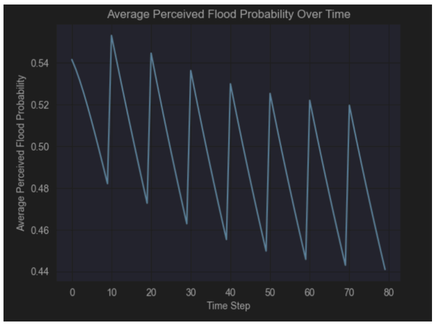
As can be seen, the residual damage is increasing with a higher discount rate. The extreme input, with the highest discount rate, has a very low perceived flood probability, low adapted households and high residual damages. This is logical as a lower discount rate has a negative effect on the perceived flood probability and therefore increases residual damages. A lower discount rate results in a higher number of adapted households, as well as higher perceived flood probabilities as can be seen in the figures. Important to take into account ins the general trend each of the discount rates have. All discount rates from 0.98 and lower have a downwards trend, while all discount rates that are higher have an upwards trend for the perceived flood probability. Preventing people from thinking that a flood probably won't happen could thus lead to a heightened sense of urgency and encourage them to invest in adaptation.



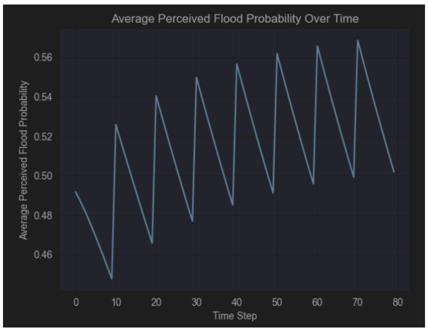
Discount rate = 0.97



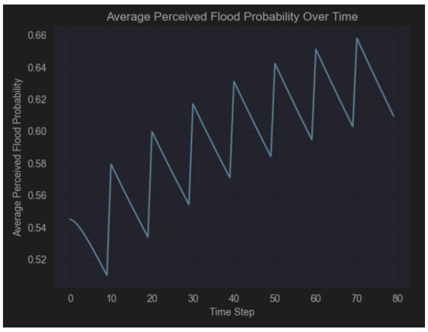
Discount rate = 0.975



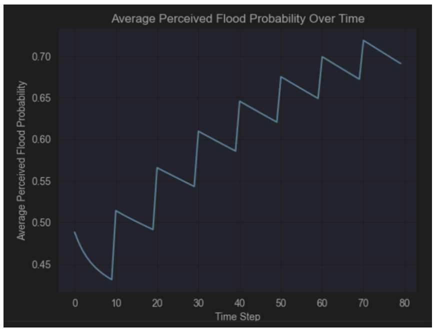
Discount rate = 0.98



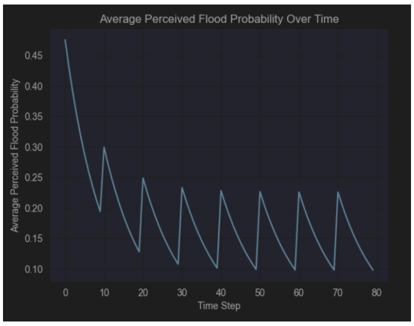
Discount rate = 0.985



Discount rate = 0.99



Discount rate = 0.995



Extreme case (Discount rate = 0.9)

Variation of fine

All other variable parameters are kept the same as the base case and the fine is varied. Also an extreme value is tested. From 15 runs the average value is taken for every indicator. The results of these runs can be seen in the table and figures below.

Table 8: *results of variation of fine*

Value	**Residual damage**	**Average taken measures at last time step**	**Number of adapted households at last timestep**
0	69,241	0.83	18
500	48,524	0.94	19
1000 (Base Case)	207,605	0.867	17
2000	111,850	0.956	18
4000	33,456	0.989	19
20000 (extreme value)	0	1.1	20

The variation of the fine leads to interesting results which could not have been predicted easily. The progression is not linear at all. Which becomes clear from these results is that the increase of fines to a very high level positively influences the adaptation of measures and therefore strongly decreases the residual damages. However when the fine is decreased to levels below the base case residual damages actually are becoming lower. This is caused by the fact that in these scenarios households do not need to pay fines, which makes them able to save money quicker and to spend this money on adaptation measures.

Variation of cost of measures

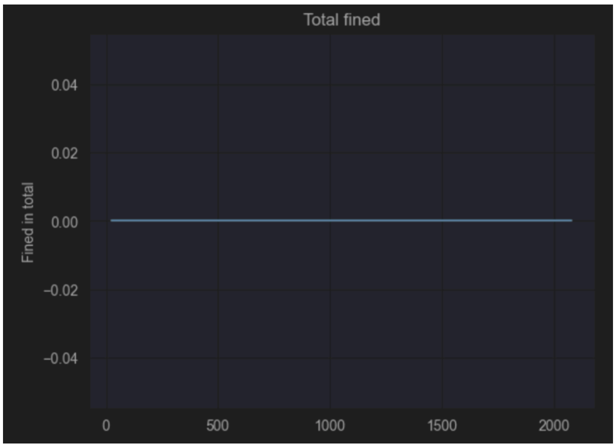
All other variable parameters are kept at the same cost as the base case and the cost of measures is varied. Also an extreme value is tested. From 5 runs the average value is taken for every indicator. The results of these runs can be seen in the table below.

Table 9: results of variation of cost of measures

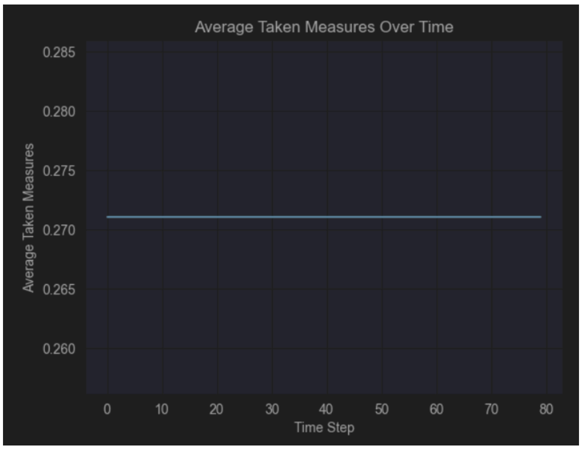
Value	**Residual damage**	**Average taken measures over time**	**Number of adapted households at last timestep**
100	43,789	0.88	19
290 (Base case)	207,605	0.867	17
400	358,890	0.632	9
1500 (Extreme input)	998,224	0.332	1

Considering the results in the table above, it is evident that as the costs of measures increase, the adoption of flood prevention measures decreases. Consequently, with a rise in the cost of measures, there is a simultaneous increase in residual damages.

In the graphs below the implications of varying the cost of measures to certain values are illustrated. If the cost of measures are a 100, this will result in everybody conforming to the certification, so everybody who is required to adapt is able to do so. The second graph shows that no flood measures are adopted at all throughout the model. This is a result of both the 'effectiveness of measures' decreasing and the financial difficulties regarding adaptation. This shows that not only people should be aware of the flooding, but should also find it financially attractive to adapt.



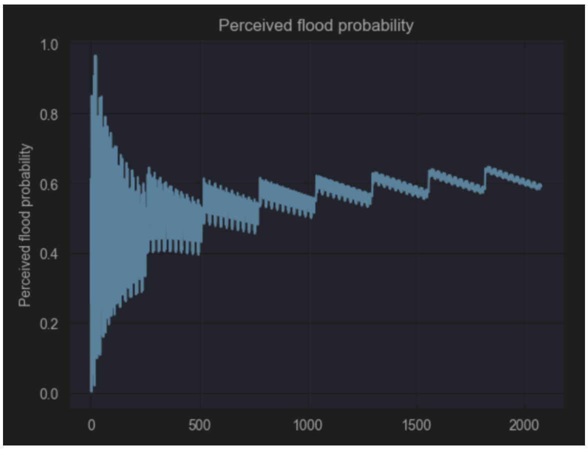
Cost of measures = 100



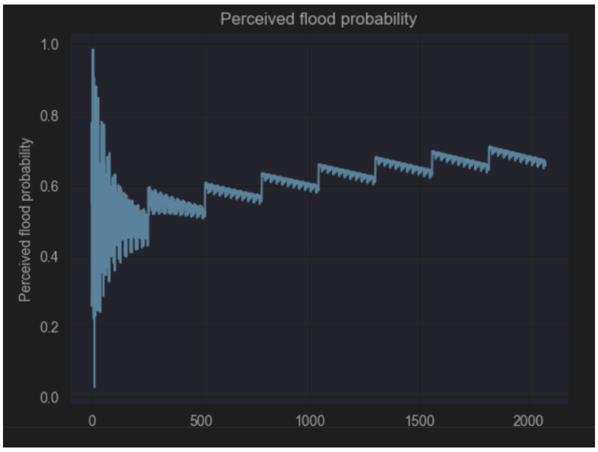
Cost of measures = 1,500

Variation of trust factor

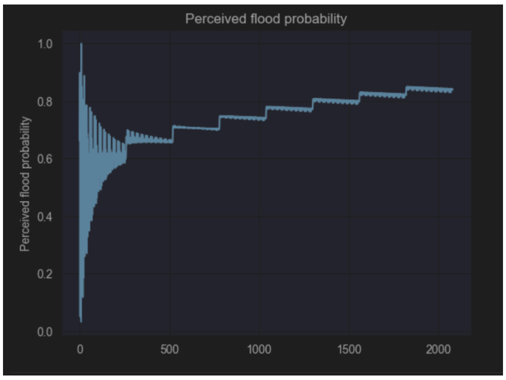
All other variable parameters are kept the same as the base case and the trust factor is varied. In the figures below it can be seen that if the range of the trust factor is increased the perceived flood probability becomes less heterogeneous much quicker. This shows that people are more aligned. Although this is not considered in the model, it could mean that people are more motivated to work together and policies concerning flood adaptations may be more easily adopted if people have the same sense of urgency.



Trustfactor = random.uniform (0, 0.1)



Trustfactor = random.uniform (0, 0.3)



Trustfactor = random.uniform (0, 0.8)

5. Conclusion, recommendation & Discussion

5.1. Conclusion and recommendation

In order to prevent excessive flood damages, it is important to know what effects can have a positive influence on the resilience of households in flood prone areas. This research has focussed on simulating the decision-making processes of a household agent engaged in urban flooding adaptation in an agent-based model, with the intention to decrease the residual damages after a flooding.
This has been done by answering the following research questions:

> *What are the model outcomes under various parameterizations?*
> *2.1 How does a social network of household agents relate to the perceived flood probability and amount of residual damages after flooding in the model?*
> *2.2 How do individual characteristics such as different perceived flood probabilities of household agents relate to the amount of residual damages after flooding in the model?*
> *2.3 How does the cost of measures influence flood adaptation and the residual damages following from this?*

From the results it can be concluded that the residual damages after a flooding are influenced by many modelled variables and the sensitivity analysis has shown that the variation of parameter values highly influences these residual damages.

The perceived effectiveness of costs remains the same throughout time, therefore the perceived flood probability is the deciding factor if households decide to adjust their desire to take adaptation measures from false to true. Constantly the results showed that a higher perceived flood probability is connected to lower residual costs and vice versa. For this reason it remains very important to constantly monitor the perceived flood probability and study what the effect of different parametrizations on this is.

An important variable is the cost of protection measures, as a high value of cost of measures results in very large residual damages values, from which it can be concluded that at a certain price level households cannot afford to purchase protection measures against flooding. Because the cost of measures is considered such an important variable for the amount of residual damages a recommendation would be that the government provides subsidies for the households, which would like to adapt, but are not able to do so as a result of limited savings. In this manner higher adaptation rates can be achieved with a financial policy instrument.

Furthermore, it can be concluded that the social network of households highly influences the perceived flood probability. The perceived flood probability of neighbours becomes similar over time. This could be a positive effect as people with the same sense of urgency may be more well willing to specific policies. A problem caused by this however is that neighbours which are not sufficiently aware of the dangers of flooding can convince their neighbours of this as well. For this reason a recommendation could be that the government launches a campaign which tackles the spread of misinformation.

What is the influence of implementing policy intervention on the awareness and preparedness of household agents against urban flooding?
3.1 In the form of certifications (fines)
3.2 In the form of government flood warnings

Government policies can have an interesting effect on the awareness and preparedness of households. From the results follow that repeated government warnings are highly influential of the perceived flood probability and therefore on the residual damages of households. With the degree of warning the government is able to influence its residents on different levels. Because a government warning is cheap, but at the same time very effective it is recommended that the government stresses the urgency to adapt and the possibility of a flooding frequently.
By releasing flood warnings the government is also able to counter the effect of the discount rate, which causes households to forget the possibility of a flooding when it has not taken place for a long amount of time. The model showed that the discount rate strongly influences the perceived flood probability and the residual damages, therefore it is important that the government warning counteracts this.

Where effective government flood warnings can minimise flood damages, certifications leading to fines may be more difficult to implement. In our model we found that while fines may be effective in encouraging households to invest in adaptation measures, it also deprives them from their means to do so when fined. This leads to an adverse effect. However the money that is fined may be able to be used for adaptation measures for these groups. This was however not modelled,

5.2. Discussion

While the agent-based model provides valuable insights, it is essential to acknowledge certain limitations in the study. The model, like any simulation, simplifies reality and is subject to inherent uncertainties. The following limitations can be identified:

- The assumptions made, such as the discount rate's constant influence on perceived flood probability, may not fully capture the complexity of real-world decision-making.
- The manner of which governments can give warnings effectively is not modelled and may require further investigation to reach out to everyone effectively.
- The model does not cover other ways to minimize damage for households like government interventions for preventing floods.
- There is only one flood in the model. While in real life more floods could happen, this model does not consider concurrent floods within a timespan of 2 years.
- Because of running in some computational limitations, the parameters were done with 5 repetitions. To actually give research with more statistically significant basis these repetitions should be increased. This however will call for some increased optimization of the model. Likewise, to see compounding effects with the sensitivity analysis, it would also be desirable to have different parameters interact with each

other. There was however an issue with these increased runs which led to using the current approach.
- In the model a household is trusted in the same amount by all its neighbours. In real life someone is trusted differently by different persons.
- Only household buildings are studied in the model, which causes the residual damages of Harris county to be actually a lot higher if other buildings would be included as well.

In future research, addressing these limitations could involve refining the model to incorporate more elements and considering additional factors that may impact household decisions. Furthermore, extra empirical validation against real-world data would enhance the model's robustness and applicability and could lead to meaningful insights.

In conclusion, our study contributes to the understanding of urban flooding adaptation and decision-making processes. The insights gained have implications for policymakers and researchers working in the field of flood risk management. By refining our model and considering additional factors, future studies can continue to advance the model built in this report to do more in-depth research about urban flood adaptation.

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