Assessing the Effect of Different Policy Interventions: An Agent-Based Modeling Approach under the Protection Motivation Theory

Elike Stoelinga [5171474]
Thomas Lautenbacher [6068677]
Jula van der Schans [5085810]

January 2024

1 Introduction

This study delves into the complexities of household decision-making in the face of flood risks, particularly in Harris County, Texas, including the City of Houston. This region is notoriously vulnerable to flooding, due to storm surges which can come in combination with very heavy rainfalls when hurricanes hit the city.

Central to this analysis is the application of Protection Motivation Theory (PMT) within an agent-based modeling (ABM) framework. PMT explains the motivational aspects behind individual and collective reactions to threats, influenced by factors such as perceived flood risk, potential damage, worry, neighbors' investment levels, and effectiveness of protective measures (response efficacy). It also considers self-efficacy or individuals' confidence in their ability to implement these measures. [1] [2]

The theory is used to explore how varying levels of neighbors' investments and heightened worry impact households' willingness to adopt flood protection measures. This willingness is quantified through two key performance indicators: the percentage of adapted agents over time and the total flood damage.

Key flooding impacts include property and infrastructure damage, economic losses, and threats to human safety, varying with flood severity, community preparedness, and response efficacy. Household adaptation decisions, influenced by protection motivation, vary based on age and income. Adaptation strategies range from structural modifications to installing permanent barriers and purchasing flood insurance. Structural measures and flood barriers are permanent home improvements. The flood insurance and adaptive building use remain valid until a household moves [1]. However, for the model, all these measures are considered permanent, as it assumes that households do not have the option to move. Where younger, high-income households favor long-term solutions, and older, lower-income households lean towards short-term, more affordable adaptations.

The ABM model will allow insights into the following research question:

What is the effect of different policy interventions measured by the share of adapted households and total flood damage using Protection Motivation Theory?

Policy

The PMT underscores the importance of government policy in amplifying worry, thereby possibly shaping households' responses to flood risks. The four policy scenarios considered in this context are:

- **No policy:** Absence of government intervention, leaving households to independently assess and respond to flood risks.
- **Policy 1 - Subsidization of adaptation costs:** This policy involves the implementation of subsidies to reduce the financial burden of adopting flood protection measures. By reducing the income threshold, this approach aims to make costlier, yet more effective, measures more appealing to households. The goal is to encourage the adoption of robust flood protection strategies by making them financially accessible.
- **Policy 2 - Increasing coping appraisal through information campaigns:** This policy involves creating informative campaigns aimed at raising awareness about the efficacy of flood adaptation measures.

The goal is to enhance confidence in these measures, thereby fostering a stronger sense of coping appraisal among households.

- **Policy 3 - Integrated approach of subsidization and information :** This policy represents a combination of financial subsidies and educational campaigns. It aims to simultaneously reduce the financial barriers and increase the level of awareness regarding effective flood protection strategies, thereby promoting a more comprehensive approach to flood risk management.

Each policy scenario has distinct implications for how households perceive and respond to flood risks, influencing their motivation and capacity to undertake protective actions.

Hypothesis

This study involves simulating a model with various parameterizations to mirror behaviors observed in real-life scenarios. Different urban contexts are represented by varying age and income demographics, including young and poor, and old and rich communities, to assess the effectiveness of policy interventions. The distinct city demographics are:

- Suburban - City with predominantly young and low-income residents
- Urban - City with predominantly older and high-income residents

Hypothesis for investigation:

1. **Hypothesis 1**
   Lever 1 will be more effective in cities with lower-income populations. In these areas, financial constraints are a significant obstacle to investing in effective flood adaptation strategies. Households in such suburban cities, when supported financially, are more willing to select costlier but more effective measures.

   - Policy lever 1 aims to provide subsidies to households, aiming to reduce the financial burden of investing in flood protection. This strategy aims to make more expensive, yet effective, adaptation options accessible to those typically hindered by income barriers.

2. **Hypothesis 2**
   Policy lever 2 will be the most effective in cities with older and wealthier populations. In these demographics, older individuals may be less inclined to invest due to a lack of perceived long-term benefits, while wealthier individuals, previously uncertain, may be persuaded to act due to a clearer understanding of their potential impact.

   - Policy lever 2 focuses on educating households about the benefits of investing in flood protection. By enhancing the perceived value of these measures, it is expected that households will be more inclined to adopt protective actions.

3. **Hypothesis 3**
   Both levers are complementary to each other, therefore the results will prove to be more effective compared to implementing one lever. The combination will have a higher impact on income, and lower-income households will be affected the most.

   - The policy levers are combined for policy interventions.

In summary, this research provides insights into the behavioral dynamics of households facing flood threats, offering a nuanced understanding of the interplay between social influences, like the behavior of neighbors, psychological aspects such as worry, and economic factors including income.

2 Method

2.1 Modelling technique

This study uses Agent-Based Modelling (ABM) utilizing the Mesa library in Python [3]. ABM is known for its ability to simulate complex behaviors and uncover system-level dynamics that emerge from the interactions of individual agents. The Mesa library facilitates the implementation of ABM, allowing for the simulation of diverse agent interactions. This approach provides insights into the collective behavior of agents and their impact on system-level dynamics.

2.2 Conceptualization

This section explores how the Protection Motivation Theory influences the minimal model. For model development, several assumptions are made, with key assumptions highlighted in the text. Additional assumptions are detailed in Appendix A, section 4.1.1. Initially, the conceptualization defines the system boundaries. Subsequently, the conceptualization is illustrated through a conceptual model, which depicts the relationships and effects among various model elements.

2.2.1 System boundaries

The focus of this study is on a specific region within Harris County, Texas - the City of Houston, home to roughly 4.8 million people. This coastal area along the Gulf of Mexico is prone to frequent flooding, often triggered by storm surges and heavy rainfall, as exemplified by Hurricane Harvey in 2017. A flood map of this area is presented in Figure 1.

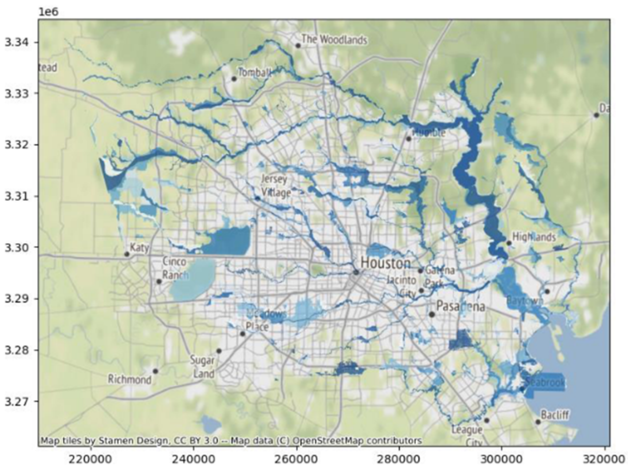


Figure 1: Flood map for coastal Harris County, Houston (retrieved from assignment description)

The agent-based model simulates over 80 ticks, which corresponds to a 20-year time frame. It focuses solely on this timeframe, without considering potential actions outside these two decades. Within the model, the only agent type is the household agent, which forms groups with its five closest neighbors.

2.2.2 Conceptual model

The model includes the Protection Motivation Theory (PMT), which consists of two main appraisals: threat and coping. The threat appraisal integrates worry, perceived flood damage, and perceived flood probability. An increase in perceived flood damage and probability increases the threat level. Worry also positively affects the height of the threat appraisal, because the more an agent worries the more threat the agent experiences.

The coping appraisal consists of the variables: self-efficacy, response efficacy, and costs of adaptation measurement. The cost of adaptation measurement is an average of the investment level of the surrounding neighbors. This is an average of the set of neighbors of the agent. The higher this level, the lower the variable cost. This reflects the notion that collaborative adaptation projects among neighbors can lower individual costs. Response efficacy and self-efficacy have a positive effect on coping appraising. The self-efficacy can even be increased by policy lever 2 (Information campaign) which focuses on educating households about the benefits of investing in flood protection.

These appraisals influence an agent's willingness to adopt protective measures. Once an agent decides to implement an adaptation measure, two primary factors influence their choice of a specific measure. Firstly, an agent's age plays a crucial role; older agents tend to be less willing to adapt, often choosing less effective measures. This is based on the assumption that younger individuals adapt more easily and older individuals may see less long-term benefits from adaptation due to their age. Secondly, an agent's income significantly impacts their choice. The more an agent earns, the easier it is to financially take a measurement, and with higher incomes, there are more opportunities for wealthy agents to execute household measurements. Additionally, the conceptual model,Figure 2, highlights another influencing factor: policy interventions. Specifically, when the model activates the policy lever where they subsidise adaptation costs. In this case, agents afford more costly adaptation measures.

When an agent selects an adaptation measurement, the agent's adaptation level rises. When an agent's adaptation level rises, the average investment of the agent's neighbors rises as well. Apart from the increased investment level, the agent's worry decreases because the agent will be less concerned once an adaptation measure is implemented. The level of adaptation of an agent will reduce the actual flood damage. The shock level influences flood damage; the higher it is, the more damage there is. This flood damage, combined with the size of the house, results in monetary loss. The larger the house, the greater the monetary loss.

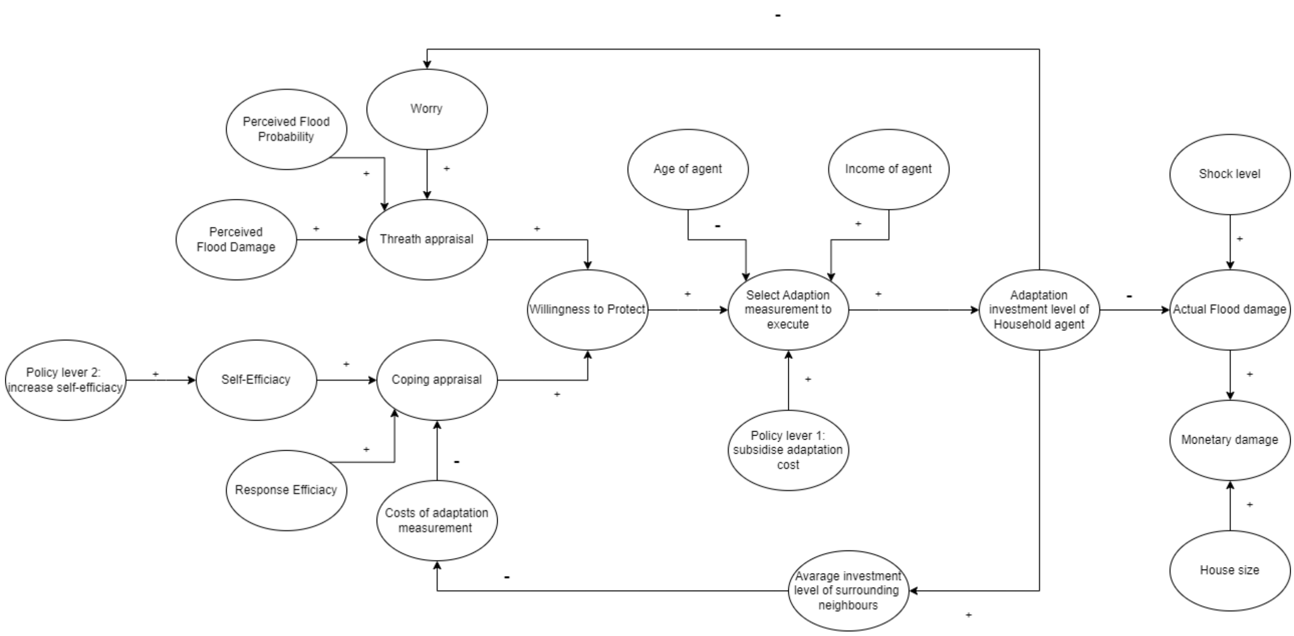


Figure 2: Conceptual model willingness to protect theory

2.3 Formalisation

This section delves into the process of transforming the conceptual model into a practical, operational model. 2.3.1 shows the visualization of the city of Houston's map within the model. 2.3.2 presents a flowchart that outlines the model's narrative, illustrating the sequence and interaction of various components. Lastly, 2.3.3 gives an overview of all the objects and variables used, including their respective ranges and functions within the model.

2.3.1 Visualisation

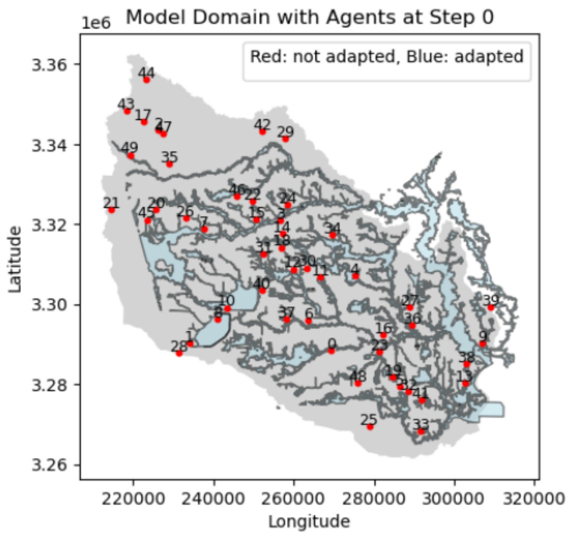


Figure 3: *Model domain of the city of Houston*

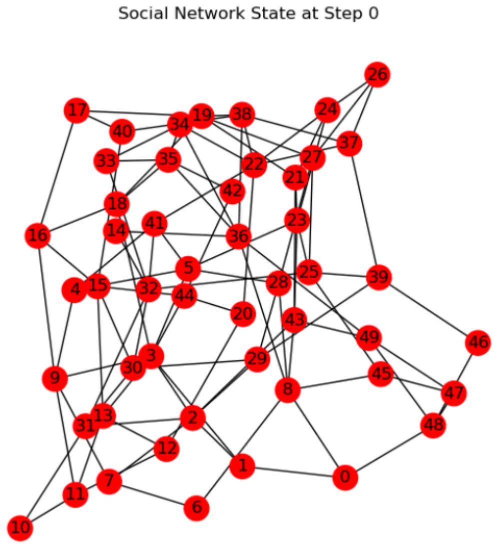


Figure 4: *The social network after initialization*

The city of Houston is modeled as a graph, where each node corresponds to a household agent, each assigned a specific geographical location defined by latitude and longitude. The positions of these nodes (x and y coordinates) are randomly generated and subsequently integrated into the attributes of the 'Households' class, effectively mapping the spatial distribution of households across the city.

2.3.2 Flowchart model

The flowchart represents the flow during one tick in the model. The model runs for 80 ticks in total (equal to 20 years).

In this implementation of the PMT, the model starts by initializing the six variables of which the threat and coping appraisals consist. Costs are derived from neighbor averages. Following the household's Willingness to Protect (W2P) is computed, this triggers actions when W2P exceeds the threshold equal to 0.5. The household has age and income attributes, influencing which action will be selected. The income is most important for deciding on the action. Secondly, the age will determine the action taken. The higher the income the younger the agent and the more effective action the agent will select. From the most effective the least effective actions are: Flood Barriers, Structural Measures, Adaptive Building Use, and Flood Insurance. If an action is taken this diminishes the worry and perceived flood damage, proportionate to their efficacy. In addition, the investment level of the set of neighbors of the agent is situated in will increase.

Additionally, policy levers can be activated or deactivated. The first policy lever is the subsidization of adaptation costs, activating this policy grants households subsidies, simulated by reducing the income threshold. Consequently, households will become more likely to implement costlier and more effective measurements. The second lever is the increasing of households' coping appraisal via informative campaigns, increasing their readiness to adopt adaptive measures.

If the threshold of 0.5 Willingness To Protect is not met the household will not take action. The worry will increase, simulating heightened concern. Once the flowchart is completely done the model will start over again with computing the Threat Appraisal and Coping Appraisal.

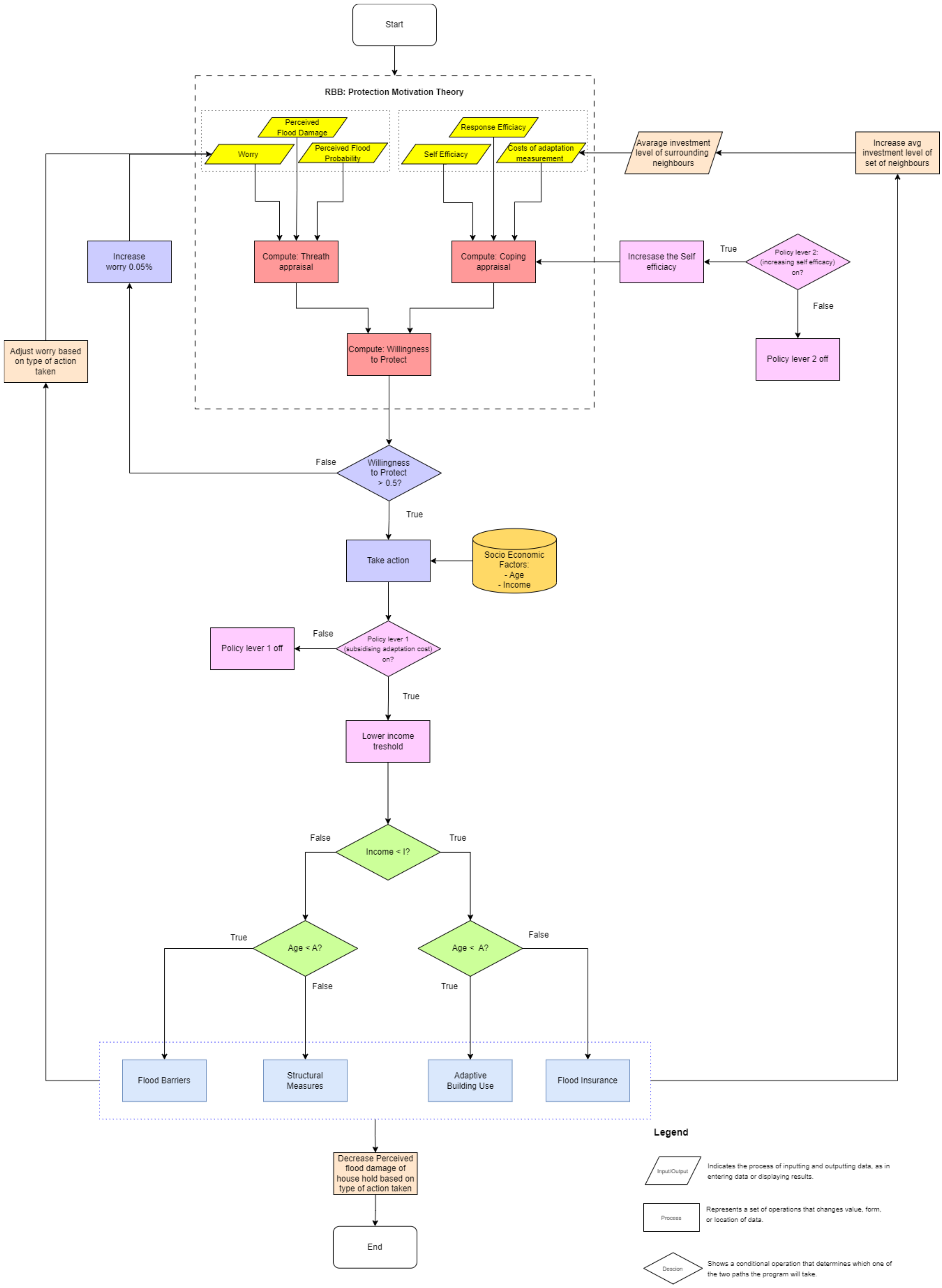


Figure 5: Flowchart model protection motivation theory

2.3.3 Variables

This section shows a list of all parameters in the model, making a distinction between the parameters that are varied during the experiments and fixed. The ranges are depicted in Table 1. None of them can get to values below zero.

Experimental parameter	**Unit**	**Value**
Income	[€/year]	Gauss $\mu = 10000; \sigma = 20000$
Age	[years]	Gauss $\mu = 50; \sigma = 10$
Fixed parameters	**Unit**	**Value**
Perceived flood probability	[-]	Gauss $\mu = 0.2; \sigma = 0.1$
Response efficacy	[-]	Gauss $\mu = 0.1; \sigma = 0.05$
Self-efficacy	[-]	Gauss $\mu = 0.1; \sigma = 0.05$
Initial value for costs of adaptation measurement	[€]	1
Initial value for worry	[-]	Gauss $\mu = 0.1; \sigma = 0.15$

Table 1: Experimental and fixed parameters of the model

The Table 2, gives an overview of the KPIs, their units, and a short description.

Key Performance Indicator	**Unit**	**Other**
Total Flood Damage	[Monetary Value]	Total flood damage, an initial model variable, decreases depending on the chosen adaptation measure's effectiveness.
Number of Adapted Agents	[%]	Households can adapt once; after adapting, they cannot adapt again.
Distribution of Adopted Measurements Over Time	[1= Flood Barrier] [2= Structural Measures] [3= Adaptive Building Use] [4= Flood Insurance]	Measures decrease worry and actual flood damage in proportion to their effectiveness, ranging from 1 (costly but effective) to 4 (cheaper and less effective).

Table 2: Experimental and fixed parameters of the model

3 Results

This section dives into the outcomes of the analysis and experimentation. Initially, section 3.2 focuses on the verification of the model. This includes a sensitivity analysis, examining how changes in input parameters influence the KPIs. Subsequently, in section 3.3, the model validation is presented, posing the fundamental question: "Did we build the right thing?". This ensures the model's efficacy in addressing the intended objectives.

3.1 Sensitivity analysis

Sensitivity analyses are important in agent-based models because they assess the robustness of the model's outcomes in response to changes in input parameters. They help in identifying influential factors, assessing the model's sensitivity to change, and improving understanding of the system's behavior. For this research, the sensitvity analysis was simplified by taking two parameters (response effiacy and self efficacy) and showing their behavior on one KPI (actual flood damage).

The parameters response efficacy and self-efficacy are varied by both -20% and +20%, each tested with 30 replications. For the response, efficacy has a Gaussian distribution in the model. For the sensitivity analysis, we changed the μ with -20% and +20%.

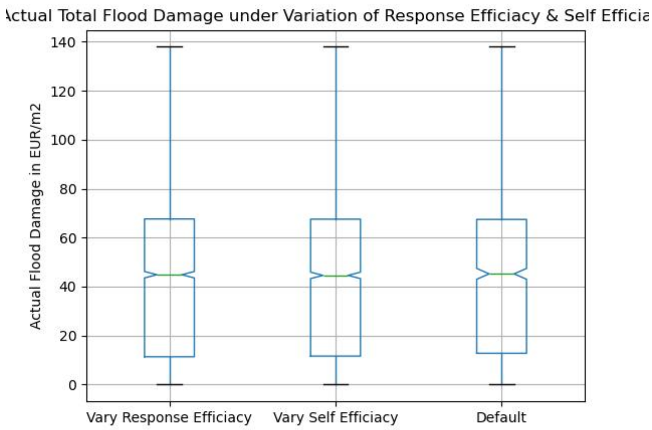


Figure 6: Sensitivity Analysis for Response Efficacy and Self Efficiacy

In Figure 6 the output of these changes in the variables can be seen in the actual flood damage. As the figure shows the vary in response efficacy and self-efficacy show very similar behavior as the default. This shows that self-efficacy and response efficacy don't significantly change the output of the KPI: actual flood damage.

3.2 Verification

Verification of an agent-based model is essential to confirm the accuracy of its structure and functionality. This process involves a thorough comparison between the model's outcomes and the conceptual model, ensuring that the model accurately and reliably represents the intended system. Such verification enhances confidence in the model's trustworthiness and relevance.

To verify the model, we focus on two key relationships identified in the conceptual model (Figure 2). The first one is the actual emergent behavior of the agent. Specifically, how an individual agent's investment in adaptation can lower the average adaptation cost for its neighbors, thereby encouraging further investment. The effect of the investment of agents on other agents is measured by the cumulative neighbor investment. According to Figure 7, once some agents begin investing, the other agents tend to follow this path. The fact that they follow each other is indicative of emergent behavior.

The other relationship that was tested in the verification is the effect of adaptation on the worry. The conceptual model states that once agents adapt the worry decreases. In the base model, half of the agents are adapted starting at step 70, and it continues to increase after that. In Figure 8, the worry begins to decrease around step 70, indicating that the worry decreases due to the agents' adaptation.

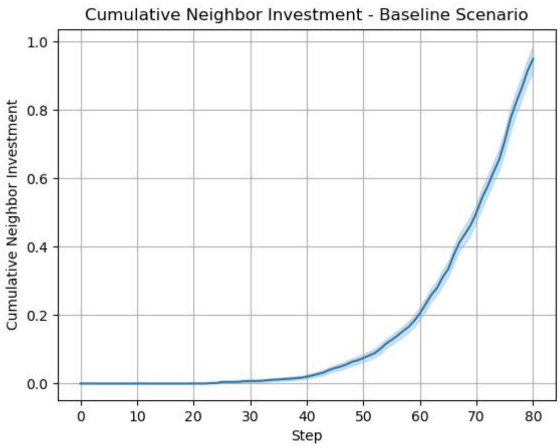


Figure 7: *Cumulative Neighbor investment over time*

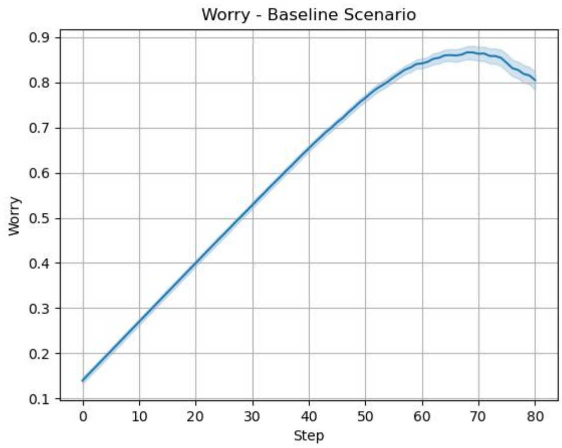


Figure 8: *Average worry of agents over time*

In summary, the verification process establishes the agent-based model's accuracy, validating its structure against the conceptual model. The observed relationships involving emergent behavior and a decrease in worry after agents are adopted are consistent with expectations, reinforcing the model's reliability. These verified connections serve as crucial benchmarks, contributing to a comprehensive understanding of the model's behavior and its alignment with the conceptualised model.

3.3 Validation

The validation of our model is critical, with the fundamental question: "Did we build the right thing?" The goal of this process is to determine whether the behavior predicted by the model is comparable to the real world. Examining the base case scenario in relation to the real world facilitates this comparison.

The base case scenario involves running the model with initial parameters and no policy interventions, essentially representing a situation where no interventions occur in the modeled scenario. Graphs displaying the mean with a 95% Confidence Interval illustrate the base case, revealing a flood in the model at step 5.

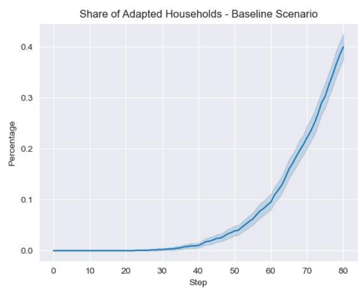


Figure 9: Base case: Share of Adapted Households

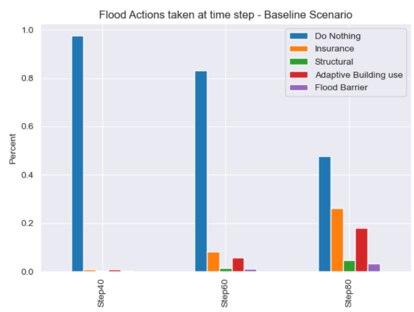


Figure 10: Base case: Flood Actions taken at time step

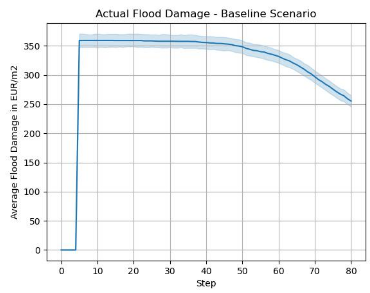


Figure 11: Base case: Actual Flood Damage

Analysing the base case scenario reveals how it aligns with the real world, in specific: Harris County. The percentage of agents adapting per time step is shown in Figure 9.In this figure, it can be seen that until step 40, almost no agents had taken measurements, with only 50% of them implementing adaptation measures at the end.

While Harris County lacks specific data, news reports indicate a concerning lack of preparedness for flooding. Research from The First Street Foundation, analyzed by ABC [4], suggests that nearly 44% of properties in southeast Texas with an 80% chance of flooding by 2053 may lack flood insurance. As flood insurance is seen as the minimal adaptation measurement that can be taken (in the model) this is roughly in line with the output of the model that around 50% has at least taken a minimal adaptation measurement.

Figure 10 shows an average distribution of low- (Flood barriers and Structural measures) and high-effort measurements (Adaptive building use and Flood insurance). This distribution is not completely in line with the data from the United States, where 28.4% have implented high-effort measures and 78.5% have implemented low-effort measures[5]. This demonstrates that in the base case scenario, the influence of income is high where, most agents earn less than the income threshold, leaving them with only two options. According to research, this modeling method appears to be correct, as income households have a significant impact on the adaptation measures that they take in the Harris County region.[6]

In Figure 11 the flood damage in euro/m2 is shown. The calculation of actual flood damage in money/m^2, based on the European Commission's average damage function for North America, uses an average of 788 euro/m^2. the calculation is based on the damage factor (see Figure 12) this factor is already implemented in the model. This is multiplied by the USA's actual flood damage value (788 euro) to get the monetary value.[7]. The model's post-flood average is slightly above 350 euro/m^2, approximately half of the USA's actual flood damage value. While in the same order of magnitude, the model's smaller scale needs consideration in this comparison.

Water depth (m)	Damage factor
0	0.20
0.5	0.44
1	0.58
1.5	0.68
2	0.78
3	0.85
4	0.92
5	0.96
6	1.00

Figure 12: : Average continental damage function for North America - residential buildings [7].

Ultimately, the model aligns with the real world, but there are a few aspects that reveal a slight divergence.

3.4 Experimental Setup

This section gives insights into the experimentation of the presented model. The study focuses on the hypothesis mentioned in section 1 and analyzes socioeconomic parameters of various demographics, as listed in Table 3, to conduct experiments.

Demographic	Average Income p.a. (mean)	Average Age (mean)
Baseline	50.000,- EUR	40 years
Urban	30.000,- EUR	30 years
Suburban	80.000,- EUR	50 years

Table 3: Scenarios under Investigation

Different policy interventions are applied to these scenarios. The "Income Threshold" and "Government Information" parameters for each policy intervention are defined as per section 1 and detailed in Table 4.

Policy Name	Description	Income Threshold	Government Information
Do Nothing	No policy intervention – default values	50.000,- EUR	1.0
Subsidy (Policy Lever 1)	Decrease of the "Income Threshold" to take an action. More income-dependent actions can be taken.	40.000,- EUR	1.0
Information Campaign (Policy Lever 2)	Increase of "Government Information". Positive Influence on Self-Efficacy. Hence, increase in W2P.	50.000,- EUR	0.8
Subsidy and Information Campaign	Simultaneous decrease of "Income Threshold" and increase of "Government Information".	40.000,- EUR	0.8

Table 4: Policy Interventions

Each policy in Table 4 is applied to the scenarios in Table 3, with 30 runs per combination to create statistically valid results, accounting for random initialization of several parameters mentioned in Table 1.

3.5 Results and Analysis

3.5.1 Baseline scenario

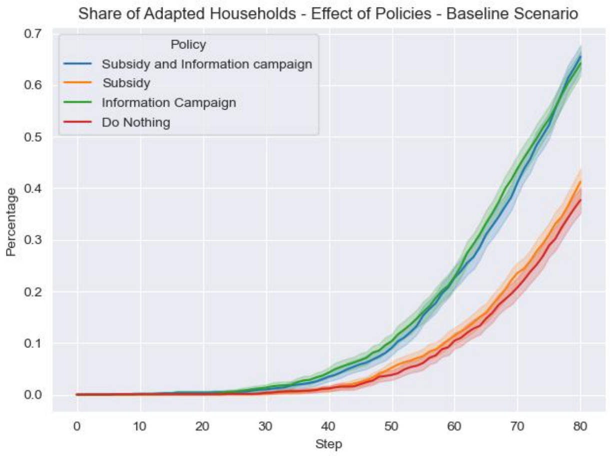


Figure 13: Effect of policies on the share of adopted households over time

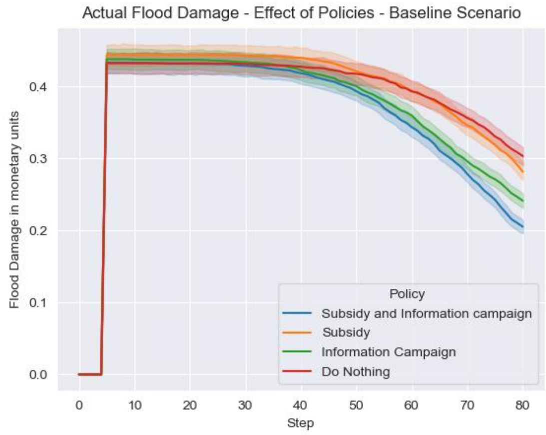


Figure 14: Effect of policies on the actual flood damage over time

The results for each scenario are analyzed in terms of the share of adapted households and actual flood damage, the KPIs. Figures illustrate the impact of different policy interventions over time, see Figure 13. Notably, "Information Campaign" significantly influences household adoption, while "Subsidy" shows a marginal additional effect. The combination of both levers demonstrates effectiveness, especially in reducing actual flood damage, indicating that government interventions leading to a higher willingness to protect, coupled with financial subsidies, result in more effective measures.

For the Actual Flood Damage (Figure 13) the insights are structured likewise and do present differences however. The results demonstrate the effect of a flood event occurring at step 5 on Actual Flood Damage. Following this event, as agents begin to adapt, the implementation of actions results in a reduction of Flood Damage. The "Subsidy" policy lever shows minimal additional impact, similar to the observations in Figure 13. However, the "Information Campaign" and the combination of both policy levers exert a more pronounced effect on reducing Actual Flood Damage.

Contrasting with Figure 13, the effect of combining "Subsidy" and "Information Campaign" outperforms using the "Information Campaign" alone. This outcome suggests that the effectiveness of flood damage mitigation is not solely dependent on the number of households adopting flood protection measures but also on the distribution of the selected measures. The selection of specific actions is heavily influenced by the financial circumstances of the households.

Therefore, in the Baseline case, the "Subsidy & Information Campaign" emerges as the most effective strategy. First, government intervention via informative campaigns leads to a higher Willingness to Protect, and consequently, the lower Income threshold - induced by the financial subsidy - leads to more effective measures being taken.

3.5.2 Suburban scenario

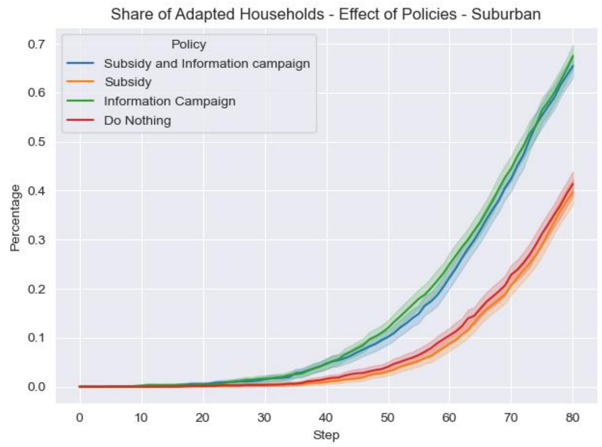


Figure 15: Effect of policies on the share of adopted households over time

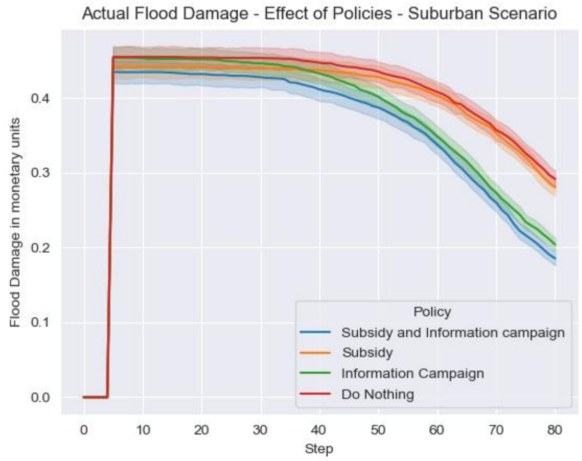


Figure 16: Effect of policies on the actual flood damage over time

The share of adapted households and the Actual Flood Damage delivers a similar picture for the Suburban scenario, compared to the baseline scenario, as depicted in Figure 27 and Figure 28, respectively.
However, some differences are remarkable: Firstly, policy lever 1 "Subsidy" seems to have even a small negative influence on the share of adapted households for the suburban region, as it leads to a lower share compared to the "Do Nothing". The difference is relatively small, this insight does strike with hypothesis 1 (section 1), which states that policy lever 1 will be most effective in the suburban demographic. This unexpected behavior needs further inquiry. A potential explanation for the "Subsidy" policy's limited impact in the Suburban area might be an insufficient generation of Willingness to Protect, which is crucial for motivating agents to take action. This observation could be linked to a modeling assumption where the "Subsidy" affects the income threshold only after an agent decides to adopt a measure. Consequently, this does not translate into a higher adoption rate, contradicting real-world expectations where a subsidy should not only enable households to choose more costly and effective measures but also increase the overall adoption rate. Further details on modeling assumptions can be found in 4.1.1.

Secondly, the additional influence of the combination of both policy levers "Subsidy and Information Campaign" is significantly smaller, compared to just the "Information Campaign". This can be explained, by the higher average income of the "Suburban" demographic. Hence, once the Willingness to Protect is generated, the lower Income Threshold - induced by the additional financial subsidy - does not have a strong additional influence on the actions taken.

3.5.3 Urban scenario

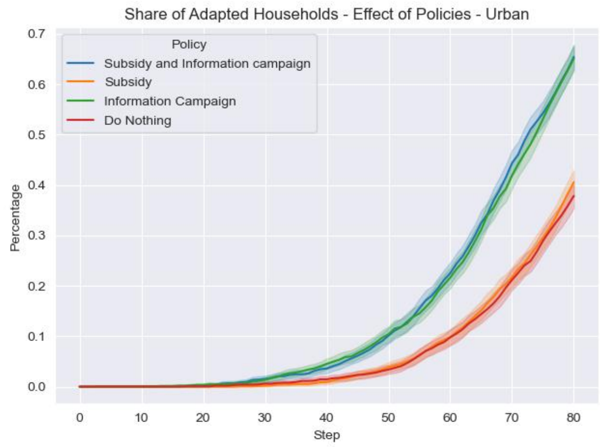


Figure 17: *Effect of policies on the share of adopted households over time*

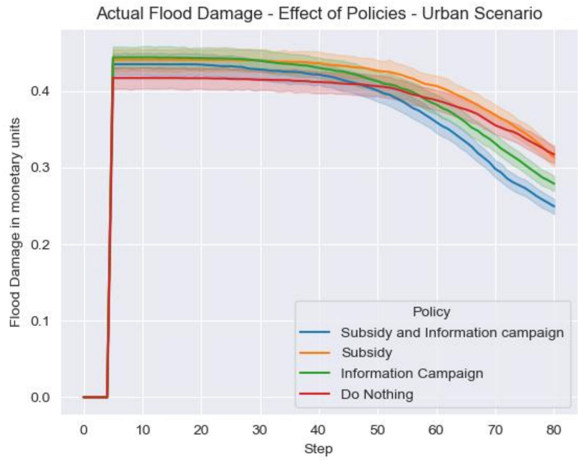


Figure 18: *Effect of policies on the actual flood damage over time*

For the "Urban" demographic the results are shown in Figure 17 and Figure 18, respectively.

For the share of adapted households, vastly similar results can be concluded as compared to the Baseline scenario. Looking at the Actual Flood Damage, however, reveals interesting insights:
Firstly, the effect of Policy 1 "Subsidy" is not visible; it does not show a substantial difference compared to the "Do Nothing" policy. This could be logically explained as people in urban regions already have a higher average income, and therefore the financial support doesn't make a difference, hence, households already select more effective measures, see Figure 20 for further details.

Even more interesting insights can be gained by a look at the Actual Flood Damage:
In general, the policy interventions have less impact on the Actual Flood Damage in the Urban demographic, compared to the Baseline or the Suburban scenario, meaning that the average actual damage is higher for the Urban demographic, independently of the policy intervention. A closer look at the Actual Flood Damage reveals that "Subsidy and Information Campaign" have the best effect on the indicator.

The analysis reveals a significant difference between the effectiveness of policy lever 2, "Information Campaign," and the combined policy approach. In the Urban scenario, the "Information Campaign" significantly increases the Willingness to Protect. However, for an optimally effective outcome, an additional financial subsidy is crucial. This financial support enables agents to take the most effective actions in flood protection. Therefore, in urban areas, the combination of raising awareness through information campaigns and providing financial support proves to be the most effective strategy for enhancing flood protection measures.

3.5.4 Scenario Comparison

A comparative analysis of scenarios with regards to the Actual Flood Damage (Figure 19) highlights the varying effectiveness of policies across demographics. Suburban regions benefit more from "Information Campaigns" and "Subsidy and Information Campaigns," leading to lower flood damage and more stable outcomes. In contrast, Urban regions require a combined approach for substantial impact. The distribution of the indicator for the "Information Campaign" and the "Subsidy and Information Campaign" in the Suburban region is more dense. This could imply that these two policies are not only effective for the Suburban demographic, but also lead to a more precise outcome.

A detailed look on **??** taken reveals that

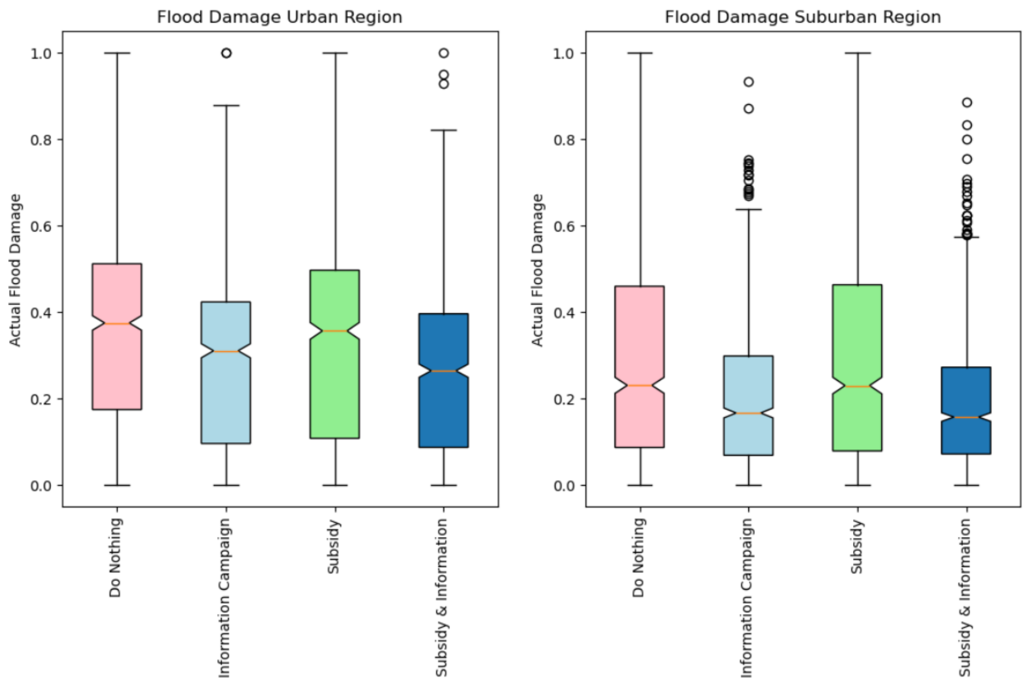


Figure 19: Comparison of Scenarios on Flood Damage and Share of Adapted Households

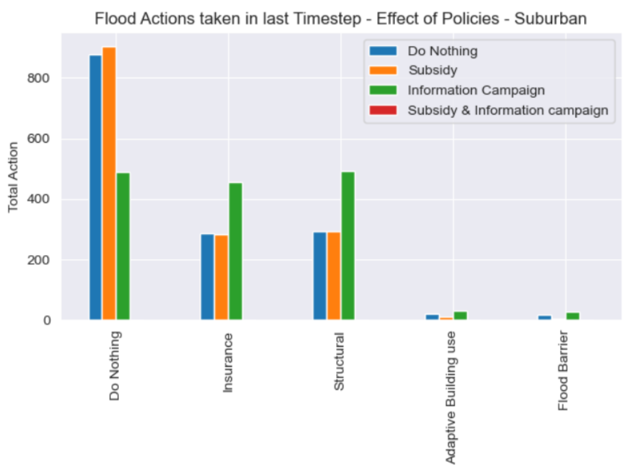


Figure 20: Flood Actions taken - Suburban

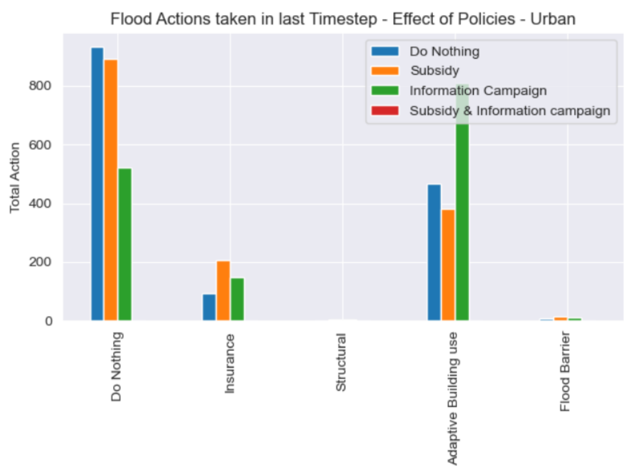


Figure 21: Flood Actions taken - Urban

4 Conclusion

4.1 Discussion

4.1.1 Limitations

Observer dependence: this model is influenced by the worldview of the creaters, this creates objectivity. Because of this objectivity in the ideal world this model would also be made multiple times by other poeple with other world views. That the model is not objective does not mean it is not useful.

Once a household has crossed the threshold of W2P and decides on an action to invest, it will be secured of protection for the rest of the timesteps run.

References

[1] Toon Haer, W. J. Wouter Botzen, and Jeroen C. J. H. Aerts. "The effectiveness of flood risk communication strategies and the influence of social networks—Insights from an agent-based model". In: *Environmental Science Policy* 60 (June 2016), pp. 44–52. DOI: 10.1016/j.envsci.2016.03.006. URL: https://doi.org/10.1016/j.envsci.2016.03.006.

[2] Brayton Noll, Tatiana Filatova, and Ariana Need. "One and done? exploring linkages between households' intended adaptations to climate-induced floods". In: *Risk Analysis* 42.12 (Feb. 2022), pp. 2781–2799. DOI: 10.1111/risa.13897. URL: https://doi.org/10.1111/risa.13897.

[3] Jackie Kazil, David Masad, and Andrew Crooks. "Utilizing Python for Agent-Based Modeling: The Mesa Framework". In: *Social, Cultural, and Behavioral Modeling*. Ed. by Robert Thomson et al. Cham: Springer International Publishing, 2020, pp. 308–317. ISBN: 978-3-030-61255-9.

[4] ABC13. "Several Houstonians focused on protecting properties for future flood events". In: (2023).

[5] B.L. Noll. *How a changing climate is changing behavior: household adaptation to floods*. 2023. URL: https://doi.org/10.4233/uuid:0d49cb3e-6dd8-4a9e-abc6-b847de938aea.

[6] Avni Pravin. "Environmental justice and flood adaptation: a spatial analysis of flood mitigation projects in Harris County, Texas". In: (2018). URL: https://scholarsbank.uoregon.edu/xmlui/bitstream/handle/1794/24540/Pravin_oregon_0171N_12381.pdf?sequence=1&isAllowed=y.

[7] J Huizinga. *Global flood depth-damage functions*. Tech. rep. European Commission, Joint Research Centre, 2017. DOI: doi:10.2760/16510.

[8] Donna L. Floyd, Steven Prentice-Dunn, and Ronald W. Rogers. "A Meta-Analysis of Research on Protection Motivation Theory". In: *Journal of Applied Social Psychology* 30.2 (Feb. 2000), pp. 407–429. DOI: 10.1111/j.1559-1816.2000.tb02323.x. URL: https://doi.org/10.1111/j.1559-1816.2000.tb02323.x.

[9] Philip Menard. "Putting the 'Motivation' in Protection Motivation Theory: An Examination of Persuasive Communication via Extrinsic and Intrinsic Means". In: 2014. URL: https://api.semanticscholar.org/CorpusID:54629223.

Appendix A: Description of Willingness to Protect and Modeling Assumptions

A1. Willingness to Protect (WTP)

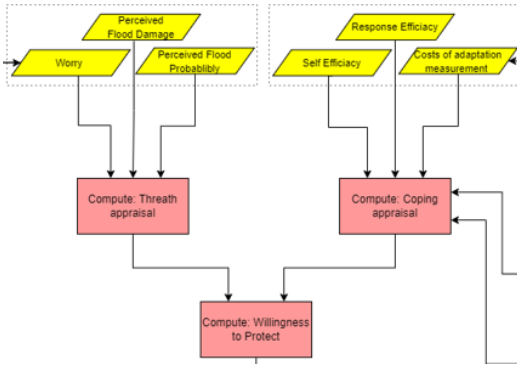


Figure 22: *Conceptualization of computing WTP*

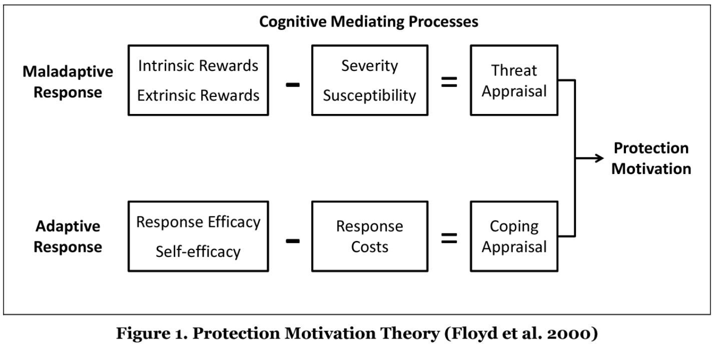


Figure 23: *Computation of Protection Motivation Theory [8]*, [9]

WTP is calculated through two primary variables: threat appraisal and coping appraisal, derived from six variables as shown in Figure 23.

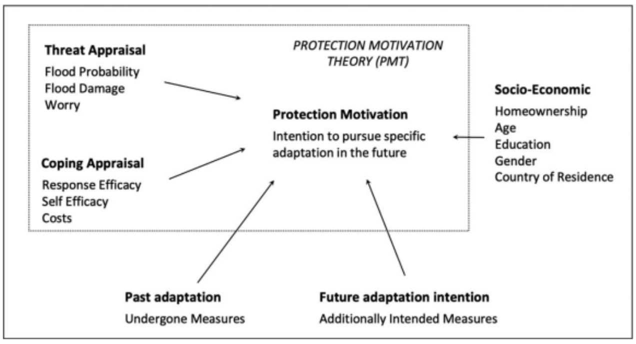


Figure 24: *Factors driving households' adaptation intentions [2]*

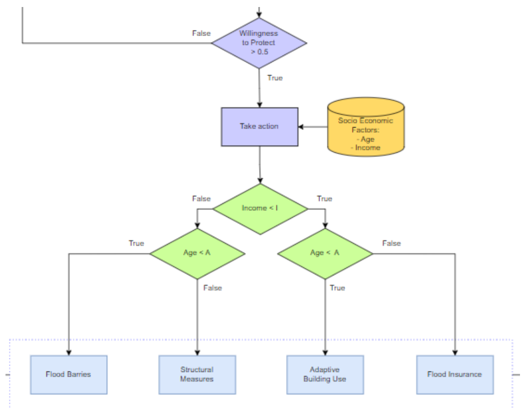


Figure 25: *Control of socioeconomic factors on the decision*

Figure 23 and Figure 24 represent the six variables that comprise the base of PMT, socioeconomic control variables, as well as the effects the past and additionally intended adaptation actions can have in influencing a protection motivation decision regarding a specific adaptation [2].
Figure 25 depicts the decision-making process on selecting an adaptation measurement.

A2. Modelling Assumptions

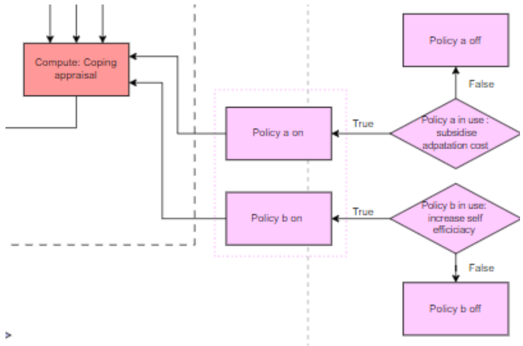


Figure 26: *Conceptualisation of the impact of policy levers on coping appraisal*

The following shows a list of all assumptions

- **Social Influence**: The more your neighbors invest, the more you are willing to adapt as well. Because of social pressure and scale of economies to get the adaptation cost down [1].
  - Initially, all agents in the model are assigned the same cost values, regardless of their differences.
  - The cost variable is always equal to one, in each time step it is updated based on the investment of neighbors by using the following formula Households.self.cost = 1−0.3×Cumulative_investment_neighbors
- **Adaptation Measures**:
  - The selection of adaptation measures, is solely influenced by their age and income, as illustrated in Figure 26. This represents a model limitation, as it does not fully represent the real-world scenario where households might use multiple adaptation strategies simultaneously.
    Adaptation options in order of effectiveness:
    * Flood barriers
    * Structural measures
    * Adaptive building use
    * Flood insurance

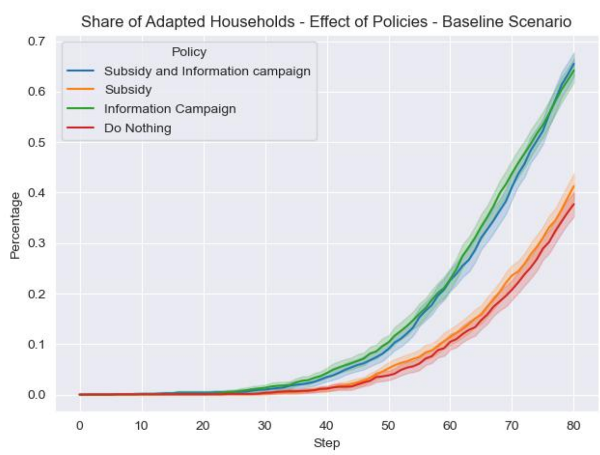
    The order is based on the different measurements that can be taken in the research of [1].
  - The effectiveness of adaptation actions (e.g., flood barriers, structural measures) is simplified and may not reflect the variety of outcomes in real scenarios.
  - The past adaptation has a generally small and insignificant effect on the future intention to adapt [1]. Consequently, this aspect is excluded from the model. In practical terms, this means once an agent in the model decides to take adaptive action, it is not able to take any further action in the following steps.
  - When an action is taken this will always have the same effect overall subsequent timesteps on the decrease in actual flood damage. However, in real life, the effect of some actions might decline over time.
- **Government Policy**:
  - Polic lever 1, "Subsidy" affects the income threshold only after an agent decides to adopt a measure. Consequently, this does not translate into a higher adoption rate, contradicting real-world expectations where a subsidy should not only enable households to choose more costly and effective measures but also increase the overall adoption rate.
  - Policy lever 2, "Informative campaigns" focuses on increasing coping appraisal, as this is considered an effective way of influencing households' decision-making [1].
  - The model assumes that government policies have a uniform impact on all agents, disregarding individual variations in response to these policies.
- **Dynamic Worry Variable**: Worry is assumed to increase over time if no adaptation measures are taken. Contrary, it decreases when households take action, with the decrease dependent on the effectiveness of the action.

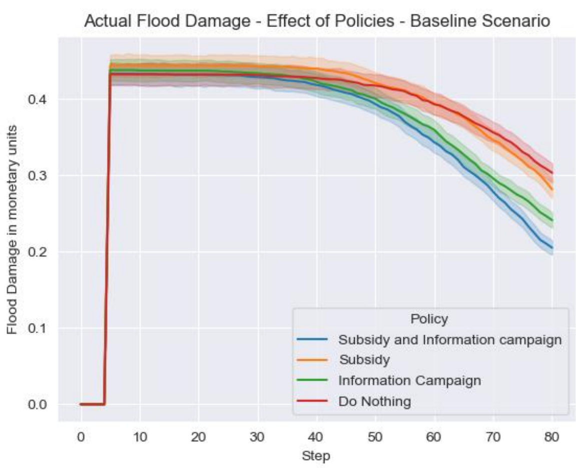
- **Static Age of Agents**: The model operates under the assumption that agents do not experience aging, despite the passage of a 20-year time frame within the simulation.
- **Exclusion of External Factors**: Factors external to the direct model environment, such as wider economic conditions, cultural influences, or long-term climate changes, are not considered.
- **One Flooding at Step 5**: Only a single flooding event at Step 5 of the simulation. The model has a static environmental response to flooding, not accounting for changes over time due to climate change.

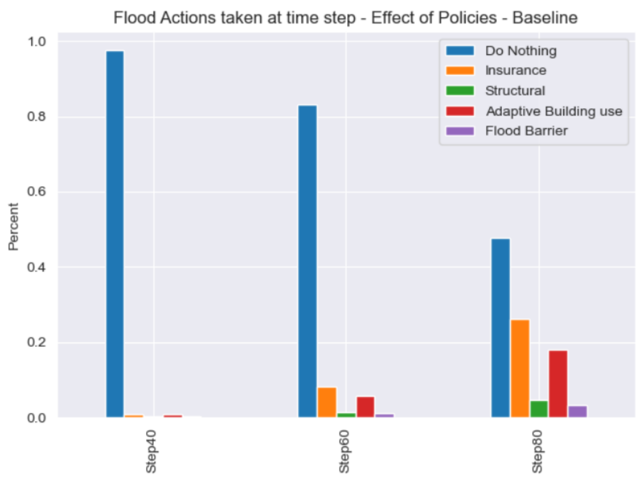
A3. List of Variables and Descriptions

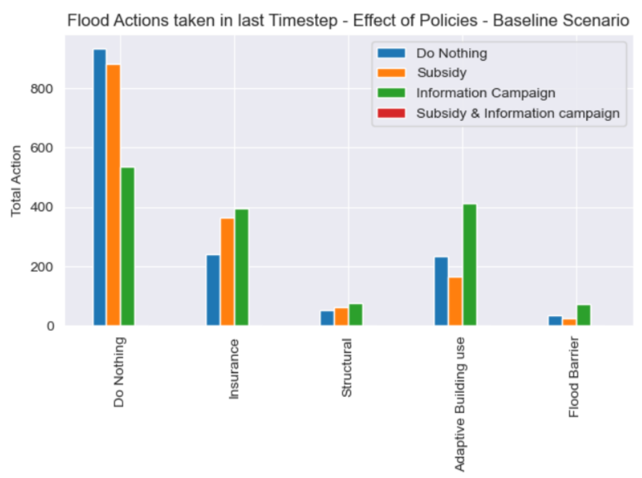
- **Perceived Flood Probability**: Perceived probability of a flood event occurring at the household's residence.
- **Perceived Flood Damage**: Perceived consequence of a flood event.
- **Worry**: It is initially set as a random variable, ranging between 0 and 1, and functions as an amplifier in the threat appraisal process. This means that worry intensifies how a household perceives the threat of a flood, potentially influencing their decision-making regarding adaptation measures. Its initial random assignment reflects the variability in individual psychological responses to potential flood risks.
- **Self Efficacy**: Household's estimate of its ability to implement a specific flood mitigation measure.
- **Response Efficacy**: Household's estimate of the effectiveness of a specific flood mitigation measure
- **Costs**: This variable represents the financial implications of flood protection measures, influenced by the average investment level of neighbors.

5 just stuff - scrap









all figures

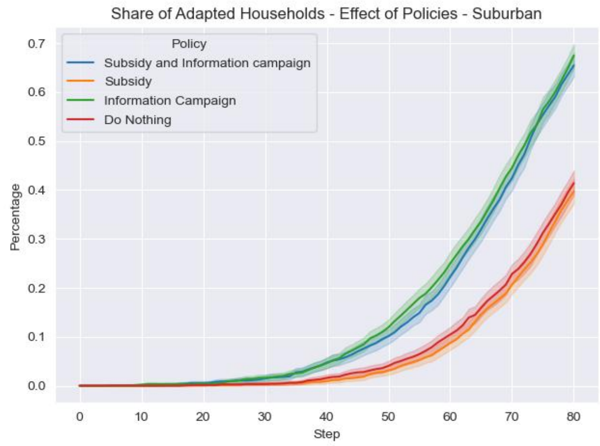


Figure 27: *Effect of policies on the share of adopted households over time*

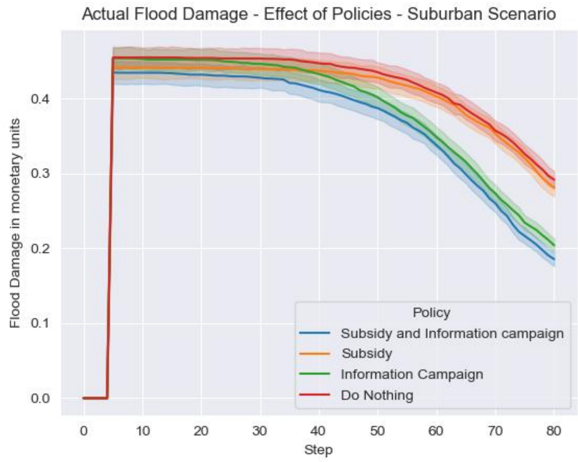
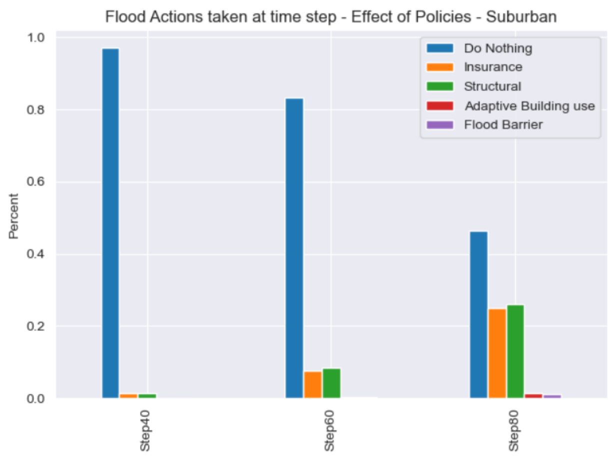
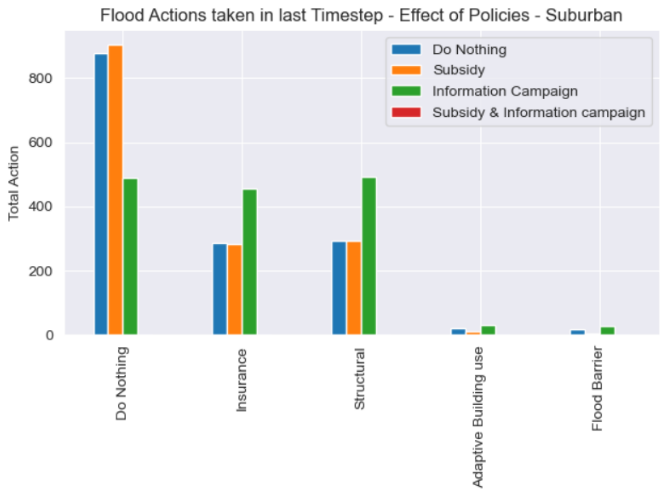
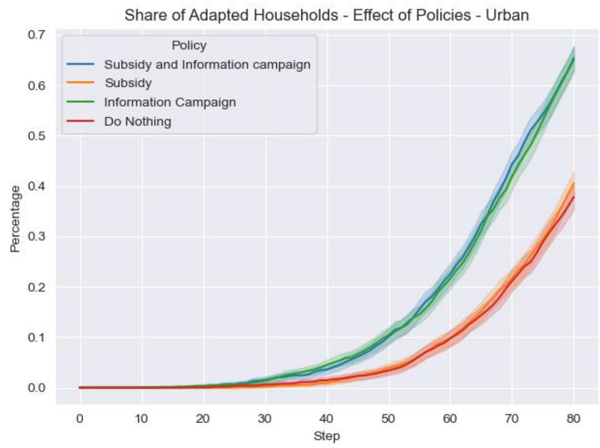
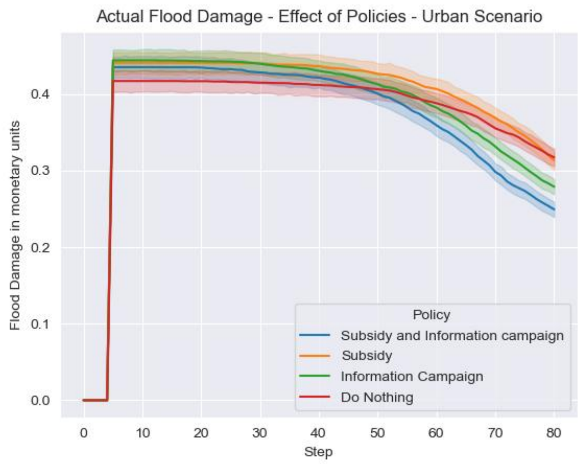


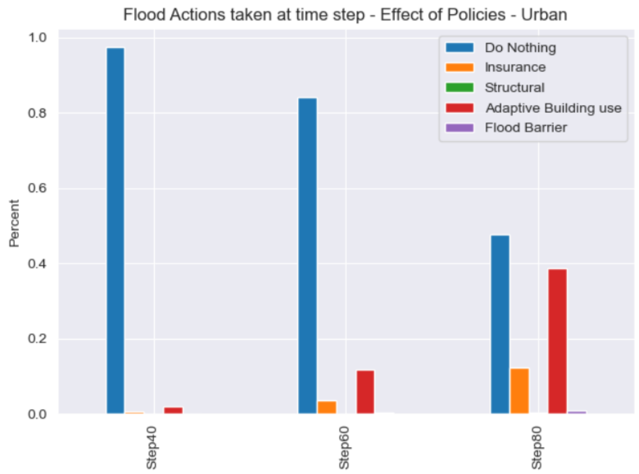
Figure 28: *Effect of policies on the actual flood damage over time*

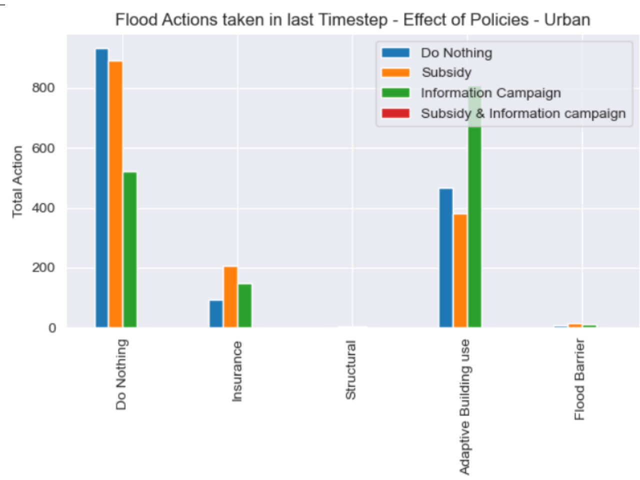





Share of Adapted Households - Effect of Policies - Urban
Policy
Subsidy and Information campaign
Subsidy
Information Campaign
Do Nothing
Percentage
Step


Actual Flood Damage - Effect of Policies - Urban Scenario
Flood Damage in monetary units
Policy
Subsidy and Information campaign
Subsidy
Information Campaign
Do Nothing
Step


Flood Actions taken at time step - Effect of Policies - Urban
Do Nothing
Insurance
Structural
Adaptive Building use
Flood Barrier
Percent
Step40
Step60
Step80


Flood Actions taken in last Timestep - Effect of Policies - Urban
Do Nothing
Subsidy
Information Campaign
Subsidy & Information campaign
Total Action
Do Nothing
Insurance
Structural
Adaptive Building use
Flood Barrier