Understanding similarities in agent biases during flood resilience

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SEN1211 Agent-based Modelling

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Table of contents

Introduction

Climate change has emerged as a critical global issue in recent years and is projected to remain a key focus into the future. Among the pressing goals is achieving climate neutrality by 2030, a target that requires adherence to numerous stringent regulations. A significant consequence of climate change is the rise in global temperatures, which contributes to higher sea levels and, consequently, an increased frequency of floods worldwide. Our project centres on Harris County in Texas, USA, where we aim to model flood adaptation strategies among different households (SEN1211 Final Project for the academic year 2023/2024) .

Floods in Harris County, Texas, have been a recurring natural disaster, posing significant challenges to residents and policymakers alike. This region, which includes Houston, is particularly prone to flooding due to its flat terrain, clayey soil, and the prevalence of tropical storms and hurricanes from the Gulf of Mexico. Notably, Hurricane Harvey in 2017 was a stark reminder of the area's vulnerability, causing catastrophic flooding and immense damage. In recent years, Harris County has experienced a notable increase in flood events. Between 2015 and 2017, the county endured three major floods. These floods resulted in billions of dollars in damages and highlighted the urgent need for flood mitigation strategies (https://www.hcfcd.org/About/Harris-Countys-Flooding-History).

Agent-Based Modeling (ABM) has emerged as a crucial tool in understanding and managing flood risks in Harris County. ABM is a computational modelling approach that simulates the actions and interactions of autonomous agents (in this case, households) to assess their effects on the system as a whole. By incorporating diverse factors such as household characteristics, economic status, geographical location, and personal experiences with flooding, ABMs can provide insights into how different households are likely to respond to flood risks and adapt over time.

This model focuses on the Reusable Building Block (RBB) of similarity bias between different agents. Similarity bias is an unconscious bias. It occurs when individuals have a preference for someone who is similar to them. In a model these could be attributes that define an agent. The model will look into the different attributes agents may have and how these attributes make an agent have different choices. Therefore the research question is:

“ How does similarity bias among agents affect flood adaptation strategies within a modelled urban environment, and what implications does this have for the resilience of different community groups?”
“How does similarity bias under various parametrizations among agents affect the total number of agents that take flood adaptation measures and the total amount of flood damage within a modelled urban environment?

To answer the question, a RBB will be made that works in the model that was given.

Method

Modelling Technique

In the scope of this research, the construction of an Agent-Based Model (ABM) is proposed. This methodology is employed to delineate complex interactions and behaviours amongst a multitude of autonomous agents. Specifically, the ABM serves to elucidate system-level dynamics that are the culmination of intricate interplays among individual entities within the model, referred to as agents. Each agent is characterised by distinct attributes and rules of engagement, facilitating interactions with other agents. These interactions are pivotal in engendering emergent behaviours within the system. The development of the model has been executed using Python as the programming language, within the integrated development environment of PyCharm. In the Agent Based model libraries like ´networkx´, ´mesa´, and ´geopandas´ are used.

Conceptualisation

In this section, we elaborate on the model's design and demarcate its system boundaries. The focus of the model is on flood adaptation strategies within Harris County, Texas. To this end, the model comprehensively encompasses the geographical and infrastructural elements of Harris County, including households, topographical features like mountains, and the river system. The urban layout of Harris County is abstracted into a graph-based representation, where various nodes symbolise specific locations or entities within the city. The connections between these nodes, represented as links, are conceptualised to for example mirror the connections between households in the region.

System boundaries

We will model de occurrences of a potential flood and therefore the flood adaptation strategies within the community of Harris county. The system boundary is therefore the region of Harris County, Texas, with its inhabitants, rivers and mountains.

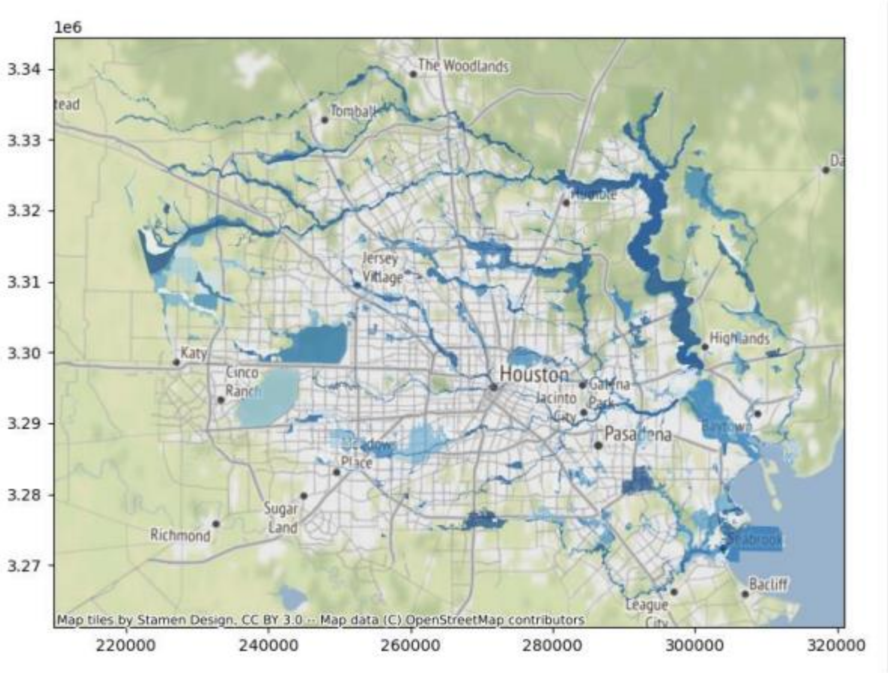

Figure 1: Map

Time

In regards to the time, the model consists of 80 timesteps. Four timesteps represent a whole year. The occurrence of the flood will be on tick 5, but can be adjusted in the initial values. So a flood can occur whenever we want. This needs to be changed in the model settings.

Description

In the model's cartographic representation, various elements such as rivers, households, and mountains are distributed across the map, each denoted by nodes. The spatial position of each household node is subject to variation in each simulation run. Initially, all households are depicted as red dots, signifying they do not have an adaptation to flood risks. The model's geographical landscape is constructed leveraging a multitude of data sources, including the selected flood map and the total number of households. Each household, represented on the map as a distinct node, maintains linkages to other nodes. These connections symbolise the social networks existing among the households and can be adjusted at any time.

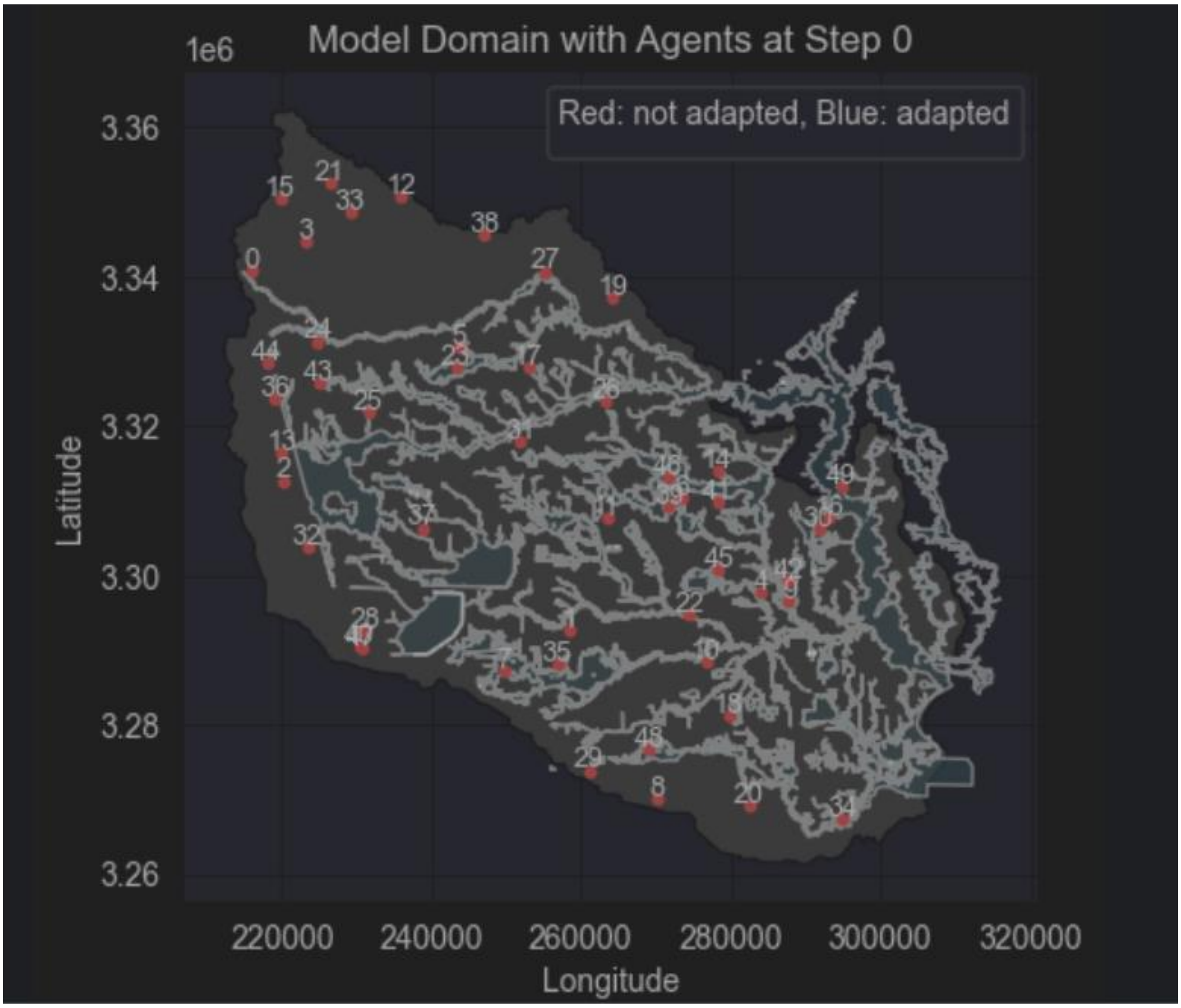

Figure 2: Model map

Like the amount of social connections, there are a few other variables in the model setting we can adjust to influence the output. For example, in the model, we can adjust the number of households in the model settings. As well as the probability of the likeliness of an edge to be created between two nodes, a network connection. Via a random function, we determine which households have children. If so, the attribute 'Household.has_child' becomes true. For each agent, an identity is calculated that consists of a few factors.

Child

As described above, the first factor is 'has_child'. If a household has no child, this factor will be false. When a household does have a child, the value becomes true. In Harris County, 40% of the households have children (Houston Public Health Data Portal, 2023). Therefore, a factor value of 0.4 is included in the model to calculate the number of households with children. This percentage is also a variable that we can adjust during modelling to examine different results.

Wealth

A second factor used in the model to calculate the identity of each household is the Wealth Factor. This factor describes the influence of wealth on a household's identity. The Wealth Factor is divided into four categories:

- Low income (Value = 0)
- Below average (Value = 1)
- Above average (Value = 2)
- High income (Value = 3)

The wealth value for each household is obtained via a uniform distribution.

House size

A third factor influencing the identity of each household is house size. For this factor, as with the wealth factor, a uniform distribution will be used to determine its value. Therefore, the house size must be divided into a few categories that represent the different types of houses in Harris County, Texas. In the model, there are two types of house sizes: small (0), medium (1), big (2).

House type

In addition to the factor of house size, we also consider different house types, which are represented using a uniform distribution. Therefore, this factor must also be divided into two categories: Apartments (assigned a value of 0) and freestanding houses (assigned a value of 1).

Education level

In the model, each household has a certain level of education, which has an influence on the possible flood adaptation strategies. It is likely to conclude that households with high education levels have a better flood adaptation strategy than households with a low level of education. The education level is also calculated with the use of a uniform distribution. Here, the different categories are:

- Low level (0)
- Medium level (1)
- High level (2)

Social preference

This factor represents whether a household is more introverted or extroverted. When a household is more introverted, it often does not speak much with neighbours or connections in their network, potentially resulting in being less influenced by other households. Being extroverted indicates that the household frequently engages in conversations with their neighbours. This factor is measured on a scale ranging from -1 (introverted) to 1 (extroverted).

Age

Each household in the model is assigned an age, which influences its identity and consequently its approach to flood adaptation. The age is determined using a normal distribution, with specified parameters for the mean age and standard deviation. The age assigned to any household must be at least 18 years.

Conceptual model

Model interactions

Figure 3 illustrates a Vensim diagram showing the interactions within the model. Various factors interact with each other, leading to different outcomes, such as varied flood adaptation strategies. In the model, each household is linked to a number of other households in this so-called social network. The extent of these connections can vary based on the model settings. For example, the social network is influenced by three factors: flood adaptation observed in others, tolerance, and similarity. Tolerance indicates the 'flexibility' of a household to be influenced by nearby households. A higher tolerance leads to a larger social network, implying that the household can form connections more easily and be more susceptible to influence. The impact of others' flood adaptation strategies on these connections within the social network is not straightforward. Additionally, similarity negatively impacts the social network; when surrounding households are already similar, it does not necessarily enhance the network.

The social network itself positively influences the factor 'Bias Influence.' Having a large social network increases the likelihood of being influenced, leading to a positive correlation. However, the relationship between the social network and flood adaptations is uncertain. This uncertainty arises because it is unknown whether households are influenced by those with extensive flood adaptations or by those who take no flood-related actions. The link between flood adaptation and damage is clear and negative: more flood adaptations typically result in less damage during floods. Regarding damage, it has a positive correlation with biassed influence. When damage from a flood is high, households are likely to be influenced to prevent similar or increased damage in the future. Damage is also affected by two other factors: floods and the household’s location on the map. Floods have a direct positive correlation with damage, as more floods lead to more damage. The relationship between a household's location on the map and damage is variable due to the differing locations of households in the model.

Finally, we consider the factor of flood estimate. This factor represents a household's expectation of the likelihood of future floods, which is based on their location on the map. Consequently, it has a positive correlation with the factor of damage. A high flood estimate often indicates that the damage following a flood will be greater, attributable to a vulnerable location. The relationship between a household's location on the map and their flood estimate is uncertain. As mentioned earlier, the variability in locations can lead to diverse flood estimates.

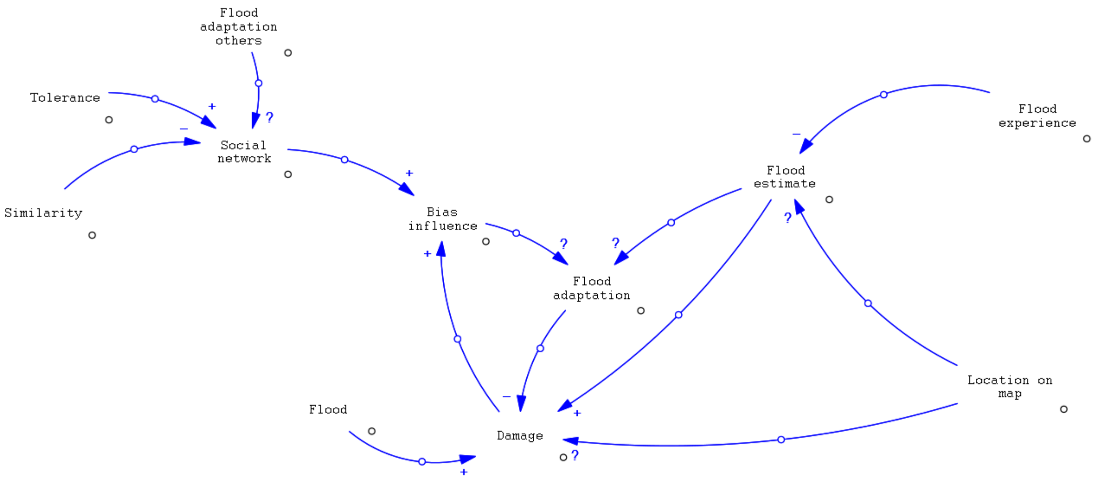

Figure 3: Vensim diagram

State diagram household

The first conceptual model presents a state diagram of the household agents who are modelled. A state diagram shows how households can change from one state to another during the model's timeframe. In the initial phase, most of the households are not yet adapted to the potential event of a flood, but some are already adapted. These are shown on the left-hand side of the model. From the initial state, the households move to the second state, the perception update. Here, households update their perceptions of flood risks. This could be influenced by a variety of factors, like their experience with flood events, whether they have children, and their biases. From this phase, we move to the third possible phase, called decision making. Based on their updated perception, households decide whether to take adaptation measures. If the household decides to take flood adaptation measures, they move to the phase called adaptation action. Once adaptation measures are implemented, the household enters a state where it is better protected against floods; this is the post-adaptation state. When a flood occurs, all households face the event, but the impact varies based on their adaptation measures. After a flood event, households can influence each other through social networks, sharing information and experiences about flood risks and adaptation measures.

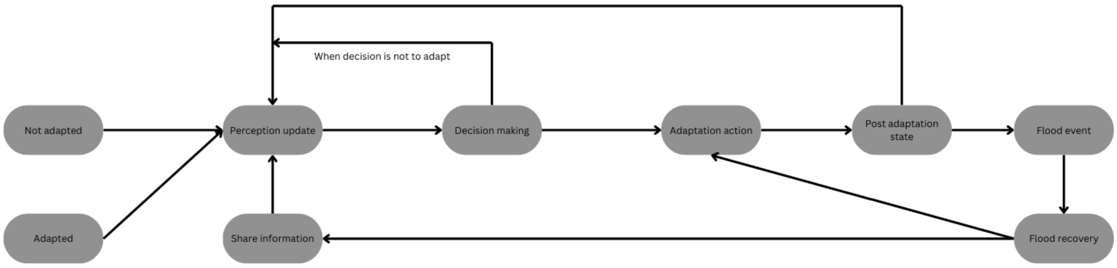

Figure 4: State diagram

Formalisation

This chapter shows a formalisation of how the conceptualisation develops in a model. The model is made in python using various libraries and packages, among the most prominent being Mesa and Networkx.

Map and visualisation

The map of Harris County has been implemented in Python using NetworkX to create a graph representation. The model domain, along with the agents at time step 0, is depicted in the figure within the model section. During this research, our focus was primarily on the connections between households, referred to as network connections, which are represented as links between the nodes. At time step 0, the connections between nodes are established, and their quantity is determined by the model settings. Initially, no household has implemented flood adaptation measures.

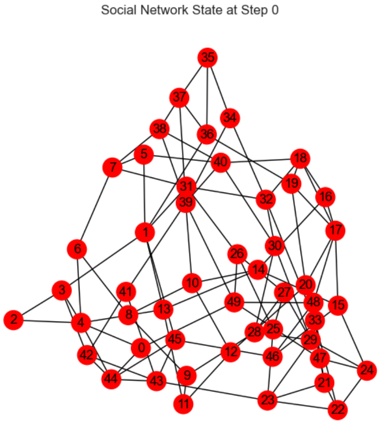

Figure 5: Social network

Environmental specifications

To ensure our model functions effectively and reflects real-world dynamics, we have integrated geographical data into the conceptual framework. This integration is achieved using the code outlined below. This choice is a simplified rationale for selecting a flood map representation.

```
flood_map_choice='harvey',
```

Figure 6: Flood map

In addition to geographical data, the model also incorporates flood risk areas into the environmental specifications. This delineates which households are situated in regions with an elevated risk of flooding. Ultimately, the network's structure is defined as a Watts-Strogatz type, facilitating the study of social connections within the community.

```
if network_type is None:
    network_type = 'watts_strogatz'
```

Figure 7: Network type

Variables

This section shows a list of all the input variables that are being used in the model. The table shows the variables with their description, the type of variable, the default value in the initial state and a brief explanation about the variable's meaning.

Variable	**Description**	**Type**	**Default value**	**Notes**
flood_map_choice	Choice of flood map (‘havey’, ‘100yr’, ‘500yr’)	String	‘Harvey’	Determines the flood risk map to use
network_type	Type of social network ('erdos_renyi', 'barabasi_albert', etc.)	String	‘watts_strogatz’	Defines the network topology
num_households	Total number of household agents	Integer	25	Initial number of agents in the model
Prob_network_connection	Probability of creating an edge between two nodes	Float	0.4	Used for network generation
num_edges	Number of edges for Barabási-Albert network	Integer	3	Relevant if 'barabasi_albert' network is chosen
num_nearest_neighbours	Number of nearest neighbours for Watts-Strogatz network	Integer	5	Relevant if 'watts_strogatz' network is chosen
flood_time_ticks	Simulation time steps when flooding occurs	List of integers	[5]	Timesteps for flood events

random_seed	Seed for pseudo-random number generation	Integer	1	Ensures reproducibility of the simulation
wealth_factor	Importance of wealth in household identity	Float	None	To be specified
wealth_distribution_type	Distribution type for wealth attribute	String	‘UI’	UI: Uniform, N: Normal, etc.
has_child_factor	Importance of having children in household identity	Float	None	To be specified
house_size_factor	Importance of house size in household identity	Float	None	To be specified
house_type_factor	Importance of house type in household identity	Float	None	To be specified
education_level_factor	Importance of education level in household identity	Float	None	To be specified
social_preference_factor	Importance of social preference in household identity	Float	None	To be specified
age_factor	Importance of age in household identity	Float	None	To be specified

household_tolerance	Level of tolerance for influence from different agents	Float	0.15	Tolerance range for agent interactions
bias_change_per_tick	Degree of bias change per simulation tick	Float	0.2	Influences the rate of change in agents' bias
flood_impact_on_bias_factor	Impact of actual vs. expected flood damage on bias	Float	1	Adjust the bias based on flood impact
prob_positive_bias_change	Probability of positive bias change towards adaptation	Float	0.5	Likelihood of increasing bias towards adaptation
prob_negative_bias_change	Probability of negative bias change away from adaptation	Float	0.1	Likelihood of decreasing bias away from adaptation
adaption_threshold	Bias threshold required for a household to adapt	Float	0.7	Threshold for adaptation decisionmaking

Table 1: Variables

Processes

This section breaks down essential steps in the model's operation. During initialisation, the social network forms, agents are placed, and attributes are assigned. In the model run, events like floods impact biases, leading to adaptive changes, and agents age over time. Agent adaptation and visualisation show how the model reacts to outside influences. Understanding these steps helps grasp the model's dynamic behaviour, offering insights into how it simulates interactions and responds to events like floods.

Processes during initialisation

1. Network initialisation

Initialization process	Description
Network type	The social network is initialised based on the specific network type "watts-strogatz"
Generate graph	A social network graph is generated with the specified number of households and parameters
Assign nodes/edges	Nodes and edges are assigned based on the social network type

Table 2: Initialization process

2. Agent initilisation

Process	Description
Create model	Create a model with a specified number of households
Place agents	Each agent (household) is placed on a node of the network graph
Generate attributes	For every household agent, attribute values will be generated based on different distributions.
Identity	All attributes will generate one number together that will result in the identity of an agent

Table 3: Agent initialisation

Processes during Model Run:

Model Run Process	Description
Flood Event	Flooding event at time step 5 that affects agents
Calculate what impact flood damage has on the bias	After the flood the actual damage minus the estimated damage is calculated and this number will be multiplied by the `flood_impact_on_bias_factor`, which will result in the impact flood damage has on the bias.
Bias change	Agents' bias is changed based on the similarity of opinions within their social network. This is done with a probabilistic change that is positive or negative
Agent Adaptation	Adaptation of agents' biases based on the actual flood impact, considering a specified threshold for adaptation.
Visualisation	Model domain visualisation, showing the floodplain and the status of each agent (adapted or not).
Age	Age of all agents will increase with 0.25 every tick.

Table 4: Model processes

Pseudocode

This code defines a simulation model of households. Each household is represented as an agent and possesses various attributes like wealth, house type, size, presence of children, age, social preferences, and education level. The model also considers geographical aspects such as location in a floodplain, estimated flood depth, and corresponding estimated flood damage. Here's a breakdown of key components:

Initialisation:

- Each household is assigned initial attributes such as wealth, house type, size, and others, based on random values.
- Geographical aspects like location and flood-related attributes are also initialised.

Social Network:

- The model establishes a social network for each household, defining connections based on proximity within a specified radius.

Conviction Calculation:

- Conviction is a measure representing the household's initial inclination towards adaptation. It is calculated based on various factors like the presence of children, house size, education level, social preferences, and age.

Bias Change:

- The code defines a mechanism for changing biases within the social network. Each household evaluates the convictions of its social connections and adjusts its own bias accordingly.

Step Function:

- The step function represents the progression of the simulation over time.
- It includes a process for adapting to potential flood risks based on estimated damage and social network biases.
- The adaptation is influenced by a combination of estimated flood damage and the household's bias, with conditions triggering the adaptation process.

The model simulates the evolution of household adaptations in response to flood risks over time. Adaptation is influenced not only by individual factors such as wealth and education but also by social dynamics within the neighbourhood.

KPI’s

This research focuses on the similarity bias of agents. Are agents going to change their flood adaptation based on other agents that have a similar identity. As a result, the key performance indicators is the total bias change of agents, the total households houses that are adapted

Key Performance Indicators (KPI’s)	Description
Total bias change agents	change in bias among all modelled agents
Total adapted households	Overall number of households that have adapted
Flood damage	Damage caused by floods within the model

Table 5: KPI's

Assumptions and model reductions

During the making of the Reusable building block assumptions were made to simplify the model and due to time limit, information gaps and resource limitations. These assumptions helped in making the model more comprehensible. Assumptions that were made by the model beforehand are not mentioned, such as the random flood depth, where the flood depth is randomly generated within a specific range.

Assumptions/ Model reductions	Clarification
Identity of agents	It is assumed that the identity is made up out of 7 attributes that all contribute the same amount. Almost every attribute is randomly given at the beginning of the model. The attributes that are being discussed are: - Age - Wealth - Has a child - House size - House type - Education level - Social preference
Flood impact calculation	Our model assumes that the impact of flooding on the agent's bias is decided by the flood depth, the bias in the network of an agent and the actual flood impact on bias.
Bias change	It is assumed that the probability of positive and negative bias change is between certain parameters.
Social network influence	We assume that agents are only influenced by agents in their social network. The social network is also formed with the ‘watts-strogatz’ type
Actual flood	The model now creates the flood at step 5 of the model.
Agent ageing	Our model assumes that everyone ages at the time time with a fixed amount (0.25)
Agent attributes	Our model assumes that attributes like wealth and house size are distributed within a specific range. Furthermore, the age of agents is normally distributed with a specific mean and standard deviation
Agent tolerance	It is assumed that agents have a tolerance of 0.15. Agents are only influenced by agents with a similar identity with the tolerance as parameter.
Flood adaptation	Our model assumes that agents cannot change their adaptation decision

Table 6: Assumptions and reductions

Results

Scenario 1: Investigating size of social circle

The first scenario that was tested was to vary the amount of connection that neighbours had. The number of neighbours varied with 2, 5 and 8 connections. As seen in the figures below, the number of neighbours has a positive effect on the bias change in the network. Further it is seen that the total number of households is higher when the number of connections are higher. In the last figure the higher number of connections also has a higher number of adapted houses, but the relation with flood damage is not really seen.

In the initial exploration, the effects of varying the number of connections among neighbours, focusing on 2, 5, and 8 connections, were tested. The results illustrated in Figures 1 to 4, offer valuable insights into the dynamics of flood adaptation strategies within our agent-based model.

To understand the impacts of social connectivity on flood adaptation, the intentional manipulation of the number of connections among neighbouring households was done. This experiment holds significance as it allows a test to look at the patterns in bias change, total household numbers, adaptation rates, and their relation to flood damage.

These findings came during the results

Positive Correlation with Bias Change:

- Figure 1 demonstrates a positive link between the number of connections and the observed bias change in the network. Simply put, more connections lead to more noticeable shifts in individual biases.

Higher Connections, More Adapted Houses:

- Figure 2 delves into the relationship between the number of connections and the adaptation of houses. In the results it is seen that more connections translate to a higher number of adapted houses, indicating the role of social networks in fostering adaptive behaviours.

Complex Dynamics of Flood Damage:

- Figure 3 introduces complexity. While more connections lead to positive changes and prepared houses, their impact on flood damage isn't so simple. Understanding this part needs more investigation.

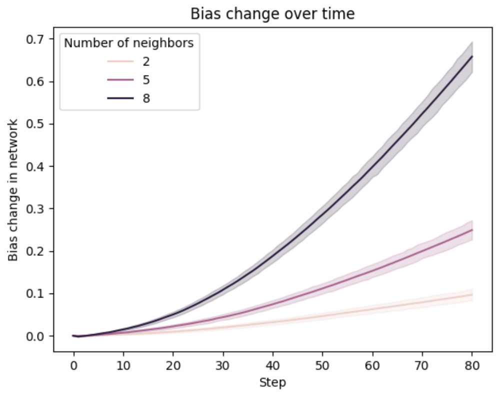

Figure 9: Scenario 1

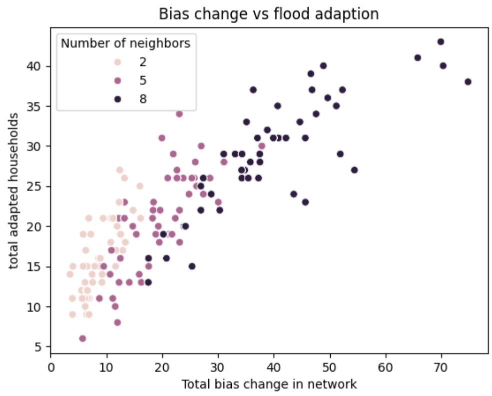

Figure 8: Scenario 1

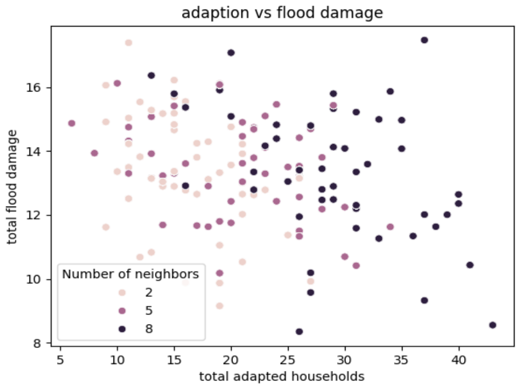

Figure 10: Scenario 1

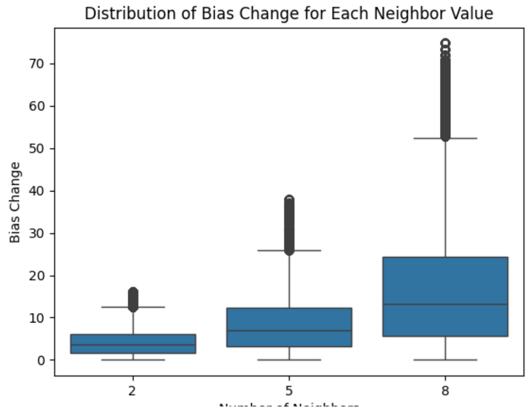

Figure 11: Scenario 1

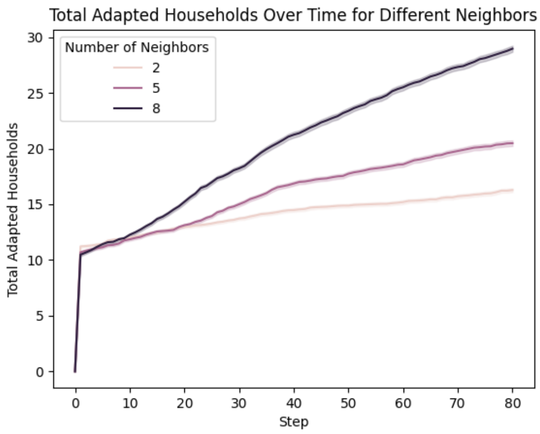

Figure 12: Scenario 1

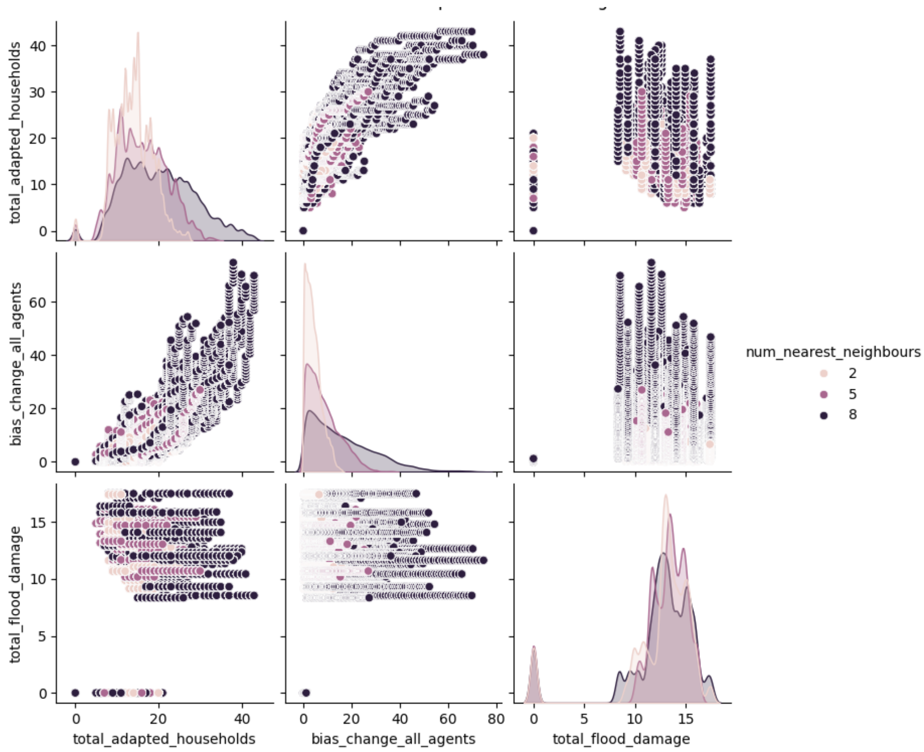

Figure 13: Scenario 1

Scenario 2: Investigating Flood Impacts

In the second scenario, the focus was on understanding the effects of floods on individuals. A total of 50 simulations were conducted in two different conditions. In the first set, under "normal" circumstances, occurring at tick 20 with factors of 0.5 and 1.2. In the second set, labelled "chance," the likelihood of severe flooding increased, with impact factors elevated to 1.5 and 2.2.

This exploration aimed to uncover how varying levels of flood impact influence the responses of individuals in the simulation. By examining these scenarios, insights about how communities adapt to different flood risks within the simulated urban environment could be analysed.

The following findings came during the experiment.

Figure 1: Flood impact on bias change
- A higher flood impact on bias correlates positively with an increased bias change in the network. Following the flood at step 20, there is a noticeable rise in the network's bias change.

Figure 2: Total adapted households
- The total number of adapted households shows an increase after the flood occurred at step 20. The heightened flood impact demonstrates a positive effect on the overall number of adapted houses.

Figure 3: Flood damage and total adapted houses adapted

- As expected, there is a higher flood damage in Figure 3. All dots representing higher flood damage are situated at the right end of the table, where a greater number of houses have adapted. This indicates a correlation between increased flood damage and a higher number of adapted houses.

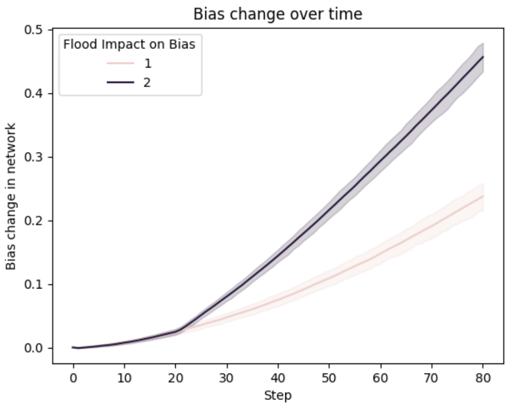

Figure 15: Scenario 2

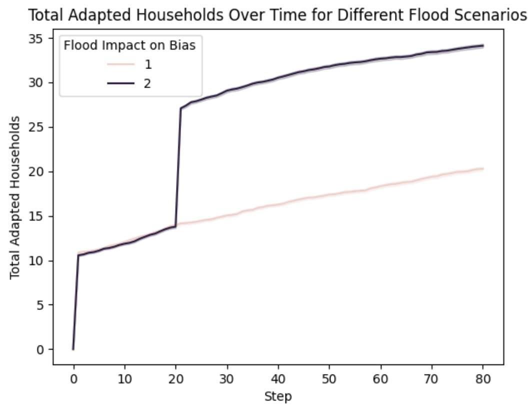

Figure 14: Scenario 2

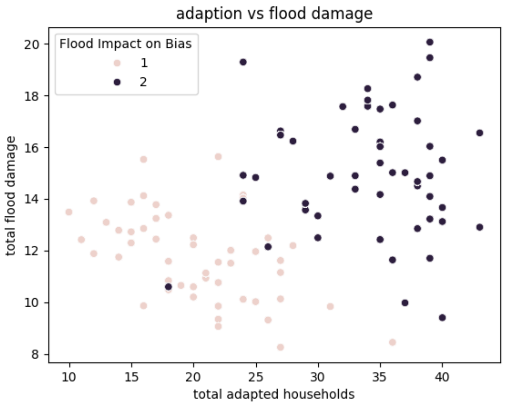

Figure 16: Scenario 2

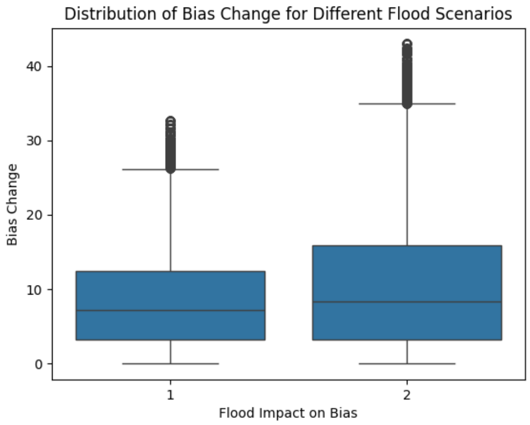

Figure 17: Scenario 2

Scenario 3: Exploring the impact of different adaptation threshold on agent bias

In the 3rd scenario, the investigations focused on the effects of varying the adaption thresholds on individual agent biases within the model. The adaption threshold was varied with 0.35, 0.7 and 1.15. The adaption threshold is calculated through a combination of estimated flood damage, network bias and actual flood impact on bias. The adaption threshold has an important role in shaping the adaptive decision of agents. By varying the threshold, more insight about the dynamics of similarity and implications for the resilience of different community groups

Findings
As seen in Figure ? a lower threshold has a positive effect on the agent bias. A higher threshold makes the agents more hesitant to adapt. It becomes clear that the threshold has an important role in the code.The scenario highlighted the challenge of finding the right balance in setting thresholds. Higher values led to collective resistance, showcasing the impact of similarity bias.

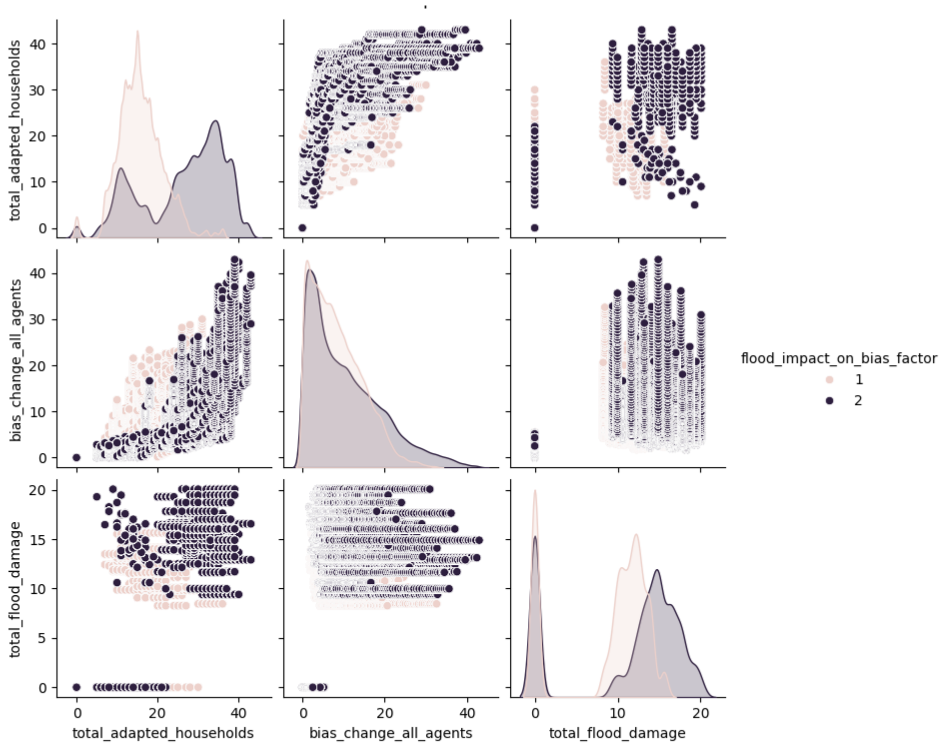

Figure 18: Scenario 3

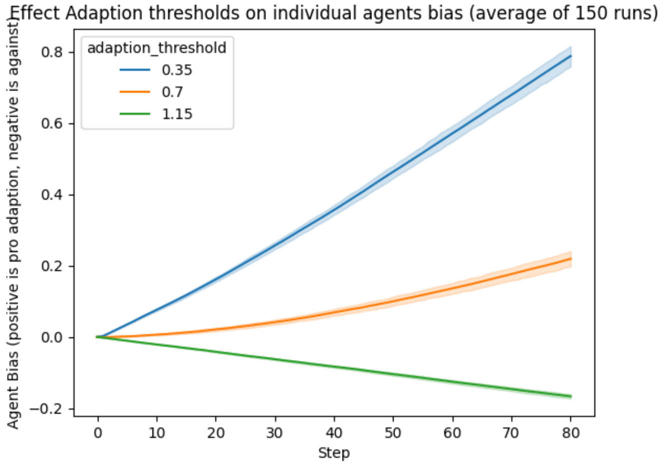

Figure 19: Scenario 3

Scenario 4: Varying Bias Change Probabilities

Introduction:
Scenario 4 delves into the impact of altering probabilities for agents to adjust biases within the flood adaptation model. By modifying these probabilities, the aim is to understand how they shape adaptive behaviours in our simulated urban environment. In the table below are the 4 combinations that were done in the experiment, to see what the effects of the positive and negative probabilities were.

	Combination 1	Combination 2	Combination 3	Combination 4
Positive	0,25	0,75	0,75	0,25
Negative	0,05	0,15	0,05	0,15

Table 7: Scenario 4 parameters

Findings:
In the two figures it can be seen that a higher positive and a lower negative probability has a higher effect on the total number of adapted households. This means that if people are more likely to respond positively to changing conditions and less likely to resist change, more households in the simulation adapt to the flood scenario.

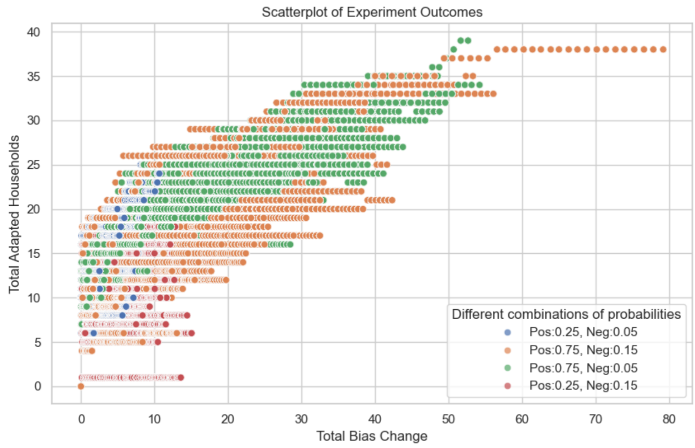

Figure 20: Scenario 4

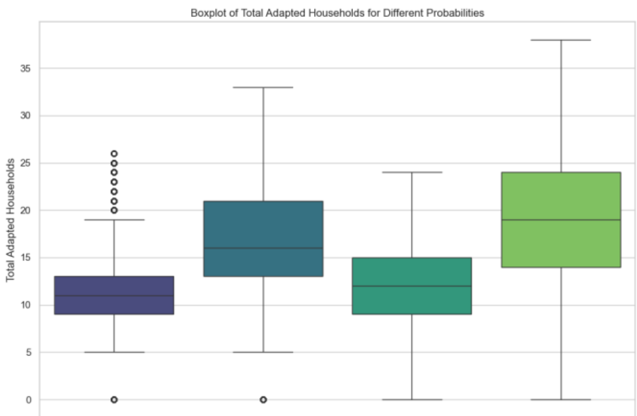

Figure 21: Scenario 4

Scenario 5: Homogeneous and Heterogeneous population

Introduction:
Scenario 5 looks at a situation where all households have the same identity. This would mean that they could interact with more people in their network, with the only different factor being the flood damage. To explore this, 2 population tests were conducted, one with a homogeneous population and another with a heterogenous population.

Findings:
Based on the 3 graphs that were made, a clear difference is seen. The homogeneous population has a higher bias change and more total adopted households. This indicates that the model is operating well and shows higher results when households share a similar identity.

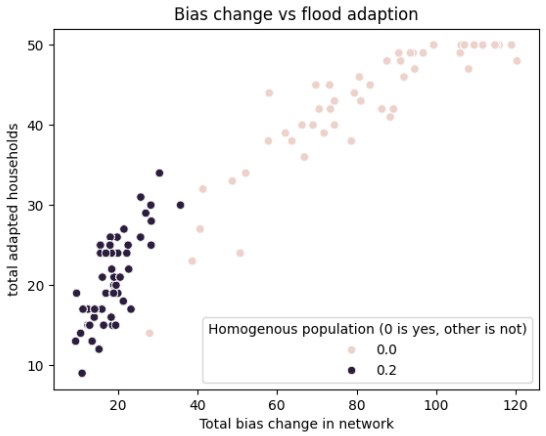

Figure 23: Scenario 5

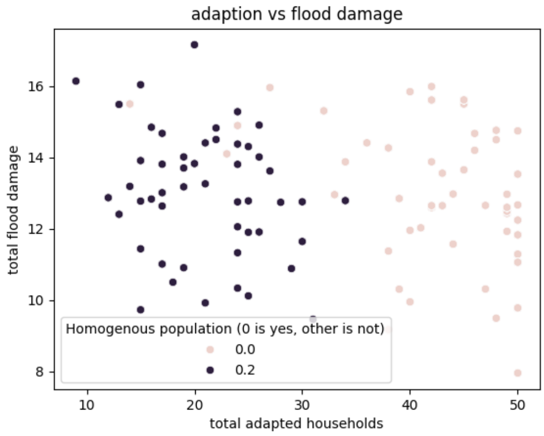

Figure 22: Scenario 5

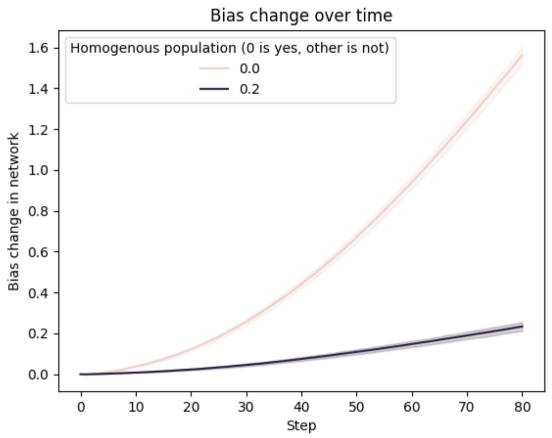

Figure 24: Scenario 5

Verification & Validation

Verification

This section demonstrates whether the model has been implemented correctly from its conceptualization. Objective verification processes involve comparing the model's output with real-world data and behaviors to ensure that the model accurately represents the system under study. During the modeling phase, small tests have been conducted to check whether the agents exhibit logical behavior. For instance, as shown below, the sensitivity of flood adaptation is tested against a threshold. It exhibits a logical behavior: more houses are adapted when there is a low number of thresholds, and as the threshold factor increases, the total number of adapted houses decreases. Parallel, we see an increase in flood damage with the increase of the threshold factor. High threshold means low adaptations means a high amount of flood damage, which are all logically results.

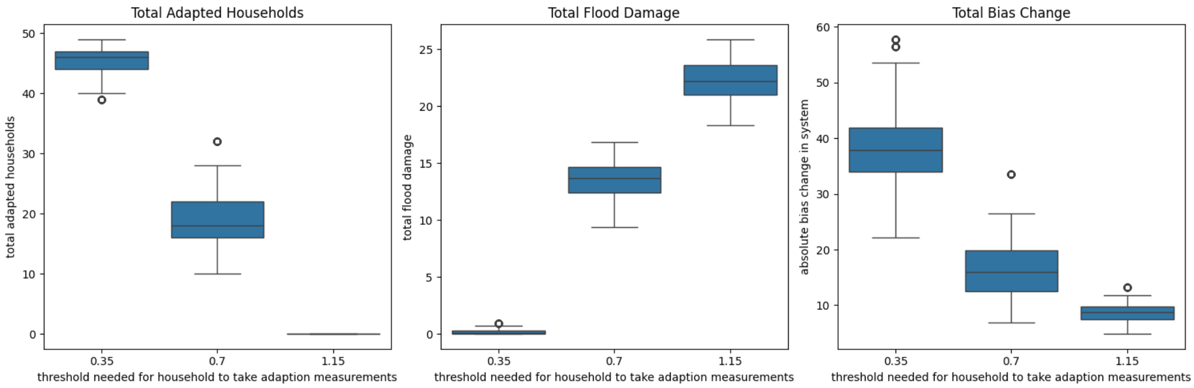

Figure 25: Verification

A second aspect of the verification process concerns the development of the social network depicted in the model. Initially, we start with a network where no household is adapted, yet all are connected to other households through network connections. As a logical result of the households' ability to communicate with each other, influenced by their introverted or extroverted tendencies, and their attempts to influence each other's biases, the network is constantly evolving. This evolution leads to the creation of more network connections, resulting in an increased number of households being flood-adapted, which are represented as red.

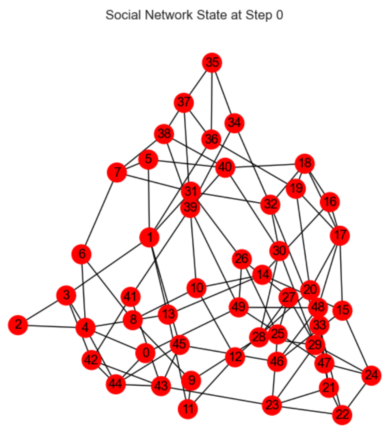

Figure 26: Verification social network

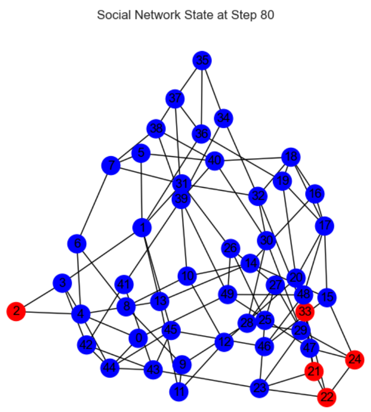

Figure 27: Verification social network

Validation

This topic is about the validation of the model. In the validation process, we will check whether the behaviour that emerges as an outcome of the model is comparable to real-life behaviour. The model has also been compared against real-world data and observed patterns of flood adaptation behaviour in Harris County. During the model's validation, we continually ask ourselves the following question:

<u>"Did we build the right thing?"</u>

The model we have employed is a simplification of the real world; therefore, the quantities of the input parameters do not always correspond precisely with actual figures. Take, for example, the number of households in the region of Harris County. In the model, the initial value was set at 25 households, whereas, in reality, Harris County has nearly 1,700 households. Incorporating the true number of households into the model would significantly increase complexity and make the analysis of results more challenging due to the multitude of interactions.

To better understand the influence of different variables incorporated into the model, a sensitivity analysis has been conducted. This analysis shows the effect of each variable on the model's outcomes and also serves as a robust method for comparing the model's predictions with real-world observations. Such comparison is critical for demonstrating the model's validity and ensuring that the results align with empirical data.

The correlation between household adaptation to flooding and the resultant damage has been well-documented in the literature. Empirical studies consistently suggest that as the number of households implementing flood adaptation measures increases, the overall damage inflicted by flooding events tends to decrease. This correlation highlights the effectiveness of proactive adaptation strategies in mitigating the adverse impacts of such natural disasters.

Furthermore, the literature indicates a direct relationship between the total number of households in a given area and the total amount of damage. Simply put, regions with a higher density of households are likely to experience greater overall damage when floods occur. This increase is due to the higher probability of more properties and infrastructures being affected, which amplifies the total impact. This is shown in the figure below with the title: 'Total Flood Damage'.

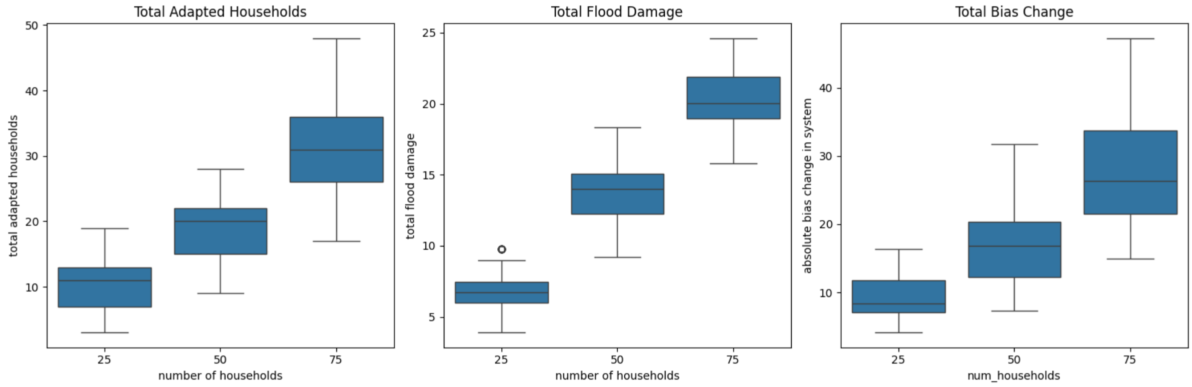

Figure 28: Validation flood damage

Additionally, a significant pattern observed in the literature is the effect of behavioural change on flood adaptation. Specifically, when the likelihood of a shift in bias towards flood adaptation increases, there is a corresponding rise in the total number of households that take proactive flood adaptation measures. This phenomenon aligns with what one would intuitively expect: as more households adjust their bias towards recognizing the benefits of flood adaptation, the level of adaptation within the community rises. This is shown in the figure below. These are results of a sensitivity analysis of the probability of a change in bias towards flood adaptations.

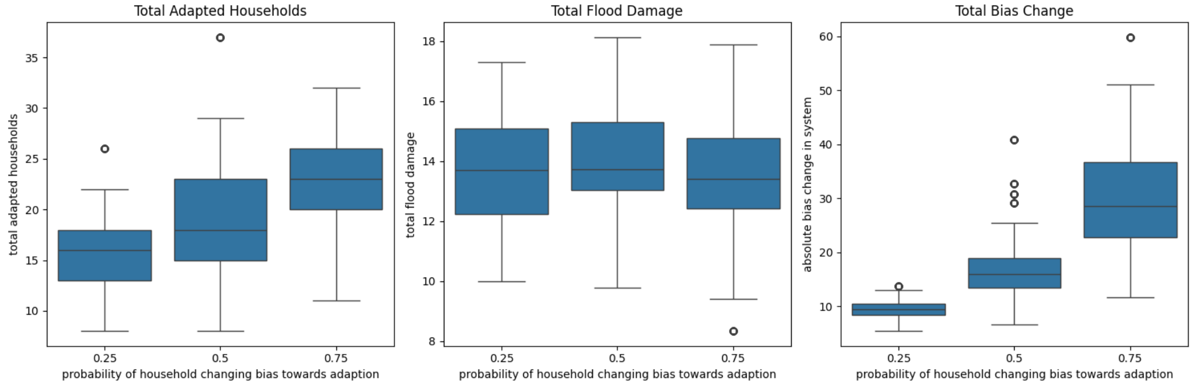

Figure 29:Validation probability change bias

This model, by incorporating such dynamics, seeks to reflect these documented patterns and offers a tool for predicting outcomes based on variations in behavioral adaptations and household density, thereby providing valuable insights for disaster preparedness and urban planning.

Conclusion & Discussion

This research has started with the following research question that was presented in the introduction of this rapport:

“How does similarity bias under various parametrizations among agents affect the total number of agents that take flood adaptation measures and the total amount of flood damage within a modelled urban environment?

In conclusion, the focus of this research was to explore the impact of similarity bias among agents on flood adaptation measures for flood damage in a simulated urban environment. Through the use of agent-based modelling, scenarios were investigated to see how the model would react with certain parameters. With variations in the size of social circles, flood impacts, adaptation threshold, bias change probabilities and similar populations.

The findings revealed insights into the dynamics of flood adaptation behaviours with the simulated community. In scenario 1 was a positive correlation between the number of social connections and bias change. This was also seen in the total number of adapted households, which showed that social networks had a big role in encouraging adaptive behaviours. Scenario 2 showed the influence of flood impacts on bias change and the total number of adapted households.

Scenario 3 provided valuable insights into the effects of adaptation thresholds on individual agent biases, which showed the challenge of finding a balance in setting these thresholds for a reasonable outcome. Scenario 4 explored the impact of varying the probabilities for agents to adjust their biases, which revealed that higher positive probabilities and lower negative probabilities resulted in a higher total number of adapted households. Scenario 5 explored homogeneous and heterogeneous populations. In this scenario came forth that homogenous population led to a higher bias change and more adapted households.

The verification and validation processes ensured that the model represented the system quite well. However a model is always wrong. Sensitivity analysis showed the model’s ability to align with real-world observations.This highlighted a link between changes in behaviour and the outcome of flood adaptation. In the end, you cannot always fully control a certain model or system.

The model simplifies certain aspects, like the flood dynamics and how households interact. Someone’s identity is based on 5 attributes that are randomly assigned. This simplification limits the model’s ability to mirror real-world household interactions. In reality multiple factors shape how households engage. While the study provides valuable insights, these simplifications show the need for caution in translating the model outcomes to real-world scenarios. Future research could explore more accurate representations of identity and social dynamics. This could enhance the accuracy to diverse urban environments.

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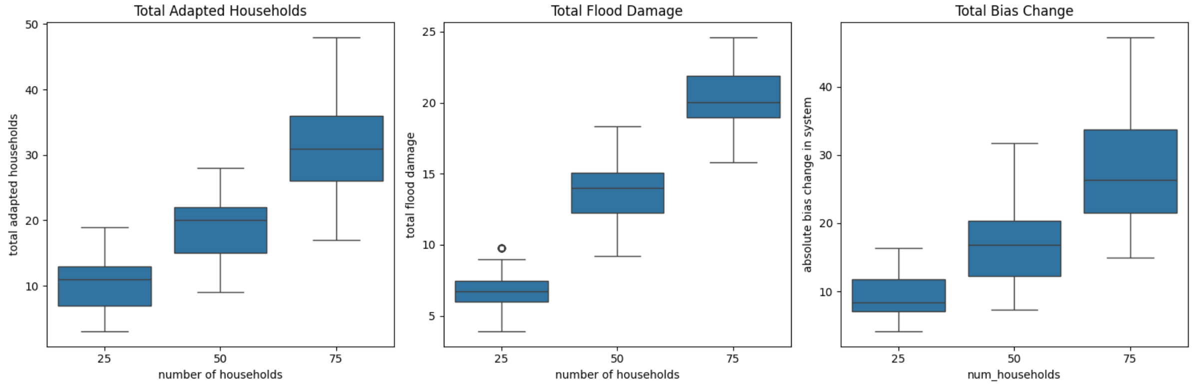
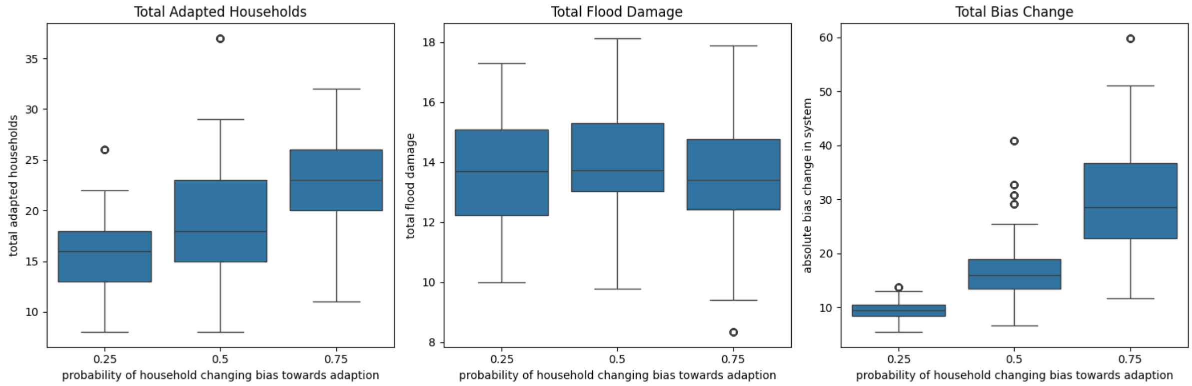
Appendix:

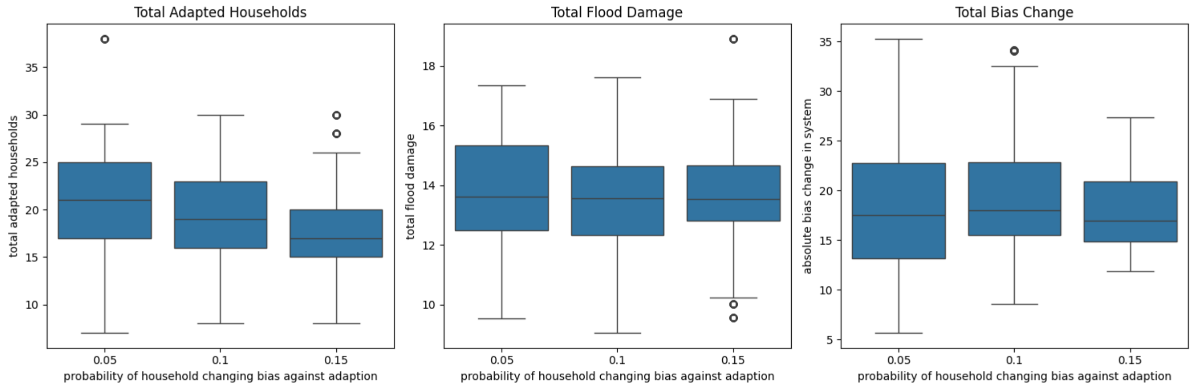
Sensitivity households:



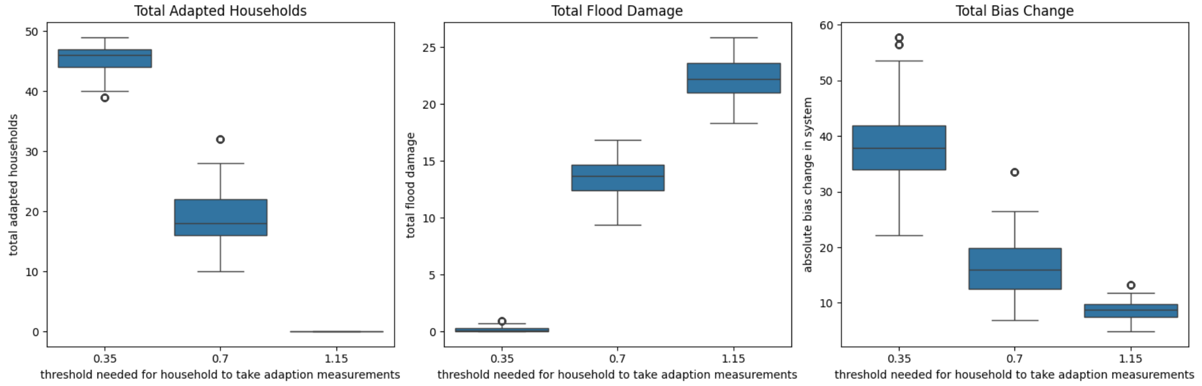
Sensitivity probability change bias towards adaption:



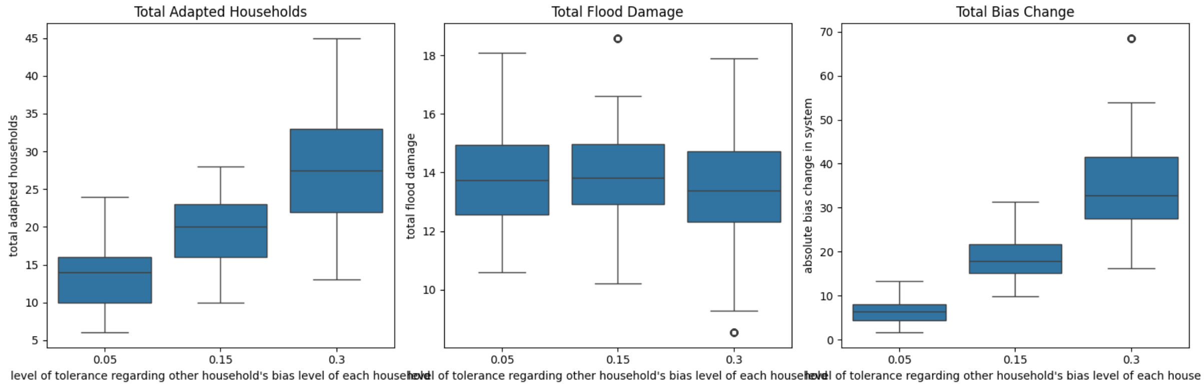
Sensitivity probability change bias against adaption:



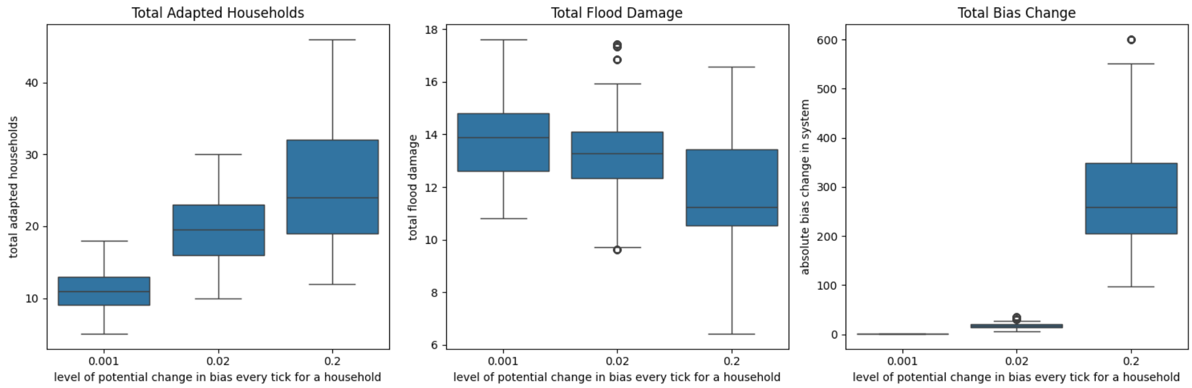
Sensitivity adaption threshold:



Sensitivity tolerance:

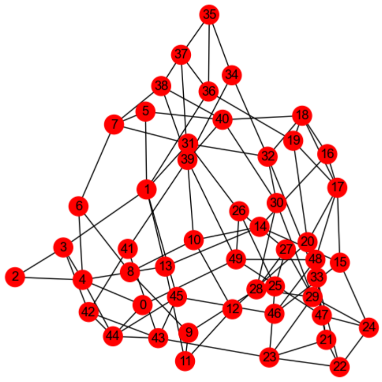


Sensitivity potential bias change per tick:

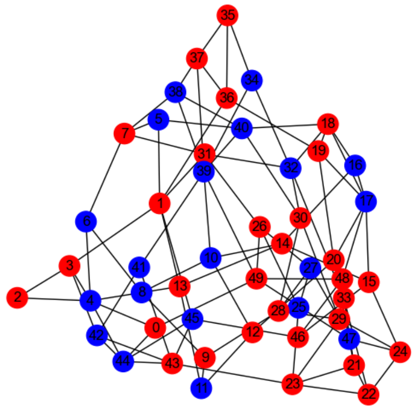


Single run homogenous population:

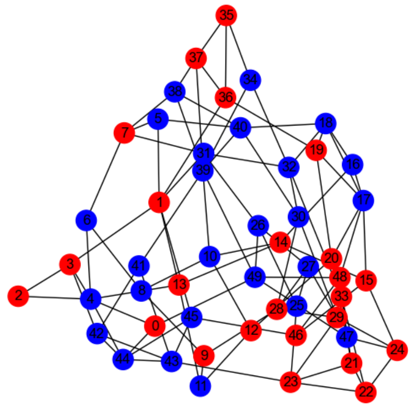
Social Network State at Step 0



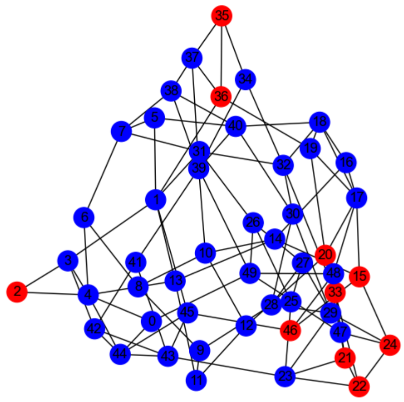
Social Network State at Step 20



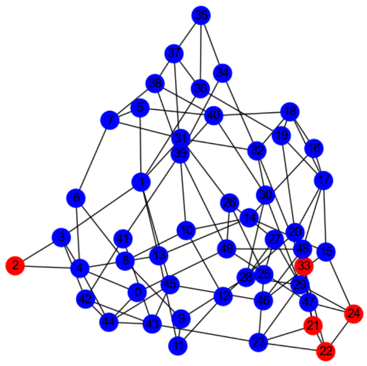
Social Network State at Step 40



Social Network State at Step 60



Social Network State at Step 80



Experiment with different amount of neighbours (so different amount of connections between households and thus different intensity of network density);