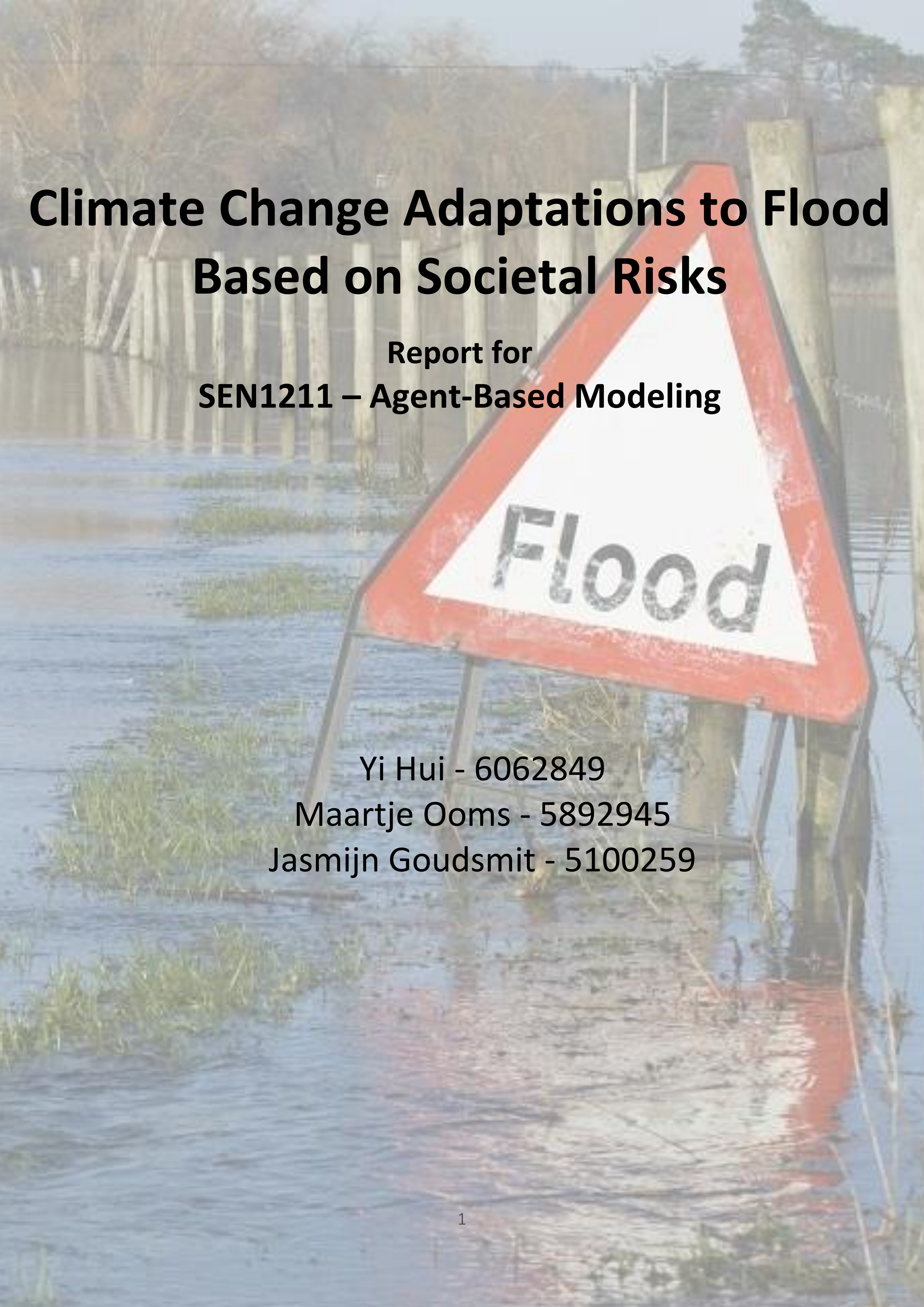

Climate Change Adaptations to Flood Based on Societal Risks

Report for
SEN1211 – Agent-Based Modeling

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Preface

This report is written for the course SEN1211 - Agent-Based Modeling. The task was to model households' dynamic adaptation to climate change, specifically flood adaptation. We chose to use Python with Mesa being the main library used for the modeling.

Before this course, we had limited knowledge of Python and agent-based modeling. As a result, we faced great challenges in coding, but we enjoyed the process of progress. While we cannot guarantee perfection in the code, we put in our best effort and truly gained valuable insights from the course.

We would like to thank Dr. Ir. Omar Kammouh, Dr. Ir. Igor Nikolic, all the lecturers, and all the TAs in this course for your contribution. Thank you for bringing us a wonderful learning experience and a new perspective to look at the world!

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1. INTRODUCTION

Human existence faces numerous hazards, with natural disasters claiming thousands of lives worldwide each year. Climate change exacerbates these challenges by increasing the impact of various natural disasters. Floods are a particularly serious threat, with damage expected to increase in the future (Yin et al., 2021). The increasing damage is causing suffering to communities, damaging homes, destroying properties, and increasing the worries among the affected individuals.

Climate change and the corresponding increase in flood damage call for adaptations from different actors. The government will make different collective adaptations such as building dikes or providing subsidies. The individual households will also make certain adaptations before and after the flood. These agents are interconnected and their behavior is integrated into the environment, into other agents, and into their own conditions. The government and societal risks, therefore, have become important factors and guidance for households to make adaptations. In such a research, with multiple actors involved, and no central control among them, agent-based modeling (ABM) becomes a possible and suitable technique to model this complex system.

For this project, we modeled the flood climate change adaptations, considering societal risks and applying the FN curve theory introduced by Jonkman et al. (2002). This project is based on the city of Harris County and the main tools used for modeling are Python and the Mesa library. The project aims to explore the application and development of an ABM rather than creating a perfect and concise model. Due to observer dependency, we focused on the societal risks and thus some elements in the minimal model will not be used. Additionally, this project might not strictly adhere to the descriptions of the assignment document, but all assumptions will be incorporated into the model. Through the developed model we aim to gain insights into the following research question:

What is the effect of societal risk factors (FN parameters, government control, etc.) on households' and government's flood adaptation strategies under the condition of different social networks and flood intensities, measured by the number of fatalities (flood damage), and diffusion of adaptation?

The report is structured as follows. In Chapter 2, the conceptualization of the model is discussed, including system boundaries, some important theories, flowcharts, (key performance indicators) KPIs, assumptions, and related parameters and experiment design. The formalization of the model is discussed in Chapter 3, where most of the important process and agent properties can be found. Chapter 4 focuses on the verification and validation of the model and in Chapter 5 the experimentation to answer the research question is shown. Lastly, in Chapter 6 the conclusion, recommendations, and future research will be discussed.

2. CONCEPTUALIZATION

In this chapter, the conceptualizations of the project will be discussed, including the system boundaries. Additionally, most of the assumptions, simplifications, parameters, and KPIs are discussed that are going to be used in the next steps of the model.

2.1 System Boundaries

Geographic boundaries

In our project, we are going to model the adaptation of households in the city of Harris County, USA, shortly before and after it was hit by the flood. As a result, the geographic boundary of this model is the city of Harris County (see Figure 2.1), including households and the government in this city. However, insurance agents will not have a specific agent class in our system, and it will be merged into the households instead. In this model, the social connections of households matter, and thus a social network will be presented as well.

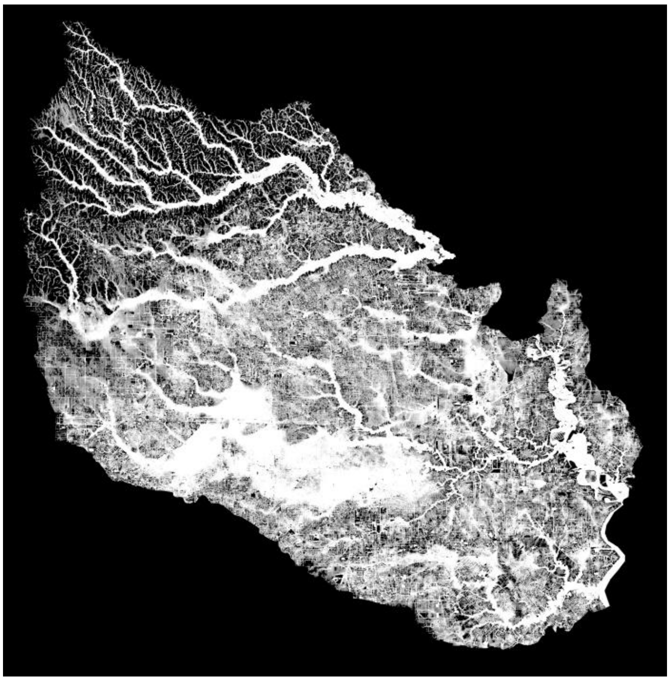

Figure 2.1 The geographic boundary of the system

Time of the system

In our model, the total time scale is 50 ticks, and one tick is a quarter of a year. The flood will occur at step 49. In this model, we will observe the change in flood damage before and after the adaptation was made, as well as governments' policies, etc. More details can be found in the model and conceptual model.

2.2 Model narrative

In this city, there will be Households in the different nodes on the map. Each node on different locations will have different flood data and these data will be assigned to the corresponding agents in the same node. We put one Government agent together with Household agents in different nodes so that the policies will be made more locally. Each Household represents a 50th of the population of Harris County.

The Households agent will have certain attributes to decide which groups they are. Such attributes include savings, the size of their house, and the level of their worries. The Government agents will have three different policies, namely communication policy, communication & providing subsidy, and communication & infrastructure. Which policy to use depends on societal risks and FN value.

There will be two types of flood damage in the model, the estimated and the actual one. Before step 49, all the data is estimated. After step 49, the flood will hit Harris County, and the actual depth is used.

The government first determines how many deaths are expected based for the whole area of Harris County on historical data mapping, the number of fatalities for the size of the event (200-year flood, 300-year flood, etc), and compares this to a societal risk limit as based on 52 records for flood damages across Korea spanning from 1994 to 2018 from the paper by Shin et al. (2021), with an international standard limit from Jonkman et al. (2002) and with an 'in between scenario', which takes risk factors that lie in the middle. This choice was made because there is not enough data on societal risk for the US and specifically Harris County. If the societal risk limit is exceeded, the government will determine the risk again for specific areas and what measure is used locally depends on how much this limit is exceeded in a specific area. The following packages can be made by the government, as taken from Wagenblast (2022): only communication, communication + subsidies, and communication + infrastructure. Communication is used in all packages, considering this has been determined through modeling to be the most effective in reducing flood damages in Harris County and it is expected that the government will always choose communication as it is affordable or low in controversy in comparison to other options, when the risk is considerably under the limit (Wagenblast, 2022). Communication + infrastructure is considered the most expensive measure and therefore the government will only do this when the societal threat is considered extremely high (above the limit). This was considered to be the most expensive, considering infrastructure projects for the area have been held back due to high costs (Wilson et al., 2014; Douglas & Foxhall, 2023). After that, communication + subsidies are considered the most expensive, and therefore only done when the societal threat is considered high (just below the limit). Subsidies do not include very high capital costs and therefore are placed least likely to be implemented after infrastructure. When the threat is considered low (below the limit), only communication is used. Regulations are considered cheap as there are no actual expenses to adaptation, yet regulations can only really be applied to newly built buildings or there will be large controversy, and therefore regulations are not included as an appropriate measure for the existing housing stock of Harris County.

How much the communication, infrastructure, and subsidies affect the results, is determined as follows, inspired by Wagenblast (2022): communication affects the results by changing the perceptions of all the households about whether they should adapt, not based on the DeGrootian model (Wagenblast, 2022) but in a simplified version, called the worry of the Household. Here, the type of network makes a difference in how the perceptions of the households actually affect each other. For infrastructure, the model of Wagenblast is simplified by saying that if a Household has other Households nearby that need strong adaptation, there will be infrastructure. For simplification, randomly the flood depth is reduced by 0.5-3 meters as the project does not help everyone in the area equally (Wagenblast, 2022). Subsidies affect the results by reducing the cost of measures by 30-75% for everyone. This is translated in the model by reducing the flood depth for households with 30-75% in the affected area but only if they are insured, as is standard for Harris County support, and if their worry is large enough that they get insured. Also, they can only get insurance if they have enough money and the expected flood risk is not very large, as insurance agents are quickly ramping up costs if the risk is high. If a Household needs strong adaptation but has no neighbors that do, they get subsidy help. Then, the actual number of fatalities can be calculated with the help of a formula by Waarts (1992) based on historical flood data (Jonkman et al., 2008).

2.3 Conceptual Model

Visual representation of the model

A visualization of the model can be seen in Figure 2.2. This Flowchart shows the conceptual model.

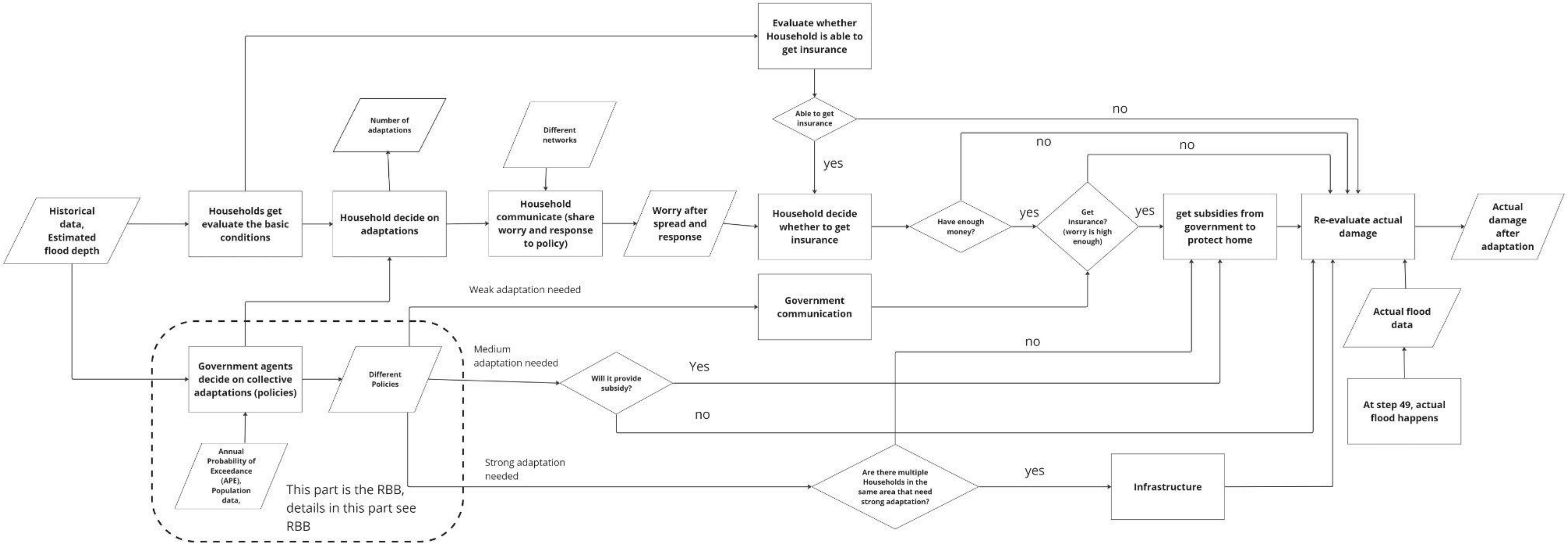

Figure 2.2 Flowchart of the model

Agents, Interactions, and Processes

In our model, only two types of agents will have their own classes, namely Households and Government. Insurance agents will not be modeled as a separate class for two reasons. Firstly, the attribute of 'getting insurance' can be directly modeled together with Households and the Government. Secondly, Insurance agents do not need to be placed on the grid necessarily, and in reality, the government can also provide official insurance.

Table 2.1 provides an overview of the general processes and interactions in the model. Some processes are carried out by a specific type of agent, while others involve interactions between two types of agents. Note that some basic processes, like placing an agent, are not detailed here. Additionally, at step 49, a flood event occurs, transforming estimated flood damage into actual flood damage.

Table 2.1 General processes and interactions in the model

Process	Interactions
The government estimates flood depth and damage and checks whether it is in the floodplain for a variety of locations and determines societal risk for the entire area of Harris County	-
The government estimates local FN value and makes policies.	-
Households communicate with their friends and government policy, change their worries.	Households and government, Different unique Households
Households decided on adaptation according to the government's policy and collective adaptation	Government and Households
Households get insurance according to their worry and their own conditions	-
The government provides subsidies to Households	Government and Households
The government provides infrastructure	Government and Households

Parameters

In this model, there are two types of parameters. The first type consists of experimental parameters, to be used later in experiments. The second type is the normal parameters used within the model. The parameters can be found in Table 2.2. Parameters C and α are varied as there is currently no societal risk limit available for Harris County. We ignore how adaptations might affect the α value in this research.

Table 2.2 Parameters

Experimental parameter	Scale
FN parameter C and α	Corresponding to different standards. The constant C acts as a scaling factor, and it is calibrated based on historical flood data, considering factors like flood intensity, duration, affected area, and historical casualty or loss rates. It sets the baseline frequency of flood events leading to a certain number of fatalities or a certain level of economic loss. For floods, alpha α how the risk of fatalities or losses decreases as the severity of the event increases. It takes into account factors like community preparedness, resilience, early warning systems, and the effectiveness of evacuation plans. A higher alpha indicates that measures in place are effective at reducing the increase in fatalities or losses as flood severity increases.
FN parameter APE (this links to the flood strength)	0.01 0.001
Network type	"erdos_renyi", "watts_strogatz"
Include societal risks?	Yes, no
Normal parameter	**Scale**
Household number	50
Exposure rate	0.1
Household's worry	[0,1]
Household's savings	low, middle, high
Household's housesize	small, medium, large
FN parameter number of people (This links to the real number of	94623

people, not the number of households)	

2.4 KPIs in the model

According to our research question, there are two main related KPIs: (1) the number of adapted households (with different adaptations) over time ticks and (2) deaths over time ticks

2.5 Assumptions and Simplifications

Table 2.3 provides a comprehensive list of all the assumptions made in the model, along with some underlying theories. It is important to note that additional assumptions may arise during the actual implementation of the model, and further details on assumptions can be found in the formalization section.

Table 2.3 Assumptions and Simplifications

Category	Assumptions	Explanations/reasons
General Model	*A global flood happens at step 49*	In our model, we assume the flood happens at step 49. The actual flood depth for each agent is calculated by multiplying the estimated depth with a factor of 0.5 to 1.2.
	Government agents and Households at the same node	In our model, we want the government to develop local policies for Households. As a result, each node will have a Household and a Government agent. This arrangement is to simplify the coding.
	No movement for agents	We assume the agents in our model will not move to other places.
Agent. Households. Attributes	*No insurance at the beginning*	We assume that no households have insurance at the initial phase, and they will buy insurance during the model run.
	Households are self-insured	No separate insurance agent will be created, and the households will have an attribute of insurance
	Only three different groups for savings	We assume that the Households will be divided into three groups of savings, and they are “low”, “middle”, and “high”. With a probability of 0.2, 0.6 and 0.2. No specific number will be assigned to them.
	Only three different groups for house size	We assume that the Households will be divided into three groups of savings, and they are “small”, “medium”, and “large”. With a probability of 0.2, 0.6 and 0.2.
	Random degree of worry	The initial worry of the households is assigned from (0, 1) randomly
	Households have three different adaptation strategies	The household agent will have three different adaptation states, weak adaptation, medium adaptation, and strong adaptation. They are not specified now, it can be specified later when it is needed.

Agent. Households. Process	*The premise of getting insurance is government has subsidies*	We assume that the government is in charge of insurance, and when it provides subsidies, the household has the premise to get insurance.
	The worry about getting insurance is 0.6	If the Households want to get insurance, the lowest requirements for them are (1) in flood plain, (2) worry > 0.6, and (3) have the premise to get insurance. Then it will be decided based on house size and savings.
	Random subsidy effects between (0.3, 0.75)	Only Households with insurance can get subsidies and the subsidy can cover (0.3, 0.75) of the actual cost by the flood.
	Both governments and Households can have effects on worry	The worries of Households depend on his/her own worries, the worries of their friends, and the government's policy. In our case, we assume weak, medium, and strong have an effect factor of 0.3, 0.6, and 0.9 on households.
Agent. Government. Attributes	*Simplified real data for social risks*	The basic data is based on the real data of Harris County. However, due to the limitation of real data, some data was simplified. For example, there are 50 locations, and then the number of people in each location would be; the population of Harris County/50.
	Only have three policies	The government only has three policies, weak, medium, and strong. Weak = Communication Medium = Communication + subsidy Strong = Communication + Infrastructure
Agent. Government. Process	*FN curve method for social risks*	The determination of different policies is based on the FN curve method. The calculation of the death rate is based on flood depth

3. FORMALISATION

In this chapter, we delve into the formalization of the conceptual model, using Python and the Mesa library. Some detailed processes and theories are described, focusing on the base scenario.

3.1 Initialization

The model is initialized by generating random locations on the map, and these locations correspond to the geographical position of the agent. In each node, one Household agent and one Government agent are created and placed. Each of the Household agents will be randomly assigned with a saving, house size, and degree of worry with a certain distribution. It is important to note that we assume that agents do not move geographically. Therefore, we use the Network Grid in Mesa, which represents our agents' social network rather than their geographic relationships. Given that the flood occurs at step 5, there is no actual flood depth at the initial stage of the model. All calculations and processes are based on estimated data. Additionally, during the model initialization, we assume that attributes with a value of True or False are initially set to False. For instance, at the initialization of the model, no Households are adapted, and none of them have insurance. These attributes will be modified during the running model. In Figure 3.1, the detailed formalization of different agents, including attributes and functions can be found.

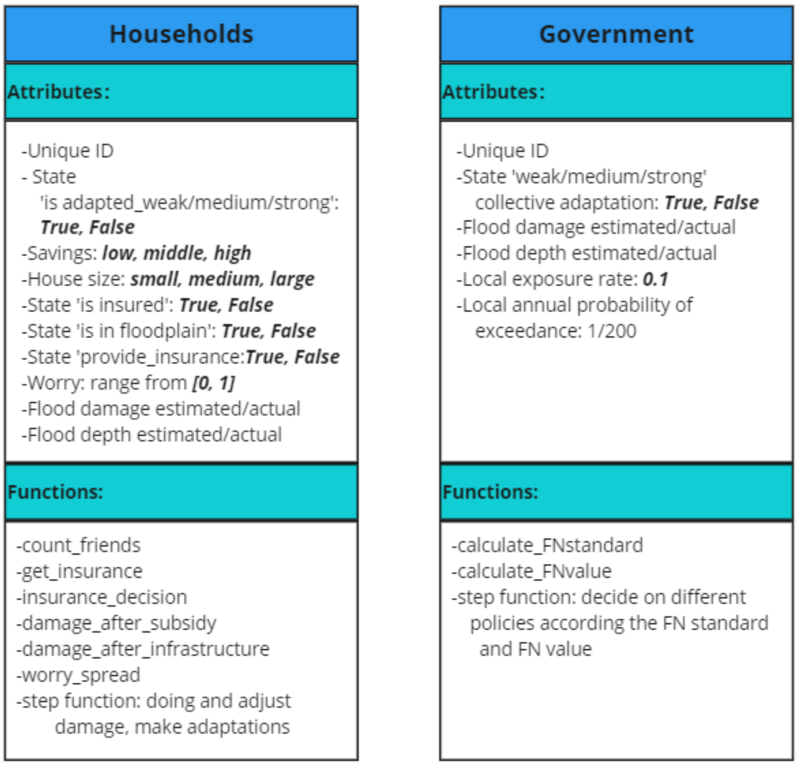

Figure 3.1 Formalization of different agents: Attributes and functions

3.2 Processes in Formalization

Processes during initialization

➢ **Generate necessary attributes**

For the Household agents, some attributes will be generated, these include:

- ***Savings***: [low, middle, high] with a probability distribution of [0.2, 0.6, 0.2].
- ***House size***: [small, medium, large] with a probability distribution of [0.2, 0.6, 0.2].
- ***Worry***: [0, 1].
- ***Social network***: based on his/her location.

For the Government agents, some attributes will be generated, these include:

- ***Local annual probability of exceedance:*** 1/200.
- ***Location:*** the government agent will be generated in the same node as the household agent.

➢ **Get flood depth and damage**

When initializing the model, the Household agents and Government agents will get flood data from the map according to their locations. A corresponding flood damage factor will be assigned according to the work by Huizinga et al. (2017), see Table 3.1.

Table 3.1 Relationships between depth and damage factor

Water depth (m)	Damage factor
0	0
0.5	0.22
1	0.38
1.5	0.53
2	0.64
3	0.82
4	0.90
5	0.96
6	1.00

However, although we assigned the damage factor to Households, it will not be used as part of the results of the data analysis. This decision is in line with the RBB requirements, which focuses on societal risks instead of economic damage. Although this exclusion is specific to our course-related objectives, it could prove beneficial in potential future applications of the model.

Processes during the model run

➢ **The Government agents make policies depending on the FN curve**

The Government's decision-making on various policies is based on FN curve theory within the field of societal risk. In this project, the FN curve used is based on the work of Shin et al (2022) and Jonkman et al. (2002). This theory involves a FN value for a specific location and a standard FN value. The Government can formulate policies by comparing the standard with the calculated FN value. This theory has the following process, with certain parameters that are pre-assigned to the agent during initialization:

1. Calculate the expected death rate according to the following function (Jonkman et al. 2008):

$$F_{\mathrm{D}}(h) = 0.665 \cdot 10^{-3} \mathrm{e}^{1.16h} \quad F_{\mathrm{D}} \leq 1$$

   Where h is the depth.
2. Calculate the number of deaths: **n= FD(h) * exposure people**
3. Calculate the FN standard based on the function, this can be done using the following function:

$$SR_{Nat} = \frac{C}{n^{\alpha}}$$

   Where SR is the standard. C is the constant defined by many criteria, and according to our calculations, C for Harris County is 0.04468. n is the number of fatalities. α is a constant, we take 0.703 in our model.
4. Calculate the FN value according to the following function:

$$\overline{F}(N > n) = 1 - \frac{R_n}{k+1}$$

   Where Rn is the ranking of the flood, and k is the annual probability of exceedance. Rn is 1 because there is only one flood in the model.
5. Compare the FN value and standard.
6. Making policies (managed through the step function). Since the medium and strong policies are policy combinations, the Government makes the policies with the following criteria:
   a) If FN value > 0.6 FN standard, weak policies can be considered;
   b) If FN value is between 0.8 and 1 FN standard and weak policies have been implemented, medium policies can be considered;
   c) If FN value > FN standard and weak policies are implemented, strong policies can be considered.

- **The Household agents communicate with friends, respond to Government, and share worries**

The Household will communicate with friends and share their worries. This process is derived from the work of Kreibich et al. (2015) and is calculated based on the following function:

$$F_{i1} = \sum_{j=1}^{k} p_{ij} F_j$$

Where Fi1 is the worry of the Households and Fj is the worry of his/her friends. If the local government made certain policies, it can be considered as the worry spread, with an effect of 0.3, 0.6, and 0.9 on weak, medium, and strong policies. The pij is the corresponding weight. For example, if an agent has a 'worry' of 0.5 with a weight of 0.6, and this agent has one friend with a worry of 0.8 with a weight of 0.4, the new 'worry' of the agent is calculated as 0.5 * 0.6 + 0.8 * 0.4 = 0.64. In our model, we assume that the weight of each is the same.

- **The Household agents evaluate whether they can get insurance or not**

Household agents will undergo an evaluation by the insurance company (not a specific agent class) to determine their eligibility for insurance. Normally, if the household agents' damage is really high, they will not be able to get insurance due to the high risk for the insurance company.

- **The Household agents evaluate to get insurance**

Household agents assess whether to get insurance based on several factors. Firstly, they verify if they are located in floodplains and assess their 'worry' level. If situated in a floodplain with a 'worry' exceeding 0.6, they may opt for insurance considering their savings and house size. It is assumed that Household agents with medium or high savings will choose to buy insurance.

- **The Household agents get subsidies and re-evaluate the damage**

If a Household agent is insured, they can get a subsidy from the Government (only when the government provides them i.e. medium policy is used). This reduces the damage by 30% to 75%. In the model, this is reflected in the reduction of flood depth.

- **The Household agents re-consider their adaptations**

After the Households re-evaluate all the factors above, they will evaluate the newest situation and make adaptations according to it. This process is managed by the step functions.

- **Calculate the actual data after adaptations and policies**

The actual flood data, including flood depth and deaths, is calculated when strong policies are implemented and adaptation occurs. The assumption is that if infrastructure is installed, the flood depth will be reduced by 0.5 to 3 meters.

4. VERIFICATION & VALIDATION

In this chapter, the actual code is examined. In the verification part, we check whether some of the important parts of the code align with the conceptual model and run properly. In the validation part, we assess whether the model fits the logic of the reality.

4.1 Verification

In this section, the 'print' function is mainly used to check some of the important functions and processes. Please note that some parameters presented here may differ from the final code to enhance clarity and understanding during the verification process.

Initialization of the model

- **Place Agent**

To verify the placement of agents, we adjusted the total number of Household agents to 50 (from 0-49). We inserted a print function in the code, as shown in Figure 4.1, and the printed result is visible in Figure 4.2. It is clear that the total number of households is 50, and there is one household and one government in the same node, which was the intended result. In Figure 4.3, a visual verification is provided to show the locations on the map (only households needed to be displayed on the map).

```
# create households through initiating a household on each node of the network graph
for i, node in enumerate(self.G.nodes()):
    household = Households(unique_id='Household'+str(i), model=self)

    self.schedule.add(household)

    self.grid.place_agent(agent=household, node_id=node)
    print ('model place',household.unique_id, 'at node', household.pos)

# And a corresponding government agent at the same node
for i, node in enumerate(self.G.nodes()):
    government = Government(unique_id='Government'+str(i), model=self)

    self.schedule.add(government)

    self.grid.place_agent(agent=government, node_id=node)
    print ('model place',government.unique_id, 'at node', government.pos)
```

Figure 4.1 Example of verification using the 'print' function.

```
model place Household0 at node 0    model place Government0 at node 0
model place Household1 at node 1    model place Government1 at node 1
model place Household2 at node 2    model place Government2 at node 2
model place Household3 at node 3    model place Government3 at node 3
model place Household4 at node 4    model place Government4 at node 4
model place Household5 at node 5    model place Government5 at node 5
model place Household6 at node 6    model place Government6 at node 6
model place Household7 at node 7    model place Government7 at node 7
model place Household8 at node 8    model place Government8 at node 8
model place Household9 at node 9    model place Government9 at node 9
model place Household10 at node 10  model place Government10 at node 10
```

Figure 4.2 Example verification of agent placement.

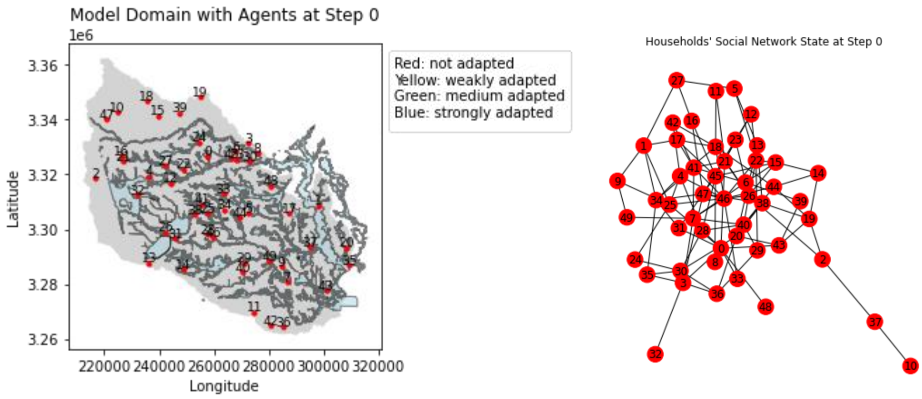

Figure 4.3 Example visual verification of agent placement.

➢ **Assign Attributes**

Figure 4.4 shows a printed result with some of the attributes of Households, including their savings, house size, and 'worry'. These results are randomly assigned and align with our expectations.

```
Household10 has savings middle , housesize medium , worry 0.5271668461790284
Household11 has savings middle , housesize medium , worry 0.8896203908815603
Household12 has savings middle , housesize medium , worry 0.7878364517927031
Household13 has savings middle , housesize medium , worry 0.7686428098236472
Household14 has savings middle , housesize medium , worry 0.678384361944247
Household15 has savings middle , housesize large , worry 0.2517981455106636
Household16 has savings middle , housesize medium , worry 0.8121818512443215
Household17 has savings high , housesize medium , worry 0.118489338537061
Household18 has savings low , housesize large , worry 0.10338446394165501
Household19 has savings middle , housesize medium , worry 0.4134209229441185
Household20 has savings high , housesize small , worry 0.9462484151932765
Household21 has savings high , housesize small , worry 0.38185293388807373
Household22 has savings middle , housesize medium , worry 0.14284216192626653
Household23 has savings high , housesize large , worry 0.38121234814810456
Household24 has savings low , housesize medium , worry 0.8761648145896072
...
Household46 has savings middle , housesize medium , worry 0.226966152016414
Household47 has savings low , housesize medium , worry 0.11732124455927995
Household48 has savings middle , housesize medium , worry 0.30604906585451475
Household49 has savings middle , housesize medium , worry 0.7237305525776142
```

Figure 4.4 Example visual verification of agent placement.

Functions and Processes

➢ **Government: FN functions and decides on policies**

The Government agents will calculate the related FN value and stand and make policies according to these two values. In Figure 4.5 the verification result for this process can be found, which is verified via a ‘print’ function. If they decide on certain policies, it will appear during the printing process. It is important to note that there is not a specific annual probability exceedance and we assume it is 1/200, which results in the same result for the FN value.

```
Government18 ,node 18 have an FN value 0.004975124378109319 and, FN standard 0.003963245618171201
there is strong adaptation
Government30 ,node 30 have an FN value 0.004975124378109319 and, FN standard 0.012392811422234147
there is no adaptation for this specific area
Government42 ,node 42 have an FN value 0.004975124378109319 and, FN standard 0.007485984077833194
there is weak adaptation
there is no adaptation for this specific area
Government35 ,node 35 have an FN value 0.004975124378109319 and, FN standard 0.012392811422234147
there is no adaptation for this specific area
Government47 ,node 47 have an FN value 0.004975124378109319 and, FN standard 0.00790428913849623
there is weak adaptation
there is no adaptation for this specific area
Government10 ,node 10 have an FN value 0.004975124378109319 and, FN standard 0.012392811422234147
there is no adaptation for this specific area
Government38 ,node 38 have an FN value 0.004975124378109319 and, FN standard 0.0065169080802230635
there is weak adaptation
there is no adaptation for this specific area
Government48 ,node 48 have an FN value 0.004975124378109319 and, FN standard 0.005966490062574945
there is medium adaptation
```

Figure 4.5 Example verification of government agent.

- **Household: worry spread**

In our model, the Household agents will talk to each other and share their worries. After they talk to their friends, they will update their risk perceptions. There are mainly two sub-processes occurring in this process. The first one is to get friends and the second is to change risk perception. These sub-processes were examined during the verification. Figure 4.6 shows the verification of getting friends and Figure 4.7 the process of the change of risk perception. In the process of changing risk perception, we observed that agents with higher worries tend to reduce their level of worry after interactions, while agents with lower worries tend to increase their worry. This aligns with the expected behavior from the functions.

```
Household 27 friend is Household 26 friend worry is 0.16460818765641583
Household 27 friend is Household 29 friend worry is 0.14496743180328164
Household 27 friend is Household 46 friend worry is 0.9770259070492865
Household 20 friend is Household 1 friend worry is 0.5978710247345331
Household 20 friend is Household 18 friend worry is 0.29905532100059884
Household 20 friend is Household 19 friend worry is 0.4895231869155444
Household 20 friend is Household 22 friend worry is 0.319205027810435
Household 36 friend is Household 5 friend worry is 0.5898467838245739
Household 36 friend is Household 17 friend worry is 0.4131615928270872
Household 36 friend is Household 35 friend worry is 0.6750455901575227
Household 36 friend is Household 42 friend worry is 0.6157375323221728
Household 36 friend is Household 43 friend worry is 0.7200949763394221
Household 36 friend is Household 44 friend worry is 0.8496884831440822
```

Figure 4.6 Example verification of getting friends.

```
Household 10 worry before spread is 0.4771946438484763
Household 10 worry after spread is 0.7741602320496671
Household 47 worry before spread is 0.17402667989739418
Household 47 worry after spread is 0.2840004758171791
Household 40 worry before spread is 0.576967051140537
Household 40 worry after spread is 0.5962934559407278
Household 33 worry before spread is 0.32618115212289645
Household 33 worry after spread is 0.4259954042575435
Household 42 worry before spread is 0.41663340101850443
Household 42 worry after spread is 0.3006065067025815
Household 7 worry before spread is 0.368649999013846
Household 7 worry after spread is 0.6017437599504745
Household 39 worry before spread is 0.852919554982791
Household 39 worry after spread is 0.7547643823705426
Household 20 worry before spread is 0.9057928394662884
Household 20 worry after spread is 0.5442287000597893
Household 2 worry before spread is 0.40876917637107435
Household 2 worry after spread is 0.3640176587833057
Household 8 worry before spread is 0.7002645378458796
Household 8 worry after spread is 0.546020209835174
```

Figure 4.7 Verification of worry spread.

➢ **Household: can I get insurance?**

By inserting a 'print' function after the *'insurance_decision'* function, we can observe whether the Household agent meets the requirement to get insurance. The result can be seen in Figure 4.8. Normally, if the damage is very high, the insurance company will not provide insurance due to the increased risk for the insurance company.

```
Household 45 is able to get insurance
Household 13 is able to get insurance
Household 29 is not able to get insurance
Household 44 is able to get insurance
Household 24 is not able to get insurance
Household 25 is able to get insurance
Household 10 is able to get insurance
Household 30 is not able to get insurance
Household 47 is able to get insurance
Household 15 is not able to get insurance
Household 11 is not able to get insurance
```

Figure 4.8 Example verification of policy response function.

➢ **Household: get insurance**

In Figure 4.9, it can be seen that when the Household meets the requirements in the function, it will get insurance. This fits our expectations.

```
Household 24 just get insured in step 5
Household 40 just get insured in step 5
```

Figure 4.9 Example verification of get insurance function.

- **Household: make adaptations**

Figure 4.10 displays a color change for the network graph, indicating the adaptation states of the Households as the steps progress.

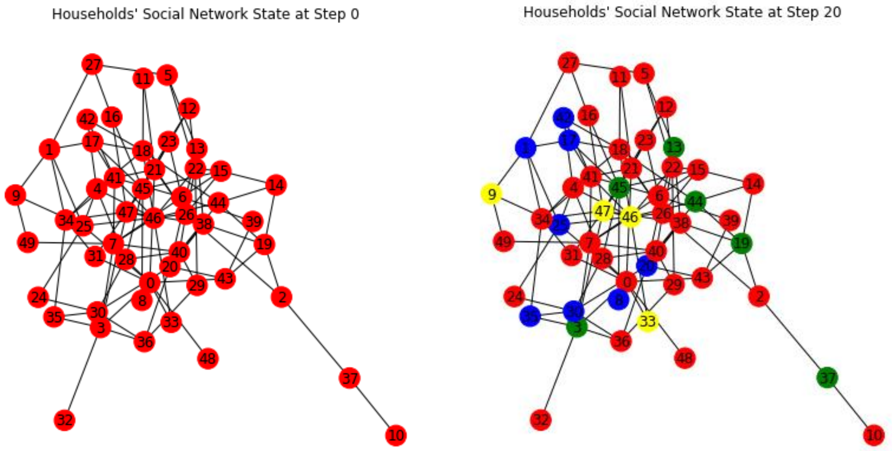

Figure 4.10 Example visual verification of adaptations.

- **Household: get the subsidy**

If one Household is insured, they will get the subsidy if the medium policy is implemented by the Government. In this case, the actual damage will be reduced. Figure 4.11 shows the flood depth (which influences the actual damage) of Household agents before and after subsidies. Household agent 8 shows no difference in flood depth as this agent does not have insurance and therefore does not have subsidies.

```
Households 8 depth before subsidy is 0.0
Households 8 depth after subsidy is 0.0
Households 34 depth before subsidy is 0.4708060698457761
Households 34 depth after subsidy is 0.30253650528859544
Households 49 depth before subsidy is 0.3830514653780647
Households 49 depth after subsidy is 0.3830514653780647
```

Figure 4.11 Example verification of subsidy function

4.2 Validation

The validation of the model aims to assess how well the model captures the real-world dynamics. The validation process is heavily dependent on the chosen criteria, considering that no model, however perfect, can fully replicate the complexity of real-world mechanisms. Given the assignment's focus on learning ABM techniques and research methods, the model's realism isn't the top priority. Acknowledging that our model is a simplified version of reality, we prioritize ensuring the completeness of the assignment. As a result, the model validation will focus on the logic of the model and its behavior under varying parameter conditions.

When solely increasing the actual flood strength in the model (multiplying the estimated flood depth between parameters a and b), as shown in Figure 4.12, we observe an increase in the total number of adapted households (based on 100 runs for each situation). This aligns with the sensitivity of flood strength and the observed trend fit the real-world expectations. Changing the government's attitude towards policy-making, specifically lowering the standard of FN value to make policies, results in a continued increase in the number of adapted households (as shown in Figure 4.13). This aligns with real-world patterns, as lower standards can lead to more policies, affecting a greater number of households and prompting adaptations. The examples provided above are not comprehensive for validation. However, this simple sensitivity analysis demonstrates the sensitivity of parameters, and the observed trends align with reality. Due to time constraints and the availability of real-world data, we will conclude the validation at this point.

	total_adapted_households
0	0
1	0
2	4
3	4
4	6
...	...
75	14
76	14
77	14
78	14
79	14

	total_adapted_households
0	0
1	0
2	1
3	3
4	4
...	...
75	19
76	19
77	19
78	19
79	19

Figure 4.12 Example validation: flood strength

	total_adapted_households
0	0
1	0
2	3
3	5
4	7
...	...
75	24
76	24
77	24
78	24
79	24

Figure 4.13 Example validation: lowering the standard

5. EXPERIMENTATION

In this chapter, the experimentation and analysis of the results are discussed. Firstly, a replicability and variability test is presented, followed by the clarification of the hypothesis for our research question. Subsequently, the experimental setup and the results of the experimentation are discussed. In the provided Excel file, the extensive results of the experimentation can be found. As most of the experiments are not seeded, the replicability of our main research results is low, though a high iteration count of 80 is used to minimize the effects of inherent stochasticity.

5.1 Replicability and variability test

A replicability test was performed to check if the model results could be replicated to improve the verifiability of the model. Although the model is not seeded for the experiment setup, the subsequent variability test is to understand how randomness affects the model.

For the reproducibility test, a variety of seeds was picked to create the same results. Below, a few runs are shown for seed 123 with the following parameters: flood_map_choice of 100yr which results in an APE of 0.01, for network erdos_renyi, for C 0.01 and alpha is 1, and societal risk is set to True. As shown in Figure 5.1, with the left being one run and the right being the next, the results are the same.

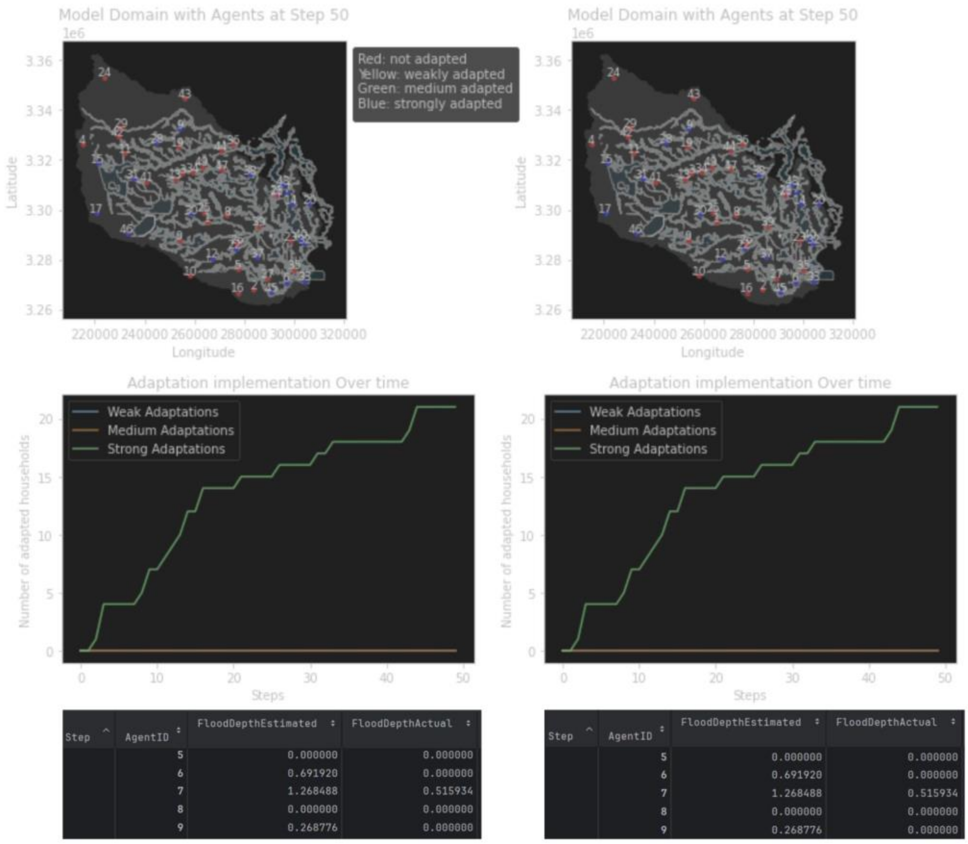

Figure 5.1: Results of replicability test for two runs on seed 123

For the variability test, the same parameters were used, except the seed was now varied across ten runs, as visible in Figure 5.2. The results of the variability test, which are shown in a log scale, show that there is a vast difference in the maximum deaths estimated, maximal deaths and the total population deaths, leading up from numbers around 10 to almost 100000. This variability can be explained by the large flood depths that were reached, as generated by the flood map and the household's location. For example, with seed 7, the estimated flood depth exceeded 13 meters, and for seeds 4 and 8, it surpassed 15 meters. Since the strong adaptation can only reduce the flood depth by a limited amount, typically a few meters, and the actual depth might be 1.2 times higher than the estimated flood depth, the actual flood depth remains high, resulting in a very high population death.

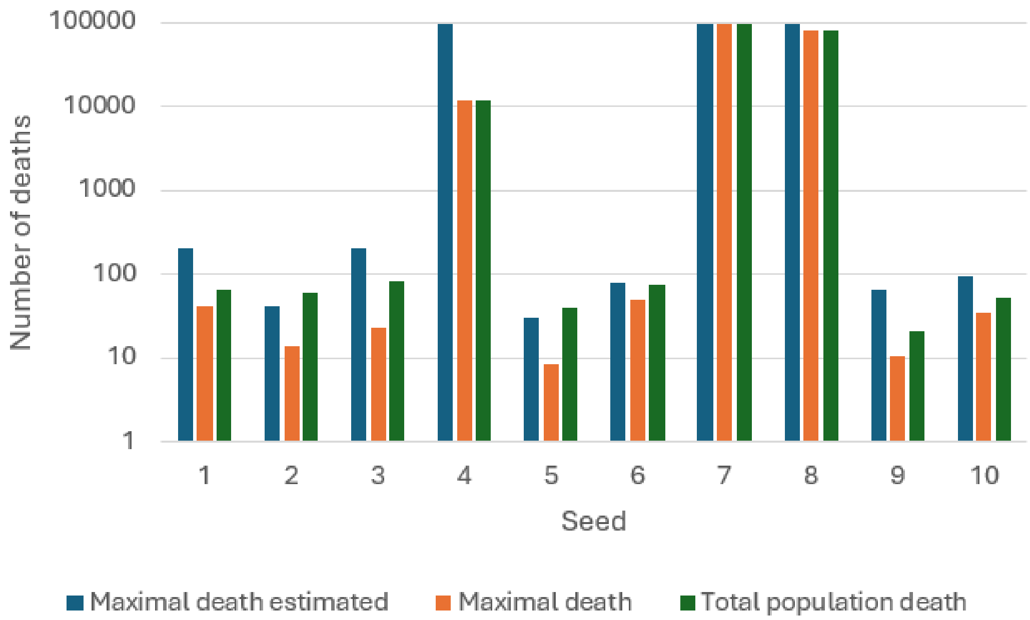

Figure 5.2 Results of variability test, using 10 different seeds

For the adaptation over time, as visible in Figure 5.3, it becomes visible that only strong adaptation takes place for all seeds and the number of adapted households varies between 14 and 21. As is visible, the graphs do not show a similar pattern. This may be the case due to variability in randomness when the adaptation is implemented – there is a 90% chance at each step that the adaptation is implemented. Yet, after reviewing how many households that should be adapted were not, it varied between 1-4 independent of how many households are already adapted. So the variability can probably be explained by the varying flood depth and randomisation in the location of households. This paragraph shows the importance of having a high iteration count, so 80 is used for further experimentation.

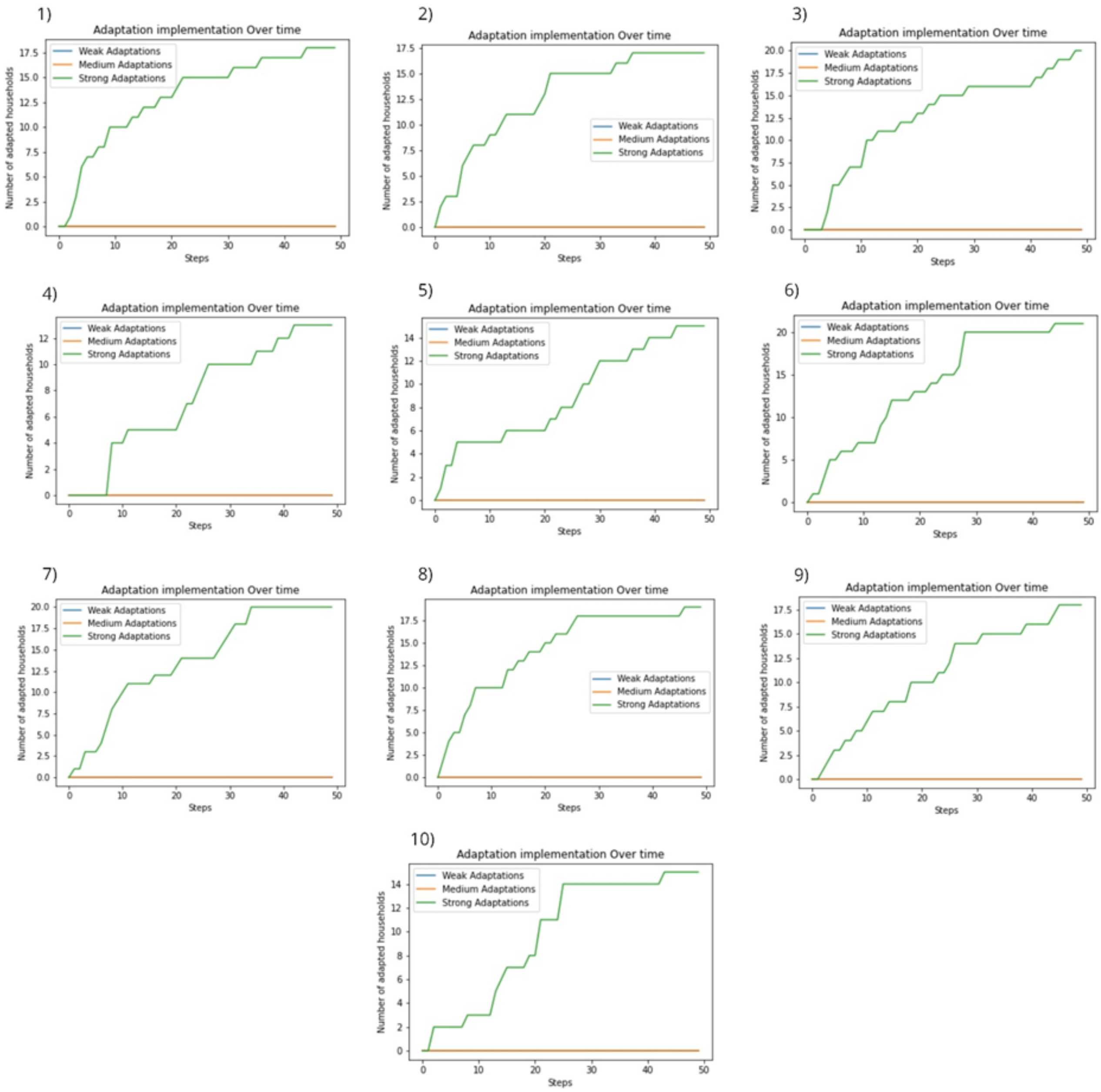

Figure 5.3: Results of variability test per seed, with the seed shown on the top left

5.2 Hypothesis

The following hypotheses were constructed from the research question below:
What is the effect of societal risk factors (FN parameters, government control, etc.) on households' and government's flood adaptation strategies under the condition of different social networks and flood intensities, measured by the number of fatalities (flood damage), and levels and strength of adaptation?
For each hypothesis, an accompanying explanation is provided below it.

Hypothesis 1:
Watts-Strogatz networks will show similar levels of adaptation as Erdős-Rényi networks.
This is due to a higher clustering coefficient and shorter path lengths in the Watts-Strogatz networks, higher worry values will be quicker to spread, but lower values as well. This will create clusters where neighbors have the same worry, but on average the worry is the same as in the Erdos-Renyi, leading to similar adaptation.

Hypothesis 2:
Flood Harvey with APE 0.001 will show similar levels of adaptation as for a hundred year flood with APE 0.01.
Because the APE (and therefore the FN curve changes) with the change of the flood size, crossing the societal risk limit might be of similar difficulty for both floods. On the other hand, logically, a higher flood risk will result in higher damage, and therefore more adaptation would be expected, which might be a limitation of using the FN curve.

Hypothesis 3:
A C value of 0.01 with an alpha value of 1 will result in more and stronger adaptations than the C value of 1 with the alpha value of 1 and therefore a lower death count. Meanwhile, the combination of a C value of 1 with the alpha value of 0.75 will lie in the middle of these.
Because the first combination results in a low societal risk limit, it will be easy to cross the limit, and the number and intensity of adaptations is high. The second combination results in the highest limit and therefore the lowest number of adaptations and the third lies in the middle.

Also, because the alpha is an exponent, changing this value will have a proportionally larger effect than changing the C value. Still, we are not able to test this within the available time-frame, and therefore this is recommended for further study.

5.3 Experiment setup

Experiments will be conducted to address the research question and test the hypotheses outlined in the previous section. The set of experiments that are conducted can be seen in Table 5.1. The parameters are linked to societal risks, which is shown in the expected size of the flood (demands adaptation in the flood map choice and the APE) and the societal risk factors C and alpha. Furthermore, the social networks (network type) in the model are varied, we chose to vary erdos_renyi and watts_strogatz, as there is uncertainty regarding the specific behavior of the actual Harris County government. This method is a factorial method, yet not a full factorial, as not a large variety of C and alpha values is tested, due to temporal limitations. Furthermore, other network types such as barabasi_albert or no_network and results for a 500 year flood were also not tested because of temporal limitations. Each experiment will run 80 times to make the results less sensitive to inherent stochasticity.

Table 5.1 Experiment setup

	Actual included societal risk?	Network type	APE & Type of flood	Societal risk parameter
1	Yes	erdos_renyi	0.01-100 years	C=0.01, α=1
2			0.001 harvey	C=0.01, α=1
3	Yes	erdos_renyi	0.01-100 years	C=1, α=1
4			0.001 harvey	C=1, α=1
5	Yes	erdos_renyi	0.01-100 years	C=1, α=0.75
6			0.001 harvey	C=1, α=0.75
7	Yes	watts-strogatz	0.01-100 years	C=0.01, α=1
8			0.001 harvey	C=0.01, α=1
9	Yes	watts-strogatz	0.01-100 years	C=1, α=1
10			0.001 harvey	C=1, α=1
11	Yes	watts-strogatz	0.01-100 years	C=1, α=0.75
12			0.001 harvey	C=1, α=0.75
13	No	watts-strogatz	0.01-100 years	C=0.01, α=1
14			0.001 harvey	C=0.01, α=1
15	No	watts-strogatz	0.01-100 years	C=1, α=1
16			0.001 harvey	C=1, α=1
17	No	watts-strogatz	0.01-100 years	C=1, α=0.75
18			0.001 harvey	C=1, α=0.75

5.4 Experiment results

The impact of societal risk factors

The results of 2, 4, and 6 (or 8, 10 & 12 or 14, 16 & 18) can be compared to show the effect of higher societal risk limit as the result of higher societal risk parameters (C and α). The result of 2, 4 & 6 can be seen in Figure 5.4.

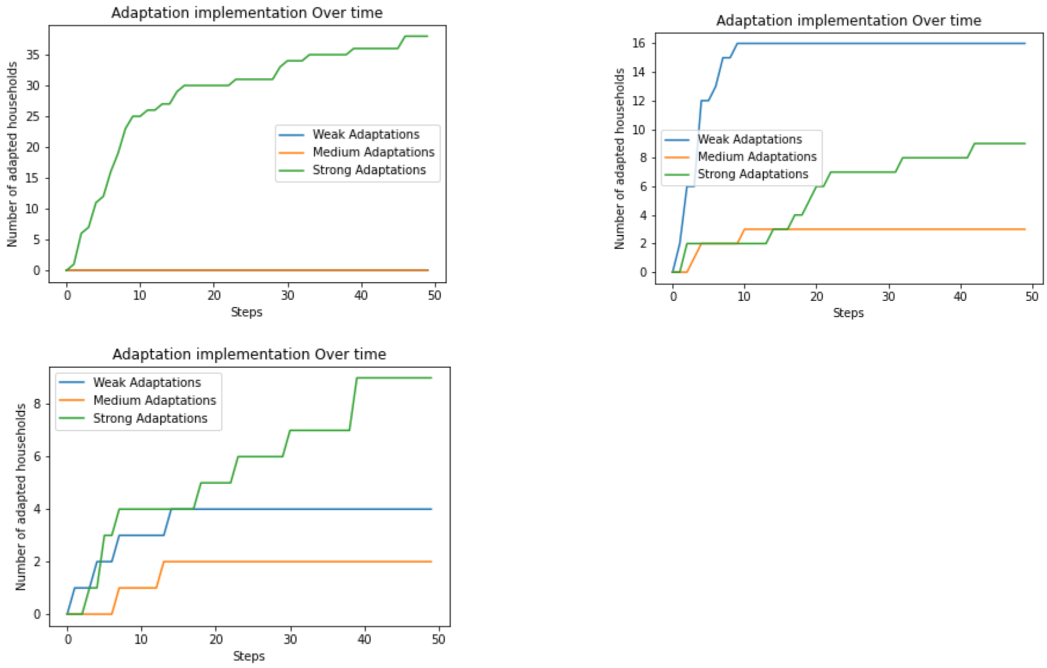

Figure 5.4 Results of scenarios 2, 4 and 6 (respectivly, left to right to bottom) when the Societal risk (FN parameter) standard keeps growing

The results are clear, when the standards keep growing, fewer households will do the adaptations. This is because when the standards are high, the government will be less likely to require any policies or collective adaptations, and thus the total number of adaptations of households will correspondingly reduce.

The impact of FN value (APE) and flood size choice

The result of each two combinations, such as 1&2 and 3&4, can show the impact of different annual probability of occurrence of flood towards the adaptations. Results of 3&4 can be an example, and they can be seen in Figure 5.5.

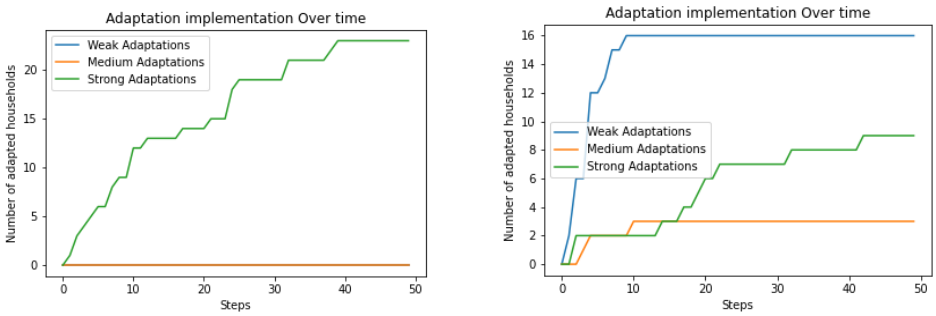

Figure 5.5 Results of scenario 3 (higher APE) & 4 (low APE) when different APEs apply.

It can be seen that when the annual probability of exceedance is low (the right one), which means the occurrence of the flood is low, the overall adaptations will mitigated in quality. That means that when the occurrence of the flood is low, the FN value is relatively low, and the government will be less likely to make policies. Thus, the households and governments are less likely or motivated to make strong adaptations when the risk is higher. This is surprising, as one would expect the adaptation to be higher when the expected flood size is higher. Still, when looking at 1&2, this conclusion can not be made and there are actually many more adaptations for the lower APE, but for 5&6 the results are similar to this graph again. Therefore, drawing definitive conclusions from these results is difficult. Similarly, for the Watts-Strogatz network, the results do not seem to follow a strong pattern.

The impact of different social networks

To check whether different social networks will have an impact on governments' and households' adaptations, experiment results of 1&7, 2&8, etc., can be compared. However, we did not consider the 'no network' scenario because, in reality, it is impossible to have a 'no network' scenario. Also, 'no network' will somehow make it less like an ABM. The results of 3&9 can be seen in Figure 5.6.

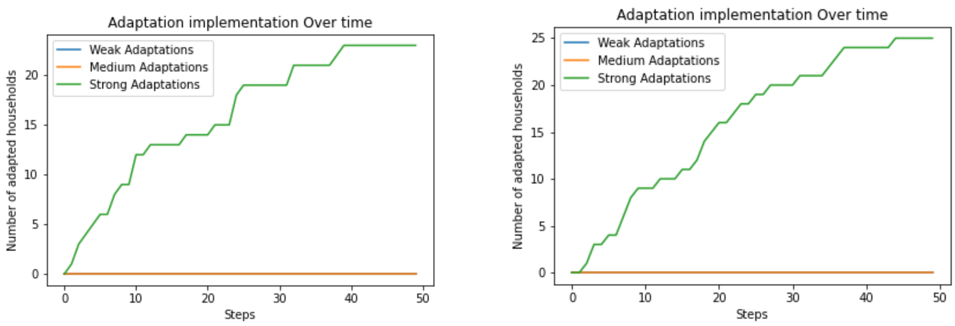

Figure 5.6 Results of scenario 3 (erdos_renyi) & 9 (watts_strogatz) when different networks apply.

As indicated, different social networks do not have a clear effect on the adaptations. As long as they communicate with each other, no huge differences will appear in how their social networks are. Next to this, the results reveal that the observed lines exibhit a notable degree of variation, which makes it difficult to make conclusion about the diffusion over time.

The impact of including societal risks or not

For the research, whether the government and societal risks will play an important role in households' adaptation will also be examined by comparing the results of 7&13, 8&14, etc. The results of the 7&13 can be seen in Figure 5.7. Notice that to implement this, we are not deleting the whole government. Instead, the FN standard was increased 10 times than it should be, and this will get rid of the impact of the societal risks.

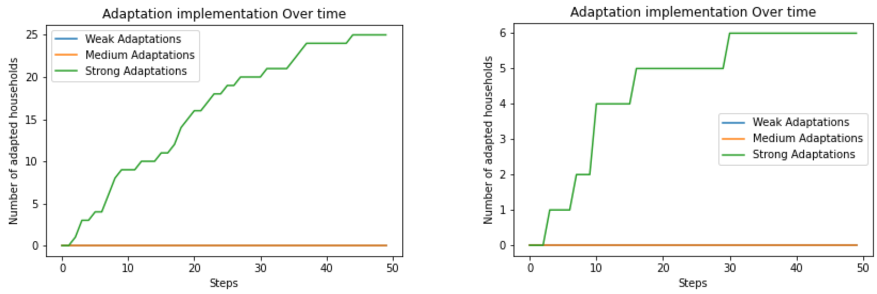

Figure 5.7 Results of scenario 9&15 when including societal risks and not.

It can be seen that when including the societal risks, households' adaptations will be much higher than not including them. Here we see a clear impact of the government and societal risks, which was also visible when comparing other results. Still, the same cannot be said when comparing e.g. 7 and 13, when the amount of adapted households appears to be approximately the same. We will describe this problem in the Limitations.

Fatalities of each scenario

In each scenario, there would be a certain number of estimated fatalities and actual fatalities. Notice that each node represents 94623 people. The results can be seen in Figure 5.8. Some of the important information can be concluded based on the graph. (1) When they do adaptations, the actual fatalities will reduce. (2) The overall death when societal risks have been applied (scenarios 1-12) is less than not including them (scenarios 14-18).

However, no specific and very clear patterns can be concluded based on this Figure, the possible reason might be that some complex interactions are ignored in the model. Or randomness in the model affected the result even with 80 iterations, as shown by the variability analysis. These limitations would be the future research for other researchers. But overall, we see that societal risks have an important role in the adaptation and each adaptation will reduce the amount of deaths. Within the available time for the project, it was not possible to perform a statistical analysis on the results.

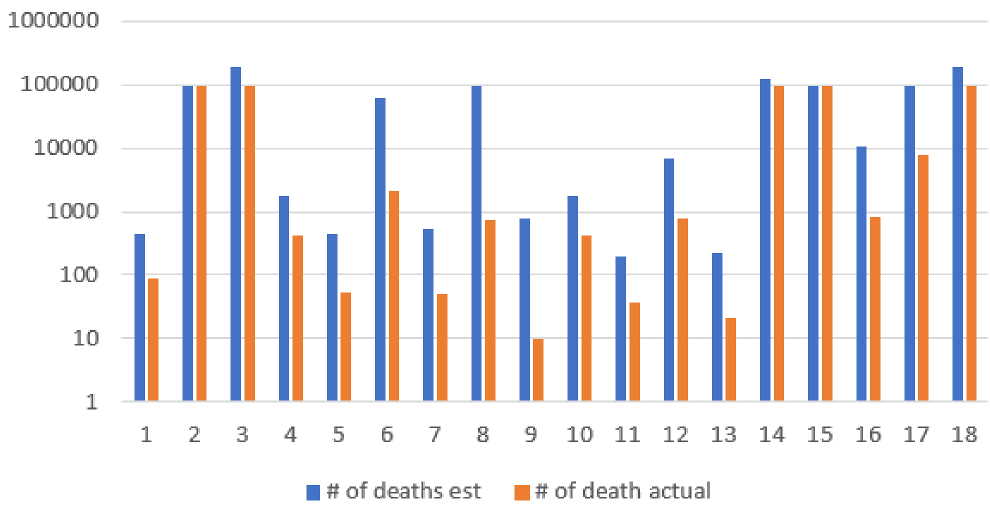

Figure 5.8 Number of total fatalities

6. CONCLUSION

Conclusion and recommendations

It is concluded that the model and its results fit hypothesis 1. The different social networks, watt-strogatz and Erdos-Renyi, did not show huge differences in adapatation. Hypothesis 2 was not consistently supported. Contrary to expectations, lower APEs did not consistently lead to higher adaptations, and definitive conclusions from the results are difficult due to the lack of a clear pattern. Hypothesis 3 was supported by the results as the standard increased, fewer household engaged in adaptations.

The research question is addressed, revealing that variations in societal risk standards considered by the government, impacts households' adaptations and damage mitigation. Lowering the government's standard for societal risks results in increased speed and number of households' adaptations, leading to a reduction in flood damage. However, social network structures do not have a clear impact on the households' adaptations.

Based on the results, it is recommended that the government incorporates societal risks into its policy-making process. Specifically, lowering the standard for societal risks is advised, as this is shown to lead to better decision-making in flood policies.

Limitations and future research

There are still limitations in this model, some of which can be concluded as follows:

- In real life, there will be more types of agents, such as separate insurance agents, rescuer agents, etc. We cannot include them all, as this system is very complicated.
- The perspective to see and analyze the question is from a societal risks perspective, and this has made the modeling extremely difficult.
- In the model, few people get insurance, because we want to link the insurance with the government policy. In real life, this could be changed, and more detailed interactions can be implemented.
- The code is not perfect, our group members are all new to Python, but we truly have learned a lot.
- Now the agents are not moving, in reality, these agents will move around, for example, they will move to avoid the flood.
- Households' attributes are not perfectly simulated. For example, in real life, they might have some attributes such as flood rescue knowledge, which could also affect their adaptations.
- The perspective of societal risks, as required by RBB. Somehow confused us a lot as in real life, these societal risks such as FN curve we used here are not very proper to use as real-life policy-making is based on more comprehensive thinking, such as political concerns (they can develop a policy only for the purpose of political propaganda.)

- The model itself also contains many limitations, for example, in order to visualize the adaptation, only 50 households and nodes are created (each indicating 94623 people). We use a number attribute to simulate the fatalities. If we had more powerful laptops and additional time, it might be feasible to simulate the actual population of Harris County and employ a state attribute with "Death" and "Alive" to model fatalities.
- The logic for societal risks could be improved. As seen in the results, most households adapt strongly in all scenarios. The reason for this is that the FN curve is often extremely large in comparison to the limit, for example 1000 times larger. For example, for {"flood_map_choice":"100yr", "network":"erdos_renyi", "APE":0.01, "C":0.01, "alpha":1,"societal_risk":True} with seed 123, you can see that the FN curve is on average more than 550 times larger than the limit. Therefore, multiplying the limit with a smaller value such as 0.25 as is done for weak adaptation, you will still see only strong adaptations. Also, for the base scenario, you can see that the multiplication of the limit with 10 barely affects the results for this reason. You need to significantly change this value for it too affect the results for many of the scenarios.
- It was not possible to do a statistical analysis within the timeframe

The future research of the project will mainly address some of the limitations mentioned above. Firstly, what if we add more agent classes to the model? We would like to add more types of agents and see how they can interact with the existing ones, and see how they can affect the results. Secondly, find more theories and combine them with the societal risk theory. Thirdly, optimize some of the attributes of the agents. For example, we might add attributes such as knowledge to the households and make the model more comprehensive. Next to this, it is possible to do more research on the reality and thus mitigate some of the randomness and assumptions in the model, which would help achieve a better experiment outcome. Last but not least, in reality, there are a lot of choices on policies and adaptation strategies, in the future, we might extend our research question and see how different policies will affect households' adaptation.

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