Faculty of Technology, Policy and Management
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Rising Tides:
Simulating the Impact of Risk Rating 2.0 on long-term Social Vulnerability

RESEARCH PROPOSAL

For the final thesis in the MS Engineering and Policy Analysis.
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Abstract

This study examines the impact of FEMA's Risk Rating 2.0 on social vulnerability in Houston, Texas. Risk-based flood insurance introduces a net increase in premium prices across policy holders, especially in high-risk areas. We expect a relative decrease in insurance and adaptation take up among vulnerable groups, potentially reinforcing already existing socioeconomic disparities and social vulnerabilities to flood hazards.

Using an agent-based model (ABM), household adaptation behavior regarding policy take up and adaptation measures are being simulated under Risk Rating 2.0 and its legacy premium framework and under varying climate change projections. The analysis focuses on adaptation outcomes with regards to flood exposure, flood risk, and social vulnerability in the long run. We will present simulation results in spatial profiles.

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Abbreviations

Acronym	Meaning
AAL	Average Annual Loss
ABM	Agent Based Model
BFE	Base Flood Elevation
BW12	Biggert-Waters Flood Insurance Reform Act (2012 legislation)
CCA	Climate Change Adaptation
CRS	Community Rating System
EDA	Exploratory Data Analysis
FEMA	Federal Emergency Management Agency
FIRM	Flood Insurance Risk Map
FMA	Flood Mitigation Assistance
GEV	Generalized Extreme Value
GIS	Geographic Information System
HFIAA	Homeowner Flood Insurance Affordability Act (2014 legislation)
NFIP	National Flood Insurance Program
NOAA	National Oceanographic and Atmospheric Administration
PRP	Preferred Risk Policy
PU	Prospect Utility
RCV	Replacement Cost Value
RR2	Risk Rating 2.0
SFHA	Special Flood Hazard Area
SLR	Sea Level Rise
SRL	Severe Repetitive Loss
SVI	Social Vulnerability Index
USACE	United States Army Corps of Engineers

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1. Introduction

Climate induced flood damages are surging. In US coastal areas, annual flood related damages are running as high as $10 billion (Jr et al., 2005). Damages from Atlantic storm surges in the US are currently doubling with each decade (Jr et al., 2005). This trend is likely to continue as sea levels rise and populations continue to flock to US coastal areas (Aerts et al., 2014; Mousavi et al., 2011).

Increasing frequency and scale of Hurricane-related natural disasters are mounting financial pressure on the National Flood Insurance Program (NFIP). The 2005 Hurricane season marked a turning point in US flood management. Hurricane Katrina alone took 1800 lives and caused over $160B in compounded damage (*Hurricane Katrina*, 2015). Two decades later, one in five residents are still displaced (*Hurricane Katrina | Deaths, Damage, & Facts | Britannica*, 2024). Since 2005, the NFIP is accumulating debt. Pressure to revise the insurance program has been mounting since.

In April 2023, the Federal Emergency Management Agency (FEMA) has fully phased in a new premium rating scheme, called Risk Rating 2.0 (RR2). (*NFIP's Pricing Approach | FEMA.Gov*, 2023). The new risk-based rating system will see an overall rise in premiums in an effort to cover consistently increasing claims payouts. FEMA claims that RR2 is also going to deliver a more socially equitable premium framework (*NFIP's Pricing Approach | FEMA.Gov*, 2023).

Nevertheless, we expect that under RR2 premiums will increase disproportionately for vulnerable groups, especially in high-risk areas. As a result, we expect a relative decrease in policy take up among such groups, potentially self-reinforcing disparity with regards to social vulnerability. This assumption poses the question: **What is the long-term impact of Risk Rating 2.0 on social vulnerability?** We will focus our case study on Houston, Texas.

1.1. Scientific Relevance

This research project is located at the intersection of three scientific fields. Climate change adaptation (CCA) is concerned with questions of flood risk, mitigation, and adaptation. Topics in economics are delivering theory for insurance markets and household-level decision making. Questions of exposure, flood risk, adaptation, and social vulnerability are best answered by literature on public policy.

By bringing these fields together, we are advancing our theoretical understanding of the links between flood insurance design and adaptation behavior. The study explores how RR2 influences household level insurance take up and adaptation outcomes under changing flood risk. **We explore the impact of this policy- and climate change-induced adaptation behavior on social vulnerability and its spatial distribution across the community.**

To the best of our knowledge, we are the first to fully replicate the premium calculations under Risk Rating 2.0 and its legacy framework. The model will be empirically informed with regards to the spatial distribution of relevant attributes across Houston, Texas. This is an improvement upon similar ABMs in the literature (Aerts et al., 2014; Han & Peng, 2019; Shao et al., 2017), which allows us to reliably use this model as a policy analysis tool for forward looking model-based decision support. Although focusing on Houston**, this policy analysis tool can generate valuable insights into the links between risk-based insurance and social vulnerability in a future in which climate change will drive policy makers around the world towards risk-based insurance, especially in the global south.**

1.2. Societal Relevance

With rising frequency and magnitude of coastal flood hazards, flood insurance becomes ever more important (Dávila et al., 2014; Shao et al., 2017; Surminski & Oramas-Dorta, 2014). The policy switch to risk-based insurance prevents adverse selection and a consequential collapse of the risk sharing mechanism (Baker, n.d.; Boudreault et al., 2020; Bradt et al., 2021; Cutler & Zeckhauser, 1997; Hudson et al., 2016). **Our research contributes to a better understanding of the effects of risk-based insurance on social vulnerability, in order to ensure access to insurance for everyone.**

2. State of the art

The literature review can be split into roughly three domains, summarized in Table 1. Reference papers are serving as a foundation for a base model upon which we will builds. To understand the underlying policy process, information on the history of the NFIP and RR2 are essential. Research domains are referring to the scientific intersections relevant to our work. We will review the project and policy process in this proposal and delve into research intersections after kick-off.

Domains of my review	**What I will review in this domain**
The model	- Reference papers - The base model
The policy process	- The National Flood Insurance Program - Risk Rating 2.0
Research domains	- Climate Change Adaptation - Insurance economics - Public Policy

Table 1: Domains of my literature review and what I will review in each domain

2.1. Search Strategy

This thesis is part of a joint research project in collaboration between Delft University of Technology and University of Texas at Austin. We will build on a replicated ABM introduced by (Han & Peng, 2019) and (Han et al., 2020). These two papers will additionally serve as a point of departure for our literature review in this proposal.

To summarize the ongoing policy process, we will perform an open search on general public search engines such as google.com (*Google*, n.d.). We will focus on government sites (*Home | FEMA.Gov*, n.d.; *Home | Homeland Security*, 2024; *U.S. Government Accountability Office (U.S. GAO)*, 2024), publications from universities (*Environmental, Social, and Governance (ESG) Initiative at Wharton School*, 2024) and the Congressional Research Service, an inhouse think tank that "serves as shared staff to congressional committees and Members of Congress" (*About CRS - Congressional Research Service (Library of Congress)*, 2024).

2.2. The model

Han & Peng (2019) and Han et al. (2020) will serve as a starting point. They introduce an ABM "to investigate adaptation strategies in coupled human and environmental coastal systems" (Han et al., 2020). The model can be seen through the XLRM framework, see Figure 1 (Jafino et al., 2021).

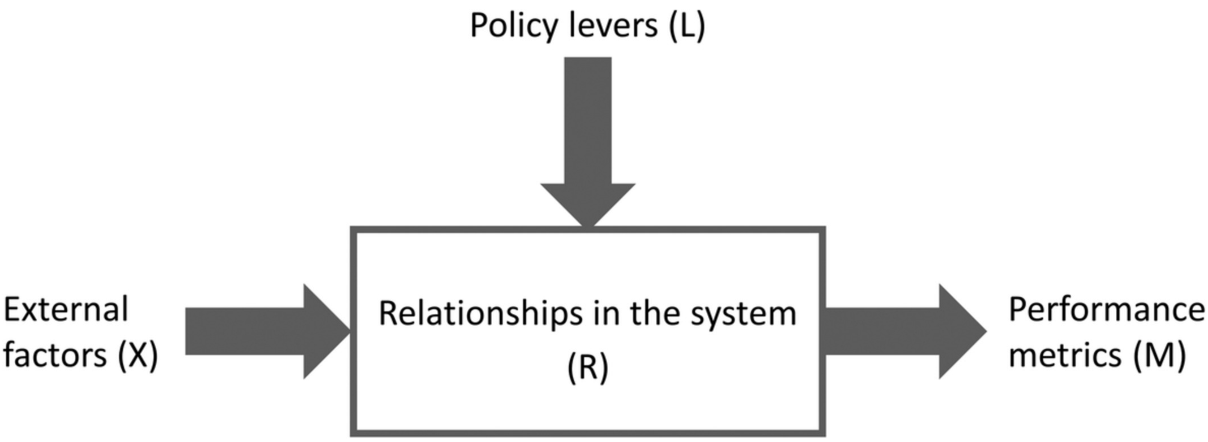

Figure 1: XLRM Framework. Figure taken from Jafino et al. (2021)

SLR introduces external pressure on the system. Interactions between three agent classes are making up the bulk of relationships in the system: Households, insurers, and the local government. The main performance metrics are insurance take up and household adaptation. Han et al. (2020) are building scenarios from combinations of the following policy levers: Risk based insurance with a voucher system for socioeconomically disadvantaged policy holders, a "twice and out" government buyout policy, a 2-ft seawall, and a 4-ft seawall. External factors are introduced into the model through a storm surge simulator, see equation 1.

$$P(z) = \left(1 + \frac{\xi(z-u)}{\sigma}\right)^{\frac{-1}{\xi}}$$

Equation 1: Flood frequency and height (Han et al., 2020)

Flood damage is modelled using the generalized extreme value (GEV) distribution P(z). z depicts the storm surge elevation. u, σ, and ξ are respective parameters for location, scale, and shape of the surge. The storm surge simulator produces data on property flood damage that is then fed into the social system. Households base their decisions on expected flood damage and a subjective risk assessment.

Households compute their prospect utilities in order to decide upon insurance and adaptation measures (see equations 2 and 3). The corresponding functions in our model are called "U" and "prospect_utility_action" (Sun, 2024a). The sum is iterating over i instances of flood events. D is depicting flood damage; RD is depicting the remaining flood damage with insurance coverage or protection from the implemented adaptation measure. C is representing adaptation costs with regards to adaptation measure j.

$$PU(NoAction) = \sum_{\mathrm{i}=1}^{\mathrm{n}} \pi_{\mathrm{i}} \mathrm{U}(-\mathrm{D}_{\mathrm{i}})$$

Equation 2: Prospect Utility if no adaptation measure implemented (Han et al., 2020)

$$PU\left(Action_j\right) = \sum_{i=1}^{n} \pi_i U\left(-C_j - RD_{i,j}\right)$$

Equation 3: Prospect Utility with adaptation measures implemented (Han et al., 2020)

π is the subjective probability weight of a storm surge event. The formula takes in the return period after a flood p, and a subjective weighing parameter γ. The corresponding function in our base model is called "pi_calculation" (Sun, 2024a). Note that it takes "risk_perception" as an input argument, see equation 5.

$$\pi_j = \frac{p_j^{\gamma}}{(p_j^{\gamma} + \left(1 - p_j\right)^{\gamma})^{1/\gamma}}$$

Equation 4: subjective probability of storm surge event (Han & Peng 2019)

Risk perception is calculated based on six socioeconomic indicators, as can be seen in equation 4. Income, race, and ownership are sourced from American Community Survey (ACS) data (*American Community Survey Data*, n.d.). The parameter for experience is set to 1 if the household has experienced a flood in the past decade. The community parameter is set to 1 if there is a community adaptation measure in place. The social parameter is modelling the impact of neighborhood behavior on risk perception by depicting the percentage of neighbors implementing an adaptation measure in the current simulation period. This parameter has been added in the 2020 paper and is missing in our base model and the 2019 paper. Risk perception is thus boundedly rational and subject to social interaction. a, b, c, d, e are set to constants (Sun, 2024b).

$$RP = \frac{aI_{income} + bI_{race} + cI_{ownership} + dI_{experience} + eI_{community} + fI_{social}}{a + b + c + d + e + f}$$

Equation 5: Risk perception (Han et al., 2020)

Han & Peng (2019) found that households in high-risk areas are more likely to implement adaptation measures indicating a certain system predisposition towards adverse selection. Furthermore, NFIP premium rates correlate with private insurance take up, indicating a risk of crowding out. A voucher coupled elevation program seems to mitigate the crowding out effect, however. Note that unlike the NIFP, private insurances have no direct interest to incentivize flood adaptation.

Han et al. (2020) found that community mitigation can bias individual risk perception and thus lead to maladaptation on the household level. That is especially the case for sea walls and owners of high-risk properties. A risk-based rating system such as RR2, a means-tested voucher system to support adaptation efforts in low-income households, and a “twice and out” government buyout program for high-risk properties are enhancing communal resilience. While the buyout program could help to overcome maladaptation, it could also promote climate gentrification. The need for a voucher program indicates a system-tendency towards social segregation.

2.3. The policy process

2.3.1. The National Flood Insurance Program

The NFIP has been called into life under the 1986 National Flood Insurance Act in an attempt to meet demand for flood insurance not covered by the private sector (Linder-Baptie et al., 2022). The NFIP is currently insuring $1.3 trillion in assets for roughly 5 million policy holders (Rogers, 2022). FEMA, as part of the US Department of Homeland Security, oversees the NFIP. Consequently, FEMA is assigned with claims handling, premium setting, sustaining NFIP’s financial stability, and flood plain management.

An integral part of flood plain management are the so-called Flood Insurance Risk Maps (FIRM). FIRMs are mapping individual flood zones. The Special Flood Hazard Area (SFHA) is defined as “the area that will be inundated by the flood event having a 1-percent chance of being equaled or exceeded in any given year” (Flood Zones | FEMA.Gov, 2020).

Identifying spatial flood risk is essential to the NFIP’s twofold purpose: Transferring risk from property owners to the federal government and mitigating overall flood risk by incentivizing individual adaptive capacities (Horn, 2024). Both, for calculating insurance premiums and targeting adaptation incentives, FEMA requires a detailed understanding of the underlying spatial flood risk distribution.

As a public body, FEMA can act as both, an a posteriori insurance provider and an a priori regulator and mitigator. To regulate risk hazards, FEMA is maintaining the Community Rating System (CRS). Households can only purchase an NFIP policy if the community they live in has applied to the CRS (Horn, 2024). Once a local community is part of the CRS, the insurance is available to homeowners as well as renters, and for residential as well as non-residential dwellings. If a local government chooses to implement flood mitigation, FEMA adjusts the CRS ranking of that community, which translates to lower premiums for policy holders.

Horn (2024) is listing several more differences between private flood insurance and the NFIP. The NFIP is actively working on reducing government cost after floods. Insurance policies are issued also to households in risk prone areas for which market-priced insurance would not be affordable. FEMA is identifying, mapping, and communicating flood risks to the public. Premium rates are used to communicate risk. FEMA is furthermore incentivizing the building of individual and communal adaptative capacities and contributing to building-code standards. Lastly, FEMA is building communal resilience through the Flood Mitigation Assistance (FMA) grant program.

NFIP insurance is financed primarily through payments by policy holders (Michel-Kerjan, 2010). NFIP flood plain management is primarily financed through congress (U.S. House of Representatives, Committee on Appropriations, 2021). The NFIP is not designed to cover "truly extreme [weather] events" (Horn, 2024). Instead, the US Treasury is expected to cover for such expanses which the NFIP then pays back with interest.

Since the 2005 Hurricane season, this finical model has been accumulating debt. Given the current trajectory of climate change and SLR, so-called truly extreme weather events are occurring ever more frequently, accelerating debt accumulation. To sustain financial stability of the program into the future, FEMA has introduced RR2 in late 2021 (Horn, 2022).

2.3.2. Risk Rating 2.0

Although Congress has cancelled $16B in debt in 2017, **the National Flood Insurance Fund is still running at a deficit of $20.5B today** (Federal Emergency Management Agency (FEMA), 2023). In an initial effort to address the NFIP's debt accumulation, Congress passed the Biggert-Waters Flood Insurance Reform Act (BW12). With BW12, FEMA was mandated to establish a fund to save at least 1% of the NFIP's total potential annual loss exposure (Linder-Baptie et al., 2022). Grandfathering and subsidies were phased out and risk based premiums were introduced (Grannis, 2012; Puente Cackley, 2013). The legislation triggered concerns over affordability and equity (Horn, 2022), resulting in the 2014 Homeowner Flood Insurance Affordability Act (HFIAA), which introduced surcharges for holders of severe repetitive loss (SRL) policies and permitted FEMA to buy reinsurance and insurance linked securities in the capital markets (Linder-Baptie et al., 2022). Despite these legislations, NFIP is continuing to lose money (Linder-Baptie et al., 2022).

RR2 is a new premium calculation framework based on up-to-date private sector actuarial standards. Flood mapping and risk modeling practices underwent an overhaul (National Flood Insurance Program Risk Rating 2.0 Methodology and Data Sources, 2022). FEMA promises the new framework to improve flood risk communication and to increase take up rate while also promoting social equitability (*NFIP's Pricing Approach | FEMA.Gov*, 2023). The primary goal, however, is to bring the NFIP back into black digits in the long run.
What does that mean for policy holders? **Premiums will rise for 77% of policy holders** and shrink for 23% (*How Have Flood Insurance Premiums Changed?*, n.d.). Over the coming years, premium rates for policy holders will increase until they reach the risk-based rate at which point **all remaining premium subsidies will be phased out**, including price cliffs and regressive cross subsidies with regards to property values (Horn, 2022; Linder-Baptie et al., 2022). 50% of policies will reach that rate in five years and 90% in ten years. The HFIAA capped individual premium increase at 18% per year for primary residencies (15% on average per year). **CRS subsidies** – the major vehicle to promote communal flood adaptation – **will continue**. The Preferred Risk Policy (RPR) will be phased out, however. The maximum chargeable premium will increase as well (Horn, 2022). Note that **26% of policy holders are low-income households** (Federal Emergency Management Agency (FEMA), 2018).

2.3.3. Calculating Risk Rating 2.0

RR2 marks the departure from a static premium calculation method towards a risk based, dynamic and property-specific one (Horn, 2022; Rogers, 2022). **The final premium is calculated by multiplying a base premium rate with property-specific rating factors**, notably including spatial metrics such as location and Base Flood Elevation (BFE) at that position, distance to waterbodies, position to drainage areas, and building characteristics such as number of floors, ground floor elevation, occupancy type, replacement cost value (RCV) of the structure, and foundation type. (Federal Emergency Management Agency (FEMA), 2022; Horn, 2022). Rating factors are provided in Appendices D and E (National Flood Insurance Program Risk Rating 2.0 Methodology and Data Sources, 2022)

Every property has a base rate assigned, based on location, peril, and occupancy type. The new base rate is derived from catastrophe models. These catastrophe models take historic loss exposure, RCV, GIS data, and market basket data to compute the property-specific average annual loss (AAL). Higher AAL correspond with higher base rates. The higher the base rate, the higher the impact of low rating factors on the final premium to be paid – for instance through elevating the structure on poles or installing flood vents.

Adjustments are made to these factors, most importantly for concentration risk, which refers to increased risk exposure through a geographic concentration of policy holders. In a disaster case, the total of claims is higher in urban centers compared to rural areas. Higher concentration risk thus leads to higher premiums.

2.3.4. Flood Insurance Risk Mapping

Up until RR2, insurance premiums were determined by FIRMs. Dwellings inside the same flood zone were roughly charged the same premium rate. Although this has changed, FIRMs are still deployed for flood plain management. FEMA is continuously updating these maps to account for SLR, advancements in risk prediction, and changes in land use (Linder-Baptie et al., 2022).

The SFHA, also known as base flood zone, is defined as the area that will be submerged in the 'once in a century' event. The chance of this area – or areas with higher elevation – being inundated by an annual flood is thus 1% (*Flood Zones | FEMA.Gov*, 2020). Unlike the SFHA that is referring to a geographic location, the BFE refers to expected flood height in that area. Adherence to certain building codes and flood insurance – for properties with federal mortgage – is mandatory inside SFHAs (Linder-Baptie et al., 2022).

The SFHA is divided into roughly two types of flood zones: Zone V is referring to flood plains with expected storm waves of up to three meters, zone A is referring to SFHA with no occurrence of storm waves. Zone A is furthermore divided into flood zones where BFE is provided (AE) and not provided (A). The suffixes O (river streams) and R (construction and maintenance) are indicating flood origins. Flood zones B, C, and X are indicating areas with flood probability below 1%. Areas with not yet determined flood risks are marked as flood zone D. For more detailed information please refer to Table 2.

Zone	**Description**
A	Base flood zone. No BFE provided
AE	Base flood zone. BFE provided
AH	Base flood zone. Shallow flood, average depth = [1;3] foot. BFE provided
AO	Base flood zone. Flood risk stemming from rivers or streams. Average depth = [1;3]. BFE provided
AR	Area with temporarily increased flood risk due to building/ maintenanve of flood control systems
A99	Base flood zone protected by federal flood control system. No BFE provided.
V	Base flood zone with storm waves ≤ 3m. No BFE provided?
VE	Base flood zone with storm waves ≤ 3m. BFE provided.
B & X	Between 1% and 0.2% chance of flood reaching this elevation or higher
C & X	Below 0.2 % chance of flood reaching this elevation or higher
D	Undetermined

Table 2 information taken from https://efotg.sc.egov.usda.gov/references/public/NM/FEMA_FLD_HAZ_guide.pdf

3. Research Gap

We recognize a growing focus on risk-based flood insurance within the CCA community (Crick et al., 2018; Díez-Herrero & Garrote, 2020; Dubbelboer et al., 2017; Han et al., 2020; Han & Peng, 2019; Jenkins et al., 2017; Kalfin et al., 2022; Shao et al., 2017). Models are being developed to explore the various consequences of a switch to risk-based flood insurance (Aerts, 2020; Crick et al., 2018; Dubbelboer et al., 2017; Han et al., 2020; Han & Peng, 2019; Hudson et al., 2016). **However, the long-term impact of risk-based flood insurance on social vulnerability has not been explored yet**.

As laid out in section 2.3.2, risk-based insurance will bring about a net increase in premiums in order to cover a climate change-related increase in actuarial expenses. We expect that under RR2 – and similar risk-based policies – **premiums will increase disproportionately for socially vulnerable groups, especially in high-risk areas**. This mechanism can lead to a relative decrease in policy take up among socially vulnerable groups, further exacerbating their vulnerability to flood risk. To explore our assumption, we formulate the following research question: **What is the long-term impact of Risk Rating 2.0 on social vulnerability across Houston, Texas?**

Due to the global nature of climate change and SLR, this knowledge gap carries importance well beyond the US. While the US is among the early-movers, **a shift to risk-based insurance is underway also in the global south** (Gao & Zhou, n.d.; Lamond & Penning-Rowsell, 2014; Surminski & Oramas-Dorta, 2014). With Risk Rating 2.0 being one of the first risk-based public flood insurances, we hope to inform the policy process elsewhere, especially in regions with high levels of social vulnerability.

Our approach is novel in three ways. Firstly, **we are the first to systematically explore the impact of risk-based insurance on social vulnerability**. Secondly, **we are the first to model an existing risk-based insurance policy by replicating the exact premium calculations.** Thirdly, we are replicating the spatial composition of Houston with regards to socioeconomic variables and policy premiums (for variables and data sources please consult section 4.2). **An empirically informed ABM allows us to explore spatiotemporal patterns.**

3.1. Research Questions

"Vulnerability of any system (at any scale) is reflective of (or a function of) the exposure and sensitivity of that system to hazardous conditions and the ability or capacity or resilience of the system to cope, adapt or recover from the effects of those conditions" (Smit & Wandel, 2006, p.5). Thus, higher exposure to hazards leads to higher vulnerability, whereas higher adaptive capacity will lead to lower vulnerability (Smit & Wandel, 2006). Social vulnerability describes the susceptibility of groups and individuals to loss, due to socioeconomic outcomes such as poverty, inequality, and marginalization (Cutter et al., 2003). Relative vulnerability scores such as the social vulnerability index, allow to quantify and compare social vulnerability across a community (CDC, 2024; Smit & Wandel, 2006).

To understand the impact of RR2 on social vulnerability across Houston, we will first study exposure and risk. Exposure refers to the susceptibility of livelihoods to adverse effects (Brooks, 2003). Households can reduce their individual exposure to flood hazards through adaptation measures and insurance. Adaptation measures such as elevating the house or floodproofing foundations reduce physical exposure. Insurance reduces financial exposure by transferring damage repair costs of physical assets to the insurer. Risk is a function of the hazard and its probability of occurrence (Brooks et al., 2005). Our model captures flood damage and allows to systematically vary flood probability.

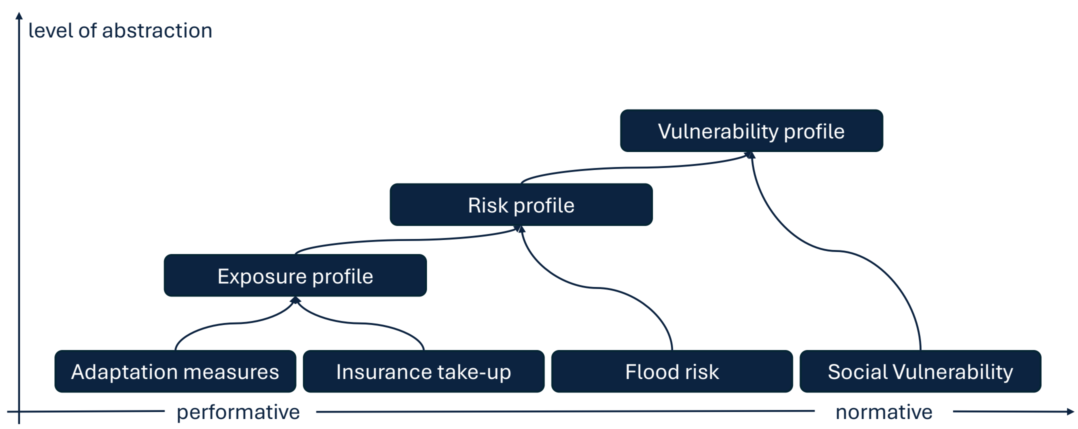

Figure 2: Model metrics (author's illustration)

Note that, while on the household level insurance reduces financial exposure and risk, on the system level it serves primarily as a risk sharing mechanism, thus redistributing rather than reducing risk. In order to study the impact of RR2 on social vulnerability, this study focuses on exposure, risk, and vulnerability for households. System level policy implications derived from our analysis will aim at improving livelihoods for vulnerable groups.

To get a holistic, spatiotemporal understanding of the flood system in Houston, we will create spatial profiles for exposure, risk, and social vulnerability, as indicated in Figure 2. These profiles will allow us to spatially compare simulation outcomes against each other and the a priori system state. The exposure profile is a function of household level adaptation behavior. The risk profile is a function of the exposure profile and flood risk. The vulnerability profile is a function of the risk profile and a social vulnerability index (see section 4.2 for data sources). With this setup of metrics, we attempt to answer the research question.

RQ: What is the long-term impact of Risk Rating 2.0 on social vulnerability across Houston, Texas?

To get an understanding of long-term system behavior, we will model annual adaptation behavior for one generation (or thirty years). To answer the research question, we will answer the following four sub-questions along the metrics introduced in Figure 2.

SQ1: What are the initial exposure profile, risk profile, and vulnerability profile in Houston Texas?

This initial step allows us to establish a baseline – or a priori system state – against which we can compare simulation outcomes later. We will answer SQ1 through an exploratory data analysis (EDA). We will analyze current insurance take up, historic flood risk, and socioeconomic variables such as income, gender, race, education, social vulnerability index, etc. (see section 4.2 for variables and data sources).

SQ2: What is the long-term impact of RR2 on the spatial exposure profile?

By simulating adaptation outcomes on the household level in comparison between RR2 premiums and legacy premiums, we attempt to answer SQ2. The model replicates both premium calculation methods, allowing us to explore the deviation in adaptation behavior based on premium prices, ceteris paribus. Note that the exposure profile incorporates household level physical and financial exposure.

SQ3: What is the long-term impact of RR2 on the spatial risk profile?

We will model changes in flood risk by manipulating frequency and scale of storm surges in line with different climate change projections. The spatial risk profile is a function of the exposure profile and flood risk. It allows us to capture changes in household level adaptation behavior (exposure profile) due to changes in flood risk. Note that we still capture the impact of a switch from legacy premiums to RR2. Unlike in SQ2, we do not hold flood risk constant. SQ3 allows us to study interaction effects between flood risk and adaptation behavior. We expect interaction to occur through households' subjective risk perception.

SQ4: What is the long-term impact of RR2 on the spatial vulnerability profile?

To understand the spatial impact of RR2 on social vulnerability, we need to analyze household level adaptation behavior along socioeconomic disparities. The vulnerability profile is a function of the risk profile and social vulnerability. Hence, the vulnerability profile will capture adaptation outcomes subject to flood risk and social vulnerability. Note that income levels and homeownership are influencing household risk perception in the model, thus influencing adaptation decisions. With SQ4 answered, we answered the research question.

4. Research Approach

This thesis will consist of three parts: A literature review, an exploratory data analysis, and a set of simulation experiments.

4.1. Literature Research

As mentioned in section 1.1, this research proposal is largely intersecting three scientific fields. Climate adaptation, insurance economics, and public policy.

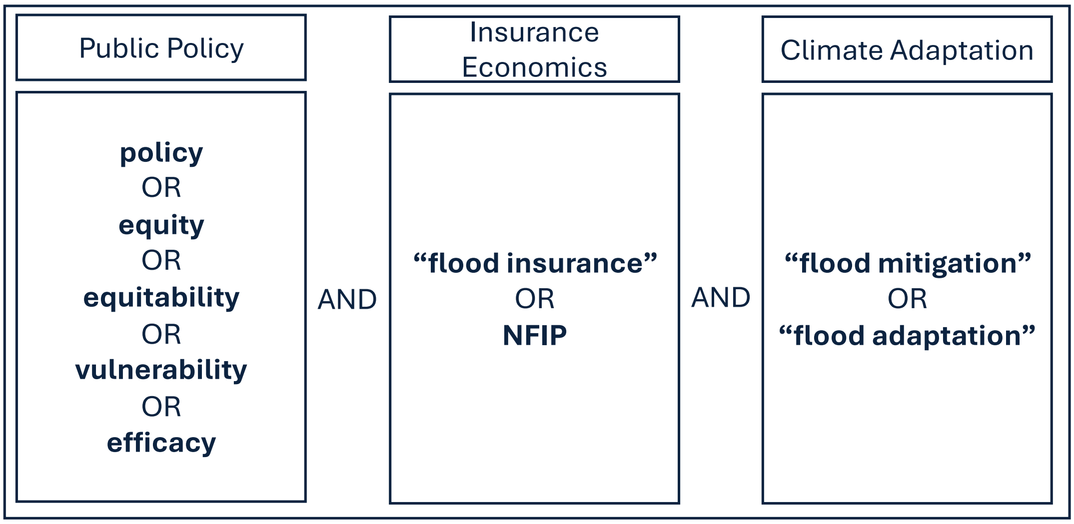

Figure 3: Key words for lit review search query, sorted by research domain (author's illustration).

In the literature review, we will identify theory and concepts important to our research gap. Based on the results, we will be able to say if the hypothesis is robust, i.e., supported by the wider knowledge body. We scoped the domains down to specific key words presented in Figure 3. The final search query combines keywords within each domain with logical OR-operators, and across domains with logical AND-operators. We will conduct our literature search on Scops and Web of Science.

4.2. Data Sources and Preparation

Variable	Source	Variable coding
Elevation	NSI	Grnd_elv_m
BFE	full_structures_data_with_BFE.csv, see structures_sampling.ipynb	
Distance to coast	USGS	
Property value/ RCV	NSI	Val_struct
Foundation type	NSI	Found_type
Foundation height	NSI	Found_ht
Number of stories	NSI	Num_story
Contents value	NSI	Val_cont
Adaptation measures	Mesa.datacollector	
CRS	Mesa.datacollector	
Drainage area	Leave out for now (USGS)	
Concentration risk	Leave out for now	
Barrier Island Indicator	Leave out for now	
RCV limit	Leave out for now	
RCV deductible	Leave out for now	
Content value limit	Leave out for now	
Content value deductible	Leave out for now	

Table 3: Data sources for rating factors

Data	Source
Census	Python package: census
Spatial mapping	Python package: US
Social vulnerability	https://www.atsdr.cdc.gov/placeandhealth/svi/index.html
FIRM zone data	https://www.fema.gov/about/glossary/flood-zones
FEMA base rates	Appendix D (National Flood Insurance Program Risk Rating 2.0 Methodology and Data Sources, 2022)
Claims history	Missing; generate synthetic data inside simulation if needed

Table 4: Other data sources

Using the sources above, we will create a geodataframe containing all addresses in Houston, their spatial position, and corresponding census tracts. We will then map elevation, FIRM data, SVI, education, income, homeownership, ethnicitiy, and insurance related variables (see table 3) to the dataframe. "structure_id" from the NSI dataset will serve as unique identifier.

In a separate dataframe we will replicate base rates and rating factors from Appendix D (National Flood Insurance Program Risk Rating 2.0 Methodology and Data Sources, 2022). We will do that for the variables in Table 3 and merge with the geodataframe.

4.3. Exploratory Data Analysis

The goedataframe as described above will be used for our Exploratory Data Analysis (EDA). As discussed under SQ1, we will create a baseline exposure, risk, and vulnerability profile. The profiles will depict a spatial distribution in form of a choropleth. The exposure profile will show RCV, insurance premiums, and insurance take up. The risk profile will show materialized flood damage and claims payout. The vulnerability profile will weigh the risk profile by SVI and income.

4.4. Modelling

We will extend the model in one crucial component: A function called "get_rate_RR2" takes an agent instance and computes the corresponding final premium for that household, replicating Appendix E (National Flood Insurance Program Risk Rating 2.0 Methodology and Data Sources, 2022). For that purpose, we will feed the rating factors from the geodataframe into the function. The function will be called with each model step, recalculating the premium based on adaptation measures implemented. This component is important for SQ2.

To study the links between flood risk and adaptation behavior, we will also extend the model to simulate different flood regimes. That can be done by extending the existing "flood_frequency" function to include different SLR projections. This component is important for SQ3.

We will also write functions to compute the spatial profiles after each simulation. To do so, we will add the relevant variables to the data collector which captures data in an exportable dataframe. The functions will take the dataframe as an argument, filter for the relevant attributes – for instance, SVI is important for the vulnerability profile but not for the risk profile.

Some more changes to the model are necessary. For instance, a spatial identifier needs to be added to the agent class in order to map adaptation outcomes back to spatial locations. By adding instantiation rules in the model class, we can ensure that the distribution of property characteristics and socioeconomic variables are replicating Houston. We can furthermore calibrate the model by checking our modelled premium values against empirical data (*All Policies by Zip Code: Projected Risk Rating 2.0 Premium Changes*, n.d.).

4.5. Experiments

We will then run the simulation experiments to answer SQ2, SQ3, and SQ4. We will compare adaptation behavior between RR2 and legacy premiums (SQ2), changes in adaptation behavior including different flood regimes (SQ3), and the impact of changes in adaptation behavior on social vulnerability (SQ4). We will additionally compare the spatial profiles from simulation output against the baseline profiles from SQ1.

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Appendix

Term	Definition	Reference
Exposure	The presence of people, livelihoods, or infrastructure that could be adversely affected	(Brooks, 2003)
Risk	A function of (the magnitude of) hazard and the probability of that hazard occurring	(Brooks et al., 2005)
Vulnerability	Function of sensitivity, exposure, adaptive capacity with regards to an exogenous shock.	(Smit & Wandel, 2006)
	"... vulnerability to environmental hazards means the potential for loss."	(Cutter et al., 2003, p.1)
	"... susceptibility to harm from exposure to stresses... and from the absence of capacity to adapt"	(Adger, 2006, p.1)
Social vulnerability	The susceptibility of social groups to potential losses from hazardous events due to factors like poverty, inequality, and marginalization	(Cutter et al., 2003)
Vulnerability index	A relative score of vulnerability across a country, region, or community	(Smit & Wandel, 2006)
Adaptation	A response to risk as a result of interaction between human adaptive capacity and vulnerability on one hand and exogenous stressors such as environmental hazards on the other.	(Smit & Wandel, 2006)
	"Adaptations are manifestations of adaptive capacity"	(Smit & Wandel, 2006, p.5)
Adaptation outcomes	Long-term impact of actions to adjust to changing conditions aimed at improving people's livelihoods, for instance through reduction in damage to assets.	(Donatti et al., 2020)
Adaptive capacity	A system's (culture's) ability to adapt fast and easily to exogenous change	(Denevan, 1983)
	"the ability of a system to prepare for stresses ... in advance ..."	(Engle, 2011, p,1)
	"...positive attribute of a system for reducing vulnerability"	(Engle, 2011, p.1)
Sensitivity	"The degree to which a system is affected, either adversely or beneficially, by climate-related stimuli..."	(IPCC, 2001, p.993)
Resilience	The magnitude of disturbance that a system in a current state can absorb before	(Adger, 2006)

	changing into a radically different system state.	
	Maintaining a desirable system state in the face of change	(Folke, 2006)

Table 5: Terms and definitions

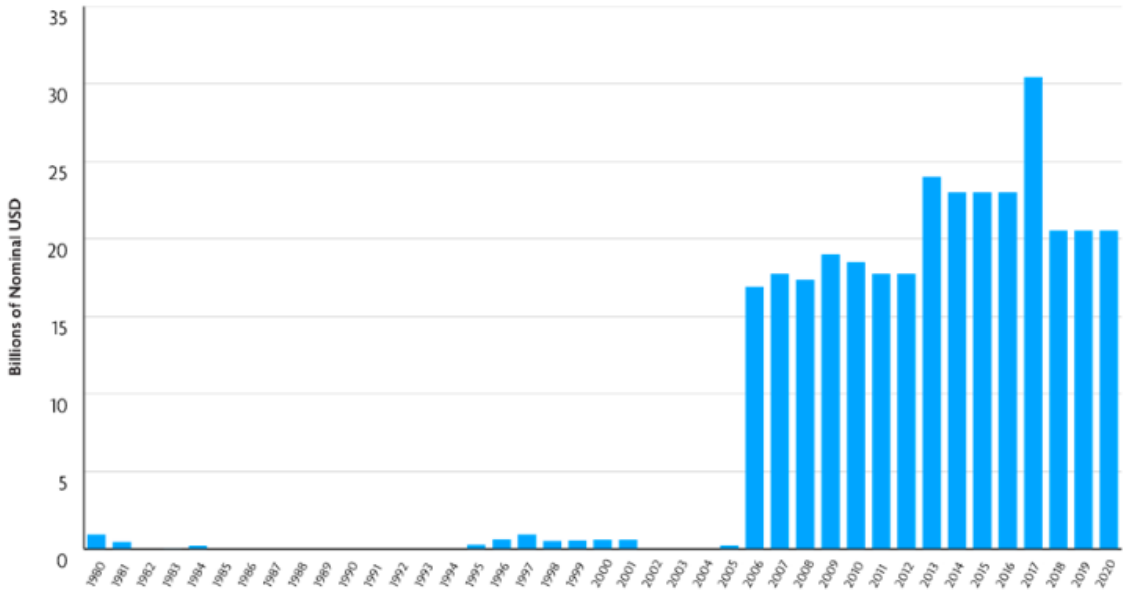

Figure 4: Year-end cumulative NFIP Debt to US Treasury (Linder-Baptie et al., 2022)

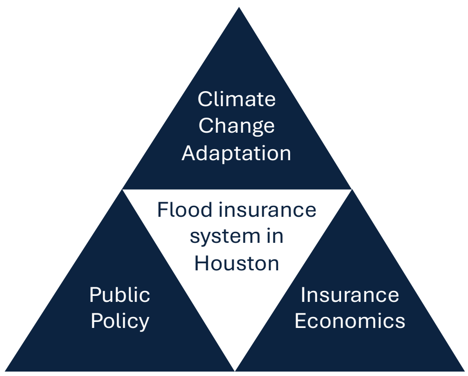

Figure 5: Research Intersections (author's illustration)