Assessing the Well-being Impacts Caused by Floods

A Case Study of Charleston, South Carolina; Addressing social vulnerability through insurance policies in the face of climate change

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by

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Preface

When I first began to work on my thesis, I was initially daunted by the prospect of undertaking this project all by myself. However, I was also motivated to challenge myself and conclude my master's programme with a project that I would be proud of. In my opinion, I have achieved these goals. I am very grateful for the results and have enjoyed the challenge of this journey. I have even learned more than I expected, I have improved my programming skills, became an expert on a whole new method, and improved my storytelling abilities. Deltares offered me a subject that ended up being very fitting for my interests, which made me very passionate about my thesis and almost always kept me motivated. I could not have achieved these goals without the guidance from my supervisors. I would like to thank Kathryn Roscoe and Maaike van Aalst for expressing their enthusiasm for this very novel method. Kathryn provided guidance in solving problems and steering me in the right direction. She also helped me by bringing me in contact with other experts for providing helpful information. I am also grateful for my supervisor from Leiden University, Carlos Felipe Blanco Rocha for always keeping the bigger picture in mind, ensuring I did not lose sight of the high-level story I was trying to find. I would like to thank my supervisor from TU Delft Saket Pande for his assistance in understanding the formulas and technical aspects of the method. Finally, I would like to thank my friends, housemates and family, who made the thesis less lonely than I had anticipated. I will miss the 'woensdag civieldag' and all the coffee and lunch breaks. I am looking back at achieving a major milestone and a few special last months of my career as a student. I am very content with the work I delivered and eager to further develop my skills in future roles.

Karien de Jonge
Delft, June 2024

Summary

Natural disasters, particularly floods, pose a significant threat to cities and communities, and their frequency and severity are increasing due to climate change. Data from the EM-DAT database reveals that floods have been the most frequent natural disasters since 2002. Projections from the Intergovernmental Panel on Climate Change suggest that heavy rainfall events will continue to increase, making floods more likely in the 21st century.

There is an urgent need to address the socio-economic impact of these disasters, particularly on the most vulnerable populations. Economic losses not only disrupt efforts to mitigate climate change, but also worsen inequalities, especially between high and low-income groups. Traditional risk assessments are based solely on property losses. Previous research highlighted that this is not sufficient to measure the socio-economic impact of floods. An interdisciplinary approach is required to integrate methodologies, improve representation of vulnerable populations and fully understand the complex challenges posed by poverty and climate change.

This study uses a modelling framework applied to a case study of Charleston, South Carolina. For the case study, an extreme hurricane was chosen to test the model. The framework aims to measure well-being losses due to flooding and to evaluate the impact of insurance policies on vulnerable groups. The well-being losses are derived from household consumption levels.

Results from the case study show that total well-being losses exceeded total asset losses. Absolute well-being losses were similar across income groups. The relative well-being losses, represented per dollar of damaged assets, were higher for the low-income groups. The implementation of insurance policies reduced overall well-being losses. When the scenario with full insurance coverage is in force, there are still well-being losses. In order to create complete resilience, it is necessary to implement multiple measures.

Further research is recommended to improve the modelling framework. Many assumptions increased the uncertainty of the model. Detailed and additional data would improve the certainty of the results. Ultimately, the research aims to provide useful evidence for policy makers and stakeholders to make more informed decisions to build resilient communities and reduce inequalities in the face of climate change.

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Nomenclature

Abbreviations

Abbreviation	Definition
EAD	Expected Annual Damage
ARIO	Adaptive Regional Input Output
NFIP	National Flood Insurance Program
FEMA	Federal Emergency Management Agency
NaN	Not a Number
SFINCS	Super-Fast INundation of CoastS
CRRA	Constant Relative Risk Aversion
CBA	Cost-Benefit Analysis
NSI	National Structure Inventory

1 Introduction

Natural disasters and extreme weather events, including flooding, have a dramatic impact on cities and communities. As climate change continues to accelerate, the frequency and severity of these events are increasing (Bai et al., 2019). Data from the EM-DAT database (for Research on the Epidemiology of Disasters (CRED), 2022) reveals that floods have consistently been the most frequent natural disasters since 2002. Projections from the Intergovernmental Panel on Climate Change (IPPC, 2012) predict a further increase in heavy rainfall events throughout the 21st century, increasing the risk of flooding. This master thesis investigates well-being losses after a flood and how an insurance policy can impact the well-being losses.

1.1. Problem introduction

Not only do floods affect more people worldwide than any other natural or technological disaster, they also cause the highest toll in terms of human suffering and economic losses (Huang et al., 2008). The vulnerability of coastal regions to flooding is amplified by rising sea levels, increasing the socio-economic impact on entire economies. Particularly vulnerable are those in low-income areas. These groups are disproportionately affected by climate-related shocks due to their greater vulnerability, limited resources, and their dependence on social safety nets (Hallegatte, Bangalore, Bonzanigo, et al., 2016). The findings of Hallegatte, Bangalore, Bonzanigo, et al. (2016) were further analysed by Hallegatte and Rozenberg (2017), which highlighted the risk of climate change pushing more people into poverty. Their findings suggest that climate change acts as a poverty multiplier, worsening income losses and growing socio-economic inequalities. Cantelmo et al. (2023) also argues that natural disasters have a greater impact on the development of low-income countries.

The economic impact of climate-related natural disasters is substantial, as demonstrated by studies such as Strauss et al. (2021), which attributed a significant portion of the economic damage from Hurricane Sandy to sea-level rise caused by climate change. Similarly, Cantelmo et al. (2023) examined the macroeconomic impact of natural disaster shocks. Welfare losses increased almost fivefold under climate change scenarios. These findings highlight the urgency of developing effective mitigation strategies to address the increasing risks, in particular to protect vulnerable communities from the devastating effects of flooding.

The standard approach to flood risk policy design is to quantify asset losses. Several studies (Allaire, 2018; Hallegatte, 2008; Kind et al., 2016; Markhvida et al., 2020; Verschuur et al., 2020; Vogt-Schilb et al., 2016; Walsh & Hallegatte, 2020) have stated that measuring asset losses alone is not a sufficient measure to assess the socio-economic impact of floods. Other indicators have been researched and measured, such as loss of income, welfare and well-being. Several studies (Agarwal et al., 2024; Groen et al., 2015; Huang et al., 2008; Nguyen et al., 2021) demonstrate a negative impact of natural hazards on income. Other studies (Hallegatte, Bangalore, & Vogt-Schilb, 2016; Markhvida et al., 2020; Verschuur et al., 2020; Vogt-Schilb et al., 2016; Walsh & Hallegatte, 2020) presented the impact on welfare losses, showing the disproportionate impact on low income groups. Meyer and Sullivan (2011) and Karim and Noy (2016) observed low levels of consumption as a result of natural disasters, which could be an indicator of other negative impacts and long-term effects. A few studies (Ahmadiani & Ferreira, 2021; Luechinger & Raschky, 2009; Navrud et al., 2012; Tamuly & Mukhopadhyay, 2022; Wang & Wang, 2022) used survey data to measure a broader loss of well-being following natural disasters. These studies will be further discussed in chapter 2.

1.2. Research gap

There is a recognised need to improve alternative methodologies to better capture losses experienced by socio-economically vulnerable populations. Large economic losses can have a negative impact on efforts to minimise climate change. These losses could also exacerbate inequalities and tensions between rich and poor populations caused by climate change. The previous literature review (Allaire, 2018) calls for an interdisciplinary approach to integrate methodologies for a comprehensive understanding of socio-economic impacts. Accurate models for estimating property damage from potential natural hazards have been developed. These results need to be further translated using other disciplines, so that socially vulnerable people are better represented. Previous research suggests that low-income households suffer disproportionately from floods. Traditional risk assessments are based solely on property losses. The use of asset loss as a metric in policy-making would be prone to bias in favour of high-income households, given that these groups tend to possess more valuable homes, resulting in the highest absolute losses. The asset loss metric is considered a valid method for insurers to design their policies, but little research has been done on the impact of these policies on well-being losses. Broader well-being analyses rely on time-consuming surveys. It is therefore beneficial to explore methods that use existing data to assess well-being losses more efficiently. A few studies have used data-driven models to estimate well-being losses. These models need to be further tested to improve their accuracy for policy making.

1.3. Research questions

To fill in the previous defined research gap in literature, this research will investigate how well-being is impacted by floods. The following research question is defined.

How do well-being losses compare to asset losses in socially vulnerable households in flood-prone areas and what role can insurance policies serve in minimising these well-being losses?

This research question can be divided into the following sub-questions:

1. What is the well-being loss compared to asset loss of a control event?
2. What is the well-being loss compared to asset loss of an extreme hurricane?
3. What is the impact of insurance policy on well-being?

To answer this research question, a novel modelling framework is used to calculate the impacts on well-being. Well-being is defined as a consumption level adjusted for the fact that 1$ is worth more to a low-income household than to a high-income household. The asset losses are the damages towards the buildings expressed in repair costs. Socially vulnerable people are those who have fewer resources to cope with natural disasters. The model will be applied to a case study. Charleston County is chosen as the case study, this county is located in a flood-prone area in the state of South Carolina; section 2.3 will further elaborate on the case study. The first sub-research question is intended to test and validate the model. The model is then applied to an extreme Hurricane, these results will be used to answer the second and third sub-questions.

1.4. Report outline

Chapter 2 explains what has been done previously in this area of research. Chapter 3 presents the methodology used in this study. Additional details of the methodology are documented in appendix A to further enhance reproducibility. The results and interpretation, together with a sensitivity analysis, are discussed in chapter 4, supplemented by additional results in appendix B. Chapter 5 compares the results with previous work and discusses limitations. Finally, chapter 6 presents the final answers to the research questions and provides recommendations.

2
Background

The first section of this chapter provides additional information on what has already been researched about the effects of natural hazards, including floods. The second section discusses current insurance policies in the United States and the problems they face. The final section briefly addresses the Charleston case study.

2.1. Impact assessment of floods

This section first describes the impact on income losses. The second section focuses on the broader economic impact on different income groups. Finally, the impact on well-being is discussed.

2.1.1. Income loss

Previous literature (Allaire, 2018) has studied the economic impact of natural disasters and found a negative impact on the economy, with income loss being one of the indicators used. The results of a meta-regression analysis presented income loss in several empirical case studies (Karim & Noy, 2016). Previous research (Agarwal et al., 2024; Groen et al., 2015; Huang et al., 2008; Nguyen et al., 2021) using different data sources, ranging from survey data to retrospective methods, found evidence of income loss after and during floods. The study by Agarwal et al. (2024) notes the role of damaged productive capital, such as factories and equipment, in contributing to income losses.

2.1.2. Broader economic impact

The literature review by Allaire (2018) found that several studies highlight the disproportionate impact on poorer households. The paper by Hallegatte, Bangalore, and Vogt-Schilb (2016) explores this further by creating a new framework that takes into account the fact that a dollar is worth more to the poor. This framework introduces a new definition of socio-economic resilience, the ratio of asset losses to welfare losses. A case study in India is used to introduce the model, followed by an assessment of socio-economic resilience in 90 countries. Vogt-Schilb et al. (2016) further developed the model with additional data and applied it to 117 countries. Verschuur et al. (2020) combined the work of Hallegatte, Bangalore, and Vogt-Schilb (2016) and Vogt-Schilb et al. (2016) and added the implementation of three policy interventions and a future sea level rise scenario. This study was applied at the district level in coastal Bangladesh. Walsh and Hallegatte (2020) developed an agent-based model based on the approach of the previous two papers. The model was applied in the Philippines and provided a multi-metric assessment that, among other things, determined the welfare loss of poor and rich households. Markhvida et al. (2020) used four models to assess household well-being losses. The household well-being was quantified by an extended version of the model from Walsh and Hallegatte (2020). It included more detail and an adaptive regional input output (ARIO) model, which improved the estimation of income losses. In some areas income losses can even exceed asset losses. The model was applied to earthquakes in 10 cities in the San Francisco Bay Area.

Low-income groups are not only more prone to natural hazards but the effects can be more prolonged and severe. Haque et al. (2020) argues that low-income populations fall into a vicious cycle, becoming even more vulnerable to the effects of floods. Research by Bista (2020) also demonstrated that disasters can increase vulnerability and redistribute household income, leading to extreme poverty. Reaños (2021) confirmed the findings of higher welfare losses in low-income households. In addition, this research found that floods increase inequality by 0.14% and that vulnerable households such as families with dependent children are most affected.

Kind et al. (2016) calculated social welfare losses for CBA (cost-benefit analysis) aimed at reducing climate-related flood risks. The framework proposed integrates risk aversion and equity considerations, addressing social vulnerability. Through a case study, it demonstrated that decisions informed by the framework differ significantly from conventional practices.

Using consumption levels as an indicator of disaster impact, (Karim & Noy, 2016) found that household save on health and education to prevent a large fall in consumption levels, which may have long-term implications. Meyer and Sullivan (2011) confirmed that low levels of consumption are indicators of poor housing quality and poor health.

2.1.3. Well-being impact

Survey data has emerged as a valuable indicator for assessing well-being in the aftermath of natural disasters, as evidenced by several studies (Ahmadiani & Ferreira, 2021; Luechinger & Raschky, 2009; Navrud et al., 2012; Tamuly & Mukhopadhyay, 2022; Wang & Wang, 2022)

Luechinger and Raschky (2009) used life satisfaction surveys to assess the impact of floods in European countries and revealed a hypothetical willingness to pay of 23.7% of annual household income to prevent a flood disaster. Similarly, Ahmadiani and Ferreira (2021), also using life satisfaction surveys, confirmed the negative impact of natural disasters on subjective well-being. Navrud et al. (2012) tested the validity of the willingness-to-contribute approach in Vietnam, where the data consisted of face-to-face household surveys and reported direct physical damage. The results confirmed that poor households are more vulnerable to floods, mainly due to their dependence on natural and agricultural resources for their livelihoods. Wang and Wang (2022) studied the aftermath of the Wenchuan earthquake in China and found a significant decline in subjective well-being independent of post-disaster relief programmes. The decline in well-being persisted for almost 10 years and was similar to an average household income loss of 67%. In addition, inequalities were found within the impact on well-being. Older adults, the less educated and those without social insurance were found to be more vulnerable to earthquakes. Tamuly and Mukhopadhyay (2022) conducted a national panel data analysis on natural disasters in India. The welfare measure used was monthly consumption expenditure adjusted for health-related expenditure. The results presented an average negative impact on adjusted consumption, yet not all socio-economic groups had a significant decline in consumption. Furthermore, the study revealed that the presence of assets, health insurance, and membership in various organizations were associated with an increase in household consumption.

2.2. Flood insurance

The current national agency for flood insurance in the US is the Federal Emergency Management Agency (FEMA). Under FEMA, the National Flood Insurance Program (NFIP) was established in 1968 to address the lack of availability of flood insurance in the private market, particularly following the Mississippi River Flood of 1927. The NFIP operates as a partnership between the federal government, local communities and insurers. Previous literature has highlighted the challenges faced by the NFIP. Despite the mandatory purchase requirement for properties in high-risk floodplains, the number of insurance purchases, also known as the take-up rate, remains low (Kousky, 2011, 2016). According to Kousky and Michel-Kerjan (2015), low insurance demand is caused by a combination of factors, including inadequate risk perception, behavioural biases, limited risk understanding, communication challenges, and misperceptions about loss rates and magnitudes. The NFIP has been criticised for not pricing premiums adequately to cover catastrophic losses. This issue has raised concerns about the programme's ability to effectively address future flood risks (Kousky & Michel-Kerjan, 2015).

Research by De Ruig et al. (2022) also addresses the NFIP's pricing problems and low take-up rates. This study refers to the NFIP's current debt of $23 billion to the US Treasury, largely due to catastrophic losses from hurricanes Katrina, Ike and Sandy. The financial sustainability of the programme is also challenged by factors such as setting premiums based on national averages that do not reflect local risk, new development in flood-prone areas, and a lack of incentives for homeowners to implement flood adaptation measures. De Ruig et al. (2022) used an agent-based model to test risk-based premiums. Results demonstrate a positive societal benefit by increasing the incentives for households to invest in risk reduction.

The extensive literature reviewed by Kousky (2019) examines the role of insurance in the recovery from natural disasters. It identifies the challenge for insurance markets to function optimally without government intervention. Nevertheless, research confirms that insurance facilitates higher recovery rates. It highlights the insurance gap, the substantial difference between total uninsured and insured losses. In addition, studies point to the persistent problem of low take-up rates, where pricing can be a major barrier. Of particular concern is the key finding that socio-economically disadvantaged or minority communities are under-insured, increasing their vulnerability and hindering recovery efforts. Those most affected by disasters often face barriers to accessing critical financial support through insurance mechanisms. These studies, which primarily examine the role of insurance through surveys, have notable limitations, such as limited external validity and challenges in establishing causal relationships. As climate change reshapes the landscape of extreme flood risk worldwide, a deeper understanding of the role of insurance in climate adaptation is essential. In addition to isolating the impact of insurance on outcomes, research is needed that compares the effectiveness of different insurance designs.

2.3. Case study Charleston

A previous case study (Zhao, 2014) in Charleston County examines the tension between risk-based premiums and the affordability of flood insurance for homeowners in flood-prone areas. Charleston was selected for this case study because of its high concentration of policies and flood risk. In Charleston, although the median income is above the state average, high property values make homeownership expensive for low- and moderate-income residents; flood insurance premiums would only add to housing costs. The risk-based premium creates strong incentives for homeowners to reduce risk, since insurance is cheaper for safer homes. Insurance companies could also provide vouchers or subsidies specifically for implementing risk reduction measures. These vouchers are argued to be a better alternative to premium discounts. It is also important to recognise that elevating homes may not be possible in certain areas, particularly in historic districts such as Charleston city, where maintaining historic architecture takes precedence over structural changes.

3 Method

This research takes as its starting point the model of Markhvida et al. (2020) that was originally developed by Hallegatte, Bangalore, and Vogt-Schilb (2016). This model calculates the household well-being losses based on the consumption level in a pre- and post-disaster situation. This research will implement simplifications to the model, which will be explained in the first section. The second section explains the data collection. The third section explains the calculations in the model. The model will be applied to two events, a control event and an extreme event, which are described in the last section. A python Jupyter Notebook is used to process the data and perform the calculations.

Figure 3.1 presents a quick overview of the method. The main result of this model are well-being losses, these will be compared to the asset losses.

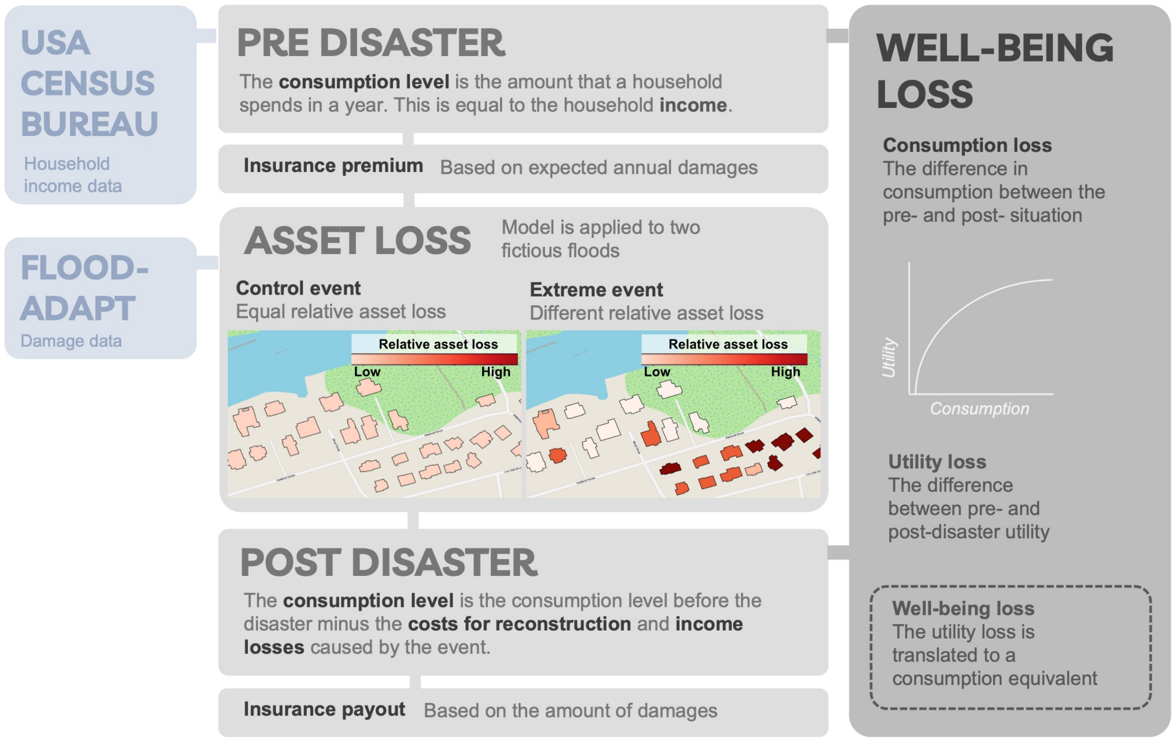


Figure 3.1: Research flow diagram of method

3.1. General assumptions and simplifications

This study excludes rented households due to uncertainties about their post-disaster circumstances. It is unclear how landlords will behave with regard to reconstruction costs and whether renters will have to pay full rent for damaged houses. In addition, this study does not consider the scenario where houses are damaged to an extent that they become uninhabitable, assuming that damage levels do not reach this threshold. Mortgage payments are excluded due to data constraints. Household savings are also excluded for simplicity.

3.2. Data collection

This research uses quantitative secondary data. The data is obtained from two sources, the US Census Bureau and FloodAdapt, an adaptation planning tool provided by Deltares. This tool uses a SFINCS (Super-Fast INundation of CoastS) model that stimulates 2D compound flooding and can accurately simulate floods. See appendix A.1 for additional details on data preparation.

3.2.1. USA Census Bureau data

Household income data is retrieved from the US Census Bureau of the year 2021. Total household income is obtained at the block group level, which is the most disaggregated level available. To account for population density, total household income is divided by the number of households in each block group. Each block group then contains an average household income. This is used as input for the model.

3.2.2. FloodAdapt

The well-being loss model requires asset loss data as input. This case study uses asset losses from an extreme version of Hurricane Ian (September 2022). Hurricane Ian was originally forecast to make direct landfall on the city of Charleston, but in the final hours it changed direction and made landfall approximately 30 to 40 km north of Charleston (news, 2022). The asset loss data from the scenario where Charleston would have been directly hit by the hurricane are used as the extreme event.

The FloodAdapt model output provides information on damage to structures and the expected annual damage (EAD). The maximal potential damage is retrieved from the National Structure Inventory (NSI) ("Technical documentation", n.d.). The data is provided at the building level for both residential and non-residential buildings. This study only considers property losses associated with residential buildings. The losses were grouped using Python, and the data were accumulated for each block group. Total asset losses, structure value and EAD were divided equally among households to assume an equal distribution of initial assets and losses. Although Hurricane Ian made landfall in 2022, the input of the NSI (also used in Floodadapt) is in 2021 prices. The income data is therefore also in 2021 prices.

3.3. Model

Data from the US census bureau and the FloodAdapt tool were merged to form one dataset used for the model. The model divides into subsections: pre-disaster situation, post-disaster situation, insurance policy, optimization of the recovery time and well-being loss. Each of these is calculated for every block group.

3.3.1. Pre-disaster

In the pre-disaster situation, households have initial capital (k_0). This study focuses only on housing capital (k_{str}), i.e. the housing assets of a household. The calculation only takes into account the structural value of the buildings, which are directly vulnerable to the effects of flooding. The land value of the houses is not considered in the assessment.

$$k_0 = k_{str} \tag{3.1}$$

Household income (i_0) includes all types of income: wages, salaries, self-employment income, interest, dividends, rental income, social security income, supplementary social security income, public assistance income and retirement income. Prior to a disaster, household consumption (c_0) is assumed to be equal to their income level (i_0), excluding mortgage payments. Both income and consumption are assumed to be constant before the disaster. Consumption is the amount that the household will consume to satisfy its needs, assuming that no income is saved.

$$c_0 = i_0 \tag{3.2}$$

3.3.2. Post-disaster

After the disaster, it is necessary to identify which components have been affected. Housing assets are directly affected by physical damage to buildings, which is registered as asset losses. Household consumption is indirectly affected. To calculate post-disaster consumption, it is necessary to define reconstruction costs and income losses over time. In the model, the disaster is assumed to occur at $t = 0$. Reconstruction starts immediately after $t = 0$.

To construct the impact over time, the asset loss ratio (ν) is calculated. The asset loss ratio (ν) is calculated by dividing the total repair costs by the total maximum potential damage (k_{str}) for each block group. It is assumed that the repair costs are equal to the asset losses.

$$\nu = \frac{repair\ costs}{k_{str}} \tag{3.3}$$

In order to define the reconstruction costs over time, it is first necessary to determine the loss of housing assets over time ($\Delta k(t)$). The reconstruction rate λ describes how fast households recover, which is optimised in section 3.3.4.

$$\Delta k(t) = \nu k_{str} e^{-\lambda t} \tag{3.4}$$

The reconstruction cost equation over time ($c_{reco}(t)$) is then defined by the rate of change of the asset loss over time ($\Delta k(t)$). For the mathematical computation see appendix A.2.

$$c_{reco}(t) = \lambda \nu k_{str} e^{-\lambda t} \tag{3.5}$$

Income is indirectly affected by physical damage to productive assets. It is assumed that the loss of income is proportional to the asset loss. The loss of income is then determined by the pre-disaster income and the asset loss ratio (ν). It is assumed that all types of income are sensitive to the disaster.

$$\Delta i(t) = \nu i_0 e^{-\lambda t} \tag{3.6}$$

The post-disaster household consumption levels are calculated by subtracting pre-disaster consumption levels from reconstruction costs and income losses. It is assumed that households have no savings to pay for the reconstruction costs.

$$c(t) = c_0 - (c_{reco}(t) + \Delta i(t)) \tag{3.7}$$

3.3.3. Insurance policy

The insurance policy used is based on De Ruig et al. (2022). This is a property flood insurance with risk-based premiums. The pre-disaster consumption and post-disaster consumption level will change due to the insurance policy.

Insurance pre-disaster

The consumption will not be equal to income anymore when the insurance policy is in force. Households will have a premium deduction from their pre-disaster consumption.

$$c_{0\ insurance} = i_0 - premium \tag{3.8}$$

The premium is determined by a pricing rule for flood insurance used in previous studies (Hudson et al., 2016; Paudel et al., 2013; Tesselaar et al., 2020a, 2020b). This method includes the expected annual damage (EAD), a deductible (D) and the number of purchasers (N), corresponding to the number of households. The (EAD) is calculated by integrating the frequency-damage curve, which represents the annual probability of damage occurrence against economic damages, see figure 3.2. The deductible is the value that the households have to pay themselves, also considered as their own risk. The deductible is set at a standard 15% (Hudson et al., 2016; Paudel et al., 2013; Tesselaar et al., 2020a, 2020b). The premium is paid annually. Each block group has a unique (EAD), resulting in different premiums for each.

$$premium = \frac{EAD - D}{N} \tag{3.9}$$

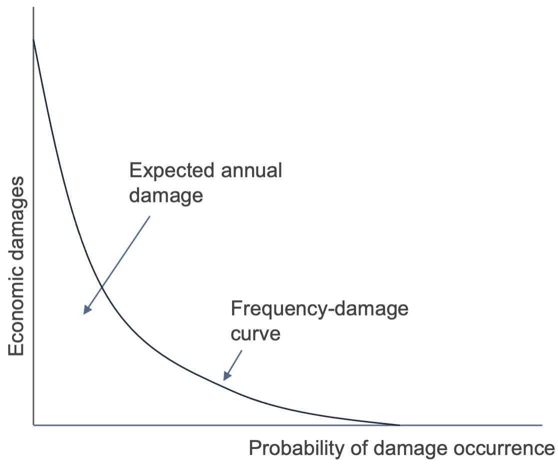


Figure 3.2: Visual presentation of the EAD

Insurance post-disaster

In the insurance scenario, the function for consumption is the same as $c(t)$ but increased by the insurance payouts. Households initiate the process by filing a claim with the insurance company, followed by the payment of the claim. As found by De Ruig et al. (2022), the NFIP pays out 45% of the claim. So the payout is 45% of the asset loss. For further details on the construction of the claim payout in the model, please refer to Appendix A.3.

$$c_{insurance}(t) = c_0 - (c_{reco}(t) + \Delta i(t)) + payout \tag{3.10}$$

$$payout = 0.45 \cdot repair\ costs \tag{3.11}$$

The model assumes an optimal payout scenario, although this may not reflect reality. Previous literature has noted several issues with insurance payouts, including uncertainties and limited availability of organized data. The complexity of the situation is beyond the scope of this study. Damage claims are processed immediately after the disaster and paid out within the first year, coinciding with the start of reconstruction efforts. After the payout, consumption levels will remain constant until the insurance payout runs out. This is the most optimal approach, taking into account that a fall in consumption is more sensitive for the well-being loss calculation.

Charleston is situated within a 100-year floodplain. De Ruig et al. (2022) assumed that 55% of households are eligible for mandatory insurance in a 100y floodplain. This model will therefore also assume that 55% of the households have insurance, also known as the take-up rate. Each calculation step of the model is done for an average household in each block group. To model this take-up rate, the payout and premium is multiplied by the take-up rate. In line with the scenario of De Ruig et al. (2022), if the premium exceeds 7.5% of their income, households will find the insurance unaffordable and decide not to purchase insurance. This implies that if the premium is higher than the average household income within a block group, the entire block group theoretically choose to refrain from insurance coverage.

3.3.4. Optimisation of the recovery time

The magnitude of income loss and reconstruction costs at a certain time is determined by the reconstruction rate (λ). This rate describes how quickly households recover. A higher rate implies a faster recovery process. Households are assumed to recover their losses exponentially over a number of years (τ). The following equation gives the relationship between time and the recovery rate, where 95% of total assets are rebuilt.

$$\tau = \ln(\frac{1}{0.05})\lambda^{-1} \tag{3.12}$$

The recovery time is optimized to maximize the well-being, ensuring that households recover while maintaining the highest possible level of satisfaction, see equation 3.13. The optimization process is constrained by lower and upper bounds. It is essential to set a lower bound to prevent an infinite recovery time scenario. The longest possible recovery time is capped at 10 years to prevent infinite recovery, see appendix A.4 for further explanation. Upper bounds represent the physically feasible fastest recovery time. The upper limit for recovery time is set at one week, based on the assumption that a faster recovery would not be physically possible.

$$\lambda_{opt} = \arg\max_{\lambda} \int_0^T u(t)\, dt \tag{3.13}$$

3.3.5. Well-being loss

The pre-disaster and post-disaster situations result in a consumption loss. This consumption loss can have very different consequences depending on the income level. A loss of $1 has a different meaning for low-income households than for high-income households. It is therefore necessary to calculate the well-being losses caused by the consumption loss. To do this, a constant relative risk aversion (CRRA) utility function is used. Utility represents the amount of satisfaction derived from a given level of consumption. Refer to figure 3.3, which illustrates that a change in consumption of the same magnitude ($A = B$) results in different utility losses ($X \neq Y$). Utility is an abstract measure of satisfaction. Pre-disaster utility is defined by (u_0).

$$u_0 = \frac{c_0^{1-\eta}}{1-\eta} \tag{3.14}$$

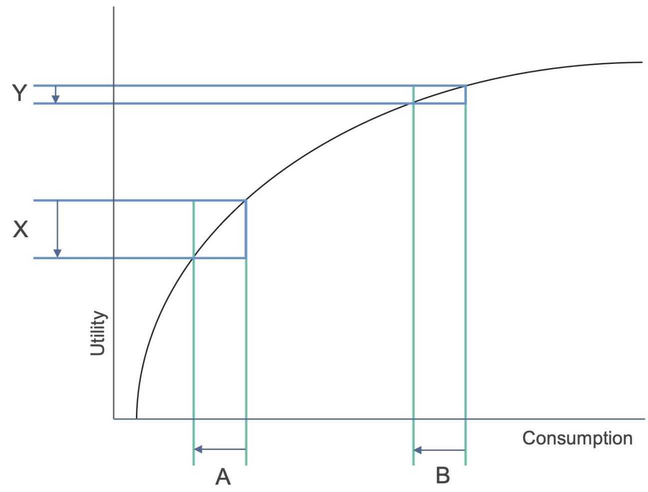


Figure 3.3: Schematic CRRA utility function with $\eta > 1$

The post-disaster utility is similarly calculated as the pre-disaster utility, instead of using c_0 the consumption over time is used.

$$u(t) = \frac{c(t)^{1-\eta}}{1-\eta} \tag{3.15}$$

The utility loss ΔU can then be calculated by the difference of the pre-disaster and post-disaster utility over the time period T. This loss is discounted over time to find the present losses. This is necessary to account for the decrease in the value of money over time.

$$\Delta U = \int_0^T (u_0 - u(t))e^{-\rho t}dt \tag{3.16}$$

In order to allow comparison with asset losses, the utility values are converted into a consumption equivalent. This equivalent represents the monetary amount by which the average household in Charleston County would have to reduce its consumption in order to experience the same level of well-being loss. In essence, it provides a monetary measure of well-being loss. The consumption equivalent is calculated by dividing the change in discounted utility by the marginal utility ($\frac{du}{dc}|c_{mean}$). The average marginal utility is used to ensure that losses are appropriately scaled for comparison between different income levels.

$$\Delta W = \Delta U / \frac{du}{dc}|c_{mean} \tag{3.17}$$

The decision has been made to evaluate the well-being losses over a 10-year period, in line with the methodology used in Markhvida et al. (2020)

3.4. Asset loss scenarios

The model will be applied to an extreme event (version of Hurricane Ian) and a control event. Both these events are hypothetical. The control event is used to validate the well-being method and to evaluate the effect that solely income has in the method. The extreme event is used to interpret the results. The relative asset loss is set equal in the control event. The average asset loss ratio (equation 3.3), of the extreme event is applied to all the block groups in the control event. The severity of the control event and extreme event are the same, they differ in the distribution of the asset losses.

4
Results and Interpretation

This chapter presents the results and their interpretation. The first section elaborates on the damages scenario presenting the input of the model. The next section discusses the general results of the asset and well-being loss for both the control event and extreme event. The following sections further analyse the results from the extreme event, including the relative asset loss, the recovery time and the recovery course of individual block groups. Thereafter, the results from the insurance scenario are presented. Lastly, the sensitivity analysis is presented. The general results are presented for the extreme and control event while all details, insurance and sensitivity analysis is only presented for the extreme event.

4.1. Visualisation input data

The extreme event is a shifted more extreme version of hurricane Ian which was suppose to make landfall very close to Charleston, figure 4.1 presents the visual presentation of the shifted version. The difference in flooding between the actual hurricane and the extreme version can be viewed in figure 4.2.

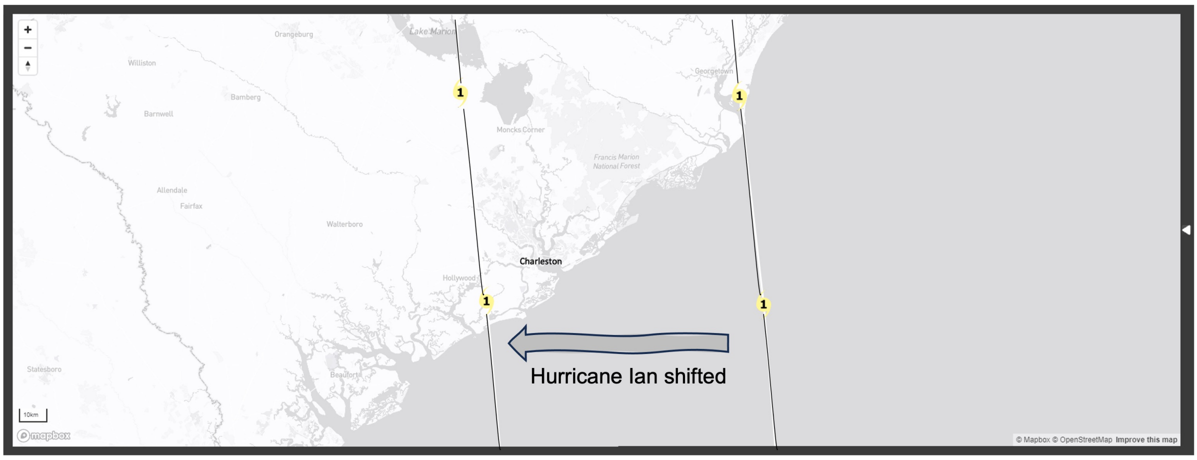


Figure 4.1: Landfall location of the extreme shifted version of hurricane Ian and the actual hurricane, source: FloodAdapt

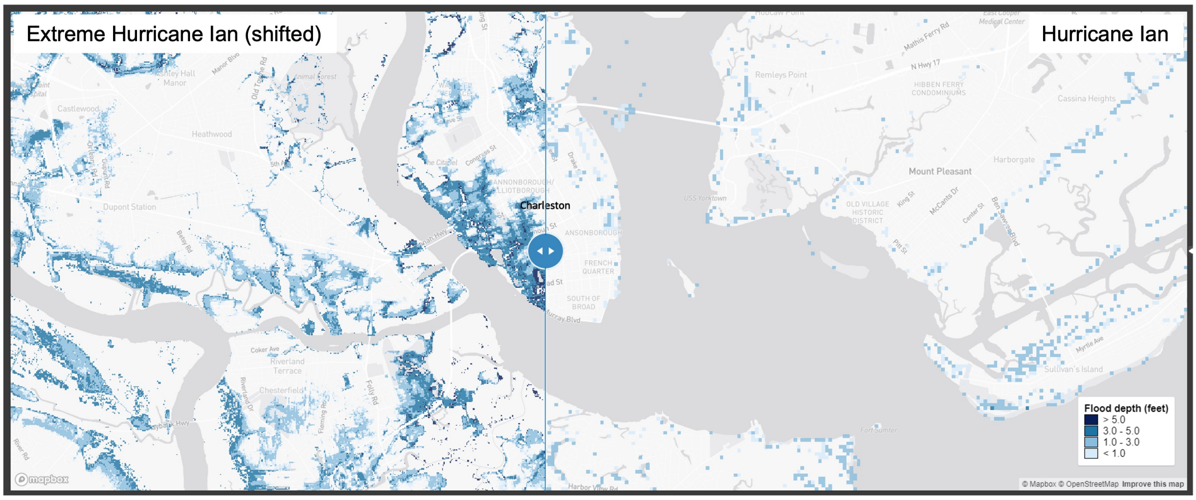


Figure 4.2: Flood depth for the extreme shifted hurricane Ian and actual hurricane Ian

The results of the well-being method depend on two input components, asset loss and household income. Figure 4.3 presents the asset losses at building level for residential buildings zoomed in on the city of Charleston. Figure 4.4 presents the household income level at block group level.

Figure 4.3: Zoomed in asset losses at building level and flood depth at subdivision level of the extreme event

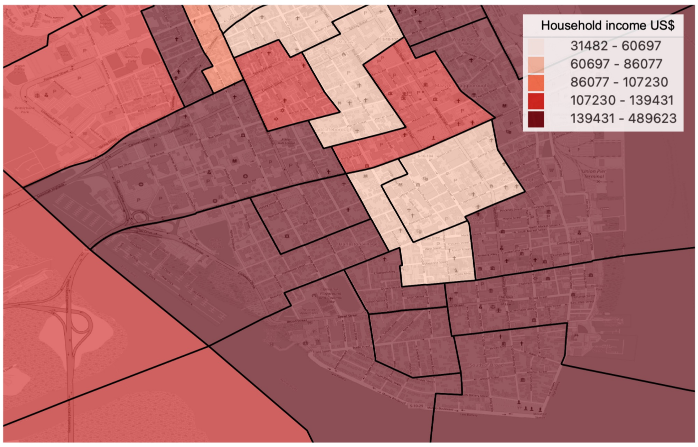


Figure 4.4: Zoomed in average household income at block group level

Figure 4.5 presents the relative asset losses for the extreme event and the control event at building level zoomed in on the city of Charleston, clearly presenting the difference between the control and extreme event.

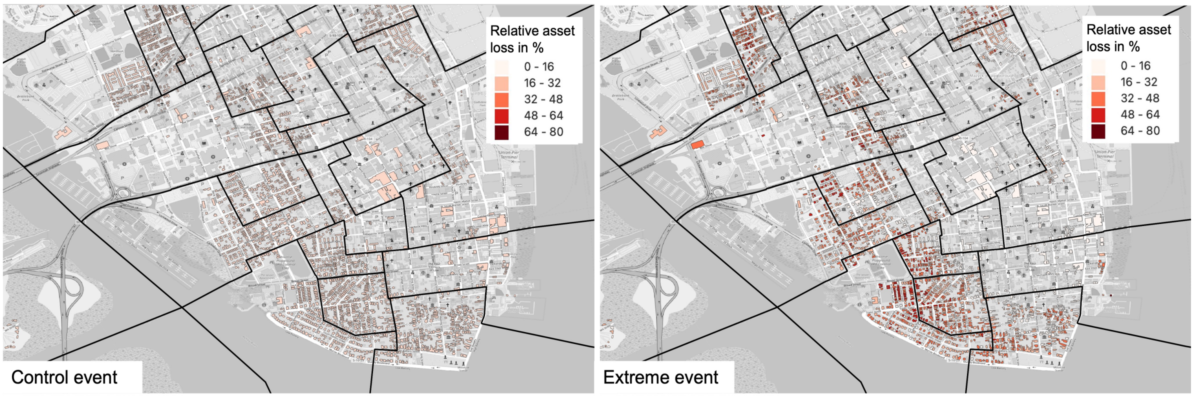


Figure 4.5: Relative asset losses for the extreme and control event at building level

4.2. General results

Figure 4.6 displays the results for the control event, while Figure 4.7 provides the results for the extreme event. These are the losses for an average household in Charleston county experiencing damage. The county consists of 246 block groups, of which 188 block groups experience losses. These 188 block groups contain 79940 households.

In the control event, well-being losses are almost twice as high as asset losses. In the extreme event, well-being losses are also higher than asset losses, but to a lesser extent. Consumption losses are smaller in the control event but lead to higher well-being losses. The next section will further explore these results by looking at different income groups.

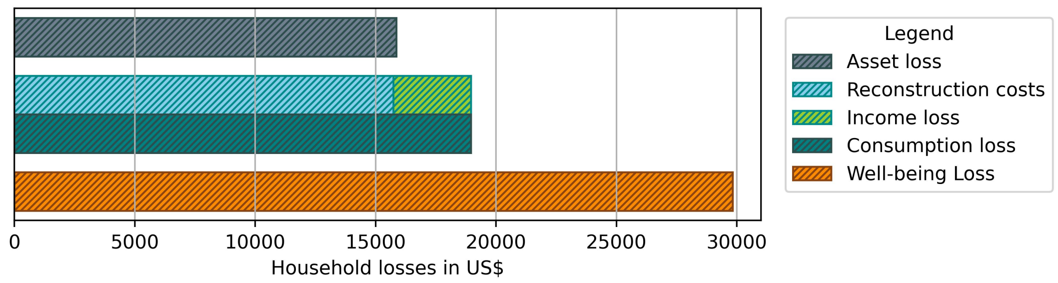


Figure 4.6: Average household losses of the control event

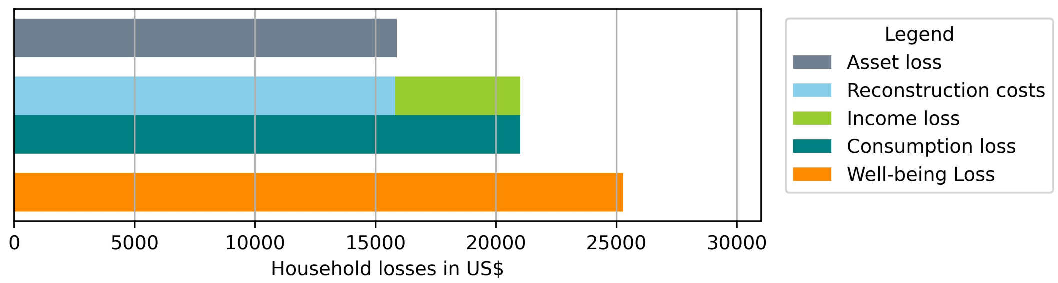


Figure 4.7: Average household losses of the extreme event

4.2.1. Results distributed by income group

Figure 4.8 presents the asset, income and well-being losses of both the control event and extreme event divided into four income quartiles. The percentages above the bars describe the share of loss in each income quartile for the extreme event and the control event. Each income quartile contains approximately 20000 households. See appendix B.1 for the income distribution per quartile and boundaries for the quartiles.

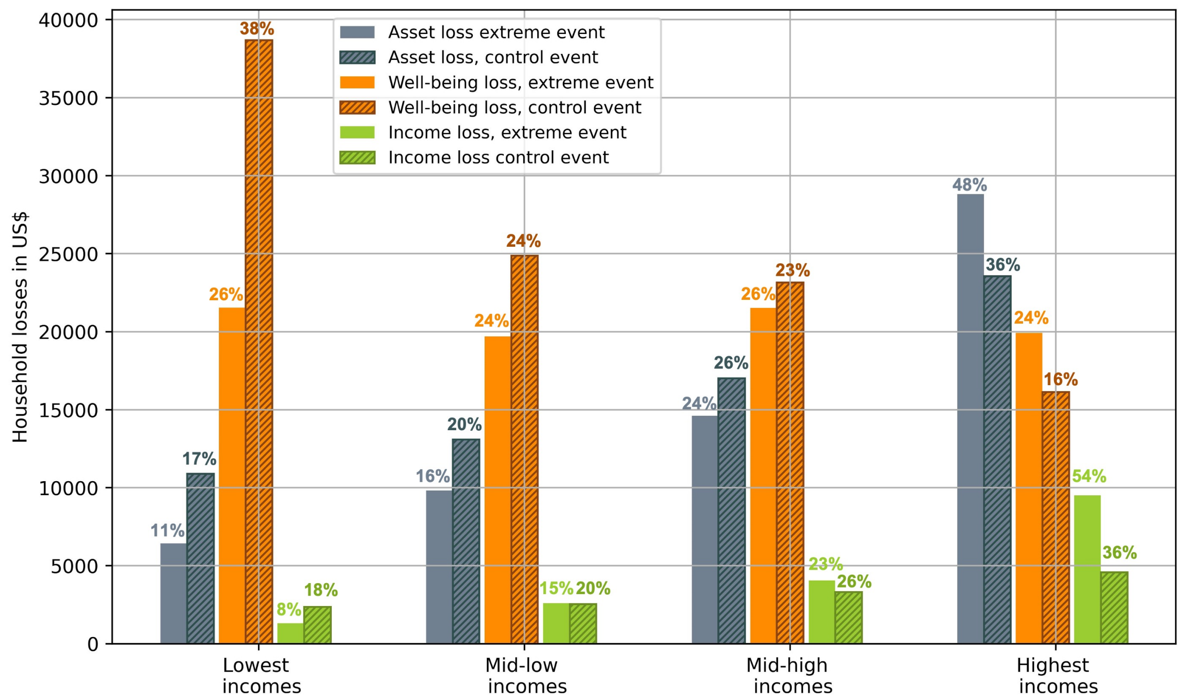


Figure 4.8: Average household losses per income quartile, extreme and control event.

Asset loss

For both the events, the asset losses are highest in the high income quartile and lowest in the low income quartile. The extreme event presents an even more concentrated asset loss in the highest income group, the lowest income group experiences 11% of the total asset loss while the highest income group experiences 48% of the total asset loss. This is partially caused by their proximity to the coast and partially because of the higher value of their properties.

Well-being loss

In the control event, well-being losses decrease by income group, with low-income households experiencing the largest well-being losses and high-income households the smallest well-being losses. These results validate the calculation of well-being loss using an utility with a higher weight on low consumption levels.

The extreme event presents a different distribution of well-being losses. The well-being losses of each income quartile are nearly equal, all around 24-26% of the total well-being losses. The higher asset loss of the high-income groups results in relatively similar well-being losses between the high-income and low-income groups. This may appear counter intuitive at first glance. However, the much lower asset loss for the lower-income groups explains this outcome. The large difference between the well-being losses of the lowest income group in the control and extreme event indicate that this income group is very sensitive towards more asset losses in their resulting well-being losses. Although the well-being losses of each income quartile are similar, the ratio between asset loss and well-being loss is different. The lowest income group has a well-being loss which is 3.3 times higher than their asset loss. The highest income group has a well-being loss which is 30% lower than their asset loss.

Income loss

Income loss is modelled proportional to asset loss. In both cases, the income loss is highest in the high income group, which is logical since this group also has more income to lose. The difference in income losses between the control and the extreme event is noticeable in the highest income group, where losses in the extreme event nearly double in the control event. This indicates that the asset loss ratio in the extreme event is higher in the highest income group, section 4.3 further elaborates this.

Well-being loss per unit of damage

The control event clearly demonstrates that, when exposure is equal, the well-being losses of low-income groups are significantly higher. Figure 4.9 illustrates these results for the extreme event, presenting the well-being loss per $100 asset loss. The well-being loss per unit of damage decrease by rising income.

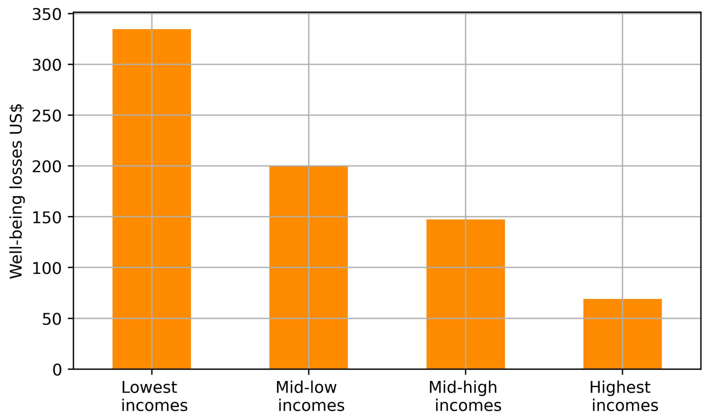


Figure 4.9: Average household well-being losses per $100 asset loss per income quartile for the extreme event.

The difference between the control event and the extreme event highlights the importance of the distribution of asset losses. These results also reveal the sensitivity of the model to the input data of asset loss and income. Note that the data set is quite small, which also increases the sensitivity of these results. It is important to define the trends rather than to focus on the absolute values of the results, as both cases show: well-being losses far exceed asset losses in low-income groups, which contrasts with the situation in high-income groups, where well-being losses are lower than asset losses.

4.2.2. Spatial results

Figure 4.10 presents the spatial results of the control event. The relative asset loss is constant, therefore the difference in asset losses between block groups is caused by a higher pre-disaster structure value of the houses. In this map the well-being losses are more distributed which is logical since every block group is affected in the same way.

Figure 4.11 presents the spatial results for the extreme event. Both asset and well-being losses are more concentrated near the coast. The highest well-being losses are experienced by a couple of block groups on the southwest coast and two block groups south of downtown Charleston.

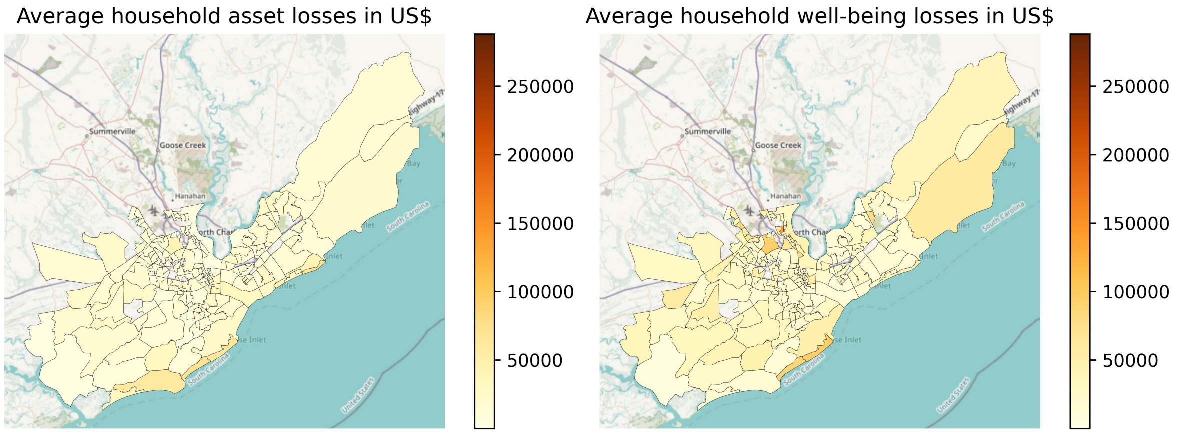


Figure 4.10: Spatial asset and well-being losses of the control event.

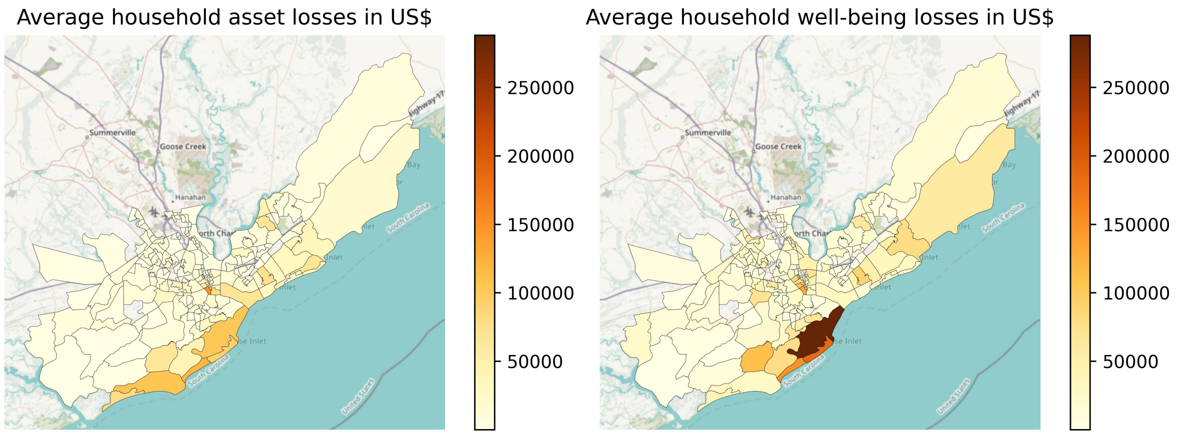


Figure 4.11: Spatial asset and well-being losses of the extreme event.

4.3. Relative asset losses

Due to the strong impact of asset losses on the results, the relative asset loss is examined in more detail in figure 4.12. The results clearly demonstrate an increase in relative asset loss as income rises. Other results have already presented the expected result that high income households lose more absolute assets, but in this case study they also have the highest relative asset loss. This implies that in Charleston high income households tend to live in more exposed areas.

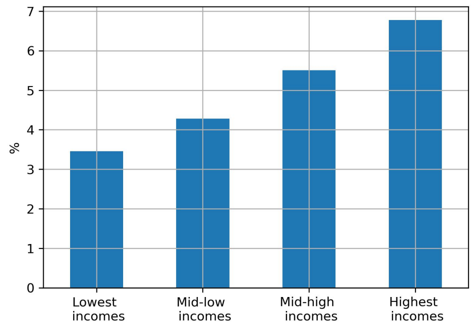
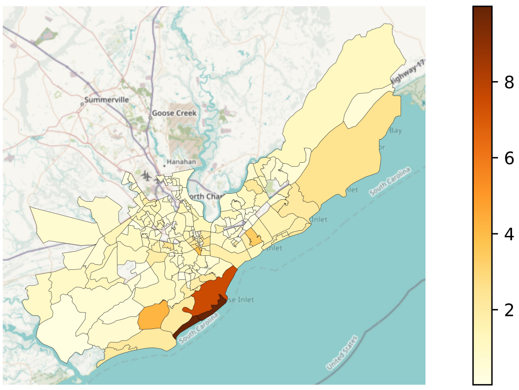


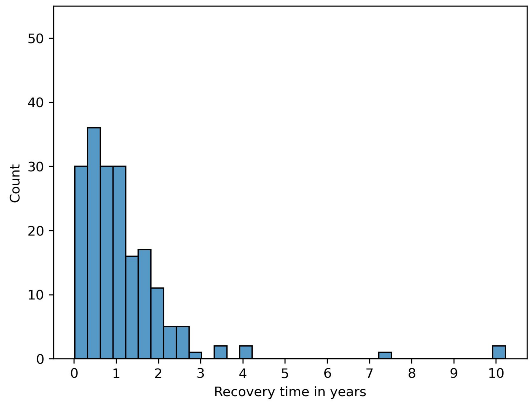
Figure 4.12: Relative asset losses per income quartile of the extreme event.

4.4. Recovery time

Figure 4.13 displays the optimal recovery time in years for the block groups that have suffered asset damage, where figure 4.13a presents the spatial distribution and 4.13b presents the frequency distribution. Notably, block groups with high levels of asset damage also tend to have longer recovery times. These block groups are located on the southwest coast. The recovery time of two block groups reached the constraint of the upper limit, meaning that their optimal recovery time is outside the 10 year limit. These block groups are not able to find an optimal recovery in these 10 years because of the high absolute asset loss compared to their income level. The longest optimal recovery after these two block groups is 7.5 years. Most households have an optimal recovery of less than 2 years.



(a) Spatial distribution of recovery time in years.



(b) Distribution of recovery time in years.

Figure 4.13: Average household recovery time in years for the extreme event.

Recovery time per $100 asset loss decreases with increasing income, as displayed in figure 4.14. These results are consistent with the expectation that higher income groups have more consumption space to quickly recovery from the disaster.

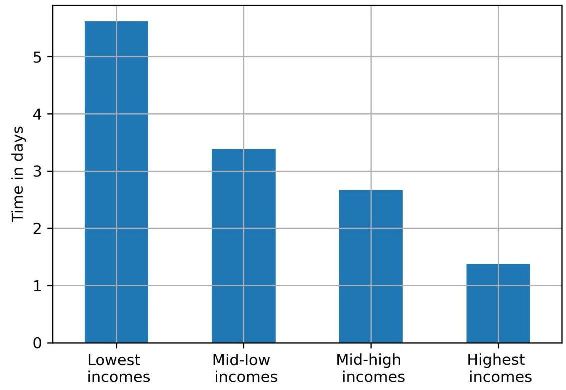


Figure 4.14: Recovery time in days per $100 asset loss per income quartile for the extreme event.

4.5. Comparison individual block groups

To facilitate comprehension of these results, a few examples are provided for individual block groups. Each figure compares two block groups in different income groups with similar relative asset losses. These figures present the consumption levels following the disaster, including the reconstruction costs, income loss, recovery time and poverty line. The recovery time line is when 95% of the initial assets have been rebuilt. Appendix B.3 presents the location of these block groups on the map of Charleston.

Figure 4.15A represents a block group with high average income, while figure 4.15B represents a block group with low average income. The block groups experienced the same relative asset loss of 13%, but the high-income group suffered substantially higher absolute asset losses. The low-income household experienced the highest well-being losses. The figure clearly presents a larger fall in consumption of the high income household, yet this consumption level is still higher than the initial consumption level of the low-income household. The fall in consumption of low-income households nearly reaches the poverty line. As a result, the loss of well-being is more severe. The optimal recovery time for the low-income household is slightly longer.

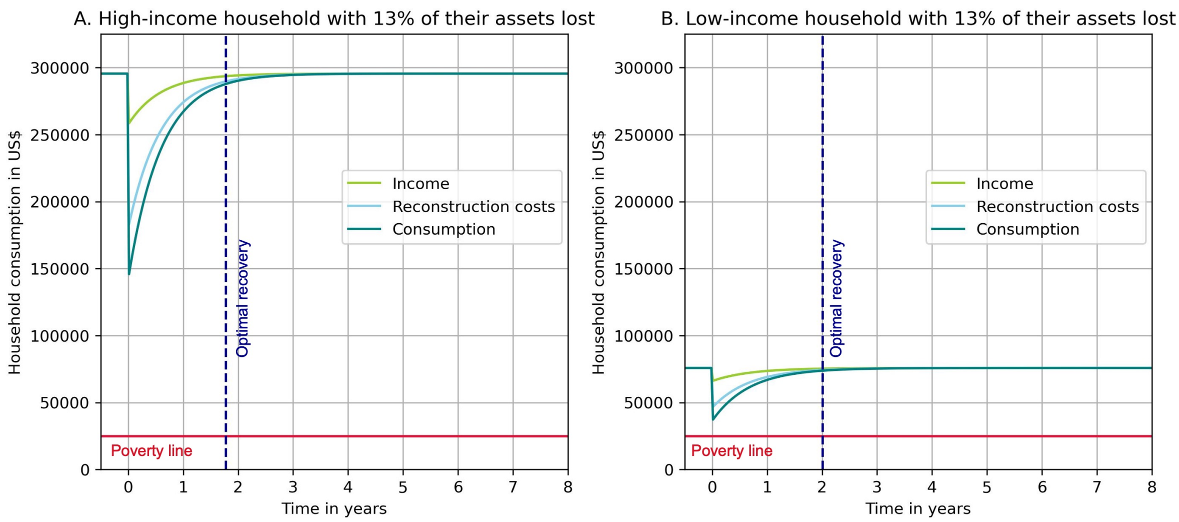


Figure 4.15: Average household consumption level of two block groups with similar relative asset losses.

Figure 4.16 presents another mid-low and high-income household. These block groups are amongst the block groups with the highest well-being losses and also among the highest relative asset losses. Similarly to figure 4.15 the high-income household (figure 4.16A) has a greater fall in consumption levels. The difference in the recovery time of these blocks is extremely high. The low-income household has slightly higher absolute losses, implying that the low-income household faces high reconstruction costs relative to its income. This explains the large difference in recovery time. Furthermore, the well-being loss of the low-income households is 2.5 times greater than that of high-income households.

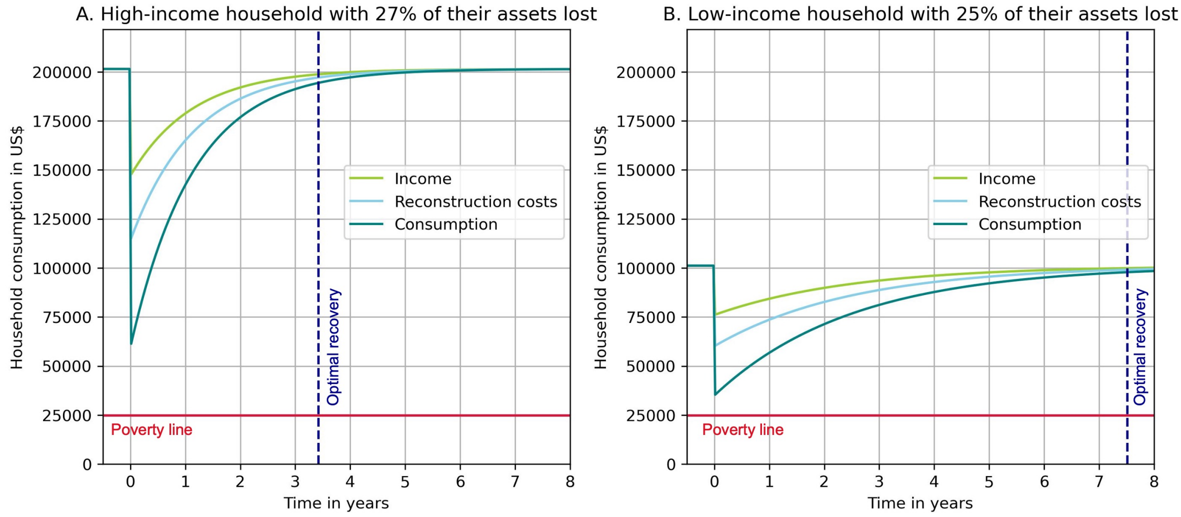


Figure 4.16: Average household consumption level of two block groups with similar relative asset losses.

Figure 4.17 displays the results of a high-income household and a low-income household, where the high-income household experiences a higher well-being loss. The recovery time of the high-income household is almost 3.5 years, while the low-income household has an optimal recovery time of less than 2 years. The high-income household has almost four times more absolute asset losses than the low-income household. In this case the extend of the absolute asset losses weigh out the greater consumption space high-income household have and leaves them with a higher well-being loss compared to a low-income household.

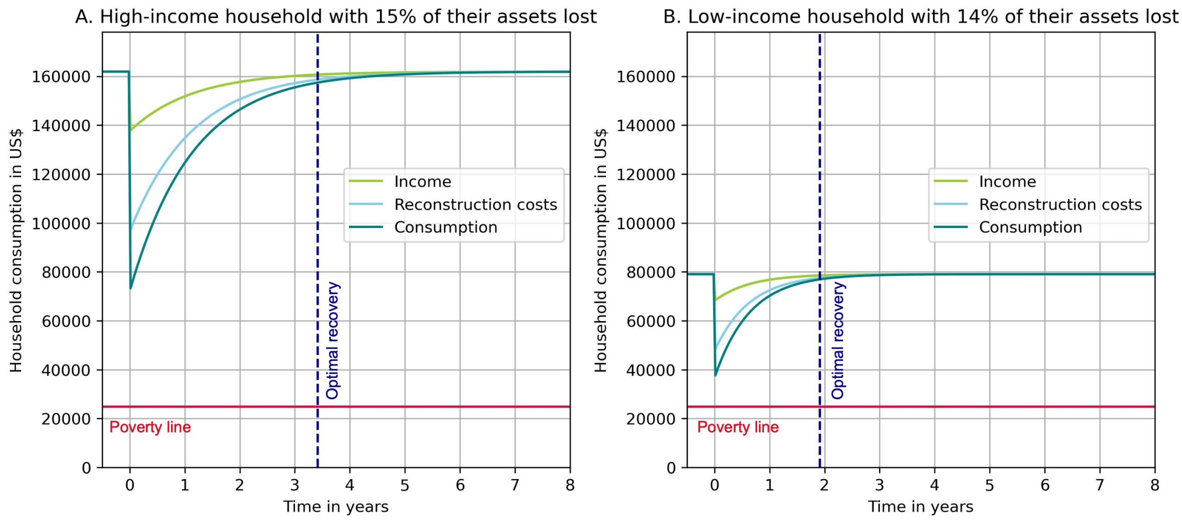


Figure 4.17: Average household consumption level of two block groups with similar relative asset losses.

4.6. Insurance

Figure 4.18 presents the well-being losses for all the block groups with and without an insurance policy. All the block groups benefit from the insurance policy, their well-being losses decrease.

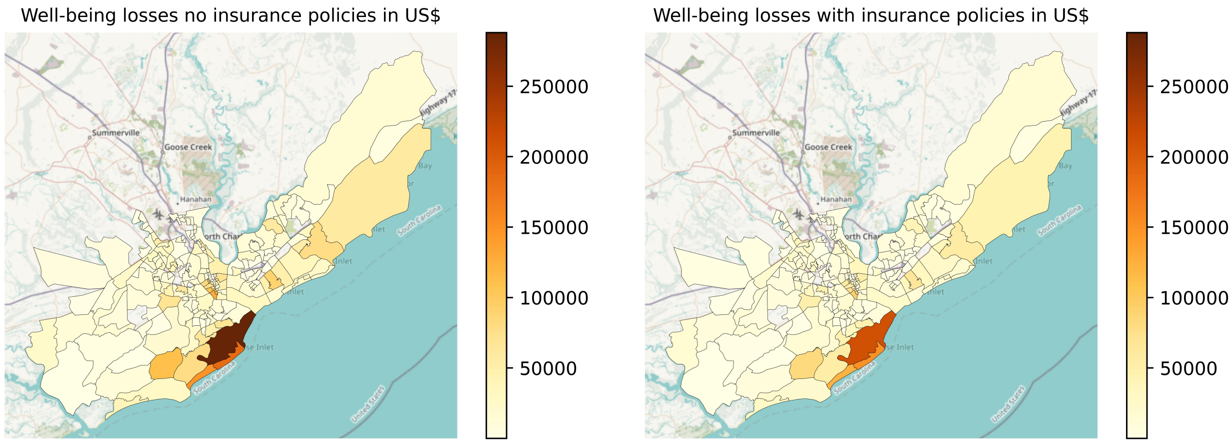


Figure 4.18: Spatial results of average household well-being losses without insurance policies and with insurance policies.

Figure 4.19 presents the recovery time in years of the block groups with and without insurance. The insurance policy also reduces the recovery time, as illustrated in figure 4.20, more block groups are concentrated in lower recovery times below 1 year. The longest recovery when insurance policy is applied, is 6 years.

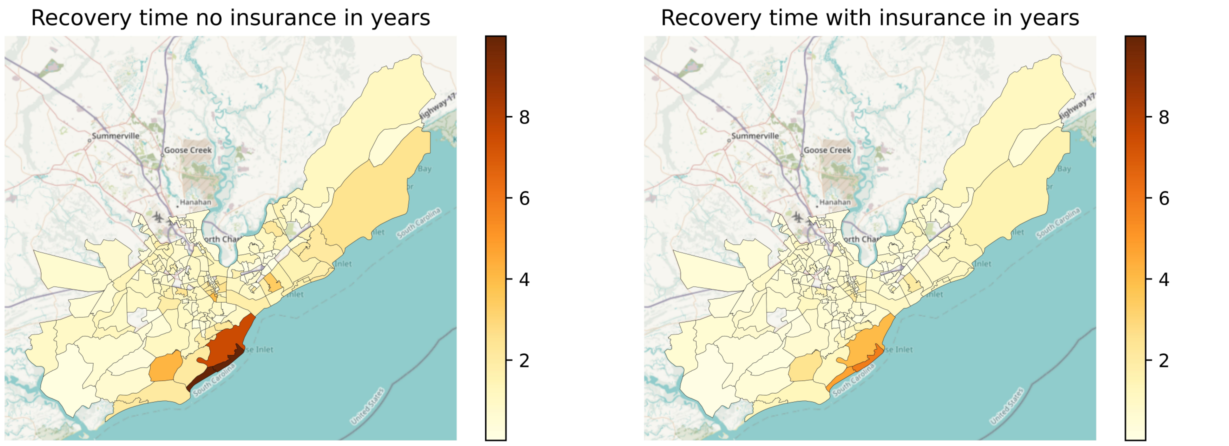


Figure 4.19: Spatial distribution of average household recovery time in years

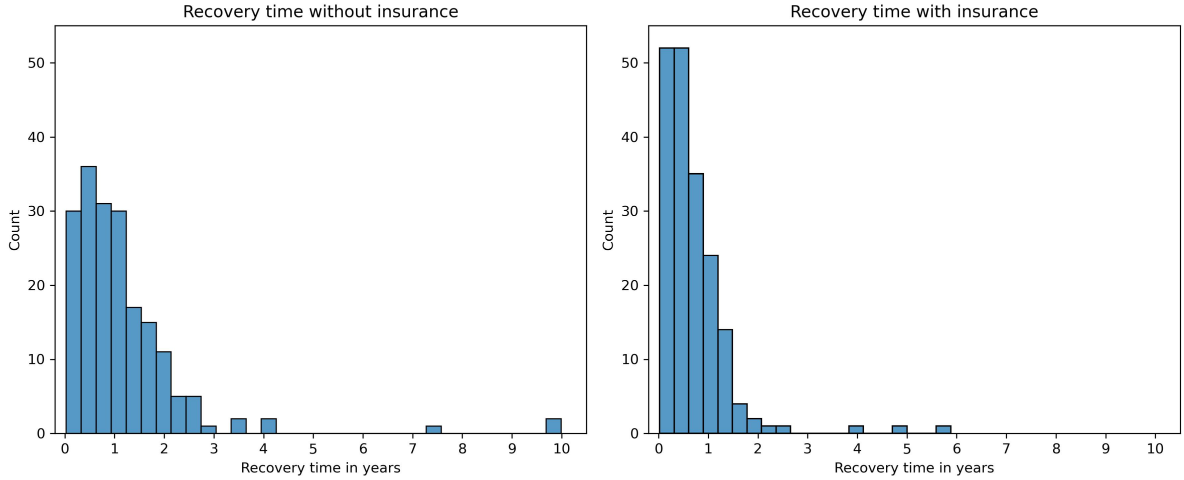


Figure 4.20: Frequency distribution of average household recovery time in years

Figure 4.21 displays the premiums for all block groups. Two block groups have premiums that exceed the 7.5% income threshold, which are marked in dark red. These two block groups are not insured. When the premium is calculated as a percentage of income, more differences between the block groups are visible, as illustrated in figure 4.21B.

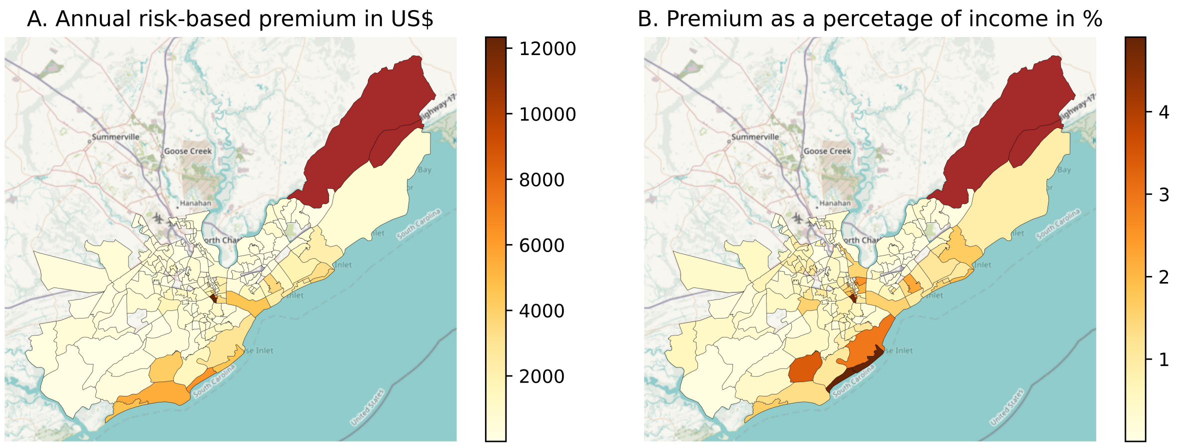
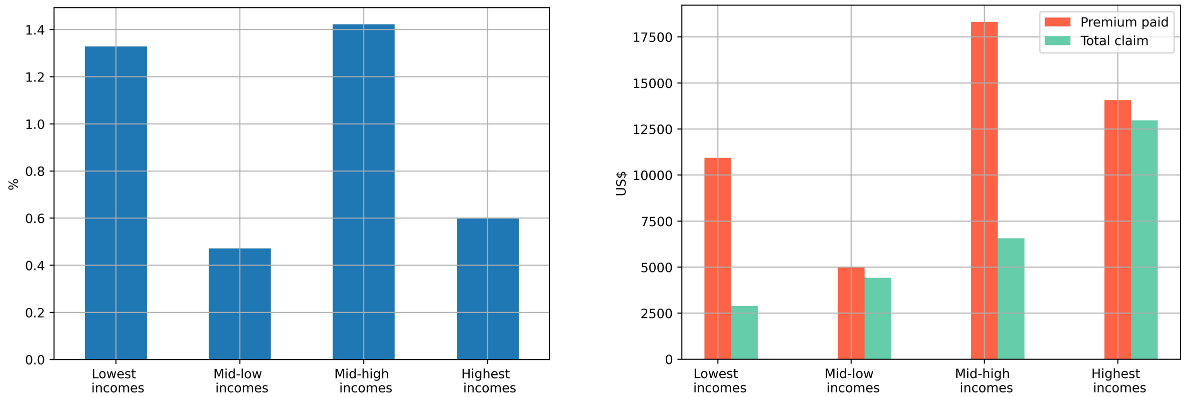


Figure 4.21: Spatial distribution of average household premiums.

Figure 4.22a further examines the relationship between income and premium. The premium is relatively high for low and middle income households. The premium is based on the EAD which explains the differences per income quartile. Figure 4.22b presents the total premium paid over a 10-year period and the claim received. The claim is 45% of the experienced damage, damage increase by income quartile, so it is logical that the claim also increases by income quartile. It is evident that the lowest income group and mid-high income group pay a disproportionately large premium relative to their received payout. All other income groups receive a higher absolute amount of claims compared to the paid premium.



(a) Average household premium as a percentage of income per income quartile.

(b) Total premium paid over a 10-year period of an average household and the one-time claim received

Figure 4.22: Average household premium and claim received as payout

Figure 4.23 presents the well-being losses with insurance base scenario for each income quartile. In all income groups there is a significant reduction in well-being losses when insurance is included. High-income households benefit slightly more from insurance than low-income households. The well-being loss of an average low income household decreases by 26% compared to 29% for a high income household.

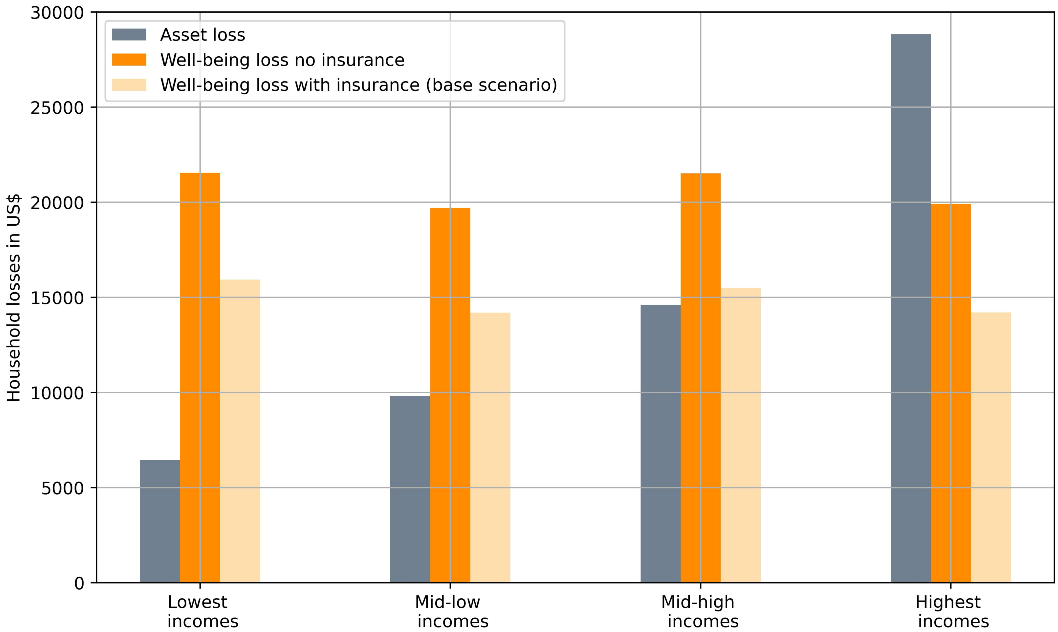


Figure 4.23: Average household well-being losses without and with insurance per income quartile.

Figure 4.24 presents the results for different take-up rates. The take-up rate is the amount of households that have insurance. A higher take-up rate of 65% presents slightly lower well-being losses. The take-up rate is not very sensitive. In a hypothetical scenario where all the household have insurance, a take-up rate of 100%, the well-being loss decreases to a certain extend but the well-being loss is still present. A comparison of the scenario without insurance to full coverage revealed a nearly halved loss of well-being. The highest relative reduction in well-being loss was observed in the mid-low income quartile.

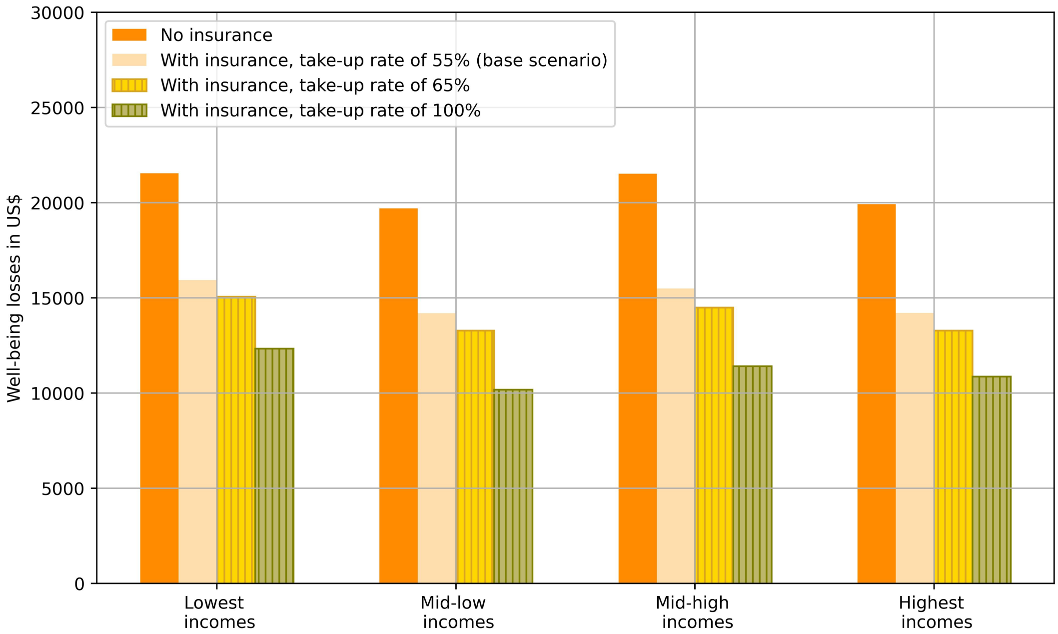


Figure 4.24: Average household well-being losses sensitivity of take-up rates per income quartile.

4.7. Sensitivity analysis

This section first discusses the sensitivity of the input parameters discount rate (ρ) and elasticity of marginal utility (η). Secondly, the sensitivity is presented of the optimisation of the recovery time. The sensitively analysis is performed on the extreme event without insurance policy.

4.7.1. Parameters

A standard discount rate (ρ) of 10% is used for the research. The discount rate is only used in calculating the well-being loss and does not affect other results. Figure 4.25 presents the results when using a discount factor of 1%. The model exhibits a small sensitivity to the discount factor, as reflected by the minor changes in well-being loss.

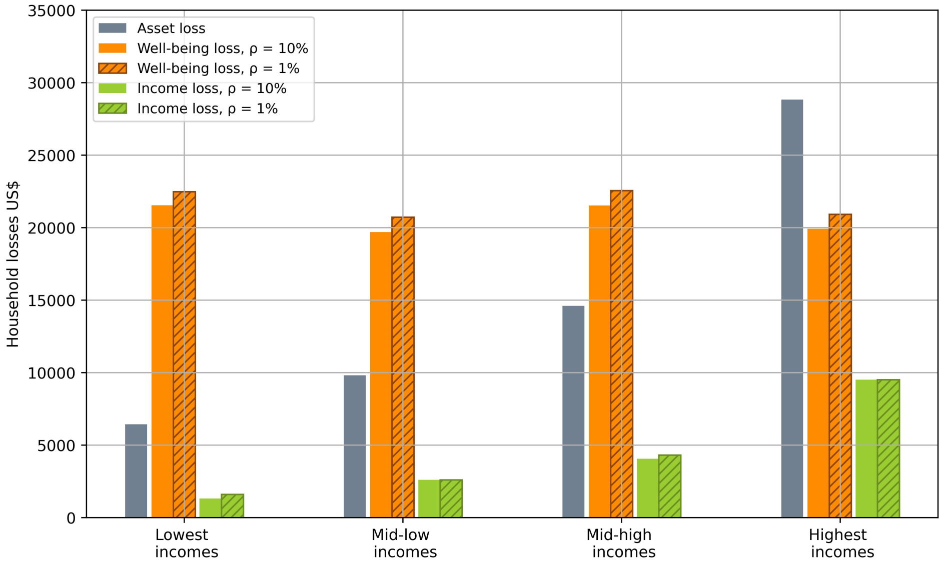


Figure 4.25: Average household losses per income quartile, sensitivity analysis of the discount rate (ρ).

The elasticity of marginal utility is the second parameter used in the model. Marginal utility is the additional satisfaction an individual receives from an increase in consumption. The elasticity of marginal utility quantifies how sensitive an individual's utility is to changes in the level of consumption. If the elasticity of marginal utility is increased, a small change in consumption will result in a much larger change in utility. In this research, a higher elasticity of marginal utility would translate into a greater weight on low levels of consumption; a small decrease in an already low level of consumption leads to a much larger decrease in well-being. Figure 4.26 compares the results with an elasticity of 2 instead of 1.5 (used in this research). The well-being loss presents the expected results: lower incomes with lower levels of consumption lead to an increase in the well-being loss, while higher incomes lead to a decrease in the well-being loss. In figure 4.27, where the effect of a higher marginal utility is visible, a higher marginal utility makes the relationship between utility and consumption more skewed.

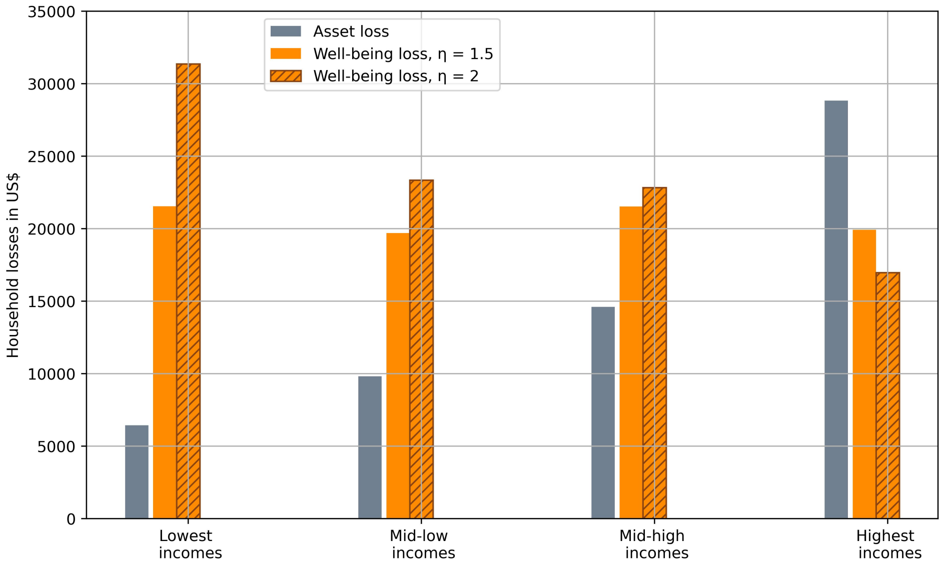


Figure 4.26: Average household losses per income quartile, sensitivity analysis of elasticity of marginal utility (η).

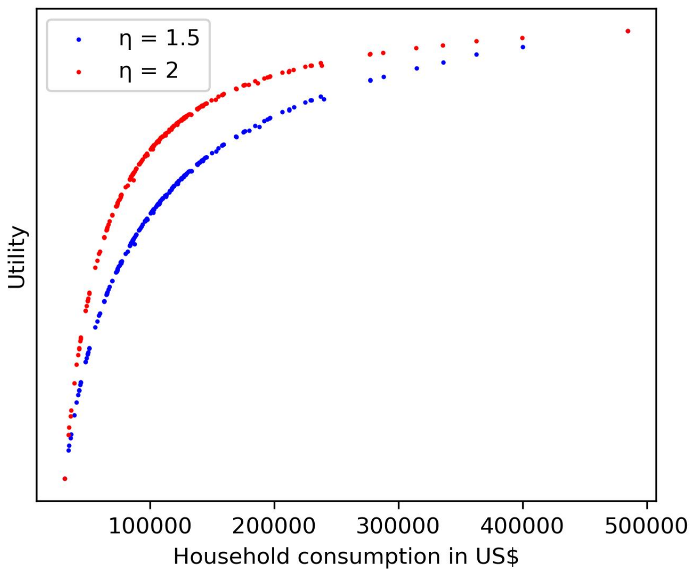


Figure 4.27: Normalized utility function for different elasticities of marginal utility (η).

4.7.2. Optimisation of the recovery time

The model optimises the recovery time to minimise the well-being loss for households. This is achieved by optimising the recovery rate λ for each individual block group. Figure 4.28 presents the results if the recovery rate was not optimised and each block group was forced to recover in 5 years. This results in a slow recovery for most block groups, since the average optimised recovery time is 1.23 years. The well-being loss is higher in each income group when the recovery rate is not optimised. These results imply that optimisation is effective.

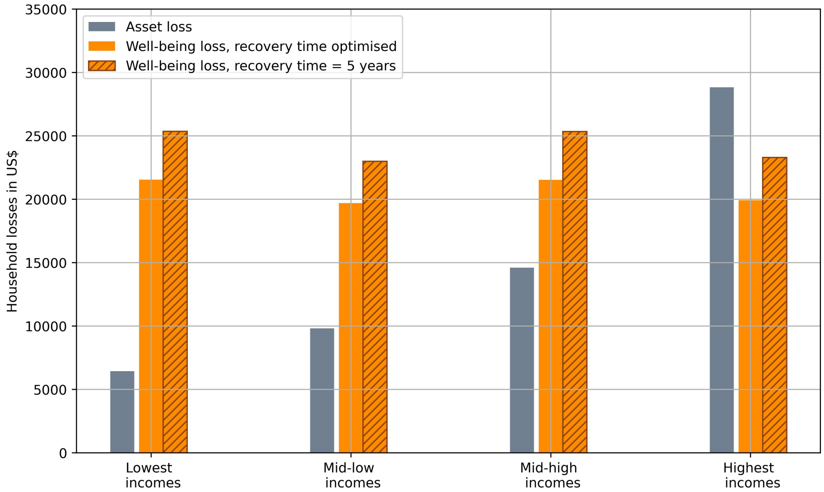


Figure 4.28: Average household well-being losses per income quartile, sensitivity recovery time.

Figure 4.29 presents the income losses when recovery is forced at 5 years, which reveals a huge increase in income loss in every income group. The loss of income is modelled proportionally to the loss of housing assets (equation 3.6). Most income loss is not directly caused by the loss of housing assets. If income loss occurs, that would be the result of productive assets loss. The model assumes that the loss of housing assets is proportional to the loss of public (productive) assets. However, public assets could recover quicker, which results in different values of income loss. Based on this information, it may seem logical to model the income loss differently. Nevertheless, this approach is necessary for the optimisation of the recovery time. The recovery time is optimized for the highest well-being. A theoretical highest well-being would be achieved when no recovery costs are paid. Therefore, the income loss is needed as a counterpart as an incentive for the model to recovery. See the limitations (5.2.3) for a further explanation.

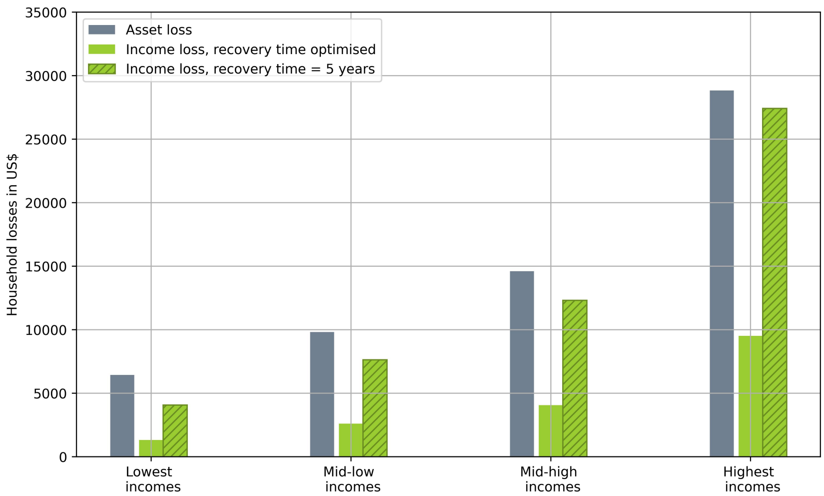


Figure 4.29: Average household income losses per income quartile, sensitivity recovery time.

In conclusion, the discount rate is not a very sensitive parameter. The elasticity of marginal utility is quite sensitive, particularly for the results of the lowest and highest income quartiles. The recovery rate is slightly sensitive in regards of the well-being losses but functions as intended. However, the recovery rate is highly sensitive for income loss, which can be identified as an uncertain part of the model.

5 Discussion

The first section of this chapter discusses how the results relate to previous work and explain how they are similar or different. The second section will discuss the limitations of the research.

5.1. Theoretical implications

The main finding that overall well-being losses exceed asset losses is consistent with the findings of previous research Walsh and Hallegatte (2020), Verschuur et al. (2020) and Markhvida et al. (2020). The general trend in these papers is that low-income groups suffer a relatively higher amount of well-being losses compared to their asset losses, which is also confirmed in this research. However, the magnitude and distribution of well-being losses are quite different.

In the research of Markhvida et al. (2020), the losses in total well-being are more than double the losses in assets, which implies that the extent of well-being losses is substantially greater. Even in the highest income quartiles, well-being losses exceed asset losses. This contradicts the findings of this research, where the well-being losses of the highest income quartile were lower than the asset losses (Figure 4.8). The study by Markhvida et al. (2020) finds that the lowest income quartile experiences 19% of the total asset losses and 41% of the total well-being losses. Similar findings are presented by Walsh and Hallegatte (2020) and Verschuur et al. (2020) regarding the share of well-being losses, however lower incomes have a smaller share of asset losses around 10%. Note that this research presents slightly different results, with the lowest incomes experiencing 11% of the total asset losses and 26% of the total well-being losses for the extreme event (figure 4.8).

Markhvida et al. (2020) and Walsh and Hallegatte (2020) also optimised the recovery time for well-being. However, it is challenging to make direct comparisons of recovery times due to to the varying levels of severity of the events of the other studies. Nevertheless, the findings are broadly consistent. Walsh and Hallegatte (2020) presented the average recovery time for two regions following a 50-year hurricane, which was found to be 3.7 and 5.3 years. The region with a longer recovery time also had higher poverty rates. This aligns with the results of this research, which indicate that recovery time decreases with rising income (see Figure 4.14). Markhvida et al. (2020) found an overall recovery of 2.5 years of the regional GDP. The recovery times observed in previous studies are slightly higher than the average in the case study of Charleston, which is 1.23 years. This may be attributed to the higher well-being losses identified in the papers of Markhvida et al. (2020) and Walsh and Hallegatte (2020). Refer to appendix C for further explanation of the methodological causes of differences in results.

Utility was also used to estimate losses in the work of the Kind et al. (2016), where risk aversion and equity weighs are integrated into cost-benefit analysis (CBA) to address social vulnerability. The results of a case study demonstrate that decisions informed by this social welfare risk framework differ significantly from conventional practices. Since these methods are not conventional, the study also discusses the concerns in the literature that such methods face.

The incorporation of equity weighs involves subjective choices in utility functions parameters, for example the elasticity of marginal utility. The results of the case study of Charleston also demonstrated that the outcomes are sensitive to the elasticity of marginal utility (figure 4.26).

5.1.1. Insurance

The results from section 4.6 are consistent with the findings of De Ruig et al. (2022), which also found positive societal benefits resulting from risk-based premiums. The study also found even higher societal benefits when combining risk-based premiums with large-scale adaptation measures. Results from survey data studies (Tamuly & Mukhopadhyay, 2022; Wang & Wang, 2022) also confirmed the positive impact of insurance on well-being. The research conducted by Markhvida et al. (2020), Walsh and Hallegatte (2020) and Verschuur et al. (2020) also found that post-disaster aid and insurance policies positively affect well-being. According to Markhvida et al. (2020), property insurance reduces well-being losses by 7%. This research reveals a 27% reduction in well-being losses in the base scenario (figure 4.23).

The results of this research indicate that risk-based premium can be relatively expansive for low-income group compared to the payout they receive (figure 4.22b). It should be noted that this model does not consider that high-income areas are more likely to have costly and structural flood insurance, as stated in previous research (Brody, Highfield, et al., 2016; Brody, Lee, & Highfield, 2016; Rufat & Botzen, 2022). Additionally, Markhvida et al. (2020) stated that low-income household are less likely to have insurance without governmental assistance. Emrich et al. (2019) also found a weaker correlation between social vulnerability and flood recovery aid. This suggests that future recovery efforts should address social vulnerability for fairer disaster recovery.

5.1.2. Scientific contribution

This study builds upon previous research by conducting further testing on the model initially developed by Hallegatte, Bangalore, and Vogt-Schilb (2016). The research includes an insurance policy with risk-based premiums to evaluate disaster relief and its effectiveness on vulnerable people. Additionally, the study aims to enhance the model's comprehensibility by presenting the interplay between the core variables used to calculate the well-being loss which have not been presented before. The distribution of relative asset losses (figure 4.12) and the optimal recovery time (figure 4.28) are important factors determining the well-being losses. Accurate results require robust income loss data, as income loss has a decisive role in optimising the recovery time in the model (figure 4.29). Another interesting finding regarding the optimisation of the recovery time, is that if no income loss is taken into account, there is no incentive to recover making it economically optimal to always postpone recovery.

5.2. Limitations

This research is limited by a number of constraints, which can be divided into data limitations, modelling choices and general limitations.

5.2.1. Data limitations

The calculations are designed to be made at the household level; however to the unavailability of detailed data the calculations are done for each block group. Although each block group contains an average of 427 households, the assumption of uniform damage and income levels within these groups overlooks the socio-economic diversity between households.

A significant limitation of the study is the exclusion of renter-occupied households, which make up 34% of all households in Charleston. This exclusion is particularly concerning due to the financial vulnerability of renters, who often lack resources and rely on landlords. Incorporating renters into the model would provide a more comprehensive understanding of vulnerability, yet presents methodological challenges beyond the scope of the study. The exclusion of renters also creates a data limitation. Income data for both owners and renters were used because it was not possible to distinguish between them. This may lead to inaccuracies as renters tend to have lower incomes. If only income data from owner-occupied households were used, the estimated well-being losses would be slightly lower.

Mortgage payments and savings were excluded from the analysis for reasons of data unavailability and simplicity. Including mortgage payments would only slightly increase the well-being losses, which would not significantly affect the overall results and interpretation. Savings could potentially reduce well-being losses, especially for high-income households, as these groups tend to have more savings.

Insurance

The assumption of immediate insurance payouts after a disaster differs from the real world, where claims processing can take much longer. To model this more accurately would require making different assumptions or extracting and analysing more data. Actual insurance data may produce different results, as high-income households may already be better insured, potentially increasing inequalities.

5.2.2. General limitations

This study focuses on a limited definition of well-being, that does not take into account a broader sense of well-being, such as injuries, loss of life, pain of loss of friends and relatives, pain of leaving the family home and being deprived of work and community activities, cultural loss, relocation, and so on. It also does not take into account that houses become uninhabitable. Besides the option of building back better is also not accounted for in the model.

5.2.3. Model limitations

The complexity of the model Markhvida et al. (2020) decreased its accessibility for practical use. Therefore, it was decided to simplify the model. However, these simplifications also impose limitations on the model. Income and income loss are the most uncertain aspects of the model. The results are very sensitive to initial income, as it determines the pre-disaster level of consumption, which is used to calculate well-being. The model assumes that all types of income are sensitive to floods. However, not all types of income are affected by asset losses. For instance, income generated from investments may be located outside the affected area. Most office jobs can be performed remotely with a computer or laptop. Income that is not reliant on productive assets is less vulnerable. Low-income types are generally more dependent on productive assets, which is not accounted for in the model. The well-being losses of low-incomes could be higher.

The assumption that income loss is proportional to housing asset loss, deviates from reality. This assumption however is necessary for the optimisation of the recovery time. The reconstruction rate is optimised for the highest well-being, which is dependent on the level of consumption. Higher consumption levels lead to higher well-being. In the post-disaster situation, reconstruction costs and income loss influence the level of consumption. If only reconstruction costs would affect the consumption level, the highest level of consumption would be achieved when no reconstruction costs are incurred (i.e. when the reconstruction rate is 0). To prevent the reconstruction rate from becoming 0, there needs to be a counterpart that has an equal or higher weight than the reconstruction cost on consumption level. Otherwise, the well-being loss without reconstruction will be the lowest. Therefore, the income must be taken into account using the same asset loss ratio used in the equation of the reconstruction costs to perform the recovery time optimisation. The optimisation of the recovery time is tailored to an income loss as incentive to recover. Not optimising the recovery time would result in higher well-being losses, especially for high-income households. Therefore the decision was made to optimise the recovery time and include income loss despite the limitations.

Lastly, households with no reported damage, which account for 24% of block groups, are not included in the results. Due to the small data set, this would change the results. As the distribution of block groups with no property damage is not evenly distributed in terms of income, it distorts the results when presenting the results by income group.

6 Conclusion

This researched aimed the answer the following research question: How do well-being losses compare to asset losses in socially vulnerable households in flood-prone areas and what role can insurance policies serve in minimising these well-being losses? To answer this question the following sub research questions were defined:

1. What is the well-being loss compared to asset loss of a control event?
2. What is the well-being loss compared to asset loss of an extreme hurricane?
3. What is the impact of insurance policy on well-being?

The control event where exposure is equal in the whole area results in nearly double well-being losses compared to asset losses. Asset losses increase with rising income. Well-being losses fall sharply as income rises. It is clear that the same relative asset loss has a very different impact on a low-income household compared to a high-income household.

The extreme event (hurricane Ian) also produced well-being losses that exceeded asset losses. Asset losses also increased with income, but to a greater extent. Relative asset losses were also concentrated in higher income areas. Absolute well-being losses were similar across income groups. When well-being losses were presented per $100 of asset loss, well-being losses decreased sharply by income group.

The insurance policy resulted in a decrease in well-being losses in each area and also for each income group after the disaster. Low-income and mid-high income groups pay a disproportional large amount of the premium compared to their received payout due differences in flood risk. Insurance is effective, but it is challenging to ensure that low-income groups also have access to affordable insurance. A hypothetical scenario, where the whole area would be insured, nearly halved the well-being losses. It can be concluded that insurance cannot eliminate all well-being losses. Therefore, other measures must be implemented to further increase resilience.

Not only absolute damages, but also relative damages have a greater impact on the well-being of low-income households. The well-being metric is useful in representing households with fewer financial resources. This model can be considered a valuable tool for assessing the impact of particular policies or mitigation measures. This research has concisely presented the interplay between core elements that cause well-being loss. This study highlights a trade-off between model complexity and usability. While increased complexity can accurate results, it can also reduce usability. The research made use of open source data, which improves reproducibility. In light of climate change and the increasing costs of floods, which have different impacts on low-income areas, methods such as these should be more widely used to better understand the consequences of natural hazards.

6.1. Recommendations

The recommendations section is divided in a section that elaborates on future research and a section that discusses suggestions for policy makers.

6.1.1. Future research

To increase the model's robustness and enable more comparison, it should be applied to more areas, as it is currently limited to only a few. If used more frequently, it could serve as a standard framework. Previous literature review highlighted the necessity of standardized frameworks to evaluate the impacts of flood damage beyond asset loss. The use of a extensive and detailed dataset could improve the accuracy of the results.

For this research, total household income has been used. However, in order to get a clearer picture, it is recommended to deduct fixed expenses from income which creates a disposable income. This approach could yield more accurate values. Currently, the numerical results are not very useful due to the number of assumptions made. The modelling framework should also be improved regarding the income loss. Income loss should be better connected to the cause. Improving this also requires a change in the method for finding the optimal recovery since the current model relies on the income loss being proportional to the asset loss ratio.

The modelling framework should be extended to include renters. Additional research is necessary to determine the impact on renters, as there is limited previous research on this topic. It is also important to investigate how landlords respond when their properties are affected. Renters are a vulnerable group, and their exclusion from the framework should be addressed.

Creating more realistic payout times would be recommend to incorporate into the model. Anticipating the impact of slow claim payouts, which is a known problem in the NFIP, would be interesting. The impact of slow payouts on well-being is not yet examined. Current data on insurance policies in force would be helpful to reflect the fact that households with higher incomes are more likely to have flood insurance. This is not included in the model and could present a different picture.

Splitting the results based on other indicators of vulnerability could extend the understanding of the impact of floods. This research is limited by the use of one indicator, which is income. However, the results are still constrained by income as input data, which makes it difficult to assess well-being losses on a broader spectrum. Nevertheless, since low-income areas are a vulnerable group to climate change, income remains a useful indicator.

6.1.2. Policy implementation

The FloodAdapt tool, which stimulates the damage scenarios, is already a very helpful tool for policy makers. It enables non-expert users to evaluate combined flood events, project future conditions and determine the effectiveness of adaptation measures. These functions can improve decision-making to reduce flood impacts and increase resilience. Incorporating the possibility of choosing the well-being metric would be a great addition to the tool. Furthermore, the option of insurance can be incorporated into the scenarios. The FloodAdapt tool can then be used to compare various climate change scenarios and assess the impact of climate change on vulnerable communities.

When implementing mitigation measures or insurance policies, it is recommended to focus on low-income communities to prevent them from entering a vicious cycle of well-being loss. It is recommended to investigate the possibility of insurance premium discounts for low-income groups. It would also be beneficial to provide low-income groups with more information about insurance. Previous literature has indicated that these groups are less aware of their risks.

It is recommended to develop a package of interventions by combining multiple pre- and post-disaster measures. Insurance can reduce the impact on well-being losses, however more can be done. Vouchers or premium discounts can function as additional policies and mitigation measures such as urban planning and infrastructure development should also be a part of a holistic approach to flood management. A cost-benefit analysis can assist in the design of such a package, with the objective of reducing the impact of climate change on vulnerable communities. This is an essential element of broader development goals.

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A
Additional methodology details

This appendix provides extra explanation of the equations used in the methodology.

A.1. Additional data preparation

The data retrieved from FloodAdapt and the USA Census Bureau were merged into a single dataset. Each row represented a block group with information on an average household within that block group. The dataset was checked for missing data and other issues. Six block groups consisting entirely of rented households were excluded from the dataset. In addition, one block group had a NaN (Not a Number) value for income, which was filled in with data from the census tract level, a higher level.

The income data retrieved from the US Census bureau includes both renter and owner-occupied households. Note that only owner-occupied households are included in the model. At the tract level (higher level), the household income can be retrieved for renter and owner-occupied households separately. This was not available at block group level. The household income, including both renter and owner-occupied households at block group level was divided by the total number of households, assuming equal income distribution between renter and owner-occupied households. This was considered as the best practice. Retrieving the data on tract level, where income solely from owner-occupied households is available, would also be an option. However this data would not have enough detail and may distort results.

A.2. Reconstruction costs

The reconstruction costs over time are the change in asset losses over time. This equation is found by determining the derivative of $\Delta k_{str}(t)$.

$$
\begin{aligned}
c_{reco}(t) &= -\frac{dk_{str}}{dt}\left(\Delta k_{str}(t)\right) \\
\Delta k_{str}(t) &= k_{str} \cdot e^{-\lambda t}
\end{aligned}
$$

Where Δk_{str} is absolute loss of structure value of the house, λ is the reconstruction rate and t time in years.

The derivative of $\Delta k_{str}(t)$ is taken by the use of the chain rule:

$$
\begin{aligned}
x &= -\lambda \cdot t, \quad \text{and} \quad y = e^x \\
k_{str}(t) &= k_{str} \cdot y \\
\frac{dk_{str}}{dt} &= \frac{dk_{str}}{dy} \cdot \frac{dy}{dx} \cdot \frac{dx}{dt} \\
\frac{dk_{str}}{dy} &= k_{str} \\
\frac{dy}{dx} &= e^x \\
\frac{dx}{dt} &= -\lambda \\
\frac{dk_{str}}{dt} &= k_{str} \cdot e^{-\lambda t} \cdot (-\lambda) \\
c_{reco}(t) &= -k_{str} \cdot e^{-\lambda t} \cdot (-\lambda) \\
c_{reco}(t) &= \lambda \cdot k_{str} \cdot e^{-\lambda t}
\end{aligned}
$$

A.3. Insurance policy

Figure A.1 presents the consumption when the insurance policy is applied. The modelling of the insurance payout is derived from the modelling of savings. Consumption after a disaster remains constant until the time $\hat{t}$, when the insurance payout is exhausted. This level of consumption is given by $c_0 - \gamma$, where γ is the consumption loss when there is an insurance payout, which is given by the following equation:

$$\gamma = \Delta c(\hat{t})$$

The total consumption loss ($\gamma \cdot \hat{t}$) and insurance payout are equal to the total consumption loss until time $\hat{t}$ with no insurance payout, see the following equation which describes the relationship between $\hat{t}$ and the payout.

$$\gamma\hat{t} + payout = \int_0^t \Delta c(t)\, dt$$

It is necessary to find the time $\hat{t}$ to create the new consumption course. The value of the insurance payout claim is given by the amount of damage a certain household has. To find $\hat{t}$ the above equation can be rewritten.

$$\hat{t} = \frac{1}{\gamma}(\int_0^t \Delta c(t)\, dt - payout)$$

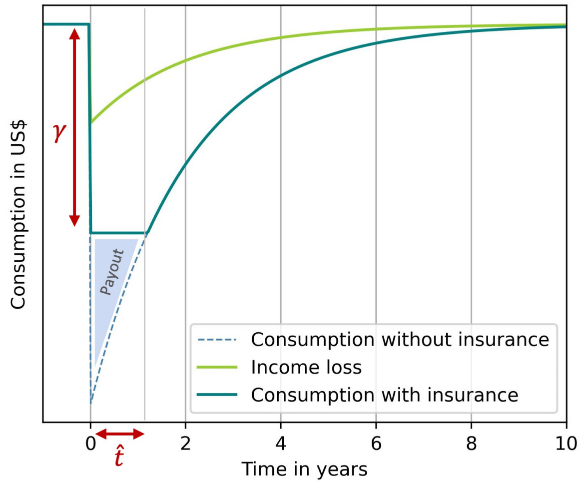

Figure A.1: Schematic overview of the household consumption when incorporating insurance policy

A.4. Explanation constraints optimisation recovery time

The optimisation of the recovery time is constrained by a lower en upper bound. The upper bound represented the fastest physical time that is possible to recover. The lower bound is essential to prevent an infinite recovery time. An infinite recovery time would occur when the optimised reconstruction rate is 0. In some cases, the optimal value for well-being is found when no reconstruction costs are paid. The well-being is based on the consumption level, the higher the consumption level, the higher well-being. The post-disaster consumption is determined by the income loss and reconstruction costs. In some case the height of the asset losses are at a certain level that the well-being decreases over time and that the highest well-being is achieved when no reconstruction costs are paid, when the reconstruction rate is 0 ($\lambda = 0$). The reconstruction rate is determined as fallows:

$$
\begin{aligned}
\lambda_{opt} &= \arg\max_{\lambda} \int_0^T u(t)\,dt \\
u(t) &= \frac{c(t)^{1-\eta}}{1-\eta} \\
c(t) &= c_0 - (c_{reco}(t) + \Delta i(t)) \\
c_{reco}(t) &= \lambda \cdot k_{str} \cdot e^{-\lambda t}
\end{aligned}
$$

If reconstruction rate λ would be 0, these equations would look like this:

$$
\begin{aligned}
\lambda_{opt} &= \arg\max_{\lambda} \int_0^T u(t)\,dt \\
u(t) &= \frac{c(t)^{1-\eta}}{1-\eta} \\
c(t) &= c_0 - (c_{reco}(t) + \Delta i(t)) \\
c_{reco}(t) &= 0 \cdot k_{str} \cdot e^{-\lambda t} \\
c_{reco}(t) &= 0 \\
c(t) &= c_0 - (0 + \Delta i(t))
\end{aligned}
$$

B

Additional results

B.1. Income distribution

Figure B.1 present the income distribution in each income quartile. Note that each income quartile approximately contains 20000 households. The income categories are defined according to annual household income (i_0) in 25th, 50th and 75th percentiles. Table B.1 presents the boundaries of the income quartiles.

Income group	Income bracket
Lowest income	$i_0 \leq$ US$91650
Mid-low income	US$91650 $< i_0 \leq$ US$119410
Mid-high income	US$119410 $< i_0 \leq$ US$147540
Highest income	$i_0 >$ US$147540

Table B.1: Boundaries of income quartiles.

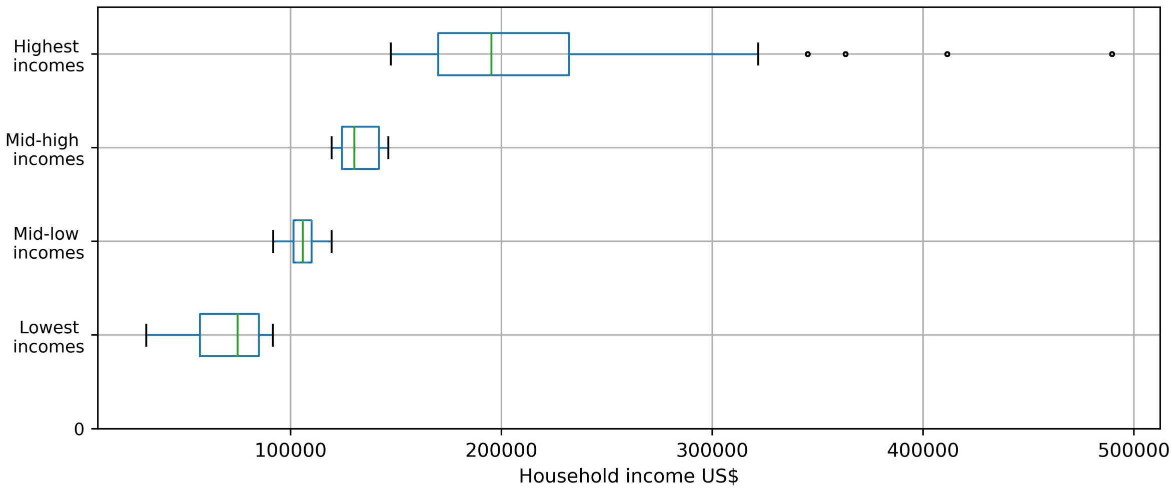

Figure B.1: Average household income Charleston county in the year 2021

B.2. Distribution of losses

Figure B.2 presents the distribution per income quartile of the absolute asset losses. Figure B.3 presents the distribution of relative asset losses. Figure B.4 presents the distribution per income quartile of the income losses. Figure B.5 presents the distribution per income quartile of the well-being losses. Figure B.6 presents the distribution per income quartile of the optimal recovery time.

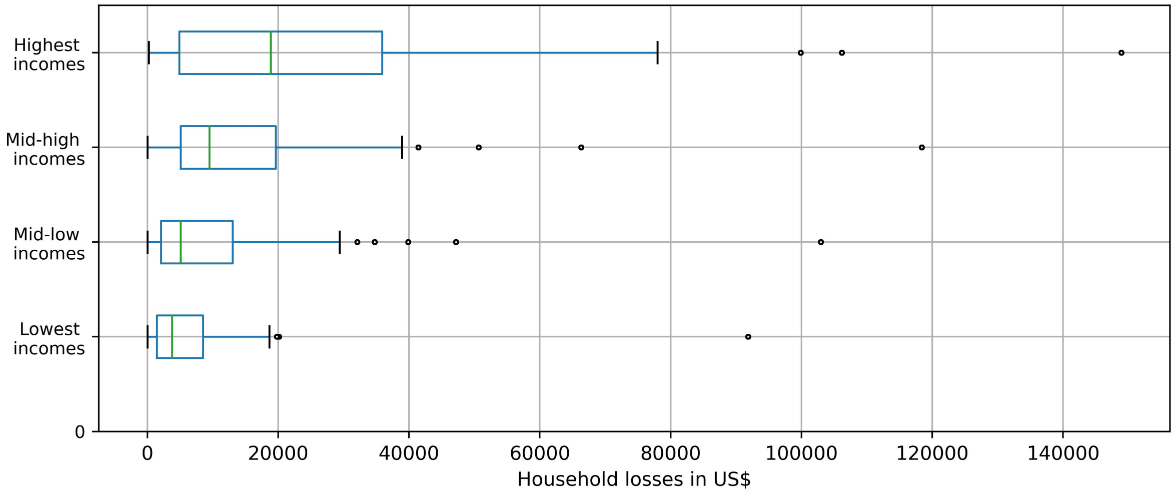

Figure B.2: Distribution of household average absolute asset loss per income quartile.

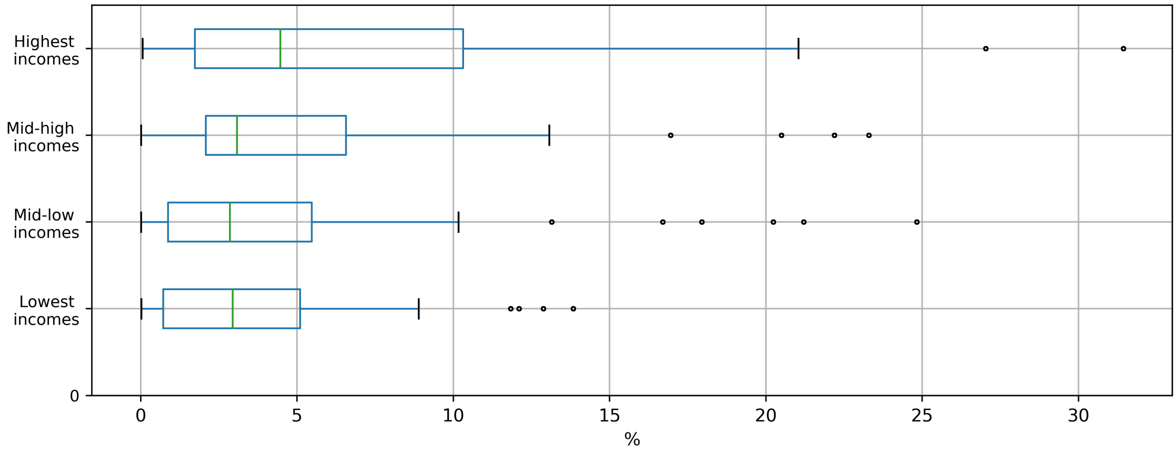

Figure B.3: Distribution of relative asset loss per income quartile

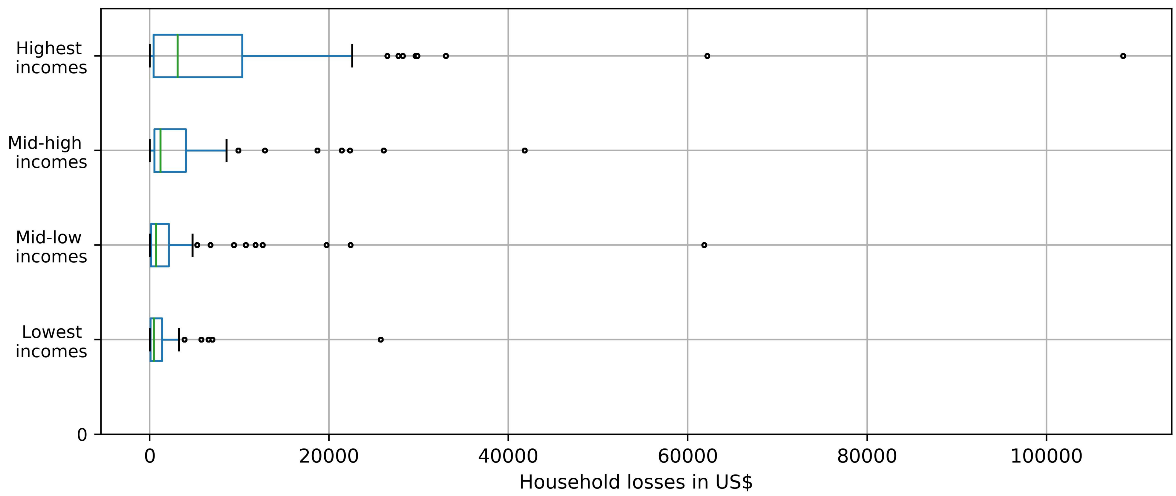

Figure B.4: Distribution of household average income loss per income quartile.

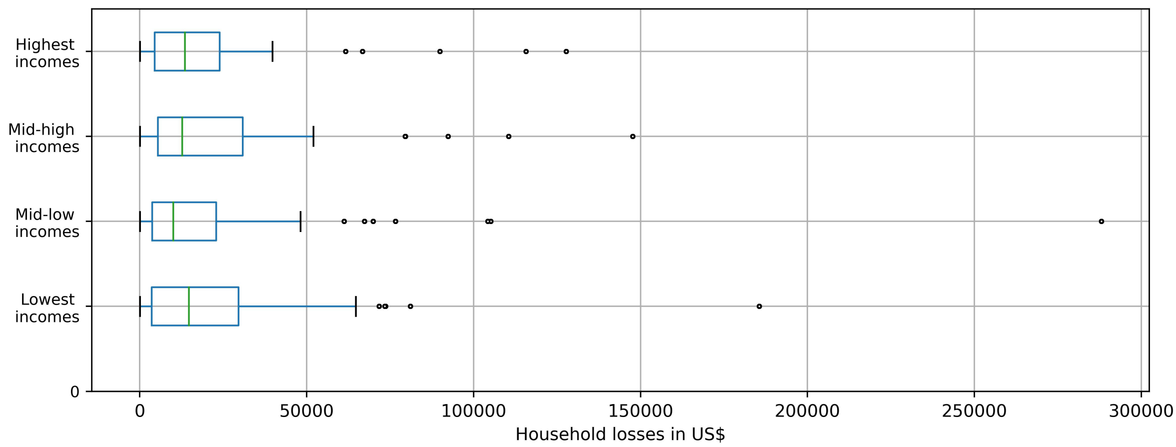

Figure B.5: Distribution of household average absolute well-being loss per income quartile.

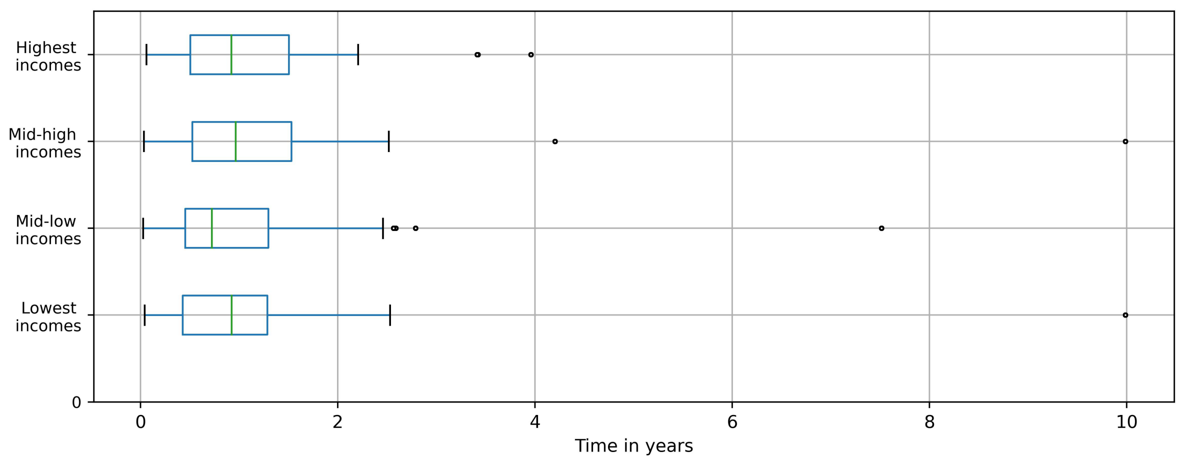

Figure B.6: Distribution of household average recovery time per income quartile.

B.3. Location of block groups individual analysis

Figure B.7 presents map the locations of the block groups which are used for individual comparison in section 4.5 of the results. Figure B.8 presents the map zoomed in on Charleston city. The corresponding figure numbers of index numbers of the block groups are stated in table B.2.

Index	Figure	Block group income type
160	Figure 4.15A	high-income
13	Figure 4.15B	low-income
1	Figure 4.16A	high-income
46	Figure 4.16B	low-income
148	Figure 4.17A	high-income
12	Figure 4.17B	low-income

Table B.2: Index numbers of block groups with corresponding figure numbers and income type.

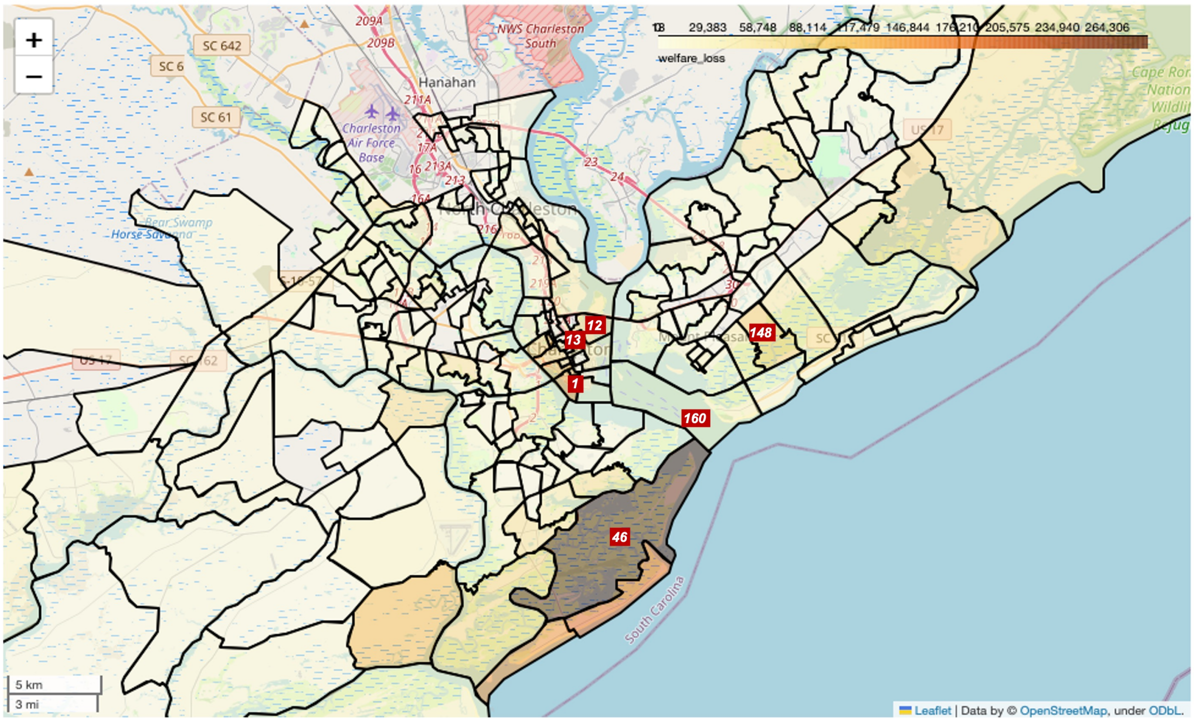

Figure B.7: Location of the block groups used for individual comparison.

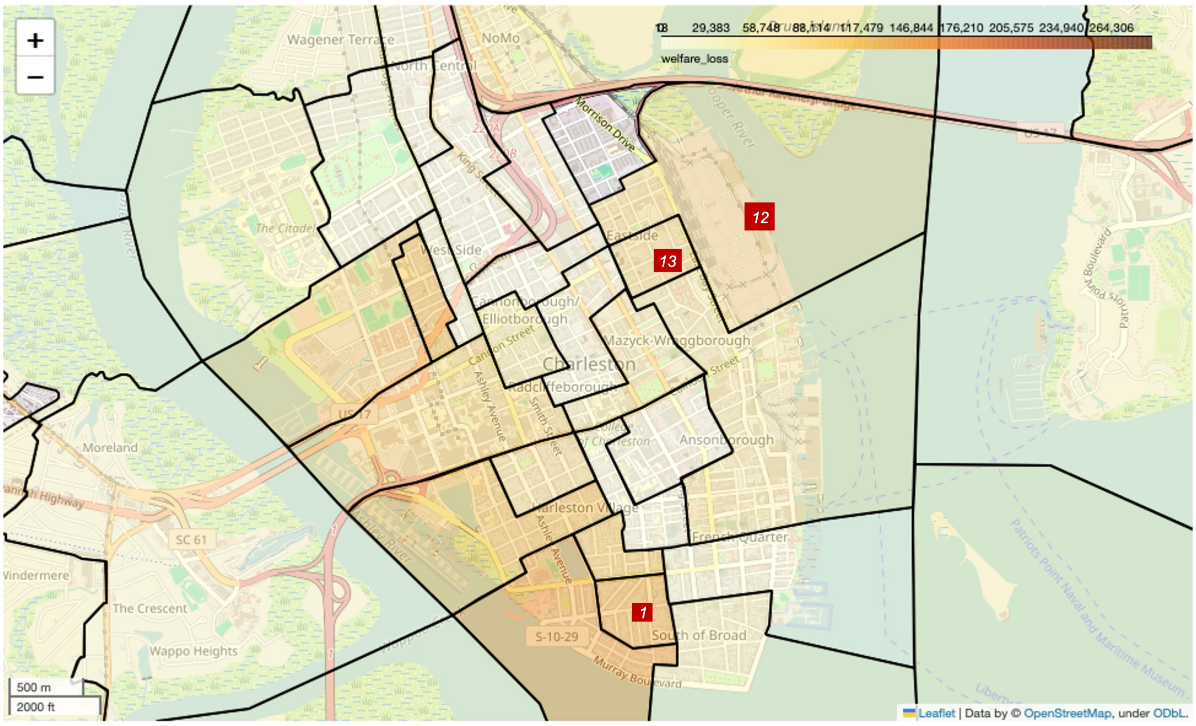

Figure B.8: Location of the block groups used for individual comparison, zoomed in on Charleston city.

C Extra explanation for discussion

The results of the case study of Charleston present differences in results with previous research; this section further elaborates on potential methodological causes of these differences.

All these papers have a larger dataset and apply the model to different types of events, which may contribute to differences in results. The total asset losses in the case study of Markhvida et al. (2020) are $115 billion asset loss, of which 56% are in the housing sector. The case study of Charleston only considers the losses in the housing sector which are $1.5 million. The simplifications made in this model could explain differences in results. Markhvida et al. (2020) model included renters, which is 56% of the total households in their dataset. The impact of including renters is difficult to assess, as Markhvida et al. (2020) assumed that renters would only partially contribute to rent payments for damaged houses, potentially reducing their well-being loss.

Moreover, the income losses are calculated differently. Markhvida et al. (2020) uses an ARIO model to estimate income losses by sector. In some areas, income losses even exceeded asset losses. Mortgage payments are included in this model as well. The inclusion of mortgage payments may intensify inequality, as wealthier households can repay their loans earlier, thereby reducing the burden of reconstruction costs. Both Markhvida et al. (2020) and Walsh and Hallegatte (2020) included household savings, which may increase inequality as high-income households tend to have more savings.

Walsh and Hallegatte (2020) and Verschuur et al. (2020) apply the model in Bangladesh and the Philippines, which are developing countries. The higher well-being losses observed in these countries can be attributed to their overall economic context, given their generally lower income levels.