COMPUTATIONAL MODELING OF HOMEOWNERS, INSURERS AND GOVERNMENT DECISION-MAKING FOR HURRICANE RISK MANAGEMENT

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COMPUTATIONAL MODELING OF HOMEOWNERS, INSURERS AND GOVERNMENT DECISION-MAKING FOR HURRICANE RISK MANAGEMENT

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In Chapter 1, we develop a computational framework for the stochastic and dynamic modeling of regional natural catastrophe losses with an insurance market to support government decision-making for hurricane risk management. The framework is comprised of a set of interacting models to (1) simulate hazard events; (2) estimate regional hurricane-induced losses from each hazard event based on an evolving building inventory; (3) capture acquisition offer acceptance, retrofit implementation and insurance purchase behaviors of homeowners; and (4) represent an insurance market sensitive to demand with strategically interrelated primary insurers. This framework is linked to a simulation-optimization model to optimize decision-making by a government entity whose objective is to minimize region-wide hurricane losses. We examine the effect of different policies on homeowner mitigation, insurance take-up rate, insurer profit and solvency in a case study using data for eastern North Carolina. Our findings indicate that an approach that coordinates insurance, retrofits and acquisition of high-risk properties effectively reduces total (uninsured and insured) losses.

Resilience to coastal hazards is inextricably intertwined with issues of equity and economic prosperity. In Chapter 2, we investigate the important and complementary roles that three primary types of risk mitigation tools (property acquisition, home retrofit, and insurance) need to play in creating a built environment that is more resilient to

hurricane events and supporting economic recovery post event, while protecting the most vulnerable among us. We propose that, though not easy, it is possible to develop sustainable, equitable, win-win solutions that are better both for each stakeholder individually and for society as a whole. Through a case study on households in eastern North Carolina, we demonstrate the importance of alignment with the natural, ingrained decision-making processes of the stakeholders involved. We examine the substantial progress that risk mitigation tools could make in reducing physical damage experienced by affected households and avoiding GDP loss when considering the economic impact of events. We also demonstrate that, when designed with considerations to favor the vulnerable population, mitigation and insurance policies can facilitate the alleviation of inequities.

In Chapter 3, we further explore the experience of different income-level households in the hurricane context, especially focusing on the low income population, and suggest the design and implementation of equitable disaster mitigation interventions.

BIOGRAPHICAL SKETCH

Cen Guo received the B.Eng. degree in Automation and the M.S. degree in Control Science and Engineering from Tsinghua University, Beijing, China, in 2014 and 2017, respectively. He continued advanced education at Cornell University and obtained the M.S. and Ph.D. degrees in Systems Engineering in 2020 and 2021, respectively.

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CHAPTER1

COMPUTATIONAL MODELING OF HOMEOWNERS, INSURERS AND GOVERNMENT DECISION-MAKING FOR HURRICANE RISK MANAGEMENT

1.1 Introduction

The U.S. has experienced more than twice the number of billion-dollar weather and climate disasters during the 2010s as compared with the 2000s [NOAA, 2019]. In 2019 alone, we saw 14 major weather and climate disasters with losses exceeding $1 billion each and totaling approximately $45 billion. The 2020 hurricane season shattered records surpassing the 2005 season with 30 named storms, 12 of which made landfall in the continental United States [NOAA, 2020]. To reduce disaster impacts, many government and private sector interventions have been implemented, including (1) the National Flood Insurance Program, (2) the Hazard Mitigation Grant Program, and (3) state insurance pools, such as the North Carolina Coastal Property Insurance Pool, also known as the Beach Plan. Despite these and other disaster mitigation measures, accelerating disaster losses suggest that we are still not able to manage disaster risks properly and adequately.

Three tools available to reduce or transfer risk for existing properties are acquisition, retrofit, and insurance. The focus of this chapter is to understand how we might deploy these tools to reduce the magnitude of the insured and uninsured losses while maintaining a robust market for insurance. A major contribution of this work is the representation of all three tools in a dynamic framework that examines insurer solvency, and the implications of retrofits and acquisition over a twenty-year time frame.

Nested and integrated models have been implemented to represent the complex interactions due to hurricane events. Disaster relief [Widener & Horner, 2011], flood risk [Akbar & Aliabadi, 2010; Lin & Shullman, 2017], hurricane evacuation [Davidson et al., 2020], infrastructure performance [Winkler et al., 2010], and insured losses [Chen et al., 2009; Hamid, 2011; Han & Peng, 2019] have been the focal points of different modeling efforts. [Taberna et al., 2020] provided a review of agent-based flood risk models and offered the observation that "most studies focus on households while representing government, insurance, and urban development simplistically." The dynamic modeling framework and case study presented here represent the government entity as balancing incentives to achieve its objective with households that make choices and respond to incentives and insurers that interact with regulatory constraints, homeowners and other insurers in an insurance market with risk-based premiums.

This study builds upon previous work that modeled the interaction between the government, insurers and homeowners recognizing their objectives that may be in conflict. [Kesete et al., 2014] and [Peng et al., 2014] provided a foundational model of insurer-homeowner interaction for the case of a single insurance provider. The framework includes a hurricane loss estimation model, a homeowner model for insurance purchase decision-making and an insurer stochastic programming model to optimize the pricing of insurance in low- and high-risk areas and purchase of reinsurance. These models, however, are static and do not consider risk mitigation options such as property acquisition and structural retrofit. Further, the government options are limited to regulation on the capital sufficiency of the insurance carrier. A third difference between the modeling effort in [Kesete et al., 2014] and [Peng et al., 2014] and the one herein is that the former characterize homeowners as expected utility maximizing with full information of their property risk. [Gao et al., 2016] expanded the insurer-homeowner interactions to include multiple providers. The resulting strategic competition under multiple firm scenarios yields a range of results characterized by premium prices, take-up rates, and profitability that vary with the number of insurers in the market.

[Wang et al., 2020] extends the single insurer model in [Kesete et al., 2014] and [Peng et al., 2014] with acquisition and mitigation grant programs as a discrete set of policy options for the government. Also, empirical models based on surveys of homeowner behaviors for insurance purchase, acquisition offer acceptance and mitigation are substituted for the utility-based decision models in [Kesete et al., 2014; Peng et al., 2014; Gao et al., 2016].

The current formulation integrates the features of [Gao et al., 2016] and [Wang et al, 2020] so that the resultant modeling framework has all the capabilities of both. That is, there is explicit representation of insurance carrier competition with pricing dependent on the inventory of homeowner demand and the number of insurers. Government decision-making is represented explicitly. Homeowner demand for insurance, retrofit and acceptance of acquisition offers is based on empirical models.

The key contribution of this research is the extension to a dynamic modeling framework. Moving to a dynamic modeling framework allows the impact of government, insurer and homeowner decision-making to manifest itself in the evolution of (1) the hurricane experiences of homeowners; (2) insurance prices; and (3) the changing building inventory (including the removal of homes from house inventory through acquisition and the upgrade of homes through retrofit). The homeowner decision-making models are dependent on these evolving homeowner experiences through such independent variables as prior hurricane experience. The dynamic character of the integrated model also allows for the explicit modeling of the financial condition of the insurance carriers. We also expand the level of detail the government can include in the specification of their acquisition and mitigation grant programs. For example, acquisition offers can vary based on the relative magnitude of the losses in the zone in which a particular home is located [Conrad et al., 1998]. The offer is also dependent on whether the home is currently damaged or not [Fraser et al., 2003]. Similar detail is also included in the specification of the grant programs for retrofit [Zhang & Nicholson, 2016]. These decisions are updated annually based on the simulated events as they occur and the evolving condition of the inventory.

The remainder of this chapter is organized as follows. Section 1.2 introduces the proposed framework and its component models. Section 1.3 presents the formulated simulation optimization problem and its solution procedure. Section 1.4 describes a case study for homes in the eastern half of North Carolina. Section 1.5 provides concluding thoughts.

1.2 Modeling framework

1.2.1 Framework components

Fig. 1-1 illustrates the modeling framework, including each of the component models. The models are of three distinct types: base or foundational models, stakeholder models and game-theoretic models. The base models provide the core input data to the analysis, namely the hurricane scenarios (hazard model) and the loss model; stakeholder models represent the decisions of the government, primary insurers, and homeowners; and game theoretic models govern the interaction between the stakeholder models.

Specifically, the government model determines, subject to a limited annual budget, the homes to which they will make acquisition offers, the terms of those offers, and the areas in which they will offer mitigation grants and the terms of those grants. The primary insurers provide insurance to the homeowners with a goal of maximizing their profits. They do this by optimizing the pricing of their policies within a Cournot oligopoly and transferring risk to a reinsurer through the optimization of the given policy parameters offered by the reinsurer. The homeowner model determines, for each homeowner, whether or not they will (1) agree to acquisition if offered to them by the government; (2) engage in retrofit and, if so, the type of retrofit; and (3) purchase insurance.

The stakeholders are involved in a Stackelberg game. The government is the Stackelberg leader, and the remainder of the stakeholders are the followers that "best respond" to options chosen by the government. The government is assumed to have full knowledge of the stakeholder followers' behaviors and reactions to its decisions. The insurers and the homeowners are also engaged in a Cournot-Nash non-cooperative game which determines insurance pricing and take-up rates. This game represents the interactions between the homeowners and the insurers as well as the competition among the insurers themselves. The arrows in Fig. 1-1 indicate the direction of influence. The remainder of this section describes these models. Detailed descriptions of the component models can be found in [Kesete et al., 2014; Peng et al., 2014; Gao et al., 2016; Wang et al., 2020].

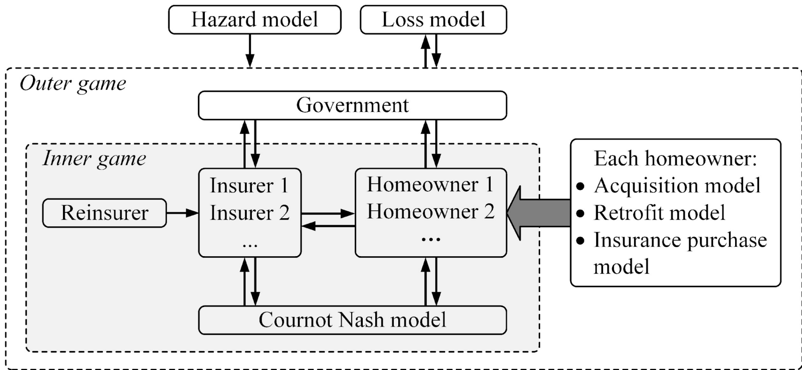


Figure 1-1 Base, stakeholder, and game-theoretic components in the modeling framework.

1.2.2 Individual models

1) Hazard model

We represent the hurricane hazard model with a set of probabilistic hurricane events abstracted from historical hurricane records first developed in [Apivatanagul et al., 2011]. Each hurricane event, denoted by h, $h \in (1, \dots, H)$, is defined by a hurricane track, several along-track intensity parameters, such as central pressure deficit and radius to maximum winds, and an annual occurrence probability P^h. Spatially defined wind speeds and surge depths associated with these hurricanes to the impacted area are estimated and exported to the loss model. In addition, we define a 20-year time period as a scenario, denoted by s, and hurricanes can occur in any of 20 time slots in each year for a total of 400 time steps in a scenario.

2) Loss model

The regional hurricane loss estimation model specifies the damage caused by different hurricanes to single-family residential buildings as developed by [Peng et al., 2013]. It builds upon a combination of a modified version of Florida Public Hurricane Loss Model for wind-related losses [FPHLM, 2005] and flood-related losses based on

[Taggart & van de Lindt, 2009; van de Lindt & Taggart, 2009]. We divide the residential buildings in the loss model into different groups based on features including their area unit i (e.g., census tract), architectural structure m (e.g., one-story home with a garage and hip roof), building resistance level c, and risk region v (e.g., high-risk region or low-risk region), and accordingly denote losses caused by hurricane h to a building of type i, m, c, and v as $L^{h}_{i,m,c,v}$. Note that flood- and wind-related losses are not separately denoted for notation simplicity. Each building is defined as a collection of several structural components (e.g., roof covering, openings), and each component is assigned a resistance value based on its physical configuration. Therefore, the resistance level c of a building is expressed as a vector of its component resistance values and is subject to change if house retrofit is implemented.

3) Homeowner model

The homeowner decision model is founded on several empirical studies designed to understand the factors that lead to different decisions. Discrete choice models based on surveys of residents of eastern North Carolina reported in [Frimpong et al., 2019; Chiew et al., 2019; Wang et al., 2017; Robinson et al., 2018] are incorporated to represent the variables that influence a homeowner's choice to insure, accept an acquisition offer or mitigate in response to a retrofit grant. Each year before the occurrence of any hurricanes, homeowners are assumed to make their own risk reduction decisions based on their characteristics including prior hurricane-related experiences, as well as policies and operational decisions from the government and insurers. The sequential decisions are (1) whether or not to accept the government property acquisition offer if offered; (2) whether or not to retrofit their home, and if a decision to retrofit is made, the type of upgrade to implement; and (3) whether or not to purchase hurricane insurance.

Homeowner acquisition decision-making is captured by a pooled probit model as in [Frimpong et al., 2019]. It should be noted that alternative-specific covariates in the model include an indicator for whether a house has been damaged in the past year and the acquisition offer price; individual-specific covariates include an indicator for whether the home is located in the floodplain, the straight-line house-to-coastline distance, homeowner income, and the length of time the homeowner has been resident in the home. In terms of notations, the simulated acquisition decision made by homeowner j is denoted by the binary variable D_j^{acq}, where $j \in J_{i,m,c,v}^{acq}$ and $J_{i,m,c,v}^{acq}$ represents a community of people whose houses are of type i, m, c, and v. To equip the model with more flexibility, we allow the acquisition price for homeowner j living in area i, denoted as $price_i^{acq}$, to vary based on the relative vulnerability of the area, and if a homeowner experienced hurricane losses in the previous year, the offered acquisition price is modified from $price_i^{acq}$ to $c_{adj}^{acq} \cdot price_i^{acq}$ with c_{adj}^{acq} being an adjustment coefficient. In this way, the acquisition decision-making model acts differently for newly-damaged and non-damaged houses and allows for heterogeneity in homeowners' willingness to accept based on the timing of the offer.

Mixed logit models are used to model homeowner retrofit and insurance purchase decision-making. The model estimation process is detailed in [Chiew et al., 2019] and [Wang et al., 2017]. For retrofit decisions, five different mixed logit models are implemented, each to predict the probability of homeowners undertaking: (1) reinforcing roof with high wind load shingles or adhesive foam, (2) strengthening openings with shutters or impact resistant windows, (3) strengthening roof-to-wall connection using straps, (4) elevating house appliances above flood level and installing water resistant insulation and siding, and (5) elevating the entire house. Covariates involved are the alternative-specific constants of revealed preference variables, the retrofit price, the maximum grant amount, the house-to-coastline distance, the number of hurricanes experienced by the homeowner, and homeowner's employment status. A simulated homeowner j's retrofit decision is denoted by the binary variable $D_{j,c'}^{ret}$, $j \in J_{i,m,c,v}^{ret}$ with the resultant variable c' being the house resistance level after retrofit.

For insurance purchase decisions, two mixed logit models are used, one for wind coverage and the other for flood coverage. Covariates involved are the insurance premium, the insurance deductible, a binary indicator as to whether or not the home is located inside or outside of the floodplain, the house-to-coastline distance, the number of hurricanes experienced by the homeowner, and homeowner's income, age, and years since the last hurricane experienced. The simulated homeowner j's insurance purchase decision is denoted by the binary variable D_j^{ins} , $j \in J_{i,m,c,v}^{ins}$. We use different superscripts in $J_{i,m,c,v}^{acq}$, $J_{i,m,c,v}^{ret}$, and $J_{i,m,c,v}^{ins}$ in the phases of acquisition, retrofit, and insurance purchase decision-making, as the community members may change along with the evolution of the building inventory.

The homeowner's decisions are subject to external constraints. For retrofit decisions, following guidelines from the Insurance Institute for Business and Home Safety FORTIFIED home program [IBHS, 2017], roof upgrades should be performed before openings upgrades; roof-to-wall upgrades must be performed with or after openings upgrades; and retrofit is applicable only if the upgrade benefit (reduced loss minus cost paid by the homeowner) exceeds a certain threshold. This threshold is typically modestly negative due to homeowners' risk aversion. For the insurance purchase decision, the homeowner only has access to a policy if the cost of the policy exceeds a given threshold η (to cover minimal transaction costs of offering the policy) (Eq. 1) Also, an affordability constraint is imposed so that the annual insurance premium cannot exceed the homeowner's budget expressed as a percentage, κ_v, of the home value, HV_m (Eq. 2). The actual deductible value $d_{i,m,c,v}^h$ beneath the deductible threshold, $\bar{d}$, is expressed in Eq. 3.

$$price_v^{ins} \cdot (L_{i,m,c,v}^h - d_{i,m,c,v}^h) > \eta \tag{1}$$

$$price_v^{ins} \cdot (L_{i,m,c,v}^h - d_{i,m,c,v}^h) < \kappa_v \cdot HV_m \tag{2}$$

$$d_{i,m,c,v}^h = \min\{L_{i,m,c,v}^h, \bar{d}\} \tag{3}$$

The insurance purchase constraints are applied to flood- and wind-related cases separately. It should be noted that we use D_j^{acq}, $D_{j,c'}^{ret}$, and D_j^{ins} to represent the final eligible homeowner decisions for notation simplicity.

4) Insurer model

The insurer's choices are based on a stochastic optimization model. Without loss of generality, we consider the case of only one insurer existing in the insurance market. The insurer's profit in scenario s and year y, $F_{s,y}$, is defined as

$$F_{s,y} = \sum_v price_v^{ins} \cdot Q_v - \tau \cdot \sum_v Q_v - \sum_t \sum_h \gamma_{s,y,t}^h \cdot I^h + \sum_t \sum_h \gamma_{s,y,t}^h \cdot B^h + \beta \cdot \sum_t \sum_h \gamma_{s,y,t}^h \cdot e^h - r_{s,y} \tag{4}$$

The first term in the right-hand side of Eq. 4 represents the total insurance premiums collected by the insurer: the premium price, $price_v^{ins}$, is defined as charge per expected dollar loss and varies by region; the insurance demand by region, Q_v, is calculated as an expectation over homeowner insurance purchase decisions, D^{ins}, as

$$Q_v = \mathrm{E}_{D^{ins}}\left[\sum_h P^h \cdot \sum_i \sum_m \sum_c \sum_{j \in J^{ins}_{i,m,c,v}} (L^h_{i,m,c,v} - d^h_{i,m,c,v}) \cdot D^{ins}_j\right] \tag{5}$$

The second term in Eq. 4 is the operational cost, which is a fixed portion, τ, of the total demand. The third and the fourth terms are the total losses across the policies written and the total value of the losses covered by the homeowners through their deductibles. $\gamma^h_{s,y,t}$ are binary indicators of whether hurricane h occurs in time slot t in year y of scenario s, and

$$I^h = \mathrm{E}_{D^{ins}}\left(\sum_i \sum_m \sum_c \sum_v \sum_{j \in J^{ins}_{i,m,c,v}} L^h_{i,m,c,v} \cdot D^{ins}_j\right) \tag{6}$$

and

$$B^h = \mathrm{E}_{D^{ins}}\left(\sum_i \sum_m \sum_c \sum_v \sum_{j \in J^{ins}_{i,m,c,v}} d^h_{i,m,c,v} \cdot D^{ins}_j\right) \tag{7}$$

are the total insured losses and the total value of the deductibles in hurricane h, expected over the homeowner insurance decisions, D^{ins}. The fifth term in Eq. 4 expresses the losses covered by the reinsurer, and

$$e^h = min\{max\{I^h - A, 0\}, M - A\} \tag{8}$$

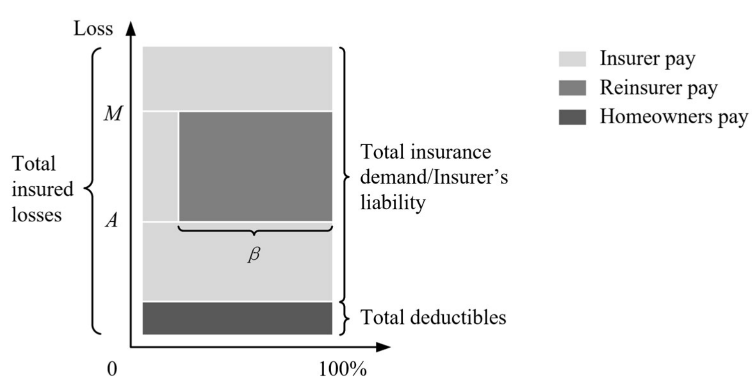


Figure 1-2 Hurricane losses coverage structure for the case of the total losses exceeding the maximum payout.

As in Fig. 1-2, hurricane losses to insured buildings are covered by homeowners, the insurer, and the reinsurer. The reinsurer's liability is a portion, β, of the total insured losses between the attachment point A and the maximum payout M. The insurer's real payment is the total demand minus the amount of losses covered by the reinsurer.

Finally, the last term in Eq. 4 corresponds to the reinsurance premium as

$$r_{s,y} = \beta \cdot \left[\left(1 + \phi + \frac{\sum_t \sum_h \gamma_{s,y,t}^h \cdot e^h}{M-A} \right) \cdot \sum_h P^h \cdot e^h + g \cdot \sigma \right] \tag{9}$$

where ϕ is a pre-defined loading factor, coefficient g represents the reinsurers' risk aversion, and σ is the standard deviation of the reinsurer's losses minus the reinstatement premium. Then

$$\max_{A,M} \mathrm{E}_s \left[\mathrm{E}_y \left(\tilde{F}_{s,y} \right) \right] \tag{10}$$

is the objective function for the insurer's optimization. $\tilde{F}_{s,y}$ is of the same value as $F_{s,y}$ if the insurer has been solvent in scenario s from the start year to year y, otherwise set as 0. The solvency is determined by the cash position of the insurer, calculated as

$$cash_{s,y} = min\left\{initial\_capital, cash_{s,y-1} + F_{s,y}\right\} \tag{11}$$

Here we assume that at the beginning of the planning horizon the insurer has $initial\_capital$ on hand equivalent to a user defined multiple of the value of the polices the carrier expects in the first year, and in the following years, the insurer can keep no more than the same amount as $initial\_capital$. Therefore, in cases when severe events occur, the insurer's cash position $cash_{s,y}$ could drop below zero due to the large negative profit $F_{s,y}$, and accordingly, the insurer would be considered insolvent.

5) Cournot-Nash model

The market concentration in the primary insurance market can lead to significant differences in the insurers' operational decisions. Therefore, a perfect information Cournot-Nash non-cooperative game is used to incorporate competition among multiple insurers for equilibrium price discovery. We extend the method developed in [Gao et al., 2016] to a dynamic setting that incorporates annual adjustments. We assume that all the insurers are homogeneous and have equal knowledge of the market. Hence, they face the same cost structure and make identical pricing decisions. Homeowner decision-making on insurance purchase is simulated at a set of hypothetical insurance price levels, followed by the resolution of the insurer optimization corresponding to the same preset prices. The output of the homeowner simulation is used to obtain demand Q_v for each risk region v, as a function of price. The demand for insurer w in risk region v, is denoted as $q_{w,v}$. The demand for the rest of the insurers in that region is denoted as $Q_{-w,v}$. And the inverse demand function is then expressed as $price_v^{ins} = ID_v(q_{w,v}, Q_{-w,v})$. The cost function for insurer w is generated by function fitting based on results from the insurer optimization and is denoted by $CF(q_{w,LR}, q_{w,HR})$. LR and HR correspond to the low-risk region and the high-risk region, respectively. The net profit for insurer w is, therefore, derived as

$$\pi(q_{w,LR}, q_{w,HR}) = \sum_v q_{w,v} \cdot ID_v(q_{w,v}, Q_{-w,v}) - CF(q_{w,LR}, q_{w,HR}) \tag{12}$$

If related functions are differentiable, the optimal $q_{w,v}$ satisfies the first order condition. For $q_{w,HR}$, we have

$$\frac{\partial ID_{HR}(q_{w,HR}, Q_{-w,HR})}{\partial q_{w,HR}} \cdot q_{w,HR} + ID_{HR}\left(q_{w,HR}, Q_{-w,HR}\right) - \frac{\partial CF(q_{w,LR}, q_{w,HR})}{\partial q_{w,HR}} = 0 \tag{13}$$

Combining $Q_{-w,HR} = (n-1) \cdot q_{w,HR}$, the equilibrium market price and demand for the high-risk region is determined. A parallel procedure is used to calculate the equilibrium price and demand in the low-risk region.

1.2.3 Government model

1) Government decisions

We assume that the core decisions of the government policy makers as they attempt to manage the regional risk are pricing policies for property acquisition and retrofit subsidization given limited budget. In property acquisition, the government offers to buy particularly high-risk properties. These properties are then demolished and the land is repurposed for open space or other appropriate use [Robinson et al., 2018]. Consistent with the way that government projects typically specify neighborhoods for acquisition rather than scattered individual houses [Wang et al., 2020], we assume that a property acquisition offer, when made, is made to all houses within a geographic zone. In retrofit subsidization, the government provides subsidies to cover a portion of homeowners' cost to encourage retrofit activities. As with the case of acquisition, we consider that the government retrofit subsidies are offered to all houses in the zones selected.

Specifically, for property acquisition, we assume that government offers are specified as a percentage of the value of the home and are denoted by $price_i^{acq}$ for homes in area i as

$$price_i^{acq} = c_{base}^{acq} + c_{prop}^{acq} \cdot \frac{\sum_h \sum_m \sum_c \sum_v P^h \cdot L_{i,m,c,v}^h \cdot X_{i,m,c,v}^{acq}}{\sum_m \sum_c \sum_v HV_m \cdot X_{i,m,c,v}^{acq}} \tag{14}$$

where $X_{i,m,c,v}^{acq}$ is the number of houses of type i, m, c, and v, and HV_m is the home value dependent only on m. Constant c_{base}^{acq} represents the base percentage price, and coefficient c_{prop}^{acq} is the proportional factor applied to the expected total hurricane losses in area i divided by the total home value in that area, both being non-negative. The actual cost for the government to acquire a house is, therefore,

$$cost_{i,m}^{acq} = price_i^{acq} \cdot HV_m \tag{15}$$

This pricing method allows prices to vary across zones through the impact of the second term on the right-hand side of Eq. 14. That is, areas of higher loss can be targeted with higher prices to incentivize acquisition more heavily. Notice that this formula implies that we need to optimize two values c_{base}^{acq} and c_{prop}^{acq}. Besides, for those who have experienced a hurricane in the previous year, they are actually offered $c_{adj}^{acq} \cdot price_i^{acq}$ instead of $price_i^{acq}$, where c_{adj}^{acq} is a non-negative variable that scales the price to reflect how the government may wish to increment or decrement the offer given that the homes are currently damaged.

The government retrofit subsidization is carried out in a similar manner as with property acquisition. The percentage price for retrofit subsidization for homeowners in area i is

$$price_i^{ret} = c_{base}^{ret} + c_{prop}^{ret} \cdot \frac{\sum_h \sum_m \sum_c \sum_v P_h \cdot L_{i,m,c,v}^h \cdot X_{i,m,c,v}^{ret}}{G \cdot \sum_m \sum_c \sum_v X_{i,m,c,v}^{ret}} \tag{16}$$

Here, c_{base}^{ret} is the base price, c_{prop}^{ret} represents the proportional factor, $X_{i,m,c,v}^{ret}$ is the number of houses, and the fractional part is the average expected home losses in area i with constant G used to adjust the scale. It should be noted that c_{base}^{ret} is a non-negative variable, but we allow c_{prop}^{ret} to take either positive or negative value since there is always a trade-off between supporting the upgrade of fewer most vulnerable houses and supporting the reinforcement of more moderately risky buildings. Moreover, the actual retrofit subsidy offered to a homeowner is

$$subsidy_{i,m,c,c'}^{ret} = min\{price_i^{ret} \cdot cost_{m,c,c'}^{ret}, \bar{J}\} \tag{17}$$

where $cost_{m,c,c'}^{ret}$ is the retrofit cost which depends on the architectural structure m and the hazard resistance level before and after the retrofit, c and c', and $\bar{J}$ is the maximum subsidy that the homeowner could receive. For convenience, higher resistance levels are coded to have larger values, so $c' > c$.

2) Grant allocation strategy

Areas that have high cost-effectiveness ratios (ratio of government spending to losses reduced by mitigation), are given priority. In practice, we calculate the cost-effectiveness ratios, regarding acquisition and retrofit, for each area based on simulated homeowner decisions and expected losses and select areas in rank order to offer grants until the budget limit is reached.

3) Government objective

The objective function of the government optimization model is to minimize a measure of the societal losses as

$$\min\ (1-\alpha) \cdot \sum_h P^h \cdot I^h + (1+\alpha) \cdot \sum_h P^h \cdot U^h \tag{18}$$

Here, the first part is the weighted, expected total insured losses, while the second part stands for the weighted, expected total uninsured losses. If α is a positive coefficient, this indicates that reducing the total uninsured losses is more appealing to the government than reducing the total insured losses. U^h here is calculated as

$$U^h = \mathrm{E}_{D^{ins}}\left[\sum_i \sum_m \sum_c \sum_v \sum_{j \in J_{i,m,c,v}^{ins}} L_{i,m,c,v}^h \cdot \left(1 - D_j^{ins}\right)\right] \tag{19}$$

4) Budget constraint

The spending on property acquisition and retrofit subsidization is constrained by the government budget. Combining Eq. 15 and Eq. 17, the budget constraint for the government optimization is

$$\mathrm{E}_{D^{acq}}\left[\sum_i \sum_m \sum_c \sum_v \sum_{j \in J_{i,m,c,v}^{acq}} cost_{i,m}^{acq} \cdot D_j^{acq}\right] + \mathrm{E}_{D^{ret}}\left[\sum_i \sum_m \sum_c \sum_v \sum_{j \in J_{i,m,c,v}^{ret}}\right.$$

$\sum_{c':c'>c} subsidy_{i,m,c,c'}^{ret} \cdot D_{j,c'}^{ret}\Big] \leq \Omega$ (20)

where the first and the second terms on the left-hand side are the acquisition spending and the total retrofit grant, expected over homeowner acquisition decisions, D^{acq}, and retrofit decisions, D^{ret}, respectively, and Ω on the right-hand side represents the user-specified total budget.

1.2.4 Dynamic modeling framework

The dynamic modeling framework is shown in Fig. 1-3. These steps are performed for each simulated hazard scenario where a scenario is a time ordered list of hurricane events over a 20-year planning horizon. Note that in each year, no hurricane events, one event or multiple events may occur.

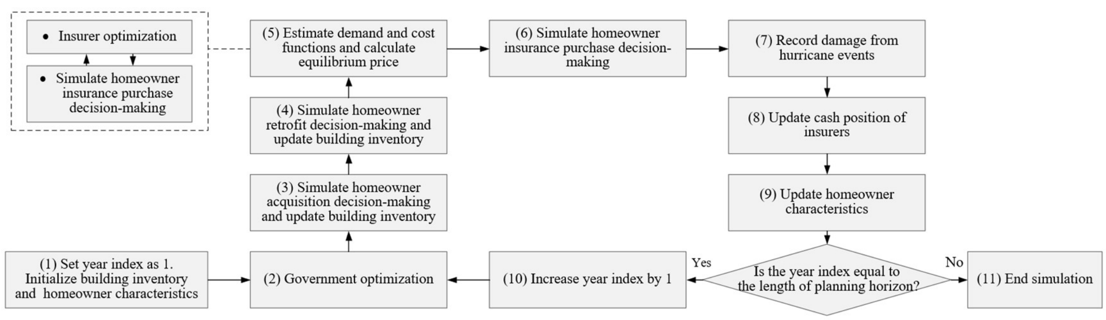


Figure 1-3 Dynamic modeling framework.

The steps corresponding to the items in Fig. 1-3 are given below.

For each scenario:

1. Set year index as 1 and initialize the building inventory and the homeowner characteristics.
2. Perform the government optimization which utilizes hurricane information from all 2,000 scenarios and generates the optimal acquisition and retrofit pricing policies. We assume the decision-makers do not have access to the actual hurricane events

that will occur in the scenario currently being explored. They only know the events that have occurred up to the year prior.

3. Simulate homeowner decisions on whether or not to accept the government acquisition offer and update the building inventory accordingly. Note that the terms of the government acquisition offered were specified in Step 2.
4. Simulate homeowner decisions on whether or not to retrofit their houses and which type of retrofit to implement and update the building inventory accordingly. Again, the terms of the government mitigation incentive programs were identified in Step 2.
5. Simulate homeowner decisions on whether or not to purchase insurance and perform insurer optimization. Then, calculate the equilibrium insurance prices.
6. Simulate homeowner decision-making on whether to purchase insurance based on the equilibrium insurance prices.
7. Calculate the impact of hurricanes in the current year of the scenario based on the hurricane loss model, the up-to-date building inventory, and homeowner insurance purchase decisions.
8. Update the insurers' financial position.
9. Update homeowner characteristics based on their experiences, and check if the year index has reached the end of the planning horizon. If not, go to Step 10; otherwise, go to Step 11.
10. Increase the year index by 1 and go back to Step 2 to start analysis for the next year.
11. End the simulation of the scenario.

Again, the dynamic modeling framework is implemented one scenario at a time by stepping through a sequence of decisions made by the government, homeowners, and insurers and updating state variables for all parties that reflect changes due to the decisions and hurricane events year by year. It is important to note that the government optimization is carried out at the beginning of each year and creates the parameters of the acquisition program and mitigation incentive programs that are used to simulate these decisions by the homeowners in Steps 3 and 4.

1.3 Simulation optimization

Simulation optimization, also known as simulation-based optimization or optimization via simulation, refers to techniques used to optimize stochastic simulations. It involves the search for those specific settings of the input parameters to a stochastic simulation such that a target objective, which is a function of the simulation output, is minimized [Amaran et al., 2016]. Given the presence of the homeowner decision-making simulation in the framework, the government optimization is a typical simulation optimization problem. The insurer optimization, on the other hand, is a stochastic programming problem as the homeowner decisions are integrated into it as constant parameters.

Formally, in the present simulation optimization problem, the optimization objective for the government is to minimize the general societal losses, which are a weighted combination of the expected total insured losses and the expected total uninsured losses. The decision variables, namely, the government policies, are the base and the proportional factors of the acquisition offer prices, c_{base}^{acq} and c_{prop}^{acq}, the adjustment coefficient used to incorporate homeowners' reaction to hurricane timings into the acquisition pricing, c_{adj}^{acq}, and the base and the proportional factors of the retrofit subsidization prices, c_{base}^{ret} and c_{prop}^{ret}. The main constraint is the government budget constraint, Eq. 20, and other constraints are either feasible ranges for variables or can be found in model descriptions in Section 1.2 and literature [Kesete et al., 2014; Peng et al., 2014; Gao et al., 2016; Wang et al., 2020; Apivatanagul et al., 2011; Peng et al., 2013].

The general simulation phase is illustrated in Fig. 1-4. Given a specific government policy (Step 1), homeowners make acquisition acceptance (Step 2) and retrofit (Step 4) decisions and cause the building inventory to change accordingly (Steps 3 and 5). A series of stochastic programming problems are then solved which maximize insurers' net profit at different hypothetical insurance price levels, and based on it the Cournot-Nash equilibrium model generates the equilibrium risk-based insurance prices (Step 6). Subsequently, the homeowner insurance purchase decision-making is simulated (Step 7) to calculate the expected total insured and uninsured losses in the objective function of the government optimization. The response surface methodology (RSM) and trust regions (TR) are combined and applied to solve the simulation optimization problem. Details of the solution method can be found in [Gao et al., 2015] and [Chang et al., 2007].

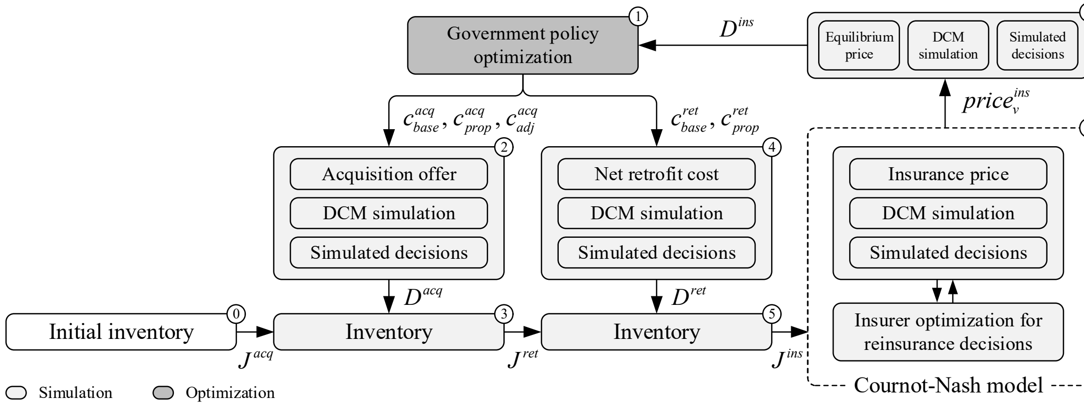


Figure 1-4 Simulation optimization structure. Marks on the top right corner of each block indicate the step numbers. DCM refers to discrete choice model.

1.4 Case study

1.4.1 Input description

The proposed dynamic modeling framework is tested and evaluated with a case study of single-family wood-frame homes in the eastern half of North Carolina. Input data are listed in Table 1-1, and key parameters are given in Table 1-2. It should be noted that a single house could do multiple component retrofits at one time, depending on the homeowner retrofit decisions. Additional details can be found in [Kesete et al., 2014; Peng et al., 2014; Gao et al., 2016; Wang et al., 2020; Apivatanagul et al., 2011; Peng et al., 2013].

Table 1-1 Data statistics

Subject	Number	Description
Building category m	8	Combinations of 2 story types, 2 garage types, and 2 roof shapes
Building resistance level c	192	Combinations of 4 flood resistance types, 2 wall resistance types, 3 opening resistance types, and 8 roof-related resistance types
Building value	8	Refer to [Gao, 2015]
Risk region v	2	High-risk region (less than two miles away from the coast) and low-risk region (more than two miles away from the coast)
Area unit i	1,509	1,006 in the high-risk region, 503 in the low-risk region
Residential building	931,902	292,890 in the high-risk region, 649,012 in the low-risk region.
Hurricane h	98	97 hurricane cases plus 1 case of no hurricane
Scenario	2,000	Each has a 20-year-long period, with 20-time steps per year

Flood-related retrofit	3	(1) Elevate appliances and electrical, (2) upgrade siding and insulation, and (3) elevate the entire house
Wind-related retrofit	6	Strengthen roof sheathing attachment and provide secondary water barrier (1) with roof cover replacement or (2) from within attic, (3) reinforce gable ends, (4) reinforce roof-to-wall connections, and protect openings with (5) impact resistant glass or (6) shutters

Table 1-2 Key user-specified model parameters

Variable	Value	Description
$\bar{b}$	\$-300	Required minimum benefit from house retrofit
$\bar{J}$	\$10,000	Maximum retrofit subsidy to each home
$\bar{d}$	\$2,500	Deductible threshold
η	\$100	Minimum insurance premium threshold
κ_{HR}	5%	Affordability parameter for the high-risk region
κ_{LR}	2.5%	Affordability parameter for the low-risk region
τ	0.35	Administrative loading factor for insurance
g	0.1	Reinsurers' risk aversion coefficient
$initial\_capital$	3 times the first-year premium	Initial capital for each insurer in the market
Ω	\$100 million	Government budget
α	0.5	Coefficient in the objective function of the government optimization
c_{base}^{acq}	$[0.75,\ 1.25]$	Government decision for acquisition pricing
c_{prop}^{acq}	$[0,\ 0.2]$	Government decision for acquisition pricing
c_{adj}^{acq}	$[0.6,\ 1.2]$	Government decision for adjusting the acquisition price based on house's damaged/undamaged status
c_{base}^{ret}	$[0.75,\ 1]$	Government decision for retrofit pricing
c_{prop}^{ret}	$[-0.1,\ 0.1]$	Government decision for retrofit pricing
G	10^4	Scale adjustment parameter for retrofit pricing

1.4.2 Results and analysis

We will report the results from analysis of a single scenario first. Examining the annual decisions from homeowners, insurers, and the government, as well as the loss reduction achieved from acquisition and retrofit measures over time for a single scenario highlights the nuanced changes in homeowner behaviors prompted by a hurricane experience. Scenario 39 was chosen to illustrate how efforts from all parties can be appropriately integrated towards hurricane risk management. Scenario 39 is a hurricane-active scenario placing it in the top 5% of scenarios for hurricane losses and measurable hurricane losses occurred in nine out of its twenty years. Fig. 1-5 summarizes the unmitigated flood- and wind-caused losses in the high- and low-risk regions for this scenario. Fig. 1-6 shows the geographic distribution of expected annual losses for homes in the study area.

After a detailed discussion of Scenario 39 we report results summarizing thirty hurricane scenarios randomly drawn from the set of 2,000 potential scenarios. The thirty scenarios were chosen to reduce computational burden of this exercise while maintaining representativeness of the loss distribution. These scenarios as a group, are a close match to original set of 2,000 scenarios in terms of mean, variance, and skewness.

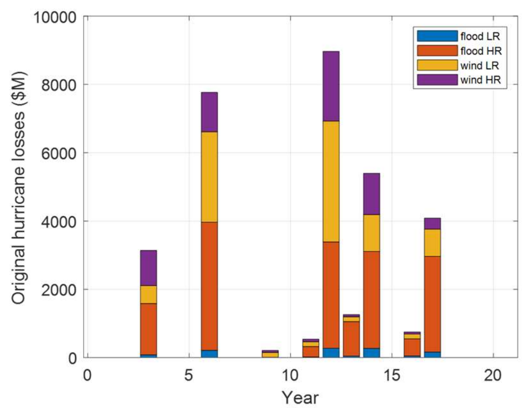


Figure 1-5 Hurricane losses in scenario 39.

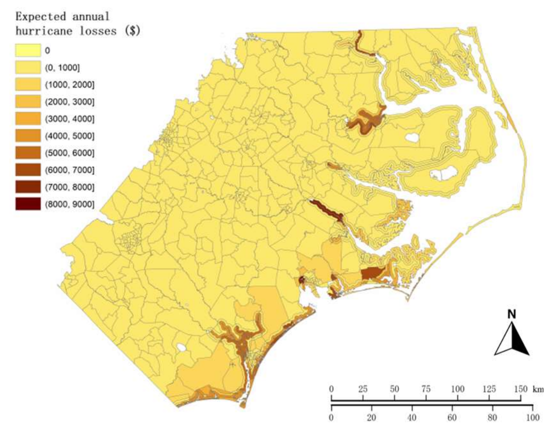
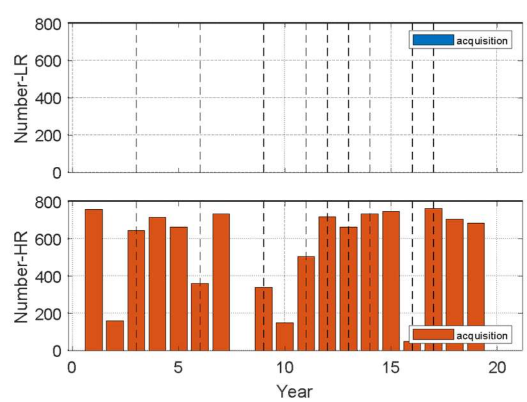


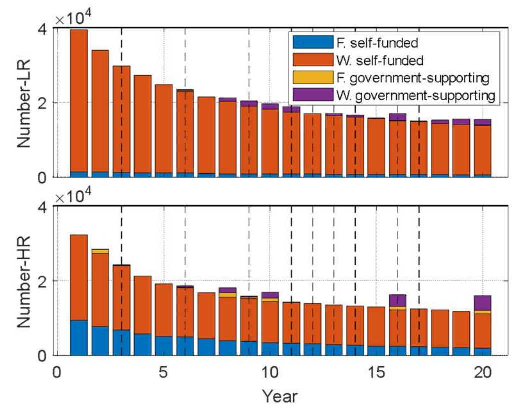
Figure 1-6 Expected annual hurricane losses, averaged over homes, for each area in eastern North Carolina.

1) Scenario 39: acquisition and retrofit decisions by homeowners

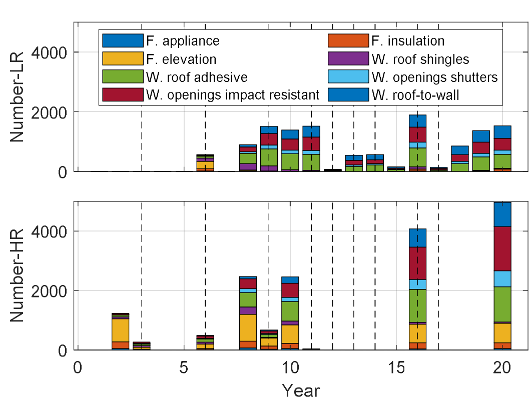
Yearly acquisition and retrofit decisions for homeowners in the study area in Scenario 39 are shown in Fig. 1-7. As can be seen from Fig. 1-7(a), optimal acquisition is only offered to and accepted by homeowners in the high-risk region. Logically, acquiring houses in the high-risk region is more effective in terms of reducing hurricane losses compared to acquiring those in the low-risk region. The number of completed offers year by year fluctuates as the tradeoff between acquisition and retrofit is close and influenced by the number of previous acquisitions. Fig. 1-7(b), (c) and (d) illustrate government-supported and fully self-funded homeowner retrofit activities. Unlike acquisition which only takes place in the high-risk region, retrofit is implemented in both the high-risk region and the low-risk region. The number of homeowners undertaking subsidized retrofit is much smaller than the number that self-fund retrofits. Retrofitting for wind represents the predominant expenditure in all cases. In addition, over time the total number of retrofit decisions made in each year decreases and the composition of specific retrofit types changes as the building stock becomes more wind and flood resistant. This reflects the order of priority in taking different retrofit actions and coincides with the constraints imposed on homeowner retrofit decisions.



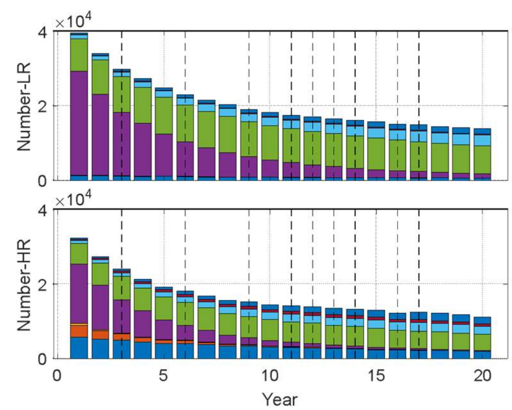
(a) Number of homeowners that accept government acquisition offers



(b) Number of homeowners that implement government-supported and self-funded retrofit



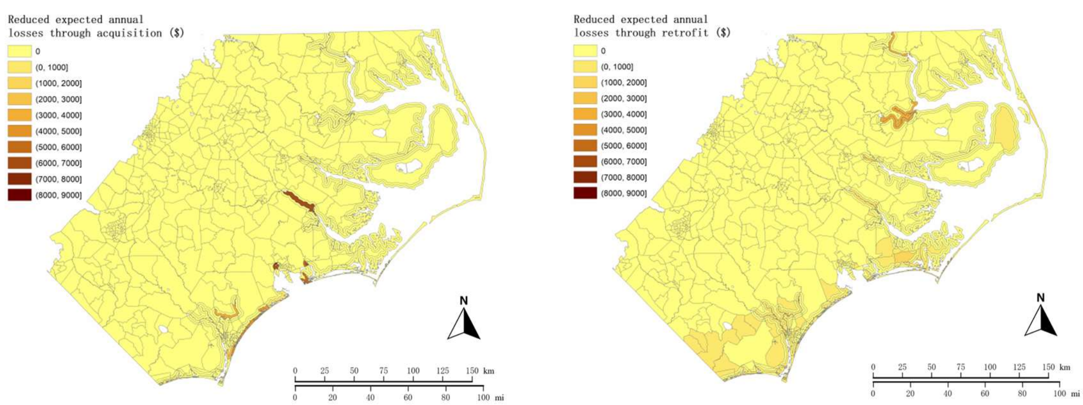
(c) Number of homeowners that implement government-supported retrofit by retrofit type



(d) Number of homeowners that implement self-funded retrofit by retrofit type (legend in Fig. 1-7(c))

Figure 1-7 Number of homeowners in low-risk and high-risk region that accept government acquisition offers (a) and implement retrofit (b,c,d) in Scenario 39. Dashed vertical lines indicate hurricane years.

Fig. 1-8 shows the reduced expected annual losses based on homeowner acquisition and retrofit decisions for Scenario 39. By comparing Fig. 1-8(a) and (b), it is apparent that the loss reduction effect is more pronounced for the measure of acquisition in the affected areas, whereas retrofit programs are carried out more broadly and benefit more homes. An interesting note is the concentrated points of large reduced annual losses for acquisition in our simulation include Kinston, NC that has in fact implemented 685 buyouts as of 2018 [Salveson et al., 2018].



(a) Reduced expected annual losses through acquisition

(b) Reduced expected annual losses through retrofit

Figure 1-8 Reduced expected annual losses by acquisition and retrofit in scenario 39. Results here are averaged over homes for each area and accumulate through 20 years.

2) Scenario 39: insurance pricing, insured and uninsured losses

The Cournot equilibrium insurance prices for Scenario 39 are shown in Fig. 1-9. The time path of equilibrium prices is relatively stable trending marginally lower in the low-risk region and similar for markets served by one to four providers. In the high-risk region price differentiation due to market concentration aligns with expectations with the single seller commanding a higher price and associated profit margin. Note that equilibrium prices are the result of the combined interaction between homeowners and insurers, the insurer competition, and the evolution of the building inventory.

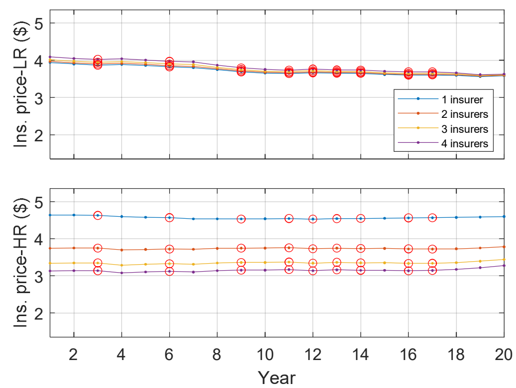
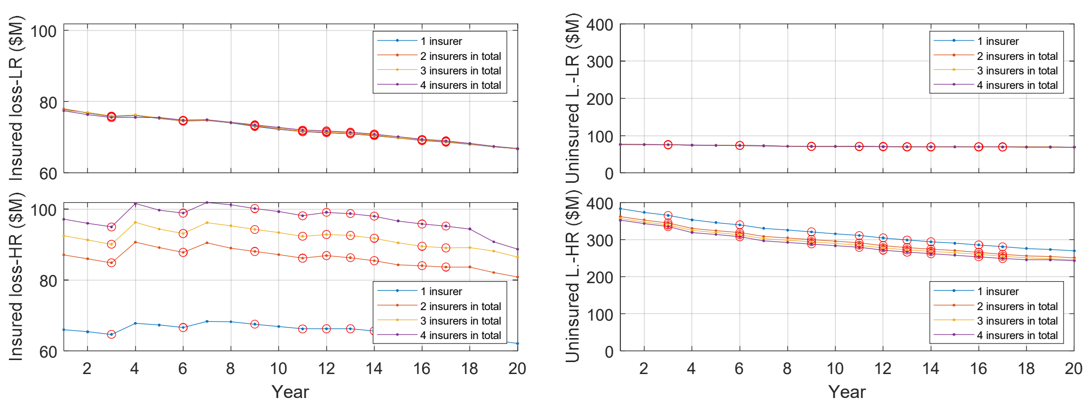


Figure 1-9 Equilibrium insurance prices in Scenario 39. Red circles indicate hurricane years.

Fig. 1-10(a) and (b) correspond to the expected total insured and the expected total uninsured losses for the high- and low-risk regions in each year of Scenario 39. In general, the timing of hurricane events and the competitiveness of the insurance market exhibit relatively strong influence on the curves for the high-risk region, but have little influence on the expected losses in the low-risk region. Specifically, in terms of hurricane timing, recent hurricane experiences stimulate homeowners to invest in insurance, with evident increase in the expected total insured losses in the high-risk region following a hurricane year. This phenomenon becomes less pronounced if (1) the related hurricane has minor impact (e.g., year 9), (2) hurricanes occur consecutively for several years and homeowner characteristics remain almost unchanged (e.g., year 11 to year 14), or (3) acquisition and retrofit implementation reduce the overall hurricane losses and therefore neutralizes the increment. In contrast, hurricane timing shows limited, even negligible influence in the low-risk region given that people in that region are less prone to flood or wind damage. In terms of market competitiveness, notable differences related to the number of insurers are found in the expected total insured and uninsured losses in the high-risk region. Logically, higher insurance prices for the single firm case affect the willingness of homeowners to buy insurance, so we observe lower insured losses and higher uninsured losses for the single seller case. Further, different prices change the eligible insurance purchase decisions as they are confined by constraints on the minimum and the maximum values of insurance policies. On the other hand, the expected total insured and the expected total uninsured losses in the low-risk region are unaffected by the number of insurers. This follows from the result that insurance prices in the low-risk region are similar at all market competitiveness levels. The lower time trend in both insured and uninsured losses is due to the cumulative effect of acquisition and retrofits adopted throughout the 20-year time horizon.



(a) Expected total insured losses (b) Expected total uninsured losses

Figure 1-10 The expected total insured and the expected total uninsured losses for each year in scenario 39. The displayed results count contributions from all insurers in the insurance market.

The number of homeowners purchasing flood and wind insurance is shown in Fig. 1-11. In the high-risk region, the take-up rate for flood insurance is higher compared to wind insurance, whereas wind insurance dominates flood insurance for homeowners in the low-risk region. Fig. 1-12 illustrates the proportion of homes that are uninsured due to the insurance policy premium affordability constraint defined as exceeding 2.5% (for the low-risk region)/5% (for the high-risk region) of the home value and the minimum annual policy premium constraint defined as less than $100. Specifically, in the low-risk region, nearly 97% of homes do not have access to flood insurance as the cost of the resultant premium would fall below $100 per year. About 46% are not offered wind insurance for the same reason. This number increases over time slightly due to adoption of risk-reducing measures. In this region, almost no households encounter the affordability constraint. This contrasts with the situation in the high-risk region. In the high-risk region, insurance policies are not offered to about 50% for flood and 14% for wind due to the $100 minimum policy premium constraint. Approximately 20% of the high-risk region homeowners are unable to purchase flood insurance due to the affordability constraint. Affordability does not constrain the purchase of wind insurance in the high-risk region. Again, these restrictions become slightly less pronounced year by year with the annual investments in acquisition and retrofit.

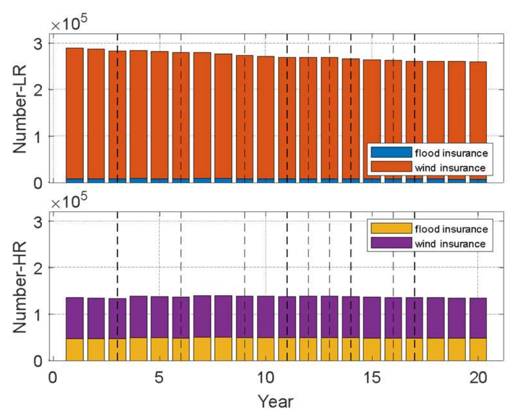


Figure 1-11 Number of homeowners that purchase flood and wind insurance in Scenario 39.

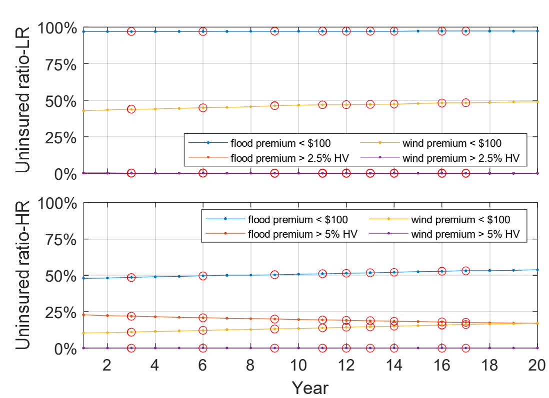


Figure 1-12 Proportion of uninsured homes due to insurance premium affordability and minimum premium constraints in Scenario 39.

3) Scenario 39: government decisions

Fig. 1-13 gives the optimal acquisition offers (Eq. 14) and retrofit subsidy (Eq. 16) for Scenario 39 (note that no acquisition offers are made to the low-risk region, and no value is given for the year if there were no acquisition offers/retrofit subsidy program in that year in that region). Results in this figure are governed by the pattern of hurricane events embedded in the scenario because each stakeholder makes decisions based on events as they occur. Acquisition offer prices for undamaged/damaged houses and retrofit subsidies in all years in this scenario are less than 100%, indicating that the efficient allocation of government resources for risk mitigation requires only partial coverage of the full cost of acquisition and retrofit activities.

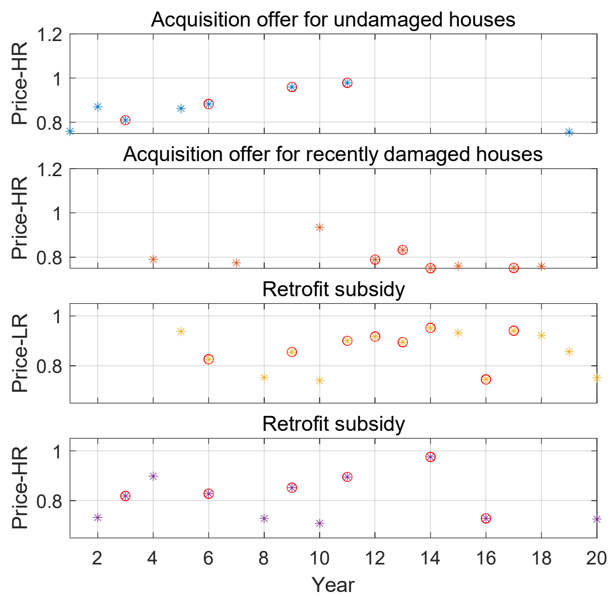


Figure 1-13 Optimal acquisition offer price (percentage of undamaged fair market value) and retrofit subsidy price (percentage of total retrofit cost) in Scenario 39.

4) Scenario 39: expected total losses

Fig. 1-14 shows the expected losses and loss ratios associated with Scenario 39. As illustrated in this figure, the flood-related losses in the high-risk region experience the most significant decrease over time. The proportion of insured losses and uninsured losses is relatively stable over time with a slight increase in the portion of total losses that are insured. From a more general view, there is a substantial reduction in the total losses with the adoption of acquisition and retrofits: the total expected loss reduction over the 20-year period is approximately $1.8 billion and is about $150 million annually thereafter.

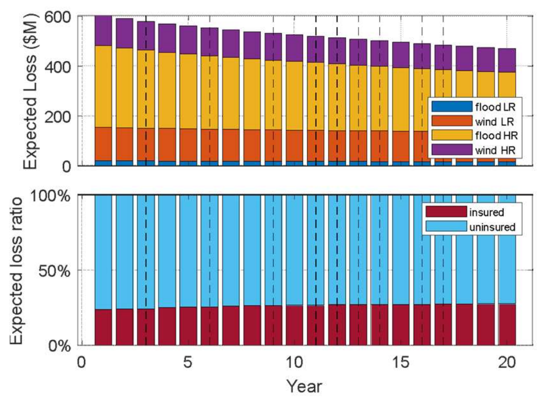


Figure 1-14 Expected total losses and loss ratio for Scenario 39

5) Summary of thirty randomly drawn scenarios

In the following two sections we provide a summary of insurance pricing, losses, government acquisition and retrofit subsidies observed for thirty scenarios randomly drawn from the set of 2,000 hurricane scenarios. The thirty scenarios preserve representativeness of the loss distribution in terms of mean, variance, and skewness.

6) Thirty scenarios: insurance pricing, government decisions and expected total losses

The risk-based insurance prices that obtain in equilibrium for the thirty selected scenarios are shown in Fig. 1-15. Although the pattern of hurricane events differs considerably from one 20-year scenario to the next, the pattern of pricing remains relatively consistent with little variation in the low-risk region. Similar to Scenario 39, the high-risk region shows the pattern of prices that is consistent with market concentration and market shares from 100% for a single firm to 25% for one of four firms.

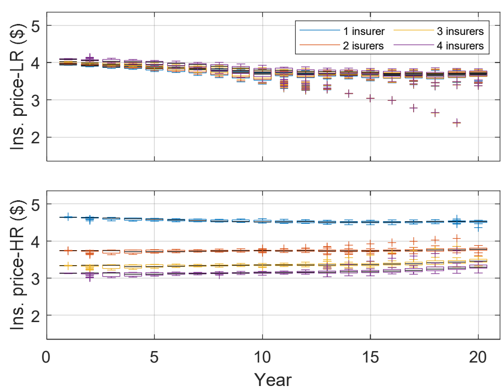


Figure 1-15 Summary of equilibrium insurance prices for thirty scenarios.

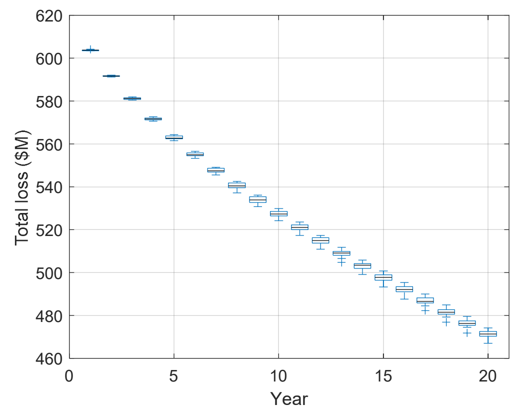


Figure 1-16 Expected total losses for thirty scenarios.

The pattern of expected total losses over the 20-year time horizon is consistent over all thirty scenarios as illustrated by the narrow distribution shown in Fig. 1-16. These benefits result from the joint effect of the constant government investment in retrofit subsidies and acquisition of vulnerable properties and the self-funded home retrofits implemented over time.

As for the pricing policies, the top two panes of Fig. 1-17 show the optimal acquisition offer prices as a percentage of fair market value for undamaged and damaged homes in the high-risk region. The acquisition offers are generally lower for damaged homes than undamaged homes. This is a function of homeowners' willingness to accept a lower acquisition offer after a damaging event and the government's optimal allocation of resources for hurricane risk management. The bottom two panes of the figure indicate retrofit subsidies that are relatively evenly distributed between high-risk and low-risk regions.

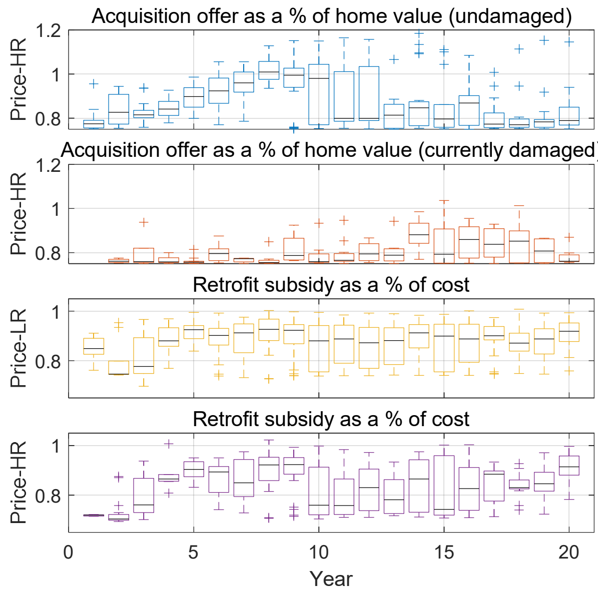


Figure 1-17 Optimal acquisition offer price (percentage of undamaged fair market value) and retrofit subsidy price (percentage of total retrofit cost) for thirty scenarios.

7) Thirty scenarios: financial status of insurers

Fig. 1-18 and Fig. 1-19 illustrates insurers' yearly cash positions for the thirty scenarios. Fig. 1-18 represents the case where a cap on the maximum cash position is assumed to be equal to 3 times the value of the policies written in that year as in Eq. 11. In contrast, Fig. 1-19 illustrates the case with no cap on the cash position meaning the insurer can maintain as much cash on their balance sheet as they accumulate. The two alternative assumptions relate to the argument in [Russell & Jaffee, 1997] that the treatment of cash carryover that is sufficient to cover a catastrophic year is subject to a number of limitations, and the formula applied to determine what proportion of earnings should be held as cash reserve can vary from company to company. Accounting requirements, tax provisions, regulatory requirements, myopic behavior of risk managers and threat of takeovers can all contribute to insufficient cash reserves. Notice that, in both cases, insurers hold better cash positions due to larger accumulated profits when there is less market competition. The absence of a cap on cash allows the insurers to accumulate balances that protect them from an extraordinarily high insured loss year. This reduces the likelihood of insolvency defined as the situation where the accumulated cash balance is negative. Without the cash position cap, there are only one or two scenarios that cause issues with insolvency; with the cap insolvency issues arise more frequently.

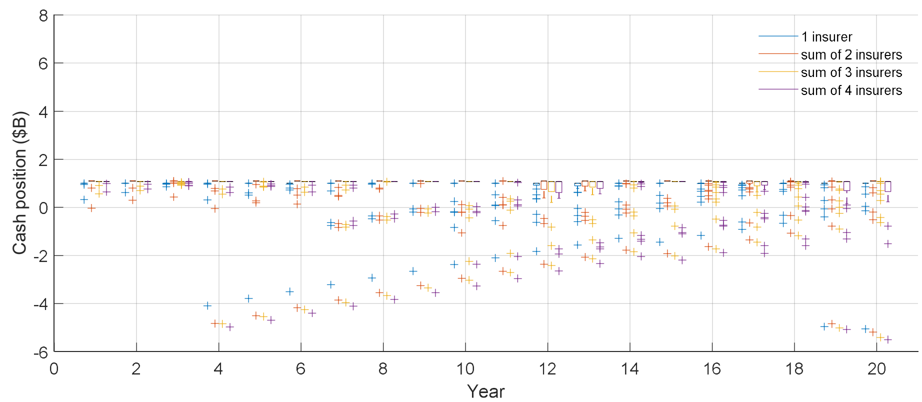


Figure 1-18 Insurer's yearly cash position, with a cap on the maximum value.

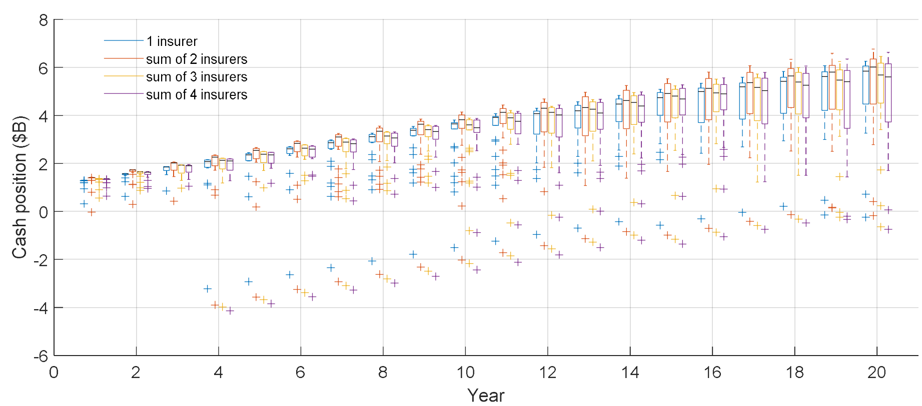


Figure 1-19 Insurer's yearly cash position, with no cap.

1.5 Summary and Conclusions

In this study, we develop a novel computational framework for the modeling of hurricane risk management, where different types of stakeholders, including the government, primary insurers, the reinsurer, and homeowners are involved in a nested dynamic game. In the outer game, the government, with knowledge of how the inner game will respond, determines what incentives to offer, including property acquisition and retrofit subsidization, to support homeowners. A simulation optimization problem is formulated to represent government decision-making and solved for the annual acquisition offer and retrofit subsidy policies. With the government decisions in place, in the inner game, primary insurers make simultaneous choices given homeowner demand and reinsurance pricing. Their behavior is captured by a stochastic program which maximizes net profit. To represent competition in the insurance market, a Cournot-Nash model is implemented to determine the equilibrium risk-based market insurance prices. Empirically-based discrete choice models are used to simulate each homeowner's response to insurance prices and government policy interventions designed to mitigate hurricane risk and reduce insured and uninsured losses. The framework is dynamic, implemented by stepping through a sequence of decisions made by the government, homeowners, and insurers year by year based on market conditions, policy offers, decision strategies, and hazard events. The state variables for all parties are updated annually to reflect changes that are due to their interactive decisions and condition changes associated with recent hazard events.

We examine the portfolio effects over time of government acquisition of high-risk properties; wind and flood mitigation through home retrofits that are self-funded and government subsidized; and risk transfer through voluntary flood and wind insurance markets. By considering how these strategies work together to reduce expected losses in an area with hurricane exposure, we find that employing a combination approach is most effective. We demonstrate that the integration of all these measures, consolidated by optimization, realizes a win-win situation for all stakeholders. We demonstrate that a viable insurance industry is possible in the region that is further improved by the relaxation of constraints on cash carryover from year to year that reduces insolvency that would a consequence of a high-hurricane-loss year. Previous empirical evidence was applied to determine acquisition prices and homeowner acceptance of acquisition offers. In addition, the take-up rate of insurance and retrofit decisions embedded in the model are also based on survey evidence. With a realistic representation of homeowner decisions, we find that undiscounted government expenditures totaling $2 billion resulted in a reduction in expected losses of $1.8 billion over the first 20 years and with a break-even time period of 23 years. This indicates the direct net benefit of public policies that combine retrofit subsidies with acquisition. Population pressure on desirable coastal regions coupled with the threat of sea level rise imply that the policy implications that we describe will likely yield even greater benefits in the future.

This dynamic model builds on previous research by combining public sector policy alternatives, household decision making, and a viable, self-sustaining insurance market. The interactions between public and private sector optimizations demonstrate win-win scenarios. Planned future research will delve into the distributional impact of hurricanes and risk management policy on households where vulnerable and low-resourced populations may require different tools to mitigate risk and prosper. Local governments across regions and within communities are also affected differentially by federal policy choices. Using distributional metrics like the Gini coefficient and other measures, comparisons across disaggregate groups could inform issues around equity and economic well-being. To expand the model, additional private sectors, different public sector optimizations will be considered, and broader representation of local and regional economies shall be included.

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CHAPTER2

HURRICANES, INSURANCE, ACQUISITION AND MITIGATION: LOOKING FOR EQUITABLE SOLUTIONS THAT SUSTAIN PROSPERITY

2.1 Introduction

Disaster losses continue to grow despite a range of government and private sector interventions, including (1) the National Flood Insurance Program (NFIP), (2) the Hazard Mitigation Grant Program, (3) FEMA's Building Resilient Infrastructure and Communities (BRIC) Program and (4) state insurance pools, such as the North Carolina Coastal Property Insurance Pool. Despite these and other disaster mitigation measures, accelerating disaster losses demonstrate that we are still losing the battle of managing disaster risks.

Many of the mechanisms created associated with providing insurance struggle financially. For example, the Congressional Budget Office (CBO) estimates that the NFIP program has an annual expected shortfall on the order of $1.4 billion, primarily resulting from expected losses in coastal counties and assuming current flood risk levels. Much of this shortfall is attributable to a mismatch between expected flood surge damage and policy pricing stemming from discounting in the most risk prone zones (about 70% of policies in the highest risk zones pay premiums that are associated with lower-risk zones through grandfathering and rate discounting). Some of these discounts are being phased out but some of the largest are scheduled to run for up to another 25 years. Given projected sea level rise, this mismatch can be expected to increase overtime (CBO, 2017).

Further, there is evidence that the most vulnerable among us experience the greatest burdens in these events. For example, low-income households are more likely to live in areas more susceptible to storm impacts and are more likely to live in housing units that are substandard. In Hurricane Harvey and in Hurricane Katrina, poor families were concentrated in flood prone areas of Houston and New Orleans, respectively (Krause 2017). Second, poor families find it difficult to afford flood insurance making them vulnerable to devastating financial loss. For example, flood insurance policyholders have significantly higher incomes than the uninsured. The median income of flood insurance policy holders in the U.S. that reside in high risk flood zones is about $77,000 whereas the median income of non-policyholders in these same high risk flood zones is about $40,000 (Grueskin 2018). Finally, natural disasters motivate those with means to leave (1.5% for severe storms) and cause a reduction in housing prices and rent on the order of 2.5-5% (Boustan et al. 2017).

Three of the primary types of tools available to reduce or transfer risk for existing properties are acquisition, retrofit, and insurance. The focus of this chapter is to demonstrate the important and complementary roles that all three need to play in creating a built environment that is more resilient to these events and supporting economic recovery post event, while protecting the most vulnerable among us.

For more than a dozen years we have analyzed regional hurricane risk management as a system using a computational modeling framework. Based on those analyses, we propose that, though not easy, it is possible to develop sustainable, equitable, win-win solutions that are better both for each stakeholder individually and for society as a whole. Based on our analyses, including full-scale applications for eastern North Carolina, we propose that such win-win solutions need to include the following features:

1. Alignment with the natural, ingrained decision-making processes of the stakeholders involved. Rather than determining what is best for the community as a whole and then convincing every stakeholder to play a specified role, we find that it is more effective to design incentives and regulations based on the way that stakeholders naturally make decisions.
2. A functioning primarily voluntary insurance market is critical to ensure insurance remains an effective part of the risk mitigation arsenal. For this to be possible, there must be a healthy competitive insurance market for which solvency of the firm and the costs of the policies are not a stumbling block.
3. Addresses dual goals of reducing total loss and equity. With spiraling losses from hurricanes, it is easy to lose sight of the fact that low income households are disproportionately affected by these events and interventions can exacerbate inequities; hence it is important to carefully consider how these households will fare under policy initiatives designed to stem these losses.
4. A combination of diverse intervention types, such as, insurance, property acquisition, and retrofit. Each reduces the consequences of hurricane events but in different ways. By removing the tail of the insured's loss distribution, insurance protects the vulnerable from financially devastating loss. It is also critical to timely regional financial recovery post-event. Physically strengthening homes actually reduces losses but not to zero and it is often expensive. Property acquisition eliminates risk but for a small number of properties.

The next section describes the models we use to conduct the analysis. Section 2.3 briefs the geographic and demographic information of the study area. Section 2.4 addresses each of the imperative features of a win-win solution, followed by conclusion remarks in Section 2.5.

2.2 Modeling framework

To explore these issues, we use a computational framework for the stochastic and dynamic modeling of regional housing stock exposed to simulated hurricane events in eastern North Carolina. The model includes a competitive, solvency-constrained insurance market and policy levers of home acquisition offers, retrofit programs, and insurance subsidies and regulation. These tools mitigate risk by removing at-risk houses from the existing stock, strengthening houses with retrofits, and shifting financial risk through purchases of insurance and reinsurance in competitive markets. The modeling framework consists of a set of interacting models that explicitly represent the objectives of individual homeowners, private insurance carriers and government organizations The models (1) simulate hurricanes; (2) estimate regional hurricane-induced losses from each hurricane based on an evolving building inventory; (3) capture acquisition offer acceptance, retrofit implementation, and insurance purchase behaviors of homeowners; and (4) represent an insurance market sensitive to demand with strategically interrelated primary insurers. These models are illustrated in Fig. 2-1.

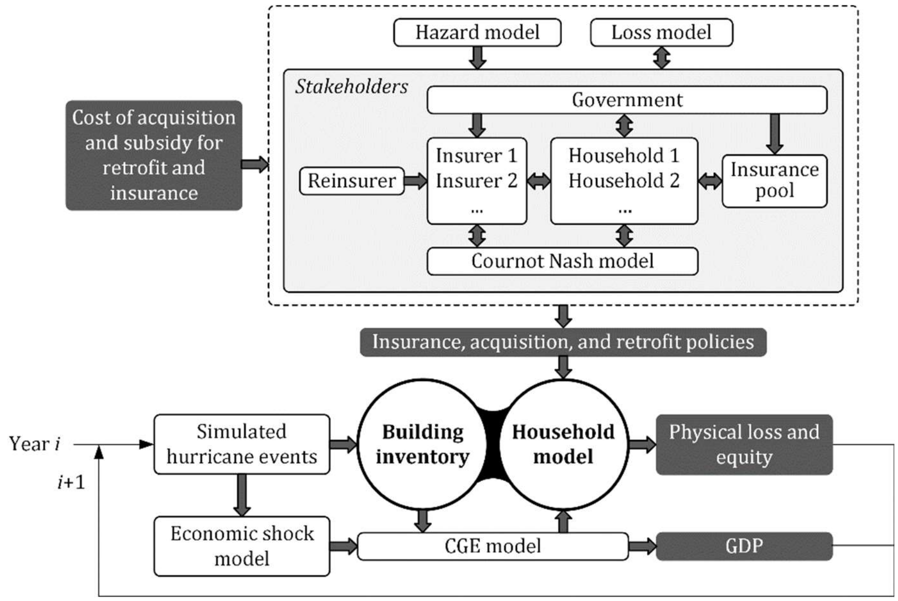


Figure 2-1 Base, stakeholder, and game-theoretic components in the modeling framework and connection to the CGE model.

The framework assumes that homeowners make decisions in their own self-interest and applies mixed logit models to incorporate homeowner retrofit, acquisition, and insurance purchase decision-making as described in [Chiew et al., 2020] and [Wang et al., 2017]. For retrofit decisions, five different mixed logit models are implemented, each to predict the probability of homeowners undertaking: (1) reinforcing roof with high wind load shingles or adhesive foam, (2) strengthening openings with shutters or impact resistant windows, (3) strengthening roof-to-wall connection using straps, (4) elevating house appliances above flood level and installing water resistant insulation and siding, and (5) elevating the entire house. Covariates involved are the alternative-specific constants of revealed preference variables, the retrofit price, the maximum grant amount, the house-to-coastline distance, the number of hurricanes experienced by the homeowner, and homeowner's employment status. Homeowner acquisition decision-making is captured by a pooled probit model as in [Frimpong et al., 2019]. Alternative-specific covariates in the model include an indicator for whether a house has been damaged in the past year and the acquisition offer price; individual-specific covariates include an indicator for whether the home is located in the floodplain, the straight-line house-to-coastline distance, homeowner income, and the length of time the homeowner has been resident in the home. For insurance purchase decisions, two mixed logit models are used, one for wind coverage and the other for flood coverage. Covariates included are the insurance premium, the insurance deductible, a binary indicator as to whether or not the home is located inside the floodplain, the house-to-coastline distance, the number of hurricanes experienced by the homeowner, and homeowner's income, age, and years since the last hurricane experienced.

The modeling framework also includes the decision making of private insurance carriers who are focused on profitability and financial sustainability. The insurer's stochastic optimization tools are their strategic residential premium pricing in low and high risk zones and selecting the parameters of a reinsurance policy.

The market concentration in the primary insurance market can lead to significant differences in the insurers' operational decisions. Specifically, we use a perfect information Cournot-Nash non-cooperative game to incorporate competition among multiple insurers to identify price equilibria. We further extend the method developed in [Gao et al., 2016] to a dynamic setting using simulation-optimization that incorporates annual adjustments of insurance prices.

We extract 100 scenarios from [Apivatanagul et al., 2011] which develops 2,000 hurricane scenarios of 20 years, each to represent the regional hurricane hazard. These scenarios, as a group, are a close match to the 2,000 in terms of mean, variance, and skewness. Across the 2,000 scenarios there are 97 unique events which are each specified by a hurricane track, several along-track intensity parameters, such as central pressure deficit and radius to maximum winds. Through the simulation of these events, spatially disaggregated peak wind gusts and flood depth are estimated.

We use a modified version of the Florida Public Hurricane Loss model to estimate wind-based losses [FPHLM, 2005] and [Taggart & van de Lindt, 2009; van de Lindt & Taggart, 2009] to estimate the flood-based losses to individual homes.

The households, insurers, and government sectors interact and react to hurricanes in terms of risk mitigation strategies and through the economic impacts of capital damage from a storm. When a hurricane event occurs the housing stock is damaged which has direct and indirect ramifications on other economic sectors. These impacts are modeled using a computational general equilibrium (CGE) model (Fig. 2-1). The hurricane event is incorporated through the social accounting matrix as a reduction in the capital stock. The rebuilding of the housing stock is financed through budget-adjusted insurance payouts and through household accumulated savings. Savings is retained as a relatively liquid asset that insulates households from financial shocks rather than an income-generating financial asset. This liquidity constraint on savings sets a lower bound for GDP estimates. Because the household decisions about retrofit, insurance, and acquisition depend, in part, on each year's simulation of storms, the damage-status of the house, and policy levers, the housing stock is updated each year to reflect these modifications to the quantity and quality of the housing stock in an iterative process. Over time, as policies and practices to mitigating risk and protecting homes are adopted, both total and marginal annual losses are reduced. As mitigation strategies are adopted, losses are reduced, insurance becomes less expensive thus, affordable for more households.

Because the data include income ranges for households, we are able to map housing loss simulations to household income groups (low, medium, and high). This delineation allows the model to include means-specific policies, such as insurance subsidies for low income groups while leaving middle and high income groups to purchase insurance at market rates. In addition, the income delineation enables the model to highlight the differential impacts of insurance, retrofit, and acquisitions by income groups and thus we can make basic inferences about equity (section 2.4.3).

2.3 Study area

We focus on census and survey data for the population residing in the eastern half of North Carolina. The study area includes the low-lying coastal counties and, extending westward, half of Raleigh, the state capital. The study region, the eastern half of North Carolina, is subdivided into low risk and high risk regions as shown in Fig. 2-2. The low risk region is areas that are within 2 miles of the coast and the high risk region are areas that are more than 2 miles from the coast. We consider 649,012 and 282,890 households inhabiting the low risk region and the high risk region, respectively, with 52%, 31%, and 17% falling into the low, middle, and high income categories, respectively. The demographic data is also cross-examined with the IMPLAN 2017 database which suggests the population considered in this work contributes to $116 Billion GDP.

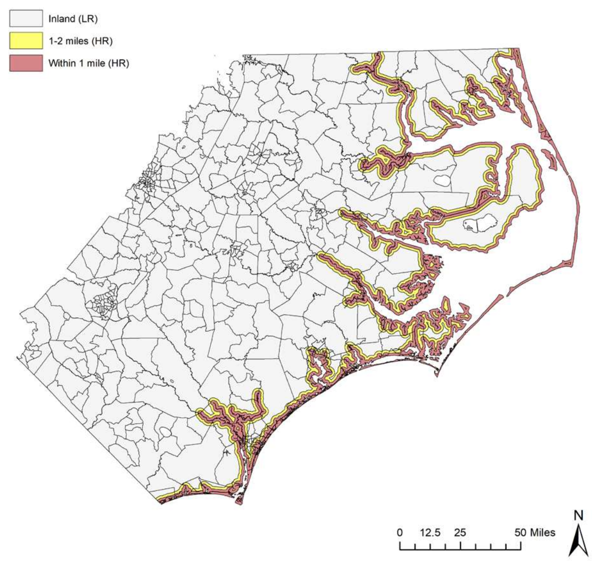


Figure 2-2 Study area of eastern North Carolina (the low risk region and the high risk region are denoted by LR and HR, respectively)

2.4 Features of a sustainable, equitable, win-win solution

2.4.1 Alignment with natural decision-making

We propose that it will be more effective to develop a system around the natural behavioral inclinations of households, insurers, and other stakeholders rather than try to alter their decisions and behaviors to conform to system-optimized recommendations.

No single stakeholder—household, insurer, or government agency, for example—can achieve community resilience on their own. Only homeowners have the authority to purchase insurance for their homes or make physical changes through retrofits. Insurers and government policies can influence homeowners' decisions by modifying pricing, providing incentives, and enforcing regulations; however, they do not physically change the building inventory themselves. Similarly, homeowners cannot decide to accept a property acquisition deal if the government does not extend one or buy insurance at a price that is not offered. Each stakeholder has a different role to play. Further, each has its own risk, objectives, alternatives, constraints, risk aversions, decision processes and timelines, and information about risk management options. Solutions will be practical and sustainable only if they are appealing from each stakeholder's perspective.

We need, therefore, to understand what governs stakeholder decision-making and configure the system in a way that leverages those behaviors rather than resists them. Research by our team and others has begun to identify some of the dimensions of this natural decision-making (e.g., Wang et al. 2017, Jasour et al. 2018, Robinson et al. 2018, Frimpong et al. 2019, Chiew et al. 2020, Stock et al. 2021).

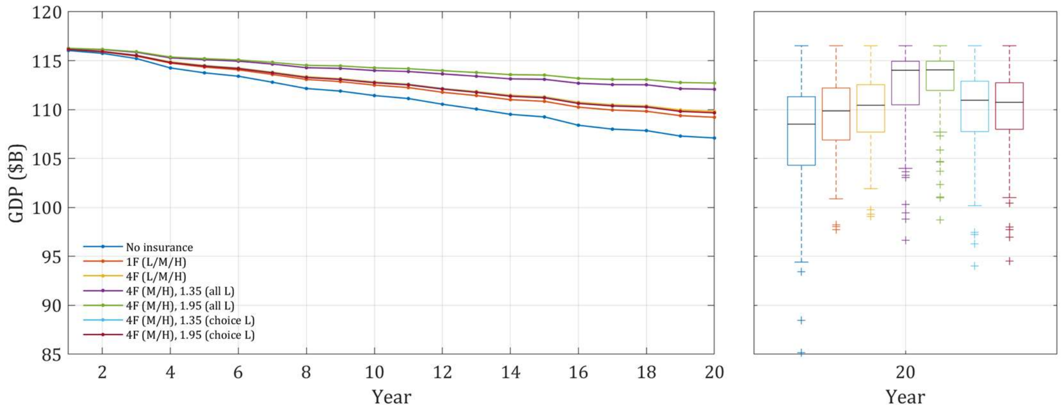
Insurers, for example, aim to maximize profit and return on equity while minimizing the chance of insolvency. The system has to allow them to achieve those goals or they will not voluntarily continue to operate in a region and help homeowners spread their risk.

Households' decision-making is much more heterogeneous and complex. Approximately one-third of people have never even engaged in the decision about whether to undertake a protective action at all. People are busy with many demands for their time, and mitigation has not sufficiently captured their attention to force thoughtful engagement about the decision (Stock et al. 2021). Even when they do engage in hurricane risk management decisions, homeowners make decisions for a wide variety of reasons. In addition to cost, decisions about undertaking retrofits, for example, depend on a number of perceived attributes of the particular retrofit, including effort required, understanding of how it works, potential to increase home value, efficacy in protecting lives and property, and effect on home appearance (Zou et al. 2020). Ultimately, no protective action will be implemented by all homeowners. Some will never accept a buyout offer, for example, no matter the price offered, although they do tend to be much more likely to accept when an offer is made after a home is damaged and before they have begun repairing it (Robinson et al. 2018, Frimpong et al. 2019). To the extent that the system to manage hurricane risk is designed to acknowledge and work around these decision-making processes, it will be more sustainable and effective. If it relies on all homeowners retrofitting, buying insurance, or accepting buyout offers, it will not succeed.

2.4.2 Criticality of a functioning insurance market

A well-functioning insurance market is critical to regional recovery post event and this criticality is investigated using the framework described above. We experiment with seven policies. The policies are 1) no insurance; 2) a monopoly firm providing insurance; 3) a four firm market (which approximates a competitive market); 4) a four firm market supplying high and middle income households and an insurance pool that provides insurance to all low income households at a reduced rate of 1.35 times the expected loss; 5) again, a four firm market for insurance serving high and middle income homeowners and a pool insurance program providing insurance to all low income households at a price of 1.95 times the expected loss; and 6) two more policies that are parallel to policies 4 and 5, but for which all low income households are not assumed to purchase insurance at the assumed reduced price but the framework uses the discrete choice models for those decisions on an individual household basis. It is important to notice that in all policies where insurance is assumed available, high and middle income households' decision making is assumed to be governed by the discrete choice models. Policy 4 and 5 assume that all low income homeowners purchase insurance at the reduced rate and do not enforce the rules that the policies exceed $100 or the affordability constraints of less than 2.5% and 5% of the home value in the low and high risk zones, respectively.

Fig. 2-3 illustrates the mean estimated annual GDP across these 100 event scenarios and a box plot of GDP by policy and scenario in year 20. With no hurricane events, the regional GDP is about $116B. The no insurance case leads to the largest reduction in GDP of about 7.9%, with the remaining policies causing losses of 6.0, 5.5, 3.6, 3.0, 5.6 and 5.6%, for policies 2 through 7, respectively. Policies 3, 6 and 7 are virtually indistinguishable with respect to mean annual impact on GDP because policies 6 and 7 bring more households into the insurance market for flood insurance through lower prices in comparison to the four firm case for all (policy 3) but result in other households being excluded for wind insurance via the $100 minimum household cost requirement, in comparison to policy 3. The policy that leads to the largest preservation of GDP is the one that provides mandatory insurance to low income households at a price of 1.93 times the expected loss with the parallel policy at 1.35 times the expected loss slightly worse. The lower price causes a slight decline in GDP because, at that price, it is difficult to maintain solvency of the pool leading to difficulty in the pool honoring policies in high loss years.



(a) (b)

Figure 2-3 GDP estimates of different insurance policies ((a): average value of GDP for 100 scenarios for 20 years; (b): distribution of GDP for 100 scenarios in year 20)

Fig. 2-3(b) illustrates the distribution in GDP by policy as of year 20. The no insurance case is of very high risk with reductions in GDP reaching about 24% in year 20. The 1 firm reduces the worst case loss across the 100 scenarios to about 16% and increases the 25% tile of GDP by about $5B in comparison to the no insurance policy. The four firm case (policy 3) improves the GDP distribution (in comparison to policy 2) through lessening the consequences of the scenarios through increased access to flood insurance, primarily. Notice that based on GDP at year 20, the four firm case for all (policy 3) appears to marginally outperform policies 6 and 7 but that requiring insurance of all low income households at a price lower than the competitive price outperforms all three (policies 4 and 5 in comparison to 3, 6 and 7). Mandatory policies for low income at 1.95 times expected loss provides a more financially stable pool program than the lower price of 1.35 which reduces the risk in the GDP substantially.

Fig. 2-4 gives boxplots for the cash position at year 20 across the seven policies for the insurers and the pool as well as a combined view across the full book of business. It's important to remember that the insurance carriers are allowed to deliver on policies even when their cash position is negative because insolvency is a relatively modest issue for these firms, making it likely they could attract short-term funds to honor the claims to weather these periods. For example, notice that in the one firm case, there is only one scenario where the carriers are insolvent at year 20. This expands to 2 scenarios in the four firm case. When the private insurers do not provide policies to low income households, the mean return is lower with similar performance when they service the entire market in the more severe couple of cases.

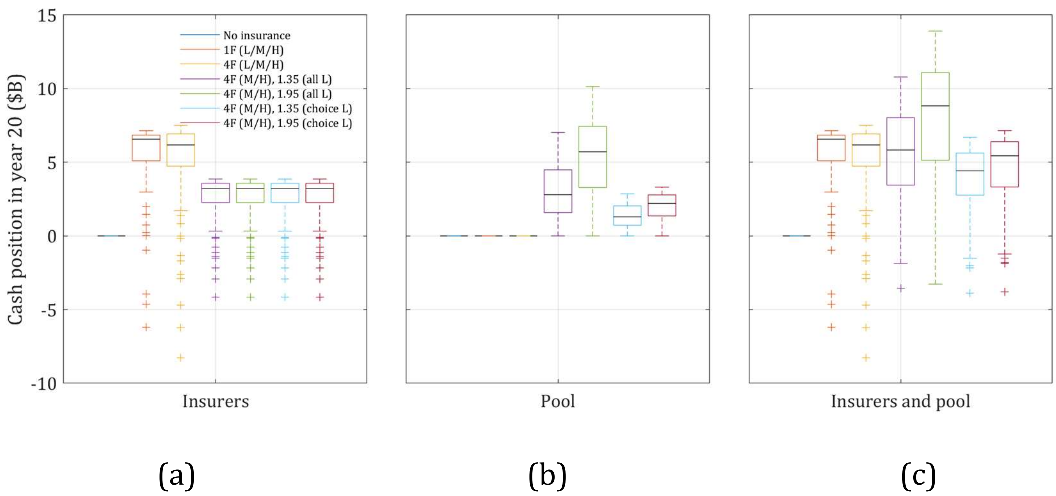


Figure 2-4 cash position in billions at year 20 for the (a) insurers, (b) pool; and (c) combination of the insurers and pool.

Fig. 2-5 gives boxplots for the dollar value ($B) of unpaid claims against the pool insurance program summed over the 20 years across the seven policies. Notice that for policy four, which is mandatory insurance for low income at the price of 1.35 times expected loss along with the four firm competitive price for high and middle income, the cash position of the pool portion is a substantial challenge. This challenge abates when we consider the full book of business that would include the returns from the policies purchased by the high and low income homeowners (Fig. 2-4). This challenge for the pools abates somewhat with the higher price (1.95) for low income. When the low income households are not assumed to purchase but are offered insurance at a reduced price, the financial risk to the pools improves.

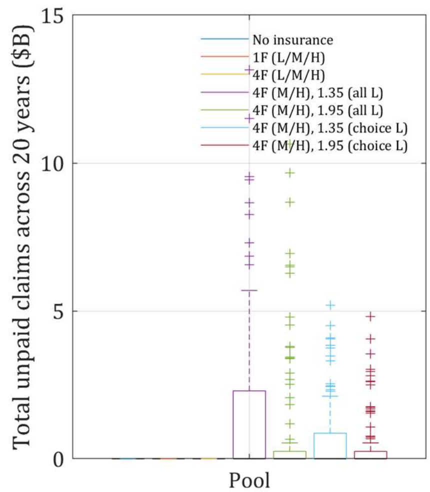
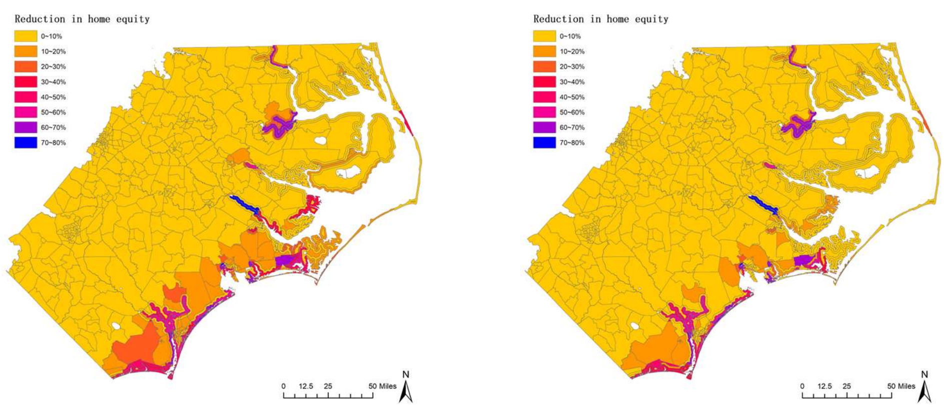


Figure 2-5 Boxplots of the sum of unpaid customer claims for pool insurance by policy.

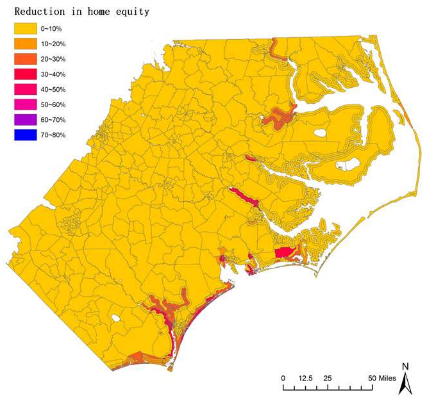
2.4.3 Total loss and equity

As mentioned previously hurricanes can have a profound impact on low income households. We explore these impacts using the seven policies described previously. The first measure of comparison is in the estimation of the decline in home equity. As has been widely discussed, the home is a very important mechanism to preserve intergenerational wealth.

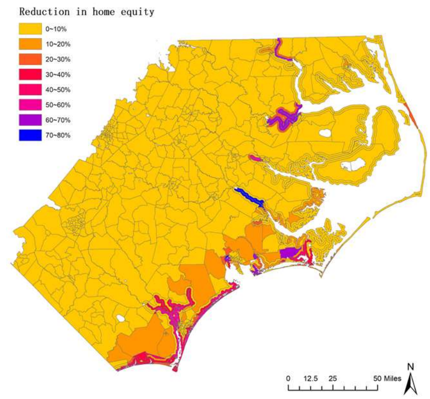
Fig. 2-6 illustrates the average impact of four of the policies on home equity after 20 years. Notice that in the no insurance case the accumulated loss is very substantial along the coastline. The four firm case reduces this loss substantially but large areas still incur very substantial losses as is the case when the low income have the option to purchase insurance at the reduced rate of 1.95 per dollar of loss. Once that insurance becomes mandatory for low income, substantial progress is made in a number of counties including Pamlico, Carteret and New Hanover Counties. This stems from the fact that many of these properties are highly vulnerable so the price of the policies in the competitive market exceeds the capacity of the homeowners to fund them. In the low income mandatory insurance scenarios, we assume that these policies are affordable even if they exceed 5% of the value of the home. As an example, consider Pamlico County. About 50% of the homeowners in this county are low income and the reduction in home equity by year 20 in this area is 32.4%, 17.2%, 9.8%, and 18% for the no insurance (1), four firm (3), four firm high and middle income and 1.95 mandatory low income (5), and the four firm high and middle income and 1.95 optional low income (7), respectively.



(a) (b)



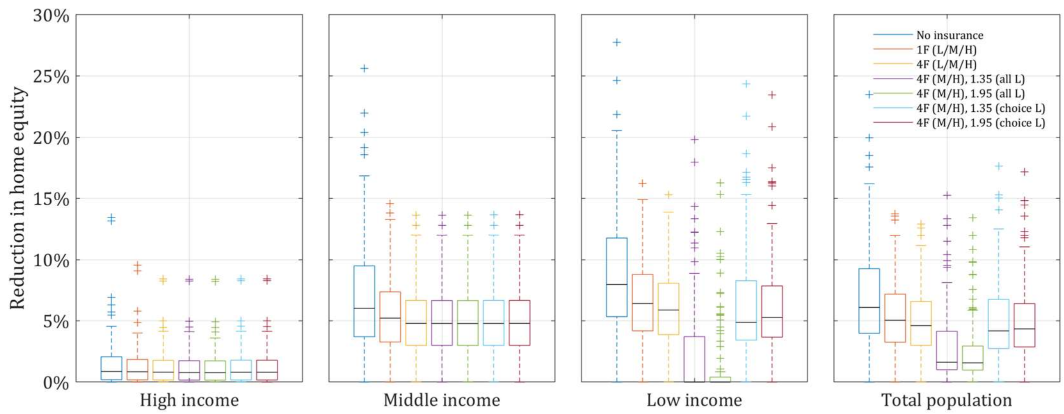
(c)



(d)

Figure 2-6 Decline in home equity (a) no insurance; (b) four firm; (c) 4 firm for high and middle income and mandatory insurance purchase at 1.95 per dollar expected loss; and (d) 4 firm for high and middle income and 1.95 per dollar of expected loss optional insurance purchase for low income.

Fig. 2-7 gives the boxplots for the reduction in home equity after 20 years in each income group and for the combined population for each of the seven scenarios. For high income households even without insurance they are able to maintain much of their home equity because their savings rates are sufficient (Cobet, 2015). For middle income, the average loss in equity is about 4%-5% in the one and four firm cases with average losses without insurance of about 6% reaching higher than 15% in some scenarios. With respect to low income households, insurance is critical with substantial gains once we assume that insurance is essentially mandatory for this segment of the population. It is worth noting that about 2% and 13% of the policies at a cost of 1.35 and 1.95 times the expected loss would exceed the 5% of home value threshold. To subsidize that portion of the insurance cost that exceeds 5% of the value of their home, would cost about $5M and $50M, respectively.



(a) (b) (c) (d)

Figure 2-7 Reduction in home equity for households in different income-level groups in year 20.

2.4.4 Combination of diverse intervention types

Insurance mitigates hurricane risk by providing financial support to aid in the recovery of the regional economy and for homeowners. However, insurance does not reduce damage to homes from hurricanes. Home retrofit and property acquisition are common risk mitigation methods which curtail and/or eliminate the hurricane loss by improving the resistance of the homes or using buyouts to demolish highly vulnerable homes, and are therefore complementary to insurance.

We investigate the effectiveness of three mitigation policies and remark on the combinations of retrofit, buyouts, and insurance. The three mitigation policies are 1) no home retrofit (including self-funded) or property acquisition; 2) a combination of government-funded home retrofit and property acquisition constrained by a limited budget, and self-funded home retrofit; 3) the integration of government-funded home retrofit and property acquisition constrained by a limited budget and applied to the high and middle income households and a parallel program for low income households with an unlimited budget but only for mitigation and acquisition opportunities with expected reduction in losses that exceeds cost.

Fig. 2-8 illustrates the annual expected hurricane loss across the 100 event scenarios by the three policies. In contrast with no mitigation or acquisition, which leaves the expected loss unchanged, policy 2 and 3 substantially reduce expected damage. The reduction in losses increases over time because 1) these are permanent changes to the building inventory reducing losses into perpetuity; 2) annually $100 M becomes available at all income levels to subsidize mitigation and fund acquisition in policies 2 and in policy 3 those funds are unlimited for the low income; and 3) household choice for mitigation occurs annually so an individual may decide to engage in a mitigation that would be beneficial but has not previously been done. It is also useful to notice that there is very little variability in loss reduction for a given policy and given year. Homeowners are somewhat influenced by their hurricane experience and to a larger extent whether or not the property has just been damaged, but across a wide region there are many homes for which these actions are highly beneficial with respect to controlling losses, and hence the budget generally limits the maximum benefit that can be realized. In year 20, the reduction in expected loss reaches about 14% and 23% of the original total expected loss for policy 2 and 3, respectively. With mitigation policy 2, about 80% of the annual budget is spent on acquisition with the remaining 20% for mitigation. With policy 3, about $1.5B is expended in the first year for property acquisition for the low income in the high risk region and no more homes get acquired thereafter. The extensive use of acquisition of low income highly vulnerable homes (2.2% of low income households in the high risk region) accounts for about 80% of the $60M gap in loss reduction between policy 2 and 3 in year 20. Also under policy 3, home retrofit is performed in multiple years to undertake all the benefit positive mitigations since there are logical orders in which mitigation on a home is conducted and we limit mitigation to one type per year per home.

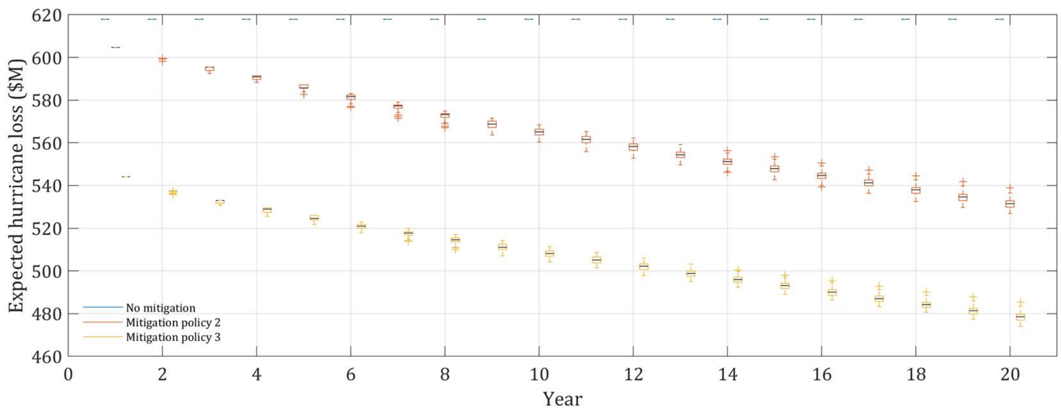


Figure 2-8 Expected hurricane loss across 100 scenarios for 20 years.

As mitigation and acquisition programs are implemented, the total cost of insurance is generally declining even though the price per dollar of expected loss may rise. Table 2-1 gives those declines in cost per home in the low risk region. In order to facilitate the comparison across mitigation options, we focus on the homes that purchase insurance for each insurance policy at year 20 when there is no mitigation. We then explore what those homeowners would pay under each of the other two mitigation strategies. For example, with mitigation policy 2 when insurance is offered at the four firm price to middle and high income households but at $1.95 per dollar of expected loss for low income households (choice), the average decline in premium is about 2% for low income households and about 4% for middle and high income households in comparison to premiums under the same insurance policy in year 20 but with no mitigation. For that same insurance policy but when it is paired with mitigation policy 3, that decline reaches almost 10% for low income in the low risk zone.

Table 2-1 also gives the average cost of the policies written (in $). In this region, as mitigation increases for a given insurance policy, the average cost of the policies decline. For example, for mitigation policy 2 for the 4 firm case, for the middle and high income, the average policy is $22 cheaper than with no mitigation. With mitigation policy 3 that decline is about $35. Note that the annual investment in mitigation measures constantly alters the building inventory and further affects the equilibrium insurance price (in the 1 firm and 4 firm cases), but in the low risk region the difference in insurance price across the three mitigation policies in year 20 is minimal.

Table 2-1 Decline in premiums at year 20 (compared to no mitigation) for population in the low risk region

% decline in premiums (average policy cost at Year 20 in $)	No mitigation		Mitigation policy 2		Mitigation policy 3	
	L	M/H	L	M/H	L	M/H
No insurance	-	-	-	-	-	-
1 firm	0 (514)	0 (521)	3 (497)	3 (504)	9 (467)	4 (499)
4 firms	0 (511)	0 (517)	4 (490)	4 (496)	11 (452)	7 (481)
1.35 all L	0 (148)	0 (517)	4 (142)	4 (496)	9 (135)	7 (481)
1.95 all L	0 (213)	0 (517)	4 (205)	4 (496)	9 (195)	7 (481)
1.35 choice L	0 (333)	0 (517)	3 (325)	4 (496)	11 (297)	7 (481)
1.95 choice L	0 (378)	0 (517)	2 (369)	4 (496)	10 (341)	7 (481)

Table 2-2 gives the parallel information as Table 2-1 but for the high risk region. Whereas the dollar cost across insurance and mitigation policies in the low risk region at year 20 is clear, it is a bit more complicated in the high risk region. For example, with four firms there is no decline in year 20 in the average cost of policy with mitigation policy 2 for the low income in comparison to no mitigation. Also the average cost of these policies is marginally higher. While at first this seems counter-intuitive, the price of insurance is marginally higher with mitigation and is offsetting the reduction in expected loss achieved through mitigation. In the one firm case the insurance carriers appear to not be as successful capturing the benefit in the reduction in expected loss through rate increases. Finally, when we consider the policies that limit the low income insurance price to 1.35 or 1.95 per dollar of expected loss, there are large reductions in insurance premiums under mitigation policy 2 and they increase further under mitigation policy 3.

It is worth noticing that when mitigation policy 3 is paired with the choice model for all income classes but the low income can purchase at 1.95 per dollar of expected loss, the decline in insurance prices is only about 4% for the low income with about 33% of low income households in the high risk region purchasing insurance. This is in contrast to the decline of about 30% when all low income households in the high risk zone purchase insurance at 1.95 per dollar of expected loss.

Table 2-2 Decline in premiums by year 20 (compared to no mitigation) for population in the high risk region*

% decline in premiums (average policy cost at Year 20 in $)	No mitigation		Mitigation policy 2		Mitigation policy 3	
	L	M/H	L	M/H	L	M/H
No insurance	-	-	-	-	-	-
1 firm	0 (2099)	0 (2136)	3 (2033)	3 (2068)	5 (2004)	2 (2089)
4 firms	0 (2112)	0 (2134)	0 (2127)	0 (2147)	0 (2130)	3 (2074)
1.35 all L	0 (1743)	0 (2134)	21 (1379)	0 (2147)	30 (1217)	3 (2074)
1.95 all L	0 (2518)	0 (2134)	21 (1992)	0 (2147)	30 (1759)	3 (2074)
1.35 choice L	0 (2236)	0 (2134)	13 (1950)	0 (2147)	21 (1775)	3 (2074)
1.95 choice L	0 (2355)	0 (2134)	5 (2240)	0 (2147)	4 (2267)	3 (2074)

* Equilibrium insurance prices in the high risk region under no mitigation, mitigation policy 2, and mitigation policy 3 in year 20 are 4.6, 4.6, 4.6 per dollar of expected loss for the 1 firm case, respectively, and 2.7, 2.9, and 3.3 per dollar of expected loss for the 4 firm case, respectively.

As loss mitigation methods and insurance complement each other in reducing hurricane risks, simultaneous application of both types of interventions further facilitates loss reduction compared to the use of any of them independently. Fig. 2-9 gives estimates of

GDP impacts under different mitigation, acquisition and insurance policies. Introducing mitigation significantly reduces GDP decline across all insurance policies examined above.

Notice that when all low income purchase insurance at 1.95 and the middle and high income purchase at the competitive price is paired with mitigation policy3, the smallest loss in GDP is experienced. That loss is on the order of 2% in comparison in year 20 for a cumulative avoided loss in GDP of about $66.2 Billion (in comparison to no insurance/no mitigation case). This avoided loss in GDP represented avoided reduction in output in construction, services, manufacturing and wholesale and retail trade of over 200%, 18%, 10% and 18.5%, respectively. These four sectors represent about 60% of GDP. The cumulative cost for insurance for low income households over the 20 years is about $6.29 Billion. It is also worth noting that cost declines by about 2% across the 20 years due to acquisition and mitigation.

Assuming that insurance is not mandatory for the low income but they do receive access to insurance at 1.95 times the expected loss, the avoided GDP loss declines to about $44.9 Billion over the 20 years. The shift to optional insurance purchase for low income households reduces the cumulative expenditures on insurance by these households of about 54%.

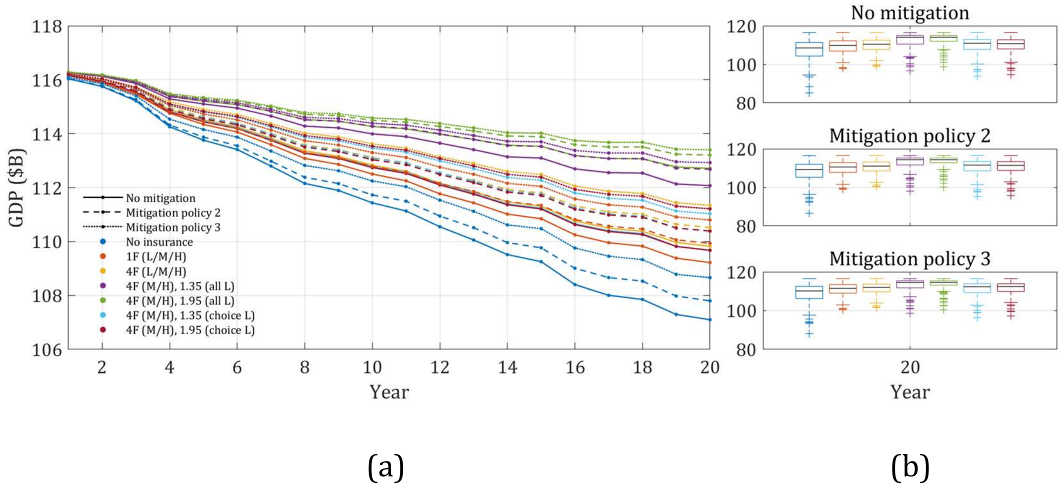


Figure 2-9 GDP for different mitigation and insurance policies. (Average GDP over 100 scenarios in (a), and box plot for 100 scenarios in (b)).

Tables 2-3 through 5 give the costs and benefits for each combination insurance and mitigation policy. The cost of mitigation that appears in tables is only the portion expended by the government through grant programs. The avoided structural loss for each mitigation that was in place prior to year 20 and is the benefit from the year it was undertaken till year 20. The final column in each table is the sum of avoided GDP loss and structural loss minus the costs for acquisition, mitigation, and all insurance purchased by low income households. It is useful to notice that the value is positive for all insurance strategies and mitigation policies, and in many cases is very large, reaching as high as $63 billion in two instances. This underscores the very large toll these events take on the regional economy and that avoiding these large scale distributions is very much in the broad interest of society.

Table 2-3 Benefits and costs of 7 insurance policies paired with no mitigation policy

($B)	Cost of Acquisition	Cost of Mitigation	Cost of Insurance for Low Income	Avoided GDP Loss	Avoided Structural Loss	Insurance Claims	Sum of Benefits Minus Costs
No insurance	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1 firm	0.00	0.00	3.38	22.80	0.00	2.82	22.24

4 firms	0.00	0.00	3.55	29.49	0.00	3.54	29.48
1.35 all L	0.00	0.00	6.11	54.04	0.00	6.29	54.23
1.95 all L	0.00	0.00	8.82	60.08	0.00	6.98	58.24
1.35 choice L	0.00	0.00	2.67	28.30	0.00	3.55	29.18
1.95 choice L	0.00	0.00	3.07	27.76	0.00	3.46	28.15

Table 2-4 Benefits and costs of 7 insurance policies paired with mitigation policy 2

($B)	Cost of Acquisition	Cost of Mitigation	Cost of Insurance for Low Income	Avoided GDP Loss	Avoided Structural Loss	Insurance Claims	Sum of Benefits Minus Costs
No insurance	0.59	0.11	0.00	6.86	1.05	0.00	7.21
1 firm	0.59	0.11	3.35	29.42	1.05	2.80	29.22
4 firms	0.59	0.11	3.55	36.04	1.05	3.51	36.34
1.35 all L	0.59	0.11	5.43	60.06	1.05	5.99	60.97
1.95 all L	0.59	0.11	7.84	65.02	1.05	6.54	64.07
1.35 choice L	0.59	0.11	2.55	35.19	1.05	3.51	36.49
1.95 choice L	0.59	0.11	3.04	34.46	1.05	3.44	35.20

Table 2-5 Benefits and costs of 7 insurance policies paired with mitigation policy 3

($B)	Cost of Acquisition	Cost of Mitigation	Cost of Insurance for Low Income	Avoided GDP Loss	Avoided Structural Loss	Insurance Claims	Sum of Benefits Minus Costs
No insurance	1.59	0.20	0.00	16.86	2.15	0.00	17.21
1 firm	1.59	0.20	3.25	39.54	2.15	2.77	39.41
4 firms	1.59	0.20	3.52	45.92	2.15	3.42	46.18
1.35 all L	1.59	0.20	4.48	62.39	2.15	5.21	63.47
1.95 all L	1.59	0.20	6.48	66.86	2.15	5.70	66.44
1.35 choice L	1.59	0.20	2.19	42.64	2.15	3.20	44.00
1.95 choice L	1.59	0.20	2.95	44.24	2.15	3.36	45.00

2.5 Concluding thoughts

Effective win-win solutions will depend on the magnitude and nature of risk in a particular region. To identify the specific combination of policies and programs best suited for a case, the system should be analyzed as a whole, considering the multiple stakeholder types and multiple intervention types together, so their interactions can be captured. In this work, we demonstrate the importance of alignment with the natural, ingrained decision-making processes of the stakeholders involved rather than assuming that we will be effective in encouraging homeowners to take actions that represent a departure from their current mindset. We examined the substantial progress that risk mitigation tools including home retrofit, property acquisition, and insurance could make in reducing physical damage experienced by affected households and avoiding GDP loss when considering the economic impact of events. We also demonstrated that, when designed with considerations to favor the vulnerable population, mitigation and insurance policies can facilitate the alleviation of inequities.

Homeowners, insurers, and policy makers are linked in pre-event mitigation and post-event recovery which is captured through the storm simulations and risk mitigation strategies. These stakeholders also interact with each other and prepare and react to storms through their economic linkages. Using a CGE model, the chapter expands previous work to include the implications of damaged capital stocks on the economy.

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CHAPTER3

IMPACTS OF HURRICANE EVENTS AND HAZARD MITIGATION INTERVENTIONS ON LOW INCOME HOUSEHOLDS IN COASTAL AREAS OF EASTERN NORTH CAROLINA

3.1 Introduction

Natural disasters, especially hurricanes, are on the rise, both in terms of frequency and severity. According to (NOAA 2020), the 2020 hurricane season shattered records surpassing the 2005 season with 30 named storms, 12 of which made landfall in the continental United States. The trend of the ever-increasing and even-accelerating disaster losses has raised broad concerns (Lavell and Maskrey 2014).

Aggravated inequity in the wake of hurricane events has been drawing wide attention in recent years (Tierney 2011, Krause 2017, Grueskin 2018, Boustan et al. 2017). In-depth investigations of how different segments of the population experience hazards differently are, however, still in great need due to difficulties caused by the natural paucity of observed data and the lack of ripeness in relevant theories and viable models. A series of work (Chiew 2020, Wang 2017, Gao 2016, Frimpong 2019) has been conducted in which a computational framework for the stochastic and dynamic modeling of regional natural catastrophe losses is proposed and used to analyze responses of different types of stakeholders to hurricane events as well as the disaster insurance market. With further development on this framework, Chapter 2 illustrated the inequitable impact of hurricane events on the different income-level households and examined the effectiveness of several risk mitigation policies in reducing hurricane loss and alleviating inequity.

In this chapter, we further explore the experience of different income-level households in the hurricane context, especially focusing on the low income population, and suggest the design and implementation of equitable disaster mitigation interventions. It is worth noticing that the metric of reduction in home equity is used throughout this chapter as home is the most valuable asset for most households and serves as the keystone to maintain the functioning of one's daily life. In addition, the study area is the eastern half of North Carolina, and we conducted the investigation with focus on single-family wood-frame homes in this area.

The remainder of this chapter is as follows. Section 3.2 introduces the modelling framework and the database. Section 3.3 investigates home equity loss by different income-level groups in the study area. Section 3.4 explores the effectiveness of insurance policies in reducing home equity loss for the low income group and Section 3.5 studies combinations of multiple risk mitigation tools. Conclusive remarks are given in Section 3.6.

3.2 Modelling framework and database

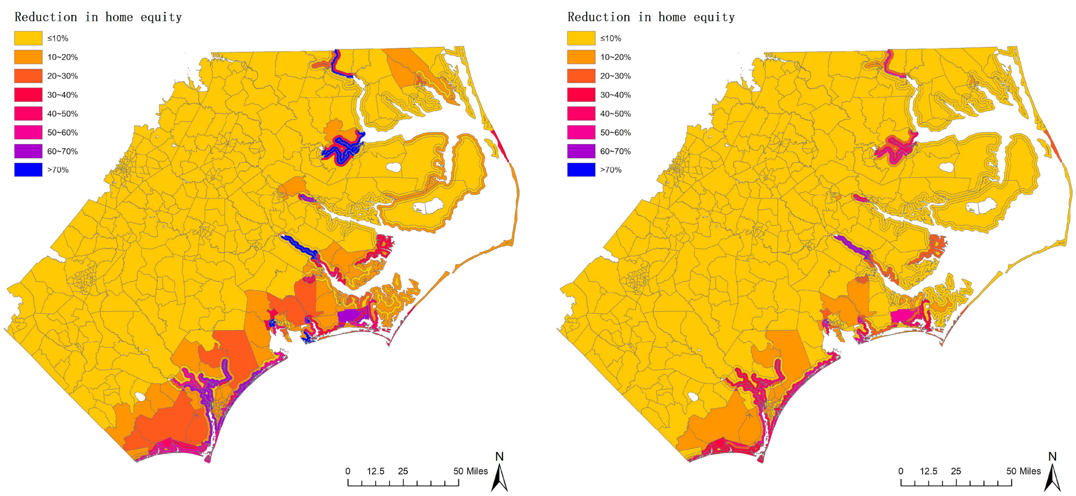
We use the same multi-stakeholder risk management framework as in Chapter 2 which is developed to inform the creation and analysis of government policies that instruct, regulate, and support individuals and organizations to properly manage hurricane risks and impact. The framework includes models (1) simulate hazard events; (2) estimate regional hurricane-induced losses from each hazard event based on an evolving building inventory; (3) capture acquisition offer acceptance, retrofit implementation and insurance purchase behaviors of homeowners; and (4) represent an insurance market sensitive to demand with strategically interrelated primary insurers. More details of the framework can be referred to in (Gao 2016, Wang 2017).

In terms of the database, we use the same census and survey data as in (Wang 2017) to investigate the disproportional impacts of hurricane events on different income-level population segments. 649,012 households in the low risk region and 282,890 in the high risk region are considered with 52%, 31%, and 17% of the total population falling into the low, middle, and high income categories, respectively.

3.3 Home equity loss by different income-level groups

We first investigate the difference in home equity loss for different income-level groups without interference from risk mitigation measures. According to simulation results, the mean percentage reduction in home equity for the low income households and the middle and high income households are 3.5% and 1.3% in the low risk region and 22.2% and 14.5% in the high risk region, respectively (average of 100 scenarios, year 20 home equity compared to undamaged home equity). The increase in house damage from the low risk region to the high risk region is due to the geographical disadvantage of the latter in the hurricane context. The avoided home equity loss for the richer group across both regions is resulted from their convenience in utilizing financial means to abate hurricane impacts (in the model, the low income, the middle income, and the high income are assumed to be able to use 0, 10%, and 30% of their annual savings to repair damaged houses, respectively).

We then explore the home equity loss after 20 years for the low income and the middle and high income by geographical areas. According to Fig. 3-1 (a) and (b), the difference in home equity loss between the richer and the less wealthy is prominent. The low income households in areas close to the coastline experience severe losses which reach more than 70% of the home equity (Fig. 3-1(a)). By contrast, the middle and high income group confront adverse impacts at lower, if not the same, intensity levels in both coastal and inland areas and the worst case of loss after 20 years is above 60% of the original home equity (Fig. 3-1(b)).



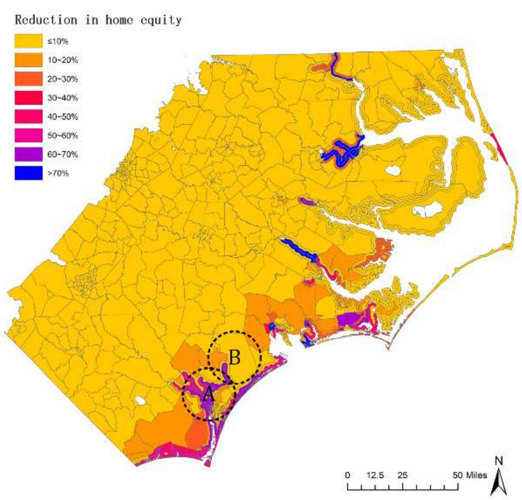
(a) Low income group (b) Middle and high income group

Figure 3-1 Home equity loss by different income-level groups (year 20 home equity compared to the undamaged home equity, average of 100 scenarios, and no hazard mitigation interventions involved).

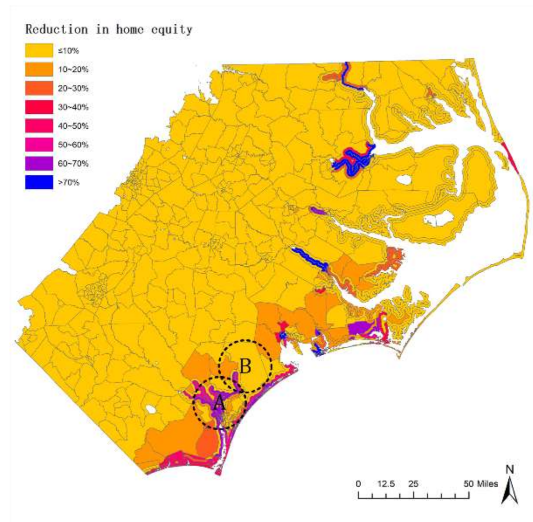
3.4 Effectiveness of insurance policies in reducing home equity loss for the low income group

We experiment with seven insurance policies to investigate the effectiveness of insurance in avoiding home equity loss for the low income population. The policies are the same as introduced in the Chapter 2, namely, 1) no insurance; 2) insurance offered by a monopoly firm; 3) insurance offered in a four firm market; 4) insurance provided by a four firm market and serving high and middle income households and mandatory insurance provided by an insurance pool and involving all low income households at a reduced rate of 1.35 times the expected loss; 5) the same policy as structured in policy 4 except that all low income households are insured at a price of 1.95 times the expected loss; and 6) and 7) two more policies that are parallel to policies 4 and 5, but for which insurance purchase decision making of the low income households are portrayed with discrete choice models on an individual household basis.

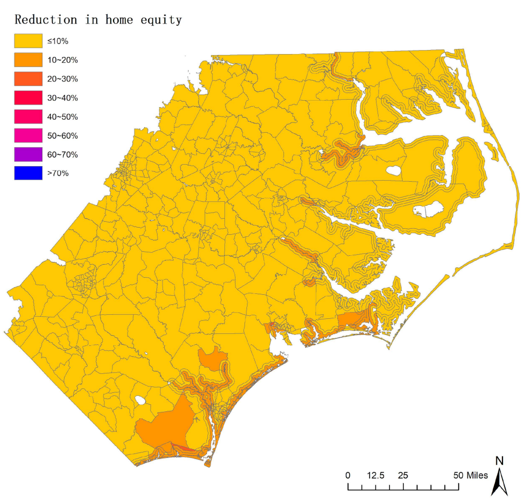
Home equity loss for low income households after 20 years under different insurance policies are illustrated in Fig. 3-2. By comparing Fig. 3-2 (a)~(f) with Fig. 3-1(a) (the no insurance case), we find that insurance policy 2 to 7 are quite effective in reducing hurricane losses, even though their performance varies greatly. Policy 3 shows slightly better effectiveness in the high risk region than policy 2, but the two of them obtain almost identical loss reduction effects in the low risk region where insurance is priced similarly in the monopoly market and the four firm market. Policy 4 and 5 have the most substantial efficacy among all seven policies as they require the involvement of all low income households. The mandatory insurance supplied at the reduced rate of 1.35 per dollar of loss confines the home equity loss of almost all areas within the 20% mark. The mandatory insurance supplied at 1.95 per dollar of loss furthers the attainment in the 1.35 case as very few areas along the coastline see home equity loss exceeding 10%. Moreover, policy 6 and 7 are more potent than policy 2 and 3 in relieving hurricane hazards in highly vulnerable areas such as in New Hanover County (area A). This advantage, however, does not exist when the four policies are implemented in less vulnerable areas such as in Pender County (area B). This can be explained by that, when using the discrete choice model, a lower insurance price enables more of those in badly exposed homes (mainly in the high risk region) to afford insurance and meanwhile prohibits more of others in safer environments (in most parts of the low risk region and a few areas of the high risk region) to get involved, all based on the assumption that households are only eligible to purchase insurance when their premiums are less than 5%/2.5% of the home value (for those in the high/low risk region) and exceed the $100 threshold.



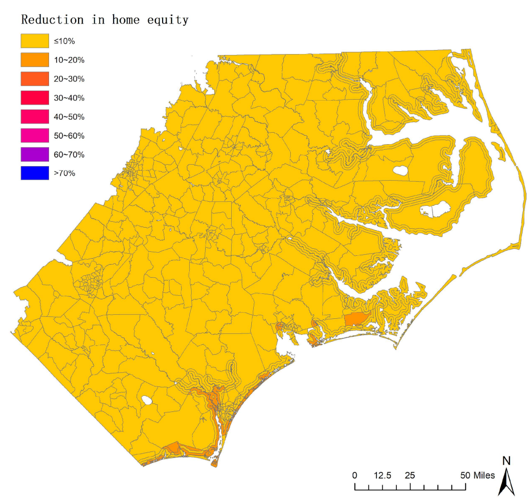
(a) 1F (insurance policy 2)



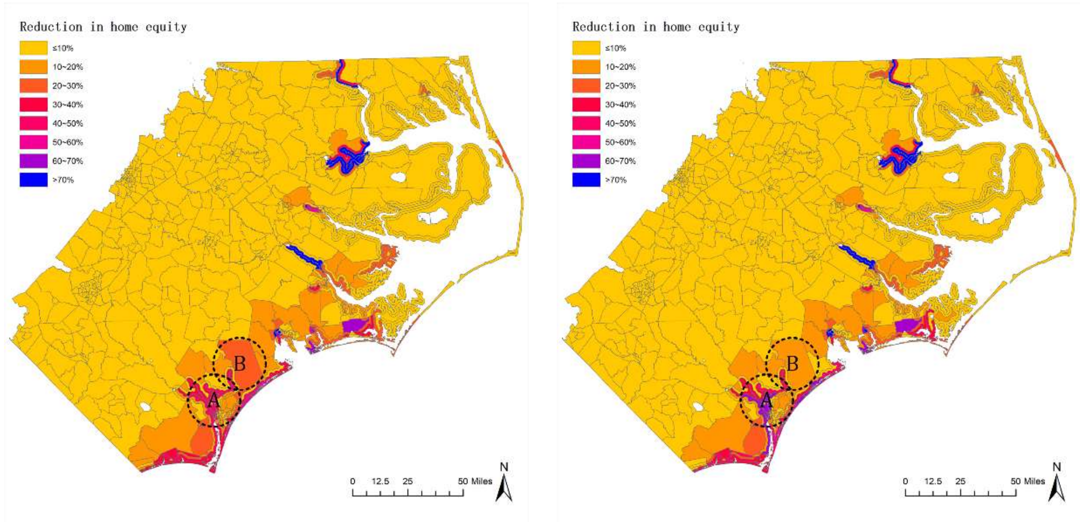
(b) 4F (insurance policy 3)



(c) 1.35 all L (insurance policy 4)



(d) 1.95 all L (insurance policy 5)



(e) 1.35 choice L (insurance policy 6) (f) 1.95 choice L (insurance policy 7)

Figure 3-2 Reduction in home equity for the low income under different insurance policies.

Reduction in home equity (average of 100 scenarios) by income groups and risk regions under different insurance policies is summarized in Table 3-1. Based on the results in this table, we notice that low income households mostly suffer from more home equity loss as compared to middle and high income households in both the low risk region and the high risk region. Exceptions are made when insurance policy 4 and 5 are carried out and only the high risk region is considered (6.8% vs. 11.0% for policy 4 and 4.2% vs. 11.0% for policy 5). This suggests that, to alleviate the situation of different income-level groups experiencing hurricanes inequitably, generally more home equity loss is posed on the low income than the middle and high income as an example, insurance needs to be designed and structured with special considerations to assist the underprivileged, especially those of less wealth and living in the high risk areas.

Table 3-1 Reduction in home equity by income groups and risk regions under different insurance policies

% reduction in home equity	LR	HR

	L	M/H	L	M/H
No insurance	3.7	1.4	21.4	14.0
1F (L/M/H)	1.9	0.7	18.0	12.0
4F (L/M/H)	1.9	0.7	16.2	10.7
4F (M/H), 1.35 (all L)	1.3	0.7	5.7	10.6
4F (M/H), 1.95 (all L)	0.9	0.7	3.2	10.6
4F (M/H), 1.35 (choice L)	2.9	0.7	14.8	10.7
4F (M/H), 1.95 (choice L)	2.6	0.7	15.4	10.7

Fig. 3-3 illustrates the distribution of home equity loss for 100 scenarios by different income-level groups and hurricane risk regions. It can be noted that the median and the variance of home equity loss in the high risk region are noticeably higher than their counterparts in the low risk region in most cases. The low income households in the high risk region are found to be in a more severe situation as compared to others under insurance policies 1, 2, 3, 6, and 7. Under policy 4 and 5, this particular group are well-protected but there are still scenarios in which they lose up to 36% of home equity after 20 years. The main reason to account for this is that the insurance pool which poses mandatory insurance on low income households can fail to honor claims after spending all funds collected from premiums, and insurance price as low as 1.35/1.95 per dollar loss can easily trigger the insolvency of the pool when severe events occur (1.95 per dollar loss is slightly better than 1.35 as suggested by the tight variation of policy 5 for the low income in the high risk region).

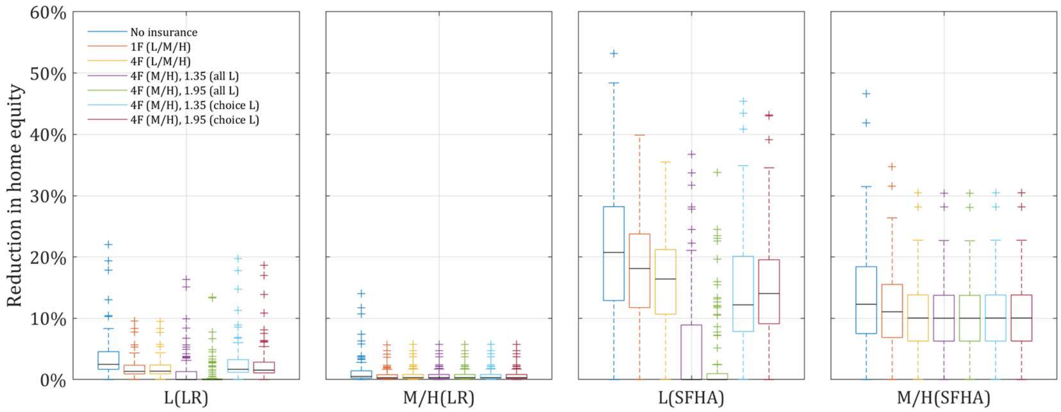
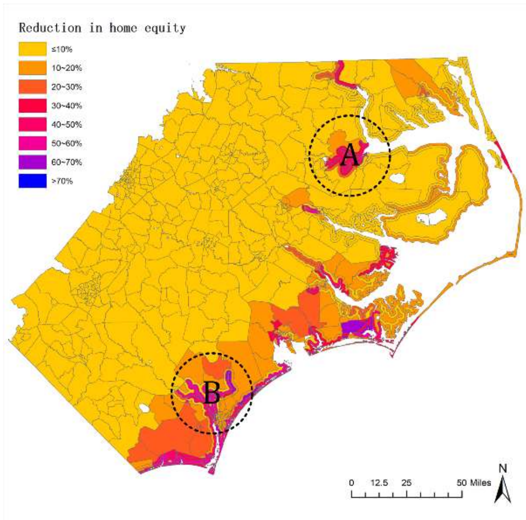


Figure 3-3 Reduction in home equity by income groups and risk regions under different insurance policies (distribution for 100 scenarios)

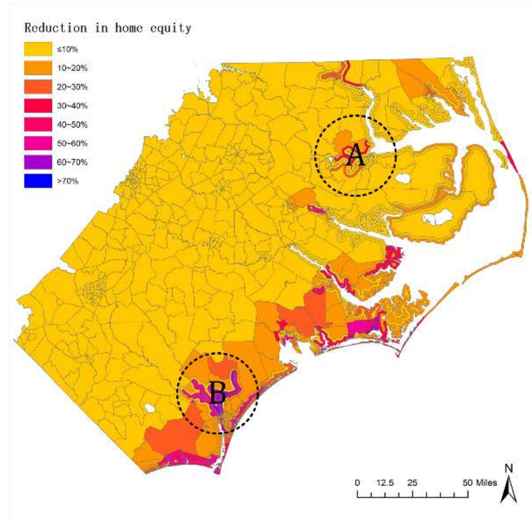
3.5 Effectiveness of hazard mitigation interventions combining mitigation measures and insurance

We further investigate the effectiveness of hazard mitigation measures that combine home retrofit, property acquisition, and insurance tools in reducing home equity loss for low income households. The mitigation policies remain the same as in previous chapters, namely, 1) no home retrofit (including self-funded) or property acquisition; 2) a combination of government-funded home retrofit and property acquisition constrained by a limited budget, and self-funded home retrofit; 3) the integration of government-funded home retrofit and property acquisition constrained by a limited budget and applied to the high and middle income households and a parallel program for low income households with an unlimited budget but only for mitigation and acquisition opportunities with expected reduction in losses that exceeds cost.

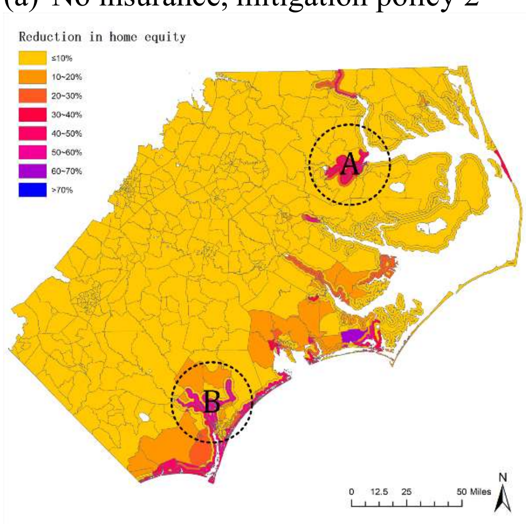
Fig. 3-4 shows reduction in home equity for low income households after 20 years under different mitigation and insurance policies. There are several points from the comparison of Fig. 3-1 (a), Fig. 3-2 (b), (d), (f), and Fig. 3-4 (a)~(h) that are noteworthy. First, the implementation of mitigation measures further improves the reduction of home equity loss achieved by only insurance policies. As an example, home equity loss for low income households in the high risk area at the junction of Bertie County, Washington County, and Martin County (area A) exceeds 70% of the undamaged home equity in insurance policy 3, and 7 in Fig. 3-2 (b) and (f). After the introduction of mitigation interventions, the reduction in home equity for this area decreases to 50~60% as shown in Fig. 3-4 (c), (d), (g), and (h). Next, mitigation policy 3 which propels home retrofit and property acquisition for the low income with unlimited budget achieves more substantial loss reduction effects in most areas prone to hazards than mitigation policy 2 in which the $100 million government budget is spent on all households (Fig. 3-4 (a), (c), and (g) compared to (b), (d), and (h)). However, in areas in Pender County and New Hanover County (area B), for the no insurance case, the decline in home equity after 20 years under mitigation policy 3 is larger than that in mitigation policy 2 (Fig. 3-4 (a) and (b)). It turns out that mitigation policy 2 realizes wide acquisition in this area (e.g., in census tract 428 in Pender County, 157 out of 180 houses get acquired in year 17 under mitigation policy 2), while no acquisition is performed here during the 20 years by mitigation policy 3. In addition, in Fig. 3-4 (e) and (f), areas in Brunswick County and Craven County (area C and D) see over 10% home equity loss after 20 years under mitigation policy 3 but less than 10% under mitigation policy 2, even though the most potent insurance policy (insurance priced at 1.95 per dollar of loss mandatory for all low income households) is applied. This stems from the fact that, in comparison to mitigation policy 2, mitigation policy 3 has a much more substantial impact on reducing the expected loss which causes the insurance pool to face higher insolvency risks since it collects less premiums. The cash position of the insurance pool in Fig. 3-5 further explains this situation as the financial status of the pool corresponding to mitigation policy 3 is outmatched by the case of no mitigation and mitigation policy 2.



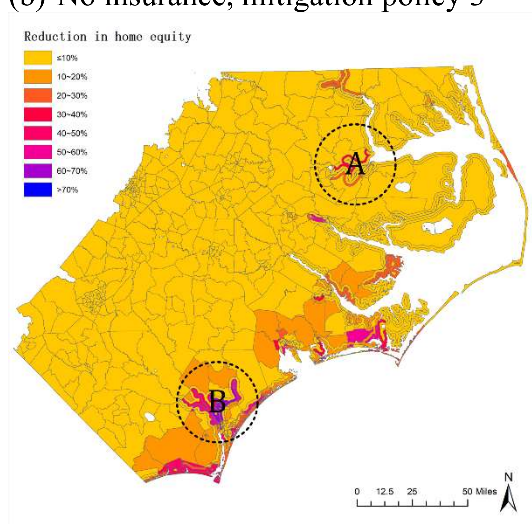
(a) No insurance, mitigation policy 2



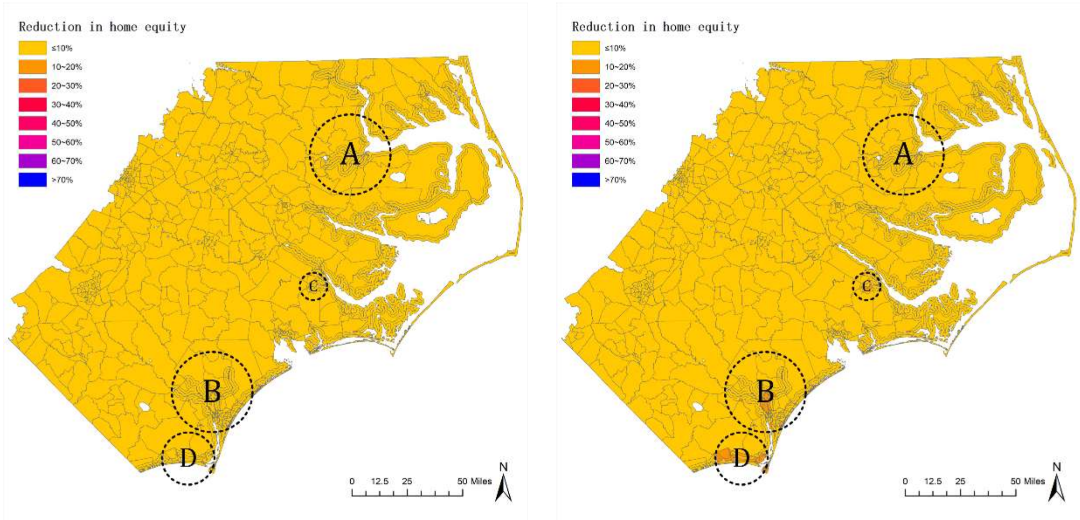
(b) No insurance, mitigation policy 3



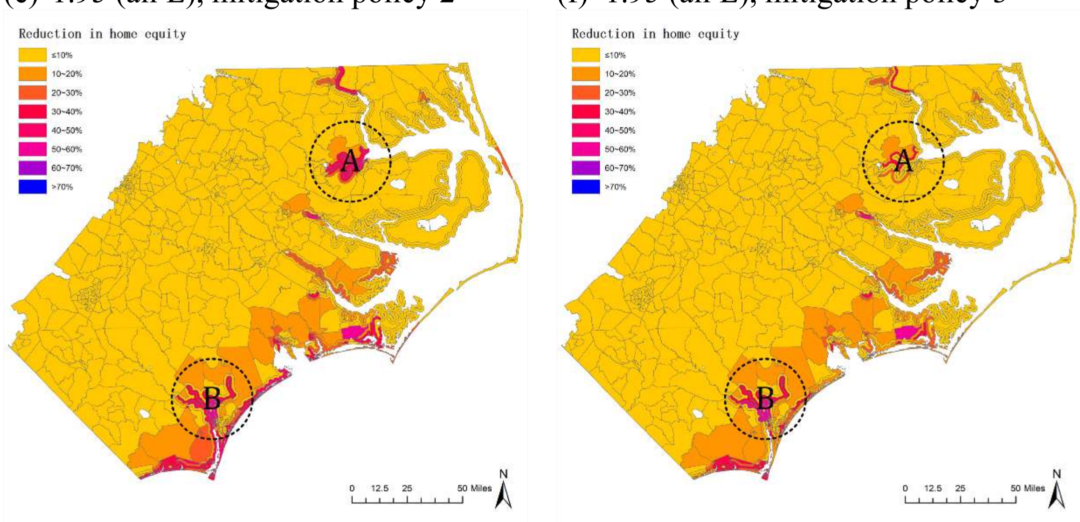
(c) 4F, mitigation policy 2



(d) 4F, mitigation policy 3



(e) 1.95 (all L), mitigation policy 2 (f) 1.95 (all L), mitigation policy 3



(g) 1.95 (choice L), mitigation policy 2 (h) 1.95 (choice L), mitigation policy 3

Figure 3-4 Reduction in home equity for low income households after 20 years under different mitigation and insurance policies (average of 100 scenarios).

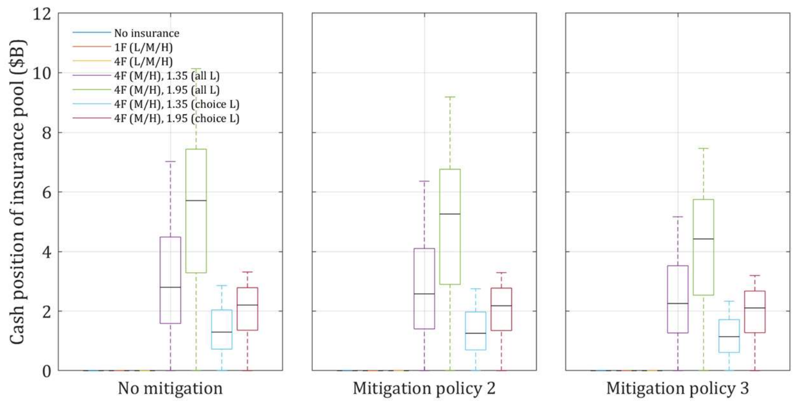
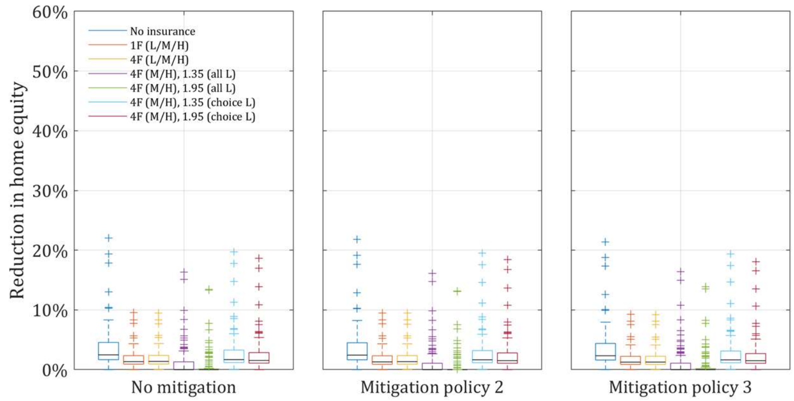


Figure 3-5 Cash position of the insurance pool in year 20 across 100 scenarios.

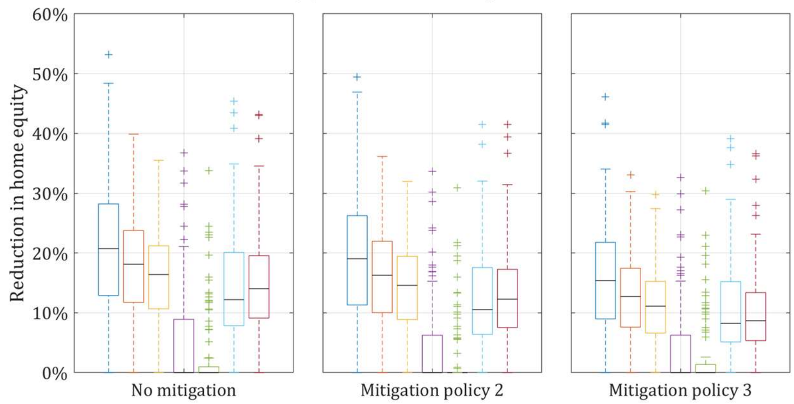
At last, the reduction in home equity after 20 years for low income households in the low risk and high risk regions under different mitigation and insurance policies is presented in Table 3-2 (average of 100 scenarios) and Fig. 3-6 (distribution for 100 scenarios). The most effective loss prevention result in the mean sense for the high risk region is attained by mitigation policy 2 paired with insurance policy 5 (1.95 per dollar of loss mandatory for all low income households). The performance of this combination is also very consistent across all the scenarios as indicated in Fig. 3-6 (b).

Table 3-2 Reduction in home equity after 20 years for low income households in the low risk and high risk regions under different mitigation and insurance policies (average of 100 scenarios)

% reduction in home equity for low income households	LR			HR		
	No mitigation	Mitigation policy 2	Mitigation policy 3	No mitigation	Mitigation policy 2	Mitigation policy 3
No insurance	3.7	3.6	3.5	21.4	19.6	16.6
1F	1.9	1.8	1.8	18.0	16.2	13.2
4F	1.9	1.9	1.8	16.2	14.4	11.6
1.35 (all L)	1.3	1.2	1.2	5.7	4.5	4.5
1.95 (all L)	0.9	0.8	0.9	3.2	2.6	2.7
1.35 (choice L)	2.9	2.8	2.8	14.8	13.0	11.0
1.95 (choice L)	2.6	2.6	2.5	15.4	13.6	10.6



(a) Low risk region



(b) High risk region

Figure 3-6 Reduction in home equity after 20 years for low income households in the low risk and high risk regions under different mitigation and insurance policies (distribution for 100 scenarios).

3.6 Conclusion

In this work, we investigate impacts of hurricane events and hazard mitigation measures on the home equity of different income-level groups in eastern North Carolina. We find that, without mitigation and insurance interventions, low income households, especially those living in the high risk region, suffer the most. Mitigation and insurance policies, when designed with special considerations to assist the most vulnerable, are proven to be effective in reducing hurricane losses and alleviating inequity. Moreover, experiments of mandatory insurance policies supplied to all low income households demonstrate the importance of increasing the low income's access to insurance and the necessity of strengthening insurance carrier's financial sustainability.

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