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FEATURE ARTICLE

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Dynamic modeling of public and private decision-making for hurricane risk management including insurance, acquisition, and mitigation policy

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Abstract

We develop a computational framework for the stochastic and dynamic modeling of regional natural catastrophe losses with an insurance industry to support government decision-making for hurricane risk management. The analysis captures the temporal changes in the building inventory due to the acquisition (buyouts) of high-risk properties and the vulnerability of the building stock due to retrofit mitigation decisions. The system 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.

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 governmental and private sector interventions have been implemented, including (1) the National Flood Insurance Program, (2) the Hazard Mitigation Grant Program, and (3) state insurance catastrophe pools. 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 paper is to understand how these tools are used in concert to reduce the magnitude of the insured and uninsured losses while maintaining a robust market for insurance. A static model that focuses on a single event or even a single year does not capture the changing nature of the housing stock or its vulnerability. To properly examine the impact of homeowner response to a portfolio of loss mitigating options, the decision must be placed in a dynamic context that extends over several years with the possibility of multiple damaging events. Furthermore, a recent damaging event affects homeowner choices. The dynamic process of updating the inventory of insured and uninsured properties to reflect these temporal changes in response to multiple loss mitigation options is a major contribution of this study. When coupled with a dynamic and temporally responsive insurance model, we produce insight on how policy to encourage retrofits and acquisition interact to affect overall losses and insurer solvency.

Government acquisition or buyout is considered one of the most effective methods of removing high-risk properties from the building stock. Under a buyout program, homeowners have the option to sell the property to the government for demolition or relocation of the structure. In our modeling framework, we consider the acquisition of properties in high hurricane risk zones. These are properties subject to storm surge, wind, hurricane-induced flooding, and possibly coastal erosion. Historically, high flood risk and repeat loss properties have been targeted for acquisition with a percentage of fair market value funded by the Federal Emergency Management Agency's Hazard Mitigation Grant Program. Contracts are voluntary, so individual homeowners may choose to accept or reject offers made by local authorities. By making offers based on predamage assessments of the home, acquisition programs provide an opportunity for homeowners to protect themselves against decreased home values in the wake of a damaging event (Frimpong et al., 2019).

For existing homes, retrofitting to improve resistance can reduce hurricane-related damages. This study considers a comprehensive set of retrofit alternatives for each house, representing the effect of each on the home's loss distribution. The wind retrofit strategies are: 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. The flood retrofit strategies are: (1) elevate appliances and electrical, (2) upgrade siding and insulation, and (3) elevate the entire house. To allow the representation of the retrofit alternatives, we defined six components: roof cover, roof sheathing, roof-to-wall connections, openings (that is, windows, doors, garage doors), walls, and flood susceptibility. The retrofit alternatives were chosen with the intent to be useful for discussion with policymakers and homeowners, associated costs can be estimated, and their effect on losses can be computed by comparing losses estimated with and without their implementation.

Nested and integrated models have been implemented to examine important aspects of 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 et al., 2011; Han & Peng, 2019) have been the foci 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 characterize the government entity as creating incentives to achieve its objective of recognizing homeowner choices and insurers that interact with regulatory constraints, homeowners, and other insurers in an insurance market with risk-based premiums.

This study builds upon prior work concerned with the interaction between the government, insurers, and homeowners. 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, an expected utility-based homeowner model for insurance purchase decision-making, and a stochastic programming model of a single insurer that optimized 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. Furthermore, the government options are limited to regulation on the capital sufficiency of the insurance carrier. Gao et al. (2016) expanded the insurer-homeowner interactions to include multiple insurance firms. The resulting strategic competition under multiple firm scenarios yields a range of premium prices, take-up rates, and profitability that vary with the number of insurers in the market.

Wang et al. (2020) extend 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 previous expected utility-based decision models.

The current formulation creates a dynamic framework that adopts the features of Gao et al. (2016) and Wang et al. (2020). There is a game-theoretic representation of insurance carrier competition; government decision-making is represented explicitly; and homeowner demand for insurance, retrofit, and acceptance of acquisition offers are based on survey-based choice models. Moving to a dynamic modeling framework allows the impact of government, insurer, and homeowner decision-making to evolve with (1) 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 hurricane experiences. 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 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 and linked to events as they occur and the evolving condition of the inventory.

The remainder of this paper is organized as follows. Section 2 introduces the framework and its component models. Section 3 presents the formulated simulation-optimization problem and its solution procedure. Section 4 describes a case study for homes in eastern North Carolina. Section 5 provides conclusions and opportunities for future research.

2 | MODELING FRAMEWORK

2.1 | Framework components

Figure 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 allocates for a predefined budget appropriation, the homes to receive acquisition offers, the terms of those offers, and the areas in which they will offer retrofit grants, and the terms of those grants. The primary insurers provide insurance to the homeowners with the goal of maximizing profit. In the homeowner model, each homeowner chooses whether or not they will (1) accept an acquisition offer; (2) engage in retrofit and, if so, the type of retrofit; and (3) purchase insurance.

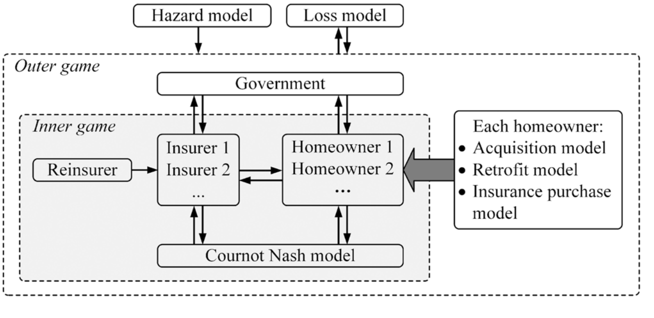

FIGURE 1 Base, stakeholder, and game-theoretic components in the modeling framework.

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 response to policy options. The insurers and the homeowners are also engaged in a Cournot–Nash noncooperative game that 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 Figure 1 indicate the direction of influence. The remainder of this section describes these models. Detailed descriptions of the component models can be found in Gao et al. (2016), Kesete et al. (2014), Peng et al. (2014), and Wang et al. (2020).

2.2 | Individual models

2.2.1 | Hazard model

We represent the hurricane hazard 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, $h \in (1, \ldots, H)$, 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 span as a scenario, denoted by s, and hurricanes can occur in any of 20-time slots each year for a total of 400-time steps in a single scenario.

2.2.2 | 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 the Florida Public Hurricane Loss Model for wind-related losses (2005) and flood-related losses based on Taggart and van de Lindt (2009) and van de Lindt and 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 a housing retrofit is implemented.

2.2.3 | 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 Chiew et al. (2019), Frimpong et al. (2019), Robinson et al. (2018), and Wang et al. (2017) 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; (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 $j \in J_{i,m,c,v}^{\text{acq}}$ and $J_{i,m,c,v}^{\text{acq}}$ 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 $\text{price}_i^{\text{acq}}$, 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 $\text{price}_i^{\text{acq}}$ to $c_{\text{adj}}^{\text{acq}} \cdot \text{price}_i^{\text{acq}}$ with $c_{\text{adj}}^{\text{acq}}$ being an adjustment coefficient. In this way, the acquisition decision-making model acts differently for newly-damaged and nondamaged 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 the homeowner's employment status. A simulated homeowner j's retrofit decision is denoted by the binary variable $D_{j,c'}^{\text{ret}}$, $j \in J_{i,m,c,v}^{\text{ret}}$ with the resultant variable c' being the house resistance level after the 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}, $j \in J_{i,m,c,v}^{\text{ins}}$. We use different superscripts in $J_{i,m,c,v}^{\text{acq}}$, $J_{i,m,c,v}^{\text{ret}}$, and $J_{i,m,c,v}^{\text{ins}}$ 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 (2017) FORTIFIED Home program, 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) (Equation 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 (Equation 2). The actual deductible value $d^h_{i,m,c,v}$ beneath the deductible threshold, d^{-}, is expressed in Equation (3):

$$\mathrm{price}^{\mathrm{ins}}_v \cdot \left(L^h_{i,m,c,v} - d^h_{i,m,c,v}\right) > \eta, \tag{1}$$

$$\mathrm{price}^{\mathrm{ins}}_v \cdot \left(L^h_{i,m,c,v} - d^h_{i,m,c,v}\right) < \kappa_v \cdot \mathrm{HV}_m, \tag{2}$$

$$d^h_{i,m,c,v} = \min\left\{L^h_{i,m,c,v}, \overline{d}\right\}. \tag{3}$$

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

2.2.4 | Insurer model

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

$$F_{s,y} = \sum_v \mathrm{price}^{\mathrm{ins}}_v \cdot Q_v - \tau \cdot \sum_v Q_v - \sum_t \sum_h \gamma^h_{s,y,t} \cdot I^h + \sum_t \sum_h \gamma^h_{s,y,t} \cdot B^h + \beta \cdot \sum_t \sum_h \gamma^h_{s,y,t} \cdot e^h - r_{s,y}. \tag{4}$$

The first term on the right-hand side of Equation (4) represents the total insurance premiums collected by the insurer: the premium price, $\mathrm{price}^{\mathrm{ins}}_v$, 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

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

The second term in Equation (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

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

and

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

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 Equation (4) expresses the losses covered by the reinsurer, and

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

As in Figure 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 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 Equation (4) corresponds to the reinsurance premium as

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

where ϕ is a predefined 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,

$$\max_{A,M} E_s\left[\left(E_y \tilde{F}_{s,y}\right)\right] \tag{10}$$

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

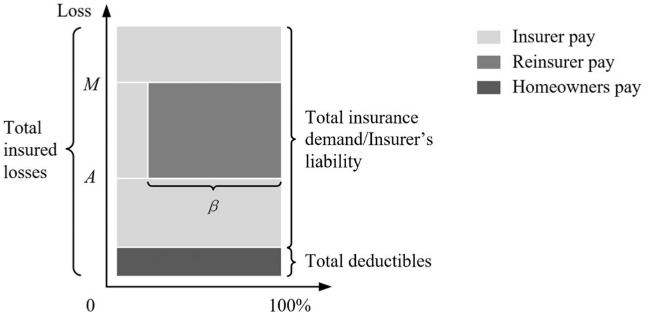

FIGURE 2 Hurricane losses coverage structure for the case of the total losses exceeding the maximum payout.

$$\text{cash}_{\text{s,y}} = \min\{\text{initial\_capital}, \text{cash}_{s,y-1} + F_{s,y}\}. \tag{11}$$

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 policies 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 $\text{cash}_{s,y}$ could drop below zero due to the large negative profit $F_{s,y}$, and accordingly, the insurer would be considered insolvent.

2.2.5 | 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 noncooperative 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 purchases 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 $\text{price}_v^{\text{ins}} = \text{ID}_v(q_{w,v}, Q_{-w,v})$. The cost function for insurer w is generated by function fitting based on results from the insurer optimization and is denoted by $\text{CF}(q_{w,\text{LR}}, q_{w,\text{HR}})$. 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

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

Assuming differentiability, the optimal $q_{w,v}$ satisfies the first-order condition. For $q_{w,\text{HR}}$, we have

$$\frac{\partial \text{ID}_{\text{HR}}(q_{w,\text{HR}}, Q_{-w,\text{HR}})}{\partial q_{w,\text{HR}}} \cdot q_{w,\text{HR}} + \text{ID}_{\text{HR}}(q_{w,\text{HR}}, Q_{-w,\text{HR}}) - \frac{\partial \text{CF}(q_{w,\text{LR}}, q_{w,\text{HR}})}{\partial q_{w,\text{HR}}} = 0. \tag{13}$$

Combining $Q_{-w,\text{HR}} = (n-1) \cdot q_{w,\text{HR}}$, 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.

2.3 | Government model

2.3.1 | Government decisions

We assume that the core decisions of the government policymaker as they attempt to manage the regional risk are the pricing of property acquisition and retrofit subsidization given a 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 typical acquisitions that specify neighborhoods for acquisition rather than a patchwork of properties (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' costs 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 $\text{price}_i^{\text{acq}}$ for homes in area i as

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

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

$$\text{cost}_{i,m}^{\text{acq}} = \text{price}_i^{\text{acq}} \cdot \text{HV}_m. \tag{15}$$

This pricing method allows prices to vary across zones through the impact of the second term on the right-hand side of Equation (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 $c_{\text{base}}^{\text{acq}}$ and $c_{\text{prop}}^{\text{acq}}$. Besides, for those who have experienced a hurricane in the previous year, they are actually offered $c_{\text{adj}}^{\text{acq}} \cdot \text{price}_i^{\text{acq}}$ instead of $\text{price}_i^{\text{acq}}$, where $c_{\text{adj}}^{\text{acq}}$ is a nonnegative 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.

A strategy similar to that used for acquisition is adopted for retrofit subsidization. The percentage price for retrofit subsidization for homeowners in the area i is

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

Here, $c_{\text{base}}^{\text{ret}}$ is the base price, $c_{\text{prop}}^{\text{ret}}$ represents the proportional factor, $X_{i,m,c,v}^{\text{ret}}$ 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 $c_{\text{base}}^{\text{ret}}$ is a nonnegative variable, but we allow $c_{\text{prop}}^{\text{ret}}$ to take either positive or negative value since there is always a tradeoff between supporting the upgrade of fewer but most vulnerable houses and supporting the reinforcement of more moderately risky buildings. Moreover, the actual retrofit subsidy offered to a homeowner is

$$\text{subsidy}_{i,m,c,c'}^{\text{ret}} = \min\left\{\text{price}_i^{\text{ret}} \cdot \text{cost}_{m,c,c'}^{\text{ret}}, \bar{J}\right\}, \tag{17}$$

where $\text{cost}^{\text{ret}}_{m,c,c'}$ 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. Higher resistance levels are coded to have larger values, so $c' > c$.

2.3.2 | Grant allocation strategy

Areas identified for grants are prioritized by cost-effectiveness ratios (ratio of government spending to losses reduced by mitigation). In practice, we calculate the cost-effectiveness ratios, regarding acquisition and retrofit, for each area based on simulated homeowner decisions and expected losses. Grants are offered to select areas in rank order until the total limit on spending is exhausted.

2.3.3 | Government objective

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

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

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

$$U^h=\underset{D^{\text{ins}}}{E}\left[\sum_i\sum_m\sum_c\sum_v\sum_{j\in J^{\text{ins}}_{i,m,c,v}}L^h_{i,m,c,v}\cdot\left(1-D^{\text{ins}}_j\right)\right]. \tag{19}$$

2.3.4 | Spending constraint

The spending on property acquisition and retrofit subsidization are constrained by an annual dollar provision for risk reduction. Combining Equation (15) and Equation (17), the constraint for the government optimization is

$$\begin{aligned}&\underset{D^{\text{acq}}}{E}\left[\textstyle\sum_i\sum_m\sum_c\sum_v\sum_{j\in J^{\text{acq}}_{i,m,c,v}}\text{cost}^{\text{acq}}_{i,m}\cdot D^{\text{acq}}_j\right]\\&\quad+\underset{D^{\text{ret}}}{E}\left[\textstyle\sum_i\sum_m\sum_c\sum_v\sum_{j\in J^{\text{ret}}_{i,m,c,v}}\sum_{c':c'>c}\text{subsidy}^{\text{ret}}_{i,m,c,c'}\cdot D^{\text{ret}}_{j,c'}\right]\le\Omega,\end{aligned} \tag{20}$$

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 spending plan.

2.4 | Dynamic modeling framework

The dynamic modeling framework is shown in Figure 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 each year, no hurricane events, one event, or multiple events may occur.

The steps corresponding to the items in Figure 3 are given below.

For each scenario:

1. Set the year index as 1 and initialize the building inventory and the homeowner characteristics.
2. Perform the government optimization based on full knowledge of the annual probability that a hurricane or multiple hurricanes occur and their expected intensity and generate the optimal acquisition and retrofit pricing policies. Decision-makers are forward-looking based on expectation and know the history of prior year events. On this basis, they offer contract terms for acquisition and retrofit subsidies to homeowners.
3. Simulate homeowner choice on whether or not to accept the government acquisition offer and update the building inventory accordingly (removing acquired homes).
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 (upgrading the storm resistance of retrofitted homes).
5. Simulate homeowner demand for insurance based on the updated inventory and perform insurer optimization to calculate the equilibrium risk-based insurance prices.
6. Enact homeowner purchase of insurance based on the equilibrium insurance prices.
7. Calculate the impact of the hurricane(s) 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, end the simulation.
10. Increase the year index by 1 and go back to Step 2 to start analysis for the next year.

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

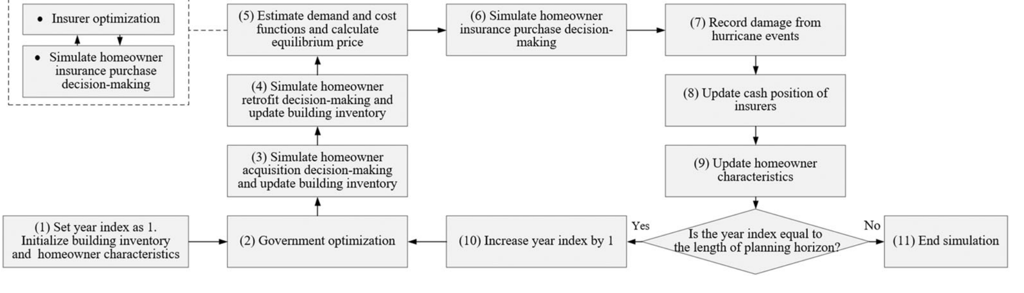

FIGURE 3 Dynamic modeling framework.

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 and mitigation incentive programs that are used to simulate these decisions by the homeowners in Steps 3 and 4.

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, 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 as constant parameters.

Formally, in the present simulation optimization problem, the optimization objective for the government is to minimize the total 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, $c_{\text{base}}^{\text{acq}}$ and $c_{\text{prop}}^{\text{acq}}$, the adjustment coefficient used to incorporate homeowners' reaction to hurricane events in the acquisition pricing, $c_{\text{adj}}^{\text{acq}}$, and the base and the proportional factors of the retrofit subsidization, $c_{\text{base}}^{\text{ret}}$ and $c_{\text{prop}}^{\text{ret}}$. The main constraint is the government spending limit, Equation (20), and other feasible ranges for variables can be found in model descriptions in Section 2 and literature by Apivatanagul et al. (2011), Gao et al. (2016), Kesete et al. (2014), Peng et al. (2013, 2014), and Wang et al. (2020).

The general simulation phase is illustrated in Figure 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 and trust regions 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).

4 | CASE STUDY

4.1 | Input description

The proposed dynamic modeling framework was tested and evaluated with a case study of single-family wood-frame homes in eastern North Carolina. Input data are listed in Table 1, and key parameters are given in Table 2. It should be noted that a single house could do multiple component retrofits at one time, depending on the homeowner's retrofit decisions.

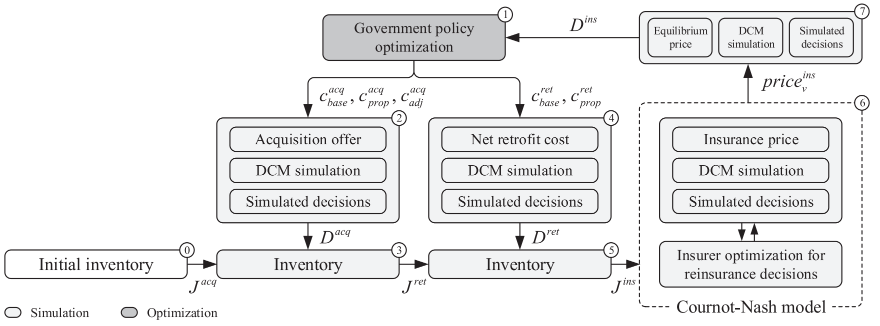

FIGURE 4 Simulation optimization structure. Marks on the top right corner of each block indicate the step numbers. DCM, discrete choice model.

Additional details can be found in Apivatanagul et al. (2011), Gao et al. (2016), Kesete et al. (2014), Peng et al. (2013, 2014), and Wang et al. (2020).

4.2 | Results and analysis

We will report the results from the 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 into hurricane risk management. Scenario 39 is a hurricane-active scenario placing it in the top 5% of scenarios for hurricane losses. Measurable hurricane losses occurred in nine out of its 20 years. Figure 5 summarizes the unmitigated flood- and wind-caused losses in the high- and low-risk regions for this scenario. Figure 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 100 additional hurricane scenarios randomly drawn from the set of 2000 potential scenarios. The 100 scenarios maintain the representativeness of the loss distribution. Additional draws from the 2000 scenario population did not change the mean, variance, and skewness of the distribution.

4.2.1 | 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 Figure 7. As can be seen from Figure 7a, the optimal acquisition is only offered to and accepted by homeowners in the high-risk region. Logically, high-risk region acquisitions provide more effective hurricane loss reduction. The number of completed offers year by year fluctuates as the tradeoff between acquisition and retrofit is close and influenced by previous acquisitions. Figure 7b–d illustrates 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 retrofits is much smaller than the number that self-fund retrofits.

TABLE 1 Data statistics

Subject	Number	Description
Building category m	8	Combinations of two story types, two garage types, and two roof shapes
Building resistance level c	192	Combinations of four flood resistance types, two wall resistance types, three opening resistance types, and eight roof-related resistance types
Building value	8	Refer to Gao et al. (2015)
Risk region v	2	High-risk region (less than 2 miles away from the coast) and low-risk region (more than 2 miles away from the coast)
Area unit i	1509	1006 in the high-risk region, 503 in the low-risk region
Residential building	931,902	292,890 in the high-risk region and 649,012 in the low-risk region.
Hurricane h	98	97 hurricane cases plus 1 case of no hurricane
Scenario	2000	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

Retrofitting for wind represents the predominant expenditure in all cases. In addition, over time the total number of retrofit decisions made 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.

Figure 8 shows the reduced expected annual losses based on homeowner acquisition and retrofit decisions for Scenario 39. By comparing Figure 8a and Figure 8b, it is apparent that the loss reduction effect is more pronounced with the 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 which has in fact implemented 685 buyouts as of 2018 (Salveson et al., 2018).

4.2.2 | Scenario 39: Insurance pricing, insured and uninsured losses

The Cournot equilibrium insurance prices for Scenario 39 are shown in Figure 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 level of insurer competition, and the evolution of the building inventory.

TABLE 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
$\bar{d}$	\$2500	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	Three times the first-year premium	Initial capital for each insurer in the market
Ω	\$100 million	Government appropriation
α	0.5	The coefficient in the objective function of the government optimization
$c^{\mathrm{acq}}_{\mathrm{base}}$	[0.75,1.25]	Government decision for acquisition pricing
$c^{\mathrm{acq}}_{\mathrm{prop}}$	[0,0.2]	Government decision for acquisition pricing
$c^{\mathrm{acq}}_{\mathrm{adj}}$	[0.6,1.2]	Government decision for adjusting the acquisition price based on the house's damaged/undamaged status
$c^{\mathrm{ret}}_{\mathrm{base}}$	[0.75,1]	Government decision for retrofit pricing
$c^{\mathrm{ret}}_{\mathrm{prop}}$	[−0.1,0.1]	Government decision for retrofit pricing
G	10^4	Scale adjustment parameter for retrofit pricing

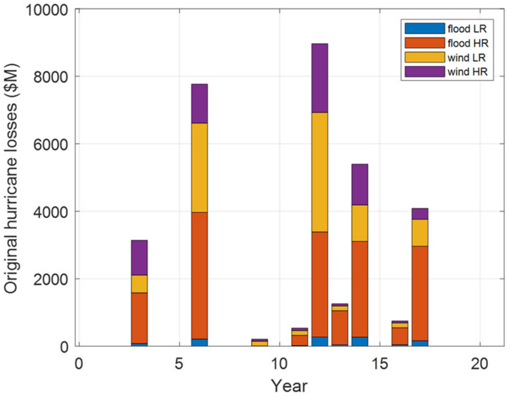

FIGURE 5 Hurricane losses in Scenario 39. HR, high risk; LR, low risk.

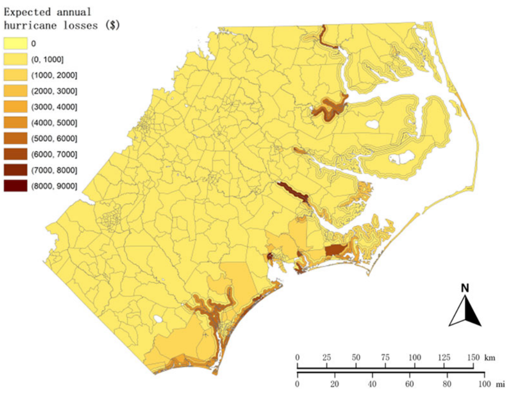

FIGURE 6 Expected annual hurricane losses, averaged over homes, for each area in eastern North Carolina.

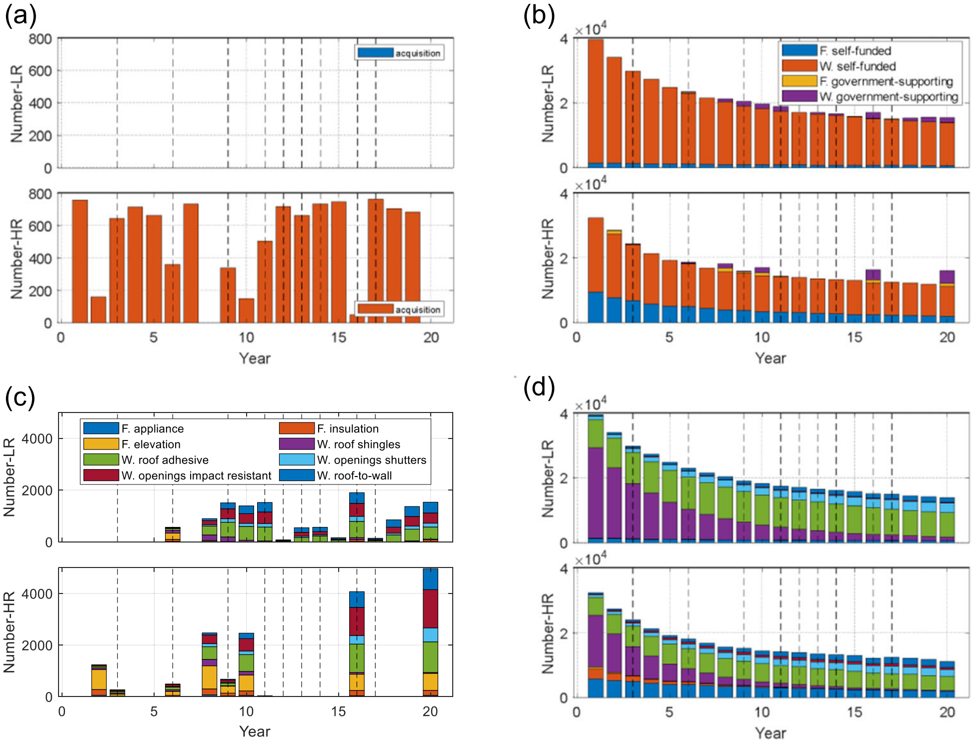

FIGURE 7 Number of homeowners in low-risk and high-risk regions that accept government acquisition offers (a) and implement retrofit (b–d) in Scenario 39. Dashed vertical lines indicate years of hurricane activity. (a) The number of homeowners that accept government acquisition offers. (b) The number of homeowners that implement government-supported and self-funded wind (W) and flood (F) retrofit. (c) The number of homeowners that implement government-supported retrofit by retrofit type. (d) The number of homeowners that implement self-funded retrofit by retrofit type. HR, high risk; LR, low risk.

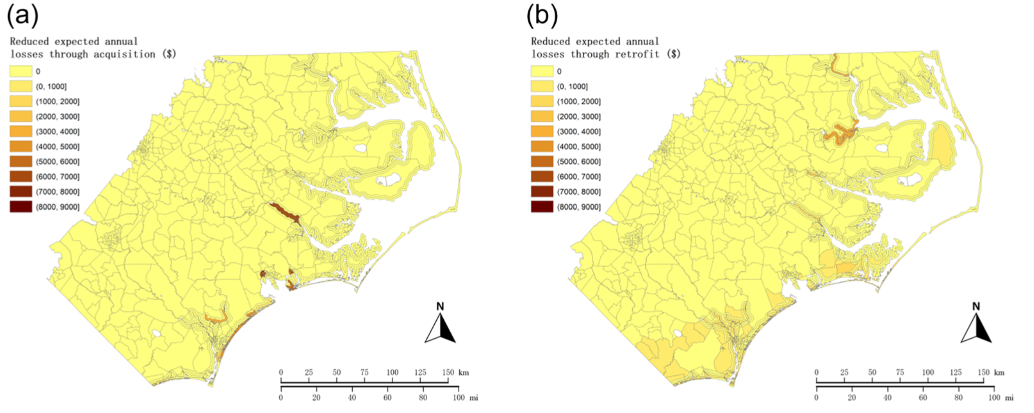

FIGURE 8 Reduced expected annual losses by acquisition and retrofit in Scenario 39. Results here are averaged over homes for each area and accumulate through 20 years. (a) Reduced expected annual losses through acquisition. (b) Reduced expected annual losses through retrofit.

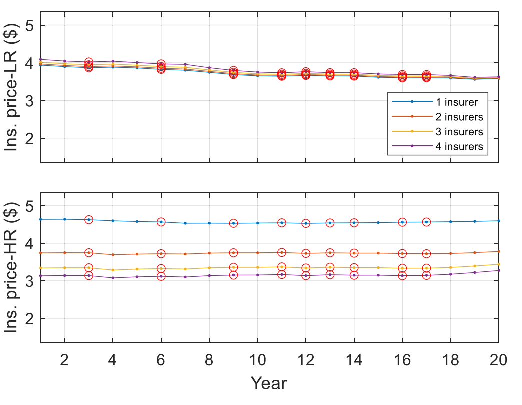

FIGURE 9 Equilibrium insurance prices in Scenario 39. Red circles indicate hurricane years. HR, high risk; LR, low risk.

Figure 10a,b shows 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 a 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 an 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 a minor impact (e.g., Year 9), (2) hurricanes occur consecutively for several years and homeowner characteristics remain almost unchanged (e.g., Year 11–14), 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-

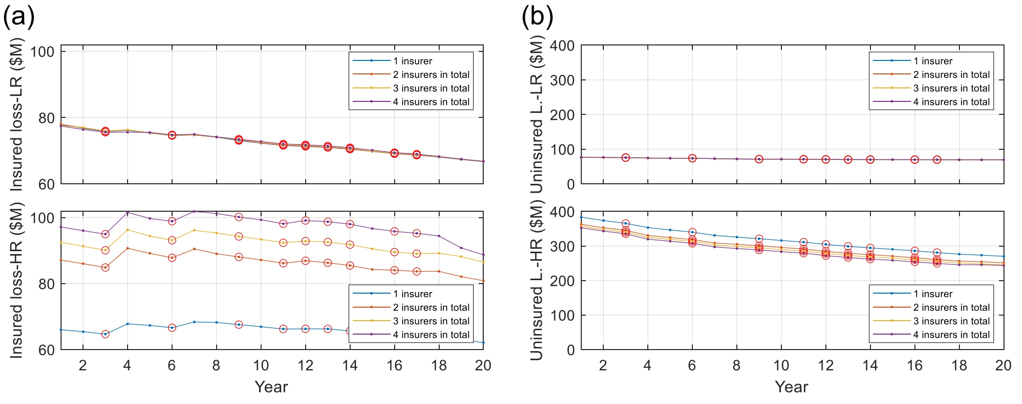

FIGURE 10 The expected total insured and the expected total uninsured losses for each year in Scenario 39. The displayed results count contributions from all insurers in the insurance market. (a) Expected total insured losses. (b) Expected total uninsured losses. HR, high risk; LR, low risk.

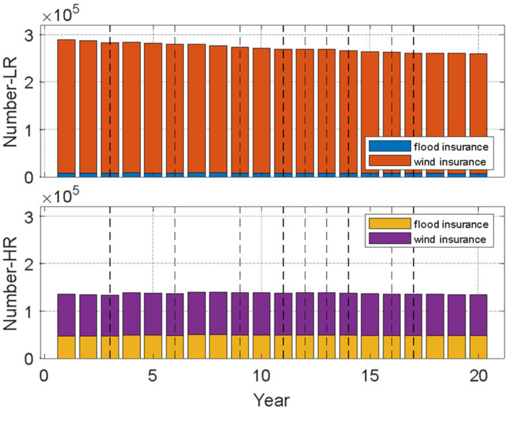

FIGURE 11 Number of homeowners that purchase flood and wind insurance in Scenario 39. HR, high risk; LR, low risk.

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. Furthermore, 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 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.

The number of homeowners purchasing flood and wind insurance is shown in Figure 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. Figure 12 illustrates the proportion of homes that are uninsured due to the insurance policy

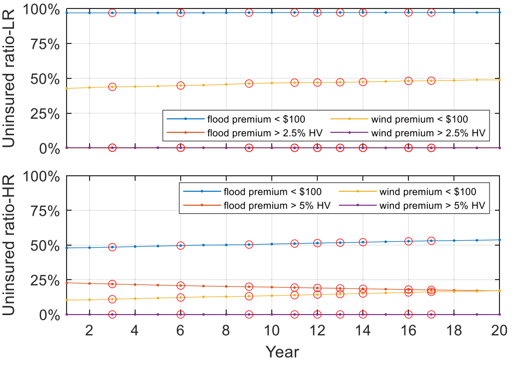

FIGURE 12 Proportion of uninsured homes due to insurance premium affordability and minimum premium constraints in Scenario 39. HR, high risk; LR, low risk.

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 the 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.

4.2.3 | Scenario 39: Government decisions

Figure 13 gives the optimal acquisition offers (Equation 14) and retrofit subsidy (Equation 16) for Scenario 39 (note that no value is given for the year if there were no acquisition offers/retrofit subsidy programs 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.

4.2.4 | Scenario 39: Expected total losses

Figure 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

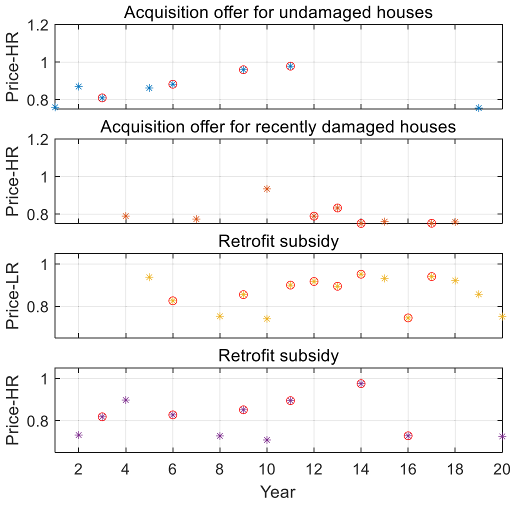

FIGURE 13 Optimal acquisition offer price (percentage of undamaged fair market value) and retrofit subsidy price (percentage of the total retrofit cost) in Scenario 39. HR, high risk; LR, low risk.

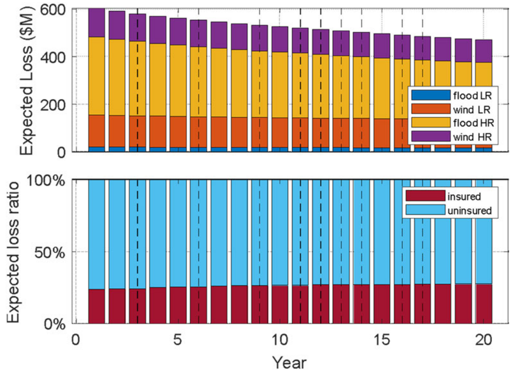

FIGURE 14 Expected total losses and loss ratio for Scenario 39. HR, high risk; LR, low risk.

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.

4.2.5 | Summary of 100 randomly drawn scenarios

In the following two sections, we provide a summary of insurance pricing, losses, government acquisition, and retrofit subsidies observed for 100 scenarios randomly drawn from the set of 2000 hurricane scenarios. A 100 scenarios preserve the representativeness of the loss distribution in terms of mean, variance, and skewness.

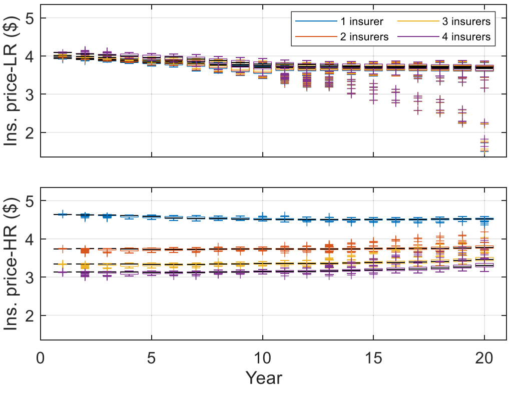

FIGURE 15 Summary of equilibrium insurance prices for 100 scenarios. HR, high risk; LR, low risk.

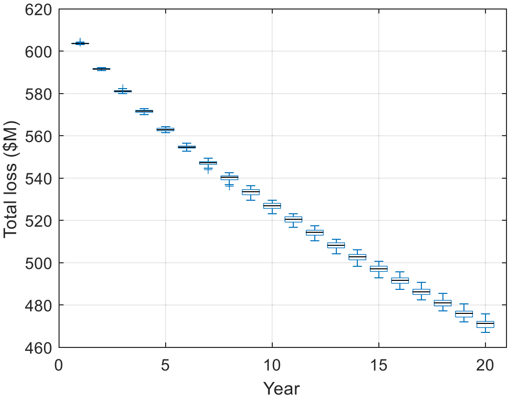

FIGURE 16 Expected total losses for 100 scenarios.

4.2.6 | One-hundred scenarios: Insurance pricing, government decisions, and expected total losses

The risk-based insurance prices that obtained in equilibrium for the 100 selected scenarios are shown in Figure 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 the market concentration and market shares from 100% for a single firm to 25% for one of four firms.

The pattern of expected total losses over the 20-year time horizon is consistent over all 100 scenarios as illustrated by the narrow distribution shown in Figure 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 Figure 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

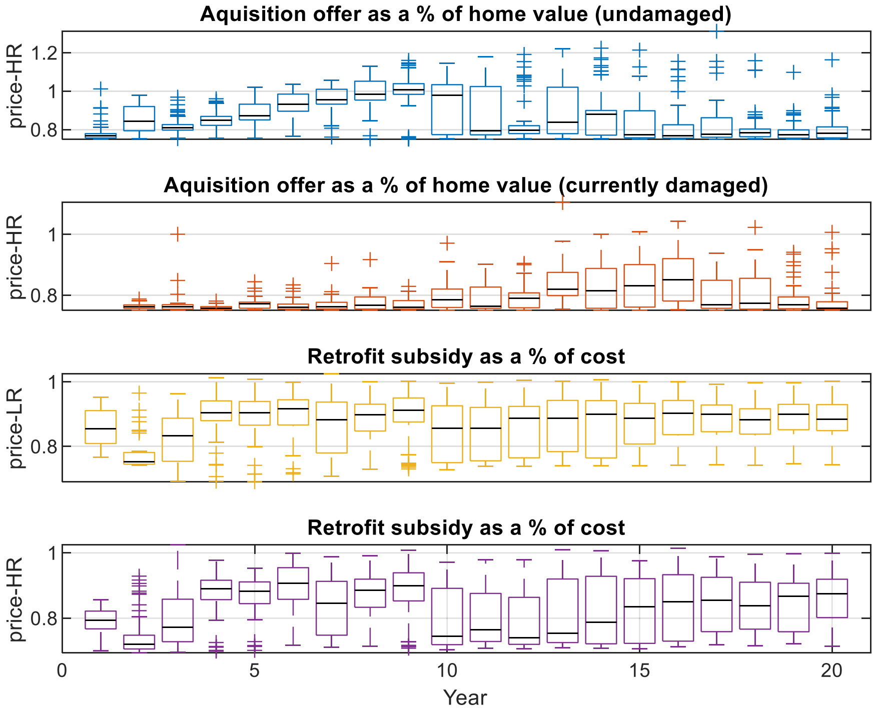

FIGURE 17 Optimal acquisition offer price (percentage of undamaged fair market value) and retrofit subsidy price (percentage of the total retrofit cost) for 100 scenarios. HR, high risk; LR, low risk.

two panes of the figure indicate retrofit subsidies that are relatively evenly distributed between high-risk and low-risk regions.

4.2.7 | One-hundred scenarios: Financial status of insurers

Figure 18 illustrates insurers' yearly cash positions for the 100 scenarios. Figure 18a represents the case where a cap on the maximum cash position is assumed to be equal to three times the value of the policies written in that year as in Equation (11). In contrast, Figure 18b 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 of Russell and 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 the threat of takeovers can all contribute to insufficient cash reserves. Notice that, in both cases in Figure 18, 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 from one to eight scenarios that cause issues with insolvency (with the four insurer cases leading to more scenarios with insolvency issues); with the cap, insolvency issues arise more frequently.

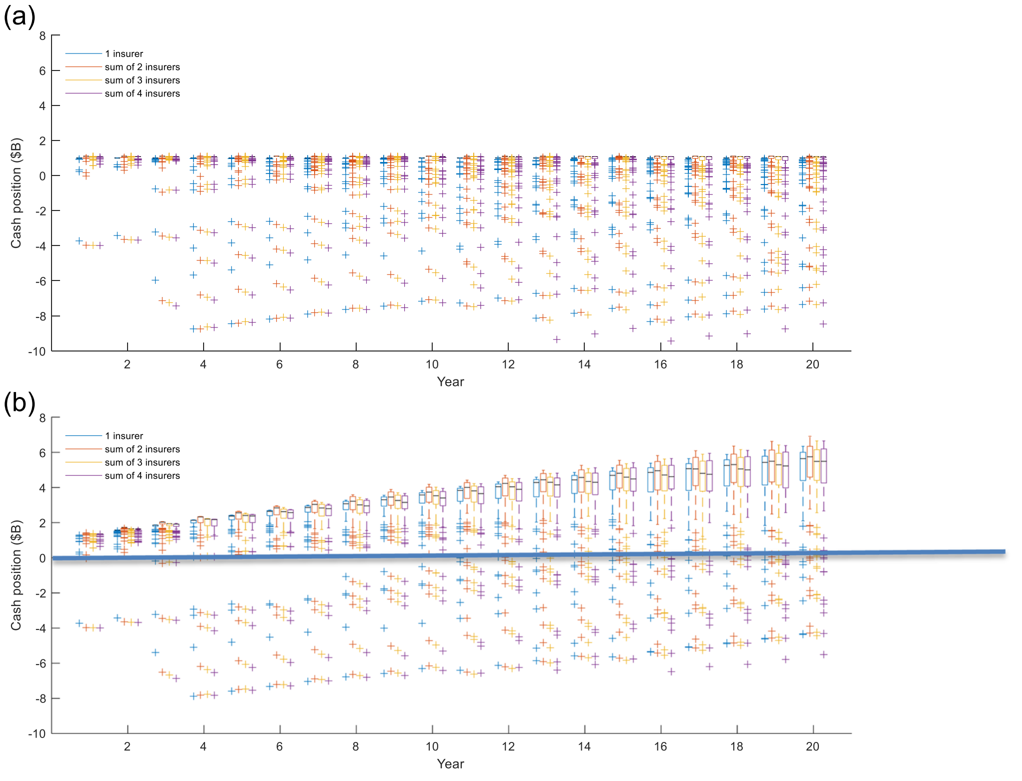

FIGURE 18 (a) Insurer's yearly cash position, with a cap on the maximum value. (b) Insurer's yearly cash position, with no cap.

5 | SUMMARY AND CONCLUSION

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 that 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, the 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 have chosen a limited set of policy options, namely acquisition/buyouts and retrofit subsidies. Other options such as zoning restrictions on development or building code requirements are most effective for new construction. Our approach was to take the existing building stock of varying resistance levels and examine the acquisitions and retrofits that the population of homeowners has indicated that they are willing to accept and adopt. This is coupled with risk-based insurance pricing derived from a voluntary insurance market. Our results indicate that a so-called win–win outcome is possible that benefits homeowners and supports a sustainable insurance industry.

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 reduction in expected insured and uninsured losses. We demonstrate that viable insurance industry is possible in the region that is further improved by the relaxation of constraints on cash carryover from year to year. Larger cash carryovers assure solvency in high-hurricane-loss years. Studies based on discrete-choice survey experiments of eastern North Carolina homeowners were 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 break-even at 23 years. This conservative estimate of net benefits does not take into account indirect economic benefits or increased risk due to climate change. Population pressure on desirable coastal regions coupled with the threat of sea-level rise implies 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 diverse groups could inform issues around equity and economic well-being. To expand the model, additional private sectors, and different public sector optimizations will be considered, and a broader representation of local and regional economies shall be included.

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