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Agent-based Modeling to Evaluate Human–Environment Interactions in Community Flood Risk Mitigation

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This article deals with household-level flood risk mitigation. We present an agent-based modeling framework to simulate the mechanism of natural hazard and human interactions, to allow evaluation of community flood risk, and to predict various adaptation outcomes. The framework considers each household as an autonomous, yet socially connected, agent. A Beta–Bernoulli Bayesian learning model is first applied to measure changes of agents' risk perceptions in response to stochastic storm surges. Then the risk appraisal behaviors of agents, as a function of willingness-to-pay for flood insurance, are measured. Using Miami-Dade County, Florida as a case study, we simulated four scenarios to evaluate the outcomes of alternative adaptation strategies. Results show that community damage decreases significantly after a few years when agents become cognizant of flood risks. Compared to insurance policies with pre-Flood Insurance Rate Maps subsidies, risk-based insurance policies are more effective in promoting community resilience, but it will decrease motivations to purchase flood insurance, especially for households outside of high-risk areas. We evaluated vital model parameters using a local sensitivity analysis. Simulation results demonstrate the importance of an integrated adaptation strategy in community flood risk management.

KEY WORDS: Adaptation; agent-based model; flood risk mitigation; protection motivation theory

1. INTRODUCTION

Traditionally, flood risk is measured by projecting flood events trends, which is a useful approach to quantifying flood risk and to facilitating the adaptation planning process. However, this traditional paradigm has been challenged by researchers for omitting consideration of uncertainties associated with flood damage and human behavior in the risk mitigation process (Chester, Underwood, & Samaras, 2020). Given the uncertainty of natural hazards and unfounded beliefs among the general public regarding climatic risk not borne out by science, a major concern of flood adaptation is the development of robust adaptation policies to improve community resilience (Oppenheimer, O'Neill, & Webster, 2008).

Successful flood adaptation and risk mitigation decisions to maintain or improve

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system resilience require understanding the interactions between physical and societal processes, which involves examining both natural and human systems (Fereshtehnejad et al., 2021). The interactions of flood risk and human adaptation comprise three related areas: the assessment of risk of the natural hazard (Nofal & van de Lindt, 2020), the human adaptive behavioral component (Scott & Lennon, 2020), and interactions between the human and natural systems (NASEM, 2018). Understanding the complex interactions and uncertainties within the natural and human systems is particularly important for managing long-term planning objectives and for sustaining the prosperity of coastal communities. Agent-based modeling (ABM), a powerful simulation technique, could capture the emergent phenomenon of the real-world through interactions of agents and the environment, and has the advantage of simulating the fine-scale, complex interactions between humans and the environment (Castle & Crooks, 2006).

The goal of this study is to enhance understanding of coastal risk management by integrating stochastic natural hazard and human risk mitigation into the evaluation of flood adaptation policies. To achieve this goal, this study developed an ABM to integrate the randomness of coastal hazards, the cognitive process of agents in risk mitigation, and alternative flood adaptation policies to evaluate community flood risk. We assume agents respond to environmental changes with private risk-reducing behaviors determined by their experience with flooding and community risk reduction. The risk-reducing behaviors of agents, including the risk transfer mechanism of purchasing flood insurance and elevating properties, were modeled based on protection motivation theory (PMT) with the risk mitigation policies of the Federal Emergency Management Agency (FEMA) (FEMA, 2020a). The developed model evaluated community adaptation outcomes by simulating agents' risk mitigation decisions under alternative policy scenarios and dynamic storm surges.

2. BACKGROUND

Two major component of flood risk management (FRM) at the design and planning level are risk transfer mechanisms and hazard mitigation measures (Brody, Gunn, Peacock, & Highfield, 2011). For example, FEMA maintains Flood Insurance Rate Maps (FIRMs) for more than 2000 communities in the United States based on a category of flood zones (Kousky & Kunreuther, 2014). FEMA identifies flood hazard areas on the FIRMs into different flood zones based on their annual probability of inundation. According to FEMA, any building located in an A or V zone is considered to be in a Special Flood Hazard Area (SFHA), while X zones have minimal flood risk and D zones are areas that have not been studied yet. Federal laws require buildings with a mortgage within the SFHA to be covered by flood insurance (Burby, 2001).

Policyholders with high insurance costs could reduce their insurance cost by elevating their houses above ground level (Xian, Lin, & Kunreuther, 2017). FEMA also provides a community rating system as a voluntary incentive program to encourage local communities to reduce flood risk (Zahran, Weiler, Brody, Lindell, & Highfield, 2009). The National Flood Insurance Program (NFIP) has been providing subsidized flood insurance to private stakeholders based on the FIRM. Insurance premiums are determined based on flood zones and base flood elevation (BFE). Although insurance premiums are risk-based, to encourage more policyholders to participate in the NFIP, a pre-FIRM subsidy is provided for households with properties built before the first flood insurance map (Kousky & Kunreuther, 2014), thus ensuring affordable flood insurance by transferring the cost of flood damage from property owners to the federal government(U.S. Government Accountability Office, 2017).

Although FEMA's flood management policies are important to alleviate flood-related impacts, given the uncertainty of climate-induced risk and divergent beliefs on risk mitigation among multiple stakeholders, variations exist between adaptation strategies (Logan, Guikema, & Bricker, 2018). Private risk mitigation has been found to substantially influence flood adaptation outcomes given their vulnerability to flood hazard (Bubeck, Botzen, & Aerts, 2012). Purchasing flood insurance is a private risk mitigation strategy for households, as flood risk and recovery is transferred risk to FEMA. Private flood mitigation behaviors, including purchasing flood insurance and house elevation, have a far-reaching effect on community resilience (Han, Ash, Mao, & Peng, 2020); however, these actions are highly influenced by homeowners' risk perceptions and capability in risk mitigation(Siegrist & Gutscher, 2008). People could either overestimate or underestimate flood risk depending on their perceived hazard frequency and intensity (Taylor, Dessai, & Bruine de Bruin, 2014).

2.1. Human Flood Risk Mitigation Behavior

The interest in understanding private risk mitigation in FRM is reflected in the number of studies focusing on the importance of human factors that drive private mitigation behaviors (Shao et al., 2017). Previous studies have identified risk perception as the perceived probability and consequences of natural hazards (Babcicky & Seebauer, 2019). Many studies found that higher risk perception increases agents' willingness-to-pay in risk mitigation (W. J. W. Botzen & van den Bergh, 2012; Zaalberg, Midden, Meijnders, & McCalley, 2009). Philip Bubeck et al. (2012) found, however, that existing empirical studies cannot explain risk perception changes over time. For example, Gallagher (2014) and Kousky (2017) found flood insurance take-up rates in the United States after a natural hazard would first increase, but taper off with time.

Over the past few decades, the influence of private risk perception and mitigation have been studied extensively within the protection motivation theory framework (Seebauer & Babcicky, 2020). For example, Grothmann and Patt (2005) explored individual adaptation actions to climate change risk using survey results. They found the self-protective behaviors of private stakeholders depend mainly on their risk perception and perceived adaptive capacity. PMT explains that agents' risk-reducing behaviors to protect themselves from natural hazards were influenced by high levels of risk appraisal and coping appraisal (Lindell & Perry, 2012; Maddux & Rogers, 1983). According to Philip Bubeck, Wouter Botzen, Laudan, Aerts, and Thieken (2018), threat appraisal describes agents' risk perception of a hazard. When the threat appraisal exceeds a certain threshold, another process, coping appraisal, will cause an agent to begin to evaluate available response measures to reduce the risk. Coping appraisal involves three components: the perceived effectiveness of certain measures, the perceived ability to reduce adverse effects, and the perceived cost of a risk-reducing measure.

Some scholars found that risk perceptions of individuals could be lessened or even somewhat negated by previous hazard experiences when impacts of the hazards are not significant, called indirect hazard experience (Kamiya & Yanase, 2019). As a result, direct and indirect flood experiences are proposed to distinguish different relationships between risk perception and hazard experiences. Gayer, Hamilton, and Viscusi (2000) found that direct and indirect experiences of natural hazards have different impacts on agents' learning of risk perceptions. Viscusi and Zeckhauser (2015) proposed a standard Beta–Bernoulli Bayesian learning model to update individuals' risk beliefs based on their flood experiences. A beta distribution, in which direct and indirect experiences are updated through Bernoulli trials and weighted differently, is proposed to analyze risk beliefs. When an agent's weight of direct experience is greater than the weight of indirect experience, others' experience counts less than one's own experiences and vice versa. Kamiya and Yanase (2019) further use this Bayesian learning model to explain the effects of direct and indirect loss experiences from extreme catastrophes on agents' hazard insurance purchasing behavior after earthquakes.

2.2. Agent-Based Modeling in FRM

ABM has been widely applied to study decision making in human-environmental systems (Bone & Dragicevic, 2010; Dawson, Peppe, & Wang, 2011). Due to heterogeneous socioeconomic characteristics of agents in ABM, it provides a bottom-up approach to evaluate collective outcomes of human behavior in risk mitigation. Compared to traditional approaches, ABM could capture emergent phenomenon through interactions between agents and the environment, and therefore, could provide more robust risk analysis to evaluate adaptation policies and strategies within the complex human and environmental systems (Abar, Theodoropoulos, Lemarinier, & O'Hare, 2017; O'Connell & O'Donnell, 2014).

Recently, ABM studies are focusing on interactions between evolving natural hazards and human behaviors under climate risk management. McNamara and Keeler (2013) linked a physical model with an agent-based behavioral model to explore the climatic risks of sea-level rise (SLR) in barrier-island communities. In their simulation, agents make decisions through evaluating tradeoffs between how much to pay for the property and for the protective measures. Haer, Husby, Botzen, and Aerts (2020) developed a large-scale ABM to explore flood risk under population growth, public adaptation, and climate change in the European Union. The dynamic adaptive behaviors of governments are based on a cost-benefit analysis, and that of households, on a discounted expected utility model with grid cells.

Tonn and Guikema (2018) developed an ABM to explore individuals' responses to evolving flood risk under stochastic flood events. In their study, a risk and coping perception rule and an adaptation rule are defined in the evaluation of private adaptation. When coping perception and risk perception exceed certain levels, agents will evaluate available risk mitigation measures. On the other hand, when community damage is above a threshold value, the community mitigation project will be implemented. The community flood damage and adaptation actions are analyzed based on Monte Carlo simulation. Tonn, Guikema, and Zaitchik (2020) further explored community flood risk under climate impacts scenarios through the ABM. Their study reveals significant impacts of future climate scenarios on agents' adaptation behaviors, where agents may relocate under extreme climate scenarios.

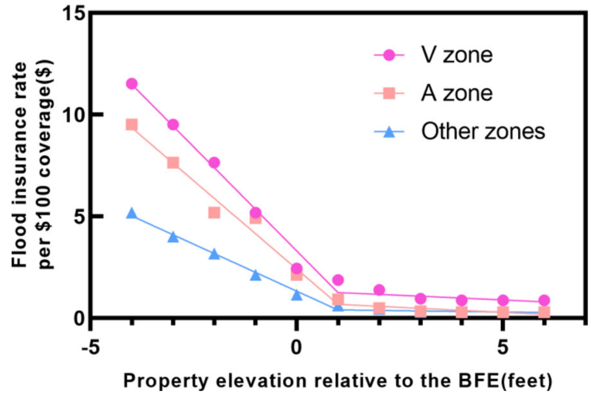

Fig 1. Flood insurance rates relative to the BFE.

3. METHODOLOGY

3.1. Model Framework

Our model considers each household as an autonomous agent that is socially connected with other agents. Agents decision-making processes are emulated based on PMT (Grothmann & Patt, 2005). According to this theory, the cognitive processes that lead to private risk reduction are driven by changes in risk perceptions of flood hazards and subsequent coping appraisal (Bubeck et al., 2012; Wouter Botzen & van den Bergh, 2009). In our model framework, an agent's cognition of risk mitigation is divided into two processes: (1) the risk perception learning process, and (2) the risk mitigation appraisal process. In the first stage, agents' risk perceptions are simulated using a Beta–Bernoulli Bayesian learning model. Agents update their risk perceptions based on Bernoulli trials of direct and indirect flood experiences in each year of the simulation. In the second stage, when an agent's risk perception is above a threshold p_t, the risk appraisal process will be initiated. The risk appraisal process evaluates risk mitigation decisions of agents based on their willingness-to-pay. A household SLR and flood risk perception survey in Miami-Dade was used to determine the flood insurance willingness-to-pay of households. Later in the process, agents will make their risk mitigation decisions by minimizing the costs of risk mitigation.

3.2. Storm Surge Modeling

The flood damage to households was measured based on flood inundation of properties under storm surges. We estimated the flood height according to the following generalized extreme value (GEV) distribution (Buchanan, Oppenheimer, & Kopp, 2017):

$$\mathrm{F}\,(\mathrm{x};\mu,\sigma,\xi) = \exp\left\{-\left(1+\frac{\xi\,(x-\mu)}{\sigma}\right)^{-\frac{1}{\xi}}\right\} \tag{1}$$

where $F(\mathrm{x};\mu,\xi,\sigma)$ represents the cumulative distribution function (CDF) function of hazards with flood height x. The distribution is characterized by the location parameter μ, scale parameter σ, and shape parameter ξ. Due to spatial variation of floods, we used the k-means algorithm to determine multiple categories of storm surge models in different areas of Miami-Dade County and fitted distribution parameters of each model to dynamically simulate storm surge heights annually. The flood height-frequency functions were fitted using the simulated inundation data from the Sea, Lake, and Overland Surges from Hurricanes (SLOSH) model and fExtremes package in R software (Coles, Bawa, Trenner, & Dorazio, 2001; Zachry, Booth, Rhome, & Sharon, 2015). The economic damage was then computed based on the inundation of storm surge and the fraction loss of a property. The damage calculation was based on methods from Yu Han and Mozumder (2021, 2022).

3.3. Risk Perception Learning

We formulated agents' risk perception model using a Beta–Bernoulli Bayesian learning model (Gayer et al., 2000; Viscusi, 1991). In particular, since the risk perception of an agent can be described as a binomial variable, the conjugate prior can be assumed as a Beta(α,β) distribution. Therefore, we used a beta distribution to update risk perception of agents through observed Bernoulli trials (Kamiya &

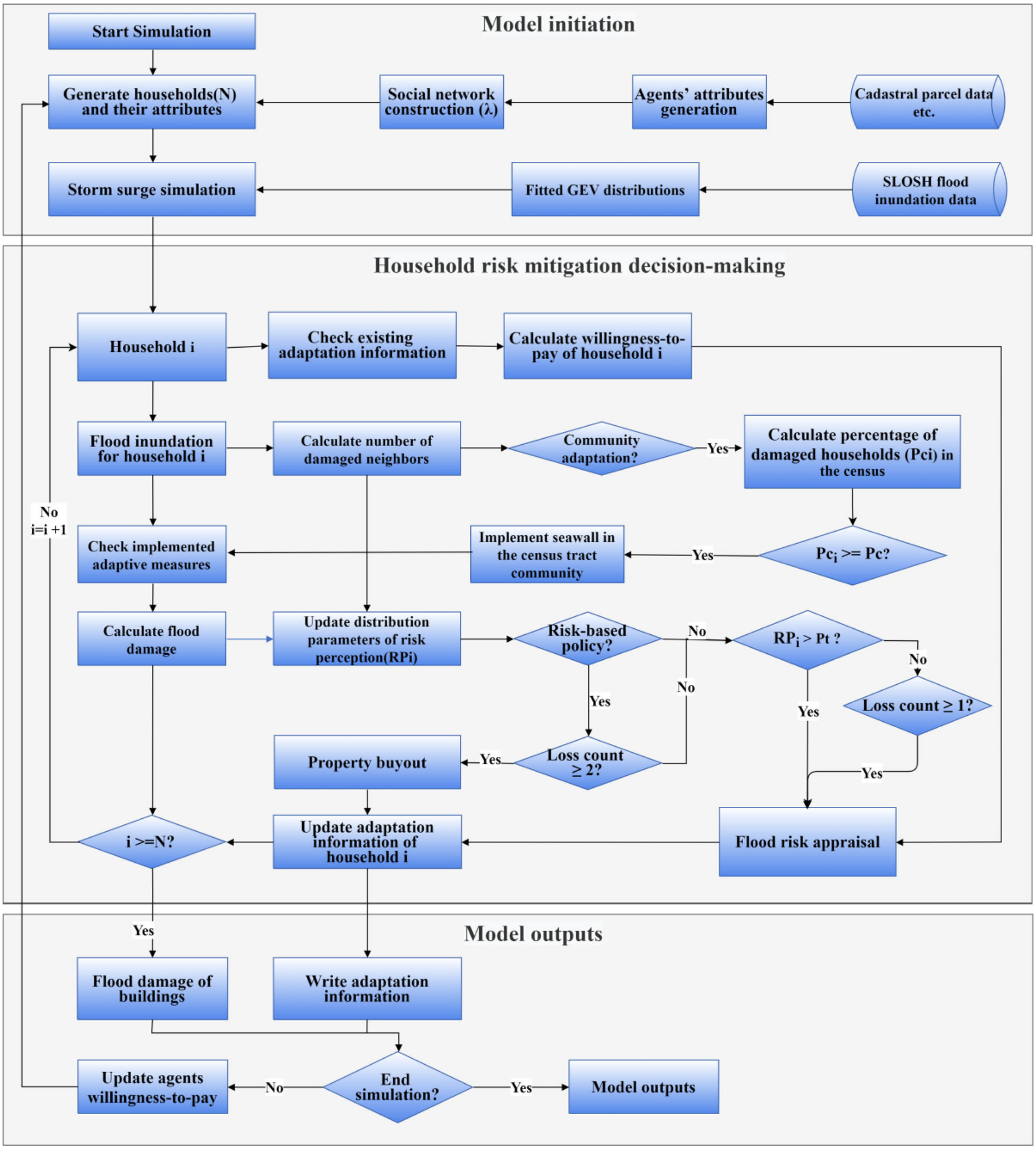

Fig 2. Model process overview.

Yanase, 2019). Viscusi and Zeckhauser (2015) consider that an agent observes not only its own trials and successes, described as $n_{i,1}$ and $m_{i,1}$, respectively, but also trials and successes from other agents, namely $n_{i,2}$ and $m_{i,2}$. As a result, the posterior belief of flood damage after all trials can be described as

$$\mathrm{RP}_i = \frac{\alpha_i + m_{i,1} + \omega * m_{i,2}}{c_i + n_{i,1} + \omega * n_{i,2}} \tag{2}$$

In Equation (2), RP_i represents the mean of the posterior risk perception of agent i, α_i and β_i are two prior distribution parameters for agent i, and

Table I. The Fitted Willingness-to-pay of Agents for Flood Insurance

Predictors	Estimate Std.	Error	t-value	Pr(>|t|)
(Intercept)	7.62398	0.41636	18.311	<2e-16***
Black	−0.78903	0.34177	−2.309	0.0224*
Hispanic	−0.20026	0.15506	−1.291	0.1986-
Asian	−0.36368	0.2611	−1.393	0.1658-
length of residence in years	−0.46588	0.10538	−4.421	1.92E-05***
Property value	0.16134	0.02957	5.456	2.07E-07***

Residual standard error: 0.7444 on 144 Degree of freedom
Adjusted R-squared 0.2707, p-value: 9.433e-09
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

$c_i = \alpha_i + \beta_i$. ω is the weight of indirect flood experiences.

Although a large and immediate change in take-up rates of FEMA flood insurance could be observed after a disaster with a standard Bayesian learning model, Gallagher (2014) found a large spike in insurance take-up rates after a hazard followed by a fast decay after a few years. This indicates that private homeowners' risk perceptions are sensitive to their flood experiences. The estimation of agents' risk perceptions in Equation (2) depends on both the frequency of direct and indirect flood experiences as well as the weight of indirect flood experiences. To measure impacts of indirect flood experiences, we constructed a social network to dynamically measure the average number of flood experiences in an agent's neighborhood. We constructed the network by randomly selecting an agent's neighbors from a Poisson distribution with the parameter λ (Yang, Mao, & Metcalf, 2019). In the simulation, the average number of flood experience within an agent's neighborhood and the total number of neighbors in a simulation year will be measured as $m_{i,2}$ and $n_{i,2}$.

We assume $\alpha_i = 0$ and $\beta_i = 1$ for the risk perception distribution parameters at the beginning of the simulation, then agents will dynamically update their risk perception parameters based on their direct and indirect flood experiences in each year of the simulation. If the risk perception of an agent is larger than a threshold value (p_t), then the agent will initiate the risk appraisal process. We calibrated the threshold p_t and weight ω using parameter sensitivity analysis in Section 5.3.

3.4. Risk Appraisal

Relying on a household SLR and flood risk perception survey, we fitted a multinomial linear model to estimate households' willingness-to-pay in purchasing flood insurance. In the model fitting, the dependent variable is the log of self-reported insurance cost and independent variables are other households' socioeconomic attributes. Based on results from the stepwise regression, we found a household's willingness to pay was strongly correlated with property value, the ethnicity of the household head, and the years of residence of that household.

We then applied the fitted model parameters and their standard deviation to randomly generate a willingness-to-pay for each household in each model replication and calculated corresponding flood insurance coverage. FEMA's flood insurance coverage for residential properties has a basic coverage of $60,000; the maximum coverage for single-family building is $250,000 (FEMA, 2020a; Kousky & Kunreuther, 2014). We determined the insurance coverage of households based on their willingness-to-pay, and the minimum coverage was set to the $60,000 basic coverage. In the risk appraisal process, when a household's willingness-to-pay is lower than the insurance cost for the minimum coverage, the household will not purchase flood insurance. Otherwise, households will choose the most cost-effective risk mitigation strategies that have the cost below or equal to their willingness-to-pay. These strategies include purchasing flood insurance or purchasing flood insurance with house elevation. Households' insurance costs may change in the model simulation. If a household's property is lost or a household living in SFHA suffers from flood damage, the household will be forced to purchase flood insurance with full coverage and elevate their property 1-foot above the BFE.

Given the above risk appraisal and coping appraisal models of agents, four states of risk mitigation are available for agents in each year, including doing nothing, purchasing flood insurance, doing nothing

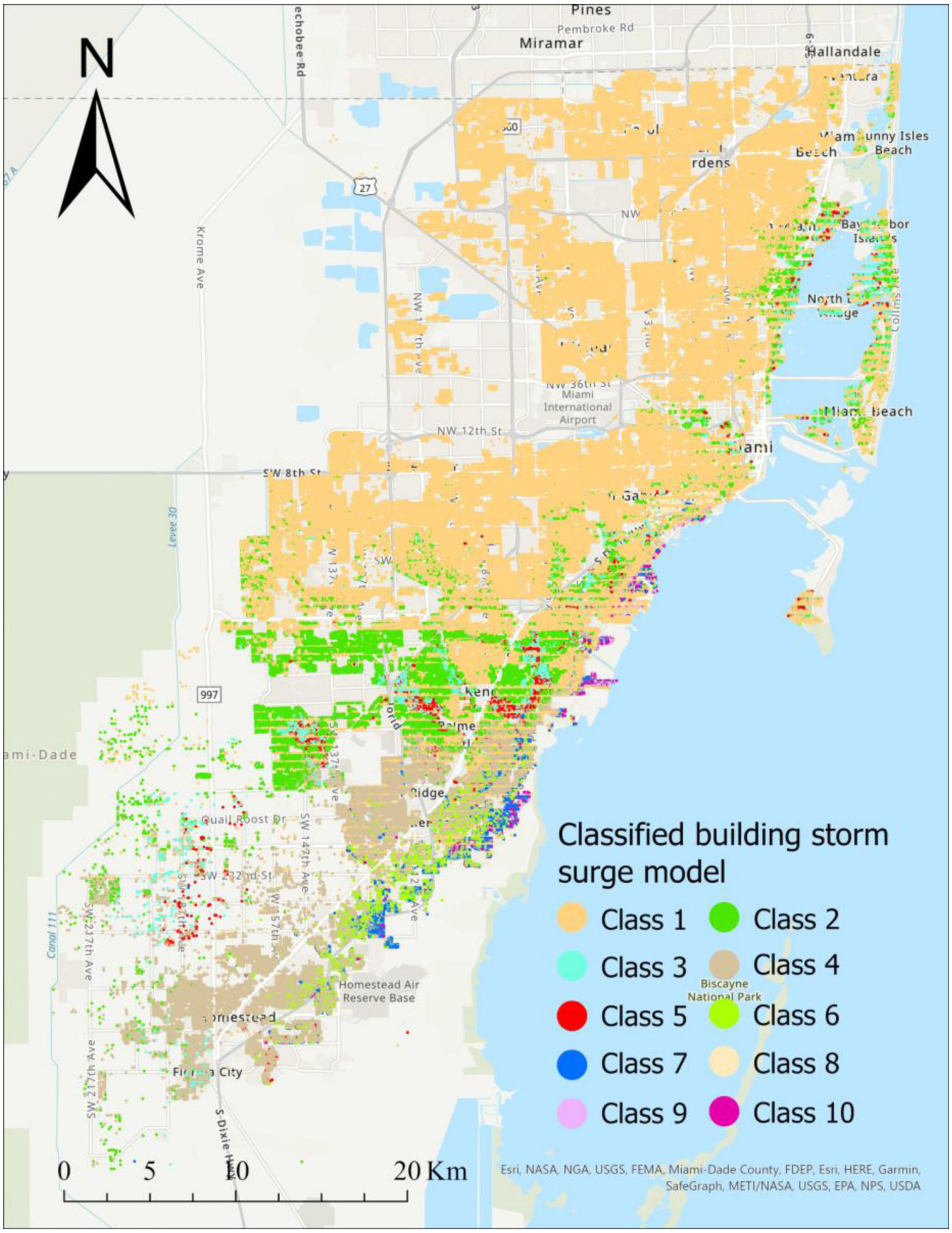

Fig 3. Properties' classified storm surge categories in Miami-Dade County, Florida.

but with elevated property, and purchasing flood insurance and effecting property elevation. In the model, flood insurance rates are determined based on FEMA's risk-based insurance rates table (FEMA, 2020a) and the elevation costs are based on Yu Han and Mozumder (2021). We assume property elevation will always be effective during the simulation period once it is implemented, while flood insurance is evaluated annually based on agents' risk perceptions.

Fig. 1 shows FEMA's risk-based insurance rates per $100 coverage in 2019 (FEMA, 2020a). We classified flood zones into three categories: Flood A zone; flood V zone, comprising two SFHAs, and flood D zone and X zone, classified into other zones. In general, the insurance rates in each flood zone can be estimated with a segmented linear model. When the difference between a property's ground elevation and the BFE is lower than 1-foot, flood insurance rates increase significantly as the property's elevation decreases. However, when a property's ground elevation is 1-foot or higher than the BFE, flood insurance rates are quite low. We then considered the grandfathered pre-FIRM insurance rates as 40% of the risk-based insurance rates if a property was built before the implementation of first FIRM (Kousky & Kunreuther, 2014).

3.5. Process Overview and Scheduling

Fig. 2 shows the data flow of the model. We generated discrete demographic attributes of households using the household SLR and flood risk perception survey data. We then classified property values into discrete categories and applied Gibbs sampling to generate a household's income, and household head's race, ethnicity and educational level (Han, Chen, Peng, & Mozumder, 2021). A social network was constructed for each agent to build his or her social connections. Each agent was assigned N social links randomly drawn from a Poisson distribution with the mean value λ, then the agent's social links were randomly connected with neighbors of the agent. Storm surges were randomly generated using the fitted GEV cumulative distributions.

In Fig. 2, each agent first measures adaptation information of his or her property, willingness-to-pay, flood inundation, direct damage, and indirect flood damage in the neighborhood. We assume census tracts to be the smallest community unit in the simulation. In scenarios with community adaptation, when the percentage of damaged properties of a census tract in any given year is above a threshold value (p_c), a 2-foot floodwall, as a public adaptive measure, is implemented in the County. Agents update his or her risk perceptions (RP_i) based on direct and indirect flood damage information. If the RP_i of the agent is greater than a predefined threshold (p_t), then the agent will begin the risk appraisal process. Otherwise, the agent will not exhibit new risk mitigation behaviors. Model parameters are defined in the Supporting Information.

If a property has been elevated in any previous year of simulation, it will be effective throughout the simulation. When property damage amounts to more than 50% of its value, we assume the property is lost. A lost property needs to be rebuilt to meet FEMA's retrofitting requirement with full flood insurance coverage (FEMA, 2020b). Thus, agents will be forced to initiate risk appraisal process when their property is lost. In the risk-based flood insurance scenario, when a property is lost twice or more, the property will be bought out by the local government, and correspondingly, the property value will be assigned as 0. After the risk appraisal process, agents will update their adaptation information. The damage and adaptation outcomes will be aggregated into model outputs and will be generated at the end of the model simulation.

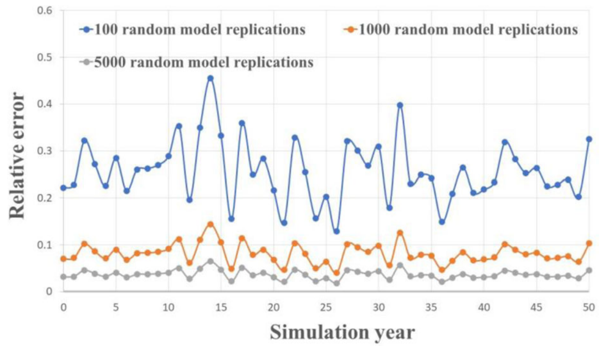

Fig 4. Model convergence calculation.

4. CASE STUDY AREA AND SCENARIOS

We chose Miami-Dade County as the case study area because it is one of regions most vulnerable to hurricane storm surge in the United States. Due to high computational burden, we randomly sampled 10% of single-family parcels and generated households as agents in this study, where a total of 37,850 properties were identified in the area.

We applied an online SLR and flood risk perception survey data to measure the willingness-to-pay of agents in purchasing flood insurance. The survey was administered by survey company Qualtrics to randomly select a representative consumer panel in Miami-Dade County between April and May 2017. At the beginning of the survey, respondents were asked about their demographics and other basic information. A total of 520 residents aged 18 and older were sampled and surveyed on their perception of sea-level rise and flood experiences, and on attitudes toward public adaptation strategies. Various survey questions regarding individuals' flood risk perception, attitude toward sea-level rise, and flood insurance purchase behavior were collected and recorded.

Table 2. The Average Model Scenario Results

Model Statistics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average annual damage per household without adaptation ($)	18,253	18,253	9,204	9,170
Average annual damage per household with adaptation ($)	8,207	5,063	4,142	3,400
Average annual total adaptation cost per household ($)	2,785	5,323	1,572	3,324
Average insurance take-up rate	43.23%	39.06%	28.66%	23.78%
Average insurance policy cost per household ($)	2,238	3,639	1,280	2,410
Average number of elevated properties	3,049	11,656	455	5,192
Discounted average annual elevation cost ($)	577	1,676	108	809

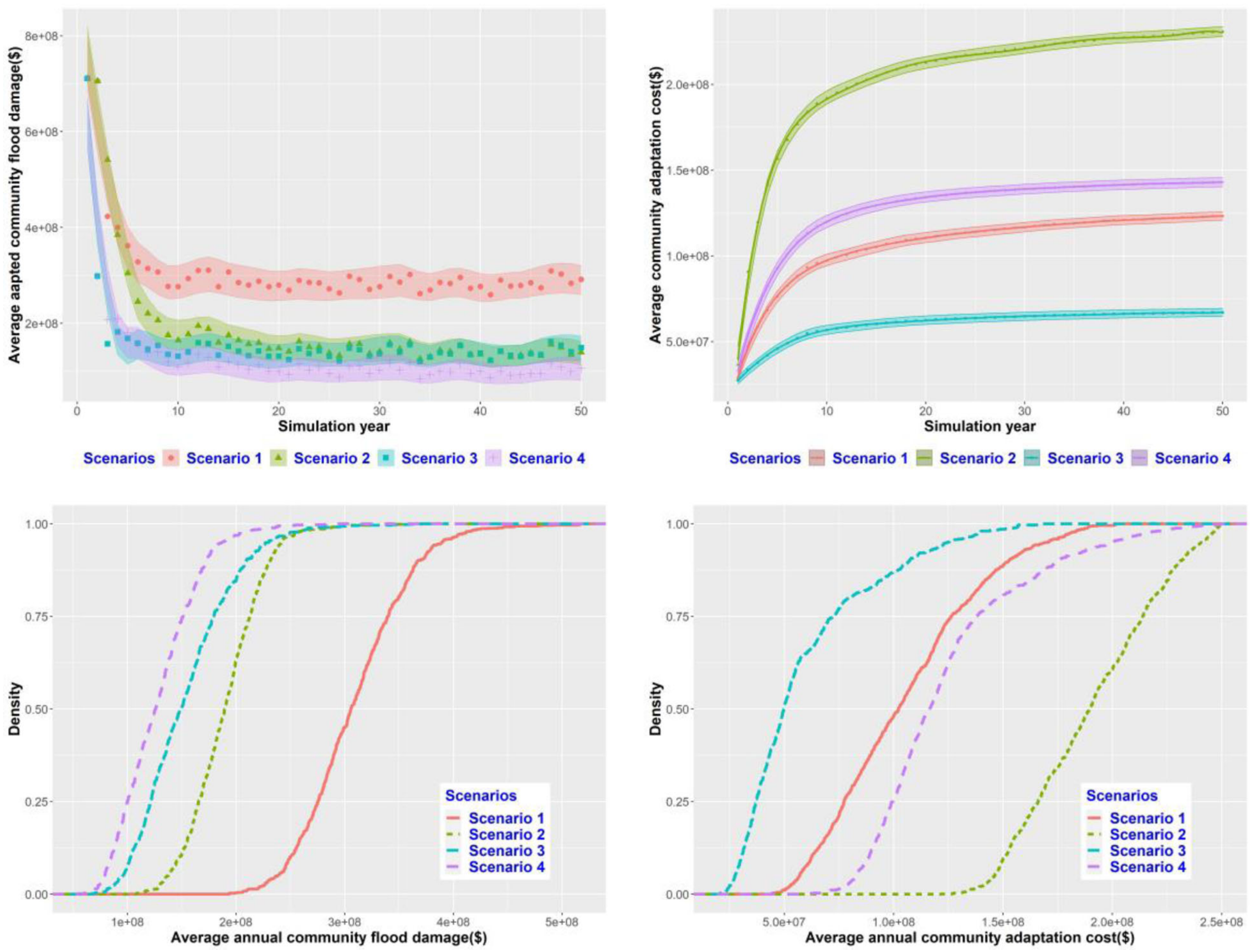

Fig 5. Average community adaptation damages and costs.

Table I shows the fitted model results for willingness-to-pay of agents. The dependent variable is the log of household insurance cost. For independent variables, property value in discrete categories is positively related with agent willingness-to-pay, while the length of residence in years in the area is negatively correlated with agent willingness-to-pay. Moreover, minorities tend to have lower willingness-to-pay compared with White populations when holding all other model parameters as constant. In the simulation, agents' length of residence and property value could change over time, and the willingness-to-pay will change accordingly.

Since spatial variations of flood inundations could yield model results more difficult to converge on a large spatial scale, we applied the *k*-means al-

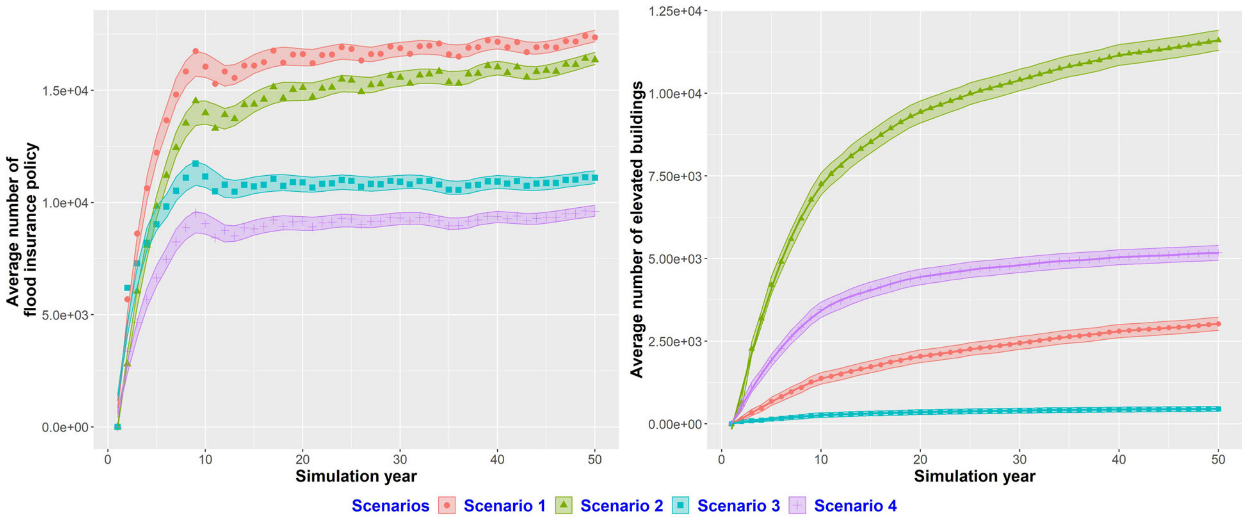

Fig 6. Average number of flood insurance policyholders and elevated buildings.

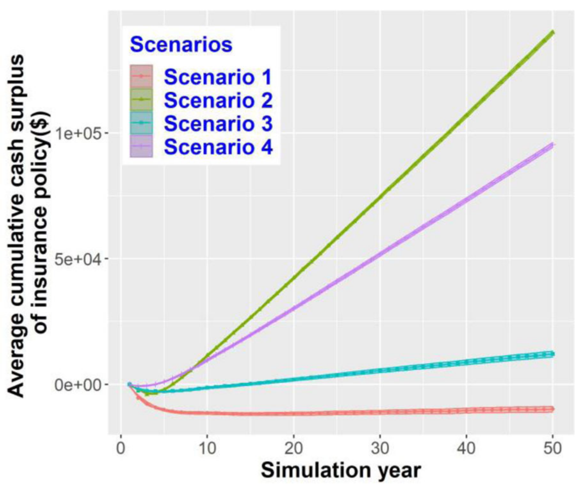

Fig 7. Average cumulative cash surplus of flood insurance policies.

gorithm to classify storm surges into 10 classes using the simulated storm surge inundations from category 1–5 in Miami-Dade County. We then fitted model parameters of the GEV distribution function for each class and assigned each property a class label. Fig. 3 shows the labeled property classes in Miami-Dade County. We labeled classes of storm surge models from low (class 1) to high (class 10) based on the value of fitted location parameter in each class. All fitted cumulative distributions of storm surge models are described in the Supporting Information. Fig. 3 shows that more than half of the properties are grouped into storm surge class 1, which has the lowest storm surge heights. In addition, properties close to each other spatially are more likely to be classified into the same class. For example, properties in Miami-Beach and south of the county are more likely to be fall into a class with higher storm surges.

We developed four model scenarios with a simulation period of 50 years. Scenario 1 was based on the NFIP policies with the pre-FIRM subsidy, where properties built before 1973, before implementation of the first FIRM, would receive a 60% insurance discount on the risk-based insurance rates. No community adaptation was considered in scenario 1. Scenario 2 uses the risk-based insurance policy to replace grandfathered insurance rates (Kousky & Kunreuther, 2014); lost properties are required to rebuild to meet the retrofitting requirement by FEMA and to be covered by flood insurance. When a property is deemed a total lost more than once, it will be bought out by the local government. Scenario 3 was designed based on the NFIP policies with the pre-FIRM subsidy, and this scenario incorporated community adaptation in risk mitigation. The local government will build a 2-foot floodwall to reduce community flood damage when the percentage of damaged properties is higher than the threshold value P_c. In the simulation, we choose $P_c = 0$, which means the entire area will be protected with a floodwall. Correspondingly, according to FEMA's community rating system, a 25% discount on flood insurance will be applied to households (Zahran et al., 2009). Scenario 4 considered both the risk-based insurance policy and the same local community adaptation actions in scenario 3.

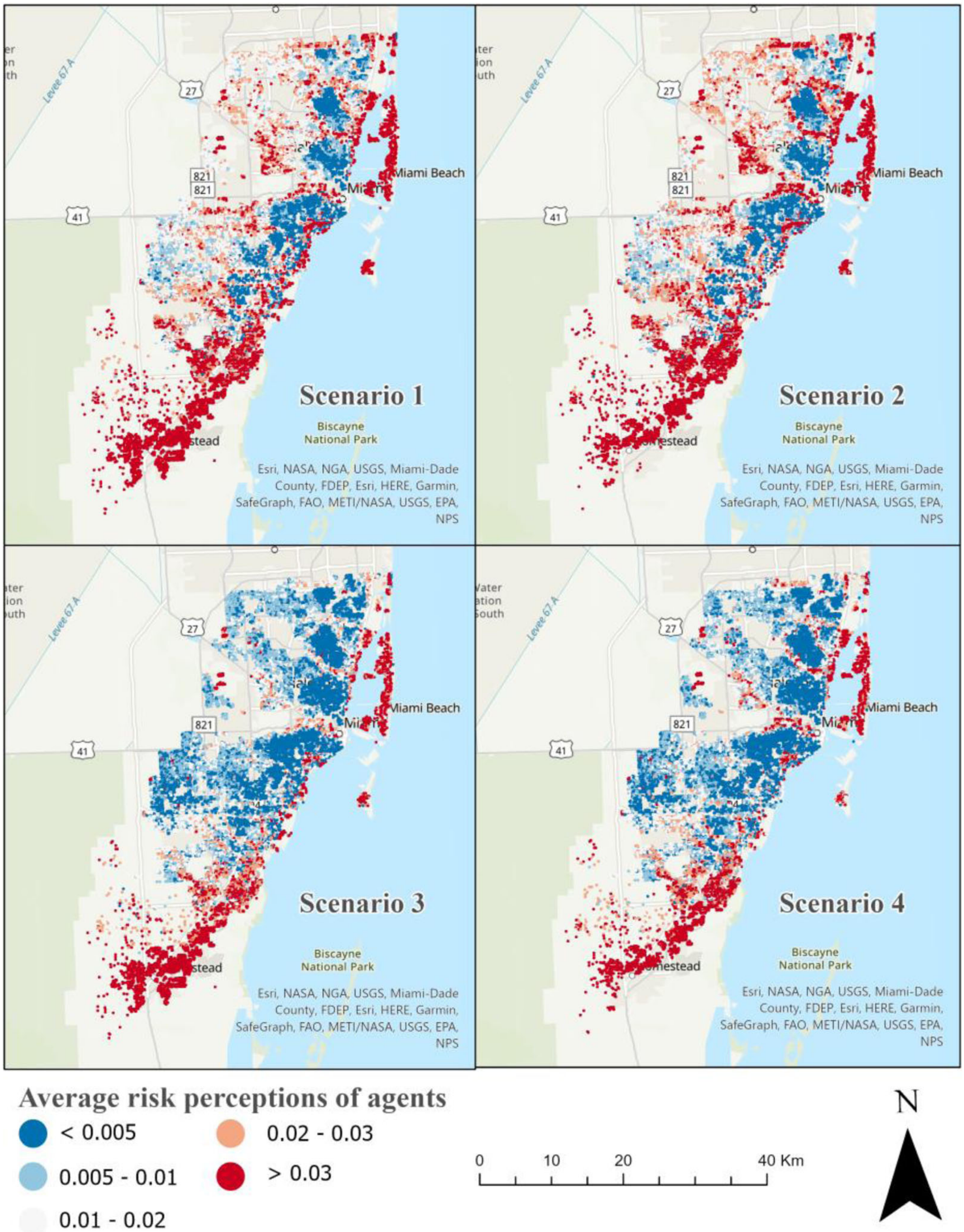

Fig 8. Average household risk perceptions.

5. RESULTS

5.1. Scenario Risk Mitigation Outcomes

We used the Monte Carlo simulation to evaluate the dynamic decision making and adaptation outcomes of agents in flood mitigation. We determined the number of model replications by calculating the convergence of results. We first randomly simulated 100, 1,000, and 5,000 replications, then calculated the adjusted relative error (Tonn & Guikema, 2018). Fig. 4 shows the calculated adjusted relative error in 50 years of simulation. A higher number of model replication could reduce model errors. When

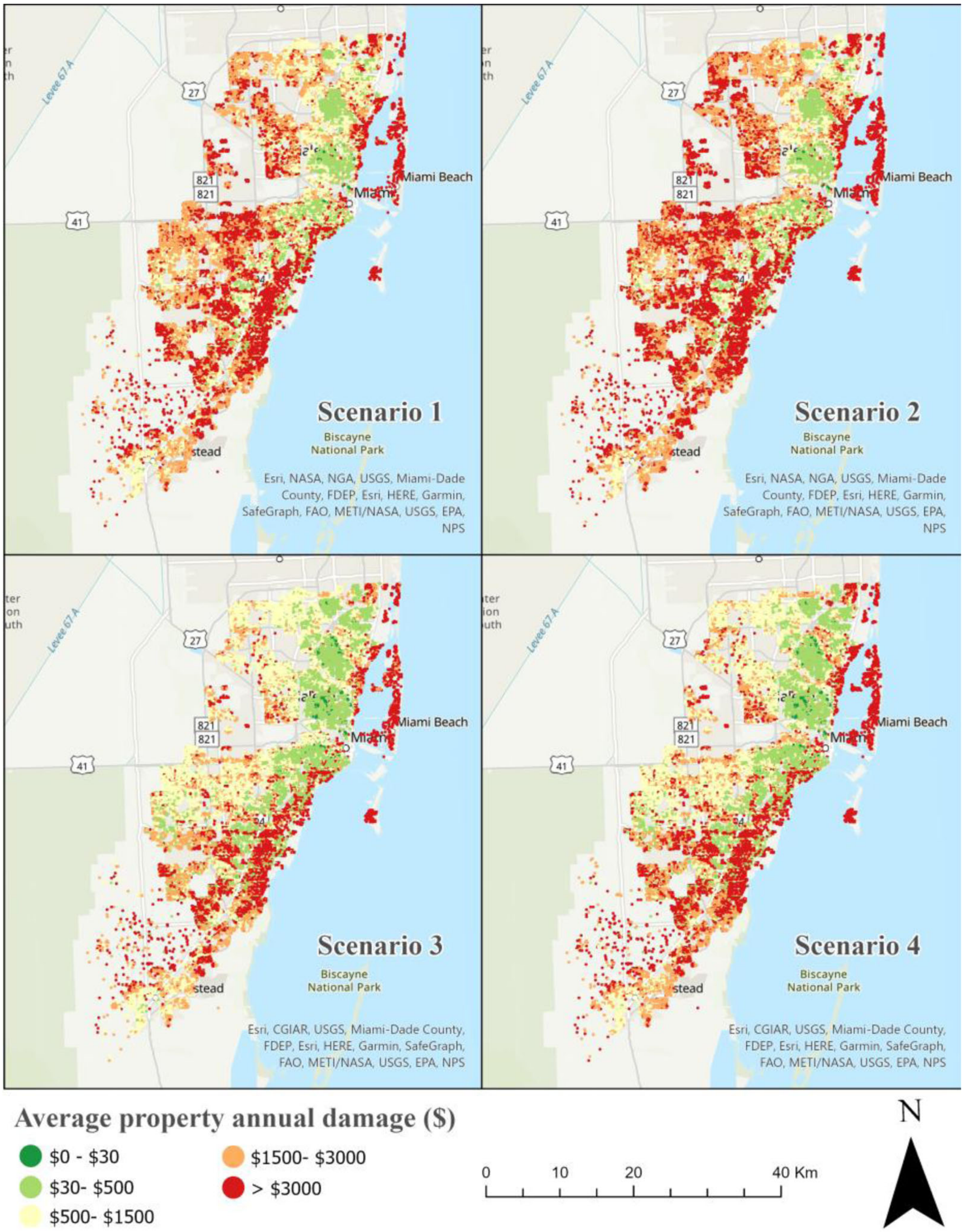

Fig 9. Average building annual damage.

the number of replications is greater than 1,000, the average adjusted relative error of model results is less than 0.1. To balance accuracy and computation burden in model evaluation, we chose 1,000 model replications in our analysis.

Table II shows the average adaptation outcomes per household for the four scenarios. The average community damages without considering risk mitigation behaviors in scenario 1 are quite similar to those in scenario 2 or between scenario 3 and scenario 4. When compared to flood damage with and without private adaptation, we found that the average annual damages in scenario 3 and scenario 4 were much lower than those in scenario 1 and scenario 2.

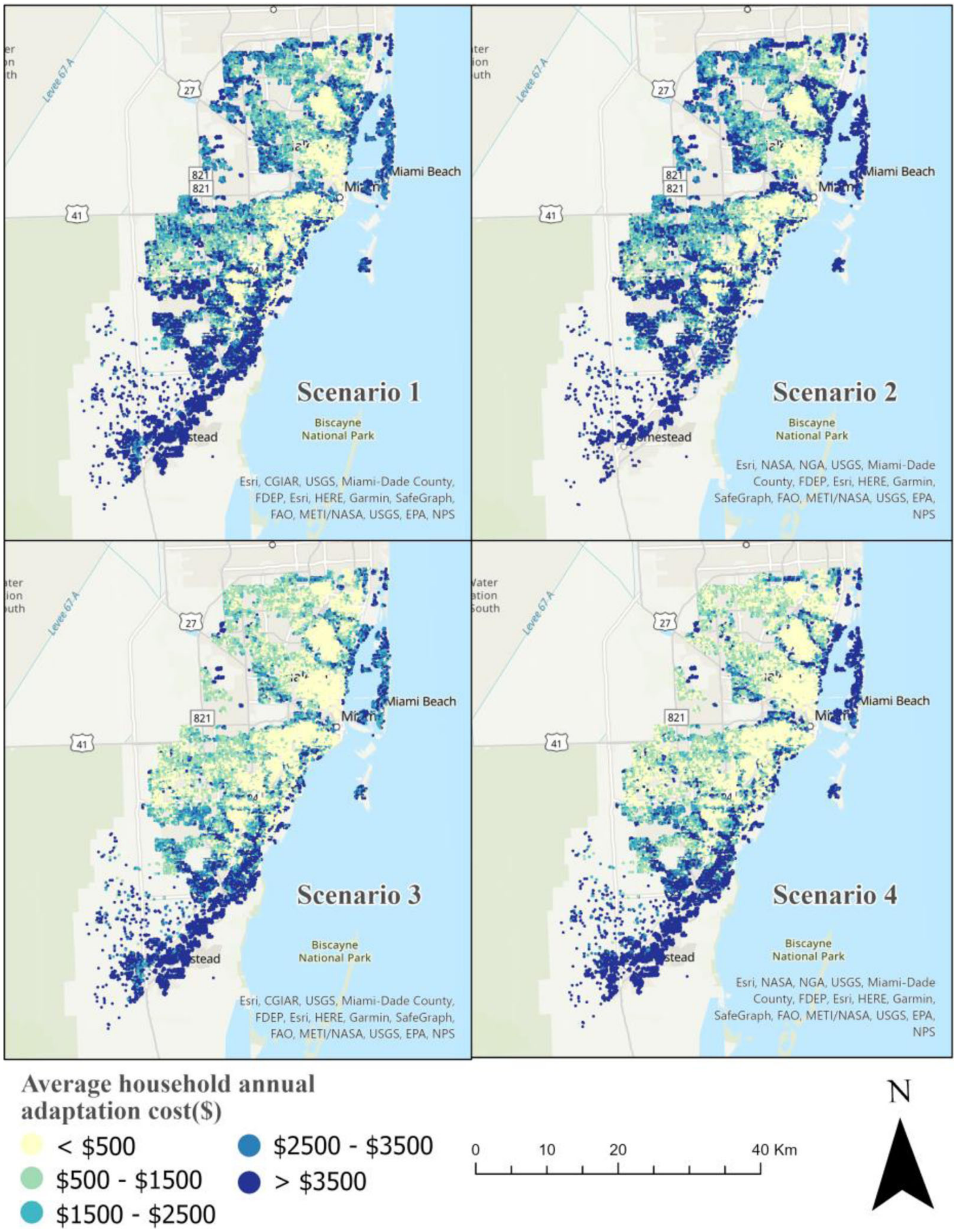

Fig 10. Average household annual adaptation cost.

This indicates the importance of community adaptation in improving community resilience in Miami-Dade County. Results also indicate that scenario 2 could be more effective in improving community resilience compared to the grandfathered insurance policy with pre-FIRM subsidies. The average annual damage with private adaptive measures in scenarios with risk-based flood insurance rates is smaller than that of scenarios with grandfathered flood insurance rates. On average, more agents will purchase flood insurance in the grandfathered insurance policy scenarios and more agents will invest in house elevation in the risk-based insurance policy scenarios. The average flood insurance take-up rates decrease from

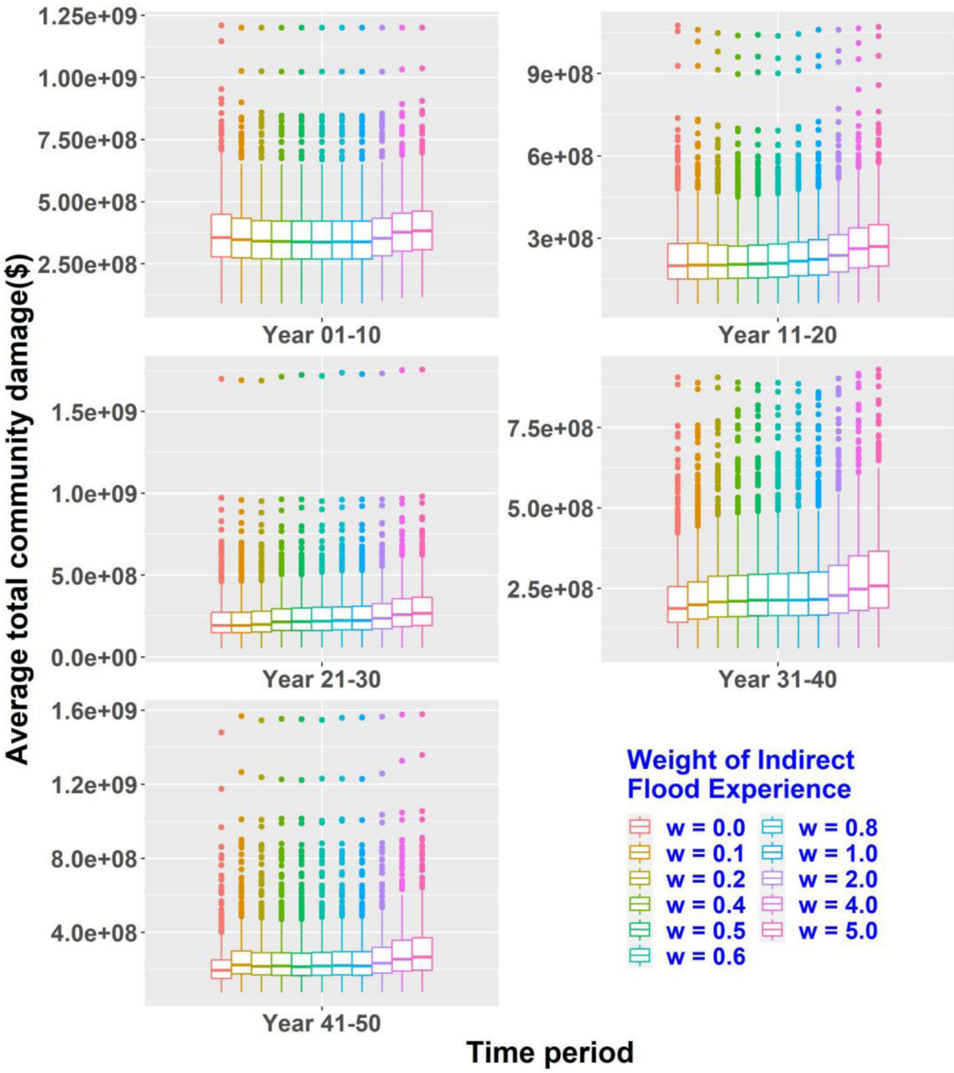

Fig 11. Model sensitivity of agents' weight of indirect flood experiences.

43.23% in scenario 1 to 23.78% in scenario 4. The average total adaptation costs per household range between $1,572 and $5,323.

Furthermore, in scenario 1 and 2, the insurance take-up rates and the number of elevated properties are both higher than those in scenario 3 and scenario 4, respectively. This indicates that community adaptation actions could reduce the motivations of agents in risk mitigation. Scenario 2 has the highest average annual adaptation cost, and scenario 4 also has a higher average annual adaptation cost than scenario 1 and 3. Nevertheless, fewer households purchased flood insurance when the flood insurance policy was transferred to risk-based rates. The discounted average annual elevation costs per household in scenario 1 and 3 are much smaller than those of scenario 2 and 4. This is because house elevation could significantly reduce flood insurance costs in scenario 2 and 4. The high flood insurance cost of the risk-based insurance policy motivates more property retrofitting behaviors.

We investigated the average community damage and adaptation outcomes of the four scenarios on the temporal scale. Fig. 5 shows the average annual community flood damage and the average annual total community adaptation costs in each scenario. The average damage ranges within a 95% confidence interval. In the first year of simulation, all scenarios have the same initial average flood damages. The average community flood damages decrease rapidly in

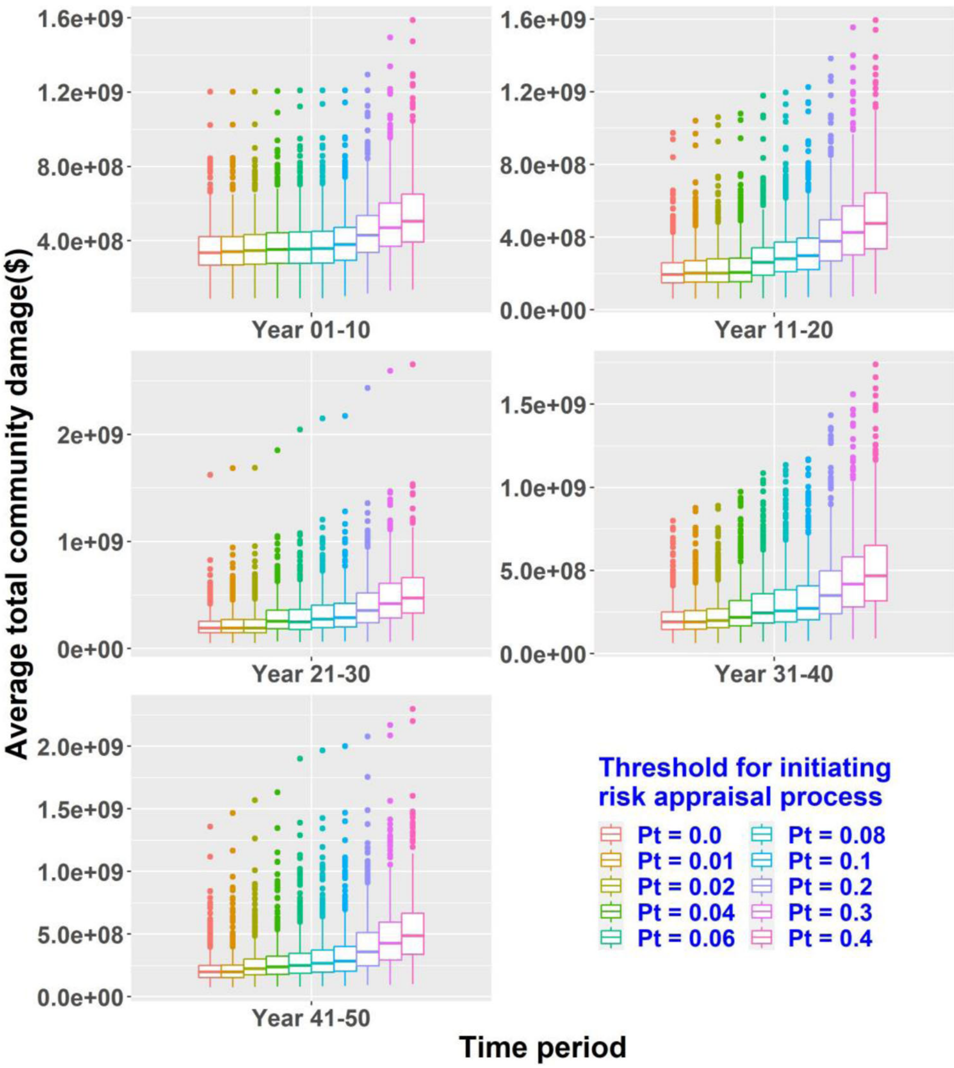

Fig 12. Model sensitivity of the threshold for initiating risk appraisal process.

the first few years. This indicates that agents are gaining their risk perceptions. The agents' learning process and the decreasing trends of community damages show the importance of private risk mitigation behaviors in community flood risk reduction. The average community damage decline rate slows after 10 years, ranging between $200 million and $280 million. The average community damages under different local and federal adaptation policies also indicate the community resilience of each scenario. Scenarios 3 and 4 have lower average damages compared to scenario 1 due to community adaptation actions. Therefore, it is important for the local government in Miami-Dade County to consider available public adaptive measures to reduce community flood risk. The average community damage in scenario 2 gradually approaches that of scenario 3. This indicated that agents could better learn flood risk knowledge under the risk-based insurance policy after a few decades in the area. Scenario 2 has the highest average community adaptation cost in all scenarios. The average community adaptation costs of agents in scenario 1 and scenario 3 are both lower than those of scenario 2 and 4. We calculated the average annual community damage and the average annual total adaptation cost for each model replication and show CDF plots for the 1000 model replications in Fig. 5. The damage distributions in all scenarios range from $140 million to $400 million. The CDFs of the average community adaptation cost indicate that flood insurance policy

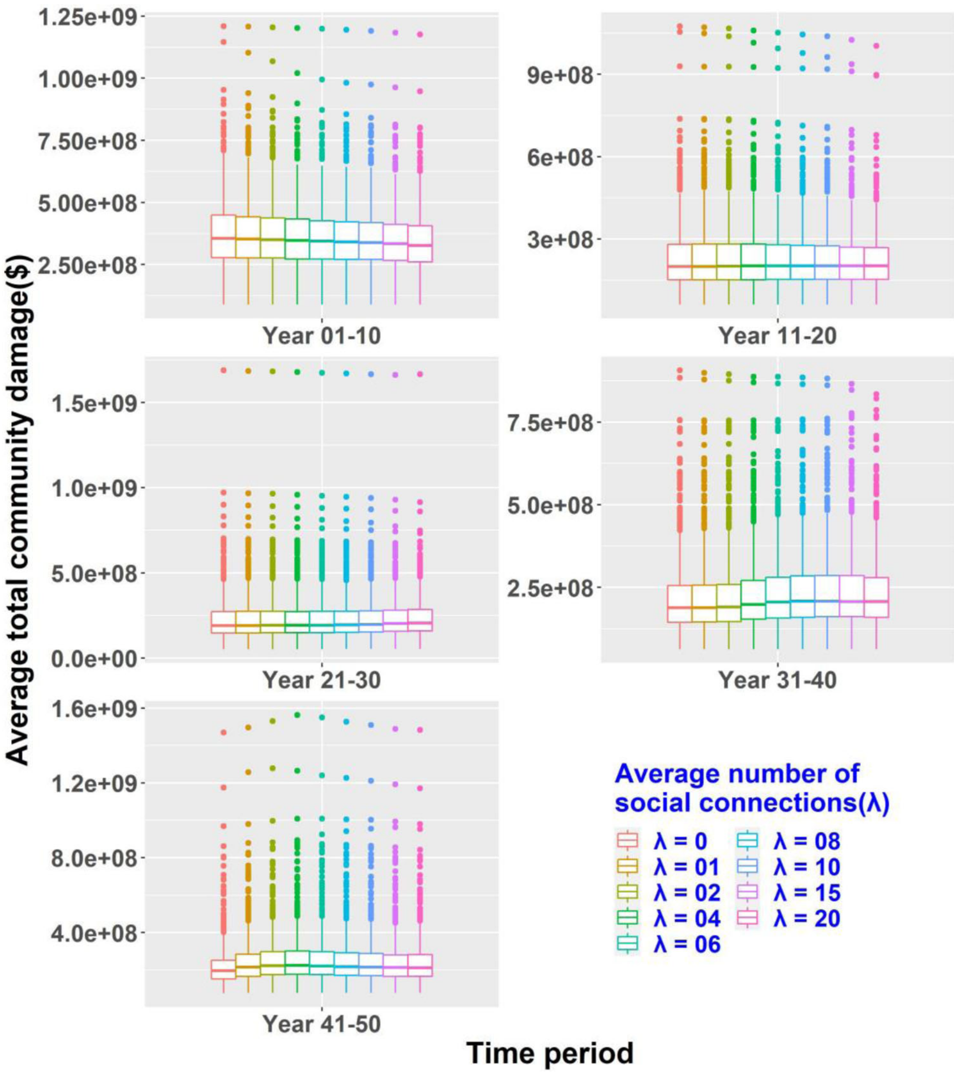

Fig 13. Model sensitivity of agents' average number of social connections.

plays an important role in determining total adaptation costs of agents. The average community adaptation cost for scenario 1 and scenario 3 ranges from \$20 million to \$200 million, and for scenario 2 and scenario 4, from \$70 million to \$250 million. Moreover, in Scenarios 2 and 4, community adaptation actions could flatten the tail of the distribution shape of the average community adaptation cost.

Fig. 6 shows the average number of policyholders and elevated properties. The average number of flood insurance policies increases very rapidly during the early years of simulation then fluctuates slightly. It can be seen that scenarios 2 and scenario 4 have fewer policyholders compared to scenario 1 and scenario 3, respectively. On the other hand, the total number of elevated properties in scenario 2 is much higher than that of other scenarios. The number of elevated properties in scenario 4 is also about twice that of scenario 1. Scenario 3 has the lowest number of elevated buildings.

We also evaluated the flood insurance surplus of each scenario in Fig. 7. The cost surplus is calculated as the difference between the cumulative insurance costs and the cumulative flood damage claims of all policyholders. This value provides only a basic financial situation in each scenario rather than the profit of the NFIP. It can be seen that the cumulative surplus in scenario 1 is negative over time. The cumulative surplus is slightly positive in scenario 3 due to community adaptation actions. Scenario 2 and scenario 4

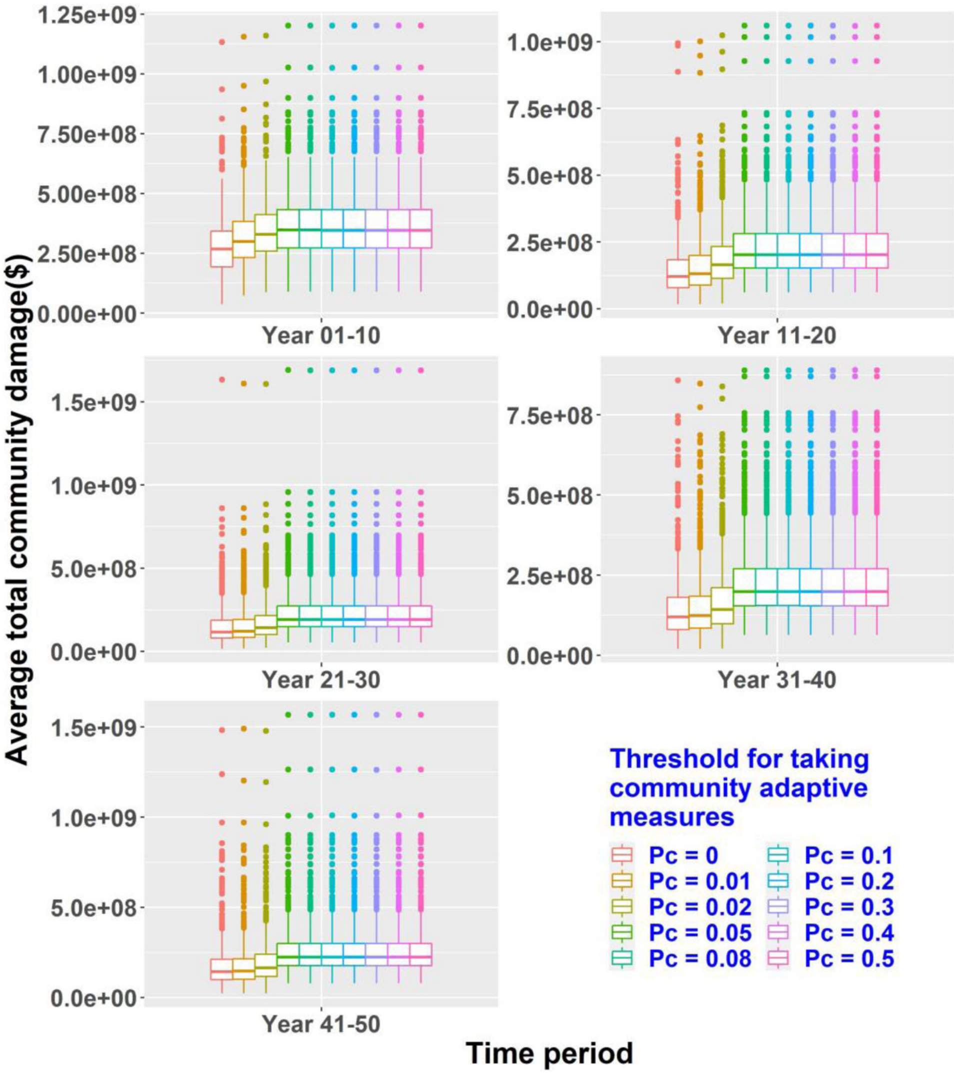

Fig 14. Model sensitivity of the threshold for taking community adaptive measures.

could provide a higher positive surplus to the NFIP. Considering additional operation costs of FEMA, it would be difficult for the NFIP to break even in scenario 1 and scenario 3.

5.2. Spatial Risk Mitigation Outcomes

Fig. 8 displays average risk perceptions of households. We estimated the average risk perceptions of households based on 1,000 model replications in the simulation. In our simulation, we choose the risk perception threshold $p_t = 0.03$, the value above which households will initiate the risk appraisal process. On average, in all scenarios, households living near the coast, such as areas around Miami Beach and east coast areas, have heightened perceptions of risk. Compared to other scenarios, more households in scenario 2 have high-risk perceptions. Households in both scenarios 1 and 2 are more likely to have high risk perceptions in areas of the east and south of the county. Because of community adaptation actions, we found risk perceptions of households in the northeast of the county are relatively lower in scenarios 3 and 4, indicating community adaptation activities will decrease households' risk perceptions.

Fig. 9 shows the spatial distributions of annual average property damage. The average annual damages are higher in scenarios 1 and 2 because of a lack of no community adaptation actions. In scenarios 3 and 4, most properties with high average damages are located in south Miami-Dade County and around the Miami Beach area. Compared to scenarios 1 and 2, it can be seen that changing insurance policies to risk-based policies could result in more damages in areas with relative low flood risk exposure. Therefore, households with low flood risk could be more affected under the risk-based flood insurance policy.

Fig. 10 shows that households in the south and northeast of the county would incur higher adaptation costs, which also indicates that agents living in those areas have higher risk mitigation behaviors. It is clear that scenario 1 and scenario 2 have higher adaptation costs on average on the spatial scale. This indicates when the local government does not invest in risk mitigation, private stakeholders incur higher costs to reduce their flood risk exposure. Fig. 10 also shows that private stakeholders within SFHA could spend more in scenarios with the risk-based insurance policy. However, when considering public risk mitigation, households in areas with low flood risk exposure, such as those in the northwest of the county, will have lower adaptation cost compared to other scenarios.

5.3. Model Parameter Sensitivity

We examined our model parameters based on one-factor-at-a-time (OFAT) sensitivity analysis, where we changed the values of one parameter at a time and kept all other parameters constant (Tonn & Guikema, 2018). Compared to other sensitivity analysis methods, the OFAT method has the advantage of relatively low computational cost and could be used to show the robustness of model outputs to changes in single parameters (ten Broeke, van Voorn, & Ligtenberg, 2016). Four parameters need to be calibrated in the model: agents' weight of indirect flood experiences (ω), agents' threshold for initiating risk appraisal process (P_t), the average number of social connections of agents (λ), and the community adaptation threshold p_c. We aggregated model results every 10 years for each model replication. Each parameter was replicated 1,000 times to include impacts of storm surges in different time periods. We used the average annual flood damage as the evaluation metric in the sensitivity analysis based on scenario 1.

Fig. 11 shows the parameter sensitivity of agents' weight of indirect flood experiences. On average, as the weight of indirect flood experiences increases, agents' risk perceptions will be more influenced by direct flood experiences. When the weight of indirect flood experiences is greater than 1, the community average annual damage increases significantly over time. This indicates that indirect flood experience would decrease the overall risk perception of the whole population when its weight is higher than that of direct flood experience.

Fig. 12 shows the model sensitivity of the threshold for initiating the risk appraisal process. It can be seen that this threshold value plays a crucial role in adjusting model results. A higher threshold value will result in fewer risk mitigation behaviors and therefore more severe average community damage.

Fig. 13 shows the number of social connections of agents. In general, when λ is larger, an agent has more connections in his or her neighborhood. When $\lambda = 0$, an agent has no social interactions. As a result, the average damages from years 1 through 10 are the highest. Nevertheless, because indirect flood experience has no influence on households' risk perceptions, households experiencing flood damages would gain higher risk perceptions. Therefore, when $\lambda = 0$, community flood damage is lower at the end of the simulation compared to other parameter values. As λ increases, more social interactions could result in lower community flood damage from years 1 through10. However, the community flood damage after 10 years increases as the increase of λ.

Fig. 14 shows the sensitivity of the threshold for taking community adaptive measures. When $P_c = 0$, the entire study area will be protected with a community floodwall, and consequently, the average community damage is the lowest. As P_c increases, the average community damage will increase in all time periods. When $P_c > 0.05$, changes in the average community damage are not significant in the simulation.

Sensitivity results of above parameters indicate model results are more significantly influenced by the threshold parameter for initiating risk appraisal. A small change in this parameter value could result significant different adaptation outcomes. We choose the entire area to be protected with floodwalls in community adaptation. We determined $P_t = 0.02$ according to empirical studies on NFIP in south Florida (Kousky, 2018). The weight of indirect flood experiences also influences model results greatly on the temporal scale. Since direct hazard experiences usually cause households to have stronger reactions (Kamiya & Yanase, 2019), we chose $\omega = 0.2$ in the model simulation. The average number of agents' social connections plays a more complicated role in adjusting model results. By referring to Yang et al. (2019), we chose $\lambda = 8$.

6. CONCLUSIONS

This article presents an ABM approach for studying evolving community flood damage and risk mitigation behavior of coastal residents under alternative adaptation policy scenarios in the United States. We developed the human risk perception model by relying on a Bayesian learning model and agents' previous experiences to simulate agents' dynamic risk perception. Parameter sensitivity results show that agents' risk perception threshold would significantly influence model results, and a higher weight of agents' indirect flood experience could discourage agents' risk mitigation behaviors and result in higher flood damage due to a false sense of resilience in the neighborhood.

We evaluated the decision making of agents on risk mitigation based on the willingness-to-pay of agents from a fitted linear model with parameter uncertainties. Results show that a household's spending on flood insurance is more influenced by the value of the property, the household's length of residence, and ethnicity of the household head. Our simulation results indicate that coastal homeowners' risk mitigation behaviors are highly influenced by flood damages from storm surges. Most households living in the south and northeast of the county are vulnerable to a high flood risk to storm surges. Consequently, these areas effect more risk-reducing behaviors.

Alternative adaptation policies could influence risk mitigation behaviors of coastal households. Our scenario results indicate that the risk-based scenario could reduce community flood damage because it delivers a clearer risk message in the form of increased insurance costs to coastal residents. Due to the high adaptation cost, the risk-based insurance rates will slightly decrease households' motivations to purchase flood insurance. This will affect households outside SFHAs and will result in greater flood damage for those households. Nevertheless, adaptation outcomes in Miami-Dade are more influenced by public risk mitigation and enforced adaptation rules, rather than flood insurance rates. Meanwhile, enhancing risk perceptions of residents in Miami-Dade County would be proactive step toward improving community resilience. Therefore, an integrated adaptation strategy with both a risk-based FEMA insurance policy and community adaptation would be necessary for improving community resilience in Miami-Dade County.

To conclude, this article presents an agent-based model to study the community flood damage with the consideration of human adaptive behaviors and alternative adaptation policies. In contrast to previous studies, we incorporated a Bayesian learning model into the protection motivation theory to evaluate households' risk perceptions and adaptive behaviors. This study improves the understanding of the natural-human systems based on the PMT. Simulation results show the community vulnerability through stochastic storm surges and the risk mitigation behaviors of agents based on the risk appraisal and coping appraisal processes of agents. Results of this study also demonstrate policy implications for flood risk management in coastal communities.

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Supplementary material