DOI: 10.1111/risa.13955

ORIGINAL ARTICLE

Individual learning as a driver of changes in community vulnerability under repeated hurricanes and changing climate

Chengwei Zhai[1,2] | **Allison C. Reilly**[3] | **Seth D. Guikema**[1]

[1]Department of Industrial and Operations Engineering, University of Michigan, Ann Arbor, Michigan, USA

[2]One Concern, Inc, Menlo Park, California, USA

[3]Department of Civil and Environmental Engineering, University of Maryland, College Park, Maryland, USA

Correspondence
Chengwei Zhai, 855 Oak Grove Ave, Menlo Park, CA 94025.
Email: czhai@oneconcern.com

Abstract
The risks from singular natural hazards such as a hurricane have been extensively investigated in the literature. However, little is understood about how individual and collective responses to repeated hazards change communities and impact their preparation for future events. Individual mitigation actions may drive how a community's resilience evolves under repeated hazards. In this paper, we investigate the effect that learning by homeowners can have on household mitigation decisions and on how this influences a region's vulnerability to natural hazards over time, using hurricanes along the east coast of the United States as our case study. To do this, we build an agent-based model (ABM) to simulate homeowners' adaptation to repeated hurricanes and how this affects the vulnerability of the regional housing stock. Through a case study, we explore how different initial beliefs about the hurricane hazard and how the memory of recent hurricanes could change a community's vulnerability both under current and potential future hurricane scenarios under climate change. In some future hurricane environments, different initial beliefs can result in large differences in the region's long-term vulnerability to hurricanes. We find that when some homeowners mitigate soon after a hurricane—when their memory of the event is the strongest—it can help to substantially decrease the vulnerability of a community.

KEYWORDS
agent-based model, hurricane mitigation, learning, repeated hazards

1 | INTRODUCTION

Natural disasters cause considerable property damage and economic loss. In 2017, three major hurricanes, Harvey, Irma, and Maria, made landfall, caused more than $300 billion (USD) in economic loss, damaged more than a million homes, and left misery in their wake (Reuters, 2017). Hurricane Irma caused approximately $70 billion (USD) in total economic loss, and half of that was due to damage to residential real estate (White, 2017). Residential building vulnerability is a critical component of a region's financial vulnerability when facing disasters. Low penetration rates of flood insurance in most coastal communities often mean that a singular event can erase a family's most valuable asset (Dixon et al., 2018; Zahran et al., 2009). Further, it can take months or even years after a disaster, depending on the availability of financial assistance, contractors, and postdisaster economic opportunities, among other factors, before displaced families return to their homes and repair houses to normal, putting the long-term future of the community at risk (Hamel et al., 2018). While there have been studies examining building stock vulnerability to hurricanes, most either (1) assume that building stock is static (Jain & Davidson, 2007) or (2) exogenously impose a change to the building stock within a hazard simulation model (Jain et al., 2005). This ignores the potential endogenous individual-level learning that stems from experience with hurricanes that could substantially alter the building stock over time.

Changes in building stock are part of the larger problem of estimating damage from repeated events. In this paper we consider repeated events to be hazards of the same type (e.g., a hurricane) that occur far enough apart in time that restoration, building, and post-storm mitigation changes to a building are completed before the next event occurs. This generally implies a separation of 1 year or more between events. Singular hazard events are well-studied, and risk analysis methods are well developed for these events. For example, hundreds of studies have been published on the aftermath of Superstorm Sandy, ranging from evacuation (Sadri et al., 2017), to nursing homes and elderly care (Lien et al., 2014), to hardening the New York City and the New Jersey coastline to reduce damage should a similar storm strike again (Smallegan et al., 2016). In contrast, relatively little is known about how repeated hazards may induce long-term changes to communities, and more specifically, how hazards change behaviors and policies which in turn influence the built environment. These alterations to the built environment change a community's ability to withstand future events.

To better understand how regional vulnerability can evolve, we must first better understand the potential contributions of individual-level learning to regional risk. This is particularly critical in communities exposed to repeated hazards as the effects of this learning, and the decisions that follow, compound over time. There is not a unified way in which individuals understand and respond to hazard risk and different beliefs about risk can lead to different mitigation behaviors. However, it is still important to understand the influence that archetypical behaviors have over time on community vulnerability to identify when interventions are warranted. For example, people who hold strong beliefs that hurricanes are infrequent and inconsequential are harder to sway even when their understanding of the hazard is updated by a new experience (Peacock, 2003). The impact of this behavior as it compounds over time differs depending on location and climate intensification. The role of memory can also influence behavior in a way that has compounding effects. More recent hazard experiences may tend to increase an individual's risk perception and decrease their risk tolerance, making individuals more likely to mitigate (Chiew et al., 2020). This is an instance of recency bias (Phillips-Wren et al., 2019). Recency bias is a type of cognitive bias that relates to systematic errors in judgment (Tversky & Kahneman, 1974).

This study investigates two specific questions: (1) When does learning from the hazard environment decrease homeowners' vulnerability to repeated hurricanes in a changing climate? and (2) How does the effect of recency bias influence a region's vulnerability in the long term? We specifically investigate the following key hypotheses, each of which is developed from the literature review (Section 2).

1. Individual-level learning can substantially change the vulnerability of the residential building stock over time as individuals update their beliefs about future damage based on damage that they experience and respond via decisions about home mitigation measures.
2. Prior beliefs about the likelihood of damaging storms can have a substantial impact on how an individual learns from experienced events and on their propensity to take additional mitigation actions.
3. Overweighting of recent events in probability updating by an individual could lead to the increased propensity to mitigate immediately after an event that is often seen in practice.

To examine these questions and hypotheses, we developed an agent-based model (ABM) that focuses on the influence of individual learning on homeowner decisions and then how these decisions affect regional building stock vulnerability. An ABM is required to address our research question to understand how complex behavior may emerge from how individuals interact with a stochastic hazard environment. This work builds conceptually from Reilly, Guikema et al. (2017), which builds an ABM to explore how homeowners interact with their hazard environment, and how their decisions could impact their risk over time. The current work expands this by considering more complex decision rules grounded in utility theory, by considering different hazard environments, and, central to this work, by considering the role that learning has on the distribution of outcomes. The model specifically evaluates the influence of prior knowledge, the effects of memory, and the confidence that homeowners have in their own beliefs about hazard risk. In the model, homeowners make decisions by choosing from a set of mitigation actions (e.g., installing hurricane shutters or hurricane straps). The approach is place-based, and developed to represent key characteristics of nine coastal counties with 357,120 homeowners in the State of Maryland. However, both the models and insights are generalizable to other areas.

An important note is needed on the role of the case study and intended use of the model. Our model is not intended to be predictive. That is, we do not and cannot make statements about how the vulnerability of the area used as the basis for our case study will evolve. There are too many additional factors beyond those considered in this paper that would need to be considered. Instead, the purpose of this work is to gain more general understanding into the possible influence of individual-level learning on the evolution of community vulnerability to natural hazards over time. Our case study provides a reality-grounded example within which to develop our model, but our model is not intended to fully represent the full reality of the area used as the basis for developing our case study. We acknowledge this tension between detail and abstractness that is always present when developing a complicated agent-based model, and we have sought to balance this tension by maintaining enough realism in our model to allow generalizable insights into the role of learning without overcomplicating the model such that it becomes completely intractable, rendering the results uninterpretable. Stating this differently, our goal in this paper is to develop scientific insight into the underlying process (individual learning in the presence of repeated hazards), not the development of a model that can be used in practice to set policies or make mitigation decisions.

The structure of this paper is as follows. We first review the literature of relevant studies as the construction of such models is highly interdisciplinary. We start by giving an overview of the literature on (1) vulnerability to and mitigation of hurricanes, (2) the use of ABMs in natural disaster studies, and (3) hurricanes and climate change. In Section 3, we introduce the framework of ABM, which includes an introduction of the case study region, a hazard model, a damage model, and models for individual learning and individual mitigation decisions. The details of model evaluation are presented in Section 5. In Section 6, we show results, including how model can be used with different climate scenarios, and discuss the role of learning, the impact of initial perception of hurricane risks, and the impact of recency bias.

2 | BACKGROUND

2.1 | Hurricane vulnerability and mitigation

Systems-level research on hurricane risk typically focuses on quantifying regional damage, the benefits and cost effectiveness of mitigation, and how federal and local policies may induce homeowners to mitigate their potential damage to reduce region-wide vulnerability. We begin with a discussion of regional damage assessment. Many studies rely on FEMA's HAZUS framework to simulate hazards and hazard impact, including estimates of economic losses from infrastructure and residential housing damage (Jain et al., 2005; Liu & Pang, 2014; Orooji & Friedland, 2017). HAZUS uses a whole-entity approach to modeling; each building class is assigned a hazard fragility curve (derived from the literature, reconnaissance, and experimental testing), which is based on a conditional probability of damage state given a hazard intensity. For example, for a hurricane, the intensity measure is typically gust windspeed. This can be too simplistic, especially when considering an individual house in a specific location. However, on a regional scale, it provides an approximation of the expected building damage given a hazard. HAZUS has additional known shortcomings, including out-of-date building stock, crude hurricane, and flooding scenarios—mostly accredited to accommodating the computational limits of most users—and deterministic hazard scenario modeling. Despite these limitations, it offers both an easy-to-use platform for researchers and practitioners to test hypotheses and its ubiquity has allowed for comparison among studies. Component-based approaches, on the other hand, are more granular. They focus on the vulnerability of individual building components, and the interactions among them, providing more accurate estimates of singular building damage (Chung Yau et al., 2011; Pinelli et al., 2004; Van De Lindt & Nguyen Dao, 2012). This approach requires significantly more knowledge of the building stock and computational resources. Our work relies on the whole-entity approach given its ubiquity and less inputs requirements. We do not use HAZUS directly, but we do use the building fragility curves provide by HAZUS. This allows us to overcome problems surrounding out-of-date building stock and crude hazard scenarios while still leveraging the HAZUS fragility functions.

Mitigation reduces the likelihood that a building experiences damage due to a hurricane. This paper focuses on household-level mitigation, such as adding wind straps or hurricane shutters. Not all mitigation is warranted based on its cost and the likelihood of damage (Wang et al., 2017). For example, Pinelli et al. (2009) studied the cost effectiveness of various mitigation strategies using a Monte Carlo simulation for different regions in Florida and created a map indicating the benefit/cost effectiveness for different combinations of housing mitigation decisions. Rose et al. (2007) contributes to this discussion on the cost effectiveness of mitigation using empirical data on hazard mitigation grants. They find a 4.7-fold return-on-investment for wind mitigation from FEMA mitigation grants—grants given to communities particularly susceptible to high windspeeds. These studies, and others like it, assume a static building stock and do not include the compounding benefits from mitigation from repeated hazard events.

Additional considerations for understanding how regional building stock vulnerability may change include homeowners' proclivity toward mitigation and federal, state, and local policies that influence homeowner mitigation behavior. Federal policies are also commonly evaluated with benefit-cost analysis or survey-based approaches (English et al., 2017), though these too are often based on a static snapshot of the situation.

Little of this past work has explicitly investigated the effects of repeated hurricanes—and their effects on mitigation behavior—on communities with the exception of Jain et al. (2005) and Reilly, Tonn et al. (2017), and Reilly, Guikema et al. (2017). Jain et al. (2005) propose a method to consider temporal changes in building inventory when estimating changes in expected losses from hurricanes over time. This simulation model considers how building vulnerability responds to changes in building codes. In Reilly, Guikema et al.'s (2017) model, homeowners from Anne Arundel County, MD can increase their home's resistance to historical hurricanes following a set of rules defined by probabilistic distributions. However, these studies do not explicitly investigate the potential role of learning as a determinant of long-term building stock vulnerability, and the modeling of decision making is intuition-based. Other studies that do consider the role of sequential hazards focus more on the degree to which learning takes place, and not the impact of learning (Colten & Sumpter, 2009). For example, Siegrist et al. (2008) explained the importance past flooding experiences and how they might change people's risk perception and motivate mitigation behavior. Their survey results suggested that negative experiences increase the likelihood of household mitigation behaviors but not necessarily when people also doubt the effectiveness of mitigation or perceive the cost as too high. Better understanding this potential role of learning is critical in understanding repeated hazards and their impacts on communities over time.

2.2 | Human learning and biases

Learning is an enduring change in the mechanisms of behavior involving specific stimuli and/or responses that results from prior experience with those or similar stimuli and responses (Chance, 2013). It has been well studied in the field of anthropology, biology, and psychology. It is one of the critical mechanisms that produces changes in behavior. To understand behaviors in a human-involved complex system must include consideration of what they learn and how they learn it.

Different types of learning have been discussed in past studies, such as individual learning, social learning, and organizational learning. Individual learning describes when the behavior itself is acquired by the result of the subject's own experience of the consequences of its actions (Feldman et al., 1996) . Social learning, on the other hand, might learn from the behavior of others, while running the risk of copying an inappropriate behavior (Feldman et al., 1996). Reed (2010) propose three requirements for a social learning process. It must (1) demonstrate that a change in understanding has taken place in the individuals involved, (2) demonstrate that this change goes beyond the individual and becomes situated within wider social units or communities of practice, and (3) occur through social interactions and processes between actors within a social network. Organizational learning describes how an organization or group can learn internally and externally as a whole (Brandi & Elkjaer, 2015). They describe how the field of organizational learning can be understood from a social learning perspective and which social learning theories add to an understanding of organizational learning that cannot be included in an individual learning theoretical approach. In the context of organizational learning, a learning loop framework is proposed to help facilitate the understanding of organizational learning (Johannessen et al., 2019). The framework describes different loops of learning that trigger different levels of retrospect of the context, assumptions, and actions that lead to the results. In the context of resilience and environmental change, outer-loop learning (i.e., which focuses on more challenging assumptions as opposed to practices and tactics) is crucial for maintaining regional resilience when environmental variability is high, such as during droughts (Yu et al., 2016).

Another potential learning source that might drive mitigation decisions is based on the experiences of neighbors. Slotter et al. (2020) used a survey approach on households' attitudes, risk perceptions, and prior experiences to understand each factor's impact on mitigation decisions. They found that both individual risk perception and neighbor experiences have a positive relationship with mitigation intention. However, the influence from factors, such as hazard experience and hazard understanding, remains under debate (Dillon et al., 2014; Mileti & Darlington, 1997; Peacock, 2003; Russell et al., 2016). While Russell et al. (2016) and Peacock et al. (2003) find a position relationship between hazard experience and an individual's motivation to mitigate, and also hazard understanding and an individual's motivation to mitigate, Mileti and Darlington (1997) and Dillon et al. (2014) did not. In Dillon et al. (2014), this is termed a "near miss" and typically arises when a disaster occurs, but by chance, the individual is unscathed, making them believe they are less vulnerable to harm than they truly are. While we acknowledge that all these types of learning are important in understanding the actual mitigation actions, we focus solely on modeling individual learning in this work, and hazard understanding and hazard experience in particular, in part because of past conflicting results.

A factor that strongly influences whether a hazard experience (or understanding) leads to mitigative action is an individual's degree of objectivity, and more specifically is the degree to which new knowledge or information is accepted and maintained over time (Underwood, 1964). One phenomenon, that we later explore with depth later in our work, is recency bias. Recency bias is a type of cognitive bias that relates to systematic errors in judgment, whereby more weight is given to events that occurred more recently than to events which occurred a long time ago (Tversky & Kahneman, 1974). It can potentially affect how the vulnerability of individuals evolves in a dynamic environment, such as one exposed to hurricanes. Individuals may, in some instances, be reactive to recent events and over-prepare compared to what they might be inclined to do had they considered a much longer hazard history. Past experiments and empirical evidence show contradictory results whether individuals actually are affected by recency bias (Royal, 2017; Wang et al., 2017). The experimental design in Royal (2017), which subjected participants to the possibility of negative income shock repetitively and offered insurance at the start of each round, found less insurance uptake, not more, when shocks occurred repetitively. This suggests that decisions were not biased toward the more recent negative outcomes in a way that would reduce vulnerability. Conversely, using surveys, Wang et al. (2017) showed that recent experience with hurricanes make homeowners more likely to purchase insurance. Similarly, using an experimental set-up where participants were asked to make mitigation decisions for a building exposed to repetitive hurricanes, Meyer found that mitigation investments were mainly driven by whether a storm occurred recently or not (Meyer, 2012). Therefore, in our study, we test both findings by generating scenarios with varying degrees of recency bias (ranging from none to strong) among the model agents.

2.3 | Agent-based models and their use in natural disaster studies

An ABM is a bottom-up modeling approach that simulates how heterogeneous intelligent agents (e.g., homeowners) interact with and learn from other agents and/or the environment and how, with this knowledge, they make decisions (Bonabeau, 2002; MacAl & North, 2010). Their decisions then change the environment and/or other entities.

Applications of ABMs span demography, the social sciences, economics, public health, and environmental science among other fields (Billari et al., 2006; Gorman et al., 2006).

ABMs have been widely used to model natural disasters and their impacts. ABMs are useful boundary objects that are able to integrate domain knowledge from multiple disciplines, making them increasingly popular (Reilly et al., 2018). The benefits of ABMs are that they (1) enable scenario-based sensitivity analysis (An, 2012), and (2) have the ability to model the compounding effects of individual actions and learning (Reilly, Tonn et al., 2017). However, most ABM work in the hazards realm centers around short-term actions after hazards occur to evaluate how agents might evacuate, take shelter, or access primary care services, and what infrastructure is needed to accommodate emergent behaviors (Chen & Zhan, 2008; Chen et al., 2006; Pan et al., 2007).

An ABM could also be used to model the long-term effects of natural disasters (Abebe et al., 2018, 2019; Haer et al., 2017, 2019; Reilly, Guikema et al., 2017; Reilly, Tonn et al., 2017; Tonn et al., 2020; Tonn & Guikema, 2018). Reilly, Tonn et al. (2017) built an ABM to quantify how hurricane-induced power outages could induce particular behaviors, and these in turn could influence a region's power system reliability in the long-run. Recent studies have also applied ABM to improve community vulnerability analyses under flood events, though the impact of individual learning has not been focused. Haer et al. (2017) built an ABM to compare how different economic behavioral models held by the agents would lead to different flood risk of the community. Haer et al. (2019) integrated different types of adaptive behavior of governments and households for river flooding under a similar framework. Households and the government as the agents would react to the environment under a combination of predefined rules, which will impact the region's long-term flood risk. Their results showed the importance of dynamic adaptive behavior and how it would lead to different flood risks under different climate projection. Abebe et al. (2018, 2019) built a coupled agent-based-flood framework and applied the model to evaluate long-term flood risk management policies. Household agents make house plans and they build houses with randomly sampled compliance toward different written formal policies. The government agent represents different levels of policy enforcement and may reduce the occurrence of flood hazard by improving the infrastructure system. The behavioral rules are relative ad hoc, which also leads to undervalidated results.

2.4 | Modeling individual learning in ABMs

People's behaviors are driven, in part, by their beliefs (Breen, 1999) and preferences (Panait & Luke, 2005). Beliefs can change over time when individuals gain additional information—perhaps through an experience or through information shared others—and then update their understanding of the process. Because learning affects how individuals make decisions over time, learning can be an essential component in an ABM framework for studying long-term implications of hazard vulnerability (Farmer & Foley, 2009). In ABMs, agents are considered autonomous and can interact with one another, meaning they can learn from both the environment and from other agents.

Learning can be viewed as a process in which beliefs are updated. In reality, this process is complex and is the subject of numerous psychological studies (Johnson & Hasher, 1987). In an ABM, however, learning is modeled in a logical structure compatible with computer coding. There are several ways to model this process in an ABMs. The primary methods include information modeling, Bayesian updating, reinforcement learning, and coevolutionary algorithms. We briefly review each below.

A common approach—information modeling or risk modeling—uses new information about disasters and risks perceived by the agents as the knowledge learned by the agents. For example, Du et al. (2017) explored evacuation processes during flooding events using an ABM. In this study, agents learn of a flood from a news broadcast, social media, and neighbor observations, which, when combined, triggers decisions by agents. In other work, Tonn et al. (2018) quantifies how different risk perception factors (i.e., flood experiences) and coping perception factors (i.e., mitigation behaviors) combine to estimate perceived risk factors. This value will then be compared with a risk tolerance threshold to determine when an agent will consider acting.

Bayesian learning or Bayesian updating is another approach for modeling learning (Breen, 1999). This method assumes an agent's beliefs about future events, such as the likelihood of a hurricane, follow specified probability distributions. These distributions are updated as new information becomes available using Bayes theorem. For example, Reilly, Tonn et al. (2017) modeled agents as having categorically distributed beliefs over the likelihood of zero, one, or more power outages in a given year. This is then combined with Dirichlet conjugate priors which are updated in a Bayesian manner every year given the number of power outages that occurred.

Another popular learning algorithm used in ABMs is reinforcement learning (Panait & Luke, 2005). In reinforcement learning, agents receive rewards from their actions, and they make decisions based on a new environment and the consequences caused by their prior actions. Krause et al. (2006) model the process of power suppliers submitting their bids to the electricity market using reinforcement learning. The agents are trying to maximize their payoffs and after each bid, they observe their gains or losses to update their behavioral policies or expected reward functions. As a result, they discover that after many rounds of bidding, the stable decisions each agent made to achieve their optimal output is the same as the existence of a unique Nash equilibrium or multiple equilibria in the system.

For each learning method, it is possible to incorporate learning and knowledge biases that individuals exhibit. For example, bandwagon effect or herd behavior is a cognitive bias in humans that people follow what others are doing instead of using their own information or making independent decisions, which is commonly observed and can be detrimental to disaster evacuations (Tsurushima, 2019). In natural hazards research, researchers have observed that the memory of events tends to fade over time (i.e., memory effect), which makes individuals less likely to take preparative actions (Logan et al., 2018; Reilly, Tonn et al., 2017), and this behavior is critical to capture in the model process. Memory fading can be a result of time or of new people moving into the area. In ABMs, the memory effect is often modeled as either a decay parameter on the awareness of the hazard (Logan et al., 2018) or as a window that allows only those events in the window to be "remembered" by the agents (Reilly, Tonn et al., 2017).

Among these models proposed, reinforcement learning, and Bayesian learning are most recognized in the field with certain limitations (Mathys et al., 2011). In this work, we choose a Bayesian model over other models, especially reinforcement learning for the following reason. Reinforcement learning is typically used under a situation to pursue for the optimal solution or policy to the agents under uncertainty. It requires repetitive simulations to train the agents to learn the optimal decision rules. This is not well-suited we our use case. Under a hurricane mitigation context, as the decision we are modeling is a one-time upgrade, they are more likely to be learned during actual hurricane experiences instead of repeated hypothetical experiments. Bayesian learning, on the other hand, is a sophisticated framework that can capture agent learning that is consistent with existing knowledge, particularly of the importance of the memory effect.

2.5 | Modeling decisions in an ABM

The decision making component of an ABM is a critical element for modeling emergent behavior. There are many different types of decision rules that can be used within ABMs. For ABMs in the hazards field specifically, we divide behavioral decision models into four groups: "if-then," descriptive, empirical, and prescriptive.

The first approach is "if-then" models which take the format of "if this happens, then one will do that with some likelihood." This approach is more ad hoc and often hard to be validated, though it is widely used in the ABM literature. The probabilities can be populated based on observation (i.e., empirical) or based on subject matter experts, but that is typically not the point. The objective is to find the marginal influence of different types of decisions on model outcomes, and these types of models require extensive sensitivity analysis (Du et al., 2017; Reilly, Tonn et al., 2017; Tonn & Guikema, 2018).

Descriptive decision theory attempts to explain the actual behaviors of decisionmakers. This is often different from their utility optimizing actions. Prospect theory is one example of a descriptive framework. Here, individuals evaluate outcomes based on possible gains and losses rather than expected utility (Kahneman & Tversky, 2018). Another well-known collection of descriptive decision theory method is bounded rationality. Models for bounded rationality assume individuals would be rational in their decision-making process, except that they are limited by the information they have, their cognitive limitations, and/or the amount of time they have to make the decision (Friedman & Rubinstein, 1998). Various heuristics and biases have also been studied to help explain observed actions. One example of using these methods in the ABM literature is a model of water scarcity management for repeated droughts (Burchfield & Gilligan, 2016).

Empirical models apply observed decision behavior (e.g., observed mitigation rates). The approach is reasonable when building an ABM for a particular region using observed data from that same region provided that the behavior is unlikely to change in the future. Then with a well-established dataset, statistical approaches can be applied to model agent's behaviors. However, individuals from different regions have been observed making different choices under similar hazards (Bouris, 2006)—likely because of different background understanding of the hazard —meaning empirical data are at times less relevant when applied to different regions. These methods are also less useful for situations in which agents must make decisions in environments they have not seen before.

Prescriptive decision theory models focus on identifying the "best" decisions by using expected utility maximization. This model assumes that a rational decisionmaker lists the actions or alternatives available to him or her, identifies the possible outcomes associated with each action along with the likelihood of occurrence of these outcomes, and finally quantifies the desirability of each outcome using a utility function. The alternative with the highest expected utility is selected. While attractive for improving individual decision making, utility theory is not necessarily a descriptive approach that captures the actual decision process people use (Rubinstein, 1988).

In this paper we use a utility-based model with subjective information for agent decision making. Given that the decision that the agents are making are both expensive and are associated with long-term changes to their homes, the agents are likely to consider costs and benefits in depth, analyzing their options. Though with certain limitations, utility-based models are well practiced in modeling decisions. It is also compatible with the Bayesian learning framework.

2.6 | Climate change and hurricanes

Climate change is likely to alter the pattern of hurricane occurrence in the next century (Walsh et al., 2015; Meehl & Tebaldi, 2004). While there is uncertainty in how climate change will affect hurricane frequency and intensity, it is likely that hurricanes will become less frequent though more intense in the Atlantic basin (Mendelsohn et al., 2012). On the other hand, climate change will also cause sea level rise, which will inundate coastal regions and result in flooding of areas that might have never seen storm surge in the past. In addition, greenhouse gas-induced warming may lead to gradually increasing risk of the occurrence of highly destructive category-5 storms (Knutson & Tuleya, 2004). Similar to Staid et al. (2014), we use a scenario-driven simulation approach and repeatedly perturb the hurricane intensity and frequency parameters for the region to better understand how individual behavior interacts with different hurricane environments to influence community vulnerability over time.

3 | METHODS

3.1 | Overview of model structure

Our agents are individual homeowners, modeled as one homeowner per land parcel and we focus on the impact of hurricane wind hazard. The model is initialized by assigning each agent attributes of their house (i.e., their house's construction type, also known as [a.k.a], building class, and the house's ability to resist wind forcing, a.k.a., resistance level) and a wealth (approximated by their house's improved value). The agents make mitigation decisions on an annual basis. Decisions are driven by an agent's perception of the risks from hurricanes. Our agents share the same alternatives in terms of mitigation actions as Reilly, Guikema et al. (2017) . We simulate how the region could evolve over 100-year periods in various hurricane scenarios. We choose 100-year as it is a sufficiently long period to allow us to see the results of individual behavior in a setting in which events happen relatively infrequently. The goal is to find the marginal contribution of decision-making related to mitigation on the vulnerability of the regional building stock. It is not to predict the building stock or its quality in 100-years. We acknowledge that 100 years exceeds the length of time for which an individual homeowner would reside in the area. We use this longer time frame to gain a more generic understanding of the potential role of learning. In the results section we highlight the results for the first 30 years to represent a more typical time span for which a homeowner would live in the area and hold a mortgage on their home.

We compare different scenarios and analyze the level of vulnerability of the community and discuss the importance of learning and initial knowledge of the agents to their decisions. Figure 1 provides an overview of the model used in this study. We first give an overview of this structure, and the subsections below provide more detail on the model's components.

We create different hurricane climate scenarios by controlling the frequency and intensity of synthetic hurricanes used in our analysis. Then we run a number of replications of the entire 100-year history using a simulation model that can be divided in to four components: the hurricane sampling model, the building damage model, the learning model, and the mitigation decision model. Many of these components have multiple steps to compute that are described in later subsections. The general process is that in a given time step (i.e., year), we sample the number and intensity of hurricanes to occur (zero hurricanes is a possibility in a given year) from distributions initially parameterized to reflect the conditions of the study area. The hurricane(s) that most closely matches the intensities are selected from a large library of synthetic but possible storms. This process is described in Section 3.3. Each house is probabilistically assigned damage (i.e., a damage level) based on the intensity of the hurricane, the downscaled 3-s 10-m peak wind gust at the parcel, and the construction type and resistance level of each home (which together, have their vulnerabilities represented by fragility curves). This process is described in Section 3.3. Agents then learn from this experience (which could include no hurricanes or no damage even if there is a hurricane) and then make mitigation decisions. This process is described in Section 3.4. This entire process repeated for 100-years under different climate scenarios. The model purposefully excludes numerous confounding factors, including recovery, insurance, disaster policy, and relocation, to isolate the impacts of learning from disasters for various climate scenarios to answer the fundamental question of what can be achieved with the learning from homeowners under climate changing. Future work could explore these effects.

The number of replications needed for stochastic convergence is determined by replicating the entire 100-year time until it meets our convergence criteria. We use the coefficient ($c_V = \frac{\sigma}{\mu}$) to calculate the output from the ABM (Lee et al., 2015). We then use Equation (1) to find the minimum number of replications, $n_{\min}$, needed to achieve desired level of convergence, E, between the coefficient of variation from n replications and m replications, where m is a large number. c_V^n and c_V^m are the corresponding coefficient of variation for n replications and m replications. We pick the potential number of iterations from a set of values, for example, 50, 100, 500, 1000, 5000, 10000. We calculate the coefficient of variation of each preselected number of iterations and select the sample size $n_{\min}$ when the convergence condition (e.g., $E = 0.01$) met for any other m greater than $n_{\min}$. As a result, we determined that when the number of iterations exceeds 1000 the convergence criteria is met for our output measure.

$$n_{\min} = \mathrm{argmax}_n \left| c_V^n - c_V^m \right| \langle E, \forall m \rangle \, n \tag{1}$$

3.2 | Case study

Our case study is based on nine counties in the state of Maryland—Anne Arundel, Calvert, St. Mary, Dorchester, Talbot, Queen Anne's, Wicomico, Somerset, and Worcester. These counties have coastlines along the Chesapeake Bay or the Atlantic Ocean (Figure 2). There are 357,120 single-family houses in this region. We identify 11 building classes based on FEMA's residential building designations. The most common building class is two-story wood-framed single-family houses. Then for each type of building, different mitigations, such as installing hurricane straps or change

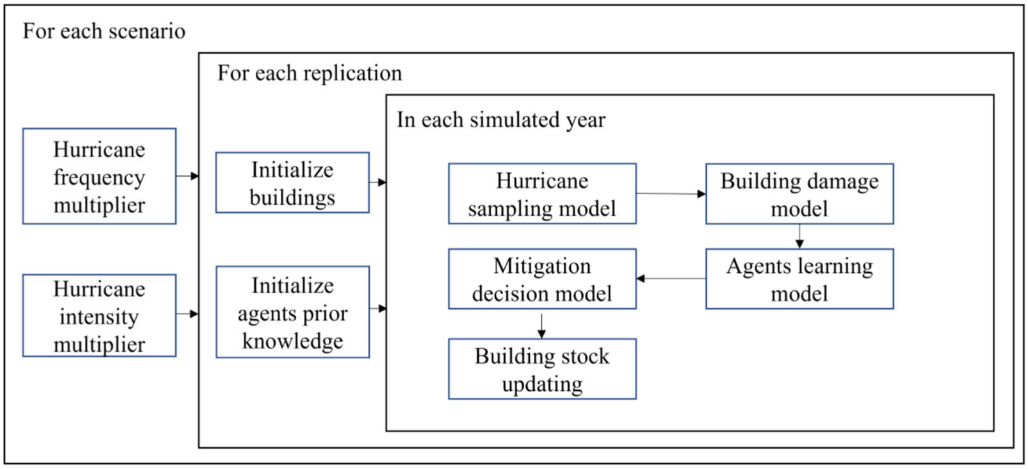

FIGURE 1 Overview of the computational flow of the ABM

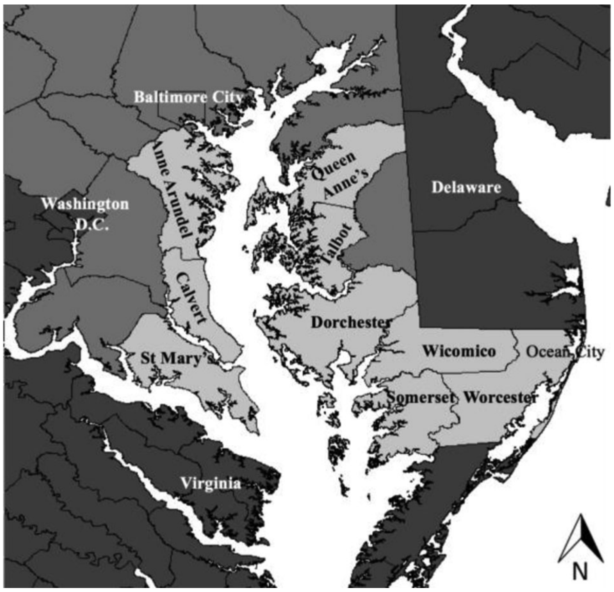

FIGURE 2 Map of region. Counties in light gray are used in the study

roof shapes, can be invested to improve the building's resistance level. A detailed description of all mitigation strategies can be found in Reilly, Guikema et al. (2017). Publicly available tax assessor data are used to spatially-locate each house and to assign each house a value (Maryland Department of Planning, 2016). The value (i.e., "improved value" from tax assessor data) combined with the building's fragility and the hurricane windspeed provide an estimate of the loss. Anne Arundel County is the most populated and is mostly suburban. Ocean City, in Worcester County, also has dense housing. The remainder of the region is either suburban or rural.

Because we do not know either income or wealth at the household level, we use the improved value as a proxy for wealth (capital) to support mitigation decisions. This is an imperfect measure. However, those with higher values are arguably more likely to have access to capital for mitigation through loans using their home's improved value as collateral. Also, this assumption can be replaced provided more detailed information on household wealth becoming available.

The case study area experiences a hurricane every 8 years on average. Most storms are Category 1 strength or below by the time they make impact in the region. The hurricane intensity tends to be greatest in the southern-most counties, such as Somerset and Worcester Counties. As the region is not as heavily influenced by hurricanes as southern states are (e.g., Florida, Louisiana), the overall hurricane resistance level is expected to be low given the current climate conditions. This provides sufficient room for the agents to learn and adapt to more intense and frequent hurricane climate scenarios.

We are not attempting to model this region in all of its detail. That is, we are not trying to model all details from these nine counties in order to support specific policy recommendations for this location. Rather, we used building stock data and historical hurricane impacts from this region to parameterize our model to provide a reasonable degree of reality and complexity to gain broader insights on the interactions among hazard frequency, damage experience, mitigation, and regional vulnerability over time.

3.3 | Hurricane sampling model

A synthetic library of possible hurricanes to affect the region, generated using the work of Staid et al. (2014a) is initially created (Reilly, Tonn et al., 2017). The library contains 36,399 synthetic storm tracks that could affect the study area, and these synthetic storms range in intensity from Tropical Depressions to Category 5 hurricanes. For each synthetic track, we then apply a hurricane wind field model to compute the 3-s 10-m peak wind gust at the centroid of each building (Holland, 1980). Next, baseline hurricane frequency and intensity distributions (Poisson and Weibull distributions, respectively) are fitted with the region's historic yearly hurricane frequency and maximum hurricane windspeeds to create the baseline hurricane climate scenario. The fitted parameters are later perturbed for different climate change scenarios (e.g., the rate parameter for the climate scenario with 25% more hurricanes is multiplied by 1.25). Once the simulation begins, in each simulated year, we sample from the intensity and frequency distributions to identify how many hurricanes affect the region that year (0 or more) and how intense each hurricane is. The hurricane in the synthetic library that is closest in intensity to the sampled intensity is selected. A more detailed description of this model is provided in Appendix A. Again, we are not aiming to model the precise future hurricane environment of the case study location under specific future climate scenarios. We are instead trying to gain a more general understanding of the potential role of individual learning in shaping a region's vulnerability over time under different possible future hazard scenarios.

3.4 | Building damage model

For each hurricane, the 3-s 10-m peak wind gust at the centroid of each parcel is computed (Holland, 1980). If more than one hurricane occurs in a year, the hurricane that is most intense is used. That is, damage from subsequent storms does not compound. Then, each house is assigned a damage state by combining building's fragility curve with the downscaled windspeed at the parcel's location.

HAZUS fragility curves are used to model each house's fragility. Each parcel is assigned to a building class based in its characteristics (e.g., number of stories, construction material). Each building class has distinct possible resistance levels, depending on the possible ways mitigation can be conducted (e.g., wind straps). As a house is mitigated, its resistance level improves. Each resistance level has five fragility curves, one for each of the possible damage states. These are as follows: Damage State 0, (DS0, no damage), Damage State 1 (DS 1, minor damage or 10% or less of the building sustained damage), Damage State 2 (DS2, moderate damage or about 25% of the building sustained damage), Damage State 3 (DS3, severe damage or about 50% of the building sustained damage), and Damage State 4 (DS4, completely destroyed) (Vickery et al., 2006). Fragility curves produce a probability that a house of a specific type and resistance level will be in one of five damage states conditioned on the windspeed.

The damage model randomly samples a number between 0 and 1 and a damage state is selected in proportion to the likelihood of being in a specific damage state given a windspeed. The losses are quantified by multiplying the improved value of the parcel by the fraction of sustained damage. Given the simplicity of these fragility curves, criticism exists (Reilly, Guikema et al., 2017). Our study is not dependent on this model and alternate fragility curves can easily be incorporated as long as they give similar output.

After a hurricane, we assume that any agents which experienced damage (from one or multiple hurricanes) would recover in a single year. That is, we do not focus on the immediate poststorm recovery process. Additionally, some or all agents may decide to mitigate. A wood-framed home, which constitutes the vast majority of the houses in our study area, could be upgraded by installing roof-wall straps, application of secondary water resistance, installing storm shutters, strengthening the roof deck attachment, or by changing the shape of the roof. Part of this decision depends on the cost of mitigation. We estimated the cost for individual homeowners to make house upgrading decisions using the RS Means cost pricing database (Plotner & R.S. Means Company., 2017).

3.5 | Agent learning and mitigation decision models

Mitigation decisions are essential components of how a community's vulnerability evolves. These decisions are partially controlled by an individual's personal beliefs about the risk a hazard poses (Siegrist & Gutscher, 2008). By observing a hazard and the damage it causes, or the lack thereof, individuals may update their beliefs about the risks posed by the hazard, and potentially change future mitigation decisions.

After each hurricane season in a simulated year, agents learn from their experience and may take mitigatory action. For instance, they may believe that the likelihood of a hurricane in any given year is now greater especially if they recently experienced a hurricane. These beliefs are combined with damage probabilities for each of the mitigation strategies and are used as inputs for a decision model on whether to mitigate.

The ABM is initialized by assigning each agent partial information or "knowledge" about the hazardscape. Specifically, each agent holds an initial belief about the frequency of each category of hurricane (including no hurricane). This is updated annually given their experiences. In each year of the ABM run, regardless if hurricane or damage occurs, agents "learn" from their experience by updating their beliefs about their risk and then decide whether to act. Based on this knowledge, agents may choose to mitigate, which, in turn, may change the vulnerability of their homes to damage in future hurricanes.

3.5.1 | Agent learning model

We model agent learning using a Bayesian updating framework. Learning in this model focuses on how likely agents believe hurricane force winds of varying magnitudes are to occur on their parcel in a given year. For example, an agent could believe that there is an 80% likelihood of no hurricane occurring in a given year, a 19% likelihood that their parcel experiences tropical storm force winds, and a 1% likelihood that a Category 1 or stronger storm would occur. If this agent were to experience Category 2 force winds, their beliefs about their chances of experiencing a Category 1 storm or greater would likely change.

We use a categorical distribution to describe each agent's belief for both hurricane frequency and intensity. We define X as a categorical random variable

$$X \sim \mathrm{Cat}\,(p_1, p_2, \dots p_7) \tag{2}$$

where p_1 through p_7 correspond to the probability of no hurricane, a tropical storm, and Category 1–5 hurricanes. While each of these divisions has a wide range of windspeeds, we select them because an individual is unlikely to know the exact windspeed they experienced, but rather an approximate windspeed such as the intensity of the storm on the Saffir–Simpson scale. The Dirichlet distribution is the categorical distribution's conjugate prior. $\alpha_1, \alpha_2, \dots, \alpha_7$ are the Dirichlet's support parameters and represent the number of observations for each of the windspeed divisions. Thus,

$$p_1, p_2, \dots p_7 \sim \mathrm{Dir}\,(\alpha_1, \alpha_2, \dots, \alpha_7) \tag{3}$$

If we treat the categorical distribution parameters as random variables, we can leverage each new windspeed observation, X_{new}, to update these parameters using Bayes rule and the Dirichlet distribution. The posterior distribution will still be a Dirichlet distribution with parameter α' given by,

$$\alpha'_i = \alpha_i + \mathrm{I}(X_{\text{new}} = i), i = 1, 2, \dots, 7 \tag{4}$$

where II is the indicator function. The posterior predictive distribution for this model is given by Equation (6).

$$f\,(X = i|\alpha) = \frac{\alpha'_i}{\sum \alpha_i{}'}, \; i = 1, 2, \dots, 7 \tag{5}$$

Before the ABM is run, priors—meaning initial beliefs over the intensity and frequency of hurricanes, $p_1, \dots p_7$—need to be assigned for each agent. We iteratively assign different starting priors in different ABM runs to test how initial beliefs influence the agents' decision process and the long-term vulnerability of the region.

We also consider the impact of recency bias in the learning models. Recency bias is a cognitive bias that occurs when an individual weighs more recent events in decision making (Phillips-Wren et al., 2019). We model the recency bias using

$$\alpha'_i = \alpha_i * w + \mathrm{I}(X_{\text{new}} = i), \tag{6}$$

where w is the weight of the long-term memory of the agents. $w < 1$ represents a decay of the long-term memory of the agent. More specifically when w decreases, it forces less weight on prior experiences and more weight on the agent's experience in that year.

As an example, consider two agents with different priors: (1,1,0,0,0,0,0) and (100,100,0,0,0,0,0), respectively. Although both indicate the agents believe there is a 50% probability of having no hurricanes and 50% probability of having a tropical storm in a given year, the underlying confidence for these two agents is distinct. Saying in the next year, both agents experienced a category 5+ hurricane, the two agents will update their beliefs by incorporating the new observations to update the underlying Dirichlet distributions' hyperparameters. If we do not consider the recency bias effect, the new beliefs will be computed with the updated distribution with hyperparameters (1,1,0,0,0,0,1) and (100,100,0,0,0,0,1). If we consider the recency bias effect with a weight of 0.9, then the hyperparameter will be updated to be (0.9, 0.9,0,0,0,0,1) and (90,90,0,0,0,0,1).

In this work, we consider the initial beliefs an agent held when making decisions by leveraging the parameters that support the Dirichlet distribution. An individual who has significant experience may be more likely to act than an individual who has much less (Siegrist & Gutscher, 2008). Table 1 shows the priors we use and what each prior implies about their beliefs. Partially uninformative priors describe agents who hold a minimum understanding of the environment. They could be, for example, agents who move to the region and thus lack knowledge of the regional risks. Partially strong priors describe agents who have lived in the region for a while, though the region is assumed to have been spared a strong hurricane for a long time. This may change at the start of the simulation, where the impact of climate change on hurricanes might make them occur more frequently or with more intensity. Wrong prior describes agents with potentially extreme experiences from previous hurricanes, who might be considered most likely to mitigate. We do not consider the effect of recency bias in these scenarios.

Similarly, recency bias also likely impacts mitigation decisions. Therefore, we modify the weight of the long-term memory (w) to represent different levels of recency biases, with a value of 1 representing no recency bias and a value close to 0 representing that they have no memory. Our hypothesis is that the loss of long-term mild and extreme hurricane experiences make recent events more meaningful for mitigation decision-making.

3.5.2 | Mitigation decision model

After agents learn, they decide whether and how to act. A detailed mathematical description of our decision model with an example of how agent learn and behave is presented in Appendix B. A brief overview follows. The agents choose from the following alternatives in each year that the model is run, for example, installing roof-wall straps, installing storm shutters, improving the roof deck attachment, installing second level water resistance, changing the shape of the roof, or simply doing nothing. Each option corresponds to a specific resistance level. Houses that are mitigated have a lower probability of being damaged when they are upgraded which is represented by differing fragility curves. However, the degree of improvement and the mitigation costs vary considerably based on the intervention. We assume agents know the probability of their house being damaged for each category

TABLE 1 Initial knowledge explanations

Priors name	Priors (No Hurr – Cat 5+ Hurr)	Implication
Partially Uninformative 1 (Baseline Prior)	(1,1,0,0,0,0,0)	Little knowledge for hurricanes events stronger than tropical storm
Partially Uninformative 2	(1,1,1,0,0,0,0)	Little knowledge for events stronger than category one storms
Partially Uninformative 3	(1,1,1,1,0,0,0)	Little knowledge for events stronger than category two storms
Partially Uninformative 4	(1,1,1,1,1,0,0)	Little knowledge for events stronger than category three storms
Partially Strong 1	(10,10,0,0,0,0,0)	Moderately strong belief that there will be no events stronger than tropical storm
Partially Strong 2	(100,100, 0,0,0,0,0)	Strong beliefs that there will be no events stronger than tropical storm
Wrong Prior (Severe Hurricanes)	(1,1,1,1,100,100,100)	Strong belief in intense hurricane events

of hurricane and for all housing mitigation options. Future iterations of the work could explore relaxing this assumption.

In each simulated year, we calculate each agent's expected utility for each mitigation alternative by combining the agent's probability distributions over hurricane frequency and intensity and the likelihood of damage for each mitigation option together with the costs of the options and the agent's utility function. An exponential risk averse utility function is used (Anand, 1993). The agent then chooses the alternative that maximizes their expected utility.

4 | MEASURE OF COMMUNITY VULNERABILITY

To compare different scenarios, it is helpful to have a measure of the overall vulnerability of the region to see the effect of different scenarios more simply. We do this through an additional calculation outside of the ABM. That is, we assessed the vulnerability of each household to six different intensities of tropical storms in that year and integrated these vulnerabilities into an overall vulnerability score for our study region. This score does not feed back to the ABM in any way. Instead, this was an extra assessment done only to provide an integrated picture of the overall vulnerability of the houses in the community. This section provides the details of how this was done.

In each simulated year, we record the state of each house in terms of its resistance level (i.e., its degree of mitigation). Then, separate from the ABM, that is, not providing any feedback into the ongoing ABM, we uniformly applied six different windspeeds (the median windspeed of each hurricane category) to each house and calculated the expected damage (in dollar value) for each house and for each windspeed. We then summed the expected damage across all of the houses to get d_i, the aggregate vulnerability measure for windspeed i.

Given that there is an upper limit of the achievable resistance of houses to hurricane winds, we also calculate the maximum and minimum expected damage, $d_i^{\max}$ and $d_i^{\min}$, which describe the most and the least damage a community could experience under windspeed level i. The maximum expected damage, $d_i^{\max}$, corresponds to all houses being in the lowest resistance level (i.e., no mitigation has been conducted). Similarly, the minimum expected damage, $d_i^{\min}$, corresponds to all houses being in the highest resistance level (i.e., no mitigation has been conducted). We then normalize and aggregate according to Equation (7):

$$\mathbf{VI} = \frac{1}{6} \sum_{i \in \text{wind level}} \frac{d_i - d_i^{\min}}{d_i^{\max} - d_i^{\min}} \tag{7}$$

Equation (7) normalizes the range of vulnerability measure to be between 0 and 1. For example, the vulnerability in Year 1 is 1, which assumes that no households have conducted mitigation and are in their initial resistance levels. If every household in the system chooses to mitigate their house to the fullest extent, the community vulnerability index will be 0. This does not mean houses are invulnerable, but they reach the max hurricane resistance as defined in the paper. The normalization is for the purpose of a better representation of the results. This value is not a representation of risk as it does not consider the likelihood of each level of storm occurring; it is a simplified measure of aggregate vulnerability. It is also not comparable across different regions or across individual buildings. The simulation for each replication of the full history always starts with no house upgrades. The Table 2 below shows the maximum and minimum damage (in U.S. dollars) for the case study region.

We use VI over time as our set of overall community vulnerability measures. The VI is not intended to reflect risk directly, as the likelihood of the hurricanes are considered only in the scenarios, but rather reflect regional building stock vulnerability conditioned on a particular scenario occurring.

5 | RESULTS

This section presents the results of our analysis. We start with the influence of hurricane frequency and intensity given weak priors (i.e., low confidence of their assessment of the hazard).

TABLE 2 Average community damages in U.S. dollars from each windspeed

Windspeed level	50 mph (∼TS)	85 mph (∼Cat 1)	103 mph (∼Cat 2)	120 mph (∼Cat 3)	143 mph (∼Cat 4)	160 mph (Cat 5+)
d^{max} ($)	1.04×10^6	8.50×10^8	7.96×10^9	2.67×10^{10}	4.87×10^{10}	5.37×10^{10}
d^{min} ($)	1.43×10^5	4.18×10^8	2.61×10^9	7.76×10^9	1.94×10^{10}	3.04×10^{10}

In the second subsection, we then vary the intensity of the priors. The priors are varied by iteratively perturbing the support parameters of the Dirichlet distribution that reflect each agent's knowledge and level of confidence when each run of the ABM is initialized. This helps us to isolate the influence of individuals who learn and gain confidence in their knowledge on regional vulnerability verses those who learn little from their experience. Similarly, we iteratively perturb the recency bias weight parameter to quantify the effect that an emphasis on more recent events has in forming beliefs on mitigation decisions.

5.1 | Influence of hurricane intensity and frequency

In this section, we first show how community vulnerability evolves in our model under different hurricane climate scenarios. We selected 100-years to understand the limit of learning and how vulnerability could decay over long periods of time for different scenarios. However, it is unreasonable to expect that homeowner would reside in a house for that length of time. To address this, blue vertical lines after the passage of 30-years are added to understand what the impact of learning may be for each scenario over a typical U.S. mortgage. We tested multiple intensities and frequencies of hurricanes. The intensity and frequency are modeled as 0.75, 1, 1.25, 1.5, and 1.75 times the historical fitted hurricane frequency and intensities. Either intensity or frequency is modified in each scenario. Again, we make no claims that these changes reflect an actual future climate scenario. Instead, we are using these discrete changes to examine potential changes in how learning influences vulnerability as a function of different hazard environments. We initialized the agents with a weak prior of (1,1,0,0,0,0,0), which assumes the agents have little knowledge with the environment, and that they believe they are equally likely to experience a tropical storm as a Category 1 storm. This is later referred to as the "baseline" priors. These priors are unlikely to induce mitigation before an agent observes additional hurricanes because an agent holding these beliefs does not believe a hurricane with force significant enough to cause substantial damage their house will occur. The results of this initial analysis are shown in Figure 3.

In Figure 3, for both plots, the x-axis is the year within simulation, and the y-axis is the vulnerability index (VI). I0.75 means hurricane intensity is 0.75 times the intensity generated from the current and baseline climate, and F0.75 means the frequency is 0.75 times the frequency in the baseline climate. The green lines for both plots are the same baseline scenario with intensity and frequency matching historical observations. Each line represents the median vulnerability index across all replications in each simulation year. We see that the community vulnerability decreases over time. This occur because we start the agents with no mitigation and any mitigation decision the agents are making will reduce the probability of damaged if a hurricane occurs. We also see that the intensity and frequency of hurricanes also substantially affect how community vulnerability evolves. As the intensity or frequency of hurricanes increases, community vulnerability to a storm of a given intensity decreases, and the higher the increase in intensity or frequency, the greater the reduction in vulnerability. This is because more mitigation takes place in response to more realized damage and this mitigation occurs sooner, meaning the benefits compound.

Based on the rate of change over time in the VI, the agents are more responsive to intensity changes than frequency changes. That is, for a given level of increase intensity, there is a greater reduction in vulnerability than for the same level of change in frequency. Furthermore, for the I1.75 scenario, the vulnerability of the region asymptotically approaches the minimum vulnerability (most resistant to hurricanes) over time. Hurricanes that are more intense tend to stimulate substantially more mitigations and reduce community vulnerability than more frequent but mild hurricanes.

5.2 | Impact of initial knowledge on the evolution of community vulnerability under different climate scenarios

To examine the effect of initial beliefs held by agents on the evolution of community vulnerability under different hurricane environments, we tested different sets of initial priors that all the agents hold at the beginning of the simulation. We compare the results from starting with each prior with the results from starting with the baseline-priors (provided in Table 1) to examine the effects of initial knowledge under each climate scenario.

The baseline evolution of vulnerability is shown in Figure 3 (with baseline climate and baseline prior) and is used to compare with each different prior scenario under the same climate. As before, we changed the intensity or the frequency, but not both together. We also controlled the hurricane records input for each hurricane climate scenario (e.g., a certain frequency or intensity comparing to the baseline scenario) with common random numbers to reduce the variance and make the results comparable for each scenario. That means the area will always be impacted by the same

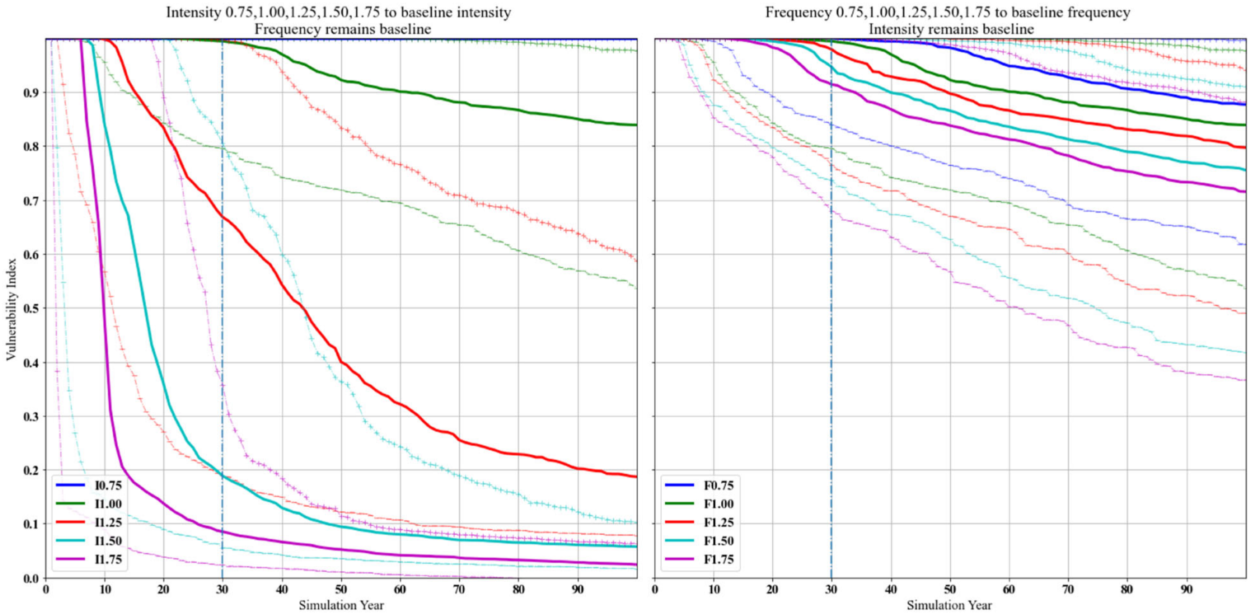

FIGURE 3 The baseline evolution of community vulnerability over a century under different hurricane scenarios. The agents are initialized with a (1,1,0,0,0,0,0) prior. Each solid line represents the median vulnerability index across all replications in each simulation year. Dashed line with the same color with '+' sign are the 85% upper bound of the output samples. Dashed line with the same color with '-' sign are the 15% lower bound of the output samples

hurricanes over 100 years in each replication for each initial knowledge priors. The common random number approach helps decrease the variance and reduce the number of replications needed for convergence when comparing different scenarios (Nelson & Matejcik, 1995).

Figure 4(A and B) shows the difference between the median VI from the baseline-priors case and the mean median for a scenario using modified priors (but the same intensity-frequency combination). Also shown are the 95% confidence intervals that are constructed by bootstrapping of all VI outputs from each replication in that scenario. The x-axis of each plot is time (years), and the y-axis is the difference between the mean VI for the baseline-priors case and the mean VI for a scenario using modified priors. When this difference is positive (negative), it means that this case resulted in a more (less) vulnerable community than the baseline-priors scenario. Sometimes, this difference is substantial. Using the difference with respect to the baseline helps us to examine how they are different from each other and explain the sensitivity.

Initial beliefs can influence agents' behaviors and community vulnerability substantially in the early years. For example, we found that under the climate scenario with hurricanes of intensity 1.75 times the initial climatic conditions, the largest difference between any two priors was more than 0.2, which is a large difference in the outcome when facing a same hurricane. When the climate intensity increases from the initial climatic conditions, cases with different initial priors begin to converge to a similar vulnerability level given a sufficient amount of time. The vulnerability indices initially diverge in earlier years and start to converge after the agents have experienced sufficient events to learn from the environment. That is, we see the effects of learning over time. Stronger hurricanes speed up the effect of learning and sway the effect of initial beliefs and led the entire community toward similar actions.

Another interesting finding is that holding strong beliefs about intense hurricanes initially (i.e., the "wrong priors case") does not necessarily imply the least vulnerability compared to other initial beliefs. The reason is that strong hurricane beliefs make the agents realize that, according to their beliefs, no matter what mitigation they undertake, damage is inevitable and cannot be reduced by much given the mitigation options we modeled. Their investment on house upgrades then would not be worth the cost. On the other hand, holding a very strong beliefs about less intense hurricanes (i.e., the "Partially Strong 2 case") impedes mitigation as well. This is because even an additional experience of a strong hurricane makes it difficult for agents to overcome their strongly held prior belief that hurricanes in the region are usually not intense. Only when the agents hold more neutral beliefs, that is, Partially Uninformative 3 and 4 cases does the community become more hurricane resistant.

Different hurricane frequency scenarios have similar rankings for different priors as the rankings for different hurricane intensities (Figure 4B). However, the differences between the "best" prior as measured by the vulnerability index (i.e., Partially strong 2) and the worst prior (i.e., Partially uninformative 4) increases as the frequency multiplier increases (*note that the range on the y-axis differs among scenarios so that we can zoom-in and show differentiation among some results*). The reason is that when hurricanes strike the area more frequently, regions that had been less likely to be impacted are more likely to be influenced at some point.

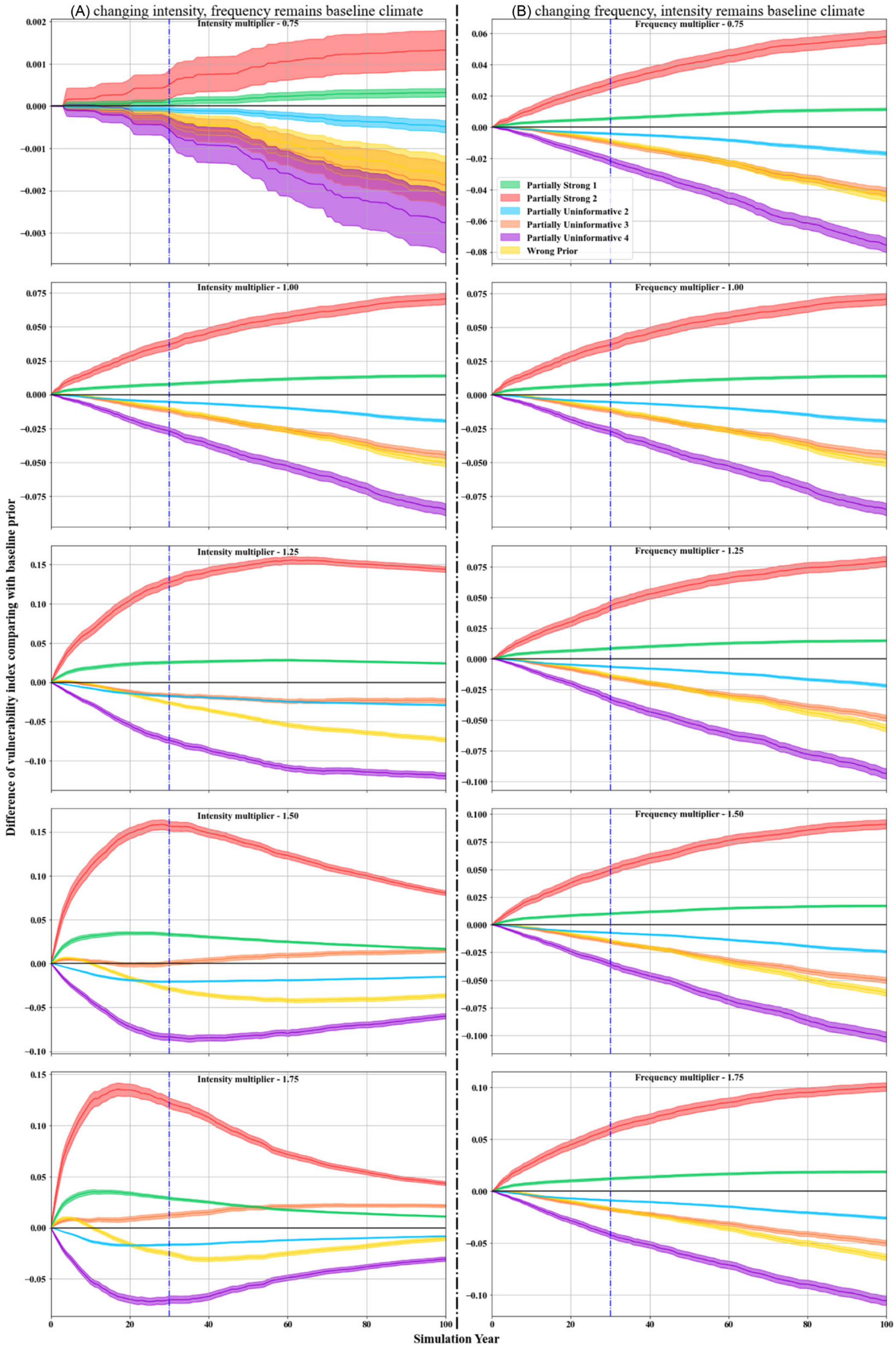

FIGURE 4 Differences in vulnerability for different initial priors compared with the baseline initial knowledge scenario over 100 years. (A) Hurricane intensity scenario changes from 0.75, 1.00, until 1.75 times the baseline climate while frequency remains baseline. (B) Hurricane frequency scenario changes from 0.75, 1.00, until 1.75 times the baseline climate while intensity remains baseline

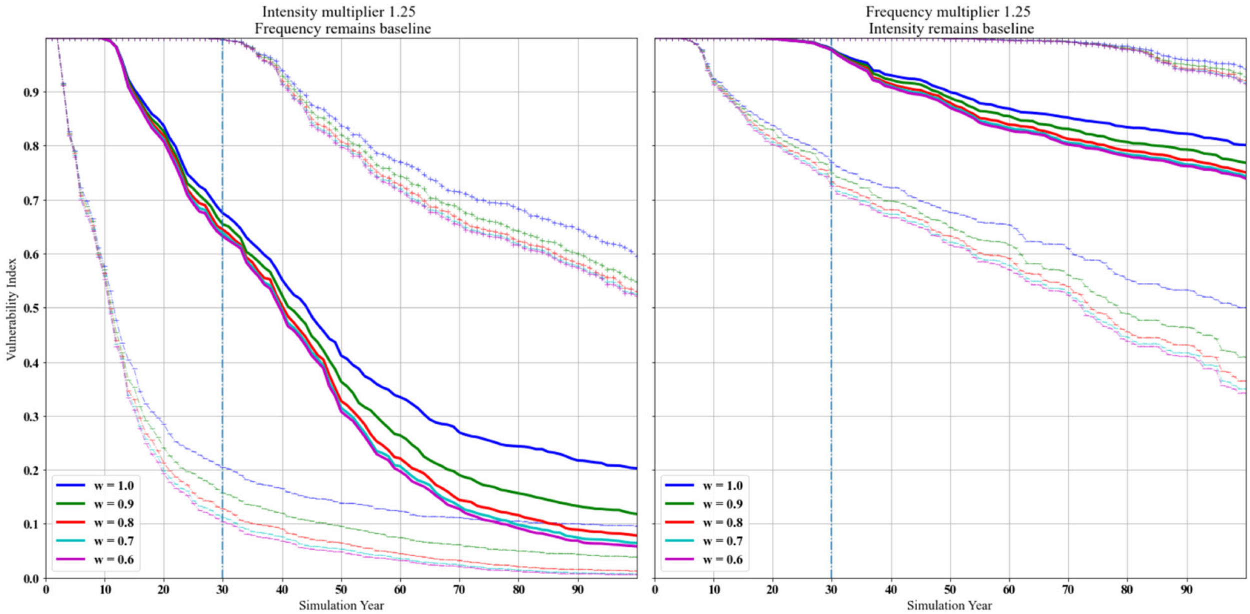

FIGURE 5 The evolution of community vulnerability under 1.25 intensity scenario (left) and 1.25 frequency scenario (right) with different recency bias weight parameter. Each solid line represents a different recency bias weight parameter. Dashed line with the same color with "+" sign are the 85% upper bound of the output samples. Dashed line with the same color with "-" sign are the 15% lower bound of the output samples

Thus, agents with little prior understanding of the risk (e.g., Partially uninformative) become likely to mitigate, because the chance that no hurricanes occur drops significantly and their perceived risk increases. On the other hand, for agents with strong priors, more frequent (though not necessarily more intense) hurricanes are unable to overcome their strongly held beliefs of low perceived risk and they continuously choose not to mitigate. Thus, over time, they experience more damage and their vulnerability index increases. In the frequency cases, initial knowledge held by the agents takes on a more significant role in determining the patterns of evolution of vulnerability over time relative to the cases in which intensity was varied. The initial differences in beliefs create a divergence in community vulnerability that does not converge by Year 100 when changes to frequency are considered.

5.3 | Impact of recency bias on the evolution of community vulnerability under different climate scenarios

Finally, we model the memory effects of agents as a weight on long-term events on their past experiences as discussed above. We chose the recency bias weight to be 1 (no weighting), 0.9, 0.8, 0.7, and 0.6. Such a process can be regarded as a result of long-term memory fading or generation replacement. This process limits the agents to make decisions based on partial information from recent events instead of using a more complete record of events. As a result, we find that this recency bias always promotes more mitigation and a less vulnerable community for any climate scenario. An example of this is shown in Figure 5. The results for other frequency and intensity scenarios are highly similar and are omitted for brevity. The blue line in both plots is corresponding to the baseline scenario in Figure 3. We are using the same partially uninformative prior as the baseline scenario as well.

We see in Figure 5 that the stronger an agent's recency bias is (or the faster the agents' long-term memory decays, reflected in a lower recency bias weight, w), the more mitigation that occurs and less vulnerable the community is. The explanation for this phenomenon is that while hurricanes usually do not occur, when they do, the agents' risk perception is weighted more heavily toward the existence of storms (and the fact that hurricanes usually do not occur is, to some degree, ignored). This, in turn, can dramatically increase their perceived risk of hurricane and damage, increasing the appeal of mitigation actions. That is, with the effect of recency bias, agents are much more sensitive to recent hurricanes. This emphasizes the importance of better understanding the degree to which limited memory is a factor in learning from the effects of past hazards.

6 | CONCLUSIONS

In this paper, we demonstrate how learning, initial knowledge, and the effect of recency bias alter the evolution of community vulnerability under different climate scenarios using an ABM. We found that individual-level learning can substantially change the vulnerability of the residential building stock over time as individuals update their beliefs about future damage based on past experience and respond via decisions about home mitigation measures. Prior beliefs about the likelihood of damaging storms can have a substantial impact on how an individual learns from experienced events and on their propensity to take additional mitigation actions; strong prior beliefs that may be wrong can increase the vulnerability compared to weaker prior beliefs. Lastly, overweighting recent events could lead to the increased propensity to mitigate immediately after an event that is often seen in practice. Incorporating the effect of learning is critical when simulating how community vulnerability may evolve under different adaptation and climate scenarios.

In our model, more intense and frequent hurricane scenarios stimulated more mitigation and resulted in a less vulnerable community overall. Different initial knowledge held by the agents had an important role in affecting the region's vulnerability, especially in early years. Limited memory can also induce more mitigation because agents are more sensitive to recent experiences. A better understanding of the learning process of individual homeowners will lead to a better understanding of their behaviors, which will benefit decisionmakers and policymakers in long-term community vulnerability mitigation decisions. For example, when a community is anchored in their beliefs of few storms (i.e., partially strong priors—the blue line) they are more vulnerable. Getting people to realize that their prior beliefs are wrong through interventions like information campaigns about hurricane frequency, intensity, and damages—admittedly a challenging task—may be useful in reducing vulnerability. Homeowners are most likely to choose to mitigate if they've recently experienced a hurricane and have sufficient resources. Government subsidies offered after a storm can help to encourage mitigation.

There are a number of limitations to this study, and additional research is needed. We explicitly did not attempt to develop a model that would predict vulnerability evolution for a real situation. Instead, we focused on develop an abstract but reality-grounded case study to better understand the potential influence of learning on the evolution of community vulnerability. Developing a model to provide accurate predictions of vulnerability evolution would require consideration of far more factors and processes. This would have to include at least land use change induced by nonhazard drivers, changes made in homes for reasons other than hazards, and the influence of social networks, government subsidies and programs, and neighbors on homeowner decisions. This is not the intention of this work. Future research into these and other aspects of this problem would be beneficial. We would also need to consider learning among peer groups and social networks, and intergenerational learning.

The results in this paper highlight the importance of understanding and modeling learning at an individual level when conducting a vulnerability assessment or risk analysis for a community facing the potential for repeated hazard events. Individual actions can substantially alter community vulnerability and learning from events is a critical part of this. Ignoring this learning effect can lead to substantial misestimation of future risk.

ACKNOWLEDGMENTS

This research was supported by the National Academies Gulf Research Program Early-Career Research Fellowship and National Science Foundation (grant number 1631409) and the National Science Foundation (grant number 1331399). The support of the sponsor is gratefully acknowledged. Any opinions, findings, conclusions or recommendations presented in this paper are those of the authors and do not necessarily reflect the views of the National Academies or National Science Foundation (contributors, 2017).

In addition, Map data copyrighted OpenStreetMap contributors and available from https://www.openstreetmap.org

ORCID

Chengwei Zhai https://orcid.org/0000-0002-8508-9838

NOTE

[1] http://planning.maryland.gov/OurProducts/downloadFiles.shtml

REFERENCES

Abebe, Y. A., Ghorbani, A., Nikolic, I., Vojinovic, Z., & Sanchez, A. (2018). A coupled flood-agent-institution modelling (CLAIM) framework for urban flood risk management. *Environmental Modelling and Software*, 1–10. https://doi.org/10.1016/j.envsoft.2018.10.015

Abebe, Y. A., Ghorbani, A., Nikolic, I., Vojinovic, Z., & Sanchez, A. (2019). Flood risk management in Sint Maarten – A coupled agent-based and flood modelling method. *Journal of Environmental Management*, *248*, 109317. https://doi.org/10.1016/J.JENVMAN.2019.109317

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling*, *229*(0), 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010

Anand, P. (1993). *Foundation of rational choice under risk.* Oxford University.

Billari, F. C., Fent, T., Prskawetz, A., & Scheffran, J. (2006). *Agent-based computational modelling: applications in demography, social, economic and environmental sciences*. Springer. https://doi.org/10.1007/3-7908-1721-X

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, *99*(3), 7280–7287. https://doi.org/10.1073/pnas.082080899

Bouris, E. (2006). Book review: Overconfidence and war: The havoc and glory of positive illusions. By Dominic D.P. Johnson. (Harvard University Press, 2004.) Balancing risk: Great power intervention in the Periphery. By Jeffrey W. Taliaferro (Cornell University Press, 2004.) *The Journal of Politics*, 68(1). https://doi.org/10.1111/j.1468–2508.2006.00382_13.x

Brandi, U., & Elkjaer, B. (2015). Organizational learning viewed from a social learning perspective. *Handbook of Organizational Learning and Knowledge Management*, 21–41. https://doi.org/10.1002/9781119207245.CH2

Breen, R. (1999). Beliefs, rational choice and Bayesian learning. *Rationality and Society*, *11*(4), 463–479. https://doi.org/10.1177/104346399011004005

Burchfield, E. K., & Gilligan, J. M. (2016). Dynamics of individual and collective agricultural adaptation to water scarcity. *Proceedings - Winter Simulation Conference*, *0*, 1678–1689. https://doi.org/10.1109/WSC.2016.7822216

Chance, P. (2013). *Learning and behavior*. https://books.google.com/books?hl=en&lr=&id=QZUWAAAAQBAJ&oi=fnd&pg=PR3&dq=Chance,+Paul.+Learning+and+behavior.+Cengage+Learning,+2013.&ots=KMhMIQaE9f&sig=BLDEVWoRKi-AbgfLQZ3pAd89owU#v=

onepage&q=Chance%2C%20Paul.%20Learning%20and%20behavior.%20Cengage%20Learning%2C%202013.&f=false

Chen, X., Meaker, J. W., & Zhan, F. B. (2006). Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys. *Natural Hazards*, *38*(3), 321–338. https://doi.org/10.1007/s11069-005–0263-0

Chen, X., & Zhan, F. B. (2008). Agent-based modelling and simulation of urban evacuation: Relative effectiveness of simultaneous and staged evacuation strategies. *Journal of the Operational Research Society*, *59*(1), 25–33. https://doi.org/10.1057/palgrave.jors.2602321

Chiew, E., Davidson, R. A., Trainor, J. E., Nozick, L. K., & Kruse, J. L. (2020). The impact of grants on homeowner decisions to retrofit to reduce hurricane-induced wind and flood damage. *Weather, Climate, and Society*, *12*(1), 31–46. https://doi.org/10.1175/WCAS-D-18-0139.1

Chung Yau, S., Lin, N., & Vanmarcke, E. (2011). Hurricane damage and loss estimation using an integrated vulnerability model. *Natural Hazards Review*, *12*(4), 184–189. https://doi.org/10.1061/(ASCE)NH.1527–6996.0000035

Colten, C. E., & Sumpter, A. R. (2009). Social memory and resilience in New Orleans. *Natural Hazards*, *48*(3), 355–364. https://doi.org/10.1007/s11069-008–9267-x

Dillon, R. L., Tinsley, C. H., & Burns, W. J. (2014). Near-misses and future disaster preparedness. *Risk Analysis*, *34*(10), 1907–1922. https://doi.org/10.1111/RISA.12209

Dixon, L., Clancy, N., Seabury, S., & Overton, A. (2018). The national flood insurance program's market penetration rate: Estimates and policy implications. *The National Flood Insurance Program's Market Penetration Rate: Estimates and Policy Implications*, https://doi.org/10.7249/tr300

Du, E., Cai, X., Sun, Z., & Minsker, B. (2017). Exploring the role of social media and individual behaviors in flood evacuation processes: An agent-based modeling approach. *Water Resources Research*, *53*(11), 9164–9180. https://doi.org/10.1002/2017WR021192

English, E. C., Friedland, C. J., & Orooji, F. (2017). Combined flood and wind mitigation for hurricane damage prevention: Case for amphibious construction. *Journal of Structural Engineering (United States)*, *143*(6), 06017001. https://doi.org/10.1061/(ASCE)ST.1943-541X.0001750

Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. *Nature*, *460*(7256), 685–686. https://doi.org/10.1038/460685a

Feldman, M. W., Aoki, K., & Kumm, J. (1996). Individual versus social learning: Evolutionary analysis in a fluctuating environment. *Anthropological Science*, *104*(3), 209–231. https://doi.org/10.1537/ASE.104.209

Friedman, D., & Rubinstein, A. (1998). Book review: Modeling bounded rationality. By Ariel Rubinstein. In *Southern Economic Journal*, 65(2). https://doi.org/10.2307/1060679

Gorman, D. M., Mezic, J., Mezic, I., & Gruenewald, P. J. (2006). Agent-based modeling of drinking behavior: A preliminary model and potential applications to theory and practice. *American Journal of Public Health*, *96*(11), 2055–2060. https://doi.org/10.2105/AJPH.2005.063289

Haer, T., Botzen, W. J. W., & Aerts, J. C. J. H. (2019). Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modelling approach. *Environmental Research Letters*, *14*(4), 044022. https://doi.org/10.1088/1748-9326/AB0770

Haer, T., Botzen, W. J. W., de Moel, H., & Aerts, J. C. J. H. (2017). Integrating household risk mitigation behavior in flood risk analysis: An agent-based model approach. *Risk Analysis*, *37*(10), 1977–1992. https://doi.org/10.1111/RISA.12740

Hamel, L., Wu, B., Brodie, M., Family, K., Sim, S.-C., & Marks, E. (2018). *One year after the storm: Texas Gulf Coast residents' views and experiences with hurricane Harvey recovery*. The Kaiser family foundation/Episcopal Health Foundation Harvey Anniversary Survey (Issue August).

Han, S. R., Guikema, S. D., Quiring, S. M., Lee, K. H., Rosowsky, D., & Davidson, R. A. (2009). Estimating the spatial distribution of power outages during hurricanes in the Gulf coast region. *Reliability Engineering and System Safety*, *94*(2), 199–210. https://doi.org/10.1016/j.ress.2008.02.018

Holland, G. J. (1980). An analytic model of the wind and pressure profiles in hurricanes. *Monthly Weather Review*, *108*(8), 1212–1218. https://doi.org/10.1175/1520-0493(1980)108<1212:AAMOTW>2.0.CO;2

Jain, V. K., & Davidson, R. A. (2007). Forecasting changes in the hurricane wind vulnerability of a regional inventory of wood-frame houses. *Journal of Infrastructure Systems*, *13*(1), 31–42. https://doi.org/10.1061/(ASCE)1076-0342(2007)13:1(31)

Jain, V. K., Davidson, R., & Rosowsky, D. (2005). Modeling changes in hurricane risk over time. *Natural Hazards Review*, *6*(2), 88–96. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:2(88)

Johannessen, Å., Gerger Swartling, Å., Wamsler, C., Andersson, K., Arran, J. T., Hernández Vivas, D. I., & Stenström, T. A. (2019). Transforming urban water governance through social (triple-loop) learning. *Environmental Policy and Governance*, *29*(2), 144–154. https://doi.org/10.1002/EET.1843

Johnson, M. K., & Hasher, L. (1987). Human learning and memory. *Annual Review of Psychology*, *38*(1), 631–668. https://doi.org/10.1146/annurev.ps.38.020187.003215

Kahneman, D., & Tversky, A. (2018). Prospect theory: An analysis of decision under risk. *Experiments in Environmental Economics*, *1*(2), 143–172. https://doi.org/10.2307/1914185

Knutson, T. R., & Tuleya, R. E. (2004). Impact of CO_2-induced warming on simulated hurricane intensity and precipitation: Sensitivity to the choice of climate model and convective parameterization. *Journal of Climate*, *17*(18), 3477–3495. https://doi.org/10.1175/1520-0442(2004)017<3477:IOCWOS>2.0.CO;2

Krause, T., Beck, E. V., Cherkaoui, R., Germond, A., Andersson, G., & Ernst, D. (2006). A comparison of Nash equilibria analysis and agent-based modelling for power markets. *International Journal of Electrical Power and Energy Systems*, *28*(9), 599–607. https://doi.org/10.1016/j.ijepes.2006.03.002

Lee, J. S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooei, B., Stonedahl, F., Lorscheid, I., Voinov, A., Polhill, G., Sun, Z., & Parker, D. C. (2015). The complexities of agent-based modeling output analysis. *Journal of Artificial Societies and Social Simulation*, 18(4). https://doi.org/10.18564/jasss.2897

Lien, C., Raimo, J., Abramowitz, J., Khanijo, S., Kritharis, A., Mason, C., Jarmon, C. H., Nash, I. S., & Carney, M. T. (2014). Community healthcare delivery post-hurricane sandy: Lessons from a mobile health unit. *Journal of Community Health*, *39*(3), 599–605. https://doi.org/10.1007/s10900-013–9805–7

Liu, F., & Pang, W. (2014). Projections of future US design wind speeds due to climate change for estimating hurricane losses. *ProQuest Dissertations and Theses*, 275.

Logan, T. M., Guikema, S. D., & Bricker, J. D. (2018). Hard-adaptive measures can increase vulnerability to storm surge and tsunami hazards over time. *Nature Sustainability*, *1*(9), 526–530. https://doi.org/10.1038/s41893-018-0137-6

MacAl, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, *4*(3), 151–162. https://doi.org/10.1057/jos.2010.3

Maryland Department of Planning. (2016). Maryland Department of Planning. http://planning.maryland.gov/OurProducts/downloadFiles.html

Mathys, C., Daunizeau, J., Friston, K. J., & Stephan, K. E. (2011). A Bayesian foundation for individual learning under uncertainty. *Frontiers in Human Neuroscience*, *5*, 39. https://doi.org/10.3389/fnhum.2011.00039

Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, *305*(5686), 994–997. https://doi.org/10.1126/science.1098704

Mendelsohn, R., Emanuel, K., Chonabayashi, S., & Bakkensen, L. (2012). The impact of climate change on global tropical cyclone damage. *Nature Climate Change*, *2*(3), 205–209. https://doi.org/10.1038/nclimate1357

Meyer, R. J. (2012). Failing to learn from experience about catastrophes: The case of hurricane preparedness. *Journal of Risk and Uncertainty*, *45*(1), 25–50. https://doi.org/10.1007/S11166-012-9146-4/FIGURES/10

Mileti, D. S., & Darlington, J. D. (1997). The role of searching in shaping reactions to earthquake risk information. *Social Problems*, *44*(1), 89–103. https://doi.org/10.2307/3096875

Nelson, B. L., & Matejcik, F. J. (1995). Using common random numbers for indifference-zone selection and multiple comparisons in simulation. *Management Science*, *41*(12), 1935–1945. https://doi.org/10.1287/mnsc.41.12.1935

OpenStreetMap contributors. (2022) https://planet.openstreetmap.org

Orooji, F., & Friedland, C. J. (2017). Cost-benefit framework to generate wind hazard mitigation recommendations for homeowners. *Journal of Architectural Engineering*, *23*(4), 1–11. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000269

Pan, X., Han, C. S., Dauber, K., & Law, K. H. (2007). A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations. *AI and Society*, *22*(2), 113–132. https://doi.org/10.1007/s00146-007-0126-1

Panait, L., & Luke, S. (2005). Cooperative multi-agent learning: The state of the art. *Autonomous Agents and Multi-Agent Systems*, *11*(3), 387–434. https://doi.org/10.1007/s10458-005-2631-2

Peacock, W. G. (2003). Hurricane mitigation status and factors influencing mitigation status among Florida's single-family homeowners. *Natural Hazards Review*, *4*(3), 149–158. https://doi.org/10.1061/(ASCE)1527-6988(2003)4:3(149)

Phillips-Wren, G., Power, D. J., & Mora, M. (2019). Cognitive bias, decision styles, and risk attitudes in decision making and DSS. *Journal of Decision Systems*, *28*(2), 63–66. https://doi.org/10.1080/12460125.2019.1646509

Pinelli, J. P., Simiu, E., Gurley, K., Subramanian, C., Zhang, L., Cope, A., Filliben, J. J., & Hamid, S. (2004). Hurricane damage prediction model for residential structures. *Journal of Structural Engineering*, *130*(11), 1685–1691. https://doi.org/10.1061/(ASCE)0733-9445(2004)130:11(1685)

Pinelli, J. P., Torkian, B. B., Gurley, K., Subramanian, C., & Hamid, S. (2009). *Cost effectiveness of hurricane mitigation measures for residential buildings*. Proceedings of the 11th Americas Conference on Wind Engineering, San Juan, Puerto Rico, June 22–26.

Plotner, S. C., & R.S. Means Company. (2017). *Building construction costs with RSMeans data 2017*. R S Means Co.

Reed, M. S. (2010). What is social learning? *Ecology and Society*, 15(4). https://www.jstor.org/stable/26268235?seq=1#metadata_info_tab_contents

Reilly, A. C., Dillon, R. L., & Guikema, S. D. (2018). Agent-based models as an integrating boundary object for interdisciplinary research. *Risk Analysis*, *41*(7), 1087–1092. https://doi.org/10.1111/risa.13134

Reilly, A. C., Guikema, S. D., Zhu, L., & Igusa, T. (2017). Evolution of vulnerability of communities facing repeated hazards. *Plos One*, *12*(9), e0182719. https://doi.org/10.1371/journal.pone.0182719

Reilly, A. C., Tonn, G. L., Zhai, C., & Guikema, S. D. (2017). Hurricanes and power system reliability-the effects of individual decisions and system-level hardening. *Proceedings of the IEEE*, *105*(7), 1429–1442. https://doi.org/10.1109/JPROC.2017.2689720

Reuters. (2017, September 03). *Hurricane Harvey damages could cost up to $180 billion*. Fortune. http://fortune.com/2017/09/03/hurricane-harvey-damages-cost/

Rose, A., Porter, K., Dash, N., Bouabid, J., Huyck, C., Whitehead, J., Shaw, D., Eguchi, R., Taylor, C., McLane, T., Tobin, L. T., Ganderton, P. T., Godschalk, D., Kiremidjian, A. S., Tierney, K., & West, C. T. (2007). Benefit-cost analysis of FEMA hazard mitigation grants. *Natural Hazards Review*, *8*(4), 97–111. https://doi.org/10.1061/(ASCE)1527-6988(2007)8:4(97)

Royal, A. (2017). Dynamics in risk taking with a low-probability hazard. *Journal of Risk and Uncertainty*, *55*(1), 41–69. https://doi.org/10.1007/S11166-017-9263-1/FIGURES/4

Rubinstein, A. (1988). Similarity and decision-making under risk (is there a utility theory resolution to the Allais paradox?). *Journal of Economic Theory*, *46*(1), 145–153. https://doi.org/10.1016/0022-0531(88)90154-8

Russell, L. A., Goltz, J. D., & Bourque, L. B. (2016). Preparedness and hazard mitigation actions before and after two earthquakes. *Environment and Behaviour*, *27*(6), 744–770. https://doi.org/10.1177/0013916595276002

Sadri, A. M., Ukkusuri, S. V., & Gladwin, H. (2017). Modeling joint evacuation decisions in social networks: The case of Hurricane Sandy. *Journal of Choice Modelling*, *25*, 50–60. https://doi.org/10.1016/j.jocm.2017.02.002

Siegrist, M., & Gutscher, H. (2008). Natural hazards and motivation for mitigation behavior: People cannot predict the affect evoked by a severe flood. *Risk Analysis*, *28*(3), 771–778. https://doi.org/10.1111/j.1539-6924.2008.01049.x

Slotter, R., Trainor, J., Davidson, R., Kruse, J., & Nozick, L. (2020). Homeowner mitigation decision-making: Exploring the theory of planned behaviour approach. *Journal of Flood Risk Management*, *13*(4), e12667. https://doi.org/10.1111/JFR3.12667

Smallegan, S. M., Irish, J. L., Van Dongeren, A. R., & Bieman, D., & J, P. (2016). Morphological response of a sandy barrier island with a buried seawall during Hurricane Sandy. *Coastal Engineering*, *110*, 102–110. https://doi.org/10.1016/j.coastaleng.2016.01.005

Staid, A., Guikema, S. D., Nateghi, R., Quiring, S. M., & Gao, M. Z. (2014a). Simulation of tropical cyclone impacts to the U.S. power system under climate change scenarios. *Climatic Change*, *127*(3–4), 535–546. https://doi.org/10.1007/s10584-014-1272-3

Tonn, G., Guikema, S., & Zaitchik, B. (2020). Simulating behavioral influences on community flood risk under future climate scenarios. *Risk Analysis*, *40*(4), 884–898. https://doi.org/10.1111/RISA.13428

Tonn, G. L., & Guikema, S. D. (2018). An agent-based model of evolving community flood risk. *Risk Analysis*, *38*(6), 1258–1278. https://doi.org/10.1111/risa.12939

Tsurushima, A. (2019). Modeling herd behavior caused by evacuation decision making using response threshold. In P. Davidsson & H. Verhagen (Eds.), *Multi-agent-based simulation XIX. MABS 2018. Lecture notes in computer science* (Vol. 11463, pp. 138–152). Springer. https://doi.org/10.1007/978-3-030-22270-3_11

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124–1131. https://doi.org/10.1126/SCIENCE.185.4157.1124

Underwood, B. J. (1964). Degree of learning and the measurement of forgetting. *Journal of Verbal Learning and Verbal Behavior*, *3*(2), 112–129. https://doi.org/10.1016/S0022-5371(64)80028-1

Van De Lindt, J. W., & Nguyen Dao, T. (2012). Loss analysis for wood frame buildings during hurricanes. II: Loss estimation. *Journal of Performance of Constructed Facilities*, *26*(6), 739–747. https://doi.org/10.1061/(ASCE)CF.1943-5509.0000270

Vickery, P. J., Skerlj, P. F., Lin, J., Twisdale, L. A., Young, M. A., & Lavelle, F. M. (2006). HAZUS-MH hurricane model methodology. II: Damage and loss estimation. *Natural Hazards Review*, *7*(2), 94–103. https://doi.org/10.1061/(ASCE)1527-6988(2006)7:2(94)

Walsh, K. J. E., Camargo, S. J., Vecchi, G. A., Daloz, A. S., Elsner, J., Emanuel, K., Horn, M., Lim, Y. K., Roberts, M., Patricola, C., Scoccimarro, E., Sobel, A. H., Strazzo, S., Villarini, G., Wehner, M., Zhao, M., Kossin, J. P., La Row, T., Oouchi, K., … Henderson, N. (2015). Hurricanes and climate: The U.S. Clivar working group on hurricanes. *Bulletin of the American Meteorological Society*, *96*(6), 997–1017. https://doi.org/10.1175/BAMS-D-13-00242.1

Wang, C., Zhang, H., Feng, K., & Li, Q. (2017). Assessing hurricane damage costs in the presence of vulnerability model uncertainty. *Natural Hazards*, *85*(3), 1621–1635. https://doi.org/10.1007/s11069-016–2651-z

White, M. C. (2017, September 16). *Why Irma's impact on the economy will be worse than Harvey's*. NBC News. https://www.nbcnews.com/storyline/hurricane-irma/why-irma-s-impact-economy-will-be-worse-harvey-s-n801696

Yu, D. J., Shin, H. C., Pérez, I., Anderies, J. M., & Janssen, M. A. (2016). Learning for resilience-based management: Generating hypotheses from a behavioral study. *Global Environmental Change*, *37*, 69–78. https://doi.org/10.1016/J.GLOENVCHA.2016.01.009

Zahran, S., Weiler, S., Brody, S. D., Lindell, M. K., & Highfield, W. E. (2009). Modeling national flood insurance policy holding at the county scale in Florida, 1999–2005. *Ecological Economics*, *68*(10), 2627–2636. https://doi.org/10.1016/j.ecolecon.2009.04.021

How to cite this article: Zhai, C., Reilly, A. C., & Guikema, S. D. (2023). Individual learning as a driver of changes in community vulnerability under repeated hurricanes and changing climate. *Risk Analysis*, *43*, 762–782. https://doi.org/10.1111/risa.13955

APPENDIX A: SYNTHETIC HURRICANE GENERATION

Synthetic hurricanes are generated outside of the ABM using the four-step process developed in Staid et al. (2014). These steps are:

a. Choose an initial windspeed and location for landfall: The U.S. coastline is divided into 50 km bins and the bins are populated by the number of hurricanes to make landfall within its boundaries. The initial location at landfall is randomly selected from these bins in proportion to historic landfall occurrences. The windspeed is sampled from the historical record.
b. Using the initial windspeed and location, generate a hurricane track from a non-parametric random forest model trained on the suite of historical U.S. hurricane tracks (Staid et al., 2014). The track reports the location of the center of the hurricane in 6-h increments.
c. Compute the peak 3-second 10-m peak wind gust at the center of each parcel in the study area using a parametric hurricane wind field and decay model (Han et al., 2009).
d. Discard any hurricane that does not impact the study region.

This is repeated until a library of 36,399 synthetic storms to impact the study region is generated. The storms range in intensity from tropical storms to Category 5 hurricanes.

Next, the case study area's historic hurricane intensity and frequency records are fitted to Poisson and Weibull distributions, respectively, to form baseline hurricane scenarios as shown in Equations (1) and (2):

$$N_i \sim \text{Poisson}\,(cF) \tag{1}$$

$$v_{\max} \sim \text{Weibull}\left(\alpha I, \beta\right) \tag{2}$$

Here N_i is the number of hurricanes that impact the case study area in year i, c is the historical annual frequency with which hurricanes make landfall in the study region and equals 0.137, and F is the multiplier that controls hurricane frequency. $F = 1.0$ implies the baseline case. $v_{\max}$ is the maximum windspeed for each sampled hurricane. The parameters α and β describe a two-parameter Weibull distribution fitted using historical maximum hurricane windspeed in this region, where $\alpha = 67.76$ and $\beta = 3.64$. I is the multiplier that controls hurricane intensity by changing the scale parameter. $I = 1.0$ implies a baseline case. These distributions are used in the ABM to sample both the number of hurricanes that occur in a year and the intensity of each hurricane. The synthetic track in the library with the maximum 3-second peak wind gust closest to the sampled hurricane landfall windspeed is selected.

APPENDIX B: DECISION MODEL

For the decision-making model, we use a decision tree to enumerate all possible alternatives that an agent can choose given their previous upgrade history. In each simulated year with at least one hurricane, each agent chooses from a set of alternatives that increases the wind resistance of their house or do nothing. We use utility theory to model each agent's preference.

In the simulation, each agent's parcel is initially assigned a building type, which is extracted from the Maryland Department of Planning[1]. There are 11 building types, defined by the building materials and number of stories. Examples of these are a single-story wood-framed homes and a two-story unreinforced masonry homes. For each building type, different upgrading options to reduce wind damages are available (e.g., adding roof-to-wall straps). For each type of building and given upgrade alternative (if any) selected, we use the fragility curve which estimates the probabilities of that building being in each of the possible damage states (i.e., damage states 1–4) from a given windspeed from HAZUS. Each agent incorporates this fragility function with their probabilistic beliefs about the frequency and intensity of hurricanes to calculate the expected utility of each alternative and then choose the alternative with the highest expected utility. Each upgrade can only be applied once, and we assume the reliability of the upgrade does not decay as time progresses in the simulation. A detailed description of build stock information can be found in Reilly, Guikema et al. (2017).

We define the current state of a house as s_0, which is the combination of its building type and upgrades previously done to that house. The potential future states of the house are denoted as s_i, $0 \le i \le n$, where n is the number of different alternatives the homeowner has for upgrading their house. A cost c_i, $0 \le i \le n$ is associated with each choice. After a storm, the house can either be not damaged or in one of four different damage states (from minor damage to completely destroyed) with damage costs c_{d0}, c_{d1}, c_{d2}, c_{d3}, c_{d4} equal to 0, 0.05,0.2,0.45, and 0.99 times the house improved value W.

The agent updates their estimates of the probability of occurrence of each category of hurricanes written as p_j, $1 \le j \le 7$, corresponding to the probability of no hurricane, a tropical storm, and Category 1–5 hurricanes. This is updated each year based on new observations by the agent in each simulated year. The probability of being in each damage state k, $0 \le k \le 4$, given the average windspeed for each category of hurricanes and the potential damage state of the house is defined as $p(d_k|s_i, \text{Hurr}\,j)$, $1 \le j \le 7$. We assume the agent knows these probabilities when making mitigation decisions.

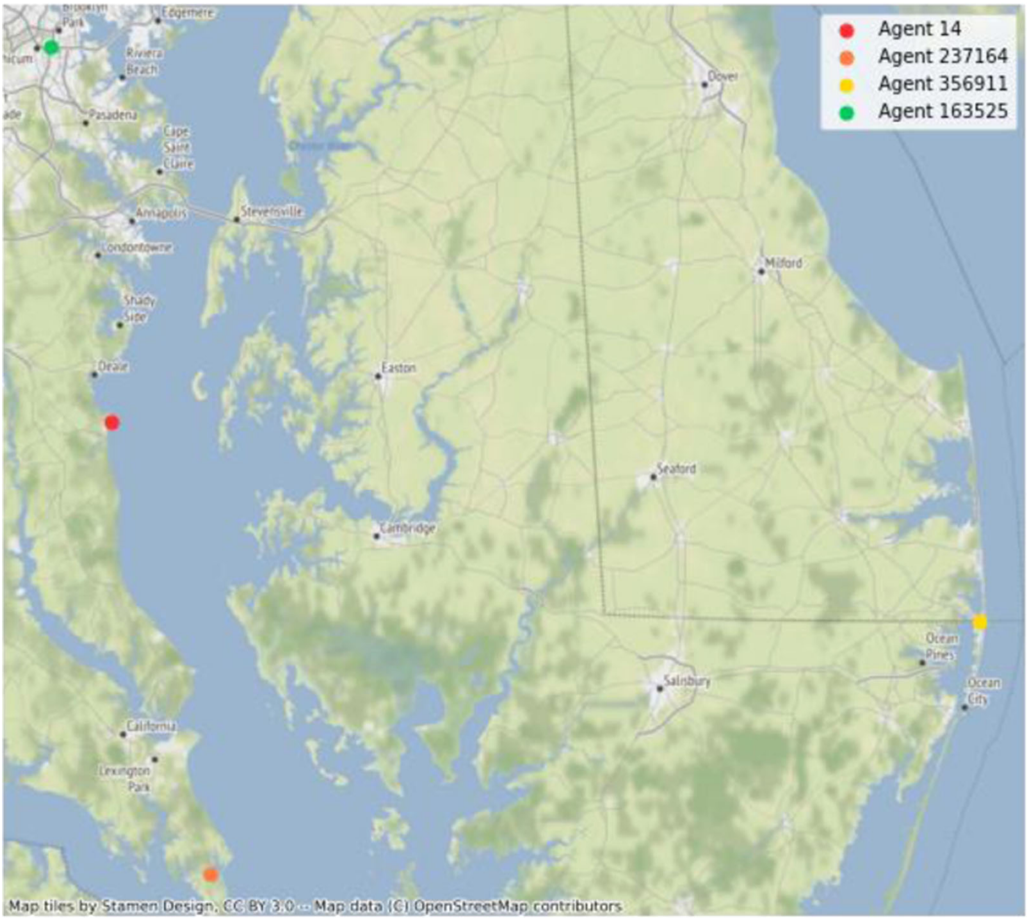

FIGURE 6 Selected agents and their locations. Map created with QGIS with OpenStreetMap, 2022 as the basemap

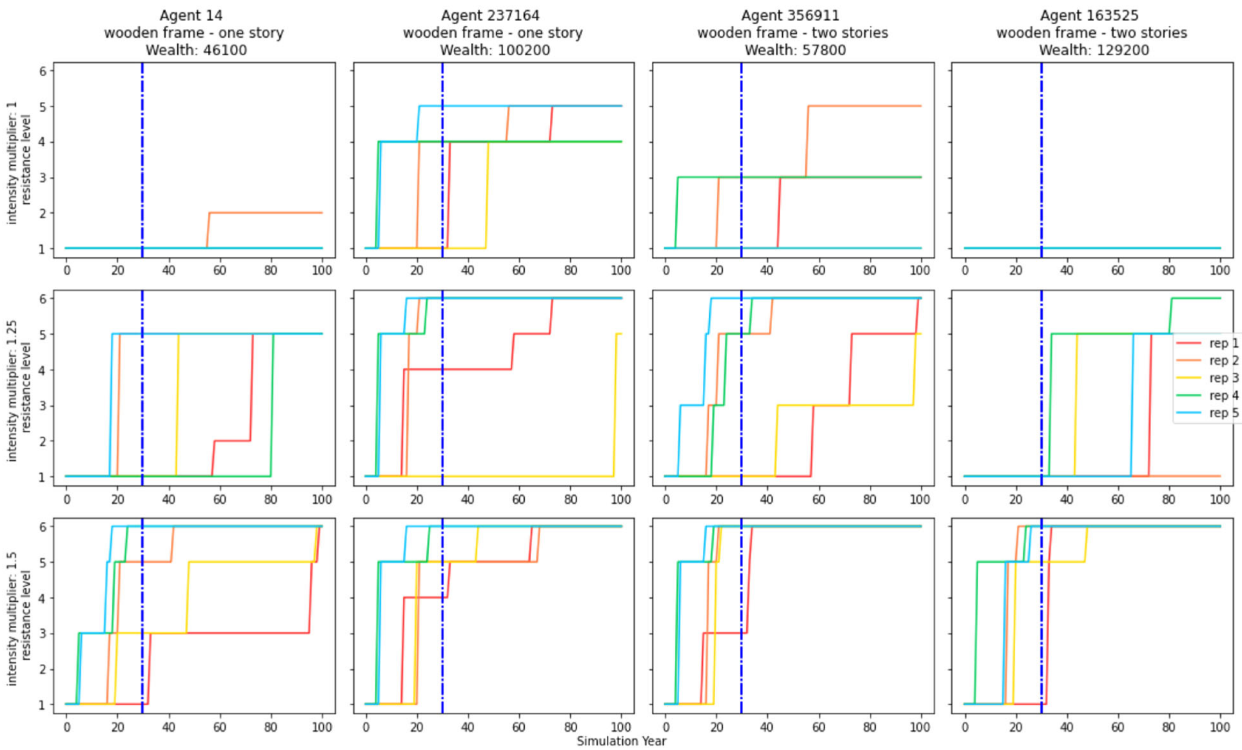

FIGURE 7 The upgrade progress of selected agents under different hurricane scenarios. Five replications are shown in this figure

We use a risk averse exponential utility function shown in Equation (1) to quantify the preference over outcomes

$$U\ (x) = \ 1 - e^{-x/R} \tag{1}$$

where R is the risk aversion factor. In the model we select R to be $0.05 * W$ where W is the wealth of each agent. We use the house's improved value as a proxy for wealth because we lack household-level net worth information. As a result, wealthy people can afford more expensive upgrades and to be more risk seeking than less wealthy people.

The agents also consider the long-term return from their investment on house upgrades, that is, what is their return over the next T years with a discount factor γ. $T\ =\ 10$ and $\gamma\ =\ 0.03$ in our model. Here the return on their investment is defined based on how much damage is reduced if they take that action given their assessment of the risk. Hence, we can calculate the expected utility considering long-term return using Equation (2).

$$EU\left(s_i|s_0\right) = \sum_{j\in[1,7]} p\left(j\right) \sum_{k\in[0,4]} p\left(d_k|s_i,j\right) LU\left(c_i, c_{dk}\right) \tag{2}$$

Where $EU(s_i|s_0)$ is the expected utility for a house in state s_0 to upgrade to s_i, and $LU(c_i, c_{dk})$ is the long-term utility if the house is in damage state k

$$LU\left(c_i, c_{dk}\right) = U\left(w - c_{dk} - c_i\ \right) + \sum_{t=1}^{T} U\left(\left(w - c_{dk}\right) * \frac{1}{\left(1+\gamma\right)^t}\right). \tag{3}$$

$U(w - c_{dk} - c_i)$ is the utility value when implementing the upgrade in the current year, and $\sum_{t=1}^{T} U((w - c_{dk}) * \frac{1}{(1+\gamma)^t})$ is the utility with this upgrade over the next T years. At the end of each year, based on the agents perception of hurricane occuring, each agent identifies the state s_i that gives them the best long-term return and upgrades their house accordingly.

To help better understand the learning and decision-making model, we provide an example running the ABM with four agents (locations and their Agent IDs shown in Figure 6) for 5 replications, with three different intensity multipliers. Agents are assumed to hold the same initial knowledge with priors (1,1,0,0,0,0,0), and their wealth varies. The same replication under different intensity scenarios has the same number of hurricanes occurring during the same years, though the tracks and intensity will be different. In the meantime, different replications have hurricanes arriving at different years. Results are shown in Figure 7. Each line represents the mitigation process for each of the five replications. When two lines are overlap, it means it is at the same resistance level as another replication during that period of time. Note that the cost of the same mitigation activities are different for different houses.

We find that agents tend to mitigate more and earlier with higher intensity scenarios. All resistance levels (or mitigation options) are adapted by agents at some point in the simulation. Agents tend to mitigate more if they hold more wealth. Agents living in different regions mitigate differently as they have different hurricane experiences. Agents 14 and 356,911 hold limited wealth, preventing them from mitigating as effectively even with more intense hurricanes. Agent 163,525 lives inland, which means they have fewer hurricane observations, leading to less mitigation overall.