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Simulating Behavioral Influences on Community Flood Risk under Future Climate Scenarios

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Flood risk is a function of both climate and human behavior, including individual and societal actions. For this reason, there is a need to incorporate both human and climatic components in models of flood risk. This study simulates behavioral influences on the evolution of community flood risk under different future climate scenarios using an agent-based model (ABM). The objective is to understand better the ways, sometimes unexpected, that human behavior, stochastic floods, and community interventions interact to influence the evolution of flood risk. One historic climate scenario and three future climate scenarios are simulated using a case study location in Fargo, North Dakota. Individual agents can mitigate flood risk via household mitigation or by moving, based on decision rules that consider risk perception and coping perception. The community can mitigate or disseminate information to reduce flood risk. Results show that agent behavior and community action have a significant impact on the evolution of flood risk under different climate scenarios. In all scenarios, individual and community action generally result in a decline in damages over time. In a lower flood risk scenario, the decline is primarily due to agent mitigation, while in a high flood risk scenario, community mitigation and agent relocation are primary drivers of the decline. Adaptive behaviors offset some of the increase in flood risk associated with climate change, and under an extreme climate scenario, our model indicates that many agents relocate.

KEY WORDS: Agent-based model; behavioral influences; climate change; flood risk; mitigation

1. INTRODUCTION

Annual flood losses have increased globally from $7 billion in the 1980s to $24 billion in years 2001 through 2011 (adjusted for inflation) (Kundzewicz et al., 2014). Flood losses have continued to increase despite the presence of both protective structures and insurance programs (Dilling, Daly, Travis, Wilhelmi, & Klein, 2015), primarily because of expanding exposure of assets (Kundzewicz et al., 2014). Future flood risk is expected to continue to increase due to both climatic and socioeconomic drivers (Alfieri, Feyen, & Di Baldassarre, 2016; DeBruin, Wong-Parodi, & Morgan, 2014). However, the increase in expected damages and population at risk can potentially be compensated for through combinations of mitigation measures (Alfieri et al., 2016). Because flood risk is so highly dependent on the combination of climate and human behavior, in the form of individual and societal actions, there is a need to incorporate both human and climatic components in models of flood risk.

Humans are both causing climate change and adapting to the changing climate (Palmer & Smith, 2014). Societal context dramatically affects vulnerability, and behavior shapes exposure, sensitivity, and adaptive capacity. Institutions can help mediate

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the impacts of climate hazards through formal approaches like regulations and information campaigns and through informal approaches like customs and cultural norms. Adaptation decisions, both on individual and societal levels, are influenced by risk perceptions, and risk perceptions that differ from the reality of risk can result in over- or underinvestment in adaptation. Furthermore, adaptation decisions can have unintended consequences for the system they are meant to protect and for the surrounding ecosystem (Dilling et al., 2015).

As such, earth-system models should capture human–climate dynamics and human–infrastructure interactions. An agent-based model (ABM) is one tool that is useful in this regard (Palmer & Smith, 2014). This study aims to simulate behavioral influences on the evolution of community flood risk under different future climate scenarios. The objective is to evaluate the usefulness of agent-based modeling for this purpose and to better understand the ways, sometimes unexpected, that human behavior, stochastic floods, and community interventions (both structural and nonstructural) interact to influence the evolution of flood risk. The intent is not to build a precise model of flood risk in an actual location but to enhance understanding of how individual and community-level behavior may influence flood risk in a future climate. The work builds on prior work that evaluates the use of ABM for simulating the evolution of community flood risk under historic climate conditions (Tonn & Guikema, 2018), and serves as a starting point for simulating behavioral influences on flood risk in a future climate. The prior work evaluated different formulations of the historic climate ABM, while this work simulates behavioral responses to future climate scenarios and their varying flood frequencies and magnitudes.

Section 2 provides background on behavioral responses to flooding and agent-based modeling. Section 3 describes methods and data. Section 4 provides results and Section 5 concludes.

2. BACKGROUND

2.1. Behavioral Response to Flooding

Decisions around flood risk management often involve engineering models and structural solutions. However, it is also vital to consider the behavioral component of flood risk. Individual mitigation decisions are often better predicted by subjective or perceptual factors than by objective risk assessment. For effective flood risk management, it is essential to consider how people think and feel about flood risk and about mitigation measures (Fox-Rogers, Devitt, O'Neill, Brereton, & Clinch, 2016). There are various strategies for dealing with increasing flood risk, including sharing the loss, bearing the loss, modifying the events, preventing the effects, or changing location (Burton, Kates, & White, 1993). In other words, flood risk can be reduced by insuring, increasing protection, reducing the hazard, reducing vulnerability, or relocating (Alfieri et al., 2016). Mitigation aims to lessen the financial impacts of floods on individuals, communities, and society as a whole (Kick, Fraser, Fulkerson, McKinney, & DeVries, 2011). To encourage effective individual and community mitigation action, it is important to consider how individuals react to flood hazards; to community policies, programs, and information; and to community mitigation measures.

Individuals react to the occurrence of floods, be it repeat flooding or lack thereof. Experiencing a flood has a large negative impact on an individual's subjective well-being (Hudson, Botzen, Poussin, & Aerts, 2017). Mitigation decisions of individuals that have withstood past flood damage are not totally rational, but are based on reasoned ideas about costs, risks, trust, and place, considering perceived costs and risks of being flooded again. Risk awareness is affected by class, prior flood experience, and length of residence (Kick et al., 2011). Floods are emotionally important and heighten flood risk awareness, and perceptions of concrete weather events like floods generally do not vary by political affiliation like climate change perceptions (DeBruin et al., 2014).

Individuals also react to community policies, programs, and information dissemination. One role of government is to trigger collective action, and governance can be an important driver for individual adaptation decision making (Adger et al., 2009). Individuals feel enabled to act responsibly and potentially to mitigate if the community has programs that encourage individuals to consider the environmental and social aspects of their behavior and provide a supportive environment for individual and community decision making (Burton et al., 1993). Buyouts and mitigation incentives also tend to come from the government. Sharing of tangible opinions by experts and other community members is a powerful influencer of mitigation action (Kick et al., 2011). Flood risk communication campaigns can increase individuals' perceived ability to implement risk mitigation strategies and willingness to take action (Fox-Rogers et al., 2016; Haer, Botzen, & Aerts, 2016).

The presence or addition of engineered flood mitigation also impacts individual risk perception and behavior. Infrastructure changes undertaken by the government may lessen flood risk, but may also create a false sense of security (Kick et al., 2011), thereby reducing individual risk perception and incentive to mitigate. Incremental flood protection measures may reduce the feasibility of future retreat from flood-prone areas (Hino, Field, & Mach, 2017). Both structural and nonstructural flood mitigation measures are typically used to manage flood risk, but nonstructural measures are becoming preferred over structural (Buss, 2005; Cummings, Todhunter, & Rundquist, 2012). Some modes of structural flood protection reduce the frequency of small floods but do not protect against rare large floods, thus exposing the community to catastrophic impacts (Alfieri et al., 2016). Furthermore, structural flood mitigation can increase exposure when land protected by the mitigation measure is developed or otherwise improved (Dilling et al., 2015).

2.2. Behavioral Response to Severe Climate Change

Floods are affected by various characteristics of a climatic system, including precipitation and temperature patterns along with drainage basin conditions, urbanization, and hydraulic structures. To date, it is likely that more regions of the United States have experienced statistically significant increases in the number of heavy precipitation events versus statistically significant decreases (Janssen, Wuebbles, Kunkel, Olsen, & Goodman, 2014; Kundzewicz, 2002; Kundzewicz et al., 2014). However, there is strong regional and subregional variation in climate change impacts to precipitation. Anthropogenic climate change has been detected in some variables that affect the hydrologic cycle, including mean precipitation, heavy precipitation, and snowpack. Temperature plays a significant role in climates where snow storage and melting significantly affect annual runoff, with resulting changes in the timing of spring peak flows. Without adaptation, future climate change will lead to increased flood losses in many regions (Kundzewicz et al., 2014).

Managed retreat is a type of transformational adaptation and is a deliberate intervention involving the abandonment of land or relocation of assets (Hino et al., 2017). Relocation of a community or portion of a community can be considered when vulnerability and risks are very sizable, as may be the case with the substantial increase in flood risk that climate change may cause in some areas (Kates, Travis, & Wilbanks, 2012). Relocation can improve the physical, social, environmental, and economic resilience of flood threatened rural communities (Cummings et al., 2012), but often is infeasible or impractical for more urban areas. Barriers to transformational adaptation such as managed retreat are substantial and include uncertainties about risks and adaptation benefits, perceived costs, and behavioral biases that tend toward the status quo (Kates et al., 2012). Other barriers to relocation or retreat from flood-prone areas include property rights, development interests, and distorted financial interests. Local governments often shy away from relocation due to fear of losing their tax base. Relocation can be forced or voluntary, and motivation for relocation often involves relocation programs, financial incentives, and awareness of high risk (Cheong, 2011). Government flood protection tends to involve incremental change instead of transformational change (Kates et al., 2012), so that construction of structural mitigation measures may lessen the drive for relocation.

Given the impracticality and barriers to transformational adaptation for nonrural areas, this study focuses on individual behavior and decisions around voluntary individual mitigation and relocation versus relocation of an entire community. Haer, Botzen, and Aerts (2019) find that household-level adaptation may provide more important risk reduction in the short term than larger scale efforts. Voluntary relocation usually happens after a catastrophic flood, and is primarily driven by economic evaluations (Alfieri et al., 2016). In a future climate, in locations where floods become more frequent and severe, both high perceived risks and economic and emotional evaluations of future flood prospects may lead more individuals to consider relocation as a preferred alternative for flood risk management. Decisions about mitigation and relocation are highly dependent on an individual's perception of flood risk and their perceived coping appraisal. Perceived risk is influenced by an individual's views of vulnerability (probability) and severity (consequences). Perceived coping appraisal is an individual's evaluation of ability to avoid a particular risk, and is influenced by perceived efficacy of mitigation measures, self-efficacy, and response cost (Bubeck, Botzen, & Aerts, 2012).

2.3. Agent-Based Modeling

An agent-based model (ABM) is a simulation model that includes both decision-making entities, called agents, and stochastic elements (Bonabeau, 2002; Epstein, 2006; Evans & Kelly, 2004). The agents are heterogeneous, spatially explicit, and autonomous, and can interact with other agents and with their environment. Agents can experience stochastic elements such as floods, and can make decisions and take action. They have learning rules and decision rules, which can vary by agent. The learning rules describe how they incorporate new information occurring in their environment and messages from other agents. The decision rules specify actions they can choose and how they make their choices. An ABM allows simulation of how individual behavior impacts other individuals and a community as a whole over time. While ABMs are generally intended to explain rather than predict, they can be used to simulate the emergence of system-level outcomes (Berglund, 2015; Crooks & Heppenstall, 2012).

ABMs are useful tools for examining systems in which individual behavior is an important driver of collective outcomes in ways that cannot be easily modeled by more aggregate models. ABMs have been used to examine coastal flooding by Dawson, Peppe, and Wang (2011) with a focus on real-time management of a coastal flooding event, not on the longer time-scales that this study focuses on. A precursor to this study focused on the longer time horizon societal changes (e.g., land use change and household level mitigation decisions) that impact the evolution of flood risk over time (Tonn & Guikema, 2018). Another study investigated the impacts of household flood risk mitigation decisions using different economic decision models (Haer, Botzen, Moel, & Aerts, 2017). Our study employs an ABM to simulate how individual behavior influences flood risk over time under future climate scenarios.

3. METHODS AND DATA

3.1. Overview

Our ABM has several distinct components, as illustrated in Fig. 1, with decisions at the agent and community scale occurring annually. First, a climate scenario is selected from four choices: historic climate and three future climate scenarios. Then, the first simulation year begins, with an initialization phase consisting of two elements. Vacant parcels are randomly populated and a flood elevation is sampled. Next, the agent simulation occurs, with the flood elevation for each agent calculated based on the agent's elevation and the sampled flood elevation. Damage is calculated for each agent, and the agent's risk and coping perception values are calculated. If risk and coping perception values exceed thresholds, the agent may decide to move out, elevate their home, elevate their mechanical equipment, or complain to the community. The next phase is the community simulation. Based on total agent damage and total agent complaints, the community decides to undertake a mitigation project and/or an information campaign or chooses to take no action. After the community simulation occurs, agent and community damage and actions are recorded, and the simulation proceeds to the next simulation year. This is repeated for a total of 50 simulation years.

Five hundred replications were run for each climate scenario, and results were recorded. This was determined to be an adequate number of replications based on convergence calculations on the average damage in the first five simulation years and total damage over the entire simulation period. Further details regarding the convergence calculations are presented in Tonn and Guikema (2018).

3.2. Case Study Location

Flood risk strongly depends on locational characteristics, and this study uses a case study approach instead of a simulated location. The city of Fargo, North Dakota, was selected as the case study location. Fargo is situated along the Red River of the North and is prone to significant, repetitive flooding. An area of the city located adjacent to the Red River consisting of 2,124 land parcels was chosen as the case study area and is illustrated in Fig. 2. Extensive GIS data for this area were obtained from the City of Fargo, including data on parcel boundaries and structure characteristics. Parcel elevations within the case study area vary within a 10-foot range, and all parcel elevations are low enough that each parcel is susceptible to flooding. While a case study approach was used, effort was made to produce methods and results that are generalizable to other locations.

3.3. Flood Elevations: Historic Climate

In the historic climate model, flood elevations are sampled from a data set that was generated using

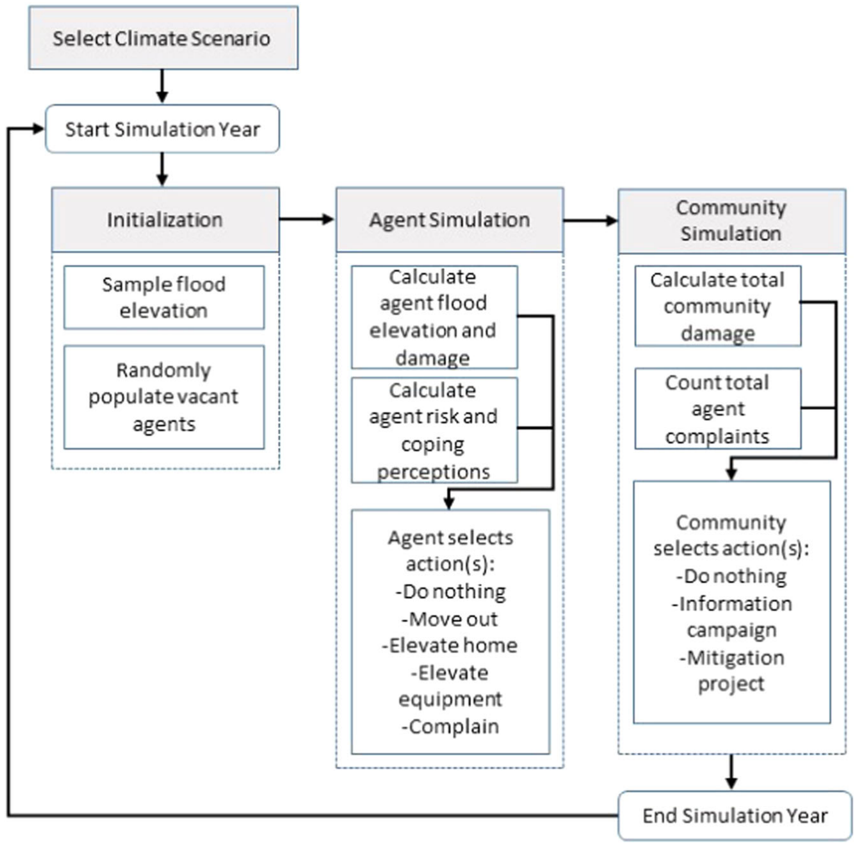

Fig. 1. Agent-based model framework.

peak annual flood elevations from U.S. Geological Survey (USGS) gauge 05054000 (Red River of the North, Fargo), years 1942–2013. This stream gauge is situated close to the midpoint of the river within the study area. Data were available for this gauge from years 1902 to 2013. However, based on a study by Villarini, Serinaldi, Smith, and Krajewski (2009) and on parameter codes in the data set, it is evident that there was a change in the data set starting in year 1942. Therefore, only data from 1942 to 2013 were included in the study, resulting in a total of 72 years of record.

A Weibull distribution was fit to this data set, and the 100-year (0.01 annual chance) flood elevation was estimated to be 902.5 feet, which is comparable to the Federal Emergency Management Agency's (FEMA's) 100-year elevation for this location. The maximum flood elevation in the data set is 903.5 feet, and to enable the simulation of a greater magnitude flood, it was necessary to add a higher flood elevation to the data set. A 500-year (0.002 annual chance) flood elevation was generated from the Weibull distribution, with an elevation of 905.1 feet. The original data set includes 72 years of record, and to generate around 500 years of record, this data set was replicated seven times ($72 \times 7 = 504$). Then, the generated 500-year flood elevation was added to the data set, for a total of 505 flood elevation data points to sample from. So that the flood elevation sample set would mimic real-world values, this process was selected instead of generating a fully synthetic data set. While floods of 100-year or greater magnitude would likely involve both pluvial and fluvial flooding, the scope of this analysis is limited to fluvial (riverine) flooding associated with the Red River of the North.

3.4. Flood Elevations: Future Climate

Future climate scenarios are based on a U.S. Army Corps of Engineers (USACE) report (Alberto, Banitt, Faber, Fleming, & Foley, 2015) titled "Red River of the North at Fargo, North Dakota, Pilot Study, Impact of Climate Change on Flood Frequency Curve." The report includes tables and figures showing the estimated climate change impact on the frequency curve for the periods 2011–2040,

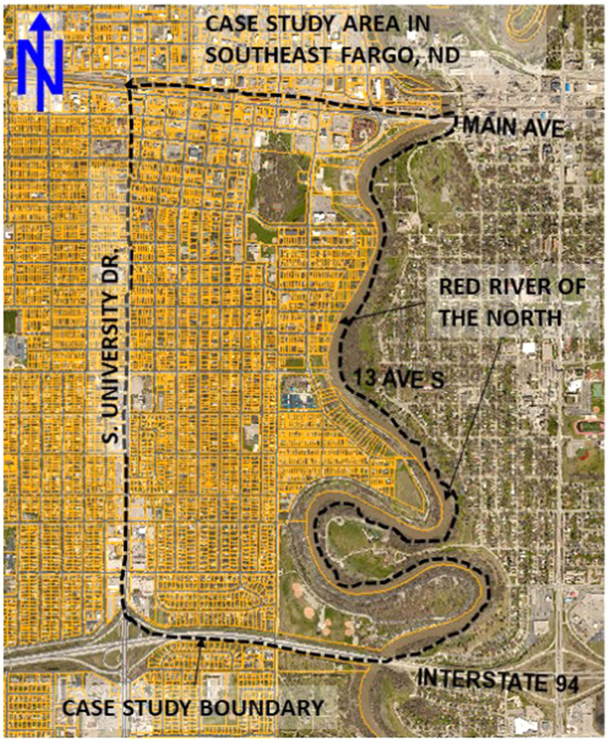

Fig. 2. Case study location with agent (parcel) boundaries.

Table I. Period 2041–2070 Future Climate Percent Change from Historic Climate Flow Rates

Exceedance Probability	Return Period	% Change Median	% Change 10%	% Change 90%
0.5	2 years	13%	−22%	58%
0.1	10 years	5%	−17%	35%
0.02	50 years	4%	−23%	56%
0.01	100 years	6%	−24%	63%
0.005	200 years	9%	−28%	70%

2041–2070, and 2071–2100. The historic (1950–1999) annual peak frequency curve is provided along with the median peak flow rate curve for each time range and the 10% and 90% confidence interval limits. The 2041–2070 time range estimates were chosen for use in this project. A table in the report provides the median, 10%, and 90% limits of the frequency curve values for this time range.

Based on the peak flow rate report values, we computed a percent change from historic climate flows for each of the return periods for the median, 10%, and 90% estimates, as shown in Table I. Then, we calculated a set of flow values for the median, 10%, and 90% scenarios, based on the historic flow values from USGS gauge 05054000 and the percent change values for each scenario. Percent change values for each flow rate were interpolated based on the percent change values specified for the return periods. In other words, sets of flow values were generated for the median, 10%, and 90% scenarios. Using the stage-discharge rating curve for the gauge, which was available from the USGS, flood elevations were estimated for each of these flow values. In some cases, the flow values exceeded the maximum flow on the rating curve. The upper portion of the rating curve is nearly linear, and we assumed that the linear trend continued beyond the maximum value on the rating curve. This linear equation was used to estimate flood elevations for flows above the maximum flow value.

Given that the future climate scenarios were provided for a range of years and uncertainty is considerable, we opted to model future climate as a set of scenarios rather than a gradually changing data set. This allowed for a level of simplicity and makes sense given that annual peak floods are stochastic occurrences, which do not gradually increase at a static rate over time. Future work could incorporate more in-depth climate modeling with a gradually changing set of flood values to sample from.

3.5. Agent Damage and Behavior

A percent damage value is calculated for each agent in each simulation year using depth–damage curves from FEMA's HAZUS program, in conjunction with structure characteristics and flood depth. Structure characteristics are based on City of Fargo GIS data, and the flood depth is calculated based on the sampled annual flood elevation versus the agent's elevation. The agent's percent damage value is multiplied by the agent's property value to estimate damage at the agent level.

Risk perception and coping perception values are calculated for each agent in each simulation year. An agent will consider taking action to reduce flood risk if the risk perception and coping perception values in a given year exceed specified thresholds. Risk perception and coping perception calculations are based on seven factors identified through extensive literature review. (1) Flood experience: how many floods has the agent experienced in prior years (Lin, Shaw, & Ho, 2008; Ludy & Kondolf, 2012; Siegrist & Gutscher, 2008)? (2) How many near-miss events has the agent experienced in prior years (Dillon & Tinsley, 2008; Dillon, Tinsley, & Cronin, 2011)?

(3) Has the community previously completed mitigation (Birkholz, Muro, Jeffrey, & Smith, 2014; Bubeck, Botzen, Kreibich, & Aerts, 2013; Ludy & Kondolf, 2012)? (4) Has the agent previously completed mitigation (Bubeck et al., 2013)? (5) Did the community disseminate information in the previous year (Poussin, Botzen, & Aerts, 2014)? (6) How many floods have the agent's neighbors experienced in prior years (Hudson et al., 2017)? (7) How many near-miss events have the agent's neighbors experienced in prior years (Dillon et al., 2011; Tinsley, Dillon, & Cronin, 2012)? Due to the small size of the study area, all agents are considered neighbors to each other for calculation purposes. Each factor value is multiplied by a beta value and summed to generate a total risk perception value. The positive or negative sign of the beta value is based on whether the factor tends to increase or decrease perceived risk. Beta values were set to reflect both the magnitude and the relative weight of the factors. More explicit discussion of each of these factors and their beta values is included in Tonn and Guikema (2018).

The risk tolerance threshold, which is the risk perception level at or above which an agent will consider taking action, was set at 60 based on professional judgment. Possible values of the risk perception factors were analyzed to identify the likely limit at which agents would perceive the risk as high enough to consider mitigation action. Each agent was randomly assigned a risk tolerance adjustment factor between 0.8 and 1.2 and the risk threshold was multiplied by this factor to reflect agent heterogeneity in risk tolerance. In addition to the risk threshold for agent action, there is a risk threshold for agents to move out. If the risk reaches this high threshold, the agent will move out, and the parcel becomes vacant. The threshold is set at 90 and is also multiplied by the agent risk tolerance factor.

Coping perception is calculated similarly to risk perception. The following five factors are included: (1) Base coping perception: A random base value is assigned to each agent for heterogeneity. (2) Home value: A value is assigned based on the agent's property value and serves as a proxy for socioeconomic factors (Bubeck et al., 2013; Lin et al., 2008; Poussin et al., 2014). (3) Prior agent mitigation: Has the agent previously completed mitigation (Bubeck et al., 2013)? (4) Information: Did the community disseminate information in the previous year (Bubeck et al., 2013; Tinsley et al., 2012)? (5) Neighbor mitigation: How many of the agent's neighbors have completed mitigation in prior years (Ludy & Kondolf, 2012; Poussin et al., 2014)?

Each of the coping factors are weighted equally and have a value from 0 to 20, and the maximum possible coping perception value is 100. Based on an analysis of possible values and professional judgment, the coping threshold is set at 30. Regardless of the agent's risk perception value, an agent will not take action unless their coping perception meets or exceeds the coping threshold.

Agent actions include complaining to the community (requesting community action), elevating mechanical equipment, and elevating the house. In each year, if the agent's coping and risk perceptions both meet the specified thresholds, the agent complains to the community. Furthermore, when the coping and risk perceptions both meet the specified thresholds, the agent considers mitigation. The agent's decision to elevate mechanical equipment, elevate the whole house, or to do nothing, is based on the lowest cost option using a utility function that includes mitigation cost and expected reduction in damage. For purposes of this analysis, the same costs for equipment elevation and for whole house elevation are used for each agent, and it is assumed that equipment or house elevation is feasible for each agent. The cost used for whole house elevation assumes that houses are constructed on masonry foundations and are elevated with courses of masonry block.

3.6. Community Action

As noted above, if an agent's risk and coping perceptions meet or exceed the threshold values in a year, they "complain" to the community. If 5% or more of the agents in the community complain in a given year, the community will implement an information campaign. The USACE provides flood risk and mitigation information to communities on a regular basis, as was indicated in conversations with a USACE staff member. However, communities do not always implement flood risk information campaigns unless prompted in some way to do so. Agents are more likely to perceive a higher risk of flooding and to undertake mitigation when they receive flood risk information from the authorities (Lindell & Hwang, 2008; Ludy & Kondolf, 2012).

Total community flood damage for each year is calculated by summing the agent damage for that year. If total community damage exceeds \$10 million in a given year, the community will implement a flood mitigation project. To establish the community damage threshold, an overall community depth-damage curve was generated, and $10 million was selected as the point on the curve in which damage begins to increase rather sharply. This corresponds to the flood elevation where damage could be considered substantial enough to justify community action. Under community mitigation conditions, the flood elevation sample set is adjusted to reflect flood elevations as impacted by the mitigation measure. Mitigation is simulated as a levee, and it is assumed that the levee will not fail over the duration of the simulation period. Therefore, once community mitigation occurs, the flood elevation sample set is adjusted by replacing all data points below the mitigation elevation with zero flood elevation.

In all 5.2% of the parcels in the study area are vacant at the beginning of the simulation period. At the start of each simulation year, there is a probability that each vacant parcel will be occupied by a new agent. If there is no community mitigation in place, the probability that a vacant parcel will be occupied in a given year is 0.01. If community mitigation is in place, the probability that a vacant parcel will be occupied is increased to 0.1, reflecting a decrease in perceived risk.

3.7. Sensitivity Analysis

Because of the subjective nature of key parameters in the study, sensitivity analysis was performed on those parameters. Prior work using a historic climate scenario included sensitivity analysis on risk perception threshold, coping perception threshold, agent complaint threshold, community damage threshold, risk threshold for moving, the probability of a vacant parcel being occupied without community mitigation, and the probability of a vacant parcel becoming occupied with community mitigation. These prior results indicated greatest sensitivity to risk and coping perception thresholds and much less sensitivity to the other parameters. As such, sensitivity analysis was performed for these two parameters for each of the four climate scenarios. For the sensitivity analysis, a single parameter was adjusted at a time, with 500 replications run for each adjustment. Changes in damage in early, middle, and late simulation years as well as changes to total damage were reviewed. Impacts to the numbers of agents mitigating and the occurrence of community mitigation were also reviewed.

Table II. Average and Total Damage under Climate Scenarios ($ Millions)

	Historic Climate	Median Climate	10% Climate	90% Climate
Average damage (years 2–6)	$4.83	$6.45	$1.80	$47.32
Average damage (years 21–25)	$1.87	$2.41	$0.53	$10.01
Average damage (years 47–51)	$2.10	$1.62	$0.36	$8.11
Total damage	$23.40	$26.13	$7.01	$144.01

4. RESULTS

4.1. Damage

The ABM was run under the historic and future climate scenarios. Table II and Fig. 3 show average damage for each climate scenario. The average damage is the sum of agent damage for the given year or simulation range averaged across 500 replications.

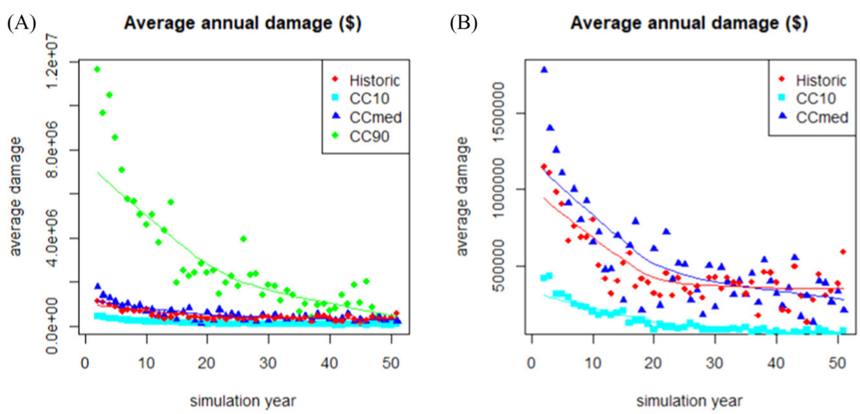

Fig. 3. Average annual damage over time: (A) all climate scenarios, (B) historic, 10% and median climate scenarios.

Damage under the 10% climate scenario was well below the historic and median climate scenarios, while damage under the 90% climate scenario was nearly an order of magnitude higher than the historic scenario. Damage declines sharply (61%–79%) between the early and middle simulation years for all scenarios. Damage declines less significantly (19%–33%) between the middle and late simulation years. The decline in damage can be attributed to agent and community mitigation measures that reduce vulnerability. For the historic climate scenario, damage actually increases in the later years, most likely due to vacant parcels being occupied.

While the future climate scenarios are uncertain, some interesting results are evident from these scenarios. The median climate scenario has higher average annual damage than the historic climate scenario in the early years. However, in the later years (years 47–51), the median climate damage is lower than the historic climate damage. This indicates that in some cases, climate change may result in increased risk perception and increased agent and community mitigation, resulting in lower total damage than under historic climate scenarios. This finding is in line with the results of Haer et al. (2019), which indicate that adaptation decisions may largely offset the increase in flood risk due to climate change.

In general, these results indicate that moderate increases in flood heights due to changes in climate may be managed through agent and community action. Very large increases in flood heights result in extremely high damage values, despite agent and community efforts to mitigate, and damage remains high despite large percentages of agents moving out of at-risk areas. Under the 10% climate scenario, damage is significantly less than under the historic climate. Even with lower flood heights, damage declines over time, primarily due to individual agent mitigation at high-risk parcels.

Table III presents per capita damage under historic and future climate scenarios. In comparing the overall damage values to the per capita damage values, the role of movement out of the study area in reducing damages starts to become evident. Under the 10% climate scenario, movement out of the study area is extremely limited, and the percentage change in damage and per capita damage across the early, middle, and late simulation years is identical. Under the historic climate scenario, the percent change in damage and per capita damage vary minimally. For the median climate scenario, the per capita percent change in damage is less than the overall percent change in damage for the early to middle years. In the middle to late years, the per capita percent change is greater than the overall percent change. The same trend is apparent and magnified for the 90% climate scenario. The role of movement out of the area is considered further in Section 4.4.

Table III. Average and Total per Capita Damage under Climate Scenarios ($)

	Historic Climate	Median Climate	10% Climate	90% Climate
Average damage (years 2–6)	$2,438	$3,275	$897	$27,669
Average damage (years 21–25)	$1,012	$1,363	$267	$17,701
Average damage (years 47–51)	$1,124	$917	$178	$6,515
Total damage	$12,510	$14,553	$3,501	$213,546

Fig. 4 provides maps of total damage over the 50-year simulation period as a percentage of property value for each agent. The lowest elevation agents, which are not all located adjacent to the river, generally experience the highest percent damage. In the 10% climate scenario, most agents experience damage only equating to 1% or less of the property value while some lower elevation agents experience more significant damage. A greater number of agents experience damage equating to 5% to 50% of the property value for the historic scenario. Mapped results look similar for the median climate, with more agents suffering damage in the 10% to 50% of property value range. Under the 90% climate scenario, nearly all agents experience damage equivalent to at least 10% of their property value.

4.2. Agent Mitigation

Household mitigation, either in the form of equipment elevation or home elevation, is undertaken by agents in some simulations. Fig. 5 shows the percentage of the 500 simulations in which the agent implemented household mitigation, either elevation of equipment or of the entire structure. In the 10% climate scenario, agent mitigation is limited and aligns well with the higher damage agents illustrated in Fig. 4. Agent mitigation is more significant under the historic and median climate scenarios, with many agents implementing household mitigation in at least 50% of the simulation runs. Under the 90% climate scenario, most agents mitigate in at least some simulation runs. However, no agents mitigate in

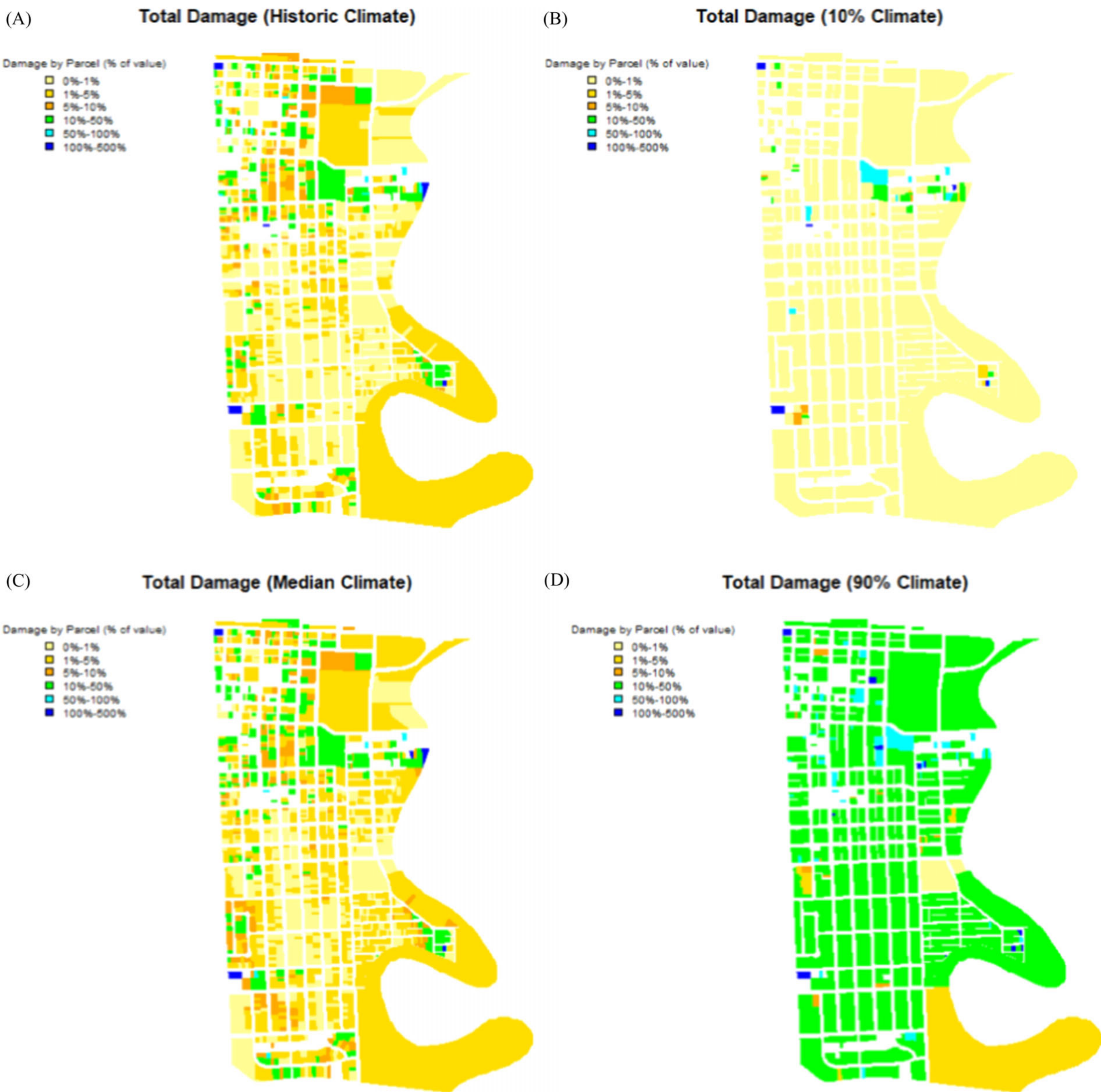

Fig. 4. Maps of average total damage: (A) historic climate, (B) 10% climate, (C) median climate, (D) 90% climate.

50% or more simulation runs under the 90% climate scenario. Under this scenario, community mitigation often happens early on due to very damaging flood events. This reduces agents' perceived risk, which results in fewer agents installing household mitigation.

4.3. Community Mitigation

When damage in a simulation exceeds the damage threshold, the community implements community mitigation. The percentage of simulations with community mitigation varies dramatically based on climate scenario, as illustrated in Table IV. Under the historic climate, 20% of replications include community mitigation, with the mitigation occurring in year 20 on average. Under the median climate scenario, 63% of replications include community mitigation, with year 16 being the average year of mitigation. Under the 10% climate scenario, community mitigation does not occur in any replication due to the lack of widespread damage. Under the 90% climate scenario, community mitigation happens

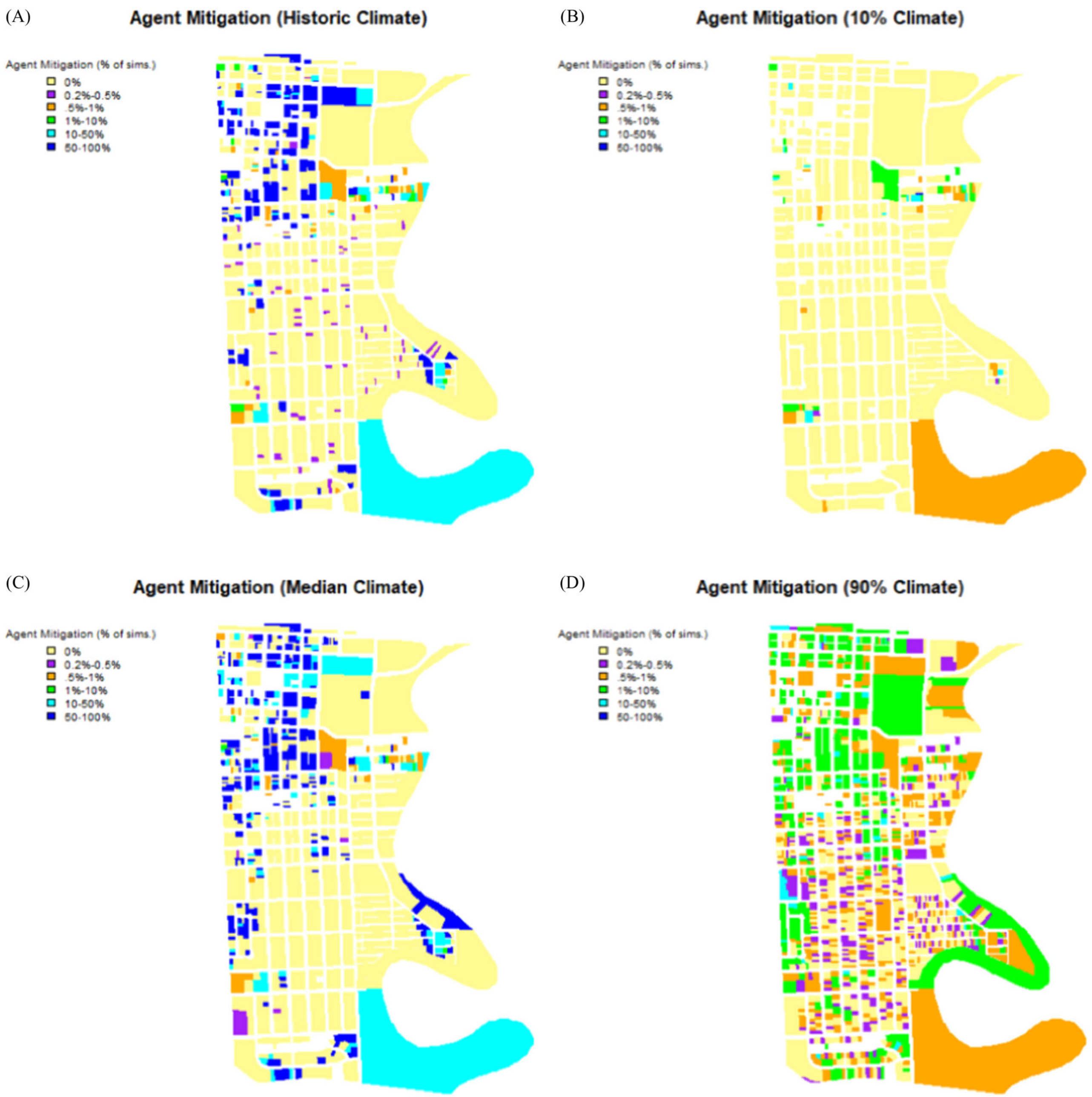

Fig. 5. Map of agent mitigation: (A) historic climate, (B) 10% climate, (C) median climate, (D) 90% climate.

in 99% of replications, with the average year of mitigation being 11. In 38% of replications under this climate scenario, more than one community mitigation occurs, meaning the height of the community flood mitigation is increased subsequent to initial installation.

In the more flood-prone climate scenarios, community mitigation plays a significant role in damage reduction over time, while agent mitigation is more significant in the scenarios that include less extreme flooding.

4.4. Vacancy

It is clear that agent movement out of the study area has a strong influence under some of the future

Table IV. Summary of Community Mitigation

	Historic Climate	Median Climate	10% Climate	90% Climate
Number of replications with community mitigation	98 (20%)	314 (63%)	0	494 (99%)
Average year of first community mitigation	20	16	N/A	11
Number of replications with more than one mitigation	4 (1%)	14 (3%)	0	191 (38%)

Table V. Average Vacancy Rates for Future Climate Scenarios[a]

	Historic Climate	Median Climate	10% Climate	90% Climate
Average vacancy rate (years 2–6)	6.7%	7.3%	5.5%	19.5%
Average vacancy rate (years 21–25)	13.3%	16.6%	5.8%	73.4%
Average vacancy rate (years 46–51)	12.2%	17.2%	5.3%	85.8%
Average vacancy rate (years 2–51)	11.9%	15.5%	5.6%	68.2%

[a]Base vacancy rate = 5.2%

climate scenarios. Table V provides a summary of vacancy rates in the simulations. The starting vacancy rate in the models is 5.2%. Under historic climate, average vacancy over the simulation period is 12%. Vacancy rates are slightly higher under the median climate scenario, and substantially increased under the 90% climate scenario, with average vacancy rates of 68% over the 50-year simulation period.

Further review of vacancy rates indicates that for the historic, median, and 10% climate scenarios, vacancy rates generally do not differ substantially amongst most replications. Under the 90% climate, there is much variation in vacancy rates in the middle simulation years, followed by consistently high

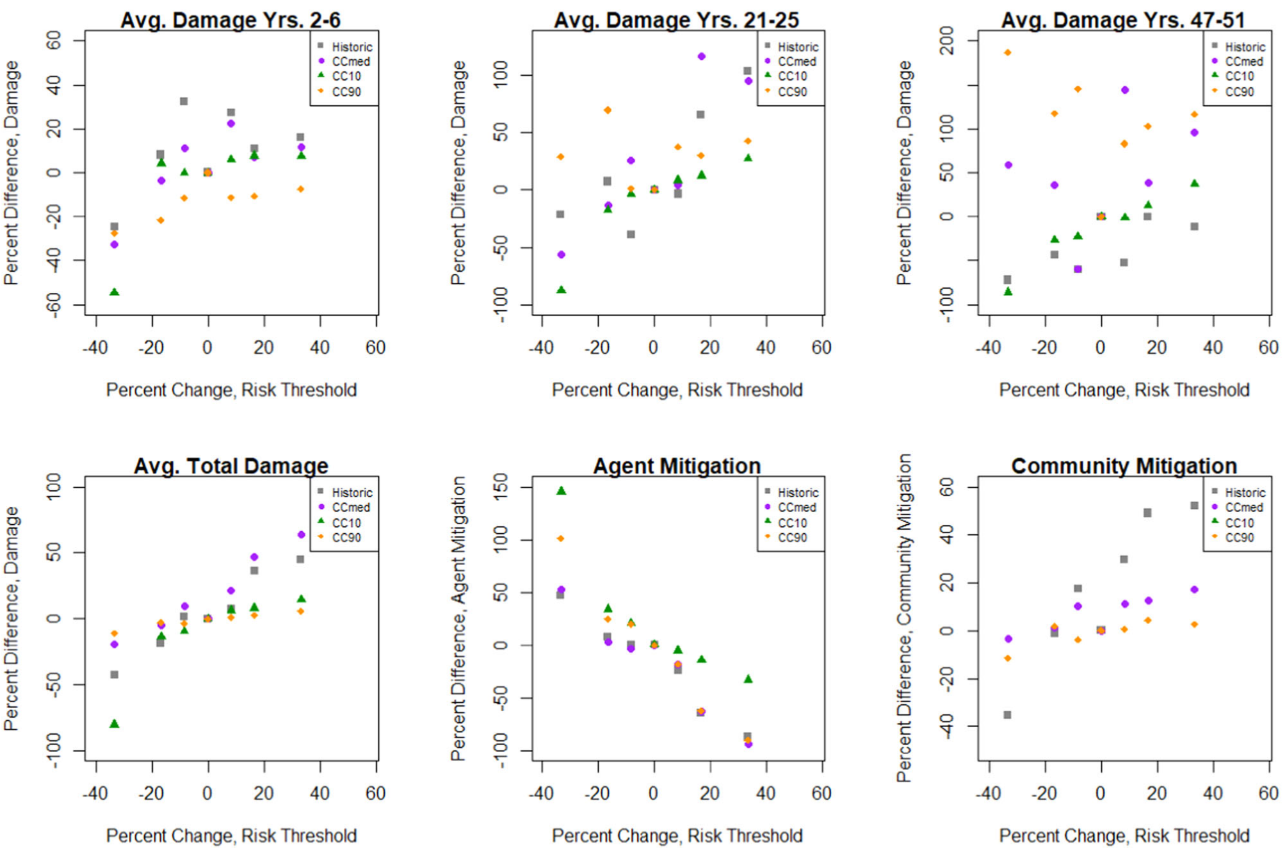

Fig. 6. Sensitivity analysis, risk threshold.

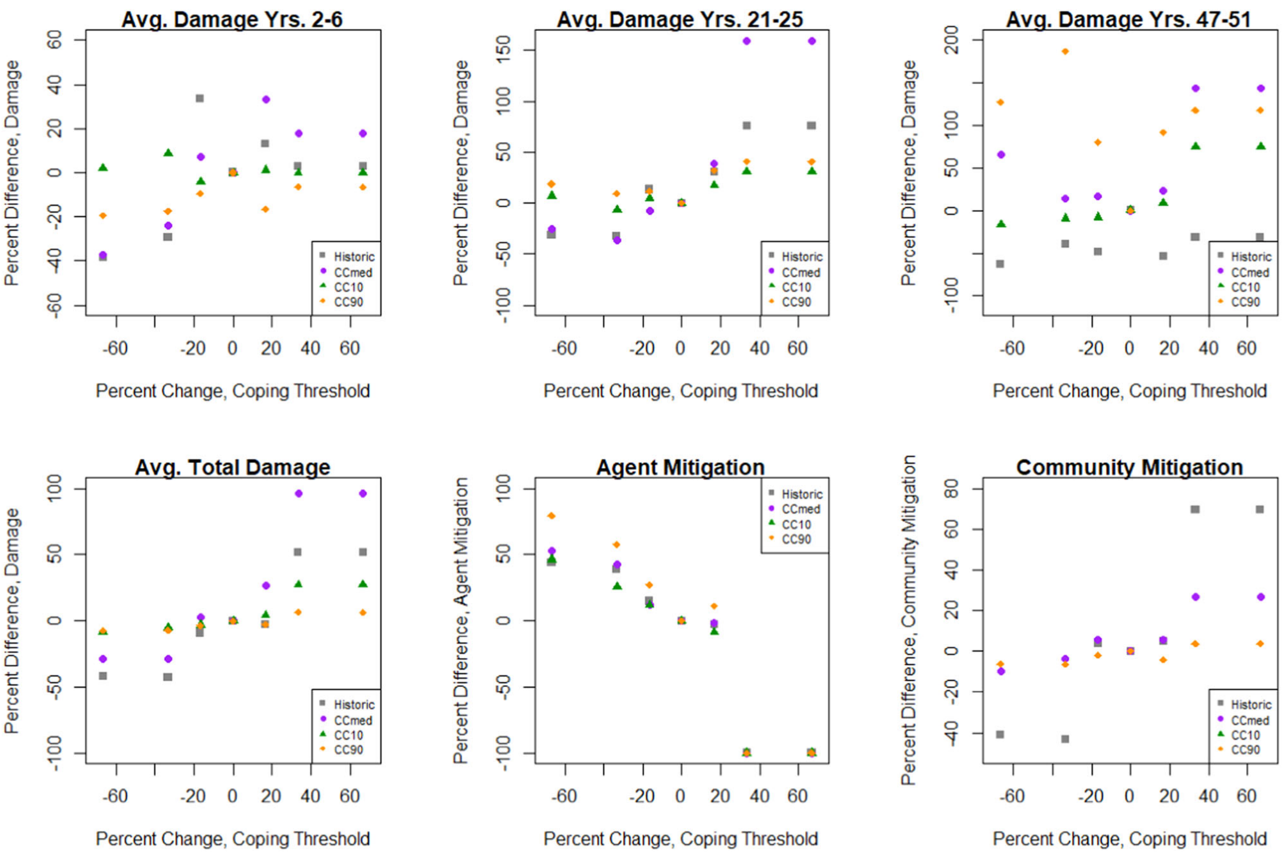

Fig. 7. Sensitivity analysis, coping threshold.

vacancy in the later simulation years. An individual's decision to move out of a flood-prone area is often heavily influenced by the availability of incentives or buyout funds, and increasing vacancy of neighboring parcels is also a significant influence. While these factors are not included in this study, it is clear that under certain future climate scenarios, vacancy can have a significant impact on flood risk.

4.5. Sensitivity Analysis

Sensitivity analysis was run to understand the impact of the subjective risk and coping threshold parameters on model results, as described in Section 3.7. Figs. 6 and 7 illustrate the percent differences in damage, agent mitigation, and community mitigation associated with changes in the risk and coping thresholds. Total damage is sensitive to variations in these parameters and tends to increase as the values of these parameters increase. At the lowest value of risk threshold, damage is low and agent mitigation is high. Community mitigation is low due to the lower damage and agent mitigation. Damage in the later simulation years is more sensitive to changes in the risk threshold than damage in the early years of the simulation. The 10% climate scenario results are most impacted by a decrease in risk threshold, while the median and historic scenarios show greatest sensitivity to increases in risk threshold.

Total damage is somewhat more sensitive to changes in coping threshold than to changes in risk threshold. With very high values of coping threshold (greater than 30% increase) no agent mitigation occurs, and community mitigation increases sharply. The 10% climate scenario exhibits the least sensitivity to changes in the coping threshold. The median climate scenario damage exhibits the greatest sensitivity to this parameter, particularly to increases in the threshold. These variations point to the importance to better understand the role of coping perception in adapting to climate risk and to better quantify this parameter for improved simulation of adaptation to climate risk. It also highlights the importance of programs like community information campaigns and of neighbor influence on overall community adaptation to climate change.

5. CONCLUSIONS

Evolving flood risk was simulated under historic climate conditions and three future climate scenarios using an agent-based model. The agent-based simulation included an initialization component, an agent action component, and a community action component. Each simulation represented a 50-year period, and 500 replications were completed for each climate scenario. Results, including damage, population, and agent and community actions, were recorded for each year of each simulation, and for each replication. The results demonstrate how flood risk can evolve in a community based on the occurrence of flood events and individual and community action.

Under the median climate scenario, total damage was generally higher than under the historic scenario. However, in some cases, damage under the median scenario was actually lower as the higher flood elevations triggered higher agent risk perception values and additional agent and community mitigation. The 10% and 90% climate scenarios are somewhat extreme, but in both cases, individual and community action result in a decline in damages over time. In the 10% scenario, the decline in damage over time is due to agent mitigation, while in the 90% scenario, community mitigation and agent relocation are primary drivers of the decline. This makes sense, because in less severe flooding, a limited number of agents are impacted, and the problem can most efficiently be dealt with at the agent level. For more pronounced flooding, community-level efforts and individual relocation are more practical. Under an extreme climate scenario with more frequent and severe floods, our model suggests that many agents move out of the study area.

This study presents a method for considering individual behavior in assessing flood risk under future climate scenarios. Individual actions, including the choice to install household mitigation measures, to request community action, and to vacate a high-risk area have a significant effect on flood risk in a community over time. Individual perceptions of the risk and of their ability to address the risk play an important part in community flood risk. ABM clearly can help illustrate, analyze, and understand these behavioral facets of flood risk. Behavioral rules in this study were based on an extensive literature review and on professional judgment. Further study on individual and community behaviors, specifically regarding risk perception, coping perception, and mitigation action, will allow for more precise quantification of agent decision rules in future work.

This study is limited in its use of four static climate scenarios. While this is appropriate to test the efficacy of using ABM as a tool to simulate climate adaptation, future studies would benefit from simulation of additional climate scenarios and gradually changing climate conditions. Further, the study is limited in its evaluation of flood risk based solely on residential damage and population at risk. To enable more holistic decision making, total societal costs could be simulated in future flood risk ABMs. Future work will include a detailed behavioral survey to gain additional information to refine the individual decision rules in this study. Flood insurance and government policies and incentives also significantly affect individual decisions on how to manage flood risk, and can have a substantial impact on community flood risk over time. The effects of policies, insurance, and incentives will be incorporated into future versions of the model. ABM can help understand, illustrate, and analyze these behavioral facets of flood risk.

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