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SEA BRIGHT, NEW JERSEY RECONSTRUCTED: AGENT-BASED PROTECTION THEORY MODEL RESPONSES TO HURRICANE SANDY

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ABSTRACT

Coastal flooding is the most expensive type of natural disaster in the United States. Policy initiatives to mitigate the effects of these events are dependent upon understanding flood victim responses at an individual and municipal level. Agent-Based Modeling (ABM) is an effective tool for analyzing community-wide responses to natural disaster, but the quality of the ABM's performance is often challenging to determine. This paper discusses the complexity of the Protective Action Decision Model (PADM) and Protection Motivation Theory (PMT) for human decision making regarding hazard mitigations. A combined (PADM/PMT) model is developed and integrated into the MASON modeling framework. The ABM implements a hind-cast of Hurricane Sandy's damage to Sea Bright, NJ and homeowner post-flood reconstruction decisions. It is validated against damage assessments and post-storm surveys. The contribution of socio-economic factors and built environment on model performance is also addressed and suggests that mitigation for townhouse communities will be challenging.

1 INTRODUCTION

Flooding from tropical storms is the most expensive natural disaster affecting the United States, and globally has only been exceeded by the Japanese Tsunami of 2011 and the earthquake of 1998 (National Oceanic and Atmospheric Administration 2019). Damages from Hurricanes Katrina in 2005 and Harvey in 2017 were 156.3 and 125 billion dollars, respectively. Mitigating the effects of future coastal flood events can reduce homeowner and community-level costs. Mitigation is a fertile area for model-based analysis, as major tropical storms are infrequent events.

Agent-Based Modeling (ABM) is one such tool for analyzing responses to natural disasters, but its efficacy is dependent upon the validity of the agents' decision making model. Through the modeling of individual actors and their actions within an environment, ABMs provide a means to identify emergent, higher-level behaviors. The actors' actions are predicated upon their perception of their environment and their subsequent decision making. The details of the decision making model and its implementation drive the model responses and are the core of the simulation (Crooks et al. 2018).

Unfortunately with ABMs, the penalties of utilizing a "bottom-up" approach to modeling are increased complexity and reduced transparency and repeatability. Confirming the correctness of each of the multitude of agents' individual stochastic actions is arduous, if even tractable. While highly recommended, model validation is often cursory or completely missing from ABM analysis and publications (Crooks et al. 2008).

This paper describes the use of Lindell and Hwang's (2008) Protective Action Decision Model (PADM) to represent homeowner responses within coastal flood mitigation modeling. It also presents an agent-based model representing Sea Bright, NJ. with a simulated hind-casting (i.e., reconstruction) of Hurricane Sandy and validates the model with post-storm homeowner survey responses (McNeil et al. 2017). Section 2 provides background into disaster response decision making theory, an overview of previous modeling efforts including ABM of coastal flooding analysis, and a summary of Hurricane Sandy and Sea Bright, NJ. The methodology used in this analysis is then presented in Section 3. Results, discussion and validation of the ABM's household damage and homeowner response modeling are described in Section 4. Finally, Section 5 provides conclusions and recommendations for future work.

2 BACKGROUND

To understand the context and methodology of this analysis, an overview of disaster response logic (Section 2.1) is provided. A review of both Agent-Based (Section 2.2) and flood (Section 2.3) modeling is beneficial. Sea Bright demographics and responses to Hurricane Sandy are presented in Section 2.4 and these were utilized as reference points during the model validation process.

2.1 Decision Making Modeling

Human reactions to natural disasters and their actions to mitigate against these hazards have been evaluated via pre-and post-disaster surveys, population shifts in census data, and changes in municipal records. The psychology of disaster responses has elicited multiple theories for victim decision making (e.g. Kahneman and Tversky 1979; Ge et al. 2011; Grothmann and Patt 2005; Bubeck et al. 2012; Lindell and Hwang 2008) and multiple vulnerability indices have been proposed (e.g. Ward 2012; Bakkensen et al. 2017). Two hazard mitigation theoretical frameworks, which are descendants of expectancy-valence models, are the protection motivation theory (PMT, Rogers 1975; Bubeck et al. 2012) and PADM.

PMT explains decision making as a sequence of three cognitive mediating processes: threat appraisal, coping appraisal, and protection motivation/avoidance (Bubeck et al. 2012). The initial step of threat appraisal may be viewed as a traditional risk assessment based upon the perceived hazard probability and consequence. The coping appraisal is similar to cost-benefit analysis utilizing the decision maker's perception of their self-efficacy (i.e., ability to affect the response), response efficacy (i.e., the responses' ability to mitigate the risk) and response cost. The final hurdle, protection motivation, involves converting perceptions into behavior, either in protective or non-protective responses. PMT's explanation for non-protective responses to beneficial mitigations is based upon fatalism, wishful thinking, and denial; but they might also be explained by competing priorities and limited resources. Where PMT bases the decision process on informational inputs of verbal persuasion, observational learning, personality variables and prior experience, PADM identifies social context, environmental cues and social information as the drivers of risk perception. In a survey of natural and man-made hazards in the coastal Houston TX area, Lindell and Hwang (2008) identified gender, ethnicity, income, and hazard experience as statistically significant factors effecting perceived risk, and perceived risk as a significant factor in hazard adjustment. Grothmann and Patt (2005) combined aspects of PADM and PMT into a climate change adaptation model. For this study, as shown in Figure 1, the Grothmann and Patt (2005) model was extended to flood mitigations and adapted to reflect Lindell and Hwang's (2008) significant factors from above.

2.2 Agent Based Modeling

ABM is a leading method to model people, organizations, and societies. Its distinguishing feature is modeling from the agent's (i.e., individual's) perspective (Macal, 2016). Agents are represented as unique entities, observing their environment at the local-level, and making decisions without external direction; which ultimately results in actions (Parker et al. 2003). The collective actions of the individuals coalesce in community-level social and organizational behavior (Macal and North 2013).

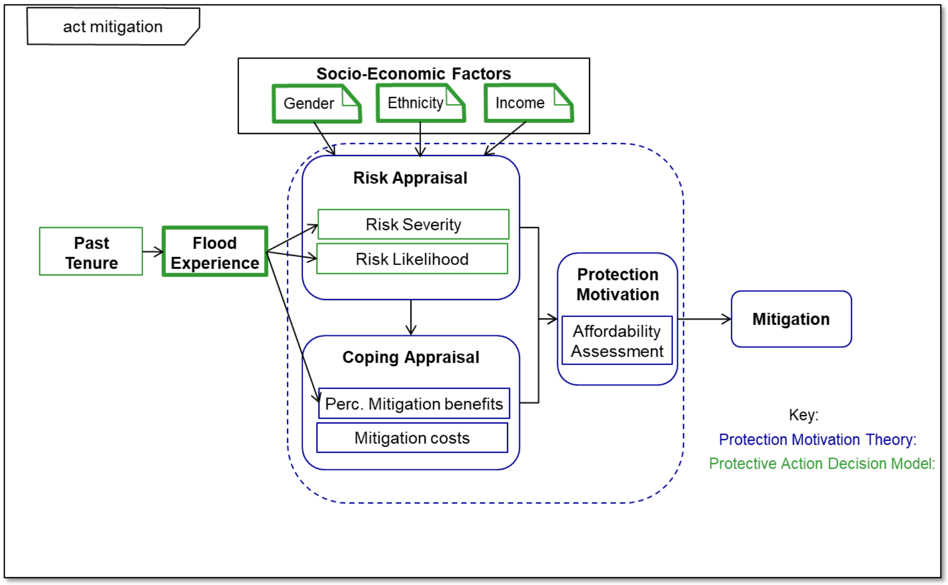

Figure 1: The authors' adaptation of the Protection Motivation Theory and Protective Action Decision Model.

Individual behavior and urban dynamics are two areas where ABM provides modeling utility (Crooks et al. 2019). Individuals are interacting autonomous entities with heterogenous characteristics, and dynamic behavior. They have the ability to learn, evolve, and adapt. In the context of coast flood modeling they can be instilled with flood experience and instantiated for each property owner with the attributes of gender, ethnicity, and income. Algorithms may be constructed to assess their perceived risk based upon current flood inundation and expected storm surge risk, their expectation of reoccurrence, and socio-economic based preferences. Cost-benefit judgements can be simulated for a constrained budget situation.

Initially, tropical storm and coastal flooding ABMs focused on transportation networks, evacuations, and shelter locations for places such as Miami, Florida (Yin et al. 2014), the Florida Keys (Chen et al. 2006, Schoenharl 2007) and in evacuation more generally (Chen et al. 2003). Dawson et al. (2011) incorporated a hydrodynamic wave model into an ABM to evaluate evacuations in the event of sea wall breaches. More recently, ABMs have expanded to evaluate flood mitigation policies for floodproofing incentives (Pei et al. 2015, Reilly et al. 2017a), electrical power reliability and hardening (Reilly et al. 2017b), and risk communication strategies (Haer et al. 2016).

2.3 Coastal Flood Modeling

Tropical storm modeling has long been the domain of Civil Engineering and Computational Fluid Dynamics (CFD), most notably for flood mapping by Federal Emergency Management Agency (FEMA). These simulation efforts provide storm surge heights and sustained wind speeds to assess potential structural damage and permit cost-benefit analysis for individual flood mitigation actions (Federal Emergency Management Agency 2016).

The CFD analyses are underpinned by well-established physics based models utilizing the shallow water wave equation, but for household-level hurricane responses the underlying theory and modeling assumptions for ABMs are less well grounded. In a review of nine coastal flood ABMs listed in the previous section, only one study referenced model validation and three others described the use of some of the four validation stages from Ngo and See (2012): face validation, sensitivity analysis, calibration, and output verification.

2.4 Hurricane Sandy and Sea Bright, New Jersey

Hurricane Sandy was the fifth most expensive natural disaster in the U.S., responsible for $68.9 billion in damages and 150 fatalities. The tropical storm reached category 3 status, but weakened and made landfall on October 29th, 2012 as a post-tropical cyclone approximately 69 miles south of Sea Bright, NJ. Maximum wind gusts at Sandy Hook, NJ (4.8 miles north of Sea Bright) were 60 knots (Blake et al. 2013). The storm tide in Sea Bright was 10.0 to 10.6 feet (North American Vertical Datum 1988) while FEMA building inundation measurements varied from 0.05 to 9.8 ft above ground level (Federal Emergency Management Administration 2015). Median damage values were $110,623 from surveys Sea Bright residents taken post-Hurricane Sandy by McNeil et al. (2017). The average damage value per surveyed household was $60,000.

The Borough of Sea Bright, NJ is a residential community and vacation location situated on the northern New Jersey barrier peninsula. Figure 2 provides an image of the area. At the time of the hurricane, the Borough contained 1019 housing units and 769 households. The majority of dwellings were two- and three-story, single family, framed homes and townhouses. 58.0% were owner occupied. The Borough was 81.1% white by household and 51.2% male by total population. Median age was 41.4 years old and median household income was $77,950 (U.S. Census Bureau 2019). In 2015, 7.0% of homes had been abandoned, condemned, or demolished; 5.6% required a complete rebuild; 66.9% had been repaired without elevation; 10.6% had been elevated; 9.9% were under repair; and 9.9% were undamaged. In determining where to live, the opinions of neighbors was not very important or not important at all for 77.6% of respondents (McNeil et al. 2017).

Figure 2: Sea Bright, New Jersey—Satellite image from Google Earth (2010), Landsat/Copernicus.

3 METHODOLOGY

A Monte-Carlo agent-based model was developed and integrated into the MASON (Luke et al. 2005) framework in order to hind-cast Hurricane Sandy's damage and compared against Sea Bright survey responses from 2014 and 2015. Analysis of Hurricane Sandy's effects was limited to the geographic constraints of the Borough of Sea Bright, while the ABM modeled individual properties, housing units, and property owners as agents within the geographic area. In what follows, we first discuss how the population was constructed (Section 3.1). Next we turn to the structural damage sustained (Section 3.2) and then to the homeowners' PMT/PADM appraisal and reconstitution decision (Section 3.3). Section 3.4 describes the calibration and verification process employed and finally Section 3.5 addresses causal analysis. The simulation's sensitivity to socio-economic factors was planned but not conducted based upon the results of the risk threshold calibration (Section 3.4) which indicated that low risk tolerances were required regardless of demographics. Due to space limitations what follows is a brief description of the model, however a more detailed description following the Overview, Design concepts, and Details (ODD) protocol by Grimm et al. (2010) and source code may be found at CoMSES/SEABrightABM (McEligot 2019).

3.1 Sea Bright and Hurricane Sandy Generation

Residential locations, building characteristics, property and building values, and homeowner names and statuses were obtained from Monmouth County Office of Records Management (2019) property records. Google Earth (2010) was used for site elevations. Flood-proofing freeboard (i.e. first floor height above ground) was estimated from Google Street View (2019) and, if imagery was not available, was supplemented with building code requirements for the home's construction year.

Property owner characteristics were derived from the American Community Survey (ACS) 2007-2011 Tract 8121 database (U.S. Census Bureau 2019) augmented with MyLife (2019), PeekYou (2019) and Facebook (2019) searches of property owner names from the property records. Differences between the ACS's population, household, and homeowner-occupier data sets were statistically analyzed to determine homeowner attributes; and 30 randomized populations of age, ethnicity, sex, and income were constructed based upon individual property value, construction date, length of ownership, owner's names, and the resolution of the ACS database. Mortgage status was based upon having purchased the home within the last 30 years.

3.2 Structural Damage

Property structural damage was determined based upon FEMA inundation levels for the nearest reference point (Federal Emergency Management Agency 2015) and utilized Hazard US-Multiple Hazards (HAZUS®-MH) 2.2 (Federal Emergency Management Agency 2003) Depth-Damage Functions (DDFs). Wind damage was considered but not included due to the moderate wind speeds in the vicinity of Sea Bright and resulting negligible damage contribution (< 0.4%) (Federal Emergency Management Agency 2003).

Inhabitant categorization of the resulting destruction was obtained from survey information (McNeil et al. 2017) and was utilized in conjunction with FEMA damage assessments to develop target percentages of units unaffected and destroyed. Flood proofing adjustments and damage bias factors were adjusted to calibrate the model against these targets.

3.3 Homeowner Response

A PMT/PADM-based decision making model was implemented at the homeowner level. Flood responses were modeled strictly on the owners interactions with their environment. Agent-to-agent interactions were not included in the study based upon the low influence level neighbor decisions had in the survey responses (McNeil et al. 2017). For the ABM, homeowner responses were mechanized in three parts. An initial risk appraisal was conducted; and, if sufficient risk was present, coping appraisal (cost benefit analysis) followed. Depending upon whether the home was damaged or destroyed, cost-benefit analysis and protection motivation (affordability assessments) were conducted on each building for repair vs. elevation and each lot for rebuilding vs. relocation or departure. The affordability assessment was implemented as a filter on these options and the most cost-beneficial affordable option was recorded and implemented.

The homeowner's risk appraisal was developed based upon both expected flood severity and risk likelihood. Bukvic and Owen (2017) and Senkbeil et al. (2010) suggest there is a 7 year flood memory and repeated flood events are necessary within this period to trigger a perception of future flood consequences; and for this study, the simulation was pre-loaded with the community experiences of Hurricane Irene (Avila et al. 2012). If a housing unit was flooded again during Hurricane Sandy the higher inundation level was taken as the future risk level, otherwise the risk height was zero. Risk likelihood was calculated incorporating Lindell and Hwang's (2008) significant socio-economic factors and a randomized variable for the uncorrelated response utilizing (1):

$$\theta = w_1 * g + w_2 * e + w_3 * h + w_4 * i + (1 - \sum w) * U(0,1) \tag{1}$$

where θ is the perceived risk level, gender g is 1 if female, ethnicity e is 1 if white, history h is 1 if the flood severity was greater than 0 (all 0 otherwise), i is income/\$200,000, and w's are the weighting factors to obtain the desired correlation levels.

A coping appraisal was conducted for each homeowner. The value of building repair, elevation, demolition with relocation within Sea Bright, and demolition with departure were determined with (2) based upon economic factors identified within the study via qualitative critical component analysis:

$$V_{j,k} = \alpha_j * P_j + S_j + C_{j,k|E(f)} * F + I_c - B_{j,k} - D_{c|d} - P_{j|r} - M_c \tag{2}$$

where $V_{j,k}$ is the value of option k for lot j, α is the perceived location premium of lot j, P is the assessed property value of lot j, S is the structural value on lot j, $C_{j,k|E(f)}$ is the cost avoidance of option k on lot j given the expected future flood consequence, F is the expected number of future floods, I_c is the insurance payout of the current dwelling, $B_{j,k}$ is the construction costs of option k for lot j, $D_{c|d}$ is the demolition cost of the current residence if destroyed, $P_{j|r}$ is the purchase cost of lot j given relocation, and M_c is the current house's mortgage balance.

The ratio of Zillow (2019) rent estimations to property values was utilized as a surrogate for water-front and water-view location premiums. Repair costs were computed based upon the assessed structural value multiplied by the percentage of structural damage. Post-construction elevation costs were \$1.50 per foot of elevation, per square foot of housing with an additional \$26 or \$57 per square feet of overhead costs for frame and masonry buildings, respectively (Aerts et al. 2013). Based upon National Flood Insurance Program guidelines (Code of Federal Regulations 2002) structural damage of 50% or greater constituted destruction and demolition was required. Demolition costs were 15% of the assessed structural value (Fixr 2019). Relocation costs within Sea Bright included the vacant lot cost and construction of a new home of equal value to the previous one. New construction costs were \$192.8 per square foot with floodproofing costs of 1.15% per foot of elevation (Federal Emergency Management Agency 2009). The outstanding mortgage was based upon a 30 year fixed interest with linear principal payment plan.

For a protection motivation assessment, reconstruction option affordability was also assessed on an annual basis utilizing a study derived calculation of available income and post-repair mortgage cost (3):

$$A_j = S * p + \Big(\big(P_c + S_c + I_c - M_c - D_{c|d} \big) - \big(P_j + S_j \big) \Big) * MR/30 \tag{3}$$

where A_j is the annual affordability, subscript c denotes current housing, S is the household annual income, p is the percentage of income for housing, and MR is the mortgage ratio of total cost to initial outlay. The percentage of income assigned to housing was an average of the current level and a randomized range based upon census property value strata, with a minimum increase of 0 to \$2000 per year. A 5% interest rate was used against the 2008-2014 national average of 4.774% (Freddie Mac 2019).

3.4 Model Validation

The simulation was verified via code reviews, test cases, and a comparison with off-line spreadsheet analysis. Validation was implemented utilizing Ngo and See's (2012) four stages for model structural validation. Prior to ABM use, the generated Sea Bright population (Section 3.1) was validated against ACS 5 year estimates utilizing paired Z-tests. During the damage analysis (Section 3.2) a face validation was conducted on the damage levels and sensitivity analysis was performed on the flood-proofing levels and DDFs. Input values for the flood-proofing bias and damage scaling factors were calibrated against historic damage levels. In conjunction with the reconstruction decisions (Section 3.3) the weighting factors from (1) were calibrated to obtain Lindell and Hwang (2008) correlation levels between sex, ethnicity, income, experience and the perceived flood risk. Sensitivity analysis was completed on risk severity, and the expected number of future storms, and the risk mitigation threshold and storm expectations were calibrated against historic mitigation levels. T-tests were conducted for the homeowner decision results against the targeted values for quantitative output validation.

3.5 Structure Elevation Analysis

The validated flood mitigation results for structure elevation were assessed to identify built environment impacts on structural elevation. Building types (Monmouth County Office of Records Management 2019) were compared against the percentage of housing units elevated in Section 3.3 and the percentage of raiseable units that were not selected for mitigation was determined.

4 RESULTS AND ANALYSIS

Results of the ABM analysis are provided below. Sections 4.1 through 4.5 provide the results corresponding to their respective Section 3.1 through 3.5 methodology section, with Section 3.4 validation as appropriate.

4.1 Sea Bright Generation

The total simulated population of 30,389 homeowners from all 30 replications was evaluated against the census and survey statistics as presented in Table 1. Of note, the survey responses' gender levels were based upon which household member responded, while the census and simulation's use of the head-of-household weighted the results toward males. All of the simulation factors are not statistically different from the ACS at $\alpha = 0.15$ or better. In general, the simulated population tracked the survey data, although it was slightly younger and less affluent. This may have occurred from limitations with the ACS data set and the use of the ACS total population and household statistics in cases where homeowner-occupier subsets were not available. Given consistency with the ACS, the simulation population is reasonable and considered adequate for the decision making analysis.

Table 1: The simulated owner population in comparison with truth data.

	ACS 2007-2011	**ACS Standard Deviation**	**Survey 2014 n = 303**	**Survey 2015 n = 142**	**Simulation Average**	**Simulation Standard Deviation**
Female	16.8%	6.1%	48.5%	47.9%	22.5%	1.0%
White	85.1%	9.5%	92.7%	89.4%	92.6%	0.6%
Under 35 years old	6.7%	8.5%	5.9%*	4.2%*	9.0%	0.9%
Over 65 years old	31.8%	8.4%	41.6%	49.3%	24.2%	1.2%
< $35,000	18.7%	8.5%	7.9%	9.8%	15.8%	1.0%
$35 – 50K	10.5%	2.1%	10.6%	7.0%	12.1%	0.6%
$50 – 100K	37.2%	2.7%	16.9%	16.2%	38.6%	1.5%
> $100K	33.6%	8.6%	49.5%	49.5%	27.3%	1.6%
Mortgage Holder	60.8%	11.6%	n/a	54.2%	61.1%	1.4%

* Under 38 years old

4.2 Structural Damage

Definitions of structural damage varied slightly between FEMA, survey responses, and the ABM simulation metrics. FEMA damage appraisals utilized flood depth as an indicator for total damage value (structure and belongings) without reference to flood-proofing heights. Four levels were identified: affected (< 2 ft above ground), minor (2-5 ft), major (> 5 ft), and destroyed. Survey responses for damage were subjective with four levels: no damage, not very extensive, somewhat extensive, and very extensive. Responses eliciting the current home status were categorized in separate terms including mitigation actions. Output metrics from the ABM consisted of the number of flooded lots, the number of housing units with flooding above their flood-proof heights, and the percentage of structural damage. Table 2 provides the breakdown of damage levels from FEMA and responses from surveys in both 2014 and 2015, and repair decisions from the 2015 survey (in the percentage of housing units).

Table 2: Hurricane Sandy damage levels and quantities.

FEMA		**Survey Damage**	**2014**	**2015**	**Survey Repair Status**	**2015**	**ABM Target**
Title	Percent	Title	Percent	Percent	Title	Percent	Percent
Affected (<2 ft)	14.2	No Damage	6.6	6.3	No Repairs Required	9.9	20.5
Minor (2 - 5 ft)	33.1	Not Very Extensive	24.1	22.5	Repaired	66.9	48.4
Major (> 5 ft)	50.3	Somewhat Extensive	37.3	37.3	Elevated	20.5	18.6
Destroyed	2.3	Very Extensive	30.7	33.1	Abandoned/ Condemned/ Rebuilt	12.5	12.5

An amalgamation of the damage data in Table 2 was utilized to develop a target value for comparison with the ABM repair decision outputs. Since FEMA's building inundation measurements are only conducted at the request of the resident as a prerequisite to obtaining disaster relief funds, it is assumed that their data does not contain significant undamaged structures, and this study utilized self-selecting survey responses as the target for undamaged units. Alternatively, survey responses likely skew the damage estimates higher. The median damage costs in the 2015 survey were 38.5% of the median Sea Bright structure's appraisal value, but the average damage cost was only 14.7% of the average appraisal value. All "not very extensively" damaged homes were assessed to have sufficient flood-proofing, and the FEMA affected domiciles were used as the target for below flood-proofing units. The study's target of destroyed units was based upon survey housing status responses (12.5%), which reduced the damaged units to the remaining 67.0% of effected homes.

The average damage percentages of the 30 simulation runs were compared against the simulation target with a flood-proofing elevation reduction of 0 to 4.5 feet Dry units were consistently 7.6% of the buildings and no units were destroyed. Considering the destroyed homes as a subset of damaged unit results, the simulation should be targeting 79.4%, which yielded a flood-proofing adjustment of -2.5 feet. This is consistent with the damage appraisals and survey responses given the definitional differences. A visual review of many of the townhouses and single family homes identified what appeared to be a furnished, wet-proofed ground floor. Flooding of this area would result in damage to the contents of the home, which would not be considered in the simulation's DDFs. Additionally, any minor damage to the structure below the flood proofing height would not be captured in the ABM's calculations.

Given a 2.5 foot flood-proofing reduction factor, scaling of the damage factors was evaluated in relationship to the number of housing units destroyed. To obtain a 13.4% destruction level, the simulation DDFs had to be increased between 60 and 70%. This increase can be accounted for due to the lack of debris, surge pressure, or foundation erosion damage in the DDFs' destruction mechanisms, which only use flood inundation.

4.3 Homeowner Responses

Utilizing the flood adjustment and damage scaling factors from Section 4.2, (1) demographic weighting factors were adjusted to obtain the PADM risk perception correlation levels, per Table 3. These resulting correlations are consistent with Lindell and Hwang's (2008). However, cross correlations between factors were not considered. This resulted in the expansion of the resulting risk perception levels to a range of -0.350 to $+1.350$.

Table 3: Demographic weighting factors and correlation with perceived risk.

	Gender (Female)	**Ethnicity (White)**	**Income**	**Flood Experience**
Weighting Factor	0.14	-0.14	-0.21	0.21
Risk Perception Correlation	0.21	-0.13	-0.17	0.27
Lindell and Hwang (2008)	0.21	-0.14	-0.18	0.27

Employing the demographic weighting factors and Section 4.2 flooding and damage factors, sensitivity analysis was conducted on the expected number of future hurricanes and perceived risk threshold required for implementing elevation mitigations compared against the Sea Bright survey data. To obtain survey levels of housing elevations with fewer than five future storms, a mitigation risk threshold level of zero or less was required, as shown in Figure 3.

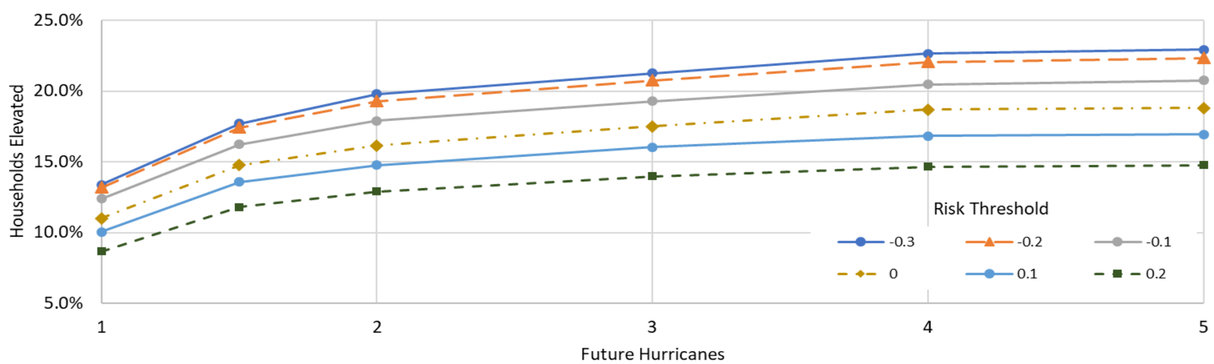

Figure 3: The Risk threshold and expected number of future hurricanes required to elevate a percentage of housing units.

Simultaneous calibration of the four previously evaluated parameters was conducted to improve overall simulation performance and increase the percentage of elevated houses. The results in Table 4 were obtained with a risk threshold of -0.1, flood-proofing decrease of 3.0 feet, a damage scaler of 0.4, and 2.0 future storms.

Table 4: The calibrated model performance compared to the targeted values.

	Dry Properties	**Undamaged**	**Repaired**	**Elevated**	**Destroyed**
Simulation Mean	7.7%	19.2%	52.0%	18.6%	10.2%
Simulation Standard Deviation	0.3%	0.2%	0.4%	0.5%	0.2%
Target Value	6.6%	20.5%	48.4%	18.6%	12.5%

4.4 Flood Mitigation Validation

The simulation elevated structure performance was statistically indistinguishable from the targeted building elevation value (α>0.92). Repaired structures were slightly overestimated at the expense of underestimating destroyed dwellings and slightly underestimating undamaged units. Attempts to spread the damage levels and shift them toward destroyed homes resulted in unrealistic destruction in the Hurricane Irene pre-processing ($\geq$4.6%) and were not implemented. Given the damage definition differences discussed in Section 4.2, the results of the ABM are statistically appropriate for investigation into the homeowner actions to mitigate future flood risks and sufficient for continued analysis.

4.5 Structure Elevation Analysis

The low risk mitigation threshold necessary to elevate historical quantities of houses (as shown in Figure 3) indicates that the risk factors are not major contributors to the flood-proofing decision. In evaluating the total replications, only 5.0% of the repaired homes could have been elevated but had risk levels below the threshold. From all of the damaged houses, 63.6% were townhouses, apartments, or duplexes which could not be individually raised. Of the remaining single family homes, 76.6% were elevated. The remaining 8.5% of all damaged houses were not elevated as shown in Figure 4. These results align with the survey respondents' comments from McNeil et al. (2017), which have repeated remarks regarding the inability to raise a townhouse. Survey results also indicate that 11.3% of the respondents did not believe they would ever have another disaster of the magnitude of Hurricane Sandy. This aligns with the ABM's response that, for low flood levels, the homeowners would not invest in major changes.

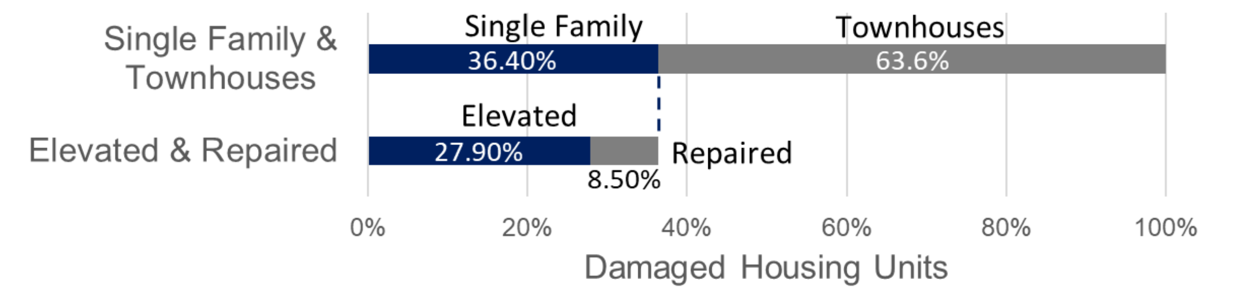

Figure 4: The percentage of houses elevated and eligible for elevation.

5 CONCLUSIONS AND RECOMMENDATIONS

Ensuring the validity of an ABM is a challenging and an often overlooked task. This study developed a methodology for conducting comparisons of modeled flood victim responses with historical data. The methodology was applied to a hind-cast of Hurricane Sandy's effect on Sea Bright, NJ and the inhabitants' reconstruction decisions. All four stages of Ngo and See's (2012) validation process where employed as discussed in Sections 3 and 4, and the ABM is appropriate for future analysis into policy decisions to mitigate coastal flood damage.

As a next step, the validated methodology from this analysis is intended for federation with the Advanced Circulation (ADCIRC) coastal flood model. The model will be extended to include community level decision making which will initiate modification of the CFD's elevation grid for large scale structural mitigations such as sea walls and berms. Changes to the ABM to include wind, water velocity, and erosion in the damage calculations are recommended to improve performance.

Several areas for additional further work were also discovered during the conduct of this work. Although agents interacted with their natural and man-made environment, interactions between agents were not modeled beyond sequentially switching lots. While their independence was partially in response to survey responses, social dependencies and dwelling resale value impacts should be considered in the future along with collective dynamics toward community level structural mitigations.

The significant take away from the analysis is the limited effect of individual risk perceptions on the decision to elevate homes to prevent future flooding (Section 4.3). Risk thresholds for flood-proofing had to be reduced to low levels to replicate the number of households which were elevated. Regardless of their demographic risk contributions, all owners with a positive risk consequence level were needed to flood-proof to match survey results. The remaining homeowners could not modify their housing unit due to adjacent units or had a "can't happen again" low risk consequence appraisal (Section 4.5). At the study level, this permits future modeling to simplify agent decisions and base them on historic flood levels and economic factors without needing to generate detailed demographically diverse populations. For larger scales, the hindrances to flood-proofing will require significant education efforts to communicate the future flood risk. Otherwise, flood mitigations will be constrained to long term community rejuvenation combined with more stringent building code requirements.

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