Integrating the Social Vulnerability of Host Communities and the Objective Functions of Associated Stakeholders during Disaster Recovery Processes Using Agent-Based Modeling

Mohamed S. Eid, S.M.ASCE[1]; and Islam H. El-adaway, M.ASCE[2]

Abstract: Disaster recovery requires the participation of the stakeholders to repair the impacted community. Nevertheless, disaster recovery remains understudied within the context of emergency management. Various models have been developed to address disaster recovery. However, those models neither considered the stakeholders' needs and preferences, nor the vulnerability of the host community. This paper presents a decision-making framework for disaster recovery that uses a bottom-up approach to capture the needs of the impacted residents and decreases the social vulnerability of host communities. The authors developed the following research methodology: (1) use a well-established community specific social vulnerability assessment tool to evaluate the society vulnerability; (2) model the multisector stakeholders through a root-to-grass technique that captures their objectives, strategies, and learning behaviors; (3) simulate the recovery progress of the impacted community using an agent-based simulation toolkit; and (4) interpret the results to provide the decision makers with optimal recovery strategies. The restorations efforts in the aftermath of hurricane Katrina in three coastal counties in Mississippi were used as the problem domain. Accordingly, the proposed model was implemented on a multiagent-based simulation toolkit with geographic information system (GIS) abilities. This research optimized the budget for the State Disaster Recovery Coordinator and the residents' insurance plans choices. As such, this study provided better social vulnerability indices than the existing conditions currently found in the areas under investigation. Further, this research provided higher disaster recovery rates within the studied host communities. For future work, other vulnerability dimensions will be simultaneously integrated into the model to provide a more accurate depiction of sustainable disaster recovery processes.
DOI: 10.1061/(ASCE)CP.1943-5487.0000680.

Introduction

Disasters are defined as "nonroutine events in societies . . . that involve conjunctions of historical conditions and social definitions of physical harm and social disruption" (Picou et al. 2004). Disaster events have led to billions of dollars in infrastructure losses because of their increasing rates and magnitudes in the last decade (Eid et al. 2015; Economics of Climate Adaptation Working Group 2009). Recent examples in the United States include: (1) Hurricane Andrew in 1992 ($20.9 billion); (2) the Northridge earthquake in 1994 ($15.9 billion); (3) the four Hurricanes Charlie, Ivan, Frances, and Jeanne in 2004 (total of $21.9 billion); (4) Hurricane Katrina in 2005 ($125 billion); (5) Hurricane Rita in 2005 ($10 billion); (6) Hurricane Wilma, also in 2005, ($16.8 billion); (7) Hurricane Ike in 2008 ($19.3 billion); and (8) Hurricane Sandy in 2012 ($68 billion) (Eid et al. 2015).

Our nation's infrastructure is highly vulnerable to natural hazards (Haimes 2012). Accordingly, decision makers are in need of sustainable disaster recovery decision support tools that decrease the vulnerability of the built environment and meet the needs of the host community (Eid and El-adaway 2016a). Even though disaster recovery dimensions were investigated (social, environmental, and economic), there is still a need to account for the complex interactions among the stakeholders who affect and are affected by the recovery processes (Kennedy 2007). The National Disaster Recovery Framework (NDRF) clearly stated that to achieve a successful redevelopment project, disaster recovery agencies need to assimilate the various participating entities and use the private insurance sector (NDRF 2011; Eid and El-adaway 2016b).

To better assist the decision makers, various post-disaster recovery models were developed. Such models used mixed integer linear programming, genetic algorithms, and numerical models to optimize the different infrastructure redevelopment projects (El-Anwar et al. 2015, 2010; Miles and Chang 2006; Bryson et al. 2002). However, the used approaches do not account for the host community needs. Moreover, the models do not consider the vulnerability of the built environment to future shocks. As such, the models only can optimize isolated projects and are unsuitable for addressing the community redevelopment at large (Eid and El-adaway 2016b).

Conversely, even though agent-based models (ABM) were used occasionally in emergency management (Crooks and Wise 2013), only few attempts were carried out within the context of disaster recovery. Fiedrich and Burghardt (2007) advocated the potential role of ABM in recovery projects. Through simulating the stakeholders of the impacted host community, decision makers can find

[1]Ph.D. Candidate, Dept. of Civil and Environmental Engineering, Univ. of Tennessee, 851 Neyland Dr., 324 John D. Tickle Bldg., Knoxville, TN 37996. E-mail: meid1@vols.utk.edu

[2]Associate Professor, Civil Engineering and Construction Engineering, Management Program Coordinator, Dept. of Civil and Environmental Engineering, Univ. of Tennessee, 851 Neyland Dr., 417 John D. Tickle Bldg., Knoxville, TN 37996 (corresponding author). E-mail: eladaway@utk.edu

Note. This manuscript was submitted on September 23, 2015; approved on January 10, 2017; published online on March 30, 2017. Discussion period open until August 30, 2017; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Computing in Civil Engineering***, © ASCE, ISSN 0887-3801.

the optimal strategies that meet the residents' needs and decrease the built environment vulnerability (Eid and El-adaway 2016a). This can be carried out through the dynamic simulation that captures the different stakeholders in the impacted host community (Nejat and Damnjanovi 2012). Thus, the use of ABM meets the aforementioned recommendation by the NDRF.

Goal and Objectives

The objective of this research was to develop a decision-making framework for disaster recovery to better guide the redevelopment processes toward increasing the communities' welfare. This paper uses a bottom-up approach that captures the needs of the impacted residents and integrates a social vulnerability assessment tool for the host communities. This study will help identify the recovery strategies that balance the short-term redevelopment objectives and the long-term goal in social vulnerability reduction.

Background Information

Overview

Active involvement of the community's stakeholders in the redevelopment planning and execution phases related to infrastructure development activities increases the participating entities' individual utilities (Boz and El-adaway 2014). Meanwhile, the slow rate in the redevelopment processes and lack of overall quality is contributed to the inadequate framework and communication between the various stakeholders (Ferdinand and Yu 2014; Chang and Rose 2012; Olshansky et al. 2006). Accordingly, the NDRF emphasizes the need to assimilate the participating entities in the decision-making processes to achieve sustainable disaster recovery (NDRF 2011).

Sustainable Disaster Recovery and Social Vulnerability

Through the last decade, research was carried out to understand the key elements to achieve a successful recovery process, and the commonly used strategies by governments and impacted residents (Cutter et al. 2006; Olshansky 2006). It was repeatedly documented that the involvement of residents' needs in the local government decisions enhanced the overall recovery output (Olshansky et al. 2006). For example, after the Kobe earthquake (1995) in Japan and hurricane Katrina (2005), higher residential approval was reported for the redevelopment plans that were previously discussed with the impacted community (Olshansky et al. 2006). This agrees with the NDRF claim that broad community involvement in the recovery decision-making processes is essential for a successful recovery project.

According to Cutter et al. (2006), the governmental recovery agencies attempt to assist the impacted residents through financial compensation, household repairs, and retrofitting the vulnerable structures. Meanwhile, residents of the impacted regions strove to (1) allocate the financial means to repair and rebuild, (2) select the optimal insurance policies that reduced their risk to future events, and (3) decide whether to sellout or stay in the host community. Various factors may affect residents' decision actions, such as social ties, socioeconomic standards, and adequate financial support by the government (Olshansky 2006).

Post-disaster insurance policies also affect the recovery processes (Eid et al. 2015; Olshansky et al. 2006), and have been reported as a key factor in the success of redevelopment projects because it provides adequate financial means for recovery (NDRF 2011; Olshansky et al. 2006). To this extent, to optimize the various disaster recovery strategies, one should understand and account for the complex interactions among the different multisector stakeholders (Eid and El-adaway 2016a).

The ultimate goal of a sustainable disaster recovery process is to decrease the vulnerability of the host community to future hazards while rebuilding the impacted infrastructure. Social vulnerability has been investigated thoroughly in the last decades to highlight the key factors affecting societies' vulnerabilities (Burton 2010; Gilbert 1995). Social vulnerability is defined as the differential capacity of groups and individuals to deal with hazards and changes on the basis of their positions within physical and social worlds (Dow 1992). A community's social vulnerability also is affected by the degrees of empowerment (ability to change strategies) and resourcefulness (Watts and Hans 1993). To this effect, social vulnerability has an inherent dimension in form of the social structure and its potential for loss because of empowerment and entitlement, plus several other factors. In addition, the external dimension of social vulnerability is contributed to a community's exposure to shocks and perturbations.

Recently, social vulnerability to hazard was quantified through different models and approaches (Burton 2010; Turner et al. 2003). The social vulnerability index (SoVI) is a widely recognized and well-established vulnerability assessment model on the basis of the host community's specific socioeconomic data (Cutter et al. 2003). To develop SoVI, socioeconomic variables for the host community must be gathered, such as household income, median age, median household value, education attained, and percentage of mobile homes. In addition, multivariate analysis (factor analysis) must be used to understand the factors that affect the host community's social vulnerability to disasters, depending on their socioeconomic specific data. The use of factor analysis allows for the calculation of relative vulnerability scores among the different regions under study. Even though the interpretation of the factors produced from factor analysis is subjective (Yang and Bozdogan 2011), this relative vulnerability scoring approach would provide decision makers with a tool to allocate the redevelopment funds depending on the relative vulnerability of the different regions affected by the natural disaster. Accordingly, the SoVI can be integrated into the disaster recovery decision support tools to optimize the budget distributions.

Agent-Based Modeling

Agent-based modeling is the result of cumulative research on the aggregated impact of individual actions on the systems' performances. Through modeling the systems in a grsssroots fashion, ABM captures the dynamics of the various participating entities. As such, ABM contributed to the body of knowledge in social science, economics, and engineering through exploring the impact of individuals' collective behavior on civil violence, social interactions, disputes, highway transportation, and negotiation (Eid and El-adaway 2016b; Mostafavi et al. 2015; Crooks and Wise 2013; Du and El-Gafy 2012; El-Adaway and Kandil 2010; Miller and Page 2004; Epstein 2002, 2001; Peña-Mora and Wang 1998; Axelrod 1986).

An agent is a computer program that acts on behalf of an individual or an organization (Nwana 1996). Agents are assumed to be (1) interdependent, and interact, influence, and affect each other; (2) follow simple rules, norms, protocols, or heuristics; and (3) adaptive, and replicate and/or learn (Eid and El-adaway 2016b). Intelligent agents are able to sense the surrounding environment, react to changes around them, choose actions that meet their needs, and learn through their (or others) past experiences

(Padgham and Winikoff 2004). Thus, those agents can represent the interactive stakeholders of a system.

To simulate the human complex behavior through experience and learning, different learning models have been developed. These models enable agents to use optimal decision actions depending on their observations of the surrounding environment. Learning is categorized into (1) individual, learning through one's own experience; and (2) social, learning through observing other similar agents. Different learning models were introduced in the last decade via multidisciplinary research in artificial intelligence, social science, and mathematics [Bayesian learning, Roth Erev reactive learning, Heuristic learning, Markov hidden process (MHP), Q-learning, particle swarm, and genetic algorithms].

Nevertheless, few ABM attempts were carried out within a disaster recovery perspective. Miles and Chang (2006) developed a post-disaster recovery model that simulates the redevelopment of the community on the basis of the interactions among the residents, businesses, and recovery agencies. Meanwhile, a multi-agent recovery simulation model was developed within a game theory context (Nejat and Damnjanovic 2012). The model simulated and analyzed the residents' sellout option, post-disastrous event. Nevertheless, the aforementioned attempts did not fully capture the ABM abilities in providing proactive decision-making support tools that decrease the vulnerability of the host communities to future disastrous events (Eid and El-adaway 2016b).

Research Methodology

The authors developed the following four step research methodology to achieve the proposed goal: (1) use well-established community specific social vulnerability assessment tools to evaluate the society vulnerability; (2) model the multisector stakeholders through a grassroots technique that captures their objectives, strategies, and learning behaviors; (3) simulate the recovery progress of the impacted community using an agent-based simulation toolkit; and (4) interpret the results to provide the decision makers with optimal recovery strategies.

The proposed model used the post-Katrina redevelopment efforts for three Mississippi coastal counties as the problem domain. As such, the authors gathered the following data sets to evaluate the host community social vulnerability, model the stakeholders' strategies and decision actions, initialize the simulation runs, and for comparison purposes. The associated data sets gathered are as follows:

- To develop the model to the pre-existing conditions, generate the initial population, and develop the comprehensive social vulnerability indicator, Ex- and post-Katrina socioeconomic data were gathered at the census tract level. The authors used U.S. Census Bureau (2012) data to collect the variables needed for each of the 78 census tracts within the three coastal counties.
- The Mississippi Development Authority's (MDA) federal reporting highlighted the commonly used disaster recovery action plans by the government recovery agencies (MDA 2015). Accordingly, three action plans were defined that directly impacted the residential sector: (1) the homeowner assistance plan, a financial aid to repair and rebuilt households with a maximum of $150,000; (2) public home assistance, a housing program for low-income families within the impacted region; and (3) elevation grants, a retrofitting plan to increase household resilience to floods by elevating the building up to 1.9 m. The authors also collected the budget distribution of the MDA through federal reporting to determine the expenditure share of each of the aforementioned plans. In addition, the authors gathered the average recovery rate per action plan to simulate how the various government redevelopment strategies affected the residential sector recovery.
- *HAZUS-MH* was used to simulate hurricane Katrina's impact on resident households. The simulation used *HAZUS* historic data sets to carry out a Level 1 analysis on the hurricane's direct and debris damage to households. As such, each household's damage was acquired depending on the resident's census tract. A tornado microhazard module was developed using historical data (1953–2012) that are publicly accessible at the Mississippi Emergency Management's website (MEMA 2016). Using the data's 150 observations, a probability density function was developed and integrated into the ABM to better simulate resident decisions in the presence of recurrent shocks.

Model Development

Model Assumptions

The proposed ABM simplified real-life redevelopment projects. Thus, this model did not explicitly capture the complete human decision-making behavior, but represented them through well-recognized social and individual learning models that simulate rationally-bounded stakeholder behaviors. To this effect, the proposed model assumed the following:

1. The objective of the resident agent was to maintain its wealth (household value and income);
2. The disaster recovery agencies' objectives were to meet residents' needs and decrease the community vulnerability;
3. All agents in the proposed model were rational; agents would never take any action that is known to themselves through decreasing their objective functions; and
4. Resident agents could mimic any other resident agent through complete observation and information about the other agent's current status and decision actions.

Comprehensive Social Vulnerability Assessment Tool

Adopting the SoVI methodology introduced by Cutter et al. (2003), this research integrated a social vulnerability indicator into the ABM to evaluate the overall social vulnerability of the host community. The SoVI model is a comprehensive socioeconomic and demographic model that evaluates the host community's vulnerability to disaster. Through relative vulnerability evaluation of the different regions understudy, this approach allows recovery agencies to allocate funds to the most vulnerable regions, as shown subsequently. This is carried out by determining the socioeconomic factors that affects residents' vulnerability to hazards.

Through the development of the SoVI, Cutter et al. (2003) pointed out the effect of socioeconomic characteristics on the vulnerability of the host community. Using the social science literature, several factors were deduced that underlines the social vulnerability attributes as follows:

Economic

The economic subcomponent in social vulnerability is related to the community's access to economic assets and household wealth. This enables the community to easily recover from damages (Blaikie et al. 1994; Tobin and Ollenburger 1993; Cutter et al. 2003; Watts and Hans 1993). Variables associated with this factor are per capita income and the percentage of high-income families.

Equity
Social equity measures the community's resourcefulness. Resourcefulness is a key factor in the social vulnerability to disaster events and exposure to damage and shocks (Smith and Wenger 2007; Watts and Hans 1993). Variables associated with this factor are percentage of the population with vehicles, percentage of home ownership, and percentage of mobile homes.

Adaptive Capacity
The social adaptive capacity is pointed out several times in the social science field, in terms of social vulnerability and resilience to disasters, as a measure for the community's ability to respond and cope with hazardous events (Cutter et al. 2003, 2006; Turner et al. 2003; Burton 2010). Variables associated with this factor; age, disabilities, and education level.

Occupation
Literature shows that type of occupation and its correlated wages and salaries affect social vulnerability (Cutter et al. 2003, 2006; Burton 2010). Variables associated with this factor include the percentage of the population that are not infirmed or institutionalized, and the percentage of the population working in service occupations.

Ethnicity
An increase in one race over another and the presence of more than one race in the same community explains the social vulnerability patterns in different regions (Cutter et al. 2003, 2006; Burton 2010). Variables associated with this factor include the percentage of African Americans, the percentage of Native Americans, the percentage of Asians, and the percentage of Hispanics or Latinos.

Following the SoVI methodology, different multivariate statistical analyses were applied to the standardized variables to measure social vulnerability indicators, as presented in Fig. 1. First, nonlinear and nonparametric statistical approaches, including multidimensional scaling, were employed to evaluate the overall structure of the data and its fitness for purpose. Second, the Cronbach's alpha reliability analysis was used to investigate the degree of correlation among the different variables that indicate a common latent variable. Third, factor analysis was used to reveal how different variables are associated with each other and how they affect community vulnerability. Finally, a simple additive model was used to calculate the relative vulnerability score of each region under study.

Disaster Recovery Agent-Based Model

Purpose
The proposed ABM was developed to represent the recovery dynamics of the impacted host community on the basis of the associated stakeholders' decision-making processes, interactions, and learning behaviors. Moreover, the impact of integrating the SoVI into the objective functions of the associated stakeholders was evaluated through the developed ABM. This approach attempted to decrease the social vulnerability of the host community to future shocks and increase the participating entities' individual utility. As such, the proposed ABM enabled the decision makers to find the strategies that meet the residents' redevelopment needs and decrease community's social vulnerability.

Agents Overview
Three different entities were depicted within the ABM: residents; insurance companies; and the government represented by the Local Disaster Recovery Management (LDRM), State Disaster Recovery Coordinator (SDRC), and Federal Disaster Recovery Coordinator (FDRC). The aforementioned stakeholders followed the NDRF's recommendations for broad community participation in the recovery processes (NDRF 2011). Nevertheless, the proposed model only considered and optimized the resident and SDRC agents' decision actions. Insurance companies, LDRMs, and the FDRC are regarded as intermediate entities that either provide services or facilitate communications between the two primary agents.

Fig. 2 presents the proposed agents interactions and basic structure. The model was initialized with the host community specific data, including number of census tracts, number of households per census tract, and SoVI per census tract. Depending on the impact of the disastrous event on the host community's households, each resident agent determined if repairs were required and whether the agent should apply for financial assistance through the LDRM. The resident agent also accounted for insurance coverage and if any had been purchased previously, which helped the resident to recover. At this point, the resident agent decided (through social learning) whether to keep the current insurance policy or apply for a more appropriate policy.

The SDRC provided residential redevelopment support through recovery plans. Through individual learning, the SDRC redistributed the available funds across the different recovery action plans. Meanwhile, the LDRMs communicated with the local residents to present them with the SDRC's residential redevelopment options. According to the NDRF (2011), the LDRMs also checked submitted applications by the local residents, only accepting the eligible resident agents, and managed the redevelopment activities and progress (NDRF 2011). Finally, the FDRC funded the SDRC and collected the redevelopment progress through the SDRC's periodic reports.

Resident Agents
The objective of the resident agents was to maintain and increase their current wealth, as show in Eq. (1). Within the disaster recovery context, the objective function was impacted by the household value and any paid expenses (repair, tax, and insurance) (Eid and El-adaway 2016b)

$$Z_i = H_i + I_i - T_i - P_{i(n,m)} + C_{i(n.m)} - R_i \quad (1)$$

where i = resident index; Z_i = objective function of resident I; H_i = household value for resident I; I_i = monthly income for resident I;

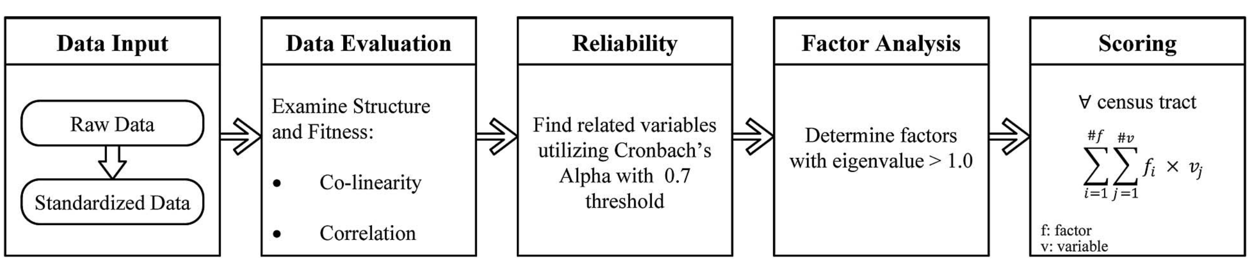

Fig. 1. SoVI methodology

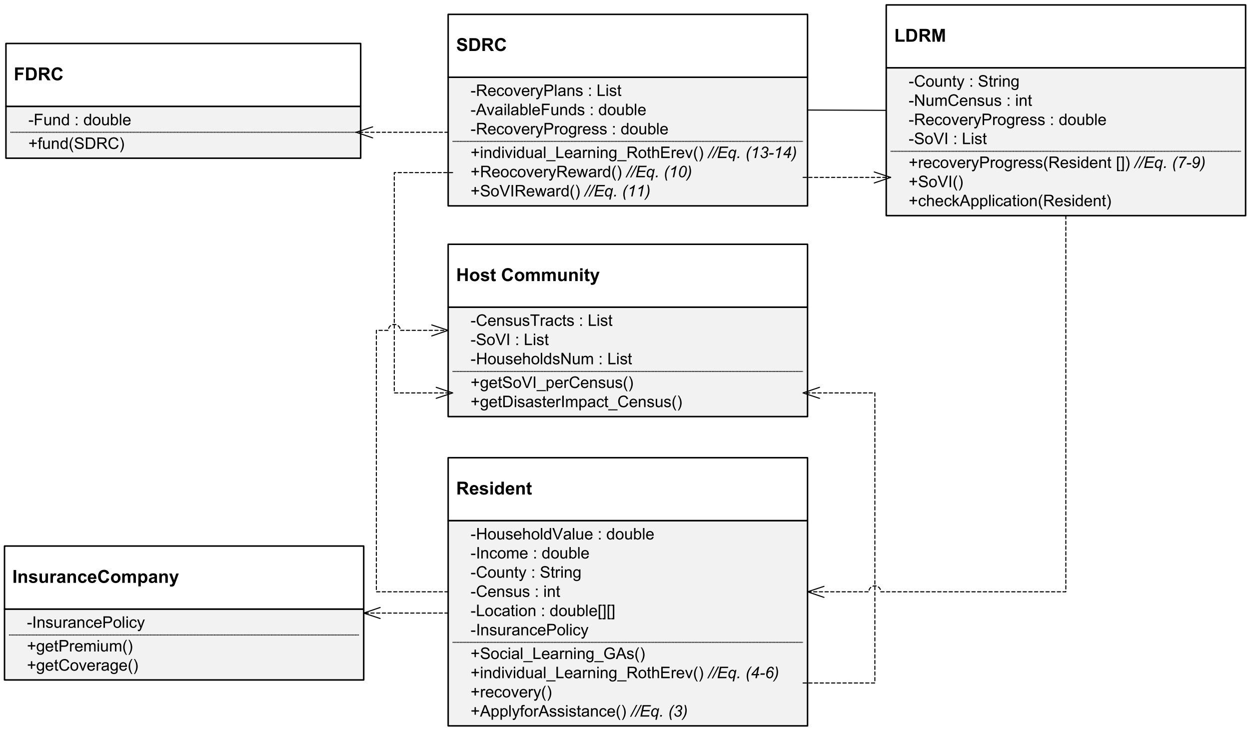

Fig. 2. Agents' interactions and basic structure

T_i = monthly distributed tax amount (income and property taxes); $P_{i(n,m)}$ = monthly distributed insurance premium cost, if any, for plan m offered by insurer n; $C_{i(n,m)}$ = insurance compensation value, if any, paid by insurer n for plan m; and R_i = self-paid repair costs.

Accordingly, the resident agents had the two following strategies to optimize and increase their objective functions: (1) decide on which insurance policy to purchase (or none), and (2) find financial means to repair the damaged household. Meanwhile, the residents' strategies expenditures were limited to their net monthly income (Eid and El-adaway 2016a). It was estimated that the monthly living costs for a household did not exceed 45% of the gross income (Federal Highway Administration 2014). Thus, the aforementioned resident's monthly expenditure (T, P, and R) should be less than the monthly net income (Eid and El-adaway 2016a) as shown in Eq. (2)

$$T_i + P_{i(n,m)} + R_i \leq (1 - 0.45)I_i \tag{2}$$

To maintain and increase the objective function through the first strategy (insurance policy), residents observed each other to determine the insurance policies that best suited them (Eid and El-adaway 2016b).

Residents Social Learning Module. To mimic the residents' social learning in their attempt to find the optimal insurance policy, the authors used genetic algorithms (GAs). Genetic algorithms can represent efficiently the agents' social-learning processes (Riechmann 2001) by simulating the social interactions among a number of residents or individuals, and imitating their observations and communication (Eid and EL-adaway 2016b; Eid et al. 2015). Genetic algorithms have been shown to be an effective optimization approach throughout the last decades (Eid et al. 2015, 2012; Hyari and El-Rayes 2006; Elbeltagi et al. 2005; Feng et al. 1997), despite consuming a long computation time (Bell and Lida 1997). The GA's algorithms allowed residents to mimic the fittest among them, following Darwin's theory of survival of the fittest (Eid and El-adaway 2016b; Riechmann 2001; Vriend 2000). Thus, residents observed all the other residents, determined the fittest, and mimicked their decision actions (insurance policy).

Residents Individual Learning Module. To secure the financial means needed for repair, the resident agent submitted an application for a governmental aid through the LDRMs. As such, the resident agent attempted to increase its objective function by choosing the plan that maximized its expected utility (Eid and El-adaway 2016b) as shown Eq. (3)

$$E(U_j)_i = (G_j \times A_j) \times pr_j \tag{3}$$

where $E(U_j)_i$ = plan j's expected utility for the resident I; G = maximum award provided by the government (SDRC) for plan j; A = government (LDRM) average acceptance probability of plan j; and pr = the learning probability used from the following reactive reinforced learning module.

Even though each resident agent chose one of the offered plans that maximized its expected utility function, the LDRMs could still deny the resident's application if the resident agent was found ineligible (not meeting the prespecified criterion) or because of a lack of funds by the SDRC. Accordingly, the resident agent needed to learn and adjust the probability associated with the selected plan to be used with the following time steps. Thus, the residents learn through their individual past experiences that can be captured through a reactive learning model.

The residents' individual learning behavior on the basis of their past experience and repetitive interaction with the LDRM was illustrated using the Roth Erev reactive reinforcement learning module (Erev and Roth 1998). The Roth Erev reactive reinforcement learning module is a game theory-based model that mimics the learning behavior of individuals playing an extensive game (Erev and Roth 1995). First, the model determined the immediate reward associated with the decision action (Eid and El-adaway 2016b), as shown in Eq. (4)

$$E_j(k) = \begin{cases} \pm 1 & \text{if } j = k \\ 0 & \text{other wise} \end{cases} \quad \forall\ j = 1, 2, \ldots, J \tag{4}$$

where E = reward of action j when using decision action k. If $j = k$, E takes the value of $+1$ or -1 if the application is approved or denied, respectively. Otherwise, $E = 0$.

At each time step, each decision action's propensity was updated using Eq. (5), and accordingly, this changed the probability of choosing each action, as shown in Eq. (6)

$$q_j(t+1) = q_j(t) \times (1 - \phi) + E_j(k) \times (1 - \varepsilon) \quad \forall j = 1, 2, \ldots, J \tag{5}$$

$$pr_j(t) = q_j(t) \bigg/ \sum_{j=1}^{J} q_j(t) \forall j = 1, 2, \ldots, J \tag{6}$$

where $q_j(t)$ = propensity of action j at time t; and ϕ and ε = forgetting and experimenting parameters, respectively. Both ϕ and ε allowed the agent to explore more options further on (Eid and El-adaway 2016b). Finally, pr = probability distribution of action j.

As such, the Roth Erev module was able to represent the individual learning process of the residents given their own experiences. Accordingly, the model weakened the probability of the strategies with poor outcomes and increased the most rewarding strategies' probabilities.

Residents Recovery Progress. Depending on the used (and accepted) government recovery plan, the residential recovery module calculated the household recovery status at each time step, as shown in Fig. 3. To evaluate and report the recovery status of the residential households, each LDRM calculated the initial households values via Eq. (7), determined the current redevelopment progress at each time step through Eq. (8), and reported the changes in the households' recovery progress through Eq. (9)

$$D_{y_o} = \sum_{i}^{I} H_{i_y} \quad \forall\ y = 1, 2, \ldots, Y \tag{7}$$

$$D_{y_t} = \sum_{i}^{I} H_{i_y} \quad \forall\ y = 1, 2, \ldots, Y \tag{8}$$

$$\Delta D_{y_t} = \frac{D_{y_t}}{D_{y_o}} \quad \forall\ y = 1, 2, \ldots, Y \tag{9}$$

where D_{y_o} = initial development status for county y; D_{y_t} = current redevelopment status at time t; ΔD_{y_t} = current change in development at time t; and H_i = household value for resident i in county y.

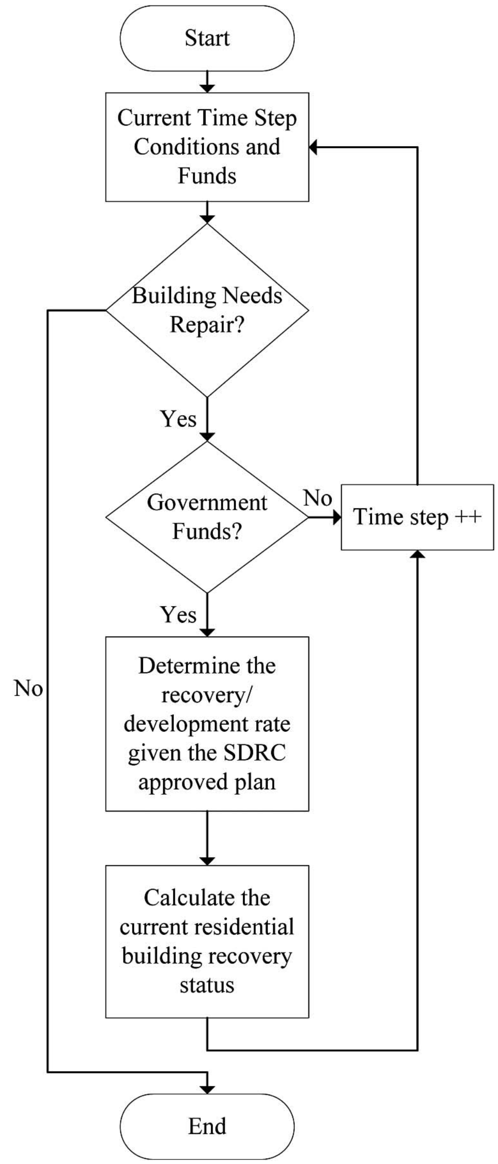

Fig. 3. Residential building recovery module

State Disaster Recovery Coordinator

Eq. (10) shows that the aforementioned SoVI was integrated into the objective function of the SDRC to decrease the host community's vulnerability. In addition, the SDRC accounted for the residents' objective functions to meet their needs, as illustrated in Eq. (11). Accordingly, the SDRC carried out a multiobjective optimization by minimizing Eq. (10) and maximizing Eq. (11). However, the total expenditure of the SDRC was constrained by the funds provided by the FDRC (Eid and El-adaway 2016a), as shown in Eq. (12)

$$\text{Average (SoVI)}_k \quad \forall\ k = 1,2, \ldots, K \tag{10}$$

$$\sum_{i}^{I} \Delta Z_{i_k} \quad \forall\ k = 1, 2, \ldots, K \tag{11}$$

$$\sum_{i=1}^{I} SG_i \leq \text{TFF} \tag{12}$$

where ΔZ_i = objective function changes of resident i when utilizing plan k; SoVI = average social vulnerability index for the residents applying for plan k; SG_i = state governmental funding for the residents I; and TFF = total federal funding for the SDRC.

As such, the SDRC needed to redistribute the funds across the different disaster recovery strategies at each time step depending on the impact of the strategies on the community's vulnerability and the objective functions on the residents. The SDRC attempted to optimize the budget distribution across the different redevelopment actions plans on the basis of its experiences, and those attempts can

Table 1. Insurance Companies Plans' Premiums and Coverage Percentages

Insurance company	Plan A		Plan B		Plan C	
	Premium (%)	Coverage (%)	Premium (%)	Coverage (%)	Premium (%)	Coverage (%)
Insurer number 1	1.8	70	2	75	2.8	85
Insurer number 2	2.2	80	2.8	85	3	95
Insurer number 3	2.8	85	3	95	3.28	100

be represented through Roth Erev reactive reinforcement learning model (Eid and El-adaway 2016b). Accordingly, Eqs. (10) and (11) were integrated into the SDRC's propensity function in the form of an immediate reward (IR_k) for each plan k, as shown in Eq. (13). IR_k is the relative fitness of each plan k given the SDRC's objective function. Thus, the module can find the Pareto-optimal budget distribution through multiobjective function optimization

$$q_k(t+1) = q_k(t)(1-\phi) + IR_k \times (1-\varepsilon) \quad \forall\ k = 1, 2, \ldots, K \tag{13}$$

where $q_k(t)$ = propensity of plan k in time t.

The plan k funding proportion (p) is its associated probability as shown in Eq. (14), which was affected by the plan's propensities. The Roth Erev learning model used ϕ and ε parameters to represent the temporal effect of the various disaster recovery strategies (Eid and El-adaway 2016b). Thus, unlike other opportunistic techniques, the Roth Erev approach can achieve optimal budget distributions that meet the residents' recovery needs and decrease the host community social vulnerability

$$p_k(t) = q_k(t) \bigg/ \sum_{k=1}^{K} q_k(t) \quad \forall\ k = 1, 2, \ldots, K \tag{14}$$

Insurance Agents

To provide residents with financial support in case of a disaster, insurance companies offered a variety of post-disaster policies. Meanwhile, the insurance premiums, coverage, and number of policies offered to the residents were optimized by the insurance companies (Eid et al. 2015). However, as previously discussed, the proposed ABM did not address the decision-making processes of the insurers, and it will be investigated in future work. The authors developed three types of myopic insurers offering different policies using Eid et al. (2015) data. Table 1 presents the various insurance policies, premiums, and compensation ratios per insurer.

Implementation Platform

The authors used *GeoMASON* as a platform for the proposed ABM. *GeoMASON* integrates geographic information systems (GIS) abilities into *MASON*, an open source multiagent simulation toolkit (Sullivan et al. 2010). Geographic information systems facilitate gathering the required attributes and inputs to initialize the agents within the model. This allows the model to be transformable to any problem domain. In addition, the visualization of the residents' location and their proximity to hazards was made easy because of GIS. Fig. 4 depicts the residents' distribution across three Mississippi coastal counties: Hancock, Harrison, and Jackson (west to east), illustrating the population distribution per census tract. The resident agents were randomly distributed within their corresponding census tract.

Model Testing

The proposed ABM was designed to be modular (flexible to alternate the various processes without negative impact on the model's

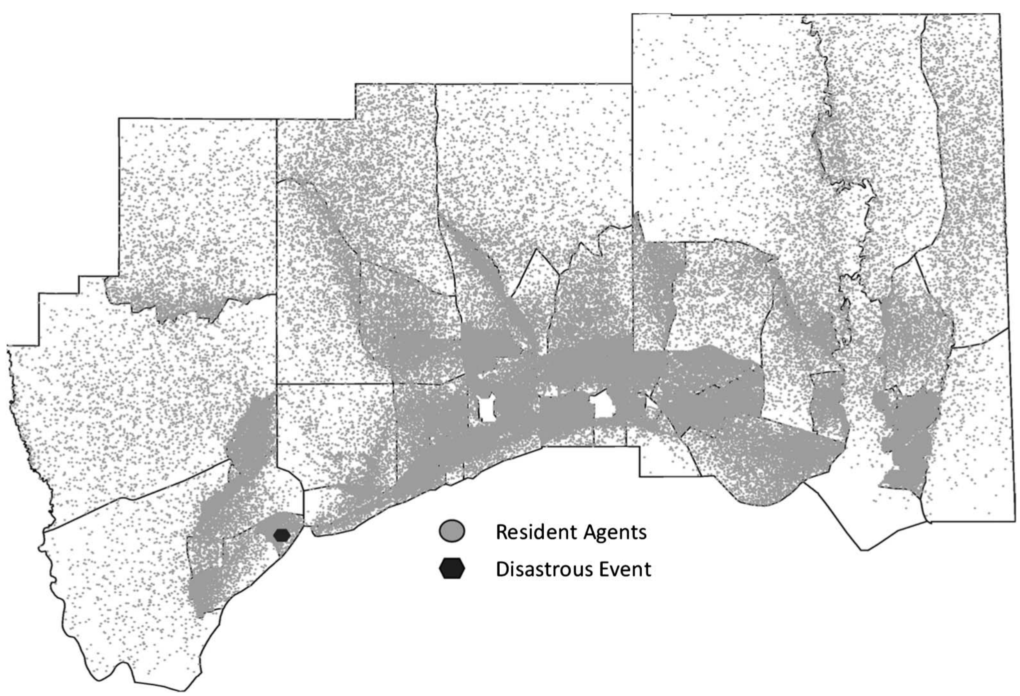

Fig. 4. Proposed model implementation on *GeoMASON*

performance) and scalable (can be used on any scale and for any number of agents/stakeholders). Incremental tests were carried out to examine agent behaviors via structural and behavioral testing. Direct empirical and theoretical tests were carried out through the structural testing. Meanwhile, to evaluate agent communication accuracy, behavioral testing was conducted. In addition, a number of regression and progression tests were used to evaluate test agents.

Most importantly, the AMB ran through two simulation scenarios (actual and uniform budget distributions). The simulation scenarios allowed for rigorous assessment on the model outcome (accounting for the needs of the residents and vulnerability of the community) in comparison with two counterfactual simulation scenarios, thus showing the model importance and potential.

Results and Analysis

The results obtained from the ABM were compared with the existing conditions of the three aforementioned counties in addition to both of the simulated scenarios (actual and uniform budget). First, using the comprehensive social vulnerability indicator, the social vulnerability resulting from the model was compared with the existing social vulnerability of the three Mississippi coastal counties and the two aforementioned scenarios. Subsequently, a discussion on the proposed budget for the SDRC is presented to highlight the reasons behind the different social vulnerability outcomes. The proposed budget was thus compared with the actual MDA expenditure distribution across the three residential recovery plans. Furthermore, to investigate the proposed SDRC's budget impact on resident recovery, the model's outcome was compared with the aforementioned scenarios illustrating the changes in the disaster recovery rate and the potential of the model. Finally, the social learning model's outcome to simulate the residents' decision on insurance policies was presented along with a discussion on its impact on household recovery. All comparisons were carried out between 2007 and 2012. This is because the socioeconomic data at the census tract level was not available until 2012, whereas the MDA federal reporting started in 2007.

Statistical Significant Sample Sizes

The authors used Lorscheid et al. (2012) and Lee et al. (2015) methodology to determine the minimum required simulation runs needed to achieve statistically significant results. Such an approach uses descriptive statistical analysis, and the means and variances of the model's distinct outcomes (Lee et al. 2015). Using the coefficient of variation proposed by Lorscheid et al. (2012), the sample size was calculated using Eq. (15)

$$n_{\min} = \operatorname{argmax}_n |c_v^{x,n} - c_v^{x,m}| \langle \text{error}, \forall x \text{and} \forall m \rangle n \qquad (15)$$

where $n_{\min}$ = minimum sample size; x = distinct outcome of interest; and m = some sample size > n, for which coefficient of variation ($c_v = \sigma/\mu$) is measured.

The authors calculated the simulation runs required to provide less than 5% margin of error for the SDRC budget distribution, residential recovery per county, and social vulnerability indicator per county. As such, seven different sample sizes were calculated. The minimum simulation runs, using Eq. (15), was found to be 175 runs, and the authors collected 180 runs.

Social Vulnerability Assessment

The SoVI is a comprehensive socioeconomic and demographic model that assesses the host community's vulnerability to disaster on the basis of their specific data (Cutter et al. 2003). To develop the SoVI, socioeconomic variables for the host community were gathered, such as average household income, household values, percentage of females, median age, percentage of mobile homes, and percentage of population speaking English. To this end, using the gathered dataset for the aforementioned three Mississippi coastal counties across the 78 census tracts, and following the SoVI methodology, 21 variables were introduced to the Cronbach's alpha reliability analysis. Afterward, 12 variables with a Cronbach's alpha value over 0.7 were retained. The elimination of nine variables reduced the attributes to economic, equity, and adaptive capacity.

Also, as previously noted, the SoVI methodology involves the use of multivariate analysis (factor analysis) to understand the factors that affect the host community's social vulnerability to disasters, depending on their socioeconomic data. The use of factor analysis allowed for the calculation of relative vulnerability scores among the different regions under study. To this effect, factor analysis was carried out on the 12 socioeconomic variables, resulting in four factors having eigenvalues greater than 1 that defined the social vulnerability of the studied region. Table 2 illustrates the retained 12 socioeconomic variables, their relation with the aforementioned social vulnerability attributes, and the factor loadings for the socioeconomic data for the three Mississippi coast counties in 2007.

Factor 1 is considered a hybrid factor representing the host community's equity and their economic standard. Factors 2 and 3 significantly relate to the economic standard and adaptive capacity. Factor 4 presents the adaptive capacity and host community equity. A simple additive factor score model was used to obtain the SoVI score for each census tract. In this way, each of the aforementioned factors was considered of an equal weight to the host community's

Table 2. Factor Analysis Loadings—2007

Attribute	Variable	Factor 1	Factor 2	Factor 3	Factor 4
Economic	Income	0.1075	0.70098	0.69642	0.08683
	Median house value	0.47794	0.5388	0.38824	0.1935
	% High income	−0.03246	0.20805	0.19926	0.0958
Equity	% With vehicles	−0.18206	0.17196	−0.04783	0.04745
	% Phone	0.11021	0.33085	−0.06504	0.48963
	% Mobile home	0.9072	−0.11693	−0.3349	−0.10942
	% Home ownership	0.748	0.09306	0.06204	0.15687
Adaptive capacity	% Speak English	0.38664	0.06612	−0.0375	0.09478
	% High school	−0.00794	0.88604	0.04583	−0.01958
	% Elderly	−0.22932	0.00888	0.86224	0.1415
	Median age	0.25112	0.29677	0.42491	0.16328
	% Female	0.08361	−0.16211	0.3319	0.92466

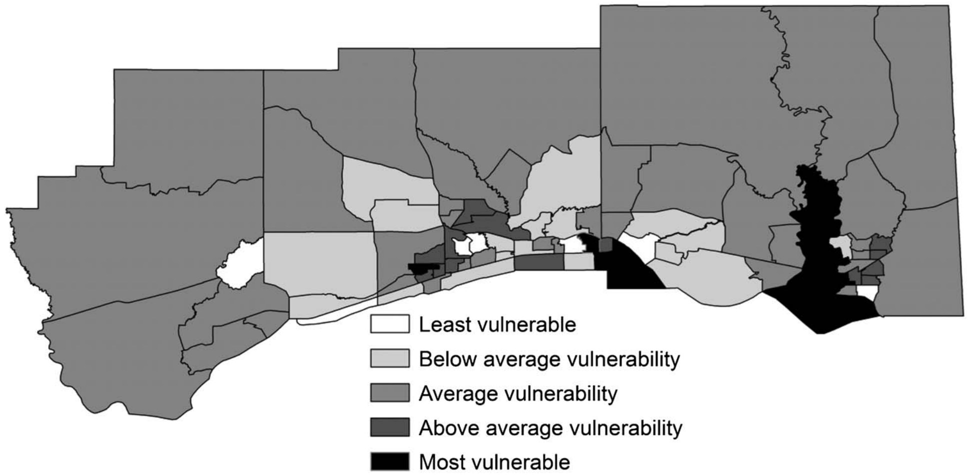

Fig. 5. Social vulnerability distribution in 2007

social vulnerability. Fig. 5 represents the three Mississippi coastal counties relative vulnerability using the SoVI scores obtained for year 2007.

Fig. 6 illustrates the existing SoVI changes through the period 2007–2012. Figs. 7–9 present the SoVI changes corresponding to the actual budget distribution scenario, the uniform budget distribution scenario, and the proposed model outcome, respectively, for years 2007–2012. The communities' social vulnerability requires a long time to change. This is because of the inherent social structure that affects the host communities' vulnerability. Accordingly, changes shown in Figs. 6–9 were generally slow. Also, the actual SoVI of the host community could not be identically replicated because of the various changes within the host community's social structure that was beyond the scope of the current model. Comparing Figs. 6–9 shows that the proposed model outperformed both the existing and actual budget distribution scenario's social vulnerability across the three counties. Meanwhile, even though the uniform budget distribution provided relatively better SoVI scores for Hancock and Jackson counties, the proposed model significantly dominated it in Harrison County, which was the most populated county.

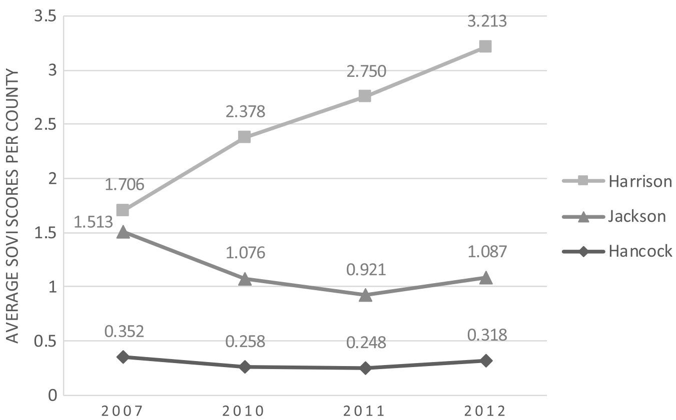

Fig. 6. Existing SoVI scores

For better visualization and comparison, Figs. 10 and 11 illustrate the actual and proposed ABM outcome, respectively, in regard to the social vulnerability. As previously discussed, SoVI is a relative vulnerability assessment of the host community. Hence, there always will remain census tracts that are more vulnerable in comparison with another. This approach, however, helped the SDRC agent shift the fund allocation to the most vulnerable residents

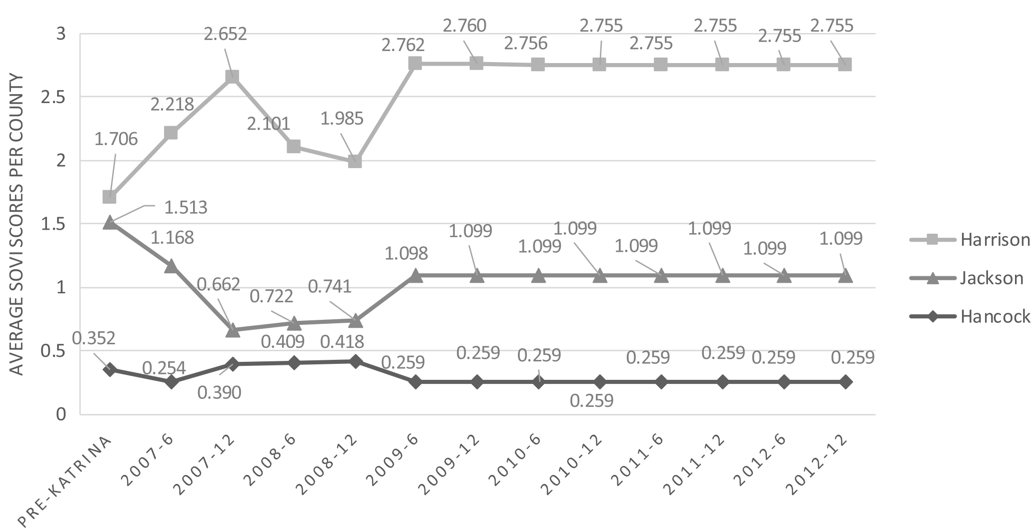

Fig. 7. Actual budget distribution SoVI scores

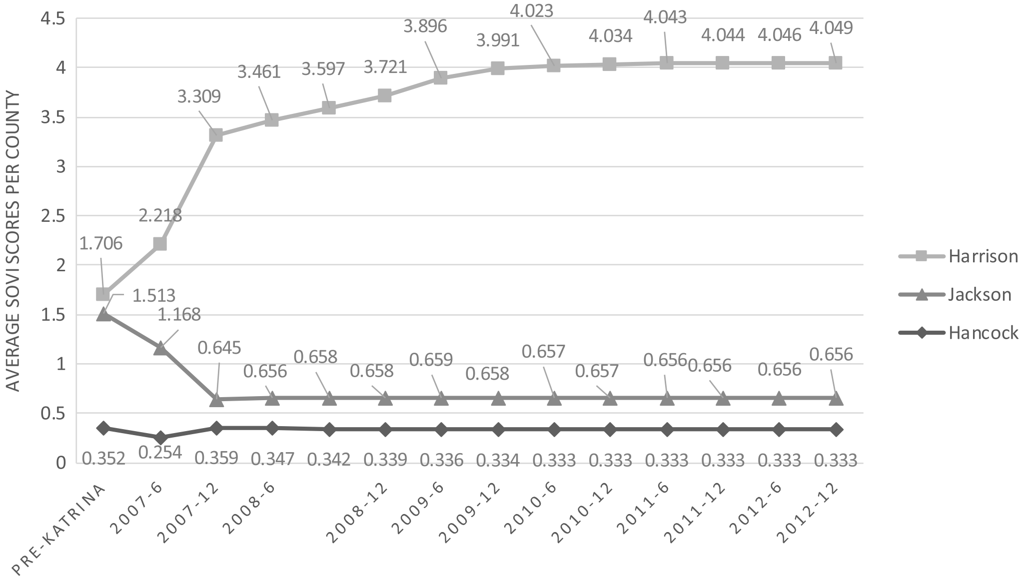

Fig. 8. Uniform budget distribution SoVI scores

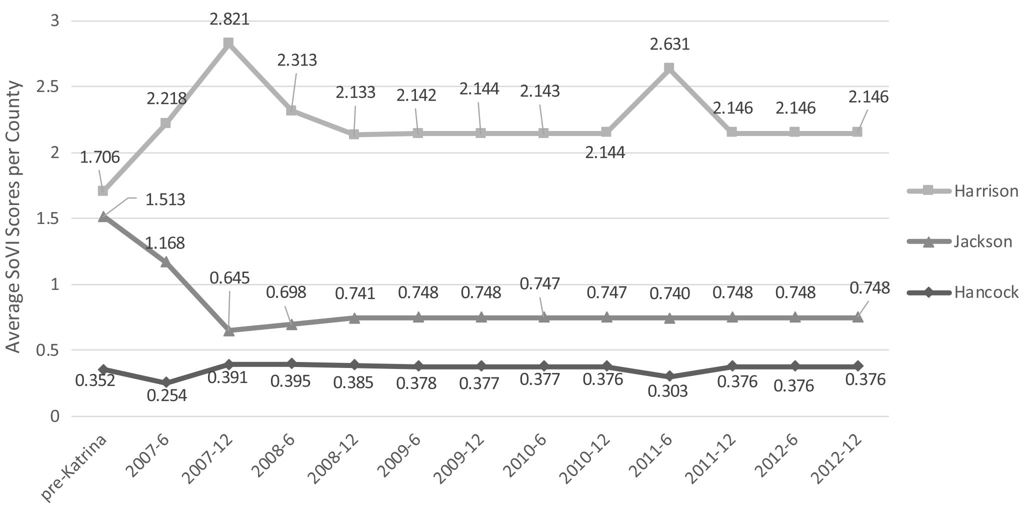

Fig. 9. ABM projected SoVI scores

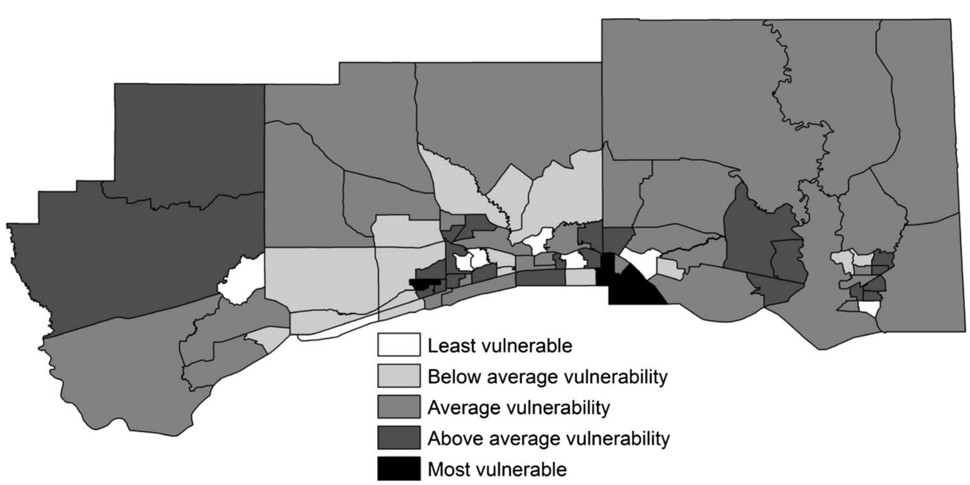

Fig. 10. Actual social vulnerability in 2012

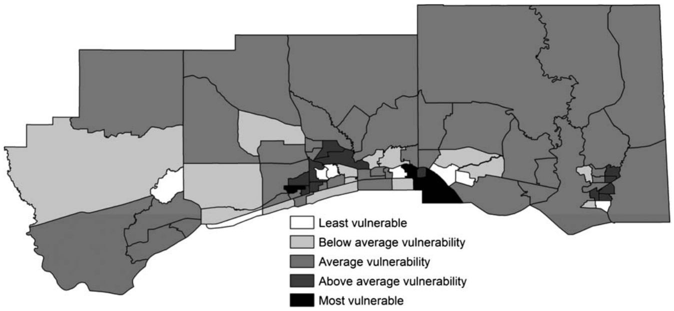

Fig. 11. Projected social vulnerability in 2012 using the ABM model

(and the most populated regions) at the current time step. As such, the model performance in regard to decreasing the counties social vulnerability was observed. The following section discusses the SDRC budget distributions that explains how the budget distribution affected the SoVI changes through the simulation run.

SDRC Funding Distribution Comparison

Fig. 12 illustrates the actual MDA's expenditure proportion for each of the three residential recovery plans. The homeowner assistance plan consumed over 80% of the total budget throughout the years. This plan provided local homeowners with financial aid to repair their damaged households. This plan thus elevated the pressure on the state's recovery agencies by awarding the local residents up to $150,000. However, such a plan does not have a significant positive

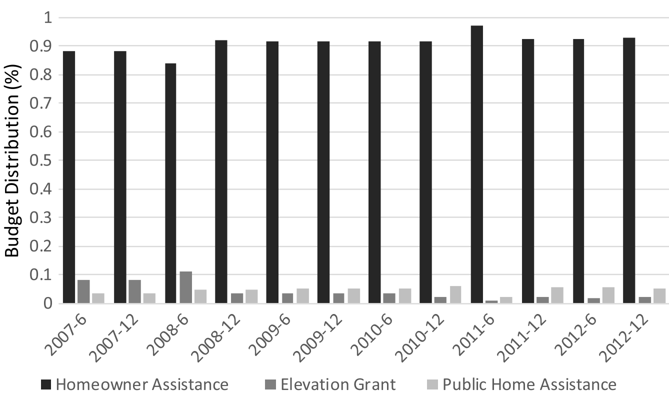

Fig. 12. Actual funding distribution

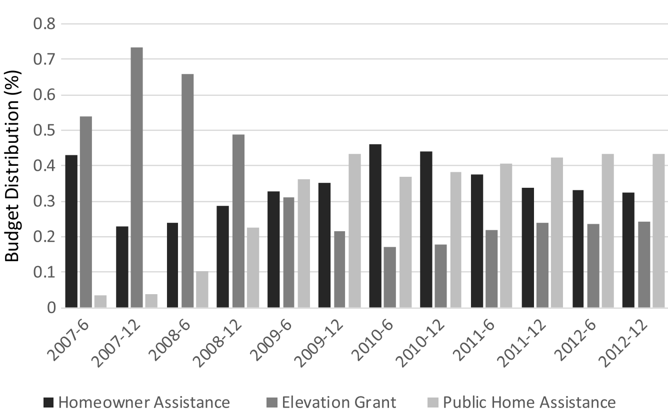

Fig. 13. Proposed ABM funding distribution

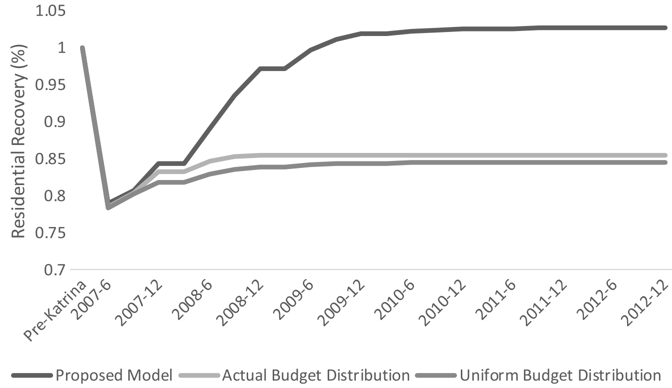

Fig. 14. Hancock recovery progress

impact on the social vulnerability of the community. Fig. 13 shows that the proposed model attempted to balance the residents' needs and the social vulnerability of the three counties. An initial uniform budget distribution was introduced to the SDRC to avoid any favoritism of one plan over the others. Fig. 13 shows that the elevation grant share increased to 70% through the first year. Such plan refers to the elevation grant retrofited the households to be more flood resilient. As such, household values increased, and, in turn, positively affected the residents' objective functions and decreased the social vulnerability of the census tract. Consequently, this decreased the social vulnerability of the three counties, as shown in Fig. 9, in comparison with Fig. 6. During the same year, an average of 30% of the budget was guided toward homeowner assistance, which gave an immediate financial relief to the affected residents. The use of disaster insurance plans affected the residents' choices. The insurance plans provided the residents with financial compensation that drove them away from government financial aid.

Through the following years (2009–2011), a decline in the elevation grant share occurred, whereas there was a significant increase for public home assistance. The latter plan provided housing assistance for low-income residents. This affected the community's social vulnerability because they were relatively and inherently more vulnerable to hazards, again as noticed in Fig. 9 in comparison with Fig. 6. Moreover, the homeowner assistance plan share also was significant because of its high reward impact on residents through financial relief. By the end of the simulation run (2012), the model tended to stabilize on a funding distribution of 43, 32, and 25% to public home assistance, homeowner assistance, and elevation grant plans, respectively.

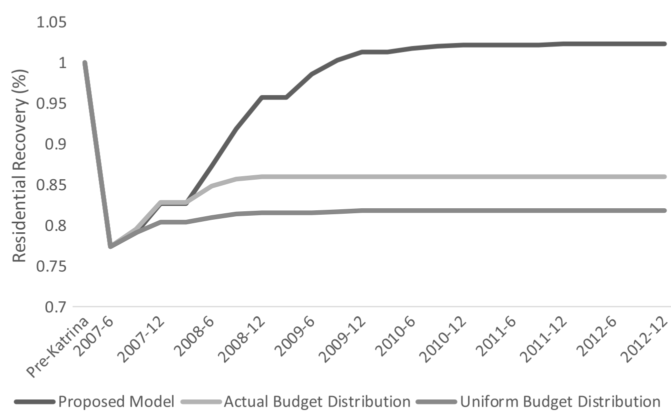

Fig. 15. Harrison recovery progress

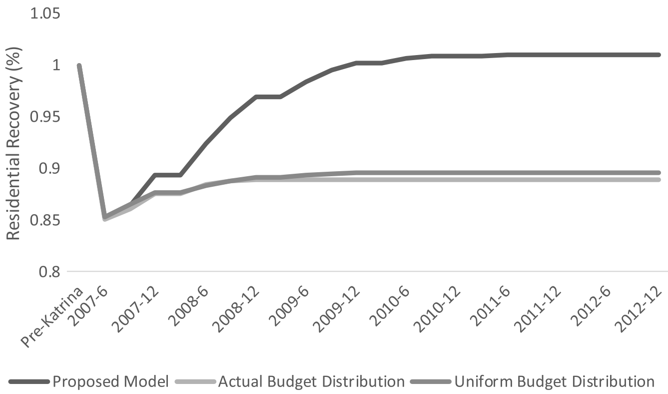

Fig. 16. Jackson recovery progress

Recovery Progress

This section illustrates the residential redevelopment progress using the proposed ABM and the two aforementioned simulation scenarios. The evaluation was carried using Eqs. (7)–(9). Figs. 14–16 present the three counties' residential redevelopment progress using the two simulation scenarios, and the proposed SDRC's budget distribution. Figs. 17–19 illustrate the upper and lower bounds of the residential recovery progress throughout the multiple simulation runs via a box plot. Accounting for the residents' needs in the SDRC's objective function allowed the model to dominate both the simulated scenarios in regard to the residents' recovery, which conforms to previously discussed literature. This provided for noticeable higher recovery rates than the other budgets. Moreover, the higher rate in recovery also is because of targeting low-income households through the public home assistance plan, which was

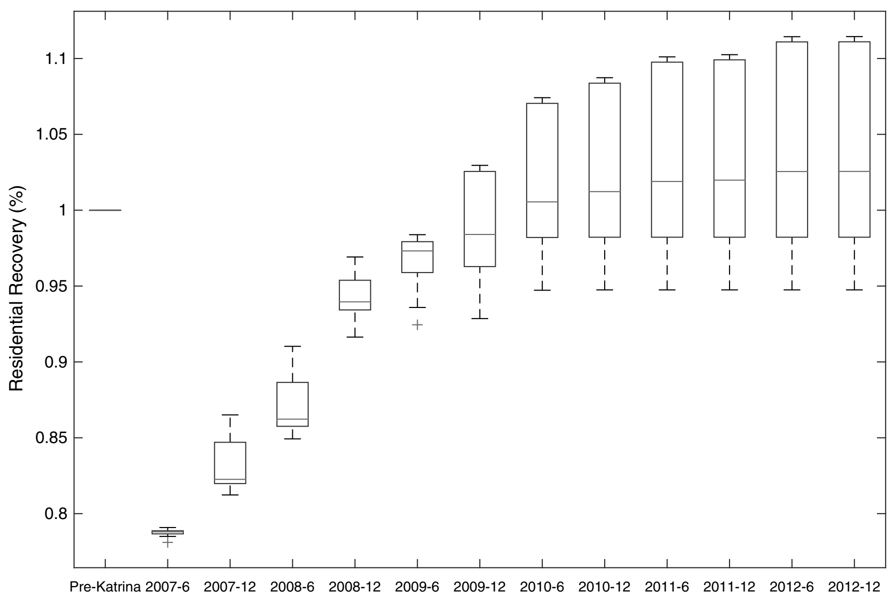

Fig. 17. Hancock recovery progress, box plot

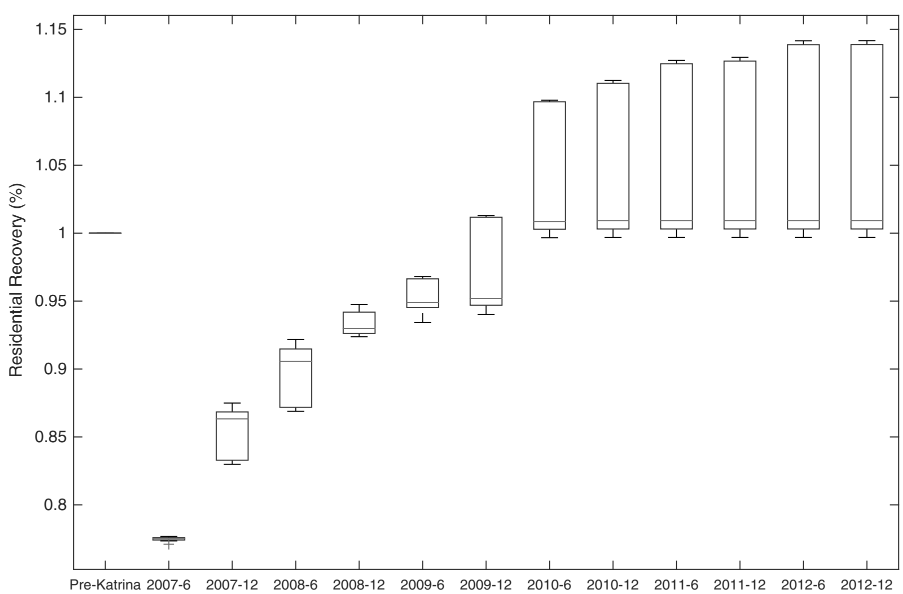

Fig. 18. Harrison recovery progress, box plot

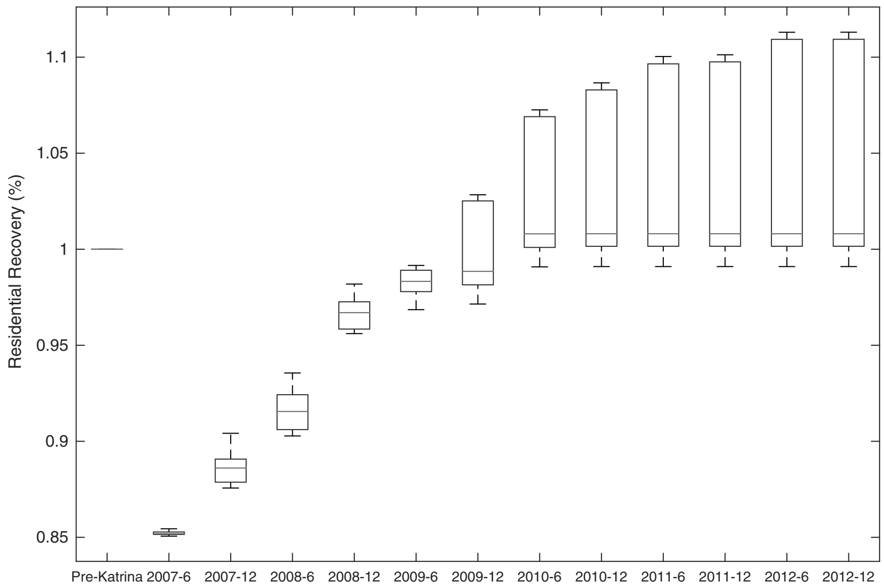

Fig. 19. Jackson recovery progress, box plot

noticeable in poor counties like Hancock. The elevation grant provided the residents with higher household values (than the initial ones) by using more resources to retrofit the households. Accordingly, the three counties achieved more than 100% recovery rate, thus making them less vulnerable to future hazards.

Residents Choices over the Different Insurance Companies

The residents were initiated with a uniformly random insurance company and policy. As the residents started to recover from the hazardous impacts, their insurance policies preferences changed because of their social learning module. The residents attempted to mimic the fittest among them who recovered faster, and, thus, had higher objective function values. Fig. 20 illustrates the number of residents per insurer (and no insurance option). Insurer No. 3 had a relatively high share of the population through the first two simulated years, shown by the fact that it compensated its customers up to 100% of their incurred losses. However, such policies are expensive, thus the residents learned through mimicking each other to use insurance policies from other insurance companies. Meanwhile, there was a decrease in those having no insurance policy because of the continuous shocks given by the tornado micromodule.

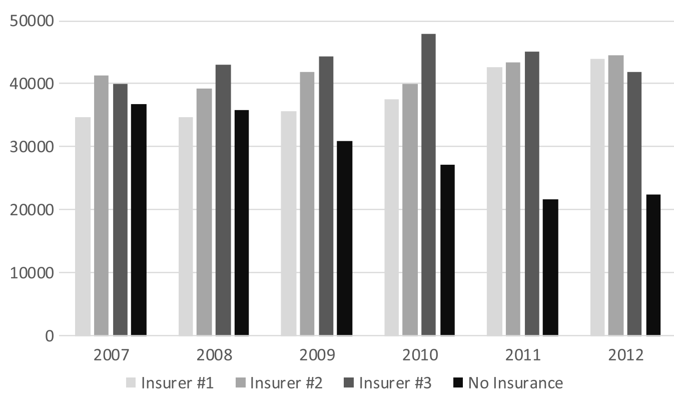

Fig. 20. Choices of residents over different insurance options

Conclusion

This paper presents a decision-making framework for disaster recovery that used a bottom-up approach to capture the needs of the impacted residents and decrease the social vulnerability of host communities. The proposed model optimized the strategies of the impacted residents and the SDRC. Nonetheless, this paper illustrated the relationship and interactions between the aforementioned stakeholders with the insurance companies, LDRM, and FDRC. The paper also presented an innovative approach to decrease community social vulnerability by using a well-established and comprehensive social vulnerability assessment tool and integrating it into the objective functions of the associated stakeholders. Thus, the proposed approach was able to meet the impacted residents' needs and decrease the host community's social vulnerability. The proposed ABM illustrated the experience-based individual learning of the residents and the SDRC through the use of the Roth Erev model that eliminated any opportunistic attitude. Moreover, GA's were used as a social learning module to mimic the residents' communication to optimize their selection of the various insurance policies.

The model implementation phase used an open-source multiagent simulation kit with GIS abilities. For the problem domain, the model used Mississippi residential redevelopment efforts. Accordingly, the ABM optimized the residential recovery budget for SDRC to meet resident needs in household redevelopment. The model budget also decreased the social vulnerability of the three Mississippi coastal counties and dominated the existing conditions found post-Katrina. Further, the proposed ABM achieved higher disaster recovery rates within the host communities under investigation. These positive results were the outcome of the innovative approach that integrated the needs of the participating entities and the social vulnerability of the built environment into the SDRC's objective functions.

Future Work

The authors will tackle the proposed model limitations and assumption to increase its potential. The proposed ABM did not model the full negotiation processes between the residents and the LDRMs. As such, the authors will develop further the modelling of the negotiation and communication processes of the SDRC and residents with the LDRMs. Moreover, the future work of this model will include the development of the FDRC's vital role in funding the SDRC and evaluation of its impact on the recovery processes. Furthermore, the learning constraints (spatial and economic standards) will be accounted for in the residents' social learning module. This will use fully the GIS potentials in defining neighborhood structures that constraint resident social learning abilities. In addition, the developed model did not account for the residents' sellout option. Accordingly, the future work will examine such decision actions and how it is affected by the government's buyout programs. Finally, the authors will implement optimization techniques to be used by the insurance companies that are considered myopic service providers within the current model.

Through the future development of the proposed model, other vulnerability dimensions will be integrated simultaneously into the model to provide an accurate depiction of the host community's sustainable recovery processes. This approach will enable further comprehensive understanding and multidisciplinary research on the factors affecting the communities' recovery activities. Moreover, uncertainty of the recovery plans' impact on the redevelopment processes needs to rigorously addressed in future work to provide for more realistic estimations on the redevelopment activities. Furthermore, through focus groups with the multisector stakeholders of the impacted region, the proposed model will provide more accurate representation of the stakeholders' decision-making parameters through calibrations. Finally, to validate the model and generalize its findings, the fully developed model will be implemented and tested on other problem domains within the nation.

Acknowledgments

The authors appreciate the constructive guidance received by the anonymous reviewers and the handling editors for the constructive feedback that helped hone and strengthen the quality of the manuscript.

Notation

The following symbols are used in this paper:

C = insurance compensation;
c_v = coefficient of variation;
D_y = residential development progress for county y;
$E_j(k)$ = plan j's reward when applying for plan k;
$E(U_j)_I$ = expected utility of plan j for resident i;
G = government reward;
I = income;
IR_k = Roth Erev immediate reward for plan k;
i = resident index;
j = recovery plan index;
k = used recovery plan index;
m = insurance policy index;
n = insurance company index;
P = insurance premium;
p_k = budget distribution for plan k, using Roth Erev model;
pr_j = Roth Erev probability for plan j;
q_j = Roth Erev propensity for plan j;
R = repair cost;
T = total taxes;
t = time step;
y = county index;
Z = resident's objective function;
ε = Roth Erev experimenting parameter; and
ϕ = Roth Erev forgetting parameter.

References

Axelrod, R. (1986). "An evolutionary approach to norms." *Am. Political Sci. Rev.*, 80(4), 1095–1111.

Bell, M. G. H., and Lida, Y. (1997). *Transportation network analysis*, Wiley, Chichester, U.K.

Blaikie, P., Cannon, T., Davis, I., and Wisner, B. (1994). *At risk: Natural hazards, people's vulnerability, and disasters*, Routledge, London.

Boz, M. A., and El-adaway, I. H. (2014). "Managing sustainability assessment of civil infrastructure projects using work, nature, and flow." *J. Manage. Eng.*, 10.1061/(ASCE)ME.1943-5479.0000203, 04014019.

Bryson, K. M. N., Millar, H., Joseph, A., and Mobolurin, A. (2002). "Using formal MS/OR modeling to support disaster recovery planning." *Eur. J. Oper. Res.*, 141(3), 679–688.

Burton, C. G. (2010). "Social vulnerability and hurricane impact modeling." *Nat. Hazards Rev.*, 10.1061/(ASCE)1527-6988(2010)11:2(58), 58–68.

Chang, S. E., and Rose, A. Z. (2012). "Towards a theory of economic recovery from disasters." *Int. J. Mass Emergencies Disasters*, 32(2), 171–181.

Crooks, A. T., and Wise, S. (2013). "GIS and agent-based models for humanitarian assistance." *Comput. Environ. Urban Syst.*, 41, 100–111.

Cutter, S. L., et al. (2006). "The long road home: Race, class, and recovery from Hurricane Katrina." *Environ. Sci. Policy Sustainable Dev.*, 48(2), 8–20.

Cutter, S. L., Boruff, B. J., and Shirley, W. L. (2003). "Social vulnerability to environmental hazards." *Social Sci. Q.*, 84(2), 242–261.

Dow, K. (1992). "Exploring differences in our common future(s): The meaning of vulnerability to global environmental change." *Geoforum*, 23(3), 417–436.

Du, J., and El-Gafy, M. (2012). "Virtual organizational imitation for construction enterprises: Agent-based simulation framework for exploring human and organizational implications in construction management." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)CP.1943-5487.0000122, 282–297.

Economics of Climate Adaptation Working Group. (2009). "Shaping climate resilient development." *A Rep. of the Economics of Climate Adaptation Working Group*, Climate Works Foundation, Global Environment Facility, European Commission, McKinsey and Company, Rockefeller Foundation, Standard Chartered Bank, and Swiss Re., Zurich, Switzerland.

Eid, M., Abdelrazek, M., and Elbeltagi, E. (2012). "Multi-objective repetitive activities projects scheduling using genetic algorithms." *Advances in civil engineering and building materials*, S. Y. Chang, S. Bahar, and J. Zhao, eds., CRC Press, Boca Raton, FL, 331–335.

Eid, M., and El-adaway, I. (2016a). "Sustainable disaster recovery decision-making support tool: Integrating economic vulnerability into the objective functions of the associated stakeholders." *J. Manage. Eng.*, 10.1061/(ASCE)ME.1943-5479.0000487, 04016041.

Eid, M., and El-adaway, I. (2016b). "Sustainable disaster recovery: Multi-agent based model for integrating environmental vulnerability into decision making processes of the associated stakeholders." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000349, 04016022.

Eid, M., El-adaway, I., and Coatney, K. (2015). Evolutionary stable strategy for postdisaster insurance: Game theory approach." *J. Manage. Eng.*, 10.1061/(ASCE)ME.1943-5479.0000357, 04015005.

El-adaway, I., and Kandil, A. (2010). "Multiagent system for construction dispute resolution (MAS-COR)." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000144, 303–315.

El-Anwar, O., El-Rayes, K., and Elnashai, A. (2010). "Maximizing the sustainability of integrated housing recovery efforts." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000185, 794–802.

El-Anwar, O., Ye, J., and Orabi, W. (2015). "Efficient optimization of post-disaster reconstruction of transportation networks." *J. Comput. Civ. Eng.*, 30(3), 10.1061/(ASCE)CP.1943-5487.0000503, 04015047.

Elbeltagi, E., Hegazy, T., and Grierson, D. (2005). "Comparison among five evolutionary-based optimization algorithms." *Adv. Eng. Inf.*, 19(1), 43–53.

Epstein, J. M. (2001). "Learning to be thoughtless: Social norms and individual computation." *Comput. Econ.*, 18(1), 9–24.

Epstein, J. M. (2002). "Modeling civil violence: An agent-based computational approach." *Proc., Natl. Acad. Sci.*, 99(suppl 3), 7243–7250.

Erev, I., and Roth, A. E. (1995). "Learning in extensive-form games: Experimental data and simply dynamic models in the intermediate term." *Games Econ. Behav.*, 8(1), 164–212.

Erev, I., and Roth, A. E. (1998). "Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria." *Am. Econ. Rev.*, 88(4), 848–881.

Federal Highway Administration. (2014). "Transpiration and housing costs: Combined transpiration and housing decisions saves money and build wealth." ⟨http://www.fhwa.dot.gov/livability/fact_sheets/transandhousing.cfm⟩ (Jan., 2015).

Feng, C., Liu, L., and Burns, S. (1997). "Using genetic algorithms to solve construction time-cost trade-off problems." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)0887-3801(1997)11:3(184), 184–189.

Ferdinand, A. V., and Yu, D. (2014). "Sustainable urban redevelopment: Assessing the impact of third-party rating systems." *J. Urban Plann. Dev.*, 05014033.

Fiedrich, F., and Burghardt, P. (2007). "Agent-based systems for disaster management." *Commun. ACM*, 50, 41–42.

GeoMASON [Computer software]. George Mason Univ., Fairfax, VA.

Gilbert, C. (1995). "Studying disaster: A review of the main conceptual tools." *Int. J. Mass Emergencies Disasters*, 13, 231–240.

Haimes, Y. Y. (2012). "Systems-based approach to preparedness for, response to, and recovery from natural and human-made disasters." *Leadersh. Manage. Eng.*, 10.1061/(ASCE)LM.1943-5630.0000183, 288–298.

HAZUS-MH [Computer software]. Federal Emergency Management Agency, Washington, DC.

Hyari, K., and El-Rayes, K. (2006). "Optimal planning and scheduling for repetitive construction projects." *J. Manage. Eng.*, 10.1061/(ASCE)0742-597X(2006)22:1(11), 11–19.

Kennedy, P. J. (2007). *Foreword for handbook of disaster research*, H. Rodriguez, E. Quarentelli, and R. Dynes, eds., Springer, New York.

Lee, J. S., et al. (2015). "The complexities of agent-based modeling output analysis." *J. Artif. Soc. Social Simul.*, 18(4), 4.

Lorscheid, I., Heine, B. O., and Meyer, M. (2012). "Opening the 'black box of simulations: Increased transparency and effective communication through the systematic design of experiments." *Comput. Math. Organiz. Theory*, 18(1), 22–62.

MDA (Mississippi Development Authority). (2015). "Mississippi disaster recovery division website." ⟨http://www.msdisasterrecovery.com/federal-reporting⟩ (Mar., 2015).

MEMA (Mississippi Emergency Management Agency). (2016). "Tornadoes." ⟨http://www.msema.org/be-prepared/tornados/⟩ (Dec. 1, 2014).

Miles, Scott B., and Chang, Stephanie E. (2006). "Modeling community recovery from earthquakes." *Earthquake Spectra*, 22(2), 439–458.

Miller, J. H., and Page, S. E. (2004). "The standing ovation problem." *Complexity*, 9(5), 8–16.

Mostafavi, A., Abraham, D., DeLaurentis, D., Sinfield, J., Kandil, A., and Queiroz, C. (2015). "Agent-based simulation model for assessment of financing scenarios in highway transportation infrastructure systems." *J. Comput. Civ. Eng.*, 30(2), 04015012.

NDRF (National Disaster Recovery Framework). (2011). "National disaster recovery framework, strengthening disaster recovery for the nation." Federal Emergency Management Agency, Washington, DC.

Nejat, A., and Damnjanovic, I. (2012). "Agent-based modeling of behavioral housing recovery following disasters." *Comput.-Aided Civ. Infrastruct. Eng.*, 27, 748–763.

Nwana, H. S. (1996). "Software agents: An overview." *Knowledge Eng. Rev.*, 11(3), 205–244.

Olshansky, R. B. (2006). "Planning after hurricane Katrina." *J. Am. Plann. Assoc.*, 72(2), 147–153.

Olshansky, R. B., Johnson, L. A., and Topping, K. C. (2006). "Rebuilding communities following disaster: Lessons from Kobe and Los Angeles." *Built Environ.*, 32(4), 354–374.

Padgham, L., and Winikoff, M. (2004). *Developing intelligent agent systems*, Wiley, Hoboken, NJ.

Peña-Mora, F., and Wang, C-Y. (1998). "Computer supported collaborative negotiation methodology." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)0887-3801(1998)12:2(64), 64–81.

Picou, J. S., Brent, K. M., and Gill, D. A. (2004). "Disaster, litigation, and the corrosive community." *Social Forces*, 82(4), 1493–1522.

Riechmann, T. (2001). "Genetic algorithm learning and evolutionary games." *J. Econ. Dyn. Control*, 25(6), 1019–1037.

Smith, G., and Wenger, D. (2007). "Sustainable disaster recovery: Operationalizing an existing agenda." *Handbook of disaster research*, H. Rodriguez, E. Quarentelli, and R. Dynes, eds., Springer, New York.

Sullivan, K., Coletti, M., and Luke, S. (2010). "GeoMason: Geospatial support for MASON." Dept. of Computer Science, George Mason Univ., Fairfax, VA.

Tobin, G. A., and Ollenburger, J. C. (1993). "Natural hazards and the elderly." Univ. of Colorado, Natural Hazards Research and Applications Information Center, Boulder, CO.

Turner, B. L., et al. (2003). "A framework for vulnerability analysis in sustainability science." *Proc., Natl. Acad. Sci.*, 100(14), 8074–8079.

U.S. Census Bureau (2012) "Population, household caracteristics, ae and sx, eucation, nmber of huseholds, homeownership, household income, employment, phone, occupation, Hancock MS, Harrison MS, Jackson MS, census tract: 2000 to 2012." ⟨http://factfinder2.census.gov⟩ (Oct. 16, 2014).

Vriend, N. J. (2000). "An illustration of the essential difference between individual and social learning and its consequences for computational analyses." *J. Econ. Dyn. Control*, 24(1), 1–19.

Watts, M. J., and Hans, G. B. (1993). "Hunger, famine and the space of vulnerability." *GeoJournal*, 30(2), 117–125.

Yang, H. Y., and Bozdogan, H. (2011). "Learning factor patterns in exploratory factor analysis using the genetic algorithm and information complexity as the fitness function." *J. Pattern Recognit. Res.*, 6(2), 307–325.