Sustainable Disaster Recovery: Multiagent-Based Model for Integrating Environmental Vulnerability into Decision-Making Processes of the Associated Stakeholders

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

Abstract: The goal of sustainable disaster recovery is to regain the built environment's functionality while decreasing the vulnerability of the society to future perturbations. This requires a new generation of decision support tools that integrate the host community's vulnerability assessment while taking into account the stakeholders' interactions, needs, and preferences. The available disaster recovery research focuses on the optimization and reconstruction of isolated projects rather than taking into account the host community's overall vulnerability and welfare. Moreover, the available research did not simultaneously take into account the stakeholders' preferences and needs. To this effect, this paper presents an agent-based model that integrates an environmental vulnerability indicator to better guide the decision-making process of the associated stakeholders. Such an approach will aid urban planners to redevelop societies into a more resilient status. This paper implements a five-step research methodology that comprises: (1) utilizing a comprehensive assessment tool to measure community's environmental vulnerability; (2) developing the objective functions and learning algorithms of the different associated stakeholders; (3) modeling the different attributes and potential strategies interrelated with the different stakeholders; (4) creating an interdependent multiagent-based model that concurrently simulates the aforementioned information; and finally, (5) interpreting and analyzing the results generated from the developed model. The proposed model adopts post-Katrina recovery as the application domain, and thus was tested using the housing and infrastructure recovery projects in three coastal counties in Mississippi. To this end, the model was able to optimize and adapt to the changing vulnerability conditions of the host community. The model also provided an optimal utilization of the infrastructure to decrease the built environment vulnerability to future natural hazards. This provided better outcomes in relation to environmental vulnerability and stakeholders' individual utility functions when compared to the actual implemented disaster recovery plans. For future work, this research will target the integration of other vulnerability indicators. This will lead to more effective representation of the host communities' complex systems, and ultimately achieving a holistic sustainable disaster recovery. **DOI: [10.1061/(ASCE)UP.1943-5444.0000349](https://doi.org/10.1061/(ASCE)UP.1943-5444.0000349).** © *2016 American Society of Civil Engineers.*

Introduction

Communities worldwide are facing an increasing rate and magnitude of disaster events causing nearly a million fatalities and billions in infrastructure losses in the last decade (Lim et al. 2016; Eid et al. 2015; Economics of Climate Adaptation Working Group 2009). This situation highlights the significant vulnerability of the built environment to perturbations and hazards. Haimes (2012) confirmed that by pointing out that more than half of the nation's transportation infrastructure is vulnerable to natural hazards, including the nation's highways, airports, marine ports, etc. As such, the vulnerability and sustainability of the host communities is regularly questioned. Moreover, the postdisaster recovery efforts affect

the vulnerability of the built environment to future shocks (Hwang et al. 2015). From an urban planning perspective, decreasing the vulnerability of communities is a key factor in disaster mitigation (Godschalk 2003). As such, it is required to (1) evaluate the vulnerability of the communities and (2) manage the physical structure redevelopment as well as the land-use patterns to decrease such vulnerabilities to future hazardous events (Schwab 1998). To this end, as both public and private sectors are concerned about their investments' vulnerability to natural hazards and sustainably for future generations, different studies were carried out within the context of infrastructure, urban planning, social, economic, and environmental perspectives (Ho and Sumalee 2014; Berke et al. 2012; Olshansky et al. 2006, 2012; Haimes 2012; Burton 2012; Karlafits et al. 2007; Meo et al. 2004).

Nevertheless, despite being one of the emergency management pillars, sustainable disaster recovery is still the least understood in the research community and among practitioners (Smith and Wenger 2007). On addressing the growing need for a holistic sustainable disaster recovery decision support tool, Haimes (2012) and Kennedy (2007) pointed out the need for research that accounts for the complexity of the sustainable disaster recovery process within the social dynamic interaction. Thus, to attain sustainable disaster recovery, a tool is required to simultaneously account for the preferences of the community's residents and stakeholders who are affected by the recovery process, the different disaster recovery agencies at the different levels, and the insurance companies

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

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

responsible for financial payouts in the case of disastrous events. Such a tool should also assimilate the vulnerability assessment of the host community to future shocks based on the community's specific data in order to better guide the recovery efforts into a more resilient built environment.

Recently, several disaster recovery models were developed to better understand, guide, and optimize the host communities' recovery process. These models utilized mixed integer linear programming for postdisaster recovery for transportation projects (El-Anwar et al. 2015), genetic algorithms for housing recovery (El-Anwar et al. 2010), evolutionary algorithms for transportation recovery fund allocation (Karlafits et al. 2007), geographic information system (GIS) to guide and manage the disaster management issues (Pradhan et al. 2007), numerical models in the earthquake recovery process (Miles and Chang 2006), and operation research in support of disaster recovery planning (Bryson et al. 2002). However, the aforementioned models focus on the optimization and reconstruction of isolated projects rather than taking into account the host community's overall welfare and vulnerability. Moreover, the tools utilized do not take into account the stakeholders' preferences and needs, which are essential for a successful and sustainable disaster recovery process, even though they might not be computationally efficient.

Agent-based modeling (ABM) has been utilized occasionally in emergency management (Crooks and Wise 2013; Chen et al. 2006). However, few attempts were made using ABM to better understand and guide the recovery efforts (Miles and Chang 2006). ABM is considered to provide a significant basis for proactive application in disaster recovery (Alesch and Siembieda 2012; Fiedrich and Burghardt 2007). This can be carried out through dynamic simulation that captures the different stakeholders in the impacted host community (Nejat and Damnjanovic 2012). This goes in line with the need to integrate the different stakeholders in the sustainable disaster recovery process.

Goal and Objectives

The objective of this paper is to present a sustainable disaster recovery decision support tool that can better guide the recovery efforts to improve the community's welfare. To this end, this paper adopts an agent-based approach to capture the objective functions of the associated stakeholders while integrating an environmental vulnerability assessment tool for the host communities. Consequently, this approach will help in understanding the effect of the different recovery strategies on the host community's vulnerability. As such, this tool will aid urban planners to redevelop societies into a more resilient status. Ultimately, this research will help in better guiding the recovery efforts to increase the community's welfare by decreasing the vulnerability of the built environment and increasing the individuals' objective functions.

Background Information

Environmental Vulnerability

In 1962, *Silent Spring* by Rachel Carson (2002) was published, which discussed the detrimental human-activity effects on the environment. It was one of the first significant publications to illustrate the environment's vulnerability and need for better sustainable actions. Consequently, environmental vulnerability, resilience, and sustainability has been widely discussed and researched in the last few decades. Furthermore, through latter research, it was pointed out that the amount of damage exerted on the infrastructure due to

the natural disaster's impact is correlated to the host communities' vulnerability and resilience. As such, several studies have been conducted to investigate and quantify the communities' environmental vulnerability and resilience to hazards (Wackernagel and Rees 1997; Nelson et al. 2007; Siche et al. 2008).

Environmental vulnerability lies at the core of the sustainable development and recovery of the host community. The environment is essential for the development process as it provides the goods and services for the economy and society. In return, the host community (residence, business, industry, etc.) exerts pressure on the environment, making it more vulnerable to perturbations and shocks. Thus, the host community's environment is vulnerable to damage due to internal and external influences. Therefore, the environmental sustainability and sustainable recovery of the host communities are closely tied to their environmental vulnerability.

The host community's environmental vulnerability is defined as the tendency for an entity to be damaged (Pratt et al. 2004). There are three main categories when evaluating the host community's environmental vulnerability: (1) the natural resilience to hazard; (2) the risk and exposure to hazard; and (3) the acquired resilience/ vulnerability to hazards from past events. In other words, environmental vulnerability possesses inherent resilient properties that allows it to resist damage, proximity properties that increase the community's exposer to environmental damage, and adaptive capacity that allows the environment to cope and rebound back to an equilibrium after a disaster event.

Due to the close relationship between resilience and vulnerability, the notion that the two terms are diametrically opposed is often promoted (Cutter et al. 2003). This paper, however, adopts a widely recognized approach where vulnerability and resilience are neither totally mutually exclusive nor totally mutually inclusive. In other words, some of the resilience properties are shared with vulnerability and vice versa. Most of the inherent properties of the host community are considered as the overlapping part between resilience and vulnerability (e.g., land size, region isolation, environmental openness, etc.). These properties are inherent and affect both the vulnerability to hazards and the ability to recover. Furthermore, this research focuses more on the concept of vulnerability, both inherent and exogenous. This will allow for understanding the host community's risk to exogenous shocks while pointing out the manageable inherent properties that would increase resilience and decrease vulnerability.

Since the 1990s, several indices has been developed to evaluate communities' environmental vulnerability to perturbation and natural hazards and its effect on the sustainability of the built environment, including the Ecological Footprint 1997 (Wackernagel and Rees 1997), Environmental Sustainability Index 2002–2005 (Esty et al. 2005), and Environmental Vulnerability Index 2004 (Pratt et al. 2004). One of the most recognized, and most fitting to the proposed model as discussed later, is the environmental vulnerability index (EVI). The EVI was developed by the South Pacific Applied Geoscience Commission (SOPAC) by the support of Ireland, Italy, New Zealand, Norway, and the United Nations Environment Program (Pratt et al. 2004; Barnett et al. 2008). Though the EVI was developed to address the vulnerability of the small developing islands, it can be applied to all countries and regions (Pratt et al. 2004).

The EVI addresses environmental vulnerability and its coupled system with human interactions in a unique approach. Unlike other vulnerability assessments, EVI considers the human impact as an exogenous factor and the human system is not the recipient of the impact, but the environment (Barnett et al. 2008). In this approach, the human system is an integrated part of the ecosystem, not a responder (Villa and McLeod 2002). Thus, unlike the other vulnerability indicators that consider the human system as a responder to

shocks, the EVI allows for capturing the true overall vulnerability of the host community. Using 50 *smart indicators*, the EVI measures the vulnerability of the environment of a country or a region to future perturbations. The indicators are considered able to summarize the most important and related environmental conditions and processes (Barnett et al. 2008). Each of the smart indicators is assigned to one of three categories (subindicators): hazards, resistance, and damage. The hazard category (or risk exposure subindex) is a comprehensive integration of the natural risk on the environment. The resistance category (inherent resilience subindex) measures the host's environmental inherent internal characteristics and its ability to cope with natural hazards. The damage category (acquired vulnerability subindex) measures the degradation of the environment due to external forces; thus the more degradation, the more the environment is vulnerable to different perturbations. Thus, EVI is able to address both the inherent and exogenous factors of the community's environmental vulnerability as previously discussed.

Sustainable Disaster Recovery and Stakeholders Interactions

The participation of the different stakeholders, in the planning and execution phases, and accounting for their needs and preferences, increases the individual utility of the associated entities (Abdalla et al. 2015; Boz and El-Adaway 2014; Boz et al. 2014; Glumac et al. 2015; Feliu 2012). More importantly, Alesch and Siembieda (2012) argue that the communities cannot recover without the integration of the stakeholders within the impacted society. Moreover, the communication between the recovery agencies, system users, and various stakeholders increases the recovery rate and quality of the outcome product and enhance the host community's resilience (Chang and Rose 2012; Olshansky et al. 2006). Consequently, recent sustainable disaster recovery studies suggest that the different stakeholders participate in both the planning and implementation phases to achieve a successful disaster recovery for the host community (Haimes 2012; Smith and Wenger 2007; Olshansky et al. 2006). Ferdinand and Yu (2014) also noted that the slow progress in redevelopment projects was due to the lack of clear framework between the different stakeholders.

To address this need, the National Disaster Recovery Framework (NDRF) outlines roles for the different stakeholders through and after a disastrous event. The NDRF indicated three main governmental agencies: (1) federal disaster recovery coordinator (FDRC); (2) state disaster recovery coordinator (SDRC); and (3) local disaster recovery management (LDRM). The FDRC is considered an essential player in the very beginning of a disaster recovery. The FDRC is mainly activated when the disaster is exceeding the SDRC's capabilities. The SDRC oversees the disaster recovery process, sets priorities, and directs necessary assistance. Finally, LDRMs play a primary role in planning, managing, and communicating with residents and businesses in the affected region.

Olshansky et al. (2006), Olshansky (2006), and Cutter et al. (2006) illustrated several disaster examples in an attempt to explain the various factors affecting the recovery process. Through their studies, one can understand patterns of successful recovery key items, the relationship between the different stakeholders in the recovery process (in addition to the government), and residents' commonly used strategies. The local governments' interaction with the different stakeholders in the host communities played a significant role in the recovery stages associated with the 1994 Los Angeles Northridge earthquake, the 1995 Kobe earthquake in Japan, and the 2005 Hurricane Katrina (Olshansky et al. 2006). The plans that had been negotiated and discussed with the residents in the

impacted regions achieved a higher approval rates by the residents and increased the host communities' welfare.

Furthermore, in regard to the different stakeholders' strategies, the commonly used government recovery plans included financial compensation, repair, rebuild, upgrade the effected infrastructure, and changes in the land use so as to decrease the host community vulnerability to future hazards (Olshansky et al. 2006; Cutter et al. 2006). On the other hand, residents of the impact regions had fewer postdisaster strategies, and lacked a plan to collaborate with local agencies for the recovery planning phase. The residents' strategies focus on (1) repairing the damaged properties, which includes means for financing the repair and rebuild processes; (2) selecting insurance policies that would best fit their needs for the future hazardous events; and (3) deciding on whether the resident should leave or stay in the impacted region. These strategies are influenced by the socioeconomic standards, the damage exerted by the disastrous events, the available government recovery plans, the social ties of the resident to the community, and their outside options (Olshansky 2006).

Preparedness also highly affects the recovery rate (Cutter et al. 2006; Smith and Wenger 2007; Olshansky et al. 2006). To this end, the impact of the insurance policies purchased by residents and/or subsidized by the government—as part of the host community's preparedness for hazardous events—played an important role in the recovery rate in the past disastrous events. Moreover, the National Disaster Recovery Framework (2011) indicated the significance and importance of adequate household insurance to achieve a successful recovery. Thus, understanding the interrelationship between the different stakeholders, whether residents, insurers, or government agencies, as well as optimizing the disaster strategies and plans for the associated stakeholders is essential to achieve a sustainable disaster recovery that would increase the host community welfare and decrease their vulnerability to future shocks.

In modeling disaster recovery, few ABM attempts have been carried out. The most recognized models were developed by Miles and Chang (2003, 2004, 2006, 2011). The developed models captured the interaction between the socioeconomic agents (residents and businesses) and the community planning after a disastrous event. Also, the model was developed to allow for estimation of the incurred damages to the community (built environment, economics, and personal). Nejat and Damnjanovic (2012) also presented a multiagent-based model with a game theory approach for the residential households' recovery. The model takes into account the social interaction between the homeowners and their neighbors. The agents' objective is to maximize their expected utility where the authors assumed a bounded rationality of the different agents. Nevertheless, the aforementioned attempts neither integrated the host community vulnerability assessment into the model nor provided a decision support tool for future disaster events. As a result, and in order to lay down the foundation for the proposed model, the following section briefly discusses agent-based modeling's history and concept as well as the several learning modules that is utilized in this research.

Agent-Based Modeling

Nobel laureate and well-known economist Thomas Schelling (1978) published a book in 1978 titled *Micromotives and Macrobehavior* discussing the relationship between the people behavior and the system collective performance. The author explained how the characteristics of the individuals, who are related to each other, compromise the "system aggregated characteristics." Since then, a lot of research has been carried out to investigate the different

individuals' behaviors and attributes and how do they build up the aggregated system. Consequently, agent-based modeling (ABM) has shown great advantages in approaching complex systems of systems, where different stakeholders contribute to the collective welfare of the system. ABM is a computational approach for simulating autonomous agents, which represent the different system's stakeholders, in order to evaluate the system performance due to the agents' interactions. ABM allows for capturing the fine grains of the systems through building it in a root to grass methodology. As Macy and Willer (2002) explain, "ABM provide theoretical leverage where the global patterns of interest are more than the aggregation of individual attributes, but at the same time, the emergent pattern cannot be understood without a bottom up dynamical model of the microfoundations at the relation level." ABM has been adopted and utilized in studying real-life applications in sociology, economics, engineering, urban development, biology, and many other fields in order to explain and model different problems like social norms, collective behavior, civil violence, the standing ovation problem, analysis of construction dispute resolution, dynamics of construction projects, collaborative negotiation, land-use forecasting, cities' walkability assessments, highway transportation infrastructure systems, urban dynamics modeling, investigating the relationship between urban form and traveling behavior, retail businesses dynamics, and humanitarian aid efforts (Mostafavi et al. 2015; Zhu 2015; Badwi et al. 2014; Zhao and Peng 2015; Yin 2013; Crooks and Wise 2013; Du and El-Gafy 2012; Du and Wang 2011; El-Adaway and Kandil 2010; Miller and Page 2004; Epstein 2001, 2002; Peña-Mora and Chun-Yi 1998; Axelrod 1986).

In defining autonomous agents, Macy and Willer (2002) stated that agents follow three assumptions: (1) agents are interdependent; agents interact and affect each other, and agents influence each other in the response they receive from others' influences; (2) agents follow simple rules; though they are complex in nature, they tend to follow rules either in forms of norms, conventions, protocols, social habits or heuristics; and (3) agents are adaptive; agents adapt through replication or learning. Moreover, Padgham and Winikoff (2004) defined an intelligent autonomous agent as a system that is reactive to the changes to the surrounding environment, follows its objectives determinedly, is flexible, learns from failures, and is able to interact with other agents.

Different learning models have been introduced to create informed and complex agents. These agents are capable to receive inputs from the surrounding environment and take different actions that affect their objective and utility functions. Agents of this sort are able to simulate complex human behavior through experience and learning, thus enabling the research to predict and evaluate the complex system at hand. Learning is categorized into two branches: (1) individual, where agents learn from their own past experience; and (2) social, where agents learn from each other's experiences. Either way, one key element in learning is the amount of anticipation (looking ahead) through the learning process. Learning anticipation can be reactive, where agents decide on an action, determine the outcome, and then can strengthen or weaken the actions' utilizing probabilities in relation to the current state. On the other hand, anticipatory learning describes when agents can determine the probabilistic outcomes of the actions given the current state. Through research in the artificial intelligence field, along with social science, phycology, and mathematics, different learning models were introduced including heuristic learning, Bayesian Learning, Roth Erev, modified Roth Erev, Markov hidden process (MHP), Q-learning, genetic algorithms, and derivative follower algorithms.

Methodology

To attain the aforementioned goal and objectives, the authors developed a five-step research methodology that comprised: (1) utilizing a comprehensive assessment tool to measure a community's environmental vulnerability; (2) developing the objective functions and learning algorithms of the different associated stakeholders; (3) modeling the different attributes and potential strategies interrelated with the different stakeholders; (4) creating an interdependent multiagent-based model that concurrently simulates the aforementioned information; and finally, (5) interpreting and analyzing the results generated from the developed model.

In order to implement the aforementioned methodology, the authors gathered five different data sets regarding the post-Katrina disaster recovery for three Mississippi coastal counties—Hancock, Harrison, and Jackson—that serve as the model's problem domain. The three counties suffered a great share of Hurricane Katrina's damage in 2005 as they were highly vulnerable to natural disasters (Burton 2012). The associated data sets gathered are as follows:

- Collecting the preexisting conditions and generating the initial population, ex-Katrina socioeconomic data for the three aforementioned counties. The socioeconomic data were collected from the U.S. Census Bureau for each of the 76 census tracts across the three counties (2000, 2009, 2010, 2011, and 2012 U.S. Census).
- The environmental data required to evaluate the three counties' environmental vulnerability were gathered on a census-tract level using GIS maps from the National Land Cover Database (2015), the National Agricultural Statistics Service Cropland Data Layers (2015), and the Mississippi Automated Resource Information System (2015). The data gathered allowed to initiate the model to ex-Katrina conditions and compare it to the post-Katrina environmental vulnerability data.
- With regard to the state disaster recovery coordinator's (SDRC) strategies and decision actions for the housing sector, data were gathered from the Mississippi Development Authority (MDA) and Mississippi Recovery Division (MRD). The data were gathered through the MDA and MRD publically accessible website for years 2007–2012. Thus, a set of action plans followed by the SDRC was determined for the housing sector recovery and restoration, which constituted more than 65% of the MRD's post-Katrina recovery budget (Mississippi Development Authority 2015). The most recognized disaster recovery strategies were (1) Homeowner Assistance, which includes repair, rebuilding, and relocation financial funding to the damaged privately owned households; (2) Public Home Assistance, which essentially targeted low-income families in order to rebuild damaged building and house them; and (3) Elevation Grants, which are an upgrade to elevate the household up to 1.9 m (6 ft, 4 in.), thus making the households' more flood resilient. Furthermore, the MDA and MRD budget and expenditure federal reports to the Federal Emergency Management Agency (FEMA) were utilized to develop the model as well as for testing and comparison purposes.
- On the infrastructure level, data were gathered for the wastewater treatment facilities (WWTF) developed after the Katrina disaster across the three aforementioned counties. The data include the projects' location, capacity, size, service coverage, and cost. The data were collected through the Mississippi Department of Environmental Quality (MDEQ), the associated counties' authorities, and the MDA federal reporting for year 2007–2012. Table 1 summarizes the different WWTFs, their capacities, and their associated counties.
- Finally, Hurricane Katrina's impact data for the three counties were calculated via *HAZUS-MH*, simulating the Hurricane

Table 1. Utilized WWTFs

WWTF number	County	Capacity [ML/day (MG/day)]
1	Hancock	5.68 (1.5)
2	Hancock	0.76 (0.2)
3	Harrison	1.51(0.4)
4	Harrison	0.76 (0.2)
5	Harrison	5.67 (1.5)
6	Harrison	0.76 (0.2)
7	Harrison	7.56 (2.0)
8	Jackson	0.47 (0.125)
9	Jackson	7.56 (2.0)

Katrina impact through wind gust, surge, and floods, with regard to the damages applied by the Hurricane on the study region's households. Thus, the different damage proportions and magnitudes were simulated and distributed on the different agents corresponding to their proximity from the hurricane. Moreover, the model also utilized the available historical data (1953–2012) by Mississippi Emergency Management related to tornados impacting the three aforementioned counties. By utilizing the data's probability density functions, a tornado hazard micromodule was integrated into the current ABM to better simulate the residents' decisions in the presence of new and recurrent shocks following the Katrina event.

Model Development

Model Assumptions

Models are simplifications of reality; as such, this model does not claim that it captures the exact human behavior or decision-making process. However, as found in the literature, the different learning modules utilized best depict the learning behaviors of rationally bounded agents through their experience. It is therefore assumed that resident agents' objectives are to maintain their wealth and the disaster recovery agencies' objectives are to increase the community welfare and decrease their vulnerability, as shown in a later section. Moreover, the proposed agent-based model assumes the rationality of the different stakeholders. Thus, no agent, resident, government, or insurance will take any action or follow any strategy that would decrease its objective function. Furthermore, in regard to the residential agents' social learning module, agents are assumed to have complete information about other residents' current objective functions' values and are able to determine the best of them.

### Comprehensive Environmental Vulnerability Assessment Tool

The proposed model adopts the environmental vulnerability index (EVI) in order to assess the host community's environmental vulnerability as well as to guide the recovery efforts by the government agencies. Such an approach aims to decrease the environmental vulnerability of the host community while achieving the individuals' objectives. The EVI is a comprehensive environmental assessment of the host community vulnerability, due to exposure to internal and external stresses, as well as the inherent system's resilience (Villa and McLeod 2002; Pratt et al. 2004). Thus, through mapping the indicators to the associated predefined scales, the model can estimate the current average vulnerability of the host community as well as the projected average change in vulnerability caused by the stakeholders' actions and strategies. Furthermore, the EVI's methodology accounts for unavailable data or inapplicable

Table 2. Utilized EVI Indicators

Indicator	Category
Loss of cover	Hazards
Terrestrial reserves	Hazards
Renewable water	Hazards
Waste production	Hazards
Vehicles	Hazards
Population growth	Hazards
Volcanoes	Hazards
Earthquakes	Hazards
Tsunamis	Hazards
Slides	Hazards
High winds	Hazards
Dry periods	Hazards
Wet periods	Hazards
Hot periods	Hazards
Cold periods	Hazards
Sea temperatures	Hazards
Sulfur dioxide emissions	Hazards
Total land area	Resistance
Vegetation cover	Resistance
Low lands	Resistance
Habitat fragmentation	Damage
Population	Damage

indicators. In case of data being unavailable, a value of zero is given to the associated indicator and average denominator is decreased by 1 (Barnett et al. 2008; Pratt et al. 2004; Villa and McLeod 2002). Moreover, in the case of an inapplicable indicator (e.g., overfishing in a landlocked country), a value of 1 is given to the indicator, thus assuming it is least vulnerable (Pratt et al. 2004; Villa and McLeod 2002).

In the data collection phase, some of the indicators were omitted as they were unavailable at the census-tract level (marine reserve, environmental openness, intensive Farming, etc.). Other indicators were also omitted as they are inapplicable to the counties in the current problem domain (isolation, relief, country dispersion, conflicts, etc.). Thus, following the EVI methodology discussed earlier, Table 2 illustrates the indicators utilized in the assessment of the host community's environmental vulnerability. Each of the indicators is mapped on a predefined scale and evaluated through a scalar form ranging from 1 to 7, where 1 indicates the least vulnerable and most resilient and 7 is the most vulnerable and least resilient as
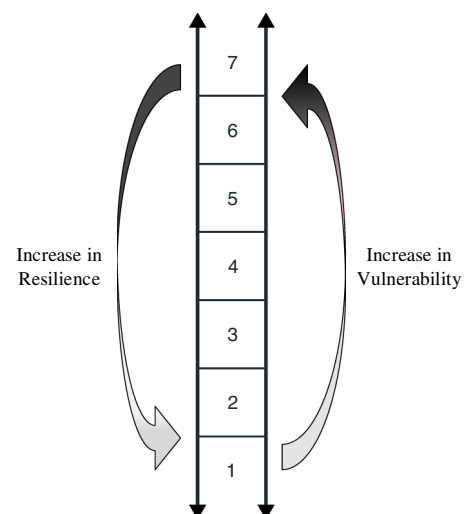
Fig. 1. EVI vulnerability scale (adapted from Pratt et al. 2004)

shown in Fig. 1. This approach is able to standardize the evaluation of the indicators, taking into account the different indicators' heterogeneity (linear, nonlinear, etc.) (Pratt et al. 2004). The scales were studied and predefined for each of the indicators by expert committees, utilizing technical literature, or by consultation with specialists in the associated fields (Pratt et al. 2004; Villa and McLeod 2002). The preset ranges of values were defined to measure the environmental vulnerability and to continue being applicable across all conditions found on the planet (Pratt et al. 2004). After all the indicators are assessed, the average of all the indicators in each subindex is calculated, resulting in an average environmental vulnerability assessment, as shown in Eq. (1)

$$\text{EVI}_c = \frac{\sum_{x=1}^{x=X} \text{Score}_y}{X} \quad \forall \ c = 1, 2, \ldots, C \qquad (1)$$

where EVI_c = average environmental vulnerability index for census tract c; X = total number of utilized indicators; and Score = associated score of indicator x mapped on the aforementioned scales.

Stakeholders' Interactions Overview

The proposed agent-based model represents the residents of an impacted community, insurance companies offering different disaster recovery plans, as well as the associated local disaster recovery management (LDRM), state disaster recovery coordinator (SDRC), and federal disaster recovery coordinator (FDRC) following the National Disaster Recovery Framework Methodology (2011). Each of the aforementioned agents has their own decision actions, strategies, and objective functions. However, the scope of this paper is limited to the residents and SDRC, leaving the optimization of LDRM and FDRC strategies for future work. Furthermore, the insurance companies were developed as myopic agents offering services to residents while observing their choices. Fig. 2 presents the model overview, illustrating the modeled host community with the different agents, residents, insurance companies, and disaster recovery agencies. The model takes as input the antecedent host community's conditions, which include population size, income level per household, education per household, household median value per region, environmental vulnerability per census tract, etc. The model also takes as an input the environmental conditions of the host community, including vegetation cover, renewable water, and waste production. This allows the model to generate the initial

conditions as well as to assess the host community's environmental vulnerability. The model then takes into account the disaster event and its effect on the host community. The agent-based model then allows for the different agents to interact, choose their strategies, and optimize and report their recovery progress along with the changes in the host community's vulnerability.

Fig. 3 illustrates the agents' interactions, which are discussed in detail through the following sections. After the encounter of a disastrous event, each resident checks the household's damage and assesses if repair is required. The resident at this point determines if he/she should apply for assistance from the local disaster recovery management (LDRM). Also, the resident agent determines the compensation amount received from the insurance policy if it had been previously purchased. The resident agent at this point gets to decide if the current insurance policy is optimal or needs to be changed for future shocks. Furthermore, the residents consider the option of repairing their damaged houses or leaving the impacted region. Meanwhile, the SDRC offers different residential disaster recovery action plans. The plans are then transmitted to the LDRMs that are in direct contact with the local residents. LDRMs propose the state's action plans to the local residents so that they can choose one that will increase their objective functions. Moreover, the LDRMs both check the residents' applications for approval as well as manage the recovery and redevelopment process (National Disaster Recovery Framework 2011). The FDRC allocates the required funding for the SDRC's disaster recovery plans. The SDRC reports back the recovery progress to the FDRC, which will affect the later funding process. Finally, the insurers offer different disaster recovery insurance policies for the host community's residents. The residents choose the appropriate policy, pay the premiums, and receive compensation if a disaster occurs.

Modeling the Different Stakeholders Objectives, Learning Behaviors, and Strategies

Residents
Resident agents tend to increase their current wealth through (1) maintaining their household value, (2) decreasing potential expenses, and (3) increasing their income. The proposed ABM illustrates the resident's objective function, shown in Eq. (2), which is updated at each time step (month)

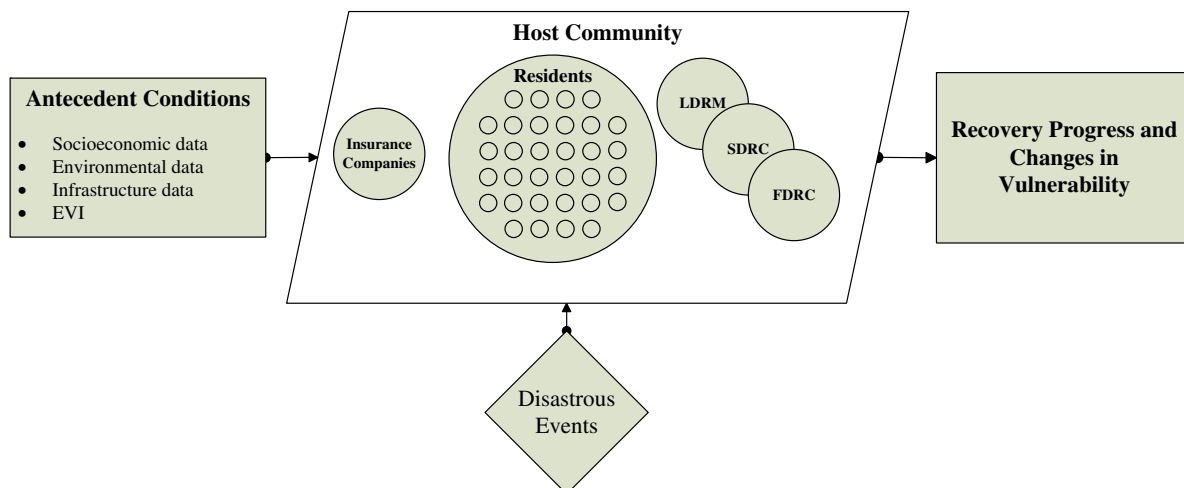$$Z_i = H_i + I_i - T_i - P_{i(n,m)} + C_{i(n.m)} - R_i \qquad (2)$$
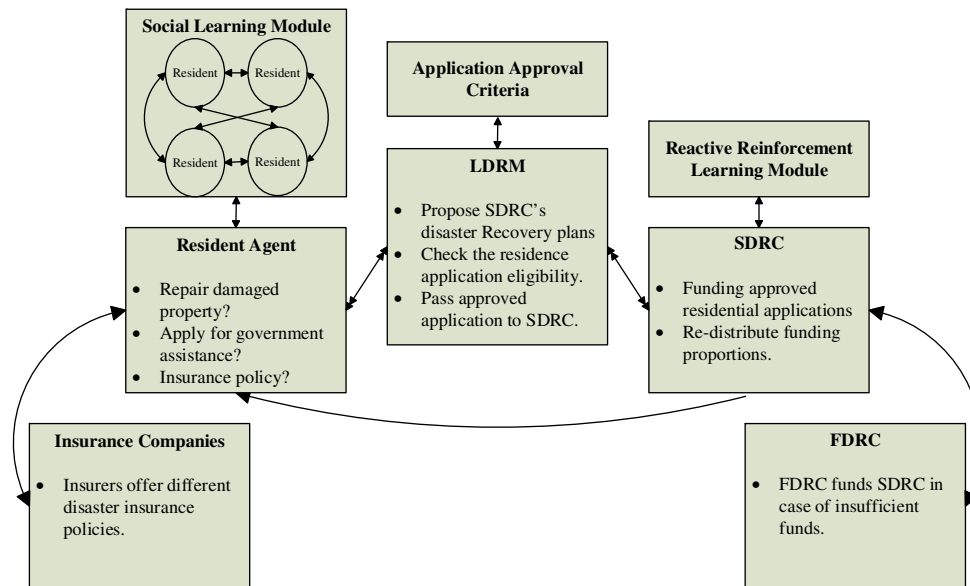

Fig. 2. Model overview

Fig. 3. Model of overall agents' interactions

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; 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 = monthly self-paid repair costs.

The residents' actions are constrained by their net income (the difference between the residents' monthly income and monthly living cost). According to the Federal Highway Administration (2014), the average household's monthly living cost does not exceed 45% of the household's income. Thus, the resident's expenses (T, P, and R) should not exceed the monthly net income as shown in Eq. (3)

$$T_i + P_{i(n,m)} + R_i \leq 0.55 I_i \tag{3}$$

As such, the resident has two decision variables: (1) purchasing an insurance policy or refrain from buying any and (2) repairing the damaged household or leave the impacted region, thus not repairing the damaged household. To this effect, and in order to maximize their objective function, residents tend to communicate with each other to learn which of the decision variables increases the other residents' utility functions. Accordingly, genetic algorithms (GAs) were used to represent the residents' social learning behavior in determining the optimum insurance plan to be purchased. Even though GAs are computationally expensive (Bell and Lida 1997), they are widely known for their high optimization capabilities (Hyari and El-Rayes 2006; Elbeltagi et al. 2005; Hegazy and Ayed 1999; Li and Love 1997; Feng et al. 1997). More importantly, GAs are considered as an efficient tool for both social and individual learning (Riechmann 2001). The selection of GAs was due to the GA's ability in demonstrating the social learning of a group of individuals from each other through simulating the communication and learning through observation (Eid et al. 2015). The algorithm works through mimicking the most fit of the residents following Darwin's theory of survival of the fittest through natural selection (Riechmann 2001; Vriend 2000).

In order for the resident agent to obtain the government recovery fund, the resident should apply for assistance through the LDRMs. As previously mentioned, LDRMs act as communicators between the SDRC and local residents. Moreover, it is the LDRM's duty to assess the submitted recovery assistance applications by the residents, only accepting that which comply with a predefined criteria, as shown in Fig. 2. Thus, the resident agent applies for one of the SDRC's disaster recovery plans that maximizes the resident's utility functions as shown Eq. (4)

$$E[U_j]_i = (G_j \times A_j) \times pr_j \tag{4}$$

where $E[U_j]_i$ = expected utility of plan j for the resident i; G = government maximum award for plan j; A = government average acceptance probability of plan j; and pr = probability utilized from the reactive reinforced learning module, discussed in the following.

The residents' choices from the different offered plans depend on the maximum expected utility function obtained across the different plans. However, in the case of denying the resident's application by the LDRM, whether for not meeting the criteria or due to insufficient funding by the SDRC for the selected plan, the resident agent should learn from this step, and thus choose a different plan in the succeeding steps. Thus, the residents' second learning module should be an individual learning one that can capture the experience-based learning process. To this end, Roth Erev reactive reinforced learning (Erev and Roth 1998) was found best to depict this learning process as it is able to capture the repetitive game between the LDRMs and residents, in addition to taking into account the experience gained through the different attempts. The Roth Erev reactive reinforcement learning model was introduced in the 1990s as a game theory approach to model the learning behavior of players based on experiments and observations (Erev and Roth 1998). The algorithm methodology is to first determine which decision action has been used and the associated immediate reward (positive or negative) by applying the selected decision action as shown in Eq. (5)

$$E_j(k) = \begin{cases} E = \pm 1 & \text{if } j = k \\ E = 0 & \text{otherwise} \end{cases} \tag{5}$$

where for each available action j, E = reward given the used action k. If $j = k$, E takes the value of +1 or −1 if the application is approved or denied, respectively; otherwise, $E = 0$.

The second step in the algorithm is to change the propensity of the decision actions and eventually their selection probabilities as shown in Eqs. (6) and (7)

$$\text{Resident action's propensity: } q_j(t+1)$$
$$= q_j(t) \times (1 - \phi) + E_j(k) \times (1 - \varepsilon) \quad (6)$$

$$\text{Resident action's probability: } pr_j(t) = q_j(t) \Big/ \sum_{j=1}^{J} q_j(t) \quad (7)$$

where $q_j(t)$ = propensity of action j in time t; and ϕ and ε = forgetting and experimenting parameters, respectively.

Both ϕ and ε allow the agent to explore more options further on. Finally, pr is the probability distribution of action j. Thus, the Roth Erev learning module can demonstrate the individual learning process, through experience and experimenting with the different strategies, weakening the poor outcome strategies, and strengthening the most rewarding strategies' probabilities.

Residents Recovery Progress. Utilizing the data gathered from MDA and MRD, the average recovery rate was calculated for each of the aforementioned SDRC's plans: Homeowner Assistance, Public Home Assistance, and Elevation Grants. Thus, as shown in Fig. 4, at each time step, if the resident was granted a government fund, the recovery module calculates the rate corresponding to the funded plan, and the recovery process takes place.

Finally, each LDRM checks for the current redevelopment progress of the local residents by (1) calculating the residents' initial households' values through Eq. (8) at the first time step; (2) at each time step, each LDRM determines the current changes in

Fig. 4. Residential building recovery module

recovery and redevelopment progress through Eq. (9); and (3) the LDRM reports the overall residents' redevelopment progress through Eq. (10)

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

$$D_{y_t} = \sum_{i=1}^{I} H_i \quad \forall \, y = 1, 2, \ldots, Y \quad (9)$$

$$\Delta D_{y_t} = \frac{D_{y_t}}{D_{y_o}} \quad \forall \, y = 1, 2, \ldots, Y \quad (10)$$

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; H_i = household value for resident i in county y; and I = total number of residents.

State Disaster Recovery Coordinator

Residential Disaster Recovery. The state disaster recovery coordinator (SDRC) is considered—along with the residents—a main controlling agent in the proposed disaster recovery ABM. Depending on the available funds, the SDRC distributes the funds for the different proposed disaster recovery plans. The proposed ABM integrates the aforementioned environmental vulnerability assessment tool into the SDRC's objective function to better guide the recovery efforts. Moreover, the funding distribution proportion is adjusted at each time step depending on changes in the residents' objective functions and the host community vulnerability corresponding to each disaster recovery strategy, as shown in Eqs. (11) and (12). To this effect, maximizing Eq. (11) and minimizing Eq. (12) act as the SDRC's objective function. Moreover, the SDRC actions are constrained by the federal agency's funds as shown in Eq. (13)

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

$$\sum_{i}^{I} \text{EVI}_i \quad \forall \, k = 1, 2, \ldots, K \quad (12)$$

$$\sum_{i=1}^{I} \text{SG}_i \leq \text{TFF} \quad (13)$$

where ΔZ_i = change in the resident's i objective function when applying for plan k; EVI = environmental vulnerability index corresponding to residents applying for plan k; SG_i = state governmental funding for the residents i; and TFF = total federal funding for the SDRC.

To this end, in order to redistribute the funding proportions as well as capturing the experience-based learning of the SDRC, Eq. (14) illustrates the utilized Roth Erev RL propensity module that assimilates the aforementioned SDRC's objective functions

$$q_k(t+1) = q_k(t)[1 - \phi] + \text{IR}_k \times (1 - \varepsilon) \quad \forall \, k = 1, 2, \ldots, K \quad (14)$$

where $q_k(t)$ = propensity of plan k in time t and IR_k = immediate reward for applying plan k.

The calculated immediate reward is the relative fitness of the SDRC's objective function when plan k is applied. This is carried out through ranking each disaster recovery plan depending on its
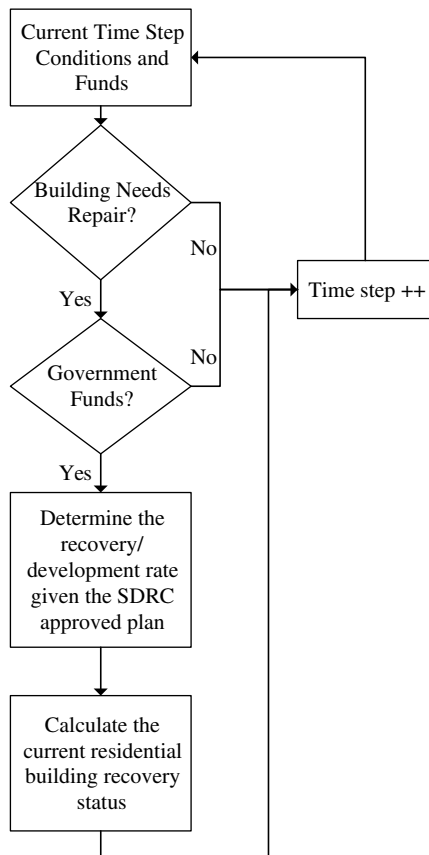
outcome in Eqs. (11) and (12). Essentially, the learning module acts as the SDRC's multiobjective function's optimization module to find the Pareto optimum strategy. Consequently, the model can re-calculate the funding distribution proportions p for each plan k using the propensities from Eq. (14) as shown in Eq. (15). In contrast to other greedy search techniques, the Roth Erev learning model is capable of representing the temporal effect of the fund allocation's impact on the host community through the utilization of ϕ and ε parameters. Thus, the learning module can guide the recovery process through (1) maximizing the residents' objective functions and (2) decreasing the host community's environmental vulnerability

$$p_k(t) = q_k(t) \bigg/ \sum_{k=1}^{K} q_k(t) \quad \forall \ k = 1, 2, \ldots, K \qquad (15)$$

Infrastructure Recovery. The proposed model aims to optimize the development of the infrastructure to minimize the environmental vulnerability of the host community while meeting the stakeholders' needs. Accordingly, and in line with the presented problem domain, the SDRC was utilized to optimize the use of the different WWTFs in the three coastal counties in Mississippi. As previously discussed, the MDA proposed nine WWTFs to be developed in the three aforementioned counties in the post-Katrina recovery. Such projects aimed to meet the increasing population growth and provide for a cleaner wastewater treatment approach. However, to the authors' knowledge, the MDA did not take into account decreasing the counties' environmental vulnerability as an outcome for the WWTF development. Therefore, the proposed model allows the SDRC agent to utilize the WWTFs and allocate their services while integrating in the SDRC's objective function of minimizing the host community's environmental vulnerability using the EVI, as shown in Eq. (16). The allocation of service location per WWTF is constrained by the capacity of the WWTF, taking into account the future population growth. Also, the WWTF service allocation is constrained by the county in which the WWTF is developed

$$\text{Minimize} \sum_{1}^{C} \text{EVI}_{c_y} \quad \forall \ y = 1, 2, \ldots, Y \qquad (16)$$

where EVI is the environmental vulnerability index for census tract c in county y.

Unlike the relationship between the SDRC and residents, which creates a stochastic outcome, the allocation of the WWTFs creates a deterministic change in the EVI outcome per county. Thus, the authors investigated several optimization techniques to be utilized for the SDRC, in order to optimize the WWTFs, including genetic algorithms, simulated annealing, taboo search, and dynamic programming. To this end, the SDRC uses a simulated annealing optimization module that decreases the host community environmental vulnerability while taking into account the population needs and expected growth. Simulated annealing was found to work best as it is able to guarantee statistical optimality (Goffe et al. 1994), unlike evolutionary algorithms, and takes into

account the multiobjective criteria of the SDRC (which dynamic programming lacks).

Insurance
In the proposed ABM, several insurance companies are considered as offering a variety of insurance plans that range from partial to full coverage. A decision for each company is to determine the distribution and pricing of plans to offer the population of resident families. Accordingly, the insurer utility function is shown in Eq. (17). It is understood that the insurers follow risk assessment in their objective functions. Nevertheless, following Eid et al. (2015), an evolutionary game theory approach can be used to determine a stable postdisaster insurance profile between residents and insurers that would increase both their utility functions

$$W_n^{t+1} = W_n^t + \sum_{i=1}^{I} \begin{cases} P_{i(x,m)} - C_{i(x,m)} & \text{if } x = n \\ 0 & \text{otherwise} \end{cases} \quad \forall \ n = 1, 2, \ldots, N$$

$$(17)$$

where W_n^{t+1} = insurance company n wealth at $t + 1$, and $C_{i(x,m)}$ = zero if no disaster has occurred at time $t + 1$. Thus, the aggregate monetary utility gained by an insurance company is the difference between the sum of the premiums paid by the resident and the sum of the indemnities paid to the resident when a natural disaster occurs.

It is worth noting two issues that may negatively affect the optimum strategy profile. The first is adverse selection as the pool will contain mostly high-risk resident families, and so the insurance company will keep the premium at a fair rate (Janssen and Karamychev 2005). It is noted though that insurers can change rates to overcome the problem of adverse election. The second issue is moral hazard as losses will always be not in the favor of the insured pool and thus the insurance will not change the situation or mitigate the damage for the insured party (Lee and Ligon 2001; Breuer 2005; Doherty and Smetters 2005).

This situation emphasizes the need of an optimum postdisaster insurance plan strategy profile where a selective value of premiums and coverage values should be determined as well. To handle these issues, the insurers were allowed to be myopic in their product offerings and then learn from their rivals given the distribution of population per contract. Thus, by utilizing the Eid et al. (2015) data, three insurance companies offering three different disaster policies were introduced from which the residents can make their choice. The different insurance companies' disaster policies' premiums and compensation ratios are found in Table 3.

Model Testing

The proposed model was developed to be modular and scalable. Modularity allows the ability to change the different algorithms and alter them without affecting the primary aspects of the model. Scalability, on the other hand, is the ability to handle any number of agents (resident, insurance ,or government) with any number of impacted regions. To this end, through the development process of

Table 3. 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

the proposed ABM, the computer model ran through incremental testing for internal and external behaviors using structure testing and behavior testing. Structure testing included (1) direct structure testing empirically (structure and parameter verification) and theoretically (structure and parameter verification as well as direct extreme-condition tests and dimensional consistency tests); and (2) structure-oriented behavior (behavior sensitivity, extreme condition, modified-behavior prediction, and boundary adequacy tests). On the other hand, behavior testing was conducted to predict the accuracy of the communication and implementation. Test agents' were utilized for a series of regression and progression tests. Regression testing was done to ensure that agents perform their stated specifications and that modifications to agents do not affect existing message handling capabilities.

Most importantly, the ABM conducted two scenarios to test the model output as well as to compare the actual results and changes in the region's vulnerability and the changes in the disaster recovery rates. This is clearly demonstrated in the forthcoming results and analysis section.

Implementation Platform

The proposed model was implemented using GeoMason on a *NetBeans IDE 7.4* platform. GeoMason is a GIS extension to the MASON multiagent based model, which was developed as an open-source Java-based discrete-event multiagent simulation toolkit by the Department of Computer Science at George Mason University (Sullivan et al. 2010). GeoMason allows for the gathering of information and editing raster and vector geospatial data. The use of GIS made it easy to gather the needed properties of the residents depending on their spatial attributes. Moreover, GIS facilitates the representation of the residents, the hazardous events, and the spatial relationship between them. Fig. 5 shows a GIS map for the three Mississippi coastal counties of Hancock, Harrison, and Jackson (west to east), along with the resident agents uniformly distributed within each census tract (depending on the population size in each census tract). The aforementioned gathered data were input to the computer model to determine the optimum funding proportions for each of the action plans introduced by the SDRC as well as the residents' choices over the different insurance policies.
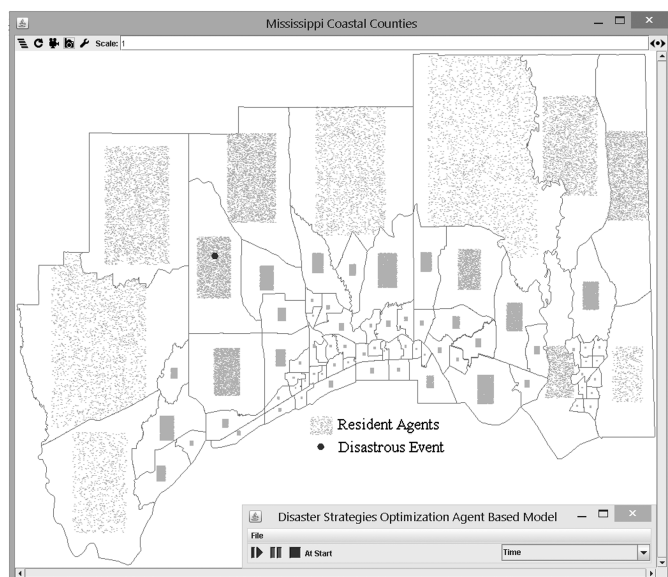

Fig. 5. Proposed model implementation on GeoMason

Results and Analysis

The results obtained from the proposed disaster recovery agent-based model are presented in this section for the actual and projected environmental vulnerability for the aforementioned three counties for Hurricane Katrina. In addition, and in order to test the model, two scenarios were simulated: (1) the SDRC's actual budget distribution and (2) a hypothetical uniform SDRC budget distribution. This approach will assess the model's outcome (with learning behaviors) in comparison to the different strategies that were actually followed or could be followed by the recovery agencies in Mississippi. Moreover, the SDRC's budget distribution is also represented and compared to the actual MDA budget distribution in order to understand the reasons behind such changes in the environmental vulnerability. Furthermore, the WWTFs' service allocation is also presented and how it was able to provide for a less vulnerable environment. Finally, the residents' choices of the different insurance companies is illustrated to indicate the significance of the insurance coverage as a preparedness strategy.

Environmental Vulnerability Assessment

As mentioned in the model development section, the EVI is a comprehensive environmental assessment of the host community's vulnerability to internal and external shocks. Moreover, in this approach, the human system is an integrated part of the ecosystem, not the responder (Villa and McLeod 2002). Thus, the model is able to assess the overall environmental vulnerability of the host community. In order to evaluate the community's overall environmental vulnerability, the values of each of the 22 collected indicators (presented in Table 2) were mapped on the predefined scale in the EVI manual (Pratt et al. 2004) in a scalar format. The 22 indicators account for the assessment of both the built environment inherited vulnerability and the risk exposure, as previously discussed. EVI scores are then calculated by taking the average of the obtained vulnerability values across all the indicators for each census tract. This allowed for a comparison of the environmental vulnerability across the 76 census tracts in the three counties. Thus, this approach will allow the SDRC to define the most vulnerable regions and allocate the funds accordingly so as to minimize the total vulnerability of the host community. It should be noted that this approach allows for prioritizing the fund allocation depending on the regions' inherent vulnerability as well as their exposure to future shocks and disasters.

The aforementioned steps were carried out on the actual collected data (for an annual basis) for the three counties on the census-tract level for pre-Katrina until 2012. Table 4 represents a sample of the census tracts' EVI values for ex-Katrina, as well as a sample of vulnerability index of some of the collected indicators (land area, vegetation cover, and population). For a better

Table 4. Ex-Katrina EVI

Census tract	County	EVI	Land	Vegetation cover	Population
1	Harrison	4	7	5	7
34.04	Harrison	3	6	1	6
39	Harrison	4	7	6	7
301	Hancock	4	7	2	7
302	Hancock	4	7	1	6
305	Hancock	5	7	2	7
403	Jackson	5	7	4	7
408	Jackson	3	6	2	4
429	Jackson	2	6	4	1

visualization, Fig. 6 illustrates the actual environmental vulnerability of the 76 census tracts for ex-Katrina conditions.

Fig. 7 presents the EVI per census tract for the year 2012. Moreover, Fig. 8 illustrates the change of EVI per county through the actual recovery process for the three counties. The EVI scores ranges between 1 (least vulnerable) and 7 (most vulnerable). It can be observed that a significant increase occurs in the vulnerability of the census tracts. Thus, it is noted that the actual budget distribution and infrastructure projects (as shown in the next section) did not improve the host community environmental vulnerability, but rather decreased it. This is observed in census tracts in Jackson County's west side and Hancock County's east side. Moreover, Hancock County's vulnerability peaked in the years 2009, 2011,

and 2012 to 3.86. This is due to the sudden increase of population and waste production, and decrease in the vegetation through the current infrastructure development. Meanwhile, Hancock County WWTFs did not significantly improve in comparison to major WWTFs carried out through Harrison County. The latter had six major wastewater treatment facilities under construction between the years 2008–2010, which improved the overall water quality and decreased the county's EVI. On the other hand, Jackson County, which faced the least impact from Katrina, did not have the major funding (both in the residential or the infrastructure sectors) in comparison to Harrison and Hancock counties. Thus, no major overall significant change in the EVI was found. Moreover, only two major wastewater treatment facilities were carried out in Jackson County following the Katrina disaster, which did not positively affect the EVI of the host community.

As discussed previously, in order to assess the proposed ABM, two simulation scenarios were introduced to compare their results to each other and to the actual vulnerability changes in the Mississippi coastal counties. To this effect, Figs. 9 and 10 illustrate the projected changes in EVI for the actual budget distribution and the uniform budget distribution. Meanwhile, the proposed model was initiated with ex-Katrina data (social and environmental), and the multiple simulation runs were utilized to determine the projected
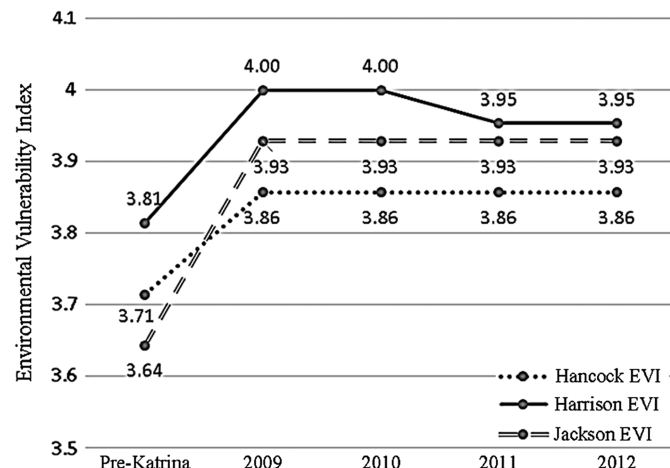

Fig. 6. Actual EVI per census tract—ex-Katrina
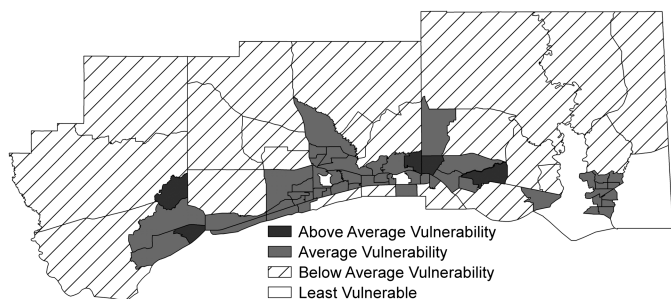
Fig. 7. Actual EVI per census tract, 2012

Fig. 9. Projected EVI per county—actual budget distribution

Fig. 8. Actual EVI change per county
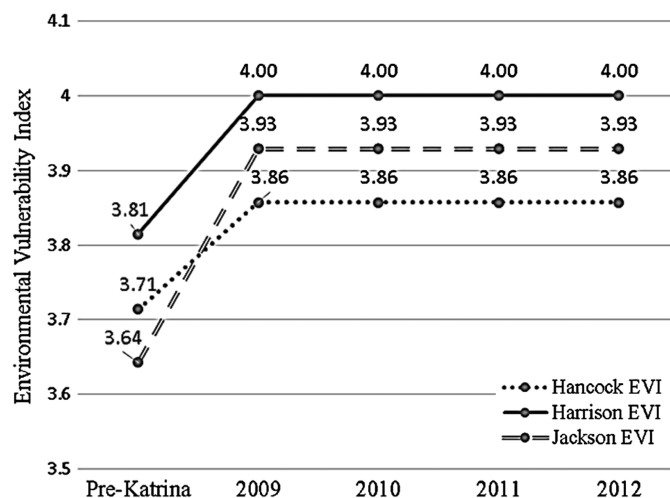
Fig. 10. Projected EVI per county—uniform budget distribution
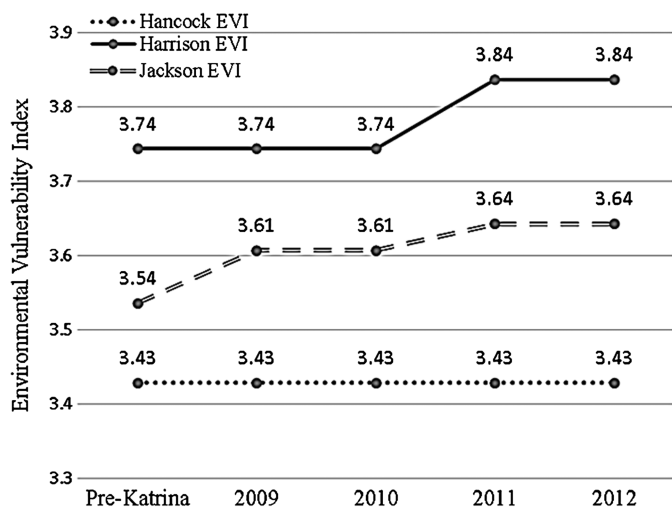
Fig. 11. Projected EVI per county—proposed model

Fig. 12. Projected EVI per census tract, 2012

EVI per census tract. These environmental vulnerability indices were affected due to the proposed SDRC budget distribution, which integrates the EVI into the SDRC's objective function, as mentioned earlier. This approach targeted decreasing the host community's environmental vulnerability while increasing the residents' individual utility functions. To this effect, Fig. 11 presents the projected change in the EVI per county. It can be observed that the proposed model's projected EVI, through the three counties, was significantly preferable than the two simulated scenarios of actual and uniform budget distribution. This is due the integration of the EVI into the SDRC's objective function to optimize the available decision actions (budget) to decrease the community's environmental vulnerability.

By comparing both Fig. 8 (actual EVI) and Fig. 11 (ABM projected EVI), several observations can be made. First, Hancock County's average EVI value did not change. This is due to minimal utilization of the Public Home Assistance by the county's residents. Such a plan decreases the vegetation cover by building new homes over existing vegetation. Moreover, the available wastewater treatment facilities proposed by the SDRC (as shown later) and optimized in the proposed model were not sufficient to decrease the host community vulnerability beyond the current values for Hancock County. Second, the Harrison County average projected EVI values are close to the actual values but started off with better values. This is due to the utilization of optimum wastewater service distribution that decreased the host community's environmental vulnerability. Nevertheless, the values peaked at 3.84 at the end of the model run due to the model's limitations, which are further discussed in the following section. Finally, Jackson County's project average EVI values were also close to the actual average EVI values. However, the values started off with better indicators due to the optimal utilization of the WWTFs' services distribution.

Nevertheless, with regard to the simulation model limitations, the model does not take into account the sudden change in the population. This will affect the population and waste production environmental indicators and may provide significant variation when comparing actual and projected EVI values, which indeed caused the aforementioned results for Hancock County. The model does however take into account the population growth by utilizing the calculated population growth rates for each census tract. The model does not take into account the regrowing of the vegetation cover, however, which affects the vegetation cover environmental indicator. In real life, public and private sectors and individuals regrow
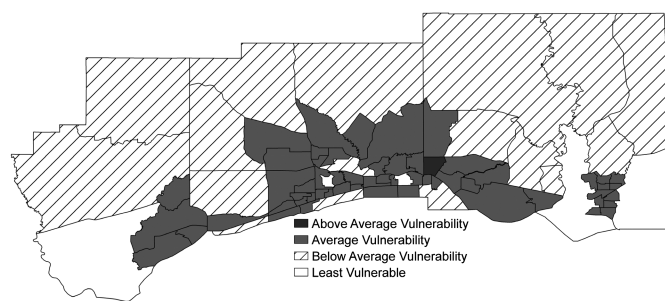
trees (vegetation cover) to accommodate for losses after construction and development as well as for many other purposes. However, there is a lack of vegetation cover regrowth data; thus, the model did not take factor this into the calculation. This will increase the EVI values acquired by the model in comparison to the actual EVI values, as shown in the end of the run for Hancock, Harrison, and Jackson counties. For a better visualization, Fig. 12 illustrates the projected EVI per census tract for the year 2012, where it can be observed that the model was able to decrease the census tracts' vulnerability, in comparison to Fig. 7.

The following section illustrates the proposed model's outcome in regard to the SDRC recovery funding distribution. Thus, a comparison between the actual and proposed model budget distribution can be carried out in the interest of understanding the reasons behind the proposed model's projected EVI for the host community.

SDRC Funding Distribution Comparison

The proposed model results were compared with the actual data gathered from the Mississippi Disaster Agency (MDA) in reference to the budget expenditure and distribution over the three residential recovery plans: Homeowner Assistance, Public Home Assistance, and Elevation Grant. The residential plans contributed more than 60% of the total Katrina recovery budget for the three counties (Mississippi Development Authority 2015). Figs. 13 and 14 illustrate the different funding proportions used by the MDA and the proposed ABM output, respectively. With regard to the actual budget distribution by MDA, it can be noted from Fig. 13 the domination of the Homeowner Assistance plan over the other two plans.
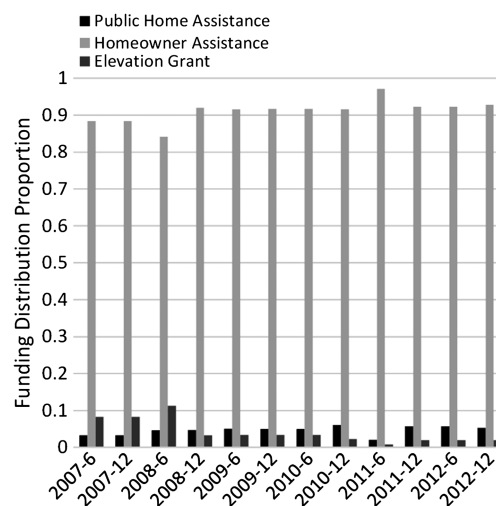

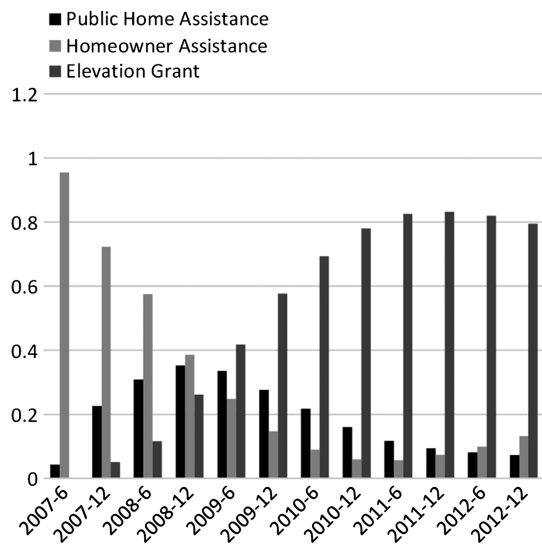**Fig. 13.** Actual funding distribution

Fig. 14. Proposed ABM funding distribution

Fig. 15. Actual WWTF service allocations

Fig. 16. Proposed WWTF service allocations

This can be justified by the pressure exerted on the disaster management by that time as the Homeowner Assistance plan has the highest demand by the residents as it awards the certified applicant with up to $150,000 (Mississippi Development Authority 2015).

Meanwhile, the model was initiated with uniform and equal budget distribution (1/3 each) for the Homeowner Assistance, Public Home Assistance, and Elevation Grant. Through the model simulation runs, the first years showed a major increase in the Homeowner Assistance plan, up to 90% in the first half of 2007. This is due to the high reward of such plan that would, temporarily, affect the residents' utility functions. However, residents tend to avoid such disaster recovery financial plans due to the presence of disaster insurance policies. Thus, this disaster recovery plan budget was decreased in later years. On the other hand, also in the first 2 years of the simulation, the Public Home Assistance plan displayed a significant increase. Such a plan affects the environmental vulnerability of the host community through decreasing the vegetation cover. Thus, the model adapted to such negative changes and decreased the Public Home Assistance plan budget in the second half of the simulation to decrease its effects on the environment. It should be noted that due to the previously mentioned model limitations, the model did not have any other corrective actions to overcome such impacts on the host community's environmental vulnerability.

The Elevation Grant showed a steady increase from the beginning of the simulation run and converged at 80% in the last quarter of the simulation. The Elevation Grant increased the host community resilience to flood, increased the residential households' values, and thus increased the residents' utility functions with no impact on the host community's environmental vulnerability. To this effect, the model reached a budget distribution of 10, 20, and 80% for the Public Home Assistance, Homeowner Assistance, and Elevation Grant, respectively. This distribution increases the residents' utility functions while maintaining and decreasing the host community environmental vulnerability.

WWTF Service Distribution

As previously mentioned, the post-Katrina recovery included the construction and development of multiple WWTFs across the three counties. As reported in the MDA annual federal reporting (2014) as well as reports from the MDEQ, the WWTFs targeted the
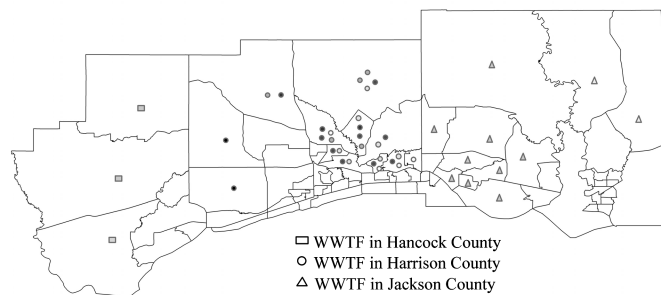
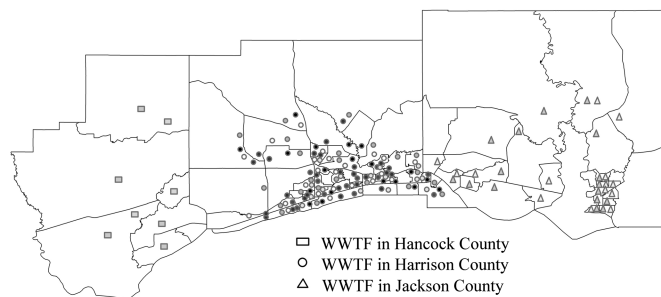population needs and projected growth. However, such an approach did not take into account the environmental vulnerability. To this effect, the proposed model recommended an optimal service allocation for each of the WWTFs to minimize the total environmental vulnerability per county, utilizing EVI methodology, while meeting the needs of the population, their expected growth, and the WWTFs' capacities. Figs. 15 and 16 illustrate the actual and proposed allocation of WWTFs services, respectively. It is clearly seen that the actual distribution of WWTFs service was minimal for Hancock County (west side), highly concentrated in the northern region of Harrison County (middle), and significantly distributed among the west side of Jackson County (east side). However, this approach did not decrease the counties' vulnerability, as seen in Fig. 7.

Meanwhile, as seen in Fig. 16, the proposed model recommended a more intense utilization of the WWTFs' full capacity to serve the population of the three counties, targeting the most environmentally vulnerable regions, thus minimizing the host community's vulnerability. This can be observed through the increase of the service allocation in Hancock County to take into account more populated regions. Furthermore, for Harrison County, the WWTFs were directed more toward the south region were the population is concentrated and is more vulnerable to perturbations. Finally, the east side of Jackson County was targeted as the population in this region had minimal WWTF services. Distributing the WWTFs' service to the most environmentally vulnerable regions helped in decreasing the host community vulnerability as shown in Fig. 7 in comparison to Fig. 12.

Recovery Progress

In order to assess the community's welfare, this section illustrates how the different disaster recovery strategies affect the host communities' redevelopment. This assessment is done through quantifying the residential damage per county, and the current recovery at each time step, as previously discussed. This approach is carried
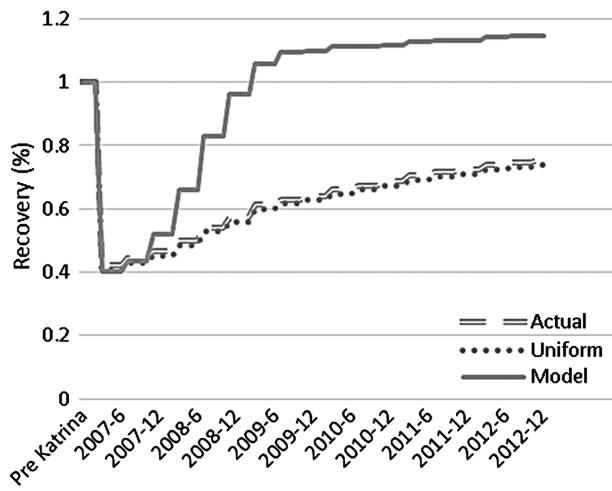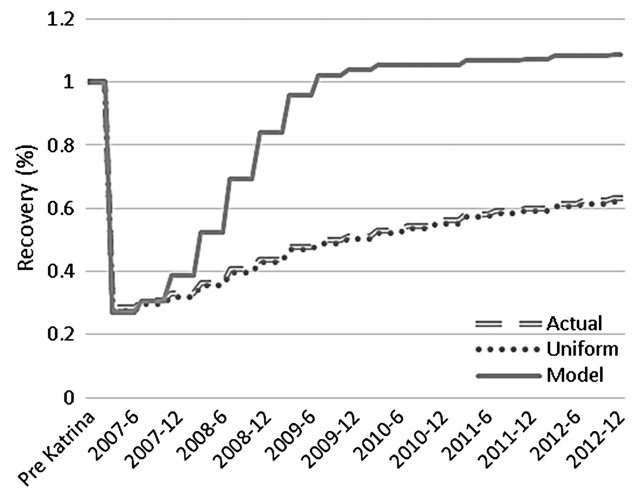
Fig. 17. Hancock recovery progress
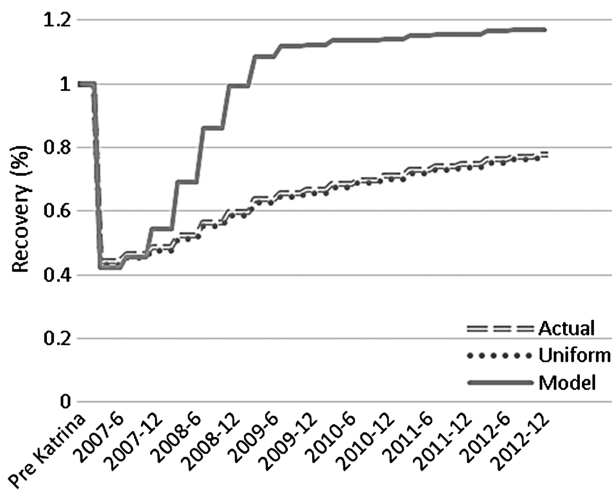

Fig. 19. Jackson recovery progress

Fig. 18. Harrison recovery progress

Fig. 20. Choices of residents over different insurance options

conditions of the household, thus increasing the households' value, and requires more resources.

Resident Choices of the Different Insurance Companies

The residents' choices of the different insurance plans differed and changed through the simulation runs. Fig. 20 illustrates the residents' choices for the three aforementioned insurers along with the choice of having no disaster insurance plan. At the beginning, the residents were randomly distributed for the three insurance companies along with the no insurance option. By using GAs as a social learning technique as previously discussed and following the game theory proposed by Eid et al. (2015), the residents changed their choices to attain the highest possible objective function through mimicking the fittest set of residents among them. To this end, the first half of the ABM simulation showed a relatively higher share for insurer #3 that would give up to 100% of the damaged property value as a compensation. As the need for such costly coverage decreased in the second half of the simulation, the residents' choices started shifting back to the other two insurance companies. Furthermore, due to the occurrence of natural hazardous events (tornados), residents tend to purchase insurance policies (a significant decrease in the strategy of not purchasing insurance is illustrated in the second half in Fig. 20). Moreover, the insurance coverage also affected the residents' choices at the beginning of the simulation, as the residents tended to avoid the Homeowner Assistance since they had the insurance financial coverage for the time being.

out for both of the disaster recovery strategies (actual and uniform budget distributions) as well as the proposed decision support agent based model. To this end, Figs. 17–19 illustrate the recovery progress for the counties Hancock, Harrison, and Jackson, respectively, when utilizing the actual disaster recovery strategies, the hypothetical uniform budget distribution, and the proposed model.

By comparing the households' recovery and redevelopment in Figs. 17–19, the model significance can be confirmed. This is due to the integration of vulnerability assessment in the SDRC's objective function, which guided the fund allocation to decrease the vulnerability of the community (as shown in a previous section) as well as to increase the community welfare (as shown in this section). The model outperformed both the actual disaster recovery strategy and the uniform budget distribution. First, the overall recovery rate of the community is higher, which is due to the distribution of the available funds depending on the needs of the community, which agrees with the findings in the previously discussed literature. Moreover, it is notid that the model achieved more than 100% recovery in each county; this is due to the implementation of the Elevation Grant that increases the households' resiliency to flood by elevating the household up to 1.9 m (6 ft, 4 in.). This type of redevelopment requires additional work to the preexisting
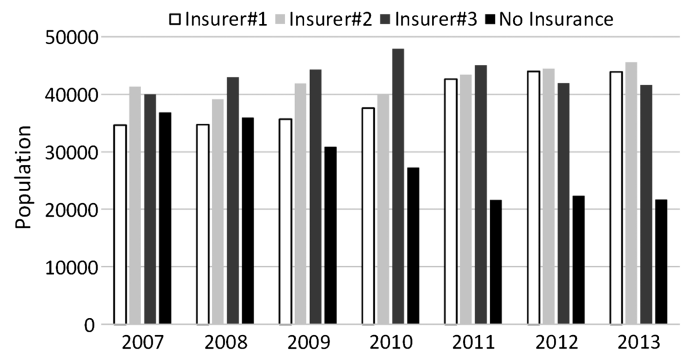
Conclusion

This paper presented a disaster recovery decision support tool through an agent-based approach that captures the objective functions of the associated stakeholders and the environmental vulnerability of host communities. This approach will aid urban planners in the postdisaster recovery of impacted communities. This will be carried out through decreasing the environmental vulnerability of the different regions while increasing the objective functions of the associated stakeholders. To this end, the model represented the residents of the impacted region as well as the local disaster recovery management (LDRM), state disaster recovery coordinator (SDRC), and federal disaster recovery coordinator (FDRC) and their interactions with each other. The model also presented the relationship between the residents and the insurance companies. Thus, the agent-based model utilized two learning modules: (1) Roth Erev reinforcement learning for the resident's individual learning and the SDRC budget distribution learning; and (2) GA social learning for the residents' attempts to achieve an optimum disaster insurance plan that would increase their utility functions. The model was implemented via a Java-based computer model utilizing a GIS interface on the post-Katrina disaster recovery for three coastal Mississippi counties: Hancock, Harrison, and Jackson. Thus, the model was able to successfully represent the interrelation between the different stakeholders in the disaster recovery process and their impacts on each other's objective functions. The model was able to optimize the SDRC actions in regard to the residential recovery budget as well as the infrastructure development. Along the same line, the model utilized a comprehensive and well established environmental vulnerability assessment tool to better guide the recovery efforts. Accordingly, the model was able to increase the community's welfare through maximizing the residents' objective function and minimizing the host community's vulnerability to future shocks and perturbations. Ultimately, the model provided better environmental vulnerability indices for the three counties in comparison to what is currently achieved by the actual disaster recovery plans carried out post-Katrina. This is due to the integration of the vulnerability assessment tool into the SDRC's objective function as well as accounting for the residents' needs. Further, the model was able to optimize the SDRC's housing sector recovery budget, the SDRC's infrastructure development, and the residents' choices over the different disaster insurance plans.

Future Work

The current model takes into account the residents and SDRC as the main controlling agents, while the LDRM acts as an assessor of the applicants eligibility. Accordingly, the model did not fully capture the negotiation process between the local government and the residents. Thus said, for future work, the authors are developing the current agent-based model to account for LDRM interactions with the residents and the SDRC. Moreover, the model will address the federal disaster recovery coordinator's (FDRC) role in the recovery process, which highly affects the recovery funding. Furthermore, the residents' social learning process will take into account the learning barriers (spatial and economic standards) that were assumed negligible in the current model. The addition of business and economic agents to the model will be beneficial to the model in order to obtain a holistic approach into disaster recovery. Finally, the insurance companies' decision-making process will be further developed as the current model illustrates them as myopic service providers.

For simplification, this model did not take into account other vulnerability dimensions (social and economic) that would affect the recovery process and model's outcome. Therefore, and in order to provide a holistic disaster recovery decision support tool, social and economic vulnerability indicators will be utilized and integrated into the proposed model. These indicators, along with the utilized environmental indicator, can give a broader understanding of the complex systems associated with the disaster recovery process. Moreover, uncertainty was not addressed in the proposed model. Thus, future work will aim to address the uncertainty and its impact on the proposed model's outcome. Also, modification and enhancements will be carried out on the infrastructure development module to capture other aspects (transportation, construction constraints, etc.). Also, in order to address the model's limitations, future work will be guided into accounting for the sudden change in population as well as accounting for the vegetation cover increase. Furthermore, understanding that the ABM's outcome is significantly affected by the agents' behaviors, the fully developed agent-based model will be calibrated to capture the actual attributes and behaviors of the different stakeholders in the host community. This will be carried out through focus groups and questionnaires distributed to the disaster recovery agencies and the residents in Mississippi after securing acceptance of associated institution review boards. Finally, and in order to provide for further testing and validation, the proposed decision support model will be implemented in other different disaster events and their associated recovery processes.

References

Abdalla, S., Elariane, S., and El Defrawi, S. (2015). "Decision-making tool for participatory urban planning and development: Residents' preferences of their built environment." *J. Urban Plann. Dev.*, 142(1), 04015011.

Alesch, D. J., and Siembieda, W. (2012). "The role of the built environment in the recovery of cities and communities from extreme events." *Int. J. Mass Emergencies Disasters*, 30(2), 197–211.

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

Badwi, I., El-Barmelgy, M., and Ouf, A. (2014). "Modeling and simulation of greater Cairo region urban dynamics using SLEUTH." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000193, 04014032.

Barnett, J., Lambert, S., and Fry, I. (2008). "The hazards of indicators: Insights from the environmental vulnerability index." *Ann. Assoc. Am. Geogr.*, 98(1), 102–119.

Bell, M. G. H., and Lida, Y. (1997). "Network design." *Transportation network analysis*, Wiley, 193–204.

Berke, P., Smith, G., and Lyles, W. (2012). "Planning for resiliency: Evaluation of state hazard mitigation plans under the disaster mitigation act." *Nat. Hazards Rev.*, 10.1061/(ASCE)NH.1527-6996.0000063, 139–149.

Boz, M., El-Adaway, I., and Eid, M. (2014). "A systems approach for sustainability assessment of civil infrastructure projects construction." *Research Congress*, ASCE, 444–453.

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.

Breuer, M. (2005). "Multiple losses, ex ante moral hazard, and the implications for umbrella policies." *J. Risk Insurance*, 72(4), 525–538.

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. (2012). "Social vulnerability and hurricane impact modeling." *Nat. Hazards Rev.*, 10.1061/(ASCE)1527-6988(2010)11:2(58), 58–68.

Carson, R. (2002). *Silent spring*, Houghton Mifflin Harcourt, Boston, MA.

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.

Chen, X., Meaker, J., and Zhan, F. B. (2006). "Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys." *Nat. Hazards*, 38(3), 321–338.

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." *Soc. Sci. Q.*, 84(2), 242–261.

Doherty, N., and Smetters, K. (2005). "Moral hazard in reinsurance markets." *J. Risk Insurance*, 72(3), 375–391.

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.

Du, J., and Wang, Q. (2011). "Exploring reciprocal influence between individual shopping travel and urban form: Agent-based modeling approach." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444 .0000084, 390–401.

Economics of Climate Adaptation Working Group. (2009). "Shaping climate resilient development." Zurich, Switzerland.

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

Esty, D., Levy, M., Srebotnjak, T., and Sherbinin, A. (2005). *2005 environmental sustainability index: Benchmarking National environmental stewardship*, Yale Center for Environmental Law and Policy, New Haven.

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⟩.

Feliu, J. (2012). "High-speed rail in European medium-sized cities: Stakeholders and urban development." *J. Urban Plann. Dev.*, 10.1061/ (ASCE)UP.1943-5444.0000123, 293–302.

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., and Yu, D. (2014). "Sustainable urban redevelopment: Assessing the impact of third-party rating systems." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000271, 05014033.

Fiedrich, F., and Burghardt, P. (2007). "Agent-based systems for disaster management." *Commun. ACM*, 50(3), 41–42.

Glumac, B., Han, Q., and Schaefer, W. (2015). "Actors' preferences in the redevelopment of brownfield: Latent class model." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000206, 04014017.

Godschalk, D. R. (2003). "Urban hazard mitigation: Creating resilient cities." *Nat. Hazards Rev.*, 10.1061/(ASCE)1527-6988(2003)4:3(136), 136–143.

Goffe, W. L., Ferrier, G. D., and Rogers, J. (1994). "Global optimization of statistical functions with simulated annealing." *J. Econom.*, 60(1–2), 65–99.

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.

Hegazy, T., and Ayed, A. (1999). "Simplified spreadsheet solutions: Models for critical path method and time-cost trade-off analysis." *Cost Eng. J.*, 41(7), 26–33.

Ho, H. W., and Sumalee, A. (2014). "Optimal recovery plan after disaster: Continuum modeling approach." *J. Transp. Eng.*, 10.1061/(ASCE)TE .1943-5436.0000668, 04014034.

Hwang, S., Park, M., Lee, H.-S., Lee, S., and Ki, H. (2015). "Postdisaster interdependent built environment recovery efforts and the effects of governmental plans: Case analysis using system dynamics." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000939, 04014081.

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.

Janssen, M., and Karamychev, V. (2005). "Dynamic insurance contracts and adverse selection." *J. Risk Insurance*, 72(1), 45–59.

Karlafits, M. G., Kepaptsoglou, K., and Lambropoulos, S. (2007). "Fund allocation for transportation network recovery following natural disasters." *J. Urban Plann. Dev.*, 10.1061/(ASCE)0733-9488(2007)133: 1(82), 82–89.

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

Lee, W., and Ligon, J. A. (2001). "Moral hazard in risk pooling arrangements." *J. Risk Insurance*, 68(1), 175–190.

Li, H., and Love, P. (1997). "Using improved genetic algorithms to facilitate time-cost optimization." *J. Constr. Eng. Manage.*, 10.1061/(ASCE) 0733-9364(1997)123:3(233), 233–237.

Lim, G., Zangeneh, S., and Kim, S. (2016). "Clustering approach for defining hurricane evacuation zones." *J. Urban Plann. Dev.*, 10 .1061/(ASCE)UP.1943-5444.0000323, 04016008.

Macy, M. W., and Willer, R. (2002). "From factors to actors: Computational sociology and agent-based modeling." *Annu. Rev. Sociol.*, 28(1), 143–166.

Meo, M., Ziebro, B., and Patton, A. (2004). "Tulsa turnaround: From disaster to sustainability." *Nat. Hazards Rev.*, 10.1061/(ASCE)1527-6988 (2004)5:1(1), 1–9.

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

Miles, S. B., and Chang, S. E. (2003). "Urban disaster recovery: A framework and simulation model." *MCEER Technical Rep. 03-0005*, Multidisciplinary Center for Earthquake Engineering Research, Buffalo, NY.

Miles, S. B., and Chang, S. E. (2004). "Foundations for modeling community recovery from earthquake disasters." *Proc., 13th World Conf. on Earthquake Engineering*, Vancouver, Canada.

Miles, S. B., and Chang, S. E. (2011). "ResilUS: A community based disaster resilience model." *Cartogr. Geogr. Inf. Sci.*, 38, 36–51.

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

Mississippi Automated Resource Information System. (2015) ⟨http://www .maris.state.ms.us/⟩.

Mississippi Development Authority. (2015). "Mississippi disaster recovery division." ⟨http://www.msdisasterrecovery.com/federal-reporting⟩ (Feb. 26, 2015).

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.*, 10.1061/(ASCE)CP.1943-5487.0000482, 04015012.

National Agricultural Statistics Service. (2015). "U.S. Department of Agriculture." ⟨https://www.nass.usda.gov/⟩.

National Disaster Recovery Framework. (2011). "National Disaster Recovery Framework, Strengthening Disaster Recovery for the Nation." Federal Emergency Management Agency (FEMA), Washington, DC.

National Land Cover Database. (2015). "Multi-resolution land characteristics consortium." U.S. Dept. of the Interior ⟨http://www.mrlc.gov/⟩.

Nejat, A., and Damnjanovic, I. (2012). "Agent-based modeling of behavioral housing recovery following disasters." *Comput.-Aided Civ. Infrastruct. Eng.*, 27(10), 748–763.

Nelson, D. R., Adger, W. N., and Brown, K. (2007). "Adaptation to environmental change: Contributions of a resilience framework." *Annu. Rev. Environ. Resour.*, 32(1), 395–419.

NetBeans IDE 7.4. [Computer software]. Sun Microsystems, Santa Clara, CA.

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

Olshansky, R. B., Hopkins, L. D., and Johnson, L. A. (2012). "Disaster and recovery: Processes compressed in time." *Nat. Hazards Rev.*, 10.1061/(ASCE)NH.1527-6996.0000077, 173–178.

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, Chichester, U.K.

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

Pradhan, A., Laefer, D., and Rasdorf, W. (2007). "Infrastructure management information system framework requirements for disasters." *J. Comput. Civ. Eng.*, 10.1061/(ASCE)0887-3801(2007)21:2(90), 90–101.

Pratt, C. R., Kaly, U. L., and Mitchell, J. (2004). "Manual: How to use the environmental vulnerability index (EVI)." *SOPAC Technical Rep. No. 383*, United Nations Environment Programme (UNEP), South Pacific Applied Geoscience Commission (SOPAC), Suva, Fiji Islands.

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

Schelling, T. C (1978). "Micromotives and macrobehavior." W. W. Norton & Company, NY.

Schwab, J. (1998). "Planning for post disaster recovery and reconstruction." *PAS Rep. No. 483/484*, American Planning Association, Chicago.

Siche, J. R., Agostinho, F., Ortega, E., and Romeiro, A. (2008). "Sustainability of nations by indices: Comparative study between environmental sustainability index, ecological footprint and the energy performance indices." *Ecol. Econ.*, 66(4), 628–637.

Smith, G., and Wenger, D. (2007). "Sustainable disaster recovery: Operationalizing an existing agenda." *Chapter 14, 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." *Technical Rep. Series*, Dept. of Computer Science, George Mason Univ., Fairfax, VA.

Villa, F., and McLeod, H. (2002). "Environmental vulnerability indicators for environmental planning and decision-making: Guidelines and applications." *Environ. Manage.*, 29(3), 335–348.

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.

Wackernagel, M., and Rees, W. E. (1997). "Perceptual and structural barriers to investing in natural capital: Economics from an ecological footprint perspective." *Ecol. Econ.*, 20(1), 3–24.

Yin, L. (2013). "Assessing walkability in the City of Buffalo: Application of agent-based simulation." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000147, 166–175.

Zhao, L., and Peng, Z.-R. (2015). "LandSys II: Agent-based land use-forecast model with artificial neural networks and multiagent model." *J. Urban Plann. Dev.*, 141(4), 04014045.

Zhu, W. (2015). "Agent-based simulation and modeling of retail center systems." *J. Urban Plann. Dev.*, 142(1), 04015004.

© ASCE

04016022-17

J. Urban Plann. Dev.