Sustainable Disaster Recovery Decision-Making Support Tool: Integrating Economic Vulnerability into the Objective Functions of the Associated Stakeholders

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Abstract: Natural disasters affect the built environment's infrastructure and disturb the economic sector's sustainability and welfare. This requires a disaster recovery decision support tool that capitalizes on the redevelopment opportunities to elevate societies to a more-sustainable and less-vulnerable status. As such, this paper presents an agent-based model approach that aims to meet the objectives of stakeholders while decreasing the community's economic vulnerability. Accordingly, the proposed model adopts a five-step research methodology: (1) implementing a comprehensive economic vulnerability assessment tool; (2) developing the objective functions and learning algorithms of the associated stakeholders; (3) modeling the different attributes and potential strategies of the various stakeholders; (4) creating an interdependent agent based model that simulates the aforementioned information; and (5) interpreting and analyzing the results generated from the developed model. The model is developed and tested on the post-Katrina residential housing and economic financial recovery in three Mississippi coastal counties. The model proposed an evolving optimal budget distribution that decreased the economic vulnerability and increased the residential and economic recovery. Ultimately, the holistic framework utilized in this study lays down the foundation for a new generation of interdisciplinary managerial decision-making support tools. **DOI: 10.1061/(ASCE)ME.1943-5479.0000487.**

Introduction

Disaster recovery is considered the restoration and repair of a damaged built environment to its predisaster conditions. However, compared to disaster preparedness, mitigation, and response, disaster recovery is considered the least-understood aspect of the emergency management processes (Smith and Wenger 2007; Berke et al. 1993). This is compounded with the fact that sustainable disaster recovery requires the nonlinear participation of different stakeholders (Smith and Winger 2007). Moreover, disaster recovery is not always achieved uniformly across different stakeholders and does not follow a clearly observable path (Sullivan 2003).

To this effect, recent studies have been conducted to understand and highlight the factors that affect the sustainable disaster recovery processes. Boz and El-adaway (2014) and Boz et al. (2014) pointed out that the participation of different stakeholders in the redevelopment planning and execution phases increases the individual utility of the participating entities. Moreover, communication between the recovery agencies, system users, and various stakeholders increases the recovery rate and quality of the outcome product as well as enhance the resilience of the host community (Chang and Rose 2012; Olshansky et al. 2006). Consequently, recent sustainable disaster recovery studies suggest that participation of the different stakeholders in both the planning and implementation phases is needed to achieve successful disaster recovery for the host community (Haimes 2012; Smith and Wenger 2007; Olshansky et al. 2006).

Furthermore, the goal of a sustainable disaster recovery process is not merely to restore the systems' functionality, but also to decrease the impacted region's vulnerability to future hazardous events (Eid and El-adaway 2016). As such, several studies have been carried out to investigate and quantify communities' resilience and vulnerability to hazards (Burton 2012; Cutter et al. 2003; Rose 2007). Various economic vulnerability assessment models were developed to evaluate countries' and cities' vulnerability and resilience to natural hazards and perturbations. Those models fall into one of two categories: (1) macroeconomics vulnerability to hazards, which focuses on the aggregated economics of a region [gross domestic product (GDP) and inflation rate, etc.], and (2) microeconomic vulnerability, which addresses the individuals' and communities' risk (per capita income, percentage of employment in nonprimary industry, and number of retail centers, etc.).

Recently, various recovery frameworks were developed to better guide and optimize the host community's recovery process. These models utilized evolutionary algorithms for multihazard project reconstruction (Flint et al. 2016), mixed integer linear programming for postdisaster recovery for transportation projects (El-Anwar et al. 2016), genetic algorithms for housing and infrastructure recovery (El-Anwar et al. 2010; Orabi et al. 2010), geographic information systems (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). Nevertheless, 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, even though they might be computationally efficient, do not take into account the stakeholders'

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preferences and needs, which is essential for a successful and sustainable disaster recovery process.

On the other hand, to the authors' knowledge, few attempts have been made to better understand and guide recovery efforts utilizing agent-based modeling (ABM). ABM is considered to provide a significant basis for proactive application in disaster recovery (Fiedrich and Burghardt 2007). This can be carried out through a dynamic simulation that captures the different needs and preferences of associated stakeholders in the impacted host community (Nejat and Damnjanovi 2012). This goes in line with the need to integrate the different stakeholders in disaster recovery decision-making processes.

Current Research Direction

The literature reviewed in the preceding section, which are discussed further in later sections, indicate that there is a knowledge gap between the recommendations of the multidisciplinary disaster recovery research and the associated recovery tools. As such, the current research direction is to bridge this gap through an innovative and transformable decision-making framework. Thus, this research tackles the need for assimilating the participating entities in the decision-making processes, in addition to achieving sustainable disaster recovery through decreasing the built environment's vulnerability.

Goal and Objectives

The goal of this paper is to present a sustainable disaster recovery decision support tool that can better guide the redevelopment efforts to increase societies' welfare. This will be achieved through decreasing the vulnerability of the built environment and increasing the individual utility of the participating entities. To this effect, this paper adopts an agent-based approach that integrates a community-level economic vulnerability assessment tool into the objective functions of the associated stakeholders. Consequently, this approach will help in better understanding the effects of the different recovery strategies on the economic vulnerability of the host communities. Ultimately, this tool will be able to highlight the restoration action plans that capitalize on the redevelopment opportunities in order to elevate the societies to a more-sustainable and less-vulnerable status.

Background Information

Economic Vulnerability to Disaster

Host communities' vulnerability and resilience has been intensively researched through the decades. The definitions have varied depending on the field of study: social, economic, or environmental. In the economic field, vulnerability is considered as "the exposure of an economy to exogenous shocks, arising out of economic openness" (Briguglio et al. 2009). Guillaumont (2009) also defined economic vulnerability as "the risk that economic growth is reduced markedly and extensively by shocks." To this effect, economic vulnerability has two dimensions: inherent (i.e., a community's market conditions and available resources); and exogenous (shocks from natural disasters or global market conditions). Resilience, from the economic perspective, is considered in general as the ability to absorb and cushion against shocks, damages, stresses, and losses (Rose 2004; Holling 1973). For example, microeconomics resilience is defined as "inherent ability and adaptive response that enables firms to avoid maximum potential losses" (Rose 2004). Thus, economic resilience has two dimensions: (1) inherent ability, which is the ability under normal circumstance to deal with exogenous shocks; and (2) adaptive response, which is the ability in crisis to cope due to ingenuity and exerting extra efforts (Rose and Liao 2005).

To this end, due to the close relationship between vulnerability and resilience, the notion that the two terms are opposite to each other is significantly promoted (Cutter et al. 2003). This research, however, adopts a widely recognized approach where vulnerability and resilience are neither totally mutually exclusive nor totally mutually inclusive. That is to say, some properties of resilience are seen as being shared with vulnerability and vice versa. Most inherent properties of the host community are considered as the overlapping part between resilience and vulnerability. These inherent properties 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 properties that would increase resilience and decrease vulnerability to future shocks.

To this effect, different types of economic vulnerability assessment models were developed in the last decade. Those models can be categorized as follows:

- Macroeconomics, where the indicators assess the economic vulnerability of countries to perturbations based on gross and aggregated data [gross domestic product (GDP), gross international trade, etc.). This category includes, the Economic Vulnerability Index for Small Islands, Economic Resilience for the Organization for Economic Co-Operation and Development (OCED) countries, and Economic Vulnerability Index for Least-Developed Countries (Röhn et al. 2015; Briguglio et al. 2009; Guillaumont 2009; Briguglio 1995); and
- Microeconomics and mesoeconomics, which focus on the economic vulnerability of individuals, firms, and industries within a specific region (Rose 2009; Rose and Liao 2005). One notable indicator in this category is a community-level economic vulnerability assessment based on statistical analysis on the community specific data in regard to natural disaster introduced by Burton (2010).

The current research approach adopts the latter category as it can represent the economic vulnerability of different stakeholders to natural hazard based on their community-specific data. Nevertheless, quantifying economic vulnerability and resilience has confronted researchers with difficulties in the last decade (Rose and Liao 2005). This is due to the following issues: (1) at the conceptual level, decision makers need to identify generalized resilient actions that sometimes do not seem feasible given that each region is unique with different inherent resilience and vulnerability properties; (2) at the operational level, it is difficult to model the different individuals, groups and community in the same single framework, which this research is attempting to achieve; and (3) at the empirical level, data are not always available or easy to gather to properly address the economic vulnerability and resiliency of the community.

Moreover, different actions and redevelopment processes affect the economic vulnerability of the host communities. Through historical data, Chandra and Thompson (2000) pointed out the impact of the infrastructure development and recovery on industries and the spatial allocation of economic activities. The infrastructure development in one county would increase the economic activities and raise the economic sector earning by 5–8% in the service and retail sectors. However, such increase in earnings within the county might draw economic activities from adjacent counties. Furthermore, Cohen et al. (2012) addressed the monetary impact of building development on different economic sectors. For example, every $1.00 spent on residential single and multifamily structures will impact the retail trade sector by $0.0912 in revenue. Thus, the residential housing recovery and redevelopment plans would impact the different economic sectors' revenue, and eventually, the host community's economic vulnerability.

Sustainable Disaster Recovery and Stakeholder Interactions

Ferdinand and Yu (2016) pointed out that the slow progress in redevelopment projects were due to lack of a clear framework between different stakeholders. To this effect, the U.S. government proposed the National Disaster Recovery Framework (NDRF 2011) to increase disaster recovery progress effectiveness and efficiency. The NDRF indicates the needs and roles of different stakeholders through and after a disastrous event. The NDRF presented 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 at the very beginning of a disaster recovery. The FDRC is mainly activated when the disaster exceeds the SDRC's capabilities. The SDRC oversees the disaster recovery process, sets priorities, and directs necessary assistance and funds. Thus, the SDRC's role is pivotal throughout the recovery process. Finally, LDRMs play a primary role in managing and communicating with residents and businesses in the affected region.

Preparedness of communities significantly impacts the recovery rate of the host community (Cutter et al. 2006; Smith and Wenger 2007; Olshansky et al. 2006). As such, the impact of the insurance policies purchased by residents and/or subsidized by the government plays an important role in the recovery rate in previous disastrous events. The National Disaster Recovery Framework (2011) indicated the significance and importance of adequate insurances for the households to achieve a successful recovery. To this effect, understanding the complex relationship between the communities' stakeholders and optimizing their disaster strategies and plans is essential to achieve a sustainable disaster recovery that would increase the host community's welfare, meet the needs of the society, and decrease their vulnerability to future shocks (Eid and El-adaway 2016).

Meanwhile, in order to understand the various factors and strategies affecting the recovery processes, Olshansky et al. (2006), Olshansky (2006), and Cutter et al. (2006) studied and analyzed several historical disaster events. It can be understood through their studies the patterns of successful recovery of key items, the relationship among the different stakeholders in the recovery process in addition to the government, and residents' commonly used strategies. The local governments' interaction with 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). To this effect, higher approval rates were achieved by the plans that had been negotiated and discussed with the residents in the impacted regions that eventually increased the welfare of host communities.

Furthermore, commonly used government disaster recovery plans have included offering financial compensation; repairing damaged infrastructure; rebuilding destroyed infrastructure; upgrading the affected infrastructure, and changing land use so as to decrease the host community's vulnerability to future hazards (Olshansky et al. 2006; Cutter et al. 2006). On the other hand, residents' strategies focus on (1) repairing 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, damage exerted by the disastrous events, available government recovery plans, social ties of the resident to the community and their outside options (Olshansky 2006). This points out the complexity and nonlinearity in the recovery process.

In order to understand and better guide the recovery efforts, different models were developed. However, few ABM attempts were carried out. The most recognized models were developed by Miles and Chang (2003, 2011) and Chang and Miles (2004). The developed models captured the interaction between the socioeconomic agents (residents and businesses) and the community planning after a disastrous event. Also the models were developed to allow for estimation of damages incurred by the community (built environment, economic, and personal). Nejat and Damnjanovic (2012) also presented a multiagent-based model with a game theory approach for the recovery of the residential households. 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 bounded rationality of the different agents. Nevertheless, the aforementioned attempts neither integrated the host community's vulnerability assessment into the model nor provided a decision support tool for future disaster events (Eid and El-adaway 2016).

To this effect, and in order to lay the foundation for the proposed model, the following section briefly discusses agent-based modeling's history and concept as well as several learning modules utilized in this research.

Agent-Based Modeling

Following the publication of *Micromotives and macrobehavior* (Schelling 1978) various researches have been carried out to investigate different individuals' behaviors and attributes and how collectively they comprise 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—that represent the different stakeholders—in order to evaluate system performance due to interactions among the agents. Furthermore,

> ABM provides 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 (Macy and Willer 2002).

ABM allows for capturing the fine grains of the systems through building it in a root-to-grass methodology. ABM has been adopted and utilized in studying real-life applications in sociology, economics, engineering, biology, agriculture, and many other fields explaining and modeling of different problems like social norms, emergence of collective behavior, civil violence, the standing-ovation problem, livestock farmers' performance, analysis of construction dispute resolution, dynamics of construction projects, collaborative negotiations, highway transportation infrastructure systems, humanitarian aid, etc. (Eid and El-adaway 2016; Mostafavi et al. 2015; Zheng et al. 2013; Crooks and Wise 2013; Du and El-Gafy 2012; El-Adaway and Kandil 2010;

Miller and Page 2004; Epstein 2002, 2001; Peña-Mora and Chun-Yi 1998; Axelrod 1986).

Agent behavior is considered to follow three assumptions (Macy and Willer 2002):

- Agents are interdependent: Agents interact and affect each other, and agents influence each other in the response they receive from others' influences;
- 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
- 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, and learns from failures as well as being able to interact with other agents.

To this effect, different learning models have been introduced to create informed and complex agents that are able 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 human complex 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 learns 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 utilization probabilities of the actions as a result of the current state. On the other hand, anticipatory learning is 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, psychology, and mathematics, different learning models were introduced including: heuristic learning, Bayesian learning, Roth-Erev, modified Roth-Erev, Markov hidden process (MHP), Q-learning, particle swarm, genetic algorithms, derivative follower algorithms, etc.

Methodology

To achieve the aforementioned goal and objectives, the authors developed a five step research methodology that entails (1) implementing a comprehensive community-level economic vulnerability assessment tool based on the community's specific data; (2) developing the objective functions and learning algorithms of the associated stakeholders; (3) modeling the different attributes and potential strategies associated with the different stakeholders; (4) creating an interdependent agent-based model that simulates the aforementioned information; and finally (5) interpreting and analyzing the results generated from the developed model.

Data Gathering

In order to attain the aforementioned methodology, the authors gathered five different data sets in regard to post-Katrina disaster recovery in three Mississippi coastal counties, namely Hancock, Harrison, and Jackson counties, which are shown in Fig. 1.

The aforementioned counties serve as the model's problem domain as all three 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 were as follows:

- In order to develop the model to the preexisting conditions and generate the initial population, ex-Katrina socioeconomic data for the three aforementioned counties were collected. The socioeconomic data were collected from the U.S. Census Bureau for each of the 78 census tracts across the three counties (U.S. Census 2000, 2009, 2010, 2011, 2012).
- The economic data required to evaluate economic vulnerability of the three counties were gathered on a census-tract level through (1) ReferenceUSA (2010, 2011, 2012), and (2) U.S. Census Bureau (2000, 2009, 2010, 2011, 2012), for the years from 2000 to 2012. The data gathered allowed the model to be initiated for ex-Katrina conditions as well as post-Katrina comparison purposes.
- Hurricane Katrina's impact data in regard to the three counties were gathered via the Hazards U.S. Multi-Hazard (*HAZUS-MH*) software. This was achieved through a Level 1 analysis

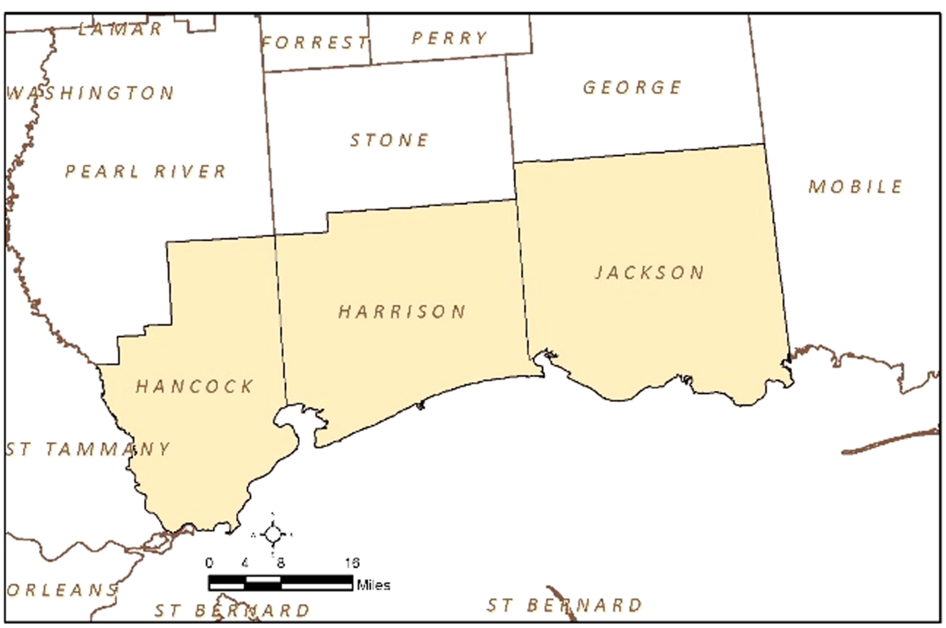

Fig. 1. Problem domain: Mississippi coastal counties

(basic losses estimates based on national databases), and accounting for direct damages on building structures (residential and businesses) as well as induced physical damages from debris on each of the 78 census tracts. *HAZUS-MH* enables for simulating past historical events like Hurricane Katrina through wind gusts, surges, and floods based on storm parameters of the hurricane, which are embedded in *HAZUS-MH* databases. To this end, *HAZUS-MH* provided damages proportions (none, minor, moderate, severe, and destruction) for each census tract, which was in return distributed among the corresponding agents. Moreover, the model also utilized the available historical data (1953–2012) from the Mississippi Emergency Management Agency (MEMA 2014) related to tornados impacting the three aforementioned counties. Through utilizing data points on the 155 tornado event occurrence, and magnitude (based on the Fujita scale), probability density functions were developed to create a tornado hazard micromodule. To this end, the micromodule was integrated into the current ABM to better simulate the agents' decisions in the presence of new and recurrent shocks post-Katrina. Such recurrent hazardous events will change the utilized insurance policies by the residents, the budget distribution by the State Disaster Recovery Agencies, etc.

- In 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 to 2012 (MDA 2015). To this end, a set of action plans followed by the SDRC was determined for the housing sector's 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, rebuild, and relocation financial funding to damaged privately owned households; (2) public home assistance, which essentially targeted low-income families so as to rebuild damaged buildings and house them; and (3) elevation grants, which is an upgrade to elevate the household up to 6 ft, and 4 in., thus making the households' more flood resilient. Furthermore, 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 (MDA 2015).
- The MDA and MRD utilized multiple of infrastructure projects that impacted the economic sector recovery. Nevertheless, only one plan was directly assigned to the businesses in the impacted region; small business loans guaranty program (SBLGP). The SBLGP plan provides capital for small businesses through providing loans through banks (MDA-FRD 2015). This plan provides small businesses (250 or less full time employees and less than $7,000,000 gross revenue) a minimum loan of $50,000 to a maximum of $500,000 for expansion, recovery or renovation. Thus, this plan increased the recovery rate of the impacted businesses and incentivized them to stay in the impacted region.

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 literature, the utilized learning modules best depict the learning behaviors of rationally-bounded agents through their experience. To this effect, it is assumed that, in the context of a disastrous event, the objective of the resident and economic agents is to maintain and increase their wealth. Meanwhile, the objectives of disaster recovery agencies are to (1) increase the community welfare, and (2) decrease built economic vulnerability, as shown in a later section. Moreover, the proposed agent-based model assumes rationality of the different stakeholders. Thus no agent—resident, economic, government or insurance—will take any action or follow any strategy that would decreases its utility value. Furthermore, in regard to the residential agents' social learning module, agents are assumed to have complete information about the current objective-function values of other residents and be able to determine the best of them.

Regarding the impact of different disaster recovery plans on the associated agents and economic vulnerability index, it is assumed that each plan will affect the stakeholders who applied for it. That is to say, residents applying for recovery plans will have faster redevelopment progress and higher objective-function values than other residents who did not apply. Meanwhile, the residential recovery plans affect the economic sector's revenue and eventually the community's economic vulnerability. The impact of residential recovery and redevelopment on the economic sector revenue follows Cohen et al.'s (2012) data, where homeowner assistance, public home assistance, and elevation grants provide for $0.05, $0.0912, and $0.0912, respectively, for each $1.00 spent in recovery.

Comprehensive Economic Vulnerability Assessment Tool

The proposed model adopts the economic vulnerability and resilience metrics developed by Burton (2010). The model is part of a multidimensional vulnerability assessment metric that is developed using community-specific data. The model was developed and validated on three coastal Mississippi counties (Hancock, Harrison, and Jackson) for the post-Katrina recovery process (Burton 2015). The model is able to measure and evaluate the built environment microeconomic and mesoeconomic vulnerability to hazards based on the community-specific data. To this end, and following the Burton model's methodology, this Economic Vulnerability Index (EconVI) was developed through gathering 11 economic variables on the census-tract level for the 78 census tracts across the three counties. Those variables are summarized in Table 1, along with their category and sources.

In order to evaluate the variables across the different census tracts, a statistical dimension-reduction technique is utilized, namely factor analysis (FA). First, the collected variables were transformed into comparable scales (per capita, percentage, or density functions). Then, using the Min-Max rescaling method, the data were standardized across the different census tracts per variable between 0 and 1, where 1 is the best value and 0 is worst value. Finally, through utilizing FA, the standardized variables can be reduced to a number of factors that summarizes the different variables and measures the latent variable (economic vulnerability). Moreover, and more importantly, this will allow for calculating a relative economic vulnerability index based on the data collected and the factor loadings. The scores are attained through a simple additive model for the factors' scores per census tract.

Even though the interpretation of the factors produced from FA is subjective (Yang and Bozdogan 2011), this relative vulnerability scoring approach nominates the EconVI to be integrated into the disaster recovery decision support tools in order to allocate redevelopment funds depending on the relative vulnerability of the different regions affected by the natural disaster.

Table 1. Economic Vulnerability Variables

Variable	Category
Percentage of home ownership[a]	Microeconomics
Percentage of working age population that is employed[a]	Microeconomics
Percentage of female labor force participation[a]	Microeconomics
Per capita household income[a]	Microeconomics
Percentage of population not employed in primary industries[a]	Microeconomics and mesoeconomics
Mean sales volume of business[b]	Mesoeconomics
Ratio of large to small businesses[b]	Mesoeconomics
Retail centers per 1,000 population[b]	Mesoeconomics
Commercial establishments per 1,000 population[b]	Mesoeconomics
Lending institutions per 1,000 population[b]	Mesoeconomics
Doctors and medical professionals per 1,000 population[b]	Mesoeconomics

[a]U.S. Census (2000, 2009, 2010, 2011, 2012).
[b]ReferenceUSA (2000, 2009, 2010, 2011, 2012).

Stakeholder Interaction Overview

The proposed agent-based model represents the residents of the impacted community, the economic sector, and the insurance companies offering different disaster recovery plans. In addition, the model presents the associated Local Disaster Recovery Management (LDRM), State Disaster Recovery Coordinator (SDRC), and Federal Disaster Recovery Coordinator (FDRC) following the National Disaster Recovery Framework (2011) methodology. The aforementioned agents all have their own decision actions, strategies, and objective functions. However, the scope of this paper is limited to the residents, economic sector, and SDRC, leaving optimization of the insurance companies, LDRM, and the FDRC strategies for future works. Moreover, regarding the economic sector, the proposed model focuses on the retail industry. Nevertheless, the model can be implemented on various other industries and services, e.g., manufacturing, construction, healthcare, etc.

Fig. 2 presents the model overview, illustrating the modeled host community that integrates the different agents, namely residents, economic, insurance companies, and disaster recovery agencies. The model takes as inputs the antecedent conditions of the host community, which include population size, income level per household, education per household, household median value per region, economic vulnerability per census tract, etc. This allows the model to generate the initial conditions based on the actual data. The model also takes as an input the economic status of the host community as this affects the aforementioned economic vulnerability assessment model; these aspects include percentage of homeownership, mean sales volume, retail centers per 1,000 of population, etc. Thus, the model is able to assess society's economic vulnerability through the agents' interaction. The model then takes into account the disaster event and its effect on the built environment. The agent-based model then allows for the different agents to interact, choose their strategies, optimize, and report their recovery progress along with changes in vulnerability. This bottom-up culture-dish approach enables the model to capture the stakeholders' interactions and how they collectively evolve, affect, and are affected by the disaster recovery process.

Fig. 3 illustrates the agents' interactions, which is discussed in detail through the following subsections. After a disastrous event, each resident and economic agent checks the damages incurred by the household or store and assesses if repair is required. The agents at this point determine if they need to apply for assistance from the LDRM. Also, the agents determine the compensation amount received from the insurance policy, if one had been previously purchased. Furthermore, the agents consider repairing their damaged structures or leaving the impacted region. Meanwhile, the SDRC offers different disaster recovery action plans. The plans are then transmitted to the LDRMs, which are in direct contact with the local residents and businesses. LDRMs propose the SDRC's action plans to the different agents so that they would choose one that will increase their objective functions. Moreover, the LDRMs both check the agents' applications for approval as well as manage the recovery and redevelopment process (National Disaster Recovery Framework 2011). Meanwhile, the SDRC manages and funds the redevelopment and recovery plans that aims to (1) increase the host community overall welfare and (2) decrease the built environment's vulnerability. The FDRC allocates the required funding for the SDRC's disaster recovery plans. The SDRC reports back on the recovery's progress to the FDRC. Finally, the insurers offer different disaster recovery insurance policies to the host community's residents and business owners. The agents thus choose the appropriate policy, pay the premiums, and receive compensation if

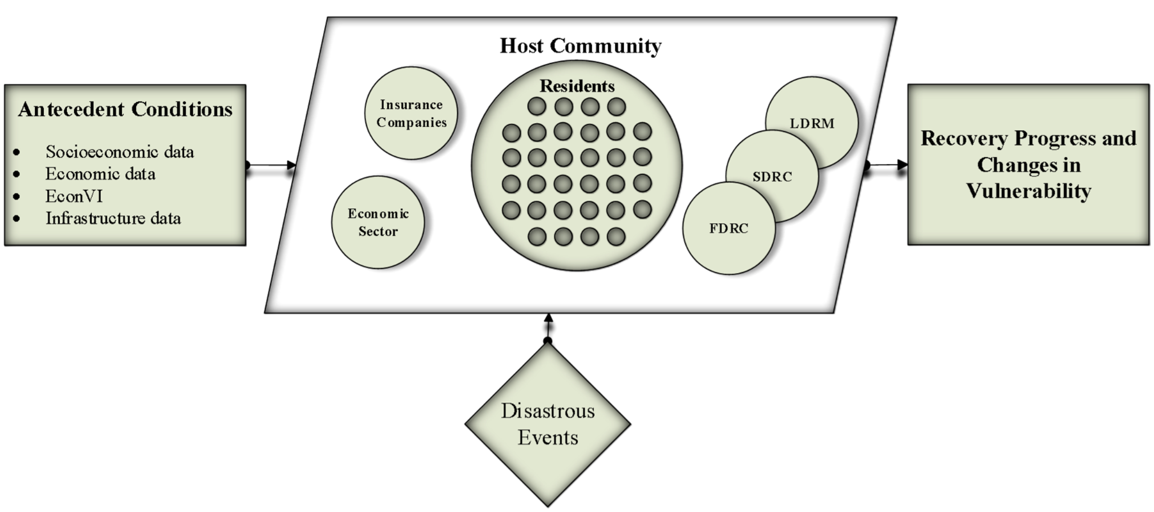

Fig. 2. Model overview

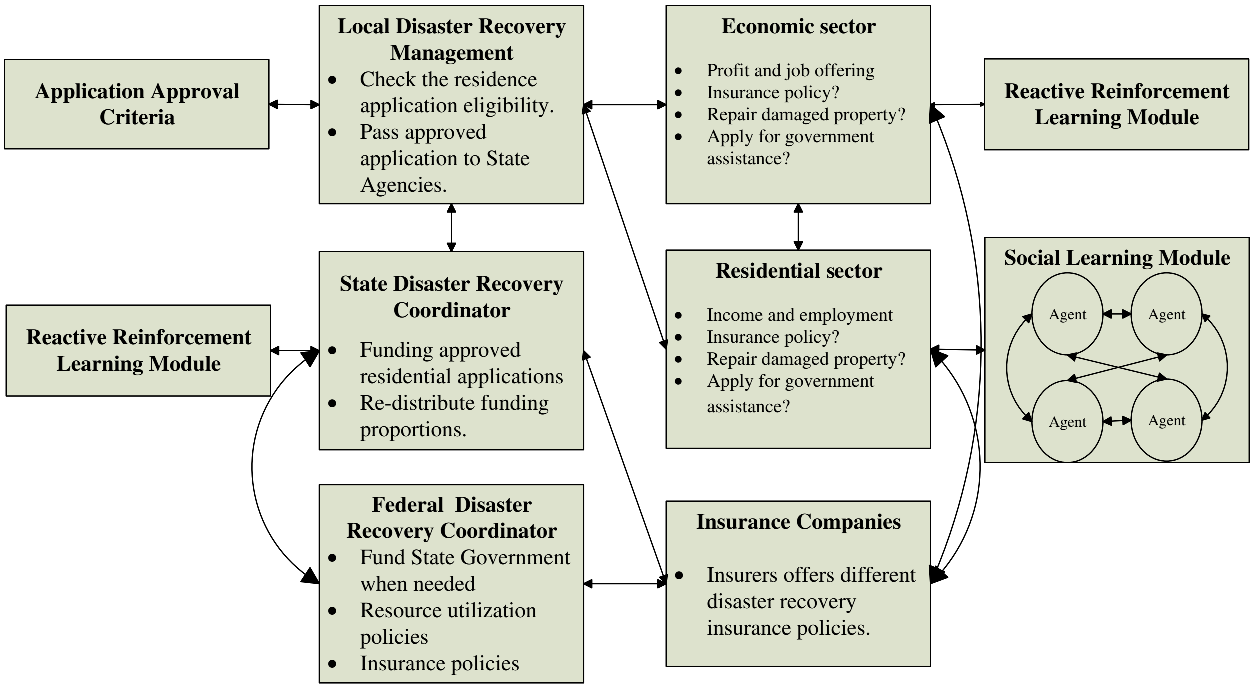

Fig. 3. Model overall: agents' interactions

a disaster occurs. The resident agents also get to decide if the current insurance policies are optimal or need to be changed to better cope after future shocks.

Modeling the Objectives, Strategies, and Learning Behaviors of the Associated Stakeholders

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 as shown in Eq. (1):

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

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

The residents' actions are constrained by their net income (difference between the monthly income and monthly living costs). According to the Federal Highway Administration (2014), the average household's monthly living cost does not exceed 45% of the household's income. Thus, a resident's expenses (T, P, and R) should not exceed the monthly net income as shown in Eq. (2):

$$T_i + P_{i(n,m)} + R_i \leq 0.55 I_i \tag{2}$$

As such, the resident has two strategies to optimize: (1) purchasing insurance policy or refrain from buying any, and (2) repairing the damaged household or leave the impacted region, thus not repairing the damaged household. For the first strategy, residents tend to communicate with each other to learn which insurance policy increases the other residents' utility functions in order to maximize their objective functions. On the other hand, the resident needs to learn through experience which disaster recovery plan should be applied for and how much they should invest to repair the damaged household. To this end, the authors investigated different learning techniques to be used for the resident agents as well as for the SDRC, as shown later on. The techniques investigated varied across the individual reinforced learning and social evolutionary learning techniques, e.g., Roth-Erev reactive learning (RL), derivative-follower, genetic algorithms, particle swarm, ant colony, Q-learning, Bayesian learning, Markov hidden process, and heuristic learning.

Particle swarm (PS) was utilized for the residents' social learning module to determine the optimum insurance plan to be purchased. PS was developed by Kennedy and Enerhart (1995) and is inspired by the migration of flocks of birds and their attempts to reach an unknown destination (Elbeltagi et al. 2005). PS is an evolutionary algorithm based on stochastic searches that mimic the social behavior of species (Elbeltagi 2013). Through collective decentralized behavior, the system can self-organize and optimize its actions to increase individuals' utility. To this effect, residents in the proposed model utilize memetic particle swarm (MPS), which was developed based on Dawkins' notion of memes (Dawkins 1976). Through this approach, each particle represents an agent who is allowed to observe surrounding agents, in a form of local search, to determine the best-fit among its peers. This will allow it to evolve through mimicking the best agent. Moreover, through mutation, new solutions can be derived that might affect the population's collective optimal output. To this end, MPS does not evolve through creating new particles as in genetic algorithms, but rather through changing individuals' social behavior and consequently moving to a better state (Elbeltagi et al. 2005). Thus, it is able to represent the social learning behavior of residents within an impacted region. PS has demonstrated its outstanding performance in social learning through different optimization and simulation models (Cheng and Jin 2015; De Oca et al. 2011)

Meanwhile, as previously mentioned, in order for resident agents to obtain government recovery funds, they should apply for assistance through the LDRMs. LDRMs act as communicators between the SDRC and local residents. Moreover, it is the LDRMs' duty to assess the submitted recovery assistance applications by the residents, only accepting those that comply with some predefined criteria, as shown in Fig. 3. To this effect, the resident agent applies for the SDRC's disaster recovery plan that maximizes the resident's utility functions as shown Eq. (3):

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

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 subsequently.

A resident's choice from among the different offered plans depends on the maximum expected utility function obtained across the different plans. However, in case the LDRM denying the resident's application either for not meeting the criteria or due to insufficient funding by the SDRC for the selected plan, the resident agent should learn to choose a different plan in the succeeding steps. Thus, residents require an individual learning model 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. The Roth-Erev reactive reinforced learning model is able to capture the repetitive game between LDRMs and residents in addition to taking into account the experience gained through the different attempts. Roth-Erev reactive reinforcement learning model was introduced in the 1990s as a game theory approach to model the learning behaviors of players based on experiments and observations (Erev and Roth 1998). The algorithm first determines which decision action has been used and the associated immediate reward (positive or negative) by applying the following selected decision action given in Eq. (4):

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

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. (5) and (6), respectively:

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

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

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

Both ϕ and ε allow the model to capture the human behavior in the trade-off between information exploration versus information exploitation (Sun and Tesfatsion 2007). Thus, the Roth-Erev learning module can demonstrate the individual learning process through experience and experimenting with the different strategies, thus weakening the poor outcome strategies and strengthening the most rewarding strategies' probabilities. However, the agents' decision-making processes are sensitive to the values of ϕ and ε (Nallur et al. 2016). As such, the authors investigated the literature utilizing the Roth-Erev learning model in order to identify the commonly utilized values for the aforementioned parameters (Nallur et al. 2016; Radhakrishnan et al. 2015; Trinh et al. 2013; Sun and Tesfatsion 2007). As such, the values of ϕ and ε were found to range between 0.5–0.5 and 0.95–0.05 for ϕ and ε, respectively. To this effect, after various experimentations and analyses, the authors utilized values of 0.85 and 0.15 for ϕ and ε, respectively.

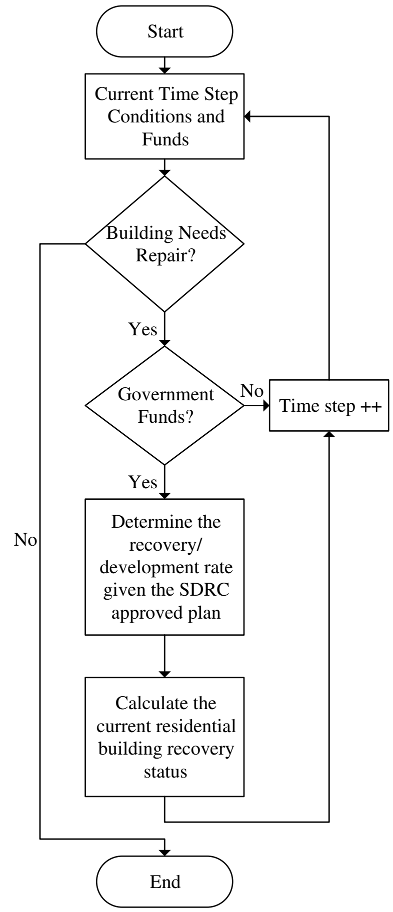

Fig. 4. Residential recovery module

Residents Recovery Progress. Utilizing the data gathered from MDA and MRD, the average recovery rate was calculated for each of the aforementioned SDRC plans, namely homeowner assistance, public home assistance, and elevation grants. Thus, if the resident was granted government funds, the recovery module calculates the rate corresponding to the funded plan and the recovery process takes place as shown in Fig. 4.

Finally, each LDRM checks for the current redevelopment progress of the local residents by (1) calculating the residents' initial households' values through Eq. (7) at the initial time step; (2) determining the current changes in recovery and redevelopment progress through Eq. (8) at each time step; and (3) reporting the overall redevelopment progress of the residents through Eq. (9)

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

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

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

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

Economic Sector

The economic sector serves the host community to which it belongs. This is manifested in offering job opportunities and providing goods and services to the residents as well as paying state and federal taxes. Like any stakeholder, the economic sector is affected by disasters and the recovery processes. The disasters affect the economic sector through (1) damaging the physical structure, which renders it incapable to serve the community and, in return, making a profit, and (2) decreasing the community's purchasing power as they are focused on the recovery processes. To this effect, the economic agent in the proposed model depicts the privately owned retail trade centers within the impacted region. The economic agent represents how the disaster and its recovery affects the economic sector's revenue, which in returns affects the community's livelihood, taxes collected, and the overall built environment's economic vulnerability. Even though the model can address different industries and services, it was found to be best to focus on one industry and reserve the other economic branches for a further study.

The economic agent's revenue is dependent on the residents' frequency of purchasing goods and or services. Also, the revenue is affected by the percentage of income spent on such goods or service by residents (Zhu 2016). To this end, the proposed model considers residents as the main driving agents in this resident/economic sector interaction. Accordingly, the economic sector is considered myopic in regard to strategies that increase their revenues. To this end, the residents' purchasing power, purchasing frequency, and expenditure ratio for each product or service determine the monthly revenue for the economic retail sector.

To this effect, as shown in Eq. (10), Freq_d demonstrates the residents purchase frequency for each product d, where the frequency takes as positive value between 0 and 1. For example, food and grocery will have a higher frequency than construction materials. Meanwhile, Eq. (11) illustrates the expenditure E by the residents per product or service d, which is governed by the ratio of the income spent on such product or service. This ratio is denoted as γ, where γ takes a positive value between 0 and 1. Such values are obtained from the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics 2014). Thus, the economic sector's revenue will be the difference between the total residents' expenditure for such product or service per month and the cost to provide such product or service CT_d, as shown in Eq. (12)

$$\mathrm{Freq}_d = [0, 1] \quad \forall\ d \in D \tag{10}$$

$$E_{i_d} = I_i \times \gamma_d \quad \forall\ d \in D, \quad \forall\ i \in I \tag{11}$$

$$\mathrm{Revenue}_d = \sum_i^I E_{i_d} - CT_d \quad \forall\ d \in D \tag{12}$$

Economic Sector Recovery and Sellout Option. The proposed model takes into account the disaster's impact on the physical structure of the economic sector depending on the location and proximity to the hazardous event. The physical damage might leave the economic agent unable to provide the community with goods and services. Thus, at each time step, if the physical recovery reached a preset threshold, the economic agent can start offering the services; otherwise, the agent will remain incapable to serve the residents or pay taxes. To this effect, at each time step, the economic agent will determine whether to stay and recover, or sell out and leave the impacted region, as shown in Fig. 5. This decision depends on (1) the disaster's magnitude and its impact on the physical structure, (2) the insurance policy's compensation, and (3) the government's recovery funds, if any.

In order to decide whether to recover from the disaster impact or leave the community, the economic agent determines the recovery cost from the disaster impact, as shown in Eq. (13) and the sellout option value, as shown in Eq. (14). If the recovery cost is greater than the sellout value, the economic agent will sell out, thus relocating and leaving the impacted region. The authors understand that this is a simplification of the economic sector's decision-making process as it does not take into consideration future projected revenues, risk factors, or heterogeneity among business owners. However, in order to provide a proper understanding of the host communities' recovery, it was found best to simplify the agents' actions in this complex built environment

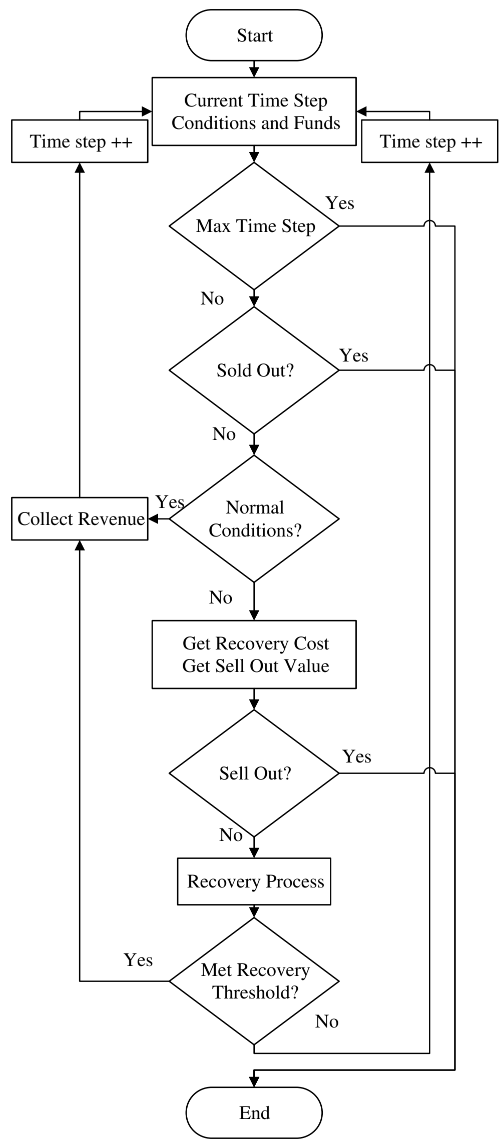

Fig. 5. Economic recovery module

$$\text{Recovery cost}_e = \text{St}_e \times \sigma_e - C_{e(\text{n.m})} - F_e \tag{13}$$

$$\text{Sell out}_e = \text{St}_e \times (1 - \sigma_e) \tag{14}$$

where St_e = structure value for economic agent e; σ = damage excreted on the physical structure as a factor of proximity of the natural hazard; $C_{e(n,m)}$ = insurance compensation value for economic agent e utilizing insurance policy m from insurer n; and F = government fund.

State Disaster Recovery Coordinator

The SDRC is considered—along with the residents—a main controlling agent in the proposed disaster recovery ABM. The SDRC redistributes the funds among the different proposed disaster recovery plans depending on the available financial capital. The proposed ABM integrates the aforementioned economic vulnerability assessment tool into the SDRC's objective function to better guide recovery efforts. Moreover, the funding distribution proportion is adjusted at each time step depending on changes in the objective functions of the residents and economic agents in addition to changes in host community vulnerability. To this effect, maximizing Eqs. (15) and (16) and minimizing Eqs. (17) and (18) serve as the SDRC's multiobjective function. Moreover, the SDRC's actions are constrained by the total federal agency's available funds as shown in Eq. (19)

$$\sum_{i}^{I} \Delta Z_{i_k} \quad \forall\ k = 1, 2, \ldots, K \tag{15}$$

$$\sum_{e}^{E} \Delta FR_{e_k} \quad \forall\ k = 1, 2, \ldots, K \tag{16}$$

$$\sum_{i}^{I} \text{Econ}VI_{i_k} \quad \forall\ k = 1, 2, \ldots, K \tag{17}$$

$$\sum_{e}^{E} \text{Econ}VI_{e_k} \quad \forall\ k = 1, 2, \ldots, K \tag{18}$$

$$\sum_{i=1}^{I} SG_i \leq TFF \tag{19}$$

where ΔZ_i = change in resident's objective function when applying for plan k; ΔFR_e = change in financial recovery rate for economic agent e; $\Delta\text{Econ}VI$ = change of the Economic Vulnerability Index corresponding to agents applying for plan k; SG_i = state governmental funding for the residents i; and TFF = total federal funding for the SDRC.

SDRC's Learning and Optimization Module. In order to optimize the SDRC's decision-making process, an individual learning module is required. This module must be able to redistribute the funding proportions of the different disaster recovery plans to achieve the aforementioned objective functions. Moreover, the module must be able to capture the experience-based learning of the SDRC. Furthermore, the learning module must allow for the temporal effect of the different disaster recovery plans. To this end, the Roth-Erev RL module was utilized. Eq. (20) illustrates the utilized Roth-Erev RL propensity module that assimilates the aforementioned SDRC's objective functions:

$$q_k(t+1) = q_k(t)[1-\phi] + \text{IR}_k \times (1-\varepsilon) \quad \forall\ k = 1, 2, \ldots, K \tag{20}$$

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. (15)–(18). In this essence, the learning module acts as the SDRC's multiobjective function's optimization model to find the Pareto optimum strategy. Consequently, the model can recalculate the funding distribution proportions p for each plan k using the propensities from Eq. (20) as shown in Eq. (21). 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, this learning module can represent the agent's information exploration and exploitation (Sun and Tesfatsion 2007). To this effect, the learning module can guide the recovery process through (1) maximizing the residents and economic sector objective functions, and (2) decreasing the economic vulnerability of the built environment

$$p_k(t) = q_k(t) \Big/ \sum_{k=1}^{K} q_k(t) \quad \forall\ k = 1, 2, \ldots, K \tag{21}$$

Insurance

In the proposed ABM, several insurance companies are offering a variety of insurance plans that range from partial to full coverage. As such, each company attempts to find the optimal distribution and pricing for the disaster policies to be offered to the population of residents and businesses. Accordingly, the insurer's utility function is shown in Eq. (22), where at each time step, 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 hazard event occurs. It is understood that the insurers follow a risk assessment in their objective functions. Nevertheless, following Eid et al. (2015), an evolutionary game theory approach can be utilized to determine a stable postdisaster insurance profile between residents and insures that would increase both their utility functions

$$W_n^{t+1} = W_n^t + \sum_{i=1}^{I} \begin{cases} P_{i(x,m)} - C_{i(x,m)}^{t+1} & \text{if } x = n \\ 0 & \text{Otherwise} \end{cases} \quad \forall\ n = 1, 2, \ldots, N \tag{22}$$

where W_n^{t+1} = insurer n's wealth at $t+1$; and $C_{i(x,m)}^t$ = zero if no disaster occurred at time $t+1$.

It is worth noting two issues that may negatively affect the optimum strategy profile. First, 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). However, insurers can change rates to overcome the problem of adverse election. Second, moral hazards as losses will always not be in 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 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, insurers were allowed to be myopic in their product offerings and then learn from their rivals given the distribution of population per

Table 2. Insurance Companies Plans' Premiums and Coverage Percentages

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

contract. To this effect, and utilizing Eid et al.'s (2015) data, three insurance companies offering three different disaster policies were introduced for residents to choose from. The different insurance companies' disaster policy premiums and compensation ratios are found in Table 2.

Model Verification and Testing

The proposed model was developed to be modular and scalable. Modularity indicates 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, economic, insurance, or government) with any number of impacted regions. More importantly, in order to provide for a rigorous model, the proposed agent-based model was subjected to several verification evaluations through a series of incremental tests. First, using test agents, a number of regression tests were carried out to ensure that the developed agents perform to their designed specifications and that their addition did not affect the existing message-handling abilities among the other existing agents. Moreover, the developed agents were tested in relation to their internal and external behaviors using structure and behavior validity testing (Vidal 2007; Vlassis 2003; Sterman 2000). Structure validity testing included structure-oriented behavior (behavior-sensitivity, extreme-condition, and modified-behavior prediction, and boundary adequacy tests). Meanwhile, behavior validity testing was conducted to predict the accuracy of communication among the different agents. On the other hand, a number of progression tests were applied through supplying definitions of all messages that a particular agent sends and receives. Such a methodology ensures that the agents in the developed model function according to their mathematical design and collectively build the ABM to its desired objectives.

Most importantly, the AMB was run through an actual budget distribution scenario to test the model's output in addition to comparison to the actual results and changes in the counties' 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 geographic information system (GIS) extension to the *MASON* multiagent-based model developed as an open source Java-based discrete-event multiagent simulation toolkit by the Department of Computer Science, George Mason University (Sullivan et al. 2010). *GeoMason* allows for the gathering of information and editing of raster and vector geospatial data. The use of GIS made it easy to gather the needed properties of the residents and economic agents depending on their spatial attributes. Moreover, GIS facilitates the representation of the residents, economic agents, and hazardous events, as well as the spatial relationship between them. Fig. 6 shows a GIS map for the three Mississippi coastal counties of Hancock; Harrison, and Jackson (west to east), along with the distribution of resident and economic agents 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. As such, the developed agent-based model simulations were performed on a

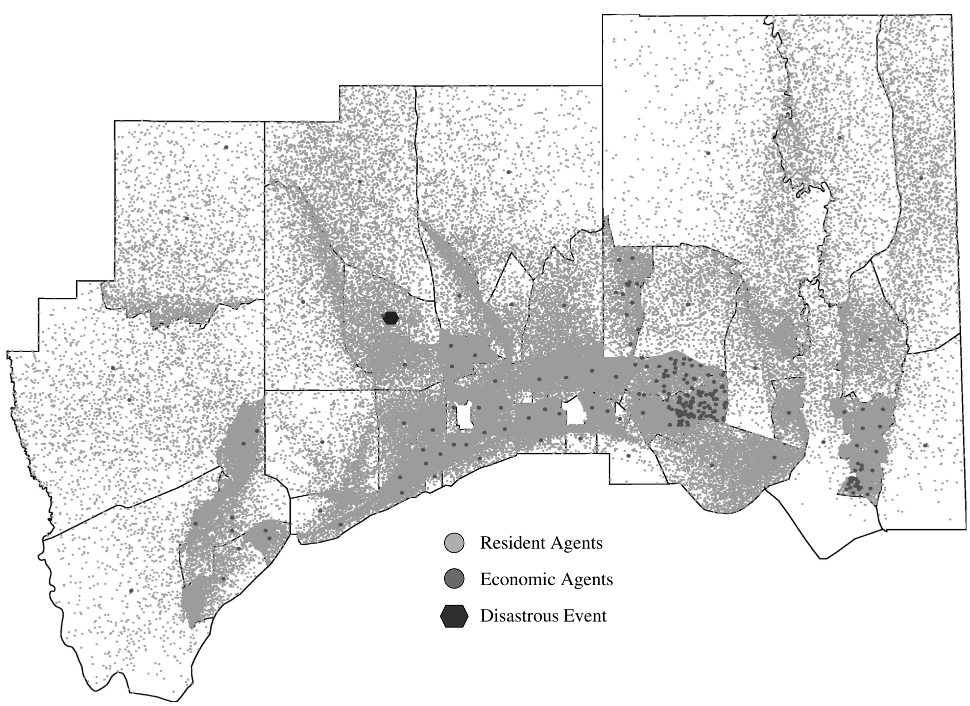

Fig. 6. Proposed model implementation on *GeoMason*

64-bit, 2.20 GHz machine with a 16 gigabytes RAM and running *Windows 8.1*. Each simulation run took an average of 15 min, with 72 time steps per simulation.

Results and Analysis

The results obtained from the proposed disaster recovery agent-based model are presented in this section in regard to (1) actual and projected economic vulnerability for the aforementioned three counties for ex-Hurricane Katrina and post-Hurricane Katrina, (2) optimized SDRC budget distribution and a comparison to the actual MDA budget distribution, (3) residential recovery progress, (4) economic agents' financial recovery, and (5) residents' choices over the different insurance companies. In addition, to test the model, an actual simulated budget distribution scenario for the SDRC is presented. This approach will assess the proposed model's outcome (with learning behaviors) in comparison to the simulated actual strategies followed by the recovery agencies in Mississippi.

To this end, and in order to achieve sound and statistically significant results, the authors utilized Lorscheid et al.'s (2012) and Lee et al.'s (2015) methodology to determine the minimum number of required simulation runs. This is achieved via descriptive statistical analysis using the means and variances of the model's distinct outcomes (Lee et al. 2015). As such, using the coefficient of variation proposed by Lorscheid et al. (2012), the sample size can be calculated using the following equation:

$$n_{\min} = \mathrm{argmax}_n |c_v^{x,n} - c_v^{x,m}| \langle E, \quad \forall\ x \quad \text{and} \quad \forall\ m \rangle n \tag{23}$$

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

To this end, the sample size was found to be 83, and the authors used a more-conservative approach by collecting 85 samples (i.e., simulation runs). In general, increasing the number of simulation runs yields more-accurate results. Nevertheless, as tempting as it may seem, such increases in the sample size will only provide small and insignificant change in accuracy (Lee et al. 2015), as long as the $n_{\min}$ criteria, stated earlier, is satisfied. As such, the authors calculated the sample sizes required for the SDRC budget distribution in addition to each county's recovery (residential and economic), and economic vulnerability indicator. To this effect, 10 sample sizes were calculated and 85 simulation runs were required to provide less than a 5% margin of error with confidence of 95% across the various results (residential and economic recovery, SDRC budget, and economic vulnerability).

Economic Vulnerability Assessment

As mentioned earlier, the EconVI is part of a multidimensional comprehensive relative economic vulnerability assessment model based on community-specific data (Burton 2010). In order to develop the EconVI, economic data for the 78 census tracts were gathered and standardized following the aforementioned methodology. To this effect, a multivariate dimension reduction technique (factor analysis) was utilized to understand the factors that affect the host community's vulnerability to hazards. The utilization of factor analysis allows for the calculation of relative vulnerability scores among the different regions under study. Even though the interpretation of the factors produced from factor analysis is subjective (Yang and Bozdogan 2011), this relative vulnerability scoring approach nominates the EconVI to be integrated into the disaster recovery decision support tools in order to allocate the redevelopment funds depending on the relative vulnerability of the different regions affected by the natural disaster.

To this effect, factor analysis was carried out on the 11 standardized economic variables resulting in three factors having eigenvalues greater than 1 that define the microeconomic and mesoeconomic vulnerabilities of the studied region. Table 3 illustrates the 11 economic variables for the three Mississippi coast counties in 2007 and their relation to each of the three factors through their loadings. Accordingly, it can be observed that Factor 1 is highly dominated by the mesoeconomic variables, namely number of retail centers, number of commercial centers, mean sales volume, and number of lending institutions. Meanwhile, Factor 2 is focused on the microeconomic vulnerability, namely percentage of female labor, percentage of employment, and per capita income. Finally, Factor 3 depicts the lending institutions, which emphasis their importance to the communities' vulnerability and preparedness to hazards. A simple additive factor scoring model is utilized to obtain the EconVI score for each census tract. Through this approach, the aforementioned factors are weighted equally in regard to their impact on the host community's economic vulnerability. Fig. 7 illustrates the three Mississippi coastal counties' relative economic vulnerability utilizing the EconVI scores obtained for year 2007. The color intensity in the figure represents the vulnerability; where areas with the lightest color are least vulnerable and those with the darkest color are most vulnerable.

As previously mentioned, in order to evaluate and compare the results obtained from the proposed ABM, an actual budget simulation scenario was introduced to the model. Thus, a sound EconVI-score comparison can be carried out between the existing conditions, the actual budget distribution scenario, and the proposed model. To this effect, Figs. 8–10 illustrate the average EconVI per county for years 2009–2012 for the three aforementioned cases.

Accordingly, it can be observed that the proposed model was able to outperform both the current and actual budget distribution scenario. At the end of the simulation run, the proposed model's EconVI reached a value of 0.319, 0.293, and 0.306 for Hancock, Harrison, and Jackson counties, respectively. In addition, the EconVI slope for Hancock County shows a rapid decrease in vulnerability. This is due to the learning module and the optimization of the SDRC's objective functions that allocate the disaster recovery funds in order to minimize the community's economic vulnerability (as shown in the following section). Meanwhile, both the existing and actual budget simulation scenarios reached

Table 3. Factor Analysis Loadings: Ex-Katrina

Variable	Factor 1	Factor 2	Factor 3
Percentage of home ownership	−0.30300	0.22506	0.03505
Percentage of employment	−0.01902	0.84857	−0.00132
Percentage of female labor	0.02838	0.87961	−0.04030
Per capita income	0.02716	0.44666	−0.02851
Percentage employed in nonprimary industry	0.19877	−0.03247	0.01315
Ratio of large to small businesses	0.01002	−0.01542	0.20185
Number of retail per 1,000 population	0.98511	0.07780	−0.11852
Number of commercial per 1,000 population	0.92027	0.02434	0.06120
Number of lending institutions per 1,000 population	0.78693	0.01826	0.61677
Doctors and medical professionals per 1,000 population	0.44153	0.00442	0.16345
Mean sales volume of business	0.86911	0.17819	0.07411

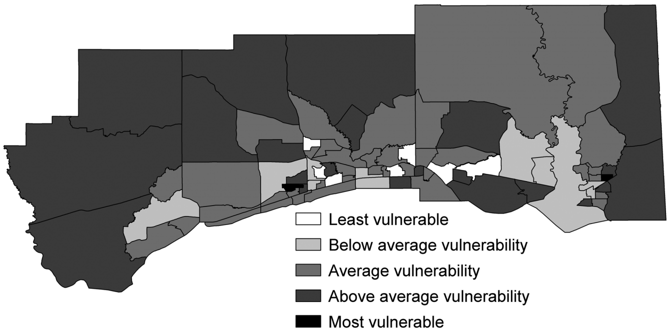

Fig. 7. Economic vulnerability distribution in 2009

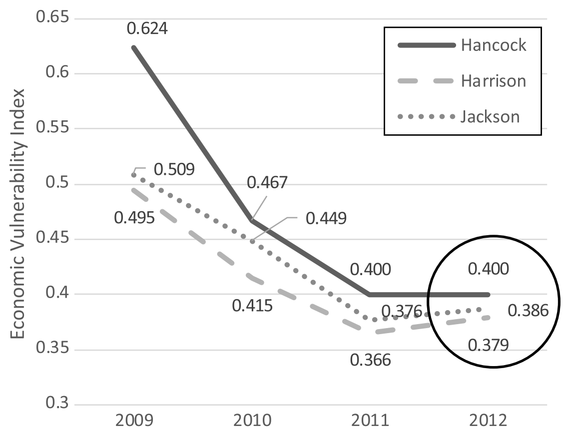

Fig. 8. Economic vulnerability index: existing condition

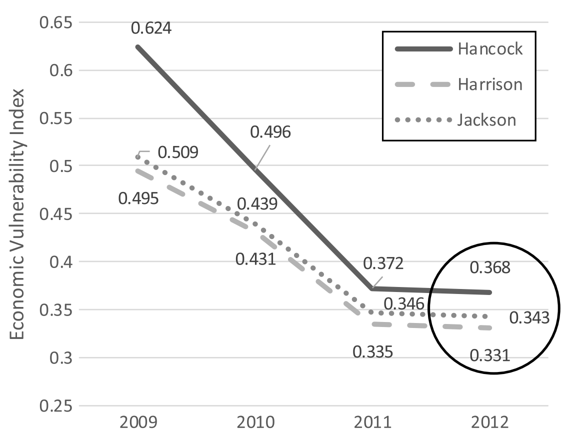

Fig. 9. Economic vulnerability index: simulated actual budget distribution scenario

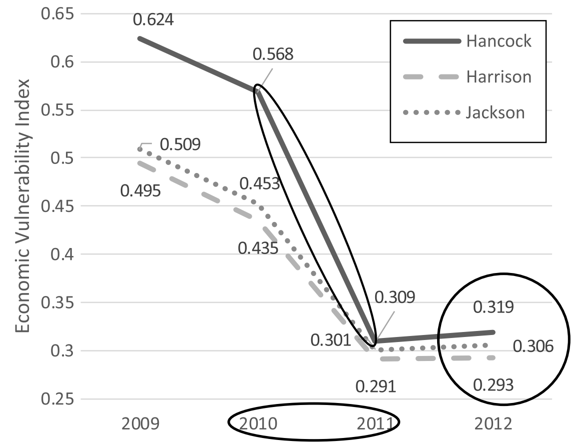

Fig. 10. Economic vulnerability index: project proposed model outcome

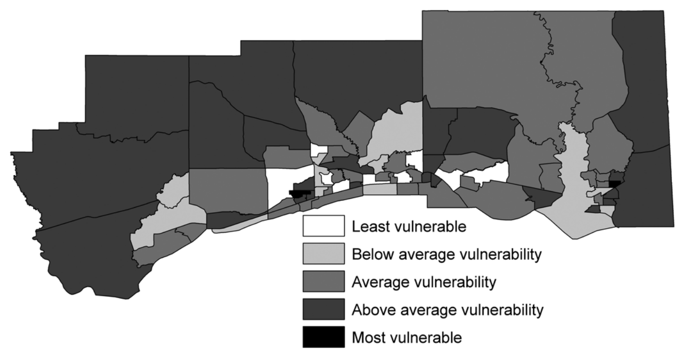

Fig. 11. Actual economic vulnerability 2012

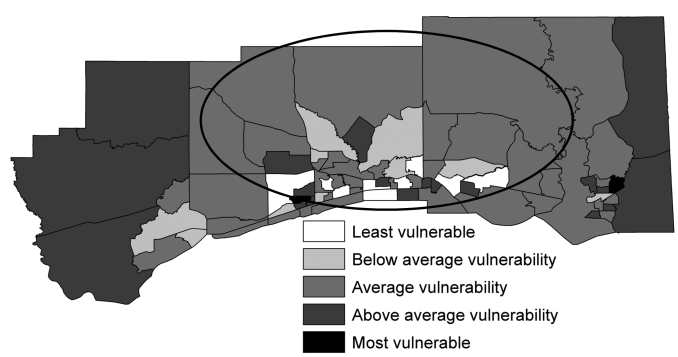

Fig. 12. ABM projected economic vulnerability 2012

significantly higher EconVI values that leave the counties more vulnerable to economic shocks due to natural disasters.

Moreover, for better visualization, Figs. 11 and 12 present both existing conditions and proposed model's relative economic vulnerability for each census tract for the year 2012. As previously mentioned, EconVI is a relative vulnerability assessment of the host community against disastrous events. To this effect, there will always remain census tracts that are more vulnerable than others. This approach, however, helps the SDRC agent to shift the fund allocation to the most vulnerable residents at the current time step.

This said, it can be observed that the proposed model was able to decrease the economic vulnerability of Harrison County, which comprises more than half of the population across the three counties. Moreover, the model also decreased the economic vulnerability of the densely populated regions in western Jackson County. To this end, it can be deduced that the ABM was able to decrease the economic vulnerability for the different census tracts in contrast to the existing scores recorded in 2012. The following section discusses the SDRC budget distributions, which explain how the SDRC's actions affected the EconVI's changes through the simulation runs, as well as the agents' recovery rates.

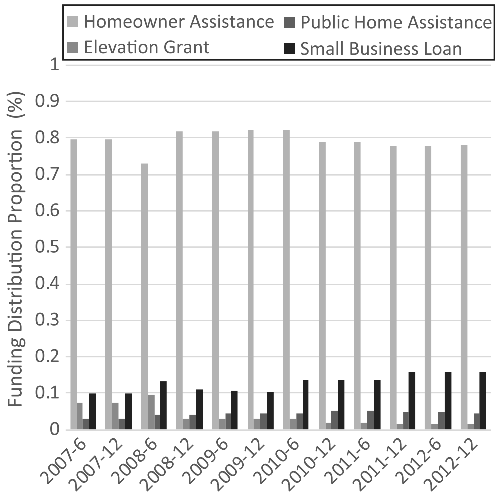

Fig. 13. Actual funding distribution

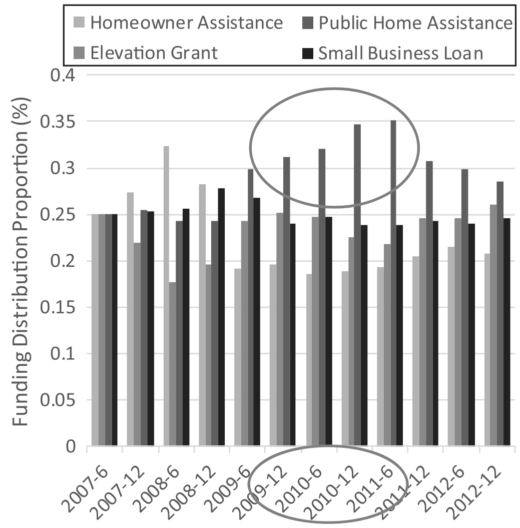

Fig. 14. ABM proposed funding distribution

SDRC Funding Distribution Comparison

The SDRC fund distribution proposed through the model was compared to the actual budget expenditure and distribution data gathered from the Mississippi Development Authority (MDA) over the four residential and economic sector recovery plans of homeowner assistance; public home assistance; elevation grants; and small business loan guaranty program. Figs. 13 and 14 illustrate the different funding proportions utilized by the MDA and proposed ABM output, respectively. In regard to the actual budget distribution by MDA, Fig. 13 indicates the domination of homeowner assistance plan over the other plans. This can be justified by the pressure exerted on the disaster management by that time as the homeowner assistance plan had the highest demand from residents as it awards a certified applicant with up to \$150,000 (Mississippi Development Authority 2015). Nevertheless, such plans did not target low-income residents or their household resilience to future hazards. Moreover, the plan contributes the least to the retail sector's revenue.

On the other hand, the proposed model presented a funding distribution pattern that evolves through time in order to address the dynamic needs of the stakeholders and decrease the built environment's economic vulnerability. To this end, the proposed model started with a uniform distribution among the four plans of 25% each. Through the first 2 years, the model increased the homeowner assistance plan's share to +30%. This plan provided for rapid household recovery through financial aid. Nevertheless, not all of the Hancock County residents could meet the homeowner assistance plan's criteria. Thus, through the following years, the model increased share of public home assistance, which eventually increased the community's recovery and decreased its economic vulnerability, as shown in the previous section. Furthermore, such a plan affects the retail sector's revenue by \$0.0912 for each \$1.00 spent on this plan, as previously discussed. Through 2009–2010, the model also increased the number of elevation grants, which increased the households' resilience to future hazards. Moreover, the elevation grants significantly contribute to retail sector revenue, as previously mentioned, which in return affected the regions' mean sales, thus impacting the economic vulnerability of the built environment. The model also increased the small business loan plan budget. Such a plan incentivized the retail sector to remain in the impacted region, thus prevented any possible increase in economic vulnerability of the host community. Such dynamic evolution in budget distribution served to increase through time the residents' and economic sector's recovery rate and objective functions while decreasing the overall built environment's economic vulnerability.

Recovery Progress

Residential Recovery

In order to assess the community's welfare, this section illustrates how the different disaster redevelopment strategies affected residents' recovery progress. The recovery progress is evaluated through quantifying the residential damage per county and the current recovery progress at each time step. For comparison purposes, this evaluation was carried out through both the simulated actual budget distribution scenario and the proposed model's optimized budget distribution. To this effect, Figs. 15–17 illustrate the recovery progress for the three counties, i.e., Hancock, Harrison, and Jackson, respectively, utilizing the simulated actual budget distribution scenario and the proposed model's outcome.

Through the household recovery and redevelopment comparisons in Figs. 15–17, the model's significance can be confirmed. The model outperformed the actual disaster recovery budget

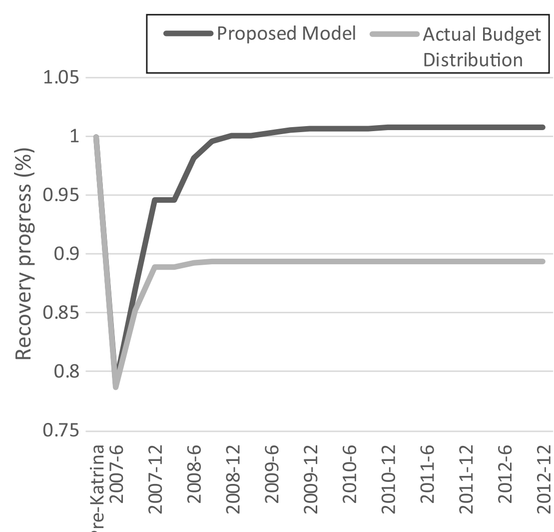

Fig. 15. Residential recovery progress: Hancock county

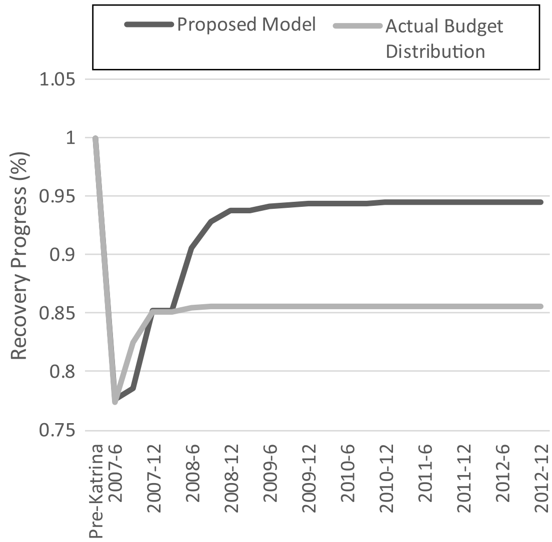

Fig. 16. Residential recovery progress: Harrison county

distribution across the three counties. First, it can be observed that the overall recovery rate is higher. This is due to the distribution of the available funds depending on the needs of the community, unlike in the actual budget distribution, which is dominated by the homeowner assistance program. To this end, the SDRC in the simulated actual budget distribution scenario was not able to address the needs of low-income residents, as shown in Hancock County. Those residents were not able to meet the homeowner assistance plan's criteria and there was not sufficient funding for the public home assistance plan. Moreover, as the budget was dominated by one plan, the SDRC was not able to address the needs of all the residents in Harrison County, resulting in just above 85% overall recovery for the county. Furthermore, this distribution of available funds depleted the SDRC's monetary resources, which could have been distributed more effectively.

On the other hand, the proposed model addressed low-income residents' needs and optimized the budget distribution to offer both public home assistance for low-income residents in addition to the homeowner assistance plan, an approach that increased the counties' overall recovery rate. Moreover, the model achieved more than 100% recovery in Hancock County. This is due to the implementation of the elevation grants, which increased household resilience to floods by elevating the household up to 1.9 m (6 ft) and 0.10 m (4 in.). This type of redevelopment requires additional work to the household's preexisting conditions, thus increasing the household's value, and requires more resources. Nevertheless, the simulated scenario had a significantly faster recovery rate than the proposed model for Harrison County through years 2007–2008. This is due to the extensive utilization of the homeowner assistance plan, which gives a higher recovery rate in comparison to the other plans. However, in the long run, this approach did not prove to be effective and an optimized budget provided a better outcome for the built environment, as shown in Figs. 15–17. Moreover, due to funds being constrained to the actual expenditure on the four aforementioned plans by the MDA (2015), not all resident agents were able to fully recover.

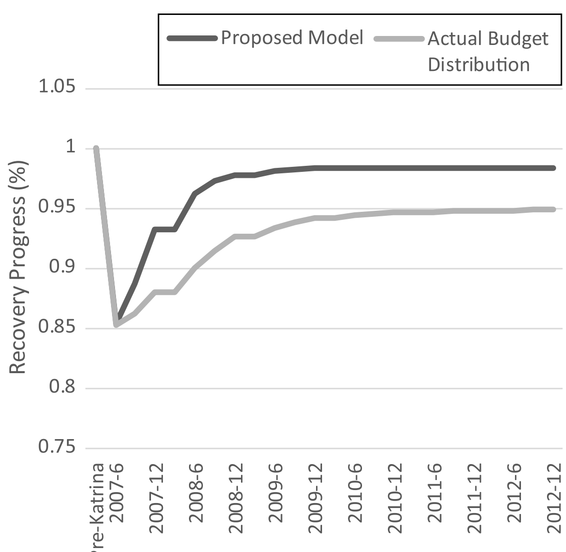

Fig. 17. Residential recovery progress: Jackson county

Economic Recovery

This section illustrates the model's ability to restore the economic sector's financial status. In parallel to the previous section, a comparison between the actual budget distribution scenario and the proposed model's outcome regarding to the retail sector's financial recovery is presented. This is carried out by measuring the retail sector's mean revenue per county, which is then evaluated against pre-Katrina mean sales revenue. To this effect, Figs. 18–20 present the financial recovery for economic agents (retail sector) for Hancock, Harrison, and Jackson counties, respectively.

It can be observed through Figs. 18–20 that the proposed model outperformed the actual budget distribution scenario in regards to the economic agents' financial recovery. As an impact of the small business loan plan offered by the SDRC, economic agents were incentivized to remain in the impacted regions. This is clear in Hancock County, which had the least number of retail center across the three counties. As shown in Fig. 18, the proposed model showed a significant increase in the recovery rate for the economic sector in this county. Moreover, the proposed model also presented a better recovery rate for Harrison and Jackson counties. This is also due to the implementation of public home assistance and elevation grant plans, which increased the counties' mean sales revenue.

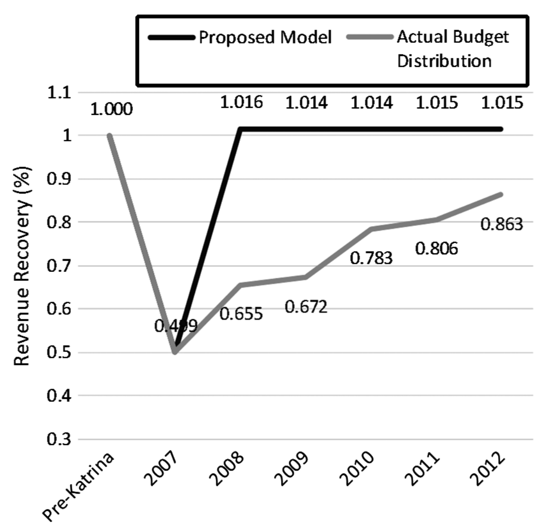

Fig. 18. Financial recovery: Hancock county

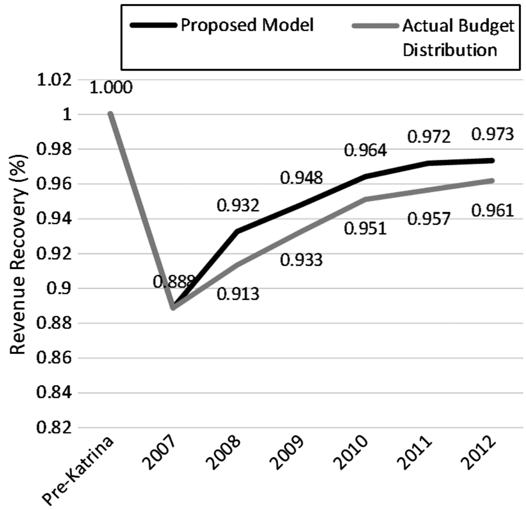

Fig. 19. Financial recovery: Harrison county

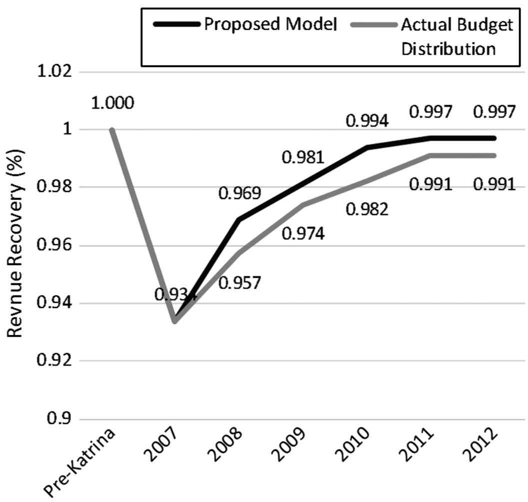

Fig. 20. Financial recovery: Jackson county

To this effect, it can be concluded that the proposed model of budget optimization through dynamic evolution provides for optimal utilization of funds. This is due to the integration of the utility functions of residents and economic agents into the SDRC's objective equations, which allows the SDRC to allocate funds in order to increase the associated stakeholders' objective functions.

Residents' Choices of Different Insurance Companies

The residents' choices of different insurance plans differed and changed through the simulation run. Fig. 21 illustrates residents' choices among the three aforementioned insurers along with the choice of having no disaster insurance plan. At the initial step, the residents were uniformly distributed among the three insurance companies along with the no insurance option. Through the utilization of MPS 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, Fig. 21 indicates that residents tend to have insurance policies that would cover their losses in case of a disastrous event. Nevertheless, residents avoided expensive insurance policies

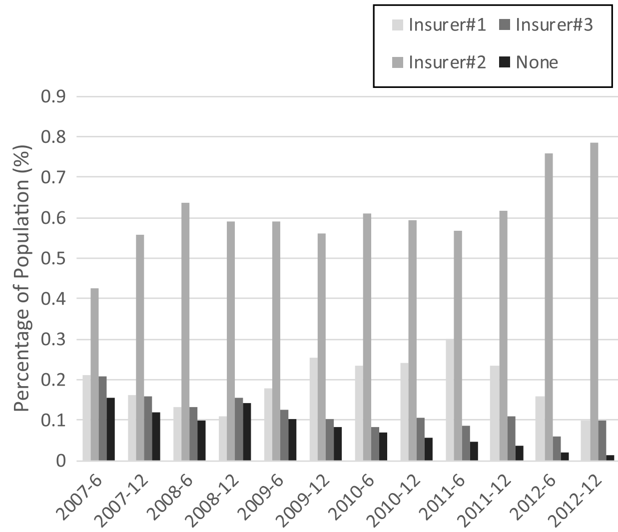

Fig. 21. Residents' choices regarding different insurance options

offered by the third insurer, even though these policies would compensate up to 100% of the damaged property's value. This is due to the relative costly premiums that rendered the residents with less costly premiums (yet less compensation ratios) more fit among their peers. Moreover, the residents also deviated from the least costly insurance plans—offered by the first insurer—as they do not sufficiently cover recovery expenses. Thus, the population converged on the second insurer. Moreover, the insurance coverage also affected the residents' choices through the simulation. The residents tended to avoid the homeowner assistance plan, as they had the insurance financial coverage and, thus, could apply for other recovery plans like the elevation grant.

Conclusion

This paper presented a disaster recovery decision support tool via an agent-based approach that integrates a comprehensive economic vulnerability indicator into the objective functions of the associated stakeholders. The model represented the residents and economic sector of the impacted region as well as the insurance companies, the local disaster recovery management (LDRM), state disaster recovery coordinator (SDRC), and federal disaster recovery coordinator (FDRC). The presented model illustrated the interactions between the different governmental entities as well as their relationship with the residential and economic sector. Moreover, the model presented the relationship between residents and insurance companies in addition to the relationship between residents and economic sector. In order to address the behavior of the stakeholders, the ABM utilized two learning modules: (1) Roth-Erev reinforcement learning for the resident's individual learning and the SDRC budget distribution learning; and (2) particle swarm social learning model that addresses the communication and learning behavior of the residents attempting to achieve an optimum disaster insurance plan that would increase their utility functions. Furthermore, the model utilized a comprehensive and well-established economic vulnerability assessment tool to better guide the recovery efforts. Such a vulnerability assessment model is able to aid the SDRC to allocate funds based on the relative vulnerability among the different impacted regions.

To this end, the model was implemented via a Java-based computer model utilizing GIS interface for the post-Katrina disaster recovery for the coastal Mississippi counties of Hancock; Harrison, and Jackson. The model also utilized an actual budget distribution scenario simulation for comparison purposes. To this end, the model was able to optimize the SDRC's actions in regard to the disaster recovery budget. The model increased the community's welfare through maximizing the objective functions of the associated stakeholders while minimizing the economic vulnerability of the built environment to future shocks and perturbations. The model provided better overall economic vulnerability indices for the three counties in comparison to those currently achieved by the actual post-Katrina disaster recovery plans. This is due to the integration of the vulnerability assessment tool into the SDRC's objective function as well as accounting for the needs and preferences of the associated stakeholders. To this end, the proposed model will enable practitioners to achieve a sustainable disaster recovery that mutually meets short-term development objectives and long-term resilience goals.

To this effect, the proposed innovative approach can be utilized in engineering and management decision-making problems where the collective behavior of the stakeholders affects the systems' performance, vulnerability, and sustainability. As such, the presented approach can be implemented not only within the context of disaster recovery, but also to other various multidisciplinary fields, like sustainable infrastructure development, urban planning, etc. Ultimately, the holistic framework utilized in this study lays down the foundation for a new generation of interdisciplinary managerial decision-making support tools.

Future Work

The current model takes into account 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 processes between the government entities and impacted stakeholders. Thus said, for future work, the authors are developing the current agent-based model to account for LDRM's interactions with residents and the economic sector. Moreover, the model will address the Federal Disaster Recovery Coordinator (FDRC) role in the recovery process, which highly affects recovery funding. Furthermore, the residents' social learning process will take into account the learning barriers (spatial, economic standards, risk perception, etc.) that were assumed negligible in the current model. Finally, the decision-making processes of the economic sector and insurance companies will be further developed as the current model illustrates them as myopic service providers.

Due to simplification, this model did not take into account other vulnerability dimensions (social and environmental) that would affect the recovery process proposed by the model. To this effect, and in order to provide for a holistic disaster recovery decision support tool, social and environmental vulnerability indicators will be utilized and integrated into the proposed model. These indicators, along with the utilized economic indicator, can give a broader understanding of the complex systems associated with the disaster recovery process. Moreover, residential and economic recovery progress rate uncertainty was not addressed in the proposed model. Thus, future work will be guided towards addressing recovery uncertainty and its impact on the proposed model's outcomes (individuals' welfare, vulnerability indicators, and budget distribution). Also, in order to address the model's limitation, future work will be guided into accounting for sudden changes in population, addition of new economic agents, and inclusiveness of other economic industries.

Furthermore, understanding that the ABM's outcome is significantly affected by the behaviors of the modeled agents, 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 among the disaster recovery agencies and impacted stakeholders in Mississippi after securing acceptance from associated institution review boards. This approach will enable empirical model validation at the agent level. Moreover, in order to provide for further testing and validation, the proposed decision support model will be implemented for various disastrous events and their associated recovery processes to generalize the model's validation. As such, the model can be utilized for decision-making purposes in regards to disaster recovery. Finally, in a future study, a rigorous sensitivity analysis will be presented on the fully developed model (social, environmental, and economic). This will provide for insightful understanding disaster recovery processes, how they are affected by the different parameters, and consequently their effects on the recovery outcome.

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