Full Length Article

Influence of testbed characteristics on community resilience using agent-based modeling

Xu Han [a,c], Maria Koliou [b,*]

[a] *Associate Professor, Department of Bridge Engineering, College of Civil Engineering, Tongji University, Shanghai, China*
[b] *Associate Professor and Zachry Career Development Professor II, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, USA*
[c] *Former Post-Doctoral Researcher, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, USA*

A R T I C L E   I N F O

A B S T R A C T

There has been a large increase in the number of days per year with numerous EF1-EF5 tornadoes. Given the significant damage incurred by tornadoes upon communities, community resilience analyses for tornado-stricken communities have been gaining momentum. As the community resilience analysis aims to guide how to lay out effective hazard mitigation strategies to decrease damage and improve recovery, a comprehensive and accurate approach is necessary. Agent-based modeling, an analysis approach in which different types of agents are created with their properties and behavior clearly defined to simulate the processes of those agents in an external environment, is the most comprehensive and accurate approach so far to conducting community resilience simulations and investigating the decision-making for mitigation and recovery under natural hazards. In this paper, agent-based models (ABMs) are created to simulate the recovery process of a virtual testbed based on the real-world community in Joplin City, MO. The tornado path associated with the real-world tornado event that occurred in May 2011 is adopted in the tornado hazard modeling for the Joplin testbed. In addition, agent-based models are created for another virtual community in the Midwest United States named Centerville using an assumed tornado scenario of the same EF-scale as that in Joplin. The effects of hazard mitigation strategies on the two communities are also explored. A comparison between the analysis results of these two testbeds can indicate the influence of the characteristics of a tornado-prone community on the resilience of the community as well as on the effects of hazard mitigation strategies. It is observed that a community's level of development significantly impacts the tornado resilience. In addition, the effects of a specific type of hazard mitigation strategy on the recovery process are contingent upon testbed characteristics.

1. Introduction

Recognized as one of the most devastating natural hazards facing human societies, tornadoes cause tremendous amounts of damage. Based on Changnon [1], the annual average loss due to tornadoes amounts to $982 million. In the late afternoon of May 22, 2011, an EF5-scale tornado hit the city of Joplin, Missouri, causing an estimated $2.8 billion in economic losses, making it the costliest tornado ever recorded in U.S. history [2]. An investigation was conducted by NOAA [3], to check if the frequency and intensity of tornadoes are on the rise, it turned out that the annual total of EF1-EF5 tornadoes has shown little to no trend over the record. On one hand, there has been a large decrease in the number of days per year with at least 1 EF1-EF5 tornado since the 1970s; on the other hand, the number of days per year with numerous EF1-EF5 tornadoes has been on the rise, which causes an increasing amount of

concern [3]. To reduce the impact of such devastating hazards on communities, community resilience simulations need to be carried out to enable risk-informed decision-making for enhancing community recovery and resilience.

Three necessary steps are needed for conducting community resilience simulations. First, a tornado hazard modeling process is needed to determine the wind fields. After that, a quantification process of damage inflicted upon the infrastructure systems of the community needs to be carried out. As the last step, the recovery process of the damaged physical and social systems of the community needs to be considered. In the damage assessment process, the damage states of each type of structure are assessed separately. During the recovery process, different systems have interactions. The development of a community model is about the development of these three key steps.

* Corresponding author.
E-mail address: maria.koliou@tamu.edu (M. Koliou).

For tornado hazard modeling, if a real tornado event has occurred in a specific location, the associated wind field can be determined via field surveying methods. Otherwise, a wind field must be generated using theoretical tornado models. Schaefer et al. [4] proposed an approach in which the probability of tornado occurrence is determined by the ratio of the total tornado area to the total area of interest. Standohar-Alfano and van de Lindt [5] generated a histogram of simulated wind speeds and fitted a Weibull distribution to the histogram to determine the probability distribution to the EF scale of a tornado. In addition, the variation of the tornado intensity along a tornado's path length and width was accounted for by Standohar-Alfano and van de Lindt [5]. The theoretical wind field proposed by Standohar-Alfano and van de Lindt [5] was later adopted in multiple studies [e.g., 6,7]. Fragility analysis is widely adopted for the damage assessment of infrastructure systems subjected to tornadoes. Fragility curves associated with various infrastructure systems have been proposed by integrating structural analysis and Monte Carlo simulation. For instance, Masoomi et al. [8] produced fragility curves associated with residential wood-frame buildings subjected to tornado hazards, Koliou et al. [9] conducted fragility analyses for big-box buildings subjected to tornado hazards and Unnikrishnan and van de Lindt [10] conducted a performance assessment for electrical power networks (EPNs) to obtain the tornado fragility curves for EPNs.

Repair time of damaged infrastructure systems is essential in the community recovery process. For the recovery of tornado-stricken communities, repair times needed for the damaged buildings and various components of the electrical power network are provided in HAZUS [11]. Koliou and van de Lindt [12] developed restoration fragility functions for different building archetypes (e.g., residential wood buildings, light industrial building, and small big box), which added a layer of uncertainty to the time needed for buildings to recover. In addition, the repair times to reach various levels of target functionality based on the different levels of initial post-hazard functionality were given in Koliou and van de Lindt [12], which can be used to determine the recovery trajectory of damaged buildings.

Hazard mitigation strategies can be involved in the community resilience analysis model. In general, the hazard mitigation strategies can be classified into two categories. The first category alleviates the damage sustained by structures during the hazard, such as conducting structural retrofits. The second category offers resources to expedite the recovery process, such as allocating funds to expedite the recovery process of businesses (also referred to as applying economic policies) after a hazard occurs. Hazard mitigation strategies of both categories are considered in this study.

Of all the community resilience analysis approaches, the agent-based modeling approach is considered the most detailed one. In agent-based models (ABMs), the properties and behavior of different types of agents (e.g., business agent, person agent, etc.) are defined. The agents are generated based on the properties and behavior defined and placed into an external environment, where the actions of agents and their interactions can be simulated. The history of agent-based modeling dates back to the late 1990s, when the Sandia National Laboratory (SNL) used agent-based modeling techniques to simulate the response of the infrastructure of the U.S. economy to financial policies [13]. Research efforts on community resilience analysis using the agent-based modeling approach include Nasrazadani and Mahsuli [14], Aghababaei and Koliou [6,15], Han and Koliou [16], and Alisjahbana [17], among others. The ABMs developed by Nasrazadani and Mahsuli [14], Alisjahbana [17], Zhao and Sun [18], Han and Koliou [19], and Sun et al. [20] are to evaluate the community resilience under seismic hazards, while the ABMs created by Aghababaei and Koliou [6,15] and Han and Koliou [16] aim to conduct resilience assessment for communities subjected to tornado hazards.

Communities are complex systems consisting of a series of interdependent social, economic, and physical subsystems. As community resilience models are essentially computer models, the community in the real world needs to be digitized into testbeds. A testbed can represent a real community such as the community in the San Francisco Bay Area, or a fictitious community such as a community in a novel or comic. The resilience of different testbeds subjected to a natural hazard (e.g., tornado) of the same intensity level may be significantly different due to various reasons. The spatial distribution of infrastructure systems in different testbeds can be different. More importantly, the level of development of different testbeds is different. A city with a high development level can have ample resources at its disposal in the recovery process and, therefore, is very likely to be more resilient than a city with a low development level. As the resilience of a community is contingent upon its characteristics, the decision-making on hazard mitigation is also contingent upon community characteristics.

The scope of this paper is to conduct resilience simulations for testbeds of different characteristics using the agent-based modeling approach and compare the findings focusing on the characteristic variability for those communities. Community resilience analysis is conducted on the Joplin testbed (the prototype of which is the community in Joplin City, MO) using the wind speed contour associated with the real-world EF5 tornado events in Joplin in May 2011. Resilience analysis is also conducted for a virtual testbed named Centerville [21] using an assumed wind speed contour of the same EF scale as the Joplin testbed. A comparison between the resilience simulation results of these two testbeds can illustrate the effect of the characteristics of the testbed on the resilience analysis results and recommendations on the recovery process. In addition, the influence of specific hazard mitigation strategies on the resilience of different testbeds is also compared to showcase the influence of the testbed characteristics on the effectiveness of a hazard mitigation strategy.

2. ABM for tornado resilience simulations

In an attempt to conduct tornado resilience simulations using the agent-based modeling approach, Aghababaei and Koliou [6] developed an ABM that accounts for multiple physical and social systems of a typical community. This agent-based modeling approach is adopted herein. The subsystems of a community in the ABMs created in this study include the electric power network (EPN), healthcare system, education system, business system, and households. Each system is associated with multiple types of agents, while each agent is associated with its properties and behavior. The relationship among agents and systems in the ABM is illustrated in the state chart of Fig. 1. In the block of each type of agent, the line starting with "-" indicates a property of this type of agent, while the line starting with "+" indicates a specific behavior of this type of agent. The decisions agents make during recovery are contingent upon these behaviors and the external environment. For instance, whether a person can go to work after the tornado events is contingent upon the agent's ability to work and the condition of the business that originally employed the agent. After the attributes of agents and behavior of agents are defined, the agents are created using object-oriented programming languages such as Java and Python. These programming languages are also used to simulate the ABM.

It is worth noting that the ABM created in Aghababaei and Koliou [6] was configured using a commercial software named AnyLogic. The ABM was later reprogrammed using the Python language in Han and Koliou [16] and was validated through a rigorous verification and validation process (V&V) by Han et al. [22]. Using the Python-based ABM model, parametric analysis can be carried out to investigate the influence of multiple distinctive parameters on community resilience. In addition, the effects of hazard mitigation strategies can also be investigated conveniently using the Python-based ABM.

The ABM developed herein consists of a set of modules. A summary of the modules of the ABM and the associated resources where detailed information is given is presented in Table 1. For the two types of hazard mitigation strategies adopted herein, i.e., structural retrofits and economic policies, the former considers modifying the fragility parameters
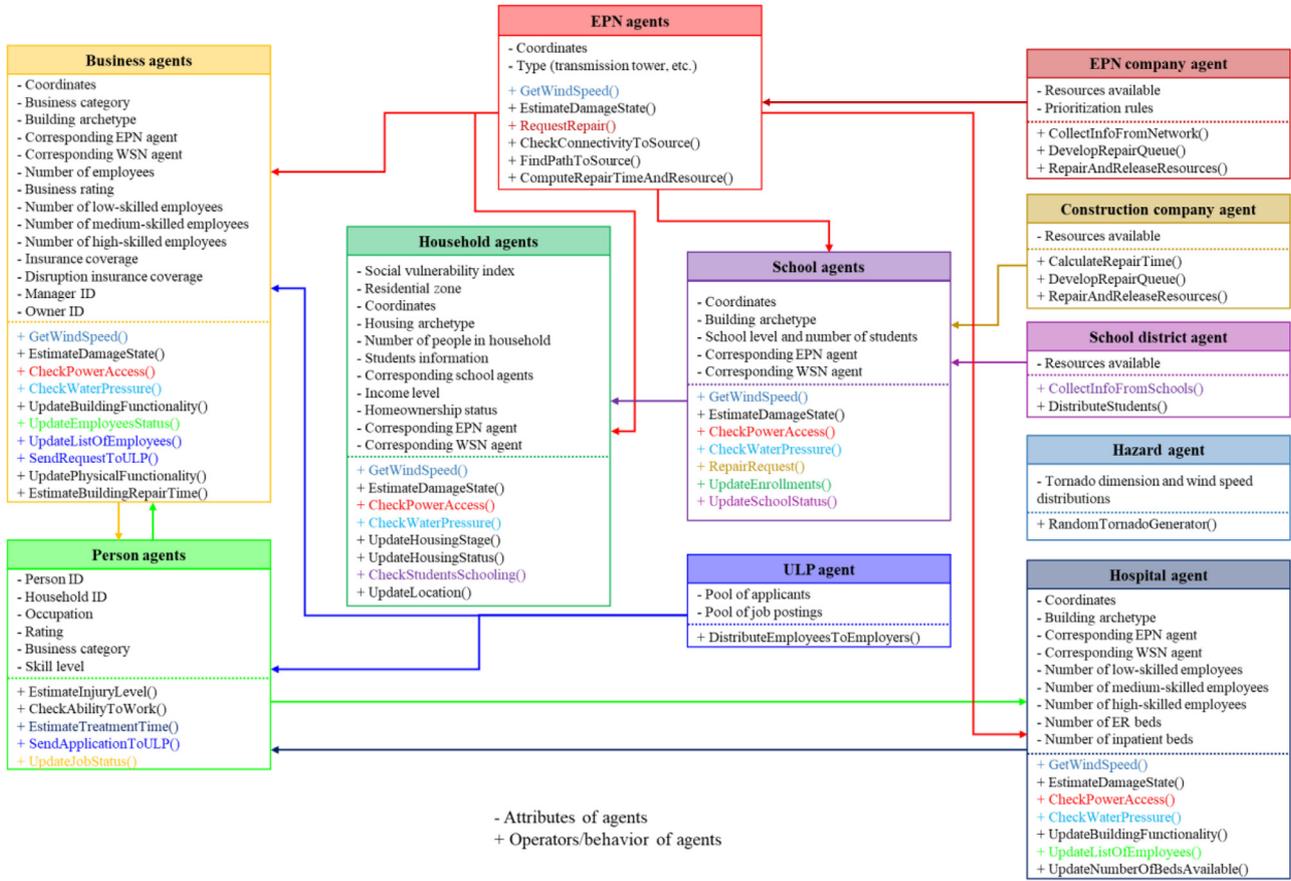
Fig. 1. Descriptions of agents in ABM for community resilience analysis (adapted from Aghababaei and Koliou [6].

Table 1
Summary of sources with detailed information on modules of the ABM.

Module	Major parameters	Source
Damage assessment for buildings	Fragility parameters	Masoomi et al. [8] and Memari et al. [23]
Damage assessment for electrical power network facilities	Fragility parameters	Unnikrishnan and van de Lindt [10]
Injury/fatality assessment	Probability of injury	IN–CORE [24]
Delay time associated with business recovery	Delay time	Almufti and Willford [25]
Building repair	Repair time	Koliou and van de Lindt [12]
Electrical power network facility repair	Repair time	IN–CORE [24]
Housing stage recovery	Stage transition probability	Sutley and Hamideh [26]
Behavior of agents in the recovery process	–	Aghababaei [27]

while the latter considers changing the recovery time needed for all the financial processes that a business is required to undergo before reopening.

In the ABM for community resilience simulations, it is of vital importance how to define and quantify community resilience. To define community resilience, the resilience of each system in the community needs to be defined in the first place. A generalized expression of the resilience of a system is calculated as follows:

$$R = \frac{1}{T_{LC}} \int_0^{T_{LC}} Q(t)\mathrm{d}t \tag{1}$$

where, R is the resilience index; T_{LC} is the control time; and $Q(t)$ is the time-variant functionality of the system.

For the EPN system, the performance metric $Q(t)$ is considered as the ratio of the number of customers with access to electricity over the total number of customers in the community. Eq. (1) is directly used to calculate the resilience index of the EPN system. For the resilience of the education and business systems, Eq. (1) is adopted to calculate the resilience of each associated entity (individual school

and business, respectively). For the resilience of the education system, the resilience index associated with a specific schooling status is calculated using Eq. (1), with the number of students in the schooling status considered as the time-variant functionality. A total of ten schooling statuses are considered herein, namely *O(Normal), O(Hosting), O(Waiting for utility), O(Minor/moderate repair and preparation), O(Dense condition), O(Temporary location), H(Open), H(Waiting for utility), H(Minor/moderate repair and preparation)*, and *enrolled outside the city*, where O indicates that a student enrolls in the original school and H indicates that the student enrolls in the hosting school. The overall resilience index of the education system is then calculated per Eq. (2).

$$R_{edu} = \sum_{i=1}^{10} \alpha_i R_{A,i} \tag{2}$$

where $R_{A,i}$ is the resilience index associated with the *i*th schooling status; α_i is the coefficient associated with the *i*th schooling status. Detailed information can be found in Aghababaei and Koliou [15].

For the business system resilience, the resilience index associated with each business is calculated using Eq. (1), with the functionality of

an individual business, i.e., *business functionality*, defined as

$$BusFunc = BuildingFunc \cdot \frac{Emps}{Emps_{needed}} \quad (3)$$

where $BuildingFunc$ is a factor indicating the physical functionality of a business; $Emps$ is the number of workers in the business, respectively; $Emps_{needed}$ is the number of workers needed to sustain the business, respectively. $BuildingFunc$ is a factor equal to 1 when the business is structurally intact and has access to utilities. The resilience index of the entire business system is finally computed per Eq. (4).

$$R_{\text{businesses}} = \frac{\sum_{i=1}^{n_b} w_{b,i} R_{b,i}}{\sum_{i=1}^{n_b} w_{b,i}} \quad (4)$$

where n_b is the number of businesses in the community; $R_{b,i}$, and $w_{b,i}$ are the resilience index and weight of the ith individual business, respectively. In the current study, the weight of a business is the number of its employees.

For the resilience of the healthcare system, the overall functionality is divided into three categories, i.e., the healthcare business system, the quality of emergency medical care, and the availability of medical resources. The resilience index associated with each category is calculated separately. Eq. (1) is used to calculate the resilience indices for two categories, which are the healthcare business system and the availability of medical resources. The resilience index associated with healthcare businesses is calculated in the same way as the business system.

The availability of medical resources is represented by the availability of emergency beds and inpatient beds. The associated functionality, $Q_h(t)$ is calculated per Eq. (5).

$$Q_h(t) = \left(\frac{n_{er}(t)}{n_{er,b}} \right)^{0.5} \cdot \left(\frac{n_{in}(t)}{n_{in,b}} \right)^{0.5} \quad (5)$$

where $n_{er,b}$ and $n_{in,b}$ are the numbers of emergency and inpatient beds prior to the disaster, respectively; $n_{er}(t)$ and $n_{in}(t)$ are the time-variant numbers of available emergency beds and inpatient beds, respectively.

For the quality of emergency medical care, the quality of urgent care, Q, is defined per Eq. (6) [28,29]:

$$Q = \min \left(\max \left(0, \frac{WT_{max} - WT}{WT_{max} - WT_0} \right), 1 \right) \quad (6)$$

where WT_{max}, WT_0, and WT are the maximum allowable waiting time, waiting time in the normal pre-disaster condition, and actual waiting time for a patient before receiving treatment. The resilience associated with the quality of urgent care is considered as the average quality of urgent care among all the patients.

The overall resilience of the healthcare $R_{\text{healthcare}}$ is then calculated per Eq. (7)

$$R_{\text{healthcare}} = \left(R_{\text{urgent}} \cdot R_h \cdot R_{nh} \right)^{\frac{1}{3}} \quad (7)$$

where R_{urgent}, R_h, and R_{nh} are the resilience indices associated with the three categories of the functionality of the healthcare system.

The control times of the EPN, education, business, and healthcare system are set as 90 days, 180 days, 730 days, and 180 days, respectively [6]. The overall community resilience is then calculated according to Eq. (8).

$$R_{\text{community}} = \left(\prod_{i=1}^{N_s} w_i R_i \right)^{\frac{1}{\sum_{i=1}^{N_s} w_i}} \quad (8)$$

where N_s is the total number of systems involved; R_i is the resilience index of the ith system; w_i is the weighting factor of the ith system. Based on Aghababaei and Koliou [6], the weighting factors herein for the EPN, healthcare, education, and business systems are set as 3, 3, 2, and 1, respectively. It should be noted that those factors can be modified based on the decision-makers'/stakeholders' priorities.

3. Joplin/Centerville community and hazard models

As previously mentioned, two testbeds are considered herein, i.e., the Joplin testbed and the Centerville testbed. The former is a testbed using the community in Joplin, MO as a prototype, while the latter is a virtual testbed representing a typical midwestern U.S. community.

The city of Joplin is in southwest Missouri, considered the center of the so-called "four-state area", which is the area where the States of Arkansas, Kansas, Missouri, and Oklahoma touch upon each other. With a total area of 81.69 square kilometers (31.54 square miles), it is the hub of the fourth largest metropolitan area in Missouri. More than 28,000 buildings are located within the boundary of the city of Joplin, including around 25,000 residential buildings and more than 3000 commercial buildings. Two hospitals are located within the city, namely the Freeman Health Systems and St. John's Regional Medical Center (SJRMC). The education system in Joplin constitutes 9 elementary schools, 3 middle schools, 6 high schools, 2 private schools offering education at both elementary and middle school levels, and 2 universities/colleges. The access to electricity is contingent upon the functionality of the 18 electrical substations and more than 24,000 electric distribution poles. The business sectors in Joplin include arts, retail, healthcare, accommodation and food, construction, finance, manufacturing, professional, wholesale, transportation and warehousing, real estate, administrative, information, utility, mining, and other types of businesses.

Table 2
Summary of archetypes of buildings in Joplin (based on Koliou and van de Lindt [12]).

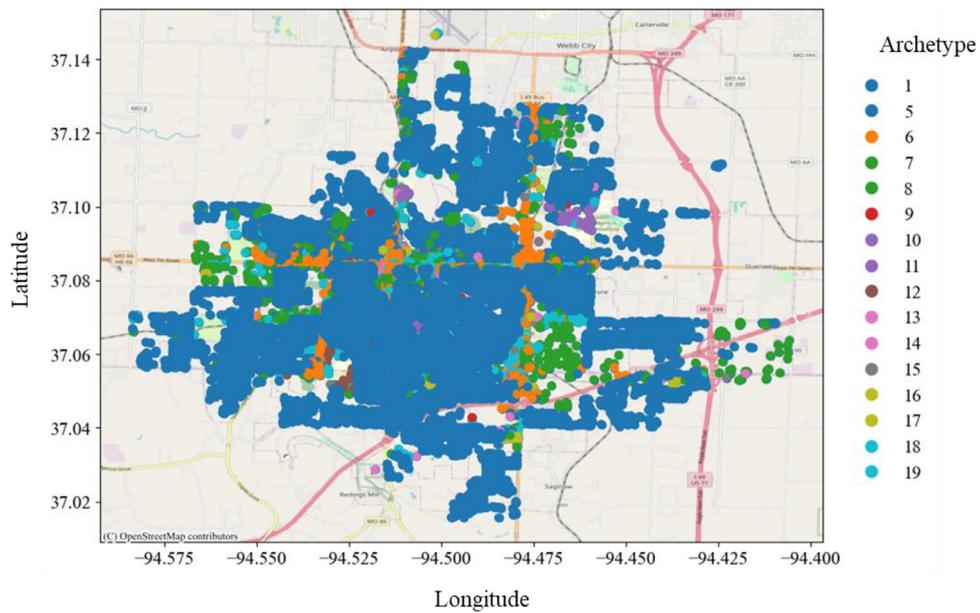| Archetype	Building description	Occupancy class
1	Wood residential building, small rectangular plan, gable roof, 1 story	Residential
2	Wood residential building, small square plan, gable roof, 2 stories	
3	Wood residential building, medium rectangular plan, gable roof, 1 story	
4	Wood residential building, medium rectangular plan, hip roof, 2 stories	
5	Wood residential building, large rectangular plan, gable roof, 2 stories	
6	Business and retail building (strip mall)	Commercial
7	Light industrial building	Industrial
8	Heavy industrial building	
9	Elementary/middle school (unreinforced masonry)	Education
10	High school (reinforced masonry)	
11	Fire/Police station	Government
12	Hospital	Commercial
13	Community center/Church	Religion/Nonprofit
14	Government building	Government
15	Large big-box	Commercial
16	Small big-box	
17	Mobile home	Residential
18	Shopping center	Commercial
19	Office building	

Fig. 2. Spatial distribution of buildings in Joplin.
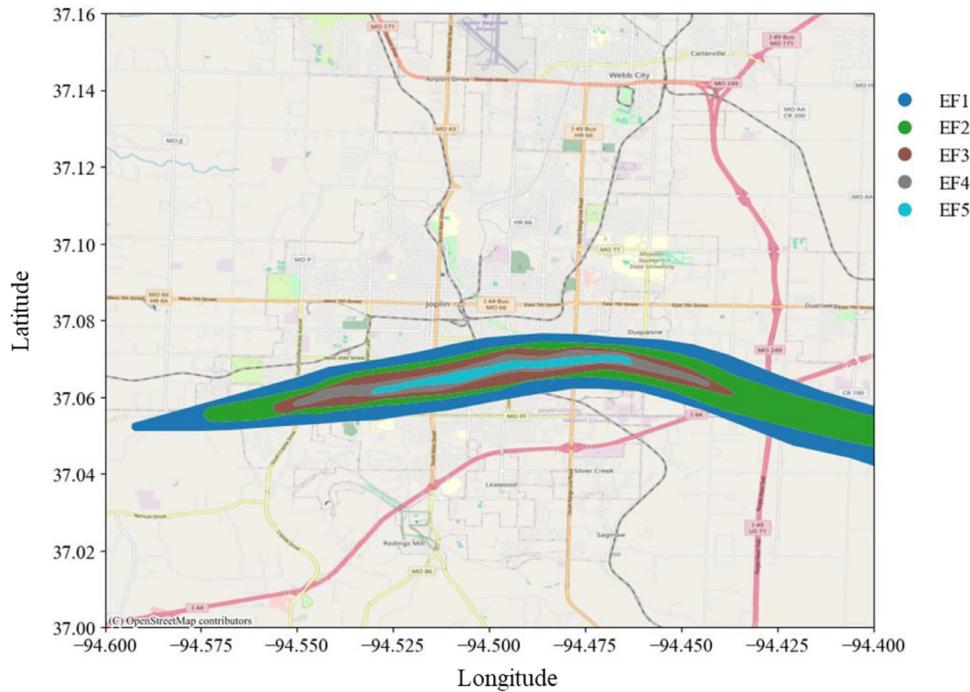

Fig. 3. Tornado path associated with the May 2011 event in Joplin.

The buildings in the city of Joplin are described in this study by 19 archetypical structures of similar US communities developed for research purposes [23]. Detailed information on the archetypes of the buildings is shown in Table 2.

Fig. 2 shows a spatial distribution of the buildings of 19 archetypes in Joplin. The tornado path associated with the tornado event in May 2011 (shown in Fig. 3) is adopted to carry out the tornado resilience simulations.

The Joplin testbed created herein is using Joplin, MO as a testbed and the building inventory and household inventory of the city are available in IN–CORE database [24]. A housing unit allocation process is conducted using the methodology proposed by Rosenheim et al. [30] to create a link between households and buildings. Detailed informa-

tion about businesses such as the business category and the number of employees is generated based on the data provided on the website of the U.S. Census Bureau [31]. Detailed information on the population in terms of business category and education level is generated also based on the website of the U.S. Census Bureau [32]. The link between people and educational institutions is created based on the age of people receiving education. The link between people and households is created based on the identity of people in households. Four identities are considered in this study, namely householder, spouse, child, and other.

The Centerville testbed is a virtual community with a population of 50,000 people, of which 10,773 are students. The plan view of Centerville is shown in Fig. 4 [21]. Seven residential zones are inside the
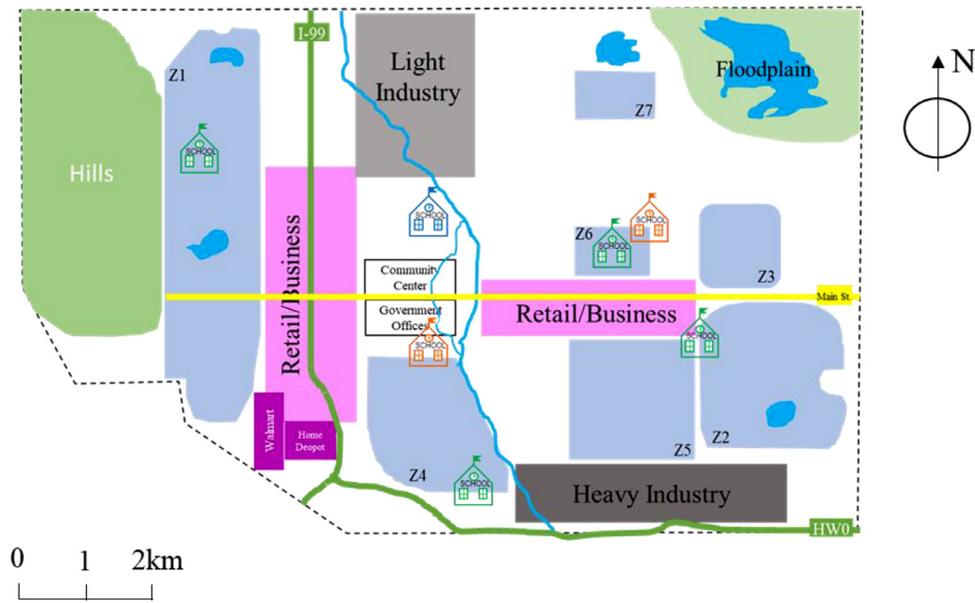
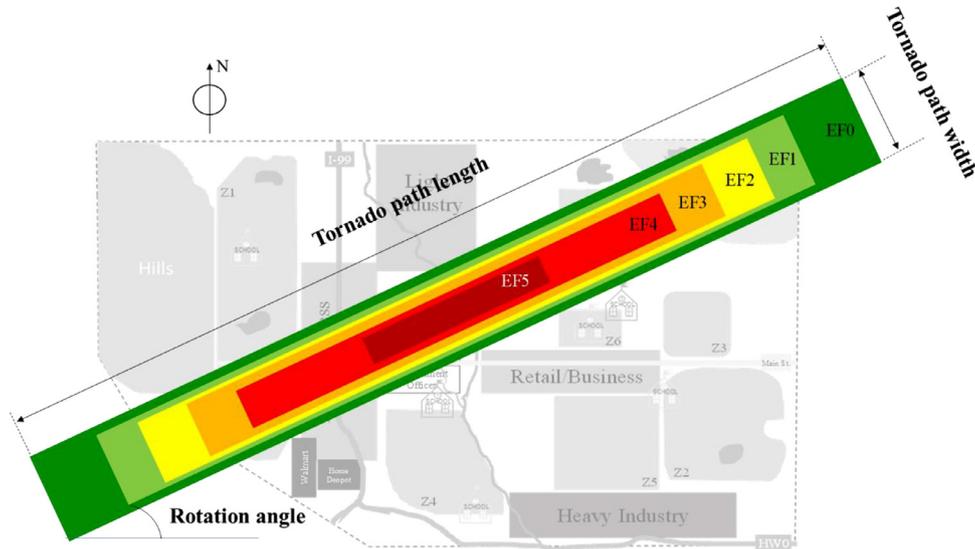**Fig. 4.** Plan view of Centerville (adapted from Aghababaei [27]).

Fig. 5. Tornado path crossing Centerville (adapted from Aghababaei [27]).

community with different demographic characteristics, income levels, and population densities. A total of 19,685 households live in Centerville, of which 10,421 households live in rental homes. The number of working people and non-working people in the working age group is 32,132 and 7708, respectively. Two commercial districts are in the community. Categories of the businesses operating inside the community include retail, manufacturing, service (non-professional), construction, healthcare, education, professional business service, utility, and governmental. A general hospital is located inside the city serving people in Centerville. The education institutions in Centerville include 4 elementary, 2 middle schools, and 1 community high school. For the EPN in Centerville, facilities include one electric power plant, six transmission substations, 25 distribution substations, 30 electric towers, and 1390 electric distribution poles. When components of the EPN are damaged, a utility company of 30 working units is tasked with repairing these damaged facilities [33]. A total of 625 vacant rentals are available based on Aghababaei and Koliou [6].

For the tornado path crossing Centerville, an EF5-scale tornado, as shown in Fig. 5, is assumed to rip through Centerville. The idealized tornado path associated with the Joplin testbed represented by the multi-layer rectangles was proposed by Standohar-Alfano and van de Lindt [5]. Utilizing the empirical dataset of tornados that occurred between 1973 and 2014, Masoomi and van de Lindt [33] generated marginal Weibull distributions for tornado width and length. The percentages of width for each tornado intensity along the tornado path width and the percentage of length for each intensity along the tornado path length were determined using observations from a number of post-tornado surveys [5]. In this manuscript, based on these distributions, the length and width of the tornado path are 33.80 km (21 miles) and 2.41 km (1.5 miles), respectively. The 3-s gust wind speed associated with each EF scale (from EF0 to EF5) is set as 120.70mph (75kph), 157.72mph (98kph), 197.95mph (123kph), 241.40mph (150kph), 294.51mph (183kph) and 378.20mph (235kph), respectively. The center of the tornado path is located at the center of
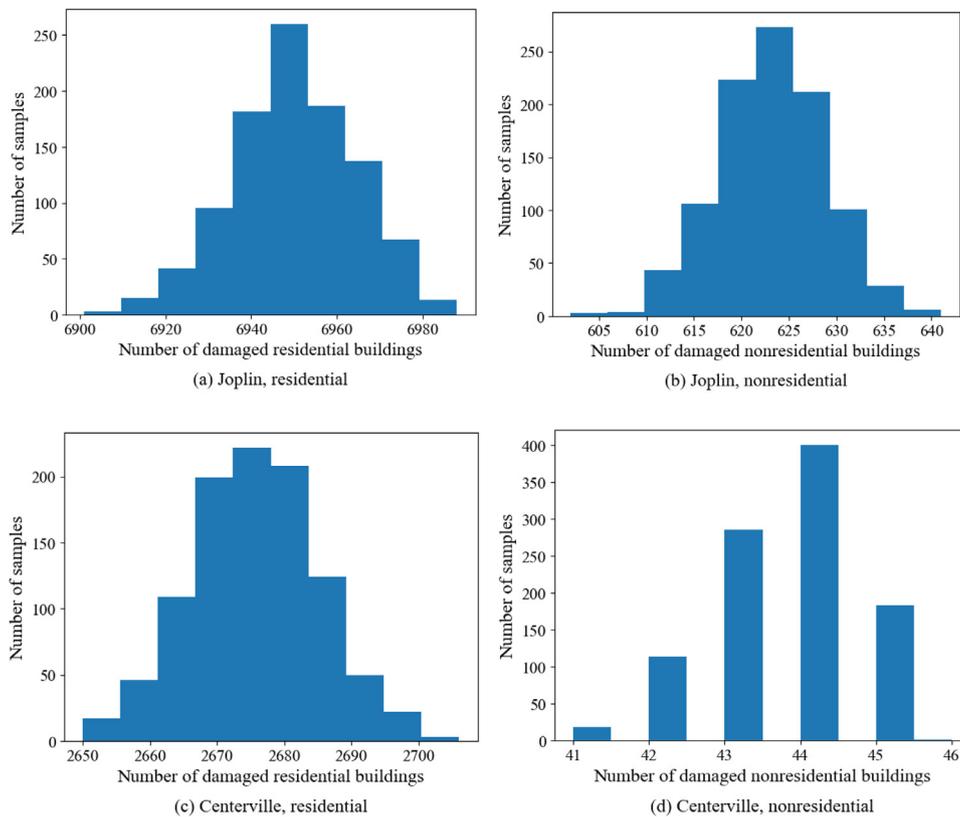
(a) Joplin, residential

(b) Joplin, nonresidential

(c) Centerville, residential

(d) Centerville, nonresidential

Fig. 6. Histograms of the number of damaged buildings.

Centerville, while the rotation angle of the tornado is 19 degrees from the east direction.

4. Recovery models implemented in ABM

In community resilience simulation, it is pivotal to generate appropriate recovery models for all the systems involved to characterize their recovery processes. The recovery models adopted herein are mostly based on those adopted by Aghababaei and Koliou [6], while required adjustments are made to adapt the recovery models to the characteristics of Joplin.

When tornado events occur, an urgent measure taken by the authorities is to restore electricity access to the users. In the present study, a repair crew consisting of multiple working units is tasked with repairing all the damaged EPN components and facilities. One working unit can only work on repairing one damaged electrical facility at a time. It is assumed that a working unit will finish repairing the current components/facility before it takes on the repair work of the next task. For a commercial hub like the city of Joplin, it is assumed that the repair crew has 500 working units, which is deemed as a large-size repair crew. For a less urbanized city like Centerville, a repair crew of 200 working units is assumed.

Another urgent measure that should be considered is the treatment of injured people. For the Centerville testbed, all the injured people are transferred to the general hospital for treatment. For the Joplin testbed, the patients are assumed to go to the Freeman Health Systems for treatment, as the SJRMC is on the tornado path and is expected to suffer severe structural damage. While in the hospital, after the triaging period, the patients will take an emergency bed where emergency medical care is offered. If it is determined that a patient needs further treatment, an inpatient bed will be assigned to them where the inpatient care will be provided. For the Joplin testbed, it is assumed that 210 emergency beds and 90 inpatient beds are available for emergency medical care, while

70 emergency beds and 30 inpatient beds are available for emergency medical care in Centerville. It should be noted that the numbers differ since the two communities have variations in the number of healthcare-providing facilities and associated capacities.

The recovery of a business hinges on three aspects. First, the building housing the business must be structurally safe so that the business can reopen. Second, the business building must have access to utilities (in which electricity access is heavily impacted in the case of tornadoes). Last but not least, the business must have an adequate number of employees to serve the business and be functioning. In the recovery mode considered herein, the business buildings that are severely damaged must be repaired so that the associated businesses can reopen. If electricity access is available by the time of business reopening, the business is considered physically functioning. After that, a hiring process will begin until the business has enough employees to operate. At that time the business is deemed as fully functioning.

For the recovery process of the education system, it is assumed that schools with no structural damage (DS0) or moderate structural damage (DS1) can reopen soon after the structural repair is conducted within a short period after the tornado hazard event. These schools can host students from other schools. If a school is in an extensive damage state (DS2), the students need to start school in a dense condition before the structural repair is completed. When a school is completely damaged (DS3), the students need to find a host school to continue their education. It is worth noting that there are higher education institutions in Joplin, such as the Missouri Southern State University for which it is assumed that an overwhelming majority of the students are from outside of Joplin. When tornado events occur, these students will stay with their families at home and return to the higher education institutions when the structural repair is completed, and the institution is functioning for in-person classes.

Household recovery is essential in the recovery of the community subjected to tornadoes. In the current study, the Markov chain model
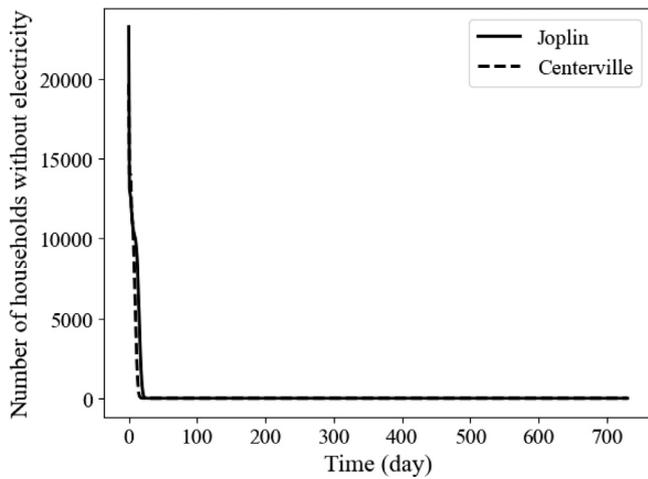
Fig. 7. Time-variant profiles of the number of households without electricity.

ery processes of all the agents involved are tracked for two years. The comparison between the resilience indices of a system or time-variant profiles associated with recovery processes of agents associated with the two testbeds can illustrate the effect of testbed characteristics on the community resilience under the tornado events of the same EF scale. It is worth noting that in the following paragraphs, all the time-variant profiles are associated with the mean results of the Monte Carlo simulation.

Histograms of damaged residential and non-residential buildings are shown in Fig. 6. As the buildings are more densely populated in Joplin than in Centerville, the number of buildings damaged in Joplin subjected to an EF5 tornado is significantly larger than in Centerville. It can also be observed that the number of residential buildings damaged is significantly larger than that of non-residential buildings, as an overwhelming majority of buildings in a testbed are residential.

Fig. 7 shows the time-variant profile of the number of households without electricity, where it is observed that as ample repair resources are allocated for the maintenance work of the EPN, the recovery time for the EPN is relatively short for both testbeds (less than one month).

The number of damaged electric distribution poles in Joplin is significantly larger than that in Centerville as shown in Fig. 8. In addition, as the electric distribution poles are vulnerable to high wind speeds, an electric distribution pole will likely be damaged if it falls within the tornado path. As a result, the dispersion of the number of electric distribution poles is small. Figs. 6 and 8 show that a community with a higher level of development is likely to have more damaged buildings and infrastructure elements under the hazard of a specific intensity.

Fig. 12 shows histograms of the education system's recovery period at elementary, middle, and high school levels for the two testbeds. The location of schools concerning the tornado path varies for the two testbeds, and the recovery periods of the education system for the two testbeds also differs significantly. The mean recovery periods for the education system at the elementary school level and the middle school level in the Joplin testbed are shorter than those in the Centerville testbed, respectively, while it is the other way around for the education system at the high school level. Please note that as the recovery process is only tracked for two years in this study, the recovery period is larger than 700 days as shown in Fig. 9 indicates that the education system still has not recovered yet two years after the tornado event.

Time-variant profiles of the number of students in normal schooling status are shown in Fig. 10. It can be seen that the profile associated with the city of Joplin is higher than that associated with Centerville, as Joplin observes a faster recovery for the education system at the elementary school level and the middle school level than Centerville. Another reason behind the quicker recovery of the education system in Joplin is that the students are more widely spread than in Centerville, as there are more schools in the former testbed. It is worth mentioning that when
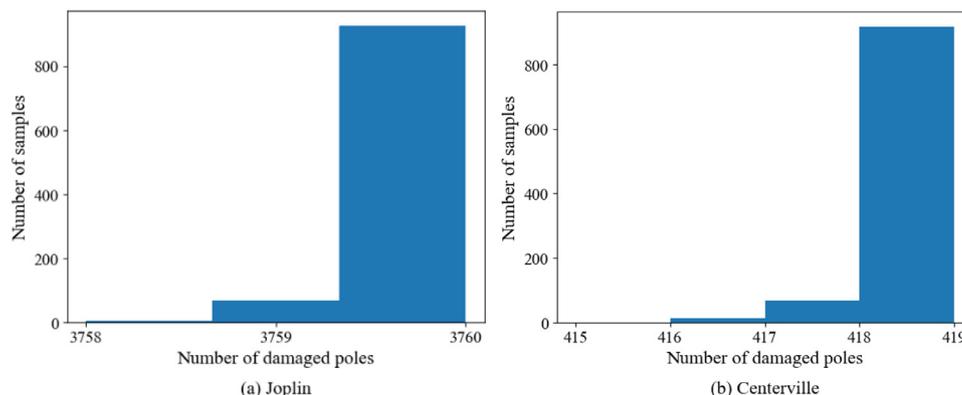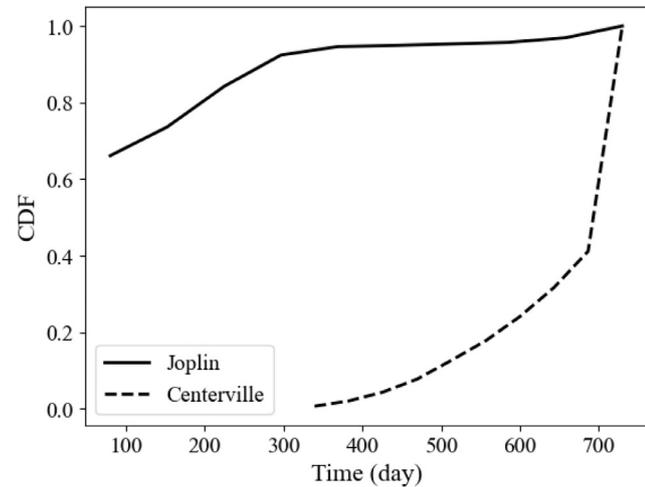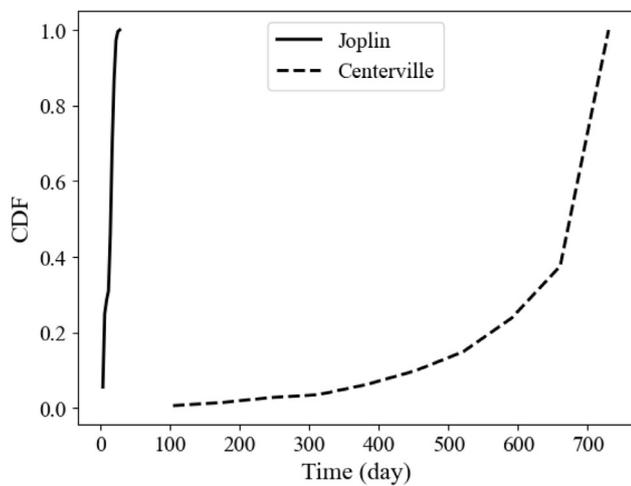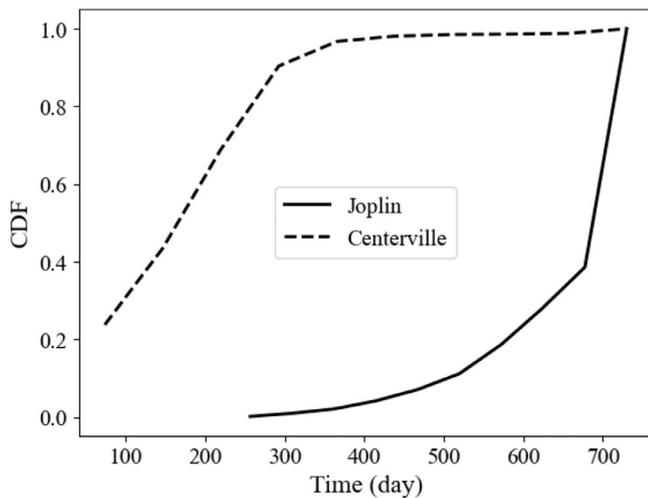
proposed by Sutley and Hamideh [26] is adopted. In this model, a total of five housing stages are considered for the households in the tornado-stricken community, namely emergency shelter, temporary shelter, temporary housing, permanent housing, and failure of housing recovery. A transition matrix is determined by Sutley and Hamideh [26] which governs the post-tornado transition between different housing stages of households. Aghababaei and Koliou [15] further defined ten specific housing statuses and mapped the five housing stages to the ten housing statuses based on factors such as household income level and home ownership. The recovery model proposed by Sutley and Hamideh [26] integrating the housing statuses per Aghababaei and Koliou [15] is adopted herein.

More detailed information on the recovery process of all the types of agents involved in the community (e.g., business, school, and household) can be seen in Aghababaei [27]. Although for a specific type of agent, the recovery process might be affected by the characteristics of the testbed (such as the number of agents and the availability and administration of resources), it is assumed that the flowcharts of recovery processes of agents in Aghababaei [27] which delineate the necessary steps that an agent needs to go through before achieving full recovery are applicable to all the testbeds investigated herein.

5. Resilience analysis results

5.1. Resilience of testbeds

A Monte Carlo simulation with 1000 samples is conducted for the resilience analysis for each testbed using the ABM approach. The recov-

(a) Joplin

(b) Centerville

Fig. 8. Histograms of the number of damaged electric distribution poles.

(a) Elementary school

(b) Middle school

(c) High school

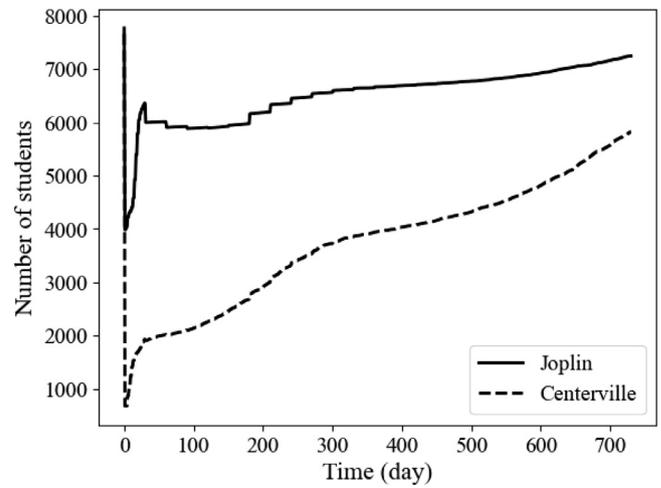**Fig. 9.** CDF plots of the recovery period of the education system.

Fig. 10. Time-variant profiles of the number of students in normal schooling status.

tornado hazards occur, the number of students originally enrolling in structurally damaged schools in Joplin is less than that in Centerville.

For the recovery process of households, time-variant profiles of housing stages for the two testbeds are presented in Fig. 11. Similarities can be observed between the housing stage distributions of the two testbeds. For both testbeds, most households remain in the permanent housing stage after the tornado. The numbers of households in emergency shelters and temporary shelters gradually decrease with time. On the other hand, for both testbeds, some households fall into the recovery failure stage about one year after the tornado event as the housing stages of those families change frequently without settling down in a permanent residence.

Time-variant profiles of the number of working-age people who cannot work are shown in Fig. 12. For both testbeds, a major reason for people unable to work is the relocation of households after the tornado event. The number of people relocated peaks about 6 months after the tornado event. Thanks to adequate medical resources, the number of injured people decreases rapidly for both testbeds. As the education system is more severely affected in Centerville than in Joplin, the number of people who need to take care of children in Centerville is about 3.4 times larger than that in Joplin.

Time-variant unemployment rate profiles for the two testbeds are presented in Fig. 13, where it can be seen that the two profiles are similar in terms of the length of the increasing phase and decreasing phase. The initial unemployment rate in Centerville is lower than that in Joplin by 5.8 percent while the peak unemployment rate in Centerville is lower by 2.5 percent.

The unemployment rate in Fig. 13 is associated with all the working-age residents in the testbeds. The employment status of the employees originally employed by the damaged businesses in the testbeds is shown in Fig. 14. As a commercial hub, the number of employees originally employed by the damaged businesses in Joplin is significantly larger than that in Joplin. Around 70 % of the employees are not affected by the structural damage sustained by businesses employing them, while the percentage is increased to around 75 % in the case of Centerville.

The mean and standard deviation (Std) associated with the resilience indices for the community and its systems in the two testbeds are shown and compared in Table 3. It can be observed that the resilience of the EPN, healthcare, and overall community of the Joplin testbed are close to their counterparts in Centerville. As students are more widely spread in Joplin than in Centerville, the resilience of the education system is about 1.3 times higher than that in Centerville. As more businesses are damaged in Joplin than in Centerville, the resilience of the business sys-
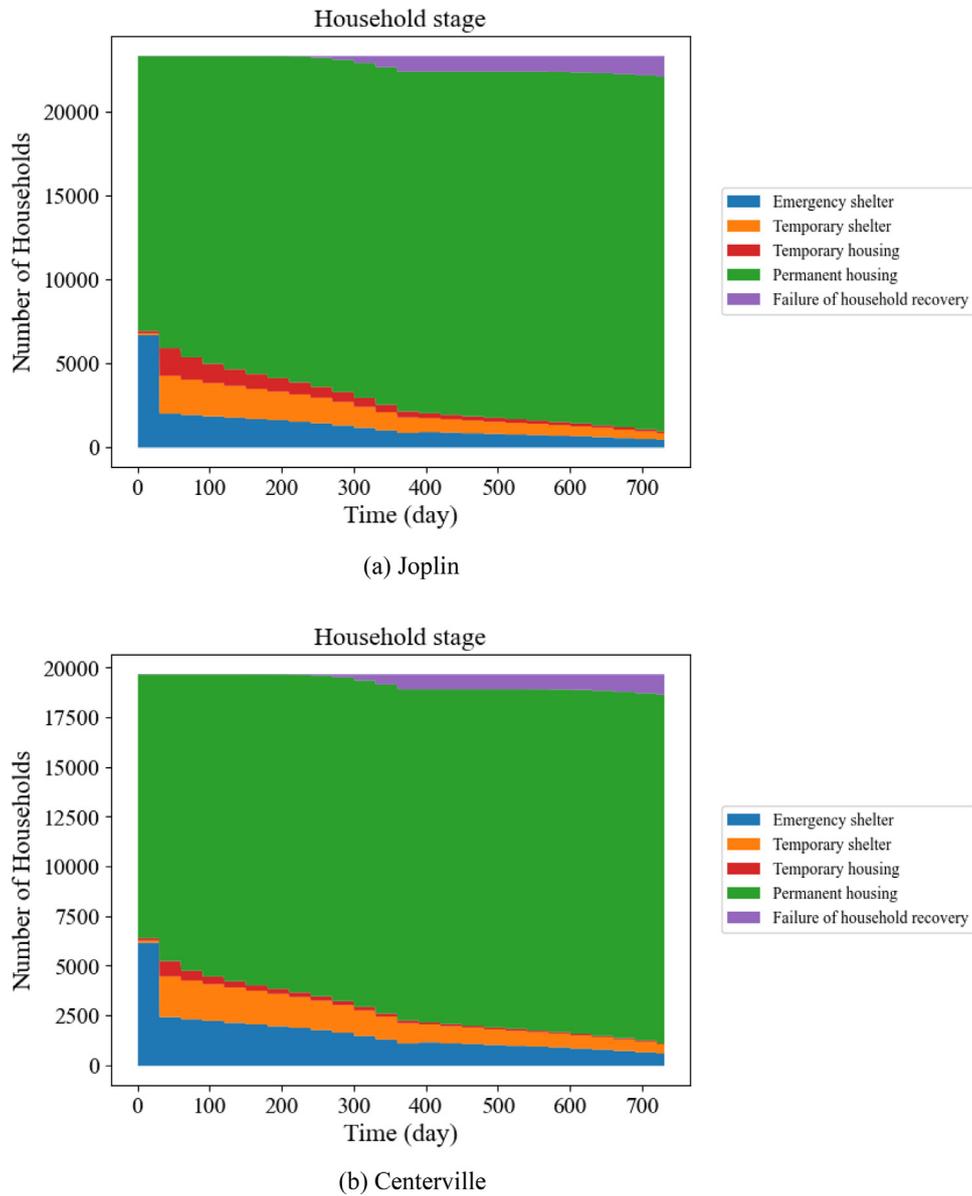
(a) Joplin

(b) Centerville

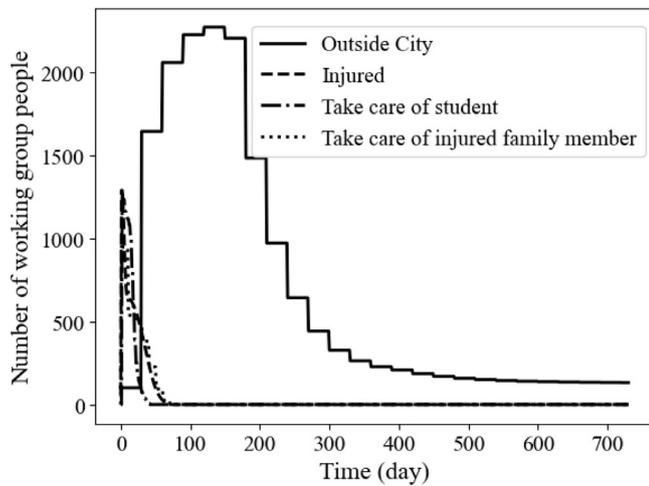**Fig. 11.** Time-variant distribution of housing stages.

Table 3
Statistical summary of resilience indices of the community and its systems.

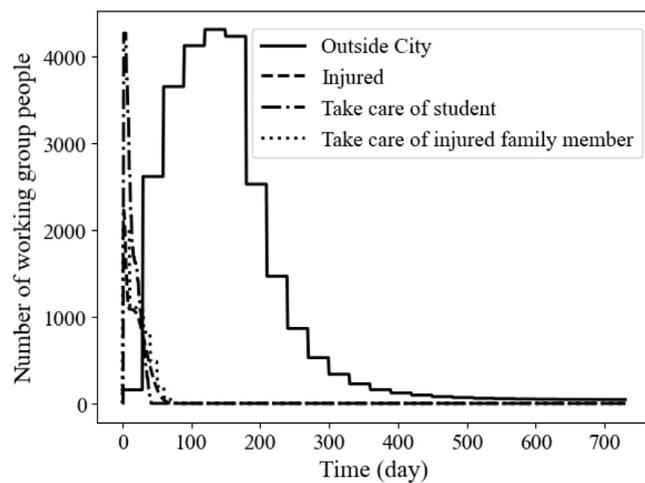| Testbeds	EPN system		Healthcare system		Education system		Business system		Community	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Joplin	0.992	0.010	0.723	0.007	0.887	0.015	0.874	0.006	0.855	0.005
Centerville	0.940	0.018	0.727	0.006	0.690	0.048	0.957	0.002	0.823	0.011

tem is about 9 percent lower than that in Centerville. Table 3 shows that a community of a higher level of development is likely to have a higher resilience in the education system due to a larger number of undamaged educational institutions, while a lower resilience in the business system due to a larger number of damaged businesses. The small COV proves that the number of samples used in this study is sufficient. The reason that the COV is not large is that the resilience index as a performance indicator measures the overall performance over a period of time. The uncertainties of the dispersion of the time-variant functionality of a system will be reduced when the functionality is integrated over time.

5.2. Validation

In the present study, the analysis results of the Joplin testbed are compared with the data provided in post-hazard investigation reports and news websites. Resilience analysis results given by the ABM in general align with data collected after the occurrence of the real-world tornado event. According to Kuligowski et al. [2], around 7500 residential buildings and 550 nonresidential buildings were damaged in the 2011 Joplin tornado event. It can be seen that both the numbers of damaged residential buildings and nonresidential buildings are close to the range of histograms (Fig. 6) associated with the number of damaged buildings

(a) Joplin

(b) Centerville

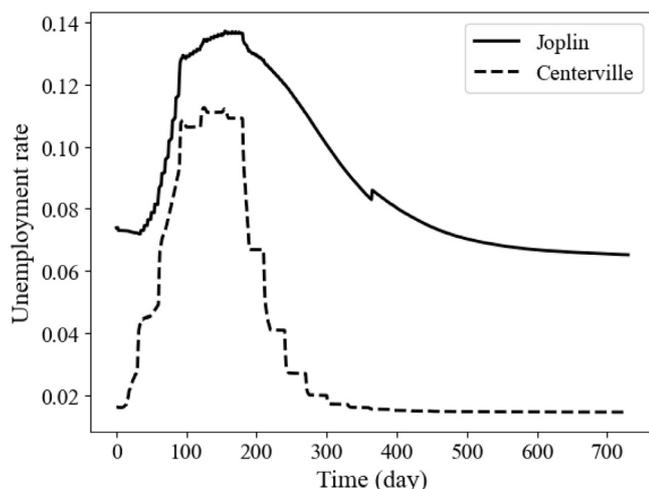**Fig. 12.** Time-variant profiles of the number of people unable to work.

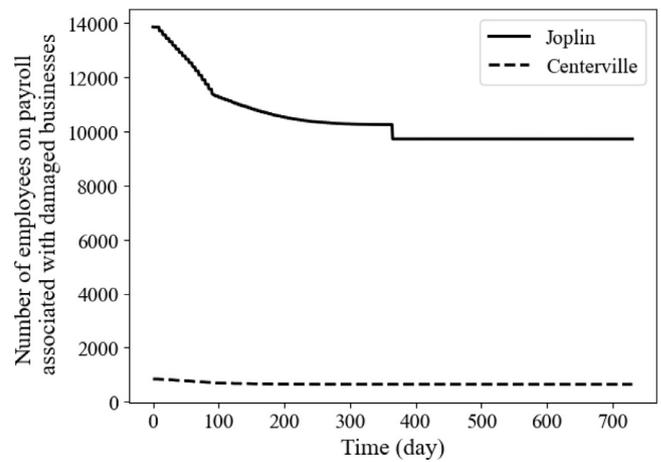**Fig. 13.** Time-variant unemployment rate profiles.

Fig. 14. Time-variant profiles of the number of people originally working in damaged businesses.

in Joplin obtained through the ABM. In addition, around 4000 electric distribution poles were damaged in the tornado event [2], which also aligns closely with the result of the ABM (the difference is about 6 percent).

For the recovery process, according to Stewart et al. [34], around 9200 people were displaced after the tornado events in 2011, which accounts for approximately 20 % of the total population in Joplin. Based on housing stage distribution results of the ABM, it can be seen that around 25 % of households live in emergency shelters after the tornado event. Therefore, the prediction of the initial housing stage distribution given by the ABM is aligned with reality. It is reported by Kuligowski et al. [2] that a quick recovery of the EPN system was achieved in Joplin and that electricity was restored to most of the customers in about 10 days. As can be seen in the recovery profile of the EPN obtained from the ABM (Fig. 7), it takes about two weeks to restore electricity to most of the customers. For the recovery of the business system, it was reported that 60 % to 70 % of the employees affiliated with the damaged business could remain on payroll [35]. Based on the profile of the number of employees on payroll obtained from the ABM in Fig. 14, it can be estimated that around 70 % of the employees affiliated with the damaged businesses can be kept on payroll and therefore, do not need to find a new employer.

It should be acknowledged that as there is a discrepancy between the characteristics and those associated with Joplin, the behavior of agents during the community recovery process stipulated in the recovery models adopted herein may also not fully reflect the real recovery process in Joplin after the May 2011 tornado event, not all the results obtained from the ABM can match the data reported. For instance, data regarding the unemployment rate reported in the news websites suggests a smaller increase in the unemployment rate after the tornado event and a faster recovery after the tornado event occur [36]. The unemployment rate profiles can be updated when a more accurate business recovery model is proposed or a reliable data source of the number of employees of businesses is provided.

It is also worth noting that the validation process can also be conducted for the ABM for virtual testbeds like Centerville. An essential step in the validation process is implementing the agent-based modeling approach using various computer programs and comparing the results obtained from different computer programs. Han et al. [22] conducted a detailed validation process on the ABM for Centerville by comparing the results obtained from open-sourced Python ABM with the ABM created using a widely used commercial software named AnyLogic. Although there is no real recovery data to compare for the recovery profile projected by the ABM, a close match between recovery processes projected by two ABMs (the difference is mainly due to the uncertainties
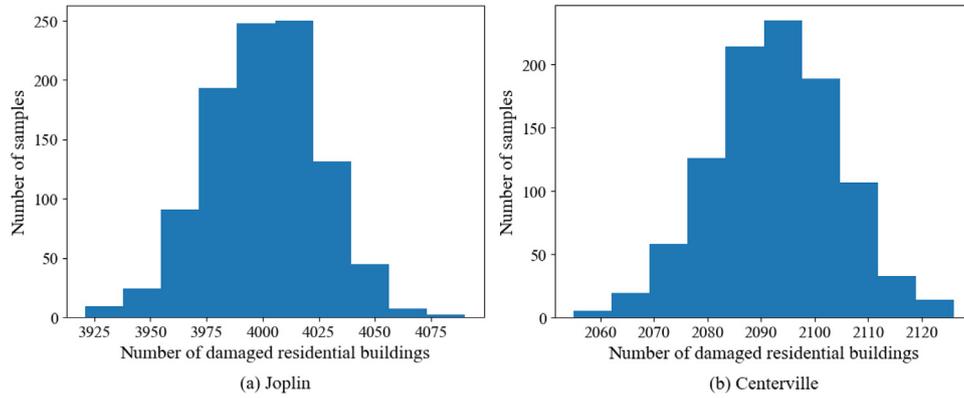
Fig. 15. Histograms of the number of damaged residential buildings with structural retrofits.

incorporated in the ABM) indicates that the agent-based modeling is implemented correctly using both computer programs. Therefore, the ABM created for Centerville can simulate the recovery process of the Centerville testbed accurately.

6. Effects of hazard mitigation strategies on the community resilience of different testbeds

A major purpose of conducting resilience analysis is to numerically quantify the effects of multiple hazard strategies on community resilience, thereby laying out effective mitigation strategies within a specified budget. Two major hazard mitigation strategies are investigated in Han and Koliou [16], namely retrofitting residential buildings and expediting the financial processes of businesses to reduce the time for businesses to reopen. For the testbeds considered herein, building archetypes 1–5 are associated with residential buildings and are subjected to structural retrofits for this case study. Structural retrofit actions for residential buildings were considered by Masoomi et al. [8] and tornado fragility curves of the five archetypes with structural retrofit actions are provided therein. Two retrofit strategies with different levels of structural resistance enhancement were considered by Han and Koliou [16] and of these two strategies, the retrofit strategy with a more significant structural resistance enhancement, referred to as "enhanced combination 2" is adopted herein. The financial processes associated with the recovery of businesses are inspection, contractor mobilization, seeking reimbursement from insurance companies, and permit issuances [25]. A total of four economic policies associated with the acceleration of multiple combinations of financial processes are considered in Han and Koliou [16]. The first policy is the default policy, in which none of the financial processes are accelerated. The second policy results in an acceleration in all the processes except financing. The third policy accelerates the financing process by setting up a credit line for the insured businesses. The fourth policy accelerates all the processes. Of these four policies, the fourth policy (referred to as "policy 4") is adopted herein. Monte Carlo simulations using the ABM of community resilience analysis are conducted for the two testbeds considering the two hazard mitigation strategies to evaluate the effects of hazard mitigation on the recovery and resilience of the communities.

Histograms of the number of damaged residential buildings of the two testbeds are shown in Fig. 15. Compared with the histograms in Fig. 6, it can be observed that applying structural retrofits can significantly reduce the number of damaged residential buildings. A direct benefit of less damaged residential buildings is that fewer people will be displaced after the hazard event, which will also reduce the spike in the unemployment rate after the hazard occurrence. As seen in Fig. 16, the peak of time-variant profiles of displaced people unable to work for the two testbeds is lowered by about 50 % after structural retrofits are implemented. The benefit of applying economic policies mainly lies
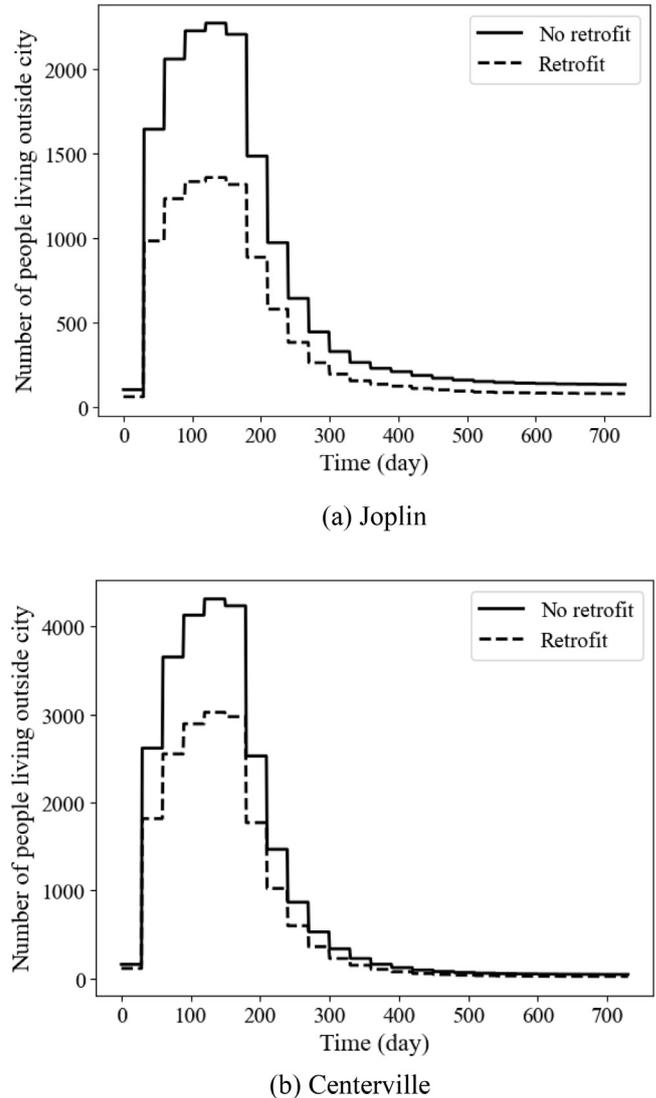

Fig. 16. Time-variant profiles of the number of people unable to work due to outside-city status.

in reducing the business reopening time. Histograms of the mean business reopening time associated with two testbeds are shown in Fig. 17, where it is observed that applying economic policies can significantly reduce the mean business reopening time. As the number of damaged
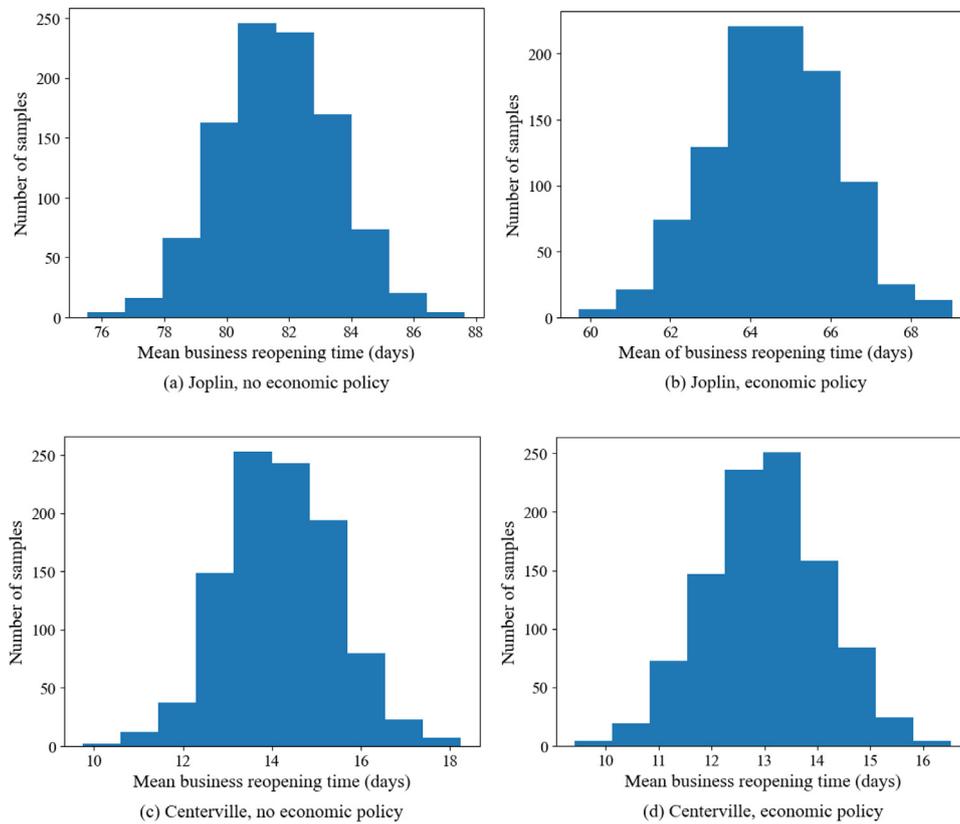
Fig. 17. Histograms of the mean business reopening time.

Table 4
Influence of hazard mitigation strategy on the resilience of the business system.

Testbed		Policy			
		No policy	Structural retrofit actions	Economic policy	Both
Joplin	Mean	0.874	0.877	0.895	0.897
	Std	0.006	0.006	0.006	0.006
Centerville	Mean	0.957	0.968	0.957	0.969
	Std	0.002	0.002	0.002	0.002

Note: Policy "both" refers to the combined mitigation strategy of implementing both structural retrofits and economic policy. "Std" refers to the standard deviation.

businesses in Joplin is much larger than in Centerville, the mean business reopening time in Joplin is much larger. Due to the same reason, the decrease in mean reopening time in Joplin due to economic policies is much larger than the decrease in Centerville.

Effects of the two hazard mitigation strategies as well as a strategy in which both structural retrofit actions and the economic policy are applied to the resilience enhancement of the business system of communities are shown in Table 4. It is shown that the effect of a specific hazard mitigation strategy on resilience enhancement is contingent upon the characteristics of the testbed. For instance, as the number of damaged businesses in Centerville is relatively small, the effect of applying economic policies is insignificant for the business resilience metric, while applying structural retrofit actions has a significant impact. On the other hand, as the number of damaged businesses in Joplin is relatively large, applying economic policies leads to a higher increase in the business resilience metric than applying retrofit actions.

7. Conclusions

In this study, resilience simulations using the agent-based modeling approach are carried out on two testbeds, namely Joplin and Centerville. The two testbeds have distinctive characteristics such as the spa-

tial layout and level of development. Both testbeds are subjected to an EF5-scale tornado and analyses are conducted to quantify their recovery and resilience and the effects of hazard mitigation strategies on them. Comparison between resilience analysis of the two testbeds can indicate the influence of testbed characteristics on community resilience. The following conclusions are drawn:

1. As communities in a metropolitan region, in general, have more maintenance resources, at least for the EPN and healthcare systems in a community, a faster recovery can be observed after tornado events of a specific EF scale in communities in a metropolitan area compared with the recovery of communities in less developed regions. In the meanwhile, the recovery period for the business system in metropolitan regions may be longer than that in less developed regions due to a larger number of damaged businesses.

2. For the tornado resilience simulation, as only the structures falling within the tornado path are likely to be damaged, the spatial distribution of structures in a community can have a significant impact on the community recovery process and resilience. For instance, a major reason behind the difference in the recovery period of schools of different education level in the two testbeds is the difference in the spatial distribution of the education institutions in the two testbeds.

As more developed communities tend to have more educational institutions, the probability that most schools fall on the tornado path is small, leading to a more resilient education system.

3. The effect of a specific type of hazard mitigation strategy on community resilience is sensitive to the characteristics of the testbed investigated. An effective maintenance strategy on one testbed may no longer be effective when applied to another testbed. For instance, whether expediting the financial processes is effective in increasing the resilience of the business system is contingent upon the number of damaged businesses in a community. The effects of structural retrofit actions on community resilience are related to the damage states of structures, which depend upon the spatial layout of structures in a community.

4. It is worth noting that the agent-based modeling methodology adopted herein can be further developed by modeling the community's recovery process in a more detailed manner. Applying the refined agent-based modeling methodology to the testbed investigated herein can be a future research direction.

5. Future research efforts also include how to achieve knowledge transfer between the resilience simulations of different testbeds using the agent-based modeling approach, i.e., trying to project the resilience of a testbed subjected to a natural hazard event based on the resilience analysis results of other testbeds subjected to a similar event. In addition, achieving knowledge transfer between the effective/optimal hazard mitigation strategies for different testbeds will be a significant future research direction. Last but not least, it is also interesting to investigate the influence of testbed characteristics on community resilience using other resilience analysis approaches and compare the results with those obtained using the agent-based modeling approach.

Relevance to resilience

The present study investigates the influence of testbed characteristics on community resilience using the agent-based modeling approach. The subject of this study correlates to the scope of the Journal of Resilient Cities and Structures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Xu Han: Writing – original draft, Writing – review & editing, Conceptualization, Methodology, Formal analysis. **Maria Koliou:** Writing – review & editing, Conceptualization, Supervision, Funding acquisition.

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