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Postdisaster Housing Stages: A Markov Chain Approach to Model Sequences and Duration Based on Social Vulnerability

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Housing recovery is an unequal and complex process presumed to occur in four stages: emergency shelter, temporary shelter, temporary housing, and permanent housing. This work questions the four-stage typology and examines how different types of shelter align with multiple housing recovery stages given different levels of social vulnerability. This article also presents a Markov chain model of the postdisaster housing recovery process that focuses on the experience of the household. The model predicts the sequence and timing of a household going through housing recovery, capturing households that end in either permanent housing or a fifth possible stage of failure. The probability of a household transitioning through the stages is computed using a transition probability matrix (TPM). The TPM is assembled using proposed transition probability models that vary with the social vulnerability of the household. Monte Carlo techniques are applied to demonstrate the range of sequences and timing that households experience going through the housing recovery process. A set of computational rules are established for sending a household to the fifth stage, representing a household languishing in unstable housing. This predictive model is exemplified on a virtual community, Centerville, where following a severe earthquake scenario, differences in housing recovery times exceed four years. The Centerville analysis results in nearly 5% of households languishing in unstable housing, thereby failing to reach housing recovery. These findings highlight the disparate trajectories experienced by households with different levels of social vulnerability. Recommendations are provided at the end for more equitable postdisaster recovery policies.

KEY WORDS: Centerville; housing recovery; recovery sequence; social vulnerability; temporary housing

1. INTRODUCTION

Assuring safe and quality housing is one of the most important individual and collective goals after a disaster (Peacock, Dash, & Zhang, 2006). Households rely upon homes for shelter, sanctuary, and often as a significant economic asset. In turn, communities rely upon a strong housing stock as a means of maintaining or enhancing political strength and social and economic growth. Buildings used for housing represent the highest percentage of all buildings in the United States (Comerio, 1998). As observed from previous U.S. disasters, housing reconstruction and housing relocation make up a significant portion of disaster losses (Peacock, Van Zandt, Zhang, & Highfield, 2014). For example, nearly $20 million of the estimated $40 million in property loss from the 1994 Northridge earthquake was attributed to

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damage to wood-frame residential buildings (Reitherman & Cobeen, 2003). Hurricane Ike was estimated to cause $3.4 billion in total damage to housing units in Texas, including damaging 80% of homes in Galveston Island (Hurricane Ike Impact Report, 2008). Hurricane Sandy, one of the largest storms on record in the United States, led to nearly $6 billion in housing damages (Blake, Kimberlain, Berg, Cangialosi, & Beven, 2013; Rutgers School of Public Affairs, 2013).

These postdisaster reports with extraordinary housing losses are becoming the norm. The National Oceanic and Atmospheric Administration (NOAA) reports 14 billion dollar disasters occurred in 2018, making it the fourth most expensive year on record for weather- and climate-related disasters in U.S. history. This is following 2017, the most expensive year on record and 2016, the third most expensive year on record (NOAA, 2019). The extent of many recent disasters is still being realized, but it is clear that rehousing victims has continued to be one of the largest challenges. New policies that support equitable housing recovery can reduce the expensive burden of rehousing victims, which will greatly improve community recovery after disaster.

This article addresses household risk of postdisaster displacement, homelessness, and several short-term and long-term potential consequences of these such as diminishing quality of life, diminishing health, diminishing wealth and financial security, and risk of widening inequality across a community. These risks are illustrated through a predictive Markov chain model of households going through the postdisaster housing recovery process. The model provides three major contributions to the housing recovery literature by (1) examining housing recovery as a process instead of merely an outcome, (2) examining the housing recovery of households instead of houses, and (3) questioning the widely accepted linear four-stage postdisaster housing typology by demonstrating that housing types used in postdisaster recovery do not necessarily fit that model, and acknowledging a fifth stage, housing recovery failure, that is often experienced by the most socially vulnerable households. The modeling and assumptions presented here are grounded in social science disaster recovery theory. The results, exemplified through a community-level analysis of the virtual community Centerville, demonstrate the vast disparities in housing recovery trajectories for different households considering their social vulnerability. Results of this model are used to recommend equitable disaster housing recovery policy in the United States.

2. POSTDISASTER HOUSING RECOVERY THEORY

Sociopolitical ecology perspective recognizes that disasters often exacerbate or accelerate processes already occurring in communities instead of changing them (Aldrich & Meyer, 2015; Bates & Peacock, 1989; Green, Bates, & Smyth, 2007; Hirayama, 2000; Kates, Colten, Laska, & Leatherman, 2006; Morrow & Peacock, 1997; Xiao & Van Zandt, 2012). Hence, preexisting inequalities can be manifested and magnified with disaster damages leading to unequal trajectories of housing recovery. Physical damage is a primary factor in explaining housing recovery disparities and it is related to disaster exposure and predisaster housing conditions associated with housing age, type, and tenure, as well as household income, race, and ethnicity (Chang, 2010; Cutter, Schumann, & Emrich, 2014; Green, Kouassi, & Mambo, 2013; Hamideh, Peacock, & Van Zandt, 2018; Highfield, Peacock, & Van Zandt, 2014; Olshansky, Hopkins, & Johnson, 2012). Physical and social concentration of damage often set the stage for different recovery trajectories for minority and inner city older neighborhoods with more older and rental housing compared to suburban and newer neighborhoods (Comerio, 1997; Green & Olshansky, 2012).

Sometimes households with the most extensive damage remain in temporary housing for years. Hamideh et al. (2018) found in Galveston following Hurricane Ike that given similar levels of damage, owner- or renter-occupied housing in low-income neighborhoods with higher concentrations of minorities and immigrants recover slower than other owner-occupied housing, which matches findings from other disasters (Weber & Lichtenstein, 2015; Wright, Rossi, Wright, & Weber-Burdin, 1979; Wu & Lindell, 2004). These homeowners and renters often have limited access to private and public recovery resources due to low-quality insurance, insurance red-lining, poor language skills and educational backgrounds, failure to apply for assistance, and inability to qualify for or repay low-interest recovery loans. Moreover, renters have limited savings and resources in their bonding social networks, and limited temporary housing options to rely on while landlords decide whether and how to rebuild (Wu & Lindell, 2004). Disaster assistance programs have largely failed to adequately consider the needs of middle- and lower income homeowners, and more particularly, renters in older and lower value housing, or provide reconstruction funding to owners of multifamily structures (Bolin & Bolton, 1986; Bolin & Stanford, 1998; Kamel & Loukaitou-Sideris, 2004; Masozera, Bailey, & Kerchner, 2007; Mueller, Bell, Chang, & Henneberger, 2011; Wu & Lindell, 2004). Disparities that result from overlooking recovery policies are also significant, and further exacerbated for people with disabilities, other special needs, health difficulties, and the homeless population, including those people living in extreme poverty and at risk of becoming homeless. Multiple studies (e.g., Cutter et al., 2014; Nejat & Ghosh, 2016) have identified insurance reimbursements, tenure, and other financial resources as the most significant factors contributing to homeowner decisions to repair, rebuild, or relocate.

It is important to study disparities in sequence and time to reach or stay in different stages of housing recovery to gain a comprehensive understanding of the actual experiences of different households throughout housing recovery. By examining household sequence through housing recovery stages, the focus of analysis shifts from only one stage, e.g., permanent housing, to the entire process of housing recovery. Housing recovery is a process with several phases rather than merely a single outcome. Quarantelli (1982) proposed a typology of four distinctive forms of sheltering and housing including emergency sheltering, temporary sheltering, temporary housing, and permanent housing. This typology has been frequently used in studies of postdisaster housing processes (e.g., Badeaux & Sutley, 2018; Bolin & Stanford, 1998; Peacock & Girard, 1997) and adopted in U.S. federal recovery programs. One of the implications of this typology is that housing recovery disparities occur not only in the final permanent housing outcome but also in different phases along the way. Consequently, households might experience differential sequencing across any or all stages of housing or shelter in the aftermath of disasters based on their socioeconomic characteristics and access to resources. For example, in a study of temporary sheltering following Hurricane Andrew, households with higher incomes were more likely to stay at hotels and motels, while those with lower incomes stayed with family (Morrow & Peacock, 1997). The limitations that lower income households face when addressing housing issues in normal situations can result in a delay or failure to transition out of temporary shelters or temporary housing into permanent housing (Fothergill & Peek, 2015; Starr Cole, 2003).

Very few studies have looked specifically at the sequence a household takes through housing recovery. Bolin (1982) and Bolin and Bolton (1986) established housing recovery as a process. Residential dislocation in those two studies is the first empirical measurement of household movement through the housing recovery process. They found disaster victims with higher incomes moved more frequently and that greater disaster losses increased the number of times disaster victims are forced to move. Starr Cole (2003) hypothesized that there were four possible sequences through the four stages of housing recovery: (1) progressive nonrepetitive (P-N), (2) progressive repetitive (P-R), (3) regressive nonrepetitive (R-N), and (4) regressive repetitive (R-R), and that sociodemographic characteristics of households and access to recovery resources are correlated with the sequence of household movements. The sample analyzed, however, only provided significant results for the two progressive sequences as the number of residents in the two regressive sequences was very small. It was concluded that as the damage to property increases, the sequence of movements of the households were more likely to be classified as P-R than as P-N. Also the sequence of movements of households that used more resources were more likely classified as P-N than as P-R (Starr Cole, 2003).

In all four postdisaster housing sequences from Starr Cole (2003), the households recover. However, Fothergill and Peek (2015), in their ethnographic study on the recovery trajectories of Hurricane Katrina–affected children observed a fifth sequence where households do not recover, particularly those who were living in precarious situations prior to a disaster. When Fothergill and Peek's study ended, one of the seven children had become homeless and was not predicted to reach stable or permanent housing; the housing recovery system had failed the child. They concluded stable housing is the most critical factor in household recovery. Here, stable housing is distinguished from permanent housing, where stable housing is achieved when a household is able to remain in the same residence for at least one year (Merdjanoff, 2015).

It is imperative for displaced residents to reach permanent housing as soon as possible following a disaster. The longer families have to spend in temporary housing and the greater the number of moves between intermediate housing stages, the greater the aggregate level of stress and financial losses experienced and the longer the persistence of mental and physical health problems. All of these processes have implications for individual and community health, long-term recovery, reinvestment, and sustainable re-development of communities.

3. EXISTING RECOVERY MODELS

Recovery is a complex phenomenon. Many quantitative studies have measured postdisaster housing recovery (or restoration) using improvement value data (Hamideh, 2015; Hamideh et al., 2018), permit data (Lester, Perry, & Moynihan, 2014; Stevenson, Emrich, Mitchell, & Cutter, 2010), or postdisaster aerial imagery of structures (Hoshi, Murao, Yoshino, Yamazaki, & Estrada, 2014) as proxy measures. Few probabilistic or predictive models exist for housing recovery including optimizing recovery outcomes from various temporary housing solutions (El-Anwar, 2010; El-Anwar, El-Rayes, & Elnashai, 2010), a decision support system for assigning families to temporary housing units and locations (Rakes, Deane, Rees, & Fetter, 2014), an agent based model of household-based decisions to rebuild (Nejat & Damnjanovic, 2012), a least absolute shrinkage and selection operator model on household decision making (Nejat & Ghosh, 2016), material resource system dynamics model on construction material supply (Diaz, Kumar, & Behr, 2015) and labor supply (Kumar, Diaz, Behr, & Toba, 2015) for rebuilding housing, and a Markov chain model for building functionality restoration that was designed generically, but could be applied to housing functionality restoration (Lin & Wang, 2017). Most of these studies focus on the physical process of rebuilding, and on recovery of houses, as opposed to recovery of households. Sutley and Hamideh (2017) took a holistic look at the housing system, its multiple stages, and its relationship with accessibility, social vulnerability, health, financial resources, household decision making, and policy interventions to develop a qualitative and scalable system dynamics model of housing. The present predictive model leverages the qualitative model Sutley and Hamideh developed (2017) by using it to depict the causal relationship of social vulnerability with a conceptualization, one that incorporates time and transition into the process of housing recovery. The interested reader is referred to Sutley and Hamideh (2017) for a thorough discussion and comparison of existing housing recovery models.

There is evidence in the literature showing that different households experience different sequences of housing stages, and that the time households spend in each of the four stages varies significantly (e.g., McIntosh, Gray, & Fraser, 2009; Mitchell, Esnard, & Sapat, 2012; Muskal, 2012; Starr Cole, 2003). However, the reasons behind these variations are largely unexplored. Social science housing recovery theory indicates housing damage, insurance reimbursements, tenure status, income level, race, ethnicity, mental health, and financial aid from local, state, and federal government and other organizations are some of the major timing contributors for a household to obtain permanent housing postdisaster. This study makes simplifications to accommodate the lack of empirical data by modeling social vulnerability as a composite construct that includes all of these factors with flexible composition and weights, and demonstrates how differing levels of social vulnerability influence the sequence and timing of a household's progression through the housing recovery stages.

4. PREDICTIVE HOUSING RECOVERY MODEL

A predictive housing recovery model was developed using a discrete state Markov chain. A Markov chain is ideal to model housing recovery as a process, rather than only an outcome; it captures the staging of the process, provides a clear visualization of the theoretical housing recovery process (as will be shown later), and accommodates and captures the inputs, outputs, assumptions, and underlying theory.

4.1. Underlying Theoretical Assumptions

Let $S(t)$ be the stochastic postdisaster housing recovery process of an individual household, denoting housing recovery stage at any time t after the hazard occurrence at t_0. $S(t)$ takes the form

$$P\left[S(t) = j|S(s) = i, S(t_{n-1}) = i_{n-1}, \ldots, S(t_1) = i_1\right] = P\left[S(t) = j|S(s) = i\right], \quad (1)$$

where s is the present time, t is a future time, $0 \leq t_1 \leq t_2 \leq \ldots \leq t_{n-1} \leq s \leq t$, and i and j are the specified stage (1 through 5) at time t or s. Meeting Equation (1) is required for a process to have the Markov property (Serfozo, 2009), i.e., the future value of the random variable (time spent in a postdisaster housing stage) depends only on the value of the random variable at the present time. This requirement assumes the time spent in temporary shelter is not dependent on the time spent in emergency shelter, for example. In general, the time spent in one stage is not dependent on

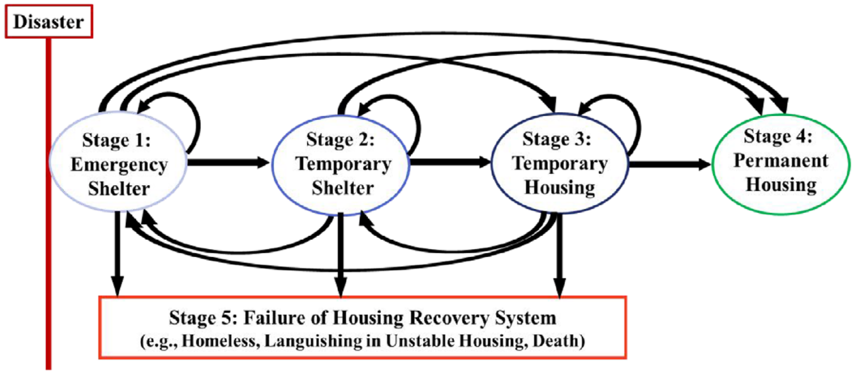

Fig 1. Markov chain realization of housing recovery stages.

the time spent in another stage. While this assumption is a simplification that has not been validated, Monte Carlo simulation (explained in the next section) overcomes any associated shortcoming with the assumption. For example, a household with limited financial resources could reach permanent housing sooner if allowed to stay in government-funded temporary housing longer such that they are able to accumulate personal savings. This scenario is still possible because of the use of Monte Carlo simulation.

The housing recovery process, $S(t)$, shown in Fig. 1, is assumed to take one of the five discrete states at any time, symbolized as S_i. The first stage, S_1, is emergency shelter; the second stage, S_2, is temporary shelter; the third stage, S_3, is temporary housing; the fourth stage, S_4, is permanent housing; the fifth stage, S_5, is failure, which can be mapped to languishing in unstable housing, becoming homeless, or death. The first three stages can be consecutive, or skipped to move into a more advanced stage. For example, a household does not have to spend any time in temporary housing in order to reach permanent housing; a household can move directly from emergency shelter or temporary shelter into permanent housing. Furthermore, a household does not have to start in emergency shelter (Stage 1). For example, with hurricanes, many households evacuate to stay with family or friends or in a hotel, which is not considered emergency shelter. Emergency shelter is defined as large group shelters that house people for the immediate first few days (or less) after a disaster impact. Rather, staying with family or friends or in a hotel is defined as temporary shelter, and thus these households will enter the model in Stage 2. Table I lists common housing types used in present-day postdisaster housing recovery in the United States, and what stage(s) these were modeled as here.

Table I. Classifying Housing and Sheltering Types

Type of Housing or Shelter	Stage
Large group shelter	1
Homeless shelter	1 or 5
Hotel or motel	2 or 3
Staying with friends or relatives	1, 2 or 3
RV or mobile home	3 or 4
Rental unit	3 or 4
Owner occupied home	3 or 4

Establishing a definition of permanent housing is a complex but necessary task for the computational model. First, permanent housing cannot be assumed to be achieved after a certain number of years considering post-Katrina experiences that left some families living in mobile housing units issued by the Federal Emergency Management Agency (FEMA), commonly identified as "FEMA trailers," for up to six years (Muskal, 2012). Second, households have different preferences somewhat dependent on their capacities to achieve different types of permanent housing, such that a wealthy family may not consider themselves in permanent housing until they are back in their own fully repaired or new single-family detached dwelling, whereas other households might feel at home and back to their normal routine in a rental unit. Third, new types of temporary housing such as Katrina cottages (El-Anwar, 2010) and RAPIDO (Van Zandt & Sloan, 2017) are intended to transition into permanent housing seamlessly by keeping the household in the temporary housing unit permanently and adding square footage onto it over time (Badeaux & Sutley, 2018). To overcome this complexity, permanent housing can be assumed to be achieved after a household self-identifies to be in permanent housing. This information is not readily available, and therefore the Markov chain assigns a household to Stage 4 permanent housing through random selection of transition probability based on social vulnerability.

Looking at Fig. 1, the first three stages can result in a progression toward Stage 4, departure to Stage 5, or digression backward to a previous stage until eventually moving into Stage 4 or 5. Both Stages 4 and 5 are absorbing stages, and Stages 1, 2, and 3 (all nonabsorbing stages) can lead to either Stage 4 or 5 through a finite number of steps, therefore this Markov chain is an absorbing Markov chain. All four sequences (i.e., P-N, P-R, R-N, R-R from Starr Cole, 2003), as well as the possibility of a household failing to reach permanent housing are accommodated through the Markov chain. To accommodate the fifth stage, a careful examination of the literature was undertaken to establish computational rules for sending a household into Stage 5 (failure). A time step equates to one month. If a household takes longer than seven years (e.g., 84 time steps) to reach Stage 4, the Markov chain automatically sends the household to Stage 5 (identified as languishing in unstable housing). Furthermore, if the household experiences more than 4 regressive steps in 12 time steps (one year), 7 regressive steps in 24 time steps (two years), or 10 regressive steps during the analysis, then the household is sent to Stage 5. Sensitivity analysis is performed in a later section to examine the sensitivity of these rules, and the end of the article translates theory to number of moves in the Markov chain.

4.2. Markov Chain of the Housing Recovery Process

The Markov chain is designed at the household level and captures the household's housing recovery trajectory given social vulnerability as the primary predictor. Let $\pi_j(t)$ denote the probability that $S(t) = S_j$ at any time t, generating a stage probability vector

$$\pi\,(t) = [\pi_1\,(t)\,;\pi_2\,(t)\,;\pi_3\,(t)\,;\pi_4\,(t)]\,, \tag{2}$$

where the initial ($t = t_0$) stage probability vector, $\pi(t_0) = [\pi_1(t_0); \pi_2(t_0); \pi_3(t_0); \pi_4(t_0)]$, can be determined by a joint probabilistic mapping from the joint effect of building damage, utility disruption, and social vulnerability following a hazard event to household dislocation rates (Lin & Wang, 2017; Sutley & Hamideh, 2017; van de Lindt et al., 2018). Such data are not readily available, but can be obtained through longitudinal postdisaster field reconnaissance (e.g., van de Lindt et al., 2018).

Let $\boldsymbol{TPM}(t)$ be the transition probability matrix that represents the household-level housing recovery process $S(t)$. The nonnegative elements of $\boldsymbol{TPM}(t)$, $p_{i,j}(t)$, defined as

$$p_{i,j}\,(t) = Prob[S\,(t) = S_j | S\,(s) = S_i] \tag{3}$$

describe the probability of a household transitioning to state S_j at any time t given their current state is S_i. Considering the underlying theoretical assumptions discussed above, that at any given time the household can remain in their current state, transition to a higher state, or transition to a lower state until permanent housing or failure are reached, $\boldsymbol{TPM}(t)$ takes the form

$$\boldsymbol{TPM}(t) = \begin{bmatrix} p_{1,1}\,(t) & p_{1,2}\,(t) & p_{1,3}\,(t) & p_{1,4}\,(t) \\ p_{2,1}\,(t) & p_{2,2}\,(t) & p_{2,3}\,(t) & p_{2,4}\,(t) \\ p_{3,1}\,(t) & p_{3,2}\,(t) & p_{3,3}\,(t) & p_{3,4}\,(t) \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{4}$$

where Fig. 1 illustrated the possible actions described in $\boldsymbol{TPM}(t)$. The housing recovery stage probability vector at any time t is

$$\begin{aligned} \pi\,(t) &= [\pi_1\,(t)\,;\pi_2\,(t)\,;\pi_3\,(t)\,;\pi_4\,(t)] \\ &= \pi\,(t_0) \times \boldsymbol{TPM}\,(t)\,. \end{aligned} \tag{5}$$

To obtain the stage a household is in at a particular time t, Monte Carlo simulation is performed using a roulette wheel. The roulette wheel was designed with slots proportionate to $\pi(t)$, where slot j is equal in size to $\pi_{\mathrm{j}}(t)$ for $j = 1, 2, 3, 4$. A random number generator fit with the bounds of the roulette wheel places the household in the aligning roulette wheel slot to determine $S(t)$. This latter step is not necessary, but is performed in the examples presented below to demonstrate finite housing recovery sequences for households. It allows households with the same social vulnerability to experience different housing recovery sequences capturing the uncertainty in the relationship between social vulnerability and recovery trajectory given the many other influential factors (e.g., initial damage level to home, incoming financial resources, material and contractor availability) that are not explicitly modeled here.

4.3. Modeling the Relationship between Social Vulnerability and Stage Transition

Social vulnerability was modeled on an arbitrary scale of 0 to 1, where 0 represents the minimal possible social vulnerability and 1 represents the

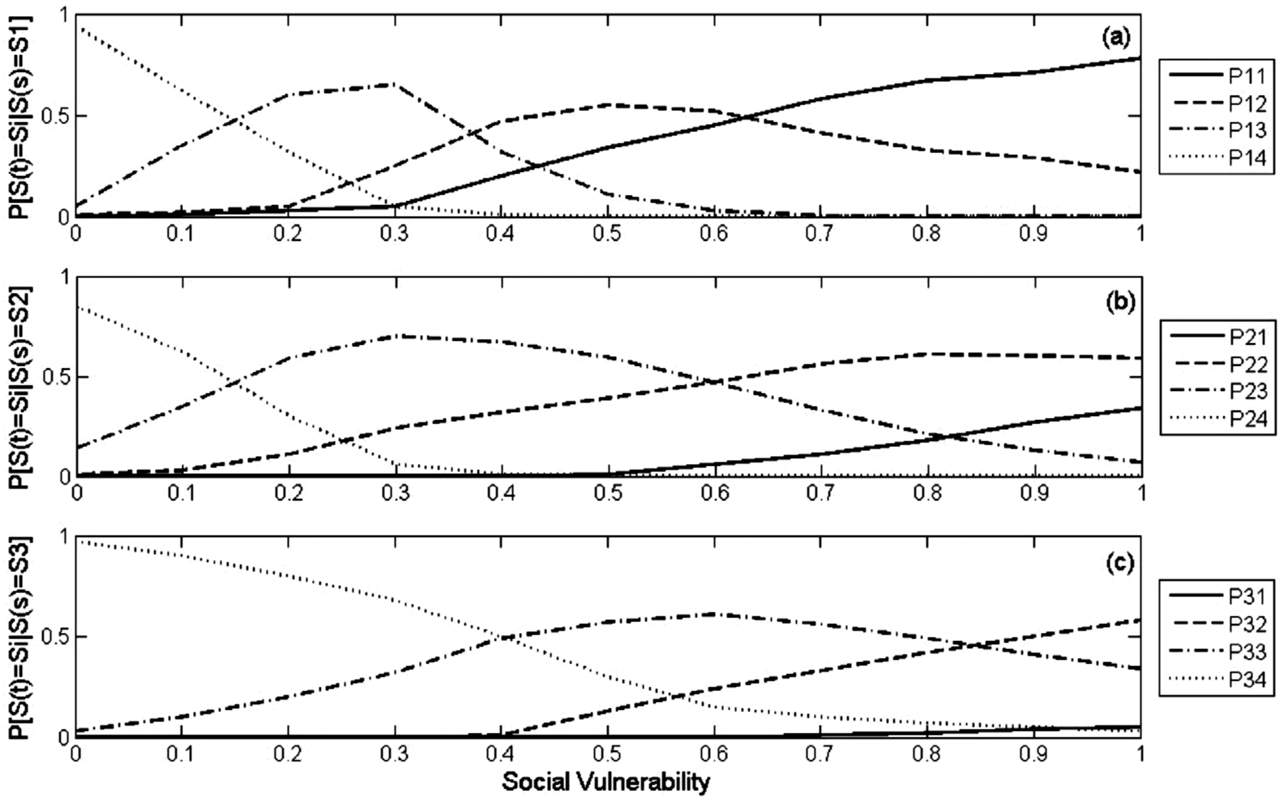

Fig 2. Stage transition probability as a function of social vulnerability.

highest possible social vulnerability. Social vulnerability is an assumed composite variable representing the increased susceptibility to negative impacts and consequences that a household experiences due to socioeconomic attributes, such as race, ethnicity, income, education tenure, and disability discussed in Section 2. Figs. 2(a)–(c) present the transition probability for each possible move as a function of social vulnerability. Fig. 2(a) presents the probability of being in Stage 1 and staying in Stage 1 (p_{11}), and being in Stage 1 and transitioning to Stage 2, 3, or 4 (p_{12}, p_{13}, and p_{14}, respectively). Fig. 2(b) presents the probability of being in Stage 2, and subsequently regressing back to Stage 1, staying in Stage 2, or progressing to Stage 3 or 4. Fig. 2(c) presents the probability of being in Stage 3, and subsequent regressing back to Stage 1 or Stage 2, staying in Stage 3, or progressing to Stage 4. Note: no probability is assigned to a household transitioning into Stage 5 (failure) as Stage 5 is assigned only through the rules established previously and presents the exception not the norm, and thus also why it does not appear in Equation (4).

The relationships presented in Fig. 2 are the authors' takeaways from interviews with residents and household surveys they have been conducted in the field after several disasters, the existing quantitative systematic housing studies in the literature and qualitative evidence in the housing recovery literature described in Section 2. For example, as shown in Fig. 2(a), the probability of being in Stage 1 and staying in Stage 1 is modeled higher for households with higher social vulnerability since households with lower social vulnerability will have access to more permanent and private housing opportunities earlier in the process. Households with low social vulnerability have the highest probability of moving into Stages 1 and 3; households with moderate social vulnerability have the highest probability of progressing to Stage 2. Similarly, looking at Fig. 2(b), once in Stage 2, it is most probable that households with low social vulnerability will transition to Stage 3 or 4, and most probable that households with high social vulnerability will stay in Stage 2 or regress back to Stage 1. Lastly, looking at Fig. 2(c), the probability of being in Stage 3 and regressing to Stage 1 or 2 increases

Table II. Sensitivity of Household Sequences to Number of Iterations

Number of Iterations, n	Social Vulnerability, SV	Minimum Recovery Time (Months)	Mean Recovery Time (Months)	Maximum Recovery Time (Months)	Number of Households Sent to Stage 5
100	0.90	0	12.50	30	40
100	0.50	0	3.40	7	0
100	0.10	0	0.35	2	0
1,000	0.90	0	13.10	43	373
1,000	0.50	0	3.48	9	0
1,000	0.10	0	0.39	2	0
10,000	0.90	0	11.40	48	3,197
10,000	0.50	0	2.60	9	0
10,000	0.10	0	0.38	3	0
100,000	0.90	0	11.36	46	31,363
100,000	0.50	0	2.60	10	0
100,000	0.10	0	0.38	3	0

as social vulnerability increases. It is less likely for a household to go from temporary housing (Stage 3) to emergency shelter (Stage 1) considering the limited time emergency shelters are open after a disaster. Thus, for households with high social vulnerability, a much higher probability is assigned for p_{32} than p_{31}, and households with low social vulnerability have a very low probability of regressing to either Stage 1 or 2. Further, households with low social vulnerability will most likely transition to Stage 4; households with moderate social vulnerability have the highest probability of staying in Stage 3—the longest documented stage of housing recovery. The relationships between social vulnerability and stage transition probability were developed using the rationale just described, and calibrated such that for any household with a given social vulnerability, the transition probability from any one stage to all other options sums to one.

4.4. Sensitivity Analysis

A sensitivity study is briefly presented here to demonstrate the analysis sensitivity to two inputs: (1) the number of iterations in the simulation and (2) the initial stage probability vector, S_0. The rules for sending a household to Stage 5 are also examined. Since the analysis employs Monte Carlo simulation, it is important to assess whether changes to the total number of iterations will give different results in potential sequences for households with the same social vulnerability. Four iteration levels ($n_1 = 100$; $n_2 = 1{,}000$; $n_3 = 10{,}000$; $n_4 = 100{,}000$) were examined each for three different social vulnerability levels ($SV_1 = 0.1$; $SV_2 = 0.5$; $SV_3 = 0.9$), holding the initial stage probability vector constant at $S_0 = [0.95\ 0.017\ 0.016\ 0.016]$. Each variation was run 10 times; in total 120 analyses were performed to test the sensitivity of the number of iterations in the analysis. The summarized results of all 120 analyses are presented in Table II with average values provided on recovery times (number of months before reaching permanent housing), and households sent to Stage 5.

Noticeably from Table II, in all cases the minimum recovery time was zero. This means that in all combinations examined, at least one household does not dislocate. Looking at the mean and maximum recovery times, these should be interpreted as recovery occurring within the time step, not necessarily at the conclusion of the time step (e.g., for the first line in Table II, all households recovered within 16 months). Examining across the increasing number of iterations, mean and maximum recovery times were fairly consistent across social vulnerability. Similarly, the number of households sent to Stage 5 was proportional to the number of iterations (40%, 37%, 32%, and 31%, respectively), but only occurred for highly socially vulnerable households ($SV = 0.90$).

To examine the sensitivity of the initial stage probability vector, S_0, three variations were examined ($S_{01} = [0.95\ 0.017\ 0.016\ 0.016]$; $S_{02} = [0.017\ 0.95\ 0.016\ 0.016]$; $S_{03} = [0.25\ 0.25\ 0.25\ 0.25]$) with the number of iterations held constant to 1,000, and three social vulnerability levels ($SV_1 = 0.1$; $SV_2 = 0.5$; $SV_3 = 0.9$) examined. Each variation was run 10 times; in total 90 analyses were performed to test the sensitivity of the initial stage probability vector

Table III. Sensitivity of Household Sequences to Input Stage Probability Vector

Initial Stage Probability Vector, S_0	Social Vulnerability, SV	Minimum Recovery Time (Months)	Mean Recovery Time (Months)	Maximum Recovery Time (Months)	Number of Households Sent to Stage 5
[0.95 0.017 0.016 0.016]	0.90	0	13.10	43	373
[0.95 0.017 0.016 0.016]	0.50	0	3.48	9	0
[0.95 0.017 0.016 0.016]	0.10	0	0.39	2	0
[0.017 0.95 0.016 0.016]	0.90	0	11.20	48	288
[0.017 0.95 0.016 0.016]	0.50	0	2.58	8	0
[0.017 0.95 0.016 0.016]	0.10	0	0.37	3	0
[0.25 0.25 0.25 0.25]	0.90	0	2.65	18	4
[0.25 0.25 0.25 0.25]	0.50	0	1.36	6	0
[0.25 0.25 0.25 0.25]	0.10	0	0.23	2	0

in the analysis. The results are presented in Table III with average values provided on recovery times, and households sent to Stage 5.

Holding the number of iterations constant, the values for all of the subsequent measures (mean recovery time, maximum recovery time, and households sent to Stage 5) are of the same order of magnitude. Similar to Table II, the minimum recovery time in Table III was zero. Different from Table II, the initial stage probability vector changes across Table III, and as such, the mean and maximum recovery times vary as expected. Looking across social vulnerability levels, when the highest proportion of households start in Stage 1, the largest number of households are sent to Stage 5; the number of households ending in Stage 5 reduces as the probability of starting in Stages 3 and 4 increases. Similarly, the maximum recovery time is highest when the highest proportion of starting places are in Stage 1. Finally, similar to Table II, only households with the highest social vulnerability ($SV = 0.90$) have households end in Stage 5. Looking across Tables II and III, this sensitivity analysis verifies the Markov chain performs consistently and as expected for its intended purpose.

5. SPATIAL DEPICTION OF DIFFERENTIAL POSTDISASTER HOUSING RECOVERY TRAJECTORIES

This section demonstrates the Markov chain of a household's housing recovery sequence through a community-level analysis. A virtual community was selected for exemplifying the model since very limited data have been collected on household housing recovery trajectory to adopt a real case study. A severe earthquake disaster is assessed for Centerville (see Lin & Wang, 2017). In the analyses that follow, the number of iterations was modeled as the number of households with a specified social vulnerability score, and the initial stage probability vector was set to $S_0 = [0.95\ 0.017\ 0.016\ 0.016]$ to capture most households starting in the first stage of emergency shelter.

5.1. The Centerville Virtual Community

Centerville, USA, is a virtual community developed by Ellingwood et al. (2016) to test integrated decision models across physical and social infrastructure systems. Centerville has a population of 50,000 people and 19,684 households. It represents a typical Midwestern city with median household income close to the U.S. average and with pockets of low-to-moderate income residents (Ellingwood et al., 2016). The Rock River runs through the center portion of the city; there are seven residential neighborhoods, three schools, a fire station, hospital, a business and retail center, and areas of light and heavy industry. Fig. 3 provides the site plan of Centerville reproduced here based on Ellingwood et al. Table IV provides the descriptions of the seven residential neighborhoods articulated in terms of average income levels and home density along with the known demographics (Ellingwood et al., 2016). Detailed information about the economy and physical infrastructure, including construction type and age of each building structure, the water system, electrical power system, and transportation system can be found in Ellingwood et al.

For the present work, residential building counts and coordinates for Centerville, obtained from Lin and Wang (2017), were used to assign social vulnerability and examine housing recovery sequence. A considerable limitation is that only one social

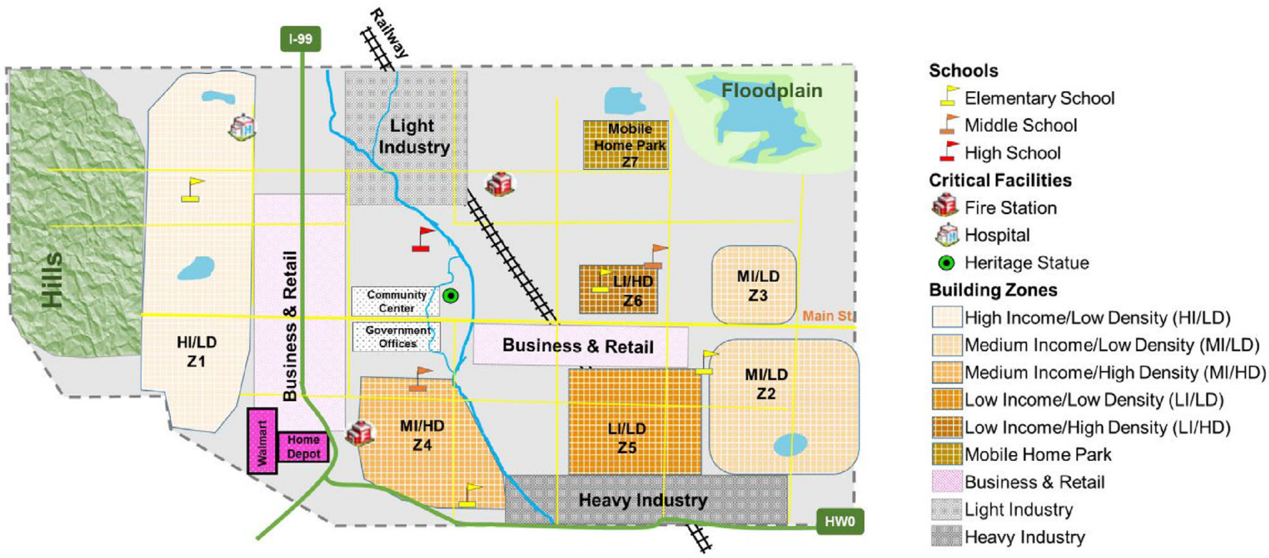

Fig 3. Plan of Centerville.

Table IV. Description of Centerville Residential Neighborhoods Zones (Ellingwood et al., 2016)

Neighborhood Zones	Description	Information Toward Social Vulnerability
Z1	High income low density	10,785 people; 4,246 households; very small percentage of families live without access to a vehicle and a small percentage use food stamps
Z2	Median income low density	7,790 people; 3,067 households; 4% live without access to a vehicle; 5% use food stamps
Z3	Median income low density	7,549 people; 2,972 households; high proportion of renter-occupied households; 8% live without access to a vehicle; 13% use food stamps
Z4	Median income high density	4,559 people; 1,795 households; mixed-majority neighborhood; 12% live without access to a vehicle; 16% use food stamps
Z5	Low income low density	4,714 people; 1,856 households; race and ethnicity is similar to that of the city as a whole; 20% live without access to a vehicle; 17% use food stamps
Z6	Low income high density	4,826 people; 1,900 households; majority–minority mixed neighborhood; somewhat higher proportion of African American and Hispanic or Latino households; 12% live without access to a vehicle; 19% use food stamps
Z7	Mobile home park	9,774 people; 3,848 households; majority–minority mixed neighborhood; 37% non-Hispanic Blacks; 34% Hispanics 23% live without access to a vehicle; 29% use food stamps

vulnerability score and sequence assessment is performed for multifamily residences, although multiple households with differing social vulnerability and experiences reside in those buildings. Due to the nature of the spatial analysis, this limited assumption was used since only one representation could be depicted in the resulting images. In total, 4,246, 2,267, 800, 3,592, 1,856, 777, and 1,352 residential buildings were modeled in neighborhoods 1, 2, 3, 4, 5, 6, and 7, respectively. Only two neighborhoods were comprised of multifamily residences, including 25 and 77 multifamily buildings in neighborhoods 4 and 6, respectively. All of these multifamily buildings were modeled in Ellingwood et al. (2016) and Lin and Wang (2017) to have 48 units each.

5.2. Assigning Social Vulnerability to Centerville Neighborhoods and Households

Limited information was provided on the social vulnerability of residential neighborhoods in Centerville, and no information was provided at the household level. Therefore, levels of social vulnerability are randomly assigned from assumed ranges

Table V. Social Vulnerability Assignments to Centerville Residential Neighborhoods

Neighborhood Zone	Percent of Households 1	Social Vulnerability Range 1	Percent of Households 2	Social Vulnerability Range 2
Z1	95%	0.01–0.15	5%	0.20–0.80
Z2	95%	0.05–0.20	5%	0.40–0.99
Z3	85%	0.10–0.50	15%	0.50–0.99
Z4	80%	0.20–0.50	20%	0.50–0.99
Z5	80%	0.40–0.80	20%	0.50–0.99
Z6	95%	0.50–0.90	5%	0.50–0.99
Z7	95%	0.85–0.99	5%	0.50–0.99

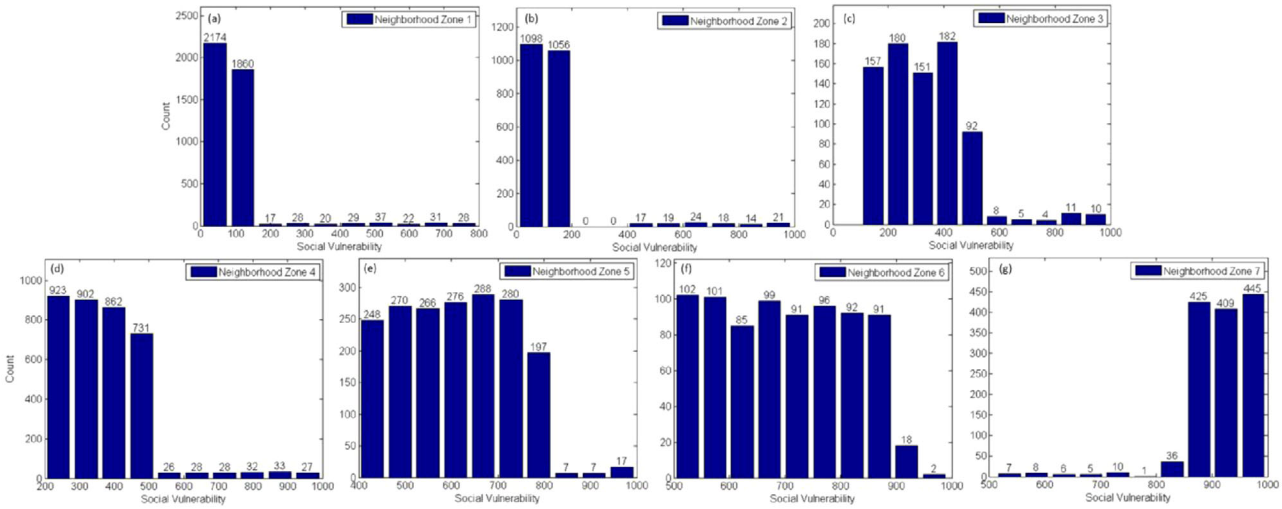

Fig 4. Social vulnerability distribution across Centerville neighborhoods: (a) Z1; (b) Z2; (c) Z3; (d) Z4; (e) Z5; (f) Z6; (g) Z7.

of social vulnerability for each of the seven neighborhoods and 14,890 residential buildings for the community-level analysis. Table V presents the social vulnerability ranges assigned to each neighborhood, where two different ranges were assigned to different proportions of households in each neighborhood such that a few households might be assigned higher or lower social vulnerability than most households in a given neighborhood. The purpose of this allocation was to generate ranges of social vulnerability in different neighbors in a way that reflects the realities of spatial clustering of different sociodemographic features in real-world communities. Figs. 4(a)–(g) present histograms of social vulnerability assigned to households in neighborhoods 1–7, respectively. In these histograms, 10 bins were used for each neighborhood. In the building-level analysis that follows, the actual social vulnerability value for each unit (household) measured to the 1,000th decimal (0.001) was used, where Fig. 4 provides an aggregate representation. Finally, Fig. 5 presents the spatial distribution of social vulnerability across Centerville neighborhoods, where blue tones align with low levels of social vulnerability and red tones align with high levels of social vulnerability. From Fig. 5, it is clear that the mobile home park (Z7) has the highest social vulnerability, although each zone is mixed.

5.3. Simulated Disaster Recovery Analysis

Centerville was subjected to a severe earthquake scenario that caused widespread disruption and dislocation (see Lin & Wang, 2017, for details on the earthquake scenario). Fig. 6 provides a spatial depiction of each household's housing stage at time t_0 ($t = 0$), immediately after the disaster. As shown in Fig. 6, and for subsequent figures, light blue dots indicate Stage 1, medium blue dots indicate Stage 2, dark blue dots indicate Stage 3, green dots indicate Stage 4, and red dots indicate Stage 5. As shown in

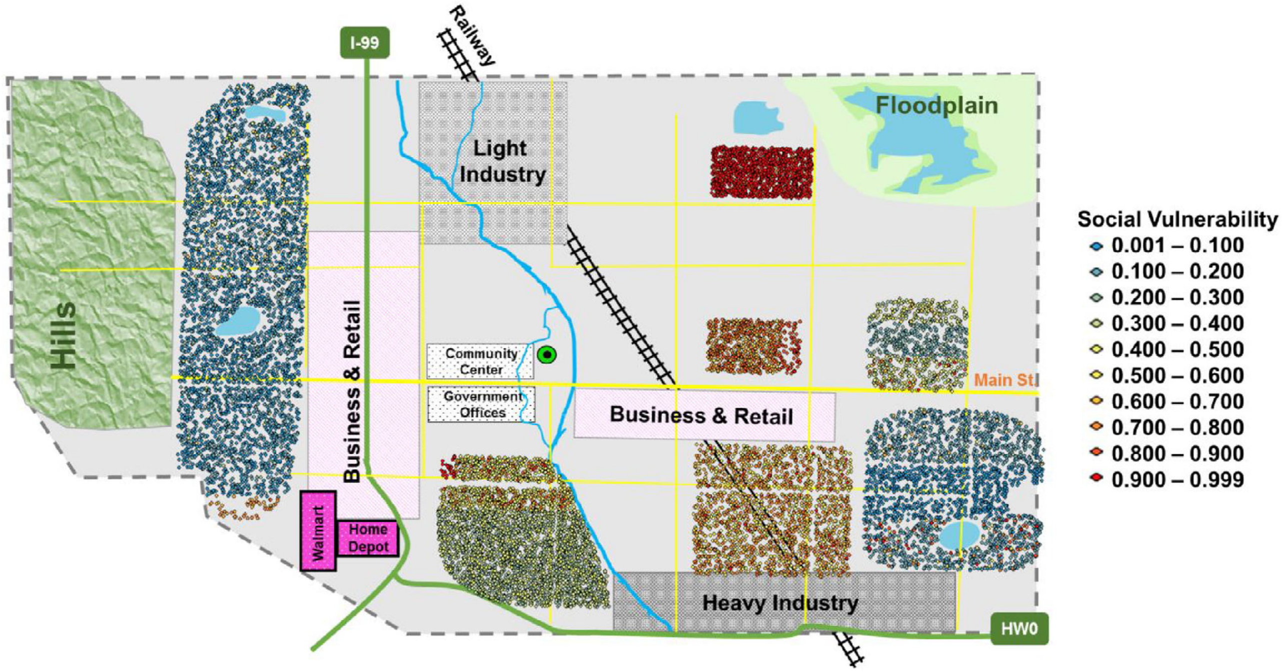

Fig 5. Spatially distributed social vulnerability across residential neighborhoods in Centerville.

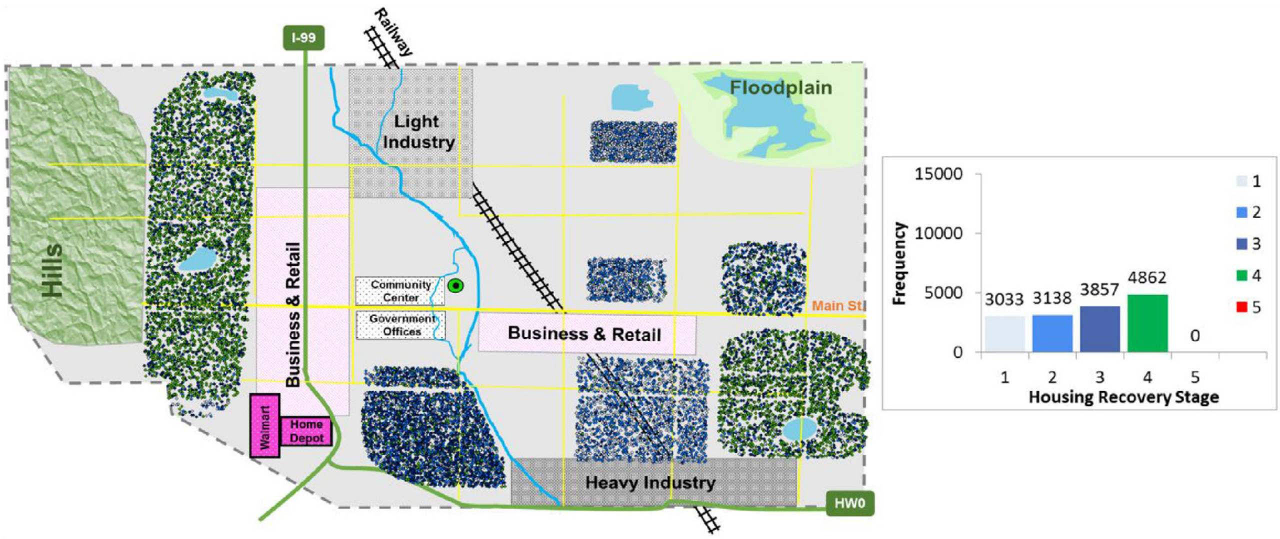

Fig 6. Housing recovery stage across Centerville households immediately after the disaster ($t = 0$).

Fig. 6, approximately 67% of all Centerville households were dislocated immediately after the disaster. Zones 1 and 2 had the largest proportion of households able to remain in permanent housing due to limited damages (68% and 61%, respectively). Zone 3 had 21% that were able to remain in permanent housing, where Zone 4 had only 9%. Zones 5 and 7 had only 2%, and Zone 6 had only 1% of households able to remain in permanent housing. The chart on the right of Fig. 6 provides a count of households in each stage at t_0. Displaced households are relatively evenly distributed across emergency shelter,

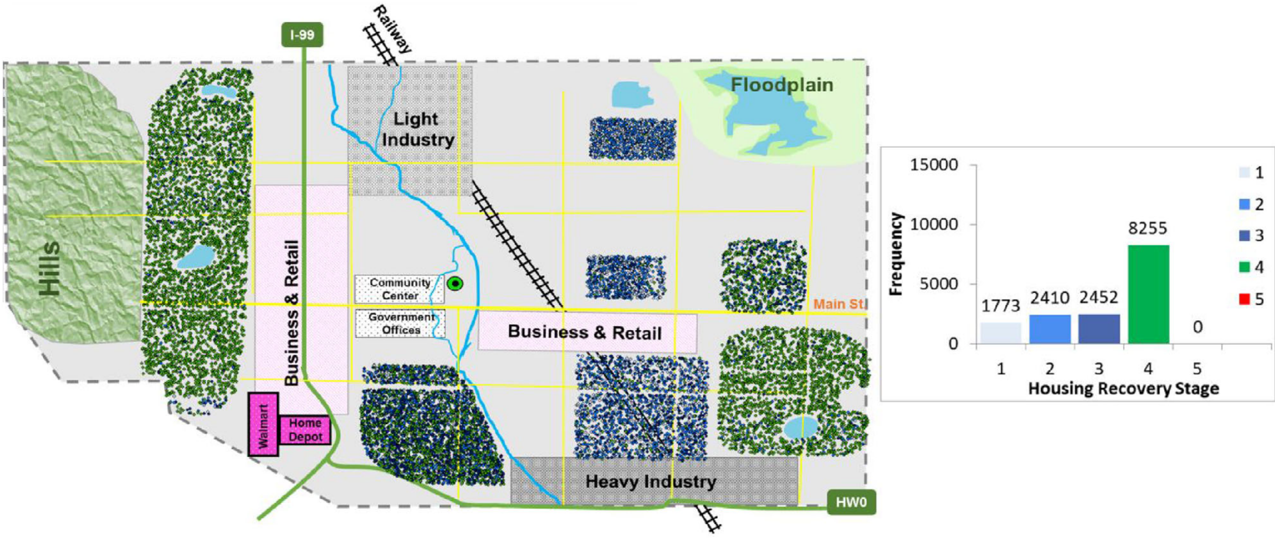

Fig 7. Housing recovery stage across Centerville households one month postdisaster ($t = 1$).

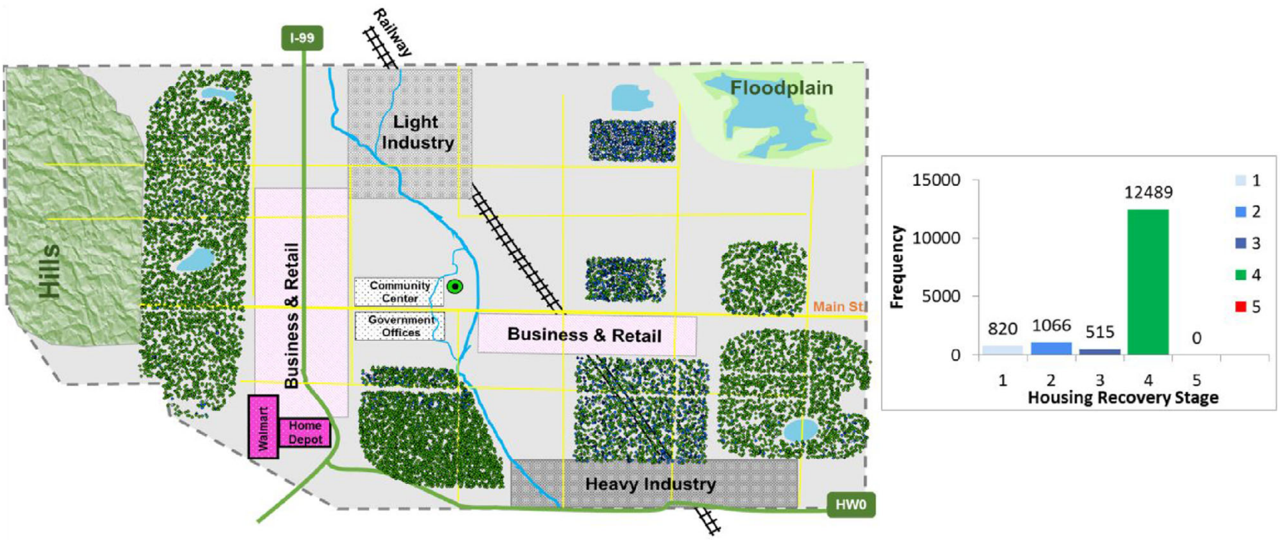

Fig 8. Housing recovery stage across Centerville households six months postdisaster ($t = 6$).

temporary shelter, and temporary housing with slightly more in permanent housing, whereas no households have entered into Stage 5 at t_0.

Fig. 7 provides the spatial distribution of housing recovery progress one month after the initial impact ($t = 1$). One month after the disaster, 44% of households are still dislocated, including 5% in Zone 1, 8% in Zone 2, 43% in Zone 3, 59% in Zone 4, 93% in Zone 5, 96% in Zone 6, and 96% in Zone 7. As evident from Fig. 7, no households have entered into Stage 5, and much fewer households are in Stage 1, and fewer in Stages 2 and 3.

Figs. 8–11 provide the spatial distribution of housing recovery progress six months, 12 months, 24 months, and 48 months after the initial impact ($t = 6$, 12, 24, 48), respectively. For this scenario, all households reached Stage 4 or ended in Stage 5 ($n = 14$ households) within 50 months. With each time step presented, the proportion of households in initial housing recovery stages (emergency and temporary shelter) decreases, while the proportion in more advanced housing recovery stages increases. Looking at Fig. 8, six months after the disaster, 16% of households are still dislocated, including 5.5% who are still

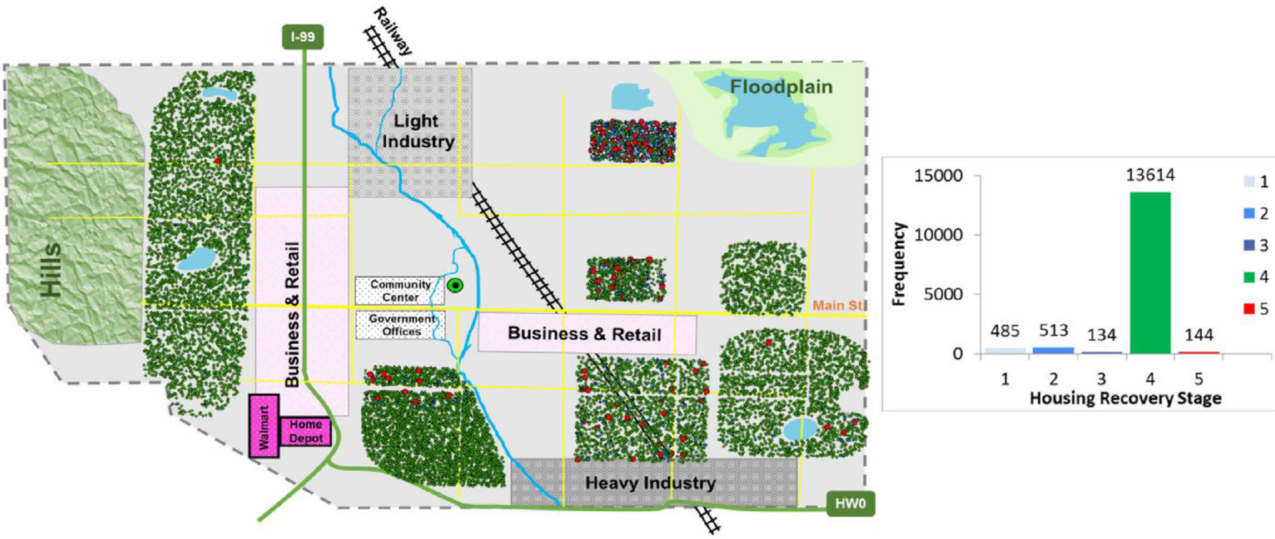

Fig 9. Housing recovery stage across Centerville households one year postdisaster ($t = 12$).

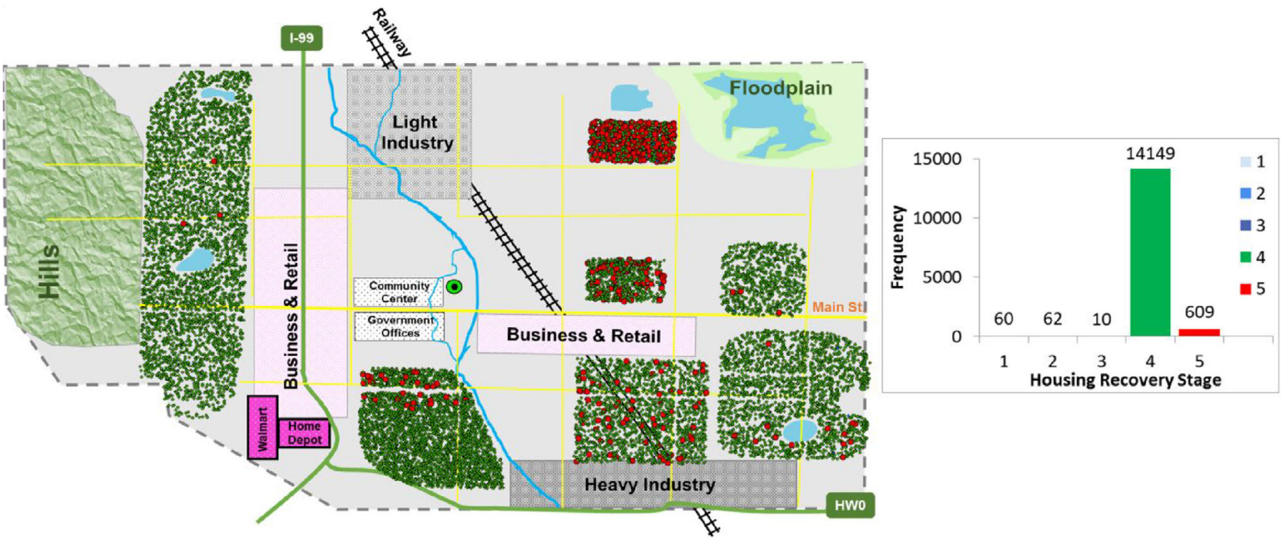

Fig 10. Housing recovery stage across Centerville households two years postdisaster ($t = 24$).

in Stage 1, where at this time period, Stage 1 likely takes the form of a homeless shelter (see Table I). Looking at Fig. 9, one year after the disaster, less than 8% of households remain dislocated, including approximately 3% in Stage 1, 3% in Stage 2, and 1% in Stage 3. Fig. 9, one year after the initial impact, is the first time shown here where households (approximately 1% of households) are observed to enter Stage 5. Although not presented here, the first household was actually sent to Stage 5 after eight months postdisaster. At two years after the disaster, 4% of households are in Stage 5, and approximately 1% are still dislocated (see Fig. 10). Finally, four years after the disaster, presented in Fig. 11, 4.6% of households are in Stage 5, 95.3% of households are in Stage 4, and a single household is still in Stage 2. The last household ended in Stage 5 (failure) at 50 months postdisaster.

5.4. Examining and Illustrating Selected Sequences

The sequences for all seven neighborhoods in Centerville are not provided here due to brevity. Fig. 12 presents the sequences for each household

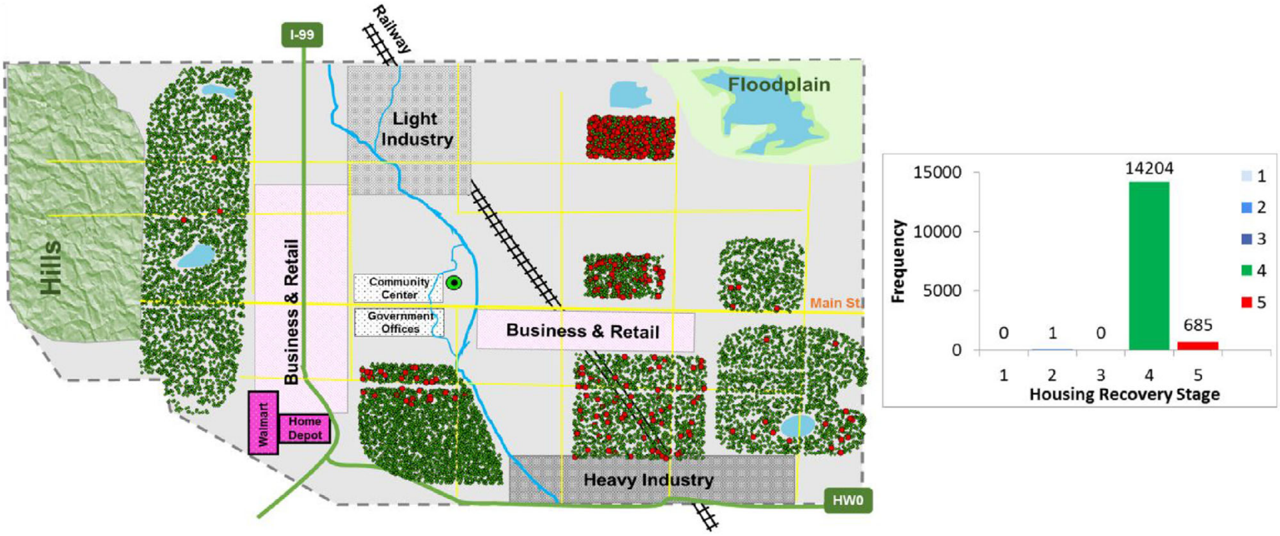

Fig 11. Housing recovery stage across Centerville households four years postdisaster ($t = 48$).

modeled in neighborhood Zones 1 and 7, the least and most socially vulnerable zones in Centerville, respectively. Note the following: (1) the individual sequences are not easily discernable in Fig. 12, rather overall trends across the two zones are the focus; (2) the households who are not dislocated are not evident in Fig. 12, since they did not experience any housing recovery sequence. As expected, there are significantly more sequences observed in Zone 7 (Fig. 12(b)) with higher social vulnerability, and fewer sequences observed for Zone 1 (Fig. 12(a)). Although not fully shown here, Zones 1, 2, 3, and 4 had less than 1% of households end in Stage 5, whereas Zones 5, 6, and 7 had 3.6%, 10%, and 36% of households end in Stage 5, respectively. This disparity is reflective of the actual recovery disparities that frequently exist within neighborhoods in the United States where not every household recovers even in neighborhoods primarily comprised of wealthy households. Zones 4 and 6 would likely have more households end in Stage 5 if each household had been modeled, rather than residential building (these were the two zones with multifamily housing). In Zone 1, the longest time to reach Stage 4 was 19 months, whereas the longest time to reach Stage 5 was 29 months. These times are much shorter than the 50 months required for the last household to reach Stage 5 in Zone 7, thus taking nearly twice as long for Zone 7 (highest social vulnerability) to complete housing recovery in comparison to Zone 1 (lowest social vulnerability).

Validating recovery models presents a significant challenge for disaster scholars. Empirical data can be used for validation, but often it is resource intensive for individual research projects to collect household-level data for more than one event in more than one community. Thus, stories and expert elicitation can be used for validation (see, for example, Browne, 2015; Morrow & Enarson, 1997; Nolen et al., 2014). From this light, a selection of sequences, presented in Fig. 13, are examined closely to relate them back to empirical and theoretical literature for model validation. The authors note that their own interview and survey experiences, alongside quantitative literature reviewed in Section 2 (e.g., Comerio, 1997; Starr Cole, 2003), were used to build the transition probabilities, whereas the qualitative literature (e.g., Fothergill & Peek, 2015; Hamideh & Rongerude, 2018; Morrow & Peacock, 1997) was used to validate sequences through stories and accounts collected through field studies. Five sequences are presented in Fig. 13 from the Centerville analysis. The first household (HH1), is dislocated from their home because of the earthquake. Their home was not damaged, but due to the widespread damage and safety concerns, HH1 chose to leave town temporarily. HH1 first stays at a hotel (Stage 3) in a town near relatives not too far away; they stay there for two months, and then return home (Stage 4) once the utility services and a sense of safety in their neighborhood are restored and emergency response across the city has subsided. This sequence and explanation are

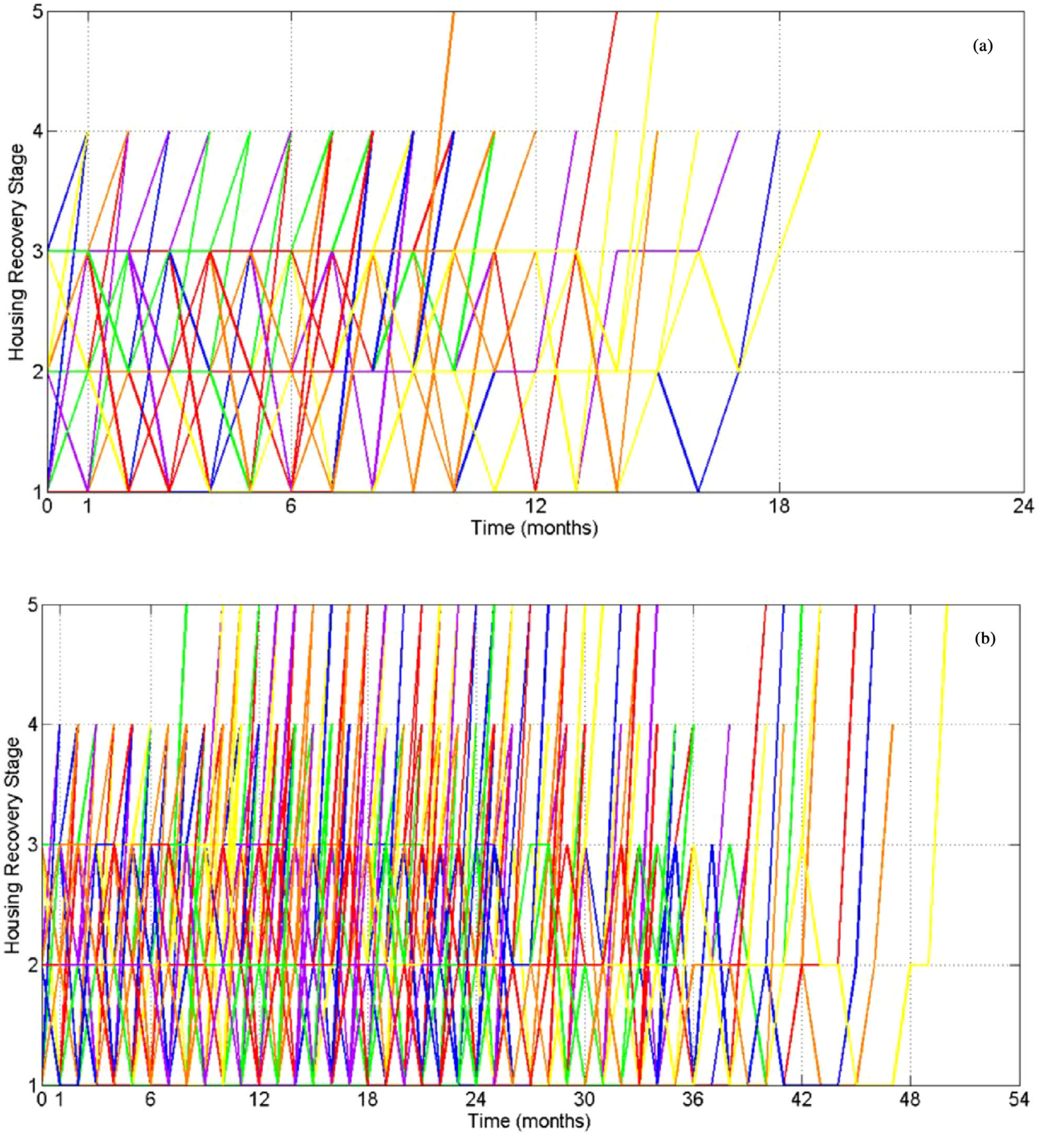

Fig 12. Housing recovery sequences across Centerville households: (a) Zone 1; (b) Zone 7.

grounded by the study referenced earlier on temporary sheltering following Hurricane Andrew, where Morrow (1997) found that households with higher incomes were more likely to stay at hotels and motels, while those with lower incomes stayed with family, and by van de Lindt et al. (2018), which documented dislocation after a catastrophic flood even for households whose homes were not damaged.

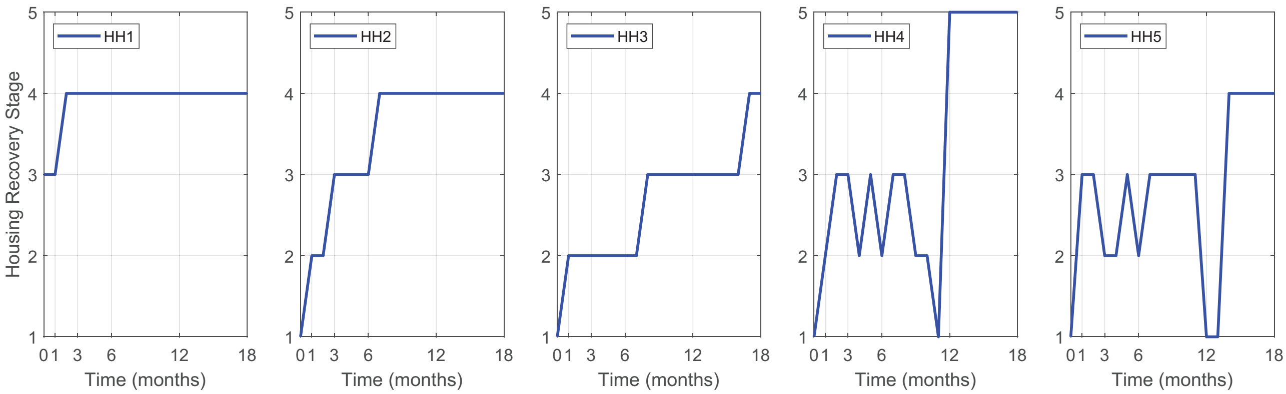

Fig 13. Selection of Centerville household housing recovery sequences.

HH2 is dislocated from their home due to minor damage and functionality issues. HH2 immediately goes to a large group emergency shelter (Stage 1) in town, soon thereafter, HH2 receives assistance from their insurance company and settles into a hotel within a few days (Stage 2). After a couple of months in the hotel, they are able to find a rental unit (Stage 3) near their place of employment. Six months after the event, HH2 buys a new home in a neighborhood that was not damaged from the earthquake and returns to permanent housing (Stage 4). This household benefited from having insurance and represents the exception, not the norm. It is more likely for households to lack adequate insurance to cover their hotel expenses and needed assistance to afford temporary shelter and temporary housing, as well as securing a permanent home. In either case, this trajectory can represent an effective combination of household resources and adequate insurance, or an effective combination of external assistance and inadequate or no insurance. It should be noted that while the model "allows" this trajectory, the geospatial figures (Figs. 6–11) do not reflect households relocating to different homes; such figures tie the household to the original home.

HH3 is also immediately dislocated from their home, but this time due to structural damage and functionality issues. In the immediate aftermath, HH3 stays in a large group emergency shelter (Stage 1). Within a month, HH3 is able to go stay with friends (Stage 2). While they are at their friends, HH3 is constantly applying for external aid; seven months after the initial impact HH3 is approved for a mobile home unit (Stage 3), where they stay for eight months. After a total of 16 months, HH3's home is repaired, and they are able to move back into permanent housing (Stage 4). In many cases assistance becomes available much later given the slow process of allocating and spending some of the government funding programs like the Department of Housing and Urban Development's Community Development Block Grant Disaster Recovery (CDBG DR) after disasters, as example experiences after Hurricanes Ike, Matthew, Florence, and Maria have demonstrated. Several of the trajectories depicted in Fig. 12(b) for Zone 7 represent consequences of such delays.

HH4 with higher social vulnerability similarly experiences structural damage and functionality loss to their uninsured older home after the earthquake. HH4 immediately goes to a large group emergency shelter (Stage 1) (Yelvington, 1997), within a month they relocate to stay with friends (Stage 2), and within another month, HH4 secures a hotel (Stage 3) on their very limited money with the expectation that a voucher will come. Previous research has shown that sometimes households with the most extensive damage remain in temporary housing for months and even years. After a few weeks of staying at the hotel, HH4 can no longer afford it and has not received any external support. HH4 packs up and goes to stay with another friend (Stage 2) in another state. HH4 is now too far away from their children's school and their own work, so they relocate to a hotel (Stage 3) back near their original home still with the expectation that external assistance is coming. HH4 still does not receive any external assistance, so they go stay with a family member (Stage 2) a few towns over. Existing research indicates that issues faced by vulnerable populations, such as overcrowding and culturally appropriate living arrangements, are often overlooked when housing options are developed (Fothergill & Peek, 2015; Pincha, 2008). Such poor arrangements have been found to disrupt the social networks on which survivors rely, resulting in an increase in psychological problems among displaced populations (Merdjanoff, 2015; Mueller et al., 2011). HH4 is experiencing significant stress from the disaster and multiple moves, and is unable to keep peace at their family member's home. HH4 relocates to a hotel (Stage 3); during this time, approximately seven months after the disaster, HH4 receives FEMA assistance for home repair. Instead of using the money to repair their home, HH4 pays for groceries, past due bills, and covers a hotel room for two months. Since HH4 did not use the home repair funds to repair their home, they are unable to get the second installment to actually repair their home. They are out of money, and leave the hotel to go stay with another friend (Stage 2). After one month at a friend's, HH4 ends up in a homeless shelter (Stage 1) leading them to four regressive moves in one year, languishing in unstable housing where the Markov chain sends them to Stage 5 for failure. The limitations many households like HH4 face when addressing housing issues in normal situations can result in a delay or failure to transition out of temporary sheltering or temporary housing into permanent housing (Morrow, 1997; Peacock et al., 2006; Peacock, Dash, Zhang, & Van Zandt, 2017).

The last selected sequence is HH5. HH5 experiences structural damage and functionality loss to their home after the earthquake. HH5 immediately goes to stay in a large group emergency shelter (Stage 1). Within a few days, HH5 is able to secure hotel vouchers (Stage 3) for about six weeks. The contractor they hired to fix their home cheated them and skipped town. Thus, when their vouchers run out, their home is still unlivable, so they relocate to stay with a family member (Stage 2). They stay with family for about a month, until they are able to obtain additional hotel vouchers. HH5 relocates to another hotel (Stage 3) for six weeks. When their vouchers run out again, their home still is not repaired, so they relocate to stay with their family again (Stage 2). HH5 is with family for only a couple of weeks when they are assigned a federally supported mobile home unit. Seven months after the disaster, HH5 moves into the mobile home unit (Stage 3), where they stay for nearly five months. The federal agency assumes recovery is complete, and retrieves all mobile housing units. HH5 is dislocated and forced to stay in a homeless shelter (Stage 1). During the month HH5 is at the shelter, a nongovernment organization helps them repair their home. Seventeen months after the earthquake, HH5 moves back home (Stage 4) (see Fothergill & Peek, 2015, for evidence of a similar housing recovery trajectory for a household after Hurricane Katrina).

6. DISCUSSION AND CONCLUSIONS

The longer families have to spend in temporary housing and the greater the number of moves between intermediate housing stages, the greater the aggregate level of stress experienced and the longer the persistence of mental health problems. All of these processes have implications for individual and population health, long-term recovery, reinvestment and sustainable redevelopment of communities. This article addresses household risk of postdisaster displacement, homelessness, diminished quality of life, diminishing health, diminishing wealth and financial security, and risk of widening inequality across a community as a function of the postdisaster housing recovery process. These risks were illustrated through a novel model of housing recovery that focuses on the experience of the household. The model captures housing recovery as both a process and an end goal. The work presented here expands the widely accepted four-stage housing recovery typology to a fifth state, failure, and captures both progressive and regressive sequences of households as a function of their social vulnerability. This work presents an important step forward in understanding how household and housing recovery interact by modeling the housing recovery process at the household level, rather than an aggregate level, such that the most socially vulnerable households cannot be overlooked. Furthermore, the ability to skip stages to advance the recovery process is a critical aspect of the model that will allow exploration of interventions that can promote quicker and more equitable recovery.

By highlighting the implications of existing recovery policies for sheltering and housing recovery stages, it is intended for this model to be used by recovery policy makers to improve postdisaster temporary housing and other housing assistance programs. Policies for postdisaster housing and sheltering should promote equity through investing in more robust infrastructure in socially vulnerable neighborhoods to mitigate housing damages, speeding up the distribution of housing and shelter assistance, particularly those aimed at low-income neighborhoods, and updating recovery policy to address the unmet housing needs of vulnerable households more explicitly and realistically. This latter recommendation includes questioning and modifying existing policies that (1) exclude renters; (2) have strict requirements on proving home ownership to receive recovery aid, which can be difficult if not impossible for those who lose all of their belongings in the disaster and discriminatory for a range of households in older, minority, immigrant, and low-income groups who have inherited a home without titles or with disputed titles/deeds, as well as those who rent to own; (3) impose strict and unclear requirements on how funds must be spent for reinstallments, such as was described for HH4 who had more immediate needs (food and immediate shelter) than repairing a home that was not livable at the time; and (4) include blanket requirements to demonstrate damage was not, even in part, caused by deferred maintenance. In addition to enhancing recovery and assistance policies, other innovative solutions that are designed to overcome the barriers created by existing recovery policy are encouraged. The RAPIDO homes discussed earlier in the article is an example of such interventions.

In the model, social vulnerability is left as a loosely defined composite variable intentionally. Many authors (e.g., Cutter, Boruff, & Shirley, 2003; Fothergill & Peek, 2004; Hamideh & Rongerude, 2018; Norris et al., 2002; Sutley, van de Lindt, & Peek, 2017; Van Zandt et al., 2012) have demonstrated or otherwise used a range of factors contributing to social vulnerability. Ultimately, social vulnerability manifests itself in different ways and is challenging to tie down to a single set of factors for all households in all communities or regions under all disaster scenarios. Further, the intersectionality of factors is poorly understood. Nevertheless, the disproportionate impact and longer recovery times for households as a function of social vulnerability is widely understood and documented in many studies—regardless of how social vulnerability is specified in each study. Using the composite social vulnerability variable provided here allows the model to be used in a wider variety of disaster scenarios.

A sensitivity analysis was performed for model verification. The model was then exemplified on a virtual community. For model validation, a selection of five sequences from the virtual community were examined closely, and explained with observed patterns and examples reported in the literature after real disasters. These selections and explanations help further demonstrate why the four-stage typology is not adequate for capturing the complexities and realities of household housing recovery. Looking back at Table I, different types of housing represent different housing recovery stages for different households. These example trajectories also help depict the disparities of experiences by different households during dislocation, obtaining external resources, securing temporary housing, repairing their permanent housing, and every step in between.

The housing recovery model proposed in this article, including its embedded rules and relationships, is based on theory and empirical observations from decades of disaster literature. There is major variance and uncertainty across those empirical observations, and there exists no single comprehensive data set on housing recovery sequences of households as a function of social vulnerability. Therefore, everything presented here needs to be more fully validated with longitudinal data collection. However, this model represents and advances the current state of knowledge on housing recovery for households with an innovative quantitative and predictive approach that can inform community resilience analyses. Adopting this model into practice for predicting outcomes in a specific community might require calibration with household-level social vulnerability input data. Nevertheless, using this model in its current state to inform more equitable housing recovery policy does not require such data. The model can be used for this purpose now. Collecting the longitudinal data across multiple disasters and communities necessary for full model validation is the long-term goal of the authors. Furthermore, reestablishing permanent housing is critical for postdisaster individual and community recovery. Thus, other future work includes linking the presented household-level housing recovery model to other models on housing reconstruction and community recovery. Such linking is the ultimate goal of the project sponsoring this work (see Acknowledgments).

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