Community-Level Framework for Seismic Resilience. I: Coupling Socioeconomic Characteristics and Engineering Building Systems

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Abstract: These two companion papers focus on the development of a coupled socioeconomic and engineering framework for community-level seismic resilience. The coupling of these two systems is used to enhance risk-informed decision making for selection of a community-level seismic retrofit plan. This first article, Part I, describes the coupled framework development, including the quantification of the effect that six socioeconomic and demographic variables—including age, ethnicity/race, family structure, gender, socioeconomic status, and the age and density of the built environment—have on four resilience metrics. Empirical data collected after previous earthquakes were used to determine relationships among these six variables and the vulnerability of the population, as understood through assessing three morbidity rates: the probabilities of injury, fatality, and posttraumatic stress disorder (PTSD) diagnosis. Prior to this study, the emotional health of the population has not been considered as an engineering metric, although social science research has established that this is one significant measure of community recovery. Initial cost, economic loss, number of morbidities, and recovery time were used as the four metrics for measuring community resilience. Part I concludes with a sensitivity study on the six variables. Based on the sensitivity study, low socioeconomic status was the highest contributor to injury and fatality, whereas a family structure with persons under 18 years old living in the household was the highest contributor to predicted PTSD diagnosis. Overall for all three morbidity rates, socioeconomic status was a higher predictor compared to ethnicity/race, and having a high percentage of females in the population caused increases in predicted morbidities. The decision-making algorithm, optimization, and several illustrative examples on Los Angeles County, California, are provided in Part II, the companion paper. **DOI: 10.1061/(ASCE)NH.1527-6996.0000239.** *© 2016 American Society of Civil Engineers.*

Author keywords: Community resilience; Socioeconomic model; Social vulnerability; Recovery time; Seismic retrofit; Woodframe buildings.

Introduction

Designing for community-level resilience is not a new research problem. However, recent calls for more complex, interdisciplinary work have refocused research in this area. Previous studies within the engineering disciplines have concentrated on single-building level designs for specific hazards in an understanding that better buildings equal a better and more resilient community. This is not a disagreeable proposition; however, the goal of the present work is to attempt to extend the above proposition. Specifically, in this paper, the focus is on a seismic hazard, where most deaths and injuries caused by earthquakes occur in buildings or are due to building damage. Therefore, again, the traditional approach of strengthening buildings is logical. But when designing for community-level resilience, there is much more to consider than just the built environment. Increasingly, researchers have started to approach the problem at the community level, often through loss-estimation models, and some of these models expanded from only considering the built environment to also considering the population (Elnashai et al. 2008). The Department of Homeland Security (DHS) and the Mid-America Earthquake (MAE) Center developed the software programs *HAZUS* (DHS 2003) and *MAEViz* (Elnashai et al. 2008), respectively, which look at loss estimation for the built environment while also including social system metrics, such as the number of fatalities and the number of displaced persons. In reality, there are many other metrics of interest, and coupling these metrics with community-level demographics is imperative for achieving a comprehensive and usable plan for community resilience.

Typically, community resilience has been approached by engineers using the process depicted in Fig. 1. A hazard is input and applied to engineering models where an engineering demand parameter is obtained. The engineering demand parameter is used as a metric for damage, which is then used to estimate losses. The damage is also input into a social science model of the community, which together output a recovery trajectory based on observed recovery trajectories from past disasters. The damage is used in multiple social science models to generate a distribution of recovery trajectories, and comparisons are made.

These models provide valuable information for recovery and general understanding of community resilience. However, if the engineering and the social science systems were appropriately coupled, then the two systems could be used together to make decisions on improving a specific community's resilience with combinations of engineering and social component modifications. Developing a coupled model for decision making is the impetus for this research. It is presented here with a focus on a seismic

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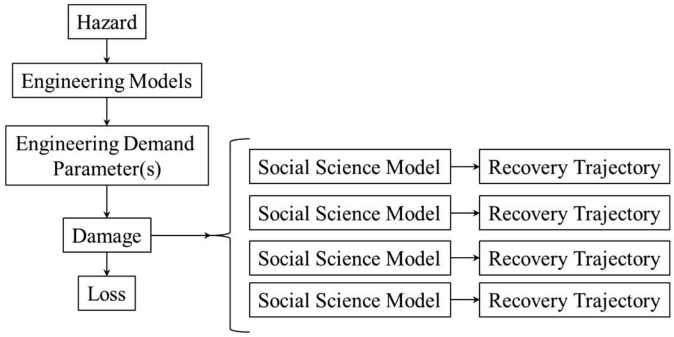

Fig. 1. Traditional (decoupled) community-level resiliency framework

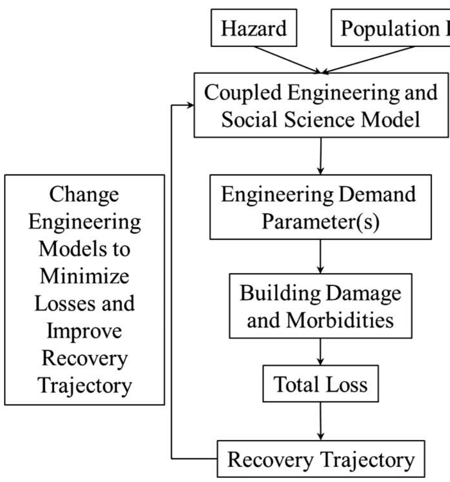

Fig. 2. Coupled community-level decision-making framework for resiliency

hazard and woodframe buildings, but the concept could be expanded in future work to other hazards and infrastructure types. The concept of the coupled model is depicted in Fig. 2.

Two major inputs are required for using the framework: the selected community's census data and the seismic hazard (or scenario earthquake) in which the community seeks to be resilient against. A set of woodframe building archetypes, thereby focusing on residential buildings, were modeled to represent the existing woodframe building stock of the community within the coupled social science and engineering framework. The archetypes were designed using the spectral parameters for Los Angeles, California, thereby using it as the focal area for exemplifying the framework. Within the framework model, these archetypes are subjected to the selected seismic hazard (i.e., scenario earthquake), and the corresponding engineering demand parameters are measured, recorded, and used to determine damage (e.g., repair costs, repair times, morbidity rates, etc.). Specifically, the morbidity rates are influenced by socioeconomic and demographic (SED) factors developed here using the demographic distribution of the community obtained from the census data. The six SED variables include age, ethnicity/race, family structure, gender, socioeconomic status, and the age and density of the built environment. Economic loss, morbidities, and recovery time are computed once the building inventory and SED factors are combined, and after applying the scenario earthquake. The end result of the optimization framework is a set of community-level seismic retrofit plans for the woodframe building stock with the associated risk of each plan. These are provided in Part II (Sutley et al. 2016), the companion paper, for the focal community.

The seismic retrofit plans may be provided to decision makers at the local or state government level, for instance, to aid in preevent seismic retrofit planning. Such plans could prove beneficial in the private sector as well, such as to housing developers working in seismic areas. Each seismic retrofit plan has associated losses, and a genetic algorithm is used to find the retrofit plans with the optimal trade-offs between the resilience metrics based on the associated losses. Part I provides the framework development, including the quantification of the effect that six SED variables have on four resilience metrics, and a sensitivity analysis on the SED variables. The companion paper, Part II (Sutley et al. 2016), to this paper provides the development of the decision-making algorithm, and several illustrative examples using Los Angeles County, California, as the focal community. The optimal seismic retrofit plans found by the search algorithm are presented with the associated losses in Part II.

Background

Perhaps the most widely used loss-estimation model in the United States is *HAZUS* (DHS 2003), which was originally developed in 1997 by the Federal Emergency Management Agency (FEMA). It is applicable to earthquakes, floods, and hurricanes, and uses damage functions to compute aggregated loss estimates. *HAZUS* estimations integrate graphical information system (GIS) software that is linked to detailed databases of the building stock and demography of the United States. The *HAZUS* model uses demographic information to estimate social losses such as the number of casualties (injuries and fatalities) and the number of persons needing temporary shelter.

The Mid-America Earthquake (MAE) Center and the National Center for Supercomputing Applications (NCSA) developed the seismic risk assessment software, *MAEViz*, in 2008 (Elnashai et al. 2008). *MAEViz* loss estimations are provided for business content loss, business interruption loss, business inventory loss, household and population dislocation, shelter requirements, and short term shelter needs. *MAEViz* computes the fiscal impact following an earthquake, and the social vulnerability of subareas within the affected region by scoring each from −9.6 to +49.51, with −9.6 being the most vulnerable, based on the demographic information of the neighborhood areas.

More recently and within the Applied Technology Council (ATC)-58 Project (FEMA 2012), the Pacific Earthquake Engineering Research (PEER) earthquake loss methodology was developed into a loss-estimation tool for its execution, the *Performance Assessment and Calculation Tool* (*PACT*) software. *PACT* provides a way to track building inventory details, and to perform the intensive probabilistic computations for accumulation of losses. Inputs include all of the building system and component information. The user may select which component fragilities to use from a database. Results from the simulation and structural analysis are used to determine three performance objectives (number of deaths, repair and replacement costs, and downtime).

In 2007, Pei and van de Lindt developed a long-term loss-estimation framework at the single building level for progression of and incorporation into performance-based seismic design (PBSD). The framework considered a response-damage-loss relationship and employed damage fragility systems to quantitatively model the uncertainty associated with that relationship. This study was the first to consider economic loss in PBSD of woodframe structures. The loss-estimation model presented in Pei and van de Lindt

(2009) was extended, applied, and used to define performance objectives for woodframe buildings in terms of economic loss in Black et al. (2010). The direct economic loss probability distribution presented did not include loss associated with downtime or casualties.

Currently available engineering resilience frameworks, hazard and vulnerability indices, and loss-estimation models often mention the importance of social context; however, explicit incorporation and/or quantification of robust SED indicators have been generally neglected. While *HAZUS* and *MAEViz* consider social losses and use demographic information for determining shelter needs, in both of those programs the social systems are completely uncoupled from the engineering systems. Neither *HAZUS* or *MAEViz*, nor other loss models, have directly incorporated robust sociodemographic variables or mental health indicators in their metrics, which is the impetus for the research presented in these companion papers. The work concludes by providing a solution strategy for achieving the preferred level of resilience through the community-level seismic retrofit plan.

Modeling Socioeconomic and Demographic Variables

Six SED variables—age, ethnicity/race, family structure, gender, socioeconomic status, and the age and density of the built environment—were incorporated into this study to be applied as adjustment factors on three baseline morbidity rates: injury, fatality, and posttraumatic stress disorder (PTSD) diagnosis. The baseline morbidity rates were computed for building occupants due to building damage alone. During an earthquake, debris can fall off of the building and onto the streets, injuring and killing pedestrians. Thus, a factor for the age and density of the built environment was developed. The age and density of the built environment was modeled as the sixth variable used in quantifying the three morbidity rates. These variables align well with the pioneering work on identifying social vulnerability factors by Norris et al. (2002a, b), Wisner et al. (2003), and Cutter et al. (2003).

The premise of this section is that based on an individual's age, ethnicity, family structure, gender, and socioeconomic status, the individual may be more vulnerable to one or more of the three morbidity rates. Measuring the difference in vulnerability due to these variables is accomplished by examining the variables at the subcategory level (i.e., male and female gender, for example) and developing subcategory factors based on information gained from the literature.

Population Studies

An extensive metadata analysis was conducted for understanding and quantifying vulnerability relationships between the morbidity rates and the six variables' subcategories. Table 1 summarizes the list of references that were used in the analytical modeling of the six variables. Studies selected for inclusion covered earthquake-affected populations only. As summarized in Table 1, there were 33 studies, focusing on 16 earthquake events, covered in the metadata analysis with much variation in terms of earthquake location and magnitude (and intensity, presumably). These earthquakes were selected due to the availability of literature and data provided in the literature on the affected population groups of interest.

Socioeconomic and Demographic Subcategory Factor Development

For the quantification of the relationships between the six SED variables and the morbidity rates, each variable was modeled at the subcategory level. The subcategories are presented in Table 2. The subcategories were selected based on the information obtained from the literature listed in Table 1 which demonstrated their influence on the morbidity rates. For example, a study listed in Table 1 may have provided the fatality count for each of the six age groups listed in Table 2 therefore demonstrating how each age group is more or less vulnerable to fatality caused by an earthquake.

The variables' subcategories were quantified as adjustment factors for the three morbidity rates. Five of the six factors were modeled by the same procedure. In each of the studies listed in Table 1, the authors surveyed members of the population in a specified area following an earthquake event. Generally, the studies reported demographic information for the surveyed population distinguishing between whichever morbidity rate(s) was relevant to their study. These reported values were then used in the present research to develop odds ratios between the subcategories used in this study. The odds ratio provides the quantity of how much more likely one subcategory was to suffer from one of the morbidities when compared to another subcategory. The odds ratios were retermed as subcategory adjustment factors.

A detailed example of how the odds ratios were computed is demonstrated using the injury and fatality data in Peek-Asa et al. (1998) collected following the 1994 Northridge earthquake. Table 3 is a regenerated version of the demographic data presented in Peek-Asa et al. (1998).

The odds ratios in the last column of Table 3 were computed using the population values for Los Angeles County to show the relative risk of injury for each demographic group over the entire population. The odds ratio is expressed as

$$OR = \frac{a/b}{c/d} = \frac{a \cdot d}{b \cdot c} \tag{1}$$

where a = number in the exposed group from demographic a; b = number in the exposed group from demographic b; c = number in the control group of demographic a; and d = number in the control group of demographic b. Using the values in Table 3, the odds ratio for male gender was computed by

$$OR_{\text{Injury,male}} = \frac{78 \times 4{,}421{,}398}{78 \times 4{,}421{,}398} = 1.00 \tag{2}$$

and the odds ratio for female gender was computed by

$$OR_{\text{Injury,female}} = \frac{93 \times 4{,}421{,}398}{78 \times 4{,}441{,}766} = 1.19 \tag{3}$$

These odds ratios indicate that females were approximately 1.2 times more likely than males to suffer from an earthquake-related injury caused by the 1994 Northridge earthquake.

Similar odds ratios were computed for all of the studies listed in Table 1, providing a range of relative risk values for each subcategory. Not all studies contributed to all three morbidity rates, as provided in Table 1. The mean value of all i odds ratios for each subcategory was taken as the subcategory factor, $f_{MR,\text{sub}}$, which is expressed as

$$f_{MR,\text{sub}} = \sum_{i=1}^{n} \frac{1}{n} \left(OR_{MR,\text{sub}(i)} \right) \tag{4}$$

where MR = respective morbidity rate; and n = total number of odds ratios for the specific subcategory. This computation was executed for all categories and subcategories listed in Table 2. The SED category factors, $F_{MR,\text{cat}}$, were computed by multiplying the subcategory factors by the percentage of the population in the respective

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Table 1. Summary of Metadata Analysis References

Earthquake	Morbidity rate	Variables gained from study	Description of data collection method	Geographic scale	PTSD prevalence (%)	Source
1993 India	PTSD	Age, gender	Semistructured interview using questions based on DSM-III-R criteria conducted 1 month post event	3 villages: Mangrul, Nandurga, and Hasalgan	23	Sharan et al. (1996)
1994 Northridge	PTSD	Gender	Interview questions based on diagnostic interview schedule/disaster supplement 32 weeks post event	City blocks with the greatest concentration of property damage, most of which were in the Northridge area	13	McMillen et al. (2000)
1994 Northridge	PTSD	Age, ethnicity, gender, SES	Computer-assisted telephone survey using Civilian Mississippi Scale conducted 8–12 months post event	Los Angeles County and Ventura County	Not provided	Siegel (2000)
1994 Northridge	Injury, fatality	Age, ethnicity, gender	Records from 78 hospitals within 2 weeks post event	Los Angeles County	N/A	Peek-Asa et al. (1998)
1994 Northridge	Injury, fatality	Age, ethnicity, gender	Records from 4 hospitals within 3 weeks post event	Los Angeles County	N/A	Mahue-Giangreco et al. (2001)
1994 Northridge	Injury, Fatality	Gender	Computer-assisted telephone survey conducted 6–24 months post event	Los Angeles County	N/A	Shoaf et al. (1998)
1995 Hanshin-Awaji, Japan	Injury, fatality	Age, gender	Records from 48 affected and 47 unaffected hospitals up to 15 days post event	48 affected and 47 unaffected hospitals	N/A	Tanaka et al. (1999)
1998 Ceyhan, Turkey	PTSD	Age, gender, family structure, SES	CAPS for DSM-IV administered 1 month and 13 months post event	Patients of the medical school of Dicle Univ. in Ceyhan	42 and 23	Altindag et al. (2005)
1999 Chi-chi, Taiwan	PTSD	Gender	Self-report administered by research psychiatrists using the ChIPS 6 weeks post event	Chungliao (worst affected region)	21.70	Hsu et al. (2002)
1999 Chi-chi, Taiwan	PTSD	Gender, SES	DTS distributed 10 months post event	2 of the most severely damaged villages	10	Chang et al. (2005)
1999 Chi-chi, Taiwan	PTSD, injury	Age, gender, SES	Interviewed using the DTS-Chinese one year post event	Victims in temporary housing units from severely affected regions	16.50	Kuo et al. (2007)
1999 Chi-chi, Taiwan	Injury, fatality	Age, gender, SES	Records through the Family Registration Database	22 municipalities officially affected by the earthquake	N/A	Chou et al. (2004)
1999 Kocaeli, Turkey	PTSD	Gender	Psychiatric interview using the CAPS for DSM-I administered 6–20 weeks post event	Schools in 2 townships of Adapazari located in the epicenter of the earthquake	60	Eksi et al. (2008)
1999 Kocaeli, Turkey	Injury, fatality	Age, gender, SES	Home interview conducted 19–21 months post event	One of the hardest hit cities, Gölcük	N/A	Ramirez et al. (2005)
2000 Iceland	PTSD	Gender, SES	Postdistributed HTQ 3 months post event	5 exposed local government areas	24	Bodvarsdottir and Elklit (2004)
2002 Molise, Italy	PTSD	Age, gender, SES	Mental Health Team administered the BSSS for PTSD six months post event	5 most affected villages	14.50	Priebe et al. (2009)
2003 Bam, Iran	PTSD	Age, family structure, gender, SES	Interviews by trained personnel using the GHQ-12 conducted 5 months post event	Bam, Iran	N/A	Montazeri et al. (2005)
2005 Pakistan	PTSD	Age, family structure, gender, SES	Trained personnel administered the DTS 30 months post event	3 districts close to the epicenter	41.30	Ali et al. (2011)
2007 Pisco, Peru	PTSD	Age, family structure, gender, SES	Interviews by trained personnel using the HTQ and PCL conducted 5 months post event	City of Pisco	25.20	Cairo et al. (2010)

Table 1. (*Continued.*)

Earthquake	Morbidity rate	Variables gained from study	Description of data collection method	Geographic scale	PTSD prevalence (%)	Source
2007 Pisco, Peru	PTSD	Age, family structure, gender, SES	PCL-C questionnaire administered by professionals 4 years post event	Urban or periurban areas of 5 districts in the province of Pisco.	15.90	Flores et al. (2014)
2008 Wenchuan, China	PTSD	Age, ethnicity, gender	PCL-C questionnaire administered by professionals 4, 6, 9, and 12 months post event	3 secondary schools in Wenchuan	11.2, 8.8, 6.8, 5.7	Liu et al. (2010)
2008 Wenchuan, China	PTSD	Age, gender	Interview with psychiatrist based on CRIES scale score, conducted 6.5 months post event	3 middle schools in Mianzhu city	2.50	Ma et al. (2011)
2008 Wenchuan, China	PTSD	Age, ethnicity, family structure, gender, SES	PCL-C administered by professionals 15 months post event	2 of the most severely affected subdistricts: 39 villages	15.20	Jia et al. (2010b)
2008 Wenchuan, China	PTSD, Injury	Age, ethnicity, family structure, gender, SES	In-person interviews by trained personnel using the CPTSD-RI conducted 15 months post event	2 of the most severely affected subdistricts: 39 villages	12.40	Jia et al. (2010a)
2008 Wenchuan, China	PTSD	Age, family structure	Professional-administered self-report PCL-C questionnaires conducted 6 months post event	9 different counties within the earthquake region	4.50	Liu et al. (2012)
2008 Wenchuan, China	PTSD	Age, ethnicity, gender, SES	Self-report using PCL-C one year post event	19 severely affected counties	40.10	Jin et al. (2014)
2008 Wenchuan, China	PTSD, Fatality	Age, ethnicity, family structure, gender, SES	Interviews by trained personnel using the HTQ 3 months post event	4 areas in Sichuan Province	47.30	Kun et al. (2013)
2009 L'Aquila, Italy	PTSD	Age, gender	TALS-SR distributed 10 months post event	Town of L'Aquila	37.50	Dell'Osso et al. (2011)
2009 L'Aquila, Italy	PTSD	Age, gender	TALS-SR distributed 10 months post event	Town of L'Aquila	41.30	Dell'Osso et al. (2012)
2009 Padang, Indonesia	Injury, fatality	Age, family structure, gender	Health records from the Health Office, Handicap International (NGO), 5 general hospitals, and a specific list of injured victims obtained from 5 villages	Padang, Indonesia	N/A	Sudaryo et al. (2012)
2010 Haiti	PTSD	Age, family structure, gender, SES	In-person interview by trained personnel using the PCL modified to include DSM-IV-TSR, conducted 2–3.5 months post event	Nazon area of Port-au-Prince	24.60	Cerda et al. (2013)
2010 Haiti	PTSD	Age, gender, SES	In-person interviews by trained personnel using the life events checklist, PDI, IES-R questionnaires conducted 30 months post event	Port-au-Prince and surrounding municipalities	36.75	Cenat and Derivois (2014)
2011 Tohoku, Japan	PTSD	Age, gender	Self-report PTSSC-15, 8 months post event	Schools in Ishinomaki City	42.60	Usami et al. (2012)

Note: BSSS for PTSD = Breslau short screening scale for PTSD; CAPS = Clinician-administered PTSD scale; ChIPS = Children's interview for psychiatric syndromes; CPTSD-RI = Child PTSD reaction index; CRIES = Children's revised impact of event scale; DSM = Diagnostic and statistical manual of mental disorders; DTS = Davidson trauma scale; GHQ-12 = 12-Item general health questionnaire; HTQ = Harvard trauma questionnaire; IES-R = Impact of event scale-revised; PCL-C = PTSD check list—Civilian; PDI = Peritraumatic distress inventory; PTSSC-15 = Posttraumatic stress symptoms for children, 15 items; TALS-SR = Trauma and loss spectrum—Self report.

Table 2. Variable Subcategories

Variable	Subcategory
Age	Child (0–9 years old)
	Adolescent (10–18 years old)
	Young adult (19–29 years old)
	Middle-aged adult (30–45 years old)
	Older adult (46–64 years old)
	Elder (65+ years old)
Built environment	New rural (not dense)
	Old rural (not dense)
	New urban (dense)
	Old urban (dense)
Ethnicity/race	White, non-Hispanic
	Non-White, non-Hispanic
Family structure	Single
	Partnered
	Person <18 years old in household
Gender	Female
	Male
Socioeconomic status	Low
	Moderate
	Upper

Table 3. Earthquake-Related Injuries and Population Rates of Injury (Data from Peek-Asa et al. 1998)

Characteristic	Number of earthquake-related injuries	Population	Odds ratio
Total	171	8,863,164	N/A
Severity			
Fatal	33	8,863,164	1.00
Hospitalized	138	8,863,164	4.18
Gender			
Male	78	4,421,398	1.00
Female	93	4,441,766	1.19
Age			
0–9 years old	5	1,384,014	1.00
10–19 years old	5	1,223,397	1.13
20–39 years old	55	3,797,209	4.01
40–59 years old	44	1,910,925	6.37
60–79 years old	36	859,369	11.60
80+ years old	25	188,498	34.58
Ethnicity/race			
White, non-Hispanic	102	3,618,850	1.00
Hispanic	38	3,351,242	0.40
African American	6	934,776	0.23
Asian/Pacific Islander	12	907,810	0.47

subcategory, $p_{\text{sub},j}$, and summing over all n_{sub} subcategories. The SED category factor is expressed as

$$F_{MR,\text{cat}} = \sum_{j=1}^{n_{\text{sub}}} f_{MR,\text{sub}(j)} \cdot p_{\text{sub},j} \tag{5}$$

This applies a factor to the population data. For example, looking at injury rate and only using the data from Peek-Asa et al. (1998), since $f_{\text{injury,female}} = 1.2$ and $f_{\text{injury,male}} = 1$, and Table 3 shows that the total population was 49.9% male and 50.1% female, then the gender category factor for injury, $F_{\text{injury,gender}}$, would be computed as

$$F_{\text{injury,gender}} = 1 \cdot (0.499) + 1.2 \cdot (0.501) = 1.1 \tag{6}$$

This is used as a predictive measure indicating that the rate of injury is expected to be 110% of the baseline rate for the specified community following the scenario earthquake, where the baseline rate is determined from building damage alone. The final predicted rate of injury will increase further, or decrease, based on the other category factors for age, ethnicity/race, family structure, socioeconomic status, and the age and density of the built environment.

There was not enough empirical information to model the subcategory factors for the built environment in the same way as the other SED variables. However this variable has been established in the literature as influencing morbidity rates and therefore was elected to still be included here. A dense built environment creates a vulnerable population to injury and fatality due to the larger potential for more buildings to collapse, collapse into each other creating debris missiles, and create a more congested area for egress. This vulnerability is exacerbated if the infrastructure is older and/or of poor quality, where *new* implies post-1994 Northridge construction. This time period was selected due to the changes adopted in seismic design following the 1994 Northridge earthquake. Additionally, as one might envision widespread building damage within a community and damage to personal property have been linked to higher rates of PTSD (Sharan et al. 1996; Shoaf et al. 1998; Siegel 2000; Ramirez et al. 2005; Altindag et al. 2005; Priebe et al. 2009; Liu et al. 2010; Usami et al. 2012). On the contrary, access to aid and resources for rural communities can be much lower, increasing their vulnerability. Due to the lack of empirical data, a set of odds ratios was assigned to each subcategory of the built environment for each morbidity rate based on engineering judgment. Very little scatter was assumed for the injury and fatality rates, and only a bit more was assigned to the PTSD diagnosis rate. All SED subcategory factors developed in this study are presented in Table 4 for the six variables and three morbidity rates. The factors presented in Table 4 were developed using the references listed in Table 1.

Table 4. SED Variable Subcategory Factors for Morbidity Rates

Variable	Subcategory	Injury	Fatality	PTSD diagnosis
Age				
	Child (0–9 years old)	0.8838	0.8838	1.2188
	Adolescent (10–18 years old)	1.5100	1.5100	1.2188
	Young adult (19–29 years old)	1.0162	1.0162	0.9379
	Middle-aged adult (30–45 years old)	0.6725	0.6725	0.9451
	Older adult (46–64 years old)	1.6712	1.6712	0.9291
	Elder (65+ years old)	2.7550	2.7550	1.3031
Ethnicity/race				
	White, non-Hispanic	—	—	1.0000
	Non-White, non-Hispanic	—	—	1.4718
Family structure				
	Single	—	—	2.0000
	Partnered	—	—	1.0000
	Person <18 years old in household	—	—	2.7065
Gender				
	Female	1.7925	2.0033	2.0486
	Male	1.0000	1.0000	1.0000
Socioeconomic status				
	Low	3.4850	3.4850	1.9403
	Moderate	1.8500	1.8500	1.2189
	Upper	1.0000	1.0000	0.9127
Built environment				
	New rural	0.9500	0.9000	1.1000
	Old rural	1.0000	1.0000	1.3000
	New urban	1.0500	1.0000	1.0000
	Old urban	1.1500	1.1000	1.2000

Table 5. Damage State Descriptions for Woodframe Buildings

Damage state	Level	Description
1	No damage	Structure can be immediately occupied, no repairs required
2	Slight	Structure can be immediately occupied, minor drywall repairs required
3	Moderate	Shelter-in-place allowed, drywall replacement required
4	Severe	Shelter-in-place prohibited, structural damage incurred
5	Collapse	Structure is not safe for entry, must be reconstructed

Damage States

The category factors developed in the previous section were applied to the baseline morbidity rates. The baseline morbidity rates vary based on the severity of building damage. If a building has little to no damage, then the morbidity rates are quite low, however if an occupied building collapses, then these rates significantly increase. In this study, five damage states—ranging from no damage to collapse (Table 5)—were modeled based on major damage categories identified for woodframe buildings. The detailed development of the mean and coefficient of variation (COV) values of interstory drift selected for the damage states is provided in Jennings (2015). The damage states are analogous to the *HAZUS* (DHS 2003) damage states for woodframe buildings. The damage states are central to the framework and provide the connection between damage measures (e.g., building performance, morbidity rates, repair costs, relocation costs, and repair times).

The damage states were defined by interstory drift, which has been shown to be well-correlated with physical damage to woodframe structures (Filiatrault and Folz 2002). Lognormal cumulative distribution functions (CDFs) were developed for each damage state and the damage states were modeled sequentially. The probability of each damage state given a specific interstory drift value was determined using the sequential damage state functions expressed as

$$P[DS=ds|ISD=x]=\begin{cases}1-P[DS\geq ds|ISD=x]ds=1\\ P[DS\geq ds|ISD=x]-P[DS\geq ds+1|ISD=x]2\leq ds\leq n_{ds}-1\\ P[DS\geq ds|ISD=x]ds=n_{ds}\end{cases}\tag{7}$$

where $n_{ds}=5$ in this study, and

$$\sum_{ds=1}^{n_{ds}}P[DS=ds|ISD=x]=1.0\tag{8}$$

Eq. (7) uses the extraction of the engineering demand parameter (i.e., peak interstory drift) based on the input seismic hazard. The probability of the sequential damage states given a peak interstory drift value is provided in Fig. 3, demonstrating the overlap of the damage states. Looking at 4% interstory drift in Fig. 3, the individual building archetype could be in any of the five damage states with the highest probability that it is in Damage State 3.

Objectives

Thus far, the SED variables and subcategory factors, and the building damage states have been discussed mostly in terms of three morbidity rates. However, the morbidity rates constitute only one of the four resilience measures used in this study to define community-level seismic resilience. Together the four resilience measures serve as objectives within the optimization, and include initial cost, economic loss, number of morbidities, and time to recovery. The resulting community-level seismic retrofit plans have associated values for each of these four objective values, and other supplementary measures computed within each objective. The analytical models for the four objectives are presented in the following subsections.

Initial Cost

Ideally, every community would be designed to be *resistant* or 100% resilient to any hazard event. Various factors may limit this in actual application, including the required initial cost, political or social will, aesthetic preferences, and so forth. Initial cost, in particular, is an imperative objective as it typically governs decision-making. The goals of decision makers—whether they be individual homeowners or political leaders—are only realized to the extent of the budget which funds the solution. Its presence here provides contrast from the other three objectives, that is to say that a community retrofit plan with lower initial cost will intuitively have more economic loss, morbidities, and a longer recovery time.

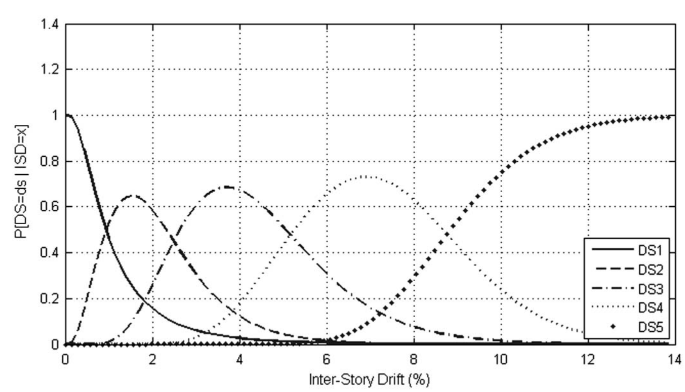

Fig. 3. Probability of sequential damage states given interstory drift

The initial cost may be computed as the cost for all new retrofits, ic_{ret}, expressed as

$$O_1 = ic_{\text{ret}} \tag{9}$$

The new retrofit costs were strict values computed using a unit cost per area, cost_{ret}, for the respective archetype and respective retrofit, multiplied by the total floor area of the archetype, fa_{arch}. The quantity of new retrofits was determined by subtracting the total number of buildings retrofitted in the projected community found by the search algorithm, $n_{\text{gen},i}$, from the original community defined by census data, $n_{\text{gen}0,i}$. This is expressed as

$$ic_{\text{ret}} = \sum_{i=i}^{n_{\text{arch,ret}}} \text{cost}_{\text{ret}} \cdot fa_{\text{arch}} \cdot (n_{\text{gen},i} - n_{\text{gen}_0,i}) \tag{10}$$

where $n_{\text{arch,ret}}$ = number of archetypes, arch, retrofitted to ret retrofit level. The initial cost, as used here, is not following a specific event. However the optimal seismic retrofit plan is determined based on the optimal trade-off between the four resilience metrics which are determined for a scenario earthquake. The initial cost is therefore representative of the initial cost necessary to plan for a specific earthquake, given the original building stock derived from census data as described in more detail in Part II (Sutley et al. 2016).

Number of Morbidities

The preservation of life is generally the central goal in any structural design code or standard (with the exceptions being in corrupt and impoverished contexts). Beyond life safety, quality of life, which encompasses mental health and well-being, should also be considered as a design goal because the mental health of a population can influence other factors that may affect overall recovery, such as ability to parent, to work, or to otherwise participate in public life, for instance. In the present research, the number of morbidities was determined using the morbidity rates for injury, fatality, and PTSD diagnoses. PTSD diagnoses were incorporated into the model to represent the mental health of the population by means of a count of the number of persons that could meet the criteria for a PTSD diagnoses.

The morbidity rates were determined as a function of the damage states and adjusted based on the socioeconomics and demographics of the population incorporated through the SED factors. The morbidity rates for the injury severity levels, including fatality, were computed as

$$MR_{is,ds} = (F_{MR,\text{age}} \cdot F_{MR,\text{gen}} \cdot F_{MR,\text{ses}} \cdot F_{MR,\text{env}}) \cdot IS_{is,ds} \tag{11}$$

and the morbidity rate for PTSD was computed as

$$MR_{pr,ds} = (F_{MR,\text{age}} \cdot F_{MR,\text{eth}} \cdot F_{MR,\text{fam}} \cdot F_{MR,\text{gen}} \cdot F_{MR,\text{ses}} \cdot F_{MR,\text{env}}) \cdot PR_{ds} \tag{12}$$

where F_{age}, F_{eth}, F_{fam}, F_{gen}, F_{ses}, and F_{env} = SED factors for age, ethnicity/race, family structure, gender, socioeconomic status, and the age and density of the built environment, respectively, as developed in Eq. (5), and where the MR subscript refers to the category factor value for either injury severity or PTSD rate. $IS_{is,ds}$ and PR_{ds} are the rate of injury severity level is and PTSD diagnosis rate for damage state ds due to building damage, respectively. Note that the category factors F_{eth} and F_{fam} were not used in Eq. (11) for determining the morbidity rates for injury and fatality. This is due to the lack of empirical data on these two variables for injury and fatality.

Table 6. Description of Injury Severity Levels

Injury severity level	Description
Minor	Self-treated injuries
Moderate	Injuries requiring basic medical aid
Severe	Hospitalized injuries
Critical	Life threatening injuries
Fatal	Deaths and nonsurvivable injuries

The morbidity rates were incorporated into the computation of three of the objectives: economic loss, number of morbidities, and time to recovery. The number of morbidities, O_3, was computed by multiplying the morbidity rates by the population size of the community, expressed as

$$O_3 = \sum_{ds=1}^{n_{ds}} \left[\left(\sum_{is=1}^{n_{is}} MR_{is,ds} + MR_{pr,ds} \right) \cdot \sum_{i=1}^{n_{\text{arch}}} (n_{i,ds} \cdot occ_i) \right] \tag{13}$$

where $n_{i,ds}$ = number of each archetype i for the damage state ds; and occ_i = occupancy for each archetype i. The number of morbidities, O_3, included the number of people in all injury severity levels, including fatalities, and the total number of PTSD diagnoses.

Injury Severity Rates

There were five physical injury severity levels considered in this study: minor injury, moderate injury, severe injury, critical injury, and fatal injury (Table 6). The fatal injuries cover both assumed instantaneous deaths caused by the earthquake and deaths occurring in the immediate days following the earthquake in hospitals due to critical injuries or other unresolved health conditions attributed to the earthquake. The latter four injury severity levels are analogous to those in *HAZUS* (DHS 2003). The minor injury severity level can be difficult to quantify due to the lack of records available; this is likely associated with most minor injuries being self-treated. Despite the difficulties, and the fact that the minor injury level was not included in *HAZUS*, it is included in the present study. The type, or specific cause of the injury was not taken into consideration.

The injury severity rates for each respective damage state, $IS_{is,ds}$, were modeled as random variables where the mean value was obtained from *HAZUS* for the latter four levels. The mean value for the minor injury severity level was determined by dividing the moderate injury severity rates by a factor of 10. The factor of 10 was chosen due to its use by *HAZUS* in several instances for increasing or decreasing from one injury severity level to the next. The rate of injury severity level, $IS_{is,ds}$, due to building damage, as shown in Eq. (11), may also be described as an exceedance probability conditioned on the damage state, shown in Fig. 4, and expressed as

$$IS_{is,ds} = P[IS \geq is | DS = ds] \tag{14}$$

where Fig. 4 was produced for the minor injury level ($is = 1$). From Fig. 4, one can see that the minor injury severity level rate is lowest at Damage State 2, with the 50th percentile value approximately equal to 0.0005. The minor injury severity level rate is highest for Damage State 5 with the 50th percentile value approximately equal to 0.04. These relative rankings across the injury levels holds consistent for the entire distribution, not only for the 50th percentile values.

Rate of PTSD Diagnosis

The rate of PTSD diagnosis was conditioned on the damage state of the building being occupied by the individual, and is expressed as a

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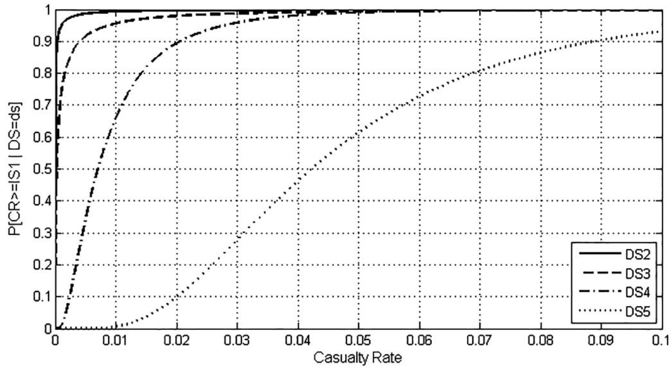

Fig. 4. Probability of minor injury given each damage state

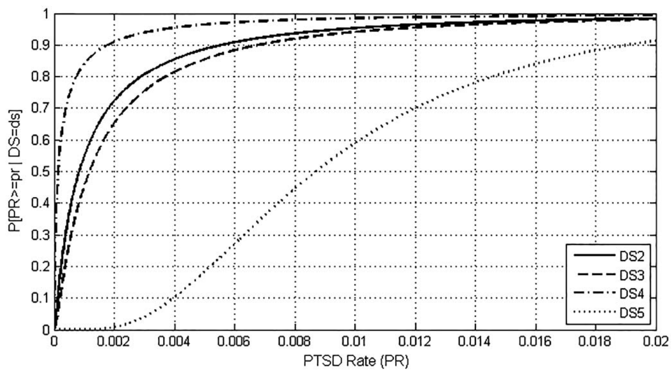

Fig. 5. Probability of the rate of PTSD diagnosis for each damage state

random variable. The mean value for each damage state was set to be the same as the severe injury rates. The PTSD diagnosis rate, PR_{ds}, due to building damage, as shown in Eq. (12), was modeled as an exceedance probability conditioned on the damage state and expressed as

$$PR_{ds} = P[PR \geq pr|DS = ds] \tag{15}$$

The probability of PTSD diagnosis given a specific damage state is expressed graphically in Fig. 5. Here again, the highest rate of PTSD diagnosis occurs at Damage State 5. To compute the number of morbidities, or a single morbidity, due to building damage alone, $MR_{is,ds}$ and $MR_{pr,ds}$ in Eq. (13) would be replaced by $IS_{is,ds}$ and/or PR_{ds} from Eqs. (14) and (15), respectively. A lognormal CDF was assumed for the morbidity rate measures due to the nature of the occurrence of morbidities, and the ability of the lognormal CDF to accurately classify other variables in this study (e.g., building damage).

Economic Loss

Economic loss may be computed as the sum of direct and indirect costs. Here, the direct costs included repair costs, EL_{RC}, and loss due to contents damage, EL_{CD}, and the indirect costs included relocation costs, EL_{RL}, and morbidity costs, EL_M, (e.g., injury costs, PTSD treatment costs, PTSD downtime costs, and the value of a lost life). The second objective, economic loss, may be expressed as

$$O_2 = EL_{RC} + EL_{RL} + EL_M \tag{16}$$

Within Eq. (16), the economic loss due to morbidity costs is the only term that incorporates the SED category factors presented in the previous section.

Repair Costs

The economic losses due to building repair costs and contents damage were grouped together in Eq. (16) as EL_{RC}. The mean values for the building repair costs were computed at the subassembly level and were obtained from Reitherman and Cobeen (2003). The subassemblies included exterior walls [5.94 m^2 (64 sq ft) unit size], interior walls [5.94 m^2 (64 sq ft) unit size], ceilings [5.94 m^2 (64 sq ft) unit size], windows (individual unit size), and water heaters (individual unit size). To compute the total building repair cost for archetype i for each damage state, $RC_{ds,i}$, the lognormal inverse CDF for the subassembly repair costs, $\phi^{-1}(RC_{ds,k})$, was multiplied by 30% of the number of subassembly units, $n_{\mathrm{unit},k}$, and summed together for all subassemblies k, expressed as

$$RC_{ds,i} = \sum_{k=1}^{5} 0.3 \cdot n_{\mathrm{unit},k} \cdot \Phi^{-1}(RC_{ds,k}) \tag{17}$$

Only 30% of the subassembly units were used in determining the repair costs because in reality not every single 2.44 × 2.44 m (8 × 8 ft) interior wall, exterior wall, and ceiling segment will be damaged in the building. The assumption of 30% of the subassembly units was based on the authors' extensive experimental testing and postearthquake damage surveys, and is likely still a conservative estimate. Damage to the water heater was determined based on the damage state information provided in Reitherman and Cobeen (2003).

Economic loss due to contents damage was set as 50% of the building repair cost value for residential structures and 100% of the mean repair cost value for commercial structures. These contents' values, CV_i, were used in DHS (2003) as percentages of the structure value. The mean contents' damage, $CD_{ds,i}$, may be expressed as

$$CD_{ds,i} = RC_{ds,i} \cdot CV_i \tag{18}$$

To compute the economic loss due to all archetypes in the community over all damage states, EL_{RC}, the sum of the archetype i repair cost for damage state ds, $RC_{ds,i}$, and the archetype i contents damage for damage state ds, $CD_{ds,i}$, was multiplied by the total number of archetypes n_i in the community and summed together for all damage states. The economic loss due to all archetypes in the community over all damage states may be expressed as

$$EL_{RC} = \sum_{ds=1}^{n_{ds}} \sum_{i=1}^{n_{\mathrm{arch}}} (RC_{ds,i} + CD_{ds,i}) \cdot n_i \tag{19}$$

All buildings were assumed to be repaired to their preearthquake state, and no option was provided for different levels of repair, opportunities not to repair, or opportunities to relocate.

Relocation Count and Cost

The ability for building occupants to shelter in place is typically important to decision makers and community leaders, and thus is considered as a design objective. If a building were to reach Damage State 4 or 5, then temporary relocation of the building occupants would be required. If persons are displaced for too long, they may decide to permanently relocate to another community, which will have a substantial impact on the community both financially and culturally. The number of relocated persons was computed as the number of buildings reaching Damage States 4 and 5 multiplied by the specific building's occupancy, expressed as

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Table 7. Relocation Cost Parameter Values (Data from DHS 2003)

Parameter	Archetype category	HAZUS value
dc (\$/sq ft)	Residential SFD	0.82
	Residential MFD	0.82
	Commercial	0.95
per (%)	Residential SFD	75
	Residential MFD	35
	Commercial	55
rent (\$/sq ft/month)	Residential SFD	0.68
	Residential MFD	0.61
	Commercial	1.36

$$n_{\mathrm{rel}} = n_{i,DS4} \cdot occ_i + n_{i,DS5} \cdot occ_i \tag{20}$$

where, n_{rel} = number of relocated persons; $n_{i,DS4}$ = number of archetypes i in Damage State 4; $n_i,_{DS5}$ = number of archetypes i in Damage State 5; and occ_i = number of persons occupying archetype i. The number of relocated persons is provided as a fragility function conditioned on the initial investment, expressed as

$$P[n\mathrm{Rel} \leq n | ic = ic_i] \tag{21}$$

where n = number of relocated persons given ic_i; ic = initial cost; and ic_i = initial cost of the specific community seismic retrofit plan i. The computation of the cost for relocation was adopted from the *HAZUS* methodology, and incorporated into the objective economic loss. The relocation cost may be expressed as

$$\mathrm{rel}_i = fa_i \cdot \left\{(1 - \mathrm{per}_i) \cdot \sum_{ds=4}^{5}(p_{ds,i} \cdot dc_i) + \mathrm{per}_i \cdot \sum_{ds=4}^{5}[p_{ds,i} \cdot (dc_i + \mathrm{rent}_i + rt_{ds,i})]\right\} \tag{22}$$

where rel_i = relocation costs for archetype i based on occupancy class; fa_i = floor area of archetype i; $p_{ds,i}$ = probability of archetype i being in damage state ds; dc_i = disruption costs for archetype i based on occupancy class in units of dollars per floor area; $rt_{ds,i}$ = recovery time for archetype i in damage state ds; per_i = percent owner occupied for archetype i; and rent_i = rental cost for archetype i based on occupancy class in units of \$/floor area/day. The values for dc_i, per_i, and rent_i were obtained from *HAZUS* and are provided in Table 7. The values for $rt_{ds,i}$ were the mean values for $RT_{ds,i}$ as discussed in the next section. To determine the economic loss due to relocation, EL_{RL}, the relocation cost for archetype i is multiplied by the total number of archetypes i in the community, and summed for all archetypes, expressed as

$$EL_{RL} = \sum_{i=1}^{n_{\mathrm{arch}}}(\mathrm{rel}_i \cdot n_i) \tag{23}$$

Economic Loss due to Morbidity

The economic loss due to morbidity, EL_M, was determined as the sum of the economic loss caused by the number of persons in each morbidity category, expressed as

$$EL_M = \sum_{is=1}^{5} EL_{Inj,is} + EL_{\mathrm{PTSD}} \tag{24}$$

where $EL_{Inj,is}$ = economic loss due to injury for injury severity level is; and EL_{PTSD} = economic loss due to PTSD. The community economic losses due to each injury severity level were modeled

Table 8. Injury Severity Costs (Data from FHWA 1994)

Injury severity level	Cost (\$)
Minor	8,000
Moderate	64,000
Severe	785,000
Critical	3,170,000
Fatality	4,165,000

as random variables. The mean value, $mEL_{Inj,is}$, was determined by multiplying the particular cost value associated with each injury severity level, $\cos t_{Inj,is}$, by the respective mean value of the injury severity rate distribution, $MR_{is,ds}$, respectively, as determined by Eq. (11). The particular cost values for each injury severity level were set as the values the U.S. government assigns to each injury severity level, including fatality (FHWA 1994), and adjusted for inflation to 2014 dollars. These values are comprehensive costs covering pain, lost quality of life, medical costs, legal costs, lost earnings, lost household production, and so forth. Table 8 provides the cost values for each injury severity level.

The economic loss due to PTSD was determined as the sum of economic losses due to treatment of PTSD, $EL_{\mathrm{PTSD,trmt}}$, and the downtime due to PTSD considering absenteeism from work, $EL_{\mathrm{PTSD,Abs}}$, and presenteeism at work, $EL_{\mathrm{PTSD,Pres}}$, based on the literature survey referenced previously, where absenteeism is the tendency to be absent from work (or school) excessively, and presenteeism is the practice of going to work (or school) while ill, injured, or otherwise distracted resulted in reduced productivity. The economic loss due to PTSD may be expressed as

$$EL_{\mathrm{PTSD}} = EL_{\mathrm{PTSD,trmt}} + EL_{\mathrm{PTSD,Abs}} + EL_{\mathrm{PTSD,Pres}} \tag{25}$$

To model the economic loss due to PTSD as a random variable, the process previously described was similarly repeated by first combining the particular costs (or mean values) for treatment, downtime due to absenteeism and downtime due to presenteeism multiplied by the rate of PTSD diagnosis determined in Eq. (12), and summing for all damage states. In this way, the economic loss due to PTSD is expressed as

$$EL_{\mathrm{PTSD}} = \sum_{ds=1}^{5}(\mathrm{cost}_{\mathrm{PTSD,trmt}} + \mathrm{cost}_{\mathrm{PTSD,Abs}} + \mathrm{cost}_{\mathrm{PTSD,Pres}}) \cdot MR_{pr,ds} \tag{26}$$

The treatment cost of PTSD was determined from a study conducted by the Congressional Budget Office (CBO) on veterans (CBO 2012) as \$5,400 per year. This is an average cost, and in CBO (2012), it was shown that the treatment cost for PTSD is highest in the first year. It should also be noted that PTSD treatment costs can last for many years, and up to a lifetime. In this study, the cost for PTSD treatment was capped at the cost for one year and set as \$5,400, and is thus a low estimate.

The downtime due to absenteeism and presenteeism is composed of the number of work loss days and work cut back days (or work-time reduced days) due to each, respectively. The equations used for determining the number of work loss days and work cut back days due to PTSD were obtained from Goetzel et al. (2004). The annual rate of absenteeism due to PTSD was computed as

$$R_{\mathrm{Abs}} = n_{\mathrm{WLD}} \cdot (P_{\mathrm{PTSD}} \cdot n_{\mathrm{pop}})/240 \tag{27}$$

where n_{WLD} = average annual number of work loss days per person obtained from Kessler and Frank (1997); n_{pop} = population size based on building occupancy; and 240 = total number of work days per year. The total loss due to absenteeism was estimated by multiplying the annual rate of absenteeism, R_{Abs}, by the average annual salary of the population, expressed as

$$\text{cost}_{\text{PTSD,Abs}} = R_{\text{abs}} \cdot \text{salary} \tag{28}$$

the annual rate of presenteeism due to PTSD is expressed as

$$R_{\text{Pres}} = n_{\text{WCBD}} \cdot (P_{\text{PTSD}} \cdot n_{\text{pop}}) \cdot hr_{\text{WCB}} \cdot 0.125/240 \tag{29}$$

where n_{WCBD} = average annual number of work cut back days per person due to PTSD (Kessler and Frank 1997); hr_{WCB} = average number of hours per day in which work is cut back due to PTSD (Kessler and Frank 1997); and 0.125 represents 8 h per work day. The total loss due to presenteeism was estimated using the average annual salary of the population, expressed as

$$\text{cost}_{\text{PTSD-Pres}} = R_{\text{Pres}} \cdot \text{salary} \tag{30}$$

Time to Recovery

As mentioned previously, the quality of life and mental health of the population is important in order for a community to successfully rebuild in the aftermath of a disaster. One way to measure the impact on the quality of life of the population is through the estimated recovery time. To compute the community time to recovery, the maximum recovery time due to either morbidity or building repair time was taken, expressed as

$$O_4 = \max \begin{cases} \text{Rec}T_M \\ \text{Rec}T_{\text{Rep}} \end{cases} \tag{31}$$

The recovery time did not consider other lifeline damage or disruption or the rate of return of residents in its computation.

Recovery Time due to Morbidity

The recovery time due to morbidity, $\text{Rec}T_M$, was determined by taking the maximum recovery time of the individual morbidity rates, mrt_{mr}, expressed as

$$\text{Rec}T_M = \max \begin{cases} mrt_{IS1} \\ mrt_{IS2} \\ mrt_{IS3} \\ mrt_{IS4} \\ mrt_{IS5} \\ mrt_{\text{PTSD}} \end{cases} \tag{32}$$

In Eq. (32), the maximum value is only taken over the morbidity rates [Eqs. (11) and (12)], which have members of the population suffering from that specific morbidity. For example, if the defined seismic hazard was for a very small earthquake, there may not be any members of the population that experience the latter three morbidity rates (e.g., critical injury, fatality, and PTSD). In this case, only the first three morbidity rates would be considered in Eq. (32). The values for mrt_{mr} were set as the values listed in Table 9 for the various morbidities. These time values were set by the authors as logical placeholders based on a review of available literature, and could be changed by the decision maker(s) using the framework. It is evident from Eq. (32) and the values in Table 9 that the recovery time due to PTSD would normally control for larger earthquakes.

Table 9. Recovery Time due to Morbidity

Morbidity rate	Time (weeks)
Injury severity Level 1	1
Injury severity Level 2	6
Injury severity Level 3	16
Injury severity Level 4	26
Injury severity Level 5	26
PTSD	52

Recovery Time due to Building Repair

The recovery time due to building repair time, $\text{Rec}T_{\text{rep}}$, was determined the same way that the economic loss due to building repair costs, EL_{RC}, was determined. The mean values for the repair times were obtained from Reitherman and Cobeen (2003). These repair times were provided at the subassembly level for exterior walls [5.94 m^2 (64 sq ft) unit size], interior walls [5.94 m^2 (64 sq ft) unit size], ceilings [5.94 m^2 (64 sq ft) unit size], windows (individual unit size) and water heaters (individual unit size). To compute the total archetype repair time, $RT_{ds,i}$, for each damage state, the lognormal inverse CDF for the subassembly repair time, $\varphi^{-1}(RT_{ds,k})$ was multiplied by the number of subassembly units, $n_{\text{unit},k}$, and summed together for all subassemblies. The total archetype repair time may be expressed as

$$RT_{ds,i} = \sum_{k=1}^{5} n_{\text{unit},k} \cdot \Phi^{-1}(RT_{ds,k}) \tag{33}$$

To compute the repair time due to all archetypes in the community, $\text{Rec}T_{\text{Rep}}$, for all damage states, the archetype i repair time for damage state ds, $RT_{ds,i}$, was multiplied by the total number of archetypes i in the community, summed over the community, and then divided by the number of repair crews, n_{rep}. The number of repair crews was determined by the percentage of the population that is in the construction industry (i.e., 5.7% on the 2010 U.S. Census for Los Angeles County) divided by three to represent a three-person crew. The actual number of repair crews is uncertain. What is known is that if a major disaster were to occur, repair crews from surrounding communities or even other states would come for work, which has been observed routinely for all types of disasters. Therefore, conservatively assuming the aforementioned approach accounts for nonprofessionals and out-of-towners offering repair work, as well as the local repair companies. The community recovery time due to building repairs may be expressed as

$$\text{Rec}T_{\text{Rep}} = \left(\sum_{ds=1}^{n_{ds}} \sum_{i=1}^{n_{\text{arch}}} RT_{ds,i} \cdot n_i \right) / n_{\text{rep}} \tag{34}$$

The strict probability of repair time given each damage state is provided in Fig. 6 for a two-story single-family dwelling. Note that the repair distributions are the same for Damage States 2 and 3. The SED factors were not used in the computation of repair time, or recovery time due to building repair due to the data limitation of being able to quantify the difference in time to repair that persons of different SED characteristics would experience. It is assumed that a difference could be found on the time a building owner takes to seek the repair based on their SED characteristics, and also possibly the response of the repair company based on the building owner's SED characteristics. Additionally, the recovery time due to repair did not include any lead time for building inspection or evaluation, finance planning, consultation, a competitive bidding process, or the mobilization of construction, which have all been

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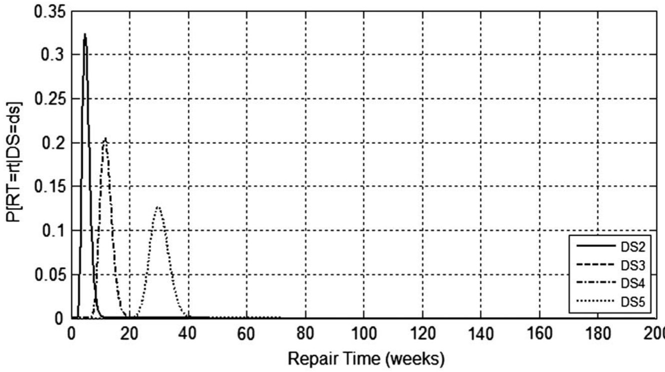

Fig. 6. Probability of repair time for each damage state

shown to influence the amount of time needed to conduct building repairs (Mitrani-Reiser 2007).

Socioeconomic and Demographic Factor Sensitivity Study

A sensitivity analysis was conducted on the SED factors developed in the previous sections. The purpose of the sensitivity analysis is to examine the influence the SED factors have on the morbidity rates. The examples presented use percentages of demographic distributions obtained from 2010 U.S. Census data (U.S. Census Bureau 2012) for three California communities. Los Angeles County, California, was selected due to its inherent seismic hazard. The subcommunity of East Los Angeles was selected due to its high population of minorities and lower-than-average socioeconomic status. Thirdly, Daly City, California, was selected for study because it also has a higher population of minorities relative to Los Angeles County, but higher-than-average socioeconomic status. The latter two communities, in comparison to Los Angeles County, allow for examination of the variables ethnicity/race and socioeconomic status in seismically active environments. Additionally, two virtual communities were designed by the authors for the investigation of two other SED variables: age and gender. The two virtual communities were not modeled after any real communities in the United States, but strictly designed to analyze the two variables of interest. All other variable distributions, aside from age and gender, were modeled to be similar to communities C1–C3. The input data for the five communities are presented in Table 10.

To perform the sensitivity analysis, the category factors determined from Eqs. (11) and (12) were modified by setting the rate of injury caused by building damage ($IS_{is,ds}$ and PR_{ds}) equal to unity to simplify the process of examining only the influence of the SED factors, and allowing the sensitivity analysis to be independent of an earthquake hazard level. Fig. 7 provides a comparison of the category factor outputs for each respective morbidity category and for the five communities. The factors for injury and fatality were very similar to each other for all five communities, where the fatality factors were shifted just higher than the injury factors. Virtual 2 (C5) had the highest injury and fatality factors of all five communities, although just more than Virtual 1 (C4). Daly City (C3) had the lowest injury and fatality factors. These results correspond well with the subcategory factors presented in Table 4. For example, C5 had the highest percentage of persons in the older two age subcategories, the lowest number of persons in the youngest and the middle-aged age groups, and the higher end of percentages of persons in the low socioeconomic status group, all of which contributed to the higher injury and fatality factors. This was very similar to C4, except the percentage of older adults was lower in C4 than C5, and the percentage of females was much higher in C4 than C5, driving up the injury and fatality factors in C4 as well. C3 had the lowest number of persons in the low socioeconomic status

Table 10. Community Input Data

Variable	Subcategory	Community input values				
		Los Angeles County (C1)	East Los Angeles (C2)	Daly City (C3)	Virtual 1 (C4)	Virtual 2 (C5)
Total population size		9,818,605	126,496	101,123	100,000	100,000
Mean annual income		$81,729	$37,982	$89,180	80,000	80,000
Mean household size		2.98	4.09	3.23	3.00	3.00
Percentage of households with children		37.2%	42.6%	35.5%	35.0%	35.0%
Age						
Child (0–9 years old)		13.1%	17.2%	10.5%	13.0%	7.0%
Adolescent (10–19 years old)		14.6%	18.1%	11.5%	15.0%	9.0%
Young adult (20–29 years old)		15.4%	16.1%	15.9%	15.0%	14.0%
Middle-aged adult (30–45 years old)		21.9%	21.6%	21.2%	22.0%	20.0%
Older adult (46–64 years old)		24.2%	18.4%	27.3%	24.0%	30.0%
Elder (65+ years old)		10.9%	8.4%	13.4%	11.0%	20.0%
Ethnicity/race						
White, non-Hispanic		27.8%	1.5%	13.9%	27.0%	27.0%
Non-White, non-Hispanic		72.2%	98.5%	86.1%	73.0%	73.0%
Family structure						
Single		32.3%	19.5%	26.7%	20.0%	20.0%
Partnered		67.7%	80.5%	73.3%	80.0%	80.0%
Person <18 years old in household		37.2%	42.6%	35.5%	35.0%	35.0%
Gender						
Female		50.7%	50.3%	50.6%	68.0%	50.5%
Male		49.3%	49.7%	49.4%	32.0%	49.5%
Socioeconomic status						
Low		27.6%	50.3%	23.8%	50.0%	50.0%
Moderate		43.4%	34.9%	37.8%	35.0%	35.0%
Upper		29.0%	14.5%	35.6%	15.0%	15.0%

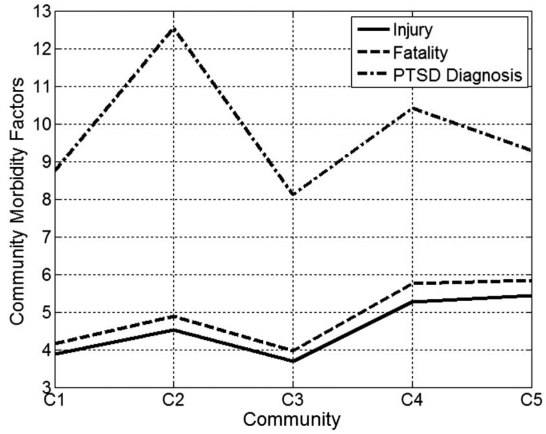

Fig. 7. Community factors for morbidity categories

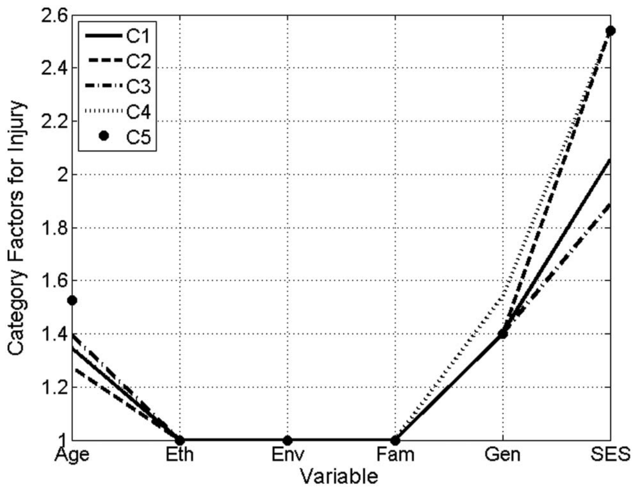

Fig. 8. Socioeconomic and demographic variable factors for injury

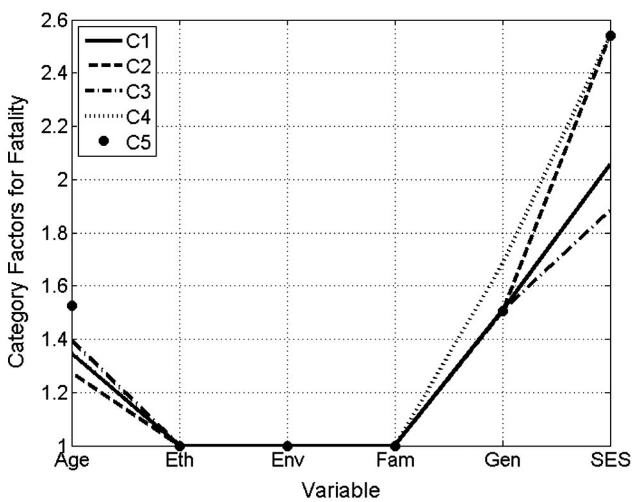

Fig. 9. Socioeconomic and demographic variable factors for fatality

group which contributed to its lower injury and fatality factors. The values for C1 were just higher than C3's due to the similar gender distributions, slightly lower socioeconomic status distributions, and a lower percentage of older adults.

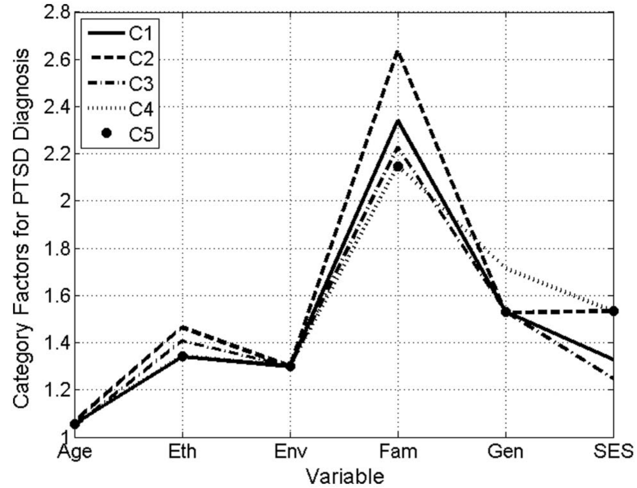

Fig. 10. Socioeconomic and demographic variable factors for PTSD diagnosis

Still referring to Fig. 7, a similar trend was noticed between the factors as a whole for injury, fatality, and PTSD diagnosis, with the exception of C5 where the factors sharply decreased for PTSD diagnosis, but slightly increased for injury and fatality. The subcategory factors for gender were very similar between morbidities (1 for male and approximately 2 for female in all cases); however, the distribution was quite different between C4 and C5. Based on Fig. 7, the gender distribution contributed to the higher PTSD factor for C4 since C4 had the highest population of females. Recall, that C5 had the highest population of elderly adults. The subcategory factors for age were very different across morbidities, as were the age distributions for C4 and C5, thus the differences in the injury and fatality factors for these two communities were controlled by the population's age.

Altogether, East Los Angeles, C2, had the highest PTSD diagnosis factor demonstrating that low socioeconomic status combined with a high population of minorities and families with persons under 18 years old living in the household contributed significantly to predicted PTSD diagnosis. C3 had the lowest PTSD diagnosis factor due to it having the highest percentage of persons in the high socioeconomic status category. The slightly higher percentage of minorities, or non-White, non-Hispanics in C3 did not appear to control over the higher percentage high socioeconomic status. It should be noted, if an analysis was conducted without using the SED variables, all of the factors in Fig. 7 would go to unity.

Figs. 8–10 present the factors for each of the SED variable categories for each of the three morbidities. Looking at the morbidity factors broken down in this way helps identify which variables controlled for which communities. The category factors for injury are shown in Fig. 8 for each community. C5 had the highest factor for age, and C2 had the lowest factor for age, which corresponds well with the age distributions for these two communities. The factors for ethnicity/race and family structure were set to unity since they do not appear in Eq. (11) for injury. In this case, the factor for the built environment was also equal to one (assuming an Old Rural built environment). C4 had the highest factor for gender even though the other four communities had very similar factor values. C2, C4, and C5 had identical factor values for socioeconomic status, which were higher than the factor values for either C1 or C3. C3 had the lowest factor value for socioeconomic status, which is attributed to it having the highest mean annual income and the highest percentage of persons in the upper socioeconomic status

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Table 11. Limitations

Limitation topic	Approach used in response to methodological challenge
Social vulnerability	Dynamic, constantly evolving measures modeled at an instance in time for a scenario event
Odds ratios	Quality ranks were assigned based on the quality of each study listed in Table 2. A reduction in quality could occur due to the data-collection process, the PTSD measurement scale, or the postevent timeline in which PTSD was diagnosed
Data collection	Data were collected from earthquakes occurring worldwide, where different cultures and economic structures are present. The user is provided the option to compute the odds ratios using only data from developed nations
Comparing losses temporality	There is discrepancy whether it is accurate to use data measured at a previous time for making loss predictions over a later period of time. Cutter and Finch (2008) demonstrated that the most influential factors to social vulnerability did not change over a period of 40 years, and therefore relationships measured in the past are applicable in the future
Comparing losses over geographic scales	There is discrepancy whether it is accurate to compare losses over geographic scales, however Schmidtlein et al. (2008) demonstrated that the most influential factors to social vulnerability did not change significantly over three geographic scales (i.e., county level, intermediate level, and census tract level)

group. An identical trend was developed for the category factors for fatality in Fig. 9 with slightly different factor values for some of the variable categories.

Fig. 10 provides the category factors for PTSD diagnosis. The trend shown in Fig. 10 varied greatly from Figs. 8 and 9. The factors for age were all very similar between communities, with C2 having the highest and C3 having the lowest, although this difference is not distinguishable from the figure. C2 had the highest factor for ethnicity, followed by C3, while the other three communities had approximately the same values. This demonstrated the idea behind the selection of those two communities, which both have high populations of minorities. The built environment factor for PTSD diagnosis was set to 1.30 for all communities for these examples to indicate an Old Rural built environment, as indicated in Table 4. There was a larger spread in the factors associated with family structure. C2 had the highest factor, which is indicative of the larger family sizes in East Los Angeles. C4 and C5 had identical family structure factors which were the lowest values. C4 and C5 both had identical family structure distributions with a relatively high percentage of partnered families, but lower percentage of families with persons under 18 years old living in the household, thus making the factors for C4 and C5 the lowest. The gender factors were approximately the same for all communities except C4 whose gender distribution had a much higher population of females. This was also exhibited in Figs. 8 and 9 for the gender category factors. Lastly, the socioeconomic status category factor was lowest for C3, followed by C1, where C2, C4, and C5 had nearly identical factor values all indicative of the socioeconomic status distributions of each community. A summary and conclusion of these results are presented in the final section.

Limitations

It is recognized that there were limitations in different areas of this study. Table 11 outlines these limitations by topic, and describes the approach used in response to the methodological challenge. It is believed that notwithstanding the limitations, the main objectives of coupling socioeconomic characteristics and engineering building systems to model resilience at the community level was achieved.

Conclusions

Following an extensive literature survey and metadata analysis, this work demonstrates that socioeconomic and demographic variables can be quantified in a meaningful way in order to be included in engineering and decision-making frameworks. Although a significant amount of uncertainty is associated with quantifying such subjective measures as posttraumatic stress disorder and loss in quality of life, there is a need to move beyond traditional casualty measurements which only include injury and/or fatality based on building damage alone. The available loss-estimation models, community disaster resiliency, and decision-making frameworks similarly lack this crucial characteristic of including social variables in their metrics. A community-level framework with a coupled socioeconomic and engineering system for community-level seismic resiliency was developed and presented. The benefit in coupling these two systems is that both are incorporated throughout the framework and thus could be used together in a much more robust manner by leaders interested in evidence-based decision making. The framework was presented for a seismic hazard, however, the conceptual framework presented in Fig. 2 may be applied to all types of hazards.

Overall, the analysis presented herein provided insight into which SED variables control decisions and outcomes for specific communities. For Los Angeles County, low socioeconomic status was the highest contributor to injury and fatality rates, and a family structure with persons under 18 years old living in the household was the highest contributor to PTSD diagnoses. Based on the comparison of C2 to C3, it was demonstrated that socioeconomic status was modeled to be a higher contributor to all three morbidity rates relative to ethnicity/race. Additionally, when population data were manipulated to have large differences in the percentages of each gender, with many more females present in the population (C4), a spike in the morbidity rates was obtained.

There are many assumptions and approximations embedded into the framework, which can lead to exacerbation of uncertainties in the estimated losses. This is further addressed in the companion paper, Part II (Sutley et al. 2016), including a calibration procedure. In Part II, the framework is applied to three communities centering on Los Angeles County, California. In particular, the optimal community-level seismic retrofit plans are identified through optimization.

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