ResilUS: A Community Based Disaster Resilience Model

Scott B. Miles and Stephanie E. Chang

ABSTRACT: A resilient community is one that does not experience serious degradation in critical services when a hazard occurs and, in the event of degradation or failure, recovers to a similar or better level of service in a reasonable amount of time. The most efficient means of making a community resilient is to make its critical services and capital robust – minimize damage/loss probability or the consequences from damage/loss through mitigation. If a community's critical services and capital are not robust, efforts must be put into recovery. Based on the measurable aspects of community capital, we have developed a simulation model called ResilUS that operationalizes community resilience across multiple, hierarchical scales in relation to a range of policy and decision variables associated with each scale. ResilUS is implemented using fragility curves to model loss and Markov chains to model recovery with respect to time. ResilUS was applied to the 1994 Northridge earthquake disaster in order to calibrate several output variables with empirical data. ResilUS represents a significant step forward for spatial decision support for disaster mitigation and recovery planning, in comparison to existing loss estimation models.

KEYWORDS: resilience, recovery, modeling, disasters, Northridge earthquake

Introduction

A resilient community is one that does not experience serious degradation in critical services when an earthquake or other disturbance occurs and, in the event of degradation or failure, recovers to a similar or better level of service in a reasonable amount of time. Critical services with respect to community resilience are those derived from and required for community capital. If a community's critical services and capital are not resilient in the face of a severe economic or natural disturbance, the result will likely be disaster and serious impairment of personal livelihoods. The most efficient means of making a community resilient is to make its critical services and community capital robust, or in other words, to minimize damage/loss probability or the consequences from damage/loss through mitigation (Bruneau et al. 2003). If a community's critical services and capital are not robust, efforts then must go towards recovery of services and livelihoods, which often requires restoration of physical infrastructure. Hazard-impacted neighborhoods within a community will recover at different rates and ultimately attain different stable states following a disaster.

This paper describes a newly developed model of community disaster resilience called ResilUS. This model represents a significant development effort, building upon the prototype model of Miles and Chang (2006). ResilUS represents hazard-related damage and recovery over time of critical services and community capital across different scales, including socio-economic agents, neighborhood, and community. ResilUS also represents how attributes and behaviors of households and businesses affect, and are affected by the built environment, policy decisions, and socio-political characteristics of a community. For example, "what if" analysis can be conducted regarding whether to retrofit a neighborhood's water pipelines or employ short-term housing instead of temporary shelters.

The following section describes the development work of ResilUS. In the third section, the updated model is applied to simulate Los Angeles' resilience with respect to the 1994 Northridge earthquake to facilitate model calibration and evaluation. The calibration of the model and its results are presented in the fourth section. The conclusion discusses potential uses for ResilUS, as well as necessary

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future model development.

Model Development

In the conceptual model of ResilUS, socio-economic agents (households and businesses) are located within particular neighborhoods, which are contained within a broader community. ResilUS explicitly represents damage associated with a hazard event to three elements of community capital: the physical built environment, economics, and personal (i.e., health). ResilUS relies on two generic indicators of recovery: the ability to perform and the opportunity to perform. These recovery indicators are specifically represented by multiple variables in ResilUS. Table 1 provides a conceptual overview of ResilUS, including input and output variables associated with each hierarchical scale. A functional overview of ResilUS is given in Table 2. Because of space limitations, the specification of each function cannot be described here. The complete model specification is included in Miles and Chang (2007).

Conceptual Model

For households, the ability to perform is represented by household health. Among other variables, health is directly influenced by availability of critical facilities and serviceability of shelter, either a person's own residence or short-term housing. Shelter serviceability is influenced not only by residence reconstruction, but availability of lifeline services. Reconstruction time is influenced by the size of the respective building in addition to the construction capacity in the community. Reconstruction can only begin after inspections have been completed in the neighborhood, which is influenced by the quality of the preparedness plan, the recovery capacity of the community, and the neighborhood's priority. Health influences a household's ability to pay off any incurred debt. ResilUS accounts for whether or not a household owns their residence so that if they do not, they do not incur debt with respect to any reconstruction loans. The opportunity to perform is represented by employment level in their neighborhood and broader community. Employment influences a household's opportunity to pay off any incurred debt. Debt is one of the main influences of whether a household is forced to leave their neighborhood.

For businesses, the ability to perform is represented by a businesses' capacity to be productive (not necessarily economic productivity or throughput). The service level of a business's physical facility influences this capacity, which is in turn influenced by a combination of infrastructure reconstruction and lifeline service restoration. Reconstruction time is influenced by the complexity or size of the respective facility, in addition to the construction capacity in the community. Reconstruction can only begin after inspections have been completed in the neighborhood, which is influenced by the quality of the preparedness plan, the recovery capacity of the community, and the neighborhood's priority. The ability to perform is also influenced community-wide health level of households and by the transportation network reconstruction level within the neighborhood, if the business's sector is locally oriented, or throughout the community if the sector is export-oriented. A business's ability to perform influences its ability to pay down any debt. Similar to households, businesses do not incur debt from reconstruction loans if they do not own their facility. The opportunity to perform is represented by the demand for a business's product or services. Recovery of demand is influenced by some proportion of household debt within the respective neighborhood or the entire community, depending on the business's size. Demand influences a business's opportunity to pay down any incurred debt, which in turn influences whether the business fails.

Whether an agent (household or business) is able to reconstruct their residence or facility is influenced by their financial resources, including the sum of insurance, reconstruction loans, disaster aid in the form of grants, and pre-event savings. If the agent owns their building or facility, the maximum level of financial resources is implicitly related to the value of the building or facility. Whether or not an agent has insurance (and what amount) is now conceptually distinct from when the insurance is outlaid. All elements of the financial resources are agent-specific, however a maximum value for loans would

Variables associated with entire community
CYR:integer [year] Year seismic code effective.
MUT:real [0,1] Probability of effective mutual aid agreement for lifeline restoration.
NBRHDS:integer [1,*] Number of neighborhoods.

Variables associated with neighborhoods
CAP:real [0,1] Recovery capacity (proxy for disaster experience, integration, and consensus). 0 to 1, with 1 being highest capacity.
CONSTR:real [0,1] Probability of available construction resources.
LL_RES:real [0, 1] Probability of available lifeline restoration resources.
LOAN_MAX:real [0,1] Limit on normalized post-event loan amount.
PLAN:real [0,1] Probability of an effective restoration plan.
PRTY:integer [1,NBRHDS] Optional restoration priority given to a particular neighborhood, with higher numbers indicating higher priority.
STH:real [0,1] Probability that short-term housing is available.
WAT_ALT:real [0,1] Alternate water source with 1 being equivalent to pre-event water service in neighborhood.
EMPL():real [0,1] Probability that employment is available.
INSP(): real [weeks] Time in weeks after event that safety inspections are completed.

Variables associated with individual households, businesses, and lifeline components
BYR:integer [year] Year building of lifeline component built.
MIT:real [0,1] Pre-event structural mitigation of building or lifeline component. 1 indicates a 25% increase is fragility curve median.
TYPE:real [0,1] Type of building or component--an indicator for size and/or complexity for reconstruction.
DMG():real [0,1] Damage of building or lifeline component expressed as ratio of building replacement value.

Variables associated with individual households and businesses
AID:real [0,1] Normalized post-event grant amount.
HAZ:real [0,10] Hazard severity; For earthquake application, USGS ShakeMap instrumental intensity.
OWNER: binary Whether household or business own's their building.
SAVINGS:real [0,1] Normalized savings or assets.
BL(t):real [0,1] Ratio of resources expended in reconstruction to building replacement value.
DEBT(t):real [0,1] Normalized level of debt. The inverse of LOAN.
INJURY():real [0,1] Degree to which household health or business demand has been injured.
INS():binary [0,1] Indicator that an agent has insurance or not.
LOAN():real [0,1] Amount of reconstruction loan taken out, normalized to building value.
LOAN_TIME() = Time in weeks after event that loan is disbursed.
MARG():real [0,1] Probability that household or business is financially marginal before event.
OUTLAY():real [0,1] Time insurance payment is made. Payment is assumed equal to building value.
RES(t):real [0,1] Normalized total financial resources.

Variables associated with individual households
INC:real [0,1] Normalized annual income.
HEALTH(t):real [0,1] Probability that household is healthy.
LEAVE(t):binary [0,1] Whether or not household has left region, Yes (1) or no (0).
SHEL(t):real [0,1] Probability that household has adequate shelter and associated services.

Variables associated with individual businesses
SECT:binary [0,1] Type of business sector: Locally-oriented (0) or export-oriented (1).
SIZE:real [0,1] Normalized number of employees.
DEMAND(t):real [0,1] Post-event demand for product with 1 indicating pre-event demand level.
FACILITY(t):real [0,1] Service level of a business's facility with 1 indicating operation at pre-event service level.
FAIL(t):binary [0,1] Occurrence of business failure, Yes (1) or no (0)
PROD(t):real [0,1] Probability that business is at pre-event production level.

Variables associated with individual lifeline components
MAINT:real [0,1] Probability that lifeline component has been well maintained.
CRIT(t); ELEC(t); TRNS(t); WAT(t):real [0,1] Probability particular critical facility, electrical, transportation, or water component is reconstructed.

Table 1. Variables in ResilUS, their definition, and conceptual association. Input variables in bold. () denotes output variable. (t) denotes time-series output variable. Variable data type indicated as real (floating point value), integer, or binary. [min, max] indicates possible numeric range of variable.

typically be applied at the community scale.

Model Implementation

Currently, ResilUS is implemented and is run inside the modeling software MATLAB/Simulink. The choice to not use conventional GIS software was because of the need to represent and manage time-series data. As a result, ResilUS currently is not topologically explicit. Input and output data compilation and visualization requires GIS software. The recovery dynamics of ResilUS are implemented using Markov chains. For a particular dynamic (time-based) output, each model state is calculated as a comparison between a uniform random number and the aggregation of all input variables, which are expressed as probabilities (e.g., the probability of restored water service in a neighborhood). Functions that Markov chains have been implemented include building and lifeline component restoration, health recovery, business demand recovery, business production recovery, and whether an agent leaves/fails. Like loss estimation models, such as HAZUS (Kircher, Whitman et al. 2006), fragility curves are used for calculating damage and injury. Each fragility curve is a lognormal cumulative distribution function. Structural mitigation of a buildings or lifeline component is represented as a uniform increase in the median value of each damage level's fragility curve. ResilUS is modular, meaning that the method in which a particular model is implemented can be changed without adversely affecting operation of the overall model. Further, the modularity facilitates substituting a data source for a model reference. Lastly, ResilUS is scalable to any number of neighborhoods or agents.

Northridge Earthquake Case Study

ResilUS was applied to model the resilience of Los Angeles, CA with respect to the 1994 M=6.7 Northridge earthquake in order to calibrate portions of the model and better understand issues such as data development requirements and model sensitivity. The data development for each scale of analysis in ResilUS is described below.

Community and Neighborhood

Community/Neighborhood
INSP = f(EQ_AVG, PLAN, CAP, REL_PRTY)
EMPL = f(PRODn, DEMn)
LOAN_TIME = f(EQ_AVG, PLAN, CAP, REL_PRTY)
REL_PRTY = f(PRTY, NBRHDS)

Businesses
BL = fm(INSP, RES, BTYPE, CONSTR)
DEMAND = fm(SECT, DEBTc, DEBTn, SIZE)
DEBT = f(DEM, SIZE, LOAN, PROD, LOAN_TIME, FAIL)
DMG = fcdf(SAVINGS, BYR, BMIT, CYR, EQ)
FACILITY = f(ELECn, BL)
FAIL = fm(FACILITY, DEM, DEBT, PROD)
INJURY = fcdf(SIZE, EQ)
INS = frand(OWNER, SIZE)
LOAN = f(OUTLAY, DMG, LOAN_TIME, MARG, LOAN_MAX, AID)
LOAN_TIME = f(INSP)
MARG = frand(SIZE)
OUTLAY = f(INS, INSP)
PROD = fm(FACILITY, TRNSn, TRNSc, SIZE, HEALTHc, FAIL)
RES = f(LOAN, AID, SAVINGS, OUTLAY)

Households
BL = fm(INSP, RES, BTYPE, CONSTR)
DEBT = f(HEALTH, INC, LOAN, NBRHD EMPL, LOAN_TIME, LEAVE)
DMG = fcdf(SAVINGS, BYR, MIT, CYR, EQ)
HEALTH = fm(CRITn, RES, SHEL, LEAVE)
INJURY = fcdf(INC,DMG)
INS = frand(MARG, INC, OWNER)
LEAVE = fm(SHEL, HEALTH, DEBT, NBRHD, EMPL)
LOAN = f(OUTLAY, DMG, LOAN_TIME, MARG, LOAN_MAX, AID)
LOAN_TIME = f(INSP)
MARG = frand(INC)
OUTLAY = f(INS, INSP)
RES = f(LOAN, AID, SAVINGS, OUTLAY)
SHEL = f(STH, ELECn, WATn, BL)

Lifelines
CRIT = fm(CRIT_TYPE, LL_RES)
DMG = fcdf(MAINT, CRIT_BYR, CRIT_MIT, CYR, EQ)
ELEC = fm(ELEC_TYPE, LL_RES, TRNSc)
LL_RES = f(MUT, CONST, PLAN, CAP, PRTY, NBRHDS)
TRNS = fm (TRNS_TYPE, LL_RES)
WAT = fm(WAT_TYPE, WAT_ALT, LL_RES, TRNSc, ELECn)

Table 2. Functional dependencies between ResilUS variables. n -- variable averaged over the neighborhood. C -- variable averaged over the community. fcdf - Function implemented using log normal cumulative distribution function fragility curve(s). frand - Function implemented using uniform random number generator. fm - Function implemented as a Markov Chain.

Based on review of the literature, the maximum probability (1) was assigned to the variables representing the recovery capacity, construction capacity resources, the effectiveness of mutual aid, the quality of a pre-disaster plan, and the use of short-term housing. Recovery capacity and general preparedness was high because of previous earthquakes in Southern California, such as the 1971 San Fernando earthquake and the 1992 Los Angeles riots. Pre-disaster planning and training was stepped up considerably immediately prior to the Northridge earthquake, with a pre-disaster plan that had been adopted soon before the Northridge earthquake (Tierney 1995; Wu and Lindell 2003). For short-term housing, high apartment vacancy rates allowed effective use of rent vouchers to provide housing (Loukaitou-Sideris and Kamel 2004; McCarty, Perl et al. 2005). Mutual aid was either in place or set in motion with respect to at least emergency management, water network repair and building inspection (Comfort 1994; EQE EQE-International 1995; Loukaitou-Sideris and Kamel 2004). We assumed neighborhood restoration priority was

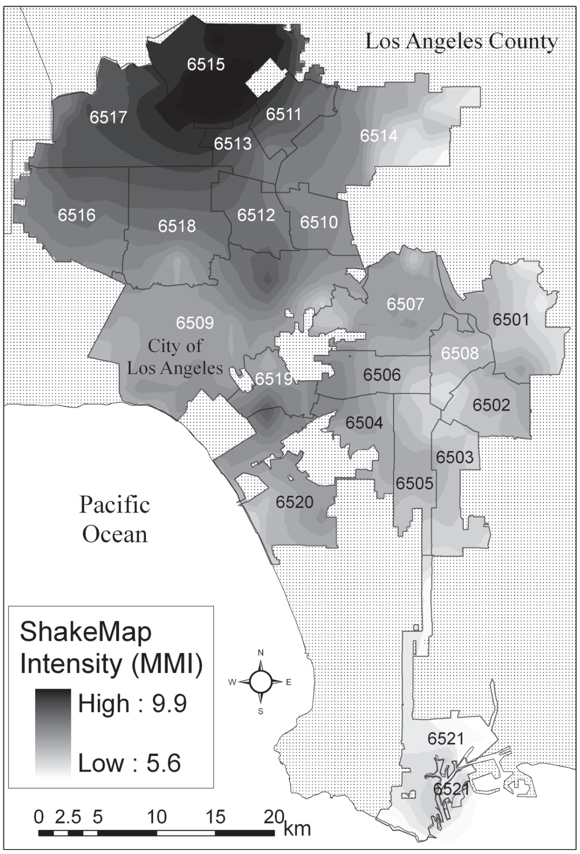


Figure 1. Instrumental intensity from the 1994 M=6.7 Northridge earthquake (USGS ShakeMap) in Los Angeles, CA. Labels indicate U.S. Census Public Use Microdata Areas (PUMAs), which were used as the case study neighborhood boundaries.

equal for all neighborhoods. To our knowledge, no major alternative water source was employed after the earthquake to aid recovery. We chose to set the building code year as 1976, reflecting the major improvements in building standards that were in place by that time as the result of the San Fernando earthquake. Data characterizing earthquake ground shaking, or instrumental intensity for the Northridge earthquake were gathered from the USGS TriNet ShakeMap system clipped to the boundary of Los Angeles and averaged for each neighborhood unit (Figure 1).

Households and Businesses

Demographics for both households and businesses were characterized using information from the U.S. Census Bureau. However, the resolution, detail, and direct sources of the data differed dramatically. For both households and businesses, the available data do not cover all agent-attribute variables of the recovery model, requiring some data to be simulated, including household and business savings, household and business structural mitigation, amount disaster aid per household (grants), business building year, business tenure, and business building type (see Miles and Chang, 2007 for algorithms).

Households

Household data available at the census tract level are an average of individual census survey response. The recovery model requires data about specific households and their attributes. We chose to use 1990 Public Use Microdata 5% State Sample from the University of Minnesota Population Center's Integrated Public Use Microdata Series (originally collected by the U.S. Census Bureau). This dataset provides individual records of households from a 1-in-20 national random sample of the population for areas no smaller than 100,000 people. These areas are referred to as PUMAs (Public Use Microdata Areas). There are 21 PUMAs within the City of Los Angeles (Figure 1). Thus, the number of neighborhoods represented in the recovery model corresponds to the 21 PUMAs in Los Angeles. The sample size across these PUMAs consisted of a total of 67,440 households. A map of household demographics for the Northridge

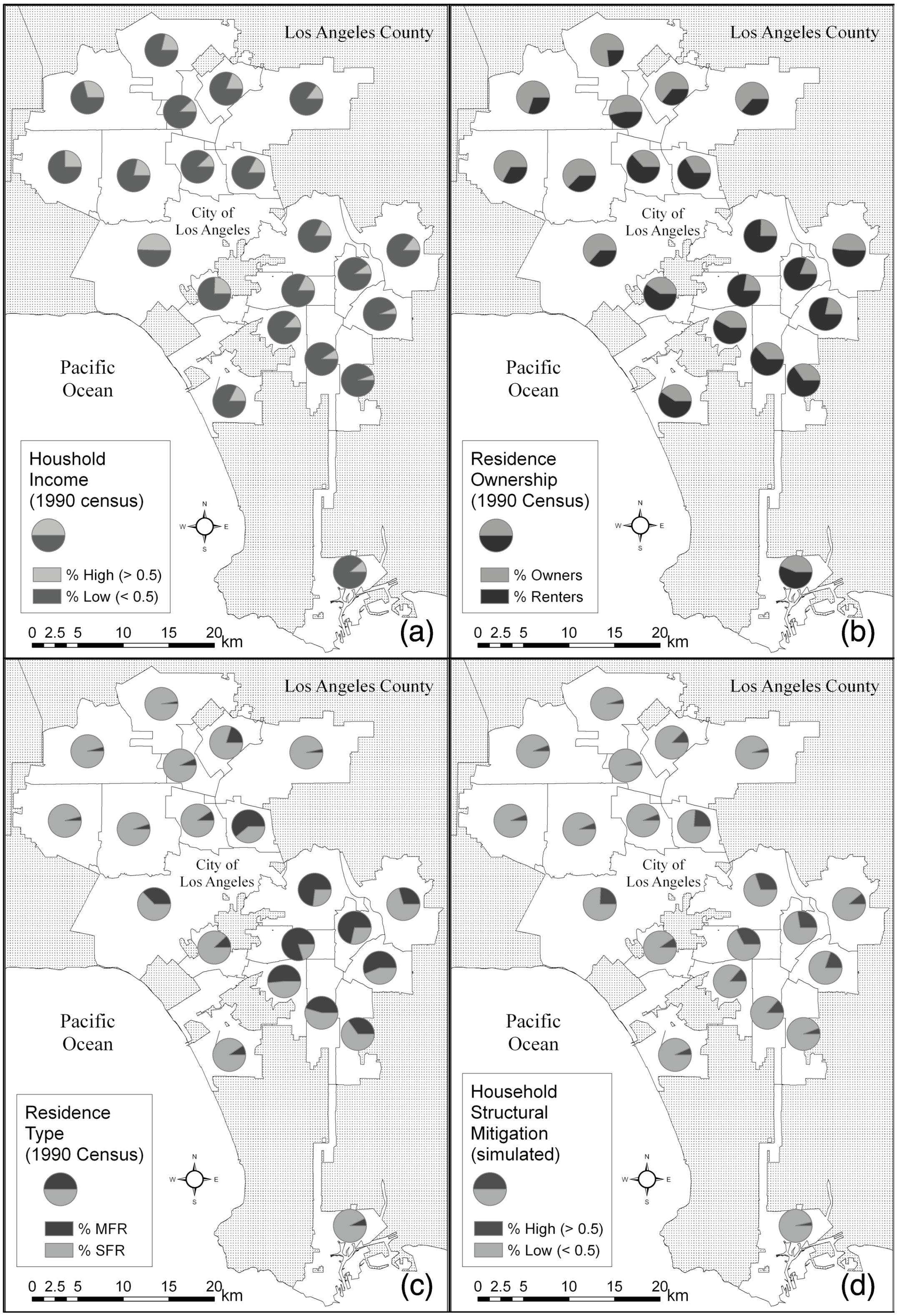


Figure 2. Household demographics (inputs) for Northridge earthquake disaster case study: (a) household income (normalized to 1990 0.95 percentile income level), (b) proportion owners versus renters (1990 census), (c) proportion of single- versus multi-family residences (1990 census), (d) proportion of households who completed high versus low level of structural mitigation (simulated data, with higher incomes having a increased likelihood of having higher levels of structural mitigation).

case study are shown in Figure 2.

Businesses

Business data readily available through the U.S. Census Bureau are much less detailed and for different spatial units than available for households. We used 1994 Zip Code Business Patterns data for parameterizing the model. These data describe the number of different businesses by size in each Standard Industry Classification sector. The data were aggregated within each PUMA to provide a common spatial unit of analysis with the household demographics. The total number of businesses in Los Angeles represented by this data is 102,684. Note that unlike the household data, these data are not a sample of the population, but instead represent the entire population. However, the data may under-represent the number of small businesses. For brevity, maps of business demographics are not shown here.

Lifelines

The modules for modeling lifeline recovery were not evaluated as part of this study. Instead, times series data were developed describing the service restoration for each lifeline network. Critical facilities (SSC 1995; Schultz, Koenig et al. 2003; FEMA 2004; OSHPD 2005), electrical network (Chang 2000; Davidson and Çagnan 2005), transportation network (Chang and Nojima 2001), and water network (LA Department of Water and Power, personal communication) were replaced by time series data describing service recovery for each lifeline network. This facilitated focusing on the household and business aspects of the model, while demonstrating the modularity of the model. In this case this means substituting data for model modules.

Model Calibration and Case Study Results

ResilUS was run to simulate the impact and recovery of the Northridge earthquake. Results of both the damage and recovery module were compared against various data gathered for evaluating the performance of each sub-module. When data were available for a particular output variable, calibration was done by either varying model parameters, revising model algorithms, or in one case (i.e., structural mitigation for businesses) the means in which the input data were simulated. Only output variables that were associated with empirical data are presented and discussed in this paper. Because of the size and complexity of the recovery module in comparison to the damage module, a different approach was taken for calibration and evaluation. For the recovery module, calibration was done on a 10% random sample of the Northridge household and business input data set. After calibration was completed, the recovery module was run on a non-overlapping 30% sample of the same original data set to ensure consistent performance of the model. All results shown here are of the 30% sample (non-calibration data set).

All damage sub-modules that could be calibrated were done so prior to calibrating modules in the recovery module. For clarity, calibration results are presented below by agent type. In actuality, there are not separate household and business modules in ResilUS.

Household Damage Module

The two major modules required calibration for the damage module with respect to households, including building damage and injury to building occupants. Calibration was done by varying the median and variance of the respective fragility curves.

Building Damage

Figure 3 shows the results of calibrating residential building damage prediction, comparing ResilUS's damage estimates averaged across each neighborhood versus average shaking intensity to observations from the Northridge earthquake (EQE-International 1995). Up to MMI 8, the damage module within ResilUS predicts a similar trend as measured after the Northridge earthquake, with slight under-prediction for single-family residences (SFRs) and slight over-prediction for the multi-family residences (MFRs). Beyond MMI 8, ResilUS predictions diverge from the empirical data, with damage for SFRs being over-predicted and damage for MFRs being under-predicted. Model predictions for these shaking intensities however are bounded by the observed trends for two types of buildings. In general, a larger proportion of MFRs were predicted to have experienced some damage than SFRs, as was generally observed.

Injury

Calibration of the module for predicting household injury was conducted similarly to that for residen-

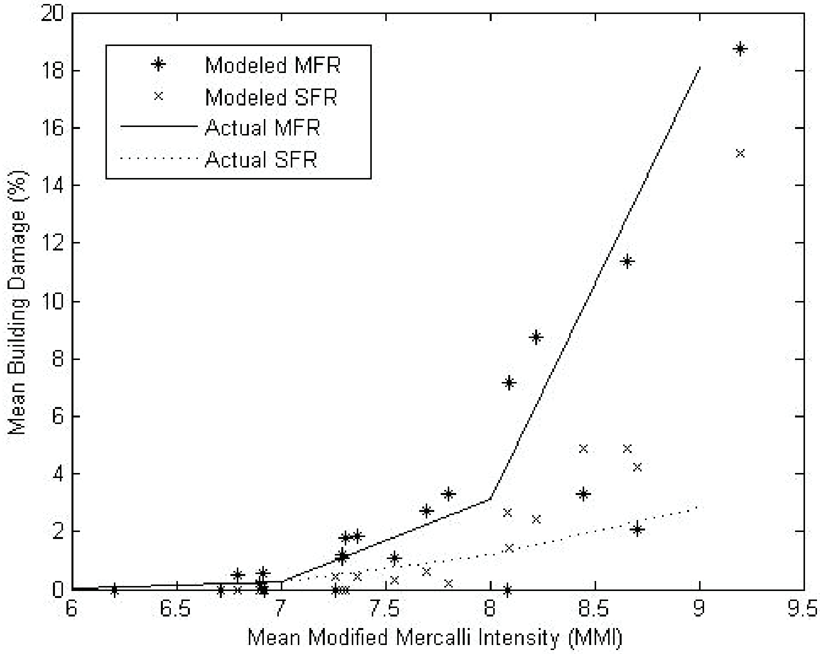


Figure 3. Comparison of modeled and actual relationship (EQE-International 1995) between mean building damage and mean Modified Mercalli Intensity (average across each study unit).

tial building damage by varying the median and variance of the associated fragility curve. In this case, there were two different data sources from which to calibrate the model. Seligson et al. (2002) conducted a survey in which they found about 8% of households that reported having experienced some injury as a result of the Northridge earthquake. As calibrated, the damage module in ResilUS predicted 3.76% of the total household population with some injury. Peek-Asa et al. (1998) collected data describing injury rate versus average shaking intensity. These data are plotted in Figure 4 with calibrated model predictions averaged over each PUMA. Through calibration, the model is able to exhibit the bilinear trend of the Peek-Asa et al. (1998) observations, but over-predicts injury rates significantly beyond MMI=8. Further adjustments to the fragility curve parameters to decrease the predicted rate lead to predictions of no injuries. Observing that the actual injury rates are quite small, this behavior may be the result of using only a 5% of the total population.

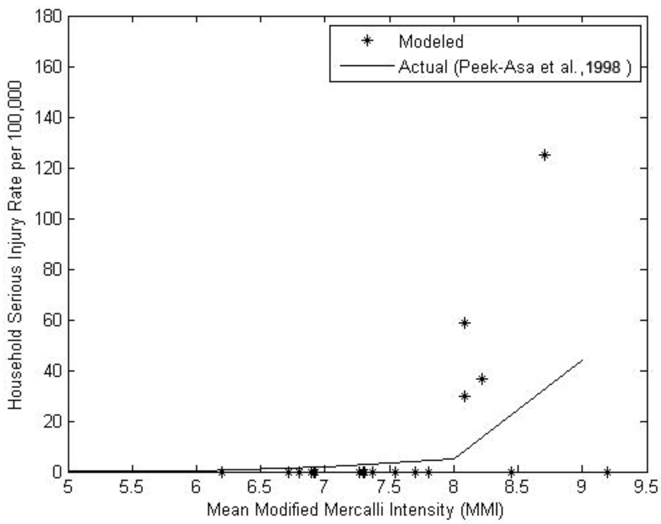


Figure 4. Comparison of modeled and actual relationship between household injury rate and mean MMI (averaged over each PUMA).

Household Recovery Module

The only widely available data for calibrating the household modules of the recovery module in ResilUS are associated with residential reconstruction. Limited data was available for calibrating the module for predicting whether residents will leave or stay as a result of a disaster. The calibration of each module is described below.

Reconstruction

The data used for calibrating the residential reconstruction in the recovery module were compiled from several sources (Comerio 1997; Comerio 1998; Wu and Lindell 2003; Loukaitou-Sideris and Kamel 2004). Calibration was done through visual comparison of plotted calibration data with various plots of the percent of residences rebuilt with time across the entire community. Calibration was done by modifying algorithm implementation—functional dependencies and Markov chain step size.

The modeled reconstruction trends, using the non-calibration data sample, for MFRs and SFRs are shown in Figure 5. Overall, the reconstruction of the MFR stock is slower than for SFR, bounding the lower-value calibration data. While only one calibration data point (Comerio 1997) is associated specifically with MFR reconstruction, post-disaster studies found a significant lag in repair to MFR units (Loukaitou-Sideris and Kamel 2004). The results of the calibrated recovery module were mapped across the Los Angeles PUMAs to further illustrate the behavior of the modeled reconstruction trends (Figure 6a). The PUMAs associated with longer repair times correspond to areas with higher rates of lower incomes, MFRs and renter-occupied units.

Leave

A poll found that 91% of homeowners within the San Fernando and Santa Clarita Valley's lived in the same place 18 months after the earthquake as they did before (Chu 1995). ResilUS was calibrated so that 18 months after the earthquake 9% of all homeowners across the study area were predicted to have left their residence. Similarly, the poll found that 25% of renters in the same area had permanently moved out of their residence 18 months after the earthquake. ResilUS was calibrated so that 25% of renters left their residence at the same time. Note that the model does not currently represent where residents move to after leaving their residence. Figure 7 shows the cumulative number of residences in owner-occupied and renter-occupied units that were modeled to have left over time. The cumulative number of residents projected to leave increases with time past the calibration point, but the rate at which residents leave decreases significantly at about 12 weeks after the earthquake, with the rate going to zero at about 140 weeks.

The spatial distribution of the percentage of households leaving their residences after the earthquake is show in Figure 6b. The higher rate of residents leaving through the central part of Los

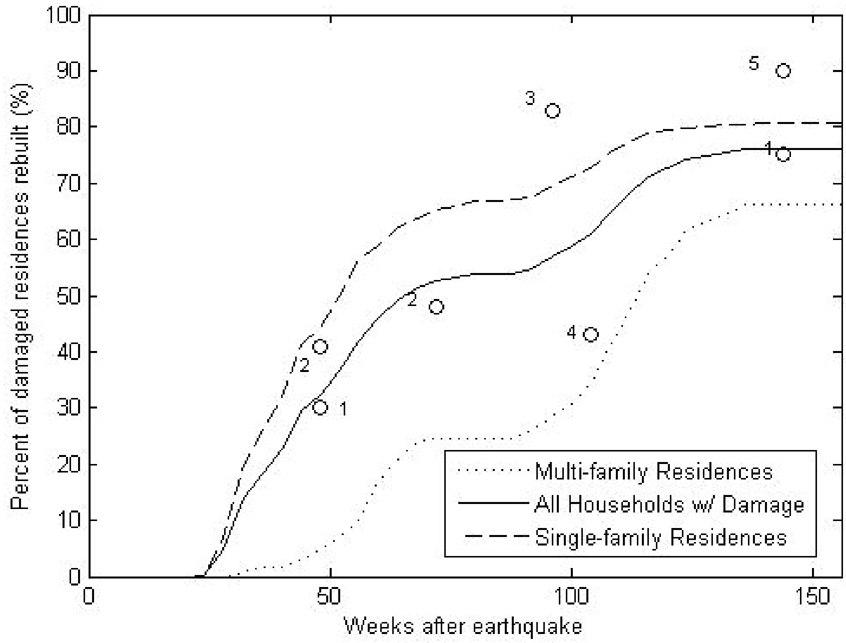


Figure 5. Residential reconstruction over time for all residences, multi-family, and single family. Labelled circles correspond to reconstruction data from respective references. (1) Comerio (1997), (2) Chu (1995), (3) Comerio (1998), (4) Wu and Lindell (2004), (5) Kamel and Loukaitou-Sideris (2004).

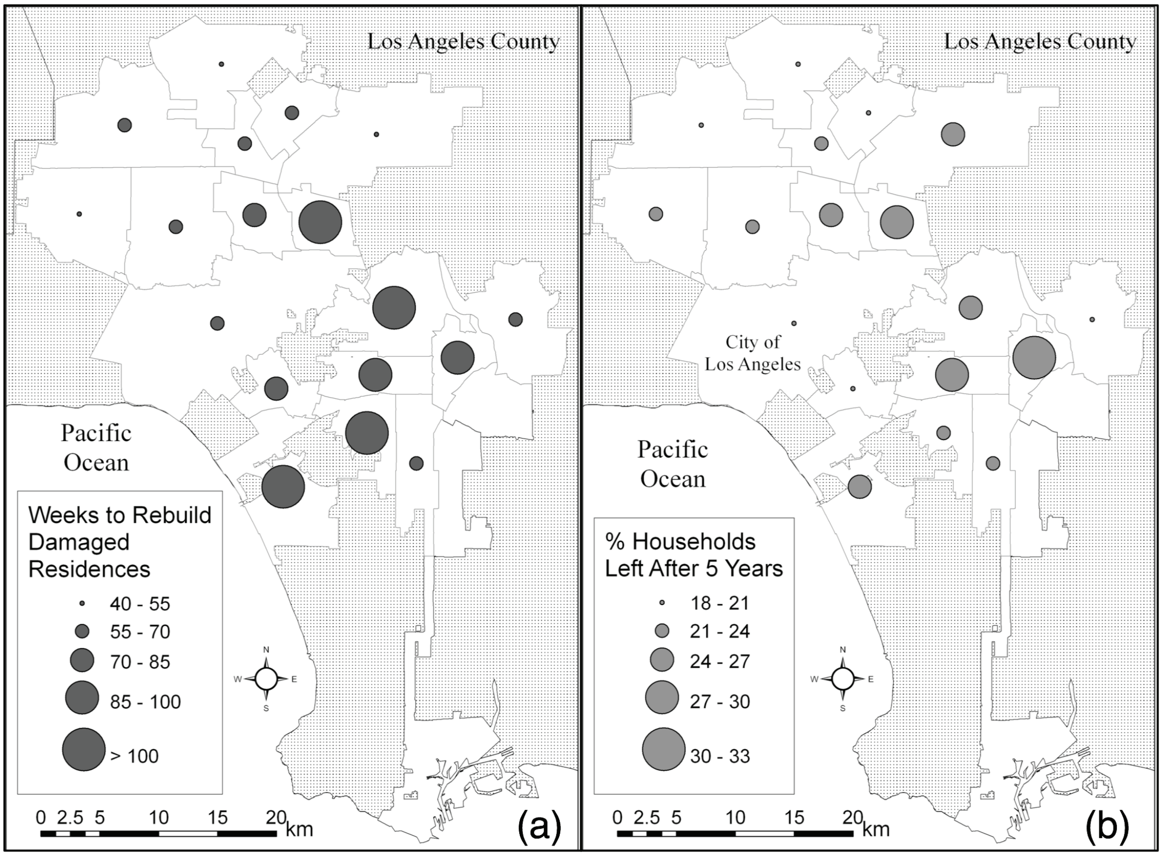


Figure 6. Partial household recovery module outputs for the Northridge earthquake disaster case study: (a) time to rebuild all damaged residential buildings. PUMAs 6502, 6503, and 6521 had no damage. (b) percentage of households modeled to have left their residence five years after the Northridge earthquake.

Angles appears associated with the slow rate of reconstruction. Loukaitou-Sideris and Kamel (2004) found that an above-average percentage of residents, especially renters, left their residences in neighborhoods with a slow pace of reconstruction. The PUMAs with a relatively high percent of residents modeled to leave that are not in PUMAs with slow reconstruction times are associated with a slow pace of health recovery. Table 3 lists statistics related to those residents projected to leave and those projected to stay, providing insight into the relative influence of various exogenous and computed variables in the model. The recovery module for modeling whether residents leave is the last module in the model hierarchy for households, and thus is influenced by all other model outputs, including outputs not described here. The greatest relative difference between average variable values of residents modeled to leave and those modeled to stay are for building type, ownership, and insurance.

Business Damage Module

The modules in the damage module associated with businesses that can be evaluated and calibrated are similar to those for households. However, the type of data that can be used in comparison to model predictions differs with respect to building damage and are not available for the immediate reduction in demand for businesses (i.e., demand

Table 3. Statistics related to households modeled to leave or stay in their residence.

	Left	Stayed
% Live in MFRs	65	29
% Renter-occupied	74	48
% Have insurance	6	13
Mean normalized income	0.25	0.31
Mean MMI	7.4	7.5
Mean mitigation	0.21	0.19
Mean damage	0.017	0.016

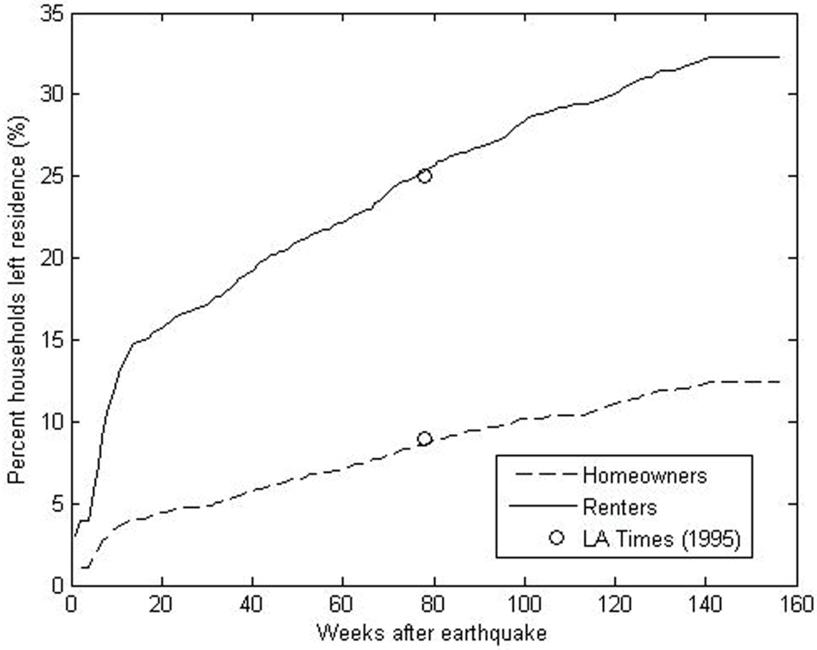


Figure 7. Cumulative number of homeowners and renters modeled to have left their residence over time show in comparison to data from a 1995 LA Times poll (Chu, 1995).

reduction). The calibration of these modules is described below.

Building Damage

Figure 8 shows the comparisons between observed (Tierney 1995) and predicted damage after calibration of the business building damage fragility curves. Yellow and red-tags are associated with 33% to 66% and 66% to 100% damage, respectively. Overall, the prediction of businesses with some damage (21%) is close to the observation (22%). The model over-predicts the percentage of buildings suffering low damage (11.6% vs. 13%), while under-predicts the percentage of red-tagged buildings (18.2% vs. 20.7%). Tierney (1995) observed that a higher percentage of small businesses suffered damage than large businesses. The model predicts a similar trend, while slightly over-predicting the absolute number of each type of businesses with some damage.

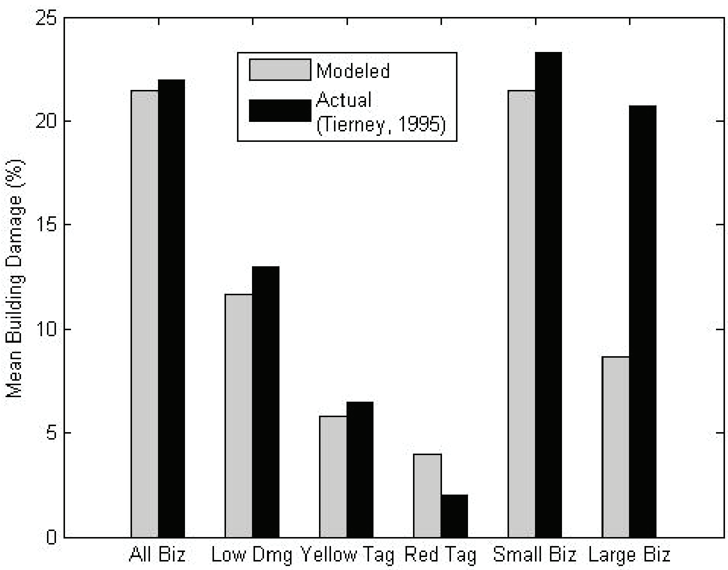


Figure 8. Comparison of modeled and actual building damage for businesses: All businesses with some structural damage, all businesses with low damage, all businesses with medium structural damage (yellow tag), all businesses with high structural damages (red tag), small businesses with some structural damage, and large businesses with some structural damage.

Business Recovery Module

Data of varying suitability were used in calibrating three modules of the recovery module with respect to business recovery. Data describing residential building reconstruction were used as a general guide for the speed of repairs for business facilities. The best available data for calibrating and evaluating the business modules of the recovery module are for employment in the Los Angeles area. Data for the entire city on gross sales receipts were used to constrain the time in which business demand recovered.

Reconstruction

The data used for calibrating the business-facility reconstruction module of the recovery module are the same as used for calibrating the equivalent residential module. These data were collected for residential reconstruction, but similar secondary data-sources for commercial and industrial reconstruction were not easily available. The assumption for calibrating the business-facility reconstruction module was that the speed of repairs should be the same or slower, on average as residential reconstruction. Calibration was done in the same way as for the residential reconstruction module, incorporating the same algorithmic modification as well.

Figure 9 shows the percentage of business facilities fully repaired over time for the City of Los Angeles with respect to business size. Currently, ResilUS is calibrated so that larger businesses repair their facilities much faster than smaller businesses. The reconstruction trend for small businesses is nearly identical to the trend for all businesses combined. This is because the large majority of businesses modeled within Los Angeles are small businesses. Large businesses make up less than 1% of the total number of businesses in each Los Angeles PUMA. Studies do not appear to have looked at the relative reconstruction speed between small and large businesses. From the standpoint of access to capital and the capacity to handle increased debt from reconstruction loans, it is logical to expect larger business have an advantage over smaller. However, many larger businesses will also have larger or more complex facilities, which require more time for repairs.

The spatial distribution of the reconstruction of business facilities is illustrated by the map in Figure 10a. The difference between PUMAs is relatively small, reflecting the large proportion of smaller, locally-oriented businesses throughout the study area.

Employment

The most readily available business-related data for evaluating the ResilUS's recovery module are associated with employment. Two different data sets were available for characterizing employment after the Northridge earthquake. Gordon et al. (1995) estimated the percent of employment days lost in 1994 after the Northridge earthquake within

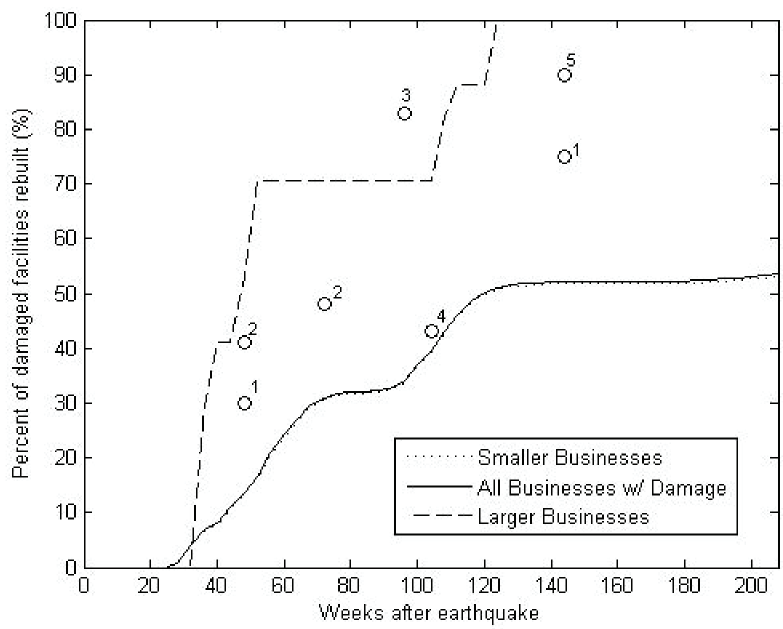


Figure 9. The percentage of business facilities reconstructed over time for small (SIZE < 0.5) and large businesses (SIZE ≥ 0.5). Labeled circles correspond to reconstruction data from respective references. (1) Comerio (1997), (2) Chu (1995), (3) Comerio (1998), (4) Wu and Lindell (2004), (5) Kamel and Loukaitou-Sideris (2004).

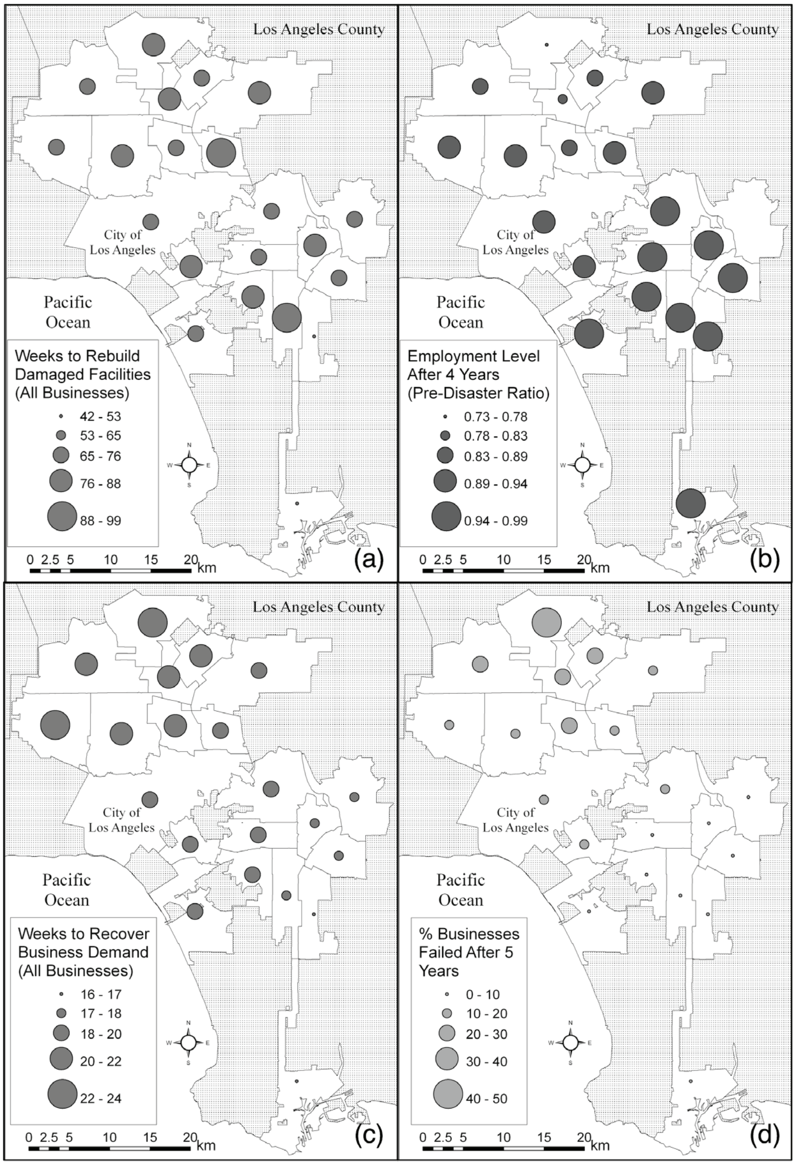


Figure 10. Partial business recovery module outputs for the Northridge earthquake disaster case study: (a) time to rebuild all damaged facilities, (b) time to recover business demand for all businesses, (c) modeled employment levels four years after the Northridge earthquake relative to pre-earthquake employment, and (d) business failure rates five years after the Northridge earthquake.

several impact zones (SCPM zones) that coincide with the community planning areas of Los Angeles. To get a sense of the relative performance of the model across PUMAs, a comparison was made by aggregating the Gordon et al. (1995) SCPM zones to roughly correspond with one or more PUMAs, resulting in six aggregate units (reclassification listed in Figure 11). The estimates of Gordon et al. (1995) were re-calculated based on aggregate counts and normalized by the mean value for the six aggregated units. The comparison is shown in Figure 11. The relative employment loss across the aggregated units appears to be similar between the model results and the estimate of Gordon et al. (1995). Because the metric of the model outputs do not match the units of Gordon et al.'s (1995) estimate, the comparison is useful only to evaluate relative spatial differences, rather than absolute employment loss. Figure 10b shows the spatial distribution of predicted employment recovery four years after the earthquake.

Time series data on employment are available from the Quarterly Census of Employment and Wages or ES202 program of the Bureau of Labor Statistics. Historical data are provided for quarterly time intervals by zip code based on this on-going census. The data were aggregated by PUMA, and an index was calculated describing the ratio of the number of people employed in a particular month after the earthquake to the number of people employed in the same month a year prior to the earthquake. Figure 12 shows the comparison between ResilUS results for 7 months after the earthquake and the ES202 data for August 1994.

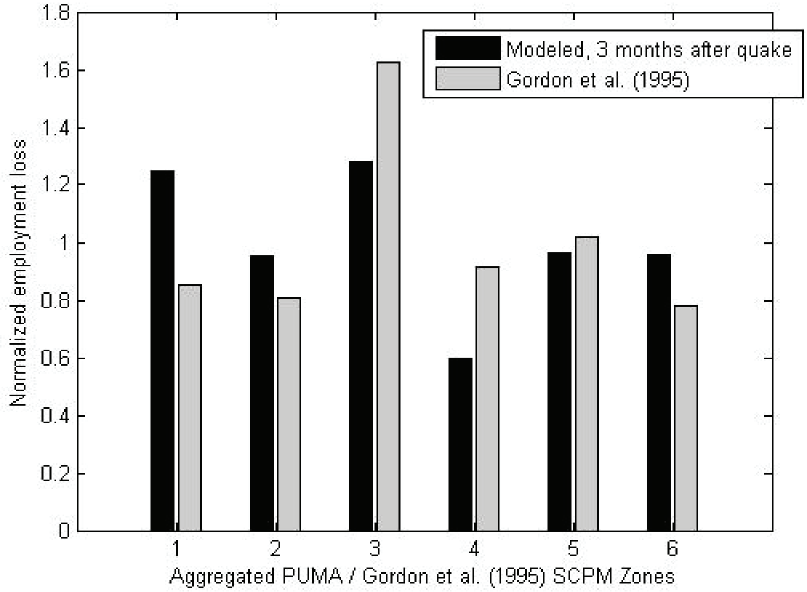


Figure 11. Normalized comparison of modeled levels in employment and employment data from Gordon et al. (1995) for selected aggregated PUMAs. 1: PUMAs 6511, 6513, 6514, and 6515;SCPM Zones 1 and 16, 2: PUMAs 6516 and 6518; SCPM Zones 5 and 13, 3: PUMA 6517; SCPM Zone 7, 4: PUMA 6507; SCPM Zone 9, 5: PUMAs 6510 and 6512, 6: PUMAs 6504; SCPM Zone 18.

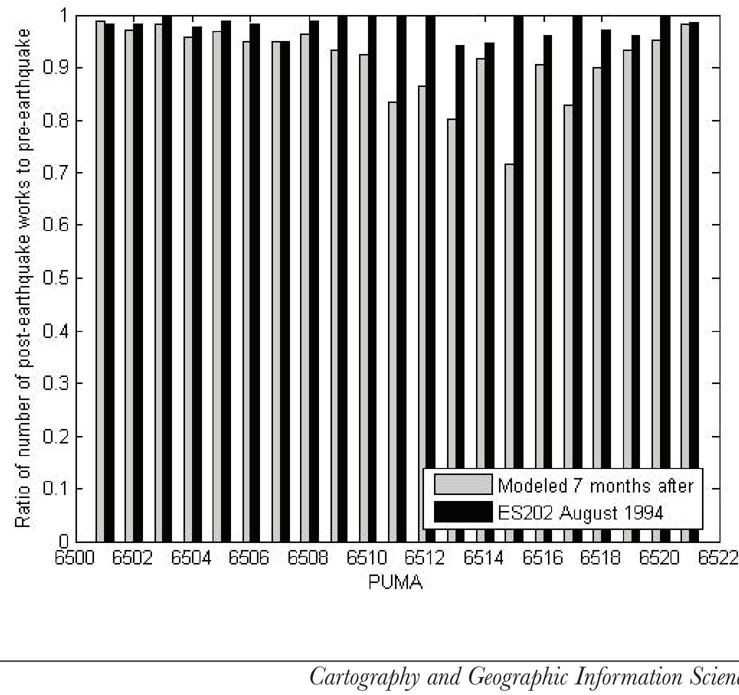
Demand

No data set associated with consumer demand for business' products and services are readily available for calibrating the corresponding recovery module. Romero and Adams (1995) noted that total taxable sales for California dipped below pre-earthquake levels in the first quarter after the earthquake, but edge above pre-earthquake levels in the second quarter. This was used as a general proxy for the time in which demand for businesses' products and services returned to pre-earthquake levels. This is a fair proxy at best because taxable sales may reflect consumer purchase spikes associated with construction and repair, rather than reflect uniform purchasing across a cross-section of business types. However, in lieu of better data, it provides an order of magnitude estimate. The spatial distribution of the number of weeks to recovery business demand is shown in Figure 10b.

Failure

General observations from studies about business failure resulting from the Northridge earthquake are useful to calibrate the failure module of the recovery module. The modeled rate of

Figure 12. Comparison of modeled employment recovery and the ratio of the number of workers, by PUMA, in August 1994 to the number in August 1993.



failure significantly drops after about 20 weeks and failures stop completely after 140 weeks (2 years, 9 months). The period of business failure is consistent with the findings of Petak and Elahi (2000), who observed that small businesses were still failing two years after the earthquake. The map of Figure 10d shows the spatial distribution of modeled business failures five years after the Northridge earthquake. The higher rate of failure in the northern PUMAs (San Fernando Valley) illustrate the influence of business debt levels, and thus business production and damage levels in the respective PUMAs. While Tierney (1995) found that businesses that suffered physical damage were more likely to report being worse off after the Northridge earthquake, Petak and Elahi (2000) note in their study that damage is not a reliable predictor of business failure. Petak and Elahi (2000) found that the locally-oriented businesses such as retail and service experienced a higher rate of failure than export-oriented businesses like manufacturing. Within ResilUS, the strong influence of damage on the business failure module of the recovery module is clear from the statistics listed in Table 4. Based on these statistics, business failure predicted by ResilUS is most sensitive to business size. Modeled businesses are also more likely to fail if they are locally oriented, don't have insurance, or did not mitigate their facility.

	Failed	Not Failed
% locally-oriented	80	74
% with insurance	11	15
Mean business size	0.02	0.2
Mean building size	0.08	0.08
Mean MMI	7.8	7.4
Mean mitigation	0.42	0.52
Mean damage	0.36	0.05

Table 4. Statistics on modeled business failure due to the Northridge earthquake.

Conclusion

In the course of this study, several limitations of ResilUS became apparent. Limitations of ResilUS included representation of decisions and policies that is probably overly simplistic and limited. It is worth considering, however, the degree to which more complex representations are warranted in light of the level of simplification in other parts of the model. The lack of a capability for modeling relocation of households within the study region is another key limitation. The overall reliability and performance of the model across a range of disasters is at present unknown. Some input variables in the model, such as household demographics are associated with relatively reliable and complete data sources, while others like mitigation status of buildings required simulation for this study. Some elements and outputs of the model simply could not be verified empirically, much less calibrated because of lack of empirical data. Work is currently ongoing to expand ResilUS so that it better represent aspects of socio-cultural and ecological capital, and to apply the modeling capabilities to the Gulf Coast of Louisiana in the context of the 2005 Hurricane Rita disaster (Miles and Chang 2008), including incorporating measures of social capital and representing natural resource dependent businesses and occupations. This work will provide further opportunity for model evaluation and calibration.

The comprehensive nature of ResilUs is one of its key strengths; yet the model limitations make it most appropriate for education, training, and public awareness purposes. Many professionals, including emergency managers, elected officials and urban planners make decisions that intentionally or unintentionally influence community recovery and resilience. Yet many of these professionals are unfamiliar with the research literature on factors that influence recovery. In an interactive setting, where users can pose "what-if" scenarios and explore their consequences, ResilUS could be used to help educate users about empirical findings from disaster studies, such as what types of businesses tend to have the most difficulty recovering. ResilUS could also raise awareness about the interconnections between different sectors in recovery, help to visualize and develop an understanding of what to expect in the event of a future disaster, and to illustrated alternative approaches to enhance recovery and resilience. ResilUS could be deployed as part of large-scale emergency response exercises to provide a basis for integrating long-term recovery planning. Lastly, if served over the World-Wide Web the public would have a rare chance to experiment with how hazard events interact with policy and demographic variables to understand how disasters unfold from more diffuse, root causes.

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