Environment and Planning B: Planning and Design 2002, volume 29, pages 281 – 301

DOI:10.1068/b2789

Linking infrastructure and urban economy: simulation of water-disruption impacts in earthquakes

Stephanie E Chang, Walter D Svekla
Department of Geography, Box 353550, University of Washington, Seattle, WA 98195-3550, USA; e-mail: sec@u.washington.edu, wsvekla@hotmail.com

Masanobu Shinozuka
Department of Civil and Environmental Engineering, University of California at Irvine, Irvine, CA 92697-2175, USA; e-mail: shino@uci.edu
Received 20 December 2000; in revised form 4 July 2001

Abstract. In this paper a simulation approach to modeling the linkages between physical infrastructure systems and the urban economy is developed. A simulation approach based on probabilistically specifying the key model relationships is effective for situations that involve substantial uncertainty, and is particularly suited to assessing risk from natural hazards. In this paper, a model of economic losses from earthquakes is developed and applied to the Memphis, Tennessee, region of the United States. We focus on water as a critical infrastructure service supporting the urban economy. The methodological approach involves systems integration of natural-science, engineering, and social-science databases and models. The concept of infrastructure services provides the linchpin in this integration process. Key spatial, temporal, and functional dimensions of infrastructure services are explicitly modeled in the simulation framework. The resulting model permits the analyst to compare the effectiveness of alternative actions, including both predisaster mitigation and postdisaster emergency-response activities. The model is calibrated in part with data from the 1994 Northridge and 1995 Kobe earthquakes. Results for several scenario earthquakes indicate the likely range of loss from economic disruption as well as uncertainties associated with the loss estimates. Sensitivity analysis indicates that one type of risk-management strategy for the water system, retrofitting pump stations, appears to be highly effective in reducing expected losses from future disasters.

Introduction

Traditional methods of regional economic-impact analysis are generally aspatial, atemporal, and deterministic. That is, typically methods such as input – output (I – O) or computable general equilibrium (CGE) analysis do not explicitly model how economic impacts propagate through space, or grow and diminish over time, and do not reflect inherent data and modeling uncertainties. These limitations represent serious shortcomings for some types of applications such as natural-disaster impact analysis.

Earthquakes, floods, and other natural disasters are inherently spatial phenomena where the distribution of primary effects—whether flooding, landslide, or ground shaking—over an urban area crucially determines the manner and extent of the ensuing economic disruption. Time also represents a key dimension; the timing of reconstruction activities, disaster assistance, and other policy interventions can significantly influence the economic-recovery process. Moreover, natural hazards are fraught with uncertainties. There are scientific uncertainties about the likelihood of events and their characteristics, engineering uncertainties about the physical destruction that the excessive natural forces will cause, and social, political, and economic uncertainties about how individuals and institutions will react to and cope with the disaster.

A growing body of research has begun to refine traditional modeling approaches to better evaluate the impacts of natural disasters on urban and regional economies. Earlier work on disaster impacts largely applied well-established I – O or econometric modeling approaches by implementing relatively minor methodological adjustments to reflect capital loss caused by the disaster (Boisvert, 1992; Cochrane et al, 1974; Ellson et al, 1984; Gordon and Richardson, 1992; Hewings and Mahidhara, 1996; Kawashima and Kanoh, 1990). In more recent research, greater attention has been paid to the complex spatial and temporal interdependencies in disasters. Particularly significant developments include methods to account for effects of congestion in the transportation network on the economy (Cho et al, 2001; Sohn et al, 2000), spatial – temporal linkages between electric power outage and economic disruption (Rose et al, 1997; Shinozuka et al, 1997), and temporally distributed impacts by using modified I – O approaches and sequential I – O models (Cochrane, 1997; Okuyama et al, 2000).

Moreover, in practice, economic disruption has been gaining attention in disaster planning. Thanks to recent developments in computer technology, including geographic informaiton systems (GIS) and faster processors, it has become feasible and increasingly common to estimate losses from future natural disasters for planning purposes (see *Earthquake Spectra* theme issue, October 1997). The Federal Emergency Management Agency (FEMA) has invested heavily in a nationally applicable loss-estimation methodology and software (called HAZUS®) for natural hazards. The version for earthquakes, released in 1997, is now being used experimentally by state and local planning agencies nationwide (www.fema.gov/hazus); versions of HAZUS® for wind and flood hazards are under development. In comparison with the paper maps and reports that were previously used for disaster planning scenarios, computerized methodologies provide numerous advantages. They can incorporate vastly more complex models, synthesize much greater quantities of information, be updated readily with new data, be adapted flexibly for multiple purposes, and be applied repeatedly for a range of scenario events (Chang et al, 2000b; Wu and Olshansky, 2000). HAZUS® includes a module for evaluating losses to the regional economy that implements an interindustry modeling approach with supply-and-demand constraints and substitutions (Brookshire et al, 1997).

Existing methodologies for evaluating economic losses from natural disasters still suffer, however, from an important common limitation: they evaluate economic impacts deterministically, thereby overlooking inherent data and modeling uncertainties. Although some studies have considered the probabilities of different disaster scenarios occurring, and some have further evaluated physical damage consequences in a probabilistic manner, models of the ensuing economic repercussions remain deterministic.

We have addressed this problem by developing a probabilistic simulation methodology for estimating the economic impact of natural disasters. We focus on the effects of urban infrastructure-system damage, which have repeatedly caused significant economic losses in earthquake disasters (Chang, 1996; Gordon et al, 1998; Platt, 1999; Rose and Lim, 2000). The methodology pays particular attention to capturing the spatial, temporal, and sectoral dimensions of the economic-loss process. The scope is limited here to direct economic losses, defined as disruptions suffered at the site of production due to physical effects of the earthquake.

Indirect losses arising from interdependencies between businesses and economic sectors are not discussed here, although they are evaluated in closely related research that is part of a larger study sponsored by the Multidisciplinary Center for Earthquake Engineering Research (MCEER) (Chang et al, 2000a; Rose and Guha, 1999). That research refines CGE modeling to accommodate different types of production adjustments to infrastructure disruption. Direct losses there are calibrated to results from the current study, presented below.

In subsequent sections of this paper, we describe the methodological approach and a case-study application of water disruption in Memphis, Tennessee, in potential earthquakes. Results from the case study provide specific insights into how infrastructure improvements can reduce potential economic losses in future disasters, as well as more general insights into the role of infrastructure in urban economies. We conclude by discussing policy implications and areas for further research.

Methodological approach

The methodological approach developed in this study is based on two fundamental insights: first, that capturing the *systems* properties of infrastructure networks (and economies) requires deterministic analysis; and, second, that many physical and economic processes of change are inherently uncertain and should be represented probabilistically. We have therefore developed a hybrid approach that simulates a large number of possible deterministic outcomes of an earthquake and sets these within a probabilistic framework. Such a 'Monte Carlo' simulation approach is not new in earthquake studies, and has been applied for many years by earthquake engineers. The innovation here consists of extending the simulation to evaluate economic impacts.

Figure 1 illustrates the framework for implementing the loss-estimation methodology. The process consists of four main stages: (1) specification of earthquake-scenario event(s) for which losses are to be estimated; (2) specification of decision variables that may influence losses, specifically mitigation and response variables; (3) modeling the losses for each scenario event with an infrastructure – economy Monte Carlo simulation model (the dashed box outlined in the figure); and (4) weighting scenario losses to derive some overall risk measure such as the expected annual economic loss from earthquake hazard.

Several features distinguish this framework from more conventional approaches. Note that the Monte Carlo simulation box encompasses both engineering and economic models. This allows much greater information flow between them than in traditional approaches. Moreover, economic loss can now be modeled with some acknowledgment of underlying uncertainties. Another innovation consists of modeling how losses change over time as the system is restored. This enables an evaluation of how postdisaster response actions can reduce economic losses. Previous studies have focused almost exclusively on predisaster mitigations.

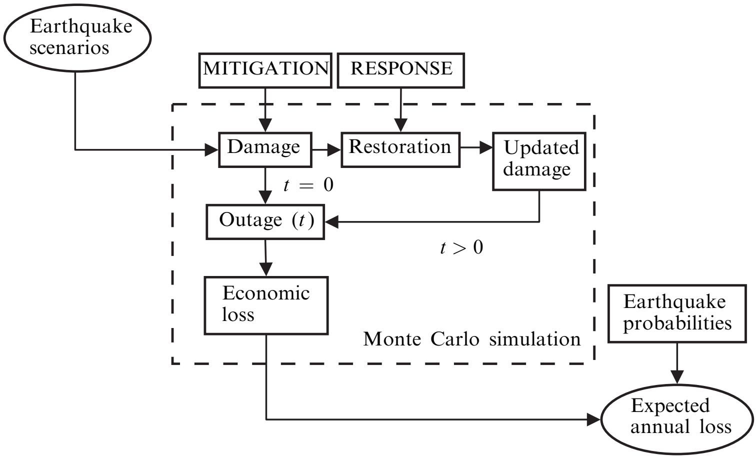

Figure 1. Loss-estimation framework (decision variables are in capitals).

Moreover, in this approach, physical infrastructure and economy are linked through the provision of infrastructure *services*. This contrasts with many macroeconomic models of infrastructure – economy relationships where infrastructure is represented as a form of public capital *stock* in dollar terms according to depreciated investment value. The key link in the current approach takes the form of the 'outage' box in figure 1 above which, on the one hand, indicates the reduction in infrastructure service due to physical damage to the network and, on the other, serves as a form of reduced or constraining input to economic activity.

Infrastructure-service provision in this framework has three important features: spatial distribution, timeframe, and functional contribution to economic activity. Spatial distribution refers to how the reduction in infrastructure service coincides in space with where production activities are concentrated, and suggests the importance of employing GIS in the approach. The explicit timeframe feature conceptualizes the linkages in a dynamic setting, where the expression of the link at a particular point in time (for example, day or week) depends upon conditions in the previous period. The third feature of infrastructure 'services', functional contribution to economic activity, requires some recognition that different economic sectors rely upon infrastructure services to varying degrees and may be differently resilient to their temporary loss.

Memphis application

Study area and scenario earthquakes

In the case study, we apply the methodology outlined above to the water-delivery system serving Memphis and the remainder of Shelby County, Tennessee (1990 population 826 000). This area is at risk from earthquakes originating in the New Madrid Seismic Zone (NMSZ) in the central United States (Johnston and Nava, 1985). Figure 2 shows the major faults in the NMSZ. The NMSZ produced the largest earthquakes in the recorded history of the United States in the winter of 1811 – 12, including at least three events with magnitude 8.0 or greater on the Richter scale. These earthquakes were

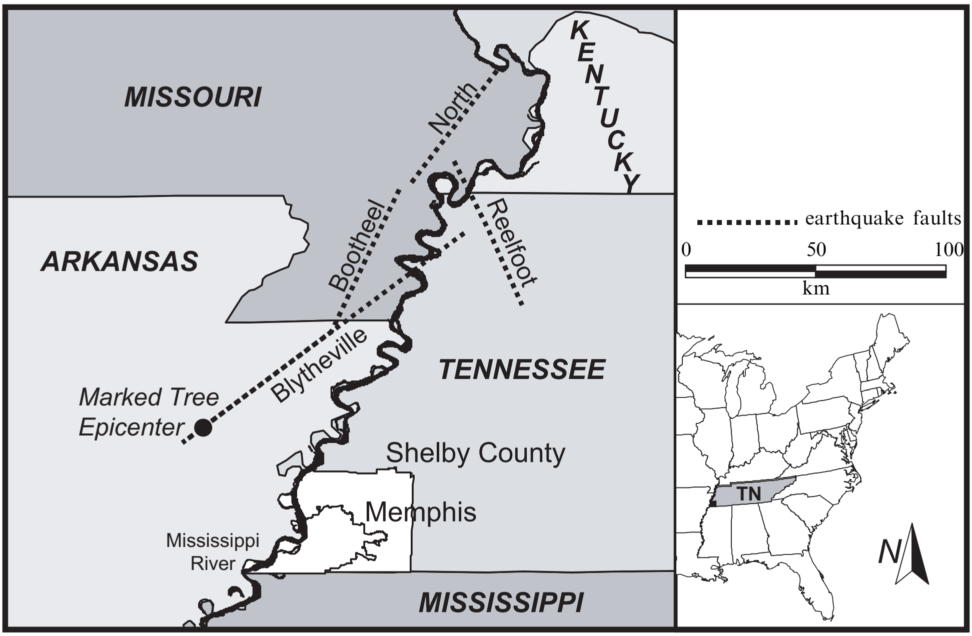

Figure 2. Study area and New Madrid Seismic Zone faults.

reported to have caused the Mississippi River to flow backwards for a time and church bells to ring as far away as Boston. In 1811–12, the region was sparsely inhabited and losses were relatively light.

We evaluate economic losses for six scenario earthquakes. Three of these have an epicentral location at Marked Tree, Arkansas, some 55 km northwest of downtown Memphis in the southern portion of the NMSZ that is closest to the study area, as indicated in figure 2. The three events are posited to be earthquakes of magnitude 6.5, 7.0, and 7.5 on the Richter scale. In addition, three other events with more distant epicentral locations from Memphis in the NMSZ are also modeled.

Memphis Light, Gas and Water Division (MLGW) supplies water to all of Shelby County, with the exception of a few unincorporated municipalities. The water source is an underground aquifer accessed by wells. The water-delivery system consists of a large low-pressure system and several high-pressure systems located on the outskirts of Memphis city. The network includes about 1370 km of buried pipes and a number of pumping stations, elevated tanks, and booster pumps.

Damage and outage

The MLGW water-delivery system is represented in the model as a network consisting of roughly 960 demand-and-supply nodes and 1300 links. An engineering model estimates the damage to system components such as pipes by using a Monte Carlo simulation approach (Hwang et al, 1998; Shinozuka et al, 1994). The essence of the damage model can be represented as follows:

$$\mathrm{p}(d_e) = D(g_e, s_e, c_e), \qquad (1)$$

where

$\mathrm{p}(d_e)$ is the probability of failure of network element e,
D is the fragility curve or failure model,
g_e is the earthquake ground-motion level at element e location,
s_e is the soil type at element e location, and
c_e is the physical characteristics of element e (for example, the construction material).

In this approach, fragility curves D provide conditional probabilities of failure for water pipes, pumping stations, and other elements constituting the network. The failure probabilities depend upon various factors that contribute to earthquake damage, including the level of ground shaking, local soil conditions, and material and structural design properties.

For each earthquake scenario, the Monte Carlo procedure simulates 100 discrete cases or realizations of systemwide damage by implementing the fragility curves indicated in equation (1). Each simulation case represents a deterministic damage pattern that is a possible outcome of the earthquake; collectively, they represent the probabilistic damage outcome of the event. Damage estimates consist of the number of pipe breaks on each network link and the (non)occurrence of failure at each of the pump stations and other supply nodes. Figure 3 (see over) shows damage results for the M7.0 Marked Tree scenario earthquake in terms of the density of pipe breaks, averaged over 100 simulations. This scenario produces an average of about 650 pipe breaks throughout the network.

For each simulation case of network damage, the model evaluates the loss of water service across the study region by undertaking a complex system-flow analysis (Hwang et al, 1998; Shinozuka, 1994); that is,

$$f_i = F(d_e), \qquad (2)$$

where f_i is the water flow at node i and F is the system-flow model. The system-flow

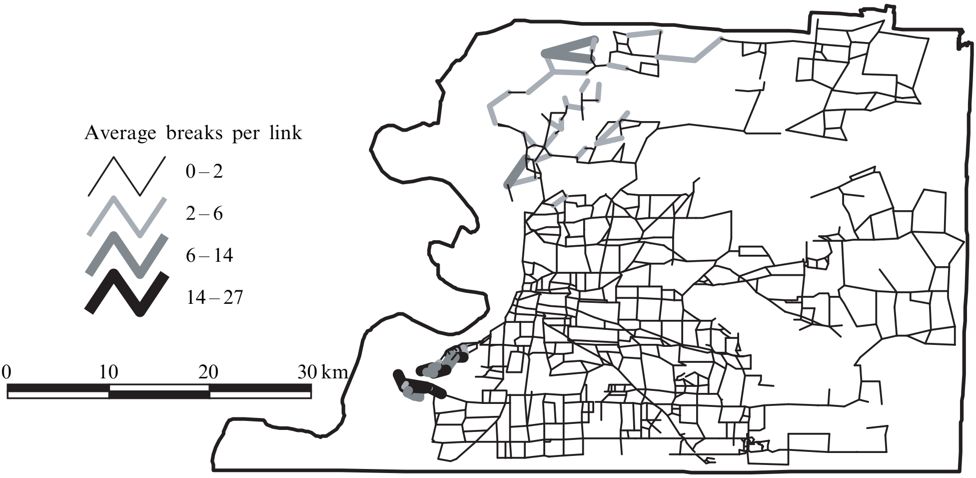

Figure 3. Network damage in M7.0 Marked Tree scenario.

model translates pipe damage into water leakage and solves for a new state of system-flow equilibrium for the damaged state of the network. This yields an estimate of water flow f at each node. The ratio of water flow in the damaged versus the intact state, or 'flow ratio' ϕ_i, is evaluated at each of the demand nodes i. This provides the basic indicator of water outage that is used in the economic-loss model below.

Restoration and temporal linkages

As noted earlier, infrastructure service provides the key link between the infrastructure system and the economy in the model, and the important features of infrastructure service as conceptualized here are its temporal, spatial, and functional dimensions. The temporal dimension is captured through modeling the restoration of the water-delivery system over time.

Economic loss depends not only on initial water outage but also on the duration and spatial pattern of water restoration to the disaster-impacted community. The model simulates repair progress over the restoration period according to specified algorithms. We have adopted a resource-constraint approach in our restoration model, and this specifies the number of repairs that can be made in any time period according to the number of repair personnel available. The damage state d ('damaged' or 'intact') for element e (for example, a particular water pipe) at time t can be characterized as:

$$d_e(t) = R[d_e(t-1), n(t-1), \rho_u, h_e], \tag{3}$$

where

t is the time-period index, in weeks,
R is the repair and restoration function,
n is the number of repair personnel available,
ρ_u is the repair rate for type u damage, in worker-days per repair,
h_e is the repair priority assigned to element e.

That is, the damage state at time t for element e depends upon the damage state in the previous time period and whether or not the element got repaired. The latter depends upon how many repair workers were available in the previous time period, the number of repairs each worker can make in a week, and the priority of element e in the repair sequence.

Note that the worker-days per repair vary with type u of damage; specifically, repairs to large pipes require more worker-days than do repairs to smaller pipes. Model parameters are based on a survey of current lifeline-restoration models and data from the Kobe earthquake (Chang et al, 1999). Here, pipes of diameter greater than 20 inches are assumed to require 14 worker days to repair if damaged, and smaller pipes are assumed to require 2.5 worker days. Following HAZUS®, the number of repair workers available is assumed to be 0.02% of the county population.

These numbers would undoubtedly be somewhat variable in an actual disaster. As seen in the Northridge earthquake and in other events, worker-days per repair could vary according to damage circumstances as well as financial incentives for speedier work. The number of workers would depend on such factors as temporary in-migration of labor, timeframe after the earthquake, and mutual-aid agreements that MLGW had established with other utility agencies.

The parameters n and ρ dictate the total number of repairs that can be made in any time period. Repair priorities h determine which damaged elements are actually repaired in that time period. The restoration model specifies the repair sequence on the basis of engineering priorities and observations from the 1995 Kobe and 1994 Northridge earthquakes. Specifically, any damage to large pipes (diameter >20 inches) is repaired first, in order to bring the transmission 'backbone' of the system online before repairing service pipes. The restoration of smaller pipes then occurs in spatial sequence, from census tracts with the least amount of damage to those with the highest.

Initial damage patterns are updated on a weekly basis until repairs have been completed. At each weekly interval, system-flow analysis F is conducted on the updated network and flow-ratio results $\phi_i(t)$ for each node i are updated. Figure 4 (see over) shows the spatial pattern of water-outage severity for the initial damage state and after one week of repairs has been completed, again for the M7.0 Marked Tree event. As before, results represent an average of the various simulated cases of the earthquake. In the figure, node-level data on flow ratio ϕ_i are spatially interpolated in GIS to yield an outage surface. Dark shadings indicate areas of greatest water loss. Outage is more severe in the western portion of the county.

Although the restoration function adopted here is reasonable given experience in recent urban earthquakes, it should be noted that other restoration algorithms could also be simulated. For example, one alternative could seek to minimize employment losses by giving priority to those subareas that utilize the lowest amounts of water, directly and indirectly, per worker (see Rose et al, 1997). Another alternative would be to give highest priority to restoring water service in downtown Memphis.

Spatial integration

Spatial integration provides the second means by which infrastructure service links the infrastructure network with the regional economy. In particular, the model utilizes GIS functions to assess the spatial coincidence of water outage and economic production activities. That is, the spatial pattern of water outage as represented in figure 4, for example, matters insofar as the economic activities that could be affected by this water loss are distributed unevenly across the region.

Data on employment location serve to indicate the spatial distribution of economic production. For Shelby County, the 1990 Census Transportation Planning Package (CTPP) from the Bureau of the Census provides employment data by place of work for traffic analysis zone (TAZ) units. Each TAZ represents a fairly homogeneous area that is meaningful for such purposes as traffic-demand modeling. Shelby County is

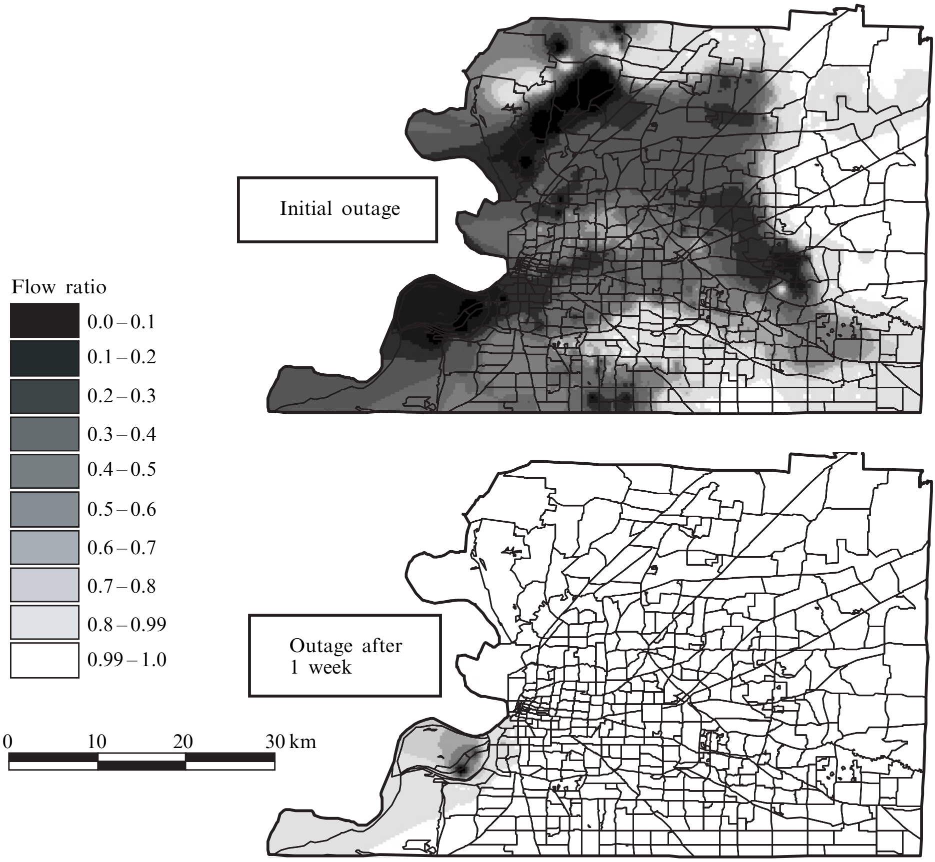

Figure 4. Water outage in M7.0 Marked Tree scenario.

comprised of 515 TAZs. These are generally smaller than census tracts, of which there are 133 in the county. Jobs data are available for an 18-sector industrial classification.

Figure 5 shows the density of jobs throughout the county, plotted by TAZ. Employment is highly concentrated: the top 10% of TAZs (located largely in downtown Memphis in the west-central portion of the county) account for nearly 50% of the jobs. Outside of Memphis, much of the county consists of agricultural land.

Integrating the spatial information on water outage and economic activity entailed defining new spatial units appropriate to this analysis. Because the water-outage results ϕ_i are produced for network nodes, whereas employment information is available for TAZs, we had to reconcile point data on the one hand with polygon data on the other. We first defined a contiguous set of 685 water-service-zone polygons for the county by performing a GIS Thiessen polygon operation on the point distribution of water-delivery nodes. Each service zone represents the inferred service area of one node on the water network. This approach implements the assumption that a particular business location will be served by the closest node on the water-delivery network. GIS overlay and intersection operations were then applied to the data sets on water service zones and TAZs to define a set of 2784 analysis zones, as shown in figure 6. Each analysis zone then contains a portion of the employment in its parent TAZ and outage data from its parent water-service zone.

Analysis zones provide modeling advantages over other spatial units such as census tracts, which are often used in earthquake loss-estimation methodologies

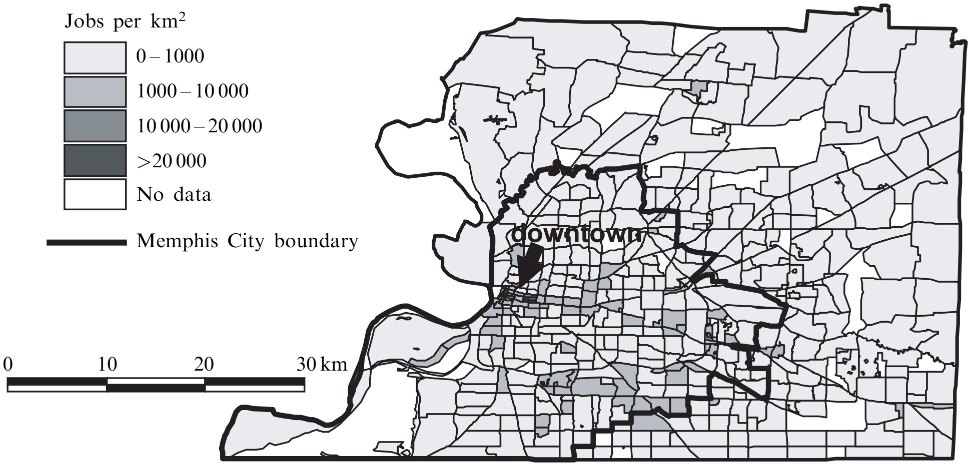

Figure 5. Employment density in Shelby County by traffic analysis zone (TAZ).

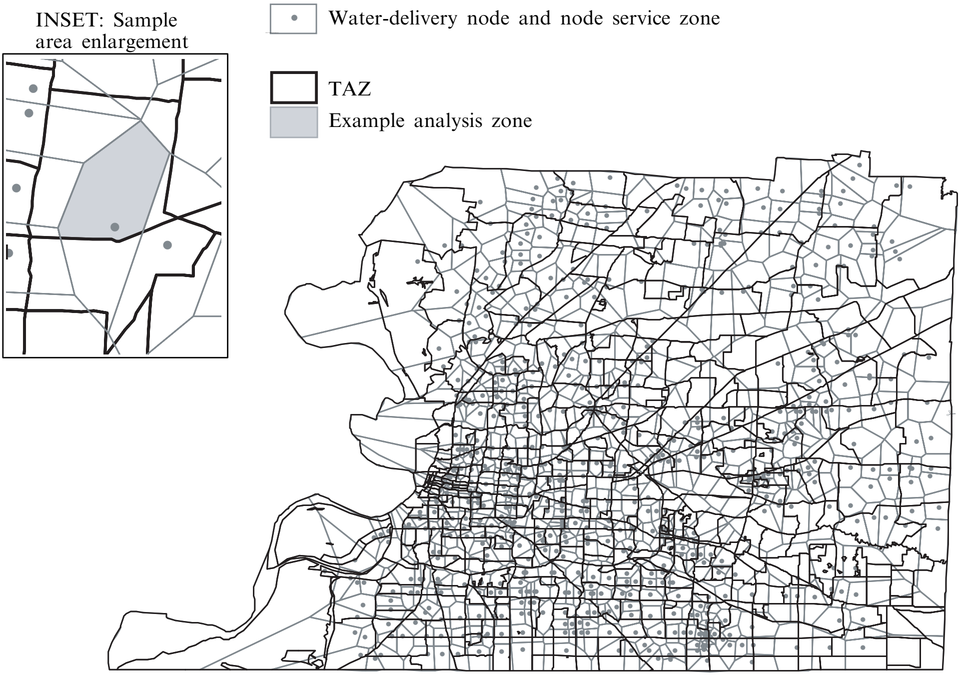

Figure 6. Formation of analysis zones from node service zones and traffic analysis zones (TAZs).

such as HAZUS®. Census tracts bear no relation to the topology of the water network and, moreover, represent fairly large spatial units. In contrast, analysis zones are defined in relation both to the water-delivery infrastructure system and to small areas designed to capture employment distribution meaningfully. Defining analysis zones therefore allows implementation of the loss model at the same spatial resolution as that of the input data and maximizes use of information on the spatial variability of factors contributing to loss.

Functional linkages

Spatial and temporal information on infrastructure service loss are alone insufficient for estimating the economic loss that would be caused by water outage in a disaster. The third dimension of infrastructure service addresses the functional linkages between infrastructure and economy, that is, how production activities rely upon water service. The production process is assumed to use water as one of many inputs. If water is curtailed, production may be cut back.

The degree to which firms would need to reduce production would depend on their *resiliency*, or their ability to withstand temporary water disruption. Resiliency varies substantially across industries and depends upon such considerations as how water is used in the production process, availability of backup supplies, substitution possibilities, and the duration of water loss. A 50% loss of water does not, in other words, necessarily reduce production by 50%.

The core of defining the functional linkage consists of quantifying business resiliency to water loss in disaster situations. The idea of resiliency parameters was first proposed in an Applied Technology Council study (ATC, 1991). However, that study and others like it have been severely limited by a lack of empirical data and have resorted, typically, to using expert-opinion data for this purpose. In contrast, the current study develops resiliency factors from empirical survey data.

Empirical basis

We have taken advantage of new data from two business surveys conducted by the Disaster Research Center (DRC) at the University of Delaware (Tierney, 1997; Tierney and Dahlhamer, 1998a; 1998b). The first survey focused on the dependency of Memphis-area businesses on infrastructure services in disaster situations. A total of 737 businesses in Shelby County responded to such questions as the importance of water to business operations and the number of days the business could operate without water service. This survey provided valuable information on the resiliency of Memphis-area businesses to water outage; however, the results are limited by the fact that the businesses surveyed had no previous experience of earthquake dislocation on which to base their responses.

The second DRC survey investigated the real experiences of businesses in the Los Angeles region in the 1994 Northridge earthquake. A total of 1110 businesses provided extremely useful information on actual resiliency and loss in the disaster. Because these data pertained to the Los Angeles region, however, their applicability to the Memphis area may be limited by regional differences in such factors as business types, practice, or disaster preparedness.

In the current study we applied data from both DRC business surveys to calibrate empirical 'resiliency factors' for use in the economic-loss model. Resiliency factors are defined as the remaining percentage output that an industry could still produce in the event of total water outage. Resiliency factors for the major economic sectors were developed separately for each of the two business surveys, then compared and combined to derive a final set of resiliency factors for the model.

In the case of the Memphis survey data, resiliency factors were developed according to responses from businesses to a specific question regarding how long they could continue to operate in the event of loss of water in a disaster (Chang, 1998). The wording of this question referred to water outage only, independent of any other disaster-related source of potential business disruption. Resiliency factors were developed for nine industries and for various outage duration periods.

The development of resiliency factors from the Northridge survey data was more complex. It required separating the effects of water loss from those of numerous other sources of business disruption such as loss of electric power, transportation problems, building damage, and so on. To accomplish this, responses from businesses to numerous questions were employed. For example, did the business lose water in Northridge, and for how long? How disruptive was this loss? Similarly, how disruptive was the loss (if any) of other specific essential services, building damage, etc? Finally, business responses regarding whether or not they closed for any period of time because of the earthquake, and the principal reasons for this closure, provided critical pieces of information.

Although the Northridge database contained 1110 businesses, only 190 of them had lost water service in the disaster. Of these, 156 lost water for less than one week. A multistep inference procedure was applied to develop industry-dependent and duration-dependent resiliency factors from the survey response of these businesses. The first step entailed cross-tabulating the disruptiveness of water outage by industry group for businesses suffering less than one week of outage. This matrix used four qualitative disruptiveness categories, based on the survey instrument: 'very disruptive', 'moderately disruptive', 'not very disruptive', and 'not at all disruptive'. Businesses were divided into seven industry groups: agriculture; mining, construction, and transportation (MCT); manufacturing; trade; finance, insurance, and real estate (FIRE); health services; and all other services. This yielded from 15 to 43 businesses in each group, with the exception of agriculture (8 businesses). Results, shown in the top portion of table 1,

Table 1. Disruptiveness level of water outage.

Industry	Percentage of businesses at each disruptiveness level				Sample size
	very	moderately	not very	not at all	
Outage <1 week					
Agriculture	0	50	25	25	8
MCT[a]	25	25	38	13	16
Manufacturing	41	6	53	0	17
Trade	32	35	19	13	31
FIRE[b]	46	31	15	8	26
Health	80	7	7	7	15
Services	33	23	33	12	43
1 week ⩽ Outage < 2 weeks					
Agriculture	41	28	21	10	na[c]
MCT	46	33	16	5	na
Manufacturing	46	41	13	0	na
Trade	61	21	12	5	na
FIRE	71	17	8	3	na
Health	85	6	6	3	na
Services	52	29	15	5	na
Outage ⩾ 2 weeks					
Agriculture	49	51	0	0	na
MCT	55	45	0	0	na
Manufacturing	58	42	0	0	na
Trade	68	32	0	0	na
FIRE	77	23	0	0	na
Health	87	13	0	0	na
Services	60	40	0	0	na

[a] Mining, construction, and transportation.
[b] Finance, insurance, and real estate.
[c] Not applicable.
Note: Rows of percentages may appear not to add up to 100—this is because of rounding errors.

indicated that some industries found water outage to be much more disruptive than others; for example, 87% of health-service businesses found water outage to be 'very disruptive' or 'moderately disruptive', even for less than one week. On the other hand, only 50% of MCT-sector businesses responded similarly.

The second step involved developing a similar cross-tabulation for longer duration outages, specifically one week and two or more weeks without water. Because few businesses had suffered such long outages in Northridge, a transition-probability inference method was used. That is, Markov-chain-type probabilities were developed to indicate the likelihood that businesses would move from one disruptiveness category (for example, 'moderately disruptive') to another (for example, 'very disruptive') as the duration of outage increased (for example, from 'less than one week' to 'one week'). These transition probabilities were based on survey data for businesses suffering outage for more than one week, as well as on the industry-by-disruptiveness matrix for those with less than one week of outage. Results for one and for two-or-more weeks of outage are also shown in table 1.

Resiliency factors

These qualitative disruptiveness categories provided the basis for developing quantitative measures of business resiliency. Making this inference used data from the entire survey sample, that is, all businesses whether or not they had suffered loss of water. An overall disruptiveness level was assigned to each business based on its highest level of reported disruption due to everything from 'loss of water' to 'need to repair building' to 'employees unable to get to work'. The overall disruptiveness level was then cross-tabulated against whether or not the business closed for any length of time as a result of the earthquake. Results were evaluated by industry. The analysis showed that they were similar for six of the seven industries, so these data were pooled to increase the sample size. The exception was the MCT group. Table 2 shows the probability of business closure for various levels of overall earthquake disruptiveness for MCT and for all other industries, respectively.

These results provide the basis for estimating business resiliency factors r for use in the economic-loss model. Equation (4) shows the derivation of r from information in tables 1 and 2. Recall that resiliency factors indicate the percentage of production in an industry j that could still be produced in the event of total water loss.

$$r_{j,t} = 1 - \mathrm{p}(Z_{j,t}) \,,$$
$$\mathrm{p}(Z_{j,t}) = \sum_{y=2}^{4} [\mathrm{p}(Z_j | Y_j = y)\mathrm{p}(Y_j = y | T_j = t)] \,, \qquad (4)$$

Table 2. Probability of business closure by earthquake disruptiveness level.

Industry group	Probability of business closure for each disruptiveness level			
	very disruptive	moderately disruptive	not very disruptive	not at all disruptive
MCT[a] (112)	0.75 (75)	0.06 (16)	0 (14)	0 (7)
All other (790)	0.86 (619)	0.21 (58)	0.11 (81)	0.06 (32)

[a] Mining, construction, and transportation industries.
Note: figures in parentheses indicate sample size.

where

$r_{j,t}$ is the resiliency factor for businesses in industry j for water outage at time t after the earthquake,

p(Z) is the probability of business closure,

y is the level of business disruption from water outage (1 = not at all disruptive, 2 = not very disruptive, 3 = moderately disruptive, 4 = very disruptive),

Y is the disruptiveness of water outage, and

T is the duration of water outage.

Note that the sum over disruptiveness levels y is taken over all levels except 'not at all disruptive'; in effect, it is assumed that businesses in this category will not close.

Equation (4) can also be applied at the scale of an individual business with slightly different interpretation. At the industry level, as noted, r represents the percentage of production that could still be produced in the event of complete water outage. At the level of the individual business in industry j, the resiliency factor indicates the probability that the business would remain open, given loss of water.

A comparison of the resiliency factors based on the Northridge data and those based on the Memphis survey showed marked differences. With one exception, resiliencies in Northridge were much higher than those in Memphis. For example, where outage is less than one week, the resiliency factors for 'retail trade' were 0.30 and 0.63 for Memphis and Northridge, respectively. The exception is in health services, where the resiliencies are quite similar, especially if outage is for less than one week. The most likely explanation for these discrepancies is that because businesses in Memphis have never experienced a damaging earthquake, the potential consequences are inflated in business owners' or managers' expectations. That is, if a Northridge-like event were to occur in Memphis, the resulting actual business resiliencies would more closely resemble the Northridge factors than the hypothetical Memphis ones. However, other explanations are also possible—businesses in Los Angeles may be much better prepared for disasters, or somehow less reliant on water than those in Memphis. In view of this ambiguity, for present purposes, the model uses resiliency factors based on a mathematical average of the Northridge and Memphis factors. These are shown in table 3 for a 16-industry classification scheme.

Table 3. Resiliency factors (based on an average of factors derived from the Northridge and Memphis business surveys).

Industry	Water-outage duration		
	<1 week	1–2 weeks	$\geqslant$ 2 weeks
Agriculture	0.53	0.35	0.30
Mining	0.73	0.48	0.44
Construction	0.68	0.47	0.43
Nondurable manufacturing	0.42	0.34	0.28
Durable manufacturing	0.42	0.34	0.28
Transportation	0.65	0.49	0.43
Communication/utilities	0.65	0.49	0.43
Wholesale trade	0.51	0.36	0.30
Retail trade	0.46	0.32	0.28
FIRE	0.44	0.27	0.24
Business/repair services	0.45	0.33	0.27
Personal services	0.45	0.33	0.27
Entertainment services	0.45	0.33	0.27
Health services	0.27	0.21	0.19
Educational services	0.45	0.33	0.27
Other services	0.45	0.33	0.27

Economic-loss model

These resiliency factors provide the basis for developing the model of direct economic loss. As noted earlier, direct economic loss refers only to business output reductions that would be caused by loss of water as a production input. This is sometimes referred to as the 'first-round' impact. It does not include the consequent upstream or downstream business interruption due to interindustry linkages, which are addressed in a separate, related study (see Chang et al, 2000a; Rose and Guha, 1999). Similarly, it does not consider household impacts and how they might affect businesses in turn via labor-input or consumption-pattern changes.

The economic-loss model implements the concept that, for the study area as a whole, loss derives from a combination of the water outage pattern, its spatial coincidence with economic activity, its duration, and the business resiliency to water loss, as shown in equation (5):

$$
\begin{aligned}
\lambda_{j,k,t} &= \frac{(1-r_{j,t})}{0.95}(w_{j,k,t}-0.05), \quad \text{if } w_{j,k,t} > 0.05\,, \\
&= 0, \qquad\qquad\qquad\qquad\qquad \text{if } w_{j,k,t} \leqslant 0.05\,,
\end{aligned}
\tag{5}
$$

where $\lambda_{j,k,t}$ is the loss factor, or proportion of output loss ($0 \leqslant \lambda \leqslant 1$), for businesses in industry j in analysis zone k for water outage at time t after the earthquake, and w is the proportion of water loss.

In equation (5) it is assumed that businesses can generally absorb the first 5% of water loss without curtailing economic activity (see ATC, 1991). This might be effected through emergency conservation efforts, for example. However, water outage in excess of 5% causes economic loss in a linear manner, up to a maximum of r percent loss (the resiliency factor) in the case of complete water outage. The same amount of water outage would cause greater disruption to industries that depend critically on water, such as health services, than to others, such as construction.

Equation (5) is implemented in the model by a Monte Carlo simulation approach which captures the probabilistic nature of economic loss. Specifically, in each simulation, a random number is generated for each of the 16 industries j in each of the 2784 analysis zones k in each weekly time period t. If the random number were greater than the relevant resiliency factor $r_{j,k,t}$, businesses of that industry in that analysis zone are modeled as closed in that time period because of water outage. If the random number is less than $r_{j,k,t}$, businesses are modeled as operating normally, despite any water loss. Partial closures are also allowed for cases where there is a 'brownout'-type situation with partial water availability.

Loss-factor results λ convert to dollar output losses in a straightforward manner:

$$
L = \sum_{j,k,t} \lambda_{j,k,t} q_{j,k}\,, \tag{6}
$$

where L is the total economic output loss from water outage (dollars), and $q_{j,k}$ is the normal or predisaster output for industry j in analysis zone k (dollars). Note that predisaster output data q are inferred from analysis-zone employment shares and total industry output in a base year. The Memphis implementation used 1996 base-year industry gross-output figures. By using employment shares as proxies for output shares, it is assumed implicitly that labor productivity is spatially invariant across the county.

As had been indicated in the procedural flowchart in figure 1 above, the model simulates economic loss within the same Monte Carlo simulation block as the estimation of water-network damage and outage. This approach thus treats both the engineering and economic portions of the problem in a probabilistic and fully consistent manner.

This kind of integrated methodology provides an important advantage over the typical approach of casting the engineering and economic portions into distinct modules that are rather tenuously linked. In particular, the effectiveness of different loss-reduction measures—for example, reducing physical damage versus enhancing business resiliency—can now be compared consistently in the current approach.

Computer application

The methodology described above, emphasizing economic loss, was implemented in a computer code written in Fortran (DIGITAL Visual Fortran Version 6.0), referred to here as *Lifeline-E*. The core of this program consists of an engineering code called *Lifeline-W(2)* designed by one of the authors, M Shinozuka, and colleagues at Princeton University for simulating water-network damage in earthquakes, conducting hydraulic analysis, and computing the resulting flow ratios (Hwang et al, 1998; Shinozuka et al, 1997). *Lifeline-E* extends *Lifeline-W(2)* by adding a restoration model and a direct-economic-loss simulation model.

Input data to *Lifeline-E* include: earthquake ground-motion values for the scenario event for each network link (in terms of peak ground acceleration, or PGA); network data; soil-type data; employment data; and any mitigation or loss-reduction actions being considered in the scenario. Outputs include: for each simulation of the earthquake and each weekly interval over the restoration period—physical damage to the network, flow ratios at each network node, and economic loss for each analysis zone; and the system-aggregate result for each of these measures. The final result consists of mean economic loss for each earthquake scenario and a distribution around this mean.

Loss-estimation results

Table 4 summarizes results for the six scenario events, including three earthquakes of varying magnitudes occuring with epicenter at Marked Tree, and three others occuring on the North or Reelfoot fault segments of the NMSZ. The scenarios chosen represent a broad range of the local seismic hazard, from minor earthquakes causing little damage to major disasters.

As expected, both the physical damage (in terms of average pipe breaks) and the restoration time increase exponentially with ground motion (as indicated by average PGA). Economic loss generally correlates positively with physical damage, but the relationship is not exact. For example, the M7.0 Marked Tree scenario event causes slightly less physical damage than the M7.5 North Fault scenario (658 versus 681 pipe

Table 4. Damage and loss in selected NMSZ events.

Location (and magnitude)	Average PGA (g)[a]	Average breaks[b]	Weeks to repair	Mean loss ($million)[c]	Mean loss (monthly %)[d]
Marked Tree (M6.5)	0.15	130	1	42	1.1
Marked Tree (M7.0)	0.21	658	2	136	3.5
Marked Tree (M7.5)	0.30	4492	11 – 12	2412	20.5[e]
North Fault (M6.8)	0.10	7	1	5	0.1
Reelfoot Fault (M6.8)	0.17	164	1	36	0.9
North Fault (M7.5)	0.22	681	2	102	2.6

[a] PGA—peak ground acceleration, averaged over mean value at each link.
[b] Number of pipe breaks, averaged over 100 simulations.
[c] Direct economic loss in gross output terms, averaged over 100 simulations.
[d] Percentage of county gross output in one month.
[e] Percentage of county gross output averaged over first three months.

breaks on average) but more economic loss ($136 million versus $102 million). This occurs because the spatial patterns of damage and outage differ between the two events. The Marked Tree scenarios generally cause more outage in the western part of the county, including downtown Memphis, than comparable events on the other faults.

Figure 7 plots the estimates of expected losses and their associated uncertainties for the same events. The six scenarios are ordered by shaking intensity (average PGA) along the horizontal axis. Uncertainty is measured by the coefficient of variation for the sample of 100 Monte Carlo simulations for each event. Loss variability is extremely high for the smaller events owing to randomness both in engineering and in economic effects. However, with increasing earthquake intensity and expected loss, the variation around the mean decreases notably. In this sense, presenting single-value loss figures—as is conventionally done—may convey a misleading sense of accuracy. The primary reason behind the high loss variability is discussed below.

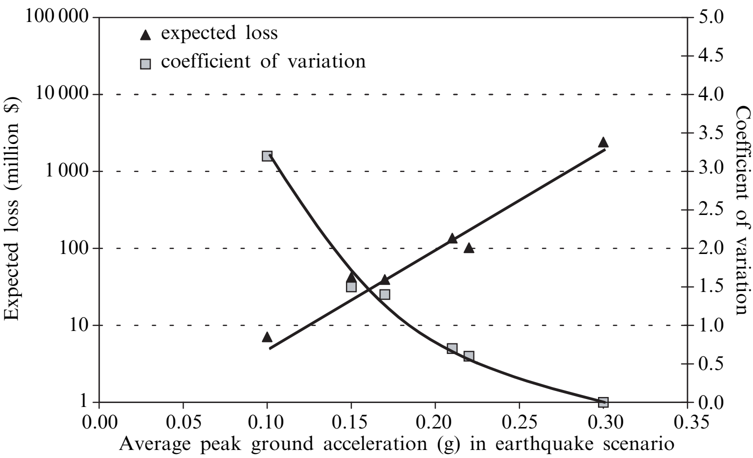

Figure 7. Loss-estimation results.

It should be pointed out that for the most damaging of the six scenarios, the M7.5 Marked Tree event, loss variability is very low for a particular reason. Extreme damage levels (nearly 4500 pipe breaks) cause the system-flow model to fail to solve for equilibrium flows in the first four weeks of this disaster. Although this may indicate a computational limitation of the program itself, it also suggests that, for the first month after an earthquake of this magnitude, the entire county would probably suffer loss of water service. In this case, maximum economic loss (defined by resiliency parameters) is assumed for the first four weeks without any randomness in the simulation.

The collective simulation results from table 4 and figure 7 show that direct loss of production because of water outage in an earthquake might range from a few million dollars to over $2.4 billion dollars in gross output terms. The total 1996 gross output in Shelby County was $47.0 billion, or $3.9 billion per month. The final column of table 4 shows expected loss as a percentage of monthly gross output. In the case of the M7.5 Marked Tree event, this is shown as an average over the first three months since restoration would require up to twelve weeks. This most severe event is expected to entail a 20% drop in monthly economic activity resulting from direct loss of water alone—a severe impact even before losses from other types of damage and indirect impacts are considered.

Are these results credible? Although there is little empirical basis for making such a judgment, Rose and Lim's (2000) assessment of the economic impact of power outage in the Northridge earthquake provides one reference data point. That study found that power outage cost \$23 million in economic-disruption loss during the hours of total blackout, including both direct and indirect disruption, even after taking into account businesses' abilities to make up production losses through overtime work. Rose and Lim's intermediate results for direct gross-output losses only—with adjustment for resiliency but without adjustment for making up production (which decreases losses dramatically), time-of-day use, and indirect effects—indicate losses of around \$74 million.

This latter number can be compared to the MLGW results obtained here. The Northridge earthquake was a moderate-sized, magnitude 6.7, earthquake that caused several hours to roughly one day of power outage that affected the entire Los Angeles area. Water outage typically lasts much longer than power outage in earthquakes—water restoration took about two weeks in Northridge and eleven weeks in Kobe. However, the economy of Shelby County is only about one-tenth that of Los Angeles. It may be reasonable to compare the M7.0 Marked Tree event—with two weeks of water outage and \$136 million direct economic loss—with Rose and Lim's estimates for Northridge. Making adjustments to the \$74 million figure to account for the duration of lifeline-service loss (14 times longer) and size of economy (one-tenth as large) yields \$104 million, which is within a reasonable range of the \$136 million Memphis estimate. Despite being very rough, this kind of reality check is useful in the absence of empirical data for validation. The result of the reality check supports the credibility of the complex model and estimation results developed here.

Sensitivity analysis

Because of the complexity of the overall loss-estimation model, no readily discernible correlation exists between model inputs and outputs. That economic losses do not increase monotonically or steadily with average ground-shaking levels—much less earthquake magnitude—testifies to the inevitable 'black box' nature of the complex model. It is therefore important to conduct a sensitivity analysis in order to confirm its credibility, on the one hand, and gain further insights into earthquake-induced economic loss, on the other. Sensitivity analysis also provides information on how losses could be reduced by various policy decisions.

Figure 8 (see over) summarizes findings from sensitivity analysis conducted for the M7.0 Marked Tree earthquake. The baseline loss was \$136 million. Loss is reduced to various extents if certain model parameters are changed. For example, we can compare how losses are reduced if soil type is altered to 'good soil' throughout the study area, if pipe fragility is reduced by 20%, if supply-link (pumping station) fragility is reduced by 20%, and if business-resiliency factors are increased by 20%. The business-resiliency change has the least impact on losses, whereas modifying the soil type and supply-link parameters have much more effect. This is not surprising, as business resiliency does not affect water outage, but simply governs how businesses respond to the outage.

Figure 8 also presents a very interesting comparison between two potential policy decisions that MLGW might undertake, labelled 'ductile-iron pipe' and 'pumping-station retrofit'. Pipe material in the network consists largely of two types of materials: cast iron, the predominant material installed until around the late 1960s and 1970s, which is brittle under seismic motion; and ductile iron, which has been employed more recently and is seismically resistant. Most of the network is cast iron. If all of this were replaced by ductile iron as a mitigation measure, total losses would be decreased by roughly a quarter. Such a mitigation measure would be a costly and long-term solution, however, that might take one or two generations to implement.

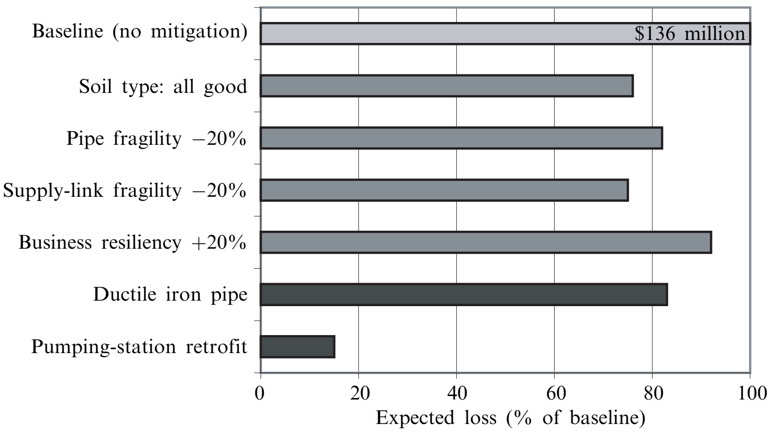

Figure 8. Sensitivity-analysis results for the M7.0 Marked Tree scenario.

An alternative mitigation approach would be to retrofit the pumping stations. Although this does not affect the number of pipe breaks, it can have a substantial impact on the amount of water delivered from the underground source to the network. If the pumping stations were retrofitted so that they did not fail in the earthquake, expected losses would be reduced by as much as 85%. Moreover, this would substantially reduce the variability of loss (not shown in figure). More detailed investigation also supported the finding that the extremely high variance for losses, indicated earlier in figure 7, can be largely attributed to variability in the simulated failures of a few of the key pumping stations that serve areas of high economic activity. This suggests that a very effective loss-mitigation strategy would be to invest in seismic retrofit of these key pumping stations. Such a strategy would not only be more effective than an alternative such as pipe replacement, but also much less costly, easier to implement, and feasible within a timeframe of a few years.

It should be noted that these sensitivity-analysis results pertain to the case of a moderately damaging earthquake such as the M7.0 Marked Tree scenario. As smaller events cause relatively insignificant damage, and larger events are relatively rare, it may be a useful approach to focus mitigation planning on such moderate-sized disasters. It is likely, however, that the sensitivity-analysis results would differ if assessed for the M7.5 Marked Tree event, for example. In such a catastrophic disaster, water outage would extend for much longer periods of time, increasing the sensitivity of results to business-resiliency factors which affect estimated losses in all weeks of the restoration after the initial one.

Conclusions

The economic-loss methodology for water lifeline systems described in this paper incorporates several significant advances in earthquake loss-estimation methodologies. It provides an approach for evaluating economic losses from lifeline disruption, a category of loss that is often overlooked. The methodology integrates engineering-damage models and economic-loss models within a Monte Carlo simulation framework. This enables consistent, probabilistic treatment of these various contributors to the loss process. GIS capabilities are used to refine the spatial resolution of analysis and more effectively use digital spatial data. Introducing a lifeline-restoration element allows the model to capture how losses change over time. Economic losses are evaluated probabilistically. Key economic model parameters are calibrated with new empirical data from the Northridge and Kobe disasters. The model allows the analyst to compare the loss reduction effectiveness of predisaster mitigations and postdisaster emergency-response decisions.

The methodology developed here also makes advances more generally in the area of modeling infrastructure – economy linkages in the urban setting. We propose the concept of infrastructure *services* as a construct to link infrastructure networks—whether measured in physical or dollar terms—with the economic system that these networks support. Infrastructure services provide this linkage spatially, temporally, and functionally. Each of these dimensions was shown to be essential in capturing how earthquake-induced damage translates into economic-disruption loss. It is argued that the economic implications of other types of changes to an urban infrastructure network, most notably new investments, can be treated similarly by considering the spatial, temporal, and functional dimensions of infrastructure-service use by economic agents.

In terms of the specific results of the earthquake application, sensitivity-analysis results demonstrated that the model can provide a useful tool to support earthquake loss-reduction decisionmaking. Preliminary results suggested that seismic safety policy for water infrastructure in Shelby County should place priority on retrofitting a few key pumping stations, as their performance largely controls economic loss. This finding is specific to Shelby County, as the criticality of these pump stations derives from their role in transmitting water from the underground aquifer to the water-delivery network. In another urban area such as Los Angeles, where water is delivered via aqueducts by using gravity, pump-station retrofitting may be much less of a priority. This observation suggests the importance of modeling the particularities of the physical infrastructure network for an urban area when evaluating investment options, even when the evaluation is conducted from the standpoint of contributions to the urban economy.

Finally, the study has indicated a number of valuable areas for further research. Several methodological refinements are warranted. For instance, in modeling the critical first week of the disaster, daily rather than weekly timesteps should be explored. Also, the analysis should be expanded from direct economic loss to also encompass indirect loss. Household impacts should be incorporated. More empirical studies are needed to clarify how different types of businesses use infrastructure services and what factors influence their resiliency to infrastructure disruptions.

Within the context of case studies such as Shelby County, seismic-safety policy implications should be investigated further. Alternative measures should be evaluated and compared in terms of earthquake loss-reduction effectiveness. Such measures include both predisaster mitigation strategies, such as seismic retrofits to various infrastructure elements, and postdisaster measures such as implementing mutual aid agreements to augment the number of repair crews available. Such comparisons may be especially helpful in regions like the Midwest where, in view of lower seismicity than places like California, focusing on disaster-response preparedness may be more advisable than investing large sums in physical retrofits.

Acknowledgements. An earlier version of this paper was published in Chang et al (2000a). This work was supported primarily by the Earthquake Engineering Research Centers Program of the National Science Foundation under Award Number EEC-9701471 to the Multidisciplinary Center for Earthquake Engineering Rearch. The authors would like to thank K Tierney at the Disaster Research Center, University of Delaware, for sharing business-survey databases, and EQE International, Inc, for use of the model EQECAT for estimating some of the scenario ground-motion levels.

References

ATC, 1991, "ATC-25: Seismic vulnerability and impact disruption of lifelines in the conterminous United States" Applied Technology Council, Redwood City, CA

Boisvert R, 1992, "Direct and indirect economic losses from lifeline damage", chapter 7, in *Indirect Economic Consequences of a Catastrophic Earthquake* Development Technologies, Incorporated under FEMA Contract EMW-90-3598; copy available from FEMA, 500 C Street, SW Washington, DC 20472, pp 207 – 266

Brookshire D S, Chang S E, Cochrane H, Olson R A, Rose A, Steerson J, 1997, "Direct and indirect economic losses from earthquake damage" *Earthquake Spectra* **13** 683 – 702

Chang S E, 1996, "Economic impact of lifeline disruption in the January 17, 1995 Hanshin-Awaji earthquake", in *Proceedings of the 11th World Conference on Earthquake Engineering* Acapulco, Mexico (Pergamon, Kidlington, Oxon)

Chang S E, 1998, "Direct economic impacts", chapter six in *Engineering and Socioeconomic Impacts of Earthquakes: An Analysis of Electricity Lifeline Disruptions in the New Madrid area, Buffalo, NY* Multidisciplinary Center for Earthquake Engineering Research, Red Jacket Quadrangle, State University of New York at Buffalo, Buffalo, NY 14261, Monograph 2, pp 602 – 611

Chang S E, Shinozuka M, Svekla W, 1999, "Modeling post-disaster urban lifeline restoration", in *Optimizing Post-earthquake Lifeline System Reliability: Proceedings of the Fifth US Conference on Lifeline Earthquake Engineering* ASCE Technical Council on Lifeline Earthquake Engineering Monograph 16, pp 602 – 611

Chang S E, Rose A, Shinozuka M, Svekla W D, Tierney K J, 2000a, "Modeling earthquake impact on urban lifeline systems: advances and integration", in *Research Progress and Accomplishments 1999 – 2000* Multidisciplinary Center for Earthquake Engineering Research, Red Jacket Quadrangle, State University of New York at Buffalo, Buffalo, NY 14261, pp 1 – 14

Chang S E, Shinozuka M, Moore J E II, 2000b, "Probabilistic earthquake scenarios: extending risk analysis methodologies to spatially distributed systems" *Earthquake Spectra* **16** 557 – 572

Cho S, Gordon P, Moore J E II, Richardson H W, Shinozuka M, Chang S E, 2001, "Integrating transportation network and regional economic models to estimate the costs of a large urban earthquake" *Journal of Regional Science* **41** 39 – 65

Cochrane H C, 1997, "Forecasting the economic impact of a Midwest earthquake", in *Economic Consequences of Earthquakes: Preparing for the Unexpected* Ed. B G Jones, National Center for Earthquake Engineering Research, Red Jacket Quadrangle, State University of New York at Buffalo, Buffalo, NY 14261, pp 223 – 248

Cochrane H C, Haas J E, Kates R W, 1974, "Social science perspectives on the coming San Francisco earthquake—economic impact, prediction, and reconstruction", WP 25 Natural Hazard, Institute of Behavioral Sciences, University of Colorado at Boulder, Boulder, CO 80309-0482

Ellson R W, Milliman J W, Roberts R B, 1984, "Measuring the regional economic effects of earthquakes and earthquake predictions" *Journal of Regional Science* **24** 559 – 579

Gordon P, Richardson H W, 1992, "Business interruption effects of a major earthquake in the Newport/Inglewood fault zone (NIFZ)", University of Southern California, School of Urban and Regional Planning; copy available from P Gordon, School of Policy, Planning and Development, University of Southern California, Lewis Hall 312, Los Angeles, CA 90089-0626

Gordon P, Richardson H W, Davis B, 1998, "Transport-related impacts of the Northridge earthquake" *Journal of Transportation and Statistics* **1** 21 – 36

Hewings G J D, Mahidhara R, 1996, "Economic impacts: lost income, ripple effects, and recovery", in *The Great Flood of 1993: Causes, Impacts, and Responses* Ed. S A Changnon (Westview Press, Boulder, CO) pp 205 – 217

Hwang H H M, Lin H, Shinozuka M, 1998, "Seismic performance assessment of water delivery systems" *Journal of Infrastructure Systems* **4** 118 – 125

Johnston A C, Nava S J, 1985, "Recurrence rates and probability estimates for the New Madrid Seismic Zone" *Journal of Geophysical Research* **90** No. B7

Kawashima K, Kanoh T, 1990, "Evaluation of indirect economic effects caused by the 1983 Nihonkai-chubu, Japan, earthquake" *Earthquake Spectra* **6** 739 – 756

Okuyama Y, Hewings G, Sonis M, 2000, "The sequential interindustry model and its application to impact analysis", paper presented at the 47th North American Meetings of the Regional Science Association International, Chicago, IL; copy available from Y Okuyama, Department of Architecture and Planning, State University of New York at Buffalo, Hayes Hall, South Campus, Buffalo, NY 14214-3087

Platt R H, 1999, "Natural hazards of the San Francisco Bay mega-city: trial by earthquake, wind, and fire", chapter 10, in *Crucibles of Hazard: Mega-Cities and Disasters in Transition* Ed. J K Mitchell (United Nations University Press, Tokyo) pp 335 – 374

Rose A, Guha G, 1999, "Regional computable general equilibrium modeling of earthquakes", paper presented at the 46th North American Meetings of the Regional Science Association International, Montreal, Quebec; copy available from A Rose, Department of Energy, Environmental and Mineral Economics, The Pennsylvania State University, 2217 Earth and Engineering Sciences, University Park, PA 16802

Rose A, Lim D, 2000, "Natural hazard loss estimation: an empirical overview and illustration"; copy available from A Rose, Department of Energy, Environmental and Mineral Economics, The Pennsylvania State University, University Park, PA 16082-5010

Rose A, Benavides J, Chang S E, Szczesniak P, Lim D, 1997, "The regional economic impact of an earthquake: direct and indirect effects of electricity lifeline disruptions" *Journal of Regional Science* **37** 437 – 458

Shinozuka M, 1994, "GIS applications in lifeline earthquake engineering", in *Proceedings of the Second China – Japan – US Trilateral Symposium on Lifeline Earthquake Engineering* Xi'an, China, pp 223 – 230, copy available from the author

Shinozuka M, Chang S E, Eguchi R T, Abrams D P, Hwang H H M, Rose A, 1997, "Advances in earthquake loss estimation and application to Memphis, Tennessee" *Earthquake Spectra* **13** 739 – 758

Shinozuka M, Rose A, Eguchi R T (Eds), 1998 *Engineering and Socioeconomic Impact of Earthquakes: An Analysis of Electricity Lifeline Disruptions in the New Madrid Area* Monograph 2, Multidisciplinary Center for Earthquake Engineering Research, Red Jacket Quadrangle, State University of New York at Buffalo, Buffalo, NY 14261

Sohn J, Hewings G, Kim T J, Jang S, Lee J S, 2000, "Benefit – cost of retrofit for transportation networks", paper presented at the 47th North American Meetings of the Regional Science Association International, Chicago, IL; copy available from T J Kim, Department of Urban and Regional Planning, University of Illinois at Urbana-Champaign, 111 Temple Buell Hall, 611 Taft Drive, Champaign, IL 61820

Tierney K J, 1997, "Business impacts of the Northridge earthquake" *Journal of Contingencies and Crisis Management* **5** 87 – 97

Tierney K J, Dahlhamer J M, 1998a, "Business disruption, preparedness, and recovery: lessons from the Northridge earthquake", in *Proceedings of the NEHRP Conference and Workshop on Research on the Northridge, California Earthquake of January 17, 1994* volume IV, California Universities for Research in Earthquake Engineering, Richmond, California, pp 87 – 97

Tierney K J, Dahlhamer J M, 1998b, "Earthquake vulnerability and emergency preparedness among businesses", chapter 5 in *Engineering and Socioeconomic Impacts of Earthquakes* Eds M Shinozuka, A Rose, R T Eguchi, Monograph No 2, Multidisciplinary Center for Earthquake Engineering Research, Red Jacket Quadrangle, State University of New York at Buffalo, Buffalo, NY 14261, pp 53 – 74

Wu Y, Olshansky R, 2000, "HAZUS-based earthquake damage analysis in Carbondale, Illinois", paper presented at the 47th North American Meetings of the Regional Science Association International, Chicago, IL; copy available from R Olshansky, Department of Urban and Regional Planning, University of Illinois at Urbana-Champaign, 111 Temple Buell Hall, 611 Taft Drive, Champaign, IL 61820