

## Research Article

**Assessing vulnerability to earthquake hazards through spatial multicriteria analysis of urban areas**

TAREK RASHED and JOHN WEEKS

Department of Geography, San Diego State University, San Diego,  
CA 92182-4493, USA  
e-mail: TRashed@mail.sdsu.edu and john.weeks@sdsu.edu*(Received 29 April 2002; accepted 29 October 2002)*

**Abstract.** Assessing urban vulnerability to natural hazards such as earthquakes can be regarded as an ill-structured problem (i.e. a problem for which there is no unique, identifiable, objectively optimal solution). A review of the literature indicates a number of contrasting definitions of what vulnerability means, as well as numerous conflicting perspectives on what should or should not be included within the broad assessment of vulnerability in cities. This paper reports on the findings from a project in which a GIS methodology has been developed to assess urban vulnerability through a spatial analytical procedure. First, we highlight the deficiencies of current GIS approaches to urban vulnerability analysis and discuss the ill-structured nature of the vulnerability problem. We then propose a working definition for vulnerability assessment in which vulnerability is thought of as a spatial decision problem under the conditions of uncertainty. Next, we present a methodology to incorporate this definition into a GIS framework that combines elements from the techniques of spatial multicriteria analysis and fuzzy logic. The application of this methodology is then illustrated with a case study from Los Angeles County. The results suggest that the proposed methodology may provide a new approach for analysing vulnerability that can add to our understanding of human/hazards interaction.

**1. Introduction**

Urban vulnerability to natural hazards such as earthquakes is a function of human behavior. It describes the degree to which socioeconomic systems and physical assets in urban areas are either susceptible or resilient to the impact of natural hazards. Over the past two decades, vulnerability has come to represent an essential concept in hazards research and in the development of mitigation strategies at the local, national, and international levels (White and Haas 1975, Hewitt 1997, Mileti 1999, Alexander 2000). Several models of urban vulnerability have been proposed to address the various ways by which society becomes subject to hazard impacts (Burton *et al.* 1978, Mitchell *et al.* 1989, Cutter 1996, Menoni and Pergalani 1996, Menoni 2001). The concept of human/nature interaction is firmly entrenched at the heart of these models representing natural hazards as dynamic phenomena that involve people not only as victims but also as contributors and modifiers (Kates

1996). Because this interaction exhibits strong spatial components, urban vulnerability is an inherently spatial problem since it almost always deals with communities within a defined urban space.

The value of GIS in supporting urban vulnerability analysis arises directly from the benefit of integrating a technology designed to support spatial decision making into a field with a strong need to address numerous critical spatial decisions (Cova 1999). For this reason, there has been a growing interest in applying GIS and spatial analytical models to vulnerability and risk analyses. This is evidenced by an increasing number of published articles on this topic (Emmi and Horton 1993, Rejeski 1993, Mejia-Navarro *et al.* 1994, Stein *et al.* 1995, Cova and Church 1997, Kehelt 1997; Kappos *et al.* 1998, FEMA-NIBS 1999, Menoni *et al.* 1999, Cutter *et al.* 2000, Radke *et al.* 2000). Nevertheless, the current state of GIS use in vulnerability analysis has been criticized for numerous theoretical and technological shortcomings that prohibit optimal vulnerability assessments, thus affecting any subsequent mitigation strategies (Rejeski 1993, Coppock 1995, NRC 1998, Cova 1999, Radke *et al.* 2000).

Coppock (1995) attributes the limitations of current GIS models to: (a) deficiencies of widely-available commercial GIS software in modeling socioeconomic data that represent the infrastructure of any vulnerability assessment procedure; (b) lack of large volumes of appropriate data typically required in vulnerability analysis; (c) inability to meet the needs of intended users adequately; and (d) lack of appropriate methods that are based on a sound understanding of the phenomena under consideration. In this paper, we focus our discussion on the latter factor concerning the lack of appropriate methods. We assert that this factor is the most critical one, since addressing other limitations depends in essence on the development of reliable assessment models that allow planners and decision makers to focus on the more vulnerable communities in their midst, and thus to help develop measures that could prevent natural hazards from becoming major human disasters.

One of the major deficiencies in current GIS approaches to vulnerability analysis is that many models apply deductive, well-structured problem-solving methodologies to the inherently ill-structured problem of vulnerability. Methodologies for solving well-structured problems typically assume a convergent solution (i.e. a single, known solution) for the problem under investigation and engage the application of a limited number of rules and principles with well-defined parameters (Sinnott 1989, Voss and Means 1989, Jonassen 1997). The implications of this type of problem-solving methodology for urban vulnerability analysis are limited because many concepts, rules, and principles associated with vulnerability in cities are not sufficiently certain, nor are all the elements and processes contributing to it acknowledged or articulated.

The Community Vulnerability Assessment Tool developed by the Coastal Services Center of the National Oceanic and Atmospheric Administration (NOAA) in the USA is an illustrative example in this regard (NOAA 1999). If one is to follow the GIS procedure suggested by NOAA to assess vulnerability, then one would first have to delineate intensity zones for each potential hazard followed by several overlay operations in order to create a composite layer of all hazards. Once this layer is created, 'vulnerability assessment' of various elements (e.g. houses, critical facilities, industry sectors, etc) can be conducted simply by overlaying the composite layer of hazards with layers that represent the spatial distribution of each element. Elements located in multi- or higher-intensity-hazard zones will be considered more vulnerable than those located in single- or low-intensity-hazard zones.

Here is where the problem arises: while the resultant GIS layer is supposed to

represent a classification of the different areas under consideration according to their degree of vulnerability (i.e. their coping ability), what it actually represents is a classification of these areas in terms of their degrees of risk (i.e. their potential losses from the hazards). Hence, the NOAA approach mixes the two notions of vulnerability and risk (a distinction between the two is given in the next section). More importantly, it does not explain the spatial variability of vulnerability—that is, why two urban communities located in the same hazard zone often experience varying degrees of loss as evidenced by past disaster experiences. One possible way to explain the spatial variability of vulnerability is to assume a causal linkage between socio-economic or demographic characteristics and various degrees of hazards according to a specific social theory. However, this imposes another dilemma because various social theories are a matter of controversy. Wisner (1993, p. 127) states that ‘while there is a strong correlation between income and access to resources ... the straight forward identification of “the poor” as vulnerable does not help planners formulate short and medium term plans’. In addition, vulnerability analysts, when working in new regions, typically lack sufficient knowledge of the degree to which the spatial variability of vulnerability corresponds to variations in societal and biophysical factors. Consequently, they find themselves faced with either one of two options. The first is to base their assessment on damage estimates from previous disasters which are often not reliable enough to capture the differential patterns of vulnerability (Emmi and Horton 1993). The second option is to treat the social and biophysical indicators as having equal weights in their contribution to the overall vulnerability of the urban place (Cutter *et al.* 2000). Clearly, both options have drawbacks.

Given these problematic issues, it is obvious that the deductive, well-structured problem-solving methodologies are inadequate when it comes to the analysis of urban vulnerability. Instead, there is a need for alternative approaches specifically designed to address the ill-structured nature of vulnerability. As is discussed in the following section, the vulnerability problem is ill-structured because there are multiple representations or understandings of vulnerability. Therefore, identifying an appropriate design structure for the assessment procedure from among the competing options is perhaps the most important part in the analysis of vulnerability. This design must recognize the divergent perspectives on urban vulnerability, and should allow us to collect evidence to support or reject the alternative hypotheses concerning the causal linkages between vulnerability, and the social and physical characteristics of urban places. In this paper, we argue that one of the useful alternatives to design a vulnerability assessment procedure is to adopt an inductive approach based on spatial multicriteria analysis. We have chosen earthquakes as a subject of this research not only because of their severe impacts on urban areas, but also because they have provided the basis for some of the fundamental physical, technological and social research in the field of natural hazards: work that has often been a model for studies of other hazardous natural agents (Alexander 1993).

We begin with a general background on several issues related to the ill-structured problem of urban vulnerability in order to provide a rationale for the methodology presented in the subsequent section. Then, we provide a working definition for the problem of urban vulnerability to earthquake hazards. Next, we present a GIS methodology for the analysis of urban vulnerability. We show the application of this methodology through a wall-to-wall exercise undertaken to classify census tracts in Los Angeles County in terms of their degree of vulnerability to earthquake hazards. We conclude with a discussion of several ways in which this methodology can be used to increase our understanding of vulnerability in urban areas.

## 2. Background

### 2.1. *The ill-structured problem of vulnerability*

Ill-structured problems can generally be defined as problems which possess multiple solutions and contain uncertainty about the concepts, rules, and principles involved to reach these solutions (Sinnott 1989, Voss and Means 1989). Therefore, such problems lack a single solution algorithm and in many cases experts may not agree regarding whether a particular solution is appropriate because it has various solutions and solution paths (Hong 1998). A review of vulnerability literature confirms that these criteria of ill-structured problems apply well to the question of vulnerability. For example, Cutter (1996: pp. 531–532) lists more than a dozen different definitions of vulnerability. Consequently, it is not surprising to find little consensus among researchers, planners, and disaster managers regarding the meanings of and approaches to undertaking vulnerability analysis (Wisner 1993). Likewise, many discrepancies are found when we examine the available models of vulnerability. On the one hand, there are socio-political theories that direct remarkably little treatment to the geographic space within which patterns of vulnerability are shaped (Quarantelli 1988, Dynes and Drabek 1994). On the other, there are more technically oriented models in which the social component is generally implicit and rarely incorporated (e.g. UN 1991, FEMA-NIBS 1999, NOAA 1999).

Among the suite of problems associated with the ill-structured nature of vulnerability analysis, perhaps the most important one is that vulnerability is often confused with the notion of risk. In fact, each of these two notions represents a distinct concept (Dow 1992, Cutter 1996). Vulnerability defines the inherent weakness in certain aspects of the urban environment which are susceptible to harm due to social, biophysical, or design characteristics, whereas risk indicates the degree of potential losses in urban places due to their exposure to hazards and can be thought of as a product of the probability of hazards occurrence and the degree of vulnerability (i.e.  $\text{risk} = \text{hazard} \times \text{vulnerability}$ ) (UN 1991). Accordingly, two communities located in hazard-prone areas with similar physical settings cannot be described as equal in risk if they differ in their vulnerabilities to the hazard in question—that is, if they differ in the adaptive and coping capacities that determine the extent to which a society can tolerate damage from extreme events without significant outside assistance (Mileti 1999).

Hence, vulnerability differs from the concept of risk in being independent from any particular magnitude of a specific natural event, but dependent on the context in which that event occurs. Such a context is manifested through a set of ecological factors that may or may not be related to the geophysical events of natural hazards, what Hewitt (1997) calls ‘the ecology of risk’. Examples of these factors include the awareness of hazards, the condition of human settlements and infrastructure, public policy and administration, the wealth of a given society and organized abilities in the field of disaster and risk management, as well as gender relations, economic patterns, and ethnic or racial stratification. Understanding the relative importance of these factors is vital to the establishment of impartial government policy and viable insurance schemes, and the identification of resources needed for emergency preparedness. However, many current models of vulnerability are essentially descriptive and too general to help in this regard (Cutter 1996). Consequently, decision makers are often obliged to limit their analysis of urban vulnerability to the technically narrow concept of risk that describes how an urban place is exposed to natural hazards, rather than how it could cope with their impacts.

In the present work, we do not limit the problem of urban vulnerability to a socially tempered response nor to a condition of potential exposure. Rather, vulnerability is thought of as a characteristic of the urban community that can be assessed through a combination of ecological factors associated with the physical conditions of the geographic space where the urban community is located (i.e. where you are), and the social conditions of the population in that place (i.e. who you are). We hypothesize that these physical and social conditions are so inextricably bound together in many disaster situations that we can use the former as indicative of the latter. The implication of this reasoning suggests a distinctly spatial approach to vulnerability analysis. Through this approach, areas with high levels of vulnerability (referred to hereafter as *hot spots*) are first located and differentiated from other areas within a defined urban region. Then, these differences are utilized to improve our understanding of the relative importance of the ecological factors. Urban vulnerability analysis is thus conceived of as a spatial problem that involves searching the urban space for evidence of hot spots of vulnerability on the basis of multiple and differentially weighted evaluation criteria. Such a spatial perspective is substantially aided by the adoption of a GIS-based spatial multicriteria analytical approach to tackle the ill-structured problem of vulnerability analysis.

## 2.2. *Vulnerability as spatial search problem*

In the present work, we attempt to address the ill-structured nature of vulnerability by proposing a methodology based on the techniques of spatial multicriteria analysis and fuzzy logic. The critical aspect in the development of this methodology is its ability to incorporate the divergent views of urban vulnerability. A potentially effective way for starting this task is to find a minimal meaningful argument that experts in the field may agree upon, and use it as a foundation for the proposed methodology. In the case of earthquake hazards, there are at least three basic points that different views of vulnerability would agree upon (Palm and Hodgson 1992, Alexander and Smith 1993, Wisner 1993, Cutter 1994, Mejia-Navarro *et al.* 1994, White 1994, SSC 1995, Hewitt 1997, Kagan 1997, Bolin and Stanford 1998, Wisner 1998, Cutter *et al.* 2000).

The first point is that although a particular earthquake may initiate the damage process, its later course depends upon complex conditions in and around the impact zone that shape the chain of potential failures in the society (figure 1). This argument ensues from the observation that major losses in urban places do not necessarily result from the immediate impact of the ground shaking. Rather, they are more likely to arise due to other hazards induced by the earthquake (e.g. the severe damages of San Francisco in 1906 and of Tokyo in 1923 were mainly due to devastating fires produced as secondary consequences of the earthquakes). This interpretation of risks suggests that impacts from earthquakes are to be largely expected in those urban areas where the society and nature interrelations are unsustainable. From a spatial perspective, this means that the problem of vulnerability can be conceptualized as a problem of searching a particular geographical region for evidence of such unsustainable relationships.

The second point shared by different models of vulnerability is that vulnerability is continuously modified by human actions and therefore it varies over space and time. Thus, at any point of time, we cannot really state that there would be an urban place that is entirely safe from the earthquake impacts. Instead, forms and severity of damage vary remarkably among different areas and groups of people, and even

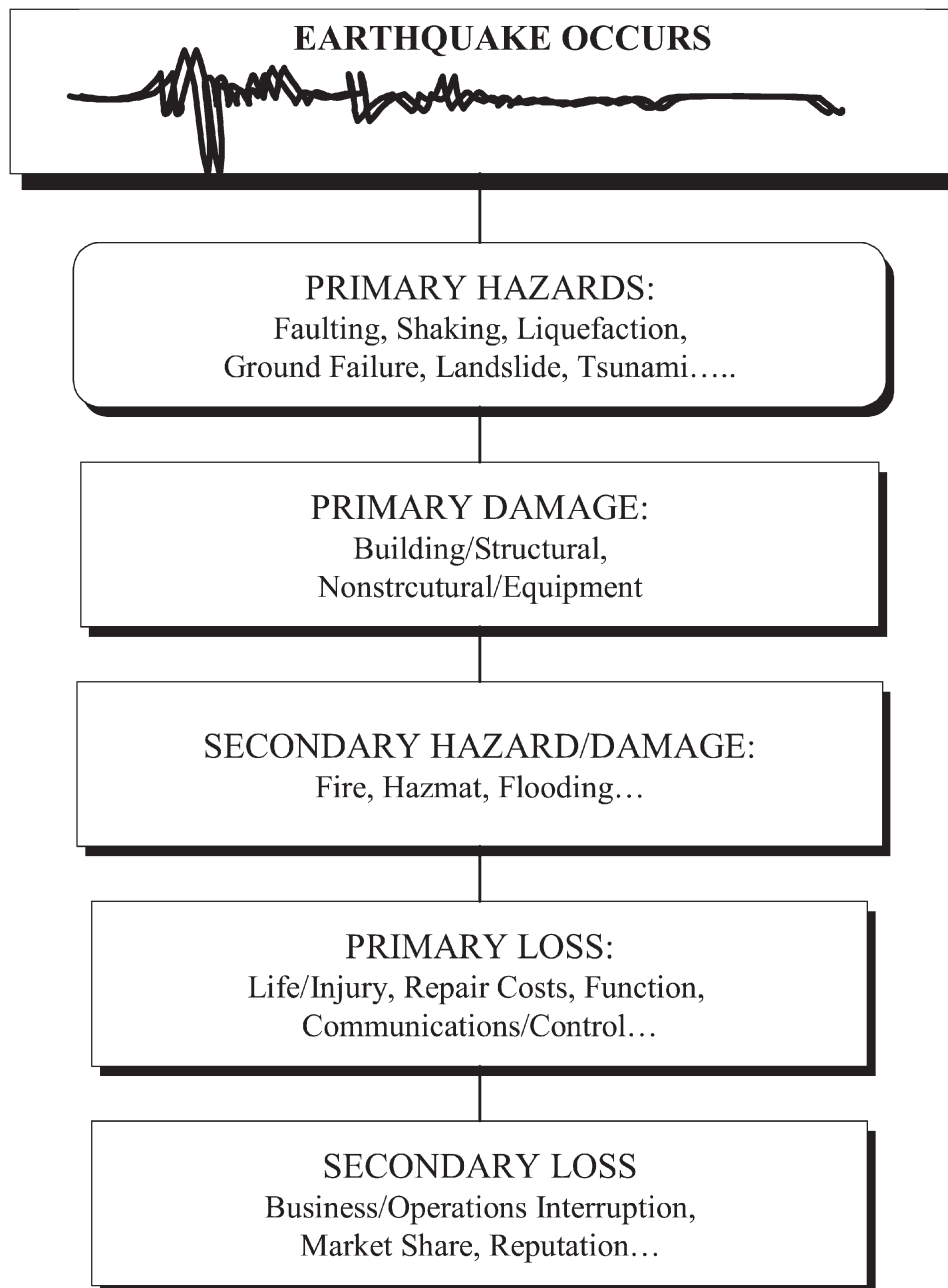


Figure 1. Earthquake risk-chain (source: (SSC 1999)).

within any local community (Hewitt 1997, Fitzpatrick and LaGory 2000). The implication of this point is that vulnerability of urban places cannot be assessed in absolute terms. Rather, the performance of the urban place should be assessed with reference to specific spatial and temporal scales. We cannot compare two places, A and B, if A represents a city and B represents a county (different spatial scales), and



the urban place, A, might be relatively more vulnerable than place B at one point of time, and less vulnerable at another point of time (different temporal scales).

Finally, different views of vulnerability do not discard the fact that knowledge of the geophysical properties of earthquakes is essential. Rather, they recognize that such knowledge is significant to the understanding of the differential patterns of urban vulnerability. Indeed, without an earthquake of such magnitude as the one that struck San Francisco in 1906, there would have been neither disaster, nor such consequences as the fire that caused 80% of the damage. Also, particular types of vulnerability can be related to, or brought about by, earthquakes (e.g. the liquefaction phenomenon) (Hewitt 1997). Thus, one cannot proceed in analyzing urban vulnerability to earthquake hazards without looking in detail at the earthquake phenomenon to understand how dangers arise at the interfaces of society and natural conditions. In doing so, however, we must be careful not to fall into what Wisner (1993: p. 128) described as ‘a dangerous lurking fallacy’ resulting from a misinterpretation of risk as vulnerability.

### 2.3. A formal definition of urban vulnerability

To put all the pieces together, we can restate a formal working definition of urban vulnerability to earthquake hazards as follows. Let  $\mathbf{S}$  be a geographical space under investigation (e.g. state, county or city) defined in terms of a finite set of  $m$  smaller spatial units (i.e. counties, census tracts or zip codes); that is  $\mathbf{S} = \{i | i = 1, 2, \dots, m\}$ . Let  $\mathbf{E}$  be a series of earthquake scenarios of different magnitudes originating from a finite set of  $n$  different epicenters such that the relationship between the epicenter and the magnitude is a one to one relationship; that is  $\mathbf{E} = \{j | j = 1, 2, \dots, n\}$ . Because of the spatial variability of hazard intensities and urban vulnerabilities, each earthquake scenario,  $j$ , will result in a potential damage state at the  $i$ th spatial unit (recall that risk = hazards  $\times$  vulnerability). Let various potential damage states resulting from each scenario be denoted by  $\mathbf{D}_j$  and expressed in three linguistic concepts; that is  $\mathbf{D}_j = \{d_j | d_j \in \{Low_j, Medium_j, High_j\}\}$ . The problem of vulnerability can then be stated as a spatial function that searches the geographic space  $\mathbf{S}$  for  $n$  number of times in order to identify the subset  $\mathbf{V}_{High} \subseteq \mathbf{S}$  which corresponds to areas with higher vulnerability (the hot spots) such that:

$$\mathbf{V}_{High} = \{i | High_j(i) > \alpha, i \in \mathbf{S}, j \in \mathbf{E}\} \quad (1)$$

where  $n$  is the number of scenarios (i.e.  $n = |\mathbf{E}|$ ) and  $\alpha$  is a certain threshold. At this point several things have to be emphasized.

First, the estimation of potential damage is surrounded by uncertainty because of the fuzziness or imprecision concerning the criteria or the factors according to which the potential damage is estimated. Although conventional Bayesian probabilities use some form of confidence factors to represent uncertainty, these approaches assign uncertainty values outside the model itself. Fuzzy logic, on the other hand, represents uncertainty and imprecision as an intrinsic part of the model, thus providing a more consistent and more mathematically sound method of handling uncertainties (for further discussion, see Cox 1999, pp. 45–65). In addition, the use of fuzzy logic for representing potential damage estimates is more appropriate than the use of Boolean logic, because the latter assumes that these estimates are certainly true. A fuzzy set differs from a Boolean or crisp set by allowing gradual memberships of damage estimates (Zadeh 1975). This gradient, which is not a probability measure

but an admitted possibility, corresponds to the degree to which an estimate is compatible with the imprecise concept of risk.

Second, in the language of fuzzy logic, the state of damage is also a fuzzy set produced by applying a 'hedge' that modifies the surface characteristic of the damage fuzzy set according to a linguistic concept (i.e. low, medium, or high). These hedged fuzzy sets represent the degree of risk, but not vulnerability, and are relative to the earthquake scenario that produces the estimates of damage. That means if an area is assigned to a membership degree of 0.30 and 0.40 in two hedged fuzzy sets  $High_{j1}$  and  $High_{j2}$  created from two earthquake scenarios  $j1$  and  $j2$  respectively, then we cannot say that the damage estimate for this area from  $j1$  is less than or greater than the damage estimate from  $j2$ .

Finally, the threshold,  $\alpha$ , in equation (1) represents the minimum degree of membership that an area can have in the fuzzy set, 'High', produced from any single scenario to be considered in the evaluation of vulnerability. For example, if  $\alpha=0.75$ . This means that the hot spots of vulnerability are those areas that maintain a degree of membership higher than 0.75 in all of the 'High' fuzzy sets generated from all the scenarios. Maintaining such a degree of membership means that these areas suffer from higher potential damage estimates regardless of the earthquake magnitude or the epicenter location. Therefore, these potential losses can be attributed directly to the higher vulnerability of these places. In the next section, we discuss how our working definition of vulnerability can be translated into a GIS analytical procedure. We then use a case study example for Los Angeles County in the following section to illustrate the application of this procedure.

### 3. Methods

#### 3.1. Approach

The spatial multicriteria analysis approach to urban vulnerability can be thought of as a process that combines and transforms spatially referenced data (input) into a resultant vulnerability score (output). As shown in figure 2, the proposed process is iterative and combines elements from the techniques of multicriteria evaluation (Malczewski 1999, Thill 1999) and fuzzy systems analysis (Leung 1997, Openshaw and Openshaw 1997, Jiang and Eastman 2000). The combination of these two techniques is very useful as it helps us address the ill-structured problem of vulnerability through a set of steps in which vulnerability is treated as a spatial decision problem under conditions of uncertainty.

The proposed process involves seven main stages. The first stage is the selection of evaluation criteria or measures that determine the scope of the analysis. The second stage is the simulation of earthquake hazards through which one can explore the possible effects of earthquakes on a particular region according to multiple deterministic and probabilistic scenarios. In the case of probabilistic simulations, the ground motion of the earthquake is statistically calculated according to the probability that an event of a given intensity will be exceeded in a given period of time. In the case of deterministic simulations, the ground motion is calculated from a hypothetical or historical source with a given strength thus excluding the spatially random effects of hazards. In the third stage, loss estimates created from each scenario run in stage two are transformed into comparable units through a 'fuzzification' process. Fuzzification is a process for standardizing the evaluation criteria through recasting values into statements about set membership using the linguistic terms identified in the first stage (Malczewski 1999). In the fourth stage, the fuzzified criteria are



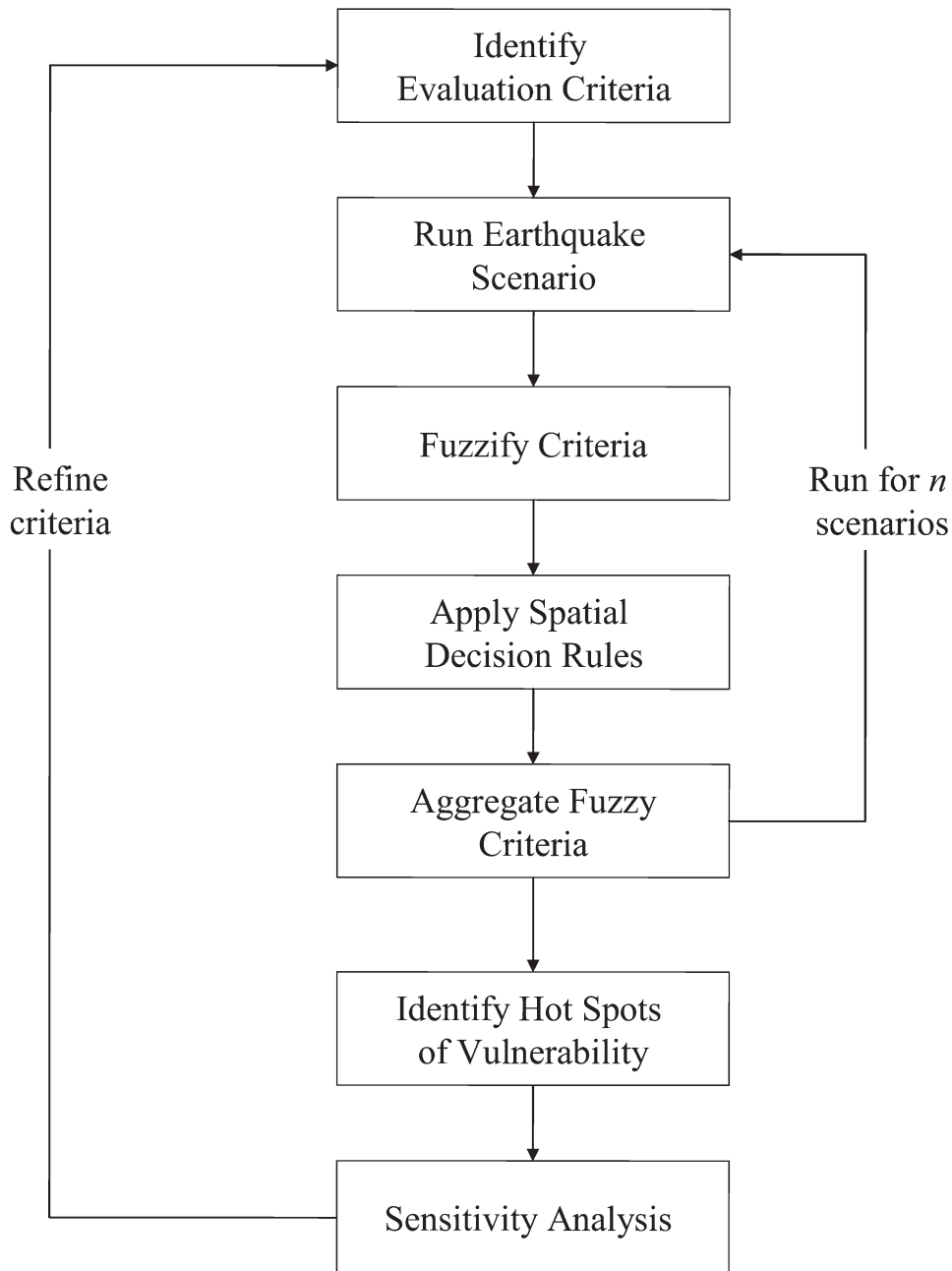


Figure 2. Framework for the study.

compared pairwise using the analytical hierarchy process (AHP) developed by Saaty (1980) in order to generate a set of fuzzy weights for the evaluation criteria. In the fifth stage, the criteria are aggregated into a one-dimensional array of rules based on a fuzzy additive weighting method. These rules are then used to calculate the membership degree of each census tract in hedged fuzzy sets representing the linguistic

expressions of the damage states (i.e. lower-risk, medium-risk, and higher-risk). Stages three to five are repeated for the rest of the scenarios. In the sixth stage, the ‘higher-risk’ fuzzy layers produced from the scenarios are used to locate hot spots of urban vulnerability based on the working definition of vulnerability introduced earlier. In the final stage, sensitivity analysis is conducted to determine the effects of simulation parameters on the final output.

### 3.2. Identify evaluation criteria

The first stage of the proposed methodology is to select a set of evaluation criteria that provides a basis for comparing the results of the earthquake simulation. In fact, this is the most critical part in the overall approach because we need to make sure that the selected criteria are sufficient to reflect the overall risk of urban areas in each scenario as a compound function of vulnerability and earthquake hazards. It is also the most time-consuming part of the methodology because it involves the collection and preparation of the data that will serve as input to the earthquake scenarios.

A good logical basis for selecting the evaluation criteria is to follow Malczewski’s (1999: pp. 107–108) recommendation that a criterion is considered good if it is: (1) comprehensive (i.e. clearly indicates the achievement of the associated objective) and (2) measurable (i.e. lends itself to a quantification/measurement). This implies that we must be able to express in linguistic terms the kind of estimates required from the simulation and to establish a measurement scale for each estimate. Likewise, a set of criteria is good if it is: (1) complete (i.e. covers all aspects of a decision problem); (2) operational (i.e. is meaningful to a decision situation); (3) decomposable (i.e. is amenable to partitioning into subsets of criteria, which may be necessary to facilitate a hierarchical approach to decision analysis); (4) non-redundant (i.e. avoids the double-counting of decision consequences); and (5) minimal (i.e. has the property of the smallest complete set of criteria characterizing the consequences of a decision).

In the present work, we suggest nine criteria upon which we base the vulnerability assessment. Our selection of these criteria has been based on the framework of ‘systemic’ vulnerability developed by Menoni and Pergalani (1996). This framework is centred on the enduring significance of the urban place as a medium in which vulnerability conditions influencing risks and damage losses are expressed, and on cities as being a dominant factor in shaping patterns of social and biophysical vulnerability (Menoni *et al.* 1999, Menoni *et al.* 2000). Hence, it helps establish a comprehensive reference against which the divergent perspectives on what contributes to vulnerability in urban places can be evaluated. Menoni and Pergalani’s (1996) framework adopts a systems-thinking approach and attempts to explain how vulnerability patterns arise from adverse interactions between and among the components of the urban system and how such patterns influence the overall risk within the urban place. Moreover, it takes into account the ‘chain of failures’ that might occur due to earthquake-induced hazards (e.g. landslides or fires). Our suggested evaluation set includes nine criteria organized under the following three categories:

- A. *Criteria for social risks*; these include: (1) percentage of households that might seek temporary shelter after an earthquake (a proxy for short-term social losses), and (2) total economic cost required for the replacement, reconstruction, and recovery of residential buildings (a proxy for long-term social losses).
- B. *Criteria for physical induced risk*; these include: (3) area of land that might be

burned due to induced fire, and (4) amount of debris measured in thousand tons.

- C. *Criteria for systemic vulnerability* which may influence the emergency response and management activities following the earthquake; these include percentage of loss in functionality for (5) hospitals, (6) fire and police services, (7) power utilities, (8) highways, and (9) bridges.

In choosing these criteria, we attempted to cover all aspects of possible risks while trying as much as possible to avoid the redundancy of measures. For example, most of the above estimates can be calculated as a function of ground failures. Therefore, we do not include a measure of liquefaction risks. Similarly, the demand on shelter can be calculated as a function of casualties, which in turn can be estimated as a function of building collapse. Therefore, neither casualties nor building collapse are chosen as criteria.

### 3.3. *Run earthquake scenarios*

As mentioned above, our conceptual approach to select evaluation criteria has been derived in part from the framework of 'systemic' vulnerability developed by Menoni and Pergalani (1996). However, Menoni and her colleagues have not yet developed an algorithm for the quantification of the variables in their framework and so we examined existing models to see which could be best adopted to generate damage estimates that represent these criteria. Several loss estimation models are available as candidates to serve this purpose and many of them use GIS software and scientifically developed algorithms to calculate, map, and display damage and loss estimates according to particular scenarios. Examples of these models include: HAZUS (HAZARDS in the US—<http://www.fema.gov/hazus/>), RADIUS (Risk Assessment tools for DIagnosis of Urban Areas against Seismic disasters—<http://www.geohaz.org/radius/>), EPEDAT (Early Post-Earthquake Damage Assessment Tool—<http://www.eqe.com/>), ROAD-1 Seismic Analysis Software (<http://mceer.buffalo.edu/research/HighwayPrj/>), and RiskLink-DLM (Detailed Loss Module—<http://www.rms.com/>). These models vary in their capabilities and scope of the analysis, and some of them are public domain software while others are commercial packages.

We chose to use HAZUS in the case study example of Los Angeles County presented in the following section for two reasons. First, it utilizes methods that have been tested by the State of California Office of Emergency Services and calibrated with data from earthquakes that occurred in sites located within our study area (FEMA-NIBS 1999). Second, HAZUS can generate loss estimates at the census tract level and this is very important to us because after we establish the basic model for our evaluation of vulnerability in this paper, the next phase of our research we will be incorporating census data into that model. Nevertheless, we believe that the proposed methodology can be replicated using other loss estimation software packages indicated above, especially if the analysis is to be conducted in places outside the North American continent.

The US government has spent over \$5 million in the development of HAZUS, designed to be used at the local, regional and state levels for estimating casualties and losses from earthquakes (FEMA-NIBS 1999). HAZUS is capable of using two separate geographic information systems (MapInfo and ArcView) to map and display the earthquake simulation results. HAZUS is essentially a 'risk' assessment tool that

generates an estimate of the consequences to a city or region of either a deterministic or probabilistic scenario earthquake (Whitman and Lagorio 1998). The resulting loss estimate generally describes the scale and extent of damage and disruption that may result from potential earthquakes. HAZUS methods have been pilot tested in Portland, Oregon and Boston, Massachusetts and calibrated with data from Northridge, Loma Prieta and other earthquakes (FEMA-NIBS 1999). While a review of these methods is beyond the scope of this paper (for a detailed discussion see HAZUS's technical manuals: FEMA-NIBS 1999), the following summarizes the main steps of using HAZUS in a simplified form:

1. Select an area of interest.
2. Specify either a probabilistic or deterministic earthquake scenario.
3. Add information delineating local soil and geological conditions. The maps for the intensity of ground shaking and the probability of permanent ground displacement are then generated by the software.
4. Use formulas embedded in the software to compute the probability distributions for damage to different classes of buildings, facilities, and lifeline system components.
5. Estimate number of ignitions and the extent of fire spread are generated with a special software subprogram.
6. Compute the expected direct economic and social losses. The latter includes estimates of casualties and shelter demand of displaced households.
7. Use the direct economic impacts on various segments of the economy as input to a user-specified model that estimates the impact on the overall regional economy.

Although HAZUS offers an opportunity to prepare comprehensive loss estimates, it should be recognized that, even with state-of-the-art techniques, uncertainties are inherent in any such damage estimations. For example, faulting, ground motions and land sliding generated by HAZUS may not occur precisely as the model anticipates (Whitman and Lagorio 1998). Therefore, results from HAZUS should obviously not be looked upon as a prediction, but rather as an indication of what the future might hold or to perform exploratory studies such as the one presented herein.

In the case study example we present later in this paper, five simulations of earthquake scenarios were run to produce damage estimates in Los Angeles County. Four of these were based on historical events that occurred in the region, ranging in magnitude from M6.1 to M7.7, while the fifth was a probabilistic simulation for a 500-year return-period earthquake of M6.5. The selection of these events was based on FEMA's guidelines (FEMA-NIBS 1999) and met our goal of determining the possible effects of earthquakes with moderate magnitude similar to the 1994 Northridge event.

#### 3.4. *Fuzzify criteria*

Because the evaluation criteria are represented by different measurement scales, they need to be standardized into a common scale. Besides the fuzzy approach, several other methods can be used for this standardization such as linear scale transformation, value/utility functions, probabilities, and revised probabilities (Malczewski 1999). We suggest the use of the fuzzy approach because of the inherent uncertainty of the damage estimates discussed earlier. In addition, fuzzy logic offers a broader family of set membership functions than other methods of standardization

(e.g. Burrough 1989, Jiang and Eastman 2000, Zeng and Zhou 2001). Finally, fuzzy models can handle linguistic, non-numeric descriptions thus offering a powerful way to resemble human reasoning in its use of approximate information and uncertainty to generate decisions.

The fuzzification of the evaluation criteria involves two steps. The first is to translate the risk concepts represented by these criteria into fuzzy sets using specific set membership function. In our case study example, we used the sigmoidal (or S-curve) membership functions that, besides being simple, are very effective in modeling continuous, nonlinear phenomena (Cox 1999). Two examples of the fuzzification process are given in figure 3. In figure 3(a), the concept of ‘amount of debris’ is represented by a ‘growth’ S-curve implying an increase in the urban risk associated with the increase in the amount of debris resulting from the collapse of buildings. In figure 3(b) the concept of ‘functionality of hospitals’ is represented by a ‘decline’ S-curve implying an increase in the urban risk associated with the loss beds in hospitals. As shown in the two figures, each S-curve is defined using three parameters: (1) a zero membership value ( $\alpha$ ) (e.g. zero tons of debris, 100% functional hospitals); (2) a complete membership value ( $\gamma$ ) (e.g. the maximum amount of debris produced from a particular earthquake simulation, 0% functional hospitals); and (3) an inflection point ( $\beta$ ) which indicates at which domain value the membership degree is 0.5 (e.g. when functionality of hospitals is 50%). The value of the curve for any domain point  $x$  is given by the following equation (Cox 1999):

$$S(x; \alpha, \beta, \gamma) = \begin{cases} 0 & \rightarrow x \leq \alpha \\ 2((x-\alpha)/(\gamma-\alpha))^2 & \rightarrow \alpha \leq x \leq \beta \\ 1 - 2((x-\gamma)/(\gamma-\alpha))^2 & \rightarrow \beta \leq x \leq \gamma \\ 1 & \rightarrow x \leq \gamma \end{cases} \quad (2)$$

The second step in the fuzzification process is to apply linguistic ‘hedges’ to these fuzzified concepts to transform them into new fuzzy sets that describe the various degrees of damage (i.e. low, medium, high) estimated for a particular criterion. In fuzzy logic, hedges represent linguistic constructs that change the surface shape of

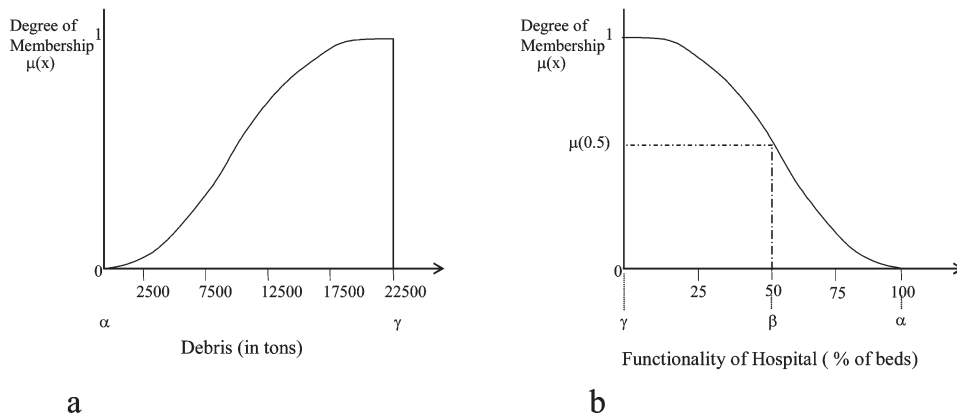


Figure 3 Examples of fuzzy concepts of damage estimates: (a) a growth S-curve representing the increase in risk associated with the increase in amount of debris (b) a decline S-curve representing the increase in risk associated with loss of hospital functionality.

fuzzy sets in the same way that adjectives change the meaning of an English sentence (Zadeh 1975). The example in figure 4 shows three new fuzzy sets produced from applying three different hedges to the 'amount of debris' fuzzy set. The 'high' fuzzy set of debris is produced through the standard Zadeh 'very' according to the following equation:

$$\mu_{very A}[x] = \mu_{very A \times A}[x] \quad (3)$$

As shown figure 4, this hedge depresses the surface of the fuzzy set so that an element from the domain that had  $x$  degree of truth in the original fuzzy set, now has square  $x$  degree of truth in the hedged fuzzy set. This means that the membership degrees for values in the original set are reduced in the hedged fuzzy set except at the set extremes, thus indicating domain values that have higher estimates of debris. Similarly, the 'medium' fuzzy set of debris was produced through approximating the average estimates of debris using a scalar approximation hedge called 'around' to result in a bell-shaped fuzzy region that represents medium estimates of debris. Finally, the 'low' fuzzy set that represents lower estimates of debris was produced by negating the 'high' fuzzy set produced earlier. In fuzzy logic, the negation of a fuzzy set is produced by inverting the truth function along each point of the fuzzy set according to the following transformation operation:

$$\sim \mu_A[x] = 1 - \mu_A[x] \quad (4)$$

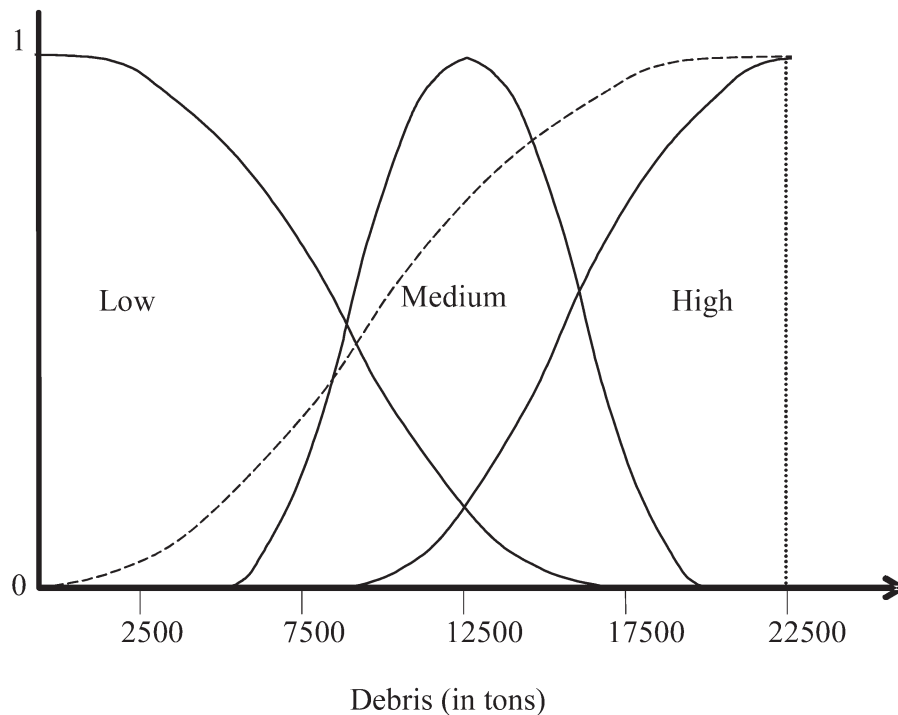


Figure 4. Low, Medium, and High fuzzy sets produced from applying three different hedges to the 'amount of debris' fuzzy set. The original fuzzy set is represented by the dashed line.



### 3.5. Apply spatial decision rules

Having created fuzzified maps for the evaluation criteria, the next task is to apply decision spatial rules based on these criteria to identify areas with higher and lower risks produced for each scenario. To do so, we need to establish the relative importance of each criterion in terms of a weight that determines its contribution to the overall risk. One of the widely adopted techniques is the analytic hierarchy process (AHP) developed by Saaty (1980), and currently implemented in the IDRISI GIS software package. The AHP approach allows one to assess the relative weight of multiple criteria in an intuitive manner. The fundamental input to the AHP is the decision maker's answers to a series of questions of the general form: 'How important is criterion A relative to criterion B?'. These are termed pairwise comparisons. Responses are gathered in verbal form and subsequently codified on a nine-point intensity scale (table 1). In the case study example of this paper, the decisions concerning the preferences were guided by the concept of chain of failures triggered by earthquakes (Menoni and Pergalani 1996). Saaty's basic method to identify the value of the weights depends on matrix algebra and calculates the weights as the elements in the eigenvector associated with the maximum eigenvalue of the matrix. Final results will include the weight of each criterion in addition to a measure of inconsistency which informs us whether or not the preferences assignment needs to be revised.

### 3.6. Aggregate fuzzy criteria

The purpose of this task is to aggregate the fuzzy criteria and their weights in additive fashion in order to identify areas with higher damage estimates in each scenario. Table 2 shows an example of criterion weights and rules used in one of the scenarios in our case study example. In this table, the goal is to maximize losses from the earthquake scenario. To do so, we want to minimize the functionality of systemic measures while maximizing values of social risks and induced hazards.

Table 1. The AHP pairwise comparison continuous rating scale.

Less important				More important				
Extremely	Very strongly	Strongly	Moderately	Equally important	Moderately	Strongly	Very strongly	Extremely
1/9	1/7	1/5	1/3	1	3	5	7	9

Table 2. An example of weights produced by the AHP. The criteria were used to produce a higher-risk fuzzy set from one of the earthquake scenarios.

Minimize functionality of bridges:	0.0388
Minimize functionality of emergency services:	0.0609
Minimize functionality of hospitals:	0.0609
Minimize functionality of power utilities:	0.0381
Minimize functionality of highways:	0.1288
Maximize costs for recover of buildings:	0.3829
Maximize demand on shelter:	0.2403
Maximize amount of debris:	0.0247
Maximize percentage of burned area:	0.0247
Consistency ratio = 0.03	

Therefore, only two damage states, 'low' and 'high', are used to generate fuzzified maps for these criteria. By applying the weights, an index of 'higher-risk' is generated for geographic units within the study area (census tracts in this example) from each scenario. Those units that are assigned to higher degrees of membership across all fuzzified criteria represented places with higher degrees of risk in that index.

### 3.7. Identifying hot spots of vulnerability

After creating the indices of higher-risk from all the scenarios, the final task is to derive the final fuzzy set that represents higher-vulnerability, thus applying the working definition introduced in equation (1) to delineate the hot spots of vulnerability according to a specific  $\alpha$ . We have investigated two possible ways of inferring the higher-vulnerability fuzzy set from the aggregation of higher-risk indices.

The first method is based on the calculation of the average membership degree of geographic units in all the higher-risk indices produced by the different scenarios. In fact, the averaging is not typically considered as a fuzzy logical operator because it lacks the property of associativity. However, in this study we have deemed it important to be examined because of the extreme cases that might be produced from the simulation (e.g. when the source of the earthquake is located on or close to a geographical unit). Indeed, the MIN-MAX compositional rules, which represent the principal method of inference in fuzzy systems, impose some limitations in decision support applications particularly when the problem under consideration is surrounded by uncertainties (Yager 1988, Cox 1999, Jiang and Eastman 2000). For example, the minimum (fuzzy-AND) operator represents a limiting factor in the analysis since the consequent fuzzy region is restricted to the minimum of the membership degree. Here a geographical unit will fail to meet our definition of vulnerability if it has a lower degree of membership in the higher-risk index produced from any single scenario. The maximum (fuzzy-OR) operator is the opposite, and can thus be thought of as a less restrictive mode of aggregation through which a geographic unit will be chosen in the result as long as it has a higher degree of membership in any single index.

Clearly, what we need in our search for hot spots of vulnerability is a global evaluation of the higher-risk indices that lies between the two extremes of MIN-MAX rules. That is, an averaging operator that permits a trade-off between the fuzzified indices of higher-risk. In our case study, the order weighted average (OWA) method implemented in IDRISI software was used for the aggregation process (Jiang and Eastman 2000 Eastman 2001). The OWA method provides continuous fuzzy aggregation operations between the fuzzy-AND and fuzzy-OR with a weighted average combination falling midway between the maximum and minimum values.

The second approach examined in the present work to locate the hot spots of vulnerability is based on the accumulating fuzzy evidence (AFE) method suggested by Cox (1999). The AFE method was originally designed to address the limitation of MIN-MAX fuzzy inference when the final fuzzy solution is arithmetically cumulative. Figure 5 outlines the steps of applying the AFE method to derive a fuzzy map of higher vulnerability. The first step in this approach is to find 'evidence' for the contribution of each higher-risk index produced from the simulation to the final higher-vulnerability fuzzy set. In doing so, we use a 'scalable monotonic chaining' to map the degree of membership of the census tract in the higher-risk to an intermediate fuzzy set representing 'vulnerability-score'. That is, for every higher-risk index, each geographical unit is evaluated for its degree of membership in that index.

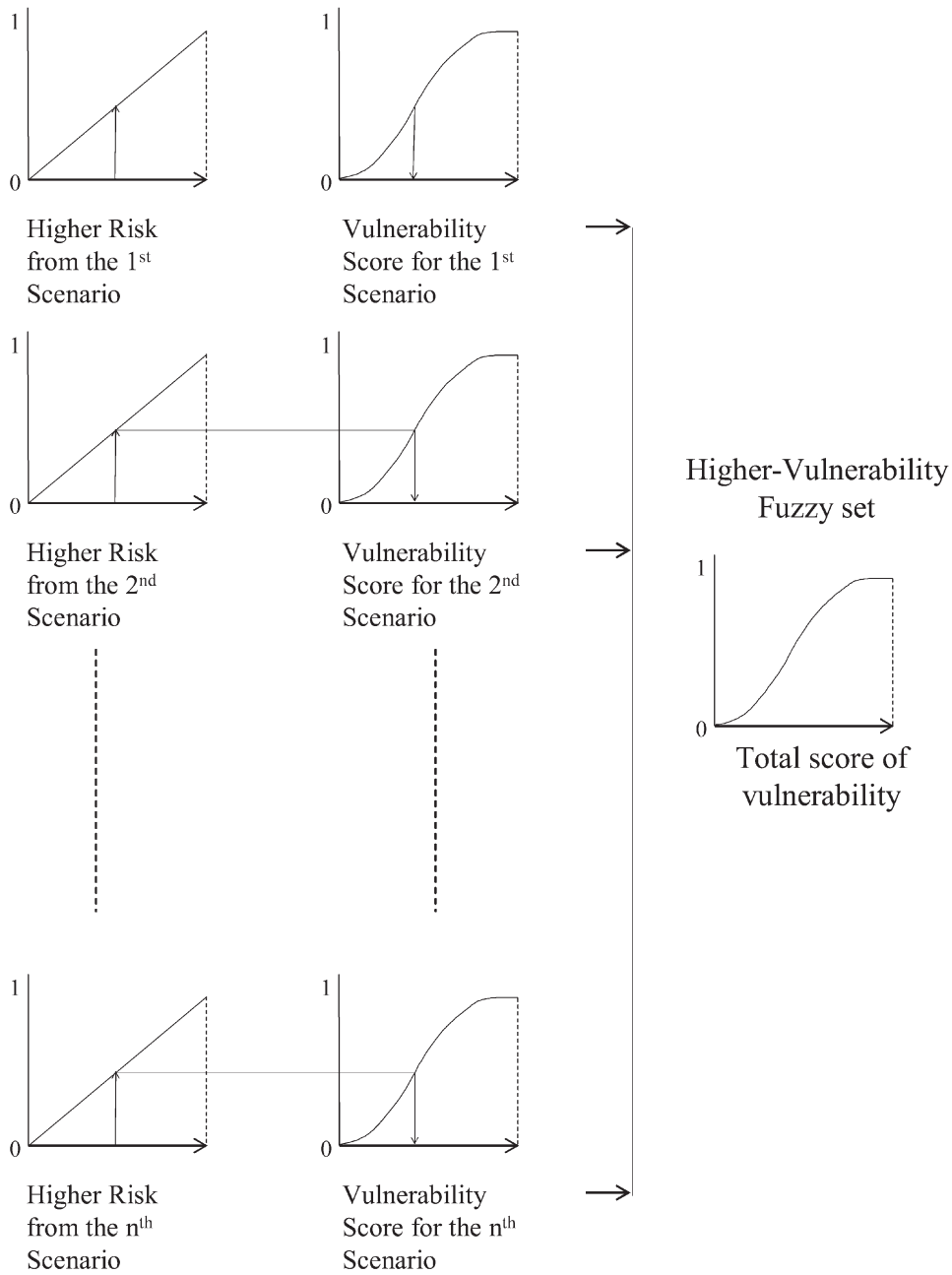


Figure 5. The accumulating fuzzy evidence (AFE) method used to derive the fuzzy set of higher-vulnerability.

This degree of membership is then used to find a point on the intermediate fuzzy set that represents a score of vulnerability associated with that particular index. This score is a value between 0 and 1000 (that is, the membership degree of the higher-risk index is multiplied by 1000). This means that if the analysis utilizes five scenarios as in our case study example and if any particular geographical unit has a maximum

degree of membership in all the higher-risk indices, then the total cumulative score of vulnerability would be 5000. After the cumulative scores are assigned to all geographical units, then the intermediate fuzzy set is used to derive the final fuzzy set that represents higher-vulnerability as shown in figure 5. In the case of utilizing 5 scenarios, the domain of the final fuzzy set will go from 0 to 5000, so that it can map the cumulative score of vulnerability to its membership degree in the higher-vulnerability fuzzy set.

The OWA and AFE methods represent two different modes for the decision making process. Therefore, which one to use depends on the objective for which vulnerability is being assessed. The OWE method approach is an averaging technique that avoids the extreme results of simulation scenarios, and thus provides a vulnerability score for the geographical units that is neither risk-averse nor risk-taking. Therefore, this method is more suitable if resultant vulnerability scores are going to be used in such decisions as the establishment of insurance plans, where insurance companies seek a trade-off between extreme cases and their business marketing. The AFE method, on the other hand, is more risk-taking as it takes into account any evidence of vulnerability produced for the geographical units by the simulation of earthquake scenarios. This method is suitable in such decisions as establishing mitigation strategies and emergency plans, where worst case scenarios should be taken into account. The implications of using these two methods will further be clarified in the results of the case study example presented in the following section.

#### **4. Analysis of urban vulnerability in Los Angeles County: A case study example for the application of the approach**

##### *4.1. Study area and data*

The study area used to test the proposed methodology in is Los Angeles County, California, a dynamic and data-rich region that has witnessed several disastrous earthquake events in the past century. The most recent one was an M6.7 earthquake which originated near Northridge on 17 January, 1994, in which 57 people were killed, 9000 were injured and damage exceeded \$25 billion (SSC 1995). The Northridge earthquake has raised many doubts with regard to levels of vulnerability in a modern urban environment generally designed for seismic resistance. The resultant damage demonstrated that questions of urban vulnerability to earthquake hazards pertain even to settings with advanced measures of social protection and high per-capita income (Bolin and Stanford 1998).

Los Angeles County is one of the most ethnically diverse places in the United States (Gordon and Richardson 1999) with a total population exceeding 9.5 million according to data from the 2000 Census, which makes it the most populous county in the nation. The segregation patterns of ethnicity and socio-economic classes in Los Angeles, accompanied by successive waves of economic restructuring and population expansion, have been reflected by the built environment and the physical structure of urban form within the region (Rubin 1977, Allen and Turner 1997, Modarres 1998). Mullens and Senger (1969), using colour infrared (CIR) aerial photos, revealed a highly consistent relationship between the physical surrogates derived from these photos (e.g. dwelling types, vegetation appearance, vacant land, lot and home sizes, pools and patios, street conditions), and the demographic and socioeconomic characteristics of urban neighborhoods in Los Angeles. Miller and Winer (1984) reported differences in vegetation species composition in Los Angeles, not only between residential and non-residential areas (e.g., commercial, industrial),

but also between residential areas with different socioeconomic profiles. Li, (1998) comparing areas in Los Angeles dominated by population groups from China and Indochina versus those dominated by groups from Taiwan and Hong Kong, showed that even the micro-divisions within the same ethnicity have their geographical expression in the spatial differentiation of urban landscape.

Therefore, the diverse social and physical character of Los Angeles makes it an ideal study site for testing the capability of our proposed methodology for deriving rigorous measures of urban vulnerability that can be utilized in subsequent research to understand the relative importance of social and physical variables in determining the overall vulnerability profile of urban communities in Los Angeles. This can help improve our understanding of vulnerability patterns in that region, and ultimately can aid in the formation of mitigation policies in anticipation of the problems that accompany urbanization processes and demographic shifts in that region.

The research's unit of analysis is the census tract, which represents the smallest geographical unit for which spatially variable data on social vulnerability can be obtained in a time series. Block-level data are available for the most recent censuses, but not for the earlier time periods that ultimately are also of interest of us in future studies. In this study, we investigated a total of 1608 census tracts covering approximately 3220 Km<sup>2</sup> that represent the entire urbanized area of Los Angeles County (see figure 6). Most of the spatial and aspatial data utilized in the analysis were obtained from the inventory datasets available from the Federal Emergency Management Agency of the US (FEMA) and built into HAZUS (FEMA-NIBS 1999). These data included inventories of building square footage and value, population characteristics from the 1990 census, costs of building repair, and certain basic economic data. Data for transportation and utility lifelines were also included as well as several layers for faults, geological conditions, and the locations of the epicenters of past earthquakes. In addition, we obtained a digital soil map of the study area from the State Soil Geographic (STATSGO) archive of the Natural



Figure 6. Study area and locations of historical earthquakes utilized in the analysis.

Resources Conservation Service at the US Department of Agriculture and processed it into a format compatible with HAZUS (USDA 2002). Similarly, maps for slope instability and liquefaction potential for the entire region were obtained from the US Geological Survey (1:24 000) and converted into GIS layers that were compatible with HAZUS.

#### 4.2. Results of the earthquake simulation

Figure 7 shows the results of the simulation of five earthquake scenarios after applying the evaluation criteria in each scenario to obtain a final fuzzy set that represents an index of higher-risk. For display purposes, the degree of membership for the census tracts in any single index was multiplied by 100. In figure 7, darker areas indicate places with higher damage estimates in the scenario. The maps shown were classified based on the natural breaks of membership degrees in the resultant indices. This classification method identifies breakpoints between classes using a statistical formula that minimizes the sum of the variance within each of the classes, thus defining those areas that hold higher degrees of risk than others. It should be emphasized at this point that the degrees of membership in these indices are scenario dependent. That is, if a census tract has a higher degree of membership in one index and a lower degree in another, we cannot assume that its risk from the former scenario is greater than its risk from the other scenario.

The resultant indices in figure 7 illustrate well the concept of risk versus vulnerability. Since vulnerability was controlled by running the simulation on the same physical and social factors, the variations observed in risk between scenarios represent changes in an earthquake hazard's parameters such as magnitude and location. In the case of the deterministic scenarios, the effect of these parameters is obvious. Those census tracts with higher degrees of membership are clustered around or near to the source of the earthquake. As we move away from the source, the degree of membership decreases. On the other hand, the index produced from the probabilistic scenario does not show any specific spatial pattern for the census tracts with higher degrees of membership in that index. This can be attributed to the underlying assumption behind the probabilistic assessment of earthquake hazards which implies uniform distribution of the seismic activity over space. Hence, the probabilistic method neglects some forms of vulnerability that exist in urban areas such as the effects of local soils. Therefore, although this method is widely adopted in many risk assessment studies, it is not highly recommended when the actual prediction of estimates is to be used to plan for emergencies or to establish mitigation policies (FEMA-NIBS 1999; Menoni *et al.* 1999).

#### 4.3. Results of the OWA and AFE methods

The results from applying the OWA and the AFE methods to higher-risk indices are presented in the maps shown in figure 8. These maps represent the fuzzy concept of higher-vulnerability in Los Angeles County. As was done with risk indices, a natural breaks classifier was applied in order to delineate those areas that are relatively more vulnerable than others (the hot spots). Thus, darker areas in figure 8 represent places with higher vulnerability while brighter areas represent places with lower vulnerability. A visual inspection of the two maps shows clearly that they both exhibit similar spatial patterns in terms of the distribution of vulnerability membership degrees. In the two maps, census tracts with a higher degree of membership in the higher-vulnerability index are clustered in the NW quadrant of Los Angeles



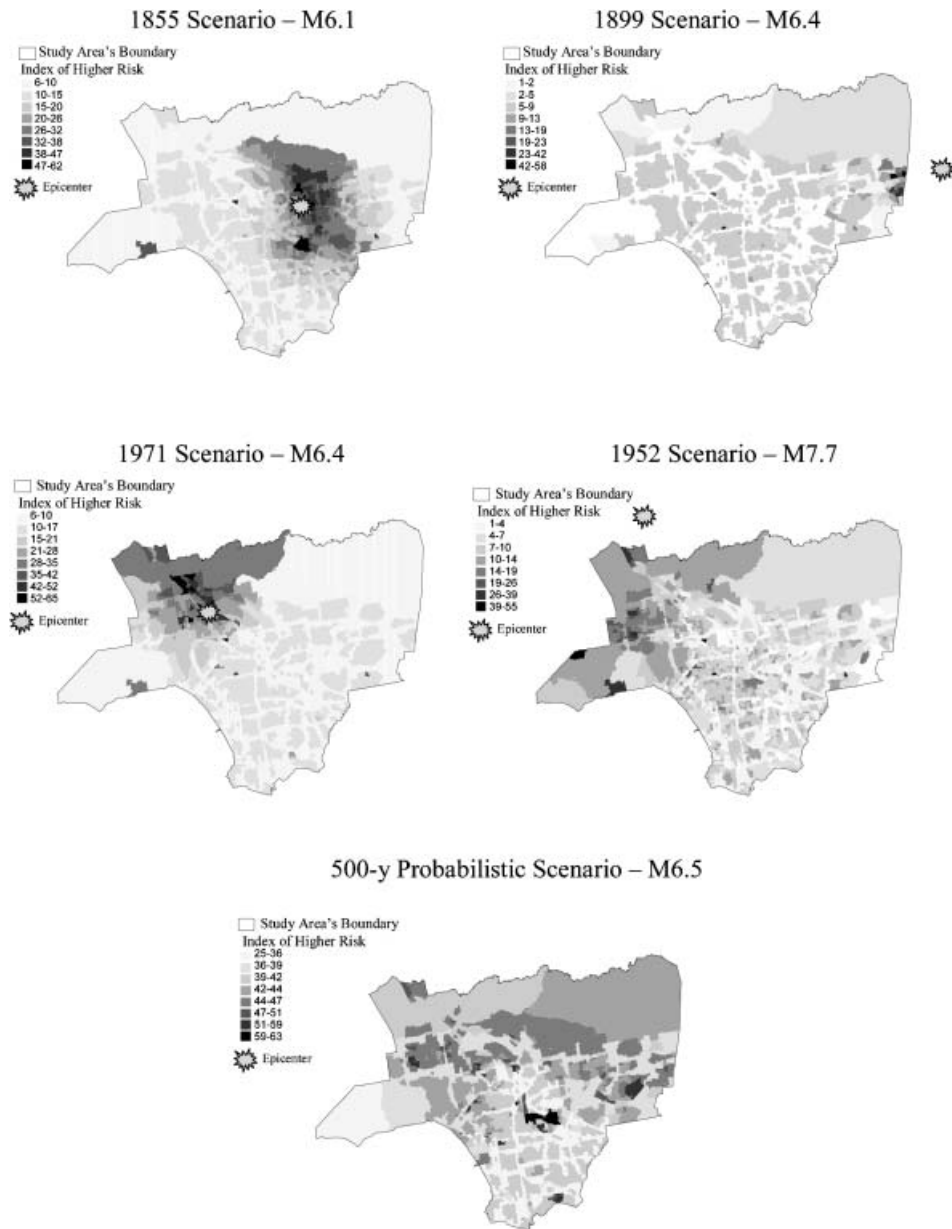


Figure 7. Fuzzified maps of Higher-Risk produced from the different scenarios. Darker areas indicate places with higher damage estimates in the scenario.

County, near the cities of San Fernando and Burbank. As we move away from this quadrant, the degree of membership decreases, and hence vulnerability decreases. Despite the similarity in the spatial pattern of vulnerability distribution in the two maps, the interpretation of their values of vulnerability is different.

In the case of the OWA-based higher-vulnerability index, the values indicate the average degree of membership in the higher-risk indices produced by the simulation of earthquake scenarios. This implies that a census tract with a lower risk in one

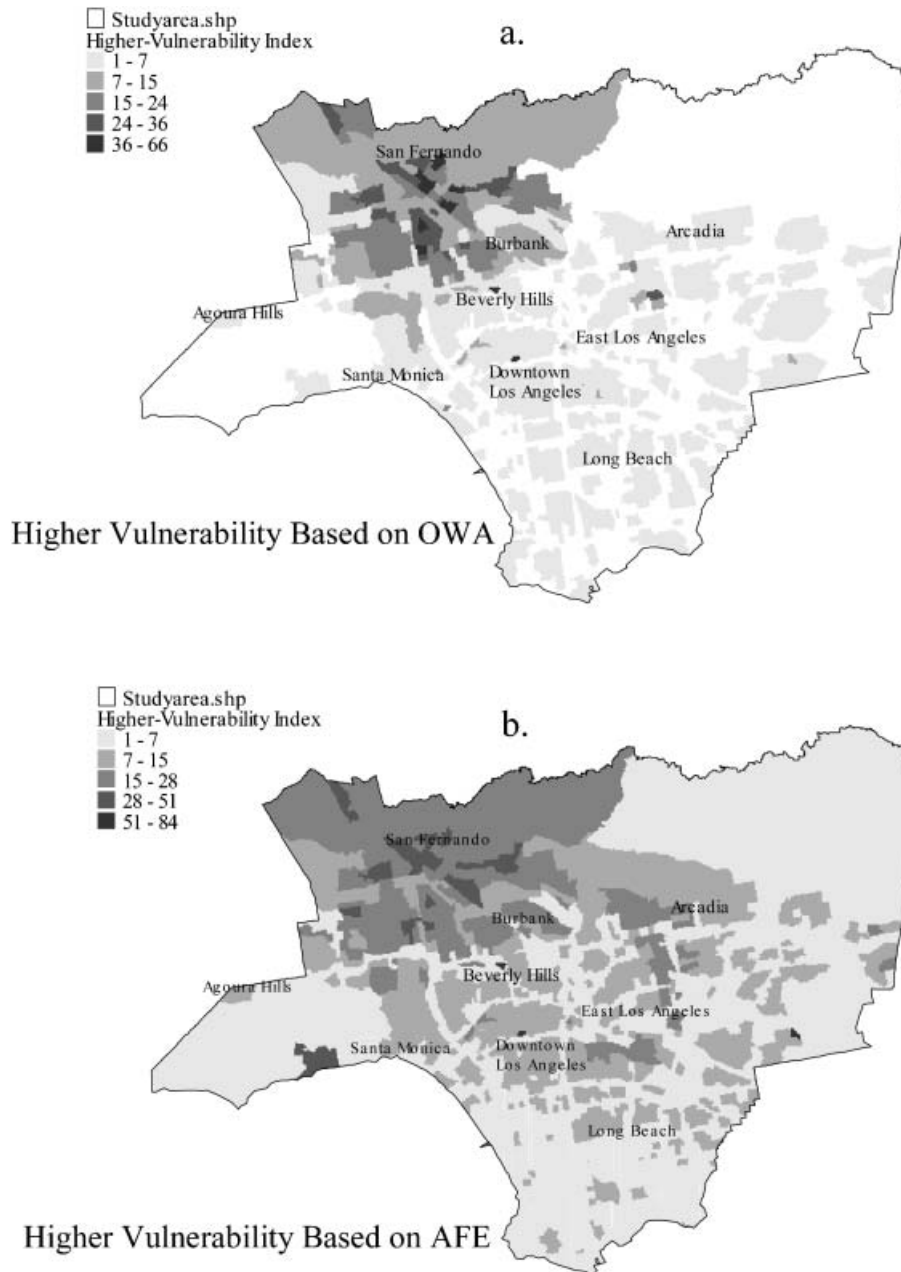


Figure 8. Results of the fuzzified maps of Higher-Vulnerability. Darker areas indicate places with higher degree of membership (see text for discussion).

scenario is compensated for by its higher risk in another. Therefore, the final averaged values imply a considerable degree of uncertainty resulting from the inability to provide a precise judgment with respect to the inference of the simulation results. This uncertainty is reflected in the range of values produced in the OWA-based map of vulnerability. As shown in figure 8, the maximum degree of membership in this

map is 0.66, implying that there is only 66% possibility that a census tract with this value would be designated as highly vulnerable. The case of the vulnerability map produced by the AFE is quite different. In this method, each higher-index produced from a specific scenario is thought of as 'imperfect' evidence for the overall vulnerability of the census tracts (i.e. the degree of imperfectness is expressed in degrees of membership in the higher-risk indices). By accumulating this evidence on an index-by-index basis in the manner discussed in the methods section earlier, we obtain a final map of vulnerability in which census tracts are assigned to values weighted by the imperfectness of the simulation results. As shown in figure 8, the AFE method yields results that are less certain and more spatially diffused than the results obtained by the OWE method.

As we indicated earlier, our primary objective from this case study was to test the proposed methodology in terms of deriving robust measures of vulnerability that can be used in subsequent research to examine the relative importance of various physical and social variables influencing vulnerability. It is, however, worthwhile to highlight here some indications about the potential linkage between variation in vulnerability scores and social and physical variability in the study area. Note that, for illustrative purposes, we only base our discussion on the general spatial distribution of vulnerability scores that have resulted from both the AFE and the OWA methods. In doing so, we utilize the network of freeways in Los Angeles (shown in figure 6) as a framework for linking variation in vulnerability scores to patterns of ethnicity and socioeconomic segregation in the study area. For example, the non-Hispanic white population is dominant in neighbourhoods that extend along the periphery, which score high on the socio-economic scale. These areas are characterized by having lower scores in vulnerability. The majority of African-American dominated neighbourhoods are associated with less affluent areas located in the urban core, which exhibits lower to medium scores of vulnerability. On the other hand, the Hispanic population is largely concentrated in the central and north-east regions. The socio-economic status of these neighbourhoods ranges from low to middle, but the scores of vulnerability in these areas are generally higher. Finally, the Asian community is divided between the south-west area of Los Angeles, where one can find highly affluent neighbourhoods such as Rolling Hills and Palos Verdes, and other areas located in the northeast part of the central city near Pasadena and Arcadia—areas that score in the middle on the socio-economic scale. In this case, vulnerability scores range between low in some neighbourhoods and high in others.

Does this mean that race and income are the sole determinants of variability in vulnerability in Los Angeles County? The answer is obviously not, but what the above description suggests is a complex interaction between the social, demographic and physical makeup of urban places that shape the vulnerability profile of the communities in Los Angeles, to which race and income may make a considerable contribution. In subsequent research, we will investigate in detail the extent to which variations in vulnerability is connected to variations in physical and social settings in Los Angeles. What concerns us this paper however, is to show the capability of our proposed methodology of deriving measures of vulnerability that have subsequent theoretical and empirical implications.

#### 4.4. *Results of sensitivity analysis*

We performed three sensitivity analysis tests on the results shown. In the first analysis, sensitivity to earthquake magnitude was examined. Then, sensitivity to

earthquake location was examined. Finally, sensitivity to simulation method was examined. Another major difference between the implications of the OWA and AFE methods can be observed in the results of the sensitivity analysis presented in figure 9. This figure shows fuzzy maps produced by excluding some scenarios from the earthquake simulation. In the first case, the sensitivity of analysis to the magnitude of the earthquakes was examined by excluding the 1952 earthquake scenario (M7.7). In the second case, the sensitivity to the location of earthquake source was examined by excluding the 1971 (M6.4) scenario whose source is located in the clustering area

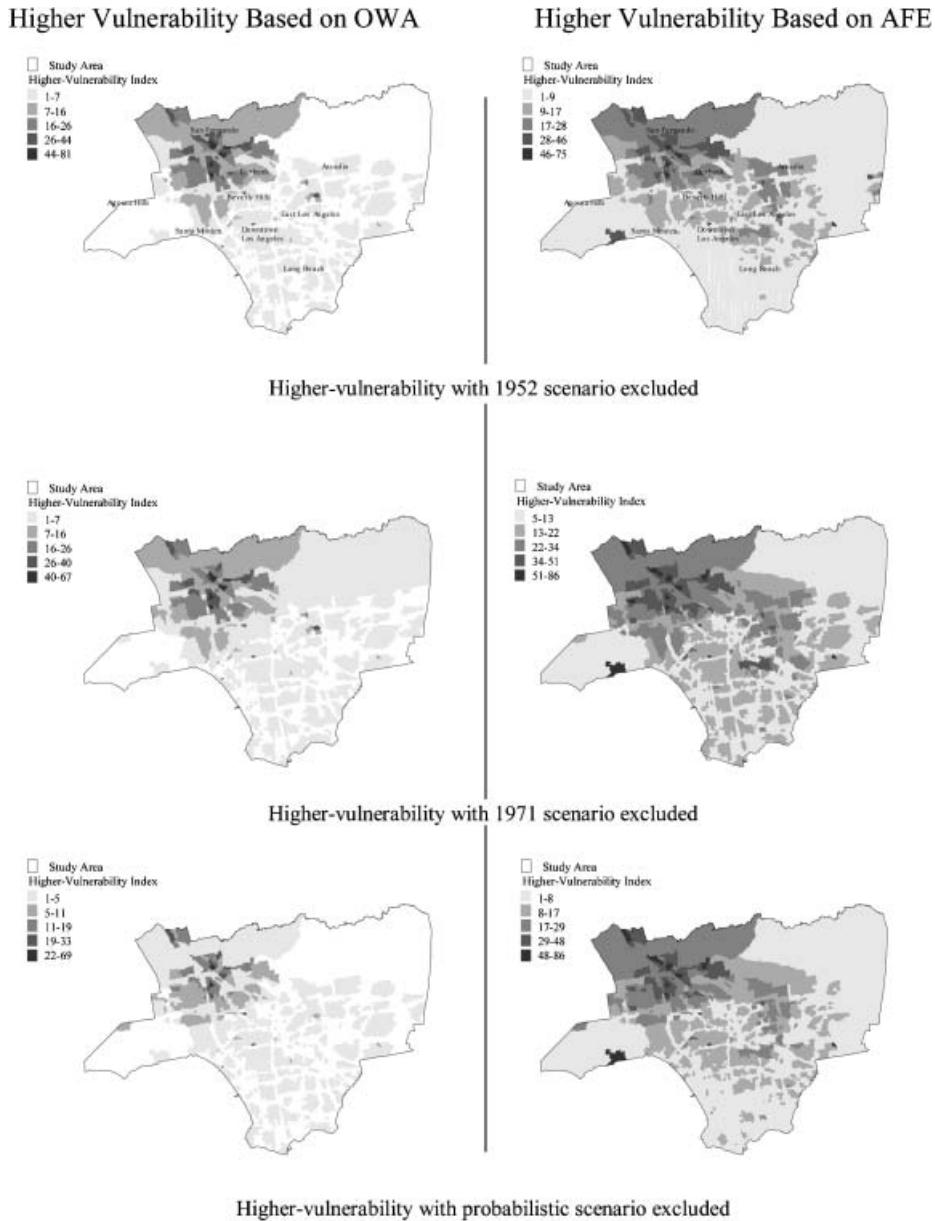


Figure 9. Results of the sensitivity analysis applied to the OWA and AFE methods.

of higher values. In the third case, the sensitivity to the simulation method was examined by excluding the probabilistic scenario. As shown in figure 9, the results of sensitivity analysis indicate no major change in the spatial distribution of vulnerability patterns in comparison to those produced from the original simulation. This observation indicates the robustness of the proposed methodology in controlling for the effects of the spatial variability in the earthquake hazards, thus attributing the variability of risk to the variations of urban vulnerability.

In terms of fuzzy aggregation methods, the OWA and AFE have responded in different degrees to the three cases mentioned earlier. In the first case, when the 1952 scenario is excluded, the overall certainty of the OWA-based vulnerability map increased, while the certainty of the AFE-based map decreased. This is due to the magnitude of the 1952 event (M7.7), which is considerably higher than the magnitudes of the other scenarios that range between M6.1 and M6.9. The exclusion of higher damage estimates produced by this scenario led to a decrease in the evidence supporting vulnerability and thus to a decrease in the certainty of the AFE-based map. In contrast, the certainty of the OWA-based map increased as the effects of extreme values on the averaging operation decreased. In the second case, the exclusion of the 1971 scenario did not result in any significant change in the results produced by the OWE method. However, examining the results produced by the AFE method, slight changes can be observed in the spatial distribution of vulnerability. As effects of the 1971 earthquake disappear, the degree of membership decreases for the areas located at or near to its source and increases for the areas located at an increasing distance from it. Finally, the exclusion of the probabilistic scenario seems to have a minor influence on the two methods, except in limiting the spatial diffusion of higher degrees of vulnerability.

## 5. Summary and conclusion

In this paper, we have demonstrated that the limitations of current GIS approaches to vulnerability analysis are not a question of data availability nor are they due to problems in current GIS software. Rather, we attributed these limitations to the adoption of methodologies that are not suitable for dealing with the ill-structured problem of urban vulnerability. We illustrated through a wall-to-wall exercise how a spatial analytical approach can be incorporated into a GIS in order provide measures of urban vulnerability in Los Angeles County. The research presented here is a work in progress, and we recognize that there are limitations in the analysis we presented. However, the aim of this paper was to pave the ground for a new approach for disaster managers to undertake vulnerability analysis, as well as for researchers to test existing theories or develop new ones. In this last section, we conclude with a discussion of the limitations and the possible contributions of the proposed methodology in terms of balancing two competing demands. The first demand is offering a replicable way for researchers as well as planners and decision makers undertaking local mitigation efforts to generate concrete profiles of vulnerable communities and to monitor changes in these profiles over time. The second is being able to bring together divergent perspectives on urban vulnerability in order to test related theories and hypotheses, thus improving our understanding of the linkage among various ecological factors that produce vulnerability patterns.

As for the first objective, the limitations of the proposed methodology can be examined against the four criteria suggested by Rejeski (1993) in his evaluation of successful GIS applications in the field of risk analysis and disaster management,

namely: *believability*, *honesty*, *decision utility*, and *clarity*. The first criterion, believability, concerns whether the models and data to be used in the analysis are properly chosen. As highlighted earlier, differences exist between different models of urban vulnerability. However, similarities also exist. In this paper, we have focused our attention on some basic points that are common among different vulnerability models. In doing so, we have adopted an ecological perspective which facilitated the selection of a comprehensive set of evaluation criteria of urban risk using an earthquake simulator to generate them. Obviously, a successful replication of this methodology depends on the existence of a variety of spatial and aspatial data that can be utilized in a damage simulation tool such as HAZUS to generate the evaluation criteria. With the rapid increase in spatial digital libraries and the wide spread of GIS in many public and private organizations, the availability of such data should no longer be problematic. Likewise, there are now many software packages that perform very sophisticated simulations of earthquake effects. We believe that the key to determining the ultimate usefulness of the proposed methodology in future application lies in testing it using simulation packages other than HAZUS. Examples of candidate simulators have been given in the methods section of this paper.

The second criterion, honesty, concerns the degree to which the accuracy of analysis and uncertainties are conveyed to the end users. The combination of spatial multicriteria analysis and fuzzy techniques offers a powerful and flexible way to handle the uncertainty associated with the unpredictable nature of earthquakes and the imprecision in translating expert knowledge into operational models. As illustrated in the case study example of this paper, uncertainties are explicitly expressed in the evaluation of vulnerability in terms of the degree to which a candidate census tract will belong to the final fuzzified set of higher-vulnerability.

The last two criteria, decision utility and clarity, address the ability to communicate the results from the analysis and whether or not these results provide a clear base for action (e.g. developing mitigation measures). While the results from the sensitivity analyses have indicated a general level of robustness of the OWA and AFE methods, they have also shown varying levels of uncertainties in the end results. As emphasized earlier, these two methods imply two different views about the way the risk is aggregated, and therefore their utilities are best set in the context of the problem under consideration. For example, if one is to plan for emergencies, then it might be suitable to delineate the hot spots of vulnerability using the OWA method. This method allows for a range of averaging operations that lie between the two extremes of MIN and MAX cases. Such operations are desired by decision makers especially when it comes to decisions that may affect human lives as in the case of disaster management. On the other hand, the AFE method better serves other kinds of applications that require more intensified results. For example, to examine the correlation between vulnerability and different ecological factors, one needs to accumulate as much evidence as possible on a factor-by-factor basis rather than obtaining the average effect of the factors.

As for the contribution of this work, we believe that the proposed methodology can help enrich our theoretical understanding of urban vulnerability. Our results indicate that hot spots of vulnerability maintain a spatial cluster in the NW quadrant of the study area regardless of the location and magnitude of the earthquake. This conforms well with vulnerability models (Mitchell *et al.* 1989, Hewitt 1997, Cutter *et al.* 2000) that suggest that vulnerability to earthquake hazards is contingent upon particular conditions that influence how well a society can cope with disasters, and



how rapid and complete its recovery from them can be. However, these conditions do not depend on the spatial distribution of the hazards as much as they depend on the characteristics of the urban place. That is, they are not from 'outside' the urban place nor do they erupt accidentally within it. Rather, they represent a product of everyday social life and ongoing urban dynamics that act upon the society and control its mutual relationship with the environment. To this end, the proposed methodology helps us identify and examine what these conditions actually are and what their relative importance might be. In future research, we will investigate the underlying causes of the spatial clustering of vulnerability hot spots. We will also examine how the spatial variations in urban vulnerability are expressed through variations in the social and physical ecological factors in the study area and whether we can use the latter as a proximate determinate of the former.

### Acknowledgments

This research has been supported by grants from the National Science Foundation (BCS-0117863 and BCS-0095641). The authors would like to thank S. Menoni, Politecnico di Milano; R. Powell, University of California Santa Barbara; J. Rogan, San Diego State University; and the anonymous reviewers for their constructive comments. An earlier version of this paper was presented at the Annual Meeting of the Association of American Geographers, Los Angeles, March 2002.

### References

- ALEXANDER, D., 1993, *Natural Disasters* (New York, NY: Chapman & Hall, Inc).
- ALEXANDER, D., 2000, *Confronting Catastrophe: New Perspectives on Natural Disasters* (New York, NY: Oxford University Press).
- ALEXANDER, D., and SMITH, K., 1993, Environmental hazards: Assessing risk and reducing disaster. *Progress in Physical Geography*, **17**, 504.
- ALLEN, J. P., and TURNER, E., 1997, *The Ethnic Quilt: Population Diversity in Southern California* (Northridge: The Center for Geographical Studies, California State University).
- BOLIN, R., and STANFORD, L., 1998, *The Northridge Earthquake: Vulnerability and Disaster* (New York: Routledge).
- BURROUGH, P. A., 1989, Fuzzy mathematical methods for soil survey and land evaluation. *Journal of Soil Science*, **40**, 477–492.
- BURTON, I., KATES, R. W., and WHITE, G. F., 1978, *The Environment as Hazard* (New York: Oxford University Press).
- COPPOCK, J. T., 1995, GIS and natural hazards: An overview from a GIS perspective. In *Geographical Information Systems in Assessing Natural Hazards*, edited by A. Carrara and F. Guzzetti, **5** (Dordrecht, The Netherlands: Kluwer Academic Publishers), pp. 21–34.
- COVA, T. J., 1999, GIS in emergency management. In *Geographical Information Systems*, edited by P. A. Longley *et al.*, **V2: Management Issues and Applications** (New York: John Wiley & Sons, Inc), pp. 845–858.
- COVA, T. J., and CHURCH, R., L., 1997, Modelling community evacuation vulnerability using GIS. *International Journal of Geographical Information Science*, **11**, 763–784.
- COX, E., 1999, *The Fuzzy Systems Handbook: A Practitioner's Guide to Building, Using, and Maintaining Fuzzy Systems* (Chappaqu, New York: Academic Press, AP Professional).
- CUTTER, S. L., editor, 1994, *Environmental Risks and Hazards* (Englewood Cliffs, NJ: Prentice Hall).
- CUTTER, S. L., 1996, Vulnerability to environmental hazards. *Progress in Human Geography*, **20**, 529–539.
- CUTTER, S. L., MITCHELL, J. T., and SCOTT, M. S., 2000, Revealing the vulnerability and places: A case study of Georgetown County, South Carolina. *Annals of the Association of American Geographers*, **90**, 713–737.

- DOW, K., 1992, Exploring differences in our common feature(s): The meaning of vulnerability to global environmental change. *Geoforum*, **23**, 417–436.
- DYNES, R. R., and DRABEK, T. E., 1994, The structure of disaster research: Its policy and disciplinary implication. *International Journal of Mass Emergencies and Disasters*, **12**, 5–23.
- EASTMAN, J. R., 2001, *IDRISI32—Guide to GIS and Image Processing* (Worcester, MA: Clark Labs, Clark University).
- EMMI, P. C., and HORTON, C. A., 1993, A GIS-based assessment of earthquake property damage and casualty risk: Salt Lake County, Utah. *Earthquake Spectra*, **9**, 11–33.
- FEMA-NIBS., 1999, *HAZUS: Users's Manual and Technical Manuals*, vols 1–3 (4 vols). (Washington DC: Federal Emergency Management Agency and Institute of Building Sciences).
- FITZPATRICK, K., and LAGORY, M., 2000, *Unhealthy Places: The Ecology of Risk in the Urban Landscape* (New York: Routledge).
- GORDON, P., and RICHARDSON, H. W., 1999, Review essay: Los Angeles, city of angels? No, city of angles. *Urban Studies*, **3**.
- HEWITT, K., 1997, *Regions of Risk: a Geographical Introduction to Disasters* (Harlow: Longman).
- HONG, N. S., 1998, The relationship between well-structured and ill-structured problem solving in multimedia simulation, PhD thesis, The Pennsylvania State University.
- JIANG, H., and EASTMAN, J. R., 2000, Application of fuzzy measures in multi-criteria evaluation in GIS. *International Journal of Geographic Information Science*, **14**, 173–184.
- JONASSEN, D. H., 1997, Instructional design models for well-structured and ill-structured problem-solving learning outcomes. *Educational Technology*, **45**, 65–95.
- KAGAN, Y. Y., 1997, Are earthquakes predictable? *Geophysical Journal International*, **131**, 505–525.
- KAPPOS, A. J., STYLIANIDIS, K. C., and PITLAKIS, K., 1998, Development of seismic risk scenarios based on a hybrid method of vulnerability assessment. *Natural Hazards*, **17**, 177–192.
- KATES, R. W., 1996, Human adjustment. In *Ten Geographic Ideas that Changed the World*, edited by S. Hanson (New Brunswick, New Jersey: Rutgers University Press), pp. 87–107.
- KEHELT, R., 1997, The Use of consequences assessment tool set for emergency management. In *17th annual ESRI user conference*.
- LEUNG, Y., 1997, *Intelligent Spatial Decision Support Systems* (Berlin, New York: Springer Verlag).
- LI, W., 1998, Anatomy of a new ethnic settlement: The Chinese ethnoburb in Los Angeles. *Urban Studies*, **35**, 479–501.
- MALCZEWSKI, J., 1999, *GIS and Multicriteria Decision Analysis* (New York: J. Wiley & Sons).
- MEJIA-NAVARRO, M., WOHL, E. E., and OAKS, S. D., 1994, Geological hazards, vulnerability, and risk assessment using GIS: Model of Glenwood Springs, Colorado. *Geomorphology*, **10**, 331–354.
- MENONI, S., 2001, Chains of damages and failures in a metropolitan environment: Some observations on the Kobe earthquake in 1995. *Journal of Hazardous Materials*, **83**, 101–119.
- MENONI, S., PERGALANI, F., PETRINI, V., LUZI, I., and ZONNO, G., 2000, Measuring the seismic vulnerability of strategic public facilities: response of the health care system. *Disaster Prevention and Management*, **9**, 29–38.
- MENONI, S., and PERGALANI, F., 1996, An attempt to link risk assessment with land use planning: A recent experience in Italy. *Disaster Prevention and Management*, **5**, 6–21.
- MENONI, S., PETRINI, V., and ZONNO, G., 1999, *Seismic Risk Evaluation through Integrated Use of Geographical Information Systems and Artificial Intelligence Techniques* (Brussels: European Commission, Environment and Climate Programme- Report No. ENV4-CT96-0279).
- MILETI, D. S., 1999, *Disasters by Design: a Reassessment of Natural Hazards in the United States* (Washington, DC: Joseph Henry Press).
- MILLER, P. R., and WINER, A. M., 1984, Composition and dominance in Los Angeles basin urban vegetation. *Urban Ecology*, **8**, 29–54.

- MITCHELL, J. K., DEVINE, N., and JAGGER, K., 1989, A contextual model of natural hazards. *Geographical Review*, **79**, 391–409.
- MODARRES, A., 1998, Putting Los Angeles in its place. *Cities*, **15**, 135–147.
- MULLENS, R. H. J., and SENGER, L. W., 1969, Analysis of Urban Residential Environments Using Color Infrared Aerial Photography: An Examination of Socioeconomic Variable and Physical Characteristics of Selected Areas in the Los Angeles Basin. Interagency report from US Geological Survey to NASA (Greenbelt: NASA).
- NOAA., 1999, *Community Vulnerability Assessment Tool: New Hanover County, North Carolina Case Study*, **2000** (National Oceanic and Atmospheric Administration's (NOAA) Coastal Services Center).
- NRC., 1998, *Reducing Disaster Losses through Better Information* (Washington, DC: National Academy Press: National Research Council).
- OPENSHAW, S., and OPENSHAW, S., 1997, *Artificial Intelligence in Geography* (Chichester: John Wiley & Sons).
- PALM, R., and HODGSON, M., 1992, Earthquake insurance: Mandated disclosure and homeowner response in California. *Annals of the Association of American Geographers*, **82**, 207–222.
- QUARANTELLI, L. E., 1988, Disaster studies: an analysis of the social historical factors affecting the development of research in the area. *International Journal of Mass Emergencies and Disasters*, **5**, 285–310.
- RADKE, J., COVA, T., SHERIDAN, M. F., TROY, A., LAN, M., and JOHNSON, R., 2000, Application challenges for GIScience: Implications for research, education, and policy for risk assessment, emergency preparedness and response. *Journal of the Urban and Regional Information Systems Association*, **12**, 15–30.
- REJESKI, D., 1993, GIS and risk: A three-culture problem. In *Environmental Modeling with GIS*, edited by M. F. Goodchild *et al.* (Oxford: Oxford University Press), pp. 318–331.
- RUBIN, B., 1977, A chronology of architecture in Los Angeles. *Annals of the Association of American Geographers*, **67**, 521–537.
- SAATY, T. L., 1980, *The Analytic Hierarchy Process* (New York: McGraw-Hill).
- SINNOTT, J. D., 1989, A model for solution of ill-structured problems: Implications for everyday and abstract problem solving. In *Everyday problem solving: Theory and applications*, edited by J. D. Sinnott (New York: Praeger), pp. 72–99.
- SSC., 1995, *Northridge Earthquake: Turning Loss to Gain* (Sacramento, California: Seismic Safety Commission of the State of California).
- SSC., 1999, *Earthquake Risk Management: A Toolkit for Decision-Makers* (Sacramento, California: Seismic Safety Commission of the State of California).
- STEIN, A., STARITSKY, I., BOUMA, J., and GROENIGEN, J. W. V., 1995, Interactive GIS for environmental risk assessment. *International Journal of Geographic Information Systems*, **9**, 509–525.
- THILL, J.-C., 1999, *Spatial Multicriteria Decision Making and Analysis* (Brookfield: Ashgate).
- UN., 1991, *Mitigating Natural Disasters: Phenomena, Effects, and Options: a Manual for Policy Makers and Planners* (New York: UNDRO (United Nations Disaster Relief Organization)).
- USDA., 2002, *State Soil Geographic Data Base (STATSGO)*—[http://www.il.nrcs.usda.gov/soils/statsgo\\_inf.html](http://www.il.nrcs.usda.gov/soils/statsgo_inf.html)., Natural Resources Conservation Service—The US Department of Agriculture).
- VOSS, J. F., and MEANS, M. L., 1989, Toward a model of creativity based upon problemsolving in the social sciences. In *Handbook of Creativity*, edited by J. A. Glover *et al.* (New York: Plenum), pp. 399–410.
- WHITE, G. F., 1994, Paths to risk analysis. In *Environmental Risks and Hazards*, edited by S. L. Cutter (Englewood Cliffs, NJ: Prentice Hall), pp. 69–74.
- WHITE, G. F., and HAAS, J. E., 1975, *Assessment of Research on Natural Hazards* (Cambridge, MA: MIT Press).
- WHITMAN, R. V., and LAGORIO, H. J., 1998, *The FEMA-NIBS Methodology for Earthquake Loss Estimation.*, **2001**, <http://www.nibs.org/hazus4a.htm>).
- WISNER, B., 1993, Disaster vulnerability: scale, power, and daily life. *GeoJournal*, **30**, 127–140.
- WISNER, B., 1998, Marginality and vulnerability: Why the homeless of Tokyo don't 'count' in disaster preparation. *Applied Geography*, **18**, 25–33.

- YAGER, R., 1988, On ordered weighted averaging aggregating operators in multi-criteria decision making. *IEEE Transactions on Systems, Man, and Cybernetics*, **8**, 183–190.
- ZADEH, L. A., 1975, The concept of linguistic variable and its application to approximate reasoning. *Information Sciences*, **8**, 199–249.
- ZENG, T. Q., and ZHOU, Q., 2001, Optimal spatial decision making using GIS: a prototype of a real estate geographical information system (REGIS). *International Journal of Geographic Information Science*, **15**, 307–321.