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An integrative GIS and remote sensing model for place-based urban vulnerability analysis

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9.1 Introduction

> It is said that many centuries ago, an Indian princess asked the Buddha to summarize his philosophy for her. The wise man obliged, but when he brought his answer to the lady, she asked for a more concise summary. This exchange was repeated several times. Whenever the Buddha complied with her latest request, the princess kept on demanding an shorter version. Eventually she asked: 'Can you express your philosophy in just *one* word?' Once more the Buddha obliged. The definition offered was 'Today' (Scheurer, 1994, p. 3).

At a glance, it appears impracticable in such a diverse and multidisciplinary area as urban vulnerability to environmental hazards to do what the Buddha did in philosophy – express the essence of the field in a single word. After all, six decades of considerable progress and outstanding achievements by hazards scholars have not succeeded in reconciling discrepancies surrounding fundamental concepts

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within the field (White and Haas, 1975; Mileti, 1999). The meaning of such basic terms as 'disaster', 'hazard', 'risk' and 'vulnerability' continues to be a matter of controversy (Dow, 1992; Cutter, 1996; Cardona, 2004). A review of the literature reveals considerable variation and fundamental conceptual differences among the numerous approaches and models developed to tackle vulnerability, risk and other hazard-related issues (Liverman, 1990; Dow, 1992; Cutter 1996; Rashed and Weeks, 2003; Cardona, 2004).

Despite all the controversies that exist in the field, we start this chapter with a proposition that urban vulnerability may indeed be summed up in one word – 'particularity'. As the literature suggests, the study of vulnerability is ecological in nature (Kates, 1971; Burton *et al*., 1978; Andrews, 1985; Hewitt, 1997; Bolin and Stanford, 1999; Fitzpatrick and LaGory, 2000; Wisner *et al*., 2004). As a result, an uneven and highly changeable complex web of dynamics and ecological factors, encompassing social, economic, cultural, political and physical variables, shape the patterns of urban vulnerability and determine the course in which these patterns evolve across space and through time. We refer to such context-dependent characteristics of vulnerability as 'particularity' to emphasize the notion that urban vulnerability can only be assessed in relation to a specific spatiotemporal context and its underlying dynamics, which interact together to produce particular forms of vulnerability.

We recognize that our attempt to describe the essence of vulnerability studies in one word is a bold step, especially when the reader is reminded that the word we use, 'particularity', has been central to philosophical tensions between various accounts of risks in hazards research (Mustafa, 2005). Accordingly, we do not expect the reader to accept our thesis as final. Rather, we invite the reader of this chapter to explore the plausibility of our thesis and its implications for the ongoing dialogue about the science of vulnerability (Cutter, 2001, 2003b) and the role of geographic information science and technology in risk and vulnerability analysis (Rejeski, 1993; Cova, 1999; Radke *et al*., 2000; Cutter, 2003a).

The approach we pursue in our inquiry in this chapter is both theoretical and empirical. We first discuss epistemological positions on the particularity of urban vulnerability, drawn from contemporary work on hazards and disasters, to make the case for a place-based approach to vulnerability analysis. Next, we introduce the theoretical constructs of an integrative GIS and remote sensing model for place-based vulnerability analysis. We discuss how the proposed model could help resolve the dilemma of devising vulnerability assessments that recognize particularities in individual contexts, yet producing quantitative indicators to facilitate comparison of vulnerabilities across time and space. We then present a case study in which the model has been applied to assess the vulnerability of the metropolitan area of Los Angeles, California. We draw upon the results of this case study and conclude the chapter with a general discussion of integration issues in GIS and remote sensing technologies, and how such integration can provide a starting point for the science of vulnerability to evolve into a more robust field.

9.2 Analysis of urban vulnerability: what is it all about?

Vulnerability studies share in common the view that disasters are a product not only of hazardous events but also of social, economic and political environments. This is a crucial point indeed, as it puts vulnerability studies together under a unique theoretical paradigm that is quite distinct from other paradigms in disaster research, such as the technological-fix paradigm, which deems the geophysical processes that produce hazardous events to be more significant. The vulnerability approach to understanding urban disasters maintains the idea that calamities are poorly explained by the character of the events that may trigger them, be they natural (e.g. earthquake, flooding), technological (e.g. chemical release, dam failure), or caused by deliberate human action (e.g. terrorism act, war). Further, it asserts that the same damaging hazard could bring widely varying losses in societies, due to variations in social and physical vulnerabilities across urban places.

Despite the general conceptual ground they share, scholars of vulnerability are nonetheless divided amongst themselves on how to approach the question of vulnerability and the goals of its analysis. There have been several takes in the literature on the epistemological positions of vulnerability scholars (for recent reviews, see Wisner *et al*., 2004, pp. 19–20; Mustafa, 2005, pp. 568–569). On the one hand, there is the realist view that emphasizes a set of common themes and elements to provide a better theoretical understanding of the 'real' root pressures in global, regional and national systems that shape the vulnerability profile of societies (Wisner *et al*., 2004). Advocates of this view do not emphasize local particularities in their studies and consider doing so as a subtle form of environmental determinism. On the other hand, there are the pragmatist and constructivist views, which share a concern for the practicality of the context in which vulnerability is analysed, although they differ considerably in their methodological and philosophical foundations (Mustafa, 2005). For pragmatists, the emphasis on context particularities helps to introduce vulnerability analysis as a tool relevant to planners and decision makers. For constructivists, it provides a better means to comprehend the reality of disasters and to connect to local people.

Mustafa (2005) suggests that these above-mentioned epistemological differences regarding the understanding and analysis of vulnerability should not be seen as being in competition but rather as important complements. We concur with Mustafa's view and see it as a foundation upon which the recent idea that calls for a science of vulnerability (Cutter, 2003b) will need to rest. At one level, the concept of vulnerability in its broadest definition directs attention to the particular conditions that influence how well a society can cope with disasters and how rapid and complete its recovery can be. Findings of previous studies endorse the notion that these conditions do not come from 'outside' the urban place, neither do they erupt accidentally within it (Fitzpatrick and LaGory, 2000). Instead, 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 (Mitchell, 1989; Wisner, 1993; Cutter, 1996; Hewitt, 1997; Turner *et al*., 2003; Tobin and Montz, 2004). At another level, there is a need to situate the finer detail brought about from examining local factors and particular patterns into a broader explanation of vulnerability, to gain deeper insights regarding the interdependence of vulnerability and differences between resources, societies and regions, and the interconnectedness among these groupings over space and time (Dow, 1992).

Reconciling the various epistemological positions on vulnerability into a more general analytical framework is therefore a central challenge to the emerging science of vulnerability and its role in 'help[ing] us understand those circumstances that put people and places at risk and those conditions that reduce the ability of people and places to respond to environmental threats' (Cutter, 2003b, p. 6). Our use of particularity as a keyword to summarize the essence of vulnerability analysis by no means negates the presence of a 'universal' knowledge with regard to vulnerability, derived from important contributions by hazards scholars over the last two decades. The argument we make by using the 'particularity' keyword, however, is that for such knowledge to be effective in advancing risk-reduction goals, it is not enough to be credible (i.e. reasonably true and generally applicable). It also has to be salient (i.e. relevant to the needs of decision makers in a given context) and legitimate (i.e. not biased to a certain research culture) (ICSU, 2002). We argue that one path to create reliable, salient and legitimate knowledge of urban vulnerability lies in devising analytical approaches capable of acknowledging the contextual particularities of vulnerability while still allowing that knowledge to be transferred from one setting to another. In this chapter, we introduce one such approach and show the role that GIS and remote sensing can play in translating this place-based approach into a replicable methodology.

9.3 A conceptual framework for place-based analysis of urban vulnerability

As we have argued above, urban vulnerability is a place-dependent process residing in the 'socio-ecological' urban context; where 'social ecology' is a term used to emphasize the people–nature relationship (Andrews, 1985; ICSU, 2002). In order for such 'place-based' knowledge of vulnerability to be salient, it cannot be simply imported from the stock of universal knowledge (ICSU, 2002). It needs to be endogenously generated. Likewise, the socio-ecological contexts vary greatly between cities and even between neighbourhoods within a given city. Consequently, the goals of urban vulnerability analysis (i.e. knowledge needs) are expected to vary too, to ensure legitimacy of the final product.

To illustrate the interrelationships between the place-based and universal levels of knowledge of vulnerability, and the way in which insights gained at local levels can

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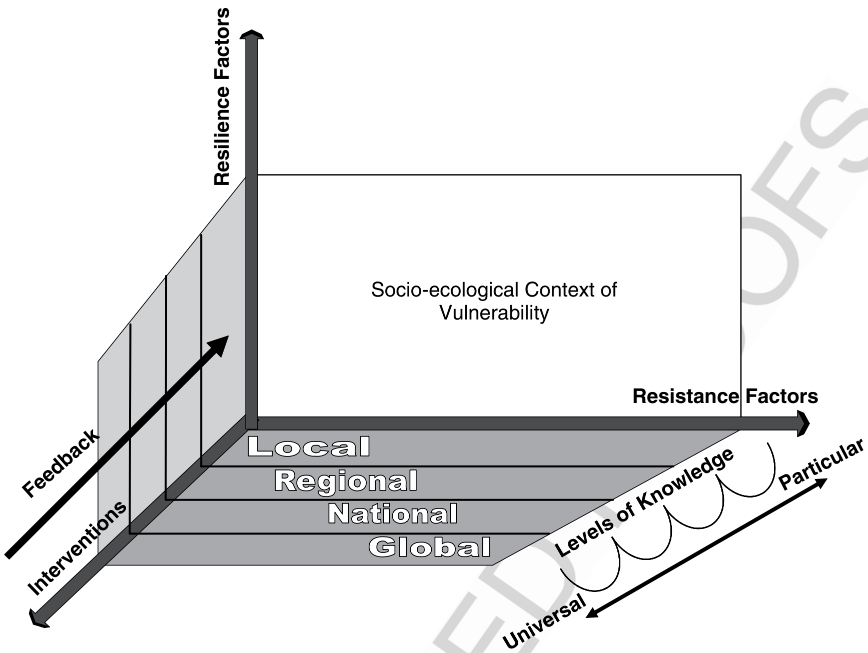

Figure 9.1 Simplified conceptual framework illustrating the interrelationships between the place-based and universal levels of knowledge of vulnerability

contribute to fundamental knowledge accumulated at the global level and vice versa, we present a simplified, general conceptual framework for vulnerability analysis in Figure 9.1. We have drawn on the insights of the vulnerability literature to establish the theoretical constructs of the proposed framework. We borrowed from Hewitt's ecological analysis of risk (Hewitt and Burton, 1971; Hewitt, 1997), Mitchell's contextual framework of hazards (Mitchell *et al.*, 1989), Cutter's hazards-of-place model (Cutter, 1996; Cutter *et al.*, 2000), and Mileti's systems approach to disasters (Mileti, 1999), the idea that patterns of vulnerability to hazards are contingent upon the physical, technological, social, economic and political realities of the system under consideration. We also have incorporated into the proposed framework some elements of Andrews' model of ecological risk intervention (Andrews, 1985) and Turner II *et al.*'s framework for vulnerability to climate change (Turner *et al.*, 2003), specifically the conception of urban areas as socio-ecological systems and the need to illuminate the nested scales of the vulnerability problem. Finally, we have used some elements of the 'pressure and release' model of vulnerability (Blaikie *et al.*, 1994; Wisner *et al.*, 2004) to convey the idea that locally focused studies and actions are of limited value if they do not account for the broader forces that affect the regional and local dynamics of vulnerability.

The framework shown in Figure 9.1 envisions the world as a hierarchy of multi-scale socio-ecological systems. A socio-ecological system at a given scale of the hierarchy encompasses the landscape of place(s) considered at this scale, i.e. neighbourhood, city, region, country, as well as the people who reside in this landscape, their culture and the way in which they organize their lives. The vulnerability of a socio-ecological system at any hierarchical level is considered a collective function of the system's resistance, its resilience, and interventions measures applied at that level. System resistance refers to the coping capacity of the system *prior* to a disaster.It represents a combination of all the strengths and resources (e.g. physical, institutional, socio-economic, skilled personal, public awareness) available within a given system to face adverse consequences that could lead to a disaster. System resilience refers to the degree to which a system is capable to return to its normal conditions *after* a disastrous event. Intervention measures denote a range of risk reduction and mitigation measures applied to both building resilience and strengthening the system's resistance.

Generally speaking, the framework sets three main characteristics for the form of knowledge that needs to be generated from urban vulnerability analysis:

1. To help explain the differential losses between people, ecosystems, and physical features due to disasters at a given level in the hierarchy (i.e. the focal system).
2. To evaluate the ability of the focal system to absorb the impact of disasters (i.e. system resistance) while continuing to function and recover from losses (i.e. system resilience).
3. Ultimately, to determine the best options available to devise risk reduction measures.

The hierarchy in the framework has important implications on the forms of knowledge that could be generated, and consequently on the above-mentioned goals of vulnerability analysis.

First, the goals of vulnerability analysis, the problems it addresses and the factors and issues considered will vary by scale. What this means is that we cannot compare two systems, A and B, if they belong to different levels in urban hierarchy (i.e. if A represents a city and B represents a county). Second, the notion of hierarchy draws attention to the fact that any system in the hierarchy, whether large or small, is made up of smaller parts (a *suprasystem*) and at the same time is part of some larger whole of which it is a component (a *subsystem*). Consequently, understanding the vulnerability of a focal system (i.e. the level chosen to receive primary attention) requires the observer to attend both to the knowledge of vulnerabilities generated at the subsystems of that focal system and to the larger processes and dynamics operating at the suprasystem to which that focal system is related (Andrews 1985; Anderson *et al*., 1999; Turner *et al.*, 2003). This means that one cannot compare the vulnerability of two focal systems, A and B, even though both are at the same level of hierarchy, unless they are part of the same suprasystem. For example, one may be able to compare the vulnerability of two cities belonging to Los Angeles County, California, but this comparison would be difficult if the cities belonged to different counties and if the processes found to be operating in these counties were different. It also means that the city A might be relatively more vulnerable than city B at one point of time and less vulnerable at another point of time, due to changes in the processes operating at the suprasystem to which they both belong.

Third, the hierarchy in the proposed framework views knowledge of vulnerability as a continuum from the particular to the universal and vice versa, as Mustafa (2005) has suggested regarding the complementary relationship among the epistemological positions in the field. As represented in Figure 9.1, the production of universal knowledge about vulnerability is accumulated and regularly updated through knowledge of vulnerability particularities generated at the lower levels of the hierarchy. These particular forms of knowledge at the lower levels are gradually generalized as we move to the upper levels in the hierarchy. In turn, the universal knowledge of vulnerability formulated at the upper levels is used to direct investigations into vulnerability conducted at lower levels. Finally, the proposed framework includes an axis for intervention measures that spans the hierarchy of socio-ecological systems. This axis emphasizes the idea that the goals of vulnerability analysis and decisions aiming at reducing risks are not quite the same across different scales in the hierarchy. At a regional scale, for example, decision makers may be concerned with the development of logistical and strategic plans to allocate resources. Therefore, it may be sufficient to crudely identify those areas that may experience higher degrees of damage in case of disasters. At the community level, on the other hand, it is necessary to have a thorough analysis of how the urban place will cope with a disaster to provide more specific intervention measures. Hence, the analysis would need to detail the behaviour of various urban subsystems, such as transportation, public facilities, infrastructure, etc.

9.4 Integrating GIS and remote sensing into vulnerability analysis

The rest of this chapter is devoted to illustrating how GIS and remote sensing can be integrated to translate the conceptual framework presented in Figure 9.1 into an applied model for place-based vulnerability analysis. The idea of context particularity implies locational variations in the outcome of vulnerability analysis as a consequence of spatial (and temporal) variations in underlying factors. These locational variations prompt the need for a spatially explicit model of vulnerability analysis. A model is said to be spatially explicit if the inputs and outputs of this model vary according to spatial location (Goodchild and Janelle, 2004). The value of using GIS and remote sensing in translating the proposed conceptual framework into an applied model for urban vulnerability analysis arises directly from the capabilities of these technologies in supporting spatial analysis and decision making, and the generation of place-based knowledge.

Based on the earlier discussion in this chapter, it can be argued that the extent to which GIS and remote sensing technologies are effectively used in the context of vulnerability analysis depends on the ability to balance two competing demands (Rashed and Weeks 2003). The first demand is offering a replicable way for researchers as well as planners and decision makers undertaking local risk reduction 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 and epistemological positions on urban vulnerability in order to test related theories and hypotheses, thus establishing links between place-based and universal levels of knowledge about vulnerability. Such links can ultimately improve our understanding of the interrelations among various contextual factors and global pressures that produce vulnerability patterns.

To meet these demands, Rashed (2006) suggests the following design criteria for integrative GIS and remote sensing place-based vulnerability analysis:

1. Emphasize the use of geospatial resources, i.e. software tools, remotely sensed images, GIS data layers, census data, etc., that are generally available to planners and decision-makers in any reasonably medium-sized urban area.
2. Recognize the divergent perspectives on urban vulnerability.
3. Be multihazards-based.
4. Incorporate policy and more explicit planning components.
5. Generate quantitative parameters that allow for the comparison of differential vulnerability within the focal system.
6. Involve a spatiotemporal modelling engine for urban dynamics that will allow us to collect evidence to support or reject alternative hypotheses concerning the causal linkages between vulnerability, and the social and physical characteristics of urban places, as well as the effects of planning policies.

Building on the above-listed criteria, Rashed (2006) proposed a procedure for place-based vulnerability analysis using GIS and remote sensing. In the following sections, we review this model of urban vulnerability analysis and then report on the findings of a case study that represents an initial attempt to test the applicability of the proposed procedure.

9.5 A GIS–remote sensing place-based model for urban vulnerability analysis

The framework in Figure 9.1 illustrates the degree of complexity involved in vulnerability analysis and draws attention to the value of a place-based analysis in

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the production of context-derived knowledge of urban vulnerability. Regardless of the spatial scale, the conception of place as a socio-ecological system entails the presence of causal linkages among an array of factors that potentially affect the vulnerability of the coupled human–environment system in a place (Turner *et al.*, 2003). Accordingly, the integrated GIS–remote sensing procedure of place-based vulnerability analysis shown in Figure 9.2 is centred on a dynamic causal model that adopts a systems-thinking approach to explain how vulnerability patterns arise from adverse interactions between and among the components of the socio-ecological system under consideration (Rashed 2006).

Causal models can be orientated in one of two ways: starting with a set of causes and examining their consequences, or starting with a set of consequences and moving down to their causes. The model shown in Figure 9.2 uses the latter path, through a distinctly spatial induction approach to vulnerability analysis. Inductive reasoning acknowledges the particularity of urban places and the need for generating place-based knowledge of vulnerability without assuming any *a priori* hypotheses. Spatial induction means that the problem of vulnerability can be conceptualized as a spatial search problem through which a particular geographic place or region is first screened for evidence of vulnerability. This is done by examining the range of potential losses that may be caused by hazards in an urban place and working back to a measure of the vulnerability of that place. The derived measure of vulnerability

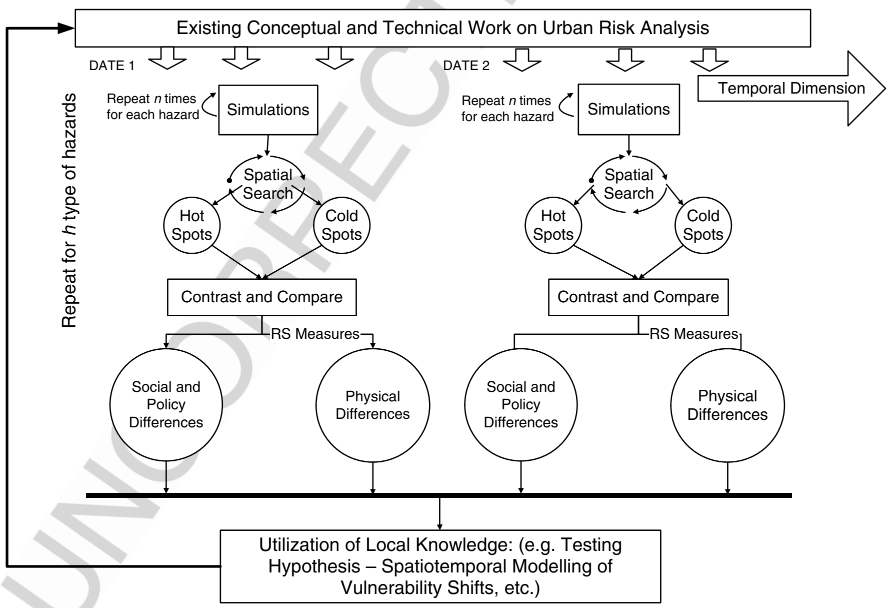

Figure 9.2 Technical framework for the integrative GIS–remote sensing model for place-based urban vulnerability analysis. Adapted from Rashed (2006)

is then utilized as an instrument to learn about the range of local factors influencing vulnerability, which might be hidden to the observer or seem quite remote from the hazardous event. This local-generated knowledge can ultimately help devise effective and sustainable risk reduction policies.

To implement the idea of spatial screening, the model proposes the utilization of current advances in geospatial techniques to simulate actual and hypothetical disaster experiences of single or multiple hazards in a particular region. Each simulation will show how potential damages or losses (risks) from a simulated hazard are distributed across the region, assuming that risk = hazard × vulnerability, when several simulations are run using a single set of data pertaining to an urban region at a given point of time (i.e. the particularities of an urban area, and hence vulnerabilities, are controlled for). Variations in simulation results then become a function of the type, location and magnitude of the hazard being simulated. Finding the most vulnerable areas (hot spots of vulnerability) within the urban region then becomes a matter of: (a) ranking urban areas based on the severity of losses calculated from each simulation and (b) searching the region for those areas that maintain relatively high ranks across all the simulation scenarios. These areas are deemed the most vulnerable because maintaining a high rank across different scenarios implies that an area is likely to experience significant losses regardless of the hazard type, originating source or magnitude. Hence, the losses in that place can directly be attributed to its vulnerability. Once areas with high levels of vulnerability are located (the hot spots), spatiotemporal comparisons to areas with lower levels of vulnerability (the cold spots) can be conducted to identify differences and commonalities in their social, physical and political characteristics. As shown in Figure 9.2, the process may be repeated using other datasets that describe the status of the urban region at other points of time. The results can then be utilized to improve our understanding of the relative importance of the various factors influencing vulnerability over space and time, and to dig deeper into the underlying processes amplifying or diminishing vulnerability.

9.6 An illustrative example of model application

To illustrate the utility of the model, we present in this section a first application in a pilot case study from Los Angeles County, California. Due to the exploratory nature of this case study, we have limited our investigation to a single context (Los Angeles County), a single hazard (earthquakes), a single date (1990) and a single question, relating to the links among differential physical and social vulnerabilities to urban earthquakes and urban environmental conditions, as measured from satellite remote sensing. The purpose of the case study is to give a practical example of carrying out place-based vulnerability using GIS and remote sensing technologies. Hence, a full discussion of the technical details encountered in the implementation of this model is beyond the scope of this chapter. We refer interested readers to

Rashed and Weeks (2003) and Rashed *et al*. (2003), in which extensive discussions of the technical developments that have contributed to the present model can be found, especially those related to the simulation of hazards, the identification of vulnerability hot and cold spots, and the quantification of urban morphology through spectral mixture analysis of remotely sensed imagery. In this chapter we will only touch briefly upon the technical issues deemed necessary for demonstrating the utility of the model and for the interpretation of its results.

9.6.1 Study area

The diverse social and physical character of Los Angeles County makes it an ideal study site for testing the capability of using GIS and remote sensing in generating context-specific knowledge of the relative importance of social and physical variables contributing to the overall vulnerability profile of urban communities in this region. Los Angeles County is one of the most populous and ethnically diverse places in the USA (Gordon and Richardson, 1999). Segregation patterns of ethnicity and socio-economic classes in Los Angeles, accompanied by successive waves of economic restructuring and population expansion, have been reflected in the built environment and the physical structure of urban form within the region (Rubin, 1977; Allen and Turner, 1997; Modarres, 1998). For example, Li (1998), comparing areas in Los Angeles dominated by population groups from China and Indochina vs. 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 the region's urban landscape.

The study area has witnessed several earthquake events in the past century. The most recent 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 (Bolin and Stanford, 1998). Therefore, formulating an understanding of the linkages among social and physical vulnerability patterns to earthquake hazards in Los Angeles County can ultimately aid in the formation of policies in anticipation of the problems accompanying urbanization processes and demographic shifts in this dynamic region.

9.6.2 Data

The unit of analysis (focal system) utilized in this case study was the census tract. In this case study, we investigated a total of 1608 census tracts covering approximately 3220 km^2 of the entire urbanized area of Los Angeles County. Most of the spatial and aspatial data utilized in the analysis were obtained from the inventory datasets available from the US Federal Emergency Management Agency (FEMA) and built into HAZUS, the software we used for simulating damage loss from earthquakes (FEMA-NIBS, 1999). 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 epicentres of past earthquakes. In addition, we utilized other population datasets from the US Census Bureau, and digital maps for soil and slope instability and liquefaction potential.

The satellite data utilized in the remote sensing analysis included a subset (3113 lines × 4801 samples) from a Landsat TM image acquired on 3 September 1990 (path 41, row 36). The acquisition date of this image corresponds reasonably well to the 1990 US Census (taken in April 1990). In addition to the multispectral image, a set of 1.0 m spatial resolution aerial photos were used to aid in the validation of the results.

9.6.3 Identifying vulnerability hot spots

Identification of vulnerability hot spots in Los Angeles was accomplished through an empirical model developed by Rashed and Weeks (2003) for the analysis of urban vulnerability to seismic hazards (Figure 9.3). The Rashed–Weeks model combines elements from the techniques of multicriteria evaluation and fuzzy systems analysis (Malczewski, 1999; Jiang and Eastman, 2000) to generate vulnerability scores for urban places. The model was built on top of a robust simulating engine of damage from earthquakes called HAZUS (HAZards in the US) developed by FEMA. HAZUS 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. It also has the capability to generate loss estimates at the census tract level, and this is very important to establish links with social measures of vulnerability derived from census data.

As illustrated in Figure 9.3, there are seven main stages in applying the Rashed–Weeks model of vulnerability analysis. The first stage is the selection of evaluation criteria based on damage estimates to be generated from the simulation. The following criteria have been used as basis of deriving the results presented below (Rashed and Weeks, 2003):

1. Criteria for social risks, including casualties, percentage of households that might seek temporary shelter after a disaster (a proxy for short-term social losses), and total economic cost required for the replacement, reconstruction and recovery of residential buildings (a proxy for long-term social losses).
2. Criteria for physically-induced and engineering risks, including collapse of structures and loss of contents, area of land that might be burned due to induced fire, and amount of debris.

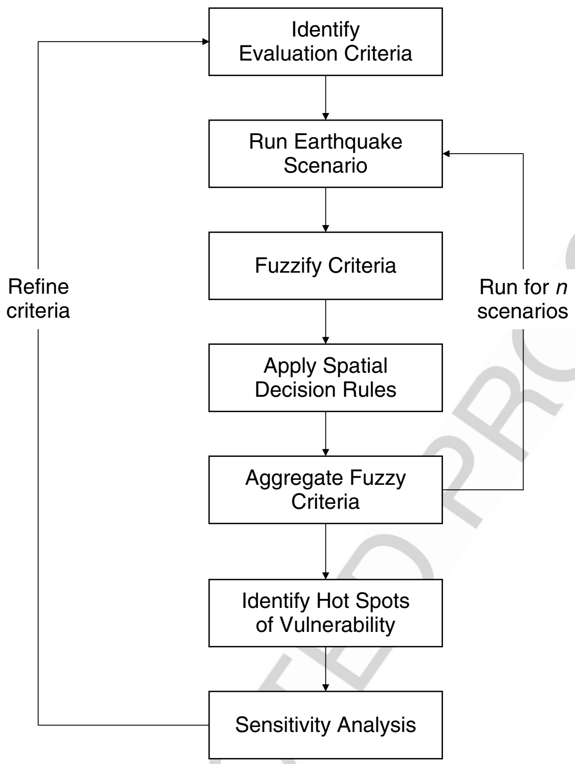

Figure 9.3 Rashed–Weeks model. Adapted from Rashed and Weeks (2003)

3. Criteria for urban systemic risks which may influence the emergency response and management activities following a disaster, including percentage of loss in functionality for hospitals, fire and police services, power utilities, highways and bridges.

The second stage of the Rashed–Weeks model is the simulation of hazards to explore the combined effects of multiple hazards on a particular region according to multiple scenarios. In the third stage, loss estimates created from a scenario are standardized through a 'fuzzification' process, which recasts values of criteria into statements about set membership using linguistic terms (high, low) (Malczewski, 1999). In the fourth stage, the fuzzified criteria are compared pairwise, using the analytical hierarchy process (AHP) developed by Saaty (1980) in order to generate a set of weights for the evaluation criteria. In the fifth stage, the weighted 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, which represent the linguistic expressions of the damage states (lower-, medium-, or higher-risk). Stages three to five can be repeated for additional scenarios. In the sixth stage, the 'higher-risk' fuzzy layers produced from all the scenarios are used to locate hot spots of urban vulnerability by identifying those locations that are frequently assigned to higher damage estimates, regardless of the hazard type or source. Finally, in the seventh stage, sensitivity analysis is conducted to determine the effects of simulation parameters on the final output.

The results from applying the Rashed–Weeks model to Los Angeles County based on data from 1990 are presented in Figure 9.4. The maps shown in Figure 9.4A represent the results of the simulation of five earthquake scenarios (four deterministic and one probabilistic). These results were produced by applying the evaluation criteria to obtain a final fuzzy set that represents an index of higher risk in each scenario. Darker areas indicate places with higher damage estimates in the scenario. The map shown in Figure 9.4B represents the distribution of higher-vulnerability values in Los Angeles County derived from the resultant simulation maps of earthquake risks. In this map, darker areas in the figure represent places with higher vulnerability, while brighter areas represent places with lower vulnerability. A visual inspection of the map shows that census tracts with a higher degree of membership in the higher-vulnerability index (i.e. vulnerability hot spots) are clustered in the NW quadrant of Los Angeles County, near the cities of San Fernando and Burbank. As we move away from this quadrant, the degree of membership decreases, and so does vulnerability.

9.6.4 Deriving remote sensing measures of urban morphology in Los Angeles

9.6.4.1 MESMA

The model in Figure 9.2 utilizes remote sensing techniques to understand how the hot and cold spots generated from the simulation physically differ in terms of land cover composition and urban spatial structure. The rationale behind this analysis is that patterns of urban morphology represent the locus of the diversity of engineering, socio-economic and political interactions within urban places. Thus, if differences are found among hot and cold spots of vulnerability in terms of the physical composition and spatial configuration, this could suggest ways in which urban morphology might be manipulated through sustainable policies, to reduce vulnerability to hazards. It could also provide a means to monitor progress toward sustainable hazards mitigation within a giving urban context.

A recurrent theme in several studies in remote sensing has been related to the derivation of summary indicators of the physical components of urban areas. This type of analysis has traditionally been limited due to the spectral heterogeneity of urban features in relation to the spatial resolution of the remote sensors (Weber, 1994), especially true in the context of multispectral images with medium spatial

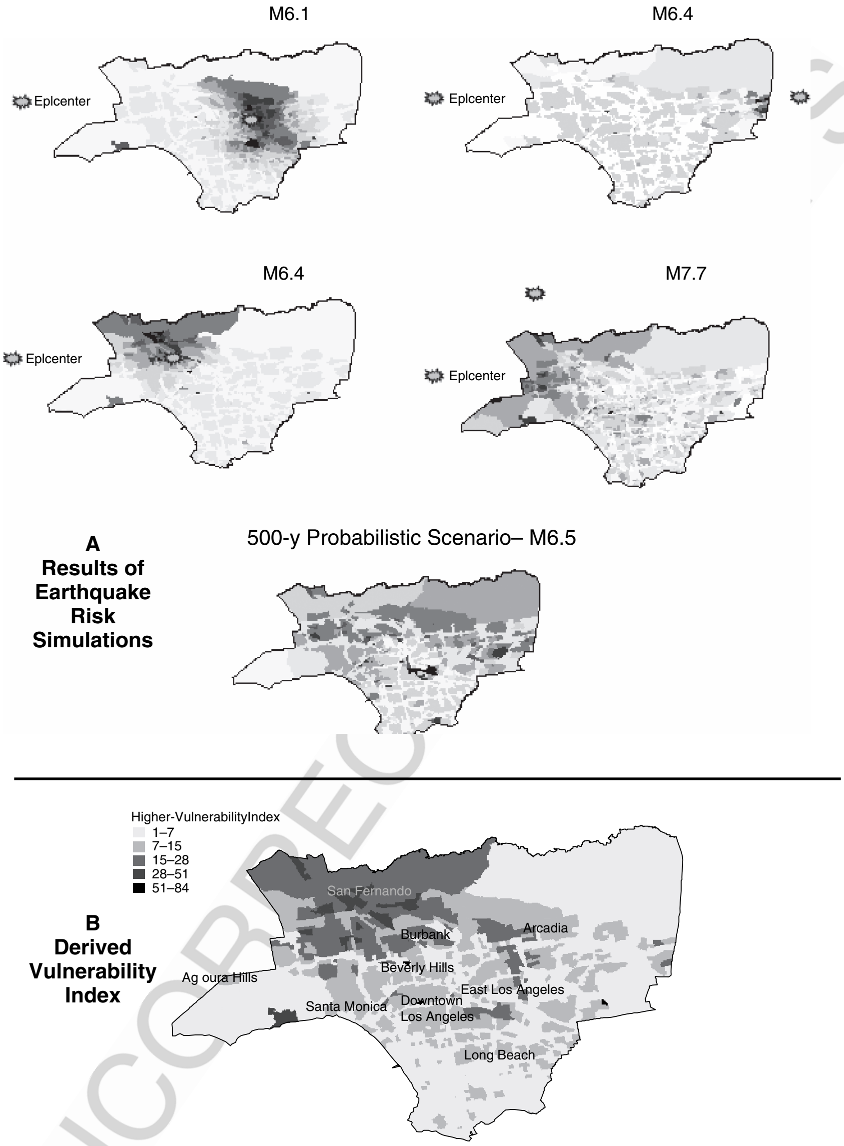

Figure 9.4 Results from applying the Rashed–Weeks model in Los Angeles. Adapted from Rashed and Weeks (2003)

resolution, such as those provided by Landsat satellites. Because of this spectral heterogeneity, there is a need to deal with a complex mixture of spectral responses (Forster, 1985).

To address the spectral mixing problem and to obtain more representative measures of the composition and structural patterns of urban land cover in the metropolitan area of Los Angeles, the remote sensing analysis task was accomplished in the present case study through the application of multiple endmember spectral mixture analysis (MESMA) (Rashed *et al*., 2003) and landscape metrics. The MESMA approach, originally developed by Roberts *et al*. (1998), is based on the concept that, although the spectrum in any individual pixel can be modelled with relatively few endmembers, the number and type of endmembers are variable across an image. In this sense, MESMA can be described as a modified linear spectral mixture analysis (SMA) approach, in which many simple SMA models are first calculated for each pixel in the image. The objective is then to choose, for every pixel in the image, which model amongst the candidate models provides the best fit to the pixel spectrum while producing physically reasonable fractions. The procedure of applying MESMA to the 1990 Landsat TM image (Figure 9.5) is described in detail in Rashed *et al*. (2003).

The results from the MESMA were used in two ways to describe spatial variation in the physical conditions between the census tracts in Los Angeles in 1990. The first way was the calculation of an average normalized measure per census tract

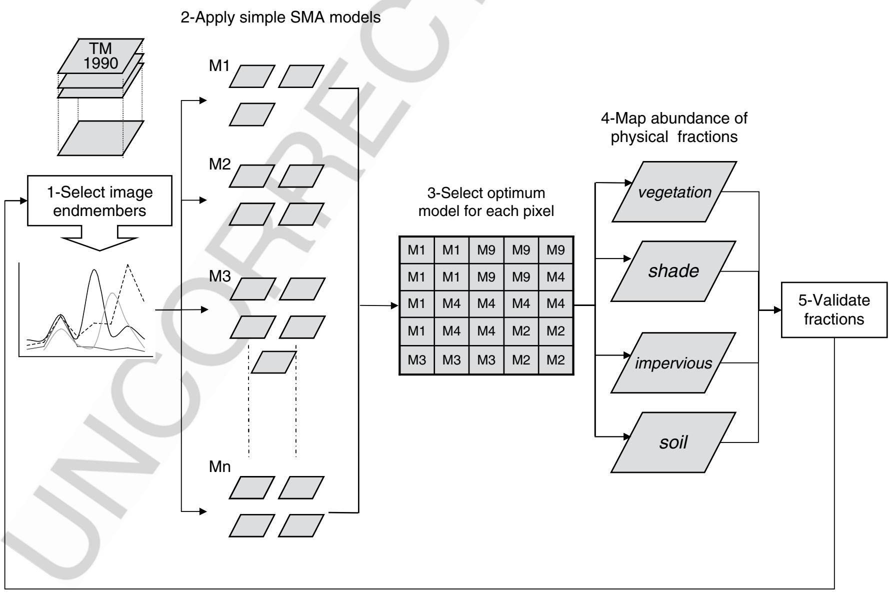

Figure 9.5 An overview of the MESMA approach. Adapted from Rashed *et al*. (2003)

for each of the four land cover categories of derived MESMA: vegetation, soil, impervious surface and water/shade (Figure 9.5). The normalization was achieved by first summing up the fractional abundance of each category within each census tract, then calculating the ratio of the total fractional abundance to the census tract's area. The product of this process was a Normalized value (range 0–100) per census tract for each of the four land cover categories, indicating the average abundance of the land cover within that tract.

The second way of utilizing remote sensing measures in the present study was the derivation of second-order measurements from MESMA fractions that described the configuration (form) of the census tracts in terms of urban land cover. The use of landscape metrics in the analysis of urban landscape patterns is one of the topics that recently received increasing attention in the urban remote sensing community (Geoghegan *et al*., 1997; Alberti and Waddell, 2000; Parker *et al*., 2001; Herold *et al*., 2002, 2003). Landscape metrics are indices developed for categorical map patterns, based on both information theory and fractal geometry (Herold *et al*., 2002; McGarigal *et al*., 2002). Categorical map patterns represent data in which the ecosystem property of interest is represented as a mosaic of patches. The definition of patches is imposed according to a phenomenon of interest and only meaningful when referenced to a particular scale (McGarigal *et al*., 2002). For example, the urban landscape of Los Angeles can be described as a mosaic of census tracts. The census tract in this case can be thought of as a patch that is relatively homogeneous in terms of social and physical conditions. Similarly, at a larger scale, a census tract can be viewed as a mosaic (or landscape) of its own, consisting of smaller patches of land cover classes represented by a collection of pixels.

Unlike the soft classification nature of MESMA results, landscape metrics operate upon a hard or crisp classification assumption. Therefore, before landscape metrics were used in the present study, MESMA fractional images had to be reclassified, such that each pixel within any census tract corresponded to one, and only one, class of land cover. A threshold of 60% was arbitrarily chosen, assuming that when a given land cover class occupies 60% or more of a pixel, then it is possible to say that this pixel generally belongs to that land cover class. When fraction values within a pixel failed to meet this criterion, then a decision role was applied to assign a class to that pixel according to what class the majority of neighbourhood pixels within a 3×3 window had.

The next step was to select a subset of landscape metrics to measure the spatial properties of census tracts in Los Angeles. Two types of metrics were used. The first was the class-level metrics, which were applied to zones of land cover types within census tracts (i.e. each zone of land cover category was considered a landscape made of individual pixels or patches). The second type was the census tract-level metrics, which treated each census tract as a landscape made of zones or patches of land cover categories. Tables 9.1 and 9.2 list the subsets of metrics that have been used on either the land cover class or census tract levels.

Table 9.1 Description of landscape metrics applied at the land cover class level within a census tract

Class metrics	
Metric	Property measured
PD (patch density)	Areal composition
LPI (largest patch index)	Areal composition
PAFRAC (perimeter-area fractal dimension)	Shape complexity
PLADJ (percentage of like adjacencies)	Degree of aggregation of land cover class
AI (index of aggregation)	Degree of aggregation of land cover class
IJI (interspersion and juxtaposition index)	Degree of interspersion or intermixing of land cover class
DIVISION	Diversity of land cover class
COHESION	Physical connectedness of the land cover class

Table 9.2 Description of landscape metrics applied at the census tract level

Landscape metrics	
Metric	Property measured
PD – (patch density)	Areal composition
LPI (largest patch index)	Areal composition
PAFRAC – (perimeter-area fractal dimension)	Shape complexity
CONTAG	Overall fragmentation of land cover classes
AI – (index of aggregation)	Degree of aggregation of land cover classes
IJI – (interspersion and juxtaposition index)	Degree of interspersion or intermixing of land cover classes
SIDI – (Simpson's diversity index)	Diversity of land cover classes

9.6.5 Deriving an index of wealth for Los Angeles County

Information on wealth was used in this case study as a proxy for access to resources, which in turn was used as an indication of the distribution of social vulnerability. Although this wealth index is not as sophisticated and comprehensive as other social vulnerability indices proposed in the literature, e.g. that of Cutter *et al*. (2003), we deem it satisfactory for the present study, given its exploratory and illustrative purposes.

To calculate an index of wealth for Los Angeles in 1990, data were used from the US Census Bureau's Survey of Income and Programme Participation (SIPP) to calculate the ratio of wealth to income at each income level by race and by age group. The next step was to use data from the 1990 Public Use Microdata Sample (PUMS) to convert the ratios derived from the SIPP data to the closest income categories that are available in the 1990 census of the study area. The averaged values represented multipliers to be applied to a table that included information on the number of households by income category and race by age for each census tract. Finally, the average household wealth was calculated for each census tract, weighted by the average income, race and age of householders in the census tract. The outcome of this process was a wealth index for Los Angeles County in 1990, which we utilized as an indication of the overall level of access to resources (and hence social vulnerability) in each census tract.

9.6.6 Spatial filtering of variables

Although spatial autocorrelation has long been a concern in geographic literature, it has not yet been routinely addressed in remote sensing applications or in vulnerability analysis (Rindfuss *et al.*, 2004). However, it is well known that data aggregated at particular spatial units, such as census tracts, will be more similar to data for other nearby spatial units than they are to more distant spatial units, because of the bias caused by spatial autocorrelation (Getis and Ord, 1992). Cliff and Ord (1981) identify two general approaches for resolving these problems: (a) filtering spatially autocorrelated data to account for spatial autocorrelation; or (b) modifying statistical models to accommodate spatial autocorrelation (such as spatially autoregressive models).

In the present study we utilized the former approach, following a method of spatial filtering suggested by Getis (1995). Getis' spatial filtering technique involves the extraction of the spatially autocorrelated portion of each of the variables to be input in an ordinary least-squares (OLS) linear regression analysis and then the use of the spatial portion as a separate factor (Getis, 1995; Scott, 1999). By solving the OLS regression model with the extracted filtered and spatial components of the variables, the spatial autocorrelation is removed from the residuals and incorporated into the model to help predict variation in the dependent variable. Summing the absolute values of the statistically significant standardized beta coefficients then allows us to determine the proportion of explained variation that is due to the spatial component, whereas the remainder of the explained variation is accounted for by the filtered (non-spatial) component. The ratio of the square of the beta coefficients for any two independent variables indicates their relative contribution to the prediction of the dependent variable.

9.6.7 Generating place-based knowledge of urban vulnerability in Los Angeles

9.6.7.1 Statistical models

Three statistical models were developed in order to: (a) demonstrate the utility of the model in generating place-based knowledge of the relative importance of the urban morphological social and physical conditions in shaping the spatial patterns of urban vulnerability to earthquakes in Los Angeles County; and (b) compare this place-generated knowledge against conventional wisdom of vulnerability. The first model tested the null hypothesis that the index of wealth (IW), used as a proxy for social vulnerability, was not significantly correlated with the index of higher vulnerability (IV), calculated from the simulation of earthquake risks. The second employed a step-wise OLS regression to examine the extent to which wealth is predicted exclusively by remote sensing measures describing urban physical characteristics. The model employed IW as a dependent variable, and the following independent variables: (a) MESMA fractional measures of vegetation, soil, impervious surface and water/shade normalized by census tract; and (b) landscape metrics calculated as second-order measures of MESMA results (listed in Tables 9.1 and 9.2). The format of this model, after applying the spatial filtering, was as follows:

$$\begin{aligned}\text{Wealth}(IW) = {} & (\text{normalized MESMA fractions filtered}) \\ & + (\text{normalized MESMA fractionsspatial}) \\ & + (\text{landscape metrics filtered}) + (\text{landscape metrics spatial}) + \text{error}\end{aligned} \tag{9.1}$$

The third model was a binary logistic regression model that examined the presence or absence of higher vulnerability (IV) based on values of a set of explanatory variables. Logistic regression was used in this part of the analysis because of the ordinal nature of the fuzzy measure of vulnerability, which allowed for a binary division of the dependent variable into high (1) and low (0) using a threshold value. The explanatory variables used in this third model included the index of wealth (IW), as well as a set of remotely sensed measures that were found to be statistically associated with wealth in the OLS regression model. The general form of this model was:

$$\text{Logit}(Pi) = \log\,[Pi/(1 - Pi)] = a + bXi \tag{9.2}$$

where *i* represents the binary value of vulnerability, *Pi* is the conditional probability of *Yi* given *Xi*, *a* is the intercept, *b* is the vector of slope parameters and *Xi* is the vector of explanatory variables (wealth and remotely sensed measures).

9.6.7.2 Results of correlation between vulnerability and wealth

Table 9.3 shows Pearson's correlation coefficients between vulnerability and wealth. The table reports a correlation value of 0.11 between vulnerability (IV) and wealth (IW), indicating a low, but nonetheless statistically significant, negative correlation at the 0.01 level, leading us to reject the null hypothesis that wealth, as a proxy for social vulnerability, is not associated with vulnerability values estimated through the simulation of biophysical risks in urban areas. The correlation between the IW and the spatial portion of the IV in Table 9.3 indicates that only the spatial components in the two indexes were significantly correlated, suggesting more evidence for the importance of 'where you are' in the distribution of vulnerability in Los Angeles. While these correlation values were not as high as one may have anticipated, based on what the literature suggests, the significance of such results becomes more apparent if we recall that the IV and IW represent the results of two totally independent methods for measuring vulnerability. Thus, while the negative correlation between wealth and vulnerability found in the model conforms to the universal wisdom, the relatively low correlation value means that the most vulnerable physical elements do not always overlap with the most vulnerable populations within Los Angeles. This finding is important because it is almost identical to what Cutter *et al.* (2000) found from an analysis conducted in Georgetown County, South Carolina, suggesting a pattern that is likely to be common in other urban places in the USA.

Further, some previous studies (e.g. Scott, 1999; Weeks *et al.*, 2000) have suggested the existence of a lag between change in the social environment and the corresponding change that may occur in the physical environment, with the former occurring first. In fact, Scott (1999, pp. 111–112), in the context of her

Table 9.3 Results of correlation analysis between vulnerability and wealth

		"IV"	"IV_sp"	"IV_f"
"IW"	Pearson Correlation	−0.111**	−0.149**	0.016
	Sig. (2-tailed)	.000	.000	.531
"IW_sp"	Pearson Correlation	−0.112**	−0.141**	0.008
	Sig. (2-tailed)	.000	.000	.769
"IW_f"	Pearson Correlation	0.045	−0.068**	0.013
	Sig. (2-tailed)	.073	.007	.601
	N	1561	1561	1561

** Correlation is significant at the 0.01 level (2-tailed) analysis of accessibility to jobs in Los Angeles, showed that the census tracts at the periphery of Los Angeles County (where higher values of IV exist) were classified as low-income tracts in the 1980 census. However, those tracts themselves became high-income in 1990. This implies a rapid social change that occurred throughout the county in the 1980s that might not yet have been reflected by a physical change in 1990. Thus, one can put forward a proposition that a wealth index based on the 1980 census data might have done a better job than the index used here, which was based on the 1990 census data. It can be suggested, then, that the statistically significant correlation results noted above in fact represent strong evidence of a possible causal linkage between the physical and social conditions of urban places with regard to vulnerability (again conforming to universal wisdom about vulnerability patterns). This is further investigated through the results of the regression models reported in the following subsection.

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9.6.7.3 Results of regression models

As a first step in examining whether remotely sensed measures can be used in conjunction with social variables to explain the variation in vulnerability, a step-wise OLS regression model was developed. The model employed the IW as a dependent variable, and a total of 40 independent variables (four Normalized MESMA variables, eight variables resulting from applying landscape metrics at the census tract level, and 28 variables resulting from applying the metrics at the four land cover class levels). The technique of spatial filtering was used to split spatially autocorrelated independent variables into their spatial and non-spatial components.

Table 9.4 Spatially filtered OLS regression for the index of wealth (IW)

Variable	Unstandardized Coefficient	Standardized β	t	Significance of t
Dependent Variable IW				
Impervious_f	−2177.326	−0.0361	−14.763	0.000
IJI_Shade_sp	526.144	0.157	5.777	0.000
Vegetation_f	1748.643	0.184	8.959	0.000
Impervious_sp	−877.699	−0.073	−2.980	0.003
IJI-Shadei_f	206.075	0.075	2.854	0.004
PD_Impervious_f	1532.003	0.394	11.253	0.000
PD_Impervious_sp	1506.867	0.340	10.008	0.000
Vegetation_sp	1475.475	0.055	2.228	0.000
R	0.767			
Adjusted R^2	0.586			
$z(1)$ For residuals	0.89			
N	1561			

Note: see text for an explanation of the variables

The results of the model are shown in Table 9.4, in which only statistically significant predictors (at the 0.05 level) are reported. The R value for this model was 0.767, with an adjusted R^2 of 0.586. An examination of the residuals showed that they were not spatially autocorrelated and exhibited no heteroscedasticity. Also, the results of the co-linearity diagnostic indicated that the independent variables had scored low (< 9) in the condition index. The results show that four of 40 variables utilized emerged as statistically significant predictors of the index of wealth. Among these, two were Normalized MESMA measures (vegetation and impervious surface) and two were derived from landscape metrics applied at the land cover class level within census tracts (PD_Imp and IJI-shd). Considering the absolute values of the statistically significant standardized beta coefficients, we can determine that MESMA measures have accounted for about 26% of the explained variation in the wealth, most of which was related to variation in vegetation. The measures derived from landscape metrics accounted for about 74%. Further, the spatial component in all variables accounted for about 52% of the explained variation in the wealth, while the filtered component accounted for the remaining 48%.

The results in Table 9.4 indicate that the most important predictors of the wealth index were the spatial and non-spatial components of PD_impervious, a landscape metric measure that describes the density of patches within the impervious land cover class in a census tract. The results show that although the density of impervious surface in census tracts is indicative of higher wealth, the abundance of impervious surface fractions derived from MESMA is negatively associated with wealth. This interesting finding highlights the value of applying landscape metrics to MESMA measures to reveal certain physical patterns within an urban place that may not otherwise be shown if one is only relying on the measurement of the physical composition in that place. Table 9.4 also lists vegetation as a strong predictor of wealth, with higher vegetation abundance associated with the more affluent census tracts – a finding that has been reported repeatedly in other urban settings (e.g. Ryznar, 1998; Rashed *et al*., 2001; Small, 2001).

Finally, results in Table 9.4 indicate that the IJI_shade, another landscape metric applied at the land cover class level, has emerged as a significant predictor of higher wealth. IJI measures the degree of the intermixing of patches within a land cover class. A lower IJI value indicates that patches belonging to a land cover class within a census tract are more aggregated and less fragmented. The results in Table 9.4 suggest that wealth increases (and social vulnerability decreases) with the increase of fragmentation in the shade within a census tract. Since shade has been used in the analysis as a proxy for building heights, one can conclude that tracts with low-rise buildings, e.g. single-family housing, would be characterized with higher IJI values. On the other hand, tracts with high-rise building will possess lower IJI values, and in Los Angeles these areas are likely to score lower on the wealth index, as in the case of downtown Los Angeles. The second regression model utilized was a binary logistic model that used the index of vulnerability (IV) as a dependent variable, and wealth and the remotely sensed measures emerged as statistically significant

Table 9.5 Logistic regression for the index of vulnerability (IV)

Variable	β	*Wald*	Significance	EXP(β)
Dependent Variable IV				
Impervious	0.1390	0.9342	0.3338	1.1491
Vegetation	0.6273	21.1980	0.000	1.8725
IJI_Shade	0.3634	5.8804	0.0164	1.4838
PD_Impervious	0.6987	19.6991	0.000	2.0112
Wealth 1	−0.0723	0.3239	0.5692	0.9303
Wealth 2	0.6018	28.5415	0.0000	1.8253
Wealth 3	0.3628	11.5632	0.0007	1.4451
Wealth 4	−0.2658	5.6609	0.0180	0.7666
Overall percent correct	63.36%			
Chi Square	15.3524		0.0317	
Nagelkerke R^2	0.102			
N	1561			

Note: see text for an explanation of the variables

predictors of the wealth index in the OLS regression model. The results of the model are shown in Table 9.5. The threshold used to determine the binary values of the IV was based on the mean value of the index. Those values that were above the mean were assigned to 1, indicating higher vulnerability, and those values that were equal to or less than the mean were assigned to 0, indicating lower vulnerability. The model was also tested using other thresholds and the results were generally consistent with those listed in Table 9.5. The overall correct prediction of the model was about 63%, with $\chi^2 = 15.34$ at a 0.05 level of significance.

The results in Table 9.5 show that three out of the four remotely sensed variables utilized emerged as statistically significant predictors of higher vulnerability. The strongest among these was again the landscape metric-based measure, PD_impervious, the higher values of which were shown to increase the odds of being highly vulnerable by a factor of 2.01, holding all other variables constant. On the other hand, as expected, being in the higher wealth category (wealth 4) reduces the odds (by a factor of 0.77) of being in the highly vulnerable category. This suggests that the wealth (social) effect is independent of the remotely sensed (physical) effect, and that both need to be taken into account if we are to understand the vulnerability of place.

9.6.8 To what extent do model results conform to universal knowledge of vulnerability?

The purpose of this case study has been to provide an applied example of the utility of an integrative GIS–remote sensing model for place-based vulnerability analysis. Generated knowledge of vulnerability was used to fulfil two objectives: first, to explore the basic hypothesis that social vulnerability is manifested through aspects from the physical environment in urban places within Los Angeles; and second, to examine the proposition that remote sensing can provide us a quantitative means to describe and assess aspects related to urban spatial structure that influence vulnerability in that region.

To address the first objective, we examined the correlation between the wealth index and vulnerability. The results showed a statistically significant negative correlation between the two indexes, although not high enough to conclude that the wealth can be taken as a sole indicator of vulnerability. Given the apparent difference between the spatial distributions of values in the two indexes, an obvious question arises: how do these results conform to theories of vulnerability found in the literature? The answer to this question can be discussed in light of the relationship between access to resources and vulnerability. This relationship was previously examined by researchers in the context of disasters in developing countries (e.g. Wisner, 1993; Blaikie *et al*., 1994). In these studies, access to resources was traditionally measured by the level of poverty determined by income (as opposed to the concept of wealth utilized here). In developing countries, spatial and physical aspects of vulnerability tend to be much more pronounced because the poor are often forced to live and work persistently in hazardous areas (Hewitt, 1997). In contrast, socially and economically marginalized populations in the USA do not necessarily live in areas at greatest risk of natural hazards (Bolin and Stanford, 1999). Indeed, the wealthy people may even choose to live in physically hazardous settings, such as earthquake-prone hillsides in California (Davis, 1998). Therefore, vulnerability in this case has little to do with systematic differences between the rich and poor in terms of their exposure to the earthquake, a finding confirmed above in the model results.

Additionally, the general literature on vulnerability draws a distinction between two patterns of vulnerability: *persistent* (or *chronic*) vulnerability and *situational* vulnerability (Bolin and Stanford, 1998). Persistent vulnerability connects to social forces that produce economically, ethnically and culturally marginalized groups. Situational vulnerability, on the other hand, occurs when some population groups (including wealthy and financially secured ones) become increasingly at risk in the face of calamity. This might happen due to a combination of circumstances related to their jobs, choice of housing, etc., but does not necessarily need to be related to social or demographic factors. That is, in situational vulnerability, a household has the option to choose not to live in a hazardous place. In persistent vulnerability, the social factor is much more noticeable, while the physical aspect of vulnerability is implicit. Situational vulnerability is quite the opposite case, in which the physical aspect of vulnerability becomes more apparent and the social aspect becomes implicit. It is our contention that these patterns of persistent and situational vulnerabilities were represented respectively by the index of wealth (IW) and the index of vulnerability (IV) produced by the simulation of physical damage resulting from earthquake scenarios. The mismatch of the spatial distribution between the two indexes implies some missing information related either to social vulnerability (in the case of the IW) or physical vulnerability (in the case of IV).

The second objective fulfilled by the knowledge generated in this case study is related to the utility of remote sensing for providing measures that can be used as surrogates for social vulnerability. The results of the OLS model showed that the remotely sensed variables accounted for about 57% of the explained variation in the IW. The results of the logistical regression showed that the remotely sensed variables emerged as significant predictors of the IV. The moral of these results is that remote sensing data can be used to derive information about the physical composition and spatial structure of the built environment in an urban place. This information reflects aspects of the social environment that will be manifested in the demography and culture of people. The built environment, represented by the arrangement of land cover classes, then interacts with the socio-economic environment (measured, at a minimum, by income, race and ethnicity) to produce the urban environment. The urban environment then creates a difference in people's vulnerability by influencing the volume and intensity of social interaction, which in turn has implications for the opportunities that exist for different social groups to access resources.

There is no doubt that a small number of statistical models based on one unique urban area in a developed country cannot be taken as a foundation upon which to build a grand theory of vulnerability to disasters, or to explain how vulnerability is reflected in the urban spatial structure. But the results of these models are still sufficient to draw the attention to the utility of place-based vulnerability analysis using GIS and remote sensing in obtaining information that addresses core issues of the social sciences such as social vulnerability.

9.7 Conclusions

The disaster caused by Hurricane Katrina in the USA in 2005, and the subsequent course of events that shaped the disaster in affected cities along the US Gulf Coast, revealed a striking example of physical and social vulnerabilities in 'western' cities in their worst-case scenario. The disaster has strongly challenged, or at least shown the need for revisiting, some popular views that are frequently portrayed in the literature in either an implicit or explicit manner, for example, the idea that 'inhabitants of less developed countries [are] more likely to die from hazards than those in more developed ones' (Bankoff, 2004, p. 29), or the emphasis on development as an exclusive means to reducing risks (UNDP, 2004). These kinds of broad generalizations with regard to vulnerabilities and risks could be misleading, because there is no place or group of people that can be thought of as entirely safe, neither is there a magic single solution for reducing urban risks. Rather, vulnerability exists in each urban society across the globe but is manifested in different forms. These could be underdevelopment in one society, lack of education and technology in a second, poor urban governance in a third, failure to translate knowledge into action in a fourth, or a combination of two or more of these and other forms.

As Hewitt (1997, p. 143) underscores, 'vulnerability analysis is essentially about the human ecology of risks'. Ecological factors that are embedded in the landscape of an urban place contribute in different ways to the overall vulnerability pattern of that place. These ecological factors represent, in varying degrees, the context-altering forces that drastically affect people's resilience and ability to cope with and recover from losses. They also provide a means to uncover and understand differential vulnerability within and between urban places. Yet, because these ecological factors are variable and do not hold a constant relationship among themselves, no two urban places are likely to be found that are identical in their vulnerabilities. As a result, it is difficult to develop a broadly applicable action plan that can be followed to diagnose vulnerability and reduce disaster impacts in every single place in the world. Therefore, as we have strongly argued throughout this chapter, revealing context particularities and being decisive for context-sensitive mitigation policies are essential goals of urban vulnerability analysis.

In this chapter, we have capitalized upon the idea of particularity and proposed a conceptual framework for analysing vulnerability across nested scales of urban socio-ecological systems. We have shown how GIS and remote sensing can be integrated to translate this framework into a replicable model for place-based vulnerability analysis. We showed through a wall-to-wall exercise an initial attempt to apply this model to analyse urban vulnerability to earthquake hazards in Los Angeles County, California. Despite the limited scope of the analysis that was carried out, the results of the model call attention to some key considerations that underline the potential of our GIS–remote sensing model for place-based urban vulnerability assessment. The first is that stratification of potential disaster impacts is strongly influenced by a range of contextual conditions, both societal and organizational, which may not be directly related to the geophysical mechanisms of the triggering of hazardous events. The second is the central role of urban dynamics modelling as a means to better understand differential vulnerabilities in cities. The third consideration is that, although vulnerability is largely a reflection of conditions created and modified by human actions, one cannot discard the fact that knowledge of the geophysical properties of natural hazards is essential to understand how dangers arise at the interface of society and natural conditions. Finally, reducing losses from hazardous events is not a problem that can be solved in isolation through a traditional urban planning model. Rather, it requires an understanding of the magnitude of shock that a given urban system is prepared to absorb while remaining capable of operating, and of the means to build management models that take into account the long-term impacts of mitigation efforts on current and future generations. Future developments and applications of our model will need to be expanded in order to ensure that these considerations are equally balanced.

Our model depends upon an integration of GIS and remote sensing. Thus far, the main stream of GIS and remote sensing integration discussions is devoted to addressing practical details. Technical issues, such as whether and how the coupling of GIS and remote sensing should be loosely or tightly implemented, common interface design, building of hybrid remote sensing-GIS databases, data sharing and interoperability, etc., have been, and continue to be, central to most of the discussions (Ehlers, 1990; Mesev, 1999; Chen *et al*. 2000; Longley and Mesev, 2001; Chen, 2002; Longley, 2002). Few researchers (e.g. Mesev, 1997; Rindfuss and Stern, 1998; Rindfuss *et al*., 2004) moved beyond the narrow technical detail to larger methodological issues involved in the integration of the technologies under the umbrella of GIS, for example, problems of spatial autocorrelation, spatial–temporal mismatch, classification compatibility, etc., but attempts made in this regard remain technical in tone and very generic, easy to acknowledge but difficult to resolve.

There is no doubt that technical issues are central to GIS and remote sensing integration. Naturally, we have encountered lots of technical details and methodological challenges in the course of developing and applying the place-based vulnerability analysis model, some of which we were able to resolve, while others remain an avenue for future developments. But we have also learned the importance of seeking guidance from the subject matter (i.e. urban vulnerability in Los Angeles) to inform the development and integration of the technologies and the selection of solution options. That is, we have learned how the fields of vulnerability and hazards can help inform the selection, development and integration of GIS and remote sensing techniques as much as we learned about the tools GIS and remote sensing can offer to vulnerability analysis. For example, the use of a simulation approach in deriving different scenarios of damage resembles to a greater extent the way in which disaster managers traditionally utilize past disaster experiences as instruments to learn about the adverse consequences of hazardous events in cities, and to infer the underlying factors that need to be addressed to promote the level of safety in the community. We used this very basic idea to develop algorithms that can screen a multitude of disaster scenarios and back into a measure of vulnerability of the place. Likewise, our use of MESMA and landscape metrics in quantifying the physical dimension of urban morphology in Los Angeles was inspired both by the characteristics of the physical settings of our study site and by discussions in the vulnerability literature about how the characteristics of the urban spatial structure (e.g. open spaces, land use/land cover, transportation layout) influence the function of the city in the immediate aftermath and during the recovery from disaster impacts (Hewitt, 1997; Menoni *et al*., 2000). This use of subject matter in guiding the development of the GIS–remote sensing integrative model exemplifies the way in which universal wisdom of vulnerability can be used to guide the investigation into the particularities of place discussed earlier in this chapter.

To this end, we suggest that the integration argument in the ongoing GIS–remote sensing literature needs to be extended further beyond its current technical and methodological focus to include the subject matter or phenomenon under consideration; how its underlying dynamics vary over space, and how established theories in such fields as economic, political and social sciences can be used to inform remote sensing–GIS integration. Earlier in the chapter, we argued that urban places can be used as an analytical basis for urban vulnerability analysis. In the conclusions of this chapter, we again argue for urban places, or space in general, but this time to be used as a basis for a wider concept of GIS–remote sensing integration, not only in terms of data but also in terms of the development of functions, algorithms and models that acknowledge the unique challenges each place brings to GIS–remote sensing analysis and can ultimately provide a basis for contextually aware decision making.

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Chapter 09

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