EXPLORING THE SPATIAL ASSOCIATION BETWEEN MEASURES FROM SATELLITE IMAGERY AND PATTERNS OF URBAN VULNERABILITY TO EARTHQUAKE HAZARDS

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ABSTRACT:

This paper discusses the implementation of an integrated set of methods used to explore the relative importance of the social characteristics and the physical conditions of urban morphology in shaping the spatial patterns of urban vulnerability to earthquake hazards in Los Angeles County. These methods include: (1) the development of an index for social vulnerability at the census tract level based on the 1990 population census, (2) the normalization of remotely sensed measures that describe the composition of census tracts in terms of the fractional abundance of urban land cover extracted through the spectral mixture analysis of a Landsat Thematic Mapper (TM) image, (3) the utilization of landscape pattern metrics for deriving new variables that describe the urban spatial structure of census tracts based on urban land cover fractions, and (4) the use of a spatial filtering technique to resolve the spatial autocorrelation problem among the independent variables. The paper begins with an introduction about urban vulnerability, highlighting the results of previous investigations conducted by the present authors, followed by an outline of the methods utilized in the present study. The remaining sections of the paper introduce the statistical models in which the remotely sensed variables are employed, demonstrate the results of such models, and discuss the conclusions that can be drawn from these results.

1. INTRODUCTION

1.1 Background

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. In this paper, we tackle the question of vulnerability within the contemporary realm of American cities. As American cities become geographically more dispersed and increasingly complex with respect to infrastructure and the built environment, more and new kinds of urban vulnerabilities are brought about by the increasing dependence of communities on technology and more complex interactions within the urban systems. Today, the geography of vulnerability in the United States stretches from coast to coast, from city to city, and from neighborhood to neighborhood within cities. Although one cannot say that there exists a non-vulnerable urban community in the United States, there are clearly places that are more vulnerable than others.

What accounts for spatial variability of urban vulnerability in and within American cities? How does the engineering of the constructed environment increase or decrease urban vulnerability, and how much of vulnerability is dependent upon the socioeconomic and demographic profile of the community? What is the vulnerability that derives from the interaction of the built and the social environments? Can we assess the relative importance of these factors in measurable and standardized ways? This paper attempts to answer some of these questions by developing an understanding of how the varying patterns of urban vulnerability and their underlying engineering factors and the social conditions are manifested in the spatial structure of urban areas.

We conceptualize urban vulnerability as a measure of the degree of coping abilities of human and physical systems of the urban place that are consistent with the principles of local sustainability. We believe that a geographically-centered approach that focuses on the vulnerability of urban place and combines elements from the engineering and social paradigms can help fill the gap between them and will pave the way for a better understanding of how vulnerability patterns evolve in urban areas. This approach emphasizes the use of geo-referenced resources that should be available to planners and decision-makers in any reasonably large urban area. These include an assessment of structural (including geologic and infrastructural) vulnerability of each neighborhood to potential earthquake hazards that might occur, and an assessment of sociodemographic vulnerability within each neighborhood to hazards. These data are drawn from engineering and land use coverages, remotely sensed data, census data, and the results of hazards risk modeling, and then are incorporated into a GIS database environment for spatial analysis and interpretation.

This paper represents the last of a three-phase ongoing project aiming at revealing the link between differential social vulnerability in urban places and unsustainable development practices as represented by features from the urban environment. In the first phase of the project, the present authors developed a GIS-prototype that combined elements from the techniques of spatial multicriteria analysis and fuzzy logic to assess the spatial distribution of vulnerability levels in

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the Los Angeles metropolitan (Rashed and Weeks, 2003). In the second phase, we adopted a multiple endmember spectral mixture analysis (MESMA) approach to map the physical composition of urban morphology in Los Angeles using Landsat TM image acquired in 1990 (Rashed *et al.*, 2003). In this paper, we report the results of the last phase of the project in which we tested the basic hypothesis that differential social vulnerability is reflected in the environmental relations and the spatial structure of urban neighborhoods (i.e., geographic conditions, building materials, structure of open spaces, housing densities, inaccessible neighborhoods, amount and types of vegetation). Many of these aspects are 'physically' represented by certain urban features and land covers, suggesting the notion that social vulnerability to urban earthquakes may be examined through advanced remote sensing data capturing and processing techniques, and validated with *in situ* data — all grounded in a remote sensing scene model (Strahler *et al.*, 1986) and integrated into a GIS-spatial analytical framework. The value of remote sensing data lies in providing timely and spatially explicit variables associated with urban attributes and human activities (e.g., Jensen and Cowen, 1999). The incorporation of these variables into a GIS with population data offers a way to analyze the spatial association between social factors and vulnerability indicators from the built and natural environments.

1.2 Results from previous studies

As indicated above, the present paper utilizes the results from two previous studies, the details of which are reported in Rashed and Weeks (2003) and Rashed *et al.* (2003) respectively. The first study originated from a pilot case study for data on the 1994 Northridge Earthquake in Los Angeles County which was used to develop and test a prototype for urban vulnerability assessment based on fuzzy logic and spatial multicriteria evaluation (Rashed and Weeks, 2003). The overall objective of the work conducted was to control for the hazards effect within the region, such that loss estimates generated by simulators of hazards effects can directly be interpreted in terms of variation in vulnerability. The work pioneered new usage of a US federally funded GIS tool called HAZUS (http://www.fema.gov/hazus/), originally developed to assess losses from seismic hazards and now expanded to encompass other hydrologic and wind hazards in the United States. The Rashed-Weeks model used HAZUS to generate a number of risk scenarios for different earthquakes within the region, through which "hot spots" of vulnerability were derived from the collective results of simulation. The model incorporated many theoretical constructs from Menoni and Pergalani's (1996) framework of urban vulnerability and integrated them with several decision-support methodologies such as Satty's (1980) analytic hierarchy process (AHP) to derive a quantitative measure of vulnerability. The resulting measures were more representative of the inherent weakness in the urban system than those resulting from the simple overlay of hazard zones and urban elements.

In the second study, the results of the model were further utilized to exploit the capabilities of remote sensing to obtain information about the composition and structural patterns of urban land cover through the application of multiple endmember spectral mixture analysis (MESMA) and landscape metrics (Rashed *et al.*, 2003). The work conducted was predicated on the idea that urban landscape results from an aggregation of different components of land cover and urban materials, none of which may be important when studied individually (Ridd, 1995; Rashed *et al.*, 2001; Rashed *et al.*, 2002). Rather, the significance of these components arises from their mutual association and from the way they interweave with each other to structure the morphology of the urban place (Pesaresi and Bianchin, 2001). A recurrent theme in several studies on urban remote sensing has been related to the derivation of summary indicators of the urban physical components from remote sensing data. 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). This is especially true in the context of multispectral images with medium spatial resolution such as those provided by Landsat, SPOT, and Indian satellites. Because of this spectral heterogeneity, there is a need to deal with a complex mixture of spectral responses (Forster, 1985). With the presence of spectral mixing in the pixels, the identification of urban land cover using per-pixel analytical techniques becomes very difficult since the continuum of land cover cannot be divided readily into discrete classes as required by these techniques.

Spectral mixture analysis (SMA) is a group of techniques that have been proposed to provide *soft* analysis of mixed pixels by transforming image values to physical variables. We used a modified SMA technique called multiple endmember spectral mixture analysis (MESMA) to derive comparable physical measures of urban places in Los Angeles County. The MESMA approach, originally developed by Roberts *et al*. (1998b) is based on the concept that, although the spectrum in any individual pixel can be modeled 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 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 resultant values can be normalized and aggregated at the urban place level to describe the composition of the urban place in terms of indices of land cover abundance that can readily be linked to measures of vulnerability and other engineering and social variables.

2. METHODS AND DATA

2.1 Overview

To test our hypothesis, that the physical and social conditions of an urban place are so inextricably bound together in many disaster situations that we can use the former as indicative of the latter, we examined the relationship between the index of higher vulnerability produced for Los Angeles County in Rashed and Weeks (2003) and the spatial distribution of wealth in this region. The distribution of wealth in society is perhaps the most obvious variable, among several possible others (such as political rights, governmental compensations, etc), that holds a direct relationship with the access to resources required to recover from the impact of a damaging event such as an earthquake hazard. We tested the hypothesis of this study first by testing the null hypothesis that the distribution of wealth (taken as a proxy for access to resources as a measure of vulnerability) and the index of higher vulnerability are not significantly correlated in Los Angeles County, and second by examining the extent to which the remotely sensed measures we produced in Rashed *et al.* (2003)

explain these two measures of vulnerability. In this section, we discuss the methods used to prepare the variables to be incorporated in the statistical models employed to answer the above-mentioned questions. These methods describe: (1) the development of an index of wealth at the census tract level in the study area based on the 1990 population census, (2) the normalization of MESMA fractions at the census tract level, (3) the utilization of landscape pattern metrics for deriving new variables that describe the urban spatial structure of census tracts in terms of urban land cover, and (4) the use of a spatial filtering technique to resolve the spatial autocorrelation problem among the independent variables.

2.2 Deriving an index of wealth for Los Angeles County

Information on wealth was used in this study as a proximate determinant of access to resources, which in turn was used as an indication of the distribution of social vulnerability. To achieve this, data were used from the US Census Bureau's Survey of Income and Program Participation (SIPP) to create an index of wealth that incorporates income in conjunction with the age and race factors. From these measures, the ratio of wealth to income was calculated 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 these two sets of data (i.e., ratio of wealth to income by race and by age group derived from the SIPP) to the closest income categories that are available in the 1990 census of the study area. The PUMS data represent a random 5% sample of the long-form questionnaires from the 1990 census, stripped of personal identifiers and grouped in geographic units of at least 100,000 people (PUMAs or Public Use Microdata Areas) to protect confidentiality. The two sets of income quintiles (those by race and those by age) derived from the SIPP data were converted to their closest income categories and 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, using the 1990 PUMS data for Los Angeles County. Finally, the average household wealth was calculated for each census tract that represented the average wealth of households in that census tract weighted by the income, race, and age of householder. The outcome of this process was a wealth index for Los Angeles County, which we utilized as an indication of the overall level of access to resources (and hence social vulnerability) in each census tract.

2.3 Normalizing MESMA fractions

The results from the remote sensing analysis conducted in our previous MESMA study (Rashed *et al.*, 2003) were used to describe spatial variation in the physical conditions between the census tracts in Los Angeles County in 1990. Two approaches have been examined to achieve this goal. The first approach, described in this subsection, was the calculation of an average normalized measure per census tract for each of four categories of urban land cover: vegetation, soil, impervious surface, and shade. The second approach, described in the following subsection, was the derivation of second-order measurements from MESMA fractions that describe the spatial structure of the census tracts in terms of these fractions.

In the first approach, fractional abundances of vegetation, impervious surface, soil and water/shade were first converted into raster grids. Next, a polygon coverage representing the census tracts was laid over each of the four grids and a census code was assigned to each pixel according to which census tract that pixel was located within. The fractional abundance of each land cover category was then summed up based on the census tract codes and the results were normalized by calculating the ratio of the summed fractional abundance to the census tract area. The end product of this process was a normalized value (ranging from 0 to 100) per census tract for each of the four land cover categories, indicating the average abundance of the land cover within that tract. Thus, these normalized values represented indices of land cover abundance that can readily be linked to the index of vulnerability and other social variables reported at the census tract level.

2.4 Applying landscape pattern metrics to MESMA fractions

The use of landscape metrics in the analysis of urban landscape patterns is a relatively new topic and few studies have been published in this regard generally (e.g., Geoghegan *et al.*, 1997; Alberti and Waddell, 2000; Parker *et al.*, 2001), and even fewer with the specific use of remotely sensed measures (e.g., Herold *et al.*, 2002; Herold *et al.*, *submitted*). In this research, we used a subset of landscape metrics as a way of quantifying the configuration and composition of spatial variation in the physical conditions in Los Angeles in terms of MESMA land cover fractions. Calculating these metrics at the census tract level (i.e., each tract is considered as collection of land cover patches) provides an additional means of establishing and testing the link between vulnerability and the social and physical conditions of urban places.

Landscape metrics are indices developed for categorical map patterns and their development has been 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. Patches represent discrete areas of relatively homogeneous environmental conditions, the definition of which is artificially 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 (or grid cells) in a remotely sensed image. While individual pixels (the construction blocks of patches) possess uniform spatial characteristics (e.g., identical size, perimeter, and shape), the aggregation of these pixels provides a rich set of properties. These properties depend on whether the pixels are aggregated over a single land cover class (patch type) or multiple classes, and whether the aggregation is considered within a specified census tract. Landscape metrics make use of these properties to reveal the spatial character and distribution of patches, and thus to quantify landscape patterns (O'Neill *et al.*, 1988; McGarigal *et al.*, 2002).

The fractions produced by MESMA are typically represented in terms of the percentage occupied by a fractional class of land cover within a pixel. However, landscape metrics operate upon the assumption that individual patches are maximally variable externally and minimally variable internally. Therefore, before landscape metrics were applied, the fractional image had to be reclassified such that each pixel within any census tract corresponded to one, and only one, class of land cover. In this regard, the use of landscape metrics requires a 'hard' view of classification as opposed to the 'soft' view represented by MESMA. However, the difference between conventional per-pixel classification techniques and the method we utilized lies in the way in which the discrete classes of land cover were derived. While conventional techniques are typically applied to the radiance or reflectance values directly, the results of MEMSA were utilized here to perform the 'hard' classification. In this sense, the discrete per-pixel classification operated in a subservient role to the sub-pixel analysis of the imagery – an approach that has been shown by other studies to produce more reliable and accurate classification of imagery (Roberts *et al.*, 1998a; Rashed *et al.*, 2001).

To do so, each pixel was screened in terms of the fractional class values assigned to it. If a fractional value (i.e., the percentage of any individual class) within a pixel was equal to or greater than 60%, that class was then assigned to this pixel. The threshold of 60% was arbitrarily chosen, assuming that when a pixel meets this condition for a certain fractional value, then it is most likely that this pixel can be classified under 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 which class the majority of neighborhood pixels within a 3 X 3 window were assigned to. This means that there may exist up to four classes (or patch types) within any census tracts: vegetation, soil, shade, and impervious surface.

The next step was to select a subset of landscape metrics that could be applied to measure the spatial properties of census tracts in Los Angeles, either in terms of the configuration of patches of pixels of a given land cover class within a census tract (i.e., class level metrics in which the landscape of interest is a specific *land cover* class within a census tract), or the configurations of patches of all the four classes that census tract may be composed of (i.e., census tract level metrics in which the landscape of interest is the census tract itself). Tables 1 and 2 list the subsets of metrics that have been used on either the land cover class or census tract levels. As shown in the tables, the same metric may measure different properties based on the level at which it is applied. For example, the PD metric in Table 1 measures the density of patches within an individual land cover class within a census tract, while in Table 2 it measures the density of all patches from all classes within that tract. On the other hand, other metrics are unique to the level at which they applied. Examples of these are the COHESION metric in Table 1 that is used to measure the connectivity of patches at the land cover class level, and the SIDI metric that measures the diversity of all land cover classes at the census tract level. Finally, there are metrics that are essentially measuring different properties in the same way at the same level such as CONTAG and AI metrics in Table 2. CONTAG measures the aggregation of individual pixels of different classes at the census tract level whereas AI measures the aggregation of patches of pixels of different classes at the same level. Thus, we should expect that some of the measures resulting from these metrics would be highly correlated with each other. Despite this redundancy, however, we have deemed it important to test them all since each one points to a slightly different aspect of the spatial structure of urban places. The calculation of all these metrics was done through a software package called FRAGSTAT (version 3), designed to compute a wide variety of landscape metrics for categorical map patterns (McGarigal *et al.*, 2002).

Table 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 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

A final remark that needs to be emphasized at this point is concerned with the relationship between those measures derived from the normalization of MESMA fractions and those produced by landscape metrics. A normalized MESMA measure of vegetation represents the average factional value of vegetation land cover within pixels belonging to a census tract. This average value, however, does not tell us about the density of vegetated pixels and how they are arranged within a census tract (e.g., fragmented or aggregated, connected or disconnected). The latter information is conveyed through the measures calculated by landscape metrics that may suffer from a drawback regarding the assumption of discrete pixels. Thus, both normalized MESMA fraction and results produced by landscape metrics represent different aspects of the physical settings of a census tract and should be looked at as being a complementary to, rather than a replacement of, each other.

2.5 Spatial filtering of variables

An important issue we had to address before we employ any statistical models was related to the implications of spatial autocorrelation on the results of these models. Spatial autocorrelation directly results from Tobler's (1979) 'First Law of Geography' that everything is related to everything else, but near things are more related than distant things. This implies that data aggregated at particular spatial units such as census tracts are more similar to data for other nearby spatial units than they are to more distant spatial units (Getis and Ord, 1992). Spatial autocorrelation may be caused by measurement problems such as the arbitrary delineation of census tract boundaries, or by the problem of spatial aggregation, or by the presence of spatial externalities (Getis, 1999). Cliff and Ord (1981) identify two general approaches for resolving these problems: (1) filtering spatially autocorrelated data to “remove” (or really to account for) spatial autocorrelation, or (2) modifying statistical models to accommodate spatial autocorrelation (such as spatially autoregressive models).

We utilized a method for spatial filtering suggested by Getis (1995). This spatial filtering technique incorporates spatial component variables into an ordinary least-squares (OLS) linear regression analysis in order to remedy the problems associated with spatially autocorrelated variables. Remediation does not involve removing all evidence of space, but rather involves extracting the spatially autocorrelated portion of each of the variables in the regression model and then reintroducing the spatial portion as a separate factor (Getis, 1995; Scott, 1999). By solving the OLS regression model with the filtered and spatial components of the variables decomposed, 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 (where you are), whereas the remainder of the explained variation is accounted for by the filtered (non-spatial) component. This is because the standardized beta coefficients in regression analysis represent the partial correlation coefficient of that independent variable to the dependent variable, controlling for all other independent variables in the equation. The ratio of the square of the beta coefficients for any two independent variables then gives us a quantitative measure of the relative contribution of each variable to the prediction of the dependent variable.

2.6 Statistical Models

The first model utilized was for testing the null hypothesis that the index of wealth (IW), used as a proxy for access to resources, was not significantly correlated with the index of higher vulnerability (IV) calculated for the study area of Los Angeles. Besides testing the basic hypothesis of this research, two regression models were employed to further examine the relationship between wealth, vulnerability, and the remotely sensed measures. The first model was a step-wise OLS regression model, which employed IW as a dependent variable. The purpose of this OLS model was to examine the extent to which wealth (as a proxy for social vulnerability) can be predicted exclusively by measures derived from remote sensing to describe the physical characteristics of an urban environment. The independent variables of that model included: (1) a set of normalized MESMA fractional measures (i.e., vegetation, soil, impervious surface, and shade) aggregated by the census tract, and (2) a set of second-order measures derived from MESMA fractions using landscape metrics (listed previously in Tables 1 and 2). The format of this model, after applying the spatial filtering, was as follows:

Wealth (IW) = (normalized MESMA fractions filtered) + (normalized MESMA fractions spatial) + (landscape metrics filtered) + (landscape metrics spatial) + error (1)

The second model was a binary logistic regression model that employed IV as a dependent variable. Logistic regression was used in this part of the analysis because of the ordinal nature of the fuzzy measure of vulnerability that allowed for a binary division of the dependent variable into high (1) and low (0) using a threshold value. In such a situation, logistic regression is useful as it helps us examine the presence or absence of higher vulnerability based on values of a set of explanatory variables. The explanatory variables for this model included the index of wealth, as well as a set of remotely sensed measures that were statistically associated with wealth in the OLS regression models. The general form of this model was:

$$\text{Logit}(Pi) = \log(Pi / (1 - Pi)) = a + b\,Xi \quad (2)$$

where i represents the binary value of vulnerability at a census tract; Pi 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).

3. RESULTS

3.1 Results of correlation between vulnerability and wealth

Table 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. This leads 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. Another interesting finding in Table 3 is related to the correlation between the IW and the spatial portion of the IV. The results indicate 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, the significance of such results becomes more apparent in light of the following facts.

First, the IV and IW represent the results of two totally independent methods for measuring vulnerability. The values of the IW were calculated exclusively based on the income information from the 1990 census, weighted by race and age. The values of the IV were derived from simulating a number of earthquake events in HAZUS, in which damage losses were calculated as a function of building types and soil conditions without taking any social factors into account. The implication of this is 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 United States.

Second, the calculations of IV and IW have been based on the physical and social characteristics, respectively, of census tracts in Los Angeles as of 1990. In this regard, these calculations implicitly assume a correspondence between physical and social change within the urban areas. However, 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 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 through the county in the 1980s that might not have been reflected yet 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.

Given these limitations, it can be suggested that the statistically significant correlation results noted above represent, in fact, strong evidence of a possible causal linkage between the physical and social conditions of urban places with regard to vulnerability. This line of reasoning is further investigated through the results of the regression models reported in the following subsection.

Table 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)

3.2 Results of regression models

Two regression models were employed in order to examine whether remotely sensed measures can be used in conjunction with social variables to explain the variation in vulnerability. The first model was a step-wise OLS regression model that employed the index of wealth as a dependent variable, and a total of 40 independent variables (4 normalized MESMA variables, 8 variables resulting from applying landscape metrics at the census tract level, and 28 variables resulting from applying the metrics at the 4 land cover class levels). Before running the model, the technique of spatial filtering was first utilized to decompose spatially autocorrelated independent variables into their spatial and non-spatial components. The second model built on the results on the first model and applied logistic regression employing the index of vulnerability as a dependent variable, and wealth and remotely sensed measures as independent variables.

The results of the first model are shown in Table 4, in which only statically 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 they were not spatially autocorrelated and exhibited no heteroscedasticity. Also, the results of collinearity diagnostic indicated that the independent variables had scored low (< 9) in the condition index. The results show that 4 out 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 β 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%. On the other hand, 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 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 within a census tract 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 can be related to the social characteristics of population in that place and may not otherwise be shown by only relying on the measurement of the physical composition in that place. The results in Table 4 also show 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, the model indicates 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 interspersion or 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. Likewise, if the land cover class in a census tract is dominated by a relatively greater number of small and highly fragmented classes, the IJI value would be high. The results in Table 4 suggest that wealth increases 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 calculated for the shade. 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. Thus, in general, the results shown in Table 4 affirm the proposition of this research that remotely sensed data can be used as a proxy for urban spatial structure that can then be used to explain variation in wealth, and hence social vulnerability.

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 that emerged as statistically significant predictors of the wealth index in the OLS regression model. The results of the model are shown in Table 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 1 indicating higher vulnerability, and those values that were equal to or less than the mean were assigned 0 indicating lower vulnerability. The model was also tested using other thresholds and the results were generally consistent with those listed in Table 5. The overall correct prediction of the model was about

63%, with 15.34 chi square value at the 95% level of significance.

The results show that three out of the four remotely sensed variables utilize emerged as statistically significant predictors of higher vulnerability. The strongest among these predictors 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 hypothesized, being in the higher wealth category (wealth 4) reduces the odds (by a factor of 0.77) of being in the high 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.

Table 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(I) For residuals	0.89			
N	1561			

Note: see text for an explanation of the variables

Table 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

4. DISCUSSION

The objective of this paper was two fold. First, to test the basic hypothesis that social vulnerability is reflected by aspects from the physical environment in urban places. 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.

To address the first objective, we examined the correlation between the wealth index and vulnerability. Vulnerability values were derived from an index of higher vulnerability for Los Angeles County, produced by Rashed and Weeks (2003). The wealth index was calculated for Los Angeles from information about income, weighted by race and age, and used in this research as a proxy for access to resources that is considered by many researchers as a major determinant of social vulnerability. The results showed a statistically significant negative correlation between the two indexes, though not high enough to conclude that the wealth can be taken as a sole indicator of vulnerability. Several reasons were listed above to explain why this difference has occurred.

Nevertheless, in light of the apparent difference between the spatial distributions of values in the two indexes, an obvious question arises: how do these results conform to the 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). These studies measured access to resources by the level of poverty (as opposed to the concept of wealth utilized here) and showed that the poor often live in less safe structures that are more likely to be damaged or destroyed by earthquake hazards. 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 US 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. Bolin and Stanford (1998, pp. 175-177), in their analysis of the impacts of the 1994 Northridge earthquake in Los Angeles, showed that while wealthy households might have suffered from losses in a hazard event, their property insurance, assets, financial credit, and stable employment had generally secured them against the destitution that befell poor families exposed to the same event (Bolin and Stanford, 1999, pp. 92).

Accordingly, a distinction can be drawn 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 (include 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 the persistent vulnerability, the social factor is much more noticeable while the physical aspect of vulnerability is implicit. The 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 of this paper was concerned with the utility of remote sensing for providing measures that can be used as surrogates for social vulnerability. To address this objective, we employed two regression models in which both first and second-ordered remotely sensed measures were utilized as independent variables. These first and second-ordered measures were respectively represented by normalized MESMA fractions and measures produced by landscape metrics. The former set of variables mainly described the physical composition of the urban place. The latter set of variables were more related to the configuration (or the physical arrangement) of land cover classes within census tracts. The results of the first model showed that the remotely sensed variables accounted for about 57% of the explained variation in the IW. The results of the second model 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 reflected in the demography and culture of people. The built environment, represented by the arrangement of land cover classes, then interacts with the socioeconomic 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 that in turn has an implication on 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 to build a grand theory of vulnerability to disasters nor 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 remote sensing and the way it can help us obtain information that address core issues of the social sciences such as social vulnerability. The results of this research have shown how remote sensing provides us with quantitative measures of the urban spatial structure that are indicative of social vulnerability and comparable from place to place. Recognition of this will help to improve the statistical association between social and physical vulnerabilities, and to carry out assessments that are comparable across spatial (and temporal) scales.

5. CONCLUSIONS

A major theme of this paper is that the analysis of vulnerability can exploit the capabilities of remote sensing to obtain information that might not be measurable in other ways. In this sense, the study builds on recent pioneering studies that attempt to take remote sensing applications beyond their current use in applied sciences, toward applications that address concerns of the social sciences (e.g., Liverman 1998). Yet, our intention is not only to introduce urban remote sensing as a meeting point for the social and physical sciences, but also to show that social applications of remote sensing can inform the research agenda of the urban remote sensing arena.

In this regard, one of the most important findings of this research is the realization that the spectral properties of conventional imagery such as Landsat TM are 'still' really useful in detecting the extent and morphology of urban land cover. Over the past few years, there has been a trend in the literature promoting the idea that further improvements in the spatial precision of satellite instrument is the only way of deriving better information for urban analysis. Our findings indicate that improved remotely sensed measures are not only a question of better spatial resolution. Rather, it is an intellectual issue which lies in bridging the gap between the two fields of remote sensing and urban analysis. This is not to say that new imagery with better spatial resolution are not important, but it is to stress the need to incorporate remote sensing within a theoretical framework that reflects that nature of urban phenomena in which resolution is only one of many other aspects that need to be considered in the analysis.

We have shown how the spectral characteristics of a Landsat TM image can provide detailed interpretation of urban form when we move beyond conventional, per-pixel classifications of imagery to the spectral unmixing approach. We have also shown the usefulness for using landscape metrics to provide information about the configuration and structures of urban morphology that supplement information about direct land cover classes derived from the imagery. The moral of this is that further progress of urban remote sensing is dependent on the thinking of new ways of using existing remotely sensed data to inform our understanding of the spatial distributions of urban phenomena, as it is on new imagery with better capabilities. Before new datasets are introduced, there is a need to develop a sold understanding of the spectral characteristics of the wide range of urban features and how they are affected by the changing spatial resolution of imagery. There is thus a need to build a solid theoretical understanding of the relationship between the pixel size and the recognition of the structural patterns of urban features. It is only through including these and other similar questions in the current agenda of urban remote sensing that we can have a full appreciation of the capabilities of existing imagery. Then, we will be in a position to set a basis for assessing data requirements for future sensors that can foster additional understating of urban systems.

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