A GIS-Based Sensitivity Analysis of Community Vulnerability to Hazardous Contaminants on the Mexico/U.S. Border

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Abstract
Growing industrial development in the Mexico/U.S. border region is creating potential health risks for citizens of both nations. Planners and policy makers working in this region must prepare for hazardous material accidents in a situation of limited information. This research develops a geographic information system-based approach for estimating and determining community vulnerability to hazardous material releases in Nogales, Sonora/Arizona. A composite mapping analysis of human-related and hazard-related variables determines high vulnerability locations. In addition, a sensitivity analysis explores a full range of vulnerability scenarios based on different weighted combinations of the human-related and hazard-related factors. Results demonstrate that a GIS-based approach can effectively compensate for much of the inherent subjectivity in a composite mapping analysis.

Introduction
Growing industrial development near human settlements at the Mexico/U.S. border concerns citizens of both nations, especially in light of the recent ratification of the North American Free Trade Agreement (NAFTA). Maquiladoras, or multinational industrial plants in Mexican communities near the U.S. border, have been attracted to the region since the mid-sixties when the Mexican Border Industrialization Program was established. This allowed multinational firms to maintain proximity to the U.S. market, but still benefit from the lower labor costs and more limited environmental regulation enforcement in Mexico. Initially, only a few plants existed, but in recent years the number of maquiladoras have increased rapidly (Perry *et al.*, 1990).

Many maquiladoras produce, store, or use a variety of hazardous materials. Accidental releases of these hazardous materials may severely affect the well-being of local communities (Perry *et al.*, 1990). To properly prepare for hazardous material emergencies, planners and policy makers in border communities must know which locations and populations are most vulnerable to potential hazardous material releases.

An important part of preparedness for potential hazardous material release incidences is *vulnerability analysis* (National Response Team, 1987). A vulnerability analysis identifies the geographic areas and populations susceptible to damage or injury should a hazardous material release occur. Planners and policy makers can use this information for both long-range development planning, as well as structuring emergency response activities such as evacuation planning and emergency response facility location.

Assessing community vulnerability typically requires gathering large amounts of primary, or "mass balance," data on the locations and amounts of hazardous material in a community. Often, smaller communities lack the resources to gather such data. The problem of gathering primary data is further confounded in trans-border communities with different political and legal systems. Therefore, a viable alternative to gathering "mass balance" data is *modeling* community vulnerability using information on the locations of potential hazard material generation sites relative to the locations of sensitive populations and institutions.

Because the spatial arrangement and intensity of human-related and hazard-related factors determine community vulnerability, a geographic information system (GIS) can provide a powerful tool for analyzing the relationships among these factors and assessing community vulnerability. A particularly useful GIS-based method is *composite mapping analysis* (CMA). CMA is a technique commonly used in environmental applications such as land-use suitability analysis or in assessing environmental sensitivity. A CMA characterizes locations based on the spatial coincidence of relevant variables that affect a proposed or existing activity (O'Banion, 1980; Hepner, 1984). Because it is based on spatial coincidence, a CMA substantially benefits from the polygon overlay or raster cell manipulation capabilities of a GIS.

A recurring question associated with CMA is how to weight the various factors which impact the phenomenon being studied. A myriad of hazard-related and human-related variables, such as release sites locations, potential contaminant pathways, population density, and the locations of sensitive institutions such as schools, can affect community vulnerability to hazardous material releases. The relative importance of each factor must be considered when combining spatial variables through a CMA. Typically, variable weights are determined through the consensus of an expert panel (Hepner, 1984). However, the availability of expert knowledge is often limited in smaller communities. Even when expert knowledge is available, a consensus is often difficult to attain, a problem that can be especially acute in a trans-

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border situation. Finally, each variable's weight can change based on the needs of the particular vulnerability analysis (e.g., long range development policy versus emergency response planning).

In this paper, we demonstrate the effectiveness of combining the spatial analytical tools in a GIS with a structured and systematic method for handling the subjectiveness often present in a community vulnerability analysis. A GIS-based CMA integrates a wide range of hazard-related and human-related factors that potentially affect community vulnerability to hazardous material releases. The GIS platform not only enhances the CMA approach to vulnerability analysis, but also allows us to develop and explore a well-structured set of vulnerability scenarios based on different weighting of the relevant variables. Results from an application of the model in the Mexico/U.S. border community of Nogales, Sonora/Nogales, Arizona indicate both the robustness of the CMA methodology as well as the flexibility of GIS for structuring inherently subjective and changeable model components such as vulnerability factor weights.

Study Background

Guidelines for Hazards Analysis

To improve planning and preparation for chemical emergencies, Congress enacted SARA (Superfund Amendments and Reauthorization Act) in 1986. Part of SARA is Title III or the Emergency Planning and Community Right-to-Know Act (EPCRA). EPCRA's purpose is to encourage cooperation among government agencies, the public, and industry in preparing for possible hazardous material accidents. Part of EPCRA requires local municipalities to prepare hazardous material emergency response plans. The *Hazardous Materials Emergency Planning Guide* (National Response Team, 1987) provides local communities guidance in preparing emergency response plans. This guide identifies *hazards analysis* as a critical part of hazardous material emergency planning.

Hazards analysis consists of three procedures: *hazards identification, vulnerability analysis,* and *risk analysis.* Hazards identification involves identifying facilities and transportation situations which may cause injury to life, or damage to property and the environment (National Response Team, 1987). Hazards identification is greatly facilitated in the U.S. by laws requiring industrial facilities to disclose information on the amounts and types of hazardous materials produced, used, or stored (US Code of Federal Regulations 40 § 302, 355, 372). This legal apparatus is not available in Mexico.

The National Response Team guide defines vulnerability as "the susceptibility of life, property, and the environment to injury or damage if a hazard manifests its potential" (National Response Team, 1987, p. 20). A vulnerability analysis identifies the geographic areas and populations susceptible to damage or injury should a hazardous materials accident occur. It includes an analysis of the extent of the vulnerable zone and populations within the zone in terms of size and types (e.g., residents, employees, sensitive populations, hospitals, schools, etc.).

Risk analysis is an assessment of the probability that a hazardous material accident may occur. Data needed for determining accident probability are often difficult to acquire, making risk analysis less feasible in smaller communities (National Response Team, 1987). This is especially true for communities on the Mexico/U.S. border.

A complete hazards analysis requires assessing all three of the components discussed above. However, a full-scale hazards analysis requires data that are often not available for a given study area. Data availability is a major problem in a trans-border situation with different legal structures, political environments, and data collection procedures. In these situations, focusing attention on the vulnerability analysis phase can still generate useful inputs for emergency planning and policy analysis. The data requirements for a vulnerability analysis are less stringent and yet its results provide local decision makers with estimates of the locations and populations at risk if an accident occurs.

Vulnerability Analysis Using GIS

A vulnerability analysis assesses spatial proximity among potential incident sites and the populations that are likely to be affected. Several published studies demonstrate effective uses of GIS for vulnerability assessment to hazardous materials. Although different in scope and purpose, these studies typically use two standard GIS techniques.

Montz (1986), Hillsman and Coleman (1986), and Gould *et al.* (1989) provide examples of a basic GIS overlay approach. This technique involves overlaying an estimated hazard zone onto several relevant GIS data sets, such as demographic, infrastructure, and institutional data. Hazard zones may be identified by buffering a potentially hazardous site (e.g., Montz, 1986), or by identifying a hazardous plume in the case of air-borne contaminants (e.g., Gould *et al.*, 1989). The second technique, composite mapping analysis, was mentioned in the introduction. This approach uses GIS overlay capabilities, but improves this strategy through scaling and weighting of the GIS data layers. The result is a final coverage consisting of cumulative vulnerability scores. These scores provide a quantitative assessment of the vulnerability *level* at each location. This contrasts with the qualitative, "binary" vulnerability levels provided by the basic GIS overlay approach. A good example of this approach is the vulnerability analysis of Santa Monica, California by McMaster (1988).

Several key data sets are essential to any GIS vulnerability study. These include hazardous material sources (i.e., geographic location and chemical properties), demographic and institutional characteristics of the community, and the physical nature of the environment. Earlier work (Montz, 1986; McMaster, 1988; Hillsman and Coleman, 1986; Gould *et al.*, 1989) has effectively addressed the first two data requirements. In the U.S. this has been accomplished using hazardous material inventories (required by EPCRA) and published census information. The third data requirement, the physical nature of the environment, has received little attention.

Study Area

The border cities of Nogales, Arizona and Nogales, Sonora are good examples of Mexico/U.S. border communities (see Figure 1). Roughly 20,000 people live in Nogales, Arizona while approximately 250,000 live in Nogales, Sonora (Zurick, 1992). The topography of Ambos Nogales ("Ambos Nogales" meaning "Both Nogales" in Spanish) consists of many hills with the primary drainage flowing from south to north. Surface runoff flows from several secondary washes into the main wash, the Nogales Wash, which flows north from Nogales, Sonora through downtown Nogales, Arizona and eventually into the Santa Cruz River basin. There are approximately 80 industrial facilities (mostly *maquiladoras* or multinational industrial firms) in Nogales, Sonora (see Figure 2). Health officials (e.g., Zurick, 1992), environmental activists

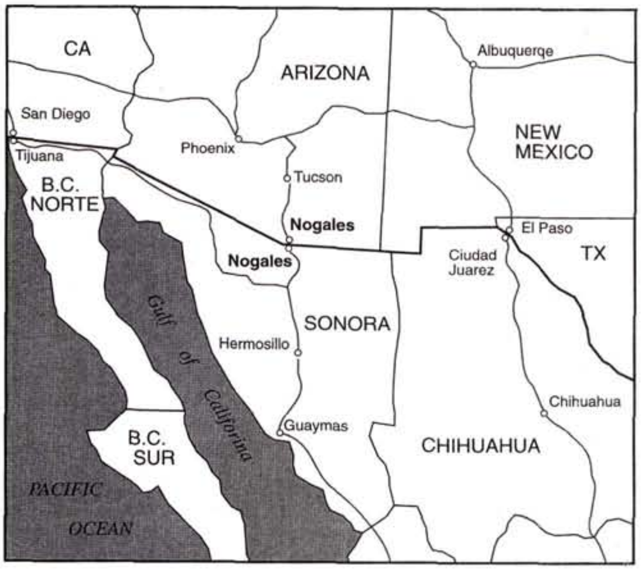

Figure 1. Location of Ambos Nogales.

(e.g., Kamp, 1991), and the media (e.g., *USA Today*, 27 October 1993) have focused attention on the risk to personal health and safety in the Nogales area due to these facilities. As recently as February 1994 over 4,000 people were evacuated from both cities when evidence of a highly flammable chemical was detected in the Nogales Wash (*New York Times*, 18 February 1994). In the U.S., local communities such as Nogales, Arizona are required by law to prepare for possible hazardous material accidents such as the February 1994 event. The GIS-based community vulnerability model provides an effective tool for hazardous release preparedness.

Methodology

Composite Mapping Analysis

In composite mapping analysis, separate thematic data layers are combined based on spatial coincidence. An advantage of composite mapping lies in its flexibility: there are many ways information in the separate thematic data layers may be combined depending on the analysis needs and postulates about the effects of different spatial variables. This also means that data preparation for composite mapping is a crucial step that affects the overall accuracy of the final map composite.

An important early step in a CMA is projecting the potential levels of a given variable onto a numeric scale reflecting the relationship between the variable's intensity and the impact on the existing or proposed land use. For example, a *scale index* can reflect the relationship between percent slope and residential land-use suitability or the relationship between population density and hazardous material vulnerability. A scaling index represents the influence of variations *within* a particular variable (O'Banion, 1980; Hepner, 1984). Often, scale indices are developed through the consensus of an expert panel (Hepner, 1984), although this is not always possible.

Before the scaled spatial data sets are combined in CMA to produce a location-specific composite score, it is also necessary to develop a set of weights that reflect the relative importance of a variable. In contrast to scale indices, *variable weights* reflect relative importance *among* different variables. If each variable is appropriately scaled, the variable weights can be stated so that the overall composite score is a simple combination of the individual (scaled) variables. An intuitive and manageable approach is to structure the weights so that the overall score is a linear combination of the scaled variables.

As in the assignment of scores in the scaling procedure, determining the appropriate weight for each data layer may typically be achieved through expert consensus. Lacking this consensus, a structured methodology must be developed that accurately models the phenomena being studied. Later in this paper we propose using sensitivity analysis to achieve this purpose. Although we could have conducted a sensitivity analysis at both levels of the CMA (i.e., scale indices and variable weights), the subjectivity and variability is substantially greater with the variable weights than with the scale indices. For example, it is clear that population density should be scaled so that higher density reflects greater vulnerability. However, it is less clear how to weight this factors relative to other human-related and hazard-related factors.

Data Sources and Preparation

The database for our GIS-based community vulnerability analysis consisted of eight spatial data layers reflecting variables that can be meaningfully partitioned into two major components: hazard-related and human-related factors. The hazard-related data layers included the location of industrial facilities (i.e., potential hazard release sites) and two modes of hazardous material transmission (surface and sewer transmission). Human-related data included data layers representing two sensitive population groups (population under 18

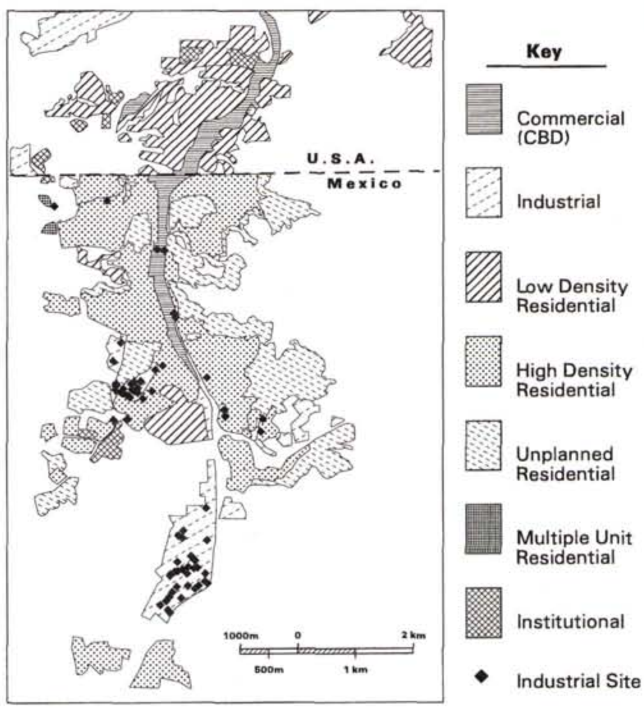

Figure 2. Land use and industrial facilities in Ambos Nogales.

years and population over 65 years), a data layer of general population density, a data layer of economic/infrastructure condition, and a data layer of sensitive institutions (schools, hospitals, and clinics). We used a linear scaling index ranging from 0 to 10 (0 representing no impact on community vulnerability and 10 represented high impact) for each GIS data layer. Because the input data layers are scaled in this ordinal fashion, the final vulnerability scores also must be interpreted as ordinal data.

Hazard-Related Data Sets

Because industrial facilities in Mexico do not publicly disclose inventories of their hazardous materials, we required a surrogate for this information. Bowen *et al.* (1994) used a computer model, the INVENT model (Ashact Ltd. & Dagh Watson, Spa., 1989), to generate estimates of hazardous waste from industrial facilities in Mexico at a regional scale. The model provides quantitative estimates of hazardous waste generation based on employment levels and manufactured products. Data on Nogales, Sonora's maquiladoras are available through *El Directorio Industrial*, published by the Colegio de la Frontera Norte (COLEF, 1990). Street addresses were used in combination with aerial photographs and field verification to digitize a GIS data layer of industrial facilities.

Using employment and product data for each maquiladora as input, the INVENT model estimated the hazardous wastes generated by each maquiladora. Estimates from INVENT were grouped into five hazard categories: (1) fire hazard, (2) sudden release or pressure, (3) reactive, (4) immediate (acute) health hazards, and (5) delayed (chronic) health hazards. Because the primary focus of this research is emergency response planning, we selected those facilities shown to generate wastes in the fire hazard and acute health hazard categories for further data preparation. Because the INVENT model is designed for regional or aggregate estimates, as a conservative measure we dismissed the quantitative output from the model and used the output only to identify the presence of a particular hazardous material type at a given site. Assuming that the amount of hazardous material associated with each facility is proportional to the size of the facility, we postulated that larger facilities posed a greater threat than smaller facilities. Using the number of employees per facility as a measurement of facility size, we ranked the facilities from lowest to highest, scaling them from 1 to 10. As a referee pointed out, this assumption may not hold in all cases. For example, larger companies may have more resources for proper handling of hazardous material and therefore pose less risk. Nevertheless, given the lack of primary data, this seemed more tenable than assuming that all facilities posed equal risk.

The next step involved defining a hazard zone for each industrial facility. The maximum initial evacuation distance suggested by the U.S. Department of Transportation for the most hazardous substances is approximately 500 metres (U.S. Department of Transportation, 1984). Although some materials require a smaller evacuation radius, we used 500 metres for all facilities. Because many industrial facilities are within 500 metres of one another, a question arises about how to score overlapping hazard zones. It is likely that hazard potential is greater in these overlap zones, but it is unclear how these potentials combine (e.g., additive versus multiplicative). Therefore, we used a conservative approach and designated the overall hazard potential in the overlap by the highest score in that zone.

Because topography significantly influences the behavior of an accidentally released hazardous material, it was important to consider the effect of the transmission of hazardous materials on potentially vulnerable populations. For example, as recently as February 1994 over 4,000 people were evacuated from Ambos Nogales because evidence of a hazardous chemical was channeled through in the Nogales Wash (*New York Times*, 18 February 1994). To represent the influence of topography on contaminant transmission, we used a least-cost-path algorithm with a raster data layer in which cell values represent elevation. Each transmission path was buffered with a 500-metre radius, creating a transmission hazard zone. Each zone was scaled from 1 to 10 depending on its release site characteristics. A similar data set was created for sewer transmission.

Human-Related Data Sets

The 1990 U.S. Census and the 1990 Mexican Census provided population data for Nogales, Arizona and Nogales, Sonora, respectively. An important objective in vulnerability analysis is to identify sensitive subpopulations (National Response Team, 1987). Two sensitive population data layers were derived from digital census coverages, *population density under 18 years* and *population density over 65 years*. A third GIS coverage was created for *general population density* (ages over 18 and under 65). By creating a separate GIS data layer for each of these subpopulations, it is possible to weight them separately in the composite model. As in the hazard-related data layers, the population density data layers were scaled from 0 to 10 based on increasing density, with unpopulated areas receiving a 0.

Two other human-related data sets were created for the community vulnerability model. The National Response Team (1987) recommends including schools, hospitals, nursing homes, and day care centers as sensitive institutions in a vulnerability analysis. For this study, we were able to create a GIS coverage of schools (preschools, elementary schools, and secondary schools), hospitals, and clinics for both sides of the border. Information for the *sensitive institutions* data layer were obtained from the Nogales, Arizona USGS 7.5-minute quadrangle and the Nogales, Sonora *Carta Urbana* (published by the Mexican Instituto Nacional de Estadistica Geografia e Informatica). These institutions were given a 100-metre buffer, and the data layer was scaled from 0 to 10. In the final coverage, all areas within 100 metres of a preschool were assigned a score of 10, while locations proximal to elementary schools, hospitals, clinics, secondary schools, and prisons received scores of 8, 6, 4, 2, and 1 (respectively).

The final human-related coverage provided a measure of the economic condition of the human landscape. Montz (1986) points out that the socio-economic status of an area or population group is an important factor to consider when preparing for an emergency situation. Due to poor warning systems and lack of effective transportation, poorer neighborhoods may be considered areas of higher risk in the event of a hazardous material accident. Socio-economic data were derived from the U.S. and Mexican censuses. For areas within the U.S., we used the mean home value as a surrogate for socio-economic status. Because the Mexican census does not provide an equivalent to mean home value, an index was derived from data on minimum monthly salary, and home construction (percent with potable water and sewage) was used for Nogales, Sonora. This index was based on a similar index for Nogales, Sonora developed by researchers at the *Colegio de la Frontera Norte* (COLEF, 1992).

Model Implementation

Traditionally, a CMA assigns a single weight to each scaled variable with the requirement that the weights are scaled such that the overall composite score is a linear combination: i.e.,

$$C = \sum_{i=1}^{n} w_i x_i \tag{1}$$

$$\sum_{i=1}^{n} w_i = 1.00 \tag{2}$$

where C is the composite score for a given spatial unit, x_i is an individual (scaled) variable for that unit (corresponding to a thematic data layer), w_i is the weight assigned to that variable, and n is the number of variables. However, in the current analysis we used a two-level approach which allows for distinctions among the components that comprise each variable's weight. This greatly facilitates the structuring of these weights in the sensitivity analysis discussed below.

The various data sets of the GIS community vulnerability model comprise two distinct components. On the one hand are human sensitivity variables, which combined produce a composite data set of human sensitivity to hazardous materials. On the other hand are hazard potential variables which combined produce a composite data set of hazard risk. The combination of these two composite data sets produces a data set which identifies community vulnerability to hazardous substance releases. Figure 3 illustrates the conceptual structure of this model.

The distinction between human-related variables and their composite factor with hazard-related variables and their composite factor suggests a two-level approach to determining individual weights. At a macro level, there is a need to create the most accurate balance in weighting the composite human-related factors against the hazard-related factors. Conversely, at a micro level the weighting combinations must truthfully represent the importance of each individual variable in representing the overall human-related and hazard-related composites. This distinction is meaningful because it highlights differences in subjectivity and variability that exist at each level. For example, at the macro-level fire department personnel may suggest that identifying hazard potential is the most important factor contributing to community vulnerability. Health officials, on the other hand, may suggest that human populations are more important. In contrast, at the micro-level subjective judgement may be required for the relative weighting of surface transmission routes versus sewer transmission routes in defining the overall hazard-related composite factor for a given material type.

In order to maintain a conceptual distinction among macro versus micro-level, we determined the overall vulnerability score for a spatial unit according to the following equation:

$$C = W H + V Z = (W \sum_{i=1}^{n} w_i h_i + V \sum_{j=1}^{m} v_j Z_j) \tag{3}$$

with the requirements

$$\sum_{i=1}^{n} w_i = 1.00 \tag{4}$$

$$\sum_{j=1}^{m} v_j = 1.00 \tag{5}$$

$$W + V = 1.00 \tag{6}$$

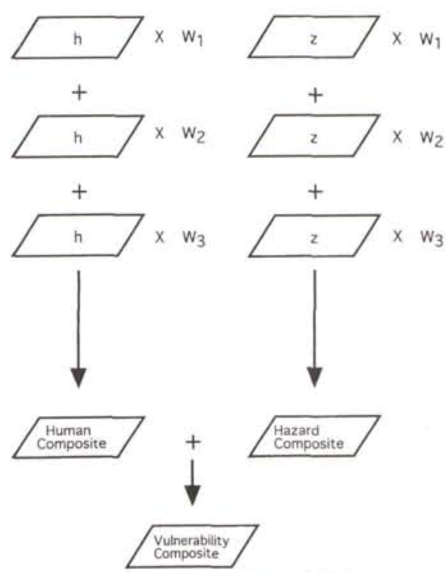

Figure 3. Conceptual view of GIS-based community vulnerability model.

where W and V represent the macro-level weights for human-related and hazard-related composite factors (respectively), H and Z represent the composite human-related and hazard-related factors (respectively), w_i and v_j represent micro-level weights corresponding to human and hazard-related variables h_i and z_j (respectively), n is the number of human-related variables, and m is the number of hazard-related variables. A sensitivity analysis explores the subjectivity and variability in variable weights at both the macro and micro-levels in a carefully structured manner.

Sensitivity Analysis

Sensitivity analysis is a technique for dealing with subjectivity and variability in model parameters. A sensitivity analysis assesses the variability of model results to changes in parameter values (Macgill, 1989). The range of parameter values used in a sensitivity analysis should represent a range of logical alternatives. In other words, the purpose of the sensitivity analysis is to test the model for output over a range of legitimate uncertainty (Minshull, 1975; Macgill, 1989). By changing the parametric inputs of the model, different yet equally valid scenarios are created. A GIS's capability to repetitively perform a task with unchanging precision makes it an effective tool for this type of modeling.

We developed a set of vulnerability scenarios based on combinations of macro-level and micro-level assumptions regarding the relative importance of variables in determining community vulnerability. At the macro-level is the broad assumption regarding the overall importance of the human component (human-related variables) versus the hazard component (hazard-related variables) of the model; we refer to these as *macro-level strategies*. On the other hand, a series of *micro-level strategies* vary the importance of human-related variables relative to other human-related variables, and hazard-related variables relative to other hazard-related variables.

We explored three macro-level strategies. First is a bal-

TABLE 1. SUMMARY OF MACRO STRATEGIES

	Description of Strategy	Proportional Weighting Coeff.	
Macro Strategy I	Human Component proportionally equal to Hazard Component.	Human: Hazard: **Total:**	0.50 0.50 **1.00**
Macro Strategy II	Human Component favored over Hazard Component.	Human: Hazard: **Total:**	0.75 0.25 **1.00**
Macro Strategy III	Hazard Component favored over Human Component.	Human: Hazard: **Total:**	0.25 0.75 **1.00**

TABLE 2. SUMMARY OF MICRO STRATEGIES FOR HUMAN COMPONENT

	Description of Strategy	Proportional Weighting Coeff.	
Micro Strategy Hum-A	All Data layers proportionally equal.	Under 18: Over 65: *General population:* Sensitive institutions: Economic condition: **Total:**	0.200 0.200 0.200 0.200 0.200 **1.000**
Micro Strategy Hum-B	Sensitive populations (under 18 & over 65) and institutions heavier than general population (19-64) and economic condition.	Under 18: Over 65: General population: Sensitive institutions: Economic condition: **Total:**	0.273 0.273 0.091 0.273 0.091 **1.000**

anced strategy, where the overall weight of the human-related variables is proportionally equal to the overall weight of the hazard-related variables. Second is a macro-strategy where the overall weight of the human-related variables are greater than the hazard-related variables. Finally, a third macro-strategy favors the contribution of the hazard component (i.e., the inverse of macro-strategy #2). Table 1 summarizes the three macro strategies and indicates relative proportions for the composite human-related and hazard-related factors. The macro coefficients were chosen with the intention of approximating legitimate assumptions about community vulnerability. Consequently, a 0.00 versus 1.00 macro-strategy is not represented because community vulnerability is by definition a function of both components (i.e., human and hazard).

The objective of the micro strategy is to develop weighting coefficients for individual data layers that reflect variability relative to other human-related or hazard-related variables. Two micro strategies are used for the human component and three for the hazard component. Micro strategy Hum-A represents a benchmark strategy where all human-related variables are weighted proportionally equal to one another. Hum-A may be referred to as a "general sensitivity" strategy. Micro strategy Hum-B represents a weighting strategy better suited to an emergency evacuation situation. The Hum-B micro strategy weights the *density under 18, density over 65,* and *sensitive institutions* data layers heavier than the *general population* and *economic condition* data layers. These variables are weighted heavier to reflect their relative importance in determining community vulnerability for an emergency evacuation situation. Table 2 summarizes the relative proportions for human-related variables in each micro strategy.

TABLE 3. SUMMARY OF MICRO STRATEGIES FOR HAZARD COMPONENT

	Description of Strategy	Proportional Weighting Coeff.	
Micro Strategy Haz-A	Hazard sites heavier than surface and sewer transmission (weighted equally).	Hazard sites: Surface transmission: Sewer transmission: **Total:**	0.500 0.250 0.250 **1.000**
Micro Strategy Haz-B	Hazard sites heavier than surface and sewer, and surface heavier than sewer.	Hazard sites: Surface transmission: Sewer transmission: **Total:**	0.500 0.333 0.167 **1.000**
Micro Strategy Haz-C	Hazard sites heavier than surface and sewer, and sewer heavier than surface.	Hazard sites: Surface transmission: Sewer transmission: **Total:**	0.500 0.167 0.333 **1.000**

TABLE 4. MACRO- AND MICRO-STRATEGY COMBINATIONS

		Macro I ΣHum = 0.50 ΣHaz = 0.50	Macro II ΣHum = 0.75 ΣHaz = 0.25	Macro III ΣHum = 0.25 ΣHaz = 0.75
Micro Strategy and Hum-A	**Micro Strategy Haz-A**	Scenario 1	Scenario 7	Scenario 13
Micro Strategy and Hum-A	**Micro Strategy Haz-B**	Scenario 2	Scenario 8	Scenario 14
Micro Strategy and Hum-A	**Micro Strategy Haz-C**	Scenario 3	Scenario 9	Scenario 15
Micro Strategy and Hum-B	**Micro Strategy Haz-A**	Scenario 4	Scenario 10	Scenario 16
Micro Strategy and Hum-B	**Micro Strategy Haz-B**	Scenario 5	Scenario 11	Scenario 17
Micro Strategy and Hum-B	**Micro Strategy Haz-C**	Scenario 6	Scenario 12	Scenario 18

All three of the hazard-related micro-strategies consider the *hazard sites* data layer to be relatively more important than transmission pathways. The rationale is an assumption of greater hazard risk near the site of a hazardous release than along its dispersion path(s). In the Haz-A micro strategy, the *hazard sites* data layer is weighted twice as heavy as the two transmission paths (surface and sewer), which are weighted equally. The Haz-B micro strategy weights surface transmission heavier than sewer transmission, and Haz-C weights sewer transmission heavier than surface transmission. Table 3 summarizes the relative proportions for hazard-related variables in each micro-level strategy.

Community vulnerability scenarios are generated by combining macro and micro strategies. For each simulation "experiment" or scenario, one macro strategy is combined with one human micro strategy and one hazard micro strategy. With three macro strategies, two human micro strategies and three hazard micro strategies, 18 possible combinations, or vulnerability scenarios, exist (see Table 4).

Given the relative weights corresponding to a macro-level and micro-level combination, the next step requires calculating the appropriate weights assigned to each data layer for every scenario. To calculate the actual weights for the data layers, the human and hazard weighting coefficients for each macro strategy are multiplied by the respective weighting coefficients of the six micro strategy combinations. The actual weights for the data layers are, in effect, a proportion of a proportion. This is more clearly indicated by examining the computational formulas for constructing each variable's "synthetic weight" in a given scenario: i.e.,

$$W_i^* = W\, w_i \tag{7}$$

$$V_i^* = V\, v_i \tag{8}$$

where W and V are the macro-level weights for the human-related and hazard-related composite factors (Table 1) and w_i and v_i are the micro-level weights for human-related and hazard-related variables (Tables 2 and 3, respectively).

Table 5 provides the resulting synthetic variable weights w_i^* and v_i^* for each vulnerability scenario. A particular vulnerability scenario is identified combining a human-related micro-strategy with a hazard-related micro-strategy and then selecting the appropriate macro-level weights for each micro-level strategy. For example, the highlighted boxes in Table 5 correspond to Scenario 10: this scenario combines the macro-strategies of Hum-B with Haz-A and gives the human-related factors an overall weight of 0.75 and the hazard-related factors an overall weight of 0.25. In contrast, Scenario 16 (which has the same micro-level strategies but the complementary macro-level weighting) can be identified by simultaneously choosing the box to the right of the upper highlighted box and the box to the left of the lower highlighted box.

We implemented the community vulnerability model using ARC/INFO GIS software. We ran the model using an arc macro language (AML)-based macro that weights the scaled data layers, adds them together, and then reclassifies the GIS composite into five ordinal levels of community vulnerability. By simply changing the weights assigned to each data layer in the AML, it is possible to use the same AML for all 18 vulnerability scenarios.

Table 5. Calculation of Scenario Coefficients (Highlighted Example of Scenario #10)

Micro Strategy	Data Layer	Micro Wt. Coeff.	Macro Strategies: I Macro Wt. Coeff. **0.50**	II & III Marco Wt. Coeff. **0.75**	III & II Macro Wt. Coeff. **0.25**
Hum-A	Under 18	**0.200**	0.100	0.150	0.050
	Over 65	**0.200**	0.100	0.150	0.050
	Gen. pop.	**0.200**	0.100	0.150	0.050
	Sen. inst.	**0.200**	0.100	0.150	0.050
	Econ. con.	**0.200**	0.100	0.150	0.050
Hum-B	Under 18	**0.273**	0.137	**0.205**	0.068
	Over 65	**0.273**	0.137	**0.205**	0.060
	Gen. pop.	**0.068**	0.046	**0.068**	0.023
	Sen. inst.	**0.273**	0.137	**0.205**	0.068
	Econ. con.	**0.068**	0.046	**0.068**	0.023
Haz-A	Sites	**0.500**	0.250	0.375	**0.125**
	Surface	**0.250**	0.125	0.188	**0.063**
	Sewer	**0.250**	0.125	0.188	**0.063**
Haz-B	Sites	**0.500**	0.250	0.375	0.125
	Surface	**0.333**	0.167	0.250	0.083
	Sewer	**0.167**	0.084	0.125	0.042
Haz-C	Site	**0.500**	0.250	0.375	0.125
	Surface	**0.333**	0.084	0.125	0.042
	Sewer	**0.167**	0.167	0.250	0.083

Results

Figures 4a, 4b, 4c, and 4d illustrate the output from the community vulnerability model for four scenarios. Figures 4a, 4b, and 4c contrast the results from the three macro-strategies (Human = Hazard, Human > Hazard, and Human < Hazard, respectively) while holding the micro-strategies (Hum-A and Haz-A) constant. Figure 4d illustrates the effect of a change in micro-strategy, specifically, Hum-B in place of Hum-A under the same macro-strategy illustrated in Figure 4a (Human = Hazard). As indicated previously, the resulting composite vulnerability scores are ordinal data classified into "very low," "low," "medium," "high," and "very high" vulnerability zones.

There are several noteworthy features of Figures 4a through 4d. Note that the different thematic data layers enter into the final composite vulnerability layer depending on the relative weights in each scenario. For example, Figure 4a indicates a spatial pattern of vulnerability that reflects an amalgamation of the buffers around hazard sites, transmission pathways, and the urban settlement pattern. However, Figure 4b illustrates that the greater weight of the human-related variables generates a spatial vulnerability pattern that strongly reflects urban development. Conversely, when hazard-related variables are given greater emphasis (Figure 4c), the composite vulnerability pattern mostly reflects site buffers and transmission pathways. A related observation is that differences due to changes in macro-strategy are much greater than differences due to changes in micro-strategy: note the minor changes in the vulnerability pattern between Figure 4a and Figure 4d.

While visually assessing output from the model is helpful in providing an initial impression of the model's behavior, an important advantage of using a GIS is its utility as a quantitative tool. Assessing the sensitivity of the model's output can be achieved by examining its *robustness*, or the variability of the model results given changes in data inputs (Macgill, 1989). We assessed the community vulnerability model's robustness by quantitatively comparing the 18 vulnerability scenarios. Particularly important to emergency evacuation planning are quantified measures of (1) the number of people in highly vulnerable zones and (2) the locations of highly vulnerable zones.

Estimates of the people most vulnerable to a hazardous substance release is important for emergency planning (National Response Team, 1987). To analyze the 18 vulnerability scenarios for quantitative differences, we calculated the number of people (all age groups) within each vulnerability zone. Figure 5 shows a plot of scenarios 1, 7, and 13 (corresponding to Figures 4a, 4b, and 4c). The large fluctuation in calculated totals for each zone provides a quantitative account of the significant visual differences in Figures 4a, 4b, and 4c. Figure 6 is a plot of scenarios 1 and 4 (corresponding to Figures 4a and 4d), representing a change in the human micro strategy weighting. Figure 7 complements these results by providing a plot of scenarios 1 and 2, representing a change

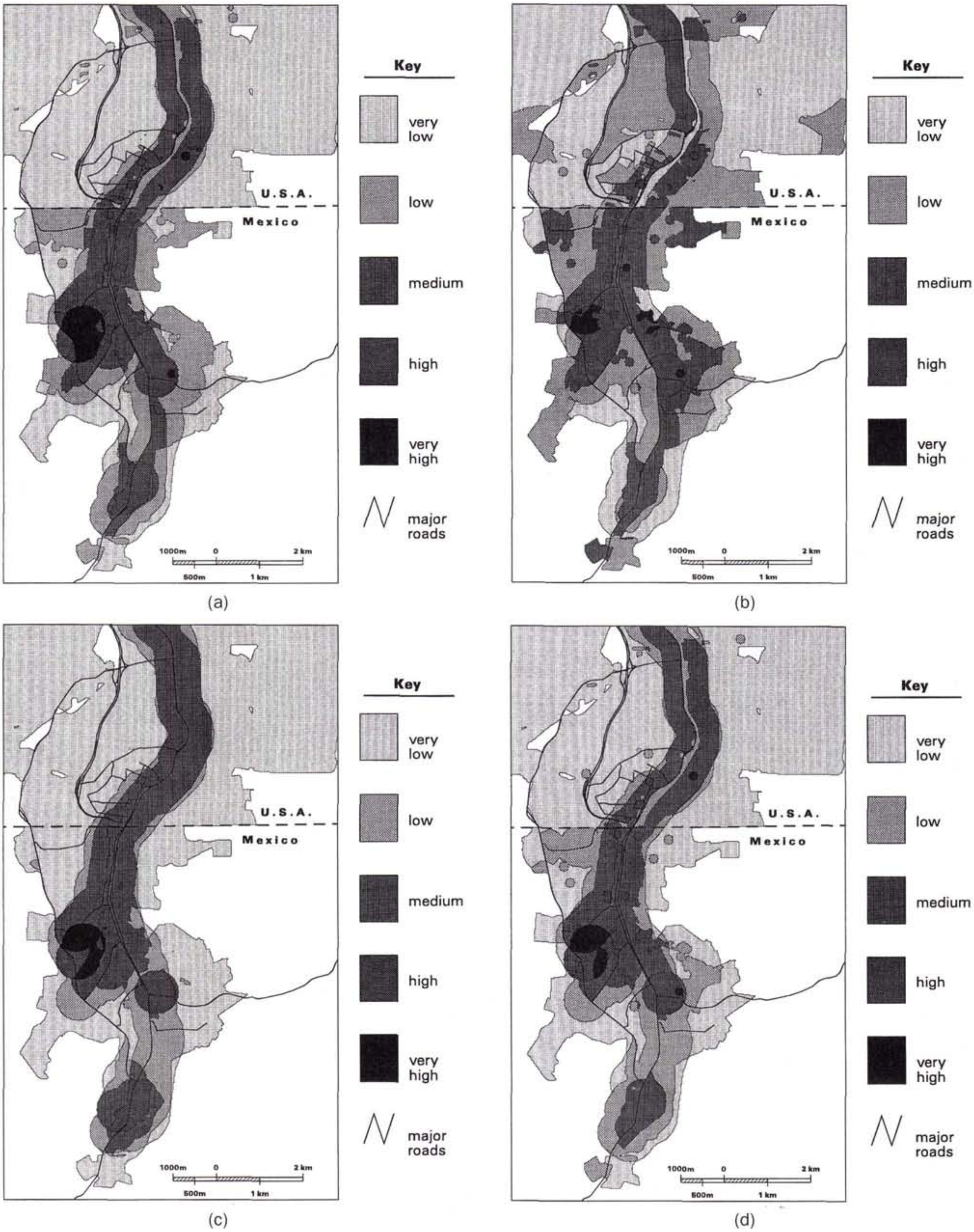

Figure 4. (a) Scenario 1 results (Human = Hazard; Hum-A and Haz-A). (b) Scenario 7 results (Human > Hazard; Hum-A and Haz-A). (c) Scenario 13 results (Human < Hazard; Hum-A and Haz A). (d) Scenario 4 results (Human = Hazard; Hum-B and Haz-A).

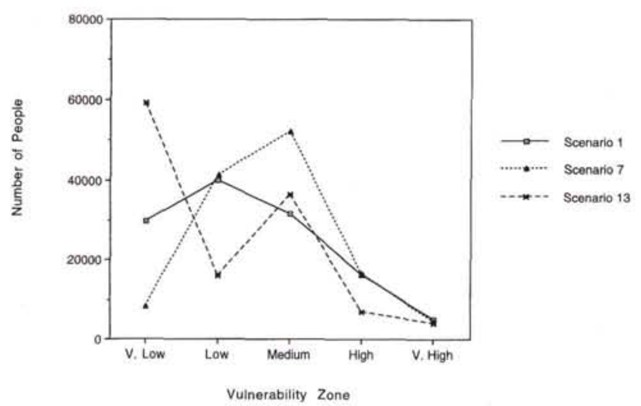

Figure 5. Population per zone: Scenarios 1, 7, and 13.

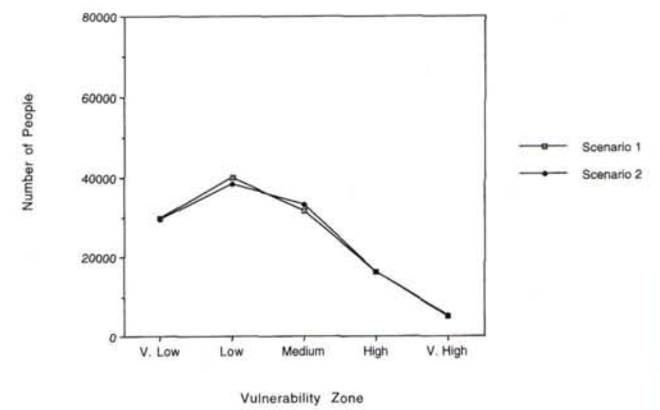

Figure 7. Population per zone: Scenarios 1 and 2.

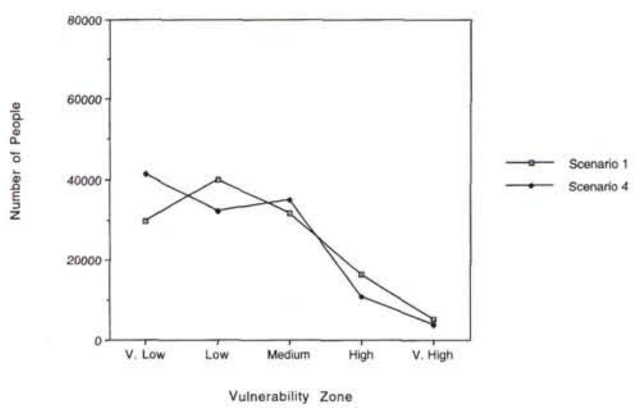

Figure 6. Population per zone: Scenarios 1 and 4.

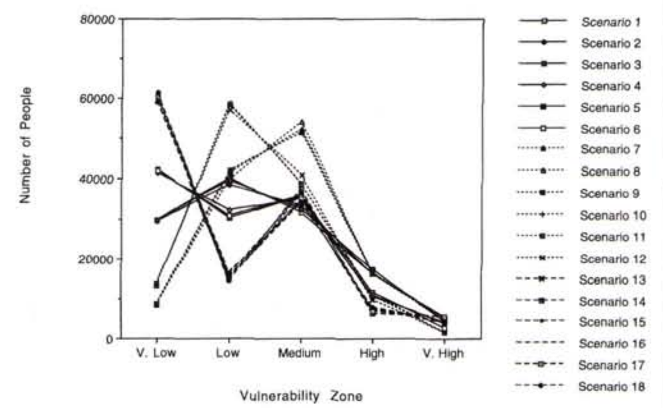

Figure 8. Population per zone: All scenarios.

in hazard micro strategy weighting (Haz-B in place of Haz-A under the Human = Hazard macro-strategy).

The influence of macro- and micro-strategy weighting, although apparent through the visual examination of the vulnerability scenarios, is more evident in the plots illustrated in Figures 5, 6, and 7. The amount of variation between these scenarios is consistent with the pattern assessed through the visual examination of the vulnerability scenarios. This quantitative analysis of differences among vulnerability scenarios confirms that changes in macro strategy influence model output the most, followed by changes in human micro strategy and changes in hazard micro strategy.

The robustness of the model can be assessed more completely by comparing all 18 vulnerability plots. Figure 8 shows the 18 vulnerability scenarios plotted simultaneously. Note that the greatest fluctuation of population estimates is for the very low, low, and medium vulnerability zones. Conversely, population estimates for the high and very high zones 4 and 5 are consistent across all vulnerability scenarios. This suggests that the GIS-based community vulnerability model is robust in predicting estimates of high and very high vulnerability, while it is less robust in predicting very low, low, and medium vulnerability. This result is encouraging: estimates for the highest vulnerability zones are more important for evacuation planning and other analysis needs than estimates for the medium to low vulnerability zones.

Descriptive statistics of the population estimates across scenarios provides a clearer assessment of model robustness. Table 6 provides the mean, standard deviation, and coefficient of relative variation (CRV) for the population estimates across vulnerability scenarios. Table 6 provides these statistical measures for aggregate population estimates as well as the critical age cohorts of less than 18 years old and over 65 years old. Note that, for the aggregate population estimates, the CRV for vulnerability zones 1 and 2 are higher than for zones 4 and 5 (57 percent and 45 percent compared to 34 percent and 31 percent). Somewhat surprising is the low CRV for the medium vulnerable zone. This indicates that the model is most robust in predicting medium vulnerability yet still resilient in predicting high and very high vulnerability. A similar pattern is evident for the population estimates of the sensitive age groups (under 18 and over 65). With the over 65 group, however, notice that the most robust results are the medium and very high categories (with CRVs of 7 percent and 18 percent). This comparison of the CRVs confirms earlier conclusions that population estimates in the high and very high categories are quite robust, especially when looking at the entire population (i.e., all age groups).

Another important aspect of analyzing the model output is determining the reliability of the population point estimates (i.e., means), because these values are often used for analysis purposes. Table 7 provides 95 percent confidence intervals for the population estimates in Table 6. An estimated 3,706 to 4,193 people are within the very high vulnerable zones of the Ambos Nogales area. Within those highly vulnerable zones, between 1,638 and 1,860 are under the age of 18, while an estimated 88 to 95 are over 65 years old. The "tightness" of these intervals indicates that estimates from the community vulnerability model are reliable across various analysis needs.

Although estimating the number of people within vulnerability zones is important to emergency planning, determining the *locations* of high and very high vulnerability zones is also crucial (National Response Team, 1987). A locational analysis of these zones will suggest the geographic areas in which efforts such as emergency response should be concentrated. Figure 9 illustrates the classified locations based on the frequency of appearance in the high or very high vulnerability zones across the 18 community vulnerability scenarios. The frequency of predictions for each cell is indicated in the map legend. These locations are based on a map resolution of 20 metres², which is the resolution of the coarsest data layer in the analysis. Figure 9 illustrates three frequency categories: cells where fewer than 6 of the 18 vulnerability scenarios predicted high or very high vulnerability, cells where 6 to 12 scenarios predicted high or very high vulnerability, and cells where greater that 12 of the 18 scenarios predicted high or very high vulnerability.

While the prediction of high or very high vulnerability may be important for a given postulated scenario, locations that consistently exhibit high vulnerability across scenarios may merit special consideration in emergency response planning. For example, a liberal assessment of community vulnerability would consider all cells predicted as highly vulnerable or very highly vulnerable in an emergency preparedness plan. That is, even if only one scenario out of 18 predicted an area to be vulnerable, it should be considered in the plan. A more conservative approach looks at those areas where more scenarios predicted vulnerability (e.g., more than 12). That is, given the range of assumptions from all 18 scenarios, these areas are most likely to be of concern to emergency planners.

Once the most vulnerable locations are identified, the GIS data sets can be used for emergency planning implementation. Each vulnerable zone, or "top priority planning area," can be analyzed separately. Information on population characteristics and sensitive institutions can be calculated easily using the GIS. For example, Figure 10 illustrates nine "top priority planning areas" based on frequency of appearance in the very high and high vulnerability zones while Table 8 illustrates the characteristic of each zone. In general, these zones are densely populated, have significant numbers of children, and contain sensitive institutions. One area (Area B) has a substantial number of elderly population and two other areas (Area D and Area E) contain a number of elementary schools. This information is useful to planners, as it identifies which parts of the city are in most critical need of attention. Once identified, the top priority zones may be used with a GIS data set of street networks to determine optimal emergency evacuation routes, or to determine the optimum location for proposed emergency response facilities.

TABLE 6. VARIATION ACROSS 18 VULNERABILITY SCENARIOS

Population: All Ages					
Vulnerable Zone	low	high	mean	s.d.	CRV
(1) Very Low	8,253	60,896	35,599	20,507	57%
(2) Low	14,346	58,684	33,360	15,019	45%
(3) Medium	31,683	54,016	38,430	6,676	17%
(4) High	6,091	17,213	11,417	3,889	34%
(5) Very High	1,547	5,433	3,949	1,242	31%
Population Under 18 Years					
Vulnerable Zone	low	high	mean	s.d.	CRV
(1) Very Low	3,197	27,239	15,471	9,379	60%
(2) Low	6,225	25,872	14,621	6,822	47%
(3) Medium	12,349	22,530	15,351	3,111	20%
(4) High	2,403	7,158	4,792	1,699	35%
(5) Very High	649	2,392	1,749	567	32%
Population Over 65 Years					
Vulnerable Zone	low	high	mean	s.d.	CRV
(1) Very Low	463	2,027	1,332	557	42%
(2) Low	511	1,846	1,079	474	44%
(3) Medium	1,760	2,224	1,966	129	7%
(4) High	169	641	389	172	44%
(5) Very High	61	117	92	17	18%

TABLE 7. ESTIMATED POPULATIONS AT 95 PERCENT CONFIDENCE LEVEL

Population: All Ages			
Vulnerability Zone	mean	s.e.	Estimated Range
(1) Very Low	35,599	2050	26,127–45,071
(2) Low	33,360	1501	26,422–40,298
(3) Medium	38,430	667	36,430–41,153
(4) High	11,417	388	9,622–13,212
(5) Very High	3,949	124	3,706–4,193
Population Under 18 Yrs			
Vulnerability Zone	mean	s.e.	Estimated Range
(1) Very Low	15,471	937	13,633–17,310
(2) Low	14,621	682	13,284–15,958
(3) Medium	15,351	311	14,741–15,961
(4) High	4,792	169	4,459–5,125
(5) Very High	1,749	56	1,638–1,860
Population Over 65 Yrs			
Vulnerability Zone	mean	s.e.	Estimated Range
(1) Very Low	1,332	55	1,223–1,441
(2) Low	1,079	47	986–1,172
(3) Medium	1,966	12	1,940–1,991
(4) High	389	17	356–423
(5) Very High	92	1	88–95

Summary and Conclusion

Community vulnerability to industrial contaminants at the Mexico/U.S. border is a serious issue concerning many people in both countries. In this paper, we demonstrate the use

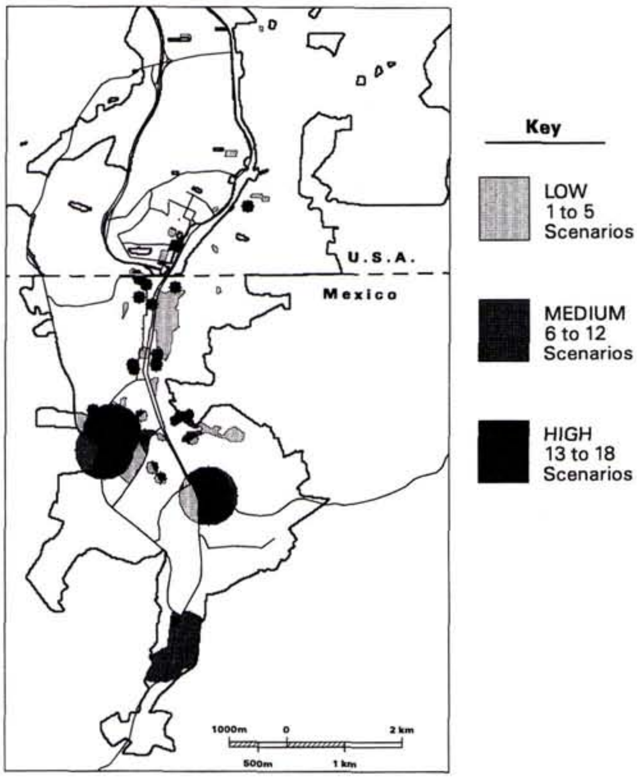

Figure 9. Frequency of predicted "very high" or "high" vulnerability by location.

of GIS to assess community vulnerability analysis in a trans-border situation. The spatial arrangement and intensity of the hazards and the demographics of the human landscape determine community vulnerability. This can be affected by the complexities of the physical landscape. This paper demonstrates the effectiveness of a GIS for modeling the interrelationships of these factors.

Another contribution is using a GIS to develop a structured and systematic method for handling the subjectiveness inherent in community vulnerability analysis. Subjective decisions are required to determine the most appropriate weighting strategy used in the community vulnerability model. At a macro level are assumptions about the relative importance of human-related variables versus hazard-related variables. Assumptions at the micro level involve the relative importance of each variable within the human or hazard component of the model. A GIS facilitates the easy re-weighting and re-assessment of model results subject to changes in these subjective weights. Because subjectivity is inherent in many planning activities, a GIS is more appropriate than strictly quantitative analyses. A structural framework using scaling indices and variable weighting strategies helps "bridge the gap" between complete subjectivity and objective analysis. As demonstrated, planners and policy makers can concentrate on locations that appear robust across many different modeling scenarios.

Although focused on technical aspects of GIS-based community vulnerability modeling, this research also highlighted practical issues associated with trans-border studies. In particular, differences in data availability, quality, and spatial resolution between the two countries affected model results. This problem is especially acute given the potentially infinite resolution of a GIS.

In theory, it is reasonable to build a model that treats Ambos Nogales as one city. The international border divides a continuous landscape of human beings, all of whom may be equally harmed by industrial contamination. In practice, however, data of equal quality for both sides of the border were difficult, and in some cases impossible, to obtain. Hazardous chemical inventories, for example, required by law in the United States and disclosed to the public, are not publicly available in Mexico. In addition, differences in the spatial resolution of available socioeconomic data existed between the two countries. More specifically, census data from Mexico had a much coarser spatial resolution than census data from the United States. This undoubtably affected model results: note the change in spatial resolution of the vulnerability pattern across the border in Figures 4a through 4d. The reliability of a GIS model such as this could be greatly improved if hazardous material inventories were available and if spatial data reporting between the two countries were standardized.

Finally, a topic for further investigation is the reliability of the GIS community vulnerability model in different physical and urban settings. Ambos Nogales was particularly well-suited for this analysis due to the channelizing effect of its physical morphology, its compact and dense urban form, and

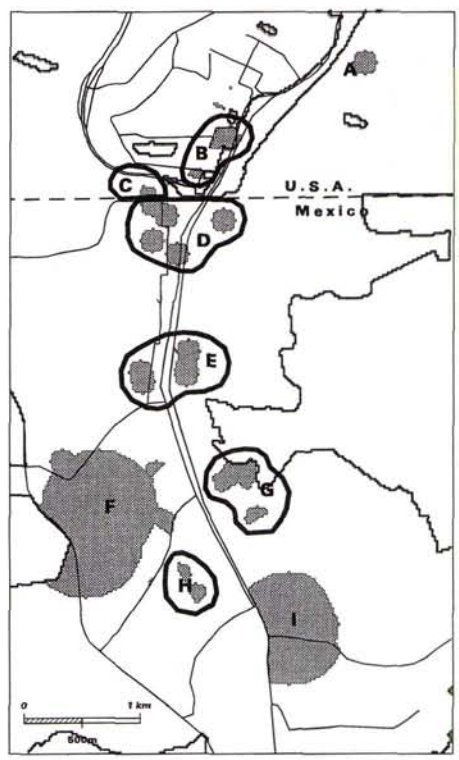

Figure 10. Top priority planning areas.

TABLE 8. CHARACTERISTICS OF TOP PRIORITY PLANNING AREAS

Area	Total population	% under 18	% over 65	Sensitive institutions	Industry within 500 meters?	Nogales Wash within 500 meters?
A	126	30	< 1	E (1)	No	Yes
B	226	34	17	E (2)	No	Yes
C	106	36	< 1		No	Yes
D	1042	40	< 1	E (4); P (1)	No	Yes
E	938	38	< 1	E (3)	No	Yes
F	5733	44	< 1		Yes	No
G	1629	44	< 1	E (1)	No	Yes
H	147	31	< 1	E (2)	No	Yes
I	4364	44	< 1		Yes	Yes

Notes: Number in parenthesis illustrate the number of institutions; E = elementary school, P = preschool.

the proximity among maquiladoras and populations and institutions at risk. Further research should assess this modeling strategy in other trans-border and non-border settings with potential vulnerability to hazardous material releases.

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