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Research Article

Modelling community evacuation vulnerability using GIS

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Abstract. We present a method for systematically identifying neighbourhoods that may face transportation difficulties during an evacuation. A classification of this nature offers a unique approach to assessing community vulnerability in regions subject to fast-moving hazards of uncertain spatial impact (e.g., urban firestorms and toxic spills on highways). The approach is founded on an integer programming (IP) model called the critical cluster model (CCM). An heuristic algorithm is described which is capable of producing efficient, high-quality solutions to this model in a GIS context. The paper concludes with an application of the method to Santa Barbara, California.

1. Introduction

The field of regional evacuation modelling has evolved along a fundamentally temporal line of inquiry, where research has centred on the problem of accurately estimating the time it might take to clear a specified zone of its population. This focus was initially motivated by the perceived threat imposed by nuclear power plants during the 1970s (WSA 1974), and the accidents at Pennsylvania's Three Mile Island in 1979 and Chernobyl in 1986 served to reinforce this emphasis. The general approach involved predefining a circular emergency planning zone (EPZ) around each nuclear site using a 10-mile radius (NRC 1980, Urbanik *et al*. 1980) and subsequently pursuing an estimate of the time it might take to clear the zone. Early static-analysis techniques for estimating network clearance time (WSA 1974, Stone 1983) have since been eclipsed by special-purpose transportation simulation models capable of dynamically modelling evacuations on the scale of entire urban areas (Sheffi *et al*. 1982, FEMA 1984, Hobeika and Jamei 1985, Pidd *et al*. 1996). A number of these simulation models have become the basis for evacuation decision support systems (Han 1990, Tufekci and Kisko 1991, de Silva *et al*. 1993, Hobeika *et al*. 1994).

In the wake of this early evacuation research on nuclear power plants, a modelling paradigm emerged (Southworth 1991, Urbanik and Jamison 1992). The standard approach was to delimit an EPZ around a known hazard and subsequently apply an evacuation simulation model to explore questions regarding the many factors that might affect network clearance time (e.g., routing, population distribution, road and intersection capacity, human behaviour). This general approach proved very useful and has been used to model the evacuation of communities at risk to chemical

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stockpile sites (Newsom *et al.* 1992), nuclear research facilities (Sinuany-Stern and Stern 1993), dams (Southworth and Chin 1987), and hurricanes (Hobeika *et al.* 1985).

A key concept that underlies this modelling approach is the notion of a credible EPZ. A credible EPZ is a valuable spatial construct, as it provides a crisp answer to the dual questions of who needs to be evacuated (population in the zone) and where they need to be routed to reach safety (outside the zone). In a sense, it serves as a formal agreement among emergency planners regarding the definition of a likely evacuation. This allows analysts to move directly to issues related to estimating and reducing the time it might take to clear a zone. As Sorensen *et al.* (1992) note, delimiting a credible EPZ can be a significant political and technical endeavour for certain hazard types.

However, a problem arises when an analyst is faced with performing an evacuation assessment for a region that is subject to a hazard with a high degree of uncertainty in its spatial impact. In short, there are many hazards where the population to be evacuated simply cannot be determined in advance. Urban firestorms, toxic spills on highways, and many other hazards routinely result in *ad hoc* evacuation zones that are established at the time of the event. For this reason, hazards with a high degree of spatial uncertainty pose an interesting modelling problem. We call this problem the indeterminable EPZ problem (IEPZ) and state it as follows: How can an evacuation assessment be performed when the population to evacuate is an unknown (i.e., when a credible EPZ cannot be established in advance)?

As the IEPZ problem is a spatial problem, it represents a significant opportunity to utilize a GIS approach. The potential role for GIS in evacuation research has been noted by a number of authors (Gatrell and Vincent 1991, Dangermond 1991, Johnson 1992, Rejeski 1993), but little work has been done in this area to date. GIS have been applied in generating alternative evacuation routes out of a given zone (Dangermond 1985, Dunn 1992) and in managing the spatial data associated with an evacuation decision support system (de Silva *et al.* 1993). In general, the wider application of GIS in hazards research has focused on modelling the physical aspects of hazards (Wadge 1988, Chou 1992, Shu-Quiang and Unwin 1992, Carrara and Guzzetti 1995, Emmi and Horton 1995, Radke 1995) and not on potential evacuation difficulties. Although evacuation vulnerability modelling is clearly related to GIS natural hazards research, it's more closely aligned with GIS research on modelling human vulnerability and risk (McMaster 1988, Estes *et al.* 1987, Hodgson and Palm 1992, Burke 1993, Emani *et al.* 1993, Brainard *et al.* 1996).

The purpose of this paper is to describe a GIS approach to the problem of identifying neighbourhoods that may face transportation difficulties during an evacuation. A secondary concern is to demonstrate that the algorithm underlying this approach is a candidate for addition to the spatial analytic toolbox of contemporary GIS (Goodchild 1987, Burrough 1990, Fotheringham and Rogerson 1993). The paper begins with a description of a methodological framework designed to address the IEPZ problem that we call evacuation vulnerability modelling. A fundamental problem is identified and formulated as an integer programming (IP) model. Solving this IP model optimally is impractical for most real-world road networks, and we describe a heuristic algorithm designed to produce efficient, high-quality solutions to the model in a GIS context. An application of the method is presented for Santa Barbara, California, and the paper finishes with a conclusion and discussion of further research.

2. Evacuation vulnerability modelling

An initial approach to addressing the IEPZ problem is to shift the emphasis from a temporal to a spatial perspective. Rather than pursuing the question as to the time it might take to clear a single zone under a particular hazard, regional evacuation can be viewed as a generic process (Perry 1985) independent of any hazard or zone. In other words, clearing people from an area can be viewed as a process independent of any particular zone or hazardous event that might warrant the evacuation. From this perspective, there would be an extremely large number of potential evacuations in any given region. An interesting problem involves classifying them regarding transportation difficulties that might arise during an urgent evacuation (e.g., congestion).

Essentially, we require a measure of evacuation difficulty at each point in the plane. One approach is to find a zone for each point that (1) contains the point, (2) is limited in size, and (3) represents the most difficult evacuation for that point. If this process was performed on a network data model at select points (i.e., intersections), it would be possible to produce a field defined along the network that represents an upper bound on potential transportation evacuation difficulties. Goodchild (1992) would consider this a process of generating a field from a discrete data model. A field of this nature would aid in assessing vulnerability, as communities that are unable to clear their immediate locale in a safe and timely manner may lead to disastrous consequences in some hazard contexts (OFD 1992).

2.1. *All possible evacuations*

Regional evacuation is a human process that occurs at the level of the individual, and it is assumed that there are a finite number of individuals in any defined region at a given point in time. As such, a set theoretic view can be adopted, where an evacuation is defined as any subset of a region's population clearing its immediate locale. The extent of the evacuation is thereby defined by the extent of the population involved. With time fixed (time-slice), there are a finite number of potential evacuations, as there are a finite number of subsets of any finite set. The cardinality of this set is given in equation (1) where n is the population of the study area and E is the set of all evacuations.

$$|E| = \sum_{i=1}^{n} \binom{n}{i} \tag{1}$$

For an area with a population as small as 50, there would be greater than 10^{15} potential evacuations (population subsets) at any point in time. A reduction of this set is required to move this problem into a computationally tractable domain (GIS).

First, the case where the evacuees are not in proximity is highly unlikely, and contiguity can be added to the definition of a valid evacuation. That is, the population must come from a contiguous area. Second, the most critical population to evacuate in the context of fast-moving hazards of uncertain spatial impact is the population within immediate proximity to the origin of the event. To focus on these frequent (Sorensen *et al.* 1987) micro-evacuations, a size limit can be included in the definition of a valid evacuation. Lastly, it's impossible to geo-reference all individuals within a study area, and a common aggregate geographic representation of population must

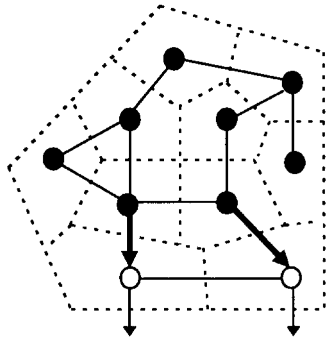

Figure 1. An example valid evacuation (black nodes) with two exits (bold arrows).

be employed. Contiguity, size, and aggregation all serve to significantly reduce the space that comprises all possible evacuations.

A common spatial data model for a transportation problem of this nature is a planar network, where the arcs represent road segments and the nodes represent street intersections. One approach to aggregating population in GIS network analysis studies is to assign and aggregate residents to their nearest street intersection using Thiessen polygons centred on the street intersections. An example network data model with one potential evacuation (black nodes) is given in figure 1. We will refer to any arc connecting the set of nodes in the evacuation to the rest of the network as an *exit* and the set of all exits for a particular evacuation as the *exit choice set*. An evacuee would be free to choose any arc in the exit choice set as a bridge to 'safety'. In graph theory, this set is commonly referred to as a *cut-set*, as the removal of this edge set results in a separation of the graph into two separate sub-graphs. At this point, the space that comprises all possible evacuations is defined as the set of all contiguous node subsets (i.e., intersections or Thiessen centroids) in a transportation network that are less than a given size.

2.2. *Evacuation difficulty*

Accurately estimating network clearance time for each evacuation using a simulation model is not possible in this context, as there are simply too many cases. However, one viable alternative is to develop a static index estimate of evacuation difficulty. To avoid confusion with estimating network clearance time, we will refer to this index as an evacuation difficulty index. Evacuation difficulty is defined as an estimate of the relative effort required to clear an area of its population. This concept embodies a composite of the potential for congestion, accidents, and general difficulty in deploying response vehicles into the evacuation zone. There are numerous approaches to operationalizing a concept like evacuation difficulty, but for our purposes, we will simply define it in equation (2) where P is the population involved and C is a measure of the capacity of the exit choice set.

$$P/C \tag{2}$$

It is clear that this definition is a highly simplified view of what is undoubtedly a complex social, spatio-temporal process. It should be noted that this method is a comparison of starting scenarios and not predicted outcomes. In other words, the comparison is between initial conditions, rather than an attempt to predict the outcome of an actual evacuation.

2.3. *Spatial evacuation vulnerability*

With the space that comprises all possible evacuations defined and an approach to scoring their potential difficulty, the focus can shift to developing a systematic spatial classification method. One approach is to inquire as to the worst-case (i.e., maximum difficulty) that each node in a network might be involved in, less than a certain size. We call this worst-case for a particular node (and size limit) its *spatial evacuation vulnerability*. The primary task is, then, to map the local variation in evacuation vulnerability throughout a network due to the unique geographical setting of individual nodes.

The definition of 'worst-case' in this context refers to the maximum value for a given difficulty measure and not the actual worst-case that might occur. For example, an actual evacuation could easily be more difficult due to the loss of exits (e.g., hazard or stalled vehicle), significant imbalances in the number of evacuees utilizing various exits, or convergence on the hazard site by response personnel and local citizens. The definition of worst-case utilized in this paper is simply an attempt to systematically reveal the geographical context in which an evacuation might take place.

An essential element in the definition of spatial evacuation vulnerability is the method for limiting evacuation size. In exploring the local neighbourhood of each node, it's necessary to formalize the notion of 'local'. We have identified five approaches to achieving this end: Euclidean distance, network distance, population, area, and node count (figure 2). In this paper, node count is utilized as the size limit, which assumes that network connectivity relations are the most critical component in defining evacuation vulnerability. This approach is particularly useful in areas subject to urban wildfires where there are very long dead-end roads extending into the urban/wildland interface. If Euclidean distance is utilized to limit evacuation size in this context, these dead-end roads appear as viable exits until the distance had been increased beyond a neighbourhood scale. It is anticipated that these various approaches to limiting evacuation size will have application in different hazard and network contexts, but we leave a thorough investigation of this issue for further research.

Figure 3 provides a theoretical example of how spatial evacuation vulnerability would be defined for a node, given that node count is the approach to limiting evacuation size. For this example, the evacuation node set must be less than or equal to six nodes. The figure shows three potential evacuations that all contain the node labelled A (note: There are many more than three node sets involving node A). Assume that each node has 100 residents, and each arc has one lane in each direction. The nodes involved are shown in black and the exits are shown as bold arrows. The

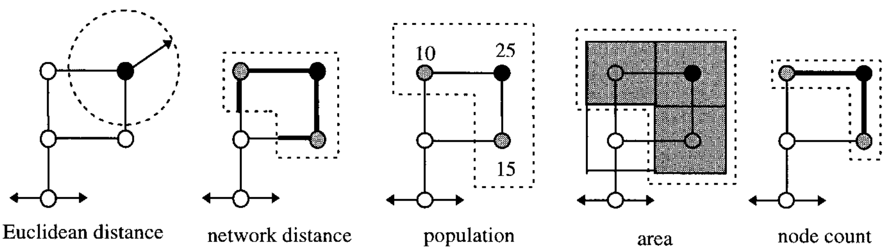

Figure 2. Five approaches to limiting evacuation size.

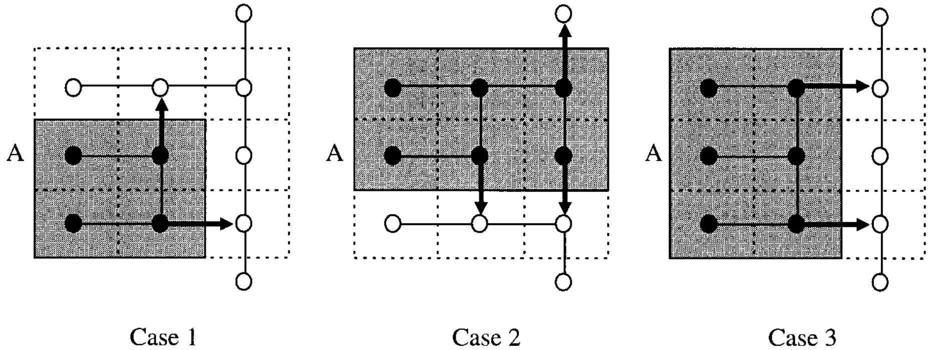

Figure 3. Three example evacuations (shaded) less than or equal to six nodes that all involve the population assigned to node A.

area assigned to each node (square Thiessen polygons) is shown with dashed lines, and the area to be cleared is shaded. In case 1, there are 400 evacuees and 2 exits (200 evacuees per exit lane). In case 2, there are 600 evacuees and three exits (200 evacuees per exit lane), and in case 3 there are 600 evacuees and only two exits (300 evacuees per exit lane). For this reason, case 3 represents node A's worst-case (maximum population per exit lane) out of the three cases (and in general as well), and node A's spatial evacuation vulnerability value would be set to 300 people per lane.

The classification of a region based on spatial evacuation vulnerability can then be achieved by iteratively posing the same query to each node in the network. An outline of this process is now offered. For a network with population assigned to its nodes and lanes on its arcs:

1. Select a method for limiting evacuation size and set the required parameters.
2. For each node, satisfy the following spatial query:
   'What is the most difficult (worst-case) evacuation starting scenario within which residents at this node might participate, where the evacuation is smaller than the specified size limit?'
3. Assign each arc in the network the higher spatial evacuation vulnerability value of its two end nodes.
4. Classify the arcs according to their spatial evacuation vulnerability value.

3. The critical cluster model

3.1. *Background*

The model formulated in this section represents the basis of our approach to modelling evacuation vulnerability. We will refer to the problem as the critical cluster problem (CCP) and the model formulated to solve it as the critical cluster model (CCM). Each individual node in a street network represents a separate optimization problem under this model. The process is akin to asking each node in the network the question posed in step 2 above. The answer to this question varies spatially as nodes do not have equivalent surroundings.

The critical cluster problem involves finding potentially the most difficult evacuation starting scenario associated with a pre-specified node, which we will call the root node. For a given root node and specified cluster size in nodes, there is at least one cluster of nodes in a network that contains the root node and maximizes the

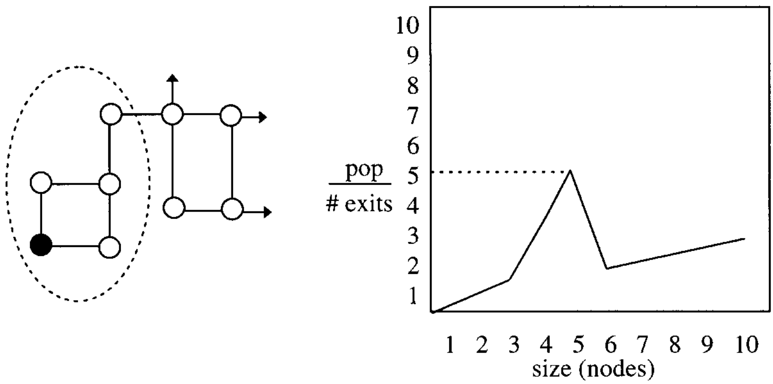

Figure 4. A network and a corresponding plot of evacuation difficulty for the black node.

ratio of cluster population to exit lanes. Solving the critical cluster problem involves finding the most extreme of these clusters for a given root node across a range of cluster sizes from one node up to a specified size limit. This optimal cluster (i.e., the cluster containing the root node that has the highest average population per exit lane) is referred to as the *critical cluster*. An example of a critical cluster is given in figure 4 for the black node. To simplify this example, each node has a population of 1 and each arc has one lane in each direction. Note that for the example root node, the critical cluster occurs at a cluster size of five; the point where the difficulty measure reaches its maximum.

The problem of finding a node's critical cluster falls within the broad category of graph or network partitioning problems. A partition is a subset of nodes within a larger network, and an optimal partitioning maximizes or minimizes some specified criteria related to the partition. In this context, we are only interested in contiguous partitions which we refer to as clusters. A related problem that is addressed widely in the operations research literature is the graph partitioning problem (Kernighan and Lin 1970, Johnson *et al*. 1989, Jin and Chan 1992, Laguna *et al*. 1994, Pirkul and Rolland 1994). This problem was originally stated by Kernighan and Lin (1970, p. 291) as:

> … given a graph *G* with costs on its edges, partition the nodes of *G* into subsets of no larger that a given maximum size, so as to minimize the total cost of the edges cut.

The graph partitioning problem arises when the goal is to divide a graph into separate sub-graphs with a minimum number of connections between the resultant sub-graphs.

This problem is related to the critical cluster problem and represents a valuable starting point from which to derive a formulation. The critical cluster problem can be stated in similar terms as:

> Given a graph *G* with costs on its edges and weights on its nodes, find a contiguous partition less than a given maximum size that contains a pre-specified node i^*, so as to maximize the total weight of the partition relative to the total cost of the edges cut.

Within the context of the difficulty measure presented in §2, node weight is population, and edge cost is the number of lanes. Note that an edge may not have the same number of lanes in each direction.

3.2. *Formulation*

To specify the critical cluster unambiguously, given a graph $G=(N, A)$ with costs, c_{ij} (lanes), on its arcs and weights, a_i (population), on its nodes, we are asked to partition N into two node sets N_1 and N_2 such that $N=N_1 \cup N_2$, $N_1 \cap N_2 = \emptyset$, where N_1 is a contiguous partition less than or equal to size s (in nodes) that contains a root node i^*, so as to maximize the total weight of N_1 relative to the total cost of the arcs cut between N_1 and N_2. This can be formulated as an integer programming (IP) problem:

Objective: Maximize: $$\frac{\sum_i a_i x_i}{\sum_i \sum_j c_{ij} y_{ij}} \tag{3}$$

Subject to: $$x_i - x_j \leqslant y_{ij} \qquad \forall i, j \text{ and } \forall j, i \in N \tag{4}$$

$$\sum_i x_i \leqslant s \tag{5}$$

$$x_{i*} = 1 \tag{6}$$

$$x_i,\ y_{ij},\ \in \{0,1\} \qquad \forall i, j \in N \tag{7}$$

Where: $$x_i = \begin{cases} 1, \text{ if node } i \text{ is in } N_1 \\ 0, \text{ otherwise} \end{cases}$$

$$y_{ij} = \begin{cases} 1, \text{ if node } i \text{ is in } N_1 \text{ and node } j \text{ is in } N_2 \\ 0, \text{ otherwise} \end{cases}$$

a_i=weight of node i (population)
c_{ij}=cost of arc ij (lanes)
s=maximum size (in nodes) of N_1
i^*=index of root node $\in N_1$

In this formulation for the CCM, the objective function (3) maximizes the ratio of the partition's total weight to the total cost of the arcs with one node in the partition and one node outside the partition. Constraint (4) ensures that if node i is in the partition and node j is not, then arc y_{ij} must be equal to 1, as it is a connection between the partition containing node i^* and the rest of the graph. If an arc's y_{ij} value is equal to 1, then the arc's number of lanes is included in the denominator of the objective function and the total number of exit lanes for the partition. Constraint (5) limits the search to partitions less than a specified size in nodes. Constraint (6) states that node i^* must be in the partition node set N_1. Constraint (7) ensures that all y_{ij} and x_i variables are binary integer variables.

There is also the condition that the critical cluster be contiguous. If we solve the above problem and the optimal critical cluster is, in fact, a multiple cluster, then additional constraints are required to ensure contiguity. Note that this problem is also a nonlinear problem, as the objective involves optimizing a ratio of two terms each with variable terms. Although we have developed an involved process for deriving optimal solutions to the CCM, finding guaranteed optimal solutions is impractical for most real world street networks. Because the goal is to solve the CCM in a practical GIS application context (i.e., arbitrarily large street networks in user time), the next section describes a heuristic algorithm designed to produce good solutions to this model in an efficient manner.

4. Heuristic algorithm

4.1. *Design*

Conceptually, the heuristic 'grows' a cluster from a specified root node in a network in an attempt to locate the node's critical cluster. Beginning with the specified node, the heuristic iteratively adds one of the currently adjacent nodes to the existing contiguous cluster. In constructing a cluster of nodes from a root node, there is one significant decision to make at each iteration: which adjacent node should be added next? A node must be assessed by the population it will add to the cluster, as well as its net effect on the cluster's total exit capacity. In the context of this paper, we have defined an arc's capacity simply to be its number of lanes. The equation for a node's gain regarding the objective value is given in equation (8):

$$\frac{P_{k+1}}{C_{k+1}}=\frac{P_k+a_i}{C_k+(o_i-c_i)}=g_i\frac{P_k}{C_k} \text{ or } g_i=\frac{C_k(P_k-a_i)}{P_k(C_k+(o_i-c_i))} \tag{8}$$

Where: k=index of iteration
g_i=gain in the objective if node i is selected
P_k=total population of cluster at iteration k
C_k=total exit capacity of cluster at iteration k
a_i=population at node i
o_i=new exit capacity node i would open, if selected
c_i=existing exit capacity node i would close, if selected

Figure 5 shows an example of growing a cluster from a root node in an attempt to find the critical cluster. To simplify this example, each node has a population of 1, and each arc has 1 lane in each direction. At step 1, the cluster began as one node (root node shown in black) with three exit lanes, giving it an objective value of 1/3. As there are three lanes leading out of the cluster, there are three adjacent nodes to evaluate with the above calculated gain value. At step 2, the node that most increased the objective value was the one to the left, and it is selected to give the cluster an objective value of 2/2=1. This added node was as isolated node (i.e., dead-end street) except for its connection to the root node. The process continues, where any adjacent node to the entire cluster is a candidate node to be added in the next iteration.

As this example relied on selecting the adjacent node that most increased the objective value, it is a greedy approach to finding the critical cluster. A greedy approach can rapidly lead to local optima, and it is likely that the best cluster found

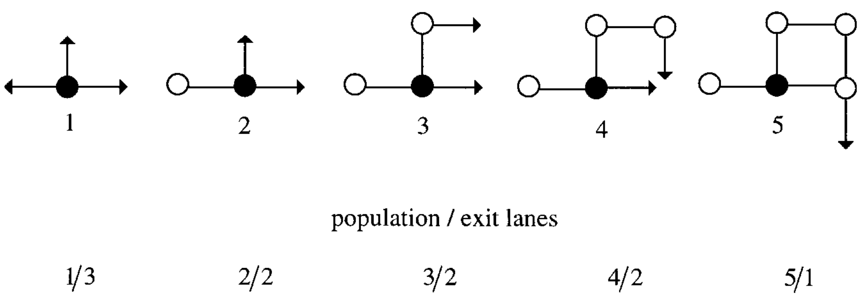

Figure 5. Growing a cluster from a root node (black node) in an attempt to find that node's critical cluster, where each node has unit population and each arc has one lane in each direction.

by this approach will not be optimal. However, solution quality can be greatly improved by modifying the procedure to use a semi-greedy approach. In a semi-greedy approach, an alpha parameter (expressed as a percentage) is used to increase the possible list of adjacent nodes that might be selected to add to the cluster. In short, the improvement factor for all adjacent nodes is calculated using equation (8), and all adjacent nodes are scanned again to produce a list of only the ones that are greater than *alpha* per cent of the best option. This implies that nodes with gain values less than the best node may be possible candidates for selection. A random selection is made from this list of candidate additions at each step. For this reason, successive runs of the heuristic for a given root node will likely result in different results. A second parameter (starts) can be added to control the number of times each node is run, where the best overall objective value is saved.

In addition to semi-greedy selection, we add the concept of adaptiveness found in the GRASP approach (Laguna *et al.* 1994). Adaptiveness is an answer to the notion that selecting one adjacent node can change the gain value of other adjacent nodes. In short, selecting one node affects the relative scores of all other adjacent nodes. This has a significant impact on the complexity of the algorithm, as it implies that the gain values for all adjacent nodes must be recalculated after every node selection. In this way, the nodes are thought to adapt their respective gain values to the changing state of the cluster.

4.2. *Implementation*

4.2.1. *GIS considerations*

The GIS query primitive that this algorithm requires is the *forward star* (Evans and Minieka 1992). A node's forward star is the set of arcs directed away from the node, which facilitates the retrieval of the set of immediately adjacent nodes. Figure 6 shows two examples of a forward star, one with undirected arcs (Case A) and one with directed arcs (Case B). The forward star query is utilized in many GIS network analysis algorithms like shortest path, routing, and tracing.

As an example, ESRI's ARC/INFO 7.0 supports the forward star query through the Arc Macro Language (AML) command SHOW with the ADJACENT and ADJACENT NEXT options. The ADJACENT option returns the number of nodes that can be reached via the undirected forward star, where subsequent calls to SHOW with the ADJACENT NEXT option return the node ids. Additional AML code can be added to remove nodes when considering street directionality (arc attribute). Although our first attempt to implement this heuristic relied on this approach, AML is an interpreted macro language and does not allow direct access to the network data structure. As such, it proved too slow for our computational

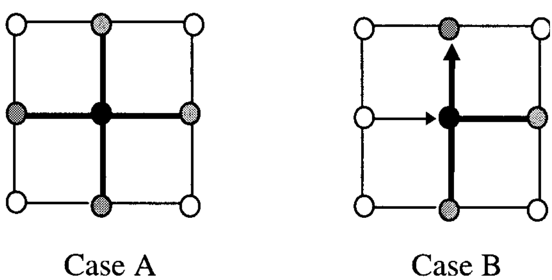

Figure 6. Two cases of a forward star (bold arcs) for the centre node.

experimental design, as we wanted to be able to grow many clusters from each node in a network of more than 5000 nodes using a variety of alternatives regarding the decision of which node to add at each step. For this reason, we implemented our own forward star network data structure (Evans and Minieka 1992) in a stand-alone *C* program and loosely coupled the program with ARC/INFO by exporting the network to text and importing the heuristic results back into ARC/INFO. In an environment where a software engineer has access to the internals of the GIS network data structure, the forward star query could be optimized, and the heuristic could be run in user-time within the GIS. A compromise between these two engineering extremes is ESRI's ARCVIEW 3.0, which has support for the forward star query through a dynamic link library (DLL) that can be called directly from a compiled *C* program (Honeycutt 1996).

4.2.2. *Specification*

The implementation of the heuristic takes as input a textual representation of a network and a set of parameters, whereby it produces an output file of node id's and their associated spatial evacuation vulnerability values. The parameters of the program are given in table 1.

There are two conditions that must be met before a network can be considered valid for an application of the heuristic: contiguity and global exit. Contiguity implies that there must exist at least one path between every pair of nodes in the network, and global exit implies that at least one node in the network be designated as an exit from the entire network. A global exit may not be selected as a component node of any cluster, and as most digital road networks are subsets of a larger network, it should be clear which nodes represent exits from the network.

The main control logic behind the algorithm is given in figure 7 as pseudocode.

```
Input:   network with weighted nodes (population) and arc (lanes),
         size limit, alpha, starts

Output: best cluster weight/cost (w/c) value achieved for each node

Main:
 for i ← 1 to n  (for all nodes in the network)
    for j ← 1 to starts ('starts' times for each anchor node)
       node ← i
       for cluster size ← 1 to size limit
          select node
          update all adjacent node gains (adaptive search)
          build candidate list of nodes within alpha percent of best
          node ← randomly select node from candidate list
          save weight/cost and node ids for best intermediate cluster
       set nodes in best intermediate cluster to at least best w/c
       unselect all nodes and reset all node gains
```

Figure 7. The pseudocode for the heuristic algorithm.

Given a size limit, the algorithm sequentially runs through the nodes in a network, in an attempt to find the critical cluster for each node. The only required parameter is the size limit, as the subsequent parameters are only used to improve the quality of the solutions produced by the algorithm. The total cluster weight over the number of exit lanes is referred to as the weight/cost value.

An important benefit of the structure of a critical cluster, in general, is that all the nodes that comprise one must have a critical cluster weight/cost ratio at least as large as the original critical cluster's. This means that when a maximum cluster is found for a particular root node, the nodes that comprise this cluster that have a critical cluster weight/cost value less than this critical cluster's value can automatically be raised up to this new value. It is still possible, however, for a subset of these component nodes to have an even higher critical cluster value. This improvement strategy is listed as step (10).

4.3. *Evaluation*

To test the performance of the heuristic algorithm, optimal solutions to the CCM were derived for 40 randomly selected nodes from 4 real-world street networks (10 each) at three evacuation size limits 10, 25, and 50 (120 problems), where the networks ranged in size from 200 to 300 nodes. The equation for evaluating the per cent from optimal for a node and size limit is:

$$\frac{O - B}{O} \tag{9}$$

where O is the optimal solution and B is the best solution achieved by the heuristic. Table 2 shows the mean per cent from optimal for the 120 problems for each combination of the semi-greedy parameters *alpha* and *starts*. A high *alpha* (e.g., near 1) constrains the growth of the cluster to greedy, where lowering *alpha* results in progressively 'wilder' cluster growth. Note that for a *starts* of 1 (row 1), the solution

Table 1. Program parameters.

Name	Range	Description
Size limit	1 … n − 1	The size limit (in nodes) to terminate growth
Alpha	0 … 1	The semi-greedy percentage parameter
Starts	1 … *x*	The number of times to start the heuristic from a root node

Table 2. Mean percentage from optimal varying *alpha* and *starts* (120 problems per cell).

	alpha									
Starts	0·975	0·950	0·925	0·900	0·875	0·850	0·825	0·800	0·775	0·750
1	12·07	10·53	11·21	11·61	11·01	12·69	12·04	15·14	15·42	17·67
2	10·57	8·56	9·32	9·14	10·23	9·52	10·27	11·18	13·06	11·93
4	9·53	7·13	8·16	7·75	7·47	8·08	8·03	8·51	9·97	8·59
8	7·72	6·12	5·92	5·08	6·73	5·92	7·35	6·82	6·65	8·04
16	7·72	6·12	5·92	5·08	6·73	5·92	7·35	6·82	6·65	8·04
32	7·81	5·25	4·95	4·29	4·34	4·53	4·45	5·06	5·02	5·02
64	6·58	4·85	4·48	3·77	4·32	3·84	4·15	4·2	3·81	3·93
128	6·58	4·74	4·13	3·95	3·69	3·87	3·61	4·02	**2·99**	3·72

quality decreases as *alpha* is decreased and the cluster growth gets wilder. Also, for all columns, solution quality improves as *starts* is increased. The best overall combination occurred at an *alpha* of 0·775 and a *starts* of 128, where the average percentage from optimal was 2·99. For our sample set of nodes, this implies that the best combination for high solution quality is moderately wild cluster growth and a large number of starts.

In evaluating the solution quality of the heuristic, it is important to keep in mind the intended purpose for the results. The goal is to produce an evacuation vulnerability map with a particular classification scheme within a user time frame. There are two additional concepts that affect the required heuristic solution quality necessary to produce an evacuation vulnerability map. Figure 8 shows how a relatively poor performance (17·5 per cent from optimal) of the heuristic for a particular node may not result in a misclassification in the output map for that node. This implies that the number of desired output map classes influences the required heuristic solution quality to produce a high quality map. The second concept that obviously influences the required heuristic solution quality is the desired heuristic classification accuracy of the output map. In other words, an output map within 99 per cent of the nodes classified correctly will require more computational effort than a map within 90 per cent classified correctly.

Putting these two concepts together introduces two additional parameters to the production of an evacuation vulnerability map: desired class granularity and heuristic classification accuracy. As solution quality can be traded for time, we want to select the avenue that results in solution quality sufficient to produce the desired map classification accuracy in the least amount of time. This implies that a two class map (e.g., high vulnerability and low vulnerability) with 90 per cent of the nodes classified correctly will undoubtedly take a fraction of the time it would take to produce a 5 class map with 99 per cent of the nodes classified correctly.

To gain insight into the relationship between solution quality and classification accuracy, a simple experiment was devised. A parameter was added that defines the number of classes of the final output map, where the classes are defined as fixed-intervals between 0 and the highest optimal value across all nodes for a particular evacuation size limit. This facilitates a comparison between the class of the optimal solution for a given node and the class assigned by the heuristic. A node is considered either correctly or incorrectly classified by the heuristic. The overall classification accuracy can be expressed as a per cent defined as the total number of correctly classified nodes divided by the total number of nodes (120). Table 3 shows the values of *alpha* and *starts* necessary to produce a map at specified levels of classification accuracy while varying the number of classes. Producing a 5 class map with 99 per cent of the nodes classified correctly was deemed impractical from a computational

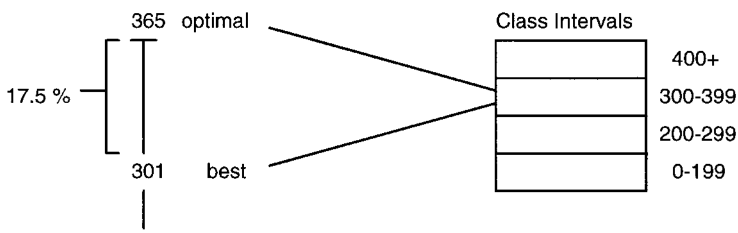

Figure 8. Poor heuristic results for a node may not result in a misclassification.

Table 3. Required (*alpha*, *starts*) pairs to produce a map at a specified heuristic classification accuracy for a specified number of classes.

	Node classification accuracy (per cent)			
No. of classes	90	95	97·5	99
2	(0·95, 1)	(0·95, 1)	(0·95, 1)	(0·95, 8)
3	(0·95, 1)	(0·95, 1)	(0·95, 8)	(0·95, 16)
4	(0·95, 8)	(0·95, 16)	(0·775, 64)	(0·775, 256)
5	(0·90, 32)	(0·775, 64)	(0·75, 512)	impractical

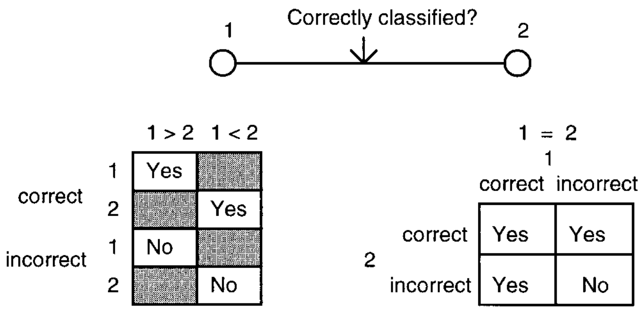

Figure 9. The relation between arc and node classification accuracy.

perspective, as producing a map with 97·5 of the nodes classified correctly required 512 starts of the heuristic at each node in the network.

One final point worth taking up before proceeding to the presentation of the method in an example case-study is arc classification accuracy. As described in §2, after the nodes of a particular network have been classified, the vulnerability level of an arc is defined to be the worst-case vulnerability level of its two end nodes. This implies that the classification accuracy of an arc depends on the classification accuracy of its two end nodes. Figure 9 shows the eight feasible cases that may occur. On the left is a table for the cases where the vulnerability level of node 1 is greater than that of node 2 and the converse. For example, the upper left corner shows that if node 1's vulnerability level is greater than node 2's and node 1 is correctly classified then, 'Yes, the arc will be correctly classified'. A more interesting table on the right side of figure 9 shows that when the vulnerability levels of node 1 and node 2 are equal (a highly likely case), then there is only one case where the arc will not be correctly classified. In short, the classification accuracy of the arcs in a evacuation vulnerability map will always be higher than the classification accuracy of its nodes. As the final map is a plot of the arc vulnerability levels, this is good. Unfortunately, it is impractical to empirically assess the arc classification accuracy of the heuristic because this requires that optimal solutions be known for a very large number of nodes in a network. However, knowledge of this factor allows one to stipulate that the classification accuracy of a particular map exceeds the value of the map's node classification accuracy (e.g., heuristic classification accuracy greater than 95 per cent).

5. Example case study: Santa Barbara, California

In the last few decades, the residents of Santa Barbara, California have endured toxic spills, firestorms, floods, and other hazards that have resulted in numerous evacuations. In addition to these fast-moving hazards, whose resulting evacuations could not have been delimited in advance, Santa Barbara is an ideal region to examine regarding evacuation vulnerability due to its wide variety of street patterns and residential configurations. This section uses Santa Barbara as a sample region to perform an example case study to highlight some of the issues that arise in a practical application of the method described in the prior sections.

5.1. *Preparation*

An initial hurdle in performing this study involved acquiring the necessary data. There are essentially two classes of geographic information required to perform a case-study, given the difficulty measure presented in § 2: streets and population. Data regarding population for the Santa Barbara area was acquired from 1990 Census Tiger files, and data on the area's roads was provided by Navigation Technologies (NavTech). Census Tiger street data would also suffice, but we found NavTech's data to be of a higher quality.

The data preparation for a study is minimal, as the model requires that all nodes have a representative population and all street segments have the number of lanes in each direction. The most involved step was transferring the population from the census data blocks to the nodes of the Navigation Technologies data. One approach to this process is depicted in figure 10, where Thiessen polygons are generated around the nodes of the street coverage and overlayed with the census Tiger blocks. The polygon 'fragments' are then each assigned to a node based on their population. A fragment's population is the fraction of the area within the block multiplied by the block's population. The shaded pieces in figure 10 would be assigned to the node in the upper left. Flowerdew and Green (1992) have researched this areal interpolation problem (zone-to-zone), and the reader is referred to this work for a complete review.

5.2. *Analysis*

Aside from selecting a measure of evacuation difficulty, the main parameter to the procedure is the size limit (s). Assuming that the measure of difficulty is the one described in § 2, and node count is the selected means for limiting size, a researcher must decide what node count limit to place on the process. In the cases of urban wildfires and toxic spills, the most critical area to clear is the immediate vicinity of the hazard. For the purposes of this example study, this was taken to be a size limit of 25 nodes. As node count is the size limit, 'vicinity' in this case refers to network

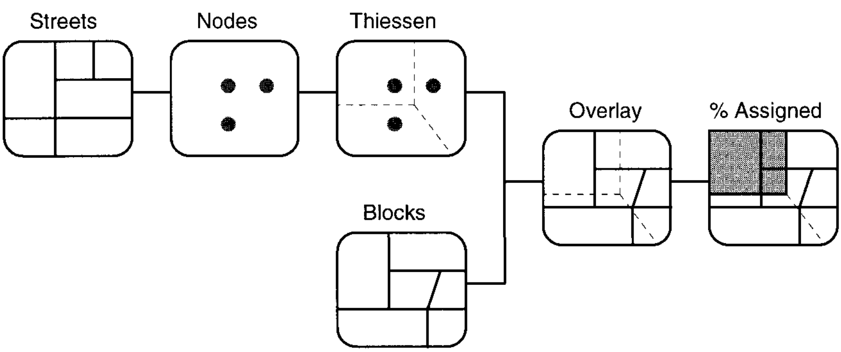

Figure 10. Thiessen polygon population interpolation process.

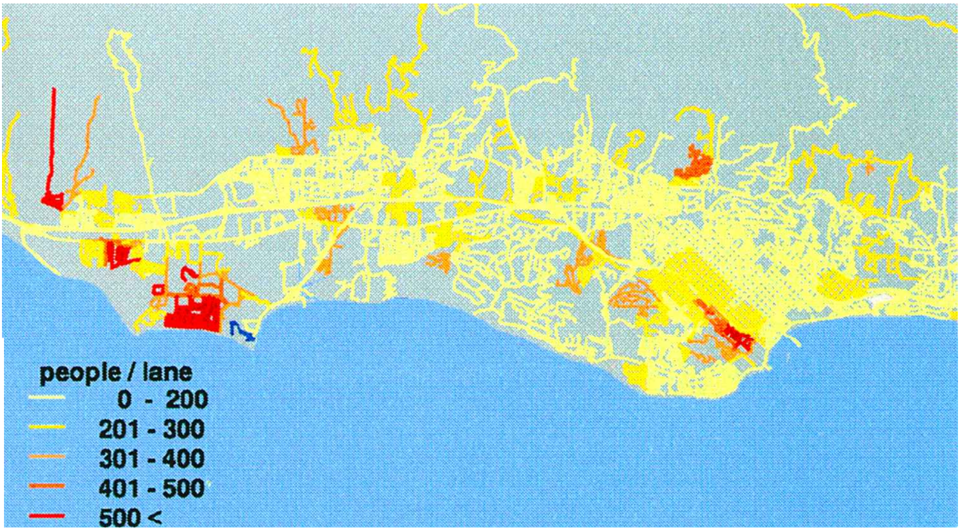

Figure 11. An evacuation vulnerability map for the Santa Barbara vicinity.

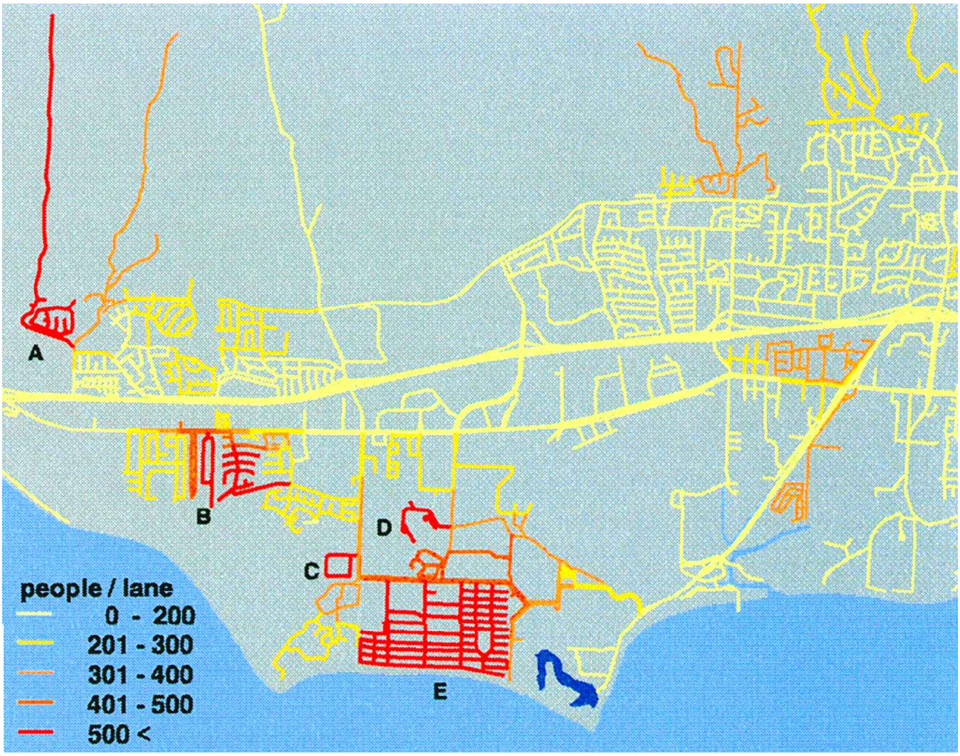

Figure 12. An evacuation vulnerability map of western Santa Barbara.

vicinity and not Euclidean distance. In other words, two nodes that are relatively far apart in Euclidean distance are considered 'close' if they are connected by a road because the potential for interaction between two evacuees starting from each of these nodes is relatively high.

Figure 11 shows the results of producing a complete map for the Santa Barbara vicinity. The thematic map unit is the number of people per lane in an road segment's worst-case evacuation (i.e., maximum difficulty value less than 25 nodes). Conceptually, the map is a discrete surface defined only along the network. Because nearby road segments are often in the same spatial evacuation vulnerability class, groups of segments organize themselves into perceivable vulnerability clusters. We call these clusters *evacuation sheds*, and they represent interesting areas for further inquiry. However, at this mapping scale the network is too dense to reveal why certain neighbourhoods are highlighted.

Figure 12 shows a larger scale view of an area just west of the Santa Barbara City limits with many evacuation 'hot spots'. Communities (A) through (D) all have more than 500 residents and only one exit lane. For this reason, there is greater potential for traffic congestion to impede an urgent evacuation of these neighbourhoods. Despite the relatively large number of exits in the larger community (E), the population density in this area is so high that the algorithm had no problem finding numerous potential evacuations where the number of residents per exit lane might be greater than 500.

Figure 13 shows a larger scale view of downtown Santa Barbara. A clear evacuation vulnerability corridor is visible along the primary artery (i.e., six lane freeway shown in gray) through this area. This is partly due to the numerous dead-end streets created by the construction of the freeway in addition to the relatively high residential density along this route. A prominent evacuation shed (A) on a relatively sharp corner of the freeway appears in red. As this neighbourhood is adjacent to the freeway, it has almost no connecting streets along its north-east side. Also, on its south-west side of this neighbourhood is a steep hillside (not shown) that results in even fewer connecting streets. Finally, its residential density is higher than other neighbourhoods in this area.

5.3. *Discussion*

As census data was used to assign population to the nodes on the network, these maps can be considered a timeslice of Santa Barbara's population at night. As in most urban areas, the population distribution during the day, night, and peak commuting hours varies considerably. In addition to population movement, these maps were constructed at one evacuation size limit (25 nodes). Table 4 shows a more comprehensive approach to a case-study, where three time periods (daytime, rush-hour, night-time) are combined with three size limits (25, 50, 100) to produce nine maps for exploring spatio-temporal evacuation vulnerability in this area. Parrot and Stutz (1991) have noted the importance of modelling daytime shifts in population in the context of emergency planning, and they provide one example approach for

Table 4. A matrix to produce nine evacuation vulnerability maps for a study area.

Evacuation size limit	Time of day (population)		
	day-time	night-time	rush hour
25	1	2	3
50	4	5	6
100	7	8	9

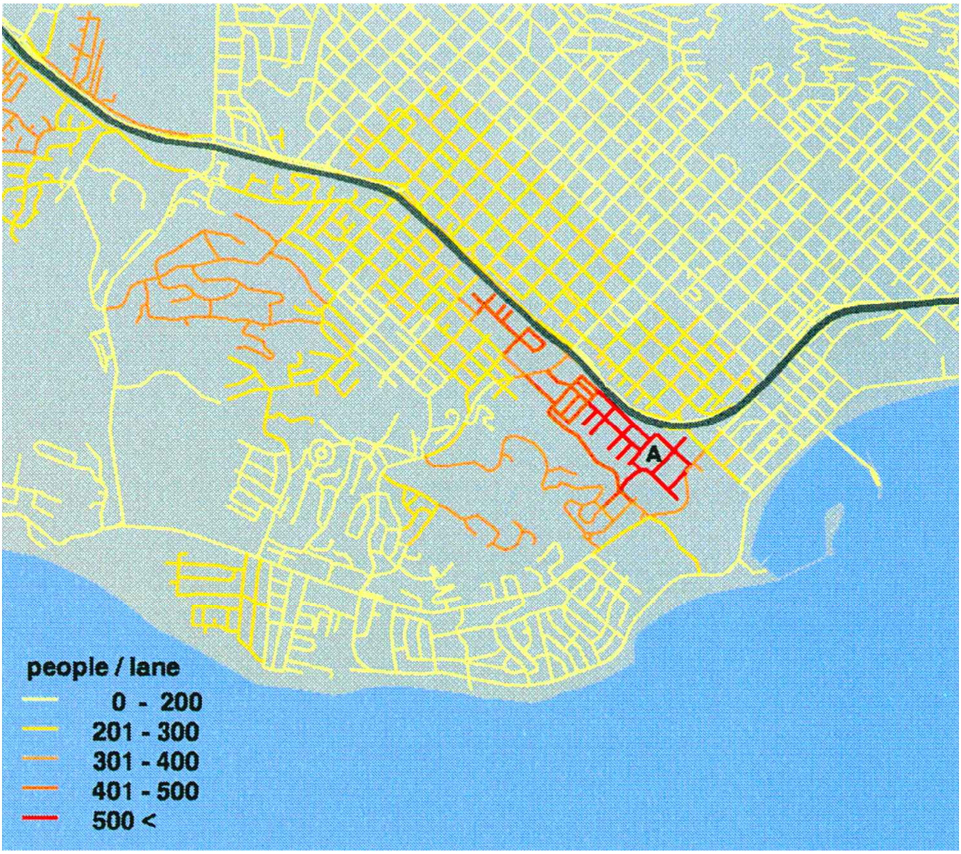

Figure 13. An evacuation vulnerability map of downtown Santa Barbara.

San Diego County. Glickman (1986) and Goodchild *et al.* (1993) have also addressed this problem from differing perspectives, but as Southworth (1991) notes, this is an area in need of further research.

6. Conclusion

The primary objective of this research was to propose one approach to the problem of performing regional evacuation analyses in areas subject to fast-moving hazards of uncertain spatial impact. When a region is subject to a hazard of this nature, it is impossible to delimit a credible emergency planning zone (EPZ) to apply any one of a host of contemporary evacuation simulation models. To overcome this problem, a new method was presented that allows a researcher to focus on the spatial variation in evacuation difficulty across a landscape. This facilitates a systematic geographical approach to studying community evacuation vulnerability.

Evacuation vulnerability modelling represents a proactive perspective for emergency planners and other parties that may be interested in disaster mitigation and preparedness. These maps can be viewed as a new vulnerability layer for hazards research. Risk can be viewed as a function of hazard and vulnerability (Alexander 1993), so if a fire hazard map represents the hazard component of risk, then an evacuation vulnerability map could be overlayed with this map to produce a risk

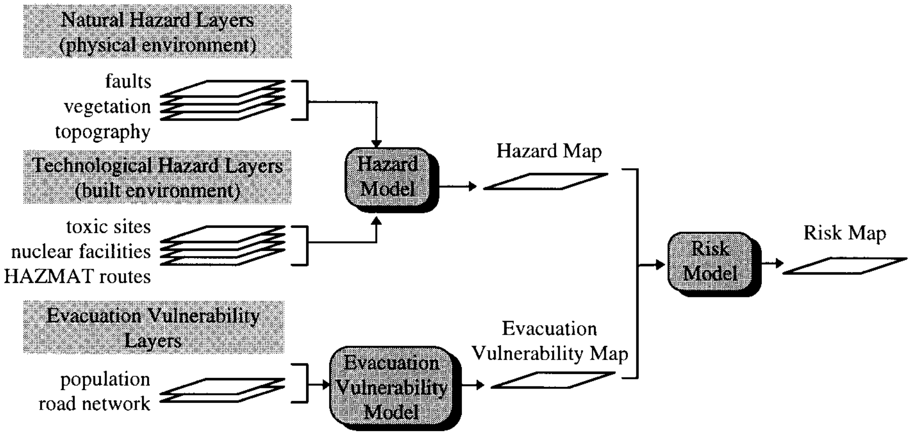

Figure 14. The potential role for evacuation vulnerability maps in risk mapping.

map. This opens the door to integrating evacuation vulnerability modelling with the numerous GIS hazard models that have been developed. Figure 14 shows example hazard layers and how they might be combined with an evacuation vulnerability layer to explore issues of risk.

Another interesting area of research that needs to be addressed in this context is developing new approaches to estimating the whereabouts of population in a city at a relatively fine-grained level (e.g., census block) for fixed points in time. This problem is extremely complex, as population fluctuations range from low-frequency seasonal migrations to the 'noise' of special events.

Also, there are also a host of interesting research questions and problems to address in developing new measures of evacuation difficulty and spatial evacuation vulnerability. First, this paper presented only one measure of evacuation difficulty, but there is a clear need to develop additional measures that take into consideration other factors that affect evacuation difficulty (e.g., number of vehicles, special populations) (Vogt and Sorensen 1992). These measures might be considered in the larger family of accessibility measures where they refer to the accessibility of a population subset out of a neighbourhood. Second, the modelling decision of how to limit evacuation size is an interesting area for further research. This paper presented five approaches that may each have application in different hazard or network contexts. An investigation into the strengths and weaknesses of these various approaches for different hazard and network contexts would be a valuable study.

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