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Including natural hazard risk analysis in an optimization model for evacuation planning

A spatial multi-objective memetic algorithm

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Abstract Decision-making in the public and private sector is often supported by geographic information systems (GIS); an implied acknowledgement of the importance of geographic information in decision support for an array of application domains. Spatial optimization methods, when integrated with a GIS, can provide facilities for providing optimal solutions to decision-making problems with explicit representation of geography. Multiple objectives are commonly present when decision tasks involve a collaboration of stakeholders. Linear programming and game programming techniques have been proposed to find exact solutions to multi-objective decision problems. However, applications in domains such as natural hazard mitigation must consider several factors that combine to form a decision problem that may be too complex for exact solution methods. This research extends work on multi-objective genetic algorithms in spatial optimization and introduces the integration of a memetic algorithm with a geographic information system for evacuation planning. An evacuation planning optimization model for Dellach, Carinthia, Austria is formulated to minimize evacuee shelter costs and risks, minimize the travel cost for evacuees, and to minimize the risk of evacuation routes. Risks in the model come from a previous multi-disciplinary risk analysis study in the federal state of Carinthia. Spatial analysis methods are incorporated to ensure a diverse set of spatial patterns in the population of decision alternatives generated by the memetic algorithm. Results of the model show the utility of the memetic algorithm to generate distinct and varying evacuation plans that can be further evaluated for emergency evacuation planning.

Keywords Evacuation · Emergency management · Spatial optimization · Risk analysis · geodesign · genetic algorithm

1 Introduction

Wildfires are a reoccurring event in Mediterranean type ecosystems around the world, and often have significant impacts on both the natural environment and

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the human population. Evacuating populations that are threatened by wildfire is a particularly difficult and time sensitive task for emergency management decision makers. When deciding on an evacuation plan, Office of Emergency Services (OES) managers must consider the dynamic complexities of wildfire progression and population distribution. Decisions must be made concerning what individuals to evacuate, when to evacuate these individuals, where to locate safe shelters, and transportation routes to shelters based on proximity. Facilities provided by a GIS can be utilized to alleviate some of the difficulty in providing reliable evacuation plans in complex events such as wildfires (Cova 1999, Dunn and Newton 1992, de Silva and Eglese 2000). A GIS may be used to compile a map of shelter locations and recommended evacuation routes as a reference for both evacuees and emergency managers. An optimal evacuation plan map is dependent on the situational context and is difficult to generate when considering the objectives of many stake-holders within the context of the hazard. Incorporating geographic results of a comprehensive hazard risk analysis into a model of evacuation routing and sheltering may lead to evacuation plans that are robust to varying hazard scenarios. Providing more detailed and up to date information to emergency management personnel can enhance their ability to make a decision on which evacuation routes and which shelter configuration to deploy.

County of San Diego, California emergency managers use GIS technology for generating evacuation maps for emergencies that involve more than one municipality. However, these maps are created based mostly on previously defined primary evacuation roads, such as highways and primary arterial roads, and no quantitative methods are used to ensure that capacities of the road network and shelters are not overwhelmed. Further, time constraints can effect whether a map is even generated at all. Cartographic products are created in response to evacuation orders for specific communities issued by the Incident Commander, typically a member of CalFire. The proposed wildfire evacuation model will provide a means of generating evacuation plans based on evacuation orders, which respect the operational constraints of transportation routes and evacuation points.The model will also extend the current emergency management practice by providing maps of the shortest path feasible routes, which in turn may inform the affected population.

A simplified process of decision making was presented by Simon (1977) to include four major steps:

1. intelligence,
2. design,
3. choice,
   and,
4. review.

These steps do not imply a linear decision making process, and may overlap or be iteratively visited(Malczewski 1999). The phase of *intelligence* involves a definition of the decision problem. In this study of evacuation planning, we are interested in answering the question: "What are the most efficient options for evacuation plans that minimize risk to the population?". Intelligence also involves designing and compiling a geographic information database of attributes related to potential or known decision making objectives.

There is complexity in representing all of the influential facets of an evacuation decision problem, even when considering only the decision objectives related

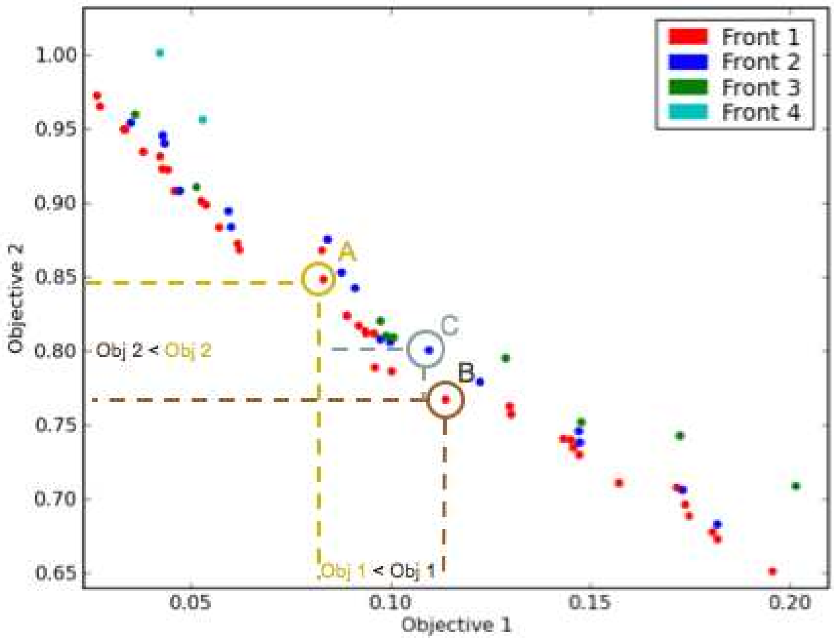

Fig. 1 An example solution set for a two-objective decision problem of minimization is shown with solutions ranked according to the Pareto-front in which they fall. *Front 1* contains all Pareto-efficient solutions. For example, solution A has a lower (more optimal) value for *Objective 1* than solution B, yet solution B has a lower (more optimal) value for *Objective 2* than solution A. Such a Pareto-efficient trade-off exists for all other solutions in *Front 1* for solution A. Solution C however is clearly dominated (in the Pareto sense) by solutions in *Front 1*, but is Pareto-efficient compared to all other solutions in *Front 2*.

to sheltering and routing. In effort to produce evacuation plans in reasonable computation times, we adopt a heuristic solution method based on multi-objective genetic algorithms. In the *design* phase of the decision process we are concerned with generating decision options. In multi-objective optimization we desire to find a set of mostly Pareto-efficient decision alternatives (Deb 2001). A solution is Pareto efficient if it performs higher in any one objective when compared to all other solutions found, or if it performs at least as well in all objectives when compared to all other solutions found (Coello 1999, Lotov et al 2005, Huang et al 2008). This concept of Pareto-efficient, or non-dominated, solutions is illustrated further in figure 1.

GIS allow databases of spatial attributes related to decision problems to be stored and analyzed. This research integrates a multi-objective algorithm for optimization with a GIS so that the algorithm may include explicitly spatial analytical functions. In doing so, we expect to improve computational performance and quality of generated solutions by leveraging geographic structure for major classes of topology representation in GIS databases:

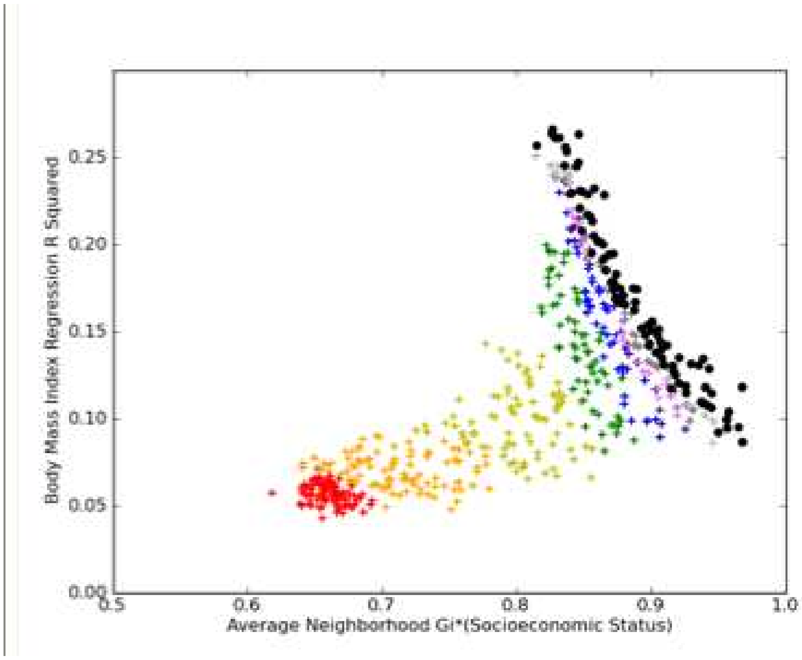

Fig. 2 An example of a two-objective decision problem where both objectives are to be maximized. Colors range in a spectral symbology from red (100) to purple (600) where each color represents the solution set at every 100 iterations. The final solution set at 800 iterations is in black, and at 700 iterations in gray. As the execution of the memetic algorithm proceeds the solution set converges and increases in diversity. Previous work (Fraley et al 2010) has achieved convergence in far fewer iterations when including problem-specific knowledge about the geographic structure of solutions.

- point,
- line or network,
  and,
- polygon or areal.

Initial studies into the use of geographic problem specific knowledge have shown promising results (Fraley et al 2010, Tong et al 2009); see figure 2 . In this study, we develop a concept of spatial diversity as a feedback mechanism in multi-objective search and optimization algorithms.

While this research focuses on the *design* phase of the decision process, the *choice* phase requires substantial focus in decision support methodologies and entails the evaluation and selection of decision alternatives. See Jankowski and Fraley (2009), Xiao et al (2007), Armstrong, Marc P, Bennett, David A, Wang, Shaowen, Xiao (2008), Bennett et al (2004) for initial work on the topic of choice among geographic alternatives generated by multi-objective algorithms. Finally a *review* phase would commence after the *design* and *choice* of alternatives and would examine the option for implementation and potentially revisiting the previous phases of the decision process.

This research adopts the framework of (Simon 1977) and uses a multi-objective memetic algorithm in the design phase. The algorithm will be tested on a problem of natural hazard evacuation routing in Dellach, Austria.

2 Evacuation planning in GIScience

This research considers the decision-making tasks of allocating wildfire evacuation shelters, and routing evacuees to appropriate shelters. Objectives in this problem are related to routing, sheltering, or both.

2.1 Sheltering

A variety of sheltering objectives have been considered in the literature. The location set covering problem (LSCP) minimizes the number facilities required to provide a certain quality of service, which is a threshold on distance from a facility (Church and ReVelle 1974). Evacuation modeling may benefit from an objective derived from the LSCP that aims to locate the minimal number of evacuation shelters to provide sufficient shelter for the evacuated population.

It is logical that locating shelters close to a hazardous area is not attractive (Kar and Hodgson 2008). When allocating shelters during planning or response to a hazard, it is useful to include objectives related to the varying risk of a future disaster occurring within a study area (Doerner et al 2008) or the current hazard extent. One may wish to place shelters close to demographics such as elderly or low-income citizens that are less mobile and in greater need of shelter, or in areas of higher population density (Kar and Hodgson 2008). Placing shelters close to highways can increase their utility and usage (Kar and Hodgson 2008, Cova and Johnson 2002, Cova and Church 1997, Chen et al 2006, Dow and Cutter 2002), and locating them near health facilities can improve the quality of care available for evacuees (Kar and Hodgson 2008). Costs related to operating or constructing a facility may be included in an evacuation model, and have been utilized by Doerner et al (2008) in an optimization model for locating public facilities with respect to potential tsunami disasters.

2.2 Routing

Routing objectives in the literature tend to include a functional relationship to the location of shelters. The maximal covering location problem (MCLP) is a class of spatial optimization problems which maximize the population of humans within a specified service distance from a fixed number of facilities (Church and ReVelle 1974). An objective rooted in the MCLP is used by Huang et al (2004) to ensure a maximum amount of evacuees will be able to reach a shelter within an acceptable travel distance or time. Evacuees may wish to be far away from a hazard, but it would be prudent for decision-makers to recommend routes and shelters that do not require long travel distances (Dow and Cutter 2002). Minimizing the sum of travel time or distance for the evacuated population is a common objective in evacuation modeling (Doerner et al 2008, Cova and Johnson 2002, Kongsomsaksakul et al 2005, Lu et al 2005, Cova and Johnson 2003), and is called a mini-sum criterion (Doerner et al 2008). Cova and Johnson (2003) present a network based model to route evacuees over the road network such that merging and intersection cross traffic is minimized. In this road lane based model, a longer distance may represent a favorable mini-sum of time with a trade-off in the mini-sum of distance criterion.

Some hazard mitigation models in the literature are formulated with routing objectives that are independent of shelter locations. Huang et al (2004) address a problem of routing hazardous materials and include consideration of route proximity to hospitals and health care. Chiu (2004) minimizes the exposure to a hazard of routed individuals during transit.

Constraints for evacuation optimization models are primarily the capacities of roads and shelters (Cova and Johnson 2003, Kongsomsaksakul et al 2005, Lu et al 2005). An analyst can also specify constraints for the number of shelters to locate, or the quality of service threshold in a MCLP or LSCP.

Once the evacuation sheltering and routing model is formulated mathematically, it can be solved using a heuristic algorithm or MCDM decision rule. Kar and Hodgson (2008) use a weighted linear sum of evacuation sheltering model objectives, which is solved directly in a GIS. However, the complexity of optimization problems that present themselves in real world scenarios typically prevent them from being solved through integer programming, or exact solution approaches (Doerner et al 2008). Simplex heuristics can be used to solve MCLP and LSCP problems, and are used by Cova and Johnson (2003) to solve an evacuation routing problem. Doerner et al (2008) note significant computational costs when solving a facility location model with a simplex solver in comparison to a genetic algorithm solver. Chen et al (2006) utilize agent-based models of evacuee behavior in response to evacuation orders to simulate evacuation processes to inform disaster planning. In other cases, problem specific heuristic software have been used for evacuation model simulation and solution (Chiu 2004, Lu et al 2005, Cova and Johnson 2002). Genetic algorithms are applied in a small number of cases in the literature on evacuation optimization models (Huang et al 2004, Kongsomsaksakul et al 2005). However, Doerner et al (2008) recently employed a MOGA, the NSGA-II, for the solution of a facility location problem of hazard mitigation.

3 Spatial multi-objective optimization

Spatial optimization problems contain a geographic structure by definition. There are several ways that genetic algorithms can be modified to integrate geographic knowledge during the search for optimal trade-off solutions (Xiao 2008, Tong et al 2009), however little research has focused on this topic. To illustrate how geographic knowledge will be integrated with a MOGA in the proposed research, the following paragraph describes the main features of how genetic algorithms search for optimal solutions to a decision problem.

Genetic algorithms contain a population, a set, of alternative solutions during their execution. Each solution alternative in the population is represented in the same manner. The solution representation is called a chromosome, and is commonly simply a list of values, each corresponding to some attribute of the solution. The primary reproductive operator of a genetic algorithm is the crossover operation, which takes pairs of parent solutions from the population and swaps a portion (for example, half) of the chromosome contents between them to create a pair of child solutions (Deb 2001). By crossing genes between high performing solutions we hope that high performing children solutions will result, and we aim for a diverse range of options among the population.

3.1 Memetic algorithms

Multiple-objective genetic algorithms (MOGA) are capable of generating a population of solutions where each solution represents a trade-off in optimality between the multiple objectives. In the nomenclature of MOGA, the algorithms decisions towards optimality are driven by natural selection, which prunes solutions towards specific objectives. This can be thought of as a global search heuristic that applies to all problems. Recent research in computer science has explored the design of memetic algorithms, which add cultural learning components into genetic algorithms (GAs) to exploit problem-specific knowledge (Knowles and Corne 2005). The notion of culture, or local social rules and norms, can adapt global search heuristics to produce specific solutions that are pertinent for the problem at hand. It is suggested that incorporating problem-specific knowledge can improve the performance of a MOGA (Corne and Knowles 2004). Specifically, geographic problems can be characterized by spatial patterns and topology, which are rarely included in MOGAs, but could be leveraged as part of a memetic algorithm for generating efficient solutions that incorporate spatial characteristics. Yet, little research has been presented which explicitly includes geographic constructs in genetic algorithms. Memetic algorithms are an extension of GAs. In a memetic algorithm, after the genetic operators are applied to the population, each solution in the population undergoes a refinement step that seeks to improve objective performance.

Spatial optimization methods belong to a class of techniques that aim at generating solutions representing a location or geographic arrangement of locations that perform well on the problem objectives. Upon formulating an optimization problem an analyst must decide how to generate a solution or even multiple alternative solutions to the problem. It is proven by No Free Lunch (NFL) theorems that all search and optimization algorithms are equal in average performance over all problems (Corne and Knowles 2004, Wolpert and Macready 1997). What follows from the NFL theorems is the supposition that incorporating problem-specific knowledge to guide the search for optimal solutions can make one algorithm perform better than another (Wolpert and Macready 1997, Corne and Knowles 2004). MOGA heuristics may require a large number of computations because many solutions are evaluated at each generation. The geographic information science literature has devoted little attention to the design of MOGAs that incorporate problem specific knowledge to improve convergence towards a Pareto set, and also reduce computation time. Xiao (2008) presents a framework to exploit spatial structure in GAs, and strives to avoid approaches that are too specific to individual problems. Tong et al (2009) introduce in their single objective genetic algorithm a crossover operation that is specific to facility location problems and incorporates the geographic arrangement of facilities to promote dispersion. In this research we introduce a memetic algorithm that leverages geographic knowledge of the diversity in the population of individuals during algorithm execution.

3.2 Diversity

A diverse solution set will facilitate more efficient inquiry of options for implementation, and cover a broader range of possibilities that can even satisfy stakeholder preferences that were not explicitly identified in the original decision problem (Xiao 2008). A large body of research exists on spatial autocorrelation statistics, which describe the global or local geographic patterns of points and polygons (geographic regions). These statistics describe the homogeneity and heterogeneity of a geographic pattern. For our purposes, the mean and standard deviation of these statistics across the entire population of decision alternatives will be used as a quality indicator of geographic diversity.

This research introduces initial results from the development of a common framework for evaluation and application of geographic operators in genetic algorithms. The evaluation framework and operators will be divided into the categories of point, line, polygon, network, and multi-structured representations.

These categories are based on the geographic structure, and thus the chromosome, of possible spatial optimization problems. Within each category, genetic operators can be designed to leverage specific geographic relations that are common to spatial optimization problems. Point representations can have locations that range from a pattern more dispersed than expected under complete spatial randomness (CSR) to a pattern that is more clustered than expected under CSR. When locations are evenly distributed throughout space, the pattern is that of CSR. For some problems, we may desire a certain level of spatial clustering, dispersion, or randomness in our solutions (Tong et al 2009). Also, it is possible to desire a range of spatial patterns where some solutions are clustered, some dispersed, and some random.

There are strong parallels between point and area representations if we consider the distribution of values across a set of polygons. For such a case, the clustering or dispersion of a polygon attribute value can be evaluated as if we are speaking of the centroid points of area polygons. However, we may also need to consider the distribution of area among polygons. If polygons have a static area size between all solutions, but their values can differ, it is important to consider the homogeneity (clustering) with respect to area coverage as well.

When the chromosome represents a network its structure is described by the degree of connectivity among locations, the network distance among locations, or the flow capacity among locations. Again, different optimization problems seek specific desired outcomes with respect to how connected or disconnected the network is, the average distance or nearest neighbor properties of locations in the network, and the distribution of flow capacities across the network.

Multi-structured representations have more than one type of chromosome representation in the problem. As multi-structured problems are simply some combination of point, area, or network spatial representations, the types of spatial patterns that are desired are composites of the aforementioned patterns.

Diversity in the solutions generated by a multi-objective algorithm can be evaluated using global measures of spatial autocorrelation for point and area representations, and global metrics from graph theory for network representations. Measures of spatial autocorrelation can describe clustering or dispersion of features and this is often done on the basis of some attribute value for area representations. Ripleys K, a measure of clustering or dispersion of point patterns, can describe the diversity of patterns in the solution set (Levine 2010). Similarly, Morans I is a statistic that indicates clustering or dispersion of point or area data with consideration of an attribute value. Because the global Morans I measure does not consider whether locations have clusters of low values or clusters of high values, the Getis-Ord G statistic can be used when it is a requirement to know the direction of magnitude of values in addition to their degree of clustering (Levine 2010). The G statistic is useful in evaluating solution sets when a decision-analyst desires hot or cold spots in the solution, or clusters of high or low values respectively.

Network diversity can be evaluated using well-developed metrics in graph theory. A network is represented as a graph by considering intersections as point locations, or nodes, that are connected by line paths, or edges. A measure of connectivity of nodes is the degree of a node, which is simply the number of edges it has to other nodes. The average degree of nodes in the networks graph is the overall connectivity of the network. The distance between two node locations in the network is the shortest path of edges between the two nodes. Thus, the average shortest path distance is a metric of closeness centrality of the network. Flow problems (for example problems involving traffic) can be evaluated based on the maximum or minimum cost flow that a network can support, or the average flow. Flow capacities are an attribute of edges in the graph. A minimum spanning tree is the set of edges in a graph that connects all nodes with the minimum flow when its edges flow capacities are summed. A maximum spanning tree is likewise the sub-graph such that the sum of flow capacities are the maximum capacity. Minimum and maximum cost spanning trees can be used to construct average flow capacities of minimum or maximum cost paths in the solution set.

4 Evacuation planning optimization

A database compiled with geographic coverage of the federal state of Carinthia, Austria was used as the basis of this research. Results from a multi-disciplinary natural hazards risk analysis were included in the database (Ward, S., Leitner, M., Paulus 2009). Geographic zones of high and medium risk to flooding, torrential currents, and landslides are outlined in figure 4. From viewing the map in figure 4 we see that roads (pink) follow the Drau river which runs west to east through the city of Dellach, centered in the map. Normally, these federal roads along the river are the primary transportation veins. Yet, they are in the highest risk zones for flooding (blue). The local roads must be used if we are to minimize the risk of transportation, however mountainous terrain, the risk of torrential currents coming from the mountains, and landslide hazards make it difficult to establish quick and direct evacuation routes.

In preparation of optimization model formulation, a network topology was constructed using the road network and building locations. Demographics and risk assessments associated with the buildings and residences become attributes of the leaf nodes of the network, and a (distance based) network travel cost was assigned to intersection nodes in the network graph (figure 6).

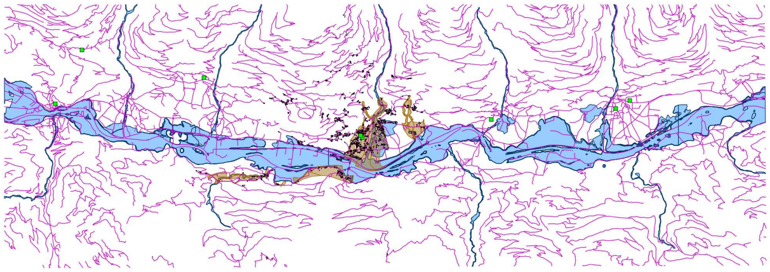

Fig. 3 The study are of this research encompasses Dellach, Austria. Federal and local roads are depicted in pink, buildings in black, and schools (potential evacuation shelters) in green. The blue areas are at high risk of flooding and torrential currents, and the brown areas are at high risk of landslide and rockfall events.

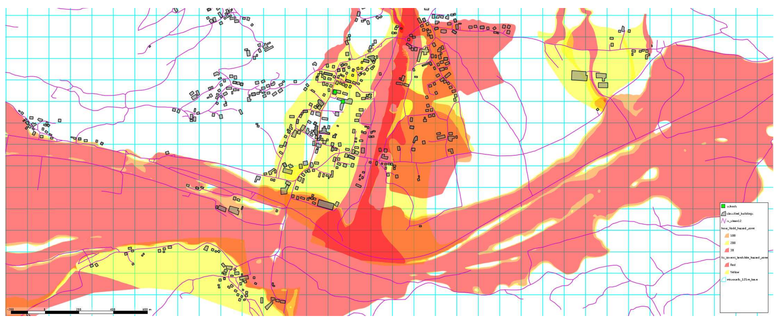

Fig. 4 Dellach, Austria lies in the center of the study area. This map is zoomed to Dellach and displays buildings (black), roads (pink), and the census enumeration grid (cyan). High risk areas are in red and moderate risk in yellow. Areas in orange are at significant risk to multiple hazards (both flooding and landslide), and areas in dark red are at high risk to both hazards. Note that some schools, which are potential shelter locations, are located within significant risk zones.

A mathematical optimization model was formulated to minimize the operation cost and risk for sheltering facilities, minimize the travel distance to shelters, and minimize the risk of routes to shelters. A linear programming model is formulated with the objectives to:

$$Minimize(\sum_{i=0}^{n}\sum_{j=0}^{n_s} s_{ij} * r_j) \tag{1}$$

where n is the size of the algorithm population, i is an individual in the population, n_s is the number of shelters in the study area, s_{ij} is a binary integer decision variable equal to 1 if shelter j is included in solution i or 0 otherwise, and r_j is the risk of natural hazard impact associated with the location of shelter j, to:

$$Minimize(\sum_{i=0}^{n}\sum_{j=0}^{n_s}\sum_{k=0}^{n_b} p_{ijk} * c_{ijk}) \tag{2}$$

where n_b is the number of buildings in the study area, k is a single building, p_{ijk} is a binary integer decision variable equal to 1 if there exists a path between building

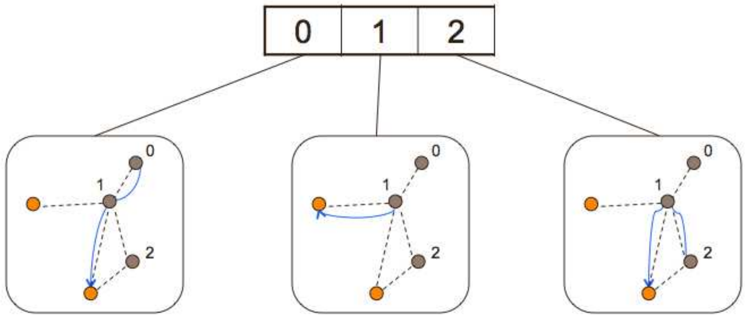

Fig. 5 A simplified version of the memetic algorithm chromosome where each gene is an index to a particular source (gray nodes) on the transportation network graph and contains a path between that source and one of the possible shelters (orange nodes).

k and shelter j in solution i and 0 otherwise, c_{ijk} is the cost of traveling along the path generated by the algorithm between k and j for solution i, and to:

$$Minimize(\sum_{i=0}^{n}\sum_{j=0}^{n_s}\sum_{k=0}^{n_b} p_{ijk} * r_{ijk}) \tag{3}$$

where r_{ijk} is the risk to hazard associated with traveling along the path between building k and shelter j in solution i.

The evacuation planning optimization model consists of binary decision variables for shelters (s_{ij}) and paths (p_{ijk}), but it should be noted that we are not selecting from a predetermined set of paths and certainly not from all possible paths between each source and destination. A heuristic path initialization strategy is utilized in the memetic algorithm described below in order to detail with the combinatorial nature of the evacuation planning optmization model. Further, s_{ij} is a function of whether shelter s_j appears in any of the paths, p_k for solution i.

5 Spatial multi-objective algorithm

We incorporate the notion of spatial diversity in addition to objective diversity to allow the probabilities of our algorithm to adapt during algorithm execution (Tarokh 2008). Further, integration with a GIS environment gives the ability to leverage topology in our algorithm operations. These two features are initial efforts towards a spatial multi-objective memetic algorithm (spatial MO-MA), which is based on the (Deb et al 2002) NSGA-II MOGA but includes problem-specific knowledge.

Chromosomes for decision problem solutions in the algorithm are represented as arrays with the source location (building or residence) as the index to the assigned route for the source to the assigned destination shelter (figure 5). Routes are initialized using a random walk along the network graph starting at the source location and continuing until a destination shelter is reached.

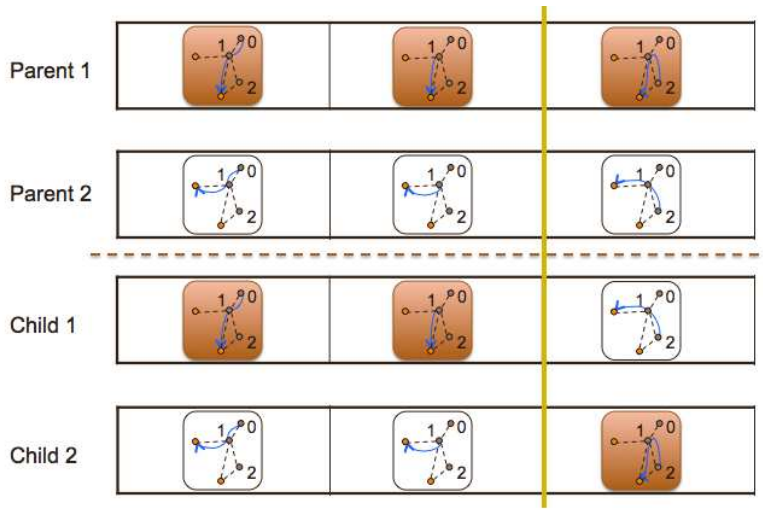

Fig. 6 A two-point crossover is implemented in the memetic algorithm. For simplicity, this figure demonstrates a single point crossover. A random splitting location (yellow line) is chosen by the genetic operator, and the genes from two parent chromosomes selected from the population are swapped about the splitting location to produce two new children.

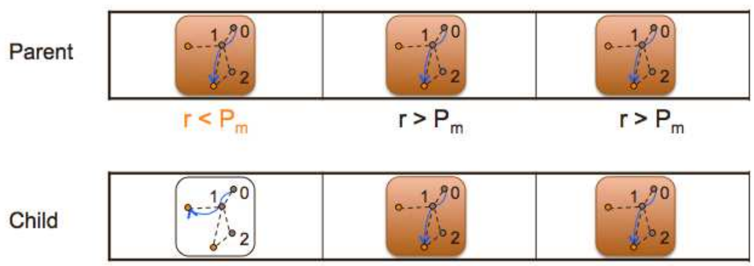

Fig. 7 Mutation in the memetic algorithm is achieved by creating a new transportation path from the starting location of a gene. While the crossover probability is applied to pairs of chromosomes, the mutation probability is applied at the scale of genes. For each gene of an individual solution in the algorithm population, if a randomly generated number, r, from a uniform distribution between 0 and 1 is less than the probability of mutation, P_m, mutation is applied.

Crossover is implemented using a two-point crossover operator (Deb 2001). Figure 5 shows a simplified version of the procedure with a chromosome of three buildings and a single-point crossover. In execution of the spatial MO-MA, a longer chromosome is used to represent all buildings, and two crossover points are utilized.

Mutation is applied on the level of genes within the chromosome. That is, each source location's route has a probability of mutation. Application of the mutation operator generates a new route for the source location to follow using the aforementioned random walk initialization strategy.

6 Results

This research demonstrates the utility of an evacuation planning optimization model and a multi-objective algorithm for generating evacuation plan designs. Trade-offs in sheltering costs, travel distance, and risk of the routes are revealed by generating a Pareto-efficient solution set. Incorporating risk analysis from expert assessment of natural hazard risk potential is a novel approach that is expected to allow more robust decision options to be considered in the *choice* phase of the decision process. Integrating the solution method with a GIS to explicitly represent geography in the memetic algorithm provides the ability to perform geographic processing in the algorithm operators and affords the monitoring of spatial diversity during algorithm execution. The algorithm discussed in the previous section was applied to the evacuation routing problem for Dellach, Austria. A population size of ten individual solutions was chosen, and the algorithm was run for 100 generations.

A scatterplot of results is displayed in Figure 6 illustrates the relationship between the travel cost objective and the travel risk objective for the solutions obtained by the algorithm. Results indicate that a larger population than 10 solutions may be required to more accurately represent the trad-off curve between travel time and travel risk. Yet, the computer random access memory required to represent the solutions prohibits much larger solution sets. Continuing work will investigate a more efficient data structure to store the evacuation paths. Furthermore, the random walk approach to initializing paths creates many turns and diversions in the paths. While this helps simulate a person's avoidance of hazardous areas, the paths are very complex and indirect, which requires a much larger amount of random access memory to store the path during algorithm execution. Alternative initialization strategies will be investigated in continuation of the research presented here, and should also allow a much larger population of solutions. The obtained solutions are however spread well across the range of cost and risk values, so the trade-offs between the cost and risk objectives are diverse as desired.

An optimal solution with high travel distance, but low risk to the hazard of flooding and torrential currents, is show in Figure 6. The most frequently traveled roads (green intersections) are in the northern reaches of the study area and there is little traffic in the hazardous area. All shelters are used in this solution, and the school within the center of Dellach, Austria is utilized heavily. An optimal solution with low travel distance, yet higher risk is displayed in Figure 6. In contrast to the lower risk solution, there is a large amount of traffic within the zone of flooding risk to reach shelters, particularly in the vicinity of the western-most shelter. There is however less traffic in general across the study area in the high risk solution example, specifically in the southern and eastern stretches (Figure 6).

7 Conclusion

Moving forward, constraints on shelter and road capacity will be included in the evacuation optimization model. Generated evacuation plans will also be evaluated using visual multi-criteria decision analysis techniques as in Jankowski and Fraley (2009). An alternative optimization model can be formulated to evaluate Pareto-

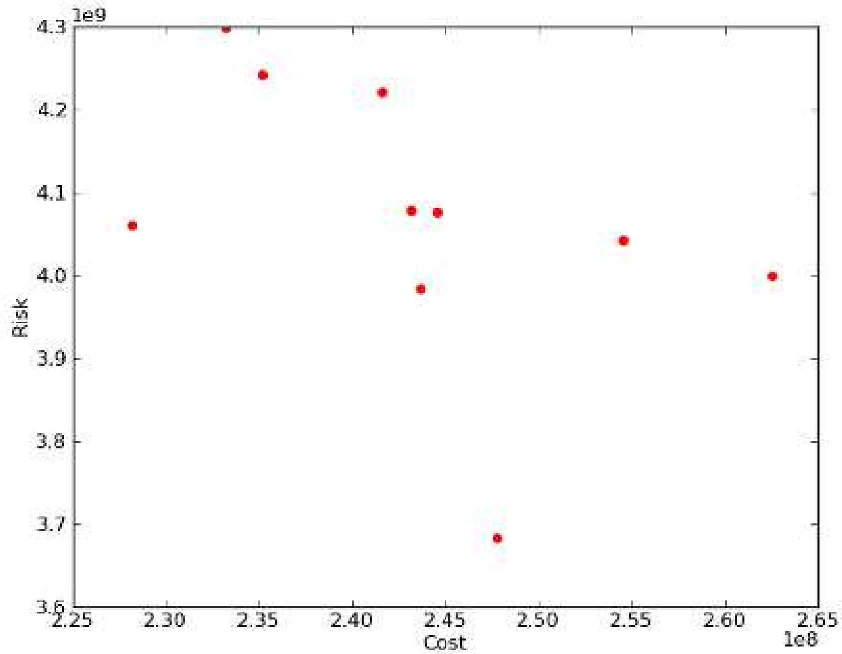

Fig. 8 Solutions obtained by applying the geographic multi-objective memetic algorithm to the Dellach evacuation optimization problem. Trade-offs in the travel distance in meters (Cost) and travel risk (Risk) objectives are evident when comparing solution points to each other.

efficient trade-offs between optimality for different types of hazards. That is, a plan that considers only the hazards of flooding may not perform well in a wildfire scenario, yet there may be compromise solutions that perform well under multiple hazard scenarios. Initial results are being computed for the Dellach, Austria study area, but other case studies in the state of Carinthia will be processed using the same model and algorithm. The work will then be extended to a scenario in southern California using HAZUS as a tool for risk analysis data.

Further work will explore the theory of memetic algorithms in Computer Science will in the context of GIScience to determine algorithm design considerations for spatial multi-objective optimization problems. This will require a sensitivity analysis and quantitative comparison of techniques for including geographic constructs in algorithm design. Possible techniques include parameter adaptation, operator spatialization, and local improvement operators. In many cases, the use of computational grid or cloud computing could be valuable to efficiently solve large geographic optimization problems.

To ensure the utility of the modeling approach, a user-centered design (UCD) approach to usability engineering will be used to integrate the model into a spatial decision support system for hazard planning and mitigation. Potential users will influence the spatial decision support system design. Inclusion of domain experts,

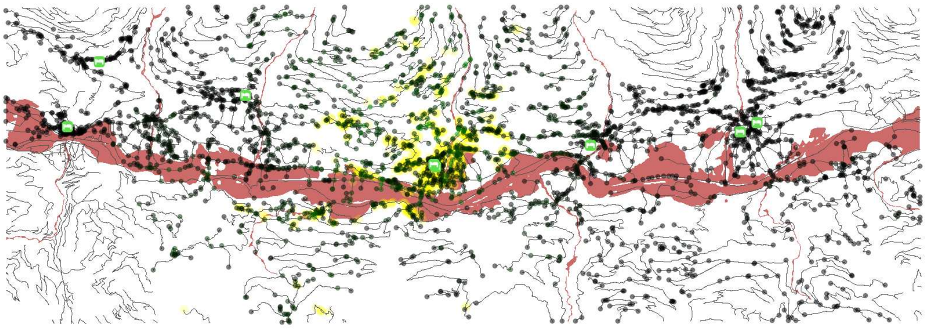

Fig. 9 A map of a high cost, low risk solution. Road segments that are most frequently traveled are show with green intersections, and the least frequently traveled road intersections are in black. The red area represents the geographic areas of high risk to flooding and torrential current. Yellow areas are the locations of evacuated populations. Green squares show the shelter locations.

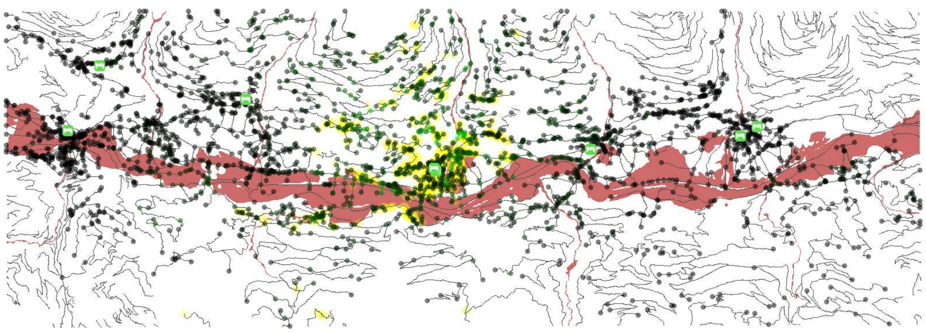

Fig. 10 A map of a high risk, low cost solution. Road segments that are most frequently traveled are in green, and the least frequently traveled road segments are in black. The red area represents the geographic areas of high risk to flooding and torrential current. Yellow areas are the locations of evacuated populations. Green squares show the shelter locations.

an initial needs and evacuation planning task assessment survey, and iterative usability study will determine the SDSS functionality and interface design.

This research has illuminated the ability of a geographic multi-objective memetic algorithm to generate trade-off alternatives for emergency evacuation planning. Results of the study are critical for consideration during the design of a computational model for evacuation simulation and planning. Through ongoing collaboration between the Carinthia University of Applied Sciences and San Diego State University, the computer model will be developed further into a decision support system that will be evaluated in both Carinthia, Austria and southern California, United States.

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