

A multicriteria spatial decision support system for solving emergency service station location problems

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Earthquakes occurring in urban areas constitute an important concern for emergency management and rescue services. Emergency service location problems may be formulated in discrete space or by restricting the potential location(s) to a specified finite set of points in continuous space. We propose a Multicriteria Spatial Decision Support System to identify shelters and emergency service locations in urban evacuation planning. The proposed system has emerged as an integration of the geographical information systems (GIS) and the multicriteria Decision-Making method of Preference Ranking Organization Method for Enrichment Evaluation IV (PROMETHEE IV). This system incorporates multiple and often conflicting criteria and decision-makers' preferences into a spatial decision model. We consider three standard structural attributes (i.e., durability density, population density, and oldness density) in the form of spatial maps to determine the zones most vulnerable to an earthquake. The information on these spatial maps is then entered into the ArcGIS software to define the relevant scores for each point with regards to the aforementioned attributes. These scores will be used to compute the preference functions in PROMETHEE IV, whose net flow outranking for each alternative will be inputted in ArcGIS to determine the zones that are most vulnerable to an earthquake. The final scores obtained are integrated into a mathematical programming model designed to find the most suitable locations for the construction of emergency service stations. We demonstrate the applicability of the proposed method and the efficacy of the procedures and algorithms in an earthquake emergency service station planning case study in the city of Tehran.

Keywords: PROMETHEE; geographical information systems; Multicriteria Spatial Decision Support System; earthquake; location planning; emergency service station

1. Introduction

Facility location planning and site selection decision problems involve a set of geographically defined alternatives from which a choice is to be made on the basis of multiple and often conflicting evaluation criteria (Kolat *et al.* 2006). The alternatives are defined geographically and the results of the analysis depend on their spatial arrangement. The problem is typically evaluated by a number of decision-makers (DMs) with unique

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preferences with respect to the relative importance of the decision criteria. Spatial Multicriteria Decision-Making (MCDM) is vastly different from conventional multicriteria analysis due to the inclusion of an explicit geographic component. Consequently, many facility location planning and site selection problems have been formulated and solved with geographical information systems (GIS)-based MCDM methods and procedures (Malczewski 1999, Chakhar and Martel 2003). Malczewski (2006) provides an excellent review of the combined GIS-MCDM methods in the literature and classifies these models according to the extent and direction of the GIS and MCDM integration, and the type of application domain and decision problem.

Multicriteria Spatial Decision Support Systems (MC-SDSS) have emerged as an integration of GIS and MCDM methods for integrating conflicting criteria and DMs' preferences into spatial decision models (Demesouka *et al.* 2013). GIS are computer systems that are capable of assembling, storing, manipulating, analyzing, and displaying geographically referenced information (Chandler and Westbrook 2002, Guo 2009). Several MCDM techniques have been used to solve facility location planning problems including ELimination Et Choix Traduisant la REalité (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Analytic Hierarchy Process (AHP), and the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), among others (Gilliams *et al.* 2005, Zhong-Wu *et al.* 2006, Reyahi-Khoram *et al.* 2007; Behzadian *et al.* 2010). A number of studies also integrated MCDM and GIS into comprehensive frameworks (Marinoni 2004, Kallali *et al.* 2007, Anane *et al.* 2008, Al-Adamat *et al.* 2010). MC-SDSS have been utilized within a large number of disciplines such as location and site planning, town and rural planning, and distribution of limited resources, among others (Malczewski and Jackson 2000, Sumathi *et al.* 2008). Although most traditional facility location models assume a discrete number of alternatives, real-life location decision problems often involve a continuous alternative space with an infinite set of options. PROMETHEE IV can be used to solve continuous MCDM problems.

The main purpose of this study is to propose a conceptual and methodological framework for combining MCDM and GIS into a single and comprehensive system that takes into account the entire emergency service station location planning process. In order to develop the MC-SDSS proposed in this article, we must integrate GIS and PROMETHEE IV into a single and comprehensive SDSS that incorporates multiple conflicting criteria and DMs' preferences. In this context, the algorithm of PROMETHEE IV is incorporated into the ArcGIS environment and a SDSS is utilized to develop emergency service station suitability maps. This MC-SDSS allows us to take into account the entire earthquake emergency service station location planning process and identify shelters and emergency service locations in urban evacuation planning.

We consider three standard structural criteria (i.e., durability density, population density, and oldness density) in the proposed model in the form of spatial maps to determine the zones most vulnerable to an earthquake. The information on these spatial maps is then entered into the ArcGIS software to define the relevant scores for each point with regard to these three criteria. The PROMETHEE IV is then used in a MATLAB model to determine the zones most vulnerable to an earthquake. The construction cost for different types of service stations in each zone is used in combination with the information on land availability in a mathematical model to find the most suitable locations for the construction of emergency service stations.

The remainder of this article is organized as follows. In [Section 2](#), we present the literature review on GIS and MCDM. In [Section 3](#), we present PROMETHEE concepts and extensions. In [Section 4](#), we describe the MC-SDSS introduced in this article. In [Section 5](#), we demonstrate the applicability of the proposed method and exhibit the efficacy of the procedures and algorithms in a real-life case study for locating earthquake emergency service station locations in the city of Tehran. In [Section 6](#), we discuss our conclusions and future research directions.

2. Literature review

The uncertainties inherent in real-life location planning problems make the use of deterministic models unrealistic from a practical standpoint. The limitation of deterministic models has been evidenced by a wide range of methods such as stochastic programming, fuzzy sets, and MCDM. [Li et al. \(2011\)](#) used stochastic programming and proposed a scenario-based model for optimizing hurricane shelter locations among potential alternatives. They considered the influence of changing the selection of shelter locations on driver route-choice behavior and the resulting traffic congestion. Stochastic programming is often used to solve problems characterized by uncertainty. There has been substantial progress developing and solving two-stage stochastic facility location models over the past 20 years ([Daskin et al. 1997](#), [Santoso et al. 2005](#), [Snyder and Daskin 2006](#)).

Fuzzy sets and logic have also been used in location planning problems. [Chou et al. \(2008\)](#) proposed a fuzzy MCDM model for international tourist hotel location selection. They used fuzzy set theory, linguistic values, hierarchical structure analysis, and fuzzy AHP to consolidate DMs' assessments about criteria weightings. They conducted an empirical study for identifying the international tourist hotel location selection in Taiwan to demonstrate the computational effectiveness of their method. [Tabari et al. \(2008\)](#) considered the tangible and intangible factors in the location selection problem and proposed a hybrid MCDM method to select the optimal location that satisfied the DM. With the aid of fuzzy AHP, their approach considered objective, critical, and subjective factors in location analysis. The last two factors, critical and subjective, were defined by the DMs in order to conform better with real-life problems. [Achillas et al. \(2010\)](#) used MCDM and ELECTRE III for location decisions of waste electrical and electronic equipment facilities. They developed a methodology aimed towards the optimal location of units of treatment and recycling, taking into consideration economical and social criteria, in an effort to combine local acceptance and financial viability. The methodology's applicability was demonstrated with a real-world case study in Greece.

Location planning problems have also been appropriately formulated and solved with MCDM methods such as AHP, ELECTRE, TOPSIS, and PROMETHEE, among others. [Briggs et al. \(1990\)](#) used MCDM and PROMETHEE for location decisions of radioactive waste for electronuclear facilities. They considered the points of view of several stakeholders: electricity companies, consumers, public bodies, and so on. A multicriteria analysis was used based on the PROMETHEE method and the Geometrical Analysis for Interactive Assistance (GAIA). These methods were well suited to this problem with many actions and few strongly conflicting criteria. [Petras \(1997\)](#) used MCDM and PROMETHEE and proposed the procedure for identifying and ranking the potential sites for disposal facilities. The potential sites were chosen on the basis of exclusionary (rejection) criteria, and PROMETHEE was used for the preliminary ranking of the sites on the basis of comparative preference criteria. The list of exclusionary and comparative criteria was given, and the weighting factors of comparative criteria were presented.

Fernández-Castro and Jiménez (2005) proposed and integrated PROMETHEE and fuzzy integer linear programming model. The PROMETHEE scores were used as objective function coefficients, in order to find the subsets of non-outranked alternatives that best satisfied a set of constraints. They argue that their integrated framework is more realistic and fits better with the fuzzy philosophy of PROMETHEE. Queiruga *et al.* (2008) described a method for the ranking of Spanish municipalities according to their appropriateness for the installation of waste electrical and electronic equipment plants. The discrete multicriteria decision method PROMETHEE combined with surveys of experts were used to rank the alternatives. Their method did not present an optimal structure of the future recycling system, but provided a selection of good alternatives for potential locations of recycling plants. Tavana *et al.* (2013) proposed a group decision support system (DSS) for the evaluation of alternative pipeline routes in the Caspian Sea region. Their proposed system decomposed the route selection process into manageable steps and combined Strength, Weakness, Opportunity, and Threat analysis with the Delphi method to capture the DMs' beliefs. A group PROMETHEE model was used to integrate these beliefs with subjective judgments and identify the most attractive pipeline route. The GAIA plane was used to further analyze the alternative routes and arrive at a group solution consistent with managerial goals and objectives.

Despite its enormous potential, the contribution of GIS to solving specific problems for DMs is marginal and other analytic capabilities must be incorporated into GIS to fill this gap (Mendas *et al.* 2010). The conceptual idea of combining MCDM and GIS is based on the use of GIS capabilities to prepare a suitable platform for the use of MCDM and remove the limitation of classical Boolean operations of data overlay (Malczewski 2004). The capacities of GIS are utilized to effectively define the alternative solutions and to identify the relevant criteria. Data overlay procedures are used to reduce the initial set of alternatives and to facilitate their evaluation by MCDM (Chakhar and Mousseau 2008).

Marinoni (2004) used AHP and GIS for land-use decision-making and proposed a model where AHP was used to derive criteria weights and GIS was used to map the land-use assessment results by a weighted summation of GIS raster datasets. Marinoni (2006) argued that the outranking methods in MCDM are subject to computational limitations with respect to the number of decision alternatives. He showed that these methods reach their computational limits quickly when dealing with large raster datasets and considering every raster cell a location alternative. Marinoni (2006) proposed an iterative approach which enabled the DMs to easily and transparently apply the PROMETHEE outranking approach for land-suitability assessment with practically no limit in the sizes of the raster datasets. Kolat *et al.* (2006) developed a geotechnical microzonation model using the MCDM method of AHP and GIS. They considered slope, flood susceptibility, soil, depth to groundwater table, swelling potential, and liquefaction potential in their problem formulation. The geotechnical microzonation maps were prepared as the output of the integrated method.

Cheng *et al.* (2007) used GIS and MCDM for shopping mall location selection. They used electronic mapping technology to produce interactive multilayer maps and find an optimal solution to their location planning problem. They combined spatial and nonspatial data to construct visualized information that was used by DMs in the selection process. They showed the applicability of their model by considering features associated with household incomes, demand points, and so on. Finally, queries were created to find solutions for four location problems: (1) minimum distance, (2) maximum demands coverage, (3) maximum incomes coverage, and (4) optimal center. Chang *et al.* (2008) presented a fuzzy MCDM model alongside a geospatial analysis for the selection of

landfill sites. They employed a two-stage analysis synergistically to form a MC-SDSS for waste management. The first stage of the analysis used the thematic maps in GIS in conjunction with environmental, biophysical, ecological, and socioeconomic variables which formed a basis for the second-stage analysis using the fuzzy MCDM. The GIS was used to perform an initial screening process to eliminate unsuitable land followed by the utilization of the fuzzy MCDM method to evaluate and select the most suitable landfill site using the information provided by the DMs with reference to the chosen criteria.

Suárez-Vega *et al.* (2011) studied a competitive network location problem and considered a proportional choice rule derived from the Huff model and multiple attributes such as size and service quality for a facility location decision. They used GIS and MCDM to determine the most promising zones on the island of Gran Canaria for locating a new hypermarket. Anane *et al.* (2012) proposed a methodology for ranking suitable locations for irrigation using fuzzy-AHP and GIS. They considered several parameters based on technical, social, economical, and environmental aspects and grouped them into five main criteria: land suitability for irrigation, resources conflicts, cost effectiveness, social acceptance, and environmental impact. AHP was used to rank these criteria and GIS was used for mapping and ranking the suitable sites based on the geographical layers obtained for the AHP criteria and subcriteria. Chu and Su (2012) show that selecting appropriate fixed seismic shelters for evacuation is fundamental to earthquake engineering in cities. They established an evaluation system which comprised three first-level indices and nine second-level indices related to important factors such as risk of hazard, location, and size of the rescue facilities. The indices were generated with AHP and entropy methods. In the final stage of their model, they use the TOPSIS method to select fixed seismic shelters for evacuation.

Othman *et al.* (2012) studied the problem of expansion of settlements over hilly areas which have largely increased the impact of natural disasters such as landslides. They used GIS and the MCDM technique of AHP to map the landslide hazard zones. Mendas and Delali (2012) integrated the MCDM method ELECTRE Tri and GIS and provided a powerful SDSS which offered the opportunity to efficiently produce land suitability maps. GIS was used for analyzing spatial data and establishing a process for decision support and MCDM was used to facilitate decision-making in situations where several solutions were available and various criteria had to be taken into consideration. They produced a land suitability map for durum wheat and showed that the ELECTRE Tri method integrated into ArcGIS was better suited to the problem of land suitability for agriculture.

Demesouka *et al.* (2013) proposed a raster-based MC-SDSS that combined the AHP and the compromise programming methods of TOPSIS GIS-based landfill suitability analysis. The procedure for identifying the disposal sites was accomplished by performing four computational models for synthesizing the DMs' preferences. They performed a comparison analysis according to suitability index estimations and showed the similarities between the Euclidean distance metric and TOPSIS. Rikalovic *et al.* (2014) showed that most of the data used by managers and DMs in industrial site selection indicate that an industrial site selection process is a spatial decision problem. They used GIS in conjunction with MCDM for an efficient spatial analysis for industrial site selection. Farahani and Hekmatfar (2010) provided a review on the recent efforts and developments in multicriteria location problems in three categories including biobjective, multiobjective, and multiattribute problems and their solution methods.

Finally, let us consider several research papers from the branch of the literature combining multicriteria and linear programming models within a GIS environment, which renders them close to our current setting for comparability purposes. Falit-Baiamonte and Osleeb (2000) developed a multiobjective mathematical location model to identify and select potential locations for environmentally hazardous facilities based on the trade-offs associated with different risk and equity criteria. Alçada-Almeida et al. (2009) incorporated a multiobjective model into a GIS-based DSS for evacuation during major fires, which can be extended to consider earthquakes, floods, and acts of terrorism. Chatzouridis and Komilis (2012) combined GIS-based methods and programming models with binary decision variables in order to locate waste transfer stations while minimizing total collection cost. Fernandes *et al.* (2014) developed a DSS embedding a GIS designed to support decision-making processes dealing with bicriteria location models where the facilities that must be located have environmental impacts.

3. PROMETHEE concepts and extensions

The PROMETHEE method was originally developed by Brans (1982). Several versions of the PROMETHEE methods such as PROMETHEE I for partial ranking of the alternatives, PROMETHEE II for complete ranking of the alternatives, PROMETHEE III for ranking based on interval, and PROMETHEE IV for complete or partial ranking of the alternatives when the set of viable solutions is continuous were proposed later by Brans *et al.* (1984). Other variations of the PROMETHEE method including PROMETHEE V for problems with segmentation constraints (Brans and Mareschal 1992), PROMETHEE VI for the human brain representation (Brans and Mareschal 1995), PROMETHEE GDSS (group DSS) for group decision-making (Macharis *et al.* 1998), the visual interactive module geometrical analysis for interactive aid for graphical representation (Brans and Mareschal 1994a, 1994b), the PROMETHEE TRI for dealing with sorting problems, and the PROMETHEE CLUSTER for nominal classification (Figueira *et al.* 2005) were developed to help with more complicated decision-making situations. The PROMETHEE methods require an appropriate multicriteria method and their success is basically due to their mathematical properties and being user-friendly (Brans and Mareschal 2005). A considerable number of successful applications of PROMETHEE in various fields (e.g., banking, industrial location, manpower planning, water resources, investments, medicine, chemistry, health care, and tourism among others) have been reported in the literature. Macharis *et al.* (1998) and Behzadian *et al.* (2010) have provided excellent reviews of the PROMETHEE methodologies and their applications. The following are the essential constructs used in the PROMETHEE methods:

A : set of alternatives;

n : natural number accounting for the total number of criteria considered;

w_j : weight of criterion j , $j = 1, \dots, n$;

$F_j(a)$: value or performance of alternative a in relation to criterion j , $j = 1, \dots, n$;

$P_j(a, b)$: preference function of criterion j , $j = 1, \dots, n$;

$$P_j(a, b) = g_j(d_j(a, b)), \quad \forall a, b \in A \quad (1)$$

where

$d_j(a, b) = a_j - b_j$, with $a_j = F_j(a)$ and $b_j = F_j(b)$ corresponding to the evaluations of the alternatives according to criterion j ;

g_j is a nondecreasing function of the deviation between the performance of alternatives;

q : indifference limit;

p : preference limit;

$\pi(a, b)$: multicriteria preference index of a in relation to b calculated as follows:

$$\forall a, b \in A \begin{cases} \pi(a, b) = \sum_{j=1}^n P_j(a, b)w_j \\ \pi(b, a) = \sum_{j=1}^n P_j(b, a)w_j \end{cases} \quad (2)$$

with

$$\sum_{j=1}^n w_j = 1$$

$$\phi^+(a) : \text{positive outranking flow expressed as } \phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a, x); \quad (3)$$

$$\phi^-(a) : \text{negative outranking flow expressed as } \phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x, a); \quad (4)$$

with $x \neq a$ in both Equations (3) and (4).

The preference function translates the difference between the evaluations obtained by the two alternatives into a preference degree ranging from 0 to 1. Brans and Vincke (1985) have proposed six different preference functions given in Figure 1: (1) usual criterion, (2) U-shape criterion, (3) V-shape criterion, (4) level criterion, (5) V shape with indifference criterion, and (6) Gaussian criterion presented to facilitate the selection of a specific preference function (see Figure 1). For each criterion, the value of an indifference threshold (q), the value of a strict preference threshold (p), and the value of an intermediate value between p and q (s) have to be fixed (Brans and Mareschal 1992).

The previous PROMETHEE methods are concerned with a set of feasible alternatives. In this section, we present a natural extension of PROMETHEE II to the case of a continuous set of alternatives A . Such a set arises when the alternatives are, for instance, percentages or dimensions of a product (Brans *et al.* 1984).

Thus, henceforth, we assume A to be a compact and connected, that is, a continuum, subset of R^n and F_1, F_2, \dots, F_n to be bounded and almost everywhere continuous functions defined on A . A multicriteria preference index $\pi(a, b)$ can be defined using all the preference functions $P_j(a, b)$. The flows are then defined as follows:

$$\phi^+(a) = \int_A \pi(a, b)db \quad (5)$$

$$\phi^-(a) = \int_A \pi(a, b)db \quad (6)$$

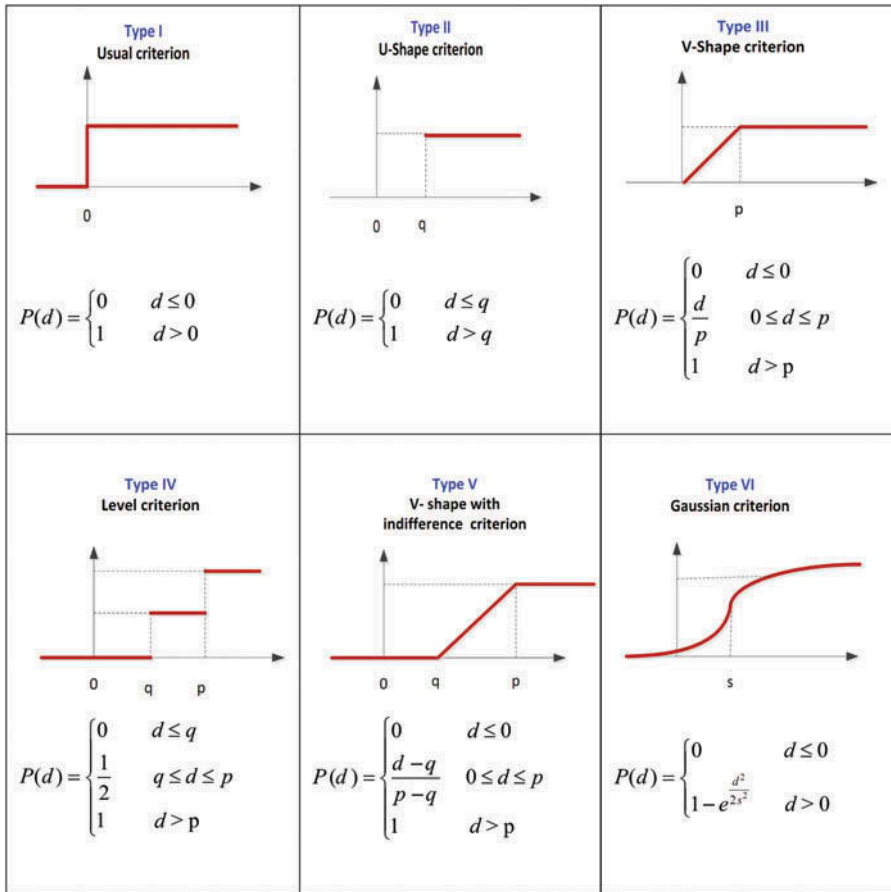


Figure 1. Preference function types.

$$\phi(a) = \phi^+(a) - \phi^-(a) \tag{7}$$

It is not always easy to integrate the preference index $\pi(a, b)$ on the set A . It may be simpler to first calculate:

$$\phi_j^+(a) = \int_A P_j(a, b) db \tag{8}$$

$$\phi_j^-(a) = \int_A P_j(a, b) db \tag{9}$$

$$\phi(a) = \frac{1}{n} \sum_{j=1}^n [\phi_j^+(a) - \phi_j^-(a)] \tag{10}$$

where $j = 1, \dots, n$.

4. The multicriteria spatial decision support system

In order to provide additional intuition regarding the implementation of our DSS, consider the following bicriteria problem used by Brans *et al.* (1984, p. 489):

$$\max \{f_1(x), f_2(x); x \in [0, 1]\} \tag{11}$$

where

$$f_1(x) = 1 - x,$$

$$f_2(x) = \left\{ \begin{array}{ll} \frac{4}{3}x & , 0 \leq x \leq \frac{3}{4}, \\ 4 - 4x & , \frac{3}{4} \leq x \leq 1. \end{array} \right\} \tag{12}$$

We obtain the net flow $\phi(x)$ shown in Figure 2, the maximum of which is obtained for $0.6 \leq x \leq 0.675$, using two-level criteria with $q = 0.1$ and $p = 0.2$. We observe that PROMETHEE IV leads to a real compromise between the two criteria.

The abovementioned functions can be used to determine an optimal point on the length of a line in continuous one-dimensional PROMETHEE problems containing one parameter (x). However, in the setting of the article, the decision alternatives are initially defined in the two-dimensional continuous space R^2 . That is, each alternative will be identified with a point of coordinates (x, y) that may initially vary in the entire continuous aerial map. Before implementing PROMETHEE IV, we divide this continuous area in

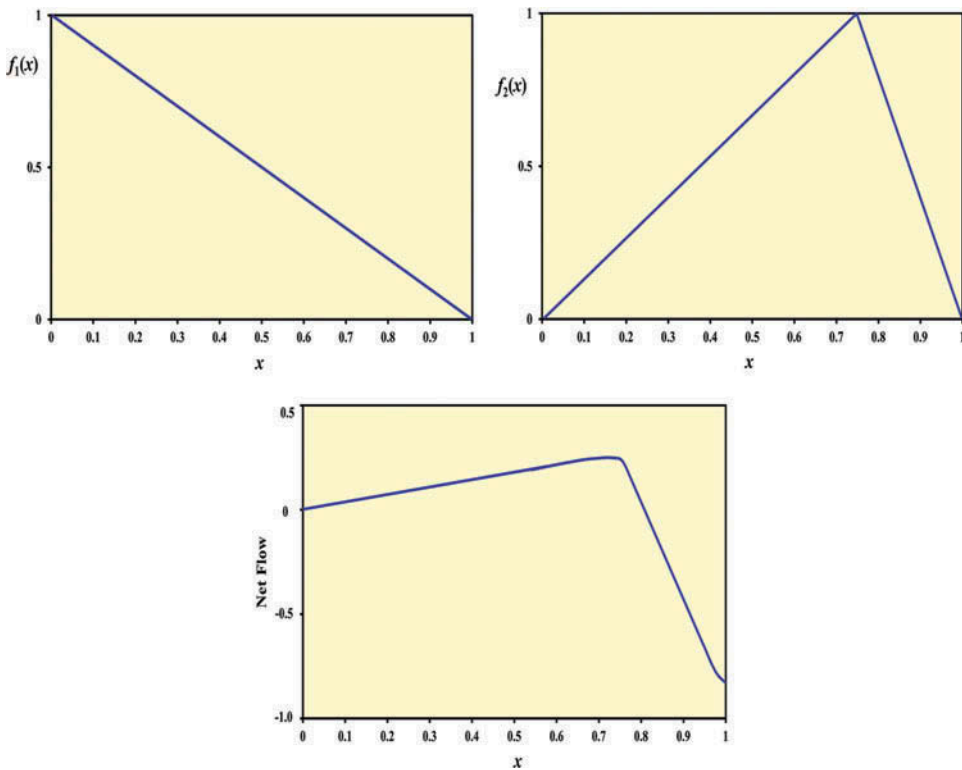


Figure 2. Bicriteria functions.

5360 pixels, we assimilate these pixels with points of the space R^2 , and use ArcGIS to assign them a value between 0 and 1 per criterion. The value assigned by ArcGIS to each point extends to its neighborhood. At this point, PROMETHEE IV is applied to evaluate the deviations between all pairs of evaluations and hence to calculate the net flow outranking for each evaluation. At the same time, note that the set of decision alternatives in PROMETHEE IV provide the domain of the continuous functions g_j , that is, the nondecreasing functions evaluating the deviation between the performance of alternatives.

The MC-SDSS proposed in the current article has been summarized in Figure 3. The main steps of the process are described below:

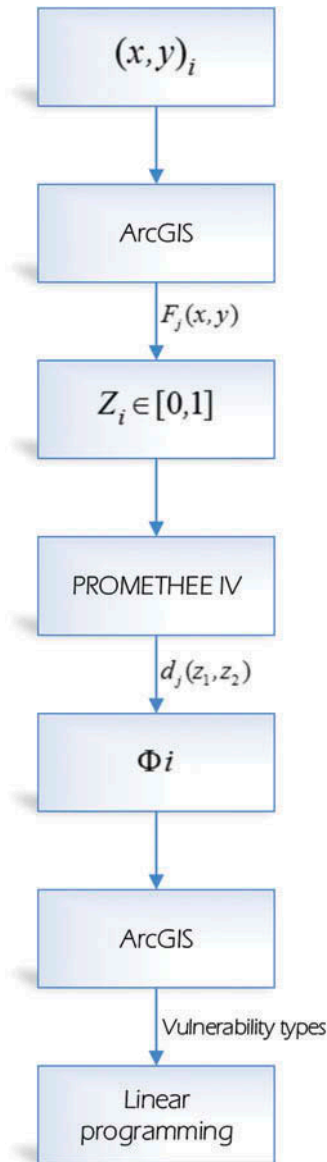


Figure 3. Summary of the proposed MC-SDSS.

- Let the set A denote the entire aerial map (i.e., a continuum subset of R^2) of the city of Tehran.
- Divide the entire map into 5360 pixels.
- Each pixel point has two coordinates, x_i and y_i , composing the pair $(x, y)_i$, for $i = 1, \dots, 5360$.
- Use ArcGIS software to assign a score value to each pixel point $(x, y)_i$. ArcGIS acts as the function $F_j(x, y)_i$ and assigns each pixel point $(x, y)_i$ a value, $z_i \in [0, 1]$, based on the criterion j being considered.
 $F_j(x, y)_i : (x, y)_i \rightarrow z_i \in [0, 1]$, for each criterion j
 $F_j(x, y)_i$ is almost everywhere continuous
- The z_i values assigned to each pixel for each criterion constitute the evaluations of each alternative that will be used to define the preference functions in PROMETHEE IV. In particular, the deviation between the evaluations of two alternatives, z_1 and z_2 , by the j th criterion, that is, $d_j(z_1, z_2)$, is defined as follows
 $d_j(z_1, z_2) : (z_1, z_2) \in [0, 1]^2 \rightarrow (z_1 - z_2) \in [-1, 1]$, for each criterion j
- The values obtained from $d_j(z_1, z_2)$ is used to determine the net flow outranking for each point, $\Phi_i(x, y)$, $i = 1, \dots, 5360$, through PROMETHEE IV.
- The net flow outranking $\Phi_i(x, y)$ is then used together with the criteria weights in ArcGIS to determine the vulnerability type of each area within the map.
- These vulnerability types will be used in the linear programming model to determine the allocation of stations based on the required construction costs. Note that these costs depend on the vulnerability type, which determines the type of station required in a given area. As will become evident when describing Figures 7 and 8, the vulnerability type data obtained using ArcGIS will be rasterized for input into the linear programming model.

Two remarks are due based on this description. First, it should be noted that in some settings one or more criteria may not be in the form of an aerial map. In order to implement the PROMETHEE outranking method in this case, we would need a homogeneous structure allowing us to compare the 5360 alternatives and obtain the net flow outranking values to be inputted in ArcGIS. In this case, the adaptive neuro fuzzy inference system could be used to approximate a surface to be used in the mathematical function for the corresponding criteria. The resulting net flow outranking values can then be combined with the aerial map in ArcGIS to obtain the vulnerability types for each area. Second, the $z_i \in [0, 1]$ evaluations of each alternative obtained using ArcGIS as a continuous map defined between each pixel point and the $[0, 1]$ interval for each criterion make PROMETHEE IV a natural choice within the set of outranking methods that could be implemented, such as TOPSIS.

5. Case study

This study was conducted for the city of Tehran to determine suitable locations for placing shelters for earthquakes that measure 6.0 or more on the Richter scale (earthquakes that have a magnitude of less than 6.0 are generally non-life-threatening). In collaboration with the city of Tehran, a group of four civil engineers was chosen to participate in this study. After several rounds of meetings with city officials, the team agreed to consider the three attributes (i.e., durability density, population density, and oldness density) proposed in this study to determine the most vulnerable zones to earthquakes and ultimately the most suitable locations for the construction of emergency service stations.

5.1. Criteria 1: durability density

The building construction department in the city of Tehran divides the residential and commercial buildings into three general categories based on the foundation and the frames used to construct the building: durable, semidurable, and nondurable. Durable buildings are constructed primarily with steel beams and concrete and can withstand earthquakes that measure 6.0 or more on the Richter scale. Semidurable buildings are constructed with steel beams, bricks, and mortar and they are most vulnerable to earthquakes measuring 6.0 or more on the Richter scale. Nondurable buildings are constructed with timber framing and clay and comprise a very small percentage of the buildings in Tehran. The main focus of the earthquake rescue teams is the semidurable buildings. According to the data collected by the engineers in the city of Tehran, the semidurable building density in the city ranges from 3% to 26%. In other words, in most parts of the city, between 3% and 26% of the buildings are semidurable. As shown in Table 1, in no parts of the city, less than 3% or more than 26% of the buildings are semidurable.

A higher semidurable building density implies a higher preference for construction of an earthquake emergency service station nearby. Consequently, the team of engineers assigned priority scores of 1, .8, .6, .4, and .2 to the densities of 23–26%, 15–22.9%, 7–14.9%, 5–6.9%, and 3–4.9%, respectively. Figure 4 presents an aerial map prepared based on the durability density data provided by the city of Tehran using satellite data.

Table 1. Durability density scores.

Durable building density (%)	Score
23.0–26.0	1.0
15.0–22.9	0.8
7.0–14.9	0.6
5.0–6.9	0.4
3.0–4.9	0.2

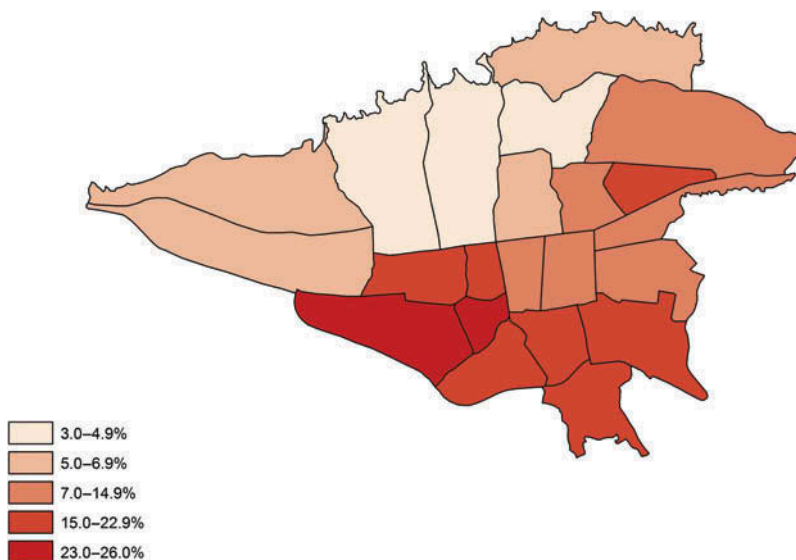


Figure 4. Durability density.

5.2. Criteria 2: population density

Population density represents the number of people living in a per unit area (hectare). The city divides the population density into five categories: 1–69, 70–129, 130–199, 200–299, and 300 or more persons per hectare. Considering that a higher population density means a higher preference for the construction of an earthquake emergency service station nearby, the team of engineers assigned priority scores of .2, .4, .6, .8, and 1 to the population densities of 1–69, 70–129, 130–199, 200–299, and 300 or more, respectively (see Table 2). Figure 5 presents an aerial map prepared based on the population density data provided by the city of Tehran.

5.3. Criteria 3: oldness density

Oldness density represents aging and wear and tear in the structural integrity of the buildings. In the newly developed sections of the city, a maximum of 57% of the building were built in the last 10 years (43% were built more than 10 years ago). In contrast, in the older sections of the city, a maximum of 22% of the buildings were built in the last

Table 2. Population density scores.

Number of people per hectare	Score
300 or more	1.0
200–299	0.8
130–199	0.6
70–129	0.4
1–69	0.2

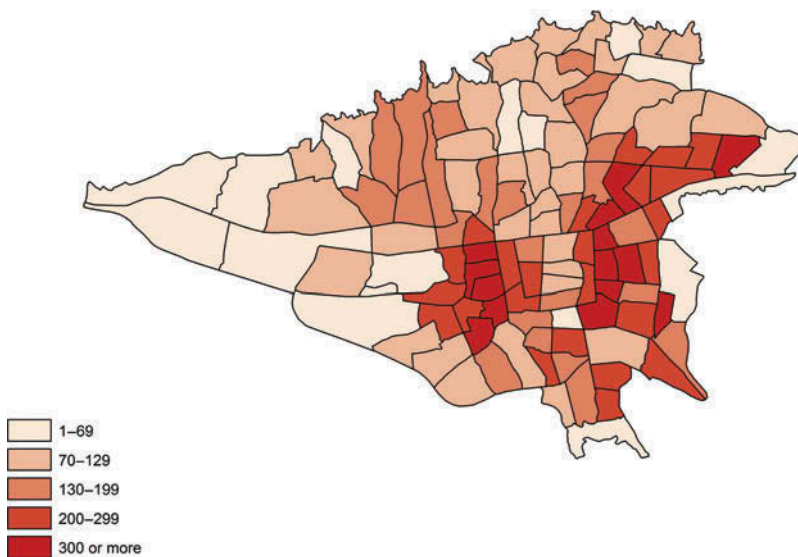


Figure 5. Population density.

Table 3. Oldness density scores.

New building percentage	Priority score
22–28.9	1.0
29–35.9	0.8
36–43.9	0.6
44–49.9	0.4
50–57	0.2

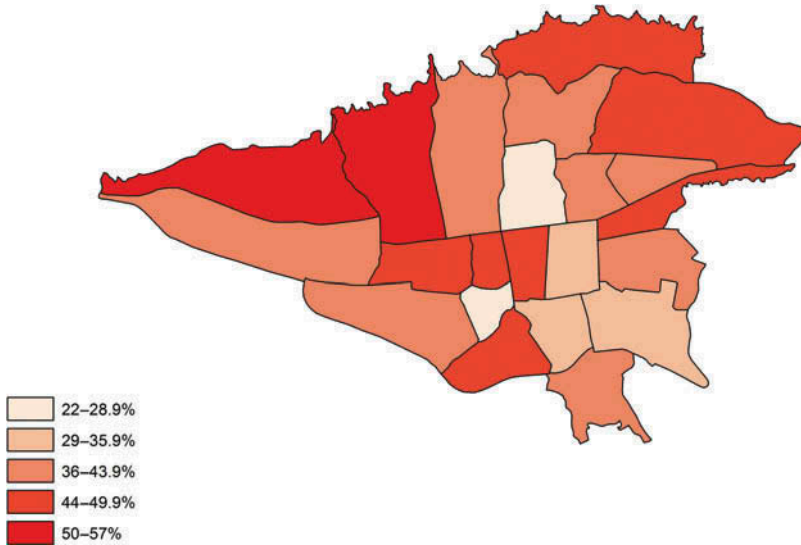


Figure 6. Oldness density.

10 years (78% were built more than 10 years ago). There are no sections of the city where you can find less than 22% or more than 57% buildings that were built in the last 10 years. Considering that the lower oldness density means a higher preference for the construction of an earthquake emergency service station nearby, the team of engineers assigned priority scores of 1, .8, .6, .4, and .2 to the oldness densities of 22–28.9%, 29–35.9%, 36–43.9%, 44–49.9%, and 50–57%, respectively (see Table 3). Figure 6 presents an aerial map prepared based on the oldness density data provided by the city of Tehran.

5.4. On land availability

Availability density represents the accessibility of the city to land for building earthquake emergency service stations. The data collected on the land availability in the city show that some parts of the city have very little land (less than 10%) and are completely inappropriate for building the emergency service stations. In contrast, some other parts of the city have plenty of available land (40% and more) and are completely appropriate for building the emergency service stations. Considering that the more appropriate availability density means a higher preference and lesser cost for the construction of an earthquake emergency service station nearby, the team of engineers assigned priority scores of 1, .8,

Table 4. Availability density scores.

Land availability	Verbal representation	Priority score
40% and more	Completely appropriate	1.0
30–39.9%	Appropriate	
20–29.9%	Relatively appropriate	0.6
10–19.9%	Inappropriate	0.4
Less than 10%	Completely inappropriate	0.2

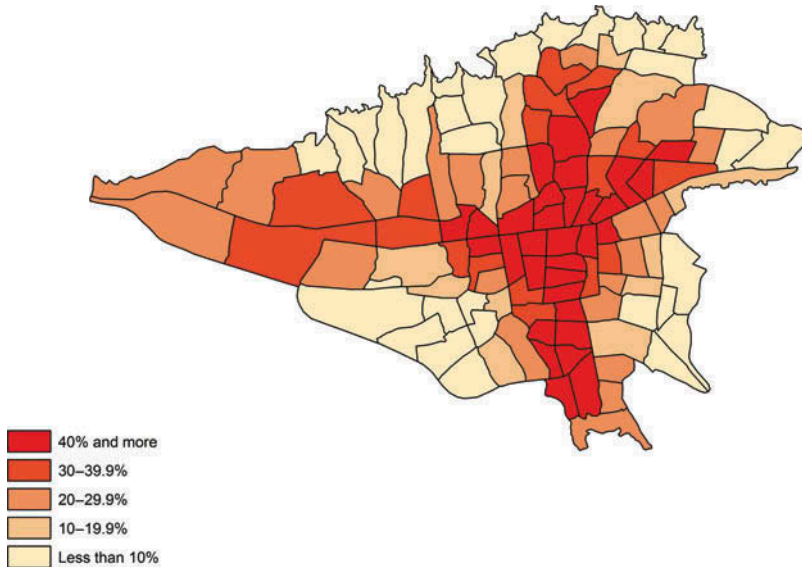


Figure 7. Availability density.

.6, .4, and .2 to the availability densities of 40% and more, 30–39.9%, 20–29.9%, 10–19.9%, and less than 10%, respectively (see Table 4). Figure 7 presents an aerial map prepared based on the availability density data provided by the city of Tehran using satellite data.

5.5. On data collection and the assignment of priority scores

Some remarks regarding the data used in the study together with the assignment of scores by the engineers follow.

The population and availability densities (represented in Figures 4 and 6) are based on the census surveys and areas defined by the city. On the other hand, the durability and oldness densities (represented in Figures 3 and 5) are based on the data provided by the 22 municipal districts composing the city of Tehran. The officials from each district have provided the required data on a district-based level, which constitutes a considerably large spatial unit.

It should be noted that each municipal district is, at the same time, subdivided into municipal regions. *Absent data limitations*, adding further divisions (segmenting the main

district units) would allow us to gain accuracy regarding the distribution of vulnerability types within the districts and, therefore, among the resulting census-based zones. However, the requirements of the fire and safety department inputted in the linear programming model will constitute the main determinant in the distribution of the stations. We have performed sensitivity analysis at the end of the current section to illustrate this point. Thus, even though the type of some of the stations and their location *within* the zones may be affected, the number of stations would remain mainly unchanged. This would be the case if, for example, we would have the data required to use the 64 postal districts composing the city of Tehran as the spatial reporting units when defining the durability and oldness attributes.

The assignment of priority scores to the interval categories defined for each attribute requires some additional explanations. The simplest case is given by the population density categories, which are defined by the city. The oldness and availability attributes have been assigned uniform interval categories defined on the range of the corresponding density values. It is the durability attribute, which constitutes one of the main sources of risk in the event of an earthquake, the one whose assignment of interval categories has been biased by the engineers. In particular, note how almost half of the range on which the density percentages are defined (from 15% to 26%) has been assigned high priority scores. Clearly, a less-biased assignment of interval categories would decrease the vulnerability scores of the riskier zones as well as the equipment of the corresponding stations assigned.

5.6. System implementation: computing the vulnerability types

In order to investigate the spatial maps using the PROMETHEE method, we considered each pixel as 300 m by 300 m and the entire map of the city of Tehran was divided into 5360 of these pixels $((x,y)_i, i = 1, \dots, 5360)$. We then assigned four scores between 0 and 1 to each pixel in the map $(F_j(x,y)_i, j = 1, \dots, 4, i = 1, \dots, 5360)$. The preference functions were considered as Type III (V-shape criterion) with $p_j = 0.1, j = 1, \dots, 4$. We use $P_j(d_j(x,y)_i)$ in place of $g_j(d_j(x,y)_i)$ to keep the notations consistent with those used in Brans and Mareschal (1992)

$$P_j(d_j(x_i, y_i)) = \begin{cases} 0 & d_j \leq 0 \\ \frac{d_j}{p_j} & 0 \leq d_j \leq p_j \\ 1 & d_j > p_j \end{cases}$$

The first three attributes were used to determine the vulnerability by constructing points. About 5360 points with the coordinates of $(x,y)_i, i = 1, \dots, 5360$, were identified on the spatial maps for criteria 1, 2, and 3 and a score was obtained for each point in each map. Consequently, a decision table with 5360 alternatives and three criteria was constructed. We then built a model with MATLAB software and performed data analysis with PROMETHEE. The results included 5360 points with coordinates $(x,y)_i, i = 1, \dots, 5360$ and a net flow outranking $(\Phi_i(x,y), i = 1, \dots, 5360)$ for each point.

The coordinates $(x,y)_i$ for each point determine the location of the point on the aerial map and the net flow outranking of a point $\Phi_i(x,y)$ determines the color of the pixel on the map. Finally, the results from the PROMETHEE method along with the criteria weights $w_1 = 0.25, w_2 = 0.4, \text{ and } w_3 = 0.35$ were used in the ArcGIS software to produce

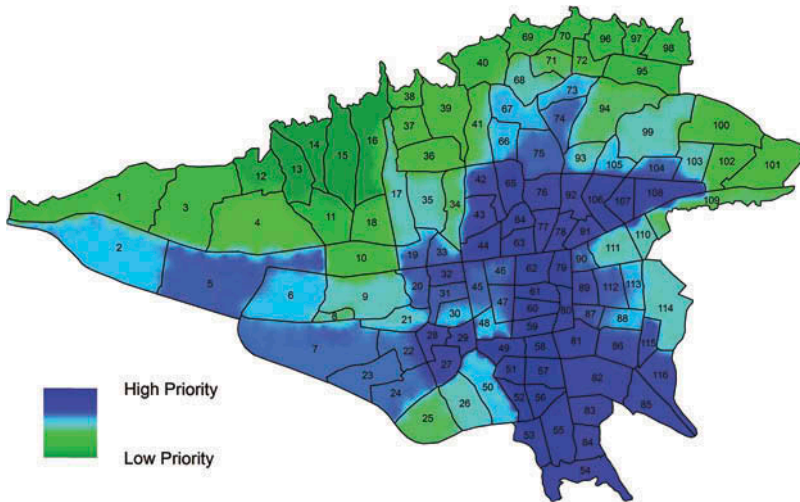


Figure 8. Vulnerability of the city zones to an earthquake.

the areas that are highly vulnerable to earthquakes (in blue) and those areas that are less vulnerable to earthquakes (in green) (see Figure 8).

As shown in Figure 8, zones that are more vulnerable to earthquakes have higher priorities. The city planners and engineers then considered the maps in Figures 7 and 8 and reached the following conclusions:

- Zones such as 7, 22, 23, 24, 27, 28, 54, 85 and 86 are highly vulnerable and at the same time very costly for building emergency service stations, because land availability in those zones is limited.
- Zones such as 58, 59, 60, 61, and 62 are also highly vulnerable and at the same time less costly for building emergency service stations, because land availability in those zones is not limited.
- Zones that are highlighted in light blue and green colors in Figure 8 are less vulnerable and at the same time require a minimally or moderately equipped emergency service station.
- Zones that are highlighted in dark blue in Figure 8 are highly vulnerable and at the same time require a high equipped emergency service station.

As shown in Table 5, the vulnerability to earthquakes in different zones was divided into five categories including very low, low, moderate, high, and very high. In response to this classification, the team considered three different types of emergency service stations (i.e., minimally equipped, moderately equipped, and highly equipped). Therefore, the team decided to consider highly equipped stations for highly and very highly vulnerable zones, moderately equipped stations for moderately vulnerable zones, and minimally equipped stations for lowly and very lowly vulnerable zones in the city.

As shown in Table 5, access to land, construction cost for different service station types, and the area are different for each zone in the city. In addition, the fire and safety department in the city had two specific requirements with regard to the distance between the emergency service station and the center of each zone. According to the first

Table 5. Zone data and requirements.

Area (km ²)	Construction cost (000 dollars)			Land availability density	Vulnerability to earthquake	Zone
	Highly equipped station	Moderately equipped station	Minimally equipped station			
13.87	2500	1667	1333	0.6	Low	1
15.35	2500	1667	1333	0.6	Moderate	2
12.52	2500	1667	1333	0.6	Low	3
13.77	1875	1250	1000	0.8	Low	4
17.73	1875	1250	1000	0.8	High	5
8.91	2500	1667	1333	0.6	Moderate	6
15.78	7500	5000	4000	0.2	High	7
1.01	7500	5000	4000	0.2	Moderate	8
8.31	3750	2500	2000	0.4	Moderate	9
5.73	1875	1250	1000	0.8	Very low	10
5.35	2500	1667	1333	0.6	Very low	11
4.36	7500	5000	4000	0.2	Very low	12
⋮	⋮	⋮	⋮	⋮	⋮	⋮
7.43	7500	5000	4000	0.2	Moderate	114
1.84	7500	5000	4000	0.2	Very high	115
4.02	7500	5000	4000	0.2	Very high	116

requirement, the (Euclidean) distance between the center of a zone to its supporting service station could not exceed 3000 m ($MaxD = 3000$). According to the second requirement, the maximum area that could be allocated to a service station could not exceed 50 km² ($MaxS = 50$). Table 6 presents the distance of the zone centers from each other in meters.

5.7. System implementation: allocation of stations

Considering the preceding data and requirements, we modeled the problem with the following variables and parameters:

- x_{ij} : if zone i is covered by stations established in zone j , 1; otherwise, 0;
- y_{jp} : if type p stations are established in zone j , 1; otherwise, 0;
- C_{jp} : construction costs of type p station in zone j ;
- p_i : station type needed for zone i (i.e., minimally, moderately, and highly equipped stations);
- s_i : area of zone i in km²
- d_{ij} : distance between center of zone i and center of zone j in meters;
- $MaxS$: maximum area (square km) that can be allocated to each station;
- $MaxD$: maximum distance between the centers of each zone and a service provider's station.

The proposed mathematical model was used for assigning zones to different emergency services stations. The optimal assignment of zones is based on their vulnerability types, computed using PROMETHEE IV, together with the logistic constraints imposed by the fire and safety department. At the same time, the availability of land conditions the construction costs of different service station types, whose minimization defines the

Table 6. Distance between the zone centers (meters).

Zone	1	2	3	4	5	...	110	111	112	113	114	115	116
1	0.0	2467.1	4447.9	7871.4	7251.0	...	27193.5	25852.4	25949.4	27062.2	28781.8	28365.6	29690.6
2	2467.1	0.0	4798.9	7643.8	6111.2	...	26945.0	25536.7	25445.3	26584.0	28238.6	27657.1	28833.0
3	4447.9	4798.9	0.0	3496.7	4002.0	...	22746.2	21410.2	21541.8	22646.5	24381.1	24026.1	25423.9
4	7871.4	7643.8	3496.7	0.0	2978.6	...	19382.0	18012.3	18078.0	19191.4	20911.4	20531.6	21929.9
5	7251.0	6111.2	4002.0	2978.6	0.0	...	21083.3	19631.6	19423.7	20571.9	22191.6	21559.7	22722.1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
110	27193.5	26945.0	22746.2	19382.0	21083.3	...	0.0	1554.8	3087.6	2548.8	3659.4	5318.9	7463.2
111	25852.4	25536.7	21410.2	18012.3	19631.6	...	1554.8	0.0	1989.9	2084.6	3790.8	4944.4	7157.1
112	25949.4	25445.3	21541.8	18078.0	19423.7	...	3087.6	1989.9	0.0	1161.5	2849.7	3259.2	5426.4
113	27062.2	26584.0	22646.5	19191.4	20571.9	...	2548.8	2084.6	1161.5	0.0	1845.9	2892.0	5098.8
114	28781.8	28238.6	24381.1	20911.4	22191.6	...	3659.4	3790.8	2849.7	1845.9	0.0	2019.4	3911.7
115	28365.6	27657.1	24026.1	20531.6	21559.7	...	5318.9	4944.4	3259.2	2892.0	2019.4	0.0	2212.7
116	29690.6	28833.0	25423.9	21929.9	22722.1	⋮	7463.2	7157.1	5426.4	5098.8	3911.7	2212.7	0.0

objective function of the corresponding linear programming model. That is, the objective of the model is to determine the zones and an appropriate equipment level for each service station with the lowest possible cost.

$$\text{Min } Z = \sum_{j=1}^{116} \sum_{p=1}^3 C_{jp} y_{jp} \quad (13)$$

$$\sum_{j=1}^{116} x_{ij} = 1 \quad i = 1, 2, \dots, 116 \quad (14)$$

$$\sum_{p=1}^3 y_{jp} \leq 1 \quad j = 1, 2, \dots, 116 \quad (15)$$

$$x_{ij} = \sum_{p=1}^3 y_{jp} \quad j = 1, 2, \dots, 116 \quad (16)$$

$$x_{ij} \leq \sum_{p \leq p_i} y_{jp} \quad \forall i, j = 1, 2, \dots, 116 \quad (17)$$

$$\sum_{i=1}^{116} s_i x_{ij} \leq \text{Max}S \quad j = 1, 2, \dots, 116 \quad (18)$$

$$d_{ij} x_{ij} \leq \text{Max}D \quad \forall i, j = 1, 2, \dots, 116 \quad (19)$$

$$x_{ij} = 0, 1 \quad (20)$$

$$y_{jp} = 0, 1 \quad (21)$$

The subscripts i and j will refer to zones of the city through the remaining of the section. Equation (13) is the objective function of the model. Equation (14) ensures that each zone is allocated to one station. Equation (15) ensures that only one type of station is established in each zone. Equation (16) ensures that if an emergency service station is established in zone j , it should provide service to that zone. Equation (17) ensures that zone i can be allocated only to those stations with the equipment level that is comparable with the requirement in that zone. The three types of station considered have been assigned the following numerical values

- $p = 3$, if the station is minimally equipped;
- $p = 2$, if the station is moderately equipped;
- $p = 1$, if the station is highly equipped.

As a result, according to Equation (17), if a minimally equipped type 3 station is required for zone i , that is, if $p_i = 3$, then

$$x_{ij} \leq y_{j1} + y_{j2} + y_{j3}$$

Consider Equation (17) and assume that the station needed for zone i must be highly equipped, that is, $p_i = 1$. If the station established in zone j is of type 1, then zone i can be assigned to the station located in zone j since

$$x_{ij} \leq y_{j1}$$

Similarly, assume that the station required for zone i must be moderately equipped, that is, $p_i = 2$. If the station established in zone j is of either type 1 or 2, then zone i can be assigned to the station located in zone j since

$$x_{ij} \leq y_{j1} + y_{j2}$$

Note that if a minimally equipped station is established in zone j , then both previous equations would be violated, that is, we would get $x_{ij} \leq 0$. Thus, Equation (17) requires the model to assign each zone only to the stations that are sufficiently equipped to cover its requirements.

Equation (18) ensures that all areas for the zones allocated to the station for zone j cannot exceed $\text{Max}S$. Equation (19) ensures that the distance between the allocated zones to the station in zone j does not exceed $\text{Max}D$. Finally, Equations (20) and (21) determine the binary decision variables. The global solution is obtained by implementing and solving the above model with (Lingo) software. Table 7 and Figure 9 show the zones assigned to each emergency service station.

For example, as shown in Table 7 and Figure 9, a highly equipped station was established in zone 6 and covered zones 6, 7, and 8; a moderately equipped station was established in zone 35 to serve zones 17, 18, 34, 35, and 36; a minimally equipped station was established in zone 95 to serve zones 94, 95, 96, 97, and 98. As shown in Table 7, the total cost of this assignment is \$58,417,000.

5.8. Sensitivity analysis

We perform sensitivity analysis to test the robustness of the results obtained in the presence of uncertainty. That is, sensitivity analysis is performed on $\text{Max}D$, $\text{Max}S$, and the resulting budget in order to help researchers and practicing managers better understand how the uncertainty in the output of the mathematical programming model can be apportioned to different sources of uncertainty in $\text{Max}D$, $\text{Max}S$, and the budget.

Assume first that the maximum area ($\text{Max}S$) that a service station can cover is fixed. If the maximum distance ($\text{Max}D$) allowed between the center of a zone and its supporting station increases, then an emergency service station located in zone j could cover a larger area. As a result, the model would assign a larger area to the station located in zone j and most of the capacity of the station would be used. In this case, a lesser number of stations would be needed and the total cost incurred would decrease.

Assume now that the maximum distance ($\text{Max}D$) allowed between the center of a zone and its supporting service station is fixed. If the maximum area ($\text{Max}S$) that a station can cover increases, then a lesser number of stations would be needed and the total cost incurred would decrease. However, a unilateral increase in $\text{Max}S$ cannot consistently decrease the number of stations required and the resulting total cost. This is due to the fact that the

Table 7. Emergency service stations and their client zones.

Service station	Service station type	Cost of construction (000 dollars)	Client zones																		
2	Moderately equipped	1667	1	2																	
3	Minimally equipped	1333	3																		
4	Highly equipped	1875	4	5	12																
6	Highly equipped	2500	6	7	8																
10	Minimally equipped	1000	10	11																	
15	Minimally equipped	4000	13	14	15	16															
20	Highly equipped	1875	9	19	20	21	28	30	31	33											
24	Highly equipped	7500	22	23	24	25	27														
35	Moderately equipped	1667	17	18	34	35	36														
39	Minimally equipped	4000	37	38	39	40	41														
46	Highly equipped	1500	32	44	45	46	47	60	61	62	63										
51	Highly equipped	1500	26	29	48	51	52	58	59												
55	Highly equipped	1500	53	54	55	83	84														
57	Highly equipped	1500	49	50	56	57	81	82													
65	Highly equipped	1500	42	43	64	65	66	75	76	77											
71	Highly equipped	2500	67	68	69	70	71	72	73	74											
95	Minimally equipped	4000	94	95	96	97	98														
102	Minimally equipped	4000	100	101	102	109															
104	Highly equipped	1500	99	103	104	105	107	108													
106	Highly equipped	1500	78	91	92	93	106	110													
112	Highly equipped	2500	79	80	87	88	89	90	111	112	113	114									
116	Highly equipped	7500	85	86	115	116															
Total cost		58,417																			

increments in MaxS would eventually lead to the redundancy of constraint (18). In this case, constraint (19) would limit the size of the area assigned to the station located in a given zone. As a result, most of the capacity of a station would remain unused.

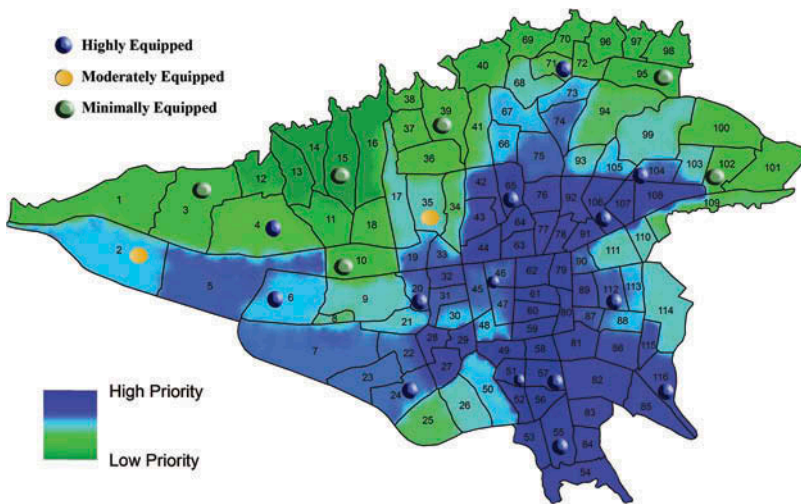


Figure 9. Earthquake emergency service station locations and their type.

Table 8. Number of stations required.

MaxD	MaxS			
	25	50	75	100 or more
1000	112	112	112	112
1500	77	77	77	77
2000	44	43	43	43
2500	32	30	30	30
3000	25	22	22	22
3500	22	17	17	17
4000	20	14	14	14

Table 9. Total cost (objective function).

MaxD	MaxS			
	25	50	75	100 or more
1000	3,09,461	3,09,461	3,09,461	3,09,461
1500	2,21,252	2,21,252	2,21,252	2,21,252
2000	1,15,001	1,14,584	1,14,584	1,14,584
2500	82,084	79,501	79,501	79,501
3000	63,292	58,417	58,417	58,417
3500	47,746	41,542	41,542	41,542
4000	38,495	33,459	33,459	33,459

Tables 8 and 9 provide a numerical illustration of the arguments just described. Note that simultaneous increments in MaxS and MaxD may lead to a substantial decrease in the number of stations required and the resulting total cost.

6. Conclusion and future research directions

The spatial nature of identifying potential emergency service station locations and the need to include multiple and often conflicting criteria along with the DMs' preferences in the analysis require a combination of GIS and MCDM methods. Spatial multicriteria decision problems generally involve a set of geographically defined alternatives from which a choice of one or more alternatives is made with respect to the DMs' preferences on a given set of evaluation criteria. In contrast to conventional MCDM, spatial multicriteria analysis requires information on the criterion values and the geographical locations of alternatives.

We propose a conceptual and methodological framework for combining GIS and MCDM in a single and comprehensive system that considers the entire earthquake emergency service station location planning process. In this context, the algorithm of PROMETHEE IV was incorporated into the ArcGIS environment and a SDSS was utilized to develop emergency service station suitability maps. We considered three attributes (i.e., durability density, population density, and oldness density) in the form of spatial maps to determine the zones most vulnerable to an earthquake. The information on these spatial maps was entered into the ArcGIS software to define the relevant scores for each point with regard to these attributes. The PROMETHEE IV method was then

used in a MATLAB model to determine the vulnerability type of the different zones of the city. These types were then incorporated in the linear programming model that was used to determine the most suitable locations for the construction of emergency service stations, as well as the type of station assigned to each location, in the city of Tehran.

Thus, the MC-SDSS introduced in this article allows us to take into account the entire earthquake emergency service station location planning process and identify shelters and emergency service locations in urban evacuation planning. Clearly, our MC-SDSS can be easily modified to incorporate any outranking method other than PROMETHEE IV, ranging from MCDM models such as TOPSIS to the discrete ELECTRE family, depending on the type of data being analyzed.

The field of MC-SDSS is far from maturity. Continued changes in computer technology are changing the way that DMs retrieve, store, and process data. The future MC-SDSS must be not only spatial but also spatiotemporal. They must be able to address concerns such as the handling of large spatial data and the development of the type of tools and techniques that are most suitable for processing these massive spatial datasets. In addition, future MC-DSS must be able to analyze spatial and space–time data so that the DMs can develop models that best represent reality.

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