Geographical & Environmental Modelling, Vol. 6, No. 1, 2002, 27–39

Carfax Publishing
Taylor & Francis Group

Fuzzy Screening for Land Suitability Analysis

JACEK MALCZEWSKI

ABSTRACT *Screening procedures are typically operationalized in GIS by means of Boolean operations using conjunctive or disjunctive decision rules. There are several conceptual and technical problems with the conventional screening methods. The methods require fairly detailed a priori information about the cut-off values, aspiration (target) levels, or preferences with respect to the relative importance of screening criteria. They may be complex, time consuming, and not totally amenable to quantitative analyses in situations involving categorical or mixed data. This paper proposes a GIS-based fuzzy screening method that avoids some of the difficulties. The method requires only a qualitative scale for land suitability evaluation with respect to a number of attributes. It also allows for assigning to each attribute a different degree of importance. The procedure results in dividing the set of alternatives (parcels of land) into two subsets: acceptable (feasible) and unacceptable (infeasible). The fuzzy screening method is illustrated using a hypothetical problem and implemented in a real-world situation involving industrial land development in the Villa Union region of the Sinealoa province on the Pacific coast of Mexico.*

Introduction

Screening procedures are useful in situations in which the decision-makers or planners must select, from a large set of alternatives, a small subset of feasible alternatives to be further examined. The procedures are typically operationalized in GIS by means of exclusionary screening methods. In general, the procedures involve (1) selecting factors (evaluation criteria or attributes) which are important (e.g. topography, soils, water, vegetation, geology, transportation network, population distribution, etc.), (2) generating individual suitability maps to indicate the areal extent and values of each factor with respect to its capability or suitability for a specified land use, and (3) combining maps using Boolean operations to identify areas suitable for a given land use. The GIS-based procedures follow the pioneering work on the cartographic sieve-mapping and overlay methods by McHarg (1969).

The conventional screening methods can be classified according to the types of constraints used to eliminate unacceptable alternatives (parcels of land). Eastman *et al.* (1993) distinguished two generic types of constraint: Boolean (or logical) and target constraints. For example, in the context of the problem of landfill facility site

Jacek Malczewski, Department of Geography, University of Western Ontario, London, Ontario N6A 5C2, Canada. Fax: +1-519-661-3750; E-mail: jmalczew@uwo.ca

1361-5939print/1469-8323online/02/010027-13
DOI: 10.1080/13615930220127279

selection we may require ‘the sites must be outside wetlands’ or ‘the sites must be 1 km away from any river’. The two limitations imposed on the set of alternatives are examples of Boolean constraints. Another example might be that ‘the area for establishing landfill facility must be approximately 200 acres’. This provides an example of a target constraint.

Constraints can also be classified into noncompensatory and compensatory constraints. The major distinction between the compensatory and noncompensatory screening is that the former takes into account the trade-offs between screening criteria, while the latter ignores the value trade-offs (Keeney, 1980). The noncompensatory approaches are typically operationalized in terms of the conjunctive and disjunctive screening methods. Under conjunctive screening an alternative is accepted if each attribute associated with a site meets a set of preset standards (thresholds or cut-offs). Disjunctive screening accepts sites that score sufficiently high on at least one of the attributes under consideration. In addition to disjunctive and conjunctive screening, the lexicographic and elimination by aspect procedures can be used to screen alternatives (Solomon & Haynes, 1984). Both methods are noncompensatory. The lexicographic method considers one attribute (map layer) at a time, beginning with the most important (Massam, 1988). Then the attributes are considered one by one in a decreasing hierarchy of importance. Like the lexicographic method, the elimination by aspects (attributes) proceeds by comparing alternatives on one attribute at a time. In elimination by aspects, however, alternatives, which fail to meet a specified standard, are eliminated from further consideration. Thus, the method combines lexicographic and conjunctive screening. For applications of the noncompensatory screening method to spatial decision problems see Massam (1988) and Carver (1991).

There are several conceptual and technical problems with using the conventional screening methods within a GIS environment (Julien & Byer, 1990; Malczewski, 1999; Munda, 1995). First, the methods require fairly detailed a priori information about the cut-offs, aspiration (target) levels, or preferences with respect to the relative importance of screening criteria. One can expect that in a complex spatial decision situation, the decision-maker will find it difficult (or even impossible) to provide the precise numerical information required by these methods. For some attributes, there exist natural dividing points (values) between acceptable and unacceptable alternatives (for example, in the case of legal requirements). However, in many situations attributes lack such natural cut-off points. For example, a cut-off may be defined, as ‘the acceptable site must be located within 5 km of a river’. Such a cut-off is not a natural one. Why would a site within 4.99 km be acceptable and a site within 5.01 km of a river would be categorized as an unacceptable one? In such situations the decision-makers are reluctant or unable to make precise statements about the cut-off points. There is usually an ambiguity and imprecision involved in defining such cut-offs. Second, the conventional exclusionary screening methods often assume that the evaluation criteria are equally important and/or the weights of importance are defined in a numerical form. Contrary to these assumptions the weights of importance are typically specified by means of some linguistic statements that provide an ordering of the evaluation criteria from the most important to the least important one. Third, in many situations a screening analysis excludes only a small portion of the study area, leaving a large number of alternatives for further examination. This undermines the capability of the method to support the decision-making process by significantly reducing the cost and time of searching for the most preferred alternative.

This paper presents a fuzzy screening method that avoids some of the difficulties associated with the conventional exclusionary screening approaches. Broadly speaking, there are two approaches to fuzzy screening: *approximation methods* and *symbolic methods* (Delgado *et al.*, 1992; Kickert, 1978). This distinction is based on the way in which the aggregation of the input data (criterion maps and preferences) is performed in a screening procedure. The approximation approach is based on the idea of representing imprecise data (information) in the form of membership functions and performing aggregation operations directly on the functions (Julien & Byer, 1990; Munda, 1995). Unlike the approximation approaches, the symbolic procedures do not require any specification of the membership functions. The aggregation operations involve direct computations on linguistic labels (qualitative statements) by taking into account the meaning and structure of the linguistic terms (Delgado *et al.*, 1992; Yager, 1993). This paper focuses on the symbolic approach to fuzzy screening.

The next section of the paper discusses a generic structure for GIS-based land/site suitability analysis and provides an overview of the GIS screening methods. The fuzzy logic concept in the context of the screening approaches is then presented and illustrated using an hypothetical site screening situation, followed by a real-world implementation of the method in the Villa Union region of the Sinealoa province on the Pacific coast of Mexico. A final section presents a summary and some conclusions of the paper.

GIS-based Land Suitability Analysis: the Problem Structure

The land or site suitability analysis can be formalized by means of the multi-attribute decision-making (MADM) problem (Eastman, 1997; Eastman *et al.*, 1993; Jankowski, 1995). Let the set of parcels of land (decision alternatives), **X**, be defined in terms of decision variables; that is $\mathbf{X} = \{\mathbf{x}_{i^*} | i = 1, 2, \ldots, m\}$. The alternatives are represented by a set of cells or pixels in a raster GIS database or a set of points, lines, and/or areal objects in a vector GIS. Thus, the index i indicates the location of the ith alternative. For the sake of simplicity we will use a single subscript to indicate the location of an alternative. Thus, each alternative is described by means of its locational attribute (coordinate data) and attribute data (attribute values associated with the location). The attribute values can be measured on qualitative or quantitative scales. We can designate by x_{ij} the level of the jth attribute with respect to alternative i. Hence, an alternative i can be characterized by the vector in equation (1), and the levels of the n attributes across an alternative are represented by the vector in equation (2).

$$\mathbf{x}_{i^*} = (x_{i1}, x_{i2}, \ldots, x_{in}), \qquad \text{for } i = 1, 2, \ldots, m \tag{1}$$

$$\mathbf{x}_{*j} = (x_{1j}, x_{2j}, \ldots, x_{mj}), \qquad \text{for } j = 1, 2, \ldots, n. \tag{2}$$

The input data for the site suitability problem (equations (1) and (2)) can be organized in a tabular form (evaluation matrix or geographical matrix). Accordingly, the data can be stored in a GIS as a set of map layers. The data consist of a set of n data layers and each object in the data layer contains an attribute value, x_{ij}. Each object (e.g. raster or polygon) in the map layer can be considered as a decision alternative or the alternatives can be determined as a combination of objects (points, lines, and/or polygons). In a particular decision situation the set of alternatives can be limited by imposing constraints on the attribute values (aspatial constraints) or on the locational attributes (spatial constraints).

Given the input data the problem is to aggregate the map layers according to a decision rule so that the alternative can be classified and ordered. The performance (suitability) of an alternative depends not only on the level of the attribute by which a location is characterized but it also involves the decision-maker(s)' preferences with respect to the attributes. The preferences are contained in the decision rule. Hence, in the most general terms, the MADM problem can be defined as follows:

$$\textit{decision rule}\ [x_{i1}, x_{i2}, \ldots, x_{in} | \mathbf{x}_{i^*} \in \mathbf{X},\ i = 1, 2, \ldots, m]. \tag{3}$$

This expression can be interpreted as follows: apply the decision rule to order the alternatives, $\mathbf{x}_{i^*}$, in the set of feasible alternatives, $\mathbf{X}$, according to the values of the attributes.

From the decision rule (3) it is obvious that the process of identifying the set of feasible alternatives is of critical importance for a land/site suitability problem. Simply, if the ordering of alternatives is to be useful and meaningful, it requires that the feasible sites are identified correctly. The set of feasible or acceptable sites is defined by means of constraints (requirements or limitations). Typically, the constraints are represented as: $x_{ij} \geqslant b_j$ or $x_{ij} \leqslant b_j$ for $j = 1, 2, \ldots, n$; where b_j is the minimum acceptable value (the cut-off value) for the jth attribute. Also, a target constraint can be used. In this case, $x_{ij} = b_j$, where b_j is a target value. An alternative is feasible (acceptable) if it satisfies the set of constraints imposed on the decision alternatives. Alternatives that do not meet the constraints are referred to as infeasible (or unacceptable).

Fuzzy Screening

Fuzziness is a type of imprecision characterizing classes that do not have sharply defined boundaries. Such imprecisely defined classes are called fuzzy sets. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth. As its name suggests, it is the logic underlying modes of reasoning which are approximate rather than exact. The importance of fuzzy logic is derived from the fact that most modes of human reasoning and especially common sense reasoning are approximate in nature.

The fuzzy modeling approaches (including the fuzzy screening methods) are based on the concept of linguistic variable. Linguistic variable is a word or sentence in a natural or artificial language (Kickert, 1978). The significance of linguistic variable is that it facilitates graduate transitions between its states and, consequently, it possesses a natural capability to express and to deal with imprecise and ambiguous statements (e.g. the decision-makers' preferences with respect to the importance of evaluation criteria are typically expressed in linguistic terms such as 'very important', 'important', 'unimportant', etc.; also, the preferences with respect to attribute values and cut-offs points are often expressed by means of linguistic terms).

To illustrate the concept of a linguistic variable, consider an evaluation criterion 'distance to a river'. It is a numerical variable that can be measured in kilometers. The variable assumes as a value any number between 0 and 10 km, for example. This is referred to as a universe (or a base variable). In general, the based variable may be measured on the quantitative (e.g. distance) or qualitative scales (e.g. ordered

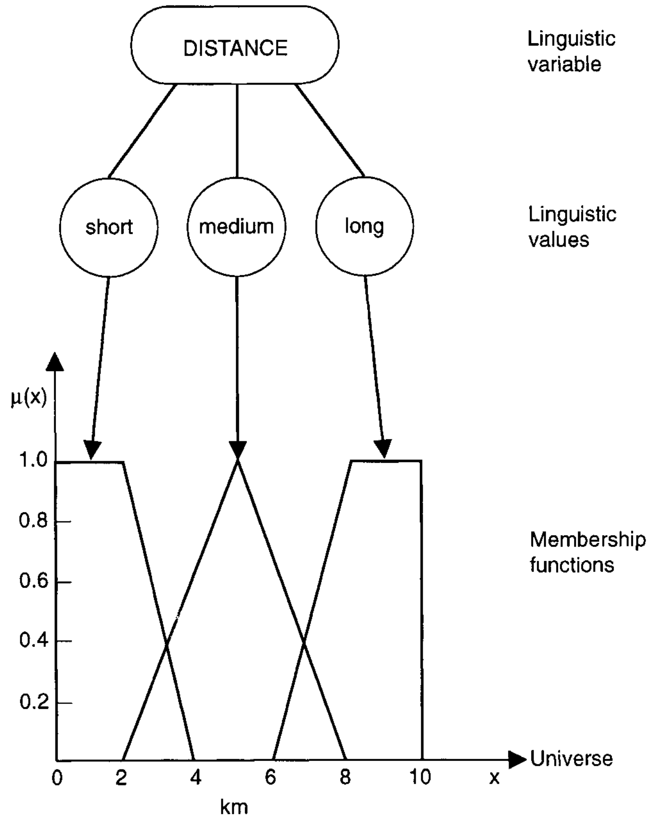

Figure 1. The linguistic variable 'distance'.

categories of land use). Now consider 'distance' as a linguistic variable (Figure 1). This variable can assume the values: 'long', 'medium', 'short', etc. Each of these terms is a linguistic value or linguistic term of the variable. The linguistic term set consists of the linguistic values. A linguistic value is characterized by a label (or syntactic value) and a semantic value (or meaning). The label is a word or sentence belonging to a linguistic term set (e.g. 'long') and the meaning is a fuzzy subset defined in a relevant interval, which is described by a membership function.

The concept of linguistic variable is not only based for operationalizing evaluation criterion and preferences, but also for the aggregation procedures in the fuzzy screening methods. There are two main approaches for performing the aggregation of linguistic information. First, the *approximation* or *indirect approach* uses the membership functions associated with the linguistic terms. The trapezoidal or triangular membership functions are typically employed to capture the vagueness of the linguistic terms (Eastman, 1997; Munda, 1995). Second, the *direct* or *symbolic approach* makes direct use of labels for computing. It is based on the premise that the set of linguistic terms is an ordered structure uniformly distributed on a scale.

Both the approximation and symbolic approaches involve two basic fuzzy operations: *MIN* (minimization) and *MAX* (maximization) operations for aggregation qualitative information. The *MIN* or intersection operator corresponds to the logical *AND*. It produces for any given fuzzy sets the largest set from among those produced by all possible fuzzy intersections. This interpretation implies no positive compensation (trade-off) between degree of membership of the fuzzy sets under consideration. It is a non-compensation operator. This means that an alternative is rejected on the basis of poor performance with respect to at least one attribute, even if it performs well above average on other attributes. On the other hand, the fuzzy *MAX* operation corresponds to the logical *OR* operation and it generates the smallest fuzzy set among the fuzzy sets produced by all possible fuzzy unions (that is, the union operation is modeled by the fuzzy *MAX* operator) (Kickert, 1978; Ross, 1995). In aggregation several evaluation criteria the *MAX* operator generates the maximum degree of membership achieved by any of the fuzzy sets representing evaluation factors. This amounts to a full compensation of lower degrees of membership by the maximum degree of membership. Consequently, it is a fully compensation operator. This means that an alternative is recognized as an acceptable one on the basis of an exceptionally high value of one attribute irrespective of poor performance with respect to other attributes. Formally, for two sets, A and B, on the universe X

$$A \cap B \rightarrow \mu_{A \cap B}(x) = MIN[\mu_A(x), \mu_B(x)] \tag{4}$$

and

$$A \cup B \rightarrow \mu_{A \cup B}(x) = MAX[\mu_A(x), \mu_B(x)] \tag{5}$$

are the intersection and union operators, respectively; $\mu_A(x)$ and $\mu_B(x)$ represent membership in sets A and B for the element x in the universe X.

One of the difficulties with the approximation approach to fuzzy screening is that it is often difficult to associate meaningful membership functions with the linguistic values. The symbolic method avoids this problem by performing aggregation operations on labels (linguistic values) directly. The method requires the decision-maker to provide his/her estimates with respect to the performance of alternatives. In particular, for each alternative, the decision-maker is asked to evaluate on a qualitative scale how well the alternative satisfies each of the evaluation criteria. There is empirical evidence to show that a seven-point scale is appropriate for multicriteria evaluation (Saaty, 1980). Specifically, the evaluation is given in labels, S_l ($l = 1, 2, \ldots, q$), from the following scale S (Yager, 1993):

S_7 Outstanding (OU)
S_6 Very High (VH)
S_5 High (H)
S_4 Medium (M)
S_3 Low (L)
S_2 Very Low (VL)
S_1 None or Negligible (N)

The use of such a scale provides a natural ordering, $S_k > S_l$ (S_k is preferred to S_l) if $k > l$ and consequently the minimum and maximum of any two labels can be defined by

$$MIN(S_k, S_l) = S_k \text{ if } S_k \leqslant S_l \tag{6}$$

and

$$MAX(S_k, S_l) = S_k \text{ if } S_k \geqslant S_l. \tag{7}$$

Thus, the ith location can be assigned a collection of n qualitative attribute values, x_{ij}. Each attribute value is an element of the set of allowable label S.

In addition, the decision-maker is required to assign a measure (weight) of importance, α_j, to each of the attributes under consideration using the same scale, S. To this end, a crucial aspect of the symbolic approach is the negation of the importance. The negation is defined as follows: $Neg(S_l) = S_{q-l+1}$. For the S scale, the negation operation provides the following:

$Neg(OU) = N$
$Neg(VH) = VL$
$Neg(H) = L$
$Neg(M) = M$
$Neg(L) = H$
$Neg(VL) = VH$
$Neg(N) = OU$

Given the set of attribute values and the set of measures of importance, the screening procedure requires finding the overall value (label) for each alternative; that is, aggregate the attributes and weights for each location. The overall value, u_i, for the ith alternative is calculated using the following screening rule:

$$u_i = MIN_i\{Neg(\alpha_j) \cup x_{ij}\} \geqslant S_* \tag{8}$$

where $Neg(\alpha_j)$ is the negation operation for the measure of importance of the jth attribute, x_{ij} is the level of the jth attribute for the ith alternative, $\cup$ is the union of the two sets, and S_* is the minimum acceptable overall value (threshold). The screening rule (8) can be interpreted as a measure of the degree to which an alternative satisfies the following proposition: *all important factors are satisfied*. In other words, if a factor is considered to be important then an alternative should perform well with respect to that factor. This is achieved by incorporating the preferences (the measures of importance), $Neg(\alpha_j)$, into the screening rule (8) (Ross, 1995; Yager, 1993). For a particular attribute, the negation of its importance acts as a cut-off value such that all ratings of alternatives below that cut-off become equal to the value of that cut-off. The screening rule disregards all distinctions less than the cut-off value while keeping distinctions above this value. For example, given the performance of the four alternatives with respect to the jth attribute: $x_{1j} = VH$, $x_{2j} = VL$, $x_{3j} = H$, and $x_{4j} = L$, and $Neg(\alpha_j) = M$, the $\{Neg(\alpha_j) \cup x_{ij}\}$ operation in the screening rule (8) will assign the cut-off value to the alternatives x_{2j} and x_{4j} (that is, $x_{2j} = x_{4j} = M$), while the values of the alternatives above the cut-off will remain the same (that is, $x_{1j} = VH$ and $x_{3j} = H$).

In general, the more important an attribute is in the screening process, the more significant its effect on the screening rule (8). Specifically, the more important the attribute, the lower the $Neg(\alpha_j)$ value, and consequently, the more levels of distinction there are. Conversely, as an attribute becomes less important the negation of the cut-off value increases, which lessens the penalty to the attribute. In the extreme cases, if the attribute becomes the most important ($\alpha_j = OU$), all distinctions remain ($Neg(\alpha_j) = N$), while if the attribute is considered totally unimportant ($\alpha_j = N$), then the cut-off value is raised to its highest level ($Neg(\alpha_j) = OU$) and all alternatives are given the same weight and no distinction is made.

The fuzzy operations can be implemented using the standard GIS overlay functions (Eastman, 1997). For a set of categorical map layers, the intersection (MIN) and the

Table 1. Class intervals for criterion maps

Minimization criterion	Maximization criterion
$0< x_{*j}^{(c1)} \leqslant x_{*j}^{(c)} \rightarrow S_7$ Outstanding (OU)	$6x_{*j}^{(c6)} < x_{*j}^{(c7)} \leqslant 7x_{*j}^{(c6)} \rightarrow S_7$ Outstanding (OU)
$x_{*j}^{(c1)} < x_{*j}^{(c2)} \leqslant 2x_{*j}^{(c1)} \rightarrow S_6$ Very High (VH)	$5x_{*j}^{(c5)} < x_{*j}^{(c6)} \leqslant 6x_{*j}^{(c5)} \rightarrow S_6$ Very High (VH)
$2x_{*j}^{(c2)} < x_{*j}^{(c3)} \leqslant 3x_{*j}^{(c2)} \rightarrow S_5$ High (H)	$4x_{*j}^{(c4)} < x_{*j}^{(c5)} \leqslant 5x_{*j}^{(c4)} \rightarrow S_5$ High (H)
$3x_{*j}^{(c3)} < x_{*j}^{(c4)} \leqslant 4x_{*j}^{(c3)} \rightarrow S_4$ Medium (M)	$3x_{*j}^{(c3)} < x_{*j}^{(c4)} \leqslant 4x_{*j}^{(c3)} \rightarrow S_4$ Medium (M)
$4x_{*j}^{(c4)} < x_{*j}^{(c5)} \leqslant 5x_{*j}^{(c4)} \rightarrow S_3$ Low (L)	$2x_{*j}^{(c2)} < x_{*j}^{(c3)} \leqslant 3x_{*j}^{(c2)} \rightarrow S_3$ Low (L)
$5x_{*j}^{(c5)} < x_{*j}^{(c6)} \leqslant 6x_{*j}^{(c5)} \rightarrow S_2$ Very Low (VL)	$x_{*j}^{(c1)} < x_{*j}^{(c2)} \leqslant 2x_{*j}^{(c1)} \rightarrow S_2$ Very Low (VL)
$6x_{*j}^{(c6)} < x_{*j}^{(c7)} \leqslant 7x_{*j}^{(c6)} \rightarrow S_1$ Negligible (N)	$0< x_{*j}^{(c1)} < x_{*j}^{(c)} \rightarrow S_1$ Negligible (N)

Note: $x_{*j}^{(c1)}, x_{*j}^{(c2)}, \ldots, x_{*j}^{(c7)}$ are the attribute values on the jth criterion map that belongs to the S_1, $S_2, \ldots, S_7$ classes, respectively.

union (MAX) are generated by using the overlay minimum and maximum operations, respectively. The GIS-based procedure for screening involves the following steps.

(i) Determine the category for criterion map layers on the basis of the seven-point scale. This procedure requires a value judgment if a categorical map is being converted to the seven-category ordinal criterion map; for example, a land category on a cover map such as residential, commercial, recreational, agricultural land, etc. should be ordered according to the scale S (of course, the ordering depends on a particular decision situation).

To convert a quantitative scale map to the seven-category map, let $x_{*j}^{(c)}$ be the class interval for the jth criterion map. The interval is defined as follows:

$$x_{*j}^{(c)} = x_{*j}^{\max}/q \tag{9}$$

where $x_{*j}^{\max}$ is the maximum value of the jth attribute, and $q = 7$ is the highest value on the S scale. Given the class interval, a criterion map can be converted to the categorical map using the seven-point ordinal scale S. Table 1 gives the class intervals for minimization and maximization criterion maps.

(ii) For each attribute, generate a new layer of data where each cell is assigned a value of 7, 6, 5, 4, 3, 2, or 1 on the basis of the scale; that is, the cells containing the Outstanding (OU) label are assigned the value of 7, the cells characterized by the Very High (VH) label are assigned 6, etc.

(iii) Assign a measure of importance to each of the attributes under consideration.

(iv) Create a map layer for each attribute where each cell contains the negation of the measure of importance defined in step (iii).

(v) Overlay each attribute layer (created in step (ii)) and the corresponding importance measure layer (step (iv)) using the MAX operation (this results in n map layers).

(vi) Overlay the n layers using the MIN operation (this results in a single layer containing a minimum value for each cell).

(vii) Specify the minimum acceptable overall value, S_*, and create a map layer where each cell contains the minimum value.

(viii) Subtract the layer created in step (vii) from that obtained in step (vi).

(ix) Assign a value of 1 to all values greater than or equal to 0, and 0 otherwise (the resulting map layer displays the cells that meet the screening rule (8) requirement; it indicates the areas where the attribute values are greater than or equal to the specified overall acceptable value of S_*).

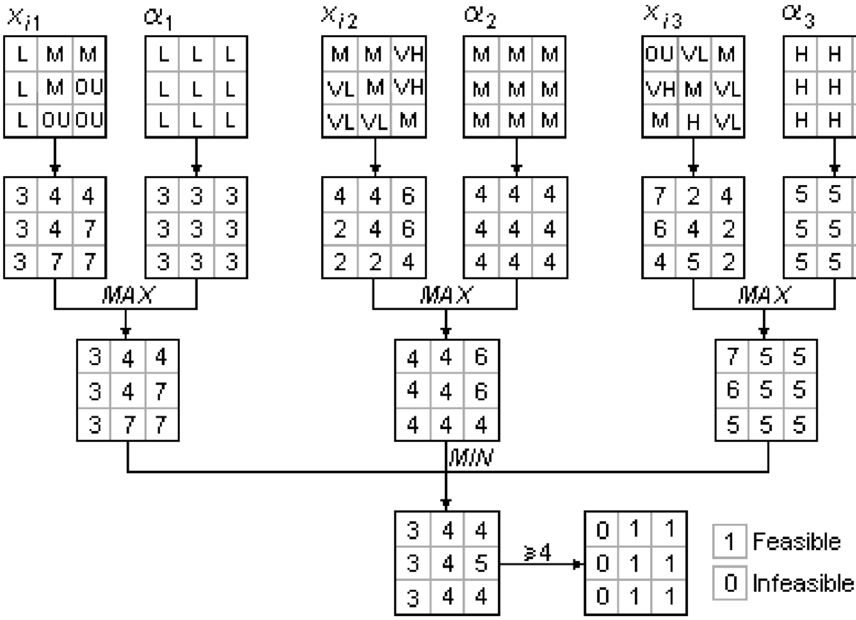

Figure 2. Fuzzy screening procedure: an illustrative example. Note: x_{i1}, x_{i2}, x_{i3} are the assessments for the ith cell and the slope, accessibility, and view criterion, respectively; α_1, α_2, and α_3 are the measurements of importance for the three criteria.

Illustrative Example

The GIS-based procedure for the fuzzy screening will be illustrated by considering a situation in which a developer must evaluate available parcels of land for a future housing development. The situation involves nine parcels of land and three evaluation criteria (slope, accessibility to a major street, and aesthetics view). The developer has conducted a field survey of the area and evaluated each parcel with respect to the three criteria in terms of its suitability for a housing development. The results of the survey are shown in Figure 2 (see the criterion map layers x_{i1}—slope, x_{i2}—accessibility and x_{i3}—aesthetics). Each cell of the input layers is assigned a value of 7, 6, 5, 4, 3, 2, or 1 according to the scale discussed earlier; that is, the cells containing the Outstanding (OU) label are assigned the value of 7, the cells with the Very High (VH) label are assigned 6, etc. In addition, the measures of importance of the three attributes have been specified as follows: $\alpha_1 = H$, $\alpha_2 = M$, and $\alpha_3 = L$. Given these measures, the $Neg(\alpha_j)$ operation is applied to obtain the $Neg(\alpha_1) = L = 3$, $Neg(\alpha_2) = M = 4$, and $Neg(\alpha_3) = H = 5$. Then, each pair of layers (the attribute layer and the corresponding importance measure layer) is combined using the MAX operation. The three resultant map layers are overlaid using the MIN operation on a cell-by-cell basis. This results in a single layer containing a minimum value in each cell. Given this layer and the specified minimum acceptable overall value, $S_* = 4$ (that is, $S_* = M$ (Medium)), a new layer is created by assigning the value of 1 to those cells that contain values greater than or equal to 4, and 0 is assigned otherwise. Notice that three cells do not meet the requirement of medium performance. The essential reason for the low performance of these cells is that they perform low on the slope attribute, which is the most important evaluation criterion.

Case Study: Screening for Industrial Site in the Villa Union Region, Mexico

The GIS-based fuzzy screening method has been implemented in a real-world situation involving industrial land development in the Villa Union region of the Sinealoa province on the Pacific coast of Mexico. A group of municipal government officials (decision-makers) was involved in the screening process, providing information on the evaluation criteria and preferences with respect to the importance of the criteria. In order to identify the most suitable industrial land development, the group identified the following criteria: proximity to rivers (x_{i1}), proximity to major roads (x_{i2}), distance from wetlands (x_{i3}), and cost of land acquisition (x_{i4}). The x_{i1}, x_{i2}, and x_{i4} criteria are to be minimized; that is, the lower the cost the better; the closer the area to major roads, and river, the better. The distance-to-wetland is a maximization criterion that requires the area for industrial development be located away from wetlands. It is important to note that the process of selection of the set of evaluation criteria was constrained by the availability and cost of acquiring data suitable for storing in GIS. To this end, the group agreed the study should be based on remote sensing data. Consequently, the base map of the study area was derived from LANDSAT TM Satellite image dated 1993. The image covers 500 km^2 (20 by 25 km) of land (each cell of the image covers 625 m^2 (25 by 25 m). It contains 800 000 cells and each cell is considered an alternative to be classified according to its suitability for industrial land development.

An unsupervised clustering using a *k*-means (minimum distance) classifier on Bands 3, 4, and 5 of the remote sensing image was applied to create the thematic map (Figure 3). The procedure was performed using EASI/PACE Image Analysis System (PCI, 1998). The infrastructure elements (city, airport, and major roads) were manually digitized using ancillary data and applied to the classified image using IDRISI (Eastman, 1997). The four criterion maps were derived from the base map using the proximity and reclassification operations (Figure 4). In addition, the fuzzy

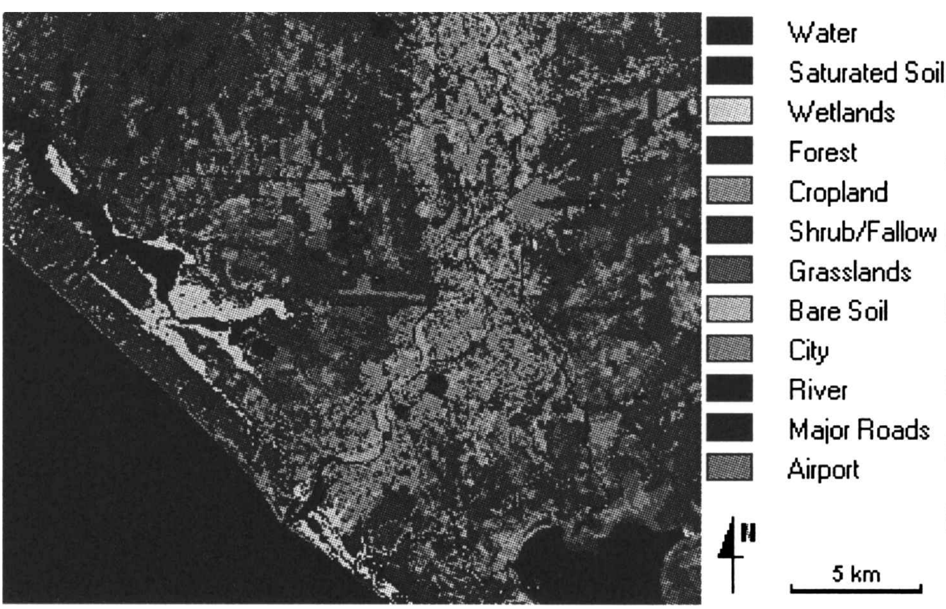

Figure 3. Base map: the Villa Union region, Mexico.

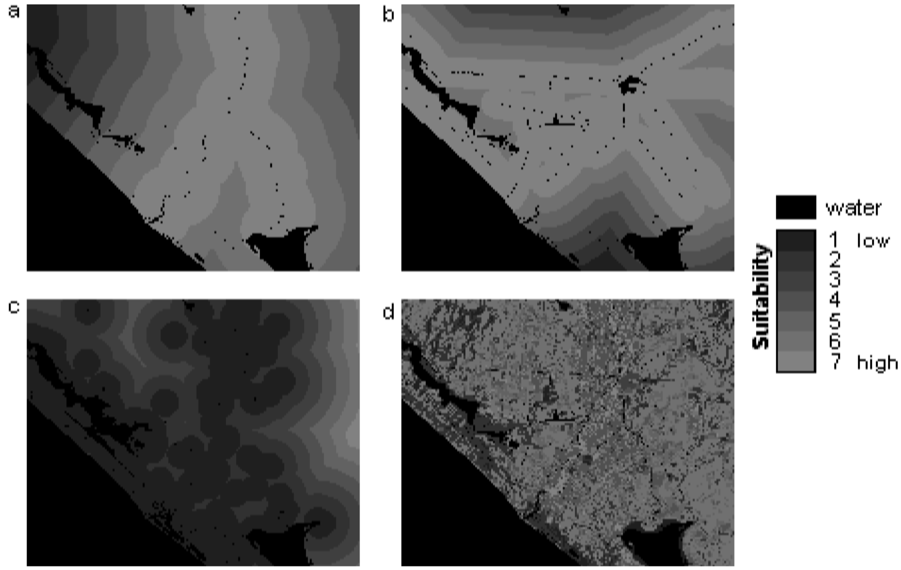

Figure 4. Suitability maps for: (a) proximity-to-river criterion, (b) proximity-to-road criterion, (c) distance-from-wetland criterion, and (d) cost of land acquisition.

screening method requires the decision-maker to provide information with respect to the levels of attributes for each of the four evaluation criteria using the S scale. Specifically, for a given criterion map, a new layer of data was generated by assigning a value of 7, 6, 5, 4, 3, 2, or 1 to each cell (see steps (i) and (ii) of the GIS-based fuzzy screening procedure and Table 1). The cells containing the value of 7 are the most suitable and the value of 1 indicates the lowest suitability for industrial land development (see Figure 4).

The decision-makers also specified the measure of importance of the *j*th attribute, $\alpha_1 = H$, $\alpha_2 = M$, $\alpha_3 = L$, and $\alpha_4 = H$, and the minimum acceptable overall value, $S_* = H$ (High). Given the categorical criterion maps, measures of criterion importance, and the minimum acceptable overall value the procedure outlined in the previous section was performed. Specifically, each pair of layers (the attribute layer and the corresponding importance measure layer) is combined using the *MAX* operation. The resultant map layers are overlaid using the *MIN* operation on a cell-by-cell basis. The output is a single map layer containing a minimum value in each cell. Given this layer and the specified minimum acceptable overall value, $S_* = 5$ (that is, $S_* = H$ (High)), a new layer is created by assigning the value of 1 to those cells that contain values equal or greater than 5, and 0 is assigned otherwise. Figure 5 shows the output map layer. The map indicates the most suitable areas for industrial land development. The suitable lands account for 3.4% (27 449 cells or 17.8 km^2) of the region.

Comparisons of the overall suitability map (Figure 5) with the individual suitability maps (Figure 4) reveal that the shape of the two suitable areas reflects the high suitability of these areas with respect to the environmental criterion (that is, the distance from wetlands) as well as moderate suitability with respect to proximity-to-rivers. In addition, the overall suitability contains land of low acquisition cost

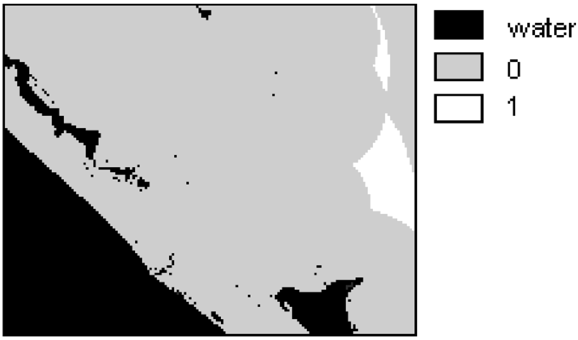

Figure 5. Land suitability for industrial development in the Villa Union region, Mexico.

(mainly, land categorized as shrub/fallow, bare soil and grasslands). These results reflect the high importance attached to the cost and proximity-to-wetlands criteria and moderate importance assigned to the proximity-to-river criterion. Since the proximity-to-road criterion was assigned low importance, it is not reflected in the shape of the two suitable areas for industrial land development. It is important to notice, however, that the suitable areas are located within the outstanding, very high and high categories for accessibility to roads.

Conclusions

The GIS-based exclusionary screening procedures conventionally used in conjunction with the land suitability analysis are of binary nature. They assume exact (crisp) input data that can be modeled by means of numerical variables and constraints. One possible way of diminishing the required amount of precision by conventional screening methods is to use linguistic variables instead of numerical values. The approach presented in this paper involves operations on linguistic variables. It requires only a qualitative scale (ordered linguistic terms) for the evaluation of alternatives with respect to a number of attributes. Both the cut-off values and the relative importance of attributes are specified as linguistic labels. Then, the symbolic approach is used to aggregate the qualitative information. The significance of the aggregation (screening) rule is that it incorporates the negation operation to transform the measure of importance. The negation operation acts as a cut-off value. Thus, unlike the conventional methods, the fuzzy screening rule contains a mechanism for dealing with the decision-maker preferences in conjunction with the cut-off values.

The fuzzy approach provides us with a meaningful representation of vague or imprecise concepts involved in defining the cut-off values and the relative importance of screening criteria. The decision-maker is no longer compelled to specify exactly the required cut-offs and his/her preferences with respect to screening criteria. If a screening problem involves a set of mixed data, quantitative data can be easily converted to the ordered linguistic terms, and the symbolic procedure can be used to aggregate the mixed data. Thus, the method provides us with a flexible framework for aggregating both qualitative and quantitative information. Notice that converting a quantitative variable to qualitative data loses much of the information in the original data. Therefore, the converting should be performed only in the case of imprecise and ambiguous information on the cut-off values and relative importance of screening criteria. The decision regarding the use of the fuzzy screening approach should be based on a careful examination of the balance between the loss of information and the advantages of the symbolic aggregation.

Another advantage of the method is that it can be performed using the standard overlay operations available in any GIS system. This implies that the symbolic (qualitative) approaches can be considered as a part of generic operations in GIS. To this end, it is important to emphasize that in the symbolic method the linguistic values are labels, which are represented as numerical scores for GIS operations. The resulting land suitability map also contains the labels (scores) measured on the same qualitative scale as the input data. Thus, the method provides a consistent way of interpreting the results in the context of the input data.

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