

# Chapter 2

## Introduction to GIS-MCDA

### 2.1 Introduction

A number of approaches for defining decision problems have been suggested in the MCDA literature (e.g., Keeney 1992; Chankong and Haimes 1983). At the most rudimentary level, a multicriteria decision problem involves a set of alternatives that are evaluated on the basis of conflicting and incommensurate criteria according to the decision maker's preferences. There are three key terms in this definition that are the main elements of any multicriteria decision problem: decision maker(s), alternatives, and criteria (Zarghami and Szidarovszky 2011).

The procedures for tackling spatial multicriteria problems involve three main concepts: value scaling (or standardization), criterion weighting, and combination (decision) rule (Eastman et al. 1993; Thill 1999; Malczewski 1999, 2006; Greene et al. 2011). These are fundamental concepts for MCDA in general and GIS-MCDA in particular. They can be considered as the building blocks of spatial decision support procedures.

### 2.2 Elements of MCDA

#### 2.2.1 Decision Makers

Decision maker is an entity with the responsibility to make decisions. It can be an individual (e.g., searching for a house or an apartment), a group of individuals (e.g., selecting a suitable site for housing development), or an organization (e.g., allocating resources for housing development). Many spatial decisions are made by groups (multiple decision makers) rather than an individual decision maker. The degree of consensus can be considered a major determinant of the nature of the decision making process (Massam 1993). Consequently, the distinction between

individual and multiple decision makers rests less on the number of individuals involved than on the consistency of the group's goals, preferences, and beliefs (Hwang and Lin 1987). If there is a single goal-preference-belief structure, then one is dealing with individual decision making, regardless of the number of individuals actually involved. On the other hand, if any of these components varies among the individuals constituting the decision making group, then we are coping with group decision making.

### 2.2.1.1 Interest Groups

Quite often, spatial decision making problems involve a number of interest groups. Massam (1988) suggests that the concept of interest group, rather than decision maker, should be used as a generic component of multicriteria decision problems. An interest group is an entity with an interest or stake in a decision concern. Interest groups can be of different form, size, and capacity. They can be individuals, organizations, or unorganized groups. One can distinguish three types of interest group: (i) the proponents of a particular plan (decision), (ii) those whose lives will be affected by the actions of the proponents, and (iii) those who have the legitimate responsibility for mediation, arbitration, or sanctioning the actions of the proponents or opponents (Massam 1988). These three types of interest group may be involved in assessing decision alternatives with respect to a set of evaluation criteria.

### 2.2.1.2 Decision Making Agents

While the conventional decision analysis focuses on the human decision maker, recent approaches to computer-based modeling provide a broader description of decision maker to include the concept of decision making agent (Parker et al. 2003; Sengupta and Bennett 2003). An agent is a computer program characterized by such properties as: autonomy (i.e., the capability of taking independent action), reactivity (i.e., the capability of sensing and reacting to its environment and other agents), and rationality (i.e., the capability of acting rationally to solve a problem at hand (Woolridge and Jennings 1995; Sengupta and Bennett 2003; O'Sullivan and Unwin 2010). Further, humanistic characteristics such as preferences, beliefs, and opinions can be a part of agent behaviour. These characteristics make it possible to represent human decision makers as agents acting in a simulated real-world environment.

Intelligent agents designed specifically for using geographic data and tackling spatial problems are referred to as geospatial agents. Sengupta and Sieber (2007) provide a comprehensive overview of geospatial agents and identify two general uses of the term in GIScience. First, the term is used in the context of modeling an individual's action in a social world. Second, the agents are autonomous software designed for supporting interaction among software components to provide assistance to users. Both perspectives are relevant for GIS-based multicriteria decision modeling (Manson 2005; Li and Liu 2007; Sengupta and Bennett 2003; Bone et al. 2011).

### 2.2.2 *Criteria*

Decision alternatives are evaluated on the basis of a set of criteria, which include attributes and objectives. Both individual criterion and a set of criteria should possess some properties to adequately represent the multicriteria nature of the decision situation (Keeney 1992). Each criterion must be comprehensive and measurable. A set of criteria should be complete (it should cover all aspects of a decision problem), operational (the criteria can be meaningfully used in the analysis), decomposable (the set of criteria can be broken into parts to simplify the process), non-redundant (to avoid the problem of double counting), and minimal (the number of criteria should be kept as small as possible).

A criterion can be spatially explicit or implicit (van Herwijnen and Rietveld 1999; Malczewski 2006; Chakhar and Mousseau 2008). Spatially explicit criteria involve spatial characteristics of decision alternatives. For example, in the context of a site search problem, site characteristics such as size, shape, contiguity, and compactness are spatially explicit criteria (Brookes 1997; Church et al. 2003). Alternatively, many decision problems involve criteria which are spatially implicit (van Herwijnen and Rietveld 1999). A criterion is said to be spatially implicit if spatial data are needed to compute the level of achievement of that criterion. Criteria such as the gross marginal return of agricultural production, equity of income distribution, public investment in the conservation reserve program, and the costs of solid waste disposing can involve spatial attributes such as distance, proximity, accessibility, elevation, and slope (MacDonald 1996; Antoine et al. 1997).

#### 2.2.2.1 **Objectives and Attributes**

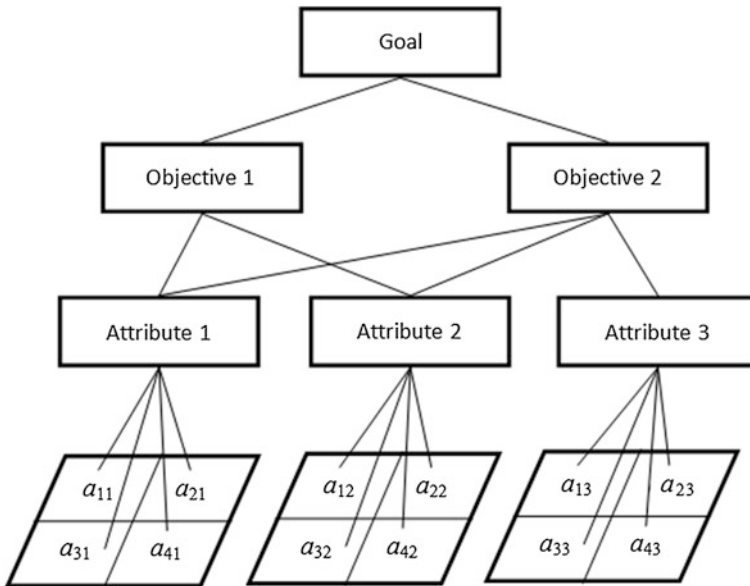
A criterion is a generic term including both the concept of objective and attribute (Malczewski 1999). An objective is a statement about the desired state of a system under consideration (e.g., a spatial pattern of accessibility to primary schools). It indicates the directions of improvement of one or more attributes. The statement about desired directions of improvement can be interpreted as either ‘the more of the attribute, the better’ or ‘the less of the attribute, the better’. This implies a maximization or minimization of an objective function. Thus, the concept of an objective is made operational by assigning to each objective at least one attribute which directly or indirectly measures the level of an achievement of the objective.

An attribute can be described as a property of an element of a real-world geographic system (e.g., transportation system, location-allocation system, or land use pattern). More specifically, an attribute is a measurable quantity or quality of a geographic entity or a relationship between geographic entities. For example, the objective of maximizing physical accessibility to central facilities such as schools, health care clinics, hospitals, or administrative centers can be operationalized by attributes such as total traveling distance, time, cost, or any other measure of spatial proximity.

### 2.2.2.2 Hierarchical Structure

The relationships between objectives and attributes have a hierarchical structure. The most general objectives are at the highest level. These general objectives may be defined in terms of more specific objectives, which are defined at lower levels. At the lowest level of the hierarchy are attributes, which are quantifiable indicators of the extent to which associated objectives are realized (Saaty 1980). The concept of hierarchical structure of criteria underlies a value-focused approach for structuring multicriteria decision problems (Keeney 1992). The approach uses the values (evaluation criteria) as the fundamental element of the decision analysis. It involves specifying criteria to evaluate a set of alternatives. Figure 2.1 shows an example of hierarchical structure of the main elements of decision problem. The top level of the hierarchical structure is the ultimate goal (or overall objective) of the decision at hand (e.g., the goal is to identify the best spatial pattern of land uses, to select the best site for a nuclear power station, to find the shortest transportation route). The hierarchy then descends from the general to the more specific until a level of attributes is reached. This is the level against which the decision alternatives of the lowest level of the hierarchy are evaluated. Each level is linked to the next-higher level.

Typically, the hierarchical structure consists of four levels: goal, objectives, attributes, and alternatives (see Fig. 2.1). However, a variety of elements relevant to a particular decision situation and different combination of these elements can be



**Fig. 2.1** Hierarchical structure of decision problem;  $a_{ik}$  is the value of the  $k$ -th attribute (criterion) associated with the  $i$ -th alternative ( $k = 1, 2, 3$ , and  $i = 1, 2, 3, 4$ )

used to represent the decision problem. For example, the following combinations of decision elements can be incorporated in the hierarchical structure:

- goal, objectives, sub-objectives, attributes, alternatives;
- goal, scenarios, objectives, attributes, alternatives;
- goal, interests groups (agents), objectives, attributes, alternatives;
- goal, interest groups, objectives, attributes, alternatives.

There have been a number of studies demonstrating the process of hierarchical structuring of spatial decision problems using the concept of analytic hierarchy process (Saaty 1980) in GIS-MCDA (Bojórquez-Tapia et al. 2001; Giupponi et al. 2004; Johnson 2005; Rinner and Taranu 2006). The concept of hierarchical structure of evaluation criteria has been implemented in several systems including CommonGIS (Rinner and Taranu 2006) and Integrated Land and Water Information System (ILWIS) (Sharifi et al. 2004).

### 2.2.3 *Decision Alternatives*

Decision alternatives can be defined as alternative courses of action among which the decision maker (agent) must choose. A geographic decision alternative consists of at least two elements: action (what to do?) and location (where to do it?) (Malczewski 1999; Chakhar and Mousseau 2008). The spatial components of a decision alternative can be specified explicitly or implicitly (Malczewski 2006). Examples of explicitly spatial alternatives include: alternative sites for locating facilities (Kao and Lin 1996; Li and Yeh 2005), alternative location-allocation patterns (e.g. Armstrong et al. 1992; Cova and Church 2000; Malczewski et al. 1997), and alternative patterns of land use-suitability (e.g. Eastman et al. 1995; Antoine et al. 1997; Brookes 1997; Bennett et al. 1999). In many decision situations the spatial component of an alternative decision is not explicitly present. However, there may be spatial implications associated with implementing an alternative decision. In such a case, the alternative is referred to as an implicitly spatial alternative (van Herwijnen and Rietveld 1999). Spatially distributed impacts can emerge, for example, through the implementation of a particular solution to minimize flood risks in which favorable impacts are produced at one location while negative consequences result at another (e.g., Vertinsky et al. 1994; Tkach and Simonovic 1997; Jumppanen et al. 2003).

The methods for defining spatial alternatives depend on the GIS data models (Malczewski 1999). In the case of raster data models, a decision alternative is often defined as a single raster of specified size or a combination of rasters. For vector data analysis, a decision alternative can be defined by a single object (point, line, or polygon) representing a geographic entity (e.g., town, highway, or region) or a combination of objects (e.g., a combination of lines and points to represent an alternative pathway between two locations).

An alternative is completely specified by defining the values of the decision variables. A variable is a measurable quantity which has a definite value at every instance. Decision variables can be classified into three categories: binary, discrete, and continuous. The simplest decision involves taking a course of action or doing nothing - the yes/no decision. This type of decision is defined by a zero-one or binary variable. Binary variables are a special case of discrete variables. A discrete variable may take on any of a finite number of values. When a gap exists between two specified values of a variable, it is called discrete. An example of a discrete variable is the number of patrons at a shopping mall. The variable is restricted to integer values. A continuous variable has an infinite number of possible values, all lying within a specified range. An example of a continuous variable is a decision variable representing facility size where any number of square feet between a minimum and maximum size may be selected. Similarly, if the monetary resources are allocated to different spatial units, there is no need to restrict them to integer values.

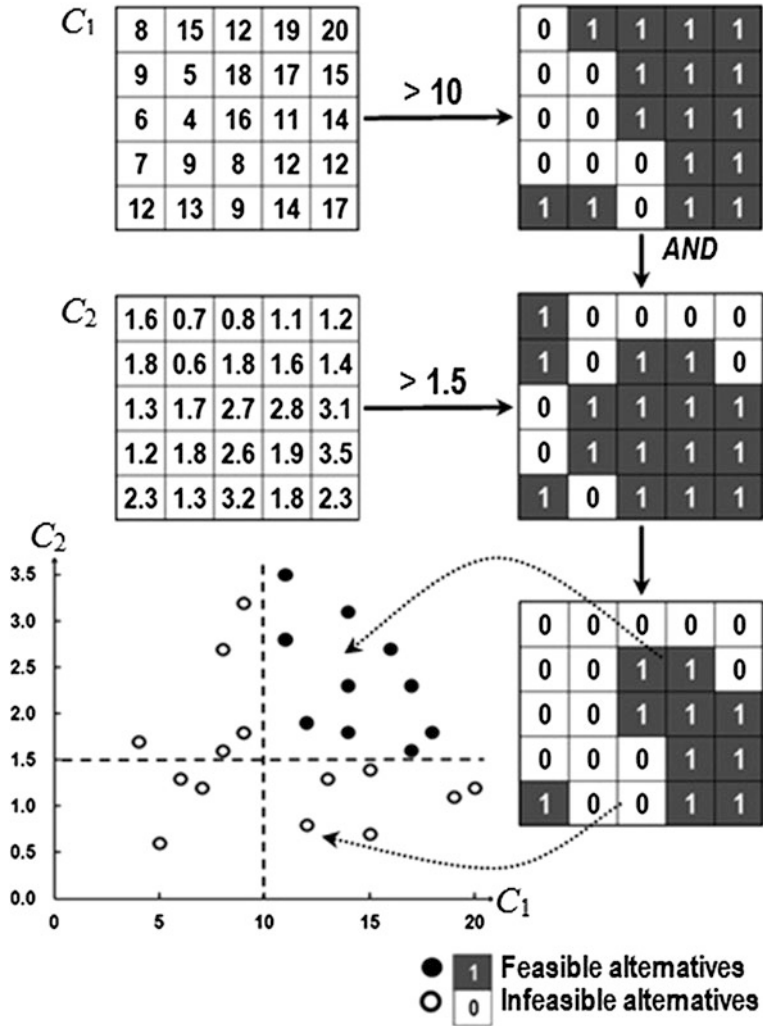
### 2.2.3.1 Feasible Alternatives

Constraints represent restrictions imposed on the decision variables (alternatives). They dichotomize a set of decision alternatives into two categories: acceptable (feasible) and unacceptable (infeasible). From the GIS perspective, the constraints eliminate geographic objects characterized by certain attributes and/or certain values of attributes from consideration. An alternative is feasible if it satisfies all constraints; otherwise, it is referred to as an infeasible (or unacceptable) alternative. The concept of Boolean (or logical) constraints is the most often used approach for identifying set of feasible alternatives in the GIS-based multicriteria procedures (Eastman et al. 1993; Malczewski 1999; Heywood et al. 2006). For example, in the context of the problem of landfill facility location, one may require that ‘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.

Figure 2.2 shows an example of two raster map layers (criterion maps  $C_1$  and  $C_2$ ) and a set of feasible decision alternatives (rasters) identified on the basis of the following constraints:  $C_1 > 10$  and  $C_2 > 1.5$ . The criterion maps are converted to 0–1 maps based on the constraints and then the Boolean *AND* operation is used to combine the maps. According to the operation, a feasible alternative must have criterion values greater than the constraints. The resulting map differentiates between feasible and infeasible alternatives.

### 2.2.3.2 Non-dominated Alternatives

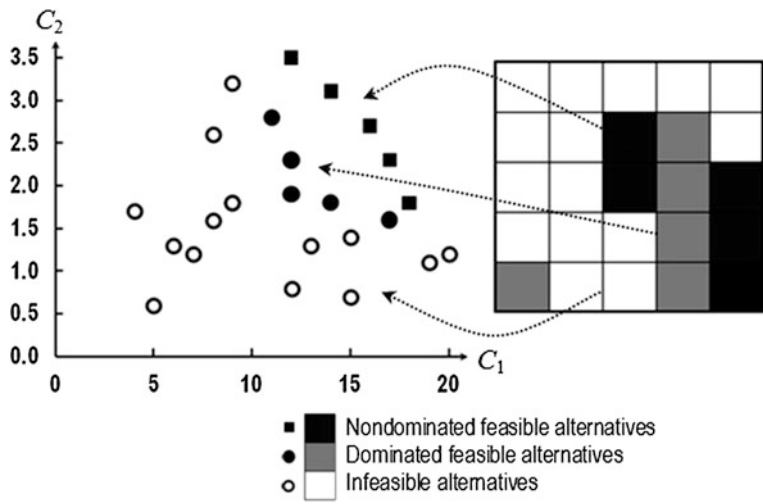
The set of feasible alternatives can be subdivided into two categories: dominated and non-dominated. This distinction is based on the Pareto optimality or efficiency principle (Cohon 1978; Goicoechea et al. 1982; Huang et al. 2008). According to



**Fig. 2.2** Feasible and infeasible decision alternatives for two criteria:  $C_1$  and  $C_2$ , and constraints  $C_1 > 10$  and  $C_2 > 1.5$

the principle: if an alternative  $A$  is at least as desirable as alternative  $B$  on all criteria and more desirable on at least one criterion, then alternative  $B$  is dominated by  $A$ . This implies that for a non-dominated solution, an increase in the value of one of the criteria under consideration is not possible without some decrease in the value of at least one other criterion. The non-dominated alternative is also referred to as the efficient or non-inferior alternative.

Figure 2.3 shows three sets of alternatives: non-dominated and dominated feasible alternatives, and infeasible alternatives for the two criterion maps shown in



**Fig. 2.3** Non-dominated, feasible and infeasible decision alternatives for two maximization criteria:  $C_1$  and  $C_2$  (see Fig. 2.2)

Fig. 2.2. Out of the 25 alternatives (rasters), only 5 are non-dominated. For example, the raster containing values of 20 and 1.2 for  $C_1$  and  $C_2$ , respectively, is a non-dominated alternative. However, it is also an infeasible alternative because it does not meet the constraint for the second criterion:  $C_2 > 1.5$ . The search for the best solution to a spatial multicriteria problem should focus on the set of non-dominated feasible alternatives.

**2.2.4 Decision Matrix**

The elements of MCDA can be organized in a tabular format (Table 2.1). The table is referred to as a decision matrix. The rows of the matrix represent the alternatives (e.g., geographic entities). Each alternative is described by its locational data and attribute data or evaluation criteria. Each attribute accounts for a column in the decision matrix. Formally, matrix  $A$  is a  $(m \times n)$  decision matrix in which element,  $a_{ik}$ , indicates the performance of alternative,  $A_i$ , when it is evaluated in terms of criterion  $C_k$ , ( $i = 1, 2, \dots, m$ , and  $k = 1, 2, \dots, n$ ). The location of the  $i$ -th alternative is defined implicitly or explicitly. For conventional (aspatial) MCDA, the location of a decision alternative is given implicitly (see Sect. 1.4.1). In the case of spatially explicit MCDA (see Sect. 1.4.2), the location of the  $i$ -th alternative,  $s_i$ , is defined by the  $(x_i, y_i)$  coordinates (for the sake of simplicity, a single subscript,  $i$ , is used to indicate the  $i$ -th location). It is also assumed that the decision maker's preferences are defined in terms of the criterion weights (denoted as  $w_k$ , for  $k = 1, 2, \dots, n$ ). Typically, it is assumed the spatial preferences are spatially homogeneous;



**Table 2.1** Decision matrix

	Criterion/attribute, $C_k$					Coordinates	
Alternative, $A_i$	$C_1$	$C_2$	$C_3$	...	$C_n$	$X$	$Y$
$A_1$	$a_{11}$	$a_{12}$	$a_{13}$	...	$a_{1n}$	$x_1$	$y_1$
$A_2$	$a_{21}$	$a_{22}$	$a_{23}$	...	$a_{2n}$	$x_2$	$y_2$
$A_3$	$a_{31}$	$a_{32}$	$a_{33}$	...	$a_{3n}$	$x_3$	$y_3$
...	...	...	...	...	...	...	...
$A_m$	$a_{m1}$	$a_{m2}$	$a_{m3}$	...	$a_{mn}$	$x_m$	$y_m$
Weight, $w_k$	$w_1$	$w_2$	$w_3$	...	$w_n$	$w_{ik}$	

consequently, a single weight,  $w_k$ , is assigned to the  $k$ -th criterion. For the spatially explicit MCDA, the value of criterion weight may vary from one location to another; consequently, the criterion weight,  $w_{ik}$ , depend on the location of the  $i$ -th alternative defined in terms of the  $(x_i, y_i)$  coordinates.

The input data for group decision-making can also be organized using the concept of decision matrix. Given an agent (decision maker, planner, expert, stakeholder),  $DM_g$  ( $g = 1, 2, \dots, z$ ), the input data consist of a series of decision matrices, each representing the  $g$ -th agent (see Sect. 8.1). The individual decision matrices can then be used to obtain a set of individual preference profiles (see Chap. 8).

## 2.3 Basic Concepts

### 2.3.1 Value Scaling

The MCDA methods require transforming the evaluation criteria to comparable units. The procedures for transforming raw data to comparable units are referred to as the value scaling or standardization methods. There is a number of methods for standardizing raw data (Hwang and Yoon 1981; Voogd 1983; Massam 1988). The score range procedure is the most popular GIS-based method for standardizing evaluation criteria (Malczewski 2006). This procedure is a special case of a more general approach for value scaling: the value/utility function method (Keeney 1992; Beinat 1997; Malczewski 1999). Conventional MCDA methods assume spatial homogeneity of preferences with respect to different levels of criterion values. Consequently, a single (global) value function is used for converting the raw criterion values to standardize form. In many situations, the preferences are spatial variable. A local form of value function can be developed to take into account the spatial varying preferences.

### 2.3.1.1 Value Function

The value function is a mathematical representation of human judgment (Keeney 1992; Beinath 1997). It relates possible decision outcomes (criterion or attribute values) to a scale which reflects the decision maker's preferences. If  $a_{ik}$  is the level of the  $k$ -th criterion ( $k = 1, 2, \dots, n$ ) for the  $i$ -th alternative ( $i = 1, 2, \dots, m$ ), then the value function,  $v(a_{ik})$ , is the worth or desirability of that alternative with respect to that criterion. Formally, for the  $k$ -th criterion (attribute) map, the value function approach transforms the raw criterion values,  $a_{1k}, a_{2k}, \dots, a_{mk}$ , into standardized scores (values),  $v(a_{ik})$ , as follows:

$$v(a_{ik}) = \left( \frac{\max_i \{a_{ik}\} - a_{ik}}{r_k} \right)^\rho, \quad (2.1)$$

for the  $k$ -th criterion to be minimized;

$$v(a_{ik}) = \left( \frac{a_{ik} - \min_i \{a_{ik}\}}{r_k} \right)^\rho, \quad (2.2)$$

for the  $k$ -th criterion to be maximized;

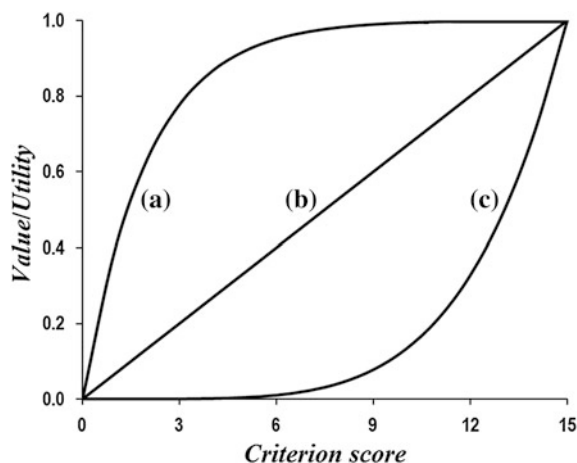
where  $\rho > 0$  is a parameter;  $\min_i a_{ik}$  and  $\max_i a_{ik}$  are the minimum and maximum criterion values for the  $k$ -th criterion, respectively; and

$$r_k = \max_i \{a_{ik}\} - \min_i \{a_{ik}\} \quad (2.3)$$

is the range of the  $k$ -th criterion. The standardized score values,  $v(a_{ik})$ , range from 0 to 1; 0 is the value of the least-desirable outcome and 1 is the most-desirable score. Since the range in Eq. 2.3 is defined for the whole study area, the  $r_k$  value is referred to as the global range (Malczewski 2011). Consequently,  $v_k(a_i)$  is the global value function.

The shape of the value function is determined by the decision maker's preferences. GIS-MCDA approaches typically assume that the value function has a linear shape (Malczewski 2000, 2006). The linear form of the value function (Eqs. 2.1 and 2.2) is obtained for  $\rho = 1$ . The linear form of the value function is the score range procedure (Voogd 1983; Massam 1988). For  $0 < \rho < 1$ , a concave value function is generated. If  $\rho > 1$ , then a convex value function is obtained. Note that the concave and convex curves obtained by selecting appropriate values of  $\rho$  are asymmetrical around the linear form; for example, the value functions for  $\rho = 0.2$  (concave curve) and  $\rho = 2$  (convex curve) are asymmetric. In order to obtain a symmetrical set of functions for  $\rho > 1$  and  $0 < \rho < 1$ , one can subtract  $v(a_{ik})$  from 1 to generate standardized values for a criterion to be maximized using Eq. 2.1. Similarly, subtracting the values of  $v(a_{ik})$  from 1 in Eq. 2.2, one can obtain standardized values for

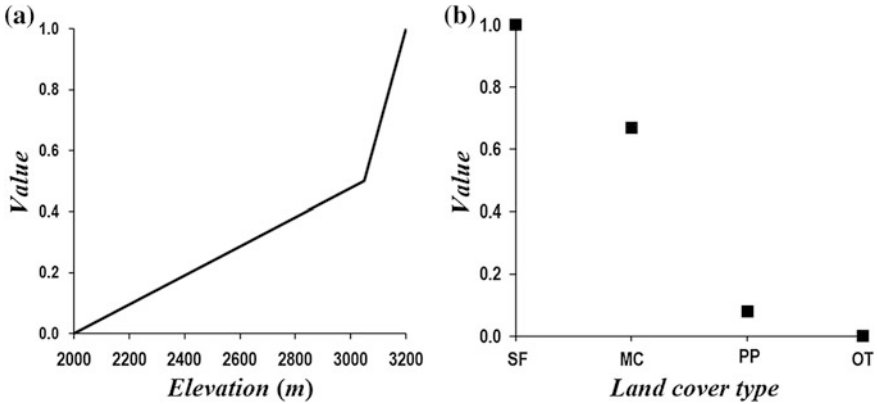
**Fig. 2.4** Value/utility function prototypes: **a** risk-aversion; **b** risk-neutrality; and **c** risk affinity



a criterion to be minimized. Figure 2.4 shows an example of symmetric concave and convex value functions.

The value function can be generalized by interpreting the  $\rho$  parameter from the perspective of behavioural decision analysis as a risk factor (Bodily 1985; Ligmann-Zielinska 2009). The  $\rho$  parameter represents the decision maker's perception of risk associated with a decision outcome. By incorporating risk factor (the decision maker's attitudes toward risk) into the process of converting the raw data into standardized values, one can interpret those values as the utility scores (or utilities). The concave utility function represents a risk-aversion (or risk-avoiding) strategy (see Fig. 2.4). It describes a situation in which one avoids the risk regardless of the payoff. If the preference curve for a decision maker is linear, then he/she is indifferent toward risk or is risk neutral. The convex utility function represents a risk-affinity strategy. It describes a situation in which there is a willingness to take the risk regardless of the payoff.

In real-world applications of GIS-MCDA, the value function is often approximated by a piecewise linear form (Pereira and Duckstein 1993; Eastman 1997). Figure 2.5 gives a sample of expert-derived value functions for the red squirrel habitat suitability evaluation (Pereira and Duckstein 1993). The value function for the elevation criterion was generated by the mid-point value method (see Fig. 2.5a). The method determines the range over which the value curve is to be assessed (that is, the minimum and maximum value on the criterion map) and assign the value of 0.0 and 1.0 to these end points; that is, 2,000 and 3,200 m, respectively. Next, the decision maker (expert) identifies the mid-value point (that is, 3,050 m) between the end points and assigns the value of 0.5 to that point. If more than one mid-value point is required for generating the value function, then the procedure can be repeated to find the mid-values of 0.25 and 0.75, and subsequent values of 0.125, 0.375, 0.625, 0.875, etc. (for more detail, see Malczewski 1999). Pereira and Duckstein (1993)



**Fig. 2.5** Expert-derived value functions for the Mount Graham red squirrel habitat suitability evaluation; *SF* spruce-fir, *MC* mixed conifer, *PP* ponderosa pine, and *OT* others (Source Based on Pereira and Duckstein 1993, p. 415)

have generated the value function using MATS (Brown et al. 1986). A similar approach for defining value function can be found in IDRISI (Eastman 1997).

The value function for categorical data can be derived using the pairwise comparison method (see Sect. 2.3.2.2). Figure 2.5b shows the value function for the land cover criterion (Pereira and Duckstein 1993). Based on a series of pairwise comparisons of the categories of land cover, the values of 1.00, 0.67, 0.08, and 0.00 are assigned to the spruce-fir, mixed conifer, ponderosa pine, and other land cover categories, respectively. Technically, the standardized values are determined by normalizing the eigenvector associated with the maximum eigenvalue of the pairwise comparison matrix (Saaty 1980).

Jiang and Eastman (2000) suggest that the concept of fuzzy set membership (Zadeh 1965) provides a basis for developing a generalized value scaling approach in GIS-MCDA. This approach can be seen as one of recasting values into statements of set memberships. The concept has been implemented in the fuzzy module of IDRISI (Eastman 1997). The ‘FUZZY’ procedure assigns a value to a decision alternative (pixel) based on its membership in a fuzzy set. This procedure involves specifying a fuzzy set membership function, which can take one of the following forms: sigmoidal, J-shaped, linear, or user-defined function.

### 2.3.1.2 Local Value Function

The global value function does not take into account spatial heterogeneity of the preferences that are represented by the relationship between the criterion score,  $a_{ik}$ , and the worth of that score,  $v(a_{ik})$  (Malczewski 2011). The preferences are assumed to be homogeneous irrespectively of the local context and factors that may affect the level of worth associated with a particular criterion score. For instance, if different

locations (households) experienced the same amount of property damage during a flood (measured in \$), then the global value function would translate the cost into the same ‘worth’ irrespective of the characteristic of the locations, such as the household income, or property value. Given the contextual characteristics, the value function may vary from one residential neighbourhood to another (Tkach and Simonovic 1997). This spatial variation of the value function can be operationalized by the concept of the local range, which can be defined as follows:

$$r_k^q = \max_{iq} \{a_{ik}^q\} - \min_{iq} \{a_{ik}^q\}, \quad (2.4)$$

where  $\min_{iq} \{a_{ik}^q\}$  and  $\max_{iq} \{a_{ik}^q\}$  are the minimum and maximum values of the  $k$ -th criterion in the  $q$ -th subset ( $q = 1, 2, \dots, g$ ) of the locations,  $i = 1, 2, \dots, m$ ;  $m > q$ , respectively.

The subset of locations  $i \in q$  can be defined using one of the two methods. First, the study area can be subdivided into discrete units (neighbourhoods, zones, or regions). For example, the subset can be specified in terms of economic regions, urban neighbourhoods, land use zones, geomorphologic units, or watersheds. For the raster data, the subset can be defined in the context of the zonal overlay functions or the non-overlapping neighbourhoods (blocks). For the vector data model, the neighbourhood can be generated using a defined  $(x_{i \in q}, y_{i \in q})$  pair falling within a given polygon (neighbourhood, zone, or region).

Second, the subset of locations can be defined using the moving windows concept (Fotheringham et al. 2000; Lloyd 2010; O’Sullivan and Unwin 2010). In this case,  $q$  consists of a focal location (alternative) and locations in its vicinity. The  $i$ -th location  $(x_i, y_i)$  is the focal alternative and the set of neighbouring locations defined by the  $(x_j, y_j)$  coordinates. There are many methods for defining the shape and size of moving windows. For example, distance and shared boundary based methods can be used. Using the shared boundary method, the  $q$ -th neighbourhood can be defined as follows:  $j \in q$  if the  $i$ -th and  $j$ -th alternatives share a common boundary, and  $j \notin q$  otherwise. This method of defining a neighbourhood can involve the Rook’s or Queen’s criteria for identifying a common boundary between two areas. Although the first order contiguity is typically used, the second or higher order neighbourhoods can also be generated. This approach is operationalized in the raster GIS environment in terms of the overlapping neighbourhood (or focal) functions (McCoy and Johnston 2001). Alternatively, a distance-based method can be used. Given the distance,  $d_{ij}$ , between two locations,  $s_i$  and  $s_j$ , and some threshold distance,  $d$ , the neighbourhood (window),  $q$ , is defined as follows:  $j \in q$  if  $d_{ij} \leq d$ , and  $j \notin q$  otherwise. This approach can be used for raster and vector (polygon centroid) data. Given the distance threshold value, all points (representing polygons or rasters) within the threshold band are included into the neighbourhood. Also, the  $p$ -nearest neighbour method can be used to define a set of overlapping neighbourhoods.

Given the definition of the local range, the local value function  $v(a_{ik}^q)$  converts different levels of the  $k$ -th attribute associated with the  $i$ -th alternative located in the

$q$ -th neighbourhood. Consequently, the local form of the global value function (see Eqs. 2.1 and 2.2) can be defined as follows:

$$v(a_{ik}^q) = \left( \frac{\max_{i,q} \{a_{ik}^q\} - a_{ik}^q}{r_k^q} \right)^{\rho_{(q)}}, \quad (2.5)$$

for the  $k$ -th criterion to be minimized; and

$$v(a_{ik}^q) = \left( \frac{a_{ik}^q - \min_{i,q} \{a_{ik}^q\}}{r_k^q} \right)^{\rho_{(q)}}, \quad (2.6)$$

for the  $k$ -th criterion to be maximized;

where  $\min_{i,q} \{a_{ik}^q\}$  and  $\max_{i,q} \{a_{ik}^q\}$  are the minimum and maximum criterion values for the  $k$ -th criterion in the  $q$ -th neighbourhood, respectively,  $r_k^q$  is the local range (see Eq. 2.4), and  $\rho_{(q)} > 0$  is a parameter for the  $q$ -th neighbourhood. The standardized values  $v(a_{ik}^q)$  range from 0 to 1, with 0 being the value of the least-desirable outcome and 1 is the value assigned to the most-desirable alternative in the  $q$ -th neighbourhood. The linear form of the value function is obtained for  $\rho_{(q)} = 1$ . For  $0 < \rho_{(q)} < 1$ , a concave value function is obtained. If  $\rho_{(q)} > 1$ , then a convex value function is obtained (see Sect. 2.3.1.1). The function provides a tool for incorporating spatially variable value/utility function (Malczewski 2011; Carter and Rinner 2014).

### 2.3.2 Criterion Weighting

A weight is a value assigned to an evaluation criterion that indicates its importance relative to the other criteria under consideration. There have been a number of methods suggested for assessing criterion weights (Hwang and Yoon 1981; Stillwell et al. 1981; Choo et al. 1999; Hobbs and Meier 2000). From the perspective of GIS-MCDA, the methods can be classified into two groups: global and local methods. The global techniques include: ranking, rating, pairwise comparison, and entropy approaches. They are based on the assumption of spatial homogeneity of preferences. Consequently, they assign a single weight to each criterion. A vast majority of the GIS-MCDA applications have used one of the three global weighting methods: ranking, rating, and pairwise comparison (Malczewski 2006). These methods require that the decision making agents specify their preferences with respect to the evaluation criteria. The entropy-based method provides an alternative criteria weighting approach. Unlike the ranking, rating, and pairwise comparison techniques, the entropy method is based on measuring information contained in the criterion values (Nijkamp and Delft 1977; Hwang and Yoon 1981). To take into

account spatial heterogeneity of preferences, spatially explicit criterion weighting methods such as the proximity-adjusted criterion weights, range-based local weighting, and entropy-based local weighting methods have been proposed (Rinner and Heppleston 2006; Malczewski 2011; Ligmann-Zielinska and Jankowski 2012).

Although the use of particular methods for assessing criterion weights is context dependent, there are some desirable properties that the criterion weights should have irrespective of the method. The criterion weights,  $w_1, w_2, \dots, w_k, \dots, w_n$ , are typically assumed to meet the following conditions:  $0 \leq w_k \leq 1$ , and  $\sum_{k=1}^n w_k = 1$ . The greater the weight, the more important is the criterion in the overall value/utility. The weights must be ratio scaled (Hobbs and Meier 2000). If criterion  $C_1$  is twice as 'important' as  $C_2$ , then  $w_1 = 2w_2$ ; that is,  $w_1 = 0.667$  and  $w_2 = 0.333$ . The weights should represent the trade-off that one is willing to make between two criteria. Assigning weights to evaluation criteria must account for the changes in the ranges of criterion values (see Sect. 2.2.1), and the different degrees of importance being attached to those ranges (Belton and Stewart 2002). Since the meaning of weights is dependent on multicriteria decision rules (see Sect. 2.2.3), the weights may have widely differing interpretations for different methods and decision contexts (Lai and Hopkins 1989; Choo et al. 1999; Belton and Stewart 2002).

### 2.3.2.1 Global Criteria Weighting

#### Ranking Method

A simple method for estimating the criterion weights is to rank the criteria in the order of the decision maker's preference (Stillwell et al. 1981). First, the straight ranking (the most important = 1, second important = 2, etc.) is used. Once the ranking is established for a set of criteria, the rank sum weights can be calculated as follows:

$$w_k = \frac{n - p_k + 1}{\sum_{k=1}^n (n - p_k + 1)} \quad (2.7)$$

where  $w_k$  is the  $k$ -th criterion weight,  $n$  is the number of criteria under consideration ( $k = 1, 2, \dots, n$ ), and  $p_k$  is the rank position of the criterion.

The ranking method has been used in a number of GIS-MCDA applications, including Proulx et al. (2007), Jankowski et al. (2008), and Zucca et al. (2008). It is also available as one of the criterion weighting methods in the ILWIS—SMCE module (Sharifi et al. 2004; see also Chap. 10). Ozturk and Batuk (2011) have implemented the ranking methods (as well as other weighting methods) into Arc-GIS-based MCDA system.

The ranking method is an attractive technique due to its simplicity. In many decision situations, the rank-order approximation provides a satisfactory approach for the criterion weights assessment (Stillwell et al. 1981). Although the usefulness of the method has been demonstrated empirically (Stillwell et al. 1981), it can be

criticized for the lack of theoretical foundation. In most cases, it is worthwhile to obtain more than rank-order approximation. Also, the practical usefulness of these methods is limited by the number of criteria to be ranked. In general, the larger the number of criteria used, the less appropriate is the method (Voogd 1983).

One particular type of ranking approach is to assign equal weights to the criteria; that is,  $w_k = n^{-1}$ . Several GIS-MCDA applications have used this approach (e.g., Biermann 1997; Carsjens and Ligtenberg 2007; Baud et al. 2008). The equal weights approach does not have any theoretical justification. Assigning equal weights does not imply that the criteria are equally important (Hobbs and Meier 2000) because the relative importance depends on the ranges of criterion values (see introduction to Sect. 2.3.2).

### Rating Method

The rating methods require the decision maker to estimate weights on the basis of a predetermined scale; for example, a scale of 0 to 100. Given the scale, a score of 100 is assigned to the most important criterion. Proportionately smaller weights are then given to criteria lower in the order. The procedure is continued until a score is assigned to the least important criterion. Finally, the weights are normalized by dividing each of the weights by the sum total. Like the ranking methods, the rating techniques may not generate appropriate criterion importance (see Sect. 2.3.2). Robinson et al. (2002) and Jankowski et al. (2008) have demonstrated the use of rating method for estimating criterion weights in the GIS-MCDA applications. The rating method is one of the weighting techniques available in the ArcGIS-based MCDA system developed by Ozturk and Batuk (2011).

### Pairwise Comparison

The pairwise comparison method was developed by Saaty (1980) in the context of the analytic hierarchy process (AHP) (see Sect. 4.3). It employs an underlying scale with values from 1 to 9 to rate the preferences with respect to a pair of criteria. The pairwise comparisons are organized into a matrix:  $\mathbf{C} = [c_{kp}]_{n \times n}$ ;  $c_{kp}$  is the pairwise comparison rating for the  $k$ -th and  $p$ -th criteria. The matrix  $\mathbf{C}$  is reciprocal; that is,  $c_{pk} = c_{kp}^{-1}$ , and all its diagonal elements are unity; that is,  $c_{kk} = 1$ , for  $k = p$ . Given this reciprocal property, only  $n(n-1)/2$  actual pairwise comparisons are needed for an  $n \times n$  matrix. Once the pairwise comparison matrix is obtained, a vector of criterion weights,  $\mathbf{w} = [w_1, w_2, \dots, w_n]$  can be computed. The weights are obtained as the unique solution to:

$$\mathbf{C}\mathbf{w} = \lambda_{\max}\mathbf{w}, \quad (2.8)$$

where  $\lambda_{\max}$  is the largest eigenvalue of  $\mathbf{C}$ . Saaty (1980) provides several methods for approximating the values of criterion weights. One of the most often used is the



procedure of averaging over normalized columns. First, the entries in the matrix  $C$  are normalized:

$$c_{kp}^* = \frac{c_{kp}}{\sum_{k=1}^n c_{kp}}, \text{ for all } k = 1, 2, \dots, n. \quad (2.9)$$

and then the weights are computed as follows:

$$w_k = \frac{\sum_{p=1}^n c_{kp}^*}{n}, \text{ for all } k = 1, 2, \dots, n. \quad (2.10)$$

The principle of transitivity provides a grounding for MCDA in general and criteria weighting in particular. For example, given three evaluation criteria,  $C_1$ ,  $C_2$ , and  $C_3$ , a transitivity relation can be defined as follows: if  $C_1 \succ C_2$ , and  $C_2 \succ C_3$ , then  $C_1 \succ C_3$  (the symbol  $\succ$  means ‘is preferred to’). According to the transitivity principle, a consistent set of pairwise comparisons would require that if  $3C_1 \succ C_2$  ( $C_1$  is three times as preferable as  $C_2$ ), and  $2C_2 \succ C_3$ , then  $6C_1 \succ C_3$ . However, one can argue that any human judgment is to some degree inconsistent (Saaty 1980). The following pairwise comparisons:  $3C_1 \succ C_2$ , and  $2C_2 \succ C_3$ , and  $5C_1 \succ C_3$  provide an example of intransitive relations. The pairwise comparison method allows for such inconsistent relations. The measure of inconsistency is based on the observation that  $\lambda_{\max} > n$  for positive, reciprocal matrices, and  $\lambda_{\max} = n$  if  $C$  is a consistent matrix. The consistency ratio ( $CR$ ) can be defined as follows:

$$CR = \frac{\lambda_{\max} - n}{RI(n - 1)} \quad (2.11)$$

where,  $RI$  is the random index, which is the consistency index of a randomly generated pairwise comparison matrix. It can be shown that  $RI$  depends on the number of criteria being compared. For example, for  $n = 2, 3, 4, 5, 6, 7$ , and  $8$ ,  $RI = 0.00, 0.52, 0.89, 1.11, 1.25, 1.35$ , and  $1.40$ , respectively (Saaty 1980). The consistency ratio,  $CR < 0.10$ , indicates a reasonable level of consistency in the pairwise comparisons; if, however,  $CR \geq 0.10$ , then the value of the ratio is indicative of inconsistent judgments. In such cases, one should reconsider and revise the original values in the pairwise comparison matrix,  $C$ .

According to Malczewski’s (2006) survey, the pairwise comparison method is the most often used procedure for estimating criterion weights in GIS-MCDA applications. The method has been tested for a variety of decision situations including site selection problems (Banai 1993, 1998; Siddiqui et al. 1996; Jun 2000; Feick and Hall 2002), land suitability analysis (Eastman et al. 1995; Stoms et al. 2002; Ceballos-Silva and López-Blanco 2003), and environmental impact assessment (Barredo et al. 2000; Bojorquez-Tapia et al. 2002). It has been used in a variety of application domains, including agriculture (Ceballos-Silva and López-Blanco 2003; Santé-Riveira et al. 2008), manufacturing (Jun 2000), transportation (Banai 1998), tourism (Feick and Hall 2002), health care (Jankowski and Ewart 1996), natural

resource management (Pereira and Duckstein 1993; Mendoza and Martins 2006; Strager and Rosenberger 2006; Hessburg et al. 2013), and waste management (MacDonald 1996; Siddiqui et al. 1996).

The pairwise comparison method is a part of multicriteria decision support modules in IDRISI (Eastman et al. 1993), ILWIS—SMCE (Sharifi et al. 2004), and CommonGIS (Rinner and Taranu 2006). In addition, the methods have been implemented in the ArcGIS/ArcView environment in several GIS-MCDA applications (Zhu and Dale 2001; Banai 2005; Boroushaki and Malczewski 2008; Chen et al. 2010; Ozturk and Batuk 2011).

The pairwise comparison method can be criticized for the ambiguity of the underlining questions (Goodwin and Wright 1998). The questions simply ask for the relative importance of evaluation criteria without reference to the scales on which the criteria are measured. This fuzziness may mean that the questions are interpreted in different, and possibly erroneous, ways by decision makers (see Sect. 4.3.2).

### Entropy-Based Criterion Weights

Unlike the ranking, rating, and pairwise comparison methods, the entropy-based criterion weighting approach does not require the decision making agents to specify their preferences with respect to the evaluation criteria. The method is based on the concept of information entropy (Shannon and Weaver 1947). Entropy is a measure of the expected information content of a message. From this perspective, the criterion weights “can be considered as successive messages which are important for evaluating” decision alternatives (Nijkamp and Delft 1977, p. 21). Given the evaluation criteria organized in the form of decision matrix (see Sect. 2.2.4, Table 2.1), one can estimate the criterion weights based on the amount of information contained in each criterion,  $a_{ik}$ , measured by the entropy,  $E_k$ , as follows (Shannon and Weaver 1947).

$$E_k = - \frac{\sum_{i=1}^m p_{ik} \ln(p_{ik})}{\ln(m)} \quad (2.12)$$

where  $p_{ik} = a_{ik} / \sum_{i=1}^m a_{ik}$ ;  $a_{ik}$  is the value of the  $k$ -th attribute for the  $i$ -th alternatives. The degree of diversity of the information contained in a set of criterion values can be calculated as:  $b_k = 1 - E_k$ . Using the degree of diversity,  $b_k$ , the entropy-based criterion weights are defined as:

$$w_{E_k} = \frac{b_k}{\sum_{k=1}^n b_k}. \quad (2.13)$$

The entropy-based criterion weights can be combined with weights,  $w_k$ , obtained using one of the other methods discussed in this section. Specifically, the new weight is defined as follows:

$$w_{E_k}^* = \frac{w_{E_k} w_k}{\sum_{k=1}^n w_{E_k} w_k}. \quad (2.14)$$

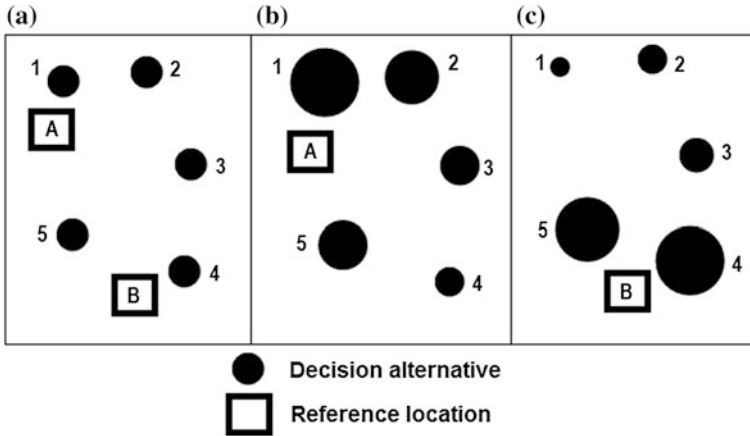
The values of the entropy-based criterion weights,  $w_{E_k}$  and  $w_{E_k}^*$  range from 0 to 1. The more diverse information is contained in the  $k$ -th criterion, the higher the value of that criterion. The smaller the value of the entropy,  $E_k$ , the higher the degree of criterion diversity,  $b_k$ , and the larger the entropy-based weight. This implies that the more information the  $k$ -th criterion provides, the more important that criterion is in the decision making procedure. If the  $k$ -th criterion is characterized by perfect homogeneity (that is,  $a_{ik}$  is a constant value for  $i = 1, 2, \dots, m$ ), then the criterion weight equals zero. Consequently, the criterion can be removed from the set of evaluation criteria because it conveys no information about the decision making situation.

The entropy-based method for estimating criterion weights has rarely been used in GIS-MCDA. Zheng et al. (2009), Berger (2006) and Li et al. (2012) provide examples of incorporating this criteria weighing method as a component of GIS-WLC (see Sect. 4.2) and GIS-TOPSIS (see Sect. 4.4.2), respectively. The method is an effective approach for estimating criterion weights in the context of local multicriteria analysis (Sect. 4.2.2) and multiscale GIS-MCDA (see Sect. 9.4). Although the concept of entropy has been suggested as an alternative method for estimating criterion weights (Nijkamp and Delft 1977; Hwang and Yoon 1981), there are some restrictive requirements underlying the proper use of this method. Jessop (1999) provides a comprehensive discussion of the concept of entropy in MCDA. The use of entropy measures should involve considerations of the requirements for estimating meaningful set of criterion weights (see introduction to Sect. 2.3.2).

### 2.3.2.2 Spatially Explicit Methods

#### Proximity-Adjusted Criterion Weights

The proximity-adjusted criterion weighting is based on the idea of adjusting preferences according to the spatial relationship between alternatives or an alternative and some reference locations (Rinner and Heppleston 2006; Ligmann-Zielinska and Jankowski 2012). Thus, the method explicitly acknowledges the concept of spatial heterogeneity of preferences. Ligmann-Zielinska and Jankowski (2012) operationalized the concept of proximity-adjusted criterion weights by introducing a reference or benchmark location. They suggest that the weights should reflect both relative importance of the criterion and the spatial position of a decision alternative with respect to a reference location. The relative importance is assessed in terms of



**Fig. 2.6** A hypothetical weight (preference) map that depicts the importance of a given criterion uniformly (a), and in a spatially heterogeneous manner (b, c). Circles represent decision alternatives, their radii are constant in (a), and proportional to weight values in cases (b) and (c); the reference locations are represented by squares (Source Adapted from Ligmann-Zielinska and Jankowski 2012)

the global criterion weight; that is, the same value of  $w_k$  is assigned to each decision alternative evaluated with respect to the  $k$ -th criterion (see Fig. 2.6a). The location effect is assessed in terms of a distance decay function; the closer a given alternative is situated to a reference location, the higher the value of the criterion weight should be (see Figs. 2.6b, c). The latter reflects a spatial bias toward a particular location.

The proximity-adjusted criterion weight,  $w_{ik}$ , assigned to the  $i$ -th alternative with respect to the  $k$ -th criterion is defined as follows:

$$w_{ik} = w_k \frac{d_{ij}^s}{\frac{1}{m} \sum_{i=1}^m d_{ij}^s}, \quad (2.15)$$

where  $w_k$  is the global criterion weight (that can be estimated by one of the methods described in Sects. 2.3.2.1),  $d_{ij}$  is the distance between the  $i$ -th alternative and the  $j$ -th reference location, and  $d_{ij}^s$  is a standardized distance for a pair of  $i$  and  $j$  locations:

$$d_{ij}^s = \frac{\min_i \{d_{ij}\}}{d_{ij}}. \quad (2.16)$$

Thus, the proximity-adjusted criterion weight is a function of the global weight modified by the normalized distance between a pair of locations. Notice that  $mw_k = \sum_{i=1}^m w_{ik}$ . This implies that Eq. 2.15 modifies the global criterion weight,  $w_k$ , by redistributing the total weight,  $mw_k$ , depending on the spatial relationship (proximity) between a reference location and decision alternative.

### Range-Based Local Criterion Weights

The critical aspect for criterion weighting methods is that the weight,  $w_k$ , is dependent on the range of the criterion values,  $r_k$  (see Eqs. 4.2–4.5). This implies that a criterion weight is intricately associated with corresponding value function,  $v(a_{ik})$ . Consequently, a meaningful estimate of a weight requires that at least the upper and lower limits of the value function (and its measurement unit) have been specified (Hwang and Yoon 1981; Malczewski 2000). The relationship is encapsulated in the range-sensitive principle (Keeney 1992; Fischer 1995). The principle is a normative proposition. It suggests that, other things being equal, the greater the range of values for the  $k$ -th criterion, the greater the weight,  $w_k$ , should be assigned to that criterion (Fischer 1995).

Given the definition of the  $q$ -th neighbourhood (see Sect. 2.3.1.2), the local criterion weight,  $w_k^q$ , for the  $k$ -th criterion can be defined as a function of the global weight,  $w_k$ , the global range,  $r_k$ , and the local range,  $r_k^q$ . Specifically,

$$w_k^q = \frac{\frac{w_k r_k^q}{r_k}}{\sum_{k=1}^n \frac{w_k r_k^q}{r_k}}, \quad 0 \leq w_k^q \leq 1, \quad \text{and} \quad \sum_{k=1}^n w_k^q = 1. \quad (2.17)$$

Since the spatial variability of the local weight,  $w_k^q$ , is a function of the local criterion range,  $r_k^q$ , the value of a local weight depends on the neighbourhood scheme used for subdividing a study area into neighbourhoods (zones or regions). Therefore, this type of criteria weighting can also be referred to as the neighbourhood-based criterion weights (Feick and Hall 2004). The method has been used as an element of local WLC model (see Sect. 4.2.2) for land suitability analysis (Malczewski 2011), and local OWA model (see Sect. 4.2.3) for evaluating residential quality of urban neighbourhoods (Malczewski and Liu 2014). Carter and Rinner (2014) have employed the local WLC model and range-based criterion weights in their case study of vulnerability to heat-related illness.

### Entropy-Based Local Criterion Weights

The concept of entropy provides an effective approach for estimating local form of criterion weights. Similar to the case of the range-based method, the local form can be obtained by incorporating the notion of neighbourhood into the procedure for entropy-based local criterion weights. Specifically, for the  $q$ -th neighbourhood (see Sect. 2.3.1.2), the local criterion weight can be defined as follows:

$$w_{E_k}^q = \frac{1 - E_k^q}{\sum_{k=1}^n (1 - E_k^q)}, \quad 0 \leq w_{E_k}^q \leq 1, \quad \text{and} \quad \sum_{k=1}^n w_{E_k}^q = 1; \quad (2.18)$$

where

$$E_k^q = - \frac{\sum_{i \in q} p_{ik}^q \ln(p_{ik}^q)}{\ln(|q|)} \quad (2.19)$$

where  $p_{ik}^q = a_{ik}^q / \sum_{i \in q} a_{ik}^q$ ;  $a_{ik}^q$  is the value of the  $k$ -th attribute for the  $i$ -th alternative located in the  $q$ -th neighbourhood;  $|q|$  is the cardinality (size) of set,  $q$  (that is, the number of decision alternatives located in the  $q$ -th neighbourhood). The entropy-based local and global criterion weights have similar interpretations (see Sect. 2.3.2.1.4).

### 2.3.3 Combination Rules

At the most fundamental level, a decision rule is a procedure or method for evaluating (and ordering) a set of decision alternatives (Hwang and Yoon 1981). In the GIS literature, the decision rules are also referred to as the rules of combination (Chrisman 1996). A combination rule integrates the data and information about alternatives (criterion maps) and decision maker's preferences (criterion weights) into an overall assessment of the alternatives. There are number of classification of decision rules. Here we focus on four dichotomic classifications: compensatory versus non-compensatory, multiattribute versus multiobjective, discrete versus continuous methods, and spatially implicit versus spatially explicit MCDA.

#### 2.3.3.1 Compensatory and Non-compensatory Methods

The distinction between compensatory and non-compensatory decision rules is based on the trade-offs between evaluation criteria: the former takes into account the trade-offs between criteria, while the latter ignores the value of trade-offs. The compensatory methods allow trade-off of a low value on one criterion against a high value on another. The weighted linear combination model provides an example of compensatory method in GIS-MCDA (Sect. 4.2).

The non-compensatory decision rules are conceptualized in GIS-MCDA using Boolean overlay operations in the form of the conjunctive and disjunctive screening methods (Malczewski 1999). Under conjunctive screening, an alternative is accepted if it meets specified standards or thresholds for all evaluation criteria. Disjunctive screening accepts alternative scores sufficiently high on at least one of the criteria under consideration. In addition, to the conjunctive and disjunctive methods, the lexicographic method has been used as GIS-based non-compensatory screening techniques (Carver 1991; Malczewski 1999).

### 2.3.3.2 Multiattribute and Multiobjective Methods

Multicriteria decision rules can be broadly categorized into two groups: multiattribute decision analysis (MADA) and multiobjective decision analysis (MODA) methods (Hwang and Yoon 1981; see Table 2.2). Multiattribute decision problems involve a predetermined, limited number of alternatives. Solving this type of decision problem is an outcome-oriented evaluation and choice process. In MADA problems, the alternatives are given explicitly rather than defined implicitly as in the case of MODA. The MODA approach is a process-oriented design and search. Unlike multiattribute approaches, the multiobjective methods make a distinction between the concept of decision variables and decision criteria. These two elements are related to one another by a set of objective functions. Also, the set of alternatives is defined in terms of causal relationships and constraints imposed on the decision variables. From the MODA perspective, the attributes can be viewed as means or information sources available to the decision maker for formulating and achieving his/her objectives (Starr and Zeleny 1977). Although the MADA and MODA methods are sometimes referred to as discrete and continuous decision problems, respectively (Hwang and Yoon 1981; Malczewski 1999), it is important to indicate that the MODA problems can be defined in terms of a set of continuous and/or discrete decision variables (Zarghami and Szidarovszky 2011).

**Table 2.2** Comparison of multiattribute and multiobjective decision analysis

Condition	Multiattribute decision analysis (MADA)	Multiobjective decision analysis (MODA)
Criteria defined by	Attributes	Objectives
Objectives defined	Implicitly	Explicitly
Attributes defined	Explicitly	Implicitly
Constraints defined	Implicitly	Explicitly
Alternatives defined	Explicitly	Implicitly
Decision modeling paradigm	Outcome-oriented evaluation/choice	Process-oriented design/search
Examples of multicriteria methods	Weighted linear combination Analytic hierarchy/network process Outranking methods Ideal point methods	Linear/integer programming Goal programming Compromise programming Heuristics/metaheuristics
Examples of spatial decision problems	Site selection Land use/suitability Vulnerability analysis Environmental impact assessment	Site search Location-allocation Transportation problem Shortest path problem Districting

Sources Based on Hwang and Yoon (1981); Malczewski (1999)

### 2.3.3.3 Discrete and Continuous Methods

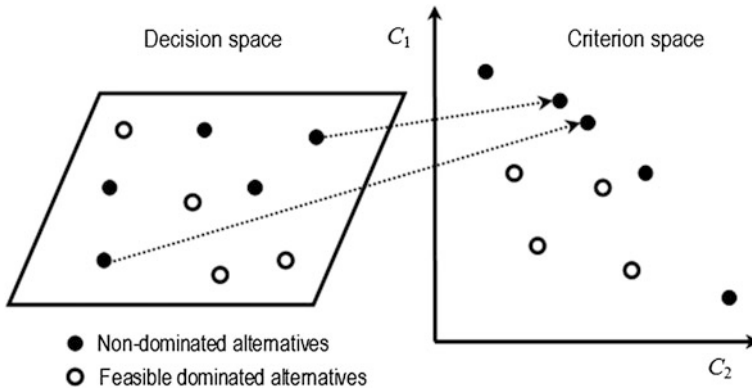
Another way of classifying the decision rules is based on the distinction between discrete and continuous decision problems (Zarghami and Szidarovszky 2011). It should be emphasized that this classification overlaps with the multiattribute/multiobjective dichotomy (see Sect. 2.2.3.2).

A good illustration of the distinction between MADA and MODA (and the discrete and continuous decision problems) is provided by the site selection and site search problems (Cova and Church 2000). The aim of site selection analysis is to identify the best site for some activity given the set of potential (feasible) sites. In this type of analysis, all the characteristics (such as location, size, and relevant attributes) of the candidate sites are known. The problem is to rate or rank the alternative sites based on their characteristics so that the best site (or a set of sites) can be identified. If there is not a pre-determined set of candidate sites, the problem is referred to as site search analysis. The characteristics of the sites (i.e., their boundaries) have to be defined by solving the problem. The aim of the site search analysis is to explicitly identify the boundary of the best site(s).

Both the site search and site selection problems assume that there is a given study area, which is subdivided into a set of basic units of analysis such as polygons or rasters. The site selection problem involves classification of the units according to their suitability for a particular activity. The analysis defines an area in which a good site might exist. The site search analysis determines not only the site suitability, but also its spatial characteristics such as its shape, contiguity, and/or compactness, by aggregating the basic units of observations according to some criteria. The site selection problem is typically tackled in the GIS environment using MADA methods, including weighted linear combination, analytic hierarchy process, ideal point methods, and outranking methods (see Chapter 4). The site search problem is typically formulated in terms of MODA problem and solved using methods of mathematical programming, including goal programming, compromise programming (see Chap. 5), or heuristic/metaheuristic algorithms (see Chap. 6).

The differences between discrete and continuous MCDA can be highlighted by examining the concept of the decision space and criterion outcome space. A set of decision variables defines the decision space for a particular decision problem. The decision space is typically limited by a set of constraints imposed on the decision variables. The constraints determine the set of feasible alternatives (see Sect. 2.2.3.1). Each alternative has at least one consequence associated with it. Accordingly, the set of decision consequences forms the decision outcome space (or the criterion outcome space or the criterion outcome space). The solution to the multicriteria decision problem can be represented and analyzed in the decision space and criterion (or objective) space. The former is a representation of the individual decision variables. The criterion space represents the performance of the solutions in terms of the criterion outcomes. For each feasible solution in decision space, there is a corresponding mapping into criterion space.

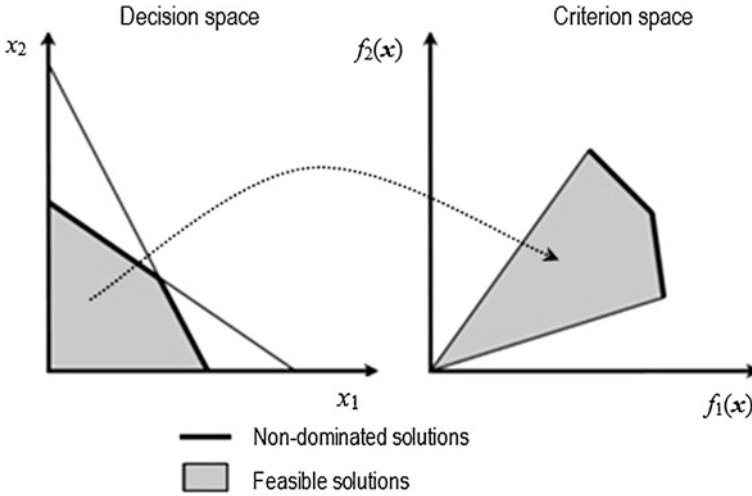




**Fig. 2.7** Discrete multicriteria decision problem: feasible and non-dominated alternatives in the decision and criterion space

Figure 2.7 illustrates the concept of decision space and criterion space for discrete MCDA. Suppose that a site selection problem involves evaluating a set of decision alternatives ( $i = 1, 2, \dots, m$ ) with respect to two criteria ( $C_1$  and  $C_2$ ), and identifying the best site. The alternatives (sites) are described by their geographic location (e.g., a coordinate system), and a binary decision variable (that is, the decision variable = 1 if the  $i$ -th site is selected, 0 = otherwise). The decision alternatives form a decision space. They can be displayed on a map where each point represents a site. Each alternative is characterized by two attributes (criteria). Thus, it can be represented in the criterion space in the form of a scatterplot. Figure 2.7 makes a distinction between the dominated and non-dominated solutions (alternatives). Notice that two alternatives can be located a distance apart in the decision space, while they may be situated nearby in the criterion space. The search for the best alternative should involve exploring the alternatives in the two spaces simultaneously. The best sites should be identified as one of the five non-dominated alternatives (see Fig. 2.7).

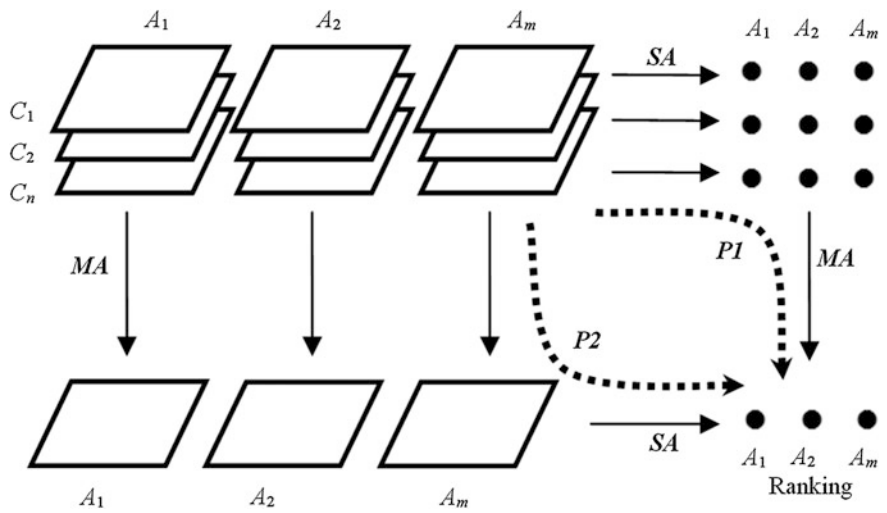
Figure 2.8 shows the concept of decision space and criterion (objective) space for the continuous MCDA. It illustrates a multiobjective linear programming problem with two decision variables ( $x_1$  and  $x_2$ ), and two objective functions ( $f_1(\mathbf{x})$  and  $f_2(\mathbf{x})$ ) to be maximized. The set of feasible solutions (decision alternatives) is determined by the linear constraints in the decision space. The set of feasible solutions can also be represented in the criterion spaces in which decision alternatives are described in terms of the values of the two objective functions (see Sect. 2.2.3).



**Fig. 2.8** Continuous multicriteria decision problem: feasible and non-dominated solutions in the decision and criterion space. *Note*  $x_1$  and  $x_2$  are decision variables, and  $f_1(x)$  and  $f_2(x)$  objective functions, which are maximized

#### 2.3.3.4 Spatially Implicit and Explicit MCDA Methods

In Sects. 2.2.2 and 2.2.3, we have made a distinction between spatially implicit and explicit elements of MCDA; that is, evaluation criteria and decision alternatives. van Herwijnen and Rietveld (1999) cross-classify these two elements of MCDA to identify four types of spatial decision problems: Type 1: both criteria and alternatives are spatially explicit; Type 2: alternatives are spatially explicit and criteria are spatially implicit; Type 3: alternatives are spatially implicit and criteria are spatially implicit; and Type 4: both criteria and alternatives are spatially implicit. von Herwijnen (1999) has suggested two distinctive approaches for representing input data for the four types of spatial multicriteria decision problems (see also Janssen and Herwijnen 1998; van Herwijnen and Rietveld 1999; Sharifi and Herwijnen 2002). First, the datasets can be represented as a map of evaluation tables. Each location has its own evaluation table with  $m \times n$  criterion (attribute) values. Second, the input data are represented as an evaluation table of maps. In this case, the performance of each alternative for a given criterion is a map. Consequently, the table contains  $m \times n$  maps. Given the two approaches for representing spatial multicriteria decision problems, von Herwijnen (1999) demonstrated that spatial MCDA involves two functions (or operations) for combining (aggregating) the input datasets into a ranking of the alternatives: (i) spatial aggregation, and (ii) multicriteria aggregation (see Fig. 2.9). Depending on the order of the two operations, one can develop two procedures (paths) for combining the input datasets. In the Path 1 procedure, each alternative is first represented by a single value for each criterion (spatially aggregated) and then multicriteria analysis is undertaken to



**Fig. 2.9** Two combination procedures (paths) for spatial multicriteria problems. *Note*  $C_1, C_2, \dots, C_n$  = evaluation criteria;  $A_1, A_2, \dots, A_m$  = decision alternatives; MA = multicriteria aggregation; SA = spatial aggregation; P1 = Path 1; P2 = Path 2 (Source Adapted from van Herwijnen and Rietveld 1999)

obtain a ranking of alternatives. The order of operations is reversed in the Path 2 procedure. MCDA is applied directly to the objects in a map followed by spatial aggregation. Boerboom et al. (2006) provide examples of the two approaches in the context of studies about evaluating and selecting the best alternative for light rail network expansions (see also Sharifi and Herwijnen 2002).

2.4 Conclusion

In the most general terms, multicriteria decision problems involve a set of decision alternatives that are evaluated on the basis of conflicting and incommensurate criteria by an individual decision maker (decision making agent) or group of decision makers. This chapter has described the three main elements of multicriteria decision problems: decision makers (decision making agents), evaluation criteria, and decision alternatives. It has underscored the spatial aspects of the elements of GIS-MCDA by making the distinction between spatially implicit and explicit evaluation criteria and decision alternatives.

The chapter has also reviewed the main concepts of MCDA from the perspective of GIS applications. It has focused on the concepts of value scaling, criterion weighting, and combination rules, as well as the importance of spatially explicit approaches for operationalizing these three concepts. Although the conventional (aspatial) decision analysis has an important role to play in GIS-MCDA, spatial

decision problems requires approaches designed specifically to take into consideration the distinctive properties of spatial data/information. This can be achieved in a number of ways by incorporating spatial considerations into the elements and concepts of MCDA (see Part II of this book).

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Multicriteria Decision Analysis in Geographic Information  
Science

Malczewski, J.; Rinner, C.

2015, XV, 331 p. 93 illus., 16 illus. in color., Hardcover

ISBN: 978-3-540-74756-7