Chapter 8
GIS-MCDA for Group Decision Making

8.1 Introduction

The GIS-MCDA methods discussed in previous chapters were concerned with decision situations involving an individual decision maker. Group decision making is not so much concerned with the number of decision makers, as it is with the homogeneity of their preferences. If a group of decision makers is characterized by a mutually consistent set of preferences, then GIS-MCDA methods can be used for solving decision problems irrespective of the number of decision makers involved (see Sect. 2.2.1). However, conflicting preferences are the norm rather than the exception. Spatial decisions are typically made by groups (multiple decision makers) consisting of individuals who are characterized by conflicting preference structures.

There are several conceptual frameworks available for multicriteria group decision making including Social Multicriteria Evaluation (SMCE), Participative Multicriteria Evaluation (PMCE), and Stakeholder Multicriteria Decision Aid (SMCDA) (Munda 2008). Although there are some differences between these approaches, the basic structure of group decision making under multiple criteria can be conceptualized in terms of the three main components: decision alternatives, evaluation criteria, and decision makers (decision making agents) (see Sect. 2.2). GIS-MCDA methods for group decision making involve a set of geographically defined alternatives (e.g., land parcels), a set of evaluation criteria on the basis of which the alternatives are evaluated, and a group of agents (decision makers, planners, experts, stakeholders). An alternative, A_i, is to be evaluated with respect to a set of criteria, C_k, $k = 1, 2, \ldots, n$ (see Sect. 2.2.4). Accordingly, each alternative is described by a set of values, a_{ik}, $A_i = \{a_{i1}, a_{i2}, \ldots, a_{in}\}$, where and a_{ik} is the level of the k-th criterion of the i-th alternative. The group of decision-makers is denoted by DM_g, where g represents an individual involved in the group decision making process: $g = 1, 2, \ldots, z$. To choose a consensus or compromise alternative, the individuals have to specify their own preferences and then the individual preferences

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are combined by means of a group choice function. Thus, there are g preference ordering sets (P_1, P_2, …, P_z) in which, for a pair of A_i and A_j from a set decision alternative, the individual DM_g prefers either A_i and A_j, or A_j and A_i, or he/she is indifferent between the two alternatives. The set of individual orderings is referred to as the preference profiles. Given the set of preference profiles, the group choice problem involves collective choice rules that produce group preferences from individual orderings.

The basic structure of group decision making under multiple criteria can be used as a component of a variety of GIS-based modeling procedures. Two distinctive types of those procedures are: (i) conventional GIS-MCDA methods for group decision making, and (ii) spatial simulation (or geosimulation) methods. One of the main distinctions between the two types of approaches is that the former methods are based on the traditional notion of decision maker (see Sect. 2.2.1.1) and tend to focuses on prescriptive-constructive modeling (see Sect. 1.2.2), while the latter group of methods involves the concept of a decision making agent (see Sect. 2.2.1.2) and descriptive-normative modeling (see Sect. 1.2.1). Furthermore, conventional GIS-MCDA methods for group decision making are spatially implicit (see Sect. 2.3.3.4), while geosimulation methods consider spatial elements of decision problems explicitly (see Sect. 1.4.2).

This Chapter provides a discussion of the most often used GIS-MCDA approaches for group decision making. Section 8.2 presents a selection of conventional GIS-MCDA methods that have been employed for tackling group decision making problems. The main objective of these methods is to support the process of identifying a consensus or compromise decision alternative by aggregating individual preferences. Section 8.3 focuses on two related geosimulation approaches: cellular automata and multi-agent based modeling from the perspective of GIS-MCDA for group decision making. It also discusses geosimulation-based multiobjective optimization approaches.

8.2 Methods for Aggregating Preferences

The main objective of a group decision making process is to reach a consensus or compromise (Massam 1988; Kangas et al. 2008). This can be achieved by aggregating individual preferences by means of a group (social or collective) scheme. The aggregation procedure can be applied in different stages of the decision making process. One can distinguish two types of GIS-MCDA procedures for group decision problems depending on the stage at which the aggregation of individual preferences is performed (Kangas et al. 2008; Boroushaki and Malczewski 2010c). First, the preferences of the individual decision makers are aggregated into a collective group preference and then the group judgment is used within the conventional GIS-MCDA (see Fig. 8.1a). In this approach, a group of individuals is considered as a decision unit and any of the GIS-MCDA methods presented in Chap. 4 can be employed for identifying an overall value for each decision alternative. Second, the

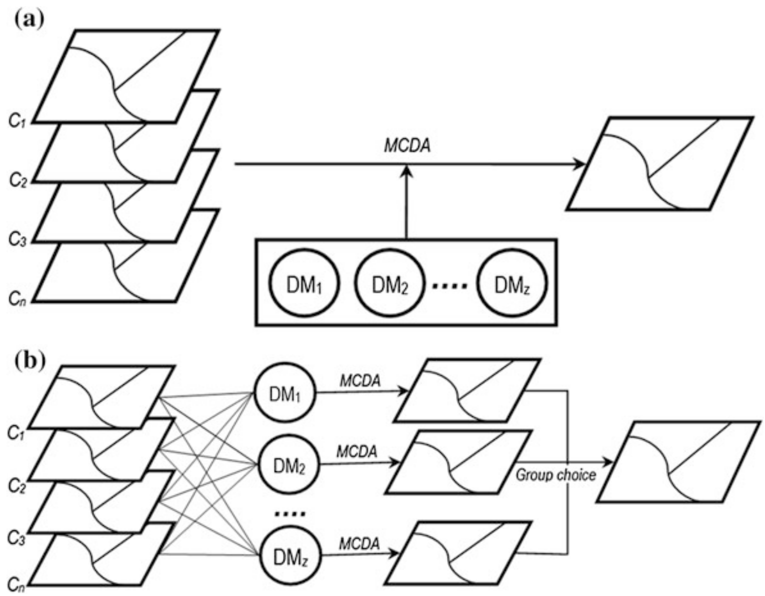

Fig. 8.1 GIS-MCDA for group decision making: **a** individual preferences aggregated external to the GIS-MCDA procedure, and **b** aggregation of individual preferences within the GIS-MCDA procedure (*Note* C_1, C_2, …, C_n = evaluation criteria (criterion maps), and DM_1, DM_2, …, DM_z = decision makers)

decision problem is tackled by each decision maker separately, and then the individual solutions are aggregated using a group choice rule (see Fig. 8.1b). In this case, the alternatives can be evaluated by each individual using a method discussed in Chap. 4, followed by a voting scheme; alternatively, an MCDA method for group decision making (such as the group value function and group AHP/ANP methods) can be used.

8.2.1 Group AHP/ANP

The AHP/ANP methods (see Sect. 4.3) are the most often used GIS-MCDA approaches for tackling spatial decision problems in the group/participatory decision making setting (Estoque 2012). There are essentially two approaches for group decision making with AHP/ANP: (i) the consensus approach involves debating the individual judgments and voting until a consensus is reached, and (ii) the aggregation approach involves synthesizing each of the individual's judgments and combining the resulting priorities. The consensus approach is based on the premise that a group of individuals can generate a single hierarchical structure for a decision problem. In the aggregation approach, each individual generates its own hierarchy (or sub-hierarchy) of the decision problem's elements.

8.2.1.1 Consensus Approach: Single Hierarchy/Network

The AHP/ANP methods can be used as consensus building tools when a group of individuals agrees on the hierarchical (network) structure of the decision problem (Saaty 1980; Dyer and Forman 1992). The consensus AHP/ANP methods follow the GIS-MCDA for group decision making framework shown in Fig. 8.1a (e.g., Levy et al. 2007; Ying et al. 2007; Hossain et al. 2009; Sharifi et al. 2009; Chow and Sadler 2010). The underlying assumption is that the group of decision makers agrees on the hierarchy structure of the problem and there is a consensus on the values contained in the pairwise comparison matrix (see Sects. 2.3.2.2 and 4.3). If it is impossible to achieve agreement on the judgments contained in the pairwise comparison matrices, then the procedure for achieving a consensus among individual decision makers can focus on the priorities of each participant. Such methods as brainstorming, nominal group, or Delphi techniques can be employed for defining the decision problem structure and deriving associated pairwise comparison matrices (e.g., Schmoldt et al. 1994; Strager and Rosenberger 2006; Ying et al. 2007). Once there is consensus regarding the problem structure and pairwise comparison matrices, the group can act as a single decision maker using conventional GIS-AHP/ANP for evaluating decision alternatives. This approach is often employed in GIS-MCDA procedures for deriving criterion weights, which are subsequently combined with criterion maps using a decision rule (see Sect. 2.3.3).

8.2.1.2 Aggregation Approach: Multiple Hierarchies/Networks

When individuals involved in a group decision making process cannot reach a consensus regarding the problem structure, then the problem must be represented by a set of hierarchies (or networks). Each member of a group acts individually and develops his/her own hierarchical (network) structure of the decision problem. Figure 8.2 gives an example of the hierarchical structure of a decision problem involving two decision makers (or two groups of individuals), DM_1 and DM_2. Although the two decision makers share a common goal, they structure the decision problem differently. The sub-hierarchical structure of DM_1 consists of two objectives (1 and 2) and three associated attributes (1, 2, and 3) to be used for evaluating four decision alternatives. The same problem is represented by DM_2 with two objectives (2 and 3) and two attributes (2 and 3).

AHP/ANP methods for aggregating multiple hierarchies/networks follow the GIS-MCDA procedure involving a set of solution maps (see Fig. 8.1b). The combination of the individual maps representing priorities obtained with AHP can be performed using either an arithmetic or geometric mean. Although either mean can be used, the geometric mean is recommended because it is more consistent with both judgments and priorities in AHP (Forman and Peniwatib 1998). Specifically, judgments are based on the pairwise comparisons that represent ratios of how many times more important one element (e.g., criterion) is than another. Synthesized

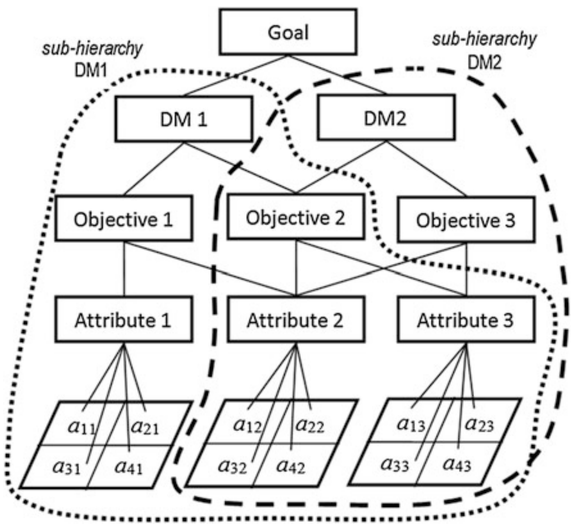

Fig. 8.2 Hierarchical structure of group decision making problem; DM_1 decision maker 1, DM_2 decision maker 2; a_{ik} is the value of the k-th attribute associated with the i-th alternative (k = 1, 2, 3, and i = 1, 2, 3, 4)

priorities assigned to decision alternatives are ratio scale measures representing how many times more preferable one alternative is than the other. However, if the individual judgments are to be aggregated, the geometric mean method must be used to preserve the reciprocal property (Forman and Peniwatib 1998). Consider, for example, two individuals with the following judgments in the pairwise comparison matrix: 5 and 1/5. Given the input data, the geometric mean method results in $1.0 = (5 \times 0.2)^{0.5}$, while the arithmetic mean is equal to: $2.6 = (5 + 0.2)/2$. The results indicate that the geometric mean value provide a sensible synthesis of the two pairwise comparisons.

To illustrate the GIS-AHP method for group decision making, consider an example involving two decision makers (DM_1 and DM_2) facing a problem of evaluating three parcels of land (A_1, A_2, and A_3). The hierarchical structures of the problem for DM_1 and DM_2 are shown in Fig. 8.3a, b. The computational procedure for obtaining the overall values of three alternatives for DM_1 and DM_2 is demonstrated in Sect. 4.3.1 (see Fig. 4.4 and Table 4.2). Figure 8.3a, b show the overall value of $V(A_3) = 0.670 > V(A_1) = 0.581 > V(A_2) = 0.266$ for DM_1, and $V(A_1) = 0.664 > V(A_3) = 0.630 > V(A_2) = 0.265$ for DM_2. Thus, the individual preferences need to be aggregated to identify the best alternative. This is achieved using the geometric mean method. For example, the weights assigned to Objectives 1 and 2 are aggregated as follows: $(0.667 \times 0.500)^{0.5} = 0.577$ and $(0.333 \times 0.500)^{0.5} = 0.408$; and then the weights are normalized $0.577/(0.577 + 0.408) = 0.586$ and $0.408/(0.577 + 0.408) = 0.414$ (see Fig. 8.3c and Table 8.1). The aggregation of individual attribute weights is obtained in a similar way using the geometric mean method.

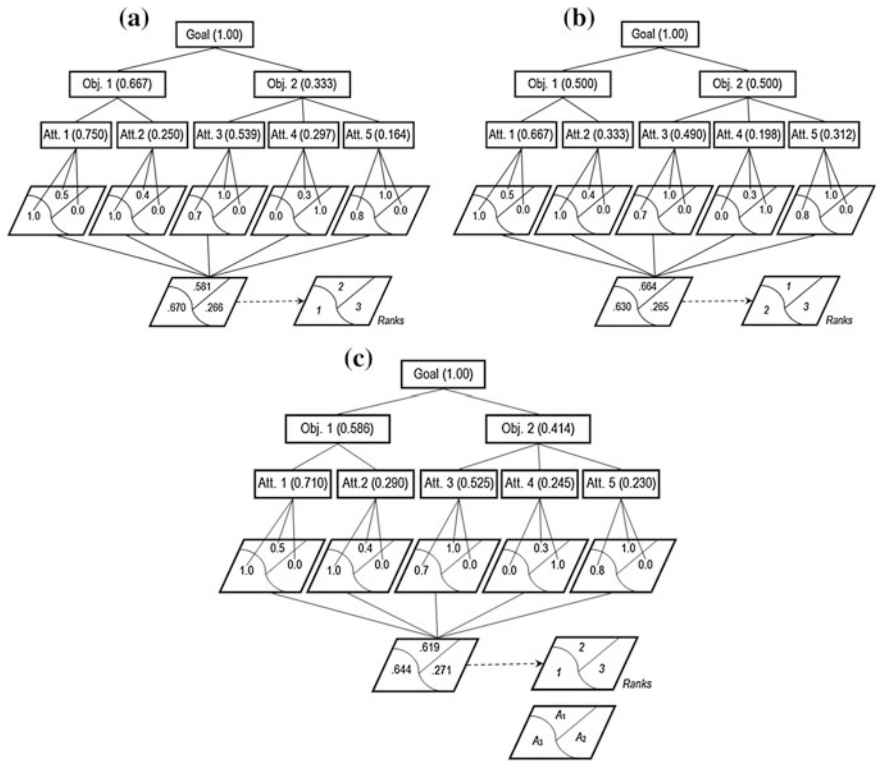

Fig. 8.3 Hierarchical structures of GIS-based AHP model for two decision makers: **a** individual decision making, DM_1, **b** individual decision making, DM_2, and **c** group decision making, DM_g—aggregation of individual preferences, DM_1 and DM_2, using geometric mean

Table 8.1 Group decision making, DM_g (see Fig. 8.3c)

Objectives w_{lg}		Attributes $w_{k(l)g}$		Standardized attribute values			Overall values		
				$v(a_{1k})$	$v(a_{2k})$	$v(a_{3k})$	$w_{lg}w_{k(l)g}v(a_{1k})$	$w_{lg}\ w_{k(l)g}v(a_{2k})$	$w_{lg}w_{k(l)g}v(a_{3k})$
1	0.586	1	0.710	0.5	0.0	1.0	0.208	0.000	0.416
	0.586	2	0.290	0.4	1.0	0.0	0.068	0.170	0.000
2	0.414	3	0.525	1.0	0.0	0.7	0.217	0.000	0.152
	0.414	4	0.245	0.3	1.0	0.0	0.030	0.101	0.000
	0.414	5	0.230	1.0	0.0	0.8	0.095	0.000	0.076
Sum							0.619	0.271	0.644

The aggregate individual preferences provide a base for calculating the overall value of decision alternatives as follows:

$$V(A_{ig}) = \sum_{k=1}^{n} w_{lg} w_{k(l)g} v(a_{ik}), \tag{8.1}$$

where $v(a_{ik})$ is the value of the i-th alternative for the k-th attribute; w_{lg} and $w_{k(l)g}$ is the weights associated with the l-th objective (l = 1, 2, …, p); and the weights assigned to the k-th attribute associated with the l-th objective. The aggregated preferences of DM_1 and DM_2 result in the following ordering of the three alternatives: $V(A_{3g})$ = 0.644 > $V(A_{1g})$ = 0.619 > $V(A_{2g})$ = 0.271 (see Fig. 8.3c and Table 8.1). The geometric mean method for aggregating individual preferences has been used in several GIS-based AHP applications (Schmoldt et al. 1994; Strager and Rosenberger 2006; Nekhay et al. 2009; Moeinaddini et al. 2010).

8.2.2 Outranking Methods

Two outranking methods, ELECTRE and PROMETHEE (see Sect. 4.5), have been integrated into GIS to support group decision making. These methods, like the AHP/ANP techniques, can be used according two schemes: (i) a consensus on the preference structure of decision makers is achieved first and then the group preferences are used within the conventional outranking methods (see Fig. 8.1a), or (ii) the individual decision makers solve the problem separately, and then the individual solutions are aggregated (see Fig. 8.1b). The former approach has often been applied by integrating GIS and ELECTRE (e.g., Joerin and Musy 2000; Joerin et al. 2001; Norese and Toso 2004), while the latter has been more popular in applications based on integrating GIS and PROMETHEE (e.g., Martin et al. 2003; Ishizaka and Nemery 2013).

8.2.2.1 ELECTRE Group Method

The ELECTRE group method is often used in situations involving an analyst (expert) and a group of agents (decision makers) (Kangas et al. 2001). Also, the expert typically identifies the threshold values (see Sect. 4.5.1) while the decision makers specify their preferences with respect to the evaluation criteria. Once the individual preferences (weights) have been identified, they can be aggregated by computing the median or mean of the individual preferences (Roy 1991). Alternatively, a group of individuals can use the conventional ELECTRE as a tool for supporting consensus among individuals with conflicting preferences. This approach is typically used in GIS-based ELECTRE applications (e.g., Joerin and Musy 2000; Joerin et al. 2001; Norese and Toso 2004; Macary et al. 2010).

Joerin and Musy (2000) and Joerin et al. (2001) provide an example of applying GIS-ELECTRE for land-use suitability assessment. They developed a system called MAGISTER (Multicriteria Analysis and GIS for Territory) for supporting a participatory (group) decision making process. The main aim of the system is to generate homogenous suitability zones for land use planning. Joerin et al. (2001) suggest that the land suitability maps obtained with MAGISTER can provide a base for integrating conflicting preferences and generating a group (consensus) solution for land use planning problems. This type of approach can be referred to as map-centered decision support (see Jankowski et al. 2001 and Chap. 11). The role of the map as a tool for supporting decision making was also highlighted by Macary et al. (2010) in the context of their GIS-ELECTRE approach for delimiting 'zones' of air pollution. Norese and Toso (2004) integrated ELECTRE and GIS to support a participatory decision process for locating an incinerator and waste disposal plant. They demonstrated that the multicriteria (ELECTRE) approach can be used as a tool for stimulating 'communication' between experts and interest groups. They also signified a central role of GIS in improving and accelerating the group decision making process.

8.2.2.2 PROMETHEE Group Method

The conventional PROMETHEE approach (see Sect. 4.5.2) has been extended to group decision making problems (Macharis et al. 1998). It is known as the Group Decision Support System (GDSS) PROMETHEE procedure. GDSS-PROMETHEE involves three phases: (i) identifying decision alternatives and evaluation criteria, (ii) evaluating alternatives by each decision maker applying the conventional PROMETHEE, and (iii) aggregating the individual evaluations by combining the individual net flows (see Eq. 4.26). The best alternative is the one characterized by the highest combined net flow.

The PROMETHEE procedure for group decision making has successfully been integrated with several GIS applications (e.g., Martin et al. 2003; Ishizaka and Nemery 2013). Martin et al. (2003) developed an integrated decision aid system for supporting land-use planning and management. Multicriteria analysis was then used to evaluate and compare the scenarios according to eleven criteria, using a combination of GIS analysis with MapInfo and multicriteria processing carried out in PROMCALC & GAIA. This process leads to a partial ranking (PROMETHEE I) and a complete ranking of the scenarios (PROMETHEE II) for each individual decision maker, as well as for the whole group. Ishizaka and Nemery (2013) used the GDSS-PROMETHEE approach for a site selection problem with GIS as a tool for visualizing the results of group decisions and negotiations.

8.2.3 Voting Methods

GIS-MCDA methods enhanced by voting procedures proved to be effective approaches for tackling spatial decision problems in group, participatory, and collaborative settings (Malczewski 1996; Jankowski et al. 1997, 2008; Chen et al. 2001; Feick and Hall 2002; Andrienko et al. 2003). The integration of GIS-MCDA and voting techniques follows the two-stage procedure shown in Fig. 8.1b. Specifically, the decision problem is tackled by each decision maker separately, and then the individual solutions are aggregated using a voting scheme. Each decision maker can generate a solution map using a GIS-MCDA method. The solution maps can then be translated into maps of ranked alternatives that can be aggregated using a voting method or vote aggregation function to generate the group solution map. One of two classes of voting schemes is typically used in the GIS-MCDA approaches for aggregating individual preferences: (i) non-ranked methods such as plurality and majority vote aggregation functions (see Sect. 8.2.3.1), and (ii) rank-based voting methods such as Borda and Condorcet aggregation functions (see Sect. 8.2.3.2).

8.2.3.1 Non-ranked Voting Rules

A non-ranked voting scheme selects an alternative that is considered the best by most individuals. It is the binary decision rule. Each individual selects one decision alternative from a set of alternatives. The alternative with the most votes is declared the best alternative. Plurality and majority rules are the simplest and most often used non-ranked methods. In the plurality voting procedure, each individual casts a single vote. The alternative with most votes is the best one. The majority rule is a specific case of plurality voting. It identifies an alternative that has been selected by a majority (more than 50 % of the votes). When there are only two alternatives, plurality is the same as majority voting.

An important consideration in aggregating individual preferences using a non-ranked voting scheme is the property of transitivity. A group that is composed of individuals with rational (transitive) preferences does not necessarily have rational collective preferences. A paradox of intransitive preferences arises from the aggregation of individual transitive preferences. For example, given a set of three decision alternatives, A_1, A_2, and A_3, a transitivity relation can be defined as follows: if $A_1 \succ A_2$, and $A_2 \succ A_3$, then $A_1 \succ A_3$ (the symbol $\succ$ means 'is preferred to') (see Sect. 2.3.2.2). Consider a decision situation involving three decision makers (DM_1, DM_2, and DM_3) and the following voting results: DM_1: $A_1 \succ A_2 \succ A_3$; DM_2: $A_2 \succ A_3 \succ A_1$; and DM_3: $A_3 \succ A_1 \succ A_2$. One can observe that in a majority vote, A_1 is preferred to A_2 by a majority of two to one (the first and third individuals preferring the alternatives in that order), and similarly A_2 is preferred to A_3 by a majority, and A_3 is preferred to A_1 by a majority. Thus, there is no simple majority winner. This result implies a circular preference among the alternatives, or the preference of the group is intransitive (Hwang and Lin 1987). It can be shown that the probability of getting intransitive result increases with an increasing number of alternatives (Arrow and Raynaud 1986). Consequently, one can suggest the chance of intransitivity of the group preference in many GIS applications is very high. This holds true especially in raster-based spatial decision making, when each location or cell represents a decision alternative.

Another limitation of the non-ranked voting rules is that these methods use a crisp value (threshold value) for defining a majority. These rules can be either absolute (majority rule, more than 50 % of the votes) or relative (plurality rule, less than 50 % of the votes). These voting methods have been extended using the fuzzy set approach to address this limitation. Specifically, a majority degree is defined using fuzzy linguistic quantifiers (see Sect. 7.3.3), which are linguistic terms such as 'most', 'at least half', 'much more than 50 %', or 'as many as possible'. A linguistic statement can then be used to indicate a combination strategy to guide the aggregation process of individual preferences. In a spatial decision setting, if Q is a linguistic quantifier, then the quantifier aggregation can take the general form of the following: Q of the decision makers are satisfied by location A_i; where Q is a term such as 'most', 'at least half', 'much more than 50 %', 'as many as possible', etc. (Yager 1996).

Faber et al. (1996) and Jankowski et al. (1997) provide the earliest applications of non-ranked voting rules to GIS-based multicriteria decision support for group decision making (see also Jankowski and Nyerges 2001; Jankowski et al. 2008). Boroushaki and Malczewski (2010c) implemented the concept of fuzzy majority in ArcGIS as a MultiCriteria Group Analyst (MCGA) extension. The MCGA procedure involves two major steps: (i) creating solution maps according to the individual decision-makers' preferences, and (ii) deriving the group solution using the fuzzy majority approach (see Fig. 8.1b). Specifically, the procedure applies a quantifier-guided OWA operator (see Sect. 7.3.3) for generating the solution maps according to the individual preferences, and then the fuzzy majority approach is employed for aggregating the individual preferences. Boroushaki and Malczewski (2010a) provide a computational example of the procedure using a hypothetical land suitability problem. The system has been applied to a real-world site selection problem (Boroushaki and Malczewski 2010a, b, c; Meng and Malczewski 2010a, b). An application of a group decision making approach for fuzzy modeling is given in Rajabi et al. (2012). They successfully applied the MCGA procedure for mapping and identifying locations (areas) at risk of a vector-borne disease.

8.2.3.2 Rank-Based Voting Rules

The main problem with the plurality method is that it takes into account only the first choices (the most preferred alternative by each individual). The rank-based voting schemas address this problem by allowing each individual to rank the decision alternatives in order of preference (Hwang and Lin 1987). The methods are also known as preferential voting. The Borda count method (or Borda social preference function) is the simplest rank-based voting system (Hwang and Lin 1987; Massam 1988). It is also the most often used in GIS-MCDA procedures for aggregating individual preferences (e.g., Malczewski 1996; Jankowski et al. 1997, 2008; Jankowski and Nyerges 2001; Feick and Hall 2002; Gorsevski et al. 2013). For a set of decision alternative (A_1, A_2, …, A_m), the Borda function assigns a point value of $m - 1$, $m - 2$, $m - 3$, …, 1, 0 to the most preferred alternative, the second most preferred alternative, …, the least preferred alternative for each individual, $g = 1, 2, \ldots, z$. The Borda score is then determined by the sum of individual point values for the i-th alternative. The alternative with the maximum Borda score is the most preferred choice according to group preferences.

The Borda count method is often used as a procedure for aggregating individual preferences according to the two-stage approach, shown in Fig. 8.2b. Specifically, a conventional GIS-MCDA method is employed for obtaining the individual rankings of alternatives (individual solution maps), which are subsequently aggregated by calculating the Borda score for each alternative (group solution map). Malczewski (1996) integrated the ideal point method (see Sect. 4.4) and the Borda social choice function in the context of land suitability problem. A set of group/collaborative/participatory spatial decision support tools has been proposed by Jankowski and associates in their GIS-MCDA systems (e.g., Jankowski et al. 1997, 2008; Jankowski and Nyerges 2001). These tools provide a combination of conventional MCDA methods (such as WLC and ideal point) and voting methods (such as the Borda choice function). Jankowski et al. (1997) demonstrate the use of a spatial decision support system for groups for prioritizing habitat site development (see also Jankowski and Nyerges 2001; Andrienko et al. 2003). Jankowski et al. (2008) proposed a Web-based spatial multiple criteria evaluation tool for individual and group decision making. The system integrates the capabilities of TOPSIS for individual MCDA and a modified version of the Borda method for aggregating individual preferences. Chen et al. (2001) developed a multicriteria evaluation system for risk-based decision making in the context of natural hazards. The system integrates WLC (see Sect. 4.2), TOPSIS, and compromise programming (see Sect. 5.3.2) as methods that can be used for generating the individual rankings, which are then combined using the Borda count method to produce a consensus ranking.

Feick and Hall (2002) developed a GIS-MCDA system to evaluate sites for a new tourism development. The system integrates two MCDA methods, WLC and concordance analysis (see Sect. 4.5), and two voting rules: the Borda and Copland counting functions for generating group-wide rankings of alternatives (see also Feick and Hall 2004). The Copland rule is an alternative to the more popular Borda function. It is a pairwise aggregation method that selects the alternative with the largest Copeland score. The Copeland score for a given alternative is defined as the difference between the number of times the alternative is ranked higher than other alternatives and the number of times that alternative is ranked lower than other alternatives when the alternatives are considered in pairwise comparisons (Hwang and Lin 1987). The results of an empirical study of a small group of individuals representing different interests show a high degree of correspondence between the Borda and Copeland rankings (Feick and Hall 2002). They also show the Borda method is more likely to promote compromise alternatives than the Copeland method. These findings support earlier comparative studies of the two voting methods (see Hwang and Lin 1987, p. 40). One drawback of the Borda scheme is that the outcome it selects is susceptible to strategic manipulation; for example, the results can be manipulated by including additional alternatives. Another drawback is that an individual can deliberately assign low ranks to alternatives, which may threaten his/her own most preferred options (Hwang and Lin 1987; Feick and Hall 2002).

The main advantages of voting approaches for GIS-based collaborative/participatory decision making are their simplicity and comprehensibility (Malczewski 2006). Janssen et al. (2005) suggest that collaborative spatial decision making does not have to involve complex multicriteria modeling. It can capture sufficient details from negotiations and deliberations in such a way that there would be no need for more sophisticated multicriteria decision modeling and aggregation (Jankowski and Nyerges 2001; Janssen et al. 2005; Nyerges and Jankowski 2010). On the other hand, simplification of the multicriteria decision modeling may result in the trivialization of the decision making process. It can also increase the risk of missing essential information about the decision making process (Carver 1999).

Both rank-based and non-ranked voting systems are subject to a number of conceptual and theoretical difficulties. The principal difficulties are the intransitivity or paradox of voting and Arrow's impossibility theorem (Arrow 1951; Hwang and Lin 1987). The decision analysis procedures, including individual preference aggregation functions, typically require the simple and logical condition of transitivity. However, individual rationality is insufficient to ensure group rationality; that is, the existence of individual preferences does not imply the existence of a group preference with properties similar to those of the individual preferences. This is illustrated by the well-known intransitivity or Condorcet paradox (see Sect. 8.2.4.1). Arrow (1951) demonstrated through his impossibility theorem that there is no acceptable mechanism for aggregating ordinal preferences that would conform to social choice. The procedures for aggregating cardinal preferences (the value/utility-based methods) have similar limitations, mainly related to the difficulty of interpersonal comparisons (Keeney and Raiffa 1976). The intransitivity problem can be avoided if alternatives are not compared simultaneously but rather one-by-one and sequentially, although it can be demonstrated that the order of comparison has a direct effect on the ranking of the alternatives (Hwang and Lin 1987).

Given the limitations of voting systems, some researchers suggest that these methods should be used as techniques for facilitating discussion and negotiation, rather than as prescriptive measures (e.g., Jankowski and Nyerges 2001; Meeks and Dasgupta 2004; Malczewski 2006; Nyerges and Jankowski 2010). This process can be supported by visualizing the collective solutions with special-purpose maps for geographically representing consensus solutions (Jankowski et al. 2001; Armstrong and Densham 2008) and argumentation mapping (Rinner 2001; Rinner et al. 2008).

8.3 Geosimulation Methods

Spatial simulation (or geosimulation) methods have recently emerged as a platform for integrating MCDA into group (social or collective) decision making. The principal purpose of using MCDA in spatial simulation approaches is to define the rules of behaviour for decision making agents (see Sect. 2.2.1.2). The MCDA methods (or multicriteria decision rules) are used for describing and understanding decision making and its consequences through a simulation model. They are employed as descriptive-normative modeling tools (see Sect. 1.2.1). Unlike the conventional GIS-MCDA methods for group decision making (see Sect. 8.2), the simulation based GIS-MCDA approaches are spatially explicit, in that the outcome of the decision process depends on spatial arrangement of decision alternatives (e.g., alternative patterns of land use). These approaches meet the requirements of spatially explicit models as specified in Sect. 1.4.2. There are two geosimulation methods: cellular automata and agent-based modeling.

8.3.1 Cellular Automata

Cellular Automata (CA) is a dynamic discrete system that typically operates on a uniform grid-based space by implementing local decision rules. At the most rudimentary level, a CA model consists of the following elements: (i) a two-dimensional cellular space divided into independent units (an array of cells or a raster grid), (ii) each cell has a *state* (the number of state possibilities is typically finite), (iii) each cell has a *neighbourhood* (e.g., the neighbourhood consists of the eight cells surrounding the centre cell), (iv) *transition rules* are applied to each cell and its neighbourhood to define the state of the cell in the next iteration, and (v) time progresses uniformly, and at each *discrete time* step, all cells change state simultaneously (Engelen et al. 1997; Liu 2009). From the perspective of MCDA for group decision making, the concepts of cell (and its state) and transition rule are of central significance.

The cells can be considered decision making agents (Li and Liu 2007). CA uses simple agent models, specified in terms of a decision rule attached to the cells. The system can involve two or more agents. In the simplest example of two possibilities of 1 and 0 (e.g., developed versus undeveloped lands), there are two groups of agents associated with the two categories of cells (Batty and Xie 1994). Similarly, in an application involving four land uses (e.g., residential, commercial, industrial, recreational), the cells can be thought of as four groups of agents representing stockholders searching for a suitable location (Li and Liu 2007; Long and Shen 2012). The states of the cells (agents) are updated according to a set of deterministic or probabilistic local decision rules. Specifically, the state of a cell at a given time depends only on its own state at the previous time step and the states of its nearby neighbours at the previous time step. All cells of an automaton are updated synchronously in parallel. Thus, the state of the entire automaton advances in discrete time steps. The global behaviour of the system is determined by the evolution of the states of all cells as a result of multiple interactions (Batty and Xie 1994; Li and Yeh 2000).

The state of the i-th cell at time $T + 1$ is defined as a function of the state of the cell and its neighbourhood at T according to the following set of transition rules (Wu 1998; Yu et al. 2011):

$$S_i^{T+1} = f(S_i^T, Q_i^T, TR) \tag{8.2}$$

where S_i^{T+1} and S_i^T are the states of the i-th cell (land use) at the time $T + 1$ and T, respectively ($i = 1, 2, \ldots, m$), the cell designated by $i = 1$ is the top left-hand corner of a grid-cell map and the cells are numbered left-to-right for each row; the cell m is located in the bottom right-hand corner of the grid); Q_i^T is the state (development situation) in the neighbourhood of the i-th location, and TR is the transition rules. The state of the i-th cell at the time $T + 1$ can be defined in terms of land conversion probability by summarising the three independent variables (S_i^T, Q_i^T, and TR) as follows:

$$S_i^{T+1} = f(P_i^T) = f(V(A_i^T)), \tag{8.3}$$

where P_i^T is the land conversion probability at the i-th location and the time T, and $V(A_i^T)$ the overall value (or land suitability) of alternative, A_i^T, at the time T. The value of $V(A_i^T)$ can be obtained using MCDA models such as WLC (see Sect. 4.5). The CA-WLC model is defined as:

$$V(A_i^T) = \sum_{k=1}^{n} w_k v(a_{ik}^T), \tag{8.4}$$

where $v(a_{ik}^T)$ is the score of development factor k at the i-th location at time t; a_{ik}^T is a feasible value of criterion k associated with the i-th location at time t (the feasible cells can be identified using one of the methods presented in Sect. 2.2.3.1); w_k is the criterion weight (see Sect. 2.3.2).

The central issue in integrating MCDA such as WLC (Eq. 8.4) into CA is the procedure for estimating the criterion weights w_k. The pairwise comparison procedure (see Sect. 2.3.2.2) has been the most often used approach for obtaining the weights (e.g., Wu 1998; Wu and Webster 1998; Li and Liu 2007; Kamusoko et al. 2009; Vaz et al. 2011; Yu et al. 2011; Ozah et al. 2012; Lai et al. 2013; Shafizadeh-Moghadam and Helbich 2013). Wu (1998) developed a system by integrating the pairwise comparison procedure into GIS-based CA for simulating land conversion in a fast growing urban region (see also Wu and Webster 1998). A similar approach has been applied for simulating an evaluation of irrigated cropland suitability (Yu et al. 2011). Myint and Wang (2006), Kamusoko et al. (2009), and Ozah et al. (2012) integrated a GIS-based CA model, the Markov chain analysis and pairwise comparison procedure, for analyzing the land-use change in a rural region (see also Munday et al. 2010; Shafizadeh-Moghadam and Helbich 2013).

There are several advantages of integrating MCDA into GIS-based CA (Wu 1998; Jiao and Boerboom 2006; Yu et al. 2011; Lai et al. 2013; Cao et al. 2014). The multicriteria approaches improve the procedures for calibrating CA parameters (Cao et al. 2014) and providing behaviour-driven transition rules, as opposed to the traditional data-driven methods such as multiple regression analysis and principal components analysis (see Liu 2009). This allows for a more realistic definition of transition rules in CA by taking into consideration the characteristics of the decision making process (Jiao and Boerboom 2006). The GIS-MCDA approach, integrated with CA, provides an effective and efficient tool for generating different planning scenarios and performing a what-if type of analysis. A disadvantage of CA modeling is that the group decision making process is present only implicitly (Ligtenberg et al. 2000). This limitation can be addressed by multi-agent modeling, which offers a conceptual and methodological approach to include the multiple actors (agents) into dynamic spatial models of decision making (Ferrand 1996; Parker et al. 2003; Torrens 2002; Ligtenberga et al. 2004).

8.3.2 Multi-agent System

Agent-based modeling (ABM) can be considered an extension of CA. Although an agent is characterized by all of the features of a basic automaton, there are some important differences between CA and ABM (Torrens 2002). In the CA model, a cell (automaton) has a fixed location in its simulated space and the capability of interacting with and diffusing state information to neighbouring cells. Unlike the case of CA, in agent-based modeling, the agents are designed as movable individual entities capable of spatial behaviour, and can manifest more complex forms than simple relocation. Consequently, the states S (see Eq. 8.2) can be designed to represent characteristics of human decision makers. Also, the transition rules (TR) can be operationalized to represent complex human-like behaviours. Real-world ABM applications typically involve a group of agents. A multi-agent system (MAS) consists of multiple heterogeneous, autonomous, goal-oriented entities that operate and interact in a common environment (Parker et al. 2003). An agent is a computational entity or small software program (see Sect. 2.2.1.2). It acts upon its environment and behaviours depending on its own experience. As an intelligent entity, an agent operates flexibly and responds to a changing environment. The agents represent individuals (e.g., households) or other actors (e.g., plants) in a simulated real world environment. For example, the environment might represent an urban area and agents might represent the interest groups involved in land use planning. Specifically, the spatial agent-based models acknowledge the fact that land use emerges from decentralized human decisions. Accordingly, ABMs attempt to capture essential features of human–environment interaction by providing means for including human decision making without losing the strength of the concept of self-organization underling the CA approaches.

The agents can act according to two basic forms of group decision making: cooperation (e.g., Bone and Dragićević 2010; Chen et al. 2010), and competition (e.g., Ligmann-Zielinska 2009). In the former case, a group of agents works together and draw on their knowledge and capabilities to attain a common goal, which can be achieved by a set of objectives (e.g., designing the best pattern of land uses or minimizing travel distance). In a competitive situation, the agents are characterized by conflicting objectives. Consequently, they act against each other attempting to maximize their own benefit. In either of the two situations, ABM involves an iterative procedure, which typically proceeds through discrete time steps. Also, like in CA, any number of transition rules can be devised to govern the activities of agents (Torrens 2002). Similarly to CA, the MAS agents exist in a geographic space and their behaviour is driven by transition rules.

Ferrand (1996) was the first to propose a framework for integrating GIS-MCDA and MAS for group decision making (multi-actor spatial planning). Subsequently, a number of studies have demonstrated the usefulness of combining these two approaches for tackling spatial decision problems (e.g., Ligtenberg et al. 2001; Ligmann-Zielinska 2009; Demircan et al. 2011; Sabri et al. 2012). Ligmann-Zielinska (2009) provides an example of using the ideal point method (see Sect. 4.5) within a multi-agent modeling approach for simulating land use patterns. The ANP and AHP methods (see Sect. 4.3) have been integrated into MAS for evaluating gentrification plans and simulating urban growth patterns, (see Sabri et al. 2012 and Arsanjani et al. 2013, respectively). While all those applications involve land use context, Demircan et al. (2011) employed GIS-MCDA and MAS for a network problem finding an optimum route for electrical energy transmission.

The synergistic effects of integrating GIS-MCDA into spatial simulation methods can be enhanced by combining CA and multi-agent modeling (e.g., Ligtenberg et al. 2001; Li and Liu 2007; Ligmann-Zielinska 2009; Sabri et al. 2012). The motivation behind integrating CA and ABM is that they are complementary modeling strategies. They can be integrated into a geographic automaton system where some agents are fixed while others are mobile (Torrens 2002). Ligtenberg et al. (2001) provide an example of an integrated CA and MAS approach and the use of GIS-based MCDA techniques for group (collective) decision making. The study aims at developing alternative scenarios for land uses in the region based on preferences of interest groups/stakeholders. The agent-based decision making procedure consists of two main steps: individual and group decision making tasks (similar to the framework in Fig. 8.1b). The individual decision making tasks involve constructing the agent-specific land use pattern. The conflicts among agents over alternative land use allocations are resolved by a progressive voting procedure (see Sect. 8.2.3).

The main advantage of an integrated geosimulation and GIS-MCDA is that it provides a tool for developing dynamic models that combine spatially explicit processes using the automaton techniques and actor (stakeholders) interactions by applying the multi-agent technology. Studies about integrating GIS-MCDA into agent-based modeling provide a significant contribution to the spatial decision analysis literature. From the perspective of spatial simulation, MCDA can be seen as a set of tools for defining the behaviour of decision making agents. On the other hand, the simulation methods provide a platform allowing for spatial aspects of multicriteria decisions to be considered explicitly. It also lends a dynamic component to the otherwise static nature of GIS-MCDA. An integrated GIS-MCDA and MAS approach can be used for exploring complex large-scale (global) spatial structures that emerge from local decision making processes. However, global patterns are unlikely to result from local decision making processes alone (Ligtenberg et al. 2004). This bottom-up approach to spatial modeling limits the capability of multi-agent simulation methods as a tool for analyzing complex spatial decision problems. This drawback can be addressed by integrating the large-scale (bottom-up) geosimulation methods and the top-down multiobjective optimization procedures.

8.3.3 Geosimulation and Multiobjective Optimization

There has recently been a growing interest in advancing GIS-MCDA by integrating geosimulation (CA and MAS) with multiobjective decision analysis (MODA) methods (e.g., Ward et al. 2003; Trunfio 2006; Castella et al. 2007; Bone and Dragićević 2009; Ligmann-Zielinska and Jankowski 2010; Chen et al. 2010; Bone et al. 2011; Fotakis and Sidiropoulos 2012; Feng and Liu 2013). Geosimulation and MODA (see Chaps. 5 and 6) have traditionally been considered two idiosyncratic approaches for analyzing and solving decision problems. The concepts of bottom-up simulation and top-down optimization are the main distinctive features of the two modeling frameworks (Castella et al. 2007; see Table 8.2). Geosimulation methods aim at describing and explaining spatial patterns in terms of principles of self-organized systems. A fundamental characteristic of geosimulation models is

Table 8.2 Selected characteristics of geosimulation and multi-objective optimization methods

Models	Characteristics
Geosimulation modeling: cellular automate (CA) and multi-agent system (MAS)	Descriptive/exploratory modeling Bottom-up approach Collective spatial decision making process Local-scale spatial process Symbolic representation of society
Multiobjective decision analysis (MODA)	Normative/prescriptive modeling Top-down approach Semi-automated designing of spatial patterns Large-scale spatial structure Non-dominance of solutions
CA/MAS and MODA	Complementarity and synergy Static form and dynamic process Multiple compromise spatial solutions Comprehensive policy modeling

Source Based on Ligmann-Zielinska and Jankowski (2010, p. 410) that they incorporate dynamic aspects of spatial structures where a large- (regional-) scale spatial pattern is generated as an outcome of local- (neighbourhood-) scale decision making processes (Ward et al. 2003; Bone et al. 2011). Spatial multiobjective optimization provides the top-down modeling framework for generating spatial structures based on a set of relevant objectives (criteria). Unlike the geosimulation approaches, the MODA models typically represent static structures rather than the decision making processes. They focus on generating non-dominated solutions and examining the trade-off between objectives (Ligmann-Zielinska and Jankowski 2010; Bone et al. 2011).

The characteristics of geosimulation and MODA suggest the two approaches are complementary methods (Ligmann-Zielinska and Jankowski 2010; Bone et al. 2011). Indeed, one can achieve a synergistic effect by integrating the two modeling frameworks. This has been demonstrated by several studies about combining CA and MODA (e.g., Ward et al. 2003; Fotakis and Sidiropoulos 2012) and MAS and MODA (e.g., Castella et al. 2007; Bone and Dragićević 2009). For example, the classic multiobjective optimization (mathematical programming) methods have been integrated with CA (Ward et al. 2003) and agent-based modeling (Castella et al. 2007; Chen et al. 2010; Ligmann-Zielinska and Jankowski 2010). Ward et al. (2003) and Castella et al. (2007) applied simulation-based multiobjective optimization models for analyzing land use changes in the context of urban growth and management of natural resources, respectively. Ligmann-Zielinska and Jankowski (2010) developed a multiobjective land use allocation model, which was employed as a tool for generating a set of solutions (or land use plans) to account for varying viewpoints of potential stakeholders. The land attributes (land value, attractiveness, and accessibility) that correspond to the objectives of the land use optimization model are then used as evaluation criteria by the developer agents. The agents operate on a cellular (raster) space to identify the best land use pattern according to their preferences and perceptions of risk associated with the property investment. An ideal point method (see Sect. 4.4) modified to account for these different attitudes to risk (see Sect. 2.3.1.1) is used by the agents as a decision rule.

Given the computational limitations of the classic optimization methods (see Chap. 5), spatial decision problems are often tackled by heuristic procedures (see Chap. 6). Bone and Dragićević (2009) developed a model in which agents representing individual stakeholders have their actions evaluated by algorithms based on reinforcement learning (RL) (see also Bone et al. 2011). The RL procedure is a multiobjective heuristic method used to reward decisions made by individual agents that lead to achieving specific objectives. The utility of this approach has been demonstrated in the context of a multiobjective decision problem for natural resource allocation. Li et al. (2011a, b), Fotakis and Sidiropoulos (2012), and Feng and Liu (2013) provide examples of coupling agent-based models with meta-heuristic procedures. Li et al. (2011a) have integrated cellular automata and ant colony optimization procedures to solve complex path optimization problems (see Sect. 6.3.4). The cellular automata approach has been coupled with a simulated annealing procedure (see Sect. 6.3.2) for modeling urban land-use changes (Feng and Liu 2013). Fotakis and Sidiropoulos (2012) proposed the CA-based spatial optimization model using non-dominated sorting genetic algorithm or NSGA-II (see Sect. 6.3.1.8) for a groundwater management problem (see also Trunfio 2006).

Chen et al. (2010) demonstrated the usefulness of MAS for tackling a land allocation optimization problem. The results of their computational experiments show that the simulation-based optimization procedure generates solutions (land allocation patterns) similar to that obtained with the exact mathematical programming methods (see Chap. 5). The approximate solution generated by MAS can be interpreted from the perspective of game theory. Compared to the game procedures, the most distinctive feature of MAS proposed by Chen et al. (2010) is related to the interactions among the individual agents. While the game procedures are typically based on the assumption of competitive agent interactions, MAS generates solutions by a joint action (cooperation) of the agents. Notice that some of the meta-heuristic methods, such as swarm intelligence procedures (see Sect. 6.3.4), are also based on strategies involving cooperation among agents.

The integrated geosimulation-multiobjective optimization methods provide a significant contribution to applied GIS-MCDA. While the multiobjective optimization procedure generates a set of non-dominated solutions and allows for analyzing trade-off between conflicting objectives, geosimulation provides an effective tool for exploring a variety of decision making scenarios and facilitating the process of identifying a compromise solution. The two modeling paradigms complement each other (Table 8.2). Complementarity is the primary source of synergy between the two methods. The synergistic effects manifest themselves in mutually reinforced conclusions that one can be derived from geosimulation and multiobjective optimization analysis. The normative results (recommendations) of multiobjective optimization can be strengthened by a complementary multi-agent, process-oriented modeling of the decision making process.

As with any heuristic method, the geosimulation-based multiobjective optimization approach is not without its problems. First, although there is some evidence to show that the methods generate good approximation of the exact solution to complex spatial problems (e.g., Chen et al. 2010), the approach does not guarantee more accurate decision making; even though one can expect that it should provide for more informed decisions. Second, the geosimulation technology can be criticized for its 'black box' style of spatial analysis (O'Sullivan and Unwin 2010). Third, the approaches are largely inaccessible to non-experts. If it is difficult to clearly present and explain the internal workings of the modeling framework, it is unlikely that a solution, or a set of solutions, obtained by geosimulation-based multiobjective optimization will be acceptable to those who make decisions.

8.4 Conclusion

This chapter provided an overview of methods for groups of decision makers. It focused on two distinctive classes of GIS-MCDA procedures for groups: conventional methods for aggregating preferences and geosimulation-based modeling.

The former includes conventional GIS-MCDA methods (see Chap. 4) that have been adapted for tackling conflicting preferences in a group decision making setting. This class of methods is based on the traditional notion of decision makers (interest groups) and tends to focus on prescriptive-constructive modeling. AHP/ANP and outranking methods, along with voting schemes, are the conventional approaches that have often been integrated with GIS capabilities. Unlike the conventional approaches, geosimulation involves the concept of decision making agents and descriptive-normative modeling. It provides a platform for spatially explicit analysis of multicriteria decision problems. When integrated with multiobjective optimization, geosimulation modeling opens up new opportunities for analyzing complex spatial problems involving a combination of bottom-up and top-down decision making processes.

GIS-MCDA methods have the potential to improve group/collaborative/participatory decision making procedures by providing a flexible problem-solving environment where participants can explore, understand, and redefine a decision problem (Malczewski 2006). By their nature, MCDA approaches integrate multiple views of decision problems to provide platforms for identifying and organizing data on alternative decisions (plans, policies) and the set of criteria for evaluating, assessing, and comparing alternatives. GIS-MCDA can support group decision processes by serving as a tool for structuring group decision problems and organizing communication in a group. The value-focused approach provides a framework for handling the debate on the identification of options, goals, criteria, objectives, and attributes; and organizing them into a hierarchy of values. The integration of GIS and MCDA allows conflict to be reduced by providing mechanisms for revealing participants' preferences, identifying and exploring compromise alternatives, and for building consensus. While GIS can influence facts in particular conflict resolution process, MCDA can make explicit the values of each individual, show where and by how much they differ, and in the process, reduce the extent of disagreements.

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