Advances in Geographic Information Science

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Multicriteria Decision Analysis in Geographic Information Science

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ISSN 1867-2434 ISSN 1867-2442 (electronic)
Advances in Geographic Information Science
ISBN 978-3-540-74756-7 ISBN 978-3-540-74757-4 (eBook)
DOI 10.1007/978-3-540-74757-4

Library of Congress Control Number: 2014955623

Springer New York Heidelberg Dordrecht London

Printed on acid-free paper

Springer Science+Business Media LLC New York is part of Springer Science+Business Media
(www.springer.com)

Preface

A growing number of scientists and practitioners are merging theories, methods, and technologies from different disciplines to extract new meaning from data and to solve complex problems using new methods. The research on integrating Geographic Information Systems (GIS) and Multicriteria Decision Analysis (MCDA) is an example of how linking concepts and methods from two distinct fields can yield new ways of tackling decision problems. At the most fundamental level, GIS-MCDA can be thought of as a collection of methods and tools for transforming and combining geographic data and preferences (value judgments) to obtain information for decision making. The main aim of this book is to contribute to GIScience by providing a comprehensive account of the theories, methods, and technologies for integrating MCDA into GIS. The book also demonstrates how the GIS-MCDA approaches can be used in a wide range of real-world planning and management situations. Indeed, we provide practitioners and students with the knowledge required for them to gain a fuller understanding of MCDA using geographic information technologies.

In recent years, there has been a considerable growth of theoretical and applied research on GIS-MCDA. The field of GIS-MCDA has strongly been adopted within the GIScience community. The efforts to integrate MCDA into GIS have also been recognized as a significant achievement in expanding MCDA into new application areas. Although the primary motivation behind the research efforts on integrating MCDA into GIS comes from the need to expand the decision support capabilities of GIS and related technologies, equally important significance is that the two distinctive areas of research can benefit from each other. On the one hand, GIS techniques and procedures have an important role to play in analyzing multicriteria decision problems. They offer unique capabilities for storing, managing, analyzing, and visualizing geospatial data for decision making. GIS allows analysts and decision makers to think about the spatial relationships in a more sophisticated and meaningful manner than is otherwise possible. This, in turn, allows for developing new ways to think about decision alternatives and considering new solutions for decision problems. On the other hand, MCDA can improve the GIS ability to tackle spatial decision problems appropriately. It provides a theoretical foundation for decision analysis and offers a wide range of methods for supporting complex decision-making processes. Although many aspects of spatial decision problems can be usefully tackled by the conventional, aspatial, MCDA methods, we believe there is a need for MCDA approaches specifically designed for dealing with spatial problems if the decision-making process is to provide meaningful results and avoid misguided recommendations.

The book is divided into three parts: Preliminaries (Part I), Spatial MCDA: Methods (Part II), and Spatial MCDA: Technologies (Part III). Parts I and II were written by Jacek Malczewski, while Part III was contributed by Claus Rinner.

Part I consists of three chapters. Chapter 1 examines the linkages between GIScience, spatial analysis, and decision support. We highlight an important distinction between conventional MCDA methods and spatially explicit multicriteria/multiobjective approaches. Chapter 2 provides an overview of generic elements of MCDA. It also examines the basic concepts of GIS-MCDA including: value scaling, criterion weighting, and combination rules. The final chapter of Part I reviews the development of GIS-MCDA research and applications in the last 20 years or so.

Part II is subdivided into five chapters dealing with spatial MCDA methods for tackling decision problems. Chapter 4 focuses on the most frequently applied GIS-based multiattribute decision analysis methods including: weighted linear combination, analytic hierarchy process/analytic network process, ideal point approaches, and outranking methods. The classic multiobjective decision methods are discussed in Chap. 5. The focus is on the most often used GIS-based multiobjective decision techniques such as: the methods for generating non-inferior solutions, the distance metric-based methods, and the interactive approaches. The complexity of many spatial multiobjective optimization problems makes it very difficult or even impossible to search every candidate solution using the classic methods. Consequently, Chap. 6 presents the heuristic algorithms. These algorithms are classified into two groups: basic heuristics (such as site suitability/location heuristics and greedy algorithms) and meta-heuristics (including evolutionary algorithms and swarm intelligence meta-heuristics). Chapter 7 explores the concept of uncertainties in GIS-MCDA. It also provides an overview of approaches for handling uncertainties in GIS-MCDA including fuzzy and probabilistic methods as well as sensitivity analysis. Chapter 8 focuses on the GIS-MCDA approaches for group decision making. It presents a selection of conventional GIS-MCDA methods that have been used for tackling group decision-making problems, and a discussion of geosimulation approaches from the perspective of GIS-MCDA for group decision making. The last chapter in Part II extends the traditional GIS-MCDA approaches to spatial/temporal multiscale analyses.

Part III addresses technologies for tackling spatial multicriteria problems. The three chapters contained therein follow the development of information technology from desktop computing to Web-based and mobile technologies. Chapter 10 explains desktop GIS-MCDA implementations and their applications. The chapter distinguishes desktop GIS-MCDA by the vector and raster data models used to represent geospatial features. Chapter 10 also includes an overview of MCDA and related modules in major commercial and open-source software packages. The chapter concludes with a case study illustrating the role of GIS-MCDA as a component in spatial decision support processes. Chapter 11 examines the combination of geovisualization and GIS-MCDA. Geovisualization is an approach to data analysis that entails multiple, linked, interactive maps that support geospatial data exploration and hypothesis development. Following an overview of geovisualization concepts, Chap. 11 distinguishes between the geovisualization of MCDA input and MCDA results. This chapter concludes with a case study, which illustrates the value of combining geovisualization and GIS-MCDA techniques to improve decision outcomes. Chapter 12 mirrors the trend of general information technology, and GIScience research and GIS development in particular, to move from desktop solutions to networked and mobile systems. The chapter outlines recent concepts and applications of Web-based and mobile GIS-MCDA technologies. This summary of ongoing research and development concludes Part III of the book.

This text is designed for researchers and practitioners in GIScience and operational research/management science, especially those conducting applied decision analysis. It is of interest to academics, students, and practitioners in both private and public sector organizations, who are interested in decision situations involving geographic datasets. In terms of pedagogical use, the book is suitable for upper level undergraduate and postgraduate teaching not only in GIScience and geography programs, but also in areas like urban and regional planning, environmental science, civil engineering, landscape architecture, and design. It can also be a valuable teaching resource for applied decision analysis and decision support systems courses offered in operational research/management science programs.

Acknowledgments

Dr. Jacek Malczewski's research in the area of GIS-MCDA was supported by the Social Sciences and Humanities Research Council of Canada (SSHRC) with two Insight Grants on "Web-based Multicriteria Spatial Decision Support Systems for Land Use Planning" (2008–2012) and "Local Multicriteria Analysis" (2012–2016). Several graduate students at the University of Western Ontario were involved in this research program, including Soheil Boroushaki, Yunliang Meng, Mohammadreza Jelokhani-Niaraki, Martin Healy, Chris Aspila, Xinyang Liu, Xue Qin, and Lucia Hussey.

Dr. Claus Rinner's GIS-MCDA research was partially funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) through two Discovery Grants on "Spatial Multi-Criteria Decision Analysis" (2004–2009) and "Developing Spatially Explicit Methods to Enhance Geovisual Analytics and Decision Support" (2011–2016). Additional funding related to one of the case studies in this book was received from a SSHRC Insight Development Grant on "Multi-Criteria Decision Analysis for Place-Based Policy-Making: Evaluating Toronto's Neighbourhood Wellbeing Indices" (2012–2014). Dr. Rinner's research was also supported by a series of NSERC Undergraduate Student Research Awards, Ontario work-study positions, and internal funds from Ryerson University's Yeates School of Graduate Studies, which allowed Dr. Rinner to work with Geography and Spatial Analysis students on projects informing the book. These students' contributions are acknowledged through references to joint publications, notably with Aaron Heppleston, John Taranu, Ben Spigel, Brian Kelsey, Olga Yermakhanova, Shiraz Nasr, Niklaus Ashton, Jacqueline Young, Martin Düren, Michael Markieta, Brad Carter, Krista Heinrich, and Steffan Voss.

Several Ryerson University students assisted us directly with completing the book manuscript. Meghan McHenry (BA cand. in Geographic Analysis) made many of the figures in Chaps. 11 and 12, and provided some text edits. Carmen Huber (BA cand. in Geographic Analysis) organized and edited the references for Chaps. 1 through 9. With a grant provided by the office of the Dean of Arts, Ryerson University, Victoria Fast (Ph.D. cand. in Environmental Applied Science and Management) edited the manuscript thoroughly and assisted with finalizing the submission. We acknowledge their valuable help, while emphasizing that any remaining errors are our sole responsibility.

Last but not least, the authors would like to thank their families and friends for their support and patience during this endeavor. Dr. Malczewski thanks his wife, daughter, and siblings for supporting him in both the high and low moments of writing this book. Dr. Rinner thanks his wife and daughter, parents, sister, and extended family as well as friends and neighbors for their encouragement, interest, impatience, and disbelief, which all helped to bring this project to completion.

Contents

Part I
Preliminaries

Chapter 1
GIScience, Spatial Analysis, and Decision Support

1.1 Introduction

Geographic Information Science (GIScience) is concerned with the nature of geographic information and geographic phenomena by providing theoretical foundations for Geographic Information Systems (GIS) and related geographic information technologies (Goodchild 1992a, 2004). The aim of GIScience is to formalize geographic principles in order to explore scientific and policy-related applications of geographic information, and to reveal and analyze the intricate relationships that individuals, organizations and society have with geographic information technologies (Mark 2003). GIScience seeks to answer fundamental questions concerning the use of GIS. These questions are often asked with reference to GIS as a decision support tool. Although GIS is conventionally seen as a set of tools for the input, storage and retrieval, manipulation and analysis, and output of spatial data, the system also contains a set of procedures to support decision making activities (Malczewski 1999; Sugumaran and DeGroote 2011). Indeed, GIS can be defined "as a decision support system involving the integration of spatially referenced data in a problem solving environment" (Cowen 1988, p. 1552). In this context, GIS is considered as a special-purpose digital database in which a common geographic coordinate system is the primary means of storing and analyzing the data to obtain information for decision making. Ultimately, the aim of using GIS is to provide support for making decisions.

A variety of theoretical and methodological perspectives on Multicriteria Decision Analysis (MCDA) in GIScience have been suggested over the last 20 years or so (Eastman et al. 1993; Laaribi et al. 1996; Malczewski 1999; Chakhar and Mousseau 2008; Nyerges and Jankowski 2010; Sugumaran and DeGroote 2011). Spatial analysis (including related fields of GIScience such as geocomputation and geovisualization), and spatial decision support systems (including related GIS-based technologies such as collaborative GIS, participatory GIS, and public

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_1

participation GIS) provide perceptive perspectives on integrating MCDA into GIS. It is the confluence of the two research areas: spatial analysis and spatial decision support where the concept of integrating GIS and MCDA can offer substantial contributions to the development of GIScience.

1.2 Spatial Analysis

GIScience owes much to developments in the field of spatial analysis, which consists of a set of techniques and models that are explicitly concerned with spatial patterns and processes (Berry and Marble 1968; Fotheringham and Rogers 1994; Goodchild and Haining 2004). A distinctive feature of spatial analysis is that its results dependent on the locations of objects (events) and their attributes. The results would be different under rearrangements of the spatial distribution of attributes or reconfiguration of the spatial structure (Godchild and Haining 2004). From the perspective of decision analysis, it is useful to classify spatial modeling approaches into two categories: statistical modeling and mathematical modeling. Although spatial analysis is viewed as being deeply rooted in statistics, a considerable portion of spatial analysis techniques and models are derived from Operations Research and Management Science (OR/MS) (Thomas and Huggett 1980; Killen 1983; Ghosh and Rushton 1986; Fotheringham and Rogers 1994). These approaches are based on mathematical modeling of decision and management problems. There are two main thrusts in mathematical modeling within the GIS environments: simulation and optimization (e.g., Malczewski 1999; Duh and Brown 2005; Langlois 2011; Li et al. 2011a, b; Tong and Murray 2012).

In a broad sense, spatial simulation is a method for performing experiments using a model of real-world spatial systems (Mather 1991; Langlois 2011). A simulation model either reproduces a process or generates a sample of many possible outcomes. Components of a system being simulated are mathematically defined and related to each other in a series of functional relationships. The result is a mathematical description of a decision process. The model is solved repeatedly, using different parameters and different decision variables every time. As those values are changed, a range of solutions are obtained for the problem and the 'best' solution can be chosen from that range.

Spatial optimization models seek to find the best (optimal) solution to well-defined spatial decision or management problems (Faiz and Krichen 2012; Tong and Murray 2012). The distinguishing characteristic of spatial optimization is that the decision/management alternatives (or decision variables) have a geographic (spatial) meaning. Common to all optimization models is a quantity (quantities) to be minimized or maximized. The quantity is often termed the objective or criterion function. In addition, optimization problems typically have a set of constraints imposed on the decision variables. The constraints define the set of feasible solutions. The solution to an optimization problem determines the values of decision variables subject to a set of constraints. Thus, in the most general terms an optimization model can be written as follows: *minimize* or *maximize* $f(\boldsymbol{x})$, subject to: $\boldsymbol{x} \in \boldsymbol{X}$, where $f(\boldsymbol{x})$ is a criterion (objective) function, $\boldsymbol{x}$ is a set of decision variables, and $\boldsymbol{X}$ is a set of feasible alternatives. If the problem involves a single criterion function, then the problem is referred to as a single-criterion (objective) model. When more than one criterion function is to be optimized simultaneously, then the model is called a multicriteria (multiobjective) model.

The primary difference between simulation and optimization procedures is the starting point. Simulation modeling starts with the actions and studies the effects on the overall system objectives by testing different policies under various external conditions. Optimization procedures start with a definition of the system objectives and specify the actions that will satisfy those objectives at the optimum level. Once the optimum conditions are established, the vicinity of the optimal points is analyzed to determine the effect of variations in the system (Thomas and Huggett 1980).

1.2.1 Descriptive and Normative Models

Each of the two modeling framework, spatial optimization and simulation, represents a fundamentally different approach for tackling decision problems. Broadly speaking, the output of spatial optimization models is a normative strategy. The normative approach is built on the basic axioms that should be considered as rational guidance for making decisions. It is concerned with 'what ought to be' (Chisholm 1979). A normative model provides a formal representation of a spatial system that determines an optimal course of action. The main use of normative theory is to provide a yardstick against which to judge the efficiency of the real word spatial system. Location analysis/theory has a prominent position within the body of spatial normative models (Berry and Marble 1968; Ghosh and Rushton 1986).

Spatial simulation modeling, on the other hand, is mainly concerned with a descriptive approach. Descriptive models attempt to describe and explain actual behaviour of decision making agents. They are based on the positive theories of spatial structures and processes that are concerned with the question of 'what is' (Chisholm 1979). Spatial simulation modeling approaches, such as Cellular Automata (CA) and Agent Based Models (ABM), provide examples of procedures that use specific decision rules to describe the behaviour of decision making agents. Those decision rules are often defined in terms of GIS-based MCDA (Wu and Webster 1998; Bone et al. 2011; Yu et al. 2011b). The integrated simulation and MCDA models can provide tools for analyzing spatial and temporal landscape dynamics, examining likely future scenarios of change, and developing and evaluating decision scenarios or plans (Ward et al. 2003; Li and Liu 2007; Liu et al. 2007; Yu et al. 2011b).

It is important to note that spatial simulation models such as ABM can be used for examining the plausibility of normative decision options generated with spatial optimization modeling (Ligmann-Zielinska and Jankowski 2010). Indeed, the distinction between the normative optimization and descriptive simulation modeling has recently been blurred by attempts to develop an integrated framework

(Bone et al. 2011; Li et al. 2011b; Plata-Rocha et al. 2011; Cao et al. 2014). For example, Bone et al. (2011) have proposed an approach for integrating multiobjective optimization analysis and simulation agent-based modeling for analyzing land-use patterns. They have also make a distinction between the normative optimization modeling and descriptive simulation analysis by suggesting that the two modeling frameworks can be represented as the top-down and bottom-up modeling approaches, respectively.

1.2.2 Prescriptive and Constructive Models

From the perspective of multicriteria analysis, it is useful to complement the traditional descriptive-normative dichotomy of decision models by prescriptive (Bell et al. 1988) and constructive approaches (Roy 1993). The distinction between these two dichotomies (descriptive-normative vs. prescriptive-constructive models) is based on the differences in which these modeling frameworks conceptualize the involvement of decision makers (stakeholders, interest groups) into the decision making procedure. The descriptive and normative models are based on an exogenous rationality; that is, the models are developed independently of the decision maker (see Table 1.1). These approaches aim at providing generic modeling formworks applicable to a wide range of decision situations. The prescriptive and constructive approaches focus the uniqueness of decision situations. This type of decision analysis aims at modeling the rationality of particular decision maker taking into accounts his/her 'subjective' view of the decision situations (Dias and Tsoukiàs 2004; Bouyssou et al. 2006).

Prescriptive models attempt to improve the decision making process by combining the theoretical foundation of normative theory with the empirical findings of descriptive theory. They are concerned with providing a recommendation on how to achieve the 'best' state suggested by the normative modeling, given the facts derived from the descriptive analysis. The prescriptive approaches focus on the

Table 1.1 Differences between approaches to decision analysis modeling

Model	Characteristics	Process to obtain the model	The criteria by which the model is evaluated
Descriptive	Exogenous rationality inductive/empirical	Observing	Empirical validity
Normative	Exogenous rationality deductive/theoretical	Hypothesizing	Theoretical adequacy/ correctness
Prescriptive	Endogenous rationality coherence with the decision situation	Revealing	Pragmatic value/usefulness
Constructive	Learning process coherence with the decision process	Consensus reaching	Pragmatic value/the user's satisfaction

Sources Keeney (1992); Bouyssou et al. (2006)

insights into the decision making process rather than on the axioms underlying the normative modeling. The process is generally fostered by the close involvement of decision makers in the modeling and analysis procedures. These insights come from understanding why a particular solution is recommended over another (Couclelis and Monmonier 1995; Jankowski and Stasik 1997). The prescriptive spatial decision modeling can be supported by the use of GIS along with MCDA. Such GIS-MCDA approaches focus on providing insights into the decision making process. These insights are enhanced by a synergetic effect of combining normative and descriptive approaches. There are a number of examples of integrating the normative multicriteria decision rules within the context of spatial simulation models (Wu and Webster 1998; Duh and Brown 2007; Li et al. 2011a, b).

There is some evidence to show that decision makers' preferences are often constructed in response to a task of selecting the best alternative (Payne 1993). This empirical finding provides a basis for organizing the concept of decision aiding around constructive approaches. The main aim of constructive approaches is to aid the decision maker in building his/her own model for a particular decision problem (Bouyssou et al. 2006). These approaches focus on the interaction and collaboration between the decision maker and analyst in order to develop a model facilitating the construction of preferences. The constructiveness of preferences underlies the concept of collective design in planning and decision making, which involves the use of information technology to stimulate social interaction and discourse in the pursuit of collective goals. In this context, GIS is seen as a tool for plan making *with* the public, rather than *for* the public (Klosterman 2001). Such perspective on the use of GIS extends the conceptual frameworks for spatial decision support to address the technological needs of collaborative/participatory decision making. Here, a specific point of emphasis is placed on integrating GIS and MCDA with computer supported collaborative work environments. Such environments enable groups of people to work together by providing a set of GIS and MCDA tools that handle many of the tasks that are required in group activities: exchange of data and information, and group evaluation, consensus building and voting (Carver 1999; Simão et al. 2009; Boroushaki and Malczewski 2010b). Jankowski and Nyerges (2001) provide a number of examples involving the use of GIS along with MCDA methods within the context of the group/participatory decision making (see also Nyerges and Jankowski 2010).

It is important to note that the classification of the modeling frameworks into the four categories—normative, descriptive, prescriptive, and constructive—is based on the different perspectives on the decision aiding processes. Bouyssou et al. (2006) argue that the differences among the four approaches are related to "their assumptions about the origin and the nature of the rationality model to be introduced in the decision aiding process" (p. 403, see Table 1.1). The classification is not based on the differences between the models, but rather on the distinctive way they are or can be used. Thus, a particular GIS-MCDA model can be considered as normative, descriptive, prescriptive or constructive, depending on the manner in which it is employed for tackling the decision making problem. For example, the weighted linear combination model (see Sect. 4.1) has been used as a normative or descriptive approach. Similarly, the GIS-based analytic hierarchy process (AHP)/analytic network process (ANP) (see Sect. 4.2) have proven to be useful for both normative and descriptive analysis. Although spatial multiobjective models (see Chap. 5) are typically used in the context of normative analysis, they can also be used for descriptive, prescriptive, or constructive modeling.

1.3 Spatial Decision Support

The concept of spatial decision support has been one of the central elements of GIScience (Densham 1991; Jankowski et al. 2006; Andrienko et al. 2007; Sugumaran and DeGroote 2011; Nyerges and Jankowski 2010). Its significance can be attributed to the need to expand GIS capabilities for tackling complex spatial decision problems. Although the concept of spatial decision support has been around for over 40 years, it was not until the early 1990s that it found a wider recognition in GIScience (Densham 1991; Janssen 1992). This development was stimulated by a series of US National Center for Geographic Information and Analysis (NCGIA) initiatives including: 'Spatial Decision Support Systems (SDSS)' (Initiative-6), 'Collaborative Spatial Decision Making' (Initiative-17), 'GIS and Society: The Social Implications of How People, Space and Environment are Represented in GIS' (Initiative-19), and the Varenius project on 'Empowerment, Marginalisation and Public Participation GIS' (NCGIA, 2014). While the first two initiatives have focused research efforts on technical/computational aspects of SDSS including participatory/collaborative GIS, the latter initiatives represent the social science perspectives by looking at the inter-relationship between GIS and society.

Over the past two decades, the concept of SDSS has evolved into a field of research, development, and practice that is made up of many different approaches and frameworks including intelligent SDSS (Leung 1997), planning support systems (Geertman and Stillwell 2002), collaborative GIS (Balram and Dragićević 2006), group SDSS (Jankowski and Nyerges 2001), participatory GIS (Craig et al. 2002), public participation GIS (Sieber 2006), spatial knowledge-based systems (Zhu et al. 1998), and spatial multi-agent systems (Parker et al. 2003). A broader perspective suggests that all these spatial information systems have a common aim: to improve the performance of decision makers, managers, and citizens when they confront spatial decision problems.

1.3.1 Spatial Decision Support Systems

A Spatial Decision Support System (SDSS) can be defined as an interactive, computer-based system designed to support a user or group of users in achieving higher effectiveness in decision making while solving a semi-structured spatial decision problem (Malczewski 1999). The essence of the SDSS concept is captured by the three terms: semi-structured spatial problem, effectiveness of decision making, and decision support. Any decision making problem falls on a continuum that ranges from completely structured to unstructured decisions. Most real-life spatial decision problems can be found somewhere between these two extremes. Such decision problems are called semi-structured (location-allocation problems, site search and selection problems, land use suitability evaluation, transportation problems, environmental impact assessment, and plan/policy evaluation). The structured part of the semi-structured problem may be amenable to automated solution by the use of a computer, while the unstructured aspects are tackled by decision makers.

Although SDSS may increase the efficiency of data-processing operations, the primary aim of the system is to improve the effectiveness of decision making by incorporating decision makers' knowledge and experience into computer-based procedures. Central to the concept of SDSS is the interaction of the user(s) with a computer-based system containing a set of tools for analyzing spatial and non-spatial data and for modeling spatial decision problems. SDSS integrates previously separate tool sets into a unified whole, which is more valuable than the sum of the parts. To this end, the ability of a GIS to handle preferences, judgments, arguments, and opinions involved in the planning process is of critical importance. This calls for a representation of this type of information in a computer-based decision support system. One way of achieving this is to incorporate MCDA techniques into the GIS-based procedures (see Sect. 1.4.1).

The concept of SDSS has often been criticized for the failure to provide suitable tools for an active public participation (Pickles 1995; Alexander 2000). The criticism has been focused on the uneven social impacts of the use of geographic information technologies. It is argued that advancements in computing hardware and GIS software have popularized geographic information technologies but achieved limited success in improving the general public's participation in community-based GIS projects due to their closed, synchronous, and place-based nature and the lack of representation from some interest groups (Sieber 2006; Dunn 2007). The GIS community has addressed this criticism by offering analytical and decision support tools that are accessible to non-experts (Craig et al. 2002). This is reflected in the increasing interest in Web-based SDSS (Rinner 2003; Sugumaran and DeGroote 2011) and related technologies such as collaborative, participatory/public participation GIS. Although the scope of those systems remains quite undefined (Jankowski and Nyerges 2001; Schlossberg and Shuford 2005), they are designed for supporting multiple parties (the general public, decision makers, stakeholders, activists) in the decision-making and planning processes, and seek to emphasize community involvement in the production and/or use of geographical information (Dunn 2007).

1.3.2 Multicriteria Spatial Decision Support Systems

Multicriteria Spatial Decision Support Systems (MC-SDSS) is a class of SDSS that is based on the concept of integrating GIS and MCDA. Similar to SDSS, the fundamental motivation for integrating GIS and MCDA stems from the need to make the GIS capabilities more relevant for decision making and planning (Sugumaran and DeGroote 2011). GIS has been designed as a general purpose technology with theories of spatial representation and computing in mind (Goodchild and Haining 2004; O'Sullivan and Unwin 2010), and with strong assumptions about the instrumental rationality as a base for decision making procedures (Alexander 2000; Sui and Goodchild 2001). As a consequence, the technology is not well-suited for acquiring, storing, processing, analyzing, and visualizing data and information critical for decision making such as value judgments, preferences, priorities, opinions, attitudes, etc. One way of alleviating this problem is to integrate MCDA methods and techniques into the suite of GIS operations. While GIS can provide a tool for handling the disagreements over facts by providing more and better information, the MCDA techniques can help in diminishing the disagreements over values among the conflicting interest parties (Feick and Hall 1999; Jankowski and Nyerges 2001).

At the most fundamental level, GIS-based MCDA (GIS-MCDA) is a procedure that transforms and combines geographic data (input maps) and the decision maker's (expert or agent) preferences into a decision (output) map. The procedure involves the use of geographical data, the decision maker's preferences, and the integration of the data and preferences according to a specified decision (combination) rule (Malczewski 1999; Chakhar and Mousseau 2007; Jankowski et al. 2008; Yatsalo et al. 2010; Reynolds and Hessburg 2014). A critical aspect of GIS-MCDA involves evaluation of the geographically defined decision alternatives based on the criterion values and the decision maker's preferences. This implies that the results of the analysis depend not only on the spatial pattern of alternatives, but also on the value judgments involved in the decision making process (see Sect. 1.4).

1.3.3 Synergy Between GIS and MCDA

The contribution of GIS-MCDA to GIScience and the opportunities for advancing research on integrating GIS and MCDA come from the synergy between the two distinctive sets of decision support tools. GIS is a system for collecting, storing, manipulating, analyzing, and presenting geographic data to obtain information for decision making. The capability of handling and geographically referenced data distinguished GIS from other information systems. They also make GIS a valuable technology in a wide range of applications, because a great variety of the public and private sector organizations use geographic data to support their activities (Brail and Klosterman 2001; Geertman and Stillwell 2002). Prominent among the enduring uses of GIS is the task of producing maps. Data outputs in both hard copy and digital map forms can be used as a basis for discussing and reviewing decision problems, which may culminate in the identification of decision alternatives and the choice of a preferred outcome. Here, the map is the source for both the dialogue and decision outcome, where the discussion and review processes are facilitated not only by analysis of spatial data, but also by review of what the map content reveals to decision participants (Jankowski et al. 2001; Andrienko et al. 2007). GIS can help in coordinating situation analysis through its ability to integrate data from diverse sources. It can enhance the MCDA capabilities for exploring decision situations and supporting the process of learning and discovery. For example, GIS enables geographic data from one sector (such as safe water supply, education, employment) to be combined with data from other sectors (such as health care) to provide a comprehensive picture of the situation in any given community, region or country, and thereby facilitating the setting of priorities for control and surveillance activities, the rationalization of the use of scarce resources, and effective planning.

The capabilities of GIS for generating a set of alternative decisions are mainly based on the spatial relationship principles of connectivity, contiguity, proximity, and the overlay methods (O'Sullivan and Unwin 2010; Chang 2011; Heywood et al. 2012). For instance, the overlay operations are often used for identifying suitable areas for new development, be it a new industrial facility, waste disposal site, school, or hospital. In this context, the functionality of GIS is essentially limited to the overlay operations in order to define areas simultaneously satisfying a set of locational criteria. However, when the selection involves conflicting preferences with respect to evaluation criteria, the overlay operations do not provide enough analytical support, because of limited capabilities for incorporating the decision makers' preferences into the GIS-based decision making process. In addition, the complexity of relationships in some spatial decision problems cannot be represented cartographically. Consequently, GIS are not flexible enough to accommodate variations in either the context or the process of spatial decision making.

Integrating MCDA into GIS can enhance the limited capabilities of GIS to store and analyze data on the decision maker's preferences. MCDA provides a methodology for guiding the decision maker(s) through the critical process of clarifying evaluation criteria (attributes and/or objectives), and of defining values that are relevant to the decision situation. The major advantage of incorporating MCDA into GIS is that a decision maker can introduce value judgments (i.e., preferences with respect to evaluation criteria and/or decision alternatives) into GIS-based decision making. MCDA can help decision makers to understand the results of GIS-based decision making procedures, including trade-offs among policy objectives, and then use the results in a systematic and defensible way to develop policy recommendations (Bell et al. 2003; Nyerges and Jankowski 2010).

Arguably, the main function of MCDA in supporting spatial decision making is to help the decision participants in developing a constructive and creative approach to the problem at hand, rather than to support them in identifying the 'best' solution (see Sect. 1.2.2). The use of argumentation maps (which combine Web-based mapping tools with a structured discussion forum to support geographically referenced discourse), in conjunction with MCDA techniques in the WebGIS environment, provides a platform for exchanging facts, knowledge, ideas, preferences, opinions, arguments, and propositions in a dynamic process of human-computer-human interactions (Rinner 2001; Sani and Rinner 2011). From this perspective, decision-making can be considered a collective learning process supported by the participatory/public participation GIS-MCDA on-line system (Carver 1999; Simão et al. 2009; Boroushaki and Malczewski 2010b).

1.4 Spatial MCDA

The GIS-MCDA procedures have mostly been derived from the general decision theory and analysis (Malczewski 1999). There has been, however, a growing trend for developing MCDA methods specifically designed for tackling spatial decision problems. To this end, it is important to identify three distinctive approaches to GIS-MCDA: (i) conventional MCDA for spatial decision making, (ii) spatially explicit MCDA, and (iii) spatial multiobjective (multicriteria) optimization. The first group of approaches uses the traditional (aspatial) MCDA for spatial problems, while the remaining two types of MCDA are methods specifically designed for tackling spatial problems.

1.4.1 Conventional MCDA

GIS-MCDA approaches typically involve the use of conventional MCDA models or decision rules for tackling spatial problems such as site selection problem and land use/suitability analysis (Malczewski 2006). A number of conventional MCDA methods have been adapted for the used in a GIS environment (see Chap. 4). The most popular MCDA methods include: the weighted linear combination and related procedures (Carver 1991; Eastman et al. 1993; Malczewski 2000), ideal/reference point methods (Pereira and Duckstein 1993; Malczewski 1996; Tkach and Simonovic 1997), the analytical hierarchy/network process (Banai 1993; Zhu and Dale 2001; Marinoni 2004), and outranking methods (Carver 1991; Joerin et al. 2001; Martin et al. 2003).

The conventional MCDA methods have largely been aspatial. They typically pay no attention to the fundamental properties of geographical data; that is, spatial heterogeneity and spatial dependency. The conventional approaches are merely extensions of existing MCDA methods to analyze spatial decision problems. They usually involve spatial variability only implicitly by defining evaluation criteria based on the concept of spatial relations such as proximity, adjacency, and contiguity (Herwijnen and Rietveld 1999; Ligmann-Zielinska and Jankowski 2008). The conventional approaches also assume a spatial homogeneity of the decision maker's preferences or value judgments within a given study area. This implies that the two main components of MCDA (that is, the criterion weights and value functions) are assumed to be spatially homogeneous (see Sects. 2.3.1 and 2.3.3). For example, the weighted liner combination procedure assigns the same criterion weight to every decision alternative (location) of a given criterion map (Eastman et al. 1993;

Malczewski 2000). Also, the procedure uses a single value function (or standardization procedure) for the whole study area, ignoring the fact that the form of the function may depend on the local context.

1.4.2 Spatially Explicit MCDA

"A model is said to be spatially explicit when it differentiates behaviors and predictions according to spatial location" (Goodchild and Janelle 2004, p. 10). This definition uses the concept of spatial location for making a distinction between conventional models and spatially explicit methods. More specifically, Goodchild (2001) suggests that there are four tests that can be used to determine if a model is spatially explicit, or if an area of investigation demands spatially explicit modeling. First, the invariance test considers a MCDA model spatially explicit if its decision outcomes (rankings or orderings of decision alternatives) are not invariant under relocation of the feasible alternatives. This implies that a change in the spatial pattern of feasible alternatives result in the changes of their rankings. Second, the representation test requires that decision alternatives in a spatially explicit MCDA model be geographically defined. Such alternatives consist of, at least, two elements: action (what to do?) and location (where to do it?). The location of an alternative can be defined using a coordinate system (e.g., geographical coordinates). Third, the formulation test declares a MCDA model spatially explicit if it contains spatial concepts such as location, distance, contiguity, connectivity, adjacency, or direction. Fourth, according to the outcome test the spatial form of outputs generated by a spatially explicit MCDA model is different than the spatial form of its inputs. For example, the input attribute (criterion) values of spatial decision problems may be assigned to various spatial objects (e.g., points and polygons), while the output maps would represent the overall values associated with each location using the raster data format.

Several approaches that conform to the four tests have been suggested (Tkach and Simonovic 1997; Herwijnen and Rietveld 1999; Feick and Hall 2004; Makropoulos and Butler 2006; Chakhar and Mousseau 2008; Ligmann-Zielinska and Jankowski 2008, 2012; Malczewski 2011). All these approaches are based on the criticism of the usefulness of conventional MCDA for spatial decision problems. In particular, they are based on the assertion that spatial decision problems require distinct modeling frameworks. Also, it is argued that the spatial decision problems cannot be effectively tackled with the same methods as non-spatial problems (Ligmann-Zielinska and Jankowski 2008, 2012; Malczewski 2011). Consequently, the spatially explicit MCDA methods go beyond the mere adaption of the conventional methods. They explicitly incorporate the properties of spatial data into the MCDA procedures and/or the components of MCDA are made spatially explicit (Herwijnen and Rietveld 1999; Makropoulos and Butler 2006; Malczewski 2011; Yu et al. 2011b; Ligmann-Zielinska and Jankowski 2012; Simon et al. 2014).

1.4.3 Spatial Multiobjective Optimization

Spatial multiobjective (multicriteria) optimization methods have been specifically designed for modeling spatial systems (Krzanowski and Raper 2001), and solving spatial problems such as land allocation (Duh and Brown 2005), site search problems (Cova and Church 2000), location allocation (Ghosh and Rushton 1986; Malczewski and Ogryczak 1995), transportation problem (Gen and Cheng 2007), vehicle routing and traveling salesman problems (Giaglis et al. 2004; Huang et al. 2006), and districting (Bong and Wang 2004). This type of modeling seeks to find the best solution to well-defined spatial decision/management problems. The distinctive feature of spatial optimization is that the decision/management alternatives (or decision variables) have a geographic meaning such as location, distance, direction, connectivity, shape of an area, districting, and length of boundaries. Consequently, the solutions to the decision/management problems can be represented on maps showing their spatial structures.

Spatial multiobjective optimization models conform to the four tests of spatially explicit modeling (see Sect. 1.4.2). The solutions of these models depend on the spatial arrangements of the feasible alternatives. The alternatives are defined geographically and contain spatial concepts explicitly; for example, the concept of location, distance, contiguity, connectivity, and adjacency are used to define the decision alternatives.

It is important to make a distinction between spatial multiobjective optimization problems (or models) and the algorithms for solving those problems. The problems can be classified according to the type of decision variables into two main categories: discrete and continuous (Goicoechea et al. 1982; Bettinger and Kim 2008; Zarghami and Szidarovszky 2011). A discrete variable is limited to a fixed or countable set of values, while a continuous variable can take on any value in a specified interval. A spatial optimization model is an integer model if any one of its decision variables is discrete. If all variables are discrete, the mode is a pure integer one; otherwise, it is a mixed–integer. A discrete problem containing only integer variable is called an integer optimization problem. Combinatorial optimization is another type of discrete modeling. This type of multiobjective optimization problems is the most often used approach for modeling spatial systems. Many spatial problems such as location allocation, travelling salesman, vehicle routing and scheduling problems fall into this category of spatial optimization (Current et al. 1990; Chang et al. 1997). If the values of all decision variables are continuous, the problem is called continuous optimization. The transportation problem is the best-known example of this type of spatial optimization (Gen and Cheng 2007). Many spatial multiobjective models involve both discrete and continuous decision variables. Such optimization problems are referred to as the mixed type. The plant location problem is typically modeled in terms of mixed optimization problem (Malczewski and Ogryczak 1996).

The solution(s) to spatial multiobjective problems can be generated using a wide range of methods (Duh and Brown 2005; Malczewski 2006; Bettinger and Kim 2008).

The methods can be classified into two categories: exact (deterministic) methods and approximate (stochastic) methods. The former are based on the theories of mathematical programming (Cohon 1978; Goicoechea et al. 1982). For example, the Simplex method in linear programming is deterministic (Goicoechea et al. 1982). However, the exact methods are inefficient in solving complex (and computationally intensive) spatial multiobjective optimization problems. To overcome the limitations of exact methods, a number of heuristics (and metaheuristics) have been proposed (Krzanowski and Raper 2001; Xiao et al. 2002; Duh and Brown 2005). These methods seek to find the best solutions by trial and error and incorporate strategies aimed at efficient exploration of a solution space (see Chap. 6). There has been a significant trend in GIScience to use metaheuristics for solving complex spatial optimization problems. A number of GIS-based metaheuristics have been developed including simulated annealing (Aerts and Heuvelink 2002; Duh and Brown 2005), evolutionary (genetic) algorithms (Krzanowski and Raper 2001; Xiao et al. 2002; Roberts et al. 2011), tabu search (Bong and Wang 2004; Bozkaya et al. 2003), and ant colony method (Li et al. 2011a; Yu et al. 2011a; Liu et al. 2012). If properly defined, metaheuristics can decrease computation times such that spatial multiobjective optimization may become a viable option for use in the interactive decision making contexts (Church et al. 2003; Duh and Brown 2005).

The metaheuristics for spatial optimization belongs to a broader field of GIScience: geocomputation (Openshaw and Abrahart 2000). Geocomputation is concerned with approaches for modeling geographical data and solving complex spatial decision problems that make use of high-speed computation methods. The scope of geocomputation overlaps with the research area of artificial intelligence (AI) or computational intelligence. AI covers a number of methods including metaheuristics (Krzanowski and Raper 2001; Xiao et al. 2002), artificial neural networks (Sui 1993; Zhou and Civco 1996; Li and Yeh 2002), cellular automata (Li and Yeh 2000; Benenson and Torrens 2004), and fuzzy logic techniques (Wang et al. 1990; Makropoulos et al. 2003). The common denominator of these methods is that, unlike conventional approaches, they are tolerant of imprecision, ambiguity, and uncertainty. All these methods have expanded the focus of GIS-MCDA by providing tools for incorporating different forms of uncertainty into spatial multiobjective optimization modeling. They also offer mechanisms for bridging the normative optimization approaches and the mostly descriptive spatial simulation methods (see Sect. 1.2.1).

1.5 Conclusion

The primary motivation behind the research efforts on integrating GIS and MCDA comes from the need to expand the decision support capabilities of GIS and related technologies. These two distinctive areas of research, GIS and MCDA, can benefit from each other. On the one hand, GIS techniques and procedures have an important role to play in analyzing multicriteria decision problems. They offer unique capabilities for storing, managing, analyzing and visualizing geospatial data for decision making. On the other hand, MCDA offer a rich collection of methods for supporting complex decision making processes. Spatial analysis and decision support are the two main areas of GIScience that can benefit most from the advancement of research about integrating GIS and MCDA. The hybrid heritage of GIS-MCDA creates new opportunities and challenges for advancing both theoretical and applied GIS-MCDA. The issue of opportunities and challenges associated with this emerging field of research will come into view in the remainder of this book.

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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

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_2

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

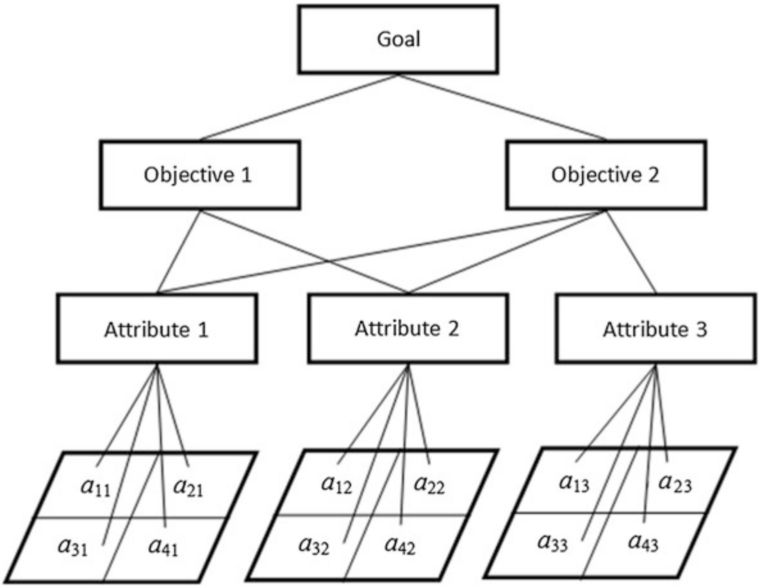

Fig. 2.1 Hierarchical structure of decision problem; a_{ik} is the value of the k-th attribute (criterion) associated with the i-th alternative (k = 1, 2, 3, and i = 1, 2, 3, 4)

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

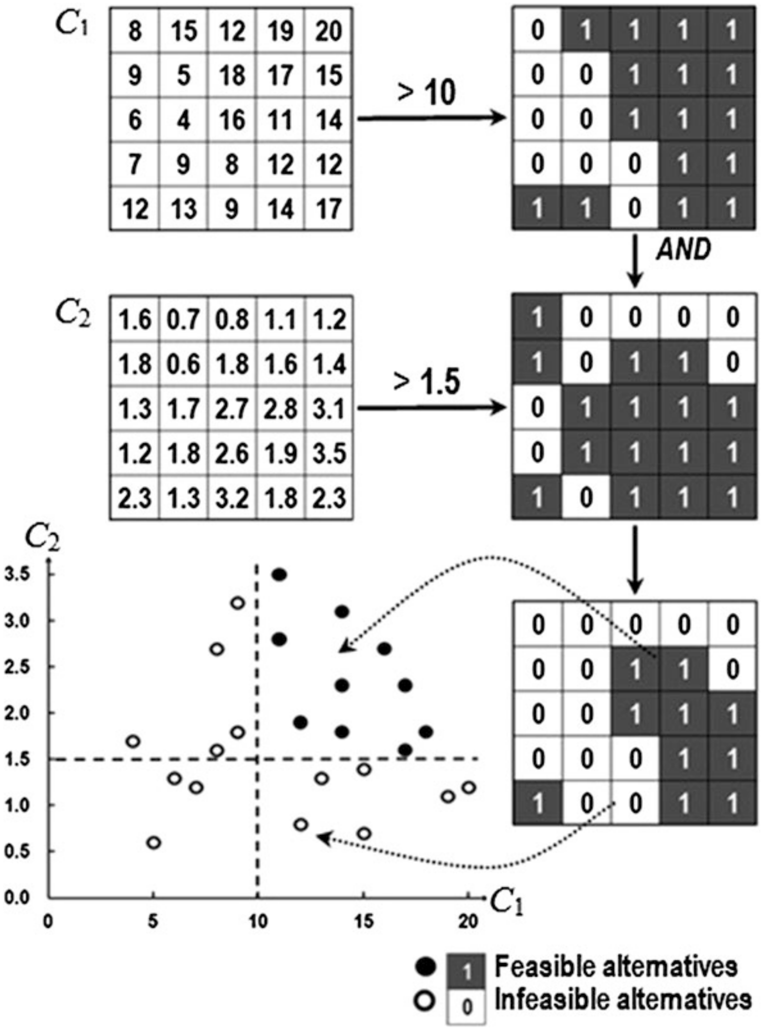

Fig. 2.2 Feasible and infeasible decision alternatives for two criteria: C_1 and C_2, and constrains $C_1 > 10$ and $C_2 > 1.5$

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

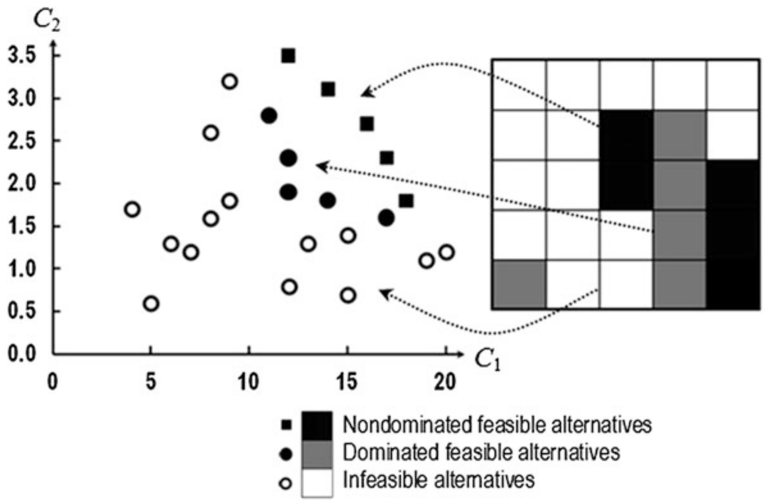

Fig. 2.3 Non-dominated, feasible and infeasible decision alternatives for two maximization criteria: C_1 and C_2 (see Fig. 2.2)

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 $\boldsymbol{A}$ 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, $(i = 1, 2, \ldots, m$, and $k = 1, 2, \ldots, n)$. 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 $k = 1, 2, \ldots, n$). 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, …, z), the input date 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; Beinat 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 ($k = 1, 2, \ldots, n$) for the i-th alternative ($i = 1, 2, \ldots, m$), 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, $a_{1k}, a_{2k}, \ldots, a_{mk}$, into standardized scores (values), $v(a_{ik})$, as follows:

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

for the k-th criterion to be minimized;

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

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

$$r_k = \max_i\{a_{ik}\} - \min_i\{a_{ik}\} \tag{2.3}$$

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 ρ 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

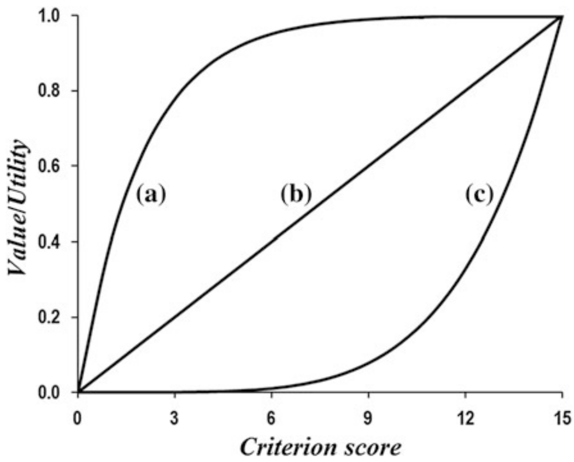

Fig. 2.4 Value/utility function prototypes: **a** risk-aversion; **b** risk-neutrality; and **c** risk affinity

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 ρ parameter from the perspective of behavioural decision analysis as a risk factor (Bodily 1985; Ligmann-Zielinska 2009). The ρ 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)

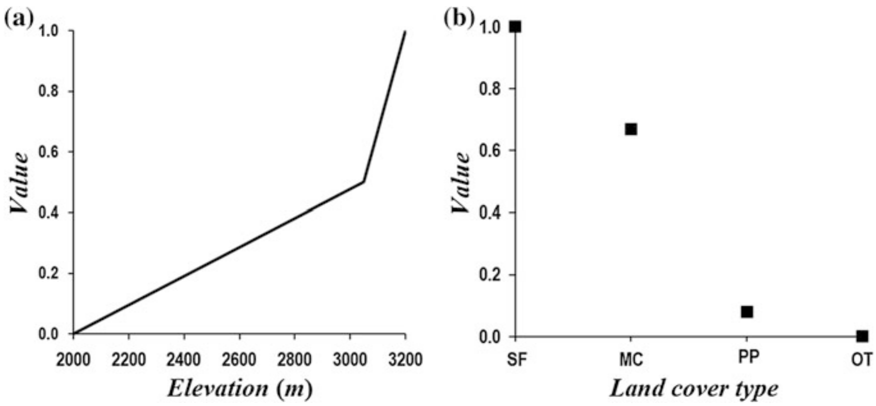

Fig. 2.5 Expert-derived value functions for the Mount Graham red squirrel habitat suitability evaluation; *SF* spruce-fir, *MC* mixed conifer, *PP* ponderosa pine, and *OT* others (*Source* Based on Pereira and Duckstein 1993, p. 415)

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:

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

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 ($q = 1, 2, \ldots, g$) of the locations, $i = 1, 2, \ldots, m$; $m > q$, 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:

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

for the k-th criterion to be minimized; and

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

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, $w_1, w_2, \ldots, w_k, \ldots, w_n$, are typically assumed to meet the following conditions: $0 \le w_k \le 1$, and $\sum_{k=1}^{n} = 1$. 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:

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

where w_k is the k-th criterion weight, n is the number of criteria under consideration ($k = 1, 2, \ldots, n$), 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 ArcGIS-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: $\boldsymbol{C} = [c_{kp}]_{n \times n}$; c_{kp} is the pairwise comparison rating for the k-th and p-th criteria. The matrix $\boldsymbol{C}$ is reciprocal; that is, $c_{pk} = c_{kp}^{-1}$, and all its diagonal elements are unity; that is, $c_{kp} = 1$, 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, $\boldsymbol{w} = [w_1, w_2, \ldots, w_n]$ can be computed. The weights are obtained as the unique solution to:

$$\boldsymbol{Cw} = \lambda_{\max}\boldsymbol{w}, \tag{2.8}$$

where $\lambda_{\max}$ is the largest eigenvalue of $\boldsymbol{C}$. 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:

$$c_{kp}^{*} = \frac{c_{kp}}{\sum_{k=1}^{n} c_{kp}}, \text{ for all } k = 1, 2, \ldots, n. \tag{2.9}$$

and then the weights are computed as follows:

$$w_k = \frac{\sum_{p=1}^{n} c_{kp}^{*}}{n}, \text{ for all } k = 1, 2, \ \ldots, \ n. \tag{2.10}$$

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:

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

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 massage. 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).

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

where $p_{ik} = a_{ik} \big/ \sum_{i=1}^{m} a_{ik}$; 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:

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

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:

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

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 $i = 1, 2, \ldots, m$), 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

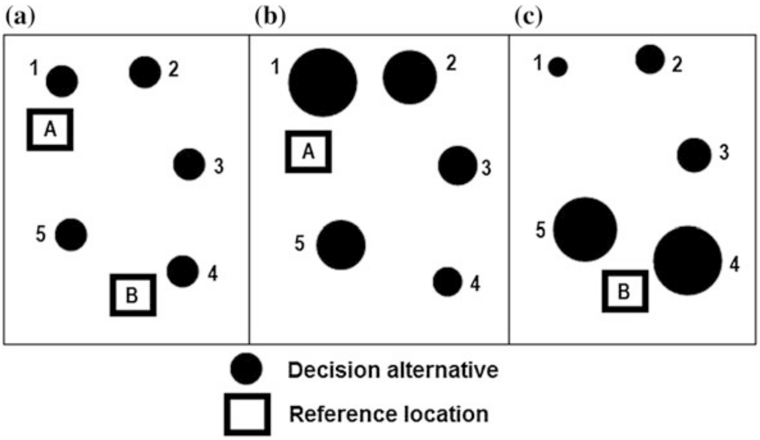

Fig. 2.6 A hypothetical weight (preference) map that depicts the importance of a given criterion uniformly (**a**), and in a spatially heterogeneous manner (**b**, **c**). *Circles* represent decision alternatives, their radii are constant in (**a**), and proportional to weight values in cases (**b**) 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:

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

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:

$$d_{ij}^s = \frac{\min_i \{d_{ij}\}}{d_{ij}}. \tag{2.16}$$

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,

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

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:

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

where

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

where $p_{ik}^q = a_{ik}^q \Big/ \sum_{i \in q} a_{ik}^q$; 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 continues 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
Constrains 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.

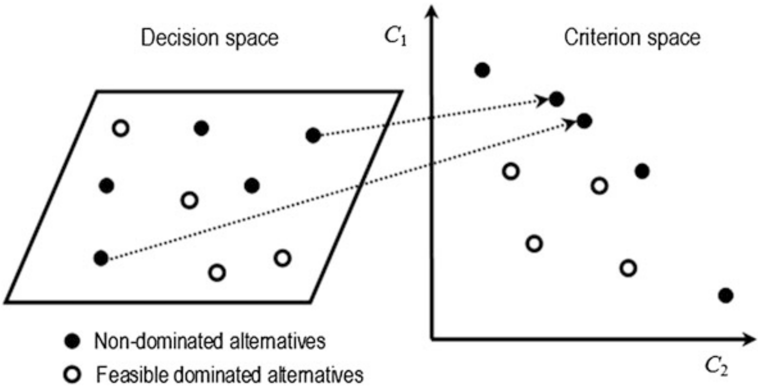

Fig. 2.7 Discrete multicriteria decision problem: feasible and non-dominated alternatives in the decision and criterion space

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, …, 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 ($f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$) 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).

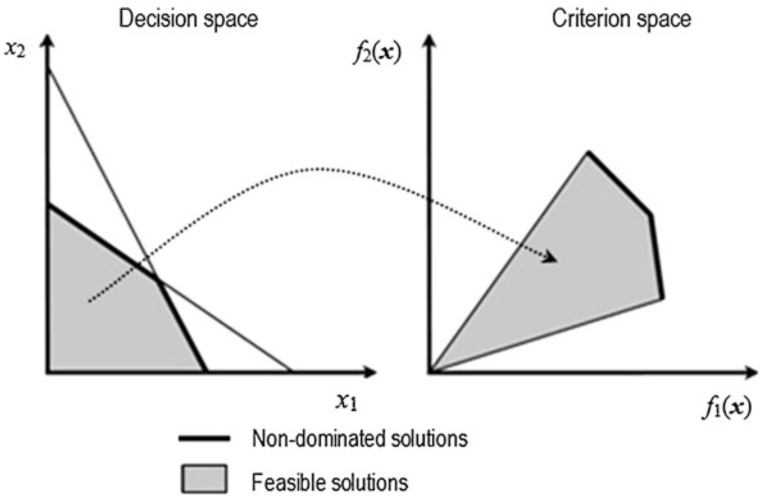

Fig. 2.8 Continuous multicriteria decision problem: feasible and non-dominated solutions in the decision and criterion space. *Note* x_1 and x_2 are decision variables, and $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$ objective functions, which are maximized

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

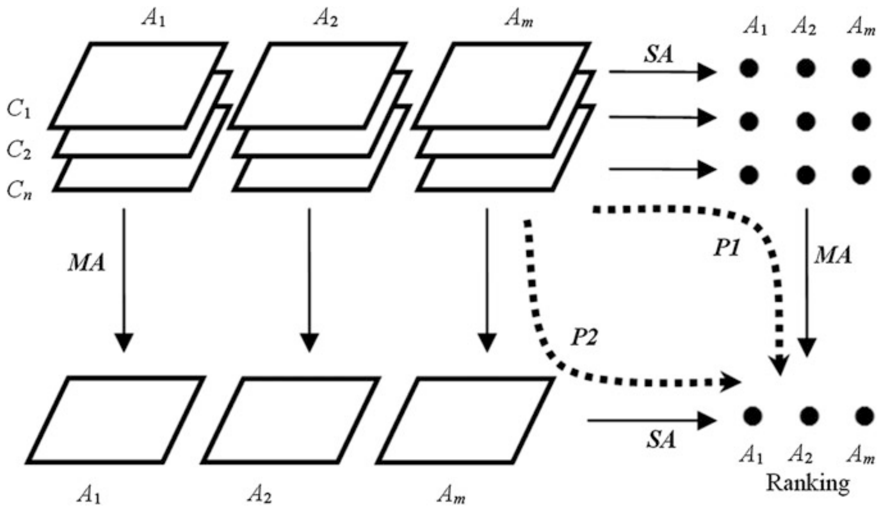

Fig. 2.9 Two combination procedures (paths) for spatial multicriteria problems. *Note* C_1, C_2, …, C_n = evaluation criteria; A_1, A_2, …, A_m = decision alternatives; *MA* = multicriteria aggregation; *SA* = spatial aggregation; *P1* = Path 1; *P2* = Path 2 (*Source* Adapted from van Herwijnen and 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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Chapter 3
Development of GIS-MCDA

3.1 Introduction

There are two main research traditions that influence methods and models of GIS-MCDA: Operations Research and Management Sciences (OR/MS) and landscape architecture/planning. OR/MS is typically associated with mathematical-based problem solving methods and approaches to decision making. Disciplines such as decision sciences, information sciences, behavioural sciences, and some aspects of systems analysis, are often included under the broad heading of OR/MS. Landscape architecture aims to apply scientific principles to the planning, designing, and managing of natural and built environments. It uses a systematic approach for analyzing social, ecological, geological, and geomorphologic conditions, and designing plans that will produce the desired outcome. The research interests of these two traditions, OR/MS and landscape architecture, meet at the application of their approaches to the land use planning and management. This common research interest resulted, *inter alia*, in establishing the GIS-MCDA paradigm.

This chapter traces the roots of GIS-MCDA and focuses on the recent developments in GIS-MCDA research. Specifically, we describe two research traditions underlying the development of GIS-MCDA: OR/MS and landscape architecture/planning. This is followed by an overview of the developments in GIS-MCDA research and applications for the last 20 years or so. The overview is based on a survey of relevant papers published in refereed journals.

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_3

3.2 Historical Background

3.2.1 The Origins of GIS-MCDA

The roots of MCDA can be traced back to the eighteenth century works on ranked preferential voting systems, which was credited to J.C. Borda and N. Condorcet. However, it was not until the second half of the nineteenth century that the fundamental concepts of MCDA were established by F.Y. Edgeworth and V. Pareto. They proposed an approach for combining conflicting criteria into a single evaluation index. Pareto also introduced one of the fundamental elements of modern MCDA theory: the concept of efficiency (also known as Pareto optimality). Pareto's work has been instrumental for the development of MCDA within the broader field of OR/MS. Indeed, one of the precursors of today's GIS-MCDA was the introduction of systems analysis, first in OR/MS and then in such disciplines as regional science (Isard 1969), urban and regional planning (Chadwick 1973), and geography (Chorley and Haggett 1967). Within OR/MS, earlier theoretical work (e.g., Koopmans 1951; Gass and Saaty 1955) provided the basis for later algorithmic developments of multicriteria programming (Charnes and Cooper 1961). Neumann and Morgenstern (1944) introduced the expected utility theory and proposed axioms of rationality, thus setting the foundations of another MCDA approach. Their work formed the core of modern decision theory. Churchman et al. (1957) were among the earlier scholars to look at the multicriteria problem formally using a simple additive weighting method. In the mid-1960s, Roy and his colleagues at SEMA METRA International developed a MCDA approach based on the concept of outranking relations (Roy 1968).

A second and quite distinct history of GIS-MCDA stems from landscape architecture and spatial planning. This perspective has its roots in the application of hand-drawn map overlay techniques used by American landscape architects in the late nineteenth and early twentieth century (Steinitz et al. 1976; Collins et al. 2001). Such landscape architects as C. Eliot and W. Manning provided detailed descriptions of the overlay procedures, but neither of them gave explicit explanations of their underlying intellectual rationales (Steinitz et al. 1976). McHarg (1969) advanced the overlay techniques by proposing a procedure that involved mapping data on the natural and human-made attributes of the environment within a study area, and then presenting this information on individual, transparent maps using light to dark shading (high suitability to low suitability) and superimposing the individual transparent maps to construct the overall suitability maps for each land use. Although McHarg's approach is widely recognized as a precursor to the classic overlay procedures in GIS, some researchers credit C. Eliot (Miller 1993) and J. Tyrwhitt (Steinitz et al. 1976) as predecessors of the modern map overlay techniques. Tomlinson (1999) suggests that it was his company, Spartan Air Services of Ottawa, which first proposed computerizing the overlay method in 1962. The overlay method was perhaps the single most important precursor to later forms of complex GIS-MCDA methods.

3.2.2 Development of GIS-MCDA

The evolution of GIS-MCDA has been a function of the development of information technologies (including geographic information technologies) and the evolving perspectives of planning/decision making. The modern GIS era can be divided into three time periods: (i) the GIS research frontier period in the 1950s–1970s, which can be referred to as the innovation stage, (ii) the development of general-purpose GIS in the 1980s, or the integration stage, and (iii) the proliferation stage, which is characterized by the development of the user-oriented GIS technology over the last 20 years or so (Foresman 1998; Waters 1998). Accordingly, the development of GIS-MCDA follow three similar stages: (i) the innovation stage (the advancements in GIS and OR/MS), (ii) the integration stage (the integration of cartographic modeling and MCDA), and (iii) the proliferation stage (the user-oriented GIS-MCDA).

3.2.2.1 Innovation: GIS and OR/MS

Although the foundations of systems thinking were developed in the 1940s, it was not until a considerable increase in accessibility to computer-based mathematical programming software in the 1960s that systems thinking became a practical proposition for decision making and planning (Isard 1969; Chadwick 1973). This development coincided with advances in computer technology, allowing for the development of automated systems for storing, manipulating, and displaying geographic data. The first systems we now call GIS were emerging in the 1960s, just as computers were becoming accessible to large government and academic institutions. Taking full advantage of the improvements in computer hardware technology required advancements in theories of spatial analysis based on computer handling of geographic data. These advancements took place during the 'quantitative revolution' in the spatial sciences in the 1950s–1960s (Berry and Marble 1968; Thomas and Huggett 1980).

During the 1970s, the usefulness of quantitative methods, including the single-objective approaches to spatial optimization problems, was increasingly questioned. The criticism was part of a broader critique of the positivist paradigm that led to the adoption of a political perspective on planning and decision making. This perspective recognized that planning deals with socio-political systems that consists of interest groups with conflicting values and preferences, and therefore must include considerations of public participation, negotiation, compromise, consensus building, and conflict management and resolution (Couclelis 1991). The development of MCDA was one of the responses to the criticism of the classic system analysis and single-criterion (single-objective) approaches to spatial decision making and planning problems (Cohon 1978; Nijkamp 1979). Planners and regional scientists were among the first to advance the idea of combining multiobjective mathematical programming techniques with GIS/computer assisted mapping (see Diamond and Wright 1988).

The complexity of many spatial multiobjective optimization problems makes it impossible to solve them using the conventional mathematical programming methods. To solve such problems, heuristic and metaheuristics (artificial intelligence or AI methods) have been proposed. A. Turning was likely the first to use heuristic algorithms in the 1940s. His report on ‘Intelligent Machinery’ in 1948 (the National Physical Laboratory, UK) contained a number of innovative AI ideas, such as machine intelligence and learning, neural networks, and evolutionary algorithms (genetic algorithms). It was not, however, until the 1980s that significant advances in developing AI algorithms for solving multiobjective optimization problems were made. In 1985, J.D. Schaffer was presumably the first to use genetic algorithms to solve multiobjective optimization. Since then, many metaheuristic algorithms, such as simulated annealing, tabu search, ant colony, and particle swarm algorithms, have been proposed for solving multiobjective optimization problems (see Burke and Kendall 2005; Talbi 2009). This area of research has also been extended to GIS-based approaches for tackling complex spatial decision making and planning problems (Duh and Brown 2005; Xiao et al. 2002).

3.2.2.2 Integration: Cartographic Modeling and MCDA

Arguably, McHarg’s transparent map overlay approach to land-use suitability analysis has had a greater influence on the development of GIS-MCDA than any other single event in GIS history. The approach analyzes land-use suitability decision problems by representing each evaluation criterion as a transparent map with the darkest gradations of tones associated with the greatest value, and the lightest tones associated with the least significant value (McHarg 1969). All of the transparent criterion maps are then superimposed upon one another to identify the most suitable land for development. In the 1970s, McHarg’s approach has been used in several computer-assisted mapping and GIS applications (Murray et al. 1971; Turner and Miles 1971; Miller and Niemann 1972; Hobbs 1980).

The development of computer-assisted mapping coincided with a rapid change in availability of computer technologies in general, and geographic information technologies in particular. Although a couple of the major commercial GIS software companies (such as Environmental Systems Research Institute and Intergraph Corporation) were established at the end of the 1960s, it was not until the 1980s that numerous commercial GIS began to develop (e.g., ARC/INFO, MapInfo GIS, and TransCAD). At the same time, the scope of GIS applications in the 1980s widened by the range of related commercially available products of information technology including CAD (computer assisted design), DBMS (database management system), remote sensing, GPS (global positioning system), as well as an increase of digital data availability to private and public organizations. Further, as computing power increased and hardware prices plummeted in the 1980s, GIS became a viable technology for state and municipal planning, and academic departments. In this context, the development of low-cost raster-based GIS was critical. This development was inspired by work on cartographic modeling and map algebra (Tomlin 1990).

The development of cartographic modeling and map algebra was a pivotal step toward integrating GIS and MCDA. Broadly defined, cartographic modeling involves a set of related, ordered map operations that act on raw data, as well as derived and intermediate data, to simulate a spatial modeling process (Tomlin 1990). It is a generic method for organizing basic GIS operations into a complex spatial model. Map algebra techniques include fundamental methods of GIS-MCDA, such as Boolean screening and weighted map combination (overlay) procedures. The procedures play a central role in many GIS applications (O'Sullivan and Unwin 2010). They also form the basis of many approaches in GIS-MCDA (Eastman et al. 1993; Malczewski 2004; Duh and Brown 2005), including techniques that are at the forefront of advances in spatial decision analysis, such as artificial intelligence (geocomputation) (Sui 1993; Zhou and Civco 1996; Xiao et al. 2002), geosimulation (Benenson and Torrens 2004; Liu 2009), geovisualization (Jankowski et al. 2001; Andrienko et al. 2007), and Web-based GIS procedures (Carver 1999; Zhu and Dale 2001).

3.2.2.3 Proliferation: The User-Oriented GIS-MCDA

The notion of user-oriented GIS-MCDA stems from the view of planning as part of the larger socio-political system. A number of studies revealed that planning is more than the collection and provision of information that can improve the policy-making process (Harris 1989). It also involves a wide range of 'intangible' activities, attitudes, and values. While some elements of the planning process may be well defined, there are significant components of subjective knowledge involved in the process Klosterman (2001). Combining the objective and subjective elements of the planning process in a computer based system lies at the core of the concept of SDSS in general and GIS-MCDA in particular (see Sects. 1.3 and 1.4).

Although the advent of desktop computing and cartographic modeling in the 1980s was instrumental in stimulating the integration of GIS and MCDA, it was not until the 1990s that GIS-MCDA established itself as an identifiable area of research within the GIScience literature (e.g., Janssen and Rietveld 1990; Carver 1991; Church et al. 1992; Banai 1993; Jankowski 1995; Malczewski 1999; Thill 1999). Until the end of the 1980s, the use of GIS remained a highly specialized professional activity. This notion changed in the 1990s, with GIS becoming regarded as a routine software application within the grasp of lay individuals. At the same time, better awareness of the value of digital spatial data and GIS-based solutions to planning and management problems produced a large market for GIS. The technological progress has been accompanied by an explosion of digital data available to private and public sector organizations.

One of the more significant trends has been the evolution from individual stand-alone computers to the highly interconnected telecommunications network environments of today. The Internet and World Wide Web, more commonly known as the Web, created an environment with almost ubiquitous access to a world of information. At the same time, many organizational decisions migrated from individual decisions to ones made by small teams and to complex decisions made by large diverse groups of individuals. In this environment, several key technological developments occurred in the area of decision support. Various tools to support collaboration and group processes have been developed, implemented, evaluated, and refined (Nyerges and Jankowski 2010; Sugumaran and DeGroote 2011). Accordingly, GIS-MCDA has been applied as a collaborative decision support system allowing interest groups to interact with public or private planning agencies (see Carver 1999).

The increasing accessibility of GIS to the general public resulted in a greater recognition of the importance of decision analysis and support within the broader field of GIScience, as exemplified by a series of the NCGIA Initiatives (see NCGIA 2014). These Initiatives have stimulated the development of spatial decision support tools including GIS-MCDA (Jankowski and Nyerges 2001). Indeed, efforts to integrate MCDA into GIS have been instrumental for developing the paradigm of spatial decision support (Eastman 1997; Malczewski 1999; Thill 1999; Ascough et al. 2002; Li et al. 2012; Reynolds and Hessburg 2014).

3.3 Recent Progress

Malczewski (2006) surveyed the GIS-MCDA literature with a comprehensive review of over three hundred refereed articles published from 1990 through 2004 (a list of these articles can be found at http://publish.uwo.ca/~jmalczew/gis-mcda.htm). The list has been updated to include articles published from 2005 through 2010. In total, 805 articles have been published in the period between 1990 and 2010. Figure 3.1 shows that the development of GIS-MCDA was rather modest in the first half of the 1990s. The second half of the 1990s witnessed an increased growth in the number of the GIS-MCDA articles. This growth accelerated over the last decade such that almost 70 % of the total was published from 2005 through 2010 inclusive.

The rapid increase in the volume of GIS-MCDA research can be attributed to two main factors. First, during the 1990s, increasingly powerful personal computer-based GIS and decision analysis software was developed, refined, and utilized in applications. Second, there was a general recognition of the importance of decision analysis and support within the broader field of GIScience. Together these factors gave impetus to considerable progress in the quantity and quality of research on integrating GIS and MCDA. During this relatively short period, there was consolidation of previous research, as well as an expansion into new substantive and technical areas. It can be argued that GIS-MCDA research has generated enough literature for it to be regarded as a legitimate subfield of research within GIScience (Thill 1999; Malczewski 2006; Chakhar and Mousseau 2008; Sugumaran and DeGroote 2011).

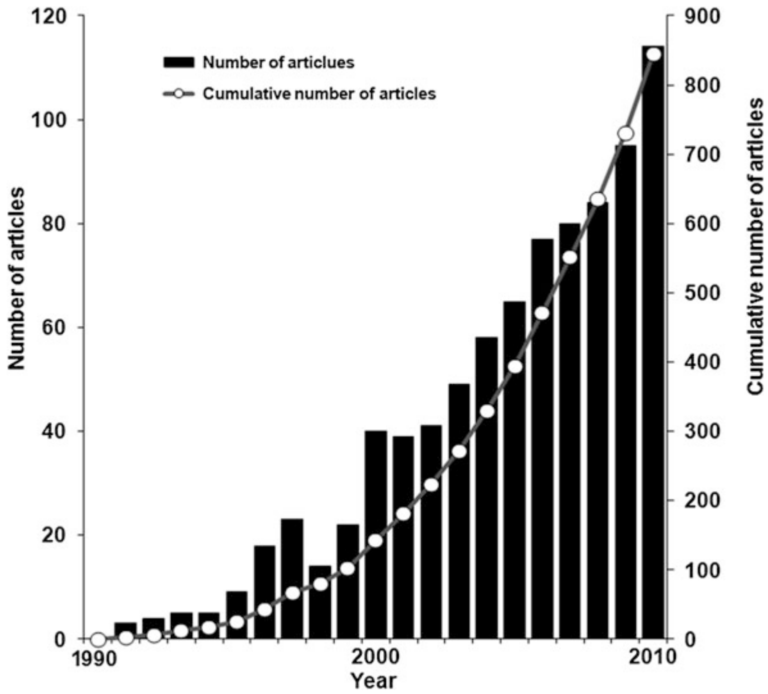

Fig. 3.1 The number of the GIS-MCDA articles published in refereed journals, 1990–2010 (*Note* the graph is based on the data for 1990–2004 taken from Malczewski (2006) and updated for 2005–2010)

3.3.1 Taxonomy of GIS-MCDA

Malczewski (2006) developed two classification schemes for the GIS-MCDA literature. First, all articles were classified based on the GIS components of GIS-MCDA methods. This classification involved the following considerations: (i) the geographic data models, (ii) the spatial dimension of the evaluation criteria, and (iii) the spatial definition of decision alternatives. Second, the articles were classified according to the elements of the MCDA methods. This taxonomy was based on the following considerations: (i) the nature of evaluation criteria, (ii) the number of individuals involved in the decision making process, and (iii) the nature of uncertainties.

3.3.2 GIS Components of GIS-MCDA

Figure 3.2 shows a classification of the GIS-MCDA approaches according to the GIS (spatial) components. There are two levels of the classification. First, the GIS-MCDA approaches can be subdivided into two groups: the raster-data-based

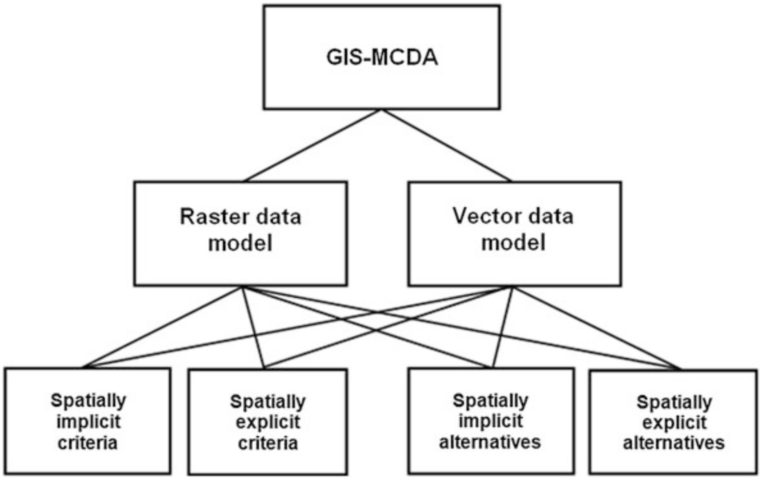

Fig. 3.2 Classification scheme for GIS components of GIS-MCDA

methods (e.g., Pereira and Duckstein 1993; Eastman et al. 1995; Malczewski 1996; Cromley and Hanink 1999; Church et al. 2003; Aerts et al. 2005), and the vector-data-based methods (e.g., Can 1992; Jankowski 1995; Laaribi et al. 1996; Rinner and Malczewski 2002; Feick and Hall 2004). It is important to note that some of the GIS-MCDA approaches have been based on the use of both the raster and vector data models. It was, however, the geographic data structure used in the multicriteria combination rules that provided the bases for classifying GIS-MCDA according to the geographic data model (Malczewski 2006). Thus, if the combination rules are performed using the raster data, then the study is categorized as the raster-based MCDA. Similarly, the vector-based multicriteria combination rules are categorized as the vector-based MCDA approaches, irrespectively of the format of the input data. Although the majority of the GIS-MCDA research has been based on the layer view of the real world represented by the raster or vector data models, an effort has also been made to use the object-oriented paradigm for integrating GIS and MCDA (e.g., Reitsma and Carron 1997; Matthews et al. 1999).

Second, the raster- and vector-based GIS-MCDA approaches can further be categorized according to the nature of decision alternatives and evaluation criteria. Both alternatives and criteria can be classified into: spatially explicit and spatially implicitly categories (Herwijnen and Rietveld 1999; Malczewski 2006). These two categories are not mutually exclusive. According to Malczewski's (2006) survey, a majority of the GIS-MCDA studies (almost 70 %) involved a combination of spatially implicit and explicit criteria (e.g., Kao and Lin 1996; Antoine et al. 1997; Lin et al. 1997; Seppelt and Voinov 2002; Wu et al. 2004). Brookes (1997), Cromley and Hanink (1999, 2003), Church et al. (2003) and Malczewski (2011) provide examples of the raster-based GIS-MCDA involving a set of spatially explicit criteria. Examples of the raster-based spatially implicit criteria are given in

Brakewood and Grasso (2000), Fuller et al. (2003), Store and Jokimäki (2003), Feick and Hall (2004), and Ligmann-Zielinska and Jankowski (2012). The vector-based GIS-MCDA methods can also involve two categories of criteria: spatially explicit criteria (e.g., MacDonald 1996; Weigel and Cao 1999), and spatially implicit criteria (e.g., Vertinsky et al. 1994; Kächele and Dabbert 2002).

The spatial components of GIS-MCDA can also be examined in the context of the three categories of GIS-MCDA: the conventional MCDA, spatially explicit MCDA, and spatial multiobjective optimization (see Sect. 1.4). A vast majority of the GIS-MCDA approaches use the conventional (aspatial) MCDA methods for tackling spatial problems (e.g., Carver 1991; Banai 1993; Eastman et al. 1993; Malczewski 2000; Zhu and Dale 2001). The most popular MCDA methods include: the weighted linear combination and related procedures (e.g., Carver 1991; Eastman et al. 1993; Malczewski 2000), ideal/reference point methods (e.g., Pereira and Duckstein 1993; Malczewski 1996), the analytical hierarchy/network process (e.g., Banai 1993; Zhu and Dale 2001; Marinoni 2004), and outranking methods (e.g., Carver 1991; Joerin et al. 2001; Martin et al. 2003). Based on the criticism of the capabilities of conventional MCDA methods to tackle spatial problems, a number of approaches have been proposed to incorporate the spatial components of MCDA explicitly (e.g., Tkach and Simonovic 1997; Herwijnen and Rietveld 1999; Makropoulos and Butler 2006; Rinner and Heppleston 2006; Chakhar and Mousseau 2008; Ligmann-Zielinska and Jankowski 2008, 2012; Malczewski 2011; Carter and Rinner 2014). Spatial multiobjective optimization methods have been specifically designed for tackling spatial decision situations in which the decision/management alternatives have a geographic connotation such as location, distance, or connectivity. Examples of the spatial multiobjective optimization methods are given in Bennett et al. (1999), Huang et al. (2006), Li et al. (2009a, b), Meyer et al. (2009), Datta et al. (2012), Coutinho-Rodrigues et al. (2012), and Maliszewski et al. (2012). Many of those approaches involve metaheuristics for solving spatial multiobjective problems (e.g., Bennett et al. 1999; Huang et al. 2006; Li et al. 2009a, b; Datta et al. 2012).

3.3.3 MCDA Components of GIS-MCDA

Criterion is a generic term including both the concept of attribute and objective (see Sect. 2.2.2). Accordingly, GIS-MCDA can be classified into two categories: multi-attribute decision analysis (GIS-MADA) and multi-objective decision analysis (GIS-MODA) (see Fig. 3.3). A majority of the GIS-MCDA approaches falls into the GIS-MADA category (see Malczewski 2006). Banai (1993), Pereira and Duckstein (1993), Jankowski (1995), Eastman et al. (1995) and Jun (2000) provide examples of GIS-MADA. The GIS-MODA approaches are presented in Antoine et al. (1997), Seppelt and Voinov (2002), Aerts et al. (2003), Xiao et al. (2002), Armstrong et al. (2003), Stewart et al. (2004), Ligmann-Zielinska et al. (2008), and Maliszewski et al. (2012), to mention a few.

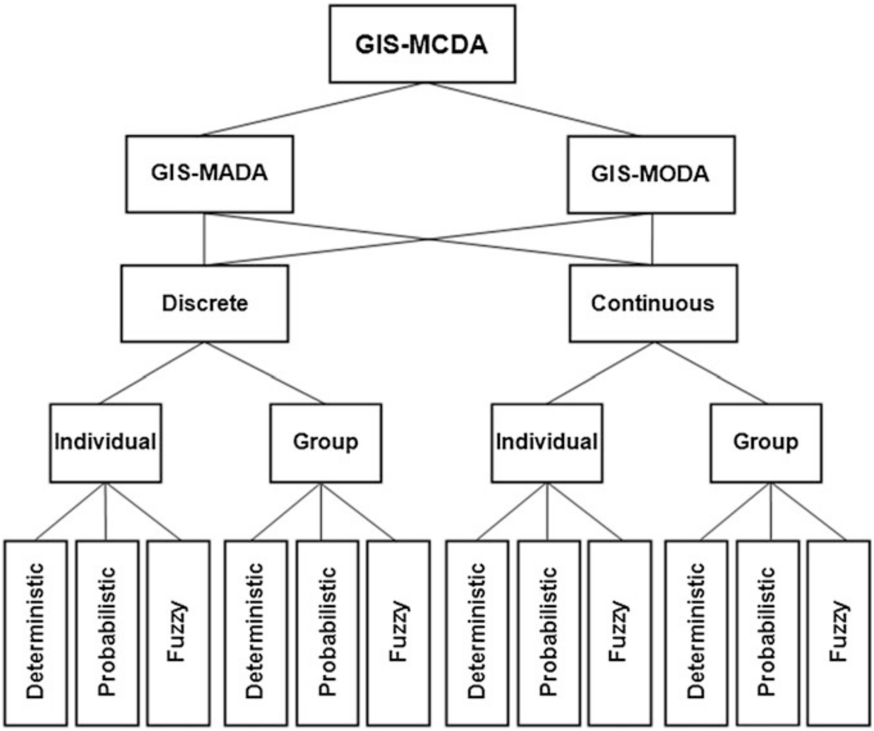

Fig. 3.3 Classification scheme for MCDA components of GIS-MCDA

GIS-MCDA approaches can also be categorized into discrete and continuous methods, depending on the definition of decision alternatives (decision variables) (see Sect. 2.2.3). The survey of GIS-MCDA shows there is an overlap between GIS-MADA and discrete multicriteria analysis on the one hand, and between GIS-MODA and continuous multicriteria analysis on the other (see Malczewski 2006). A vast majority of the GIS-MADA approaches have been used for tackling talking discrete spatial decision problems (e.g., Carver 1991; Banai 1993; Pereira and Duckstein 1993). There have been a few studies representing the GIS-continuous MADA (e.g., Varma et al. 2000; Prato 2008). This type of approaches typically involves a multiattribute utility mathematical programming based on an assessment of utility functions (see Goicoechea et al. 1982). In addition, there have been several GIS-MADA studies involving the mixed-integer mathematical programming models (e.g., Lin and Kao 2005; Wu and Murray 2005; Eiselt 2007; Ligmann-Zielinska et al. 2008). The continuous models have typically been used in the context of multiobjective mathematical programming (e.g., Lanta et al. 2005; Roetter et al. 2005; Santé-Riveira et al. 2008).

The GIS-MADA and GIS-MODA approaches can be further subdivided into two categories: individual and group decision making. This classification is based on the goal-preference structure of the decision maker. If there is a single goal-preference structure, then the problem is referred to as a single decision maker's problem, regardless of the number of individuals actually involved (see Sect. 2.2.1). On the other hand, if the individuals involved in the decision making process are characterized by different goal-preference structures, then the problem becomes that of group decision making. A majority of the GIS-MCDA articles represented the individual decision maker's approaches (Malczewski 2006). These approaches can be found in both GIS-MADA (e.g., Carver 1991; Banai 1993; Pereira and Duckstein 1993; Eastman et al. 1995; Jun 2000) and GIS-MODA (e.g., Church et al. 1992; Xiang 1993; Kao 1996; Antoine et al. 1997; Aerts et al. 2003). The group/participatory approaches are presented in Malczewski (1996), Feick and Hall (2002), Bailey et al. (2003), Jankowski et al. (2008), and Boroushaki and Malczewski (2010b). These studies are based on the GIS-MADA methods. There is a relatively small number of applications using GIS-MODA for group decision making (e.g., Bennett et al. 1999; Seppelt and Voinov 2002; Bayliss et al. 2003). The group decision making category includes the participatory decision making approaches (Jankowski and Nyerges 2001). Participatory GIS-MCDA is a general concept that includes Group GIS-MCDA and Public Participation GIS-MCDA. This distinction is based on the size of group involved in the decision making process (Balram and Dragićević 2006). The Group GIS-MCDA applications typically involve a small group of participants (e.g., Feick and Hall 2004; Norese and Toso 2004). The Public Participation GIS-MCDA applications are based on the involvement of a large group of participants (e.g., Bojorquez-Tapia et al. 2004; Jankowski and Nyerges 2001; Boroushaki and Malczewski 2010a).

The GIS-MCDA studies can also be categorized according to the amount of information about the decision situation that is available to the decision maker/analyst. To this end, one can distinguish three categories of decision problems: deterministic, probabilistic, and fuzzy. If the decision maker has perfect knowledge of the decision environment, then the decision is made under conditions of certainty (deterministic decision making). Many analysts deliberately choose to model spatial decisions as occurring under a condition of certainty because of insufficient data or because the uncertainty is so remote that it can be disregarded as a factor (see Hwang and Yoon 1981; Malczewski 1999). Consequently, majority of the GIS-MCDA studies fall into the deterministic category (e.g., Carver 1991; Jankowski and Richard 1994; Brookes 1997; Marinoni 2004).

There are two basic types of uncertainty that may be present in a decision situation: (i) uncertainty associated with limited information about the decision situation, and (ii) uncertainty associated with fuzziness (imprecision) concerning the description of the semantic meaning of the events, phenomena or statements themselves (Malczewski 1999). Consequently, both multiattribute and multiobjective problems under uncertainty can be further subdivided into: *probabilistic* (or stochastic) (e.g., Klungboonkrong and Taylor 1998; Seppelt and Voinov 2002; Prato 2008) and *fuzzy* decision making problems depending on the type of uncertainty involved (e.g., Banai 1993; Jiang and Eastman 2000; Joerin et al. 2001; Bailey et al. 2003; Makropoulos et al. 2003; Chen et al. 2010; Qiu et al. 2014).

3.3.4 Integration of GIS and MCDA

From the perspective of MC-SDSS (see Sect. 1.3.2), it is useful to identify the different approaches for integrating GIS and MCDA. These approaches can be categorized according to: the extent of integration and the direction of integration of GIS and MCDA. Three categories can be identified based on the extent of integration: (i) loose-coupling, (ii) tight-coupling, and (iii) full integration (Goodchild 1992; Nyerges 1992; Jankowski 1995; Jun 2000). In the loose coupling approach, two systems (GIS and multicriteria modeling system) exchange files such that a system uses data from the other system as the input data (e.g., Guimarães Pereira et al. 1994; Jankowski 1995). A tight coupling strategy is based on a single data or model manager and a common user interface. Thus, the two systems share not only the communication files but also common user-interface (e.g., Bennett et al. 1999; Riedl et al. 2000). A more complete integration can be achieved by creating user-specified routines using generic programming languages. The routines then can be added to the existing set of commands or routines of the GIS package. This coupling strategy is referred to as a full integration approach (e.g., Eastman et al. 1995; Matthews et al. 1999; Yatsalo et al. 2010).

The GIS-MCDA approaches can also be classified in terms of the direction of integration. This type of classification includes four categories: (i) one-directional integration with GIS as principal software, (ii) one-directional integration with MCDA system as principal software, (iii) bi-directional integration, and (iv) dynamic integration (see Nyerges 1992; Jun 2000). One-directional integration provides mechanisms for importing/exporting information via a single flow that originates either in the GIS or MCDA software. This type of integration can be based on GIS or MCDA as the principal software. Jun (2000) and Malczewski et al. (2003) provide examples of the one-directional integration with GIS as the principal software. MCDA as the principal software for integrating MCDA and GIS was used in Antoine et al. (1997), and Kächele and Dabbert (2002). In the bi-directional integration approach, the flow of data/information can originate and end in the GIS and MCDA modules. While bi-directional integration involves one-time flow of information, dynamic integration allows for a flexible moving of information back and forth between the GIS and MCDA modules according to the user's needs (Jun 2000; Yatsalo et al. 2010).

3.3.5 Application Domains

One of the most remarkable features of the GIS-MCDA approaches is the wide range of decision and management situations in which they have been applied. Table 3.1 shows the major areas of the GIS-MCDA applications and a sample of relevant studies. According to Malczewski's (2006) survey, the major application areas include: environmental planning/management, transportation, urban and regional planning, waste management, hydrology and water resource, agriculture,

Table 3.1 Application domains of GIS-MCDA

Application domain	References
Environmental planning/management	Pereira and Duckstein (1993), Bojórquez-Tapia et al. (2001), Noss et al. (2002), Seppelt and Voinov, 2002, Geneletti (2007), Lesslie et al. (2008), Çelik and Türk (2011) and Hessburg et al. (2013)
Transportation planning/management	Church et al. (1992), Weigel and Cao (1999), Jha et al. (2001), Farhan and Murray (2008), Alçada-Almeida et al. (2009), Coutinho-Rodrigues et al. (2012) and Maliszewski et al. (2012)
Urban/regional planning	Wu (1998), Feng and Lin (1999), Gomes and Lins (2002), Ward et al. (2003), Ligmann-Zielinska et al. (2008) and Plata-Rocha et al. (2011)
Waste management	Carver (1991), Kao (1996), Kao and Lin (1996), MacDonald (1996), Charnpratheep et al. (1997), Leão et al. (2004) and Ferretti (2011)
Hydrology and water resource management	Reitsma and Carron (1997), Tkach and Simonovic (1997), Giupponi et al. (1999), Lee et al. (2000), Makropoulos et al. (2003), Martin et al. (2003), Chen et al. (2011)
Natural hazard	Rashed and Weeks (2003), Ayalew et al. (2004), Gorsevski et al. (2006), Ozturk and Batuk (2011) and Lai et al. (2013)
Agriculture	Matthews et al. (1999), Kächele and Dabbert (2002), Ceballos-Silva and Lopez-Blanco (2003), Meyer et al. (2009), Chen et al. (2010) and Cisneros et al. (2011)
Forestry	Vertinsky et al. (1994), Kangas et al. (2000), Riedl et al. (2000), Schlaepfer et al. (2002), Gilliams et al. (2005) and Zeng et al. (2007)

and forestry. These domains account for more than 70 % of all GIS-MCDA applications (Malczewski 2006). In addition, the GIS-MCDA methods have found their applications in such diverse domains as: recreation and tourism management (e.g., Feick and Hall 1999, 2004), housing and real estate (e.g., Can 1992; Johnson 2001; Malczewski and Rinner 2005), geology and geomorphology (e.g., Araújo and Macedo 2002; Burton and Rosenbaum 2003), industrial facility management (e.g., Jun 2000; Vlachopoulou et al. 2001), and cartography (e.g., Huffman and Cromley 2002; Armstrong et al. 2003).

Some decisions are more important than others in terms of their immediate impact or significance. Therefore, it is instructive to look at the GIS-MCDA applications from the perspective of the decision levels. One can identify three levels of decision: *operational*, *tactical,* and *strategic*. The operational (or routine) decision problems are those that occur frequently and they are almost identical (a high degree of replication). The vehicle routing and scheduling problems are examples of this type of spatial optimization (e.g., Bowerman et al. 1995; Chang and Wei 1999; Lopes et al. 2008; Choi et al. 2009). The tactical level decisions tend to be medium range, medium significance, and with moderate consequences. Districting problems provide an example of a spatial optimization problem at the tactical level (e.g., November et al. 1996; Bong and Wang 2004). Strategic decisions are concerned with general direction, long-term goals, and values. These decisions are the least structured with the most uncertain outcome, partly because they reach far into the future and partly because they are of great significance. There are a number GIS-MCDA applications that are concerned with strategic decisions, such as locating major facilities (e.g., Carver 1991; Negi and Jain 2008; Zucca et al. 2008), land allocation (e.g., Aerts et al. 2005; Duh and Brown 2005), choice of environmental strategies (e.g., Martin et al. 2003; Bryan and Crossman 2008), and urban/regional development (e.g., Wu and Webster 1998; Plata-Rocha et al. 2011).

3.4 Conclusion

The multidisciplinary field of GIS-MCDA has been widely and strongly adopted within the GIScience community. The decision analysis community has also recognized it as an important area of application. The chapter overviewed recent development in GIS-MCDA, and also provided a brief historical background of the research traditions that have influenced the evolution of GIS-MCDA. Based on the survey of relevant publications, this chapter has presented taxonomy of GIS-MCDA research and applications. The survey suggests that the research and applications have focused on relatively small number of multiattribute methods including the weighted linear combination, ideal point methods, the AHP/ANP, and outranking methods. Also, a few multiobjective programming methods have been used for tackling spatial problems within the GIS environment. Another finding of the survey suggests that artificial intelligence approaches have increasingly been employed for solving complex spatial multiobjective problems. Part II of this book will discuss the most often used GIS-MCDA methods.

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Part II
GIS-MCDA: Methods

Chapter 4
Multiattribute Decision Analysis Methods

4.1 Introduction

Although a large number of multiattribute decision analysis (MADA) methods is available (Hwang and Yoon 1981), the theoretical and applied research about GIS-MADA has focused on a relatively small number of multiattribute procedures including: the weighted linear combination, ideal point methods, the analytic hierarchy process/analytic network process, and outranking methods (see Sect. 3.3.2). These four methods are discussed in this Chapter. We introduce the conventional MADA methods and discuss their extensions to the spatially explicit models (see Sect. 1.4). The chapter also provides a brief overview of GIS-based applications for each of the four methods.

4.2 Weighted Linear Combination

The weighted linear combination (WLC) and related models are the most often used GIS-MADA methods (see Sect. 3.3.2). Other terms such as simple additive weighting, weighted summation, weighted linear average, and weighted overlay have also been used to describe WLC (see Malczewski 2006a). The WLC model consists of two components: criterion weights, w_k, and value functions, $v(a_{ik})$ (see Sect. 2.3). It is a map combination procedure that associates with the ith decision alternative (location) a set of criterion weights, w_1, w_2,…,w_n, and combines the weights with the criterion (attribute) values, a_{i1}, a_{i2}, …, a_{in}, (i = 1, 2, …, m) as follows:

$$V(A_i) = \sum_{k=1}^{n} w_k v(a_{ik}), \tag{4.1}$$

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_4

where $V(A_i)$ is the overall value of the ith alternative at location, s_i, defined by the (x_i, y_i) coordinates (for the sake of simplicity a single subscript, i, is used to indicate the location of the ith alternative); $v(a_{ik})$ is the value of the ith alternative with respect to the kth attribute measured by means of the value function. The alternative characterized by the highest value of $V(A_i)$ is the most preferred one.

The WLC model is based on the assumptions of linearity and additively. The former assumption means that desirability of an additional unit of an attribute is constant for any level of that attribute, which implies constant marginal values/ utilities of a_{i1} and a_{i2}. The additively assumption means the attributes under consideration are mutually preference independent of each other; that is, the preferential independence property exists if the ranking for one attribute does not depend on fixed values of other attributes.

It should be emphasized that one cannot meaningfully assess the value of a criterion weight without identifying the value function (the range of criterion values) (Keeney 1992; Hobbs and Meier 2000; Munda 2008). To demonstrate the relationships between the criterion weights and ranges, let us consider two locations, s_1 and s_2, evaluated by means of two criteria to be minimized; that is, $s_1 = \{a_{11}, a_{12}\}$ and $s_2 = \{a_{21}, a_{22}\}$. If one is indifferent between the two decision alternatives, then the overall value of s_1 should be the same as the value of s_2; that is,

$$w_1 v(a_{11}) + w_2 v(a_{12}) = w_1 v(a_{21}) + w_2 v(a_{22}). \tag{4.2}$$

Using the definition of value function in Eq. 2.2, Eq. 4.2 is rewritten as follows:

$$\begin{aligned} & w_1\left(\frac{a_{11} - \min\limits_{i1}\{a_{i1}\}}{r_1}\right) + w_2\left(\frac{a_{12} - \min\limits_{i}\{a_{i2}\}}{r_2}\right) \\ & = w_1\left(\frac{a_{21} - \min\limits_{i}\{a_{i1}\}}{r_1}\right) + w_2\left(\frac{a_{22} - \min\limits_{i}\{a_{i2}\}}{r_2}\right) \end{aligned} \tag{4.3}$$

After some algebra, we obtain:

$$\frac{w_1}{r_1}a_{11} + \frac{w_2}{r_2}a_{21} = \frac{w_1}{r_1}a_{12} + \frac{w_2}{r_2}a_{22}, \tag{4.4}$$

and

$$\frac{w_1}{w_2} = -\frac{r_1(a_{21} - a_{22})}{r_2(a_{11} - a_{12})}. \tag{4.5}$$

Thus, the ratio of the two weights, w_1 and w_2, should be inversely proportional to the rate at which one is willing to trade two criteria off. This principle should be applied irrespectively of the method used for assessing the criterion weights. The most often used approach for assessing the criteria and value function in GIS-WLC is the pairwise comparison method (Sect. 2.3.2.1) and the criterion range standardization method (Eqs. 2.1 and 2.2) (see Malczewski 2006a).

GIS-WLC is often used without full understanding of the assumptions underlying this approach. Hobbs (1980), Lai and Hopkins (1989), Heywood et al. (1995), and Malczewski (2000) provide discussions of the incorrect use of GIS-WLC. One should notice, however, that the assumptions behind WLC are often very difficult to apply in spatial decision making problems (Malczewski 2000). Furthermore, there is evidence to show that the WLC method yields "close approximations to very much more complicated non-linear forms, while remaining far easier to use and understand" (Hwang and Yoon 1981, p. 103; see also Massam 1993; Stewart 1996). One of the main advantages of WLC is that the method can easily be implemented within the GIS environment using map algebra operations (Tomlin 1990). The method is also intuitively appealing to decision makers. Consequently, GIS-WLC has been applied for analyzing decision and management situations in a variety of application domains (e.g., Eastman et al. 1995; Jankowski 1995; Geneletti 2005). Several GIS (such as IDRISI, ILWIS, and CommonGIS) feature decision support modules performing the WLC procedure (Eastman 1997; Rinner and Malczewski 2002; Boerboom et al. 2006).

4.2.1 Proximity-Adjusted WLC

The proximity-adjusted WLC model 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). It is argued that a choice of a particular decision alternative depends not only on the relative importance of criteria (measured by the global weights) but also on the location of the alternative with respect to other alternatives and/or some reference location (Ligmann-Zielinska and Jankowski 2012). The concept of spatial heterogeneity of preferences can be operationalized by the proximity-adjusted criterion weights (see Sect. 2.3.2.2). Given the definition of the proximity-adjusted weight, w_{ik}, assigned to the ith alternative with respect to the kth criterion, one can write the proximity-adjusted WLC model as follows:

$$V(A_i^p) = \sum_{k=1}^{n} w_{ik} v(a_{ik}). \tag{4.6}$$

Unlike the conventional (spatial or global) WLC (Eq. 4.1), the proximity-adjusted WLC is a spatially explicit MCDA model (see Sect. 1.4.2). It explicitly introduces spatial heterogeneity of preferences in calculating the overall value of the ith decision alternative.

Ligmann-Zielinska and Jankowski (2012) have analyzed a real-world decision situation involving a house selection problem to demonstrate and evaluate the proximity-adjusted WLC model. They found that the results of proximity-adjusted WLC were significantly different from those obtained using conventional models. The study suggests that the proximity-adjusted preferences (weights) have an integrative and non-linear effect on the ranking of decision alternatives.

4.2.2 Local WLC

The critical aspect of the global WLC model is that a criterion weight is intricately associated with the corresponding value function (see Eqs. 4.2–4.5). The interrelated concepts of the criterion range (value function) and criterion weight provide the foundation for developing the local form of WLC (Malczewski 2011; Carter and Rinner 2014). The relationship is encapsulated in the range-sensitive principle (e.g., Keeney 1992; Fischer 1995). Range sensitivity is a normative property, which is concerned with the dependence of criterion weights on the ranges of criterion values. The range sensitivity principle suggests that, other things being equal, the greater the range of values for the kth criterion, the greater the weight, w_k, that should be assigned to that criterion (e.g., Fischer 1995). Thus, the criterion weights vary as a function of the range of criterion values, r_k (see Sect. 2.3.2).

Given the definitions of local weight (see Sect. 2.3.2.2) and the local value function (see Sect. 2.3.1.2), the local form of WLC can be defined as follows:

$$V(A_i^q) = \sum_{k=1}^{n} w_k^q \, v(a_{ik}^q), \tag{4.7}$$

where $V(A_i^q)$ is the overall value of the ith alternative estimated locally (in the qth neighbourhood), $v(a_{ik}^q)$ is the value of the kth criterion measured by means of the local value function in the qth neighbourhood, and w_k^q the local criterion weight. The decision alternative with the highest value of $V(A_i^q)$ is the most preferred alternative in the qth neighbourhood.

Figure 4.1 compares the results of global and local WLC models for analyzing spatial pattern of heat vulnerability in the City of Toronto. The result of the global model shows that the most vulnerable neighbourhoods are arranged in a ‘U’-shaped pattern around the centre of Toronto, a pattern which has been identified in previous studies of socio-economic inequality in the city. In contrast to the global result, the local form of WLC demonstrates a more dispersed pattern. The local WLC thus creates isolated vulnerability “hot spots” in local neighbourhoods.

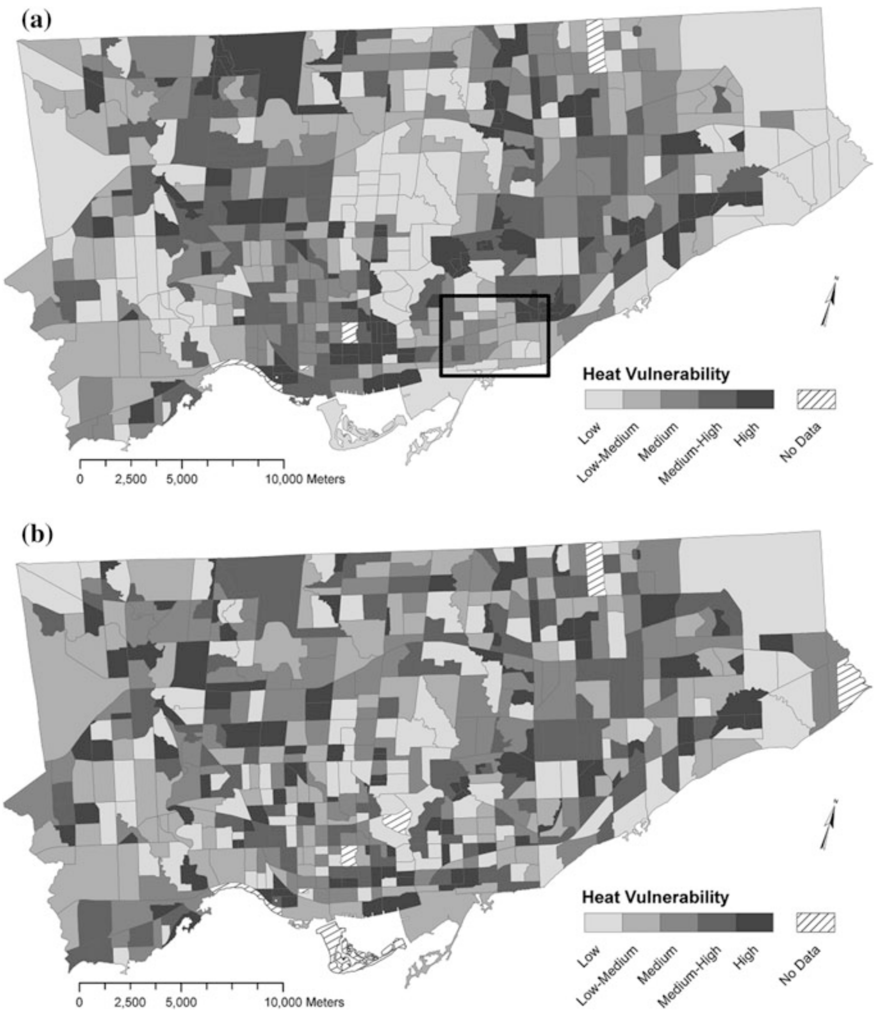

Fig. 4.1 Heat vulnerability in Toronto modelled using: (**a**) global WLC, and (**b**) local WLC (first-order contiguity). Map inset frame in global WLC map is from original source and not used here (*Source* Carter and Rinner 2014, Figs. 2 and 3, reprinted with permission)

4.2.3 WLC and Ordered Weighted Averaging

The Ordered Weighted Averaging (OWA) is a generalization and extension of the WLC model (Jiang and Eastman 2000). It is a family of multicriteria combination procedures developed by Yager (1988) and extended to GIS applications by Eastman (1997). For a given set of criterion (attribute) maps, OWA is a map combination procedure that associates with the maps two types of weights: a set of criterion weights, $w_1, w_2, \ldots, w_n$, and a set of order weights $\lambda_1, \lambda_2, \ldots, \lambda_n$ ($0 \leq \lambda_k \leq 1$, and $\sum_{j=1}^{n} \lambda_j = 1$). Given the set of attribute values $a_{i1}, a_{i2}, \ldots, a_{in}$ at the ith location ($i = 1,2, \ldots, m$), OWA can be defined as follows (Yager 1988):

$$V(A_i^o) = \sum_{k=1}^{n} \frac{\lambda_k u_k z_{ik}}{\sum_{k=1}^{n} \lambda_k u_k}, \tag{4.8}$$

$V(A_i^o)$ is the overall value of the ith decision alternative at location, s_i; $z_{i1} \geq z_{i2} \geq \ldots \geq z_{in}$ is the sequence generated by reordering of the standardized criterion values; that is, for the kth criterion the attributes, $a_{1k}, a_{2k}, \ldots, a_{mk}$ are transformed to $v_k(a_1), v_k(a_2), \ldots, v_k(a_m)$ using a value function approach (see Sect. 2.3.1.1); u_k is the criterion weight reordered according to the attribute value, z_{ik}. The reordering procedure is central to the OWA operator. It involves associating an order weight, λ_k, with a particular ordered 'position' of the attribute values a_{i1}, $a_{i2}, \ldots, a_{in}$. The first order weight, λ_1, is assigned to the highest attribute value for the ith location; λ_2 is associated with the next lower value for the same location, and so on; λ_n is assigned to the lowest attribute value.

Equation 4.8 can be recognized as the conventional WLC (see Eq. 4.1) with modified criterion weights, which are obtained by multiplying the criterion weights by the order weights. For example, given a set of criterion values at the ith location, $v(a_{ik}) = (0.6, 0.3, 0.2, 0.9)$, a set of order weights, $\lambda_k = 0.25$ for all k, and the following set of criterion weights, $w_k = (0.1, 0.5, 0.3, 0.1)$, the overall value $V(A_i^o) = 0.36$ (see Table 4.1). One can verify that the conventional $V(A_i) = (0.6 \times 0.1) + (0.3 \times 0.5) + (0.2 \times 0.3) + (0.9 \times 0.1) = 0.36$.

The generality of OWA is related to its capability to implement a wide range of combination operators by selecting appropriate order weights, λ_k (Yager 1988). The family of OWA operators includes the most often used GIS-base map combination procedures: the conventional WLC and Boolean overlay operations, such as intersection (AND) and union (OR) (Jiang and Eastman 2000). A set of equal order weights ($n^{-1}, n^{-1}, \ldots, n^{-1}$) does not affect any position in the re-ordered weighted standardized criterion values, resulting in the WLC scores; the order weights (1.0, 0.0, …, 0.0) assign a weight of 1.0 to the highest (best) criterion value for each

Table 4.1 Example: computing OWA

k	Criterion values $v_k(a_i)$	Criterion weights w_k	Ordered criterion values z_{ik}	Reordered criterion weights u_k	Order weights λ_k	$\lambda_k\ u_k$	$\lambda_k\ u_k\ z_{ik}$	$\frac{\lambda_k u_k z_{ik}}{\sum_k \lambda_k u_k}$
1	0.6	0.1	0.9	0.1	0.25	0.025	0.0225	0.09
2	0.3	0.5	0.6	0.1	0.25	0.025	0.0150	0.06
3	0.2	0.3	0.3	0.5	0.25	0.125	0.0375	0.15
4	0.9	0.1	0.2	0.3	0.25	0.075	0.0150	0.06
Σ						0.250		0.36

location, resulting in an OR-type combination; the order weights (0.0, …, 0.0, 1.0) assign a weight of 1.0 to the lowest (worst) values, resulting in the Boolean AND combination (Jiang and Eastman 2000; Malczewski et al. 2003). The *AND* and *OR* operators represent the extreme cases of OWA and they correspond to the MIN and MAX operators, respectively (Jiang and Eastman 2000; Malczewski 2006b; Malczewski and Rinner 2005).

The behaviour of the OWA operators can be described in two dimensions: the degree of *ORness* and *trade-off*. The measure of *ORness* is defined as follows (Yager 1988):

$$ORness = \sum_{k=1}^{n} \left(\frac{n-j}{n-1} \right) \lambda_k, \; 0 \leq ORness \leq 1. \tag{4.9}$$

The degree of *ORness* indicates the position of OWA on a continuum between the AND or OR operators. It emphasizes the higher (better) values or the lower (worse) values in a set of attributes associated with the *i*th alternative. There are both theoretical and empirical evidence to show that individuals (decision-makers) with optimistic (or risk-taking) attitudes tend to emphasize good properties of alternatives, while pessimistic or risk-averse decision-makers tend to focus on bad properties of alternatives (Bodily 1985; see Sect. 7.3.3).

The trade-off is defined as follows (Jiang and Eastman 2000):

$$tradeoff = 1 - \sqrt{n \sum_{k=1}^{n} \frac{\left(\boldsymbol{\lambda_k} - \frac{\boldsymbol{1}}{\boldsymbol{n}}\right)^2}{n-1}}, \; 0 \leq tradeoff \leq 1. \tag{4.10}$$

According to Jiang and Eastman (2000), the trade-off measure specifies the degree of compensation or substitutability between criteria. It indicates the compensation of low values on one criterion by high values on another criterion.

These two dimensions form a decision strategy space (see Fig. 4.2; Eastman 1997; Jiang and Eastman 2000; Rinner and Malczewski 2002). Note that the degrees of *ORness* and *trade-off* depend on the number of criteria, n, being included in the OWA procedure. Except for the special cases of *ORness* = 1.0, 0.5, and 0.0, the greater the number of criteria, the higher the level of trade-off that can be obtained for a given degree of *ORness*. For the special cases of AND, OR, and WLC operators, the measures of *trade-off* and *ORness* are fixed irrespectively of the number of criterion maps. For $n = 2$, the decision space has a triangular form. As the number of criteria increases from $n = 2$ to $n \rightarrow \infty$, the decision strategy space gradually changes its shape from a triangular to a rectangular form (see Malczewski 2006b).

A key issue associated with using OWA is the method for determining the order weights. In the GIS-OWA applications the weights are often defined 'intuitively' based on the degree of *ORness* and *trade-off* (Eastman 1997; Jiang and Eastman 2000; Rinner and Malczewski 2002; Bell et al. 2007; Valente and Vettorazzi 2008). The maximum entropy method (O'Hagan 1990) has been used in Malczewski et al.

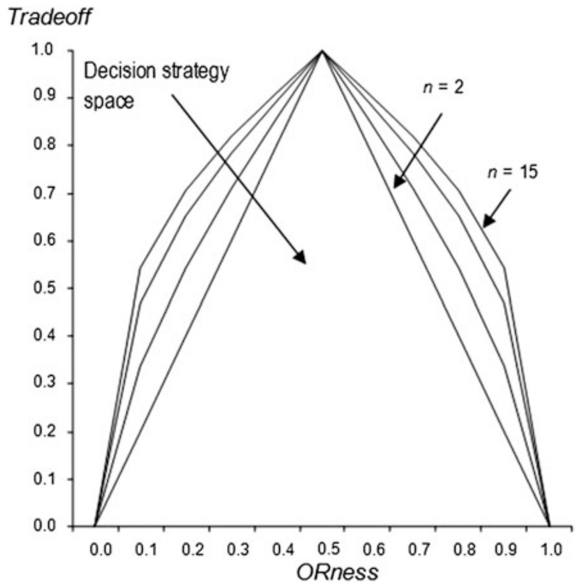

Fig. 4.2 Relationships between the measures of *trade-off* and *ORness* for the number of criterion maps $n = 2$, 5, 10, and 15

(2003), Makropoulos and Butler (2006), and Makropoulos et al. (2007). This method allows for determining the optimal values of order weights by maximizing the measure of entropy (dispersion of the order weights), subject to a specify degree of *ORness* (O'Hagan 1990). Yager's (1996) approach for defining order weights with the linguistic quantifiers has been extended to GIS-OWA by Malczewski (2006) (see also Malczewski and Rinner 2005; Carrara et al. 2008; Chen and Paydar 2012). The linguistic quantifiers based OWA has been implemented in Common-GIS (Rinner and Malczewski 2002) and ArcGIS (Boroushaki and Malczewski 2008). Figure 4.3 provides an example of the CommonGIS-OWA application. It shows a series of maps displaying different patterns of residential quality depending on the degree of *ORness* specified in terms of linguistic quantifiers.

The OWA concept (Yager 1988) has been extended to the GIS applications by Eastman (1997) as a part of decision support module in GIS-IDRISI. The development of the IDRISI-OWA module has also stimulated the implementation of OWA in the ArcView/ArcGIS environment (Malczewski et al. 2003; Malczewski 2006b; Makropoulos and Butler 2006; Boroushaki and Malczewski 2008; Ozturk and Batuk 2011; Chen and Paydar 2012; Rahman et al. 2012; Zubaryeva et al. 2012; Eldrandaly 2013). In addition, an effort has been made to implement GIS-OWA as a Web-enabled system using CommonGIS (Rinner and Malczewski 2002; Malczewski and Rinner 2005). The OWA procedure has also been integrated into the location-based services (Rinner and Raubal 2004) and personalized route planning (Nadi and Delavar 2011).

Although OWA is a relatively new concept, there have been a number of GIS-OWA applications. The method has most often been employed for land-use suitability analysis (Eastman 1997; Jiang and Eastman 2000; Melo et al. 2006;

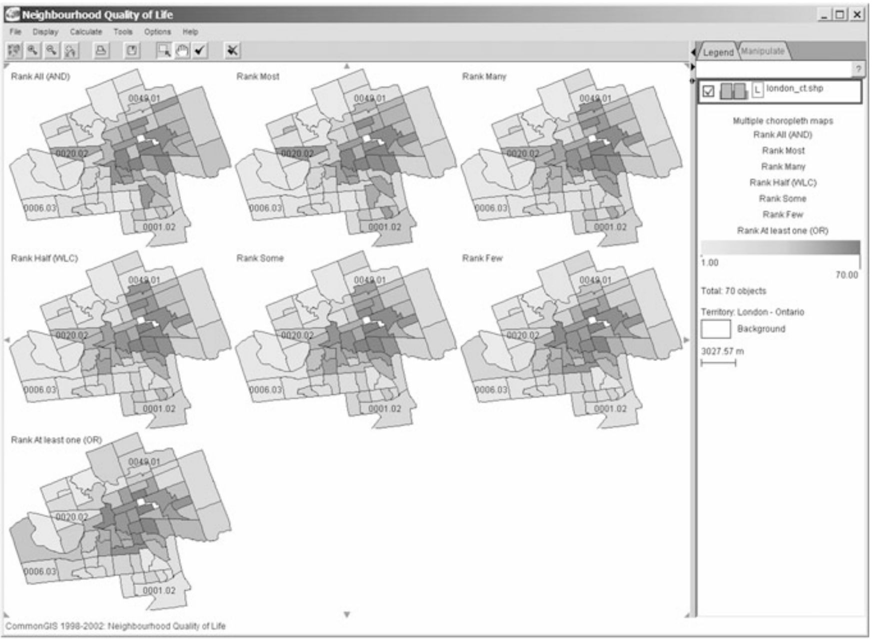

Fig. 4.3 Evaluating residential quality in London, Ontario: multiple choropleth maps of quantifier-based OWA method in CommonGIS (*Source* Malczewski and Rinner 2005, Fig. 4b, reprinted with permission)

Boroushaki and Malczewski 2008; Chen and Paydar 2012). The GIS-OWA approach has also been used as a tool for urban and rural planning (Gao and Asami 2005; Tassinari and Torreggiani 2006; Taleai et al. 2007). Several authors offer the GIS-OWA approach for evaluating residential quantity (Mendes and Motizuki 2001; Malczewski and Rinner 2005; Stimson et al. 2006). GIS-OWA has also been employed in health care research (Clements et al. 2006; Bell et al. 2007). Rinner and Malczewski (2002) and Rinner and Raubal (2004) have demonstrated applicability of GIS-OWA as a decision support tool in the area of tourism. GIS-OWA has been applied in a variety of environmental study domains including: environmental monitoring (Carrara et al. 2008), conservation planning (Thackrah et al. 2004; Valente and Vettorazzi 2008), analyses of vulnerability to earthquake hazards (Rashed and Weeks 2003), and landslide hazards (Gorsevski et al. 2006; Gemitzi et al. 2007). Rahman et al. (2012) provided an example of using GIS-OWA for aquifer recharge sites selection, while (de Araújo and Macedo 2002) applied GIS-OWA to analyze geological favorability. Melo et al. (2006) and Gemitzi et al. (2007) used the method to find the best location for landfill site.

Makropoulos and Butler (2005, 2006) and Makropoulos et al. (2007) have proposed a GIS-OWA-based spatial decision support system for urban water management. These studies are of particular significance for GIS-MCDA. Makropoulos and Butler (2005) developed an approach, termed spatial OWA (SOWA). The main advantage of SOWA is that it incorporates a spatially variable degree of *ORness* (or the attitude toward risk) into the decision analysis procedure. This implies that different types of OWA can be applied to different locations depending on their characteristics. While Makropoulos and Butler (2005) have focused on spatially explicit GIS-OWA model using the degree of *ORness*, Malczewski and Liu (2014) proposed an approach for developing the local form of GIS-OWA based on the concepts of spatially explicit value functions and criterion weights (see Sects. 2.3.1.2 and 2.3.2.2). These two approaches are complementary. One can suggest that an integration of these two spatially explicit multicriteria modeling frameworks would provide advancement of research on GIS-OWA.

4.3 Analytic Hierarchy/Network Process

The analytic hierarchy process (AHP) is one of the most comprehensive methods of multicriteria decision analysis (Saaty 1980). The method is based on three principles: decomposition, comparative judgment, and synthesis of priorities. The decomposition principle requires that a decision problem be decomposed into a hierarchy that captures the essential elements of the problem. The principle of comparative judgment requires assessment of pairwise comparisons of the elements within a given level of the hierarchical structure, with respect to their parent in the next-higher level. The pairwise comparison is the basic measurement mode employed in the AHP procedure (see Sect. 2.3.2.1). The synthesis principle takes each of the derived ratio-scale priorities in the various levels of the hierarchy and constructs a composite set of priorities for the elements at the lowest level of the hierarchy (that is, alternatives). Given these principles, the AHP procedure involves three main steps: (i) developing the AHP hierarchy (see Sect. 2.2.2.2), (ii) assigning weights of importance to each element of the hierarchical structure using the pairwise comparison method (see Sect. 2.3.2.1), and (iii) constructing an overall priority rating.

4.3.1 Analytic Hierarchy Process

The conventional AHP is a global method. For a typical hierarchical structure (which consists of a goal, objectives, attributes, and alternatives), the global AHP model defines the overall evaluation score (or priority rating) as follows:

$$V(A_i) = \sum_{k=1}^{n} w_l w_{k(l)} v(a_{ik}), \tag{4.11}$$

where $v(a_{ik})$ is the value function; w_l is the weights associated with the lth objective ($l = 1, 2,\ldots, p$), and $w_{k(l)}$ is the weights assigned to the kth attribute associated with the lth objective. The weights as computed using Eqs. 2.9 and 2.10 (see Sect. 2.3.2.1).

There have been a number of approaches for integrating GIS and AHP (see Malczewski 2006a). They can be classified into two groups. First, AHP is integrated into GIS as a tool for estimating the weights associated with attribute/criterion map layers. Once the weights are estimated, they are combined with the attribute map layers using a combination rule such as WLC (Eastman et al. 1993). This approach is of particular importance for problems involving a large number of alternatives, when it is impossible to perform a pairwise comparison of the alternatives. Second, the AHP method is employed as a procedure for combining the priority for all levels of the hierarchy structure including the level representing alternatives. In this case, a relatively small number of alternatives can be evaluated (e.g., Jankowski and Richard 1994).

The AHP-GIS approaches can also be categorized into two groups depending on the extent to which the AHP principles are integrated into GIS. The first group includes GIS-AHP systems having the capabilities of estimating criterion weights based on the comparative judgment principle (Eastman et al. 1993; Jun 2000; Gemitzi et al. 2007; Karnatak et al. 2007; Ozturk and Batuk 2011). However, the systems do not have the capabilities of representing decision problem using the decomposition principle and calculating the overall evaluation score according to the AHP synthesis of priorities model. They typically use some form of additive weighted model for calculating the overall evaluation scores. IDRISI Multi-Criteria Evaluation (MCE) module provides a good example of this category of GIS-AHP (Eastman et al. 1993). The second group of GIS-AHP includes systems that are based on the three principles of AHP: decomposition, comparative judgment, and synthesis of priorities. CommonGIS (Rinner and Taranu 2006), ILWIS-SMCE (Boerboom et al. 2006), and the Ecosystem Management Decision Support System/Criterium DecisionPlus (Reynolds et al. 2003; Reynolds and Hessburg 2014; Murphy 2014) exemplify this type of GIS-AHP.

Figure 4.4 shows an example of the GIS-based AHP procedure. A problem of evaluating three parcels of land (A_1, A_2, and A_3) is first decomposed into a hierarchy, which descends from the general goal to the more specific elements of the problem: two objectives and five attributes. The relative importance of the two objectives is assessed based on the pairwise comparison. Let us assume that Objective 1 is twice as important as Objective 2. Using Eqs. 2.9 and 2.10, one can compute the objective weights as follows: $w_1 = (1/2) \times ((1/1.5) + (2/3)) = 0.667$ and $w_2 = 0.333$ (see Table 4.2a). There are two attributes associated with Objective 1. Table 4.2b shows that Attribute 1 is three times as important as Attribute 2. Consequently, $w_{1(1)} = 0.75$ and $w_{2(1)} = 0.25$. The attribute weights associated with Objective 2 have been calculated in similar ways (see Table 4.2c). Since the consistency ratio (CR) for each of the pairwise comparison tables is less than < 0.10, the weights can be used for calculating the overall value of each alternative using Eq. 4.11. For example, the overall value of $V(A_1) = (0.667 \times 0.75 \times 0.5) + (0.667 \times 0.25 \times 0.4) + (0.333 \times 0.539 \times 1.0) + (0.333 \times 0.297 \times 0.3) + (0.333 \times 0.164 \times 1.0) = 0.581$. The overall values of $V(A_2) = 0.266$, and $V(A_3) = 0.670$ are calculated in similar way. The results are shown in Fig. 4.4.

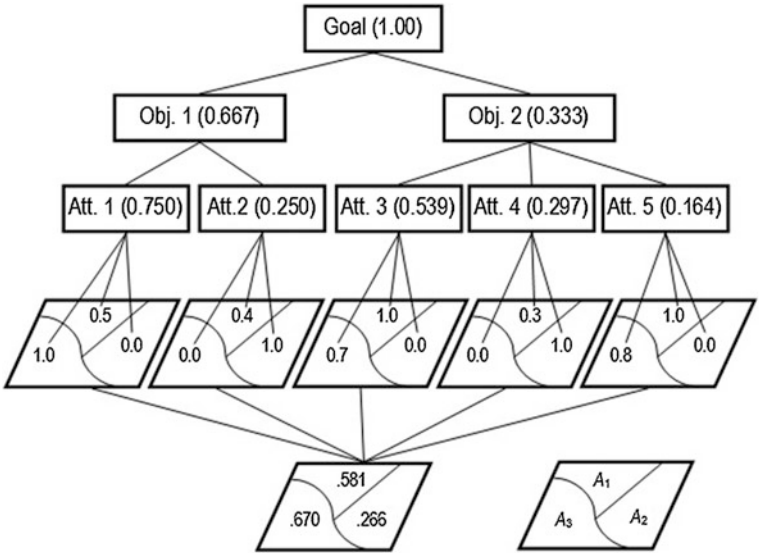

Fig. 4.4 Example of hierarchical structure of GIS-based AHP model (*Note* A_1, A_2, and A_3 are alternatives, *Obj.* Objective, *Att.* Attribute, the maps show standardized attribute values for each parcel of land)

Table 4.2 Pairwise comparisons of: (a) objectives with respect to goal, (b) attributes with respect to objective 1, and (c) attributes with respect to objective 2

(a)			
Goal			
Objectives	Obj.1	Obj. 2	w_l
Obj.1	1	2	0.667
Obj.2	0.5	1	0.333
Sum	1.5	3.0	1.000
$CR = 0.00$			
(b)			
Objective 1			
Attributes	Att.1	Att.2	$w_{k(1)}$
Att.1	1	3	0.750
Att.2	0.33	1	0.250
Sum	1.33	4.00	1.000
$CR = 0.00$			

(c)				
Objective 2				
Attributes	Att.3	Att.4	Att.5	$w_{k(2)}$
Att.3	1	2	3	0.539
Att.4	0.5	1	2	0.297
Att.5	0.33	0.5	1	0.164
Sum	1.83	3.50	6.00	1.000
$CR = 0.01$				

The AHP model is a form of WLC (see Sect. 4.2). If the hierarchical structure consists of three levels (the goal, attributes, and alternatives), then the AHP method is an equivalent of WLC with criterion weights defined by the pairwise comparison method. The major advantage of using AHP rather than WLC is the former provides a tool for focusing decision maker attention on developing a formal structure to capture all the important elements of a decision situation. The pairwise comparison method is generally found to be readily accepted in practice, as a means of establishing information about the relative importance of criteria and the relative performance of options. Like WLC, AHP (Eq. 4.11) is an additive weighting model. Consequently, a valid implementation of the method requires that the underlying assumptions of additive weighting model be met (see Sect. 4.2).

4.3.2 Analytic Network Process

One of the underlying assumptions of AHP is that the elements of the hierarchical structure are independent. This is a rather strong assumption especially in the context of spatial decision problems. Real-world spatial decision situations typically involve a complex pattern of the interactions and dependences among elements of the decision problem. Saaty (1996) proposed a method, analytic network process (ANP), for tackling decision problems in the presence of the dependence among elements of decision situation. The method is an extension and generalization of AHP. Like AHP, ANP is based on the principles of decomposition, comparative judgment, and synthesis of priorities (see Sect. 4.3).

The principle of decomposition involves problem structuring by a network rather than a hierarchy (see Fig. 4.5). A network consists of clusters (components or levels). Each cluster is made up of elements (or nodes). The clusters are connected by links (or arcs). The directions of the arcs signify dependence, indicating a one-way-dependence or two-way-dependence (influence or interaction) between a pair of clusters. A loop associated with a component indicates feedback into the component itself. An element of a given cluster can interact with some or all elements of that cluster or of elements of another cluster. Thus, the ANP method allows both interaction and feedback within clusters of elements (inner dependence) and between clusters (outer dependence). Those clusters with no entering or leaving arc are referred to as source or sink clusters, respectively. Those components which arrows both enter and exit are known as transient components, such as the objective and attribute clusters. Notice that a hierarchy is a special case of a network with links going only in one direction (see Figs. 4.5a and 4.5b).

The ANP and AHP procedures use a similar principle of comparative judgment (see Sect. 4.3.1). Both methods derive ratio scale priorities for elements and clusters of elements by making paired comparisons of elements. Thus, the pairwise comparison method (see Sect. 2.3.2.1) is employed to generate matrices of dependent clusters and elements. In ANP, like in the case of AHP, pairwise comparisons of the elements in each cluster are conducted with respect to their relative importance

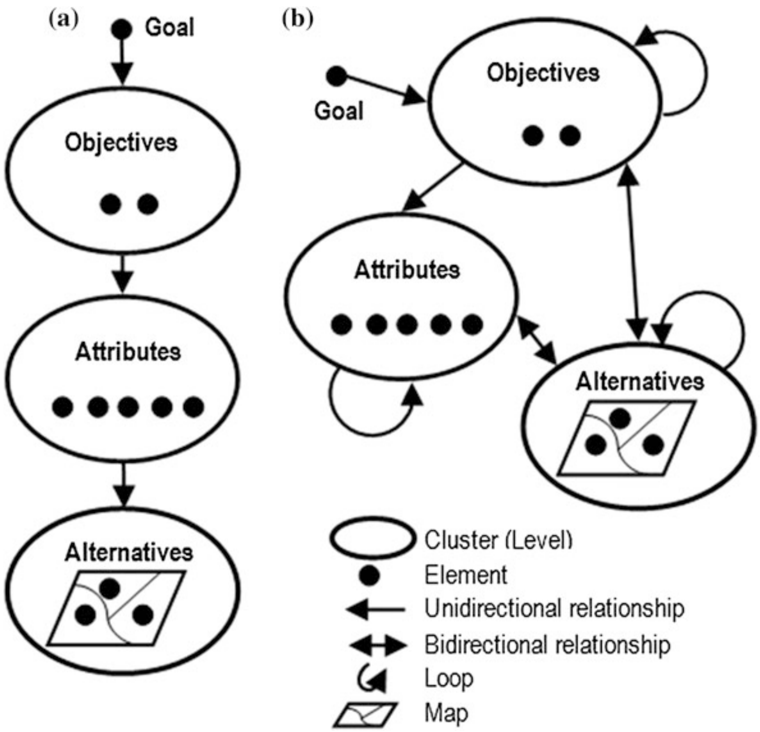

Fig. 4.5 **a** Hierarchical structure, and **b** network structure of the hypothetical example of land use/suitability problem (see Fig. 4.4)

toward their 'control component'. The control hierarchy is a hierarchy of criteria and sub-criteria, for which priorities are derived using the principle of comparative judgment with respect to the goal (Saaty 1996). The criteria are used to compare the clusters, and the sub-criteria are employed in the process of comparing the elements. The generic question of the comparative judgment can be formulated as follows: given a cluster or an element (in the same component or in another component) or given a component, how much more does a given element (component) for a pair influence that element (component) with respect to a control subcriterion (criterion)? The weights of the components are used to weight the blocks (or submatrices) of the supermatrix corresponding to the components being influenced.

The synthesis of priorities in ANP is obtained by using the concept of super-matrix. Saaty (1996) explains the concept as a parallel to the Markov chain process (see also Banai 2010). The super-matrix approach allows a resolution of the effects of dependence that exists between the clusters and elements. It is a partitioned matrix, where each sub-matrix (block) is composed of a set of relationships between two clusters/elements of the graphical network model (see Fig. 4.5b). The super-matrix is a two-dimensional matrix of elements by elements. The priorities from the pairwise comparisons are entered in the appropriate column of the super-matrix. The sum of each column corresponds to the number of comparison sets. The super-matrix needs to be column stochastic. This means that the sum of each column in the super-matrix must be one (that is, the matrix must be normalized). This is achieved by a procedure for obtaining a limiting super-matrix. The procedure involves raising the super-matrix to the power 2 N + 1, where N is an arbitrarily large number to obtain the convergence of the interdependent relationship. It repeatedly takes the power of the matrix, its square, its cube, etc. until the limit is attained (converges), in which case the sum of each column is equal one.

The linear hierarchy shown in Fig. 4.5a can be represented by the following super-matrix:

$$M_H = \begin{bmatrix} 0 & 0 & 0 & 0 \\ w_{21} & 0 & 0 & 0 \\ 0 & W_{32} & 0 & 0 \\ 0 & 0 & W_{43} & I \end{bmatrix}.$$

The super-matrix for the hierarchy, M_H, consists of: a vector, w_{21}, representing the impact of the objectives on the overall goal, a sub-matrix, W_{32}, representing the relationship between objectives and underlying attributes, a sub-matrix, W_{43}, representing the impact of the attributes on each of the alternatives, an identity matrix, I, and the zero entries indicate that the levels are unrelated.

The network shown in Fig. 4.5b can be described by corresponding super-matrix:

$$M_N = \begin{bmatrix} 0 & 0 & 0 & 0 \\ w_{21} & W_{22} & 0 & W_{24} \\ 0 & W_{32} & W_{33} & W_{34} \\ 0 & W_{42} & W_{43} & W_{44} \end{bmatrix}.$$

For the network super-matrix, M_N, any zero entred in the hierarchy super-matrix, M_H, is replaced by a sub-matrix if there is an interrelationship of the elements within a cluster or between two clusters. For example, W_{22}, W_{33}, and W_{44} are sub-matrices representing the interrelationships between elements of the objective, attribute, and alternative clusters, respectively. The bidirectional relationships between the elements of the attribute and alternative clusters are represented by the sub-matrices W_{34}, and W_{43}.

In order to compare the super-matrix approach for AHP and ANP, we use the land use/suitability problem shown in Fig. 4.4. Since the linear hierarchy (AHP) is a specific case of the network (ANP), it can be represented in the form of super-matrix (see Table 4.3). The priorities of the criteria with respect to the goal, and those of the alternatives with respect to each criterion, are clearly discernible in the super-matrix (see Fig. 4.4). Note that there is an identity sub-matrix for the alternatives with respect to the alternatives in the lower right hand part of the matrix. The level of

Table 4.3 Super-matrix, M_H, for the hierarchical structure in Fig. 4.5a (see also Fig. 4.4)

	Goal	Obj.1	Obj.2	Att.1	Att.2	Att.3	Att.4	Att.5	A_1	A_2	A_3
Goal	0	0	0	0	0	0	0	0	0	0	0
Obj.1	0.667	0	0	0	0	0	0	0	0	0	0
Obj.2	0.033	0	0	0	0	0	0	0	0	0	0
Att.1	0	0.750	0	0	0	0	0	0	0	0	0
Att.2	0	0.250	0	0	0	0	0	0	0	0	0
Att.3	0	0	0.539	0	0	0	0	0	0	0	0
Att.4	0	0	0.297	0	0	0	0	0	0	0	0
Att.5	0	0	0.164	0	0	0	0	0	0	0	0
A_1	0	0	0	0.286	0.297	0.557	0.286	0.571	1	0	0
A_2	0	0	0	0.143	0.164	0.123	0.571	0.143	0	1	0
A_3	0	0	0	0.571	0.539	0.320	0.143	0.286	0	0	1
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1	1

Note Obj. Objective, *Att.*Attribute, A_1, A_2 and A_3 are alternatives

alternatives in a hierarchy is a sink cluster of nodes that absorbs priorities but does not pass them on.

Tables 4.3 and 4.4 give the super-matrix, M_H, and its limit super-matrix, respectively. All the priority vectors obtained by pairwise comparisons are placed in the appropriate columns of the super-matrix, M_H, associated with the network (see Table 4.4 and Fig. 4.4). Notice that the sum of entries for each column of the super-matrix equals 1. This indicates that there are no dependences in the linear hierarchical structure shown in Fig. 4.5a. Therefore, the super-matrix does not have to be weighted to convert it to the stochastic super-matrix. The synthesis of priorities is generated by raising the super-matrix to the power of 15. The results are precisely what one obtains by hierarchic composition using the AHP method (see Fig. 4.4

Table 4.4 Limiting super-matrix of M_H in Table 4.3

	Goal	Obj.1	Obj.2	Att.1	Att.2	Att.3	Att.4	Att.5	A_1	A_2	A_3
Goal	0	0	0	0	0	0	0	0	0	0	0
Obj.1	0	0	0	0	0	0	0	0	0	0	0
Obj.2	0	0	0	0	0	0	0	0	0	0	0
Att.1	0	0	0	0	0	0	0	0	0	0	0
Att.2	0	0	0	0	0	0	0	0	0	0	0
Att.3	0	0	0	0	0	0	0	0	0	0	0
Att.4	0	0	0	0	0	0	0	0	0	0	0
Att.5	0	0	0	0	0	0	0	0	0	0	0
A_1	0.352	0.289	0.479	0.286	0.297	0.557	0.286	0.571	1	0	0
A_2	0.185	0.148	0.259	0.143	0.164	0.123	0.571	0.143	0	1	0
A_3	0.463	0.563	0.262	0.571	0.539	0.320	0.143	0.286	0	0	1
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1	1

Table 4.5 Super-matrix, M_N, for the network structure in Fig. 4.5b

	Goal	Obj.1	Obj.2	Att.1	Att.2	Att.3	Att.4	Att.5	A_1	A_2	A_3
Goal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obj.1	0.667	0.333	0.500	0.000	0.000	0.000	0.000	0.000	0.100	0.667	0.500
Obj.2	0.333	0.667	0.500	0.000	0.000	0.000	0.000	0.000	0.900	0.333	0.500
Att.1	0.000	0.750	0.000	0.313	0.253	0.245	0.216	0.163	0.110	0.113	0.298
Att.2	0.000	0.250	0.000	0.313	0.293	0.285	0.321	0.146	0.162	0.119	0.298
Att.3	0.000	0.000	0.539	0.154	0.219	0.216	0.225	0.190	0.280	0.113	0.158
Att.4	0.000	0.000	0.297	0.087	0.096	0.145	0.128	0.190	0.162	0.541	0.089
Att.5	0.000	0.000	0.164	0.133	0.138	0.109	0.111	0.312	0.287	0.113	0.158
A_1	0.000	0.328	0.400	0.286	0.297	0.557	0.286	0.571	0.000	0.333	0.833
A_2	0.000	0.261	0.400	0.143	0.164	0.123	0.571	0.143	0.250	0.000	0.167
A_3	0.000	0.411	0.200	0.571	0.539	0.320	0.143	0.286	0.750	0.667	0.000
SUM	1.000	3.000	3.000	2.000	2.000	2.000	2.000	2.000	3.000	3.000	3.000

and Table 4.2). Thus, the overall value of $V(A_1)$ = 0.352, $V(A_2)$ = 0.185, and $V(A_3)$ = 0.463 (see the goal column of the limiting super-matrix in Table 4.4). A_3 is the best alternative.

Let us demonstrate the super-matrix approach for analyzing the land use/suitability problem represented as a network in Fig. 4.5b. Table 4.5 shows the super-matrix, M_N, for the network structure. Since all columns of M_N, except the goal column, contain more than a single priority block, the super-matrix must be weighted or transformed into a column stochastic matrix. This requires pairwise comparisons for the three clusters to determine their influence on each other with respect to the control criterion (that is, land suitability). The resulting weighted super-matrix is column stochastic (see Table 4.6) and can be used for deriving the overall priorities (that is, the land suitability or the overall $V(A_i)$ values) by raising it

Table 4.6 Weighted (stochastic) super-matrix, M_N, in Table 4.5

	Goal	Obj.1	Obj.2	Att.1	Att.2	Att.3	Att.4	Att.5	A_1	A_2	A_3
Goal	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obj.1	0.667	0.179	0.270	0.000	0.000	0.000	0.000	0.000	0.062	0.416	0.312
Obj.2	0.333	0.360	0.270	0.000	0.000	0.000	0.000	0.000	0.561	0.207	0.312
Att.1	0.000	0.223	0.000	0.209	0.169	0.163	0.144	0.108	0.026	0.027	0.071
Att.2	0.000	0.074	0.000	0.209	0.196	0.190	0.214	0.098	0.039	0.028	0.071
Att.3	0.000	0.000	0.160	0.103	0.146	0.144	0.150	0.126	0.067	0.027	0.038
Att.4	0.000	0.000	0.088	0.058	0.064	0.097	0.085	0.126	0.039	0.130	0.021
Att.5	0.000	0.000	0.049	0.089	0.092	0.073	0.074	0.208	0.069	0.027	0.038
A_1	0.000	0.054	0.066	0.095	0.099	0.186	0.095	0.190	0.000	0.046	0.114
A_2	0.000	0.043	0.066	0.048	0.055	0.041	0.190	0.048	0.034	0.000	0.023
A_3	0.000	0.067	0.033	0.190	0.179	0.107	0.048	0.095	0.103	0.091	0.000
Sum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 4.7 Limiting priorities of the network super-matrix, M_N, in Table 4.5

Clusters	Elements	Priorities from the limiting super-matrix	Priorities normalized by clusters
Objectives	Objective 1	0.131	0.410
	Objective 2	0.189	0.590
Attributes	Attribute 1	0.114	0.253
	Attribute 2	0.106	0.233
	Attribute 3	0.101	0.224
	Attribute 4	0.065	0.144
	Attribute 5	0.066	0.146
Alternatives	A_1	0.091	0.387
	A_2	0.055	0.231
	A_3	0.090	0.382

to powers until convergence is reached. The priorities obtained from the limiting super-matrix are given in Table 4.7. The results reflect the complex pattern of relationships in the network system shown in Fig. 4.5b.

Comparing the normalized priorities (Table 4.7) with the results obtained for the hierarchical system (see Fig. 4.4 or Table 4.4), the ordering of the alternatives for the network system: $V(A_1) > V(A_3) > V(A_2)$ is different than that obtained for the liner hierarchy: $V(A_3) > V(A_1) > V(A_2)$. This can be attributed to the presence of the complex pattern interactions and feedbacks within clusters of elements and between clusters of the network system.

GIS-AHP/ANP has proved to be an effective approach for a wide variety of decision and management situations such as: land use/suitability analysis (Banai 1993; Abdullah et al. 1994; Tseng et al. 2001; Hill et al. 2005; Hood et al. 2006; Gemitzi et al. 2007; Anagnostopoulos et al. 2010; Chen et al. 2010; Eldrandaly 2013), site selection problem (Jun 2000; Siddiqui et al. 1996; Sumathi et al. 2008), vulnerability analysis (Thirumalaivasan et al. 2003; Gorsevski et al. 2006), and plan/impact evaluation (Klungboonkrong and Taylor 1998). The method has been used in a broad range of application domains. The most popular areas of application include: agriculture and fisheries (Tseng et al. 2001; Hill et al. 2005; Hood et al. 2006; Rahmarv and Saha 2008; Nekhay et al. 2009; Chen et al. 2010; Feizizadeh and Blaschke 2013), transportation (Banai 1998; Klungboonkrong and Taylor 1998; Sadeghi-Niaraki and Kim 2009), waste management (Banai 1993; Gemitzi et al. 2007; Sumathi et al. 2008; Ferretti and Pomarico 2012), and geomorphology (Komac 2006; Neaupane and Piantanakulchai 2006).

According to the survey of AHP/ANP literature by Sipahin and Mehpare (2010), the GIS-AHP applications are among the most often used approaches for integrating AHP with other decision support techniques. The GIS-AHP approach ranks third. It accounts for about 11 % of all the AHP-based integrated applications (while the first and second ranking methods, simulation and TOPSIS, account for 15 and 12 %, respectively). Indeed, the popularity of AHP/ANP is due to its flexibility and ease-of-use, as well as the availability of software packages such as EXPERT CHOICE (expertchoice.com), HIPRE3+, and Web-HIPRE (www.hipre.hut.fi). In addition, and more importantly, the AHP (pairwise comparison) approach has been incorporated into GIS including IDRISI (Eastman et al. 1993), ILWIS – SMCE (Sharifi et al. 2004), and CommonGIS (Rinner and Taranu 2006). The method has also been implemented in the ArcGIS/ArcView environment in several GIS-MCDA applications (e.g., Reynolds et al. 2003; Banai 2005; Boroushaki and Malczewski 2008; Zhu and Dale 2001; Chen et al. 2010b; Ozturk and Batuk 2011; Eldrandaly 2013).

The use of the AHP/ANP method as a tool for both normative and descriptive modeling (see Sect. 1.2.1) and prescriptive and constructive modeling (see Sect. 1.2.2) of spatial patterns and systems is another testimony for its applicability in a wide range of research areas. For example, Banai (1993) has employed the AHP method as a normative approach for GIS-based land evaluation to find the best location of a public facility. The ANP method has been used for describing spatial and socio-economic interrelationships in a metropolitan area and for prescribing policy recommendations (see Banai and Wakolbinger 2011). The use of AHP as a component of a Web-based participatory spatial decision support can be considered an implementation of a constructive approach (e.g., Boroushaki and Malczewski 2010; Meng and Malczewski 2010).

Despite the widespread use of AHP/ANP, the method has not been without criticism (Belton and Gear 1983; Goodwin and Wright 1998; Barzilai 1998). The criticisms include: the ambiguity in the meaning of the relative importance of one element of the decision hierarchy when it is compared to another element, the number of comparisons for large size problems, and the use of a 1-to-9 scale. Some decision analysts argue that the type of questions asked during the process of pairwise comparisons are meaningless (Belton and Gear 1983). In addition, it is argued that for large problems, there are too many pairwise comparisons that must be performed. Another criticism is related to the so-called 'rank reversal' problem (Belton and Gear 1983). Specifically, the AHP analysis may indicate that alternative A_1 is preferred to alternative A_2 when alternative A_3 is not being considered; but when alternative A_3 is included as an option, it may indicate that alternative A_2 is preferred to alternative A_1.

4.4 Ideal Point Methods

The ideal point methods are based on the premise of evaluating decision alternatives with reference to some specific target or goal (Zeleny 1982). Unlike the additive decision rules presented in Sects. 4.2 and 4.3, the ideal point methods order a set of decision alternatives on the basis of their separations from some ideal/reference point. The terms ideal point method and compromise programming are sometimes used interchangeably. For example, Carver (1991) and Pereira and Duckstein (1993) have used the concept in their GIS-based ideal point method and compromise programming, respectively (see also Tkach and Simonovic 1997; Santé-Riveira et al. 2008; Ligmann-Zielinska 2009; Elaalem et al. 2011). To avoid confusion, we distinguish between these two terms. Although GIS-based compromise programming has typically been used as multiattribute (discrete) approaches, one should indicate that it has been derived from the multiobjective (continuous) programming method (see Sect. 5.3.2). Indeed, compromise programming methods have originally been proposed as multiobjective methods of progressive articulation of preferences (Zeleny 1982). Subsequently, the compromise programming method has been adapted to discrete settings as well. Here, we use the term ideal point methods to cover the GIS-MADA methods that are based on the concept of the ideal/reference point including the compromise programming approach for discrete decision problems.

4.4.1 Reference Points and Separation Measures

A reference point represents a hypothetical alternative (decision outcome). It can be any significant target or goal against which the decision alternatives are evaluated. This hypothetical alternative is often defined in terms of the positive ideal (utopia) point, or negative ideal (or anti-ideal or nadir) point (Zeleny 1982). Formally, the positive ideal alternative, A^+, and the negative ideal, A^-, are determined as follows: $A^+ = t_1^+, t_2^+, \ldots, t_n^+$, and $A^- = t_1^-, t_2^-, \ldots, t_n^-$; where $t_k^+ = \max_i\{v(a_{ik})\}$, $t_k^- = \min_i\{v(a_{ik})\}$. Thus, the positive and negative ideal points are determined as the best- and worst-possible value achievable by any alternative, respectively. If the value function $v(a_{ik})$ is defined by Eq. 2.1 or 2.2, then $A^+ = (1,1,\ldots,1)$ and the negative ideal, $A^- = (0, 0, \ldots, 0)$ (see Carver 1991; Pereira and Duckstein 1993).

A separation of the ith decision alternative from a reference point can be defined by means of the L_p distance metric as follows:

$$L_p(A_i) = \left[\sum_{k=1}^{n} (w_k|t_k - v(a_{ik})|)^p\right]^{\frac{1}{p}}, \tag{4.12}$$

where w_k is the kth criterion weight; $v(a_{ik})$ is the value function of the kth criterion; $|\;|$ is the absolute value operator; t_k is the reference value for the kth criterion, e.g., t_k^+ and/or t_k^-; $v(a_{ik})$ is the value of the ith alternative with respect to the kth attribute measured by means of the value function; and p is a power parameter ranging from 1 to ∞. If the p parameter is set at 1, then the rectangular distance (or Manhattan metric) is obtained; that is,

$$L_1(A_i) = \sum_{k=1}^{n} w_k|t_k - v(a_{ik})|. \tag{4.13}$$

For $p = 2$ the straight-line distance is calculated; that is,

$$L_2(A_i) = \sqrt{\sum_{k=1}^{n} (w_k|t_k - v(a_{ik})|)^2}. \tag{4.14}$$

If $p = \infty$, then the minimum of the maximum weighted deviation is sought; that is,

$$L_\infty(A_i) = \min\{\max[(w_1|t_1 - v(a_{i1})|), (w_2|t_2 - v(a_{i2})|), \ldots, (w_n|t_n - v(a_{in})|)]\}. \tag{4.15}$$

In general, a larger value of p reflects greater concern for minimizing the maximum separation from the ideal point; that is, as the parameter p tends toward ∞ one is increasingly concerned with larger deviations or regrets (Zeleny 1982; Pereira and Duckstein 1993). The regrets can be interpreted as the 'inability' to achieve the ideal solution. It is the difference between what one actually achieved and what one could have achieved, or the difference between the actual payoff and the payoff that would have been obtained if a different course of action had been chosen. This is also called difference regret or opportunity loss.

The p parameter is a 'balancing factor' between the two extreme cases when $p = 1$ and $p = \infty$. If $p = 1$, then the solution minimizes the total regret (or it maximizes the total weighted benefits). When $p = \infty$, then the maximum discrepancy or regret is minimized, which implies the avoidance of large regrets for any of the criteria (Karni and Werczberger 1995). It also implies that Eq. 4.15 is a non-compensatory decision rule.

The overall value of $L_1(A_i)$ is a solution that minimizes the total regret; that is, the weighted sum of the regrets associated with all the criteria. The deviation from the ideal can be interpreted a measure of disutility of the ith alternative. The $L_1(A_i)$ value is a complement of the overall value (utility) of a given alternative; that is, $L_1(A_i) = 1 - V(A_i)$. For $p = 1$, all weighted deviations are assumed to compensate each other perfectly; that is, a decrease of one unit in a given criterion value can be compensated by an equivalent increase in any other criterion (Zeleny 1982; Baja et al. 2007). For $p = 2$, each deviation is accounted for in direct proportion to its size. This implies a partial compensation between criteria. As p approaches infinity, the alternative with the largest deviation completely dominates the distance measure resulting in a mini-max, non-compensatory decision rule (Zeleny 1982). In practice, if p is greater than a value of approximately 10, then the largest deviation totally dominates the evaluation (Pereira and Duckstein 1993; Karni and Werczberger 1995). Since the p parameter varies according to the assessment's compensatory level, the value is context dependent. Karni and Werczberger (1995) provide suggestions on choosing appropriate value of p.

4.4.2 Ideal Point Models

Given the definitions of the reference points and separation measures, one can design a number of decision rules using the family of the L_p distance metrics and the positive and negative ideal points. Here we limit our discussion to the most popular GIS-based methods: the ideal point approach (Carver 1991; Pereira and Duckstein 1993; Malczewski et al. 1997) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Jankowski and Ewart 1996; Malczewski 1996; Chen et al. 2001).

The ideal point approach rates the decision alternatives under consideration according to their multidimensional distance to the ideal point using the distance metric (Eq. 4.12). Two versions of the ideal point model can be defined: the positive and negative ideal models. For the value function, $v(a_{ik})$, defined in Eqs. 2.1 or 2.2, the positive ideal point $A^+ = (1,1, \ldots,1)$. Accordingly, the ideal point model can be defined as follows:

$$L_p^+(A_i) = \left[\sum_{k=1}^{n} (w_k|1 - v(a_{ik})|)^p\right]^{\frac{1}{p}}. \tag{4.16}$$

The best alternative is that one which minimizes the value of $L_p^+(A_i)$. A family of ideal point models can be defined by changing the p parameter (see Sect. 4.4.1).

If the value function, $v(a_{ik})$, is defined by Eqs. 2.1 or 2.2, then the negative ideal point $A^- = (0, 0, \ldots, 0)$; and, consequently, the negative ideal point model can be written as follows:

$$L_p^-(A_i) = \left[\sum_{k=1}^{n} (w_k v(a_{ik}))^p\right]^{\frac{1}{p}}. \tag{4.17}$$

The best alternative is that one which maximizes the value of $L_p^-(A_i)$. One can develop a series of negative ideal point models by varying the p parameter (see Sect. 4.4.1).

Notice that there is equivalence between the conventional WLC model (see Eq. 4.1) and the ideal point models (Eqs. 4.16 and 4.17). For the value of $p = 1$, $L_p^+(A_i) = 1 - V(A_i)$ and $L_p^-(A_i) = V(A_i)$. Thus, the negative ideal model for $p = 1$ is completely equivalent to WLC. To demonstrate the relationship between the three models, $L_p^+(A_i)$, $L_p^-(A_i)$, and $V(A_i)$, let us consider a simple problem of evaluating 16 location (rasters) based on two criteria (see Fig. 4.6). The criteria are to be maximized. The criterion weights are given as follows: $w_1 = 0.6$ and $w_2 = 0.4$. Then, the separation measures (Eqs. 4.13-4.15) are used for the computing the overall values of $L_1^+(A_i)$, $L_2^+(A_i)$, and $L_\infty^+(A_i)$. The results are shown in Fig. 4.7. For example, the computations for the alternative A_1 involve the following: $v(a_{11}) = (12.0 - 5.5)/(12.0 - 0.0) = 0.542$, and $v(a_{12}) = (4.2 - 0.0)/(4.2 - 0.0) = 1.0$. Given the standardized attribute values, the

a_{i1}

5.5	5.0	3.0	1.0
3.5	6.5	10.5	9.5
1.0	0.0	8.5	6.0
3.5	1.5	12.0	10.5

a_{i2}

0.0	1.0	2.0	3.0
1.0	1.4	2.2	3.2
2.0	2.0	2.8	3.6
3.0	3.2	3.6	4.2

Fig. 4.6 A hypothetical example of two criterion maps (*Note* Each raster contains criterion values a_{i1} and a_{i2}, i = 1, 2, 3,…,16; the criteria are minimized)

(a)

.275	.345	.340	.336
.270	.458	.735	.780
.240	.210	.692	.643
.461	.380	.943	.925

(b)

.275	.268	.242	.290
.199	.351	.565	.564
.197	.210	.502	.456
.335	.314	.691	.660

(c)

.275	.250	.192	.286
.175	.325	.525	.476
.190	.210	.425	.351
.286	.305	.600	.528

Fig. 4.7 The overall values of alternatives using the ideal point, A^+ = (1.0, 1.0): (**a**) the $L_1^+(A_i)$ model (**b**) the $L_2^+(A_i)$ model, and (**c**) $L_\infty^+(A_i)$ model (*Note* xxx the best alternative)

overall value of the alternative: $L_1^+(A_i) = (0.6 \times |1.0–0.542|)^1 + (0.4 \times |1.0–1.0|)^1 = 0.275$. Notice that $L_1^+(A_i) = L_2^+(A_i) = L_\infty^+(A_i) = 0.275$. This is due to the value of $v(a_{12}) = 1.0$. Similar computations are performed to evaluate the alternatives using the negative ideal model (Eq. 4.17). The results are given in Fig. 4.8. It can be shown that $L_1^+(A_i) = 1 - V(A_i) = 1 - [(0.6 \times 0.542) + (0.4 \times 1.0)] = 0.275$, and $L_1^-(A_i) = V(A_i) = 0.725$. Consequently, $L_1^+(A_i) + L_1^-(A_i) = 1$.

(a)

.725	.655	.660	.664
.730	.542	.265	.220
.760	.790	.308	.357
.539	.620	.057	.075

(b)

.515	.464	.496	.562
.523	.383	.205	.157
.587	.630	.220	.305
.440	.534	.057	.075

(c)

.405	.358	.450	.550
.427	.291	.190	.126
.550	.600	.176	.300
.425	.525	.057	.075

Fig. 4.8 The overall values of alternatives evaluated using the negative ideal point, A^+ = (0.0, 0.0): (**a**) the $L_1^-(A_i)$ model (**b**) the $L_2^-(A_i)$ model, and (**c**) $L_\infty^-(A_i)$ model (*Note* xxx the best alternative)

A comparison of the results (Figs. 4.7 and 4.8) indicates that the best solution (the ordering of the alternatives) is model dependent. For example, the $L_2^+(A_i)$ and $L_2^-(A_i)$ models identify different best locations (rasters) (see Fig. 4.7.b and 4.8.b). To avoid these 'ambiguous' results, the Technique for Order Performance by Similarity to the Ideal Solution (TOPSIS) was proposed (Hwang and Yoon 1981).

TOPSIS involves a combination of $L_p^-(A_i)$ and $L_p^+(A_i)$ into a composite measure. It defines the best alternative as the one that is simultaneously closest to the ideal alternative and furthest away from the negative ideal point. Formally, the composite measure is written as follows (Hwang and Yoon 1981):

$$L_p^{\pm}(A_i) = \frac{L_p^-(A_i)}{L_p^+(A_i) + L_p^-(A_i)}, \tag{4.18}$$

$0 \leq L_p^{\pm}(A_i) \leq 1$. $L_p^{\pm}(A_i)$ measures the relative closeness of the ith alternative to the ideal point, A^+. The alternative with the highest value of $L_p^{\pm}(A_i)$ is the best alternative.

Figure 4.9 shows the results of the TOPSIS model for the data in Fig. 4.6. Note that the results indicate that the best alternatives for the three models are 'compromise' selections between those obtained using of the $L_p^-(A_i)$ and $L_p^+(A_i)$ models. Also, it is interesting to note that for the standardized value, $v(a_{ik})$, defined by Eqs. 2.1 or 2.2, $L_1^{\pm}(A_i) = L_1^-(A_i)$. Consequently, $L_1^{\pm}(A_i) = V(A_i)$. Thus, the TOPSIS model $L_1^{\pm}(A_i)$ is equivalent to the WLC model (see Sect. 4.2).

The conventional ideal point methods (Eqs. 4.16–4.17) consider the spatial dimension of the multicriteria problems implicitly. In these types of MCDA models, the locations (the x, y coordinates) of decision alternatives do not affect the outcome of the ideal point procedures. Tkach and Simonovic (1997), Koo and O'Connell (2006), and Qin (2013) have proposed spatially explicit ideal point (compromise programming) methods. Tkach and Simonovic (1997) have advanced the conventional GIS-IP method by considering spatially explicit decision alternatives (see also Simonovic and Nirupama 2005). Koo and O'Connell (2006) have

(a)

.725	.655	.660	.664
.730	.542	.265	.220
.760	**.790**	.308	.357
.539	.620	.057	.075

(b)

.652	.634	.672	.659
.724	.522	.266	.218
.749	**.750**	.305	.401
.568	.630	.076	.102

(c)

.595	.589	.701	.658
.709	.472	.266	.209
.743	.741	.293	.461
.598	.633	.087	.124

Fig. 4.9 The overall values of alternatives using the TOPSIS method: (**a**) the $L_1^{\pm}(A_i)$ model, (**b**) the $L_2^{\pm}(A_i)$ model and (**c**) the $L_\infty^{\pm}(A_i)$ model (*Note* xxx the best alternative)

focused on the spatial variability in the criterion weights. Based on the proposed extensions of the ideal point method (Eq. 4.16), the spatial ideal point model can be written as follows:

$$L_p^+(A_{i(x,y)}) = \left[\sum_{k=1}^{n} \left(w_{i(x,y)k}\left|1 - v(a_{i(x,y)k})\right|\right)^p\right]^{\frac{1}{p}}. \tag{4.19}$$

where $w_{i(x,y)k}$ is the weight associated with the kth criterion and the ith alternative at the x, y location; $v(a_{\ i(x,y)k})$ is the value of the ith alternative at the x, y location for the kth criterion; and other terms have been defined previously (see Eq. 4.16).

Unlike the conventional GIS-IP method, which determines a single overall score (separation from the ideal point) for each alternative (location), the spatially explicit model identifies a distance metric for each location and for each alternative. It determines the best decision alternative for each location. Tkach and Simonovic (1997) have used the spatially explicit GIS-IP method to evaluate potential flood protection alternatives. Using the spatially explicitly GIS-IP model, Tkach and Simonovic (1997) demonstrated that the best flood protection strategy identified by the conventional GIS-IP method may not necessarily be the best for all locations in a study region. They have shown that the best strategies (alternatives) vary from one location to another. The study also demonstrated that the choice of the best alternative is sensitive to the criterion weights. Tkach and Simonovic (1997) have used a set of global criterion weights; that is, a single weight has been assigned to a particular criterion. Koo and O'Connell (2006) have extended the conventional GIS-IP approach by making the criterion weights spatial variable. They have used the spatial or site-specific weights as a component of a spatially explicit GIS-IP model for evaluating land use scenarios. It is important to note, however, that the criterion weights have not been defined based on stakeholders' preferences. The weights have been estimated for each location (raster) using environment variables such as temperature, ground elevation, or soil properties (Koo and O'Connell 2006). While Koo and O'Connell (2006) have focused on spatially variable criterion weights in the GIS-IP model, Qin (2013) has advanced spatially explicit ideal point method by developing the local form of GIS-OWA based on the concepts of spatially explicit value functions and criterion weights (see Sects. 2.3.1.2 and 2.3.2.2).

The ideal point models have a prominent place in the area of GIS-MCDA applications (Malczewski 2006a). In particular, this type of GIS-MCDA has made significant contribution to the development of GIS-based land-use suitability analysis (Eastman et al. 1995; Malczewski 2004; Santé-Riveira et al. 2008). For example, the ideal point approaches have been used for land-use suitability analysis in a wide variety of application domains including: environmental assessment and management (Pereira and Duckstein 1993; Berger 2006; Koo and O'Connell 2006; Liu et al. 2006; Strager and Rosenberger 2007), radioactive waste management (Carver 1991; Salt and Culligan Dunsmore 2000), water resources management (Tkach and Simonovic 1997), rural land use planning (Elaalem et al. 2011), and housing evaluation and residential development (Natividade-Jesus et al. 2007; Ligmann-Zielinska 2009). The methods have also been used for locating service facilities such fire stations (Malczewski et al. 1997), health practitioner clinics (Jankowski and Ewart 1996), and seawater therapy resorts (Crecente et al. 2012).

Although the ideal point approaches have predominantly been used as normative modeling tools, Pereira and Duckstein (1993) have demonstrated their utility as predictive models. They have also shown the capabilities of the GIS-IP approach for performing sensitivity analysis based on the p parameter. Several researchers have emphasized that an important advantages of the ideal point method is that it does not assume preference independence of attributes (Zeleny 1982; Pereira and Duckstein 1993; Prato 2008). It can be argued, however, that the ideal point approach involves some of the difficulties associated with the assumption underlying WLC (see Sect. 4.1). Since the model for $p = 1$ is completely equivalent to WLC, one can argue that the ideal point method is “subject to any assumptions, pros, and cons” of WLC (Hobbs and Meier 2000, p. 88; see also Munda 2008).

4.5 Outranking Methods

The outranking methods are based on a pairwise comparison of alternatives for each evaluation criterion (Roy 1968). The underlying assumption of these methods is that the decision maker’s preference structure can be represented by outranking relations, which are defined for each pair of alternatives A_i and A_j. The ith alternative outranks the jth alternative if there is enough evidence to declare that A_i is at least as good as A_j on the majority of the criteria, while there is no essential evidence to show that the statement is false with respect to the remaining criteria (Vincke 1989). The pairwise comparison procedure involves determining the extent to which criterion scores and associated weights confirm or contradict the pairwise relationships between alternatives. The procedure typically uses the concordance and discordance measures. The former are based on the concordance set; that is, the subset of all criteria, for which the ith alternative is not worse than the competing alternative, j. The latter measures are based on the discordance set; that is, the subset of all criteria, for which alternative, i, is worse than the competing alternative, j (Nijkamp and Van Delft 1977). There are a wide variety of formulas available to calculate the overall score for each alternative on the basis of the two indicators (Voogd 1983). The most popular outranking methods are: ELECTRE (ELimination Et Choix TRaduisant la REalité) (Benayoun et al. 1966) and PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) (Brans et al. 1984). These two outranking methods have also been most often used for integrating into GIS (e.g., Can 1992; Joerin 1995; Joerin and Musy 2000; Joerin et al. 2001; Martin et al. 2003; Marinoni 2005; 2006; Chakhar and Mousseau 2007; 2008; Aissi et al. 2012; Massei et al. 2013).

4.5.1 ELECTRE

Over the last forty years or so, ELECTRE has evolved into a family of methods including: ELECTRE II, ELECTRE III, ELECTRE IV, ELECTRE IS, and ELECTRE TRI (Roy 1968; Figueira et al. 2005, 2010). These methods address different types of problems such as: the choice problem (ELECTRE I, IS), ranking (ELECTRE II, III, IV), and sorting/classification (ELECTRE TRI). Here, we will focus on the classic ELECTRE I (henceforth called ELECTRE). The method compares each pair of alternatives (a_i, a_j) using the concept of concordance and discordance. The concordance index, c_{ij}^{+}, for two alternatives, i and j, is defined as follows:

$$c_{ij}^{+} = \sum_{k \in q} w_k + \sum_{k \in p} 0.5 w_k \tag{4.20}$$

where q is the criterion for which $A_i > A_j$, and p is the criterion for which $A_i = A_j$. The concordance index is a weighted sum of the number of criteria in which A_i is better than A; and the ties receive on-half of the weights.

Consider a set of alternatives, A_i, described by a set of criterion values, a_{ik}, ($i = 1$, 2, 3, 4 and $k = 1$, 2, 3) and associated criterion weights, w_k (Table 4.8). Given the hypothetical input date, the concordance index, c_{ij}^{+}, for each pair of alternatives is computed using Eq. 4.20. For example, the concordance indices between alternatives 1 and 4, and 4 and 1 are computed as follows: $c_{14}^{+} = 0 + 0.35 + 0 = 0.35$, and $c_{41}^{+} = 0.45 + 0 + 0.20 = 0.65$ (see Table 4.9).

The discordance index is based on a constructed interval scale common to all criteria (Goicoechea et al. 1982). The procedure for creating such scale aims at assessing the level of importance associated with improving one criterion by a given interval at the expense of worsening another criterion by a particular interval. This is achieved by assigning a maximum score of 100 (or any other suitable

Table 4.8 Input data for the ELECTRE example

		Criteria		
		C_1	C_2	C_3
		%	km	Scale
Alternatives	A_1	18	1.2	M
	A_2	10	1.5	L
	A_3	5	1.8	H
	A_4	12	2.0	H
Weights	w_k	0.45	0.35	0.20
Min or max		min	min	max
Scale intervals		100	60	30

Note L = low, M = medium, H = high

Table 4.9 Concordance matrix

Alternatives		j			
		A_1	A_2	A_3	A_4
i	A_1	–	0.55	0.35	0.35
	A_2	0.45	–	0.35	0.80
	A_3	0.65	0.65	–	0.90
	A_4	0.65	0.20	0.10	–

number) to every criterion, and then, a particular number of points is assigned to each criterion according to the level of importance the decision maker attaches to the range between the best and worst levels of each criterion. This can be interpreted as the level of discomfort associated with moving from one level to the next for each criterion. Given the interval scale, the discordance index, c_{ij}^{-}, is defined as follows:

$$\begin{aligned} c_{ij}^{-} &= \frac{\text{maximum interval for } j \text{ prefered over } i}{\text{total range of scale}} \\ &= \frac{\text{maximum interval for } j \text{ prefered over } i}{100}. \end{aligned} \tag{4.21}$$

Suppose that the following maximum scale intervals have been specified by the decision maker: 100, 60, and 30 for C_1, C_2, and C_3, respectively. These scale intervals can be used for converting the original criterion values (Table 4.8) into the assessments shown in Table 4.10. The first criterion has 4 levels; therefore, 100/4 = 25 points. The levels of C_2, and C_3 are worth 60/4 = 15 and 30/3 = 10 points, respectively. Given the points associated with each criterion, one can convert the original criterion values for C_1 as follows: (i) since the criterion is to be minimized, then the minimum value, a_{i1}, receives the maximum scale interval of 100, and then (ii) each decrease in the value of a_{i1} is worth—25 points; i.e., 10, 12, and 18 associated with alternative A_2, A_4, and A_1 is converted to 100 − 25 = 75, 75 − 25 = 50, and 50 − 25 = 25, respectively (see Table 4.10). The values for C_2, and C_3 in Table 4.10 are obtained using similar procedure.

The discordance index is computed for each pair of alternatives using Eq. 4.21. For example, the discordance index between alternative 1 and 3 is computed as follows. Since the values associated with A_3 are greater than values associated with

Table 4.10 Rescaled criterion values according to the scale intervals

		Criteria		
		C_1	C_2	C_3
Alternatives	A_1	25	60	20
	A_2	75	45	10
	A_3	100	30	30
	A_4	50	15	30

Table 4.11 Discordance matrix

Alternatives		*j*			
		A_1	A_2	A_3	A_4
i	A_1	–	0.50	0.75	0.25
	A_2	0.15	–	0.25	0.20
	A_3	0.30	0.15	–	0.00
	A_4	0.45	0.30	0.50	–

A_1 for C_1, and C_3, then Eq. 4.21 is used for the two criteria; thus, c_{13}^- for C_1 = (100−25)/100 = 0.75, and c_{13}^- for C_3 = (30−20)/100 = 0.10. Therefore, c_{13}^- = maximum of (0.75, 0.10) = 0.75. The complete set of indices is given in the discordance matrix (Table 4.11).

ELECTRE makes use of the concordance and discordance indices for identifying the outranking relations and creating a dominance matrix. The relation for a pair of alternatives is assigned a value of 1, if the *i*-th alternative is preferred to the *j*-th alternative under the following conditions: $c_{ij}^+ \geq c^+$ and $c_{ij}^- \leq c^-$, where c^+ and c^- are the thresholds representing the minimum acceptable concordance and the maximum acceptable discordance values, respectively; otherwise, the relation between *i* and *j* is assigned a value of 0.

Suppose that the minimum concordance condition c^+ = 0.6 (that is, $c_{ij}^+ \geq 0.6$) and the maximum discordance condition c^- = 0.3 (that is, $c_{ij}^- \leq 0.3$). Give the two conditions, one can construct the dominance matrix (Table 4.12), and identify the following pairs of alternatives satisfying the two conditions: (2, 4), (3, 1), (3, 2) and (3, 4). The analysis shows that A_3 is the best alternative. It dominates (outranks) remaining alternatives. A_2 dominates A_4. A_1 and A_4 do not dominate any alternative; they are the least preferred alternatives. Thus, $A_3 > A_2 > A_1 = A_4$. Notice that the ELECTRE I procedure resulted in a partial ordering of the alternatives. Since the introduction of ELECTRE I, more advanced outranking methods have been proposed. For example, ELECTRE II generates a complete ordering of the alternatives by using multiple levels of the c^+ and c^- values to construct two extreme outranking conditions: strong and weak outranking relations. These conditions are then used to identify a complete ordering of the alternatives (Goicoechea et al. 1982).

Carver (1991) and Can (1992) have implemented the outranking/concordance analysis within the ARC/INFO environment. They applied the method to analyze

Table 4.12 Dominance matrix

Alternatives		*j*			
		A_1	A_2	A_3	A_4
i	A_1	–	0	0	0
	A_2	0	–	0	1
	A_3	1	1	–	1
	A_4	0	0	0	–

suitable radioactive waste disposal sites (Carver 1991), and for constructing residential quality scores as a preliminary step toward defining neighbourhoods in urban area (Can 1992). Over the last decade or so, there has been a considerable increase in the number of studies on integrating the ELECTRE methods into GIS. Proulx et al. (2007) used the GIS-based ELECTRE approach to identifying vulnerable locations in a drinking water system. Natividade-Jesus et al. (2007) developed a GIS-based decision support system for housing quality evaluation using a variety of MCDA methods including ELECTRE I and ELECTRE TRI. Aissi et al. (2012) proposed a GIS-based ELECTRE approach for a problem of locating transportation corridor. The GIS-based ELECTRE TRI method has been used for analyzing spatial patterns of agro-environmental risk (Macary 2013) and tackling land use planning problem (Sobrie et al. 2013). Joerin and Musy (2000), Joerin et al. (2001), and Chakhar and Mousseau (2007, 2008) have integrated the ELECTRE TRI method into GIS to analyze land suitability and land use planning problems. These studies are of particular significance for the GIS-based outranking methods because they address the problem of defining spatial decision alternatives in the context of outranking analysis.

One of the advantages of the outranking methods is their ability to consider both quantitative and qualitative criteria. Furthermore, the methods require relatively small amount of information from the decision maker. Since the outranking relations are based on a voting analogy, the ELECTRE methods can be used without reference to a challenging analysis of trade-offs between attributes in the value function approaches. They are mainly concerned with the use of the ordinal scale measurements and are based on the principles of non-compensatory preferences structures (Bouyssou and Vansnick 1986). Stewart (1992) suggests that ELECTRE is a valuable tool when the number of alternatives under consideration is small. In the cases of decision problems involving a large number of alternatives, the method can be used as a screening procedure for generating a subset of desirable yet diverse decision alternatives (Hobbs and Meier 2000). Although the concepts underlying the outranking methods are intuitively appealing (Gilliams et al. 2005), they are "difficult to verify empirically as models of human preferences" (Stewart 1992, p. 583). Another disadvantage of ELECTRE is that the c^+ and c^- threshold values are essentially arbitrary (Hobbs and Meier 2000), although Rogers and Bruen (1998) suggest some guidelines for their selection.

4.5.2 PROMETHEE

There are several variants of the PROMETHEE method including PROMETHEE I, II, III, IV, V, and VI (Brans et al. 1984). PROMETHEE I and II have been integrated into GIS (see Malczewski 2006a). Therefore, we will focus on these two forms of the method. The methods use the following procedure for identifying the outranking relation for a pair of alternatives (A_i, A_j):

$$P(A_i, A_j) = \sum_{k=1}^{n} w_k p_k(a_i, a_j), \tag{4.22}$$

where $P(A_i, A_j)$ is the outranking degree of a pair of alternatives, w_k is the kth criterion weight, and $p_k(a_i, a_j)$ is the preference function of the kth criterion. The form of the preference function is determined by the type of the criterion and the threshold values, which take into account the impreciseness (fuzziness) of the criterion values. Brans et al. (1984) suggest six types of the preference: the usual (or strict), U-shape (threshold), V-shape (linear over range), level (stair-step), V-shape with threshold (linear with threshold), and Gaussian functions. The simplest form is the usual preference function, which does not involve any threshold value. It is defined as follows:

$$p_k(a_i, a_j) = \begin{cases} 1 & \text{if } a_{ik} \text{ preferrd over } a_{jk} \\ 0 & \text{otherwise} \end{cases} \tag{4.23}$$

where a_{ik}, and a_{jk} are the values associated with the ith and jth alternatives for the kth criterion, respectively. Table 4.13 gives the preference values, $p_k(a_i, a_j)$, for the data shown in Table 4.8. For example, for the criterion to be minimized, the value of a_{21} = 10 % is preferred over a_{11} = 18 %, and consequently, $p_1(a_1, a_2) = 0$ and $p_1(a_2, a_1) = 1$ (see Table 4.13a). Given the preference structures for the three criteria, the value of $P(A_i, A_j)$ can be computed using Eq. 4.22. For example, $P(A_1, A_2) = (0 \times 0.45) + (1 \times 0.35) + (1 \times 0.20) = 0.55$ (see Table 4.14).

Given the outranking values, $P(A_i, A_j)$, the PROMETHEE procedure evaluates each alternative based on the leaving and entering preference flows:

$$F^{+}(A_i) = \frac{\sum_{j=1, i \neq j}^{n} P(A_i, A_j)}{m - 1} \tag{4.24}$$

$$F^{-}(A_i) = \frac{\sum_{j=1, i \neq j}^{n} P(A_j, A_i)}{m - 1} \tag{4.25}$$

Table 4.13 The preference values, $p_k(a_i, a_j)$, for the data in Table 4.8

(a)					(b)					(c)				
C_1	A_1	A_2	A_3	A_4	C_2	A_1	A_2	A_3	A_4	C_3	A_1	A_2	A_3	A_4
A_1	–	0	0	0	A_1	–	1	1	1	A_1	–	1	0	0
A_2	1	–	0	1	A_2	0	–	1	1	A_2	0	–	0	0
A_3	1	1	–	1	A_3	0	0	–	1	A_3	1	1	–	0
A_4	1	0	0	–	A_4	0	0	0	–	A_4	1	1	0	–

The pairwise comparisons of four alternatives with respect to three criteria: (a) C_1, (b) C_2, and (c) C_3

Table 4.14 The results of PROMETHEE for the data in Table 4.8

Alternative		j				$F^+(A_i)$	$F(A_i)$	Rank
		A_1	A_2	A_3	A_4			
i	A_1	–	0.55	0.35	0.35	0.417	−0.166	3
	A_2	0.45	–	0.35	0.80	0.533	0.066	2
	A_3	0.65	0.65	–	0.80	0.700	0.467	1
	A_4	0.65	0.20	0.00	–	0.283	−0.367	4
	$F^-(A_i)$	0.583	0.467	0.233	0.650			

The outranking degree for pairs of alternatives, $P(A_i, A_j)$, the leaving flow, $F^+(A_i)$, the entering flow, $F^-(A_i)$, and the net flow, $F(A_i)$

where $F^+(A_i)$ and $F^-(A_i)$ are the leaving (or positive) and entering (or negative) flows, respectively, and m is the number of alternatives. The preference of an alternative over all other alternatives is measured by the leaving flow, whereas the preference of all other alternatives over an alternative is measured by the entering flow. The positive outranking flow expresses how each alternative is outranking all the others. The alternative is better if it has higher positive flow. The negative outranking flow expresses how each alternative is outranked by all the others. The alternative is better if it has smaller negative flow.

In the PROMETHEE I method, the alternatives are ranked using the leaving and entering flows. This results in a partial ordering of the alternatives. A complete ordering in PROMETHEE II is obtained by calculating the net flow:

$$F(A_i) = F^+(A_i) - F^-(A_i). \tag{4.26}$$

The most preferred alternatives are the ones with the higher net flows, whereas the alternatives with the lower net flows are considered as the least preferred ones. Table 4.14 shows the values of $F^+(A_i)$,$F^-(A_i)$ and $F(A_i)$. For example, the flows alternative A_1 are obtained as follows: the leaving flow $F^+(A_1)$ = (0.55 + 0.35 + 0.35) /3 = 0.417, the entering flow $F^-(A_1)$ = (0.45 + 0.65 + 0.65) / 3 = 0.583, and the net flow $F(A_1)$ = 0.417 − 0.583 = − 0.166. The PROMETHEE procedure results in the complete ordering of the alternatives: $A_3 > A_2 > A_1 > A_4$ (see Table 4.14).

The GIS-based PROMETHEE methods have been applied in a variety decision situations including: land-use planning and management (Martin et al. 2003; Gilliams et al. 2005; Marinoni 2005), natural hazards assessment and monitoring (Lin 2008), environmental pollution assessment (Ilić et al. 2011), and retail and service facility location (Guimarães Pereira et al. 1994). Marinoni (2005, 2006) provides a comprehensive discussion of approaches for integrating the PROMETHEE method into a GIS. He has integrated the conventional and stochastic versions of PROMETHEE into ArcGIS and used the integrated system for land use suitability analysis. Marinoni (2005) suggests that PROMETHEE is the most attractive outranking method due to its ‘mathematical simplicity and transparency’. Gilliams et al. (2005) developed a SDSS called AFFOREST that integrates GIS capabilities and MCDA methods, including PROMETHEE and ELECTRE. They have also made comparison of the methods in the context of policy and planning decisions related to the problem of agricultural land afforestation. One of the conclusions of the study was that the GIS-based PROMETHEE performs slightly better than the GIS-based ELECTRE with respect to such considerations as: user friendliness, simplicity of the model strategy, variation of the solution, and implementation.

The PROMETHEE methods have been integrated with artificial intelligence techniques (see Chapter 6). For example, Lin (2008) integrated the self-organizing map (SOM) neural network and PROMETHEE into GIS for monitoring and assessing earthquake-induced landslide hazard. Guimarães Pereira et al. (1994) used GIS-based approach to PROMETHEE in conjunction with a genetic algorithm for generating location alternatives for retail and service facilities. They suggest that the integrated approach improves the theoretical principles upon which the genetic algorithm fitness function is based, leading to the construction of a robust set of locational alternatives.

The integration of the PROMETHEE methods into GIS is often based on a loose coupling approach (see Sect. 3.3.4), with PROMETHEE system as principle software. This can be attributed to the availability of PROMETHEE software such as the D-Sight system and its earlier versions: PROMCALC and DECISION LAB 2000 (http://www.d-sight.com). Indeed, the D-Sight Maps Plugin has the capabilities of displaying alternative decisions on a map and interacting with all the results of the multicriteria analysis. The software is based on the PROMETHEE-GAIA approach (GAIA stands for Geometrical Analysis for Interactive decision Aid), developed by Brans and Mareschal (1994). Furthermore, the PROMETHEE-GAIA software has been integrated into GIS (e.g., Martin et al. 2003; Lidouh et al. 2009; Ilić et al. 2011). Yatsalo et al. (2010) developed a standalone GIS-MCDA system with the PROMETHEE method as one of the options for performing multicriteria analysis. The system has been applied to land use planning (Yatsalo et al. 2010) and site selection problem (Ishizaka et al. 2013).

The PROMETHEE methods share a similar set of advantages and disadvantages with the ELECTRE approaches (Marinoni 2006; Chakhar and Mousseau 2008). One advantage of the outranking methods is the ability to consider both quantitative and qualitative criteria in the process of pairwise comparisons of alternatives. The methods do not require assumptions underlying the weighted additive models. Arguably, the major limitation of the GIS-based outranking methods is the problem of a large number of pairwise comparisons alternatives with respect to each evaluation criterion (e.g., Pereira and Duckstein 1993; Joerin and Musy 2000; Joerin et al. 2001; Marinoni 2005, 2006; Chakhar and Mousseau 2007, 2008; Aissi et al. 2012). For example, given a problem of evaluating m decision alternatives with respect to n criteria, the total number of input elements for the PROMETHEE method is equal to $(n + 1)(m + m^2)$ (Marinoni 2006). A problem involving four evaluation criteria and 1,000 alternatives would require 5,005,000 input elements. This amount of input information seriously limits applicability of the method in the GIS environment, especially when the decision problems involve large raster-based datasets.

There have been several attempts to find a solution to the limitation of outranking methods (e.g., Joerin et al. 2001; Marinoni 2006; Chakhar and Mousseau 2007; 2008). The proposed approaches are based on the concept of spatial aggregation of the basic geographic units of criterion maps to reduce the number of decision alternatives. Joerin et al. (2001) used a homogeneity index to define decision alternatives. One disadvantage of this approach is a substantial loss of information associated with the process of spatial aggregation. Marinoni (2006) also proposed an iterative method for reducing the number of alternatives based on the concept of raster aggregation. Chakhar and associates provided a comprehensive approach for dealing with the computational limitation of outranking methods in the GIS environment (Chakhar et al. 2005; Chakhar and Mousseau 2007, 2008). The approach is based on the concept of a decision map, which involves the process of overlaying criterion maps, using the ELECTRE TRI method for classifying the result of the criterion map overlay procedure, and aggregating adjacent (similar) spatial units. Given the 'homogenous' spatial units, Chakhar and Mousseau (2008) have demonstrated the procedure for generating spatial decision alternatives using a constraint-based suitability analysis for point, line, and polygon features or their combinations.

4.6 Conclusion

In this chapter, we discussed four MADA methods: the weighted linear combination, AHP/ANP, ideal point methods, and outranking methods. We outlined conventional MADA methods and emphasized that they are merely extensions of existing models to analyze spatial decision problems. The conventional MADA methods are often inadequate for tackling spatial decision problems because of their limited capabilities to operationalize and analyze spatially heterogeneous preferences. Consequently, we presented several spatially explicit models that are capable of incorporating the spatial preferences into GIS-based decision analysis procedures. In addition, the chapter provided an overview of GIS-based applications of the four methods. The overview indicated a wide range of decision situations in which the GIS-MADA methods can be used.

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Chapter 5
Multiobjective Optimization Methods

5.1 Introduction

Multiobjective optimization methods, or multiobjective decision analysis (MODA), define decision alternatives in terms of a model consisting of a set of objective functions and a set of constraints imposed on the decision variables. Formally, MODA problems are formulated as follows:

$$\text{maximize}\, F(\boldsymbol{x}) = \{f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_n(\boldsymbol{x})\}, \tag{5.1}$$

$$\text{subject to: } \boldsymbol{x} \in \boldsymbol{X}, \tag{5.2}$$

where $F(\boldsymbol{x})$ is the n- dimensional objective function; $f_k\,(\boldsymbol{x})$ is an objective (criterion) function ($k = 1, 2, \ldots, n$); $\boldsymbol{X}$ is the set of feasible alternatives, and $\boldsymbol{x} = (x_1, x_2, \ldots, x_m)$ is a vector of decision variables, $x_i \geq 0$, for $i = 1, 2, \ldots, m$. One can assume without lost of generality that all objective functions in Eq. 5.1 are to be maximized. In spatial optimization problems, there is at least one set of spatially explicit decision variables. The variables can be used in many different ways to define spatial decision alternatives. For example, the concept of location-allocation is often employed for defining a set of spatial alternatives. Specifically, any locational alternative can be defined as a binary vector, $\boldsymbol{x} = (x_1, x_2, \ldots, x_m)$, where a decision variable, x_j, is defined as follows: $x_j = 1$, if an activity (e.g., health service facility) is located at the ith site; and $x_j = 0$, otherwise. Also, a vector of allocation variables associated with the jth location can be defined in terms of a binary variable as follows: $x_{ij} = 1$, if an activity (e.g., demand for health services) at the ith location is allocated to the jth location; and $x_{ij} = 0$, otherwise.

Given that the multiobjective optimization models (5.1)–(5.2) include conflicting and often non-commensurate criteria, the problem involves finding a set of Pareto optimal solutions (which is also known as a set of efficient, non-dominated, and non-inferior solutions). In Sect. 2.2.3.2 we have outlined the concept of Pareto optimal (or non-dominated) alternatives. Here, we define the concept formally.

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_5

A vector of decision variables $\boldsymbol{x}^*$ is said to be Pareto optimal if there exist no other feasible vector $\boldsymbol{x}$ such that $f_k(\boldsymbol{x}) \geq f_k(\boldsymbol{x}*)$ for all $k = 1, 2, \ldots, n$ and $f_k(\boldsymbol{x}) > f_k(\boldsymbol{x}*)$ for at least one k. This implies that $\boldsymbol{x}^*$ is Pareto optimal if there is no feasible vector that would improve some objective without causing a simultaneous deterioration of at least one other objective. The non-dominated set in the objective space is referred to as the Pareto front. In the absence of any preference regarding the objectives, all non-dominated solutions are assumed equivalent or indifferent. However, the multiobjective decision problems often require that a single non-dominated alternative is selected from the set of Pareto optimal solutions. This type of problems has traditionally been handled by combining the objectives into a scalar function and then solving the equivalent single-optimization problem to identify a best-compromise alternative (or a set of non-dominated alternatives). Once the multiobjective problem is specified in terms of single-objective model, it can be solved using conventional mathematical programming algorithms (Cohon 1978; Goicoechea et al. 1982; Huang et al. 2008).

This chapter focuses on the most often used conventional optimization approaches in GIS-MCDA, which can be classified into three groups: (i) methods for generating non-dominated solutions (the weighting and constraint methods), (ii) the distance-based methods (such as compromise programming, goal programming, and reference point methods), and (iii) interactive methods (Hwang and Masud 1979). This classification is based on the ways in which the decision maker's preference information is incorporated into the modeling procedure. Efficient solution generation methods do not require the preference information to be provided before performing the optimization procedure.

These techniques are also referred to as a posteriori methods, because the solution procedure is performed first and the decision maker preferences can then be elicited from the generated set of solutions. In distance-based methods, the preferences are specified a priori; that is, all decision maker preferences are specified before the solution process. The interactive methods assume that the preferences can be provided progressively in the modeling procedure.

5.2 Weighting and Constraint Methods

Several techniques for generating non-dominated solutions are available (Cohon 1978; Goicoechea et al. 1982; Zarghami and Szidarovszky 2011). A common feature of these techniques is that the multiobjective problem is first transformed into a scalar problem and then solved as a single-objective optimization problem. The basic difference among the methods lies in how they make the transformation from a multi- to single-objective model (Cohon 1978). The most often used methods for tackling spatial multiobjective problems are the *weighting* and *constraint methods* (Diamond and Wright 1988; Malczewski and Ogryczak 1995; Church et al. 1992; Maliszewski et al. 2012).

The weighting method involves assigning a weight, w_k ($k = 1, 2, \ldots, n$), to each objective function, $f_k(\boldsymbol{x})$. The multiobjective function (5.1) can then be converted into a single-objective form through the linear combination of the objectives together with the corresponding weights. Thus, the problem (5.1)–(5.2) can be transformed as follows:

$$\text{maximize}\, F(\boldsymbol{x}) = \{w_1 f_1(\boldsymbol{x}) + w_2 f_2(\boldsymbol{x}) +, \ldots, + w_n f_n(\boldsymbol{x})\}, \tag{5.3}$$

$$\text{subject to: } \boldsymbol{x} \in \boldsymbol{X}. \tag{5.4}$$

where the weights $w_k \geq 0$ and $w_1 + w_2 +, \ldots, + w_n = 1$. The set of non-dominated solutions to the problem (5.3)–(5.4) is generated by parametric variation of the weights. An approximation of the non-dominated solution set can be generated by systematically varying the weighting coefficients and solving the associated single-objective model. Figure 5.1a illustrates the concept of weighting method for the two objective functions. It shows the feasible solution region and the non-dominated alternatives (or the Pareto-optimal front). For a bi-objective problem, there are two weights, and one of them is independent. Since F is a linear combination of f_1 and f_2, the contour of F in the objective space is a line, l_s. The value of F is the same at any point of the contour line; therefore, the line is referred to as the linear indifference curve. The slope of the line is defined by the value of the weights; specifically, the slope is equal to $-w_1/w_2$. The value of F depends on the location of the line. By changing the values of the weights one can obtain different values of F represented by the parallel indifference curves, l_1, l_2, and l_3. Since model (5.3)–(5.4) involves maximization of the objective functions, the indifference curve

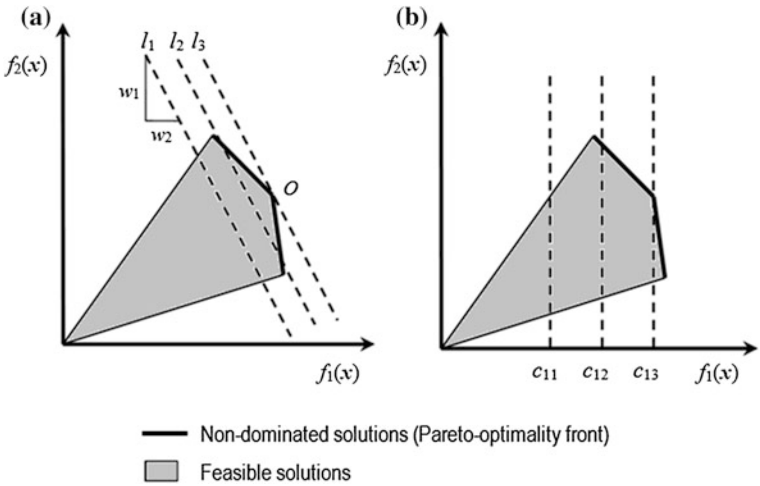


Fig. 5.1 The concept of **a** weighting method, and **b** constraint method (*Note* the objective functions $f_1(x)$ and $f_2(x)$ are maximized; O = optimal solution; w_1, w_2 = weights; l_1, l_2, l_3 = linear indifference curves; c_{11}, c_{12}, c_{13} = constraints imposed on $f_1(x)$)

with the maximum value of F determines the optimal solution. Specifically, the solution to the problem (5.3)–(5.4) is to move the contour line northeastwards in parallel as far as possible until it becomes tangent to the feasible objective space. The point of tangency, O, located on the indifference curve l_3 indicates the optimal solution.

Note that if some value (or utility) functions (see Sect. 2.3.1.1) and associated objective weights are estimated according to the principles described in Sect. 2.3.2, then the weighting method becomes multiobjective *value function* method. Given the value functions, $v(f_k(\boldsymbol{x}))$, for $k = 1, 2, \ldots, n$, the problem (5.1)–(5.2) can be stated with the following value function program:

$$\text{maximize}\, F(\boldsymbol{x}) = \{\Sigma\, w_k\, v(f_k(\boldsymbol{x}))\}, \tag{5.5}$$

$$\text{subject to: } \boldsymbol{x} \in \boldsymbol{X}, w_k \geq 0 \text{ for } k = 1, 2, \ldots, n. \tag{5.6}$$

where w_k is the weight of importance assigned to the kth objective. Note that there is a difference between the value function models (5.5)–(5.6) and the weighting method for generating non-dominated solutions (5.3)–(5.4). The value function method incorporates the decision maker's preferences by assigning weights of importance to the objective functions, while in the weighting method the weights are parameters that may be varied systematically to yield points that are non-dominated solutions. Also, the weighting model (5.3)–(5.4) is used for generating a set of non-dominated alternatives by changing the weighting coefficients, while the problem (5.5)–(5.6) results in a unique non-dominated solution. Thus, strictly speaking, the value function model is not a method for generating a set of non-dominated alternatives. If the objective weights w_1 and w_2 represent the decision makers' preferences with respect the objective functions $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$, and the assumption of a linear value function is accepted, then point O would indicate the best (compromise) solution (see Fig. 5.1a).

One limitation of the weighting method is that certain non-dominated solutions cannot be detected when the Pareto-optimal front is non-convex (Cohon 1978). The constraint method can alleviate this problem. The method involves maximizing only one of the objective functions while all others are converted into inequality constraints. Thus, the multiple objective problem (5.1)–(5.2) can be transformed to the following single-objective problem:

$$\text{maximize}\, f_s(\boldsymbol{x}), \tag{5.7}$$

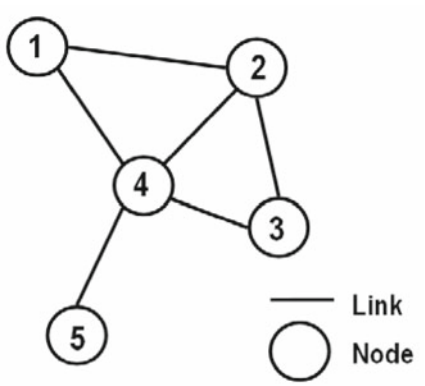
$$\text{subject to: } \boldsymbol{x} \in \boldsymbol{X}, \text{ and } f_k(\boldsymbol{x}) \geq c_k, \text{for all } k \neq s, \tag{5.8}$$

where c_k is a lower bound on objective k.

The set of non-dominated solutions can be generated by solving the single-criterion problem (5.7)–(5.8) with the parametric variation of the c_k value. Like the weighting method, the constraint problem can be solved with standard mathematical programming techniques (Cohon 1978).

Figure 5.1b demonstrates the concept of the constraint method. It shows situations involving two objective functions, where $f_2(\boldsymbol{x})$ is to be maximized and $f_1(\boldsymbol{x})$ is converted to a constraint $f_1(\boldsymbol{x}) \geq c_{1b}$, for $b = 1$, 2, and 3. The constrain divides the original feasible objective space into two portions: feasible and infeasible; for example, the portion of the original feasible space right from the c_{11} line constrains all feasible solutions, while the left portion becomes infeasible solution space for the problem (5.7)–(5.8). By changing the values of the constraint, c_{1b}, one can obtain different values of the objective function, $f_2(\boldsymbol{x})$. Since the model (5.7)–(5.8) represents a maximization problem, the maximum value of $f_2(\boldsymbol{x})$ determines the optimal solution. A set of non-dominated solutions to the problem can be generated by moving the constraint line eastwards in parallel.

Computational examples of the weighting and constraint methods are given in Goicoechea et al. (1982) and Malczewski (1999). Goicoechea et al. (1982) illustrates the methods by solving resource allocation and watershed management problems. Malczewski (1999) provides a computational example of the methods using a spreadsheet-based solver for tackling a location-allocation problem. Here we give another example of the weighting (value function) method to demonstrate the procedure of generating non-dominated solutions. We consider a hypothetical example of the p-median problem on a network. The problem is to locate p facilities on a network of m nodes and allocate each node to exactly one of them so that the total distance (and other relevant attribute) is minimized (or maximize). We consider a problem of locating two service facilities ($p = 2$) for supplying components to five manufacturers (towns) ($m = 5$) (Fig. 5.2). The demand for the services, z_i, is measured by the number of units required by the ith manufacturer. The problem involves optimizing three objective functions: (i) total distance, (ii) total environmental impact associated with transportation of the components (measured by an index assigned to links of the network), and (iii) total risk of accident. The raw datasets for the attributes (objectives) were normalized using Eq. 2.1. Table 5.1 shows normalized values of the three attributes.



Town i	Demand, z_i (in millions)
1	18
2	12
3	25
4	30
5	15

Fig. 5.2 Network of five demand nodes representing towns and six links representing roads

Table 5.1 Standardized values of (a) distance, d_{ij}, (b) environmental impact, e_{ij}, and (c) risk of accident, r_{ij}, associated with the i,jth link (arc) of the network consisting of five nodes; i = demand node (i = 1, 2, .., 5), and j = node for potential location of facility (j = 1, 2, .., 5)

(a)

i \ j	1	2	3	4	5
1	1.0	0.4	0.2	0.6	0.0
2	0.4	1.0	0.6	0.8	0.2
3	0.2	0.6	1.0	0.8	0.2
4	0.6	0.8	0.8	1.0	0.6
5	0.0	0.2	0.2	0.6	1.0

(b)

i \ j	1	2	3	4	5
1	0.5	0.4	0.1	0.9	0.0
2	0.4	1.0	0.3	0.7	0.7
3	0.1	0.3	0.1	0.6	0.3
4	0.9	0.7	0.6	0.0	0.4
5	0.1	0.7	0.3	0.4	1.0

(c)

i \ j	1	2	3	4	5
1	0.0	0.25	0.25	1.0	0.0
2	0.25	1.0	0.5	1.0	0.75
3	0.25	0.5	1.0	0.5	1.0
4	1.0	1.0	0.5	0.25	0.25
5	0.0	0.75	1.0	0.25	0.0

Formally, the problem can be written as follows:

$$\text{maximize} f_1(\boldsymbol{x}) = \sum_{i=1}^{m}\sum_{j=1}^{n} z_i d_{ij} x_{ij} \tag{5.9}$$

$$\text{maximize} f_2(\boldsymbol{x}) = \sum_{i=1}^{m}\sum_{j=1}^{n} z_i e_{ij} x_{ij} \tag{5.10}$$

$$\text{maximize} f_3(\boldsymbol{x}) = \sum_{i=1}^{m}\sum_{j=1}^{n} z_i r_{ij} x_{ij} \tag{5.11}$$

subject to:

$$\sum_{j=1}^{n} x_{ij} = 1, \quad \text{for } i = 1, 2, 3, \ldots, m; \tag{5.12}$$

$$x_{ij} - x_{jj} \leq 0, \quad \text{for } i = 1, 2, 3, \ldots, m,\ j = 1, 2, 3, \ldots, n; \tag{5.13}$$

$$\sum_{j=1}^{n} x_{jj} = p; \tag{5.14}$$

$$x_{ij} = 1 \text{ or } 0, \quad \text{for } i = 1, 2, 3, \ldots, m,\ j = 1, 2, 3, \ldots, n; \tag{5.15}$$

where z_i = the number of units demanded by the ith manufacturer; d_{ij} = standardized value of distance between node i and j; e_{ij} = standardized environmental impact index assigned to the link (road) between i and j; r_{ij} = standardized risk of accident associated with the link (road) between i and j.

The objective functions $f_1(\boldsymbol{x})$, $f_2(\boldsymbol{x})$, and $f_3(\boldsymbol{x})$ maximize the total weighted standardized values of distance, environmental impact, and risk of accident, respectively. Equation (5.12) ensures that each demand node (manufacturer) is allocated to a service facility. Inequality (5.13) guarantees that the demand nodes are allocated only to those candidate nodes where facility will be established. Equation (5.14) indicates the number of facilities to be located (that is, p = 2). According to Eq. (5.15), each of the allocation (decision) variables must be equal to 1 or 0; specifically, x_{ij} = 1 if the components required by the ith manufacturer are supplied at the jth facility, and x_{ij} = 0 otherwise;

In order to generate a set of non-dominated solutions, the multiobjective problem (5.9)–(5.15) is converted to the following singe-objective form:

$$\text{maximize } F(\boldsymbol{x})\left(w_1 \sum_{i=1}^{m}\sum_{j=1}^{n} z_i d_{ij} x_{ij}\right) + \left(w_2 \sum_{i=1}^{m}\sum_{j=1}^{n} z_i e_{ij} x_{ij}\right) + \left(w_3 \sum_{i=1}^{m}\sum_{j=1}^{n} z_i r_{ij} x_{ij}\right), \tag{5.16}$$

$$\text{subject to: } (5.12)-(5.15). \tag{5.17}$$

This problem can be tackled using a standard mathematical programming solver. We use a spreadsheet based LINDO system (www.lindo.com).

As suggested, a set of non-dominated solutions can be generated by varying the objective weights, w_k. One way of varying the weights is to assign a weight of 1 to one of the objective functions and 0 to all other functions. The problem (5.16)–(5.17) is solved with three different sets of the objective weights; that is, if w_1 = 1, w_2 = 0, and w_3 = 0, then $f_1(\boldsymbol{x})$ is optimized; if w_1 = 0, w_2 = 1, and w_3 = 0, then $f_2(\boldsymbol{x})$ is optimized; and, if w_1 = 0, w_2 = 0, and w_3 = 1, then $f_3(\boldsymbol{x})$ is optimized.

The results are organized in the form of a pay-off matrix (see Table 5.2). The matrix allows us to identify the maximum and minimum values of each objective function; that is, the *ideal* (utopia) and *anti-ideal* (nadir) solutions can be defined. The ideal solution is usually not attainable but it can be presented to the decision maker as a limit to the best numerical values of the objectives; that is, it provides the decision maker with lower limits for minimized criterion functions and upper limits for the functions to be maximized. The anti-ideal point is the worst criterion value. It is the lower limits and upper limits for criterion functions to be maximized and minimized, respectively.

Figure 5.3 shows the optimal location-allocation patterns associated with the results of the three solutions displayed in the pay-off matrix (Table 5.2). The results indicate that there are substantial differences between the three non-dominated solutions. Furthermore, the differences are present in the objective and decision space. Notice that the optimal value of $f_1(\boldsymbol{x})$ and $f_3(\boldsymbol{x})$ are similar. However, the associated location-allocation patterns are considerably different. This remark

Table 5.2 The pay-off matrix for the problem (5.16)–(5.17)

Optimized objective functions	Objective function value		
	$f_1(x)$	$f_2(x)$	$f_3(x)$
$f_1(x)$ ($w_1 = 1$, $w_2 = 0$, $w_3 = 0$)	86.6	38.4	35.8
$f_2(x)$ ($w_1 = 0$, $w_2 = 1$, $w_3 = 0$)	58.4	66.9	64.0
$f_3(x)$ ($w_1 = 0$, $w_2 = 0$, $w_3 = 1$)	71.2	47.2	86.5
Ideal vector	86.6	66.9	86.5
Nadir vector	58.4	38.4	35.8

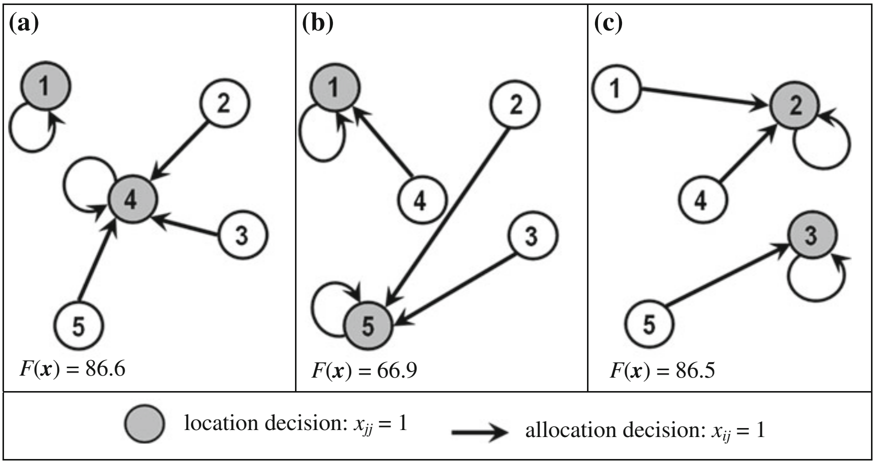


Fig. 5.3 Location-allocation patterns for solution of the multiobjective optimization problem (5.9)–(5.15) for: **a** $w_1 = 1$, and $w_2 = w_3 = 0$; **b** $w_2 = 1$, and $w_1 = w_3 = 0$, and **c** $w_3 = 1$ and $w_1 = w_2 = 0$

underscores the importance of examining the results of spatial multiobjective modeling both in the objective and geographic (decision) space.

In addition to the non-dominated solutions obtained by generating the pay-off matrix, one can solve the problem (5.16)–(5.17) for different sets of the objective weights to analyze the non-dominated set of alternatives. Table 5.3 shows the objective function values for a sample of four sets of weights. The associated location-allocation patterns are given in Fig. 5.4. Notice we obtained the same solutions for $w_1 = 0.5$, $w_2 = 0.25$, $w_3 = 0.25$, and $w_k = 0.33$ (see Fig. 5.4a and d). There are, however, substantial differences between these location-allocation patterns and those displayed in Fig. 5.3b and c. Note also that the values of the objective functions are similar for $w_1 = 0.5$, $w_2 = 0.25$, $w_3 = 0.25$ and $w_1 = 0.25$, $w_2 = 0.25$, $w_3 = 0.50$. This suggests that similar solutions to multiobjective decision problem in the objective space may be substantially different in the geographic space, and vice versa.

The results of the weighting method provide important information about the set of non-dominated alternatives, the range of possible decision outcomes, and the trade-offs involved. In spite of the fact that this information is very useful in searching for the best decision outcomes and corresponding location-allocation pattern, a decision maker would likely find it difficult to choose the best alternative even for a very small spatial (location-allocation) problem. Therefore, an a priori or interactive method has to be applied to identify the best (compromise) alternative (Sect. 5.3).

Several GIS-MODA applications have used the weighting method (e.g., Church et al. 1992; Kao and Lin 1996; Wu and Murray 2005; Farhan and Murray 2008; Herzig 2008; Ligmann-Zielinska and Jankowski 2010; Maliszewski and Horner 2010; Maliszewski et al. 2012). Church et al. (1992) integrated the weighting method into a raster based GIS for generating and exploring spatial alternatives for a corridor location problem. Kao and Lin (1996) also used a raster-based GIS in their spatial analysis of landfill sitting problem with the weighting method. Wu and Murray (2005) integrated the weighting method with GIS to analyze the trade-off between public transit service quality and access coverage in a bus-based transit system. Farhan and Murray (2008) integrated spatial multiobjective model into ArcView GIS and used the weighting method to analyze the trade-offs involved in locating park-and-ride facilities. Maliszewski and Horner (2010) used standard mathematical programming software CPLEX (see www.aimms.com/features/solvers/cplex) and ArcGIS to solve multiobjective problem of sitting critical

Table 5.3 The weighting method: the location-allocation problem results for selected sets of objective weights

Weights			Objective functions			
w_1	w_2	w_3	$f_1(x)$	$f_2(x)$	$f_3(x)$	$F(x)$
0.50	0.25	0.25	71.2	53.2	82.8	69.59
0.25	0.50	0.25	66.0	66.0	65.8	65.94
0.25	0.25	0.50	71.2	47.2	86.5	72.85
0.33	0.33	0.33	71.2	53.2	82.8	69.05

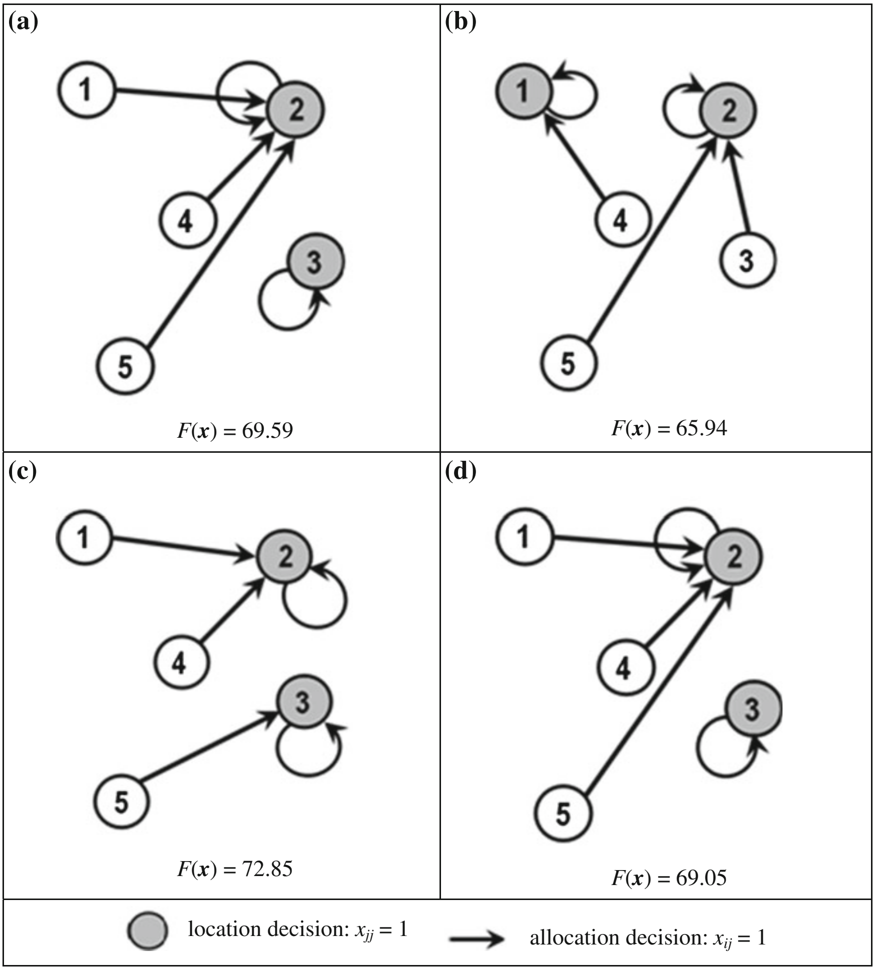


Fig. 5.4 Location-allocation patterns for solution of the multiobjective optimization problem (5.9)–(5.15): **a** $w_1 = 0.5$, $w_2 = 0.25$, $w_3 = 0.25$; **b** $w_1 = 0.25$, $w_2 = 0.5$, $w_3 = 0.25$; **c** $w_1 = 0.25$, $w_2 = 0.25$, $w_3 = 0.5$; and **d** $w_1 = 0.33$, $w_2 = 0.33$, $w_3 = 0.33$

supply facilities (see also Maliszewski et al. (2012)). Herzig (2008) developed LUMASS (Land Use Management Support System), which integrates ArcMap GIS and the open source mixed-integer linear programming system called *lp_solve* (see http://lpsolve.sourceforge.net) for tackling land use allocation problems. The system offers the techniques for generating the set of efficient solutions: the weighting and constrain methods.

One important advantage of the weighting and constraint procedures is that the methods reduce the multiobjective optimization problem to a scalar valued function. This means that the vast body of algorithms, software, and experience that exist for single-objective optimization models can be directly applied to multiobjective problems. This is of major importance considering the extent to which single-objective optimization has influenced the development of spatial analysis methods, such as spatial interaction and location analysis (Thomas and Huggett 1980; Killen 1983).

The weighting and constraint methods are easily used and intuitively appealing. There are, however, some major concerns associated with the use of the methods. They are very intensive computationally. The computational requirements for the weighting and constraint methods depend on the number of objective functions and the number of weights or constraints. There is an exponential relationship between the number of objective functions and computational burden (Cohon 1978). Since the resulting subset of efficient solutions depends on the particular weights or constraints applied, the methods may not generate a good representation of the entire non-dominated set. One possible way of handling this problem is to reduce the scale of weights or the intervals of the constraints. However, this will increase the computational burden. There is no generic rule for varying the weights or constraint intervals for generating a representative subset of non-dominated solutions.

5.3 Distance Metric Based Methods

The distance metric based MODA methods aim at minimizing a function of the distance between the desired (usually unachievable) and achieved solutions (Jones and Tamiz 2010; Zarghami and Szidarovszky 2011). The desired solution (target values) can be defined as an ideal point, some reference point, or a set of goals. The most often used distance metric approaches include: goal programming (Charnes and Cooper 1961), compromise programming (Zeleny 1982), and the reference point method (Wierzbicki 1982). These methods are also the most popular distance metric procedures implemented in the GIS environment (e.g., Church et al. 1992; Antoine et al. 1997; Agrell et al. 2004; Zeng et al. 2007; Huang et al. 2008; Meyer et al. 2009; Li and Leung 2011; Coutinho-Rodrigues et al. 2012).

The distance based methods are also referred to as the L_p-norm approaches. Indeed, the definition of distance metric is the main procedural difference between the different types of those methods. A generic form of the distance metric model can be written as follows (Jones and Tamiz 2010):

$$L_p = \left[\sum_{k=1}^{n}\left(\frac{|f_k(x) - a_k|}{h_k}\right)^p\right]^{\frac{1}{p}}, \tag{5.18}$$

where $f_k(\boldsymbol{x})$ is the achieved value of the kth objective ($k = 1, 2, \ldots, n$); a_k the target value; h_k is the normalisation constant associated with the kth objective; and p is a power parameter ranging from 1 to ∞ (see Sect. 4.4.1).

5.3.1 Goal Programming

The goal programming methods require the decision maker to specify the most desirable value (goal) for each objective (criterion) as the aspiration level or target value. The objective functions (5.1) are then transformed into goals as follows:

$$f_k(\boldsymbol{x}) + d_k^- - d_k^+ = a_k, \text{ for } k = 1, 2, \ldots, n, \tag{5.19}$$

$$d_k^-, d_k^+ \geq 0, \ (d_k^-, d_k^+) = 0, \tag{5.20}$$

where a_k is the aspiration level for the kth objective, d_k^-, d_k^+ are negative and positive goal deviations, respectively; that is, non-negative state variables that measure deviations of the achieved value of the kth objective function from the corresponding aspiration level. Thus, two types of variables are part of any goal programming formulation: the decision variables, x_i, and the deviational variables, d_k.

A number of measures of multidimensional deviations (achievement functions) and corresponding goal programming forms have been proposed by Jones and Tamiz (2010). The achievement function, $g(\boldsymbol{d}^+, \boldsymbol{d}^-)$, can be formulated in terms of the weighted L_p norm as follows:

$$g(d^+, d^-) = \left[\sum_{k=1}^{n} \left(w_k^- d_k^- + w_k^+ d_k^+ \right)^p \right]^{\frac{1}{p}}, \tag{5.21}$$

where w_k^- and w_k^+ are weights corresponding to the kth goal deviations. The weights represent additional information reflecting the decision maker's preferences with respect to the deviation variables. One can generate a number of models by changing the value of p. The *weighted goal* and *Chebyshev goal programming* have been the most often used goal programming methods in the GIS environment (see Malczewski 2006a). For $p = 1$, the achievement function (5.21) takes the form of the weighted goal programming:

$$g(\boldsymbol{d}^+, \boldsymbol{d}^-) = \sum_{k=1}^{n} \left(w_k^- d_k^- + w_k^+ d_k^+ \right), \tag{5.22}$$

The weighted goal programming assumes that the positive deviations and negative deviations of the criterion outcomes from the aspired goals are equally undesirable.

One can also use the L_p norm to develop weighted Chebyshev goal programming. Specifically, for $p = \infty$ the achievement function of the Chebyshev goal programming takes the following form:

$$g(\boldsymbol{d}^+, \boldsymbol{d}^-) = \max_{k=1,2,..,n} \left(w_k^- d_k^- + w_k^+ d_k^+ \right), \tag{5.23}$$

This type of goal programming minimizes the deviation from those aspiration levels so that the worst deviation from any single-goal aspiration level is minimized.

It is important to note that the models (5.22) and (5.23) are related to other L_p based multiobjective methods. Section 5.3.2 provides an example of a spatial multiobjective optimization problem to demonstrate the relationship between the distance metric based models. A computational example of goal programming is given in Malczewski (1999). He considers a location-allocation problem in the context of transporting and disposing hazardous waste. There have been a number of studies on integrating goal programming methods into GIS. The weighted Chebyshev goal programming was used by Church et al. (1992) for tackling multiobjective corridor location problem. November et al. (1996) integrated TransCAD GIS and goal programming for analyzing alternative patterns of school districting. Ghosh (2008) used a loose coupling approach for integrating a goal programming method into SPANS GIS to analyze alternative patterns of land use. The location-routing problem using standard mixed integer linear programming modeling have been tackled in several studies, including Coutinho-Rodrigues et al. (1997), Alçada-Almeida et al. (2009), and Coutinho-Rodrigues et al. (2012). For example, Coutinho-Rodrigues et al. (2012) used the weighted goal programming method within GIS environment to solve a location-routing problem in the context of designing urban evacuation plans. Meyer et al. (2009) and Cisneros et al. (2011) applied GIS-based goal programming approaches for analyzing spatial patterns of agricultural land use. Meyer et al. (2009) developed a weighted goal programming model for analyzing alternative spatial patterns of farming systems. The distance metric based methods, including the weighted goal programming model, have been employed by Cisneros et al. (2011) to analyze the conflicts and trade-off among environmental, economic, and social interests in the context of agricultural land use.

The major advantage of goal programming is its computational efficiency. While dealing with the multi-objective decision problems, goal programming approaches allow us to stay within an efficient linear programming computational environment. There are, however, several conceptual and technical problems with using goal programming methods for tackling spatial multicriteria optimization problems. The standard goal programming methods require the decision maker to specify fairly detailed a priori information about his/her aspiration levels, and the importance of goals in the form of weights. One can expect that in a complex spatial decision situation, the decision maker will find it difficult (or even impossible) to provide the precise information required by these methods. Another weakness of weighted goal programming is its poor control over the interactive process in the case of discrete problems. For example, in the case of multiobjective location problems, this may mean some efficient locational decisions are likely to be selected for various aspiration levels and weights, whereas other decisions, despite being efficient, are selected only for aspiration levels defined very close to their outcomes (Malczewski and Ogryczak 1996). This problem associated with a priori information required by standard goal programming methods can be overcome, at least partially, by an interactive approach (see Sect. 5.4).

5.3.2 Compromise Programming

The compromise programming method is based on the assumption that the performance of decision alternatives can be evaluated with respect to a point of reference (Zeleny 1982). The obvious choice for a point of reference is the ideal solution (or ideal point), which defines the optimal value for each objective considered separately. The method identifies the non-dominated solution closest to the ideal point using various weighted L_p norms as follows:

$$\text{minimize}\left\{L_p(x)=\left[\sum_{k=1}^{n} w_k^p\left(\frac{f_k^+ - f_k(x)}{f_k^+ - f_k^-}\right)^p\right]^{\frac{1}{p}}\right\}, \tag{5.24}$$

$$\text{subject to: } \boldsymbol{x}\in\boldsymbol{X}, w_k \geq 0 \text{ for } k=1,\,2,\,\ldots,\,n. \tag{5.25}$$

where $L_p(\boldsymbol{x})$ is the distance metric; w_k is the weight associated with the kth objective function ($k = 1, 2, \ldots, n$); $f_k(\boldsymbol{x})$ is the value of the kth objective function; f_k^+ is the ideal value of the kth objective function; f_k^- is the nadir or anti-ideal value of the k-the objective function; and p is a power parameter ranging from 1 to ∞. The compromise set consists of all compromise solutions determined by solving (5.24)–(5.25) for a given set of weights (w_1, w_2, …, w_n) and for $p \geq 1$. The parameter p reflects the importance of the maximum deviation from the ideal point (see Sect. 4.3). In general, larger values of p reflect greater concern for minimizing the maximum deviation. For $p = 1$, all deviations are weighted equally; for $p = 2$, each deviation is weighted in proportion to its magnitude. For the value of $p = \infty$, the problem involves minimizing the maximum deviation, which is known as the min-max problem or the weighted Chebyshev problem. Note that the compromise programming approach involves a double-weighting scheme (Karni and Werczberger 1995). The parameters w_k and p reflect the importance of the maximal deviation and the relative importance of the kth objective, respectively. The weights, w_k, weigh deviations according to objectives but irrespective of their magnitudes. The parameter p weights the individual deviations according to their magnitudes and across the objectives.

It is general practice to use compromise programming models for $p = 1$, 2, and ∞ (Goicoechea et al. 1982). In order to identify the compromise set, we need to determine the pay-off matrix. Let us illustrate the concept of compromise programming for $p = 1$, 2, and ∞, and $w_1 = w_2 = w_3 = 0.33$ using the location-allocation problem (see Sect. 5.2). Given the pay-off matrix (see Table 5.2), the location-allocation problem (5.9)–(5.15) for $p = 1$ can be written as follows:

$$\text{minimize}\left\{L_1(x)=\left(0.33\frac{86.6-f_1(x)}{86.6-58.4}\right)+\left(0.33\frac{66.9-f_2(x)}{66.9-38.4}\right)+\left(0.33\frac{86.5-f_3(x)}{86.5-35.8}\right)\right\}, \tag{5.26}$$

subject to: (5.12)–(5.15).

Likewise, compromise programming models for $p = 2$ and ∞ can be formulated. Given the operational definition of the compromise programming models for $p = 1$, 2 and ∞, the solution of the problem always results in a non-dominated point for $1 \leq p < \infty$. However, for $p = \infty$, one can obtain a dominated solution (Goicoechea et al. 1982). This general remark is confirmed by the results shown in Table 5.4 Also, the value of $L_p(\boldsymbol{x})$ suggest that the compromise programming model for $p = 2$ generates a non-dominated solution closest to the ideal point.

Tables 5.3 and 5.4 show the same values of the objective functions for the compromise programming model for $p = 1$ and the weighting methods for $w_k = 0.333$. Also, the corresponding location-allocation patterns are identical (see Figs. 5.4d and 5.5a). This finding can be generalized. Indeed, it can be shown that the compromise programming model for $p = 1$ and the weighting (value function) methods (see Sect. 5.2) result in an equivalent solutions for the same set of objective weights (see Li and Leung 2011). Furthermore, the compromise programming resembles goal programming (Goicoechea et al. 1982; Jones and Tamiz 2010). The solution for the weighted goal programming (see Sect. 5.3.1) corresponds to the solution of compromise programming for $p = 1$ if the same weights

Table 5.4 Compromise programming: the location-allocation problem for $p = 1$, 2, and ∞, and $w_1 = w_2 = w_3 = 0.333$

p	$L_p(x)$	$f_1(x)$	$f_2(x)$	$f_3(x)$
1	0.367	71.2	53.2	82.75
2	0.234	72.0	60.0	65.75
∞	0.432	50.0	46.5	44.50

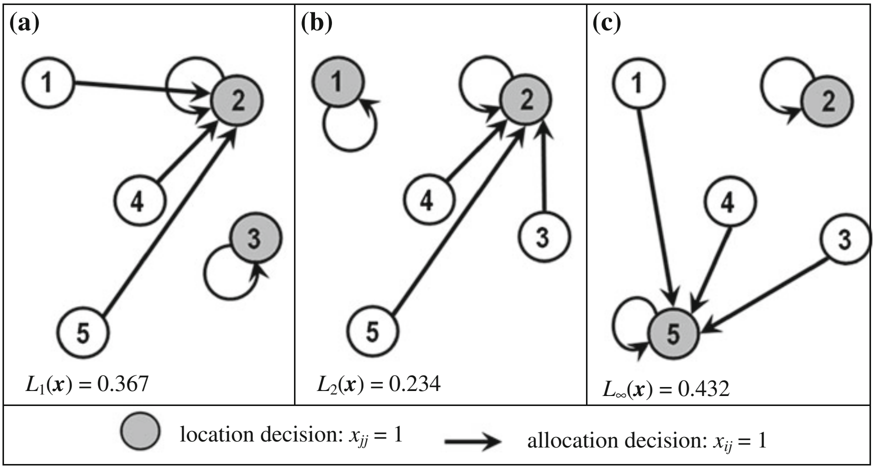


Fig. 5.5 The location-allocation patterns generated by the compromise programming method for $w_1 = w_2 = w_3 = 0.333$ and selected p values: **a** $p = 1$, **b** $p = 2$, and **c** $p = \infty$

and the same ideal (aspiration) levels are chosen. Also, the Chebyshev goal programming model is equivalent to compromise programming for $p = \infty$ (Jones and Tamiz 2010).

There have been several applications of GIS-based compromise programming methods for solving spatial multiobjective optimization problems (e.g., Church et al. 1992; Chang et al. 1997; Shih and Lin 2003; Huang et al. 2008; Li and Leung 2011). All the studies focus on tackling problems in the transportation sector, such as locating transportation corridors and routing problems. Church et al. (1992) have used the weighted Chebyshev distance model as a method for dealing with some of the concerns associated with the use of the weighting method (see Sect. 5.2). They used the method for analyzing a corridor location problem. This study is of particular significance because of its approach for exploring spatial alternatives in both decision space and objective space. Chang et al. (1997) developed an ArcGIS-based compromise programming model for tackling vehicle routing and scheduling problems. The limitations of the weighting method, in the context of spatial multiobjective optimization, have also been highlighted by Huang et al. (2008), and Li and Leung (2011). They demonstrated the relationship between the utility/value function approach and compromise programming, and used the weighted Chebyshev model for tackling routing problems using GIS. Shih and Lin (2003) used GIS and a combination of multiobjective methods, including compromise programming, for tackling routing and scheduling problem.

One advantage of the compromise programming approach is its simple conceptual structure. In addition, the set of preferred compromise solutions can be ordered between the extreme criterion outcomes, and consequently, an implicit trade-off between criteria can be performed. A disadvantage of this approach is that, except for the two extremes (that is, when $p = 0$ and ∞), there is no clear interpretation of the various values of the parameter p. Therefore, the selection of the "best" alternative within the reduced set of compromise alternatives must be made based on a further insight into the compromise set of non-dominated alternatives. One way to achieved this is using the approach as a component of an interactive procedure (see Sect. 5.4).

5.3.3 Reference Point Method

From the perspective of behavioural decision theory, the reference point method can be recognized as an approach that combines the classical optimizing and satisficing decision rules (Wierzbicki 1982, 1983). It is argued that an individual has some tendency toward maximization of his/her utility even if he/she behaves according to satisficing rationality principles; that is, he/she forms aspiration levels as a guide for decision making (Malczewski and Ogryczak 1996). Such type of behaviour is referred to as quasi-satisficing rationality. The concept of quasi-satisficing rationality can be considered as an attempt to generalize the underlying behavioural principles of the distance based multiobjective methods. Indeed, the compromise programming approach is based on the optimizing rationality principle, while the satisficing behaviour is underlying philosophy of goal programming (Romero et al. 1998).

The key element of the quasi-satisficing decision framework is the relationship between the non-dominated set of solutions and aspired goals. According to the quasi-satisficing principle, the decision maker should identify the best (most preferred) alternative as the one which belongs to the set of non-dominated solutions, irrespective of the attainability of his/her aspiration levels. Although the aspired levels may not be achievable, they can be projected onto the Pareto optimal front by using the achievement scalarizing function (Wierzbicki 1982; Romero et al. 1998). Using the achievement scalarizing function, the reference point model can be written as follows:

$$\text{minimize}\left\{\max_k\left[\frac{w_k}{h_k}(a_k - f_k(x))\right] - \varepsilon\sum_{k=1}^{n}\frac{w_k}{h_k}f_k(x)\right\} \tag{5.27}$$

$$\text{subject to: } \boldsymbol{x} \in \boldsymbol{X}, w_k \geq 0 \text{ for } k = 1, 2, \ldots, n. \tag{5.28}$$

where ε is an arbitrary sufficiently small positive number; it guarantees a non-dominated solution of the problem (5.1)–(5.2). The objective function (5.27) has two components: (i) the difference between the weighted Cherbyshev norm of the discrepancies between reference levels, a_k, and the achieved value of the k-th objective $f_k(\boldsymbol{x})$, and (ii) a small regularization term of the weighted sum of the n objectives.

Malczewski and Ogryczak (1996) provide a computational example of the reference point method using a hypothetical plant location problem. They also demonstrate the use of the method within the framework of goal programming. Specifically, the reference point approach can be operationalized within a goal programming framework as an initial Chebyshev goal programme followed by the $L_1(\boldsymbol{x})$ Pareto restoration phase (Romero et al. 1998). Zeng et al. (2007) integrated reference point based systems into ArcGIS for tackling forest planning and management. Antoine et al. (1997) developed a decision support system called Aspiration-Reservation Based Decision Support (ARBDS) (see also Malczewski and Ogryczak 1996). The system integrates the FAO Agro-Ecological Zones/GIS package and the reference (aspiration-reservation) point method (see also Agrell et al. 2004). Antoine et al. (1997) and Agrell et al. (2004) used the system for land use planning. Maniezzo et al. (1998) and Rozakis et al. (2001) employed the reference point method as a component of spatial decision support systems for locating waste management facilities and bio-energy projects, respectively.

One advantage of the reference point method is that it has the capability to capture every Pareto optimal solution by using appropriate aspiration levels. For this reason, the method is especially suitable as a component of interactive multi-objective modeling. However, the reference point model shares some of the drawbacks associated with the other distance metric based approaches. The method requires the decision maker to specify fairly detailed a priori information regarding the reference point(s) and the objective weights. This information may be difficult to elicit for the decision maker. This problem can be alleviated, at least partially, by using the method within the framework of an interactive modeling (see Sect. 5.4).

5.4 Interactive Programming Methods

The main idea behind interactive multiobjective programming methods is to determine the best (compromise or satisficing) decision outcome among the set of efficient solutions by means of a progressive communication process between the decision maker and the computer based system (Nijkamp 1979; Steuer 1986). Interactive multiobjective programming methods do not require a priori information about the decision maker's preference structure. The existence of a utility/value function is implicitly assumed and the function is maximized by means of a formal mechanism that involves an interactive exchange of information between a substantive model of the decision situation (computer-based decision support system) and the user. An interactive procedure consists of two phases: (i) in the dialogue phase, the decision maker analyzes and evaluates information provided by a computer-based system and articulates his/her preferences, and (ii) in the computational phase, a solution (or a group of solutions) that meets the decision maker's requirements specified in the dialogue phase, is generated. This interactive exchange of information is continued until an outcome is deemed acceptable to the decision maker.

Although there is a number of interactive multiobjective programming methods available (Steuer 1986; Korhonen and Wallenius 2010), the interactive approaches to spatial decision problems have been mostly limited to distance metric base methods (see Sect. 5.3). Examples of integrating GIS and interactive goal programming approaches are given in Coutinho-Rodrigues et al. (1997), Roettera et al. (2005), Santé and Crecentea (2007), and Alçada-Almeida et al. (2009). The reference point method is the core of spatial interactive decision support system developed by Antoine et al. (1997) and Agrell et al. (2004). Malczewski and Ogryczak (1996) provide a computational example of an interactive multiobjective approach to plant location problem (see also Malczewski and Ogryczak 1990).

Since the decision maker is an essential part of the multicriteria decision making process, an interactive method is a natural approach for tackling multiobjective decision problems (Korhonen and Wallenius 2010). Also, the methods are amenable to the use of graphical representation of alternative solutions to support the interactive process of decision making. This feature of interactive procedures is of particular significance as a component of spatial decision support (Church et al. 1992; Malczewski and Ogryczak 1996). There is evidence to show that GIS-based interactive methods provide valuable support for understanding and analyzing complex spatial decision problem (Alçada-Almeida et al. 2009).

5.5 Conclusion

This chapter discussed classic multiobjective optimization methods. It focused on those approaches that have been most often integrated into GIS: methods for generating non-inferior solutions, distance metric-based methods, and interactive methods. We overviewed GIS-based applications of multiobjective optimization methods, and signified relationships between different methods. First, we indicated that the weighting method for generating non-dominated solution can be considered the value/utility function method providing that suitable value/utility functions and associated objective weights have been elicited from the decision maker. Second, we demonstrated the links between the distance metric based methods. Specifically, compromise programming models with the $L_1(\boldsymbol{x})$ and $L_\infty(\boldsymbol{x})$ distance metrics are equivalents to the weighted and Chebyshev goal programme methods with the target values set at ideal levels. Also, the reference point method can be considered within the framework of goal programming as a Chebyshev goal programme, along with the $L_1(\boldsymbol{x})$ Pareto restoration procedure. Third, we indicated that distance metric based methods are often used as components of interactive approaches for tackling spatial decision problems. We emphasised the importance of displaying alternative solutions using GIS within the framework of interactive decision support procedures.

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Chapter 6
Heuristic Methods

6.1 Introduction

The complexity of many spatial optimization problems makes it difficult, or even impossible, to search every candidate solution using the classic mathematical programming methods (see Chap. 5). Such complex problems are often tackled by heuristic algorithms. This class of methods is based on a trial-and-error approach. The algorithms aim at finding good solution in an acceptable timescale by iteratively trying to improve a candidate solution with regard to a given measure of quality. However, the methods do not guarantee that an optimal solution is ever found.

Heuristic algorithms include a group of methods referred to as meta-heuristics (Burke and Kendall 2005; Yang 2010). No agreed definitions of heuristics and meta-heuristics exist in the literature. The two terms are often used interchangeably. However, we make a distinction between these two groups of methods. Meta-heuristics are relatively sophisticated heuristic methods (Burke and Kendall 2005). They are sometimes referred to as advanced or modern heuristics, as opposed to the traditional basic heuristic methods. Accordingly, the methods can be classified into: basic heuristics (or heuristics) and meta-heuristics.

Although generic heuristic methods do exist, GIS-based applications of basic heuristics tend to be problem specific. For example, there is a number of basic heuristics that involve land-use suitability analysis in the raster GIS environment. One can distinguish two categories of these heuristics. First, site suitability heuristics involve allocating competing land uses to parcels of land based on land use suitability scores (e.g., Eastman et al. 1995). This type of heuristics does not consider the spatial properties of areas (regions or patches) of land uses, such as compactness and connectedness, explicitly. Second, site location heuristics are search procedures concerned with land suitability and spatial objectives. In this case, an optimal patch or region contains cells having the highest suitability scores; and it is also characterized by some desirable spatial properties such as shape, orientation, compactness, and contiguity (see Brookes 1997a; Church et al. 2003). In addition to the land

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_6

suitability-raster-based heuristics, a few other heuristic methods, such as the greedy algorithms, Lagrangian Relaxation heuristics, and HERO heuristic optimization, have been employed for tackling spatial multiobjective optimization problems within the GIS environment. In contrast to the site suitability/location heuristics, these methods are more applicable to vector-data-based spatial problems.

There is a wide range of meta-heuristics available for tackling multiobjective optimization problems (Talbi 2009). Some of these meta-heuristics have been integrated with GIS. Evolutionary algorithms are the most popular GIS-based implementations. They include meta-heuristics, such as genetic algorithms, evolution strategies, and evolutionary programming methods. Other meta-heuristic procedures that are considered to be a part of the family of evolutionary algorithms are simulated annealing and tabu search (see Xiao et al. 2007; Talbi 2009). The genetic algorithms are by far the most popular methods for tackling spatial multiobjective problems using GIS (e.g., Bennett et al. 1999; Armstrong et al. 2003; Stewart et al. 2004; Aerts et al. 2005; Xiao et al. 2007). Thus, the concept of genetic algorithms is discussed in detail. The chapter also provides an outline of the swarm intelligence meta-heuristics, which have recently been employed for solving complex spatial multiobjective problems. The ant colony and particle swarm optimization procedures are the two best known swarm intelligence meta-heuristics.

6.2 Basic Heuristics

6.2.1 Site Suitability Heuristics

Eastman et al. (1995) proposed a heuristic method for land-use suitability analysis. The method is designed to operate with raster GIS. It has been implemented in the IDRISI Multi-Objective Land Allocation (MOLA) module. The basic principle underlying MOLA is a reclassification of ranked suitability maps with a subsequent conflict resolution between competing land uses (activities) allocated to a parcel of land (raster). The procedure involves three main steps. First, the land use allocation problem is represented in a form of a simple hierarchical structure consisting of four levels: the goal, objectives, attributes, and alternatives (see Sect. 2.2.2.2). Figure 2.1 provides an example of the hierarchical structure of decision problem used in the MOLA procedure. Second, the weighted linear combination (see Sect. 4.2) is performed for each objective (e.g., land use suitability for manufacturing, agricultural, commercial, residential, and recreational activities). Each suitability map contains value ranging from 0 to 1 (in the procedure described by Eastman et al. (1995), the standardized suitability maps contain values ranging from 0 to 255 because they are in the form of an 8-bit integer image). The suitability scores are ranked for each objective. Third, given the areal target (the size of the area allocated to particular land use) and the weight of importance assigned to each objective (activity), an iterative procedure is performed. It involves allocating the best ranked cells to each activity according to the specified areal targets and resolving conflicts based on the weighted minimum-distance-to-ideal point representing hypothetical cell having maximum suitability value for one objective and minimum value(s) for other objective(s).

Eastman et al. (1995) demonstrated the utility of MOLA for resolving conflict between the spatial pattern of land suitability for manufacturing and agricultural activities. In similar application of MOLA, Aguilar-Manjarrez and Ross (1995) analyzed the conflict involved in allocating land for aquaculture and agriculture. Bergena et al. (2005) and Wang et al. (2012) employed MOLA for simulating land cover changes. The MOLA procedure can also be used as an element of participatory GIS for land use management (Kyem 2001, 2004).

One of the main drawbacks of MOLA is that the procedure may not generate the best spatial pattern of land uses according to spatial criteria, such as contiguity and compactness (Brookes 1997a; Church et al. 2003; Ligmann-Zielinska et al. 2008). This shortcoming stimulated research on developing heuristic procedures to take into account both spatial (land use suitability) and spatially explicit criteria for land use allocation and site search problems (see Sect. 6.2.2). Furthermore, Cromley and Hanink (1999) have shown that MOLA is most efficient when the suitability scores for different land uses are inversely correlated. In such a case, one can expect a low level of conflict between competing land uses because it is likely that a cell having a high suitability score for one activity will be characterized by low suitability for the other land use(s). However, it is unlikely that the method will generate a near optimal solution for highly correlated objectives (land suitability values). Cromley and Hanink (1999) argue that the use of heuristics, such as MOLA, for tackling spatial problems is only justified if they result in near optimal solutions and if an efficient exact method cannot be developed. Consequently, they demonstrated that suitability based land use allocation analysis can be operationalized in terms of a generalized assignment problem (see also Çelik and Türk 2011; Türk and Çelik 2013) and solved using exact methods (see Chap. 5). Brookes (1997a) suggested an extension of the MOLA method with a different stopping condition. The method, called the iterative relaxation heuristics, addresses the need for identifying sites that meet an area requirement. However, the approach does not generate sites of a particular size; only ones greater than a specified areal threshold value. Also, it may not generate sites of desirable compactness and shape, and the sites may contain holes.

6.2.2 Site Location Heuristics

To overcome the criticism levelled at the site suitability heuristics, Brookes (1997a) proposed the parameterized region-growing (PRG) heuristic for locating sites with particular spatial characteristics on raster suitability maps. This approach consists of two components: simple region-growing and parameterized shape-growing. The algorithm (the simple region-growing procedure) starts with a seed cell (raster) and then interactively adds neighbouring cell that have the highest suitably score, until the region (site) has grown to the required size. In the case of two or more cells with equal suitability values, the cell closest to the seed location is selected. The procedure has also built-in mechanism for eliminating a call that would create a hole in the growing region. The parameterized shape-growing involves a similar iterative procedure as the simple region-growing algorithm, using a shape-suitability score defined by the direction and distance between two cells. It starts with the most suitable neighbouring cell in terms of the shape suitably score, and interactively add cells based on re-evaluated shape suitability scores of the cells neighbouring the growing region at each step of the procedure. The PRG algorithm computes the overall value of the ith cell, ST_i, as a weighted average of the two scores; that is,

$$ST_i = (w_1 \times SA_i) + (w_2 \times SS_i), \tag{6.1}$$

where SA_i and SS_i are the non-spatial and spatial suitability scores associated with the ith cell, respectively; and w_1 and w_2 are the weights assigned to the non-spatial and spatial suitability criteria, respectively. Thus, the algorithm trades off the types of suitability in the process of searching for a region located near optimal regions.

An alternative to the parameterized region-growing heuristics is the use of the patch growing process (Church et al. 2003). The procedure starts with a seed raster cell, and then sequentially adds contiguous raster cells until a pre-specified area of the patch is achieved. It is an iterative process that involves capturing neighbouring cells to the patch and placing them in a list in a random order. Each cell in the neighbourhood list is examined for the number of edges, e, that it shares with the current patch. The e value ranges from 1 to 4 (based on the edges in cardinal directions). Then, the composite suitability (CS_i) for each cell in the neighbourhood list is calculated as follows:

$$CS_i = SS_i + (N \times e_i), \tag{6.2}$$

where SS_i is the suitability value for the ith cell, e_i is the number of edges that cell i shares with the existing patch, and N is the weight attached to sharing edges with the existing patch. The value of N controls the level of compactness desired in the overall shape of the patch. The CS_i scores are sorted in descending order. Next, the top X percent of the cells in the sorted list is added to the patch.

Figure 6.1 gives a computational example of the CS_i scores. There are ten cells (including seven cells with the identical composite suitability score) that can be included in the patch. Since X = 40 %, the four cells having the highest values of CS_i are selected. Note that the cells selected to be a part of the resulting patch may not contain the highest suitability scores, SS_i. This is because of the random nature in which the cells are listed. The six cells left behind are not added in this iteration of the procedure, but they might be added in future iterations. Also, Fig. 6.1 shows how some cells with lower suitability, SS_i can be added to the patch based on the value of the N multiplier.

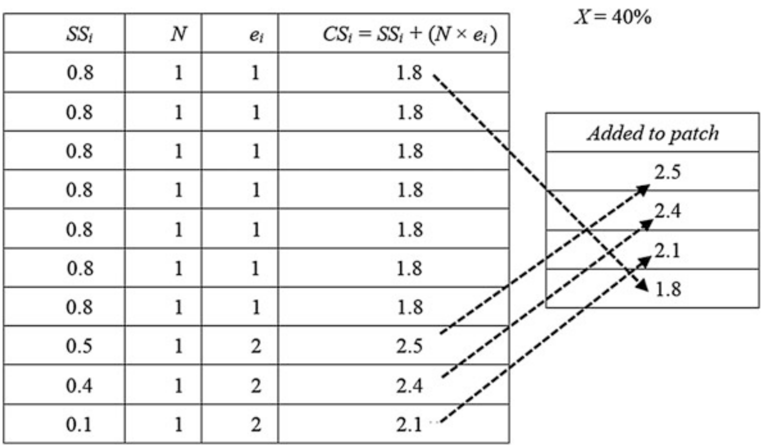

Fig. 6.1 A hypothetical scenario of selecting cells included in the patch by the parameterized region-growing procedure

Vanegas et al. (2011) proposed a modified version of the parameterized region-growing procedure, called heuristic for multiple criteria site location (HMSL) (see also Vanegas et al. 2008). There are three distinctive elements of the HMSAL procedure. The initial step of the procedure identifies a number of seed cells using a quadtree based search approach. All suitability criteria, including the compactness scores, are normalized, and then the region-growing procedure proposed by Church et al. (2003) is applied to each initial seed cell to generate several candidate solutions. Each candidate solution is represented as a binary map, where the cells that have been identified as a part of solution patch are assigned a value of 1; otherwise, the cells contain a value of 0. The overall suitability value, SV_i, is computed according to the following equation:

$$SV_i = w_N \sum_{i=1}^{p} 0.25 g_i + \sum_{i=1}^{p} \sum_{k=1}^{n} w_k v(a_{ik}), \tag{6.3}$$

where w_N is weight border (which is the parameter N in Eq. 6.2); g_i is the number of edges that the ith cell shares with adjacent cells containing a value of 1 (a constant value of 0.25 is used for normalizing the g_i value); w_k is the weight associated with the kth criterion; and $v(a_{ik})$ is the value function (the normalized suitability scores for the ith cell with respect to the kth criterion). Notice that the second component of the SV_i model (Eq. 6.3) is a weighted linear combination for land suitability (see Sect. 4.2). The accumulated composite suitability is calculated for each patch, and the one corresponding with the highest value is chosen as the best.

The three heuristics have been tested using environmental planning/management problems, such as designing nature reserves and wildlife corridors (Brookes 1997a), delineating habitant patches for conservation planning (Church et al. 2003), identifying areas for developing management strategies for rehabilitation and enhancement projects (Healy and Malczewski 2005), and providing support for policy and planning decisions concerning the afforestation of agricultural land (Vanegas et al. 2008). Empirical studies have shown that site location heuristics successfully tackle the problem of generating feasible alternative regions of the required size (Brookes 1997b; Healy and Malczewski 2005; Vanegas et al. 2008). According to Brookes (1997a), the regions generated by the PRG method are characterized by considerably better utility than regions generated by the aspatial heuristics (see Sect. 6.2.1). Furthermore, Church et al. (2003) demonstrated that the PGP method tends to generate more realistic habitat patches as compare to those obtained with the PRG algorithm. Vanegas et al. (2008) compared the quality of solutions generated with the HMSL procedure and mathematical programming algorithms. Their findings suggest that the approaches generate similar solutions, both in the objective outcome and decision (geographic) space (see also Brookes 1997a).

One of the difficulties with the application of the site location heuristics is the requirement to specify a set of parameters. There is some evidence to show that planning practitioners may find it difficult to specify the input parameters (Healy and Malczewski 2005; Vanegas et al. 2011). One way to alleviate some of the problems associated with the parameters is to perform a sensitivity analysis (Vanegas et al. 2011), which can provide valuable information about the site location heuristics. For example, Vanegas et al. (2011) show that the computation time and quality of the results is predominantly affected by the percentage of cells added to the growing patch in each iteration. They suggest a low value of this parameter guarantees high quality solutions. Furthermore, the weighting parameters in the PRG method (see Eq. 6.1) should reflect the trade-off between the spatial and non-spatial criteria. Consequently, the principles for identify a valid set of criterion weights described in Sect. 2.3.2 are applicable here as well.

6.2.3 Greedy Algorithms

The greedy algorithms are examples of constrictive heuristics methods, which are also referred to as successive augmentation algorithms. A greedy method constructs a good feasible solution in stages. The construction process is based on a simple idea of making choices repeatedly to get closer to a good feasible solution. The algorithm uses a heuristic style local search at every stage of its execution, with the intention of finding the global optimum. It starts from scratch (with an empty solution) and constructs a solution by assigning values to one decision variable at a time, until a complete solution is generated. The greedy heuristic needs not find a best solution, but rather terminates in a reasonable number of steps; finding an optimal solution for a real-world problem using this heuristic typically requires unreasonably many steps.

For example, in the travelling salesman problem, a solution can be defined by the set of arcs of a network representing routes that connect nodes (e.g., cites) to be visited by the salesman. The problem is to find the most 'cost' efficient sequence of cities in a given region, stopping once at each and returning to the initial starting location. A greedy strategy for the problem involves identifying an unvisited city nearest to the current city at each step of the procedure. This strategy is referred to as the nearest-neighbour greedy heuristics. Figure 6.2a illustrates the travelling salesman problem for a network consisting of 6 nodes (*A*, *B*, *C*, *D*, *E*, and *F*) and 8 links. A value of multiobjective function $F(\boldsymbol{x})$ is associated with each link (or arc). For instance, the objective function can be a combination of travel cost and time. The sum of values associated with a route is to be minimized. Figure 6.2b shows a solution to the problem using the nearest-neighbour greedy heuristic method; that is, starting with node *A*, at each step of the procedure, an unvisited node nearest to the current city is selected. The solution is {*A*–*D*–*F*–*E*–*B*–*C*–*A*}. It results in the objective function value of 14. However, it is not difficult to see that this is not the best solution. Figure 6.2c shows a better solution {*A*–*B*–*C*–*E*–*F*–*D*–*A*}, with a value of objective function of 12.

There are a few applications that have used greedy algorithms for tackling multiobjective spatial problems in a GIS environment (e.g., Siitonen et al. 2002, 2003; Davis et. al 2003, 2006; Fischer and Church 2005). Siitonen et al. (2003) provide an example of using a GIS-based multiobjective greedy heuristics algorithm for tackling a forest management problem (see also Siitonen et al. 2002). Davis et al. (2003) developed a framework for prioritizing sites (rasters) for land conservation. The framework applies GIS and a greedy heuristic procedure, in which the site that provides the greatest utility per conservation dollar is chosen first, all resources and values are recalculated on the basis of that conservation action, and the procedure is repeated until the budget constraint has been met (see also Fischer and Church 2005;

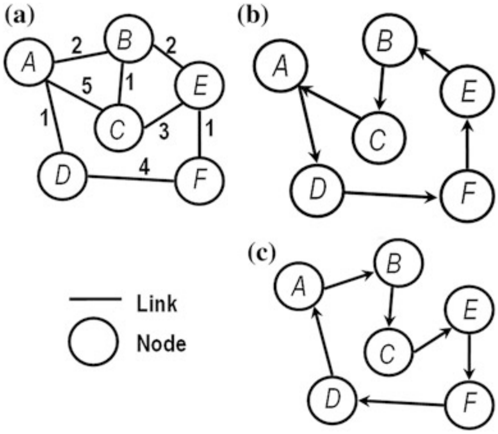

Fig. 6.2 Greedy strategy for the travelling salesmen problem with *A* as the starting node: **a** network consisting of nodes and links (arcs), **b** a solution to the problem using the nearest-neighbour greedy heuristic method, and **c** a better solution to the travelling salesmen problem (*Note* The values of multiobjective function are associated with each link)

Davis et al. 2006). Davis et al. (2003) justified the use of the greedy heuristics on a practical ground, arguing that the procedure fits the way the conservation budgets are often allocated in practice. However, they recognized that other search methods, such as simulated annealing or genetic algorithms (see Sect. 6.3), can be used to generate better solutions (e.g., Possingham et al. 2000; Fischer and Church 2005).

One way of improving the performance of the basic greedy heuristics is to design a greedy procedure with multiple starting solutions. The Greedy Randomized Adaptive Search Procedure (GRASP) is an extension of the simple greedy approach. In the GRASP procedure, the local search is repeated from a number of initial solutions generated by a randomized greedy heuristic. It is an adoptive procedure because the greedy heuristic takes into account the decisions of the precedent iterations (Feo and Resende 1995).

6.2.4 Other Heuristic Methods

There are a few other heuristic methods integrated into GIS to solve spatial multiobjective problems, including the HERO heuristic optimization and Lagrangian relaxation methods. The HERO heuristic optimization procedure has been specifically developed for tackling forest planning and management problems (Pukkala and Kangas 1993). It is a multicriteria iterative procedure that consists of two main phases: (i) generating a set of initial solutions that involves a random selection of a treatment schedule for each stand (a relatively homogeneous forest area for management purposes), and (ii) using a direct ascent method for improving the best initial solution (see Kangas et al. 2001, 2008). The method has been integrated into GIS and applied to solving spatial forest management problems (e.g., Pukkala et al. 1995; Kurttila et al. 2002; Store and Antikainen 2010). The HERO heuristic provides an efficient and effective tool for examining complex spatial problems. One of its main advantages is it integrates multiattribute methods, including additive and multiplicative utility function (see Sects. 2.3.1 and 7.4.1), and AHP (see Sect. 4.3), with the heuristic optimization method to generate solutions to spatial problems using GIS (Kangas et al. 2001, 2008; Store and Antikainen 2010).

The main idea behind the Lagrangian relaxation method is to incorporate some constrains multiplied by Lagrange multipliers into the objective function of an optimization model. The Lagrangian relaxation of the original optimization problem is solved interactively to obtain optimal values of the multipliers. A solution to the relaxed problem is an approximate solution to the original problem (see Eqs.5.1–5.2). The Lagrangian relaxation method has been predominantly applied as an approximation approach for solving single-objective spatial optimization problems. Some of those applications have used the Lagrangian relaxation as a core element of a heuristic procedure. This type of approach is referred to as the Lagrangian relaxation heuristics. There are a few applications of this heuristics for tackling spatial multiobjective optimization problem using GIS as a component of the procedure (e.g., Nozick 2001; Zografos and Androutsopoulos 2008). Nozick (2001) used the method for tackling a facility location problem. Zografos and Androutsopoulos (2008) proposed a new Lagrangian relaxation heuristic algorithm for solving the problem of locating emergency response units.

6.3 Meta-Heuristics

6.3.1 Genetic Algorithms

Evolutionary algorithms are meta-heuristic methods inspired by biological principles of natural selection and survival of the fittest. They operate on a population of individuals (potential solutions) instead of single solutions. In this way, the meta-heuristic search is performed in a parallel manner. By applying the principle of survival of the fittest, the algorithms produce a set of improved solutions at each generation (iteration). Each generation contains a new set of solutions created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators borrowed from natural processes, such as selection, recombination, mutation, and replacement. This process leads to the evolution of populations of individuals that are better suited to their environment (optimization problem) than the individuals that they were created from. The procedure is terminated when some condition is satisfied. This type of procedure, with some modifications, is used by a number of evolutionary meta-heuristics. Specifically, the family of evolutionary algorithms include three main groups of approaches: (i) genetic algorithms, (ii) evolution strategies, and (iii) evolutionary programming methods (Talbi 2009). Other meta-heuristic methods that are considered to be a part of the family of evolutionary algorithms are tabu search and simulated annealing (see Xiao et al. 2007; Talbi 2009). Genetic algorithms have been the most often used meta-heuristics for dealing with multi-objective optimization problems. They are also by far the most popular methods for tackling spatial multiobjective problems using GIS (e.g., Zhou and Civco 1996; Brookes 1997b, 2001; Balling et al. 1999, 2004; Bennett et al. 1999; Armstrong et al. 2003; Stewart et al. 2004; Aerts et al. 2005; Zhang and Armstrong 2008; Cao et al. 2011, 2012; Datta et al. 2012; Jankowski et al. 2014).

The basic feature of genetic algorithms is a multi directional and global search, while maintaining a population of potential solutions from generation to generation. The population based approach is especially useful for exploring the set of Pareto solutions. Figure 6.3 shows a flowchart of genetic procedure (Deb 2001). The procedure begins with defining a multiobjective optimization problem, which typically involves specifying two or more objective functions and a set of constraints (see Eqs. 5.1–5.2). In order to execute a generic algorithm, each potential solution to the optimization problem must be encoded. According to genetic algorithm terminology, a solution vector of decision variables is referred to as a chromosome or an individual. Chromosomes are made of discrete units. These units

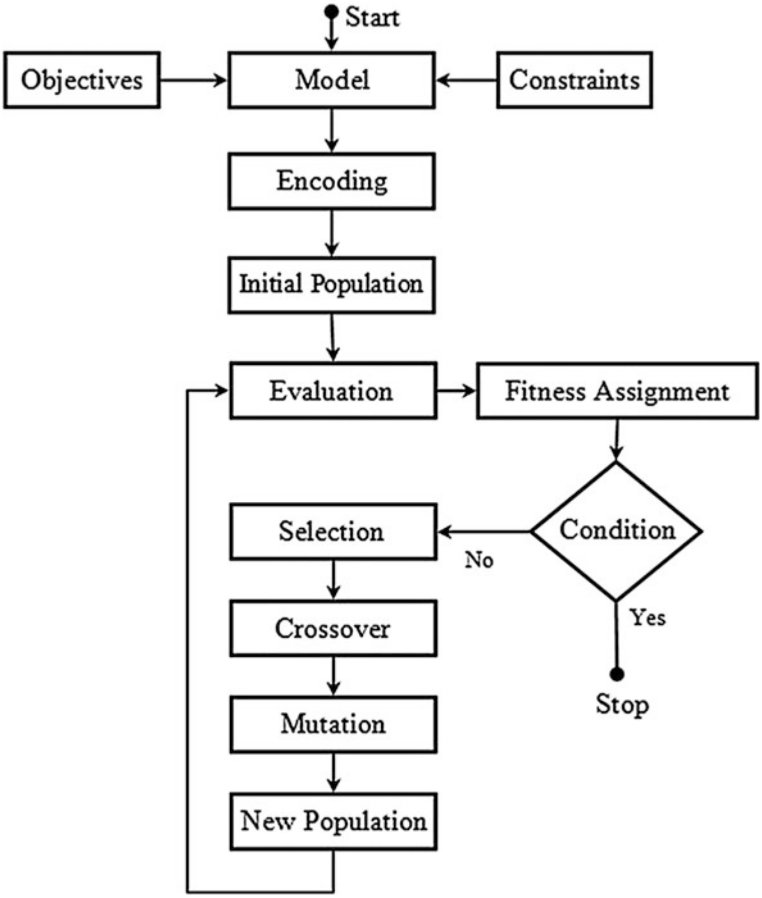

Fig. 6.3 A flowchart of genetic procedure (*Source* Adapted from Deb 2001, p. 83)

are called genes. Each gene controls one or more features of the chromosome. In the basic form of genetic algorithm, genes are defined by binary digits. Normally, a chromosome corresponds to a unique solution in the solution space. This requires a mapping (or encoding) mechanism between the solution space and the chromosomes. In fact, a genetic algorithm works on the encoding of a problem (strings representing the decision variables), not on the problem itself. Once an encoding strategy has been developed, the procedure defines a set of initial chromosomes or solutions. The initial population is created by using a random method. After the initial population is created, the genetic algorithm is executed iteratively. First, the solutions are evaluated using a fitness function. Since the goal of generic algorithm is to maximize the fitness within the population, the function determines a candidate solution's relative fitness, which is subsequently used by the algorithm to guide the evolution of good solutions. If the termination condition is not satisfied, then the population is modified using three genetic operators: selection, crossover, and mutation.

The selection operator chooses the best performing individuals (parents) in each successive iteration. Crossover and mutation operators are applied to these parent chromosomes to produce a pair of offspring solution chromosomes. The crossover is the main operator by which new individuals, with better fitness values, are created for the new generation. Mutation is used to maintain genetic diversity from one generation of solutions to the next. The iterative process is continued until a termination condition is satisfied. The termination condition is often defined as a maximum number of generations (iterations) that has to be completed (e.g., Talbi 2009).

6.3.1.1 Encoding

GIS-based implementations of genetic algorithms typically use one of the following encoding schemes: (i) binary representation (Bennett et al. 1999; Feng and Lin 1999; Lourenço et al. 2001; Li and Yeh 2005; Halfawy et al. 2008; Xiao 2008; Indriasari et al. 2010), (ii) discrete representation (e.g., Balling et al. 1999; Chandramouli et al. 2009; Lowry and Balling 2009; Roberts et al. 2011), and (iii) order- (or permutation) based representation (Xiao et al. 2002; Huang et al. 2006b; Mooney and Winstanley 2006; Fang et al. 2011). The choice of the encoding strategy is problem dependent (Matthews 2001; Xiao et al. 2002; Stewart et al. 2004; Cao et al. 2012). An overview of GIS-based genetic algorithms reveals there are two major groups of encoding strategies, depending on the type of spatial multiobjective optimization problems. First, there is a group of encoding schemes designed for representing land use patterns (e.g., Matthews et al. 1999; Stewart et al. 2004; Cao et al. 2011, 2012). Second, there are methods for representing solutions to network problems, such as shortest path, travelling salesman, vehicle routing, location-allocation, and districting problems (e.g., Gen and Cheng 2000; Hunag et al. 2006a, b; Halfawy et al. 2008; Zäpfel et al. 2010). This classification is by no means exhaustive. Depending on the spatial data models (raster vs. vector data format), similar schemes to represent different land use and network problems can be used. For example, one can apply a binary encoding for representing a land use problem. Each solution (that is, alternative land use pattern or plan) is represented as a string of bits. A decision variable, or a gene, is defined for each parcel of land; that is, the variable determines the land use type to be allocated to a particular parcel. The number of possible land uses defines the length of the gene. For example, if four land uses are considered (e.g., residential, commercial, industrial, and recreational), then a gene of two bits is required to represent all four types of land use; that is, 00, 10, 01, and 11. Accordingly, the length of a bit string representing a potential land use plan for a study area consisting of m parcels of land is $2m$ (see Fig. 6.4a, b). Halfawy et al. (2008) used similar encoding for representing network-based plans.

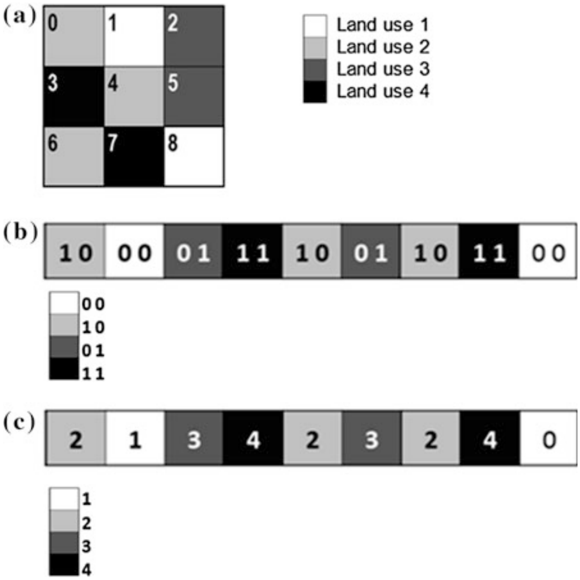

Fig. 6.4 Encoding a potential land use plan: **a** land use pattern (ID = 0, 1, 2, …, 8), **b** binary encoding, and **c** integer encoding

The discrete encoding strategy is often employed in the GIS-based land use applications (e.g., Balling et al. 1999; Chandramouli et al. 2009; Lowry and Balling 2009; Roberts et al. 2011). Figure 6.4c shows an example of discrete encoding of a land use pattern (alternative solution) for a study area consisting of nine parcels of land. Each land-use variable can take on an integer value from 1 to 4. These values correspond to the four land uses. Each chromosome is a numeric code describing the details of a land use pattern (see Lowry and Balling 2009; Roberts et al. 2011).

The differences (and similarities) in encoding schemes for the raster- and vector-data design approaches can be illustrated using a grid-based corridor location problem (Zhang and Armstrong 2008) and a vehicle routing network-based problem (Zäpfel et al. 2010). Figure 6.5 shows an example of a feasible corridor alignment (a chromosome consisting of a string of genes). Each feasible corridor is encoded as a sequence of positive integers (genes), which are represented by the IDs of the nodes (rasters): $ID = 0, 2,\ldots, p$. The IDs define the location of each raster on a grid surface. The cell designated by $ID = 0$ is the top left-hand corner of a grid-cell map, and the cells are numbered left-to right for each row; the cell p is located in the bottom right-hand corner of the raster map. Each feasible decision alternative (corridor) is defined by its origin and destination nodes, and all of the cells through which the corridor passes on the way from the origin to destination (see Zhang and Armstrong 2008). For example, corridors (chromosomes) A and B are encoded by the following string of cells (or genes): (0, 1, 2, 8, 14, 20, 26, 32, 33, 34, 35) and (0, 6, 12, 18, 24, 25, 26, 27, 28, 29, 35), respectively.

In the most general terms, the vehicle routing problem can be defined as follows: given the locations of a depot (and its capacity) and customers (and their demand), the vehicle routing problem involves designing optimal set of routes for a fleet of

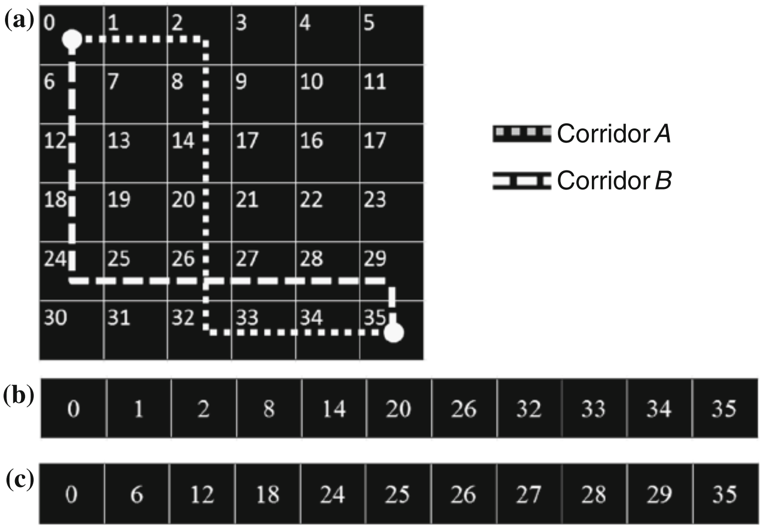

Fig. 6.5 **a** Two alternative corridors (*routes*) between location (*raster*) 0 and location 35 in the geographical space, **b** chromosome representation of corridor *A*, and **c** chromosome representation of corridor *B*

vehicles in order to serve the customers. Each potential route starts and ends in the depot. The alternative solutions (routes) for the vehicle routing problem can be encoded using a permutation-like approach (Zäpfel et al. 2010). Each permutation decodes a unique solution. Figure 6.6 shows a feasible solution for a hypothetical

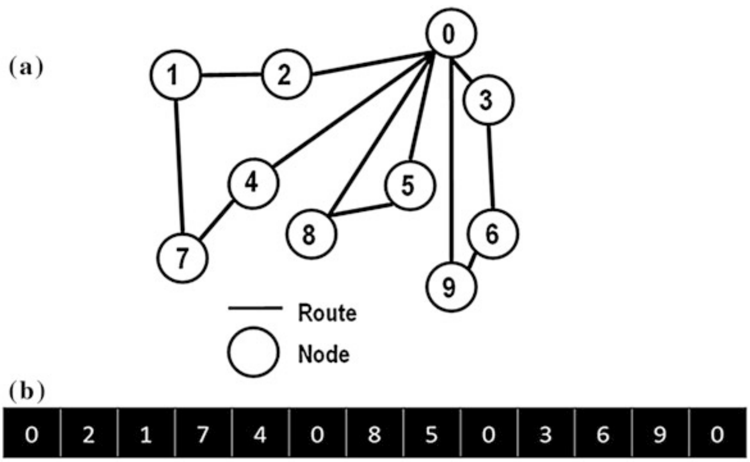

Fig. 6.6 A feasible solution of vehicle routing problem for depot located at node 0: **a** network representation, and **b** chromosome representation

vehicle routing problem on a network of 10 nodes (the depot is represented by node 0, and the customers are located at nodes 1, 2,…9). The permutation encoding of the solution results in the following string of nodes: (0, 2, 1, 7, 4, 0, 8, 5, 0, 3, 6, 9, 0). This encoding scheme indicates that the first vehicle beings its route at the depot (node 0), and then goes to customer 2, 1, 7, 4 and ends its tour at the depot. The second vehicle goes to customer 8 first, and returns to the depot via node 5. The third route includes the depot and three customer nodes in the following order: 0, 3, 6, 9, and 0. These solutions can also be represented equivalently using a set notation: {(0, 2, 1, 7, 4, 0), (0, 8, 5, 0), (0, 3, 6, 9, 0)}.

6.3.1.2 Initialization

The quality of results generated by a genetic algorithm depends on the size of the initial population and the way it is constructed. The main consideration in the process of constructing the initial population is diversification (Talbi 2009). If the population is not well diversified, a premature convergence (a convergence toward a suboptimal result or local optimum) can occur. A number of methods can be employed to construct the initial population including: random generation, sequential diversification, parallel diversification, and heuristics (Talbi 2009). For GIS-based applications of genetic algorithms, the initial population of candidate solutions is usually generated randomly, allowing the entire range of possible solutions in the search space (e.g., Bennett et al. 1999; Mooney and Winstanley 2006; Zhang and Armstrong 2008; Roberts et al. 2011; Wu et al. 2011; Fotakis et al. 2012). The random generation is typically performed using pseudo-random numbers or a quasi-random sequence of numbers (Talbi 2009).

For spatial multiobjective problems, a domain-specific knowledge is often incorporated into the procedures for generating an initial set of alternatives (e.g., Bennett et al. 1999; Mooney and Winstanley 2006; Datta et al. 2012). For example, Datta et al. (2012) suggest that a heuristic method for generating an initial set of solutions for a combinatorial problem is more effective than a random assignment method. They propose a greedy algorithm (see Sect. 6.2.3) for designing initial solutions for a spatial aggregation problem by minimizing the amount of violation of constraints imposed on the size/population of a zone (region). The algorithm works as follows: a zone is first formed with a single randomly selected spatial unit (represented by a node), and then it is expanded to the neighbouring nodes, which have not yet been included in any other zone. The expansion is continued until the maximum size of the zone, or its minimum population, is reached, or each node is assigned to a zone.

Zhang and Armstrong (2008) also found some limitations of the traditional approach for generating a set of initial solutions to corridor selection problems. They have implemented three techniques for generating the initial population: random, heuristic, and seeding the genetic algorithm with results from the Dijkstra's shortest path procedure. The initialization procedure typically starts with an origin and randomly chooses a valid cell based on the connectivity information of the network. The procedure keeps selecting a valid cell that can be connected to the last node of the current route that has not been included in it so far, until a destination is reached. There is, however, empirical evidence to show that the random walk procedure often leads to poor performance (e.g., extremely long chromosomes) when applied to larger datasets. Consequently, Zhang and Armstrong (2008) proposed a heuristic method to tackle the problem associated of random procedure by combining random and biased walk approaches. The biased walk procedure is based on the idea of a 'directionally biased walk'; that is, the direction leading from the origin toward the destination has a higher probability of being selected as the next node. This procedure generates a better initial population of solutions (routes) while maintaining its diversity. Zhang and Armstrong (2008) also suggested the efficiency and effectiveness of the procedures for generating initial population can be improved by introducing a set of seeds systematically generated from Dijkstra's shortest path algorithm. The seeding procedure allows for generating a well-formed Pareto front (a diverse population) in a reasonable amount of time.

The size of the initial population is an important consideration. If the population is too small, the algorithm has a few possibilities to perform crossover and only a small part of search space is explored. On the other hand, if there are too many potential solutions, the algorithm can be inefficient. An overview of GIS-based genetic algorithm implementations suggests that in many applications, the size of initial population was fixed at 100 (e.g., Balling et al. 1999; Makropoulos and Butler 2005; Ducheyne et al. 2006; Chandramouli, et al. 2009; Lowry and Balling 2009; Wu et al. 2011; Cao et al. 2012). A population of 50 solutions was used by Lanta et al. (2005), Zeng et al. (2007), and Indriasari et al. (2010). Some applications employed procedures involving several hundred solutions; for example, the population size was equal to 200 and 500 in studies by Roberts et al. (2011) and Saadatseresht et al. (2009), respectively. In general, the population size depends on the nature of the problem. For example, Matthews (2001) determined the population size as a function of the number of objectives and the niche-size (which defines the average expected spacing of solutions in the final population). The population size increases along with the increasing number of objectives and decreasing niche-size. For a bi-objective optimization problem and a niche-size of 0.25, 0.1, and 0.025, the population size is 9, 21, and 81, respectively; for a problem involving four objective functions and a niche-size of 0.25, 0.1, and 0.025, the population size is 369, 4,641, and 265,761, respectively (see Matthews 2001).

6.3.1.3 Evaluation and Fitness Assignment

One of the critical issues associated with applying a genetic algorithm to multi-objective optimization problems is the question of determining the solution's fitness value. The aim of this procedure is to assign a fitness value to measure the quality of each solution. In general, the techniques for fitness assignment are based on the concepts and methods of the conventional multiobjective optimization procedures (see Chap. 5). Accordingly, they can be classified into the following categories:

(i) weighted-sum (value function) approaches, (ii) the metric-based approaches, and (iii) Pareto-based (or dominance-based) approaches (see Gen and Cheng 2000).

The weighted-sum approach transforms the multicriteria decision problem into a single criterion one. All the principles outlined with respect to the discrete and continuous weighting methods are applicable here, as well (see Sects. 4.2 and 5.2). These approaches have been used in the GIS-based genetic procedures by Li and Yeh (2005), Makropoulos and Butler (2005), and Mooney and Winstanley (2006). Like the weighted-sum methods, the metric-based converts multicriteria decision problems into a single criterion fitness value. These approaches include compromise programming, goal programming, and reference point methods (see Chaps. 4 and 5). Bennett et al. (1999) employed the ideal-point method (see Sect. 4.4) to identify the fitness value of solutions in their GIS-based implementation of genetic algorithm for tackling land use problem involving multiple decision making agents. A reference point method has been implemented in land use analysis by Stewart et al. (2004), Aerts et al. (2005), and Janssen et al. (2008).

The Pareto-based approaches are the most often used in GIS-based multiobjective genetic algorithm applications (e.g., Balling et al. 1999; Ducheyne et al. 2006; Lowry and Balling 2009; Roberts et al. 2011; Datta et al. 2012). The underlying designing principle of these methods is that the procedure should guide the search toward the Pareto front. This is illustrated in Fig. 6.7, which shows patterns of non-dominated alternatives in the objective space for a problem involving two objective functions (see Balling et al. 1999). Figure 6.7a, b show the pattern at the beginning and end of the genetic procedure, respectively. The starting generation is characterized by a fairly random pattern. The fitness assignment mechanism should guide the genetic procedure toward a well-formed pattern of solutions, shown in Fig. 6.7b. Note that the number of non-dominated solutions

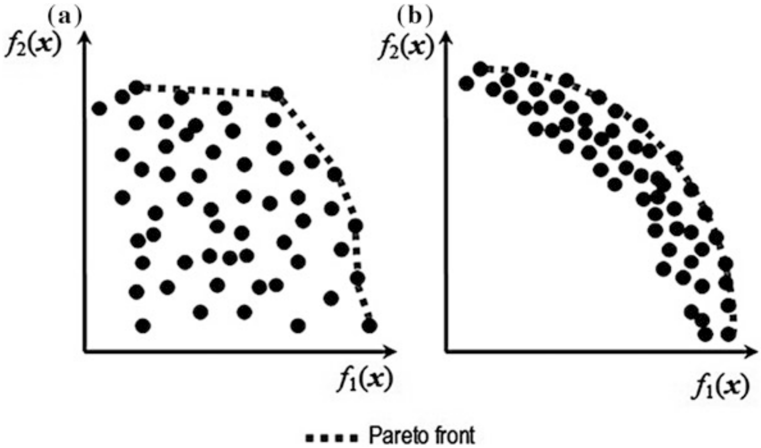

Fig. 6.7 Distribution of alternative solutions to a hypothetical bi-objective problem: **a** starting generation, and **b** final generation (*Note* the objective functions $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$ are maximized)

(the Pareto-front) increases from six in the starting generation to 14 in the final generation.

Ranking methods are often applied to identify relative fitness of solutions. The Pareto-based ranking procedures include: dominance rank, dominance depth, and dominance count fitness assignment (Talbi 2009). Figure 6.8 illustrates the three methods for fitness assignment. In the dominance rank, the fitness value of a given solution is the number of individuals in the population that dominates that solution. Matthews (2001) provides an overview of the ranking methods in the context of multiobjective land use planning.

In the dominance depth method, the set of solutions is subdivided into several groups (or fronts). The Pareto-optimal solutions are assigned rank 1; they form the first front, ϕ_1. The solutions that are only dominated by ϕ_1 solutions are assigned rank 2; they form the second front, ϕ_2. The solutions that are dominated by the solutions of ϕ_1 and ϕ_2 are assigned rank 3; they form the third front, ϕ_3; and so forth. This fitness assignment strategy has been employed in the GIS-based implementations of genetic algorithms including Armstrong et al. (2003), Kim et al. (2008), and

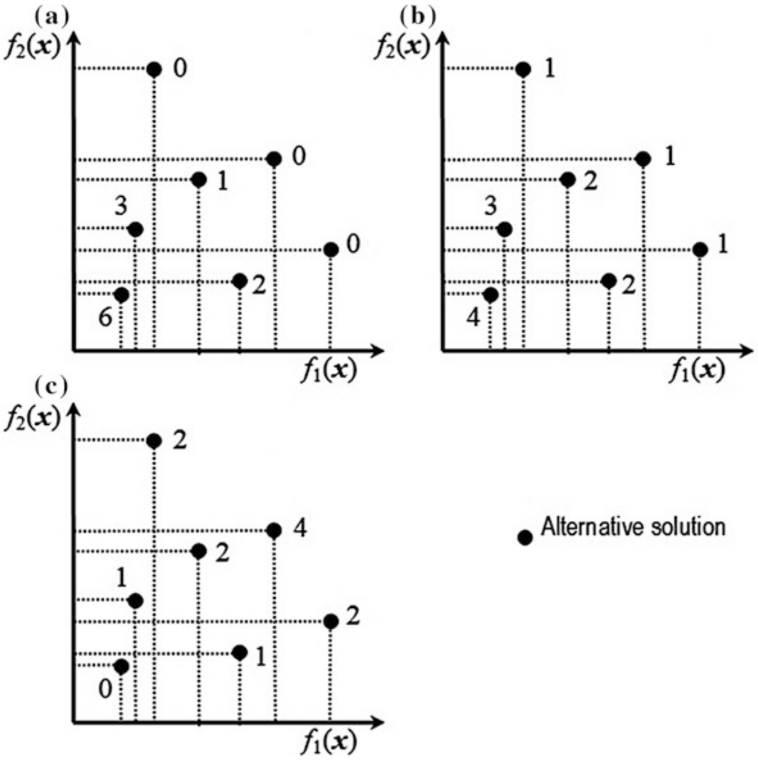

Fig. 6.8 Fitness assignment methods: **a** dominance rank, **b** dominance depth, and **c** dominance count (*Note* the objective functions $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$ are maximized)

Datta et al. (2012). The dominance depth method is a part of the NSGA-II algorithm (see Sect. 6.3.1.8).

The dominance count fitness assignment identifies the number of solutions that are dominated by a given individual in the population. Matthews et al. (2000) used this approach in their implementation of a genetic algorithm as a component of Land Allocation Decision Support System (see also Matthews 2001). The dominance count fitness value can be used in combination with other measures. For example, in the family of SPEA (Strength Pareto Evolutionary Algorithm) procedures, the dominance count can be employed in combination with the dominance rank. Lanta et al. (2005) provide an example of GIS-based application of the SPEA algorithm (see also Matthews 2001).

6.3.1.4 Selection

The selection operator employs the survival-of-the-fittest principle to choose "high-quality" individuals (solutions) from the current population. At each successive generation, the existing solutions are selected based on their fitness; the higher the fitness of the individual, the higher the probability of it being selected into a mating pool (temporary population). The selection procedures can be grouped into two categories: (i) fitness proportionate selection, such as roulette-wheel selection, and (ii) rank-based selection, such as tournament selection methods (see Talbi 2009). Zhang and Armstrong (2008) provide examples of the roulette-wheel and tournament selection methods in their implementation of the multiobjective genetic algorithm for tackling corridor location problems.

In the roulette-wheel selection, each individual in the current population is assigned a roulette-wheel slot size in proportion to its fitness. This implies that a chromosome is selected from the population with a probability proportional to its fitness. The roulette-wheel is spun to obtain a reproduction candidate. One of the disadvantages of this method is that it could reduce the search space if there are outliers (individuals with exceptionally higher fitness values) in the population (Porta et al. 2013). Furthermore, if the interval of fitness function values of the solutions is relatively small, then each solution would have a nearly equal chance to be selected. To address this limitation, an alternative method, such as the tournament selection approach, can be used.

The tournament selection method involves a random selection of s individuals for a tournament against each other. The fittest individual in the group of k chromosomes wins the tournament and is selected as the parent for the next generation. Using this scheme, n tournaments are required to select n individuals. A tournament selection procedure was applied in Makropoulos and Butler (2005), Mooney and Winstanley (2006), Indriasari et al. (2010), and Datta et al. (2012). For example, the crowded tournament selection operator (Deb 2001) was used in the procedure for designing optimal census areas by Datta et al. (2012). This operator compares two randomly selected solutions, i and j (each solution consists of a group of areal units) at a time, and stores the 'winning' solution i in a temporary population. The ith solution is declared a winner if it ranks higher than j, or if it has a better crowding distance in the case when two solutions are characterized by the same rank (see Sect. 6.3.1.8).

6.3.1.5 Crossover

Given the mating pool of solutions, individuals are recombined (or crossover) to make new offspring. The main aim of crossover operators is to exploit the existing (best) solutions. The operators typically involve two individuals recombined with a crossover probability, p_c. Specifically, a uniform random number, r, is first generated, and then for $r \leq p_c$, the two randomly selected parents are recombined to generated two offspring; otherwise, the offspring are exact copies of their parents. There are a number of crossover methods available for implementing into GIS-based genetic procedures (e.g., Sastry et al. 2005; Xiao 2008). Some of these methods are generic (problem independent) and some of them are specifically design for spatial problems. The most often used generic crossover methods include: one-point, two-point, and uniform crossover operators (Sastry et al. 2005). A crossover operator that randomly selects a crossover point within a chromosome, and then interchanges the two parent chromosomes at that point to produce two new offspring is referred to as the one-point crossover method. Figure 6.9a illustrates this method with the recombining of two vehicle routing patterns (see Sect. 6.3.1.1, Fig. 6.6). The two-point crossover operator selects two points randomly and then

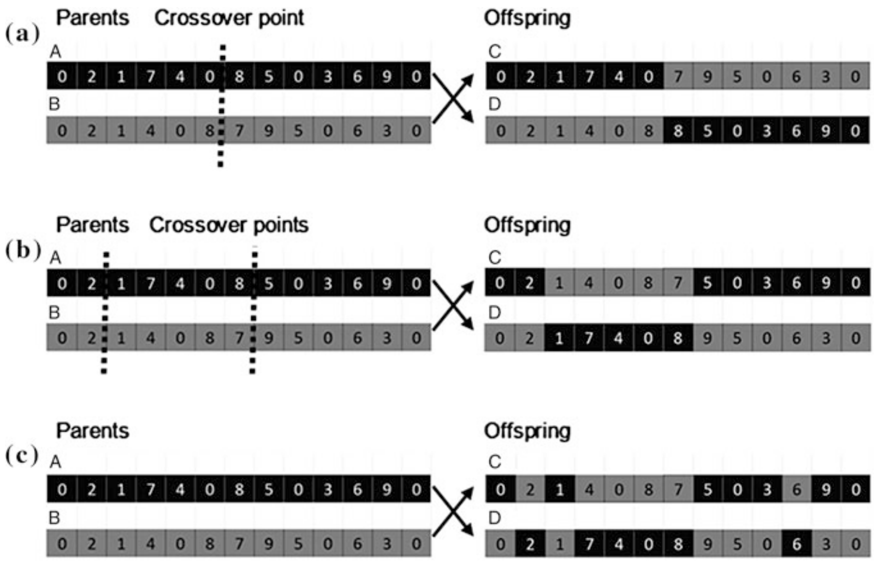

Fig. 6.9 Crossover methods for vehicle routing patterns (see Fig. 6.6): **a** one-point crossover, **b** two-point crossover, and **c** uniform crossover

the elements outside the selected points are inherited from one part of the offspring, and the other elements are placed in the other parent (see Fig. 6.9b). Uniform crossover evaluates each gene in the parent's chromosomes for exchange with some probability defined by the mixing ratio (or the swapping probability). Typically, the probability of 0.5 is used. Specifically, a value of the A parent's gene is assigned to the C offspring and the value of the B parent's gene is allocated to the D offspring with the probability of 0.5. Unlike the one- and two-point operators, this method allows the parent chromosomes to be mixed at the gene level, rather than the segment level (see Fig. 6.9c).

The three methods are of limited applicability to spatial problems with permutation codes, such as the routing and traveling salesman problems. They cannot guarantee feasibility of the offspring. This can be demonstrated by an inspection of offspring generated by the one-point method. The solutions are infeasible because they do not meet the constraint of visiting every location only once (in offspring C and D, locations 7 and 8 are visited twice, respectively). Figure 6.9b, c show that the two-point and uniform crossover methods generate feasible offspring. However, the probability of obtaining a feasible solution is very low. There are methods for addressing this type of problem, including the greedy crossover procedures (see Xiao et al. 2007; Zäpfel et al. 2010). These methods are typically some modifications of the conventional approaches. The modified procedures ensure that only feasible solutions are encoded, and only feasible solutions may result from crossover operators (Xiao et al. 2007). The *p*-median location-allocation analysis provides an example of a spatial problem that has been tackled using genetic algorithms with traditional single- or multi-point crossover mechanisms modified to ensure that the results of a recombination yield a feasible solution (e.g., Dibble and Densham 1993; Bennett et al. 2004).

The one-dimensional representation crossover can also be used as a recombination procedure in GIS-based land use analysis (Balling et al. 1999; Matthews et al. 1999, 2000). For example, Balling et al. (1999) demonstrate the one-point crossover method for recombining land use plans. Given that each plan is represented as a string of 155 genes, an integer between 1 and 155 is randomly selected to serve as a crossover point. Each of the two parent's chromosome is cut at the crossover point and then the portions of the chromosomes following the crossover point are swapped to generate two new chromosomes (offspring) (see also Bennett et al. 2004; Lowry and Balling 2009). Porta et al. (2013) provide an example of two-point crossover procedure for land use planning problems. The procedure randomly selects two crossover points and then swaps the genes of both parents between those two positions (see also Matthews 2001). Matthews (2001) discusses the uniform crossover operator, which can be implemented using a crossover mask, with the crossover proportion set to 0.5. This value means that the offspring contain, on average, equal proportions of genes from each parent, maximizing the operator's exploratory power (see also Matthews et al. 1999).

It can be argued, however, that conventional one-dimensional representation approaches are of limited applicability for tackling spatial problems in general, and land use problems in particular (Bennett et al. 1999; Stewart et al. 2004). Spatial problems require that the traditional linear data structure for genetic operations be extended to a two-dimensional representation of space (Bennett et al. 1999). A number of procedures for two-dimensional representation have been proposed (Bennett et al. 1999; Matthews 2001; Stewart et al. 2004; Cao et al. 2011, 2012). Figure 6.10 gives an example of a spatially explicit two-point crossover procedure. It involves a random selection of two locations and shape of the crossover patches. These are used to recombine two parent solutions (land use patterns, *A* and *B*). The offspring *C* and *D* inherit the land use structure in the patches of parent *B* and *A*, respectively. Although a vast majority of crossover procedures for genetic algorithms involve a two-parent recombination, a single-parent crossover procedure has been proposed by Cao et al. (2012).

6.3.1.6 Mutation

Mutation procedures operate on a single solution (offspring). It aims at diversifying the search (that is, maintaining genetic diversity from one generation to the next) and preventing premature convergence of the genetic algorithm (that is, preventing

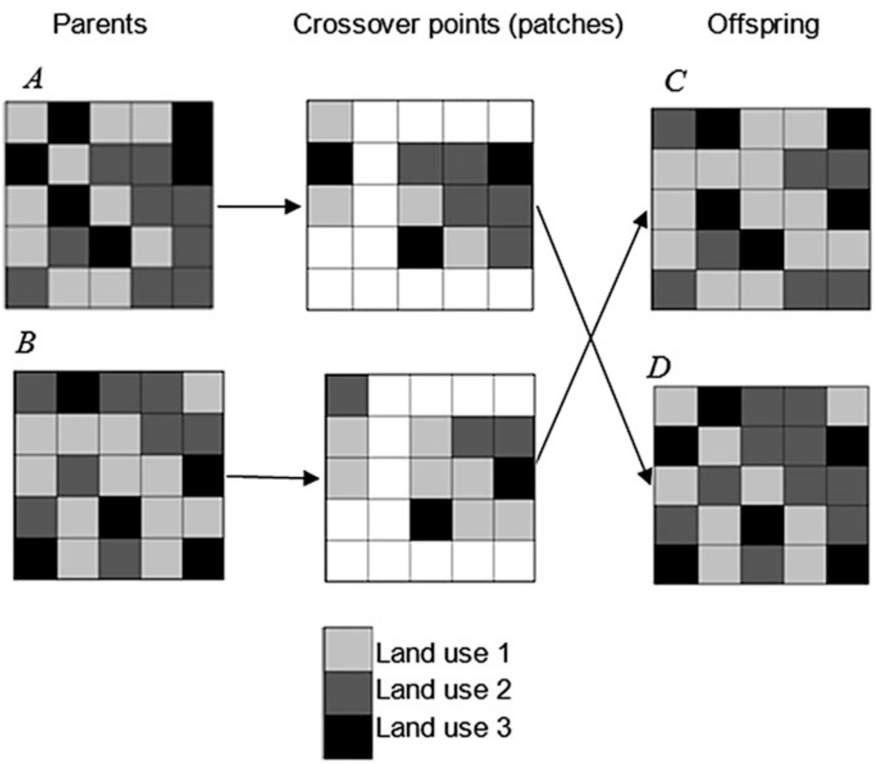

Fig. 6.10 Spatially explicit two-point crossover procedure

all solutions in a population to fall into a local optimum). This is accomplished by exploring those parts of a solution space that have not been represented in current solutions, and by altering one or more gene values of individuals in the current generation to create new solutions. The operator is performed according to a given mutation probability, p_m. In general, it is recommended that $0.001 < p_m < 0.01$ (Talbi 2009). The mutation probability is an important parameter of genetic algorithms, as its value influences the quality of solutions generated by the mutation operators. There is some evidence to show that the smaller the value, the better the solution. An empirical study of land use planning suggests that mutation procedures with a high value of p_m results in poor solutions (Porta et al. 2013). This is due to the presence of too many changes in individuals' genes, which make the mutation behaviour almost random. Porta et al. (2013) also demonstrated that for a low value of $p_m = 1/L = 0.000013174$ (where L is the individual size), the algorithm generates the best solutions.

Similar to the crossover operations, mutation depends on the encoding. Accordingly, three types of mutation procedures can be identified: (i) mutation in binary representation can be performed by swapping a few randomly selected bits from 1 to 0 or from 0 to 1; (ii) mutation in discrete representation involves changing the value associated with an element by another value; and (iii) mutation in permutations is performed by the swapping, inversion or, insertion operators (Talbi 2009).

Feng and Lin (1999) and Xiao (2008) demonstrate the use of the binary representation based mutation operator. Feng and Lin (1999) employ the following procedure: a random number ranging between 0 and 1 is generated first, and then if the random number $< p_m = 0.01$, then the gene changes its value from 0 to 1 or from 1 to 0. Xiao (2008) uses the single-point mutation. The procedure involves selecting a mutation element at random and then the binary digit of that element is changed from 1 to 0 or 0 to 1 with a probability of p_m. Lowry and Balling (2009) and Roberts et al. (2011) provide examples of the mutation procedure involving a discrete representation. For instance, Lowry and Balling (2009) use $p_m = 0.01$ for integrated land use plans. This implies that 1 % of the genes of an offspring solution (land use patterns) are randomly changed to a new value.

The simplest mutation operator involving permutation-based solutions can be performed by swapping two randomly selected adjacent nodes in a single solution (route or path) (see Fig. 6.6). The adjacency of nodes can be defined in the decision (geographic) space or the objective space. For example, given the routing patterns shown in Fig. 6.11 (offspring C), randomly selected nodes 8 and 7 can be exchanged to generate a new routing pattern, E. This simple approach does not guarantee the feasibility of solutions, unless it is modified in such a way that only feasible solutions are processed with the mutation procedure. There is a number of more advanced mutation procedures for spatial multiobjective problems involving the permutation encoded solutions. For example, Xiao et al. (2002), and Mooney and Winstanley (2006) developed mutation procedures specifically designed to deal with the problem of infeasible solutions in the graph-based site selection and shortest path problems.

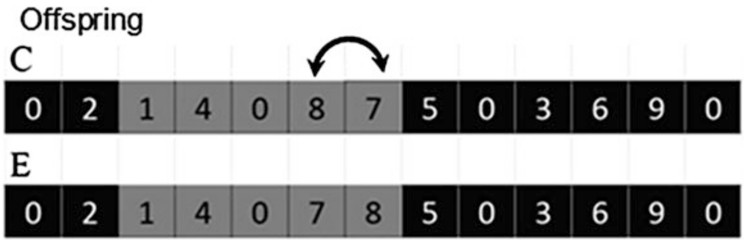

Fig. 6.11 Mutation: swapping two randomly selected nodes (see Figs. 6.6 and 6.9b)

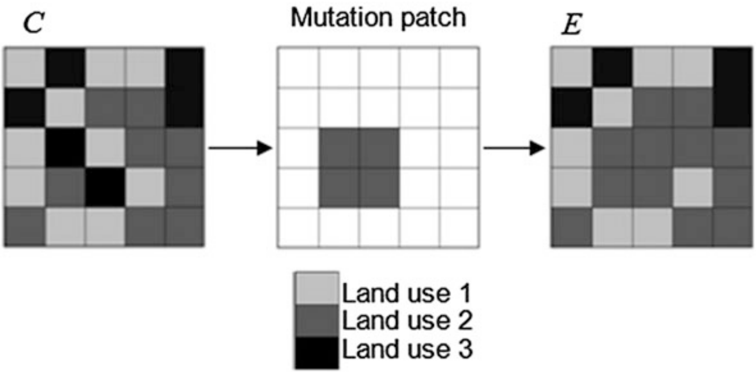

Fig. 6.12 Spatially explicit mutation for land use pattern (see Fig. 6.10)

Figure 6.12 shows an example of a spatially explicit mutation operator for a hypothetical grid-based land use pattern. The procedure defines the location and shape a mutation patch (window) at random. The new solution, *E*, is then generated by deleting the patch in the offspring solution, *C*, and replacing it with randomly selected land use(s). Matthews (2001), Stewart et al. (2004), and Cao et al. (2011, 2012) provide detail discussions of this type of mutation operators and their real-world applications.

6.3.1.7 New Population

Once the new offspring solutions are created with the crossover and mutation operators, they need to be introduced into the population. There are a number of replacement strategies that can be used to create a new population (Matthews 2001; Sastry et al. 2005). One strategy is the delete-all approach, where the parent population is eliminated and replaced by the offspring population. Another is the steady-state strategy, where a portion of parent solutions is deleted and replaced by the offspring individuals. Deb (2001) noted that the elitism strategy, which is concerned with preserving and using of elite solutions (e.g., Pareto optimal solutions), enhances the performance of multiobjective genetic algorithms (see also Matthews 2001). Most of the elitist strategies make use of a secondary population (or archive), in which a certain number of Pareto optimal solution can be stored. Several GIS-based multiobjective studies use elitism as a part of the generic algorithm implementation (e.g., Mooney and Winstanley 2006; Lowry and Balling 2009; Cao et al. 2012). The concept of elitism is an element of the NSGA-II procedure (see Sect. 6.3.1.8).

6.3.1.8 Non-dominated Sorting Genetic Algorithm II (NSGA-II)

Many variants of the multiobjective genetic algorithm have been suggested, with different schemes for chromosome representation, fitness function, selection, crossover, and mutation. One of the most popular genetic procedures is the Non-dominated Sorting Genetic Algorithm II (NSGA-II), developed by Deb and associates (Deb 2001). It is also the most often used procedure in GIS-based applications of genetic algorithms (e.g., Makropoulos and Butler 2005; Ducheyne et al. 2006; Maringanti et al. 2009; Saadatseresht et al. 2009; Cao et al. 2011; Datta et al. 2012; Fotakis et al. 2012; Jankowski et al. 2014).

The NSGA-II procedure involves two main stages: (i) the parent and offspring populations, P_t and O_t are combined and then sorted using the non-dominated sorting method (see Sect. 6.3.1.3; Fig. 6.8b), and (ii) the Pareto-fronts are identified and then the individuals are sorted according to the crowding distance method to identify the best individuals to be included in the new population P_{t+1} in such a way

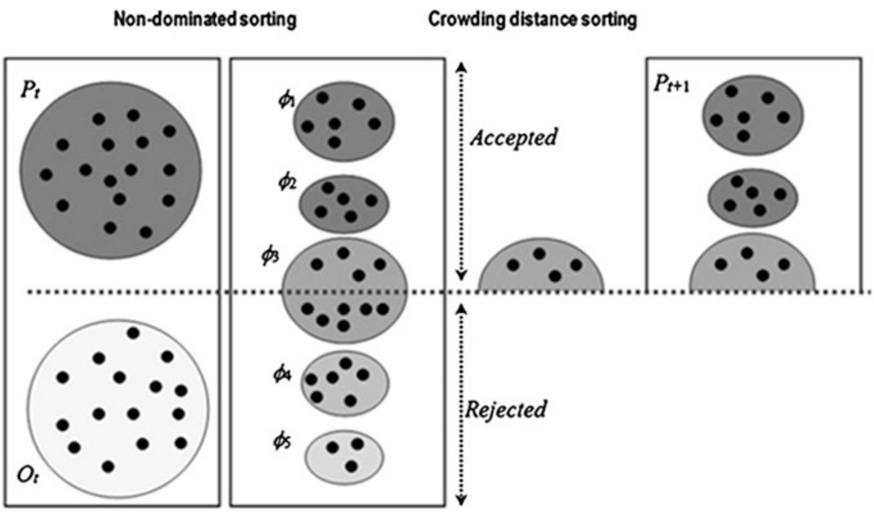

Fig. 6.13 The NSGA-II procedure (*Note* P_t parent population; O_t offspring population; P_{t+1} new parent population; ϕ* Pareto-front)

that the sizes of P_t is equal the number of individuals in P_{t+1}. Figure 6.13 illustrates this process. The parent, P_t, and offspring, O_t, populations include 15 individuals each. The individuals are then combined to form a population of 30 solutions. Five Pareto-fronts are identified in the combined population; the fronts are sorted by the non-dominated method. Next, the number of individuals in the combined population must be reduced to the size of P_t; that is, the new population must include the top 15 individuals. First, all the solutions of the first two Pareto-front, ϕ_1 and ϕ_2, are included into P_{t+1}. The sizes of ϕ_1 and ϕ_2 are 6 and 5; thus, to create the new population of 15 individuals, four solutions from the set of ϕ_3 must be included. Crowding distance sorting is used to rank the individuals forming ϕ_3 and then the top 4 ranking individuals are included into the new population, P_{t+1}.

The NSGA-II procedure considers individuals with a higher value of crowding distance a better solution because they introduce more diversity into the population. Figure 6.14b illustrates the concept of the crowding distance method. According to Deb (2001), crowding distance is an estimate of the density of solutions in the vicinity of solution i in the objective space, calculated as half of the perimeter of the enclosing cuboid (Fig. 6.14b; see also Makropoulos and Butler 2005; Kim et al. 2008; Roberts et al. 2011; Cao et al. 2011). Technically, it is an estimate of the size of the largest cuboid enclosing i without including any other point in the population (see Cao et al. 2011). For a bi-objective problem, the crowding distance of the ith individual is calculated as follows:

$$i_{dis} = \frac{f_1(x)_{i+1} - f_1(x)_{i-1}}{\max f_1(x) - \min f_1(x)} + \frac{f_2(x)_{i-1} - f_2(x)_{i+1}}{\max f_2(x) - \min f_2(x)} \tag{6.4}$$

The two ranking methods are used in the NSGA-II replacement procedure. Specifically, the old population and set of offspring solutions are combined and ranked according to non-dominance and crowding distance. The individuals that perform about average in the combined population form the new generation.

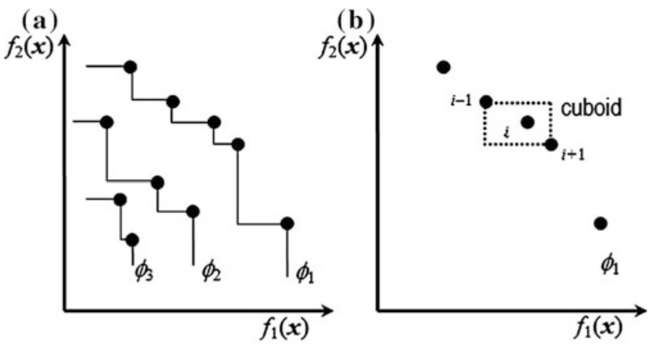

Fig. 6.14 The NSGA-II ranking methods: **a** dominance-depth ranking; ϕ_1, ϕ_2, and ϕ_3 = Pareto-front 1, 2, and 3 respectively, **b** crowding distance ranking for the Pareto front, ϕ_1, consisting of five non-dominated solutions

Table 6.1 The values of two objective functions $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$ for (a) parent population, P_t, and (b) offspring population, O_t

Solution	$f_1(\boldsymbol{x})$	$f_2(\boldsymbol{x})$
(a)		
1	0.50	1.00
2	0.20	0.75
3	0.80	0.40
4	0.10	0.40
5	1.00	0.50
6	0.10	0.85
7	0.25	0.10
(b)		
A	0.80	0.90
B	0.25	0.60
C	0.90	0.60
D	0.90	0.30
E	0.35	0.90
F	0.60	0.15
G	0.65	0.60

The NSGA-II procedure is illustrated using a bi-objective problem. Table 6.1 shows the standardized values of two objective functions, $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$, for parent and offspring populations of seven individuals. First, the two populations are combined and then a non-dominated sorting procedure is performed. Four Pareto-fronts are obtained: $\phi_1 = \{1, A, C, 5\}$, $\phi_2 = \{E, G, 3, D\}$, $\phi_3 = \{6, 2, B, F\}$, and $\phi_4 = \{4, 7\}$ (see Fig. 6.15 and Table 6.2).

To create a new population of seven individuals, one has to consider only the first two fronts: ϕ_1 and ϕ_2; that is, the new population, P_{t+1}, should include four

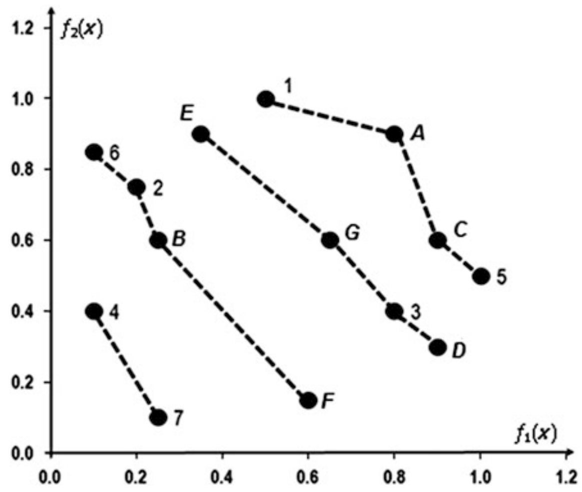

Fig. 6.15 Pareto fronts for bi-objective problem (*Note* the objective functions, $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$, are maximized)

Table 6.2 The parent/offspring population sorted according to the Pareto-fronts

Solution	$f_1(\boldsymbol{x})$	$f_2(\boldsymbol{x})$	Pareto front #
1	0.50	1.00	1
2	0.20	0.75	3
3	0.80	0.40	2
4	0.10	0.40	4
5	1.00	0.50	1
6	0.10	0.85	3
7	0.25	0.10	4
A	0.80	0.90	1
B	0.25	0.60	3
C	0.90	0.60	1
D	0.90	0.30	2
E	0.35	0.90	2
F	0.60	0.15	3
G	0.65	0.60	2

individuals of ϕ_1 and three best solutions of ϕ_2. Since the combined set of ϕ_1 and ϕ_2 consist of eight individuals, we need to identify three best solutions of ϕ_2 using the crowding distance procedure. By definition, the value of crowding distance for the boundary solutions, *E* and *D*, is equal to infinity (Fig. 6.15). The crowding distance for the solutions, *G* and *3*, are calculated according to Eq. 6.4. Given the objective functions, $f_1(\boldsymbol{x})$ and $f_2(\boldsymbol{x})$, are standardized, their minimum and maximum values are 0 and 1, respectively. Then, the value of crowding distance for individual *G* is calculated as follows:

$$G_{dis} = \frac{0.8 - 0.4}{1 - 0} + \frac{0.9 - 0.35}{1 - 0} = 0.95 \tag{6.5}$$

The value of crowding distance for alternative 3 is calculated in a similar way using Eq. 6.4. Given the results (Table 6.3), the individuals of ϕ_2 are sorted according to the descending order of the crowding distance as follows: {*D*, *E*, *G*, *3*}. The first three solutions are selected and included into the new population. Thus, the

Table 6.3 The values of crowding distance for the offspring population O_t

Solution	$f_1(\boldsymbol{x})$	$f_2(\boldsymbol{x})$	Pareto front #	Distance
1	0.50	1.00	1	∞
5	1.00	0.50	1	∞
A	0.80	0.90	1	0.80
C	0.90	0.60	1	0.60
3	0.80	0.40	2	0.55
D	0.90	0.30	2	∞
E	0.35	0.90	2	∞
G	0.65	0.60	2	0.95

population P_{t+1} = {*1*, *5*, *A*, *C*, *D*, *E*, *G*}. This set of solutions is then used for generating a new set of offspring individuals, O_{t+1}. For example, let us consider a set of pairs selected in such a way that each individual is listed twice: (*1*, *A*), (*1*, *G*), (*5*, *C*), (*5*, *A*), (*E*, *G*), (*D*, *E*), (*D*, *C*). Next, a binary tournament procedure (see Sect. 6.3.1.4) is performed to identify the offspring population. An individual *i* is a better solution than *j*, if it ranks higher than *j* in terms of non-dominance. If the non-dominance rankings are the same, then the individual with largest crowding distance is selected.

Table 6.4 shows the results of selecting the offspring population. For example, the alternatives *1* and *A* are equally good with respect to the non-dominance ranking (they rank 1); however, solution *1* is declared the winner because it is characterized by larger value of crowding distance than *A*. Given the tournament results, the new set of offspring solutions includes: {*1*, *1*, *5*, *5*, *E*, *A*, *C*}. These solutions can be recombined and mutated to complete one generation of the NSGA-II procedure.

Cao et al. (2011) have proposed a spatial NSGA-II for multi-objective optimization of land use (or NSGA-II-MOLU). This method modifies the conventional NSGA-II by introducing spatial components into the crossover and mutation operators. The crossover operators typically involve a recombination of two parent chromosomes. Cao et al. (2011) suggest that single parent crossover operators provide a more effective approach for land use analysis. Figure 6.16 illustrates the concept of single parent crossover. First, the size of the crossover window is selected, and then a continuous set of cells (patch) is randomly selected; for example, in a 3 by 3 cell window, seven cells are randomly selected to form a patch (see Fig. 6.16a). Second, two locations for the patches are chosen at random within the study area (see Fig. 6.16b). Third, the land use patterns of the two patches are swapped to create an offspring solution (see Fig. 6.16c).

Figure 6.17 shows an example of the mutation approach for NSGA-II-MOLU suggested by Cao et al. (2011). First, the size of the mutation window is selected; then, the shape of the patch with some probability is chosen and one land use type as the mutation direction is identified at random (see Fig. 6.17a). Second, a location for the patch is selected at random (see Fig. 6.17b). Third, if the same land use types

Table 6.4 Selecting the offspring population using a tournament procedure

Pair of solutions	Pareto front #	Crowding distance	Tournament: winning solution
1, *A*	1 and 1	∞ and 0.80	*1*
1, *G*	1 and 2	∞ and 0.95	*1*
5, *C*	1 and 1	∞ and 0.60	*5*
5, *E*	1 and 2	∞ and ∞	*5*
E, *G*	2 and 2	∞ and 0.95	*E*
D, *A*	2 and 1	∞ and 0.80	*A*
D, *C*	2 and 1	∞ and 0.60	*C*

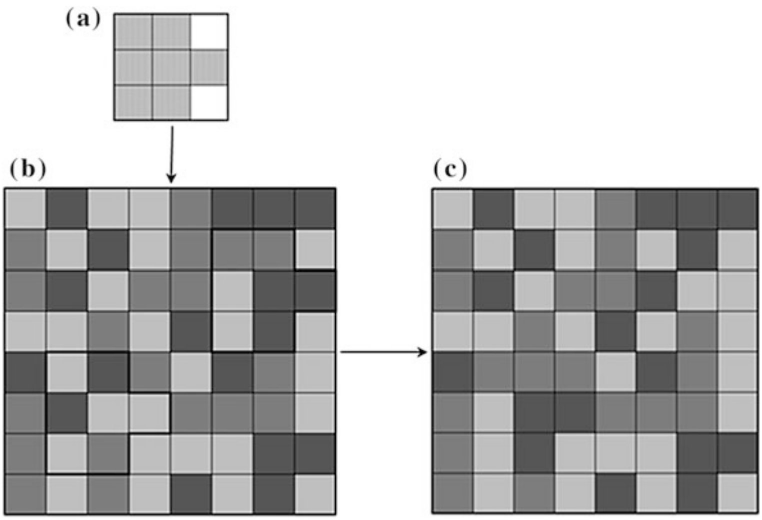

Fig. 6.16 Single parent crossover operator for land use pattern: **a** crossover window (patch), **b** locations of crossover patches, and **c** swopping patches

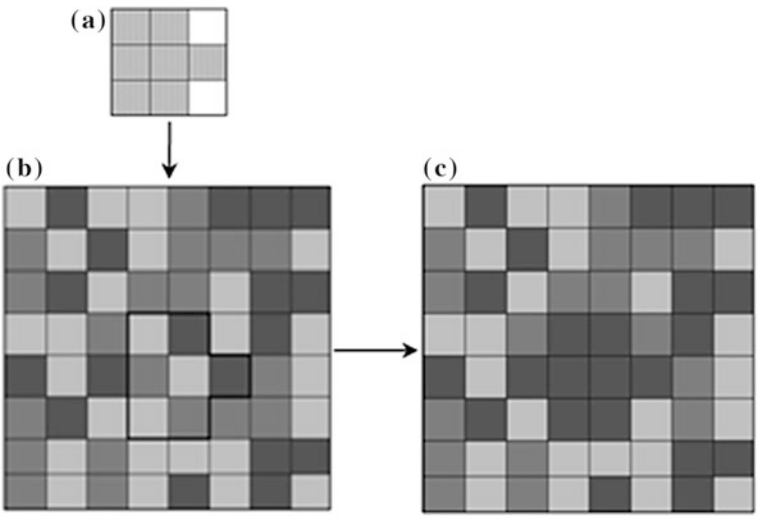

Fig. 6.17 Mutation operator for land use pattern: **a** crossover window and patch, **b** location of mutation patch, and **c** introducing new land use type within the patch

surround the mutation patch, then the mutation patch replaces the original solution; otherwise, the procedure returns to the first step (see Fig. 6.17c).

One of most remarkable features of GIS-based approaches to multiobjective analysis using genetic algorithms has been the wide range of application domains.

The NSGA-II procedure provides a good example of the diversity of applications. It has been applied to: urban water management (Makropoulos and Butler 2005), forest management (Ducheyne et al. 2006; Fotakis et al. 2012), non-point source pollution control (Maringanti et al. 2009), evacuation planning (Saadatseresht et al. 2009), land use allocation (Datta et al. 2007; Cao et al. 2011, 2014), scheduling joint participation with variable spatiotemporal preferences and opportunities (Fang et al. 2011), spatial aggregation problem (Datta et al. 2012), and alternative spatial patterns of sensors for monitoring radioactivity (Jankowski et al. 2014).

One of the advantages of NSGA-II is that it uses the concept of elitism and crowded distance operator, which preserves diversity without specifying any additional parameters. The elitism mechanism consists of combining the best parents with the best offspring. If the crowding comparison operator is not used, then the elitism mechanism preserves Pareto optimal solutions that have already been found. However, when the operator is employed to restrict the population size, the algorithm loses its convergence property (Deb 2001). One disadvantage of genetic algorithms (including NSGA-II) is that the abstract genetic algorithm framework may be difficult to implement efficiently and effectively in the context of spatial multiobjective problems (O`Sullivan and Unwin 2010).

6.3.2 Simulated Annealing

Simulated annealing (SA) is a generic meta-heuristic method, which mimics the process of arranging atoms when a material (steel or glass) is heated and then slowly cooled (Kirkpatrick et al. 1983). During the process of crystallization, the temperature controls the arrangement of atoms in their lowest-energy configuration. When the temperature is high at the beginning of the procedure, the material is characterized by a disordered configuration of atoms and high energy. As the temperature decreases, the material is gradually reaching a crystalline solid state with low energy. Eventually, when the material approaches zero temperature, the atoms approach their minimum energy state.

The SA algorithm imitates the annealing process to solve an optimization problem. Specifically, it generates moves randomly in the solution space searching for a solution that minimizes the value of an objective function. As the result of a move from one point of the solution space to another, the value of objective function may increase, decrease, or remain the same. The algorithm always accepts moves that decrease the value of the objective function. However, changes that increase the value of the objective function are accepted with a small probability that depends on a control parameter called the temperature. The probability of accepting a worse point is given by $\exp(-\Delta E/T)$, where ΔE is the energy difference (that is, the difference in the value of objective function between the current and next point), and T is the control parameter. This is the Metropolis step, the fundamental procedure of simulated annealing (Metropolis et al. 1953). As the SA algorithm progresses, the probability that such moves are accepted decreases, giving worse solutions a lesser chance of replacing the current solution. This results in convergence to an optimal point. The stopping criterion is often defined by the following inequality: $T < T_{\min}$, where $T_{\min}$ is a given minimum value of the temperature parameter. Other examples of stopping criteria are iteration limits, or some changes in the objective function for the last several accepted points (Talbi 2009).

Figure 6.18 illustrates the main concepts of the SA procedure using an example of land use pattern. The initial solution is generated by random allocation of land uses satisfying the area requirement for each land use alternative (Sharma and Lees 2004). A new land use pattern is constructed by selecting two rasters and exchanging the land uses between them. If the value of objective function (the energy) of this new land use pattern is lower than that of the previous one, the change is accepted unconditionally and the land use pattern is updated. If the energy is greater, the new configuration is accepted probabilistically according to the

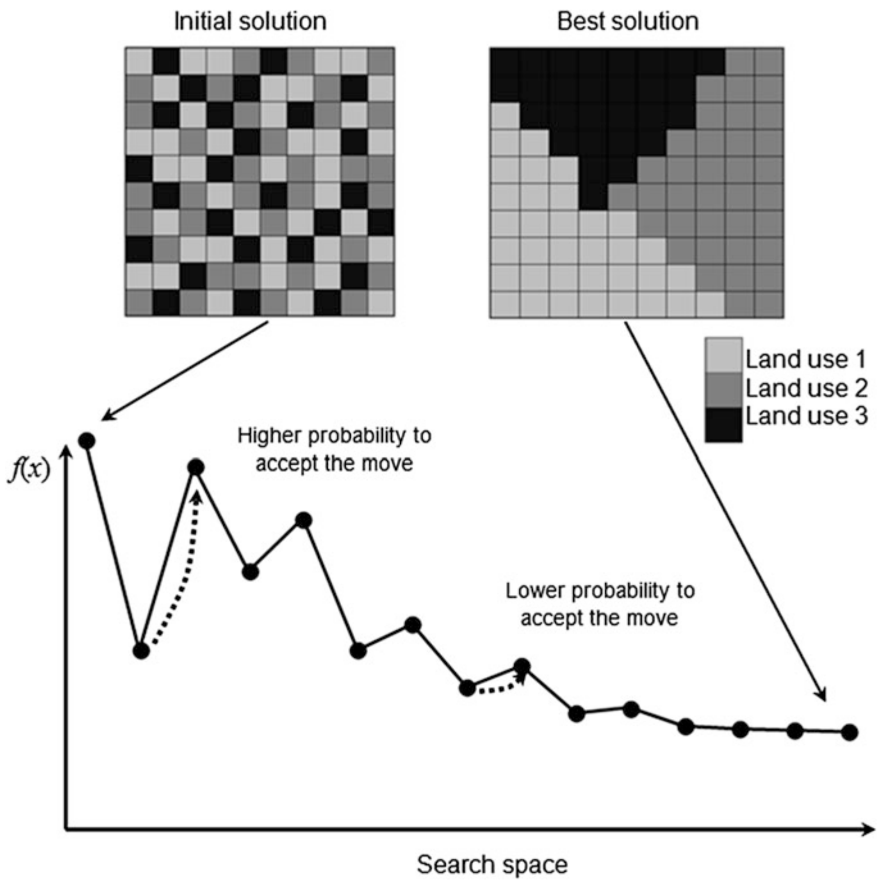

Fig. 6.18 Simulated annealing procedure; the solutions are represented in the decision spaces (the land use patterns) and the search space

Metropolis step. This procedure allows the system to move consistently toward lower energy states, yet still move out of local minima due to the probabilistic acceptance of some upward moves. The algorithm eventually reaches a near minimum when swaps of land use between two rasters are unable to reduce the objective function. The resulting land use pattern is a higher degree of spatial organization, measured in terms of clustering of units with the same land use type.

Although SA for multiobjective optimization problems is conceptually identical to a single-objective SA, there are some procedural differences between the single- and multi-objective SA methods (Suman and Kumar 2006; Duh and Brown 2007; Duh 2008). Specifically, one can distinguish two approaches for tackling GIS-based multiobjective optimization problems with SA. First, the different evaluation criteria (objectives) are combined into a single-objective cost function, and then the problem is solved using the single-objective SA procedure (e.g., Macmillan and Pierce 1994; Aerts and Heuvelink 2002; Sharma and Lees 2004; Santé-Riveira et al. 2008a, b). Second, the conventional SA algorithm is modified for multiobjective problems to search for Pareto-optimal solutions (e.g., Duh and Brown 2005, 2007; Duh 2008).

Several multiobjective SA procedures are available (Suman and Kumar 2006). The methods use modifications of the acceptance criteria to increase the probability of accepting Pareto-optimal solutions. For example, Duh and Brown (2007) have employed Pareto simulated annealing (PSA), which uses a set of interacting solutions (the generating set) at each iteration to propagate new solutions (see Czyzak and Jaszkiewicz 1998). The algorithm creates subsequent generating sets by a random swapping method based on the results at the previous phase. If solution y is not dominated by its preceding solution x, then it is tested for Pareto optimality with respect to the solutions in a non-dominated set; and when it is verified to be the Pareto-optimal solution, it is added to the non-dominated set. Concurrently, if the newly added solution dominates any solution in the set of non-dominated solutions, the dominated solution is removed from the set. The probability of retaining a new solution y in the generating set equals 1.0 when y dominates or is equal to the current solution x. Otherwise, the following function is used: $p = \min\{1, \exp(\sum_{k=1}^{n} \lambda_k^x(\Delta/T)\}$, where $\Delta = f_k(x) - f_k(y)$ is the change in the value of the kth objective function ($k = 1, 2, \ldots, n$); T is the annealing temperature; and λ_k^x is the weighting parameter associated the kth objective function for solution x generated in the prior iteration. The higher the value of λ_k^x, the lower the probability of accepting swaps that decrease the value of the kth objective function and the greater is the probability of improving the value of this objective (see also Duh 2008). Duh and Brown (2007) have incorporated auxiliary knowledge in the structure of spatial patterns to improve the performance of PSA in solving multiobjective spatial allocation problems. The knowledge-informed PSA uses: (i) auxiliary rules that preferentially generate subsequent solutions in order to improve the effectiveness and efficiency of approximating the Pareto front, and (ii) solutions optimized by the single-objective SA algorithm as the initial solutions of PSA to encourage the diversity of Pareto solutions (see Duh and Brown 2005).

GIS-based multiobjective approaches in the area of spatial planning and decision making with the support of the SA algorithms are most often used for tackling land use allocation and related problems (e.g., Aerts and Heuvelink 2002; Sharma and Lees 2004; Aerts et al. 2005; Duh and Brown 2007; Duh 2008; Santé-Riveira et al. 2008a, b). GIS-based SA procedures have also been employed for solving districting problem (Macmillan and Pierce 1994; Bergey et al. 2003) and identifying the best location pattern of emergency facilities (Indriasari et al. 2010).

One of the advantages of using SA for tackling spatial multiobjective optimization problems is that the algorithm is easy to implement. It is also a robust, flexible, and versatile tool for solving different types of complex spatial problems (Duh 2008). Sharma and Lees (2004) compare the SA and MOLA methods for a land use allocation problem (see Sect. 6.2.1). Overall, SA provides a superior solution. In addition, the quality of the final land allocation can be assessed easily by comparing the cost functions between the initial and final land use allocation. In case of MOLA, there is no means to assess the quality of the solution since the original suitability values are lost during the ranking operation. Indriasari et al. (2010) compared the performance of three meta-heuristics: SA, genetic algorithm (see Sect. 6.3.1), and tabu search (see Sect. 6.3.3). Although SA generated a solution that was significantly better than the existing location pattern of emergency facilities, the SA algorithm was inferior compared to the tabu search in term of solution quality and computation time. The genetic algorithm and SA procedure were comparable in computation time, but the former was better in solution quality. The performance of these procedures can be improved by developing a hybrid meta-heuristics. Bergey et al. (2003) provide an example of a hybrid multi-objective method called simulated annealing genetic algorithm. The method is based a composite concept of a population based evolutionary search and a point based local search, similar to simulated annealing. The simulated annealing genetic algorithm outperformed SA in its ability to identify non-dominated solutions.

6.3.3 Tabu Search

The development of the tabu search (TS) method was inspired by the mechanics of human memory (Glover 1989). Given an initial solution, x, the algorithm finds a new solution by making local moves over the current solution at each iteration. A move is an operation on a current solution, which aims at transforming the solution into a neighbouring solution (Duh and Brown 2005). The moves are context dependent. Figure 6.19 gives two examples of neighbouring move strategies for a raster-data-based optimization problem. The algorithm uses a neighbourhood search procedure to iteratively move from one potential solution x to an improved solution y in the neighbourhood of x, until some stopping criterion has been satisfied. Typically, the memory structure is divided into categories: (i) a short term memory (containing a list of visited tabu moves, as the search is not allowed to revisit solutions), and (ii) a long term memory (it records the regions of the search

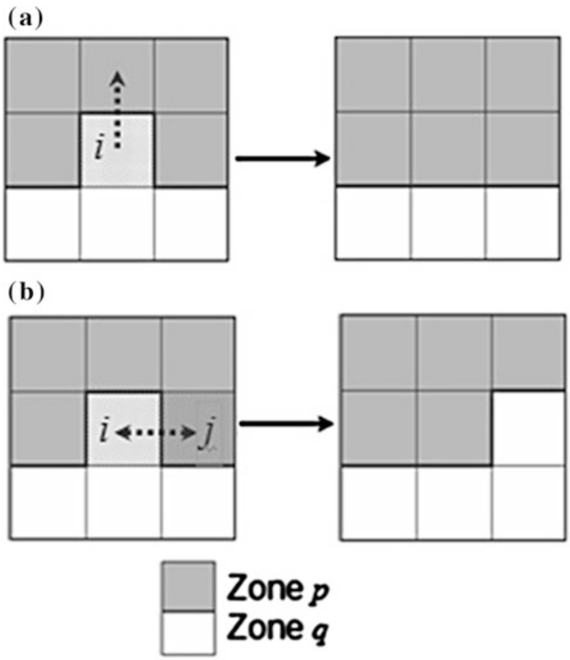

Fig. 6.19 Two neighbouring move strategies for a raster data: **a** the transfer strategy (the *i*th raster is transferred from zone *q* to *p*, and **b** the exchange strategy (the two rasters, *i* and *j*, are swopped between the two zones *q* and *p* (see Bong and Wang 2004)

space which have been explored, and is used for directing the search to regions which are under-explored). In addition, the algorithm can use an intermediate-term memory, which is a list of rules intended to bias the search toward promising areas of the search space. For example, this type of memory can store locally Pareto-optimal solutions and be used to select points for search intensification, focusing the search on regions of the search space with known good objective function values. At each iteration, the best solution from the set of non-tabu solutions is selected as the new current solution. The algorithm is terminated when a stopping condition is met; for example, when it reaches a specified number of iterations, or the number of iterations since the last improvement is larger than a specified number.

Although there is empirical evidence to show the TS algorithms generates quality solutions to spatial multiobjective optimization problems (see Sect. 6.3.2), there have been few applications of GIS-based TS (e.g., Bettinger et al. 1997; Lourenço et al. 2001; Bozkaya et al. 2003; Bong and Wang 2004; Zhang and Wright 2004; Indriasari et al. 2010). Bettinger et al. (1997) applied TS to solve a spatial planning problem in forestry. Lourenço et al. (2001) used the TA algorithm for solving a bus scheduling problem. Bozkaya et al. (2003) and Bong and Wang (2004) employed TS supported by the GIS capabilities to tackle districting problem. A comparative study of GA, SA, and TS, in the context of the problem of locating emergency facilities, can be found in Indriasari et al. (2010). It is important to note that Lourenço et al. (2001) and Bong and Wang (2004, 2006) developed hybrid meta-heuristics, which combined two meta-heuristic methods, including TS. The results of their applications provided evidence of high efficiency and effectiveness of hybrid meta-heuristics in solving spatial multiobjective problems.

6.3.4 Swarm Intelligence

Swarm intelligence optimization methods are inspired by social behaviours in flocks of birds, schools of fish, herds of buffalo, colonies of ants, and so forth. A colony or swarm is a self-organized, multi-agent system in which the individuals (agents) cooperate to accomplish complex tasks. This cooperation is distributed among the entire population, without any centralized control. The global pattern of agents emerges from local interactions between agents, which occur through direct (agent-to-agent) or indirect (via the environment) communication. Each agent follows a set of rules influenced by locally available information. Ant colony and particle swarm optimization methods are the most successful swarm intelligence inspired optimization algorithms (Talbi 2009; Yang 2010).

6.3.4.1 Ant Colony Optimization

Ant Colony Optimization (ACO) is based on an imitation of the behaviour of ants in their search for food (Dorigo et al. 1991). Although it seems that each ant in a colony has its own agenda, the colony (population) behaves as a self-organizing system. This behaviour is exemplified by the way in which ants search for a food source. Ants form and maintain a line to their food source by laying a trail of pheromone (a chemical to which other ants are sensitive). They deposit a certain amount of pheromone while walking, and each ant prefers to follow a direction marked by high concentration of pheromone. This enables the colony of ants to quickly find the shortest route. At the beginning of the searching process, the ants explore all the paths or routes (see Fig. 6.20a). Gradually the shortest path is marked with more pheromone than other routes because the self-regulating mechanism attracts more and more ants to the route characterized the highest level of pheromone. Sooner or later, nearly all the ants are choosing the shortest path (Fig. 6.20d).

The main idea behind the ACO meta-heuristics is to use repeated and often recurrent simulations of a set of software agents (mobile agents inspired by real ant behaviour) to generate solutions to a given problem. At each iteration, the agents collect relevant information, which is used in subsequent iterations to direct their search for the best solution. The information for permutation problems (such as shortest path, vehicle routing, and traveling salesman problems) is usually encoded in an n by n pheromone matrix $[\tau_{ij}]$, $i, j = 1, 2, \ldots, n$. In any given iteration, an ant chooses its route probabilistically. The choice is based on the pheromone level and

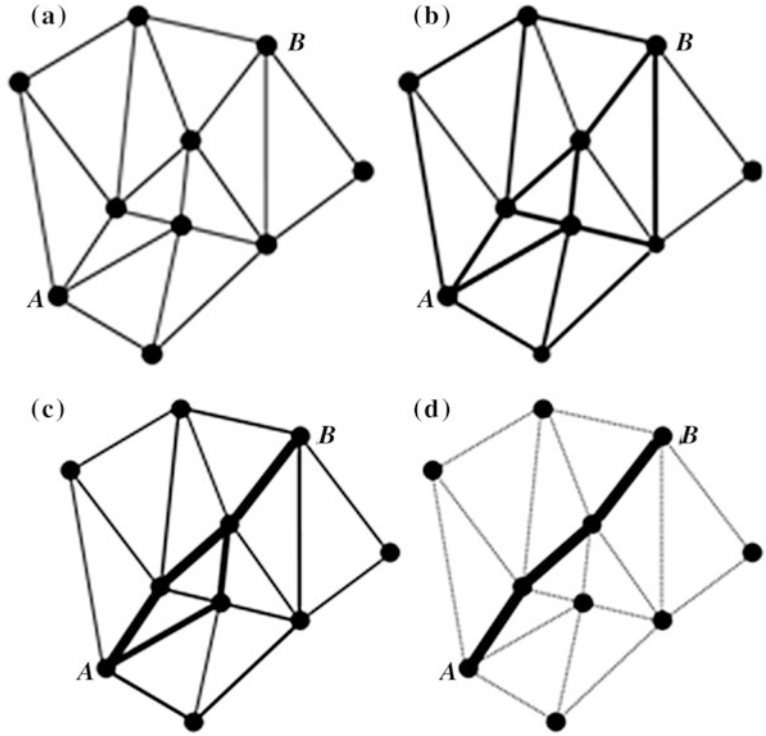

Fig. 6.20 The shortest path between node A and B identified by the ant colony optimization: **a** a hypothetical network of nodes (cities) and links or arcs (highways); **b** initially all the paths between a pair of nodes, A and B, are explored; **c** the shortest path between A and B is reinforced by the large quantity of pheromone deposited by the ants; and **d** all potential paths except the shortest one are eliminated due to the evaporation process

the distances between two nodes, i and j. Specifically, the probability is defined as follows:

$$p_{ij} = \frac{\tau_{ij}^{\alpha}\eta_{ij}^{\beta}}{\sum_{p \in S} \tau_{ip}^{\alpha}\eta_{ip}^{\beta}}, \quad \text{for } j \in S; \tag{6.6}$$

where τ_{ij} is the pheromone concentration on the route between i and j; η_{ij} is the desirability of the route between nodes i and j (the value of η_{ij} is typically inversely proportional to the distance between i and j; that is, $\eta_{ij} = 1/d_{ij}$); and α and β are parameters which determine the relative influence of the pheromone concentration and route desirability, respectively. All solutions (alternative paths) that are constructed by the ants in a single iteration are evaluated using the respective objective function and then the best alternative is identified.

The pheromone concentration can change with time due to the process of evaporation. Therefore, a procedure for the pheromone update must be specified. It involves two steps (Dorigo et al. 1991). First, according to the classical evaporation procedure, the level of pheromone is updated by a reduction rate, $\rho \in (0,1)$ as follows: $\tau_{ij} = (1-\rho)\tau_{ij}$; for $i, j = 1, 2, \ldots, n$. Second, the pheromone value associated with the best solution, π, is updated according to the following formula: $\tau_{i\pi(i)} = \tau_{i\pi(i)} + \Delta$, for $i = 1, 2, \ldots, n$; where $\Delta = 1/f(\pi)$. The ACO procedure is performed iteratively until a specified stopping criterion, such as a predefined number of iterations or a specified quality of solution, has been reached.

Li et al. (2009a, b) modified the conventional ACO algorithm to make it capable of addressing spatial multiobjective optimization problems in a GIS-raster environment (see also Li et al. 2011a, b, c). They used the concept of utility for aggregating objective functions and introduced a direction function as a tool for exploring the search space to increase efficiency of the ACO algorithm (Li et al. 2009a). The conventional ACO method has also been advanced by adopting the strategies of neighbourhood pheromone diffusion, tabu table adjusting, and multi-scale optimization (Li et al. 2009b). These advances of GIS-based ACO have been part of an integrated system, called the geographical simulation and optimization system or GeoSOS (Li et al. 2011a). The system has been successfully applied to tackling site selection problems (Li et al. 2009b), path-finding problems (Li et al. 2009b, 2011c), and problems of zoning design (Li et al. 2011b, 2012a, b). The ACO methods have also been used for solving the problem of searching for the best location of public facilities such as emergency services (Liu et al. 2005) and fire stations (Liu et al. 2006; Huang et al. 2006a). Yu et al. (2011) and Hou et al. (2014) developed an ArcGIS-based ACO for multicriteria land-use suitability assessment and water resources allocation, respectively. Liu et al. (2012b) applied ACO for tackling land use allocation problem. The forest land management has been another area of successful application of GIS-based multiobjective modeling with the ACO methods (Zeng et al. 2007).

6.3.4.2 Particle Swarm Optimization

Particle swarm optimization (PSO) is inspired by the social behaviour in flocks of birds, schools of fish, and swarms of insects such as termites, bees, and wasps (Kennedy and Eberhart 1995). In this context, an individual (e.g., a bird, fish) is referred to as a particle (or an agent). Each individual in a swarm behaves according a combination of its own intelligence and the collective intelligence of the population. In PSO, individual particles of a swarm represent potential solutions (e.g., spatial patterns of land uses). Each particle has its own velocity and position (location) in a multi-dimensional search space. The particles move through the space seeking a good solution. The particles communicate their current locations to neighbouring particles. The position of each particle is adjusted according to its velocity (i.e., rate of change) and the difference between its current position and the best position found by its neighbours, and the best position it has found so far. More specifically, the velocity is defined by three elements: 'inertia' based on the current velocity value of the element; 'personal influence' based on the solution element of the particle's own best solution so far, called local best; and 'social influence' based on the solution element of the best particle found in the population during the search process, called global best. As the model is iterated, the swarm focuses more and more on an area of the search space containing high-quality solutions.

Ma et al. (2011) and Masoomi et al. (2013) provide two notable applications of GIS-based PSO for land use allocation problems. Although the general concept of PSO is the same for all kinds of optimization problems, there are some distinct considerations associated with extending PSO to spatial multiobjective modeling. First, there is the issue of how to maintain good solutions found so far. Second, one should define the global and local best particles to guide particles toward Pareto-optimal solutions. Third, a procedure for incorporating spatially explicit objectives (such as compactness and contiguity) into the GIS-based PSO modeling framework has to be developed. All of these issues are discuss in the context of land use modeling in Ma et al. (2011) and Masoomi et al. (2013).

The integration of swarm intelligent optimization methods into GIS offers enhanced spatial analytical capabilities involving the concept of a simple self-organized system of agents cooperating to solve a problem. Ma et al. (2011) indicate that an attractive feature of PSO is its simplicity and flexibility. Unlike the genetic algorithm that involves complex coding, a swarm intelligent optimization algorithm is able to perform all the operations using a few parameters. Zeng et al. (2007) compare the performance of ACO with other heuristics such as simulated annealing and genetic algorithm, and conclude that the three methods result in a similar final output. However, one can argue that the performance of conventional swarm intelligence algorithms can be significantly improved when they are modified to take into account specific features of spatial multiobjective decision problems (e.g., Ma et al. 2011; Liu et al. 2012a, b). Indeed, the results of comparative studies by Liu et al. (2012a, b) show that a modified ACO is considerably more efficient than simulation annulling (see Sect. 6.3.2), genetic algorithm (Sect. 6.3.1), and the MOLA method (6.2.1) in solving a zoning problem. Other computational experiments and comparisons of different algorithms reveal that the ACO procedure designed for solving a site section problem shows a stable performance under different parameter settings and it outperforms the conventional genetic algorithm (Liu et al. 2006).

6.4 Conclusion

This chapter has shown a wide range of heuristic methods for tackling spatial multicriteria decision problems. Although the methods do not guarantee optimal solution to a given decision problem, they are capable of finding good solutions in an acceptable computing time by iteratively improving a candidate solution with regard to a given measure of quality. We have classified the GIS-based heuristic approaches into two groups. First, there is a group of basic heuristic methods that tend to be designed for solving specific spatial problems. This group includes such methods as: site suitability heuristics, site location heuristics, and greedy algorithms. Second, there is a large collection of meta-heuristics. These approaches typically employ conventional meta-heuristics for solving spatial optimization problems using GIS. This group of methods include: genetic algorithms, simulated annealing, tabu search, and swarm intelligence methods. Since genetic algorithms are the most often used heuristics for tackling spatial multiobjective decision problems, a considerable portion of the chapter was devoted to the concepts and procedures of genetic algorithm.

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Chapter 7
Dealing with Uncertainties

7.1 Introduction

In the previous chapters, we have often made an implicit assumption that complete information about the decision problems is available. Such assumption underlies the deterministic approaches to GIS-MCDA discussed in Chaps. 4 and 5. It is important to note that some of the metaheuristics (see Chap. 6) can be referred to as stochastic approaches because they involve random numbers, and different results may be obtained upon running such algorithms repeatedly. This should not, however, be confused with stochastic programming, which refers to methods for solving optimization problems involving stochastic or probabilistic variables. Some of the metaheuristics of Chap. 6 make use of stochastic operations, but they may operate on a deterministic or stochastic structure of the optimization problem.

We recognize that in real world situations, the information available is often uncertain because of measurement and conceptual errors. This lack of complete information should be taken into account in the procedures for tackling spatial multicriteria decision problems. The term 'uncertainty' can have many different connotations. Stewart (2005) defined the concept based on an application-oriented view of modeling uncertainty (Zimmermann 2000) as follows: "Uncertainty implies that in a certain situation a person does not possess the information which quantitatively and qualitatively is appropriate to describe, prescribe or predict deterministically and numerically a system, its behaviour or other characteristics" (p. 446). This definition is of particular relevance for MCDA, as it focuses on the major elements of MCDA (see Chap. 2): the decision maker (his/her preferences), and the quantitative and qualitative attributes of a system being modelled and analyzed using MCDA approaches. The uncertainties in decision analysis are related to a number of sources, which can be internal or external to the process of problem structuring and analyzing. Internal uncertainty can come from an incomplete understanding of the decision problem, model specification, and input data.

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_7

External uncertainty are related to the nature of the decision environment, and thereby the consequences of a particular course of action which may be outside of the control of the decision maker (Stewart 2005). Here we are primarily concerned with the internal uncertainty associated with GIS-MCDA.

There are essentially two approaches for handling uncertainties in MCDA: direct and indirect methods. The former incorporates uncertainty into the multicriteria decision rules directly (some aspects of this approach have been discussed in Chaps. 4–6). Specifically, any of the deterministic methods discussed in the previous chapters, such as WLC, AHP, ideal point, compromise programming, and goal programming, can be extended to take into account uncertainties involved in the decision making process. To this end, it is useful to distinguish two types of uncertainty that may be present in a decision situation: (i) uncertainty associated with fuzziness (imprecision) concerning the description of the semantic meaning of the events, phenomena, or statements themselves, and (ii) uncertainty associated with limited information about a decision situation (see Sect. 3.3.3). Consequently, both multiattribute and multiobjective problems under uncertainty can be further subdivided into: fuzzy (e.g., Banai 1993; Jiang and Eastman 2000; Makropoulos et al. 2003), and probabilistic (or stochastic) decision making problems, depending on the type of uncertainty involved (e.g., Kangas et al. 2005; Marinoni 2005; Prato 2008).

Sensitivity analysis is an alternative method of incorporating uncertainties into MCDA. It is concerned with the way uncertainties in a set of input data affect the multicriteria decision model output. Sensitivity and uncertainty analysis can be considered as integral parts of broadly defined sensitivity analysis (Saltelli 2000; Crosetto and Tarantola 2001). The analysis of uncertainty is a prerequisite for sensitivity analysis. Sensitivity analysis can be performed either comprehensively (global sensitivity analysis) or just partially, by considering selected input factors only (local sensitivity analysis).

7.2 Sources of Uncertainty in GIS-MCDA

The type of uncertainty analysis in spatial MCDA depends on the decision rule (method) employed for tackling a decision problem. For example, discrete and continuous MCDA methods (see Sect. 2.3.3.3) typically involve different types of uncertainties. However, the two major components of multicriteria analysis, the criterion values and criterion weights, are the main sources of uncertainty. Consequently, uncertainty analysis in spatial MCDA aims at identifying and evaluating the effects of errors (uncertainties) associated with the criterion maps, and the decision maker's preferences (weights) on the decision outcomes (ordering the alternatives). The criterion map and preference errors are interrelated.

7.2.1 Model Uncertainty

A considerable amount of theoretical and empirical evidence indicates that the application of different multicriteria decision rules to the same decision problem yields inconsistent results (e.g., Goicoechea et al. 1982; Hobbs and Meier 2000). The disagreement among MCDA methods is a source of uncertainty associated with the choice of the most suitable method for a particular decision problem. There is no commonly accepted set of rules for selecting the 'best' MCDA model. The process of selecting an MCDA method should be concerned with such factors as the nature of the decision problem, data requirements, consistency of results, and computational complexity (Goicoechea et al. 1982).

An overview of GIS-MCDA applications suggests there has been a limited amount of research on uncertainly associated with selecting the 'best' GIS-MCDA methods (Malczewski 2006a). A vast majority of GIS-MCDA applications have been based on an unverified assumption that a particular GIS-MCDA model (such as WLC or AHP) is the most appropriate method for the decision problem at hand. There are a few examples of GIS-MCDA applications involving the use of more than one method to analyze the model uncertainty (e.g., Carver 1991; Heywood et al. 1995; Elaalem et al. 2011). These studies emphasized the importance of analyzing the sensitivity of the results to the choice of one decision rule over another. Correlation coefficients and map comparison techniques can be used for identifying differences in results generated by different GIS-MCDA methods (e.g., Heywood et al. 1995; Malczewski and Rinner 2005; Elaalem et al. 2011). CommonGIS is an example of a system with capabilities of comparing results generated by several methods (Andrienko and Andrienko 1999). Malczewski and Rinner (2005) used CommonGIS to demonstrate the importance of exploring decision or evaluation problems in geographic space and criterion outcome space in conjunction with the use of a family of OWA decision rules (see Sects. 4.2.3 and 7.3.3). Using an example of residential quality evaluation, they have demonstrated that the criterion outcome space may not capture some vital geographical components. Some spatial units may be similar in criterion space, but they may be different when analyzed in geographic space, and vice versa. Furthermore, there are considerable differences between the rank-orders and associated spatial patterns generated by different models such as the Boolean and WLC models (see also Jiang and Eastman 2000).

The model uncertainty in GIS-MCDA should be seen as an opportunity to better understand the decision problem, rather than a 'superfluous' complication of the GIS-MCDA procedures (Massam 1988). The results of a well-selected set of GIS-MCDA methods for tackling a particular problem can stimulate discussion about the reasons for disagreements and lead to new insights into the decision problem. Hobbs and Meier (2000) recommend that one should be concerned with the relative validity of results generated by different methods only if the results are significantly different. If the results converge, then the differences are of secondary importance. In such a case, an ease-of-use rule can be employed for selecting a GIS-MCDA method.

7.2.2 *Criterion Map Uncertainty*

One can identify several types of uncertainty associated with criterion maps. Broadly speaking, they are related to the GIS database and MCDA method. Consider for example the WLC model (see Sect. 4.2). The set of criteria to be included into the model (Eq. 4.1) is associated with the following types of uncertainty: (i) the choice of criteria, (ii) criterion values, and (iii) standardization procedures/value functions (Malczewski 2000; Chen et al. 2011).

7.2.2.1 Selecting Criteria

There are two tendencies in defining the set of criteria in the context of a particular decision problem. First, the number of evaluation criteria is defined in such a way that the decision model describes the problem as close as possible to the real-world system under consideration. This may lead to a formidable number of criteria being included in the decision model. Second, the problem situation can be described by a small number of criteria. This may lead to an oversimplification of the decision problem, which is usually related to data availability and data quality. Even if the decision maker (analyst) is aware that some evaluation criteria are important for a decision problem, the required data may not be available, or they may be of poor quality. This oversimplification can, however, be a source of uncertainty about the appropriate description of the decision problem and specification of the MCDA model.

The procedures for selecting a set of criteria (attributes) should be based on some desirable properties (Keeney and Raiffa 1976; Keeney 1992a). Both individual criterion and a set of criteria should possess some properties to adequately represent the multicriteria nature of the decision problem. Each attribute must be comprehensive and measurable. A set of attributes should be complete (the attributes should cover all aspects of a decision problem), operational (they can be meaningfully used in the analysis), decomposable (they can be broken into parts to simplify the process), non-redundant (they avoid problems of double counting), and minimal (the number of attributes should be kept as small as possible). Each of these requirements can be a potential source of uncertainty. Empirical studies have shown that different sets of criteria for a decision problem might result in significantly different rank-orderings of alternatives (e.g., Alexander 1989; Hobbs and Meier 2000).

7.2.2.2 Criterion Values

Criterion map errors are referred to as the uncertainty associated with the GIS datasets (see Sect. 2.2.2). The errors can be classified into positional (or locational) and attribute (or criterion) errors (e.g., Burrough and McDonnel 1998). They can also be categorized into measurement and conceptual errors. The former are associated with imprecision in the measurement of criterion values, while the latter are attributed to the process of translating real-world entities into map objects.

The error of measurement is defined as the difference between the measured value and the true value. For example, if one measures a distance between two points on a map to the nearest millimeter, any distance between two measurements (say 99.5 and 100 mm) will be recorded as one value or the other. This means that a value of 99.5 or 100 mm may be recorded, but the choice could be random, giving either positive or negative deviations from the true value. The differences between the true distance and the measured values are errors. The distribution of errors is assumed to be a normal distribution. Typically, a sampling of locations on the ground provides a means for identifying the 'true' value. Once the ground truth has been undertaken at the sample locations, the error can be assessed using root mean square (RMS) (Burrough and McDonnel 1998; Bolstad 2008). RMS is the base for a number of spatial error models for point, line, and polygon objects, as well as attributes associated with those objects. For example, errors associated with digital elevation models are typically defined in terms of RMS. For categorical data, the errors are usually described by a confusion matrix or classification error matrix (Jensen 1996). A number of measures of error based on the confusion matrix are available. One of the most often used is the Kappa statistic, which is a measure of agreement between the predicted spatial pattern and the observed pattern for a systematic spatial sample.

7.2.2.3 Value Scaling

Uncertainty associated with the multicriteria model output may have its source in the value scaling (or standardization) of the criterion maps (see Sect. 2.3.1). First, the relationship between the criterion value and the value (utility) score is based on an expert or decision maker's subjective judgment, and therefore the form of the relationship (e.g., a linear vs. non-linear form) is intrinsically uncertain (Janssen 1992; Chen et al. 2011). Second, there is a number of methods for standardizing the criterion values, and a value function can take a number of forms (see Sect. 2.3.1). The different methods may result in different rank-orderings of the alternative decisions (Janssen 1992; Young et al. 2010). Third, the results of value scaling procedures are sensitive to the spatial (and temporal) extent and resolution (see Sect. 9.2). Specifically, the extent and resolution scales affect the extreme criterion values (e.g., the value of criterion range), which are used in the criterion standardization procedures. Thus, the results of GIS-MCDA are scale dependent. Chapter 9 provides a detailed discussion about the sensitivity of GIS-MCDA results to spatial and temporal scales.

7.2.3 Criterion Weight Uncertainty

GIS-based MCDA methods often assume that the decision maker is able to provide precise judgments with respect to the importance of evaluation criteria. In some situations, this can lead to a misspecification of the MCDA model (e.g., the criterion weights). Indeed, the decision maker may be unable to exactly specify his/her preferences due to limited or imprecise information and knowledge. Also, it is common that inconsistencies can be found while elucidating the decision maker's preference (Saaty 1980; Keeney 1992a).

As mentioned earlier, the uncertainty associated with criteria weights can be incorporated into multicriteria decision procedures. The probabilistic and fuzzy procedures take into account the inherent uncertainty and imprecision in assessing the decision maker preferences (see Sects. 7.3 and 7.4). In many situations, however, the only solution to the problem of preference uncertainty is to specify the degree of confidence for a preference measurement. To this end, the preference uncertainty can be defined in terms of the preference error as the difference between the assessed value of criterion weight and its true value. Error in this technical usage does not imply that there is any mistake in the preference measurement process. Typically, we can never really know the error measurement. What the analyst can estimate, however, is the uncertainty interval of the preference (criterion weight) measurement. In this sense, the uncertainty is an estimate (with some level of confidence) of the limits of error in the measurement. The criterion weights can be expressed in terms of the ranges and error format. For example, it might be stated with 95 % confidence that the true value of the weight assigned to the k-th criterion is within the range between 0.5 − 0.01 and 0.5 + 0.01, or $w_k \pm \Delta w_k = 0.5 \pm 0.01$. Uncertainty can also be associated with fuzziness (imprecision) concerning the criterion weight assessment (see Sect. 3.2.3). The decision maker may specify his/her preferences with respect to the evaluation criteria using set of linguistic terms such as: 'unimportant', 'important', 'very important', or 'extremely important'. One way of dealing with verbal statements is to use fuzzy set theory (see Sect. 7.3).

7.3 Fuzzy Methods

Fuzziness is a type of imprecision describing a set of objects or elements that do not have sharply defined boundaries. Such imprecisely defined sets of objects are called fuzzy sets (Zadeh 1965). The concepts of fuzzy number and linguistic variable provide the base for the fuzzy MCDA. There are two main types of approaches for performing a combination of linguistic information: approximation and symbolic methods (Malczewski 2002). The approximation, or indirect approach, uses the membership functions associated with the linguistic terms. The trapezoidal or triangular membership functions are typically employed to capture the vagueness of the linguistic terms (Klir and Yuan 1995; Munda 1995). This approach can be used to ‘fuzzify’ the conventional GIS-MCDA methods discussed in Chaps. 4 and 5. For example, there have been a number of applications aiming at implementing fuzzy forms of the WLC model (e.g., Paez et al. 2006; Vadrevu et al. 2010), AHP (e.g., Elaalem et al. 2011; Anagnostopoulos and Vavatsikos 2012; Kordi and Brandt 2012), compromise programming (Simonovic and Nirupama 2005), and PROMETHEE (e.g., Chou et al. 2007). Section 7.3.2 provides an example of this type of fuzzy approach to GIS-MCDA. The direct or symbolic approach makes direct use of labels for computing. It is based on the premise that the set of linguistic terms is an ordered structure uniformly distributed on a scale. An extension of OWA (see Sect. 4.2.3) using the concept of fuzzy linguistic quantifiers (see Sect. 7.3.3) provides an example of the direct approach to GIS-MCDA.

7.3.1 Fuzzy Sets

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth. It is a multi-valued logic that allows intermediate values to be defined between conventional evaluations like yes/no, true/false, or black/white. A fuzzy set allows objects to belong partly to multiple sets. It is defined in the framework of some ordinary (crisp) sets called the universe of discourse (Zadeh 1965; Klir and Yuan 1995). Specifically, the theory of fuzzy sets deals with a subset M of the universe of discourse X, where the grade of membership is described by the membership function $\mu_M(x)$. The function represents any elements x of X partially belonging to M, or the grade of membership of x in M. An object’s membership value, or degree to which it belongs to a set, can be any number between one and zero. An element x clearly belongs to M if $\mu_M(x) = 1$ and does not belong to M if $\mu_M(x) = 0$. The higher the membership value of an element, the more it belongs to the set. By way of illustration, assume that $X = \{x_1, x_2, x_3\}$, and $M = \{0.4/x_1, 0.1/x_2, 0.6/x_3\}$ is an example of a fuzzy subset of X, where the numerical values indicate the membership value of x. In this expression, x_1, x_2, and x_3 have a membership grade of 0.4, 0.1, and 0.6 in the fuzzy subset M, respectively.

The capability of fuzzy sets to articulate gradual transitions from membership to non-membership has a broad utility not only for representing geographical entities with imprecise boundaries (Burrough and McDonnell 1998), but also for GIS-based operations and analyses including MCDA (Malczewski 1999). In Sect. 2.3.1.1 we described the concept of membership function as a tool for standardizing criterion maps (see Eastman 1997; Jiang and Eastman 2000). Here we define two terms, fuzzy number and linguistic variable, which play a fundamental role in fuzzy MCDA.

A fuzzy number is a fuzzy set defined on the domain of real numbers (Klir and Yuan 1995). Since any fuzzy set is a family of ordinary (crisp) sets, the arithmetic and algebraic operations on fuzzy numbers can be defined so that they may be manipulated in an analogous manner to crisp numbers (Chen and Hwang 1992; Klir and Yuan 1995). The operations are based on the extension principle. The principle allows for any algebraic operations defined for crisp sets to be extended to fuzzy sets. However, the use of extension principle operations on fuzzy numbers tends to be cumbersome. Therefore, special fuzzy numbers have been suggested to simplify fuzzy modeling. For the sake of computational efficiency and ease of data acquisition, the most often used fuzzy numbers include trapezoidal and triangular types (Chen and Hwang 1992; Klir and Yuan 1995). These categories of fuzzy numbers are sometimes referred to as standard membership functions (or standard fuzzy numbers). Here we limit our discussion to the trapezoidal numbers. An example of a trapezoidal fuzzy number is given in Fig. 7.1. The number is designated by M, where $M = \{(x, \mu_M(x)\}$, where x is a real number and $\mu_M(x) = [0, 1]$. The membership function indicates the degree of truth that M takes a specific number x (Chen and Hwang 1992). The shape of the fuzzy number is defined by four parameters: a, b, c, and d (see Fig. 7.1). Note that the trapezoidal fuzzy numbers include specific cases of crisp numbers (for $a = b = c = d$), interval numbers (for $a = b$ and $c = d$), and triangular numbers (for $b = c$).

The concept of a fuzzy number provides the basis for defining linguistic or fuzzy variables (Klir and Yuan 1995). Specifically, the fuzzy numbers are states of a linguistic variable. The states are represented by linguistic concepts such as 'very short', 'short', 'medium', 'long', or 'very long'. These concepts are defined in terms of a base variable, the values of which are real numbers within a specific range. A base variable is a variable in the conventional sense; for example, distance, slope, elevation, temperature, moisture, or precipitation.

Let us consider 'distance' as a linguistic variable (Fig. 7.2). This variable can assume the values: 'short', 'medium', and 'long'. Each of these terms is a linguistic value or linguistic-term of the variable. A linguistic value is characterized by a label (or syntactic value) and a meaning (or semantic value). The label is a word or sentence belonging to a linguistic term set (e.g. 'long') and the meaning is a fuzzy subset defined in a relevant interval, which is described by a membership function, $\mu_M(x)$. The fuzzy subset is defined in terms of a base variable; the distance that can take any value between 0 and 10 km, for example.

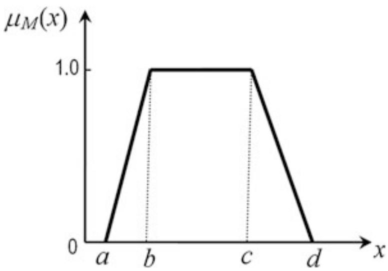
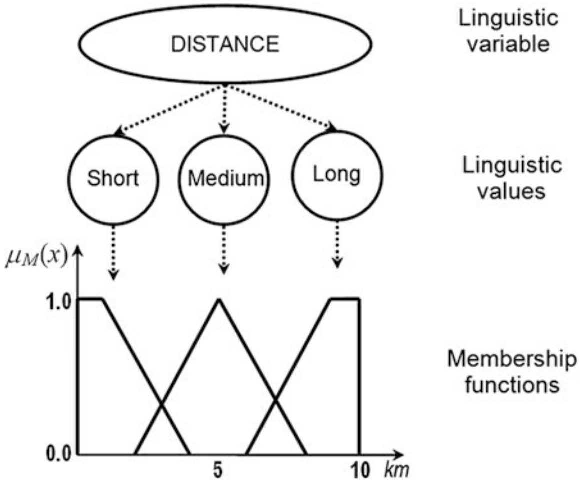


Fig. 7.1 Trapezoidal fuzzy number, M, with continuous membership function; the terms a, b, c, and d are real numbers

Fig. 7.2 An example of linguistic variable of distance



7.3.2 Fuzzy Additive Weighting

The fuzzy simple additive weighting (FSAW) method is similar to the conventional simple additive weighting or weighted linear combination method (see Sect. 4.2). Both methods use the weighted average as the combination operator. The difference between these two methods is that FSAW operates on fuzzy data; that is, the criterion values and weights are specified in terms of fuzzy numbers. Specifically, FSAW uses the concept of the trapezoidal (or triangular) fuzzy numbers (see Fig. 7.1). If the attributes, $\widetilde{v}(a_{ik})$, and weights, $\widetilde{w}_k$, are represented in the trapezoidal number format, then the value of the i-th alternative is given by:

$$\widetilde{V}(A_i) = \sum_{k=1}^{n} \widetilde{w}_k \widetilde{v}(a_{ik}). \tag{7.1}$$

The method can be implemented within the GIS environment using fuzzy arithmetic operations (see Malczewski 1999). This requires that the criterion values, $\tilde{v}(a_{ik})$, are represented in the form of the fuzzy criterion map. Specifically, each object (e.g., polygon or raster) on the map is assigned a single element of the trapezoidal fuzzy number; that is, the values of a, b, c, and d (see Fig. 7.2). Accordingly, a single criterion map is represented by a set of four map layers in GIS. This strategy for storing fuzzy data in GIS allows us to operationalize the fuzzy multicriteria decision analysis using the standard GIS overlay operations. This is effectively accomplished by manipulation of fuzzy numbers through the process of fuzzy arithmetic (Klir and Yuan 1995):

$$\widetilde{V}(A_i) = \widetilde{w}_1 \otimes \widetilde{v}(a_{i1}) \oplus \widetilde{w}_2 \otimes \widetilde{v}(a_{i2}) \oplus \cdots \oplus \widetilde{w}_n \otimes \widetilde{v}(a_{in}), \tag{7.2}$$

where $\otimes$ and $\oplus$ are the fuzzy multiplication and addition operations, respectively.

Consider a problem of evaluating three parcels of land (A_1, A_2, and A_3) with respect to two evaluation criteria (or attributes): slope and type of soil. Table 7.1 gives the values (linguistic terms) assigned to the three parcels of land with respect to the two attributes. For example, the suitability of A_1 is evaluated as 'low' and 'high' with respect to the two criteria: slope and type of soil, respectively. These linguistic terms can be converted to fuzzy numbers using a three-term conversion scale (see Chen and Hwang 1992, p. 467). The results are shown in Table 7.2. The weights associated with the two attributes are: $\widetilde{w}_1$ = 'important' and $\widetilde{w}_2$ = 'very important'. These linguistic terms can be converted to fuzzy numbers using a two-term conversion scale as follows: $\widetilde{w}_1 = (0.4, 0.6, 0.6, 0.8)$, and $\widetilde{w}_2 = (0.4, 0.8, 0.8, 1.0)$.

Given the input fuzzy numbers, the overall value, $\widetilde{V}(A_i)$, is calculated using Eq. 7.2. For example, $\widetilde{V}(A_1) = (0.4, 0.6, 0.6, 0.8) \otimes (0.0, 0.0, 0.2, 0.4) \oplus (0.4, 0.8, 0.8, 1.0) \otimes (0.6, 0.8, 1.0, 1.0) = (0.24, 0.64, 0.92, 1.32)$ (see Table 7.2). The overall scores can be ranked using the d values of the fuzzy numbers, $\widetilde{V}(A_i)$. Accordingly, A_3 is the most preferred alternative. Alternative A_1 ranks second and A_2 ranks third. One disadvantage of this approach is that the use of the d element to rank the alternatives may result in inconsistent and misleading ordering of the alternatives because the fuzzy numbers may not be linearly ordered. This depends on the spreads of the trapezoidal (triangular) fuzzy numbers. Thus, the d-element based method can be used only if large spreads are tolerable. Alternatively, defuzzification (or conversion of the fuzzy numbers to crisp scores) can be applied for ranking the alternatives. A number of approaches (such as centroid index, fuzzy mean, and spread) have been suggested to convert fuzzy numbers to crisp scores (for an overview see Chan and Hwang 1992).

An advantage of the FSAW method is its simplicity. It can be performed using standard GIS overlay operations. Notice that the linguistic values are labels, which

Table 7.1 Fuzzy data for hypothetical problem of evaluating three parcels of land: criterion values $\widetilde{v}(a_{i1})$ and $\widetilde{v}(a_{i2})$, and criterion weights, $\widetilde{w}_k$, defined by linguistic terms

i	Slope, $\tilde{v}(a_{i1})$	Type of soil, $\tilde{v}(a_{i2})$
1	Low	High
2	Medium	Low
3	High	Medium
$\tilde{w}_k$	Important	Very important

Table 7.2 Fuzzy numbers of the linguistic terms criterion values $\widetilde{v}(a_{i1})$ and $\widetilde{v}(a_{i2})$, and criterion weights $\widetilde{w}_k$ (Table 7.1) and the overall value, $\widetilde{V}(A_i)$, for the three parcels of land

i	$\tilde{v}(a_{i1})$	$\tilde{v}(a_{i2})$	$\tilde{V}(A_i)$
1	(0.0, 0.0, 0.2, 0.4)	(0.6, 0.8, 1.0, 1.0)	(0.24, 0.64, 0.92, 1.32)
2	(0.2, 0.5, 0.5, 0.8)	(0.0, 0.0, 0.2, 0.4)	(0.08, 0.30, 0.46, 1.04)
3	(0.6, 0.8, 1.0, 1.0)	(0.2, 0.5, 0.5, 0.8)	(0.32, 0.88, 1.00, 1.60)
$\tilde{w}_k$	(0.4, 0.6, 0.6, 0.8)	(0.4, 0.8, 0.8, 1.0)	

are represented as numerical scores for GIS operations. The resulting land suitability map also contains the labels (scores) measured on the same qualitative scale as the input data (fuzzy numbers). Thus, the method provides a consistent way of interpreting the results in the context of the input data. A disadvantage of the method is that it is limited to a specific (trapezoidal) form of fuzzy numbers, which limits its applicability and may impose some degree of inconsistency in ordering of the overall values.

7.3.3 Fuzzy Linguistic OWA

Zadeh (1983) introduced the concept of fuzzy linguistic quantifiers. This concept allows for converting natural language statements into formal mathematical specification of the multicriteria functions (Munda 1995). There are two general classes of the linguistic quantifiers: absolute and relative (proportional) quantifiers. Absolute quantifiers can be used to represent linguistic terms such as 'about 4', 'less than 5', or 'more than 10'. The relative quantifiers are closely related to imprecise proportions. They can be represented as fuzzy subsets over the unit interval with proportional fuzzy statements such as 'few', 'half', or 'many'. There is no empirical evidence to show which of the two classes of linguistic quantifiers are more suitable for spatial multicriteria analysis. The use of one of the two types of quantifiers depends on the decision situation. Also, the absolute quantifiers can be transformed to a corresponding proportional quantifier (Malczewski 2006b). Consequently, one can focus, without loss of generality, on one of the classes of proportional quantifiers. Here, we limit ourselves to the Regular Increasing Monotone (RIM) quantifiers. We employ one of the simplest and most often used methods for defining a parameterized subset on the unit interval (Yager 1996). Specifically, $Q(p) = p^{\alpha}$, $\alpha > 0$. $Q(p)$ is represented as a fuzzy set in interval [0, 1]. It can be applied for generating a whole family of RIM quantifiers (see Fig. 7.3 and Table 7.3).

Table 7.3 shows a selection of the RIM quantifiers and their characteristics. By changing the parameter α, one can generate different types of quantifiers and associated operators between the two extreme cases of the 'all' and 'at least one' quantifiers. The choice of particular value of α can be interpreted in the context well established concept of the decision maker attitudes toward risk (Bodily 1985). According to the theory, an essential component of any evaluation/choice process is the attitude of the decision maker toward risk (see Sect. 2.3.1.1). Risk perception or propensity is the consistency of a decision maker to either take or avoid actions that he/she perceives as risky. An individual with low risk-taking propensity (risk aversion) will typically weigh low criterion values associated with the i-th location more highly and an individual with high risk-taking propensity (risk acceptance) is more likely to weigh high criterion values more highly.

For $\alpha = 1$, the value of Q is proportional to α and therefore, it is referred to as the 'identity' quantifier. This quantifier represents an individual who is indifferent toward risk or is risk neutral. As α tends to zero, the quantifier Q approaches its

Fig. 7.3 A family of the regular increasing monotone (RIM) quantifiers (*Source* Malczewski 2006b, Fig. 1, reprinted with permission from Elsevier)

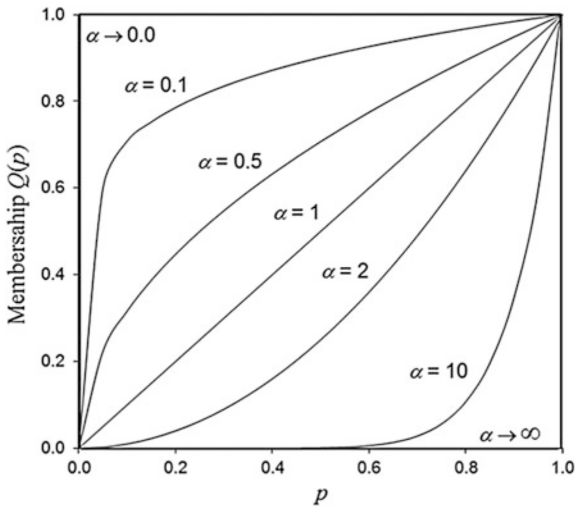


Table 7.3 Some properties of the Regular Increasing Monotone (RIM) quantifiers for selected values of α

α	Fuzzy quantifier (Q)	Attitudes toward risk	OWA weights (λ_k)
$\to 0$	At least one	Extremely optimistic (risk- acceptance)	$\lambda_k = 1$; $\lambda_k = 0$, for $k = 2, 3, \ldots, n$
0.1	At least a few	Optimistic	*
0.5	A few	Moderately optimistic	*
1.0	Identity	Neutral	$\lambda_k = 1/n$, for $k = 1, 2, \ldots, n$
2.0	Most	Moderately pessimistic	*
10.0	Almost all	Pessimistic	*
$\to \infty$	All	Extremely pessimistic (risk-aversion)	$\lambda_n = 1$ $\lambda_k = 0$, for $k = 1, 2, \ldots, n - 1$

*Depended on the number of criterion maps

Source Malczewski (2006b), Table 2, reprinted with permission from Elsevier

extreme case of 'at least one'. Moving from the 'identity' toward the 'at least one' quantifier increases the degree of risk-acceptance (the level of optimism). The curves above the 'identity' quantifier represent these situations (see Fig. 7.3). On the other hand, any curve below the 'identity' quantifier represents the degree of pessimistic decision strategies. The closer the curve is to the extreme case of 'all', the higher is the degree of risk avoidance. The 'all' quantifier represents an extremely pessimistic decision strategy.

The parameter, α, can be used to calculate a set of order weights, λ_k (see Sect. 4.2.3). The weights are defined as follows (Yager 1996; Malczewski 2006b):

$$\widetilde{\lambda}_k = \left(\sum_{h=1}^{k} u_h\right)^{\alpha} - \left(\sum_{h=1}^{k-1} u_h\right)^{\alpha} \tag{7.3}$$

where u_k is the criterion weight, w_k, reordered according to the attribute value, z_{ik} (see Sect. 4.2.3). Given the order weights, the quantifier-guided OWA can be defined as follows:

$$V(A_i^O) = \sum_{k=1}^{n} \widetilde{\lambda}_k z_{ik}. \tag{7.4}$$

$V(A_i^O)$ is the overall value of the i-th decision alternative.

Malczewski (2006b) and Boroushaki and Malczewski (2008) provide computational examples of the linguistic quantifier-guided OWA. The model has been implemented in CommonGIS (Malczewski and Rinner 2005) and ArcGIS (Boroushaki and Malczewski 2008); and applied to problems of evaluating the residential quality of urban neighbourhoods (Malczewski and Rinner 2005), and land suitability for housing developments (Malczewski 2006b; Boroushaki and Malczewski 2008). It has also been used in a variety of multicriteria evaluation problems for assessing the prospect for expanding irrigation systems (Chen et al. 2010a), potential markets for electrified vehicles (Zubaryeva et al. 2012a), local biomass availability (Zubaryeva et al. 2012b), solar energy resources (Charabi and Gastli 2011), and seismic hazards (Bordogna et al. 2007).

Fuzzy MCDA approaches provide us with a meaningful representation of uncertainties in GIS-based procedures. The significance of using linguistic variables in GIS-MCDA applications is that it facilitates gradual transitions between its states and, consequently, it possesses a natural capability to express and deal with imprecise and ambiguous statements. The decision maker is not required to specify 'exactly' his/her preferences with respect to the evaluation criteria. If a decision problem involves a set of mixed-data, quantitative data can be easily converted to ordered linguistic terms, and the symbolic procedure can be used to aggregate the mixed-data. Thus, the method provides us with a flexible framework for aggregating both qualitative and quantitative information (Malczewski 2002, 2006b). Furthermore, the fuzzy quantifier-guided OWA procedure provides a built-in mechanism for the analysis of model uncertainty by applying different linguistic quantifiers (changing the value of the α parameter) to obtain a wide range of decision/evaluation scenarios, and examine the differences (and similarities) between solutions generated by GIS-based multicriteria combination rules such as the Boolean operations and WLC (see Sect. 4.2).

7.3.4 Fuzzy Programming Methods

There are many approaches for introducing fuzziness into classic multiobjective decision models (see Chap. 5). Given the MODA problem (see Eqs. 5.1 and 5.2), one can distinguish three classes of fuzzy MODA models consisting of: (i) fuzzy objectives (goals) and a set of deterministic constraints, (ii) deterministic objectives and a set of fuzzy constraints, and (iii) fuzzy objectives and a set of fuzzy constraints (Leung 1988). In a fuzzy decision environment, the fuzzy objectives are characterized by their membership functions, and so are the constraints. The fuzzy objectives and fuzzy constraints are combined to form a decision. The relationship between objectives (criteria) and constraints in a fuzzy decision is symmetric in the sense that the two are treated operationally in the same way (Bellman and Zadeh 1970; Klir and Yuan 1995). Both objectives and constraints are defined as subsets of the decision space. According to the classic fuzzy model (Bellman and Zadeh 1970), the best decision alternative is characterized by the highest grade of membership in the intersection of the objectives and constraints.

There have been a few GIS-based applications of fuzzy multiobjective programming models (e.g., Maness and Farrell 2004; Wang et al. 2004; Simonovic and Nirupama 2005; Baja et al. 2007; Maeda et al. 2009). These applications focused on extensions of deterministic optimization methods such as linear programming (e.g., Maness and Farrell 2004; Maeda et al. 2009) and compromise programming (e.g., Simonovic and Nirupama 2005; Baja et al. 2007) into the area of fuzzy multiobjective modeling. The approach developed by Simonovic and Nirupama (2005) is of particular significance to GIS-based fuzzy multiobjective modeling because it proposes spatially explicit fuzzy compromise programming (FCP). Specifically, deterministic compromise programming (see Sect. 5.3.2, Eq. 5.24) is extended to a spatially explicit form (Tkach and Simonovic 1997) and then the spatially explicit model is fuzzified by introducing the concept of fuzzy distance metric, $\widetilde{L}_{i(x,y)\tilde{p}}$ for the i-th alternative at the x, y location (raster) and a given fuzzy parameter, $\widetilde{p}$ (Simonovic and Nirupama 2005). The fuzzy distance metric is determined for each location based on the fuzzy criterion values and the decision maker's preferences (fuzzy weights). The best decision alternative is determined for the x, y location by minimizing the distance metric value. Simonovic and Nirupama (2005) demonstrated the advantages of spatial FCP in the context of water resource management. The major contribution of the GIS-based FCP method is that it allows for examining the spatial patterns of preferred decision alternatives. This provides a valuable decision support tool for spatial planning and management (e.g., for determining future flood protection options). In addition, the results show that the ranking of decision alternatives is sensitive to the shape of the fuzzy membership function (Simonovic and Nirupama 2005). This discussion is applicable to other fuzzy methods discussed in this Section.

7.4 Probabilistic Methods

Probabilistic (or stochastic) MCDA methods incorporate the concept of uncertainty into multicriteria decision rules explicitly. The methods discussed in Chaps. 4 and 5 can be extended to the probabilistic framework (e.g., Levy 2005; Marinoni 2005; Prato 2008; Benke and Pelizaro 2010; Chen et al. 2011). The stochastic MCDA methods use a probability distribution rather than a single number for describing the overall performance of each alternative. One can compare the score distribution of the alternatives, and identify the preferred decision alternative probabilistically. Probabilistic approaches in GIS-MCDA can be classified into three groups: (i) utility function models, (ii) analytical methods for models simulating from probability distributions, and (iii) belief network methods.

7.4.1 Utility Function Methods

The utility function method is based on multiattribute utility theory (Keeney and Raiffa 1976). The term ‘utility’ is a generic one. It includes both the concepts of utility and value functions (see Sect. 2.3.1). The distinction between these two functions is based on the assumption concerning the nature of the decision problem. While the value function describes preferences with respect to levels of the attributes in deterministic situations, the utility function captures not only preferences regarding the attribute levels, but also relative risk attitudes. The concept of utility is a classic method of including uncertainty (risk preference) into the decision making process. It is inherently probabilistic in nature.

An additive multiattribute utility method has a similar form to the weighted linear combination (see Sect. 4.2), except that the values are replaced by utilities. Although the method has a prominent place in classic decision analysis and theory, it has rarely been applied for tackling spatial decision problems using GIS (e.g., Keisler and Sundell 1997; Store and Kangas 2001; Vacik and Lexer 2001; Ligmann-Zielinska 2009). One of the barriers in applying the utility function method for solving spatial decision problems is a set of underlying assumptions such as preferential independence and utility independence (Keeney and Raiffa 1976). Usually, it is quite difficult, impractical, or even impossible to obtain a mathematical representation of the decision maker’s preferences in the form of utility functions (ReVelle et al. 1981; Lai and Hopkins 1989). The procedures for assessing utility functions with even a moderate number of attributes can be time consuming and tedious. Also, they place considerable information processing demands on the decision maker. It can be argued that decision makers are unable or reluctant to articulate their preferences without knowing the possible consequences associated with alternative decisions (ReVelle et al. 1981).

7.4.2 Analytical Methods

Analytical methods are typically used in situations where the uncertainty in outcomes can be described as a function of the uncertainty of the input (Chen et al. 2011). These approaches are similar to the uncertainty analysis methods used as a part of sensitivity analysis procedures (see Sect. 7.5). One can develop a framework for MCDA using a simulation method, such as Monte Carlo for generating probability distributions of the inputs. Specifically, this approach identifies probability distributions using a simulation method to generate values from the distributions and uses these simulated values as inputs to a multicriteria decision model (Durbach and Stewart 2012). The Monte Carlo simulation involves the following basic steps: (i) formulate a MCDA deterministic model, (ii) identify the probability distribution, (iii) use random numbers to simulate the probabilistic events, and (iv) simulate the MCDA model by combining the probabilistic events (Openshaw et al. 1991). After running a large number of trials, the results are collected and can be represented in the form of a probability distribution for one or more of the input values and spatial distribution of the errors (error maps).

Marinoni (2005) provides an example of the Monte Carlo simulation approach for the GIS-based multicriteria modeling. He proposes an extension of the conventional PROMETHEE method (see Sect. 4.5.2) by using probability distributions for the input parameters. Specifically, the stochastic PROMETHEE method assigns theoretical distributions to the i-th alternative or location ($i = 1, 2,\ldots, m$) with respect to the k-th criterion ($k = 1, 2, \ldots, n$). The probability distribution models are then used as inputs in the Monte Carlo simulations to randomly generate N sample values for each criterion. The number of simulations should be sufficiently large; for example, $N \geq 500$. The random values are drawn from the [0, 1] interval and then the probability distributions are used to identify the actual criterion (sample) values. A matrix of m by n cells is obtained by using the sampling procedure repeatedly. Since each cell contains N values, the total number sample (criterion) values is equal to $N(m \times n)$. The matrix is the input data for the PROMETHEE procedure, which is performed N times resulting in the N orderings of alternatives. The orderings are then examined and compared using a mean stochastic rank and stochastic rank index (see Marinoni 2005, 2006). These measures can be used for identifying the best alternative. Marinoni (2005) gives a computational example of the procedure, and demonstrates implementation and use of the stochastic PROMETHEE method in the ArcGIS environment. He also provides an application of the method to analyze the suitability of parcels of land for residential development (Marinoni 2005, 2006).

The family of Stochastic Multi-criteria Acceptability Analysis (SMAA) models (Lahdelma et al. 1998) provides another example of the Monte Carlo simulation from probability distributions approach. The main idea behind SMAA is to explore the criterion weight space. It is an inverse-preference method that provides information about the types of preferences (criterion weights) that would lead to the selection of particular alternatives. The method represents uncertain (inaccurate) criterion values by a joint probability distribution, and decision-makers' unknown or partly known preferences are simulated by choosing weights randomly from appropriate distributions (Kangas et al. 2005, 2008). The SMAA models differ in terms of the type of preference information. Variants are available for value function, outranking, and reference point methods. SMAA generates three measures for each alternative: (i) an acceptability index (a measure of the variety of different preferences resulting in a certain rank for an alternative), (ii) a central weight vector (a measure of the typical preferences favoring each alternative), and (iii) a confidence factor (a measure of accuracy of the input data for making an informed decision) (Lahdelma et al. 1998; Kangas et al. 2005). Kangas et al. (2003, 2005) applied the SMAA methods to tackle forest management problems using GIS as a tool for supporting the process of generating alternatives. One of the advantages of the GIS-SMAA approach is it can be employed as an exploratory approach for examining spatial patterns of decision/management alternatives using the rank acceptability indices, central weight vectors, and confidence factors. However, a successful implementation of the SMAA method largely depends on the functional relation and forms of the probability distribution functions (Chen et al. 2011).

Arguably, any of the multiattribute methods discussed in Chap. 4 can be extended to the probabilistic framework using Monte Carlo simulation (e.g., Openshaw et al. 1991; Prato 2008; Benke and Pelizaro 2010; Kangas et al. 2003, 2005; Grandmont et al. 2012; Tenerelli and Carver 2012). Openshaw et al. (1991), Tenerelli and Carver (2012) provide examples of uncertainty (error propagation) analysis in the context of GIS-based weighted linear combination models. Prato (2008) developed stochastic multiple attribute evaluation method based on the conventional deterministic TOPSIS (see Sect. 4.4). The Monte Carlo simulation approach is used as the basis of probabilistic framework for GIS-AHP (Benke and Pelizaro 2010; Grandmont et al. 2012).

A shortcoming of the Monte Carlo simulation is that it can be computationally demanding due to the large number of samples required to generate the inputs (Marinoni 2005). Therefore, a practical application of the method is limited to problems of relatively small sizes, in terms of the number of alternatives and criteria, even if the simulation procedures are automatically performed using suitable software such as @RISK (Palisade Corporation 2012).

7.4.3 Belief Networks

A Bayesian belief network (or Bayesian network) is an approach for modeling uncertainties in the input data and the interactions between elements of multicriteria decision (Fenton and Neil 2001; Watthayu 2009). The Bayesian network procedure involves identifying elements of multicriteria decision problem including decision alternatives, objectives, criteria, and constraints. These elements are organized using an influence diagram. The diagram consists of a decision node representing decision alternatives, a utility node that represents the set of objectives, and the evaluation criteria along with factors that may affect them, which are represented by chance nodes. The Bayesian network uses links to represent the relationships (interdependencies) and conditional probability tables associated with the nodes. The procedure then provides a method for computing a value (within some probability distribution) for each decision alternative, with respect to each criterion. The values are combined to assign overall utility to a given alternative; and then the alternatives can be ordered (ranked) to identify the alternative characterized by the maximum expected utility.

Bayesian network has proven to be an effective method for tackling uncertainties and complex interdependencies in spatial decision problems. The procedure has been employed to analyze a variety of spatial decision and management problems including: non-point source pollution (Dorner et al. 2007), risk assessment of desertification (Stassopoulou et al. 1998), land use changes (Kocabas and Dragićević 2007), and marine planning (Stelzenmüller et al. 2010). Although Bayesian network approaches have been successfully integrated with GIS (e.g., Stassopoulou et al. 1998; Stelzenmüller et al. 2010), there has been no attempt to demonstrate the synergetic effects that one would expect by combining the complementary capabilities of MCDA and Bayesian networks in the GIS environment. In addition, the method does not provide an explicit mechanism for dealing with ignorance. The Dempster–Shafer theory (DST) of evidence (Shafer 1976) provides such a mechanism by replacing subjective probabilities with 'degrees of belief.' By combining evidence from different sources, the DST procedure identifies a degree of belief (represented by a belief function) that takes into account all of the available evidence. The procedure has been successfully integrated into GIS (Eastman 1997) and used for tackling multicriteria evaluation problems (e.g., Burton and Rosenbaum 2003; Clements et al. 2006; Feizizadeh et al. 2014). For example, Feizizadeh et al. (2014) proposed GIS-OWA (see Sect. 4.2.3) integrated with the pairwise comparison method for estimating criterion weights (see Sect. 2.3.2.2), and DST for analyzing uncertainty in the landslide susceptibility mapping (see also Feizizadeh and Blaschke 2014).

7.5 Sensitivity Analysis

Sensitivity analysis in MCDA is a set of methods for assessing uncertainty in the multicriteria model output and importance of the model input factors (such as the criterion values and weights). One can distinguish two interrelated components of the analysis: uncertainty analysis and sensitivity analysis. The objective of uncertainty analysis is to evaluate the effects of uncertainty associated with the multicriteria model input factors on the uncertainty in the model output (e.g., the rank-ordering of decision alternatives). On the other hand, sensitivity analysis focuses on how the uncertainty in the output is affected by the uncertainty in the model input factors. It aims at partitioning the uncertainty in output to different sources of uncertainty associated with the input factors (Saltelli 2000; Crosetto and Tarantola 2001). The term sensitivity analysis is used here to cover both uncertainty and sensitivity analyses.

A number of frameworks and approaches for sensitivity and uncertainty analysis were proposed for spatial modeling in general (Heuvelink et al. 1989; Lodwick et al. 1990; Burrough and McDonnell 1998; Crosetto et al. 2000; Crosetto and Tarantola 2001; Lilburne and Tarantola 2009), and GIS-based multicriteria modeling in particular (Malczewski 1999; Gómez-Delgado and Bosque-Sendra 2004; Gómez-Delgado and Tarantola 2006; Ligmann-Zielinska and Jankowski 2008, 2014; Chen et al. 2010a, 2011). Uncertainty analysis is often considered as an error propagation approach (Heuvelink et al. 1989; Burrough and McDonnell 1998). Lodwick et al. (1990) suggest that the essential difference between sensitivity analysis and error propagation analysis depends on the way in which the errors in the input factors are defined; the former requires a priori knowledge of the error associated with the input data, while the latter imposes perturbations or variations on the inputs. Although it is useful to make a distinction between uncertainty (or error propagation) analysis and sensitivity analysis, it can be argued that the two types of analysis form a complementary two-stage procedure (Crosetto et al. 2000; Saltelli 2000; Crosetto and Tarantola 2001). In brief, the uncertainty associated with model inputs are propagated through the model for uncertainty analysis and their relative importance is assessed using sensitivity analysis.

Figure 7.4 shows a generic procedure for uncertainty and sensitivity analysis. The procedure involves a sequence of steps starting with identifying sources of uncertainty associated with the input factors, $\boldsymbol{X} = (X_1, X_2, \ldots, X_h)$, of a specified GIS-MCDA model. The input factors represent all sources of uncertainly that influence the outcome. They often include a set of evaluation criteria and associated criterion weights (e.g., Gómez-Delgado and Bosque-Sendra 2004). The input factors are then specified as random variables having probability density functions. For example, each raster cell or polygon of a criterion map is assigned with a random variable value from a normal distribution (Tenerelli and Carver 2012). A decision model is assumed to have one output, Y. The relationship between the input factors and the model output is defined as a function: $Y = f(X_1, X_2, \ldots, X_h)$. The output has its own probability density function that provides us with the tool for assessing the model output. Specifically, one can assess whether the model output meets the requirements for effective support of the decision process (Crosetto and Tarantola 2001). Uncertainty and sensitivity analysis is terminated if the decision model meets the requirements; otherwise, sensitivity analysis is performed to define how the model output is affected by the uncertainty in the input factors. This can be represented by a chart displaying information about the relative influence of the input factors on the uncertainty in the model output.

Conventional sensitivity analyses can be categorized into two groups: local and global methods. While local sensitivity analysis methods focus on selected input factors, global approaches allow all the input factors to vary over their range of uncertainty. The conventional distinction between global and local methods does not imply any spatial connotation (see Sect. 4.2.2). It is based on the scope of sensitivity analysis ranging from the local one-at-a-time experiments to global testing of interdependencies among the input factors (Ligmann-Zielinska and Jankowski 2008). The conventional methods are the most often used approaches for

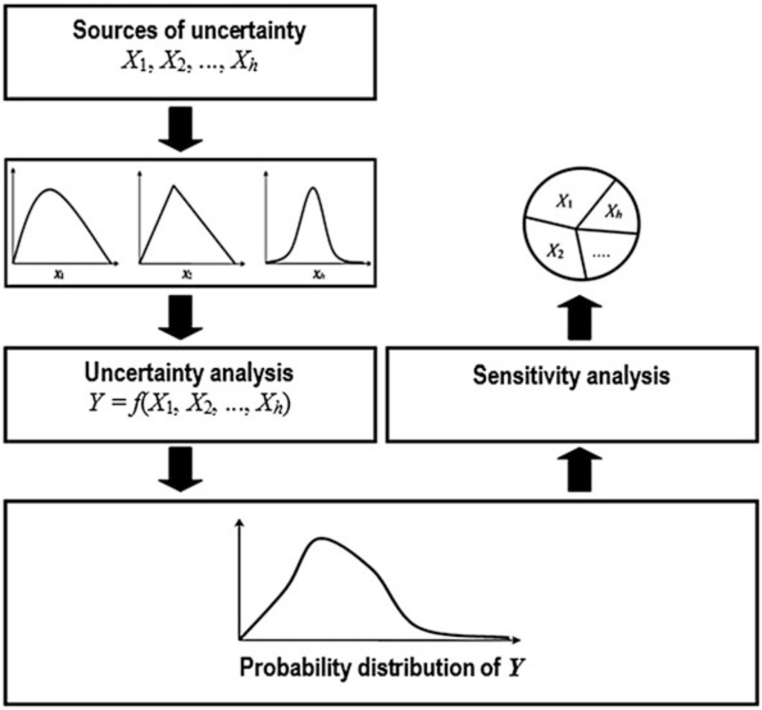


Fig. 7.4 A framework for a sampling-based uncertainty and sensitivity analysis (*Source* Based on Crosetto et al. 2000; Saltelli 2000; Crosetto and Tarantola 2001)

performing sensitivity analysis of the GIS-MCDA models (Gómez-Delgado and Bosque-Sendra 2004; Ligmann-Zielinska and Jankowski 2008). One can distinguish two groups of approaches to sensitivity analysis in GIS-based multicriteria modeling: (i) one-at-a-time experiments, and (ii) variance-based methods.

7.5.1 One-at-a-Time Method

A vast majority of the studies about sensitivity analysis in GIS-MCDA use a factor screening method, in which the impact of changing the values of each factors is evaluated in turn (Gómez-Delgado and Bosque-Sendra 2004). The most common procedure is to vary selected input components (or a single component), rerun the model, and record the corresponding changes in the result (Lilburne and Tarantola 2009). The model components responsible for the largest relative changes in the model output are then considered to be the most important. This method is a local and one-at-a-time approach in that the other parameters are fixed at nominal values, and the sensitivity analysis is limited to a small area of the parameter space. Within this category of sensitivity analysis, the input factors most often analyzed are: the number of evaluation criteria and criterion values (Jankowski 1995; Chen et al. 2011; Plata-Rocha et al. 2011; Grandmont et al. 2012; Tenerelli and Carver 2012), criterion weights (e.g., Jankowski et al. 1997; Store and Kangas 2001; Feick and Hall 2004; Chen et al. 2010a, 2013, 2011; Tenerelli and Carver 2012; Gorsevski et al. 2013), MCDA models (Laaribi et al. 1996; Geneletti and Duren 2007; Makropoulos et al. 2007), other factors such as criterion standardization and model parameters (Pereira and Duckstein 1993; Makropoulos et al. 2007; Natividade-Jesus et al. 2007; Young et al. 2010), and choice of spatial and temporal extent and resolution (see Chap. 9).

The impact of changing criterion weights on the MCDA model output is, by far, the most often used type of sensitivity analysis in GIS-based multicriteria modeling (Gómez-Delgado and Bosque-Sendra 2004). The criterion weight sensitivity is typically examined using the one-at-a-time approach (e.g., Jankowski et al. 1997; Store and Kangas 2001; Andrienko et al. 2003; Feick and Hall 2004; Chen et al. 2010a, 2011). The sensitivity of the model output (the overall value associated with a decision alternative) to the criterion weight variation is determined by dealing with a single weight at a time and changing its value from 0 to 1 by a given factor. For example, for the WLC model (see Eq. 4.1), the overall value of the i-th alternative, $V(A_i,w_t)$, is a function of the overall score of the alternative, A_i, with w_t as its independent variable (see Chen et al. 2011). Specifically,

$$V(A_i, w_t) = w_t v(a_{it}) + \sum_{k \neq t} w_{k*} v(a_{ik}), \tag{7.5}$$

where $w_{k*} = \frac{(1-w_t)w_k}{\sum_{k \neq t} w_k}$, and w_k, w_{k^*}, and w_t is the k-th criterion weight, the adjusted k-th weight, and the addressed weight, respectively; $v(a_{ik})$ and $v(a_{it})$ are the value functions for the k-th and t-th criterion, $k \neq t$.

Consider a problem involving the evaluation of five sites (decision alternatives) with respect to three criteria using the WLC model. The standardized criterion values, $v(a_{ik})$, criterion weights, w_k, and the overall values, $V(A_i)$, are given in Table 7.4. The overall values indicate the following ordering of the alternatives: $A_2 > A_1 = A_3 > A_5 > A_4$. Next, let us focus on the impact of changing w_1 on the WLC model output, $V(A_i)$. One can use Eq. 7.5 to calculate the overall value, $V(A_i, w_t)$, while changing w_1 from 0 to 1. Figure 7.5 shows the results. Alternative A_4 or A_2 are

Table 7.4 Standardized criterion values, $v(a_{i1})$, $v(a_{i2})$, and $v(a_{i3})$ for five decision alternatives and the overall value of each alternative $V(A_i)$ based on the WLC model

i	$v(a_{i1})$	$v(a_{i2})$	$v(a_{i3})$	$V(A_i)$
1	0.70	0.00	0.70	0.49
2	1.00	0.60	0.40	0.82
3	0.50	0.30	1.00	0.49
4	0.00	1.00	0.00	0.30
5	0.35	0.50	0.60	0.42
w_k	0.6	0.3	0.1	

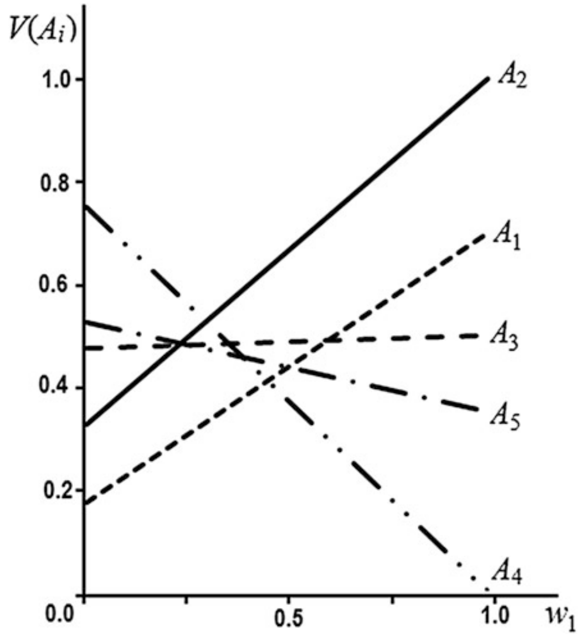


Fig. 7.5 Sensitivity of the weighted linear combination output, $V(A_i, w_1)$, to changes of criterion weight, w_1, ranging from 0 to 1

the best options, depending on the value of w_1. The crossover point between the two alternatives is 0.298. Alternative A_4 is the first-ranking alternative for $0 \leq w_1 < 0.298$. For $w_1 = 0.298$, $V(A_2, w_1) = V(A_4, w_1)$. When $0.298 < w_1 \leq 1.0$, A_2 is the best alternative. Similar sensitivity analysis can be perform for w_2 and w_3, and for criterion values, $v(a_{ik})$ (see Chen et al. 2011).

The one-at-a-time methods have been implemented in several GIS-MCDA systems (Jankowski et al. 1997; Store and Kangas 2001; Andrienko et al. 2003; Feick and Hall 2004; Jankowski et al. 2008; Plata-Rocha et al. 2010; Chen et al. 2010b, 2011, 2013; Tenerelli and Carver 2012). For example, Chen et al. (2010b; 2013) developed a GIS-based AHP-sensitivity analysis in the ArcGIS environment using the one-at-a-time method (see also Grandmont et al. 2012). Andrienko et al. (2003) extended CommonGIS by adding sensitivity analysis capabilities to test the influence of shifting criterion weights on the stability of decision option rankings. The sensitivity analysis in CommonGIS can be performed with respect to several decision rules including WLC, ideal point, and AHP methods. Choice Modeler is a Web-based spatial multicriteria evaluation system with a range of sensitivity analysis procedures including the one-at-a-time approach (Jankowski et al. 2008).

7.5.2 Variance-Based Methods

A number of methods are available for performing global sensitivity analysis from a set of Monte Carlo simulations (Lilburne and Tarantola 2009; Ligmann-Zielinska and Jankowski 2014). The methods are often based on some decomposition of the variance of the model output. Specifically, the aim of the variance-based global sensitivity analysis is to identify both the main sensitivity effects or first-order effects (the contribution to the variance of the model output by each factor input) and the total sensitivity effects (the first-order effect plus interactions with other inputs) (Saltelli et al. 2008). Given a model $Y = f(\boldsymbol{X})$, where Y is the model output, and $\boldsymbol{X} = (X_1, X_2, \ldots, X_k)$ are the input factors, a variance decomposition is defined as:

$$V = V(Y) = \sum_{i=1}^{k} V_i + \sum_{i}\sum_{j} V_{ij} + \sum_{i}\sum_{j}\sum_{k} V_{ijk} + \cdots + V_{1,2,\ldots,k} \tag{7.6}$$

where $V(Y)$ is the total unconditional variance (the total variance of the model's output); V_i is part of the variance or the main (direct) effect of X_i on Y, and V_{ij} is the joint impact of X_i and X_j on the total variance minus their first-order effects. The contribution of each input factor to the variance of the output is defined in terms of the first-order sensitivity index:

$$S_i = \frac{V_i}{V(Y)}. \tag{7.7}$$

The total effect index, S_{Ti}, accounts for the total contribution to the outputs variation due to factor X_i, and all of the higher order effects, due to their interactions (Saltelli et al. 2008). The index is defined as follows:

$$S_{Ti} = S_i + \sum_{i \neq j} S_{ij} + \cdots \tag{7.8}$$

For example, for three input factors, X_1, X_2 and X_3, the total effect S_{T1} can be expressed as: $S_{T1} = S_1 + S_{12} + S_{13} + S_{123}$; where S_{T1} is the total sensitivity index of X_1, S_1 is the main effect of X_1, S_{12} is the interaction effect between X_1 and X_2, and S_{123} is the interaction effect among X_1, X_2, and X_3.

The most popular variance-based methods include the Fourier amplitude sensitivity analysis test (FAST), extended FAST (E-FAST) and the Sobol' method (Saltelli et al. 2008). Gómez-Delgado and Tarantola (2006) provide an overview of the variance-based sensitivity analysis methods in GIS-MCDA modeling. They applied the Sobol' and E-FAST methods in a case study of identifying the most suitable area for a hazardous waste landfill site using the WLC model (see Sect. 4.2). The sensitivity of WLC (or simple weighted composition index) to the input factors was also examined by Lilburne and Tarantola (2009) in the context of a groundwater contamination using an improved version of the Sobol' method.

The main advantage of the variance-based methods is that they allow for exploring the entire spectrum of the input factors. The methods also provide a set of sensitivity measures for assessing the relative importance of the input factor. This point has been highlighted in Gómez-Delgado and Tarantola (2006). Their study shows that three out of 22 input factors jointly account for 97 % of the output variance. Gómez-Delgado and Tarantola (2006) suggest that this type of information can be employed to simplify the original WLC model, retaining only the three most prominent factors (see also Lilburne and Tarantola 2009).

The spatial components of GIS-MCDA have often been considered only implicitly in the conventional approaches to sensitivity analysis. One can argue, however, that the spatially explicit input factors of GIS-based multicriteria modeling can substantially influence the model output (Herwijnen and Rietveld 1999; Ligmann-Zielinska and Jankowski 2008; Lilburne and Tarantola 2009; Ligmann-Zielinska et al. 2012). Ligmann-Zielinska and Jankowski (2008) provide a comprehensive account of spatially explicit approaches to sensitivity analysis for GIS-based multicriteria evaluation methods. Ligmann-Zielinska and Sun (2010) and Ligmann-Zielinska et al. (2012) advanced variance-based methods by considering temporal and spatially explicit components of sensitivity analysis. Ligmann-Zielinska and Sun (2010) applied a time-dependent variance-based method to represent the dynamics of an agent-based model. They employed the ideal point method as a decision rule for modeling land use change (see Sect. 4.4). The results of this study provide evidence that the conventional static sensitivity analysis is inadequate because of its inability to capture the dynamics of model sensitivity to various input factors. Ligmann-Zielinska et al. (2012) applied the generic framework for sensitivity analysis of a GIS-based multicriteria land suitability problem involving an evaluation of the potential for habitat restoration. They use a hypothetical scenario

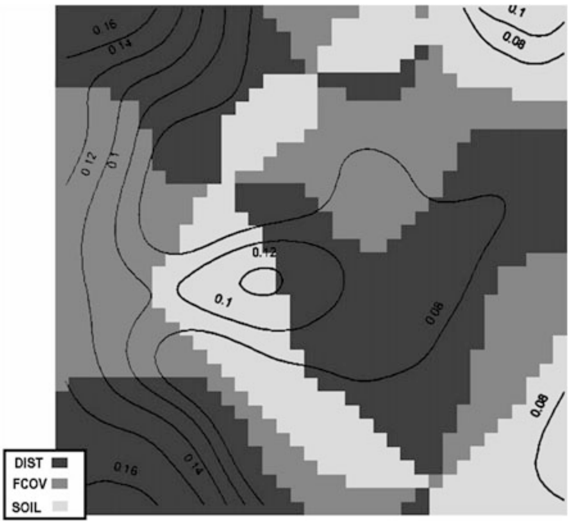


Fig. 7.6 Sensitivity analysis of a GIS-MCDA model: dominating weights based on total-effect sensitivity maps. *Note DIST* distance to known plant community, *FCOV* forest cover, and *SOIL* soil suitability; contour lines represent the amount of uncertainty measured by the standard deviation of land suitability scores (*Source* Ligmann-Zielinska et al. 2012, Fig. 3, reprinted with permission)

with three criterion inputs: distance to plant community, forest cover, and soil suitability (see Fig. 7.6).

The results of the first stage of the procedure (that is, uncertainty analysis) were displayed in the form of an average suitability surface and an associated uncertainty surface representing a standard deviation of suitability maps. In the second stage of the procedure, the variability of suitability maps was broken down and apportioned for every input weight to generate first-order and total-effect sensitivity indices for each criterion weight (see Eq. 7.6). The variance decomposition was employed to every pixel of the suitability map to generate a sensitivity map for each of the three criterion weights. Finally, the three total-effect sensitivity maps were overlaid, which partitioned the study area into regions of dominating weights (see Fig. 7.6). Given the spatial heterogeneity of criterion weights, the results of this study underscore the importance of spatially explicit sensitivity analysis (see also Sect. 1.4). This type of analysis facilitates an assessment of spatial robustness of the multicriteria model based on the average suitability and associated uncertainty maps. In general, areas characterized by high average suitability scores and low standard deviation values indicate robust suitability sites (see Ligmann-Zielinska et al. 2012).

7.6 Conclusion

In real-world decision situations, the available information is often uncertain. This lack of complete information should be taken into account in the procedures for tackling spatial multicriteria decision problems. In this chapter, we overviewed the sources of uncertainty in GIS-based multicriteria modeling and discussed a variety of approaches for handing uncertainties in GIS-MCDA methods. We demonstrated that the deterministic methods discussed in Chaps. 4–6 (such as WLC, AHP, compromise programming, and goal programming) can be extended to take into account uncertainties associated with fuzzy (imprecise) and limited information about the decision situation. The fuzzy and probabilistic methods can be referred to as direct approaches, incorporating uncertainty into the GIS-MCDA procedures.

Sensitivity analysis is an alternative approach for handling uncertainties in GIS-MCDA. Two most often used sensitivity analyses in GIS-based multicriteria modeling were presented: one-at-a time and variance-based methods. We stressed the importance of spatially explicitly approaches to sensitivity analysis of GIS-MCDA models. The analysis should be seen as an integral part of GIS-based multicriteria procedures. This is because it not only provides a tool for examining robustness of the model output (e.g., the rank-ordering of decision alternatives), but also an opportunity to better understand the decision problem. The results of sensitivity analysis can stimulate discussion about the decision problem at hand and lead to new insights into the nature of the problem. The new insights might be of particular importance in situations involving group/participatory decision making. The concepts and methods of participatory GIS-MCDA will be discussed in the next chapter.

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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

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_8

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

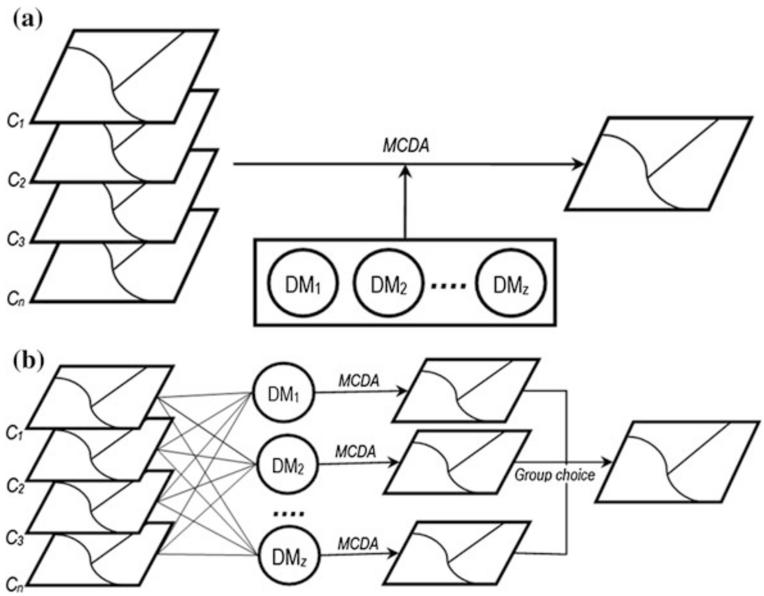

Fig. 8.1 GIS-MCDA for group decision making: **a** individual preferences aggregated external to the GIS-MCDA procedure, and **b** aggregation of individual preferences within the GIS-MCDA procedure (*Note* C_1, C_2, …, C_n = evaluation criteria (criterion maps), and DM_1, DM_2, …, DM_z = decision makers)

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

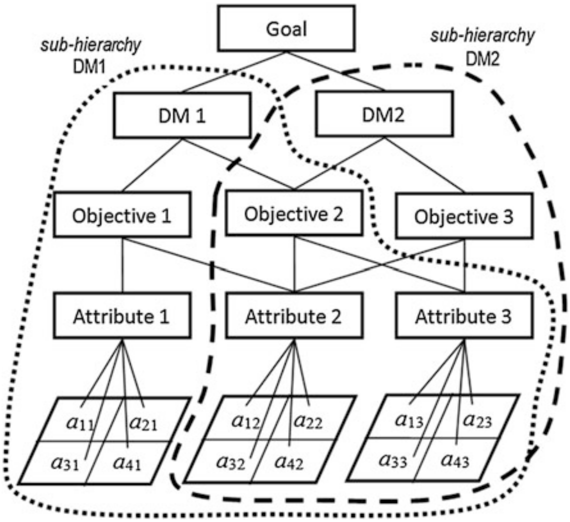

Fig. 8.2 Hierarchical structure of group decision making problem; DM_1 decision maker 1, DM_2 decision maker 2; a_{ik} is the value of the k-th attribute associated with the i-th alternative (k = 1, 2, 3, and i = 1, 2, 3, 4)

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.

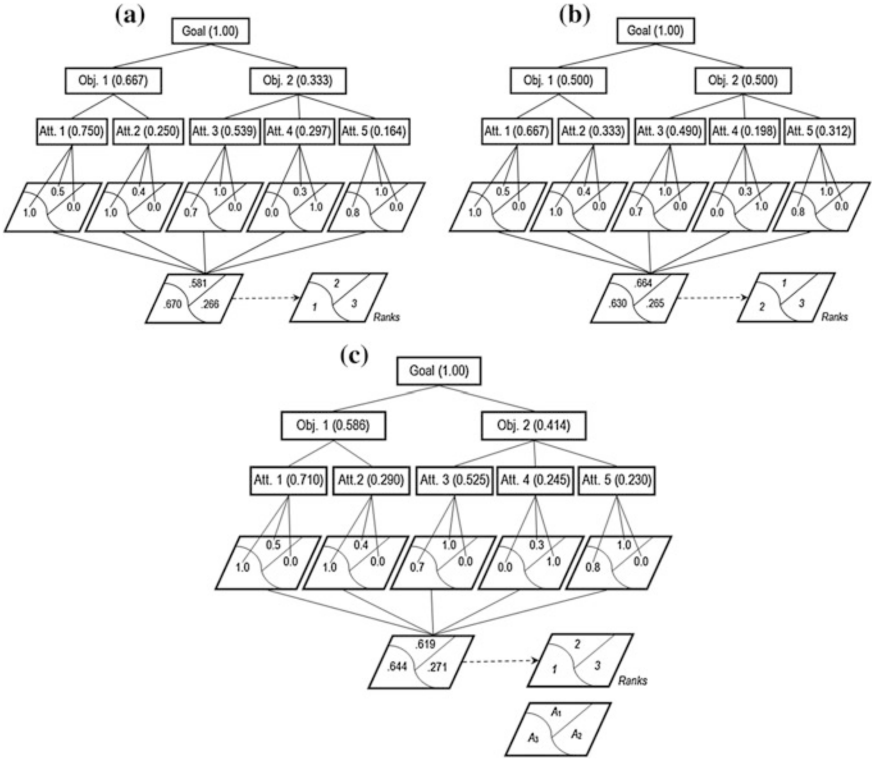

Fig. 8.3 Hierarchical structures of GIS-based AHP model for two decision makers: **a** individual decision making, DM_1, **b** individual decision making, DM_2, and **c** group decision making, DM_g—aggregation of individual preferences, DM_1 and DM_2, using geometric mean

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 nondominated 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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Chapter 9
Scale Issues and GIS-MCDA

9.1 Introduction

Decision making is a process. In many decision situations, the process operates across geographic, temporal, and organizational scales. Every change in scale brings about a new decision/evaluation problem, and consequently, the results of GIS-MCDA are scale dependent. The scale consists of extent (observational or geographic scale) and resolution (measurement scale). Each of these scales has spatial and temporal dimensions. Multiscale GIS-MCDA approaches tend to focus on issues of spatial scale and, in particular, the influence of resolution on the results of GIS-MCDA. This can be attributed to two interrelated issues of scale in spatial analysis. First, geographic (areal) datasets collected for analyzing decision situations (e.g., spatial patterns) may have little or no connection to the underlying decision making processes. The GIS-MCDA procedure executed on such data is not independent of how these areal units are configured. This situation is referred to as the modifiable areal unit problem (MAUP). MAUP has two components: (i) the scale effect; that is, the sensitivity of GIS-MCDA results due to the changing number (size) of spatial units of analysis, and (ii) the zoning effect; that is, the results of GIS-MCDA are influenced by the changing shape of the spatial units.

Second, a major source of scale effects is spatial heterogeneity. Accordingly, the methods for analyzing the effects are based on the premise that the variability of geographic data is scale dependent and the processes underlying a spatial pattern are best represented at the scale characterized by maximum variability. In the context of decision/evaluation problems, the measure of variability should be related to the main components of multicriteria analysis: the value function (the criterion standardization procedure) and the criterion weights. We suggest that the criterion range value can provide a measure for identifying the most appropriate scale of GIS-MCDA. This Chapter will discuss the two issues of scale in the context of GIS-MCDA. It will also provide an overview of approaches for tackling multiscale decision situations using GIS-MCDA.

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DOI 10.1007/978-3-540-74757-4_9

9.2 Meanings of Scale

The term scale has a wide variety of meanings (see Lam 2004; Wu 2004; Schneider 2009). Lam (2004) identified four connotations of scale commonly used in spatial sciences: cartographic scale, geographic (or observational) scale, measurement scale, and operational scale (see also Lam and Quattrochi 1992). *Cartographic* scale is defined as the relationship between the distance on a map and the corresponding distance in the real world, which is often expressed by the representative fraction; i.e., a numerical ratio of map distance to earth distance (for example, the representative fraction of 1:50,000 means that one unit of measure on the map equates with 50,000 same units on the ground). A 'large-scale map' shows a relatively small area of the earth, such as a county or city, and a 'small-scale map' shows a relatively large area such as a continent. The cartographic meaning of scale is often felt, to some extend, contradictory and confusing when used in spatial decision analysis.

In the context of spatial analysis and modeling, it is useful to denote scale as "the resolution within the range or extent of measured quantities" (Schneider 2009, p. 21). This definition indicates that scale consist of both extent and resolution. Furthermore, it is a comprehensive definition that can be applied to the notion of both spatial and temporal scale. Spatially, scale refers the spatial resolution relative to the geographic extent. Temporally, scale is the time-based resolution relative to the temporal extent. For the spatial extent, a small-scale decision problem means a small area of analysis, and a large-scale decision problem implies a large area of analysis. This connotation of spatial scale is referred to as an *observational* or *geographic* scale (Lam 2004). The temporal extent is the time-span of decision problems; small-scale decision problems are characterized by a short duration and large-scale problems imply long-term decisions.

The *measurement* or *resolution* scale defines the smallest spatial/temporal unit of analysis (measurement) employed in a given decision making procedure. Large-scale decision problems typically incorporate coarse resolution (coarse-scaled data) while small-scale problems are usually based upon fine resolution (fine-scaled data). Finer resolution decision analyses usually have smaller spatial and temporal extents, while large extents typically require coarser resolutions. Some routine decision problems (such vehicle routing and scheduling problems) exemplify small-scale decision making in terms of spatial and temporal extents. Strategic decisions, such as selecting a site for a major facility or choosing an environmental protection plan, are large-scale decision problems. They are concerned with achieving long-term goals (see Sect. 3.3.5).

Table 9.1 shows a cross-classification of spatial/temporal and observational/measurement scales in the context of decision making processes, conceptualized in terms of operational scale. The effects of scales on the spatial pattern of decision alternatives may occur by changing the spatial resolution and/or geographic extent. Likewise, the pattern may change according temporal resolution and/or extent. *Operational scale* corresponds to the level at which relevant (natural and social)

Table 9.1 Spatial/temporal resolution and extant and operational scale

Scale	Spatial	Temporal	Operational
Measurement	Smallest spatial unit of analysis (resolution)	Shortest temporal unit of analysis (time step)	Agent
Observational	Total relevant geographic area (extent)	Total relevant period of time (duration)	Jurisdictional domain
Operational	Spatial scale of action	Temporal scale of action	

Source Agarwa et al. (2002), (Lam 2004)

processes operate. This connotation of scale can be referred to as the scale of the decision making problem or the scale of action (Lam 2004). It involves identifying the spatial/temporal extent and resolution of a set of decision alternatives relevant for a particular decision situation. From the perspective of decision making, the operational and measurement scales converge at the concept of the decision making agent(s); the basic decision making unit(s) can be defined as a human decision maker (see Sect. 2.2.1.1) or an artificial intelligence agent (see Sect. 2.2.1.2). A discrepancy between the operational and measurement scales results in spatial/temporal misrepresentation of the decision making agent. A group of agents (decision makers) forms a jurisdictional domain (Agarwa et al. 2002). The notion of jurisdictional domain provides a common ground for identifying the relationship between observational and operational scales. A mismatch between the operational scale and extent results in spatial/temporal misrepresentation of the jurisdictional domain. The domain provides a framework for decision making and defines its spatial and temporal scopes. Finding the operational scale of a decision problem is a crucial component of GIS-MCDA. It is the operational scale that has to be identified first in order to appropriately define the observational and measurement scales of the decision situation.

9.3 Multiple Scale Approaches in GIS-MCDA

GIS-based multiscale MCDA is an approach in which a GIS-MCDA model (decision rule) is used at two or more spatial and/or temporal scales simultaneously or sequentially to analyze a complex decision/evaluation problem. A vast majority of GIS-based multiscale MCDA applications focus on spatial multiscale decision/evaluation analysis (e.g., Can 1992; Store and Jokimäki 2003; Deng and Wilson 2008; Zubaryeva et al. 2012a; Sacchelli et al. 2013; Karydas et al. 2014). There have been a few attempts to consider time as an element of GIS-MCDA (Ratsiatou and Stefanakis 2001; Pfeffer 2002; Chen et al. 2003; Young et al. 2010). The approaches for tackling spatial and temporal multiscale/multicriteria problems should be framed in the context of operational scales; that is, the spatial and temporal scales of action (see Sect. 9.2 and Table 9.1). The need to structure a decision problem and to effectively solve the problem comes from the hierarchical organizations of many geographic systems of economic, political, and social activities. For example, any land use related decision/evaluation problem involves not only spatial patterns of land use, but also a complex set of policies and regulations at national, regional, and local level of governments.

9.3.1 Spatial Multiscales

There are at least two types of approaches for examining multicriteria decision/evaluation problems at multiple spatial scales: (i) sensitivity analysis of GIS-MCDA results across spatial scales, and (ii) integrative GIS-based multiscale MCDA approaches. First, the multiscale analysis is used for testing sensitivity of GIS-MCDA results to changes in the spatial scale of analysis (see Sect. 7.5). Can (1992) and Zubaryeva et al. (2012a, b) provide examples of this type of multiscale approach. One can perform multiscale sensitivity analysis by changing the geographic scale or extent (e.g., Zubaryeva et al. 2012a), changing the resolution scale (e.g. Can 1992), or changing both resolution and extent (e.g., Hill 2005). In this type of multiscale analysis, the GIS-MCDA model is applied to each level of spatial aggregation and then the results are compared. This procedure aims at identifying the most suitable scale at which the GIS-MCDA model should be used (see Sect. 9.4.3). For example, Can (1992) compared the outcomes of GIS-based outranking methods (concordance and discordance scores) at two levels of aggregation of census data (census tracts and block groups), in the context of evaluating residential quality of neighbourhoods, and concluded that the block group (smaller areal units), rather than the census tract scale, should be used in the analysis. This conclusion was derived by examining the spatial autocorrelation of concordance and discordance scores at the two census scales.

Second, the GIS-MCDA procedure is used as an integrative element of multiscale analysis (Store and Jokimäki 2003; López-Ridaura et al. 2005; Nobrega et al. 2011, 2012; Scolozzi and Geneletti 2012). López-Ridaura and associates (2005) provide a comprehensive approach to multiscale GIS-MCDA (see also Delmotte et al. 2013). They developed a framework for multiscale evaluation of natural resource management systems. The framework consists of two main stages: the analytical phase (analyzing information about multiscale systems) and the synthesis phase (synthesising information about multiscale systems). The analytical phase aims at deriving case-specific criteria (systems objectives and attributes) for multiscale evaluation. It identifies the spatial scales for evaluating alternatives (or impact scales) by considering the geographic extent/resolution and operational scales of stakeholders or decision making agents (see Sect. 9.2; Table 9.1). Figure 9.1 gives an example of impact/action scales for natural resource management systems. It shows the geographic extent, resolutions (parcels of land), and the agents operating at different scales: regional (e.g., regional administration), sub-regional (e.g., non-governmental organizations), municipal (e.g., municipal governments), and individual parcels of land (e.g., farmers). The agents are characterized by a set of

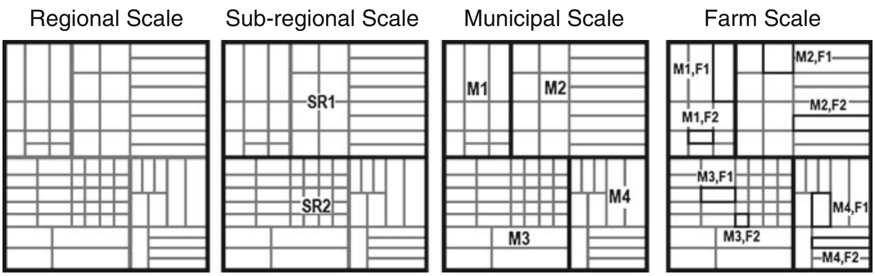

Fig. 9.1 A hypothetical example of a nested hierarchical structure of administrative areas and parcels of land: regional (*R*), sub-regional (*SR*), municipal (*M*), and farm (*F*) scales. (*Source* Adapted from López-Ridaura et al. 2005)

objectives and associated attributes for measuring performance of the natural resource management systems.

The second phase involves a set of procedures for evaluating alternative decisions by means of scenario analyses. It aims at describing the intra- and inter-relationships for the systems at different scales of analysis. This can be achieved by using a GIS-MCDA approach. López-Ridaura et al. (2005) employed the multiple goal linear programming (MGLP) method (see Sect. 5.3.1) by nesting MGLP models designed for each scale of analysis (see Fig. 9.1). The basic principle underlying this multiscale/multicriteria model is that the objectives of stakeholders at one scale can be included as constraints for optimisation at other scales. One can generate a set of alternative decision scenarios using the multi-scale MGLP models and perform a sensitivity (or 'what if' type of) analysis for examining the objectives/attributes trade-offs within and across scales.

Although the framework has specifically been designed and applied for evaluating and making recommendations for managing natural resource systems, it can be considered as a generic procedure for multiscale GIS-MCDA, applicable to tackle a wide range of multiscale/multicriteria evaluation problems. From this perspective, the main component of the framework is the GIS-MCDA modeling component, which aims at integrating relevant data/information and agent/stakeholder preferences to analyze and evaluate decision alternatives. Depending on the decision/evaluation situation, different GIS-MCDA models can be used. For example, Groot et al. (2007) and Store and Jokimäki (2003) used heuristic methods (see Chap. 6). Groot et al. (2007) developed a GIS-based land-use optimization procedure called Landscape IMAGES (Interactive Multi-goal Agricultural Landscape Generation and Evaluation System) for exploring multiscale trade-offs between multiple objectives using a heuristic search method (evolutionary strategy algorithm—see Sect. 6.3.1). Store and Jokimäki (2003) employed the HERO method (see Sect. 6.2.4) as an integrative element of their multiscale approach to habitat suitability modeling. Nobrega et al. (2011, 2012) used the AHP method (see Sect. 4.3.1) for integrated multiscale environmental impact assessment of transportation corridors.

9.3.2 Temporal Multiscales

Multiscale GIS-MCDA approaches can also be used for tackling multicriteria problems involving temporal scales of decision/evaluation situations. As with spatial scale, any temporal scale has two meanings: extent and resolution. The temporal concepts of time step and duration are analogous to spatial resolution and extent (see Sect. 9.2). The temporal extent scale is the timeframe for the decision/evaluation procedure; that is, a specified period of time for which the procedure is concerned. The temporal resolution defines the time steps. The complexity of multiscale GIS-MCDA models tends to increase with a longer timeframe and a greater number of time steps (Agarwal et al. 2002). The GIS-MCDA models involving multiple temporal scales are often referred to as spatiotemporal models (e.g., Ratsiatou and Stefanakis 2001; Poff et al. 2010; Young et al. 2010). In this type of approach to the decision/evaluation problem, the spatial scales do not change over time; that is, the geographic extent and resolution are the same for each time step. As far as the authors are aware, there has been no attempt to develop a GIS-MCDA model for multiple spatial and temporal scales.

The temporal multiscale GIS-MCDA studies typically involve a time series; a sequence of datasets (e.g., the values of evaluation criteria) measured at successive points in time. Two approaches for incorporating temporal scales into GIS-MCDA procedures are identified: (i) temporal aggregation methods, in which the temporal datasets are aggregated to obtain an overall evaluation of each decision alternative (e.g., Pfeffer 2002; Young et al. 2010), and (ii) time series methods, which use GIS-MCDA procedures for multicriteria combination of evaluation criteria and decision making agents preferences in subsequent time steps (e.g., Poff et al. 2010; Sabri et al. 2012).

Pfeffer (2002) proposed a generic approach for incorporating temporal scale into the GIS-MCDA procedures. The approach is an extension of the framework developed by Herwijnen (1999) (see Sect. 2.3.3.4). Herwijnen's framework integrates two methods of combining criterion maps: the spatial aggregation (*SA*) and multicriteria aggregation (*MA*) (see Fig. 2.14). Given spatiotemporal data, a third method of combining the input datasets, the temporal aggregation (*TA*), can be added (Pfeffer 2002). Depending on the order of operations one can identify six procedures for combining spatiotemporal datasets: (i) $SA \rightarrow MA \rightarrow TA$, (ii) $SA \rightarrow TA \rightarrow MA$, (iii) $MA \rightarrow SA \rightarrow TA$, (iv) $MA \rightarrow TA \rightarrow SA$, (v) $TA \rightarrow SA \rightarrow MA$, and (vi) $TA \rightarrow MA \rightarrow SA$ (where the symbol $\rightarrow$ reads 'is followed by'. Pfeffer (2002) applied the $SA \rightarrow TA \rightarrow MA$ and $TA \rightarrow SA \rightarrow MA$ procedures for evaluating potential locations of alpine ski runs using WLC as the main multicriteria combination method and performing sensitivity analysis by comparing the results of WLC, TOPSIS, and ELECTRE (see Sects. 4.2, 4.4, and 4.5, respectively).

Zhou and Chen (2011) advanced Pfeffer's (2002) framework by suggesting different ways of aggregating temporal data, according to the decision making agents' preferences. They have applied their temporal aggregation approach, in conjunction with the OWA method (see Sect. 4.2.3), with the $TA \rightarrow SA \rightarrow MA$ procedure for evaluating emergency management systems using one-year-interval time series for the period 2005–2009. Similarly, Young et al. (2010) employed the $TA \rightarrow SA \rightarrow MA$ method for developing an area-based composite score using the AHP procedure (see Sect. 4.3) and exploring spatiotemporal patterns of social deprivation and health-care needs for three 10-year time steps between 1981 and 2001. The central element of the procedure is the spatiotemporal method for standardizing criterion values. The study modifies the conventional standardization methods (see Sect. 2.3.1) to make the evaluation criteria comparable over time. Specifically, the overall maximum and minimum values across the three time steps are used to standardize the evaluation criteria.

In the time series methods for tackling temporal multiscale multicriteria decision/evaluation problems, GIS-MCDA is used as the multicriteria combination procedure. It is employed at each time step to combine the values of evaluation criteria and decision making agents preferences (e.g., Lesslie et al. 2008; Poff et al. 2010; Zheng et al. 2010). Poff et al. (2010) provide a good example of applying GIS-MCDA for analyzing time series datasets. They have employed the time series method to a forest management problem involving a total of thirteen 10-year time steps and the temporal extent of 130 years (the time period 1997–2127) using the compromise programming procedure (see Sect. 5.3.2).

The geosimulation models (cellular automata and multi-agent system) are the most significant application of the time series methods involving GIS-MCDA (see Sect. 8.3). The critical element of integrating geosimulation, GIS-MCDA, and time series is the transition rule of geosimulation models. It determines the spatial dynamics of the system being modelled. There are a number of studies in which the transition rules are derived from multicriteria procedures that are employed at each time step of the geosimulation modeling (e.g., Wu 1998; Wu and Webster 1998; Ligtenberg et al. 2001; Li and Liu 2007; Sabri et al. 2012—see discussion on GIS-MCDA and geosimulation in Sect. 8.3.1and 8.3.2). Equation 8.4 provides an example of the WLC-based time series multicriteria model (a transition rule) in the geosimulation procedures (see Sect. 8.3.1).

9.4 The Modifiable Areal Unit Problem

GIS-MCDA models often use datasets representing evaluation criteria, which are reported for arbitrary and modifiable areal units (regions, zones, parcels of land). The arbitrary and modifiable nature of geographic data implies that the results of GIS-MCDA (i.e., the overall values of decision alternatives or evaluation scores associated with areal units) depend on the particular areal units that are evaluated using a set of criteria. In the context of spatial multicriteria analysis, the different types and levels of aggregation can lead to entirely different criterion outcomes and associated preferences, and consequently one can obtain substantially different overall values of decision alternatives and their rank-orderings. This sensitivity of analytical results to changing shape and size of areal units is referred to as the modifiable areal unit problem (Openshaw 1984; Wong 2009). It states that changing the size (the *scale effect*) and shape of the spatial units of analysis (the *zoning effect*) can change the results of the modeling procedure. The scale effect is concerned with the question of how many zones should be used. The zoning effect focuses on the question of which zoning scheme should be used at a given level of aggregation.

9.4.1 The Scale Effect

The results of GIS-MCDA depend on the scale at which the analysis is performed. Given a study area (the geographic/operational scale—see Sect. 9.2), any change in the resolution scale affects the number of areal units; and consequently, the size of areal units and their criterion values. This implies a different multicriteria decision/evaluation problem involving a different (smaller or larger) set of decision alternatives. Evaluating decision alternatives represented by areal units may result in different, and in some cases very different, overall values of alternatives (their rank-orderings) depending on the spatial resolution or (dis)aggregation of the areal units. The differences in the ordering of alternatives, due to the resolution scale, can be referred to as a scale based 'rank reversal' problem (see Sect. 2.3.2). Specifically, the results of GIS-MCDA may indicate the following ordering of four decision alternatives (areal units): $A_1 > A_2 > A_3 > A_4$ (where, > means 'alternative A_i is preferred to A_j'); but when A_1 and A_2 are aggregated to form a new areal unit $A_{(12)}$, and A_3 and A_4 are aggregated into $A_{(34)}$, then $A_{(34)}$ could be preferred to $A_{(12)}$.

Furthermore, the results of GIS-MCDA are influenced by the changes in the range of criterion values (the difference between the maximum and minimum values) due to the changing spatial scale. The criterion range is important because it affects both the results of criterion standardization (or value function) and the criterion weighting procedures (see Sects. 2.3.1 and 2.3.2). The criterion weights are intrinsically related to the criterion ranges (see Eqs. 4.2–4.5). Accordingly, any change in the criterion range values should result in a different set of criterion weights, and subsequently in different overall values of alternatives.

An effective way of illustrating the scale effect in GIS-MCDA is to use a raster dataset at different levels of geographic resolution. Let us consider two evaluation criteria: elevation (in meters) and proximity (distance) to water (in kilometers) at three levels of resolution (Fig. 9.2). The 16 km study area is divided into 16 areal units of equal size (Fig. 9.2a); the units are then aggregated into eight zones of 2 km^2 (Fig. 9.1b), and four zones of 4 km^2 (Fig. 9.2b). The three aggregation schemes results in considerably different values of key parameters of MCDA: the criterion ranges and criterion weights (see Table 9.2). The criterion ranges, r_1 and r_2, decline as the number of zones decreases. This, in turn, affects the criterion weights for the elevation criterion, w_{E_1}, and distance criterion,w_{E_2}, which are

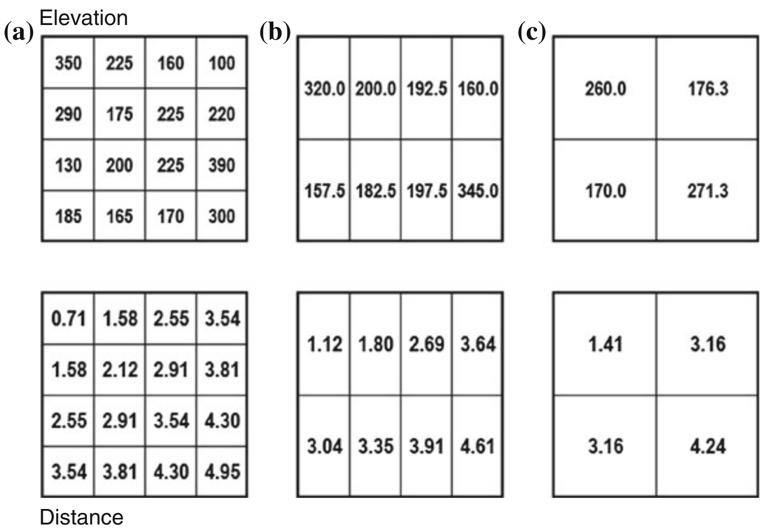

Fig. 9.2 Two criterion maps for study area (extent) of 16 km^2: elevation (in meters) and proximity (distance) to water (in kilometers) at three levels of resolution: **a** 1 km^2, m = 16 areal units; **b** 2 km^2, m = 8 areal units; **c** 4 km^2, m = 4 areal units

Table 9.2 The scale effect: three levels of resolution of a 16 km^2 study area (the number of area units, m = 16, 8, and 4)

Criteria	Elevation		Distance		r_2/r_1	w_{E_2}/w_{E_1}
# of units (rasters)	Range r_1 (m)	Weight w_{E_1}	Range r_2 (km)	Weight w_{E_2}		
16	290.00	0.436	4.24	0.564	0.015	1.294
8	187.50	0.389	3.49	0.611	0.019	1.571
4	101.25	0.262	2.83	0.738	0.028	2.817

r_1 = the range of elevation criterion values; r_2 = the range of proximity (distance) criterion values; w_{E_2}/w_{E_1} = trade-off between the distance and elevation criteria

estimated using the entropy based method (see Sect. 2.3.2.1.4 and Eq. 2.12). Specifically, the increasing values of r_2/r_1 correspond to the increasing trade-offs between the two criteria along with decreasing number of zones from 16 to 4 (Table 9.2). For example, the trade-off value for m = 16 is equal to 1.294; this means that one is willing to trade-off one unit of elevation for 1.294 units of distance. The increasing trade-off values due to the aggregation process indicate that the distance criterion is becoming relatively more importance with the increasing size of areal units (or decreasing number of units). Indeed, this is the scale effect regarding the relative importance of criterion weights.

Given the criterion weights, the two criterion maps are standardized (see Eq. 2.2) and then combined using the WLC model (see Eq. 4.1). As expected, the overall WLC scores assigned to each areal unit are sensitive to the resolution. Figure 9.3

Table 9.3 The zoning effect: three zoning systems for the number of zones, $m = 8$

Criteria	Elevation		Distance		r_2/r_1	w_{E_2}/w_{E_1}
Zoning systems	Range r_1 (m)	Weight w_{E_1}	Range r_2 (km)	Weight w_{E_2}		
Z_1	187.50	0.389	3.49	0.611	0.019	1.571
Z_2	178.00	0.341	3.49	0.659	0.020	1.860
Z_3	245.00	0.620	2.55	0.380	0.010	0.613

r_1 = the range of elevation criterion values, r_2 = the range of distance criterion values, w_{E_2}/w_{E_1} = trade-off between the distance and elevation criteria

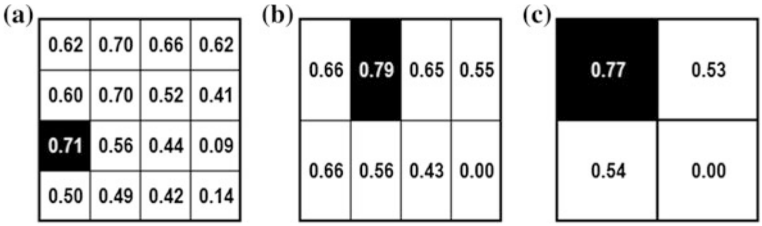

Fig. 9.3 The scale effect: the results of WLC for two evaluation criteria (see Fig. 9.1) and entropy-based criterion weights (see Table 9.2). *Note* Highlighted values: the best alternative

indicates that not only the location of the best units depends on the resolution scale, but also the rank-ordering of the areal units is sensitive to the number of zones. This is the scale effect concerning spatial patterns of the WLC scores and their rank-orderings.

9.4.2 The Zoning Effect

The zoning effect is any variations in the outcomes of GIS-MCDA due to alternative aggregation of basic areal units (or building blocks) to delineate boundaries of zones (decision alternatives). It involves keeping the same number of zones but changing the shapes and sizes. For any specified number of zones, there is often an enormous number of alternative zoning systems that need to be considered (Openshaw 1984; Wong 2009). As in the case of scale effect, the changes of zoning systems affect the results of GIS-MCDA. First, the different zoning systems are often characterized by different criterion ranges. This, in turn, influences the results of the related procedures of value function and criteria weighting. Second, the overall value scores and rank-orderings of alternative decisions are sensitive to the changing zoning patterns. The zoning effect can be illustrated using an example of two criteria: elevation and proximity to water (see Sect. 9.3.1). Figure 9.4 shows three zoning configurations generated by aggregating 16 areal units into 8 zones.

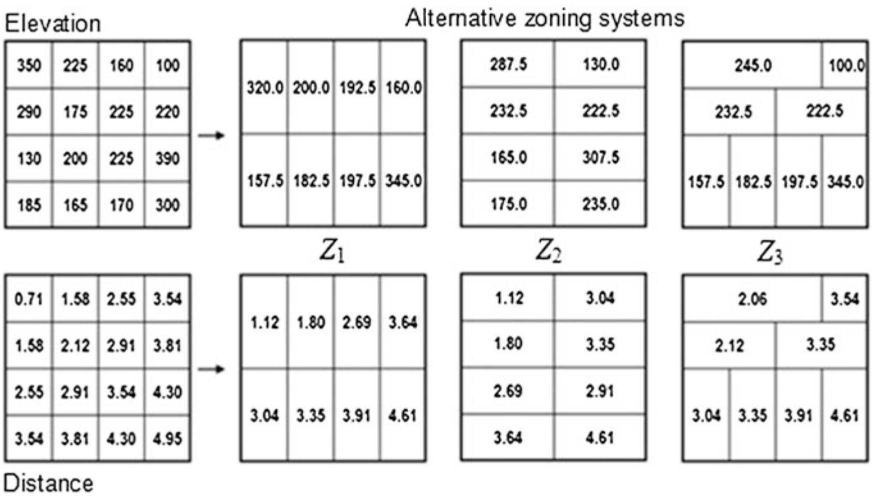

Fig. 9.4 Three alternative zoning systems Z_1, Z_2, and Z_3 obtained by aggregating 16 areal units for two criterion maps of the study area at a resolution of 1 km^2: elevation (in meters) and distance to water (in kilometers); number of zones m = 8

The changing pattern of zones affects the criterion range values and criterion weights generated by the entropy method. Accordingly, the trade-off values are very different depending on the zoning pattern. For the zoning systems Z_1 and Z_2, the distance criterion is more important than the elevation criterion, as indicated by the trade-off value of greater than 1.0 (see Table 9.4). However, the zoning system Z_3 is characterized by the trade-off value of less than 1.0. This indicates the elevation criterion is more important than the distance criterion. This, in turn, leads to inconsistent results of GIS-WLC. Figure 9.5 shows considerable differences between the spatial patterns of the overall WLC values for the three zoning schemes. Also, the rank-orderings of the areal units are dependent on the zoning system.

Table 9.4 Two evaluation criteria for an area of 16 km^2: elevation (in meters) and proximity to water (in kilometers) at four levels of measurement scales (resolution)

Scale level	Scale		Criterion range, r_k	
	Number of units	Unit size (km^2)	Elevation r_1 (m)	Distance r_2 (km^2)
0	256	0.0625	320.00	5.30
1	64	0.25	315.00	4.95
2	16	1.00	290.00	4.24
3	4	4.00	101.25	2.83

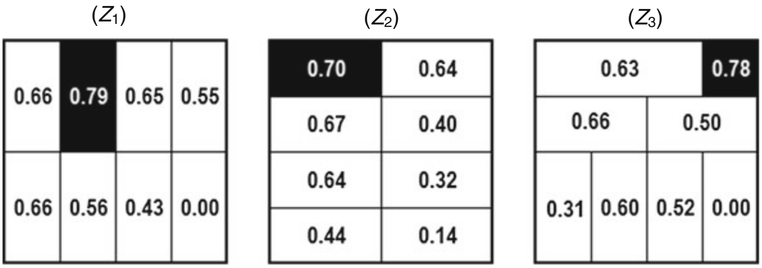

Fig. 9.5 The results of WLC for two evaluation criteria (see Fig. 9.4) and the entropy-based criterion weights for three zoning systems, Z_1, Z_2, and Z_3 (see Table 9.3). *Note* Highlighted values: the best alternative

9.4.3 Dealing with the MAUP

There are a number of procedures available for detecting the most appropriate (characteristic) scale or scales of spatial analysis (see Quattrochi and Goodchild 1997; Tate and Atkinson 2001). Although there has been no attempts to develop a systematic method for dealing with the MAUP of multicriteria decision/evaluation problems, one can suggest that the variance based methods (Cao and Lam 1997) provide the most promising procedures for modeling scale of GIS-MCDA. The variability of geographic data changes with the extent and resolution (Lam 2004; Wu 2004; Schneider 2009). The scale of maximum variability is where most of the processes underlying a spatial pattern operate (Cao and Lam 1997).

The variance based approaches, with some modification, can be used for exploring the scale problem in GIS-MCDA. Specifically, we argue that an effective method for detecting the most appropriate scale of spatial multicriteria analysis should involve the range of criterion values (the difference between the largest and smallest values in a dataset), rather than the value of variance or standard deviation. The criterion range is one of the basic concepts in GIS-MCDA. Importantly, the criterion range value is used as a component of the fundamental procedures in multicriteria analysis, such as the methods for identifying value functions (see Sect. 2.3.1) and estimating criterion weights (see Sect. 2.3.2). To illustrate the relationship between the criterion ranges and spatial scales, let us consider a study area of 16 km^2 to be evaluated with respect to two criteria: elevation (in meters) and proximity to water (in kilometers) (see Sect. 9.4.1; Fig. 9.2) at four spatial scales (see Table 9.4). The smallest unit of analysis is a raster of 0.0625 × 0.0625 km (the spatial resolution level 0). The basic units are aggregated to obtain the resolution levels of 0.25, 1, and 4 km. The elevation values of the l-th level are the average value of the four nested rasters of the $l - 1$ level. The proximity to water criterion is measured by the distance between the upper-left-hand corner of the raster grid and the raster's centroid. A plot of the criterion value ranges against the resolution scales shows that the ranges rise monotonically as a function of the numbers of areal units (Fig. 9.6). Note that the curve climbs steeply at the low resolution levels

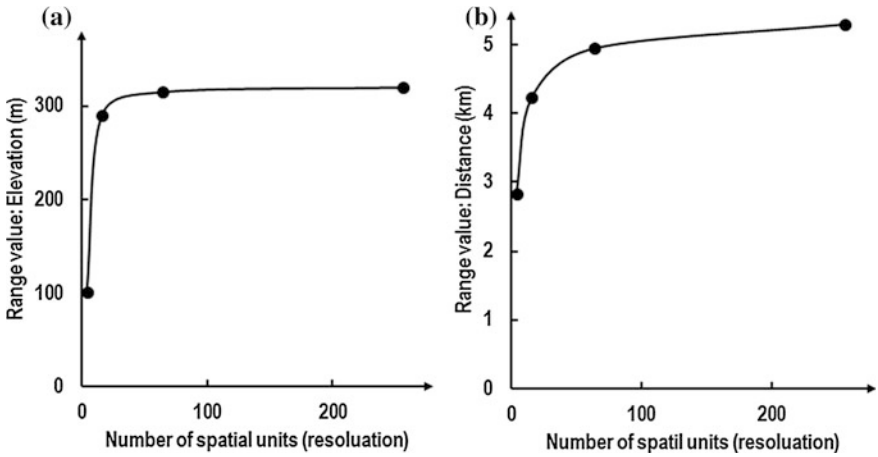

Fig. 9.6 The value of criterion range as a function of the number of spatial units: **a** the elevation criterion, and **b** the proximity (distance) to water criterion

but quickly tapers off at the higher (finer) levels of resolution. The criterion range values are increasing negligible at the high resolution levels. This relationship shows a progressive increase in the range value until some resolution (a point on the curve), beyond which a large increase of the number of areal units corresponds to a near zero increase in the range value. The 'threshold' point beyond which there is no significant increase of the range value can be used for identifying the appropriate scale of analysis. For example, Fig. 9.6 suggests that the resolution level of 0.25 (64 areal units) can be consider the most appropriate scale for GIS-MCDA involving the two criteria: elevation and proximity to water.

The selection of the spatial scale of multicriteria analysis is an outcome of a process that takes into consideration two main factors: the value of criterion range (the higher is the value, the more suitable is the resolution scale) and the availability of data. One can apply a simple rule: select the level of resolution that maximizes the values of criterion range from the set of available datasets. This rule is supported by empirical studies involving the use of census data. For example, Can (1992) suggests that among the available geographical datasets of the U.S. census data, the smallest areal units are the most suitable datasets for multicriteria analysis of residential quality. Likewise, an empirical study of area-based deprivation indices using datasets derived from Statistics Canada determined that the smallest unit of analysis is the most appropriate for examining spatial patterns (Schuurman et al. 2007). There are no empirical studies involving remote sensing datasets that would support the principle of maximum criterion range value. We suggest that the results of geographical/local variance based research about the principle of maximum variability for detecting the operational scale (e.g., Cao and Lam 1997) can be extended to examine the principle of maximum criterion range value in the context of GIS-MCDA.

Furthermore, the range of criterion values is a pivotal element of the local forms of GIS-MCDA models (Malczewski 2011; Malczewski and Liu 2014; Carter and Rinner 2014). We suggest that the local methods can provide an effective platform for modeling scale in multicriteria analysis (see Sect. 4.2.2). There is some evidence to show that the results of the local procedures are sensitive to the definition of the size and shape of the units of analysis (Liu 2013; Qin 2013). One can identify the relationship between the criterion range values and resolution by gradually changing the size of the units of analysis in the local GIS-MCDA model, and then determine the most appropriate scale for the evaluation criterion by finding the maximum range value. This does not imply that local GIS-MCDA modeling 'solves' the scale problem. We suggest, however, that the results of local GIS-MCDA models may provide a tool for exploring the scale effects and, at least partially remove the uncertainty associated with the scale problem in GIS-MCDA procedures.

The general principle of designing an 'optimal' zoning system is to minimize the intra-zonal variances and to maximize inter-zonal variances (Wong 2009). However, it would be an unsuitable approach to apply the same principle for tackling MAUP in GIS-MCDA (see Sect. 9.4.1). Although the variance and range of criterion values might be related, it is the latter measure that is of crucial importance for multicriteria analysis. Therefore, we suggest that the underlying principle for generating zoning systems is to maximize the local and global criterion range values simultaneously. This involves solving a bi-objective optimization problem: (i) to maximize the value of the local range, and (ii) to maximize the value of the global range, subject to a set of constraints regarding the number of zones and spatial properties of zones such as contiguity and compactness. This optimization task can be recognized as a constrained non-linear integer problem that can be solved using the methods described in Chaps. 5 and 6 (see Alvanides and Openshaw 1999).

To illustrate the optimization task of designing a zoning system, let us consider the problem discuss in Sect. 9.4.2. Given the 16 areal units (rasters of 1 km^2) and their attributes (criterion values of elevation and proximity to water), the task is to find the 'best' system of 8 zones that maximizes the local and global range values. For the sake of illustration, we consider only three zoning systems (see Fig. 9.4) out of a set of 12,870 feasible aggregations of the 16 basic units into 8 zones. Table 9.5 shows the local and global criterion range values for the three zoning systems. The conflicting nature of this bi-objective optimization problem is displayed in Fig. 9.7. For the elevation criterion, there are two non-dominated solutions: Z_2 and Z_3 (Z_1 is dominated by Z_3). In the case of the proximity criterion, the three solutions to the zoning problem are non-dominated. Note that Z_1 and Z_2 are characterized by the same value of the global and local ranges, however, the systems display different spatial patterns of zones (see Fig. 9.4). The property of non-dominance indicates that there does not exist a single solution that simultaneously optimizes the global and local range (see Sect. 2.2.3.2). Thus, there are trade-offs that one is faced with; a higher value of one range can be achieved only at the expense of a lower value of the other range. To identify which of the non-dominated solution is the 'best'

Table 9.5 The values of global and local ranges of two evaluation criteria: elevation (in meters) and proximity (distance) to water (in kilometers) for three zoning systems

Criteria	Elevation		Distance	
Zoning systems	Global range r_1 (m)	Average local range $r_{1(q)}$ (m)	Global range r_2 (km)	Average local range $r_{2(q)}$ (km)
Z_1	187.50	66.25	3.49	0.67
Z_2	178.00	86.25	3.49	0.67
Z_3	245.00	68.13	2.55	0.82

Note r_k = global range for the k-th criterion, k = 1, 2; $r_{k(q)}$ = local range for the k-th criterion in the q-th zone, q = 8

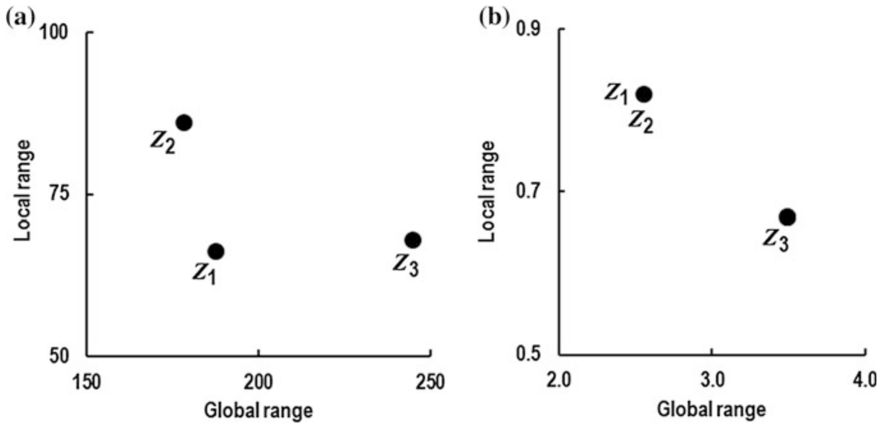

Fig. 9.7 Alternative zoning systems Z_1, Z_2 and Z_3 and the criterion ranges for: **a** the elevation criterion, and **b** the proximity to water criterion

zoning system, one can use the multiobjective weighting method (see Sect. 5.2). Depending on the set of weights assigned to the two objective functions, Z_2 or Z_3 is identified as the 'best' zoning system for the evaluation criterion. In the case of the proximity to water criterion, the 'best' zoning system can be selected between: Z_1 and Z_3 or Z_2 and Z_3.

It is important to emphasize that the scale and zoning effects should not be regarded solely as problems, but as a potentially useful contribution to GIS-MCDA (Alvanides and Openshaw 1999). The methods for detecting an appropriate scale of analysis should be considered an essential component of the toolset for exploratory analysis of decision situations. The challenge is to develop a systematic and operational modeling approach for exploring MAUP and integrate it with the GIS-MCDA procedures. At the very minimum, the capabilities of GIS should be used to assist in reducing scale and zoning effects. The system allows for access to geographic data at various levels of spatial aggregation. The data can be processed, analyzed, and displayed at the lowest possible level of aggregation, and the modifiable areal unit effects can be explored by reaggregating and reanalyzing. While this can only be done at levels of aggregation above the lowest available, the results allow GIS-MCDA users realize the degree of scale and zoning effects.

9.5 Conclusion

This Chapter was concerned with the issues of scale in GIS-MCDA. It defined the different meanings of scale and provided a discussion of the connotations of spatial, temporal, and operational scales in the context of decision/evaluation problems. It also provided an overview of approaches for tackling the spatial and spatiotemporal multiscale decision situations using GIS-MCDA. One of the most challenging aspects of GIS-MCDA modeling is the modifiable areal unit problem (MAUP). This Chapter discussed the two components of the problem (the scale and the zoning effects) in GIS-MCDA procedures. It focused on demonstrating how MAUP influences the results of GIS-MCDA. We suggested that the methods for tackling the scale and zoning problems in GIS-MCDA should focus on the range of criterion values as the pivotal measure of procedures for exploring MAUP.

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Part III
Spatial MCDA: Technologies

Chapter 10
Desktop GIS-MCDA

10.1 Introduction

The implementation of GIS-based MCDA has evolved in step with advances in GIS and information technology in general (see Chap. 3). Historically, implementations were isolated through the use of specific scripting or programming languages and incompatible GIS data structures. The question of whether the MCDA module was tightly or loosely coupled with GIS modules was an important one. Today's software design allows for seamless integration of functional modules across computing platforms—at least in principle. Therefore, the focus of this chapter is placed on GIS concepts and techniques that directly influence the implementation of MCDA procedures within GIS.

The representation of a multicriteria decision problem in GIS depends on the representation of the geospatial phenomena that define the problem, in particular the decision alternatives and evaluation criteria (see Sects. 2.2.2 and 2.2.3). Commonly, the geometric dimension, the attribute dimension, and sometimes the temporal dimension of geospatial phenomena are being distinguished (e.g., Worboys 1995). These dimensions present somewhat different modeling challenges. The attribute dimension, in particular, is of critical importance to MCDA. There are two approaches to representing geography and attaching attributes to locations: the raster model and the vector model. The raster model is used for field-like phenomena that are measured (or interpolated) continuously across space. These phenomena are represented by attribute values attached to a regular grid of cell locations. The vector model is used for phenomena that occur at distinct locations or are assigned to distinct physical or conceptual features. In this case, attribute values are attached to geometric features, i.e. points, lines, or polygons.

In the raster model, every cell is typically considered as a decision alternative. In contrast, in the vector model there is usually a well-defined, much smaller set of features that represent the decision alternatives. In the raster model, each criterion requires a separate raster layer, albeit all layers have to be transformed to the same

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_10

grid resolution in order to be combined. Thus the multiple criterion layers represent the same set of alternatives, the grid cells. In the vector model, each criterion is represented by a column (field) in a data table associated with the set of alternatives. Through simple table join operations, all criteria can be integrated in a single data table, even if they originate from multiple sources. Thus, in the vector model there is usually only one map layer representing the decision alternatives as features that are linked to a multi-column attribute table, much like the concept of the decision matrix outlined in Sect. 2.2.4.

Malczewski (1999) notes that multiattribute decision making is well served by the raster model, while the vector model may better support multiobjective decision making. Indeed, the well-defined combination procedures in raster data analysis discussed in the following section fit with the structure of multiattribute decision problems. In addition, some multiobjective decision problems require advanced data models such as traffic flow models in transportation planning and hydrological models in environmental studies. However, the association between the data model and type of MCDA problem usually results from a complex interplay of characteristics of the decision problem on the one hand, and the domain-specific approach to geospatial data modeling on the other hand. For example, the network vector model is common in transportation planning where decisions typically are multi-objective decision problems. In contrast, hydrological modeling may be addressed with either a vector-based network model or a raster-based terrain model, and therefore the association between decision problem type and data model is not as straightforward.

The following Sect. 10.2 explains the commonalities and differences of implementing MCDA procedures in vector-based or raster-based data structures using generic GIS functionality. Section 10.3 then introduces examples of dedicated MCDA modules in desktop GIS packages. Section 10.4 completes the chapter with a case study that integrates vector- and raster-based GIS-MCDA.

10.2 MCDA Implementation in Vector- and Raster-Based GIS

A key processing step in MCDA is the combination of multiple criterion values into a single evaluation score for each decision alternative (see Chap. 4). The required calculations can be implemented using generic GIS functionality. In the vector model, the feature attribute table represents the decision matrix, and its columns are combined to obtain evaluation scores as a new column referring to the same alternatives (rows). In the raster model, each single-value map layer corresponds to a column in the decision matrix (see Sect. 2.2.4), and layers are combined using map algebra, resulting in a new layer that refers to the same alternatives (grid cells). Other processing steps in MCDA can be implemented using the same generic functions, including adding or removing attributes/layers to be used as decision criteria, and rescaling and weighting criterion values. In the following examples, we go through these steps using the Field Calculator and the Raster Calculator in the open-source software package QGIS (formerly Quantum GIS). Similar functionality exists in commercial GIS such as Esri's ArcGIS or Pitney Bowes' MapInfo.

10.2.1 MCDA Implementation Through Table Calculations

In the vector data model, GIS-MCDA often starts with a data table, in which the rows refer to geographic locations and the columns refer to selected characteristics of these locations. The data used in the following example of MCDA implementation through table calculations originated from the Human Development Index (HDI) created annually for most countries in the World by the United Nations Development Program (UNDP). The 2013 Human Development Report includes statistical tables for download (UNDP 2013). We selected the table 'Human Development Index and its Components', which includes the 2012 HDI rank, name, and abbreviated code of each ranked country, 2012 HDI value, and the corresponding index components, namely life expectancy at birth, mean years of schooling, expected years of schooling, and gross national income per capita.

Like these HDI data, the data used in other GIS-MCDA projects often are secondary data that are obtained as an aspatial data table. To complete the data collection, we also needed to procure a geospatial data file of locations or boundaries that the tabular data refer to. The HDI data table includes a three-letter code for each country, for which we needed a matching code in the geospatial data file. The 'World Borders Dataset' available at http://thematicmapping.org/downloads/world_borders.php has such a code and is available under a 'Creative Commons Attribution-Share Alike License'.

Both datasets were loaded into QGIS, as illustrated in Fig. 10.1. To combine the aspatial and spatial datasets, we performed a table join operation that attaches each row in the HDI data table to the corresponding country in the world boundary dataset (see Fig. 10.2). In the resulting table, the components of the HDI were not recognized as numeric variables, as can be seen by their alignment within the table cells (left alignment is customary for text data while numeric data are typically displayed with right alignment in spreadsheet software) or by analyzing the table's metadata. Additionally, the field names from the original attribute table were changed to automatically generated cryptic names. To convert the text fields to numeric fields with proper names for further processing, new fields were created and filled using the 'toreal()' and 'toint()' conversion function in the Field Calculator in QGIS, as shown for the life expectancy field in Fig. 10.3. To conclude the preparation of a spatially explicit decision matrix, we saved the joined data to a new, integrated geospatial dataset, such as a Shapefile, to avoid issues in the following data processing steps.

To replicate the HDI, we examined its composition from three simple indices—a life expectancy index, an education index, and an income index–, and four underlying variables—life expectancy at birth [in years], mean years of schooling

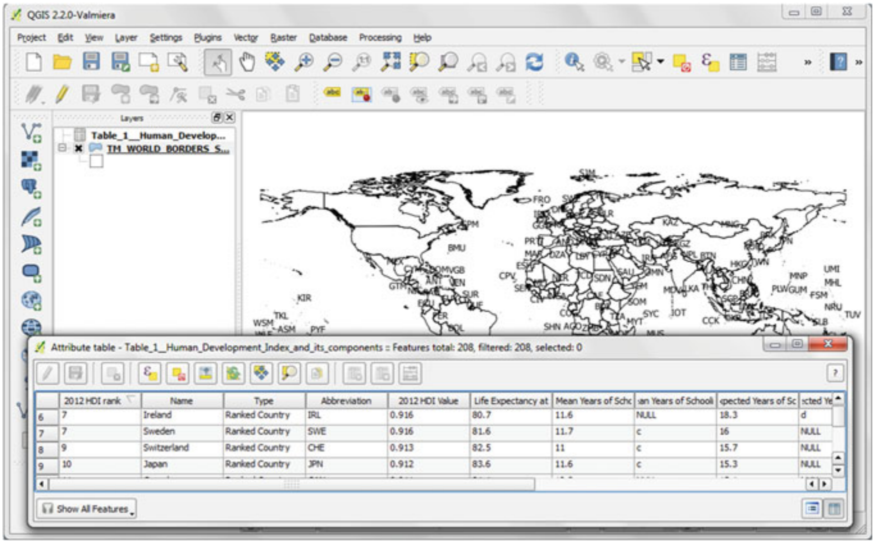

Fig. 10.1 Human development index data table and world boundary datasets in QGIS

for ages 25 and above [in years], expected years of schooling [in years], and gross national income (GNI) per capita [in purchasing power parity US$]. The four individual variables were already normalized as required to exclude effects of area or population size on the GIS-MCDA results. The component indices were then calculated as follows (see Excel tool at http://hdr.undp.org/en/content/excel-tool-calculating-indices for the original calculations):

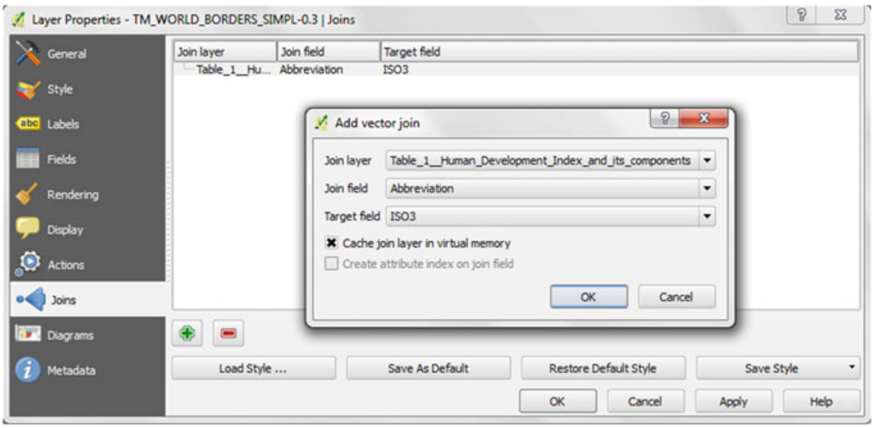

Fig. 10.2 Table join operation to attach tabular data to geospatial boundary layer

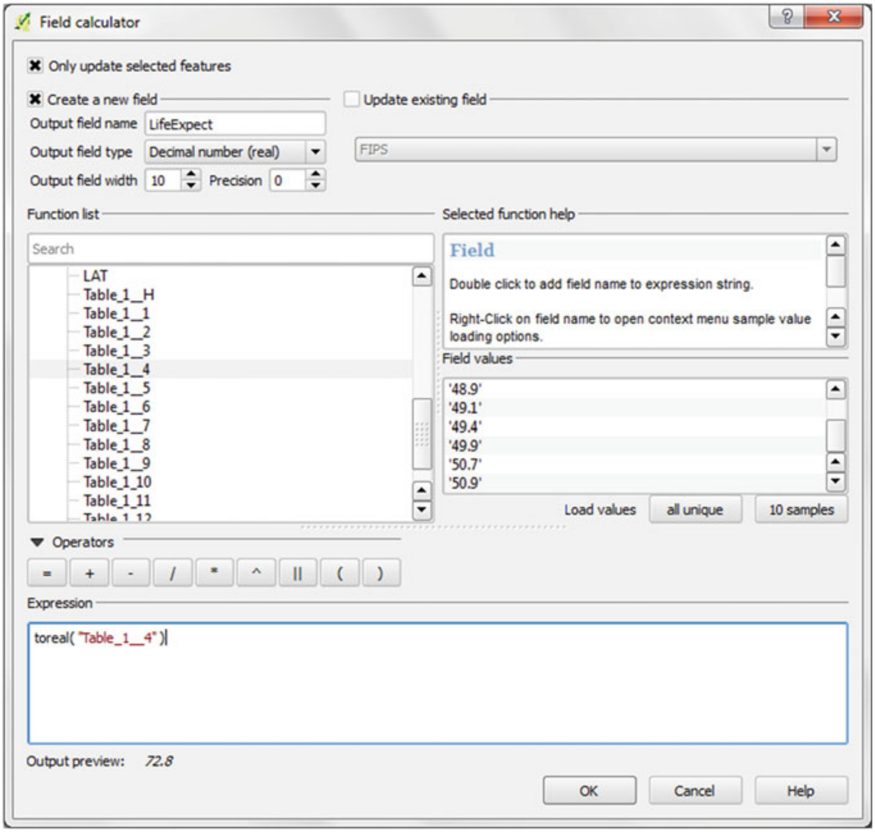

Fig. 10.3 QGIS field calculator used for creating a new, numeric field for life expectancy data copied from imported text field

- Life expectancy index = (life expectancy at birth−20 years)/(83.57 years −20 years)
- Education index = *sqrt*((mean years of schooling/13.27) * (*min*(expected years of schooling,18)/18))/0.971
- Income index = (*ln*(GNI per capita)−*ln*(100))/(*ln*(87,478)−*ln*(100))

The creation of these component indices served the purpose of value scaling in GIS-MCDA (see Sect. 2.3.1). In fact, the life expectancy index and the income index are variations of score-range transformation to obtain values within the 0–1 range, and the education index is a variation of the geometric mean. The transformations use theoretical or de facto minimum and maximum values; e.g., a minimal life expectancy of 20 years for a sustainable human population and a minimum of US$100 for GNI per capita, as well as a maximum number of expected years in schooling capped at 18 years (see FAQ HDI at http://hdr.undp.org/en/faq-page/human-development-index-hdi for further explanations). The example of the

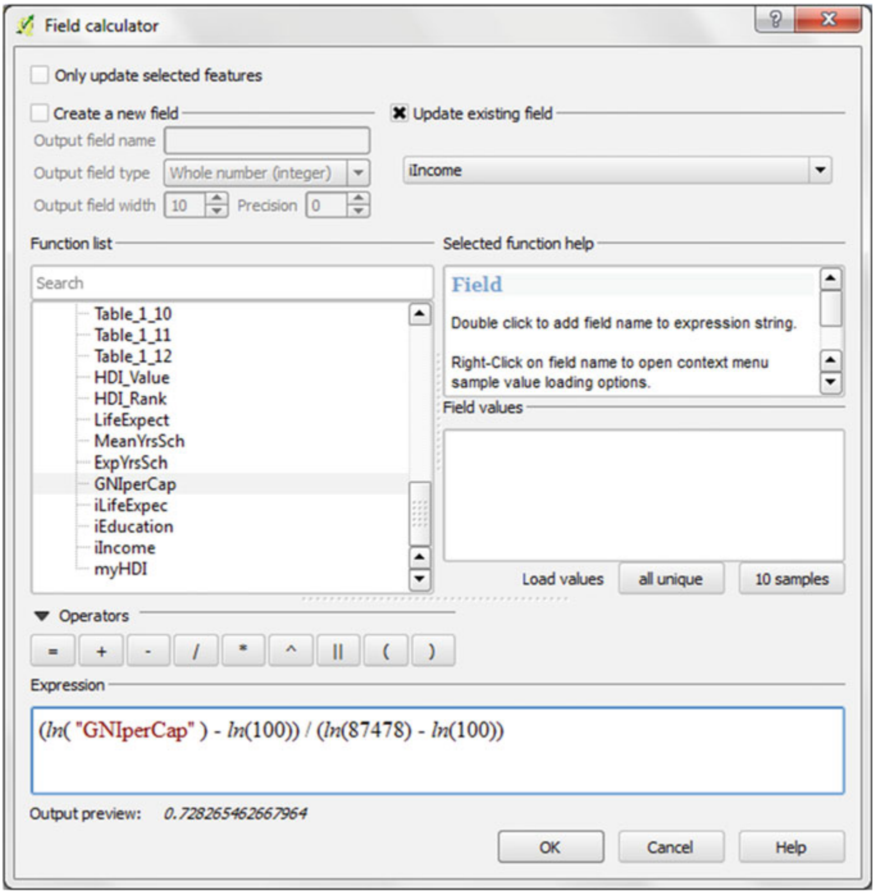

Fig. 10.4 Logarithmic score-range transformation of GNI per capita to obtain income index as a component of the HDI

income index calculated as a score-range transformation of the variable GNI per capita on a logarithmic scale is shown in Fig. 10.4.

The HDI was then calculated as a geometric mean of the three component indices as follows and as shown in Fig. 10.5:

- HDI = *cube root* (life expectancy index * education index * income index)

The component indices were equally weighted and combined multiplicatively. Up until 2009, the HDI was calculated as an unweighted arithmetic mean, or in other words, a weighted linear combination with equal weights. It must be noted that using equal weights is not consistent with MCDA theory, since weights should be determined in conjunction with criterion value ranges (see Sect. 2.3.2.1.1).

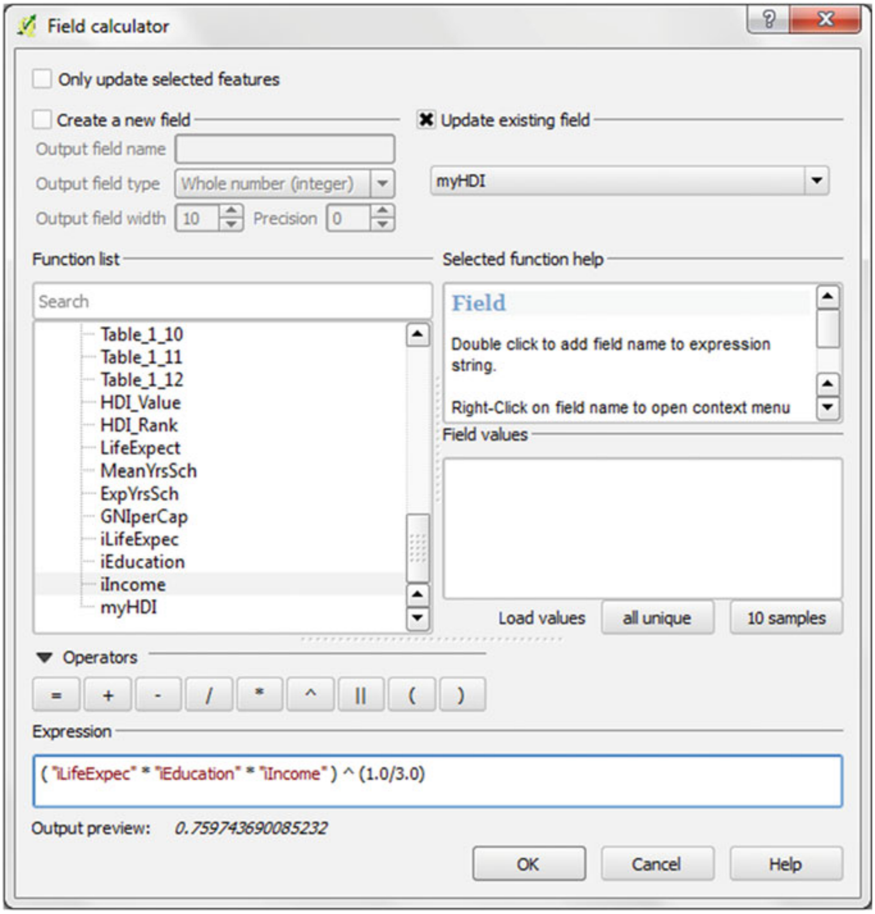

Fig. 10.5 Calculation of the HDI as an unweighted geometric mean in QGIS field calculator

10.2.2 MCDA Implementation Through Map Algebra

In the raster data model, GIS-MCDA primarily consists of an overlay of raster data layers, each of which represents one decision criterion. The example used in this section is a simple index of wildfire risk for the Province of Ontario, Canada. The index is composed of just two indicators (criteria): one representing the locations of historic wildfire occurrences, and the other representing road access both for fire-fighting crews and for evacuation of residents.

To establish the ‘decision matrix’ as a stack of criterion layers, the Canadian Disaster Database (2013) was searched for wildfire occurrences within the Province of Ontario for the available time period from the year 1900 to present day. This search

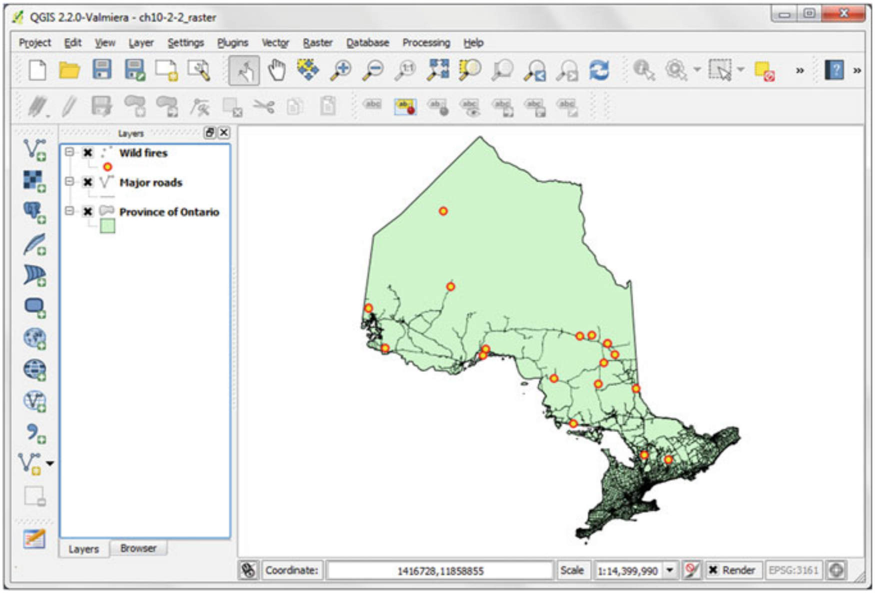

Fig. 10.6 Initial data layers for wildfire risk index

resulted in 18 point locations coded in KML format, which was loaded into QGIS and converted to a point Shapefile. The road access criterion was developed from DMTI Spatial Inc.'s major roads dataset for 2013, which was available through an academic site license. A provincial boundary file was retrieved from Statistics Canada, also under an academic license. The screenshot in Fig. 10.6 shows these layers.

A number of raster operations followed in order to rasterize the source data, create distance surfaces, clip the new layers to the Provincial boundary, and rescale them for the final index calculation. Figures 10.7 and 10.8 show the rasterization dialog, which uses the QGIS interface to GRASS functionality, and the QGIS project with rasterized criterion layers added to the source data layers. Rasterization was needed because the distance/proximity functions in QGIS require a raster layer as input. A distance surface was created using the r.grow.distance function from GRASS, available within QGIS processing toolbox (Fig. 10.9). The distance surface was created for the bounding box of the study area and, therefore, needed to be clipped to the actual shape of the Province, as shown in Fig. 10.10. This is important for the following rescaling (standardization) step, in which the actual maximum distance within the study area is needed. Rescaling was achieved using the raster calculator in QGIS. Road distance was rescaled as a benefit (maximization) criterion, while wildfire distance was rescaled as a cost (minimization)

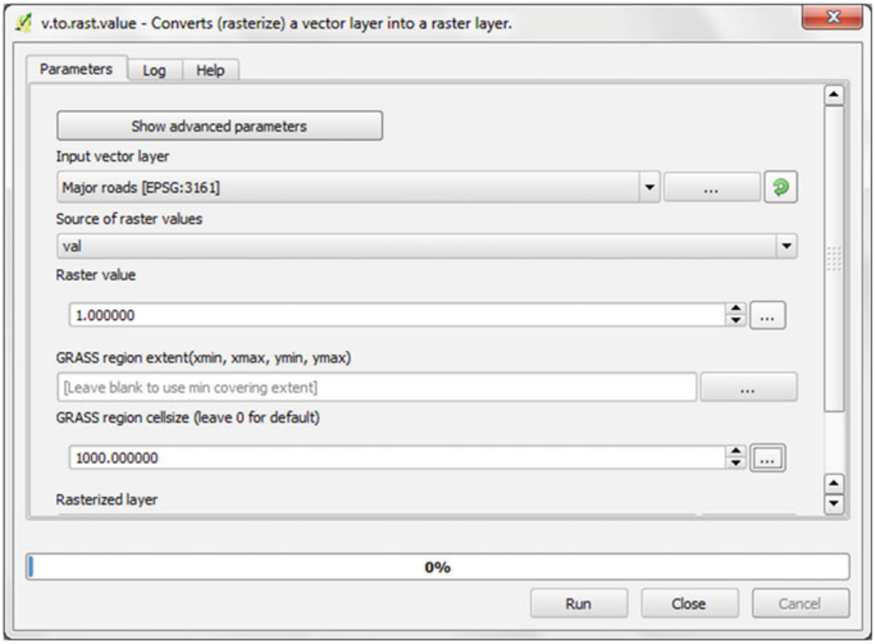

Fig. 10.7 Rasterizing major roads using GRASS vector-to-raster tool within QGIS

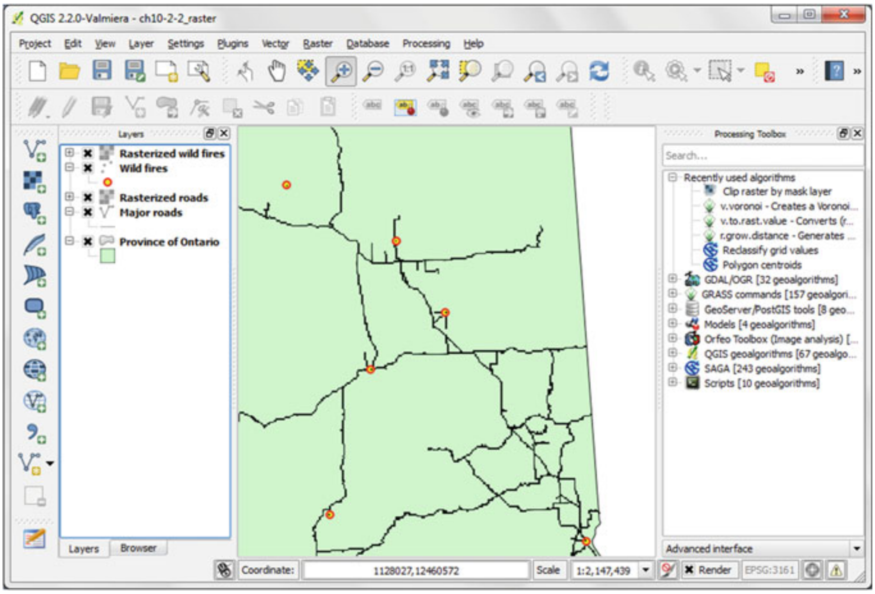

Fig. 10.8 QGIS project with rasterized criterion layers added

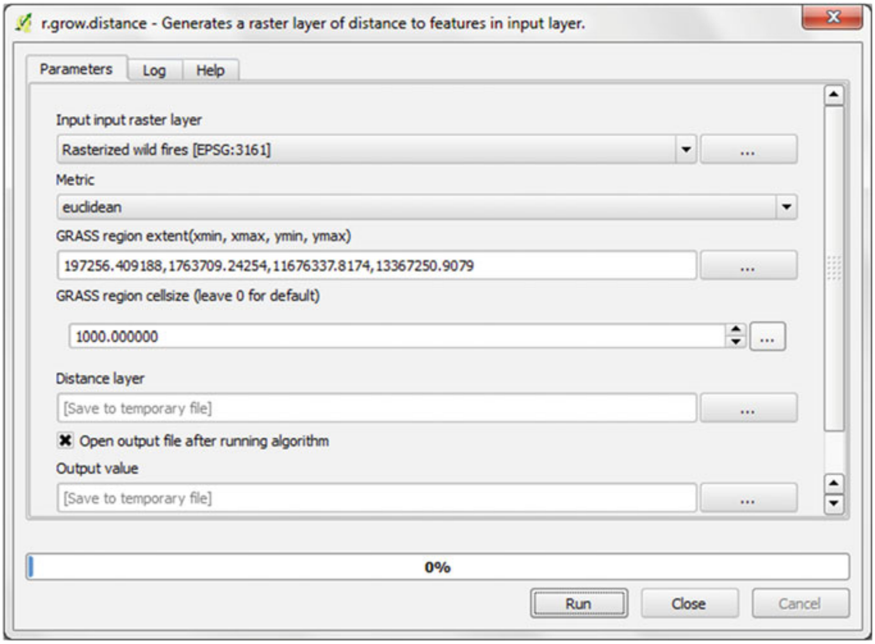

Fig. 10.9 Calculation of a distance surface from historic wildfire incidents

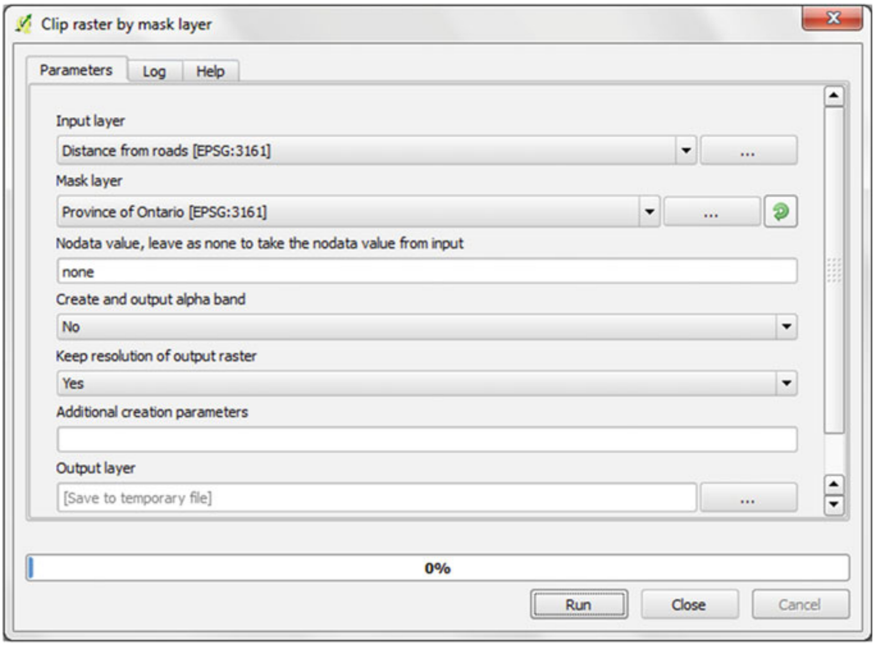

Fig. 10.10 Clip of raster distance surface to boundary of study area

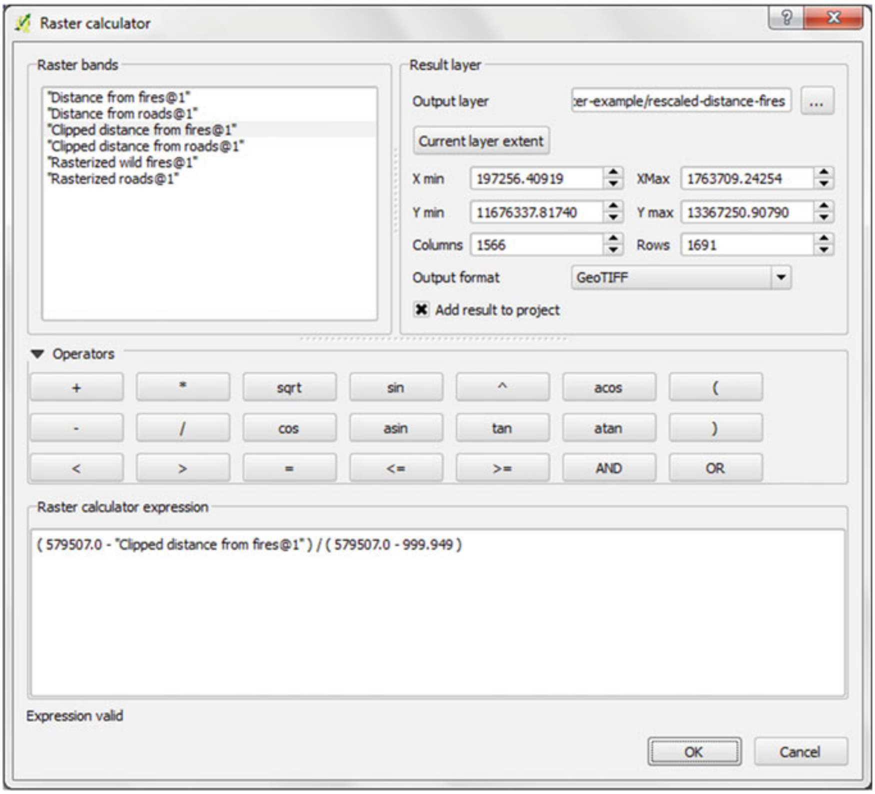

Fig. 10.11 Rescaling (standardization) of wildfire distance as a cost (minimization) criterion in QGIS' raster calculator

criterion (see Fig. 10.11). As a result, the larger the distance to roads, and the smaller the distance to wildfires, the larger the rescaled criterion values are.

Using the rescaled criterion layers, a weighted linear combination was performed using the raster calculator in QGIS. The resulting risk index is composed from a 60 % of historic wildfires occurrences and 40 % road access. The MCDA calculation for the risk index is shown in Fig. 10.12 and the resulting map appears in the screenshot of the QGIS project in Fig. 10.13.

The core GIS-MCDA algorithm in the raster model is performed as a local raster operation, where an arithmetic or logical operation is applied to the coincident cells of two or more raster datasets (criterion layers). For example, the percentage weight is multiplied with the first cell of the first input layer, and the second weight multiplied with the first cell of the second layer. These two terms are then added up to form the composite index value of the first cell of a new layer, which is the final

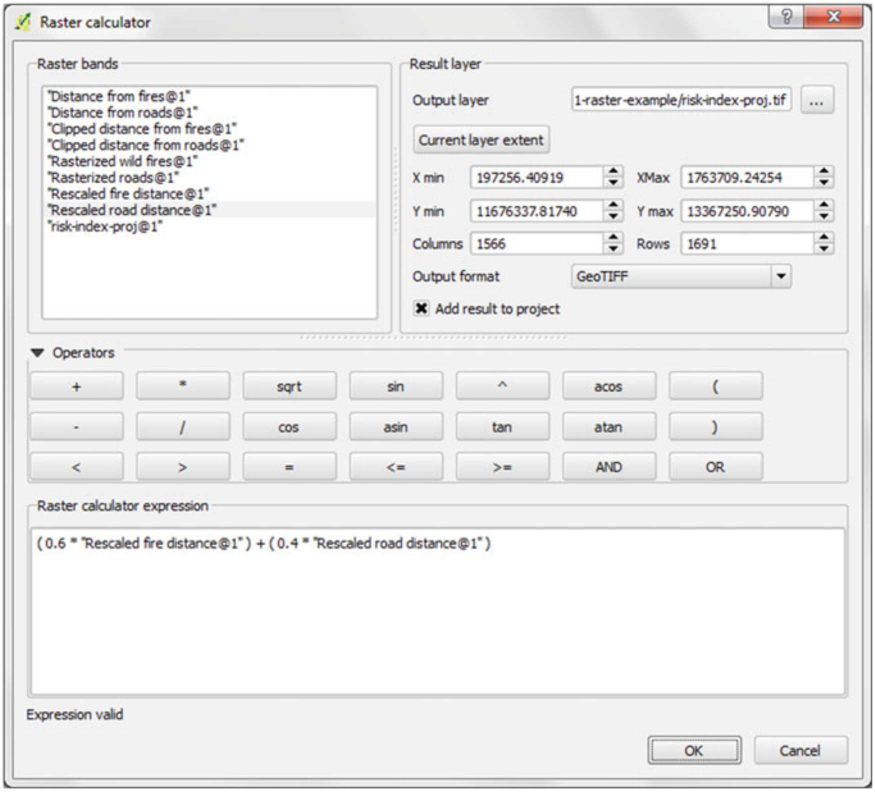

Fig. 10.12 Composite wildfire risk index as a weighted linear combination in QGIS' raster calculator

risk index. This process is repeated for each pair of corresponding cells in the two input rasters. The output raster layer represents a weighted linear combination, or weighted average, of the two input rasters.

10.3 MCDA Modules in Commercial and Open-Source GIS

The IDRISI GIS software package includes, arguably, the most comprehensive MCDA functionality among commercial GIS packages. IDRISI has been developed by Clark Labs at the Graduate School of Geography at Clark University in Worcester, Massachusetts (see http://www.clarklabs.org). It includes a 'Decision

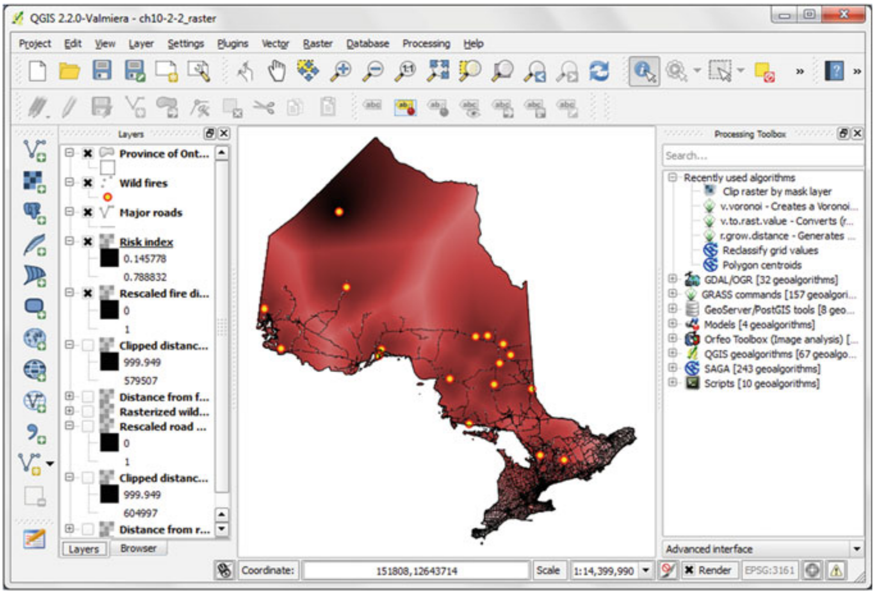

Fig. 10.13 QGIS project with final index map and layers from intermediate raster processing. Note that this simple wildfire risk index is for illustration of desktop GIS-MCDA techniques only!

Wizard' with tools for weighting, ranking, and multiattribute and multiobjective decision analysis. IDRISI's MCE (multi-criteria evaluation) module has been applied to land use planning, risk and vulnerability assessment, sustainable forest management, hazardous material transportation planning, and emergency planning, as illustrated on the Clark Labs Web site. IDRISI terminology distinguishes decision criteria into hard 'constraints' and soft 'factors' (Eastman 1997). Constraints are used for Boolean masking, which removes unsuitable alternatives from further processing. Factors are the compensatory decision criteria, which allow for trade-offs between high and low values. The criterion weights are interpreted as the parameters that control the trade-off between factors. An example of the process of inspecting the available data for decision making, developing constraints and factors, and conducting a multi-criteria evaluation with IDRISI is described in Rinner (2003). The IDRISI workflow for MCDA is graphically outlined in Fig. 10.14.

Within Esri's ArcGIS software package, the 'Overlay toolset' in the 'Spatial Analyst toolbox' includes three tools that support suitability modeling and site selection: weighted overlay, weighted sum, and fuzzy overlay. Similarly to the IDRISI MCE module, the overlay tools in ArcGIS are limited to operating on the raster data model. According to the ArcGIS Help 10.1 (Esri 2012), weighted overlay rescales all input raster layers to the user-selected scale (e.g., 1–9);

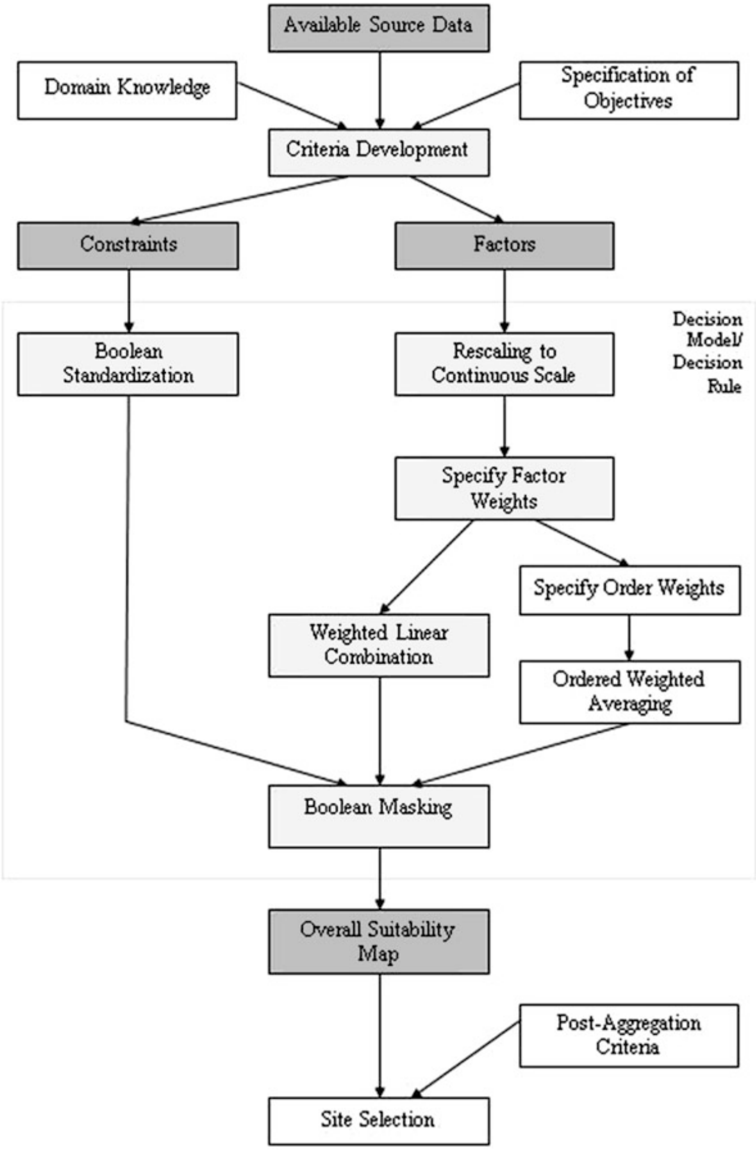

Fig. 10.14 The IDRISI approach to MCDA

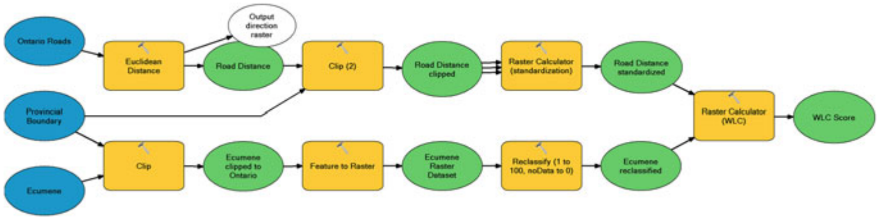

Fig. 10.15 Sample GIS-MCDA workflow in Esri's modelbuilder

multiplies the rescaled criteria with user-defined weights out of 100 %; and adds these values up to create a resulting raster layer, in which high values represent the most desirable locations. The weighted sum function is only slightly different from weighted overlay, in that it does not rescale input layers and does not impose the restriction of a 100 % sum on the user-defined weights. However, the weighted overlay function suffers from several conceptual issues, which are not present in the weighted sum tool. The input raster layers in the weighted overlay function have to be "discrete integer rasters" (Esri 2012), and therefore, any continuous-value criteria would have to be reclassified to the nominal or ordinal measurement level with a corresponding loss of accuracy. The rescaling of both, the input data and the weighted MCDA result, to a limited integer range such as 1–9 introduces inconsistencies. While the weighted sum tool preserves continuous or integer input and the original range of the MCDA result, its unconstrained weighting scheme is problematic. Because of the contradictions to the rescaling and weighting principles outlined in Sect. 2.3, results from the ArcGIS overlay toolset have to be carefully analyzed.

Esri's ModelBuilder application acts like a visual scripting environment within ArcGIS. It can, therefore, play an important role in making GIS-MCDA processing steps such as data preprocessing, rescaling, weighting, and combination efficiently re-producible. Figure 10.15 shows a sample GIS-MCDA workflow in Esri's ModelBuilder. The workflow, which is similar to the raster processing example in the previous section, includes two source files, a road network layer, and the polygons of settled areas in Canada, as well as the boundary of the Province of Ontario as a third input file. The road lines are used to create a distance surface and the settlement areas are rasterized. The study area boundary is then used in clip operations to limit the extent of the two criterion layers. The settlement criterion is then reclassified to 0 (no settlement) or 100 (settlement), while the distance surface is rescaled using the raster calculator in ArcGIS to stretch the real-world distance from roads to the same 0–100 value range. Finally, the raster calculator is used once more to combine the two rescaled, weighted criteria into an MCDA result raster representing weighted linear combination scores. Using ModelBuilder, the

Table 10.1 MCDA-related add-ins on the phased-out Esri 'ArcScripts' Web site (http://arcscripts.esri.com/)

Title	Software	Language	Author	Modified	Downloads
AHP 1.1—Decision support tool for ArcGIS	ArcGIS—ArcView	Visual Basic	Oswald Marinoni	Feb 13 2009	10,374
AHP-OWA 2.0—multicriteria evaluation	ArcGIS desktop	VB.net	Soheil Boroushaki	May 30 2008	3,922
MultiCriteria group analyst	ArcGIS desktop	VB.net	Soheil Boroushaki	Oct 16 2008	789
Multi criteria evaluation	ArcView GIS	Avenue	C Heather	Sep 19 2003	1,475
Multiple criteria decision analysis system (MCDAS) 1.0.2	ArcGIS engine runtime	C#	Randal Greene	Mar 9 2010	455
Multiple criteria (SAW, TOPSIS) spatial decision support for ArcGIS	ArcGIS desktop	Python	Andrius Kucas	Jun 16 2010	1,853
Weighted_spatial	ArcView GIS	Avenue	Ayad Faris	Dec 6 2008	232

parameters of the desktop GIS-MCDA process can be easily modified and the analysis re-run.

Due to its long-standing popularity as a desktop GIS, Esri's ArcGIS group of products also benefits from numerous add-ins developed by end-users and GIS professionals. Add-ins used to be published on the 'ArcScripts' Web site, which is still maintained and includes 5,712 entries. A quick search for MCDA-related keywords yields the seven add-ins listed in Table 10.1. However, as of April 2010, the site was closed and updates to the existing user scripts, as well as newly developed add-ins, have to be shared through the 'ArcGIS Resources' Web site. That site does not have a consistent search function and no MCDA-related add-ins could be found upon a quick search. Instead, developers may be using generic open source software platforms such as SourceForge or CodePlex to publish their ArcGIS add-ins, as in the case of the MCDA4ArcMap tool (Rinner and Voss 2013) described in Chap. 11.

An example of a small, commercial GIS-MCDA product is DECERNS (Decision Evaluation in Complex Risk Network System). The tool was originally developed at Obninsk State Technical University in Russia. A current Web-based implementation includes the AHP, TOPSIS, and PROMETHEE methods, as well as fuzzy and other advanced MCDA techniques (see http://deesoft.ru/lang/en/product-decerns-mcda/).

An MCDA package was implemented in the open-source GRASS GIS (Neteler and Mitasova 2008), and is therefore also available in the popular open-source QGIS package (see http://qgis.org/en/site/). The 'r.mcda' package operates on raster data and offers five MCDA techniques: AHP, Electre, Fuzzy/OWA, Regime, and dominance-based Rough Sets (Massei et al. 2012). The developers specifically highlight the 'r.mcda.roughsets' module, which implements Greco et al.'s (2001) dominance-based rough set approach to MCDA, which can handle inconsistent information. Another open-source MCDA toolkit is available in the Integrated Land and Water Information System (ILWIS). ILWIS is a GIS and remote sensing software, which was originally developed as a commercial, yet low-cost, product at ITC, the International Institute for Geo-Information Science and Earth Observation in Enschede, Netherlands. It was later released as an open source project with a community Web site maintained by 52° North (see http://52north.org/communities/ilwis). The SMCE (Spatial Multiple Criteria Evaluation) module in ILWIS has been used for land use suitability analyses and water management.

The Spatial Decision Support Knowledge Portal at the University of Redlands, http://www.spatial.redlands.edu/sds/, provides a large collection of spatial decision support methods, tools, and case studies. The portal's "Multi-Criteria Decision Analysis" section lists Idrisi along with a few other tools that implement MCDA techniques. The portal also helps users to integrate decision theory into real-world planning and decision making problems, which also is the purpose of the following case study.

10.4 Case Study: Desktop GIS-MCDA in Spatial Decision Support

In 2010/11, the City of Toronto, Ontario, Canada, implemented a heat vulnerability assessment and decision support system using a GIS-MCDA approach (Toronto Public Health 2009, 2011a). Heat vulnerability was defined as a combination of exposure and sensitivity variables. Exposure to extreme heat was modeled predominantly through variables representing the bio-physical and housing environment, while sensitivity was modeled through socio-economic and public health variables. Thematic maps played an important role in analyzing and conveying the results of the Toronto heat vulnerability assessment to decision makers. In this detailed case study description, we review other critical steps in desktop GIS-MCDA for the heat vulnerability assessment from the report by Toronto Public Health (2011a).

Table 10.2 Heat vulnerability index composition and indicator weighting

40 % Exposure index	30 %	Surface temperature
	10 %	Access to green space
	10 %	Tree canopy shading
	17.5 %	Dwellings in high-rises (five or more storeys)
	17.5 %	Rented dwellings in older high-rises (built before 1986)
	15 %	Population density
60 % Sensitivity index (general population)	25 %	Low-income persons (2005, after tax LICO)
	5 %	Low-income among children (age 0–5)
	5 %	Renter households spending > = 50 % on housing
	5 %	Low-income renters spending > = 50 % of income on housing
	10 %	Persons not speaking English
	5 %	Recent immigrants (2001–2006)
	5 %	No high school certificate among adults (age 25+)
	5 %	Racialized groups
	10 %	Disability among persons age 25–64
	5 %	Emergency visits 2004–2008 for circulatory disease
	5 %	Emergency visits 2004–2008 for respiratory disease
	15 %	**Seniors sensitivity index (see separate table)**

Source adapted from Toronto Public Health (2011a)

The heat vulnerability assessment project was designed by Toronto Public Health as a spatially explicit, intra-urban analysis focusing on social vulnerability of residential population to extreme summer heat (Rinner et al. 2010). The project objective was to support prioritization among hot weather outreach options. The approach included the creation of composite indices of heat vulnerability using GIS and MCDA methodology applied to Toronto-specific datasets. The data were to be integrated to administrative boundaries representing city neighbourhoods and the 531 Census tracts from the 2006 Canadian Census were selected as the spatial units, representing a compromise between level of detail and manageability of the data layers. The project included a pilot phase (Toronto Public Health 2009) and an implementation phase (Toronto Public Health 2011a), as well as the collection of user feedback on a series of draft maps; the refinement of the 30-criteria index shown in Tables 10.2 and 10.3; the creation of a series of maps of heat exposure and sensitivity indicators, subindices, and indices (i.e., geovisualization of MCDA input and output, see Chap. 11); and the development of a GIS-based decision support system.

Table 10.3 Seniors sensitivity subindex composition and indicator weighting

Seniors sensitivity index (to be included in heat vulnerability index)	10 %	Frail seniors (age 75+ with a disability) among total population in private households
	10 %	Low income (2005, after tax LICO) and living alone among seniors (age 65+)
	20 %	Low income among seniors
	10 %	Low income among seniors living alone
	5 %	Senior families paying > = 30 % on housing
	5 %	Unattached seniors paying > = 30 % on housing
	10 %	Seniors not speaking English
	5 %	Recent immigrants (1996–2006) among seniors
	5 %	No high school certificate among seniors
	5 %	Seniors in racialized groups
	5 %	Unattached seniors with disability
	5 %	Disability among persons age 65–74
	5 %	Emergency visits 2004/05 among persons age 65–74

Source adapted from Toronto Public Health (2011a)

The Toronto heat vulnerability assessment provides examples for the considerations around criterion selection, data availability, transformation of variables between geographic representations, and data maintenance issues in desktop GIS-MCDA, which are briefly summarized in this section. The geospatial data processing, mapping, and decision support functionality were implemented in the commercial ArcGIS desktop GIS software, while the MCDA calculations were implemented in the Microsoft Excel spreadsheet software.

An important indicator of heat exposure was the surface temperature obtained from thermal remote sensing images. Although high surface temperatures do not directly affect human health, they are usually associated with high outdoor and indoor temperatures that can cause heat-related illness. Of more than a dozen thermal images taken over a period of 11 years, only two images were ultimately deemed suitable due to their currency, in-season capture, and cloud-free coverage of the study area. The two images from June 2007 and September 2008 were averaged resulting in surface temperatures of between approximately 15 and 40 for each 30 m by 30 m pixel.

To be compatible with vector-based indicators and the objective of supporting hot weather outreach planning and decision making by administrative units, the surface temperature data were allocated to Census tracts. For this purpose, zonal statistics in ArcGIS were used to create the average surface temperature per Census tract from the pixel values falling within the tract, and reassigning the average

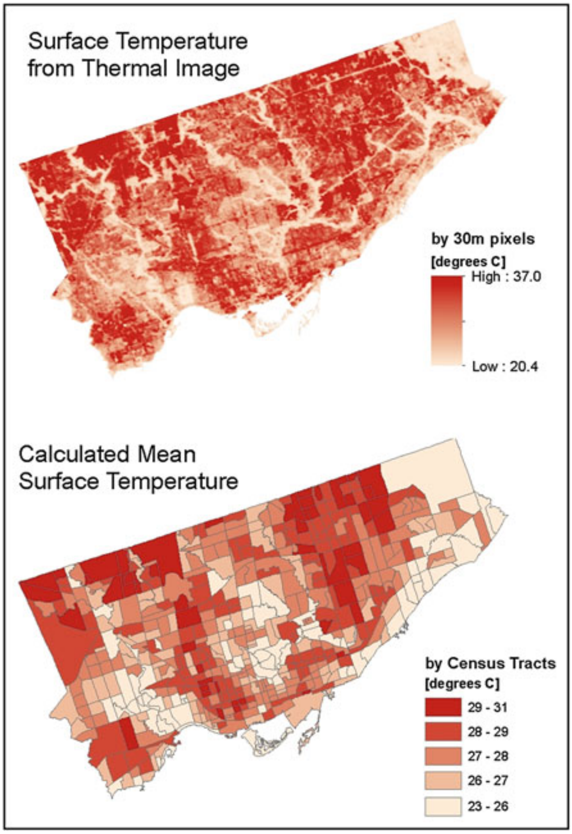

Fig. 10.16 The effect of raster/vector representation on the spatial patterns of a heat exposure indicator (*Source* modified from Rinner et al. 2010)

temperature to the Census tract boundary file (see Fig. 10.16). A similar process was used to assign the proportion of tree canopy coverage to each Census tract originating from the land cover pixel values of a City of Toronto grid dataset. In addition, the accessibility of green spaces to local residents was modeled as the average distance from a park. For that purpose, a distance raster was calculated in ArcGIS based on the City's green space boundary dataset. The distance pixels were then reaggregated to Census tract boundaries using zonal statistics, which were limited to the residential areas within each Census tract, as can be seen in Fig. 10.17.

As part of the heat vulnerability assessment, a mapping tool was developed as an ArcMap customization to enable Toronto Public Health to view and modify the heat vulnerability maps, interactively zoom to individual neighbourhoods of interest, and create custom heat vulnerability reports for internal outreach and communication with hot weather response stakeholders and other community organizations. Figure 10.18 shows the customized ArcMap user interface with query fields for Toronto neighbourhoods, wards, and priority areas. Figure 10.19 shows a custom

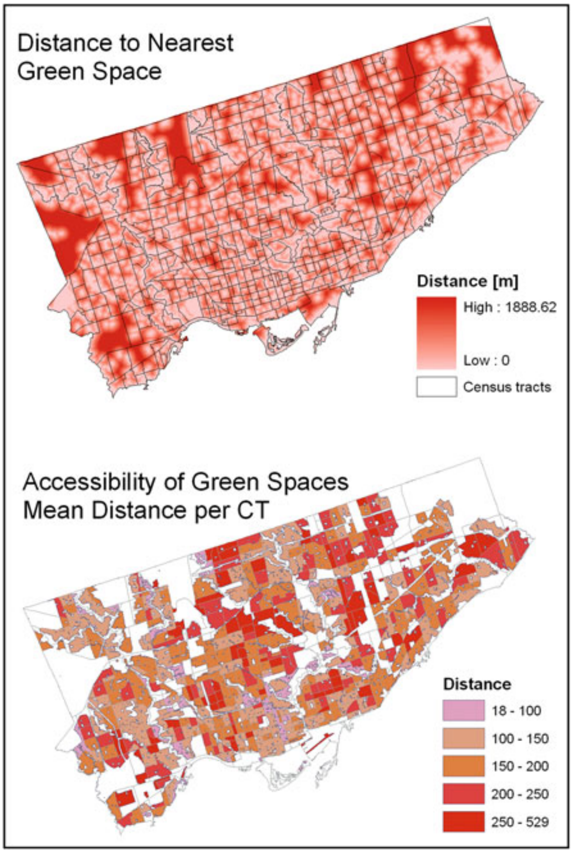

Fig. 10.17 Development of area-based heat exposure indicators from a distance surface (*Source* Toronto Public Health, 2011a, Figs. 4-9 and 4-11, reprinted with permission from Toronto Public Health)

report for a selected neighbourhood, which includes an extract of the heat vulnerability index map for the Census tracts comprising the neighbourhood as well as reference statistics for populations of interest to Toronto Public Health. The custom nature of the mapping tool, the query functionality, and the report generation function illustrate important components of a spatial decision support system (e.g., Densham 1991; Sugumaran and DeGroote 2010)—see also Sect. 1.3.1.

10.5 Conclusion

In summary, desktop GIS-MCDA, as used in the case study project, included the exploration of potential decision criteria (indicators of heat exposure and heat sensitivity); generation of ancillary data (e.g., distance surfaces); conversion of raster datasets to the common unit of analysis in the vector data model (i.e., Census tracts); rescaling, weighting, and summation of indicators to subindices and indices

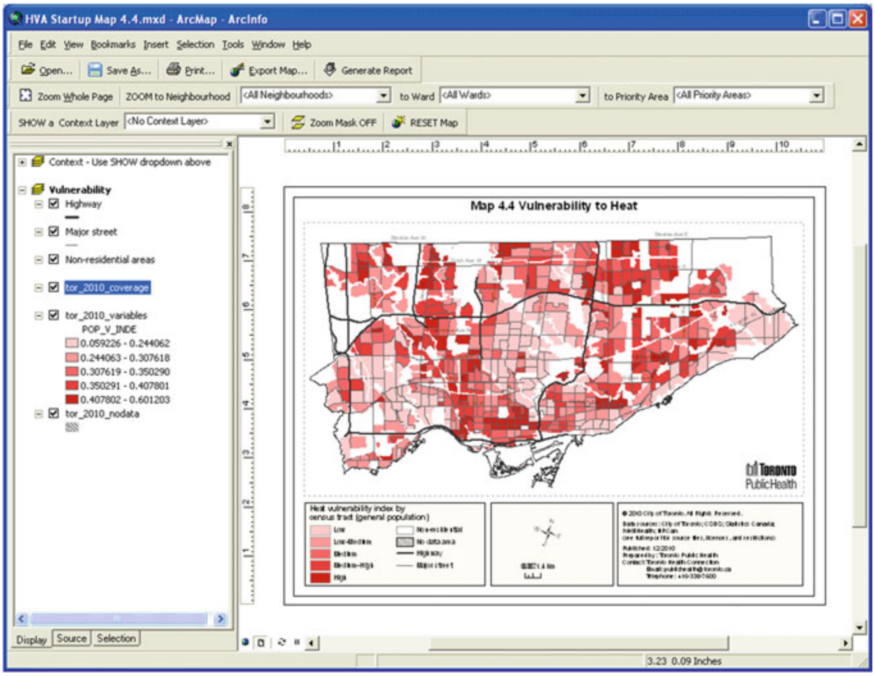

Fig. 10.18 Customized GIS tools for Toronto's heat vulnerability assessment and decision support system (*Source* Toronto Public Health 2011b, Fig. 10.1, reprinted with permission from Toronto Public Health)

(performed in spreadsheet software); reintegration of external calculations with units of analysis; mapping of input data and results; and interactive examination and reporting of results. While the MCDA calculations could have been tightly coupled within the desktop GIS software as outlined earlier in this chapter, the convenience of the spreadsheet software for numeric data manipulation outweighed the drawbacks of the loose coupling approach (see Sugumaran et al. 2011).

In this chapter, desktop GIS-MCDA implementation was presented with a distinction between vector- and raster-based techniques. Goodchild et al. (2007) note that the field (raster) versus object (vector) views are interchangeable, when we just consider the appearance of a scene. However, if the scene is subject to a process, the analyst has to make a critical decision about spatial representation. GIS-MCDA is a process that requires careful consideration of suitable representation. Examples from the vector and raster worlds and their combination were provided. However, the analyst may be constrained by available tools, which in turn are influenced by the underlying GIS software. GIS packages serving the environmental community are likely raster-oriented to support the field-based processes common in environmental studies. In contrast, GIS supporting the study of socio-economic phenomena

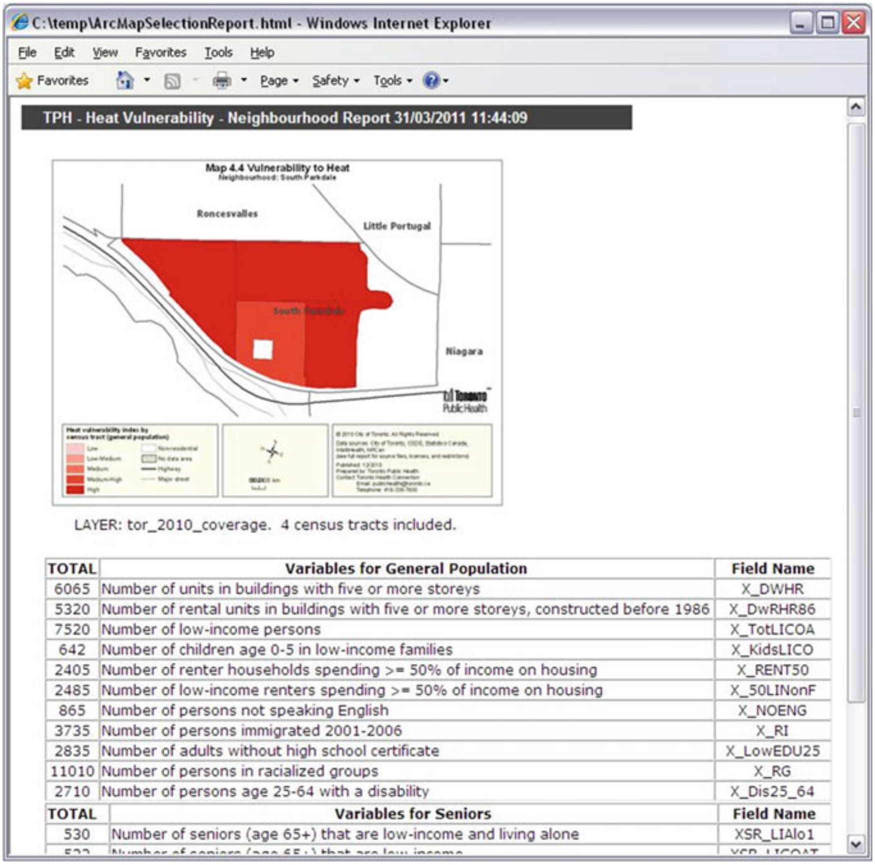

Fig. 10.19 Custom neighbourhood report from Toronto's heat vulnerability assessment and decision support system (*Source* Toronto Public Health, 2011b, Fig. 10.10, reprinted with permission from Toronto Public Health)

are more likely vector-oriented to be able to represent discrete objects of analysis such as Census geographies.

Desktop GIS is the traditional platform for implementing MC-SDSS (see Sect. 1.3.2). Despite the recent emergence of geovisualization-focused MCDA, as well as Web-based and mobile GIS-MCDA, which are discussed in the following two chapters, desktop GIS-MCDA remains a critical resource for informed decision making across a variety of fields. It is expected that desktop GIS-MCDA will continue to be the domain of expert analysts, while the newer approaches will expand the accessibility of GIS-MCDA techniques to non-experts.

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Chapter 11
Geographic Visualization and MCDA

11.1 Introduction

Geographic Visualization, or geovisualization, refers to specific approaches to the cartographic display of geospatial data. Going beyond traditional thematic mapping, geovisualization environments are characterized by their interactive nature. This interactivity allows for multiple perspectives on the same data, thereby supporting an analyst to explore the underlying phenomena and developing scientific hypotheses about them. Geovisualization technology has been combined with MCDA techniques to support decision analysts with advanced human-computer interaction tools.

This chapter first outlines the development of geovisualization within GIScience and summarizes its basic tenets. Examples from the literature that use the CommonGIS tool are presented in more detail. The use of geovisualization to explore MCDA inputs, as well as MCDA results and MCDA parameter space, is then discussed using the ArcGIS add-on 'MCDA4ArcMap' and a deprivation index for the City of Toronto as an example. The chapter concludes with a discussion of the role of geovisualization and MCDA in public planning and decision making.

11.2 Overview of Geovisualization

11.2.1 The Development of Geovisualization Within Cartography

The concept of geovisualization emerged in the Cartography and GIScience literature in the early 1990s. DiBiase (1990) suggests that visualization plays an important role along the continuum of scientific methods, and associates the visual methods in exploration and confirmation with a scientist's 'visual thinking' in a

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_11

'private realm', while visual methods for synthesis and presentation act as 'visual communication' tools in a 'public realm'. MacEachren (1994) extends DiBiase's concept by proposing the map use cube, or cartography-cubed representation. MacEachren (1994) argues that maps are useful along a range of tasks, from 'revealing unknowns' in a private environment using highly interactive mapping tools, to 'presenting knowns' in a public setting using less interactive (i.e., static) maps. MacEachren (1994) thereby emphasizes the data exploration function of maps as complementary to the traditional communication function of maps. Finally, MacEachren and Kraak (2001) coined the term 'geovisualization' and outlined a research agenda for the field.

Based on related research in the area of information visualization, the process of geovisualization can be characterized as one of "overview first, zoom and filter, then details-on-demand", as posited by Shneiderman (1996, p. 337). In their taxonomy of tools for interactive data display, Buja et al. (1996) distinguish focussing, linking, and arranging functions. Spatial data exploration tasks have also been separated into the following groups (Zhou and Feiner 1998; Andrienko et al. 2002; Keim 2002; Plaisant 2005; Kelsey and Rinner 2009):

- identifying the attribute value of an object;
- querying objects by specified attribute values;
- clustering objects by similar attribute values;
- ranking objects by an attribute;
- comparing objects by their attribute values, as well as comparing spatial patterns of two or more attributes at one point in time, or of a single attribute over time (change); and
- quantifying the association (correlation) between two attributes.

The CommonGIS thematic mapping tool (Andrienko and Andrienko 1999) implements many of the principles of geovisualization. For example, its choropleth map allows the user to interactively modify class breaks, the number of classes, and the classification method. It also supports interactive highlighting of one or more selected classes, removing outliers at both ends of the value range, and comparing values to a reference value or reference object with a single click on the map. These interactive functions change the map symbology ad hoc without delay, as required to support visual thinking with maps. With a view on this functionality, Rinner and Taranu (2006, p. 647) suggest that "an interactive mapping tool is worth a thousand numbers".

11.2.2 Geovisualization of Large Geospatial Datasets

Visualization is often recommended to explore large, multi-dimensional datasets. Examples in Keim (2001) include stock trading data and satellite imagery with approximately 200,000 and 16,000 data records, respectively. A short decade later, the term 'big data' was coined to describe datasets in the order of gigabytes (GB), terabytes, or larger, with their implication on data storage, management, retrieval, analysis, and visualization. For example, Jacobs (2009) shows how a dataset in the order of 100 GB is easily imported into a standard database management system, but turns out to be too large to be queried. Jacobs (2009) also notes that ‘big data’ often only become big through “repeated observations over time and/or space” (p. 40).

Remote sensing, as well as ground surveying, have traditionally yielded voluminous geospatial datasets depending on the spatial and temporal resolutions, at which the data are collected. An example of a large raster dataset originating from remote sensing is the City of Toronto’s 2007 land cover dataset, which represents eight land cover classes at a 60 cm pixel resolution, and is stored in a 3.5 GB image file. An example of a large vector dataset is the OpenStreetMap raw dataset covering the extent of the Province of Ontario, which (at the time of writing) is stored in a 5.44 GB XML file.

Geospatial data are inherently multi-dimensional with usually two (increasingly three) spatial dimensions combined with one or more attribute dimensions. An early model was the ‘geographical matrix’ proposed by Berry (1964), in which places (that are nested within different levels of regions) are associated with multiple characteristics measured by variables (that are also nested in a thematic hierarchy). Geospatial data become even more complex if their temporal dimension is considered (e.g., Andrienko and Andrienko 2005). Recent research in geovisualization examines spatio-temporal data through trajectories of movement of objects. For example, Andrienko et al. (2010) propose space-in-time and time-in-space visualizations for traffic data from GPS tracking of over 17,000 cars during one week.

11.2.3 Geovisualization of Parameters of Analytical Processes

Geospatial datasets that are important for government and business planning and decision making are not always large or complex. For example, the City of Toronto is tracking neighbourhood demographics on the basis of 140 geographic units, to which demographic and socio-economic variables can be attached. The 140 neighbourhood boundaries stored in Shapefile format are 422 kB large, while a sample data table with 14 variables from the City’s Wellbeing Toronto tool for each of the 140 neighbourhoods occupies a mere 13 kB in comma-separated format. However, complexity arises when such data are used in analytical processing. The degrees of freedom in analytical models result in numerous possible solutions, if input parameters are uncertain. This is the case in MCDA, where parameters such as criterion weights depend on decision makers’ preferences and different input settings will result in different outcomes. The potential of geographic visualization for exploring decision space, attribute space, and parameter space in MCDA simultaneously was first suggested by Armstrong et al. (1992), Church et al. (1992), and later comprehensively illustrated by Jankowski et al. (2001).

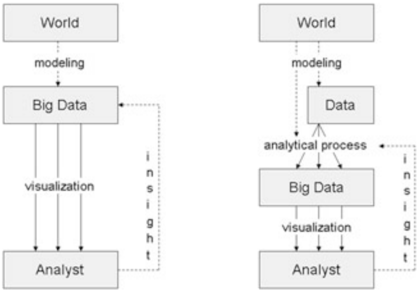

Fig. 11.1 (Geo)visualization used to gain insight from large datasets (*left*) or from analytical processes applied to not-so-large data (*right*) (*Source* modified from Rinner 2007)

The diagram in Fig. 11.1 contrasts the 'traditional' use of geovisualization to explore large datasets ('big data', left column) from its use to explore the complex output of an analytical process, which was applied to any dataset, large or small (right column). In the first case, geovisualization is used to support the development of hypotheses about the real-world phenomena represented by a large dataset. In the second case, geovisualization is used to gain insight into the effects of parameter settings in an analytical process, such as an MCDA model. Rinner (2007) also relates this application of geovisualization techniques to the emerging research fields of visual analytics (Thomas and Wong 2004) and geovisual analytics (Andrienko et al. 2007).

The two approaches illustrated in Fig. 11.1 can also be associated with the geovisualization of MCDA input and MCDA results, respectively. The geovisualization of MCDA input uses human-map interaction to manipulate graphical displays of 'raw' input data, including criterion values and model parameters (such as local weights). In contrast, the geovisualization of MCDA results refers to the interactive graphical display of evaluation scores or a derived ranking of alternatives, which changes with the analyst's modification of model parameters. The remainder of this chapter presents concepts, tools, and applications for geovisualization of both, MCDA input and MCDA results.

11.3 Geovisualization of MCDA Input

The elements of GIS-MCDA introduced in Chap. 2 include the decision makers, criteria, and alternatives (see Sect. 2.2). This formal framework also includes the decision makers' preferences regarding value scaling, criterion weighting, and combination rule (see Sect. 2.3). Most of these components can have spatial dimensions (Rinner and Heppleston 2006) and be visualized geographically, as outlined in the following sections.

11.3.1 Visualizing Decision Alternatives

Geovisualization, as introduced in this chapter, implies that an analyst works with cartographic displays interactively. This requires systematic changes of data or display parameters. In the case of MCDA elements, maps can be used to view the spatial distribution of decision alternatives, and the way in which constraints reduce the set of alternatives (see Sect. 2.2.3.1). For example, the analyst could initially view point locations of alternatives (vector model) or a gridded area of interest (raster model), in conjunction with a basic reference map, and then successively add constraints and view the diminishing set of feasible alternatives. This would help identify thresholds where constraints are becoming too narrow by not leaving a sufficiently large set of feasible alternatives to choose from. An implementation of this interactive approach is available with the ‘dynamic query’ tool in the CommonGIS software mentioned earlier (Andrienko and Andrienko 2001). However, this form of geovisualization is limited to manipulating the presence or absence of decision alternatives, since we have not included characteristics of these locations in the display yet.

11.3.2 Visualizing Criteria

The evaluation criteria in the form of criterion outcomes assigned to decision alternatives are perhaps the most common element of GIS-MCDA to be explored with geovisualization tools. The criteria are represented in a decision matrix (vector model) or through a set of criterion maps (raster model). Here, geovisualization occurs through interactive thematic mapping, where the data can be viewed from multiple perspectives using different map symbologies and zoom levels, allowing the focusing on, or highlighting of, data subsets, and linking different map displays so that the analyst can take advantage of the full scope of map-centred data exploration methods. Within CommonGIS, Andrienko and Andrienko (2001) introduce interactive visual tools to support MCDA, including ‘utility signs’. These thematic map symbols include standardized bar charts and pie charts, which represent the relative performance of decision alternatives on multiple, weighted criteria. For example, a frame around bar charts indicates the maximum performance in the decision matrix, while the width of the bars increases with the corresponding criterion weight. An example with three criteria is shown in Fig. 11.2 (Rinner and Malczewski 2002).

Another mapping technique to visualize evaluation criteria is ‘small multiples’. Multiple small single-criterion maps allow the analyst to examine the spatial association between criteria. In CommonGIS, this approach is further supported through dynamic linking of the small multiples, which ensures that objects highlighted or selected on one map are highlighted or selected on all other maps. Griffin et al. (2006) presented an interesting study of small multiples compared to animated

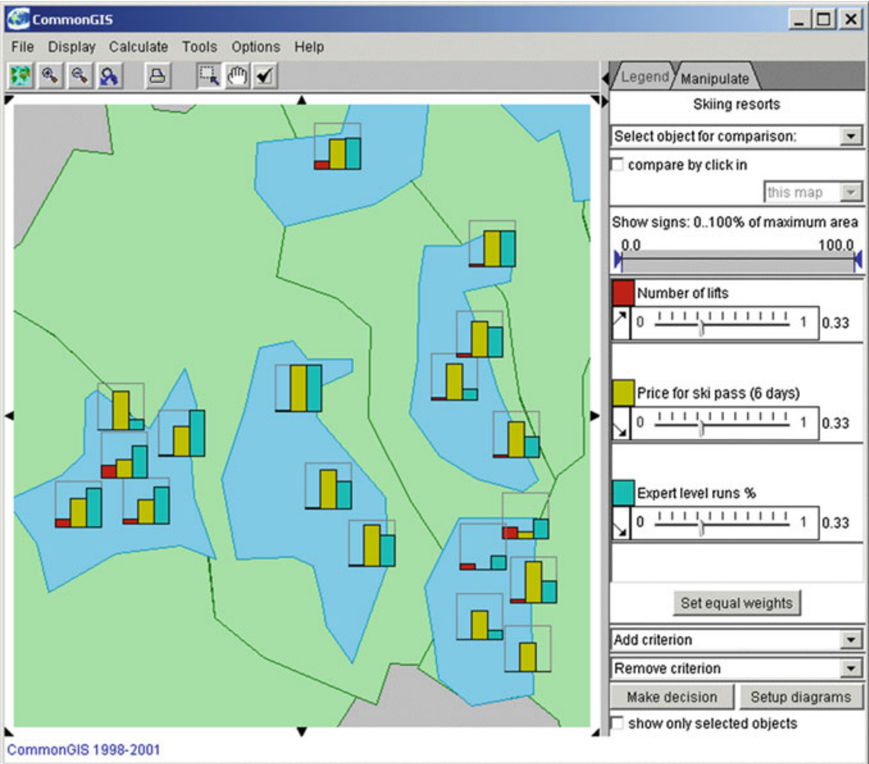

Fig. 11.2 The use of interactive standardized bar charts to visualize criterion values (*Source* Rinner and Malczewski 2002, Fig. 4, used with permission)

maps, and found that animated maps were more effective for cluster identification than static small multiples. However, the interactive small multiples available in select geovisualization software, such as CommonGIS, may overcome the limitations of static small multiples.

11.3.3 Visualizing Scaled Values and Criterion Weights

A basic GIS-MCDA concept that can benefit from geovisualization is the value scaling (or criterion standardization) process (see Sect. 2.3.1). For example, Young et al. (2010) explored the effects of switching between different value functions (standardization procedures) by mapping the corresponding standardized values on interactive maps in CommonGIS. Specifically, two approaches for the scaling of cost criteria using the maximum-score procedure were compared, which resulted in considerable differences in scaled criterion values, although these did not significantly change the MCDA results. An additional example for visually exploring value scaling is provided as part of the case study in Sect. 11.5.

Geovisualization can also be applied to another key concept of GIS-MCDA: criterion importance weighting (see Sect. 2.3.2). While criterion weights are usually globally defined, Malczewski (2011) proposed local weighted linear combination (LWLC) with locally varying weights (see Sect. 2.3.2.2). These local weights can be mapped in order to understand the LWLC procedure (Malczewski 2011; Carter and Rinner 2014). Geovisualization principles could be applied to compare the spatial patterns of multiple sets of local weights. An example of visually exploring local weights is provided in the case study in Sect. 11.5.

11.4 Geovisualization of MCDA Results

11.4.1 Visualizing Combination Rules and Parameters

Results of a multicriteria analysis typically take the form of evaluation scores and ranks for decision alternatives. In the context of a geovisual approach to MCDA, these results are understood to be tentative and subject to adjustment and fine-tuning (Rinner 2007). Interactive changes of the cartographic display are not only triggered by the analyst's manipulation of map symbology, but more importantly, by iterations of the MCDA process with different input and processing parameters. The effects of changes to any of the parameters discussed in the previous section (alternatives, criteria, scaled values, and weights) can in principle be explored using geovisualization. Additionally, the choice of a combination rule, and the parameters that are specific to each rule, can be explored using interactive maps. This map-centred exploration of tentative MCDA results can provide feedback into the MCDA process as outlined in Fig. 11.1.

Jankowski et al. (2001) provide one of the most comprehensive studies using geovisualization of MCDA results. These authors developed tools within the CommonGIS platform that help analysts explore decision space (geography) along with criterion space (attributes). The integrated geovisualization offers interactive map manipulation, linked displays, and immediate response when changing map symbols, map classification, or criterion weights in an ideal point analysis (see Sect. 4.4).

Rinner and Malczewski (2002) and Malczewski and Rinner (2005) extended this research to include the geovisualization of decision making strategies defined by the ordered weighted averaging (OWA) operator and equally implemented within CommonGIS (see Sect. 4.2.3). An example from Malczewski and Rinner (2005) is shown in Fig. 11.3, in which the rankings of neighbourhood quality of life using two distinct combination rules are compared in geographic space (i.e., map) and MCDA result space (i.e., classified scatter plot).

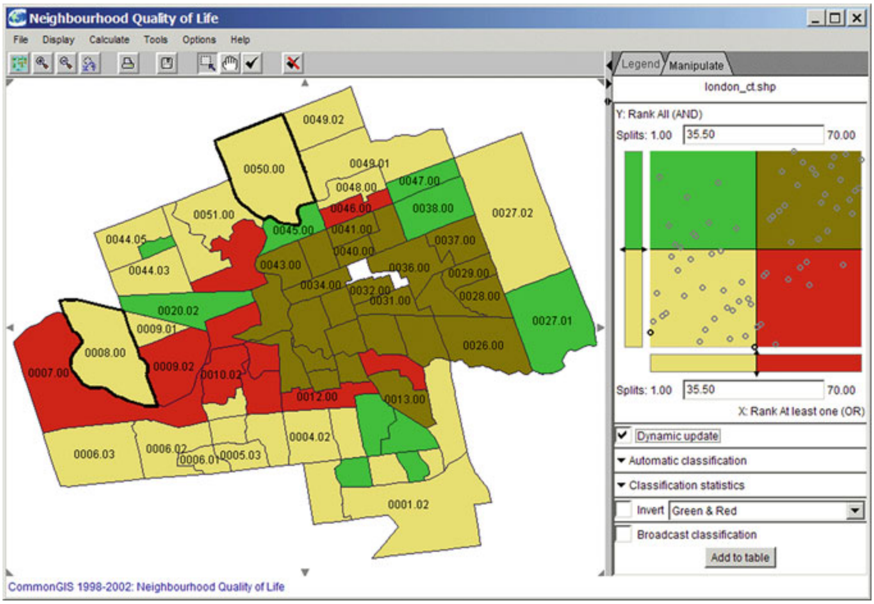

Fig. 11.3 Comparison of neighbourhood quality of life rankings under two distinct MCDA combination rules, using a map (*left*) and linked scatterplot (*right*) in CommonGIS (*Source* Malczewski and Rinner 2005, Fig. 5a, used with permission)

Rinner and Taranu (2006) added an implementation of the AHP method (see Sect. 4.3.1) to CommonGIS, and illustrated how analysts could interactively explore the effects of changes in the criterion hierarchy and weighting on tentative MCDA results. The geovisualization of the effects of modifying combination rules and their parameters is further illustrated in the case study in Sect. 11.5.

11.4.2 Visualizing Model Sensitivity

To deal with uncertainties in GIS-MCDA, it is recommended to conduct sensitivity analyses on model input factors (see Sect. 7.5). Sensitivity analysis changes the input parameters and examines the resulting effects on MCDA results, much like geovisualization. However, while geovisualization leaves it to the analyst to visually assess the effects, sensitivity analysis provides quantitative measures of effects. In fact, geovisualization, as presented in Fig. 11.1, could itself be labelled as 'visual sensitivity analysis'. In addition, geovisualization can assist with quantitative sensitivity analysis.

While sensitivity analysis is commonly conducted using global (i.e. spatially invariant parameters), recent work by Ligmann-Zielinska and Jankowski (2008) and others adds spatiality to a framework for sensitivity analysis in GIS-based

MCDA (see Sect. 7.5.2 for details). The authors argue that spatial criteria and spatial weights should be explicitly considered in sensitivity analysis within MCDA. Similar to the introduction of local weights, spatially explicit sensitivity analysis opens the door to the application of geovisualization. For example, the visual exploration of spatial patterns in MCDA outcome sensitivity could yield important insight into sources of uncertainty in a given GIS-MCDA problem.

11.5 Case Study: Geovisualization in Spatial Decision Support

In this section, a case study is used to illustrate the principles of geovisualization of MCDA inputs and results, including the effects of modifying MCDA model parameters. A deprivation index is a composite measure of socio-economic status, attempting to identify socially disadvantaged areas. In this case study, a sample deprivation index was composed of nine variables aggregated to the 140 social planning neighbourhoods for the City of Toronto, Canada. The variables were retrieved through the Wellbeing Toronto tool and include:

(a) Average household income after taxes (Canadian $)
(b) Gini coefficient
(c) Proportion of rented dwellings
(d) Proportion of seniors living alone
(e) Proportion of children living in low income homes
(f) Proportion with no high school education
(g) Proportion of unemployed persons
(h) Rate of teen (age 15–19) pregnancy
(i) Rate of deaths that occurred before the age of 75

The geovisualization tool used in this case study is MCDA4ArcMap (Rinner and Voss 2013). MCDA4ArcMap is an add-in for the commercial ArcGIS software. It includes functions for loading a data layer, selecting attributes as decision criteria, choosing a decision rule and standardization technique, and assigning criterion ‘directions’ and weights. The decision rules available in the tool include the WLC, LWLC, and OWA methods (see Sect. 4.2). The standardization, or value scaling, techniques available include score-range transformation and maximum-score procedures (see Sect. 2.3.1). The MCDA4ArcMap tool also includes an interactive mapping dialog that supports classified and unclassed choropleth mapping of criteria and MCDA scores with ad hoc changes to the map’s colour scheme, classification method, and number of classes.

The interactive thematic mapping function is first used to explore the nine case study criteria individually. Figure 11.4 shows the MCDA4ArcMap user interface to explore the household income indicator. Figure 11.5 shows screenshots of the additional eight quintile maps. In an interactive session, these maps show the

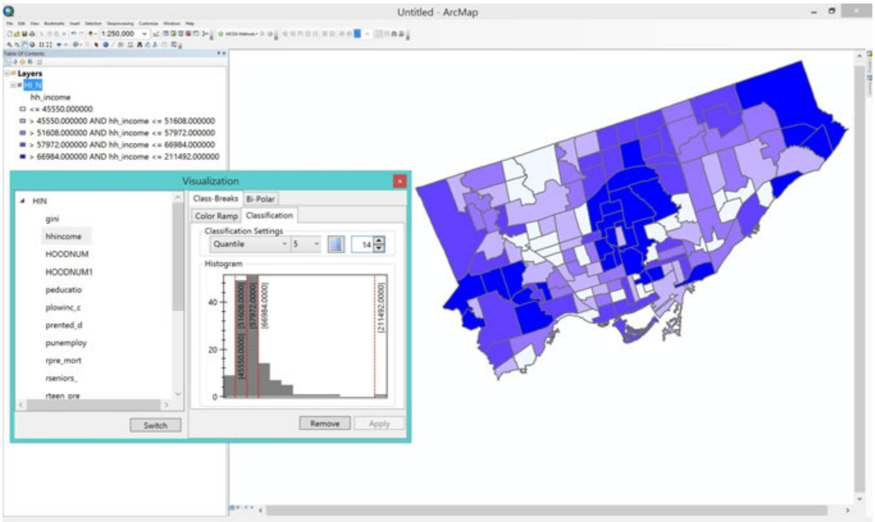

Fig. 11.4 Screenshot of the MCDA4ArcMap tools used to visualize MCDA input data (criterion values)

analyst that the spatial patterns of most of the criteria are similar, with lower values in the centre of the city and toward the southwest and northeast, and higher values arranged in a U-shaped pattern around the centre. However, all criteria have somewhat different spatial distributions, providing locally different contributions to the composite deprivation index. The most distinct pattern is shown in the proportion of seniors living alone, where some of the high (problematic) values coincide with the wealthy neighbourhoods in the centre of the City.

These deprivation indicators were combined using the OWA and LWLC methods (see Sect. 4.2). Figure 11.6 shows the OWA dialog window, along with screenshots of the MCDA results, using the seven predefined values of the alpha parameter of the OWA method. The quintile maps suggest that the variation of outcomes is relatively stable, since the general spatial pattern of higher deprivation in neighbourhoods to the west and east of the centre of the City persists from one end of the parameter range to the other.

A different finding emerges from the exploration of the LWLC parameters. Figure 11.7 shows the LWLC tool with the parameters that can be changed by the user. Figure 11.8 shows screenshots of the MCDA results using four different settings for the k parameter in the nearest-neighbour definition of the LWLC method. A high number of nearest neighbours (k = 15) yields a spatial pattern of deprivation that is similar to the pattern observed using the OWA method. However, the smaller the parameter and processing window become, the more distinct the pattern that emerges. For example, a few neighbourhoods in the centre of Toronto show greater deprivation, as they are directly compared with the adjacent wealthy neighbourhoods.

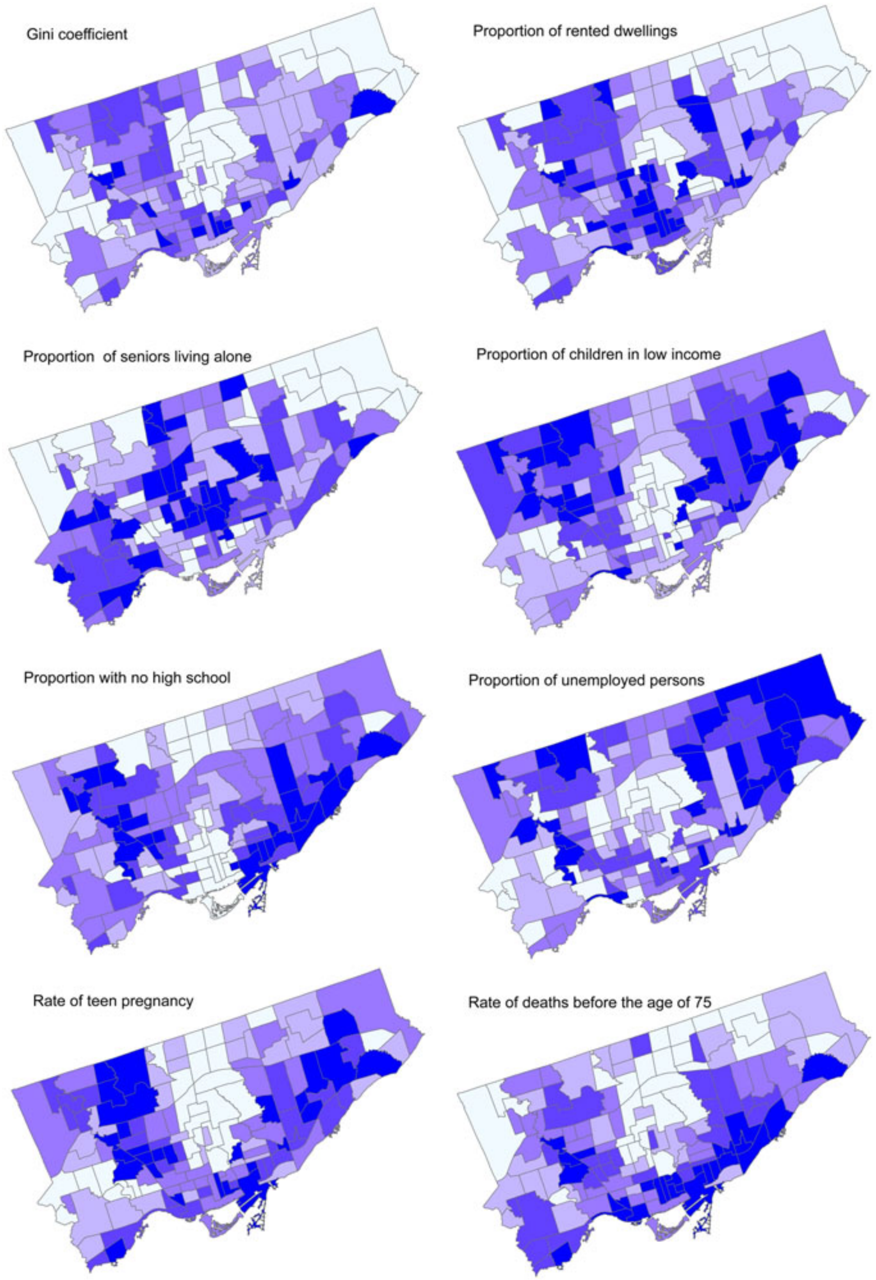

Fig. 11.5 Screenshots of maps of additional input data (criterion values) from the MCDA4ArcMap tool

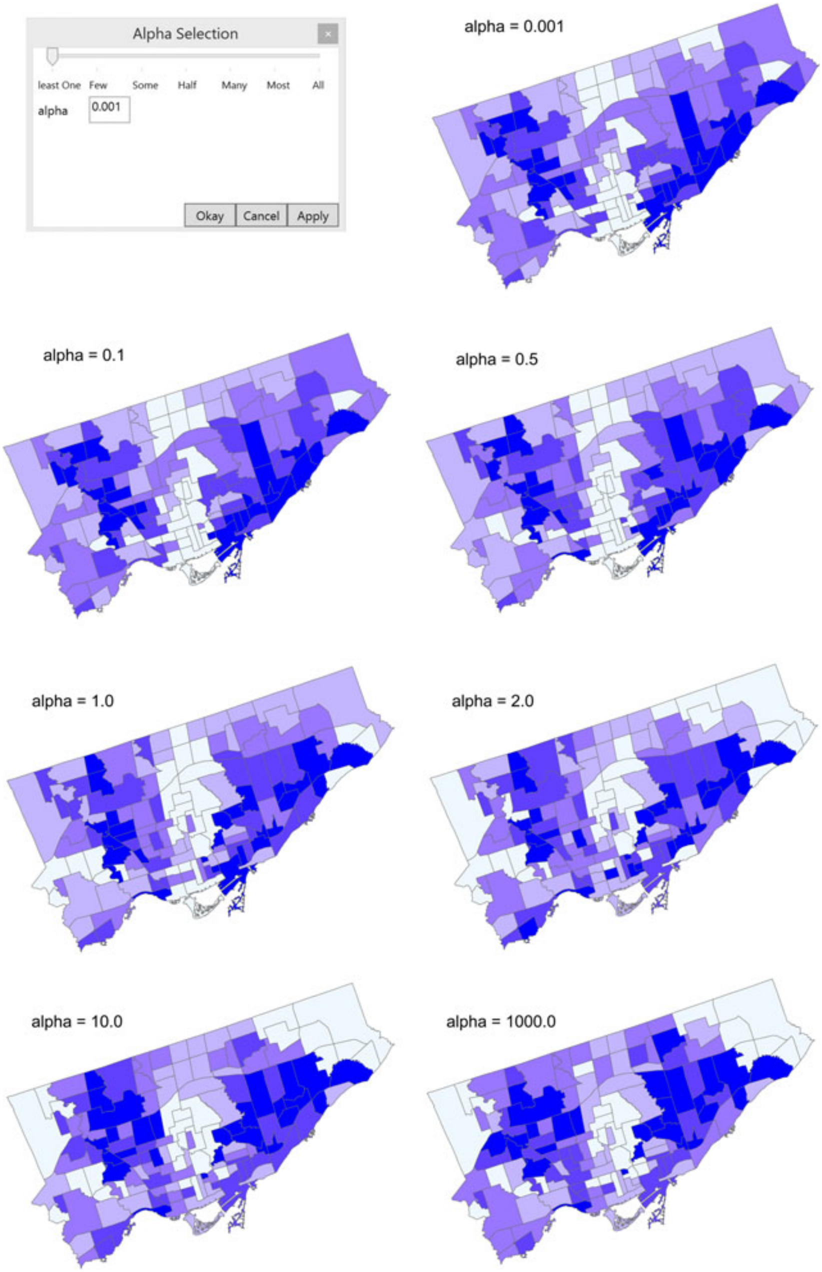

Fig. 11.6 Screenshots of the OWA tool and maps of deprivation index (MCDA result) using seven different settings of the alpha parameter

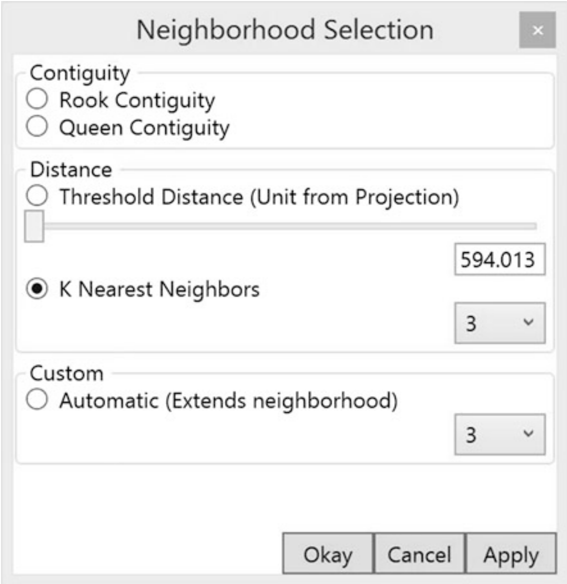

Fig. 11.7 Screenshots of the MCDA parameters to be set in the LWLC tool

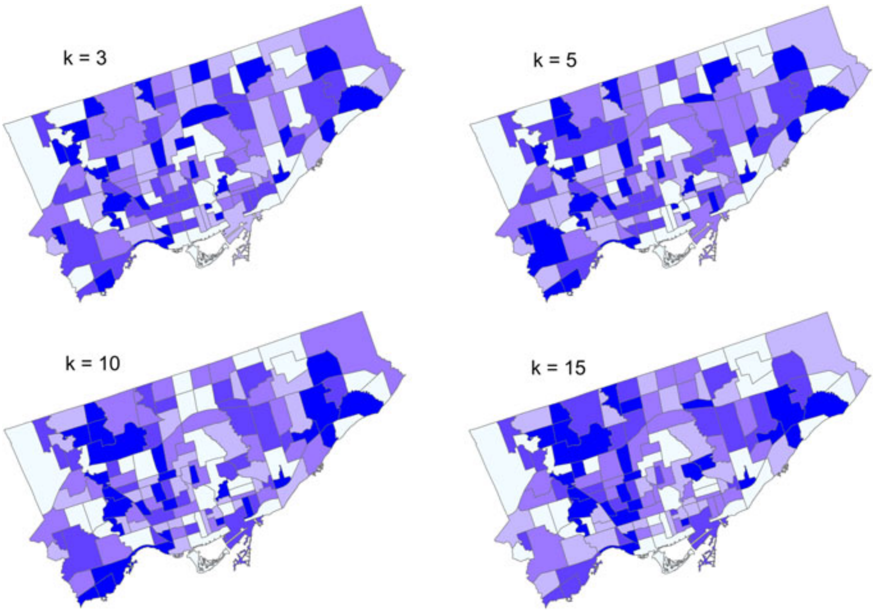

Fig. 11.8 Screenshots of deprivation index (MCDA result) using four different settings of the *k*-nearest neighbour definition in the LWLC tool

In a similar fashion, the MCDA4ArcMap tool allows the analyst to explore other model parameters such as the standardization (value scaling) technique, the criterion weighting in the WLC and other methods, and alternate neighbourhood definitions in the LWLC method. In addition, visual comparison of the MCDA results across the different methods can be conducted. Thereby, the analyst will gain insight into the options for modeling deprivation, enabling an informed decision with respect to the creation of the composite index.

11.6 Conclusion

This chapter's case study illustrates the benefits of combining principles of geovisualization with MCDA techniques. The interactive exploration of thematic maps of MCDA input and MCDA results allows the analyst to better understand the decision problem, generate working hypotheses about spatial relationships between criteria, and conduct sensitivity analysis to examine the impact of gradual parameter changes in the MCDA approach. These benefits grow as geospatial datasets become increasingly large and pervasive across numerous fields of government and business operations.

The visual analysis approach, however, also comes with limitations. Most notably, visual examination of spatial patterns on maps is imprecise and relies on the analyst's experience and impartiality. While maps in data analysis and decision making can effectively support reasoning, the reliance on maps alone is often found to be unsatisfactory by quantitative analysts. In a group decision making scenario, Jankowski and Nyerges (2001) found that maps were used to present results of analysis rather than in the problem formulation stages. In contrast, Andrienko et al. (2003) determined that maps, combined with interactive tools, worked well in a collaborative site selection role-play.

The workflow shown in Fig. 11.9 illustrates the use of MCDA techniques and maps in the project described in Sect. 10.4 (see also Toronto Public Health 2011). Decision support was aimed at prioritizing hot weather outreach, as well as planning for longer-term climate change adaptation. Maps of individual exposure and sensitivity indicators, and of composite indices, allowed analysts, outreach managers, and research consultants at Toronto Public Health to assess the spatial distribution of potential heat vulnerability across city neighbourhoods (Toronto Public Health 2011). This map-centred analysis supported a first reduction of the set of decision alternatives (neighbourhoods) to those with the highest potential vulnerability (e.g., highest quintile).

The bottom half of Fig. 11.9 shows how geovisualization of MCDA input and results was integrated in a broader analytical and decision making process. First, adaptation maps were created by overlaying hot weather response facilities, such as cooling centres, with the indicator and index maps. These adaptation maps give the public health agency an indication of accessibility of facilities by people living in the most vulnerable areas. Furthermore, three different 'lenses' were applied to the

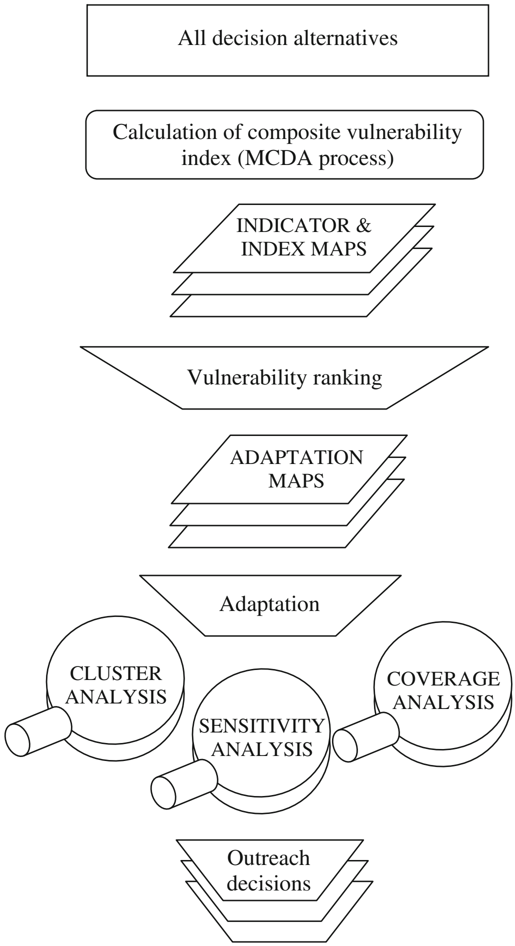

Fig. 11.9 Workflow for heat vulnerability assessment and decision support using maps of MCDA input and result (*Source* modified from Toronto Public Health 2011)

results, as indicated by the magnifying glasses near the bottom of Fig. 11.9. Cluster analysis was used to identify local clusters of heat vulnerability across multiple neighbourhood boundaries; sensitivity analysis was proposed as a way to assess the stability of the heat vulnerability index under changes to the indicator weights; and coverage analysis provided a way to combine the heat vulnerability index, which was based on normalized indicators such as proportions and rates, with raw-count data for populations of interest. All of the additional steps in this workflow were supported by maps showing descriptive statistics or analytical results, thereby confirming the importance of geovisualization and map-centred MCDA in this public planning and decision making case study.

Ultimately, the role of interactive maps and MCDA in public and private sector planning and decision making has yet to be determined. However, the status of MCDA as an established analytical modeling technique, and of geovisualization as an increasingly popular approach to data analysis, will create sustained interest in combining these technologies. The emerging ‘big data’ phenomenon will further increase this interest, as growing databases provide the necessary input for MCDA and geovisualization facilitates making sense of the results.

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Chapter 12
Web-Based and Mobile GIS-MCDA

12.1 Introduction

In analogy to GIS and decision support systems technology, Sugumaran and Sugumaran (2007) distinguish traditional GIS and SDSS (see Chap. 10) from Web-based/distributed SDSS, mobile SDSS, and service-based SDSS. With more specific reference to MCDA tools within SDSS, this chapter outlines the state of the art in Web-based MCDA tools, including those using service-oriented software architectures, and mobile MCDA.

Web-based GIS-MCDA encompasses a range of applications, in which GIS-MCDA functionality is distributed in a computer network and made available remotely through a Web interface. The key question in Web-based GIS-MCDA is about the goal: why make a GIS-MCDA application accessible online? In the broader context of online spatial decision support systems, Rinner (2003a) notes that a common motivation is to support group decision making. In his early review of Web-based multi-criteria evaluation, Carver (1999) highlights the goal of providing public access to data and tools for planning and decision making, while Greene et al. (2011) position Web-based GIS-MCDA as a collaborative tool and foresee its integration as a component of participatory GIS. In such an environment, the purpose of combining GIS-MCDA with deliberative elements is to develop consensus among decision makers (Boroushaki and Malczewski 2010a).

Mobile GIS-MCDA shares many technical considerations with Web-based GIS-MCDA, but presents a different focus. Mobile GIS-MCDA assists mobile users on mobile devices, and often employs information on the user's current location as input for decision support. The technical commonalities between Web-based and mobile GIS-MCDA stem from the underlying technology, which is often discussed in combination (e.g., Peng and Tsou 2003). Increasingly, Web applications offer mobile versions that are adapted to the smaller screens of handheld devices and the

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_12

fleeting context, in which they are used while someone is on the move. Additionally, Web applications increasingly use information on the user's current location, whether they are being accessed from a mobile device or from a desktop computer. Thus, the two technological domains seem to be all but conflating with implications on GIS-MCDA applications developed for either.

In addition to shared technology, mobile GIS-MCDA also shares the decision support capabilities of Web-based GIS-MCDA, which were classified by Rinner and Malczewski (2002) as follows:

1. Level 1 tools support the evaluation of a single, fixed criterion or optimisation function. Examples include the minimization of driving distance in a route planner or minimization of cost in the recycling decision support system outlined below. Thus, this class does not constitute Web-based or mobile GIS-MCDA in the proper sense, since there is no compensation between multiple criteria, and the input of decision maker preferences is limited.
2. Tools at level 2 support user-defined queries with a combination of criteria using a logical AND operator. An example can be found in online real-estate listings, where users can search for properties that are within a given price range, have a minimum number of bedrooms, and are located at a waterfront. These tools process multiple, user-selected criteria, yet always in a non-compensatory fashion.
3. Level 3 is comprised of tools that allow users to set decision criteria and importance weights. Examples include some of the research prototypes as well as the neighbourhood wellbeing index site described in this chapter.
4. Finally, tools at level 4 support the selection of the decision rule in addition to criteria and weights. At the time of Rinner and Malczewski's (2002) publication, no such tools were known to the authors. In the meantime, however, some of the Web-based and mobile GIS-MCDA tools described in the following sections include elements of a user-defined decision rule.

The remainder of this chapter discusses Web-based and mobile GIS-MCDA tools and applications that fall into Rinner and Malczewski's (2002) levels 3 and 4, in which users can interactively determine criteria, weights, and decision rules. Within Web-based GIS-MCDA (Sect. 12.2), representative implementations of Web-based GIS-MCDA with a focus on interactive geovisualization are reviewed in Sect. 12.2.1. Then, Web Services-based GIS-MCDA applications are outlined in Sect. 12.2.2. Finally, collaborative and participatory GIS-MCDA implementations are discussed in Sect. 12.2.3. Within mobile GIS-MCDA (Sect. 12.3), we distinguish between the generic decision support functions of mobile GIS (Sect. 12.3.1) and explicitly location-based MCDA (Sect. 12.3.2).

12.2 Web-Based GIS-MCDA

12.2.1 Interactive Web-Based Spatial Decision Support Systems

The technical foundations and early applications of Web-based spatial decision support systems (SDSS) are summarized in Rinner and Jankowski (2002), Rinner (2003a), and Sugumaran and Sugumaran (2007). Web-based SDSS extend the concepts of SDSS, which Densham (1991) introduced as "a framework for integrating database management systems with analytical models, graphical display and tabular reporting capabilities, and the expert knowledge of decision makers" (p. 404). Bhargava et al. (2007) review the progress of Web technology for non-spatial decision support, calling for more empirical research toward developing guidelines for effective decision support computation on the Web. These authors also discuss payment models and organizational integration of online decision support.

The most important information technology characteristic with respect to Web-based application is the client/server architecture. It distinguishes multiple client computers from comparatively few server computers that communicate with each other over a network. The schematic Web-based SDSS architecture in Fig. 12.1 shows the user interface on the client computer (Rinner and Jankowski 2002). The

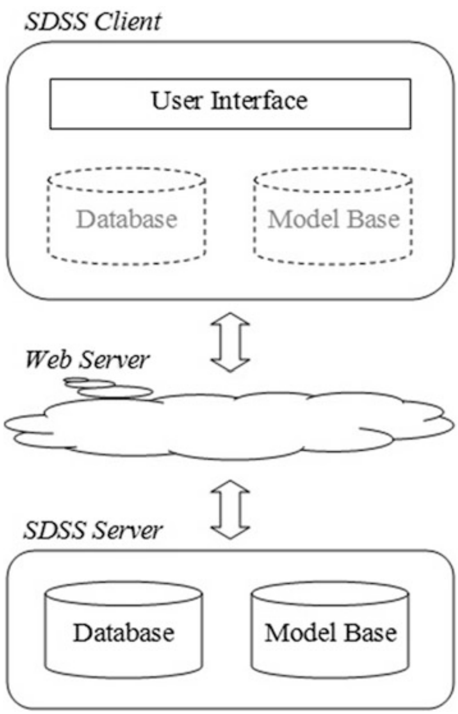

Fig. 12.1 Components of a Web-based SDSS, with MCDA functionality included in the model base (*Source* modified from Rinner and Jankowski 2002)

user interface corresponds to Densham's (1991) display and reporting functions. The database and model base components can either be moved to the client or stay on the server side, depending on whether the system includes a 'thick client' or 'thin client'. All GIS-MCDA functionality is included in the model base.

Rinner (2003a) describes a conceptual framework for the development of Web-based SDSS based on toolboxes and generators. The framework refers to Sprague's (1980) framework for standalone SDSS. An example of the Web-based SDSS framework is given with the Idrisi32 application programming interface (API) as a toolbox that offers access to IDRISI's functions including the multi-criteria evaluation module. An online version of IDRISI, developed by Rinner (2003b), serves as the Web-based SDSS generator through which application developers can create specific Web-based SDSS.

Early applications of Web-based GIS-MCDA include a nuclear waste site selection that uses Boolean constraints and weighted overlay of compensatory criteria (Carver et al. 1997); a decision support system to direct consumers to recycling facilities that best suit their disposal needs and reduces their travel times (Bhargava and Tettelbach 1997); and a regional vegetation management and decision support system, VegMan (Zhu et al. 2001). Subsequent Web-based GIS-MCDA applications started to exhibit more advanced functionality. For example, Mustajoki and Hamalainen's (1999) Web-HIPRE supports individual and group decision making with multiple weighting techniques and value functions to choose from; Jankowski et al.'s (2001) spatial decision support prototype DECADE integrates geovisualization techniques with MCDA and data mining; Rinner and Malczewski (2002) introduce decision strategies to the set of parameters that users can define in Web-based GIS-MCDA; and finally, Jankowski et al. (2008) extend their Choice Modeler's functionality to sensitivity analysis and voting.

State-of-the-art Web-based GIS-MCDA is characterized by using mainstream GIS and/or Web technologies. This includes commercial software such as ArcIMS and Oracle used by Karnatak et al. (2007) in a biodiversity conservation application, or ArcGIS Server described by Sugumaran and DeGroote (2010) in an analysis of environmentally sensitive areas. The Wellbeing Toronto tool (http://www.toronto.ca/wellbeing/) is a modern, highly interactive Web-based GIS-MCDA application. It was implemented using Hypertext Markup Language (HTML), Cascading Style Sheets (CSS), and Javascript. Markieta and Rinner's (2014) visual GIS-MCDA tool is an example of using prevailing open-source Web technologies, including OpenLayers and jQuery, for the client and UMN MapServer for the server components.

12.2.2 Web Services-Based GIS-MCDA

A Web service is a computer program that is accessed by other programs on a computer network. The Open Geospatial Consortium (OGC) and the International Standards Organization (ISO) are standardizing Web services in the area of geo-processing. Online, interoperable, geo-processing services make GIS tools compatible when they are used by different decision makers on different computing platforms (including hardware and operating system). The first and most popular OGC specification dealt with Web Map Services (OGC 2006). Web Map Services can be used to overlay map layer images from different remote sources in a single client application. Similar specifications have since been published for Web Feature Services and Web Coverage Services for the interoperability of vector and raster data access and visualization, respectively. The OGC's Web Services initiative Phase 4, started in the Fall of 2005, includes "Geo-Decision Support Services" to "provide interoperable access to distributed geospatial web services to aid decision makers in forming, analyzing, and selecting alternatives" (OGC 2007). Up to this point in time, the international standardization activities have focused on the exchange of geospatial datasets and imagery, and do not explicitly distinguish between analysis and decision support functions. However, as Ascough et al. (2002) argue, "existing spatial toolsets will be radically affected by current trends toward OpenGIS and interoperability" (p. 178).

An important aspect of OGC's 'Geo-Decision Support Services' is related to service chaining. Service chaining refers to the combination of Web services, by which more complex geo-processing tasks can be constructed from simple ones. Bernard et al. (2003) outlined two variants of using OpenGIS service chaining to create an online 'assessment and decision support system' for GIS-MCDA: (1) a specialized MCDA client uses Web Coverage Services and/or Web Feature Services and catalogue services to perform an MCDA operation; (2) an aggregate MCDA service chain includes both, the basic services from variant 1, and additional, yet-to-specify processing services for the actual MCDA operation. Holzmeier and Ostländer (2005) describe the first specification and implementation of a Web Map Algebra Service that combines criterion maps from distributed sources in an interoperable fashion. The Web Map Algebra Service performs algebraic operations such as difference or ratio on datasets originating from different Web Coverage Services. The case study in Holzmeier and Ostländer (2005) combines these service requests to perform simple additive weighting on environmental and socio-economic data layers to assess vulnerability to climate change in the Barents Sea region.

To overcome issues with distributed data access, Zhang et al. (2008) develop a forest conservation decision support system using geospatial semantic Web service techniques. Their prototype implementation uses Esri's ArcGIS and the open-source PostGIS and GeoServer tools as heterogeneous data sources; an MCDA module implemented as a Web processing service through Java servlets; and an ontology service to provide a semantic data catalogue based on the Protégé framework and a custom Java servlet within the Apache Tomcat container. Zhang et al.'s (2008) client module was implemented using the OpenLayers JavaScript library and OpenGIS Web Map Service, Web Feature Service, and Web Coverage Service. A weighted linear combination function was implemented in the Java programming language using an OpenGIS Web Processing Service.

We anticipate that explicit decision support tools such as MCDA operators will increasingly be conceptualized and implemented in the context of spatial data infrastructures. A framework for service-oriented architecture for distributed decision support systems was proposed by Zhang (2010). Her 'Decision Processing Services' are conceived as service chains, which illustrate an MCDA model implemented through OGC Web Processing Services. Rinner and Düren (2011) replicate McHarg's (1992) semi-transparent layer overlay idea, which dates back to 1967, using OGC Web Map Services. Markieta and Rinner (2014) used an improved map overlay and opacity tool to explore a composite index of human influence on the environment. Such distributed GIS-MCDA tools complement the decision support capabilities of integrated geospatial data and on-the-fly mapping that are promoted in current standardization efforts. Interoperable geo-processing services provide the tools, and service chaining acts as the generator, to model MCDA operations for specific spatial decision support services.

12.2.3 Collaborative and Participatory GIS-MCDA

One of the most recent trends in GIS-MCDA has been its integration in larger systems for collaboration or public participation. Due to the nature of collaborative and participatory processes, these systems often employ the two-way communication techniques of the second-generation World-Wide Web, known as 'Web 2.0' (e.g., Rinner et al. 2008). GIS-MCDA represents the analytical aspects of decision making, while the collaborative or participatory functions support the deliberative aspect. The combination of these two functional groups was termed the 'analytic-deliberative approach' by Stern and Fineberg (1996), which was adapted to the participatory GIS realm by Jankowski and Nyerges (2003).

Several authors have combined GIS-MCDA with participatory tools. Voss et al. (2004) presented a combination of CommonGIS, a Web-based GIS with MCDA and group voting capabilities, and Dito, a participation platform. The authors conducted several site selection case studies, in which participants combined rounds of map annotation, geographically referenced discussion of criteria and decision maker preferences, and moderated consensus-finding in the Dito forum, with map exploration, attribute visualization, and MCDA-based ranking of locations in CommonGIS. Simao et al. (2009) developed a wind farm siting application by adding a series of Web pages to weight and combine 19 decision criteria to Keßler et al.'s (2005) argumentation map, a map-centred discussion forum. Simao et al.'s (2009) Web application created composite maps that showed the dominant result and the degree of controversy resulting from the analytical stage of the user's decision making process. These MCDA results could then be discussed as part of the deliberative stage. A similar combination of tools was proposed by Taranu (2009), who developed an MCDA module called 'MapChoice' for the map annotation tool 'MapChat' (Hall and Leahy 2006). Taranu (2009) implemented a weighted linear combination function to be used in conjunction with group deliberation of criterion weights.

Boroushaki and Malczewski (2010b) explicitly refer to analytic-deliberative decision support. Their 'ParticipatoryGIS' integrates a Web-based OWA as the MCDA component, a fuzzy majority approach for group-based MCDA, and Rinner et al.'s (2008) 'Argoomap'. ParticipatoryGIS was then used by Malczewski et al. (2013) in a site selection case study. Another combination of the analytic and deliberative components of decision making is provided by Mansourian et al. (2011) in an urban planning application. Their prototype 'Web-based participatory urban planning' framework includes the AHP and concordance analysis techniques for use by the public and by municipal authorities, respectively. Non-conforming land use change applications are being submitted to a public discussion forum for deliberation. Despite promising developments, a conceptual framework for combining deliberative elements with MCDA is still missing. Such a framework would identify the workflow and exchange of information between system elements, and the mechanisms, by which a final decision can be derived.

The most recent trends in developing collaborative and participatory GIS-MCDA include empirical studies (Jelokhani-Niaraki 2013; Swobodzinski and Jankowski 2014) and the inclusion of Semantic Web technologies (Jelokhani-Niaraki and Malczewski 2012). Jelokhani-Niaraki (2013) presents the findings of an extensive human-computer interaction study using a collaborative GIS-MCDA application. Process tracing and Web logs were used to record the participants' decision making activities. Jelokhani-Niaraki (2013) found that with increasing task complexity, decision makers tended to favour non-compensatory decision strategies. Individual and group decision making were found to employ significantly different information acquisition procedures. Finally, Jelokhani-Niaraki (2013) observed that participants made more use of data tables than of maps representing the decision problem. In a similarly complex study of a participatory transportation planning exercise, Swobodzinski and Jankowski (2014) examine the impact of decision maker characteristics, such as socio-economic status, attitudes toward decision making, and travel behaviour, on the human-computer interaction with the transportation planning Web application. Acknowledging the emerging Web 3.0 as "the integration of Semantic Web (Web of meaning) technologies with the principles of Web 2.0 (Web of people)" (p. 3), Jelokhani-Niaraki and Malczewski (2012) implement another prototypical GIS-MCDA application with an ontological framework. The goal of this work is to represent the domain knowledge of collaborative GIS-MCDA in a machine-readable form. The description of a collaborative GIS-MCDA ontology in the Ontology Web Language supports automatic reasoning and guides Jelokhani-Niaraki and Malczewski's (2012) site selection case study.

12.3 Mobile GIS-MCDA

12.3.1 General Decision Support Functions of Mobile GIS

In their opening editorial for the then-new Journal of Location-Based Services, Raper et al. (2007) posit the utility of mobile devices and services for decision making as the highest objective in the research field of the journal. They also point to very limited research completed at the time on mobile and location-based decision support. We distinguish between the general decision support functions of mobile GIS discussed in this section and specific MCDA techniques that consider the mobile user's current location outlined in the following section.

GIS vendors position Mobile GIS as a component of enterprise-wide GIS, which allows for data collection and access during outdoor fieldwork. Examples of research into mobile GIS include the search for suitable cartographic representations on handheld devices (Reichenbacher 2001); field data collection and the relation between data quality and semantics (Pundt 2002); and mobile GIS integration with wireless Internet technology and its application in environmental monitoring (Tsou 2004). Thus defined, mobile GIS do not provide direct decision support, although they may contribute to the data used for office-based decision support with desktop GIS.

In addition, Web-based GIS-MCDA applications may run on mobile devices and in some circumstances, the use of such applications while traveling may qualify as mobile decision making. For example, the use of the Wellbeing Toronto Web application on a tablet computer (see Fig. 12.2) via a wireless network could guide an on-site visit of a neighbourhood that is identified as disadvantaged by the composite neighbourhood wellbeing indices in the tool. Similarly, a route planner such as MapQuest Open is a Web-based decision support application that can be accessed from a mobile device such as a smartphone (see Fig. 12.3).

12.3.2 Location-Based MCDA

Raubal and Rinner (2004) identify single-attribute queries as the typical decision support application of mobile devices. They note that location-based services at the time were not able to consider multiple criteria or take personal user preferences into account. User preferences are then linked with the input parameters of MCDA, and Raubal and Rinner (2004) devise a prototypical, location-based MCDA application, called 'HotelFinder', which supports travelers in finding a hotel with user-defined compensatory criteria in a weighted linear combination procedure.

Several applications were derived from the original HotelFinder. Rinner and Raubal (2004) added the OWA technique in order to represent personal decision strategies as another element of mobile user preferences. Rinner et al. (2005) examined the constraints imposed by the limited screen size and resolution of

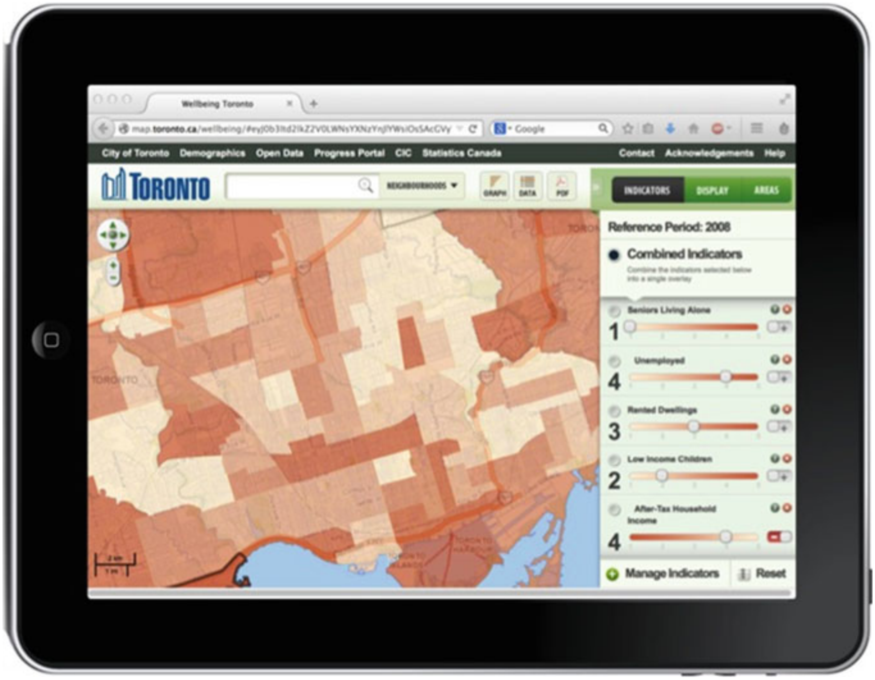

Fig. 12.2 The Wellbeing Toronto web application on a mobile device

mobile devices and the limited attention that mobile users can afford to pay to their devices in every-day situations. The authors then reduced the MCDA processing steps and devised simplified MCDA parameter settings, including a single screen to select and weigh decision criteria on a qualitative scale using drop-down menus rather than numeric sliders. Bäumer et al. (2007) presented another derivative of the HotelFinder and conducted an extensive real-world user test. This experiment yielded positive feedback on the utility of a mobile decision support service and illustrated the need for additional decision criteria.

More recent work on location-based MCDA has also focused on route planning applications. In an attempt to illustrate a more 'serious' application of mobile decision support, Rinner (2008) developed an emergency shelter finder scenario. The work by Park et al. (2008) integrates various context variables into a restaurant recommendation system for groups of users. These authors use a Bayesian network approach to model individual decision maker preferences and an AHP for the selection of a restaurant based on four criteria, including a location-dependent distance variable. Sadeghi Niaraki and Kim (2009) present a route planner with a personalized AHP using an ontology-based approach. The ontology is used to assign user-specific costs to road segments. Völkel and Weber (2008) use a weighted average cost function to combine a shortest-path algorithm with additional criteria that are specific to users with restricted mobility. Emrich et al. (2013) also

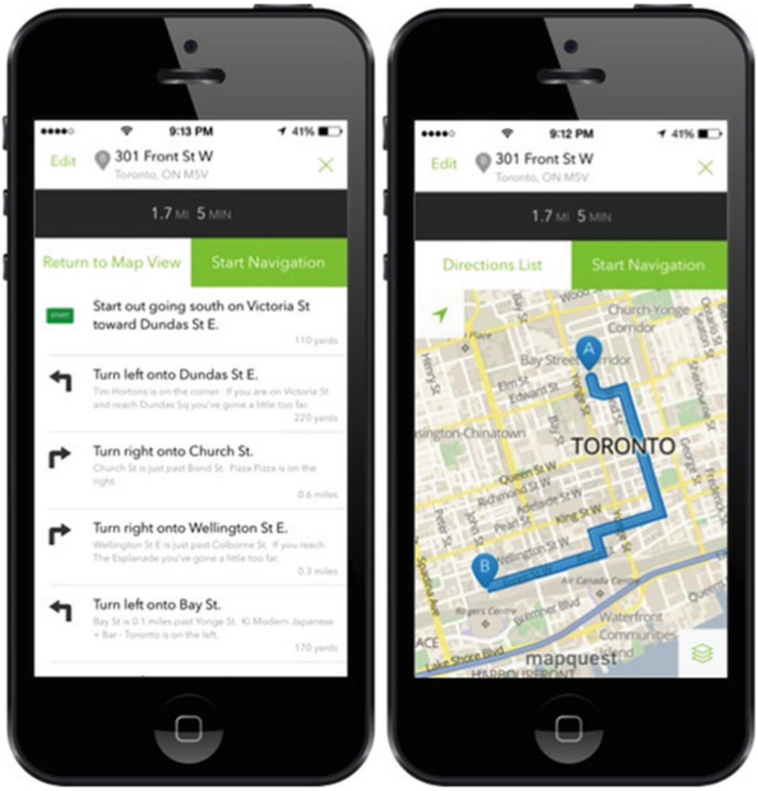

Fig. 12.3 The MapQuest Open route planner on a mobile device (stepwise instructions on the *left*, map view on the *right*)

use an ontological approach to present an adaptive location-based service that takes into account the users' social context—"preferences, interactions and usage patterns of people or places" (p. 1165)—in order to provide recommendations for places of interest. Further, Emrich et al. (2014) presented a hybrid between a traditional route planner and a personalized location-based decision support tool.

In terms of technology, the HotelFinder application consisted of a thick client implemented in Esri's ArcPad mobile GIS tool using the ArcPad Studio development environment. In contrast, Bäumer et al.'s (2007) reimplementation in the .NET framework using the C# language presented a thin client that accesses Microsoft's Virtual Earth tile server for background map layers. Espeter and Raubal (2009) take another step toward state-of-the-art mobile computing technology by implementing a restaurant finder for groups of mobile users. These authors used asynchronous JavaScript and XML (AJAX), the Web technology that made so-called 'slippy maps' possible. AJAX handles client-server communication in the background of a Web application, thereby enabling continuous, smooth client interaction, such as map pan and zoom, while additional information is transferred from the server. Espeter and Raubal (2009) developed the restaurant finder as HTML pages with cascading style sheets and JavaScript code on the mobile client side, and Java servlets within an Apache Web server. Google Maps was used to provide the background for visualizing origin and destination. Yu and Chang (2009) also use Google Maps, along with Microsoft's IIS Web server, the .NET programming framework, the SQL Server 2005 database, and ASP.NET 2.0 for the development of dynamic Web pages for their tour planning service. Emrich et al.'s (2013) tool was implemented using HTML5 to keep it independent of different users' mobile computing platforms.

12.4 Conclusion

Both Web-based and mobile GIS-MCDA hold the promise of spreading the use of GIS-MCDA as a rational decision support method for spatial planning and decision making. While Web applications cater to the need for providing greater accessibility, engaging the public, and supporting distant collaboration, mobile applications are more geared toward individual decision making, often with respect to route planning and leisure/social activities. The 'serious' applications of location-based MCDA are sparse and may remain so, as GIS-MCDA continues to be primarily suitable for expert analysts.

Broader use of mobile and Web-based GIS-MCDA will require carefully designed tools, clearly defined processes, and user training. Its limitations arise from issues with digital literacy of users, lack of formal processes, and a shortage of user-friendly tools. Additionally, concerns regarding the actionability of composite MCDA scores, as well as the danger of stigmatization of poor performing decision options in public planning, can override potential benefits of GIS-MCDA in expanded use cases. Still, Web-based and mobile implementations of GIS-MCDA could ultimately lead to better-informed, participatory, and evidence-based decision making in the public and private realm.

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Chapter 13
Conclusions

13.1 Summary

The aim of this book was to provide a comprehensive account of theories, methods, and technologies involved in GIS-MCDA procedures. This was achieved by: (i) explaining the fundamental concepts of MCDA and integrating those concepts into GIS-based methods, (ii) overviewing GIS-MCDA methods and demonstrating their applications in a wide variety of decision situations, and (iii) presenting a set of information technologies and decision support tools available for integrating GIS and MCDA methods. Specifically, the discussion of relevant concepts, methods, and technologies was organized into three parts: Preliminaries (Part I), Spatial MCDA: Methods (Part II), and Spatial MCDA: Technologies (Part III).

Part I examined the linkages between GIScience, spatial analysis, and decision support (Chap. 1). It then provided an overview of generic elements of MCDA and the basic concepts of GIS-MCDA including: value scaling, criterion weighting and combination rules (Chap. 2). Part I also outlined the development of GIS-MCDA research and applications (Chap. 3). We emphasized the spatial aspects of GIS-MCDA by making a distinction between spatially implicit and explicit evaluation criteria, criterion weights, and decision alternatives. This distinction was central for identifying two groups of MCDA methods integrated into GIS: conventional (spatially implicit) and spatially explicit MCDA methods.

Part II discussed GIS-MCDA models and procedures including: multiattribute methods (such as the weighted linear combination, ideal point methods, the analytic hierarchy/network process, and outranking methods), and multiobjective optimization methods (such as generating non-dominated solutions, distance-based, and interactive methods) (Chaps. 4 and 5, respectively). In addition to the conventional methods, we presented a selection of basic heuristics (such as site suitability and site location heuristics, and greedy algorithms) and meta-heuristics (such as genetic algorithms, simulation annealing, tabu search, and swarm intelligence methods) for tackling complex decision situations (Chap. 6). We emphasized the relevance and

J. Malczewski and C. Rinner, *Multicriteria Decision Analysis in Geographic Information Science*, Advances in Geographic Information Science,
DOI 10.1007/978-3-540-74757-4_13

applicability of these methods for solving spatial optimization problems. This, in turn, is related to a number of considerations including: methods for dealing with uncertainties, group (participatory/collaborative) decision making, and scale issues in GIS-MCDA (Chaps. 7, 8 and 9, respectively). We overviewed the sources of uncertainty and discussed a variety of approaches for handing uncertainties in GIS-MCDA methods. We demonstrated that conventional, deterministic GIS-MCDA methods (such as WLC, compromise programming, and goal programming) can be extended to take into account uncertainties associated with fuzzy and limited information about the decision situations. We also discussed sensitivity analysis as a method for handling uncertainties in GIS-MCDA. We stressed the significance of spatially explicitly approaches to sensitivity analysis, and suggested that the analysis provides insights of particular importance in situations involving group/participatory decision making. Part II focused on two distinctive classes of GIS-MCDA procedures for groups: (i) conventional methods for aggregating preferences, which are based on conventional GIS-MCDA procedures adapted for tackling conflicting preferences in a group decision situation, and (ii) geosimulation methods, which are based on the concept of decision making agents. The problem of identifying appropriate spatial, temporal, and operational scales of analysis was examined in the last chapter of Part II. The discussion paid particular attention to the two components of the modifiable areal unit problem (scale and zoning effects) in GIS.

Part III turned the reader's attention to the technologies supporting the implementation of spatially implicit and explicit MCDA models and procedures in a GIS environment. GIS-MCDA technologies were organized by two dimensions: spatial representation and decision making environment. Desktop GIS-MCDA was separated into raster-based and vector-based implementations, depending on the underlying GIS data model (Chap. 10). While a case study illustrated transitions between the data models, there is still no seamless combination of the two approaches in GIS technology, and consequently GIS-MCDA has to be implemented with a focus on one or the other. Often, this decision goes along the lines of application domains, where environmental applications tend to use field-based models represented as raster data, while socio-economic applications are more likely to use object-based models represented as vector data. We also provided an overview of GIS-MCDA tools including classical applications such as IDRISI's MCE module and ArcGIS' overlay toolbox. However, open-source GIS, such as QGIS, are becoming competitive alternatives to these commercial packages, even though dedicated open-source GIS-MCDA tools are still limited with respect to versatility and documentation. Part III then turned to new developments regarding the decision making environment where GIS-MCDA is implemented. The combination with geovisualization opens GIS-MCDA to visual data exploration techniques (Chap. 11). We outlined the use of interactive maps and linked graphical displays to simultaneously explore decision space and criterion space, and within the latter, raw and scaled criterion values and weights (MCDA input), as well as parameters of decision rules and model sensitivity (MCDA results). Part III also accounted for the general trend of information technology moving toward distributed and mobile systems and applications (Chap. 12). In analogy to recent development in GIS, both Web-based GIS-MCDA and mobile GIS-MCDA were reviewed. Accessibility of GIS-MCDA technology to a broader range of users was highlighted as the main driver behind the development of Web-based and mobile GIS-MCDA.

13.2 Contribution to GIScience

The last 20 years or so have witnessed remarkable progress in the quantity and quality of research about integrating GIS and MCDA (Janssen and Rietveld 1990; Malczewski 2006; Chakhar and Mousseau 2008; Tong and Murray 2012). The contributions of GIS-MCDA to GIScience have come from the synergy between the two distinctive sets of decision support tools (see Sect. 1.3.3). On the one hand, GIS techniques and procedures have an important role to play in solving multicriteria decision problems. They offer unique capabilities for storing, managing, analyzing, and visualizing geospatial data to provide useful information for decision making. GIS can help in coordinating situation analysis through its ability to integrate data from diverse sources. It can enhance the MCDA capabilities for exploring decision situation and supporting the process of learning and discovery. On the other hand, MCDA offer a rich collection of methods for supporting decision making procedures. The multidisciplinary field of GIS-MCDA has been widely and strongly adopted within the GIS community (Malczewski 2006, 2010). Quite correctly, the GIS community recognizes the benefits to be gained by incorporating MCDA into a suite of GIS capabilities. The efforts to integrate MCDA into GIS have also been recognized as a considerable accomplishment in expanding MCDA into new application areas (Wallenius et al. 2008).

The primary motivation behind the efforts to integrate GIS and MCDA has come from the need to expand the decision support capabilities of GIS (see Sect. 1.3). The efforts to integrate MCDA into GIS were instrumental for developing the paradigm of spatial decision support (Sugumaran and DeGroote 2011; Li et al. 2012). This development has been paralleled by the evolution of GIS from a ‘close’-expert-oriented to an ‘open’-user-oriented technology, which in turn has stimulated a movement in the GIScience community toward using the technology to increase the democratization of decision making processes via public participation. By their nature, MCDA tools allow the integration of multiple views on decision problems. They can improve the communication and understanding of a decision problem among multiple decision makers and facilitate numerous ways of building consensus and reaching policy compromises. Consequently, the GIS-MCDA methods can contribute to improving collaborative decision making procedures by providing flexible problem-solving approaches where those involved in collaborative tasks can explore, understand, and redefine a decision problem. The integration of MCDA into GIS can support collaborative work by providing a means of structuring group decision making problems and organizing communication within a group setting, as MCDA offers a framework for handling debates on the identification of components of a decision problem, organizing the elements into a hierarchical structure, understanding the relationships between components of the problem, and stimulating communication among participants.

By integrating MCDA into GIS, one can enhance the limited capabilities of GIS to store and analyze data on the decision maker's preferences. MCDA can guide the decision maker(s) through the critical process of clarifying evaluation criteria, and of defining values that are relevant to the decision situation. The major advantage of incorporating MCDA into GIS is that a decision maker can introduce value judgments into GIS-based decision making. MCDA can provide assistance in understanding the results of GIS-based decision making procedures, including trade-offs among conflicting evaluation criteria/objectives, and then use the results in a systematic and defensible way to develop policy recommendations (Nyerges and Jankowski 2010).

Recent developments in spatial analysis show that GIS-MCDA can make substantial contributions to the development of geo-computation (computational intelligence) methods (Aerts et al. 2005; Li et al. 2011; Xiao 2008; Lai et al. 2013). One can identify two areas where GIS-MCDA has added to geo-computational research: spatial optimization and geosimulation. First, the contribution comes from the use of fundamental concepts of GIS-MCDA, such as value function and criterion weighting (see Sect. 2.2), to develop a number of heuristic and meta-heuristic procedures for solving complex spatial optimization problems (Chap. 6). Although the methods have often been developed by adapting conventional, aspatial heuristics and meta-heuristics, some of these methods have specifically been designed for tackling spatial multiobjective optimization problems. Second, the advantage of integrating GIS-MCDA into geosimulation modeling is that it provides a set of tools for defining the behaviour of decision making agents. At the same time, the simulation methods provide a platform allowing for spatial aspects of multicriteria decisions to be considered explicitly. This, in turn, has inspired research on integrating spatial simulation and optimization methods. The integrative modelling framework combines the bottom-up approach of geosimulation methods and the top-down multiobjective optimization procedures as a tool for analyzing complex spatial decision problems (see Sect. 8.3.1).

Another significant contribution of GIS-MCDA to GIScience is the development of spatially explicit multicriteria models. A number of approaches have been proposed for developing spatially explicit methods using the concepts of GIS-MCDA, including the local forms of multicriteria models. The local forms of the conventional, global models are of particular significance because they have been developed based on well-established MCDA concepts. The local forms of multicriteria models open up new opportunities for GIScience and spatial analysis. The results of conventional GIS-MCDA are unmappable, with exception of the overall evaluation scores. Alternatively, the results of local MCDA modelling can be mapped and further examined with GIS (Malczewski 2011).

13.3 Challenges and Prospects

Notwithstanding the remarkable growth of research on GIS-MCDA (Chap. 3) and the synergistic effects gained by integrating MCDA into GIS (see Sect. 13.2), one can identify some limitations associated with combining these two distinctive sets of methods. Because of the hybrid origin GIS-MCDA, research has tended to concentrate on the technical issues of integrating MCDA into GIS. As a consequence, our understanding of the benefits of such integration is limited by the scarcity of research on empirical substantiation of the use of GIS-MCDA in tackling real-world problems (Jankowski and Nyerges 2001). There are also other, more general, concerns surrounding the use of MCDA in GIS that require careful consideration. More attention should be paid to the theoretical foundations and operational validity of GIS-MCDA methods. Some MCDA procedures are lacking a proper scientific foundation and some methods involve a set of stringent assumptions, which are difficult to validate in real-world situations. These problems have, to a large extent, been ignored by the GIS-MCDA community. If a primary purpose of GIS-MCDA is to process and synthesize large spatial datasets and value judgments, and to examine the implications of those value judgments for planning and policy making, then more careful consideration must be given to the assumptions underlying the MCDA procedures (Malczewski 2010).

Recent developments in spatial analysis show that geo-computation (computational intelligence) offers new opportunities for GIS-MCDA (see Sects. 6.3 and 8.3). Geo-computational tools can potentially help to model and describe complex systems for decision making (Li et al. 2011; Tong and Murray 2012). An integration of MCDA and geo-computation can enhance GIS-MCDA capabilities of handling larger and more diverse spatial datasets. Another significant trend has been associated with developing map-centred exploratory approaches to GIS-MCDA (see Chap. 11). The main purpose of these approaches is to provide the decision maker with insights into the nature of spatial decision problems not readily obtained by conventional methods (such as tabular displays). The power of map-centred exploratory analysis comes from the confidence in the GIS-MCDA procedures that grows as decision makers see the procedures confirm their understanding of the decision problem at hand.

One of the most challenging aspects of GIS-MCDA has been the problem of identifying an appropriate scale of analysis. There are several issues here, which should be addressed to advance GIS-MCDA. First, there is a very limited research base upon which to make generalizations and develop a generic framework of multi-scale GIS-MCDA (see Chap. 9). Second, to avoid confusion surrounding the different meanings of scale, there is a need for empirical studies of the different connotations of spatial, temporal, and operational scales in the context of spatial multicriteria decision/evaluation problems. Third, there is the question of how to deal with the MAUP effects in GIS-MCDA. Although, the problem can possibly be tackled by computationally intensive techniques proposed in GIScience/spatial analysis, we suggest that modelling procedures specifically designed to deal with

MAUP in GIS-MCDA are needed. The challenge is to develop a practical and operational modelling approach for exploring MAUP and integrate it into GIS-MCDA procedures.

There is a need for advancing spatially explicit methods of GIS-MCDA. Although considerable progress has been made to develop spatially explicit methods for dealing with multicriteria decision problems, the practical potential is yet to be substantiated. Furthermore, there is the question of how to develop spatially explicit MCDA models (Xiao 2008; Tong and Murray 2012). Most of the spatially explicit GIS-MCDA methods are designed for solving spatial multiobjective optimization problems that involve spatially defined decision alternatives. Another way to proceed is to 'spatialize' or 'localize' the fundamental concepts of MCDA, such as value functions and criterion weights. The main challenge here is to develop an approach that is consistent with the underlying principles of MCDA and at the same time, conforms to the tests for spatially explicit models (see Sect. 1.4.2). The capabilities of GIS for generating decision alternatives are mainly based on the spatial relationship principles of connectivity, contiguity, proximity, and overlay methods. However, when a decision situation involves conflicting preferences with respect to evaluation criteria, the overlay operations do not provide enough analytical support because of limited capabilities for incorporating the decision makers' preferences into the GIS-based decision making process (Sugumaran and DeGroote 2011). In addition, the complexity of relationships in some spatial decision problems cannot be represented cartographically. Consequently, GIS are not flexible enough to accommodate variations in either the context or the process of spatial decision making. We suggest that the aim of GIS-MCDA is to support spatial decision making by assisting in a constructive approach to the problem at hand (see Sects. 1.2.2 and 1.3.3). This approach can be greatly enhanced by Web-based collaborative learning processes supported by participatory/public participation GIS-MCDA (Carver 1999; Simão et al. 2009; Boroushaki and Malczewski 2010) and the use of argumentation maps in conjunction with MCDA techniques in an online environment (Rinner 2001; Sani and Rinner 2011).

Embracing novel computing technologies holds the promise of GIS-MCDA access by a broader audience. However, this prospect comes with challenges resulting from general software and data access issues. For example, commercial GIS packages are generally not affordable by average citizens, or even by many smaller businesses and organizations. In addition, geospatial datasets represent a major cost in most GIS projects and therefore in GIS-MCDA. The increasing availability of professional-quality open-source GIS software alleviates the upfront costs for new GIS-MCDA users. In another major trend in GIScience and policy, government data are increasingly opened to the public in support of transparency and democratization of decision making. The emerging open data catalogues promise to foster evidence-based decision making and public review of decisions, both of which call for including GIS-MCDA procedures. The technical developments in geovisualization, Web-based, and mobile GIS-MCDA will benefit experts and lay users alike by making GIS-based multicriteria analyses more effective and efficient.

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