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GIS-Based Multiple-Criteria Decision Analysis

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Abstract

Important and complex spatial decisions, such as allocating land to development or conservation-oriented goals, require information and tools to aid in understanding the inherent tradeoffs. They also require mechanisms for incorporating and documenting the value judgements of interest groups and decision makers. Multiple-criteria decision analysis (MCDA) is a family of techniques that aid decision makers in formally structuring multi-faceted decisions and evaluating the alternatives. It has been used for about two decades with geographic information systems (GIS) to analyse spatial problems. However, the variety and complexity of MCDA methods, with their varying terminologies, means that this rich set of tools is not easily accessible to the untrained. This paper provides background for GIS users, analysts and researchers to quickly get up to speed on MCDA, supporting the ultimate goal of making it more accessible to decision makers. A number of factors for describing MCDA problems and selecting methods are outlined then simplified into a decision tree, which organises an introduction of key methods. Approaches range from mathematical programming and heuristic algorithms for simultaneously optimising multiple goals, to more common single-objective techniques based on weighted addition of criteria values, attainment of criteria thresholds, or outranking of alternatives. There is substantial research that demonstrates ways to couple GIS with multi-criteria methods, and to adapt MCDA for use in spatially continuous problems. Increasing the accessibility of GIS-based MCDA provides new opportunities for researchers and practitioners, including web-based participation and advanced visualisation of decision processes.

1. Introduction

People often make spatial decisions, in both personal and professional matters: what route to take on a daily commute, where to locate a new branch office, or which forest stands to harvest. Selecting an alternative usually requires trading off different considerations. Route selection, for instance, may be a trade-off among distance, driving time, road quality and scenery. Different people facing the same problem may apply different values and motivations and reach different conclusions. As decisions increase in complexity and importance, so does the need to formalise them using available information, and to document the rationale.

Multiple-criteria decision analysis (MCDA) can be defined as 'a collection of formal approaches which seek to take explicit account of [key factors] in helping individuals or groups explore decisions that matter' (Belton and Stewart 2002, 2). For approximately 20 years, MCDA methods have been used for spatial problems by coupling them with geographic information systems (GIS) (Carver 1991; Malczewski 2006a). The goal of this paper is to make the GIS-based MCDA field more accessible to a wider audience. This includes the GISciences community of researchers, analysts, and users, and ultimately experts and decision makers in many fields. The GIS literature is filled with tools, scenarios and cases involving spatial decision support (Dragićević 2008; Nyerges and Jankowski 2010), so there is a major challenge for newcomers in even identifying GIS-based MCDA research and tools. It requires an understanding of the concepts of non-spatial MCDA, hence a related goal is to make sense of the sheer variety of MCDA methods and the many ways they can be integrated with GIS.

Section 2 introduces MCDA, and Section 3 lists a number of factors used to categorise decision scenarios and select formal methods. These selection factors are used to build a methods decision tree in Section 4, which organises brief descriptions of key MCDA methods. We then discuss the spatial extension of MCDA in Section 5, particularly spatially continuous problems that are ideally suited to modelling with GIS. Research trends in the field of GIS-based MCDA are also reviewed. Section 6 is geared towards the practitioner, covering available software and coupling strategies for integrating MCDA with GIS. The Conclusion identifies opportunities related to making the field more accessible.

2. MCDA Background

Multiple-criteria decision analysis aids decision makers in analysing potential actions or alternatives based on multiple incommensurable factors/criteria, using decision rules to aggregate those criteria to rate or rank the alternatives (Eastman 2009; Figueira et al. 2005; Malczewski 1999a). Although the decision criteria normally cannot all be maximised in selecting an alternative or action, MCDA researchers and practitioners do not view it simply as a quantitative optimisation problem that identifies the best potential 'solutions'. Instead, the focus is on eliciting and making transparent the values and subjectivity that are applied to the more objective measurements, and understanding their implications (Belton and Stewart 2002; Roy 2005). The field is often referred to as multiple criteria decision making, but decision 'analysis' or 'aiding' (MCDA) better reflects the more subtle and broader-ranging intentions.

Multiple-criteria decision analysis grew out of and in reaction to single-criterion optimisation techniques, most notably linear programming. These were developed during World War II and honed in the early days of the business management field of Operations Research, in both contexts without considering secondary consequences that require multiple criteria (Zeleny 1982). Simple and somewhat crude approaches to reconciling multiple criteria require alternatives to meet one, some or all criteria based on cut-off values. These approaches are named non-compensatory methods, in that increases in the value of one criterion cannot be offset by decreases in the value of another (Hwang and Yoon 1981).

Among advocates of more sophisticated compensatory approaches that facilitate criteria tradeoffs, two prominent schools of MCDA (American and European, summarised in Table 1) evolved simultaneously but somewhat separately during the 1960s and 1970s. Both schools shared the concepts of decision alternatives and criteria, but differed in their philosophy and approach to aggregating criteria. The early American school of MCDA followed the Operations Research tradition. One set of its methods used a value or utility function based on multi-attribute utility theory (Keeney and Raiffa 1976), multiplying weights by normalised criteria values (for instance converted to a continuous 0–1 scale) and summing these to derive a score or rating for each alternative. Another set of methods within the American school centred on the idea of specifying desirable or satisfactory outcomes and using mathematical programming to come as close as possible to these in criteria outcome space (multi-dimensional space where each dimension represents the

Table 1. Early schools of multiple-criteria decision analysis.

	American school	European (French) school
Assumptions	Precise knowledge and judgements, optimal decisions	Imprecision in evaluating criteria, optimal decisions not achievable
Goal	Rating and selection of alternatives	Ranking of alternatives
Aggregation approaches	Value/utility function, multi-criteria and multi-objective optimisation	Outranking
Key institutions	Decision Sciences Institute – http://www.decisionsciences.org/	LAMSADE – http://www.lamsade.dauphine.fr/
	Institute for Operations Research and the Management Sciences – http://www.informs.org	EURO Working Group – Multicriteria Decision Aiding – http://www.cs.put.poznan.pl/ewgmcda/

possible values of one criterion) (Dykstra 1984). The word 'programming' is used in the sense of the program of action that is recommended as a result of the analysis. The European school moved away from the Operations Research idea of obtaining an optimum, and developed outranking relationships to help decision makers compare alternatives in a pair-wise manner to rank their preferences for the alternatives in various ways (Roy 1968a cited in Roy and Vanderpooten 1996; Vincke 1992). A key assertion in this approach is that decision makers do not have precise preconceptions of the relative importance of the criteria, and that decision aiding should help them develop this insight. A somewhat less prominent school of MCDA, based on fuzzy sets (Zadeh 1965) and value-function aggregation, is the analytic hierarchy process (AHP) developed by Saaty (1980). AHP uses pair-wise comparison of criteria to derive relative weights.

As MCDA has grown, the clear divisions among the schools have diminished. For instance, subtleties introduced by the European school, such as recognition of subjectivity and imperfect knowledge (Roy and Vanderpooten 1996), are now widely recognised and are reflected in the accepted definitions of MCDA. The various techniques are considered tools in the analyst's toolkit to be applied as appropriate to different problems or phases of the same problem. Consequently, the primary research challenges moved from development of methods, to such issues as frameworks for method integration (Belton and Stewart 2002) and application in distributed collaborative environments (Carver 1999; Malczewski 1999a). There has been a steady growth in MCDA's range of application, for instance in environmental and resource fields such as forest management (Diaz-Balteiro and Romero 2008; Mendoza and Martins 2006).

Perhaps MCDA's greatest strength is its ability to simultaneously consider both quantitative and qualitative criteria, as long as the latter can be represented using an ordinal or continuous scale. One result is that MCDA is an alternative to decision analysis based solely on economic (monetary) valuation. There is substantial literature on economic valuation of non-monetary phenomenon, such as ecosystem goods and services (van Kooten and Bulte 2000; Turner et al. 2008). A practical challenge of such approaches is avoiding dismissal by decision makers of these often very large and theoretical valuations when pitted against hard economic criteria like jobs and exports. MCDA approaches can help overcome economic biases (Herath and Prato 2006) by either using a non-monetary common denominator (a continuous scale like 0–1) or avoiding altogether the need to convert criteria from their original values.

3. Method Selection Factors

One approach to succinctly categorising virtually all MCDA scenarios is their association with various problem types, or *problématiques*. These include choice (making a single selection or recommendation), ranking (establishing a preference order for some or all of the alternatives), sorting (separating alternatives in classes or groups), description (learning about the problem), design (developing new alternatives for possibly addressing the problem) and portfolio (selecting a subset of alternatives) (Belton and Stewart 2002; Roy 1996).

Other factors that describe decision problems or affect the choice and implementation of MCDA methods include:

1. *Number of decision makers*: MCDA techniques designed for individuals can be applied for group decisions where consensus can be achieved through education or negotiation (Malczewski 2006a). Otherwise, the methods must be extended using approaches such as aggregated weighting (Malczewski 1999b) or voting (Hwang and Lin 1987). Group approaches open up a variety of issues, often studied in Collaborative GIS research (Balram and Dragićević 2006; Joerin et al. 2009; Rinner 2001).
2. *Decision phase*: The phase or phases of the decision process to be supported. There are many ways to organise and describe decision phases (Anderson et al. 2003; Bouyssou et al. 2006; Turban and Aronson 2001), with a critical distinction for MCDA between the problem exploration/structuring phase and the evaluation/recommendation phase.
3. *Number of objectives*: With a single objective (such as recommending the site for a new fire station), the decision maker(s) can focus on relevant criteria or factors with measurable attributes, and thus corresponding techniques are often called multiple-criteria evaluation (MCE) or multiple-attribute decision making (MADM) (Jankowski 1995; Malczewski 1999a). With multiple-objective decision making (MODM), it is necessary to establish whether the objectives are in synergy or conflict (for instance allocating urban land either to housing or green space) and to group the criteria by objective (Eastman et al. 1995; Malczewski 2004).
4. *Number of alternatives*: Scenarios with a limited number of clear alternatives (like analysing three pre-selected locations for a new fire station) are discrete problems that usually culminate in a single selection (Chakhar and Mousseau 2007). A large or infinite number of alternatives (like identifying all possible sites for the new fire station) signifies a continuous problem usually characterised as screening, search, or suitability rating (Eastman 2009; Malczewski 1999a).
5. *Existence of constraints*: Limitations on solutions, either in the form of alternatives/areas to be excluded from consideration or conditions that the recommended solution must meet. Common constraints in spatially continuous problems are that recommended areas must be a minimum contiguous size (Eastman 2009) or provide corridors of connectivity (Chakhar and Mousseau 2008).
6. *Risk tolerance*: The decision makers' level of risk tolerance (Eastman 2009) and desire to quantify the risk inherent in a choice (Chen et al. 2001; Eastman 2005). For instance, when screening alternatives, a risk-tolerant decision maker might be willing to accept alternatives that meet just a few criteria or even one criterion. A risk-averse decision maker, on the other hand, may accept only alternatives that meet all criteria.
7. *Uncertainty*: Whether the criteria and weighting should be modelled with certainty (i.e. deterministically) or uncertainty (i.e. probabilistically or fuzzily) (Jiang and East-

man 2000; Malczewski 1999a; Shepard 2005). This may be based on the nature of the criteria or simply a matter of modelling preference. For instance, in a land-classification problem, the transition from woodland to wetland could be modelled with crisp boundaries (either one or the other) or fuzzy boundaries (with one or more classification levels where the land is partially wooded and partially wet).

8 *Measurement scales and units*: Whether it is possible to convert heterogeneous criteria based on various measurement scales (such as currency and qualitative survey results) to a common scale, and whether decision makers are comfortable with representing criteria numerically (Chakhar and Mousseau 2008; Joerin et al. 2001).

9 *Experience*: The training and experience of the analyst and decision makers (Belton and Stewart 2002). Given the large number of methods and their vastly different assumptions (see discussion of the early schools of MCDA in the Introduction), this is a very practical consideration that results in technique biases.

10 *Computational resource capacity*: Another practical consideration is available software (Malczewski 1999a; Weistroffer et al. 2005) and hardware, and these can have budget implications.

11 *Direction of problem solving*: Typically, problems are worked forward in support of a new decision. However, existing decisions can be worked backward to elucidate the value judgements that would be needed to support them, in a process called preference disaggregation (Jacquet-Lagrèze and Siskos 2001; Siskos 2005).

4. MCDA Methods

Given the diversity of MCDA methods, selection of an appropriate method or combination of methods depends on the context. The decision tree of Figure 1 is, therefore, not intended to be comprehensive or definitive, but provides one approach to simplifying the selection process. The clearest separation of methods is based on whether or not there are multiple objectives. If the decision maker or analyst determines that the multiple objectives are either complementary or can be prioritised, then MADM methods can be applied repeatedly in a two-level or stepwise fashion (Eastman 2009; Malczewski 1999a). If the multiple objectives are in conflict, MODM methods are required. The choice is based on the number of alternatives, between mathematical programming for locating an optimal solution, and heuristic methods for locating a satisfactory solution close to the optimum. Unfortunately, there is no easy definition of what constitutes a 'large' number of alternatives as it depends on the computational capacity of the software or algorithm being used.

The MADM side of the tree is divided based on the question of trading off criteria. Non-compensatory approaches are easier to understand and apply, but they require including or excluding alternatives based on hard cut-offs. Compensatory approaches are more realistic and subtle in their modelling, as they allow criteria outcomes to be traded off against each other on a continuous scale, so that a loss in one criterion can be compensated for by a gain in another. Note that MODM methods are generally compensatory by nature, and therefore always support criteria tradeoffs. Like MODM, selection of compensatory MADM methods is also differentiated based on the number of alternatives.

It is important to realise that the methods are not mutually exclusive, due to the complexities and multiple phases of decision analysis. For instance, non-compensatory techniques could be used for preliminary screening of alternatives, followed by a compensatory method to support final selection. Multiple techniques can also be applied

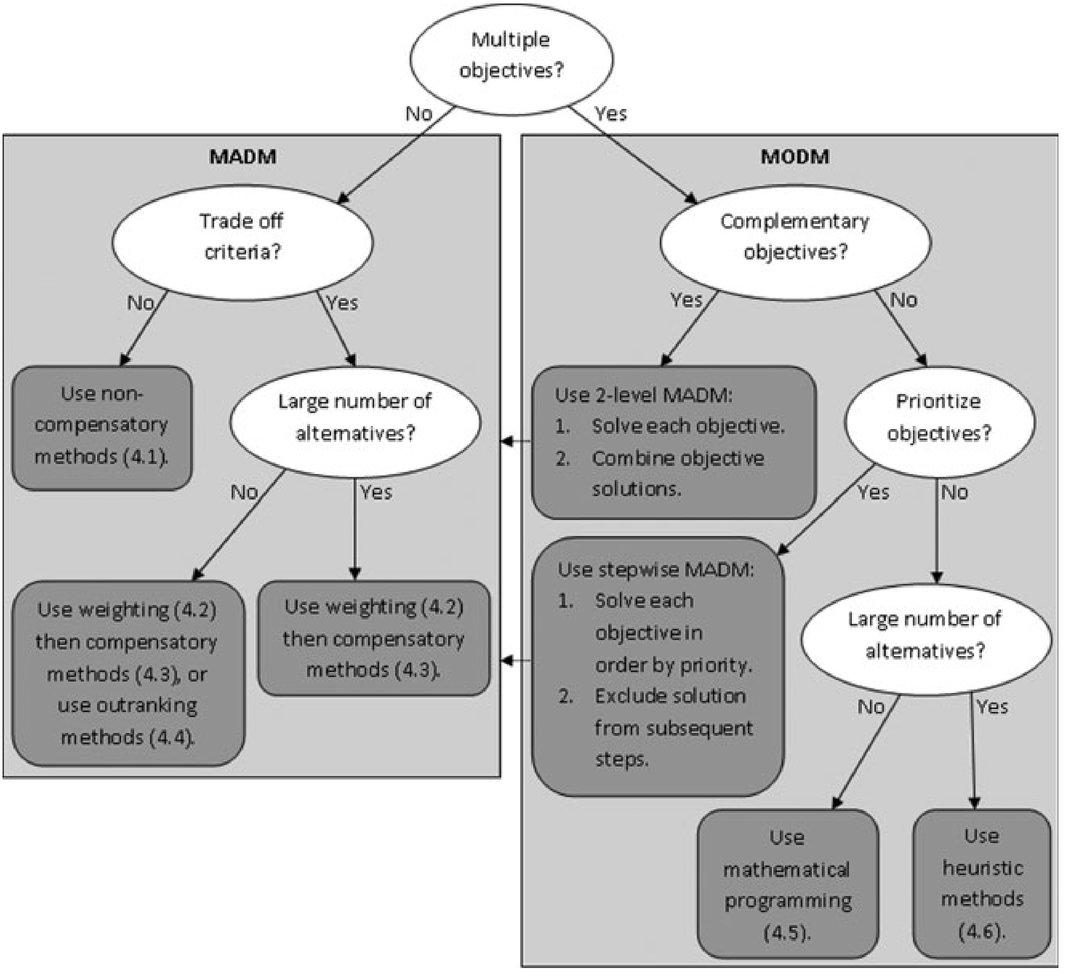

Fig. 1. Multiple-criteria decision analysis methods decision tree. Shaded action nodes (dark grey) indicate the numbered subsection of the paper that describes the set of methods.

in parallel as part of a strategy to validate the robustness of the recommendations (Carver 1991; Roy 2005). A more common approach to sensitivity analysis is to run multiple iterations using the same method, each time making slight adjustments in the inputs (such as the selection and weighting of criteria) to assess the sensitivity of the resulting outputs (Feick and Hall 2004; Malczewski 1999b; Store and Kangas 2001).

4.1. NON-COMPENSATORY AGGREGATION METHODS

Often used for screening as well as selection, non-compensatory methods include:

1 *Conjunctive*: Accept alternatives if they meet a cut-off value on every criterion. Implementations involving spatial problems often use binary overlay (Jankowski 1995; McHarg 1969), where the objects or cells in each layer are set to 1 if they pass the cut-off for that criterion and 0 otherwise. The layers are combined using an intersection operation (logical AND) to identify 'solution areas' that meet criteria, as shown in Figure 2. Conjunctive methods are risk averse because all criteria must be fully met (Eastman 2009).

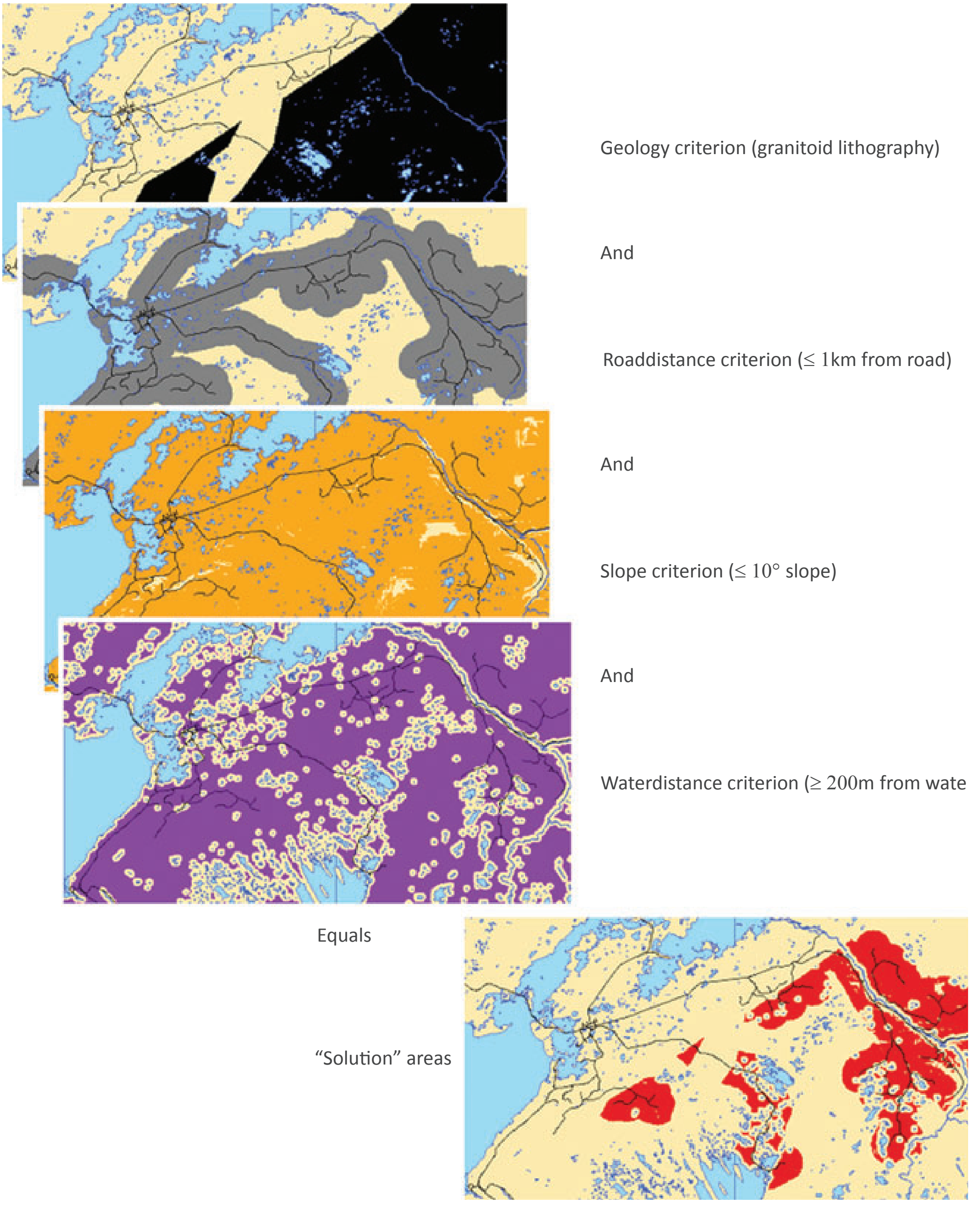

Fig. 2. Conjunctive example. Binary overlay for mineral exploration site identification, showing areas that meet the selected cut-off on all criteria.

2 *Disjunctive*: Accept alternatives that meet a cut-off value on at least one criterion (Hwang and Yoon 1981). It can also be implemented for spatial problems using binary overlay, where the map criteria layers are combined using a union (logical OR) operation. It is a risk-taking method, because only one criterion must be met (Eastman 2009).
3 *Lexicographic*: Rank/order the criteria, then eliminate alternatives hierarchically by comparing them on the highest ranked criterion, followed by the second highest ranked, etc. (Carver 1991; Jankowski 1995).
4 *Elimination by aspects*: Use a lexicographic approach, but also enforce a conjunctive cut-off for each criterion (Malczewski 1999a).
5 *Dominance*: Look for dominant alternatives that score at least as high as every other alternative on every criterion (Jankowski 1995).

4.2. WEIGHTING METHODS

The following methods are used to derive relative criteria weights/importance before applying a compensatory aggregation method (Belton and Stewart 2002; Malczewski 1999a; Nyerges and Jankowski 2010):

1 *Ranking*: Ranks/orders the criteria, then converts the ranks to weights using:
  (i) Rank sum – each rank value divided by the sum of all rank values.
  (ii) Rank reciprocal – 1 divided by each rank value.
  (iii) Rank exponent – a rank sum with the numerator and denominator raised to a power between 0 and 1, thereby reducing the resulting weight differences.
2 *Rating*: Rates the criteria using a common scale (such as any value between 0 and 1) or point allocation (for instance allocating 100 points among all criteria).
3 *Trade-off analysis*: Directly assesses tradeoffs between pairs of criteria to determine the cut-off values at which they are considered equally important.
4 *Analytic hierarchy process*: Compares criteria pair-wise on a fuzzy-linguistic ratio scale and subsequently computes overall relative weights based on aggregate calculations of all pair-wise ratios (Eastman 2009; Saaty 2005; Schmoldt et al. 2001). AHP is more than a criteria weighting method, as it also provides an additive, hierarchical aggregation of criteria. Figure 3 shows AHP weighting of three of the criteria from the mineral exploration example.

4.3. COMPENSATORY AGGREGATION METHODS

Compensatory decision rules not requiring pair-wise comparison of alternatives are of two types:

1 Additive methods that normalise criterion scores to enable comparison of performance on a common scale:
  (i) *Weighted linear combination* (*WLC*): Also known as simple additive weighting, this approach multiplies normalised criteria scores by relative criteria weights for each alternative (Geldermann and Rentz 2007; Nyerges and Jankowski 2010). WLC can sum all weighted criteria values in a single step, or proceed hierarchically so that each group of related criteria (such as wildlife, tourism and agriculture in a rural land-management problem) is first aggregated before being combined with other groups. In Figure 4, the earlier mineral exploration example is analysed using single-step WLC, showing criteria normalisation and weighting, and the

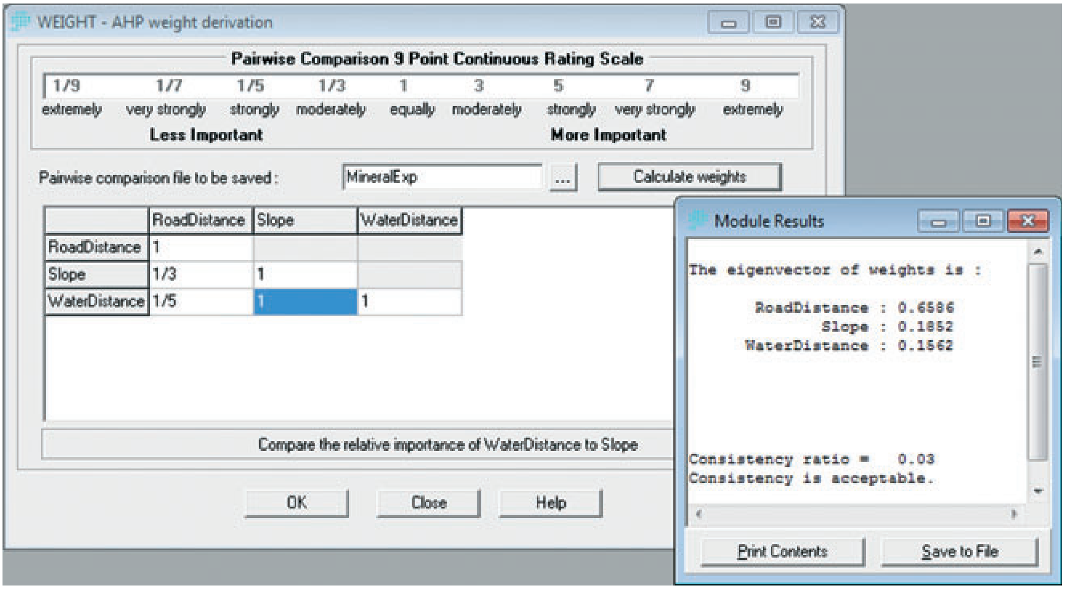

Fig. 3. Weight derivation using analytic hierarchy process in IDRISI GIS (http://www.clarklabs.org/). First, the criteria are compared pair-wise. For instance, WaterDistance is considered to be strongly less important than RoadDistance (1/5). Then the eigenvector of the pair-wise comparisons is used to determine the overall criteria weights. The consistency ratio ensures, in this example, that the comparisons Slope/RoadDistance (1/3) and WaterDistance/RoadDistance (1/5) are sufficiently consistent with the comparison WaterDistance/Slope (1/1).

resulting map of aggregated suitability scores. Because it supports full trade-off or compensation among criteria values, WLC is mid-way on the risk tolerance continuum between conjunctive and disjunctive approaches and is thus considered a risk-neutral technique (Eastman 2009).

(ii) *Fuzzy additive weighting*: Adapts WLC using non-crisp criteria and weight values derived from fuzzy-linguistic quantifiers such as 'high', 'medium' and 'low' (Gemitzi et al. 2007; Malczewski 1999a; Zadeh 1965).

(iii) *Ordered weighted averaging* (*OWA*): Also based on fuzzy methods, OWA extends WLC using criteria-order weights to control the levels of criteria trade-off, allowing decision makers to place themselves along a continuous spectrum of risk tolerance (Jiang and Eastman 2000; Malczewski 2006b; Rinner and Malczewski 2002; Yager 1988).

2 Non-additive methods that use the original criteria scores:

(i) *Ideal point*: Identifies a point in criteria outcome space by specifying the preferred value of each criterion (Malczewski 2004; Nyerges and Jankowski 2010). This ideal point may not be close to a feasible alternative, but there are a number of methods for selecting one, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Chen et al. 2001; Liu et al. 2006).

(ii) *Non-dominated set*: Identifies the set of alternatives that score at least as high as every other alternative on at least one criterion, also called the efficient set or Pareto set (Lotov et al. 2004; Malczewski 1999a).

(iii) *Reasonable goals method*: Extends the non-dominated set to help visually select from the alternatives using a series of two-dimensional graphs of criteria outcome space (Jankowski et al. 1999).

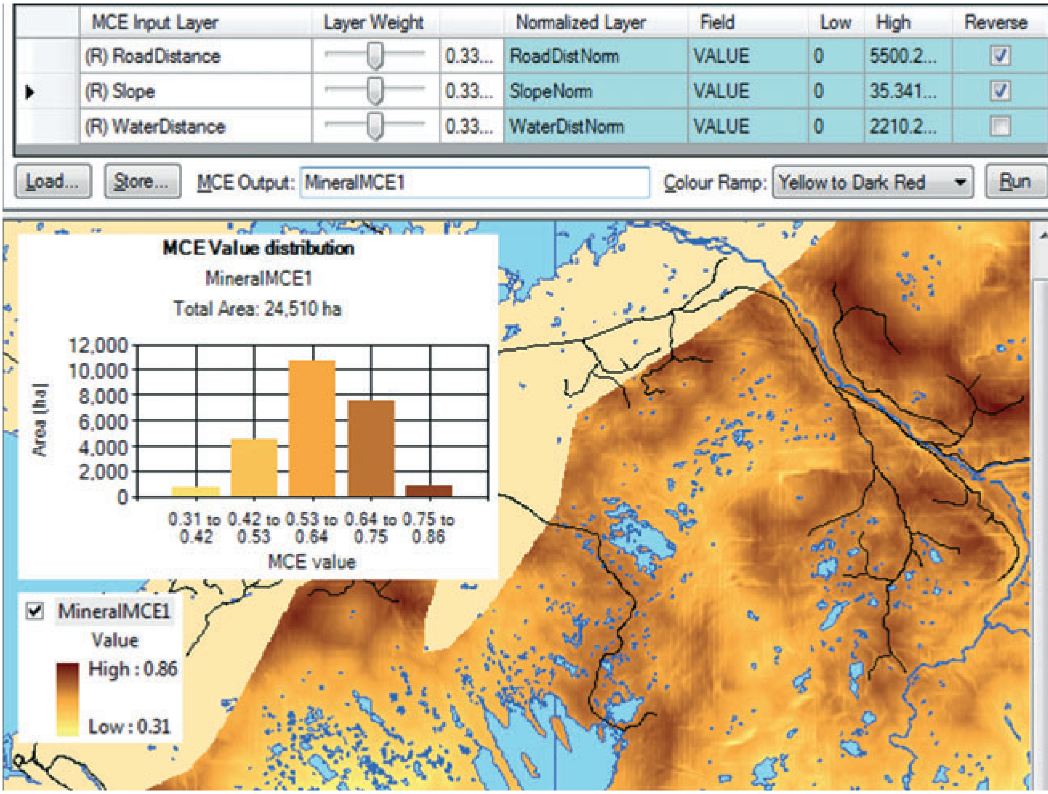

Fig. 4. Weighted linear combination example. Mineral exploration site identification based on the inputs from Fig. 2, leaving the Geology criterion as a hard constraint, but using continuous values for the RoadDistance, Slope and WaterDistance criteria. Continuous values are normalised to a 0–1 scale, with optional scale reversal for criteria where less is better. Then they are weighted (in this case equally) and summed to produce the continuous output shown. Darker areas are more suitable, with the highest rated area scoring 0.86 (of a possible maximum of 1).

4.4. OUTRANKING AGGREGATION METHODS

Outranking methods undertake pair-wise comparison of a discrete set of alternatives to rank them based on concordance (the set of criteria for which one alternative dominates another) and discordance (the opposite set) (Belton and Stewart 2002). The outranking philosophy recognises that decision makers are subject to ambiguous and evolving value judgements, even during the MCDA process. Well-known methods of this type include:

1. *ELECTRE*: A family of outranking methods (ELECTRE I, II, III, IV and TRI) that have evolved along with the European school of MCDA (Bouyssou et al. 2006; Joerin et al. 2001). ELECTRE can handle various problem types (choice, ranking, sorting) and approaches to decision modelling. It introduced thresholds for declaring indifference or preference between two alternatives on a particular criterion, and support for criteria that cannot be weighted (Belton and Stewart 2002).
2. *PROMETHEE*: An outranking method that supports various criterion preference functions such as U-shaped, linear and flat (no threshold) (Brans and Mareschal 2005; Geldermann and Rentz 2007; Marinoni 2006).

4.5. MATHEMATICAL PROGRAMMING METHODS

The following methods attempt to find the optimal way to satisfy goals by solving systems of equations:

1. *Linear/integer programming*: Mathematically optimises by maximising or minimising a single-criterion value using constraints, commonly employed in Operations Research and Management Science (Anderson et al. 2003; Wisniewski 2002). An example is to minimise the driving time to visit a specific set of customers, subject to speed limit constraints. To apply this approach, multi-objective problems are converted to a single objective using value functions (in the case of deterministic models) or utility functions (in the case of probabilistic models) (Malczewski 1999a).
2. *Goal/compromise programming*: Finds the alternative that minimises overall deviation or distance from user-specified ideal points or aspiration/reservation levels simultaneously for multiple objectives (Anderson et al. 2003; Baja et al.2007; Ghosh 2008).
3. *Interactive programming* (*reference point*): Uses successively refined aspiration/reservation levels for each objective to select a feasible alternative (Janssen et al. 2008; Malczewski 1999a; Zeng et al. 2007).

4.6. HEURISTIC METHODS

Due to computational limitations, mathematical optimisation is not possible when there are a large number of alternatives, such as in spatially continuous problems modelled using raster layers, where every possible outcome of every raster cell is an alternative. The following methods can be used to allocate cells among conflicting objectives, with the aim of a close to optimal 'solution':

1. *Multiple-objective land allocation* (*MOLA*): Allocates each cell to the objective with the closest ideal point. Objectives can optionally be weighted unequally, so that a cell may be allocated to an objective with a higher weight even when there is an objective with a closer ideal point (Eastman 2009; Eastman et al. 1995).
2. *Genetic algorithms* (*GA*): Allocates cells based on a trial-and-error process that introduces small changes (evolutionary mutations) and tests for solution improvement (Aerts et al. 2005; Bone and Dragićević 2009; Malczewski 2004).
3. *Simulated annealing* (*SA*): Allocates cells based on an iterative random process that tests for overall improvement at each step (Possingham et al. 2000; Duh and Brown 2007; http://www.uq.edu.au/marxan/).

Genetic algorithms, SA and other techniques such as cellular automata (CA) (Malczewski 2004; Myint and Wang 2006; White et al. 2004) are collectively referred to as *geocomputation* when used in spatial problems. They can be applied to related aspects of spatial decision support, such as time series used to predict the future outcome of proposed alternatives resulting from MCDA.

5. GIS-Based MCDA

The basic intention underlying *spatialised* applications of MCDA is to augment the traditional question of 'what' with the additional question of 'where' (Malczewski 1999a). GIS-based MCDA also facilitates calculation and analysis of spatial criteria such as distance, travel time and slope. Virtually all MCDA methods can be applied to spatial problems, as shown by the examples and the many GIS-oriented references in the methods just elaborated. As discussed earlier, many MCDA methods can only be applied to a small number of alternatives due to computational limitations (in the case of mathematical optimisation) or practical considerations (in the case of pair-wise comparisons). This limits the choice of methods in spatially continuous problems, which attempt to rate or allocate swaths of land (i.e. where every cell or parcel of land is potentially part of the recommended solution). One approach to opening up additional methods for these problems is to convert them to a smaller number of discrete alternatives. For instance, strategic regional planning exercises (e.g. http://www.geog.leeds.ac.uk/papers/99-8/; http://www.cbhvregionalplan.ca/) can employ representative scenarios showing a few possible land configurations for debate and discussion. A risk of this approach, though, is potentially biasing subsequent analyses by excluding good alternative configurations (Belton and Stewart 2002). Another option for spatially continuous study areas is classification into homogeneous zones based on criteria values or categories (Chakhar and Mousseau 2008; van Herwijnen and Rietveld 1999; Joerin et al. 2001). This limits the number of alternatives to the combination of possible outcomes for the zones, although often with a loss of spatial resolution.

An important element of accessibility for any field is a vibrant research community. Use of MCDA with and in GIS has been an active and growing topic of research since the early 1990s (Malczewski 2006a,c). These literature reviews also reveal use of many different combinations of methods and approaches. Leading application areas include environment/ecology, transportation, urban/regional planning, waste management, hydrology/water resources, agriculture and forestry. The reader is encouraged to refer to Malczewski (2006a; http://publish.uwo.ca/~jmalczew/gis-mcda.htm) for case studies in their areas of interest.

Despite the breadth of methods and applications, GIS-based MCDA can still be categorised as a niche field. A field-specific research group and related journal (http://publish.uwo.ca/~jmalczew/gimda/) did not survive. Non-GIS publications such as *Journal of Multi-Criteria Decision Analysis*, *Operations Research*, *Decision Sciences* and *Management Science* are important sources of information, but rarely publish GIS-oriented material. GIS-based MCDA publishing typically occurs in the general GISciences literature or in application-oriented journals. These trends were confirmed with a search of the Scopus citation database using the query ['GIS' AND ('multiple criteria decision' OR 'multi-criteria decision' OR 'multicriteria decision' OR 'MCD*' OR 'multiple criteria evaluation' OR 'multi-criteria evaluation' OR 'multicriteria evaluation' OR 'MCE')] resulted in 279 articles, broken down by year in Figure 5. Other combinations of search terms could yield additional relevant articles, but these results are representative of the steady progression of the publications in the field.

Figure 6 lists the journals containing three or more of the 279 articles. They are overwhelmingly in the GIS, Environmental and Planning fields, with the leader being the *International Journal of Geographical Information Science*. One of the few noteworthy academic conferences for the field is the Urban and Regional Information Systems Association (http://www.urisa.org/) annual conference. Again, researchers have to look to general GISciences, general decision research, application-specific fields or industry events for dissemination. No academic institution is a clear leader in GIS-based MCDA, although a selection of leading researchers based on their apparent prominence, stated research interests and publications in the field is provided in Table 2.

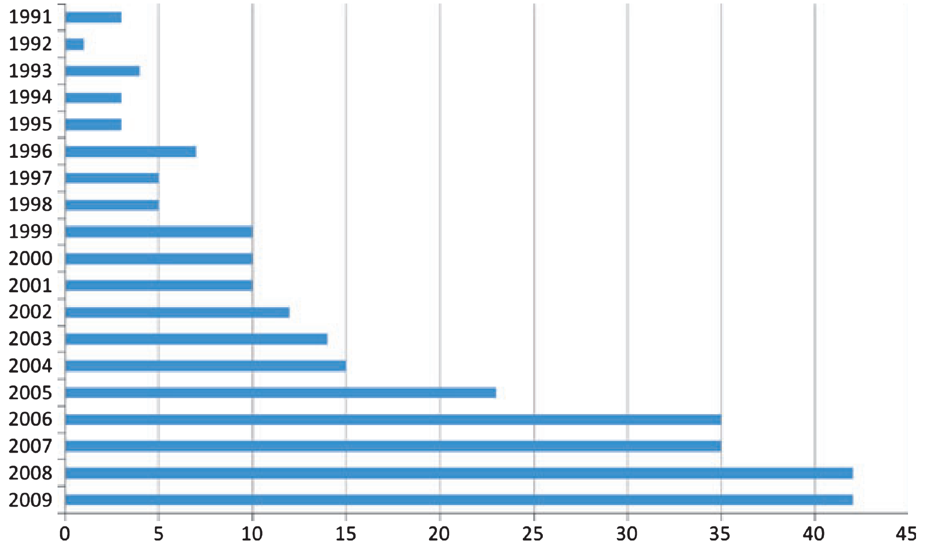

Fig. 5. Geographic information system-based multiple-criteria decision analysis article count by year (from http://www.scopus.com).

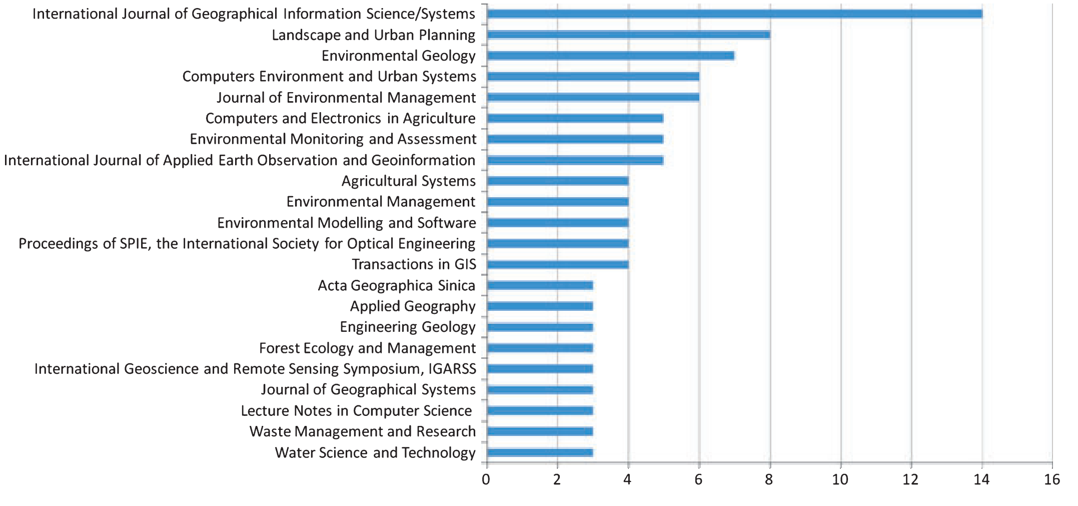

Fig. 6. Geographic information system-based multiple-criteria decision analysis article count by journal (from http://www.scopus.com).

6. GIS-Based MCDA Software

An important factor in the accessibility of research and methods is the availability of tools that implement them. GIS-based MCDA software can be categorised based on the level of integration of MCDA capabilities within GIS. Jankowski (1995, 2006) defines three levels of GIS-MCDA coupling: *full* (a single software package provided by the vendor), *tight* (a common user interface and data management, achieved through package customisation) and *loose* (based on data exchange between packages). Most MADM techniques can be implemented in most GIS packages without custom programming (Malczewski

Table 2. Selected geographic information system-based multiple-criteria decision analysis researchers.

Researcher	Institution	Link
Steve Carver	University of Leeds	http://www.geog.leeds.ac.uk/people/s.carver/
Salem Chakhar	Université Paris-Dauphine	http://www.lamsade.dauphine.fr/~chakhar/
Suzana Dragićević	Simon Fraser University	http://www.sfu.ca/dragicevic
Ronald Eastman	Clark University	http://www.clarku.edu/academiccatalog /facultybio.cfm?id=61
Piotr Jankowski	San Diego State University	http://geography.sdsu.edu/People/Faculty /jankowski.html
Florent Joerin	Université Laval	http://www.adt.chaire.ulaval.ca/1_chaire /presentation_titulaire.php
Jacek Malczewski	University of Western Ontario	http://geography.uwo.ca/faculty/malczewskij
Oswald Marinoni	Commonwealth Scientific and Industrial Research Organisation	http://www.csiro.au/people/Oswald.Marinoni.html
Timothy Nyerges	University of Washington	http://faculty.washington.edu/nyerges
Claus Rinner	Ryerson University	http://www.ryerson.ca/~crinner

1999a). For instance, ESRI's ArcGIS suite of products (http://www.esri.com) provides the building blocks needed to implement WLC, including weighting overlay and map algebra. There are numerous free and commercial ArcGIS add-ons implementing other GIS-based MADM techniques (Boroushaki and Malczewski 2008; Marinoni 2004; http://arcscripts.esri.com). Only two packages, IDRISI and CommonGIS, provide full integration of MCDA (Nyerges and Jankowski 2010).

IDRISI (http://www.clarklabs.org) is a commercial GIS that includes decision-support modules based on WLC, AHP, OWA, MOLA and CA, among others, plus a wizard to assist in selection of appropriate decision techniques (Eastman 2009). It also encourages and supports identifying contiguity of 'solution' areas, helping address the fragmentation problem in raster-based MCDA. Figure 7 shows a spatially continuous example of IDRISI's WLC capabilities (Rinner 2003a). CommonGIS (http://www.commongis.com), originally called 'Descartes', is a Java-based program that runs in a web browser or as a desktop application, and provides a number of multi-criteria decision capabilities including Ideal Point, WLC, OWA and Pareto Sets. Figure 8 shows a discrete WLC example from Jankowski et al. (2001), depicting interactivity and map-graph linking.

IDRISI is the only GIS package to have full coupling of a MODM method, the MOLA heuristic described in Section 4.6. Mathematical optimisation is typically integrated by loose coupling of GIS with packages or libraries such as those provided by Lindo (Malczewski 1999a; http://www.lindo.com/), or using custom programs to tightly couple the algorithms (Ghosh 2008). An important question is the order of integration (van Herwijnen and Rietveld 1999; Malczewski 2006a), as it can introduce biases related to the steps performed by each tool. Fully integrated GIS-based MODM is required to flexibly address this issue. Progress towards this goal has been made in the realms of nature conservation and land-use planning, as several organisations have developed packaged add-ons tightly coupled with ArcGIS (http://www.natureserve.org/prodServices/vista/overview.jsp; http://gg.usm.edu/pat/overview.htm; http://www.placeways.com). Customisation and integration generally also hide technical complexity, and therefore, work towards the goal of accessibility. It is important, however, that the underlying methods and assumptions are

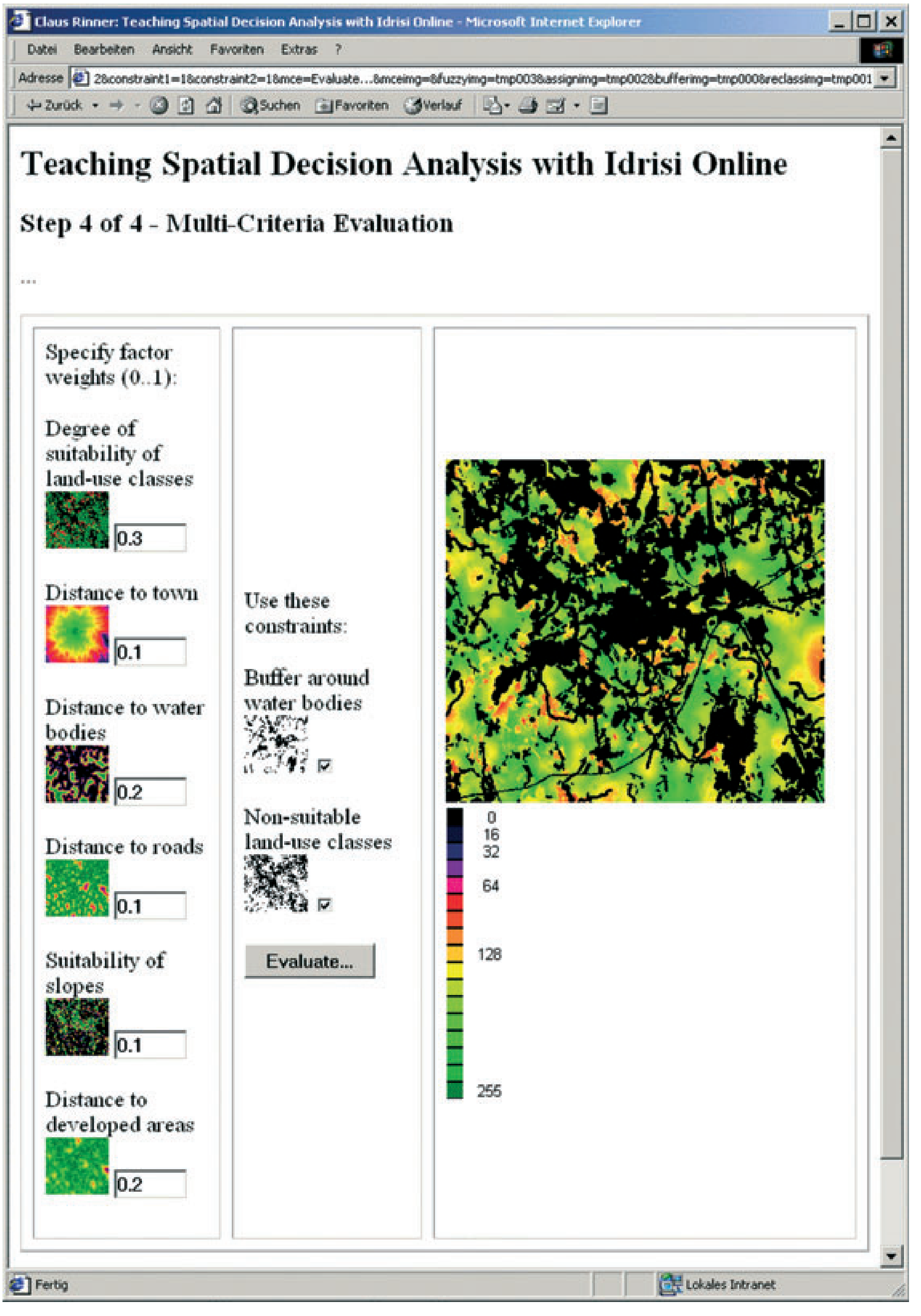

Fig. 7. IDRISI multiple-criteria evaluation example (from Rinner 2003a, reproduced with permission of the publisher). Users specify criteria weights and optionally select constraints, then evaluate all locations within the study area using a 0–255 rating scale. It employs a custom web-based interface to the non-Web IDRISI package.

well documented, to avoid creating a black box that is not trusted. Trust in MCDA may also be compromised if it is applied *a posteriori* to support preconceived decisions (Voogd 1983).

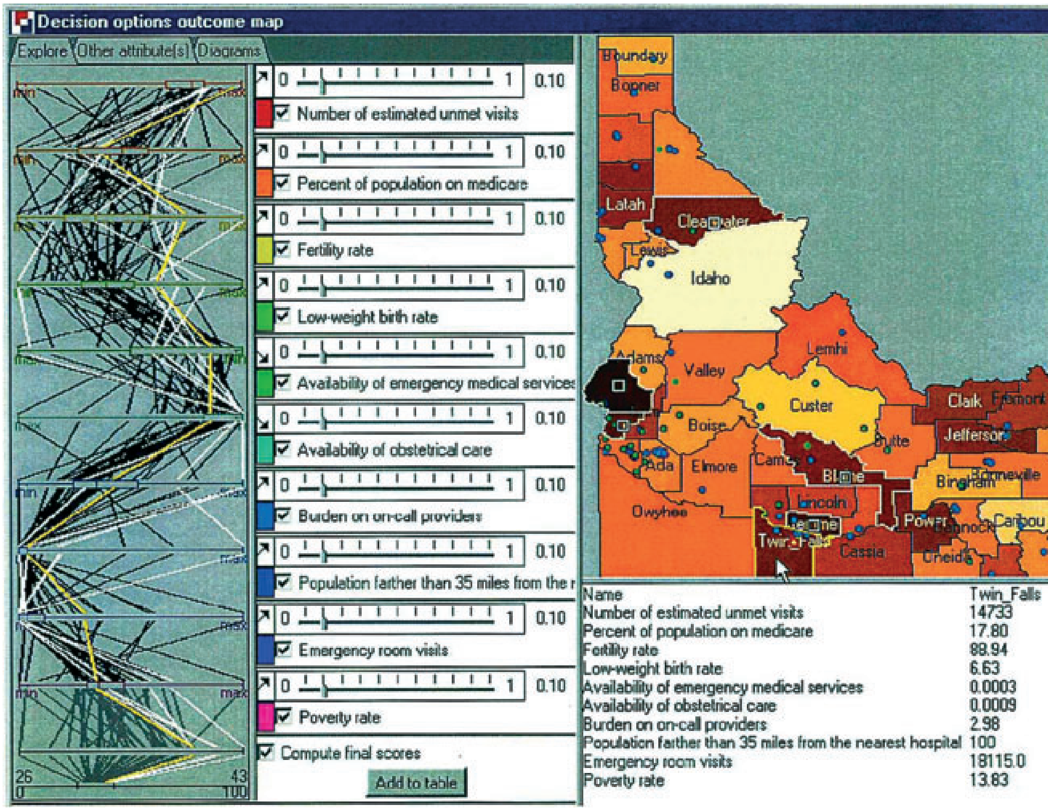

Fig. 8. CommonGIS multiple-criteria evaluation example (from Jankowski et al. 2001, reproduced with permission of the publisher), showing counties of Idaho measured on ten healthcare criteria. Interactivity includes the ability to visually select counties in the map, and to set criteria weights using sliders. Links can be seen (i) between the selected county and the textual information in the bottom right, (ii) between the highlighted counties in the map and the parallel coordinates graph to the left, and (iii) among the criteria weights, the overall county score at the bottom of the graph and the county shading in the map.

7. *Conclusion*

This paper has provided an overview of the background and methods of MCDA, and its spatial extension using GIS. Although research output, tools and applications in GIS-based MCDA continue to expand, the field has not achieved widespread acceptance. One reason is that it is often considered to be just an element of spatial decision support. Another reason is the breadth and complexity of available methods, particularly when viewed from the perspective of someone with little or no background in formal decision analysis. This introduction to the field is but one step towards making GIS-based MCDA more accessible. The need for cursory treatment of the methods selected for presentation here, and the exclusion of many other techniques and important issues, speaks to the richness that awaits those who choose to delve further into this field. In addition to continued refinement of the underlying methods and improved integration of MCDA with GIS software, there are many other opportunities for increasing accessibility. We conclude by highlighting two of them: web-based delivery and improved visualisation.

The Internet is an obvious deployment platform for collaborative GIS-based MCDA and decision support, and this approach is not new (Carver 1999; Mason and Dragićević

2006; Rinner 2003b; http://www.collaborativegis.com/). Web-based applications have certainly helped the momentum of Participatory GIS (PGIS), a newer sub-discipline that emerged from the GIS and society debates (Pickles 1995) as a broad research umbrella regarding socio-political aspects of interest group engagement using GIS (Craig et al. 2002; Haklay and Tobón 2003; Jankowski and Nyerges 2001; Weiner and Harris 2008). Researchers are beginning to explicitly combine MCDA and PGIS (Boroushaki and Malczewski 2010; Simão et al. 2009) and it is possible that GIS-based MCDA will be increasingly positioned as a component of PGIS. Regardless, an important element of PGIS that GIS-based MCDA practitioners could embrace in order to promote broad acceptance is incorporating traditional and local knowledge (McIntyre et al. 2008; Rantanen and Kahila 2009; Sheppard and Meitner 2005). Doing this effectively requires approaches that support the exploration/structuring phase of decision processes, not just the evaluation/recommendation phase, to avoid a biased pre-selection of criteria and alternatives (Ramsey 2009). Beyond the PGIS realm, GIS-based MCDA can look to Web 2.0 (Haklay et al. 2008; http://oreilly.com/web2/archive/what-is-web-20.html) for developments like *crowdsourcing* (Hudson-Smith et al. 2009; Poore 2010), whereby members of the public could suggest novel alternatives in a decision problem.

Geographic information systems and map-based applications have always provided visual appeal. However, the visual element of the platform is far from stagnant, being driven by the increasing expectations of web users and those performing advanced interactive analysis. GIS-based MCDA could add to its limited visualisation research (such as Jankowski et al. 2001; Lidouh et al. 2009; Rinner 2007), by considering how to incorporate visualisation advances from other fields.

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