Multi-attribute Decision Analysis in GIS: Weighted Linear Combination and Ordered Weighted Averaging

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Decision analysis can be defined as a set of systematic procedures for analysing complex decision problems. Differences between the desired and the actual state of real world geographical system is a spatial decision problem, which can be approached systematically by means of multi-criteria decision making. Many real-world spatially related problems give rise to geographical information system based multi-criteria decision making. Geographical information systems and multi-criteria decision making have developed largely independently, but a trend towards the exploration of their synergies is now emerging. This paper discusses the synergistic role of multi-criteria decisions in geographical information systems and the use of geographical information systems in multi-attribute decision analysis. An example is provided of analysis of land use suitability by use of either weighted linear combination methods or ordered weighting averages.

Povzetek: V prispevku predstavljamo porabo tehnologije GIS pri večkriterijskih odločitvenih postopkih.

1 Introduction

Decision making is based on numerous data concerning the problem at hand. It has been estimated that 80% of data used by managers and decision makers are geographical in nature [37]. Decision problems that involve geographical data are referred to as *geographical* or *spatial decision problems* [21].

Informed decision making and problem solving rely on the effective communication and exchange of ideas and information, the type and amount of information available and necessary to tackle a particular decision problem being related to the complexity of the situation. Spatial decision problems often require that a large number of feasible alternatives be evaluated on the basis of multiple criteria. Spatial decisions are multi-criteria in nature [4, 26, 28].

The types of decision problems that are referred to as geographical involve a large set of feasible alternatives and multiple conflicting and incommensurate evaluation criteria. Accordingly, many real world spatial problems give rise to multi-criteria decision making (MCDM) based on geographical information system (GIS). These two distinct areas of research, GIS and MCDM, can benefit from each other. GIS techniques and procedures have assumed an important position in decision making in the sense that they offer unique capabilities for automating, managing, and analysing a variety of spatial data for decision making. On the other hand, MCDM and a wide range of related methodologies, such as multi-objective decision making (MODM), multi-attribute decision making (MADM), multi-attribute utility theory (MAUT), public choice theory, and collaborative decision making, offer a rich collection of techniques and procedures with which to reveal decision makers' preferences and allowing their incorporation into GIS-based decision making [21].

Spatial multi-criteria decision analysis can be thought of as a process that combines and transforms geographical data (input) into a resultant decision (output). Geographical information can be defined as georeferenced data that has been processed into a form meaningful to the recipient. The data in geographical information systems are most commonly organized by separate thematic maps or sets of data, referred to as a *map layer, coverage* or *level*. The alternative to the layer approach is object-oriented GIS, where the objects are intended to closely represent real world elements. Irrespective of spatial data organisation, the ultimate aim of GIS is to provide support for spatial decisions. The multi-criteria decision-making procedures define a relationship between "input maps" and "output maps" [21].

Maps have a long history of use in support of decision making. Ever since they first appeared as a means of navigation, they were also used as a form of decision support tool. Good maps often meant the differences between success and failure and it is not unusual to find that maps have played a very important role in modern decision making. The GIS environment allows aggregation of qualitative and quantitative geo-referenced data [14]. In this paper, the GIS capabilities for supporting spatial decisions are analyzed in the context of the major phases of the decision-making process, each stage of which requires different types of information. Tools such as GIS offer a unique opportunity to tackle spatial problems traditionally associated with more efficient and effective data collection, analysis, and alternative evaluation.

Two methods of multi-criteria evaluation (MCE) in GIS, the Weighted Linear Combination (WLC) and the Ordered Weighted Average (OWA) methods are discussed. A generalised framework of GIS-based spatial decision-making procedure is defined and following the procedure proposed, an example of multi-attribute decision analysis (MADA) in GIS is performed using both WLC and OWA. A comparison of these two different approaches has been made, based on results of land-use suitability analysis for the study area, the municipality of Ig, Slovenia.

2 Multi-criteria decision making and GIS

2.1 Multi-criteria decision making

It is generally assumed that multi-criteria decision analysis (MCDA) originated at the beginning of 1960s. Most of practitioners of MCDA consider that their field stems largely from the early work on goal programming and research of Simon [35]. He suggests a structure for analyzing human decision-making processes by distinguishing between the *intelligence*, *design*, and *choice* phases.

Any decision-making process begins with the recognition of the problem to be decided. In the intelligence phase, a situation is examined for conditions calling for a decision. In the design phase, decision makers develop alternative solutions to the decision problem already identified. Typically, a formal model is used to support a decision maker in determining the set of alternatives. In the choice phase, decision makers evaluate the decisions and choose the best alternative. In the context of decision problems with a spatial connotation, the potential for application of spatially enabled methods in Simon's decision phases has already been examined [21]. While the intelligence and design activities can mostly be covered by multi-purpose spatial analysis methods, the choice phase requires specific methods still absent from most GIS [2, 21, 24, 25, 32].

The choice phase requires formal methods (decision rules) to select feasible alternatives and to rank them with respect to the decision-makers' preferences. As humans tend to base rational decisions on an assessment of multiple decision criteria, MCDA methods have become important tools in management sciences and operations research. By incorporating quantifiers (i.e. the relative importance of different criteria) for the decision-maker's preferences, these types of decision rules are capable of solving semi-structured decision problems.

2.2 Geographical information and GIS

Most of definitions of GIS focus on two aspects: technology and/or problem solving. The technological approach defines GIS as a set of tools for the input, storage and retrieval, manipulation, analysis and output of spatial data. This approach however ignores the problem solving aspects of GIS and it has been argued that GIS functionality can play a crucial role in a comprehensive decision-making process [11, 12, 13, 20, 21].

GIS have the ability to perform numerous tasks utilizing spatial and attribute data. Such functions distinguish GIS from other management information systems. Furthermore, GIS as an integrated technology allows for integration of a variety of geographical technologies (such as remote sensing, global positioning systems, computer-aided design, automated mapping and facilities management) that can be in turn integrated with analytical and decision-making techniques. The way in which data are entered, stored and analyzed must mirror the way in which information will be used for analysis or decision-making tasks. GIS should therefore be viewed as a process rather than as merely software or hardware. The system possesses a set of procedures that facilitate the data input, data storage, data manipulation and analysis, and data output to support decision-making activities [13].

In general, a GIS has three main components and is a *computer system* that includes hardware, software and appropriate procedures (or techniques and orders for task implementation). In addition, GIS are distinguished by their use of *spatially (geographically) referenced* data, and for carrying out various *management and analysis* tasks on these data. By allowing data to be organised, presented and analyzed efficiently, by integrating them with other data and by the creation of new data that can be operated on in turn, GIS creates useful information t which can help decision making [14]. Geographical information can be defined as georeferenced data that has been processed into a form that is meaningful to the recipient decision-maker and which is of real or perceived value in the decision-making process. In general, the MCDA in GIS should be viewed as a process of conversion of data to information that adds extra value to the original data [21, 22].

2.3 Multi-criteria decision problems

Multi-criteria decision-making problems can be classified on the basis of the major components of multi-criteria decision analysis: *multi-objective* decision making (MODM) versus *multi-attribute* decision making (MADM), *individual* versus *group* decision-maker problems, and decision under *certainty* versus decision under *uncertainty*. The distinction between MODM and MADM is based on the classification of evaluation criteria into attributes and objectives.

A *criterion* is the basis for a decision and can be measured and evaluated. In case of the spatial decision problem, attributes are the properties of geographical entities. More specifically, an attribute is a measurable quantity or quality of a geographical entity or a relationship between geographical entities. In the context of a decision-making problem, the entities and the relationships are referred to as the objects of decisions.

Multi-attribute decision making methods are data-oriented. An *attribute* is a concrete descriptive value, a measurable characteristic of an entity, including inter-entity relationships. Multi-attribute techniques are referred to as discrete methods because they assume that the number of alternatives is explicit. Multi-attribute decision problems require that choices be made among alternatives described by their attributes. This implies that attribute-objective relationships are specified in such a form that attributes can be regarded as both objectives and decision variables. Attributes are used as both decision variables and decision criteria [21].

An *objective* is a more abstract variable with a specification of a relative desirability of the levels of that variable. The multi-objective methods are mathematical programming model-oriented, where the alternatives, identified by solving a multi-objective mathematical programming problem, must be generated [16]. Multi-objective methods define the set of alternatives in terms of a decision model consisting of two or more objective functions and a set of constraints imposed upon the decision variables. The model implicitly defines the alternatives in terms of decision variables. Multi-objective models are often approached by converting them to a single objective problem solvable by standard linear/integer programming methods [33]. It is significant however, that the definition of "objective" is somewhat broader than is typically encountered in the mathematical programming literature. In mathematical programming, the term objective is often used to refer to a specific objective function. An objective is a statement about the desired state of the system under consideration and includes purposes and perspectives of a decision making. It serves as the defining role as to how the decision is structured. Purposes define the number of alternatives to be considered and the nature of decision set; perspective determines the decision rule: what criteria will be chosen, how they are evaluated, and how the final decision is made [8].

Objectives are functionally related to, or derived from, a set of attributes. An objective indicates the directions of improvement (change) of one or more attributes. For a given objective, several different attributes might be necessary to provide a complete assessment of the degree to which the objective might be achieved. If there is a direct correspondence between attributes and objectives, the multi-objective problem becomes a multi-attribute problem. In multi-attribute decision analysis, attributes are used both as decision variables and decision criteria. Generally speaking, MADM approaches are searched-based approaches and in GIS they use raster-based data structure, while MODM are choice-based approaches and use vector-based data structure [21, 23].

2.4 Framework for spatial decision making

Decision making is a sequence of activities starting with decision problem recognition and ending with a recommendation, and eventually with a final choice of alternative. As the storage and processing capacity of human memory is limited, humans develop simplifying cognitive shortcuts or processing rules to solve complex problem [5]. There being a number of alternative ways to organize the sequence of activities in the decision-making process, the quality of the decision making arguably depends on the sequence in which the activities are undertaken [21].

According to Kenney [19], two major approaches include the alternative-focus approach, which focuses on generating decision alternatives, and the value-focus approach, which uses the values (evaluation criteria) as a fundamental element of the decision analysis. The differences between these two approaches are related to the question of whether alternatives should be generated first followed by specification of the value structure, or conversely, the alternatives should be derived from the value structure (Figure 1). The general principle for structuring the decision-making process is that decision alternatives should be generated in such a way that the values specified for the decision situation are best achieved [19].

Any decision-making process begins with the recognition and definition of the decision problem, which is the perceived difference between the desired and existing states of a system. The intelligence phase of decision-making involves searching the decision environment for conditions requiring a decision: raw data are obtained, processed, and examined for clues that may identify opportunities or problems (Figure 1).

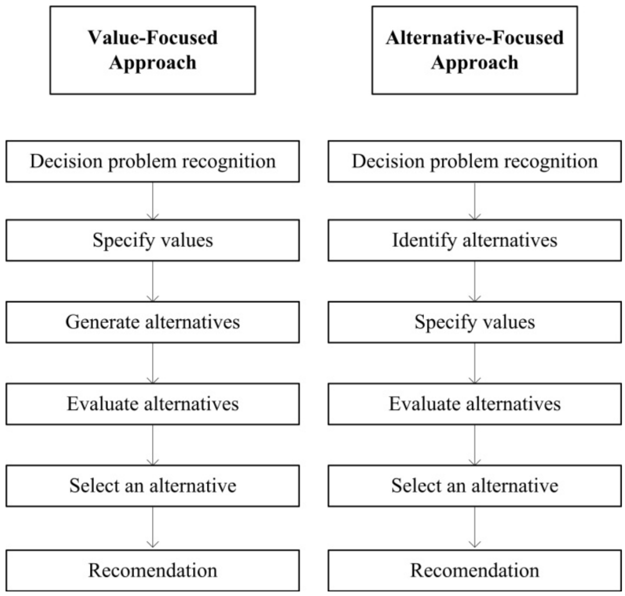

Figure 1: The sequences of alternative- and value-focused approaches (based on Kenney [19]).

A significant proportion of human problems have a geographical component. Decision making as a scientific discipline has a much longer history than GIS. Within the wider field of decision research, computers have been used to develop decision-support systems (DSS). GIS has been referred to as a specific kind of decision-support system dealing with problems which involve a high degree of spatiality [14] and which can provide a framework for the development of spatial decision-support system (SDSS), particularly when coupled either loosely or tightly coupled with other model software. Spatial decision-support system and decision-support system share the same characteristics but the former (SDSS) presents in fact an extension of DSS (Figure 2).

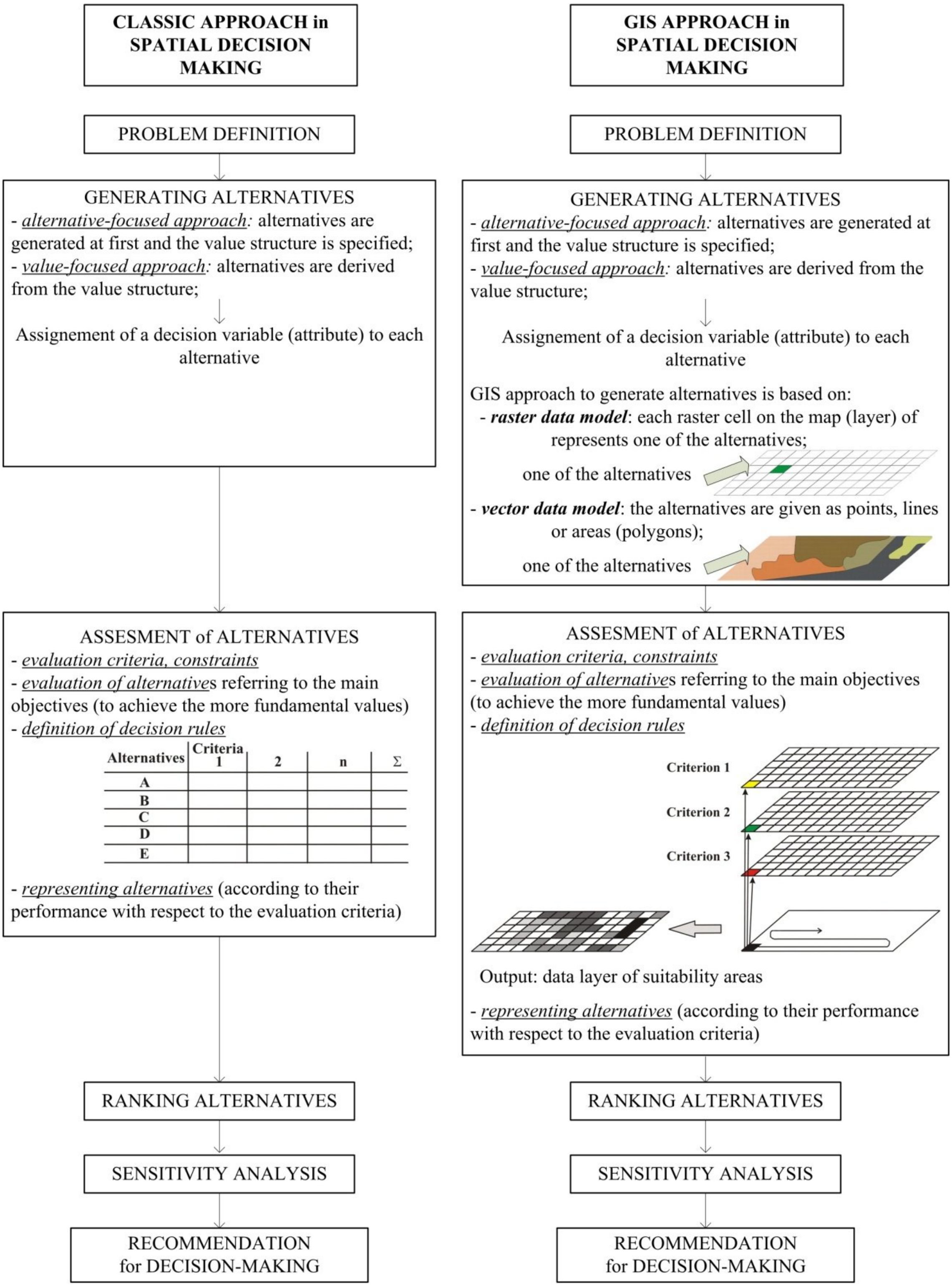

Figure 2: Classic and GIS-based spatial decision-making procedures.

One of the most important rules governing the use of GIS for SDSS is that GIS themselves do not make decisions – people do. In SDSS the emphasis is on the use of spatial data and in GIS it is on supporting decision makers in the decision-making process to choose the alternative (decision) which is the best solution to the problem that needs to be solved. Multi-criteria spatial decision support systems (MC-SDSS) integrate GIS-based data processing and analysis techniques and multi-criteria decision analysis. MC-SDSS, which is discussed more in detail below, can be viewed as a part of a broader field of spatial decision support systems.

Figure 2 shows the sequence of actions in classic spatial decision making and in GIS-based spatial decision making. Although the alternative-focused approach is mentioned in connection with the generation of alternatives, values are in general more fundamental than alternatives with respect to a decision problem. In other words, alternatives are the means to achieving the more fundamental values. Once the decision problem is defined, the spatial multi-criteria analysis focuses on evaluation criteria, which means specifying a comprehensive set of objectives that reflects all concerns relevant to the decision problem, and measures for achieving those objectives. Such measures are called *attributes*. A measurement scale must be established for each attribute. The degree, to which the objectives are met, as determined by the attributes, is the basis for comparing alternatives. The evaluation criteria are associated with geographical entities and relationships between entities and therefore can be represented in the forms of maps (a raster or a vector model). GIS data-handling and analysis capabilities are used to generate inputs to spatial multi-criteria decision analysis [21].

During the process of multi-criteria decision making, a decision variable is assigned to each alternative. Variables or "attributes" are used by the decision maker to measure the performance of alternative decisions. With respect to the evaluation criteria, the decision maker's preferences are incorporated into the decision model. The preferences are typically expressed in terms of the weights or relative importance assigned to the evaluation criteria under consideration. Given the set of alternatives, attributes and associated weights, the input data can be organized in the form of decision matrix or table. Eventually, the one-dimensional measurements (in GIS geographic data layers) and judgments (preferences and uncertainty) must be integrated to provide an overall assessment of alternatives. This is accomplished by an appropriate decision rule or aggregation function. Since a decision rule provides an ordering of all alternatives according to their performance with respect to the set of evaluation criteria, the decision problem depends on the selection of the best outcome (or an ordered set of outcomes) and the identification of the decision alternatives leading to this outcome [21].

After obtaining a ranking of alternatives, sensitivity analysis should be performed to determine robustness. This is aimed at identifying the effects of changes in the inputs (geographical data and the decision makers' preferences) on the outputs (ranking of alternatives). It helps to learn how the various decision elements interact to determine the most preferred alternative and which elements are important sources of disagreement among decision makers or interest groups. Spatial decision making typically involves a large numbers of alternatives evaluated on the basis of multiple, possibly conflicting criteria, and some systematic method of identifying the best alternatives (or classifying or ranking alternatives) is required.

The final result of a decision-making process is a recommendation for future action. The decision or recommendation should be based on the ranking of alternatives and the sensitivity analysis. It may include the description of the best alternative or a group of alternatives considered candidates for implementation. Visualisation techniques such as maps are of major importance in presenting and communicating the results to decision makers and interest groups [21].

3 Multi-attribute decision analysis

GIS-based multi-criteria decision analysis can be thought of as a process that combines and transforms spatial data into a resultant decision. The MCDM procedures are decision rules which define a relationship between the input maps and an output map. The procedures use geographical data, the decision maker's preferences, data manipulation, and preferences according to decision rules. Two considerations of critical importance for spatial MCDA are the GIS capabilities of data acquisition, storage, retrieval, manipulation and analysis, and the MCDM ability to combine the geographical data and the decision maker's preferences into one-dimensional values of alternative decisions [22].

There are many ways in which decision criteria can be combined in MCDA. A *Weighted linear combination* (*WLC*) and its variants [3, 7, 9, 31] requires summation of the weighted criteria. The *Analytical hierarchical process* (*AHP*), an adoption of WLC, can be used in two distinctive ways within the GIS environment: first, it can be employed to derive the weights associated with criteria map layers, and second, the AHP principle can be used to aggregate the priority for all hierarchical levels including the level representing alternatives [1, 34]. *Concordance-discordance analyses* are methods in which each pair of alternatives, represented as raster pixels or polygons, is analysed for the degree to which one outranks the other in the specified criteria [3, 18, 27, 29, 36]. The *ideal point methods* avoid some of the difficulties associated with the multi-attribute methods [15, 30]. These approaches order a set of alternatives on the basis of their distance from an ideal point. Recently, Malczewski [23] established a very good body of literature on GIS-based multi-criteria decision analysis.

Over the last decade, a number of multi-attribute (or multi-criteria) evaluation methods have been introduced in the GIS environment. Among these procedures, the WLC and Boolean overlay operations, such as intersection (AND) and union (OR), are considered the most straightforward and the most employed in the GIS environment [22]. The Ordered Weighted Averaging

(OWA) and its variant, Weighted Linear Combination (WLC) are discussed in this paper.

3.1 Weighted linear combination (WLC)

Weighted linear combination, or simple additive weighting, is based on the concept of a weighted average in which continuous criteria are standardized to a common numeric range, and then combined by means of a weighted average. The decision maker assigns the weights of relative importance directly to each attribute map layer. The total score for each alternative is obtained by multiplying the importance weight assigned to each attribute by the scaled value given for that attribute to the alternative and then summing the products over all attributes. The scores are calculated for all of the alternatives and that with the highest overall score is chosen. The method can be executed using any GIS system with overlay capabilities, and allows the evaluation criterion map layers to be combined in order to determine the composite map layer which is output. The methods can be implemented in both raster and vector GIS environments. Some GIS systems, e.g. Idrisi [9], have built-in routines for the WLC method, and there are available freeware modules or scripts, e.g. for ArcGIS [2], to perform that kind of MCDA of this sort.

With the weighted linear combination, factors are combined by applying a weight to each followed by a summation of the results to yield a suitability map:

$$S = \sum w_i x_i \tag{1}$$

where S is suitability, w_i is weight of factor i, and x_i is the criterion score of factor i. In cases, where Boolean constraints also apply, the procedure can be modified by multiplying the suitability calculated from the factors by the product of the constraints:

$$S = \sum w_i x_i \cdot \prod c_j \tag{2}$$

where c_j is the criterion score of the constraint j.

All GIS software systems provide the basic tools for evaluation of such a model [9].

3.1.1 Standardization of criterion scores

The first step in this process is digital GIS database development. Because criteria are measured on different scales, it is necessary that factors be standardized before combination, and that they be transformed, if necessary, so that all factor maps are positively correlated with suitability.

Voogd [36] reviewed a variety of procedures for standardization, typically using the minimum and maximum values as scaling points. The simplest is a *linear scaling* such as:

$$x_i = \frac{(R_i - R_{\min})}{(R_{\max} - R_{\min})} \cdot SR \tag{3}$$

where R_i is the raw score of factor i, $R_{\min}$ is the minimum score, $R_{\max}$ the maximum score, and SR is the standardized range.

The process of standardizing evaluation criteria can be seen also as one of recasting values into a statement of set membership [7, 9]. If the continuous factors are really fuzzy sets, this is easily recognizable as just one of many possible set membership functions. Eastmann [7] suggested the standardization of factors using a range of *fuzzy set membership functions* to either a 0-1 real number scale or a 0-255 byte scale. The latter option is recommended because it optimizes the computation. Importantly, the higher value of the standardized scale must represent the case of being more likely to belong to the decision set. Besides this deterministic (linear scaling) and fuzzy approach, there are other processes for standardizing evaluation criteria, such as the *value/utility function approach*, and the *probability approach* [21].

A critical issue in the standardization of factors is the choice of the end points at which set membership reaches either 0.0 or 1.0 (0 or 255). Blind use of linear scaling (or indeed any other scaling) between the minimum and maximum values of the image is ill advised. In setting these critical points for the set membership function, it is important to consider their inherent meaning.

3.1.2 Evaluation of criterion weights

MCDM problems involve criteria of varying importance to decision makers and information about the relative importance of the criteria is required. This is usually obtained by assigning a weight to each criterion. The derivation of weights is a central step in defining the decision maker's preferences. A weight can be defined as a value assigned to an evaluation criterion indicative of its importance relative to other criteria under consideration. The larger the weight, the more important is the criterion in the overall utility [21].

A variety of techniques exist for the development of weights. In very simple cases, assignment of criteria weights may be accomplished by dividing 1.0 among the criteria. When more than a few criteria are involved and many considerations apply, it becomes difficult to make weight evaluations on the set as a whole. The weights are then usually normalized so that they sum to 1. In the case of n criteria, a set of weights is defined as follows:

$$w = (w_1, w_2, ..., w_j, ..., w_n) \text{, and}$$

$$\sum w_j = 1 .$$

There are four main groups of techniques for the development of weights [21]:

- *ranking methods*, which are the simplest methods for assessing the importance of weights: every criterion under consideration is ranked in the order of the decision maker's preferences;
- *rating methods,* which require the estimation of weights on the basis of predetermined scale;
- *pairwise comparison methods,* which involve pairwise comparison to create a ratio matrix;
- *trade-off analysis methods,* which make use of direct trade-off assessments between pairs of alternatives.

In this paper, we focus on a pairwise comparison method which has the added advantages of providing an organized structure for group discussions, and helping the decision making group focus on areas of agreement and disagreement when setting criterion weights.

The technique of pairwise comparisons has been developed by Saaty [34] in the context of a decision making process known as the Analytical Hierarchy Process (AHP). This technique was developed outside the GIS software using a variety of analytical resources and its first use with a GIS application was in 1991 [31]. In Saaty's technique, weights of this nature can be derived by taking the principal eigenvector of a square reciprocal matrix of pair-wise comparisons between the criteria. The comparisons deal with the relative importance of the two criteria involved in determining suitability for the stated objective. Ratings are provided on a nine-point continuous scale (Table 1).

Table 1: Scale for pairwise comparison [34].

Intensity of Importance	Definition
1	Equal importance
2	Equal to moderate importance
3	Moderate importance
4	Moderate to strong importance
5	Strong importance
6	Strong to very strong importance
7	Very strong importance
8	Very to extremely strong importance
9	Extreme importance

In developing weights, an individual or group compares every possible pairing and enters the ratings into a pairwise comparison matrix or *ratio matrix*. Since the matrix is symmetrical, only the lower triangle actually needs to be filled in. The remaining cells are then simply the reciprocals of the lower triangle. Eastmann [9] noted that if empirical evidence about the relative efficacy of a pair of factors exists, this evidence can also be used.

The procedure then requires that the principal eigenvector of the pairwise comparison matrix must be computed to produce the best fit set of weights. A good approximation to this result can be achieved by following the operations below [21]:

- sum the values in each column of the pairwise comparison matrix;
- divide each element in the matrix by its column total (the resulting matrix is referred to as the *normalized pairwise comparison matrix*); and
- compute the average of the elements in each row of the normalized matrix, that is, divide the sum of normalized scores for each row by the number of criteria.

These averages provide an estimate of the relative weights of the relevant criteria. Here, the weights are interpreted as the average of all possible ways of comparing the criteria.

Since the complete ratio matrix contains multiple paths by which the relative importance of criteria can be assessed, it is also possible to determine the degree of consistency that has been used in developing the ratings. Saaty [34] describes a procedure by which an index of consistency, and a *consistency ratio* (CR), can be produced. The consistency ratio (CR) defines the probability that the matrix ratings were randomly generated and Saaty suggests that matrices with CR ratings greater than 0.10 should be re-evaluated. In addition to the overall consistency ratio, it is also possible to analyze the matrix to determine where the inconsistencies arise.

Estimation of the consistency ratio involves the following operations:

- determination of the weighted sum vector by multiplying the weight for the first criterion times the first column of the original pairwise comparison matrix, then multiplying the second weight times the second column, the third criterion times the third column of the original pairwise matrix, and so on to the last weight, and finally summing these values over the rows; and
- determination of the consistency vector by dividing the weighted sum vector by the criterion weights determined previously.

The consistency ratio is defined as:

$$CR = \frac{CI}{RI} \tag{4}$$

where RI is the *random index*, and CI is the *consistency index* which provides a measure of departure from consistency.

The consistency index is calculated as:

$$CI = \frac{\lambda - n}{n - 1} \tag{5}$$

where λ is the average value of the consistency vector, and n is the number of criteria.

The random index is the consistency index of the randomly generated pairwise comparison matrix. and depends on the number of elements being compared. Table 2 shows random inconsistency indices (RI) for different numbers of criteria.

Table 2: Random inconsistency indices (RI) for different number of criteria [34].

n	RI	n	RI	n	RI
1	0.00	6	1.24	11	1.51
2	0.00	7	1.32	12	1.54
3	0.58	8	1.41	13	1.56
4	0.90	9	1.45	14	1.57
5	1.12	10	1.49	15	1.59

3.1.3 Evolution using the WLC decision rule

The procedure by which criteria are selected and combined to produce a particular evaluation, and by which evaluations are compared and acted upon, is known as a *decision rule*. A decision rule might be as simple as a threshold applied to a single criterion or it may be as complex as one involving the comparison of several multi-criteria evaluations. Decision rules typically contain *choice function* for combining criteria into a single composite index and a *choice heuristics*, which is a statement of how alternatives are to be compared. Choice functions and heuristics provide a mathematical means of comparing alternatives. Since they involve some form of optimization such as maximizing or minimizing some measurable characteristic, they theoretically require that each alternative must be evaluated in turn. *Choice heuristics* specify a procedure to be followed rather than a function to be evaluated and are commonly used because they are often simpler to understand and also easier to implement [9].

Once the criteria maps (factors and constraints) are developed, an evaluation (or aggregation) stage is undertaken to combine the information from the various factors and constraints. The simplest type of aggregation is the *Boolean intersection* or logical AND. This method is used only when factor maps have been strictly classified into Boolean suitable/unsuitable images with values 1 and 0. The evaluation is simply the multiplication of all the images.

The weighted linear combination (WLC) aggregation method multiplies each standardized factor map (i.e., each raster cell within each map) by its factor weight and then sums the results. Since the sum of the set of factor weights for an evaluation must be one, the resulting suitability map will have the same range of values as the standardized factor maps that were used. This result is then multiplied by each of the constraints in turn to "mask out" unsuitable areas.

3.1.4 Limitations of WLC

There are some fundamental limitations, discussed by Jiand and Eastman (see [17]) in the use of weighted linear combinatorial procedures in a decision making process.

The first problem in using WLC as a decision rule concerns the different aggregation methods employed in decision making. Despite an expectation that the WLC method and Boolean method should yield similar results, they very often fail to do so because they cause logically methods of aggregation. In the WLC method, a low score on one criterion can be compensated by a high score on another; this is known as *trade-off* or *substitutability* and is quite different from the Boolean options, which are absolute in nature.

The second problem of the WLC stems from its *standardization of factors.* The most common approach to this is to rescale the range to a common numerical basis by simple linear transformation. However, the rationale for doing so is unclear [10, 36] and in some cases, a non-linear scaling may seem appropriate.

The third problem concerns *decision risk* which may be considered to be the likelihood that the decision will be wrong. For a Boolean procedure, decision risk can be estimated by propagating measurement error through the decision rule, thereby determining the risk that the decision made for a given location is wrong. Continuous criteria of weighted linear combination would appear however to express a further uncertainty that is not so readily estimated with stochastic methods. The standardized factors of WLC each express suitability: the higher the score, the more suitable the location is for the intended land use. There is no real threshold, however, that allows definitive allocation of areas to be chosen and areas to be excluded. Jiang and Eastmann [17] suggested that those kinds of problems could be solved by considering decision-making as a set problem and through the application of *fuzzy measures* in multi-criteria evaluation. They suggested that the ordered weighted averaging approach may provide an extension to and generalization of the conventional map combination methods in GIS.

3.2 Ordered weighted averaging (OWA)

Ordered Weighted Averaging (OWA) uses a class of multi-criteria operators [38] and involves two sets of weights: criterion, or importance weights and order weights [2]. A criterion weight is assigned to a given criterion or attribute for all locations in a study area to indicate its relative importance, according to the decision-maker's preferences, in the set of criteria under consideration. The order weights are associated with the criterion values on a location-by-location basis. They are assigned to a location's attribute values in decreasing order with no consideration of the attribute source of each value. The re-ordering procedure involves associating an order weight with a particular ordered position of the weighted attribute values. The first order weight is assigned to the highest weighted attribute values for each location, the second order weight to the second highest values, and so on.

Order weights are central to the OWA combination procedures. They are associated with the degree of ORness, which indicates the degree to which an OWA operator is similar to the logical connective OR in terms of its combinatorial behaviour. Order weight is also associated with a trade-off measure indicating the degree of compensation between criteria. The parameters associated with the OWA operations serve as a mechanism for guiding the GIS-based land-use suitability analysis. The ORness measure allows for interpreting the results of OWA in the context of the behavioural theory of decision making. OWA operations for example facilitate the development of a variety of land use strategies ranging from an extremity pessimistic (the minimum-type strategy based of the logical AND combination) through all intermediate neutral-towards-risk strategise (corresponding to the conventional WLC) to an extremely optimistic strategy, the maximum-type strategy based on the logical OR combination.

Thus, OWA can be considered as an extension and a generalization of the conventional combination procedures in GIS [17]. Indeed, WLC is just one variant of the OWA technique [9].

3.2.1 Order weights, trade-off and risk using OWA

In Weighted Linear Combination, factor weights are weights that apply to specific factors; all the pixels of a particular factor image receive the same factor weight in the raster data model. They indicate the relative degree of importance of factor in determining the suitability for an objective. In the case of WLC, the weight given to each factor also determines how it trades-off relative to other factors but, as described below, order weights in OWA determine the overall level of trade-off allowed. The use of order weights allows for aggregation solutions that fall anywhere along the risk continuum between AND and OR.

Order weights are quite different from factor weights because they do not apply to any specific factor. Rather, they are applied on a pixel-by-pixel basis to factor scores as determined by their rank ordering across factors at each location, or pixel. Order weight 1 is assigned to the lowest-ranked factor for that pixel (i.e., the factor with the lowest score), order weight 2 to the next higher-ranked factor for that pixel, and so forth. It is possible that a single order weight could be applied to pixels from any of the various factors depending upon their relative rank order.

Boolean approaches are extreme functions that result either in very risk-averse solutions when the AND operator is used or in risk-taking solutions when the OR operator is used. The WLC approach is an averaging technique that softens the hard decisions of the Boolean approach, avoiding the extremes. In a continuum of risk, WLC falls exactly in the middle; it is neither risk-averse nor risk-taking. But, any assignment of order weights results in a decision rule that falls somewhere in a triangular decision strategy space that is defined by the dimensions of risk and trade-off as shown in Figure 3.

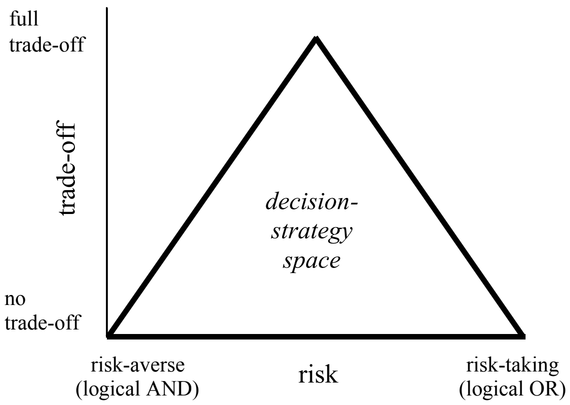

Figure 3: Triangular decision-strategy space defined by the dimension of risk and trade-off.

Table 3 shows, how order weights alter MCE results by controlling levels of trade-off and risk (see also [9]). Consider the case where factor weights are equal for three factors A, B, and C. Holding factor weights equal will make the effect of the order weights clearer. If a single pixel has factor scores A (210), B (197), and C (224), the factor weight for each of the factors will be 0.33. Ranking from minimum to maximum value, the order of these factors for this pixel is [B, A, C]. For this pixel, factor B will be assigned order weight 1, A order weight 2 and C order weight 3. In Table 3, there are thirteen sets of order weights that have been applied to this set of factor scores [197, 210, 224]. Each set yields a different MCE result even though the factor scores and the factor weights are the same in each case.

Table 3: Example of applied order weights to the set of factor scores (197, 210, 224).

Order weights			**Result**
min (1)	(2)	max (3)	
1.00	0.00	0.00	197
0.90	0.10	0.00	198
0.80	0.20	0.00	200
0.70	0.20	0.10	202
0.50	0.30	0.20	206
0.40	0.30	0.30	209
0.33	0.33	0.33	210
0.30	0.30	0.40	212
0.20	0.30	0.50	214
0.10	0.20	0.70	219
0.00	0.20	0.80	221
0.00	0.10	0.90	223
0.00	0.00	1.00	224

The first set of order weights in Table 3 is [1, 0, 0]. The weight of factor B (the factor with the minimum value in the set [B, A, C]) will receive all possible weight while factors A and C will be given zero weight. Such a set of order weights makes the factor weights irrelevant. Indeed, the order weights have altered the evaluation such that no trade-off is possible. As it can be seen in the Table 3, this has the effect of applying a minimum operator to the factors, thus producing the traditional intersection operator (AND) of fuzzy sets. Similarly, the last set of order weights [0, 0, 1] has the effect of a maximum operator, the traditional union operator (OR) of fuzzy sets. Again, there is no trade-off and the factor weights are not employed. Where the order weights are equal [0.33, 0.33, 0.33], all ranked positions are assigned the same weight; this makes trade-off fully possible and locates the analysis exactly midway between AND and OR. Equal order weights produce the same result as WLC.

In each of these three cases, the order weights have determined not only the level of trade-off but have situated the analysis on a continuum from (risk-averse, minimum, AND) to (risk-taking, maximum, OR). The order weights are not restricted to these three options, but instead any combination of values that sum to 1.0 can be assigned. As already noticed any assignment of order weights results in a decision rule that falls somewhere in a triangular decision strategy space (see Figure 3).

The degree of trade-off in OWA is governed by the relative distribution of order weights between the ranked factors. If the sum of the order weights is evenly spread between the factors, there is strong trade-off, whereas if all the weight is assigned to a single factor rank, there is no trade-off. Order weights of [0.5, 0.3, 0.2] would indicate a strong (but not perfect) degree of risk aversion and some degree of trade-off. Weights of [0, 1, 0], would imply neither risk aversion nor acceptance, and no trade-off because all the weight is assigned to a single rank [9].

3.2.2 Evolution using OWA decision rule

There have already been several implementations in the last decade of OWA in GIS environments. As an example, OWA is already included for more than a decade in Idrisi GIS software [7]. Eastmann suggested the following guidelines for the use of the OWA option of MCE: (a) their criteria should be divided into three groups: hard constraints, factors that should, or should not trade-off. For example, factors with monetary implications typically trade-off, while those factors associated with some safety (or environment) concern typically do not; (b) if factors both trade-off and do not trade-off, their consideration should be separated into two stages of analysis. In the first stage, aggregate the factors that trade-off using the OWA option. The degree of trade-off can be controlled by manipulation of the order weights. In the second, use the result of the first stage as a new factor that is included in the analysis of those that do not trade-off; (c) if you run an analysis with absolutely no trade-off, the factor weights have no real meaning and can be set to any value.

Boroushaki and Malczewski have implemented an OWA-approach in the ArcGIS environment, pointing out that OWA combination operators can be recognized as the conventional AHP combination with modified criterion weights [2]. The weights are obtained by multiplying the criterion weights by order weights. With different sets of order weights, one can generate a wide range of OWA operators including the three aforementioned $S = \sum w_i x_i$ special cases of the WLC, Boolean overlay combination AND and OR.

4 Application of WLC and OWA

To demonstrate the WLC and OWA techniques for development of factor weights, let us consider an actual suitability problem. The objective is to find the suitable areas for residential development in the small municipality of Ig, which is a semi-rural community located near the Slovenian capital Ljubljana.

The whole procedure of decision rule (the procedure by which criteria are selected and combined to arrive at a particular evaluation, and by which evaluations are compared and acted upon) will not be presented here. The evaluation of criterion weights, trade-off and risk using OWA as well as WLC techniques of real problem is discussed. An example has been implemented in Idrisi Andes GIS [9], using MCE and OWA modules.

4.1 Application of WLC

A group of professionals who had developed a professional basis for the spatial plan of municipality of Ig, identified seven factors as the most important in searching for suitable areas for residential development in the municipality; those were: (1) distance from an existing residential zones, (2) slope, (3) solar illumination radiation, (4) distance from state and municipal roads, (5) distance from bus stops, (6) distance from flowing water, and (7) distance from forest. Table 4 shows pairwise comparison matrix (or ratio matrix) for these seven factors.

One of the advantages of the WLC method is the ability to give different relative weights to each of the factors by aggregation. Factor weights, sometimes called trade-off weights, are assigned to each factor. They indicate the importance of a factor relative to all other factors and they control how factors will trade-off or compensate for each other. In the case of WLC, where factors fully trade-off, factors with high suitability can be compensated for other factors with low suitability in a given location. The degree to which one factor can compensate for another is determined by its factor or trade-off weight.

Table 4: Ratio (or pairwise) matrix for seven factors.

	(1) resid. zones	(2) slope	(3) solar rad.	(4) roads	(5) bus stops	(6) flow. water	(7) forest
(1) resid. zones	1						
(2) slope	3	1					
(3) solar rad.	1	1/3	1				
(4) roads	3	1/3	4	1			
(5) bus stops	2	1/4	1/3	1/4	1		
(6) flow. water	1/3	1/6	1/3	1/6	1	1	
(7) forest	3	1/6	1/3	1/6	1/3	1	1

Table 5: Factor weights using the WLC method (A - factor weights derived by the approximation method; B - factor weights resulting from eigenvector using module WEIGHT, Idrisi Andes; CR – consistency ratio).

Factor	Factor weight - A	Factor weight - B
(1) distance from existing residential zones	0.0806	0.0839
(2) slope	0.3375	0.3512
(3) solar illumination radiation	0.1228	0.1204
(4) distance from state and municipal roads	0.2596	0.2653
(5) distance from bus stops	0.0851	0.0953
(6) distance from flowing water	0.0463	0.0457
(7) distance from forest	0.0680	0.0382
		CR = 0.06

After entry of the ratio matrix, factor weights were calculated in two ways: (A) using the approximation method described in 3.1.2, or (B) using the module WEIGHT in Idrisi Andes GIS, which calculates the eigenvector directly. WEIGHT utilizes a pairwise comparison technique to develop a set of factor weights that will sum to 1.0. Factors are compared two at a time in terms of their importance relative to the stated objective (locating residential development). When all possible combinations of two factors have been generated, the module calculates a set of weights and, importantly, a consistency ratio. This ratio indicates any inconsistencies that may have been arisen during the pairwise comparison process. The module allows repeated adjustments to the pairwise comparisons and reports the new weights and consistency ratio for each iteration. Table 5 shows both factor weights as well as consistency ratio calculated in Idrisi Andes GIS.

One of the most common procedures for aggregating data by WLC method is to multiply each standardized factor by its corresponding weight. These data are then summed and the sum is divided by the number of factors [9]. Once this weighted average is calculated for each pixel, the resultant image is multiplied by the relevant Boolean constraints to mask out areas that should not be considered at all. The final image is a measure of aggregate suitability that ranges from 0 to 255 for non-constrained locations (Figure 5a). The WLC aggregation method allows standardization of the criteria in a continuous fashion, retaining important information about degrees of suitability. It also allows differentially weighted criteria to trade-off with each other. In the next application, another aggregation technique, ordered weighted averaging is explored. This allows control of the amount of risk and trade-off to be included in the result.

4.2 Application of OWA

The aggregation method of ordered weighted averaging (see 3.2) offers control over the position of the MCE along the risk and trade-off continuum. Using OWA, we can control the level of risk we wish to assume in our MCE, and the degree to which factor (trade-off) weights will influence the final suitability map [9]. OWA offers a wealth of possible solutions for our residential development problem. In our application, seven order weights were applied corresponding to the seven factors that were rank-ordered for each location after the modified factor weights were applied. Table 6, gives six typical sets of order weights for the seven factors: (a) average level of risk and full trade-off, (b) low level of risk and no trade-off, (c) high level of risk and no trade-off, (d) low level of risk and average trade-off, (e) high level of risk and average trade-off, (f) average level of risk and no trade-off. Figure 4 shows the locations of typical sets of order weights in the decision-support space.

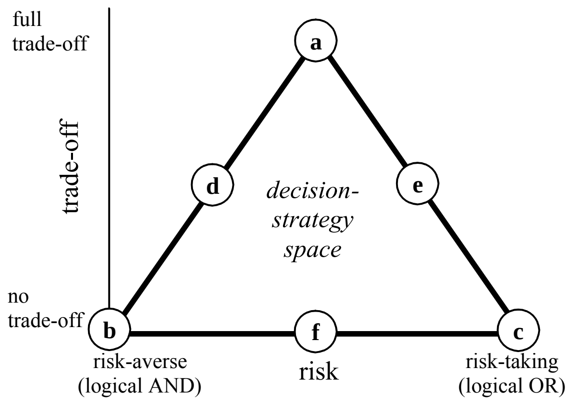

Figure 4: Decision-strategy space and typical sets of order weights (see Table 6).

It is evident that the set of order weights are in accordance with factor weights derived by WLC. The weight is distributed evenly among all factors regardless of their rank-order position from minimum to maximum for any given location. They are not skewed toward the minimum (AND operation) or the maximum (OR operation). As in the WLC procedure, the result of order weights (a) is exactly in the middle in terms of risk. In addition, because all rank order positions are given the same weight, no rank-order position will have a greater influence over another in the final result. Set (a) gives full trade-off between factors, allowing the factor weights to be fully employed.

Table 6: Typical sets of order weights for seven factors.

	(**a**) Average level of risk and full trade-off						
order weight	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428	0.1428
rank	1st	2nd	3rd	4th	5th	6th	7th
	(**b**) Low level of risk and no trade-off						
order weight	1	0	0	0	0	0	0
rank	1st	2nd	3rd	4th	5th	6th	7th
	(**c**) High level of risk and no trade-off						
order weight	0	0	0	0	0	0	1
rank	1st	2nd	3rd	4th	5th	6th	7th
	(**d**) Low level of risk and average trade-off						
order weight	0.4455	0.2772	0.1579	0.0789	0.0320	0.0085	0
rank	1st	2nd	3rd	4th	5th	6th	7th
	(**e**) High level of risk and average trade-off						
order weight	0	0.0085	0.032	0.0789	0.1579	0.2772	0.4455
rank	1st	2nd	3rd	4th	5th	6th	7th
	(**f**) Average level of risk and no trade-off						
order weight	0	0	0	1	0	0	0
rank	1st	2nd	3rd	4th	5th	6th	7th

To produce a low risk result for the residential development problem, the one close to AND (minimum) on the risk continuum, then greater order weight is given to the lower rank-orders (the minimum suitability values) – set (b) in Table 6. Such a weighting results in no trade-off. If a high risk result (OR (maximum)), is sought, then greater order weight has to be given to the higher rank-orders (the maximum suitability values) – set (c).

Using the OWA approach, the order weights can be altered in terms of their skew and dispersion. It is possible to produce an almost infinite range of possible solutions to the problem. In our residential development problem, the decision-makers and administrators may be interested in a conservative or low-risk solution to the identification of suitable areas for development. They also know that their estimates for how different factors should trade-off with each other are important and worthy of consideration. An AND operation will not let them consider any trade-off, and the WLC operation, where they would have full trade-off, is too liberal in terms of risk. They will then want to develop a set of order weights that would give them some amount of trade-off but would maintain a low level of risk in the solution.

There are several sets of order weights that could be used to achieve this. Let us consider the set of order weights (d). These specify an operation midway between the extreme of AND and the average risk position of WLC. In addition, they set the level of trade-off to be intermediate between the no trade-off situation of the AND operation and the full trade-off situation of WLC.

While it is clear that suitability generally increases from AND to OR for any given location, the character of the increase between any two operations is different for each location. The extremes of AND and OR are clearly dictated by the minimum and maximum factor values, however, the results from the middle trade-off operations are determined by an averaging of factors that depends upon the combination of factor values, factor weights, and order weights [9]. In general, in locations where the heavily weighted factors (slopes and roads) have similar suitability scores, the three results with trade-off will be strikingly similar. At the locations where these factors do not have similar suitability scores, the three results with trade-off will be more influenced by the difference in suitability (toward the minimum, the average, or the maximum).

4.2.1 Grouping factors by trade-off

Eastmann [9] suggested that the OWA approach could also be used to aggregate the suitability maps of groups of factors. Our factors are of two distinct types: factors relevant to *development cost* and factors relevant to *environmental concerns*, which do not necessarily have the same level of trade-off. Factors relevant to the cost of development clearly can fully trade-off. Where financial cost is the common concern, savings in development cost in one factor can compensate for a high cost in another. Environmentally relevant factors on the other hand, do not easily trade-off. To cope with this discrepancy, we treated our factors as two distinct sets with different levels of trade-off specified by two sets of ordered weights. This yields two intermediate suitability maps, one the result of combining five financial factors, and the other the result of combining both environmental factors. We then combined these intermediate results using a third MCE operation.

We decided that factors relevant to cost (1-5) could fully trade-off and selected an average risk; for this reason, the WLC procedure to combine them has been used. For the second group of factors, those relevant to environmental concerns, we decided to use the same procedure as for those relevant to costs – however, environmental factors were treated separately. Table 7 shows the revalued factor weights and the old factor weights, when all factors together (1-7) have been calculated (see 4.1).

Table 7: Re-valued factor weights using WLC (relevant to development cost) and OWA (relevant to environmental concerns) (B - factor weights as the result of eigenvector using module WEIGHT, Idrisi Andes GIS before grouping).

Factors	**Factor weight – B (from Table 4)**	**Revalued factor weight**
Cost factors		
(1) distance from existing residential zones	0.0839	0.1040
(2) slope	0.3512	0.3834
(3) solar illumination radiation	0.1204	0.1314
(4) distance from state and municipal roads	0.2653	0.2896
(5) distance from bus stops	0.0953	0.0916
Environmental factors		
(6) distance from flowing water	0.0457	0.5447
(7) distance from forest	0.0382	0.4553

The final step in defining the suitable areas for residential development was to combine two intermediate results using a third MCE operation. In that aggregation, factors relevant to costs and factors relevant to environment were treated as factors in a separate aggregation procedure. There is no clear rule how to combine these two results [9] and so we assumed that decision-makers would be unwilling to give more weight to either the developers' or the environmentalists' factors, these factor weights being equal, and they would not allow the two new consolidated factors to trade-off with each other, nor did they want anything but the lowest level of risk when combining the two intermediate results. For these reasons, we used an OWA procedure that yielded a low risk result with no trade-off (the order weights were 1 for the 1st rank and 0 for the 2nd).

Figure 5 shows both results of MCE: (a) using WLC approach, and (b) using OWA approach. Constraints including built-up zones, electric mains and water bodies have been applied to the final suitability maps to mask out unsuitable areas. The darker colours denote more suitable areas for residential development in the municipality of Ig.

4.3 Discussion

In this paper, two methods for MCE in GIS, weighted linear combination (WLC) and ordered weighted averaging (OWA), were presented and tested. Both techniques are used most effectively with factors that have been standardized to a continuous scale of suitability and weighted according to their relative importance. The relative importance weights of factors were estimated using the analytical hierarchy process (AHP). Constraints were defined as Boolean masks. The methods have some similar procedures but, in this paper, they were based on different statements about how criteria dealing with land use suitability analysis could be evaluated. Consequently, they yielded to two different results (Figure 5).

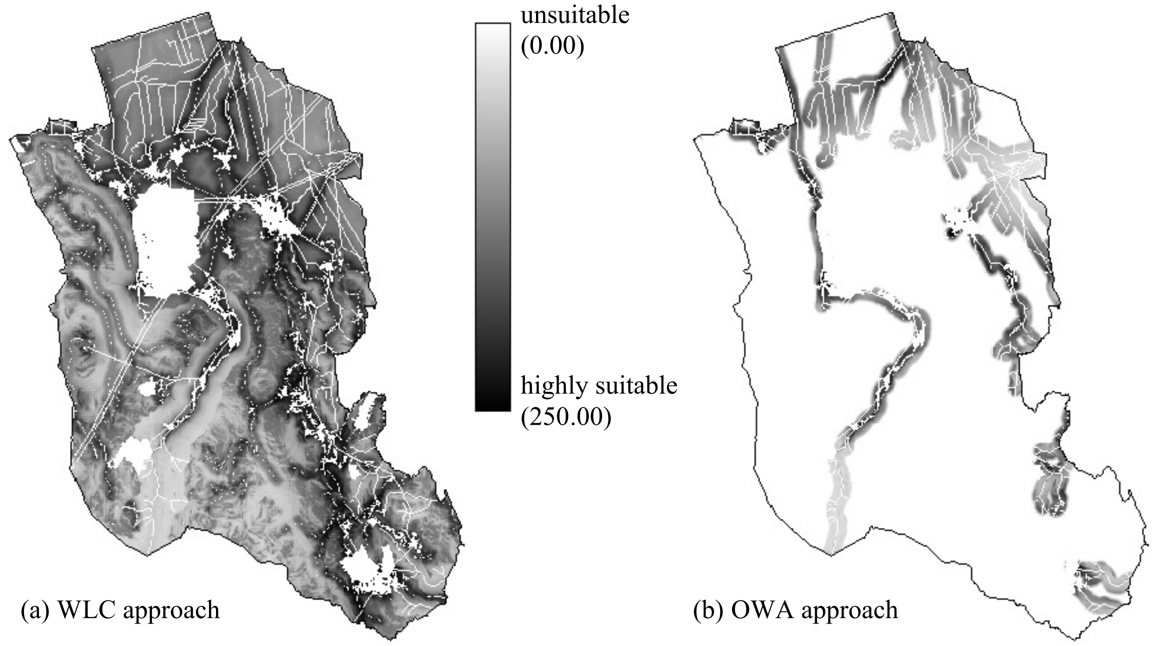

Figure 5: Results of aggregation of weighted factors and constraints using WLC and OWA approaches (suitability for residential development).

The land evaluation was performed on a cell by cell basis. WLC allowed us to use the full potential of our factors as continuous surfaces of suitability. The identified factors were standardized using fuzzy functions, and then weighted and combined using an averaging technique. The factor weights used expressed the relative importance of each criterion to the overall objective, and they determined how factors were able to trade off with each other. The final map of continuous suitability for residential development (image (a) on Figure 5) is a result that is neither extremely risk-averse nor extremely risk-taking. In WLC, all factors were allowed to fully trade-off. Any factor could compensate for any other in proportion to its factor weight.

The second aggregation method we used OWA, gave us control over the position of the MCE along both the risk and trade-off axes (see Figure 4). It allowed control of the level of risk we wished to assume in our application, and the degree to which factor weights (trade-off weights) influenced the final suitability map. Control over risk and trade-off was made possible through a set of order weights for the different rank-order positions of factors at every location (pixel). With order weights we combined costs and environmental factors with a very low level of risk and no trade-off between them. So, the order weights first modified the degree to which factor group weights had influence in the aggregation procedure, thus they governed the overall level of trade-off. After weights were applied to the factor groups (to some degree dependent upon the overall level of trade-off used), the results were ranked from low to high suitability for each location. This had the effect of weighting factor groups based on their rank from minimum to maximum value for each location. The relative skew toward either minimum or maximum of the order weights controlled the level of risk in the evaluation. Additionally, the degree to which the order weights were evenly distributed across all positions controlled the level of overall trade-off, i.e., the degree to which factor group weights had influence.

In our application of WLC we used factor weights defined in Table 5 and Table 7, and in OWA we applied the order weights (1 for the 1^{st} rank and 0 for the 2^{nd}) that yielded a low risk result with no trade-off. Defined and fully traded-off weights in the WLC approach led to a result in which a larger proportion of the municipality area was indicated as highly suitable for residential development, as compared to the result of OWA approach (see Figure 5). However, with the continuous result of WLC, the best locations for residential development can be defined by setting the lowest degree of suitability; e.g. 200 in Figure 5 (a).

The standardization and aggregation techniques discussed here are important in exploration of any multi-criteria problem and they result in images that show the suitability of locations in the entire study area. Multi-criteria problems often concern eventual site selection for some development, land allocation, or land-use change and there are many techniques for site selection using images of suitability. However, the main purpose of this application was not to suggest the best areas for residential development in tested area. It was rather to define and apply two methods of MCE (WLC and OWA) in GIS as the generalised framework of GIS-based spatial decision-making procedure, and to show the policy makers and decision makers what kind of tools useful for calculations of images of suitability. When our results are compared with the professional basis for spatial plan in Ig, made by classical approach as defined in Figure 2, the most similar result was from the OWA approach with low risk and no trade-off between costs and environmental factors.

The results of our research indicate that applications of decision making in GIS are multifunctional and can incorporate different levels of complexity of the decision problem. In this case, the choice of weights and weighting techniques played a crucial role. It is obvious that decision makers with a preference for a subjective scale may not arrive at the same weights for the factor criteria. This may lead to different results for suitability maps and can affect the final decision with regard to the overall objective. However, it must be noted that the presented methods are only tools to aid decision makers; they are not the decision itself.

5 Conclusions

Spatial multi-criteria analysis, with its explicit geographic component represents a significant departure from the conventional MCDM techniques. In contrast to the conventional multi-criteria decision making, spatial multi-criteria analysis requires both data on criterion values and the geographical location of alternatives. Increasing computer power, user-friendly GIS and decision support software, and increased access to and familiarity with computers among decision makers are a few of the reasons for the rapid growth in both research and practice in GIS-based multi-criteria spatial decision making. GIS technology provides the capabilities of data acquisition, storage, retrieval, manipulation, and data analysis to develop information that can support decisions. MCDM techniques provide the tools with which to integrate the geographical data and the decision maker's preferences into one-dimensional value array of alternative decisions. The use of GIS in SDSS in addition provides spatial data models, the means of entering and displaying spatial data and additional spatial analysis tools. A significant contribution of the SDSS concept to geographic information science is that it integrates distinct tool sets (data and models) into a unified whole more valuable than the sum of the parts.

The results presented in this paper demonstrate the application of weighted linear combination (WLC) and ordered weighted averaging (OWA) within a GIS for the purpose of determining the most suitable locations for residential areas in the municipality of Ig (see also [6]). It is clear that integrated decision support tools in the GIS software system allow exploration of variety of rationales and perspectives in suitability evaluation and land allocation. The test study of suitability analysis for a residential area is a simple case with only seven main attributes. In the real world, the situation is much more complex. There are still several topics referring to the spatial multi-criteria decision analysis in GIS that must be investigated and developed. These include selection of attributes, which must take account of their completeness, independence and real influence, or weight; the scale and methods of aggregation of attributes; error assessment and finally, the incorporation of database and decision rule uncertainty and sensitivity analysis. The tools currently available however, offer significant advantages for decision makers in spatial decision problem fields.

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