Comparison of Multicriteria Methods for Land-use Suitability Assessment

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Abstract— *In this paper we investigate properties of multicriteria methods that are used for building land-use suitability assessment criteria. We identify and describe fundamental properties that are of interest in the land-use suitability analysis and the design of suitability maps. The existing multicriteria methods can be evaluated from the standpoint of their ability to support the desirable properties that affect the expressive power of evaluation methods. In this paper we investigate simple additive scoring, MAVT, MAUT, AHP, OWA, outranking methods and LSP.*

Keywords— GIS, land-use, MCDM.

1 Introduction

This paper has two main goals. The first goal is to identify properties that affect the expressive power of multicriteria decision methods (MCDM) that can be used to create suitability maps of a specific geographic region. The second goal is to investigate land-use suitability assessment methods that are based on simple additive scoring (SAS), multiattribute value technique (MAVT), multiattribute utility technique (MAUT), analytic hierarchy process (AHP), ordered weighted average (OWA), outranking methods (ELECTRE, PROMETHEE), and logic scoring of preference (LSP) in view of satisfaction of the identified properties.

We assume that the analyzed geographic region is divided into cells and that each cell with coordinates x, y is characterized by an array of suitability attribute values $a_1(x,y), \ldots, a_n(x,y)$, $n \geq 1$ [5]. The attributes are defined as quantitative parameters that affect the suitability of a cell for some specific land-use (e.g. housing, recreation, agriculture, industrial development, etc.). The set of attributes must be complete, i.e., it must include *all* relevant components. Generally, the attributes must be justifiable and not redundant with each other.

The purpose of MCDM is to provide a criterion function $\sigma : \mathbb{R}^n \to [0,1]$ for computing an overall degree of suitability $S(x,y) = \sigma(a_1(x,y), \ldots, a_n(x,y))$ that reflects the suitability of location x, y for specific land-use. The overall suitability is a matter of degree: $0 \leq S(x,y) \leq 1$. As in all soft computing models, here 0 denotes a completely unsuitable location, and 1 denotes the highest level of suitability. A suitability map is defined as a distribution of the overall suitability $S(x,y)$ for a specific geographic region [7].

Nowadays suitability maps are assumed to be dynamically created using data from GIS databases in a way illustrated in Fig. 1. The multicriteria decision model must be interfaced both with the user and with the GIS database. An attribute ETL interface is necessary to Extract, Transform, and Load the set of cell attribute values from the GIS database. The multicriteria decision model is used to implement the criterion function σ and to generate the overall suitability $S(x,y)$. The user input includes a specification of desired suitability attributes and parameters of the decision model. A suitability criterion interface is necessary for accepting user input and for rendering the resulting suitability map.

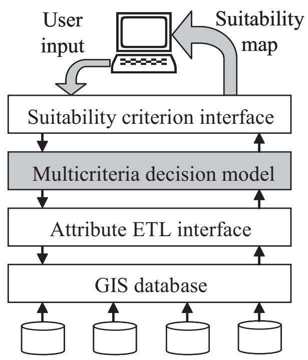

Figure 1: Dynamic generation of suitability maps using GIS.

Suitability maps introduced in GIS literature use a variety of decision models [16, 9, 11, 5, 20]. The emphasis of such efforts is primarily (and naturally) on the selection of attributes and the use of suitability maps. So far the GIS literature avoided problems of evaluating the credibility of MCDM used for the development of suitability maps.

Except for interfacing with GIS components, the land-use suitability assessment problems do not differ from evaluation problems in other areas. All multicriteria decision models are ultimately models of human decision making in the area of evaluation of complex alternatives. Therefore, the credibility of MCDM used in GIS context depends on their ability to express observable properties of human evaluation logic [4]. The primary purpose of this paper is to evaluate the expressive power of GIS-related MCDM based on the level of their ability to support the concepts of human evaluation logic.

The remainder of this paper is structured as follows. In Section 2, the logic properties of GIS-related MCDM are studied. In Section 3, the logic properties of the selected decision meth-

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ods are investigated. The major contributions of the paper are summarized and some conclusions are presented in Section 4.

2 Ten fundamental properties of MCDM

The properties of human evaluation logic are easily observable, and they are also observable in the context of land-use evaluation. Our goal is to first identify properties that are frequently encountered in all worth assessment problems. The most important properties include the following:

1. Ability to combine any number of attributes.
2. Ability to combine objective and subjective inputs.
3. Ability to combine absolute and relative criteria.
4. Flexible adjustment of relative importance of attributes.
5. Modelling of simultaneity requirements.
   (a) Modelling of soft simultaneity.
   (b) Modelling of hard simultaneity.
6. Modelling of replaceability requirements.
   (a) Modelling of soft replaceability.
   (b) Modelling of hard replaceability.
7. Modelling of balanced simultaneity/replaceability.
8. Modelling of mandatory, desired, and optional requirements.
9. Modelling of sufficient, desired, and optional requirements.
10. Ability to express suitability as an aggregate of usefulness and inexpensiveness (separation of the usefulness analysis and the cost analysis).

2.1 Ability to combine any number of attributes

We assume that the analyzed geographic region is divided into cells and that each cell is characterized by attributes $a_1, \ldots, a_n$, $n \geq 1$. In special cases $n = 1$. For example, the acoustic pollution (noise) maps presented in [11] uses in each cell a single scalar value, the level of noise. However, in all cases of more complex suitability maps we have $n > 1$. For example, the housing suitability maps discussed in [5] use $n = 11$. If we want to develop maps of complex suitability indicators that depend on variety of inputs it is reasonable to expect that the number of inputs can be large. So, in a general case, MCDM used to compute the land-use suitability must be able to support any number of inputs.

It should be noted that this requirement indirectly transforms into a requirement to use nonlinear MCDM models. Indeed, in the case of linear weighted aggregation models, the overall suitability $S(x, y)$ is a dot product of a vector of n suitability components $\mathbf{s} = [s_1(x, y), \ldots, s_n(x, y)]$ (one component for each attribute) and a corresponding vector of relative weights $\mathbf{W} = [W_1, \ldots, W_n]$: $S(x, y) = \sum_{i=1}^{n} W_i s_i(x, y)$ where $0 \leq s_i(x, y) \leq 1$, $0 < W_i < 1$, $i = 1, \ldots, n$, and $W_1 + \cdots + W_n = 1$.

Obviously, a large value of n yields a low significance of individual components. For example, if $n = 100$ the average significance (the ability to change the overall suitability S) of each input is only 1%, and in the case of unequal weights some inputs will have the significance considerably below 1% which means that such inputs may (and should) be neglected. This is not acceptable since credible decision models must be equally applicable for any number of inputs.

2.2 Ability to combine objective and subjective inputs

Some input attributes are objectively measurable values (e.g., distances, slopes, altitudes, temperatures, etc). Other inputs are subjective and must be assessed by experts (e.g., aesthetic quality of an area, the quality of educational and/or medical institutions, quality of public transportation, development costs, etc.). MCDM for GIS applications must be able to combine and aggregate objective and subjective inputs.

2.3 Ability to combine absolute and relative criteria

Each suitability attribute must satisfy specific requirements. The requirements can be defined as elementary criterion functions $g_i : \mathbb{R} \rightarrow [0, 1]$, $i = 1, 2, \ldots, n$. By definition, the attribute suitability $s_i(x, y) = g_i(a_i(x, y))$ is the degree of satisfaction of the attribute requirements. The suitability of an attribute is a component of the overall suitability of the evaluated location x, y.

Suppose that a decision maker (DM) needs a suitability map for housing in a rural area where it is possible to buy land and build a house. Let the attribute $a_i(x, y) = t$ denote the traveling time between location $L(x, y)$ and the closest elementary school (or hospital, or airport, or any other point of interest). An absolute criterion is a criterion that evaluates location L regardless of other competitive locations. E.g., a DM may specify the absolute requirements as threshold times t_{min} and t_{max} so that all times $t \geq t_{max}$ are considered unacceptable and all times $t \leq t_{min}$ are considered perfectly acceptable. Then the elementary criterion function might be defined as follows: $g_i(t) = \max(0, \min(1, (t_{max} - t)/(t_{max} - t_{min})))$. So, $g_i(t)$ specifies the attribute suitability for any value of t. If DM wants to compare locations L_1 and L_2, with respect to the access to school then the comparison can be based on $g_i(t_1)$ and $g_i(t_2)$. If t_{min} and t_{max} are well justifiable values, then $g_i(t_1)$ and $g_i(t_2)$ are very credible results.

Another approach is to define a relative criterion. In the case of k locations an example of such a criterion could be $g_i(t) = t_{min}/t$, $t_{min} = \min(t_1, \ldots, t_k)$. The relative criterion evaluates relationships between competitors regardless of DM's actual needs: the closest location is considered perfectly suitable ($g_i(t_{min}) = 1$) and a location where $t = 2t_{min}$ gets $g_i(t) = 0.5$. Obviously, the credibility of relative criteria is much less under DM's control than the credibility of corresponding absolute criteria. E.g., if only two locations are available, then the location that is 2 minutes from the closest school is likely to be equally attractive as the location that is 1 minute from the school, and locations that are 1 hour and 2 hours from the closest school might be equally unacceptable; in both cases the suitability levels of 1 and 0.5 are inappropriate. For some other values, e.g., $t_{min} = 7$ minutes, the presented relative criterion might be appropriate.

It is highly unlikely that DM knows what is better, but does not know what is good. In other words, if DM can specify a justifiable relative criterion, it is very likely that DM can also specify a justifiable absolute criterion. Absolute criteria can be used to evaluate a single alternative (e.g., a single location), while relative criteria can be applied only if we have multiple alternatives. Relative criteria are appropriate only in situations where expected values of attributes are unknown. Such situations are not frequent, but exist, and MCDM must be able to combine and aggregate absolute and relative attribute criteria.

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2.4 Flexible adjustment of the relative importance of attributes

In a general case, multiple attributes are not equally important. The relative importance of an attribute is usually expressed using multiplicative or implicative weights [3]. The relative importance has two roles in suitability criteria: it defines the level of contribution of an attribute to the overall suitability, and it defines compensatory properties between attributes. Assuming that the overall suitability is a function of attribute suitability degrees, $S = \lambda(s_1, \ldots, s_j, \ldots, s_k, \ldots, s_n)$, we expect that if the suitability s_j is more important than the suitability s_k, then $\partial S/\partial s_j \geq \partial S/\partial s_k$. Under the same assumptions, if some compensation is possible, then $\lambda(s_1, \ldots, s_j, \ldots, s_k, \ldots, s_n) = \lambda(s_1, \ldots, s_j - p, \ldots, s_k + q, \ldots, s_n)$ and $p < q$. In other words, a suitability decrement p of an attribute can be compensated by the suitability increment q of a less important attribute, but the increment q must be greater than the decrement p. These properties are essential in human reasoning and must be supported by MCDM.

2.5 Modelling of simultaneity requirements

Function $\lambda : [0,1]^n \rightarrow [0,1]$ that aggregates all attribute suitability degrees and computes the overall suitability degree is essentially a logic function. In human decision making the aggregation of suitability degrees is usually a stepwise process where small groups of related suitability degrees are aggregated and replaced by an aggregated suitability degree. The process of stepwise aggregation terminates when the suitability degrees of subsystems at the highest level are aggregated yielding the overall suitability degree S as a compound function of attribute suitability degrees.

Let us investigate an aggregation step where DM aggregates m suitability degrees using an aggregation function $\mu : [0,1]^m \rightarrow [0,1]$. In human decision making $\mu(s_1, \ldots, s_m)$ is most frequently a model of simultaneity. E.g., a homebuyer regularly prefers locations that are both close to schools for children *and* to jobs for parents. Such a simultaneity requirement can be modelled using some form of partial conjunction [3], i.e., μ is expected to have an adjustable degree of similarity with conjunction $s_1 \wedge \cdots \wedge s_m$. A normalized degree of proximity between $\mu(s_1, \ldots, s_m)$ and $s_1 \wedge \cdots \wedge s_m$ is called andness and it can be defined by: $\alpha = \frac{(s_1 \vee \cdots \vee s_m) - \mu(s_1, \ldots, s_m)}{(s_1 \vee \cdots \vee s_m) - (s_1 \wedge \cdots \wedge s_m)}$. Since $(s_1 \wedge \cdots \wedge s_m) \leq \mu(s_1, \ldots, s_m) \leq (s_1 \vee \cdots \vee s_m)$ it follows that $0 \leq \alpha \leq 1$ and $\mu(s_1, \ldots, s_m)$ is a model of simultaneity if $0.5 < \alpha \leq 1$ and $(s_1 \wedge \cdots \wedge s_m) \leq \mu(s_1, \ldots, s_m) < (s_1 + \cdots + s_m)/m$. This form of andness depends on input degrees of suitability and humans usually think globally using an average andness, e.g., $\overline{\alpha} = \int_{[0,1]^m} \alpha(s_1, \ldots, s_m) ds_1 \ldots ds_m$, $0 \leq \overline{\alpha} \leq 1$. If DM needs a high simultaneity (e.g., $\overline{\alpha} > 0.7$), that usually means that all inputs must be at least partially satisfied. In other words, $\mu(s_1, \ldots, s_m) = 0$, $s_i = 0$, $i \in \{1, \ldots, m\}$ and it is mandatory to satisfy all inputs. This kind of simultaneity is called a *hard simultaneity*. In other cases DM may need a *soft simultaneity*, where the average andness is slightly above 0.5 and $\mu(s_1, \ldots, s_m) > 0$, $s_i > 0$, $i \in \{1, \ldots, m\}$. Supporting models of simultaneity is an important requirement that MCDM must satisfy.

2.6 Modelling of replaceability requirements

Replaceability requirements are symmetrical and complementary to simultaneity requirements. Replaceability means that a high suitability in a group of attributes can be achieved using any one of the attributes (i.e., they can replace each other). E.g., a home location can be considered suitable for recreational activities if it is close to lake, *or* close to ski terrains. The intensity of replaceability can be determined using the orness indicator that is a complement of andness: $\overline{\omega} = 1 - \overline{\alpha}$. Replaceability aggregators satisfy conditions $0.5 < \overline{\omega} \leq 1$ and $(s_1 + \cdots + s_m)/m < \mu(s_1, \ldots, s_m) \leq (s_1 \vee \cdots \vee s_m)$. High orness means low andness and vice versa. Similarly to the case of simultaneity, a high level of replaceability (e.g., $\overline{\omega} > 0.7$) may be combined with the requirement for hard replaceability where $\mu(s_1, \ldots, s_m) = 1$, $s_i = 1$, $i \in \{1, \ldots, m\}$. Soft replaceability is any form of replaceability that does not satisfy the hard replaceability requirements. In the case of soft replaceability we have $\mu(s_1, \ldots, s_m) < 1$, $s_i < 1$, $i \in \{1, \ldots, m\}$.

2.7 Modelling of balanced simultaneity/replaceability

If the simultaneity and replaceability are balanced then $\alpha = \omega = 0.5$. In the case of two variables, from definition $\alpha = \frac{(s_1 \vee s_2) - \mu(s_1, s_2)}{(s_1 \vee s_2) - (s_1 \wedge s_2)} = 0.5$ it follows that $\mu(s_1, s_2) = ((s_1 \vee s_2) + (s_1 \wedge s_2))/2 = (s_1 + s_2)/2$. This result indicates that the arithmetic mean is a soft computing logic function that combines simultaneity and replaceability requirements in a balanced way: DM would like that all attributes are simultaneously satisfied, but at the same time s/he accepts that any attribute can compensate any other attribute. It is important to understand that the arithmetic mean represents a model of this specific logic condition and nothing more. MCDM that use the arithmetic mean are acceptable only in cases where DM can justify the use of this specific logic condition.

According to Malczewski [16], "GIS implementations of the weighted summation procedures are often used without full understanding of the assumptions underlying this approach."

2.8 Modelling of mandatory, desired, and optional requirements

Using models of simultaneity, replaceability and negation ($x \mapsto 1 - x$) it is possible to create a variety of compound soft computing logic functions that precisely reflect the needs of DM. A compound aggregator that is most frequent in human reasoning is used to combine mandatory and nonmandatory attributes. Most frequently there are one mandatory attribute and one or two nonmandatory attributes. E.g., a DM may reject home locations that do not have good ground transportation, but accept locations that are far from an international airport. In such cases the ground transportation is a mandatory requirement, and the vicinity of an international airport is desired, but not mandatory. Optional attributes are also nonmandatory and have lower significance than desired attributes. To model such requirements we need aggregators $\mu(s_{man}, s_{des}, s_{op})$ that satisfy the conditions $\mu(s_{man}, s_{des}, s_{op}) = 0$, $s_{man} = 0$, $s_{des} > 0$, $s_{op} > 0$ and if the compensation between s_{des} and s_{op} is possible, then $\mu(s_{man}, s_{des}, s_{op}) = \mu(s_{man}, s_{des} - p, s_{op} + q)$, $s_{man} > 0$, $p < q$. Optional attributes can be omitted, and in such cases

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we use only mandatory and desired inputs. An aggregator with these properties is a partial absorption function introduced in [2] and expanded in [19].

2.9 Modelling of sufficient, desired, and optional requirements

Sufficient, desired and optional requirements are a disjunctive counterpart of mandatory, desired and optional requirements. If the sufficient input is completely satisfied then the desired and optional inputs have no effect. If the sufficient attribute has low or even zero suitability degree, this can be partially compensated by the desired and optional attributes. The corresponding aggregator $\mu(s_{suf}, s_{des}, s_{op})$ satisfies conditions $\mu(s_{suf}, s_{des}, s_{op}) = 1, s_{suf} = 1, s_{des} < 1, s_{op} < 1$, and if the compensation between s_{des} and s_{op} is possible, then $\mu(s_{suf}, s_{des}, s_{op}) = \mu(s_{suf}, s_{des} - p, s_{op} + q)$, $s_{suf} < 1$, $p < q$.

2.10 Ability to express suitability as an aggregate of usefulness and inexpensiveness

Land-use is regularly related to a variety of costs (e.g., the cost of land, the cost of building infrastructure and objects, the cost of financing, etc.). The overall suitability depends on two simultaneous requirements: finding locations that are very useful for specific purpose and at the same time inexpensive. A convenient way to solve that problem is to define *usefulness* as a non-financial part of the overall suitability, and *inexpensiveness* as an overall result of cost analysis (an aggregate of cost components only). Then, the overall suitability can be conveniently expressed as an aggregate of usefulness and inexpensiveness. Separation of cost and usefulness attributes reflects human reasoning where the overall cost is compared with the corresponding overall satisfaction. Of course, there are cases where the overall suitability does not depend on cost. In such cases the overall suitability reduces to usefulness.

The presented list of properties is not proved to be necessary and sufficient in all cases. However, the presented conditions are relevant for many land use decision problems and show that logic aggregation of attribute suitabilities is a frequently needed property. For detailed analysis of mathematical conditions see [4], and for sample applications see [4, 5].

The necessary properties of MCDM's do not change if attributes of a cell are functions of time, or functions of the values of attributes in other cells.

3 Properties of GIS related MCDM

Several GIS related MCDM approaches have been presented in literature [15, 16]. Among the decision methods used in these approaches we selected a representative set that consists of the following techniques: *simple additive scoring* (SAS) [8, 6], *multiattribute value technique* (MAVT) [22, 13, 14], *multiattribute utility technique* (MAUT) [13, 10], *analytic hierarchy process* (AHP) [18, 1], *ordered weighted average* (OWA) [21, 17], *outranking methods* [12] and *logic scoring of preference* (LSP) [4, 5].

The ten fundamental features presented in the previous section can be used to investigate the selected decision methods in view of their appropriateness for land-use evaluation and suitability map construction.

3.1 Simple additive scoring

The SAS technique [8, 6] is based on the concept of a weighted average in which weights are used to denote relative importance of suitability attributes. A DM directly assigns a weight w_i to each suitability attribute a_i, $i = 1, \ldots, n$. These assigned weights are rescaled to normalized weights W_i, $i = 1, \ldots, n$, such that $\sum_{i=1}^{n} W_i = 1$. The overall score or overall degree of suitability $S(x, y)$ of each cell x, y is then computed by:

- Determining the n suitability components $s_1(x, y), \ldots, s_n(x, y)$ that are obtained from the evaluation of the n attributes for the cell.
- Multiplying each suitability component $s_i(x, y)$ with the normalized weight W_i of its corresponding attribute.
- Summing the products over all attributes, i.e., $S(x, y) = \sum_{i=1}^{n} W_i s_i(x, y)$.

Therefore, SAS uses a simple linear weighted aggregation model.

3.2 Multiattribute value technique

In MAVT [22, 13, 14] suitability attributes a_i, $i = 1, \ldots, n$ are evaluated using value functions that aim to mathematically represent human judgements. A single-attribute value function translates the performance of the alternative attribute values into a value score which represents the degree to which a decision objective is achieved. As such, value function v_i associates a number (or 'value') $v_i(a)$ with each alternative value a of attribute a_i in such a way that a preference order on the alternatives consistent with DM value judgements is obtained.

For aggregation, more complex value functions are used. The most commonly used function is the simple additive weighting function $S(x, y) = \sum_{i=1}^{n} W_i v_i(a_i(x, y))$ where W_i is the weight of suitability attribute a_i and $v_i(a_i(x, y))$ is the value of suitability attribute value $a_i(x, y)$ (of cell x, y). This approach is valid if suitability attributes are preferentially independent.

The weights W_i are scaling constants that have to be derived with reference to the attribute ranges. These need to be elicited through questions which capture acceptability of trade-offs (e.g., 'how many units of one suitability attribute are worth how many of units of another suitability attribute?'). Weights must sum up to 1, i.e., $\sum_{i=1}^{n} W_i = 1$.

As such, the MAVT approach is similar to the 'scoring method', except that the scores $s_i(x, y)$ are replaced by values $v_i(a_i(x, y))$ that are obtained with the value function v_i.

3.3 Multiattribute utility technique

MAUT [13, 10] is used and treated separately from MAVT when 'risks' or 'uncertainties' have a significant role in the definition and assessment of alternatives. The attitude of the DM toward risk is incorporated into the assessment of a single-attribute utility function u_i, which is obtained through utility analysis and translates the values of suitability attribute a_i into 'utility units'. A 'utility unit' is a relative value between 0 and 1 (where 0 and 1 resp. denote the worst and best values). The concept of a utility function is inherently probabilistic in nature.

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Aggregation is done by an overall utility function. A simple additive weighting function is most commonly used. In such a case $S(x,y) = \sum_{i=1}^{n} W_i u_i(a_i(x,y))$. Suitability attributes must be preferentially independent. The weights W_i, $i = 1, \ldots, n$ have to sum up to 1, i.e., $\sum_{i=1}^{n} W_i = 1$.

From aggregation point of view, the MAUT approach is similar to the MAVT and 'scoring' approaches.

3.4 *Analytic hierarchy process*

AHP [18, 1] uses a different approach. Cognitive psychology has found that people are poor at assimilating large quantities of information on problems. The subsequent steps in AHP can be summarized as follows:

- Model the problem as a hierarchy containing the decision goal, the alternatives for reaching it, and the suitability attributes for evaluating the alternatives.
- Establish priorities (normalized weights) among the elements of the hierarchy by making a series of judgments based on pairwise comparisons of the elements.
- Synthesize these judgments to yield a set of overall weights for the hierarchy. This is done by means of a sequence of multiplications of the matrices of relative weights at each level of the hierarchy.
- Check the consistency of the judgments.
- Come to a final decision based on the results of this process.

Suitability attributes are subdivided in subattributes and hierarchically structured. Overall suitability $s(x,y)$ for an attribute a is computed by an additive weighting function $s(x,y) = \sum_{j=1}^{m} W_{s_j(x,y)} s_j(x,y)$ where $s_j(x,y)$, $j = 1, \ldots, m$ denote the suitability components of the subattributes of a. All weights $W_{s_j(x,y)}$ must to sum up to 1, i.e., $\sum_{i=j}^{n} W_{s_j(x,y)} = 1$.

3.5 *Ordered weighted averaging*

In an OWA approach [17], the DM specifies the decision-relevant suitability attributes to be used as evaluation criteria; identifies preferred criteria values on a qualitative scale; and defines the relative importance of each criterion by assigning weights. The weighted criterion values are then combined using an OWA aggregation operator [21], resulting in an evaluation score for each cell. OWA allows the DM to specify a decision strategy that reflects his decision-related preferences.

The OWA operators [21], provide a parameterized class of mean type aggregation operators. Many notable mean operators such as the max, arithmetic average, median and min, are members of this class. OWA operators allow to model linguistically expressed aggregation instructions.

An OWA operator of dimension n is a mapping function $F : [0,1]^n \rightarrow [0,1]$ that has an associated collection of weights $\mathbf{W} = [W_1, \ldots, W_n] \in [0,1]^n$, for which it holds that $\sum_{i=1}^{n} W_i = 1$, and with $F(s_1, \ldots, s_n) = \sum_{i=1}^{n} W_i s'_i$ where s'_i is the ith largest value of the s_i.

By choosing different $\mathbf{W}$, different aggregation operators can be implemented. The OWA operator is a non-linear operator as a result of the process of determining the values s'_i.

3.6 *Outranking methods*

Outranking methods, such as variants of ELECTRE and PROMETHEE are used in the areas of GIS and environmental planning [12]. The basic idea of these methods is to use strictly relative criteria that express a range from indifference to strong preference of one alternative over another alternative separately for all individual attributes. The attribute preferences are then averaged using the arithmetic mean to generate the credibility of the outranking relation of two alternatives (PROMETHEE). In such a case no input is mandatory. The overall degree of outranking of two alternatives can also be computed using a product (ELECTRE III), making all attributes mandatory.

3.7 *Logic scoring of preference*

With the LSP method [4, 5] suitability maps are created with the following main steps:

1. Creation of an attribute tree. This tree contains and structures all parameters that affect the overall suitability and is build by the DM.
2. Definition of elementary criteria. The DM has to provide an elementary criterion for each attribute involved in the decision process. These criteria will be evaluated during suitability map construction. For each analyzed cell x, y, the evaluation of each attribute a_i, $i = 1, \ldots, n$ will result in an elementary satisfaction degree $s_i(x,y)$.
3. Creation of the aggregation structure. For each analyzed cell, all associated elementary satisfaction degrees must be aggregated. Therefore, the DM has to create an aggregation structure, which adequately reflects his domain knowledge and reasoning.
4. Computation of the overall suitability degree. Once the attribute tree, the elementary criteria and the aggregation structure are available, the suitability map construction can start. The elementary criteria are evaluated and their resulting elementary satisfaction degrees can be aggregated in order to compute the overall satisfaction degree of each analyzed cell.

Aggregation in LSP is done via the aggregation structure, build by the DM. The basic building blocks of the aggregation structure are the simple and compound LSP aggregators. The DM can use them to construct an easily understandable aggregation schema which is consistent with observable properties of human reasoning in the area of evaluation.

The simple LSP aggregators are all graded preference logic functions and based on a superposition of the fundamental *Generalized Conjunction/Disjunction* (GCD) function. Most frequently, GCD is implemented by the weighted power mean function $GCD(s_1, \ldots, s_n) = (W_1 s_1^r + \cdots + W_n s_n^r)^{1/r}$ where $r \in [-\infty, +\infty]$ and $0 < W_i < 1$ such that $\sum_{i=1}^{n} W_i = 1$ [5]. The parameter r determines the logical behavior of the function. As such a continuous variety of logical functions ranging from full conjunction to full disjunction can be modelled. The simple LSP aggregators can be used to construct more complex, compound operators like the conjunctive partial absorption which can be used to aggregate a mandatory and a desired criterion.

For suitability map construction, the overall suitability degree of each analyzed cell x, y must be computed. This is

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done in two steps: First, the elementary satisfaction degrees $s_1(x,y),\ldots,s_n(x,y)$ are aggregated using the logic aggregation structure. This results in the overall satisfaction degree $s(x,y)$ of the cell. Second, cost (if applicable) is taken into account. Cost is dealt with separately. This better reflects human reasoning and allows for more efficient cost/satisfaction studies. Cost is considered to be a function c of the analyzed cells. For each cell x,y the cost function returns the associated cost $c(x,y)$ of the cell. If the importance of high satisfaction of criteria is the same as the importance of low cost, then the overall suitability degree $S(x,y)$ of the cell can be computed by $S(x,y) = s(x,y)/c(x,y)$. Alternative definitions of $S(x,y)$ are possible.

4 Conclusions

All multicriteria decision methods should be models of human decision making and the only way to prove their credibility is to show their proximity to human evaluation logic. Our analysis shows that the majority of existing MCDM are not derived with an explicit goal to model observable properties of human reasoning. Indeed, human reasoning is neither restricted to the use of arithmetic mean nor restricted to relative criteria only. Humans use a spectrum of absolute and relative elementary criteria and a spectrum of soft computing logic aggregators, such as soft and hard simultaneity and replaceability with nonmandatory, mandatory and sufficient attributes, conjunctive and disjunctive partial absorption, as well as other compound aggregators.

Decision methods that are used in land-use evaluation problems cannot be randomly selected, without appropriate justification. The justification for using a specific evaluation method in a GIS environment should be based on investigating the capability of the method to support features that are proved to characterize human decision making. Many oversimplifications that are frequent in GIS literature [16] (particularly those based on simple additive models) are based on the fact that they are "easy-to-understand and intuitively appealing." Unfortunately, that is not enough. Before using mathematical models it is first necessary to prove that they are appropriate.

LSP is a method developed with the goal to support logic operators observed in human reasoning. Consequently, it is realistic to expect that the LSP method can provide highly accurate and justifiable models for GIS applications, such as land-use evaluation, suitability maps, and natural resources planning.

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