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A new fuzzy multi-criteria evaluation method for group site selection in GIS

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ABSTRACT

Multiple criteria group site selection problems involve a group of individuals evaluating a set of alternative sites on the basis of multiple criteria. This paper presents an application of a new fuzzy algorithm for finding and exploring potential solutions to these problems in a raster Geographical Information System (GIS) environment. Linguistic assessments from decision-makers are represented as triangular fuzzy numbers (TFN's), which are adjusted for uncertainty in the source data and its relationship to suitability by using an approach based on type-2 fuzzy sets. The first aggregation of inputs is a compensatory one based on fuzzy multi-attribute decision-making (MADM) theory. An adjusted aggregation then factors in conflicts, risks and uncertainties to enable a variety of compensatory and non-compensatory outcomes to be generated based on decision-maker preferences. The algorithm was implemented in ArcView GIS as part of an ongoing collaborative project with Brisbane Airport. This paper outlines the fuzzy algorithm and its use in site selection for a recycling facility on the Brisbane Airport site.

KEY WORDS: Geographic information system, Fuzzy logic, Group decision-making, Multicriteria evaluation

1. INTRODUCTION

Site selection for facilities such as airports, highways, and heavy industry is often extremely complex. As multiple stakeholders are usually involved in the selection of a given location, there is a strategic need to take into account multiple criteria, which are often conflicting, incommensurate and subject to uncertainty. Complexity is further increased as the spatial variation of suitability and the weighting of each criterion may form the basis of disagreements amongst a group of heterogeneous decision-makers. There has been much literature on multiple criteria evaluation in GIS (Eastman, Jin et al. 1995; Jankowski 1995; Malczewski 1999), and it has been noted that achieving consensus requires that complete information is available to all parties (Sharifi, Toorn et al. 2002). However most GIS-based analysis methods assume or require consensus among decision-makers (Malczewski 1996) and have little capacity for dealing with conflicts, risks and uncertainty, thereby losing potentially important information in the aggregation phase.

Fuzzy multiattribute methods have been widely used and recommended as decision-making tools (Bonissone 1982; Liang and Wang 1991; Ribeiro 1996; Herrera and Herrera-Viedma 2000), but have been largely overlooked in GIS applications. One possible reason for this is the need to avoid a large computational burden. In raster GIS the decision area may contain millions of cells, with each cell representing an alternative that will ideally be analyzed in a real-time interactive environment. Literature on fuzzy decision-making in a GIS environment has largely been based upon inference systems (Zeng and Zhou 2001), non-compensatory methods (Malczewski 2002), or the use of fuzzy sets to describe crisp utility functions (Jiang and Eastman 2000). Other fuzzy approaches to spatial problems can be found in (Banai 1993; Stefanakis, Vazirgiannis et al. 1996; Makropoulos, Butler et al. 2003). However there remains a need for a computationally efficient algorithm that maximizes information value while minimizing calculation time.

This paper advances existing work on multicriteria group site selection in GIS by providing a new fuzzy algorithm to aid the selection of an optimal site that does not rely on consensus from decision-makers, and handles quantitative and linguistic uncertainty. Quantitative uncertainty is defined here as uncertainty based on the source data and its relationship with suitability, and is separate from the linguistic uncertainty inherent in the vagueness of linguistic suitability assessments. The algorithm also differs from other approaches such as using Borda's choice rule or TOPSIS, by providing an easy mechanism to explore and minimize conflicts and risks linguistically.

The remainder of this paper is organized as follows: Section 2 provides a functional description of the type of problem focused on in the paper, Section 3 details the algorithm, Section 4 illustrates its implementation, Section 5 provides a discussion of advantages and disadvantages, and lastly conclusions are drawn.

2. GROUP MULTICRITERIA LOCATION PROBLEMS (GMCLP'S)

The algorithm described in this paper was developed to aid in the solution of a specific type of site selection problem, the GMCLP. GMCLP's are complex real world decision problems with the objective of finding an optimal site for a facility or service from multiple alternatives, using multiple evaluation criteria and the opinions of multiple stakeholders. They contain four key attributes:

1. A large number of spatial alternatives:
The alternatives under consideration are numerous enough to make manual analysis impractical i.e. the problem is non-trivial
2. A heterogeneous group of decision-makers:
Multiple parties are involved in the decision process and there is no guaranteed consensus among them
3. Multiple evaluation criteria with an explicit spatial component
The decision is based on multiple, conflicting criteria that vary across space
4. Uncertainty
The relationship between the available raw data and site suitability is subject to some kind of uncertainty

A real world example of a GMCLP is illustrated and worked through in Section 4.

3. ALGORITHM DESIGN

3.1 Framing the problem

The core components of a site selection problem are represented in the following notation:

A = $(A_1, A_2, \ldots\ldots A_I)$	The set of I feasible alternatives
C = $(C_1, C_2, \ldots\ldots C_J)$	The set of J criteria
D = $(D_1, D_2, \ldots\ldots D_K)$	The set of K decision-makers
$\boldsymbol{W_k} = (W_{k1}, W_{k2}, \ldots\ldots W_{kJ})$	The set of criterion weights based on the k^{th} decision-maker's preferences
R = $\begin{bmatrix} R_{11}\ldots\ldots\ldots R_{1K} \\ \vdots \\ R_{J1}\ldots\ldots\ldots R_{JK} \end{bmatrix}$	The matrix of relevance of the k^{th} decision-makers opinion with respect to criterion j. *(values are scaled after input so each criterions relevance values sum to 1)*

N.B. Deriving the relevance matrix is ideally achieved via consensus, and should be based on the competency of a decision-maker to make assessments relating to each criterion. However it may also be derived via a non-weighted averaging of each decision-maker's assessments of the competencies of others in the group.

$\mathbf{O_k} = \begin{bmatrix} O_{11k}\ldots\ldots\ldots O_{1Ik} \\ \vdots \\ O_{J1k}\ldots\ldots\ldots O_{JIk} \end{bmatrix}$	The matrix of criterion outcomes for alternative i and criterion j, based on decision-maker k's suitability and uncertainty assessments.

At a basic level the process is tailored to strategic decisions, and follows a sequence of steps. The first step involves accepting linguistic suitability and uncertainty inputs (O_{ijk}) from decision-makers to generate a set of raster suitability maps, where each cell is treated as an alternative (A_i). Secondly a fuzzy MADM aggregation is performed using the suitability maps, relevance scores (R_{jk}), and criterion weightings (W_{kj}). The next step is to derive output parameters quantifying compensatory suitability ($R_s(i)$), conflicts ($R_c(i)$), risks ($R_r(i)$), and uncertainties ($R_u(i)$). An adjusted aggregation is then performed to include all output parameters in an adjusted rating ($A_s(i)$), and the final step is to interactively explore alternatives and reduce them in an iterative process. The full procedure is shown in more detail in Figure 1.

3.2 Linguistic term set operations

The linguistic approach to decision-making was chosen here because it has been shown to be an effective tool for modeling qualitative information in real world decision-situations. For background on the linguistic approach, see (Zadeh 1976; Bonissone 1982; Ribeiro 1996; Herrera and Herrera-Viedma 2000). Linguistic processing provides an easy method for decision-makers to input preferences, and generates easily understandable natural language outputs.

Four linguistic term sets are used for decision-maker input and natural language outputs:

T(S)	site suitability terms *(as triangular fuzzy numbers (TFN (a,b,c)) on [0,1])*
T(W)	terms for weighting of criteria and decision-maker relevance *(as crisp numbers on [0,1])*
T(U)	terms describing the level of uncertainty *(as labels U_0, U_n, …. U_{N-1} , where N is the number of uniformly distributed, ordinal uncertainty terms)*
T(G)	terms for generating new suitability terms in T(S) *(as crisp numbers on [0,1])*

Herrera and Herrera-Viedma (2000) offer advice on choosing term sets, see (Herrera and Herrera-Viedma 2000). Generally the sets will have an odd cardinality between five and nine, with the middle term centered on 0.5. Table I gives some sample linguistic terms and their semantic values.

Two operations are performed on the linguistic suitability terms prior to aggregation. The first is generation of new suitability terms to enable decision-makers to utilize context specific words and increase the resolution of the set. Secondly, uncertainty scaling of suitability terms provides a means to quantify uncertainty based on source data separate from the linguistic uncertainty of the suitability term.

Table I: Linguistic term sets

Suitability *(as a TFN)*		**Weighting**		**Uncertainty**	
Totally unsuitable	(0,0,0)	*Irrelevant*	.1	*Very Certain*	0
Bad	(0,.2,.4)	*Unimportant*	.3	*Certain*	1
Indifferent	(.3,.5,.7)	*Moderately Important*	.5	*Moderately Certain*	2
Good	(.6,.8,1)	*Important*	.7	*Uncertain*	3
Perfect	(1,1,1)	*Very Important*	.9	*Very Uncertain*	4
		Critical	1		

Term generation is facilitated by a hedging procedure that enables the addition of up to four new suitability terms to a set of around five primary terms, whilst still preserving the ordinal quality of the set. The first step in this process is choosing the term that will immediately precede the new term in utility. The semantic value of the new term will take the form of a TFN, with its center of gravity situated between this term and the next term above. Equation 1 defines the breakpoints of the new term:

$$x' = x_{-} + (x_{+} - x_{-})g \tag{1}$$

Where:

x' is the value of the new breakpoint

x_{-} is the value of the breakpoint in the lower term

x_{+} is the value of the corresponding breakpoint in the higher term

g is the generation term

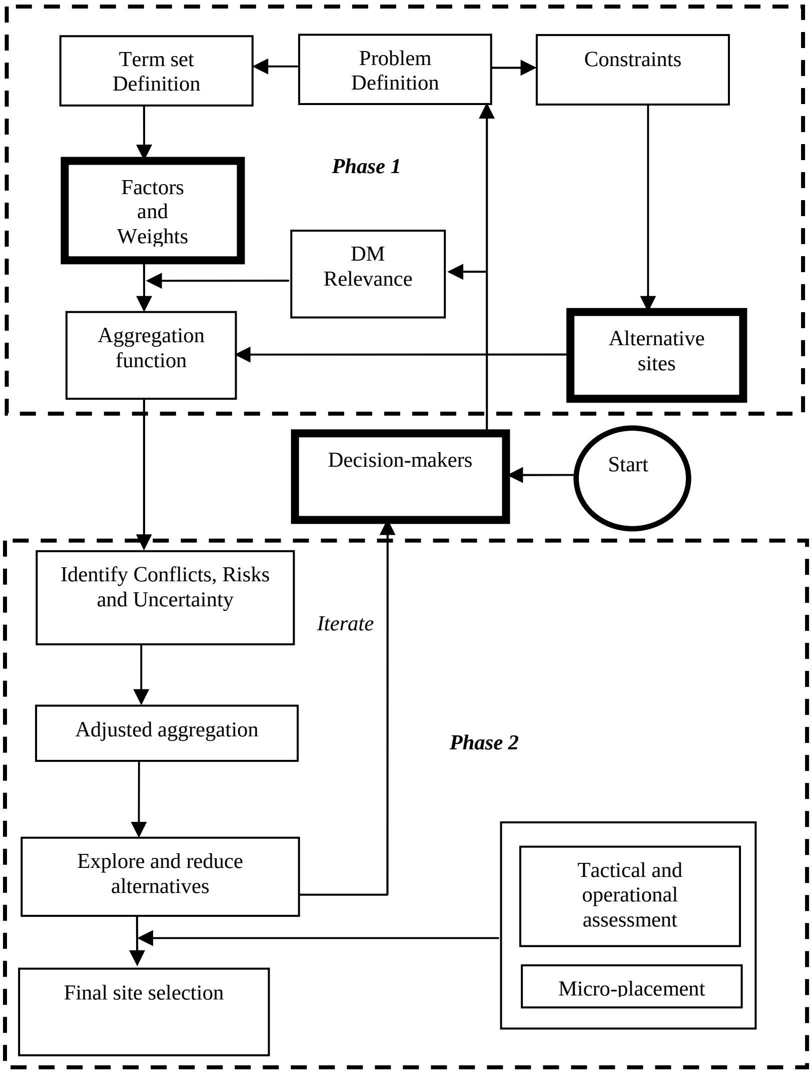

Figure 1: The site selection process

There are two types of uncertainty inherent in decision-maker suitability assessments, which are defined here as linguistic and quantitative. Linguistic uncertainty is represented by the fuzziness of the primary suitability term (TFN(a,b,c)), whereas quantitative uncertainty is represented using the concept of a type-2 fuzzy set and its footprint of uncertainty (FOU). Quantitative uncertainty has also been referred to as ambiguity, nonspecificity or strife (Mendell and John 2002). The FOU of the suitability term is defined here by moving vertices a and c of the primary TFN outwards to the boundary of [0,1], see Figure 2. Primary vertices a and c are reallocated according to the uncertainty assessment, see Figure 3. These points are defined as follows:

$$Supp = \left(\frac{1-c+a}{N-1}\right)n + c - a \tag{2}$$

$$a = \begin{cases} 0 & \text{if } b < \dfrac{Supp}{2} \\ 1 - Supp & \text{if } 1-b < \dfrac{Supp}{2} \\ b - \dfrac{Supp}{2} & \text{Otherwise} \end{cases} \tag{3}$$

$$c = \begin{cases} Supp & \text{if } b < \dfrac{Supp}{2} \\ 1 & \text{if } 1-b < \dfrac{Supp}{2} \\ b + \dfrac{Supp}{2} & \text{Otherwise} \end{cases} \tag{4}$$

Where:

Supp is the width of the support of the new primary membership

n is the term number chosen by the decision-maker from a set of N-1 uniformly distributed uncertainty terms

The scaled term now envelops both suitability and quantitative uncertainty information in a type-1 fuzzy number, enabling the use of relatively simple type-1 processing procedures whilst increasing information value.

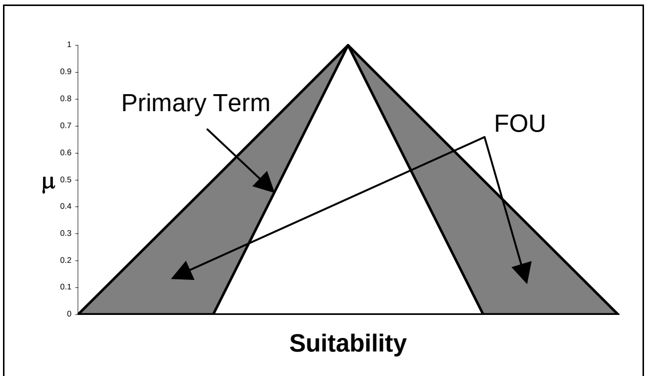

Figure 2. FOU

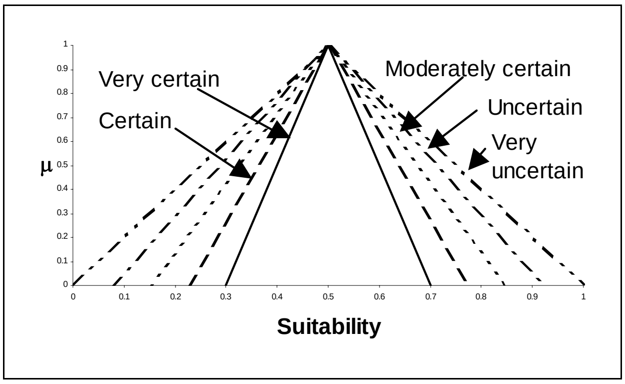

Figure 3. The effect of uncertainty assessments on the primary MF

Weighting coefficients may also be dynamic, whereby one criterion per decision-maker (W_{jk} j=1..J), and one decision-maker per criterion (R_{jk} k=1..K), may be deemed 'critically important'. This enables one set of criterion outcomes to outweigh all others combined, whilst still allowing other outcomes to contribute to the overall score. The weighting coefficient for critical importance is calculated prior to aggregation via Equation 5.

$$W_c = 2N\sum_{n=1}^{N} W_n \tag{5}$$

Where:

W_c is the critical weighting coefficient

W_n is the static weight of factor n (the static weight of critical is 1)

N is the number of weights in the set

The final step is to normalize all weights in the set by dividing by W_c.

3.3 Information input

The procedure requires each decision-maker to generate a set of suitability maps representing how they perceive each criterion spatially varies in suitability and uncertainty. Categorical criteria such as land use are easily classified using a suitability term scaled for uncertainty. Input would be of the form *'I am very certain that areas zoned residential are totally unsuitable'*. However continuous variables such as proximity are difficult to represent via fuzzy terms without breaking the raw value into discrete categories. In this case input takes the form *'I am moderately certain that 100m from the residence is unsuitable'* and *'I am certain that 1000m from the residence is perfect'*. Here both the continuous nature of the variable and the fuzziness of its utility value are preserved using a fuzzification procedure. Decision-makers classify points on the domain of the source variable according to their suitability and uncertainty, and values that lie at a point x, in between the classified points, are given a fuzzy rating as follows:

$$Supp_x = \frac{(Supp_h - Supp_l)(x - x_l)}{x_h - x_l} \quad (6)$$

$$b = \frac{(b_h - b_l)(x - x_l)}{x_h - x_l} \quad (7)$$

$$a = \begin{cases} o & \text{if } b < \dfrac{Supp_x}{2} \\ 1 - Supp_x & \text{if } 1 - b < \dfrac{Supp_x}{2} \\ b - \dfrac{Supp_x}{2} & \text{Otherwise} \end{cases} \quad (8)$$

$$c = \begin{cases} Supp_x & \text{if } b < \dfrac{Supp_x}{2} \\ 1 & \text{if } 1 - b < \dfrac{Supp_x}{2} \\ b + \dfrac{Supp_x}{2} & \text{Otherwise} \end{cases} \quad (9)$$

Where:

$Supp_x$ is the width of the support of the suitability TFN at point x

$Supp_h$ is the width of the support of TFN (a_h,b_h,c_h) at the next highest rated point

$Supp_l$ is the width of the support of TFN (a_l,b_l,c_l) at next lowest rated point

x_h is the next highest rated point

x_l is the next lowest rated point

3.4 Aggregation and output parameters

The aggregation used here is based on fuzzy multiattribute decision-making theory. In order to process linguistic variables, procedures for performing arithmetic operations on the parameter based fuzzy numbers are needed. A comprehensive set of operations was developed by (Bonissone 1982) and is used here. The aggregation uses inputs from all decision-makers, and each decision-maker's assessments are weighted using the relevance matrix. This first aggregation is compensatory, as described by Equation 10.

$$S_i = \sum_{j=1}^{J} \sum_{k=1}^{K} O_{ijk} \times R_{jk} \times W_{jk} \mid \quad i = 1 \ldots I \quad (10)$$

Where:

S_i is the suitability of alternative i.

O_{ijk} is the criteria outcome for alternative i with relation to criterion j and decision-maker k, including quantitative uncertainty.

R_{jk} is the relevance of decision-maker k's opinion with respect to criterion j.

W_{jk} is the weight assigned to criterion j by decision-maker k

The aggregation output is a fuzzy number representative of each alternative's overall compensatory suitability and uncertainty. To enable the derivation of a linguistic rating for each alternative it is first necessary to carry out a simple score range normalisation using Equation 11.

$$\mathrm{N}(TFN(x)) = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (11)$$

Normalisation of TFN's is accomplished by using crisp numbers for x_{max} and x_{min}, with x_{min} set to 0 and x_{max} set to c_{max}, the third breakpoint of the highest possible score using the defined weighting and relevance parameters in an aggregation.

The method used here to rank fuzzy numbers is a scoring function that measures a TFN's centre of gravity along the x-axis. For fuzzy numbers with a non-zero area the score is calculated using Equation 12.

$$R_s(i) = R_s(\mathrm{TFN}(a,b,c)) = b + \frac{\left(1 - \frac{1}{\sqrt{2}}\right)\left(\frac{(c-b)^2}{2} - \frac{(b-a)^2}{2}\right)}{\frac{b-a}{2} + \frac{c-b}{2}} \quad (12)$$

Where:

$R_s(i)$ is the suitability score for alternative I

Rating a fuzzy number via a linguistic approximation is essentially a pattern recognition problem, solved by extracting a set of features for comparison. As the suitability term set is ordinal, a single feature can be used to ascertain the position of the closest term. The score from Equation 12 is used here, as shown in Equation 13:

$$\ell_s(S_i) = s_n \quad \text{If} \quad \left|(R_s(s_n) - R_s(S_i))\right| = \mathop{\Lambda}_{n=0}^{N-1} \left|(R_s(s_n) - R_s(S_i))\right| \quad (13)$$

Where:

ℓ_s is the linguistic suitability term approximation operator

s_n is the n[th] term in a set of N-1 suitability terms

S_i is the overall suitability of alternative i as a TFN

Risk is defined here as the probability of making a decision that does not satisfy all criteria according to some minimum standard. It is therefore apparent in alternatives that rate poorly on at least one criterion, and this may not be adequately represented in a compensatory aggregation procedure. A risk score is derived via Equation 14 and a linguistic assessment of risk for each alternative is generated using the result from Equation 14 in Equation 15:

$$R_r(i)=\begin{cases}0 & \text{if} \quad R_s\left(\bigwedge_{j=1}^{J}\bigwedge_{k=1}^{K}O_{ijk}\right)\geq R_s\left(O_{Min}\right)\\ \dfrac{R_s\left(O_{Min}\right)-R_s\left(\bigwedge_{j=1}^{J}\bigwedge_{k=1}^{K}O_{ijk}\right)}{R_s\left(O_{Min}\right)} & \text{Otherwise}\end{cases} \quad (14)$$

$$\ell_r(R_r(i))=r_n \quad \text{If} \quad \left|\left(r_n-R_r(i)\right)\right|=\bigwedge_{n=0}^{N-1}\left|\left(r_n-R_r(i)\right)\right| \quad (15)$$

Where:

$R_r(i)$ is the risk score for alternative i

O_{Min} is the minimum outcome required to eliminate risk *(specified linguistically by decision-makers)*

ℓ_r is the linguistic risk term approximation operator

r_n is the n^{th} element of a set of N-1 risk terms *(we use the term generation term set here)*

$\wedge$ is the minimum operator

Conflict occurs when an alternative is rated poorly and weighted highly on a criterion by one decision-maker, and is rated well, or weighted poorly on the same criterion by another decision-maker. Risk is a necessary but not sufficient condition for conflict, so the analysis is limited to those alternatives with a risk measure greater than zero. Conflict is assessed using Equation 16, and a linguistic assessment of the level of conflict is obtained in an identical way to that of Risk. Again the term generation terms are used.

$$R_c(i)=\frac{\bigvee_{j=1}^{J}\left(\bigvee_{k=1}^{K}R_s(O_{ijk})-w_{jk}-\bigwedge_{k=1}^{K}R_s(O_{ijk})-w_{jk}\right)}{2} \quad (16)$$

Where:

$R_c(i)$ is the conflict score for alternative i

$\vee$ is the maximum operator

The uncertainty score $R_u(i)$ is the width of the support of the aggregated output, and uncertainty is rated linguistically by Equation 17.

$$\ell_u(i)=u_n$$

$$\text{If} \quad \left|Supp\left(U\left(l_s(S_i),u_n\right)\right)-Supp\left(S_i\right)\right|=\bigwedge_{n=0}^{N-1}\left|Supp\left(U\left(l_s(S_i),u_n\right)\right)-Supp\left(S_i\right)\right| \quad (17)$$

Where:

$\ell_u(i)$ is the linguistic uncertainty approximation for alternative I

$U((l_s(S_i),u_n)$ is the TFN of the linguistic suitability term approximation for S_i, scaled for uncertainty using u_n

u_n is the n^{th} term in a set of N-1 uncertainty terms

3.5 Exploring alternatives

Decision-makers can now decide which parameters are most important as they explore and reduce the set of feasible alternatives in an interactive, iterative process. Alternatives are reduced by selecting minimum standards for each of the four parameters or creating an overall adjusted suitability value via Equation 18. The adjusted suitability score is then used to generate an adjusted linguistic suitability rating using equation 13. Weighting of the four parameters is via consensus, or a non-weighted averaging of each decision-maker's preferences, which enables a variety of non-compensatory outcomes to be generated.

$$A(i)=\frac{R_s(i)w_s+(1-R_u(i))w_u+(1-R_r(i))w_r+(1-R_c(i))w_c}{w_s+w_u+w_r+w_c} \quad (18)$$

Where:

$A(i)$ is the adjusted suitability value of alternative i

w_s is the weighting of the suitability score

w_u is the weighting of the uncertainty score

w_r is the weighting of the risk score

w_c is the weighting of the conflict score

4. IMPLEMENTATION

A real world site selection decision at Brisbane Airport, Queensland State, Australia, is worked through here using a set of GIS tools based on the algorithm just described. The GIS tools, collectively referred to as 'InfraPlanner', were developed within ArcView GIS. They consist of interfaces created by Visual Basic customisation of the standard package, and are an example of a closely coupled Spatial Decision Support System (SDSS). InfraPlanner currently exists in prototype form, and further details are available from the authors.

4.1 The problem

The problem worked through here concerns the location of a new recycling facility on the Airport grounds. The Airport occupies 2700ha of land, located 13km north east of the State Capital, Brisbane, adjoining Moreton bay. The site is flat and low lying, occupying part of the original Brisbane river delta, which has undergone extensive changes since the 1830s, with most of the original network of tidal waterways being replaced with constructed drains. Much of the vegetation on the site has been planted in the last 15 years, and was chosen to reduce the attraction of birds. There are, however, some environmentally sensitive areas to consider when locating new developments, as well as issues associated with airport facilities, Government legislation and the effects of airport operations on local communities.

There are three separate groups with an interest in the outcome. The Brisbane Airport Corporation (BAC), The Commonwealth Government (for regulatory compliance), and a local residential community adjoining the Airport (whose inputs were provided by an Airport representative with knowledge of their concerns). The groups differ considerably in their priorities and suitability assessments, creating a rich decision-making environment.

4.2 Decision-maker input

Data input primarily consists of the creation of a set of maps detailing the suitability and uncertainty assessments of each group. The first step in the process is the definition of constraints (Boolean criteria) that serve to limit the number of alternatives under consideration. After an initial consultation with BAC, and the Governments Airport Environment Officer (responsible for compliance with government regulations) a set of five constraints emerged:

1. Airport Boundary: The site must lie within the airport boundary
2. Existing Buildings: Sites already occupied are excluded
3. Road access: The site must be within 200m of selected access roads.
4. Zoning: The site must lay in a zone designated ‘General Industry’ or ‘Light Industry’ as defined by the BAC 1998 Master Plan.
5. Conservation: The site must not occupy an area of high conservation value.

The map of unconstrained alternatives is derived using standard GIS Boolean overlay functionality and is shown in Figure 4.

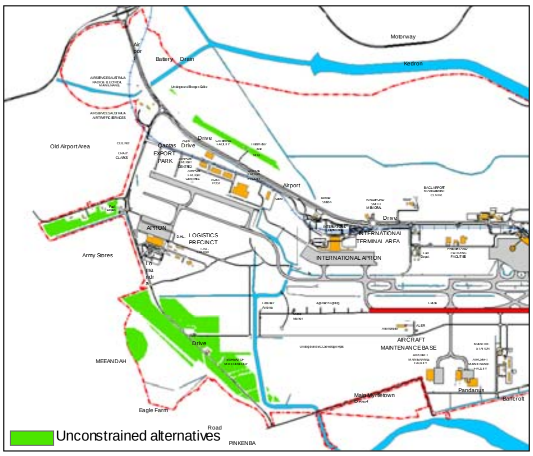

Figure 4. Unconstrained alternatives

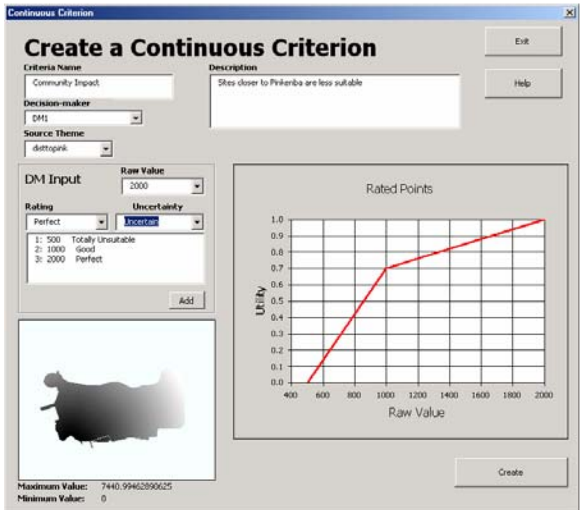

Figure 5: Creating a suitability map from a continuous variable

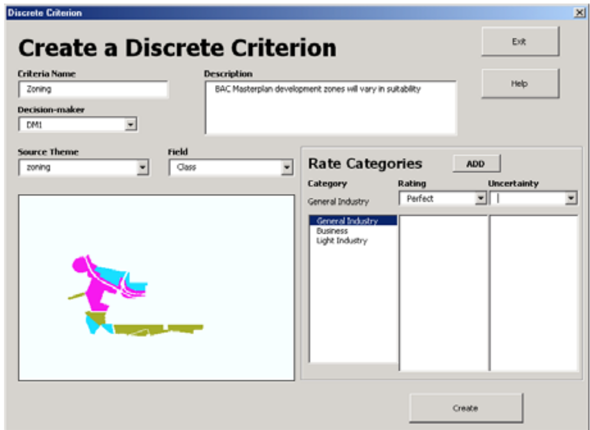

Figure 6: Creating a suitability map from a discrete (categorical) variable

The next step in the process involves the definition and linguistic assessment of criteria that vary on a suitability scale from ‘Totally Unsuitable’ to ‘Perfect’. These criteria (referred to as factors) are represented as a set of suitability maps, created using interfaces that convert linguistic inputs from each decision-maker to a spatially explicit format as shown in Figures 5 and 6. In the case of continuous variables, users see a crisp utility function generated from their assessments, which is fuzzified as the map is created. To illustrate how the linguistic input is structured factor definition from BAC is provided below:

BAC factor definition

1. **Environmental value** is ‘important’: It is ‘moderately certain’ that sites of moderate conservation value are ‘good’ whilst it is ‘very certain’ that all others are ‘perfect’.
2. **Zoning** is ‘very important’: It is ‘very certain’ that general industry zones are ‘perfect’ whilst it is ‘moderately certain’ that light industry zones are ‘good’.

3. **Tenant Amenity** is 'important': It is 'very certain' that sites less than 50m from sensitive tenants are 'totally unsuitable'. It is 'moderately certain' that sites 100m from sensitive tenants are 'good'. It is 'certain' that sites 500m from sensitive tenants are 'perfect'.
4. **Community Impact** is 'important': It is 'very certain' that sites less than 500m from Pinkenba are 'totally unsuitable'. It is 'uncertain' that sites 1000m from Pinkenba are 'good'. It is 'very uncertain' that sites 2000m from Pinkenba are 'perfect', and 'certain' that sites 4000m from Pinkenba are 'perfect'.
5. **Proximity to BAC Landfill Requirement** is 'moderately important': It is 'very certain' that sites on Lomandra Dr are 'perfect'. It is 'moderately certain' that sites on Randle Rd, Sugarmill Rd and Viola Pl are 'good'. It is 'moderately certain' that sites on Airport Dr are 'indifferent'.
6. **Traffic impact** is 'important': It is 'very certain' that sites on Airport Drive are 'bad'. It is 'moderately certain' that sites on Lomandra Drive and Viola Pl are 'good'. It is 'certain' that sites on Randle Road and Sugarmill Rd are 'perfect'.

InfraPlanner takes the linguistic assessments and generates raster maps, where each raster cell has a corresponding fuzzy number representative of the suitability and uncertainty assessment for each criterion from each decision-maker. A compensatory weighted aggregation then provides overall compensatory outcomes, as shown in Figure 7 which illustrates semantic results for five sample alternatives.

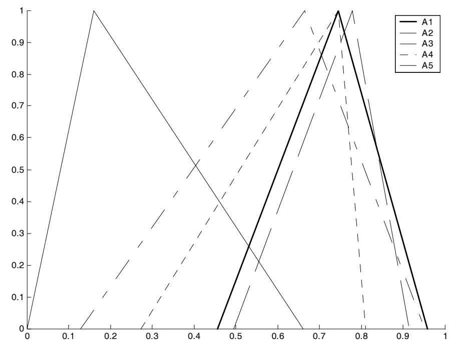

Figure 7. Semantic values for compensatory suitability

An adjusted aggregation based on decision-maker preferences for the importance of minimizing conflicts risks and uncertainty, or maximizing compensatory suitability is now performed to enable an adjusted overall suitability estimate to be derived. An adjusted aggregation is described for the five alternatives from Figure 7 in Table II.

Interactive alternative exploration is shown in Figure 8. Users can view the decision area as a regular map or use raster maps of criterion outcomes, conflict, risk, uncertainty or aggregated suitability. Clicking on a particular location produces a natural language analysis in real time.

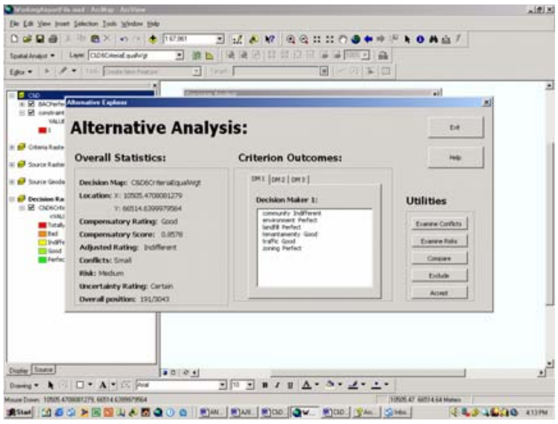

Figure 8: Alternative exploration and feedback

Table II. Compensatory and adjusted outcomes

	Compensatory Rank	*Compensatory Suitability*	*Uncertainty*	*Risk*	*Conflict*	*Adjusted Suitability*	*Adjusted Rank*
A1	2	Good	Certain	Zero	Zero	Good	1
A2	4	Indifferent	Uncertain	Zero	Zero	Good	2
A3	1	Good	Totally certain	Very large	Large	Indifferent	3
A4	3	Indifferent	Certain	Large	Very large	Indifferent	5
A5	5	Bad	Moderately certain	Very Large	Medium	Indifferent	4
Wgts		*Moderately important*	*Irrelevant*	*Unimportant*	*Important*		

As expected the system highlighted differences in preferred sites for the different priorities and suitability criteria of the three groups. The best compensatory solution was acceptable to only two of the parties, and performing a second aggregation to minimise conflict found a slightly different solution that the third party also rejected. It was quickly ascertained that disagreement was primarily due to the third decision-maker placing primary importance on satisfying a single criterion. Unfortunately this left no locations available that were completely satisfactory to all, and the primary benefit gained in from the system was the clear identification of the source of conflict, which has become the subject of negotiation between parties.

5. DISCUSSION

The nature of the site selection problem presented here is typical of many real world situations. A fundamental problem in designing systems to solve such problems is that there is often no universally accepted solution to find, and it is not always possible to derive the best compromise from initial assessments. Most GIS based decision-making methods assume that crisp numerical suitability assessments can be processed according to a pre-determined algorithm to derive a solution. However the complex nature of many site selection decisions make such assumptions unrealistic. It was noted during the selection process that decision-makers were reluctant to place their faith in a derived solution without fully understanding how that solution was obtained. This creates a significant hurdle for system designers whose aim is to replicate, and by default replace, the decision-making process.

Using a pre-determined optimization algorithm is standard procedure in many areas of problem solving, and works particularly well when the exact utility of a solution can be precisely measured and used as feedback to improve performance. However the exact utility of a solution in site selection is seldom known. Multiple, conflicting criteria, and the added human element of conflicting opinions of measurement and importance create an ill-structured problem that is often dynamic, in that assessments may change as the solution space is examined. It is also relevant to note that problem-solving strategies vary from person to person, making the group situation a particularly dynamic environment.

InfraPlanner was designed as an intelligent spatial decision support system to provide decision-makers with relevant, understandable processed information, whilst leaving them in control of the decision-making process. To this end it was noted that decision-makers expressed satisfaction with outputs, as they enabled the group to find the core elements behind their conflicting assessments. In a real world situation, where political issues can dominate operational concerns, it is often most beneficial to identify these core areas as they may be traded off for concessions outside the sphere of the site selection task. Outcomes from the site selection task discussed in this paper confirm this point of view.

Giving decision-makers the ability to generate a variety of solutions that maximized aggregated suitability or minimized risk, conflict and uncertainty provided an easily understandable way for decision-makers to take more control of the analysis, rather than accepting imposed heuristics. Moreover, whilst the system makes computationally deriving a solution from input data possible, its major strength was the high information value of outputs. The experiment confirmed that a focus on a meaningful, interactive exploration of alternative outcomes, as opposed to attempting to derive a solution from initial inputs, is a valid way to support decision-makers in their task.

There are some important limitations of the current ‘InfraPlanner’ system: Firstly, the method used is currently limited to analyzing problems with the objective of locating a single facility, which makes it unsuitable for situations where multiple land uses are considered. Secondly, the use of single cells as alternatives does not accurately represent the true size and spatial configuration of a proposed development, which has been surprisingly seldom noted (Brookes 1997). Lastly, utilizing linguistic terms for data input may unnecessarily limit the accuracy of results in those cases where hard quantitative data is available.

Another difficulty noted in the group situation was the requirement to define discrete criteria. As an example, some decision-makers noted overlap in their perception of community impact versus environmental impact. Some authors have described multicriteria decisions, particularly those with multiple objectives, in terms of a hierarchical structure, whereby some criteria encompass others, eg (Saaty 1980). In a group situation this provides another area for disagreement and/or misunderstanding.

6. CONCLUSIONS

The experience gained from the example at Brisbane Airport proved the validity of an approximate reasoning approach to group site selection problems under uncertainty. The InfraPlanner system enabled decision-makers to express their assessments linguistically and receive meaningful linguistic feedback, whilst taking more control of the process than other methods allow, and satisfaction with outputs was expressed.

The results indicated a definite benefit from utilizing a multi-decision-maker framework, as consensus was unattainable. An emphasis on providing meaningful processed information, rather than offering a heuristically derived solution was also found to be beneficial.

Further work is needed to design site selection algorithms that are capable of handling multiple facility problems, and explicitly include the size and spatial configuration of the required land parcels. Genetic algorithms offer a promising method to explore feasible alternatives without resorting to the massive number of calculations required to fully examine the solution space of such problems.

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