Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in ArcGIS

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Received 26 January 2007; received in revised form 1 April 2007; accepted 4 April 2007

Abstract

This paper focuses on the integration of GIS and an extension of the analytical hierarchy process (AHP) using quantifier-guided ordered weighted averaging (OWA) procedure. AHP_OWA is a multicriteria combination operator. The nature of the AHP_OWA depends on some parameters, which are expressed by means of fuzzy linguistic quantifiers. By changing the linguistic terms, AHP_OWA can generate a wide range of decision strategies. We propose a GIS-multicriteria evaluation (MCE) system through implementation of AHP_OWA within ArcGIS, capable of integrating linguistic labels within conventional AHP for spatial decision making. We suggest that the proposed GIS-MCE would simplify the definition of decision strategies and facilitate an exploratory analysis of multiple criteria by incorporating qualitative information within the analysis.

Keywords: Analytical hierarchy process; Ordered weighted averaging; GIS; Multicriteria evaluation; Linguistic quantifiers

1. Introduction

Spatial multicriteria decision problems typically involve a set of feasible decision alternatives that are evaluated on the basis of multiple, conflicting and incommensurate criteria. GIS-based multicriteria decision analysis (GIS-MCDA) can be defined as a process that integrates and transforms geographic data (map criteria) and value judgments (decision maker’s preferences and uncertainties) to obtain overall assessment of the decision alternatives (Malczewski, 1999, 2006a).

Central to GIS-MCDA is the concept of decision rules or evaluation algorithms. A decision rule is the procedure that dictates the order of alternatives or which alternative is preferred to another in a decision problem (Starr and Zeleny, 1977). In the context of GIS-MCDA, a decision rule is a procedure that enables the decision maker to order and select one or more alternatives from a set of available alternatives (see Malczewski, 1999). There are two fundamental classes of decision (or combination) rules in GIS: the Boolean overlay operators...
and weighted summation procedures. They have been the most often used decision rules in GIS (Janssen and Rietveld, 1990; Eastman, 1997; Heywood et al., 2002; O’Sullivan and Unwin, 2003; Malczewski and Rinner, 2005). These approaches can be generalized within the framework of ordered weighted averaging (OWA) (Jiang and Eastman, 2000; Makropoulos et al., 2003; Malczewski et al., 2003; Malczewski and Rinner, 2005; Malczewski, 2006b). OWA is a family of multicriteria aggregation procedures. It has been developed in the context of fuzzy set theory (Yager, 1988). OWA involves two sets of weights: the weights of criterion importance and order weights. By changing the order weights, one can generate a wide range of outcome (decision strategy) maps. Over the last decade or so, several applications of OWA have been implemented in the GIS environment (Jiang and Eastman, 2000; Araújo and Macedo, 2002; Rinner and Malczewski, 2002; Makropoulos et al., 2003; Malczewski et al., 2003; Rashed and Weeks, 2003; Calijuri et al., 2004; Makropoulos and Butler, 2005; Malczewski, 2006b).

The analytical hierarchy process (AHP) proposed by Saaty (1980) is another well-known procedure which is based on the additive weighting model. The AHP method has been employed within the GIS environment in two distinct ways. First, it can be employed to derive the importance weights associated with criterion map layers. Then the weights can be aggregated with the criterion map layers in a way similar to weighted combination methods. This approach is of particular importance for spatial decision problems with a large number of alternatives that make it impossible to complete pairwise comparisons of the alternatives (Eastman et al., 1993; Marinoni, 2004). Second, the AHP method can be used to combine the priority for all levels of the hierarchical structure, including the level representing alternatives. In this case, a relatively small number of alternatives can be evaluated (Jankowski and Richard, 1994).

Yager and Kelman (1999) introduced an extension of the AHP using OWA operators (AHP-OWA), suggesting that the capabilities of AHP as a comprehensive tool for decision making can be improved by integration of the fuzzy linguistic OWA operators. The inclusion of AHP and OWA can provide a more powerful multicriteria decision-making tool for structuring and solving decision problems including spatial decision problems.

Both AHP and OWA procedures have been implemented individually in GIS environments. Eastman (1997) and Jiang and Eastman (2000) implemented OWA operators in GIS-IDRISI. Malczewski et al. (2003) implemented parameterized OWA procedures in ArcView 3.2 environment as a GIS-OWA module. Also, the AHP has been part of the IDRISI functionality for years. It also has been implemented in the ArcGIS environment as a VBA macro (Marinoni, 2004). However, there is still no implementation of the AHP-OWA operators using fuzzy linguistic quantifiers in GIS solutions.

There are two objectives of this paper: (1) to adapt the AHP-OWA procedures using fuzzy linguistic quantifiers for GIS-based multicriteria evaluation (MCE) procedures, and (2) to demonstrate the implementation of AHP-OWA procedures as an additional command in ArcGIS environment. Sections 2 and 3 provide an introduction to the concept of the AHP and OWA operators in a spatial decision-making context. Section 4 presents an illustrative example of the AHP-OWA. Then, in Section 5, we demonstrate the GIS-based linguistic quantifier-guided AHP-OWA. Section 6 exemplifies a real-world application of the GIS-based AHP-OWA. The final section presents concluding remarks.

2. The AHP

The AHP is a flexible and yet structured methodology for analyzing and solving complex decision problems by structuring them into a hierarchical framework (Saaty, 1980). The AHP procedure is employed for rating/ranking a set of alternatives or for the selection of the best in a set of alternatives. The ranking is done with respect to an overall goal, which is broken down into a set of criteria (objectives, attributes). The AHP procedure involves three major steps: (i) developing the AHP hierarchy, (ii) pairwise comparison of elements of the hierarchical structure, and (iii) constructing an overall priority rating.

2.1. The AHP hierarchy

The first step in the AHP procedure is to decompose the decision problem into a hierarchy that consists of the most important elements of the decision problem. In developing a hierarchy, the top level is the ultimate goal of the decision at hand. The
hierarchy then descends from the general goal to the more specific elements of the problem until a level of attributes is reached. Although the hierarchical structure typically consists of goal, objectives, attributes and alternatives, a variety of elements relevant to a particular decision problem and a different combination of these elements can be used to represent the problem (Saaty, 1980). In a GIS-based multicriteria analysis the alternatives are represented in GIS databases. Each layer contains the attribute values assigned to the alternatives, and each alternative (e.g. cell or polygon) is related to the higher-level elements (i.e. attributes). In the context of this paper, a typical four-level hierarchy of goal, objectives, attributes and alternatives has been considered in order to demonstrate the spatial AHP procedure (Fig. 1). Accordingly, the spatial decision problem here involves a set of geographically defined alternatives (e.g. parcels of land), a set of evaluation criteria (goal, objectives and attributes) and its associated weights (or preferences). The set of alternatives is denoted here by \( A_i \) for \( i = 1, 2, \ldots, m \). The alternatives are to be evaluated with respect to a set of \( p \) objectives \( O_q \) for \( q = 1, 2, \ldots, p \). The objectives are measured in terms of the underlying attributes. Thus, there is a set of \( n \) attributes (criterion map layers), \( C_j \) for \( j = 1, 2, \ldots, n \), associated with the \( p \) objectives. A subset of attributes associated with the \( q \)th objective is denoted by \( C_k(q) \) for \( k = 1, 2, \ldots, l \); \( l \leq n \). To indicate the importance of the criteria, two sets of weights, \( W_q = (w_1, w_2, \ldots, w_p) \) and \( W_k(q) = (w_1(q), w_2(q), \ldots, w_l(q)) \), are assigned to the objectives and attributes, respectively. The weights have the following properties: \( w_q \in [0, 1] \), \( \sum_{q=1}^{p} w_q = 1 \), and \( w_k(q) \in [0, 1] \), \( \sum_{k=1}^{l} w_k(q) = 1 \). The performance of alternatives \( A_i \) with respect to attributes \( C_j \) is described by a set of standardized criterion values: \( X = [x_{ij}]_{m \times n} \), \( x_{ij} \in [0, 1] \) for \( j = 1, 2, \ldots, n \).

### 2.2. Pairwise comparisons

The pairwise comparison is the basic measurement mode employed in the AHP procedure. The procedure greatly reduces the conceptual complexity of a problem since only two components are considered at any given time. It involves three steps: (i) developing a comparison matrix at each level of the hierarchy, beginning at the top and working down, (ii) computation of the weights for each element of the hierarchy, and (iii) estimation of the consistency ratio.

The pairwise comparison method employs an underlying semantical scale with values from 1 to 9 to rate the relative preferences for two elements of the hierarchy (Table 1). The pairwise comparison matrix for objective level has the following form: \( A = [a_{qt}]_{p \times p} \) where \( a_{qt} \) is the pairwise comparison rating for objective \( q \) and objective \( t \). The matrix \( A \) is reciprocal—that is, \( a_{qt} = a_{qt}^{-1} \)—and all its diagonal elements are unity—that is, \( a_{qq} = 1 \), for \( q = t \). The same principles apply to the attribute level as well. At the attribute level, a pairwise comparison matrix is obtained for each of the objectives by comparing associated attributes; thus,

<table>
<thead>
<tr>
<th>Intensity of importance</th>
<th>Verbal judgment of preference</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
</tr>
<tr>
<td>5</td>
<td>Strong importance</td>
</tr>
<tr>
<td>7</td>
<td>Very strong importance</td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>Intermediate values between adjacent scale values</td>
</tr>
</tbody>
</table>

*Note: Adapted from Saaty (1980).*
$A_{ij} = [a_{ij}]_{n \times n}$ for $q = 1, 2, \ldots, p$, where $a_{ij}$ is the pairwise comparison rating for attribute $k$ and attribute $h$ associated with objective $q$.

2.3. Criterion weights

Once the pairwise comparison matrix is obtained, our aim is to summarize preferences so that each element can be assigned a relative importance. This can be achieved by computing a vector of the weights and priorities, $\omega = [w_1, w_2, \ldots, w_p]$ for objectives and $\omega_i(q) = [w_{1(q)}, w_{2(q)}, \ldots, w_{n(q)}]$ for attributes associated with the $q$th objective.

This can be accomplished by normalizing the eigenvector associated with the maximum eigenvalue of the pairwise comparison matrix. The eigenvector then gives the relative weights of the objectives (or attributes). This normalized eigenvector can be composed by an iterative process; first the matrix $\hat{A}$ is computed by normalizing the columns of $A$:

$$\hat{A} = \left[ a_{ij}^* \right]_{n \times n},$$

where

$$a_{ij}^* = \frac{a_{ij}}{\sum_{q=1}^{n} a_{ij}^q} \quad \text{for all} \quad i, j = 1, 2, \ldots, n. \quad (1)$$

Then $\hat{A}$ is computed and normalized in $\hat{A}_2$, next $\hat{A}_3, \ldots, \hat{A}_n$ are computed until the columns of the obtained matrix are all identical. This column then gives the vector of $\omega$:

$$w_q = \frac{a_{q(i)}}{a_{q(1)}}, \quad \text{for all} \quad q = 1, 2, \ldots, p. \quad (2)$$

The attribute weights, $w_{h(q)}$, are calculated in a similar way; thus:

$$a_{ih(q)}^* = \frac{a_{ih(q)}}{\sum_{l=1}^{n} a_{ih(q)}} \quad \text{for all} \quad h = 1, 2, \ldots, l. \quad (3)$$

Then the attribute weights are given by

$$w_{h(q)} = \frac{a_{ih(q)}}{a_{i1(q)}}, \quad \text{for all} \quad h = 1, 2, \ldots, l. \quad (4)$$

One can expect that any human judgment is to some degree imperfect (or inconsistent). Therefore, it would be useful to have a measure of inconsistency associated with the pairwise comparison matrix $A$. In order to measure the degree of consistency, we can calculate the consistency index (CI) as

$$CI = \frac{\lambda_{\text{max}} - p}{p - 1}, \quad (5)$$

where $\lambda_{\text{max}}$ is the biggest eigenvalue that can be obtained once we have its associated eigenvector and $p$ is the number of columns of matrix $A$. Further, we can calculate the consistency ratio (CR), which is defined as follows:

$$CR = \frac{CI}{RI}, \quad (6)$$

where $RI$ is the random index—the consistency index of a randomly generated pairwise comparison matrix. It can be shown that $RI$ depends on the number of elements being compared (Table 2). The consistency ratio (CR) is designed in such a way that if $CR<0.10$ then the ratio indicates a reasonable level of consistency in the pairwise comparison; if, however, $CR\geq0.10$, then the values of the ratio are indicative of inconsistent judgments. In such cases one should reconsider and revised the original values in the pairwise comparison matrices.

2.4. Constructing an overall priority rating

The final step is to aggregate the relative weights of objectives and attribute levels to produce composite weights. This is done by means of a sequence of multiplications of the matrices of relative weights at each level of hierarchy. The global weights of each criterion, $w_j$, are calculated as follows:

$$w_j = w_q \times w_{k(q)}. \quad (7)$$

For the hierarchical structure defined in Section 2.1, the overall evaluation score, $R_i$ of the $i$th alternative is
calculated as follows:

\[ R_i = \sum_{j=1}^{n} w_j^q x_{ij}. \]  

(8)

3. Ordered weighted averaging (OWA)

OWA is a class of multicriteria combination operators developed by Yager (1988). OWA involves two vectors of weights: criterion importance weights \((w_j, j = 1, 2, \ldots, n)\) and order weights \((v_j)\). The importance weight \(w_j\) is assigned to the \(j\)th criterion map (attribute) for all locations to indicate the relative importance of the attribute according to the decision maker’s preferences. The order weights are associated with the criterion values on a location-by-location basis. They are assigned to the \(i\)th location’s attribute value in decreasing order without considering from which criterion map the value comes.

Considering the same spatial decision problem defined in Section 2.1 (same hierarchical structure), the OWA combination operator associates with the \(i\)th location (e.g. raster or point) and a set of order weights \(V = (v_1, v_2, \ldots, v_n)\) such that \(v_j \in [0, 1]\) for \(j = 1, 2, \ldots, n\), and \(\sum_{j=1}^{n} v_j = 1\), and is defined as follows (see Yager, 1988; Malczewski et al., 2003; Malczewski, 2006b):

\[ OW A_i = \sum_{j=1}^{n} \left( \frac{v_j x_{ij}}{\sum_{j=1}^{n} v_j x_{ij}} \right) z_j, \]  

(9)

where \(z_1 \geq z_2 \geq \cdots \geq z_m\) is obtained by reordering the criterion values \(x_{i1}, x_{i2}, \ldots, x_{im}\), and \(u_j\) is the reordered \(j\)th criterion weight, \(w_j\).

Considering \(w_j = w_j^q\), Eq. (9) can be recognized as the conventional AHP combination defined in Eq. (8) with modified criterion weights. 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 special cases of the WLC, Boolean overlay combination (AND) and (OR) (Yager, 1988; Malczewski et al., 2003; Malczewski, 2006b).

3.1. Quantifier-guided OWA combination

Zadeh (1983) introduced the concept of fuzzy linguistic quantifiers. This concept allows for the conversion of natural language arrangements into formal mathematical formulations, directly leading to the formulation of the MCE functions (Munda, 1995).

There are two general classes of the linguistic quantifiers: absolute and relative quantifiers. Absolute quantifiers can be defined as fuzzy subsets of \([0, +\infty[\). They can be used to represent linguistic terms such as about 4 or more than 10. The relative quantifiers are closely related to imprecise proportions. They can be represented as fuzzy subsets over the unit interval, with proportional fuzzy statements such as few, half, many, etc. Here, we will only consider a class of the relative quantifiers known as the relative quantifiers: absolute and relative quantifiers. Absolute quantifiers can be defined as fuzzy subsets of \([0, +\infty[\). They can be used to represent linguistic terms such as about 4 or more than 10. The relative quantifiers are closely related to imprecise proportions. They can be represented as fuzzy subsets over the unit interval, with proportional fuzzy statements such as few, half, many, etc. Here, we will only consider a class of the relative quantifiers known as the regular increasing monotone (RIM) quantifiers.

In this setting, if \(Q\) is a linguistic quantifier, then it can be represented as a fuzzy subset over the unit interval \([0, 1]\), where for each \(p\) in the unit interval, the membership grade \(Q(p)\) indicates the compatibility of \(p\) with the concept denoted by \(Q\). To identify the quantifier, we employ one of the most often used methods for defining a parameterized subset on the unit interval (Yager, 1996):

\[ Q(p) = p^z, \quad a > 0. \]  

(10)

It can be applied for generating a series of the RIM quantifiers. We can associate the quantifier with a value of a single parameter, \(a\), and by changing the value of the parameter one can generate different types of linguistic quantifiers between two extreme cases of the at least one and all quantifiers (Table 3).

In the context of spatial multicriteria decision making, it can be assumed that the relationship between the criteria or objectives (based on decision-maker judgment) can be described as: “\(Q\) of the important criteria (objectives) are satisfied by an acceptable alternative”, where \(Q\) is a RIM linguistic statement (for example, \(Q = \text{“Many”}\)). The concept of linguistic quantifiers provides a method for generating ordered weights based on the RIM linguistic quantifiers (see Eq. (10)). They are defined

<table>
<thead>
<tr>
<th>Linguistic quantifier ((Q))</th>
<th>At least one</th>
<th>Few</th>
<th>Some</th>
<th>Half</th>
<th>Many</th>
<th>Most</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>0.0001</td>
<td>0.1</td>
<td>0.5</td>
<td>1</td>
<td>2</td>
<td>10</td>
<td>1000</td>
</tr>
</tbody>
</table>
as follows (Yager, 1996):

\[ v_j = \left( \frac{\sum_{k=1}^{l} u_k}{\sum_{k=1}^{n} u_k} \right)^x - \left( \frac{\sum_{k=1}^{j-1} u_k}{\sum_{k=1}^{n} u_k} \right)^x. \] (11)

It is important to mention that criterion weights, in most of the GIS-based MCE procedures, have the property \( \sum_{j=1}^{n} w_j = 1 \). Accordingly, \( \sum_{j=1}^{n} u_j = 1 \) and Eq. (11) can be simplified to

\[ v_j = \left( \sum_{k=1}^{j} u_k \right)^x - \left( \sum_{k=1}^{j-1} u_k \right)^x. \] (12)

Given the criterion weights, \( w_j \), and order weights, \( v_j \), the quantifier-guided OWA can be defined as follows:

\[ \text{OWA}(q) = \sum_{j=1}^{n} \left( \left( \sum_{k=1}^{j} u_k \right)^x - \left( \sum_{k=1}^{j-1} u_k \right)^x \right) z_{ij}. \] (13)

4. AHP_OWA procedure

We introduced two approaches to GIS-based MCE, the AHP and OWA. However, these two procedures do not operate at the same level. The AHP is a *global* tool for creating a hierarchical model of the spatial decision problem, analyzing the whole process and evaluating each alternative. The evaluation process in the AHP uses a simple weighted linear combination to calculate the local scores of each alternative as a cell (raster format) or a polygon.

The OWA operators, alternatively, provide a general framework for making a series of *local* aggregations used in the AHP. The very nature of these two procedures gives rise to their combination and create a more powerful decision making tool (Yager and Kelman, 1999).

In this framework, we shall assume that the two first steps of the AHP have been achieved, which are formation of the hierarchical structure and calculating the relative weights of the elements (objectives and attributes) of the hierarchy by conducting pairwise comparisons. At this point, the quantifier-guided OWA procedures take the lead for the rest of the analysis. The procedure at this stage involves three main steps (Malczewski, 2006b): (i) specifying the linguistic quantifier \( Q \), (ii) generating a set of ordered weights associated with \( Q \), and (iii) computing the overall evaluation for each alternative at each level of the hierarchy by means of the OWA combination function.

Considering the same four-level hierarchy spatial decision problem introduced in Section 2.1, the overall score of the \( i \)th alternative can be calculated in two steps: first, the score of the \( i \)th alternative regarding each objective will be calculated as follows:

\[ s_{iq} = \sum_{k=1}^{l} u_{k(q)} \cdot z_{ik(q)} \]

for all \( i = 1, 2, \ldots, m \) and \( q = 1, 2, \ldots, p \) (14) and

\[ v_{k(q)} = \left( \sum_{k=1}^{l} u_{k(q)} \right)^{x_q} - \left( \sum_{k=1}^{l} u_{k(q)} \right)^{x_q}, \] (15)

where \( z_{ik(q)} \) is obtained by reordering attribute values associated with the \( q \)th objective, \( x_{k(q)} \), and \( u_{k(q)} \) is the reordered \( k \)th attribute weight associated with the \( q \)th objective. \( x_{q} \) is the parameter linked to the linguistic quantifier associated with the \( q \)th objective.

Given the score of each alternative regarding each objective, \( s_{iq} \), the overall score of the \( i \)th alternative can be calculated as follows:

\[ \text{AHP_OWA}(i) = \sum_{q=1}^{p} v_q s_{iq} \quad \text{for all} \quad i = 1, 2, \ldots, m \] (16)

and

\[ v_q = \left( \sum_{q=1}^{p} u_q \right)^{x_q} - \left( \sum_{q=1}^{p} u_q \right)^{x_q}, \] (17)

where \( s_{iq} \) is obtained by reordering of the alternative scores at the \( q \)th objective level, \( s_{iq} \), and \( u_q \) is the reordered \( q \)th objective weight. \( x_q \) is the parameter linked to the linguistic quantifier associated with the goal of the spatial decision problem according to the hierarchal structure.

5. Illustrative example

To demonstrate AHP_OWA using linguistic quantifiers, we consider a hypothetical site-suitability problem. The problem involves evaluating a set of sites (parcels of land: A, B, C) for development on the basis of economic and environmental objectives. The objectives are measured in terms of five criteria: (i) price, (ii) proximity to major roads, (iii) slope, (iv) distance from wetlands and (v) view.
The overall goal here is to identify the best parcel for development. This requires assessing the relative importance (weights) of the elements at each level of the decision hierarchy and assigning a linguistic quantifier to the levels of goal and objectives.

Table 4
Pairwise comparison matrix of the level of objectives and calculated weights

<table>
<thead>
<tr>
<th></th>
<th>Economic</th>
<th>Environmental</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic</td>
<td>1</td>
<td>2</td>
<td>0.667</td>
</tr>
<tr>
<td>Environmental</td>
<td>0.5</td>
<td>1</td>
<td>0.333</td>
</tr>
</tbody>
</table>

Table 5
Pairwise comparison matrix of economic attributes and calculated weights

<table>
<thead>
<tr>
<th></th>
<th>Price</th>
<th>Prox. to road</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>1</td>
<td>3</td>
<td>0.75</td>
</tr>
<tr>
<td>Prox. to road</td>
<td>0.333</td>
<td>1</td>
<td>0.25</td>
</tr>
</tbody>
</table>
The economic objective has been judged to be two times as important as the environmental objective. This results in assigning weights of 0.667 and 0.333 to the two objectives, respectively (Table 4).

The economic objective is measured by two attributes, price and proximity, to major roads. The price attribute has been estimated to be three times more important than the proximity to major roads. Consequently, weights of 0.750 and 0.250 have been assigned to price and proximity to major roads, respectively (Table 5). The environmental objective is measured in terms of three attributes, slope, distance from wetlands and view. Table 6 shows the pairwise comparison matrix and calculated weights for the attributes of environmental objectives. In addition, linguistic quantifiers “Many”, “All” and “Many” are assigned to the goals of decision problem, economic objective and environmental objective, respectively. This means that “All” of the important criteria (according to their relative weights) associated with economic objective (price and proximity to roads) must be satisfied by an acceptable solution. In terms of environmental objective, an acceptable alternative should satisfy “Many” of the important criteria associated with the objective (slope, distance to wetlands and view) and finally, for the goal of the decision problem, “Many” of the important objectives must be satisfied.

Given the standardized criterion maps and corresponding objectives and criterion weights, we apply AHP_OWA operators (Eqs. (14)–(17)) for assigned fuzzy linguistic quantifiers. Given the final scores of AHP_OWA, the parcels of land can be ranked. Alternative A is the most suitable, followed by alternative B. The C site is least suitable for development (Fig. 2).

6. Implementation of AHP_OWA in ArcGIS

The AHP_OWA module has been implemented within ArcGIS 9.1 as a command. Commands are components that implement the ICommand interface of ArcObjects, ArcGIS development platform.

In order to deliver AHP_OWA customization as a command, a COM-Compliant component is created as a Dynamic Link Library using Visual Studio 2005 and ArcObjects. There are some advantages of developing customized components by using a COM-Compliant environment such as Visual Studio 2005, than by using VBA macros in ArcGIS. The main advantages are: (i) a wider range of functionalities can be integrated within the customization, (ii) codes are hidden with DLL files, (iv) it would be possible to extend and customize all aspects of ArcGIS application and (v) the customization can be easily delivered to client machines (ESRI, 2004).

The AHP_OWA procedure starts with reading all the raster layers within the current map document of ArcGIS. This enables the user to select the relevant map criteria layers for the decision problem (Fig. 3). Then, the maximization and minimization criterion maps can be selected and standardized (Fig. 4). Step three of the procedure involves definition of the hierarchical structure of the decision problem by selecting the number of objectives, naming the objectives and selection of the associated criteria to each objective (Fig. 5).
Given the hierarchical structure of the problem, the pairwise comparisons of objectives and the criteria corresponding to each objective, the relative weights for objectives and criteria can be generated. The user can input the preference values using the given scale in Table 1. Since the pairwise comparison matrix is reciprocal, the transpose cell is filled with the reciprocal value whenever a preference enters into a cell. The weights are generated using Eqs. (1)–(4) (Fig. 6).

Within the following steps of the module, the user can change or refine the calculated weights of the objectives and the corresponding criteria (Fig. 7). Finally, in the last step of the module, the linguistic quantifiers are assigned to the goal of the decision problem and each objective. Using Eqs. (14)–(17), a result map layer of AHP_OWA scores is created and added to the map document of ArcGIS. By changing the linguistic quantifiers associated with the objectives and attributes, a wide range of decision scenarios can be generated and the corresponding map layers are added to the map document (Fig. 8).

7. Example application

To illustrate the application of AHP_OWA in a real-world decision problem, we use data for a land suitability problem in Arva and Ilderton region, north of London, in the province of Ontario, Canada. In order to identify the most suitable lands for housing development, the same four-level decision hierarchy, objectives and criteria as mentioned in Section 4 are considered. Except for distance from wetlands, which is a maximization criterion, the rest of the criteria are to be minimized.

The importance of the objectives and criteria has been judged and weights are calculated according to Tables 4–6. In addition, linguistic quantifiers “All” and “Many” are assigned economic objective and environmental objective, respectively. Given the weights for objectives and corresponding criteria and linguistic quantifiers for economic and environmental objectives, we apply AHP_OWA operators for selected values of fuzzy linguistic quantifiers: at least one, few, some, half, many, most and all for the goal of the decision making.

Fig. 9 shows the seven alternative land suitability scenarios for housing development. Each pattern is associated with a given linguistic quantifier and the corresponding \( z \) parameter. The scenario associated with the quantifier “all” for the goal of the decision problem represents the worst-case scenario, in that...
the lowest \( s_q \) value (Eq. (14)) is assigned to each location. The land suitability scenario associated with fuzzy quantifier “half” (\( x = 1.0 \)) represents the strategy corresponding to the conventional weighted linear combination on the level of objectives (\( s_q \)). The end of the continuum represents another extreme scenario. Under this scenario, the land suitability pattern is composed of the best possible outcomes (that is, the highest possible value of \( s_q \) is selected at each location). The alternative scenarios have been developed under the assumption that only the linguistic quantifier associated with the goal of the decision problem changes. Ultimately, for the decision problem here, \( 7^3 \) alternative scenarios can be developed.

8. Conclusions

This paper has presented the theoretical basis for the GIS-based AHP_OWA approach and its integration with a customized command within the ArcGIS environment. The AHP_OWA implementation in ArcGIS extends the work of Marinoni (2004) on the AHP method for spatial multicriteria decision analysis and addresses the suggestion by Yager and Kelman (1999) to improve the capabilities of the conventional AHP method by integration of the fuzzy linguistic OWA operators.

The fusion of AHP and OWA enables AHP to include quantifier-guided aggregation instead of simple weighted averaging into the process of

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Fig. 9. Land suitability maps of the Arva and Ilderton region in Ontario: AHP_OWA results for selected linguistic quantifiers.
aggregation of criterion values, which in turn brings natural language quantification to spatial decision analysis. Fuzzy linguistic quantifiers, as part of the human language, are a significant part of computer–human interactions. Fuzzy logic has contributed to the challenge of the interpretation and translation of natural language specifications into formal mathematical expressions, which paved the way to the formulation of the OWA procedure.

The fuzzy linguistic OWA has the capability of capturing qualitative information which the decision maker may have regarding the discerned relationship between the different evaluation criteria. Within the AHP_OWA procedure, the qualitative information will be combined with the quantitative preferences of the AHP method.

This paper demonstrated how, by applying different linguistic quantifiers, a decision maker could obtain a wide range of decision strategies and scenarios. The described AHP_OWA module brings the capabilities of fuzzy quantifiers within the ArcGIS environment, enhances the existing AHP module and improves ArcGIS functionalities by integrating a multicriteria decision analysis module into its environment.

Acknowledgments

This research was supported by the GEOIDE Network (Project: HSS-DSS-17) of the Canadian Network of Centers of Excellence. The authors would like to thank anonymous reviewers for their constructive comments on an earlier version of this paper.

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