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Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis

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Abstract

The objective of this paper is to incorporate the concept of fuzzy (linguistic) quantifiers into the GIS-based land suitability analysis via ordered weighted averaging (OWA). OWA is a multicriteria evaluation procedure (or combination operator). The nature of the OWA procedure depends on some parameters, which can be specified by means of fuzzy (linguistic) quantifiers. By changing the parameters, OWA can generate a wide range of decision strategies or scenarios. The quantifier-guided OWA procedure is illustrated using land-use suitability analysis in a region of Mexico.

Keywords: GIS; Fuzzy quantifiers; Ordered weighted averaging; Multicriteria evaluation; Land-use suitability analysis

1. Introduction

Land-use suitability mapping and analysis is one of the most useful applications of GIS for spatial planning and management (Collins et al., 2001; Malczewski, 2004). The analysis aims at identifying the most appropriate spatial pattern for future land uses according to specify requirements, preferences, or predictors of some activity (Hopkins, 1977; Collins et al., 2001). In general, the GIS-based land suitability analysis assumes that a given study area is subdivided into a set of basic unit of observations such as polygons or rasters. Then, the land-use suitability problem involves evaluation and classification of the areal units according to their suitability for a particular activity. Over the last 10 years or so, land-use suitability problems have increasingly been conceptualized in terms of the GIS-based multicriteria evaluation procedures (e.g. Banai, 1993; Jankowski and Richard, 1994; Joerin, 1995; Barredo, 1996; Beedasy and Whyatt, 1999; Malczewski, 1999; Barredo et al., 2000; Mohamed et al., 2000; Bojorquez-Tapia et al., 2001; Dai et al., 2001; Joerin et al., 2001).

There are two fundamental classes of multicriteria evaluation methods in GIS: the Boolean overlay operations (noncompensatory combination rules) and the weighted linear combination (WLC) methods (compensatory combination rules). They have been the most often used approaches for land-use suitability analysis (Heywood et al., 1995; Jankowski, 1995; Barredo, 1996; Beedasy and Whyatt, 1999; Malczewski, 2004). These approaches can be generalized within the framework of the ordered weighted averaging (OWA) (Asproth et al., 1999; Jiang and Eastman, 2000; Makropoulos et al., 2003; Malczewski et al., 2003; Malczewski and Rinner, 2005). OWA is a family of multicriteria combination procedures (Yager, 1988). It involves two sets of weights: the weights of relative criterion importance and the order (or OWA) weights. By specifying an appropriate set of the OWA weights, one can generate a wide range of different land-use suitability maps.

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Although OWA is a relatively new concept (Yager, 1988), there have been several applications of this approach in the GIS environment (Asproth et al., 1999; Jiang and Eastman, 2000; Mendes and Motizuki, 2001; Rasmussen et al., 2001; Araújo and Macedo, 2002; Makropoulos et al., 2003; Malczewski et al., 2003; Rashed and Weeks, 2003; Calijuri et al., 2004; Makropoulos and Butler, 2005; Rinner and Malczewski, 2002). All those applications use the conventional (quantitative) OWA. Specifically, research into GIS-OWA has so far focused on the procedures that require quantitative specification of the parameters associated with the OWA operators. However, there is some evidence to suggest that the conventional OWA operators are of limited applicability in situations involving a large set of evaluation criteria (Yager, 1996). One might expect that in a complex spatial decision situation, the decision makers might find it difficult (or even impossible, especially for problems involving a large number of criteria) to provide the precise numerical information on the OWA parameters. For a large set of evaluation criteria one faces a difficult problem of combining the criterion maps in a way that the results correspond to the decision maker's preferences with respect to the criteria. In such situations, the key aspects of the decision problem may be specified in terms of some fuzzy linguistic quantifiers such as: most of the criteria must be satisfied or at least 80% of the criteria must be satisfied, etc. This calls for an extension of the conventional OWA so that it can accommodate situations involving qualitative statements in the form of fuzzy quantifiers (Yager, 1988, 1996).

The aim of this paper is to combine the advantages of fuzzy linguistic quantifiers and OWA operators for GIS-based multicriteria evaluation procedures. Section 2 defines the GIS-based OWA. Section 3 discusses the concept of fuzzy linguistic quantifiers and the use of the quantifiers in the GIS-OWA procedures. Then, Section 4 presents an illustrative example of the linguistic quantifier-guided OWA. Finally, Section 5 provides conclusions.

2. Definition of OWA

The GIS-based multicriteria evaluation procedures involve a set of geographically defined alternatives (e.g. parcels of land) and a set of evaluation criteria represented as map layers. The problem is to combine the criterion maps according to the criterion (attribute) values and decision maker's preferences using a decision rule (combination rule). Here it is assumed that an alternative is represented as a cell (raster) or a polygon. Each alternative ($i = 1, 2, \ldots, m$) is described by a set of standardized criterion values: $a_{ij} \in [0, 1]$ for $j = 1, 2, \ldots, n$. A multicriteria evaluation problem involves also preferences which are typically specified as the criterion weights, $w_j \in [0, 1]$ for $j = 1, 2, \ldots, n$, and $\sum_{j=1}^{n} w_j = 1$. Given the input data (a set of criterion map layers and criterion weights), the OWA combination operator associates with the i-th location (e.g., raster or point) a set of order weights $v = v_1, v_2, \ldots, v_n$ such that $v_j \in [0, 1]$, $j = 1, 2, \ldots, n$, $\sum_{j=1}^{n} v_j = 1$, and is defined as follows (see Yager, 1988; Malczewski et al., 2003):

$$\mathrm{OWA}_i = \sum_{j=1}^{n} \left(\frac{u_j v_j}{\sum_{j=1}^{n} u_j v_j} \right) z_{ij}, \tag{1}$$

where $z_{i1} \geq z_{i2} \geq \ldots \geq z_{in}$ is the sequence obtained by reordering the attribute values $a_{i1}, a_{i2}, \ldots, a_{in}$, and u_j is the criterion weight reordered according to the attribute value, z_{ij}. It is important to point to the difference between the two types of weights (the criterion weights and the order weights). The criterion weights are assigned to evaluation criteria to indicate their relative importance. All locations on the j-th criterion map are assigned the same weight of w_j. The order weights are associated with the criterion values on the 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.

Eq. (1) can be recognized as the conventional weighted linear combination (WLC) with modified criterion weights. The weights are obtained by multiplying the criterion weights by the order weights. For example, given a set of criterion values at the i-th location on the j-th criterion, $a_{ij} = (0.1, 0.0, 0.6, 0.8, 0.3)$, a set of order weights, $v_j = 0.2$ for all j, and the following set of criterion weights, $w_j = (0.07, 0.27, 0.33, 0.13, 0.20)$, the modified criterion weight method results in $\mathrm{OWA}_i = 0.369$ (see Table 1).

With different sets of order weights, one can generate a wide range of OWA operators including the most often used GIS-base map combination procedures: the weighted linear combination (WLC) and Boolean overlay operations, such as intersection (AND) and union (OR) (Yager, 1988; Malczewski et al., 2003). The AND and OR operators represent the extreme cases of OWA and they correspond to the MIN and MAX operators, respectively. The order weights associated with the MIN operator are: $v_n = 1$, and $v_j = 0$ for all other weights. Given the order weights, $\mathrm{OWA}_{i(\mathrm{MIN})} =$

Table 1
Illustrative example: calculating OWA

j	Criterion values a_{ij}	Criterion weights w_j	Ordered criterion values z_{ij}	Reordered criterion weights u_j	Order weights v_j	$u_j v_j$	$u_j v_j z_j$	$u_j v_j z_{ij} / \sum_j u_j v_j$
1	0.1	0.07	0.8	0.13	0.2	0.026	0.021	0.104
2	0.0	0.27	0.6	0.33	0.2	0.066	0.040	0.198
3	0.6	0.33	0.3	0.20	0.2	0.040	0.012	0.060
4	0.8	0.13	0.1	0.07	0.2	0.014	0.001	0.007
5	0.3	0.20	0.0	0.27	0.2	0.054	0.000	0.000
Σ						0.200		0.369

$\mathrm{MIN}_j(a_{i1}, a_{i2}, \ldots, a_{in})$. The following weights are associated with the MAX operator: $v_1 = 1$, and $v_j = 0$ for all other weights, and consequently $\mathrm{OWA}_{i(\mathrm{MAX})} = \mathrm{MAX}_j(a_{i1}, a_{i2}, \ldots, a_{in})$. Assigning equal order weights (that is, $v_j = 1/n$ for $j = 1, 2, \ldots, n$) results in the conventional WLC, which is situated at the mid-point on the continuum ranging from the MIN to MAX operators (Yager, 1988). Thus, $\mathrm{OWA}_{i(\mathrm{WLC})} = \sum_{j=1}^{n} w_j a_{ij}$. Also, one can verify that the conventional $\mathrm{WLC}_i = (0.1 \times 0.07) + (0.0 \times 0.027) + (0.6 \times 0.33) + (0.8 \times 0.13) + (0.3 \times 0.20) = 0.369$.

3. Quantifier-guided OWA combination procedure

Given a set of criterion maps and a fuzzy linguistic quantifier Q, one can perform a procedure for combining the criteria based on a statement regarding the relationship between the evaluation criteria. For example, the combination procedure may be guided by such statement as: most of the criteria should be satisfied, at least half of the criteria should be satisfied, all criteria must be satisfied, etc. This type of procedure is referred to as the quantifier-guided multicriteria evaluation (Yager, 1996). The procedure involves three main steps: (i) specify the quantifier Q, (ii) generate a set of order weights associated with Q, and (iii) compute the overall evaluation for each i-th location (alternative) by means of the OWA combination function.

3.1. Linguistic quantifies

Based on the type of linguistically quantified statements one can distinguish between: the absolute linguistic quantifiers and the relative (or proportional) linguistic quantifiers (Zadeh, 1983). Statements such as at least about 4, about 5, almost 10, not much more than 10, more than 5, etc. provide examples of the absolute quantifiers. The relative linguistic quantifiers indicate a proportional quantity such as most, many, a few, almost all, about half, about 60%, etc. They can be represented as fuzzy sets of the unit interval [0, 1]. They measure a proportion of a set, where 0 means 0% and 1 means 100%. Thus if Q is a linguistic quantifier, then it can be represented as a fuzzy set Q of the unit interval [0, 1], where for each $p \in [0, 1]$, $Q(p)$ indicates the degree of compatibility of p with the concept denoted by Q. For example, if Q is most and if $Q(0.95) = 1$, then we would be saying that 95% is completely compatible with the idea conveyed by the linguistic quantifier most, while $Q(0.60) = 0.75$ would indicate that 60% is only 0.75 compatible with the concept of most.

There is no empirical evidence to show which of the two classes of linguistic quantifiers is more suitable for multicriteria evaluation. Here we will focus on a class of the proportional quantifiers known as the regular increasing monotone (RIM) quantifiers (Yager, 1996). To identify the quantifier we employ one of the simplest and the most often used methods for defining a

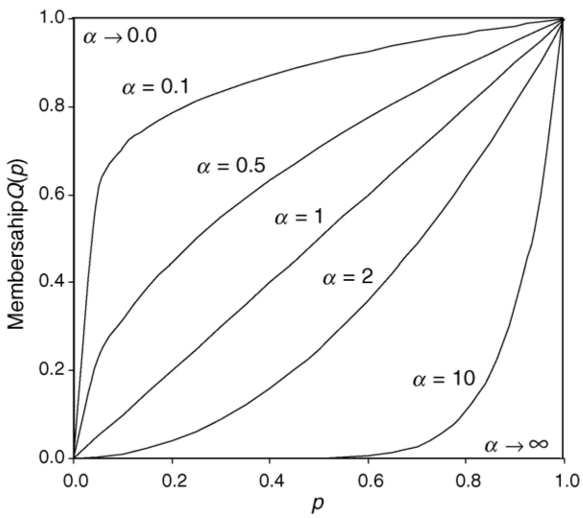

Fig. 1. A family of the regular increasing (non-decreasing) monotone (RIM) quantifiers.

Table 2
Some properties of the regular increasing monotone (RIM) quantifiers for selected values of the α parameter

α	Quantifier (Q)	OWA weights (v_j)	ORness	Tradeoff	GIS combination procedure
$\alpha \to 0$	At least one	$v_1 = 1$; $v_j = 0$, for all other weights	1.0	0.0	OWA (OR, MAX)
$\alpha = 0.1$	At least a few	[a]	[a]	[a]	OWA
$\alpha = 0.5$	A few	[a]	[a]	[a]	OWA
$\alpha = 1$	Half (identity)	$v_j = 1/n$, for all j	0.5	1.0	OWA (WLC)
$\alpha = 2$	Most	[a]	[a]	[a]	OWA
$\alpha = 10$	Almost all	[a]	[a]	[a]	OWA
$\alpha \to \infty$	All	$v_n = 1$; $v_j = 0$, for all other weights	0.0	0.0	OWA (AND, MIN)

[a] These measures are problem-specific.

parameterized subset on the unit interval (Yager, 1996). Specifically,

$$Q(p) = p^{\alpha}, \quad \alpha > 0 \tag{2}$$

$Q(p)$ is represented as a fuzzy set in interval [0, 1] (see Fig. 1). It can be applied for generating a whole family of the RIM quantifiers. Table 2 shows a selection of the RIM quantifiers and their characteristics. By changing the parameter, α, one can generate different types of quantifiers and associated operators between the two extreme cases of the all and at least one quantifiers. For $\alpha = 1$, $Q(p)$ is proportional to α and therefore it is referred to as the identity quantifier. As α tends to zero, the quantifier $Q(p)$ approaches its extreme case of at least one, which corresponds to the MAX operator. As α tends to infinity, the quantifier $Q(p)$ approaches its extreme case of all, which corresponds to the MIN operator.

3.2. The order weights

The concept of fuzzy quantifiers provides a method for generating the order weights. The weights are based on the RIM quantifier (see Eq. (2)). They are defined as follows (Yager, 1996):

$$v_j = \left(\frac{\sum_{k=1}^{j} u_k}{\sum_{k=1}^{n} u_k}\right)^{\alpha} - \left(\frac{\sum_{k=1}^{j-1} u_k}{\sum_{k=1}^{n} u_k}\right)^{\alpha}. \tag{3}$$

It is important to notice that in the GIS-based multicriteria evaluation procedures, the criterion weights have typically the following property: $\sum_{j=1}^{n} w_j = 1$. Consequently, $\sum_{j=1}^{n} u_j = 1$ and Eq. (3) can be simplified to:

$$v_j = \left(\sum_{k=1}^{j} u_k\right)^{\alpha} - \left(\sum_{k=1}^{j-1} u_k\right)^{\alpha}. \tag{4}$$

Thus, the order weights, v_j, are derived from the criterion weights, w_j. There a number of methods for estimating criterion weights; that is, the decision maker's preferences with respect to the evaluation criteria (see Malczewski, 1999). In the context of the quantifier-guided OWA combination procedure, an appropriate method for estimating criterion weights should be based on an ordering of the evaluation criteria (see Stillwell et al., 1981; Malczewski, 1999). Denoting the rank position of the j-th attribute by r_j, the most important attribute is ranked first ($r_j = 1$), the second most important attribute ranks second ($r_j = 2$), and so on; the least important attribute is assigned a rank of $r_j = n$. Then, the j-th criterion weight can be defined as follows:

$$w_j = \frac{n - r_j + 1}{\sum_{j=1}^{n} n - r_k + 1}, \quad \text{for}\, k = 1, 2, \ldots, n. \tag{5}$$

Stillwell et al. (1981) have demonstrated empirically that in many situations the rank-order approximation is a satisfactory approach to the criterion weight assessment.

3.3. The OWA operators

Given the criterion weights, w_j, and order weights, v_j, the quantifier-guided OWA is defined as follows:

$$\mathrm{OWA}_i = \sum_{j=1}^{n}\left(\left(\sum_{k=1}^{j} u_k\right)^{\alpha} - \left(\sum_{k=1}^{j-1} u_k\right)^{\alpha}\right) z_{ij}. \tag{6}$$

Table 3 provides a computational example of the OWA procedure for the i-th location and five criterion values and for three linguistic quantifiers: at least one ($\alpha \to 0$), identity ($\alpha = 1$), and all ($\alpha \to \infty$). Given the criterion values $a_{ij} = (0.1,\ 0.0,\ 0.6,\ 0.8,\ 0.3)$, the procedure involves: (i) ranking the criterion according to their importance; that is, criterion $j = 3$ ranks first and

Table 3
Illustrative example: computing OWA_i for the i-th location and five criterion values for the linguistic quantifiers

j	Criterion values a_{ij}	Criterion ranks r_j	Criterion weights w_j	Ordered criterion values z_{ij}	Criterion weights u_j	$\left(\sum_{k=1}^{j} u_k\right)^{\alpha}$	$\left(\sum_{k=1}^{j} u_k\right)^{\alpha} - \left(\sum_{k=1}^{j-1} u_k\right)^{\alpha}$	$\left(\left(\sum_{k=1}^{j} u_k\right)^{\alpha} - \left(\sum_{k=1}^{j-1} u_k\right)^{\alpha}\right) z_{ij}$
(a) At least one ($\alpha = 0.0001$)								
1	0.1	5	0.07	0.8	0.13	1.00	1.00	0.8
2	0.0	2	0.27	0.6	0.33	1.00	0.00	0.0
3	0.6	1	0.33	0.3	0.20	1.00	0.00	0.0
4	0.8	4	0.13	0.1	0.07	1.00	0.00	0.0
5	0.3	3	0.20	0.0	0.27	1.00	0.00	0.0
Σ			1.00		1.00		1.00	$\mathrm{OWA}_i = 0.8$
(b) Identity ($\alpha = 1$)								
1	0.1	5	0.07	0.8	0.13	0.13	0.13	0.104
2	0.0	2	0.27	0.6	0.33	0.46	0.33	0.198
3	0.6	1	0.33	0.3	0.20	0.66	0.20	0.060
4	0.8	4	0.13	0.1	0.07	0.73	0.07	0.007
5	0.3	3	0.20	0.0	0.27	1.00	0.27	0.000
Σ			1.00		1.00		1.00	$\mathrm{OWA}_i = 0.369$
(c) All ($\alpha = 1000$)								
1	0.1	5	0.07	0.8	0.13	0.0	0.0	0.0
2	0.0	2	0.27	0.6	0.33	0.0	0.0	0.0
3	0.6	1	0.33	0.3	0.20	0.0	0.0	0.0
4	0.8	4	0.13	0.1	0.07	0.0	0.0	0.0
5	0.3	3	0.20	0.0	0.27	1.0	1.0	0.0
Σ			1.00		1.00		1.00	$\mathrm{OWA}_i = 0.0$

criterion 1 ranks fifth; (ii) calculating the criterion weights according to Eq. (5), $w_j = (0.07, 0.27, 0.33, 0.13, 0.20)$; (iii) ordering the criterion values; that is, $z_{ij} = (0.8, 0.6, 0.3, 0.1, 0.0)$; (iv) reordering the criterion weights according to z_{ij}; that is, $u_j = (0.13, 0.33, 0.20, 0.07, 0.27)$; (v) calculating OWA according to Eq. (6) (see Table 3). Notice that the at least one operator identifies the maximum criterion value (i.e., $\mathrm{OWA}_i = 0.8$), while the all operator identifies the minimum criterion value (i.e., $\mathrm{OWA}_i = 0.0$) (see Table 3a and c). For the identity operator $\mathrm{OWA}_i = 0.369$. This is the value obtained for the OWA operator defined by (1) with $v_j = 1/n$ for all j (see Section 2 and Table 1).

3.4. Land-use suitability patterns: decision strategy space

The GIS-based OWA provides a tool for generating a wide range of decision strategies (alternative land-use suitability patterns) by specifying an appropriate linguistic quantifier (the α parameter) and the associated set of the OWA weights. The position of the OWA operator can be identified on the continuum ranging from the all quantifier to the at least quantifier. There are two commonly used measures for identifying the position of the OWA operator on the continuum: the tradeoff and ORness measures (Yager, 1988, 1996; Jiang and Eastman, 2000).

The tradeoff is a measure of compensation (criterion substitutability). It indicates the degree to which a poor performance on one criterion can be compensated by a good performance on other criteria under consideration (Jiang and Eastman, 2000). The tradeoff measure takes values in the interval from 0.0 to 1.0 (see Table 1 and Fig. 2). The value of 0.0 indicates no tradeoff among criteria. If the value equals 1.0, then there is a full tradeoff. The measure can be interpreted as degree of the OWA weights dispersion. Specifically, the degree to which the weights are evenly distributed across all criteria controls the level of overall tradeoff among criteria (see Table 2).

The position of OWA on the continuum between the quantifier all and at least one can also be identified by specifying the degree of ORness (Yager, 1988, 1996). The degree of ORness ranges from 0.0 to 1.0 (see Table 1 and Fig. 2). It measures the degree to which an OWA operator is similar to the logical OR (or the at least one quantifier) in terms of its combination behaviour (Malczewski et al., 2003). ORness is also related to the RIM quantifier (see Section 3.1). Specifically, one can obtain different degrees of ORness by changing the α parameter (Yager, 1988, 1996).

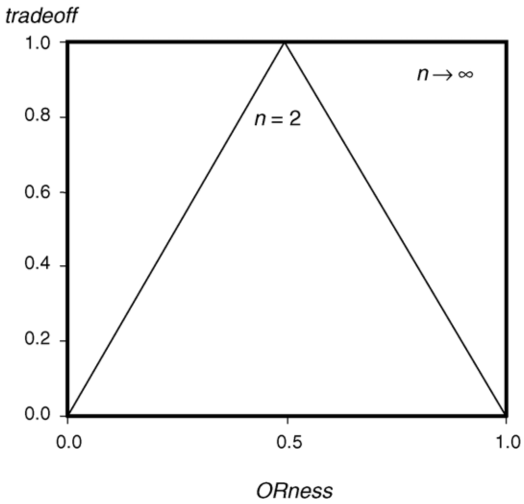

Fig. 2. Decision strategy space: the relationship between the tradeoff and ORness measures.

The decision strategy space is defined by the two OWA measures: tradeoff and ORness. Fig. 2 shows the relationship for two extreme cases of $n = 2$ and $n \to \infty$. The degree of the ORness and tradeoff depends of the number of criterion maps being included into a combination procedure. Except for the special cases of ORness = 1.0, 0.5 and 0.0, the greater the number of criterion maps, the higher the level of tradeoff for a given degree of ORness (Table 2). For the special cases, the measures of tradeoff and ORness are the same irrespective of the number of criterion maps. For $n = 2$, the decision space has a triangular form. Any point of the triangle represent a decision strategy defined by the dimensions of ORness and the tradeoff among criteria. As the number of criterion maps increases from $n = 2$ to $n \to \infty$ (a large number), the decision strategy space gradually changes its shape from a triangular to a rectangular form. This implies that for a large number of criterion maps the tradeoff approaches 1.0 irrespective of the level of ORness.

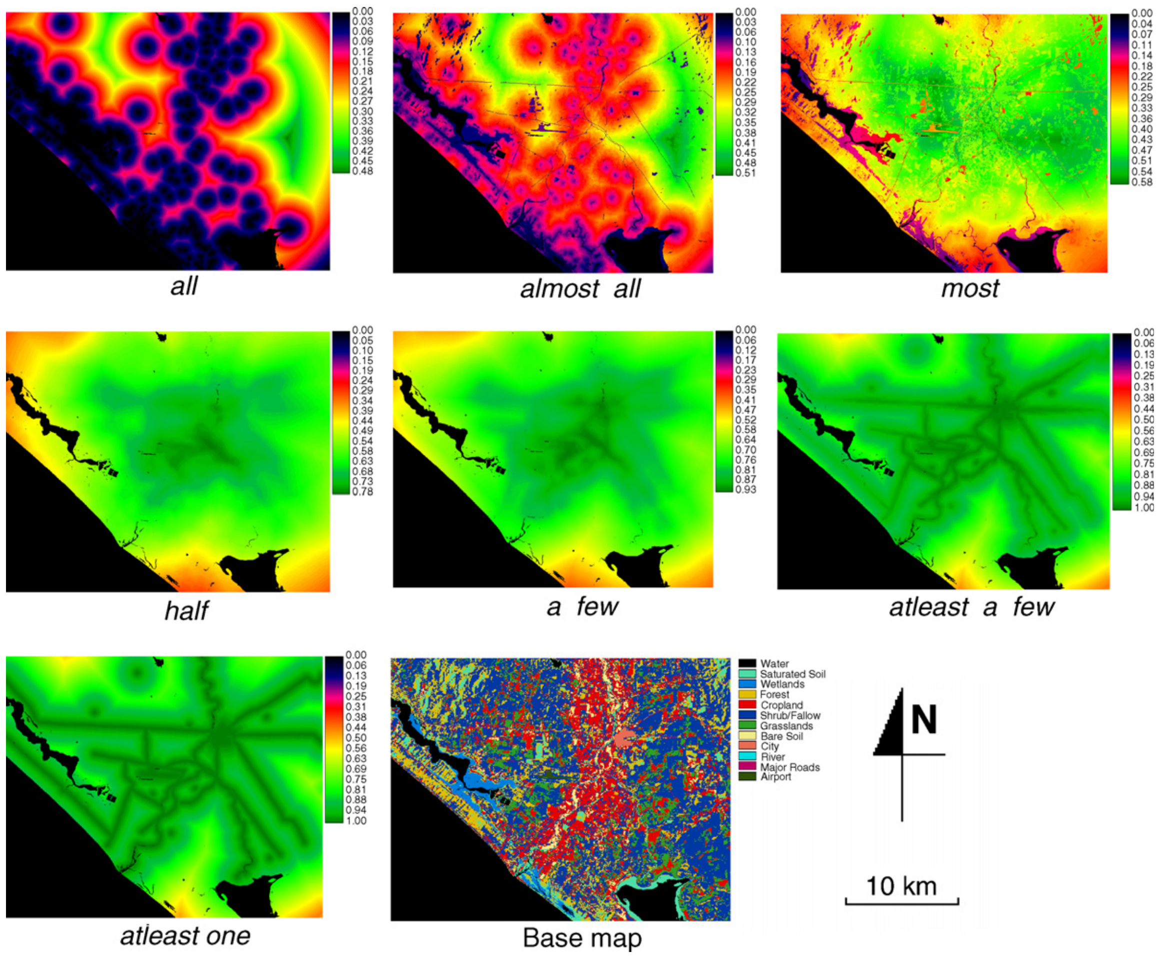

Fig. 3. Land suitability maps of the Villa Union region in Mexico: the OWA results for selected fuzzy linguistic quantifiers.

4. Example application

To illustrate the fuzzy quantifiers-guided OWA we use data for a land-use suitability problem in the Villa Union area, in the Sinaloa province on the Pacific coast of Mexico. In order to identify the most suitable lands for housing development, the following criteria are considered: (i) proximity to the city, (ii) proximity to the airport, (ii) proximity to major roads, (iii) proximity to rivers, and (v) distance from wetlands. The first four criteria are to be minimized; that is, the closer the area to the city, major road, and river, the better. The fifth factor is a maximization criterion that requires the suitable areas to be located away from wetlands. The criterion maps were derived from LANDSAT TM Satellite image dated 1993 (see Fig. 3; Base map) by an unsupervised clustering using a *k*-means (minimum distance) classifier on bands 3–5. The procedure was performed using EASI/PACE Image Analysis System. The infrastructure elements (city, airport, and major roads) where manually digitized using ancillary data and applied to the classified image using IDRISI. The map covers an area of 25 by 20 km.

The five criteria were ranked as follows: the proximity to major roads (the most important criterion ranked first), the proximity to the city, the proximity to the airport, the proximity to rivers, and the distance from wetlands (the least important criterion). Using Eq. (5), the following estimated values for the criterion weights were obtained: 0.33, 0.27, 0.20, 0.13, and 0.07 for the proximity to major roads, proximity to the city, proximity to the airport, proximity to rivers, and distance from wetlands, respectively. Given the standardized criterion maps and corresponding criterion weights, we apply the OWA operator (6) for selected values of fuzzy quantifiers: at least one, at least a few, a few, identity, most, almost all, and all. Each quantifier is associated with a set of order weights that are calculated according to Eq. (4).

Fig. 3 shows the seven alternative land suitability patterns for housing development. Each pattern is associated with a given quantifyer, the α parameter, and the measure of tradeoff. The strategy associated with the fuzzy quantifier all (the MIN operator) represents the worst-case scenario (the lowest criterion value is assigned to each location). According to this strategy, the most suitable areas for housing developments are located away from the wetland (Fig. 3). Increasing the value of α from 0.0 to 1.0 corresponds to increasing the degree of ORness as well as increasing tradeoff between evaluation criteria (see Table 2 and Fig. 2). This implies that relatively higher and higher values are assigned to the higher-ranking criterion values at the expense of lower-ranking criteria at a given location.

The land suitability pattern associated with the identity quantifier ($\alpha = 1.0$) represents the strategy corresponding to the conventional weighted linear combination. This strategy is characterized by ORness = 0.5 and a full tradeoff. Increasing the value of α from 1.0 to a large number represents decreasing degree of ORness and decreasing level of the tradeoff among criteria. Comparison of corresponding maps in Fig. 3 indicates that along with decreasing ORness, the areas that could be recommended for housing development get larger and larger. The end of the continuum represents the extreme (MAX) strategy. Under this strategy, the land suitability pattern is composed of the best possible outcomes (that is, the highest possible value is selected at each location). The MAX operator (the at least one quantifier) produces the most suitable areas along the main roads and near the city.

5. Conclusions

This paper has presented an application of natural language quantification to GIS-based land-use suitability analysis. Natural language is a principal means of human communication. Fuzzy (or linguistic) quantifiers are at the heart of human language and they are an important means of computer–human interaction. How people process information represented in natural language is still a challenge to computer sciences in general and to GIScience in particular. It is clear that, for a computer with the conventional processing paradigm to process natural language formalism is required. The fuzzy quantifiers provide an example of such formal concept. Applying fuzzy logic via the theory of approximate reasoning has facilitated the translation of natural language specifications into formal mathematical expressions, which subsequently led to the formulation of the OWA procedure. The paper demonstrated how one could obtain a wide range of multicriteria decision rules (strategies) by applying appropriate fuzzy quantifiers. The family of OWA operators includes the conventional GIS-based Boolean overlay operations and weighted linear combination methods.

The fuzzy-quantifier-based OWA approach is capable of capturing qualitative information the decision maker or analyst may have regarding his/her perceived relationship between the different evaluation criteria. It is in this effort one can see the benefit of the fuzzy quantifier approach to GIS-based multicriteria analysis. This is especially true in situations involving a large number of criterion maps. In such situations, it is impractical or even impossible to specify the exact relationships between evaluation criteria. The OWA approach provides a mechanism for guiding the decision maker/analysis through the multicriteria combination procedures. It allows him/her to explore different decision strategies or scenarios. Consequently, the approach facilitates a better understanding of the alternative land-use suitability patterns.

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