

A Soft Approach to Conflict Resolution in Multi-Criteria Evaluation of Urban Land Use Suitability

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Abstract: The objective of this paper is to incorporate the concept of fuzzy quantifiers into the GIS-based urban land suitability analysis via ordered weighted averaging (OWA) as a soft approach to conflict resolution. Conflicts arise when certainty of included layers in the suitability assessment and their weights are objectionable and experts differ in their views as to the importance and rank of these layers. 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 which is much needed in managerial arenas. This paper presents a collection of seven quantifiers with their associated weight functions to explore their effects on the ranking of alternatives. This is illustrated through using urban land suitability analysis in Tehran Province, Iran. The results indicate that the OWA method is flexible and easy to implement in urban land use suitability analysis and provides a framework which is analogous to accuracy assessment. Also, the results can help the decision makers to choose the preferred type of linguistic quantifiers according to their degree of optimism and consensus to achieve the best solution on urban land development scenarios. We show the approach provides a means of arriving at consensus among different stakeholders and helps remove major conflicts among decision makers.

Key words: Multi-criteria evaluation · Ordered Weighted Averaging · Fuzzy linguistic quantifiers · Urban land suitability analysis · GIS

INTRODUCTION

Land suitability analysis and mapping is one of the most useful applications of GIS for spatial planning and management. Suitability assessment means finding the most appropriate spatial location and pattern for future land uses according to specific requirements, preferences or predictions of certain activities [1-3]. Naturally, when implementing land suitability assessment using various data resources and maps, RS and GIS techniques become very useful. Most of these land suitability assessments are multi-criteria by nature, as suitability for different land uses is influenced by a number of parameters at the same

time. Mainly, there are two fundamental classes of multi-criteria evaluation methods in GIS: the Boolean overlay operations which are non-compensatory and the weighted linear combination (WLC) methods which allow for trade-offs between different layers. These methods have been the most often used approaches for land use suitability analysis. A more advanced approach, yet mostly untested is the ordered weighted averaging [4] which has been developed to bring more flexibility to the assessment and which provides a means for tradeoff and risk taking when assessing land suitability. Yager introduced the ordered weighted average (OWA) aggregation method in which linguistic quantifiers are used in the aggregation function.

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This approach allows for using linguistic quantifiers such as ‘all’, ‘most’, ‘at least half’ and similar terms as quantifiers for the decision. So, the decision can be made based on linguistic requirements such as ‘choose the best alternative based on most of the criteria’, or based on ‘all of the criteria’ or ‘few of the criteria’ and, etc. Hence, the OWA approach generates a range of alternatives which means more flexibility. It can provide a decision support medium for decision makers to achieve a consensus on the best possible development plans. By using this approach, it is also possible to estimate sensitivity of the alternatives’ ranking to the type of linguistic quantifier. Although OWA is a relatively new concept, there have been several applications of this approach in the GIS environment and it has been used in many fields including neural networks, database systems, fuzzy logic controllers, expert systems, market research, linguistic quantified propositions, mathematical programming, lossless image compression and also in solving MCDM problems [5]. Unfortunately, there are not many applications of the procedure to urban land use planning. Although, many studies of urban land use management have been conducted over the past years [6-14] but, the need to apply novel methods of urban land use planning that can: (1) resolve controversies among stakeholders (2) include uncertainties in data, decisions and natural changes in environmental setting and (3) provide a means of consensus making among decision makers in Iran is strongly felt. Like other developing countries, Iran has experienced a high level of urbanization which has transformed the physical fabric of urban areas. Tehran Province is one of the most rapid growing regions of the country in which strong economic state and allocation of many facilities and infrastructures creates a mass immigration pull. Thus, it is no wonder that the area has experienced rapid population growth and continuous

expansion in recent years. As the area is in high demand for other uses as well, the degree of conflict among stakeholders is high, which necessitates a collaborative consensus building method to be implemented for land development. This study showcases such an approach for Tehran Province through application of the OWA method. It also tries to amend the shortage of linkage between knowledge producers (scientists in universities and institutes) and users of such knowledge (decision makers, stakeholders and common people) through a softer approach to land use planning.

Study Area Description: Tehran province is one of the 31 provinces of Iran, with a total area of 12981 km². It is located to the north of the central plateau of Iran (Fig. 1) spanning over 34° to 36°5'N and 50° to 53°E. Its population is around 13,281,858 million and the Province is composed of 10 Cities. (Tehran, Rey, Robat Karim, Shahriar, Eslamshahr, Varamin, Pakdasht, Damavand, Firouzkouh, Shemiranat). Tehran province is the richest province as it contributes to approximately 29% of the country's GDP (Gross Domestic Product). Furthermore, it houses approximately 18% of the country's population. It is the most industrialized province in Iran and 86.5% of its population resides in urban areas with the remaining 13.5% living in rural areas. Tehran Province has over 17,000 industrial units employing 390,000 people, 26% of all units in Iran. The metropolis of Tehran is the capital city of the province and of Iran. Tehran, with a population of more than 7 million, is ranked amongst the 20 most populous metropolitan cities of the world already suffering from all the illnesses of large metropolises such as air, noise and scenery pollution and over-crowding [15]. So, scientists and high ranking officials already feel the need to direct population and urban growth to other suitable areas within the Province in the hope to lift the pressure off Tehran.

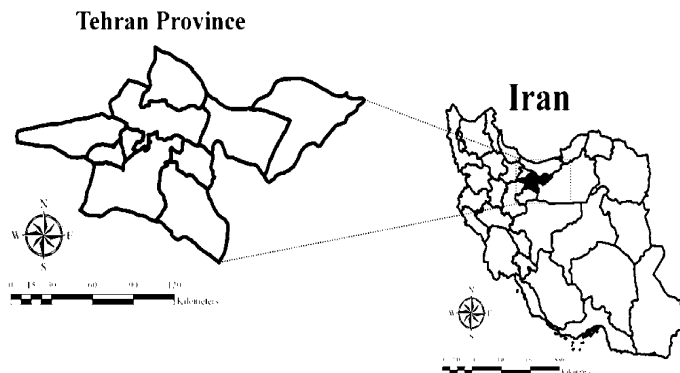


Fig. 1: The location of Tehran province

MATERIAL AND METHODS

Multi-criteria Analysis and the GIS-based Land Use Suitability Assessment: The approach of breaking the environment into different layers, analyzing and integrating them according to pre-defined models for the given development presented in this paper is analogous to the approach discussed by Makropoulos and Butler [16]. Although in a traditional sense, the three steps has been applied manually for many years using McHarg’s [17] method, which has been modified for Iran by Makhdoum [18]. However, in the more modern computerized multi criteria version of land capability assessment, the initial, ill-defined fuzzy set can be decomposed to better-defined sets, for easier and safer identification of fuzzy membership functions. After identifying the individual fuzzy membership functions for the decomposed sets, an integration method is used to generate the combined fuzzy set’s membership function. The general framework of MCA is shown in Fig. 2 and the process can be described as a three-step algorithm as below:

1-Breaking up of the Complex Environment (Fuzzy Information) – Selection of Evaluation Criteria: There are various issues that affect the selection of evaluation criteria for multi criteria decision making (MCDM).

Normally, the question at hand, availability, scale of the problem, flexibility of the computer package used and the extent of the area being analyzed affects criteria selection. When choosing criteria, care should be exercised not to make the problem unnecessarily complex or over simplified such that the assessor is made sure that the affected area is adequately represented in the process. Keeney and Raiffa [19] identified a number of properties of a set of evaluation criteria. They suggested that each evaluation criterion must be comprehensive and measurable and the set must be complete (cover all aspects of the problem), operational (meaningful in analysis), decomposable (broken into parts to simplify the process), non-redundant (avoid double counting) and minimal. The selection process has to target the problem at hand and represent the characteristics of the environment that is being analyzed. According to the main objective of this study--which is urban land-use suitability assessment-- a large number of environmental, economic and social factors are relevant. After literature reviews and discussions with researchers and local experts in 2011, the criteria for urban land-use suitability assessment in Tehran Province were selected from a long list that included natural and ecological attributes and socio-economic factors. Clearly, each criterion should be carefully chosen with respect to the local conditions. Totally, 15 factors were selected for the assessment.

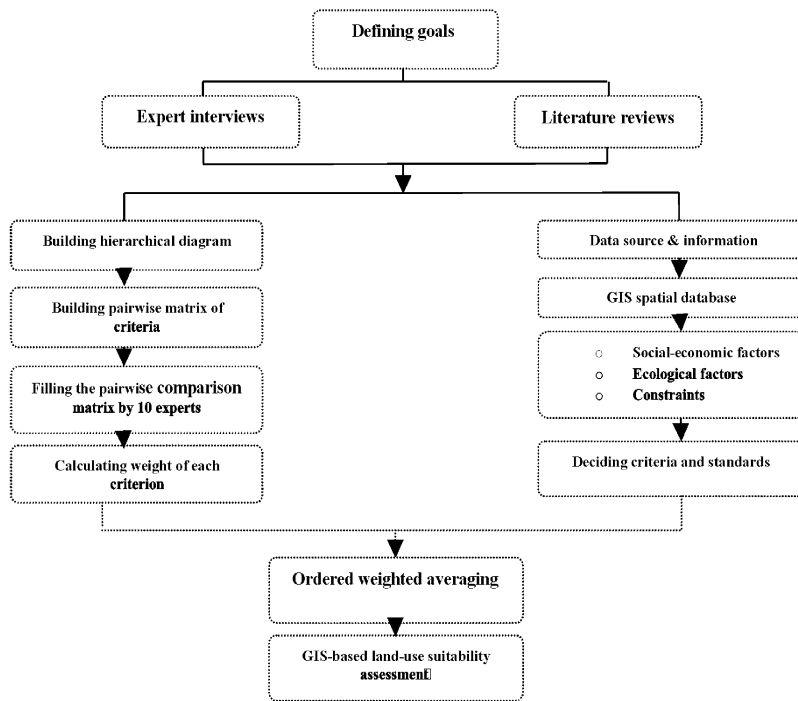


Fig. 2: General framework of the MCA

Table 1: Weights for criteria and sub-criteria

Criteria	Weights	Sub- criteria	Weights
Elevation	0.0229		-
Aspect	0.0157		-
Slope	0.1434		-
Soil attributes	0.0937	Soil type	0.25
		Sensitivity to erosion	0.4
		Land capability	0.35
Climate types	0.0229		-
Vegetation	0.0575		-
Distance from river	0.0937		-
Ground water depth	0.0575		-
Distance from fault lines	0.2022		-
Wind speed	0.0229		-
Geology	0.0937	Sensitivity to erosion	0.6
		Foundation capacity	0.4
Distance from roads	0.0575		-
Distance from power sources	0.0229	Electricity lines	0.4
		gas lines	0.35
		Power plants	0.25
Distances from existing land uses	0.0361	Industries	0.65
		Mines	0.35
Distance from residential lands	0.0575		-

The 15 criteria and their sub-criteria that have been used are shown in Table 1. These include slope, aspect, elevation, geology, soil attributes, climate types, ground water depth (m), wind speed (knots), vegetation type, distance from: (1) rivers (m), (2) fault lines (m), (3) existing land uses such as industries and mines (m), (4) urban infrastructures and power supply facilities such as power plants, gas lines and power lines (m), (5) the main roads (m) and (6) residential and urban areas (m) [1, 9, 11, 18, 20-26].

2-Generation of the Individual Fuzzy Sets – Criterion Maps and Their Standardization: After breaking up the affected environment into relevant information layers, maps should be generated for each of the layers known as criteria. In doing so, maps with different scales from various governmental departments were collected and projected into the standard projection system (WGS_1984_UTM_Zone_39N) and converted into grids with a pixel size of 30m×30m.

To be able to utilize criteria and their spatial representation, they should be associated with a common scale of measurement. For this reason, we need to standardize criteria maps during which the values of different layers are changed to a common scale so that all fall within a predefined range. Hence, in the next stage, a standardization process of the factors to a continuous

scale and a byte-level range of 0-255 by the user-defined fuzzy set membership function were implemented. These transforming standards were considered through literature reviews and discussions with researchers and local experts on land resources, environmental protection, urban planning, geology and social development.

3-Weighting – Integration: All criteria that are taken into account in the decision process are generally not equally important to the expected outcome. This relative importance should therefore be identified and the criteria should be prioritized – typically through the application of a weighting scheme. Weights should be considered to be an expression of decision maker’s choices or experience and can illustrate conflicts of interests where multiple decision makers are involved [16]. In order to obtain the criterion importance weights we considered the pair wise comparison method, developed by [27] in the context of the analytic hierarchy process (AHP). Based on the hierarchical structure shown in Table 1, the relative importance of factors was analyzed according to the advice given by 10 experts with related backgrounds. Through AHP, pair-wise comparison matrices were filled by experts and the weights for factors were determined. The important point of this stage is the consistency ratio in comparisons. Saaty suggests that in a scientific study, consistency ratio should be less or equal to 0.1 to be sure

about our judgments. This figure was less than 0.1 for all the pair-wise matrices filled by the experts. Then, by averaging the weights, the single rank of each factor was determined and so was the total rank (Table 1).

Another concept in the spatial multi criteria decision analysis (SMCDA) is the 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. In the context of GIS-MCDA, a decision rule is the order chosen by decision makers and other evaluators to select one or more alternatives from a set of available alternatives [28]. Depending on the nature of the alternatives and the information (criteria), the rules can be applied in a deterministic, probabilistic or fuzzy context [16]. A variety of rules from simple additive weighting to ordered weighted averaging methods can be found in the literature [29-33]. Here, we briefly describe the weighted linear combination and then move on to the ordered weighted averaging method, which forms the basis of our approach.

Weighted Linear Combination (WLC): A common compensatory method used for the estimation and implementation of numerous criteria in a GIS is the Weighted Linear Combination (WLC). By using this method, the total score of land use suitability for one assessment unit is calculated using the following equation:

$$S_i = \sum_{j=1}^n w_j \times x_i(j) \quad (1)$$

Where S_i is the integrated evaluation value of grid i , w_j is the weight for factor j and $x_i(j)$ is the value of factor j of grid i . The reason why this is the most frequently used technique lies in the fact that Eq. (1) can be applied through any GIS with fundamental overlay capabilities. Eastman [34] as well as Malczewski [35], emphasize that WLC implies the acceptance of two assumptions: linearity and additivity. Linearity implies that the benefit from more input of a criterion is constant and independent on the characteristics of the problem and additivity implies independency between the variables (criteria). In practice, these assumptions are generally not valid. Direct weight assignment, relying exclusively on the experience of the decision maker can be often misleading [16]. On the other hand, multi criteria decision making (MCDM) problems are usually affected by uncertainty. One of these uncertain parameters is the decision maker's degree of optimism,

which has an important effect on the results. In this way, the application of other methods which can remove such errors seems necessary. To achieve the cited flexibility and remove the error, we apply the ordered weighted averaging method for Tehran Province which is in very high demand for land development.

Definition of OWA: Yager [4] introduced a special aggregation technique based on the ordered weighted averaging (OWA) operator, which is a common generalization of the three basic aggregation functions (Max, Min and average). For a given set of n criterion (attribute) maps, an OWA operator can be defined as function $OWA: I^n \rightarrow I$, where $I=[0, 1]$ with an associated set of order weights $v = [v_1, v_2, \dots, v_n]$ such that $v_j \in [0, 1], j= 1, 2, \dots, n, \sum_{j=1}^n v_j = 1$. In this method, it is assumed that an alternative is represented as a cell (raster) or a polygon. Each alternative ($i = 1, 2, \dots, m$) is described by a set of standardized criterion values: $\alpha_{ij} \in [0, 1]$ for $j= 1, 2, \dots, n$. The OWA operator is defined as follows:

$$OWA_i(\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{in}) = \sum_{j=1}^n v_j z_{ij} \quad (2)$$

Where $z_{i1} \geq z_{i2} \geq \dots \geq z_{in}$ is the sequence obtained by reordering the attribute values $\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{in}$. We have to be careful about 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 but the order weights are associated with the criterion values on the location-by-location basis and depend on the decision maker's degree of optimism which is known as Orness degree. By defining an appropriate set of the OWA weights, a wide range of different land-use suitability maps can be generated that softens the procedure of decision making.

Quantifier-guided Owa Combination Procedure: Zadeh [36] introduced the concept of fuzzy linguistic quantifiers. Using this concept one can convert natural language arrangements into formal mathematical formulations. 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, which are used in this study, are closely related to imprecise proportions and are represented as fuzzy subsets over the unit interval, with

proportional fuzzy statements such as few, half, many, at least 0.5 and more than 0.3 and etc. With a batch of criterion maps and a fuzzy linguistic quantifier Q , we can combine 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 shows that how many criteria the decision maker wants to consider. Yager [37] categorized the relative quantifiers into three classes:

1. *Regular monotonically non-decreasing.* In this type of quantifiers, the more criteria are satisfied, the higher the value of the quantifier. The quantifier $Q(r)$ can be thought of as the degree that the concept Q has been satisfied by r . Examples for this type of quantifier are ‘Most’, ‘All’, ‘More than α ’, ‘There exists’ and ‘At least α ’. This type of quantifier has the following properties: $Q(0) = 0, Q(1) = 1$, If $r_1 > r_2$ then $Q(r_1) \geq Q(r_2)$.
2. *Regular monotonically non-increasing.* These quantifiers are used to express linguistic terms such as ‘Few’, ‘Less than α ’, ‘Not all’ and ‘None’ in which the quantifier prefers fewer criteria to be satisfied. Such a quantifier has the following properties: $Q(0) = 1, Q(1) = 0$, If $r_1 < r_2$ then $Q(r_1) \geq Q(r_2)$.
3. *Regular unimodal.* These quantifiers are used to express linguistic terms such as ‘About α ’ or ‘Close to α ’ which implies that the maximum satisfaction is achieved when exactly α is satisfied. This quantifier is characterized by: $Q(0) = Q(1) = 0, Q(r) = 1$ for $\alpha \leq r \leq b, r_2 \leq r_1 \leq \alpha$ then $Q(r_1) \geq Q(r_2), r_2 \geq r_1 \geq b$ then $Q(r_2) \leq Q(r_1)$.

Calculation of the Order Weights: A number of methods have been suggested for determining the order weights in the OWA operator. In this study, we focus on the method that allows us to obtain the order weights from functional forms of the proportional monotone linguistic quantifier such as few, more than α , less than α , most, etc. see [38]. One approach for generating the weights has been proposed by [38, 39] for the regular monotonically increasing and decreasing quantifiers. For the regular monotonically increasing quantifiers, the order weights are defined as follows:

$$v_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right), \quad j=1, \dots, n. \quad (3)$$

The weights for the regular monotonically non-increasing quantifiers are the antonyms of the regular monotonically increasing quantifiers. Thus, these weights are defined as:

$$v_j = Q\left(\frac{j-1}{n}\right) - Q\left(\frac{j}{n}\right), \quad j=1, \dots, n. \quad (4)$$

Calculation of the order weights in this stage is analogous to [40]. Here, we will work on both the regular monotonically non-decreasing and non-increasing quantifiers by using seven families of quantifiers to study their effect on urban land suitability analysis. The selected fuzzy quantifiers are: “at least one”, “less than 50%”, “few”, “average”, “most”, “more than 50%” and “all”. We focus on the most suitable and risk aversion quantifiers to decrease the undesirable consequences of urban development. By studying the distribution of evaluation criteria (factors) in different suitability patterns through applying different linguistic quantifiers, the risk aversion quantifiers can be determined and recommended for further work.

RESULTS AND DISCUSSION

Urban Land Suitability Assessment: Given the standardized criterion maps and their corresponding weights, described in ‘Material and method’ section, we applied the OWA operator for the selected fuzzy quantifiers. Each quantifier is associated with a set of order weights. Table 2 shows different sets of order weights associated with seven linguistic quantifiers (at least one, less than 50%, few, average, most, more than 50% and all) for 15 criteria. In this procedure, it is necessary to order the criterion values for the i -th location in descending order. The criterion ranks (r_j) shows the descending order of criterion values for the i -th location and the other columns show the associated set of order weights accompanied by this rank. Finally, Fig. 3 shows the seven alternative land suitability patterns for urban land use suitability analysis in Tehran Province.

As it is shown in Fig. 3, the suitability assessment through different linguistic quantifiers leads to nearly the same suitable sites, though with different value ranges. All the suitable sites are approximately located in the southern part of the Province. However, the main point is the degree of suitability which is absolutely different in these maps.

Table 2: Order weights for 15 criteria by seven linguistic quantifiers for the i-th location

Criterion ranks (r_j)	OWA weights (v_j)						
	At least one	Less than 50%	Few	Most	Average	More than 50%	All
1	1	0.1334	0	0	0.0666	0	0
2	0	0.1333	0	0	0.0666	0	0
3	0	0.1333	0	0	0.0666	0	0
4	0	0.1334	0.1334	0	0.0666	0	0
5	0	0.1333	0.1333	0.0666	0.0666	0	0
6	0	0.1333	0.1333	0.1334	0.0666	0	0
7	0	0.1334	0.1334	0.1333	0.0666	0	0
8	0	0.0666	0.1333	0.1333	0.0666	0.0666	0
9	0	0	0.1333	0.1334	0.0666	0.1334	0
10	0	0	0.1334	0.1333	0.0666	0.1333	0
11	0	0	0.0666	0.1333	0.0666	0.1333	0
12	0	0	0	0.1334	0.0666	0.1334	0
13	0	0	0	0	0.0666	0.1333	0
14	0	0	0	0	0.0666	0.1333	0
15	0	0	0	0	0.0666	0.1334	1
Σ	1	1	1	1	1	1	1

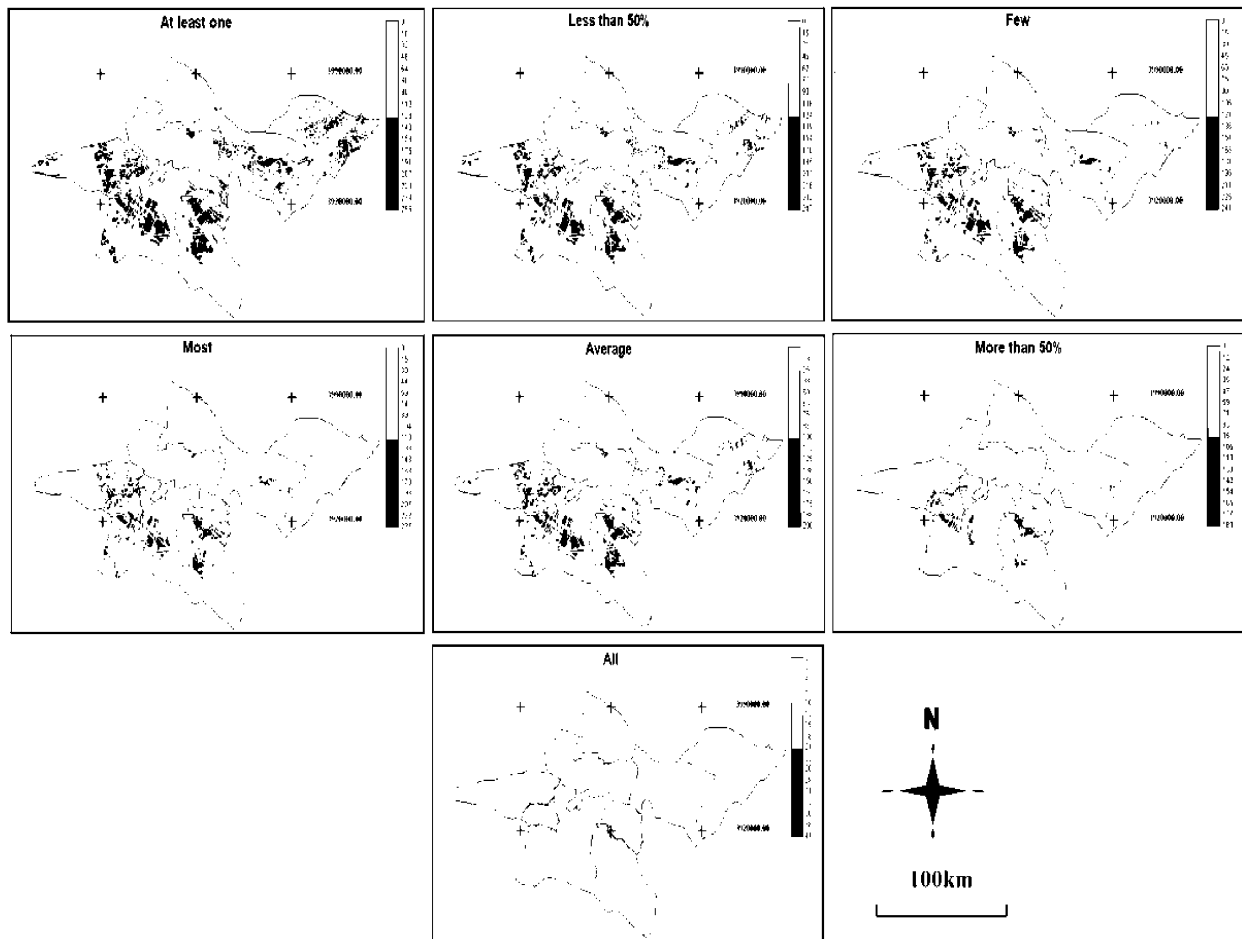


Fig. 3: The OWA results for the selected fuzzy linguistic quantifiers

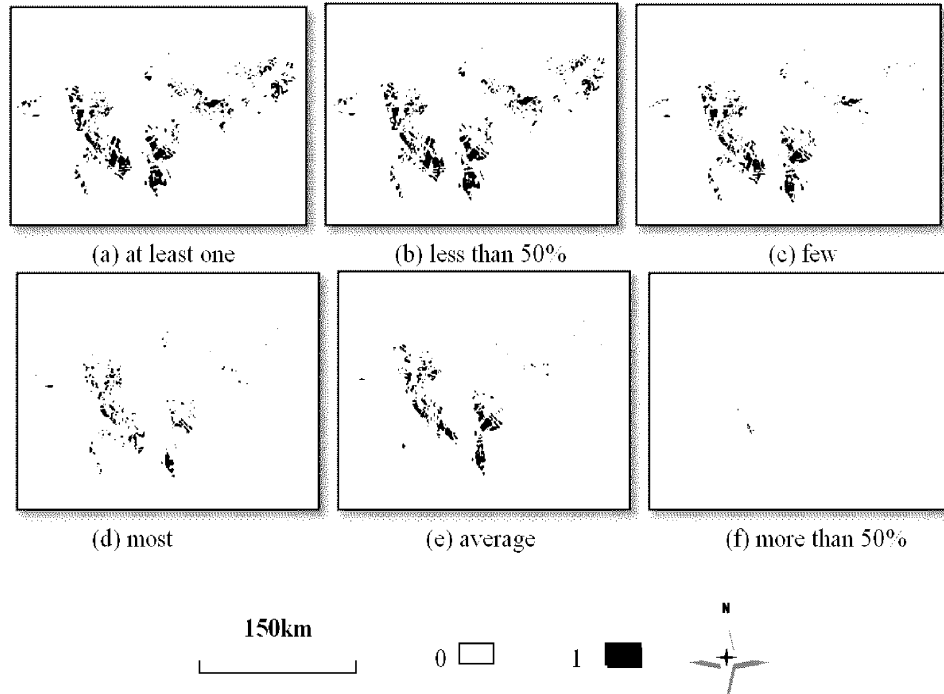


Fig. 4: The Boolean maps of land suitability patterns with pixel values of more than 150

Obviously, the strategy associated with the fuzzy quantifier ‘at least one’ (the MAX operator) represents the best-case scenario (the highest criterion value is assigned to each location). With this strategy, the land suitability pattern has the best possible results and the suitability values change between 0 - 255. By moving through this continuum (from ‘at least one’ to ‘all’ quantifier) the land suitability scores decreases. This means that at the beginning of this continuum, relatively higher and higher values are assigned to the higher-ranking criterion values at the expense of lower-ranking criteria at a given location that leads to higher-ranking values. In the case of ‘less than 50%’ and ‘few’ quantifiers (when order weights are more inclined towards the higher-ranked factors) risk taking is higher (more of an OR approach). In the case of ‘most’ and ‘more than 50 %’ quantifiers (when order weights are mostly assigned to the lower-ranked factors) risk aversion is higher (more of an AND approach). On the other end of this continuum is the ‘all’ strategy. ‘All’ (the MIN operator) represents the worst-case scenario (the lowest criterion value is assigned to each location). In this case, the suitability values range between 0-41 that shows the lowest suitability score.

Now we want to restrict the sites to the more suitable lands. So, by considering a threshold of 150, the pixels with suitability values of less than 150 were omitted. So, all of the maps with the exception of ‘All’ (the MIN

operator) were reclassified to Boolean maps with pixel values of 0 (for pixel values of less than 150) and 1 for (for pixel values of more than 150). This reclassification for the ‘All’ (the MIN operator) cannot be done because of its pixel values. The result for the other six suitability maps can be seen in Fig. 4.

Therefore, the suitability maps from different linguistic quantifiers were applied and the overlap among them studied. In this way, it was possible to delimit areas where the results of the different suitability patterns were similar and where they were different. This helps to pinpoint the most suitable sites based on the highest overlapping areas and facilitates arriving at consensus among stakeholders with different opinions. In doing so, the results of OWA calculations using different linguistic quantifiers were cross-tabulated and the common areas were derived and shown in Fig.5, where (a) shows the common areas from the four linguistic quantifier suitability maps, (b) shows the common areas from the five linguistic quantifier suitability maps and (c) shows the common areas from the six linguistic quantifier suitability maps.

Here, by extracting the more suitable lands, we can compare the factor distribution in different suitability maps. It is assumed that risk taking quantifiers may have higher range of factor distribution and vice versa, risk aversion quantifiers may have limited distribution of the factors that is more inclined to the best condition.

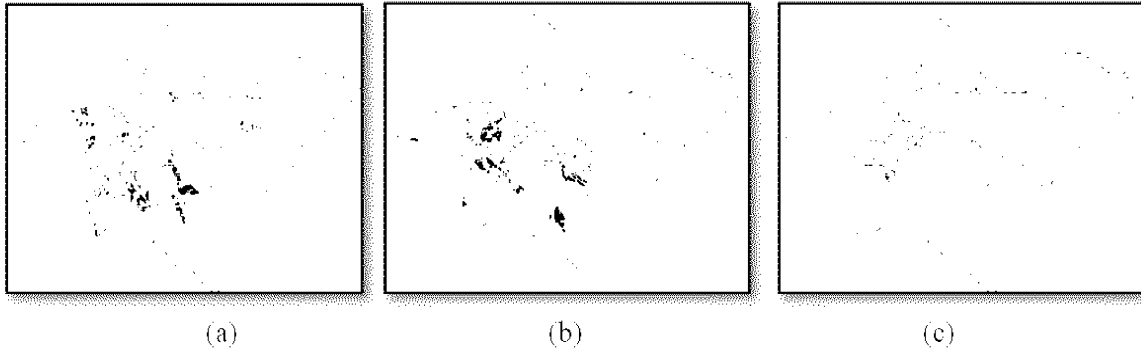


Fig. 5: Overlap among different Boolean suitability maps

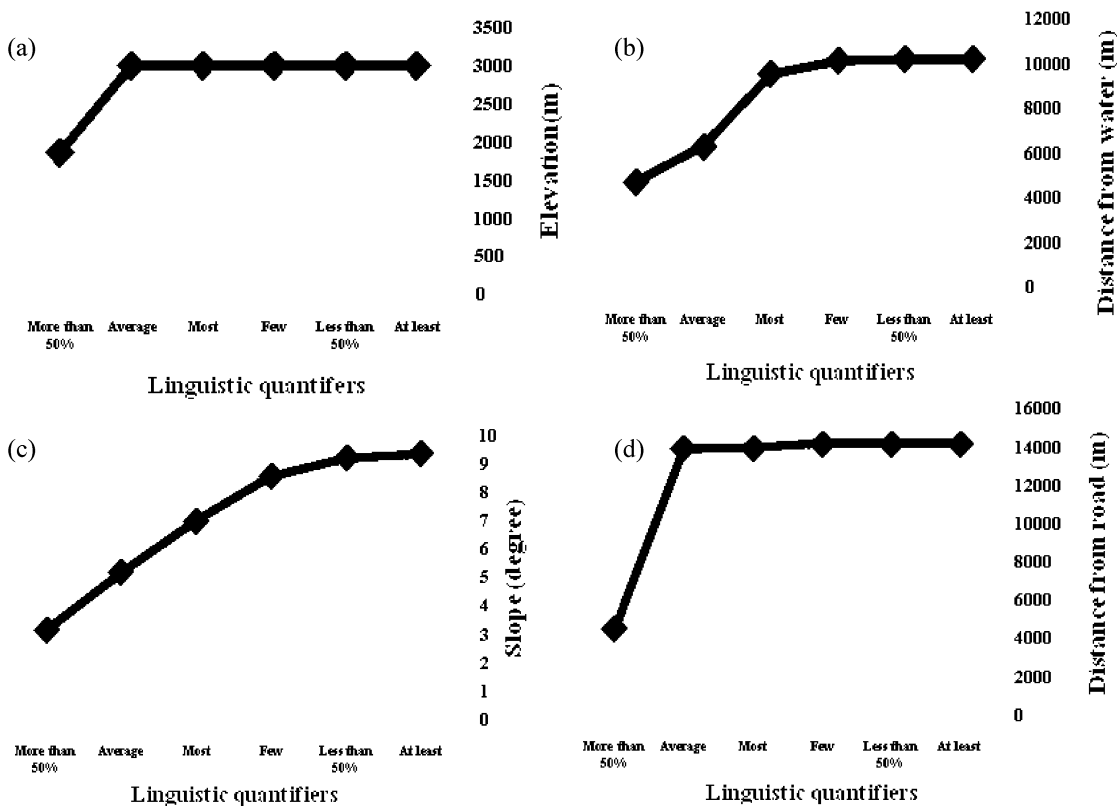


Fig. 6: The distribution of four important factors through different linguistic quantifiers

As it is shown in Fig. 6, this concept is found to be true. We have mostly the best condition in the case of risk aversion quantifiers (in these examples, the less criterion value leads to high suitability score for land development). We can show this fact by comparing four important factors in urban land use management including: slope, elevation and distance from water and road.

Totally, the OWA method is helpful as it provides this spectrum of summation procedures. At one extreme (the logical OR), each criterion is sufficient on its own to

support inclusion in the decision set without modification by other factors. At the other extreme (the logical AND), each criterion is considered necessary (but not sufficient on its own) for inclusion in the decision set. The final results indicate that the OWA method is flexible and easy to implement in urban land use suitability analysis. The method provides a framework which is analogous to accuracy assessment in other GIS and RS applications. In other words, when deliberate and arbitrary criteria and their weighting are used in the process of site selection, there is no way one

can provide traditional accuracy measures. In these circumstances, the degree of optimism and pessimism and consensus among decision makers when changing criterion weights and order weights reflects the accuracy in the traditional sense. Hence, to decide the best scenarios of urban land development, the overlapping areas among different runs of the OWA with various weights provides such a means. These results can help the decision maker to choose the preferred type of linguistic quantifiers according to their degree of optimism and consensus to achieve the best solution on urban land development scenarios.

CONCLUSION

This paper presents an application of natural language quantification to GIS-based urban land suitability analysis via ordered weighted averaging and demonstrates how one can obtain a wide range of urban land development scenarios by applying appropriate fuzzy quantifiers. The fuzzy-quantifier-based OWA approach is capable of absorbing qualitative information offered by the decision makers or analysts regarding their perceived relationship between the different evaluation criteria. Through this process, we aim to show the usefulness and necessity of the approach to the relevant audience. The method has proved successful when applied to the case study of Tehran Province.

The results indicate that fuzzy quantifier approach can provide an appropriate framework for solution of the complicated issues and contradicting interests' when planning for urban development. We have also demonstrated that the OWA method is flexible and easy to implement which facilitates a better understanding of urban land use suitability analysis. On the other hand, the results can help the decision makers to choose the preferred type of linguistic quantifiers to achieve the best solution on urban land development scenarios and thus avoid conflicts with other stakeholders. Also, as the results derived from the approach are systematic and reproducible, it can be considered a means of collaboration and interaction among urban developers and decision makers for achieving consensus on the best development scenarios. The results can be used as a policy-support document for governmental authorities who have direct or indirect connections to land development and the planners and especially the consulting engineers who design the city master plans. It is also expected that the method can be used for other provinces and cities, as well.

REFERENCES

1. Liu, Y., X. Lv, X. Qin, H. Guo, Y. Yu, J. Wang and G. Mao, 2007. An integrated GIS-based analysis system for land-use management of lake areas in urban fringe. *Landscape and Urban Planning*, 82: 233-246.
2. Malczewski, J., 2004. GIS-based land-use suitability analysis: a critical overview. *Progress in Planning*, 62: 3-65.
3. Malczewski, J., 2006. Ordered weighted averaging with fuzzy quantifiers: GIS-based multicriteria evaluation for land-use suitability analysis. *International Journal of Applied Earth Observation and Geoinformation*, 8; 270-277.
4. Yager, R.R., 1988. On ordered weighted averaging aggregation operators in multicriteria decision making. *IEEE Transactions on Systems, Man and Cybernetics*, 18: 183-190.
5. Zarghami, M. and F. Szidarovszky, 2008. Revising the OWA operator for multi-criteria decision making problems under uncertainty. *European Journal of Operational Research*, 198: 259-265.
6. Adhvaryu, B., 2010. Enhancing urban planning using simplified models: SIMPLAN for Ahmedabad, India. *Progress in planning*, 73: 113-207.
7. Awad, A.R. and M.T.A. Ela, 2003. Urban planning for low-income groups with developed optimization models. *Advances in Engineering Software*, 34: 607-619.
8. Dai, F.C., C.F. Lee and X.H. Zhang, 2001. GIS-based geo-environmental evaluation for urban land-use planning: a case study. *Engineering Geology*, 61: 257-271.
9. Merwe, V.D. and J. Hendrik, 1997. GIS-aided land evaluation and decision-making for regulating urban expansion: A South African case study. *Geo Journal*, 43: 135-151.
10. Pütz, M., 2011. Power, scale and Ikea: analyzing urban sprawl and land use planning in the metropolitan region of Munich, Germany. *Procedia Social and Behavioral Sciences*, 14: 177-185.
11. Svoray, T., P. Bar and T. Bannet, 2005. Urban land-use allocation in a Mediterranean ecotone: Habitat Heterogeneity Model incorporated in a GIS using a multi -criteria mechanism. *Landscape and Urban Planning*, 72: 337-351.

12. Taleai, M., A. Sharifi, R. Sliuzas and M. Mesgari, 2007. Evaluating the compatibility of multi functional and intensive urban land uses. *International Journal of Applied Earth Observation and Geoinformation*, 9: 375-391.
13. Yang, F., G. Zeng, C. Du, L. Tang, J. Zhou and Z. Li, 2008. Spatial analyzing system for urban land use management based on GIS and multi criteria assessment modeling. *Progress in Natural Science*, 18: 1279-1284.
14. Zhang, X., Y. Wu and L. Shen, 2011. An evaluation framework for the sustainability of urban land use: A study of capital cities and municipalities in china. *Habitat International*, 35: 141-149.
15. Wikipedia, 2011. [http:// en.wikipedia.org/ wiki/ Tehran_Province](http://en.wikipedia.org/wiki/Tehran_Province). Last accessed April 25.
16. Makropoulos, C.K. and D. Butler, 2006. Spatial ordered weighted averaging: incorporating spatially variable attitude towards risk in spatial multi-criteria decision-making. *Environmental Modelling and Software*, 21: 69-84.
17. McHarg, I.L., 1969. *Design with Nature*. John Wiley & Sons, Incorporated. ISBN 0-471-11460-X.
18. Makhdom, M., 2003. *Fundamental of Land use Planning*. University of Tehran Press, pp: 203-207.
19. Keeney, R.L. and H. Raiffa, 1976. *Decisions with Multiple Objectives: Preferences and Value Trade Offs*. Wiley, NewYork.
20. Abasspour, M. and A. Gharaguzlu, 2006. Urban Development Model by Using Environmental Modeling and GIS and RS. *Geo Sciences*, 57: 54-61.
21. Ahsan, M., 2003. *Collection of urban planning regulations and laws*. Tehran: Ministry of Housing and Urban Development, Urban Planning and Architecture Adjutancy, Urban Planning and Architecture Research Center of Iran, pp: 672.
22. Karam, A., 2005. Land suitability analysis for physical development in north west of Shiraz, applying Multi Criteria Analysis (MCE) with GIS. *Geographical Researches*, 54: 93-106.
23. Lotfi, S., K. Habibi and M.J. Koohsari, 2009. An Analysis of Urban land development using Multi-Criteria Decision Model and Geographical Information System (A Case Study of Babolsar City). *American Journal of Environmental Sciences*, 5: 87-93.
24. Mansor, S., N. Ahmed and R. Shiriff, 2006. GIS based multi-criteria approaches to housing site suitability assessment. *shaping the Change, XXIII FIG Congress, Munich, Germany*.
25. Monavari, M. and S. Tabibian, 2006. Identification of environmental factors for site selection of new cities in Iran. *Journal of Environmental Sciences and Technology*, 8(3) 1-9.
26. Tofigh, F., 2005. *Spatial Planning: International Experience and Its relevance for Iran*. Tehran: Urban Planning and Architecture Research Center of Iran, pp: 474-495.
27. Saaty, T., 1980. *The Analytic Hierarchy Process*. McGraw-Hill, New York.
28. Boroushaki, S. and J. Malczewski, 2008. Implementing an extension of the analytical hierarchy process using ordered weighted averaging operators with fuzzy quantifiers in Arc GIS. *Computers and Geosciences*, 34: 399-410.
29. Boroushaki, S. and J. Malczewski, 2010. Using the fuzzy majority approach for GIS-based multi criteria group decision-making. *Computers & Geosciences*, 36: 302-312.
30. Chang, N.B., G. Parvathinathan and J.B. Breeden, 2008. Combining GIS with fuzzy multicriteria decision making for landfill sitting in a fast-growing urban region. *Journal of Environmental Management*, 87: 139-153.
31. Chen, S.M. and C.H. Wang, 2009. A generalized model for prioritized multicriteria decision making systems. *Expert Systems with Applications*, 36: 4773-4783.
32. Chen, Y., K.W. Li and S. Liu, 2011. An OWA-TOPSIS method for multiple criteria decision analysis. *Expert systems with Applications*, 38: 5205-5211.
33. Nadi, S. and M.R. Delavar, 2011. Multi criteria, personalized route planning using quantifier-guided ordered weighted averaging operators. *International Journal of Applied Earth Observation and Geoinformation*, 13: 322-335.
34. Eastman, J.R., 1997. *IDRISI for Windows. Version 2.0, Tutorial Exercises*, Graduate School of Geography, Clark University, Worcester, MA.
35. Malczewski, J., 1999. *GIS and multicriteria decision analysis*. John Wiley & Sons, Canada.
36. Zadeh, L.A., 1983. A computational approach to fuzzy quantifiers in natural languages. *Computers and Mathematics with Applications*, 9: 149-184.

37. Yager, R.R., 1991. Connectives and quantifiers in fuzzy sets. *Fuzzy Sets and Systems*, 40: 39-76.
38. Yager, R.R., 1996. Quantifier guided aggregation using OWA operators. *International Journal of Intelligent Systems*, 11: 49-73.
39. Yager, R.R., 1993. Families of OWA operators. *Fuzzy Sets and Systems*, 59: 125-148.
40. Arieh, D.B., 2005. Sensitivity of multi-criteria decision making to linguistic quantifiers and aggregation means. *Computers & Industrial Engineering*, 48: 289-309.