Susceptibility mapping of visceral leishmaniasis based on fuzzy modelling and group decision-making methods

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Abstract. Visceral leishmaniasis (VL) is a vector-borne disease, highly influenced by environmental factors, which is an increasing public health problem in Iran, especially in the north-western part of the country. A geographical information system was used to extract data and map environmental variables for all villages in the districts of Kalaybar and Ahar in the province of East Azerbaijan. An attempt to predict VL prevalence based on an analytical hierarchy process (AHP) module combined with ordered weighted averaging (OWA) with fuzzy quantifiers indicated that the south-eastern part of Ahar is particularly prone to high VL prevalence. With the main objective to locate the villages most at risk, the opinions of experts and specialists were generalised into a group decision-making process by means of fuzzy weighting methods and induced OWA. The prediction model was applied throughout the entire study area (even where the disease is prevalent and where data already exist). The predicted data were compared with registered VL incidence records in each area. The results suggest that linguistic fuzzy quantifiers, guided by an AHP-OWA model, are capable of predicting susceptive locations for VL prevalence with an accuracy exceeding 80%. The group decision-making process demonstrated that people in 15 villages live under particularly high risk for VL contagion, i.e. villages where the disease is highly prevalent. The findings of this study are relevant for the planning of effective control strategies for VL in northwest Iran.

Keywords: visceral leishmaniasis, environmental modelling, geographical information system, fuzzy modis, group decision-making, Iran.

Introduction

Visceral leishmaniasis (VL), also known as kala-azar, is an important tropical disease affecting up to half a million new cases worldwide every year (Zakeri et al., 2004). On the Indian subcontinent, the *Leishmania donovani* parasite commonly causes transmission from person to person by phlebotomine sand flies, while a reservoir host is involved in the New World, the Mediterranean region and East Africa (Abdou, 2000; Morris et al., 2002). Although VL is restricted to specific localities, few studies of environmental factors have been performed to explain its focal distribution (Brooker et al., 2002).

Unlike cutaneous leishmaniasis (CL), which is highly prevalent in Iran and already mentioned as "Salak" in Avicenna's famous medical encyclopaedia Canon almost a thousand years ago, the history of VL is short. The first three human cases of VL (two children and one adult) were reported from the Tonekabon District in northern Iran some 60 years ago (Pouya, 1950). The diagnosis of VL in Iran is currently based on active or passive search for patients with the characteristic clinical symptoms combined with a positive serological response. At present, almost 10,000 VL patients have been diagnosed from all over the country with the great majority (about 3,600) coming from two provinces: Fars in the south and Ardabil in the north-west. Hundreds of districts and thousands of villages are affected and the number of affected cities has reached 300 according to the Ministry of Health (MOH, 2008).

The VL focus recently revealed in Iran seems to be an extension of the Mediterranean infantile form of leishmaniasis (Mazloumi Gavgani et al., 2007). The epidemic in the north-western focus began in the 1980s in the Kalaybar district and has since spread to another district, Ahar. Since 1976, the number of annually reported cases has increased considerably (MOH, 2006). All parasites isolated from humans or dogs infected with VL in this region have been diagnosed as *L. infantum* by isoenzyme typing (Maruashvili and Bardzhade, 1966; Zakeri et al., 2004). The average

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occurrence of *L. infantum* infection in the endemic districts of Ardabil (e.g. Meshkin-Shahr) and East Azerbaijan (e.g., Kalaybar) since 1985 has been about 3% per year with all ages equally at risk (Zakeri et al., 2004). Four sand fly species, *P.* (*Larroussius*) *kandelakii*, *P.* (*Larroussius*) near *major*, *P.* (*Larroussius) perfiliewi* and *P.* (*Adlerius*) near *chinensis*, are the likely vectors in the north-western part of Iran, as determined by the relative abundance and isolation of *Leishmania* from related species (Feliciangeli et al., 2003). As in most endemic countries in both the Old and New Worlds, dogs are apparently the principal reservoir hosts for *L. infantum* in Iran, but other canids (e.g. foxes, jackals and wolves) are also commonly infected (Gebre-Michael et al., 2004). *L. infantum* was isolated and identified in dogs at the study site, which directly incriminated this species as a reservoir host in this region (Mazloumi Gavgani et al., 2007).

VL is currently sporadic in 31 provinces of Iran but endemic in at least six provinces. In the latter, over 50% of all VL patients are children less than 2 years old, and 90% are under 12 years (MOH, 2006). The sex ratio is only marginally male-biased with about four males for every three female cases (MOH, 2006). In the provinces where VL is sporadic, the disease is clearly more common in males and the mean age of the cases is also slightly higher than in the other endemic areas (Edrissian, 1996). The reason for the lower risk in adult females may be associated with the traditional covering clothing worn by women in this region, which may reduce the chance of sand fly bites.

A number of studies in other parts of the world have demonstrated that statistical associations with environmental variables can be used to generate reliable risk maps of the sand fly vector and VL occurrence (Peterson and Shaw, 2003; Gebre-Michael et al., 2004). No such studies have been conducted in Iran or the neighbouring trans-Caucasus countries, but there is good evidence that the distribution of VL and its vectors in this region depend on environmental variables (Castillo Riquelme et al., 2006; Salahi-Moghaddam et al., 2010). Although multy criteria decision making (MCDM) methods have only been sparsely used for Health-GIS applications based on geographical information systems (GIS), Clements et al. (2006) used this approach to obtain a greater understanding of uncertainty related to the geographical distribution of Rift Valley fever (RVF). They highlighted the potential of methods developed in the decision sciences to improve the understanding of uncertainties surrounding the geographical distribution of diseases in animals. New health-GIS modelling approaches have not been much used either. Because of their poten-

tial utility, this type of integrated methods needs to be tested in the field. Fuzzy analytical hierarchy process_ordered weighted averaging (AHP_OWA) has been combined with GIS applications by Boroushaki and Malczewski (2008) in a synthetic approach that was shown to alleviate most of the weaknesses of previous attempts. In the present research, this new MCDM method was used to model the development of VL. As a first application in health, an integrated fuzzy AHP_OWA method was used to develop a prediction map for VL. The main reason for this choice was the crucial need for the application of expert knowledge and VL data together in a single model.

The aim was to apply GIS-based multi-criteria decision-making analysis (MCDA) methods and to produce a spatial prediction model of VL. To investigate the current status and risk level in the villages epidemic for VL, the knowledge of local experts and physicians were directly entered into the model. Since the expert opinions about the degree of influence of the various factors differed, an aggregating approach was considered to achieve the best decision. A GIS-based group decision-making method was chosen and the analysis was performed using a GIS platform.

Material and methods

Study area

East Azerbaijan is a province in northwest Iran covering an area of 49,287 km² and bordering Azerbaijan and Armenia. With an altitude of 3,722 m above the mean sea level (MSL), Sahand Peak, 50 km south of Tabriz, is the highest mountain in the province, while the lowest point is the Urmia Lake at 1,220 m above MSL. There are many cold and dry mountainous areas, but the lowlands enjoy temperate weather. The lowest average temperature of the last 10 years (8.9 °C) was recorded in the city of Tabriz, while the highest occurred in the city of Maragheh (20.2 °C). The lowest average temperature for the whole province was -1 °C. These variations are caused by the effect of solar radiation and air masses of different origins in combination with the topography and the proximity of the Caspian Sea. The mountain chains surrounding the province contain cold air from the north, limiting subtropical climate to foothills and plains. In this study we focused on two districts: Kalaybar in the western part of the province centred on longitude 47.043° E and latitude 38.864° N, and Ahar, situated immediately south of Kalaybar around the geographical coordinates 47.068° E and 38.472° N (Fig. 1).
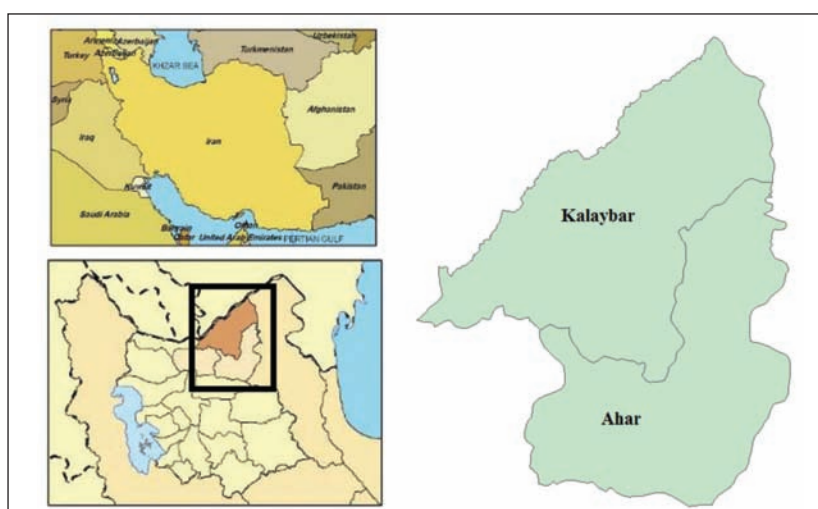
Fig. 1. Study area in East Azerbaijan-Iran.

Data collection

In collaboration with the Infectious and Tropical Diseases Research Center of the Ministry of Health (MOH), we collated VL notification data at the village level, either from central registers or from district centres between 2000 and 2008 (or even earlier whenever possible) integrating the information into a common database. Digitised data corresponding to the coordinates of each of the study villages were extracted from the National Centre of Cartography (NCC) maps (scale 1:50,000) and fed into ArcGIS 9.3 software (ESRI, Redlands, CA, USA). Data on rainfall and temperature were extracted from mapping of gathered data from the East Azerbaijan Meteorological Organization. Available village-level medical data were integrated into a GIS, incorporating demographic, socioeconomic, environmental and healthcare access data. Table 1 represents a sample collection of the massive volume of the data that was gathered during the research.

Statistical associations between the environmental and socioeconomic variables, detected from the above mentioned data and VL occurrence, were sought using spatial analysis, adjusted by year, taking into account spatial autocorrelations and validated by comparing predictions against independent data (i.e. occurrence data not used to generate the models) (Figs. 2 and 3). The final model was used to generate prediction of VL occurrences based on the integrated fuzzy, multi-criteria, decision-making method introduced in the next section.

Approach

The records of the Communicable Diseases and Health Centres in East Azerbaijan and Ardabil

Table 1. A sample of tabular gathered data from MOH, Meteorological Organization and NCC.

| Village	Dogs	Gender ratio (♀/♂)	Health centre distance (km)	Distance to river (km)	Average altitude (m)	Rainfall (mm)	Mean temperature (°C)	No. of VL cases (%)
Abdolrazagh	34	1.36	1	2	1,000	350	10	3
Abootorab	20	0.82	4	5	1,000	350	15	8
Abrigh Sofla	17	1.08	10	5	1,000	350	10	5
Agh Baraz	79	0.87	1	1	1,000	350	10	8
Abash Ahmad	27	1.42	1	3	1,400	500	10	14
Abas Abad	74	0.96	10	5	1,800	350	10	19
Afil	72	1.03	10	1	1,800	350	10	9
Agh Balagh	59	1.08	10	1	1,800	350	7.5	6
Agh Dareh	85	0.91	10	2	1,800	350	7.5	6
Aballoo	282	1.11	10	2	2,200	500	5	4
Abrigh	201	0.78	10	1	2,200	350	7.5	3
Agh Daraghe Ghadim	64	0.84	10	2	2,600	500	5	1
Agh Daraghe Jadid	92	0.93	10	5	2,600	500	5	1
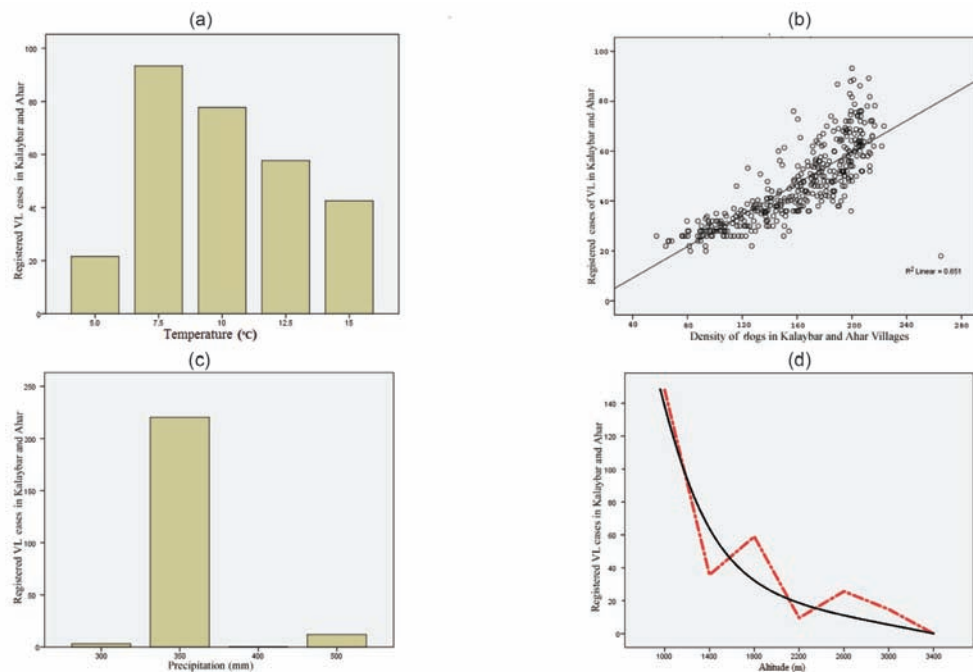
Fig. 2. Four environmental factors associated with VL.

provinces suggest that VL is spreading to the neighbouring cities and villages in the north and north-west. In addition, VL is especially prevalent among the nomadic population of the area (MOH, 2006). This study is based on reliable estimates deduced from statistical analysis of MOH data accomplished by the authors regarding various parameters of *L. infantum* infection in humans. Risk factors for infection at the individual level including gender, climate (temperature, rainfall), geographical factors (elevation, distance from rivers), reservoir host (dogs), vector (sand fly) and socioeconomic factors (including nomadic conditions) were gathered together to provide input for the spatial modelling.

Decision-making can be defined as the cognitive processes resulting in the selection of a course of action among several alternative scenarios. Every such process produces a final choice. MCDA is a transparent process supporting decision-makers faced with making numerous (sometimes conflicting) evaluations
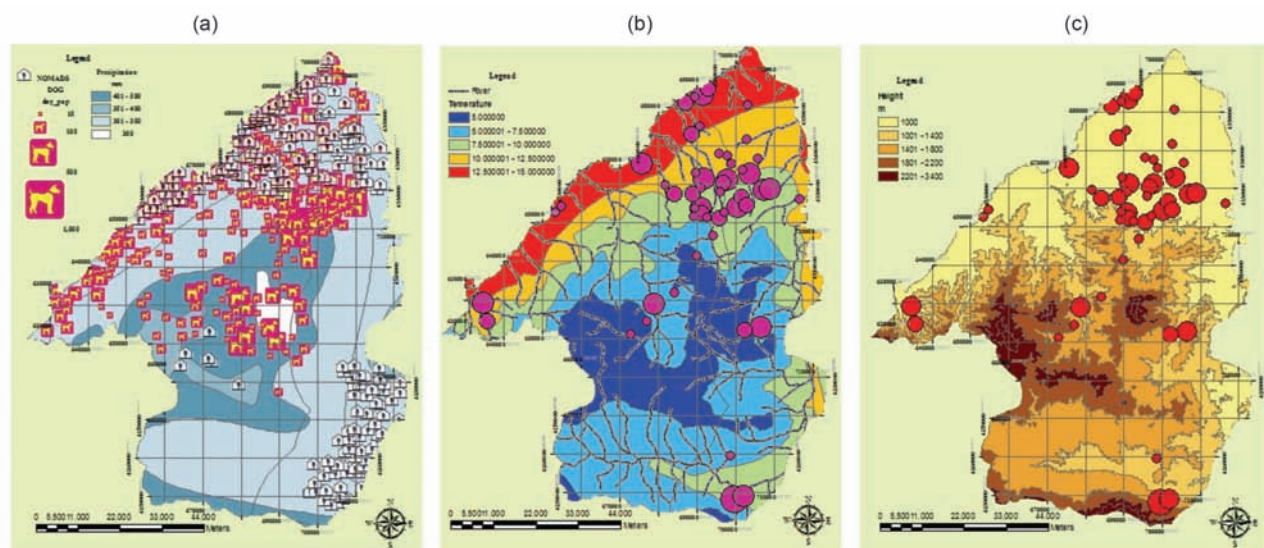

Fig. 3. Environmental factors associated with VL incidence in Kalaybar and Ahar. (a) Dogs and nomads; (b) river, temperature and VL incidence; (c) altitude and VL incidence.

by highlighting these conflicts aiming to find a compromise. GIS–MCDA is a process that combines geographical data (map criteria) and value judgments (decision-maker preferences and uncertainties) to obtain appropriate and useful supporting documentation. The main idea behind integrating GIS and MCDA is that these two distinct areas of research can complement each other (Malczewski, 2006a). The GIS–MCDA procedures offer a structure that can handle different opinions on the identification of the elements of a complex decision problem, arrange the elements into a hierarchical structure, and study the relationships among the elements of the problem. Applying GIS–MCDA for group decision-making forms aggregating individual judgments into a group preference in a manner in which the best compromise can be recognised (Boroushaki and Malczewski, 2010). Although the GIS–MCDA approaches have traditionally focused on the MCDA algorithms for individual decision-making, significant efforts have been made to integrate MCDA with GIS for group decision-making settings (Kyem, 2004). According to Malczewski (2006b), the voting methods are the most common approach for generating a group solution in a GIS-based, multi-criteria, group decision-making.

The analytical hierarchy process (AHP), proposed by Saaty (1980), is a structured technique for organising and analysing complex decisions. It provides a comprehensive and rational framework for structuring a decision problem, representing and quantifying its elements, relating those elements to overall goals, and evaluating alternative solutions. The AHP procedure is employed for rating or ranking a set of alternatives for the selection of the best with respect to the overall goal. It is broken down into a set of criteria (objectives, attributes) (Boroushaki and Malczewski, 2008) producing pair-wise comparisons based on forming judgments between two particular elements (Saaty, 1980). GIS has been combined with various MCDA methodologies in recent years and AHP has frequently been used (Marinoni, 2005), especially in rating and weighting criterion maps. Traditional AHP, however, does not show the uncertainty or fuzziness of decision-making (Vahidnia et al., 2009). In spite of its popularity, this method is often criticised for its inability to arrive at exact numbers and to adequately handle the inherent uncertainty and imprecision associated with the mapping of the perception of decision-makers (Deng, 1999).

The ordered weighted averaging (OWA) operators, proposed by Yager (1988), provide a parameterised class of mean-type aggregation operators, which have been widely used in computational intelligence because of their ability to model linguistically expressed aggregation instructions. The performance of the OWA operators has been demonstrated in two dimensions: the degree of "OR" ness (or risk) and trade-off (Malczewski and Rinner, 2003). The degree of "OR" ness specifies the situation of OWA on a continuum between the "AND" or "OR" operators and highlights the higher (better) values or the lower (worse) values in a set of attributes associated with the ith alternative. There is both theoretical and practical evidence to confirm that individuals (decision-makers) with optimistic (risk-taking) attitudes tend to select good alternatives, while pessimistic or risk-averse decision-makers tend to emphasise the bad properties or alternatives (Mellers and Chang, 1994). According to Jiang and Eastman (2000), the trade-off measure identifies the degree of compensation between criteria.

The concept of linguistic quantifiers was introduced by Zadeh (1983). The quantifiers are represented as fuzzy sets and are also referred to as fuzzy quantifiers, a concept which allows the translation of natural language specifications into formal mathematical expressions, directly leading to the formulation of the multicriteria, decision/evaluation functions (Munda, 1995). There are two generic classes of linguistic quantifiers: absolute and relative ones (Yager, 1996). The former are defined as fuzzy subsets and can be used to signify linguistic statements, e.g. "approximately five" or "more than ten". The relative quantifiers are closely associated with imprecise proportions and are defined as a fuzzy subset (0, 1) with proportional terms such as a "few", "half", "many", and "most".

AHP and OWA have been introduced as two GIS-based multi criteria evaluation (MCE) approaches, but these two procedures do not operate at the same level (Malczewski, 2006b). The AHP is a comprehensive tool for creating a hierarchical model of the spatial decision problem, analysing the whole process and evaluating each alternative. The OWA operators, alternatively, provide a general framework for making a series of local aggregations used in the AHP. The nature of these two techniques gives rise to their combination and creates a more powerful decision-making tool (Yager and Kelman, 1999). The main issue in OWA procedures is the step of reordering the arguments. The reordering process used in the conventional OWA is based on the values of the arguments to be aggregated, Yager and Filev (1999) proposed induced ordered weighted averaging (IOWA) operators as an extension of the conventional OWA by considering a more general approach for the reordering stage.

The voting schemes are rank-order methods (Hwang and Lin, 1987) that involve two steps: (i) the individual judgments are converted into a ranking of the alternatives; and (ii) the individual rankings are combined into a group solution (Boroushaki and Malczewski, 2010). A solution map can therefore be generated by each decision maker using an MCDA decision rule, at which point the solution maps can be translated into maps of ranked alternatives to be aggregated using a voting method to generate the solution map of the group preference (Feick and Hall, 2004).

A fuzzy majority approach has been introduced by Pasi and Yager (2006) to model the concept of majority opinion in group decision-making problems. Using a linguistic quantifier, the fuzzy majority concept can generate a group solution that corresponds to the majority of the decision-makers' preferences. The linguistic quantifier leads the aggregation process of the individual judgments in such a way that there is no need for rankings of the alternatives of individual solutions. Accordingly, the approach addresses the above mentioned difficulties encountered by the voting schemes in relation to the combination process.

Methodology

AHP

Any human judgment is to some degree inconsistent. It would therefore be useful to have a measure of inconsistency associated with the pair-wise comparison matrix (A) (Sadeghi-Niaraki et al., 2010). To measure the degree of consistency, we can calculate the consistency index (CI) as:

$$CI = \frac{\lambda_{max} - p}{p - 1} \qquad \text{(Eq. 1)}$$

where λ_{max} is the biggest eigenvalue that can be achieved once we have its associated eigenvector and p is the number of columns of matrix A.

The consistency ratio (CR), i.e. the consistency index of a randomly generated pair-wise comparison matrix, is calculated as:

$$CR = \frac{CI}{RI} \qquad \text{(Eq. 2)}$$

where *RI* is the random index. If *CR* <0.10, the ratio specifies a reasonable level of consistency in the pair-wise comparison. If, however, *CR* ≥0.10, the values of the ratio reveal inconsistent decisions. In such cases, one should reconsider the original values in the comparison matrices (Boroushaki and Malczewski, 2008).

OWA

Given a set of n weighted standardised criterion (attribute) values ($w_1 a_{i1}$, $w_2 a_{i2}$, ..., $w_n a_{in}$) for each alternative *i*, and a set of order weights (v_1, v_2, ..., v_n, $0 \le v_j \le 1$, and $\Sigma_{j=1}^{n} v_j = 1$), OWA can be defined as follows:

$$OWA_i = \Sigma_{j=1}^{n} v_j b_{ij} \qquad \text{(Eq. 3)}$$

where $b_{i1} \ge b_{i2} \ge ... \ge b_{in}$ is the sequence achieved by reordering the weighted criterion values $w_1 ai_1$, $w_2 a_{i2}$, ... $w_n a_{in}$ (Rinner and Malczewski, 2002). According to the standard assumptions behind multi-criteria decision analysis, the criterion weights have the following properties: $0 \le w_j \le 1$, $= \Sigma_{j=1}^{n} w_j = 1$, and the attribute values are standardised so that $0 \le a_{ij} \le 1$ for the ith alternative (*i = 1, 2, ..., m*) and the jth attribute (*j=1, 2, ..., n*) (Malczewski, 1999).

Linguistic quantifiers and OWA weights

Here, we limit ourselves to a class of relative (proportional) quantifiers, and we employ one of the most often used methods for defining a parameterised subset on the unit interval (Yager, 1996):

$$quantifier\ (p) = p^{\alpha}, \alpha\ f\ 0 \qquad \text{(Eq. 4)}$$

For a series of linguistic quantifiers that include monotonically increasing proportions of elements, we can associate the quantifiers with a value of a single parameter, α, which specifies the degree of the inclusion. This parameter can be used to calculate a set of order weights as follows:

$$v_j = \left(\frac{j}{n}\right)^{\alpha} - \left(\frac{j-1}{n}\right)^{\alpha}, for\ j = 1, 2, ..., n \qquad \text{(Eq. 5)}$$

The order weights are generic in the sense that they are independent of particular multi-criteria problems. The order weights depend only on the number of criteria that are being used in the combination procedure and the specified linguistic quantifiers, which are associated with the parameter. By changing the parameter, one can generate different types of quantifiers and related OWA operators between the two extreme cases of *at least one* and *all* quantifiers (Boroushaki and Malczewski, 2008).

The AHP-OWA procedure

In this structure, we assume that the two first steps of the AHP have been accomplished. The hierarchical

structure has been formed, and the relative importance of the components (objectives and attributes) of the hierarchy has been determined by conducting pair-wise comparisons. At this point, the quantifier-guided OWA methods take the lead for the rest of the analysis. The procedure at this stage involves three main steps (Malczewski, 2006b): (i) identifying the linguistic quantifier Q; (ii) generating a set of ordered weights associated with Q; and (iii) computing the overall evaluation for each ith location (alternative) at each level of the hierarchy by means of the OWA combination function.

IOWA

In IOWA, in addition to argument values (elements to be combined), a_i, and order weights, v_i, which are presented in OWA operators, the argument values have been associated with another set of values, t_i, called order-inducing values (Boroushaki and Malckzewski, 2010). Consequently, IOWA procedures consist of pairs of (a_i, t_i) so that order inducing values, t_i, are used to guide the reordering of the argument values. In this case, IOWA can be defined as:

$$IOWA\ (a_i, t_i) = \Sigma_{j=1}^{n}\ v_j\, a_{t\text{-}index\ (i)} \qquad (Eq.\ 6)$$

where the t-index (i) is the index of the ith largest t.

Group decision making

The approach utilises a modified IOWA operator with a set of inducing order values on the basis of the similarities of the arguments to be aggregated (Boroushaki and Malczewski, 2010). The similarities between pairs of preference values can be computed using a support function Sup (a, b), which can be signified as the support for *a* from *b* where:

$$Sup\ (a, b) \geq Sup\ (x, y)\ if\ |a\text{-}b|\ p\ |x\text{-}y| \qquad (Eq.\ 7)$$

The nearer (more similar) the two argument values are, the more they support each other (Yager, 2001). In addition, Pasi and Yager (2006) suggest a way for generating the order weights in such a way that the most supported values have more influence (weight) in the aggregation procedure. They demonstrate that the fuzzy majority technique produces the majority semantic of preferences in a group decision-making process (Fig. 4).

Results and discussion

From a public health perspective, a key safeguard against zoonoses consists of well-designed surveillance, including human infections and animal reservoir host populations. From the scientific perspective, there is a need to develop a better understanding of the spatial patterns concerning the epidemiology of humans and animals as well as the spatial synchrony between these two populations. This information is essential for rational and cost-effective targeting of control measures. Recent advances in GIS provide an opportunity to map vector-borne diseases (e.g. malaria, trypanosomiasis, onchocerciasis, leishmaniasis, schistosomiasis, etc.) analyse the environmental factors affecting their spatial distribution and develop surveillance approaches as done by Davies and Mazloumi-Gavgani (1999).

The general distribution of endemic and non-endemic villages relative to altitude, rainfall, temperature patterns and location was explored. Clear clustering of
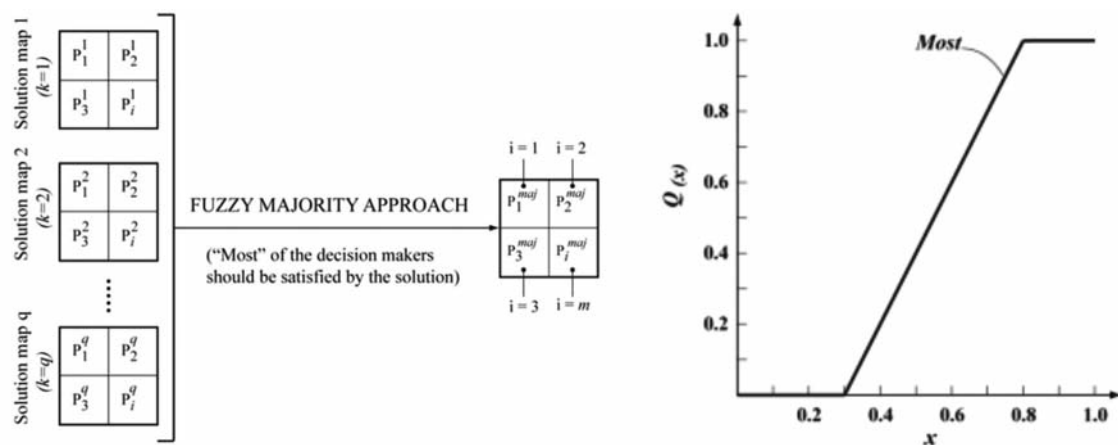

Fig. 4. (a) Schematic procedure of GIS-based fuzzy majority approach; (b) function Q corresponding to linguistic quantifier "most" (Boroushaki and Malczewski, 2010).

high-occurrence villages at low altitudes and correlation with low rainfall values as well as moderate temperature zones was found (Fig. 2). The spatial pattern of villages with VL cases indicated that many of the cases also occurred in riverside villages or villages in close proximity to rivers (Fig. 3b). The significant effect of the river on the presence of VL is thus obvious, but many other factors also play a role. For example, the distribution of VL cases indicates that reported cases in districts occur mostly in villages without health centres or located far from them. The presence of health centres and the impact of educational and control programmes on environmental factors and on individual behaviour is an important factor that can influence the incidence of most diseases, including VL.

Fig. 3 indicates the relationship between VL incidence and different factors in a geographical schema. The original data in these maps were the statistical datasets from the MOH. This information was georeferenced and saved in ESRI shape file format (http://www.esri.com/library/whitepapers/pdfs/shapefile.pdf).

The effect of altitude on the occurrence of VL is remarkable. The maps in Fig. 3 show no reported VL cases in the villages at altitudes 2,200 m above MSL and few cases of VL are seen in the villages situated at altitudes between 1,800 m and 2,200 m above MSL. Almost all reported VL cases are observed in villages in the plains or at relatively low altitudes, i.e. below 1,400 m above MSL (Fig. 3c). However, the probability of finding VL in lowland villages still appears to be significantly correlated with altitude, but the influence of other parameters on this significant effect needs more consideration (Fig. 2d).

The spatial pattern of average temperatures during 10 years in the Kalaybar and Ahar districts is demonstrated by temperature isoclines (Fig. 3). The mapping of isoclines and the georeferenced VL occurrence indicate highly prevalent areas of endemic villages situated in areas where the temperature varies between 7.5 °C and 15 °C. The probability of VL occurrence seems to be significantly correlated with particular temperatures, as the maps show that villages with a low prevalence are located in places with temperatures generally lower than 5 °C (Fig. 3b). This correlation may exist due to the effect of the climate on vectors and reservoirs. Our survey on the spatial pattern of annual average rainfall during last ten years in the Kalaybar and Ahar districts demonstrates that places with rainfall between 300 to 350 mm have a high prevalence of VL (Fig. 3a), while rainfall ranging between 350 and 500 mm are only weakly correlated

with VL prevalence. Average rainfall above 500 mm seems to suppress the occurrence of VL (Fig. 2d) making the probability of finding a case of VL strongly negatively correlated with rainfall average above this level (MOH, 2006).

Fig. 2 confirms that both dog and sand fly abundance as reservoir host and vectors can serve as the main risk factor for transmission. The correlation of the dog population and VL occurrence in the study area was demonstrated in several data analyses and maps in the region during this study. The strong relationship detected between the transmission rate in humans and dogs in different villages provides further evidence for the role of infected dogs in the transmission of VL to humans (Fig. 2b). The significant association between the abundance of dogs in a village and the transmission rate has been shown not to depend on the human population size (MOH, 2006). Instead, the investigations showed that VL cases were mostly reported from nomadic villages, indicating that there is a lifestyle and habitat effect on VL occurrence and that the environment, in particular the presence of dogs (every household of nomads keeps many dogs), has an effect (MOH, 2006). The high correlation between the abundance of dogs and nomadic villages suggests that both dogs and nomadic living conditions are strong risk factors in this region (Fig. 3a).

According to our studies, the environmental factors that affect the incidence, distribution, spatial modelling of VL are the most important. Therefore the environmental factors were first entered into a fuzzy AHP-OWA algorithm to identify susceptive areas in relation to the prevalence of VL. Then the knowledge of five local experts in the field of VL was generalised in a fuzzy group decision-making process. The main objective was to investigate the current situation of the villages at risk to provide urgent emergency services. Because of the limitation of AHP in problems with a high number of factors, the fuzzy weighting method was very helpful in this stage. Most of the local experts and medics were not familiar with AHP; therefore, when asked to enter their knowledge into the model during an AHP process, the reliability of their comments might have decreased to a significant extent.

Developing a prediction model to identify areas susceptive for VL prevalence using a fuzzy AHP-OWA approach

Prevention is particularly important in areas characterised by unsafe conditions and where the risk for infection is the highest. The disease may not yet have

reached epidemic proportions in these places, but if preventive measures are ignored, a widespread public health problem could occur. For example, after confirmation of several cases of VL in Kalaybar city, spatial processing models were used to identify areas at risk but not yet seriously involved.

Focusing on factors affecting the incidence of VL in the Kalaybar region, based on reports about suspected infection of the disease in some areas in East Azerbaijan (especially Ahar city), the identification of susceptive areas for widespread prevalence of VL in the East Azerbaijan area was accomplished. Modelling of the problem was designed on the basis of the identification of the environmental and non-environmental factors that affect VL. Eight factor maps were prepared: distance to health centres, distance to nomads, distance to areas with high parasite resources (dogs), villages with higher percentage of females, areas with altitudes lower than 1,400 m above MSL, areas with annual precipitation below 350 mm, distance to rivers, and areas with an average temperature of 7.5 °C. The factors were then classified as "climate" and "intensity of contagion" classes. Temperature, precipitation, rivers and altitude factors were considered to belong to the "climate" class. The impact of health centres, nomads, density of dogs and gender was assigned to the "intensity of contagion" class. In the next stage, after structuring the criteria, a pair-wise comparison between factor maps was performed according to their

effects on VL. The process was indirectly dependent on the knowledge of experts (Fig. 5). By weighting of the AHP, the relative importance of each criterion was obtained. In the "climate" class, the weights that were achieved by AHP were as follows: altitude = 0.45, precipitation = 0.263, distance to river=0.103 and temperature = 0.155. Considering the coefficient CR = 0.015, i.e. < 0.1, the weight values were validated and remained in the calculations (Fig. 5a).

For the factors that are associated with the contagion of VL, the relative importance of criteria was also calculated. The health centre was assigned a weight of 0.271, nomads 0.505, gender 0.061, and the vector density factor gained a weight about 0.162. After this stage, the consistency ratio was calculated to examine the reliability of the values. CR = 0.023 indicates the proportion of the comparison (Fig. 5b). Considering that the main purpose of this part of the research was to determine the most likely areas for the prevalence of VL, the contagion factor's importance was considered twice of the factors in the climate class. After calculating the relative weights of the criteria for each factor and sub-layers, they would be spatially combined with regard to the amount of compensation (trade-off) and risk.

Various combinations of criteria and factors can be generated using OWA and fuzzy linguistic quantifiers. Because of the nature of the criteria in the "contagion class" that accompanied a high level of risk, the "all"
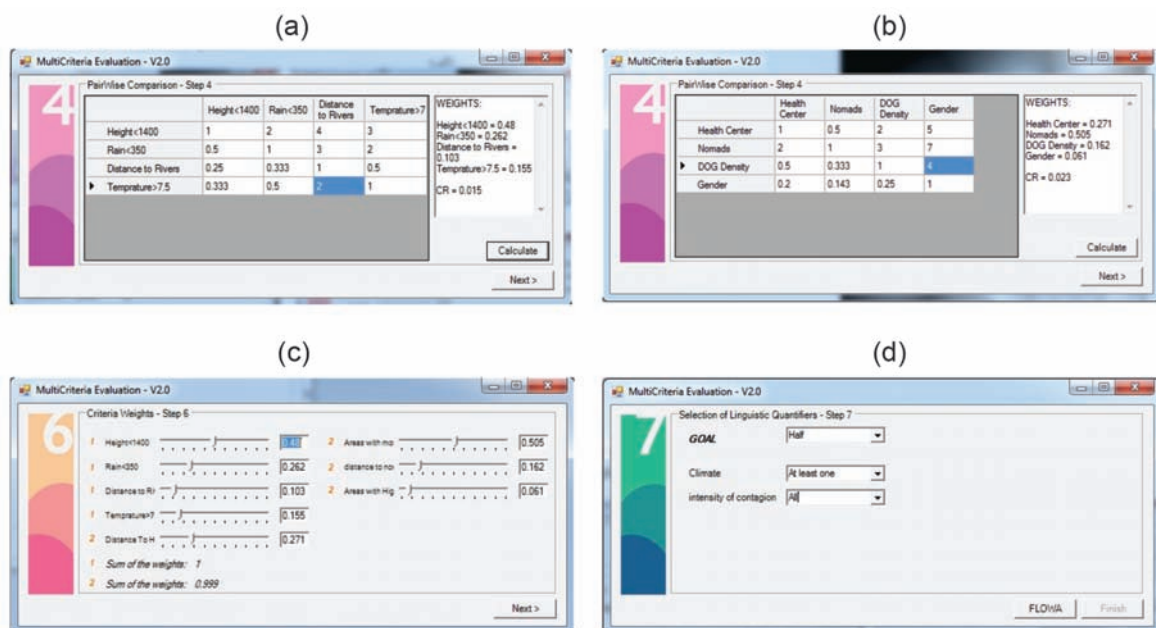

Fig. 5. Using AHP and fuzzy linguistic quantifiers for criteria weighting (Boroushaki and Malczewski, 2008).
Legend: (a) Pairwise comparison of "climate" criteria; (b) pairwise comparison of "intensity of contagion" criteria; (c) criteria weights for "climate" and "intensity of contagion" classes; (d) selection of fuzzy quantifier for "climate" and "intensity of contagion" classes and final goal.

Half-At least One-All   **Half-At least One-Most**   **All-Half-All**
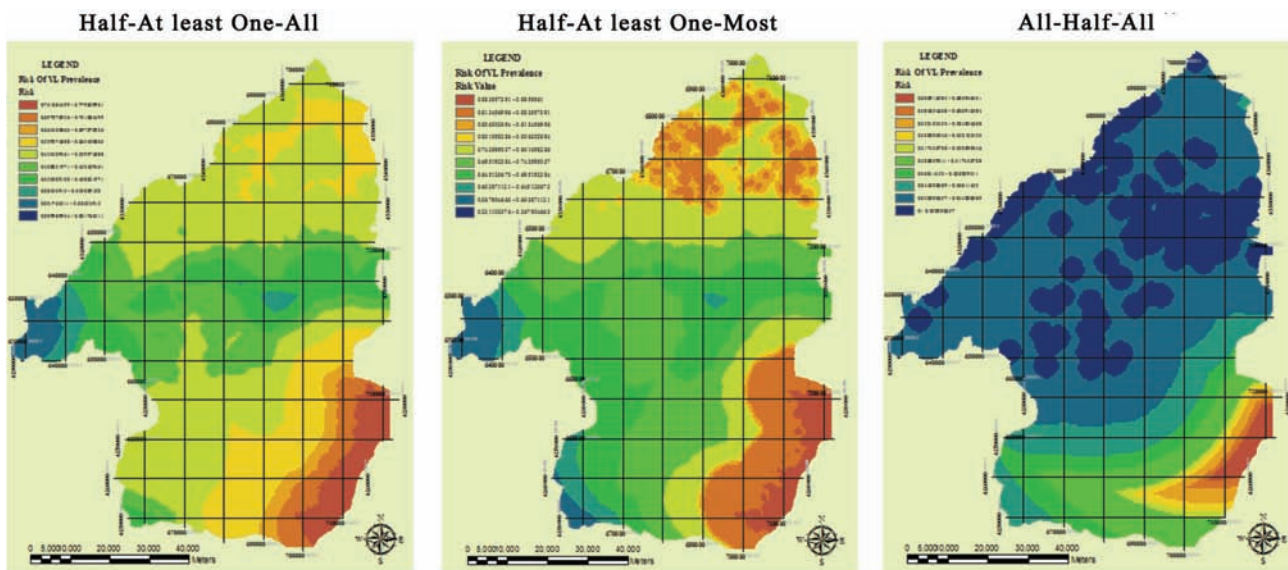

Fig. 6. Predicted risk map of VL widespread prevalence.

and "most" quantifiers were assigned to this class (Fig. 5d). Considering that the aim of this part of the research was to identify the foci of renewed prevalence of VL in the study area, the contagion factors are therefore more risky. The linguistic fuzzy quantifiers of "all" and "most" have a high compatibility with these factors. There were two approaches involving the climate-related factors. According to the first approach, factors associated with climate had low compensation (trade-off) and lower levels of risk associated with them. If one region does not meet one of the four regional climatic conditions, its deficiency cannot be compensated by the other factors. In this case, the fuzzy linguistic quantifier of "at least one" was used for modelling and combination of the relative importance of the affective factors (Fig. 5d). The second approach suggests that climatic criteria with a low level of risk and high level of trade-off should be considered. If a high-altitude area that is not supposed to have the appropriate environmental conditions for prevalence of VL meets the temperature term, the level of risk in the area increases. The height and temperature factors are related to trade-off. Similarly, there is a high level of trade-off in other climatic factors. For modelling the low risk and high trade-off, the "half" fuzzy quantifier was used (Fig. 6).

After entering information about factor maps and their relative importance into the VL prediction model, some evaluation was accomplished. Effective factors and parameters associated with VL outbreak have been entered in the prediction model spatially (even where VL was epidemic). The achieved prediction data and the registered cases of VL in infected

areas have been compared together. The differences between the predicted risk values and the real risk values could show the reliability of the predicted data appropriately. When relating risk maps with the infected villages and available information about the patients, the outputs indicated that all of the current highly infected villages were predicted to be hazardous areas by fuzzy AHP-OWA. Approximately 81% of the highly infected villages (more than 20 cases) were classified in the highest risk category (risk of more than 70%). Fig. 7 indicates that the real risk values and the predicted VL risk values according to the fuzzy AHP-OWA model in the study area were almost at same level. In this stage, according to the user interfaces and tools provided, various fuzzy quantifiers were assigned to the criterion map layers. Different maps were obtained from these processes. All the maps indicate
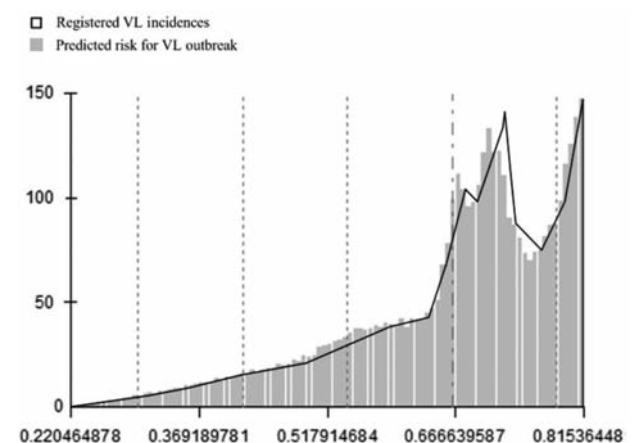

Fig. 7. Predicted level of risk and VL incidence in the study area.

that the villages southeast of Ahar have the highest risk for a widespread incidence of VL (Fig. 6). Further investigations showed that this region has suitable climatic conditions for VL parasites, and nomad villages were noticeably deployed there. The disease is not yet seriously epidemic in this area, but there is a lack of health and medical facilities that influences this negatively. Because of the importance of the problem, preventive measures and training should be instituted as soon as possible.

Identifying the villages most at risk using a fuzzy group decision-making process

Group decision-making is an underlying process in many of the applications. Because of the uncertainties associated with this kind of decision making, Pasi and Yager (2006) proposed a new group decision-making method based on the fuzzy majority approach and Borouskhaki and Malczewski (2010) introduced this method in GIS-based models. There are many differences and unities in group decision-making affairs investigating an epidemic disease like VL. To achieve an aggregating decision from different types of ideas is very helpful in these applications. In this paper, this new decision-making method was entered into the health-GIS modelling for the first time.

In the previous section of this study, unsafe areas in which VL could become epidemic in the near future were predicted by AHP, OWA and fuzzy linguistic quantifiers. To assess the current status of the highly infected villages in an effective disaster management process, a general investigation should be considered. Expert knowledge has been used in fuzzy AHP_OWA to estimate the logical degree of risk and trade-off between the criteria and sub-criteria indirectly. Fig. 6 shows the indirect modelling of the expert's knowledge would not cause a significant difference in output

maps and, as can be seen, all the maps in this figure consider the south-east of the study area as a susceptive area for a VL outbreak. To have an appropriate prioritization in preparing aid measures for infected villages, the degree of contagion should be determined in each area. Because the lack of information the experts' knowledge was very important at this stage and we used it in our model directly. Therefore the final result has a strong dependency on their comments. However, there was not an aggregation about the efficacy of factors between local experts and medics. Comparison between Fig. 9a and Fig. 9b indicates that the differences between comments were salient in maps. To achieve an aggregation about the current situation of the infected villages we used a fuzzy group decision-making approach. Providing information about eight effective factors on VL, health experts were asked to use fuzzy terms such as "very high", "high", "medium", "low" and "very low" to declare the efficacy of each factor (Fig. 8).

After gathering information and opinions of five local experts about VL and weighting factors by converting the fuzzy terms to hard numbers, the information was combined at various levels of risk and trade-off using fuzzy linguistic quantifiers (Table 2). On the basis of the knowledge of each of the experts, one thematic map was generated. The main objective in this part of the study was to introduce the villages already in a critical condition where the disease was almost epidemic. In each of the generated maps, different levels of risk were assigned to the villages (Figs. 9a and 9b). There should therefore be a fuzzy group decision-making process to identify the villages in which most of local experts and medics agree about the severity of the crisis. The weighting values of experts and doctors were used in a grid map with cell size of 1,000 m². Then, the degree of compatibility for five different weighting values was obtained in each cell using IOWA. The risk level for

Fig. 8. Criteria weighting using fuzzy terms and local experts' opinions (Boroushaki and Malczewski, 2010).

Table 2. The opinions of 5 local VL specialist about the degree of effect of 8 parameters on VL.

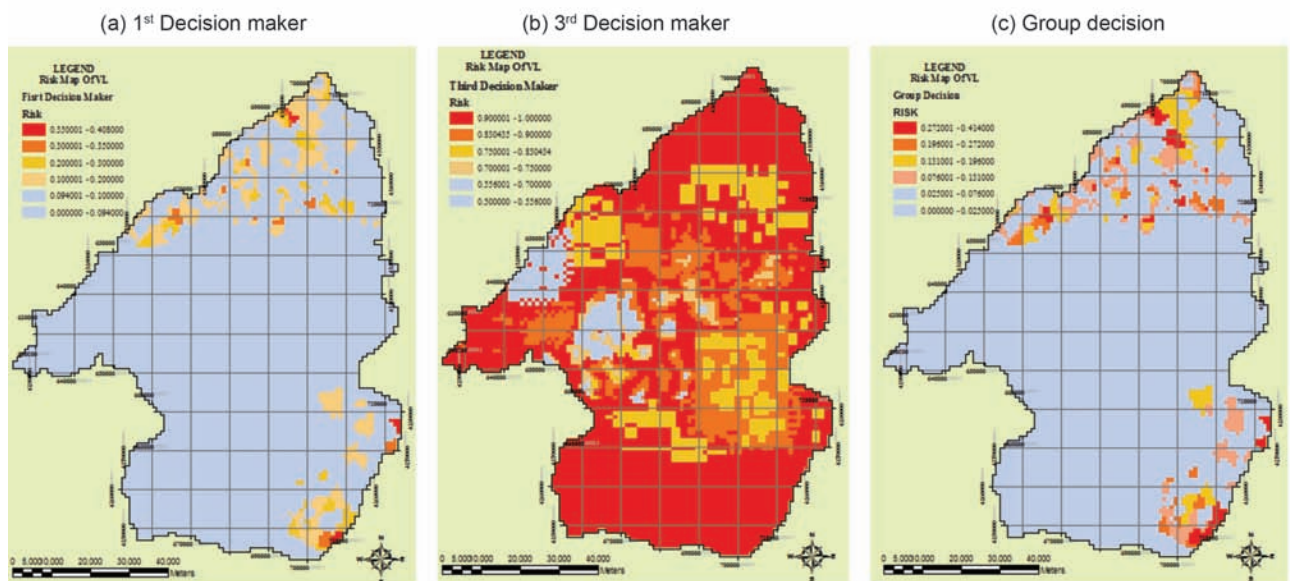| Decision maker	Nomads	Altitude	Temperature	Rain	River	Health center	Dogs	Gender
1	Very high	High	Medium	High	High	Medium	Very high	High
2	High	Medium	Medium	Medium	Medium	Medium	Very high	Low
3	Very high	Very high	High	High	High	High	Medium	Very low
4	High	High	Medium	Low	Low	Very high	High	Low
5	High	Medium	Medium	Medium	Medium	High	Very High	Medium

Fig. 9. Produced risk map from experts' opinions by fuzzy terms and IOWA.

each area was calculated using a fuzzy majority approach in a fuzzy group decision-making process. At this stage, a risk value was obtained for each location that represents the opinions of the majority of medics and health professionals. A new map was generated that indicates the level of danger for each village. The new map should be useful for prioritizing the provision of the health measures for each village (Fig. 9c). Further investigations showed that the residents of 15 villages were living under conditions, clearly undesirable with respect to the health services. Indeed, the situation in certain villages, e.g. Guy Darre, Khorde Qeshlagh and Dash Qayeli, are at the stage rendering them highest priority status (Fig. 10).
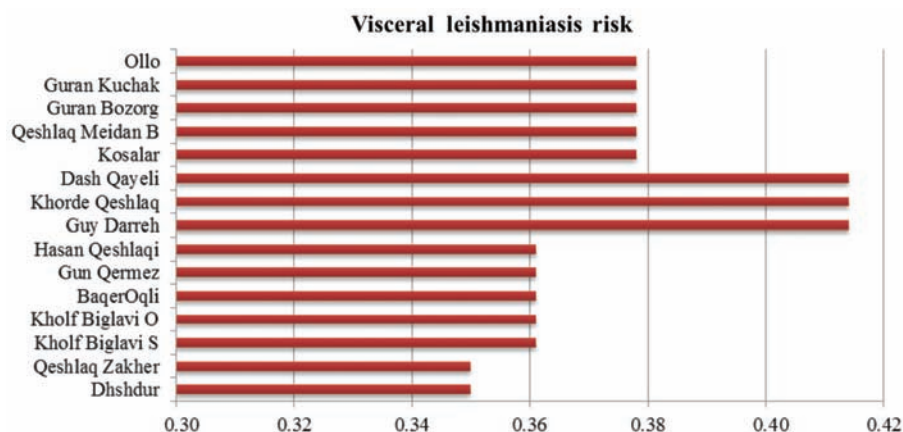

Fig. 10. Villages highly infected with VL.

Conclusion

GIS can be regarded as a decision-supporting tool providing appropriate facilities for modelling, both for environmental and non-environmental factors. The following ideas and recommendation were felt to be important:

(i) Guiding the OWA process by linguistic fuzzy quantifiers leads to better modelling in terms of risk and trade-off. Assessment of the results of the fuzzy AHP-OWA model indicates a reliability of 81% for the predicted information.

(ii) A group decision-making process based on the fuzzy majority approach, utilised on the basis of the IOWA algorithm, is capable of reliably mapping areas of high risk for VL.

(iii) With regard to spatial modelling of vector-borne diseases, there is a strong dependence of final results on the data collected. This is particularly important for vector datasets. The application of data-driven methods such as neural networks should be useful to model the spatial behaviour of the vectors. This information could be used as the input data for the disease analysis which will be present in future work.

Acknowledgement

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