Comparisons between Different Multi-criteria Decision Analysis Techniques for Disease Susceptibility Mapping

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Abstract

Geographic information system multi-criteria decision analysis (GIS-MCDA) procedure can combine criterion maps together and associated the criterion weights to acquire an overall value for each spatial location in the research area. Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Ordered Weighted averaging (OWA) are three generic algorithms of multi-criteria decision analysis. These have been combined with GIS to tackle wide range of spatial problems.

In this research, the comparison of AHP, TOPSIS, and OWA methods for susceptibility mapping in spatial communicable disease study had been made through testing the sensitivity of each model. The methods are compered by two concrete case studies: modelling of visceral leishmaniasis in north-western Iran for mapping of risky areas and modelling of dengue disease in Ecuador for mapping of risky areas. In regard to testing the algorithms, prediction-rate method was utilized to draw the receiver operating characteristic (ROC) curve. Comparing the tendency of ROC curves and the risk-prone areas of the disease from susceptibility maps, also considering the realistic situations of two infectious diseases, evaluations of these three algorithms had been done.

In this research, at least in this application, AHP model offers the best predictive accuracy in both of these two case studies.

Keywords: multi-criteria decision analysis, AHP, TOPSIS, OWA, disease susceptibility mapping

Acknowledgements

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List of Acronyms

AHP	Analytical Hierarchy Process
AUC	Area Under the ROC curve
CI	Consistency Index
CR	Consistency Ratio
DEX	Decision Expert
DF	Dry Farm
DMs	Decision Makers
FC	Forest with Canopy Cover
FN	False Negative Fraction
FP	False Positive Fraction
GIS	Geographic Information System
GIScience	Geographic information science
IF	Irrigated Farming and Orchards
ITDRC	Infectious and Tropical Diseases Research Center
LR	Lakes and Water Reservoirs
MCDA	Multi Criteria Decision Analysis
MoH	Ministry of Health
NIS	Negative Ideal Solution
OWA	Ordered Weighted averaging
PAHO	Pan American Health Organization
PIS	Positive Ideal Solution
RC	Rangelands with Canopy Cover
RB	Large River Beds
ROC	Receiver Operating Characteristic
ST	Health Center Nomads and Settlement
TN	True Negative Fraction
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TP	Ture Positive Fraction
VL	Visceral Leishmaniasis
WLC	Weighted Linear Combination

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Chapter 1

1. Introduction

1.1 Background

Global changes in earth system influences patterns of human health, international health care, and public health activities (McMichael 2013). Specifically, some vector borne diseases like communicable diseases always reminded as global disease burden. GIS are being used with enhancive frequency in spatial epidemiology researches. As advances GIS technology make it much easier to connect spatially referenced physical and social-economic phenomena to patterns of health, disease and well-being (Krieger 2003). Disease risk mapping has become an established technique in spatial epidemiology study, it aims to summarize spatial and geographical variations in disease risk, for purpose of assessing and quantifying the amount of true spatial heterogeneity and the associated patterns, to highlight areas of elevated or lower risk and to obtain clues as to disease etiology (Best,N., et al. 2005). Descriptive disease risk mapping aims at illustrating the spatial variation, the data being used in these maps are always earned by surveys or surveillance. For the existing data-sparse situations, GIS-based multi-criteria decision analysis (GIS-MCDA) can be used to analysis the disease risk maps. The variety of influencing factors (criteria) and the need to use experts' knowledge on how to integrate these factors is also the main reason for using MCDA.

Combination of GIS and MCDA gives decision makers not only the single strategy for geographical region but also different weights for different strategies. Many spatial decision problems lead to the GIS-based multi-criteria decision analysis. Spatial analysis and decision support systems provide perspectives among both MCDA and GIS, concept of totalization GIS and MCDA contribute a lot to the GIScience development. The integration between GIS and multi-criteria decision analysis (MCDA), had significantly developed over the last 25 years. GIS plays an essential role in decision problem analysis. In the same time, MCDA also provide a rich mixture of procedures to structure the decision problems, among this the alternative decisions will be designed and evaluated (Malczewski 2006). Indeed, most of the fundamental level GIS-MCDA is processed as the transformation and combination of geographical data and criteria judgement (which comes from the decision maker's preferences), in order to achieve successful decision making. Using GIS-based MCDA methods for health-GIS application improve the understanding of uncertainties surroundings. With this in mind, in this research, MCDA technique was selected to deal with the influencing factors in the disease risk mapping.

Susceptibility maps combine different factors that contribute to a hazard together, aimed at achieving the most likely occurred hazard area; it can understand and predict future hazards, based on statistical or deterministic methods. Mapping the areas that are susceptible to some existed disasters or diseases is essential for effective management and can control the spread of the damage cause by them. It could be the basis for decision maker to help people

reduce the losses caused by disasters or diseases. In a creation of susceptibility map, mapping method integrates many factors and weights the importance of different variables, using subjective decision-making rules, based on the experience of the experts involved (Zhu,L. and Huang,J.F.2006). The GIS-based MCDA methods can be used to solve the factors and weights problems during creating susceptibility map.

In order to find an efficient method to obtain high accuracy disease susceptibility maps, we test three models to solve this problem. The three models being implemented in this research are AHP, TOPSIS, and OWA respectively.

1.2 Research objectives
(1) The main objective of this study is to use three of GIS-MCDA methods namely Analytical Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Ordered Weighted averaging (OWA), in susceptibility mapping.
(2) Secondary aims of this study were to compare these three methods by analyzing the difference between their potential risks of diseases shown from the susceptibility mapping. To discuss the suitability one of the techniques for disease risk prediction from these three methods.

1.3 Methodology
To investigate the status and risk level of the disease, experts and physicians' knowledge were directly entered into these three models. The algorithms were developed in MATLAB to achieve values in each model. All the data tested by these three models were produced in ArcGIS.

To obtain the weights for these methods, questionnaires of the factors firstly sent to the experts. Questionnaire for each method is in the appendix; OWA and TOPSIS have the same questionnaire. AHP method has different one, pairwise comparison was used in this questionnaire. Factors were identified via literature review. To test the liability of the models, two case studies, visceral leishmaniasis (VL) in north-western Iran and dengue disease in Ecuador were used for testing. In order to validate these three models, prediction-rate method was used, the results of the susceptibility maps from different models, were validated by comparing them with the existing infected areas. ROC curves of the three models were draw to analyze the models in statistical level.

1.4 Outline
This thesis is organized in 5 chapters. Chapter 1 is introduction, which includes background, research objectives, methodology and outline. Chapter 2 is literature review, which contains both GIS for health study and MCDA techniques. In GIS health study section, the development and combination of GIS and health study was introduced. In MCDA techniques segment, the three methods AHP, TOPSIS, OWA were introduced by detail. Chapter 3 is implementation, two cases: VL disease in northwest Iran and dengue disease in Ecuador were used for implement the models. In chapter 4, validations and discussions about the three models were drawn. In final chapter, conclusions of the all studies were presented.

Chapter 2

2. Literature review

2.1 GIS in health study (spatial epidemiology)

Communicable disease study is the study of health and disease in human populations, time, person, place are the first 3 important epidemiologic variables in this analysis; place, however always been the most difficult one to illustrate (Melnick Al, et al. 1999). Spatial analysis methods and GIS has been combined together to enhance the understanding and visualization of spatial and health data. GIS in spatial epidemiology study is a field dealing with spatial (spatial-temporal) data that linked to the disease spread or population at risk. The objective of spatial epidemiology study is to identify disease causes and correlates by relating spatial disease patterns to geographic variation in health risks (Jacquez,G.M. 2000).

Disease mapping studies have become an established technique in health GIS study, which aims to summarize spatial variation in disease risk to assess and quantify the spatial heterogeneity, highlight areas of risk area and to gain the disease prediction. When applying spatial communicable disease analysis methods as part of disease management to forecast and assess the potential of the disease, the information decision makers expect to acquire from risk includes both the level of disease risk and information on risk factors.

For the modelling techniques, it can be categorized into two kinds of methods: data-driven and knowledge-driven. The former one is characterized by statistical methods to define relationships between factors and disease risk, however the later approach is based on existing knowledge about the relationships with the disease risk of interest. Receiving and integrating the knowledge of experts is very important and challenging, knowledge-driven techniques provide the solutions for this problem. It is useful for identifying risk factors, which also means the statistical regression models that being used in knowledge-driven approach eliminate proxy risk factor variables related to unobserved disease transmission procedures. Transmission dynamics can be directly modelled in knowledge-driven techniques. More detailed description about knowledge-driven techniques is discussed in 2.2.

2.2 Multi-criteria decision analysis techniques

Multi-criteria decision analysis (MCDA) considers multiple criteria together into the decision-making environment; it is a sub-discipline of operations research. A variety of approaches and methods have been already developed for the implementation of MCDA in an array of disciplines, which range from social science to natural science. There is a large number of methods in MCDA, for instance, Analytic hierarchy process(AHP),Decision Expert (DEX), Data envelopment analysis, Technique for the order of Preference by Similarity to Ideal Solution(TOPSIS),etc. More than 33 methods can be listed for conducting MCDA. However many of them are applied on a small number of alternatives, due to the limitation in computation or practice (Greene et al. 2011). Spatial decision problem can also be sloved by the implementation of MCDA. Spatial decision problem involves a huge set of alternatives

are often evaluated by decision-makers, managers, stake-holders, etc.

MCDA is knowledge-driven technique. Different from data-driven technique, the activity progress in knowledge-driven technique is not compelled by data. In knowledge-driven technique, the generation and use of knowledge is the major part in the creation of the procedure (Figure2-1). In this study, three GIS-MCDA models were implemented, which were AHP, TOPSIS and OWA.
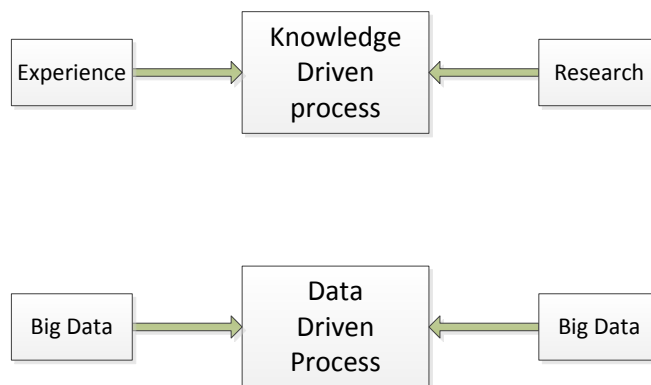
Figure 2-1.Knowledge driven Vs Data driven

AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology developed by Thomas L. Saaty in the 1970s and has been extensively studied and refined since then. TOPSIS is a multi-criteria decision analysis method, which was originally developed by Hwang and Yoon in 1981 and further developed by Yoon in 1987, and Hwang, Lai and Liu in 1994.The ordered weighted averaging (OWA) operators provide a parameterized class of mean type aggregation operators. They approved by Ronald R.Yager(1988). Many notable mean operators such as max, arithmetic average, median and min, are members of this class.

2.2.1   Analytical Hierarchy Process (AHP)

AHP method (Saaty 1977, 1980; Saaty and Vargas 1991) is a well-known method in multi-criteria techniques, which has been incorporated into GIS-based suitability procedure (Marinoni 2004; Jankowski and Richard 1994). In this method, both quantitative and qualitative information about decision-making problems can be organized (Saaty 1980; Malczewski 1999). AHP is a flexible, quantitative method for selecting among alternatives which are based on their relative performance to more than one interest criteria (Boroushaki and Malczewki 2008; Linkov et al. 2007). The ratio scales of criteria can be driven from paired comparison in AHP method. After the weights were determined through the pairwise comparison method, the resulting evaluation scores are used to order the decision alternatives from the most to the least desirable, followed by an aggregation criterion technique (Jiang and Eastman 2000; Gorsevski et al. 2006).

As a structured technique organizing analyzing complex decisions based on mathematics and psychology, the AHP method works as a flow chart (Figure 2-2) (Saaty and Vargas 1991). Step 1, define alternatives: define the complete list of alternatives which come from your

choices. Step 2, organize criteria: brainstorm the decision-making criteria and make sure the stakeholder understand and buy into the criteria. Step 3, build surveys: express the opinions with pairwise comparisons and obtain the weights of each criterion. Step 4, collect input: participants fill surveys, ask participants whom an expert on the related domain. Step 5, check consistency: calculate the consistency ratio and check if it is within the allowances. In AHP method, the consistency ratio (CR) value is always below 0.1. Step 6, find group values: find common values after the comparisons. Step 7, weights of criteria: the values acquire from the pairs comparison, which can represent priorities of experts who participated into the decision. Step 8, ranking the alternatives, get access to the final scores of alternatives then distribute them to criterion. Finally, step 9, the final decisions achieved.

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│    Step 1: Define alternatives   │
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│    Step 2: Organize criteria     │
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│ Step 3: Bulid Surveys (Pairwise comparison)  │
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│      Step 4:Collect input        │
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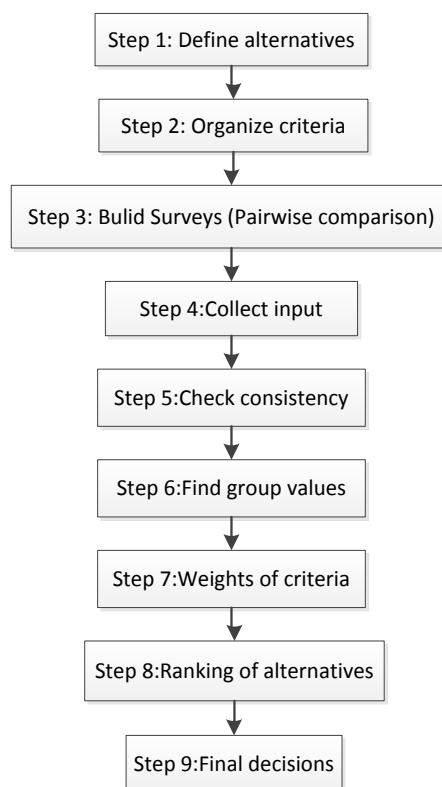
Figure 2-2.AHP process flow chart

As far as the pairwise comparison being concerned, it plays an essential role in AHP method. The development of pairwise comparison based on the ratio of two criteria at a time, each comparison works as a two-part comparison. For instance, if the ratio value between criterion A and criterion B is 3, the ratio value between criterion B and A is 1/3. The AHP comparison matrix consists of an equal number of rows and columns, where scores are recorded on one side of the diagonal, while values of 1 are placed in the diagonal of the matrix (Gorsevski et al. 2006). In order to make the comparison, the scale of numbers that indicates how many times one element is more dominant over another is indexed by Saaty (2008). Table 2-1 introduces the scale.

Table 2-1.Scales for pairwise comparisons (Saaty 2008)

Intensity of importance	Description	Explanation
1	Equal importance	Two activities contributes equally to the object
2	Weak or slight	
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another, its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
Reciprocals	Values for inverse comparison	A reasonable assumption

Human judgment sometimes can violate the transitivity rule and thus cause an inconsistency; therefore the consistency ratio (CR) is computed to check the consistency of the conducted comparisons (Gorsevski et al. 2006). If the comparison matrix is neither totally consistent nor contradictory, a different situations will appears ,to solve this, one suitable measurement was described by Saaty(1980), the consistency index(CI) is calculated as follows:

$$CI = \frac{\lambda \max - n}{n - 1} \tag{1}$$

Where, λ_{max} is the biggest principal eigenvalue, n is the number of compared alternatives. Occasionally, the referee is not absolutely consistent; Saaty defined the consistency ratio (CR) to measure this level of inconsistency:

$$CR = \frac{CI}{RI} \tag{2}$$

Where RI is random index, this value can be obtained from a lookup table. Saaty had required that only the CR value below 0.1 is acceptable.

2.2.2 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS, originally developed by Hwang and Yoon (1981), is a crucial MCDA method which is widely used in different decision making problems. The basic concept of TOPSIS contains the chosen of the shortest geometric distance between alternative and positive ideal solution (PIS), and the longest geometric distance between alternative and negative ideal solution

(NIS). According to this the original idea of TOPSIS is straightforward: originates from the concept of a displaced ideal point from the compromise solution with the shortest distance(Belenson, S.M.,Kapur, K.C), both the distance to positive ideal solution and negative ideal solution being considered simultaneously by TOPSIS . The final ranking is obtained by means of the closeness index.

Actually, TOPSIS is a utility-based method that compares each alternative directly. It depends on data in the evaluation matrices and weights (Cheng, S., Chan, C.W., Huang, G.H 2002). To make group environment more manageable, many operations in the processing of TOPSIS are scrutinized to be established. The operation inside TOPSIS includes: establish decision matrix, decision matrix normalization, distance measure, aggregation operations. The procedure of TOPSIS shown in flow chart(Figure 2-3).
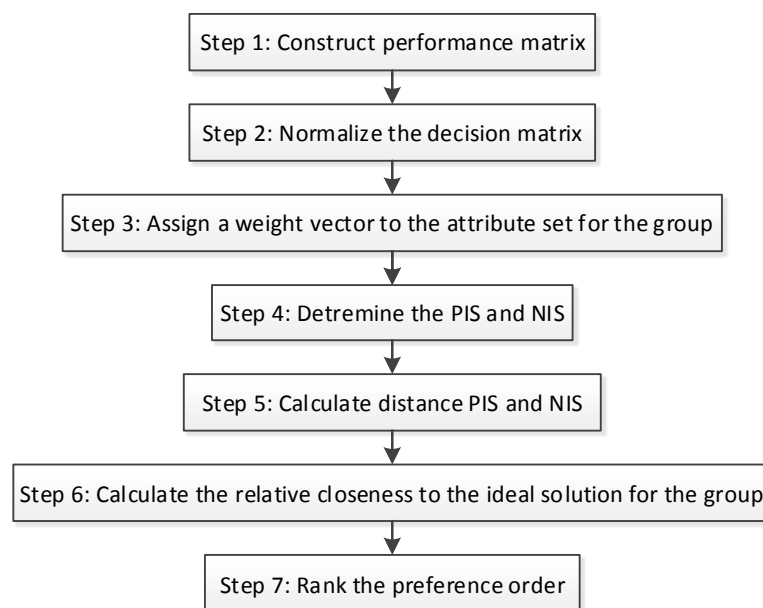
Figure 2-3.TOPSIS process flow chart

Step 1: performance matrix is constructed, create an evaluation matrix consisting of m alternatives and n criteria, with the intersection of each alternative and criteria given as X_{ij} , we therefore have a matrix $(X_{ij})_{m \times n}$ .the structure of the matrix can be expressed as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{3}$$

Step 2: normalize the decision matrix, using the normalization method:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \tag{4}$$

Step 3: assign a weight vector to the attribute set for the group, construct the weighted

normalized decision matrix:

$$v_{ij} = w_j r_{ij}, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \tag{5}$$

Step 4: detremine the positive ideal and negative ideal solutions.
Positive ideal solution:

$$A^* = \{v_1^*, \ldots, v_n^*\}, v^* = \{\max(v_{ij}), j \in J; \min(v_{ij}), j \in J'\} \tag{6}$$

Negative ideal solution:

$$A^- = \{v_1', \ldots, v_n'\}, v' = \{\min(v_{ij}), j \in J; \max(v_{ij}), j \in J'\} \tag{7}$$

Step 5: calculate the separation measure for each alternative (calculate distance).The separation from positive ideal alternative is:

$$S_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2}, i = 1, \ldots, m \tag{8}$$

The separation from negative ideal alternative is:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j')^2}, i = 1, \ldots, m \tag{9}$$

Step 6: Calculate the relative closeness to the ideal solution C_i^*:

$$C_i^* = S_i' / (S_i^* + S_i^-), 0 < C_i^* < 1 \tag{10}$$

Step 7: rank the preference order, the larger the index value, the alternative performs better, which also means the more C_i^* value close to 1 the better.

2.2.3 Ordered Weighted averaging (OWA)

The ordered weighted averaging (OWA) is a class of multi-criteria aggregation or combination operations developed by Yager (1988) which involves two set of weights: criterion importance weights and ordered weights. The criterion weight W_j is assigned to the j_{th} criterion map for all locations to indicate the relative importance of the evaluation criteria's attribute according to the decision maker's preferences. The ordered weights are associated with the criterion values on the location-to-location basis. They are assigned to a given i_{th} location's attribute value in decreasing order with no consideration from which criterion map value comes. The ordered weights are central to the OWA combination operators.

The OWA method has been developed in the context of fuzzy set theory (Yager,1988) in the beginning. Eastman (1997) and Jiang implemented the OWA operations as a part of a decision support module in GIS-IDRISI. Several authors offer the GIS-OWA approach to urban planning and management (Asproth et al. 1999; Mendes 2000;Mendes and Motizuki 2001). Fritz et, al. (2001) proposed that GIS-OWA operations could be used for wild-land perceptual decision making. In most of the studies that mentioned before, the OWA method is test by hypothetical decision scenarios. Jiang, H. and Eastman, J.R. (2000) remind that as a relatively new research, OWA should be tested in a variety of decision making situations to make sure

how it may help decision maker in the real day life. The appeal of OWA is reordering and changing criterion parameters, for that one can generate different solution maps and scenarios. Different with the Boolean overlay AND operator which means the lowest risk while the OR operator represents the highest risk in decision making, OWA method contains a full spectrum of risk scenarios bounded between the AND and OR operators (Gorsevski, P.V., Donevska, K.R, et al. 2012). Since the order weights are associated with the criterion values on a location-to-location basis. The location's attribute values are assigned to them in decreasing order.

Yager (1988) proposed OWA as a parameterized family of combination operators. For a given set of n criterion maps, the OWA function defined as follows, formally an OWA operator of dimension n is a mapping F: $R_n \rightarrow$ R that has an associated collection of ordered weight W= [w_1, w_2,..., w_n] lying in the unit interval and summing to 1, given the set of attribute value $a_1, a_2, ..., a_n$, and the OWA equation is that:

$$F\left(a_1, a_2, ..., a_n\right) = \sum_{j=1}^{n} w_j b_j \tag{11}$$

Where, b_j is the j_{th} largest of the a_i. For example, with a particular position of the attribute values, the first order weight, w_1, is assigned to the highest suitability attribute value; w_2 is assigned to the second highest suitability attribute value while w_n is assigned to the lowest suitability attribute value. The aggregation in OWA is achieved since the reordered weights determined by the attribute values that are combined with the set of ordered weights. The OWA operator provides a rich family of aggregation operators which are parameterized by the weighting vector. Due to the OWA operator is a mean operator. It is bounded, monotonic, symmetric, and idempotent.

Yager (1988) introduced two characterizing features associated with the weighting vector w of OWA operator. The first is the attitudinal character (ORness), it is defined as:

$$A-C\left(W\right) = \frac{1}{n-1} \sum_{j=1}^{n} (n-j) w_j, A-C\left(W\right) \in \left[0,1\right] \tag{12}$$

In addition, A-C(max) is 1, A-C(med) is 0.5, A-C(min) is 0. Thus the A-C changes from 1 to 0 as we go from Max to Min aggregation. The attitudinal character characterizes the similarity of aggregation to OR operation, which OR defined as the Max. The second feature is the dispersion. This defined as:

$$H\left(W\right) = -\sum_{j=1}^{n} w_j \ln\left(w_j\right) \tag{13}$$

This value characterizes the degree of the arguments that being used.

There are several researches proposing that the position of order weights can be identified based on the concepts of trade-off and risk. It can be achieved by varying the ordered weights, and what's in return, would generate a continuous aggregation procedure. The ordered weights is W= [w_1, w_2,..., w_n] ,where w_n represents the ordered rank. When w_{min}= [1,

0,..., 0] , it is AND operator (andness). When w_{max}= [0, 0,..., 1], it is OR operator (ORness). When w_{mean}= [1/n, 1/n,..., 1/n], it has the same solution as the WLC(weighted linear combination). The degree of the dispersion of the weights donates the level of TRADE-OFF, representing the compensation measurement. The trade-off defined as:

$$TRADE-OFF = 1 - \sqrt{\frac{n\sum_r (w_r - 1/n)^2}{n-1}}$$ (14)

Where n is the number of criteria, r is the order of criteria, w_r is the weight of the r-th order criteria.

In GIS-OWA model, the OWA combination operator associates with the J_{th} location and a set of order weights V=($v_1,v_2,...,v_3$) ,where $v_j \in [0,1]$ for $j=1,2,...,n$ and $\sum_{j=1}^{n} v_j = 1$, Malczewski(2006) had defined the GIS-OWA method as follows:

$$OWA_i = \sum_{j=1}^{n} \left(\frac{u_j v_j}{\sum_{j=1}^{n} u_j v_j} \right) z_{ij}$$ (15)

Where z_{ij} obtained by reordering the criterion values decreasingly, and u_j is the reordered j_{th} criterion weight. About the ordered weight, it can be estimated using a number of methods (Yager, 1996). In this study, based on Yager (1996) the OWA order weights are computed using equation:

$$W_j = \left(\frac{j}{n} \right)^\alpha - \left(\frac{j-1}{n} \right)^\alpha$$ (16)

Where α is the degree of optimism that indicates the decision strategy. α is related to the ORness as the following equation:

$$ORness = \frac{1}{1+\alpha}, \quad \alpha \geq 0$$ (17)

The aggregation corresponding to specific ORness(α parameter) describes detailed in Table 2-2.

Table 2-2.The decision strategies corresponding to specific ORness Value (Jelokhani-Niaraki 2015)

α	ORness	Aggregation strategy	Decision Strategy
0	1	Logic OR(MAX)	Extremely optimistic
0.1	0.9	----	Very optimistic
0.4	0.7	----	Optimistic
1	0.5	WLC	Neutral
2	0.3	----	Pessimistic
10	0.1	----	Very pessimistic
∞	0	Logic AND(Min)	Extremely pessimistic

The operations about the OWA methods are shown step by step in the flow chart(Figure2-4).

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│   Step 1:Reordered attribute value   │
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│ Step 2:Reordered criterion weights according to the attribute value │
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│  Step 3 :Calculate the Ordered weights  │
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│     Step 4:Calculate OWA value        │
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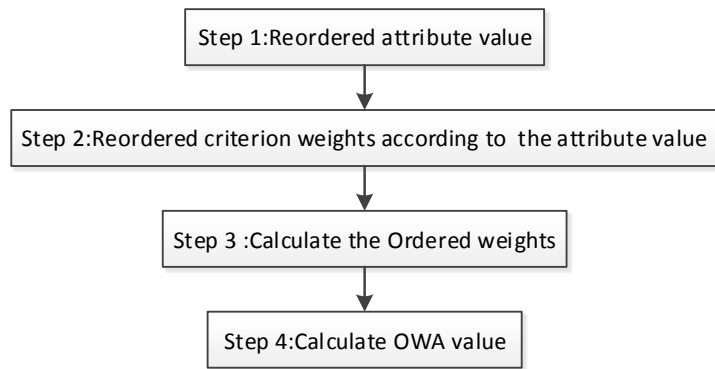
Figure 2-4.The OWA process flow chart

Chapter 3

3. Implementation

The aim of the implementation is to test the three methods: AHP, TOPSIS, OWA and compare the results of these methods, by evaluating the susceptibility maps of these three models in two case study areas : northwest Iran and mainland of Ecuador. One case study is visceral leishmaniasis in north-western Iran; the other case study is dengue disease in Ecuador (mainland). The study area was classified into seven categories of susceptibility: extremely low, very low, low, medium, high, very high, and extremely high. Accordingly, the final susceptibility map relies a lot on their controlling factors, the selection of the criteria factors is important in this research. From some formal researches, both in social and physical environment several factors strongly influence the VL disease, such as nomadic lifestyle, climate condition, altitude of the area, etc.(Edrissian et al.,1988, Mirsamadi et al., Salahi-Moghaddam et al.).

For the visceral leishmaniasis in this research , 13 factors were defined, including river, altitude, large river beds(RB),lakes and water reservoirs(LR), temperature, precipitation(Rain),Irrigated farming and orchards(IF), dry farm(DF),rangelands with canopy cover(RC),forest with canopy cover(FC),health center, nomads ,and settlement (ST) (Figure 3-1).As for environmental factors, people who live in high-temperature and high-precipitation areas are more susceptible to VL disease; people who live in areas have more IF and DF are more susceptible to VL disease; people live in area have less RC and FC are more susceptible to VL disease. As for Socioeconomic factors, nomads and settlement will increase people's susceptibility to VL disease; people whose living area have more health centers are more susceptible to VL disease. As for geographical factors, low elevation and short distance to river will increase people's susceptibility to VL disease; people who are living more close to RB and LR are more susceptible to VL disease. For layers RB, LR, IF, DF, RC, FC, ST, they are different classes in land cover layer, we extracted them from land cover layers. Many factors were responsible for epidemic dengue disease during the past 20th century, even though there still exits some non-understood ones (Gubler 1998), it still clear that some geographical factors influence a lot on the spread of dengue. For dengue disease in this case study, 4 factors were identified with the highest impact on the spread of disease including temperature, precipitation, elevation, and distance to river (Figure 3-2).People who are living in high temperature and precipitation area are more susceptible to dengue disease; people who are living in low elevation and short distance to river area are more susceptible to dengue disease. Experts have already decide the classification for the factor layers.
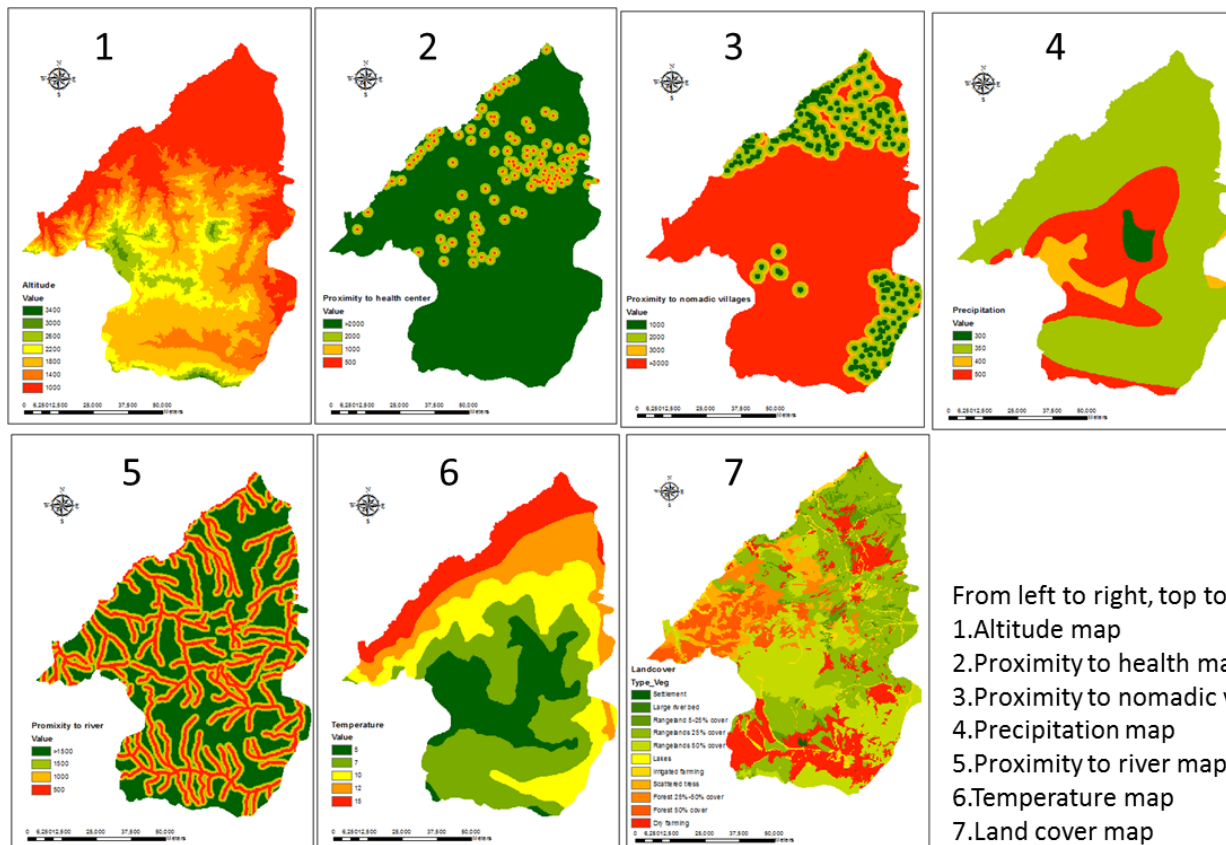
From left to right, top to bottom
1. Altitude map
2. Proximity to health map
3. Proximity to nomadic villages map
4. Precipitation map
5. Proximity to river map
6. Temperature map
7. Land cover map

Figure 3-1.Factors maps of VL disease in northwest Iran
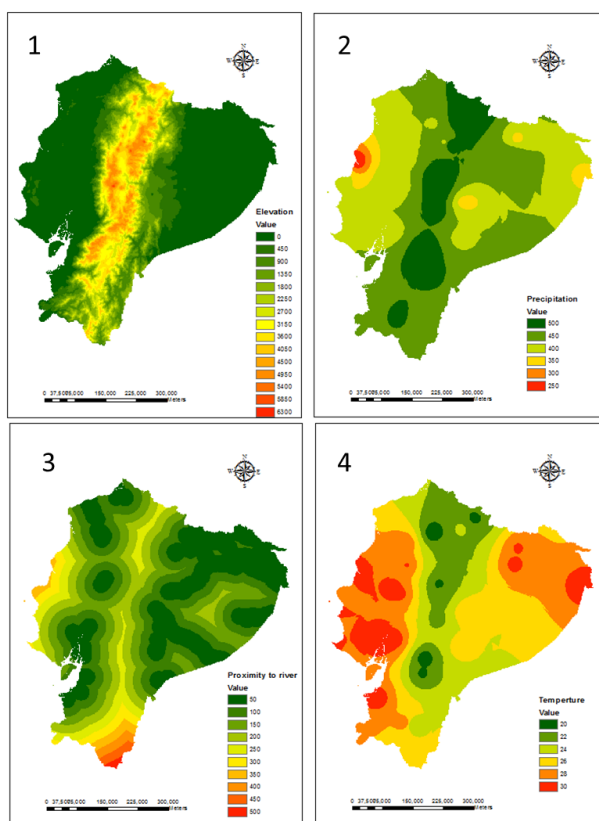
From left to right, top to bottom
1. Altitude map
2. Precipitation map
3. Proximity to river map
4. Temperature map

Figure 3-2.Factors maps of dengue disease in Ecuador (mainland)

13

3.1 Study area

The first study area is inside Iran, mainly on two parts: Kalaybar(western part of East Azerbaijian province;47°04´E, 38°29´N), Ahar(south of kalaybar; 47°02´E,38°52´N). The second study area is Ecuador (mainland; 1°46´S, 78°12´W).
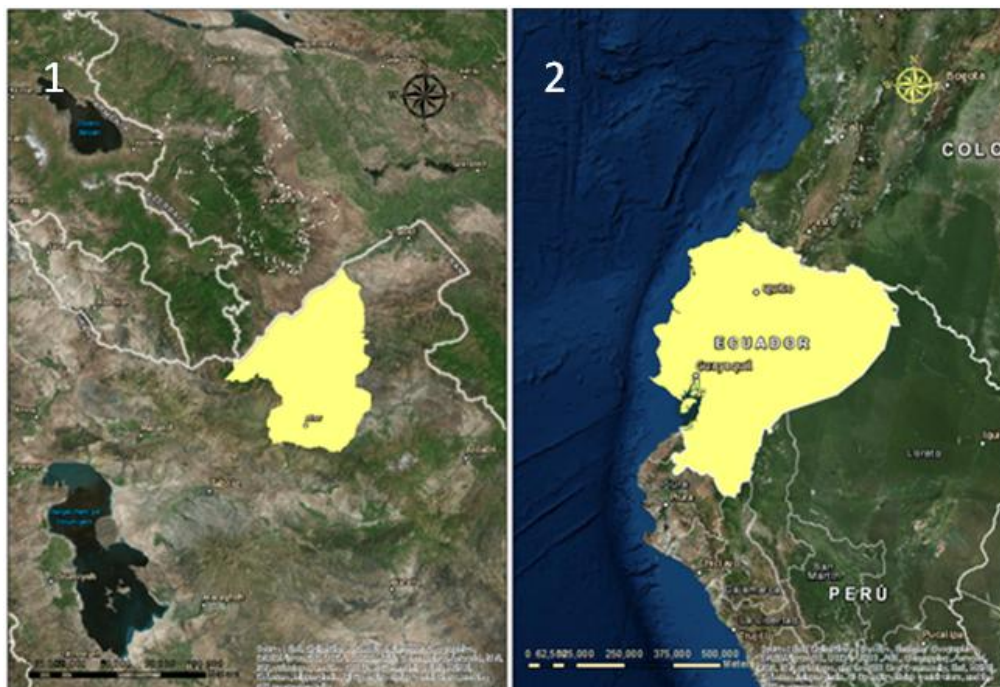

Figure 3-3.(1) Study area in East Azerbaijian,Iran; (2)Study area in the mainland of Ecuador.

3.2 Data source

The geographic data used in Iran comes from Iranian National Cartographic Center, Meteorological Organization, Infectious and Tropical Diseases Research Center (ITDRC) of MoH. The data used in Ecuador comes from the Ministry of health of Ecuador. The data for Iran was collected from 2000 to 2008; the data for Ecuador was in 2015.The geographic data are in the raster format. ArcMap 10.2.2 is applied to manipulate the spatial data. MATLAB is applied to run the figures from the data in three models. The weights that used in the study are acquired from experts.

3.3 VL disease In northwest Iran

Visceral leishmaniasis (VL), also known as black fever, is the most severe form in leishmaniasis. This disease is the second-largest parasitic killer in the world endemic. Leishmania infantum is the principal agent of human and canine VL in Iran (Mohebali et al.,2002, 2004). The disease has been reported adventitiously in Iran with the southern and north-western part being the primary epidemic. The physical and social environment of northwest Iran have many factors associated with the Visceral leishmaniasis disease heavily (Rajabi M,et al. 2014).

3.3.1   AHP results and map

In order to apply the AHP method described above, breaking of the complex unstructured problem into its component factors is necessary. Geography, environment and social economy are three mainly part that influence the spread of VL disease. So the influence factors were classified into these three hierarchies. After the 13 factors being arranged in hierarchic order, numerical factors will be assigned to them to make sure the judgment of the relative importance of each factor is subjective. The judgements are then synthesized. The factors compared against other factors is assigned a relative dominant value between 1 and 9 to the intersecting cell (Table 3-1).

Analyzing all these 13 factors in topography, meteorology and human environment, we decide that the main criteria level in this AHP method contains three parts: Geographical factors, Environmental factors, Socio-economic factors. In the sub criteria level , there is 4 factors under geographical factors(River, Altitude, Large river beds(RB),Lakes and water reservoirs(LR)).For environmental factors, six factors including temperature, precipitation(Rain),Irrigated farming and orchards(IF), dry farm(DF),rangelands with canopy cover(RC),forest with canopy cover(FC) were considered. For Socio-economic factors, health center, nomads and settlement (ST) were included. The main structure of the AHP criteria level is drawn in Figure 3-4.
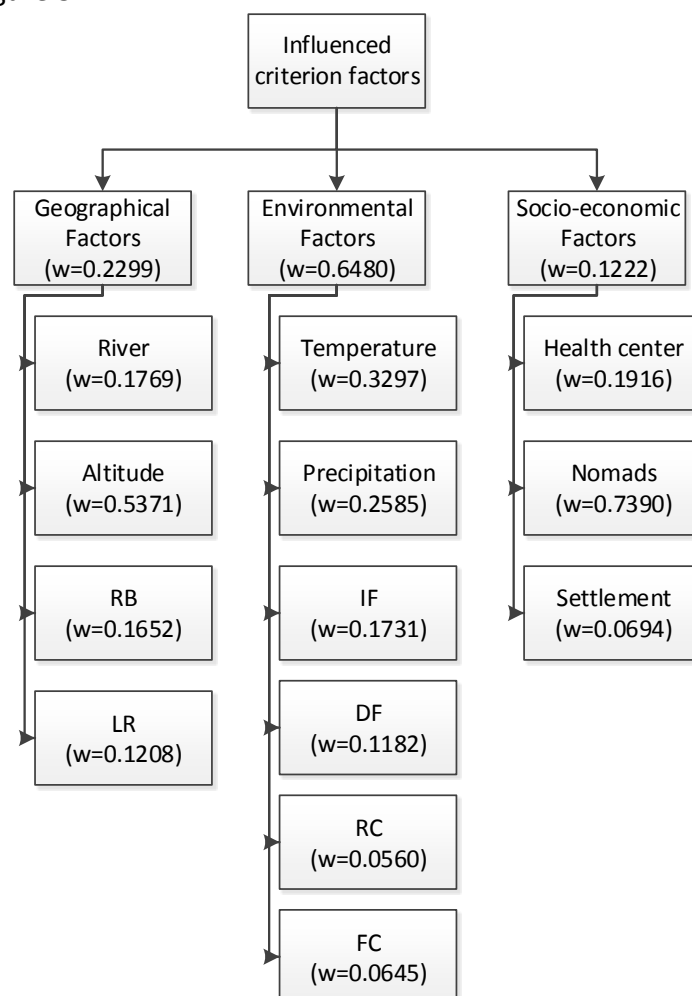

Figure 3-4.APH hierarchy associated with VL

The weights in this research were gained from VL modeling expert. The weight values were determined by AHP pairwise matrix for the datasets (Table 3-1). After that, CR value was calculated to determine if the pairwise comparisons are consistent (this value should be less than 0.1). One of the strengths of the AHP method is that it considers for inconsistent relationships while at the same time, providing a CR as an indicator of the degree of consistency or inconsistency (Forman and Selly 2001; Chen et al. 2009). In this study, the CR results for the pairwise comparison matrix for these thirteen dataset layers were 0.0032(Table 3-2). It justifies the comparison of the characteristics were perfectly consistent. And the relative weights were appropriate to be used in the VL susceptibility model.

Table 3-1.Pairwise comparison matrix, factor weights and consistency ratio of the data layers used

Factors	1	2	3	4	5	6	Eigen values
Geographical							
*River	1						0.1769
*Altitude	2	1					0.5371
*Large river beds(RB)	1	1/5	1				0.1652
*Lakes and water reservoirs(LR)	1	1/5	1/2	1			0.1208
Consistency ratio : 0.0627							
Environmental							
*Temperature	1						0.3297
*Precipitation(Rain)	1/2	1					0.2585
*Irrigated farming and orchards(IF)	1/4	1/4	1				0.1731
*Dry farm(DF)	1/3	1/3	1/3	1			0.1182
*Rangelands with canopy cover(RC)	1/4	1/4	1/4	1/3	1		0.0560
*Forest with canopy cover(FC)	1/3	1/3	1/4	1/3	1	1	0.0645
Consistency ratio : 0.0972							
Socio-economical							
*Health center	1						0.1916
*Nomads	6	1					0.7390
*Settlement(ST)	1/4	1/8	1				0.0694
Consistency ratio : -0.0952							

Table 3-2.Pairwise comparison matrix for dataset layers of VL analysis

Factors	1	2	3	Eigen values
Geographical	1			0.2299
Environmental	3	1		0.6480
Socio-economical	1/2	1/5	1	0.1222
Consistency ratio : 0.0032				

There are 4 pairwise comparison matrices in all. One for the main criteria level shown in Table 3-2, three for the sub-criteria level, the first sub-criteria is under geographic: river, altitude, large river beds(RB), lakes and water reservoirs(LR), given in Table 3-1. The second matrix for sub-criteria is under environment. The third matrix for sub-criteria is under socio-economy. All the eigenvalues in each matrix should sum to be 1. Susceptibility mapping using AHP model in this research was constructed using the following equation:

$$VL_{AHP} = W_{AHPgeo}(River \times W_{AHP} + Altitude \times W_{AHP} + RB \times W_{AHP} + LR \times W_{AHP}) +$$
$$+ W_{AHPenv}(Temperature \times W_{AHP} + \Pr ecipitation \times W_{AHP} + IF \times W_{AHP} + DF \times W_{AHP} + RC \times W_{AHP} + FC \times W_{AHP}) \quad (18)$$
$$+ W_{AHPsoc}(Healthcenter \times W_{AHP} + Nomads \times W_{AHP} + Settlement \times W_{AHP})$$

The AHP method was implemented in ArcGIS. First, all layers were normalized. The resolution is 100(m) ×100(m).Then under spatial analysis tool, raster calculator was chosen to acquire the susceptibility mapping. Three sub level criterion maps were calculated: geographical factor map, environmental factor map, socio-economic factor map. At last, continue to choose the raster calculator to achieve final AHP map (Figure 3-5).
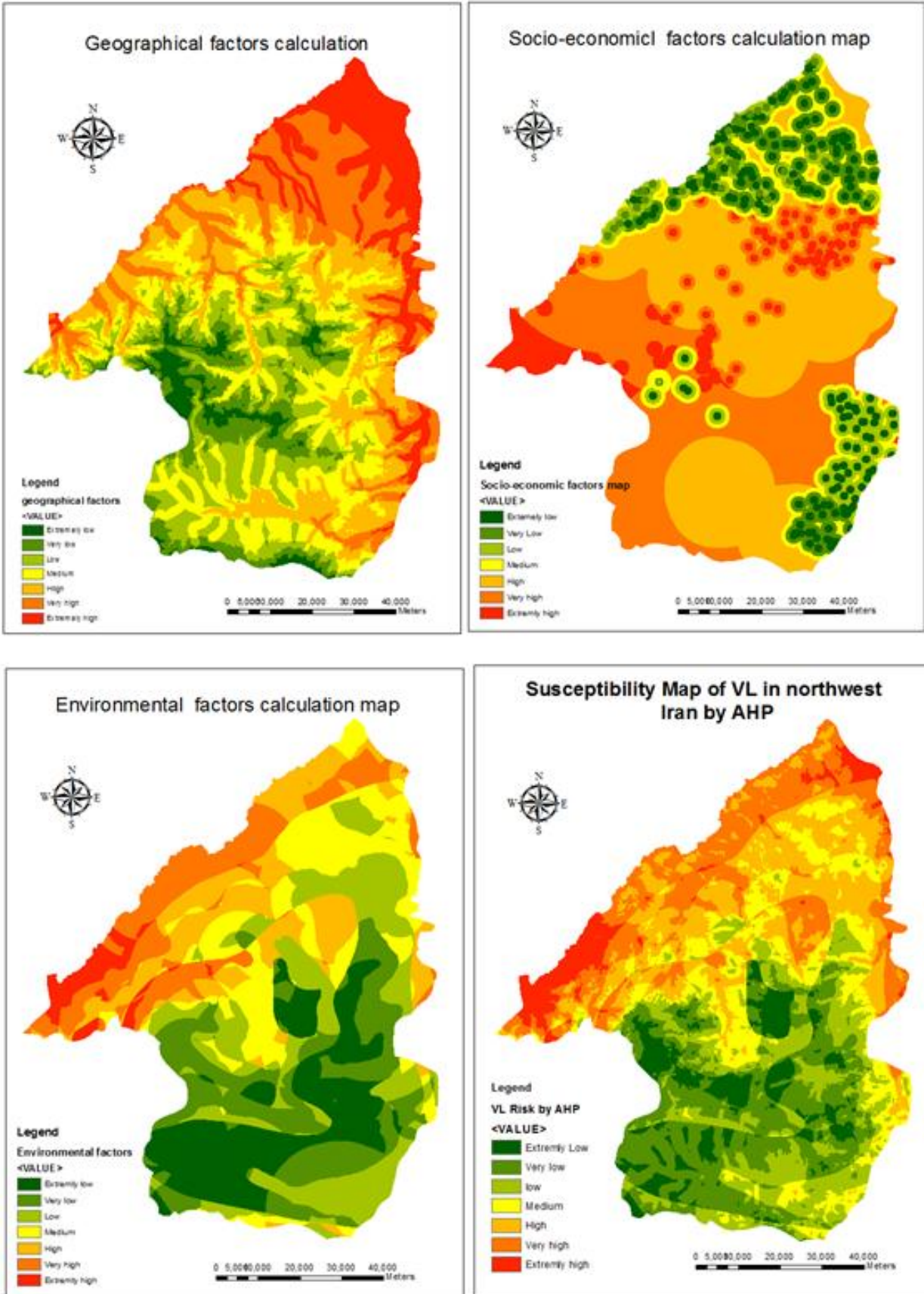
Figure 3-5.Susceptibility map of VL in northwest Iran by AHP

3.3.2 TOPSIS results and map

TOPSIS is a useful technique in dealing with multi-criteria problems. It helps decision makers (DMs) to organize the problems into a logical structure to solve them in a more efficient way. During this processing, analysis, comparisons, and alternatives rankings will be carried out. In this research, the 13 criteria factors that mentioned in the AHP method were used.

According to the basic TOPSIS model, the 13 layers of different factors were normalized first. Then they were combined into one layer with the cell size: 100(m) ×100(m). The attribute table of the combined 13 factors layer included an 8145×13 table with the normalized value of each reclassified cell. Considering the matrix form which is required in TOPSIS model, transform the table value to a matrix shown as equation (19), the 13 columns represents the 13 evaluation goal factors; the number of the rows is 8145:

$$D = \begin{array}{cccccc} f_1 & f_2 & f_3 & f_4 & & f_{13} \\ \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & x_{1,4} & \cdots & x_{1,13} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{6,1} & x_{6,2} & x_{6,3} & x_{6,4} & \cdots & x_{6,13} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{8145,1} & x_{8145,2} & x_{8145,3} & x_{8145,4} & \cdots & x_{8145,13} \end{bmatrix} \end{array} \qquad (19)$$

Data processing was performed using ArcGIS 10.2.2. Calculation of TOPSIS model was performed using MATLAB. After combine all 13 factors layers into one, a matrix using for TOPSIS model can be transformed from this layer's attribute table. Chapter2.2.2 has described the TOPSIS procedure, run this 8145×13 matrix within the TOPSIS algorithm in MATLAB, the ideal closeness results were chosen to represent the TOPSIS final value. Because this matrix has 8145 rows, the number of ideal closeness drawn from the TOPSIS model is 8145(20 of them are selected randomly as a present Table 3-4).Then join the TOPSIS value as a new column in the attribute table of the combined layer. The final susceptibility map come from TOPSIS model was drawn by classified TOPSIS value in properties symbology (Figure 3-6). The weights used in this model are listed in Table 3-3.

Table 3-3.Factors weights for TOPSIS model

Factors	Weights
Settlement(ST)	0.1
Lakes and water reservoirs(LR)	0.05
Large river beds(RB)	0.05
Forest with canopy cover(FC)	0.01
Rangelands with canopy cover(RC)	0.01
Dry farm (DF)	0.04
Irrigated farming and orchards(IF)	0.04
Temperature	0.15
River	0.05
Precipitation(Rain)	0.1

Nomads	0.2
Health	0.05
Altitude	0.15

Table 3-4.The PIS NIS and ideal closeness value in TOPSIS model(pick 20 of 8145 figures as example)

| ID	Positive ideal distance	Negative ideal distance	Ideal closeness
2000	1.6158e-04	6.5688e-05	0.2890
2001	1.4879e-04	6.2943e-05	0.2973
2002	1.9096e-0.4	5.6275e-05	0.2276
2003	1.9694e-0.4	5.0294e-05	0.2034
2004	1.8356e-0.4	5.0294e-05	0.2567
2005	1.7237e-0.4	6.4834e-05	0.2733
2006	1.7569e-0.4	5.5750e-05	0.2409
2007	1.8576e-0.4	6.0936e-05	0.2470
2008	1.4540e-0.4	7.6041e-05	0.3434
2009	1.6292e-0.4	8.3117e-05	0.3378
2010	1.6508e-0.4	6.7984e-05	0.2917
2011	2.0158e-0.4	4.2755e-05	0.1750
2012	1.8103e-0.4	5.0410e-05	0.2178
2013	1.5917e-0.4	6.7564e-05	0.2980
2014	1.3446e-0.4	9.3202e-05	0.4094
2015	1.4821e-0.4	6.9282e-05	0.3186
2016	1.6988e-0.4	5.0806e-05	0.2302
2017	1.8639e-0.4	5.7190e-05	0.2348
2018	1.7294e-0.4	5.8495e-05	0.2527
2019	1.3193e-0.4	7.8736e-05	0.3738
2020	1.6281e-0.4	6.7955e-05	0.2945
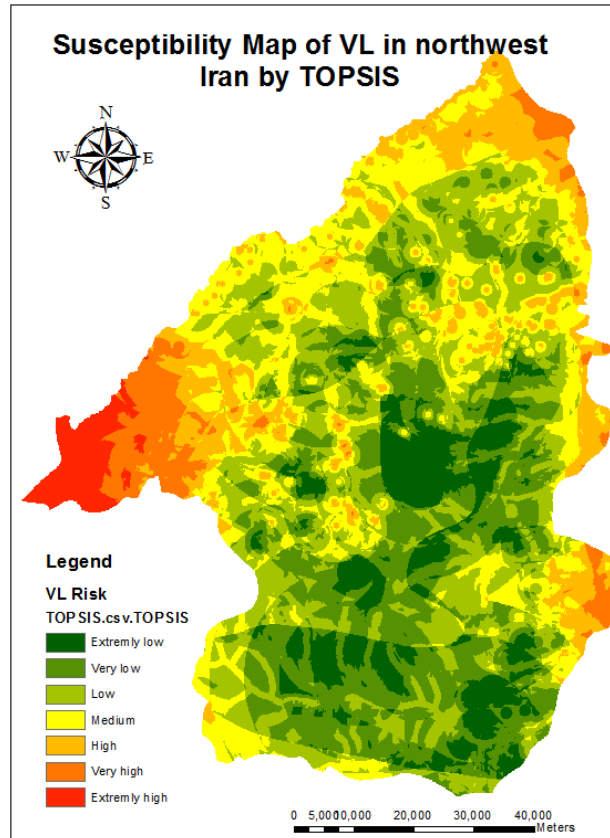
Figure 3-6.Susceptibility map of VL in northwest Iran by TOPSIS

3.3.3 OWA results and maps

According to the basic concept described in chapter 2.2.3, equations (15), (16) were selected to develop the OWA method. The criteria weights are the same as TOPSIS ones. In OWA model, firstly the normalized 13 layers should combined to be one layer (the same one as TOPSIS), then the same 8145×13 matrix was load into MATLAB, run the matrix under the OWA function, according to equation 15 in this research. The standardization and calculation in the OWA method were all done by this function. Different α values produces different set of ordered weights, and set of ordered weights are related to a trade-off and ORness, which means a decision scenario. Table 2-2 had discussed the relationships between α and ORness. α is the degree of optimism that indicates the decision strategy. If ORnees is 0, α will equal to ∞, strategy corresponding to MIN operation; if ORness is 1, α will equal to 0, strategy corresponding to MAX operation; if ORness is 0.5, α will equal to 1, strategy corresponding to conventional WLC. α value and ORness value used in this case study listed in Table 3-6, it guides the user along the continuum from extremely optimistic to extremely pessimistic decision strategies. Ordered weights were calculated according to equation (16).Table 3-5 shows 7 different α values and associated optimal order weights. According to the ordered weights, trade-off values under different α values list on Table 3-6. Different α value will come to different ordered weights, so different OWA maps will be gained by the change of α value. Joining the final OWA values as a new column to the attribute table of the combined layers (Figure 3-7). Since it has 7 α values in this research, there would be 7 OWA maps in the end. The susceptibility mapping in OWA method was shown by classified OWA value in
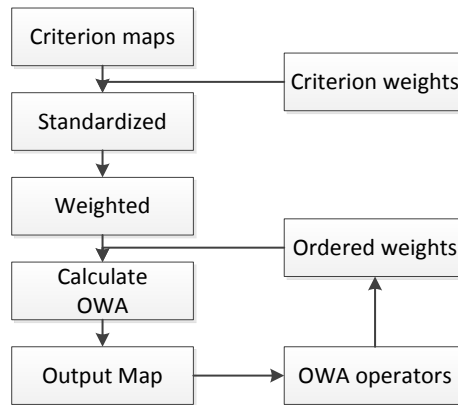
properties symbology (Figure 3-8 to Figure 3-14).

Figure 3-7.Flow chart of OWA

Table 3-5.Optimal order weights for selected values of the parameter α and the number of map layers.

	α						
	0	0.1	0.4	1	2	10	∞
V_1	0	0.7738	0.3584	0.0769	0.0059	7E-12	1
V_2	0	0.0555	0.1145	0.0769	0.0178	7E-09	0
V_3	0	0.0343	0.0833	0.0769	0.0296	4.2E-07	0
V_4	0	0.0252	0.0678	0.0769	0.0414	7E-06	0
V_5	0	0.0201	0.0583	0.0769	0.0533	6.3E-05	0
V_6	0	0.0167	0.0516	0.0769	0.0651	0.0004	0
V_7	0	0.0144	0.0467	0.0769	0.0769	0.0016	0
V_8	0	0.0126	0.0428	0.0769	0.0888	0.0057	0
V_9	0	0.0113	0.0397	0.0769	0.1006	0.0175	0
V_{10}	0	0.0102	0.0372	0.0769	0.1124	0.0472	0
V_{11}	0	0.0093	0.0350	0.0769	0.1243	0.1156	0
V_{12}	0	0.0086	0.0331	0.0769	0.1361	0.2610	0
V_{13}	1	0.0080	0.0315	0.0769	0.1479	0.5509	0

Table 3-6.Some properties for selected values of the α parameter (Jelokhani-Niaraki 2015)

α	ORness	Tradeoff	Aggregation strategy	Decision Strategy
0	1	0	Logic OR(MAX)	Extremely optimistic
0.1	0.9	0.2435	OWA	Very optimistic
0.4	0.7	0.6833	OWA	Optimistic
1	0.5	1	WLC	Neutral
2	0.3	0.8338	OWA	Pessimistic
10	0.1	0.4199	OWA	Very pessimistic
∞	0	0	Logic AND(Min)	Extremely pessimistic

Figure 3-8 to Figure 3-14 shows seven decision strategies. Each strategy is associated with a given α value and the measurement of trade-off between evaluation criteria. The strategy associated with α=0 refers to the extremely optimistic strategy. This strategy is characterized by a dispersion of 0, which implies no trade-off between evaluation criteria. Increasing α value from 0 to 1 corresponds to increasing the degree of optimism, increasing the trade-off between criteria. This implies higher and higher ordered weights are assigned to the higher-ranking criterion values at a certain location. As a result, low risk area gets larger and larger. The strategy associated with α=1 represents a neutral work. It is also a strategy with full trade-off between evaluation criteria. Assigning same criteria weight 0.0769 to every criterion in this case study. Increasing α value from 1 to ∞ means increasing degree of pessimistic and decreasing the trade-off between criteria. The strategy with α=∞ refers to an extremely pessimistic strategy. This strategy assigns an ordered weight of 1 to highest value at each location. Under this strategy, most of the area should be considered for high risk. However extremely optimistic strategy and extremely pessimistic strategy would beyond the limited resources and be prejudice (Malczewski, J. 2005).So, the optimistic strategy (α=0.4) was selected for VL modeling (the same reason for dengue disease section 3.4.3). This strategy is also with moderate trade-off between criteria. From the OWA map with α=0.4, it is clear that the area of highest risk are situated at the north east of our study area, the central part are the lowest risk area.
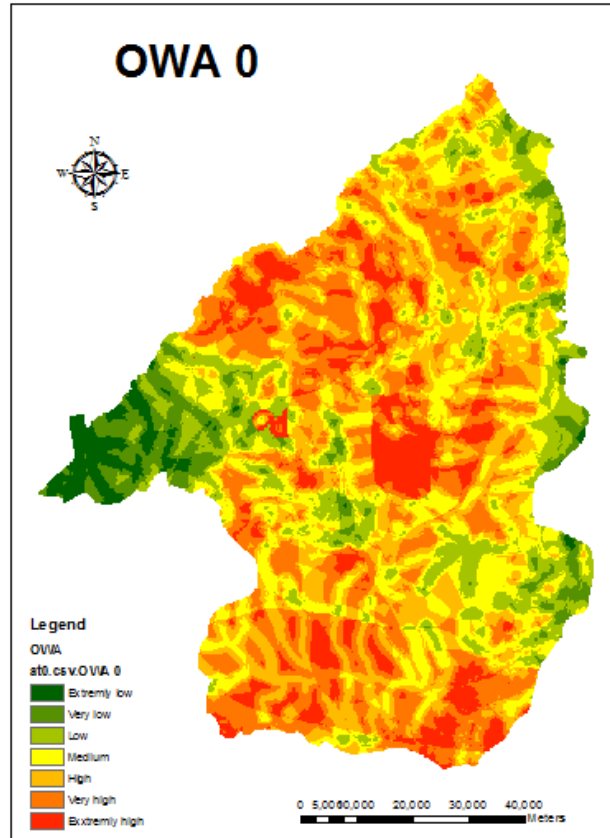
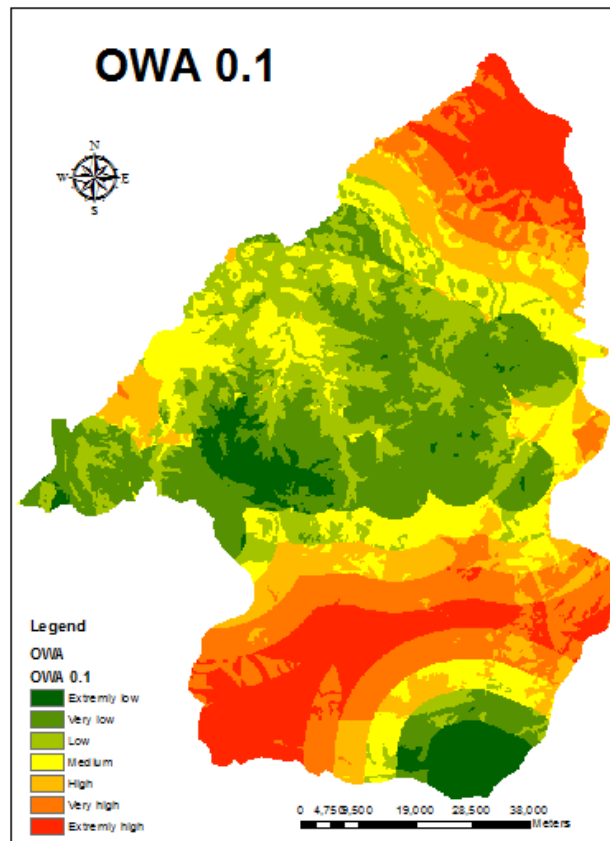Figure 3-8.Susceptibility map of VL in northwest Iran by OWA0 method

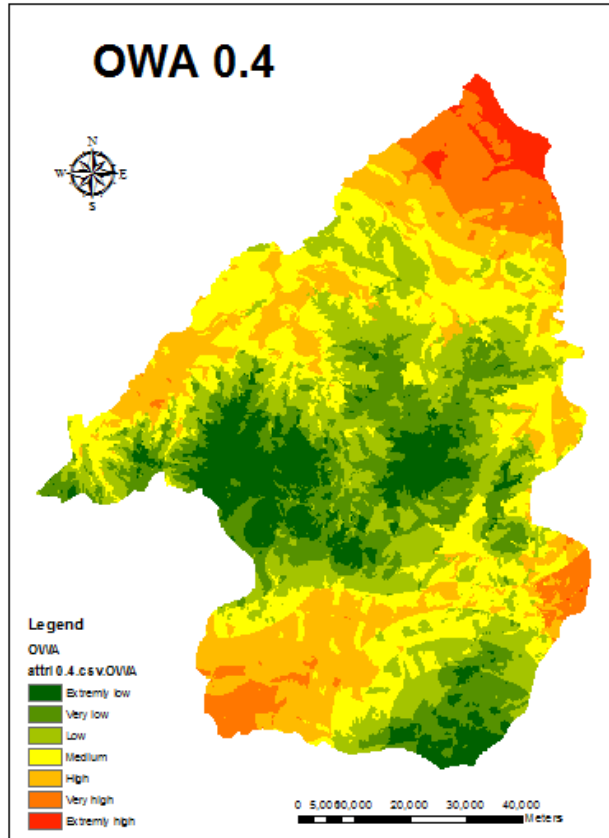Figure 3-9. Susceptibility map of VL in northwest Iran by OWA0.1 method

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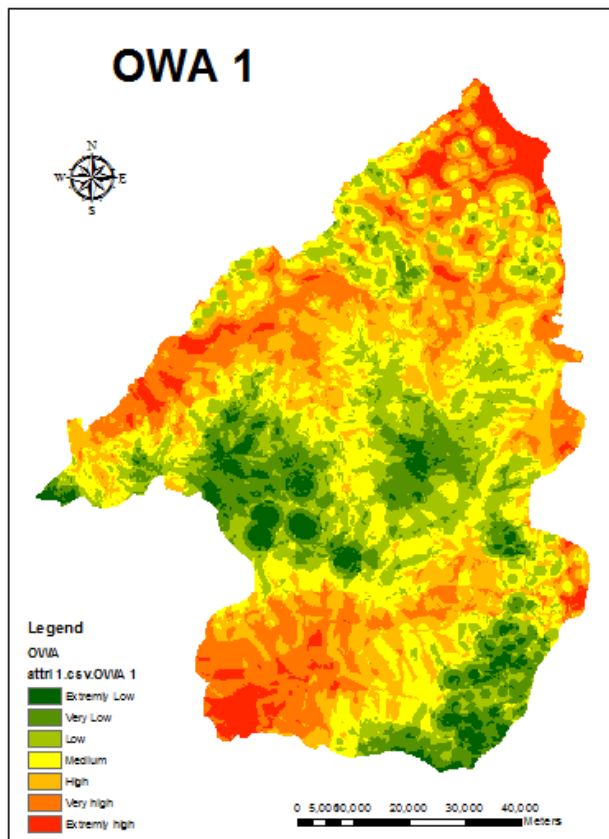Figure 3-10. Susceptibility map of VL in northwest Iran by OWA0.4 method

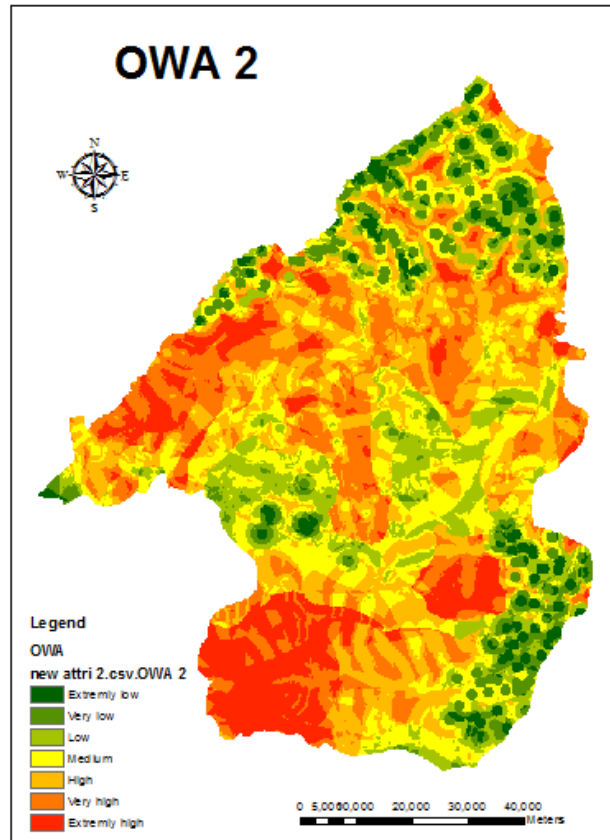Figure 3-11. Susceptibility map of VL in northwest Iran by OWA1 method

25

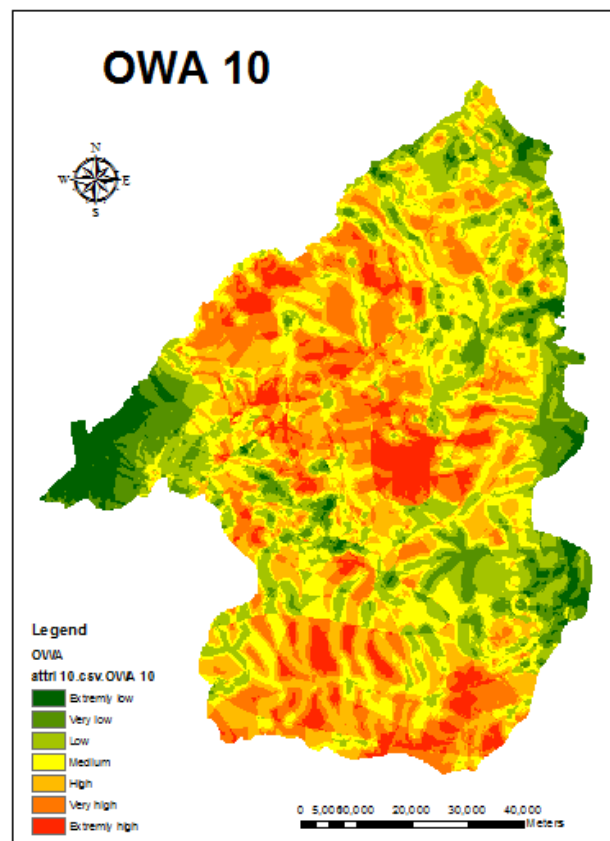Figure 3-12. Susceptibility map of VL in northwest Iran by OWA2 method

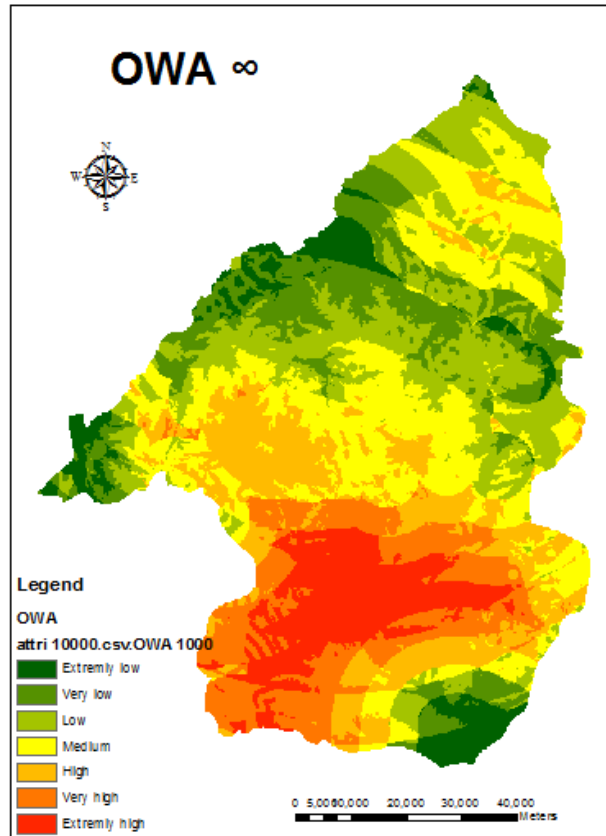Figure 3-13.Susceptibility map of VL in northwest Iran by OWA10 method

Figure 3-14.Susceptibility map of VL in northwest Iran by OWA∞ method

3.4 Dengue disease In Ecuador

Dengue fever (DF) is a global disease burden that infects an estimated 50-100 million individuals in tropical and sub-tropical areas every year (Halstead 2007). It has rapidly increased in geographic distribution, incidence in recent years. Through the bite mosquitoes, the viruses are transmitted. Dengue is widely distributed in more than 100 countries in the Americas, the Middle East, the Asia-Pacific region and Africa. The geographical limits correspond approximately to a winter isotherm of 10°C, mostly between latitude 35°N and 35°S (World Health Organization 2009). Approximately 50 million epidemics occur each year. In 2000, an outbreak of dengue in Ecuador included 22,937 cases reported to PAHO (Dick, O.B., et al. 2012). It is now hyper-endemic in the coastal regions in Ecuador.

3.4.1   AHP results and map

According to the data in Ecuador, the case study of the dengue disease only had 4 factors within one level, which are temperature, precipitation, elevation, and distance to river respectively. The weight of each factors were gained from the questionnaire which we collect suggestions from dengue modeling expert. The results of pairwise comparison are shown in Table 3-7.

Table 3-7.Pairwise comparison matrix for dataset layers of Dengue analysis

Factors	1	2	3	4	Eigen values
Temperature	1				0.3142
Precipitation	2	1			0.4172
Elevation	1/4	1/5	1	1/5	0.0649
Distance to river	1/3	1/2	5	1	0.2037
Consistency ratio : 0.0880					

The susceptibility map using AHP model in this research was constructed using the following equation:

$$Dengue_{AHP} = Temperature \times W_{AHP} + \Pr ecipitatuon \times W_{AHP} + Elevation \times W_{AHP} + Dis \tan ce \times W_{AHP} \quad (20)$$

All the procedures for Ecuador data in AHP method are the same as VL disease in northwest Iran. Final susceptibility map by AHP method is shown as Figure 3-15.
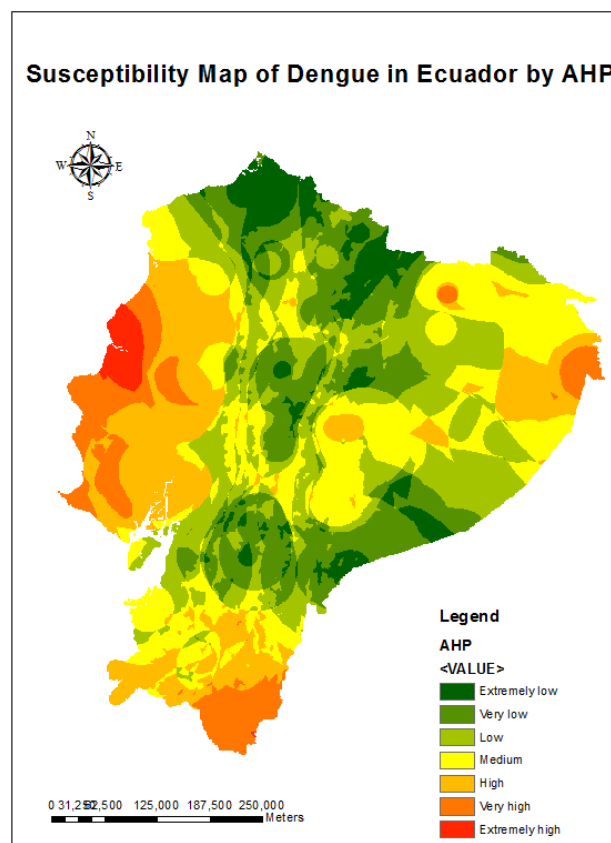

Figure 3-15.Susceptibility map of Dengue in Ecuador by AHP

3.4.2 TOPSIS results and map

Regards to the weights used in TOPSIS, the experts' weights were utilized directly in this model (Table 3-8).

Table 3-8.Factors weights for TOPSIS model (Dengue)

Factors	Weights
Temperature	0.3
Precipitation	0.4
Elevation	0.1
Distance to river	0.2

The procedure in TOPSIS is the same as VL disease in northwest Iran. The matrix in this case study is a 542×4 matrix. Final susceptibility map of dengue disease in Ecuador by TOPSIS method is shown as Figure 3-17 to Figure 3-24.
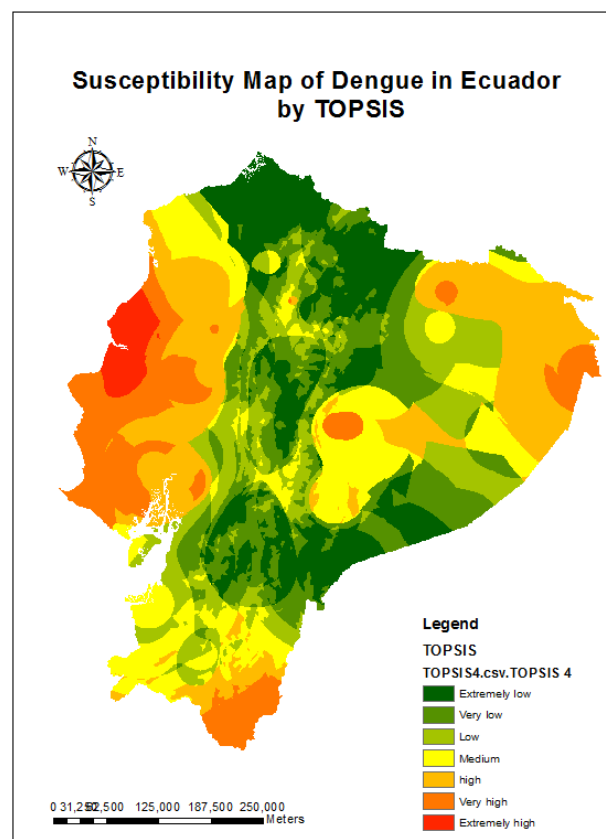

Figure 3-16.Susceptibility map of dengue in Ecuador by TOPSIS

3.4.3   OWA results and map

With the same process as in VL disease, the ordered weighs (Table 3-9), trade off (Table 3-9), and final susceptibility map (Figure 3-15) given as below. It is clear the central part are low risk area, the left and right side of Ecuador mainland are high risk area.

Table 3-9.Order weights for selected values of the parameter α and trade-off values

	α						
	0	0.1	0.4	1	2	10	∞
V_1	0	0.8706	0.5743	0.2500	0.0625	9.5E-07	1
V_2	0	0.0625	0.1835	0.2500	0.1875	0.0009	0
V_3	0	0.0386	0.1334	0.2500	0.3125	0.055	0
V_4	1	0.0284	0.1087	0.2500	0.4375	0.9437	0
Trade off	0	0.1721	0.5631	1.0000	0.6773	0.0736	0

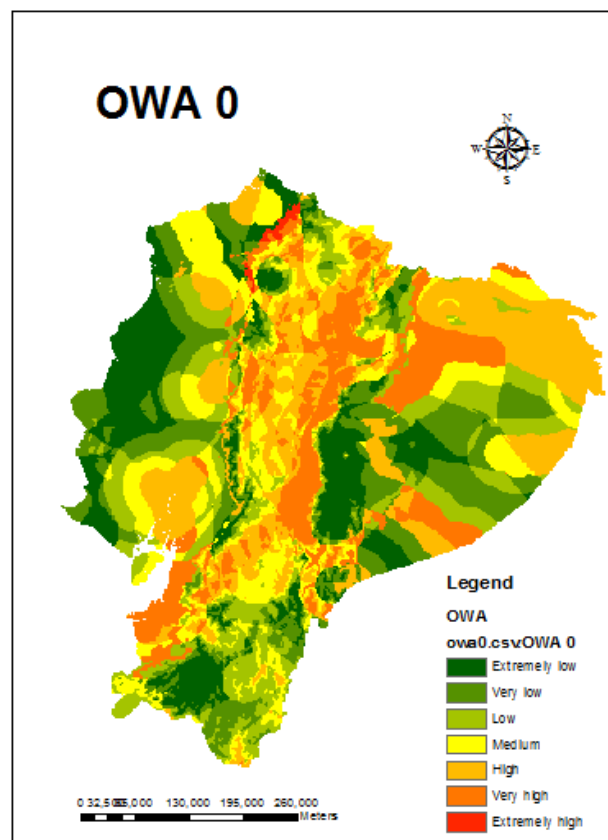
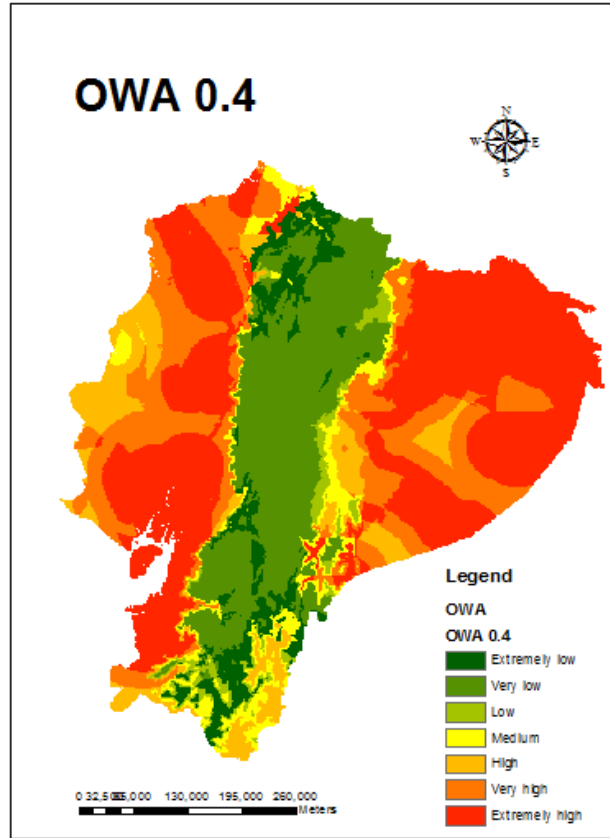Figure 3-17.Susceptibility map of dengue in Ecuador by OWA0

Figure 3-18. Susceptibility map of dengue in Ecuador by OWA0

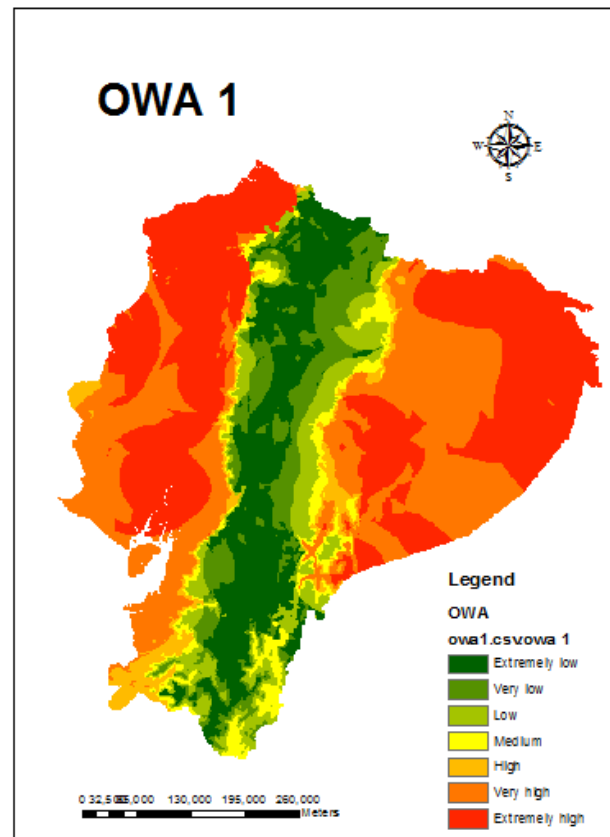

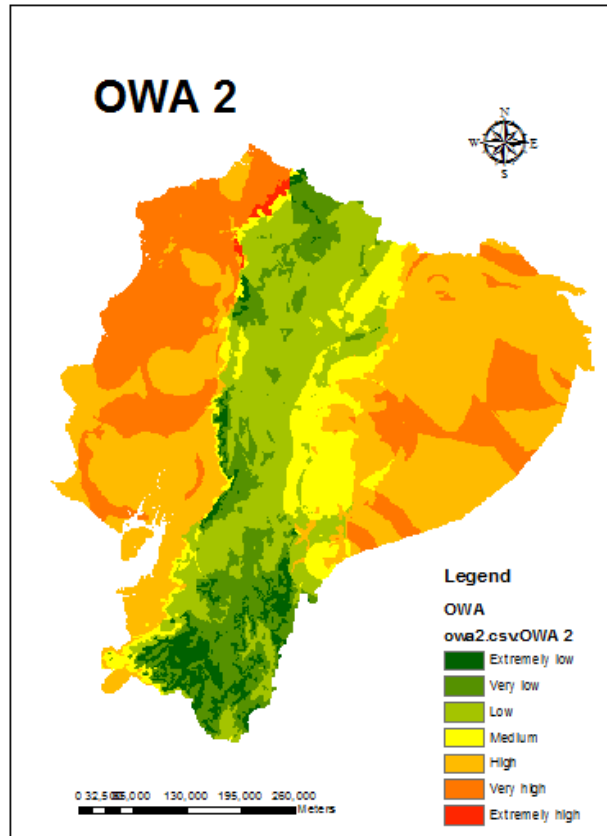Figure 3-19.Susceptibility map of dengue in Ecuador by OWA1

Figure 3-20. Susceptibility map of dengue in Ecuador by OWA2
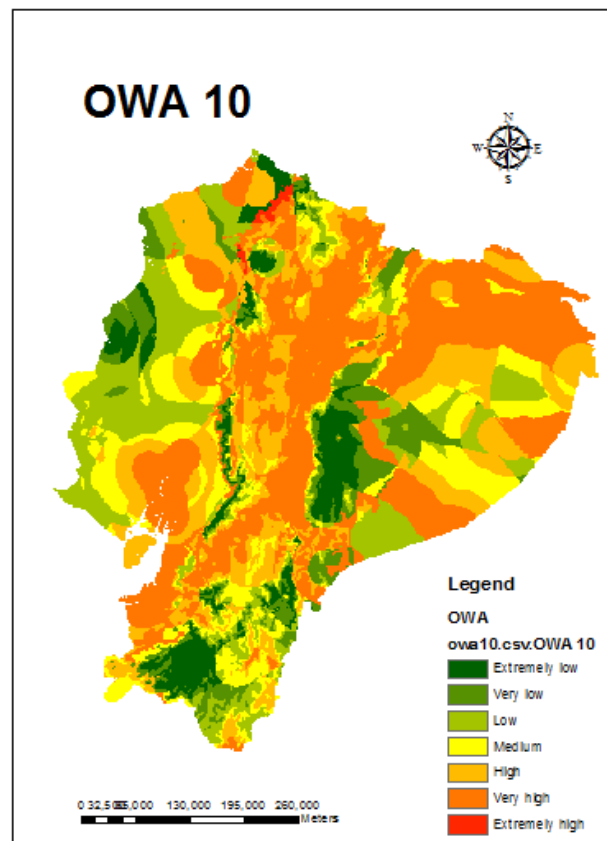

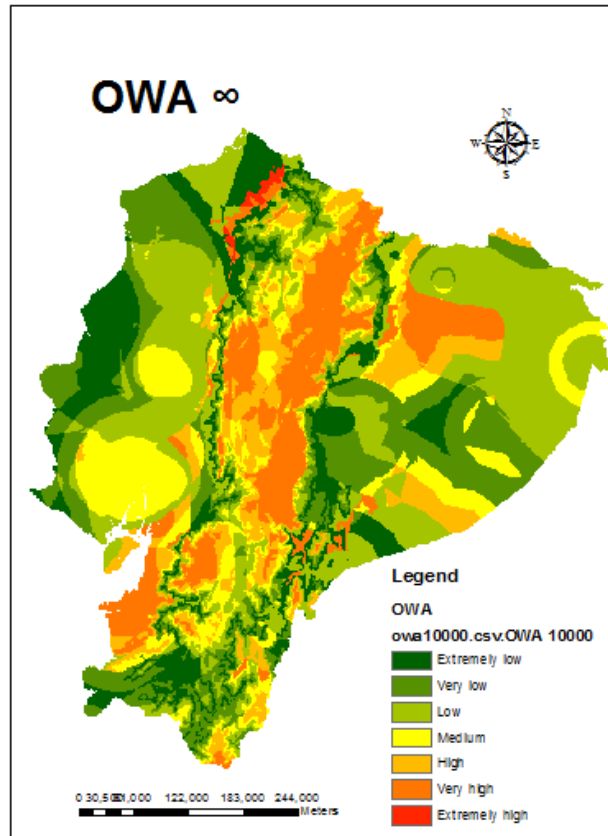Figure 3-21.Susceptibility map of dengue in Ecuador by OWA10

Figure 3-22. Susceptibility map of dengue in Ecuador by OWA ∞

Chapter 4

4. Results and Discussion

4.1 Validation of models used

4.1.1   VL disease in northwest Iran

Existing VL disease inventory points were used for the validation of these three models to make comparison. 5 endemic points and 5 non-endemic points. Table 4-1 lists the figure of area under category for each method; all the susceptibility categories for AHP, TOPSIS, OWA (0.4), and WLC (OWA 1) are clearly listed by certain numbers in the table.

In OWA method, owing to different α parameter, a wide range of OWA solutions can be generated. In this case study, exploring 7 scenarios of order weights by different parameter: α= 0, 0.1, 0.4,1,2,10 and ∞ respectively (Section3.3.3). Increasing α value from 0 to ∞ corresponds to increasing ORness degree and trade-off between evaluation criteria. The criterion substitutability expressed by the trade-off value, it illustrates the degree of the performance. Comparing all of 7 corresponding maps in Figure 3-8 to Figure 3-14, along with decreasing the ORness (increasing trade-off), the VL disease high risk areas get smaller and smaller. It has already mentioned in Section3.3.3, α equals 1 represents WLC, this strategy characterized by full trade-off and 0.5 ORness. Considering all the trade-off values of different α value, as it mentioned in section3.3.3, OWA0.4 were chosen to represent the

OWA method, because OWA 1 also represents WLC, we also choose this one.

For instance, AHP method (Figure 4-1) was interpreted as follows(Table 4-1): (i) the sum of the extremely high, very high and high susceptibility zones account for 40.65% (4.40%+16.87%+19.38%) of the entire study area, contained 40% non-endemic validation points and 100% endemic validation points . (ii) the moderate susceptibility zones account for 14.32% of the study area and no endemic and non-endemic points in this category. (iii) the sum of extremely low, very low and low susceptibility zones occupied 45.03% (8.57%+20.24%+16.22%), contained no endemic validation and 60% of the non-endemic points.

Table 4-1.Areas under category (%) for each method

Method	Susceptibility category (%)						
	Extremely low	Very low	Low	Medium	High	Very high	Extremely high
AHP	8.57%	20.24%	16.22%	14.32%	19.38%	16.87%	4.40%
TOPSIS	10.16%	23.77%	26.28%	20.70%	11.44%	5.07%	2.58%
OWA (0.4)	10.35%	16.25%	21.55%	23.42%	18.90%	7.75%	1.78%
WLC(OWA1)	4.00%	11.25%	17.92%	22.46%	21.97%	17.38%	5.02%

Figure 4-1 shows the susceptibility map from AHP methods and add 10 validation points in this map. The black points are endemic, and green points are non-endemic. The predictions confirm to the calculation of the model, except 2 validation points (non-endemic) in the southwest area.
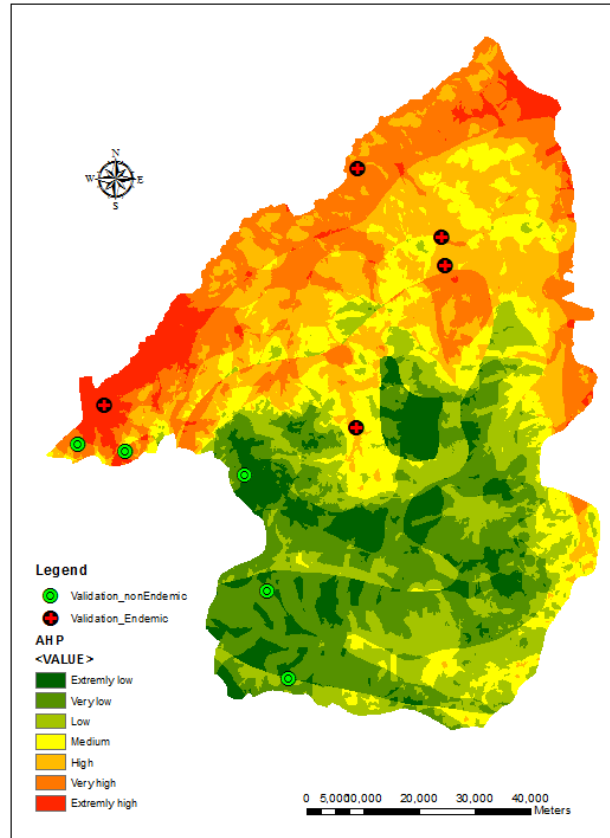
Figure 4-1.AHP multiclass susceptibility map with validation points for VL

To compare these three methods, prediction-rate method is used to validate the models. The prediction rate method explains how well the model and predictor variable predicts the disease. This method is widespread used to measure the performance of a predictive rule (Yesilnacar and Topal 2005; Van Den Eeckhaut et al.2006; Pourghasemi et al. 2012). In prediction-rate method, ROC (receiver operating characteristic) curves are used to assess the performance of models. PubMed search exposit that ROC analysis has been widely used in epidemiology for the assessment and tests of the disease from the healthy disciplines (Kummar R, et al. 2011; Daubin C, et al. 2011; Darmon M, et al. 2011,;Reddy S, et al. 2008;Zuo KH, et al. 2007). ROC curve plots the different accuracy values gained against the whole range of possible threshold values in the functions. This curve obtained by plotting both proportions of false negatives (1-specificity) and all combinations of sensitivities.

In order to perform ROC curve analysis, measurement of interest (=the communicable disease being studied) and independent diagnosis (classify the study subjects into 2 groups: disease group, non-disease group) should be provided. Endemic points were defined as 1; non-endemic points were defined as 0. The predicted scores of validation data from AHP, TOPSIS, OWA0.4, and WLC are listed in Table 4-2.

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Table 4-2.Validation data used for AHP, TOPSIS, OWA 0.4, WLC

State	AHP	TOPSIS	OWA 0.4	WLC
0	3.7795	0.6424	0.0581	-0.2506
0	3.8998	0.5692	0.1156	-0.2000
0	2.7465	0.2282	0.0386	-0.2471
0	2.9185	0.1916	0.1498	-0.1394
0	2.7263	0.2060	0.1977	-0.1131
1	3.8992	0.3768	0.1320	-0.1849
1	3.6063	0.2624	0.1165	-0.1702
1	3.7959	0.2803	0.1485	-0.1597
1	3.6782	0.3410	0.1422	-0.1645
1	4.4530	0.7433	0.1563	-0.1481

The area under ROC curve (AUC) which as a one-dimensional index, were calculate to measure the classification performance. AUC value varies from 0 to 1.The maximum value 1 means that the diagnostic test is perfect. 0.5 represents a worthless test. 0 indicates the result is completely wrong. AUC value from 0.5 to 1 means a good fit, while value below 0.5 presents a random fit (Swets 1988).

Figure 4-2 shows the ROC curves of the three models for VL disease in northwest Iran. Table 4-3 lists the AUC values of the three models.
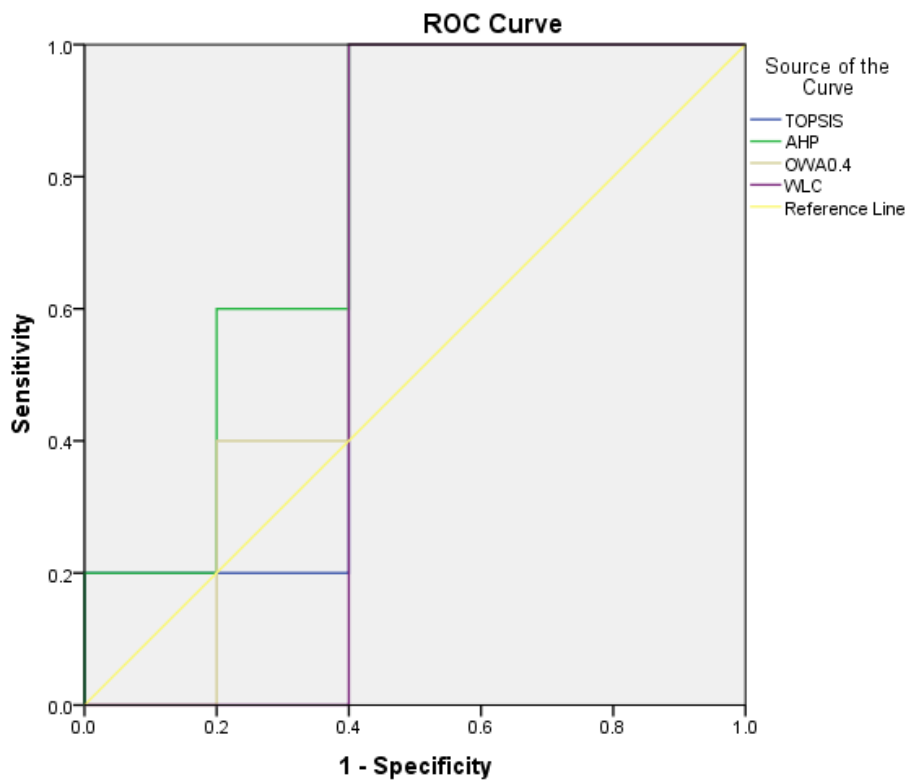

Figure 4-2.The ROC curves for AHP, TOPSIS, OWA 0.4, WLC

Table 4-3.AUC values of TOPSIS,AHP, OWA 0.4, WLC for VL disease in northwest Iran

Test Result Variable(s)	AUC
TOPSIS	0.680
AHP	0.760
OWA 0.4	0.640
WLC	0.600

Consider ROC curves of these three models together; it is obvious that their overall performance of the curves is close to each other. For more strict accuracy control, the comparison of AUC value is necessary. As a result, AHP (0.760) has higher prediction performance than TOPSIS (0.680), OWA 0.4(0.640) and WLC (0.600).From this plot, it can be concluded that AHP is the best one.

As to reason, it might be mainly caused by the factors: the number of the factors, the processing mode of the factors weights. For the number, too many factors were analyzed in this disease (some comparison will be made in 4.1.2). For the procedure, in AHP method, pairwise comparison was used to balance the weights from the expert, which made the factors weights more objective. TOPSIS and OWA invest the expert weights directly from the questionnaire. That make the weights depends more on experts' own opinion. It is also one shortcoming of knowledge-driven techniques.

4.1.2 Dengue disease in Ecuador

For dengue disease in Ecuador, validation areas were added to test the models, 4 non-endemic areas and 6 endemic areas were selected for the validation. The results are listed in Table 4-4. For OWA method results, comparing all of 7 corresponding maps in Figure 3-11, along with decreasing the ORness (increasing trade-off), the dengue disease high risk areas get larger and larger. Take AHP model as an example, it was interpreted as follows: (i) the sum of extremely high, very high and high susceptibility zones account for 27.82% (1.50%+8.11%+18.21%) of the entire study area. (ii) the moderate susceptibility zones account for 23.31% of the entire study area. (iii) the sum of extremely low, very low and low susceptibility zones account for 48.87% (7.00%+18.38%+23.49%).

Table 4-4.Areas under category (%) for each method

	Susceptibility category (%)						
	Extremely low	Very low	Low	Medium	High	Very high	Extremely high
AHP	7.00%	18.38%	23.49%	23.31%	18.21%	8.11%	1.50%
TOPSIS	16.23%	17.66%	15.49%	16.47%	20.30%	11.63%	2.23%
OWA (0.4)	6.10%	21.82%	2.61%	5.55%	8.54%	18.08%	37.31%
WLC(OWA1)	14.19%	9.35%	7.68%	4.74%	3.85%	26.02%	34.17%

Figure 4-3 shows the susceptibility map resulted from AHP method and add the validation areas in this map. 10 areas were selected from east west south north and middle part of Ecuador. Due to the lack of data in the east of Ecuador, so the northeast part was selected to represent that area. The darker the red color is, the more risk of dengue export in that area has. The same to VL disease, endemic areas were given state as 1, non-endemic area were given state as 0. The predicted scores of validation data from AHP, TOPSIS, OWA0.4, and WLC are listed in Table 4-5.Table 4-6 lists the AUC values of these four models.
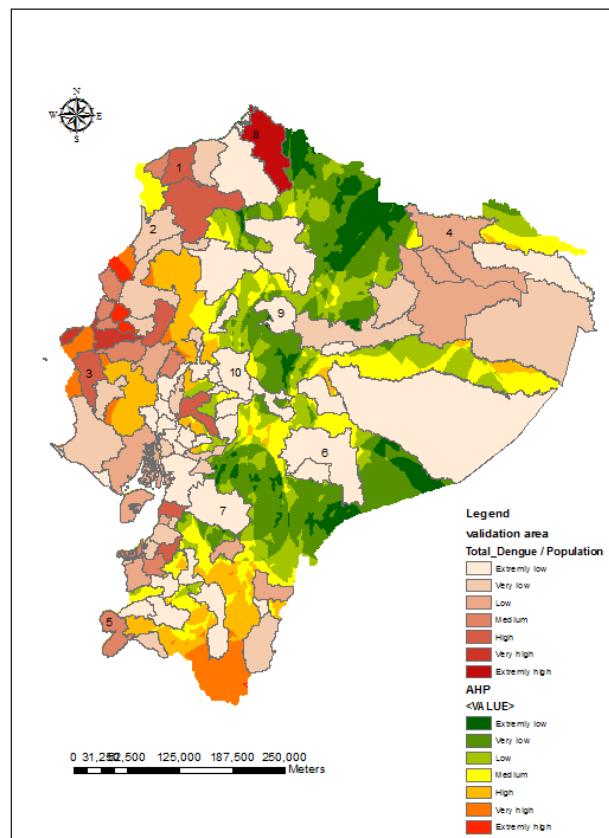

Figure 4-3.AHP multiclass susceptibility map with validation areas for dengue

Table 4-5.Validation data used for AHP, TOPSIS, OWA 0.4, WLC

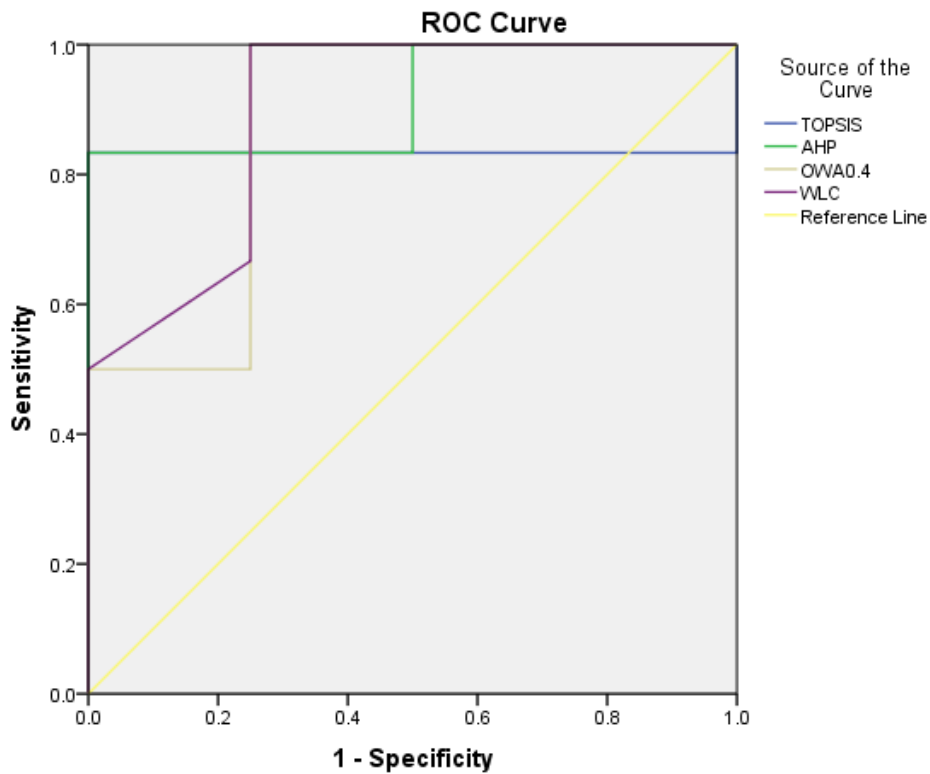| State	AHP	TOPSIS	OWA 0.4	WLC
1	2.3598	0.1985	0.7425	0.3000
1	3.0814	0.2706	0.7586	0.2449
1	3.5537	0.3723	0.4934	0.1567
1	2.6740	0.2494	0.7715	0.3153
1	3.0716	0.2341	0.6069	0.0728
1	1.7775	0.0337	0.6761	0.3464
0	1.8321	0.0804	0.7273	0.2449
0	1.6482	0.0872	0.1036	-0.3618
0	2.2027	0.1644	0.1292	-0.1225
0	1.6482	0.0826	0.1213	-0.3548

Figure 4-4 .The ROC curves for AHP, TOPSIS, OWA 0.4, WLC

Table 4-6.AUC values of TOPSIS, AHP, OWA 0.4 WLC for Dengue disease in Ecuador

Test Result Variable(s)	AUC
TOPSIS	0.833
AHP	0.917
OWA 0.4	0.875
WLC	0.896

It is obvious that these four lines are close to each other. Even though changing the data, AHP method also perform the best comparison with others. The AUC values of dengue disease being concerned (Figure 4-4), OWA and AHP don't have that huge discrepancy, they are almost equal to each other. Considering VL disease' values, there can be a conjecture, the subjective judgment of the factors weights from experts influence the results, otherwise OWA method can results a perfect prediction.

The GIS-MCDA methods provide a framework to deal with complex decision problem. In this study, the results indicated that AHP method performed best comparing to OWA and TOPSIS method. However when analyzing the dengue disease in Ecuador, the OWA-derived results are close to AHP result.

Comparing to VL disease, the precision of AUC value in dengue is higher. One reason is that the number of the factors in VL disease (13 factors) is much more than dengue disease's (4

factors). Because the huge amount of criteria and heterogeneity of data, results' uncertainty remains unclear. Even some small changes in weights may have a significant impact on the final results. Another reason is that the study area for VL disease is smaller than the study area for dengue disease; in general, enough data will provide a high accuracy test.

4.2 limitation

As mentioned above, within the three models, the best results can be gained by using AHP methods. One reason of these may cause by the weights given by experts. It is also one of the intrinsic deficiencies of knowledge driven technology, different experts will probably give different weights based on their own opinion.

From the AUC value of these models in VL disease and dengue disease, it can also be conclude that the lack of data influences the validation of the models. In the other words, for VL disease in Iran, the study area is only the northwest of Iran, for dengue disease the data tested in the models were the all Ecuador (mainland), but the study area in Iran is somewhat not large enough. That's why the test results in Ecuador is conspicuous than that in Iran.

Chapter 5

5. Conclusion

This thesis has focused on comparing Multi-criteria decision Analysis methods for susceptibility mapping in spatial communicable disease study. Related terminologies (literature review) are first introduced in Chapter 2, which contains the processing of the AHP, TOPSIS and OWA methods. Followed by the case study chapter, two case studies are presented to illustrate the methods: VL disease in northwest Iran, dengue disease in Ecuador (mainland). Finally the results (susceptibility maps) from these three methods are compared by the AUC values from ROC curves.

When using GIS-MCDA methods, it is evident that each method has advantages and limitations (Kritikos and Davies 2011).Based on this idea, in this study, the accuracy of the three GIS-MCDA methods had been compared. TOPSIS and OWA method were implemented in the same way: the ideal closeness values for TOPSIS and OWA values under different α values were calculate in MATLAB first, then join the value in ArcGIS to obtain the susceptibility maps of the disease. AHP method used the spatial analysis tools: raster calculator to combine all the factor layers to gain the susceptibility map of the disease. These investigations expose the capabilities of the three methods for susceptibility mapping in spatial communicable disease study. The results indicate that, in this particular application, the AHP method obtained the best predictive accuracy. However, it still be found if the data is enough OWA method almost have the same predictive accuracy as AHP. Analyzing the results from both VL disease and dengue disease, although TOPSIS performed worst in these three methods, it still had high AUC values. In conclusion, AHP method has the most concise procedures and highest accuracy in the prediction of infectious disease.

The limitation of this study can be concluded in two aspects: model limitation and data limitation. With respects to model limitation, the numbers of factors influence the final results, complicated factors in VL disease generate all the AUC values in these three methods lower than that in dengue disease. For data limitation, one is the restriction of experts' weights. Another data limitation is the lack of validation data, for VL disease validation we only have 10 points. For dengue disease validation, even though the patient and population rate area created as the validation area, but the deficiency of patients data in some regions still confine the precision of validation.

For future study, temporal prediction can be added to draw the risk prediction maps. Different with other risk map, no time factors is associated with a susceptibility map. All the prediction in this study is in a non-specified time span. If enough data provided, spatial-temporal prediction can be made from maps, which will provide more accurate prediction of the communicable disease.

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Appendix

Questionnaires for VL disease

- AHP method

A pilot study for development of a questionnaire for exploration of expert opinions on potential risk factors for VL in Northwest Iran, using a multi-criteria decision making (MCDM) method

You are cordially invited to participate in a pilot study, for development of a questionnaire which explores expert opinions on potential risk factors for VL in northwest Iran.

This questionnaire is designed to evaluate AHP's role in the susceptibility mapping of visceral leishmaniasis in northwest Iran. All your professional suggestions will be considered during the research, and will influence the final result of our research. Thank you for spending time doing the questionnaire.

Analytic Hierarch Process (AHP) was used in our research to identify and weight the risk factors. AHP is one kind of Multi-Criteria Decision making Method help the decision-makers choosing the criteria. Your tasks for this questionnaire are shown as below:

A: fill in the questionnaire (part 1- 2)
B: give your comments (part 2) as to clarity of instructions, important items that are left out etc.

Yours sincerely,
Shuzhi Dong
Dept of Physical Geography and Ecosystems Science
Lund University, Sweden

Method

In the AHP method each pair of criteria should be compared and weighted from 1 to 9 according to your view its influence on VL. The scale to comparing each pair of criteria is shown in Table q1.

Table q1: Values for the experts for pair wise comparison of criteria

Choice	Importance Value
Equally preferred	1
Moderately preferred	3
Strongly preferred	5
Very Strongly preferred	7
Extremely preferred	9
Values in between preferences	2, 4, 6, 8

Source: Ali Mansourian(2015)

This questionnaire is designed to perform a pair wise comparison of the available factors affecting the VL, the 8 factors shown as follow:
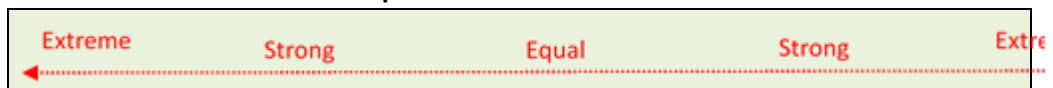
1. **Main criteria level**:
   1) Geographical factors
   2) Environmental factors
   3) Socio-economic factors
2. **Sub criteria level**:
   1) Geographical factors
      ➢ River
      ➢ Altitude
      ➢ Large river beds (RB)
      ➢ Lakes and water reservoirs (LR)
   2) Environmental factors
      ➢ Temperature
      ➢ Precipitation(Rain)
      ➢ Irrigated farming and orchards (IF)
      ➢ Dry farm (DF)
      ➢ Rangelands with canopy cover (RC)
      ➢ Forest with canopy cover (FC)
   3) Socio-economic factors
      ➢ Health center
      ➢ Nomads
      ➢ Settlement (ST)

Your task: Please compare the relative importance of each pair of factors affecting the VL using the scale below:

Part 1: Comparison of main criteria factors

		Extreme			Strong					Equal					Strong			Extre	
		9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
1	**Geographical factors**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	**Environmental factors**
2	**Geographical factors**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	**Socio-economic factors**
3	**Environmental factors**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	**Socio-economic factors**

Part 2: Comparison of sub criteria factors
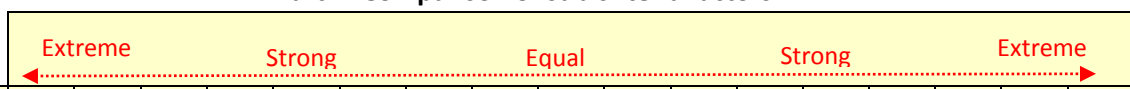
		Extreme			Strong					Equal					Strong			Extreme	
		9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	

		Extreme		Strong				Equal				Strong				Extreme			
		9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
1	River	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	Altitude
2	River	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	RB
3	River	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	LR
4	Altitude	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	RB
5	Altitude	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	LR
6	RB	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	LR

Part 3: Which statement do you agree with regards to each factor?

Environment factors	
Temperature	
People who are living in the high-temperature areas are more susceptible to VL	☐
People who are living in the low-temperature areas are more susceptible to VL	☐
Precipitation	
People who are living in the high-precipitation areas are more susceptible to VL	☐
People who are living in the low-precipitation areas are more susceptible to VL	☐
IF	
People who are living in the areas have more Irrigated farming and orchards are more susceptible to VL	☐
People who are living in the areas have less Irrigated farming and orchards are more susceptible to VL	☐
DF	
People who are living in the areas have more dry farm are more susceptible to VL	☐
People who are living in the areas have less dry farm are more susceptible to VL	☐
RC	
People who are living in the areas have more rangelands with canopy cover are more susceptible to VL	☐
People who are living in the areas have less rangelands with canopy cover are more susceptible to VL	☐
FC	
People who are living in the areas have more forest with canopy cover are more susceptible to VL	☐

People who are living in the areas have less forest with canopy cover are more susceptible to VL	☐
Socioeconomic factors	
Health center	
People whose living areas have more health centers are more susceptible to VL	☐
People whose living areas have less health centers are more susceptible to VL	☐
Nomads	
People whose living areas have more nomads factors are more susceptible to VL	☐
People whose living areas have less nomads factors are more susceptible to VL	☐
Settlement	
People whose living areas have more settlement factors are more susceptible to VL	☐
People whose living areas have less settlement factors are more susceptible to VL	☐
Geograpical factors	
Altitude	
People who are living in the high-elevation areas are more susceptible to VL	☐
People who are living in the low-elevation areas are more susceptible to VL	☐
Distance from river	
People who are living in the areas have long distance from river are more susceptible to VL	☐
People who are living in the areas have short distance from river are more susceptible to VL	☐
RB	
People who are living more close to Large river beds are more susceptible to VL	☐
People who are living far from Large river beds areas are more susceptible to VL	☐
LR	
People who are living more close to Lakes and water reservoirs are more susceptible to VL	☐
People who are living far from Lakes and water reservoirs are more susceptible to VL	☐

Part 4: Please, give your comments as to selection of groups and items

The aim of the study was   Suggestions for improvement:

□ 1 Very difficult to understand

□ 2

□ 3

□ 4

□ 5 Very easy to understand

The instructions for the questionnaire were   Suggestions for improvement:

□ 1 Very difficult to understand

□ 2

□ 3

□ 4

□ 5 Very easy to understand

Other comment

- TOPSIS and OWA method

A questionnaire for Multi Criteria Decision Making for studies of VL with the help of TOPSIS and OWA Process

You are cordially invited to participate in a study, for development of a questionnaire which explores expert opinions on potential risk factors for VL in northwest Iran.

Please give the weight of each of the factors below according to your experience.

Factors	Weights
Health centre	
River	
Altitude	
Temperature	
Precipitation(Rain)	
Nomads	
Large river beds(RB)	
Lakes and water reservoirs(LR)	
Irrigated farming and orchards(IF)	
Dry farm(DF)	
Rangelands with canopy cover(RC)	
Forest with canopy cover(FC)	
Settlement (ST)	

Questionnaires for dengue disease

- ## AHP method

A pilot study for development of a questionnaire for exploration of expert opinions on potential risk factors for

Dengue disease, using a multi-criteria decision making (MCDM) method

You are cordially invited to participate in a pilot study, for development of a questionnaire which explores expert opinions on potential risk factors for dengue disease in Ecuador.

This questionnaire is designed to evaluate AHP's role in the susceptibility mapping of for dengue disease in Ecuador. All your professional suggestions will be considered during the research, and will influence the final result of our research. Thank you for spending time doing the questionnaire.

Analytic Hierarch Process (AHP) was used in our research to identify and weight the risk factors. AHP is one kind of Multi-Criteria Decision making Method help the decision-makers choosing the criteria. Your tasks for this questionnaire are shown as below:

A: fill in the questionnaire (part 1- 2)

B: give your comments (part 2) as to clarity of instructions, important items that are left out etc.

Yours sincerely,

Shuzhi Dong

Dept of Physical Geography and Ecosystems Science

Lund University, Sweden

Method

In the AHP method each pair of criteria should be compared and weighted from 1 to 9 according to your view its influence on VL. The scale to comparing each pair of criteria is shown in Table q2.

Table q2: Values for the experts for pair wise comparison of criteria

Choice	Importance Value
Equally preferred	1
Moderately preferred	3
Strongly preferred	5
Very Strongly preferred	7
Extremely preferred	9
Values in between preferences	2, 4, 6, 8

Source: Ali Mansourian(2015)

This questionnaire is designed to perform a pair wise comparison of the available factors affecting the VL, the 8 factors shown as follow:
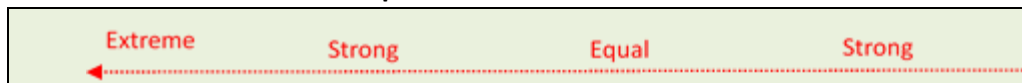
3. **Criteria level**:
   4) Temperature
   5) Precipitation

6) Elevation
7) Distance to river

Your task: Please compare the relative importance of each pair of factors affecting the VL using the scale below:

Part 1: Comparison of main criteria factors

	Extreme			Strong				Equal				Strong					
Temperature																	**Precipitation**
Temperature																	**Elevation**
Temperature																	**Distance to river**
Precipitation																	**Elevation**
Precipitation																	**Distance to river**
Elevation																	**Distance to river**

Part 2: Which statement do you agree with regards to each factor?

Environment factors	
Temperature	
People who are living in the high-temperature areas are more susceptible to Dengue	☐
People who are living in the low-temperature areas are more susceptible to Dengue	☐
Precipitation	
People who are living in the high-precipitation areas are more susceptible to Dengue	☐
People who are living in the low-precipitation areas are more susceptible to Dengue	☐
Elevation	
People who are living in high-elevation areas are more susceptible to Dengue	☐
People who are living in low-elevation areas are more susceptible to Dengue	☐
Distance from river	
People who are living in the areas have long distance from river are more susceptible to Dengue	☐
People who are living in the areas have short distance from river are more susceptible to Dengue	☐

Part 4: Please, give your comments as to selection of groups and items

The aim of the study was   Suggestions for improvement:

□ 1 Very difficult to understand

□ 2

□ 3

□ 4

□ 5 Very easy to understand

The instructions for the questionnaire were   Suggestions for improvement:

□ 1 Very difficult to understand

□ 2

□ 3

□ 4

□ 5 Very easy to understand

Other comment:

- TOPSIS and OWA method

A questionnaire for Multi Criteria Decision Making for studies of VL with the help of TOPSIS and OWA Process

You are cordially invited to participate in a study, for development of a questionnaire which explores expert opinions on potential risk factors for Dengue disease in Ecuador.

Please give the weight of each of the factors below according to your experience.

1. Temperature

2. Precipitation

3. Elevation

4. Distance to river