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To cite this article: Bakhtiar Feizizadeh, Thomas Blaschke & Hossein Nazmfar (2012): GIS-based ordered weighted averaging and Dempster–Shafer methods for landslide susceptibility mapping in the Urmia Lake Basin, Iran, International Journal of Digital Earth, DOI:10.1080/17538947.2012.749950

To link to this article: http://dx.doi.org/10.1080/17538947.2012.749950

International Journal of Digital Earth
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tjde20
GIS-based ordered weighted averaging and Dempster–Shafer methods for landslide susceptibility mapping in the Urmia Lake Basin, Iran

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Received 17 March 2012; final version received 12 November 2012

In this paper, GIS-based ordered weighted averaging (OWA) is applied to landslide susceptibility mapping (LSM) for the Urmia Lake Basin in northwest Iran. Nine landslide causal factors were used, whereby the respective parameters were extracted from an associated spatial database. These factors were evaluated, and then the respective factor weight and class weight were assigned to each of the associated factors using analytic hierarchy process (AHP). A landslide susceptibility map was produced based on OWA multicriteria decision analysis. In order to validate the result, the outcome of the OWA method was qualitatively evaluated based on an existing inventory of known landslides. Correspondingly, an uncertainty analysis was carried out using the Dempster–Shafer theory. Based on the results, very strong support was determined for the high susceptibility category of the landslide susceptibility map, while strong support was received for the areas with moderate susceptibility. In this paper, we discuss in which respect these results are useful for an improved understanding of the effectiveness of OWA in LSM, and how the landslide prediction map can be used for spatial planning tasks and for the mitigation of future hazards in the study area.

Keywords: GIS-multicriteria decision analysis; OWA; uncertainty analysis; belief; landslide susceptibility mapping; Urmia Lake Basin

1. Introduction

Landslides are one of the most serious natural disasters that occur worldwide. Landslide susceptibility mapping (LSM) is very important in order to mitigate the effects of landslide hazards, safety planning, and disaster management (Yilmaz 2010). There has been a significant progress in the development of landslide researches, LSM, and hazard zoning, whereby much of this progress is based on the extensive use of ‘Digital Earth’ and ‘Geoinformatics’ using GIS, GPS and remote-sensing techniques (Van Westen, Castellanos, and Kuriakose 2008; Gorsevski and Jankowski 2010; Yilmaz 2010; Althuwaynee, Pradhan, and Lee 2012; Feizizadeh, Blaschke, and Rezaei Moghaddam 2012b; Feizizadeh and Blaschke 2012a; Gorsevski et al. 2012; Pourghasemi, Pradhan, and Gokceoglu 2012a; Pourghasemi et al. 2012b).

Over the past years, GIS has generally been used as the basic analysis tool for spatial management and data manipulation, due to its ability to handle large

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amounts of spatial data (Oh and Pradhan 2011). GIS-based multicriteria decision analysis (GIS-MCDA) provides a rich collection of techniques and procedures for structuring decision problems, as well as designing, evaluating, and prioritizing alternative decisions. At the most rudimentary level, GIS-MCDA can be defined ‘as a process that transforms and combines geographical data and value judgments (the decision-maker’s preferences) in order to obtain information for decision making. The synergetic capabilities of GIS and MCDA are believed to have a high potential of the decision rules’ (Malczewski 2006a, 703). Although the GIS-MCDA approaches have traditionally focused on the MCDA algorithms for individual decision-making, significant efforts have recently been made to integrate MCDA with GIS for group decision-making settings (Malczewski 1996; Jankowski et al. 1997; Nyerges et al. 1997; Bennett, Wade, and Armstrong 1999; Feick and Hall 1999; Jankowski and Nyerges 2001a, 2001b; Kyem 2004).

Ordered weighted averaging (OWA) is a GIS-MCDA technique which was developed by Yager (1988). It is useful for MCDA because problems in MCDA often require the inclusion of information about the importance associated with the different criteria (Yager 2004). The OWA operators can convert multi-attribute values into aggregated single values, with different weights assigned to each. It can be applied to assign different weights to each attribute. There are, however, some limitations associated with the use of these procedures in an OWA decision-making process, whereby uncertainty is inevitable making it challenging to accept the results that are offered by OWA.

For any MCDA it is necessary to assess the reliability of the methods and hence the validity of the results. Uncertainty analysis can be used to determine the probability of the outcomes and therefore to turn uncertainty into an assessment of ‘risk’ in decision-making (Chen et al. 2011). Dealing with imprecision and uncertainty requires techniques that go beyond classical logic (Gorsevski and Jankowski 2005). Based on the probability theory, the Dempster–Shafer theory (DST) is a well-known uncertainty analysis method used to examine uncertain judgments by experts (Rakowsky 2007). The DST provides a unifying framework for representing uncertainty, since this can include both the cases of risk and ignorance in the same formulation (Tayyebi et al. 2010). It introduces uncertainties in modeling and allows probability judgments to be made in order to capture the imprecise and vague information entailed in the modeling evidence (Gorsevski and Jankowski 2005). In the context of LSM and ‘Digital Earth’, we want to make it more explicit to stakeholders that landslide databases and input parameters often contain imprecisions and uncertainties which will influence the modeling process and the resulting landslide susceptibility maps (Gorsevski and Jankowski 2005). Thus it is important to evaluate the reliability of resulting susceptibility maps with respect to unknown future landslide events (Chung and Fabbri 2003; Park 2011). The main objectives of this paper are to produce a GIS-based OWA for LSM and to develop a DST uncertainty analysis framework to qualitatively evaluate the validity of the OWA model.

2. Case study area

The study area was the Urmia Lake Basin. This area, with a size of 19,913 km$^2$, is located in the East Azerbaijan province of Iran. The Urmia Lake Basin, with 35 cities and 1018 villages totaling 3.2 million inhabitants (Iranian Census Center 2007),
is important in terms of housing, industrial, and agricultural activities for the East Azerbaijan province (Feizizadeh and Blaschke 2012a; Feizizadeh et al. 2012a). In the Urmia Lake Basin, the elevation increases from 1260, at Urmia Lake, to 3710 meters above sea level in the Sahand Mountains. The climate of this area is semi-arid, and the annual precipitation amounts to approximately 300 mm (Alijane 2000). The area’s geology is complex, and the lithological units comprise several formations causing volcanic hazards, earthquakes, and landslides. This geophysical setting makes slopes of this area potentially vulnerable to landslides and mass movements (Figure 1).

3. Methodology

3.1. Data processing

In this study, landslide susceptibility was evaluated by using GIS spatial analysis and techniques based on GIS-OWA. The LSM process was performed using nine causal criteria including elevation, slope, aspect, distance to roads, distance to steams, distance to faults, land use/cover, precipitation, and geology. After the preprocessing and preparation of the spatial datasets, all necessary geometric thematic editing was done on the original datasets. Respectively, all vector layers were converted into raster format with a 20-m resolution, and the spatial datasets were processed. The

Figure 1. Location of the case study area within Iran and the Persian Gulf region (left) and northwestern Iran (right).
methodology of our research aims to standardize landslide criteria, the pairwise comparison technique which uses the AHP in order to elicit weights concerning the relative importance of the variables, and the OWA aggregation method to compute and map landslide hazards. In this respect, the pairwise approach uses a-priori membership functions based on expert knowledge. Expert knowledge and beliefs are codified and applied in order to produce continuous fuzzy classifications by incorporating imprecise semantics (Gorsevski, Jankowski, and Gessler 2006; Gorsevski et al. 2012). This technique is an extension of the classic binary logic, with the possibility of defining sets without sharp boundaries and allowing for partial assignation of elements to a particular set.

A fuzzy set is essentially a set whose members may have degrees of membership between 0 and 1, as opposed to a classic binary set in which each element must have either 0 or 1 as the membership degree. A pairwise comparison technique is typically used for rating and standardizing the ordinal values (Malczewski 2004). The first step involves standardizing the predictor variables to a common numeric range using fuzzy membership functions (Jiang and Eastman 2000). In our LSM research, the criteria used relate to topography, climate, geology, vegetation, and anthropogenic factors, all of which were represented by separate GIS data-set layers. These criteria were standardized at the lowest level using the maximum eigenvectors’ approach on a scale of 0–1, resulting in memberships to multiple different potential classes. After the standardization of the predictor variables, a predictor data-set of landslide locations was used to measure the goodness-of-fit of the individual predictor variables and to derive the relative weights for subsequent aggregation of the predictor variables.

3.2. Ordered weighted average

OWA has the ability to optimally weight the attributes based on the rank of these weighting vectors after processing aggregation (Cheng, Wang, and Wu 2009). The appeal of OWA is that, by reordering and changing criterion parameters, one can generate a wide range of different solution maps and predictive scenarios (Feizizadeh and Blaschke 2012a; Gorsevski et al. 2012). The OWA operator is a technique for ranking criteria and addressing the uncertainty from their interaction. The robustness of the OWA approach is that it yields continuous scaling scenarios between the intersection (risk adverse) and the union (risk taking) operators. This continuous scaling is accomplished by global and local weights. The global weights are assigned either based on decision-makers’ judgments or through a pairwise comparison for controlling the level of criteria trade-off relative to other criteria, while the local weights are incrementally added and removed from the criteria and provide a means for controlling the level of uncertainty and risk taking (Chen and Zhu 2010). In the OWA method, $z_{ij}$ is the sequence of attribute values for one cell (spatial location or pixel). By reordering from the maximum value, $v_j$ is the $j$-th order weight, $u_j$ is the $j$-th criterion weight, and OWA is defined as follows (Chen and Zhu 2010):

$$\text{OWA}_i = \sum_{j=1}^{n} \left( \frac{u_j v_j}{\sum_{j=1}^{n} u_j v_j} \right) z_{ij}$$  \hspace{1cm} (1)
The key is to calculate order weights and criterion weights. The criterion weights are
assigned to evaluation criteria in order to indicate their relative importance. All
locations on the \( j \)-th factor are assigned the same weight of \( u_i \). The order weights are
associated with criterion values, and the order weights are determined by their rank.
The \( j \)-th factor at a different location with a different rank order is assigned a
different order weight (Chen and Zhu 2010).

### 3.3. Calculation of the order weights

The OWA combination operator in Equation (1) disregards the fact that most of the
GIS-based decision-making problems require a set of different weights in order to be
assigned to criterion map layers. In order to extend the conventional OWA approach,
it is necessary to incorporate the ‘criterion weights’ (importances), \( W_i \), into the OWA
procedure. Yager (1997) proposed a criterion weight modification approach for the
inclusion of criterion weights into the OWA operator as shown in Equation (2)
(Boroushaki and Malczewski 2010):

\[
V_j = Q \left( \frac{\sum_{i=1}^{j} u_i}{\sum_{i=1}^{n} u_i} \right) - Q \left( \frac{\sum_{i=1}^{j-1} u_i}{\sum_{i=1}^{n} u_i} \right)
\]  

(2)

where \( u_j \) is the reordered \( j \)-th criterion weight, \( w_j \), according to the reordered \( z_{ij} \).

When considering \( Q(p) = p^x \) for \( x > 0 \), Equation (2) can be simplified to:

\[
V_j = \left( \frac{\sum_{i=1}^{j} u_i}{\sum_{i=1}^{n} u_i} \right)^x - \left( \frac{\sum_{i=1}^{j-1} u_i}{\sum_{i=1}^{n} u_i} \right)^x
\]  

(3)

Accordingly, given the sets of criterion weights, \( W_i \), and order weights, \( V_i \), the OWA
operator can be defined as shown in equation (4) (Boroushaki and Malczewski 2010):

\[
\text{OWA}_j = \sum_{j=1}^{n} \left( \left( \frac{\sum_{i=1}^{j} u_i}{\sum_{i=1}^{n} u_i} \right)^x - \left( \frac{\sum_{i=1}^{j-1} u_i}{\sum_{i=1}^{n} u_i} \right)^x \right) z_{ij}
\]  

(4)

OWA provides a tool for generating a wide range of decision strategies in a decision
strategy space, by applying a set of order weights to criteria that are ranked in
ascending order on a pixel-by-pixel basis. The number of order weights is equal to the
number of criteria and must sum up to one. The position of a set of order weights can
be identified in a decision strategy space based on the concepts of tradeoff and risk
(Yager 1988; Jiang and Eastman 2000). Tradeoff indicates the degree to which a low
standardized value on one layer can be compensated for by a high standardized value
on other considered criteria. Risk refers to how much each criterion affects the final
solution (Jiang and Eastman 2000; Malczewski 2006a; Robinson, van Klinken, and
Metternicht 2010). In order to calculate the order weights \( (v_i) \) given in formula (1),
the order weights are determined according to their rank position \( r_k \), and \( v_k \) is
expressed as follows:

\[
v_k = \frac{n - r_k + 1}{\sum_{j=1}^{n} (n - r_k + 1)} \quad (k = 1, 2, \ldots, n)
\]  

(5)
where \( r_k \) is the rank order position according to the criterion attribute values, 1 for maximum, 2 for second, and \( n \) for minimum. A measure of ‘ORness’ and tradeoff, associated with a particular set of weights, can be obtained by Equations (6) and (7) (Chen and Zhu 2010):

\[
\text{ORness} = \sum_{j=1}^{n} \frac{n-j}{n-1} v_j
\]

where, \( \text{ORness} = (0, 1) \) (7)

Therefore, another effective method is to calculate order weights \( v_i \) according to ORness (changing from 0 to 1) (Chen and Zhu 2010). The levels of tradeoff between criteria are directly controlled by the ordered weights (Malczewski 1999). This is achieved by varying the ordered weights, which, in turn, would generate nonlinearity into the continuous aggregation procedure. The ordered weights \( V = [v_1, v_2, \ldots, v_n] \) where \( v_n \) represents the ordered rank take \( v_{\text{min}} = [1, 0, \ldots, 0] \) for the ‘AND’ operator \( v_{\text{max}} = [0, 0, \ldots, 1] \) for the ‘OR’ operator and \( v_{\text{mean}} = [1/n, 1/n, \ldots, 1/n] \). The relative skewness of the ordered weights dictates the level of risk associated with ‘AND’ and ‘OR’, while the position of OWA on the continuum between ‘AND’ and ‘Or’ can be achieved through Equations (8–10):

\[
\text{ANDness} = \frac{1}{n-1} \sum_{r}^{\infty} (n-r)w_r
\]

\[
\text{ORness} = 1 - \text{ANDness}
\]

\[
\text{Trade-off} = \sqrt{\frac{n \sum_r (w_r - 1/n)^2}{n-1}}
\]

where \( n \) is the number of criteria, \( r \) is the order of the criteria, and \( w_r \) is the weight for the criterion of the \( r \)-th order. As given in the above equations, the ‘ANDness’ measures the degree to which an OWA operator is similar to the logical ‘AND’, while the ‘ORness’ measures the degree to which an OWA operator is similar to the logical ‘OR’ (Jiang and Eastman 2000; Rinner and Malczewski 2002). The degree of the dispersion of the weights controls the level of trade-off which represents the compensation measurement (Gorsevski et al. 2012).

3.4. Calculation of criterion weights

Criterion weights are the weights assigned to the objective and attribute maps (Meng, Malczewski, and Boroushaki 2011; Feizizadeh and Blaschke 2012b, 2012c). In order to calculate criterion weights given in Equation (1), the AHP provides the possibility of ranking the criteria based on their relative important degrees (Chen and Zhu 2010). This method is based on mathematical functions for analyzing complex decision problems (Saaty 1977). GIS-based AHP has gained popularity because of its capacity to integrate a large quantity of heterogeneous data, and because obtaining the required weights can be relatively straightforward, even for a large number of criteria. It has been applied to a variety of decision-making problems (Tiwari, Loof, and Paudyal 1999; Nekhay, Arriaza, and Guzmán-Álvarez 2008; Hossain and Das 2010). Using the AHP, the indicators are structured in hierarchical order with the assigned ‘weight’ obtained from the ‘pairwise comparison’ technique.
The pairwise comparison method employs an underlying semantic scale with values from 1 to 9 in order to rate the relative preferences for two elements of the hierarchy (Table 1). The pairwise comparison matrix for the objective level has the following form:

$$A = \begin{bmatrix} a_{qt} \end{bmatrix}_{p \times p}$$

where $a_{qt}$ is the pairwise comparison rating for objective $q$ and objective $t$. The matrix $A$ is reciprocal – that is, $a_{qt} = a_{qp} - 1$ – and all its diagonal elements show unity – that is, $a_{qq} = 1$ for $q = t$.

The same principles apply to the attribute level as well. At the attribute level, a pairwise comparison matrix is obtained for each of the objectives by comparing associated attributes, thus,

$$A_{(q)} = \begin{bmatrix} a_{kh(q)} \end{bmatrix}_{|x| \times |x|} \quad \text{for} \quad q = 1, 2, \ldots, p$$

where $a_{kh(q)}$ is the pairwise comparison rating for attribute $k$ and attribute $h$ associated with objective $q$ (Boroushaki and Malczewski 2008).

This construction of the comparison matrix is the most critical step in the AHP. In our case, a nine-point continuous rating scale is adopted, which is shown in Table 1. Thus, the comparison matrix produced by this technique is a positive reciprocal matrix. Therefore, only the higher/lower triangular half which includes $n(n-1)/2$ elements needs to be filled in (Chen and Zhu 2010). The maximum latent root of $\lambda_{\text{Max}}$ in the comparison matrix $A$ has an eigenvector of $W$; the estimation of criterion weights is to calculate eigenvector $W$, which makes:

$$AW = \lambda_{\text{Max}} W \quad (11)$$

The calculation of the eigenvector is as follows:

$$\tilde{a}_{ij} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \quad i, j = 1, 2, \ldots, n \quad (12)$$

Then adding by row:

$$\overline{W}_i = \sum_{j=1}^{n} \tilde{a}_{ij} \quad i, j = 1, 2, \ldots, n \quad (13)$$

**Table 1. Scales for pairwise comparisons (Saaty and Vargas 1991).**

<table>
<thead>
<tr>
<th>Intensity of importance</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
</tr>
<tr>
<td>5</td>
<td>Strong or essential importance</td>
</tr>
<tr>
<td>7</td>
<td>Very strong or demonstrated importance</td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
</tr>
<tr>
<td>2, 4, 6, and 8</td>
<td>Intermediate values</td>
</tr>
<tr>
<td>Reciprocals</td>
<td>Values for inverse comparison</td>
</tr>
</tbody>
</table>
Vector $\mathbf{W} = [\mathbf{W}_1, \mathbf{W}_2, \ldots, \mathbf{W}_n]^T$ is standardized as follows:

$$W_i = \frac{w_i}{\sum_{j=1}^{n} w_i}, \quad i, j = 1, 2, \ldots, n$$

(14)

Eigenvector $\mathbf{W}_i = [W_1, W_2, \ldots, W_n]^T$ is obtained. But consistency verification is necessary, and maximum latent root $\lambda_{\text{Max}}$ is calculated firstly as follows:

$$\lambda_{\text{Max}} = \sum_{j=1}^{n} \frac{(\mathbf{AW})_i}{nW_i}$$

(15)

where $(\mathbf{AW})_i$ represents the $i$-th element in $\mathbf{AW}$, and consistency index (CI) is calculated as follows:

$$\text{CI} = \frac{\lambda_{\text{Max}} - n}{n - 1}$$

(16)

The consistency ratio (CR) is calculated with a random consistency index (RI) as follows:

$$\text{CR} = \frac{\text{CI}}{\text{RI}}$$

(17)

Since human judgment can violate the transitivity rule and thus cause an inconsistency, the CR is computed in order to check the consistency of the conducted comparisons. In case of high inconsistency the most inconsistent judgments can be revised (Gorsevski, Jankowski, and Gessler 2006). A random index (RI) is the CI of a randomly generated pairwise comparison matrix. It is clearly demonstrated in Table 2 that the RI depends on the number of elements being compared. The CR is designed in such a way that if $\text{CR} < 0.10$ then the ratio indicates a reasonable level of consistency in pairwise comparison; if, however, $\text{CR} \geq 0.10$, then the values of the ratio are indicative of inconsistent judgments. In such cases one should reconsider and revise the original values in the pairwise comparison matrices (Boroushaki and Malczewski 2008). To achieve a pairwise comparison matrix in our study, ‘expert’ opinions informed the relative weight of the factors and the criteria involved. The comparative results of the landslide susceptibility sub-criteria and criteria are shown in Tables 3 and 4, respectively.

### 3.5. DST (Belief)

The DST based on evidence proposed by Shafer (1976) has been regarded as an effective spatial data integration model. It is a powerful tool for probabilistic reasoning based on a formal calculus for combining evidence (Martin, Zhang, and Liu 2010). The DST is well known as evidence theory and provides a mathematical

<table>
<thead>
<tr>
<th>Number of criteria</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>RI</td>
<td>0</td>
<td>0</td>
<td>0.58</td>
<td>0.9</td>
<td>1.12</td>
<td>1.24</td>
<td>1.32</td>
<td>1.41</td>
<td>1.45</td>
<td>1.49</td>
</tr>
</tbody>
</table>

Note: Adapted from Saaty (1980).
Table 3. Pairwise comparison matrix, factor weights, and consistency ratio of the data layers used.

<table>
<thead>
<tr>
<th>Factors</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Eigen values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Lithology</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1) Altered zone</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.045</td>
</tr>
<tr>
<td>(2) Metamorphic–plutonic</td>
<td>1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.036</td>
</tr>
<tr>
<td>(3) Plutonic</td>
<td>3</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.020</td>
</tr>
<tr>
<td>(4) Volcanic</td>
<td>6</td>
<td>5</td>
<td>7</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.101</td>
</tr>
<tr>
<td>(5) Metamorphic–volcanic</td>
<td>6</td>
<td>5</td>
<td>4</td>
<td>4</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>0.120</td>
</tr>
<tr>
<td>(6) Volcanic–sedimentary</td>
<td>5</td>
<td>3</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>1</td>
<td></td>
<td></td>
<td>0.200</td>
</tr>
<tr>
<td>(7) Sedimentary–volcanic</td>
<td>7</td>
<td>6</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td></td>
<td>0.208</td>
</tr>
<tr>
<td>(8) Sedimentary</td>
<td>8</td>
<td>6</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.270</td>
</tr>
<tr>
<td><strong>Consistency ratio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.061</td>
</tr>
<tr>
<td><strong>Precipitation (mm)</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(1) &gt;250</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.083</td>
</tr>
<tr>
<td>(2) 251–300</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.098</td>
</tr>
<tr>
<td>(3) 301–350</td>
<td>4</td>
<td>3</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.116</td>
</tr>
<tr>
<td>(4) 350–400</td>
<td>7</td>
<td>4</td>
<td>1/3</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.301</td>
</tr>
<tr>
<td>(5) 401–485</td>
<td>8</td>
<td>3</td>
<td>7</td>
<td>5</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>0.402</td>
</tr>
<tr>
<td><strong>Consistency ratio</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.075</td>
</tr>
<tr>
<td><strong>Land use/cover</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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framework for information representation and combination. The robustness of Dempster–Shafer approach is represented by handling the capability of incomplete data coverage. The DST confirmed that output result of belief, disbelief, uncertainty (doubt), and plausibility has to be defined as precisely as possible, in that case we can get a reasonable result (Carranza 2009; Althuwaynee, Pradhan, and Lee 2012). With this theory, a belief interval, along with mass functions, is used for information representation (Park 2011). The DST provides additional flexibility for the specification of uncertainty in probabilistic models and hypothesis testing (Ducey 2001). It has mostly focused on uncertain reasoning in artificial intelligence and expert systems (Shafer and Pearl 1990).

The evidence for the DST is based on approximate reasoning where imprecision and uncertainties are introduced into the decision-making process by considering probability intervals with lower and upper bounds (Mertikas and Zervakis 2001; Table 3 (Continued))

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Table 4. Pairwise comparison matrix for dataset layers of landslide analysis.

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<td>1/3</td>
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<td>1/3</td>
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Consistency ratio: 0.053
Gorsevski and Jankowski 2005). The DST evidence provides framework for estimation of EBFs (Dempster 1967; Shafer 1976), which are integrated according to Dempster’s (1968) rule of combination. Because the theoretical formalization of EBFs is involved, the following discussion for its application will be simplified (Park 2011). The EBFs are the compound of Bel (degree of belief), Dis (degree of disbelief), Unc (degree of uncertainty), and Pls (degree of plausibility). According to Dempster (1967), the main parts of the theory are represented by Bel = lower probability, and Pls = upper probability. There are three important functions in DST (Althuwaynee, Pradhan, and Lee 2012, 128):

1. Basic probability assignment function (bpa or m)
2. Belief function (Bel)
3. Plausibility function (Pls)

Dempster’s rule of combination provides a tool to combine multiple spatial data layers. The interval between belief and plausibility presents the uncertainty of the knowledge about the target proposition (Park 2011). Figure 2 shows the schematic representation of DST combinations for uncertainty analysis. In this theory, a frame of discernment \( \Theta = \{T_1, T_2, \ldots, T_n\} \), which is a set of mutually exclusive and exhaustive propositions, is first established. Then, a mass function \([m(T)]\) assigns the belief committed to each proposition, as shown in the following equation (Park 2011):

\[
M: 2^\Theta \rightarrow [0, 1] \left\{ \sum_{T \in \emptyset} m(T) = 1 \right\}
\]

where \( \emptyset \) is the empty set.

Based on the mass function, the belief (Bel) and plausibility (Pls) functions are defined, respectively, by:

\[
\sum_{T \in \Theta} m(T) = 1
\]

\[
\sum_{T \in \Theta \neq} m(T)
\]

Figure 2. Schematic relationships of evidential belief functions (Althuwaynee et al. 2012).
where, for every $H \subseteq \Theta$, $Bel(H)$ is a measure of the total amount of beliefs committed exactly to every subset of $H$ by $m$. $Pls(H)$ represents the degree to which the evidence remains plausible. These two functions, which are regarded as the lower and upper probabilities, respectively (An, Moon, and Bonham Carter 1994; Park 2011), have the following properties:

$$Bel(H) \leq Pls(H)$$
$$Bel(H) = 1 - Bel(\bar{H})$$

where $\bar{H}$ is the negation of $H$, and $Bel(\bar{H})$ is also called the disbelief function. The above properties indicate that the unknown true probability or likelihood lies somewhere between the belief and plausibility functions. The difference between these two functions, also called the belief interval or ignorance, represents the ignorance of one’s belief of the target proposition $H$, and can be regarded as a measure of uncertainty. This belief interval or ignorance is the main distinct characteristic of the DST of evidence compared to the traditional probability theory. The commitment of belief to a subset $H$ does not force the remaining belief to be committed to its complement (i.e. $Bel(H) + Bel(\bar{H}) \leq 1$) (Shi 1994; Park 2011).

Dempster’s rule of combination is used for the combination of information in the mathematical theory of evidence. Let $m_1$ and $m_2$ be two mass functions, respectively; then a combined mass function is defined by Dempster’s rule of combination (Park 2011).

$$m(H) = m_1 \oplus m_2 = \frac{\sum_{A \cap B = H} m_1(A_i) \cdot m_2(B_j)}{1 - K}$$

(21)

$$K = \sum_{A \cap B = \emptyset} m_1(A_i) \cdot m_2(B_j) < 1$$

(22)

Dempster’s rule of combination is commutative and associative. Thus, the order and grouping of combinations are immaterial. In Equation (22) $K$ is often interpreted as a measure of conflict between different sources. This term provides the degree to which the combined information is contradictory toward the target proposition (Shafer 1976; Park 2011). The most important features of DST are divided into two parts (Althuwaynee, Pradhan, and Lee 2012):

1. The model is generally designed to handle with varying precision levels of information; no further assumptions are needed to represent the information.
2. It allows for the direct representation of uncertainty of system responses; an imprecise input can be considered by a set or an interval, and the resulting output is a set or an interval.

4. Results and validation of the model

Figure 3 depicts the landslide susceptibility map derived based on GIS-MCDA. However, in any landslide susceptibility map it is necessary to assess the reliability of results. In order to validate the landslide susceptibility maps the derived maps were tested using the known landslide locations (Yilmaz 2010). This is a critical
strategy in prediction models which can provide meaningful interpretation with respect to future landslides (Pourghasemi et al. 2012b). In our research the validation was performed by comparing the known landslide location data (132 landslide events in the case study area) in order to qualitatively evaluate the validity of the OWA method within the LSM process. The results of this comparison indicated that the highly susceptible category covers about 20.16% of currently occurring landslides, while the category of moderate susceptibility covered about 76.74% of current landslides. The low susceptibility category covered about 3.1% of currently occurring landslide events; however, there was no landslide observed in the category of no susceptibility.

4.1. Uncertainty analysis based on DST

In our research the IDRIS software was used to implement DST and carry out uncertainty of the results. Figure 4 depicts the spatial distribution of the belief or support for landslide susceptibility map. Based on the results obtained using the belief function, very strong support (0.85–0.89) was established in the high susceptibility category of the landslide susceptibility map while a strong support (0.65–0.80) was achieved in the moderately susceptible category, and moderate support (0.45–0.60) was achieved in the low susceptibility category. However, relatively weak support (0.40–0.24) was determined in the no susceptibility category.
5. Discussion

Uncertainty analysis provides a measure of the level of confidence that the decision maker can place in the ranking of alternatives based on the determinative MCDA (Chen et al. 2011). Using the OWA method one can select any degree of tradeoff among the criteria ranging between no tradeoff and full tradeoff according to the decision-making strategy. It is due to the fact that the OWA operators can combine multi-attribute values into single aggregated values. It can be used to assign different weights to every attribute. The OWA operator assesses different effects between the different attributes in order to extract relevant information from the data (Cheng, Wang, and Wu 2009). The GIS-based OWA provides a tool for generating a wide range of decision strategies (such as LSM, land suitability analysis, and so on), and the position of the OWA operator can be set anywhere along the continuum ranging from the all quantifier to the least quantifier (Malczewski 2006b). Indeed, uncertainty in results may have significant impacts on the MCDA results and may lead to inaccurate outcomes and undesirable consequences. The importance of a subsequent uncertainty analysis has been increasingly recognized due to the influence of uncertainties in data, models and expert judgments (Chen et al. 2010). Uncertainty within a decision-making process may be broken down into three basic elements within which uncertainty can occur, namely the evidence, the decision set, and the relation that associates them (Chen and Zhu 2010). The DST can be used as a knowledge-driven approach for map combination. Several authors confirmed that it is well suited for representing and manipulating aleatory and epistemic uncertainties (Fabre,
Appriou, and Briottet 2001; Sallak, Schön, and Aguirre 2010; Althuwaynee, Pradhan, and Lee 2012). The belief module can be used to implement the Dempster–Shafer logic. Belief constructs and stores the current state of knowledge for the full hierarchy of hypotheses which form the frame of discernment (Chen and Zhu 2010).

The belief model aggregates different sources of information to predict the probability that any phenomenon might occur. Because the tool provides the user with a method of reviewing the relative strength of the information gathered to establish belief values, it is useful for applying anecdotal information to an analysis since one can acknowledge ignorance in the final outcome produced. With this flexibility, it becomes possible to establish and evaluate the relative risk of decisions made based on the total information that is available (IDRISI 2009). The belief decision support model in Idrisi software generates three outputs: belief, plausibility, and belief interval. The support image represents the degree to which the evidence provides concrete support for the proposition. It is important to interpret it with the plausibility and belief interval images. The plausibility image shows the degree to which the evidence does not refute the proposition. The relationship between the two output images is significant for evaluating what decisions to make about the gathering information. Even if the concrete evidence for a proposition is not significant, i.e. belief values are low, it is still possible to have high plausibility values in those areas. This would suggest possible spaces where enough information exists in order to make a concrete decision about the use of these spaces or the allocation of resources to them. At the very least, it suggests where to narrow down the selection of areas and where the gathering of more evidence seems necessary (Tangestani and Moore 2002). The advantage of the belief is its capability to handle uncertainties and establish valuable information for devising a data gathering strategy in order to reduce the uncertainties from the predicated models (Eastman 2001; Gorsevski and Jankowski 2005). Furthermore, since evidence is not without uncertainties, belief handles uncertainties (Gorsevski and Jankowski 2005). Based on the DST (belief) approach, the uncertainty represents the difference between plausibility and support. The ignorance value can be used to represent the lack of evidence (complete ignorance is represented by 0). Thus, the belief and plausibility function values all lie between 0 and 1 (Althuwaynee, Pradhan, and Lee 2012). The DST-based uncertainty acts as a measure of the uncertainty of a proposition. The ignorance value can be used to represent the lack of evidence (complete ignorance is represented by 0). Based on DST the susceptibility map is a result of integrated map of degree of belief (Althuwaynee, Pradhan, and Lee 2012), and the belief function shows the spatial distribution of the belief or support for landslide susceptibility map (see Figure 3).

Using DST into account LSM defines a mass function by employing quantitative relationships between the known landslides and input conditioning factors (Mohammady, Pourghasemi, and Pradhan 2012). Based on the belief results the uncertainty of the produced landslide susceptibility map produced is not significant. Unlike the Boolean overlay where the intersection ‘AND’ operator represents the lowest risk while the union ‘OR’ represents the highest risk in the decision-making, the OWA method can obtain a full spectrum of risk scenarios bounded between the intersection ‘AND’ and the union ‘OR’ operators (Gorsevski et al. 2012). The degree of ‘ORness’ indicates the degree to which an OWA operator is similar to the logical connective ‘OR’, in terms of its combination behavior. The parameter is also associated with a tradeoff measure indicating the degree of compensation between
criteria. The ‘ORness’ measure allows the OWA results to be interpreted in the context of the behavioral theory of decision-making. The OWA operations make it possible to develop a variety of strategies ranging from extremity pessimistic (the minimum-type strategy based on the logical ‘AND combination,’ through to an intermediate neutral-toward-risk strategy, to an extremely pessimistic strategy (the maximum-type strategy based on the logical ‘OR’ combination). Thus, OWA can be considered as an extension and a generalization of the conventional combination procedures in GIS (Jiang and Eastman 2000; Feizizadeh and Blaschke 2012a).

6. Conclusions

Natural disasters have become major threats to human life and the world economy (Guo 2010). Landslides are a type of hazards which particularly causes economic losses, property damages, and high maintenance costs, as well as injuries or fatalities (Das et al. 2010). In order to mitigate the landslide hazard, understanding the processes that lead to landsliding and the effort for subsequent susceptibility mapping provides the fundamental knowledge about the evolution of landscapes, and lays the foundation for hazard management and creation of safety measures (Althuwaynee, Pradhan, and Lee 2012). We started from the hypotheses that (1) these damages can be mitigated if the cause and effect relationships of the events are known (Intarawichian and Dasananda 2010) and (2) LSM is a solution to understanding and predicting future hazards, appropriately portraying the spatial distribution of future slope failure susceptibility (Lei and Jing-feng 2006). Therefore, the main objective of this research was an uncertainty analysis for LSM in order to determine the reliability of the results. The landslide susceptibility map for the Urmia Lake region in Northwest Iran derived using the OWA method could be successfully evaluated using the belief method. A very interesting detail of the research carried out was the relatively weak support (0.40–0.24) found for the no susceptibility category. Since this is in contrast to all other categories we may conclude that our LSM is less reliable in errors of omission. A few even very small and isolated known landslides may already contradict the results of the no susceptibility category. We are therefore very cautious in using these results and communicating this category as ‘less likely’. In fact, when passing on these results to the planning agencies we highlighted the high susceptibility areas and the moderate susceptibility areas as first and second priorities for planning and mitigation measures.

Making maps available to decision makers and the public may help to mitigate some effects and to be prepared to counteract disastrous situations. It is not so much the lack of scientific and technological tools as to why so many hazards become disasters (Guo 2010). As it has been demonstrated in this article – and in many others – scientific methods and tools exist to analyze, map, monitor hazards, and to model susceptibility. There is a problem of ‘access to and sharing of information and data, and a need for science to be incorporated into social and political decision-making. In order to (a) reduce risks and vulnerability, (b) mitigate the effects of natural disasters, and (c) improve rescue operations, a multidisciplinary approach is necessary involving natural, social, and political sciences. These issues are of global concern and fit well into the Digital Earth concept’ (Guo 2010, 228).

The research output could offer the susceptibility map with good degree of confidence which can be used for land use planning to mitigation and emergency...
decisions of landslide risk. Further, the results of this research are useful in understanding the capability of the OWA-MCDA method in LSM. The results of this research will be passed on to regional authorities and shall help citizens, planners, and engineers to reduce losses caused by current and future landslides (see Figure 5) by means of prevention, mitigation, and avoidance. In conjunction with earlier research the results are useful for explaining the relationship between known existing landslides and landslide susceptibility and shall therefore be used to support emergency decision mitigation plans in the Urmia Lake Basin, Iran.

Acknowledgements

Authors would like to thank the anonymous reviewers for their helpful and constructive comments on earlier versions of the manuscript and the department of Geoinformatics (Z_GIS), University of Salzburg for partial financial support. This work was carried out as part of a PhD study funded by the Iranian Ministry of Science, Research and Technology and including a study period at the University of Salzburg.

References


Figure 5. Policy level map of high landslide susceptibility in the Urmia Lake Basin.


