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An heuristic approach for mapping landslide hazard by integrating fuzzy logic with analytic hierarchy process

by

Pece V. Gorsevski[1], **Piotr Jankowski**[2] and **Paul E. Gessler**[1]

[1] Department of Forest Resources, College of Natural Resources
University of Idaho
Moscow, ID 83843, USA
email: peceg@uidaho.edu, paulg@uidaho.edu

[2] Department of Geography, San Diego State University
San Diego, CA 92182 USA
email: piotr@geography.sdsu.edu

Abstract: This study presents an integration of fuzzy sets theory with analytic hierarchy process (AHP) to model landslide hazard. The approach involves developing expert knowledge from existing landslide datasets which are used for standardizing digital terrain attributes, a pairwise comparison method for the elicitation of attribute weights, and their subsequent aggregation through weighted linear combination (WLC) and ordered weighted average (OWA) function to generate landslide hazard maps. The approach enhances the methodology for modeling landslide hazard in roaded and roadless areas through the derivation of probabilistic maps. The maps can be used as a decision support tool in forest management and planning. A case study from the Clearwater National Forest in central Idaho, USA, illustrates the application of the approach in a practical setting.

Keywords: landslide, multiple criteria evaluation, analytic hierarchy process, weighted linear combination, ordered weighted averaging, modeling.

1. Introduction

In recent years the impact from road related and non-road related landslides has attracted substantial attention in the Pacific and Inland Northwest U.S. The road related (RR) landslide hazard with spatial locations within roaded areas is often initiated by a combination of triggers such as rain or rain-on-snow events and human activities such as careless or improper road-building or poor road maintenance in steep mountainous regions. The non-road related (NRR) landslide hazard with spatial locations within non-roaded areas is initiated by the same triggers as the RR landslide hazard except that human activities are not present. Irrespective of the nature of the cause of the landslides the impacts from landslides are often reflected through downstream sediment that affects water quality, water quantity, and aquatic habitat.

Mapping landslide hazard for sound management decision-making is necessary in these mountainous regions to protect water quality and to reduce or prevent loss of aquatic habitat. Preferably, given the mapping of landslide hazard, decision-makers should avoid human activities such as road construction in vulnerable areas prone to landslide susceptibility. The ability to model landslide susceptibility is a valuable resource for conducting integrated management practices at any level of the decision-making process.

A variety of approaches have been used to assess landslide hazard. Quantitative techniques include: stability ranking based on criteria such as slope, parent material, and elevation (McClelland et al., 1997); statistical models linking environmental attributes using spatial correlation (Carrara, 1983; Carrara et al., 1991; Chung et al., 1995; Chung and Fabbri, 1999; Dhakal et al., 2000; Dai and Lee, 2002; Gorsevski, 2002; Gorsevski et al., 2000, 2003, 2004, 2006; Gorsevski and Gessler, 2003); process models that combine the infinite slope equation and hydrological components (Montgomery and Dietrich, 1994; Wu and Sidle, 1995; Gorsevski, 2002); and hybrid models combining qualitative and quantitative methods such as the weighted linear combination method, which involves pairwise comparison to create weights for predictor variables (Ayalew et al., 2004). For instance, the approach of Ayalew et al. (2004) is based on categorizing predictor variables that are coded by computing landslide density and are ordered on the basis of related significance of landslide hazard before assigning weights for each individual class from the predictor variables. The weights are derived using expert knowledge and the pairwise comparison technique to elicit the relative importance of landslide predictor variables for computing a single landslide hazard map. The final map of landslide susceptibility is divided into five categories using the mean and standard deviations.

In this paper, we expand upon the previous efforts of Ayalew et al. (2004) by proposing probabilistic maps as a decision support tool for mapping RR and NRR landslide hazard. In the approach presented here a heuristic framework incorporates the fuzzy set theory (Zadeh, 1965, 1978) to standardize landslide predictor variables, the pairwise comparison technique applied in the context of the AHP (Saaty, 1980) to elicit weights concerning relative importance of the variables, and the WLC and OWA aggregation methods (Yager, 1988) to compute and map landslide hazard. A similar approach was applied by Eastman (2001) and Jiang and Eastman (2000) in the context of multi-criteria evaluation of residential development and industrial land use allocation in Kenya. Other examples of similar frameworks have been described by Juan et al. (2004) in a decision support system for forage selection and Chen and Hwang (1992) in multiple attribute decision making context. The contribution of the proposed approach lays in the application of this framework in a decision support system for mapping landslide hazard while deriving unbiased weights through goodness-of-fit and ratio values that are used to obtain the relative importance of landslide predictor variables. The first step involves standardizing the predictor variables to a common numeric range using fuzzy membership functions (Jiang and Eastman, 2000). This approach uses *a priori* membership functions based on expert knowledge. Expert knowledge and beliefs are codified and applied to produce continuous fuzzy classifications by incorporating "imprecise semantics" (Burrough and McDonnell, 1998; MacMillan et al., 2000). After the standardization of the predictor variables a predictor dataset of landslide locations is used to measure the goodness-of-fit of individual predictor variables and to derive relative weights for subsequent aggregation of the predictor variables. The next step is to construct a pairwise comparison matrix using the previous knowledge of goodness-of-fit in assigning the relative importance of predictor variables before the map of landslide hazard is derived. Finally, the standardized predictor variable values are aggregated with weights in the WLC method. In addition to WLC method the OWA method is used to present the sensitivity of landslide hazard map to different beliefs in the importance of predictor variables.

The proposed approach (Fuzzy/AHP) is illustrated using a case study of the Clearwater National Forest (CNF) in central Idaho. The focus of this paper is not on validating the model but on demonstrating a decision support methodology, in which expert knowledge is actively involved in the process of developing the model. The results of the presented approach are compared with another approach to modeling landslide hazard by integrating fuzzy k-means classification with the Bayesian theorem (Gorsevski et al., 2003).

2. Modeling Theory

2.1. The fuzzy set theory

Fuzzy logic (Zadeh, 1965) is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth-values between "completely true" and "completely false." In conventional logic the degree to which individual (z) is a member or is not a member of a given set (A) is expressed by the membership function MF^B. The membership function MF^B can take the value 0 or 1 shown in (1) and (2) for an example of a set being an interval $[b_1, b_2]$:

$$MF^B(z) = 1, \quad \text{if } b_1 \leq z \leq b_2 \tag{1}$$

$$MF^B(z) = 0, \quad \text{if } z < b_1 \text{ or } z > b_2 \tag{2}$$

where (b_1) and (b_2) define the exact boundaries of the set (A). For instance, if the boundaries (b_1 and b_2) for "steep" slope were defined between 45% and 70%, then the conventional set theory would assign value 1 for each individual belonging to the set and 0 otherwise (Fig. 1). On the other hand, the idea behind fuzzy logic is to describe the vagueness of entities in the real world, where belonging to a set is really a matter of degree (Malczewski, 1999). For instance, linguistic terms and qualitative data such as, "gentle," "moderate," "steep," and "very steep" land can be translated into fuzzy sets. A fuzzy set is a class of elements or objects without well-defined boundaries between these objects that belong to the class and those that do not. Fuzzy logic allows objects to belong partially to multiple sets and it is multivalued logic that allows intermediate values to be formulated mathematically. The fuzzy set is specified by a membership function, and the function represents any elements on a continuous scale from 1 (full membership) to 0 (full-non-membership). Mathematically a fuzzy set (A) is defined as follows: If (Z) denotes a space of objects, then the fuzzy set (A) in (Z) is the set of ordered pairs

$$A = \{z, MF_A^F(z)\}, \quad z \in Z \tag{3}$$

where the membership function $MF_A^F(z)$ is referred to as the "degree of membership of (z) in (A)". The higher the membership value of $MF_A^F(z)$, the more z belongs to the set.

Fuzzy sets for developing spatial decision support systems for mapping landslide hazard can be used to design standardized criterion maps. There are two basic methods for building fuzzy membership functions: the fuzzy k-means clustering (Burrough and McDonnell, 1998; Burrough et al., 2000, 2001; Gorsevski et al., 2003, 2005) and fuzzy semantic import (*SI*) model (Burrough and McDonnell, 1998; MacMillan et al., 2000). Fuzzy k-means cluster analysis can be viewed as an extension of traditional cluster analysis that is not dependent on prior knowledge. On the other hand, the use of the *SI* model depends on the existence of well-defined expert knowledge. It can be applied when users have a good, qualitative idea of how to group data, but have difficulties with the exactness of using the standard (Boolean) method (Burrough and McDonnell, 1998). For instance, standardized criterion maps can be developed by computing a landslide density function for a predictor variable (if other expert knowledge is nonexistent) in order to understand and formulate the fuzzy membership function using the *SI* model.

The *SI* approach uses various fuzzy membership functions such as linear increasing, linear decreasing, triangular, sinusoidal, and j-shaped (Burrough and McDonnell, 1998). Selecting appropriate shape and form of those functions is crucial because those functions affect the results used for decision-making purposes (Stefanakis et al., 1999). Therefore, one should have a clear understanding that fuzzy classes created by the *SI* approach may not be optimal. The selection of an appropriate function is not always easy and the selection of the mathematical function can vary among individuals. However, probability theory can often be used to help select an appropriate function (Burrough and Frank, 1995).

Although similarities exist between fuzzy membership functions and probability functions the two concepts are quite different. Rather than defining probability, the fuzzy membership functions define possibility (Zadeh, 1987). Possibility is a type of deterministic uncertainty that measures the degree to which an event occurs, not whether it occurs. This is different than probability, which deals with the question of whether or not an event occurs (Bezdek and Sankar, 1992). Therefore, it should be clear that similarities of objects with respect to imprecisely defined properties are quantified by possibility while expectations of outcomes (i.e., over a large number of experiments) are quantified by probabilities. However, in the absence of expert knowledge the possibility values are derived by transforming probability density function into a fuzzy membership function. The transformation is achieved through the shape of an appropriate fuzzy membership function that closely describes a particular probability density function while transformations in many instances will vary between individuals because they capture the subjectivity of human judgment and model imprecision that is neither random nor stochastic.

The fuzzy functions used to transform probability density function in this paper are described below: For instance, linear transformation function is given by two components, including linear increasing (*MLI*) and linear decreasing (*MLD*) component, and is used where simple linear mapping is needed. Equations 4 and 5 show the *MLI* and the *MLD* functions.

$$MLI(z) = \frac{z - c_0}{c_1 - c_0} \qquad \text{if } z > c_1 \quad MLI(z) = 1 \tag{4}$$

and

$$MLD(z) = \frac{z - c_2}{c_2 - c_3} + 1 \qquad \text{if } z > c_2 \quad MLI(z) = 1 \tag{5}$$

where $[c_0, c_1, c_2, c_3]$ are the control points that govern the shape of the fuzzy function. When one of these functions is used only two control points are needed. In the case of a monotonically increasing linear function, the first control point (c_0) indicates the location where the membership function starts to linearly increase above zero until maximum of one is reached at the second control point (c_1) and values above this point take value of one on the measurement scale. In the case of a monotonically decreasing linear function, the values below the first control point (c_2) on the measurement scale take on value of one. In addition, this is the location where the membership function starts to linearly decrease below one until minimum of zero is reached at the second control point (c_3). A symmetrical form to describe triangular or trapezoidal distributions is also possible by merging the monotonically increasing and the monotonically decreasing linear functions.

For example, constructing a fuzzy boundary for the "steep" slope in Fig. 1 (between 45% and 70%) one could use the symmetric linear function, which is described by the first control point at 40% to mark the location where the membership function begins to rise above zero, the second point at 50%, which indicates the maximum value of the function; values of one are assigned between the second and the third control (65%) points, followed by a decrease of the function reached in the last control point (75%) with the value of zero.

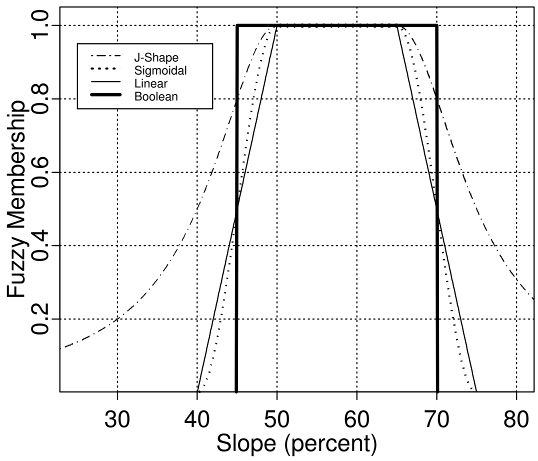

Figure 1. Fuzzy vs. Boolean membership functions

The j-shaped function also has symmetric, monotonically increasing or monotonically decreasing forms. Fig. 1 illustrates the j-shaped function, which is controlled by four breakpoints ordered from low to high on the measurement scale (i.e., 40%, 50%, 65%, and 75%). Characteristic for the j-shaped function is that the first and the last control points (c_0 and c_3) are set at a 0.5 membership value, which makes the function asymptotic with zero reached at infinity. The j-shaped function is derived by Burrough (1989) and defined in equations (6) and (7) where in the monotonically increasing case the function is:

$$MJI(z) = 1/(1 + ((z - c_1)/(c_1 - c_0))^2) \quad \text{if } z > c_1 \quad MJI(z) = 1 \tag{6}$$

and in the case of monotonically decreasing the function is:

$$MJD(z) = 1/(1 + ((z - c_2)/(c_3 - c_2))^2) \quad \text{if } z > c_2 \quad MJD(z) = 1 \tag{7}$$

The sigmoidal membership function can be used to fit Boolean sets of any widths and a symmetric form is used to approximate a bell-shaped distribution (Fig. 1). The use of a monotonically increasing or monotonically decreasing form allows skewed distributions from frequency histograms to be also represented by the function. The sigmoidal function is given by the following equations:

$$MS(z) = \cos^2 \alpha \tag{8}$$

where in case of monotonic increase the function is:

$$\alpha = (1 - (z - c_0)/(c_1 - c_0)) * \pi/2 \quad \text{if } z > c_1 \quad MSI(z) = 1 \tag{9}$$

and in case of monotonic decrease the function is:

$$\alpha = (z - c_2)/(c_3 - c_2) * \pi/2 \quad \text{if } z > c_2 \quad MSD(z) = 1. \tag{10}$$

However, in situations when none of the previous fuzzy functions are applicable for a desired fit, a user-defined function can be used. The fuzzy membership in the user-defined function can be linearly interpolated between any two control points.

2.2. Analytic Hierarchy Process

Quantitative and qualitative information about the decision problems may be organized using the AHP (Saaty, 1980; Malczewski, 1999) method. The AHP offers a flexible and robust multiple criteria evaluation (MCE) approach to decision situations involving decision alternatives, decision criteria, and trade-offs. The AHP reduces the complexity of a decision problem to a sequence of pairwise comparisons which are synthesized in a ratio matrix that provides a clear rationale for ordering the decision alternatives from the most to the least desirable.

Specifically, the process builds a hierarchy of decision criteria and through the pairwise comparison of each possible criterion pair a relative weight for each decision criterion within the hierarchy is produced. The development of pairwise comparison is based on the rating of relative preferences for two criteria at a time. Each comparison is a two-part question determining which criterion is more important, and how much more important, using a scale with values from the set: {1/9, 1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 1/2, 1, 2, 3, 4, 5, 6, 7, 8, 9} from 1/9 representing the least important (than), to 1 for equal importance, and to 9 for the most important (than), covering all the values in the set.

The comparison matrix consists of an equal number of rows and columns where scores are recorded on one side from the diagonal while in the diagonal of the matrix values of 1 are placed. The weights are determined by normalizing the eigenvector which corresponds to the largest eigenvalue of the ratio matrix (Malczewski, 1999). Since human judgments can violate the transitivity rule and thus cause an inconsistency, the consistency ratio (CR) is computed to check the consistency of the conducted comparisons. In case of high inconsistency the most inconsistent judgments can be revised.

After the weights are 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. For example, individual standardized criterion maps of potential landslide hazard could represent decision criteria. Assigning relative weights to these criteria can be done by the pairwise comparison method. After the relative weights are generated, the standardized criterion maps and their resulting weights can be used as an input for the WLC function or the OWA function (Jiang and Eastman, 2000).

Because of its simplicity and robustness in obtaining weights and integrating heterogeneous data, the AHP has been used in a wide variety of applications, including multiattribute decision making, total quality management, suitability analysis, resource allocation, conflict management, and design and engineering (Vargas, 1990; Chen and Hwang, 1992; Jiang and Eastman, 2000; Vaidya and Kumar, 2004). However, it should be remarked that AHP has been criticized for its inability to adequately handle the ambiguity and imprecision associated with the conversion of linguistic labels, attached to the ratio scale, to crisp numbers used in the comparison matrix. The other criticisms concern the axiomatic foundation of the method, the correct meaning of priorities, the measurement scale, and the rank reversal (Lootsma, 1993; Barzilai, 1998; Leskinen, 2000; Mikhailov, 2003). Despite these shortcomings the AHP has been widely used for practical applications and integrated with other methodologies such as fuzzy sets to represent human judgments and capture their inconsistencies.

2.3. Weighted Linear Combination

Once the criterion scores have been standardized and weights have been computed, WLC method (Voogd, 1983) is the simplest method that aggregates criteria to form a single score of evaluation. In the WLC method each criterion is multiplied by its weight from the pairwise comparison and the results are summed:

$$S = \sum_i w_i \mu_i \tag{11}$$

where S is the final score, w_i is the weight of the criterion i, and μ_i is the criterion standardized score. Weights can have a tremendous influence on the solution. Because the criterion weights are summed to one, the final scores of the combined solution are expressed on the same scale. Also, weights given to each criterion determine the trade-off level relative to the other criteria, which implies that high scores and weights from standardized criteria can compensate for low scores from other criteria. However, when scores from standardized criteria are low while the weights are high, they can only weakly compensate for the poor scores from other criteria (Jiang and Eastman, 2000).

2.4. Ordered Weighted Average

Yager (1988) introduced the OWA operation, which represents a continuous fuzzy aggregation bounded by the hard rigor of the MIN or the AND operator and the extremely liberal rigor of the MAX or the OR operator. In the spatial implementation of OWA, using the raster data structure as a complete and exhaustive representation of geographical space, one define OWA as a combination operator associating with an i-th location (raster cell) a set of ordered weights $v = v_1, v_2, ..., v_n$ such that

$$v_j \in [0,1] \quad \text{where} \quad j = 1, 2, \ldots, n, \quad \text{and} \sum_{j=1}^{n} v_j z_{ij}. \tag{12}$$

Given the set of attribute values a_{i1}, a_{i2}, …, a_{in} at the i-th location and a set of n criterion maps represented by rasters:

$$OWA_i = \sum_{j=1}^{n} v_j z_{ij} \tag{13}$$

where $z_{i1} \geqslant z_{i2} \geqslant \ldots z_{in}$ is the sequence obtained by reordering the attribute values $a_{i1}, a_{i2}, \ldots, a_{in}$. The reordering involves associating an order weight, v_j, with a particular position of the attribute values such that the first order weight, v_1, is assigned to the highest attribute value for the i-th location, v_2 is assigned to the next highest attribute value for the i-th location, and so on; v_n is assigned to the lowest attribute value for the i-th location. Thus ordered weights do not apply to any specific criterion, but are assigned to a location in the order determined by the attribute values. Given that there are m locations in a raster there are m sets of ordered weights – one set per each location.

The levels of trade-off between criteria are directly controlled by the ordered weights (Malczewski, 1999). For instance, while in WLC the trade-off is fixed between criteria and the levels of trade-off are controlled by the weights of the criteria, in OWA the criteria weights are adjusted according to the level of trade-off through the aggregation procedure (Jiang and Eastman, 2000). This is achieved by varying the ordered weights, which, in return, would generate a continuous fuzzy aggregation results between fuzzy MIN and fuzzy MAX. The ordered weights $v = [v_1, v_2, ..., v_n]$ where v_n represents the ordered rank take $v_{\min} = [1, 0, ..., 0]$ for the AND operator, $v_{\max} = [0, 0, ..., 1]$ for the OR operator, and $v_{\text{mean}} = [1/n, 1/n, ..., 1/n]$ for the arithmetic mean. In the last case, where the ordered weights are equal the full trade-off is still possible while the final solution is located exactly between the AND and OR operator. In fact, this solution yields the same results as the WLC. Furthermore, the relative skew to the right or to the left of the ordered weights dictates the level of risk associated with the minimum (ANDness) and the maximum (ORness), while the degree of the dispersion of the weights controls the level of TRADE-OFF (Jiang and Eastman, 2000). Obtaining proper OWA operators in (12) and (13) with respect to the level of risk between AND and OR is achieved through equations (14), (15), and (16) that characterize the OWA measures:

$$ANDness = \frac{1}{n-1} \sum_{r} (n-r) w_r \tag{14}$$

$$ORness = 1 - ANDness \quad (15)$$

$$TRADE - OFF = 1 - \sqrt{\frac{n \sum_r (w_r - 1/n)^2}{n-1}} \quad (16)$$

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. According to Eastman (2001), the assignment of ordered weights leads to the decision rule that falls in a triangular decision space where the risk aversion decision rule is generated by using the AND operator, while a risk taking decision rule is generated by the OR operator. On the other hand, any intermediate solution between the AND and OR operators allows for trade-off between the criteria.

Applying OWA in the context of landslide hazard evaluation could be a very useful tool for evaluating different prediction scenarios that often need to be customized based on different decision priorities given that the attitudes towards risk can be quantified and expressed by ordered weights.

3. Study area and modeling approach

The proposed methodology (Fuzzy/AHP) for mapping landslide hazard in Idaho's CNF was tested and compared against another approach described in Gorsevski et al. (2003). The study area and the modeling approach are discussed in the following sections.

3.1. Study Area

The study area is within the CNF, located on the western slopes of the Rocky Mountains in north central Idaho. The CNF is located west of the Montana border and is bounded on three sides by four other National Forests; the Lolo in Montana; the Bitterroot in Montana and Idaho; the Nez Perce in Idaho; and the Panhandle in Idaho. The CNF map is shown in Fig. 2. Nearly 5200 km^2 including wilderness areas are designated as roadless areas, while 2235 km^2 has been developed with roads. The topography is highly dissected with elevations ranging from 485 m to 2700 m and slopes varying between 0 and 100 percent. The climate is characterized by dry and warm summers, and cool wet winters (McClelland et al., 1997). Annual precipitation ranges between 600 mm at low elevations to more than 2000 mm at high elevations. Much of the annual precipitation falls as snow during winter and spring, while peak stream discharge occurs in late spring and early summer. The soils are highly variable but typically well drained and primarily derived from parent materials such as granitics, metamorphic rocks, quartzites, and basalts or surface colluvium. The land cover is predominately forested with coniferous species such as grand fir (*Abies grandis*), Douglas fir (*Pseudotsuga menziesii*), subalpine fir (*Abies lasiocarpa*), western red cedar (*Thuja plicata*), western white pine (*Pinus Monticola*), and various

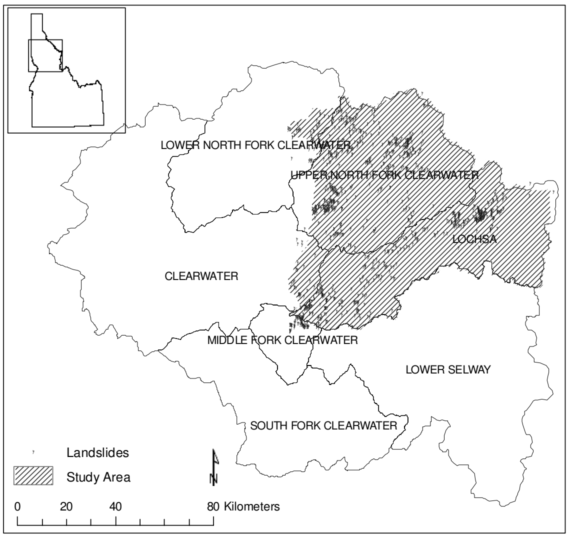

Figure 2. Distribution of landslides over the CNF drainage during winter 1995/96 storm events (area of interest is the shaded area)

other shrubs and grasses that have short growing seasons, particularly at the higher elevations.

3.2. Methods

Landslides were assessed through aerial reconnaissance flights and field inventory in July 1996. Aerial photography was acquired at a scale of 1:15840 (4 inches = 1 mile) followed by photo interpretation between October 1996 and February 1997 (McClelland et al., 1997). The landslides interpreted from aerial photos were classified into RR and NRR. A total of 865 landslides were recorded, with 55% RR and 45% NRR landslides. The presence or absence of a landslide was represented as a (30-m) grid coverage with values of 1 for presence and 0 for absence. The initiation area of each landslide (i.e., the area where the main scarp of the landslide occurred) was interpreted as the point representing the presence of a landslide. The RR landslides, which are associated with forest roads, were coded separately from the NRR landslides. This enabled the development of independent quantitative models for each dataset (RR, NRR). Also, RR landslides and NRR landslides were separated into a predictor and test datasets based on two sub-basins within the study area. The predictor datasets were used to develop the model while the test datasets were used only to validate the final predictions of landslide hazard.

A total of six topographic attributes were used in the development of the model. These topographic attributes included: elevation, slope, profile curvature, tangent curvature, wetness index or compound topographic index (CTI), and solar radiation (Moore et al., 1993; Gallant and Wilson, 2000). In previous work by Gorsevski et al. (2003, 2005) the same topographic attributes have been consistently used for prediction of RR and NRR landslide hazard. Derivation of expert knowledge from these topographic attributes involved computing the probability density functions (PDF's) to describe presence and absence of RR and NRR landslide hazard. This step was aimed to assist in choosing appropriate fuzzy functions and their control points for fitting the shape of the fuzzy functions associated with the presence of RR and NRR landslide hazard. For instance, examining a frequency histogram of landslides associated with elevation could help to understand the distribution and the level of the hazard across the elevation range. Therefore, this information could be used in concert with the expert knowledge to define the type and the shape of the membership function.

The next step employed standardization, which involves the rescaling of each criteria (topographic attribute) using its suitable fuzzy function developed in the previous step. The resulting fuzzy maps produced a continuous landslide hazard for each topographic attribute where membership values were reduced to the range between 0 and 1. At this point the goodness-of-fit between individual fuzzy maps and the predictor dataset was evaluated. The instances of presence and absence for RR and NRR landslide hazard were cross-tabulated with fuzzy membership values for each grid location to aid in assigning the importance of the criteria in the pairwise comparison matrix. Since our goal was to maximize the presence of landslides (predict the maximum number of landslides) while minimizing the absence of landslides (minimize the area associated with the landslides) in the high probability range, we derived the importance of each criterion based on a ratio value. The ratio value was obtained by setting an arbitrary cut-off (i.e., high probability hazard ranging between 0.5 to 1) where firstly proportions of areas of absence and proportions of correctly identified landslides (presence) were individually summed before the ratio value was computed (absence divided by presence). Lower ratio values suggested higher importance for individual criteria. For example, the ratio value for the slope criterion was derived when standardized slope criteria with membership values of 0.5 and higher were cross-tabulated with the predictor datasets from RR and NRR landslides to determine the magnitude of area associated with absence and the number of landslides associated with presence.

After that, the construction of the pairwise comparison matrix followed. Here, the relative importance suggested by the ratio value of one criterion relative to another was established by using a scale from Saaty (1980). Lastly, from the pairwise comparison matrix the criteria weights were developed, and then were used with the WLC and OWA functions for subsequent aggregation of all criteria resulting in continuous mapping of landslide hazard.

4. Results and discussion

Expert knowledge was used to define the characteristics and standardize each criterion associated with RR and NRR landslide hazard. The type of membership functions and control points used in the study are given in Tables 1 and 2, while the fit of the predictor datasets with the membership functions is illustrated in Fig. 3(*b*) and 4(*b*).

Table 1. Fuzzy set membership functions and controlling points for development of NRR landslide hazard

Input data	$\mathbf{c}_0$	$\mathbf{c}_1$	$\mathbf{c}_2$	$\mathbf{c}_3$	**Fuzzy function**
Elevation (m)	600	1000	1200	1700	Sigmoidal - Symmetric
Slope (deg)	5	20	24	40	Sigmoidal - Symmetric
CTI (no units)	5.5	5.7	6.3	7.3	J-Shaped - Symmetric
Solar Radiation (KWH/m^2)	100	400	700	1200	Linear - Symmetric
Profile Curvature (rad/100m)	-0.1	-0.02	0.02	0.1	J-Shaped - Symmetric
Tangent Curvature (rad/100m)	-0.14	-0.05	0.06	0.16	J-Shaped - Symmetric

a)

b)

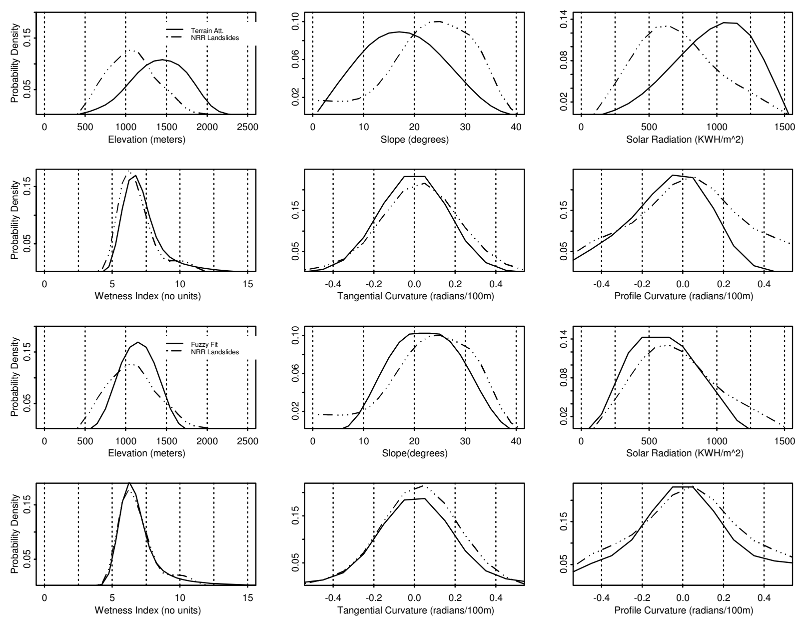

Figure 3. PDF's of *a*) NRR landslides associated with individual topographic attributes and *b*) Fuzzy membership functions applied on the NRR landslide distributions

Table 2. Fuzzy set membership functions and controlling points for development of RR landslide hazard

Input data	$\mathbf{c_0}$	$\mathbf{c_1}$	$\mathbf{c_2}$	$\mathbf{c_3}$	**Fuzzy function**
Elevation (m)	600	1000	1300	1700	Sigmoidal - Symmetric
Slope (deg)	0	18	24	32	Sigmoidal - Symmetric
CTI (no units)	5.7	5.9	6.3	7.4	J-Shaped - Symmetric
Solar Radiation (KWH/m^2)	350	600	800	1400	Linear - Symmetric
Profile Curvature (rad/100m)	-0.12	-0.02	0.02	0.1	J-Shaped - Symmetric
Tangent Curvature (rad/100m)	-0.14	-0.5	0.4	1.3	J-Shaped - Symmetric

a)

b)

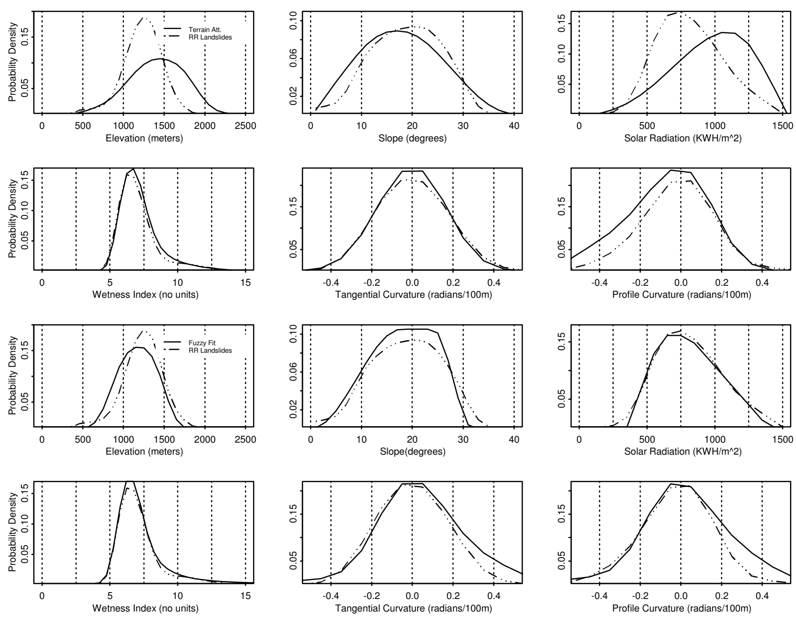

Figure 4. PDF's of *a*) RR landslides associated with individual topographic attributes and *b*) Fuzzy membership functions applied on the RR landslide distributions

Fig. 3(*a*) and 4(*a*) also display the relative PDF's for all topographic attributes and corresponding RR and NRR landslides. For example, in Table 1 for the topographic attribute slope using the equations for the sigmoidal function (8, 9, and 10) and the controlling points in the table 5, 20, 24, and 40, fuzzy representation of NRR landslide hazard was derived. The fuzzy membership function which fits the PDF associated with slope landslides is shown in Fig. 3(*b*) where the first point '5' marks the location where the membership function begins to rise above zero, the second point '20' indicates where it reaches the value of one, the third point '24' indicates the location where the membership grade begins to fall below one, and the last point '40' marks the location where zero is reached again.

Tables 3 and 4 show the importance of individual topographic attributes based on ratio values for estimating RR and NRR landslide hazard. In the tables the cross-tabulation (goodness-of-fit) for presence (Pre) and absence (Abs) between the fuzzy models and the predictor data is presented.

Table 3. Importance of individual topographic attributes for building an NRR landslide hazard based on the ratio value

Fuzzy	**Elevation**		**Slope**		**Solar**		**Cti**		**Tg. Curv.**		**Pr. Curv.**	
Membership	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**
0	32.9	5.6	5.7	4.8	22.3	5.6	0.2	1.6	0.2	2.4	0.3	2.4
.1	22.7	33.9	25.8	25.8	21.8	47.6	33.9	41.9	43.8	33.9	28.1	29.8
.2	5.2	5.6	4.3	3.2	6.9	1.6	7.8	4.0	5.6	13.7	8.0	10.5
.3	4.4	2.4	4.8	4.8	7.1	2.4	7.1	2.4	6.1	5.6	7.1	6.5
.4	3.9	0.8	5.4	4.0	6.7	0.8	6.2	9.7	4.3	4.0	7.7	5.6
.5	4.0	6.5	3.6	5.6	6.8	5.6	5.7	0.0	4.3	4.0	3.2	2.4
.6	3.8	0.8	5.5	7.3	6.3	6.5	5.9	8.1	5.2	8.9	7.7	7.3
.7	4.1	6.5	6.8	6.5	6.2	9.7	5.7	7.3	6.3	4.0	4.6	2.4
.8	4.3	4.8	7.3	4.0	5.6	10.5	6.0	6.5	3.6	2.4	5.3	4.8
.9	5.3	10.5	9.3	10.5	5.4	4.8	7.5	4.0	5.9	6.5	12.6	13.7
1	9.4	22.6	21.5	23.4	4.8	4.8	14.0	14.5	14.7	14.5	15.4	14.5
Sum (.5 -1)	30.9	51.6	54.0	57.3	35.1	41.9	44.8	40.3	40.0	40.3	48.8	45.2
Ratio	**0.60**		**0.94**		**0.84**		**1.11**		**0.99**		**1.08**	

Table 4. Importance of individual topographic attributes for building an RR landslide hazard based on the ratio value

Fuzzy	**Elevation**		**Slope**		**Solar**		**Cti**		**Tg. Curv.**		**Pr. Curv.**	
Membership	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**
0	32.7	3.6	4.2	2.3	3.7	0.9	0.2	1.4	0.2	1.4	0.3	1.4
.1	28.8	39.4	33.4	33.5	20.5	35.3	27.2	32.1	39.4	24.9	26.4	29.0
.2	4.2	3.6	3.9	3.6	6.4	3.2	7.9	5.9	6.5	9.0	7.2	10.9
.3	3.6	2.7	3.7	2.7	8.3	1.8	7.4	6.8	7.4	7.7	6.8	7.2
.4	3.2	1.8	4.3	1.8	8.7	4.5	6.6	6.8	4.1	6.3	6.6	3.6
.5	3.2	4.1	4.9	4.5	9.4	3.6	6.3	6.3	4.9	5.0	4.0	6.3
.6	3.2	4.1	5.4	5.0	9.0	7.7	6.3	5.4	5.9	8.1	6.9	4.5
.7	3.5	9.0	4.3	2.7	9.2	7.2	6.4	5.9	7.1	10.9	6.2	4.5
.8	3.7	3.6	8.5	8.6	8.6	10.4	6.9	4.1	4.1	5.4	4.9	6.8
.9	4.8	6.8	8.3	12.7	8.5	12.2	8.7	5.9	7.0	8.1	11.9	8.1
1	9.1	21.3	19.1	22.6	7.6	13.1	16.1	19.5	13.4	13.1	18.8	17.6
Sum (.5 -1)	27.5	48.9	50.4	56.1	52.3	54.3	50.7	47.1	42.4	50.7	52.7	48.0
Ratio	**0.56**		**0.90**		**0.96**		**1.08**		**0.84**		**1.10**	

For instance Table 3 shows that fuzzy membership of 1.0 for elevation is associated with 9.4% of the total study area while 22.6% of the landslide population was correctly predicted. The table also shows that summed presence and absence for fuzzy membership of 0.5 and higher for elevation is associated with 30.9% for absence and 51.6% for presence. The ratio value obtained by the division of the absence by the presence is also shown. In Table 3 the elevation has the lowest ratio value (0.60) which represents the most important criterion for achieving the specified goal in this study. The next most important criterion for NRR landslide hazard is solar radiation followed by slope, tangent curvature, profile curvature, and CTI. The most important criterion for RR landslide hazard (Table 4) is elevation followed by tangent curvature, slope, solar radiation, CTI, and profile curvature.

Pairwise comparison matrices and scores for computing the criterion weights are shown in Tables 5 and 6 for the NRR landslide hazard and Tables 7 and 8 for the RR landslide hazard. Because the pairwise matrix is symmetrical, only the lower triangular half is shown. To account for imperfections with conversions of linguistic expressions we ran two different scenarios each with slightly different scores that are shown for both RR and NRR landslide hazard. In each cell of the matrix the relative importance of the row criterion is compared to its corresponding column criterion. For example, in Table 5 the slope criterion (1/3) is moderately less important than elevation, or solar radiation (2) is equal to moderately more important then slope. The weights for each criteria and *CR* are also shown in the tables. The value of the *CR* is less than 0.10 in all matrices which indicates a good consistency.

Table 5. A pairwise comparison matrix for calculation criteria weights for NRR landslide hazard

	Pairwise Comparison with 9 Point Continuous Rating Scale							
1/9	**1/7**	**1/5**	**1/3**	**1**	**3**	**5**	**7**	**9**
extreme	**v.strong**	**strong**	**moderate**	**equal**	**moderate**	**strong**	**v.strong**	**extreme**
	Less Important					**More Important**		
Elev	**Slope**	**Solar**	**Cti**	**TgCurv**	**Pr Curv**	**Weights**	**CR**	
Elevation	1						0.3449	0.01
Slope	1/3	1					0.1729	
Solar	1/2	2	1				0.1953	
Cti	1/3	1	1/2	1			0.0806	
Tg Curv	1/4	1/2	1/3	1/2	1		0.1357	
Pr Curv	1/4	1/2	1/3	1/2	1	1	0.0705	

Table 6. A pairwise comparison matrix for calculation criteria weights for NRR landslide hazard

	Pairwise Comparison with 9 Point Continuous Rating Scale							
1/9	**1/7**	**1/5**	**1/3**	**1**	**3**	**5**	**7**	**9**
extreme	**v.strong**	**strong**	**moderate**	**equal**	**moderate**	**strong**	**v.strong**	**extreme**
	Less Important					**More Important**		
Elev	**Slope**	**Solar**	**Cti**	**TgCurv**	**Pr Curv**	**Weights**	**CR**	
Elevation	1						0.3825	0.02
Slope	1/3	1					0.1596	
Solar	1/2	2	1				0.2504	
Cti	1/6	1/4	1/5	1			0.0428	
Tg Curv	1/4	1/2	1/3	3	1		0.1006	
Pr Curv	1/5	1/3	1/4	2	1/2	1	0.0641	

Table 7. A pairwise comparison matrix for calculation criteria weights for RR landslide hazard

	Pairwise Comparison with 9 Point Continuous Rating Scale							
1/9	**1/7**	**1/5**	**1/3**	**1**	**3**	**5**	**7**	**9**
extreme	**v.strong**	**strong**	**moderate**	**equal**	**moderate**	**strong**	**v.strong**	**extreme**
	Less Important					**More Important**		
Elev	**Slope**	**Solar**	**Cti**	**TgCurv**	**Pr Curv**	**Weights**	**CR**	
Elevation	1						0.3174	0.01
Slope	1/2	1					0.1781	
Solar	1/2	1	1				0.1781	
Cti	1/3	1/2	1/2	1			0.0874	
Tg Curv	1/2	1	1	2	1		0.1659	
Pr Curv	1/4	1/3	1/3	1	1/2	1	0.0731	

Table 8. A pairwise comparison matrix for calculation criteria weights for RR landslide hazard

	Pairwise Comparison with 9 Point Continuous Rating Scale							
1/9	**1/7**	**1/5**	**1/3**	**1**	**3**	**5**	**7**	**9**
extreme	**v.strong**	**strong**	**moderate**	**equal**	**moderate**	**strong**	**v.strong**	**extreme**
	Less Important					**More Important**		
Elev	**Slope**	**Solar**	**Cti**	**TgCurv**	**Pr Curv**	**Weights**	**CR**	
Elevation	1						0.3825	0.02
Slope	1/3	1					0.1596	
Solar	1/4	1/2	1				0.1006	
Cti	1/5	1/3	1/2	1			0.0641	
Tg Curv	1/2	2	3	4	1		0.2504	
Pr Curv	1/6	1/4	1/3	1/2	1/5	1	0.0428	

Fig. 5 illustrates the spatial implementation of the WLC model for the NRR landslides, while Fig. 6 shows the spatial implementation of the WLC model for the RR landslides. RR and NRR predictor and test landslides were overlayed for visualization of the prediction whereas the legends in both figures represent the probabilities of landslide hazard on a scale from 0 to 1. Fig. 5 is associated with Table 6, and Fig. 6 is associated with Table 8. Furthermore, the goodness-of-fit between the models and the independent test data is shown in Table 9. The table presents the cross-tabulation of the independent test data for the RR and NRR landslides against the results from the WLC models. The table is organized by showing categorized probabilities of presence/absence of NRR landslide hazard calculated by the independent test data and models derived from criteria weights from Tables 5 and 6 and presence/absence of RR landslide hazard calculated by the independent test data and models derived from criteria weights from Tables 7 and 8. Table 9 shows high probabilities (0.8 – 1) for the NRR landslides associated with Table 6 where 12.9% are classified as absent and 34.9% as present, while for high probabilities (0.6 – 1) 34.9% are classified as absent and 75.1% as present. In the same table, high probabilities (0.8 – 1) for the RR landslides are associated with Table 8, where 17.4% are classified as absent and 48.0% as present, while for high probabilities (0.6 – 1) 45.9% are classified as absent and 86.8% as present.

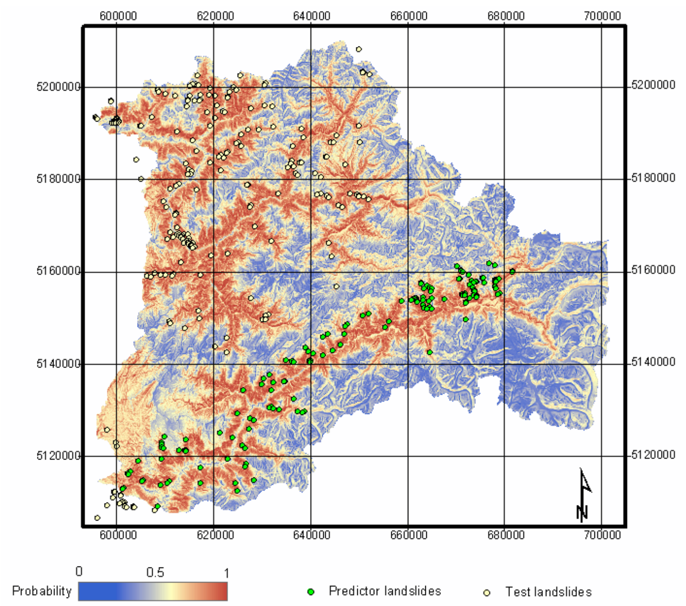

Figure 5. Probabilities of NRR landslide hazard derived by WLC model with criteria weights from Table 6

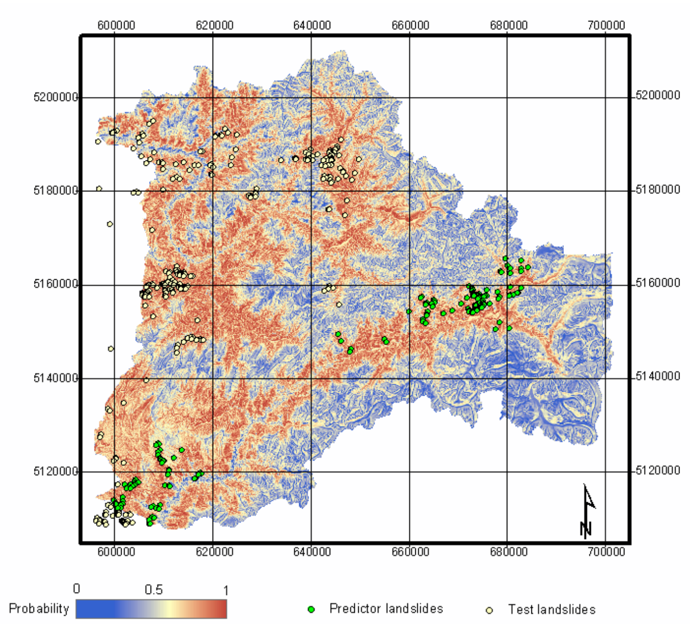

Figure 6. Probabilities of RR landslide hazard derived by WLC model with criteria weights from Table 8

Table 9. Proportion of presence/absence associated with probabilities for NRR (Tables 5 and 6) and RR (Tables 7 and 8) landslides

Probability	**Non-road related (%)**				**Road related (%)**			
	(Table 5)		(Table 6)		(Table 7)		(Table 8)	
	Abs	**Pres**	**Abs**	**Pres**	**Abs**	**Pres**	**Abs**	**Pres**
0 - 0.2	2.7	0.0	6.9	0.5	0.4	0.4	0.8	0.4
0.2 - 0.4	23.3	4.8	28.5	5.3	12.7	1.1	14.9	1.5
0.4 - 0.6	36.7	20.6	29.8	19.1	38.1	11.7	38.4	11.4
0.6 - 0.8	25.4	48.8	22.0	40.2	34.1	44.0	28.5	38.8
0.8 - 1	11.9	25.8	12.9	34.9	14.7	42.9	17.4	48.0

However, the same predictors with a different methodology (Fuzzy/Bayesian) were used by Gorsevski et al. (2003) where final results showed much better overall fit with better discrimination between high and low hazard areas of the RR and NRR landslide hazard (Table 10). For instance, it is interesting to point out that very low hazard (0 – 0.2) for the NRR landslide was associated with 60.8% of the area where 11.1% of the actual landslides were present. For the high hazard (0.8 – 1) 18.4% of the areas were associated with 62.1%

of the actual landslides. Although high discrimination was not obtained with the Fuzzy/AHP methodology it is interesting to note that the results achieved with both methodologies are somewhat comparable for the RR landslide hazard. Similar ratio values were obtained for the prediction of the high hazard (0.8 – 1) with the Fuzzy/AHP method. Ratio values of 0.34 (using Table 7) and 0.36 (using Table 8) are comparable with the ratio value of 0.34 for the Fuzzy/Bayesian methodology. Also, using the Fuzzy/AHP methodology for the probability of 0.6 and lower 51.2% of the areas were linked to 13.2% of the landsides using Table 7 and 54.1% of the areas were linked to 13.3% of the landsides using Table 8 whereas by using the Fuzzy/Bayesian methodology 76.6% of the areas were linked to 37.4% of the landsides. Even though the comparison between both methodologies may be further analyzed, we should keep in mind that the Fuzzy/AHP methodology was based on a heuristic approach, which can be further improved as additional information becomes available and that the comparison here was done based on the current state of knowledge about the topographic factors explaining the landslide hazard in forested areas.

Table 10. Proportion of presence/absence associated with probabilities for NRR and RR landslide hazard using Fuzzy/Bayesian approach

	Non-road related		**Road related**	
Probability	**Abs**	**Pres**	**Abs**	**Pres**
0 – 0.2	60.8	11.1	45.6	8.6
0.2 – 0.4	6.1	5.3	11.4	8.1
0.4 – 0.6	4.5	4.2	19.6	20.7
0.6 - 0.8	10.3	17.4	11	26.1
0.8 - 1	18.4	62.1	12.4	36.5

The differences between the results obtained by the Fuzzy/AHP and the Fuzzy/Bayesian methodology may be the consequence of the categorization of memberships associated with the fuzzy k-means in the Fuzzy/Bayesian method, whereas with the Fuzzy/AHP approach the fuzzy predictors were continuous. In the Fuzzy/Bayesian method probabilities from the relative frequency of association between the knowledge of presence and absence of landslide locations and categorized membership values of fuzzy k-means classes were calculated before being combined by the Bayes theorem. Also, assigning weights and different importance to the predictors could have contributed to the discrepancies between the results obtained with both methods.

Moreover, the WLC solution is only one scenario which represents an average solution with full trade-off within the continuous nature of the OWA procedure as mentioned earlier. In order to explore other possible solutions of landslide hazard in the decision strategy spectrum, Table 11 shows the ordered weights that were applied to generate these solutions. For example, in Table 11 the solution AND is associated with the MIN operator where the distribution of ordered weights is skewed. In the solution the value of 1 for the ANDness means that the solution coincides with the AND while the value of 0 for the ORness means that the solution is the most distant from OR. The trade-off measure set to 0 represents no trade-off while 1 represents the full trade-off. The MIDAND is the solution between the AND and the WLC where some trade-off is allowed, the AVG solution is slightly different than the WLC because some trade-off is allowed, the MIDOR solution is the solution between the WLC and the OR where some trade-off is allowed, and OR is the opposite extreme of the AND solution.

Table 11. OWA evaluation solutions for both RR and NRR landslide hazard

Solution	**Order Weights**	**ANDness**	**ORness**	**TRADE-OFF**
AND	[1, 0, 0, 0, 0, 0]	1	0	0
MIDAND	[.5, .3, .125, .05, .025, 0]	.84	.16	.95
WCL	[.16, .16, .16, .16, .16, .16]	.50	.50	1
AVG	[0, 0, .5, .5, 0, 0]	.50	.50	.84
MIDOR	[0, .025, .05, .125, .3, .5]	.16	.84	.95
OR	[0, 0, 0, 0, 0, 1]	0	1	0

Tables 12 and 13 were generated from the pairwise comparison Tables 6 and 8 and OWA and show the proportions of presence/absence associated with the probabilities of RR and NRR landslide hazard under different decision rules. Although a few different possible solutions are demonstrated in this paper between the extreme AND and OR, there are many other solutions that a decision-maker can generate and accept while adjusting decisions and associated risk based on other knowledge of contextual information. For example, a comparison between the WLC solutions in Table 12 and 13 and the OWA solutions in Table 14 shows better prediction generated by OWA based on the ratio of absence and presence for both RR and NRR landslide hazard. The ratio value for the prediction of the high hazard (0.8 – 1) associated with the OWA is 0.36 for the NRR landslides and 0.35 for the RR landslides, while the same ratio value associated with the WLC is 0.37 for the NRR landslides and 0.36 for the RR landslides. For hazard ranging 0.6 to 0.8 the ratio value associated with the OWA is 0.51 for the NRR landslides and 0.71 for the RR landslides, while the same ratio value associated with the WLC is 0.55 for the NRR landslides and 0.73 for the RR landslides.

In Table 14 the following OWA weights [.2 .15 .15 .2 .15 .15] were used with the NRR landslide hazard while [.17 .15 .15 .23 .15 .15] were used with the RR landslide hazard. In the case of the NRR landslide hazard the ANDness corresponded to a value of 0.52 while ORness corresponded to a value of 0.48, which suggests the solution leans slightly toward the AND operator. The trade-off value coupled with the NRR landslide hazard equaled 1, which means that

Table 12. Proportion of presence/absence associated with probabilities for NRR landslides generated through the OWA method

	AND		MIDAND		WLC		AVG		MIDOR		OR	
Probability	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**
0 - 0.2	78.1	64.6	51.5	18.2	6.9	0.5	13.0	9.1	0.7	1.0	0.0	0.0
0.2 - 0.4	13.4	19.6	26.4	37.3	28.5	5.3	14.6	6.2	0.5	0.0	0.1	0.0
0.4 - 0.6	5.6	10.5	13.5	28.2	29.8	19.1	20.5	16.7	4.9	2.9	0.6	0.0
0.6 - 0.8	2.2	3.8	6.0	11.5	22.0	40.2	24.6	26.3	28.0	17.7	1.9	1.0
0.8 - 1	0.7	1.4	2.6	4.8	12.9	34.9	27.3	41.6	66.0	78.5	97.3	99.0

Table 13. Proportion of presence/absence associated with probabilities for RR landslides generated through the OWA method

Probability	**AND**		**MIDAND**		**WLC**		**AVG**		**MIDOR**		**OR**	
	Abs	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**	**Abs**	**Pre**
0 - 0.2	72.4	51.6	42.0	11.7	0.8	0.4	2.3	1.5	0.0	0.4	0.0	0.4
0.2 - 0.4	16.9	23.4	30.5	33.0	14.9	1.5	10.5	3.3	0.2	0.4	0.0	0.0
0.4 - 0.6	7.4	15.8	17.2	30.0	38.4	11.4	20.3	10.6	2.5	0.0	0.3	0.4
0.6 - 0.8	2.6	5.1	7.7	17.2	28.5	38.8	28.3	23.8	18.4	4.8	1.5	0.4
0.8 - 1	0.7	4.0	2.6	8.1	17.4	48.0	38.6	60.8	78.9	94.5	98.2	98.9

Table 14. Proportion of presence/absence associated with probabilities for NRR and RR landslide hazard using OWA method

	Non-road related		**Road related**	
Probability	**Abs**	**Pres**	**Abs**	**Pres**
0 – 0.2	7.5	0.0	0.7	0.4
0.2 – 0.4	30.5	6.7	14.6	1.5
0.4 – 0.6	29.4	20.1	39.7	12.1
0.6 - 0.8	21.1	41.1	29.2	41.4
0.8 - 1	11.5	32.1	15.8	44.7

a full trade-off is possible. In the case of the RR landslide hazard both the ANDness and the ORness corresponded to a value of 0.50 and the trade-off corresponded to a value of 1 which is equivalent to the WLC values. Although this solution lies in the middle as the WLC solution, because of the trade-off possibilities by applying different sets of ordered weights, we were able to generate a better solution in achieving our goal.

5. Conclusion

This paper implements the concept of predicting RR and NRR landslide hazard using the heuristically-based integration of the fuzzy set theory and AHP and the subsequent aggregation through WLC and OWA methods. The strength of the approach tested in this study is its flexibility in using expert knowledge for mapping landslide hazard. For instance, in the MCE of landslide hazard different criteria may be used for assessing RR or NRR hazard, or perhaps different criteria may be used for solving different regional problems. There are many different fuzzy membership functions that could be used in the process of criteria standardization where continuity and uncertainty could be recognized through assignment of fuzzy membership sets. Also, through setting a clear, objective goal the methodology offers a systematic way of assigning the importance of criteria. The flexibility offered by the Fuzzy/AHP approach combined with an automated knowledge base about the appropriate criteria for local conditions and the selection of appropriate fuzzy membership functions could become the bases for spatial decision support system helping to predict and map landslide hazard.

The results from this study demonstrate that calculating ratio values based on a specific goal for criteria derived by fuzzy membership functions could help to order the criteria from the most to the least desirable and to be used in conjunction with the pairwise comparison. In the matrices the relative importance of one individual criterion against another criterion using a 9-point rating scale was expressed, where that same relative importance indirectly suggested the contribution of landscape processes driving the RR and the NRR landslide hazard. The criteria weights obtained with the pairwise comparison techniques were then used with the WLC and the OWA function to aggregate the criteria and present the space for the decision rule available to the decision-maker.

Compared to the Fuzzy/Bayesian technique (Gorsevski et al., 2003) this methodology showed weaker prediction for the NRR landslide hazard while the results for RR landslide hazard were comparable. However, the advantages of this modeling technique include the ability to integrate heterogeneous data such as quantitative and qualitative criteria using expert knowledge, the flexibility to select specific criteria for different study areas or different problems under consideration, the flexibility to change the importance level of criteria, and the freedom to develop various modeling scenarios for acceptable levels of decision risk when mapping landslide hazard.

In summary, the presented application of the Fuzzy/AHP showed the capability of the approach to produce flexible site-specific information for decision-makers. We believe that this approach with its relative simplicity and cost-efficient analysis has the potential to support decision-makers in the real world mapping of landslide hazard areas.

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