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# COMBINING FUZZY LOGIC AND INFORMATION THEORY FOR PRODUCING A LANDSLIDE SUSCEPTIBILITY MODEL

**Tsangaratos P.[1] and Ilia I.[1]**

*[1]National Technical University of Athens, School of Mining and Metallurgical Engineering, Department of Geological Science, Iroon Polytechniou 9, Zografou 15780, Athens, Greece, ptsag@metal.ntua.gr, gilia@metal.ntua.gr*

## Abstract

*The main objective of the present study was to develop a landslide susceptibility model by combining Fuzzy logic and Information Theory in order to estimate the spatial probability of landslide manifestation, in the mountains of central Tzoumerka, Greece. Specifically, Fuzzy logic was enabled for weighting the landslide related variables based on expert knowledge and in respect to landslide susceptibility, while the Shannon's entropy index, an index from Information Theory, was calculated to weight the significance of each landslide related variable based on the available data. The final landslide susceptibility map was produced by applying the weighted sum method. Engineering lithological units, slope angle, slope aspect, distance from tectonic features, distance from river network and distance from road network were among the six landslide related variables that were included in the landslide database used in the training phase. The landslide inventory map was constructed by interpreting aerial photographs, satellite images and field surveys and was separated into two datasets, one for training and one for validating the model. The outcomes of the validation process illustrated that the developed methodology efficiently provided the most susceptible areas and was in good agreement with the actual landslide locations. The area under the curve was estimated to be for the training and validating datasets 0.7575 and 0.7828 respectively. The produced landslide susceptibility map could be regarded from local and national authorities as a valuable mean to evaluate strategies or to prevent and mitigate the impact of landslides.*

***Keywords:*** *slope stability, fuzzy weighting, Shannon's entropy index, Tzoumerka, Greece.*

## Περίληψη

*Ο κύριος στόχος της παρούσας μελέτης ήταν η ανάπτυξη μιας μεθοδολογιάς για την εκτίμηση της κατολισθητικής επιδεκτικότητας η οποία συνδυάζει την ασαφή λογική και τη Θεωρία της Πληροφορίας, στα βουνά της κεντρικής περιοχής των Τζουμέρκων. Συγκεκριμένα, η ασαφής λογική χρησιμοποιήθηκε για την εκτίμηση των συντελεστών βαρύτητας των κλάσεων των μεταβλητών που επιλέγθηκαν στην οποία εκτίμηση λαμβάνεται υπόψη η γνώση των εμπειρογνωμόνων. Ο δείκτης εντροπίας του Shannon, χρησιμοποιήθηκε για τον υπολογισμό των συντελεστών βαρύτητας της κάθε μεταβλητής με βάση τα διαθέσιμα δεδομένα. Ο χάρτης κατολισθητικής επιδεκτικότητας κατασκευάστηκε με εφαρμογή της μεθόδου του σταθμισμένου αθροίσματος. Οι τεχνικογεωλογικές ενότητες, η γωνία κλίσης, η διεύθυνση της γωνίας κλίσης,η απόσταση από τα τεκτονικά χαρακτηριστικά, η απόσταση από το υδρογραφικό δίκτυο και η απόσταση από το οδικό δίκτυο ήταν μεταξύ των έξι μεταβλητών που επιλέγθηκαν.*

*Η βάση δεδομένων με τη καταγραφή των κατολισθητικών φαινομένων έγινε μετά από τη σχετική ερμηνεία αεροφωτογραφιών, δορυφορικών εικόνων καθώς και τη διεξαγωγή ερευνών πεδίου. Χωρίστηκε σε δύο σύνολα δεδομένων, ένα για εκπαίδευση και ένα για επικύρωση του μοντέλου. Τα αποτελέσματα της διαδικασίας επικύρωσης έδειξαν ότι η μεθοδολογία που αναπτύχθηκε ήταν σε καλή συμφωνία με την πραγματική θέση των καταγεγραμένων κατολισθήσεων. Συγκεκριμένα, η περιοχή κάτω από την καμπύλη (AUC curve), ένας στατιστικός δείκτης, εκτιμήθηκε ότι είναι για την εκπαίδευση 0.7575 και για την επικύρωση και 0.7828. Ο παραγόμενος χάρτης κατολισθητικής επιδεκτικότητας θα μπορούσε να θεωρηθεί από τις τοπικές και εθνικές αρχές ως ένα πολύτιμο μέσο για την αξιολόγηση των στρατηγικών ή για την πρόληψη και τον μετριασμό των επιπτώσεων των κατολισθήσεων.*
***Λέξεις κλειδιά:*** *Κατολισθητική επιδεκτικότητα, ασαφής λογική, Θεωρία της Πληροφορίας, Τζουμέρκα, Ελλάδα.*

## 1. Introduction

Landslides involve a wide variety of processes that result in the gravitational movement of slope-forming materials that may occur in offshore, coastal or/and inland areas. They are considered among the most frequent natural hazards with significant consequences to human life and incalculable social - economic consequences. Its general accepted that natural hazards cannot be prevented; however their impacts can be reduced. In this context, the spatial distribution of future landslides that is estimated during a landslide susceptibility analysis provides information and knowledge that aids land – use planning, decision making and overall landslide risk reduction. Thus, the estimation of the likelihood of a landslide occurring in an area is a fundamental process defined by a set of geological, tectonic and hydrologic conditions, morphological characteristics, soil and vegetation features, land use and human practices. The analysis of landslide phenomenon is attempted through qualitative or expert - driven models and quantitative or data - driven models. Relatively recently, new techniques and methods derived from the domain of Machine Learning and Data Mining where utilized as promising tools to evaluate the susceptibility and risk against landslides (Korup and Stolle, 2014). These methods are characterized by the ability of learning and discovering hidden and unknown patterns from large multi-thematic databases. Numerous papers could be found through the scientific literature that take advantage of their ability to sufficiently assess data, including: the logistic regression approach (Pourghasemi *et al*., 2013a; Regmi *et al*., 2014), fuzzy logic method (Pourghasemi *et al*., 2012a; Tien Bui *et al*., 2012a; Feizizadeh and Blaschke, 2013; Zhu *et al*., 2014), artificial neural network method (Ermini *et al*., 2005; Ferentinou and Sakellariou 2007; Yilmaz 2010; Tien Bui *et al*., 2012b; Conforti *et al*., 2014; Tsangaratos and Benardos, 2014), Bayes theorem based on weights of evidence (Regmi *et al*., 2010a, 2010b; Kouli *et al*., 2014; Ilia and Tsangaratos 2015), neural–fuzzy method (Vahidnia *et al*., 2010; Oh and Pradhan, 2011), support vector machines (Yilmaz 2010; Tien Bui *et al*., 2012c; Pourghasemi *et al*., 2013b; Pradhan 2013), index of entropy (Bednarik *et al*., 2010; Constantin *et al*., 2011; Pourghasemi *et al*., 2012b; Devkota *et al*., 2013; Youssef *et al*., 2015) and decision tree method (Saito *et al*., 2009; Yeon *et al*.,2010; Nefeslioglu *et al*., 2010; Tien Bui *et al*., 2012c; Pradhan, 2013; Tsangaratos and Ilia, 2015). The main objective of the present study is to produce a landslide susceptibility map based on the combination of Fuzzy logic and Information Theory. The Fuzzy logic approach was applied in order to weight the variables according to expert opinion, while the Information Theory was applied to estimate the influence of each variable has on the landslide susceptibility calculation based on the data. The study area covers the mountains of Central Tzoumerka, which are located at the administrative unit of Epirus Greece, where serious landslides events have been encountered. The computation process was carried out using SPSS 16.0 (SPSS, 2007) for validating the model, while ArcGIS 10.1 (ESRI, 2013) was used for compiling the data and producing the landslide susceptibility maps.

## 2. Study area

The main research area is located at the eastern part of the Pindus administrative unit covering approximately an area of 222 $km^2$ clarified as the Kallaritikos watershed, a sub - basin of the Greek Water District Epirus (Fig. 1a).

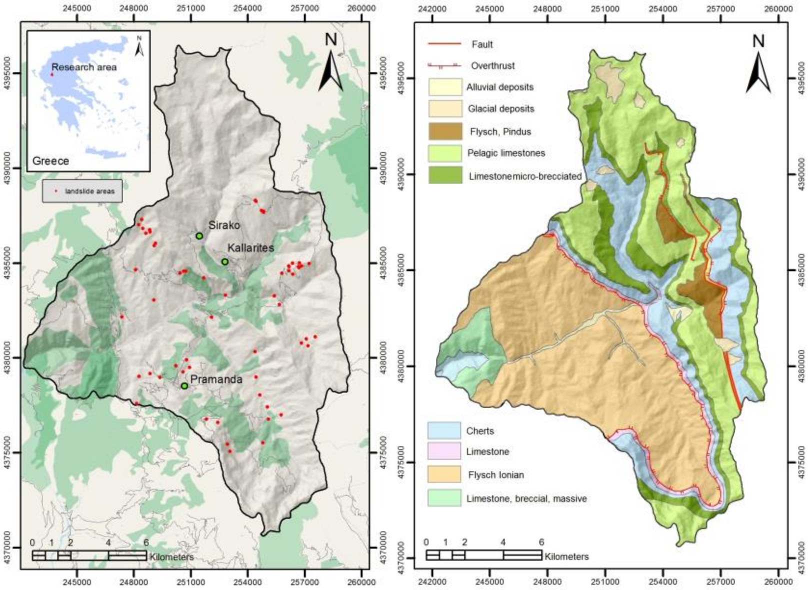


**Figure 1a - The study area, 1b - The geology of the area.**

Concerning the topography of the area it's characterized as mountainous, with the highest altitude observed in the area reaching 2354m while the lowest point is at 325m above sea level. The geological profile of the wider region consists of formations that are part of the Ionian tectonic zone, mainly constituted by Upper Eocene - Lower Miocene sedimentary sequences, as well as part of the Pindus tectonic zone, where Upper Cretaceous - Eocene sedimentary sequences outcrop (Brunn, 1956; Aubouin, 1959). About 43.40% of the research area is covered by chert formations with limestone interbeds, 37.20 % covered by limestone formations and about 17.35% covered by flysch formations. The area is characterized by a dense dendritic drainage pattern, while large successive anticlines and synclines overthrusts to the west.

## 3. Materials and Methods

### 3.1. The developed methodology

The developed methodology consisted of a four phase procedure; (a) classifying and weighting the predictor variables based on fuzzy logic and expert knowledge, (b) calculating the weight of each variable based on the Shannon's entropy index, (c) applying the weighted sum model to produce the landslide susceptibility map and (d) validating the produced model. Details of each phase are provided in the following paragraphs. The first phase, involves the application of a fuzzy logic approach in order to estimate the weight of each predictor variable. The developed methodology collects the opinions of a group of experts in reference to the importance each predictor factor has to the estimation of landslide susceptibility. Each expert assigns a linguistic value (very important, quiet important, important, neutral, unimportant, quite unimportant and very unimportant) when asked about the importance of the factor that is transformed into a triangular fuzzy number (Table 1).

**Table 1 - Scale of importance.**

| Intensity of importance | Fuzzy triangular number |
|---|---|
| Very important (VI) | (1, 2, 3) |
| Quiet important (QI) | (2, 3, 4) |
| Important (I) | (3, 4, 5) |
| Neutral (N) | (4, 5, 6) |
| Unimportant (UnI) | (5, 6, 7) |
| Quite unimportant(QUnI) | (6, 7, 8) |
| Very unimportant (VUnI) | (7, 8, 9) |

The aggregated triangular fuzzy number is calculated using the geometric mean model of mean general model proposed by Klir and Yuan (1995). The computing formula is illustrated as follows:

Assume the linguistic value assigned to the j$^{th}$ predictor factor (j=1, 2... n) by the i$^{th}$ expert (i=1,2,..k) and the equivalent triangular fuzzy number that corresponds to that linguistic value $\tilde{v}_{ij} = (a_{ij}, b_{ij}, c_{ij})$

The aggregated triangular fuzzy number for the j$^{th}$ predictor factor is $\tilde{v}_j = (a_j, b_j, c_j)$ where,

$$a_j = \underset{i=1}{\overset{k}{Min}}\{a_{ij}\} \quad b_j = \frac{1}{n}\sum_{i=1}^{k} b_{ij} \quad c_j = \underset{i=1}{\overset{k}{Max}}\{c_{ij}\}$$

The next step is to use the simple centre of gravity method to defuzzify the aggregated triangular fuzzy number of each predictor factor and to estimate the Intensity of importance ($I_j$) (Equation 1), while the weighting of each predictor variable is obtained by the equation 2.

**Equation 1 - Intensity of importance**

$$I_j = \frac{a_j + b_j + c_j}{3}$$

**Equation 2 - Weight of variables**

$$wi_j = \frac{\max\{I_j\} - I_j + 1}{\sum_{k=1}^{n} \max\{I_j\} - I_k + 1}$$

The next phase involves the estimation of weight of influence of each variable based on Shannon's entropy index. The Shannon's entropy index has been used in the Information Theory as a measure originally proposed by Claude Shannon to quantify the entropy, uncertainty or information content in strings of text (Shannon, 1948). It proposes that the more information one has the more certain one becomes, likewise we can postulate that the more diverse something is the more uncertain we become in knowing its decision or outcome. The information coefficient is an index that ranges between 0 and 1, with values closer to 0 indicating less influence of the variable while values closer to 1 indicating more influence. The equations used to calculate the information coefficient Wj representing the weight value for the parameter as a whole (Bednarik *et al.*, 2010; Constantin *et al.*, 2011) are given in Table 2.

**Table 2 - Equation for determining the Weight coefficient based on Shannon's entropy index.**

| Number of equation | Explanation | Equation |
|---|---|---|
| **Equation 3** | Landslide probability | $p_{ij} = \frac{L_{ij}}{A_{ij}}$ |
| **Equation 4** | Landslide Probability density | $P_{ij} = \frac{p_{ij}}{\sum_{j=1}^{c_j} p_{ij}}$ |
| **Equation 5** | Entropy value | $H_j = -\sum_{i=1}^{c_j} P_{ij} \otimes \log_2 P_{ij}$ |
| **Equation 6** | Maximum entropy value | $H_{j\max} = -\log_2 c_j$ |
| **Equation 7** | Information coefficient | $I_j = \frac{H_{j\max} - H_j}{H_j}$ |
| **Equation 8** | Weight coefficient of each class of j$^{th}$ factor | $w_{ij} = \frac{1-(P_{ij} \otimes \log_2 P_{ij})}{H_{j\max} - H_j}$ |

The third phase involves the application of the weighted sum method in order to calculate the landslide susceptibility index, according to equation 9:

**Equation 3 - Landslide susceptibility index**

$$LSi_{pi} = \frac{1}{j}\sum_{j=1}^{n} w_{ij} * wi_{cij}$$

The result of the summation is a continuous interval of values which represent the various levels of susceptibility and forms the landslide susceptibility map that is reclassified according to the natural break method for the determination of the class intervals (Feizizadeh and Blaschke, 2013). Classes identified are described as follows: very high susceptibility (VHS), high susceptibility (HS), moderate susceptibility (MS), low susceptibility (LS) and very low susceptibility (VLS). The final phase involves the validation of the developed model by means of the success-rate and prediction-rate methods (Fawcett, 2006). Using the landslide grid cells in the training dataset, the success-rate results were obtained, while the validation dataset were used for the construction of the prediction-rate curves (Chung and Fabbri, 2003). The area under the ROC curve (AUC) has been used as a metric to access the overall quality of the predictive models by evaluating the models ability to anticipate correctly the occurrence or non-occurrence of predefined events (Hanley and McNeil, 1982; Fawcett, 2006). If AUC is close to 1, the outcomes of the analysis are excellent, while if the AUC is closer to 0.5, the less accurate the result of the analysis is.

## 3.2. Data

Concerning the landslide inventory which includes information about the location, features and abundance of landslide areas, it was based on historical information concerning landslide incidence, the interpretation of aerial photos, the use of satellite imagery and extensive field observations. A total of 116 sites where identified and partitioned into two datasets, one for training and one for validating purpose, containing 93 and 23 sites, respectively. The landslide related variables that was selected for the assessment of the landslide susceptibility of the research area are described by the following six variables: engineering geological units, slope angle, slope aspect, distance from tectonic features, distance from river network and distance from road network. Particular, the geological formations that cover the research area were grouped into four categories based on their engineering geological behavior, the spatial distribution of failures identified in the region, but also the experience and knowledge that has been recorded in related studies. Specifically, the following were found and classified: A) quaternary loose, fine grained deposits that consist mainly of cobbles, pebbles, grits and sands with low proportions of fines, such as clayey silts and sandy silts; B) limestones formations, that are characterized as Pelagic, thin to medium – bedded, often micro - brecciated with nodules or lenticular silica layers and local thin intercalations of shales; C) flysch formations with alternating siltstones and sandstones and frequent participation of conglomerates and intermediate lithological types, and D) chert formations with limestone interbeds. The fault density maps were also constructed based on the geological map (IGME, 1961) and was classified into three zones of influence: A) < 250m, B) 251-500m and C) > 501m. A digital elevation model (DEM) with a spatial resolution of 20x20m was generated from national topographic maps in scale 1:50.000. Based on the DEM data, slope angle, slope aspect and distance from the river network were constructed. Specifically, five classes for slope angle have been identified and classified: A) $0^0$-$15^0$, B) $16^0$-$30^0$, C) $31^0$–$45^0$, D) $46^0$–$60^0$ and E) slopes greater than $61^0$. In accordance to the previous, five classes for slope aspect have been identified and classified: A) $226^0$-$270^0$, B) $46^0$-$90^0$, C) $91^0$-$135^0$, $271^0$-$315^0$, and D) $316^0$-$45^0$, $136^0$-$225^0$ (Fig.4d). Concerning the river network density map, it was formed using the DEM data and further classified into three zones of influence: A) < 100m, B) 101-300m, and C) > 301m. Finally, the distance from the road network was constructed based on the national topographic maps and classified into three zones of influence, characterizing the distance of landslide incidence from the road network: A) < 100m, B) 101-300m, and C) > 301m.

## 4. Results

According to the weighting process conducted in the first phase (Table 2), that was based on fuzzy logic and expert knowledge, the most susceptible class was estimated to be class A (<100m) in the variable Distance to road network (0.5714), followed by the class A (<100m) in the variable Distance to river network (0.5000). The least susceptible class was class A (<$15^0$) in the variable Slope (0.0667), followed by the class A ($226^0$-$270^0$) in the variable Aspect (0.1000). From the analysis performed during the second phase (Table 3), that was based on the Information Theory and the Shannon index, the most uncertain variable was estimated to be Distance to river network (0.0133), followed by Aspect (0.0307), Engineering lithological units (0.0490), Slope (0.1426), Distance to tectonic features (0.3995 ) and Distance to road network (0.4087).

**Table 4 - Weight of variables according to expert knowledge and Information Theory.**

| Landslide related variable | Class | Fuzzy Logic $W_j$ | Information Theory $w_{ij}$ |
|---|---|---|---|
| **Engineering lithological units** | A | 0.1176 | 0.0490 |
| | B | 0.1765 | |
| | C | 0.3529 | |
| | D | 0.3529 | |
| **Slope** | A | 0.0667 | 0.1426 |
| | B | 0.1667 | |
| | C | 0.2000 | |
| | D | 0.3000 | |
| | E | 0.2667 | |
| **Aspect** | A | 0.1000 | 0.0307 |
| | B | 0.1667 | |
| | C | 0.2000 | |

| Landslide related variable | Class | Fuzzy Logic $W_j$ | Information Theory $w_{ij}$ |
|---|---|---|---|
| | D | 0.2667 | |
| | E | 0.1333 | |
| **Distance to tectonic features** | < 250m | 0.4737 | 0.3995 |
| | 251- 500m | 0.4211 | |
| | > 501m | 0.1053 | |
| **Distance to river network** | < 100m | 0.5000 | 0.0133 |
| | 101-300m | 0.3571 | |
| | > 301m | 0.1429 | |
| **Distance to road network** | < 100m | 0.5714 | 0.4087 |
| | 101-300m | 0.4286 | |
| | > 301m | 0.2143 | |

The third phase involved the application of the weighted sum method in order to calculate the landslide susceptibility index, according to equation 9. The outcome of the estimation is illustrated in Figure 2a in which the various levels of susceptibility are presented and reclassified according to the natural break method for the determination of the class intervals. Following the developed methodology five classes of susceptibility where identified. Very high susceptibility (VHS) that covered approximately 8.59%, high susceptibility (HS) covering 20.42%, moderate susceptibility (MS) covering 29.65%, low susceptibility (LS) covering 27.29% and very low susceptibility (VLS) covering 14.05% of the total research area. As illustrated in figure 2b, the landslide probability density within the zones high and very high susceptibility was calculated to be over 81.00%, while within the zones very low and low susceptibility was calculated to be less than 5%. The results of the implementation of the developed methodology was validated using the training and validation dataset through the use of the ROC graphs and the success and prediction rate curves, which are summarized by the calculation of AUC values. Figure 2b shows the results indicating that the model has good prediction capabilities. In particular, the AUC value for the training and validating datasets was calculated to be 0.7575 and 0.7828 respectively.

## 5. Discussion and conclusion

It is well established that for the assessment of landslide phenomena, the majority of the applied methods are based either on the experience and knowledge provided by experts or on statistical or probabilistic theories or even the use of deterministic models (Aleotti and Chowdhury, 1999). Each procedure has advantages and disadvantages that are influenced by the quality and quantity of the available data and also the experience, judgment and the time engagement of the expert. In this context, the development of a hybrid method that combines the two procedures can be thought as a valuable tool in order to produce more accurate predictive models. Particularly, in the present study a landslide susceptibility map was produced by applying Fuzzy logic and Information Theory. The Fuzzy logic approach was applied in order to weight the variables according to expert opinion, while the Information Theory was applied to estimate the influence of each variable has on the landslide susceptibility calculation based on the data.

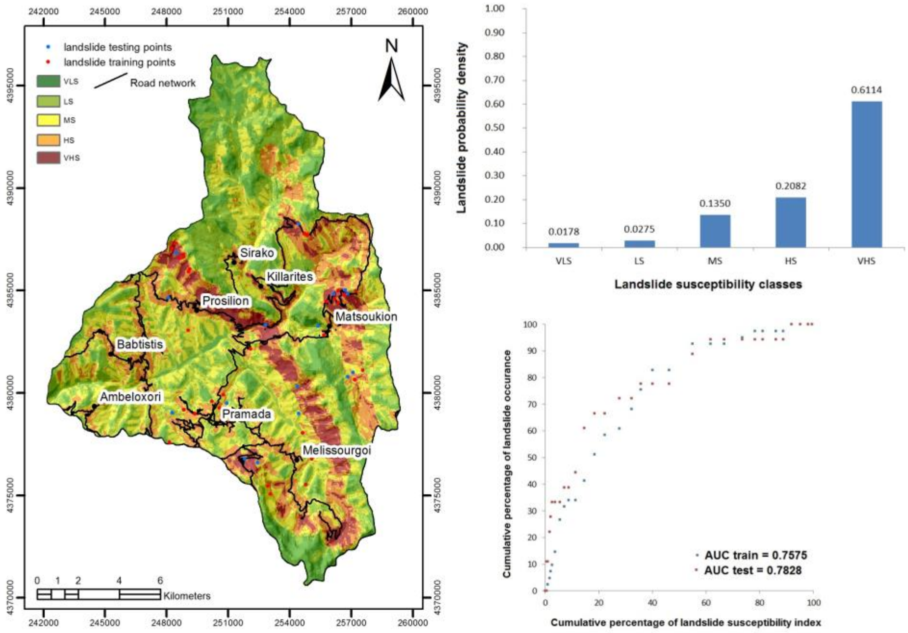


**Figure 2a - The landslide susceptibility map, 2b - Validation graphs.**

The study area covers the mountains of Central Tzoumerka, an area considered as one of the historical centres of the Vlach culture in Pindus, Greece, with a cluster of significant historical villages, such as Sirako, Killarites and Pramanda. From the visual inspection of the produced landslide susceptibility map it is obvious that the spatial pattern of susceptibility mainly follows the spatial distribution of the landslide conditioning variable, Distance to tectonic features. Furthermore, major sections of the road network that connect those historical villages intersect areas of very high landslide susceptibility. Concerning the accuracy of the developed model, the combination of the two procedures produced highly accurate predictive models. Specifically, the AUC value for the training and validating datasets was 0.7575 and 0.7828 respectively. In conclusion, the produced landslide susceptibility map could be regarded from local and national authorities as a valuable mean to evaluate strategies or to prevent and mitigate the impact of landslides.

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