A COMPARATIVE ASSESSMENT OF NEURAL NETWORK, FUZZY AND NEURO-FUZZY APPROACHES FOR LANDSLIDE SUSCEPTIBILITY ZONATION IN GARHWAL HIMALAYAS

M. K. Arora, [1] S. Chauhan, [2] M. Sharma [3]

[1]Professor, Department of Civil Engineering, IIT Roorkee, ROORKEE, India
(manojfce@iitr.ernet.in)
[2]Geo-Information Analyst, Shell Projects and Technology, BENGALURU, India
[3]Asst. professor, Dept. of Geology, H.P. Univ. Regional Center, Dharamshala, India

Abstract. *Availability of accurate and objective landslide susceptibility maps depicting zones defined on the basis of probability of occurrence of landslides is one of the critical inputs in assessing risk to property and lives in any mountainous region, particularly in the Himalayas. The aim of this study is to assess the utility of soft computing tools, namely, neural network, fuzzy and neuro-fuzzy approaches for for landslide susceptibility zonation and risk assessment in a rigorous mountainous terrain in India.*

Key words: *Landslide Susceptibility Zonation, Artificial Neural Network, Fuzzy Set*

1.   INTRODUCTION

Landslides in the Himalaya are one of the major and widely spread natural hazards that often strike life and property and are a major concern. One of the requirements for effective landslide mitigation and management programme is the availability of an accurate Landslide Susceptibility Zonation (LSZ) map. LSZ maps categorize a region according to their potential stability or instability, based on geological, geomorphological and topographical factors. The need for LSZ maps at different scales has increased in recent past to support decision makers at various levels of the territorial planning management.

Preparation of LSZ maps requires evaluation of the relationships between various terrain conditions and instances of landslide occurrence. A skilled earth scientist, through his vast experience based on the assessment of the overall terrain conditions usually identifies the causative factors affecting the occurrence of landslides in a region. On their assessment, these factors and their categories are assigned weights and ratings respectively as per their importance in landslide occurrences. The knowledge in the form of weights and ratings is typically input to any LSZ process in several different ways.

In this study, a landslide susceptibility zonation study has been carried out using neural, fuzzy and neuro-fuzzy approaches in remote sensing and GIS domain. A set of raster

thematic data layers, each pertaining to a selected causative factor, have been created through digitization of past maps or derived from remote sensing images using an image processing and GIS software. These data have been input to an inhouse developed software namely LaSaRiZ (Landslide Susceptibility and Risk Zonation) software. The outputs from this software are the landslide susceptibility zonation maps produced from various approaches. The evaluation of landslide susceptibility maps derived from the implemented approaches has been performed through landslide density analysis and interpretation of Receiver Operating Characteristic (ROC) curves.

2.   Literature Review

The data integration for various causative factors and their categories to carry out LSZ mapping can either be manual or in a Geographic Information System (GIS) environment as is evident from a number of in-house studies (e.g., Gupta *et al.* 1993, Saha *et al.* 2002, Saha *et al.* 2005, Pareek *et al.*, 2010, Chauhan *et al.*, 2010a). Thus, in these studies, the weights have usually been assigned on the basis of the knowledge domain of the expertise about the subject and the area. This weight assignment strategy, at times, may however be highly subjective and may therefore contain some implicit biasness.

Therefore, in order to reduce the subjectiveness in the weight assignment procedure, a number of alternative strategies (e.g., Saha *et al.* 2005, Mathew *et al.* 2007, Champati Ray *et al.*, 2007, Pradhan *et al.* 2009) have been attempted in recent years for LSZ mapping in Himalaya and other parts of the world. Most of these studies are based on establishing the relationships between categories of the causative factors and incidences of the existing landslides in a given region through spatial data analyses. Thus, a range of data driven approaches have been proposed, which include logistic regression and multivariate statistical methods (Dai *et al.* 2001; Van Den Eeckhaut *et al.* 2006, Akgun *et al.*, 2008; Mathew *et al.* 2009; Akgun and Turk, 2010; Chauhan *et al.*, 2010b), decision tree approach (Nefeslioglu *et al.*, 2010), artificial neural network (Arora *et al.* 2004; Kanungo *et al.* 2006; Pradhan and Lee, 2010; Pradhan *et al.*, 2010a), fuzzy relations (Kanungo *et al.* 2006; Pradhan 2010, 2011) and neuro-fuzzy approaches (Kanungo *et al.* 2006; Pradhan *et al.*, 2010b; Sezer *et al.*, 2011). Each approach is based on a different mathematical concept but has been used with an ultimate aim to produce an LSZ map in an objective manner thereby reducing the subjectivity in the weight assignment procedure.

For the last one decade, several ANN based LSZ studies have been conducted (e.g., Lee *et al.,* 2003; Arora et al., 2004; Kanungo *et al.*, 2006; Nefeslioglu et al., 2008; Pradhan and Lee, 2010; Pradhan et al., 2010a, b; Sezer *et al.*, 2011). In these studies, the ability of an ANN to learn non-linear functions has been exploited for landslide susceptibility mapping in

a region where the data pertaining to causative factors may not be approximated by a normal distribution and are non-linearly related.

In addition, fuzzy set theory has also been found useful for landslide mapping (e.g., Chi *et al.* 2002). Here, a fuzzy set can be utilized to assign varying degree of memberships to the categories of causative factors according to their importance in landslide occurrence. Recently, attempts (e.g., Kanungo *et al.*, 2006) have also been made to combine the ANN and fuzzy set approaches wherein weights to be assigned to causative factors are determined objectively through ANN and ratings are assigned to categories of factors using fuzzy set theory (e.g., Kanungo *et al.*, 2006; Pradhan et al., 2010b; Sezer *et al.*, 2011).

In this study, the traditional backpropagation ANN has been implemented for the determination of weights of causative factors *via* a connectionist weighting process (Olden *et al.* 2004). The backpropagation ANN, as implemented in the software, can also be used as a black box to independently produce an LSZ map. A fuzzy relation concept based on cosine amplitude method has been implemented to determine ratings (equivalent to fuzzy membership values) of categories of causative factors. The fuzzy relation concept can be used to independently produce a fuzzy-set based LSZ map and can be combined with neural network to produced a neuro-fuzzy based LSZ map.

## 3.	BRIEF ACCOUNT ON LSZ APPROACHES USED

3.1 Back-propagation neural network (BPNN) approach

A typical neural network architecture for LSZ mapping may be a three layer design with seven input neurons corresponding to seven thematic data layers (one for each causative factor affecting landslide) in the input layer and one output neuron corresponding to presence or absence of landslide in the output layer. The number of neurons in the hidden layer is determined by trial and error.

The back propagation neural network (BPNN) is based on the mathematical background given in Arora *et al.* (2004) and Kanungo *et al.* (2006). The flowchart of implementing BPNN as black box for LSZ as implemented in LaSaRiZ is given in figure 1.
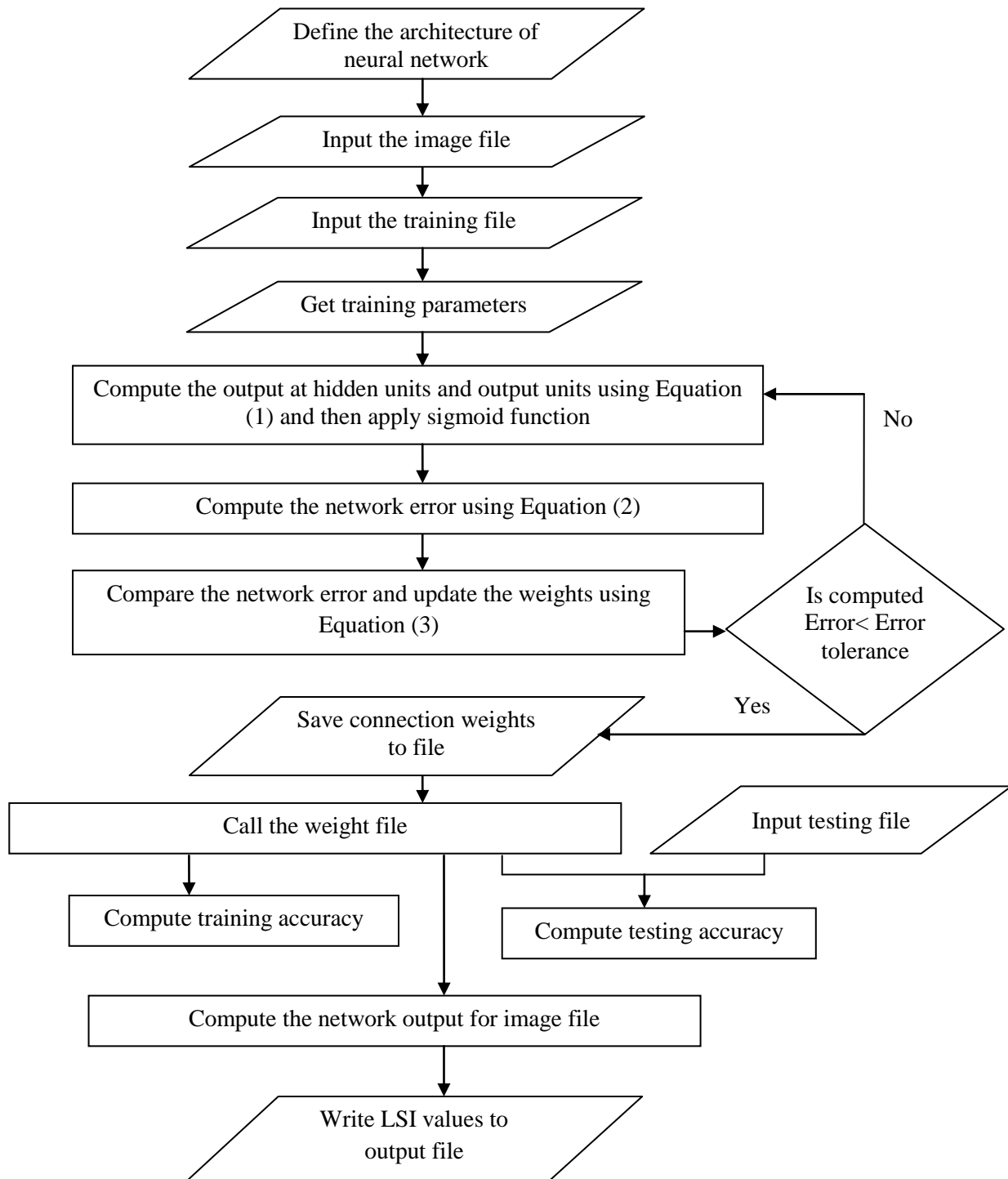
Figure 1: Flow chart to perform LSZ using BPNN

The network architectural parameters (i.e., number of units in input layer, hidden layers and output layer) are given as input. The three stages involved in ANN data processing for a classification problem are; the training stage, the weight determination stage and the classification stage. The training process is initiated by assigning arbitrary initial connection

weights, which are constantly updated until an acceptable training accuracy is attained. While developing an ANN, the data are commonly partitioned into two subsets; training for the development of the model and testing for the validation of the model. It is expected that the training data will represent all the characteristics belonging to the problem domain (e.g., LSZ). The training data *via* input neurons are processed through hidden neurons to generate an output at the output neuron.

In the ANN black box approach, the adjusted weights obtained from the trained network are subsequently used to process the testing data to assess the accuracy and generalization capability the network. Once the network is trained and tested to the desired accuracy, the adjusted weights are used to simulate the complete dataset. In the present context, the network output values for the whole dataset has been categorized into one of the five landslide susceptible zones to produce the LSZ map from ANN. This approach has been referred to as ANN black box approach, since, in this case, the weights remain hidden (Arora *et al.* 2004).

3.2   Fuzzy set based cosine amplitude approach

The cosine amplitude approach is a fuzzy relation concept to compute ratings, which define the degree of relationship between category of causative factors and landslide occurrence. The flowchart of this approach, as implemented in the software, is shown in figure 3.
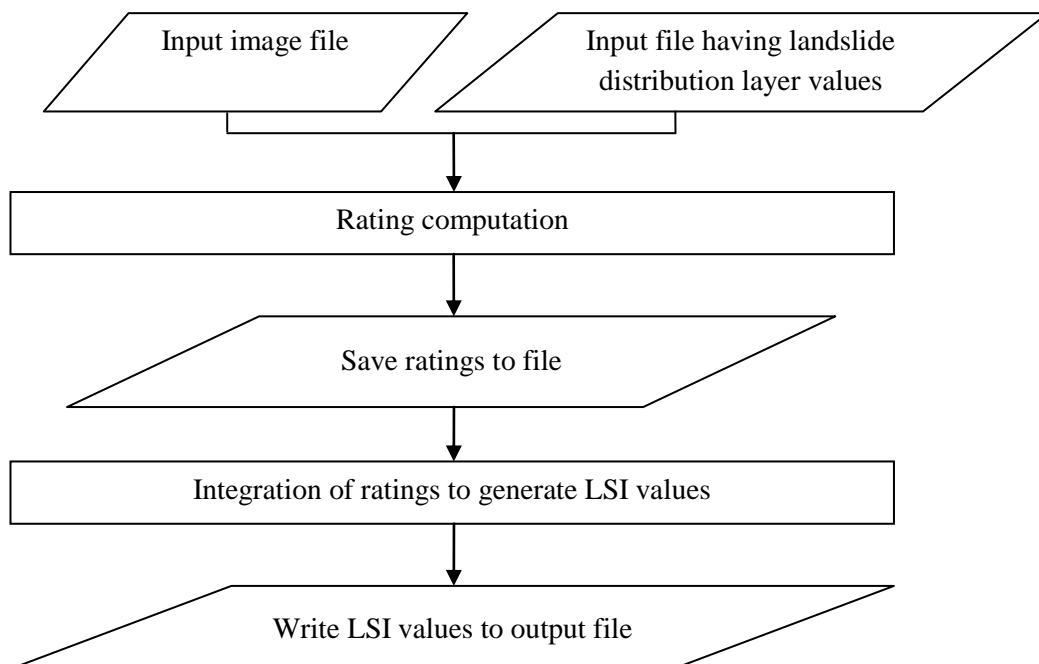

Figure 2: Flow chart to perform LSZ using fuzzy set based cosine amplitude approach

The approach evaluates the relation between the existing landslide occurrence and the categories of each causative factor considered. The categories of existing landslide distribution layer and categories from each thematic data layer (corresponding to each causative factor) taken one at a time have been considered as two binary datasets for the computation of ratings or strength of relationship. The ratings, thus obtained, have been integrated to estimate the Landslide Susceptibility Index (LSI) values. The LSI values have been categorised in an ordinal manner to produce an LSZ map.

3.3 Combined neural network and fuzzy approach

A combined neural network and fuzzy approach takes advantage from both to integrate ANN derived weights and fuzzy set derived ratings to produce an LSZ map. This map is expected to be more accurate than the LSZ maps produced either from ANN or fuzzy relation concept. The implementation of this approach can be understood with the help of the flowchart given in Figure 3.
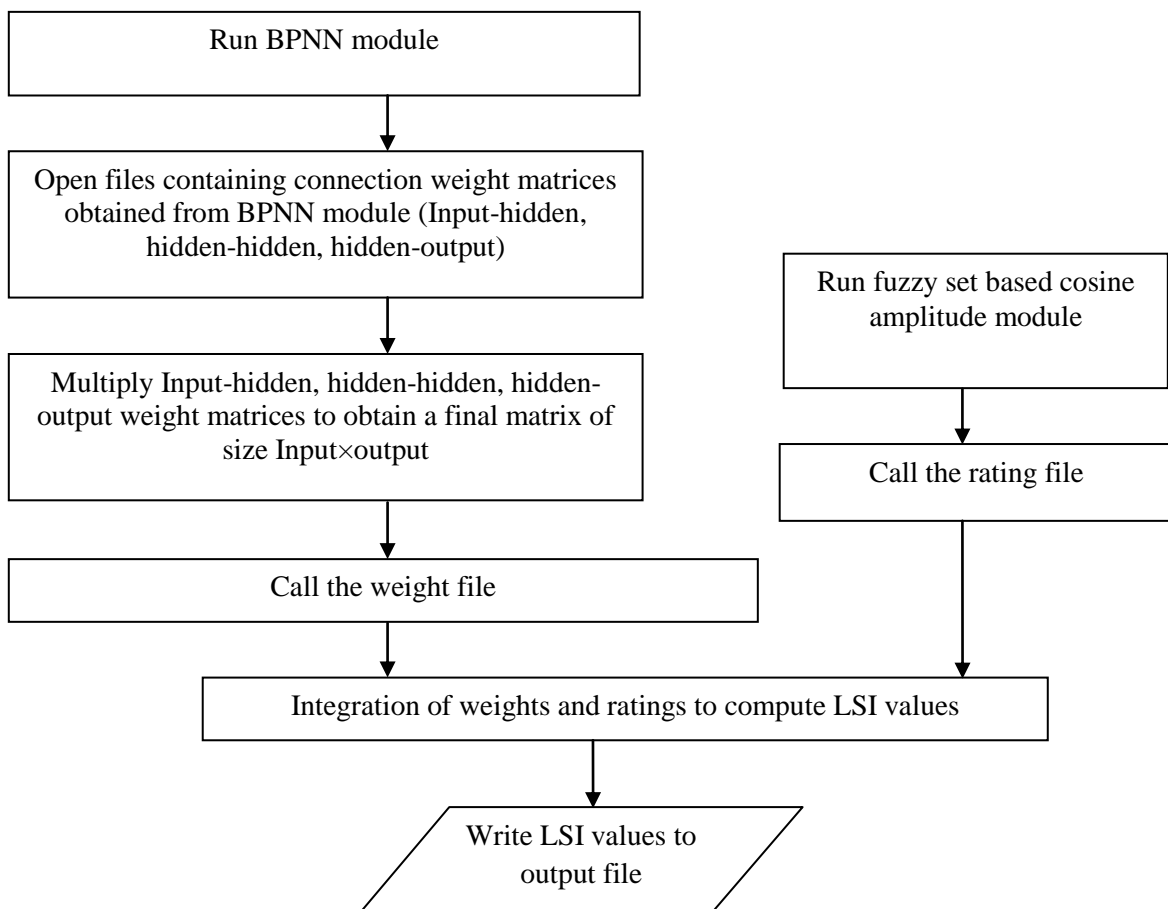

Figure 3: Flow chart to perform LSZ using combined neural network and fuzzy approach

The combined neural and fuzzy approach involves three steps, (i) Determination of weights of causative factors through ANN connection-weight approach; (ii) Determination of ratings for categories of causative factors using cosine amplitude method; and (iii) The integration of weights and ratings to produce the LSZ map. The processing steps in defining the architecture of the ANN, its training and testing are similar to those of ANN black box approach. The connection weight matrices from the trained two-hidden layer network for input-hidden, hidden-hidden and hidden-output layers are extracted. Simple matrix multiplications of these weight matrices are performed to achieve a weight matrix representing weights corresponding to the causative factors (Olden *et al.* 2004). The ratings of the categories of causative factors are determined from the cosine amplitude method. The weights, derived from ANN and ratings computed from cosine amplitude method are integrated to compute LSI values, which have been further categorized to produce the LSZ map.

4. Study Area and Data

The study area belongs to parts of Chamoli and Rudraprayag districts of the State of Uttarakhand, India, in the Himalayan region and covers about 600 sq km. There are a number of thrusts and faults passing through the area which has rendered the rock mass weak. The area is also characterized by fragile geology and complex tectonics. The region had also witnessed two major earthquakes in the recent past one; Uttarakashi in 1991 and Chamoli in 1999, which caused extensive damages to the life and property. These seismic ground movements make the lithology fragile and cause landslides.

All these factors along with torrential rainfall make the slopes inherently unstable, which lead to occurrences of landsides in the region. Based on the past studies on LSZ in the region, seven key causative factors, namely, slope, aspect, relative relief, lithology, structural features, land use land cover and drainage density, were considered.

Spatial data pertaining to these causative factors were collected from satellite remote sensing images (IRS-1C and P6 satellite sensors - PAN, LISS-III and LISS IV), Survey of India (SOI) topographic maps, Valdiya's geological map (Valdiya, 1980) and the field campaigns. Table 1 provides the details of these data along with their usage in the study.

Table 1: Data sources and specific use

Data types	Description			Specific Use
	Satellite/Sensor	Spatial Resolution	Year of Acquisition	
Remote Sensing Data	IRS PAN	5.8m	1999	Land use/ Land cover, Structural Features Landslide distribution
	IRS LISS-III	23.5m	2001	
	IRS LISS-IV	5.8m	2008	
Google Earth Data	Various images of study area Google Earth Data			Landslide distribution
Topographical maps (1963)	Scale: 1:50000			DEM: Slope, Aspect, Relative Relief Drainage network
Geological map (1980)	Scale: 1:326000			Lithology, Structural Features
Field Data	GPS Surveys			Landslide distribution, Land use/Land cover

These spatial data were appropriately processed and analyzed in an image processing and GIS software to prepare seven thematic data layers. Further details on the study area, causative factors and their justification, and the process of preparation of thematic data layers can be found in Chauhan *et al.* (2010ab). The seven thematic data layers have been named as slope, aspect, relative relief, structural buffer, lithology, drainage density and landuse landcover. These layers are stacked as a single database to be input to LaSaRiZ for various operations.

The identification and mapping of existing landslides is a pre-requisite to develop any data-driven model for LSZ. Therefore, existing landslide locations have been interpreted visually and mapped from high-resolution LISS IV (MX) image and PAN sharpened multi-spectral image. A total of 154 landslides of varying dimensions have been mapped, which were subsequently digitized and rasterized to create a landslide distribution data layer. From this landslide distribution data layer, the pixels of landslide and no-landslide attributes are extracted, which are then used for training and testing of the three approaches for LSZ mapping implemented in the LaSaRiZ software.

5.   Creation of LSZ maps

5.1   LSZ using back-propagation neural network approach

The database of landslide and non-landslide pixels consist of a total of 2621 pixels denoting the presence of landslide and an equal number of pixels denoting the absence of landslide. This dataset is divided into two mutually exclusive datasets; 80% for training and 20% for testing. A number of ANN architectures have been designed, which are trained with back-propagation learning algorithm, with learning rate of 0.01 and a momentum factor of 0.2. The training parameters have been kept fixed across various neural networks for their effective comparison. The training process is initiated by assigning arbitrary initial connection weights, which are constantly updated until an acceptable training accuracy is achieved. The adjusted weights obtained from the trained network are subsequently used to process the testing data to assess the accuracy and the generalization capability of each network. The training and testing data accuracies of each network are listed in Table 2.

Table 2: Training and testing data accuracies (I: input layer, H1: first hidden layer, H2: second hidden layer and O: output layer). Bold values indicate the highest accuracy

ANN Architecture (I×H1×H2×O)	Training Accuracy (%)	Testing Accuracy (%)	Difference in training and testing data accuracies
7×4×1×1	64.9	63.2	1.7
7×5×2×1	67.4	65.0	2.4
7×6×3×1	68.0	65.3	2.7
7×7×4×1	71.0	69.3	1.7
7×8×5×1	73.9	70.0	3.9
7×9×5×1	**75.2**	**71.7**	**3.5**
7×9×6×1	75.1	68.0	8.1
7×10×5×1	74.9	67.6	8.3
7×10×6×1	73.3	67.1	10.2
7×11×5×1	72.4	66.8	11.6

From this table, it can be observed that as the neural network architecture changes, the training and testing data accuracies increase up to a certain neural network design, after which a decrease in accuracy occurs. This shows that there is an optimum ANN architecture for this

dataset. Moreover, the training data accuracies differ from testing data accuracies for various architectures. Larger is the difference between training and testing data accuracies, lesser may be the generalization capability of an ANN. Keeping this in view, an ANN with 7×9×5×1 architecture, producing a training accuracy of 75.2% and a testing accuracy of 71.7%, which not only depicts less difference between the training and testing data accuracies but attained high absolute values, has been considered as the most appropriate one for the current dataset. Thus, the adjusted weights from this ANN have been used to determine the network output of all the pixels of the image. The values of neural network outputs for each pixel have been found to vary from 0.01 to 0.998, which reflect the LSI values of pixels. Higher the value of LSI, more susceptible is that pixel towards the occurrence of landslide. These LSI value have been categorized arbitrarily into five landslide susceptibility zones in an ordinal fashion (Table 3) to produce an LSZ map.

Table 3: Classification of LSI values obtained from ANN black box approach into landslide susceptible zones

Range of LSI values	Landslide Susceptibility Zones
≤0.1	VLS
>0.1 and ≤0.25	LS
>0.25 and ≤0.8	MS
>0.8 and ≤0.9	HS
>0.9	VHS

5.2   LSZ using cosine amplitude based fuzzy relation approach

The categories of landslide distribution layer and categories of a thematic data layer, taken one at a time, have been considered as two datasets for the computation of ratings or strength of relationship. The pixels in the landslide areas have been assigned a value of 1, whereas remaining pixels are assigned a value of 0 in the landslide distribution layer. Similarly, a value of 1 has been assigned to a particular category of a thematic layer and a value of 0 to remaining pixels. Hence, in total, there are 43 data layers in binary form (i.e., 42 layers of categories of causative factors and 1 layer of landslide distribution category). With the help of these data layers, fuzzy memberships or ratings of all the 42 categories have been determined using the cosine amplitude method and are given in Table 4.

Table 4: Fuzzy ratings for different categories of causative factors as obtained from cosine amplitude approach

Causative Factors	Categories	Fuzzy Ratings (r_{ij})
Aspect	North	0.004
	Northeast	0.013
	East	0.034
	Southeast	0.031
	South	0.023
	Southwest	0.018
	West	0.017
	Northwest	0.002
	Flat	0
Drainage Density	<3.72 m/m^2	0.038
	3.72-7.45 m/m^2	0.029
	7.45-11.17 m/m^2	0.014
	11.17-14.90 m/m^2	0.006
	>14.90 m/m^2	0.003
Sructural Features (buffer)	0-500 m	0.039
	500-1000 m	0.020
	1000-1500 m	0.014
	1500-2000 m	0.012
	2000-2500 m	0.002
	>2500 m	0
Land use/ Land cover	Sparse vegetation	0.023
	Dense forest	0.001
	Snow	0
	Water	0.006
	Settlement	0.035
	Barren land	0.074
	Fallow land	0.034
	Agriculture	0.013
Relative Relief	<25	0.004
	25-50	0.023
	50-75	0.025
	75-100	0.020
	100-125	0.017
	>125	0.026
Slope	0-15°	0.019

	15-25°	0.025
	25-35°	0.023
	35-45°	0.028
	>45°	0.017
	Granite-Grandiorite-Gneiss	0.024
	Granite	0.019
Lithology	Quartzite with Slate	0.045

By assigning the ratings of the 42 categories (*t*) in the corresponding binary layers of categories, 42 images of r_{ij} have been generated. These 42 rated images (R_l) have been integrated to LSI values, which are found to range between 0.045 and 0.274. A probability distribution curve with mean (μ_0) value of 0.15 and standard deviation (σ_0) value of 0.026 of these LSI values has been produced. A success rate curve approach, as described in Saha *et al.* (2005), has been adopted to categorize the LSI values into five ordinal landslide susceptible zones. Accordingly, the boundaries of landslide susceptible zones have been fixed at LSI values of 0.107, 0.136, 0.164 and 0.193 and an LSZ map.

5.3 LSZ using combined neural network and fuzzy approach

ANN architecture with one input layer, two hidden layers and one output layer has been adopted. Similar to earlier ANN approach, the number of neurons in the hidden layers have been varied in this case also by running the networks several times to achieve the desired training and testing data accuracies. The training and testing accuracies of 10 networks is shown in Table 5.

Table 5: Training and testing accuracies in combined neural network and fuzzy approach

ANN Architecture	Overall Accuracy (%)		
	Training	Testing	Difference in training and testing accuracies
7×6×5×1	71.2	65.0	6.2
7×7×6×1	72.5	66.3	6.2
7×8×7×1	73.8	67.5	6.3
7×9×8×1	74.0	68.3	5.7
7×10×9×1	77.3	70.4	6.9
7×11×10×1	78.8	72.2	6.6
7×12×10×1	**79.3**	**74.8**	**4.5**
7×13×9×1	78.6	72.7	6.9
7×14×10×1	77.0	69.6	5.9

7×15×9×1	76.6	68.8	7.8

From this table, a variation in both training and testing accuracies can be noticed as the neural network architecture changes. This suggests that there exists optimal neural network architecture for a given dataset. An ANN with 7×12×10×1 architecture with training accuracy 79.3% and testing accuracy 74.8% has been found to be the most appropriate one, as it provides the least difference between training and testing accuracies. The updated weights of input-hidden, hidden-hidden and hidden-output connections for this network have been captured for further analysis. Simple matrix multiplications of these weight matrices are performed to obtain the final weight matrix corresponding to the factors. The weights of the causative factors thus obtained after connection weight analysis, are given in Table 6.

Table 6: Weights of causative factors derived through ANN in combined neuro-fuzzy approach

Causative Factors	ANN derived Weights
Land use/ Land cover	3.14
Structural Features	2.07
Aspect	1.43
Drainage Density	1.11
Lithology	0.99
Slope	0.78
Relative Relief	0.48

It can be observed from this table that causative factor land use land cover has the most influencing effect with highest value of weight as 3.14. This is followed by the structural features factor with the value of 2.07. Thus, unlike ANN blackbox approach, the importance of each causative factor on the basis of ANN derived weights, can be ascertained in this approach. Further, the ratings of each category of the factor have been determined from fuzzy relation based cosine amplitude method. The weights are integrated with ratings to compute LSI values, which range from 0.0582 to 0.3849 with a mean value of 0.22 and standard deviation value of 0.048. These LSI values have been categorized using success rate curve

method. Accordingly, the boundaries of landslide susceptible zones were fixed at LSI values of 0.148, 0.196, 0.244 and 0.292 to produce the LSZ map.

6.   RESULTS AND DISCUSSION

The LSZ maps produced from the three approaches through LaSaRiZ software have been evaluated with each other in respect of the distribution of existing landslides in the area, i.e. on the basis of landslide density, and then through ROC curves. Landslide density has been defined as the ratio of the existing landslide area (in percent) obtained from landslide distribution layer to the area of each landslide susceptibility zone (in percent) obtained from an LSZ map. The distribution of landslide susceptibility zones and the landslide densities for all the three approaches are given in Table 7.

Table 7: Landslide distribution in various landslide susceptible zones

Landslide Susceptible Zones	ANN black box approach			Fuzzy set based approach			Combined neural network and fuzzy approach		
	% area of identified zones (a)	% area of observed landslides per class (b)	Landslide density (b/a)	% area of identified zones (a)	% area of observed landslides per class (b)	Landslide density (b/a)	% area of identified zones (a)	% area of observed landslides per class (b)	Landslide density (b/a)
VHS	11.60	29.3	2.52	4.0	24.33	6.08	5.1	33.1	6.49
HS	27.40	42.7	1.56	20.9	40.32	1.93	23.9	41.4	1.73
MS	46.15	27.4	0.59	41.1	27.62	0.67	41.4	21.9	0.53
LS	8.80	0.26	0.29	29.3	7.13	0.24	25.9	3.6	0.14
VLS	6.05	0.34	0.05	4.7	0.6	0.13	3.7	0	0

It can be seen that in case of back-propagation neural network approach, 72% of the observed landslides fall in 39% of the total area categorized into very high and high susceptibility zone. Also, a very large area of about 29% is obtained as very high susceptibility zone in neural network approach, which does not show any defined pattern and is found to be distributed overall in the map. In case of the cosine amplitude based fuzzy relation approach, 64.65% of observed landslides fall in 24.9% of identified very high and high susceptibility zones. However, in case of combined neural network and fuzzy approach, 74.5% of observed landslides fall in 29.0% of identified very high and high susceptibility zones, which in fact should be the case (i.e., areas belonging to very high and high susceptibility zones have been further narrowed down). This outcome can also be

corroborated from the study of landslide density values. Usually, an ideal LSZ map should have the highest landslide density for VHS zone, as compared to other zones and there ought to be a decreasing trend of landslide density values successively from VHS to VLS zone. It has also been ascertained that the landslide density values for VHS zone of LSZ maps are higher than those obtained for other susceptibility zones. There is also a decreasing trend of landslide density values from VHS zone to VLS zone. Thus, based on the landslide density values of different landslide susceptibility zones and their trend from VHS to VLS zones for all the LSZ maps, it can be inferred that the combined neural network and fuzzy approach performs significantly better than the other two approaches for LSZ mapping.

The acceptability of LSZ map produced from the combined neural network and fuzzy approach has further been strengthened through ROC curves (Swets, 1988, Mathew *et al.* 2009). In the present context, the true positive rate has been defined as the number of correctly classified predicted landslide pixels over the total predicted landslides and is represented on the Y-axis of ROC curve. The false positive rate was defined as the number of incorrectly classified landslide pixels over the total predicted no-landslide pixels and is represented on the X-axis of the ROC curve. The area under curve (AUC) constitutes one of the most commonly used accuracy statistics for the prediction models in natural hazard assessments (Begueria 2006). The minimum value of AUC is 0.5 signifies that the model does not accurately predict the occurrence of landslide while a maximum value of AUC is 1 denotes perfect prediction.

To assess the performance of all the three LSZ approaches, the ROC curves have been generated using the SPSS 16.0 software. For this purpose, a test data set consisting of randomly selected pixels from landslide and no landslide pixels has been considered. The ROC curves for the LSZ maps from the ANN black box (AUC=0.84), fuzzy relation based (AUC=0.86) and combined neural network and fuzzy (AUC=0.92). These curves clearly depict that the combined neural network and fuzzy based approach model is the most successful one in predicting the probability of landslide susceptibility for the study area, since the AUC value for the LSZ map derived from this approach is higher than that obtained from other two approaches.

7.   CONCLUSION

In this paper, a comparative study on landslide susceptibility zonation using three soft computing approaches, namely, ANN black box approach, fuzzy relation based approach and combined neural network and fuzzy approach was presented. The efficacy of the approaches was examined through a case study in the Himalayan region. The LSZ map produced by the combined neural network and fuzzy approach showed systematic and a decreasing trend of variation in landslide density values from VHS to VLS zones in the region. Thus, for the

study area considered, the combined neural network and fuzzy approach provided an accurate representation of the actual scenario of landslide occurrences in the region.

8.   REFERENCES

[1] Akgun, A., Dag, S., Bulut, F., "Landslide susceptibility mapping for a landslide-prone area (Findikli, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models". *Environmental Geology*. 54, 1127-1143, 2008.

[2] Akgun, A., Türk, N., "Landslide susceptibility mapping for Ayvalik (Western Turkey) and its vicinity by multicriteria decision analysis. *Environmental Earth Sciences*". 61, 595-611, 2010

[3] Arora, M.K., Das Gupta, A.S., Gupta, R.P., "An artificial neural network approach for landslide hazard zonation in the Bhagirathi (Ganga) Valley, Himalayas". *International Journal of Remote Sensing*, 25, 559–572, 2004.

[4] Champati ray, P. K., Dimri, S., Lakhera, R. C. and Sati, S., 2007, Fuzzy-based method for landslide hazard assessment in active seismic zone of Himalaya, *Landslides*, 4, 101-111.

[5] Chauhan, S., Arora, M. K., and Gupta, N. K., 2010a, Landslide Susceptibility Zonation through ratings derived from Artificial Neural Network, *International Journal of Applied Earth Observation and Geo Information*, 12, 340-350.

[6] Chauhan, S., Sharma, M and Arora, M. K., 2010b, Landslide Susceptibility Zonation of Chamoli region, Garhwal Himalayas,using Logistic Regression Model, *Landslides*, Published Online.

[7] Chi, K.-H., Park, N.-W., Chung, C.-J., 2002b. Fuzzy logic integration for landslide hazard mapping using spatial data from Boeun, Korea. Proc. of Symp. on Geospatial Theory, Processing and Applications, Ottawa.

[8] Dai, F.C., Lee, C.F., Li, J., Xu, Z.W., 2001. Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong. *Environmental Geology*, 40, 381– 391.

[9] Gupta, V., Sah, M.P., Virdi, N.S., Bartarya, S.K., 1993. Landslide Hazard Zonation in the Upper Satlej Valley, District Kinnaur, Himachal Pradesh. *Journal of Himalayan Geology*, 4, 81–93.

[10] Kanungo DP, Arora MK, Sarkar S, Gupta RP (2006) A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas. *Engineering Geology*, 85, 347–366

[11] Lee, S., Ryu, J.H., Lee, M.J. and Won, J.S., 2003. Use of an artificial neural network for analysis of the susceptibility to landslides at Boun, Korea. *Environmental Geology*, 44, 820-833.

[12] Mathew J., Jha V. K., Rawat G. S., 2007. Weights of evidence modelling for landslide hazard zonation mapping in part of Bhagirathi valley, Uttarakhand. *Current Science*, 92, 628–638.

[13] Mathew, J., Jha, V.K. and Rawat, G.S., 2009. Landslide susceptibility zonation mapping and its validation in part of Garhwal Lesser Himalaya, India, using binary logistic regression analysis and receiver operating characteristic curve method. *Landslides*, 6, 17-26.

[14] Nefeslioglu, H.A., Sezer, E., Gokceoglu, C., Bozkir, A.S., Duman, T.Y., 2010. Assessment of Landslide Susceptibility by Decision Trees in the Metropolitan Area of Istanbul, Turkey. Mathematical Problems in Engineering.

[15] Olden, J.D., Joy, M.K., Death, R.G., 2004. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modeling*, 178, 389–397.

[16] Pareek, N., Sharma, M. L., Arora, M. K., 2010, Impact of seismic factors on Landslide Hazard Zonation: A case study in part of Indian Himalayas, *Landslides*, 7, 191-201.

[17] Pradhan, B. and Lee, S., 2009. Use of geospatial data and fuzzy algebraic operators to landslide-hazard mapping. *Applied Geomatics*, 1, 3–15.

[18] Pradhan, B., 2010. Application of an advanced fuzzy logic model for landslide susceptibility analysis. International Journal of Computational Intelligence Systems 3, 370-381.

[19] Pradhan, B., 2011. Use of GIS-based fuzzy logic relations and its cross application to produce landslide susceptibility maps in three test areas in Malaysia. Environmental Earth Sciences 63, 329-349.

[20] Pradhan, B., Lee, S., 2010. Landslide susceptibility assessment and factor effect analysis: backpropagation artificial neural networks and their comparison with frequency ratio and bivariate logistic regression modelling. Environmental Modelling & Software 25, 747-759.

[21] Pradhan, B., Lee, S., Buchroithner, M.F., 2010a. A GIS-based back-propagation neural network model and its cross-application and validation for landslide susceptibility analyses. Computers Environment and Urban Systems 34, 216-235.

[22] Pradhan, B., Sezer, E.A., Gokceoglu, C., Buchroithner, M.F., 2010b. Landslide Susceptibility Mapping by Neuro-Fuzzy Approach in a Landslide-Prone Area (Cameron Highlands, Malaysia). IEEE Transactions on Geoscience and Remote Sensing 48, 4164-4177.

[23] Saha, A.K., Gupta, R.P., Arora, M.K., 2002. GIS-based landslide hazard zonation in a part of the Himalayas. *International Journal of Remote Sensing*, 23, 357–369.

[24] Saha, A.K., Gupta, R.P., Sarkar, I., Arora, M.K., Csaplovics, E., 2005. An approach for GIS-based statistical landslide susceptibility zonation—with a case study in the Himalayas. *Landslides* 2, 61–69.

[25] Sezer, E.A., Pradhan, B., Gokceoglu, C., 2011. Manifestation of an adaptive neuro-fuzzy model on landslide susceptibility mapping: Klang valley, Malaysia. Expert Systems with Applications 38, 8208-8219.

[26] Valdiya, K.S. 1980. *Geology of Kumaun Lesser Himalaya*. Wadia Institute of Himalayan Geology, Dehra Dun. 292p.

[27] Van Den Eeckhaut, M., Vanwalleghem, T., Poesen, J., Govers G., Verstraeten, G. and

Vandekerckhove, L., 2006. Prediction of landslide susceptibility using rare events logistic regression: A case-study in the Flemish Ardennes (Belgium). *Geomorphology*, 76, 392-410.