# Landslide Susceptibility Assessment at a Part of Uttarakhand Himalaya, India using GIS – based Statistical Approach of Frequency Ratio Method

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Abstract - Frequency Ratio has successfully applied as statistical approach for landslide susceptibility assessment in many regions over the world. In the present study, a part of Uttarakhand Himalaya has been selected as a case study to apply the FR model for landslide susceptibility assessment. For this, landslide inventory map was firstly constructed with 430 landslide locations identified from various sources with the help of GIS technology. These landslide locations were then randomly split into two parts (i) for training process (70% landslide locations) and (ii) for validation process (30% landslide locations). Presently, the total of six landslide conditioning factors (slope, aspect, elevation, curvature, land use, and rainfall) has been selected for analyzing the spatial relationship with landslide occurrences. Using training dataset, the FR model was then built to assess landslide susceptibility in the study area. Finally, success rate curve and predictive rate curve have been employed to validate the performance of the FR model. The results show that the FR model indicates fairly well in the present study. Overall, the FR model is an effective method for the landslide susceptibility assessment of hilly areas. It can be applied in other areas of Himalayas for the assessment and management of landslide hazards

Keywords: Landslides; GIS, Frequency Ratio, Uttarakhand, India

# 1. INTRODUCTION

Landslide is a natural geological phenomenon which is described as a massive movement of materials (soils, rocks, organics, etc.) from up to down slope [1] causing loss of life and properties. It usually occurs under different conditions depending on characteristics of study region such as geology, topography, hydrology, meteorology, vegetation, human activities, etc. Landslide is a complex phenomenon thus researchers all are trying to understand its mechanism in order to mitigate their harmful impaction.

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Landslide susceptibility map is a useful tool in landslide hazard management via land use planning and decision makings. It shows degree of susceptibility of area to landslide occurrences. Landslide susceptibility map could be produced based on the spatial prediction of landslides that is carried out on the base of an assumption that landslides in the future will occur under same conditions with which occurred in the past [2]. Therefore, landslide susceptibility could be assessed through evaluation of the spatial relationship between a set of conditioning factors and previous landslide occurrences. In recent years, many landslide susceptibility maps have been generated in many regions over the world using Geographic Information System (GIS) technology as a standard tool.

Presently, statistical approach is the most popular for landslide susceptibility assessment. It is known as subjective approach to produce reliable results. Many methods have been applied using this approach such as frequency ratio [3-5], weights of evidence [4, 6, 7], logistic regression [6, 8, 9]. Out of these methods, frequency ratio is used widely for landslide susceptibility assessment with good performance [5, 10].

The main objective of the current study is to create a detailed landslide susceptibility map at a part of part of Uttarakhand Himalaya (India) using the FR model. The performance of the FR model has been evaluated using success rate curve and predictive rate curve.

#### 2. STUDY AREA

The study area (Fig 1) is located between Pauri Garhwal and Tehri Garhwal districts in Uttarakhand state of India (longitudes of 78o29'01'E to 78o37'06''E and latitudes 29o56'38''N to 30°09'37''N) covering an area of of

study area is very steep with slope angles ranging from 0 to 70 degrees. About 85.45% of the study area belongs to slope angles of 15 to 45 degrees.

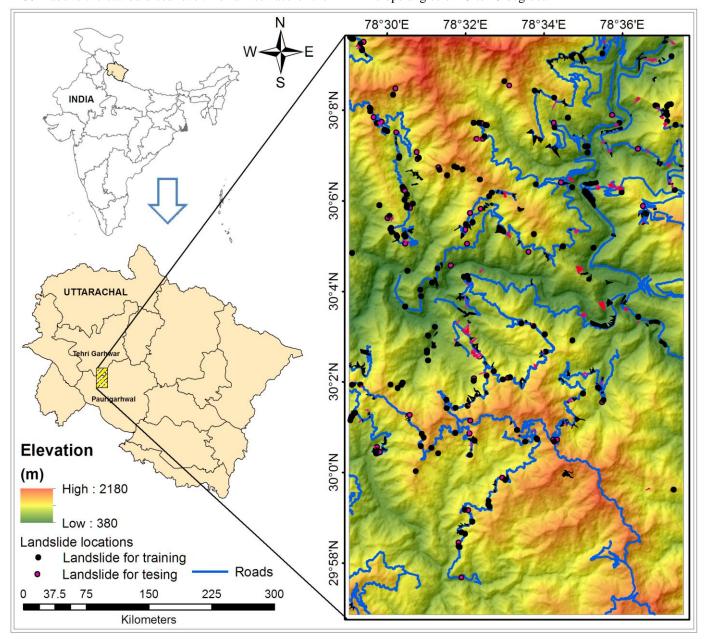


Fig. 1 Landslide inventory map of study area

In the study area, there are four main land use patterns such as dense forest, open-forest, non-forest, and scrub land. Non-forest occupies the biggest area (39.02%). The study area occupies by two types of soil namely silt and loamy. Loamy soil is predominant in the area (73.73%).

The study area is situated in subtropical moon soon region having three separate seasons including winter (October to February), summer (March to June), and moon soon (June to September). Rainfall usually occurs heavily in moon soon season with annual mean rainfall ranging from 770mm to 1684mm. The temperature in this region varies from 1.3°C to 45°C whereas the humidity varies between 25% and 85%.

#### 3. METHODOLOGY

#### 3.1. Data collection and interpretation

Regional scale topographical and land use map on the scale of 1:1000.000 have been used in the present study (http://www.ahec.org.in/wfw/maps.htm). Meteorological data was studied for 30 years from 1984 to 2014 obtained from Global Weather data for SWAT [11]. Landslide susceptibility assessment has been done using GIS software 10.2 versions.

#### 3.1.1. Preparation of landslide inventory map

Landslide inventory map has been constructed with 430 landslide locations identified using interpretation of Google Earth images up to 10m spatial resolution in Google Earth pro 7.0 (Fig 1). These landslide locations have been then validated from historical landslide reports, newspaper records, and extensive field data. Landslide inventory has

been then divided into two parts to generate training dataset (70% landslide inventory, i.e 301 landslide locations) and testing dataset (30% remaining landslide inventory, i.e 129 landslide locations)

#### 3.1.2. Development of various thematic layers

Landslide conditioning factors such as slope angle, slope aspect, elevation, curvature, land use, rainfall have been taken into account to evaluate the spatial relationship between them and landslide occurrences in the study area. Slope angle map, slope aspect map, elevation map, and curvature map have been constructed using DEM with 20m generated from regional scale topographic map. Land use map has been extracted from state land use map. Rainfall map has been generated based on spline interpolation method [12] using meteorological data.. All classes of these maps are shown in Table 1. Also, Fig 2 shows the slope angle map, Fig 3 shows land use map.

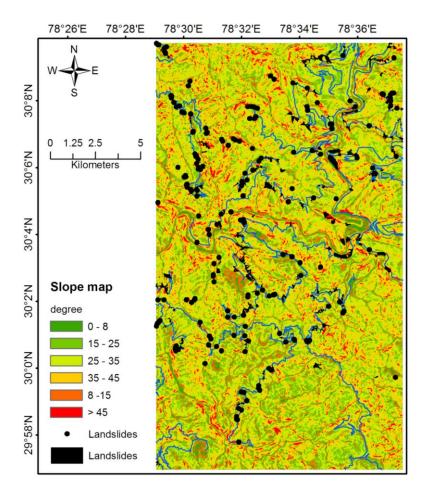


Fig. 2 Slope map with landslide locations

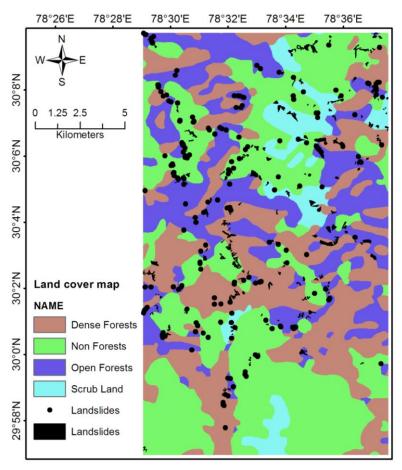


Fig. 3 Land use maps with landslide locations

## 3.2. Background of the Frequency Ratio method

Frequency Ratio (FR) is a statistic approach that has been applied to evaluate landslide susceptibility in this study. The main principle of this method is based on assessment of observed spatial relationship between past landslides and a set of landslide conditioning factors [13]. FR is carried out based on the frequency ratio values that are a ratio of the probability of present and absence of landslide occurrences for each landslide conditioning factor class. Higher FR value indicates stronger observed spatial relationship between the landslide occurrence and landslide conditioning factor [14]. FR values are calculated by applying the following equation:

$$FR = \frac{P_i}{PL_i} = \frac{N_i^{pix}/N}{N_i^{Lpix}/N^L} \tag{1}$$

Where  $P_i$  is the percentage of pixels in each landslide conditioning factor class,  $PL_i$  is the percentage of landslide pixels in each landslide conditioning factor class.  $N_i^{pix}$  is the number of pixels in each landslide conditioning factor class, N is the number of all pixels in total the study area.  $N_i^{Lpix}$  is the number of landslide pixels in each landslide

conditioning factor class,  $N^L$  is the number of all landslide pixels in total the study area.

# 3.3. Development of the Frequency Ratio model for landslide susceptibility assessment

In order to assess landslide susceptibility in the study area using the FR model, landslide inventory map (70% landslide location) has been first overlaid separately with thematic data layers to calculate the frequency ratio values (FR). Thereafter, the FR values have been converted into Normalized Frequency Ratio values (NFR) in the range from 0.01 to 0.99 to facilitate the final analysis and interpretation [15]. The NFR values were then used to reclassify all landslide conditioning factors for landslide susceptibility analysis. The results are shown in Table 1.

Table 1 Landslide conditioning factors and its Normalized Frequency Ratio values

| Data layers             | Class                        | Pixels | Landslide pixels | %<br>Class Pixels | %<br>Landslide Pixels | FR    | NFR   |
|-------------------------|------------------------------|--------|------------------|-------------------|-----------------------|-------|-------|
| Slope angle<br>(degree) | 0-8                          | 23380  | 0                | 2.89              | 0                     | 0     | 0.01  |
|                         | 8-15                         | 51036  | 182              | 6.31              | 2.97                  | 0.47  | 0.161 |
|                         | 15-25                        | 172508 | 587              | 21.34             | 9.57                  | 0.449 | 0.154 |
|                         | 25-35                        | 307836 | 1752             | 38.08             | 28.57                 | 0.75  | 0.25  |
|                         | 35-45                        | 210478 | 2608             | 26.03             | 42.52                 | 1.633 | 0.533 |
|                         | > 45                         | 43250  | 1004             | 5.35              | 16.37                 | 3.06  | 0.99  |
| Slope aspect            | Flat (-1)                    | 2995   | 0                | 0.37              | 0                     | 0.000 | 0.010 |
|                         | North (0-22.5 and 337.5-360) | 91903  | 823              | 11.37             | 13.42                 | 1.181 | 0.670 |
|                         | Northeast (22.5-67.5)        | 110190 | 505              | 13.63             | 8.23                  | 0.604 | 0.348 |
|                         | East (67.5-112.5)            | 103550 | 403              | 12.81             | 6.57                  | 0.513 | 0.297 |
|                         | Southeast (112.5-157.5)      | 99163  | 661              | 12.27             | 10.78                 | 0.879 | 0.501 |
|                         | South (157.5-202.5)          | 102376 | 986              | 12.66             | 16.08                 | 1.270 | 0.720 |
|                         | Southwest (202.5-247.5)      | 110327 | 1467             | 13.65             | 23.92                 | 1.753 | 0.990 |
|                         | West (247.5-292.5)           | 93966  | 749              | 11.62             | 12.21                 | 1.051 | 0.597 |
|                         | Northwest (292.5-337.5)      | 94018  | 539              | 11.63             | 8.79                  | 0.756 | 0.433 |
| Elevation (m)           | < 600                        | 69962  | 1745             | 8.65              | 28.45                 | 3.288 | 0.990 |
|                         | 600 - 750                    | 87839  | 804              | 10.86             | 13.11                 | 1.207 | 0.370 |
|                         | 750 - 900                    | 111735 | 694              | 13.82             | 11.32                 | 0.819 | 0.254 |
|                         | 900 - 1050                   | 120840 | 1042             | 14.95             | 16.99                 | 1.137 | 0.349 |
|                         | 1050 - 1200                  | 119901 | 953              | 14.83             | 15.54                 | 1.048 | 0.322 |
|                         | 1200 - 1350                  | 105343 | 511              | 13.03             | 8.33                  | 0.639 | 0.201 |
|                         | 1350 - 1500                  | 86345  | 192              | 10.68             | 3.13                  | 0.293 | 0.097 |
|                         | 1500 - 1650                  | 57348  | 121              | 7.09              | 1.97                  | 0.278 | 0.093 |
|                         | 1650 - 1800                  | 34539  | 71               | 4.27              | 1.16                  | 0.271 | 0.091 |
|                         | > 1800                       | 14636  | 0                | 1.81              | 0                     | 0.000 | 0.010 |
| Curvature               | Concave (<-0.05)             | 368974 | 3572             | 45.64             | 58.24                 | 1.276 | 0.990 |
|                         | Flat (-0.05 - 0.05)          | 71506  | 0                | 8.84              | 0                     | 0.000 | 0.010 |
|                         | Convex (>0.05)               | 368008 | 2561             | 45.52             | 41.76                 | 0.917 | 0.714 |
| Land use                | Dense Forests                | 258794 | 1730             | 68.07             | 56.25                 | 0.826 | 0.275 |
|                         | Non Forests                  | 315891 | 1931             | 7.36              | 22.49                 | 3.057 | 0.990 |
|                         | Open Forests                 | 181011 | 1637             | 15.09             | 20.76                 | 1.376 | 0.451 |
|                         | Scrub Land                   | 53964  | 835              | 4.5               | 0.5                   | 0.110 | 0.045 |
| Rainfall<br>(mm)        | < 900                        | 68200  | 914              | 8.44              | 14.92                 | 1.768 | 0.990 |
|                         | 900 - 1000                   | 127765 | 1288             | 15.8              | 21.02                 | 1.330 | 0.739 |
|                         | 1000 - 1100                  | 123612 | 1275             | 15.29             | 20.81                 | 1.361 | 0.757 |
|                         | 1100 - 1200                  | 111966 | 1064             | 13.85             | 17.36                 | 1.254 | 0.695 |
|                         | 1200 - 1300                  | 104849 | 970              | 12.97             | 15.83                 | 1.221 | 0.676 |
|                         | 1300 - 1400                  | 94066  | 486              | 11.63             | 7.93                  | 0.682 | 0.368 |
|                         | 1400 - 1500                  | 81107  | 89               | 10.03             | 1.45                  | 0.145 | 0.060 |
|                         | > 1500                       | 96923  | 42               | 11.99             | 0.69                  | 0.057 | 0.010 |

## 3.4. Landslide Susceptibility Map

Landslide susceptibility map has been constructed by calculating and classifying landslide susceptibility indexes (LSI) for whole study area. LSI indicates the degree of susceptibility of area to landslide occurrences. Areas with smaller LSI indicate less susceptibility to landslide occurrence. LSI has been calculated based on the NFR values that have been determined in training process (Table 1). The calculation of LSI is shown in E.q (2):

$$LSI = \sum_{i=1}^{6} NFR_{i}$$
 (1)

Where NFR<sub>i</sub> are the normalized frequency ratio values of slope, aspect, elevation, curvature, land use, and rainfall, respectively

Many methods can be employed for classification of landslide susceptibility indexes such as the equal interval, the natural break and the standard deviation [16]. Out of these, the natural break method is the most widely used [17] thus it has been selected for classifying the landslide susceptibility indexes in this present study. Using this method, landslide susceptibility indexes were classified into 5 intervals with respective susceptible classes as: (1) Very low (LSI =  $0.06 \div 1.905$ ), (2) Low (LSI =  $1.905 \div 2.481$ ), (3) Moderate (LSI =  $2.481 \div 3.035$ ), (4) High (LSI =  $3.035 \div 3.703$ ), (5) Very high (LSI =  $3.703 \div 5.94$ ). Landslide susceptibility map developed using the FR model in the study area is shown in Fig. 4.

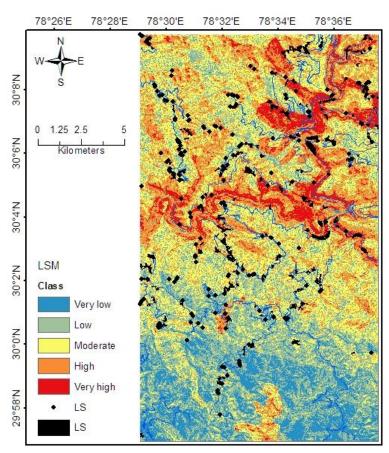


Fig. 4 Landslide susceptibility map (LSM) of the study area using the FR model  $\,$ 

#### 3.5. Validation of the Frequency Ratio Model

The performance of the FR model has been evaluated using the success rate and predictive curves which were proposed by Chung and Fabbri [18]. Success rate curve indicates the relationship between the percentage of landslide susceptibility map and the percentage of landslide pixels used for training process. In contrast, predictive rate curve presents the relationship between the percentage of landslide susceptibility map and the percentage of landslide pixels employed for testing process. The area under success rate curve (AUC) illustrates the degree of fit of the

Frequency Ratio model with the training dataset whereas the area under predictive rate curve (AUC) shows prediction capability of the Frequency Ratio model [18]. Higher AUC values indicate better performance of the FR model.

The results are shown in Fig. 5. It can be observed that the AUC of success-rate curve is 0.75 indicating quite good degree of fit of the Frequency Ratio model with the training dataset. Whereas, the AUC value of prediction rate curve is 0.70 indicating that prediction ability of the Frequency Ratio model are also fairly good.

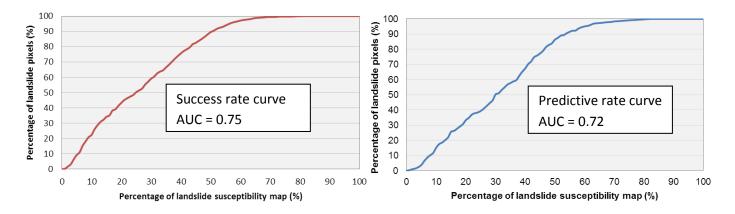


Fig. 5 The performance of the FR model using success rate curve and predictive curve in this study

#### 4. DISCUSSIONS AND CONCLUSIONS

Landslide susceptibility assessment at a part of Uttarakhand Himalaya, India has been carried out in this study using the Frequency Ratio (FR) model which has been applied widely in literatures. A total of 236 landslide locations have been utilized to construct landslide inventory map. Six landslide conditioning factors (slope angle, slope aspect, elevation, curvature, land use, rainfall) have been taken into consideration for evaluation of the relationship between them and spatial landslide occurrences. The performance of the FR model has been validated using success rate and predictive rate curves. The results show that the FR model is applicable for landslide susceptibility assessment. Its performance is fairly good (AUC = 0.72). The results of the present study are comparable with other studies [5, 19, 20].

Overall, the FR model is an effective method for landslide susceptibility assessment of hilly and mountainous areas. It can be applied in other landslide prone areas for assessment and management of landslide hazards.

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#### REFERENCES

- Van Westen, C., T. Asch, and R. Soeters, Landslide hazard and risk zonation-why is it still so difficult. Bull Eng Geol Environ 2006.
  p. 67–184.
- [2] Pradhan, B., A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS. Computers & Geosciences, 2013. 51(0): p. 350-365.
- [3] Mohammady, M., H.R. Pourghasemi, and B. Pradhan, Landslide susceptibility mapping at Golestan Province, Iran: a comparison between frequency ratio, Dempster–Shafer, and weights-ofevidence models. Journal of Asian Earth Sciences, 2012. 61: p. 221-236
- [4] Ozdemir, A. and T. Altural, A comparative study of frequency ratio, weights of evidence and logistic regression methods for landslide susceptibility mapping: Sultan Mountains, SW Turkey. Journal of Asian Earth Sciences, 2013. 64: p. 180-197.
- [5] Poudyal, C.P., et al., Landslide susceptibility maps comparing frequency ratio and artificial neural networks: a case study from the

- Nepal Himalaya. Environmental Earth Sciences, 2010. **61**(5): p. 1049-1064.
- [6] Devkota, K.C., et al., Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling-Narayanghat road section in Nepal Himalaya. Natural Hazards, 2013. 65(1): p. 135-165.
- [7] Kayastha, P., M.R. Dhital, and F. De Smedt, Landslide susceptibility mapping using the weight of evidence method in the Tinau watershed, Nepal. Natural hazards, 2012. 63(2): p. 479-498.
- [8] Bai, S., et al., GIS-based rare events logistic regression for landslide-susceptibility mapping of Lianyungang, China. Environmental Earth Sciences, 2011. 62(1): p. 139-149.
- [9] Yilmaz, I., Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: conditional probability, logistic regression, artificial neural networks, and support vector machine. Environmental Earth Sciences, 2010. 61(4): p. 821-836.
- [10] Shahabi, H., et al., Landslide susceptibility mapping at central Zab basin, Iran: A comparison between analytical hierarchy process, frequency ratio and logistic regression models. CATENA, 2014. 115(0): p. 55-70.
- [11] NCEP, Global Weather data for SWAT. http://globalweather.tamu.edu/home, 2014.
- [12] Kawamura, H., T. Sasaki, and T. Otsuki, Spline interpolation method. 1992, Google Patents.
- [13] Choi, J., et al., Combining landslide susceptibility maps obtained from frequency ratio, logistic regression, and artificial neural network models using ASTER images and GIS. Engineering Geology, 2012. 124(0): p. 12-23.
- [14] Pradhan, B. and S. Lee, Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia. Landslides, 2010. 7(1): p. 13-30.
- [15] Umar, Z., et al., Earthquake induced landslide susceptibility mapping using an integrated ensemble frequency ratio and logistic regression models in West Sumatera Province, Indonesia. CATENA, 2014. 118(0): p. 124-135.
- [16] Ayalew, L. and H. Yamagishi, The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. Geomorphology, 2005. 65(1): p. 15-31.
- [17] Irigaray, C., et al., Evaluation and validation of landslidesusceptibility maps obtained by a GIS matrix method: examples from the Betic Cordillera (southern Spain). Natural hazards, 2007. 41(1): p. 61-79.
- [18] Chung, C.-J.F. and A.G. Fabbri, Validation of spatial prediction models for landslide hazard mapping. Natural Hazards, 2003. 30(3): p. 451-472.
- [19] Choi, J., et al., Combining landslide susceptibility maps obtained from frequency ratio, logistic regression, and artificial neural network models using ASTER images and GIS. Engineering Geology, 2012. 124: p. 12-23.
- [20] Yalcin, A., et al., A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey. Catena, 2011. 85(3): p. 274-287.