Indian Journal of Spatial Science
Autumn Issue, 10 (2) 2019 pp. 65 - 72

Indian Journal of Spatial Science
Peer Reviewed and UGC Approved (Sl No. 7617)
EISSN: 2249 - 4316 homepage: www.indiansss.org ISSN: 2249 - 3921

Landslide Hazard Zonation using Frequency Ratio Model and Fuzzy Logic: A Case Study of New Tehri Region, India

Ashutosh Mishra#
Post Graduation Student, Land Resources Management, Central University of Jharkhand

A.C. Pandey
Professor, Land Resources Management, Central University of Jharkhand

K.K.Ramachandran
Scientist at National Centre for Earth Science Studies, Thiruvananthapuram

Vincent A Ferrer
Scientist at National Centre for Earth Science Studies, Thiruvananthapuram

 # Corresponding Author

Article Info

Article History

Received on:
31 December 2018
Accepted in *Revised Form* on:
31 July, 2019
Available *Online* on and from:
23 September, 2019

Keywords

Frequency Ratio Model
GIS
Fuzzy Logic
Remote Sensing
Information System
Landslide Hazard Zones

Abstract

The present study uses Remote Sensing and GIS for finding susceptible zones of landslide hazards in the Tehri region which has an area of 798 sq.km. Six-factor layers responsible for landslide occurrence, such as road, slope, lineaments, geology, drainage, landuse are assigned membership functions and appropriate rules were assigned to them in Fuzzy Inference System. Frequency Ratio Method is applied in the same area and both the method is assessed for the accuracy. The Fuzzy Inference based landslide susceptibility mapping has been classified into five zones. These results have been compared with the landslide hazard zonation map generated by frequency ratio method and the results were presented in detail. A comparison of the total area under each class in both the methods has been revisited with the landslide density in each class of hazard. It has been found that the frequency ratio has given better results than the fuzzy method. It is to be highlighted that the present study has not used any prior information into the Inference system for hazard zonation however in the frequency ratio method landslide inventory (previous instances of landslide occurrences in the study area) was used as one parameter for hazard zonation.

Introduction

The Indian subcontinent has an exceptionally varied range of natural landscape, among which the Himalayas are the young folded mountain and where the phenomena of slope failure are very common. The state of Uttarakhand state lies in the Himalayas which is primarily divided into four parallel ranges of the Greater Himalayas, the Middle Himalayas (also known as the Inner or Lesser Himalayas), the Siwalik and the Tarai-Bhabhar region (CGWB, 2014). The combination of the varied terrain, different glaciers, rivers, and other climatic and geological condition make Uttarakhand a vulnerable state.

In the present study, remote sensing techniques and GIS tools have been used to assess the magnitude of susceptibility to landslide and its spatial distribution and also for the quantitative analysis of landslide inducing parameters like slope, lineament density, drainage density, geology, landuse, road density as these are of great significance for the scientific management of mountain river basin. Landslide Hazard Zonation Mapping is an important technique to figure out the spatial distribution of landslides and helps to take site-specific proper remedial measures in a rational manner (Sarkar and Anbalagan *et. al.* 2008). Hence, the interaction of different factors is studied separately and ultimately final coordination is made through fuzzy inference system and frequency ratio model.

The frequency ratio technique is a statistical approach to simulate environmental conditions. It also uses to take into account the factors related to the dependent variable. It is applied here to generate a landslide susceptibility map. Pixel landsliding and non-landslide have been computed in terms of six factors related to a landslide (Baharin Bin Ahmad *et. al.* 2014). The landslide susceptibility map results in five distinctive classes, insensitive to very high sensitive one. Unlike the frequency ratio method which is data-driven, the Mamdani Fuzzy Inference System is dependent on expert opinion and does not require landslide inventory which makes it unbiased.

The Study Area

The study area extends between 78°17'7.5"E - 78°35'52"E longitudes and 30°23'87"N - 30°36'50"N latitudes respectively. Its administrative limits are covered within the domain of the Tehri Garhwal district of Uttarakhand state. The area is covered in Survey of India Topographical Sheet No 53J / 7 NW on 1:25,000 scale. Here, the climate is hot and temperate. In winter, there is much less rainfall than in summer with an annual average of 1934 mm. The average annual temperature is 15.3 °C.

The area is a highly undulating lesser Himalayan terrain, represented by high ridges/spurs, deep valleys, and abrupt/sharp slopes. In general, ridges have thick/ dense to open forest on the northern side while the southern face is mostly covered by agricultural land (Rohan Kumar *et al.* 2016). The area is a compound network of plentiful streams, which are making dendritic to the sub-dendritic pattern. A major part of the area is unapproachable due to tremendously rugged topography and thick forest cover. The regional trend of major ridges is NNW-SSE, which is generally parallel to the strike of the country rocks.

Methodology

Data Preparation

In this study, the major thematic layers are generated as input. A number of processes were performed to prepare these layers. The following sections are going through the main steps which have been done.

Landslide Inventory Mapping

On an image, landslides are easily recognized immediately after an event. Its boundaries are usually distinct, making it relatively easy to identify and map. Fresh landslides are devoid of vegetation cover. As time passes, vegetation grows and cover the landslides and sometimes, human activity results in the destruction of its evidence. Many landslides appear to have been revived and moved as time progressed. The landslide Inventory prepared here is of April 2018.

Landslides can be mapped either as points or as polygons. Landslide point mapping is much faster and lets the interpreter include larger areas. This is useful when instant mapping has to be carried out, in a little time after the prevalence of a major event, such as tropical storm, hurricane or earthquake. The point should be located in the scarp of the landslide, and not in the center of the accumulation area because otherwise, it will be difficult to associate the landslide with the causal factors. When mapping landslides as a point, no information is stored on the size of the landslide, and therefore it will be very difficult to use a point-based landslide inventory in subsequent susceptibility and hazard assessment. Landslide polygon mapping is preferred here as it gives a much better representation of the landslide features (Norbert Simon, *et. al.* 2017). A total of about 194 incidences of the landslide have been identified in the area with size varying between 288 m^2 to 147160 m^2. The total area which contributes to landslides is 2.8 km^2 which is 0.35% of the total area under study (Fig.5).

Generation of Thematic layers of Causative Factors

The digital images of SENTINEL 2A with a high resolution (10 m) were used. These images were downloaded from the Earth Science Data Interface (ESDI) at the Global Land Cover Facility and opened on ERDAS Imagine 10 and saved as one compiled imagine (*.Img) file to be imported to ArcGIS Environment with correct georeference. The used DEM is SRTM with a spatial resolution of 30m. The SRTM DEM has been downloaded for generating the slope map. It was then added to the ArcGIS platform in order to generate drainage map and slope map using the spatial analyst tools. The study area was then clipped according to its known coordinates (fig.6, 7 and 8).The geological map of the area was then added to ArcGIS and georeferenced with the first reference map for digitization and raster mapping (Fig.9).

Density Maps

The distance to roads, urban areas, production wells, and treatment plants are one of the eight parameters affecting the artificial recharge locations. These maps have been generated by using the Spatial Analyst Straight Line Distance function in ArcGIS which calculates the straight line (Euclidean) distance from the main objective site (in this case, roads, urban areas, production wells, and treatment plants). The result is a raster dataset in which every cell represents the distance to the main objective site in meter (Fig.10).

Landslide Hazard Zonation Methods

There are various approaches and techniques that exist for landslide susceptibility mapping. The simplest one is the frequency ratio method wherein the landslide inventory plays a key role in hazard zonation. The statistical index model, weights of evidence, certainty factor and entropy models are some of the bivariate statistical methods followed in landslide susceptibility mapping. With the introduction of great computational facilities, soft computational techniques like neural networks, fuzzy logic, support vector machine, Adaptive neuro-fuzzy inference systems (ANFIS) were introduced which were capable of dropping the statistical limitations of susceptibility mapping. As a follow-up, this study uses the fuzzy inference system for susceptibility mapping using the various geo spatial layers generated using Remote sensing and GIS techniques. This paper details the susceptibility mapping discussing the Mamdani fuzzy and Frequency Ratio techniques of landslide susceptibility mapping and assessing the accuracy of these models.

Frequency Ratio Model

The frequency ratio (FR) is a statistic approach that has been applied to evaluate landslide susceptibility in this study. The FR model is an observation-based approach for the preparation of landslide susceptibility maps. For the construction of FRM landslide conditioning factors and training data set were used. The calculation of FR is as follow:

$$FRV \quad \frac{L_1 / L}{C_1 / C}$$

Where, L_1 = area affected by landslide in each class, L = total area affected by landslide, C_1 = area of each class and C = total area.

Fuzzy Inference System (FIS)

In this study, six conditioning parameters characterizing topographical, geological, and geomorphic conditions were included in the FIS. After completing the data production stage of the study, the data were processed using a soft computing approach, i.e., a Mamdani-type fuzzy inference system. Thus, an Excel file depicting the susceptibility degrees for the study area was produced using the Mamdani FIS. These values were then exported into a GIS environment and a landslide Inventory map.

The Mamdani FIS for the assessment of landslide susceptibility Tehri includes a total of 6 inputs: Landuse, Landform, Slope, Relative relief, Drainage density, and Lineament Density. Landuse and Landform inputs are constructed using three crisp triangular membership functions. Other four Inputs are formed by two membership functions. A total of 22 Landuse/Landcover and 5 landform types are cropped out in the study area. These classes are reclassified under three classes in the present study. When applying these classifications, the BIS rating standards for landslides hazard zonation are considered.

To minimize the uncertainty, a 50% overlap is applied between the fuzzy sets for each input parameter, and triangular membership functions are used for each fuzzy set. To provide a generalization for the study area, the minimum number of the fuzzy sets is considered. This also affects the number of if-then rules. The output includes five fuzzy sets in the form of triangular membership. One of the main parts of a Mamdani FIS is the fuzzy if-then rules. A total of 144 if-then rules are implemented in this fuzzy set.

Results and Discussion

Landslide Hazard Zonation Maps

Landslide susceptibility map has been constructed by calculating and classifying landslide susceptibility index (LSI) for the study area. LSI indicates the degree of susceptibility of the area to landslide occurrences. Areas with smaller LSI indicate less susceptibility to landslide occurrence. LSI has been calculated based on the FR values that have been determined using the following equation:

.
$$LSI = \sum_{k=1}^{6} FR_k$$

Where, L_1 = area affected by landslide in each class, L = total area affected by landslide, C_1 = area of each class and C = total area.

For visual interpretation, the raster dataset needs to be classified into categorical susceptibility classes. For this purpose, different types of classifiers have been considered. While categorizing, the distribution of the data should be taken into account because class intervals change based on the chosen classifier. If the data distribution is close to normal, equal interval or standard deviation classifiers should be used. If the data distribution has a positive or negative skewness, the quantile or natural break distribution classifiers could be chosen. In this study, before choosing the best data classifier for the obtained data, the data distribution histogram was taken into consideration. Then, all of the classifiers noted above were applied to the data. In this study, the quantile classifier is found to be accurate. Table - 4 gives the elaborate information about the different classes of 'landslide hazard zones' along with the areal extent in which landslide occurs. The blue line follows the more ideal path as it increases its density values more frequently with increasing vulnerability of landslide in predicted landslide hazard classes (fig.18). On the other hand, the red line follows the same trend but it lacks a less increase in landslide densities with respect to their corresponding class. The reason for this can be easily explained as the FIS does not take Landslide Incidences as input.

Conclusion

The Mamdani FIS can be constructed completely based on expert opinion without a thorough data analysis process. An expert can reflect opinions on landslides in a region in the model via fuzzy if-then rules. The computational load is low, and results can be obtained in a short time. A Mamdani FIS can be constructed, and production of the degrees of landslide susceptibility can be easily obtained. Restrictions in the landuse practices can be imposed in the high-risk zones. Effective mitigation measures like slope correction, regeneration of natural vegetation, provision for smooth natural drainage are to be carried out. All kinds of disaster preparedness have to be initiated in these high risk zones with the involvement of the Panchayat Officials and the public.

Recommendations for further Research

Certainly, there is the scope of further improvement of the FIS model. The following points should be considered for any further research to be carried out:

1. Identification of landslide location with previous data and assigning membership functions based on those incidences.
2. Involvement of more of the causative factors.
3. Development of the MATLAB program to make the process of assigning rules more simple and easy and less time-consuming.
4. Deciding accurate rules according to ground conditions of the study area with field verification.

Limitations

Landslide Mapping has been entirely based on Google Earth and Satellite image visual data and analysis. A major limitation is that there is no on-field validation of the landslide events due to steep slope and inaccesible nature of the slides.. Although utmost care is taken in considering the landslide mapping, still there are chances of wrong interpretations. Interpretation of the visual scars may be exaggerated sometimes while small landslides may not be visible or difficult to analyze.

References

1. Akgun, A., et al.2011, An easy-to-use MATLAB program (MamLand) for the assessment of landslide susceptibility using a Mamdani fuzzy algorithm. Computers and Geosciences. V38 i1. 23-34
2. Baharin Bin Ahmad et al 2014, Using Frequency Ratio Method for Spatial Landslide Prediction), Research Journal of Applied Sciences, Engineering, and Technology 7(15):3174-3180
3. Gokceoglu and Sezer, 2009.A statistical assessment of international landslide literature (1945-2008). Landslides. v6. 345-351.
4. Gokceoglu and Zorlu, 2004. A fuzzy model to predict the uniaxial compressive strength and the modulus of elasticity of a problematic rock. Engineering Applications of Artificial Intelligence. v17 i1. 61-72.

5. Gokceoglu et al., 2005.The 17 March 2005 Kuzulu landslide (Sivas, Turkey) and landslide-susceptibility map of its near vicinity. Engineering Geology. v81. 65-83.
6. Gokceoglu et al., 2009a.Estimating the uniaxial compressive strength of some clay-bearing rocks selected from Turkey by nonlinear multivariable regression and rule-based fuzzy models. Expert Systems. v26 i2. 176-190.
7. Gokceoglu et al., 2009b.A comparative study on indirect determination of the degree of weathering of granites from some physical and strength parameters by two soft computing techniques. Materials Characterization. v60. 1317-1327.
8. Ground Water Scenario of Himalayan Region, India, Central Ground Water Board
9. Juang et al., 1992.Mapping slope failure potential using fuzzy sets. Journal of Geotechnical Engineering ASCE. v118. 475-494.
10. Kanungo et al., 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. v85 i3-4. 347-366.
11. Kayabasi et al., 2003. Estimating the deformation modulus of rock masses: a comparative study. International Journal of Rock Mechanics and Mining Science. v40 i1. 55-63.
12. Lamelas et al., 2008.Doline probability map using logistic regression and GIS technology in the central Ebro Basin (Spain). Environmental Geology. v54. 963-977.
13. Lee and Juang, 1992.Evaluation of failure potential in mudstone slopes using fuzzy sets. ASCE Geotechnical Special Publication 31, Stability and Performance of Slopes and Embankment-II, 1992.
14. Lee and Pradhan, 2006.Probabilistic landslide hazards and risk mapping on Penang Island, Malaysia. Earth System Science. v115 i6. 661-672.
15. Lee et al., 2004.Determination and application of the weights for landslide susceptibility mapping using an artificial neural network. Engineering Geology. v71. 289-302.
16. Lee, 2005.Application of logistic regression model and its validation for landslide susceptibility mapping using GIS and remote sensing data. International Journal of Remote Sensing. v26. 1477-1491.
17. Norbert Simon, 2017 Representing Landslides as Polygon (Areal) or Points? How Different Data Types Influence the Accuracy of Landslide Susceptibility Maps Sains Malaysiana 46(1)(2017): 2734
18. Pandey A.C. Unpublished P.hd. Thesis
19. Rohan Kumar, R Anbalagan *et al* 2016 Landslide Susceptibility Mapping Using Analytical Hierarchy Process (AHP) in Tehri Reservoir Rim Region, Uttarakhand Journal of the Geological Society of India 87(3) · April 2016
20. Sonmez et al., 2003.An application of fuzzy sets to the GSI system in rock engineering. Engineering Applications of Artificial Intelligence. v16 i3. 251-269.
21. Sonmez et al., 2004. Models to predict the uniaxial compressive strength and the modulus of elasticity for Ankara agglomerates. International Journal of Rock Mechanics and Mining Science. v41 i5. 717-729.
22. Stephen A. Nelson,2014, Tulane University, Natural Disasters, EENS3050.

Table – 1: Computation of Frequency Ratio Values and Normalized Values

Classes/Factors	Landslide Area	Class Area	L1/L	C1/C	F.R.	Normalized Values
Slope						
0-10	39802	78570000	0.0142	0.098462	0.144792	0.257609367
10-20-	146099	290790000	0.0523	0.364412	0.143603	0.25549434
20-10-	314444	603450000	0.1126	0.756232	0.148935	0.264981484
30-45	345861	1294380000	0.1238	1.622092	0.076372	0.135879302
<45	40427	238950000	0.01448	0.299447	0.048357	0.086035559
Lineament Density						
Very low	533700	159575400	0.191164	0.199977	0.955933	0.191637386
Low	403200	159071400	0.144421	0.199345	0.724477	0.145237043
Moderate	421200	161048700	0.150868	0.201823	0.747528	0.149858063
High	620100	158241600	0.222112	0.198305	1.12005	0.2245381
Very High	806400	160032600	0.288842	0.20055	1.440251	0.288729418
Drainage Density						
Very low	272700	34055100	0.097678	0.042677	2.288754	0.015096829
Low	540900	36198000	0.193743	0.045363	4.27099	0.028171836
Moderate	491400	89253000	0.176013	0.11185	1.573651	0.010379946
High	712800	3688200	0.255316	0.004622	55.23946	0.364364431
Very High	766800	2484000	0.274658	0.003113	88.23212	0.581986969
Road Density						
Very low	252900	312744600	0.090585	0.391925	0.231129	0.024517918
Low	170100	122799600	0.093012	0.15389	0.604404	0.064114454
Moderate	386100	123491700	0.211122	0.154757	1.364213	0.144714024
High	822600	120591000	0.449803	0.151122	2.976419	0.31573476
Very High	1152900	118342800	0.630413	0.148305	4.250793	0.450918846
LU/LC						
Built up Area	10800	2282400	0.003868	0.00286	1.352472	0.16916335
Barren Land	703800	46791000	0.252092	0.058638	4.299155	0.537726223
Evergreen Forest	103500	404295300	0.037072	0.506655	0.073171	0.009151998
Agriculture	1922400	299335500	0.688579	0.375121	1.835616	0.229593618
Degraded Forest	44100	28999800	0.015796	0.036342	0.43465	0.054364809
Waterbody	0	16265700	0	0.020384	0	0
Geology						
Alluviam	136800	18972900	0.049	0.023776	2.06086	0.071670956
Paturi Quartize	0	2502000	0	0.003135	0	0
Slates	1681200	25298100	0.602184	0.031703	18.99449	0.660575247
Quartzite	501300	33490800	0.179559	0.04197	4.278272	0.14878632
Quartzite	93600	81476100	0.033526	0.102104	0.328354	0.01141922
Augen Gneiss	277200	68751000	0.099289	0.086157	1.152419	0.040077906

Table – 2: Characteristics of Membership Functions

Input	Minimum Range	Maximum Range	Membership Functions		
Lineament Density	0	1.62	High	Triangular	[0 0 1.62]
			Low	Triangular	[0 1.62 1.62]
Drainage Density	0	4.90	High	Triangular	[0 0 4.90]
			Low	Triangular	[0 4.90 4.90]
Landuse	1	3.00	Low	Triangular	[1 1 1]
			Moderate	Triangular	[2 2 2]
			High	Triangular	[3 3 3]
Geology	1	3.00	High	Triangular	[1 1 1]
			Moderate	Triangular	[2 2 2]
			Low	Triangular	[3 3 3]
Road Density	0	11.90	High	Triangular	[0 0 11.9]
			Low	Triangular	[0 11.9 11.9]
Slope	0	73.10	High	Triangular	[0 0 73.10]
			Low	Triangular	[0 77.1 73.1]
Output	0	1.00	Very Low	Trapezoidal	[1 0 0.1 0.3]
			Low	Triangular	[0.1 0.3 0.5]
			Moderate	Triangular	[0.3 0.5 0.7]
			High	Triangular	[0.5 0.7 0.9]
			Very High	Trapezoidal	[0.7 0.9 0.11]

Table – 3: Landslide Density Table

	Frequency Ratio				
	Very Low	Low	Moderate	High	Very High
Class Pixels	169735	187286	180289	176625	172698
L	88200	151200	395100	898200	1251900
C	152761500	168557400	162260100	158962500	155428200
l/L	0.03167420	0.05429864	0.141887524	0.32255979	0.449579832
c/C	0.19143772	0.21123283	0.203341179	0.19920869	0.194779576
Landslide density(F.R)	0.16545437	0.25705588	0.697780571	1.61920542	2.308146679
Normalized L.D.	0.03278252	0.05093210	0.138255681	0.32082342	0.457327711
Fuzzy Inference System					
	Very Low	Low	Moderate	High	Very High
Class Pixel	172360	184409	169626	176475	183763
L1	272700	337500	513000	700200	961200
C1	155124000	165968100	152663400	158827500	165386700
L1/L	0.09793148	0.121202327	0.184227537	0.25145443	0.345184228
C1/C	0.194398359	0.207987972	0.191314783	0.19903951	0.207259373
Landslide Density (FIS)	0.503767012	0.582737192	0.962955054	1.26333925	1.665469802
Normalized L.D.	0.101193229	0.117056212	0.193431742	0.25377084	0.33454804

***L1**= Area of a landslide in each class in sq m.**L**= Total area of landslides in sq. m.=2.8sq. km. **C1**= area of each class in sq.m..**C** = total area =789 Sq.km*

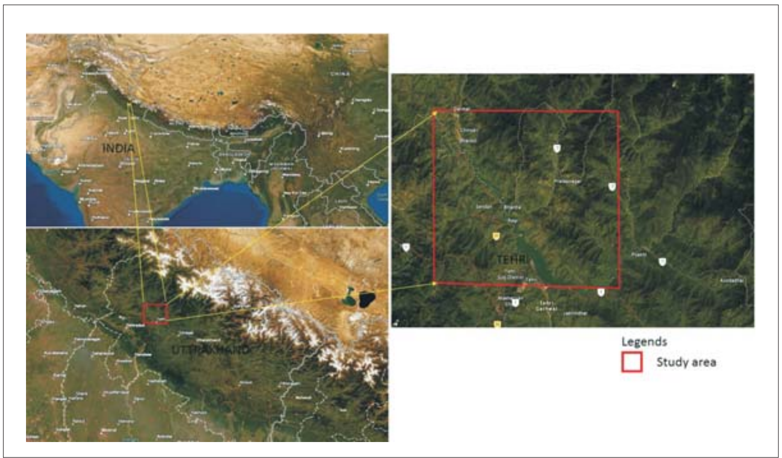

Fig.1: Location of the Study Area

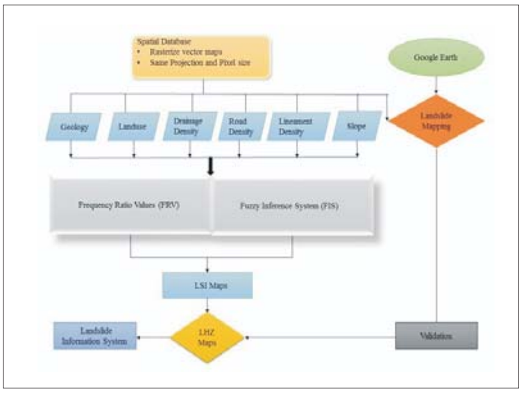

Fig. 2 Methodology Flowchart

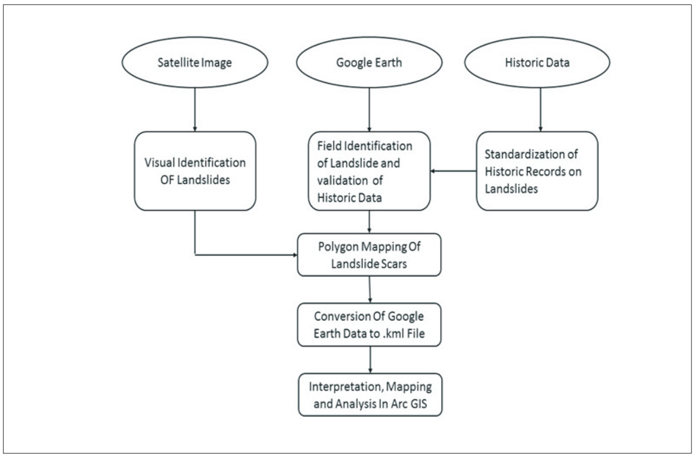

Fig. 3: Methodology for Mapping Landslides

Fig. 4: Google Earth Imagery showing Landslide

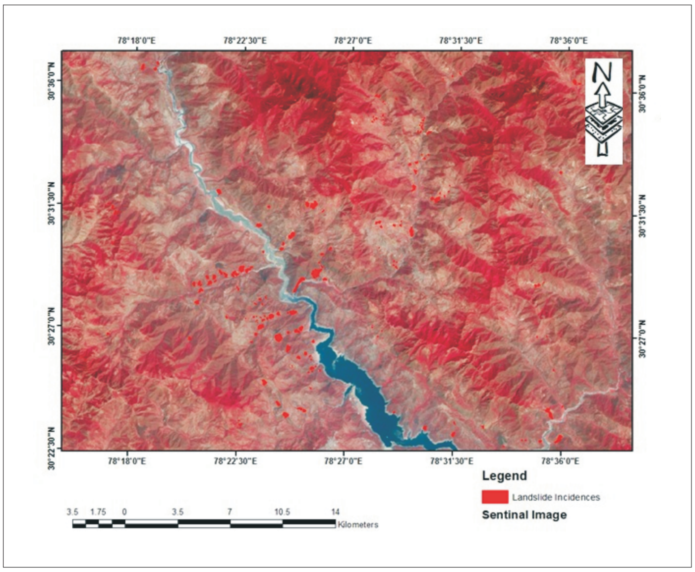

Fig. 5: Landslide Inventory

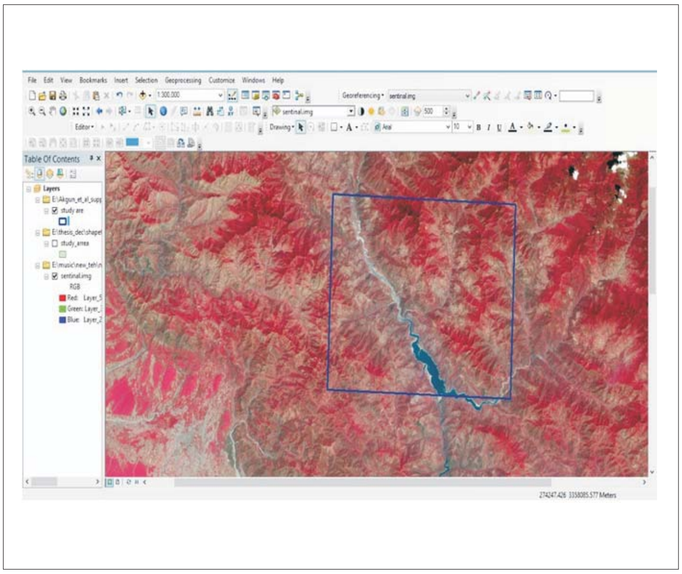

Fig. 6: The imported Image Map and the Study Area

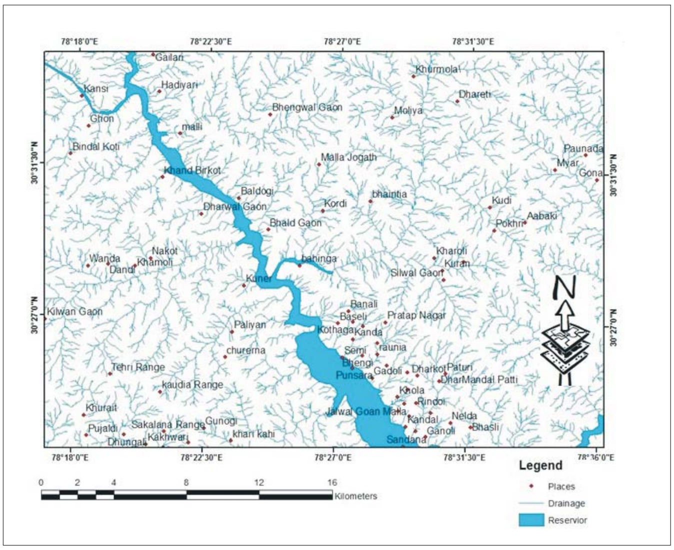

Fig. 7: Drainage Map

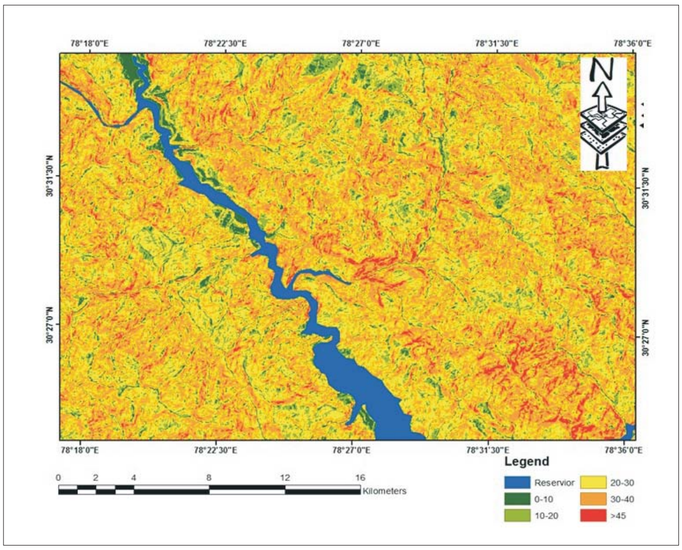

Fig. 8: Slope map

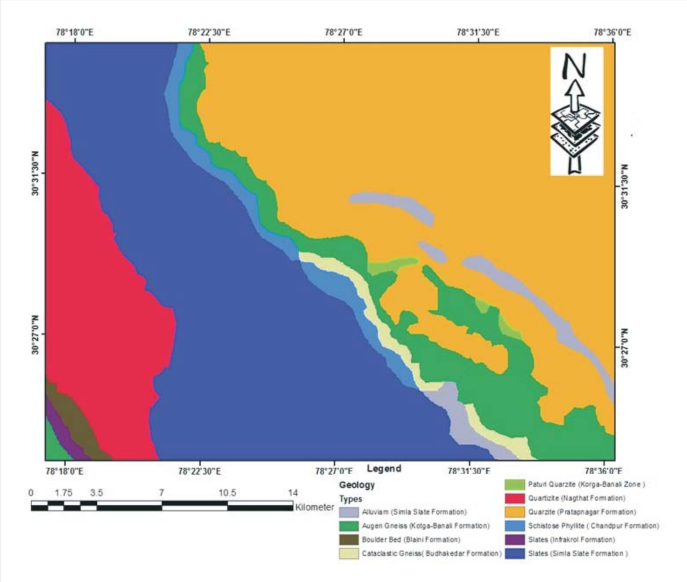

Fig. 9: Geology Map

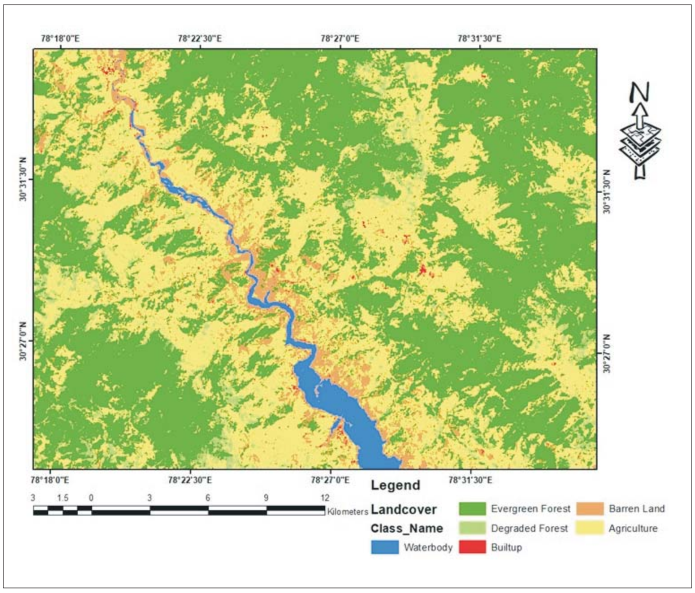

Fig.10: Landcover Map

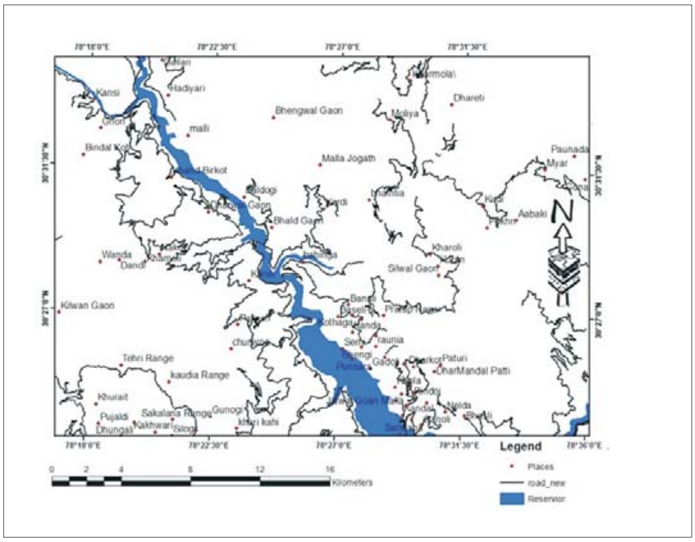

Fig. 11: Drainage Map

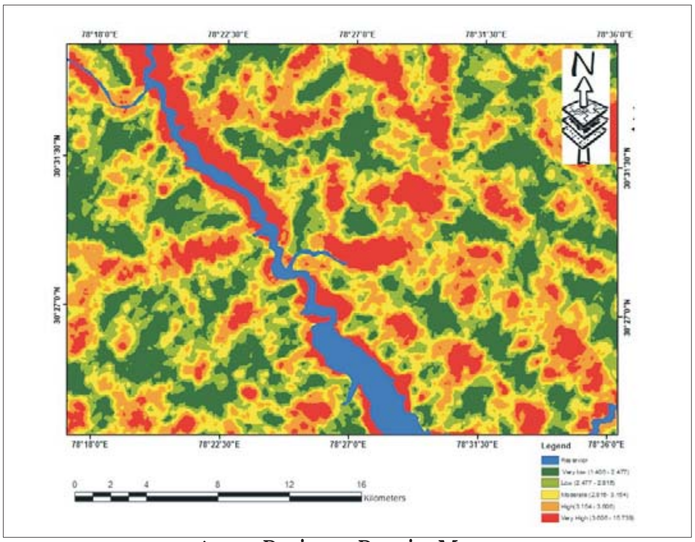

Fig. 12: Drainage Density Map

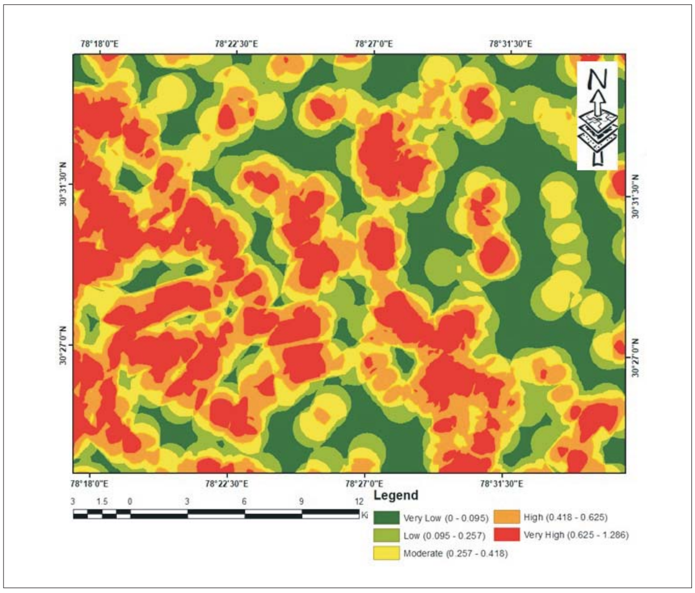

Fig. 13: Lineament Density Map

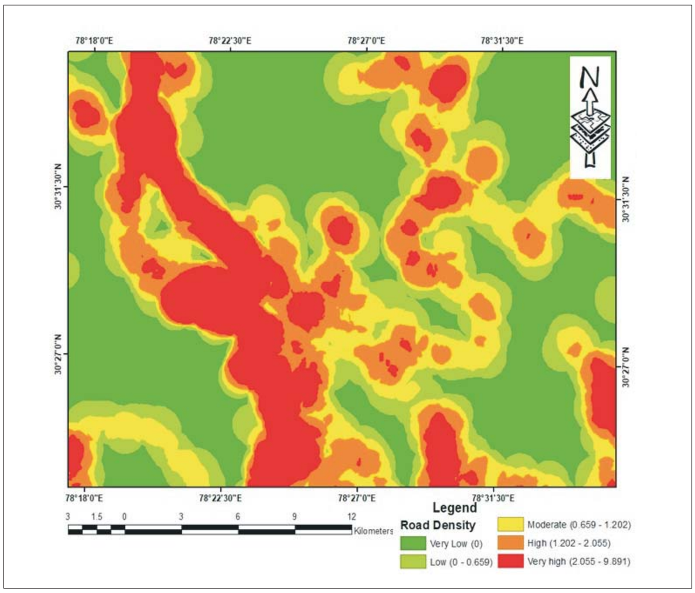

Fig. 14: Road Density Map

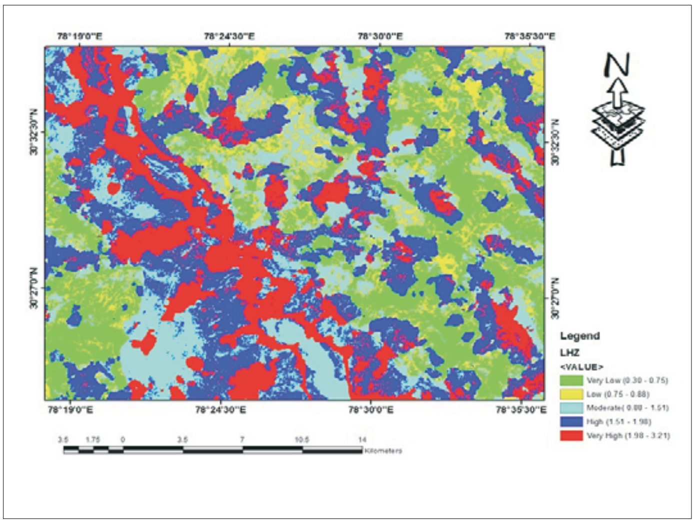

Fig.15: Frequency Ratio LHZ Map

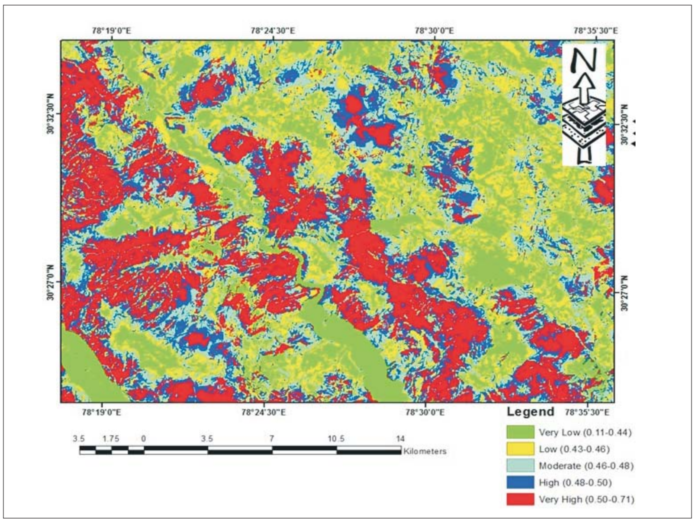

Fig.16: Landslide Hazard Zonation (FIS Method)

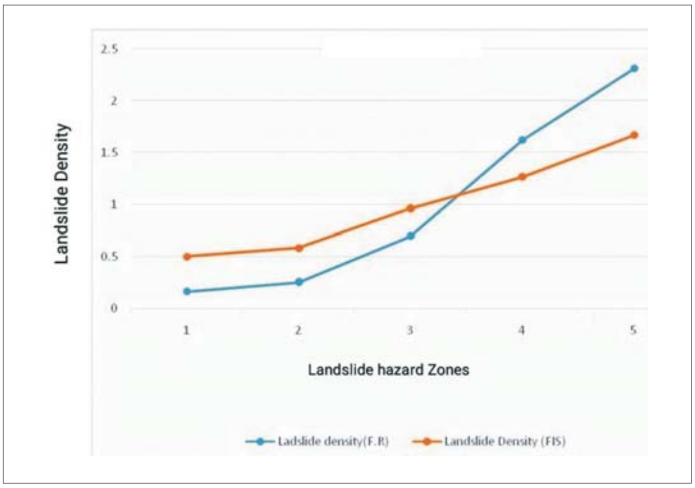

Fig. 17: Comparison Graph

Ashutosh Mishra#
Post Graduation Student
Land Resources Management
Central University of Jharkhand
Email: ashutosh242225@gmail.com

A.C. Pandey
Professor,
Land Resources Management,
Central University of Jharkhand
Email: arvindchandrap@yahoo.com

K. K. Ramachandran
Scientist
National Center for Earth Science Studies
Thiruvananthapuram
Email: raman.kk@ncess.gov.in

Vincent A Ferrar
Scientist
National Center for Earth Science Studies
Thiruvananthapuram
Email: vincent@ncess.gov.in