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A Comparative Study of Frequency Ratio, Shannon's Entropy and Analytic Hierarchy Process (AHP) Models for Landslide Susceptibility Assessment

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Abstract: Landslide susceptibility maps are very important tools in the planning and management of landslide prone areas. Qualitative and quantitative methods each have their own advantages and dis-advantages in landslide susceptibility mapping. The aim of this study is to compare three models, i.e., frequency ratio (FR), Shannon's entropy and analytic hierarchy process (AHP) by implementing them for the preparation of landslide susceptibility maps. Shimla, a district in Himachal Pradesh (H.P.), India was chosen for the study. A landslide inventory containing more than 1500 landslide events was prepared using previous literature, available historical data and a field survey. Out of the total number of landslide events, 30% data was used for training and 70% data was used for testing purpose. The frequency ratio, Shannon's entropy and AHP models were implemented and three landslide susceptibility maps were prepared for the study area. The final landslide susceptibility maps were validated using a receiver operating characteristic (ROC) curve. The frequency ratio (FR) model yielded the highest accuracy, with 0.925 fitted ROC area, while the accuracy achieved by Shannon's entropy model was 0.883. Analytic hierarchy process (AHP) yielded the lowest accuracy, with 0.732 fitted ROC area. The results of this study can be used by engineers and planners for better management and mitigation of landslides in the study area.

Keywords: landslide susceptibility mapping; AHP; Shannon's entropy; frequency ratio; landslide inventory

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1. Introduction

Hilly regions are frequently affected by landslide disasters. Landslides are responsible for huge loss of life and damage to infrastructure [1,2]. A landslide is the result of movement of a slope under the effect of gravity, but the movement can be triggered by the factors such as rainfall, earthquakes, erosion, etc. [3,4]. The accurate prediction of landslides can help in the planning and management of landslide hazards, and can ultimately be used for the reduction of risk [5]. Landslide susceptibility maps help in the identification of landslide prone areas. Landslide susceptibility maps can be very efficient tools for planners and risk managers [5]. The occurrence of landslides is a complex phenomenon which depends upon various factors. Geological factors, drainage characteristics, land-use of the region, construction activities, etc., can all be responsible for the occurrence of landslides [6]. Anthropogenic activities and the development of infrastructure in landslide prone areas can disturb natural slopes, resulting in massive disaster [7,8].

The study area selected in this study is the Shimla district in Himachal Pradesh (H.P.), India. The study area is developing at a very rapid rate. Anthropogenic activities have been increasing in the study area, resulting in the instability of natural slopes. Landslide occurrence is very frequent in the study area due to rugged topographic and the typical climatic conditions in the region. Therefore, there is a need for the preparation of a landslide susceptibility map for the region which can be used by planners and engineers.

In different regions of the world, landslide susceptibility mapping has been undertaken by various researchers, using geographic information systems (GIS) and remote sensing [2,4,6,9–14]. Qualitative and quantitative approaches are both widely used. Qualitative techniques consider expert opinion, while quantitative approaches establish a mathematical relationship between causative factors and the occurrence of landslide [2,5,13,15–17]. Landslide inventory-based methods utilize a direct approach in which susceptibility maps are prepared by considering the geomorphological characteristics of the region. Ranking and weightage are introduced to improve direct susceptibility mapping, through analytic hierarchy processes (AHP), analytic network processes (ANP), fuzzy logic, etc. [15–18]. These methods can be categorized as semi-qualitative methods. Quantitative methods such as the bivariate method [19–21], multi-variate method [22–24], weight of evidence [25,26], etc., are widely used with the development of GIS techniques. GIS platforms help in the calculation and visualization of the cumulative effects of causative factors on landslides. Qualitative techniques are based on the subjective judgment of experts, while the output in quantitative techniques depends on the availability of historical landslide data [27].

Landslide susceptibility mapping has not been undertaken for the study area until now. There is a need for the preparation of an accurate landslide susceptibility map for the region. In this study, we used three techniques for landslide susceptibility mapping, i.e., frequency ratio (FR), Shannon's entropy model and analytic hierarchy process (AHP). Shannon's entropy model is an improvement over the frequency ratio model and is rarely used in the Indian continent for landslide susceptibility mapping. The results of this study can help in the delineation of landslide prone regions in the study area. Construction planners, environmental engineers and risk managers can use the results of this study for the planning and mitigation of landslide hazards in the study area.

2. Study Area

Figure 1a shows the methodology adopted in this study. In the first step, the study area is selected. Shimla is the capital of Himachal Pradesh (H.P.) province in India. The region lies between longitudes 77°0' E and 78°19' and latitudes 30°45' and 31°44'. The elevation of the region varies from 300 m to 6000 m and shows variation in the vegetation [28,29]. The study area lies in the Kashmir and Western Himalayas seismic region. Shimla district lies in a high damage risk zone in the case of seismic activity (MSK VIII) [28,29]. Major earthquakes that have occurred in Himachal Pradesh (H.P.) are the Kangra earthquake 1905 ($M = 8$), the Chamba earthquake 1945 ($M = 6.5$), the Kinnaur earthquake ($M = 6.8$), etc. The study area is predominantly covered by rock from the Jutogh, Shali, Simla and Rampur groups. The study area consists of lithological units of shale, siltstones, quartzite, dolomites, phyllite, schist, conglomerate, etc. The region is predominantly covered by the Proterozoic age group, Palaeo-proterozoic age group and Neo-proterozoic age group. The study area is mainly forest and cultivated land. Some of the study area in upper Shivaliks consists of hill tops with snow. The temperature varies from 4 °C to 31 °C [28,29]. Therefore, the region is cool in winter and moderately warm in summer. Figure 1b shows the study area and landslide inventory.

2.1. Landslide Inventory

A landslide inventory plays an important role in the mathematical modelling and validation of the final output [13]. Landslide inventories consist of information regarding the location of landslides, area of landslides, activity and date of landslides, etc. [30]. A landslide inventory can be simple to complex, depending upon the requirement of study. A landslide inventory is prepared from previous literature, Google Earth and field visits. The field visits cannot be undertaken frequently due to restricted movement in the current COVID-19 pandemic. The landslide inventory consists of more than 1500 landslides in the study area. The landslides are represented by polygons. Figure 1 shows the landslide inventory.

(a)

Figure 1. Cont.

(b)

Figure 1. (a) Flow chart of methodology, (b) Study area and landslide inventory.

2.2. Landslide Conditioning Factors

Understanding the causative factors of landslides for the preparation of landslide susceptibility maps is very important. The data for the preparation of thematic layers of causative factors were obtained from different sources. An ASTER digital elevation model (DEM) was obtained from the USGS website. The resolution of the DEM used in this study is 1 arc second, which is approximately equal to 30×30 m. The average root mean square error (RMSE) in the measurement of elevation is ± 13.31 m. In terms of absolute positioning, the ASTER DEM models have a tendency for displacement by 5.3 m in our study. Landsat 8 data was used for the preparation of a land-use map for the study area. The resolution for Landsat bands 1–7 is 30×30 m. Hydrogeological and topographical maps were used for the digitization of faults, lithology and the road network. The land cover of the study area was obtained from Landsat 8 data.

Selection of condition factors depends on the availability of data, ease of use and the results of a literature survey. In many studies, DEM based factors are considered to be major causative factors, but in recent studies, land use, drainage networks and faults or lineaments are also considered to be responsible for landslide occurrence. The factors considered in this study are explained as follows. The relative importance of the causative factors can be found using Shannon's entropy and the AHP model.

2.2.1. Slope Gradient

Slope gradient may be defined as the rate of change in elevation with respect to horizontal surface. When the shear stresses in a downward direction exceed the shear strength of soil or rock mass, the failure of slopes occur. Therefore, the slope angle directly affects the stability of slope [31]. The slope of the study area was extracted from a digital elevation model (DEM) of the study area. The study area is comprised predominantly of steep slopes greater than 60° . As the slope angle increases, the possibility of slope failure increases. Figure 2a shows slope gradient of the study area.

Figure 2. Causative factors: (a) Slope gradient (b) Slope aspect (c) Relative relief (d) Topographic wetness index.

2.2.2. Slope Aspect

Slope aspect gives the direction of maximum slope with respect to magnetic north. Slope aspect affects erosion, evapotranspiration, desertification, solar heating and soil moisture [5]. Slope aspect indirectly shows the impact of water on the mass. Figure 2b shows the slope aspect of the study area.

2.2.3. Relative Relief

Relative relief shows the change in elevation. The change in elevation indicates variation in vegetation type and topographical characteristics of the region [13]. Vegetation roots hold the rock and soil mass together and make it more stable. The relative relief varies from 0 to 254 m in the present study. Figure 2c shows the relative relief of the region.

2.2.4. Topographic Wetness Index (TWI)

The topographic wetness index (TWI) is the tendency of terrain to accumulate water. It indicates variation in soil moisture [32]. Figure 2d shows the TWI of the region. If SCA is specific catchment area and ϕ is the angle of slope, TWI is given by the following formula:

$$TWI = \ln \left(\frac{SCA}{\tan \phi} \right) \quad (1)$$

2.2.5. Lithology

Lithology is an important causative factor of landslides. Variation in rock characteristics and age prominently affect landslide events [33]. Detailed information about the lithological and geological character of the region is given in Table 1. Figure 3a shows the lithology of the region.

Table 1. Lithology of the study area.

Age	Group Name	Geological Formation	Lithology
Mesoproterozoic	Shali	Tatapani	Pink and grey dolomite, phyllite, shale
Neoproterozoic	Shali	Sorgharwari	Pink and grey limestone, sporadic shale
Palaeocene-Eocene	Sirmur Dharmshala Group	Subathu	Green carbonaceous shale, limestone, quartzite
Palaeoproterozoic	Kulu	Khokhan	Schist and quartzite
Palaeozoic	Not available	Not available	Medium to coarse biotite granite
Proterozoic (Undiff)	Jutogh	Manal, chor, pabar	White grey quartzite, schist, carbonaceous dolomite, granite, gneiss

2.2.6. Drainage Density

The drainage characteristics of the region significantly affect the occurrence of landslides. River water erodes the soil at the toe of the slope and weakens the base, which may result in slope failure [33,34]. Drainage density is divided into four categories for the study area. Higher drainage density increases the risk of landslides. Figure 3b shows the drainage density of study area.

2.2.7. Distance from Roads

Road construction disturbs the natural slopes along highway corridors. Road construction activities involve significant cutting and filling activities. The bottom section of a slope is weakened by the soil and rock cutting activities during highway construction [35]. Vehicular vibrations, excessive excavations and disturbed natural slopes all induce instability and increase the risk of landslide occurrence. Slopes existing near roads are more prone to experience landslides [13,35]. A detailed analysis of slope stability during the planning of construction of projects can reduce the risk of landslide occurrence. Distance from roads indirectly represents the effects of human interference on natural slopes. If proper slope protection is provided and the slopes along highways are planned properly, the risk of landslides along highways can be reduced. Figure 3c shows the distance from roads.

Figure 3. Causative factors: (a) Lithology (b) Drainage density (c) Distance from road (d) Distance from faults.

2.2.8. Distance from Faults

Cracks, faults, fissures and lineament can increase pore pressure in the rock and soil mass, and can induce instability in slopes [36,37]. In this study, faults were digitized from NRSA data. Proximity to faults is considered a causative factor in this study, and Euclidean distance from faults was calculated in ArcGIS. Figure 3d shows distance from faults.

2.2.9. Land Cover

Land cover is an important factor that affects the occurrence of landslides. Vegetation area, forest area, barren land, etc. are shown in a land cover map, and may affect the occurrence of landslides due to their diverse characteristics. A land cover map was extracted from Landsat 8 imagery. The land use was classified using a supervised learning technique of image classification in ArcGIS. The study area is predominantly covered with the cropland and forests. In the upper elevations, there are glaciers and snow covered hill tops as well. Figure 4 shows the land cover map of the region.

Figure 4. Land-use/land cover map.

3. Modelling Approach

3.1. Frequency Ratio

Frequency ratio models are based upon the relationship between the occurrence of landslide events and the causative factors [38,39]. A relationship between the landslide inventory and causative factors can be established in a GIS environment. A landslide will occur under the same conditions as past landslides [5]. The frequency ratio is the ratio between the percent areas where landslides have occurred in a class to the percent area of the influencing class relative to the whole study area as shown in the following formula [40].

$$Fr = \frac{\left(\frac{M_i}{M}\right)}{\left(\frac{N_i}{N}\right)} \quad (2)$$

where M_i = Number of pixels containing landslides in a class; M = Total number of pixels in a class; N_i = Total number of pixels containing landslides; N = Total number of pixels in the study area.

The landslide susceptibility index is calculated by summing up the Fr for each sub-factors:

$$\begin{aligned} &\text{Landslide Susceptibility Index (LSI)} \\ &= Fr_1 + Fr_2 + Fr_3 + Fr_4 + \dots + Fr_n \end{aligned} \quad (3)$$

where Fr is frequency ratio and n is number of causative factors. Table 2 shows the frequency ratio (FR) calculation.

Table 2. Frequency ratio and Shannon's entropy weightage.

Conditioning Factor	Classes	No. of Pixels in Class	Percentage in Class (a)	No. of Landslide Pixel in Class	Percentage of Landslide Pixel (b)	FR (b/a)	Pij	Eij	Hij = 1 – Eij	Wj
Slope										
	<30	107,718.000	1.710	13.000	0.800	0.468	0.115	−0.108	0.442	0.120
	30–45	246,772.000	3.900	13.000	0.800	0.205	0.050	−0.065		
	45–60	1,001,205.000	15.910	91.000	5.950	0.374	0.092	−0.095		
	60–75	3,779,957.000	60.050	803.000	52.510	0.874	0.214	−0.143		
	More than 75	1,158,974.000	18.410	609.000	39.830	2.163	0.530	−0.146		
		6,294,626.000		1529.000		4.085		−0.558		
Aspect										
	Flat	105.000	0.002	0.000	0.000	0.000	0.000	0.000	0.124	0.033
	North	916,307.000	14.560	210.000	13.730	0.943	0.116	−0.108		
	Northeast	792,179.000	12.590	156.000	10.200	0.810	0.100	−0.100		
	East	627,294.000	9.970	255.000	16.680	1.673	0.206	−0.141		
	South East	804,073.000	12.770	290.000	18.970	1.486	0.183	−0.135		
	South	900,237.000	14.310	230.000	15.040	1.051	0.129	−0.115		
	South West	809,177.000	12.860	135.000	8.830	0.687	0.084	−0.091		
	West	643,538.000	10.220	150.000	9.810	0.960	0.118	−0.109		
	North West	801,716.000	12.730	103.000	6.740	0.529	0.065	−0.077		
		6,294,626.000		1529.000	100.000	8.139		−0.876		
Relative relief										
	0–50	2,612,642.000	41.660	804.000	52.580	1.262	0.323	−0.159	0.408	0.110
	50–100	691,263.000	11.023	145.000	9.480	0.860	0.220	−0.145		
	100–150	710,948.000	11.337	186.000	12.160	1.073	0.274	−0.154		
	More than 150	2,256,417.000	35.980	394.000	25.770	0.716	0.183	−0.135		
		6,271,270.000		1529.000		3.911		−0.592		
TWI										
	Low	2,810,725.000	44.650	712.000	46.560	1.043	0.340	−0.159	0.500	0.135
	Moderate	2,473,126.000	39.290	596.000	38.980	0.992	0.323	−0.159		
	High	855,581.000	13.590	207.000	13.540	0.996	0.325	−0.159		
	Very High	155,194.000	24.650	14.000	0.910	0.037	0.012	−0.023		
		6,294,626.000		1529.000		3.068		−0.500		
Lithology										
	Neoproterozoic	1,364,515.000	21.680	415.000	27.150	1.252	0.408	−0.159	0.401	0.109
	Proterozoic (Undiff)	3,023,399.000	48.030	415.000	27.140	0.565	0.184	−0.135		
	Mesoproterozoic	502,058.000	7.970	143.000	9.350	1.173	0.382	−0.160		
	Plaeoproterozoic	1,384,339.000	22.000	556.000	36.360	1.653	0.539	−0.145		
	Palaeozoic	10,282.000	0.160	0.000	0.000	0.000	0.000			
	Palaeocene-eocene	7564.000	0.130	0.000	0.000	0.000	0.000			
	Meghalayan	2469.000	0.030	0.000	0.000	0.000	0.000			
		6,294,626.000		1529.000		4.643		−0.599		
Drainage density										
	0–15	2,309,122.000	36.680	320.000	20.930	0.571	0.186	−0.136	0.403	0.109
	15–30	2,194,591.000	34.860	628.000	41.070	1.178	0.384	−0.160		
	30–45	1,441,690.000	22.900	438.000	28.640	1.251	0.408	−0.159		
	More than 45 (up to 66)	349,223.000	5.550	143.000	9.350	1.685	0.549	−0.143		
		6,294,626.000		1529.000				−0.597		

Table 2. Cont.

Conditioning Factor	Classes	No. of Pixels in Class	Percentage in Class (a)	No. of Landslide Pixel in Class	Percentage of Landslide Pixel (b)	FR (b/a)	Pij	Eij	Hij = 1 – Eij	Wj
Distance from road										
	0–1.5 KM	1,743,800.000	27.700	531.000	34.720	1.253	0.409	−0.159	0.547	0.148
	1.5–5.5 km	2,114,630.000	33.590	286.000	18.700	0.557	0.181	−0.134		
	More than 5.5	2,436,196.000	38.700	712.000	46.560	1.203	0.392	−0.159		
		6,294,626.000		1529.000				−0.453		
Distance from faults										
	0–1.5KM	2,790,363.000	44.330	674.000	44.080	0.994	0.324	−0.159	0.587	0.159
	1.5 km–3.0 km	1,295,638.000	58.660	298.000	19.490	0.332	0.108	−0.105		
	more than 3 km	2,208,625.000	35.090	557.000	26.420	0.753	0.245	−0.150		
		6,294,626.000		1529.000				−0.413		
Landuse/landcover										
	Snow	440,046.000	6.990	220.000	14.390	2.059	0.671	−0.116	0.287	0.078
	Settlement	604,702.000	9.610	104.000	6.800	0.708	0.231	−0.147		
	Agricultural Land	1,800,554.000	28.600	246.000	16.080	0.562	0.183	−0.135		
	Forest	3,148,252.000	50.010	855.000	55.910	1.118	0.364	−0.160		
	Barren Land	301,072.000	4.790	104.000	6.800	1.420	0.463	−0.155		
		6,294,626.000		1529.000				−0.713	3.700	

3.1.1. Shannon's Entropy

Shannon's entropy model is an improvement on the frequency ratio model. The frequency ratio model only considers the weightage of sub-factors, and does not consider the weightage of causative factors. Shannon's entropy measures the uncertainty or instability of a system [41]. With landslide susceptibility mapping, it measures the influence of causative factors on the occurrence of landslides [42–45]. Weightage of causative factors is calculated using the following procedure:

$$P_{ij} = FR / \sum_{i=1}^m FR \quad (4)$$

$$\sum_{i=1}^m E_{ij} = \sum_{i=1}^m (P_{ij}) \times (\ln P_{ij}) \quad (5)$$

$$H_{ij} = 1 + \sum_{i=1}^m E_{ij} \quad (6)$$

$$W_j = H_{ij} / \sum_{i=1}^n H_{ij} \quad (7)$$

where P_{ij} is the probability density and FR is the frequency ratio of sub-factors. W_j is the weightage of causative factors obtained from Shannon's entropy technique. These values can then be used for assigning weight to causative factors, while frequency ratio values are used for sub-factors. Table 2 shows Shannon's entropy weightage of causative factors.

3.1.2. Analytic Hierarchy Process (AHP)

Analytic hierarchy process (AHP) is a decision-making tool which helps to solve complex problems with simple criteria. AHP is based upon three principles i.e., decomposition of the problem, comparative judgment, and synthesis of relative importance or rankings [43]. In AHP, the problem is broken down into hierarchical criteria. These criteria are compared to each other. This process of relative comparison is called pair-wise com-

$$\text{Consistency Ratio (CR)} = \frac{CI}{RI} \quad (8)$$

CI is calculated as follows:

$$\text{Consistency Index (CI)} = \frac{\lambda_{max} - n}{n - 1} \quad (9)$$

Randomness index values are given by Saaty, which is dependent on the value of n . RI is the result of extensive experimentation on large dataset samples. If the CR values are less than 10%, the pairwise comparison is considered consistent. If the CR value is more than 10%, the solution is considered inconsistent and weights are reassigned in a pairwise comparison matrix. Tables 3 and 4 show the relative comparison matrix of AHP for causative factors and sub-factors.

[illegible]

Conditioning Factor	Classes	1	2	3	4	5	6	7	8	9	Weightage (Wi)
Slope	>30	1									0.04
	30–45	2	1								0.054
	45–60	3	3	1							0.102
	60–75	5	5	3	1						0.209
	More than 75	9	8	7	5	1					0.596
						CR = 0.059					
Aspect	Flat	1									0.023
	North	2	1								0.047
	Northeast	7	4	1							0.204
	East	4	2	0.33	1						0.082
	South East	9	8	3	4	1					0.362
	South	5	3	0.5	2	0.25	1				0.125
	South West	4	2	0.25	1	0.2	0.5	1			0.078
	West	3	0.5	0.25	0.5	0.14	0.33	0.5	1		0.046
	North West	2	1	0.14	0.33	0.12	0.25	0.33	0.5	1	0.033
					CR = 0.025						

Table 4. Cont.

Conditioning Factor	Classes	1	2	3	4	5	6	7	8	9	Weightage (Wi)
Relative relief	0–50	1									0.581
	50–100	0.33	1								0.255
	100–150	0.2	0.33	1							0.114
	More than 150	0.11	0.2	0.33	1						0.05
	CR = 0.028										
TWI	Low	1									0.565
	Moderate	0.33	1								0.262
	High	0.2	0.33	1							0.118
	Very high	0.14	0.2	0.33	1						0.055
	CR = 0.043										
Lithology	Neoproterozoic	1									0.194
	Proterozoic (Undiff.)	0.33	1								0.098
	Mesoproterozoic	0.5	4	1							0.168
	Palaeoproterozoic	5	7	3	1						0.43
	Palaeozoic	0.2	0.33	0.33	0.2	1					0.053
	Paleocene-eocene	0.17	0.2	0.2	0.14	0.5	1				0.033
	Meghalayan	0.2	0.14	0.14	0.11	0.33	0.5	1			0.024
	CR = 0.085										
Drainage density	Low	1									0.046
	Moderate	3	1								0.094
	High	5	5	1							0.203
	Very high	9	7	5	1						0.657
	CR = 0.063										
Distance from road	Low	1									0.751
	Moderate	0.2	1								0.178
	High	0.11	0.33	1							0.07
	CR = 0.03										
Distance from faults	Low	1									0.751
	Moderate	0.2	1								0.178
	High	0.11	0.33	1							0.07
	CR = 0.03										
Landuse/Landcover											
	Snow	1									0.5
	Settlement	0.14	1								0.046
	Agricultural land	0.11	0.5	1							0.034
	Forest	0.2	5	5	1						0.137
	Barren land	0.33	9	7	3	1					0.284
CR = 0.072											

4. Results and Discussion

4.1. Frequency Ratio

The frequency ratio (FR) of the causative sub-factors is shown in the Table 2. The relative importance of the sub-factors can be evaluated from the weightage calculated in the Table 2. The impact of slopes less than 45° is very low, but as the slope increases above 45°,

the frequency ratio increases sharply. More than 39% of landslides occur in regions where the slope is more than 75° , while such slopes only cover 18% of the study area. Higher slope values trigger the effect of gravity and also increase shear stress. The maximum frequency ratio (FR) value for slopes is 2.163. East, south-east, south, and North Slope aspects affect the occurrence of landslides more compared other directions. The frequency ratio (FR) is highest for the east direction (1.673), followed by the south east direction (1.486). These aspects receive more rainfall and are also subjected to erosion, which makes them more prone to landslides. The areas of low (0–50 m) and high (100–150 m) relative relief were more prone to landslides. The frequency ratio value for relative relief was highest (1.262) for 0–50 m relief, followed by 1.073 for 100–150 m relief. Lower values of topographic wetness index (TWI) have a significant effect on landslide occurrence, with a frequency ratio of 1.043, while very high values of TWI (FR = 0.037) had minimal effect on landslide occurrence. As TWI increases, FR decreases. Neoproterozoic age deposits had the highest FR values (1.252), followed by Mesoproterozoic deposits (FR = 1.653). The frequency ratios follow an increasing trend as the drainage density increases. For very high drainage density, the FR value was 1.685. Smaller distance from roads had a significant effect on the occurrence of landslides. Small distances from roads have the highest FR value i.e., 1.253, and similarly, smaller distances from faults also showed maximum FR (0.994) values in its category. Cutting activities performed during road construction reduced strength at the toe of slopes, making them more prone to landslides. Snow covered land (FR = 2.059) was more prone to landslides, while agricultural land (FR = 0.562) had the least effect on landslide occurrence. After snow cover, barren land due to less vegetative cover was found to be more prone to landslides, with an FR value of 1.420.

The landslide susceptibility index (LSI) for the frequency ratio model varied from 3.173 to 13.297. The landslide susceptibility map is shown in Figure 5. The map is divided using natural breaks in ArcGIS showing very low, low, moderate, high and very high susceptibility zones. It is observed that high and very high landslide susceptibility zones cover around 45% of the study area, but more than 70% landslides occur in these regions. The very high susceptibility zone covers only 16.62% of the total study area but it is subjected to 40.7% of the total landslide area. 11% of the total landslide area occur in very low and low susceptibility zones while these zones cover more than 25% area.

4.2. Shannon's Entropy Model

The weightage of sub-factors in Shannon's entropy model was based on frequency ratio (FR) values. The weightage of causative factors was evaluated from FR values of sub-factors. It is found that distance from faults and distance from roads are the major causative factors which have a very high impact on the occurrence of landslides. The weightage of distance from faults is 0.159 and weightage of vicinity to roads is found to be 0.148. The anthropogenic activities of road cutting and development have significantly increased landslide activities in the study area. The topographic wetness index (TWI) is also an important factor, with a weightage of 0.135 as per Shannon's entropy model. Slope has a weightage of 0.120. Lithology, drainage density, and relative relief have almost equal weightage.

Figure 5. Landslide Susceptibility Map using Frequency Ratio.

The results of the FR model have been changed a little following the implementation of Shannon's entropy weightage to major causative factors. The simplest landslide susceptibility equation for this model is given as follows:

$$\begin{aligned}
 \text{Landslide Susceptibility Index (LSI)} &= 0.120 \times \text{Slope} + 0.033 \times \text{Aspect} \\
 &+ 0.110 \times \text{Relative Relief} + 0.135 \times \text{TWI} \\
 &+ 0.109 \times \text{Lithology} + 0.109 \times \text{Drainage Density} \\
 &+ 0.148 \times \text{Distance from Roads} \\
 &+ 0.159 \times \text{Distance from Faults} + 0.078 \times \text{Land use}
 \end{aligned} \tag{10}$$

LSI varies from 0.402 to 1.412 for Shannon's entropy model. The final landslide susceptibility map is divided into five categories, i.e., very low, low, moderate, high and very high, using natural breaks. The landslide susceptibility map by Shannon's entropy is shown in the Figure 6. Shannon's entropy model shows that 12.06% of the area has very high susceptibility, which contains 31.93% landslide area of the region. The model shows that 23.66% of the area has high susceptibility, which contains 34.45% landslide area. Very low and low landslide susceptibility zones cover 9.84% and 24.85% of study area, respectively.

Figure 6. Landslide susceptibility map using Shannon's entropy.

4.3. Analytic Hierarchy Process (AHP) Approach

According to the AHP model, distance from roads and drainage density are the major factors which have high weightage, i.e., 0.280 and 0.205 respectively. Higher weightage of distance from roads shows the significance of anthropogenic activities towards occurrence of landslides. Lithology has a weightage of 0.096 in the AHP model. Neoproterozoic and mesoproterozoic deposits have been more responsible for occurrence of landslides compared to other lithological units, as per the AHP model. Distance from faults has a weightage of 0.161, which states the high significance of this factor in the occurrence of landslides, while aspect has the lowest weightage, i.e., 0.016. Slope (weightage = 0.105) and (weightage = 0.081) are important DEM-based factors which affect the landslide phenomenon. Lower TWI values are more responsible for the occurrence of landslides compared to higher values. Tables 3 and 4 show the AHP weightage for all the factors and sub-factors, respectively.

The landslide susceptibility index (LSI) for the AHP approach is given by following equation:

$$\begin{aligned}
 \text{Landslide Susceptibility Index (LSI)} &= 0.105 \times \text{Slope} + 0.016 \times \text{Aspect} \\
 &+ 0.036 \times \text{Relative Relief} + 0.081 \times \text{TWI} \\
 &+ 0.096 \times \text{Lithology} + 0.205 \times \text{Drainage Density} \\
 &+ 0.280 \times \text{Distance from Roads} \\
 &+ 0.168 \times \text{Distance from Faults} + 0.020 \times \text{Land use}
 \end{aligned} \tag{11}$$

The landslide susceptibility index (LSI) for the landslide susceptibility map obtained from the AHP approach varies from 0.061 to 0.648. The landslide susceptibility map is divided by natural breaks based on the landslide susceptibility index shown in Figure 7.

Figure 7. Landslide susceptibility map using analytic hierarchy process.

It is found that 23.05% area lies under very low landslide susceptibility according to the AHP approach, and contains around 10% landslide area. Around 24% area lies under high susceptibility and contains around 29% landslide area, while around 8% area lies under very high susceptibility containing 9.24% of the landslides. It seems evident that the AHP model remains less efficient in the classification of landslide susceptibility as compared to the previous two models. The relative importance of the causative factors has been selected based on the subjective approach of experts. There is no mathematical relationship for the comparison of the relative importance of causative factors and sub-factors. In qualitative techniques such as AHP, the input can be varied for better output. The lower accuracy in the AHP may be due to underestimation and overestimation of the impacts of some causative factors and sub-factors.

4.4. Validation of Results

The results were validated using a receiver operating curve (ROC). Figure 8 shows the ROCs for the landslide susceptibility maps prepared with different techniques. The ROC curves show a relationship between sensitivity and (1-specificity). The area under curve (AUC) value for the frequency ratio model is 0.925, which shows very high accuracy. The frequency ratio model shows very encouraging results in the study area. Shannon's

entropy model shows an accuracy of 0.883. The analytic hierarchy process (AHP) based landslide susceptibility map shows an AUC value of 0.732, which is the lowest among all the models.

Figure 8. Receiver operating characteristic curve for validation.

5. Conclusions and Future Scope

Landslides are one of the most disastrous phenomena in the Himalayan region. In this study, statistical approaches and expert based approaches are compared for landslide susceptibility mapping in a GIS environment. The frequency ratio (FR) model shows better accuracy i.e., 0.925 compared to Shannon's entropy model and the AHP. Shannon's entropy model had an accuracy of 0.883, and AHP model had an accuracy of 0.732 using the ROC technique. The FR model and Shannon's entropy model have inputs based on landslide inventories which cannot be varied, while in the AHP model, the input can be varied to improve accuracy. The relative importance of each factor and sub-factor can be observed from these models. It can be concluded that frequency ratio is the most efficient method, and is the simplest to implement in quantitative methods. An accurate and extensive

landslide inventory is required for the efficient implementation of frequency ratio models. The results from qualitative methods like AHP depend upon the selection of weights, so need additional research. AHP can be used in the regions for which historical landslide data is not available. There is evidence of rock fall, debris flows and landslides in high and very high susceptibility zones. Landslide susceptibility maps using these models have not previously been prepared in this study area. Therefore, the results of this study can provide a very useful input for the planner and risk managers.

The study could be extended to predict landslide hazard and risk assessment of the study area. The seasonal variation in causative factors such as rainfall, land-use variation and vegetation cover variation can be studied and their impact on the occurrence of landslides can be observed.

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