M.tech (Geotechnical Engineering) Dhiren Sagar (23/GTE/09) 2025

A Comparative Study of Empirical, Statistical, and Analytical Models for Landslide Susceptibility in Kullu District, Himachal Pradesh

MAJOR PROJECT I REPORT

A Dissertation Submitted
In Partial Fulfillment of the Requirements for the Degree of

MASTERS OF TECHNOLOGY

IN
GEOTECHNICAL ENGINEERING
BY

DHIREN SAGAR
(2K23/GTE/09)

Under the Supervision of

Prof. RAJU SARKAR
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Department of Civil Engineering
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CANDIDATE'S DECLARATION

I, **DHIREN SAGAR,** M. Tech (Geotechnical Engineering) student, having **Roll no: 2K23/GTE/09,** hereby certify that the work which is being presented in the dissertation entitled "**A Comparative Study of Empirical, Statistical, and Analytical Models for Landslide Susceptibility in Kullu District, Himachal Pradesh**" in partial fulfillment of the requirements for the award of the Degree of **Master Of Technology in Geotechnical Engineering**, submitted in the **Department of Civil Engineering, Delhi Technological University**, Delhi Technological University is an authentic record of my work carried out under the supervision of **Prof. Raju Sarkar,** Professor, Department of Civil Engineering, Delhi Technological University, Delhi.

I have not submitted the matter presented in this dissertation for the award of any other degree from this or any other institute.

(DHIREN SAGAR)

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and that the statement made by the candidate is correct to the best of our knowledge.

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(Supervisor)

Place: Delhi, Date:

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CERTIFICATE BY THE SUPERVISOR(s)

Certified that **DHIREN SAGAR (2K23/GTE/09)** has carried out his research work presented in this thesis entitled "**A Comparative Study of Empirical, Statistical, and Analytical Models for Landslide Susceptibility in Kullu District, Himachal Pradesh**" for the award of the Degree of **Master of Technology in Geotechnical Engineering** from the Department of Civil Engineering, Delhi Technological University, Delhi, under our supervision. The thesis embodies the results of the original work, and the student himself carries out studies. The contents of the thesis do not form the basis for the award of any degree to the candidate or anybody else from this or any other University/Institution.

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Date:

ABSTRACT

Kullu district of Himachal Pradesh, India, is highly susceptible to landslides due to its rugged terrain, complex geological conditions, and heavy seasonal rainfall. This study evaluates and compares three different modeling approaches for landslide susceptibility mapping—empirical (Frequency Ratio), statistical (Shannon Entropy), and analytical (Analytical Hierarchy Process)—to determine the most effective technique for predicting landslide-prone areas.

A comprehensive landslide inventory comprising 428 landslide events and ten Landslide Conditioning Factors (LCFs), including slope, elevation, aspect, lithology, and proximity to streams, was used to develop susceptibility maps. The Frequency Ratio (FR) model demonstrated the highest predictive accuracy with an AUC value of 0.738, followed closely by the Shannon Entropy (SE) model (AUC = 0.735). The AHP model (AUC = 0.635) exhibited lower predictive performance, suggesting limitations in its weighting scheme for this region. Validation techniques, including AUC-ROC analysis and Success-Prediction Rate curves, confirmed the reliability and generalizability of the models.

The findings emphasize the effectiveness of statistical and empirical models over analytical methods for landslide susceptibility assessment in mountainous terrains. The generated susceptibility maps are a valuable tool for disaster risk management, infrastructure planning, and sustainable development in the Kullu district. This research improves landslide prediction methodologies and supports targeted mitigation strategies for high-risk regions.

ACKNOWLEDGEMENT

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Lastly, I would like to express my immense gratitude towards god. I wouldn’t have been what I am today without his/her blessing. Please, god, always keep me on the list of your much-loved children.

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CHAPTER 1

INTRODUCTION

The Kullu district of Himachal Pradesh, located in northern India, is renowned for its scenic landscapes but is also highly susceptible to landslides due to its steep terrain, complex geological formations, heavy monsoon rainfall, and increasing human activities such as construction and deforestation. Landslides pose significant threats to life, property, infrastructure, and the environment, making accurate susceptibility mapping crucial for disaster preparedness, risk reduction, and sustainable development.

Landslide Susceptibility Mapping (LSM) helps identify high-risk areas by analyzing various environmental, topographical, and geological factors. It is a vital tool for disaster management, infrastructure planning, and land-use regulation. Researchers have employed empirical, statistical, and analytical models to assess landslide-prone regions, each offering distinct advantages and limitations. This study evaluates three widely used methods:

- Empirical Model (Frequency Ratio - FR): Determines susceptibility based on the observed correlation between past landslide occurrences and Landslide Conditioning Factors (LCFs).
- Statistical Model (Shannon Entropy - SE): Measures the contribution of each LCF by analyzing its information gain in reducing uncertainty.
- Analytical Model (Analytical Hierarchy Process - AHP): Uses expert-driven pairwise comparisons to assign relative importance to LCFs.

The study area exhibits challenging topographical conditions, with elevations ranging from 1,200 m to over 6,000 m, deep valleys, and narrow gorges. Heavy monsoon rainfall, snowmelt, and human-induced slope modifications further increase landslide susceptibility. The research integrates a landslide inventory of 428 documented events and ten LCFs, including slope, aspect, elevation, lithology, curvature, and distance from streams, derived using geospatial tools.

Findings indicate that the Frequency Ratio and Shannon Entropy models outperform the AHP model in predictive accuracy, as validated by AUC-ROC analysis. The FR model achieved the highest AUC value of 0.738, followed closely by the SE model (AUC = 0.735), while the AHP model exhibited a lower predictive performance (AUC = 0.635), suggesting limitations in its factor weighting. Success Rate and Prediction Rate curves further confirmed the reliability of the statistical-based approaches.

The study underscores the importance of data-driven and statistical models for landslide prediction in mountainous regions. The generated susceptibility maps provide valuable insights for disaster management, infrastructure development, and environmental protection. These findings contribute to enhancing geomorphological hazard assessment and support targeted mitigation strategies for landslide-prone areas in Kullu district.

CHAPTER 2

LITERATURE REVIEW

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Chen, W., Guo, C., Lin, F., Zhao, R., & Li, T. (2024). Exploring advanced machine learning techniques for landslide susceptibility mapping in Yanchuan County, China. *Earth Science Informatics.* The dataset comprises 311 landslide points with a training-to-validation ratio of 7:3.

Chen, Z., Tang, J., & Song, D. (2024). Modeling landslide susceptibility using alternating decision tree and support vector. *Terrestrial, Atmospheric and Oceanic Sciences.* Employs ROC analysis to test ADTree and SVM models.

Dorji, L., & Sarkar, R. (2024). Hydrological modeling using CN method and satellite images in the Barsa River Basin, Bhutan. *Springer Nature Singapore.* Highlights hydrological modeling for ungauged basins.

Gayen, A., & Haque, S. M. (2024). Gully erosion susceptibility using advanced machine learning method in Pathro River Basin, India. *Springer Nature Singapore.* This study evaluates susceptibility using SAGAGIS and ArcGIS tools with training (70%) and testing (30%) data splits.

Ha, H., Bui, Q. D., & Tran, D. T. (2024). Improving forecast performance of landslide susceptibility mapping using gradient boosting algorithms. *Environment, Development and Sustainability.* Uses ensemble gradient boosting methods for susceptibility forecasting.

Khatun, S., Saha, A., & Sarkar, R. (2024). Assessment of landslide vulnerability using statistical and machine learning methods in Uttarakhand, India. *Springer Nature Singapore.* Uses statistical tools for susceptibility modeling.

Lau, R., Seguí, C., Waterman, T., & Veveakis, M. (2024). Quantitative assessment of Interferometric Synthetic Aperture Radar (INSAR) for landslide monitoring and mitigation. *Springer Nature Singapore.* Employs RMSE for evaluating INSAR-based landslide assessments.

Lv, J., Zhang, R., Shama, A., & Hong, R. (2024). Exploring the spatial patterns of landslide susceptibility assessment using interpretable Shapley method. *Journal of Environmental Management.* Conducts assessments using RF, SVM, and XGBoost models.

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Roy, B., Gogoi, P., & Saha, S. (2024). Assessment of shifting of River Ganga along Malda district of West Bengal using satellite images. *Springer Nature Singapore.* Uses temporal satellite imagery to assess geomorphic changes.

Saha, A., Saha, S., & Sarkar, R. (2024). Novel ensemble of M5P and deep learning neural network for predicting landslide susceptibility: A cross-validation approach. *Springer Nature Singapore.* Focused on hybrid machine learning models with MAE and RMSE validation.

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Sameen, M. I., Sarkar, R., Pradhan, B., Drukpa, D., & Alamri, A. M. (2020). Landslide spatial modeling using unsupervised factor optimization and regularized greedy forests. *Computers & Geosciences, 134*, 104336. Focuses on spatial modeling with 952 landslide points using RGF.

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Sharma, A., & Prakash, C. (2023). Impact assessment of road construction on landslide susceptibility in mountainous region using GIS-based statistical modeling. *Journal of the Geological Society of India.* Focused on road-induced landslide susceptibility in Mandi district.

Thapa, R., Sarkar, R., & Gupta, S. (2024). Geospatial study of river shifting and erosion-deposition in the River Damodar, West Bengal. *Springer Nature Singapore.* Analyzes geomorphological risks using geospatial tools.

Wei, Y., Qiu, H., Liu, Z., & Kamp, U. (2024). Refined and dynamic susceptibility assessment of landslides using InSAR and machine learning. *Geoscience Frontiers.* Integrates RF, LR, and GBDT for improved susceptibility assessment.

CHAPTER 3

METHODOLOGY

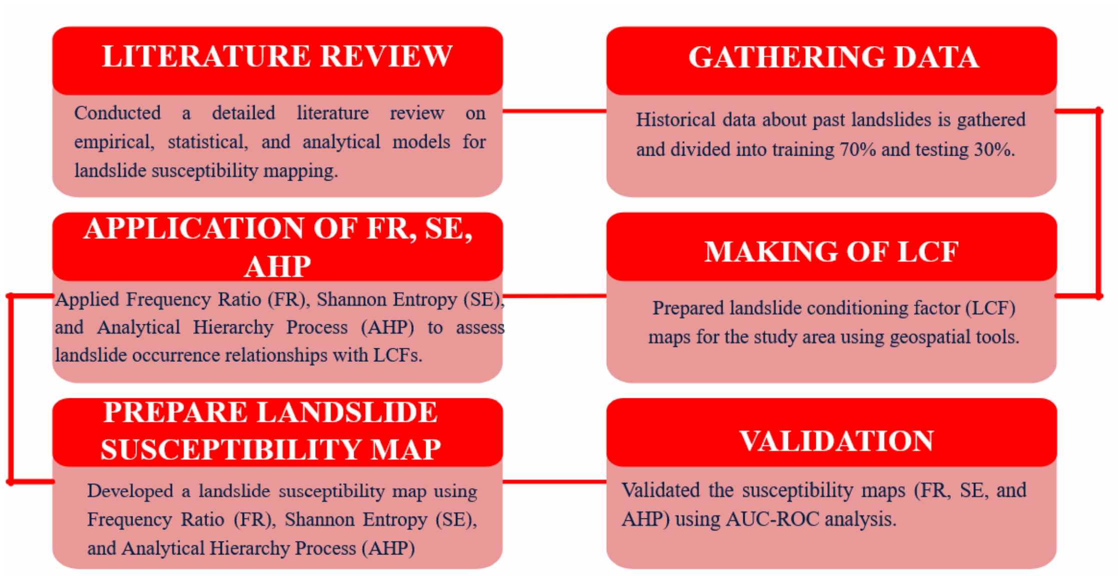

Figure 3. 1: METHODOLOGY

CHAPTER 4

DATA SOURCE

TABLE 4.1: DATA SOURCE

MAP	**DATA SOURCE**
INDIAN MAP	https://www.indianremotesensing.com/2017/01/Download-India-shapefile-with-kashmir.html
LANDSLIDE POINTS	https://bhukosh.gsi.gov.in/Bhukosh/Public
DISTRICT AND SUB-DISTRICT MAPS	https://esriindia1.maps.arcgis.com/home/item.html?id=b89de19cafb94ea38552a55eb5b2d13d
SLOPE, ASPECT, ROUGHNESS, TWI	https://opentopography.org/
DISTANCE FROM DRAINAGE	https://www.hydrosheds.org/products/hydrorivers#downloads
LITHOLOGY	https://certmapper.cr.usgs.gov/data/apps/world-maps/
CURVATURE, CONTOUR, HILLSHADE, ELEVATION	https://earthexplorer.usgs.gov/

CHAPTER 5

STUDY AREA: KULLU, HIMACHAL PRADESH

Kullu district is located in the state of Himachal Pradesh, in northern India. It lies between latitudes 31°20' to 32°25' N and longitudes 76°56' to 77°52' E. The district is part of the Western Himalayas and covers an area of approximately 5,503 square kilometers.

Kullu is characterized by a rugged and mountainous terrain, with altitudes ranging from 1,200 meters to over 6,000 meters above sea level. The district is known for its steep slopes, deep valleys, and narrow gorges, making it highly susceptible to landslides, particularly during the monsoon season.

The district experiences a temperate climate with significant rainfall during the monsoon season (July to September).

The region also receives heavy snowfall in higher altitudes during the winter. The average annual rainfall ranges from 800 mm to 1,000 mm, which, combined with steep terrain, increases the risk of landslides.

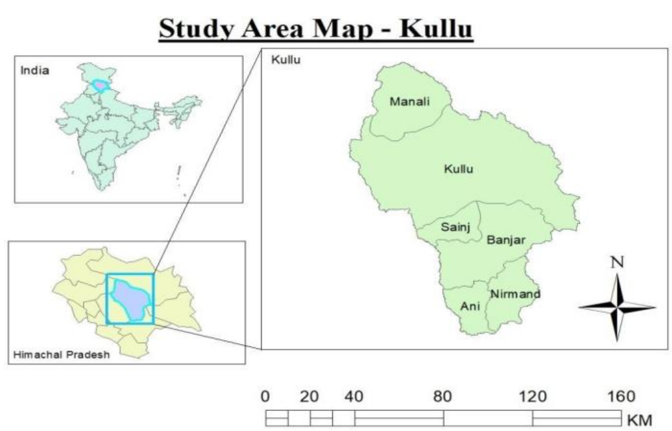

Figure 5.1: STUDY AREA MAP

CHAPTER 6

LANDSLIDE INVENTORY MAP

This landslide inventory map provides a spatial record of past landslide occurrences in the Kullu district. Historical landslide data was acquired in the form of polygon shapefiles from the Bhukosh by the Government of India, which is designated as one of the nodal agencies responsible for collecting past landslide incidence data in India.

A total of 399 landslide locations were obtained for the region. This landslide inventory data is critical for developing landslide susceptibility models, serving as a foundation for training and validating machine learning algorithms. By correlating the historical landslide locations with topographical, geological, and environmental variables, the inventory provides a basis for identifying landslide-prone areas.

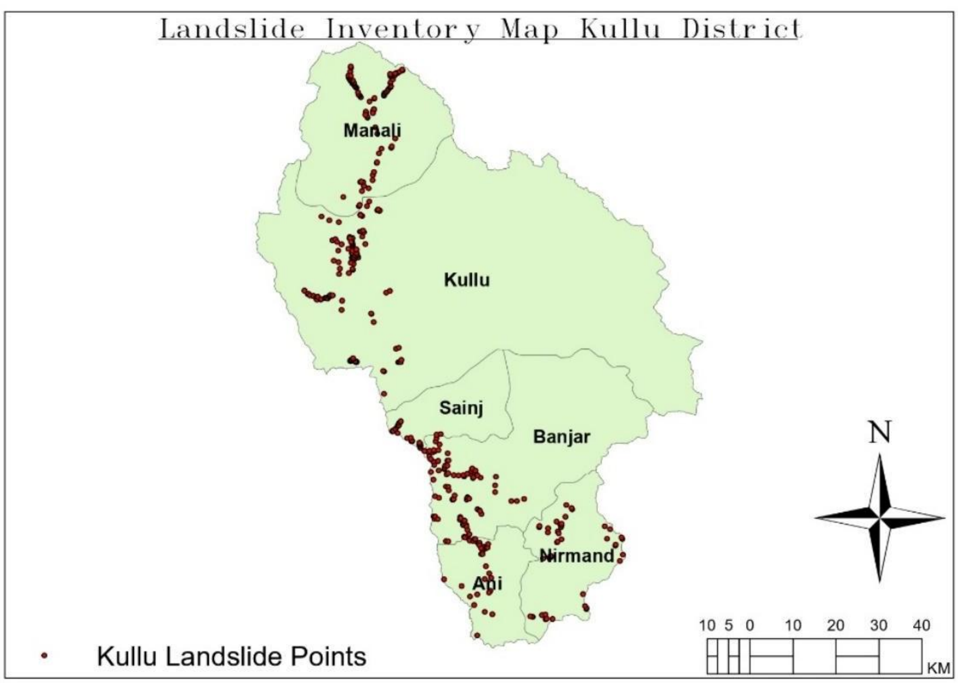

Figure 6.1: LANDSLIDE INVENTORY MAP

CHAPTER 7

LANDSLIDE CONDITIONING FACTORS

7.1 SLOPE

Known to depict the inclination of prevailing slopes in an area, the slope map was derived from the DEM in degrees using the spatial analyst surface tool of the GIS software and is said to have an impact on surface runoff and contribute to slope instability. The resulting map was then categorized into five classes, namely; 0°–15°, 16°–25°, 26°–35°, 36°–45° and >45°.

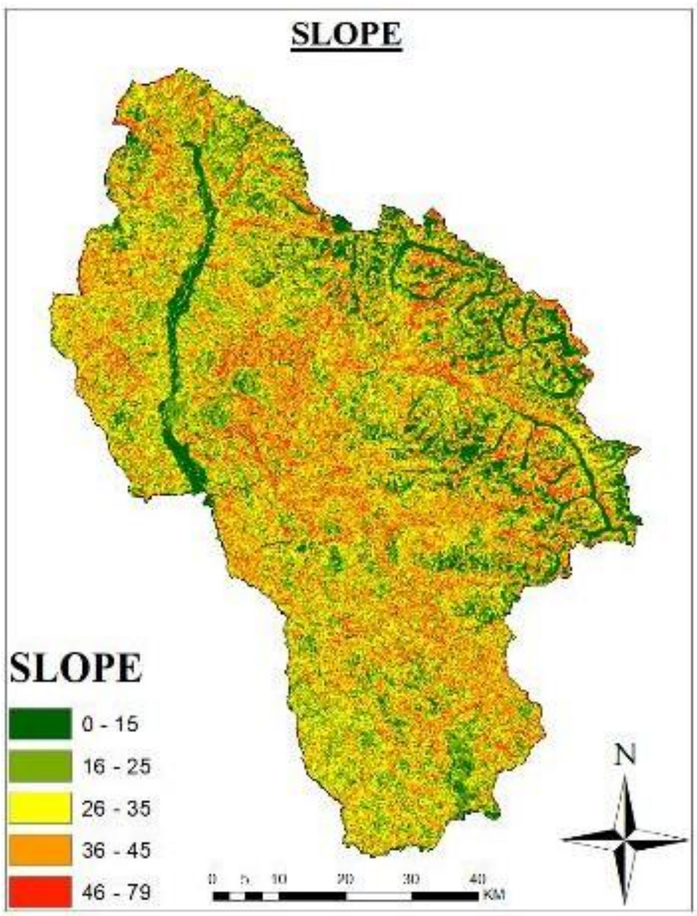

Figure 7.1: SLOPE

7.2 ASPECT

The aspect factor, which describes the spatial distribution of each topographical direction, is critical in determining slope stability. Furthermore, the curvature factor refects topographical morphology. The aspect map was calculated from the DEM in ArcGIS 10.7 software. The aspect map was divided into five groups.

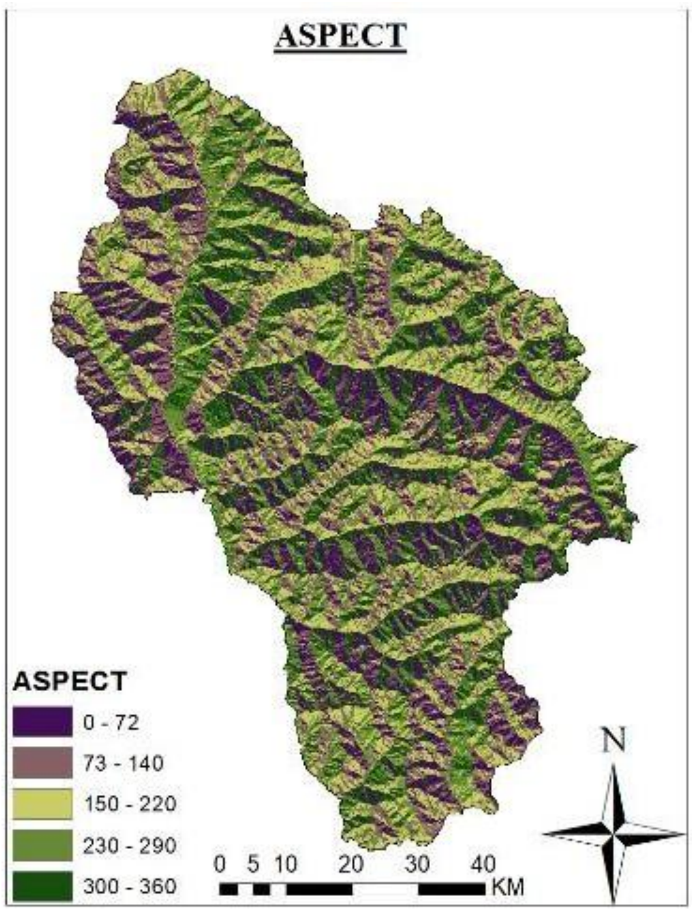

Figure7.2: ASPECT

7.3 DISTANCE FROM STREAM

Drainage does play an important role in slope instability, due to the action of under-cutting and increase in slope saturation. Also, bank erosion caused by high stream discharge velocity as well as toe erosion have a consequential impact on the area's landslide activity which is further enhanced by heavy rainfall.

The hydrology tools of the GIS platform were used to delineate the river networks, more specifically, by using the stream order tool. The Euclidean distance tool was then employed to create a buffer distance of 100 m intervals from the generated stream network. Five distinct classes resulted namely, 500 m, 1000 m, 1500 m, 2000 m and >2000m.

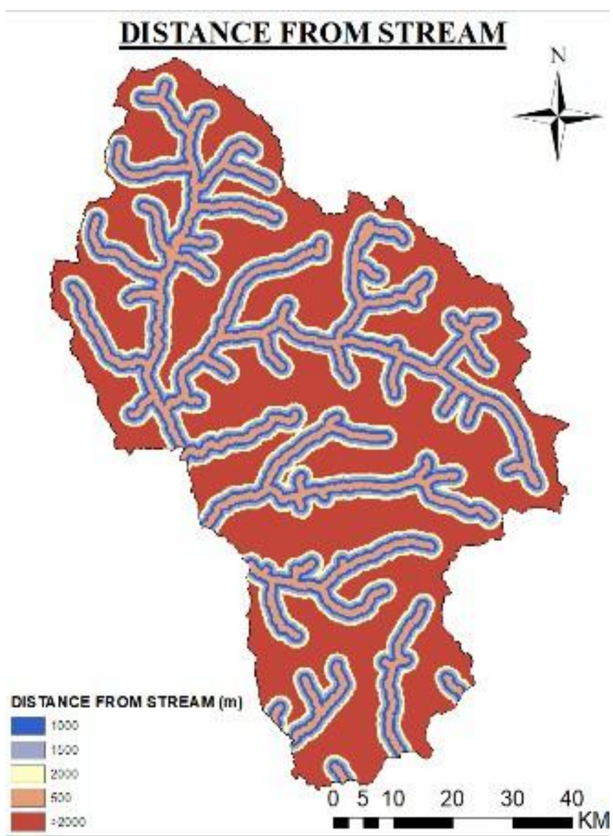

Figure7.3 : DISTANCE FROM STREAM

7.4 CURVATURE

Curvature, a key factor influencing slope stability, was classified into five categories: **Highly Concave** (high water accumulation and susceptibility), **Moderately Concave** (moderate susceptibility), **Flat** (neutral influence), **Moderately Convex** (low susceptibility), and **Highly Convex** (minimal susceptibility). These classes were derived using curvature analysis in ArcGIS to support the study of landslide susceptibility.

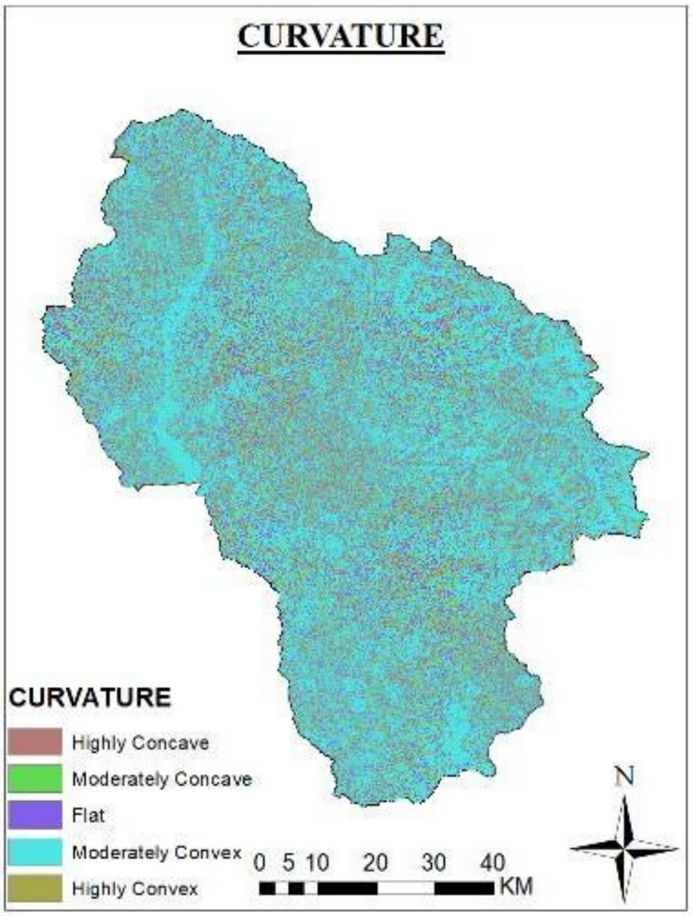

Figure 7.4: CURVATURE

7.5 ELEVATION

Elevation plays a significant role in influencing slope stability and landslide susceptibility. For this study, the elevation was classified into six categories: **<1500 m**, **1500–2500 m**, **2500–3500 m**, **3500–4500 m**, **4500–5500 m**, and **>5500 m**. These classes were created using GIS tools to reflect the varying topographical features of the region. Lower elevations (<1500 m) are more prone to human intervention and development, increasing landslide susceptibility, while higher elevations (>5500 m) generally exhibit reduced susceptibility due to limited accessibility and less anthropogenic activity.

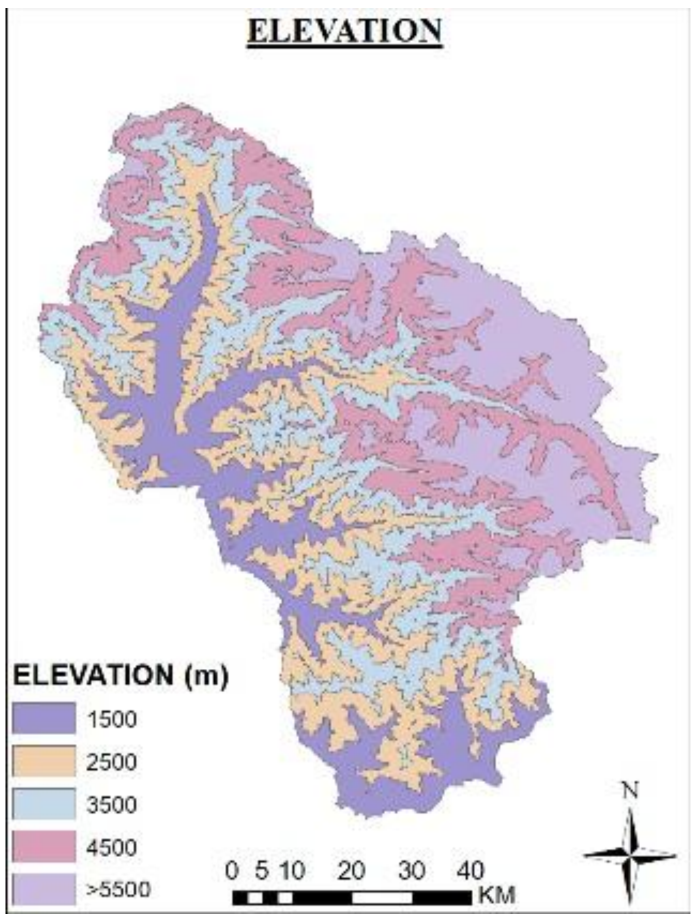

Figure 7.5 :ELEVATION

7.6 LITHOLOGY

The lithology shapefile, acquired from the USGS, contained four lithological units, each having distinct structure, strength, plasticity potential, and composition. The influence of each of these lithostratigraphic units on slope instability was therefore evaluated for deeper insight into their relationship to previous landslide occurrences. The lithology map was finally prepared after a process of extraction, rasterization, and resampling into 10 m cell resolution.

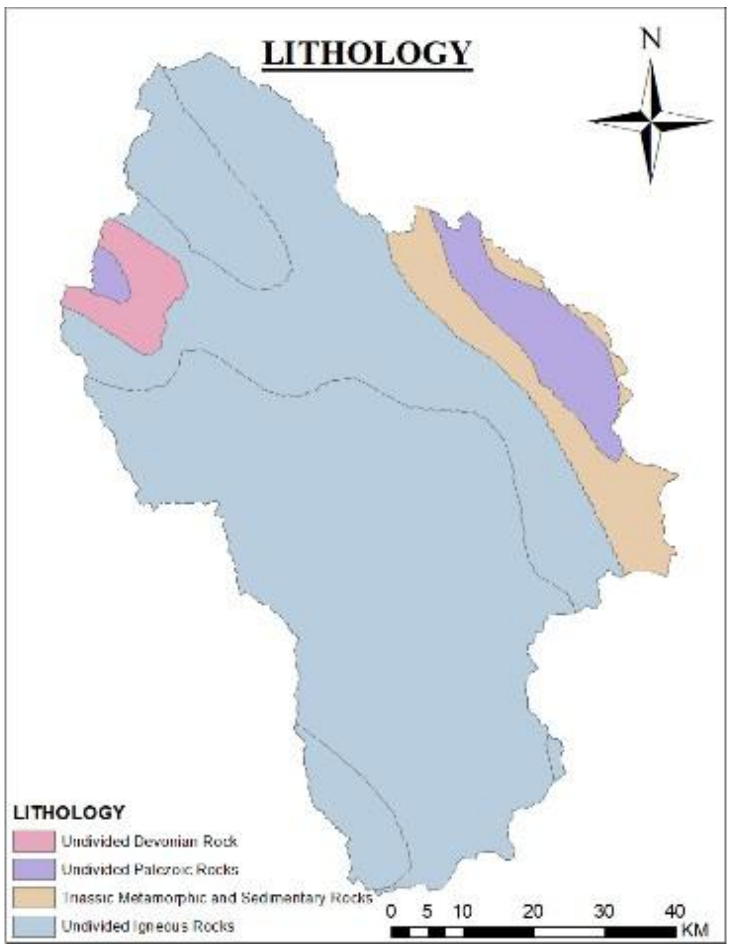

Figure 7.6: LITHOLOGY

7.7 HILLSHADE

Hillshade, an important parameter for terrain analysis, was classified into five categories based on illumination intensity: **Low Illumination**, **Moderate Low Illumination**, **Moderate Illumination**, **High Illumination**, and **Very High Illumination**.

These classes represent variations in sunlight exposure, with low illumination corresponding to shadowed, north-facing slopes that retain more moisture and may be more prone to instability, while high illumination areas are typically well-exposed, drier, and more stable. The classification aids in providing critical insights for topographical and geomorphological studies.

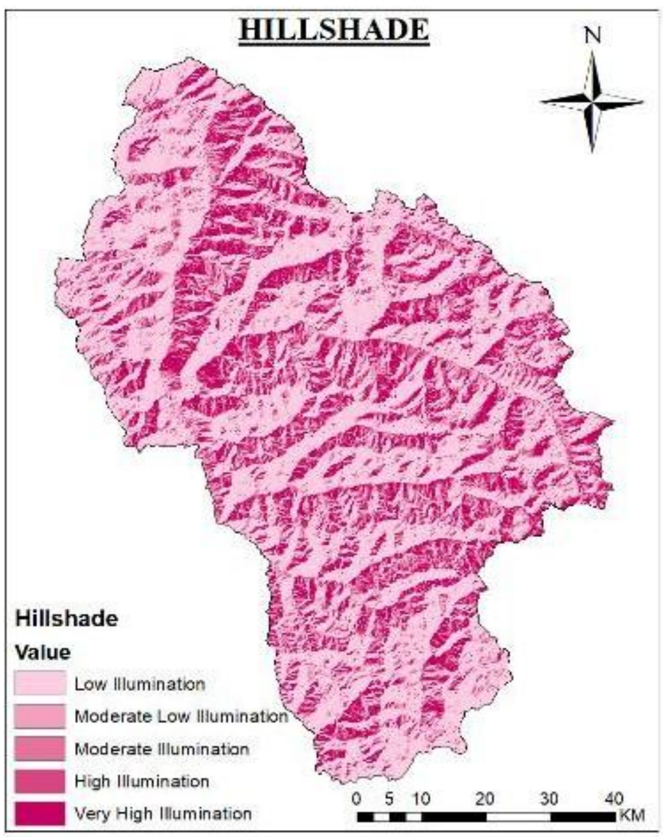

Figure 7.7: HILLSHADE

7.8 CONTOUR

Contours, essential for understanding topographical variation, were classified into five elevation categories: **800.00–1600.00 m, 1600.01–2800.00 m, 2800.01–4000.00 m, 4000.01–4800.00 m, and 4800.01–6400.00 m.** These categories represent altitudinal differences, with lower elevations often associated with river valleys, agricultural activities, and human settlements, while higher elevations correspond to rugged terrain, alpine ecosystems, and potential snow-covered regions.

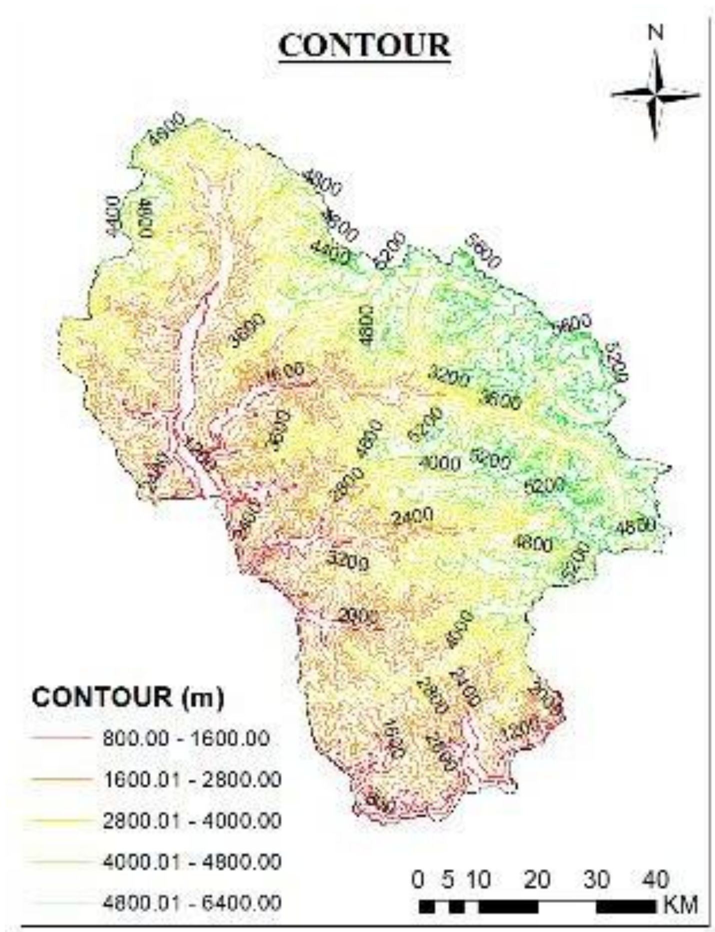

Figure7.8 : CONTOUR

7.9 TOPOGRAPHIC WETNESS INDEX (TWI)

The Topographic Wetness Index (TWI) is a crucial factor in assessing slope stability, as it measures the potential for water accumulation in a given area. TWI is influenced by both the local slope and upstream contributing areas, representing the tendency of soil to become saturated. Higher TWI values indicate areas where water is likely to accumulate, which in turn increases the potential for landslides due to reduced soil strength.

A classification scheme was applied in the GIS platform, creating several TWI categories that represent different levels of soil moisture saturation. These categories help in understanding the variation of landslide susceptibility across the region.

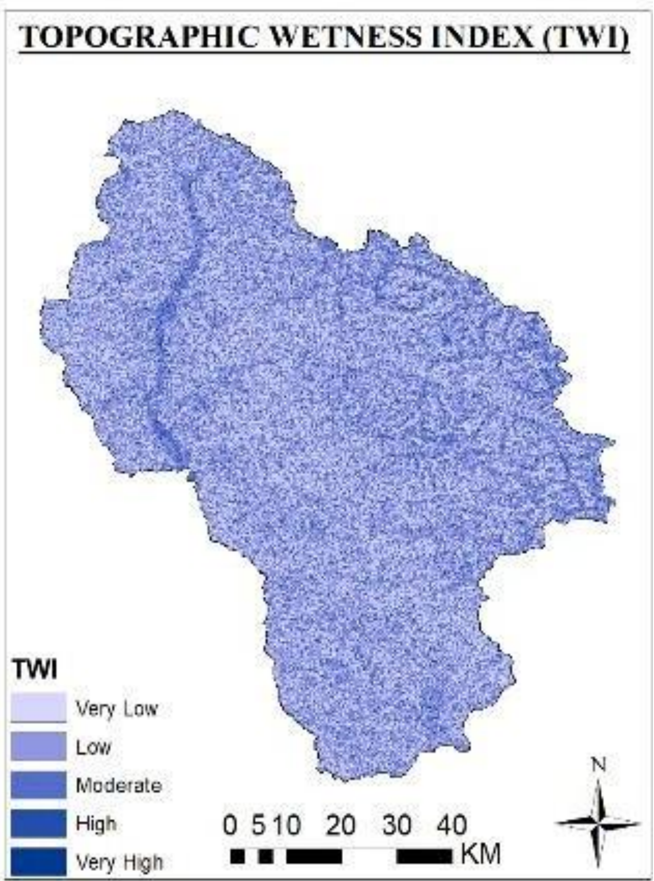

Figure 7.9: TWI

7.10 ROUGHNESS

Roughness is a critical topographic factor that influences the stability of slopes and the occurrence of landslides. It measures the irregularity and variability of the terrain surface, with higher roughness values indicating more rugged and uneven terrain. In mountainous regions like Kullu, roughness plays a significant role in determining how rainfall, vegetation, and soil interact with the slope surface.

For this study, roughness was calculated using Digital Elevation Model (DEM) data within a GIS platform. Areas with higher terrain roughness tend to experience more slope instability due to the uneven distribution of surface water runoff and soil mass movement.

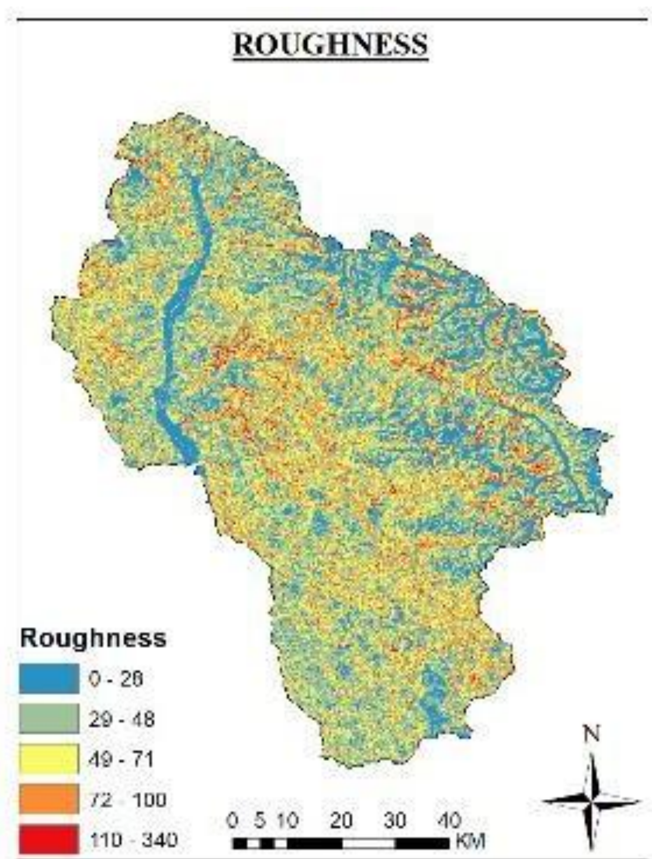

Figure 7.10: ROUGHNESS

CHAPTER 8

EMPIRICAL TECHNIQUE

8.1 Introduction

Frequency Ratio is an empirical technique used to assess the relationship between landslide occurrences and conditioning factors.

It calculates the likelihood of landslide occurrence based on the distribution of each factor class.

8.2 Formula

FR = (Landslide Pixels in Factor Class / Total Landslide Pixels) ÷ (Total Pixels in Factor Class / Total Pixels in Study Area)

The resulting ratio represents the correlation strength between the factor class and landslide occurrence.

$$FR = \left(\frac{P_L}{\sum_{i=1}^{n} P_L}\right) / \left(\frac{P_C}{\sum_{i=1}^{n} P_C}\right) \tag{8.1}$$

where P_L = Landslide pixels contained in a factor class, P_C= Pixels of a factor class.

Categorize landslide conditioning factors (e.g., slope, aspect, elevation) into classes. Calculate the FR value for each class of the conditioning factors. Assign weights to the classes based on FR values.

8.3 Outcome

Generates weighted maps for each conditioning factor. Helps in creating a combined **landslide susceptibility map** by summing up weighted factors.

8.4 Application

Due to its data-driven approach, the Frequency Ratio (FR) method is widely used in landslide susceptibility mapping. It evaluates the relationship between past landslide occurrences and Landslide Conditioning Factors (LCFs) by calculating the probability of landslide presence within different factor classes. This method helps quantify each factor's contribution and assigns weights accordingly.

FR is commonly applied in geospatial analysis using GIS tools to generate landslide susceptibility maps. The method enables accurate zoning of landslide-prone areas by integrating historical landslide data with environmental and topographical parameters. These susceptibility maps assist in disaster preparedness, infrastructure planning, and risk assessment, helping policymakers make informed decisions for mitigation strategies.

8.5 Advantages of Frequency Ratio

One of the key advantages of the Frequency Ratio method is its simplicity and efficiency in analyzing landslide susceptibility. Since it is based on historical data, it provides objective and quantifiable results without relying on subjective expert opinions. Additionally, it is easy to implement using GIS software, making it a preferred choice for regional-scale susceptibility assessments.

Another significant advantage is its flexibility, which can be applied to various terrains and environmental conditions. The method also allows for comparative analysis with other models, helping researchers and planners evaluate the effectiveness of different susceptibility assessment techniques. Furthermore, the statistical nature of FR improves accuracy, ensuring reliable hazard predictions in landslide-prone regions.

TABLE 8.1: FREQUENCY RATIO CALCULATION

Parameter	**Classes**	**Class Pixels**	**% Class Pixels**	**Landslide Pixels**	**% Landslide Pixels**	**FR**	**RF**	**RF (non%)**	**RF (INT)**	**Min RF**	**Max RF**	**Max-Min RF**	**(Max-Min) Min RF**	**PR**
Slope	1	647471	9.568	3680.639941	11.261	1.1769	0.16959	16.9593	16					
	2	964952	14.260	5663.519909	17.328	1.2151	0.17510	17.5100	17					
	3	1301951	19.240	6894.71989	21.094	1.0964	0.15799	15.7989	15					
	4	1417203	20.944	6803.999891	20.817	0.9939	0.14323	14.3231	14					
	5	1252030	18.503	4821.119923	14.750	0.7972	0.11488	11.4879	11					
	6	839960	12.413	3499.199944	10.706	0.8625	0.12428	12.4284	12					
	7	343165	5.071	1321.919979	4.044	0.7975	0.11492	11.4923	11					
		6766732		32685.12		6.9394				0.11488	0.17510	0.06022	0.00692	**8.70**
Distance From Stream	1	889849	13.124	14359.67977	43.916	3.3461	0.55315	55.3149	55					
	2	837689	12.355	3784.319939	11.574	0.9367	0.15485	15.4853	15					
	3	815942	12.034	2838.239955	8.680	0.7213	0.11923	11.9235	11					
	4	798463	11.777	1697.759973	5.192	0.4409	0.07288	7.2884	7					
	5	3438134	50.709	10018.07984	30.638	0.6042	0.09988	9.9879	9					

		6780077		32698.08		6.0492				0.09988	0.55315	0.45327	0.04527	**10.01**
	1	2366120	34.967	9447.839849	28.917	0.827	0.11921	11.9213	11					
	2	2594022	38.335	13504.31978	41.333	1.078	0.15543	15.5427	15					
	3	1284051	18.976	6324.479899	19.357	1.020	0.14705	14.7052	14					
	4	426583	6.304	1982.879968	6.069	0.963	0.13878	13.8778	13					
Topographic Wetness Index	5	95956	1.418	1412.639977	4.324	3.049	0.43953	43.9529	43					
		6766732		32672.15948		6.937				0.11921	0.43953	0.32032	0.03819	**8.39**
	1	1296996	19.129	6985.439888	21.372	1.117	0.21087	21.0866	21					
	2	2095440	30.906	12000.95981	36.717	1.188	0.22423	22.4230	22					
	3	1764161	26.020	7270.559884	22.244	0.855	0.16135	16.1355	16					
	4	1075089	15.856	4250.879932	13.006	0.820	0.15481	15.4806	15					
	5	447110	6.594	1982.879968	6.067	0.920	0.17363	17.3634	17					
Roughness	6	101333	1.495	194.3999969	0.595	0.398	0.07511	7.5110	7					
		6780129		32685.12		5.298				0.07511	0.22423	0.14912	0.01120	**13.31**

	1	3861905	57.119	19090.08	58.383	1.022	0.20729	20.7292	20					
	2	456610	6.753	1516.32	4.637	0.687	0.13926	13.9259	13					
	4	500197	7.398	2643.84	8.086	1.093	0.22165	22.1652	22					
	6	607601	8.987	3589.92	10.979	1.222	0.24777	24.7767	24					
Hillshade	7	1334849	19.743	5857.92	17.915	0.907	0.18403	18.4030	18					
		6761162		32698.08		4.931				0.13926	0.24777	0.10851	0.01511	**7.18**
	1	106375	1.569	194.40	0.595	0.379	0.02995	2.9951	2					
	2	223904	3.302	2462.40	7.531	2.280	0.18024	18.0238	18					
	3	206797	3.050	4250.88	13.000	4.262	0.33689	33.6887	33					
	4	345180	5.091	4626.72	14.150	2.779	0.21967	21.9673	21					
	5	1256230	18.528	4911.84	15.022	0.811	0.06408	6.4080	6					
	6	1302007	19.203	3499.20	10.702	0.557	0.04405	4.4046	4					
	7	1667651	24.596	4821.12	14.744	0.599	0.04738	4.7380	4					
Elevation	8	1671985	24.660	7931.52	24.257	0.984	0.07775	7.7745	7					
		6780129		32698.08		12.652				0.02995	0.33689	0.30694	0.00919	**33.39**

	1	698080	10.316	2838.24	8.680	0.841	0.09307	9.3069	9					
	2	655031	9.680	3123.36	9.552	0.987	0.10915	10.9149	10					
	3	619183	9.150	3019.68	9.235	1.009	0.11164	11.1635	11					
	4	786613	11.625	4250.88	13.000	1.118	0.12370	12.3702	12					
	5	857871	12.678	4160.16	12.723	1.004	0.11101	11.1006	11					
	6	881251	13.023	4341.60	13.278	1.020	0.11277	11.2774	11					
	7	737241	10.895	4445.28	13.595	1.248	0.13802	13.8022	13					
	8	716266	10.585	4536.00	13.872	1.311	0.14496	14.4963	14					
Aspect	9	815196	12.047	1982.88	6.064	0.503	0.05568	5.5679	5					
		6766732		32698.08		9.041				0.05568	0.14496	0.08928	0.00497	**17.96**
	1	1501061	22.139	7374.24	22.553	1.019	0.34935	34.9348	34					
	2	3790293	55.903	19271.52	58.938	1.054	0.36156	36.1562	36					
Curvature	3	1488775	21.958	6052.32	18.510	0.843	0.28909	28.9090	28					
		6780129		32698.08		2.916				0.28909	0.36156	0.07247	0.02095	**3.46**
	1	3861905	57.119	19090.08	58.3829	1.022	0.20729	20.7292	20					
Contour	2	456610	6.753	1516.32	4.6373	0.687	0.13926	13.9259	13					

	3	500197	7.398	2643.84	8.0856	1.093	0.22165	22.1652	22					
	4	607601	8.987	3589.92	10.9790	1.222	0.24777	24.7767	24					
	5	1334849	19.743	5857.92	17.9152	0.907	0.18403	18.4030	18					
		6761162		32698.08		4.931				0.13926	0.24777	0.10851	0.01511	**7.18**
	0	1873815	27.637	10018.08	30.6381	1.109	0.21531	21.5312	21					
	1	502077	7.405	0.00	0.0000	0.000	0.00000	0.0000	0					
	2	408960	6.032	2734.56	8.3631	1.386	0.26929	26.9289	26					
	3	631	0.009	0.00	0.0000	0.000	0.00000	0.0000	0					
	4	358169	5.283	0.00	0.0000	0.000	0.00000	0.0000	0					
	5	3198499	47.175	18519.84	56.6389	1.201	0.23319	23.3186	23					
	6	196269	2.895	194.40	0.5945	0.205	0.03989	3.9889	3					
	7	37035	0.546	0.00	0.0000	0.000	0.00000	0.0000	0					
Lithology	8	204618	3.018	1231.20	3.7654	1.248	0.24232	24.2324	24					
		6780073		32698.08		5.149				0.03988924995	0.26929	0.22940	0.00915	**25.07**

CHAPTER 9

STATISTICAL TECHNIQUE

9.1 Introduction

Shannon Entropy is a statistical approach used in landslide susceptibility mapping to measure the uncertainty in data distribution. It helps determine the significance of Landslide Conditioning Factors (LCFs) by analyzing their probability and contribution to landslide occurrences. Factors with higher entropy values indicate more randomness, while those with lower entropy strongly influence landslide susceptibility.

This method assigns weights to each LCF by calculating entropy and information gain, ensuring an objective and data-driven assessment. The weighted factors are then combined to generate a landslide susceptibility map, improving the accuracy of hazard prediction and reducing biases in factor selection.

9.2 Formula

$$P_{ij} = \%\ \text{landslide pixels} / \%\ \text{class pix} \qquad (9.1)$$

Where Pij from Eq. (9.1) represents the frequency ratio values, and (Pij) from Eq. (9.2) gives the probability density value of each class.

$$(P_{ij}) = P_{ij} / \Sigma_{j=1}^{n_j} P_{ij} \qquad (9.2)$$

Hj and Hjmax from Eqs. (3) and (4) denote the entropy values for each class, whereas nj is the number of classes in each factor.

$$H_j = \Sigma_{i=1}^{n_j} (P_{ij}) \log_2(P_{ij}) \quad (9.3)$$

$$H_{j\max} = \log_2(n_j) \qquad (9.4)$$

The information coefficient, Iij, and the final weight index, Wj, were evaluated using

Eqs. (5) and (6), respectively.

$$Iij = (Hjmax - Hj) / Hjmax \quad (9.5)$$

$$Wj = Iij \times Pj \quad (9.6)$$

9.3 Outcome of Shannon Entropy

The Shannon Entropy method provides a quantitative and objective landslide susceptibility assessment by measuring the uncertainty and significance of Landslide Conditioning Factors (LCFs). By analyzing the probability distribution of landslide occurrences, it assigns weights based on information gain, ensuring an accurate and data-driven susceptibility map.

The final landslide susceptibility map categorizes the study area into different risk zones, helping identify regions with high landslide potential. This approach enhances predictive accuracy, reduces bias in factor selection, and supports effective disaster management, risk assessment, and land-use planning.

9.4 Application in Landslide Susceptibility Mapping

Shannon Entropy plays a crucial role in landslide susceptibility mapping by evaluating the importance of each Landslide Conditioning Factor (LCF). By analyzing the probability distribution of landslide occurrences, it helps in assigning appropriate weights to different factors based on their contribution to landslide susceptibility.

This ensures a more data-driven and objective approach, leading to more accurate susceptibility predictions and improved hazard assessment.

9.5 Advantages

One of the main advantages of Shannon Entropy is its objective approach to factor weighting, which reduces subjective biases in susceptibility assessment. It also considers the information content of each factor, ensuring that influential factors are appropriately weighted.

Additionally, this method can be integrated with other statistical and machine learning techniques, further enhancing the accuracy and reliability of landslide susceptibility

TABLE 9.1: SHANNON ENTROPY CALCULATION

Parameter	**Classes**	**Class Pixels**	**% Class Pixels**	**Landslide Pixels**	**% Landslide Pixels**	**FR**	**Shannon Entropy**			
							Pij	**Ej**	**1-Ej**	**Wj (Percentage)**
	1	647471	9.568	3680.64	11.261	1.1769	0.1696	-0.1307		
	2	964952	14.260	5663.52	17.328	1.2151	0.1751	-0.1325		
	3	1301951	19.240	6894.72	21.094	1.0964	0.1580	-0.1266		
	4	1417203	20.944	6804.00	20.817	0.9939	0.1432	-0.1209		
	5	1252030	18.503	4821.12	14.750	0.7972	0.1149	-0.1080		
	6	839960	12.413	3499.20	10.706	0.8625	0.1243	-0.1125		
Slope	7	343165	5.071	1321.92	4.044	0.7975	0.1149	-0.1080	0.161	**0.054**
Total		6766732		32685.12		6.9394		-0.8392		
	1	889849	13.124	14359.68	43.916	3.3461	0.5531	-0.1422		
	2	837689	12.355	3784.32	11.574	0.9367	0.1549	-0.1254		
Distance From Stream	3	815942	12.034	2838.24	8.680	0.7213	0.1192	-0.1101	0.439	**0.147**

	4	798463	11.777	1697.76	5.192	0.4409	0.0729	-0.0829		
	5	3438134	50.709	10018.08	30.638	0.6042	0.0999	-0.0999		
Total		6780077		32698.08		6.0492		-0.5606		
	1	2366120	34.967	9447.84	28.917	0.827	0.1192	-0.1101		
	2	2594022	38.335	13504.32	41.333	1.078	0.1554	-0.1257		
	3	1284051	18.976	6324.48	19.357	1.020	0.1471	-0.1224		
	4	426583	6.304	1982.88	6.069	0.963	0.1388	-0.1190		
Topographic Wetness Index	5	95956	1.418	1412.64	4.324	3.049	0.4395	-0.1569	0.366	**0.122**
Total		6766732		32672.16		6.937		-0.6341		
	1	1296996	19.129	6985.44	21.372	1.117	0.2109	-0.1425		
	2	2095440	30.906	12000.96	36.717	1.188	0.2242	-0.1456		
	3	1764161	26.020	7270.56	22.244	0.855	0.1614	-0.1278		
Roughness	4	1075089	15.856	4250.88	13.006	0.820	0.1548	-0.1254	0.242	**0.081**

	5	447110	6.594	1982.88	6.067	0.920	0.1736	-0.1320		
	6	101333	1.495	194.40	0.595	0.398	0.0751	-0.0844		
Total		6780129		32685.12		5.298		-0.7579		
	1	3861905	57.119	19090.08	58.383	1.022	0.2073	-0.1417		
	2	456610	6.753	1516.32	4.637	0.687	0.1393	-0.1192		
	4	500197	7.398	2643.84	8.086	1.093	0.2217	-0.1450		
	6	607601	8.987	3589.92	10.979	1.222	0.2478	-0.1501		
Hillshade	7	1334849	19.743	5857.92	17.915	0.907	0.1840	-0.1353	0.309	**0.103**
Total		6761162		32698.08		4.931		-0.6913		
	1	106375	1.569	194.40	0.595	0.379	0.0300	-0.0456		
	2	223904	3.302	2462.40	7.531	2.280	0.1802	-0.1341		
	3	206797	3.050	4250.88	13.000	4.262	0.3369	-0.1592		
Elevation	4	345180	5.091	4626.72	14.150	2.779	0.2197	-0.1446	0.231	**0.077**

	5	1256230	18.528	4911.84	15.022	0.811	0.0641	-0.0765		
	6	1302007	19.203	3499.20	10.702	0.557	0.0440	-0.0597		
	7	1667651	24.596	4821.12	14.744	0.599	0.0474	-0.0628		
	8	1671985	24.660	7931.52	24.257	0.984	0.0777	-0.0862		
Total		6780129		32698.08		12.652		-0.7687		
	1	698080	10.316	2838.24	8.680	0.841	0.0931	-0.0960		
	2	655031	9.680	3123.36	9.552	0.987	0.1091	-0.1050		
	3	619183	9.150	3019.68	9.235	1.009	0.1116	-0.1063		
	4	786613	11.625	4250.88	13.000	1.118	0.1237	-0.1123		
	5	857871	12.678	4160.16	12.723	1.004	0.1110	-0.1060		
	6	881251	13.023	4341.60	13.278	1.020	0.1128	-0.1069		
	7	737241	10.895	4445.28	13.595	1.248	0.1380	-0.1187		
Aspect	8	716266	10.585	4536.00	13.872	1.311	0.1450	-0.1216	0.0575	**0.019**

	9	815196	12.047	1982.88	6.064	0.503	0.0557	-0.0698		
Total		6766732		32698.08		9.041		-0.9425		
	1	1501061	22.139	7374.24	22.553	1.019	0.3493	-0.1596		
	2	3790293	55.903	19271.52	58.938	1.054	0.3616	-0.1597		
Curvature	3	1488775	21.958	6052.32	18.510	0.843	0.2891	-0.1558	0.5249	**0.176**
Total		6780129		32698.08		2.916		-0.4751		
	1	3861905	57.119	19090.08	58.3829	1.022	0.2073	-0.1417		
	2	456610	6.753	1516.32	4.6373	0.687	0.1393	-0.1192		
	3	500197	7.398	2643.84	8.0856	1.093	0.2217	-0.1450		
	4	607601	8.987	3589.92	10.9790	1.222	0.2478	-0.1501		
Contour	5	1334849	19.743	5857.92	17.9152	0.907	0.1840	-0.1353	0.3087	**0.103**
Total		6761162		32698.08		4.931		-0.6913		
Lithology	0	1873815	27.637	10018.08	30.6381	1.109	0.2153	-0.1436	0.3505	**0.117**

	1	502077	7.405	0.00	0.0000	0.000	0.0000	0.0000		
	2	408960	6.032	2734.56	8.3631	1.386	0.2693	-0.1534		
	3	631	0.009	0.00	0.0000	0.000	0.0000	0.0000		
	4	358169	5.283	0.00	0.0000	0.000	0.0000	0.0000		
	5	3198499	47.175	18519.84	56.6389	1.201	0.2332	-0.1474		
	6	196269	2.895	194.40	0.5945	0.205	0.0399	-0.0558		
	7	37035	0.546	0.00	0.0000	0.000	0.0000	0.0000		
	8	204618	3.018	1231.20	3.7654	1.248	0.2423	-0.1492		
Total		6780073		32698.08		5.149		-0.6495		

CHAPTER 10

ANALYTICAL TECHNIQUE

10.1 Introduction

The Analytical Hierarchy Process (AHP) is a multi-criteria decision-making method used in landslide susceptibility mapping to assign relative weights to Landslide Conditioning Factors (LCFs). It is based on expert judgment and pairwise comparisons, ensuring a structured evaluation of factor importance.

AHP calculates weights through a comparison matrix, ranking factors based on their influence on landslides. A Consistency Ratio (CR) is used to validate the reliability of judgments. This method effectively incorporates expert knowledge but may introduce subjectivity compared to data-driven statistical approaches.

10.2 Formula

AHP calculates weights through pairwise comparisons, forming a judgment matrix. The weight (W) of each factor is determined using the eigenvector method:

$$AW = \lambda_{max} W \tag{10.1}$$

Where:

A is the pairwise comparison matrix

W is the weight vector

λ_{max} is the maximum eigenvalue

The Consistency Ratio (CR) ensures the reliability of judgments and is computed as follows:

$$CR = CI / RI \tag{10.2}$$

where:

$CI = (\lambda_{max} - n) / (n - 1)$ (Consistency Index)

RI is the Random Index for a given matrix size n is the number of factors

A CR value ≤ 0.1 indicates an acceptable level of consistency.

10.3 Outcome

The Analytical Hierarchy Process (AHP) generates a weighted landslide susceptibility map, categorizing areas into different risk zones based on factor importance. Incorporating expert judgment ensures a systematic prioritization of Landslide Conditioning Factors (LCFs), allowing for a more structured evaluation. This method aids in identifying high-risk areas, enabling authorities to implement effective landslide mitigation strategies and make informed decisions for disaster management.

10.4 Application

The Analytical Hierarchy Process (AHP) is widely used in landslide susceptibility mapping to assign relative importance to Landslide Conditioning Factors (LCFs). Using pairwise comparisons and expert judgment, AHP systematically ranks factors such as slope, elevation, lithology, and distance from streams based on their influence on landslides.

AHP is applied in geospatial analysis using GIS tools to generate weighted susceptibility maps. These maps help in risk assessment, infrastructure planning, and disaster mitigation by identifying high-risk zones. Additionally, AHP can be integrated with other statistical and machine learning models to enhance prediction accuracy and improve landslide hazard assessment in complex terrains.

10.5 Advantages

One of the key advantages of the Frequency Ratio method is its simplicity and efficiency in analyzing landslide susceptibility. Since it is based on historical data, it provides objective and quantifiable results without relying on subjective expert opinions.

Another major advantage is its flexibility, which can be applied to various terrains and environmental conditions. The method also allows for comparative analysis with other models, helping researchers and planners evaluate the effectiveness of different susceptibility assessment techniques.

TABLE 10.1 AHP MATRIX

Factors	Slope	Aspect	Curvature	Hillshade	Roughness	Contour	Elevation	TWI	Distance from Stream	Lithology
Slope	1	3	2	4	2	3	0.5	0.5	2	0.33
Aspect	0.33	1	0.5	2	0.5	1	0.33	0.33	0.5	0.25
Curvature	0.5	2	1	3	1	2	0.5	0.5	1	0.33
Hillshade	0.25	0.5	0.33	1	0.33	0.5	0.25	0.25	0.33	0.2
Roughness	0.5	2	1	3	1	2	0.5	0.5	1	0.33
Contour	0.33	1	0.5	2	0.5	1	0.33	0.33	0.5	0.25
Elevation	2	3	2	4	2	3	1	1	2	0.5
TWI	2	3	2	4	2	3	1	1	2	0.5
Distance from stream	0.5	2	1	3	1	2	0.5	0.5	1	0.33
Lithology	3	4	3	5	3	4	2	2	3	1
SUM	10.41	21.5	13.33	31	13.33	21.5	6.91	6.91	13.33	4.02

TABLE: 10.2 CI VALUES

Factors	Slope	Aspect	Curvature	Hillshade	Roughness	Contour	Elevation	TWI	Distance from stream	Lithology	Average	Lemda	CI	RCI	CR
Slope	0.10	0.14	0.15	0.13	0.15	0.14	0.07	0.07	0.15	0.08	**0.12**	10.21	0.024	1.49	0.016
Aspect	0.03	0.05	0.04	0.06	0.04	0.05	0.05	0.05	0.04	0.06	**0.05**	10.07	0.008	1.49	0.005
Curvature	0.05	0.09	0.08	0.10	0.08	0.09	0.07	0.07	0.08	0.08	**0.08**	10.10	0.011	1.49	0.007
Hillshade	0.02	0.02	0.02	0.03	0.02	0.02	0.04	0.04	0.02	0.05	**0.03**	10.11	0.013	1.49	0.009
Roughness	0.05	0.09	0.08	0.10	0.08	0.09	0.07	0.07	0.08	0.08	**0.08**	10.10	0.011	1.49	0.007
Contour	0.03	0.05	0.04	0.06	0.04	0.05	0.05	0.05	0.04	0.06	**0.05**	10.07	0.008	1.49	0.005
Elevation	0.19	0.14	0.15	0.13	0.15	0.14	0.14	0.14	0.15	0.12	**0.15**	10.31	0.035	1.49	0.023
TWI	0.19	0.14	0.15	0.13	0.15	0.14	0.14	0.14	0.15	0.12	**0.15**	10.31	0.035	1.49	0.023
Distance From Stream	0.05	0.09	0.08	0.10	0.08	0.09	0.07	0.07	0.08	0.08	**0.08**	10.10	0.011	1.49	0.007
Lithology	0.29	0.19	0.23	0.16	0.23	0.19	0.29	0.29	0.23	0.25	**0.23**	10.30	0.033	1.49	0.022

CHAPTER 11

RESULTS

11.1 DISCUSSION

Landslide Susceptibility Maps were generated using three different methods: Frequency Ratio (FR), Shannon Entropy (SE), and Analytical Hierarchy Process (AHP). These models help in identifying landslide-prone areas by analyzing environmental factors such as slope, elevation, aspect, and lithology.

Each technique applies a unique approach to weigh the contributing factors, resulting in different susceptibility classifications.

Frequency Ratio (FR): A data-driven empirical method that calculates landslide probability based on historical landslide occurrences within different factor classes.
Shannon Entropy (SE): A statistical method that measures the randomness of factor distribution and assigns weights based on information gain.
Analytical Hierarchy Process (AHP): A structured decision-making technique that uses expert judgment and pairwise comparisons to assign relative importance to conditioning factors.

The results of this study provide a comparative analysis of three landslide susceptibility mapping techniques: Frequency Ratio (FR), Shannon Entropy (SE), and Analytical Hierarchy Process (AHP). Each model was evaluated based on its predictive accuracy and ability to classify landslide-prone areas effectively. The Frequency Ratio model achieved the highest accuracy with an AUC value of 0.738, followed closely by the Shannon Entropy model (AUC = 0.735). Both models demonstrated strong predictive capabilities, highlighting the effectiveness of data-driven and statistical approaches. In contrast, the AHP model yielded a lower AUC value of 0.635, indicating limitations in factor weighting based on expert judgment.

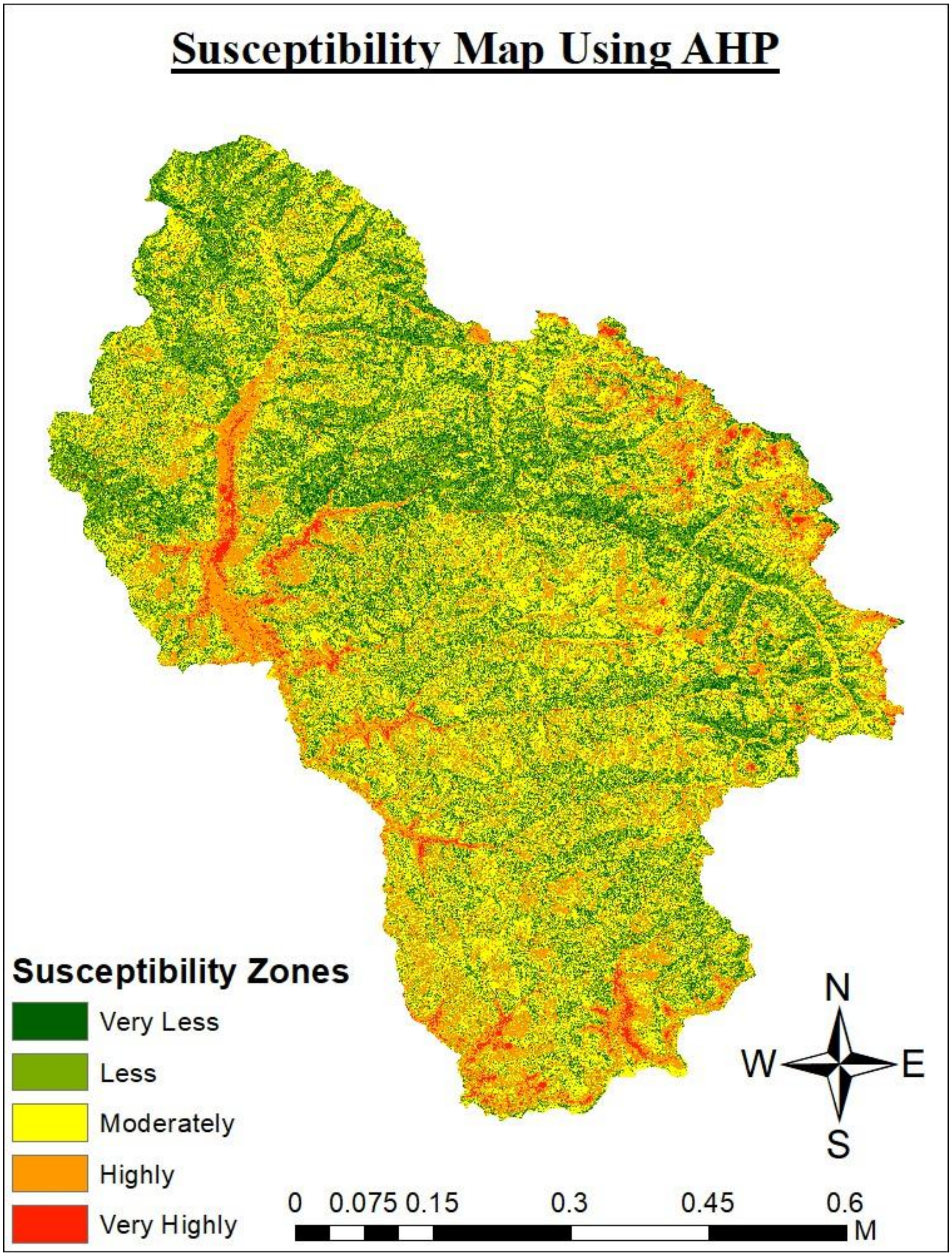

Figure 11.1 Susceptibility map using AHP

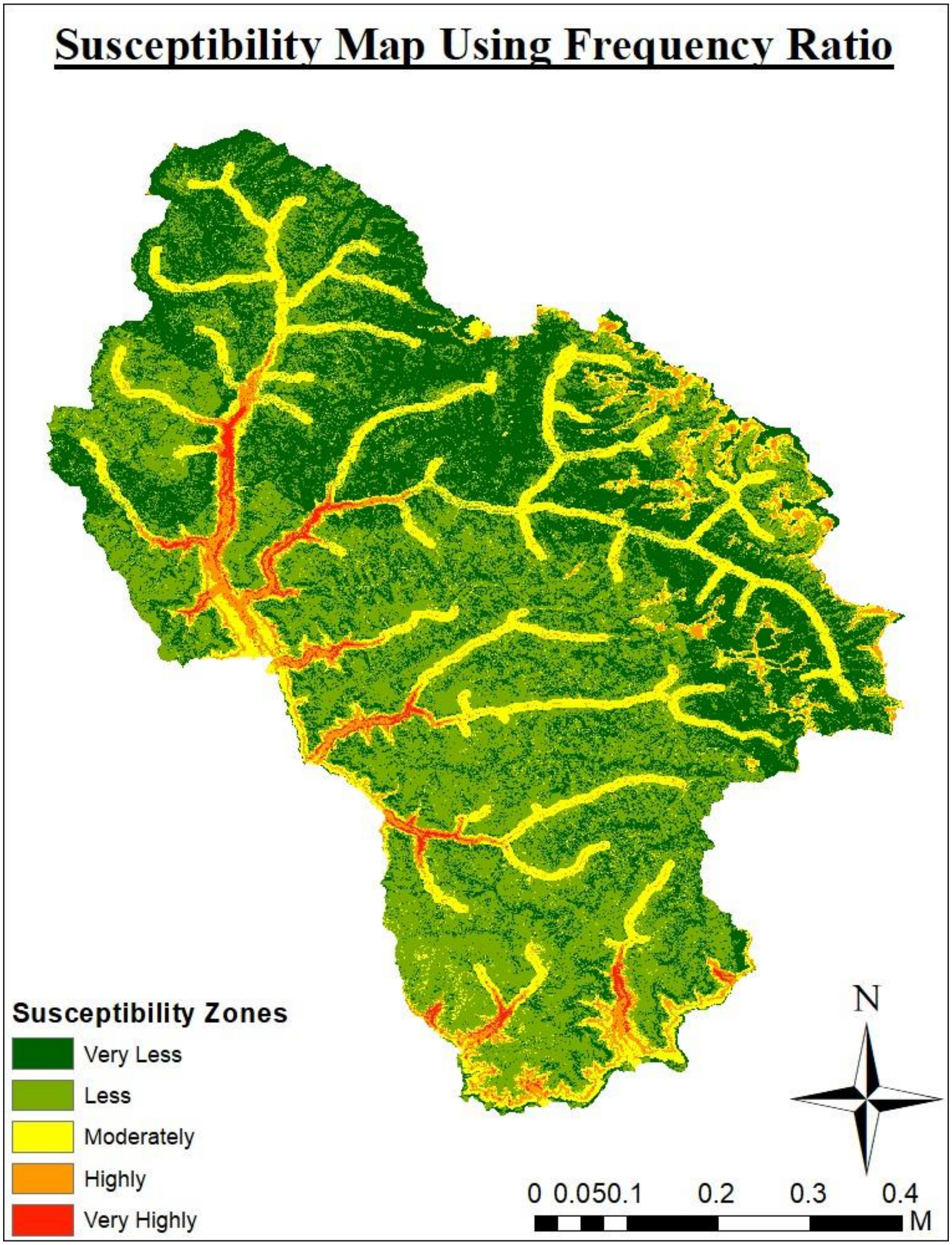

Figure 11.2 Susceptibility map using Frequency Ratio

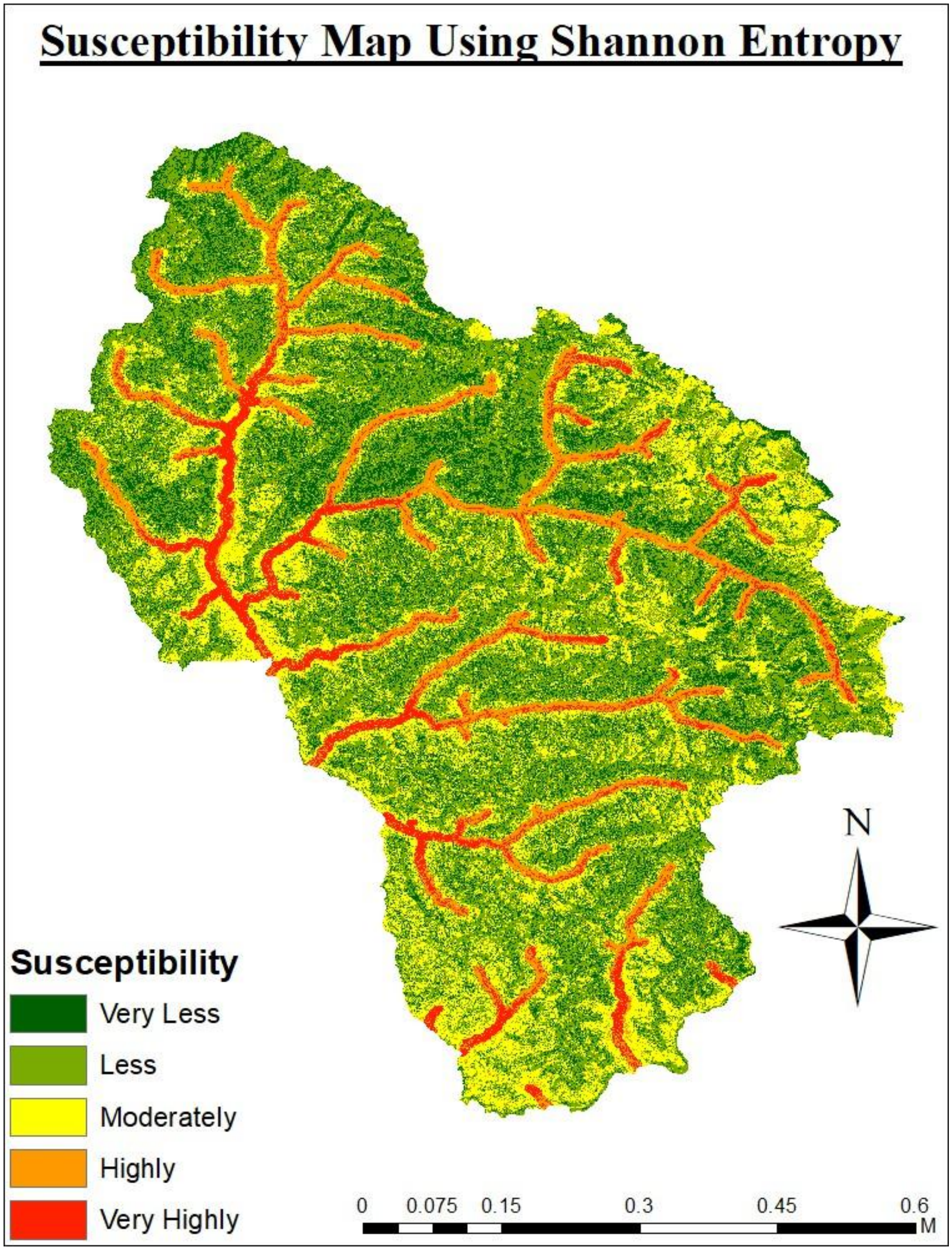

Figure 11.3 Susceptibility map using Shannon Entropy

11.2 VALIDATION

Validation is a crucial step in assessing the performance and reliability of a predictive model. It ensures that the model is effective on training data and performs well on unseen data. In landslide susceptibility mapping and other machine learning applications, validation helps in determining how accurately the model classifies areas as susceptible or non-susceptible. Various validation techniques, such as k-fold cross-validation, hold-out validation, and statistical metrics, are used to evaluate model effectiveness.

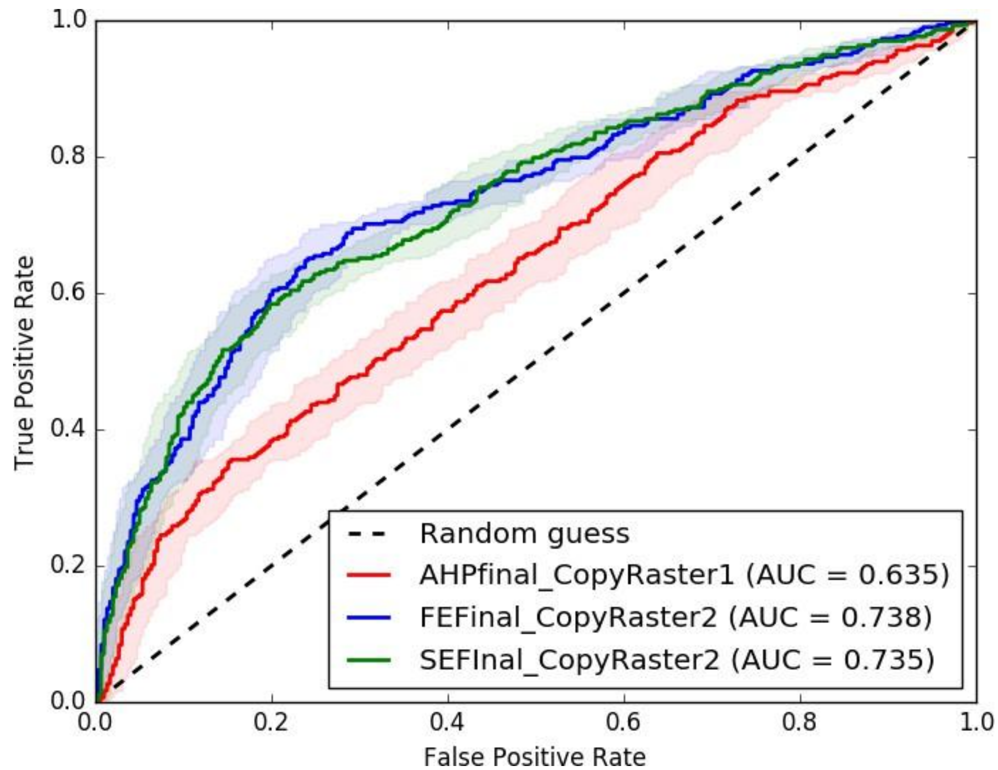

Figure 11.4 Success Rate Curve

One crucial measure of validation is the success rate curve, which assesses how well the model predicts landslide-prone areas based on the training dataset. It is generated by plotting the cumulative percentage of correctly predicted landslide areas against the total study area. A higher success rate indicates that the model effectively captures patterns in the training data and is well-calibrated for mapping susceptibility.

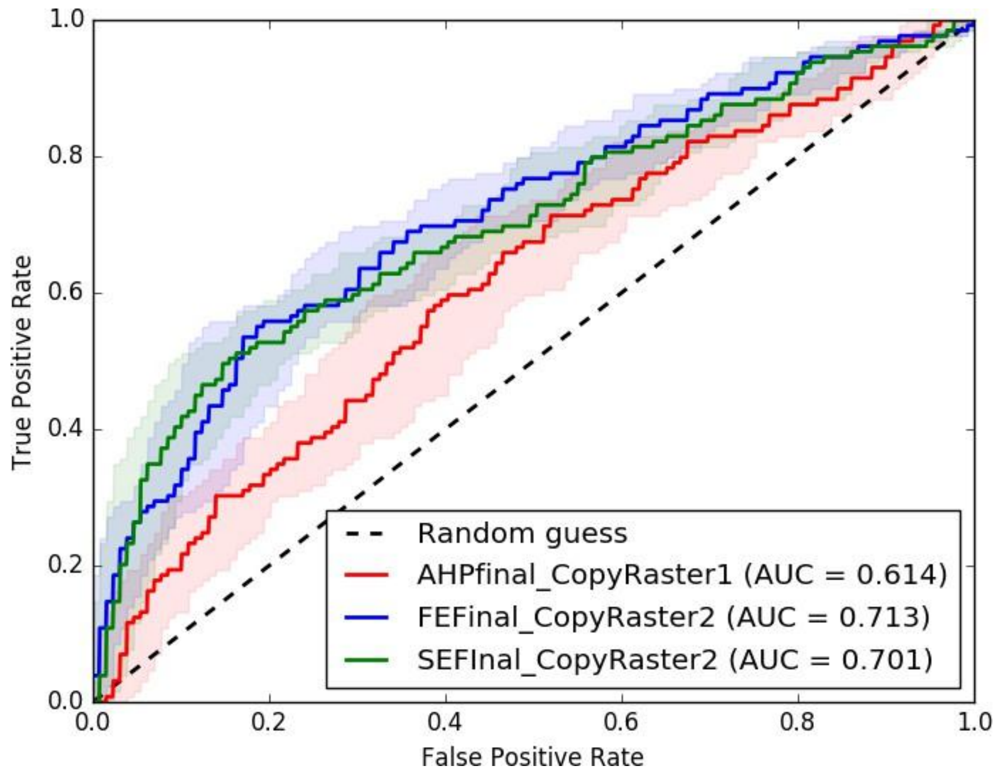

Figure 11.5 Prediction Rate Curve

Similarly, the prediction rate curve evaluates the model's ability to predict landslide occurrences on test data. It is derived from an independent dataset and helps determine how well the model generalizes beyond the training dataset. A model with a high prediction rate is considered robust and reliable for practical applications, as it indicates strong generalization capabilities.

In addition to these curves, true positives and negatives play a critical role in validation. True positives (TP) refer to areas correctly identified as landslide-prone, while true negatives (TN) indicate non-landslide areas correctly classified by the model. These values are crucial for calculating performance metrics such as accuracy, sensitivity, specificity, and the area under the curve (AUC). A well-validated model should have a high TP rate while maintaining a low false positive and false negative rate to ensure accurate susceptibility mapping.

CHAPTER 12

CONCLUSION AND FUTURE FOCUS

12.1 CONCLUSION

Landslide susceptibility mapping was conducted in the Kullu District of Himachal Pradesh using three techniques: Frequency Ratio (FR), Shannon Entropy (SE), and Analytical Hierarchy Process (AHP). The generated susceptibility maps were validated using Area Under the Curve (AUC) values, where the FR model achieved the highest predictive accuracy (AUC = 0.738), followed closely by the SE model (AUC = 0.735), indicating their strong predictive capabilities. In contrast, the AHP model exhibited lower accuracy (AUC = 0.635), suggesting limitations in factor weighting through expert judgment. To further evaluate model performance, Success Rate and Prediction Rate curves were developed, helping to assess both the model fit with training data and its predictive capability with testing data.

The results highlight that statistical-based models (FR and SE) outperform AHP in predicting landslide-prone areas, making them more reliable for hazard assessment. The generated landslide susceptibility maps play a crucial role in disaster risk management, infrastructure planning in high-risk zones, and early warning systems, supporting sustainable land-use planning. This study provides a scientific foundation for decision-making, aiding in reducing landslide-related risks in mountainous regions such as Kullu District, Himachal Pradesh.

12.2 FUTURE FOCUS

The performance comparison **of** Frequency Ratio (FR), Shannon Entropy (SE), and Analytical Hierarchy Process (AHP) has been successfully completed, showing that statistical models (FR and SE) outperform AHP in landslide susceptibility mapping. Future research can focus on integrating machine learning techniques like Random Forest, Support Vector Machines, and Deep Learning to enhance prediction accuracy.

Additionally, incorporating environmental factors such as soil moisture, vegetation index, and rainfall variability can improve model precision.

Further advancements can include hybrid model**s** combining statistical, analytical, and machine learning approaches for more reliable susceptibility mapping**.** Temporal analysis of landslides can help assess changes over time, while field validation will ensure models align with real-world conditions. These improvements will lead to more adaptive and data-driven models**,** strengthening disaster preparedness and risk mitigation strategies in landslide-prone area.

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PUBLICATIONS

1) International Conference on Geological and Environmental Sustainability

Sagar, D., Sharma, S., & Sarkar, R. A Comparative Study Of Empirical, Statistical, And Analytical Models For Landslide Susceptibility In Kullu District, Himachal Pradesh. International Conference on Geological and Environmental Sustainability (ICGES-25), 03rd-May-2025, Chandigarh, India

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03rd-May-2025 | Chandigarh, India

Acceptance Letter

Paper ID: SFE_56120

Paper Title: A Comparative Study Of Empirical, Statistical, And Analytical Models For Landslide Susceptibility In Kullu District, Himachal Pradesh

Authors Name: Dhiren Sagar, Shivakar Sharma, Raju Sarkar

Dear Author,

With heartiest congratulations I am pleased to inform you that based on the recommendations of the reviewers and the Technical Program Committees, your paper identified above has been accepted for publication and oral presentation by **International Conference on Geological and Environmental Sustainability (ICGES-25)**

This conference received number of submissions from different countries and regions, reviewed by international experts and your paper cleared all the criteria, got accepted for the conference. Your paper will be published in the conference proceeding after the registration.

For registration: https://www.sfe.net.in/conf/registration.php?id=3331560

Herewith, the conference committee sincerely invites you to come to present your paper at our conference.

Sincerely,

Dr. James Crusoe
President
Society for Education (SFE)

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CERTIFICATE

OF PRESENTATION

International Conference on Geological and Environmental Sustainability (ICGES-25)

03rd May 2025 | Chandigarh - India

This is to certify that **Dhiren Sagar** affiliated with Delhi Technological University, India has presented a paper titled A Comparative Study of Empirical, Statistical, and Analytical Models for Landslide Susceptibility in Kullu District, Himachal Pradesh at the conference organized by the Society For Education (SFE) held on 03rd May 2025 at Chandigarh - India.

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2) International Conference on Interdisciplinary Academic Research and Innovation (IARI-25)

Sagar, D., & Sarkar, R. Empirical Modelling of Landslide Susceptibility in Kullu District Using Frequency Ratio and GIS. International Conference on Interdisciplinary Academic Research and Innovation (IARI-25) 18th May 2025 Agra, India

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International Conference on Interdisciplinary Academic Research and Innovation - IARI-25

18th May 2025 | Agra

Acceptance Letter

Paper ID: SFE_62709

Paper Title: Empirical Modelling of Landslide Susceptibility in Kullu District Using Frequency Ratio and GIS Integration

Authors Name: Dhiren Sagar, Raju Sarkar

Dear Author,

With heartiest congratulations I am pleased to inform you that based on the recommendations of the reviewers and the Technical Program Committees, your paper identified above has been accepted for publication and oral presentation by **International Conference on Interdisciplinary Academic Research and Innovation - IARI-25**

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at the conference organized by the Society For Education (SFE) held on 18th May 2025 at Agra - India.

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