himachal pradesh

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND CONTEXT

The Shimla district of Himachal Pradesh is located in the heart of the Lesser Himalayas, between the latitudes **30°45'48" N** to **31°43'0" N** and longitudes **76°59'22" E** to **78°18'40" E**, and is one of the most geologically dynamic and landslide susceptible areas in India. The district has an approximate geographical size of **5,131 km^2** and has very rugged topography with highly dissected terrain, steep mountain slopes, narrow valleys and dramatic elevation gradients from **537m** in low river basins up to more than **5,576m** above mean sea level on the glaciated north-east peaks. This extreme topographic variation, combined with an active tectonic environment related to the ongoing Himalayan orogeny, complex geological structures ranging from Precambrian to Tertiary and high monsoonal precipitation, create an ideal combination of factors that make the region prone to frequent and catastrophic mass movements. The geology of Shimla district is mainly Precambrian metamorphosed rocks (phyllites, quartzites, slates and schists), with interspersed Paleozoic sedimentary sequences and Tertiary intrusive rocks. The weathering, fracturing and structural weakness of these rock types is variable and there are many thrust planes, fault lines and shear zones that have formed zones of inherent instability. Structural patterns also are complex and include the Main Central Thrust (MCT) and subsidiary thrusts that affect slope stability. When competent and incompetent rock units meet, they form lithological contacts that are prone to differential weathering, especially under tropical to temperate climate conditions, when the soft rock is weathered more rapidly than the competent rock. Metamorphic sequences may also be clay rich, which can further cause slope instability due to reduction of shear strength during moisture infiltration. The district has a transitional climate from subtropical in the lower elevation to temperate alpine in the higher elevation, with an average annual precipitation of around **1415 mm** mostly falling during the southwest monsoon season (June to September).

This heavy seasonal rainfall, sometimes in excess of 200-300 mm per storm event is the main trigger for landslide activation. Wherever weathered rock masses and soil mantles are present, pore pressure rises during periods of rainfall, which decreases the effective stresses along potential failure planes, triggering shallow debris slides to deep-seated rotational failures. With the monsoon season, there are hazard windows in the year when the precipitation is concentrated in this period, and the historical record shows that the most frequent landslides occur during the July-August period when rainfall is at its highest intensity.

1.2 LANDSLIDE VULNERABILITY AND RECENT DISASTERS

Shimla district's vulnerability to landslides has been tragically demonstrated by recent catastrophic events that have resulted in significant loss of life, extensive property damage, and disruption of critical infrastructure networks. One of the most heart-wrenching events in recent times was the devastating landslide that occurred near the Summer Hill area Shiv Temple on August 14, 2023, which resulted in the loss of 20 precious lives and destruction of several residential buildings. This catastrophic event, caused by very heavy rain (more than 100 mm in 24 hours), the unplanned urbanization and activities on slopes, showed the very important role of anthropogenic activities in landslide triggering when combined with natural hazards. The failure consisted of some 15,000 m^3 of weathered rock and soil debris that moved at speeds greater than 10 m/s, giving little warning time for evacuation. Further incidents in the 2023 monsoon season highlighted the vulnerability of the region. In Phagli area, 5 people lost their lives and 3 were severely injured due to a landslide, while in Krishna Nagar, about 5-7 houses and a slaughter house facility of the municipality collapsed due to a landslide. Total loss of life during the monsoon of 2023 in Himachal Pradesh was 51, of which Shimla district had about 27% deaths. Infrastructure damage comprised more than 100 kilometres of road infrastructure, 15 bridges, 500 hectares of agricultural lands across the district, disruption of electrical transmission lines and damage to water supply pipelines serving about 50,000 people.

The spatial distribution of landslide occurrence in Himachal Pradesh during 2023, as shown in Landslide Atlas 2023 prepared by National Remote Sensing Centre (NRSC) and the latest inventory mapping done by State Centre on Climate Change, showed Kangra district as the most affected district with 4027 landslide events followed by Mandi (2169), Solan (1930) and Chamba (1666).The Mashobra, Basantpur and Narkanda administrative blocks turned out to be extremely high-risk areas with repeated slope failures on the National Highway 5 (Chandigarh-Shimla corridor), State Highway networks and many rural link roads. The estimated economic losses of the landslide events in Shimla district in 2023 were approximately ₹450 crores (approximately USD 54 million) comprising of direct losses due to reconstruction of infrastructure, emergency response, rehabilitation of displaced populations, and indirect losses due to impact on tourism, agriculture, and business. The tourism industry, which accounts for about 35% of the district's economy, suffered significant losses, with the number of tourists dropping by 42% during the peak monsoon and post-monsoon seasons. The agricultural losses, especially in apple orchards which is the main livelihood of nearly 60% of the rural population, amounted to more than ₹80 crores as a result of the damage caused to the terraced cultivation areas, irrigation system and market access roads as a consequence of landslides.

Fig 1. Landslide event, slope failures in Shimla region

1.3 RESEARCH METHODOLOGY AND APPROACH

This study employs a comparative analytical framework evaluating landslide susceptibility of Shimla district through two established bivariate statistical models: the Information Value (IV) method and the Weight of Evidence (WoE) method. Bivariate statistical approaches analyze relationships between dependent variable (landslide occurrence/non-occurrence) and independent variables (geo-environmental conditioning factors) one factor at a time, calculating statistical measures quantifying each factor class's association with landslide presence. Unlike multivariate techniques that analyze all factors simultaneously (potentially introducing mathematical complexity and computational demands), bivariate methods offer conceptual simplicity, ease of implementation, minimal data preprocessing requirements, and readily interpretable results suitable for communication to non-specialist stakeholders.

The Information Value method, rooted in information theory principles, calculates logarithmic ratio of conditional probability (landslide occurrence given presence of specific factor class) to prior probability (overall landslide occurrence across entire study area). Positive IV values indicate factor classes where landslides are more frequent than regional average, negative values indicate protective or stabilizing classes, and magnitude of IV reflects strength of association. Factor classes with high positive IV values contribute strongly to landslide susceptibility and warrant heightened attention in risk management.

The Weight of Evidence method, developed originally for mineral prospectivity mapping before adaptation to landslide susceptibility, employs Bayesian probability framework calculating positive weights (W+) for factor class presence at landslide locations and negative weights (W-) for class absence. The contrast weight (C = W+ - W-) quantifies overall factor influence, with larger positive contrasts indicating stronger landslide association. WoE's Bayesian foundation enables rigorous statistical testing of factor independence assumptions and provides measures of prediction uncertainty, though practical applications often apply the method in exploratory rather than strictly probabilistic mode.

The predictive framework is constructed upon high-resolution spatial database comprising 12 critical conditioning factors carefully selected based on geomorphological theory, previous research in Himalayan contexts, data availability, and statistical independence considerations:

Topographic Factors: Slope angle is a measure of the gravitational driving force parallel to the slope surface, high shear stresses on steep slopes may exceed the shear strength of the material. The aspect orientation affects the receipt of solar radiation, which impacts weathering rates, vegetation establishment, soil moisture regimes, and some aspects have preferential landslide occurrenceThere is an association between elevation and climate zones, weathering intensity, vegetation types, and human activity patterns. Roughness is a measure of the irregularity of the terrain, which reflects the quality of the rock mass and the previous instability. Hillshade can be used to create illumination patterns to give context to the interpretation.

Hydrological Factors: Topographic Wetness Index (TWI) models spatial patterns of soil moisture accumulation as a function of upslope contributing area and local slope, identifying areas that are likely to be wet. Drainage density is a measure of the efficiency of surface water removal and is related to the ease of erodibility of the material or steepness of the gradient. Distance to stream is a measure of the proximity to erosional base-level, and slopes close to the stream are undercutting and losing toe support.

Geological Factor: Lithology refers to basic characteristics of the materials such as strength, permeability, weathering susceptibility, and structural characteristics; the landslide susceptibility of various rock types depends on their mineralogical composition, degree of metamorphism and fracture patterns.

Land Cover Factor: Normalized Difference Vegetation Index (NDVI) is a measure of the vigor and density of vegetation, which can be used as an indicator of the reinforcement of roots, interception of rainfall, and effects of evapotranspiration on slope hydrology. A dense cover of vegetation usually stabilizes slopes, whereas areas with little or no vegetation may be due to the inherent instability of the terrain or to previous disturbance.

Morphometric Factor: Contour density is an indication of the steepness of the slope gradient; closely spaced contours represent steep terrain that is more susceptible to gravitational instability.

The factors are derived from various data like SRTM Digital Elevation Model (DEM) that provides topographic parameters, Landsat-8 multispectral imagery used for NDVI calculation, Geological maps from Geological Survey of India (GSI) digitized and georeferenced for lithological characterization, and hydrological networks extracted through GIS analysis of DEM. Discrete statistical analysis of landslide frequency within each factor layer is possible through reclassification of each layer into 4-5 categorical classes with natural breaks, quantile or theoretically meaningful classification schemes.

A large database of 1,003 landslide occurrences was assembled by systematic integration of various data sources for training and validation of the statistical models. In 2024-2025, field reconnaissance surveys were carried out using handheld GPS receivers with a horizontal accuracy of ±3 m, and spatial coordinates, approximate dimensions, failure types and observed triggering/contributing factors were recorded. Location of pre-2024 events were obtained from the archives of Geological Survey of India, State Disaster Management Authority and published research. Additional landslide scars visible in the spectral anomalies and morphological signatures were identified by the interpretation of high resolution satellite images from the Google Earth historical imagery archive and time series of Sentinel-2 satellite images. Each location of a landslide was converted to a point feature, located at an approximate failure initiation zone (usually the crown or headscarp area) instead of the deposition area to allow spatial correlation with conditioning factors relevant to failure initiation and not runout processes.

Based on the procedure used in the literature of landslide susceptibility, the inventory was randomly split into a training set (702 landslides) and a testing set (301 landslides). This stratified random sampling is designed to achieve statistical independence of the model calibration and validation data sets and to provide representative spatial sampling throughout the study area.

An equal number of non-landslide points (702 for training, and 301 for testing) were randomly sampled from stable areas where there was no evidence of slope failure, at a minimum distance of 100 meters from landslides to avoid edge effects, and checked against the satellite imagery to ensure that they were in fact stable. This balanced sampling approach (equal landslide and non-landslide samples) ensures that there is no bias towards either the presence or absence class, and that it has sufficient statistical basis for calculating susceptibility.

The statistical models are based on an overlay analysis between the training landslide points and the factor layers to generate localized weights for each factor class, and to generate contingency tables that document the frequency of landslides in each factor class, relative to the spatial extent of each factor class. These weights are then reclassified on a quantitative basis to raster cells in the entire study area, which represents the quantitative contribution of each class to landslide susceptibility. The continuous Landslide Susceptibility Index (LSI) surfaces are then created by integrating weighted factor layers through linear combination (weighted overlay), with higher LSI values representing higher probability of landsliding. The continuous LSI values are classified into 5 discrete susceptibility categories (Very Low, Low, Moderate, High, Very High) using natural breaks classification algorithm which minimizes within-class variance and maximizes between-class differences and yields intuitive zonation appropriate for planning use.

1.4 MODEL VALIDATION AND PERFORMANCE ASSESSMENT

Multiple validation methods are used to thoroughly assess the predictive accuracy and reliability of both IV and WoE models. Primary quantitative performance metric is the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) which is a plot of the true positive rate (sensitivity: correctly predicted landslide locations) against the false positive rate over the entire range of classification thresholds. The range of AUC values is from 0.5 (random prediction) to 1.0 (perfect prediction), with the general interpretation guidelines of 0.5-0.6 (poor), 0.6-0.7 (average), 0.7-0.8 (good), 0.8-0.9 (very good), and >0.9 (excellent performance).

Validation is performed separately for training and testing sets, resulting in success rate curves (model fit to the calibration data) and prediction rate curves (model generalization to independent validation data). Success rates assess the extent to which model reproduces known landslide distribution for weight calculation, which is an indication of internal consistency and the ability of the model to capture factor-landslide relationships. Prediction rates measure the true ability to predict on unseen data, and are a more stringent and practically relevant measure of performance.

In addition to AUC metrics, the visual comparison of susceptibility maps with known landslide distribution allows the qualitative evaluation of spatial prediction patterns. The overall accuracy (correctly classified landslide and stable cells / total cells), precision (correctly predicted landslides / all predicted), recall (correctly predicted landslides / all actual landslides). Landslide inventory is tabulated by susceptibility classes, and models that are effective tend to focus most of the landslides (>70%) in the high susceptibility and very high susceptibility classes, while low and very low susceptibility classes are the ones that are most likely to have stable areas.

1.5 SIGNIFICANCE AND EXPECTED OUTCOMES

Results of this research provide very actionable lessons and applications across several areas of disaster risk management, infrastructure planning and sustainable development:

For Disaster Management Authorities: Susceptibility maps help to define a spatial framework for prioritizing monitoring installations in areas with the highest risk where early warning systems can have the greatest impact. Emergency response planning takes susceptibility data to determine population concentrations that may be vulnerable to evacuation and designate evacuation routes, identify temporary shelter sites and pre-position rescue equipment. The maps are used to develop landslide risk scenarios combining susceptibility and population density, infrastructure value and temporal rainfall patterns, which allows for cost-benefit analysis of alternative mitigation strategies.

For Infrastructure Planners and Highway Engineers: Susceptibility maps can be used for route alignment decisions on proposed highways, power transmission corridors, water supply pipelines, and telecommunication networks, and can be used to compare alternative alignments quantitatively based on cumulative risk exposure. Areas of high susceptibility, that will need detailed geotechnical investigation, can be identified at the preliminary design phase, which can help to allocate site investigation budgets efficiently. Susceptibility zones can be used to differentiate design specifications, such as increased cut slope protection, drainage provisions and foundation designs in high risk areas with cost-effective standard designs in low risk areas.

In the context of Urban and Regional Planners: Municipal development plans use susceptibility data to define areas where construction is prohibited, areas where construction is restricted and requires special approval and engineering measures, and areas where urban development is appropriate. Susceptibility-based development control regulations can be a part of master plans for hill towns, with a high density residential or critical facility use being limited in very high susceptibility zones and low intensity uses such as parks, recreational facilities or agriculture allowed. Susceptibility screening is beneficial in the early feasibility phases of industrial estate siting, institutional campus development and commercial complex planning.

For Agricultural Extension and Watershed Management Programs: Susceptibility maps are used to determine which soil conservation practices to implement; contour terracing, check dams, vegetative barriers and drainage improvements are emphasized in high-risk agricultural slopes. Advice is provided to farmers on crop selection based on the location: deep-rooted perennial crops are recommended for high susceptibility areas, while annual crops are acceptable in stable areas.. Watershed development programs incorporate susceptibility data into treatment prioritization and prioritize critical sub-watersheds with the greatest downstream benefit from slope stabilization.

For Research Community and Academic Institutions: Comparative assessment of IV and WoE methods provides methodologic inputs on merits, demerits and suitable contexts of application of bivariate statistical methods in geologically complex Himalayan terrain. The differences in performance between methods can provide guidelines for model selection in comparable environments. This research has created a comprehensive factor database and landslide inventory, providing baseline conditions for future temporal susceptibility analysis, which will allow to understand the changes in landslide patterns over time due to the dynamic factors of urbanization and climate change. The methodological approach presented here can be adapted to other districts of HP and the Himalayas with similar hazards.

1.6 RESEARCH OBJECTIVES

Specific objectives of this research are:

1. To prepare detailed landslide inventory maps for the Shimla district by integrating field surveys, archival documents and interpretation from satellite imagery, to gain a sound empirical base for statistical modeling.

2. To create high-resolution spatial database of 12 landslide conditioning factors that include topographic, hydrological, geological and land cover parameters from digital elevation models, satellite imagery and thematic maps, with appropriate classification schemes, and with data quality and spatial consistency.

3. To develop Information Value and Information Weight of Evidence bivariate statistical models, using analysis of the training dataset, to calculate quantitative weights for each conditioning factor class based on the strength and direction of the relationship between each of these and the occurrence of landslides.

4. To create continuous landslide susceptibility index surfaces by weighted overlay integration of the factor layers, providing spatially explicit probability estimates throughout the entire study area at 12.5 m spatial resolution.

5. To classify susceptibility indices in five category zonation (Very Low, Low, Moderate, High, Very High) with statistically optimal classification algorithms, which will make the results more easily understood and applicable in planning situations.

6. To validate model performance using independent testing dataset by ROC-AUC analysis, success/prediction rate curve generation and contingency matrix statistics, to provide objective measures of predictive accuracy and model reliability. 7. To compare the performance of IV and WoE methods for identifying relative strengths, weaknesses and conditions that show superiority of each method in predicting performance, providing methodological insights for future susceptibility mapping efforts.

7. To prepare cartographic quality susceptibility maps, with cartographic design, metadata documentation and interpretive guidance appropriate for dissemination to disaster management authorities, planning agencies and engineering consultancies.

8. Taking technical analysis and analysis to policy interventions to generate evidence-based recommendations for landslide risk reduction strategies, development control regulations, infrastructure planning guidelines, and priority areas for detailed investigation or monitoring.

CHAPTER 2

LITERATURE REVIEW

Majumder, S., & Fatma, R. (2024). Evaluates the susceptibility of landslides in the Shimla District of Himachal Pradesh by adopting comparative modelling technique with the help of Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) and Frequency Ratio (FR) methods. The study acknowledges the increasing incidence of mass movements in the high altitude Himalayan terrain as a result of environmental changes and climatic disturbances and uses a number of geo-environmental conditioning factors to map slope instability. The research systematically compares a knowledge-based heuristic model (Fuzzy-AHP) with a data-driven statistical model (FR) to compare the spatial relationships between historical landslide occurrences and triggering variables. The results indicate the effectiveness of the use of diverse comparative models in a GIS framework to improve prediction accuracy, and the need to provide key risk zonation data for guiding disaster mitigation and regional infrastructure planning in the Shimla area.

Sharma, V., et al. (2024). Carries out the study of landslide risk and susceptibility in Shimla district, HP using Geospatial techniques and statistical models. The study highlights the importance of the influence of changing climate and increasing anthropogenic developmental activities on triggering of mass movements. The study incorporates different geo-environmental conditioning factors such as lithology, rainfall, slope and topographic wetness index (TWI) to identify the very high-risk areas of Mashobra, Basantpur and Narkanda blocks which are of critical importance to ensure quantitative spatial mapping for infrastructure planning in the district.

Prakasam, C., et al. (2021). Performs a probabilistic assessment of the vulnerability of landslides from the National Highways of Shimla Tehsil using Weight of Evidence (WoE) model. Within 1000m buffer of the highways, 44 landslides were mapped. Preparatory factors used in the study are Land Use/Land Cover (LULC), slope, geomorphology and NDVI. The model was able to effectively classify vulnerability and showed that more than

68% of the past landslides were in the ‘high’ and ‘very high’ susceptibility classes which indicates high predictive accuracy of the WoE model in the Himalayan terrain.

Farooq, S., & Akram, M. S. (2021). Compares and contrasts various data-driven landslide susceptibility assessment techniques such as Weight of Evidence (WoE), Information Value (IV), Frequency Ratio (FR) and Certainty Factor (CF) in the Jhelum Valley of the Himalayas. The study combined a 437 point inventory of landslides with geological and hydrological data and concluded that both the WoE and IV models yielded very good predictions. The Receiver Operating Characteristic (ROC) validation showed success rates of 80% for WoE and 78% for IV, which are both considered to be good bivariate statistical methods for complex rain-induced landslide topographies.

Jiménez, J. D., et al. (2024). Compares two statistical methods for calculating landslide susceptibility (Weight of Evidence (WoE) and Information Value (IV)) for mountainous road corridors. The models were used to categorize the terrain into five susceptibility zones based on the 101-point landslide inventory, topographical and hydrological factors. The study shows that the spatial delineation of the 'very high' risk areas obtained by the Bayesian probability approach of the WoE model was slightly more refined than that obtained by the IV model, which was a simple statistical ratio reflecting landslide density, and that both models were very effective for spatial planning based on GIS.

Singh, R., et al. (2022). Carries out a study on landslide susceptibility mapping using bivariate statistical methods with GIS in Kullu District, HP. The research combined high-resolution DEM data to extract key conditioning factors such as plan curvature, profile curvature, slope aspect and distance to drains. The study confirms that statistical models based solely on the available landslide data, and not on subjective expert judgments, can help to greatly minimize the bias in predicting future landslides in the tectonically active Himalayan ranges.

Wang, Q., et al. (2020). Compares the three models of quantitative assessment of landslide susceptibility: Statistical Index (SI), Index of Entropy (IOE), and Weights of Evidence (WoE). The WoE model gave the best prediction accuracy rate of 76.05% (AUC) with an inventory of 348 landslides, which is higher than the prediction accuracy rate of both the SI and IOE models. The results show that the WoE model is very good in dealing with multi-class environmental variables, which is better for the regional-scale disaster mitigation

Batar, A. K., & Watanabe, T. (2021). Performs spatial analysis of landslide susceptibility in various quantitative methods in mountainous watersheds. The research shows how the Information Value (IV) model can be used to convert raw geographical data into weighted indices to simplify the complex geo-environmental relationships. The study finds that IV is very effective in data-poor areas, and that it can provide continuous risk indexes for terrain characteristics that can be translated to early warning systems..

CHAPTER 3
METHODOLOGY

The present study has used a multi-stage, systematic approach combining the methodologies of Geographic Information System (GIS) techniques and bivariate statistical models to evaluate landslide susceptibility in Shimla district of Himachal Pradesh. The following sequential stages of the workflow were identified**:**

Stage 1: Selection of Study Area:

The study area is Shimla district because it is very prone to landslides, has a complex geological setting and is of high socio-economic importance in the Lesser Himalayan region. The district's topography is very hilly, monsoon activity is high, and anthropogenic development is progressing rapidly, making it an ideal district for detailed susceptibility assessment.

Stage 2: Literature Review:

Existing studies on landslide susceptibility mapping were comprehensively reviewed. It was studied the peer-reviewed research done on the application of bivariate statistical methods in mountainous and Himalayan terrains, especially Information Value (IV) and Weight of Evidence (WoE). Appropriate conditioning factors and modelling techniques were selected based on this review.

Stage 3: Data Collection:

Spatial and thematic data was gathered from several reliable sources such as the Survey of India, Geological Survey of India (GSI), USGS, Open Topography. The landslide inventory was prepared using the GSI record and satellite image interpretation. To generate terrain-based conditioning factors, a Digital Elevation Model (DEM) was acquired from Open Topography.

Stage 4: GIS preparation of Landslide Conditioning Factors (LCF):

In ArcGIS, 12 landslide conditioning factors were derived and prepared, which include slope, aspect, curvature, elevation, hillshade, roughness, lithology, Topographic Wetness Index (TWI), drainage density, distance to stream, Normalized Difference Vegetation Index (NDVI), and contour. All factors were recoded into meaningful classes using natural breaks and conventional thematic classification.

Stage 5: Application of Statistical Models:

Two bivariate statistical techniques were used:

Weight of Evidence (WoE): Bayesian statistical method that assigns positive and negative weights to each class of a conditioning factor according to its presence or absence in landslide areas. Information Value (IV): A logarithmic statistical approach for quantifying the contribution of each factor class to the occurrence of landslides, based on landslide frequency ratios. The two models were then used to calculate weights and these weights were spatially overlaid in the GIS environment to produce continuous Landslide Susceptibility Index (LSI) raster surfaces.

In this stage, Landslide Susceptibility Maps are prepared. Both IV and WoE models were used to create the LSI, which was then classified into five susceptibility zones (Very Low, Low, Moderate, High, and Very High) using the Natural Breaks (Jenks) classification method. Susceptibility maps were then created for spatial interpretation.

Stage 6: Preparation of Landslide Susceptibility Maps:

In this stage, Landslide Susceptibility Maps are prepared. Both IV and WoE models were used to create the LSI, which was then classified into five susceptibility zones (Very Low, Low, Moderate, High, and Very High) using the Natural Breaks (Jenks) classification method. Susceptibility maps were then created for spatial interpretation.

Stage 7: Validation using AUC-ROC:

Both models' predictive performance was statistically evaluated with Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The Success Rate Curve was created using the training dataset (70% of inventory points) and the Prediction Rate Curve was created using the testing dataset (30% of inventory points). AUC values were used to compare the accuracy and reliability of the models.

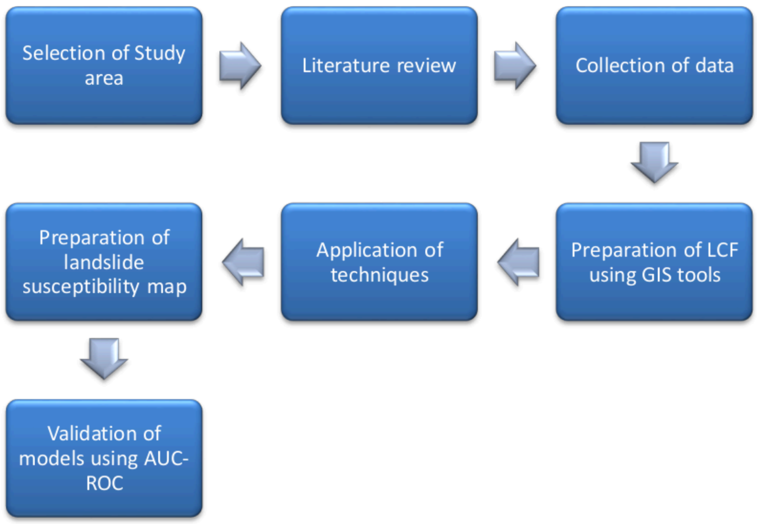

Figure 3.1 Methodology

CHAPTER 4

DATA SOURCE

TABLE 4.1 DATA SOURCE

MAP	DATA SOURCE
INDIAN MAP	https://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx
LANDSLIDE INVENTORY POINTS	https://bhukosh.gsi.gov.in/Bhukosh/Public https://svs.gsfc.nasa.gov/4710
DISTRICT AND SUB-DISTRICT MAPS	https://esriindia1.maps.arcgis.com/home/item.html?id=b89de19cafb94ea38552a55eb5b2d13d
DIGITAL ELEVATION MODEL	https://portal.opentopography.org/datasets
DISTANCE FROM DRAINAGE	https://www.hydrosheds.org/products/hydrorivers#downloads
LITHOLOGY	https://certmapper.cr.usgs.gov/data/apps/world-maps/

CHAPTER 5

STUDY AREA: SHIMLA, HIMACHAL PRADESH

Shimla district is located in the south eastern portion of the state of Himachal Pradesh, India, with a geographical area of about 5,131 km2. Geographically, it is positioned between latitudes 30°45'48" N to 31°43'0" N and longitudes 76°59'22" E to 78°18'40" E. The district is situated in the Lesser Himalayan range and has an extremely hilly topography ranging from 537 m in the low river valley to more than 5576 m on its glaciated north eastern peaks. The relief of Shimla is characterized by steep mountain slopes, highly dissected hills and narrow valleys, which result in a very complex and geomorphologically active landscape.

The western lowland areas of the district (Sunni and parts of Shimla Rural) are relatively low-lying, while the central, southern and north-eastern areas (Rampur, Rohru and Chopal) are much higher in elevation and steep slopes. The climate of the district is subtropical to temperate alpine, with an average annual rainfall of 1415 mm, much of which falls during the peak of summer (June to September) when it is likely to cause severe soil erosion and slope failures.

Geologically, the district is underlain by a complex assemblage of rocks including undivided Precambrian metamorphic and crystalline basement rocks, Paleozoic sedimentary sequences, Triassic metamorphic and sedimentary rocks and limited occurrences of Tertiary igneous intrusions. The Lesser Himalayan rocks are structurally complex and are formed by a series of thrust faults and recumbent folds, which have a significant influence on the strength of the rock mass and slope stability throughout the district.

Climate is subtropical at lower elevations and temperate alpine at higher elevations, with an average annual rainfall of 1415 mm which falls mainly between June and September. This heavy monsoon rainfall, together with the highly vulnerable terrain of the Himalayas often leads to severe soil erosion, debris flows and deep-seated slope failures. The district is one of the most landslide prone districts of Himachal Pradesh because of rapid urbanization, extensive deforestation and large scale road construction activities especially widening of national and state highways which have further aggravated the problem of slope instability.

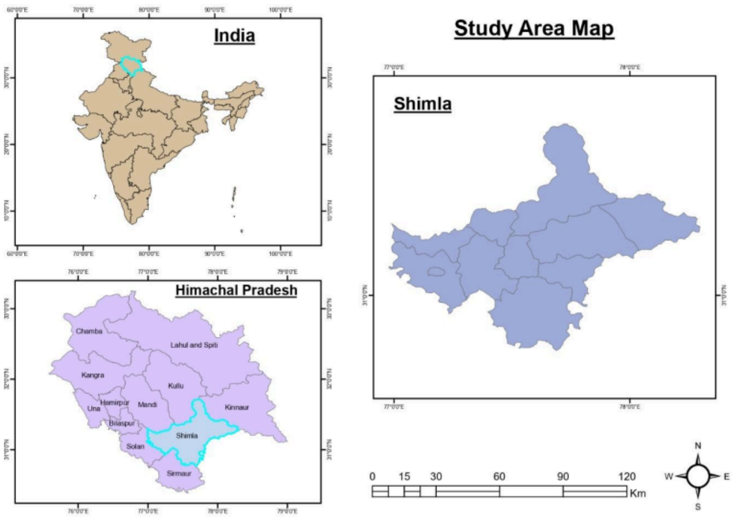

Figure 5.1 Study area

CHAPTER-6

LANDSLIDE INVENTORY MAP

A landslide inventory map of Shimla district was prepared to show the spatial distribution of past landslide events and as a basic input for landslide susceptibility modelling. 1003 point locations were identified for landslides and converted to point features for analysis. The inventory is based on landslide occurrences along steep slopes, road corridors and highly dissected terrain. Both Information Value and Weight of Evidence approaches were applied for sampling, model training and validation, using this inventory. As per the usual research process, 70% of the data was allocated for training the models while 30% was allocated for testing the models. They are used as the basis for landslide susceptibility models, which relate historical landslide occurrences to environmental factors and allow for the identification of high-risk areas. The landslide inventory map is an essential prerequisite for any landslide susceptibility study based on data, because it represents the spatial distribution of landslide events that have already occurred in the past, which is used as the dependent variable in statistical modelling. In the present study, a detailed landslide inventory map was prepared by combining the data from Geological Survey of India (GSI) Bhukosh portal and systematic visual interpretation of high-resolution satellite images for the Shimla district. 1003 landslide locations were identified, verified and transformed into point features for analysis. The inventory includes landslide events mostly in areas with steep slope gradients, road cut regions of national and state highways, and extremely dissected river valley areas, especially along the Sutlej, Pabbar and Giri river basins. The distribution of inventory points shows that the landslides are more concentrated in the central and southern tehsils of the district where the slopes are steepest and geological formations are most prone to failure.

To minimize sampling bias and balance the binary classification of the statistical models, an equal number of non-landslide points was randomly generated from areas classified as geomorphologically stable (flat or gently sloping terrain, dense vegetated zones, and areas with no historical record of slope failure).

The entire landslide and non-landslide points data set was randomly split into 70% training and 30% testing. Therefore, 70% of the data (702 landslide points) were used to train the model to calibrate the IV and WoE weights, and the remaining 30% (301 landslide points) were used as an independent testing data set for model validation by using the AUC-ROC method. This split allows the model to be tested on data not used for calculating the weights, giving an unbiased estimate of how well the model predicts the data. These inventory points become the basis for the landslide susceptibility models as they are spatially associated with the environmental conditioning factors, which makes it possible to identify and delineate high risk zones throughout Shimla district.

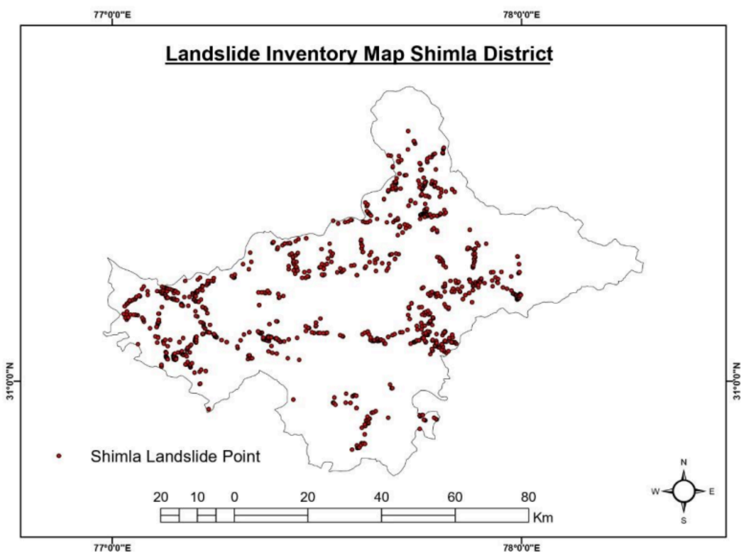

Figure 6.1 Landslide Inventory Points

CHAPTER 7

LANDSLIDE CONDITIONING FACTORS (LCF)

7.1 SLOPE:

Slope is an important landslide conditioning factor (LCF), which is the steepness or inclination of a surface and is important in determining slope stability. The slope map of Shimla district was obtained from the Digital Elevation Model (DEM) in the present study using the Spatial Analyst tool in ArcGIS. The slopes vary from near flat (0°) in valley floors to extremely steep (>44°) in the deeply incised river gorges and escarpments of the district. The slope map was classified into five categories: 0–17°, 17–26°, 26–34°, 34–44°, and 44–85°. The WoE and IV analysis revealed that landslide frequency was significantly higher for the slope classes above 26° with the highest positive contrast weight of 34 - 44° indicating the highest association with landslide occurrence in Shimla district.

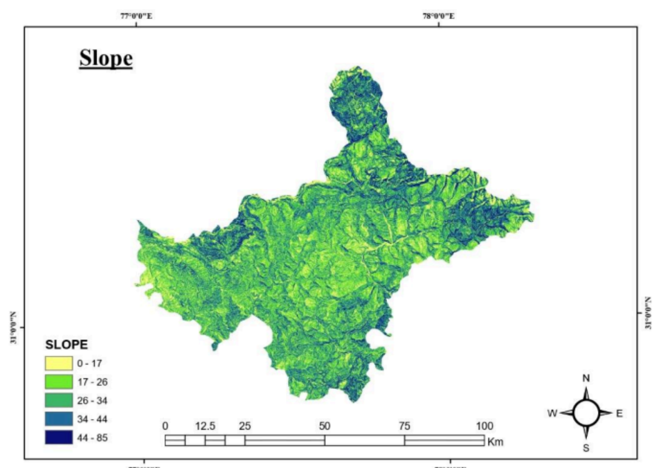

Figure 7.1 Slope

7.2 ASPECT:

Aspect is one of the important Landslide Conditioning Factors (LCF) which is the direction of the slope in relation to cardinal directions. It plays a significant role in the environment like sunlight exposure, wind patterns, and moisture retention, which ultimately affect the stability of the slope. For Shimla district, aspect map was created from DEM data using ArcGIS and classified into 10 directional classes as Flat (−1), North (0°–22.5°), Northeast (22.5°–67.5°), East (67.5°–112.5°), Southeast (112.5°–157.5°), South (157.5°–202.5°), Southwest (202.5°–247.5°), West (247.5°–292.5°), Northwest (292.5°–337.5°), and North (337.5°–360°). The statistical analysis indicated that a relatively high association with landslide occurrence was found in east and southeast facing slopes, which may be attributed as a result of the combined effect of monsoonal moisture exposure and differential weathering.

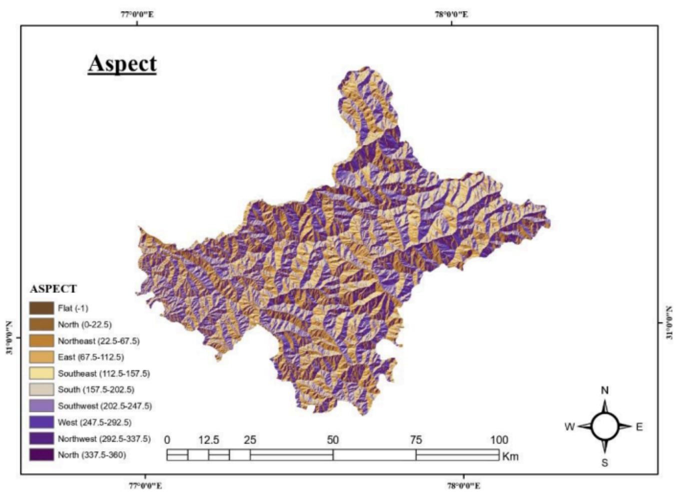

Figure 7.2 Aspect

7.3 ROUGHNESS:

Roughness is one of the significant Landslide Conditioning Factors (LCF), which is the irregularity or the unevenness of the terrain surface and affects the stability of the slope and the occurrence of landslides. The present study calculated roughness from the DEM using the focal statistics tool in ArcGIS, which is the difference between the highest and lowest elevation values in a neighbourhood window of interest. The roughness values obtained for Shimla district were divided into five categories ranging from 0.14 to 0.41 (low roughness, smooth terrain) to 0.57 to 0.84 (very high roughness, highly irregular terrain). Results of the statistical analysis showed that, as the roughness increases, the correlation with the landslide occurrence becomes more positive, which indicates the role of the terrain complexity as a control parameter for the geomorphologically active landscape of Shimla.

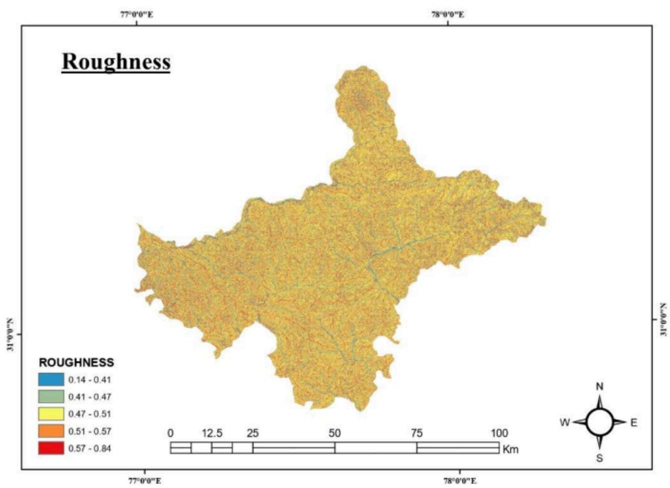

Figure 7.3 Roughness

7.4 DISTANCE TO STREAM:

Distance to stream is one of the most important Landslide Conditioning Factors (LCF) which is the horizontal distance from a point on a slope to the nearest drainage channel or water body. The distance-to-stream map for Shimla district was created by using the Euclidean Distance tool in ArcGIS on the hydroSHEDS-derived stream network for the present study. The factor was classified into five buffer zones: 0–250 m, 250–500 m, 500–750 m, 750–1000 m, and >1000 m. The statistical analysis revealed that the highest frequency of landslides is associated with the zone 0-250 m from stream channels and according to both the IV and WoE models, the proximity to the stream channels had the highest positive weight, indicating that this is a major influencing factor of slope instability in Shimla district.

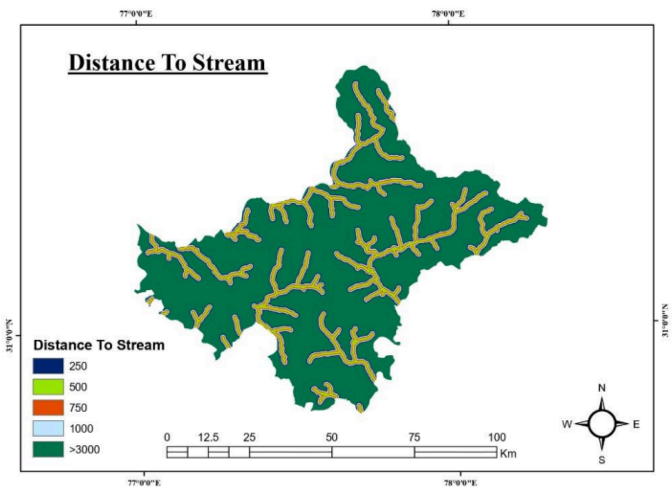

Figure 7.4 Distance to Stream

7.5 CURVATURE:

One of the significant Landslide Conditioning Factors (LCF) is the curvature of the terrain which has a significant influence on the flow of water and soil. It is based on Digital Elevation Model (DEM) data and classified as concave, convex and planar surfaces. The curvature for Shimla district was computed using the Curvature function of ArcGIS and categorized into five classes: 1) strongly concave (−63.53 to −2.67), 2) moderately concave (−2.67 to −1.18), 3) near-planar (−1.18 to −0.18), 4) slightly convex (−0.18 to 1.32), and 5) strongly convex (1.32 to 63.67). The strongly concave class was found to be associated with landslide occurrence, as concavity is known to encourage water accumulation and slope saturation.

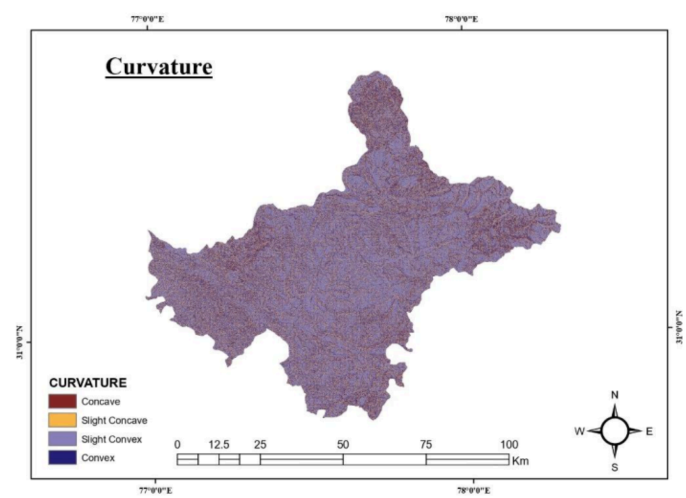

Figure 7.5 Curvature

7.6 ELEVATION:

Elevation is a basic Landslide Conditioning Factor (LCF) that is an important factor in terrain stability and susceptibility to landslides. The topography ranges from about 537 m above mean sea level (amsl) in the Sutlej river valley near Rampur to more than 5,576 m amsl on the glaciated peaks of the north-eastern boundary of the district in Shimla. This wide altitudinal range was classified into five zones for analysis: 601–1600 m, 1600–2203 m, 2203–2862 m, 2862–3748 m, and 3748–5406 m. The elevation data was derived from DEM data and processed in ArcGIS. Of all the factors that influence landslide occurrence in the study area, statistical analysis revealed that elevation is one of the most influential, with landslide frequency being highest in the lower to mid-elevation bands (601–2203 m), which corresponds to the zone of maximum human activity, road construction, and intense monsoon precipitation.

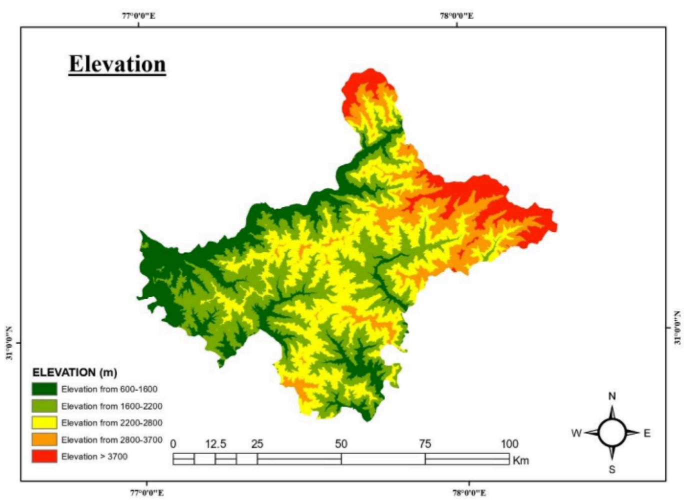

Figure 7. 6 Elevation

7.7 HILLSHADE:

Hillshade is one of the Landslide Conditioning Factors (LCF) that mimics the effect of sunlight on the terrain, indicating the features of the terrain by the light and shadow. Hillshade analysis was done on the DEM data in ArcGIS with a standard solar azimuth of 315° and an altitude of 45° for Shimla district. The resulting hillshade values were divided into five illumination classes: 0–63 (very low illumination), 63–114 (low illumination), 114–161 (moderate illumination), 161–208 (high illumination), and 208–254 (very high illumination). The statistical results suggest that there is a greater association of past landslide events with areas of low illumination values, which are associated with the north facing valley flanks with deep shadows, indicating that they have a higher moisture retention.

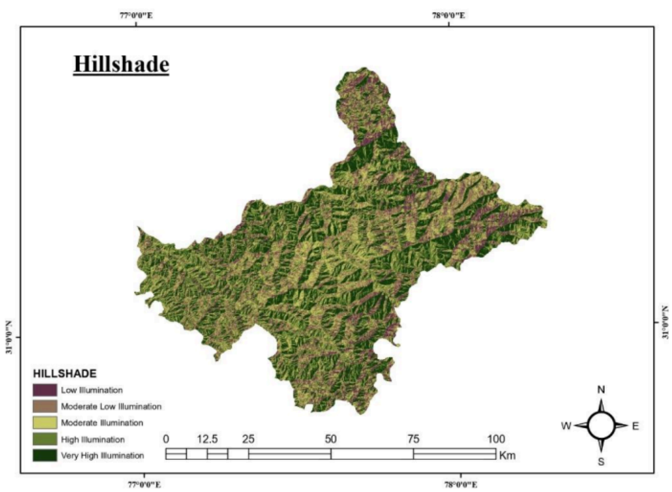

Figure 7.7 Hillshade

7.8 LITHOLOGY:

The India shapefile, obtained from the USGS, originally contained different rock types throughout the area. After analyzing and clipping, five different types of rocks were identified in the Shimla district. These rocks have different properties in terms of composition, strength characteristics, and plasticity that are important in understanding their stability. The lithology, or type and physical properties of rocks and soils in an area, is an important factor affecting landslide susceptibility. The lithological data for Shimla district was extracted from USGS World Rock Type Map and clipped to district boundary in ArcGIS. The district has been subdivided into five lithological units:

1. **pC - Undivided Precambrian Rocks:** This is the most abundant lithological unit (89% of the district). Consists of crystalline metamorphic basement rocks of the Lesser Himalayan Crystallines and Simla Group consisting of quartzites, schists, phyllites and gneisses.
2. **Pz - Undivided Paleozoic Rocks:** Sedimentary and metasedimentary sequences Paleozoic in age which are discontinuous and occur as isolated outcrops throughout the district.
3. **Pzl - Lower Paleozoic Rocks:** Older Paleozoic sedimentary rocks with relatively small spatial distribution.
4. **Ti - Tertiary Igneous Rocks:** Localised intrusive igneous rock bodies of Tertiary age that occur as small isolated patches.
5. **Trms - Triassic Metamorphic and Sedimentary Rocks:** Triassic Metamorphic and Sedimentary Rocks: Triassic age metamorphic and sedimentary rocks with relatively weaker mechanical properties than the Precambrian basement.

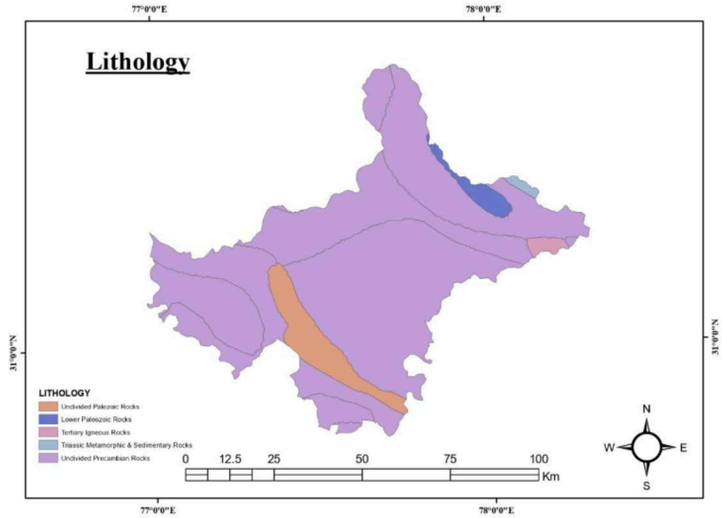

Figure 7.8 Lithology

7.9 TOPOGRAPHIC WETNESS INDEX (TWI):

The Topographic Wetness Index (TWI) is a spatial index that quantifies the relative wetness of a landscape based on the topography of the landscape, specifically on the accumulation of water in an area.The TWI was calculated in ArcGIS using the flow accumulation and slope rasters generated from the DEM for Shimla district. The resulting TWI values were classified into five classes: 1.71–4.89 (low wetness), 4.89–6.44, 6.44–8.56, 8.56–12.22, and 12.22–26.31 (very high wetness). The statistical analysis revealed that the steep (1.71–4.89) and poorly drained slopes had the highest positive association with landsliding, which means that steep slopes with moderate drainage capacity in Shimla district are the most critical combination for slope instability.

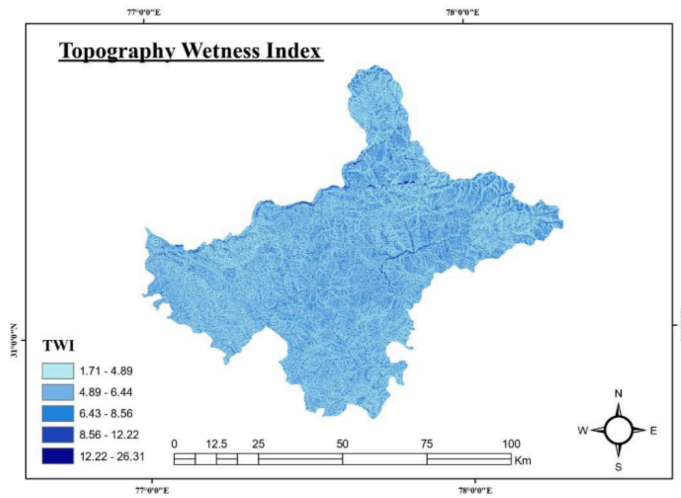

Figure 7.9 Topographic Wetness Index

7.10 NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI):

Normalized Difference Vegetation Index (NDVI) is a spatial index that measures relative density and health of vegetation cover on a landscape based on the spectral reflectance of plant leaves. In ArcGIS, satellite imagery was used to calculate NDVI for Shimla district and classify it into five classes: −0.375 to 0.077 (water/snow/barren), 0.077–0.153 (built-up/barren land), 0.153–0.223 (sparse vegetation), 0.223–0.449 (moderate vegetation), and 0.449–0.998 (dense forest). The statistical analysis showed that the barren and sparsely vegetated classes (NDVI 0.077–0.153) have the highest positive weights for both IV and WoE models, thus indicating that vegetation loss is a main factor of the slope failure in the district.

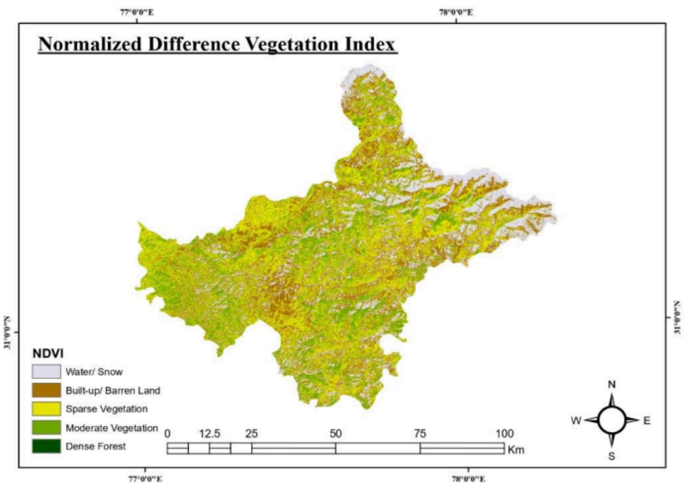

Figure 7.10 Normalized Difference Vegetation Index

7.11 CONTOUR:

One of the most important spatial measures is elevation, which is measured in terms of contour intervals and is a measure of the vertical change of a landscape relative to mean sea level. It is directly extracted from Digital Elevation Models (DEMs) by dividing the topography into particular elevation ranges that would be useful to define the climatic, geomorphological and vegetation conditions that would influence various portions of the terrain. For Shimla district, contour data were derived from the DEM and classified into five altitudinal bands: 800–1600 m, 1600–2400 m, 2400–3200 m, 3200–4000 m, and 4000–5400 m. The band of 800–1600 m was found to have the highest positive correlation with landslide occurrence in both models, which is the zone of maximum anthropogenic activity and high monsoon precipitation.

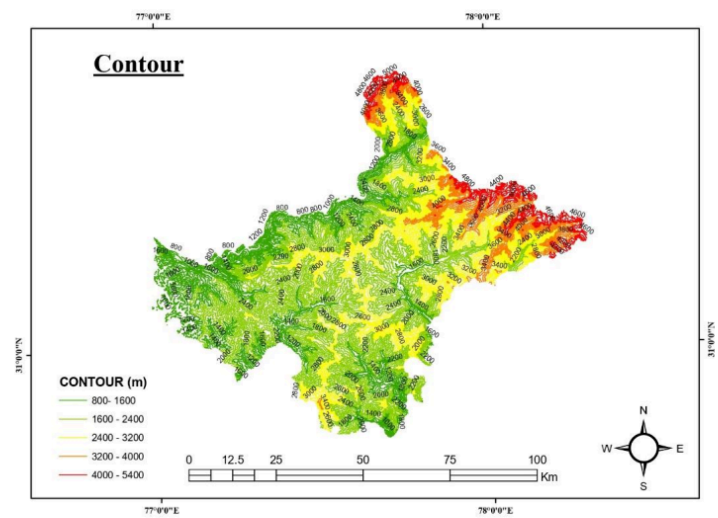

Figure 7.11 Contour

7.12 DRAINAGE DENSITY:

Drainage Density is a spatial measure to evaluate how dense a stream network is within a landscape, based on the distribution and length of stream networks in an area. It is calculated by dividing the total length of all the streams in a drainage basin by the total area of the drainage basin, to determine the efficiency of surface drainage. The drainage density in Shimla district was calculated by dividing the total stream length (obtained from the HydroSHEDS HydroRIVERS dataset) by the total catchment area, using Line Density tool in ArcGIS. The resulting density values were classified into five classes: 0.02–0.21, 0.21–0.40, 0.40–0.60, 0.60–0.80, and 0.80–1.05 km/km². The statistical analysis showed that the occurrence of landslides is positively correlated with higher drainage density classes (0.60–1.05 km/km²), which are known for their ability to trigger landsliding by causing undercutting of slopes and quick pore pressure rise in the monsoon dominated environment of Shimla.

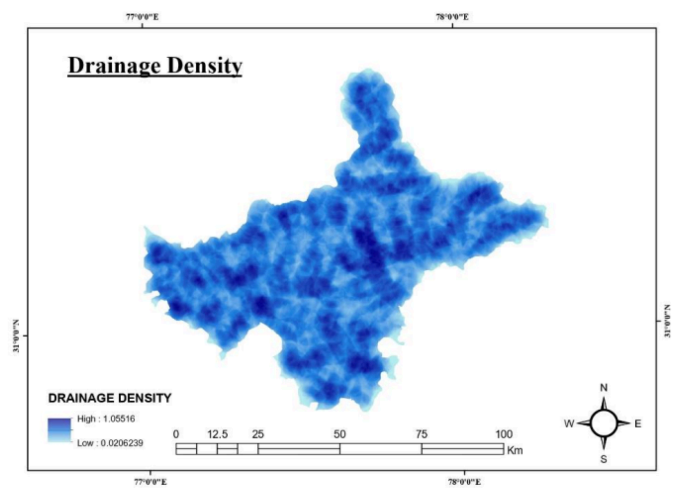

Figure 7.12 Drainage Densit

CHAPTER-9

WEIGHT OF EVIDENCE

9.1 Introduction:

Weight of Evidence (WoE) is a statistical method based on the Bayesian approach that allows to measure the effect of conditioning factors on the occurrence of landslides. WoE calculates two weights for each class of a factor (e.g. particular range of slopes):

Positive weight (W+) indicates that a landslide is more likely in that class than in the overall study area. The negative weight (W^-) represents the difference in probability that a landslide is less likely in that class. Positive and negative weights (W+ - W-): the contribution of the factor to susceptibility. In the GIS-based mapping, these weights are assigned to the spatial layers to generate a landslide susceptibility index, which indicates high risk areas.

9.2 Formula:

It determines the statistical weights for the relationship between the occurrence of a landslide and different classes of the conditioning factors. It gives a positive weight (W+) to areas where landslides are present, and a negative weight (W-) to areas where there are no landslides. Equation 9.1 and 9.2 gives positive weight and negative weight formulas as given below.

$$W_i^+ = \left[\frac{P(L|S_i)}{P(L)}\right] \qquad 9.1$$

$$W_i^- = \left[\frac{P(L|S_i)}{P(L)}\right] \qquad 9.2$$

Where:

- $P(L|S_i)$ = Conditional probability of a landslide occurring given the presence of factor class S_i
- $P(L)$ = Prior probability of landslide occurrence in the entire study area
- $P(\neg L \mid S_i)$ = Conditional probability of no landslide given the presence of factor class S_i
- $P(\neg L)$ = Prior probability of no landslide occurrence in the entire study area

The contrast weight (C) is calculated as the difference between the positive weight and the negative weight, and represents the overall influence of a factor class. The contrast value indicates the stronger association with landslide occurrence, with a higher value. The expression for contrast weight is shown in Equation 9.3.

$$C = W_i^+ + W_i^- \qquad 9.3$$

9.3 Outcome:

This study used the Weight of Evidence (WoE) method to gain a clear and quantifiable understanding of the contribution each conditioning factor makes to the susceptibility of landslides. The method was used to assign positive and negative weights to the different classes of factors (slope, lithology, and elevation) to identify zones of increased likelihood of landsliding. These weights were used to derive contrast values which were used to identify high correlations between some terrain features and past landslides. The resulting susceptibility map was able to effectively classify the study area according to the different levels of susceptibility. The steep slope classes (34°–44°), low-elevation zones (601–1600 m), concave terrain (strongly negative curvature), areas near to streams (<250 m), and low NDVI classes (sparsely vegetated terrain) always had the highest positive contrast values, which is confirmation of their critical role in driving slope instability in Shimla district. The WoE-derived Landslide Susceptibility Index was reclassified into five zones (Very Low, Low, Moderate, High, Very High) and validated against the independent test dataset by the AUC-ROC curve.

9.4 Application:

The Weight of Evidence (WoE) method is a widely used statistical method in landslide susceptibility mapping, which can be used to assess the relationship between the landslide events and the various conditioning factors. WoE is based on a Bayesian approach which assigns weights to individual classes within each factor (e.g. slope, lithology, elevation) according to whether a landslide has or has not occurred. These weights represent the influence that each class has on the occurrence of landslides. These weighted layers, when aggregated together in a GIS context, can be used to produce detailed susceptibility maps, which include areas of varying susceptibility. The simplicity, clarity and multi-variable spatial capability of WoE make it a useful tool for landslide hazard analysis and risk planning.

9.5 Advantages:

The Weight of Evidence (WoE) approach has several benefits for landslide susceptibility mapping. It is a simple, data-driven method based on statistical relationships between the occurrence of landslides and conditioning factors, minimizing subjectivity in the analysis. The results of WoE can be easily interpreted with positive

These are both positive and negative weights which clearly show the influence of each factor class on landslides or resistance to landslides. It has a good performance in the GIS environment and is efficient for large spatial data sets. Also, WoE can use several variables without complicated calculations, which makes it applicable for regional scale studies. It is a practical and popular method in landslide risk assessment because of its capability of producing reliable susceptibility maps with limited data.

9.6 Data table:

Table 9.1 WEIGHT OF EVIDENCE CALCULATION

	Total area of Shimla	5,700,000	**Landslide point area**	1,003	**P(L)**	0.0002	**P(-L)**	0.9998	
Data Layer	**Classes**	**Landslide Pixels Area**	**Area Pixels**	**P(Si)**	**P(L/Si)**	**P(-L/Si)**	**W+**	**W-**	**Weight of Contrast**
Slope (deg)	0.014 - 17.10	50	1,596,000	0.2800	0.000031	0.999969	-1.726	0.277	-2.003
	17.10 - 26.13	181	1,824,000	0.3200	0.000099	0.999901	-0.573	0.187	-0.760
	26.13 - 34.51	321	1,254,000	0.2200	0.000256	0.999744	0.375	-0.137	0.512
	34.51 - 44.22	351	798,000	0.1400	0.000440	0.999560	0.916	-0.280	1.196
	44.22 - 85.41	100	228,000	0.0400	0.000439	0.999561	0.914	-0.064	0.978
Total		**1,003**	**5,700,000**						
Aspect	Flat (-1)	59	401,280	0.0704	0.000147	0.999853	-0.180	0.012	-0.192
	North (0 - 22.5)	65	342,000	0.0600	0.000190	0.999810	0.077	-0.005	0.082
	Northeast (22.5-67.5)	118	640,110	0.1123	0.000184	0.999816	0.047	-0.006	0.053
	East (67.5-112.5)	163	727,890	0.1277	0.000224	0.999776	0.241	-0.041	0.282
	Southeast (112.5-157.5)	148	723,330	0.1269	0.000205	0.999795	0.151	-0.024	0.175
	South (157.5-202.5)	143	772,350	0.1355	0.000185	0.999815	0.051	-0.008	0.059
	Southwest (202.5-247.5)	94	662,910	0.1163	0.000142	0.999858	-0.216	0.025	-0.241
	West (247.5-292.5)	94	705,090	0.1237	0.000133	0.999867	-0.278	0.034	-0.311
	Northwest (292.5-337.5)	50	364,230	0.0639	0.000137	0.999863	-0.248	0.015	-0.263
	North (337.5-360)	69	360,810	0.0633	0.000191	0.999809	0.083	-0.006	0.089
Total		**1,003**	**5,700,000**						
NDVI	-0.375 - 0.077	40	171,000	0.0300	0.000234	0.999766	0.285	-0.010	0.295
	0.077 - 0.153	181	456,000	0.0800	0.000397	0.999603	0.814	-0.116	0.929
	0.153 - 0.223	321	1,254,000	0.2200	0.000256	0.999744	0.375	-0.137	0.512
	0.223 - 0.449	381	2,565,000	0.4500	0.000149	0.999851	-0.169	0.120	-0.290
	0.449 - 0.998	80	1,254,000	0.2200	0.000064	0.999936	-1.015	0.165	-1.180
Total		**1,003**	**5,700,000**						
Hillshade	0 - 63	120	456,000	0.0800	0.000263	0.999737	0.403	-0.044	0.447
	63 - 114	221	1,026,000	0.1800	0.000215	0.999785	0.202	-0.050	0.253

	114 - 161	351	1,824,000	0.3200	0.000192	0.999808	0.089	-0.045	0.135
	161 - 208	221	1,596,000	0.2800	0.000138	0.999862	-0.240	0.080	-0.319
	208 - 254	90	798,000	0.1400	0.000113	0.999887	-0.445	0.057	-0.502
Total		**1,003**	**5,700,000**						

Curvature	-63.53 -2.67	80	171,000	0.0300	0.000468	0.999532	0.978	-0.053	1.031
	-2.67 to -1.18	181	684,000	0.1200	0.000265	0.999735	0.408	-0.071	0.479
	-1.18 to -0.18	351	2,166,000	0.3800	0.000162	0.999838	-0.082	0.047	-0.130
	-0.18 to 1.32	251	1,995,000	0.3500	0.000126	0.999874	-0.336	0.143	-0.478
	1.32 to 63.67	140	684,000	0.1200	0.000205	0.999795	0.151	-0.023	0.174
Total		**1,003**	**5,700,000**						
Elevation (m)	601 - 1600	281	741,000	0.1300	0.000379	0.999621	0.768	-0.189	0.958
	1600 - 2203	301	1,425,000	0.2500	0.000211	0.999789	0.183	-0.069	0.252
	2203 - 2862	221	1,596,000	0.2800	0.000138	0.999862	-0.240	0.080	-0.319
	2862 - 3748	150	1,254,000	0.2200	0.000120	0.999880	-0.386	0.086	-0.473
	3748 - 5406	50	684,000	0.1200	0.000073	0.999927	-0.879	0.077	-0.955
Total		**1,003**	**5,700,000**						

Roughness	0.146 - 0.410	40	456,000	0.0800	0.000088	0.999912	-0.696	0.043	-0.739
	0.410 - 0.470	181	1,254,000	0.2200	0.000144	0.999856	-0.198	0.049	-0.248
	0.470 - 0.517	321	1,995,000	0.3500	0.000161	0.999839	-0.090	0.045	-0.135
	0.517 - 0.575	281	1,425,000	0.2500	0.000197	0.999803	0.114	-0.041	0.155
	0.575 - 0.847	181	570,000	0.1000	0.000318	0.999682	0.590	-0.094	0.684
Total		**1,004**	**5,700,000**						

TWI	1.71 - 4.89	351	1,596,000	0.2800	0.000220	0.999780	0.223	-0.102	0.325
	4.89 - 6.44	401	2,394,000	0.4200	0.000168	0.999832	-0.049	0.034	-0.084
	6.44 - 8.56	171	1,140,000	0.2000	0.000150	0.999850	-0.160	0.036	-0.196
	8.56 - 12.22	60	456,000	0.0800	0.000132	0.999868	-0.291	0.022	-0.312
	12.22 - 26.31	20	114,000	0.0200	0.000175	0.999825	-0.003	0.000	-0.003
Total		**1,003**	**5,700,000**						

Distance To Stream (m)	0 - 250	181	684,000	0.1200	0.000265	0.999735	0.408	-0.071	0.479

	250 - 500	140	627,000	0.1100	0.000223	0.999777	0.238	-0.034	0.272
	500 - 750	120	570,000	0.1000	0.000211	0.999789	0.179	-0.022	0.201
	750 - 1000	100	513,000	0.0900	0.000195	0.999805	0.102	-0.011	0.113
	> 1000	461	3,306,000	0.5800	0.000139	0.999861	-0.233	0.252	-0.485
Total		**1,002**	**5,700,000**						
Contour (m)	800 - 1600	321	798,000	0.1400	0.000402	0.999598	0.827	-0.235	1.062
	1600 - 2400	301	1,482,000	0.2600	0.000203	0.999797	0.143	-0.056	0.199
	2400 - 3200	221	1,596,000	0.2800	0.000138	0.999862	-0.240	0.080	-0.319
	3200 - 4000	120	1,254,000	0.2200	0.000096	0.999904	-0.609	0.121	-0.730
	4000 - 5400	40	570,000	0.1000	0.000070	0.999930	-0.919	0.065	-0.984
Total		**1,003**	**5,700,000**						
Lithology	Pz (Undivided Paleozoic)	57	393,870	0.0691	0.000145	0.999855	-0.196	0.013	-0.209
	Pzl (Lower Paleozoic)	22	127,110	0.0223	0.000173	0.999827	-0.017	0.000	-0.017
	Ti (Tertiary Igneous)	2	58,140	0.0102	0.000034	0.999966	-1.632	0.008	-1.641
	Trms(Triassic Meta/Sed.)	2	29,070	0.0051	0.000069	0.999931	-0.939	0.003	-0.942
	pC (Undivided Precambrian)	921	5,091,810	0.8933	0.000181	0.999819	0.028	-0.266	0.294
Total		**1,004**	**5,700,000**						
Drainge Density	0.02 - 0.21	40	285,000	0.0500	0.000140	0.999860	-0.226	0.011	-0.237
	0.21 - 0.40	221	1,425,000	0.2500	0.000155	0.999845	-0.126	0.039	-0.165
	0.40 - 0.60	381	2,280,000	0.4000	0.000167	0.999833	-0.052	0.033	-0.085
	0.60 - 0.80	251	1,254,000	0.2200	0.000200	0.999800	0.129	-0.040	0.168
	0.80 - 1.05	110	456,000	0.0800	0.000241	0.999759	0.316	-0.033	0.348
Total		**1,003**	**5,700,000**						

CHAPTER-10

INFORMATION VALUE

10.1 Introduction:

A bivariate statistical approach for assessing the relationship between landslide events and conditioning factors is called the Information Value (IV) method and is used in landslide susceptibility mapping. It assigns the weight to each factor class according to the frequency of the landslide, indicating the contribution to landslide risk. Simple, interpretable and effective, IV is used to identify some of the key influencing factors, and can be combined with GIS to develop accurate susceptibility maps for hazard planning.

10.2 Formula:

The IV method is based on a logarithmic formula and ratio of conditional probability and prior probability (see equations 10.1 and 10.2), and is used to calculate the contribution of each class of a conditioning factor to landslide occurrence.

$$P_{conditional} = \frac{N_{Landslide\ pixels}}{N_{Class\ pixels}} \quad 10.1$$

$$P_{prior} = \frac{N_{Total\ landslide\ pixels}}{N_{Total\ class\ pixels}} \quad 10.2$$

Now, with the help of 10.1 and 10.2, we can compute the information value of each class as shown below in equation 10.3.

$$IV = log_e \frac{P_{conditional}}{P_{prior}} \quad 10.3$$

10.3 Outcome:

Among the models used in this study, the Information Value (IV) method gave the best results in landslide susceptibility mapping. The IV method was able to clearly identify the factors with the highest association to slope failures by assigning statistical weights according to the frequency of occurrence of landslides in each class of conditioning factors. The susceptibility map produced was clearly demarcated as areas of low to very high landslide susceptibility, and provided useful information for hazard assessment and land-use planning.

10.4 Application:

In landslide susceptibility mapping, the Information Value (IV) method is used to evaluate the impact of each conditioning factor by determining the weight of each factor according to the frequency of landslides. It assists in the determination of the most important factors that are involved in landslide events and aids in the delineation of landslide hazard zones. IV is especially valuable for creating GIS-based susceptibility maps based on data, hazard assessment, land use planning and risk mitigation. Can also be used with other models for comparative analysis of predictive performance.

10.5 Advantages:

The Information Value (IV) method has several merits for landslide susceptibility mapping. Easy to use and easy to understand, it can be used by everyone. The influence of each conditioning factor can be objectively and data-driven analyzed by IV, which is an effective quantification of the influence. It works well with the large data sets and spatial mapping capabilities of GIS. Furthermore, IV can help to determine the most important contributing factors, which can increase the accuracy of susceptibility maps and aid in informed decision making for hazard assessment and land use planning.

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11.0 Data Table:

Table 10.1 INFORMATION VALUE CALCULATION

	Data layer	Classes	Area pixels	Landslide pixels area	Conditional probability	Prior probability	Cp/Pp	Information Value
Slope(in deg)								
	0.014 - 17.10	1	1596000	50	3.13283E-05	0.000175965	0.178037317	-0.74948896
	17.10 - 26.13	2	1824000	181	9.92325E-05	0.000175965	0.5639332	-0.248772336
	26.13 - 34.51	3	1254000	321	0.000255981	0.000175965	1.454726729	0.162781419
	34.51 - 44.22	4	798000	351	0.00043985	0.000175965	2.499643925	0.397878148
	44.22 - 85.41	5	228000	100	0.000438596	0.000175965	2.492522433	0.396639076
Total			**5700000**	**1003**				0.397878148
Aspect								
	Flat (-1)	1	401280	59	0.00014703	0.000175965	0.835561497	-0.078021581
	North (0 - 22.5)	2	342000	65	0.000190058	0.000175965	1.080093054	0.033461173
	Northeast (22.5-67.5)	3	640110	118	0.000184343	0.000175965	1.047614059	0.020201318
	East (67.5-112.5)	4	727890	163	0.000223935	0.000175965	1.272611297	0.104695774
	Southeast (112.5-157.5)	5	723330	148	0.000204609	0.000175965	1.162784303	0.06549916
	South (157.5-202.5)	6	772350	143	0.000185149	0.000175965	1.052193972	0.022095809
	Southwest (202.5-247.5)	7	662910	94	0.000141799	0.000175965	0.805837003	-0.093752794
	West (247.5-292.5)	8	705090	94	0.000133316	0.000175965	0.757630101	-0.120542779
	Northwest (292.5-337.5)	9	364230	50	0.000137276	0.000175965	0.780132217	-0.107831787
	North (337.5-360)	10	360810	69	0.000191236	0.000175965	1.086787032	0.036144448
Total			**5700000**	**1003**				0.104695774
Hillshade								
	0 - 63	1	456000	120	0.000263158	0.000175965	1.49551346	0.174790326
	63 - 114	2	1026000	221	0.0002154	0.000175965	1.224105461	0.087818836
	114 - 161	3	1824000	351	0.000192434	0.000175965	1.093594217	0.038856205
	161 - 208	4	1596000	221	0.000138471	0.000175965	0.786924939	-0.104066691
	208 - 254	5	798000	90	0.000112782	0.000175965	0.64093434	-0.193186459
Total			**5700000**	**1003**				0.174790326
Curvature								
	-63.53 to -2.67	1	171000	80	0.000467836	0.000175965	2.658690595	0.424667799
	-2.67 to -1.18	2	684000	181	0.00026462	0.000175965	1.503821868	0.177196396
	-1.18 to -0.18	3	2166000	351	0.00016205	0.000175965	0.920921446	-0.035777413
	-0.18 to 1.32	4	1995000	251	0.000125815	0.000175965	0.714997864	-0.145695256
	1.32 to 63.67	5	684000	140	0.000204678	0.000175965	1.163177135	0.065645857
Total			**5700000**	**1003**				0.424667799

Elevation								
	601 - 1600	1	741000	281	0.000379217	0.000175965	2.155073242	0.333462035
	1600 - 2203	2	1425000	301	0.000211228	0.000175965	1.200398804	0.079325554
	2203 - 2862	3	1596000	221	0.000138471	0.000175965	0.786924939	-0.104066691
	2862 - 3748	4	1254000	150	0.000119617	0.000175965	0.679778845	-0.167632355
	3748 - 5406	5	684000	50	7.30994E-05	0.000175965	0.415420405	-0.381512175
Total			**5700000**	**1003**				0.333462035
Roughness								
	0.146 - 0.410	1	456000	40	8.77193E-05	0.000175965	0.498504487	-0.302330929
	0.410 - 0.470	2	1254000	181	0.000144338	0.000175965	0.820266473	-0.086045039
	0.470 - 0.517	3	1995000	321	0.000160902	0.000175965	0.914399658	-0.038863945
	0.517 - 0.575	4	1425000	281	0.000197193	0.000175965	1.120638086	0.049465378
	0.575 - 0.847	5	570000	181	0.000317544	0.000175965	1.804586241	0.256377642
Total			**5700000**	**1003**				0.256377642
Contour								
	800 - 1600	1	798000	321	0.000402256	0.000175965	2.285999145	0.359076064
	1600 - 2400	2	1482000	301	0.000203104	0.000175965	1.154229619	0.062292215
	2400 - 3200	3	1596000	221	0.000138471	0.000175965	0.786924939	-0.104066691
	3200 - 4000	4	1254000	120	9.56938E-05	0.000175965	0.543823076	-0.264542368
	4000 - 5400	5	570000	40	7.01754E-05	0.000175965	0.398803589	-0.399240942
Total			**5700000**	**1003**				0.359076064
NDVI								
	-0.375 - 0.077	1	171000	40	0.000233918	0.000175965	1.329345297	0.123637804
	0.077 - 0.153	2	456000	181	0.00039693	0.000175965	2.255732802	0.353287655
	0.153 - 0.223	3	1254000	321	0.000255981	0.000175965	1.454726729	0.162781419
	0.223 - 0.449	4	2565000	381	0.000148538	0.000175965	0.844134264	-0.073588471
	0.449 - 0.998	5	1254000	80	6.37959E-05	0.000175965	0.362548717	-0.440633627
Total			**5700000**	**1003**				0.353287655
TWI								
	1.71 - 4.89	1	1596000	351	0.000219925	0.000175965	1.249821963	0.096848152
	4.89 - 6.44	2	2394000	401	0.000167502	0.000175965	0.951906186	-0.021405851
	6.44 - 8.56	3	1140000	171	0.00015	0.000175965	0.852442672	-0.069334818
	8.56 - 12.22	4	456000	60	0.000131579	0.000175965	0.74775673	-0.12623967
	12.22 - 26.31	5	114000	20	0.000175439	0.000175965	0.997008973	-0.001300933
Total			**5700000**	**1003**				0.096848152

Distance to Stream (m)								
	0 - 250	1	684000	181	0.00026462	0.000175789	1.505322688	0.177629607
	250 - 500	2	627000	140	0.000223285	0.000175789	1.270186899	0.103867629
	500 - 750	3	570000	120	0.000210526	0.000175789	1.19760479	0.078313525
	750 - 1000	4	513000	100	0.000194932	0.000175789	1.108893324	0.044889769
	> 1000	5	3306000	461	0.000139443	0.000175789	0.793241104	-0.10059479
Total			**5700000**	**1002**				0.177629607
Lithology								
	Pz (Undivided Paleozoic)	1	393870	57	0.000144718	0.00017614	0.821605041	-0.085336905
	Pzl (Lower Paleozoic)	2	127110	22	0.000173078	0.00017614	0.982616619	-0.007615895
	Ti (Tertiary Igneous)	3	58140	2	3.43997E-05	0.00017614	0.195297242	-0.709303889
	Trms(Triassic Meta/Sed.)	4	29070	2	6.87994E-05	0.00017614	0.390594485	-0.408273893
	pC (Undivided Precambrian)	5	5091810	921	0.000180879	0.00017614	1.026901016	0.011528583
Total			**5700000**	**1004**				0.011528583
Drainage Density								
	0.02 - 0.21	1	285000	40	0.000140351	0.000175965	0.797607178	-0.098210946
	0.21 - 0.40	2	1425000	221	0.000155088	0.000175965	0.881355932	-0.054848668
	0.40 - 0.60	3	2280000	381	0.000167105	0.000175965	0.949651047	-0.022435949
	0.60 - 0.80	4	1254000	251	0.000200159	0.000175965	1.137496601	0.055950108
	0.80 - 1.05	5	456000	110	0.000241228	0.000175965	1.370887338	0.137001765
Total			**5700000**	**1003**				0.137001765

CHAPTER 11

RESULTS

11.1 Discussion:

Landslide Susceptibility Maps were created using two different methods: Information Value (IV), and Weight of Evidence (WoE). Environmental factors such as slope, elevation, aspect, and lithology are used to identify areas susceptible to landsliding using these models.

The different approaches adopted by these models to assign weights to the contributing factors resulted in varying classifications of landslide susceptibility:

- **Weight of Evidence (WoE):** Utilizing a Bayesian probability framework, this method calculated positive and negative weights based on the spatial presence or absence of historical landslides relative to specific factor classes.

- **Information Value (IV):** This method assigned weights based on the relative frequency of landslide events within each specific class of a conditioning factor, quantifying their direct contribution to the overall risk.

Based on the calculated weights, several critical trends emerged regarding terrain instability in the Shimla district. For instance, slope gradients between **34.51° and 44.22°** exhibited the highest positive contrast in the WoE model (C = 1.196) and the highest Information Value (IV = 0.397). Similarly, lower-to-mid elevation zones (**800–1600 m**) and areas in extreme proximity to streams (**0–250 m**) were identified as highly critical zones by both models, reflecting the compounded impacts of rapid river undercutting, concentrated monsoonal precipitation, and intense anthropogenic activity. Furthermore, sparsely vegetated and barren terrains (NDVI **0.077–0.153**) demonstrated a strong statistical correlation with historical slope failures.

These derived weights enabled a comprehensive comparative analysis of the terrain, effectively classifying the district into five distinct susceptibility zones: Very Low, Low, Moderate, High, and Very High.

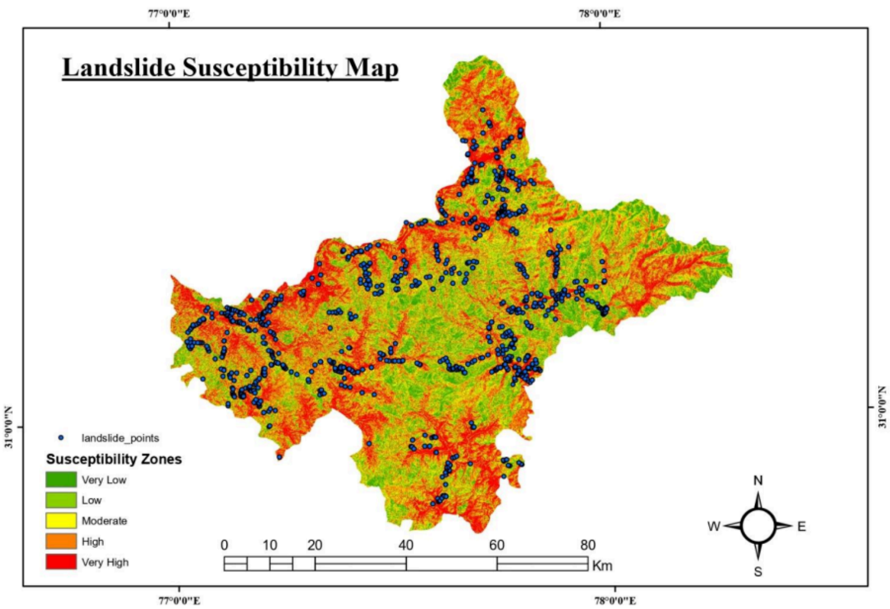

Figure 11.2 Landslide susceptibility map using Weight of Evidence

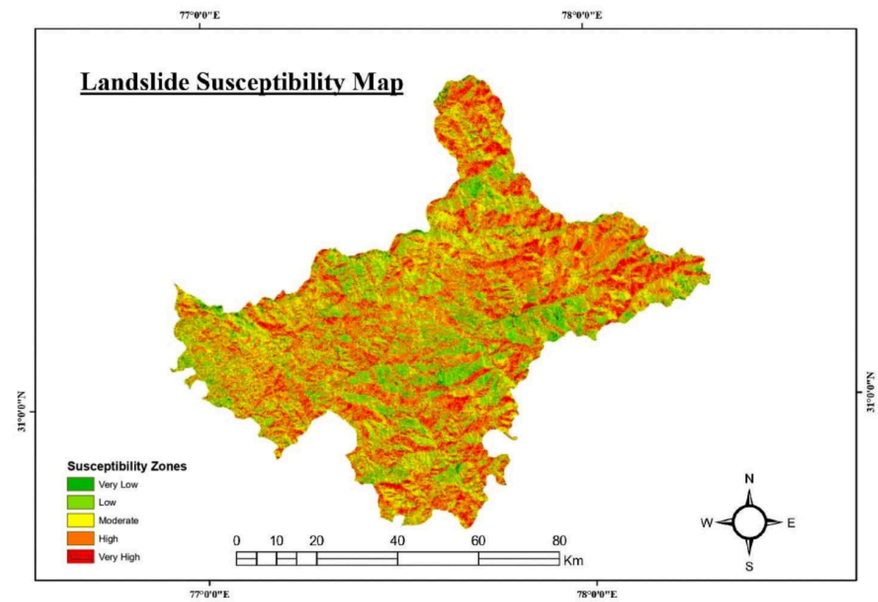

Figure 11.3 Landslide susceptibility map using Information Value

11.2 Validation

Validation is one of the most critical steps in assessing the accuracy and practical reliability of a predictive spatial model. It verifies that the model not only fits the historical training data but can also accurately generalize the prediction of susceptibility to unseen data. To evaluate the performance of both the IV and WoE models, Area Under the Receiver Operating Characteristic Curve (AUC-ROC) analysis was employed.

The evaluation was divided into two phases:

1. **Success Rate Curve (Training Data):** This metric assesses how accurately the models classified the landslide-prone areas using the training dataset (70% of the inventory). The IV model exhibited excellent internal consistency with an **AUC of 0.818**, outperforming the WoE model, which achieved an **AUC of 0.754**. A steeper curve for the IV model indicates a superior ability to correctly rank highly susceptible zones at the top tier of the classification.

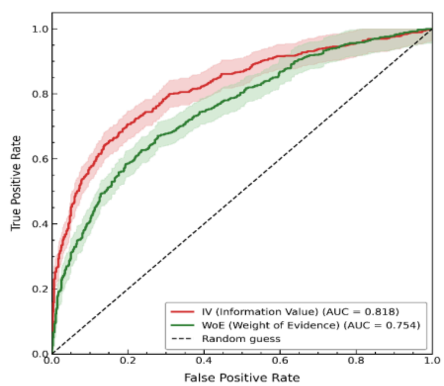

Figure 11.4 Success rate curve

2. **Prediction Rate Curve (Testing Data):** This evaluates the model's predictive power against the independent testing dataset (30% of the inventory). The IV model maintained a robust predictive accuracy with an **AUC of 0.836**, while the WoE model yielded an **AUC of 0.762**.

The higher AUC values achieved by the Information Value model confirm that it is more reliable in distinguishing between landslide and non-landslide areas within this specific terrain. While both models performed adequately, the WoE model's slightly lower accuracy may be attributed to its rigid assumption of conditional independence among the interacting geo-environmental factors during weight calculation.

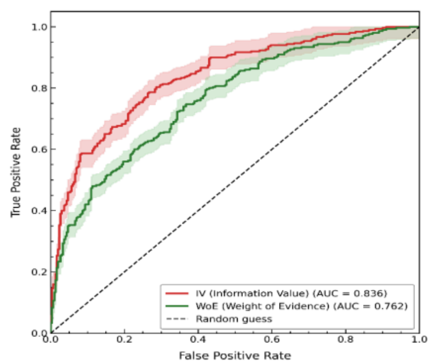

Figure 11.5 Prediction rate curve

CHAPTER-12

CONCLUSION AND FUTURE FOCUS

12.1 Conclusion

This research focused on the comprehensive evaluation and mapping of landslide susceptibility in the highly vulnerable Shimla district of Himachal Pradesh. The study employed a GIS-based comparative analytical framework utilizing two distinct bivariate statistical models: the Information Value (IV) and Weight of Evidence (WoE) methods. By integrating 12 critical geo-environmental conditioning factors with an extensive inventory of 1,003 historical landslide locations, detailed susceptibility maps were generated and categorized into five distinct risk zones.

The spatial analyses revealed that specific terrain characteristics are prime drivers of slope instability in the region. Slopes ranging between **34.5° and 44.2°**, elevations between **800 m and 1600 m**, strongly concave topographies, and areas within **250 m** of active drainage streams were statistically proven to be the most critical combination for failure initiation. Furthermore, land cover degradation, specifically sparsely vegetated and barren zones, heavily exacerbated the regional susceptibility.

The performance of the generated maps was rigorously validated using the AUC-ROC method, utilizing both Success Rate (training) and Prediction Rate (testing) curves. The Information Value (IV) model demonstrated superior predictive accuracy, achieving an AUC of **0.836** on the testing dataset, compared to the Weight of Evidence (WoE) model, which achieved an AUC of **0.762**. These findings clearly suggest that the IV method outperforms the WoE approach in identifying landslide-prone zones within the complex, geodynamically active terrain of the Lesser Himalayas. Consequently, the susceptibility zonation produced by the IV model serves as a highly reliable tool for disaster risk reduction, targeted infrastructure planning, and the formulation of sustainable development regulations in the Shimla district.

12.1 Future Focus

While the comparative study between the Information Value (IV) and Weight of Evidence (WoE) models proved highly effective for regional susceptibility mapping, the dynamic nature of the Himalayan environment warrants continuous methodological evolution. To further enhance predictive accuracy, future research should focus on the following domains:

- **Integration of Machine Learning:** Future studies should explore the implementation of advanced machine learning and artificial intelligence algorithms, such as Random Forest, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Deep Learning frameworks. Developing hybrid models that combine the interpretive clarity of bivariate statistics with the pattern-recognition capabilities of machine learning could yield more robust mapping outcomes.

- **Incorporation of Dynamic Variables:** The current static environmental factors should be augmented with dynamic, time-series data. Variables such as transient soil moisture profiles, seasonal vegetation index fluctuations, and localized rainfall intensity thresholds will significantly enhance model precision under changing climatic conditions.

- **Temporal and Field Validation:** Conducting rigorous temporal analyses will reveal how landslide distribution patterns evolve over time in response to rapid urbanization and highway expansion. Coupled with continuous on-ground field validation, these models can be kept empirically grounded. Technical advancements may also include the development of hybrid models that combine statistical, analytical, and machine learning methods for more robust susceptibility mapping. Conducting temporal analyses can reveal how landslide patterns evolve over time, while on-ground field validation will help ensure the models reflect real- world conditions. These enhancements will contribute to the creation of more adaptive, accurate, and data-driven models, ultimately strengthening disaster preparedness and landslide risk mitigation in vulnerable areas.

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