# Evaluating the impact of road construction on landslide susceptibility- A case study of Mandi district, Himachal Pradesh, India.

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**Abstract**

Landslide susceptibility mapping has proved to be crucial tool for effective disaster management and planning strategies in mountainous regions. The present study is perused to investigate the changes in the landslide susceptibility of the Mandi district of Himachal Pradesh due to road construction. For this purpose, an inventory of 1723 landslides was generated from various sources. Out of these, 1199 (70%) landslides were taken in the training dataset to be used for modelling and prediction purposes, while 524 (30%) landslides were taken in the testing dataset to be used for validation purposes. Eleven landslide causative factors were selected from numerous hydrological, geological and topographical factors and were analyzed for landslide susceptibility mapping using three bivariate statistical models, namely; Frequency Ratio (FR), Certainty Factor (CF) and Shanon Entropy (SE). Two sets of LSM maps i.e. landslide susceptibility map natural (LSMN) and landslide susceptibility map road (LSMR), were generated using the above mentioned bivariate models and were divided into five landslide susceptibility classes namely; very low, low, medium, high and very high. These maps were analyzed for accuracy of prediction and validation using receiver operating characteristic (ROC) curves and area under curve (AUC) technique which indicated that all three bivariate statistical models performed satisfactorily with the SE model had the highest prediction and validation accuracy of 83-86%. Further analysis LSM maps confirmed that the percentage area in high and very high classes of land-slide susceptibility increased by 2.67-4.17% due to road construction activities in the study area.

**Evaluating the impact of road construction on landslide susceptibility- A case study of Mandi district, Himachal Pradesh, India.**

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## Abstract

Landslide susceptibility is crucial for effective hazard management, planning mitigation and risk reduction strategies. In the present study, impact of road construction on landslide susceptibility is assessed for Mandi district. 1723 landslides data for Mandi district was compiled from the various sources with eleven causative factors. The eleven landslide causative factors were selected from numerous hydrological, geological and topographical factors. The landslide susceptibility analysis was carried out using three bivariate statistical models, namely, Frequency Ratio (FR), Certainty Factor (CF) and Shanon Entropy (SE). Two sets of Landslide Susceptibility Maps were generated for assessing the impact of road construction and were divided into five landslide susceptibility classes. The SE model had the highest prediction and validation accuracy of (83-86%). The percentage area in high and very high classes of landslide susceptibility increased by 2.67-4.17% due to road construction activities in the study area.

**Keywords:** Landslide; Bivariate Models; ROC; Multicollinearity; Remote Sensing

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# 1. Introduction

The adverse impacts of landslides on the socio-economic environment are increasing rapidly on a local and global scale. Due to complex physiography and increasing anthropological activities, Himachal Pradesh is recognised for frequent landslide occurrences, especially during the monsoon season. Rainfall induced landslide of Kotrupi on 13 August 2017 was one such devastating incidence. At least 46 people lost their lives as two state transportation busses got buried under a massive landslide along National Highway-154. The highway construction in mountainous regions significantly influences landslide occurrences (Dugonji, 2014). As many highways are under construction and many are in the planning phase in Himachal Pradesh which continuously interfere and destabilise the natural bed slope. The deforestation along the highway alignment also enhances the risk of landslides in Himachal Pradesh.

To quantify and manage the risk due to landslides, the landslide susceptibility analysis and mapping is of utmost importance. Landslide susceptibility of a region can be described as the probability with which a landslide can occur in a region based on that region's topographical and geographical conditions (Brabb, 1984) and the previous occurrences of landslides in the region (Nohani et al., 2019). Generally, landslide susceptibility is shown on maps that display multi-layered spatial and temporal distribution and the probability with which landslides can occur (Nagarajan et al., 1998). The susceptibility analysis and zonation of landslide hazard is considered as a complex process. It is a readily perceived research area in recent times, and experts have proposed various techniques and methodologies in different geological and meteorological settings (Nayak, 2010; Reichenbach et al., 2018). The multiple stages of landslide risk analysis and management, as compiled by (Fell, 1993), are widely accepted in evaluating and analysing landslide hazard. Various studies have shown the suitability of remote sensing and geomatics-based approaches for susceptibility analysis on a regional scale due to availability of spatially and spectrally varied temporal data (Prakash and Nagarajan., 2018). The remote sensing and GIS-based approaches using high/medium-resolution satellite imagery and Digital Elevation model allows a cost effective and rapid extraction of geological and topographical data on the regional scale (Prakash and Nagarajan., 2017). The first stage in most of the landslide susceptibility mapping methods is to develop a comprehensive landslides inventory map by compiling landslide event data from the various sources for the region. (Pradhan et al., 2014). Landslide hazard assessment and susceptibility analysis are highly dependent on the accuracy of landslides data acquisition and mapping (Henriques et al., 2009; Guzzetti, 2005). Landslide inventory map can be prepared from satellite image by visual interpretation and computer processing of the imagery, field inspections, aerial photographs, high resolution DEM and available data from various published reports (Remondo et al., 2003).

The next phase in landslide susceptibility analysis is to formulate layers of thematic variables of landslide causative factors leading to slope instability. The factors affecting land surface include regional geology, slope curvature, aspect, soil, distance to road, elevation, lineament density, drainage network, NDVI etc. These factors can be extracted and mapped using high resolution remote sensing images, arial photographs, published maps and digital elevation models (DEM) using geospatial tools and techniques. Remote sensing data has been accepted as the most accurate and authentic source of Earth's surface data (Banshtu and Prakash, 2014). Remote sensing provides the benefit of mapping landside areas according to research demand using updated satellite images (Jaiswal, 2009). These satellite images and aerial photographs being stereoscopic provides three dimensional perspectives for the characterisation of landslides based on their spatial and temporal features of the region (Mantovani et al., 1996; Chakraborthy, 2008). This spatial and temporal thematic dataset needs to be integrated with ground based information (Nagarajan et al., 1998).

For this purpose, GIS is a widely accepted tool to store extensive data (Rengers et al., 1992; Soeters et al., 1991). GIS can manipulate and analyse remotely sensed data for assessing landslide hazard (Carrara et al., 1991; McKean et al., 1991). The factors can then be ranked according to available codes, expert opinions, statistical modelling and multicriteria evaluation based techniques (Reichenbach et al., 2018). Hence using GIS in analysing remotely sensed images and DEM's can be considered as a highly efficient tool for landslide susceptibility mapping (Van Westen, 2000; Jebur et al., 2014b).

Geo-physical laws generally control landslides occurrence, and statistical, empirical and deterministic methods can be used for their analysis (Crozier, 1989; Hutchinson, 1988; Dietrich et al., 1995). The key to predicting landslides of the future is to analyse the past and present scenarios (Varnes, 1984). Along with this, various quantitative and qualitative approaches have been developed, helping determine the frequency and probability of a landslide event (Frangov et al., 2017). Some of the most accurate statistical techniques in landslide susceptibility modelling include logistic regression analysis, data overlay analysis, multi criteria analysis, the weight of overlay analysis, bivariate analysis and entropy based analysis etc. (Huabin et al., 2005; Kanungo et al., 2009; Reichenbach et al., 2018).

The present study is perceived with the motivation that road construction activities significantly influence the study area's landslide susceptibility. Despite ever increasing landslide incidences along the highways, there is still a significant research gap in comprehensive studies regarding road construction's impact on landslide susceptibility of a mountainous region like the Mandi District of Himachal Pradesh. Hence this study aims to compare the change in Landslide Susceptibility of Mandi district due to construction of roads in the district using Frequency Ratio (FR), Certainty Factor (CF) and Shanon Entropy (SE) models.

# 2. Study Area

Mandi district is located at the central region of Himachal Pradesh between 31°13' and 32° 05' North latitudes and 76°37' and 77°25' East longitudes. The district is the second most populated district of Himachal Pradesh, with a total area of 3,951 km$^2$ and a population density of 250 persons/km$^2$ having a road density of 155 km per 100 km$^2$. Two major National Highways that run across the district's length and breadth are NH-3 (Atari-Manali-Leh) and NH-154 (Pathankot-Sundernagar-Bilaspur). The climate of the region is sub-tropical in the valleys but tends to be temperate near the hilltops. The annual average rainfall in the district is 255 mm with average monthly rainfall extremities ranging from 10 mm in November to 345 mm in July. The elevation increase from west to east and south to north with altitude of the area ranging from 500 m to 3400 m. The soils of Lesser Himalayas and Siwaliks are mainly found in the district, which is generally high in organic matter and characterised by rugged topography. Hydro-geologically, the district has two distinct and well defined units, viz. porous formations constituted by unconsolidated sediments and the fissured formations. Forests, sparse and dense vegetation cover the majority of the district area. The Beas river runs through the northern part of the district whereas the southern part is drained by the Satluj river as shown in Figure 1.

# 3. Materials and Methods

## 3.1 Data Sources

The Operational Land Imager (OLI) and Thermal Infrared Sensor (TRIS) of Landsat-8 satellite having 12-Band multispectral images of the 30-m resolution were downloaded from United States Geological Survey (USGS) Earth Explorer website. The multispectral images from the year 2015 to 2020 from the first week of October to the last week of November, just after the monsoon season is over as maximum landslides incidences in the Mandi district occurred during the monsoon season, were considered adequate due to the availability of cloud-free data. These high resolution multispectral images were already terrain corrected and were suitable for analysing the study area's terrain characteristics. Advanced Land Observing Satellite-Phased Array Type L-band Synthetic Aperture Radar (ALOS-PALSAR) Digital Elevation Model (DEM) of 12.5m resolution was downloaded from the Alaska Satellite Facility website. This DEM was used to derive topographical information such as slope, curvature, aspect and drainage density etc., of the study area. A geological map of the study area was obtained from India's Geological Survey (GSI) Bhukosh portal. The Mandi district's soil map was generated using published Soil Map of Himachal Pradesh procured from the Indian Council of Agricultural Research-National Bureau of Soil Survey and Land Use Planning (ICAR-NBSS-LUP). The road network for the study area was developed from the published maps from the portal of Ministry of Road Transport and Highways (MoRTH). Table 1. Depicts various data sources used and their purpose in the present study.

## 3.2 Landslide Inventory Dataset

In the present study, landslide occurrences in the study area were detected and mapped using three sources (a) landslide data from Himachal Pradesh government disaster revenue reports and various documented sources such as Bhukosh portal of GSI (b) High resolution Google Earth images were used as an auxiliary data source and are analysed through visual interpretation to identify landslides and (c) through extensive field surveys using handheld GPS. The analysis of factors responsible for triggering landslides is necessary as it gives a relationship between various conditions that might be responsible for disrupting the stable slope conditions. (Crozier and Glade, 2003). The various triggering factors in study area are earthquakes, soil erosion, deforestation, mining infrastructure development etc. It was found that the most common triggering factor for all the landslides in the region was rainfall. Hence all landslides are treated as rainfall induced landslides in the present study. A total of 1723 landslides and their location, type and other required information were documented for developing a GIS based landslide inventory of the district. The landslide inventory was subdivided into a training set of 1199 landslides (70%) for landslide susceptibility analysis and a validation set of 524 landslides (30%) using random sampling in ArcGIS as shown in Figure 2.

## 3.3 Landslide Causative Factors

The interaction between geological, morphometric, topographical and hydrological factors in a region influences landslides' occurrence. Hence the appropriate selection of these causative factors is a primary step in landslide susceptibility analysis ( Lee et al., 2004; Dou et al., 2015). In the present study, based upon the previous studies and expert opinions, eleven landslide causative factors namely slope gradient, plan curvature, aspect, elevation, drainage density, lineament density, geology, NDVI, soil, TWI and distance from the road were selected for the analysis. As there were variable scales of various causative factors, therefore all these were resampled into a raster format of 30 m resolution to commensurate the diversity for geoprocessing and map algebra analysis through ArcGIS.

The slope gradient is considered a significant factor that influences landslides in a particular area as it quantifies the amount of shear force acting on a specific area of sliding. (Saha et al., 2005; Pradhan and Lee, 2010). The slope gradient map prepared from the 12.5 m ALOS PALSAR DEM of the Mandi district is shown in Figure-3. The study area exhibits a considerable variation in slope gradients with slopes ranging from 0° to 82° which gives rise to flatter terrains along the valleys to extremely steep terrains along the mountains. The relief features of the region are extensively used in landslide susceptibility analysis as it affects rainfall, seismicity, etc. (Pham, 2017). The north eastern part of the Mandi district is dominated by a higher elevation which ranges from 3000 to 6000 m. The northern part of the Mandi district is surrounded by Beas river which is characterised by a lower elevation, including Balh Valley. The slope aspect of the area tends to be relatively evenly distributed in all directions, although southward directions have slight predominance. The plan curvature of the area is predominantly flat to slightly concave. The Plan Curvature of slope represents the direction of maximum slope and helps identify the morphology of the area's topography (Erener and Düzgün, 2012; Pourghasemi et al., 2012). The drainage density, the measure of the density of streams and rivers in a drainage basin, directly influences slope's erodibility dissected by channels and influences the surface runoff (Demir et al., 2014). The drainage density of the Mandi district ranges from 0 - 2.4 and is subdivided into five classes. Hydrological impact of drainage networks on the wetness/saturation of the soils on the slopes is assessed and quantified using Topographic Wetness Index (TWI) (Beven and Kirkby, 1979). The TWI map of study area was prepared by combined arithmetic application of morphometric variables, including the slope gradient and flow accumulation parameters, using Equation (1) with values ranging from 4.0 – 28.0. Normalised Difference Vegetation Index (NDVI) map is one of the most fundamental and widely accepted index to detect vegetation and landcover changes caused by infrastructural developmental activities. (Carrara et al., 1982; Ceballos and Lopez, 2003; Ahmad et al., 2013). Normalised Difference Vegetation Index (NDVI) map was prepared using image analysis techniques on high resolution Landsat-8 images of the study area using ERDAS IMAGINE software using Equation (2). The primary NDVI zone of the study area was shrubs and grasslands (45%), followed by sparsely vegetated (28%) and urban area (12%). Lineaments are the linear weaknesses or fracture planes such as cracks, faults, bleeding planes, joints etc. which represents the underlying geology of the area (Ramakrishnan et al., 2013). It was found that almost 35% of the total area had high to very high lineament density, and 26% of the total area had a moderate density of lineaments. Geological boundaries of an area are closely related to slope and rock strength, and such boundaries may lead to increased landslide activity. Mandi district lies within the lesser Himalayan and Siwalik region and was classified into five zones based on their slopes and terrain characteristics (Choubey et al., 2007; Dou, 2014). Different types of soils have different cohesion values, and the infiltrated water might be able to erode the soils with lesser cohesion values. (Mzuku et al., 2005; Godt et al., 2009; Baum, 2010). The Mandi district's soil map was classified into five categories of soils based on their depth, drainage, and erosion properties. The construction of roads in mountainous terrain often includes excavation along the natural bed slope. This usually results in loss of support and cracks development due to increased strain in the upper soil mass. (Devkota et al., 2013; Pradhan et al., 2018) As a result, landslides occurrences are mostly distributed near the road network. (Ayalew and Yamagishi, 2005; Tuan and Dan, 2012). The road network distribution was reclassified into five road buffer zones from 0-500 m at 100 m intervals.

$\mathrm{TWI} = [\mathrm{Ln}\ (\mathrm{As})\ /\ \mathrm{Tan}\ (\beta)]$ (1)

Where Ln is natural log, $A_s$ = Flow Accumulation, $\beta$ = Slope in Radians

$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED})\ /\ (\mathrm{NIR} + \mathrm{RED})$ (2)

NIR (Near Infra-Red Band) and RED Band represent the electromagnetic spectrum's spectral reflectance bands.

## 3.4 Statistical Landslide Susceptibility Models

Statistical bivariate models are widely accepted methods of quantitative analysis of landslide data. They generate a statistical relationship between the dependent variable (known landslides distribution) with a set of independent variables (landslide causative factors) to predict landslide susceptibility of an area. (Carrara et al., 1991; Chung et al., 1995; Guzzetti et al., 2006b; Rossi et al., 2010). In this study, landslide susceptibility analysis was carried out using three statistical models, i.e. Frequency Ratio (FR), Certainty Factor (CF) and Shanon Entropy. The data of all landslide causative factors were resampled into raster format of spatial resolution of 30 m. The accuracy of these models was validated by plotting the Receiver Operating Characteristics Curve (ROC) using Monte Carlo Simulation in the SDM tool in ArcGIS. The detailed methodology used in the present study is described using a flowchart as shown in Figure 4.

### 3.4.1 Frequency Ratio Model

Frequency ratio (FR) is an observation based statistical model representing the probability of occurrence of landslides for a given influencing parameter by correlating them with the existing distribution of landslides (Lee and Pradhan, 2007; Bonham and Carter, 2014). FR model associates the pixel data with and without landslides with pixels of input raster data layers of causative factors. The FR value is then computed for each class of particular causative factor using Equation (3). FR values greater than 1 indicate a higher proportion of landslide occurrence and a high correlation with that specific class of causative factor. On the contrary, FR value less than 1 indicates a lower correlation with that particular causative factor. (Akgun, 2008; Karim et al., 2011)

$FR(i) = \frac{Npix(li)\ /\ Npix(ci)}{\sum Npix(li)\ /\ \sum Npix(ci)}$(3)

Npix(li) = Number of pixels containing landslides in each class (i) of the causative factor

Npix(ci) = Total number of pixels in each class (i) of the causative factor

[?]Npix(li) = Total number of pixels containing landslides in the study area

[?]Npix(li) = Total number of pixels in the whole study area

To prepare final LSM maps, the FR values of all the landslide causative classes have to be integrated using Equation (4)

$\mathrm{LSM_{FR}} = \mathrm{FR_1}+ \mathrm{FR_2}+ \mathrm{FR_3}+\ldots+ \mathrm{FR_n}$ (4)

### 3.4.2 Certainty Factor Model

The Certainty Factor (CF) model is one of the most fundamental and widely accepted model for landslide susceptibility mapping. (Kanungo et al., 2011; Liu et al., 2014). It provides a rule based favourability function to consolidate heterogeneous data layers using Equation (5).

CF =

$$\begin{matrix} \frac{\mathrm{ppa\ -pps}}{\mathrm{ppa(1-pps)}} & amp;\ \text{when ppa} \geq \text{pps} \\ \frac{\mathrm{ppa-pps}}{\mathrm{pps(1-ppa)}} & amp;\ \text{when ppa} < \text{pps} \end{matrix} \ (5)$$

Where CF is the Certainty Factor, ppa is the conditional probability of having a landslide event occurring in class "a", and pps is the prior probability of having the total number of landslides in the study area "A".

The CF value ranges between -1 and +1, where +1 is the measure of belief (definitely true) or increasing certainty of landslide occurrence and -1 is the measure of disbelief (definitely false) or decreasing certainty of landslide occurrence. CF value nearby 0 indicates that the conditional probability is very close to the prior probability, and hence it is difficult to ascertain any certainty of landslide occurrence (Lee and Talib, 2005; Pourghasemi et al., 2012e). The pairwise data layers of all landslide causative factors were combined based on "Z" values obtained from Equation (6) (Dou et al. 2014; Ilia et al. 2015).

$$Z = \begin{matrix} A+B-AB & amp; A,B \geq 0 \\ (A+B)/(1-min(|A|,|B|)) & amp; A*B < 0 \\ A+B+AB & amp; A,B < 0 \end{matrix} \ (6)$$

These pairwise combinations have to be persistently performed on all causative factors using the integration rule until all data layers were combined to prepare final LSM maps.

### 3.4.3 Shanon Entropy Method

The entropy of a system conceptually measures the degree of randomness, disorder, uncertainty or instability. Thermodynamically as Boltzmann described, entropy is used to represent the direction of the spontaneity of a process. Claude Shannon in 1948 developed the concept of entropy to analyse a fundamental communication problem of information theory. The Shanon Entropy (SE) model can be used to measure the uncertainty in the information of various landslide causative parameters (Bednarik, 2010; Pourghasemi, 2012; Nohani et al., 2019). The probability density $P_{\mathrm{ij}}$values for each class is calculated using Equation (7), which are further used to calculate the information coefficients $H_j$ using Equation (8).

$P_{\mathrm{ij}} = \frac{\mathrm{FR}}{\sum_{j=1}^{N_j} \mathrm{FR}}$ (7)

where $P_{\text{ij}}$ represents the probability density of each sub class, and FR represents the frequency ratio of each class.

$$E_j = -\sum_{i=1}^{N_j} P_{\text{ij}}\ P_{\text{ij}}, j = 1, \ldots, n$$

$E_{\text{jmax}} = N_j, j = number\ of\ sub\ classes$

$H_j = (E_{\text{jmax}} - E_j/E_{\text{jmax}}),\ H = (0,1),\ j = 1, \ldots,$ n

$W_j = H_j * FR$ (8)

Where $E_j$ and $E_{\text{jmax}}$ are the entropy values, $H_j$ is the information coefficient, $N_j$ is the number of classes in each landslide causative factor. $W_j$ calculated from Equation (8) is the relative weight assigned to each landslide causative factor on the whole. $W_j$ values closer to 1 represent higher uncertainty or inconsistency, whereas values closer to 0 represents higher certainty or consistency. The final LSM maps were prepared by using Equation (10)

$\text{LSM}_{\text{SE}} = W_1 * \text{FR}_1 + \text{W}_2 * \text{FR}_2 + \text{W}_3 * \text{FR}_3 + \ldots + \text{W}_n * \text{FR}_\text{n}$(9)

# 4. Results

## 4.1 Multicollinearity Analysis

Multicollinearity analysis is a statistical concept and is generally carried out to check for correlation between various independent variables (Nohani et al., 2019; Roy et al., 2019). In this study, a multicollinearity test was conducted to analyse the correlation between 11 independent landslide causative factors using IBM SPSS Statistics software. The Variance Inflation Factor (VIF) and tolerance values obtained from the multicollinearity analysis are shown in Table 2. The VIF values $> 10$ or tolerance values $< 0.1$ suggest the problem of collinearity among the independent variables. It can be seen from Table 2. that there is no issue of collinearity among independent variables as all values of tolerance and VIF were found satisfactory. Hence all selected landslide causative factors were found suitable for landslide susceptibility analysis.

4.2 Relationship between Landslide Causative Factors and Landslide Occurrence

LSM maps of the study area were prepared using three bivariate statistical models and were further analysed for landslide susceptibility change due to road construction. This was done by preparing two types of LSM maps. The first map, termed as Landslide Susceptibility Map Natural ($\text{LSM}_\text{N}$), was formulated, taking into account only ten landslide causative factors excluding distance from road factor. Similarly, the second map, termed as Landslide Susceptibility Map Road ($\text{LSM}_\text{R}$), was prepared, taking into account all the eleven landslide causative factors, including distance from the road factor, using Equation (4). The $\text{LSM}_\text{N}$ and $\text{LSM}_\text{R}$ maps were classified into five landslide susceptibility zones: very low, low, moderate, high, and very high susceptibility, as shown in Figure 5.

The FR values of each class of eleven landslide causative factors based on their correlation with the landslide occurrences are shown in Table 3. The $\text{LSM}_\text{N}$ and $\text{LSM}_\text{R}$ maps analysis indicates that drainage density, TWI, NDVI and distance from road (for $\text{LSM}_\text{R}$ only) were the critical factors that affect the study area's landslide susceptibility. While analysing the hydrological parameters, the highest FR values were obtained for areas with very high drainage density (14.7) and very high TWI (49.7). Such areas were found to be more susceptible to landslides. Also, it was found that areas near the vicinity of roads are generally more prone to landslides. Further, the FR values of the distance from the road classes of 0-100 m (6.4) and 100-200 m (5.7) were found to be highest therefore, such areas were found to be more landslide prone. The study area was categorised into five NDVI classes: waterbodies, urban area, barren land, shrubs and grasslands, and sparse and dense vegetation. The areas closer to waterbodies had the highest FR value (7.7), followed by urban areas where human interference with natural slopes was observed.

The analysis of CF values indicated a similar trend with classes of very high drainage density (0.93), very high TWI (0.98), NDVI waterbodies (0.87) and 0-100 m (0.84) distance from road indicating the highest correlation with landslide occurrence. Further, the slope gradient directly relates to landslides occurrence as steeper slopes tend to be more unstable than flatter terrains. It was interpreted from the data that slope gradient classes, namely; steep (35°-45°) and very steep (>45°), had the highest CF values and were more prone to landslides, whereas no landslides were reported for flat (<15°) slope gradient class. Similarly, it was observed that the probability of landslides was moderate at lower elevations (400m-1000m) due to modest terrain characteristics. The highest probability of landslides was observed at high elevations (2000m-2500m). At very high elevations (2500m-3500m), the probability of landslides again decreases. This might be attributed to lesser reporting of landslides due to rugged terrain at areas with higher elevations. Regarding the geological aspects, the Middle Siwalik Group was found to have the highest CF values (0.74). This group predominantly consists of medium to coarse grained sandstone and red clay alternation, soft pebble with subordinate claystone and a locally thick prism of the conglomerate which might be attributed to its higher landslide susceptibility. During the analysis of soil classes, the highest CF was obtained for the lesser Himalayan soils of fluvial valleys (0.75), followed by Siwalik soils of side and reposed slopes (0.62). Both these soil types are described as loamy to loamy-skeletal soils, facilitating moderate to severe erosion.

The analysis of the Shanon Entropy model indicated that the highest $W_{ij}$ values were obtained for drainage density, TWI, NDVI and distance from road factors and highest $P_{ij}$ values were attributed to very high drainage density (0.58), very high TWI (0.42), NDVI waterbodies (0.57) and 0-100 m distance from roads (0.35). Hence these factors had the highest influence on landslide occurrence. Along with these, the areas with steep (35°-45°) and very steep (>45°) slopes and moderately high elevation class was found to have the highest $P_{ij}$ values and had a moderate influence on landslides occurrence. The geology map analysis again confirms that the Middle Siwalik Group, with the highest $P_{ij}$ value (0.15), was highly prone to landslides, followed by the Dharmasala Group. Similarly, soil classes analysis confirms that the fluvial valley soils of lesser Himalayas with the highest $P_{ij}$ value (0.70) were highly prone to landslides because of their shallow depth and excessive drainage characteristics. All other landslide causative factors such as aspect, curvature, lineament density etc. and their classes with the highest FR, CF and SE values had low to moderate influence on landslides occurrence.

### 4.3 Accuracy Assessment and Validation of Models

In this study, the $LSM_N$ and $LSM_R$ maps prepared using FR, CF and SE models were evaluated for accuracy of prediction and validation using ROC curves and AUC technique. These are well known techniques to determine the quality of a statistical model by plotting the fraction of true positives values out of total positives values and false positives values out of total negatives values by determining Sensitivity and Specificity (Devkota et al., 2013; Nohani et al., 2019). Each model's prediction rate curve was plotted using training data set of 1199 landslides (70%), and the validation rate curve of each model was plotted using a validation data set of 524 landslides (30%). The relative ROC curves of the three models are shown in Figure 6. Based on the ROC results and AUC evaluation, all three models offer the satisfactory prediction and validation accuracy. However, the Shanon Entropy model was found to have the most accurate prediction and validation for landslide susceptibility mapping of $LSM_N$ and $LSM_R$ maps.

## 5. Discussion

The process of generation of LSM maps is complex and requires multistep in depth analysis. This study analyses three main issues: (a) the mapping of landslide susceptibility of Mandi district based on relevant landslide causative factors (b) the comparison of three statistical models, namely Frequency Ratio (FR), Certainty Factor (CF) and Shanon Entropy (SE) for their accuracies in predicting landslides and (c) the assessment of landslide susceptibility change due to road construction in Mandi district.

An appropriate selection of landslide causative factors requires extensive knowledge of geographical and topographical aspects of the study area and triggering mechanisms associated with them (Guzzetti et al., 1999; Costanzo et al., 2012). Generally, the optimal approach is manual selection based on expert opinion, but there are no universal guidelines for identification and selection of landslide causative factors (Dou et al., 2015). Based on this criterion, eleven landslide causative factors were identified, all of whom had a strong association with landslide occurrence. Further, the interdependence of these factors was investigated using a multicollinearity test, which indicated that the selected factors were independent and credible. Analysis of the three statistical models results revealed that drainage density, distance from the road, TWI and NDVI were the most influential factors for landslide occurrence. At the same time, the slope curvature and aspect were the least influential factors on landslide occurrence. The rest of the parameters, such as elevation, lineament density, geology and soil, had a moderate impact on landslide occurrence. A high density of drainage networks and steeper slopes, and sedimentary rocks like medium to coarse grained sandstone and conglomerate can be attributed as principle factors of landslide occurrence in the study area. These factors, especially when combined with excessively drained soils, high lineament density and improper road construction activities, tend to increase the study area's landslide susceptibility. Further, the NDVI map analysis suggested that the areas near waterbodies and the areas interfered with by human settlements, road construction or any other infrastructure development activities tend to be more prone to landslides. On the contrary, regions having very high elevations, a higher percentage of vegetation and flatter slope gradients have minimum susceptibility to landslides. These results conform with the findings of similar research reports. (Dou et al., 2015; Hong and Bui, 2015; Roy, 2019).

Statistical modelling is an essential component in determining the landslide susceptibility of an area. The accuracy of statistical models is primarily dependent upon the data quality and model structure. In this study, three statistical models, namely: FR, CF and SE, were used to determine the Mandi district's landslide susceptibility. The validation of these models was done using ROC curves and the AUC technique, assuming that landslides were dependent only on the given spatial parameters with rainfall as the common triggering factor. The results indicate that all three models have satisfactory values for prediction and accuracy. Still, the relative contribution of the landslide causative factors varied with the models, as shown in Figure 6. The highest accuracy of prediction and validation was demonstrated by Shanon Entropy (83-86%). The SE model is an entropy based data driven model which directly stores information of variables and correlates with the probability of landslide occurrence. This might be the reason for its higher accuracy in comparison to the other two models. The SE model indicated that drainage density and distance from roads as the two major contributing factors towards landslide susceptibility. The SE model also suggested a strong correlation between higher slope gradient and TWI and landslide occurrence. Some other factors like NDVI, soil, geology and elevation also indicated significant contribution. The geology Dharmasala Group, Dagshai and Kasauli Formations combined with soils of fluvial valleys at moderate to high elevations showed the highest correlation with landslide occurrence. FR model being on the observation model had (75-79%) accuracy of prediction and validation. As a rule-based model, the CF model had a relatively good accuracy of predicting and validating (75-82%). These models also suggested drainage density and road construction as two fundamental factors with maximum impact on landslide susceptibility in the study area. The comparison of these models was found to be in accordance with recent studies of landslide susceptibility analysis. (Devkota et al., 2013; Lee and Pradhan, 2007; Nohani et.al, 2019; Wang et al., 2015).

In this study, the $\mathrm{LSM_N}$ and $\mathrm{LSM_R}$ maps were prepared using FR, CF and SE models. The results of all the models indicated that the road construction activities in the Mandi district appear to be a primary factor responsible for an increase in landslide susceptibility of the study area. For comparison, ten common landslide causative factors were considered for preparing two susceptibility maps. The additional factor of the distance from the road was only considered for the $\mathrm{LSM_R}$ map. These susceptibility maps are further classified into five zones of susceptibility: very low, low, moderate, high and very high susceptibility. The analysis of change in susceptibility was done by comparing each class's percentages in both $\mathrm{LSM_N}$ and $\mathrm{LSM_R}$ maps, as shown in Table 4. The analysis of $LSM_N$ and $LSM_R$ maps of FR model indicates that the percentage of area in high susceptibility zone increases from 22.9% in $LSM_N$ map to 24.5% in $LSM_R$ map and the percentage of area in very high susceptibility zone increases from 13.2% in $LSM_N$ map to 15.8% in $LSM_R$ map.

Similarly, for the CF model, the high susceptibility zone area increases from 23% in the $LSM_N$ map to 24% in the $LSM_R$ map. The area is very high susceptibility zone increases from 7% in $LSM_N$ map to 8% in $LSM_R$ map. Likewise, in the SE model having the highest prediction accuracy, it was observed that the percentage of area in high susceptibility zone increases from 19.3% in $LSM_N$ map to 21.6% in $LSM_R$ map, and the percentage of area in very high susceptibility zone increases from 10.8% in $LSM_N$map to 12.5% in $LSM_R$ map. It can be observed from the $LSM_R$ maps in Figure 5. that the areas in the vicinity of the road, particularly in classes (0-100m) and (100-200m), witnessed an increase in landslide susceptibility. This can be attributed to the fact that the cutting and tempering of natural bed slope for road construction increases the risk of slope failure in that area. Additionally, road construction may change or block the natural drainage networks operating in mountainous terrains. This might further increase the probability of landslide occurrence in that area.

# 6. Conclusions

Landslide susceptibility mapping is crucial, keeping in mind the futuristic development plans in mountainous regions. In the present study, 1723 landslides and 11 causative factors with high correlation to landslide occurrences were used for landslide susceptibility analysis. The landslide susceptibility maps were prepared using frequency ratio (FR), certainty factor (CF) and Shanon Entropy (SE) models and were further classified into five classes i.e. low, moderate, high, and very high susceptibility zones. The accuracy of these models were assessed using Receiver Operating Characteristics (ROC) method and area under the curve (AUC) technique. The FR model's prediction and validation accuracy lie between (75-79%) and for the CF model lies between (75-82%). The highest accuracy of prediction and validation was observed for the SE model (83-86%), and hence SE model is recommended for similar studies in the future. The analysis of three models indicate that very high drainage density and TWI, NDVI waterbodies and a distance of (0-100 m) from roads are the four most predominant factors influencing the landslide susceptibility in mountainous region. Further analysis of $LSM_N$ and $LSM_R$ maps implied a 2.67-4.17% increase in the areas with high and very high susceptibilities due to road construction in the study area. Hence, the road construction in hilly region increases the landslide susceptibility so a better planning and construction management is required to mitigate the impact of road construction on landslide susceptibility.

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