Landslide Susceptibility Mapping along Manipur-Assam NH-37

Kanwarpreet Singh  (kanwarpreet.e9570@cumail.in)
Chandigarh University  https://orcid.org/0000-0002-7012-1815

Sukhajit Khaidem
Chandigarh University

Research Article

Keywords: LANDSAT, GIS, Quantitative, LSZ, AUC

Posted Date: May 26th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1520393/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License
Abstract

Landslides are the most catastrophic geological natural hazard in mountainous terrain. To minimise and mitigate these threats, comprehensive landslide mitigation and management, landslide assessment, and susceptibility zonation are required. Various methods are established based on different assessment methodologies, which are classified into qualitative and quantitative approaches. GIS based landslide susceptibility mapping was carried out along the National Highway 37, which connects Assam and Manipur and is a vital lifeline for the state. Field visits, LANDSAT bands, and Google Earth were used to create a landslide inventory map along the road corridor. To perform landslide susceptibility zonation modelling based on Frequency Ratio, Shannon’s Entropy, and Weight of Evidence, thematic layers of several landslide causative elements were delineated. The study area has been categorized into five vulnerable zones: very low, low, moderate, high, and very high. The landslide susceptibility zonation map was validated using the area under curve and landslide density methods. The final map will be helpful for various stakeholders, including town planners, engineers, geotechnical engineers, and geologists, for development and construction activities along NH-37.

1. Introduction

Due to high topography, poor land cover, and climatic circumstances conducive to landslides, landslides are one of the most catastrophic natural catastrophes, causing significant damage to residential areas, economic losses, and human casualties all over the world, but notably in hilly terrain (Akgun et al., 2008; Solaimani et al., 2013; Ahmed, 2014). Landslides are impacted by the structural, lithological, geomorphological, climatic, environmental, hydrological, and seismological variables of the affected area, among other factors. The majority of landslides are caused by oversaturation of the slope-forming materials (Prakash et. al 2020; Balasubramani K. and Kumarswamy K. 2013; Bera et. al., 2019). The susceptibility of landslides is determined by bedrock geology, geomorphology, soil depth, soil composition, slope gradient, slope aspect, slope convexity and concavity, elevation, engineering properties of the slope content, land use pattern, drainage patterns, anthropogenic activities, and other intrinsic variables (Anbalagan et. al., 2015; Bappaditya et. al., 2020 Raghuvaishi et. al., 2014). Landslides are frequently caused by extrinsic factors such as severe rainfall, earthquakes, and volcanoes in a given zone of susceptibility. It is often accepted in literature that a combination of these elements could produce landslides in a particular area. As a result, evaluating these elements and their relationship to historical landslides in a given area can aid in the prediction of future landslides (Akgun et al., 2008; Wu and Chen, 2009; Solaimani et al., 2013; Dou et al., 2017). The spatial relationship between landslides and influencing factors can be used to create a landslide susceptibility map (C.J Westen 2000).

Varnes (1984) defined landslide hazard as the probability of a potentially devastating landslide occurring within a particular time frame and inside a specific area. In addition, intrinsic and extrinsic characteristics are utilised to evaluate the risk of landslides in a particular area (Dai et. ai., 2001; Hawas et. al., 2018; Lakshmi et. al., 2019). It is important to assess those factors which can cause landslides to mitigate the damage caused by landslides. The three primary components of a landslide analysis are landslide
vulnerability, landslide danger, and landslide risk (Ioan et. al., 2017; Reichenbach et. al., 2018). A review of different approaches for assessing and mapping landslide risk has been carried out (Akgun et al., 2008; Wu and Chen, 2009; Tareq et. al., 2011; Solaimani et al., 2013).

There are variety of approaches to delineate landslide susceptibility maps (LSMs) categorized as “statistical, soft computing, and analytical methodologies (Pardeshi et. al., 2013; Saaty T. 2008; Lee S 2007). In case of large study area, the implementation of the analytical approaches is difficult where the statistical methods can be employed. The weights depending upon the dependent and independent variables can be predicted (Wubalem et al., 2020; Bopche and Rege 2021).

There are four primary processes to creating a landslide susceptibility map: (1) A landslide inventory map will be created; (2) Landslide controlling factor maps will be created; (3) The most appropriate method for evaluating the weights of each element will be used; (4) a GIS platform will be used to create a landslide susceptibility map (Sarda et al., 2019; Meten et. al. 2021; Salman and Akram 2021). Furthermore, incorporating these techniques into GIS is a relatively easy and simple. It assesses the interdependencies and relative importance of the components that cause slope failure activities in the area in order to create landslide susceptibility map for its use in urban planning and development (Fell et al., 2008; Osadebe et. al. 2019). Landslide susceptibility assessment and zonation procedures can be used to determine the risk of landslides in a given area (Mengistu et. al. 2019; Sarkar et. al., 2013). Various researchers have entailed inventory-based methodologies, expert assessment, statistical, deterministic, probabilistic, and distribution-free approaches (Dai and Lee, 2001; Fall et al., 2006; Kanungo et al., 2006; Arora et. al. 2009; Raghuvanshi et al., 2014; Achour et al. 2018; Singh et al. 2018; Abdo 2021; Magd et al. 2021).

The current study focuses on GIS-based landslide susceptibility mapping along National Highway 37 from Imphal to Nungba, which connects Assam and Manipur in India and serves as a vital artery between the two states. Using statistical concepts and methodologies, this method measures and evaluates the Landslide Susceptibility Index.

2. Study Area

Manipur is a small state in northeast India with a little portion of the valley in the centre part of the state. It has a monsoon climate that lasts only for four months from June to September. The main source of rain is the southwest monsoon, with June being the wettest month. Winter, summer, and rainy season are the three seasons in the area. Landslides and other natural calamities routinely disrupt Manipur's hilly roadways, particularly the state's national highways, during and after periods of heavy and protracted rains. The state's lifeline is the NH-39 (now renamed NH-2) and NH-37, which connect the state to the rest of the country. Any obstruction on these two routes has a wide range of consequences for the citizens of the state.

The current investigation spans a total distance of 113 kilometres, from Imphal, the state capital, to Nungba. The brittle nature of the Litho units, which emerge from the rock types and structures that characterise these rocks, is one of the key factors contributing to frequent landslides in Manipur. However,
certain areas are found to be covered with thick soil columns, causing instability. The engineering qualities of rocks, as well as soils and moisture content variations, all play a part in the initialization of slides on this slope. In the present study, Authors tried to locate hazard prone zones in the study area along the National Highway-NH-37. At 24°74'96"N and 93°42' 21"E, the current investigation area is covered by Survey of India Toposheet No. 83 H/5. Nungba lies at an elevation of 400 metres above sea level.

Nungba is a small town on the eastern edge of the Indian Himalayas, covering around 120 square kilometres. It is located in India's most seismically active zone, Seismic Zone V. The most recent seismic activity, with an epicentre 50 kilometres from Nungba, was observed in the early hours of 3 January 2016. Nungba is defined by its hills and rivers. It has a sharp slope in the east and becomes more gently elongated in the west and south. Rwangdai, Rengpang, Taodaijang, Mukti, Namgaylung (known as Mukti Naa), Tajeikaiphun, and Puiluan are a few of the hill settlements that surround Nungba. Rivers such as the Lemga, Khatha, Thingdingluangthuak, and Luangphai flow out of and encircle Nungba. Alang (Irang), Agu, and other rivers serve as natural boundaries in the study area. The climate of Nungba is subtropical. It has a pleasant and temperate climate all year, with temperatures ranging from 5 to 20 degrees Celsius in the winter and 15 to 30 degrees Celsius in the summer.

3. Data Collection

Data collection and preparation is important for each research project. In depth understanding of an area's influence in factors that need to be recognised and mapped is required for landslide susceptibility mapping. The data availability influences the choice of landslide causative factors for susceptibility evaluation. The database collected for LSZ modelling from various sources is mentioned in the flow chart (Figure 2) and Table 1. Ten landslide causative factors were turned into thematic maps: slope, aspect, curvature, drainage density, soil, lithology, land use-land cover (LULC), rainfall, geology, elevation, and lineament density. The slope, aspect, curvature, and elevation maps of the study area were extracted from digital elevation model. The lithology and lineament maps were produced using database available at Geological Survey of India website. LISS 3and Google Earth satellite imagery are used to create the LULC map. Rainfall map of the study area has been prepared using CHRS based database. All the thematic layers were re-sampled into a 30m*30m resolution raster format for LSZ modelling.

3.1 LANDSLIDE INVENTORY

The landslide inventory map has been used as a foundation for LSZ, as it shows the sites of landslides and allows for easy identification. It could also be employed on a regional scale to reduce landslide dangers and risks. A thorough landslide inventory can provide valuable insight into the failure mechanisms of landslides.

| Table 1. Data use in present study |
The landslide inventory map was created using LISS 3 satellite images, Google Earth, and extensive field visits. Rockfall, debris flow, and debris/earth slide are among the several types of failures seen in the area. Some of the landslide occurrences in the study area are shown in Figure 3.

4. Landslide Causative Factors

Data collection and the creation of a spatial database from which important parameters are extracted are required for landslide susceptibility analysis. Selecting the independent variables that play a significant effect, on the other hand, is a difficult undertaking. There are no general norms or requirements. As a result, factor selection must take into account the study area’s characteristics as well as data availability. The eleven factors considered for the susceptibility analysis are described in the following paragraphs as mentioned in Figure 4. Landslide causative factors were subdivided into different classes to best reflect the diversity of the data source and scale differences, and to clearly delineate their role in the mechanism.

4.1 CURVATURE

The rate of change in slope gradient (profile curvature) and/or aspect (plan-form curvature) in a specific direction is theoretically described as curvature. Convexity is defined by positive profile curvatures, while slope concavity is defined by negative profile curvatures. Ridges have positive topographic curvature values, while valleys have negative ones. Values near zero indicate level surfaces, regardless of slope. The profile and plan-form curvatures are combined in the topographic curvature map. The mountain locations with scarp, ridges, deep valleys, and gorges, where rockfalls and landslides are possible, have the highest values.

4.2 SLOPE

Because land-sliding is directly related to this element, the slope angle is widely utilised in landslide susceptibility research. The slope has been categorised into five classes in this study. The predominant
class is 0–15°, which is uniformly present in flat places. Slope values range from 0–15° to 30–45° in some large areas of the lowlands and uplands, with steep slopes influenced by landslides and earth flows. The higher slope values are associated with mountain peaks and ridges that have sub-vertical slopes (above 60°) and are subject to rockfall.

**4.3 ASPECT**

The down slope direction of the highest rate of change in value from each cell to its neighbours is identified by this aspect. In landslide susceptibility studies, aspect is considered a less essential feature. Nonetheless, aspect-related variables like as sunlight exposure, drying winds, and rainfall may have an impact on the occurrence of landslides. 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 (0-22.5) are the 10 classes of the aspect map based on direction (337.5-360).

**4.4 DRAINAGE DENSITY**

The drainage network, which is heavily influenced by the underlying lithology, can be used to extract data on the general direction of surface water flows towards individual basin outlets, the angle of intersection between tributaries and main channels, all of which can be used to control drainage discharge and related instability, especially in critical environments. The drainage system was broken down into three distinct drainage patterns. The most common pattern is sub-dendritic, yet due to the high permeability of lavas, it is absent in some areas.

**4.5 SOIL**

The soil deposit of study area are fine loamy, fine silty soil, fine clay, fine silty, clayey skeletal, fine loamy soil, and clayey soil. Because distinct lithological units may be affected by different landslide types with varying susceptibility degrees, lithology and soil cover are essential considerations in landslide susceptibility analysis. Furthermore, as thematic literature has shown, soil cover layers, which are largely exposed to weathering, can alter land permeability, geotechnical parameters, and hence the landslide type.

**4.6 LANDUSE AND LANDCOVER**

Slope stability is greatly influenced by vegetation cover. Sparsely or weakly vegetated areas, in general, experience faster soil erosion and instability than wooded areas. A vegetation map was created in the study area using the photo-geological analysis and the land-use map. Vegetation cover was divided into six categories, including populated flat terrain, agricultural land, aquatic bodies, barren ground, densely vegetable forest land, and sparsely vegetable forest land, with areas without vegetation corresponding to urban areas. The primary vegetation type are shrub crops, including Banana plant, wheat sugar-cane, etc. which cover most of the plains, the central and southern highlands, whereas forests cover large parts of the mountain areas.
4.7 ELEVATION

Elevation is having a crucial role in landslide conditioning. In general, slope stability is influenced by other elements such as vegetation types, soil types, rainfall, and vegetation coverage. In order to create landslide susceptibility maps, several researchers use the elevation factor. Elevation is classified into five divisions in this study: 52m-380m, 380-572m, 572m-781m, 781m-1052m, and 1052m-1493m.

4.8 RAINFALL

Rainfall events are crucial in the landslide mechanism process. This phenomenon is reliant on rainfall intensity distribution and is influenced by relation between several factors such as geography and hydrography, land use and vegetation, lithology and so on. The annual rainfall in Nungba is approximately 1152 millimetres. From April/May through August/September, the rainy South West Monsoon produces showers, which is beneficial to agriculture. The monsoon season is marked by frequent landslides, with the National Highway 37 occasionally impeding traffic flow.

4.9 LITHOLOGY

The lithology of a given location is a significant intrinsic factor in slope instability. Because unconsolidated materials are directly related to instability, the researchers deemed it to be a significant causal component. The area's lithology includes shale, siltstone, greywacke rhythmite and sandstone, flaggy sandstone with subordinate shale. Sand, silt, and clay, flaggy sandstone with subordinate shale, rare coal, carbonaceous sandy shale, sandstone, and coal seams, shale, siltstone, greywacke rhythmite, and sandstone.

4.10 LINEAMENT DENSITY

Lineaments are structural elements that represent weak points. The surface topography of the underlying structural structures is expressed by these features. Landslides are more likely to occur near lineaments because they aid in fostering selective erosion and limited water circulation. The geology map and high-resolution satellite data were used to create the lineament map (GSI). The current region has been divided into three groups based on its proximity to the lineament.

4.11 GEOLOGY

For landslide hazards assessment, geology is an essential causal factor. The lithology of the Nungba region was extracted in the raster domain using a district geological map obtained from the Geological Survey of India (GSI) and processed with GIS software. The Surma Group, Barial Group, Disang Group, and Alluvium geological units were used to classify the research region. The Barial Group covers a large portion of the territory, accounting for 66.85% of the total, with Alluvium accounting for 23.7 percent.

5. Methodology
5.1 Frequency Ratio Method

The frequency ratio is a quantitative technique that uses GIS and spatial data to measure landslide susceptibility. The frequency ratio technique is routinely and efficiently used for landslide susceptibility mapping. It is based on a quantifiable link between the inventory of landslides and the factors that cause them. The most extensively used tool in bivariate statistical approaches is frequency analysis (Lee and Min 2001; Chimidi et al. 2017; Girma et al. 2015; Raghuvanshi et. al. 2014). This technique takes into account the relationship between each of the responsible causative factor groups and the spatial distribution of prior landslides in the area (Chimidi et al. 2017; Girma et al. 2015; Akgun et al. 2012; Lee 2005). The frequency ratio is the ratio of landslides in a factor class as a percent of all landslides to the factor class's area (Shano et al. 2020; Tao et. al., 2016). The frequency ratio has been adjusted to one. Thus, a frequency ratio more than one suggests a strong relationship between the parameter class and landslide incidence, whereas a frequency ratio less than one shows a weaker relationship between the factor class and landslide occurrence (Girma et al. 2015; Chimidi et al. 2017, Lee and Min 2001). The frequency ratio (FR) for each class of causative factors has been calculated using the Equation below, which combines the landslide inventory map with the factor map.

\[
Fr = \frac{Npix(1)}{Npix(2)} \times \frac{P}{Npix(3)} \times \frac{P}{Npix(4)}
\]  

(1)

\[Npix(1) = \text{pixels no. that contain landslide in a class}\]
\[Npix(2) = \text{Total pixels count of every class}\]
\[P \text{Npix (3)} = \text{Total pixels count that contain landslide}\]
\[P \text{Npix (4)} = \text{Total pixels count}\]

The calculated frequency ratio is added all together to obtain a Landslide Susceptibility Index (LSI) map using Eq. below

\[LSI = Fr1 + Fr2 + Fr3 + Fr4 + \ldots + Frn\]  

(2)

where Fr is the frequency ratio, and n is the total number of selected causative factors.

The ratio, according to the methodology, is the area where the landslides occurred divided by the total area, with 1 being the average value. If the value is greater than 1, the percentage of the landslide is greater than the area, suggesting a higher correlation; if the value is less than 1, the correlation is lower (Akgun et al., 2007; Sharma et. al., 2014). The weights for each landslide causative factor class are shown in Table 2.

5.2 Shannon’s Entropy Model
Shannon’s entropy model is an improvement on the frequency ratio model. The frequency ratio model only considers the weightage of sub-factors, and does not consider the weightage of causative factors. Shannon’s entropy measures the uncertainty or instability of a system (Roodposhti et al. 2016). With landslide susceptibility mapping, it measures the influence of causative factors on the occurrence of landslides (Getachew and Meten 2021). Weightage of causative factors is calculated using the following procedure and the weights evaluated were shown in Table 2.

\[ P_{ij} = \frac{FR}{\sum FR} \]  
\[ E_{ij} = (P_{ij}) \times (\ln P_{ij}) \]  
\[ W_{ij} = \frac{1 - E_{ij}}{\sum (1 - E_{ij})} \]

where \( P_{ij} \) is the probability density and \( FR \) is the frequency ratio of sub-factors. \( W_{ij} \) is the weightage of causative factors obtained from Shannon’s entropy technique. These values can then be used for assigning weight to causative factors, while frequency ratio values are used for sub-factors.
| Slope   | Count(C) | Landslide (L) | FR = L%/C% | Pij | Eij | 1-Eij | Wij |
|---------|----------|---------------|------------|-----|-----|--------|-----|
| 0–15    | 71259    | 10            | 0.02895    | 0.00404 | -0.00967 | 1.4885 | 0.09034 |
| 15–30   | 48232    | 122           | 0.52191    | 0.07287 | -0.08288 |
| 30–45   | 60968    | 301           | 1.01868    | 0.14222 | -0.12046 |
| 45–60   | 51112    | 350           | 1.41293    | 0.19727 | -0.13906 |
| >60     | 22017    | 446           | 4.17978    | 0.58358 | -0.13649 |

**Aspect**

| Flat    | 27960    | 11            | 0.08117    | 0.00789 | -0.01659 |
|---------|----------|---------------|------------|--------|---------|
| North   | 30013    | 102           | 0.70124    | 0.06819 | -0.07953 | 1.9342 | 0.11738 |
| Northeast | 28125   | 104           | 0.76298    | 0.07420 | -0.08381 |
| East    | 25096    | 112           | 0.92085    | 0.08955 | -0.09384 |
| Southeast | 21112   | 114           | 1.11417    | 0.10835 | -0.10458 |
| South   | 23728    | 119           | 1.03481    | 0.10063 | -0.10036 |
| Southwest | 25681   | 127           | 1.02039    | 0.09923 | -0.09956 |
| West    | 24180    | 133           | 1.13493    | 0.11037 | -0.10564 |
| Northwest | 23677   | 122           | 1.06318    | 0.10339 | -0.10189 |
| North   | 24016    | 285           | 2.44861    | 0.23813 | -0.14840 |

**Curvature**

| Concave | 52319    | 633           | 2.49643    | 0.51855 | -0.14789 |
|---------|----------|---------------|------------|--------|---------|
| Flat    | 156470   | 130           | 0.17143    | 0.03560 | -0.05157 | 1.3558 | 0.08228 |
| Convex  | 44799    | 466           | 2.14631    | 0.44583 | -0.15641 |

**LULC**

| Populated Flat Land | 80717    | 84            | 0.21472    | 0.02729 | -0.04268 |
|---------------------|----------|---------------|------------|--------|---------|
| Agriculture Land    | 19421    | 102           | 1.08369    | 0.13775 | -0.11859 | 1.6013 | 0.09718 |
| Water Body          | 21096    | 140           | 1.36931    | 0.17405 | -0.13216 |
| Thickly Veg Forest Land | 54486  | 103           | 0.39005    | 0.04958 | -0.06468 |
| Slope                     | Count(C) | Landslide (L) | FR = \(L\% / C\%\) | Pij   | Eij   | 1-Eij | Wij      |
|---------------------------|----------|---------------|-----------------------|-------|-------|-------|----------|
| Sparsely Veg Forest Land  | 45535    | 160           | 0.72502               | 0.09215 | -0.09542 |
| Barren Land               | 32333    | 640           | 4.08423               | 0.51915 | -0.14780 |
| **Soil**                  |          |               |                       |       |       |       |          |
| Fine Loamy                | 93206    | 243           | 0.53794               | 0.02590 | -0.04110 |
| Fine Silty Soil           | 8454     | 62            | 1.51323               | 0.07288 | -0.08289 | 1.5185 | 0.09215 |
| Fine Clay                 | 8083     | 50            | 1.27103               | 0.06147 | -0.07446 |
| Fine Silty                | 5441     | 330           | 12.5144               | 0.60274 | -0.13252 |
| Clayey Skeletal           | 79606    | 243           | 0.62985               | 0.03033 | -0.04605 |
| Fine Loamy soil           | 14475    | 301           | 4.29066               | 0.20665 | -0.14150 |
| Clayey soil               | 30092    | 0             | 0                     | 0      | 0      |       |          |
| Fine Clayey soil          | 14231    | 0             | 0                     | 0      | 0      |       |          |
| **Geology**               |          |               |                       |       |       |       |          |
| Surma Group               | 5622     | 37            | 1.35796               | 0.17423 | -0.13221 |
| Barial Group              | 169523   | 476           | 0.57936               | 0.07433 | -0.08390 | 1.4554 | 0.08832 |
| Disang Group              | 18348    | 435           | 4.89189               | 0.62764 | -0.12696 |
| Alluvium                  | 60095    | 281           | 0.96481               | 0.12378 | -0.11231 |
| **Lithology**             |          |               |                       |       |       |       |          |
| Shale, Siltstone, Greywacke Rhythmite & Sandstone | 4565 | 426 | 19.25509 | 0.90496 | -0.03924 |
| Flaggy Sandstone with Subordinate Shale | 85654 | 374 | 0.90096 | 0.04238 | -0.05814 | 1.1647 | 0.07068 |
| Undiff. Fluvial Sediments-Sand, Silt and Clay | 78954 | 429 | 1.12114 | 0.05269 | -0.06735 |
| Flaggy Sandstone with Subordinate Shale Rare Coal | 56456 | 0 | 0 | 0 | 0 |
| Slope | Count(C) | Landslide (L) | FR = L%/C% | Pij   | Eij   | 1-Eij | Wij   |
|-------|----------|---------------|------------|-------|-------|-------|-------|
| Carbonaceous Sandy Shale, Sandstone & Coal Seams | 27959 | 0 | 0 | 0 | 0 | |

**Lineament**

| | | |
|---|---|---|
| Low | 154695 | 215 | 0.28677 | 0.06323 | -0.075818 |
| Medium | 50175 | 375 | 1.5421 | 0.34002 | -0.15929 | 1.3689 | 0.0830 |
| High | 48718 | 639 | 2.7063 | 0.59673 | -0.13379 | |

**Elevation**

| | | |
|---|---|---|
| 52–380 | 39542 | 116 | 0.60530 | 0.11393 | -0.10747 |
| 380–572 | 67238 | 150 | 0.46031 | 0.08664 | -0.09203 | 1.6475 | 0.09998 |
| 572–781 | 65094 | 501 | 1.58808 | 0.29891 | -0.15676 |
| 781–1052 | 57588 | 260 | 0.93157 | 0.17534 | -0.13257 |
| 1052–1493 | 24126 | 202 | 1.72759 | 0.32517 | -0.15864 |

**Drainage**

| | | |
|---|---|---|
| Low | 156169 | 213 | 0.28142 | 0.05292 | -0.06754 |
| Medium | 62501 | 371 | 1.22479 | 0.23033 | -0.14686 | 1.3180 | 0.07999 |
| High | 34918 | 645 | 3.81142 | 0.71675 | -0.10366 |

**Rainfall**

| | | |
|---|---|---|
| 1034–1088 | 59307 | 60 | 0.20874 | 0.04021 | -0.05612 |
| 1088–1135 | 34205 | 117 | 0.70578 | 0.1359 | -0.11781 |
| 1135–1164 | 75630 | 380 | 1.03673 | 0.1997 | -0.13971 | 1.6243 | 0.09857 |
| 1164–1193 | 39236 | 249 | 1.30945 | 0.25224 | -0.15088 |
| 1193–1259 | 45210 | 423 | 1.9305 | 0.37188 | -0.15975 |

### 5.3 Weight Of Evidence Method

The relative density for each causal factor category and the total density for the entire area were computed using the 1229 training landslide cells. The WOE model was then used to estimate the relevant statistics for each of these factor groups (Table 3). The statistical association between landslide events and each causal factor (evidence) may be quantified and assessed to determine whether and how
significant the factor is responsible for the occurrence of historical landslides (Dilip et. al., 2017). For each category of each causal component, a pair of weights, \( W^+ \) and \( W^- \), is calculated.

\[
W^+ = \ln\left(\frac{L}{L + A}ight) \quad \text{(6)}
\]

\[
W^- = \ln\left(\frac{A}{B + D}\right) \quad \text{(7)}
\]

Where,

L “pixels number that show the appearance of both predictive factor of landslide and landslides”

A “pixels number that show the appearance of landslides presence and absence of landslide predictive factor”

B “pixels number that show the appearance of landslide predictive factor and absence of landslides”

D “pixels number that show absence of both landslide predictive factor and landslides”

The contrast, \( X \), between these weights (\( W^+ \), \( W^- \)) is a helpful measure of the spatial relationship between the category of causal component and the occurrence of landslide occurrences. The value of \( X \) is positive for a positive spatial relationship and negative for a negative spatial association.

The overall value of LSI for each cell can be calculated by adding the contrast values of the causal factors:

\[
\text{LSI} = \sum X \quad \text{(8)}
\]

Where \( X \) is the contrast value for the category of all the factor.
Table 4
Relation between landslide and controlling factor

| Class (Slope) | C   | L     | A    | B    | D     | W+   | W-   | X    |
|---------------|-----|-------|------|------|-------|------|------|------|
| 0–15          | 71259 | 10 | 1219 | 71249 | 181110 | -3.546 | 0.323 | -3.870 |
| 15–30         | 48232 | 122 | 1107 | 48110 | 204249 | -0.652 | 0.106 | -0.759 |
| 30–45         | 60968 | 301 | 928  | 60667 | 191692 | 0.018  | -0.005 | 0.024 |
| 45–60         | 51112 | 350 | 879  | 50762 | 201597 | 0.347  | -0.110 | 0.458 |
| > 60          | 22017 | 446 | 783  | 21571 | 230788 | 1.445  | -0.361 | 1.807 |

| Class (Aspect) | Flat       | North     | Northeast | East       | Southeast | South    | Southwest | West       | Northwest  | North     |
|----------------|------------|-----------|-----------|------------|-----------|----------|-----------|------------|-----------|----------|
|                | 27960      | 30013     | 28125     | 25096      | 21112     | 23728    | 25681     | 24180      | 23677     | 24016    |
|                | 11         | 102       | 104       | 112       | 114       | 119      | 127       | 133        | 122       | 285      |
|                | 1218       | 1127      | 1125      | 1117      | 1115      | 1110     | 1102      | 1096       | 1107      | 944      |
|                | 27949      | 29911     | 28021     | 24984      | 20998     | 23609    | 25554     | 24047      | 23555     | 23731    |
|                | 224410     | 222448    | 224338    | 227375     | 231361    | 228750   | 226805    | 228312     | 228804    | 228628   |
|                | -2.515     | -0.356    | -0.271    | -0.082     | 0.108     | 0.034    | 0.020     | -0.127     | 0.061     | 0.902    |
|                | 0.108      | 0.039     | 0.029     | 0.008      | -0.010    | -0.003   | -0.002    | -0.014     | -0.006    | -0.165   |
|                | -2.623     | -0.395    | -0.300    | -0.091     | 0.119     | 0.038    | 0.022     | 0.141      | 0.068     | 1.067    |

| Class (Curvature) | Concave | Flat | Convex |
|-------------------|---------|------|--------|
|                   | 52319  | 156470 | 44799 |
|                   | 633    | 130   | 466    |
|                   | 596    | 1099  | 763    |
|                   | 51686  | 156340 | 44333 |
|                   | 200673 | 96019  | 208026 |
|                   | 0.922  | -1.767 | 0.769  |
|                   | -0.494 | 0.854  | -0.283 |
|                   | 1.416  | -2.622 | 1.052  |

| Class (LULC) | Populated Flat Land | Agriculture Land | Water Body | Thickly Veg Forest Land |
|--------------|---------------------|------------------|------------|------------------------|
|              | 80717               | 19421            | 21096      | 54486                  |
|              | 84                  | 102              | 140        | 103                    |
|              | 1145                | 1127             | 1089       | 1126                   |
|              | 80633               | 19319            | 20956      | 54383                  |
|              | 801726              | 233040           | 231403     | 197976                 |
|              | -1.542              | 0.080            | 0.316      | -0.944                 |
|              | 0.314               | -0.006           | -0.034     | 0.155                  |
|              | -1.856              | 0.087            | 0.350      | -1.099                 |
| Class                      | C    | L    | A    | B    | D    | W+  | W-  | X    |
|----------------------------|------|------|------|------|------|-----|-----|------|
| Sparsely Veg Forest Land   | 45535| 160  | 1069 | 45375| 206984| -0.322| 0.058| -0.381|
| Barren Land                | 32333| 640  | 589  | 31693| 220666| 1.422| -0.601| 2.023|
| Class(Soil)                |      |      |      |      |      |     |     |      |
| Fine Loamy                 | 93206| 243  | 986  | 92963| 159396| -0.622| 0.239| -0.861|
| Fine Silty Soil            | 8454 | 62   | 1167 | 8392 | 243967| 0.416| -0.017| 0.434|
| Fine Clay                  | 8083 | 50   | 1179 | 8033 | 244326| 0.245| -0.009| 0.254|
| Fine Silty                 | 5441 | 330  | 899  | 5111 | 247248| 2.584| -0.292| 2.876|
| Clayey Skeletal            | 79606| 243  | 986  | 79363| 172996| -0.464| 0.157| -0.621|
| Fine Loamy soil            | 14475| 301  | 928  | 14174| 238185| 1.472| -0.223| 1.695|
| Clayey soil                | 30092| 0    | 1229 | 30092| 222267| 0    | 0.126| -0.126|
| Fine Clayey soil           | 14231| 0    | 1229 | 14231| 238128| 0    | 0.058| -0.058|
| Class (Geology)            |      |      |      |      |      |     |     |      |
| Surma Group                | 5622 | 37   | 1192 | 5585 | 246774| 0.307| -0.008| 0.315|
| Barial Group               | 169523| 476  | 753  | 169047| 83312| -0.547| 0.618| -1.166|
| Disang Group               | 18348| 435  | 794  | 17913| 234446| 1.606| -0.363| 1.969|
| Alluvium                   | 60095| 281  | 948  | 59814| 192545| -0.035| 0.010| -0.046|
| Class (Lithology)          |      |      |      |      |      |     |     |      |
| Shale, Siltstone, Greywacke Rhytmite & Sandstone | 4565 | 426  | 803  | 4139 | 248220| 3.050| -0.409| 3.459|
| Flaggy Sandstone with Subordinate Shale | 85654| 374  | 855  | 85280| 167079| -0.104| 0.049| -0.154|
| Undiff. Fluvial Sediments- Sand, Silt and Clay | 78954| 429  | 800  | 78525| 173834| 0.114| -0.056| 0.171|
| Flaggy Sandstone with Subordinate Shale Rare Coal | 56456| 0    | 1229 | 56456| 195903| 0    | 0.253| -0.253|
| Carbonaceous Sandy Shale, Sandstone & Coal Seams | 27959| 0    | 1229 | 27959| 224400| 0.117| -0.117|      |
| Class (Lineament)          |      |      |      |      |      |     |     |      |
6. Results And Discussions

6.1 Frequency Ratio Model and Shannon Entropy

The results of the geographic link between landslide locations and landslide conditioning factors using the FR model are shown in the Table 4. The angle of slope > 60° has a greater FR value of 4.17, followed by 45–60° (1.41), whereas remaining slope classes have a relatively low FR value. Gentle slopes were typically observed to have lower weight values of FR because of the lower shear stresses associated with low gradient locations (Yalcin et al.2011; Mohammady et al.2012; Hamid et al.2020). The FR value is higher for areas that face north, west, and southeast in terms of slope aspect. The altitude and landslide probability shows a great relationship between them that the class of 1052–1493 m has the maximum
FR value (1.72), which indicates that this elevation range is more prone to landslides. This finding is consistent with field studies, as landslides were frequently seen in the research area's high-elevation ranges. Convex as well as concave areas have greater FR values of 2.14 and 2.49, respectively, in the event of plan curvature, but the flat class are low in FR value (0.17). In general, instability slope of the curvature areas is linked to high soil moisture levels. Soil stability reduces when there is increase in moisture content (Hamid et al. 2020).

When drainage density is high, landslide occurrence is also high (3.81), however when drainage density is low, the FR is 0.28, indicating that landslides are unlikely to occur. Only populated flat land area class has a lower FR value (0.214), followed by densely vegetable forest land area with a FR value of 0.39, and barren land with FR value of 4.084 is more susceptible to landslides. The orientation and mechanical strength of the discontinuities have a significant impact on the landslide triggering phenomena (Duo et al. 2017). The FR value for the three different classes of lineament density viz. low, medium, and high, is 2.706 for the high class, 0.286 for the low class, and 2.706 for the medium class. The Fine Loamy soil type of soil has the highest FR value (4.29) for landslide occurrence among the different types of soils observed in the study region, whereas slopes with fine Clayey soil are less prone to landslides 0. Finally, the resulting FR value weights are combined together to create a final LSZ map. The LSI equation in its simplest version, which was used to create an LSZ map using a raster calculator in a GIS map algebra tool, is as follows:

\[ \text{LSI FR} = (\text{FR Slope gradient}) + (\text{FR Slope aspect}) + (\text{FR Curvature}) + (\text{FR Drainage density}) + (\text{FR Lineament density}) + (\text{FR Soil}) + (\text{FR LULC}) + (\text{FR Lithology}) + (\text{FR Elevation}) + (\text{FR Geology}) + (\text{FR Rainfall}). \]

Table 5 depicts the distribution of the research area into various categories, revealing that 17.38 percent of the region under investigation falls into the extremely low hazard zone, with landslides occurring in this zone in the fewest quantity (11.8 percent). On the other hand, 12.2% of the chosen region is in a very high danger zone, with landslides accounting for 27% of all landslides (Fig. 5).

Low, medium, and high hazard zones, which covered 21.99 percent, 27.25 percent, and 21.15 percent of the study area, respectively, had 17.085 percent, 19.3 percent, and 23.85 percent of the landslides (Fig. 6). It's worth noting that Noney and its surroundings are in a high-risk landslide zone, whereas the risk of landslides in the Nungba area and its surroundings is rather low.

To validate the data obtained from the FR approach discussed above, the area under curve (AUC) strategy was employed. In this process, the AUC value is utilised to estimate the model's accuracy. For the validation phase, the landslide susceptibility index map was delineated using Arc GIS' natural break approach. To produce prediction rate curves, the landslide inventory has been plotted against the LSI values in Microsoft Office Excel 2007. The curves provide an assessment of model fitness based on their AUC values. The AUC for the FR-developed LSZ map is 0.86, implying an overall prediction rate of 86.95 percent for the LSZ map as shown in Fig. 7. The landslide density has also been evaluated susceptibility zone wise depicting an increasing trend with respect to the criticality of susceptibility class (Table 5).
The weightage of sub-factors in Shannon’s entropy model was based on frequency ratio (FR) values. The weightage of causative factors was evaluated from FR values of sub-factors. It is found that aspect is the major causative factor which has a very high impact on the occurrence of landslides having weightage of 0.117. The curvature is also an important factor, with a weightage of 0.082 as per Shannon’s entropy model. Slope has a weightage of 0.090. Lithology, drainage density, and relative relief have almost equal weightage. The weightages for the other causative factors are shown in the LSI equation. The results of the FR model have been changed a little following the implementation of Shannon’s entropy weightage to major causative factors. The simplest landslide susceptibility equation for this model is given as follows:

\[
\text{LSI Shannon’s Entropy} = 0.090 \times \text{Slope (FR Slope gradient)} + 0.117 \times \text{FR Slope aspect} + 0.082 \times \text{FR Curvature} + 0.098 \times \text{FR Drainage density} + 0.083 \times \text{FR Lineament density} + 0.092 \times \text{FR Soil} + 0.097 \times \text{FR LULC} + 0.070 \times \text{FR Lithology} + 0.099 \times \text{FR Elevation} + 0.088 \times \text{FR Geology} + 0.0985 \times \text{FR Rainfall}. 
\]

The final landslide susceptibility map based on Shannon’s entropy model is divided into five categories, i.e., very low, low, moderate, high and very high, using natural breaks (Fig. 8). Shannon’s entropy model shows that 12.06% of the area has very high susceptibility, which contains 26.53% landslide area of the region. The model shows that 22.36% of the area has high susceptibility, which contains 24.28% landslide area. Very low and low landslide susceptibility zones cover 14.26% and 24.73% of study area, respectively as shown in Fig. 9.

To validate the data obtained from the Shannon Entropy approach discussed above, the AUC method was employed. In this process, the AUC value is utilised to estimate the model’s accuracy. The AUC of the LSZ map is 0.80, implying an overall prediction rate of 80.47 percent for the LHZ map as shown in Fig. 10. Validation of the LHZ model has also been analysed using Landslide Density method showing increasing order of landslide density with increase in the susceptibility index as mentioned in Table 6.

| Hazard zones | Frequency Ratio model | Frequency Ratio model | Frequency Ratio model |
|--------------|-----------------------|-----------------------|-----------------------|
|              | Zone Area (km$^2$)    | Landslide area (km$^2$) | Landslide density     |
| Very low     | 39.638                | 0.130605265            | 0.118077267           |
| Low          | 50.149                | 0.188982869            | 0.170855139           |
| Medium       | 62.14                 | 0.213534889            | 0.193052065           |
| High         | 48.2                  | 0.263873534            | 0.238562096           |
| Very high    | 27.82                 | 0.309103443            | 0.279453434           |
Table 6
Comparison of predicted landslide hazard zones and observed landslides

| Hazard zones | Shannon Entropy model |
|--------------|-----------------------|
|              | Zone Area (km$^2$) | Landslide area (km$^2$) | Landslide density |
| Very low     | 32.5539             | 0.130715538             | 0.118176963      |
| Low          | 56.4561             | 0.172404103             | 0.155866651      |
| Medium       | 60.6438             | 0.240875744             | 0.217770313      |
| High         | 51.0489             | 0.268615897             | 0.242849559      |
| Very high    | 27.5265             | 0.293488718             | 0.265336514      |

6.2 Weight of Evidence Model

The various roles of each predisposing factor in the spatial occurrence of landslides can be analysed by analysing $W^+$, $W^-$, and final weight ($W$) values assigned to each of the classes of predictive variables. The angle of slope $> 60^\circ$ has a greater WOE value of 1.807, followed by $45^\circ - 60^\circ$ (0.458), whereas remaining slope classes have a relatively low WOE value. The WOE value is higher for areas that face north, west, and southeast in terms of slope aspect. In case of elevation, the altitude and landslide probability showed relationship in the elevation class of 572-781m and 1052-1493m showing these classes as more prone to landslides having weights 0.69 and 0.63. This finding is consistent with field investigation, as landslides were frequently seen in the study area's high-elevation ranges.

In case of curvature, the convex as well as concave areas have greater WOE values of 1.416 and 1.052, respectively, whereas the flat class is having low WOE value (-2.622). The populated flat land area class has a lower WOE value (-1.856), followed by densely vegetable forest land area with a WOE value of -1.099, whereas the barren land has been found as highly prone to landslide (2.023). The orientation and mechanical strength of the discontinuities have a significant impact on the landslide triggering phenomena (Duo et.al. 2017). The WOE weight value for the three different classes of lineament density viz. low, medium, and high is 1.523 for the high class, -2.007 for the low class, and 0.588 for the medium class. The Fine silty soil type of soil has the highest WOE value (2.876) among the other soil types, whereas slopes with fine Clayey soil are less prone to landslides (-0.058). The Disang Group geology class has been found as highly susceptible to landslides showing 1.969 weight while Barial group is less prone to landslides (-1.16). The drainage density classes of High, Medium, and Low are having 1.94, 0.28, -2.043 weight values depicting the criticality of high drainage density class. The rainfall classes of 1164–1193 and 1193–1259 are having higher potential of landslides with respect to other rainfall classes which all are having low WOE weight. The lithology class of Shale, Siltstone, Greywacke Rhytmite & Sandstone is highly prone to landslide in the study area having 3.459 weight of evidence value in comparison to other lithology classes. The LSZ map was created by adding the values of contrast of all of the causal components in the chosen combination. Based on the "Natural Breaks" technique, this map was divided into five groups (Very Low, Low, Moderate, High, and Very High susceptibility) as shown in
Fig. 11. A total 48 percent of landslides are in the high to very high susceptibility zone. The Nungba's high susceptibility zones are mostly found in the NE and E zones. About 31% of instabilities occur in zones of low to extremely low susceptibility as shown in Fig. 12.

The accuracy of the LSZ map has been evaluated as 84.98% based on AUC as shown in Fig. 13.

| Hazard zones | Weight Of Evidence model |
|--------------|--------------------------|
|              | Zone Area (km²) | Landslide area (km²) | Landslide density |
| Very low     | 37.77718         | 0.140758              | 0.127256          |
| Low          | 51.74556         | 0.205585              | 0.185865          |
| Medium       | 59.83366         | 0.223463              | 0.202028          |
| High         | 53.02417         | 0.243625              | 0.220256          |
| Very high    | 25.61943         | 0.292669              | 0.264595          |

7. Conclusions

Landslides are one of the most disastrous phenomena in the hilly region of Manipur. In this study, statistical approaches were compared for landslide susceptibility mapping along NH-37. However, a total of 57 landslides were mapped utilising aerial images and image interpretation with field inspection for susceptibility evaluation across the entire study area. The lithology, aspect, curvature, slope angle, landuse or land cover, soil, drainage density, geology, lineament density, elevation, and rainfall are some of the influencing characteristics taken into account for LSZ models. To obtain the map of landslide susceptibility for the entire study area along the road corridor, this study used three different approaches: frequency ratio, shannon's entropy, and weight of evidence. Because these methods are totally field based, they were also utilised to validate the resulting susceptibility map. The AUC for the FR and Shannon's entropy-developed landslide hazard zonation map is 0.86 and 0.80, implying an overall prediction rate of 86.95 and 80.47 percent for the LSZ map while the accuracy of the WOE model has been evaluated as 0.8498, implying an overall prediction rate of 84.98%. The FR model based LSZ map is highly preferred as its accuracy is higher in comparison to the other models. The study can be extended to predict landslide hazard and risk assessment of the study area. The seasonal variation in causative factors such as rainfall, land-use and vegetation cover variation can be studied and their impact on the occurrence of landslides can be observed.

Declarations

STATEMENTS AND DECLARATIONS
Authors are not having any financial or non-financial interests that are directly or indirectly related to the work submitted for publication.

**ACKNOWLEDGEMENT**

The authors are thankful to the public works department of Manipur for giving required landslide related database. The support and encouragement given by local public during the field visits is also appreciable.

**References**

1. Abija, F.A., Nwosu, J.I., Ifedotun, A.I. and Osadebe, C.C. “Landslide susceptibility assessment of Calabar, Nigeria using geotechnical, remote sensing and multi-criteria decision analysis: implications for urban planning and development.” Journal Earth Science Environment Student (2019) DOI:10.25177/jeses.4.6.ra.617

2. Abdo, H.G. 2021. Assessment of landslide susceptibility zonation using frequency ratio and statistical index: a case study of Al-Fawar basin, Tartous, Syria. Int. J. Environ. Sci. Technol. 1–20.

3. Abu El-Magd, S.A., Ali, S.A., Pham, Q.B., 2021. Spatial modeling and susceptibility zonation of landslides using random forest, naïve bayes and K-nearest neighbor in a complicated terrain. Earth Sci. Inf. 14 (3), 1227–1243.

4. Bayes, A. 2014.”Landslide susceptibility mapping using multi-criteria evaluation techniques in Chittagong Metropolitan Area, Bangladesh.” Springer link. DOI:10.1007/s10346-014-0521

5. Anbalagan, R., Kumar, R., Lakshmanan, K., Parida, S. & Neethu, S. “Landslide hazard zonation mapping using frequency ratio and fuzzy logic approach, a case study of Lachung Valley, Sikkim. Geology environment Disasters (2015). DOI 10.1186/s40677-014-0009-y.

6. Wubalem, A. and Meten, M.”Landslide susceptibility mapping using information value and logistic regression models in GonchaSisoEneses area, north-western Ethiopia.” Springer Nature Switzerland AG (2020). DOI: 10.1007/s42452-020-2563-0.

7. Balasubramani, K., Kumaraswamy, K. “Application of geospatial technology and information value technique in landslide Hazard zonation mapping: a case study of Giri Valley, Himachal Pradesh.” Disaster Adv (2013).

8. Bera, A., Mukhopadhyay, B.P., Das, D.”Landslide hazard zonation mapping using multi-criteria analysis with the help of GIS techniques: a case study from eastern Himalayas, Namchi, South Sikkim.” Natural Hazards (2019).DOI:10.1007/s11069-019-03580-w

9. Bappaditya, K., Anindita, N., Srabanti, B., Subhajit, S. and Chandra, R. B. “GIS based Landslide Hazard Zonation Mapping by Weighted Overlay Method on the Road Corridor of North Sikkim Himalayas, India.” research square (2020).DOI:10.21203/rs.3.rs-56087/v1

10. Chimidi, G., Raghuvanshi, T.K., Suryabhagavan, K.V. (2017) Landslide hazard evaluation and zonation in and around Gimbi town, western Ethiopia – a GIS-based statistical approach. ApplGeomat (Springer) 9(4):219–236
11. C.J Westen. “The modelling of land hazard using GIS.” Environmental Science (2000).
12. Duo, G.L, Zhang, Y.S, Iqbal, J. “Landslide susceptibility mapping using an integrated model of information value method and logistic regression in the Bailongjiang watershed, Gansu Province, China”. Journal of Mountain Science (2017). DOI:10.1007/s11629-016-4126-9
13. Dai, F.C., Lee, C.F. “Landslide characteristics and slope instability modelling using GIS, Lantau Island, Hong Kong.” Geomorphology (2002).
14. Dilip, K., Neha, L., Anita, R. “Study and Prediction of Landslide in Uttarkashi, Uttarakhand, India Using GIS and ANN.” American Journal of Neural Networks and Applications 2017; 3(6): 63-74
15. F.C. Dai, C.F. Lee, Jiadi Li, & Z.W. Xu. “Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong.” Environmental Geology (2001). DOI:10.1007/s002540000163
16. Girma, F., Raghuvanshi, T.K., Ayenew, T. and Hailemariam, T. (2015) Landslide hazard zonation in Ada Berga district, Central Ethiopia – a GIS based statistical approach. J Geom 9(i):25–38.
17. Hawas, K., Muhammad, S., Muhammad, A. K., Mian, A. B., Safeer, U. S., & Chiara C. “Landslide susceptibility assessment using Frequency Ratio, a case study of northern Pakistan.” The Egyptian Journal of Remote Sensing and Space Sciences (2018). DOI: 10.1016/j.ejrs.2018.03.004
18. Hamid, R.P., Narges, K., Mahdis, A., Mohsen, E., Mehrdad, Z., Thomas, B. & Artemio, C. “Assessing and mapping multi-hazard risk susceptibility using a machine learning technique.” Scientific Reports (2020).
19. H. Lakshmi Ram Prasath, K. N. Kusuma, S. Chaitanyaa, & Balamurugan G. “Frequency ratio modelling using geospatial data to predict Kimberlite Clan of rock emplacement zones in Dharwar Craton, India.” International Journal Applied Earth Obs Geoinformation (2019). DOI: 10.1016/j.jag.2018.08.019
20. Ioan, A., Sanda, R., Ioana, M. R., Flavia, L. M., Ștefan, B. “Landslide susceptibility assessment in almas basin by means of the frequency rate and GIS techniques.” Geographia Technica (2017).
21. Kanwarpreet, S. & Virender, K. “Hazard assessment of landslide disaster using information value method and analytical hierarchy process in highly tectonic Chamba region in bosom of Himalaya.” Journal of Mountain Science (2018). DOI:10.1007/s11629-017-4634-2
22. Kanungo, D.P., Arora, M.K., Sarkar, S. and Gupta, R.P. “A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas.’ Engineering Geology (2006), pp.347-366
23. Kanungo, D.P, Arora, M.K, Sarkar, S, Gupta, R.P. “Landslide susceptibility zonation (LSZ) mapping: a review.” Journal of South Asia Disaster (2009).
24. Saaty, T. “Decision making with the analytical hierarchy process.” International Journal of Services Science (2008).
25. Lee, S. “Application and verification of fuzzy algebraic operators to landslide susceptibility mapping. Environment Geology (2007).
26. Lee, S. and Min, K.”Statistical analysis of landslide susceptibility at Yongin.” Korean Environment Geology (2001).DOI:10.1007/s002540100310

27. Litesh, B. and Priti, P. R.”Feature-based model for landslide susceptibility mapping usinga multi-parametric decision-making technique and the analytic hierarchy process.” Indian Academy of science (2021).DOI:10.1007/978-981-15-8391-9_22

28. Shano, L., Raghuvanshi, T.K. and Matebie, M. “Landslide susceptibility evaluation and hazard zonation techniques – a review.” Geoenvironmental Disasters (2020).DOI:10.1186/s40677-020-00152-0

29. Mohammady, M., Pourghasemi, H.R, Pradhan, B.”Landslide susceptibility mapping at Golestan Province, Iran: a comparison between frequency ratio, Dempster– Shafer, and weights-of-evidence models.” J Asian Eart Science (2012). DOI:10.1016/j.jseaes.2012.10.005

30. Mengistu, F, Suryabhagavan, K.V, Raghuvanshi, T.K, Lewi, E. “Landslide Hazard zonation and slope instability assessment using optical and InSAR data: a case study from Gidole town and its surrounding areas, southern Ethiopia.” Remote Sensing of Land (2019).DOI:10.21523/gcj1.19030101

31. Getachew, N. & Matebie, M.”Weights of evidence modeling for landslide susceptibility mapping of Kabi-Gebro locality, Gundomeskel area, Central Ethiopia”. Geoenvironmental Disasters (2021).DOI:10.1186/s40677-021-00177-z

32. Prakash, B., Binoy, K.B., Varun, J., K. Srinivasa Rao. “Landslide Susceptibility Mapping in East Sikkim Region of Sikkim Himalaya Using High Resolution Remote Sensing Data and GIS techniques.” Applied Ecology and Environmental Sciences (2020).DOI:10.1269/aees-8-4-1

33. Pardeshi, S.D., Autade, S.E., Pardeshi, S.S.”Landslide hazard assessment: recent trends and techniques. Springer Plus (2013).

34. Fell, R., Jordi, C. & C. Bonnard. “Guidelines for landslide susceptibility, hazard and risk zoning for land use planning.” Engineering Geology (2008).DOI:10.1016/j.enggeo.2008.03.014

35. Raghuvanshi, T.K, Ibrahim, J., Ayalew, D. (2014).”Slope stability susceptibility evaluation parameter (SSEP) rating scheme—an approach for landslide hazard zonation.”Journal of African Earth Science (2014).

36. Reichenbach, P, Rossi, M., Malamu, B.D, Mihir, M., Guzzetti, F. “A review of statistically-based landslide susceptibility models.” Earth Science Reviews (2018).DOI:10.1016/j.earscirev.2018.03.001

37. Roodposhti, M.S.; Aryal, J., Shahabi, H., Safarad, T. “Fuzzy Shannon Entropy: A Hybrid GIS-Based Landslide Susceptibility Mapping Method. Entropy 2016,18, 343.DOI:10.3390/e18100343

38. Sharma, L.P.; Patel, N., Ghose, M.K., Debnath, P. Development and application of Shannon’s entropy integrated information value model for landslide susceptibility assessment and zonation in Sikkim Himalayas in India. Nat. Hazards 2014,75, 1555–1576.

39. Salman, F. & Mian, S. A. “Landslide susceptibility mapping using information value method in Jhelum Valley of the Himalayas”. Arabian Journal of Geosciences (2021).DOI:10.1007/s12517-021-07147-7
40. S. Sarkar, A. Roy, T. R. Martha. “Landslide susceptibility assessment using Information Value Method in parts of the Darjeeling Himalayas.” Geology Journal of the Geological Society of India (2013). DOI: 10.1007/s12594-013-0162-z

41. Samaneh, R., Solaimani, K., Matteo, M., & Ataollah, K. “Mapping landslide susceptibility with frequency ratio, statistical index, and weights of evidence models: a case study in northern Iran.” Environment Earth Science (2017). DOI: 10.1007/s12665-017-6839-7

42. Solaimani, K., Mousavi, S.Z. and Kavian, A. “Landslide susceptibility mapping based on frequency ratio and logistic regression models.” Arab Journal of Geoscience (2013). DOI: 10.1007/s12517-012-0526-5

43. Tareq, H.M., Juhari, M.A., Abdul, G.R. and Ibrahim, A. “Landslide Susceptibility Assessment using Frequency Ratio Model Applied to an Area along the E-W Highway.” American Journal of Environmental Sciences (2011). DOI: 10.3844/AJESSP.2011.43.50

44. Chen, T., Ruiqing, N. & Xiuping. “A comparison of information value and logistic regression models in landslide susceptibility mapping by using GIS.” Journal of Environment Earth Science (2016). DOI: 10.1007/s12665-016-5317-y.

45. Sarda, V.K. and Deepak D. “Landslide Susceptibility Mapping Using Information Value Method.” Jordan Journal of Civil Engineering (2019) 13(2):2019-335.

46. Wu, C.H., Chen, S.C (2009) Determining landslide susceptibility in Central Taiwan from rainfall and six site factors using the analytical hierarchy process method. Geomorphology 112: 190–204. DOI: 10.1016/j.geomorph.2009.06.002

47. Yacine, A., Sonia, G. & Victor, C. “GIS-based spatial prediction of debris flows using logistic regression and frequency ratio models for Zezere River basin and its surrounding area, Northwest Covilhã, Portugal.” Arabian Journal of Geosciences (2018) DOI: 10.1007/s12517-018-3920-9

48. Yalcin, A. (2008) “GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): comparisons of results and confirmations.” Catena 72:1–12. DOI: 10.1016/j.catena.2007.01.003.

**Tables**

Tables 3, 7, and 8 not available with this version.

**Figures**
Figure 1

Study Area showing NH-37 connecting Imphal and Nungba
Figure 2

Flow chart showing methodology of the whole work.
Figure 3

Landslide field photographs in the study area, a) The Imphal-Jiribam highway in Manipur got broken between Sinam and Laijan village. Around 60 feet of the NH-37  (b) A stretch of 50 meters of NH-37 was covered with landslides in the sub-division of Kangpokpi (c) A 300 meters long stretch of NH 37 was covered with debris of the landslide at Tintong village, July 27, 2019 (d) Landslide affected Sirarakhong villagers in Noney District (which is 85 kms from Imphal) on 6th April 2017 (e) On Aug 01, 2015, 20 people were killed in the landslide at the village under Khangbarol sub-division of the district (f) Two landslides at Sinam village in Tamenglong district have dislocated traffic along NH 37, 2017.
Figure 4

Thematic maps showing landslide causative factors
Figure 5

Landslide hazard zonation map generated using Frequency Ratio method

Low, medium, and high hazard zones, which covered 21.99 percent, 27.25 percent, and 21.15 percent of the study area, respectively, had 17.085 percent, 19.3 percent, and 23.85 percent of the landslides (Figure 6). It’s worth noting that Noney and its surroundings are in a high-risk landslide zone, whereas the risk of landslides in the Nungba area and its surroundings is rather low.
Figure 6

Landslide area percentage in the different hazard zones

Figure 7

Area Under Curve showing accuracy of FR model
Figure 8

Landslide hazard zonation map generated using Shannon's Entropy method

The final landslide susceptibility map based on Shannon's entropy model is divided into five categories, i.e., very low, low, moderate, high and very high, using natural breaks (Figure 8). Shannon's entropy model shows that 12.06% of the area has very high susceptibility, which contains 26.53% landslide area of the region. The model shows that 22.36% of the area has high susceptibility, which contains 24.28% landslide area. Very low and low landslide susceptibility zones cover 14.26% and 24.73% of study area, respectively as shown in Figure 9.
Figure 9

Landslide area percentage in the different hazard zones

Figure 10

SE Model (80.47)
Area Under Curve showing accuracy of Shannon's Entropy model

Figure 11

LHZ map generated using Weight of Evidence method
Figure 12

Percentage landslide area in the different hazard zones

Figure 13

Area Under Curve showing accuracy of WOE model