MASTER THESIS

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Landslide Susceptibility Assessment in Tanahu District, Nepal

By

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Science Pledge

By my signature below, I certify that my project report is entirely the result of my own work.

I have cited all sources of information and data I have used in my project report and indicated their origin.

Kathmandu, December 2019 Signature

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Abstract

Landslides are one of the most recurrent natural hazard occurring each year in the hilly and mountainous ranging from mid to northern part of Nepal causing massive loss of life and property. Nepal is a mountainous country lying in one of the most seismically active zone. It sits on the boundary of two massive converging tectonic plates, the Indian Plate and the Eurasian Plate. In addition to the earthquakes caused due to the converging tectonic plates, the rugged topography, unstable geological conditions along with the concentrated and prolonged rainfall during monsoon seasons, Nepal has been considered as a place which is particularly vulnerable to natural hazards. Natural hazards such as landslides cannot be avoided completely but the processes and consequences can be mitigated. For this, it is necessary to understand overall processes leading to the landslide including its triggering mechanism, and then identifying the susceptible zones of landslides and their consequences within specified region. In Nepal, few numbers of studies have been done particularly focused on small territories like sub-basin, certain road section, or small administrative unit of municipal level. The current study takes a broader field of study and models landslide susceptibility at a regional scale in Nepal.

The study focuses on the application of Geographic Information System (GIS), and statistical calculations for landslide susceptibility modelling of Tanahu District, Nepal. Here, landslide susceptibility models of the district have been successfully developed and applied for the study area. The models were derived using three different statistical approaches including Frequency Ratio (FR), Shannon Entropy (SE) and Statistical Information Index (SII). It was assumed that the landslides may occur in future under similar geophysical, geological and hydrological conditions and triggering factors that influenced them in the past. A landslide inventory of Tanahu district was developed. The landslide inventories were used to derive the quantitative relationships between landslide occurrences and landslide causative factors. The major triggering factors considered in this study are based on the various previous studies and literatures of similar scope. Ten landslide conditioning factors

were included in present study: slope, aspect, curvature, lithology, geology, land use, distance from river, distance from road, and distance from fault and soil type. Individual factor map were prepared as thematic layers. The landslide points were divided into 70/30 ratio for training and validation purpose with equal number of non-landslide pixels. After determining the weights of each classes from the proposed three models, the landslide susceptibility maps were prepared with five classes (very low hazard, low hazard, moderate hazard, high hazard and very high hazard) using ArcGIS. The overall performance of the resulting models were compared based on the accuracy value using the Area under the Curve (AUC). The values of AUC of success rate for FR, SE and SIII methods were found to be 78.73%, 77.09% and 79.23% respectively. Moreover, the values of AUC of prediction rate for FR, SE and SIII methods were found to be 76.31%, 74.08% and 76.38% respectively. The result showed that the SII model has the highest prediction capability compared to the other two models in present case of study.

The model shows that more than 41% of the area falls under low and very low susceptibility level while only 30% of area has high probability of landslide occurrence. Out of ten (10) local administrative unit of Tanahu district, Aanbukhaireni and Devghat Rural Municipality have most of the areas in high susceptibility while Byas, Ghiring, Bhimad and Bhanu Municipality have very dominant area in very low to moderate susceptibility of landslide occurrence.

The result of the present study indicates that integration of GIS has increased the quality and effectiveness of overall process of susceptibility modelling and prediction mapping. To enhance the planning strategies for disaster mitigation, reduced economic losses, build safer communities and ensure sustainable development a reliable landslide hazard forecasting and risk assessment is a key component.

TABLE OF CONTENTS

LIST OF MAPS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AUC	Area Under the Curve
Cme	Eutric Cambsiols
CMg	Gleyic Cambsiols
CMo	Ferralic Cambsiols
CMx	Chromic Cambsiols
DEM	Digital Elevation Model
FR	Frequency Ratio
GIS	Geographic Information System
GLOFs	Glacial Lake Outburst Floods
HFT	Himalayan Frontal Thrust
ICIMOD	International Centre for Integrated Mountain Development
LSI	Landslide Susceptibility Index
LSM	Landslide Susceptibility Map
LvX	Chromic Lewisols
MBT	Main Boundary Thrust
MCDA	Multi Criteria Decision Analysis
MCT	Main Central Thrust
MS	Master’s
PHh	Eutric Regosols
SAR	Synthetic Aperture Radar
SE	Shannon Entropy
SII	Statistical Information Index
SWI	Soil Water Index
UNESCO	United Nations Educational Scientific and Cultural Organization
UTM	Universal Transverse Mercator
USGS	United States Geological Survey

CHAPTER 1: INTRODUCTION

1.1 Background

Landslide is one of the most common natural hazards that has caused massive damages to infrastructure, property as well as loss of lives around the world. The country which is mostly affected by landslide was China with 695 landslide-persuaded deaths that is followed by Indonesia with 465 deaths, India - 352, Nepal - 168, Bangladesh - 150 and Vietnam - 130 (ILC, 2007). Approximately 89.6% of the total fatalities around the world were caused by landslides set off by prolonged or intense rainfall. (Petley D. , 2008).

Nepal is prone to variety of human induced disasters and natural hazards. More than 80 percent of the total population of Nepal is likely to suffer from natural hazards such as landslides, floods, earthquakes, fires, windstorms hailstorms and GLOFs (NDRR, 2019).

Among various natural hazards, landslide is very common in hilly region of Nepal. Two third of total area of Nepal lies in mountainous and hilly region, one of the several reasons leading to landslide. Landslides in Nepal causes significant number of fatalities, economic losses and is one of the major restraint in development (Petley et al., 2007). The various reasons causing landslides as mentioned by Varnes (1958) are listed below:

1. Geological causes
    a) Weak or sensitive materials
    b) Sheared, jointed, or fissured materials
    c) Weathered materials
    d) Contrast in permeability and/or stiffness of materials
    e) Adversely oriented discontinuity (bedding, fault, unconformity, contact, and so forth)
2. Morphological causes
    a) Tectonic or volcanic uplift

b) Fluvial, wave, or glacial erosion of slope toe or lateral margins

c) Glacial rebound

d) Deposition loading slope or its crest

e) Subterranean erosion (solution, piping)

f) Vegetation removal (by fire, drought)

g) Shrink-and-swell weathering

h) Freeze-and-thaw weathering

i) Thawing

3. Human causes

a) Loading of slope or its crest

b) Excavation of slope or its toe

c) Drawdown (of reservoirs)

d) Deforestation

e) Irrigation

f) Artificial vibration

g) Mining

h) Water leakage from utilities

The major agents causing critical landslides and related phenomena in the mountains and hilly part of Nepal are rugged topography, frequent earthquakes, soft and fragile rocks, heavy rainfall during monsoon and unstable geological structures (Dahal & Hasegawa, 2008). The deformation of land occurs due to slow but continuous seismic activities and also sudden change in geographic structure due to sudden change such as earthquakes. This type of deformation of land can cause severe landslides. According to (NDRR, 2019), the landslide hazard risks is further aggravated by anthropogenic activities like encroachment into vulnerable land slopes, improper land use and unplanned and random development activities such as construction of canals, roads, tunnels without convenient protective measures in the vulnerable hilly and mountain belt. NDRR (2019) also claims that on the basis of Himalayan range and their geology, the hilly area of Nepal located in Mahabharata range, Siwalik, Mid-land and higher altitude of Himalayas are more vulnerable to landslide.

A detailed knowledge about the expected frequency, character, pattern and magnitude of slope failures in an area can lead to successful mitigation of landslide hazards. For conducting quicker and safer mitigation programs over a specific area identification of landslide-prone regions is essential. In recent years, greater awareness of disasters due to landslides has brought attention to the government level. Despite many researches, there have been limited standard methods that can develop reliable model for prediction of landslide events. Only few attempts have been made to predict the landslides or prevent the losses due to such events. Hence, the probable land slide hazard and their impacts on various aspect of geo-environment becomes a remarkable issue of study. The new technology resources and software in the field of geographic information domain have provided sophisticated functionalities to integrate spatial/non spatial data to study, model, analyse and predict the consequences of such disasters. For the purpose of the MS Thesis, a study will be made on the different landslide causative factors, determination of their weights, preparation and analysis of the landslide susceptibility model and accuracy assessment while using three GIS-based statistical methods.

1.2 Problem Statement

According to the Disaster Report prepared by Ministry of Home Affairs of Nepal, in the last two years, 2940 disaster events were recorded with 13 different type of disaster in Nepal. Among the 2940 disaster events, 290 were landslides. The same report specifies that in terms of impact of environment and resources, 2780 landslides were triggered due to earthquake and 31 districts were affected by ground cracks, naturally damaging built up areas, forest, infrastructure, water resources and agriculture lands. Many small scale landslides are barely taken into account until and unless they result in loss of lives.

The census (2011) of Nepal shows the population growth rate of Tanahu District is 0.25% per year. The exploitation of natural resources like agricultural and forest land for development of new settlements, roads, and construction activities and material extraction over the hills and river banks is increasing. Haphazard development works especially- rural roads, has increased the unplanned surface excavation in potentially hazardous area. At present, overwhelming number of rural roads are being expanded and constructed by local units. Such un-engineered road cut has created severe surface crack and sliding problems even in dry season.

Figure 1: Photographs of Landslides in the study area

For this study, a case of Tanahu District is considered. Geologically this district lies in lesser Himalayan region which is composed with many characteristics that make it prone to frequent and severe landslides. The both Mahabharata Range and Midlands have many numbers of deep seated landslides. Many of them are still active and slow moving creep.

Likewise, most of the shallow landslides in Mahabharata Range and Midlands basically occur on deep seated landslides mass (Hasegawa et al.2008).

This research study is basically aimed at investigating the areas with potential of occurrence of future landslides and predicting the vulnerable areas. Also this district is one of the district with significant hydropower potential and agricultural product. Due to landslides, the agricultural lands are being diminished. Also, the debris cause the heavy siltation in the river which severely affects the river ecosystem. This impacts the storage capacity of the reservoir and affects the regular performance of hydropower generation plant.

A part of this research work will result in landslide susceptibility maps which will be key to create awareness among the people in the concerned territory. This can be the basis of decision making and infrastructure development planning, resettlement planning in order to minimize future disaster that may come due to unplanned activity. The findings of this study can remain as an important asset to the stake holder organizations who work in the field of disaster control and prevention. Also, the offices for planning and infrastructure development may use it to know more about vulnerability level in the area under study and plan developmental projects accordingly.

1.3 Objectives

The overall goal of the present research work is to perform landslide susceptibility assessment in Tanahu district of Nepal. The specific objectives of the research are:

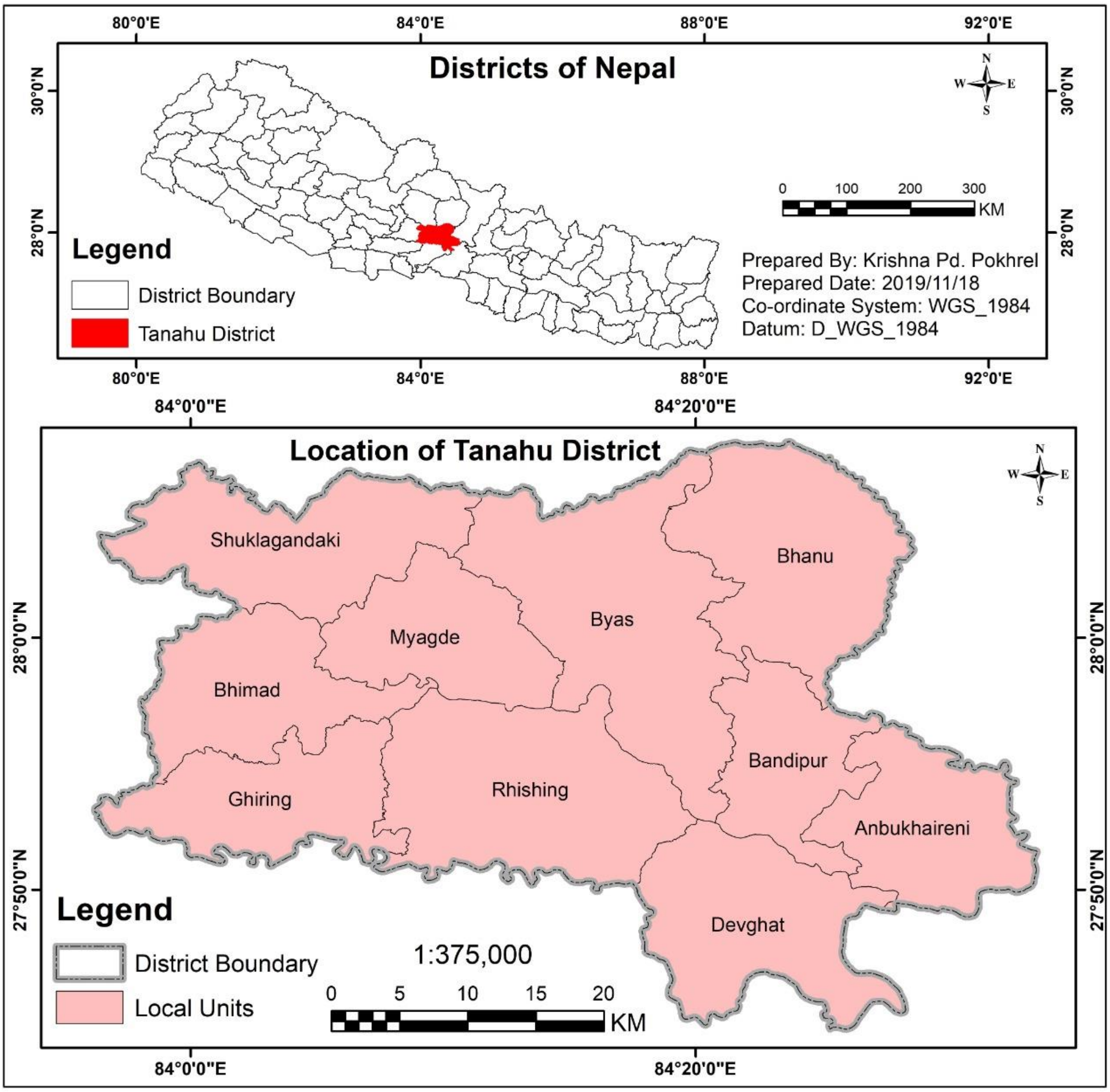
- To prepare the landslide inventory.
- To assess landslide conditioning factors in the study area based on analysis of previous landslides.
- To develop and apply models for spatial prediction of landslide hazard, assess the applicability of different conditioning factors in the susceptibility assessment, and validate and compare the results of three approaches (namely Frequency Ratio, Shannon Entropy and Statistical Information Index Method).

1.4 Description of Study Area

1.4.1 Description of General Profile

Tanahu district is one of the seventy seven districts of Nepal. It lies in Gandaki Pradesh. The district with Damauli as its district headquarters, covers an area of 1571 square kilometres. According to the census data, 2011 the total population of Tanahu district is 323,288 comprising 143,410 male (44.4%) and 179,878 female (55.6%) residing in 78,309 households. It has average population density of around 209 per square kilometres while the average family size is 4.13. This district lies in mid-hilly region of Nepal. Geographically the district spreads from 83° 50' E to 84° 34' E longitude and 27° 44' N to 28° 08' N latitude. This district is rich with its geographic, biologic, social, economic, religious and cultural diversity and has abundant potential of tourism. It consists of ten local units: Bhanu, Byas, SuklaGandaki and Bhimad as municipality, Aanbukhaireni, Bandipur, Devghat, Myagde, Rishing and Ghiring as rural municipality. It is bounded by Chitwan, Gorkha in east, Syanja in west Kaski and Lamjung in north and Palpa, Chitwan, Nawalpur districts in south. The main trading centres within this district are Aabukhaireni, Damauli, Dumre, Dulegauda, Bhimad, Khairenitar, Bandipur, Tharpu Kalesti, Turture, Bhansar, Purkot,Jamune etc. Other major historical and touristic places are Ghansikuwa, Bhanu- birthplace, Tanahusur Palace, Manungkot, Mirlungkot, Kotdarbar, Bandipur, Chhimkeswori, Thaprek. Most of these places are reachable by major highways, and fender roads, excavated tracks and trails. The district has average length of 52.9 km and average width of 33 km. (CBS, 2012)

Tahanu district mostly belongs to the Mahabharat Range and partly in the Churia Range. It forms the rugged, semi-matured terrain with sharp crests and gentle to steep slopes with various steep streams and semi-wet gulley. The northern slopes are less steep than the southern .The climate of the area is semi-alpine, sub-tropical and warm. The peak temperature reach up to 37°C in Jun/July and the lowest temperature reach up to 3°C in December/January. There are various small to medium sized streams joining to the major rivers that are originated from Mahabharata Range. Overall river structure is dendritic with steep gradients and deep valley cut. The total average length of small and big rivers inside this district is 864 km. Average rainfall of the area is recorded to be 1761 mm and the elevation ranges from 181-2130m. The general topography of this district is rugged with small to medium relief and complex geological structures resulting from active tectonic processes and seismic activities thus, the area is susceptible to landslides (Paudyal, 2014). The map of the study area is shown in Map 1:



Map 1: Study Location

1.4.2 Geological structure of study area

According to the geological map of the area published by Department of Mines and Geology (Amatya & Jnawali, 1994) the geological description has been done in the following paragraph.

Tanahu District, consist of un-fossiliferous sedimentary and low grade metamorphic rock of midland group (Lesser Himalayan Rock) like slate, phyllite, schist, quartzite, limestone and dolomite. Geologically it is composed of Phulchoki and Lakharpata sub Group of rock consisting of Lakharpata, Syanja, Sangram, Galyang, Ghanpokhara, Naudada, Ranimata, Kusma and Seti Formations. Siwalik group of rock is located at southern part of this district near to Devghat area separated by Main Boundary Thrust (MBT). Tectonically it is located in between HFT in south and MCT in north. Main Frontal thrust is located just 5 km from Devghat village at Chitwan district. It is also active thrust. MBT separate the Sub Himalaya and Siwalik Group of rock. General dipping of the rock is toward North East (NE) direction with low angle 20 to 35 degree. It passes near to Kota, Devghat, and Kalimati village. Due to tectonic movement (sharing through shearing line) of MBT at the rate of 50 mm per year (Patriat and Achache, 1984), frequent landslides are observed in this area. Main Central Thrust (MCT) extends in east-west direction at the northern boundary of Tanahu district near to Kunchha Village. There are many local thrusts that exist within Tanahu District. One major thrust passes through the Seti river section from Gaighat (Conflunce of Seti and Trishuli River) up to Pokhara valley along the strike of rock. It crosses many times Seti River mainly near to Damauli area. Due to passing of low grade metamorphic rock like slate, dolomite, this region is prone to small to large scale land slide. The extensively thrusted and faulted rocks give rise to steeper, unstable hill slope in this area.Phulchoki Sub Group of rock is well exposed at the Kahun Village in the form of Kahun Klippe. Low grade metamorphic rock like slate and phyllite is main lithology of Galyang formation which underlined by Markhu formations and Tistung formation of rocks. Due to upper high grade and basal low grade rocks; small to medium scale landslides are present over that area.

1.5 Literature Review

Every study project requires a review and analysis of the related works, articles and tools. During preparation of this report various literatures, journal articles from different scholars, software manuals etc. were studied to gather the information on concepts and working procedures for landslide susceptibility assessment using different statistical methods. Brief summary of the literatures reviewed are presented in the paragraphs below.

1.5.1 Concept on Landslide

Based on the knowledge and experience, the term “Landslide” has been defined in multiple ways by different researchers. Landslides can be regarded as "mass wasting," in which a large amount of soil and rock has down-slope movement under the direct influence of gravity (USGS, 2019). When forces acting down-slope (mainly due to gravity) exceed the strength of the earth materials that compose the slope the slope failure occur. Such movements are caused due to the influence of multiple factors acting on the earth surface which increase the effects of down-slope forces.

Landslides occur in smaller scales than other natural disasters, but have higher distribution and are more dangerous in many cases. Hence, this elaborates that landslides occur mostly in the slopes due to huge movement by changes in water level, stream erosion, rainfall, snowmelt and changes in ground water, disturbance by human activities earthquakes, volcanic activity or any combination of these factors. Landslide hazard can also be considered as probability of occurrence of a potentially damaging landslide within a specified period of time and within a given area (Varnes, 1984; Van Westen et al., 2006). This definition highlights a need to foresee both location based spatial probability and time/frequency based temporal probability while analysing, assessing and researching landslide hazards (Tien, 2012).

Varnes (1978,) described the features for a complex earth slide-earth flow, which has been illustrated in the following *Figure 1*.

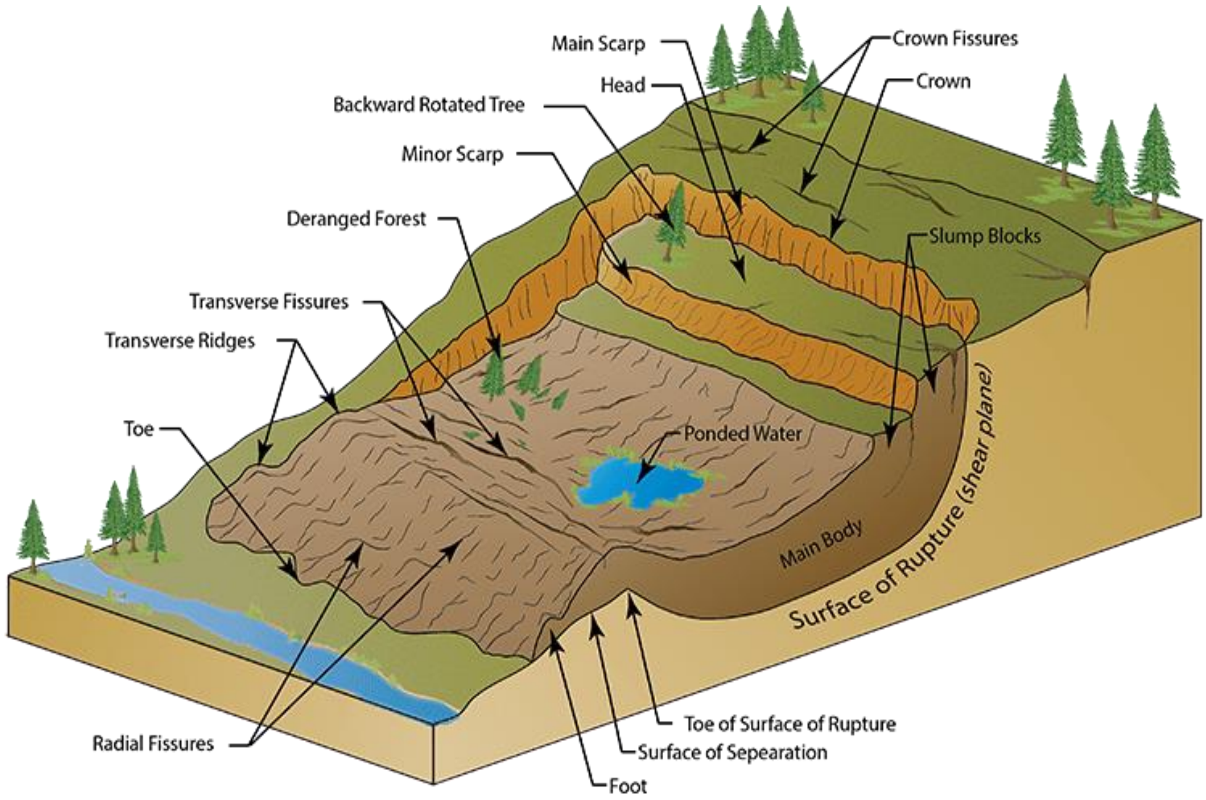


Figure 2: Illustration of landslide features

*Source: (*Gavanjanecee, 2018)

1.5.2 Causes of Landslides

Landslide are related to several causes and triggering factors. The three major cause for the landslide are briefly explained below:

1.5.2.1 Landslides and Water

Conners (2019) describes that soil congestion is the major cause of landslides. The effect of soil saturation can occur in the form of snowmelts, intense rainfalls, and variation in ground-water levels and change in water level along earth dam, coastlines and the banks of reservoir, lakes, rivers and canals. According to Khanh (2009), the term flooding and land sliding are nearly allied as both of them are related to runoff, precipitation and saturation of soil and ground by water.

Flooding can be one of the effect of landslide because floods in the form of sheet flow, overland flow, groundwater ridging etc. are connected to landslides as mentioned by Recare (2018). The landslide dams can block stream channels and valleys allowing huge amount of stream water to back up. This can cause flooding of backwater and if dam cannot withstand the pressure of backwater flooding there would be subsequent downstream flooding. The landslides can overtop in the reservoirs and caused in reduce potential of reservoirs and basin to store water (Khanh, 2009).

1.5.2.2 Landslides and Seismic Activity

The mountainous region that are highly risk of landslides can experience seismic activity i.e. earthquake. The types of landslides that are initiated by weakest shaking are rock falls, soil falls, rock slides and disrupted soil slides whereas the strongest shaking may result in deeper-seated slides, rock avalanches and soil avalanches (Keefer, 1984). Similarly, Khanh (2009) affirms that the landslides tend to take place when there is occurrence of earthquake in the steep landslide probable region because of dilation of soil materials due to shaking which allows quick infiltration of underground water. The Great earthquake of Alaska of 1994 caused the landslides on a large scale and other ground failure. Thus, the landslides that took place due to the earthquakes have killed people and damage infrastructure at a greater rate all around the world (Khanh, 2009).

1.5.2.3 Landslides and Volcanic Activity

Landslides can be caused due to the volcanic activities and some of them are destructive types. Khanh (2009) states that the process of volcanic lava can melt snow at a high rate, causing deluge of ash, soil, water and rock that simulates swiftly on the steep slopes of volcanic mountains. The most affected region is flat area around the volcanoes. The break out of Mount St. Helens of 1980 in Washington provoked the gigantic landslide on the northern region of volcano which is reckoned to be the biggest landslide in recorded times (Khanh, 2009).

1.5.3 Landslide Classification

In late twentieth century, Varnes (1978) landslide classification system was adapted by the Commission on Landslides and other Mass Movements on Slopes (IAEG, 1990) in order to standardize landslide nomenclature. Based on that classification, the International Geotechnical Society's UNESCO Working Party on World Landslide Inventory (WP/WLI), established under the IAEG Commission, developed a series of ways to report a landslide (WP/WLI I. G., 1990) prepare a landslide outline (WP/WLI I. G., 1991), explain the activities of a landslide (WP/WLI I. G., 1993), and compute the rate of mass movement (WP/WLI I. G., 1995). According to Li & Mo (2019), the Varnes (1978) landslide classification system has achieved worldwide recognition by various institutions in different dates as USGS (1985), IAEG (1990), EPOCH (1993) and USGS (2008).

Usually, shallow landslides involve only the upper regolith zone and soil layer, while deep-seated landslides additionally involve substratum at higher depth. The volume of landslide can vary from some tens of cubic meters to several cubic kilometers for giant landslides, while landslide speed may range from a few centimeters per year for slow-moving landslides and tens of kilometers per hour movement of mass for fast landslides which are highly destructive (Guzzetti, 2005). The existing landslides can be classified as inactive (often relict or fossil), dormant (potentially reactivated) or active according to the state of activity or movement. Multiple landslides, for example, occur almost simultaneously when steep slopes are shook up by an earthquake or over a period of hours or days when faults are triggered by snow melting or intense rainfall (Guzzetti et.al., 2005).

The most applied landslide classification was the one outlined by the late D.J. Varnes (Cruden and Varnes, 1996, Varnes, 1958, Varnes, 1978). This classification distinguishes five types of mass movement: fall, topples, slides, spreads, and flows combined with types of material: bedrock, coarse soils, and predominant fine soils.

There are 32 landslide types in the modified version of the Varnes classfiifaion which is reiterated by Hungr et al., (2014) which is shown in the Table 1:

Table 1: An update of Varnes landslide classification system

<table>
<tr><th>Type of movement</th><th>Rock</th><th>Soil</th></tr>
<tr><td>Fall</td><td>1. Rock and ice fall</td><td>2. Boulder, debris, and silt fall</td></tr>
<tr><td rowspan="2">Topple</td><td>3. Rock block topple</td><td rowspan="2">5. Gravel, sand, (fell) silt topple</td></tr>
<tr><td>4. Rock flexural topple</td></tr>
<tr><td rowspan="5">Slide</td><td>6. Rock rotational slide</td><td>11. Clay and silt rotational slide</td></tr>
<tr><td>7. Rock planar slide</td><td>12. Clay and silt planar slide</td></tr>
<tr><td>8. Wedge slide</td><td>13. Gravel, sand, debris, and slide</td></tr>
<tr><td>9. Rock compound slide</td><td rowspan="2">14. Clay and silt compound slide</td></tr>
<tr><td>10. Rock irregular slide</td></tr>
<tr><td rowspan="2">Spread</td><td rowspan="2">15. Rock slope spread</td><td>16. Sand, silt, and liquefaction spread</td></tr>
<tr><td>17. Sensitive clay spread</td></tr>
<tr><td rowspan="9">Flow</td><td rowspan="9">18. Rock and ice avalanche</td><td>19. Sand, silt, and debris dry flow</td></tr>
<tr><td>20. Sand, silt, and debris flowslide</td></tr>
<tr><td>21. Sensitive clay flowslide</td></tr>
<tr><td>22. Debris flow</td></tr>
<tr><td>23. Mud flow</td></tr>
<tr><td>24. Debris flood</td></tr>
<tr><td>25. Debris avalanche</td></tr>
<tr><td>26. Earthflow</td></tr>
<tr><td>27. Peat flow</td></tr>
<tr><td rowspan="3">Slope deformation</td><td>28. Mountain slope deformation</td><td>30. Soil slope deformation</td></tr>
<tr><td rowspan="2">29. Rock slope deformation</td><td>31. Soil creep</td></tr>
<tr><td>32. Soil flection</td></tr>
</table>

Source: Hungr et al. , 2014

Although landslides occur in smaller scales than other natural disasters, but have higher distribution and are more dangerous in many cases. Landslides lead to the evolution of landforms and are considered as the biggest threat in a great number of regions all around the world (Tien, 2012). UNESCO (1993) described the activity of landslide based on the state, style and distribution. The state is defined based on time, the style indicates spatial distribution and distribution being the movement of landslide. Different landslide activities are presented in the Table 2

Table 2: A glossary of activities of landslides

State of activity	Distribution of activity	Style of activity
○ Active: ○ Reactivated ○ Suspended ○ Inactive : Dormant : Abandoned : Stabilized Relict	○ Retrogressing ○ Advancing ○ Widening ○ Confined ○ Enlarging ○ Diminishing ○ Moving	○ Complex ○ Composite ○ Multiple ○ Successive ○ Single

Source: WP/WLI I. G., 1993

1.5.4 Landslide Conditioning Factors

The event-controlling factors are known as “predisposing factors”, “causative factors”, “causal factors”, “intrinsic factors”, “conditioning factors”, “quasi-static factors” and “preparatory factors” (Zhu et al., 2014). The features that influence driving and resisting forces and their balance are commonly called conditioning factors. In regional scales, these are different geological, geomorphological and environmental properties of the ground. The main factors which influence land sliding are discussed by Varnes(1978) and Hutchinson (1988). Normally, the most important factors are bedrock geology (lithology, structure and degree of weathering), geomorphology (slope gradient, relative relief and aspect), soil (depth, porosity, permeability, and structure), hydrologic conditions and land use and land cover (LULC). Landslides are sparked by many causative factors. Most landslide-triggering factors can be divided into 4 major groups including geological, topographical, hydrological factors and loading conditions (Anbalagan et al, 2014).

In every declined surface (i.e. slope), there is gravitational force that tends to contribute for downslope movement and opposing force that tend to resist the movement. A basic definition of factor of safety of a slope is a resultant which is comparison of the shear stress of the downslope and shear strength of the soil along with known or assumed rupture surface. Terzaghi (1950) opines from this general definition, landslide causes are divided into external causes which result in an escalation of the shearing stress (e.g. unloading the slope toe, geometrical changes, loading the slope crest, shocks and vibrations, changes in water regime, drawdown) and internal causes which result in a reduction of the shearing resistance (e.g. weathering, progressive failure, seepage erosion). However, Varnes (1978) revealed that there are a variety of internal or external causes which may be operating either to escalate the shearing stress or to decrease the shearing resistance. The huge variety of movements of slope reflect the diversity of circumstances that cause the slope to become non rigid and eventually this process trigger the movement.

According to Brabb (1981) it is more relevant to consider causal factors (including both “processes” and “conditions”) than “causes” per se alone. Hence, the ground conditions (sensitive fabric, degree of weathering, weak strength and fracturing) are not causes but are influential criteria. These weak ground conditions are responsible for an unstable slope to evolve, to which must be added the environmental criteria of stress, temperature and pore water pressure. It does not matter if the ground is fragile as such, failure will only take place as a result if there is an adequate causal phenomena which acts as well. Such causal phenomena may be natural or anthropogenic, but practically change the stable ground conditions amply to cause the slope system to failure, i.e. to skeptically change the stability state (Popescu, 1984).

Following are the list of conditioning factors considered in different researches:

- Geomorphological factors: elevation/altitude, relative relief, slope, aspect, general curvature (plan, profile), tangential curvature, longitudinal curvature, cross-section curvature, roughness index, topographic wetness index, stream power index, stream transportation index, slope length, diagonal length.
- Geological factors: lithology (texture, weathering), fault density, distance from faults / lineaments.

- Soil factors: depth, inner texture, surface texture, erosion, slope, stoniness, drainage and hydraulic conductivity, permeability, porosity, effective thickness.
- Land use/cover factors: land cover, normalized difference vegetation index, forest (type, age, diameter, and density of timber), road density, distance from road.
- Climatic factors: annual total rainfall, annual maximum rainfall, average annual rainfall.
- Hydrological factors: river density, distance from river.

Landslide causal factors can be divided in accordance to their effect (triggering or preparatory) and their origin (physical or man-made processes, ground conditions and geomorphological). Ground conditions or the mass and material characteristics of the ground, can be mapped on the landslide surface and the neighboring ground and analyzed in the subsurface by drilling and smashing. Popescu (2002) mentions the foloowing testing procedures to determine mechanical characteristic of surface material:

- Geomorphological processes can be defined as changes in the morphology of the ground. It can be analyzed by pre-existing maps, surveys of the landslide area, aerial photographs or attentive observation at different epoch by the local population.
- Physical processes involve the surrounding and can be analyzed at the landslide site by instrumentation, such as seismographs, rainfall gauges or piezometers. Careful observations over different time of damage from earthquakes or water wells may be acceptable backup. The alternation in mechanical properties with distance from the surface at different period of time may, in some circumstances, illustrate changes of these properties.
- Man-made processes can be analyzed by landslide site observations and from construction or excavation records from various parties at the site.

1.5.5 Landslide Susceptibility Assessment

Landslide susceptibility can be defined as possibility of occurrence of a landslide in an area due to various geo-environmental factors. It is regarded as the proneness of terrains to produce slope failures. Landslide susceptibility (LS) assessment helps to quantify the volume or area and the spatial probability of a landslide event, by providing a relative estimation of the spatial events of landslides in a mapping unit based on the conditions of local terrain, and it may also include the information related to the temporal probability of the expected landslide event, the intensity and velocity rates of the existing or potential landslide events (Fell et al., 2008; Guzzetti et al. 1999; Lepore et al. 2011; Rossi and Reichenbach 2016). So, a landslide susceptibility map shows the correlation between causative factors that contribute to landslides with the past distribution of slope failures (Brabb, 1984). Identifying areas with higher risk of landslides requires evaluation of the distribution and frequency of historical landslides. Quantitative spatial analysis can be used for assessing the landslide susceptibility of a region and providing the scientific information relevant for mitigation and prevention of future landslides in that region (Yilmaz, 2009).

In the past two decades, substantial research studies on LSM have been conducted worldwide. According to Chen et al. (2013), Landslide Susceptibility Map (LSM) is the typical output of the combination of all factor maps according to their weight. This is the generated by categorizing landslide susceptibility Index into different levels of susceptibility classes. Cheng et al. (2013), then reiterates GIS provides a reliable platform for generation of LSM by defining weight of each landslide conditioning factors and assigning rating for each factors. Such

Guzzetti et al. (2000) and Van Western et al. (2006) consider that extent of study area, purpose of inventory, scale, characteristics and resolution of aerial imagery and the resources available paly important role in the preparation of LSM which are created after combination of different landslide factor maps.

The following *Figure 4* shows the basic steps for preparation of LSI as mentioned by Khanh (2009):

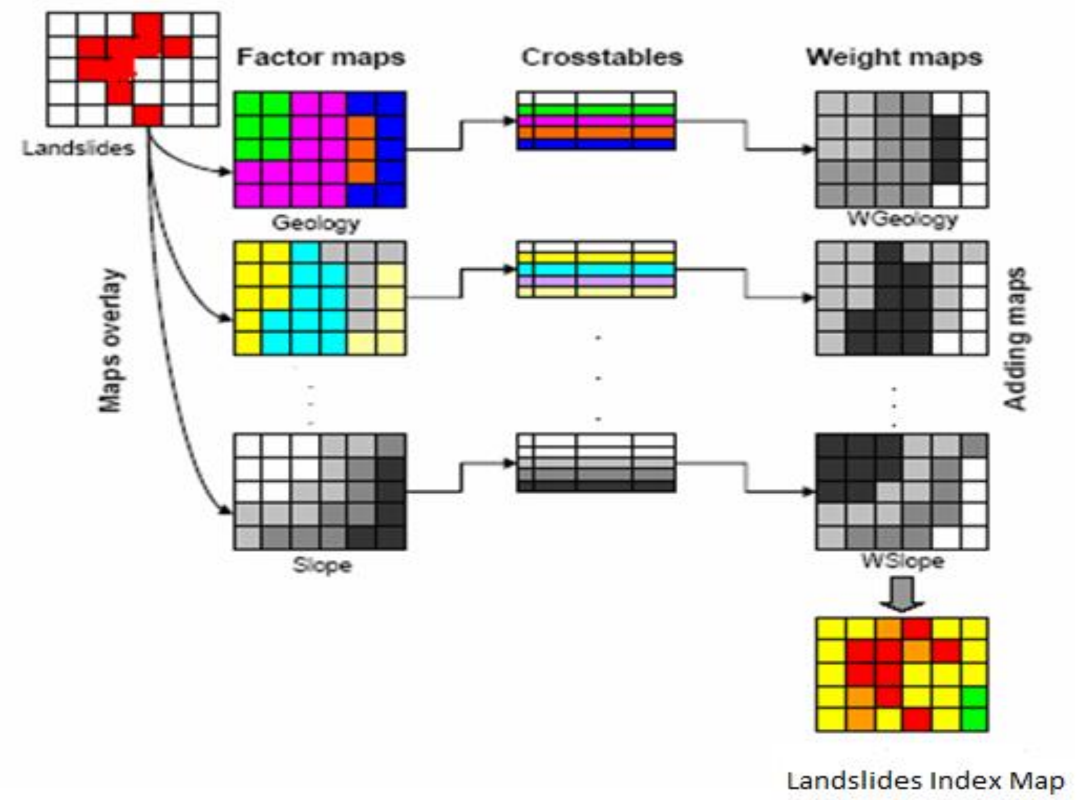


Figure 3: Schematic representation of LSI preparation steps

Source: Khanh, 2009.

1.5.6 Hazard, Vulnerability and Risk

Landslide hazard (H) can be expressed as probability of occurrence of a potentially damaging landslide within a given area and a specified period of time (Pt) (van Westen et al., 2006, Varnes and IAEG, 1984). Hazard zonation mapping is one of the technique to outline the zones that has potential probability of occurrence of landslide within a certain period of time within an area. Vulnerability is a concept that elaborates certain factors or constraints related to physical, economic, social or geographic elements concerned susceptible with impact of a hazard. Landslide risk is defined as the interaction of hazard and vulnerability that may arise negative consequences to the environment, people and their property. To identify the spatial and temporal extent of landslide hazard requires identifying the areas that are, or could be, affected by a landslide and assessing the probability of such land sliding occurring within a specified period. Specifying a precise period for the future occurrence of a landslide can be difficult. As a result, landslide hazard has often been represented by landslide susceptibility, where preparatory landslide causes are described (Acharya, 2016).

The following *Figure 2* shows the relationship between hazard, risk and vulnerability:

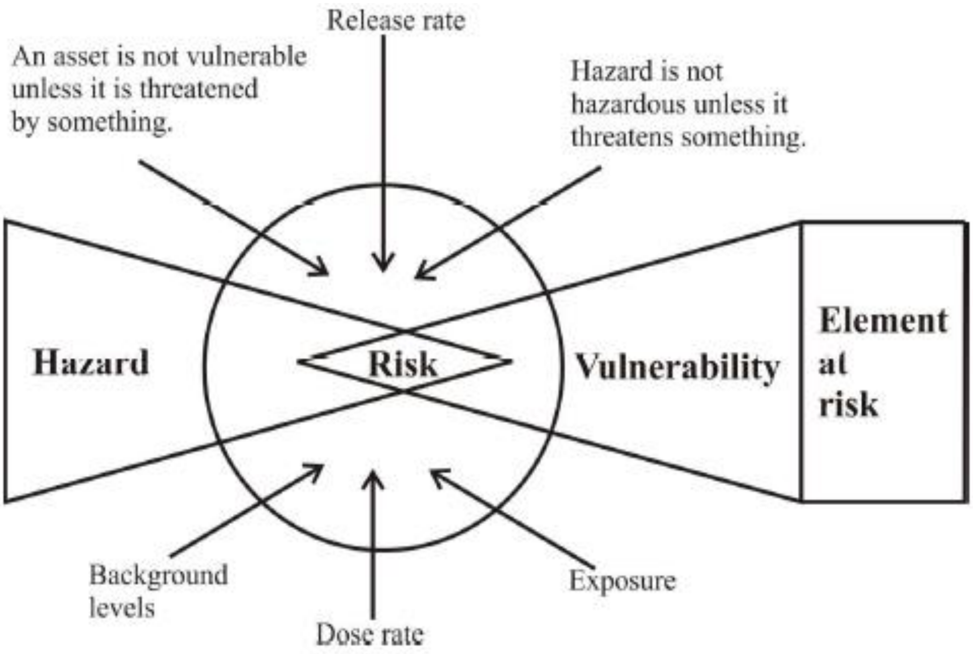


Figure 4: Conceptual relationship between hazard, risk and vulnerability

Source: Alexander, 2002

Hazards create risks by exposing pre-existing vulnerabilities. The risk that a community faces is mitigated by its level of preparedness, response and recovery or readiness (ADPC). There are various approaches to define landslide hazards for landslide investigation and its risk management (Acharya, 2016). Landslide susceptibility assessment is one of the important part of investigation for landslide hazards.

1.5.7 Landslide Susceptibility Assessment Methods

Over the last two decades, many models for landslide susceptibility mapping have been proposed with the assumptions that landslide susceptibility is related to causal factors and can be evaluated as long as the causal relationship is known (Zhu et al., 2014). In recent years, assessment of landslide susceptibility in the form of hazard zonation has been attempted in a wide variety of environments and using diverse approaches. The different methodologies developed were influenced by the scale of analysis, the availability of input data, and the required details of the hazard map (Brabb, 1984; Nilsen et al., 1979; Varnes, 1984; Wagner et al., 1988; Pachauri and Pant, 1992; Anbalagan, 1992; Sarkar et al., 1995).

The different landslide susceptibility assessment methods can be presented as *Figure 3*.

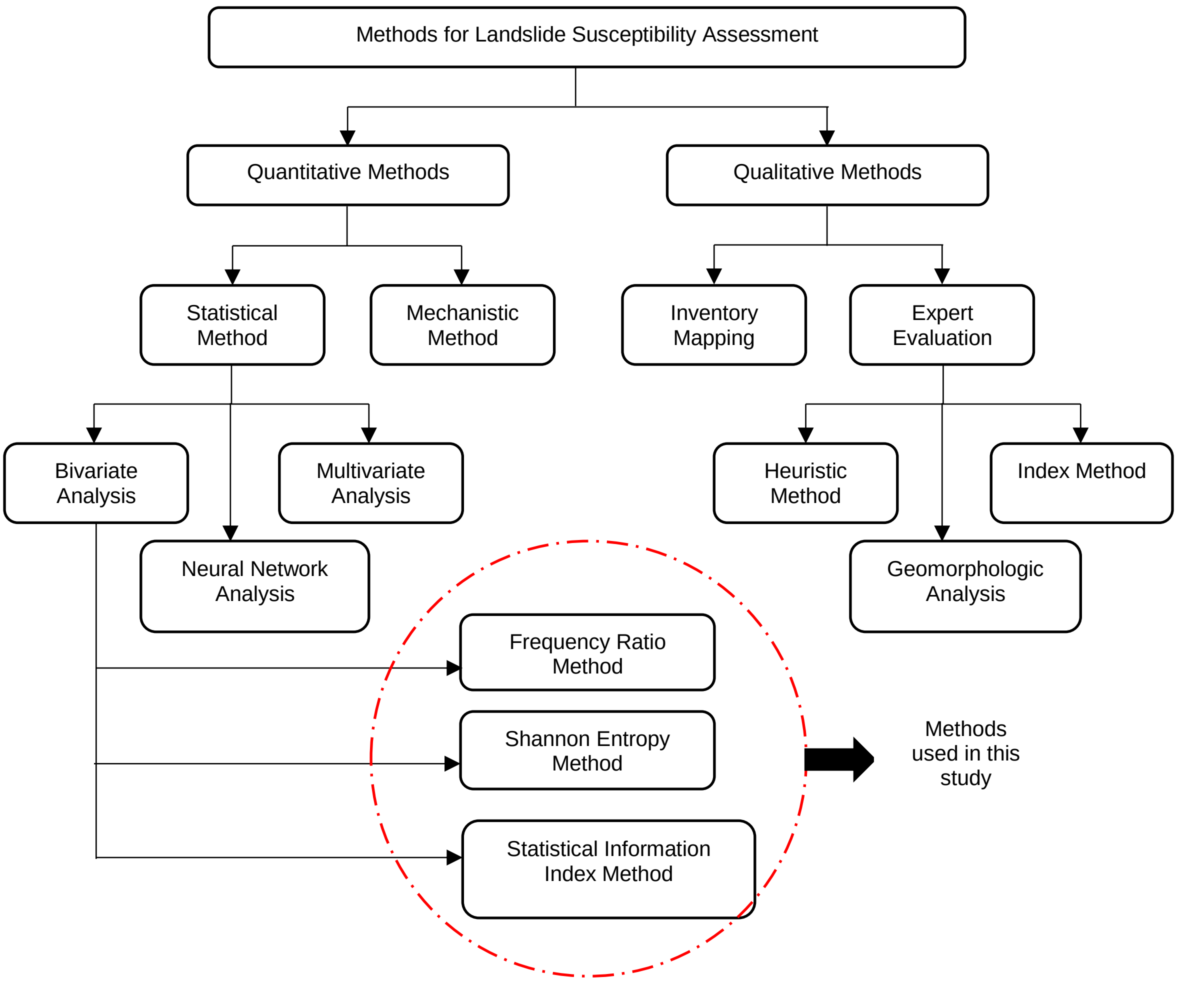


Figure 5: Landslide Susceptibility Assessment Methods

It is seen that, there are two different landslide susceptibility analysis techniques used widely; quantitative and qualitative methods. Qualitative methods are subjective methods that are based on opinions of expert and characterize hazard zoning in detailed terms. Quantitative methods employ mathematical models to estimate the probability of landslide occurrence in a region, and thus define hazard zones on a continuous scale (Guzzetti et al., 1999). To achieve accurate estimation of the probability of slope failure, an up-to-date landslide inventory map and complete information on the past mass movements are required.

Although the methods for landslide susceptibility assessment can be qualitative and quantitative, they all need to follow the steps (Clerici et al., 2002; Süzen and Doyuran, 2004) as listed below to successfully implement the assessment:

- Mapping past landslides in a target region,
- Mapping a set of geological/geomorphological factors that are supposed to be directly or indirectly correlated with slope instability.
- estimating the correlations of these factors with slope instability, and
- differentiating the target region into areas of different landslide susceptibility (hazard zoning)

In which landslides can be identified and mapped using a variety of techniques including:

- geomorphological field mapping (Brunsden, 1928),
- analysis of oblique or vertical stereoscopic aerial images (Rib & Liang, 1978) surface and under-surface observing, and
- innovative remote sensing tools and technologies (Mantovani et.al., 1996), for example the interpretation of SAR images, the interpretation of multispectral images (Zinck et.al., 2001) having high resolution or the interpretation of space or airborne sensors having high quality DEMs (Kaab, 2002).

The quality and accuracy of the landslide susceptibility maps is very crucial as it affects the reliability of the predicted results which are obtained from various inventories.

Quantitative methods can be classified into statistical and deterministic analysis. The deterministic methods are usually focused on evaluating the mechanical equilibrium probable slide block and computing the slope safety factor (Zhou et.al., 2003). They are mostly appropriate when the pattern of landslide is simple and homogeneous in geologic and geomorphic properties.

Statistical method is a quantitative method which is based on study and analysis of the functional relation between existing landslide and its instability. A huge amount of data are required in this method to develop reliable outcomes. Some of the techniques of statistical methods are bivariate statistical analysis, multiple linear regression, discriminant analysis and logistic regression (Bui et al., 2011). Bivariate statistical analysis usually involves the computation of two variables for the purpose of establishing the empirical relationship between them. The weight of individual class are assigned according to statistical relationship between previously occurred landslide and different factor maps (Pradhan et al., 2012). Bivariate method is a statistical analysis in which each factor map (for example slope, vegetation, land use, geology, soil, distance to river, and distance to road) is combined with landslide inventory. The weights are assigned to each landslide factors considering their landslide densities or abundance in each attribute class (Adhikari, 2011).

Different statistical methods have been developed over the years for landslide susceptibility assessment. The current study is aimed at assessing three bivariate models, namely the Frequency Ratio (FR), Shannon Entropy (SE) and Statistical Information Index (SII). Brief description of which are presented in the *Methodology* section and assessments results are discussed in Result and *Discussion section* below.

1.5.8 Landslide Susceptibility Assessment and GIS

Geographic Information Systems (GIS), as a computer-based system for data capture, input, manipulation, transformation, visualization, combination, query, analysis, modeling and output, with its excellent spatial data processing capacity, has made easy to the overall process of disaster assessment (Carrara, 1983). GIS functionalities has provided a reliable platform to ease the problem of slope stability through various geotechnical analysis tools. Extraction of relevant spatial information related to landslide occurrence is an integral part of hazard assessment. Statistical methods combined with GIS are proved to be effective tools for generating and processing spatial information. The advancement in earth Observation (EO) techniques facilitate effective landslide detection, mapping, monitoring and hazard analysis (Tofani et al. 2013). Most of the methods currently used in assessing and mapping landslide susceptibility are based on an accurate evaluation of the spatial distribution of both the "causal factors", and/or of the landslides occurred in reality. Such process involve handling, interpretation and graphical representation of a large amount of territorial data (Magliulo & Russo, 2009). Thus, GIS represent a powerful tool in landslide susceptibility assessment.

Diverse GIS techniques are used to perform landslide susceptibility assessment for the research. GIS procedure provide functionalities like look up tables, clipping, tabulating area, buffering, classification, resampling, overlay analysis, raster calculations and visualization of results which are vital during susceptibility assessment. Chalkias et al. (2014) has also used GIS for landslide mapping by calculating the landslide density in each parameter class by crossing the respective layer with the landslide inventory map. He had used the GIS methodologies for landslide susceptibility mapping while utilizing different statistical approaches for weight calculation. So, application involves integration of the LSI values of multiple factors by means of overlay analysis using the different equations for each methods used and these are key functions provided by GIS.

1.5.9 Validation of Landslide Susceptibility Assessment

Validation implies a comparison between the maps obtained from the models and the independent dataset (Deng et al., 2017). Landslide susceptibility maps can be verified by comparing the susceptibility maps with both the training data with the test data. For this purpose success rate and prediction rate curves are calculated where the values provide the base for testing the model compatibility and prediction capacity. The success rate curve is derived by comparing the predicted model and the landslides data used in the modeling, and this indicates how well the resulting landslide susceptibility maps have classified the areas of existing landslides (Tien et al. 2012). Whereas the prediction rate curve illuminates how well the model and predictor variables predict the results.

1.5.10 Area under the Curve (AUC)

AUC is one type of accuracy in statistics for prediction models (probabilities) in the assessment or analysis of natural disaster events. Mathematically, AUC is a graph of varying index numbers usually between a maximum value of 1 or equal to 100% and 0.5

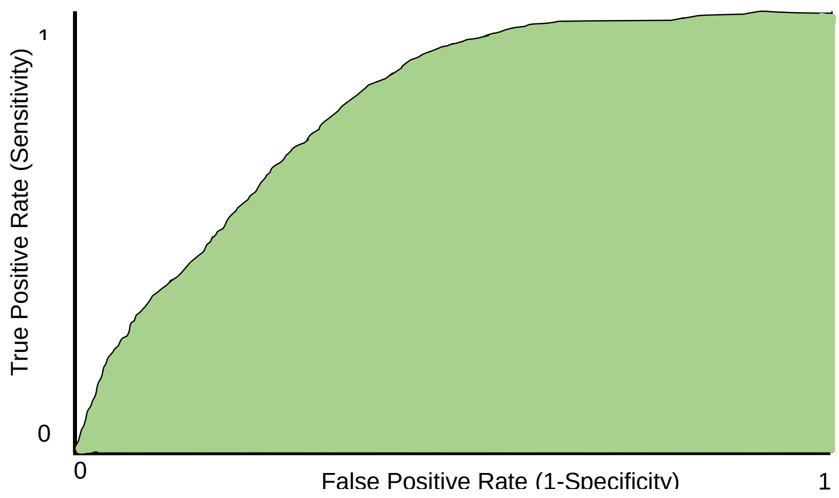


Figure 6: Relationship of True Positive Rate vs False Positive Rate

Or equal to 50%. In an ideal model, AUC is very close to 1.0 which means the model is perfect fit whereas in a random prediction model, AUC is close to 0.5 (Swets, 1988). AUC is used as measurement to determine the comprehensive quality of the model.

When the area of the curve is large, it represents the best performance of the model over whole area of potential cutoffs (Hanley & McNeil, 1982). AUC measure the quality of the prediction of model regardless of what distribution threshold is chosen.

1.5.11 Previous Studies

In the study by Nohani et al. (2019) comparison of four bivariate models namely the frequency ratio (FR), Shannon entropy (SE), weights of evidence (WoE) and evidential belief function (EBF), in Landslide susceptibility assessment of Klijanrestagh Watershed, Iran was performed. All methods gave similar results however WoE model out performed among them.

For the validation process different techniques has been used by different authors. Generally area under the curve being the main validation process different techniques have been used for generating AUC curves. Receiver operating characteristic in one of the main validation techniques used similarly other curve like success rate curve and prediction rate curve are also used for validation (Chalkias et al., 2014). The study suggests that an area under curve with value of more than 70% is good for the validation of the model (Khanh, 2009).

Khanh (2009) on his report has used statistical index method for creating landslide susceptibility map of his study area. Landslide inventory was correlated with each factor to calculate the final landslide susceptibility of the study area. The validation showed a competitive accuracy with the logistic regression method with the accuracy being 79% and 82% from statistical information index method and logistic regression method. One of the main advantages of using this method is it allows to calculate the weight of each class separately. The use of logarithm function for weight calculation gives both positive and negative values which helps in clear determination of which class has maximum impact on landslides than other classes (Abidine & Abdelmansour, 2019). Pourghasemi et al. (2012) applied Shannon's entropy approach was to analyze the landslide susceptibility in Kalaleh town using eighteen landslide conditioning factors and results of AUC evaluation yield 82.15% of validation accuracy. Similarly, Abidine & Abdelmansour (2019) has also used the same method for landslide susceptibility mapping alongside frequency ratio method. Similar process mentioned earlier was used to create landslide susceptibility map of the study area using both the methods. The accuracy of the model was checked through AUC methods with FR showing accuracy of 85.57% and SII showing accuracy of 89.03%.

Bui et al. (2011) has also used two methods for landslide susceptibility mapping statistical index and logistic regression. Despite some of the author considering logistic regression method above this method it shows high comparison with other methods. The area under the curve from logistic regression show value of 95 % accuracy and statistical index method showing 94.02 accuracy. Chalkias et al. (2014) has also used statistical indexing method. Since the method of model preparation is same AUC values was determined using success rate curve and prediction rate curve. The result shows success rate has accuracy of 82 % whereas prediction rate has 75%. The accuracy of this model depends on more landslide surveys. Despite being suppressed by other mapping technique it is one of the main technique in landslide mapping with good validation of the model.

1.6 Concluding remarks

The concept of landslide, its classification, terms and terminologies, its relation with different geo-environmental factors, mechanism, and theories behind the assessment methods are thoroughly reviewed in this chapter. The necessity for the landslide assessment, general information and geological description about study area has been provided shortly. Literatures showed several approaches that can be used for susceptibility assessment. Among which FR, SII and SE are deterministic bivariate statistical methods that have provided satisfactory prediction results under similar type of study area and causative factors in the previous studies. The methodological steps for overall assessment has been described in the Methodology section.

CHAPTER 2: METHODOLGY

Various methods for landslide susceptibility assessment have been studied in the scientific literatures. Assessment is accompanied by GIS analysis in combination with the statistical calculations. Three bivariate statistical methods have been used for the present study. The basic methods, procedural phases, data and software used for the assessment are described in the following sub headings.

2.1 Work Flow:

Overall methodology for land slide susceptibility assessment of Tanahu district with the application of GIS and statistical calculations consists of the following procedures described briefly below:

- Creating landslide polygons to prepare Landslide inventory
- Sampling the landslide data in training and testing subset
- Preparation of thematic layers for each of the landslide factors used for current study
- Resampling all the factor layers into raster of same pixel and classification based on specific theme.
- Overlay and clip operation to calculate the pixel statistics of landslide over each class of specific factor
- Calculation of the weight of each factors based on the landslide inventory for each methods.
- Combining all the thematic layers based on their weight to derive landslide susceptibility index map using raster calculator tool in ArcGIS to produce the Landslide Susceptibility Index (LSI) map
- From the calculation, the study area was divided into five zones of relative landslide susceptibility, i.e., very low susceptibility, low

The general workflow diagram for the current study is presented in Figure 7 below:

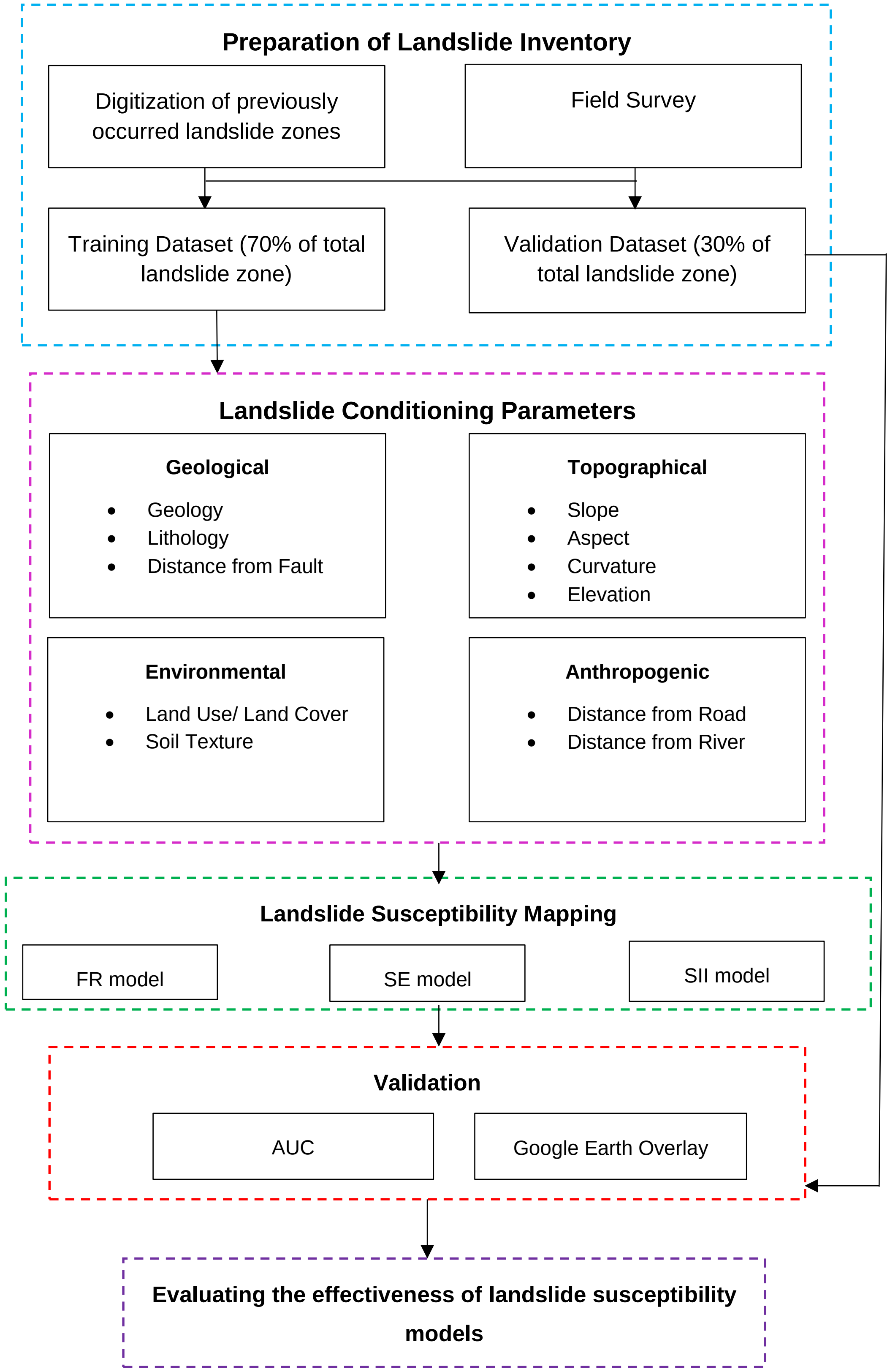


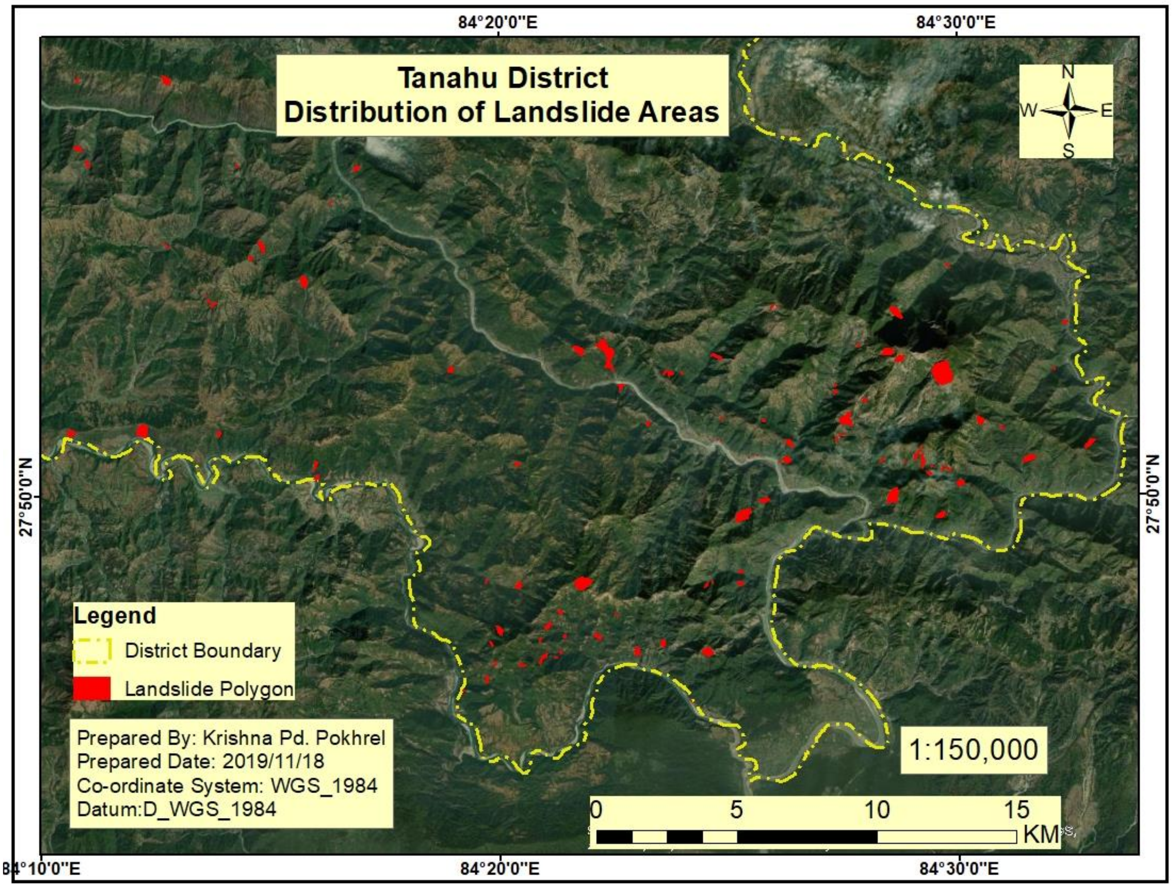
Figure 7: Methodology Flow Chart

2.2 Data Used

The data required for the overall assessment were obtained from different sources. The brief description the data, their sources, features and analysis procedures are presented as below:

2.2.1 Preparation of Landslide Inventory

The elemental step in landslide susceptibility mapping is developing the inventory map based on past landslides. The accuracy of the data heavily depend on the past and present landslides for predicting the future landslides (Reichenbach et al., 2018). The following Map 1Map 2 shows the sample of digitized landslide polygons in the south eastern part the district:



Map 2: illustration of overlaying landslide polygons in world base imagery

The landslide inventory provides insights into the types, failure mechanism, location, trigger as well as frequency of occurrence, its density and damage related with landslide (Van Westen et al., 2008). In this research, in total 136 landslide areas were collected and mapped for preparing landslide inventory map. The historic images of different years were interpreted visually to locate the slipped area. World base imagery that is available online were also taken as base for demarking the landslide polygons.

The verification of such areas was done with field visits. Some of the landslide polygons were obtained from the measurement during the field and GPS location of those were taken to plot them. Some digitized sample polygons were measured for verification. The spatial location of those sample were found in acceptable accuracy. Later the polygons were randomly split into two subsets as training and testing data using Subset Features tool in ArcGIS version 10.4 where data were divided into 70% and 30% as a training and testing data set. The two subset of landslide inventory are explained shortly below

2.2.2 Training Data

Among the total landslide data, 70% of the data were used for developing the model as training data. A sum of 95 landslide locations were used for prediction of future landslide. The training data were determined by digitizing the landslide areas using Google Earth, online word base imagery and field visit. The polygon data was then converted to raster format for further analysis. The total landslide pixels covered by training data is 2796.

2.2.3 Validation Data

Among the total landslide data, 30% of the data were used for validating the model as test data. A sum of 41 landslide locations were used for validating the predicted landslide area. The validation data were also determined by digitizing over the world base imagery available online within ArcGIS and field measurement. The polygon data was converted to raster format for further analysis.

2.3 Landslide Conditioning Parameters

The factors that causes large mass of rock, debris or earth to move down a slope are landslide conditioning parameters. To obtain an assessment method for the analysis of susceptibility to landslides, identifying the landslide conditioning factors is crucial (Ercanoglu & Gokceoglu, 2002).

In this study, the for various landslide conditioning factors have been collected from different sources like USGS earth explorer, Humanitarian Data Exchange, ICIMOD, Department of Mines and Geology, Survey Department of Nepal, digitation from Google Earth and direct field survey to validate the result obtained from this analysis. All the calculations and analysis work are done with the raster data. So the vector data were converted to raster format using *feature to raster* function within spatial analyst tool. Hence the data set were in different pixel sizes. All the raster were then resampled into 30*30 m pixel size in order to bring consistency and to increase the confidence in the final product.

The data obtained from different sources were first projected into a common projection system using *project raster tool*. The MUTM_84 projection system was used as adopted by Nepal. The details of the projection system has given in the following Table 1

Table 3: Detail parameters of MUTM_84 Projection system

Projected Coordinate system: MUTM_84		
S.N.	**Parameters**	**Value**
1	False Easting	500,000.00
2	False Northing	0.00
3	Central Meridian	84.00
4	Scale factor	0.9999
5	Latitude of Origin	0.00
Geographic Coordinate System: GCS_Nepal_Nagarkot		
1	Datum	D_Nepal_Nagarkot
2	Prime meridian	Greenwich
3	Angular Unit	Degree

This study has included four sets of major parameters under which ten (10) landslide conditioning parameters affecting the occurrence of landslides were taken in to account for analysis. These are classified as geological, topographical, environmental and anthropogenic parameter and that are explained below:

2.3.1.1 Geological parameters

There are three geological parameters that are used in this study i.e. Geology, Soil type and Fault lines of Tanahu district. The description of the features of different geological formations are given in *Annex 1* of this report. The short explanation about these data is presented in the paragraphs below:

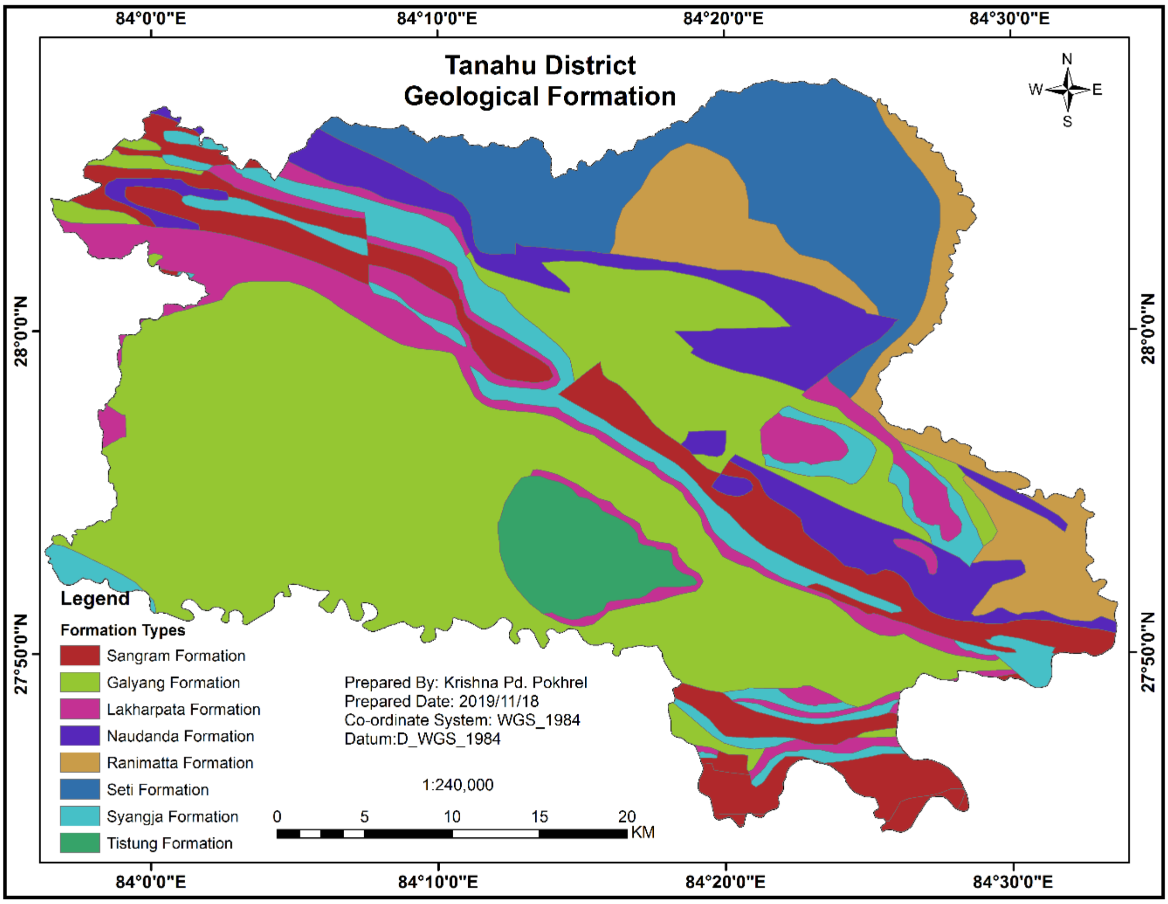
Geology

Geology plays vital role in the occurrence of landslide. As the study area consists of different geological formation which have the different mechanical and chemical properties some of which more vulnerable to slope instability. The different formation has different composition, structure and permeability which affect the formation materials strength (Pradhan et al., 2016).

The geological map of scale 1:200,000 was obtained from Department of Mines and Geology, Nepal. The data was in vector format. So it was converted to raster format to calculate the number of landslide pixels falling in each geological formation types.

In this analysis, geological data was categorized into 8 classes based on the geological formations. These are Galyang Formation, Lakharpata Formation, Markhu Formation, Naudanda Formation, Ranimatta Formation, Recent, Sangram Formation, Seti Formation, Syangja Formation and Tistung Formation. The characteristics of these formations and mechanical properties is presented in Annex 1.

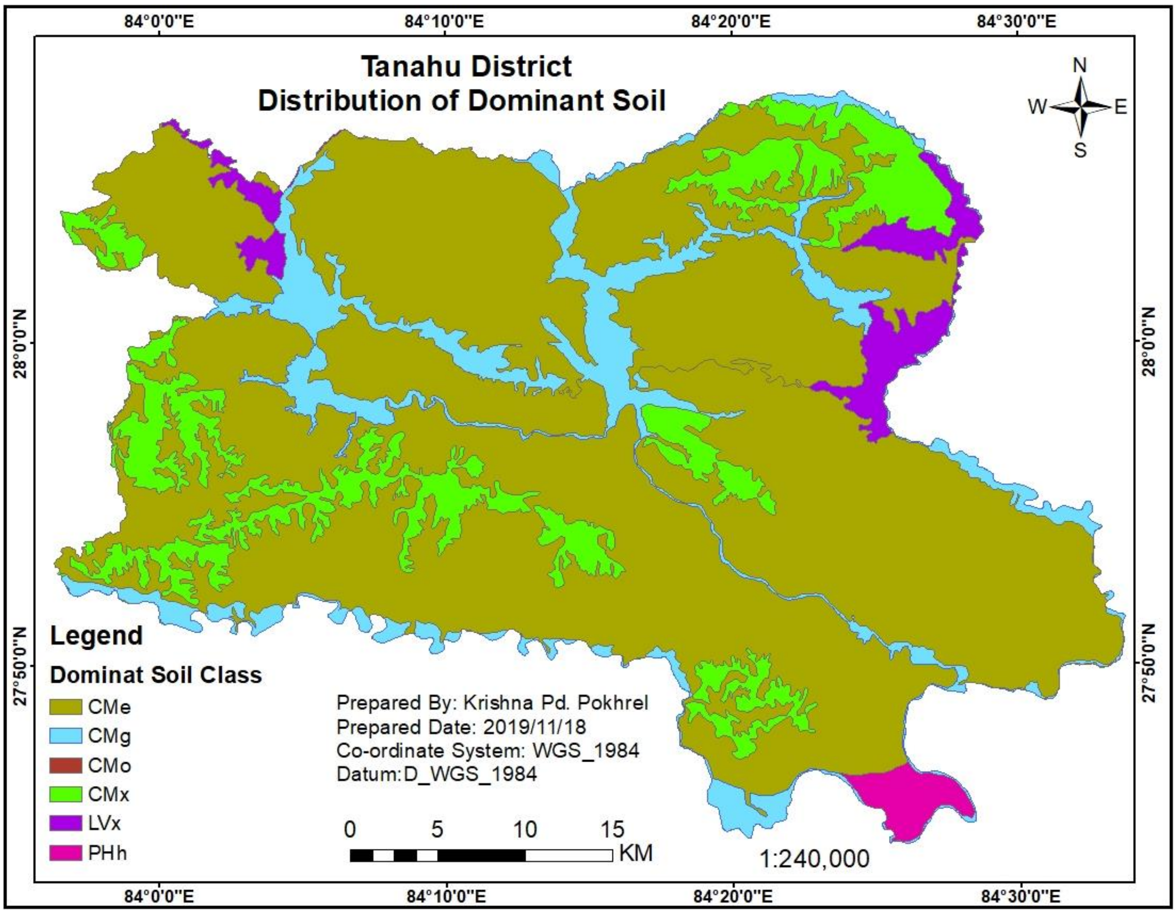
The following Map 3 shows the different geological formation that lie in study area.



Map 3: Geological Formations of Tanahu District

Soil Type

Soil plays major role in instability of earth surface. Like the geology, different classes of soil have different physical and chemical properties that influence the strength of formation soil (Hong H. et al., 2016), so that convergence of these parameters with curvature and slope steepness has a remarkable influence on landslide occurrences (Nguyen, et al., 2019). Since soil is heterogeneous and part of the area is mountainous, soil type was considered as one of the important factors that may contribute to landslide. Steep soils are likely to be eroded and lose their topsoil as they form. Dominant Soil and Parent material maps were clipped form the Soil and Terrain database (SOTER) for Nepal. It is a generalization of Nepal's Soil and Terrain database at a scale of 1:50 000 compiled in 2004 by FAO and the Survey Department of Nepal together. It was also converted to raster format to calculate the number of landslide pixels falling in each dominant soil types in order to investigate the pattern of landslide occurrence in each soil types. The soil map was classified in to 6 classes based on fertility and chemical composition (dominant soil) of soil namely Cme, CMg, CMo, CMx, Lvx and PHh and presented in Map 4



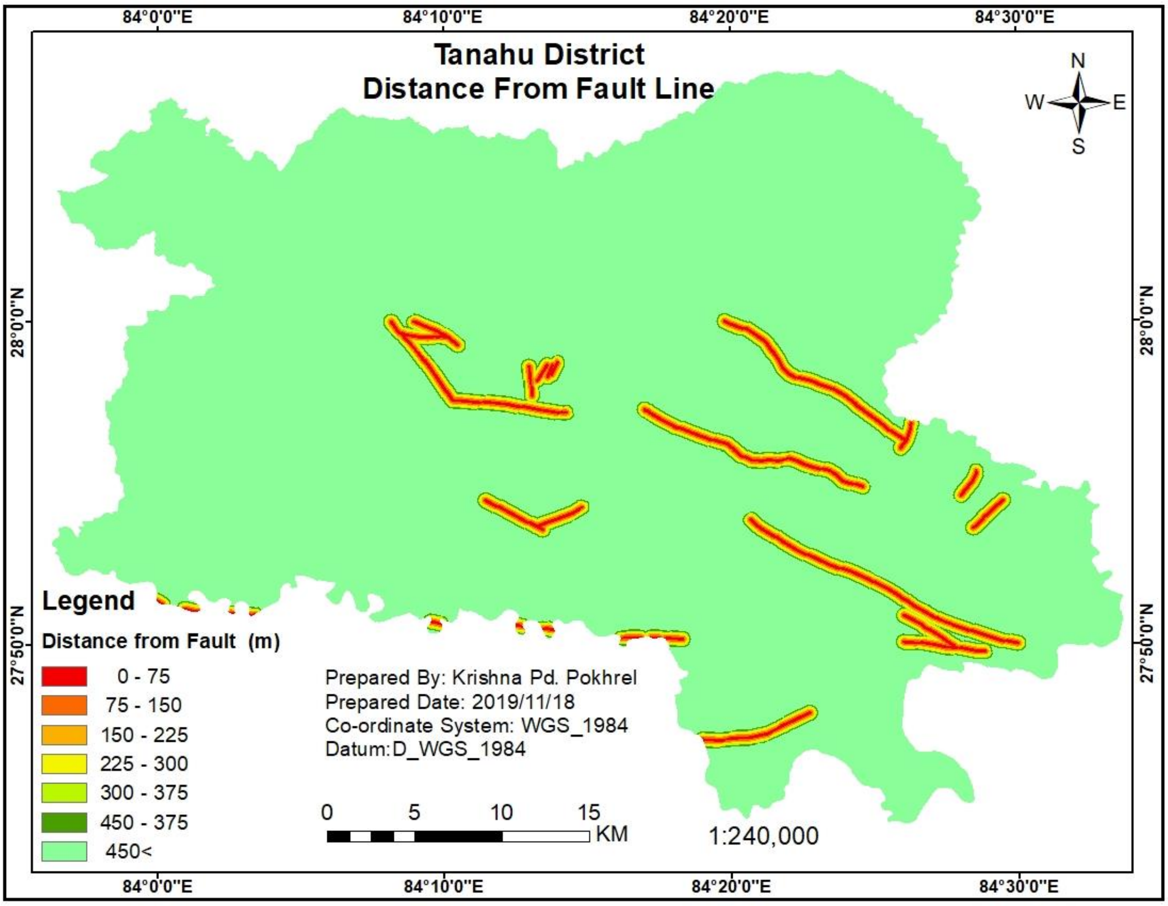
Map 4: Dominant Soil Types of Tanahu District

Distance from fault

The fault means the discontinuity between the soils and rocks (Ayalew & Yamagishi, 2005). The rocks around the faults are more disturbed so that strength is highly reduced and hence, the region around these tectonic features more susceptible for failure (Poudel et al., 2016). The areas which are fragile and weak in formations are more vulnerable to landslide occurrence. So it has been taken as one of the factor.

The fault map was also derived from the geological map of the area published by Department of Mines and Geology, Nepal. For the calculation purpose the Euclidean distance tool of Spatial Analyst extension of ArcGIS was used to create buffer zones of fault line. The buffer zone of each 75 meters were created. The buffer was zones consisting overall six classes 0-100, 100-200, 200-300, 300-400, 400-500 and >500 were used for calculation.

The overall buffer zones of fault line is presented in following Map 1



Map 5: Distance from Fault line in Tanahu District

2.3.1.2 Topographical parameters

Topography is a broad term which is used to describe the detailed study of the earth's surface. This includes changes in the surface such as mountains and valleys as well as the steepness or the degree of incline of a surface and direction that a slope faces. There are four topological parameters that are derived from SRTM DEM in this analysis. SRTM of 1 Arc Second (app. 30 meters) spatial resolution is available for free download from Earth Explorer platform of United States Geological Survey (USGS) as tiles of 1 by 1 degree spatial coverage. A rectangular tile that covers Tanahu district was downloaded and was clipped by boundary of Tanahu district to get DEM of study area. This data set has been used for assessing the slope, aspect and curvature variation over study area. The basic specification of DEM used is given in Table 4.

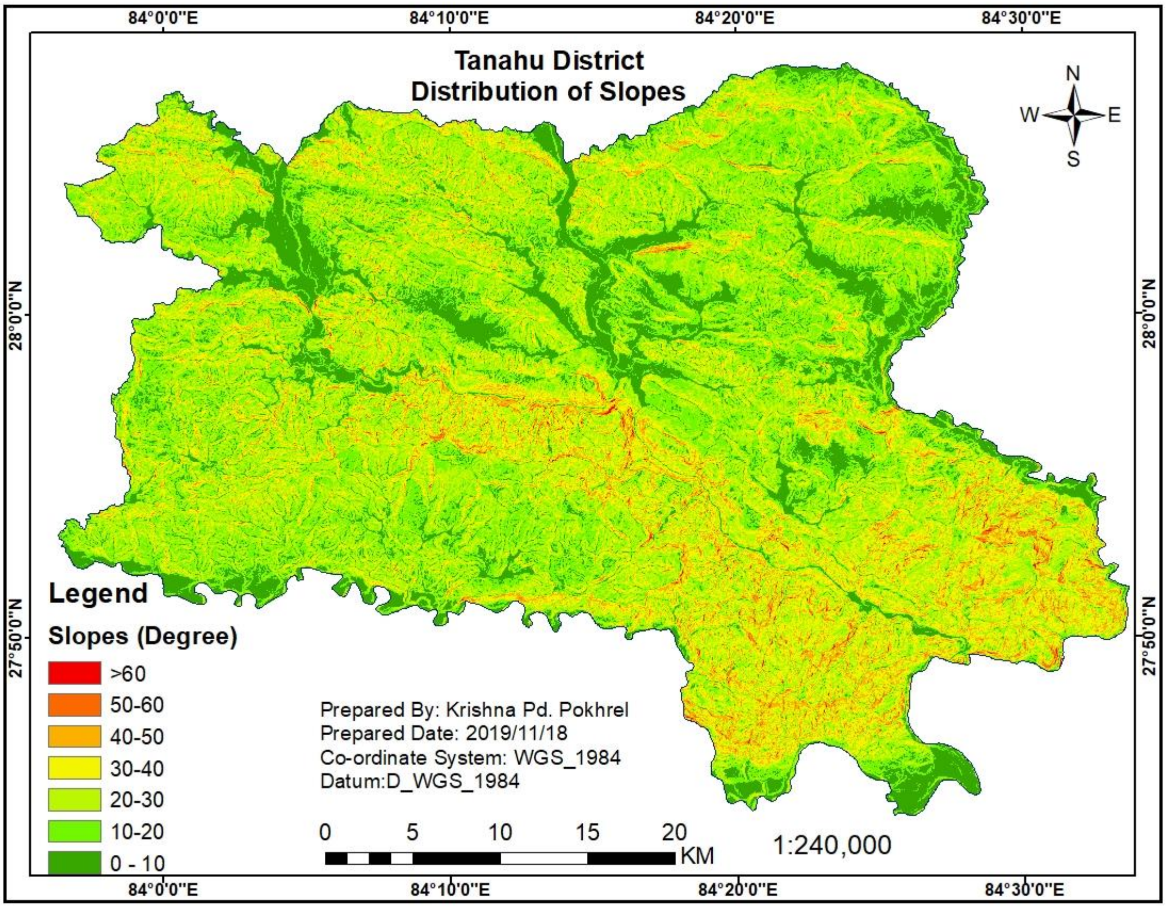
Table 4: General Specification of DEM used

DEM Details	
Projection	Geographic
Horizontal Datum	WGS84
Vertical Datum	EGM96 (Earth Gravitational Model 1996)
Vertical Units	Meters
Spatial Resolution	1 arc-second for global coverage (~30 meters)
Raster Size	1 degree tiles
C-band Wavelength	5.6 cm

Source: USGS, Earth Explorer

Slope

Slope is among the most significant factors in the occurrence of landslide. Slope affects the soil water content (surface and subsurface) and formation of soil, erosion potential. It has been widely shown that landslides tend to occur more frequently on steeper slopes (Poudel et al., 2016). The increase in slope angle results in unstable terrain. For the calculation of purpose the slope values was reclassified into seven groups 0-10, 10-20, 20-30, 30-40, 4-55, 55-65, >65 degrees. This range of classification has also been used by Acharya (2016) in the study of Landslide hazard zonation of Sindhupalchok district, Nepal. The overall slope distribution within study area is as shown in Map 6*.*



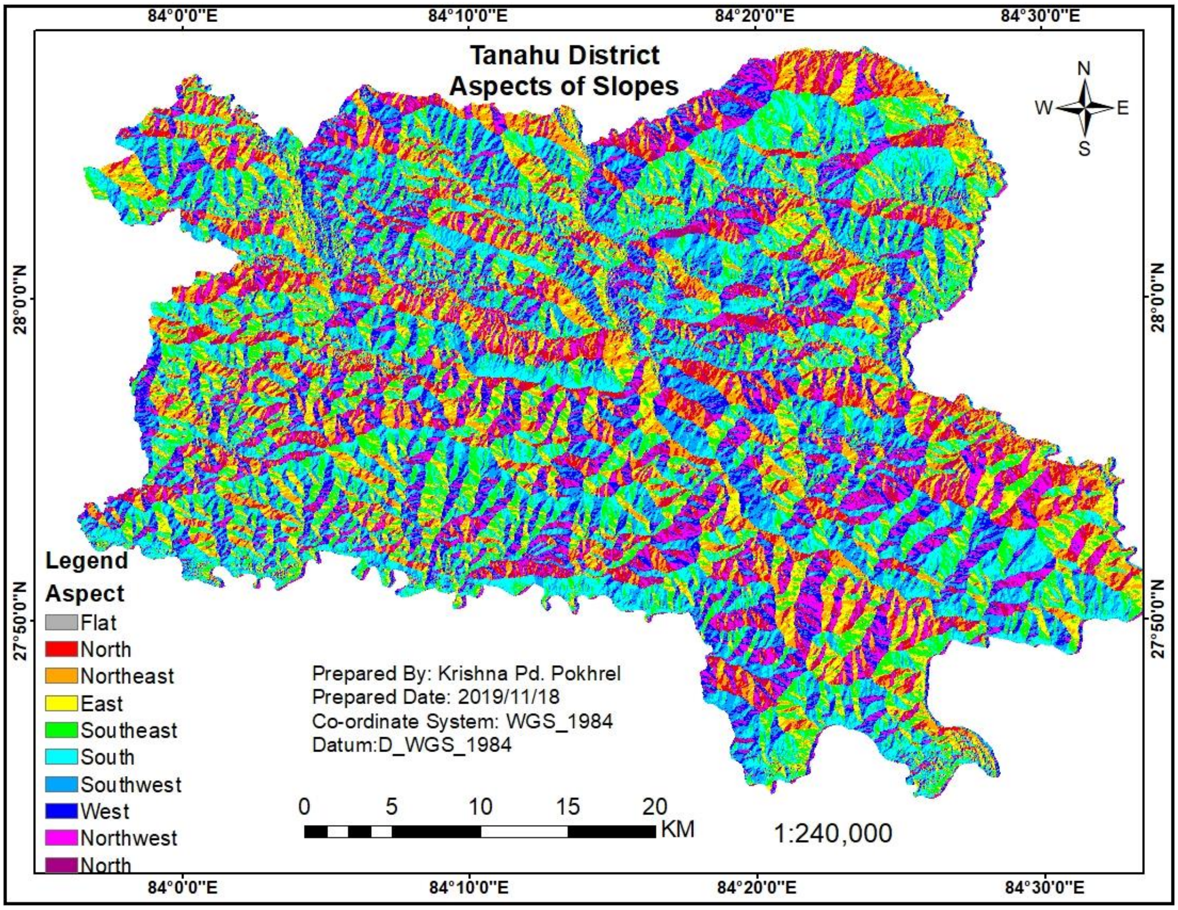
Map 6: Variation of Slope in Tanahu District

Aspect

Aspect is the direction of slope and is expressed in degrees. The slope aspect is also one of the most significant factors affecting the occurrences of landslide due to various wetness of the aspect (Pham et al., 2018). Aspect related parameters such as exposure to sunlight, drying winds, rainfall (degree of saturation), and discontinuities may control the occurrence of landslides (Dai et al., 2001; Cevik and Topal, 2003).

The aspect map was also produced from DEM. For the study purpose the aspect values were classified into nine (9) classes as Flat:-1, North: 0-22.5 and 337.5-360, North-east: 22.5-67.5, East: 67.5-112.5, South-east: 112.5-157.5, South: 157.5-202.5, South-west: 202.5-247.5, West: 247.5-292.5, North-west: 292.5-337.5 where the class values are in degrees and number of landslide occurrences in each category was identified by tabulate area tool of ArcGIS.

The overall distribution of Aspects of Slopes within study area is presented in Map 7*:*

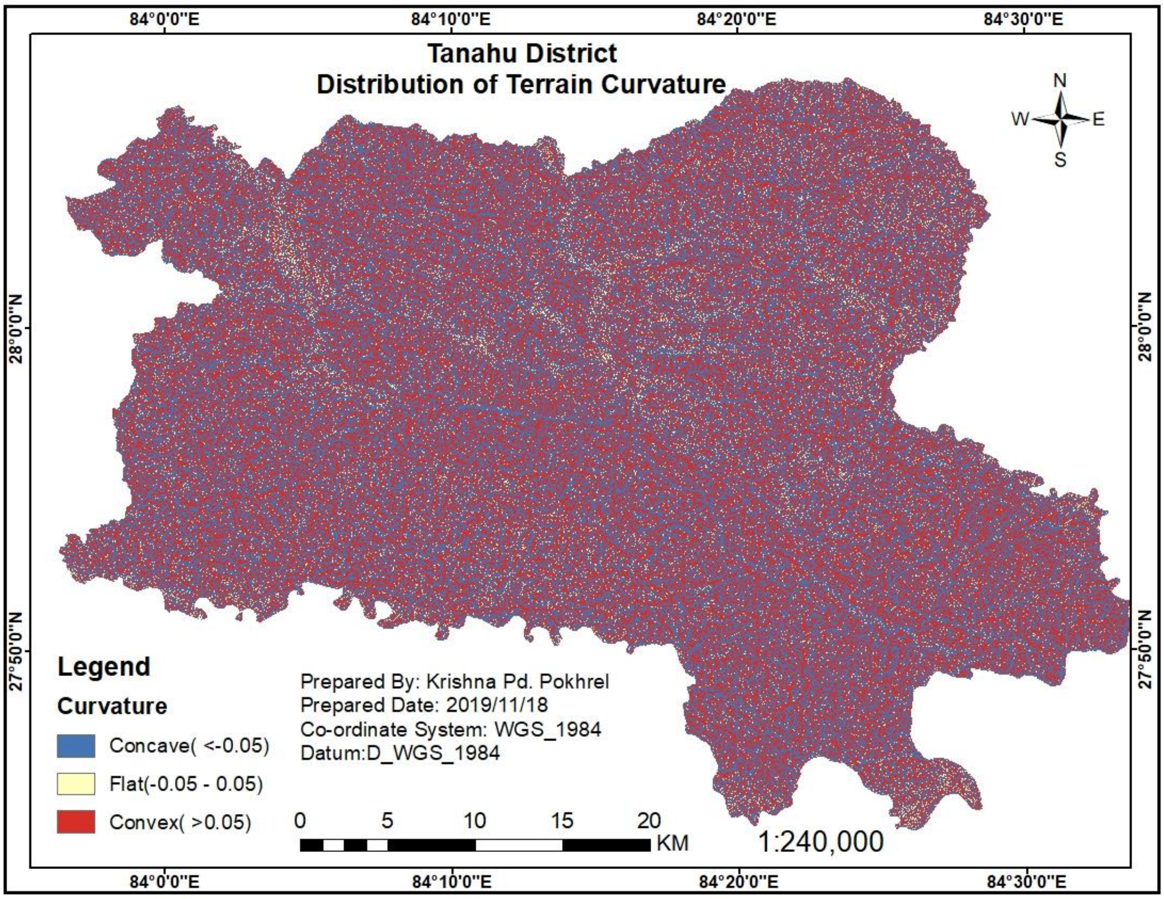


Map 7: Distribution of Aspects of Slope in Tanahu District

Curvature

Curvature is parallel to the direction of the maximum slope. A negative value specifies that the terrain is upwardly convex at that cell, positive profile value specifies that the terrain is upwardly concave at that cell and zero value specifies that the terrain is flat/linear. Curvature affects the acceleration or deceleration of flow across the surface (Buckley, 2010). The morphology of the topography was identified by curvature (Pourghasemi et al., 2013). It controls the surface runoff so that it has an impact on the landslide occurrences (Pham, et al., 2018) .The curvature was derived from DEM and divided into three classes of negative curvature (<-0.05), zero curvature- flat (-0.05-0.05) and positive curvature (>0.05) (Nohani et al., 2019). Then the landslide area falling under each curvature classes were assessed using *tabulate area* tool of ArcGIS.

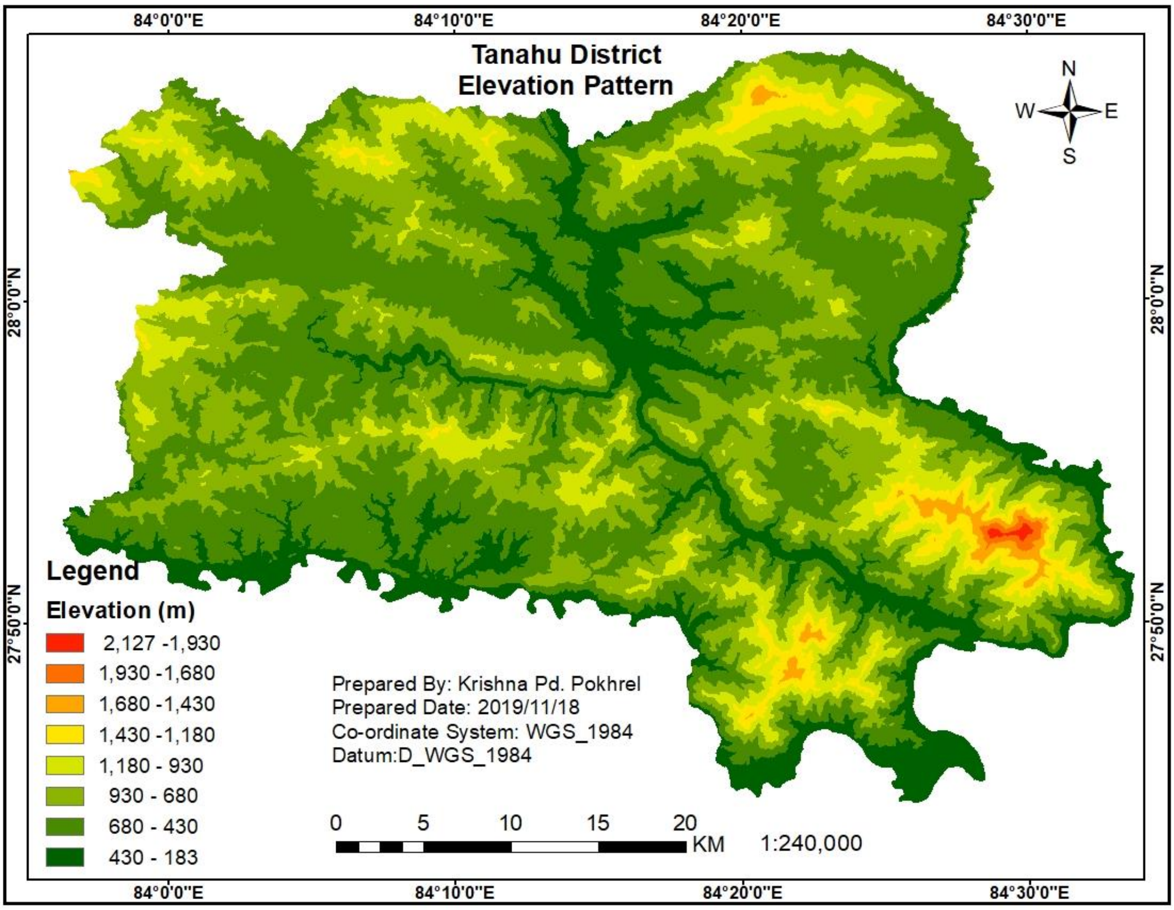
The distribution pattern of curvature within study area is shown in Map 8.



Map 8: Curvature Pattern of Terrain in Tanahu District

Elevation

Elevation is widely used factor for the assessment of landslide susceptibility. Elevation affect large number of biophysical parameter and anthropogenic activities (Poudel et al., 2016). Elevation is also related to different environmental parameters such as vegetation cover, rainfall, temperature etc. The strong statistical relationships between elevation and landslide occurrence have been cited in many studies Pachauri& Pant (1992); Dai & Lee, (2002); Lineback, et al. (2001). In general, altitude or elevation are usually associated with landslides by virtue of other factors such as slope gradient, lithology, weathering, precipitation, ground motion, soil thickness and land use. For example, higher mountainous areas often experience larger volumes of precipitation, both rain and snow falls (Khanh, 2009). Elevation map was produced from DEM with 30m*30m grid size. For the calculation purpose the elevation map was reclassified into 8 classes from lowest 181 to 2130 with 250 m interval. The variation of elevation within study area is presented in Map 9:



Map 9: Elevation Pattern of Tanahu District

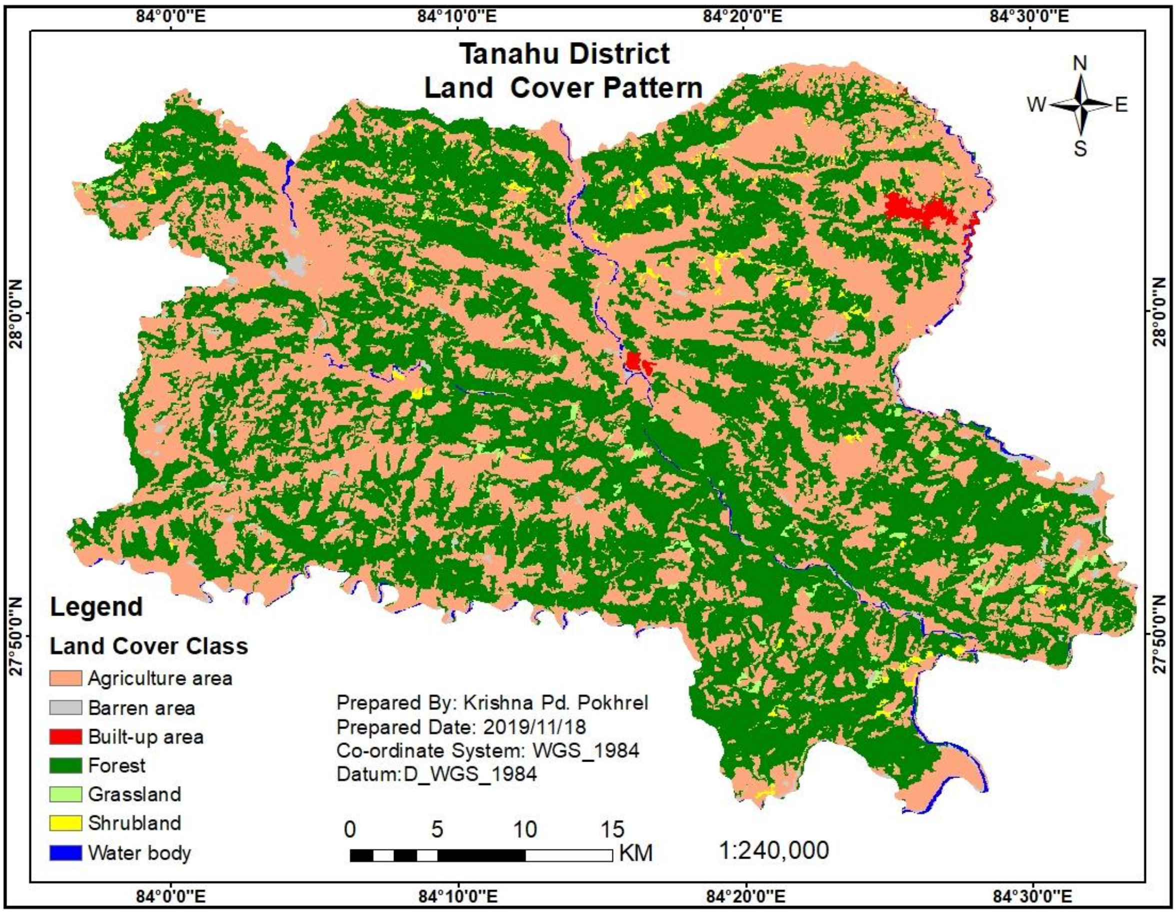
2.3.1.3 Environmental parameters

There are two environmental parameters that are taken into account which are Land use/Land cover (LULC) and soil texture of Tanahu district. The explanation of these parameters are given below.

Land use/Land cover

It is a significant factor that affects the landslides. The effect of vegetation on landslide susceptibility is complex and depends on mechanical stabilization due to the presence of roots, soil moisture depletion as a result of transpiration, surcharge from the weight of trees, and wind-breaking (Nilaweera and Nutalaya, 1999). However it is obvious that the land cover pattern and type hugely impact the rate and extent of landslide. For landslide susceptibility mapping, it is required to understand the current land use/ land cover and how it is being used, along with accurate means of monitoring over time (Caldwell, 2019).

A 30-meter resolution national land cover database of Nepal (Uddin et al., 2015) derived using the Landsat imagery was downloaded from RDS (Regional Database System) portal of ICIMOD (International Centre for Integrated Mountain Development) which freely available. This data has 7 land cover classes. The resolution of the map was itself 30*30 and was projected in WGC_84 which was converted to MUTM for uniformity and consistency in work. The land use land cover pattern within the study area is demonstrated in *Map 10*.



Map 10: Land Cover pattern of Tanahu District

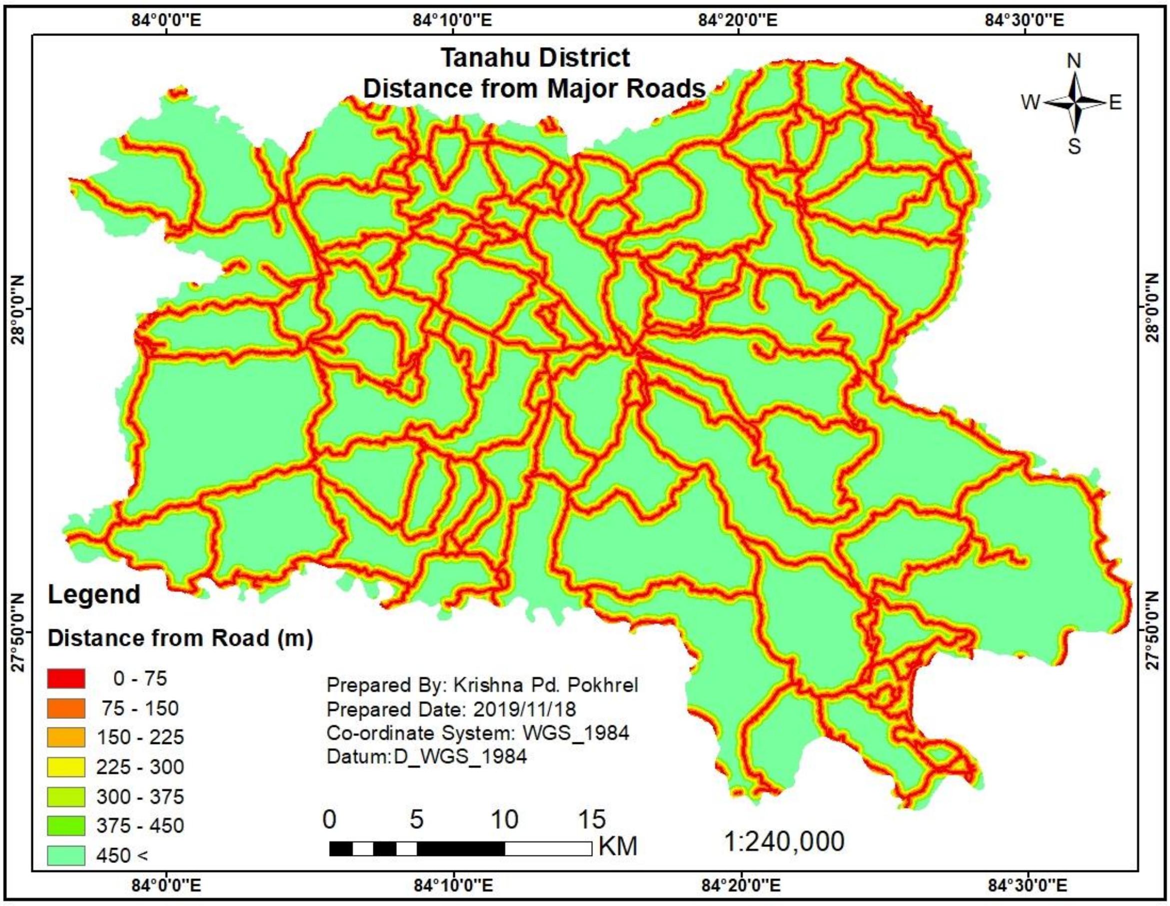
The above land use map was categorized into 7 different land use types namely Agriculture Area, Barren Area, Buildup Area, Forest, Grassland, Shrub land and Water Body. The areas of landslide falling under each land cove categories are assessed in order to establish the correlation between landslide occurrence and land cover types.

2.3.1.4 Anthropogenic parameters

Anthropogenic parameters are important in analyzing the landslide susceptibility. In this study, two anthropogenic parameters are taken as distance from road and distance from river. Explanation of these parameters are given below:

Distance from Road

Tuan & Dan (2012) explains that landslides were mostly distributed near the road system. By cutting more than 10 degrees of slope in hills to build roads, discontinuity is created in soil and rock. During the construction roads in hilly terrain the natural slope is disturbed which therefore, the area nearer to road can be prone to landslides (Ayalew & Yamagishi, 2005). The road data was downloaded from web page of open street map i.e. www.openstreetmap.org/. The data was then rectified in order to remove the redundant road data. For the calculation purpose, the buffer zones were created by assigning the values of distance from the road using Euclidean distance function under spatial analyst tool in ArcGIS. Buffer classes of each 75 m were obtained. The classes include six categories 0-75, 75-150, 150-225, 225-300, 300-375, 375-450 and >450 meters. This classification was used by Khanh et al. (2009) and (Acharya, 2016) in their research. The weight for each class were calculated based on the training pixels falling inside each classes of road buffer. The major road buffer zones within study area displayed in Map 11 below:

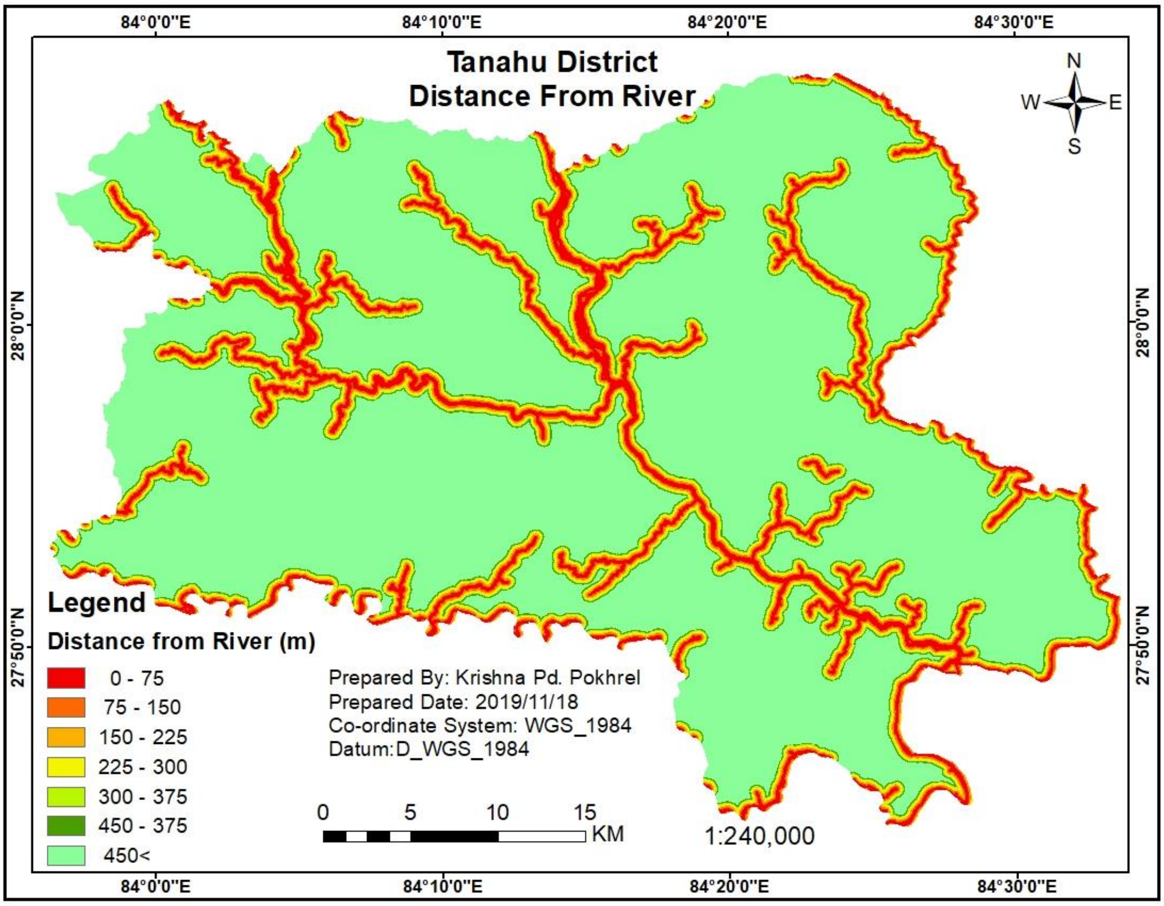


Map 11: Road Buffer Zones of Tanahu Distrct

Distance from River

River is considered as main source of soil moisture (Nohani, et al., 2019). In the research, (Binh Thai et al., 2017) found that 65.12% of landslides occurred at the vicinity of first class of river at a distance of 0-40m. The closeness of the slope to drainage structures is another important factor in terms of stability. Streams may adversely affect stability by eroding the slopes or by saturating the lower part of material until resulting in water level increases (Gokceoglu and Aksoy, 1996; Dai et al., 2001; Saha et al., 2002). So, proximity to river is also considered as a very important parameter in LSM. The data was extracted from the river layer of National topographic database prepared by Survey department of Nepal.

The buffer zones of 75 meters were created using the Euclidean distance function under spatial analyst tool. The weight for each class were calculated based on the training pixels falling inside each classes. The same classification system was adopted by Khanh (2009). The six classes are 0-75, 75-150, 150-225, 225-300, 300-375, 375-450 and >450 meters. The buffer zones of main stream and river networks is demonstrated in Map 12.



Map 12: River Buffer Zones of Tanahu Distrct

Hence the each factor were classified in their stated classes. Different classes of each causative factors has different level of impact on inducing the slope instability of a specific area. Landslide is caused with the effect of solely one factor or combined effect of different factors. This relation is established by using the previously occurred landslide inventory. For the assessment number of pixels in each class of a factor having landslide area and total number landslide pixels in study area were calculated. The total number of pixels in the study area were also obtained using summary statistics in ArcGIS. The details of the calculation procedure and calculation of weight values using three different method has been discussed below.

2.4 Landslide Susceptibility Assessment

The important part of the landslide susceptibility assessment is the combination different causative factors based on their weight calculated using different statistical methods. The calculation procedures and involved algorithm differ from one method to another. So the final result may vary accordingly. Susceptibility map is one of the product of overall assessment procedure. The unique sequence of various spatial and statistical datasets develop a susceptibility map which characterize the whole study area into several susceptible classes such as: very high, high, moderate, low and very low (Soeters & van Westen, 1996; Brabb et al., 1999).

Various literatures have used different methods for the study of landslide susceptibility zonation. In this study, the statistical model was chosen because it has been largely used to assess LS and widely used by combining and integrating statistical models with the geographical data and open source of GIS applications. Many studies have tried to assess landslide susceptibility by increasing GIS applications using different models also.

Among those reference of some studies Khan et al. (2019); Fayez et al.(2018); Yilmaz (2009) using FR model, Roodposhti et al.(2016); Pourghasemi et al. (2012); Sharma et al (2012) for SE model and Khanh (2009); Regmi et al. (2014) for SII model, Acharya (2016) has been taken for overall procedure. Also these three models were selected in such a way that the geography, frequency of occurrence of landslide, elevation range and topological structure were similar to the study area.

Applied methods and their calculation procedure for the purpose of landslide susceptibility assessment are described in the sections below:

2.4.1 Frequency Ratio

FR was chosen for this study as a basic analysis for a preliminary probabilistic assessment due to the mathematical simplicity and comparatively rapid assessment time. Future landslide hazard can be assumed to occur from the similar conditions as past landslides.

From this assumption, the relationship can be developed between area of occurrence of landslide and landslides not occurring in an area with factors relating to landslide. It can be expressed as a Frequency Ratio that represents the quantitative relationship between landslide occurrences and different causative parameters (Pradhan et al., 2012). The formula for the calculation by frequency ratio is as follows:

$$FR = \frac{N_l^p \;/\; N}{N_i^{lp} \;/\; N^l}$$

Where, N_l^p = number of pixels in each landslide conditioning factor class

N = number of all pixels in total the study area

N_i^{lp} = number of landslide pixels in each landslide conditioning factor class

N^l = number of all landslide pixels in total the study area

The relative frequency was calculated as:

$$RF = \frac{FR_i}{\sum_{n=1}^{i} FR}$$

Where, FR_i = Frequency Ratio of each class of a factor

$\sum_{n=1}^{i} FR$ = summation of Frequency Ratio of each class

The prediction rate was computed as:

$$PR = \frac{Max_{RF} - Min_{RF}}{(Max - Min)_{Min_{RF}}}$$

Where, Max_{RF} = Maximum Relative Frequency

Min_{RF} = Minimum Relative Frequency

$(Max - Min)_{Min_{RF}}$ = Minimum Relative Frequency of subtraction of Min_{RF} from Max_{RF}

Meena et al. (2019) has prepared landslide susceptibility maps using the statistics-based approach. In their study, FR model was implemented using GIS tools. The weight was defined as the area in for landslide occurrence to the total study area. According to Meena et al. (2019), the FR value which is greater than 1 shows high correlation and lower than 1 shows lower correlation.Yilmaz (2009) has used FR model for LSM along with logistic regression and artificial neural networks. Further, the results explain that the frequency ratio is one of the best tool in landslide susceptibility assessment if there are sufficient number of input data. The input process, computations and output procedures are readily understood in the FR model.

2.4.2 Shannon Entropy

In information theory, the entropy is the measure of system imbalance, instability, disorder and uncertainty and thus, can predict or forecast the development trend of certain specified system (Lotfi & Fallahnejad, 2010). In present days, the Shannon Entropy has been used widely to determine the weighted in index in natural hazards (example landslide hazard) and in integrated estimation of natural-environment phenomena such as droughts, debris flows, sandstorms and so on (Mon et al., 1994).

In case of landslides, the Shannon Entropy assesses the diversity or dissimilarity in the natural environment. Further, the extent of various factors that influence landslide is also referred as entropy of landslides. Greater the influence of landslide factors, greater is the entropy index (Sujatha, 2012). The steps for the calculation of Shannon Entropy is shown below:

1. Normalizing the frequency of landslide occurrence:

   Normalization is the process to make an adjustment in the certain weights. The formula for calculating the normalized weight is shown below:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$$

Where, P_{ij} = normalized weight of the landslide occurrence zone

x_{ij} = frequency rate of landslide occurrence of class of certain factor

2. Computation of entropy:

The entropy of the diverse sets of value is calculated by following formula:

$$E_j = -k \sum_{i=1}^{m} P_{ij} \ln(P_{ij})$$

$$k = \frac{1}{\ln{(m)}}$$

Where, E_j = entropy of a class of certain factor

k = a coefficient

m = number of classes of a factor

P_{ij} = normalized weight of the landslide occurrence zone

3. Defining weight:

Finally, the weight is computed in Shannon Entropy analysis is shown below:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)}$$

Where, E_j = entropy of a class of certain factor

w_j = weight of the factor using Shannon Entropy

In order to prepare the accurate landslide susceptibility mappng, Roodposhti et al. (2016) has used Shannon Entropy method because of its flexibility of fuctions of fuzzy membership and the objective evaluation of criteria weights. The greater influecne of landslide factors is indicated by greater entropy index. The SE method was used by Pourghasemi et al. (2012) to locate the landslide probable zone in Kalaleh township of Golestan province, Iran. Altogether 18 landslide conditioning factors were applied to calculate LSI which was compared with field-verified landslide locations. The verification was done by AUC and the results showed accuracy of 82.15%.

2.4.3 Statistical Information Index

Statistical information index method also commonly known as information value method is one of the most common methodology in landslide susceptibility modelling. It was first proposed by Van Westen (1997). Later on, with the successful validation of model it was used by other researchers such as Cevik, Topal and Oztekin for their studies (Oztekin & Topal, 2005). It is one of the bivariate statistical models in which weight for each input factor is determined based on the comparison between a landslide inventory and all the parameter factor map. The factor basically used in this index method are rainfall, slope, elevation, geology. According to Van Westen (1997), the statistical technique is one of the most preferable models in the medium scale of 1:25000 to 1:500000.

In the statistical index method, a weight value for a parameter class, such as a geological unit or a certain slope class is defined as the natural logarithm of the landslide density in the class divided by the landslide density in the entire map (Van Westen, 1997). Finally integration of the various factors and classes into a single landslide susceptibility index is achieved by procedure based on weighted linear sum. The formula for landslide modelling using statistical information model.

$$\mathrm{Wij} = \ln\left(\frac{\mathrm{Densclass}}{\mathrm{Densmap}}\right) = \ln\left(\frac{\mathrm{D_{IJ}}}{\mathrm{D}}\right) = \ln\left(\frac{\frac{\mathrm{Npix\ (Si)}}{\mathrm{Npix\ (Ni)}}}{\frac{\sum_{i=1}^{n}\mathrm{Npix\ (Si)}}{\sum_{i=1}^{n}\mathrm{Npix\ (Ni)}}}\right)$$

Where, Wij – The weight given to a certain class i of parameter j.

Dij – Densclass – the landslide density within the class i of parameter j.

D – Densmap – The landslide density within the entire map,

Npix (Si) – Number of pixels that contain landslide in a certain parameter class.

Npix (Ni) – Total number of pixel in a certain parameter class.

∑Npix (Si) – Total number of landslide pixels.

$\sum Npix (Ni)$ – Total number of studied parameter pixels.

The statistical information index method is based on the statistical correlation of the landslide inventory map with attributes of different maps. The Wij value in the equation is only calculated for classes that have landslide occurrences. In the case of no landslide occurrences in a parameter class the value Wij would be minus infinite. Therefore, an arbitrary value according to the parameter classes least weights calculated is given to that types of pixel (Saha, 2005).

2.5 Validation

2.5.1 Validation using AUC curve

After the development of the models, validation was carried out in order to check and analyze the success and prediction rates. The validation is required to ensure that the models are correct and can be useful for the future estimation of landslide. The accuracy assessment was performed by comparing the existing landslide dataset with landslide susceptibility results in terms of rate curves and areas under the rate curve (Chung and Fabbri, 1999).

The success rate is a calculation of the success of a model that shows how well the model matches the prior events (Chung and Fabbri 2003; Wahono 2010). To generate the success rate curve, the calculated index values of all cells in the study area were arranged in order and were divided into 100 equal classes ranging from highly susceptible classes to non-susceptible classes. The success rate curve was created by plotting the susceptible classes starting from the highest values to the lowest values on the X-axis and the cumulative percentage of landslides occurrence on the Y-axis.

Sensitivity = TP/ (TP + FN)

Specificity = TN / (FP + TN), (Nohani et al., 2019)

Where true positive (TP) is the number of observed landslides predicted accurately and true negative (TN) is the total non-occurring landslides that have been predicted accurately. On the other hand, false positive (FP) is considered as the number of occurring landslides inaccurately categorized in the non-landslide classes and false negative (FN) is considered as the number of non-occurring landslides inaccurately categorized in the landslide classes

Also, prediction rate is the validation of calculations on predictive assessments that show how well the model can predict unknown upcoming events or posterior events (Mezughi et al. 2011; Pimiento 2010). The prediction rate curve was prepared using those landslides polygon which were separated as test data set.

$$AUC = \sum_{i=0}^{n} (x_i - x_{i-1})\, y_i - \left[(x_i - x_{i-1})\,(y_i - y_{i-1})\,/2\right],$$

Where xi is the percentage of area and yi is the area of the landslide

2.5.2 Satellite Imagery Overlay

Google Earth overlay is one of the methods for assessing the accuracy by overlaying the models in the Google Earth image. Google Earth can be a reliable tool for checking and visualizing the results over series of historic images. Thus, Google Earth was used for validating purpose by taking sample of certain portions of the model and overlaying them over Google Earth for visual interpretation and prediction accuracy.

2.5.3 Evaluating the Effectiveness of Models

The AUC can identify the model’s accuracy and ability in predicting future landslides. The AUC was used to assess the accuracy of the models. The results of success rate was obtained on the basis of training data and the results of prediction rate was obtained on the basis of validation data.

The higher the percentage of the area below the curve, i.e. the steeper the curve's slope, the better is the prediction. For e.g. a value of 0.9 for the AUC would indicate a very good model, in which 90% of the landslides falls in the 10% highest susceptibility area (Lee and Talib, 2005; Remondo et al., 2003). The evaluation of effectiveness of models were executed after validation process. The accuracy of each models were obtained from the AUC along with success rate and prediction rate.

The assessment of the models were also performed to assess the suitable method for the determination of the landslide susceptible zone of the study area. The predicted areas under different susceptibility classes were also presented. At the same time the density of the actually occurred landslide over the predicted susceptibility classes were also calculated in order to determine the distribution pattern of landslide polygon over the generated susceptibility model. This helped to infer whether predicted model confirms the actual ground reality.

2.6 Software Used

The software that are used in this research work are as follows:

- ArcGIS 10.4
- Google Earth
- Microsoft Excel

2.7 Concluding Remarks

The data of ten (10) different conditioning factors were collected and processed using GIS. The conditioning factors include slope gradient, slope aspect, elevation, curvature lithology, soil type, land cover (land use), distance from road, and distance from river. Susceptibility assessment is performed using FR, SII and SE methods. The results have been validated by comparing each factor with the landslide validation set, and have been tested by calculating the prediction rate curve. The curve provides a basis to distinguish the prediction capacity of different models into five susceptibility zones.1 very low; low; moderate; high and very high.

CHAPTER 3: RESULTS AND DISCUSSIONS

This chapter explains the results obtained from the assessment of landslide susceptibility levels by different methods which are presented in this chapter.

3.1 Results

All the methods adopted in this study are based on the number of pixels in each class of different factors and number of landslide pixels falling within each class of those factors under study. The data help to establish the relation between landslide occurrence and influence of each class on the event by deriving the weight value. Based on the factor layers and the training sample of landslide inventory the total number of pixels in each class of different factors as well total number of landslide pixels falling within each classes are computed using tabulate area tool in ArcGIS. A summary of the calculation of weight value using three different method is presented in the following *Table 5*.

Table 5: Weight Calculation for Each Factor and their classes using different methods

SN	Factors	Weight Calculation For Each Factor and their classes							
		Class	Class pixel	Landslide pixel	FR Method		SE Method	SII Method	
					FR	PR	SE	ConP/Prop	Inf. value
1	Slope (Degree)	0-10	266446	9	0.021	2.517	0.175	0.021	-3.857
		10-20	465773	52	0.07			0.07	-2.662
		20-30	558377	679	0.761			0.76	-0.274
		30-40	401557	1712	2.666			2.666	0.981
		40-50	49189	271	3.446			3.446	1.237
		50-60	6763	64	5.919			5.918	1.778
		>60	588	9	9.573			9.572	2.259
2	Plan Curvature	Concave	840390	1441	1.072	1.028	0.168	1.072	0.07
		Flat	82744	81	0.612			0.612	-0.491
		Convex	825648	1274	0.965			0.965	-0.036
3	Aspect	Flat	513	0	0	1.497	0.032	0	-4
		North	220344	148	0.42			0.42	-0.867
		North-East	204634	354	1.082			1.082	0.079
		East	191059	413	1.352			1.352	0.301
		South-East	244035	738	1.891			1.891	0.637
		South	278119	793	1.783			1.783	0.578
		South-West	243764	290	0.744			0.744	-0.296
		West	185400	52	0.175			0.175	-1.741
		North-West	180825	8	0.028			0.028	-3.587

4	Elevation (m)	181-430	227336	106	0.292	3.551	0.167	0.292	-1.232
		430-680	743945	614	0.516			0.516	-0.661
		680-930	523116	797	0.953			0.953	-0.048
		930-1180	186478	571	1.915			1.915	0.65
		1180-1430	49996	229	2.865			2.865	1.052
		1430-1680	13372	352	16.464			16.463	2.801
		1680-1930	3255	82	15.756			15.755	2.757
		1931-2130	1195	45	23.552			23.55	3.159
5	Land Use	Agricultural	732268	659	0.613	2.964	0.129	0.563	-0.575
		Barren Area	15349	4	0.177			0.163	-1.814
		Builup Area	9127	0	0			0	-4
		Forest	935661	1814	1.32			1.212	0.193
		Grassland	25295	87	2.341			2.151	0.766
		Shrubland	19626	3	0.104			0.096	-2.348
		Water Body	11442	2	0.119			0.109	-2.214
6	Distance from Fault	0-75	36901	252	4.27	1.168	0.023	4.271	1.452
		75-150	33961	184	3.388			3.388	1.22
		150-225	34327	227	4.135			4.136	1.42
		225-300	34095	203	3.723			3.724	1.315
		300-375	34741	144	2.592			2.592	0.953
		375-450	35834	73	1.274			1.274	0.242
		>450	1539187	1714	0.696			0.696	-0.362
7	Soil	Cme	1302375	2063	0.991	2.143	0.163	0.991	-0.009
		CMg	172751	331	1.198			1.198	0.181
		CMo	4	0	0			0	-4
		CMx	202786	403	1.243			1.243	0.217
		Lvx	52358	0	0			0	-4
		PHh	18772	0	0			0	-4
	Geology (Formation)	Galyang	680410	360	0.331		0.103	0.331	-1.106
		Lakharpata	140836	0	0			0	-4
		Markhu	10501	19	1.131			1.132	0.124
		Naudanda	168219	177	0.658			0.658	-0.419
		Ranimata	309037	0	0			0	-4
		Sangram	165597	0	0			0	-4
		Seti	39582	576	9.1			9.101	2.208
		Syangja	120038	71	0.37			0.37	-0.995
		Tistung	59509	0	0			0	-4
9	Distance from Roads	0-75	352559	849	1.506	1.138	0.02	1.506	0.409
		75-150	260939	476	1.141			1.141	0.132
		150-225	222147	356	1.002			1.002	0.002
		225-300	187601	300	1			1	0
		300-375	156247	75	0.3			0.3	-1.203
		375-450	128294	78	0.38			0.38	-0.967
		>450	441259	663	0.94			0.94	-0.062
10	Distance from Rivers	0-75	193993	127	0.409	1	0.015	0.409	-0.893
		75-150	127324	101	0.496			0.496	-0.701
		150-225	118015	125	0.662			0.662	-0.412
		225-300	110844	181	1.021			1.021	0.021
		300-375	104427	239	1.431			1.431	0.359
		375-450	98511	132	0.838			0.838	-0.177
		>450	995932	1892	1.188			1.188	0.172

Where,

FR = Frequency Ratio; PR = Prediction Rate, SE = Shannon Entropy;

ConP = Conditional Probability; ProP = Prior Probability;

3.1.1 Landslide Susceptibility Assessment Using Frequency Ratio

The weight of each landslide conditioning factors were assigned using Frequency Ratio for the preparation of LSM. The higher value of FR represents the stronger correlation of the parameters with landslide occurrence. The values of FR greater than 1 indicates a strong correlation whereas the values of FR lower than 1 indicates a weak correlation (Pradhan B.). Below ***Error! Reference source not found.*** shows the results of FR method showing the weights obtained for each classes of various factors.

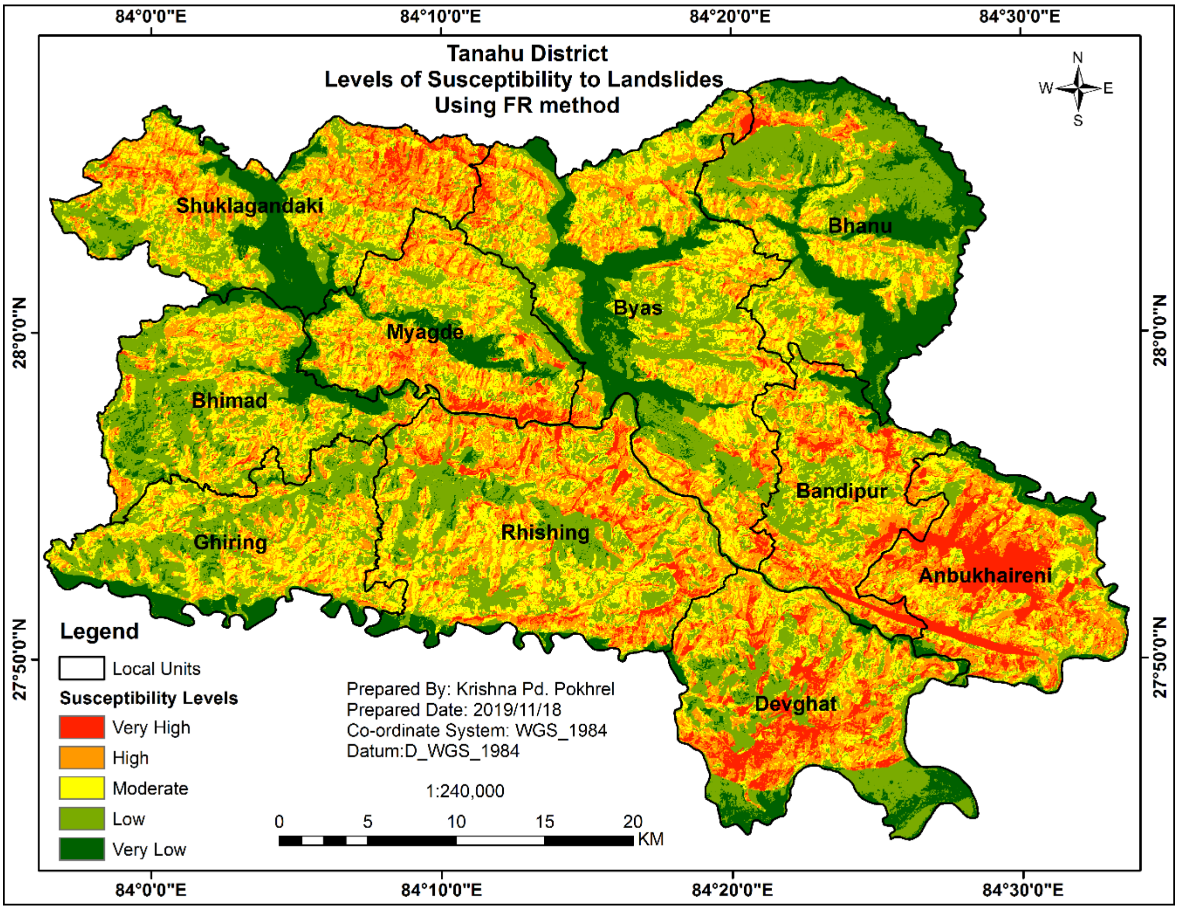
The result signifies that the most frequent landslide occurrences are observed in steep slopes among which the steepest slope has frequency ratio of 9.573. Regarding the landslide conditioning parameter of curvature, concave curvature has the highest impact with value 1.072 and convex and flat curvatures has smaller impact on the landslides weighing 0.965 and 0.612 respectively. The impact of aspect is higher in the North-East, South and South-East weighing 1.082, 1.783 and 1.891. Furthermore, another important factor for landslide occurrence is elevation. The lowest elevation that ranges from 181-431 has lowest impact with a weight of 0.262 whereas the highest elevation that ranges from 1931-2130 has highest impact with a weight of 23.552. It can be interpreted as low elevation usually has flat regions and high elevation usually has sloppy land.

The Table 6 illustrates that the less distance from the fault (i.e. 0-75) has high impact weighing 4.270 and the greater distance from the fault (i.e. >450) has less impact weighing 0.696. Similarly, the land covered with grassland is observed to have strong impact with a weight of 2.341. The soil type of CMx which is considered as non-fertile has high impact for landslide occurrence with a weight value of 1.243. Another affecting factor for landslide is distance from road. The effects of landslide seems to be higher for the first class (from 0 m to 75 m) which weighs 1.506 and lower as the distance from road increases. Similarly, the area in between 225 m – 300 m distance from the river is highly susceptible to landslide as shown by frequency ratio.

Using the above *Table 6*, the values for each factors was developed which was finally used to prepare the LSI map using raster calculator. When the LSI is classified into specific classes defining susceptibility level, the resulting map is the Landslide susceptibility Map.

LSM_{Fr} = *Total Sum of (weight* factor map)*

.The distribution of landslide susceptibility using FR method is shown hereunder in Map 13:



Map 13: Levels of Landslide Susceptibility in Tanahu Using FR Method

The above Map 13 illustrates the landslide susceptible zone which is shown by five class i.e. very low, low, moderate, high and very high. The area covered by each classes of landslide susceptible map using FR method is tabulated below in Table 6:

Table 6: Illustration of Area Covered by each Landslide Susceptibility classes using FR method

Class	Pixel Count	Area (in sq. km)	% of Covered
Very Low	225096	202.6	13
Low	520285	468.3	30
Moderate	434272	390.8	25
High	415152	373.6	24
Very High	154241	135.8	8
Total	**1749046**	**1571.1**	**100**

The Table 6 demonstrate that among total area of 1571.1 sq. km, the landslide probable area under classification very high and high are 135.8 sq. km and 373.6 sq. km respectively. The Table 6 also emphasizes the difference between values. The comparison can be interpreted by change in area in different classes of landslide susceptible zone.

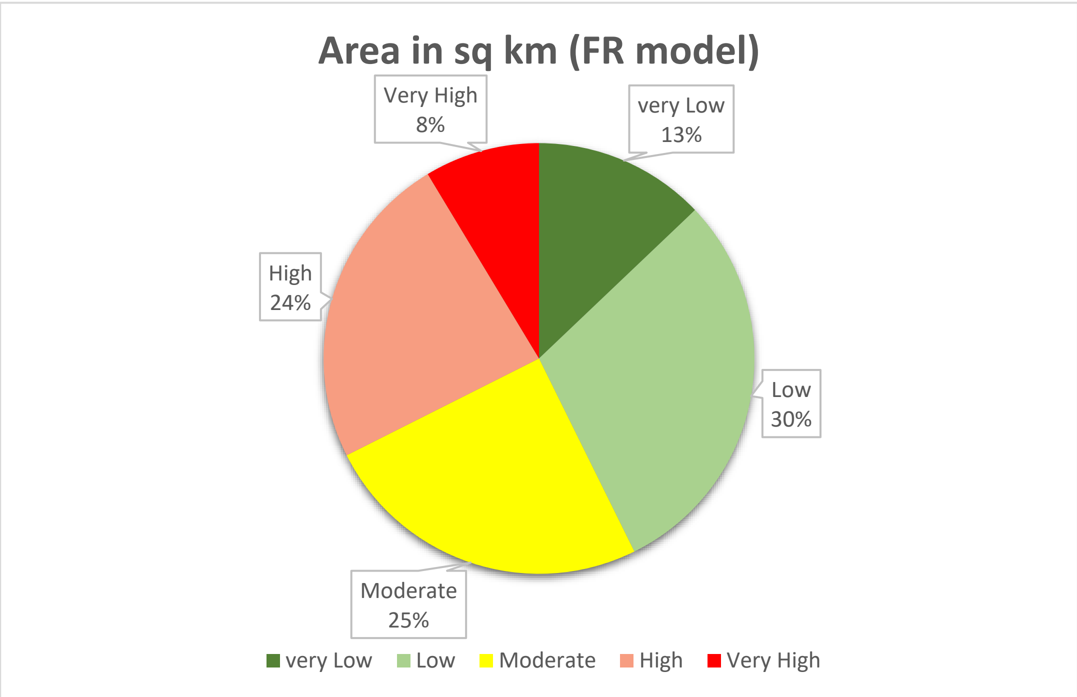


Figure 8: illustration area covered by each class using FR method (in percentage)

The pie chart in **Error! Reference source not found.** describes the area of different classes in percentage in which the landslide susceptible zone for very high and high classes are 8%

and 24% respectively. Most of the area lies in low susceptible zone which has highest percentage of 30%.

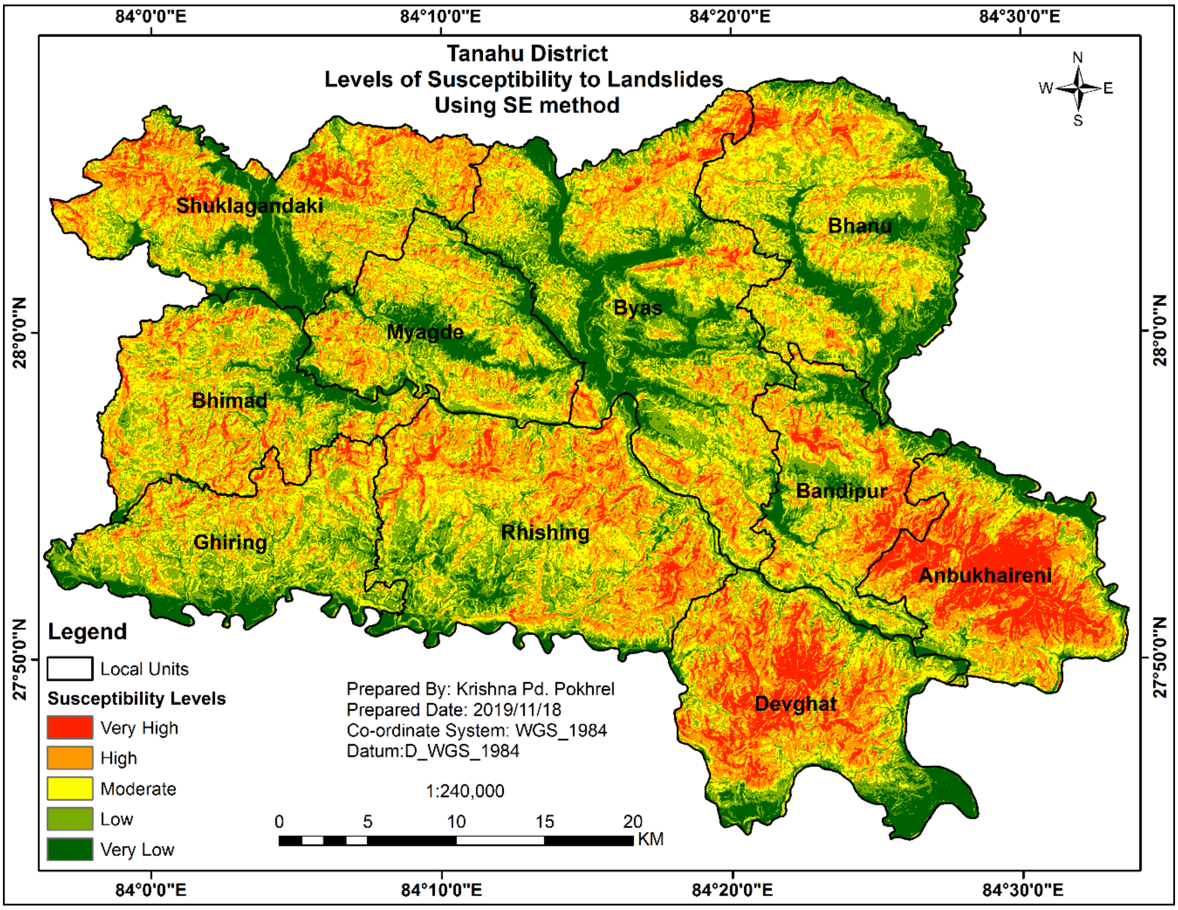
3.1.2 Landslide Susceptibility Assessment Using Shannon Entropy

Another result was obtained using Shannon Entropy method which is usually preferred for LSM because of its flexibility of fuzzy memberships and ambitious evaluation of factors weights. In MADM, the greater the value of the entropy corresponding to an special attribute, which imply the smaller attribute's weight, the less the discriminate power of that attribute in decision making process (Lotfi & Fallahnejad, 2010). The *Table 5 above* shows the weight of each classes using Shannon Entropy method

From the weight values in the *Table 5*, it is seen that the factor slope having the SE value 0.175 among other value is the highest factor supporting the landslide susceptibility. From the result, it is also clear that the factors plan curvature, elevation, soil, land use and geology having values 0.168, 0.167, 0.163, 0.129 and 0.103 respectively are the factors which highly boost probability of occurrence of landslide. Similarly, the factors such as aspect, distance to fault, distance to road, distance to river have low values 0.032, 0.023, 0.020 and 0.001 respectively in comparison to other factors which indicate that these factors have less effect on landslide occurrence. Using the above table, SE values for each factors was developed which was finally used to prepare the LSI map using following equation:

LSM_{SE} = *0.175973*Slope* $_{FR}$ + *0.168044*Plan Curvature* $_{FR}$ + *0.032152*Aspect* $_{FR}$ + *0.167234* Elevation* $_{FR}$ + *0.129656* Land use* $_{FR}$ + *0.023615* Distance to Fault* $_{FR}$ + *0.163923* Soil* $_{FR}$ + *0.103139* Geology* $_{FR}$ + *0.020657* Distance to Road* $_{FR}$ + *0.015607* Distance to River* $_{FR.}$

The distribution of different landslide susceptibility levels using Shannon Entropy method is shown hereunder in Map 14



Map 14: Levels of Landslide Susceptibility in Tanahu Using SE Method

Likewise in landslide susceptibility map using FR model, the probable zone of landslide occurrence using SE model was developed in which there are five classes (i.e. very low, low, moderate, high and very high).The area covered by each classes of landslides susceptibility map using SE method is presented in Table 7.

Table 7: Illustration of Area covered by each levels of Landslide Susceptibility using SE method

Class	Pixel Count	Area (in sq. km)	% of Area Covered
Very Low	265268	238.7	15
Low	412668	371.4	24
Moderate	502348	452.1	29
High	400546	360.5	23
Very High	168216	148.4	9
Total	1749046	1571.1	100

The Table 7 demonstrate that among total area of 1571.1 sq. km, the landslide high risk area under the classification very high and high are 148.4 sq.km and 360.5 sq. km respectively. It elaborates the characteristic difference of area of various classes. It provides the insight that the most probable landslide occurrence region is 208.9 sq. km.

The Pie diagram in Figure 9 has been drawn to visualize the relative relationship of area distributed over different landslide susceptibility levels. It describes the area of different classes in percentage in which the landslide susceptible zone for very high and high classes are 9% and 23% respectively. Most of the area lies in moderate susceptible zone which has highest percentage of 29%.

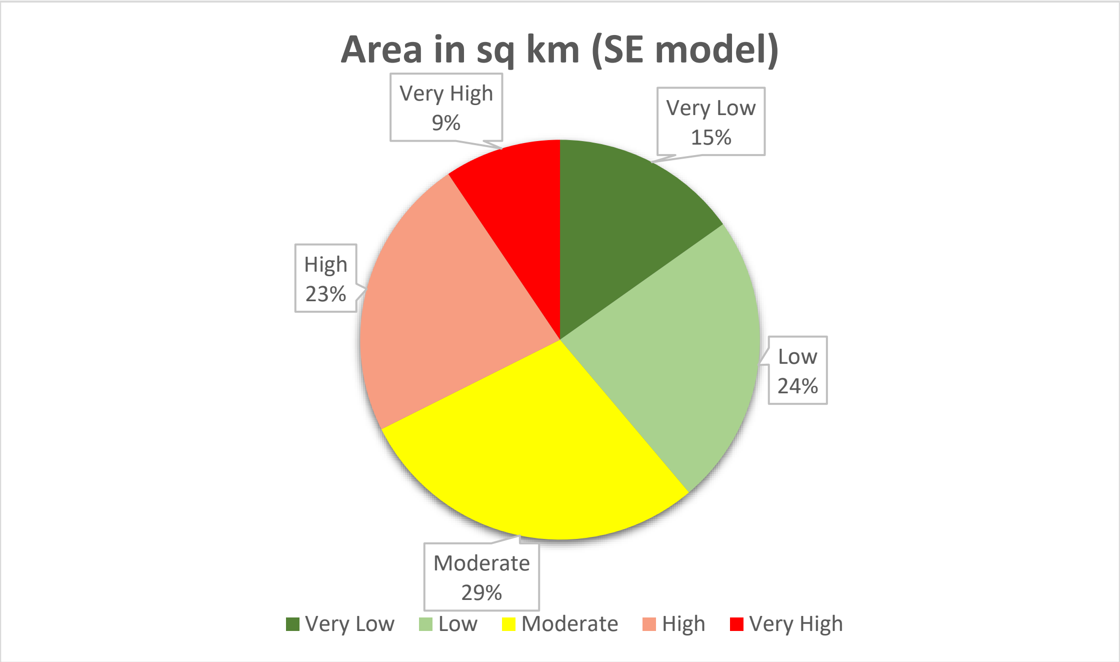


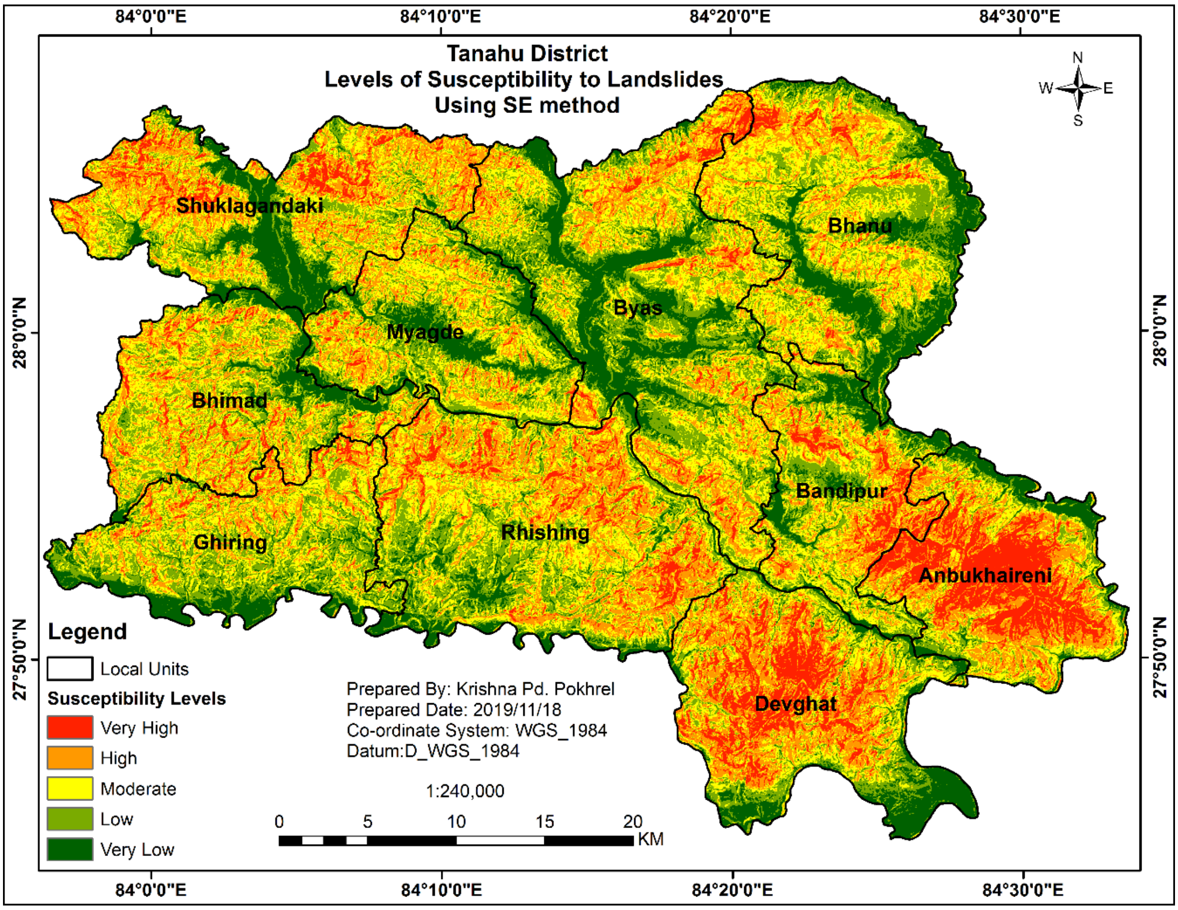
Figure 9: Illustration of area covered by each Susceptibility class using SE method (in percentage

3.1.3 Landslide Susceptibility Map Using Statistical Information Index

The result was obtained from SII method which shows statistical correlation of the landslide conditioning factors along with attribute. The weights calculated for the individual factor map was used to assess which map are important fort the prediction. So, it is very important to link the weighted value of each parameter class with the factor maps. For the very reason weight calculation is done in attribute tables. The *Table 5* above shows the weight calculated for each classes of causative factors using SII method.

The landslide susceptibility index map is created by the raster calculator which is method of GIS function in which each factor map were combined. In the *Table 5*, weight of each class factor or information value is calculated using the Statistical information index method. From the Table it can be seen that the main advantage is this method shows individual correlation of class with landslide which makes this more effective than other. The logarithm gives the both negative and positive impact of class on the susceptibility. The class with 0 landslide pixel illustrated that no correlation exist between the class and landslide occurrence. From the table it can be seen that factors like slope, elevation, distance to fault, geology which has a high positive information value up to 2.25, 3.15, 1.49, 3.8 has high correlation with landslide occurrence and has high impact on landslide susceptibility. Slope have maximum positive value in greater than 65 degree whereas elevation has maximum positive values above 900 meters. Distance to fault have maximum value in range 150 to 225 from the fault whereas geology has maximum weight among other factors which has basic rock formation. So, these are the factors which has high probability in landslide susceptibility mapping. The factors like road, rivers have high negative values which predict that they have minimum effect on landslide occurrence.

SII values for each factors was finally used to prepare the LSI map using raster calculator. The corresponding landslide susceptibility map (LSM) was generated using ArcGIS software. It is clear that the probability of landslide occurrence rises with the enlargement of the LSI. In the present study, the natural break method, which seeks to reduce the variance within classes and maximize the variance between classes was used to the reclassify the LSI values into five categories, namely very low, low, moderate, high and very high. The distribution of landslide susceptibility level within the study area as obtained using SII method is presented below in Map 15:



Map 15: Levels of Landslide Susceptibility in Tanahu using SII method

The *Map 15* illustrates the distribution of landslide susceptible zone of study area in which the landslide zone is categorized into very low, low, moderate, high and very high classes. The area covered by each classes of landslide susceptible map using SII method is tabulated below in Table 8:

Table 8: Illustration of Area covered by each Landslide Susceptibility Levels using SII method

Class	Pixel Count	Area in sq km	% of Area Covered
very Low	202537	182.3	12
Low	536797	483.1	31
Moderate	561614	505.5	32
High	348377	313.5	20
Very High	99721	86.7	5
Total	**1749046**	**1571.1**	**100**

The Table 8 demonstrate that among total area of 1571.1 sq. km, the landslide probable area under classification very high and high are 86.7 sq. km and 313.5 sq. km respectively. Also it shows the information about variation of classes in term of area. It provides the insight that the region which is in risk of probable landslide is 400.2 sq. km.

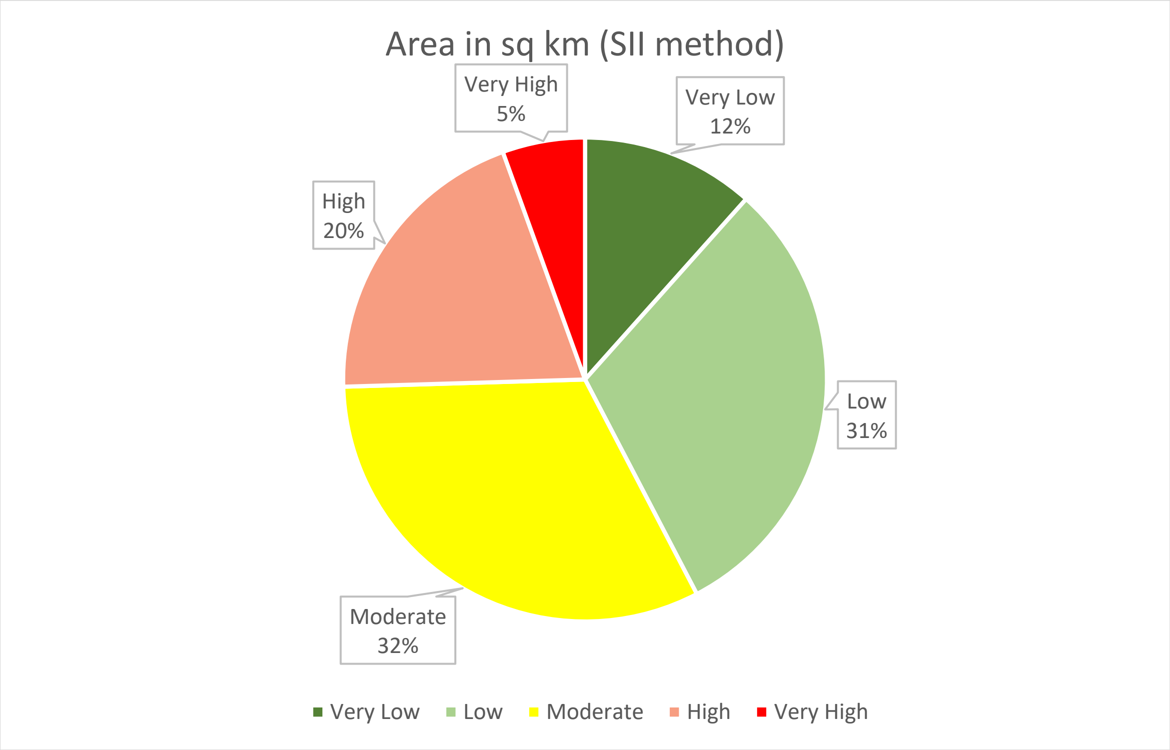


Figure 10: Illustration of area covered by each susceptibility class using SII method (in percentage)

The pie chart in Figure 10 highlights the area of different classes in percentage in which the landslide susceptible zone for very high and high classes are 5% and 20% respectively. Most of the area lies in moderate susceptible zone which has highest percentage of 32% whereas low and very low susceptibility classes cover 43 % of the total study area. It signifies that the susceptibility classes as predicted by this method lie in same line with other two methods stated above.

Another Analysis was done based on the distribution of landslide occurrence in five susceptibility classes. The landslide area for five susceptibility classes of the two datasets are presented in the Table 9*:*

Table 9: Area of landslide in each susceptibility class of two datasets (Training and Testing Data sets)

Class	**Area(in sq. km)**					
	FR Method		**SE Method**		**SII Method**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Very Low	0.01	0.01	0.03	0.01	0.01	0.02
Low	0.24	0.09	0.17	0.13	0.10	0.08
Moderate	0.62	0.16	0.44	0.16	0.30	0.32
High	0.87	0.40	0.72	0.31	0.83	0.40
Very High	1.21	0.88	1.17	0.32	1.31	0.53

A simple method for checking the distribution of landslide susceptibility classes in the study area in terms of actual landslide area has been used. The Table 9 explains the landslide areas corresponding to each five susceptibility classes for the training dataset and test dataset for three methods (FR, SE and SII). It is clear that most of the landslides occurred in the area of “high” and “very high” susceptibility level whereas very less landslide has occurred in the areas of predicted low to very low susceptibility classes.

The comparison of landslide area with the LSM reveals when the susceptibility level increases, the landslide area grows accordingly. It means that the predicted areas of higher susceptibility also hit by higher number/area of actual landslide in the ground. This signifies that predicted landslide areas are directly related to the landslide occurrence and hence landslide susceptibility models adopted in this study can be useful for forecasting the landslide susceptibility. The relationship is observed for both the training and test landslide data with different susceptibility classes.

The relationship between landslide occurrence and each susceptibility classes as assessed by different methods has been plotted and presented in Figure 11

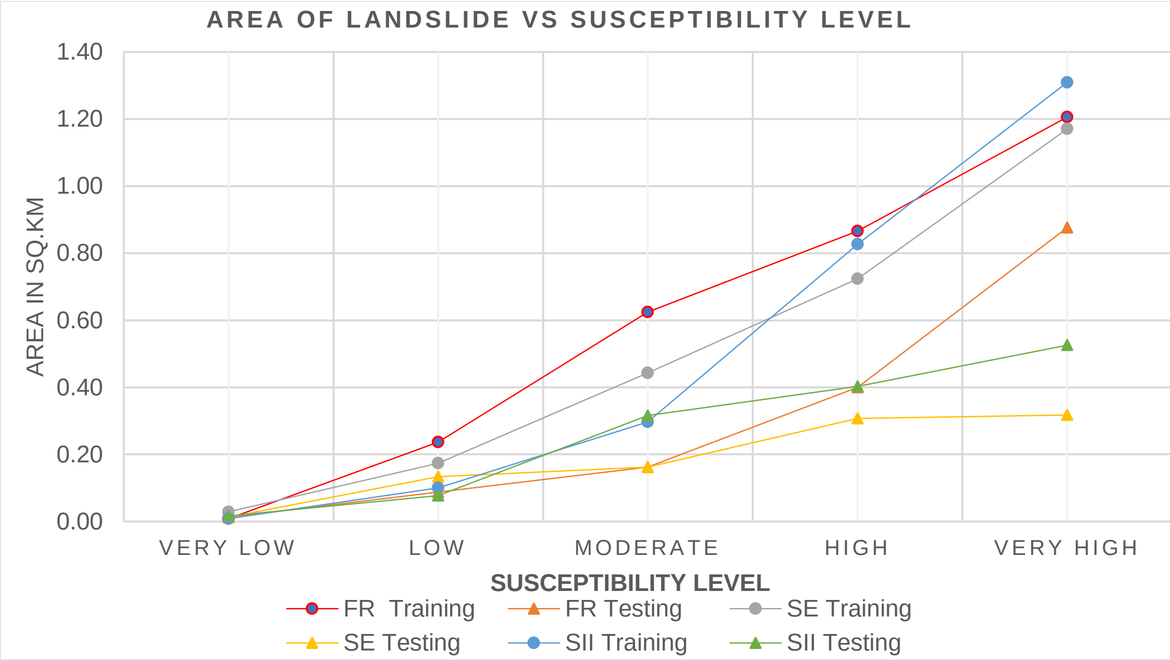


Figure 11: Relationship between Areas of landslide vs susceptibility level

3.2 VALIDATION

The receiver operating characteristic (ROC) curve is the sensitivity or specificity curve which is used to illustrate the prediction accuracy of a landslide susceptibility model (Saha et al., 2005; Conoscenti et al., 2008; Kamp et al., 2008; Bălteanu et al., 2010; Song et al., 2012).

In this study interpretation of the ROC curve was made by calculating the area under the curve (AUC), i.e., the area between the horizontal axis and the ROC curve. To assess this, the resulting susceptibility values of the entire study area were arranged in the descending order along the X-axis and cumulative landslide occurrence is plotted on the Y-axis.

3.2.1 Validation by AUC

After the development of three models, AUC technique was used to validate and compare their accuracy. The two evaluations are done in AUC for defining accuracy of model which are success rate evaluation and prediction rate evaluation. The success rate and prediction rate can be determined by correlating the results of landslide susceptibility at well-known landslide positions. The closeness of success rate and prediction rate highlights how these models helps in predicting the occurrence of landslides in future. The AUC curve that is determined by training dataset should be approximately equal to the AUC curve determined by using validation dataset. However, the AUC curve of training dataset is higher than the prediction curve because the validation data on landslide area are not used in modeling process (Dahal et al., 2013). The curve is prepared by plotting false positive rate in x- axis against true positive rate in y- axis.

True Positive Rate= Sensitivity

False Positive Rate= 100- Specificity

The graphs showing the comparison of three models with success rate and predict rate are shown in *Figure 12*:

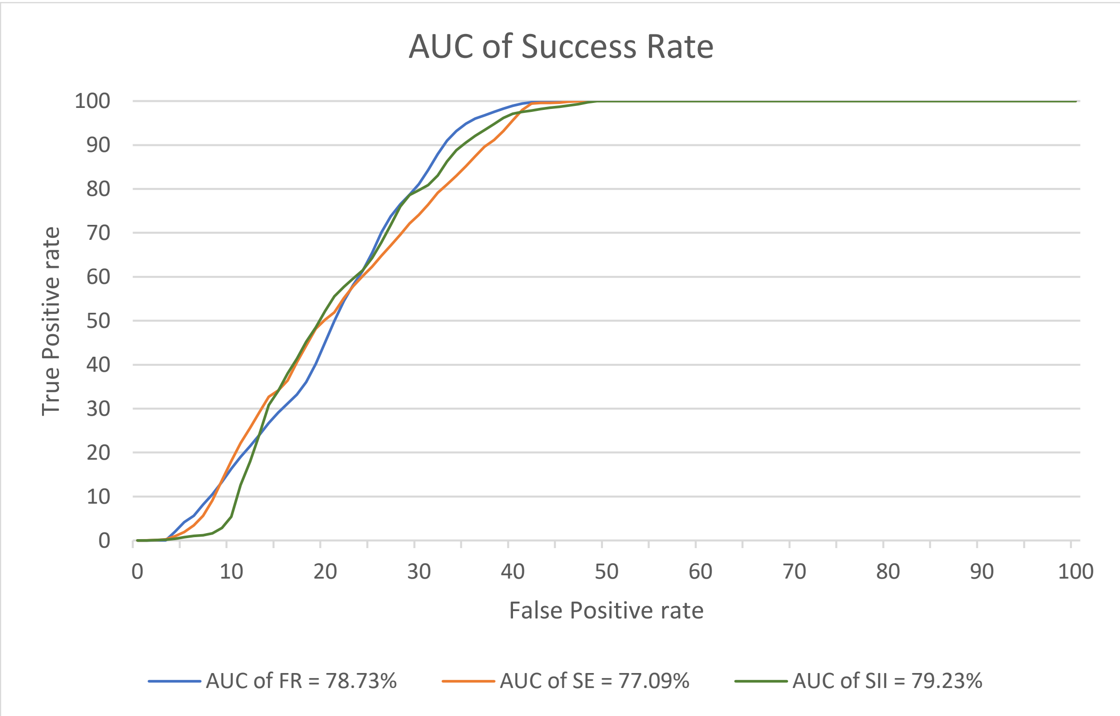


Figure 12: Graph showing AUC of success rate of FR, SE and SII method

The graph in *Figure 12* and Figure 13 reveal that the entire test fall in the category 70% - 80% because the AUC value ranges from 77.09% to 79.23% in the success rate and 74.08% to 76.38% in the prediction rate. The values of AUC of success rate for FR, SE and SIII methods were found to be 78.73%, 77.09% and 79.23% respectively

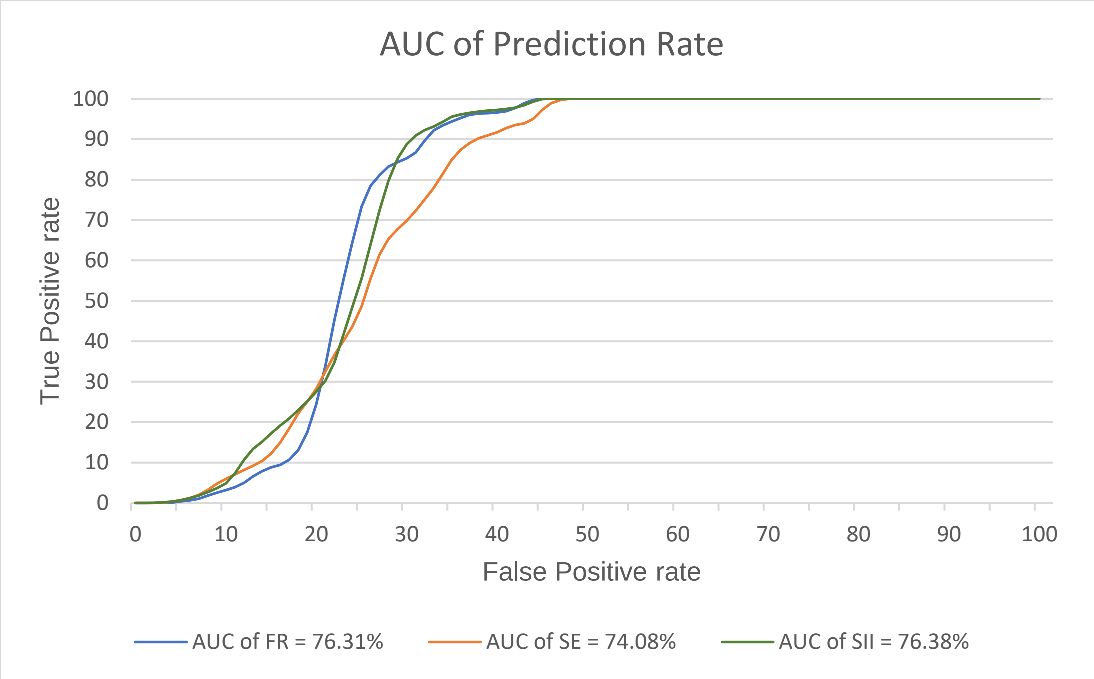
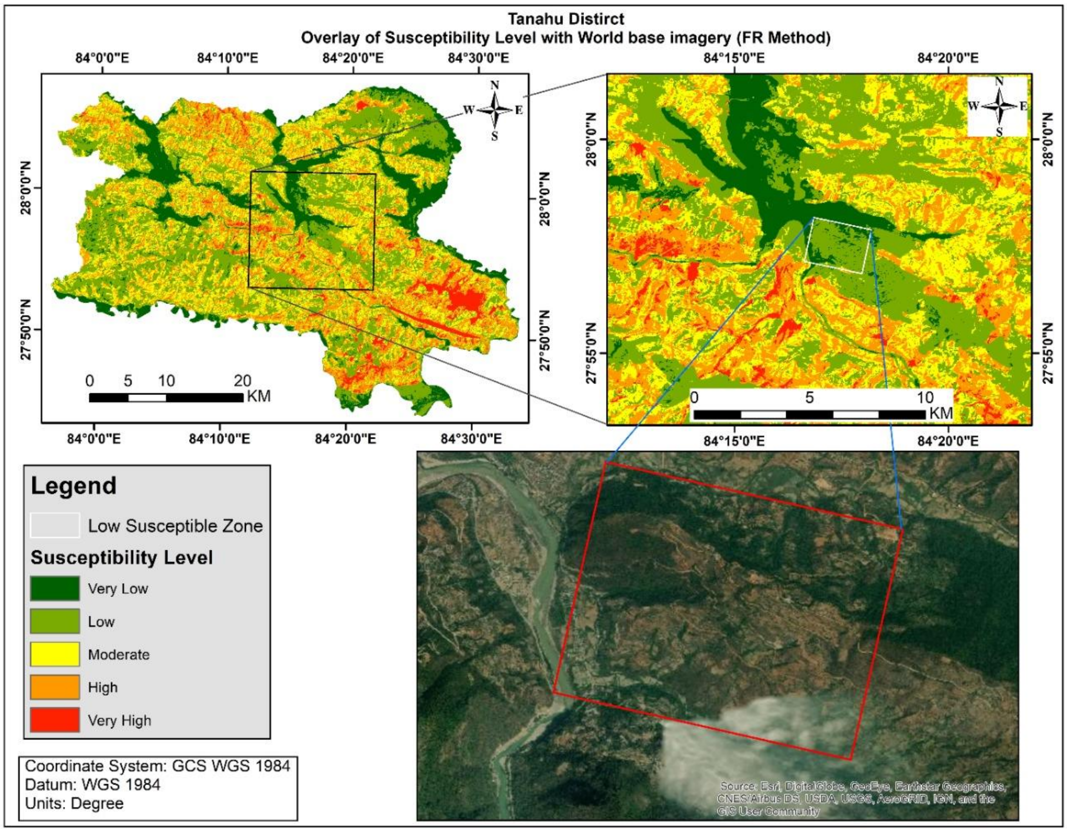


Figure 13: Graph showing AUC of prediction rate of FR, SE and SII method

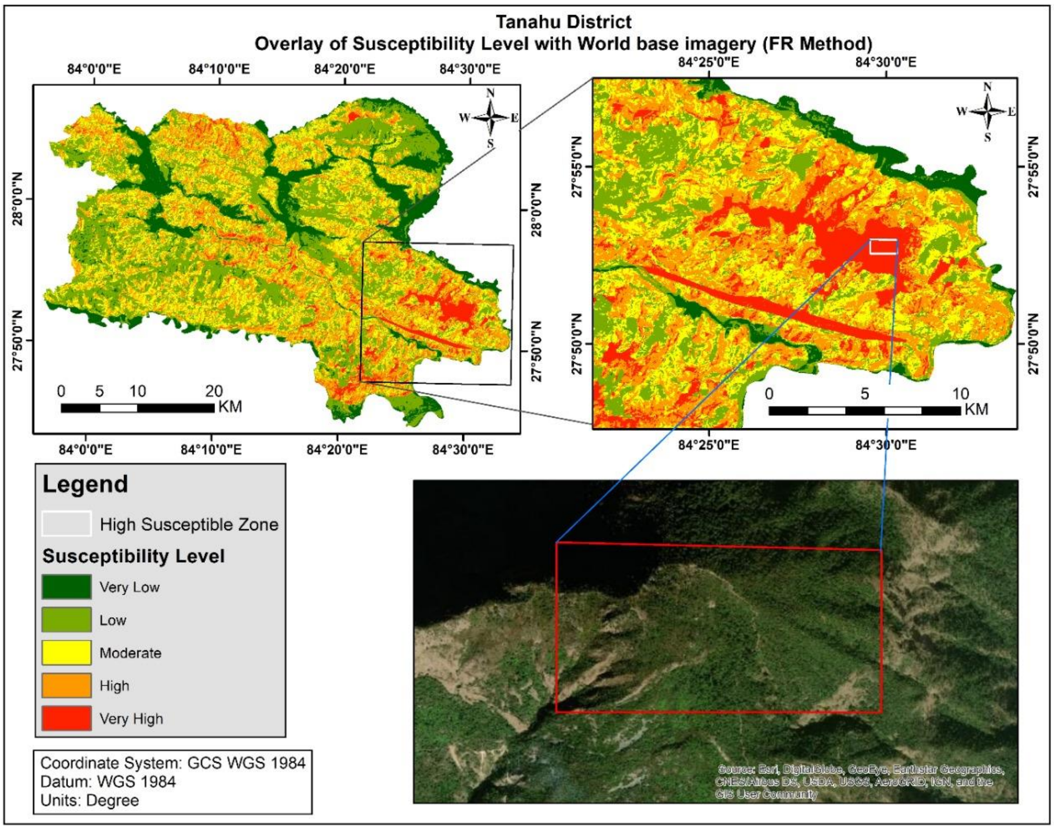
Moreover, the values of AUC of prediction rate for FR, SE and SIII methods were found to be 76.31%, 74.08% and 76.38% respectively. Therefore, it can be inferred from the accuracy assessment that Statistical Information Index method employed in this study demonstrated reasonably good accuracy for estimating the susceptible zone for landslide occurrence of the study area followed by FR and SE method. However, the general prediction accuracies of these proposed three models are comparable reasonable.

3.2.2 Validation by World Base Imagery Overlay

The resultant landslide susceptibility maps were overlaid on World Base Imagery to check the correctness through visualization. The results after comparison with the base imagery verifies the facts presented in the paragraphs above. The areas with higher relative altitude, barren and steeper slope seem to fall in highly susceptible zone and the areas with comparatively low elevation with gentle slope, high vegetation cover and hard lithological formations seem to fall in low risk zone of landslide. The demonstration of high susceptibility and low susceptibility and corresponding imagery are shown in Map 16 and Map 17 with the help of World Base Imagery.



Map 16: High landslide susceptible zone using online world imagery



Map 17: Low landslide susceptible zone viewed over online world imagery

3.3 Discussion

One of the most practical approaches for landslide hazard assessment and proper management responsibility is the preparation of landslide susceptibility model. Although, there exist different methods to prepare the LSM, there is no a universal guideline from model selection to prepare better LSMs (Nohani et al., 2019). In this study, three popular and widely used state-of-the art statistical bivariate models (i.e., FR, SE, and SII) were applied for the assessment susceptibility within stud area. The key beginning of statistical-based method is to prepare the landslide inventory map. Therefore, the identification and selection of landslide conditioning factor should be carefully noted since the quality of factors and geo-physical characteristics of the study area affects the completeness of landslide inventory maps.

Modeling results mostly depend on both the model's structure and quality of data (Pham et al., 2017). The common advantage in all these three methods used in the study is that they show a simple and honest way for preparing and updating the data and assessment of landslide susceptibility processes by using GIS. Another absolute advantage of these methods is they can be easily applied in land-use planning and policies. The applied methods that are used for developing LSM are reasonable to use. Also they are identified as fully objective sine they are based on real and field based spatial distribution of landslides which increase their reliability.

In the existing literature, the bivariate methods often compute the weights of each values on the basis of density of landslides. The some of the parts of the study area are characterized by geophysical factor classes that are not prone to landslide. As example landslide toes generally have very low slope angles which may increase the landslide density, resulting in increase in weighting value. This type of result may induce the overestimation of landslide susceptibility. But most of the results have shown that the frequent landslide in steeper, barren and high elevation range which is usually valid. In the distances of 0 to 75 m from the road the greatest impact on landslides occurring may happen since the closer to the road the natural slope is disturbed during excavation which produces higher landslide occurring probability. The direction a slope faces also affect the physical and biotic features of the terrain. The results showed that the south aspect had the highest effect on landside occurrences, and the main reason may be that the south aspect has the most dryness among other aspects resulting from more solar radiation. Regarding the curvature, concave has the most effect on landslide occurrences. The reason behind may be the concave surface gives the pathway to surface runoff during rainy season which swipes the surface soil and vegetation causing landslide. Similarly Lower Siwalik and Middle Siwalik have problem from alternating beds of mudstones and sandstone. The annual rainfall in Lesser Himalaya zone is comparatively higher and the frequency of high intensity rainfall is also high. Thick soil formations are found in slopes of the Midlands because of deeply weathered rocks (Dahal, 2010). As a result, the slopes are very prone to landslides after intense rainfall. These results are approximately consistent among the FR, SE and SII models. These findings are consistent with results of other similar literature studies.

The landslide susceptibility map and the relative pie-charts illustrating the spatial distribution of the landslide susceptibility classes highlight that, on average, 30% of the total study area fall under high and very high susceptible zones where as 41% of the total area fall under low and very low susceptible zones. The remaining 29% of the total area is moderately susceptible to landslide. The land surfaces characterized by the highest susceptibility are scattered in the study area, even if they are mainly concentrated in the South-east and North western part of district. However, in the middle and west part of the district, low and very low susceptible areas are generally predominated.

Among the 10 local unit of Tanahu district, Devghat and Aabhukhaireni rural municipality and Shuklagandaki municipality are most vulnerable to landslide hazard. In South-western region, moderately low susceptible areas are generally predominated. The Byas municipality contains more areas that are very less to null vulnerable to the future landslide.

This contains the area that are mostly flat and relatively less steep, in low lands, and falls in the Ranimatta formation which has relatively hard and compacted lithology. An overlay of the landslide inventory maps on the landslide susceptibility map has demonstrated that the predicted high susceptibility class contain more actual landslide area and similarly, low susceptibility class has less or null actual landslide area.

In this study, the weight for different landslide conditioning factors were calculated and elevation was observed to have the highest weight value. This is followed by slope, land use, soil type, and geology which gave similar effect in susceptibility prediction. The distance from river and distance from fault show the lowest impact in landslide occurrence. Based on the distribution analysis of landslide susceptibility classes for the factors of elevation, slope, lithology, land cover and soil type, it can be seen that the barren land, agricultural area and sparse forest area with lithology of Galyang, Naudanda and Sangram having the concave topography would be most likely to have slope failure. Whereas the areas with flat or gentle slope (< 20°), dense forest with Syanja and Ranimata formation which are basically composed of quartzite and gneiss would have the stable geology. This shows the low and moderate landslide susceptibility. The study by Zhang et al. (2016) and Nohani et al. (2019) show the similar result. Geologically, Naudanda formation, Sangram formation and Galyang formations are compose of limestone, green phyllite, quartzite, grey siliceous dolomites and grey slates making them more fragile to slope failures. These formations are more favorable to high and very high susceptibility. So the areas of the Aabukhaireni, Bandipur and Shuklaganadaki local units are observed to be more susceptible to landslide.

Among the statistical methods used in this study, each methods are acceptable since they have good results as suggested by the fact in the above percentage of AUC curve. To sum up, the most efficient method among these models is SII method however, these three models can be used for landslide susceptibility mapping

CHAPTER 4: CONCLUSION AND RECOMMENDATION

4.1 Conclusion

A large proportion of the areas in Tanahu consists of high hills and mountains where fragile and rugged topography itself is a challenge to slope stability. Where increasing development activities like rural road construction, cutting down trees for wise purpose and unplanned expansion of settlement are undergoing in fast pace. The material extraction from river and hilly terrain has being taken place in increasing rate. They all are posing the risks of landslides hazards. A proper assessment on landslide susceptibility in a regional scale has become a necessary task at present. Landslide Susceptibility Modeling is one of the most important and challenging tasks in the assessment of risk of landslides. Since many methods are proposed for the landslide predictability, an appropriate method is a must for the susceptibility and risk analysis. The detailed process of landslide susceptibility assessment in this work is an example set for the regional scale implementation.

Geospatial data and methodologies in collaboration with statistical methods provide base for susceptibility assessment. So, the study was carried out by combining GIS based approach with a different statistical bivariate method. Three bivariate statistical modelling approaches namely FR, SE and SII were used in landslide susceptibility assessment of Tanahu district in Gandaki province, Nepal.

A total of 136 locations of landslides were determined by Google Earth digitization and field surveys which was used to create a landslide inventory map of the study area. Out of total landslides polygons, 70% (95) were used for training whereas rest 30% (41) were applied for validation. On the basis of characteristics of the area under study and availability of data 10 landslide conditioning factors :1) land cover; 2) slope; 3) geology; 4) distance from fault; 5) aspect; 6) elevation; 7) distance from road; 8) distance from river; 9) curvature and 10) soil type were considered for analysis. Finally, a series of landslide susceptibility index were prepared based on 3 approaches mentioned above. The obtained LSI were then classified into five categories of susceptibility levels namely: very high, high, moderate, low and very low.

The results show that a total of 32%, 32 and 25% of area are under the high and very susceptible zone, 43%, 39% and 43% are under low and very low susceptible zones whereas 25%, 29% and 32% of area are predicted as areas of moderate susceptibility using FR, SE and SII method respectively. The produced maps were evaluated using both training and testing datasets with AUC method. The evaluations show that the success rate and prediction rate for FR model is 78.73% and 76.31%, SE model is 77.09% and 74.08% and SII model is 79.23% and 76.38% respectively. The SII model having the highest AUC and was evaluated as the most accurate model among the 3 applied models. The AUC value of these three models are relatively high with model predictions, therefore the results of landslide susceptibility modelling are accurate and can be used in real-world landslide risk and vulnerability assessment.

The outcomes of this research can be used in predicting future landslides. Similarly it can be helpful in planning for infrastructure development and resettlement activities. For the effective land use planning and implementing engineering works various geo environmental factors such as slope, elevation, geology, land cover, soil type etc. of that region should always be considered. Hence, such study can be of great utility to land use planners, policy and decision makers as well as implementing agencies. To sum up, the findings of this study can remain as an important asset to stakeholder organizations who work in the field of landslide related disaster control and management such as:

- Ministry of Home Affairs
- Department of Hydrology and Meteorology
- Department of Water induced Disaster Management
- Department of Mines and Geology
- Department of Survey, Central Bureau of Statistics (CBS)
- International Center for Integrated Mountain Development (ICIMOD)
- Related UN agencies

4.2 Limitations of Study

The limitations of this research work are as follows:

- This research was analyzed based on medium resolution SRTM DEM from which landslide conditioning factors such as slope, aspect, curvature and elevation were generated. Hence, the overall results were based on DEM resolution which may affect accuracy.
- In practice land use, land cover, geology, soil type are more impacting factor landslide occurrence but the available data are of small scale and variation is only observed in large spatial extent which affects in overall prediction accuracy.
- The land use data used in this study was prepared in 2010 by ICIMOD. The land use data could poorly describe the updated land features of present scenario.
- Rainfall is one of the major triggering factor for landslide however, precipitation data is not used in this study because the data was very sparse.
- All old landslide scars may not have been accounted during the preparation of landslide inventory due to unavailability existing inventory. So, it was based on available images from google earth, world base imagery, and some field visits.

4.3 Recommendations

The recommendations to any other researchers and analysts in order to increase the quality of the landslide susceptibility modelling are listed below:

- Landslide inventory data is a key source of information for many research, analytical work and disaster management plan. So, a proper, reliable and updated landslide inventory of the district should be maintained. The study area is more susceptible to landslides in some of geological formations Naudanda formation, Sangram formation and Galyang formations. So, further study is recommended in reliable scale to focus on such formations.

- Geomorphological inventory are valuable asset for susceptibility, hazard and risk studies. So, accurate event inventory maps need to be prepared after each landslide triggering event (e.g., rainstorm, prolonged rainfall, seismic activity, or rapid snowmelt event).
- The landslide conditioning factors such as elevation, curvature, aspect slope, TWI etc., are derived from DEM which affects the overall accuracy. Therefore, updated DEM with relevant resolution is recommended.
- More landslide conditioning factors can be considered for better result such as precipitation, sediment transport index, stream density, Soil Water Index (SWI) and so on.
- For cross validation and reliability, the landslide susceptibility modelling can be done using other methods such as weight of evidence, logistic regression, certainty factor and machine learning approaches.
- From this research, the study area is observed as vulnerable zone of landslide. So, policy makers and planners should focus on developing proper plans for land use, settlement, infrastructure development and building bylaws and their timely implementation. Local government bodies should conduct awareness programs to the people of those areas
- The detailed process of landslide susceptibility assessment in this work is an example set for the regional scale implementation in future. This work shows that with the current available data, a reliable hazard map for landslide occurrence can be produced using optimum model among various data mining techniques. The procedure is quite easy to understand and implement in GIS. With these data updates, landslide assessments can be more reliable and the results can be further improved

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APPENDICES

APPENDIX A: General Characteristics of Geological Formations of Tanahu

Table 10: Geology Formation

Geological Formation	Description
Tistung Formation	Dull green grey colored phyllites pink purplish tinted sandstones with sandy limestone. Ripple marks, clay cracks, worm tracks are abundant pebbly beds near base.
Lakharpata Formation	Fine grained, light blue, grey limestone & dolomites with thin interactions of grey shales, white, pink dolomite limestone, purple quantizes & green shales at the top
Syangja Formation	White pale orange pinkish or purplish or calcareous quartzite & quarzitic limestone intercalated with dark grey purple & green shales strongly ripple marked quartzites at the base.
Galyang Formation	Dark grey slates intercalated with thin grey calcareous slates & lamillqe of carbonates. Thick beds of grey siliceous dolomites are found at place.
Sangram Formation	Black, dark grey to greenish grey shales with interaction of limestone & quartzites.
Naudanda Formation	White massive fine to medium grained quartzites with ripple marks interbedded with green phyllites. Basic intrusions are noted.
Ranimatta Formation	Grey greenish grey gritty phyllites grilstones with conglomerates & white massive quartzites in the upper parts. Basic intrusions are abundant.
Seti Formation	Grey greenish grey gritty chlorite muscovite sandstones gritstones with conglomerates & white massive quartzites in the upper parts .Basic intrusions are noted.

APPENDIX B: Soil Type

Table 11: Soil Type

Dominant component of soil	Fertility
CMx/PHh	Non fertile
CMo	Least fertile
CMg	Fertile
LVx/ CMe	Highly fertile

APPENDIX C: Photographs of Field Visists