Landslide Susceptibility Mapping of East Sikkim Employing AHP Method

Md Nawazuzzoha, Md. Mamoon Rashid, Mohammed Ihtesham Hussain, Adnan Shakeel, and Hasan Raja Naqvi

Abstract The occurrence of landslides is a frequent phenomenon in the hilly terrain of the Indian Himalayan region leading to severe environmental and socio-economic issues by distorting ecological balance and damaging human lives and property. The present work intends to identify the landslide susceptibility zones of Sikkim Himalaya using the ensembles of important knowledge-driven technique, i.e., Analytical Hierarchy Process (AHP) with Landslide Numerical Risk Factor. The Shuttle Radar Topography Mission (SRTM) DEM, Landsat 8, and GSI datasets were used. The landslide inventory map has been considered as the dependent factor and the geo-environmental factors like rainfall, slope, aspect, altitude, geology, soil texture, distance from the river, lineament, and road, Stream Power Index (SPI), topographic wetness index (TWI), Topographic Roughness Index (TRI), and Sediment Transport Index (STI), Normalized Difference Vegetation Index (NDVI) have been considered as independent factors. A landslide susceptibility map was prepared based on the AHP method and classified into high, moderate, and low-risk zones in a GIS environment. Results reveal that, about 29% of areas highly susceptible to landslide and past landslide inventories were also overlaid to observe the accuracy of susceptibility mapping.

Keywords Landslide · Susceptibility · AHP · East Sikkim Himalaya

1 Introduction

Landslides are dangerous natural hazards that occur suddenly and cause considerable damage (Guzzeti et al. 1999). It is defined as the downslope mass movement of rock, earth, and debris under the direct influence of gravity (Cruden 1991), that are triggered by the earthquake, volcanic eruptions, rainfall, slope failures, and human

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activities like excavation and slope cutting (Bahrami et al. 2021). Landslides belong to the most distributed natural disasters in the world with the potential to cause loss of human lives as well as severe damage to the infrastructure (Vojtekova and Vojtek 2020). Snow avalanches are a form of a landslide that happens in snow-covered areas at higher elevations and are caused by the bulk movement under gravity's impact. Identification of avalanche hazard is necessary for planning future developmental activities in mountain areas (Athick et al. 2015). Landslide occurrence is affected by two types of factors, i.e., Predisposing factors which create the condition and Triggering factors which initiate the landslide. Predisposing factors include elevation, slope, aspects, LULC, curvature, and geology, whereas Triggering factors are earthquakes, seismic activity, heavy or prolonged rainfall, excavation, and slope cutting (Guzzeti et al. 2012; Chen et al. 2017a, b; Rabby and Li 2020). Soil erosion considerably contributes to the landslide as it weakens the slope material. The rate of mean soil loss is higher in elevated zones and decreases toward the lower region, also increase in the slope gradients accelerates the rate of sediment loss (Naqvi et al. 2015; Agegnehu et al. 2020), higher elevation and steeper slope areas are more prone to landslide occurrence. The changes in land cover, biomass, and hydrologic regimes subsequently affect erosion which is more pronounced on hill slopes (Naqvi et al. 2013, 2019; Emiru et al. 2018). Analysis of the landslide and predictor factors correlation are used to estimate the susceptibility of landslide. Generally, landslide susceptibility is the spatial probability of land sliding in a given area, depending on a combination of various factors such as geology, land use and land cover, tectonics, slope, aspects, vegetation, etc. (Guzzeti et al. 2006; Wu et al. 2016). For rainfall-induced landslide, drainage density is an important susceptibility index. High drainage density indicates a highly dissected landscape that has undergone intense slope cutting (Latief et al. 2015). Landslide hazard zonation (LHZ) is an important content of landslide hazard prediction modeling. Identifying landslide-prone locations can assist decision-makers in reducing landslide risks (Boroumandi et al. 2015). The aim of landslide susceptibility mapping is to identify landslide-prone areas for the purpose of disaster management, spatial planning, and developmental process. Till now various qualitative (knowledge-driven) and quantitative (statistical) techniques and methods have been proposed for landslide susceptibility modeling (Dai and Lee 2002; Lazzari and Danese 2012). Quantitative and semi-quantitative methods consider weighing and rating based on logical tools such as AHP, fuzzy logic, combined landslide frequency ratio, and weighted linear combination (Pradhan and Lee 2009; Kayastha et al. 2013; Zhu et al. 2018). Landslide accounts for 9% of the world's disaster (Galli et al. 2008). According to various researches, China, India, Nepal, and Philippines are the most affected countries by landslides on the basis of severity, losses, and frequency of occurrence (Kirschbaum et al. 2009). Indian Himalayan Region has been the site of frequent landslides. The present study area lies in the East Sikkim Himalaya. In the past, there have been frequent and catastrophic landslides that caused heavy losses of lives and property in Sikkim. Due to the increase in population in hilly areas, economic activities like infrastructural development and construction of roads have increased making this region vulnerable to landslides (Biswakarma et al. 2020). So it is very demanding to prepare an updated landslide susceptibility map for the East Sikkim region.

2 Study Area

East Sikkim is one of the districts of the state of Sikkim. Geographically, it is located in northeastern India and a part of Sikkim Himalaya of the Indian Himalaya that lies between 27.274° N to 27.322° N latitudes and 88.778° E to 88.732° E longitudes (Fig. 1). The study area covers 954 sq km and has an average elevation of 610 m above mean sea level. The capital of Sikkim state is Gangtok city which lies in this area. It has a population of 283,583 and is one of the most populous districts among the four districts in the state (Census 2011). The climate of the district has been divided into tropical, temperate, and alpine zones. The climate is cold and humid for most of the period, and rainfall occurs almost each month. Due to its proximity to the Bay of Bengal, the Study area experiences heavy rainfall.

The mean temperature varies from 1.5 to 9.5 degree centigrade. In the entire state, fog is the common attribute between May to September and biting cold in the winter. During the month of May to October, rainfall is heavy and well distributed. The study area is mainly drained by the perennial Tista River with its tributaries such as Dik Chhu, Rate Chhu, and Rangpo Chhu. The surface area is generally roofed by forests, agricultural land, rocky and barren land, and settlements. The thickness of soil varies from steep slopes to valleys and terraces. The study area lies in the seismic zone IV and geological formation is as old as Proterozoic Eons.

3 Data and Methodology

For the accomplishment of the present work, a variety of significant data have been collected and followed different methods to achieve the landslide susceptibility mapping (Fig. 2). The rainfall data was obtained from Indian Meteorological Department, population data from the District Statistical Handbook, Census of India (2011), SRTM DEM from NASA, drainage and road networks from Open series Topographical Sheets (2015), Soil data and Geological data from the Geological Survey of India (Table 1).

3.1 Landslide Conditioning Factors

Significant and efficient mapping required an appropriate set of conditioning factors correlated to landslide events that need prior knowledge of the main contributors to the landslides (Guzzeti et al. 1999). These conditioning factors are terrain, geology

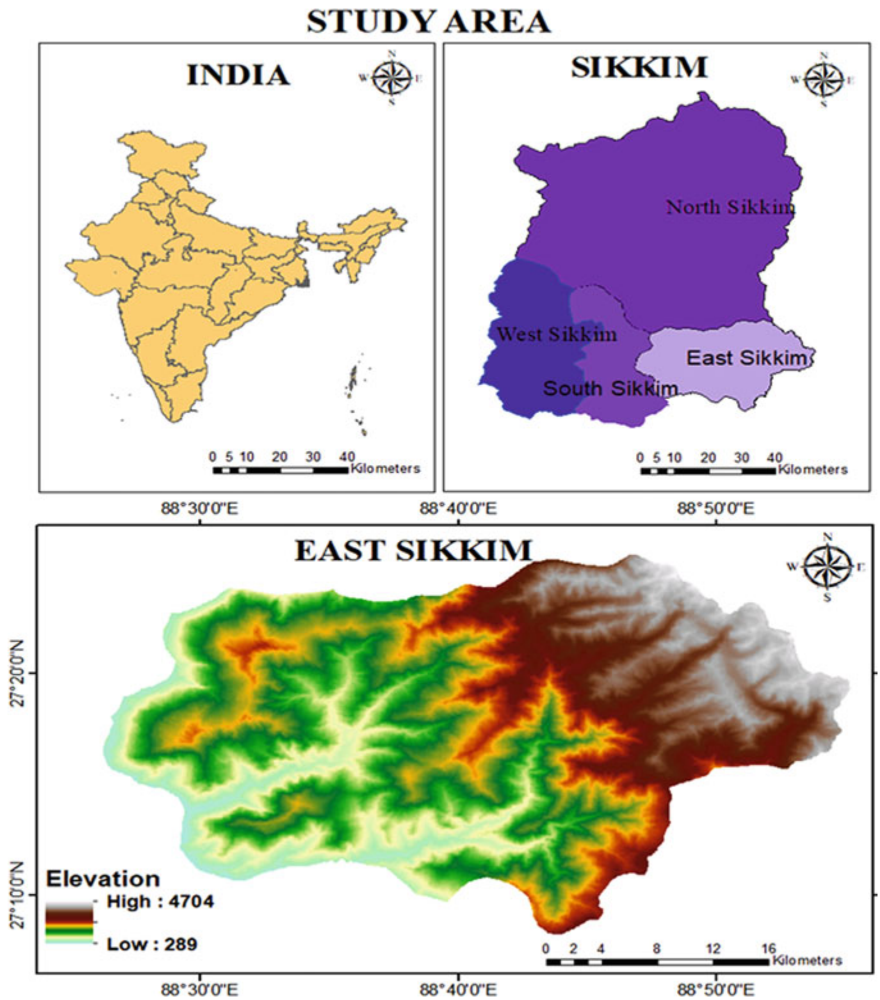

Fig. 1 Study area East Sikkim

and morphology, slope, weather conditions, vegetation density, LULC, and man-made influences. In this study, we have used 15 conditioning factors such as slope, elevation, curvature, aspect, normalized difference vegetation index (NDVI), land use land cover (LULC), topographical roughness index (TRI), topographical wetness index (TWI), sediment transport index (STI), distance from lineament, distance from the road, distance from the fault, lithology age, and Geomorphological landform.

The elevation change of each place is one of the most essential factors in the creation of soil erosion and slope mass movement. This factor has a significant impact on the direction of runoff as well as the rate at which drainage density accumulates (Hosseinzadeh et al. 2009). The highest point in the region is 4704 m, whereas

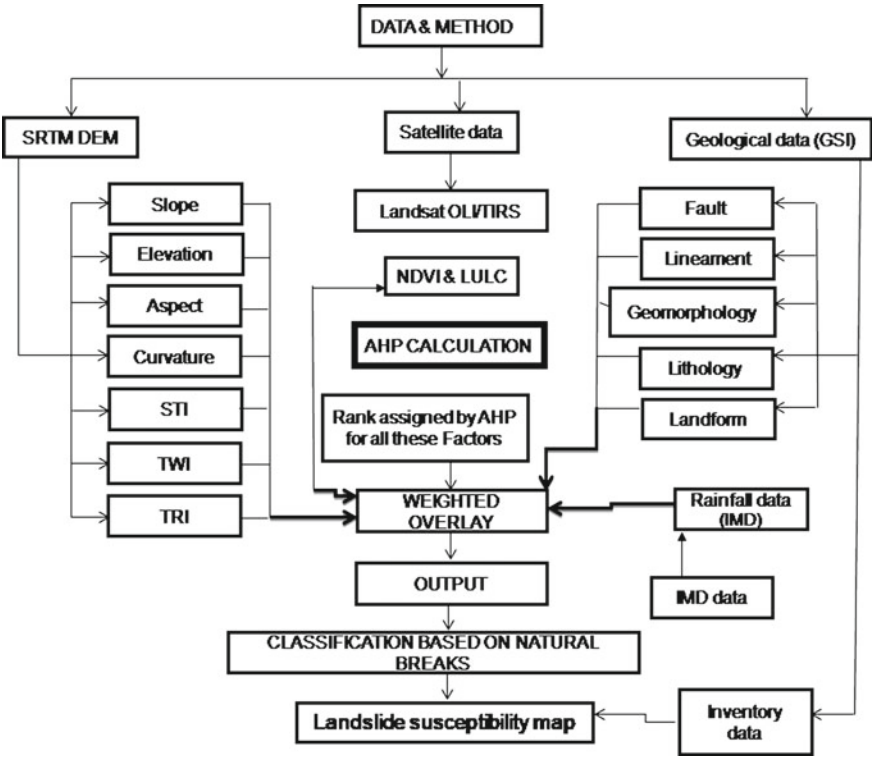

Fig. 2 Schematic flowchart depicts the datasets and methods used for the study

Table 1 Datasets and their sources employed for the study

Datasets	Data structure	Spatial resolution	Source
SRTM (DEM)	Raster	30 m	USGS, Earth Explorer, http://www.dwtkns.com/srtm30m/
Rainfall (mm)	Raster	0.05°	CHIRPS (https://chg.geog.ucsb.edu/data/chirps)
Landsat 8–OLI	Raster	30 m	(USGS) https://earthexplorer.usgs.gov/
Landslide inventory	Vector	National scale	https://bhukosh.gsi.gov.in/Bhukosh/MapViewer.aspx
Geological data	Vector	National scale	https://bhukosh.gsi.gov.in/Bhukosh/MapViewer.aspx

the lowest point is 289 m from mean sea level (MSL). In most of the landslide susceptibility studies, slope percentage is one of the most important predisposing factors (Abedini et al. 2017). Technically, as the slope rises, shear stress increases, resulting in an increase in the potential for slope instability. The aspect factor is vital in maximizing the quantity of rainfall, sun energy, and suitable wind blowing in any region, as well as reflecting the influence of soil thickness, vegetation, wetness, and other factors. Another contributor, the curvature is defined as the rate of change of slope angle or aspect which has a significant impact on slope stability. A general curvature map can be used to describe slope morphology and flow (Nefeslioglu et al. 2008). Concave, flat, and convex curvatures are the three types of curvature found in the research area.

Slope failure is complicated by the presence of lineaments (Ramli et al. 2010). Lineaments describe the weaker plane or zone, and most landslides occur in this zone (Kannan et al. 2013; Thapa et al. 2017). Active faults are significant in landslides from two perspectives: first, they are the source of earthquakes, and second, active faults play a key role in breaking stones and causing instability. The shear resistance of the slide lowers as a result of discontinuity in the geological formation, and landslides are more likely to occur. In this case, highways play the most important role in concentrating runoff, therefore, experience and current data on landslides during road reconstruction and widening demonstrate the need of including this component in landslide sensitivity zoning. In the ArcGIS environment, the three parameters stated above were determined using Euclidean distance.

The nature of land use land cover (LULC) is a key indicator of slope inconstancy which influences the earth's characteristics and causes variations in its activity. As a result, mapping the LULC and its monitoring is a critical undertaking that has a significant impact on the frequency of these dangers. Rainfall is a highly influential factor that has been considered as a landslide triggering factor. The annual rainfall map was created for this study using data from eight meteorological stations in the area and the inverse distance weighted (IDW) interpolation method was employed. Landslides are thought to be caused by a variety of factors, including geomorphology that was created using geological maps and only a few field checks (Kannan et al. 2013). In landslide susceptibility, lithology age is one of the most prominent determinant factors since different lithological units have varying weightage scores, which can provide valuable information about a region's landslide susceptibility (Yalcin and Bulut 2007). Other important and crucial aspects were also considered, and their computations were based on the following equations:

Topographic Roughness Index (TRI)

Topographic roughness index (TRI), one of the morphological factors which is broadly utilized in landslide analysis was computed by using Eq. (1).

$$\mathrm{TRI} = \sqrt{Abs\left(\max^2 - \min^2\right)} \tag{1}$$

where max and min are the biggest and smallest values of the cells in the nine rectangular neighborhoods of altitude, respectively.

Sediment Transportation Index (STI)

Sediment transportation index (STI) defines the procedure for slope failure and deposition (Eq. 2).

$$\mathrm{STI} = \left(\frac{As}{22.13}\right)^{0.6}\left(\frac{\mathrm{Sin}\beta}{0.0896}\right)^{1.3} \tag{2}$$

where β is the slope at each pixel and As is the upstream area.

Topographic Wetness Index (TWI)

Topographic Wetness Index (TWI) is an index that quantifies how topography controls the hydrological processes of an area and is derived using Eq. (3)

$$\mathrm{TWI} = \mathrm{Log}[\mathrm{A}\tan(\alpha)] \tag{3}$$

where A is the catchment area and α is the local slope gradient corresponding to a specific cell.

TWI increases with the decrease of slope and the highest TWI value is usually on floodplains (Yilmaz and Keskin 2009).

Normalized Difference Vegetation Index (NDVI)

The NDVI (Normalized Difference Vegetation Index) is a frequently used metric for describing vegetation and plant health (Chen et al. 2019a, b; Abedini and Tulabi 2018). Because the root system links to the soil and keeps it from wasting after rains, vegetation coverage helps to prevent erosion and landslides (Chen et al. 2019a, b). The NDVI was calculated using Eq. (4) and Landsat 8 level 2 images from March 7, 2018, where IR is the infrared band and R is the red band.

$$\mathrm{NDVI} = (\mathrm{IR} - \mathrm{R})/(\mathrm{IR} + \mathrm{R}) \tag{4}$$

The NDVI scale runs from 1 to 1, with a positive value of 0.2–0.8 indicating vegetation and forests, a negative value indicating water bodies, and a low positive value (0.2 and below) indicating bare land and urban areas (Chen et al. 2017a, b; Althuwayee and Pradhan 2018).

Table 2 Saaty's fundamental scale (1980)

1	Equal importance on the scale
3	Importance of moderate value
5	Significant importance
7	Extremely important
9	Extremely high influence
2, 4, 6, 8	Values in the middle of the two adjacent judgments

3.2 Analytic Hierarchy Process (AHP)

An important multi-criteria decision analysis (MCDA) method for allocating weights to specific parameters is the analytical hierarchy process (AHP) proposed by Saaty and Vargas (1998). The AHP approach employs a pair-by-pair comparison matrix. The consistency ratio (CR) value varies from 0 to 1 when the matrix is created (Saaty 1980, 1990, 1994). The AHP method can be used to do a general linear combination method to determine the potentiality index (Malczewski 1999). The fundamental scale of Saaty (1980) was used to create the pairwise matrix (Table 2). The weight of parameters was computed using the AHP approach in this example.

3.3 Application of the AHP Model

The AHP is used in this study to identify landslide vulnerability zones using a criteria-based judgment technique. For zoning landslide susceptibility, AHP can provide a good and reliable method. AHP is a single procedure that assists in determining the relative importance of various aspects based on the expert's knowledge and opinion. The AHP approach was used to assign weights to the landslide determining elements (Table 3) for this study. For mapping the landslide probability, the slope has the most weight (0.218), followed by rainfall (0.112), elevation (0.109), and TWI (0.101).

4 Result and Discussion

4.1 Mapping and Assessment of Factors Responsible for Landslide Occurrence

The various factors were considered that could be significantly responsible for landslide occurrences, and accordingly, thematic maps of all parameters were prepared for the AHP model. The most influential factor for landslide trigger is topography and all the possible thematic layers were extracted through DEM data (Fig. 3a–g). The degree of slope is more important, and the majority of the pixels indicated by blue hue

Table 3 Parameters wise weights, matrix, and consistency ratio using AHP

Parameters	Elevation	Rainfall	Slope	TWI	Curvature	Distance from fault	Distance from lineament	Distance from road	Aspect	LULC	STI	NDVI	TRI	Lithology age	Geomorphology	Weight
Elevation	1															0.109
Rainfall	0.5	1														0.112
Slope	1	1	1													0.218
TWI	0.5	1	0.33	1												0.101
Curvature	1	0.5	0.17	0.5	1											0.079
Distance from fault	0.5	0.5	0.17	0.25	0.5	1										0.048
Distance from lineament	1	0.25	0.12	0.5	0.25	0.5	1									0.053
Distance from road	0.25	0.5	0.12	0.5	0.5	1	1	1								0.064
Aspect	0.25	0.5	0.17	0.25	1	0.5	0.5	0.5	1							0.06
LULC	1	0.25	0.25	0.5	0.5	1	1	0.5	1	1						0.056
STI	0.33	0.25	0.17	0.5	0.25	1	0.33	0.5	0.17	0.5	1					0.029
NDVI	0.5	0.17	0.17	0.2	0.5	0.5	0.5	0.17	0.33	0.33	1	1				0.027
TRI	0.2	0.25	0.11	0.25	0.17	0.25	0.25	0.12	0.11	0.17	0.5	0.5	1			0.015
Lithology age	0.25	0.17	0.17	0.14	0.25	0.33	0.17	0.17	0.17	0.12	0.33	0.33	0.5	1		0.013
Geomorphology	0.33	0.25	0.14	0.17	0.17	0.5	0.25	0.25	0.12	0.17	0.25	0.25	0.5	1	1	0.015

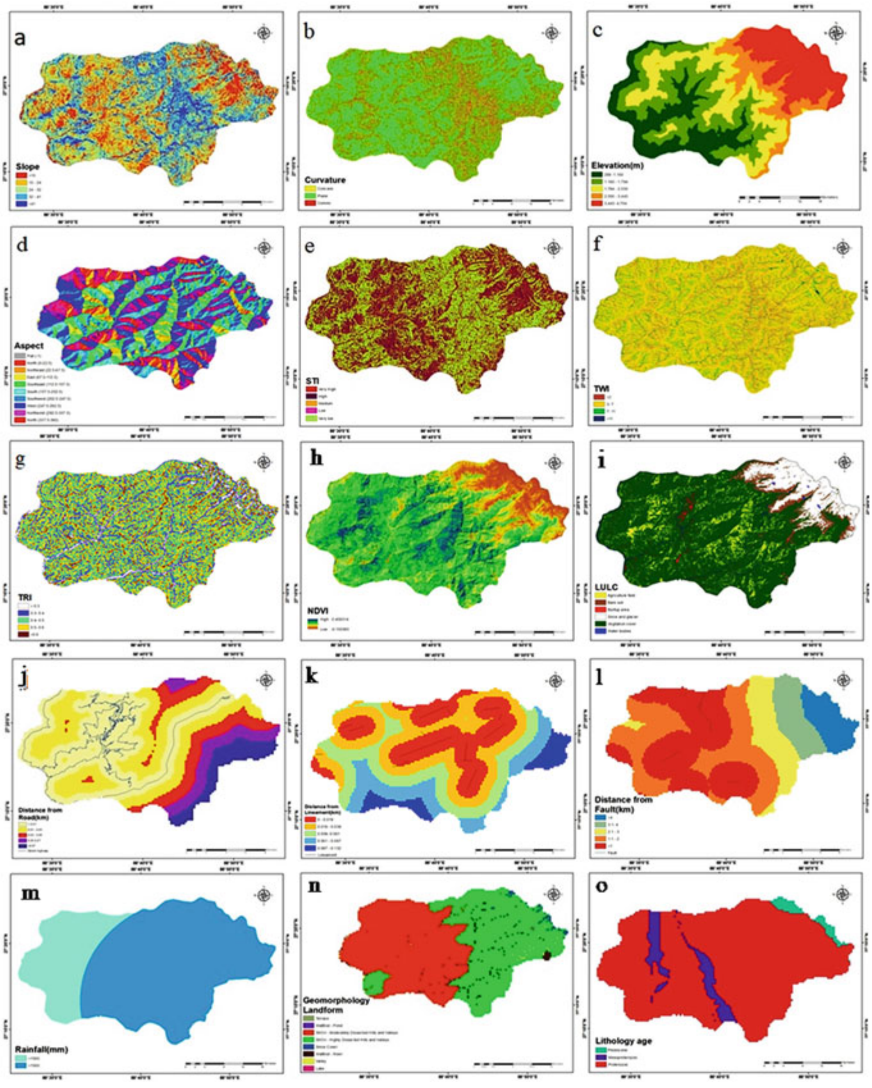

Fig. 3 Parameters such as **a** Slope, **b** Curvature, **c** Elevation, **d** Aspect, **e** STI, **f** TWI, **g** TRI, **h** NDVI, **i** LULC, **j** Distance from Road, **k** Distance from Lineament, **l** Distance from Fault, **m** Rainfall, **n** Landforms, and **o** Lithology used for landslide susceptibility mapping

had values greater than 40° and ranged between 0° to 70° (Fig. 3a). The study area has concave, plain, and convex curvatures, among them plain is dominant followed by convex and concave curvatures (Fig. 3b). The altitude of the study area ranges from 289 to 4704 m and the eastern part has the greatest variation in topography and almost half of the area has elevation >2500 m. Therefore, the study region is classified into five zones, viz., very low (289–1160), low (1160–1794), medium (1794–2550), high (2550–3443), and very high (3443–4704) (Fig. 3c). The aspect (slope orientation) affects the exposure to sunlight, precipitation, and wind, thus inversely affecting other factors that could be responsible for triggering the landslides such as vegetation cover, soil moisture, and thickness (Clerici et al. 2006). Accordingly, aspect has been categorized into flat, north, northeast, east, southeast, south, southwest, west, northwest, and north (Fig. 3d). The sediment transport index (STI), reflecting the erosive power of the overland flow depends on slope and upstream area that has been derived by considering the transport capacity limiting sediment flux and catchment evolution erosion theories (Devkota et al. 2013; Pradhan and Kim 2014). Higher STI scores denote that the area has more probability for the occurrence of a landslide (Fig. 3e), and accordingly, STI has been classified and considered in the AHP model. TWI has been calculated and results generated through DEM data denote that wherever the TWI is high, that area is considered more susceptible to landslide. The composite scores of TWI are categorized into four classes such as <2, 3–7, 7–11, and >11 (Fig. 3f). Moreover, TRI has also been calculated through DEM which too showed the similar criteria adopted in STI and TWI. The pixels under different scores of TRI have been categorized into five classes, viz., <0.3, 0.3–0.4, 0.4–0.5, 0.5–0.6, and >0.6 where higher score has more probability for the occurrence of landslide (Fig. 3g).

The NDVI and LULC thematic layers are prepared through Landsat 8–OLI dataset and these are also indicating factors that can help in finding the landslide susceptible area. The highly dense vegetative cover (>0.5), sparse vegetation (0.2–0.5), and bare land (0–0.2) areas are possibly extracted through NDVI. The NDVI scores have great potential to identify the more prone region in terms of landslide on the basis of land coverage, thus the values near 0 to 0.2 are highly susceptible (Behling et al. 2014), and accordingly, the mentioned range of NDVI values are prone within a range of our NDVI results from −0.156 to 0.459 (Fig. 3h). The spatial distribution of LULC showed that almost 2.27% of the area is covered by water bodies, 70.75% area is covered by vegetation, and 0.16 by built-up area (Fig. 3i). The remaining LULC areas such as agriculture fields (8.31%), bare lands (5.42%), and snow/glacier (13.08%) areas are exposed and make these regions highly susceptible to landslides. Other parameters such as distance from the road, lineament, and fault have also been considered and calculated through Euclidean distance (in km) into a few categories. The lowest (<0.01, <0.01, and <1) and highest (>0.07, >0.1, and >4) scores for the distance from the road, lineament, and fault are, respectively, (Fig. 3j–l). Road building activity in mountain areas is regarded as an infrastructure improvement that may be very detrimental to landslides. These lower scores suggest that the minimum distance from lineament, road, and fault makes the region more susceptible to landslides (Cao et al. 2021).

Rainfall is one of the significant triggering factors of landslides. Often, a heavy rainfall spell of 1 or 2 h can cause mass movement, or sometimes it can be an antecedent rainfall over the past few days (Dutta et al. 2021). The study area experiences an abundance of rainfall and recorded a value >1500 mm (Fig. 3m). The geomorphologic map depicts important geomorphic units, processes, landform, and structure that controls landslide. The geomorphological landforms are of eight categories: Terrace, WalBond-Pond, StrOri-Moderately Dissected Hills and Valleys, StrOri-Highly Dissected Hills and Valleys, Snow cover, WatBod-River, Valley, and Lake (Fig. 3n). Literature suggests that the dissected hills and valleys are more prone to landslides (Sonker et al. 2021). Most of the portion of this study area has moderately and highly dissected hills and valleys. It is recognized that geology is also one of the significant parameters that greatly influence landslide occurrence and lithological variation leads to a difference in the strength and permeability of rocks. Although lithology falls into three categories of geological age, i.e., Pleistocene, Mesoproterozoic, and Proterozoic periods (Fig. 3o), studies have suggested and was found that the Proterozoic age group in the Lesser Himalayan sequence is most prone to landslides (Tiwari et al. 2017).

4.2 Landslide Susceptibility Mapping

The various studies have been conducted and used weight combining methods for landslide susceptibility mapping (Abedini and Tulabi 2018). Identifying the landslide-prone area is not an easy task, as its mapping is very important for decision makers. The previously published researches have suggested that the AHP method is more suitable than the frequency ratio method. Therefore, in this study, a landslide susceptibility map was produced by combining all the influential factors according to weightage criteria using the AHP model (Table 3). Further, it was classified into low, medium, and high susceptible zones (Fig. 4). In light of the produced results, it was found that nearly 29% area of this region has been highly susceptible to landslides. The medium and low risks have shared 18 and 53% area, respectively, under the susceptible zones (Table 4).

The study area is undoubtedly not new to the phenomena of gravitational instability, as expected, the geologic setting and the characteristics of the terrains are a part of the Himalayas. Thus, the susceptibility to landslides is inbuilt in the natural characteristics of this landscape and there is a definite relationship between landslide occurrence and geophysical setup. Morphology of the hill slope has a great effect on the landslide events (Dai and Lee 2002). The Slope is considered as an important factor and the main reason for terrain instability (Haeri and Samiei 1996). In this study, high instability occurred in those regions where slopes were between 24° and 41°, whereas slopes less than 24° and higher than 41° angles were noticed to be less prone to landslide occurrences. Duration of rainfall and its intensity have a major role in the occurrence of landslides that, of course, depends on factors such as topography and geological structure of the slopes and their permeability (Lydia and Espizuajorge 2002). Heavy rainfall increases TWI, as well as STI, of a place due to water invasion in the gaps that leads to the slope deformation. The area where the values of STI, as well as TWI, were high has been found to be more susceptible to landslides. The instability is high in the valley area and along the roadsides. The city of Gangtok, which is the capital of Sikkim experiences great human interference and

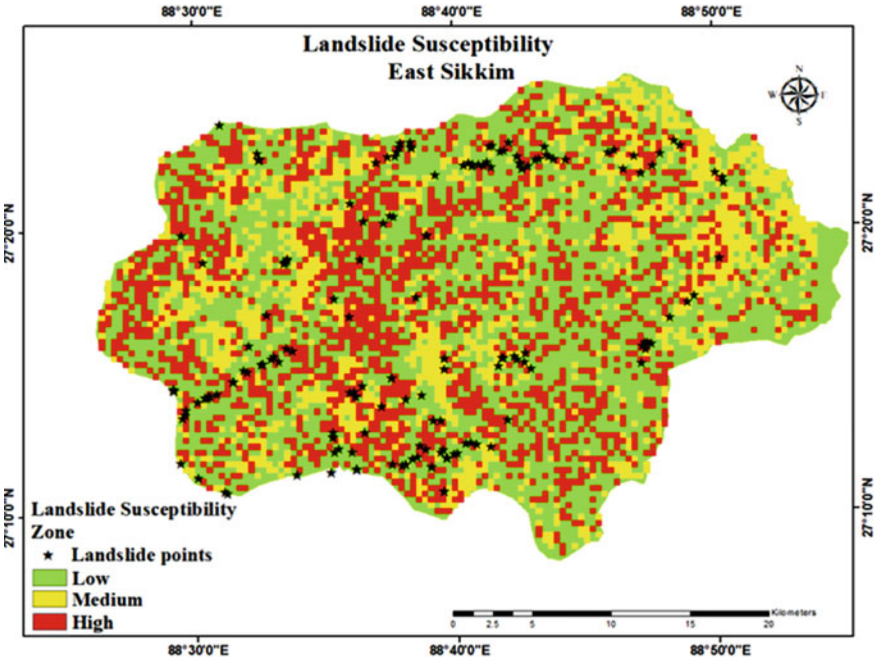

Fig. 4 Generated landslide susceptibility zones and overlaid point locations of past landslides

Table 4 Landslide susceptible zones with respective spatial coverage

Landslide susceptibility zone	Area in km^2	Area (%)
Low	510.42	52.948
Medium	165.54	17.172
High	288.04	29.88

goes through a phase of drastic development activities that ultimately influence the land cover and encroachments. This uncontrolled settlement and rampant expansion of roads and other land use practices encroached on the vulnerable land significantly increases not only the area under susceptible zones, but also the landslides frequency. The results showed that built-up areas, bare land areas, and agricultural field areas mostly fall into the high susceptibility zone. Road networking activity in mountain areas is regarded as an infrastructural enhancement, which may develop the ground for change in the stability of the landscape over there. The results reveal that the high susceptible zone is dominant along the roads and its periphery. The region is a part of an active continent–continent collision zone and the prime locations of all human activities enhance the risk potential of landslides. The area which lies within a 2 km buffer zone of the fault line falls under the high susceptible zone. Therefore, these all-important reasons are collaboratively responsible for landscape deformation.

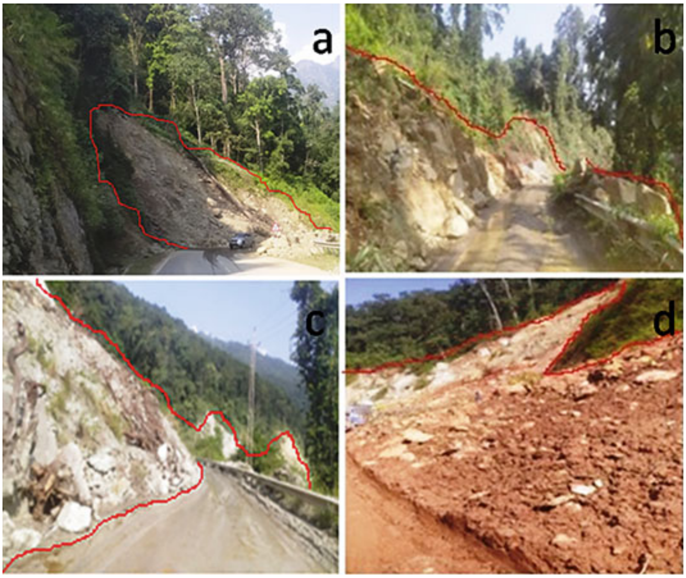

Fig. 5 Few samples of photographs of different types of slides. The Creep **a**, **b** Rockfall, **c** Debris flow cum rockfall, and **d** Debris flow pictures were taken during a field visit to validate the locations of landslides over susceptibility mapping

4.3 Landslide Inventories Validation Over Susceptibility Map

The landslide susceptibility map has been validated by superimposing the GSI landslide distribution point layer and supported by field photographs taken during the field visit (Figs. 4 and 5). According to GSI data, the study area had experienced approximately 167 landslides that differ in terms of width, length, and height. The overlaid analysis showed that most of the earlier landslides fall into the high susceptible zone followed by the medium and low susceptible zone. The different types of landslides photographs were also taken in the field in order to validate the present study (Fig. 5, panel a–d).

5 Conclusions

Disaster is a serious disruption that unstabilizes the general condition of the physical, social as well as economic environment. The young mountain region is more vulnerable to earthquakes and landslides. This study area is a part of the young folded mountain Himalaya, where landslide is a vast growing hazard that poses a great threat to human lives, properties, and rising infrastructure. Therefore, mapping landslide-susceptible zones is the first step to be taken as preventive measure. In this study, the AHP method has been used in the GIS environment by considering slope, LULC, NDVI, TWI, rainfall, Distance from (road, fault, and lineament), and elevation factors. AHP method is applied to assign the weight of each factor causing the landslide. Based on the AHP calculation, the four most influencing possible factors found for landslide occurrence are slope, rainfall, elevation, and TWI. The obtained susceptibility map and its related data show that the high susceptible zones cover an area of 29% followed by medium (17%) and low (53%) area. The map was validated by earlier landslides event data taken from GSI as well as supported with field photographs. However, the field visit was in the initial days to take an overview of the area, and the photographs taken for validation and to assess the types of slides are not sufficient enough to conclude the results very accurately in terms of field data. Although, landslide inventories dataset is highly recommendable to validate our landslide susceptibility mapping. This attempt would be helpful for planners and decision makers to follow the proper land use planning and slope management for sustainable development that could possibly minimize the upcoming landslide events in the study area.

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