



Landslide probability mapping by considering fuzzy numerical risk factor (FNRF) and landscape change for road corridor of Uttarakhand, India

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Abstract

Landslide poses severe threats to the natural landscape of the Lesser Himalayas and the lives and economy of the communities residing in that mountainous topography. This study aims to investigate whether the landscape change has any impact on landslide occurrences in the Kalsi-Chakrata road corridor by detailed investigation through correlation of the landslide susceptibility zones and the landscape change, and finally to demarcate the hotspot villages where influence of landscape on landslide occurrence may be more in future. The rationale of this work is to delineate the areas with higher landslide susceptibility using the ensemble model of GIS-based multi-criteria decision making through fuzzy landslide numerical risk factor model along the Kalsi-Chakrata road corridor of Uttarakhand where no previous detailed investigation was carried out applying any contemporary statistical techniques. The approach includes the correlation of the landslide conditioning factors in the study area with the changes in land use and land cover (LULC) over the past decade to understand whether frequent landslides have any link with the physical and hydro-meteorological or, infrastructure, and socioeconomic activities. It was performed through LULC change detection and landslide susceptibility mapping (LSM), and spatial overlay analysis to establish statistical correlation between the said parameters. The LULC change detection was performed using the object-oriented classification of satellite images acquired in 2010 and 2019. The inventory of the past landslides was formed by visual interpretation of high-resolution satellite images supported by an intensive field survey of each landslide area. To assess the landslide susceptibility zones for 2010 and 2019 scenarios, the geo-environmental or conditioning factors such as slope, rainfall, lithology, normalized differential vegetation index (NDVI), proximity to road and land use and land cover (LULC) were considered, and the fuzzy LNRF technique was applied. The results indicated that the LULC in the study area was primarily transformed from forest cover and sparse vegetation to open areas and arable land, which is increased by 6.7% in a decade. The increase in built-up areas and agricultural land by 2.3% indicates increasing human interference that is continuously transforming the natural landscape. The landslide susceptibility map of 2019 shows that about 25% of the total area falls under high and very high susceptibility classes. The result shows that 80% of the high landslide susceptible class is contained by LULC classes of open areas, scrubland, and sparse vegetation, which point out the profound impact of landscape change that aggravate landslide occurrence in

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that area. The result acclaims that specific LULC classes, such as open areas, barren-rocky lands, are more prone to landslides in this Lesser Himalayan road corridor, and the LULC-LSM correlation can be instrumental for landslide probability assessment concerning the changing landscape. The fuzzy LNRF model applied has 89.6% prediction accuracy at 95% confidence level which is highly satisfactory. The present study of the connection of LULC change with the landslide probability and identification of the most fragile landscape at the village level has been instrumental in delineation of landslide susceptible areas, and such studies may help the decision-makers adopt appropriate mitigation measures in those villages where the landscape changes have mainly resulted in increased landslide occurrences and formulate strategic plans to promote ecologically sustainable development of the mountainous communities in India's Lesser Himalayas.

Keywords Landslide susceptibility mapping (LSM) · Landscape · Fuzzy landslide numerical risk factor (FLNRF) · GIS · Land use land cover (LULC) change · Village hot spot

1 Introduction

Development of landscape is a long-term process affected by several factors, both natural and anthropogenic, at a local scale to a regional scale. The natural factors that influence the primary and secondary natural landscape are mainly governed by the geomorphological processes of weathering and erosion (Geertsema et al. 2009). Conversely, among the anthropogenic factors, the construction of roads, extraction of minerals, growing habitation, and deforestation are some prevailing activities that are often found to alter the landscape within a short period. To understand the changing behavior of a landscape, it is imperative to investigate the changing nature of land use and land cover (LULC) in an area.

Landslides in the Himalayas are among the most dangerous natural hazards that threaten human lives and livelihood and adversely affect the environmental condition and socioeconomic status of the people living there. Many landslides are activated every year in the Himalayan ranges during the monsoon season (June–August) due to its unique geotectonic setup (Pachauri 2010; Pandey and Sharma 2017; Sur and Singh 2019). The steeper slopes, profound weathering of bedrocks, and intense southwest monsoon rainfall in the Middle and the Lesser Himalayas are aggravated with growing development, increasing economic activities, and investments in landslide-prone areas (Gabet et al. 2004; Ambrosi et al. 2018; Sharma et al. 2020). According to the Geological Survey of India (GSI), about 0.14 million sq. Km area in Uttarakhand, Himachal Pradesh, and Jammu and Kashmir (North West Himalayas) are prone to landslide hazard (GSI Bhukosh 2020). The Lesser Himalayas of India's Uttarakhand state has observed a considerable rise in developmental activities in the past decade. Such anthropological influence resulted in increasing number of natural hazards together with extreme climate conditions (Allen et al. 2015). Most often the landslides are triggered by torrential heavy rainfall, seismic activities, or, anthropological reasons such as heavy vehicles' movement or, usually, human activities on unstable slopes (Kwan et al. 2014; Li et al. 2014). Many of the past literature reviews suggest that the complex hydro-geological settings and increasing anthropogenic activities are among the key factors that often influence the landslide occurrences in India's Himalayan region (Rai et al. 2014; Singh and Sharma 2020).

The Kalsi-Chakrata road corridor in the Dehradun district of India's Uttarakhand state, experiences a substantial amount of damages to roads, buildings, and other infrastructure elements and, sometimes, loss of lives due to rain-induced landslides during the monsoon period (June–August). This hazard incurs significant economic losses that affect the livelihood of the village communities residing in those rugged mountainous regions of Garhwal Himalayas. The incidents of roadblocks and damages during the monsoon months have been reported by national and local news agencies almost every year (Sur et al. 2020). The Amraha landslide between Kalsi and Sahiya town is recurring every year for more than a decade, disrupting the road connectivity and often bringing life to a complete standstill. A thorough literature review reveals that no in-depth and holistic scientific research has been conducted on landslide hazard mapping in the Kalsi-Chakrata road corridor. Hence, it is imperative to perform a comprehensive landslide hazard assessment concerning the landscape regarding environmental and social parameters applying advanced geospatial techniques. This paper's primary purpose is to investigate whether the landscape change has any impact on landslide occurrences in the Kalsi-Chakrata road corridor by detailed investigation through correlation of the landslide susceptibility zones and the landscape change and finally demarcate the hotspot villages where influence of landscape on landslide occurrence may be more in future.

The variations in land use and land cover (LULC) in mountainous terrain can increase or decrease a landscape's probabilities. In several studies, it has been noted that a positive relationship exists between the alterations in the landscape and the incidence of landslides (Chen et al. 2019). The correlation of the changes in LULC in the past may help to understand whether frequent landslides have any link with the physical and hydro-meteorological causes or due to the increasing economic activities in an area. Landslides primarily occur by dislocation of soils on steep slopes by heavy rains, aggravated by several hydro-geomorphological processes and anthropogenic activities. The areas with added forest and vegetation cover have soil more stabilized than the regions that experience many developmental activities through deforestation, construction on hill slopes, etc. (Sartohadi et al. 2018). The hilly terrain of the tropical belt, such as the Lesser Himalayas, often faces the pronounced impact of climate change. Such implications may result in volatile precipitation that increases the risk of landslide occurrence many folds, thus threatening people's lives and infrastructural damages and left a profound impact on an area's environment and ecology (NASA/Goddard Space Flight Center 2020; Dikshit et al. 2020).

It is evident from the literature survey that human activities often lead to reforms and alterations in the natural landscape, which may lead to the activation of complex hydro-geomorphological processes resulting in landslides (Sur and Singh 2019). All over the world, more emphasis has been put on the impact of landslides on human lives and infrastructure; however, little attention has been paid to its impact on the natural environment and ecology (Schuster and Highland 2007; De Sy et al. 2013). In some of the significant past studies, environmental degradation and socioeconomic indicators that play a crucial role in landscape change has been emphasized as possible reason behind the increased landslide occurrences (Abbas et al. 2019). It is also evident from studies that the fragile Himalayan landscape are highly susceptible to natural hazards, leading to increasing concern among the scientists on current and future climate change scenarios (World Bank 2013). The latest studies also emphasized the impact of physiography and climate change as significant parameters that aggravate the landscape changes in the mountainous areas (Abbas et al. 2020). In this context, the manmade process such as road/railway construction, dumping, undercutting of slopes, quarrying and mining,

excavation for building and structure construction, etc., on slopes often modifies the landscape and sometimes aggravates the factors responsible for landslides in hilly terrain (Kumar and Gorai 2018; Nseka et al. 2019). As a result, in some cases, landslides in various forms may be experienced in a newer, previously non-existent anthropogenic landscape where the direct and indirect impacts of landslides may sometimes persist in the long term. The direct impact of a landslide is damages and losses attributable to the areas of occurrence due to the landslide (Heping et al. 2019; Chen et al. 2019). In contrast, indirect costs include environmental impacts, livelihood changes, changes in agricultural practices, transport disruption, economic restrictions, etc. In a highly dynamic environment like the Himalayas, landslides change the landscape and often substantially influence human lives and activities. In the mountainous rural areas, significantly the changes in the landscape and economic losses due to landslide sometimes inflict a substantial threat to the societies (Fu et al. 2020).

As depicted above, the Himalayas in the tropics is a comparatively recent formation that is seismically active rugged and hilly terrain is highly fractured and weathered due to intense folding and faulting (Pachauris 2010). Caused by a higher degree of human interference in the form of continuous construction activities, deforestation, improper cultivation practices, increased vehicular movements, mining, more and more areas of the Lesser Himalayas are becoming focal points for increased economic activities. All these factors, coupled with hydro-geological and climatological parameters, induce more frequent landslide events in the Himalayas (Khanduri 2017). Therefore, it is imperative to investigate the occurrences of landslides concerning the landscape in such areas so that necessary fortification and mitigation methods may be adopted to reduce the landslide hazards and reduce the landscape's fragility.

There are several advanced approaches and techniques for predicting landslides applied in different parts of the globe that try to address other aspects of landslide prediction (Singh et al. 2015). Those techniques' accuracy and prediction capability often vary widely (Chen et al. 2016; Meena et al. 2019). In the past decade, there has been quite a few proper research works carried out based on a contemporary approach to prepare landslide susceptibility assessment based on qualitative and quantitative methods (Guzzetti et al. 1999; Pradhan and Lee 2010; Tien Bui et al. 2015, 2019; Haoyuan et al. 2016; Pham et al. 2017; Gao et al. 2019; Dikshit et al. 2020; Sharma et al. 2020). One general and essential procedure for spatially predicting the landslide hazard is developing landslide susceptibility index (LSI) mapping. The statistical models, in particular, are based on the data-driven methodology that is well capable of predicting the landslide susceptible areas spatially. Such techniques provide a useful prediction for the decision-makers and authorities in adopting appropriate approaches in minimizing the potential damages and losses from existing and future landslides (Pourghasemi and Rahmati 2018; Sur and Singh 2019; Singh et al. 2020).

The present study has followed the GIS-based multi-criteria decision making (MCDM) approach like fuzzy landslide numerical risk factor (FLNRF) model for mapping the landslide susceptibility. The FLNRF or fuzzy LNRF is a contemporary statistical model based on the data-driven methodology that spatially predicts the landslide susceptible zones. The fuzzy set theory has been implemented to allow greater flexibility to resolve the uncertainty and imprecision and provides more accurate results using fuzzy membership functions to address this issue. Several other researchers have applied the FLNRF model considering important landslide conditioning factors such as slope, rainfall, altitude, aspect, geology, soil, distances from road, fault, and river in their work and generated the

landslide susceptibility maps having considerably higher accuracy (Torkashvand et al. 2014; Roy and Saha 2019).

The rationale of this work is to delineate the areas with higher landslide susceptibility using the ensemble model of FLNRF along the Kalsi-Chakrata road corridor of Uttarakhand where no previous detailed investigation was carried out previously applying any contemporary statistical techniques. In the present study, the remote sensing technique was used to spatially delineate the past landslide locations followed by detailed field investigation. To assess the landslide susceptibility zones, the geo-environmental or conditioning factors such as slope, rainfall, lithology, normalized differential vegetation index (NDVI), proximity to road and land use and land cover (LULC) were considered, and the fuzzy LNRNRF technique was applied. In order to do this, the fuzzy membership function (MF) value was estimated for each factor and afterward, the MF value of parameters using the fuzzy gamma operator has been assembled with the LNRNRF model for producing the LSM. The output LSM was then validated using landslide test locations based on receiver operating characteristic (ROC) curve. The novelty of this research is that though many of the researchers have applied LNRNRF method for LSM; however, this is the first instance when the knowledge-driven technique (fuzzy logic) assembled with LNRNRF model has been applied in a Lesser Himalayan road corridor in Uttarakhand. Likewise, the present study was the first instance when a detailed geospatial investigation has been carried out to correlate the landscape change with the landslide probability. This has been done by considering the LULC map of 2010 and 2019 in the FLNRF model considering all the remaining conditioning factors as constant. The landslide susceptibility map of 2010 and 2019 generated has been analyzed in the light of landscape change at village level so that inferences can be drawn to find out the village priorities where more attention is required for appropriate mitigation measures.

2 Study area

The study area includes 34 villages located in the Dehradun district of Uttarakhand state in India through which the 42-km long Chakrata-Kalsi road corridor passes. Chakrata is a popular hill station and a famous tourist destination at the height of 2118 m above sea level in the Lesser Himalayan ranges. Kalsi, on the other hand, is a small cantonment town located at the bank of the Yamuna River. According to the Census of India (2011) village boundary data, the study area spreads over 83 sq. Km area with a population of more than 16,600 residing in 2700 households. As per the Bureau of Indian Standards (BIS), the entire study area falls in seismic zone V, and the Main Boundary Fault (MBT) passes through the road corridor. The study area has a very rugged topography with altitude ranging between 433 m (near Yamuna River) and 2456 m (near Chakrata). The mean altitude of the area is 1445 m above mean sea level. The temperature ranges from 1.4 °C in winter to 34 °C in summer, with an average annual rainfall varying between 1339 and 1479 cm. The road corridor is situated in the Siwalik and Middle Himalayas, one of the most seismically active regions. The geology, structures, and lithology of the area have been mapped using geological maps acquired from GSI. In the study area, the outer sedimentary belt consists of the Krol belt, while the inner belts constitute thick sequences of unmetamorphosed sediments. There are seven geological formations observed in the study area, of which the Jaunsar group is the predominant formation that covers more than 90% of the geographical area. During the field investigation, the Mandhali-Chakrata Formation (Proterozoic II) and Chandpur Formation (Proterozoic III lower), where most of

the landslides occurred, were studied concerning other landslide conditioning factors. The Main Boundary Thrust (MBT) can be easily distinguished near the Kalsi town. The study area typically experiences three seasons. Agriculture, social forestry, and mining activities are among the villagers' essential means of livelihood (Fig. 1).

The common types of rain-induced landslides in this area include debris slide, debris flow, rock slide, and rockfall (Fig. 2). A substantial number of landslides occur between June and August every year when the torrential monsoon rain saturates the surface soil and rocks, which often leads to slope failure under the influence of the geo-environmental factors. The most widespread and threatening landslide is the Amraha landslide that has increased in size by more than ten times in the previous two decades (Fig. 2). This often causes blockade of the village roads during the monsoon resulting in a disruption in the vehicular movements and economic loss. Apart from direct damages to assets and damages to infrastructure, there are often significant indirect losses that significantly impact the communities residing in the study area. These indirect losses usually occur due to the interruption of road transport and obstacle in economic activities (rotten fruits and vegetables). Overall, the collective influence of the newer geologic formation, rugged terrain,

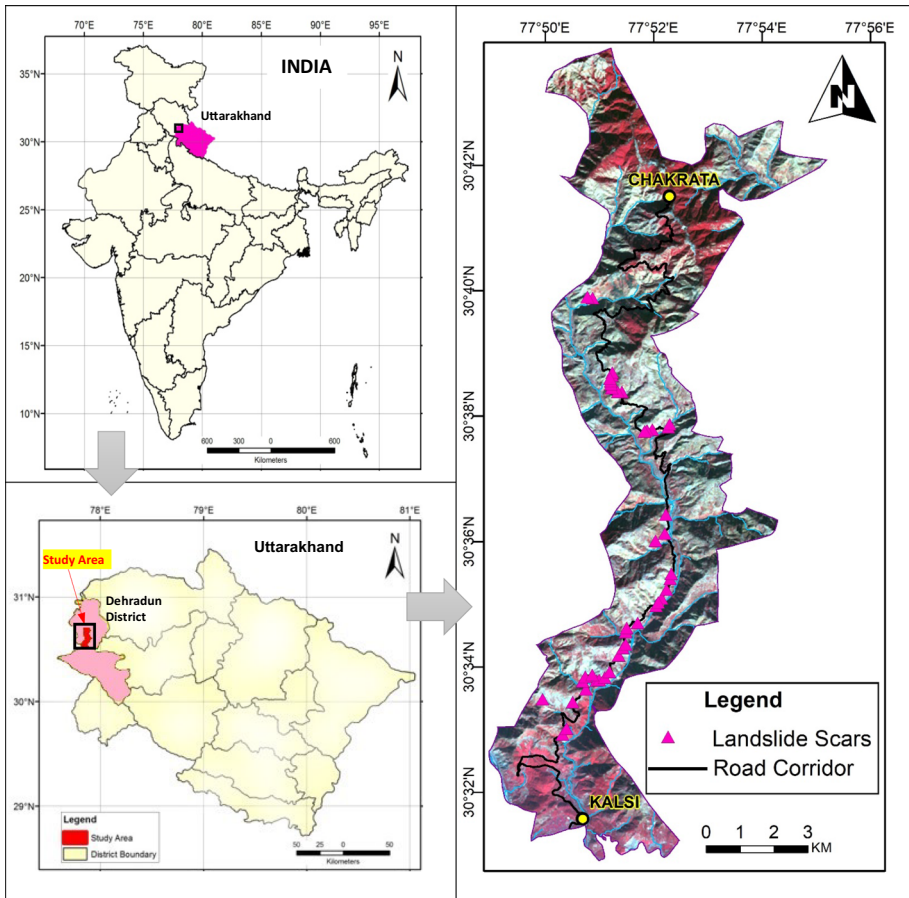


Fig. 1 Location of the study area

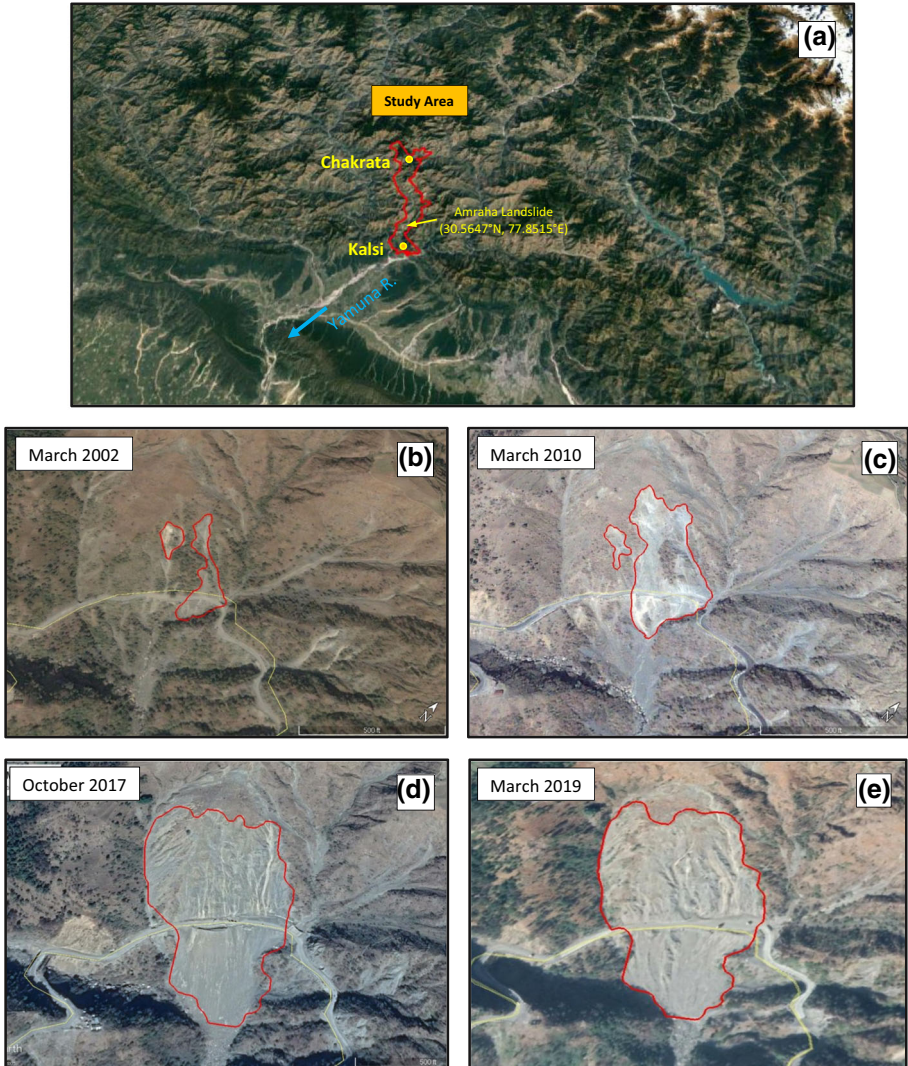


Fig. 2 Expansion of Amraha landslide over the past two decades. **a** Panoramic view of the study area with Amraha landslide; **b–e** advancement of Amraha landslide near Sahiya town over the past two decades delineated from Google Earth satellite images

high seismicity, higher monsoonal rainfall, deep weathering, and intense anthropogenic activities on unstable slopes most likely have a substantial influence on periodic landslides.

3 Materials and methods

The first step in any LSI mapping is to organize a detailed landslide inventory by interpreting the high-resolution satellite data, which was further validated through intensive field investigation (Guzetti et al. 1999, 2012; Deng et al. 2017; Ambrosi et al. 2018). Next, the critical conditioning factors (geo-environmental factors) were identified through

literature review and field data analysis for further consideration in predictive models (Marinos et al. 2019). These are the factors that might have been responsible for triggering a landslide in the past. The conditioning factors usually considered are topography, geo-hydrology, climate, and anthropogenic activities (Wang et al. 2019). More efforts have been made to generate thematic layers using higher-resolution and the latest vintage data for selected geo-environmental factors after a thorough literature review and necessary validation in the present study. The detailed information of the data source is presented in Table 1. The following sub-sections present the data and materials used in this study and the methodology adopted for generating LSI maps.

Table 1 Detail of thematic layers and their data sources

Thematic Layers	Sub-classes	Data description	Vintage	Data source
Land use/land cover (LULC)	LULC 2010	Landsat 7 enhanced thematic mapper plus (ETM ⁺)	10.3.2010	http://earthexplorer.usgs.gov
	LULC 2019	Resourcesat-2/linear imaging self-scanning system IV (LISS-IV) (5.8 m)	17.3.2019	National Remote Sensing Centre (NRSC), India
Landslide inventory	Test and training data sets	Cartosat (2.5 m)	2017	NRSC, India
		Resourcesat-2/LISS4 (5.8 m)	2019	NRSC, India
		Google earth, public works department (PWD), Published reports, Bhukosh from Geological Survey of India (GSI)	2006–2017	https://earth.google.com ; Geological survey of India (http://bhukosh.gsi.gov.in) Public Works Dept., Uttarakhand
DEM/DTM	DTM	Cartosat (2.5 m), Resourcesat-2/LISS4 (5.8m)	2017	NRSC, India
Topographical	Slope	Slope angle (10 m)	2017	NRSC, India; (processed digital terrain model (DTM) by the researcher)
Geological	Lithology	Lithological classes (1:25,000)	2015	Geological Survey of India
Meteorological	Rainfall	Indian meteorological department (IMD) rainfall data	1947–2017	https://data.gov.in ; https://mausam.imd.gov.in
Vegetation	Normalized difference vegetation index (NDVI)	Resourcesat-2/LISS4 (5.8 m)	2017	NRSC, India
Road	Road proximity	Resourcesat-2/LISS4 (5.8 m) Google Earth	2017	NRSC, India https://earth.google.com ;

3.1 Data sources

For carrying out the current investigation, various essential information has been acquired from various sources, e.g., the Cartosat digital elevation model (DEM) from the National Remote Sensing Centre (NRSC), Hyderabad, rainfall data from the Indian Meteorological Department (IMD), lithology data from Geological Survey of India (GSI). The land use/land cover (LULC) data were generated from Landsat 7 Enhanced Thematic Mapper Plus (ETM⁺) and Resourcesat-2/Linear Imaging Self-Scanning System IV (LISS-IV) for the year 2010 and 2019, respectively. The LISS-IV data of NRSC were used to generate the normalized differential vegetation index (NDVI) and road network thematic layers. The overview of the procedure adopted here is shown in the flowchart in Fig. 5.

3.2 Software used

To predict the landslide susceptible areas, the thematic data layers were prepared using ArcGIS 10.8, ENVI 4.7, and GEOMATICA software for selected landslide conditioning factors, namely slope, lithology, rainfall, NDVI, road proximity, and LULC. The mathematical calculation has been done in SPSS software. The final aggregation of LSM values has been carried out in ArcGIS 10.8.

3.3 Landslide inventory mapping

Landslide inventory mapping helps to comprehend the factors or conditions that might have been accountable for triggering a past landslide or signify the incidence of an active landslide (Marinos et al. 2019). The landslide inventory, in this study, was prepared using three primary sources supported by in-depth field surveys and laboratory investigations:

- i. The landslide records collected from Uttarakhand public works department (PWD)
- ii. Bhukosh: Online data sharing platform of GSI
- iii. Identification of possible past landslide scars delineated from higher-resolution periodic earth observation data (LISS-IV satellite images captured in March 2019 and Google Earth satellite images between 2001 and 2017)

The boundaries of the landslide events were delineated as precisely as possible. The records collected in this process were examined through extensive field surveys mostly along the road corridor, including the connecting village roads using the Global Positioning System (GPS) instrument and geo-tagged camera during the monsoon and post-monsoon periods (Fig. 3). It was observed that the common types of rain-induced landslides in this area include debris slide, debris flow, topple failure, rock slide, and rockfall. The landslide inventory comprises the type of movement, type of material, the slide's dimension, the damages/losses caused by past events. There were 56 prominent landslide locations demarcated as in 2019, along with descriptions of the landslide hazard. For both modeling and validation purpose, the landslide point locations were used in the model. In the absence of any defined procedures for selecting the ratio of the training (for model preparation) and validation dataset (for verification of model's performance) (Guzzetti et al. 2012), the most commonly selected sample ratio is 70/30 for training and validation (Tsangaratos and Ilia 2016; Deng et al. 2017; Sur et al. 2020). Following this process, 38 sites (70%) were selected randomly as training dataset to develop the model and the remaining 17 landslides (30%) sites were considered to test the prediction accuracy. Similarly, for the year 2010, 35

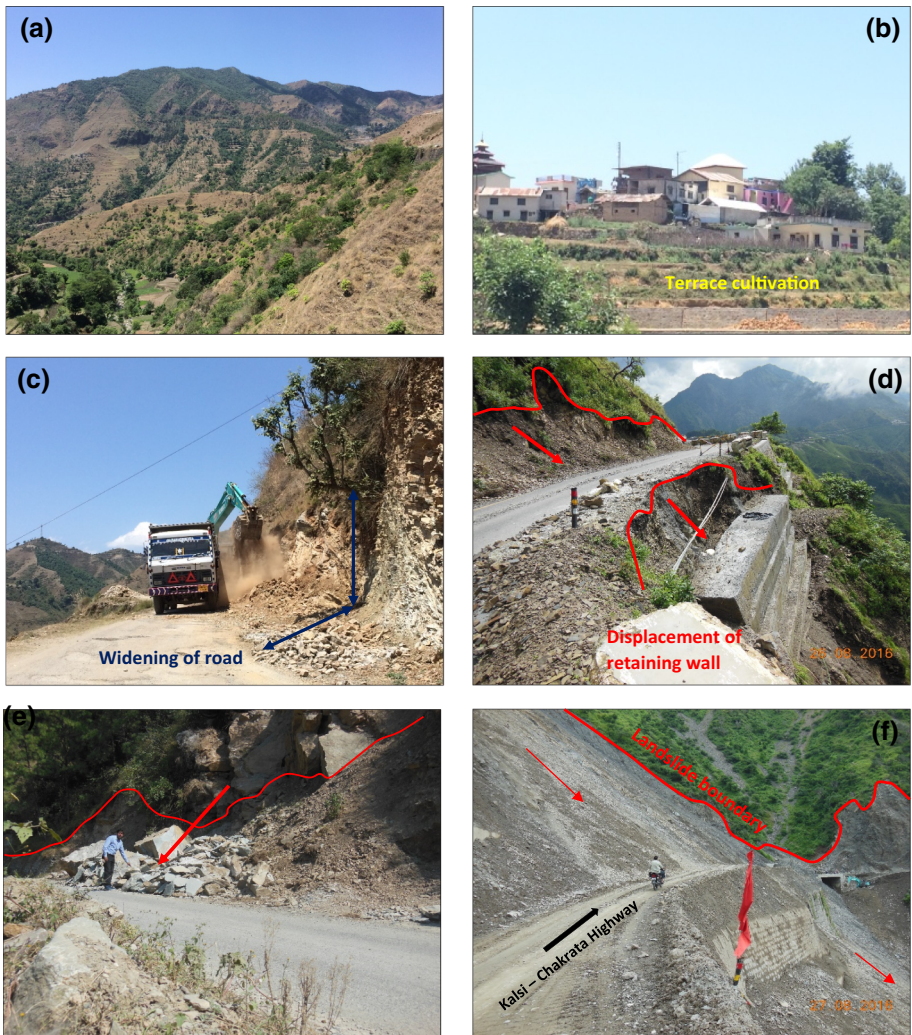


Fig. 3 Photographs demonstrating overview of the landscape and spatial location of landslides. **a** The landscape along the Kalsi-Chakrata road corridor near Chakrata; **b** view of typical village in near Sahiya; **c** cutting of slope for road widening near Sahiya; **d** lateral displacement of retaining wall near Amraha; **e** rockfall and fragmentation near Dhaira village; **f** debris slide in Amraha area, the prevalent landslide in the road corridor

landslide locations were delineated for comparative study and expansion of the landslides. These data were also chosen for correlation between the landscape and the landslides.

3.4 Landslide conditioning factors

The landslide conditioning factors are nominated based on in-depth literature review, and their numbers selected for LSM may vary from a small number of factors (Pradhan and Lee 2010; Akgun 2012) to a large number of factors (Catani et al. 2013; Tien Bui et al. 2015;

Xu et al. 2016; Zhang et al. 2018; Sharma et al. 2020; Singh et al. 2020; Sur et al. 2020). In this study, the most influencing conditioning factors in the Himalayan terrain, such as slope, rainfall, lithology, normalized differential vegetation index (NDVI), proximity to road and land use and land cover (LULC), were picked up. The thematic layers for these factors were prepared from authentic sources using remote sensing and GIS software with a pixel size of 10 m and categorized applying Jenks natural breaks. The digital terrain model (DTM) was generated from Cartosat digital elevation model (DEM) (10 m resolution) and LISS-IV satellite images (5 m resolution) in Global Mapper software at a 10 m resolution. The quality of the DTM was checked through the Survey of India (SOI) spot heights, GPS reading collected during field visits, and differential global positioning system (DGPS) points already used in other published reports in the Chakrata-Kalsi area. The thematic layers for the remaining factors were generated using ArcGIS 10.3 software from secondary sources selected carefully based on their authenticity, scale, and vintage.

Rainfall is one of the most significant conditioning factors stimulating the landslide's occurrence in the Himalayas as rain affects slope stability through runoff and pore water pressure (Wang et al. 2019). The daily rainfall data for eight sub-districts headquarter stations surrounding the study area were obtained from the Indian Meteorological Department (IMD) for the past 70 years (from 1947 to 2017). The mean annual rainfall data, using the inverse distance weighted (IDW) method, were interpolated to produce the annual rainfall map. Next, the rainfall map has been categorized into five distinct classes such as very low (1339–1371 mm), low (1372–1398 mm), moderate (1399–1426 mm), high (1427–1453 mm), and very high (1454–1479 mm), respectively. About 75% of the past landslides occurred in the high and very high landslide categories (Fig. 4a).

The slope is another major contributory factor for landslides in the Lesser Himalayas for landslide initiation. The slope angle directly influences shear strength, and more material disintegrates for given material strength on the steeper slopes. Such a condition often produces more massive landslides (Zhang et al. 2018; Wang et al. 2019; Sur and Singh 2019; Sur et al. 2020). In this study, the slope map has been generated from the Cartosat DTM and classified into five classes ($< 10^\circ$, 10° – 20° , 20° – 35° , 35° – 50° , $> 50^\circ$) applying Jenks natural breaks method (Fig. 4b).

In the Himalayan terrain, another significant contributory factor for landslides is lithology that determines rocks' strength and permeability (Wang et al. 2019). In this study, the lithological data were captured from the GSI map available at 1:25,000 scale using ArcGIS software that comprises eight distinct categories. The literature shows that the rock stratum having less shear strength and lesser permeability produces more number of landslides. Another noteworthy finding from the lithological map is that most past landslides occurred in the Mandhali-Chakrata Formation and Chandpur Formation. These two formations cover large areas along the road corridor containing highly weathered and less amalgamated greywacke rock materials (Fig. 4c).

NDVI strongly influences the likelihood of land sliding. This study's NDVI map was generated from LISS-IV satellite imagery and classified into five categories from very low to very high: -0.24 – 0.19 , 0.19 – 0.31 , 0.31 – 0.39 , 0.39 – 0.48 , and 0.48 – 0.77 (Fig. 4d). NDVI value varies between -1 and $+1$, and the high positive NDVI value (near to $+1$) indicates a higher and healthier vegetation cover. In contrast, areas with negative NDVI values (near -1) indicate that the bare earth surface is devoid of vegetation. It has been observed that the areas with a steeper slope, higher rainfall, and less vegetation are more susceptible to frequent landslides (Singh et al. 2015; Sur et al. 2020).

The road-building activity and movement of heavy vehicles in the Lesser Himalayas road corridors are among the causes of frequent landslides. A considerable number of

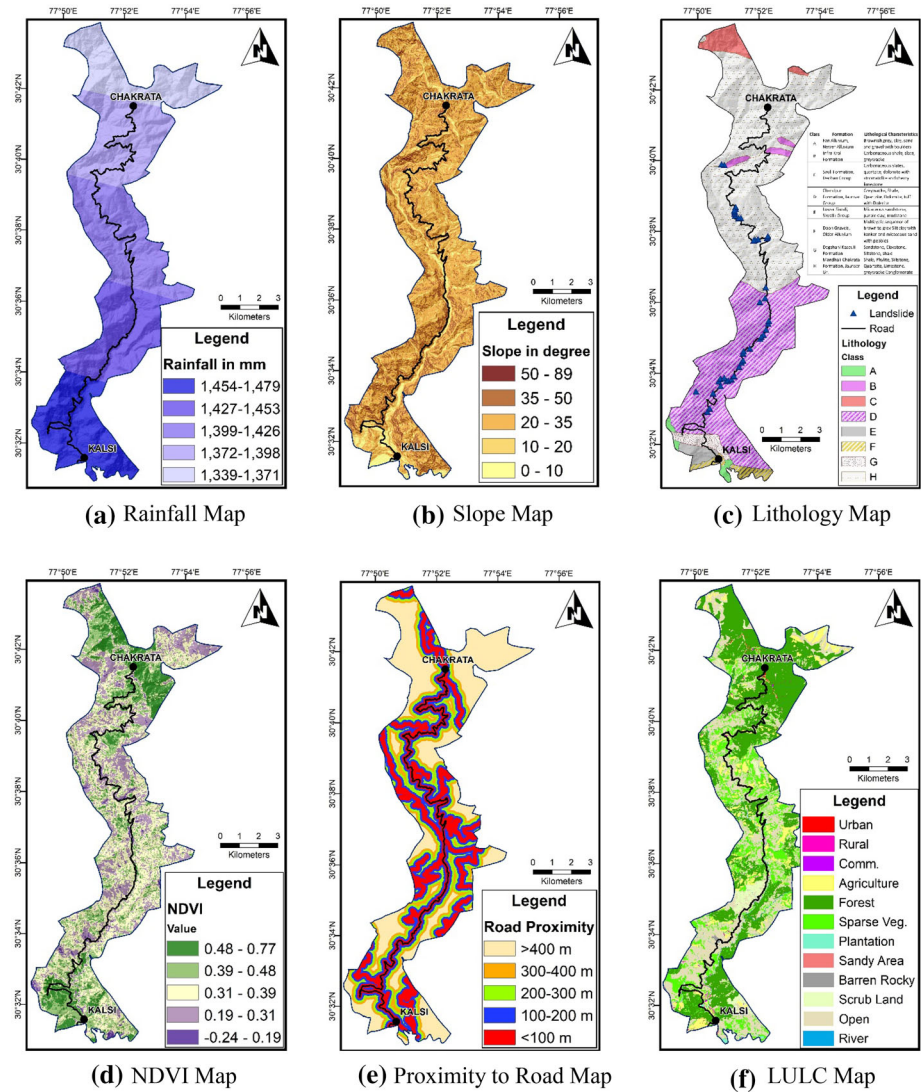


Fig. 4 Landslide conditioning factors (a–f) considered

landslides across the Himalayas occur in the road cuts mainly due to excavation, hydrologic load change, and deforestation that disturbs the stability of the slope (Wang et al. 2019). The study area’s road network, extracted from LISS-IV satellite images, was divided into state highway, main road, and village roads. The proximity to the road map was carried out in the ArcGIS software at < 100 m, 100–200 m, 200–300 m, 300–400 m, 400–500 m, and > 500 m. In this regard, it may be considered that there is no standard procedure to determine the proximity to roads as a landslide conditioning factor in the literature (Sur et al. 2020). By changing the distance to any of these parameters, the output will be different. Hence, based on expert opinion, past studies, and observations during the field investigation, the road proximity has been determined in this study too. It was seen

that out of 55 cataloged landslides in the study area, as many as 48 are located within a distance of 100 m from the roads (Fig. 4e). It indicates road proximity as a significant contributory factor for landslides in the Kalsi-Chakrata road corridor.

The LULC layer was generated from the LISS-IV satellite image applying the pixel-wise classification technique, further validated with available SOI topographical sheets and the published LULC data from NRSC. Following the classification scheme adopted by the National Remote Sensing Centre (NRSC), India, 14 distinct LULC classes were derived for the study area. It has been noted that 67% of the landslide incidents occurred in LULC classes of sparse vegetation, scrubland, and barren rocky areas where weathering of rocks and erosion process influence the land sliding (Fig. 4f).

3.5 Land use/land cover layers for landscape change analysis

An effort has been made to evaluate the interface between landscape and landslides in the study area by studying the change in land use/land cover patterns in the study area. The LULC data were generated from Landsat 7 Enhanced Thematic Mapper (ETM) for 2010 at 15 m spatial resolution and from IRS P-6 LISS-IV satellite image for 2019 at 5.8 m spatial resolution applying the supervised classification technique through maximum likelihood (Shastri et al. 2020). The selected training sets were collected through an intense field survey to attain the classified data's desired accuracy. The thematic LULC layer was categorized into 14 classes following the NRSC scheme. The landslide areas shown in the inventory were overlaid on the LULC layer to observe whether the landslides shifted from one class to another over time.

3.6 Landslide susceptibility modeling approach using fuzzy landslide numerical risk factor (FLNRF)

Landslide susceptibility may be expressed as the possibility of landslide in an area, and it represents the degree to which a place can be affected by future slope movements (Guzzetti et al. 1999). As described in the introduction section of this paper, applying geospatial techniques, the index weights for the landslide conditioning factors have been assessed using the fuzzy landslide numerical risk factor (FLNRF) model. The LNRF model is a contemporary landslide probability model where landslide risk is determined by using the past landslide slip surface in a unit compared to the mean past occurrence slip in the whole unit.

$$\text{LNRF} = A/F \quad (1)$$

where A : landslides in every unit, F : mean area of landslide contained by the whole unit.

The $\text{LNRF} > 1$ value signifies the higher probability of a conditioning factor in contributing to the landslide occurrence. At the same time, $\text{LNRF} < 1$ indicates less likelihood of a conditioning factor to stimulate a landslide occurrence. Next, the concept of fuzzy logic was applied in the LNRF model. The FLNRF technique is an advanced statistical technique for predicting the landslide hazards that embeds the fuzzy theory applied to the traditional LNRF model using the concept of membership function (MF). The calculation of FLNRF that was carried out in this study may be expressed as:

$$A = \{m, \mu_A, (m)\} \text{ for each } m \in M \quad (2)$$

where μ_A is the MF, i.e., the membership of (m) in fuzzy set A .

This means

$\mu_A = 0$ when m does not belong to A .

$\mu_A = 1$ when m belongs completely to A .

$0 < \mu_A(m) < 1$ when m belongs in a certain degree to A .

Accordingly, the MF used for the conditioning factors is:

$$\mu_A(m) = f(m) = \begin{cases} 0 & m \leq a \\ m - a/b - a & a > m > b \\ 1 & m \geq b \end{cases} \quad (3)$$

where m is the input data and a, b are the limit variables.

For combining the MF, a fuzzy gamma operator value of 0.975 has been considered in a GIS environment while generating the landslide susceptibility map at 10 m \times 10 m grid cells.

Finally, to assess the influence of LULC change on landslide spatial probability, the landslide susceptibility index (LSI) has been computed applying the fuzzy LNRF or FLNRF model considering the change in LULC classes between 2010 and 2019, while all the remaining conditioning factors (slope, lithology, rainfall, NDVI, and proximity to the road) remain unchanged (Fig. 5). The LSI values were further categorized into five distinct LSM classes (very high, high, moderate, low, very low) using Jenks natural breaks. The results attained from the fuzzy LNRF model were validated through receiver operating characteristics (ROC) curve.

4 Results

As discussed in this paper's introduction and methodology section, landslides can have a long-term impact on the environment. Even the topographic changes caused by some giant rock slides may persist for hundreds of years. Therefore, to assess the impact of landslides in this study, the changes in LULC over about 10 years were studied considering the past landslide events and the conditioning factors in the FLNRF model. Finally, the landslide susceptibility was spatially interrelated with the landscape of the area.

4.1 Land use and land cover maps and decadal change detection

It has been observed that significant changes occurred in the natural landscape in a period of the past 10 years, and the same is reflected from the analysis of LULC maps of 2010 and 2019 (Fig. 6). In 2010, the Kalsi-Chakrata road corridor had more vegetation cover, which accounts for > 59% of the total area in the forest and sparse vegetation classes. Among the other LULC classes, open areas constitute for about 28%, while agriculture and scrubland covered about 7.4% and 3.5% of the total study area, respectively. Significantly, the forest cover of the area has been reduced by more than 6% in 2019 compared to 2010 (Table 2). Since vegetation cover has a positive impact on lowering the landslides, the rapid exhaustion of such green belts' in the study area may aggravate more landslides in future. Figure 5 shows that the landscape, such as open areas, barren land, and scrubland that have more potential in producing frequent landslides, has increased by about 6% during the last decade. It has also been observed that the human settlement in the study areas has been increased from 0.4% in 2010 to 0.6% in 2019, which indicate more amount of anthropogenic interventions in the form of increased vehicular movement, widening of roads,

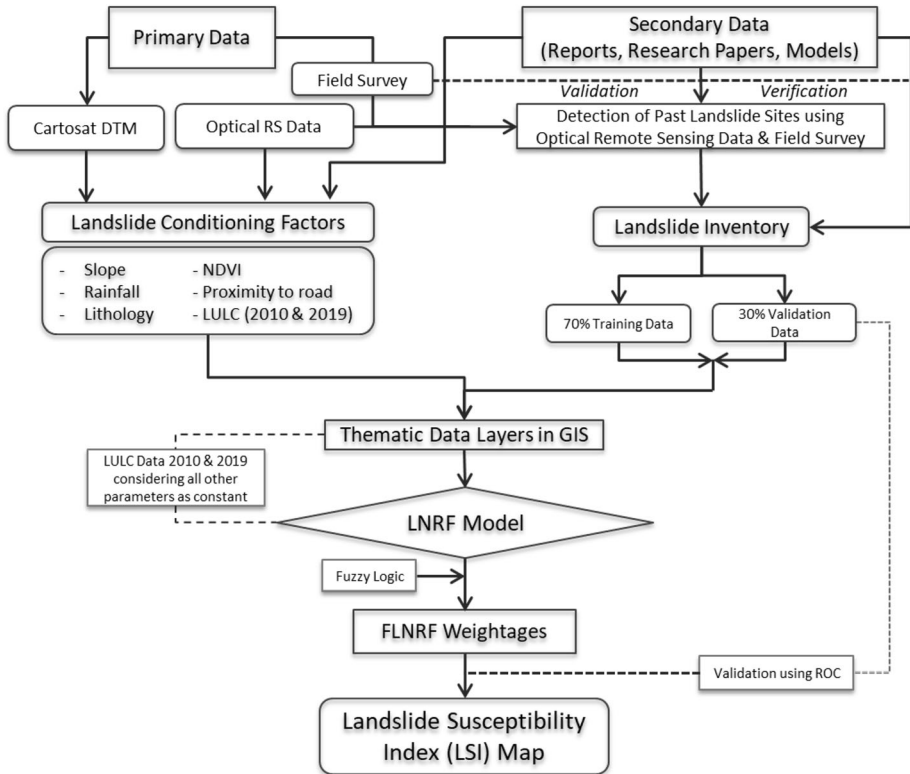
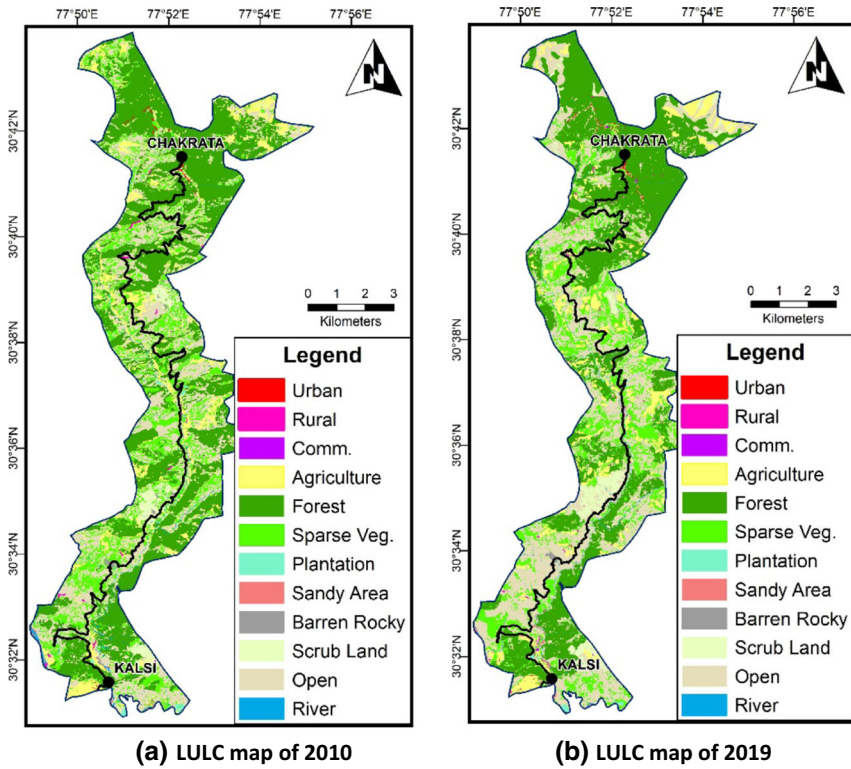


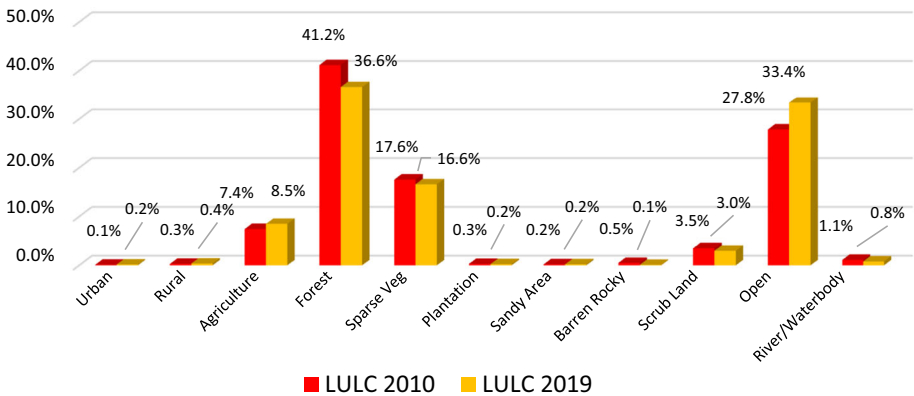
Fig. 5 Fuzzy LNRF methodology adopted in this study

other developmental activities in the study area. Another significant observation is conversion of forest and sparse vegetative areas into agricultural land. As a result, more than 1% of the latter increased compared to the agricultural area observed in 2010. The forest cover depletion suggests considerable impact on flora and fauna, and this indicates an urgent need to investigate the habitat of wildlife residing in the study area.

To better understand the changes and impacts on the landscape in the study area from landslide points of view, the landslide’s spatial distribution was overlaid on the LULC map. It has been observed that about 51% of the past landslides occurred in open areas, followed by 26% and 14% in areas covered by sparse vegetation and scrubland, respectively (Table 3). Out of 55 landslides, two landslides (4%) are formed on the rocky barren topography, while only one landslide was found in the forest area. Next, the LULC change detection between 2010 and 2019 was correlated with the landslide inventory in detail (Table 3). It has been observed that the landslide occurrence in the LULC class of open area, barren rocky land, and arable land was increased by 10.9% in 2019 compared to 2010. Conversely, there has been a considerable reduction in the LULC class of sparse vegetation and forest cover in the same way. This observation indicates that the conversion of LULC from vegetative areas to open lands has positively influenced landslides.



Change in LULC Area between 2010 & 2019



(c) Land use/ Land cover change detection

Fig. 6 Spatial change of LULC in the study area between 2010 and 2019, and change in area by LULC classes

Table 2 Spatial change in land use/land cover between 2010 and 2019

LULC classes	2010		2019		Change	
	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
Urban	0.09	0.11	0.13	0.16	0.04	0.05
Rural	0.22	0.26	0.30	0.36	0.08	0.10
Agriculture	6.15	7.40	7.09	8.53	0.94	1.13
Forest	34.19	41.17	30.44	36.65	− 3.75	− 4.51
Sparse veg	14.58	17.56	13.79	16.61	− 0.79	− 0.95
Plantation	0.24	0.28	0.18	0.22	− 0.05	− 0.07
Sandy area	0.15	0.18	0.17	0.20	0.02	0.02
Barren rocky	0.42	0.50	0.08	0.10	− 0.34	− 0.40
Scrub land	2.91	3.50	2.48	2.99	− 0.43	− 0.51
Open	23.20	27.93	27.72	33.39	4.53	5.45
River/waterbody	0.92	1.11	0.66	0.79	− 0.26	− 0.32
Total area	83.04	100.00	83.04	100.00		

Table 3 Comparison of existing landslide event areas covered by LULC classes of 2010 and 2019

LULC classes	2010		2019		Change	
	AREA sq. m	% Area	AREA sq. m	% Area	AREA sq. m	% Area
Urban	0	0.0	0	0.0	0	0.0
Rural	0	0.0	0	0.0	0	0.0
Commercial and Industrial	0	0.0	0	0.0	0	0.0
Agriculture	248	5.6	298	6.7	50	1.1
Forest	190	4.3	86	1.9	− 104	− 2.3
Sparse veg	1637	36.9	1255	28.3	− 382	− 8.6
Plantation	0	0.0	0	0.0	0	0.0
Sandy area	2	0.0	0	0.0	− 2	0.0
Barren rocky	378	8.5	564	12.7	186	4.2
Scrub land	100	2.3	120	2.7	20	0.5
Open	1850	41.7	2097	47.2	247	5.6
River/waterbody	36	0.8	21	0.5	− 15	− 0.3
Total area	4441	100.0	4441	100.0		

4.2 Progression of landslide events and their extent

As presented in the landslide inventory section above, the landslide occurrence in the study area was increased almost by 57% in past decade, which is quite alarming and invites an in-depth analysis of the landslide genesis across the road corridor. The extent of the landslides varied across the road corridor besides their occurrences. It was observed that the largest landslide, namely the Amraha landslide, has grown exponentially from about

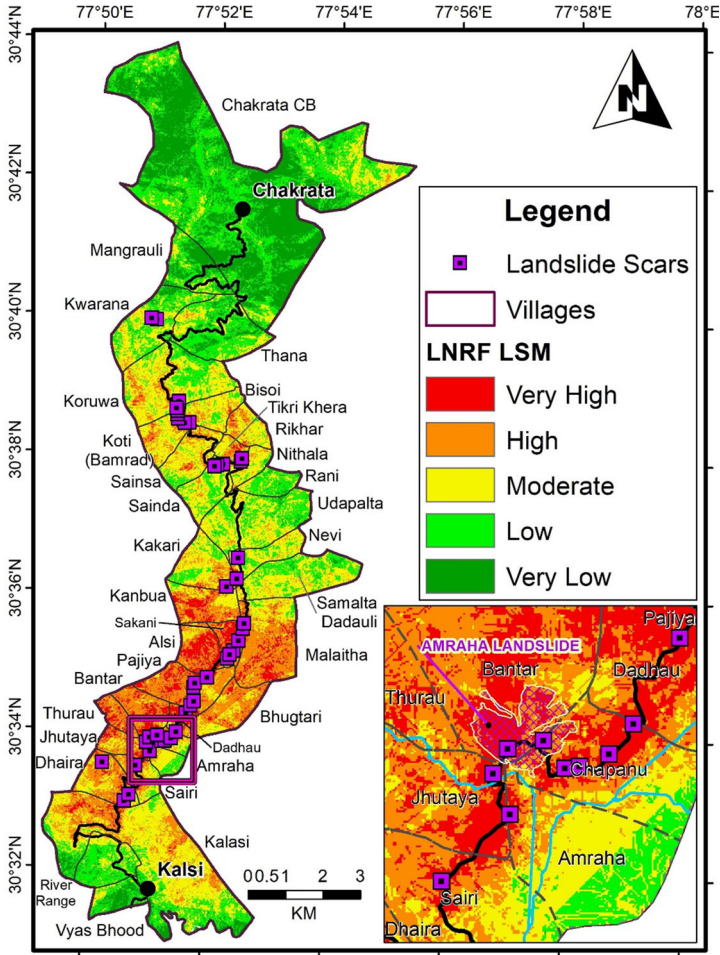
5200 sq. m. in 2002 to 16,900 sq. m. in 2010, which has been further increased in size to approximately 52,200 sq. m. in 2019. This indicates about ten times increase in extent of the Amraha landslide over the past decade. It was also observed that though sparse vegetation was the main LULC class in 2010, most of those areas have been transformed into open areas in and around the Amraha landslide. The spatial analysis suggests more than 70% of the sparsely vegetative areas converted into open areas. Moreover, because of the expansion of the landslide size, about 2600 sq. m. active landslide areas now contained agricultural land in 2010. In the absence of appropriate mitigation measures, the Amraha landslide progression may consume additional areas having LULC class of agricultural land, village settlements and roads, and areas under sparse vegetation cover. The above indicates the severity of the landslide hazard in the event of landscape change. The following sections are focused on assessing the correlation of landslides with the landscapes to a greater extent and finding out the potential impact of landslides on other environmental and anthropological concerns. This study further recommends a thorough investigation of such massive recurring landslides for adaptation of appropriate mitigation measures.

4.3 Landslide susceptibility zonation

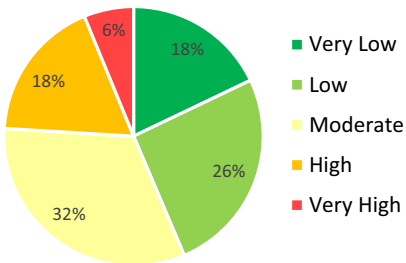
As illustrated in the methodology, the landslide susceptibility index (LSI) map was generated using the FLNRF model by integrating LSI values applying GIS techniques for 2010 and 2019 (Fig. 7a and b). LSI's higher value specifies higher degree of landslide susceptibility and vice versa. The LSI output was classified into five landslide susceptibility categories, viz. very low, low, moderate, high, and very high, using the Jenks natural breaks method. The result depicts that the areas having $> 35^\circ$ slope, greywacke type of lithology, > 1427 mm average annual rainfall, NDVI value < 0.3 , rocky-barren topography, sparse vegetation cover and, the proximity of 100 m from the road has more correlation with the occurrence of the landslide. The vegetation on steep slopes binds the soil and reduces erosion, and thus, the lesser the vegetation cover, the more chances of landslide combined with other conditioning factors. This study analyzes the spatial correlation of the future landslide probabilities through investigation of various landslide conditioning factors. It pinpoints the sets of conditioning factors that may influence future landslides over others in the study area. The results indicates that the south and south-central areas, particularly along the Kalsi-Chakrata road corridor, are more susceptible to landslide hazards.

Figure 7a and b present the landslide susceptibility maps generated for the year 2010 and 2019 to recognize and quantify the effect of LULC change over the past ten years. It has been observed that about 6% (5.1 sq. km.) and 18% (14.7 sq. km) of the study area falls within very high and high landslide hazard zones in 2010, respectively, while in 2019, it was only about 8% (6.6 sq. km.) and 17% (14.4 sq. km) for the same susceptibility zones. The moderate landslide susceptibility zone accounted for about 32% (26.7 sq. km.) in 2010, which was further reduced by 1% in 2019. The above result suggests that considering all the other landslide conditioning factors except LULC as static, the model outcome shows an increase of about 2% in very high landslide susceptible areas, which require being investigated spatially by correlating the LULC change for the study area.

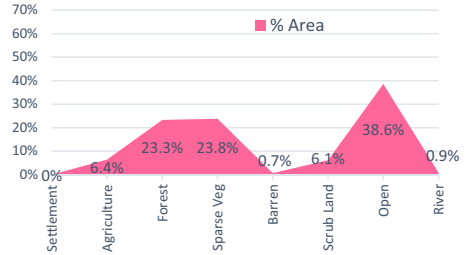
At the village level, the hazard map from the FLNRF model depicts that Sakani village and Dadhau village, located adjacent to the start of the Lesser Himalayas, are greatly susceptible to landslide hazard, having 61% and 57% of its areas fall within very high LSI zones, respectively. The output reveals that among the other villages, Alsi (52%), Chapanu



DISTRIBUTION OF LANDSLIDE SUSCEPTIBILITY ZONES



High+Very High Landslide Susceptibility Area by 2010 LULC



(a)

Fig. 7 a Landslide susceptibility map using FLNRF model for 2010 and distribution of high susceptibility area by LULC classes of 2010. **b** Landslide susceptibility map using FLNRF model for 2019 and distribution of high susceptibility area by LULC classes of 2019

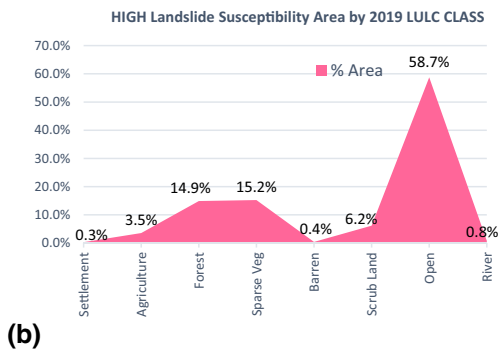
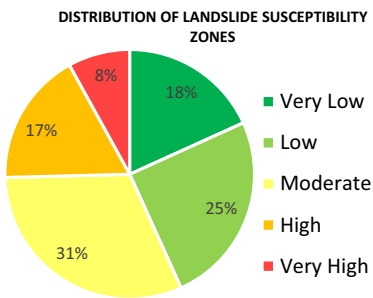
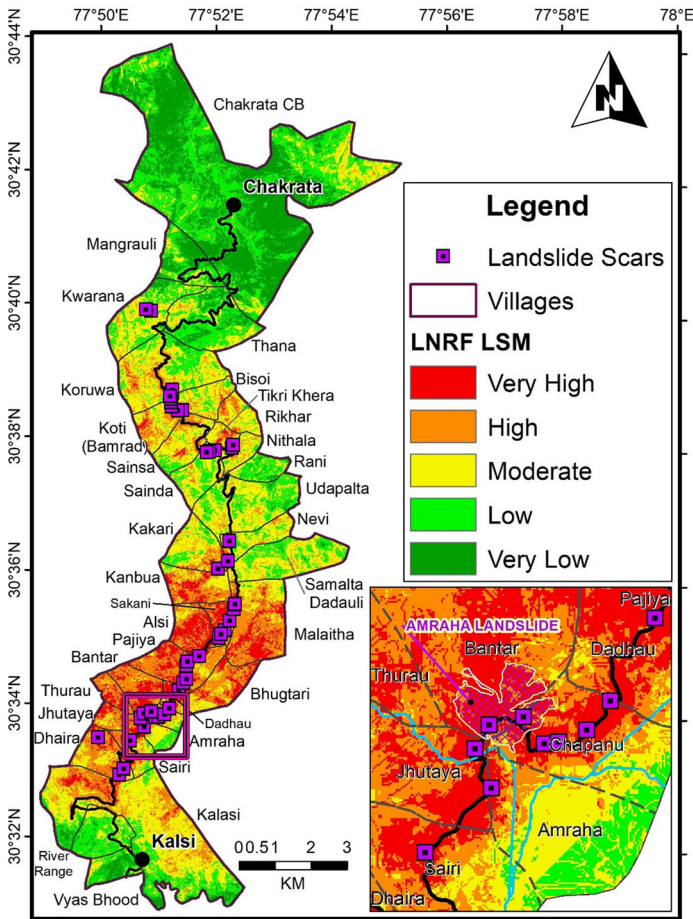


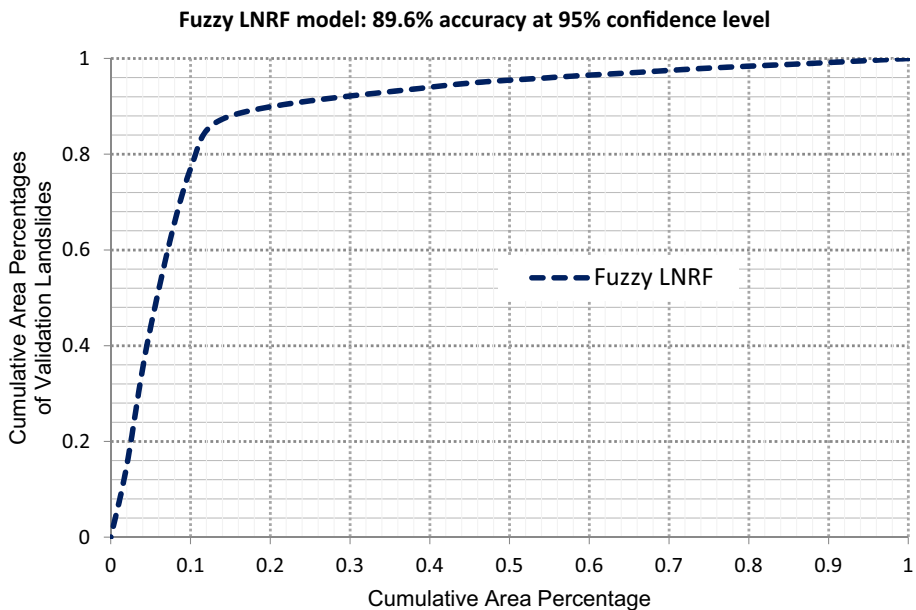
Fig. 7 continued

Table 4 Spatial distribution of highly susceptible landslide areas by LULC classes in 2019

LULC-2019	Very high susceptibility class		High and very high susceptibility class	
	Area sq. km	% Area	Area sq km	% Area
Rural	0.01	0.19	0.06	0.29
Agriculture	0.11	1.65	0.74	3.54
Forest	0.38	5.67	3.13	14.86
Sparse veg	0.53	8.04	3.21	15.25
Sandy area	0.00	0.00	0.01	0.04
Barren rocky	0.05	0.82	0.08	0.36
Scrub land	0.66	9.90	1.30	6.16
Open	4.87	73.26	12.36	58.74
River/waterbody	0.03	0.48	0.16	0.76
Total area	6.64	100.00	21.03	100.00

(47%), Pajiya (41%), and Jhutaya (40%) villages have higher exposure to very high landslide hazard (Table 4).

The prediction probability of the FLNRF model was validated using the area under the curve (AUC) approach using the receiver operating characteristics (ROC) method. The AUC value from the FLNRF model shows an AUC value of 89.60%, which indicates higher model accuracy in classifying the areas of existing landslides, which signifies the excellent prediction capability of the FLNRF model (Fig. 8).

**Fig. 8** ROC curve evaluation of success rate of the FLNRF model

4.4 Connection of LULC and landslide susceptibility

In this section, the authors appraised the landslide susceptibility results by associating the spatial distribution of the conditioning factors in the high and very high landslide susceptibility classes across the road corridor. Table 4 shows that most of the very high landslide susceptible areas are contained by open areas (73%), followed by scrubland, sparse vegetation, and forest cover, which account for 9.9%, 8%, and 5.7% of the total very high landslide susceptibility areas, respectively. Likewise, let us consider the combined areas under very high and high landslide susceptibility classes. About 57% out of the total landslide hazard areas fall within the open area LULC class, followed by sparse vegetation (15.2%), forest (14.9%), scrubland (6.2%), and agricultural land (3.5%). This study's statistical model also substantiates that the landscape with open areas, sparse vegetation, scrubland, and rocky barren land classes is more susceptible to landslides.

4.5 Villages priority ranking and future mitigation needs

For this purpose, the study also attempted to detect the most fragile landscape at the villages by overlaying the LSM classes (very high and high) on the LULC layer. The combined areas under open areas, sparse vegetation, scrubland, and rocky barren land LULC classes are also considerably higher than the others (Table 5). From this perspective, a priority ranking system to identify the hotspot villages has been proposed based on the percentage of higher landslide susceptible areas and the LULC classes that have been found responsible for producing frequent landslides. Following this process, the Sakani, Bantar, Thurau, Pajiya, and Alsi have been marked as the top five villages where the landscape is fragile enough to produce future landslide. Hence, the requirement is to further investigate the landscape and landslides to decide the appropriate landslide mitigation measures. This provides a strong basis for the decision-makers to interpret the landscape of the study area in relation to the landslide hazard to minimize the environmental impacts, damages to assets, casualties, and loss of livelihood at the village level in the future.

5 Discussion

The study outcomes reveal that the GIS-based fuzzy LNRF technique adopted in this study is a powerful and essential MCDM tool for mapping the landslide susceptibility in the Kalsi-Chakrata Road corridor in relation to the changing landscape. As presented in the introduction section of this paper, the knowledge-driven fuzzy logic technique has been pulled together with the LNRF model for predicting the landslide susceptible areas in a Lesser Himalayan road corridor in Uttarakhand first time. The FLNRF method is a compatible technique, and the output LSM has a greater likeness with the prevalent landslide sites noted during the field examination. Moreover, the comparison of the LSM map of 2010 and 2019 indicates that the spatial relationship of LULC change on landscape probability and the village priority ranking has been made for compelling mitigation needs.

In the past, the impact of LULC on landslide has been studied with the geological, topographical, and drainage conditions. Many of these past studies have advocated for the influence of hydro-geomorphological settings and environmental conditions, including terrain, climate, geology, lithology, hydrology, soil, LULC, and human interferences on the spatial occurrences of landslides. The natural slope's stability can be improved or

Table 5 Village Hotspot ranking through comparison of higher landslide susceptible areas and LULC classes for detailed investigation of landscape change and landslide mitigation

NAME	LULC Classes-2019					High + Very High Landslide Susceptible Areas	Village Hotspot
	Sparse Veg	Barren Rocky	Scrub Land	Open	Barren + Sparse Veg + Open + Scrubland		
Sakani	34.8%	3.2%	17.0%	14.8%	69.8%	97.1%	1
Bantar	33.3%	0.0%	0.0%	36.5%	69.8%	95.4%	2
Thurau	29.5%	0.0%	0.0%	63.3%	92.8%	94.2%	3
Pajjya	17.8%	0.5%	17.5%	11.8%	47.7%	91.3%	4
Alsi	19.8%	1.5%	47.2%	8.1%	76.6%	90.7%	5
Jhutaya	44.0%	2.0%	0.0%	43.8%	89.8%	87.5%	6
Dadhau	19.1%	0.0%	1.1%	60.3%	80.4%	86.3%	7
Malaitha	18.4%	0.3%	0.0%	29.6%	48.3%	76.7%	8
Chapanu	33.0%	6.2%	0.0%	40.3%	79.5%	76.3%	9
Bhugtari	3.6%	0.0%	0.7%	14.2%	18.5%	73.9%	10
Dhaira	28.2%	0.0%	0.0%	55.4%	83.6%	73.9%	11
Kanbua	19.3%	0.0%	1.0%	15.4%	35.7%	70.4%	12
Sairi	36.4%	0.0%	0.0%	29.4%	65.8%	61.6%	13
Tikri Khera	28.4%	0.0%	0.0%	37.4%	65.8%	52.5%	14
Koti (Bamrad)	25.7%	0.0%	0.0%	34.6%	60.2%	50.3%	15
Sainsa	22.8%	0.0%	0.0%	40.5%	63.3%	32.3%	16
Rikhar	31.2%	0.0%	1.1%	33.2%	65.5%	31.1%	17
Kakari	31.4%	0.0%	1.3%	40.4%	73.1%	29.9%	18
Nithala	24.6%	0.0%	0.0%	32.4%	56.9%	29.2%	19
Bisoi	26.4%	1.3%	10.8%	48.1%	86.7%	28.1%	20
River Range	20.1%	0.0%	5.3%	36.1%	61.5%	25.2%	21
Koruwa	20.7%	0.4%	6.7%	28.6%	56.5%	21.4%	22
Amroha	8.3%	1.6%	0.1%	20.0%	30.0%	19.3%	23
Nevi	23.2%	0.0%	0.3%	31.9%	55.3%	17.6%	24
Sainda	23.6%	0.0%	0.0%	26.2%	49.8%	14.6%	25
Kwarana	28.5%	0.0%	0.0%	30.5%	59.1%	5.8%	26
Samalta Dadauli	10.0%	0.0%	0.0%	30.3%	40.3%	5.8%	27
Udapalta	23.5%	0.0%	0.0%	31.9%	55.4%	5.5%	28
Kalasi	11.0%	0.0%	0.0%	13.0%	24.0%	2.0%	29
Rani	21.5%	0.0%	0.0%	53.7%	75.1%	1.7%	30
Thana	12.3%	0.0%	0.0%	28.2%	40.5%	1.5%	31
Vyas Bhood	10.2%	0.0%	0.0%	11.7%	21.9%	0.4%	32
Chakrata CB	10.2%	0.0%	2.1%	18.2%	30.4%	0.3%	33
Mangrauli	12.1%	0.0%	0.0%	27.8%	40.0%	0.3%	34

worsened because of such impacts, which may intensify or pacify the landslide events' frequency and magnitude (Galve et al. 2015; Schmaltz et al. 2017; Chen et al. 2019). The lithological and geological structures can be considered static in slope stability analysis. Simultaneously, the transformation of LULC and change in morphology and climate may happen seasonally or over a decade (Reichenbach et al. 2014). Specifically, the changes in LULC and their spatial variations are often induced or controlled by anthropological activities. Recent studies have supported the fact that in populated areas, the occurrence and aggravation of landslides are associated with the land use changes by human interference (Vanacker et al. 2003; Geertsema et al. 2009; Bruschi et al. 2013). It is well known

that slope stability is improved by vegetation cover, whereas unplanned human actions may worsen the slope stability. A considerable amount of research has been carried out on how the plant root system can sturdily stabilize the soil and improve the slope stability; however, there are limited studies available for assessing the impact of landscape change on landslides in the Indian Himalayan region. (Randall et al. 1997; Glade et al. 2003; Stokes et al. 2008; Pisano et al. 2017; Meneses et al. 2019; Dikshit et al. 2020). It has also been studied that except for some landslides that occurred due to the undercutting of slopes, commonly, the shallow landslides are directly triggered by land use changes in an area (Chen et al. 2019). These studies support the fact that landslide susceptibility in many areas has a strong correlation with the changing land use pattern, and hence, it will be imperative to investigate the relationship of LULC and landslide susceptibility in the landslide-prone Lesser Himalayan terrain. In this context, it should be kept in mind that the change in the landscape should be viewed integrated with the persistent socioeconomic development and climate change scenarios that may lead to ecological degradation and substantial landscape disintegration (Abbas et al. 2020). Hence, a more robust and detailed investigation may be carried out considering the climate change impacts and socioeconomic variations concerning the landscape change and landslides in continuation of the present study.

To better understand the influence of LULC change on the spatial occurrence of landslides in the Kalsi-Chakrata area, a statistical correlation has been established. The result shows that over the past decade (2010–2019), the forest cover in the study area has been reduced by 6%, while the open areas have risen by more than 5%. The increase in settlement areas by 1.1 sq. km. is considerably higher for the Lesser Himalayas' hilly terrain. It has probably resulted not only in the increasing number of landslides from 35 nos. in 2010 to 56 nos. in 2019, but also most of the newer landslides (51%) occurred in the LULC category of open areas. Such an example strongly supports the fact that the conversion of LULC from vegetation cover to open land and sparse vegetation has a positive influence on aggravating the landslides. Table 4 shows that the majority of the very high landslide susceptible areas are contained by open areas (73%), followed by scrubland, sparse vegetation, and forest cover, which account for 9.9%, 8%, and 5.7% of the total very high landslide susceptibility areas, respectively.

Although the present study considers a small road corridor as a test area, the findings are significant and promising because it could establish the correlation between the decrease in vegetation cover with increasing landslide susceptible areas. Due to increased human interference on the land cover through road widening, increased vehicular movements, expansion of agriculture, and mining in the study areas, high landslide susceptible areas have increased considerably, which has expanded the threat of landslides in the settlement areas and agricultural lands. While adopting the current study for applying in other geographies, it should be kept in mind that the other landslide conditioning factors other than LULC were considered to be static while correlating the LULC and landslide occurrences temporally and spatially. In reality, the other factors are dynamic though the pace of change may vary significantly in a few decades. Even in a short period, the populated areas like in the Lesser Himalayan terrain, the conditioning factors such as the slope angle, aspect, rainfall distribution, and intensity can be altered by earth movement processes of soil erosion, undercutting of slopes, landslides, etc. To compensate for such variations, the present study focused on the use of high-resolution and latest vintage datasets (including DTM, lithology, rainfall data, etc.) applying integrated remote sensing data and GIS techniques to establish the finding of the study in a more comprehensive manner. The use of a fuzzy algorithm has also helped overcome some of the uncertainties

that authors have faced in some past reviews. As a whole, this study promotes an easily interpretable contemporary multi-criteria decision-making process that integrates the fuzzy method with the RS and GIS technique to provide a strong basis for understanding the landscape of the study area concerning the landslide occurrences. Furthermore, extending the outcome of LULC and landslide susceptibility connection at the village level opens the path for a detailed investigation that has not been thought of as an essential means for intensive and comprehensive landslide mitigation measures and sustainable development local scale.

6 Conclusion

In the past two decades, landslides have been observed quite calamitous, combined with extreme climate events in India's Himalayas. The rapid changes in landscape categories in the Lesser Himalayan regions have been inevitable with the recent developmental and economic activities. Therefore, to systematically evaluate the impact of the landscape changes on landslide hazards in both the short and long term, this study adopted an integrated GIS-based fuzzy LNRF–MCDM approach to understand the processes that contribute to landslides landslide-prone Lesser Himalayas.

The proposed fuzzy LNRF approach ascertains that this method of GIS-based MCDM can be effectively instigated for landslide susceptibility assessment in other areas of the Lesser Himalayas. The combined use of detailed landslide inventory and high-resolution landslide conditioning factors layers justifies the geo-spatial aspect to capture the minute information across the study area. Regarding choosing the probabilistic LSI model for a complex geo-environmental setup, the fuzzy membership approach provides more comprehensive, flexible, and substantial results when the decision criteria are qualitative, as in the landslide risk assessment. The FLNRF model can help identify the groups of conditioning factors in relation to the LULC classes that may have more influence on future landslides. The decrease in vegetation cover and increase in human activities escalate the risk of frequent landslides. It was observed that the LULC class of rocky and barren land devoid of vegetation coupled with steep slopes ($> 50^\circ$) and greywacke type lithology are among the main contributing factors responsible for landslide occurrence in the study area. Moreover, the higher torrential rainfall, recent geological formation, and anthropogenic impacts (nearness to roads) certainly intensify landslides' chances along the Kalsi-Chakrata road corridor.

The present study contributes significantly to providing a useful prediction for the decision-makers and authorities in adopting appropriate approaches in minimizing the potential damages and losses from existing and future landslides by studying the landscape changes. Due to the uncertainties inherent in the landslide conditioning factors, certain uncertainties will always persist in landslide susceptibility assessment. Therefore, the fuzzy LNRF approach in the future may consider other significant conditioning factors such as spatiotemporal change of rainfall distribution and frequency under the climate change scenarios as well as other causative factors responsible for landscape change. The fuzzy LNRF model applied has 89.6% prediction accuracy at 95% confidence level. Thus, the current model has an excellent prediction capability, and the LSM generated for this study has a close resemblance for future landslide scenarios at specified locations. Furthermore, the study of the connection of LULC change with the landslide probability and identification of the most fragile landscape at the village level has been instrumental in studying the spatial landslide occurrences in the study area. Such an exercise may help the decision-

makers adopt appropriate mitigation measures in those villages where the landscape changes have mainly resulted in increased landslide occurrences and formulate strategic plans to promote ecologically sustainable development of the mountainous communities in India's Lesser Himalayas. Hence, the present fuzzy LNRF-based methodology coupled with the GIS technique applied herein may be encouraged for landslide susceptibility assessment to the landscape changes in the other Lesser Himalayan road corridors.

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