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Dynamic association of slope movements in the Uttarakhand Himalaya: a critical review on the landslide susceptibility assessment

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ABSTRACT

Slope movement, the surface expressions as seated scars are the variety of surface deformation mechanisms on the earth's outer crust. These slow-deformation mechanisms can be visualized easily, if in-situ geotechnical observations, GNSS synopticity (regional), and space-borne (Microwave) spatio-temporal data structured and interpreted accordingly. Globally, several techniques are adapted for the slope failure analysis and their zonation. Thus, the most directed with geospatial technologies. Wide area assessment, mapping, and monitoring are some complex tasks only possible and could be addressed with the space borne datasets. Their outcomes help users to implement area strategies viz. in susceptibility and vulnerability. Landslide Susceptibility mapping (LSM) quantify the problem very effectively. In LSM, soft computing analytical skills among various participatory and triggering factors for the application of complex models are required for ground simulation. In this article critical review of LSM over Uttarakhand Himalaya was primarily focussed which analyze various sections including- participatory/triggering factors, datasets, different models, and validation practices. The study exhibits multiple avenues and future pathways for various research windows, such as LSM-SAR refinement, orographic climatic and changing factor relationship, high-quality data coupling with drone/ Unmanned Aerial Vehicle (UAV) data, etc. Such analysis implicates the cost-effectiveness of strategies in effective planning and management.

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Uttarakhand Himalaya;
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surface deformation;
triggering stipules; factor of
safety

1. Introduction

Mass movement is the surface expression as seated scars on the outer crust are the primary step of a variety of surface deformation mechanisms. such processes concealed and initiate with the ground slope and its direction and later on their

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development to the point of surface deformation (earth surface elevation transformation by regional denudation and downward displacement of land) over the earth surface may involve and escalate with the presence of external stimulus over the period (Allen 1984). Bibliographic records express a different way of explanation of such mechanisms: Landslide, in terms of Varnes (1978), is a relative displacement of the outer most surface concerning the stable ground state underneath. Similar to this, Crozier (1986) explained it as the gradient apparent and descent gravitational shift of earth elements that occur without the aid of water. While (Guzzetti 2002) interpreted it as the downward slope mobilization of earth material with the presence of antecedent variables, such as slope, aspect, elevation, lithology, soil, terrain channeling, etc. oftentimes slope movement started and get escalated with the triggering agent (rainfall, earthquake, anthropogenic acceleration). Well-documented records from Campbell (1975) and Ellen et al. (1988) from California, Jibson (1989), Simon et al. (1990), Larsen and Torres Sanchez (1992) from Puerto Rico, Wilson et al. (1992) and Ellen et al. (1993) from Hawaii, Dikshit et al. (2020) and Das and Ganguli (2022) from India revealed the activation of landslides close association and relationship with the rainfall intensity. Despite García-Rodríguez et al. (2008) from El Salvador, Kamp et al. (2008) from India, Fan et al. (2019) from China, Kargel et al. (2016) from Nepal, Pourghasemi and Rahmati (2018) from Iran supports the role of the earthquake in triggering the landslides. Furthermore, anthropogenic acceleration to affecting slopes includes rapid infrastructure framework (Barnard et al. 2001; Petley et al. 2007) conjointly with ground shaking (caused during mining, tunneling, and cutting roads) enhance the landslide occurrences in the hilly region (Süzen and Kaya 2012; Robinson et al. 2017). Due to its multimodal morpho-dynamic process and the improper interaction of humans with the environment, especially in terrain ecosystems, landslides have been identified as one of the fast-spreading epidemics affecting hill ecosystems (Metha et al. 2015; Sharma and Sanjeevi 2015; Sarkar et al. 2016).

The current review intent is to carry out a critical analysis of the techniques used to simulate slope failure susceptibility and the accompanying terrain zonation. It is noticed while preparing the database that, Parallel phrases ‘susceptibility’ is often used with the ‘Hazard’ and exists collinearly. Despite the definition, it stands differently. ‘Susceptibility’ is contemplated as the spatial occurrence and landslide propensity under certain topography and climate conditions in any area. While, the ‘hazard,’ denotes the probability of slope failure and its magnitude with its occurrence in a given period and place.

When addressing the earlier work, it reveals that the study of the landslide impacts with the climatic and triggering variables is attempted and adopted using various GIS heuristic-knowledge-driven (qualitative) and data-driven (quantitative) approaches as illustrated in Tables 1 and 2. It is noticed that all of the assumptions used in the proposed methodologies and methods to determine landslide susceptibility have been taken directly from the source texts (Varnes and IAEG 1984; Carrara et al. 1991; Hutchinson 1991, 1995; Turner and Schuster 1996; Guzzetti et al. 1999).

In this article, sometimes we use the alternative term ‘Ground movement’, ‘slope movement’, ‘mass movement’, and ‘slope failure’ as ‘landslide’ synonyms.

Table 1. A basic approach for susceptibility modeling.

Approaches	Qualitative (heuristic on knowledge-driven) approach	• It is Subjective, the user generates heuristic determinations of susceptibility and characterizes the ranges of susceptibility using descriptive (qualitative) terms. • Representation ability depends on an expert/investigator, interpreting the map for actual and potential slope un-isostatic conditions. • Experts assign ranks and weights to the known un-isostatic components based on assumptions or expected importance.
	Quantitative (data-driven) approach	• It works based on Numerical estimates. • The functional linkages are built between known or inferred un-isostatic factors. • It requires a Training set as considers the temporal and present distribution of landslides.

In the Himalayan orogeny, the land mass distribution in highly elevated areas dominantly hinges on the mechanical characteristics of rock formation with their spatial attributes. Particularly, when dealing with ground movements area-specific geometry is extremely important. The review reveals that landscape geometry evolves through the interaction between exogenic and endogenic earth processes. Later on the process complexes and initiates the mechanisms, such as folding, faulting, basin tilting, and fluvial mechanics within it. When these mechanics together interact and initiate along the geomorphic alignments (*viz.* slope; its length, curvature, aspect, and roughness) with the superimposed land mass characteristic (including a loaded drainage network, man-made fill, or the artificial overburden), it may fail if one of any alignment gets unstable (Gruber et al. 2004; Huggel et al. 2010).

In the Himalayan region, landslides are more frequent and severe than global events. Documented database of Geological Survey of India (GSI) (<http://www.gsi.gov.in>) scales, about 12.6% (0.42 M km²) topography in the Indian subcontinent is prone to landslide hazards, to which 33% (0.14 M km²) falls in the North-western (NW) Himalayas. Particularly, the active boundaries of the states Uttarakhand, Himachal Pradesh, and Jammu and Kashmir are prone to such hazards. Because of its destructive potential, it poses a significant threat to the lives and socio-economic assets of humans as well as to nature’s prosperity (Corominas et al. 2013). Landslides with varying frequencies are reported in these terrains. According to recent evidences on landscape creation, it is a widely discussed subject when it comes to high-magnitude with low-frequency landslides and low-magnitude with high-frequency landslides. The identification, measurement, and dating of significant landslides allow for Ist-order estimations of mountain denudation caused by large-scale mass-movements, which can relate further with denudation caused by fluvial and glacial erosion.

Uttarakhand, Garhwal-Kumaun Himalaya (UGKH) an integral part of the Himalayan mountain system occupies a total of 93% of land in the mountainous region. The mentioned complex interactions among several primary factors (Slope, Geology, Geomorphology, Aspect, terrain roughness, vegetation, terrain channelling) with the secondary response (cohesion, friction, changes of the water table and groundwater, and their multiple intensifying stimulus range by magnitude, intensity, and frequency of climatic, earthquake, anthropogenic cause) makes the terrain so

Table 2. Classification of basic approaches used in landslide susceptibility assessment/modelling.

Approach	Types	Classification	References
Qualitative (heuristic on knowledge-driven) approach	Direct method (inventory-based approaches)	Field geomorphological and Morpho-dynamic analysis	Numada et al. 2003; Bai et al. 2019
		Distribution analysis	Chang et al. 2016; Roşjan et al. 2016
Alternative-semi quantitative approach	Indirect method (index-based method)	Analytic hierarchy process (AHP)	Lee et al. 2004; Yalcin et al. 2011; Pourghasemi et al. 2012; Park et al. 2013; Kumar and Anbalagan 2016; Saha et al. 2020; Sur et al. 2020; Feizizadeh et al. 2013
		Fuzzy-set based analysis	Champati Ray et al. 2007; Kanungo et al. 2009; Feizizadeh 2013
		Ordered weighted-averaging function (OWA)	Feizizadeh et al. 2014
		Weighted linear combination	Feizizadeh and Blaschke 2012
		Artificial neural networks (ANNs)	Arora et al. 2004; Yesilnacar and Topal 2005; Chauhan et al. 2010; Pradhan et al. 2010; Yilmaz 2010; Park et al. 2013; Pradhan and Lee 2010; Wang et al. 2019; Chen et al. 2019
Quantitative approach (data-driven)	Artificial intelligence (AI) and machine learning (ML)	Support-vector machine (SVM)	Yilmaz 2010; Pradhan 2013; Goetz, Brenning, et al. 2015; Tien Bui et al. 2016; Chen et al. 2017; Zhang et al. 2018; Chang et al. 2019; Wang et al. 2019
		Random forest (RF)	Trigila et al. 2015; Pourghasemi and Kerle 2016; Youssef et al. 2016; Ada and San 2018; Chang et al. 2019; Tang et al. 2020; Hong et al. 2018
		Decision tree (DT)	Pal and Mather 2003; Nefeslioglu et al. 2010; Akgun 2012; Tien Bui et al. 2012; Pradhan 2013; Pham et al. 2016
		AdaBoost (AB)	Micheletti et al. 2014
		Classification and regression trees (CART)	Vorpahl et al. 2012; Felicísimo et al. 2013
		Maximum entropy (MaxEnt)	Felicísimo et al. 2013; Park 2015; Konejady et al. 2017; Hong et al. 2018
		Fuzzy logic	Chung and Fabbri 2003; Park 2004; Champati Ray et al. 2007; Vahidnia et al. 2010; Oh and Pradhan 2011; Sezer et al. 2011; Pourghasemi et al. 2012; Guettouche 2013; Sharma et al. 2013; Pourghasemi and Rahmati 2018
		Naive Bayes	Lee 2004; Bhargavi and Jyothi 2009; Tien Bui et al. 2012; Pham, Tien Bui, Pourghasemi, et al. 2015; Pham, Tien Bui, Prakash, et al. 2015
		Boosted regression trees	Dickson and Perry 2016; Youssef et al. 2016; Binh Thai et al. 2017
		Adaptive neuro-fuzzy inference system (ANFIS)	Bui et al. 2012; Aghdam et al. 2016; Polykretis et al. 2019; Choi et al. 2011

(continued)

vulnerable for the landslide and subsidence. This sometimes results in their aftermath effects, such as induced flash floods (due to landslide dam, debris-glacial flood) or vice versa (Ermini and Casagli 2003; Gruber et al. 2004; Jomelli et al. 2004; Huggel et al. 2010; Allen and Huggel 2013; Fischer et al. 2013; Paranunzio et al. 2015; Weidner et al. 2019).

Observations of the last two decades with RS and GIS and field-based analysis show the remarkably increasing trends of such calamities in the region. According to the Vulnerability Atlas of India (link <https://vai.bmtpc.org/>) and (USDMA 2016) report (link <https://www.usdma.uk.gov.in>), the frequency and number of such disasters have recorded an alarming exponential rise with a 2900% increase in last five years. Most of these occurred between June and October, during the monsoon season, and during the region's peculiar seismic episodes. Similarly, flash flood-triggered landslides have wreaked havoc on Uttarakhand. According to the (USDMA 2016) database, the state saw significant cloudburst incidents in the years 2002, 2004, 2007, 2008, 2009, 2010, 2012, 2014, 2016, 2019, 2020, 2021, and 2022.

As the practices conducted over the decade's tells us these hazards can be curbed, but the projection cannot be avoided especially in the Uttarakhand Himalaya. Since it is an earthquake-prone area (Zone-IV and V), Where soil and rocks get disturbed by constant geo-tectonic shift.

Therefore, to map prone areas and their assessment before their occurrence is important in minimizing their hazard impact using spatial distribution and velocity analysis and simultaneously from the inventory outcome by LSM/LHZ assessment. The effort involved in effective hazard susceptibility provides end users, planners, and policy-makers for rapid movement identification, suitable risk assessment, preparedness, and management against such events. However, the reliability of such maps as LSM/LHZ primarily depends on the criteria scrutinized for hazard evaluation. For an evaluation of the landslide susceptibility it is necessary and important to answer the following ground question:

- How will the slope failure occur?
- When and where it will occur?
- What type of slope failures will occur?
- What will be the frequency and magnitude of slope failure? ... etc.

The most recent archives with the current subject show the synoptic diversity of the isostatic adjustment, stabilization, and consolidation state about the region. Therefore, a comprehensive review of the recent work done in consideration of Landslides inventory their updation, LSM/LHZ status, and rate of movement calculation as a subpart. Literatures reviewed to ensure the pattern of occurrence, pattern of movement (annual and temporal), dynamic relationship with the climate, and the long-term impacts/effects of landslides on nearby urbanization for safe operation about landslide awareness and for providing mitigation measures. Therefore, the review was conducted with the scientific published records especially focused on the current criteria of the manuscript subject. Key role as remote sensing and GIS, field, instrumentation, etc. with a different bandwidth of investigation were reviewed for

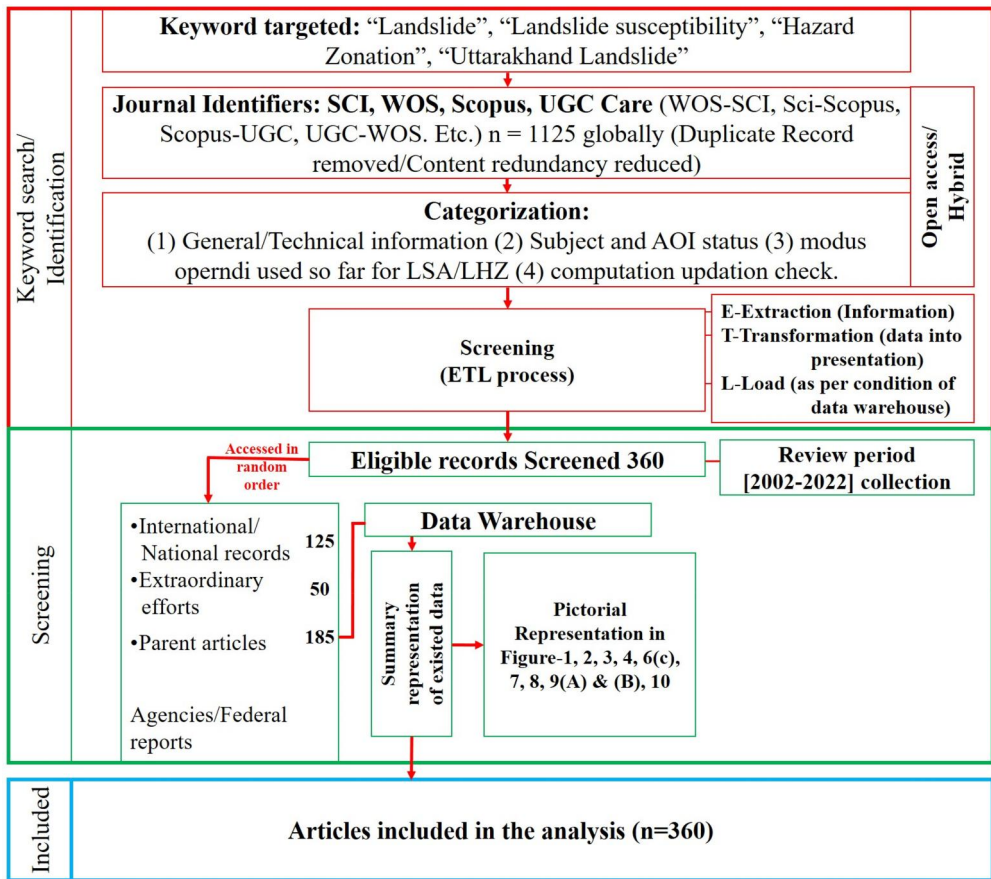


Figure 1. Flowchart of the systematic review for the study.

the past, current, and future (expected, projected) through undertaken 360 articles. Out of the numbers a stretch of 185 international/national articles primarily focussing extra-peninsular India, 125 articles focused their views on the same problem globally for the period of 2000–2022 was studied. Fifty articles are considered for basic understanding and their extraordinary efforts. The flowchart adopted for the current systematic analysis is shown in Figure 1.

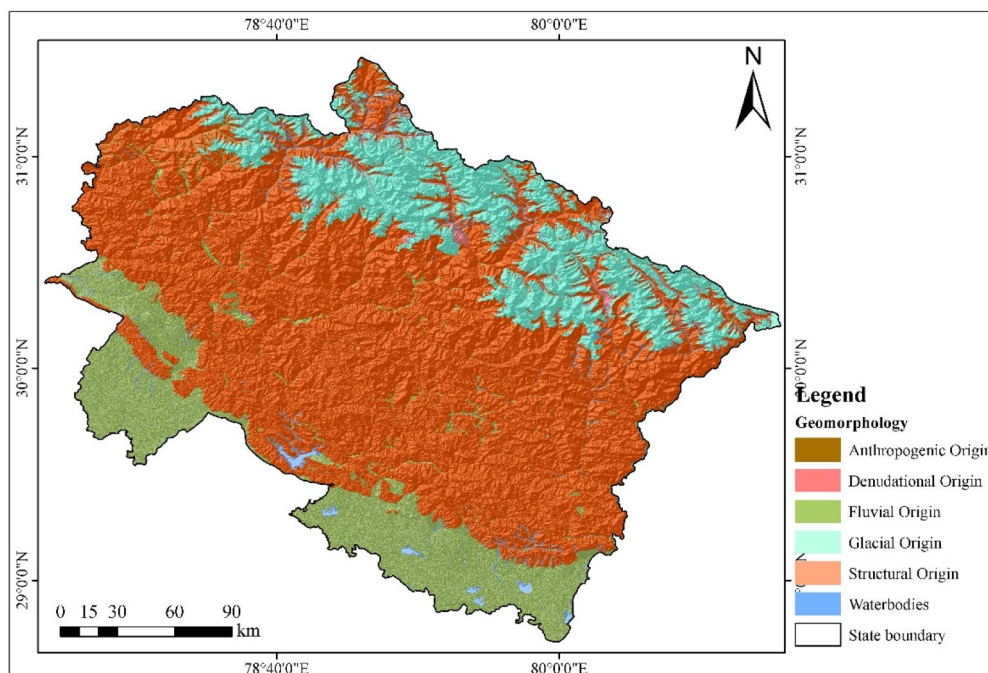
The literature on the burning issue is broad and diversified, so we limit this process by review of the published articles in various scientific journals, proceedings, conferences, and book chapters technically relying on the GIS, and field integrating approach. An exhaustive analysis of the most recent developments in slope stability and failure mechanisms can provide a reliable foundation for stability prediction, early warning, and emergency risk mitigation in mountainous regions. For this paper, a comprehensive perspective addressing the landslide is organized in the sections as follows:

2. Region characteristics: relationship with litho-morphological attribute

Uttarakhand Himalaya (UH), a major framework within Extra Peninsular India (EPI) is one of the most diversified landmasses in terms of the complex morphological

Table 3. Classification of the failure associated with the composition.

Movement type	Bedrock/clast predominantly (coarse size)/clast (fine size)
Fall	Rock/debris/earth-fall
Topple	Rock/debris/earth-topple
Slide	Rock/debris/earth-slide
Spread	Rock/debris/earth-spread
Flow	Rock/debris/earth-flow

**Figure 2.** Major geomorphological classes in the Uttarakhand Himalaya.

setup and the dynamic tectonostratigraphic column. It occupies $\sim 1.63\%$ area of the Indian total 12% EPI, out of which 93% represents the typical terrain. The region is very prone to ground movements, such as landslide activity. Such slope failures take place due to fragile-complex litho units and presence of the dynamic structures over the region. Further, the associated damage depends upon the size and the rate of movement of the landslide. Morphologically, the region represents a wide spectrum of high energy along its steep topographic slopes also representing the high topographic roughness. Thus, it results in a different range of frequency and magnitude of failures sparsely around the varying geographic units in this region. The terminology of the failure is different with material composition (Table 3).

UH shows a variety in the landform pattern (erosional/denudational, depositional) throughout the region due to their origin and the state geographic location, thus it is classified into six major landform classes (GSI and NRSC 2012) (Figure 2).

In addition to the slope failure, these movements escalate denudational (erosion) processes along the highly undulated Himalayan terrain, which contributes to the long-term evolution of terrain-slope morphology. Precursor-like various surface

expressions develop, such as structural discontinuities, micro topographic deformations, etc. within a moving mass due to the acting tensile/compressional stresses. These can be seen in the bulged slope due to sagging further accompanied by a linear series of depressions before the development of the slip surface.

With the current ability of the space-borne datasets mapping, monitoring, and the overall susceptibility and risk analysis of these prone sites became easy and cost-effective with time. With RS and GIS, mapping the slip surfaces may define their spatial patterns, movement, and their spatiotemporal evolutionary patterns of surface deformation even for the individual evaluation of the slide surface with their kinematics and mechanics. By observing the in-situ surface pattern of the active slope failures one can identify the type of movement and predict their near future dynamic behaviour, such as velocity, the distance of travel, and their pattern in response to the climatic variables, etc.

Geologically, in the Himalayan mountains-Uttarakhand Himalayan system provides unique research space for the study to ensure the continental lithosphere response in favour of its destructive Collision history (Dewey and Burke 1973; LeForté 1975). In context of mass movement, the effective role of geological sequence (formation, litho units) cannot be ignored from the literatures (Middlemess 1885; Holland 1908; Auden 1935; Heim and Gansser 1939; Misra and Sharma 1967; Jain 1971; Rupke 1974; Valdiya 1979, 1980; Srivastava and Mitra 1994; Searle et al. 2003; Richards et al. 2005). It is observed that the Himalayan geology has been studied for over a century by many geologists. In sequence to that (Heim and Gansser 1939) first introduced the major Himalayan physiographic sequence as The Sub-Himalayan Seq. (SHS), the Lesser Himalayan Seq. (LHS), the Central Himalayan Crystalline (HCS), and the Tethyan Himalayan Seq. that aged from Cenozoic (quaternary) to Archean and dipping to its north with the alternating dipping thrust-fault systems as Himalayan Main Frontal Thrust (MFT), Main Boundary Thrust (MBT), Main Central Thrust (MCT), and later recognized South Tibet Detachment fault (STDF). Each tectonic unit is not only representing its physiography (average elevation) but also separated by the boundaries of intra-crustal fault zones (thrusts and wrench faults). Stratigraphic association is shown in Figure 3. Here the map dimension intends to introduce Himalayan geology as a whole with the diverse regional geological setup (Uttarakhand Himalaya) alongside regional structures to elucidate the relationship between landslides and geology. Based on the section review it is observed that the regional setup ranges from the late Proterozoic-recent quaternary age. UH, stretched from south to north elaborates: the late tertiary to a recent quaternary group of rocks. Heterogenic lithology comprised of thickly bedded sandstone, siltstone and mudstone, weakly cemented conglomerate beds, and permeable quaternary deposits on moderate to steep slopes are primarily responsible for the landslide in the lower part region. It has been observed that the intensity usually occurs high along the active tectonic zones, specifically between the MBT–MCT in its south and north. The Proterozoic (mid)–Cambrian (early) age Lesser Himalaya (LH) rocks are bounded between these fault systems. Due to the intense structural presence (folding and faulting) along such rugged-hilly terrain, it becomes highly fractured, highly weathered (Pachauri 2010), sheared, and less consolidated. furthermore, compared to other Himalayan sequences,

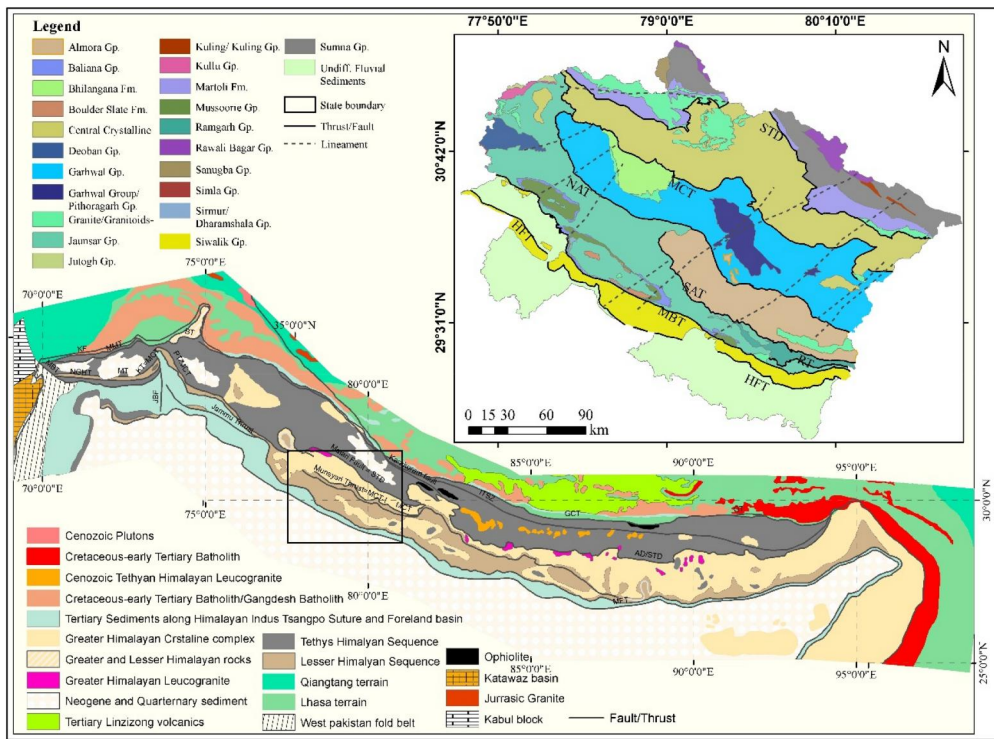


Figure 3. Geological map view of Uttarakhand Himalayan and Himalayan geological stretch (modified after Yin 2005 and GSI 2021).

the LHS experiences a higher amplitude of human temporal interference through construction-development activities, such as cultivation, deforestation, construction of roads cutting on complex slopes, more vehicular movements, mining, and other economic activities etc. These elements weaken and fragile the LH terrain, which frequently exacerbates the landslide phenomenon, especially during the monsoon season (Khanduri 2017). Similarly, Central Himalaya (HCH) is a region that is highly sensitive to tectonic instability. It is further negatively impacted by anthropogenic intervention, but not up to that greater extent than LHS. It is bounded by STD-MCT from its North-south. Similarly, Tethyan Himalaya (TH) (Figure 4) is strongly influenced by glacial and periglacial processes, with diverse landforms, such as active glaciers, moraines, and loosely-sedimented alluvial fans. Thus, resulting in various incidents of landslides, avalanches, or snow-induced rock avalanches.

2.1. Slope failure: vulnerability with the climate

As previous mentioned, different terrestrial phenomenon influences the slope instability which causes the associated threat, out of them climate play a very crucial role. In natural conditions climate and its variations at different temporal and geographical scales influence the rate and movement and velocity and chiefly by precipitation and temperature (Crozier 2010).

Heavy precipitation, like the kind that happens during the monsoon season from mid-June through late September. Thus, it also triggers landslides on the steep

	North		
	Trans Himalaya (Tibetan plateau, batholith)	Average width of the region is around 40km at the extremities and 225km in the central part. Average elevation is 3000m	
	Tethyan or Tibetan Himalaya	Marine, fossiliferous strata. comprising of Proterozoic, Mesozoic and Eocene age rocks.	
	Greater/Higher/Central Himalaya	Crystalline complex consisting of gneisses and aplitic granites. High grade crystalline rocks (Granite and gneisses) overlain by metamorphosed sediments (limestone), elevation range from 5-8km and approx. average elevation of 6100m with average width 25-30km	
	Lesser Himalaya	Non-fossiliferous low-grade metamorphic rocks or Partially metamorphosed sedimentaries and low-high grade crystalline rocks of Proterozoic age. Also thin deposits of early tertiary marine sediments exposed in outliers and windows. Average elevation varies from 2-3km, and average width 60-80km.	
	Sub Himalaya	Cenozoic (late tertiary to early quaternary aged sediment) Average elevation range differs 500-800m (autochthon) to 2.5-3km (parautochthon), width vary with the exposures along the foothill.	
	Indo-gangetic Foredeep		
	South		

Figure 4. Major structural division of the UH.

terrain. Although, regional setup sometimes drives off-season (early/an extended period) precipitation in a different part of the region and helps in gaining trigger. Furthermore, a scientific study says if the amount released in the preceding seven days is abnormally high in any high mountains, then the potential occurrence of landslides increases. When determining the intensity of precipitation as an aggressive factor, only the immediate preceding rainfall event will be considered. In special terms, landslides may result from moisture content variations in continuous precipitation and are difficult to monitor accurately at a finer scale. Studying the impact of rainfall that precedes a landslide is the simplest way to establish a threshold for them. Globally, records from (Pasuto and Silvano 1998; Kanungo and Sharma 2014; Dikshit and Satyam 2017) explain the antecedent period from 3 to 120 days for the seasonal threshold. For the study area, it can be better conceptualized in Figure 5, which describes the annual cumulative distribution of rainfall. In Figure 6 area-specific plot for the administrative blocks can easily be conceptualized.

The graphical representation shows the cumulative-intense variation in the UH precipitation throughout the period of (2010–2022), Source (<https://indiawris.gov.in>). The red portion differentiates the peak monsoon frequency attributed to the sudden rising peak in the year's trend. The yellow line represents the average value calculated for the months defining year show remarkable changes in the pattern, especially for the years 2010, 2012, 2013, and 2021, respectively in the post-monsoon phase. Various studies suggest the combined impact of more frequent intense rainfall and a warming-environment interaction is affecting the delicate structures around the natural and artificial reservoirs/lakes. Over time add-some effects of such cumulates can affect such structures. It may result in the release of flash floods and downstream

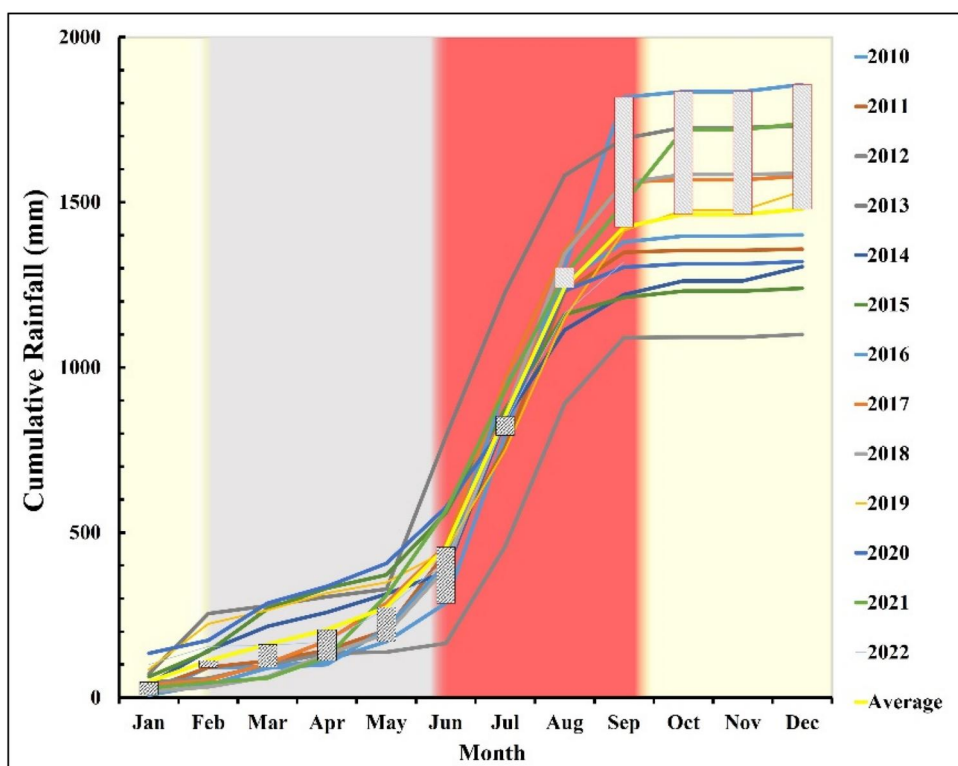


Figure 5. Cumulative rainfall distribution in UH.

flooding, activation/reactivation of landslides by the rapid flow, toe cutting, and associated infrastructure damage with the loss of water resources. For the climatic review, an interpretation with the ‘Climatic reanalysis product-ECMWF produced-ERA5 Daily Aggregates (2017) (C3S 2017) with vectorized 95 Administrative blocks was made to get the total precipitation pattern. The understanding was synchronized using the Google earth engine (GEE)—a cloud platform. It displays the temporal high intensified precipitation of the region for the study years. Figures 6(A,B) represent the single day-max intense precipitation beyond the torrential limit, which was obtained for all 95 administrative blocks of the state. The Red dotted encircled represents the excess limit of precipitation that happened in a single day max range beyond 125 mm in each administrative unit. As per the technical definition of the cloud burst >100 mm (Dimri et al. 2017). The further rising and falling trends in every single block represent the seasonal or monsoonal fluctuation for the study period.

From Figure 6, the understanding of the basic pattern was further summarized into three parts and illustrated in its continuation in Figure 7: where (A) represents antecedent prolonged (preceding 7 days) intense rainfall pattern with a day hour’s stretch—it defines the example of the observed precipitation for the particular administrative block number ‘86’ as ‘Champawat’ with a significant positive rate of excess delivers in the area. The graphical plot was made for the year 2012 and the year selection was random to obtain the trend. (B) Illustrates the number of frequent-intense precipitation

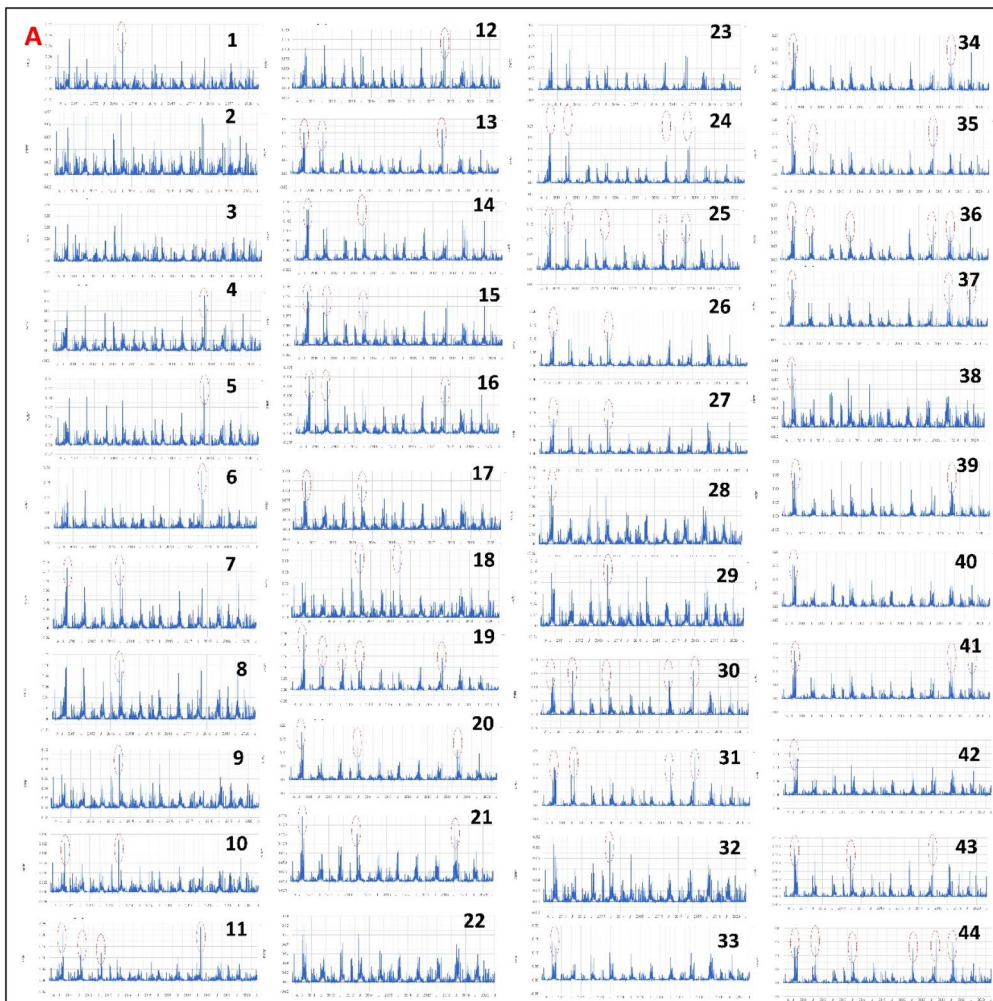


Figure 6. (A,B) Representation of precipitation day hour max trend in 95 administrative blocks of Uttarakhand.

events that have been encouraged geographically due to hill characteristics—it represents an area day mean total precipitation, which shows multiple extreme event peaks in the same administrative blocks for the study period. This results in the activation and reactivation of thousands of landslides concerning their potential threat (C) Region Classification w.r.t the stability defining potential vulnerability. Combining the results from the current evaluation and the information obtained from past studies show that a combined 72% of articles provide information based on the landslide event as a trigger, out of which 58% of articles directly relate climatic influence as the major trigger and used station- and satellite-based rainfall data as event information. Similarly, 67% of articles focused on the seismic results as the triggers for the explanation. Similar statistics have been computed with the current area specific, here 78% of articles were prepared with the triggers as the influence along with the preparatory response. Relatively comparing the figures 77% revealed and lightening the events on the Area-specific

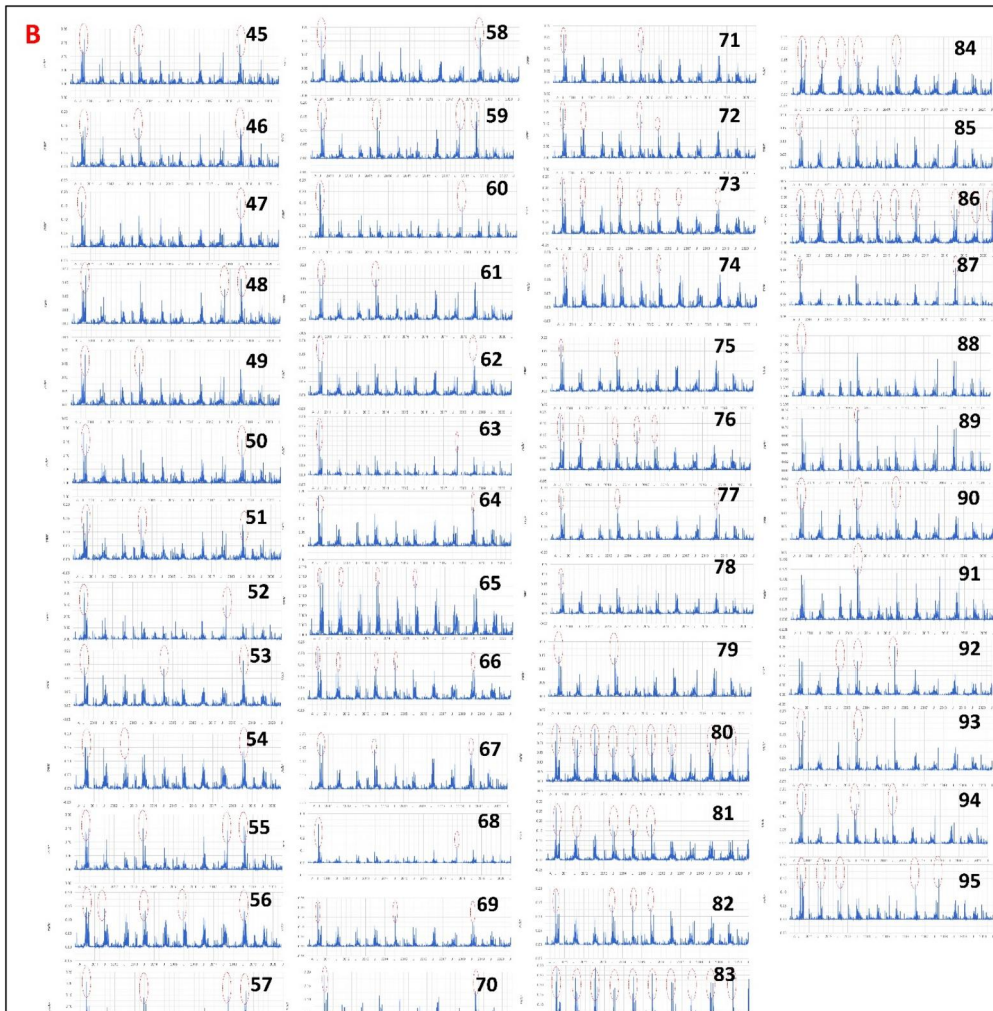


Figure 6. Continued

studies with precipitation factors rest focussing and relating it with anthropogenic (road cutting, manmade river damming, mining and quarrying, heavy construction on an undefined slope, forest fire, etc.).

Although there have been numerous studies of slope failures attributed to rainfall in seismically active terrain, such as Uttarakhand (Sangeeta and Maheshwari 2019; Gupta and Satyam 2022; Khanduri 2022). There have been relatively few studies predicting the potential effects of both factors.

2.2. Slope failure: vulnerability with the interplate seismicity

It is concluded that co-seismic slope failures are the most dangerous geological hazards in seismically active mountainous regions (Javed et al. 2017). As the result of the 1999 Chamoli earthquake, Barnard et al. (2001) reported 56 triggered landslides after

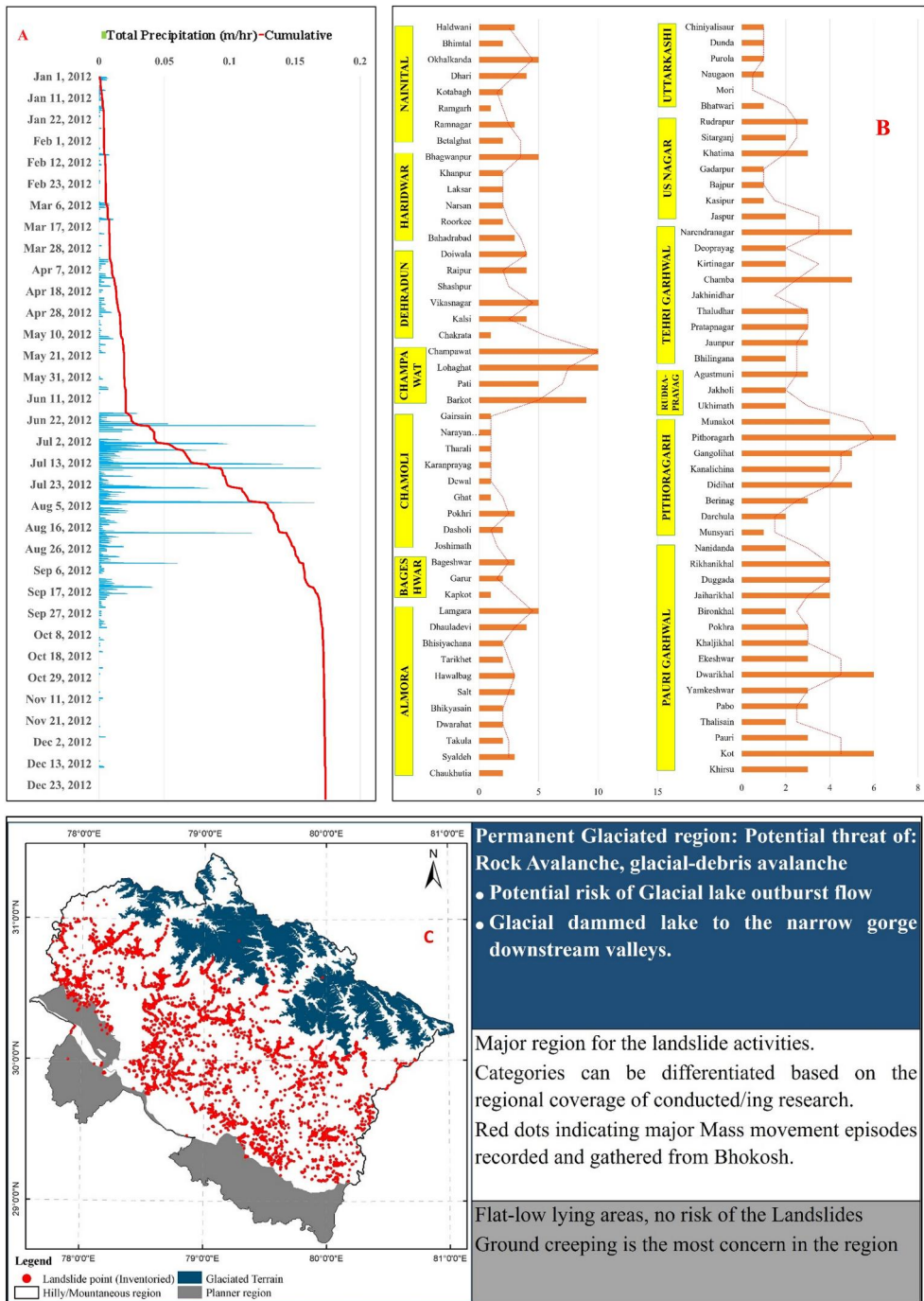


Figure 7. (A) ERA-5 modelled based precipitation observed for the administrative block-Champawat (ID-86), (B) extreme precipitation events in 95 administrative blocks for the study period, and (C) landslide distribution in the region with their vulnerability.

the earthquake in the region. Although, the review conducted here since 2010 depicts relatively fewer/no current record of greater than $M_w=6$ earthquakes in the region. Based on data obtained from <https://seismo.gov.in/data-portal>, shows only two seismic events occurred greater than $M_w=5-6$ with a depth ranging of 5–10 km and ~30 events of $M_w=4-5$ having 5–30 km depth in the region. Several earthquakes below $M_w<4$ have been found in the inventory displayed in Figure 8. Along with the background as seismic density plot in the close periphery.

The majority of the seismic event shows their inclination and dynamics along the active tectonics margins, particularly their majority along the Main Central Thrust (MCT) and North Almora Thrust (NAT). MBT and other regional fault systems are also sensitive to their confluence with regional faults. Such dynamics led to a nucleation process to trigger the weak zone (along the high slope, unconsolidated soil overburden, barren land, vulnerable directional slope, near geological structures/weak planes), which further results in significant slope failure or in form of an avalanche in the region. Table 4 represents the slope class (% distribution), landslide (frequency), and seismic events distribution concerning the seismic zonation of Uttarakhand. The database indicates slope movements and seismic episode occurrences majorly along the slope range of 15–30 and 30–45°. It is also obtained that the central part (Lesser Himalayan group of rocks) are more vulnerable to such type of activities. Detailed information about the specific slope class percent distribution, Seismic history (earthquakes along the slope classes), Landslides (along the slope classes), Slope failure vulnerability of the region, and a few publications detail those using slope range as a critical parameter for their study given below in Table 4 with further their extension down in the list.

3. Slope movement: region-specific classification

The above representations Figures 1, 2, 6(c), and 7 represent the supporting characteristics of Uttarakhand. Here, the most common natural slope failures and their activation shows potential sensitivity and inclination towards the water level changes, intense rainfall, rapid snowmelt, and earthquake shaking. In such terrain, it is frequently observed that sudden drops in the water level against the slope also cause landslides. This happened particularly near to earth dams, along dam margins, and along the banks of lakes, reservoirs, canals, and rivers. Similarly, it is noticed with the rapid snow melt which get saturates more to the hillside soil and recharged the shallow fractured basement. It raises pore fluid pressure beneath regolith, thus triggering the landslide (Mathewson et al. 1990).

Further, taking as region-specific failures- can be differentiated into two basic categories: ‘landslide’ and ‘rapid slope failure’. As described in Table 5, the division elaborates on the classified failure mechanism based on the gradient, nature of the movement, rate with moving mass (rock, debris, and earth), and the possible aforementioned triggering stipules which support the geographical location of Uttarakhand followed by the overburden mass, topography, geology, soil, over the region. Additionally, landslides and rapid slope failures differ from one another in terms of

the size of the incident, slope inclination, and point of origin. Table 5 describes the following as an extended form (Red and Blue outlined).

The slope morphometry presents great variations along the geological units in this region. Failures along the slope valued between min-max (usually above 20° and rarely exceeding $>55^\circ$) can directly relate to the (Varnes 1978) slope morphometric classification. Based on that landslides, slope classes are characterized into six broad classes grouped as a very gentle, gentle, moderately steep, steep, very steep, and escarpment/cliff. The slope angle $>45^\circ$ is represented as falls and topples. Similarly, a slope angle $>15\text{--}35^\circ$ as the slides, and $<15^\circ$ considers slides with creep movement. As per the rate of failure, velocity scale has been proposed by the (Varnes 1978). It is estimated that the landslides generally move at a slow rate (less than cm/min.) with a longer duration (over 100 h) and these are frequently repeated movements with the typical slope angle (Gentle-Moderately steep). In contrast, rapid slope failure typically moves at a rate of more than 1 m per second (with high slope angles that are steep and very steep) and takes less than an hour.

As opposed to weathered materials in their natural state, high slope values exceeding 45° consist of sturdy rocks, and these types of rocks are stable, high slope values are very rare in terms of landslides. It is because of the width of weathering zone which is found too few in such slope settings thus it reduces the susceptibility of landslides. The only thing that heavily triggers these incidents over such slope conditions is the sudden shaking of the earth slab by earthquake and volcanism or by the anthropogenic vibration during the mega-scale development projects. Tanoli et al. (2017) reported that 76% of landslides occurred at slope range between 20 and 50° before earthquakes, whereas 78% occurred at slopes of $30\text{--}80^\circ$ after earthquakes. It determines the effectiveness of such triggers.

4. Slope susceptibility analysis: remote sensing and GIS approach for LSM

From this analysis, varying variable selection with new and modern product refinement techniques, numerous modeling approaches along with differing validation performance. These were applied to the earlier research which gives nearly accurate/positive sign of model adaptability. Irrespective of the modeling approach used, the selection of the thematic raster defining extensive variables particularly if seasonal derivatives—is important and a pre-requisite for LSM. From the records, author extracted information on causative factors for the respective theme preparation. In sequence to that Space-borne data, product types, ground-based events information, and other valuable data as a source for inventory were identified and listed. This can help one with further sorting and inventory arrangement. The scale, mapping unit, and resolution of these inputs are also very important for production and model development.

4.1. Landslide inventory, causative factors, thematic selection-preparation for the LSM

We have listed 100+ papers specifically focussing their views on the landslide incidents covering UH. Similarly, several other published records project the same

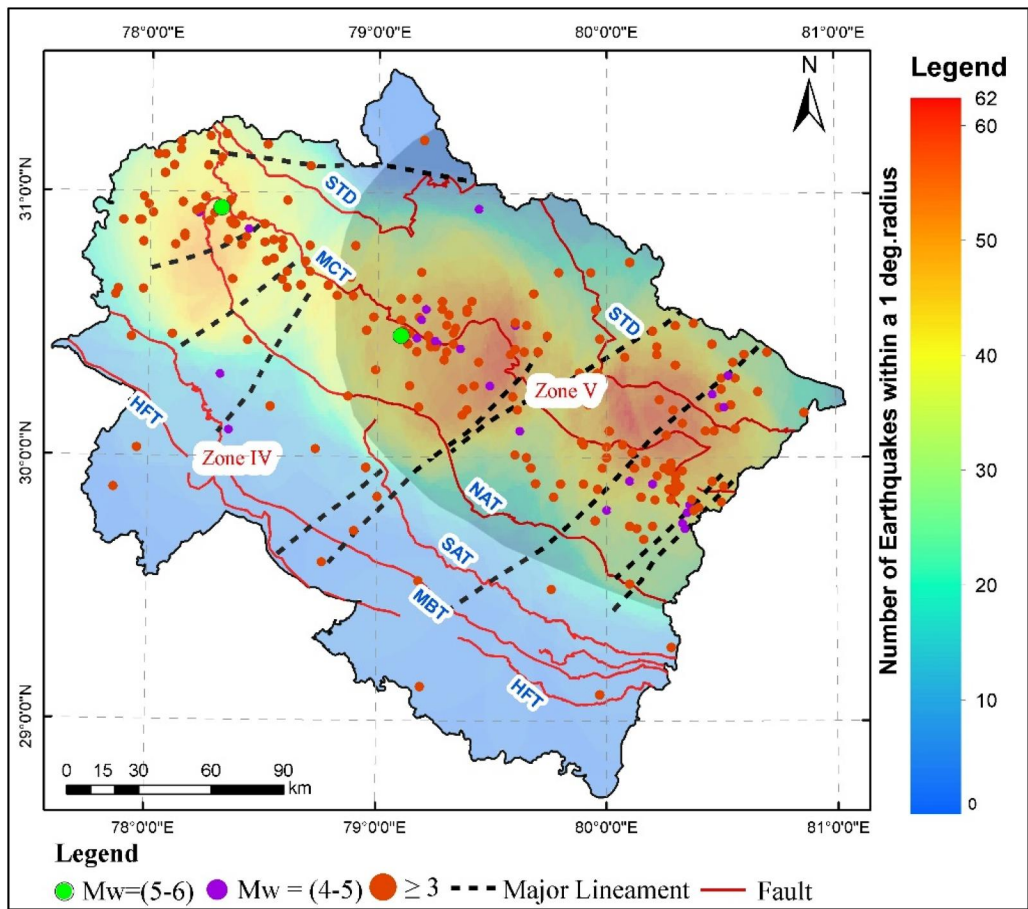


Figure 8. Seismic zonation, archival seismic density map with the structural framework of Uttarakhand Himalaya.

worldwide. These are separated into six major groups geological, morphological, hydrological, land cover, climatic triggering, and geo-technical, and represented in Figure 11. Further, the vertical bar diagram shows the effectivity and potency of the specific while defining the susceptibility.

These groups may be combined or cascaded in the space and time. Sometimes it results in 'complex-movements,' which include more than one type of movement or those in which one type of movement develops into another. Most of the cases, behaviour of slope movement is highly controlled by the nature of the geological material and so on by physical, hydrological, and geotechnical properties. It demands further exploration for their establishment.

Although these groups were selected and studied based on the un-stability caused by the single controlling parameter 'Slope' which is greatly preferred and often initiates such un-stability. Finally, insights from the records enlighten the behavior of such slope failures, which is time-dependent. So, according to Crozier (1986) the safety factor (FoS) of the slope, by comparing the shear strength (act to resist

Table 4. Slope class distribution concerning the seismic zone and archives of seismic and landslide with rock type of the region.

Slope (in degree)	Slope percent in the seismic zone. (approx.)	Rock type	Seismic history (earthquakes along the slope classes)	Landslides along the slope classes	Slope failure vulnerability of the region
Zone IV					
0–15	77.31	Ph, St, Sl, Qtz, Sle, Lst, Lcgrt	11	221	Low
16–30	53.57	Gnlis, Ph, St, Sl, Qtz, Sle, Lst, Lcgrt	30	1292	Moderate
31–45	46.16	Ph, St, Sl, Qtz, Sle, Lst, Lcgrt, Gnlis, grt, Sdt., Lst, Dlmnt, DnGrvl, Uncslst st	33	1528	High
46–60	28.05	Ph, St, Sl, Qtz, Sle, Lst, Lcgrt, Gnlis,grt, Sdt., Lst, DnGrvl, Uncslst st	04	240	Moderately high
61–75	14.70	Ph, St, Sl, Qtz, Sle, Lst, Lcgrt, Dlmnt DnGrvl, Clmrt, Uncslst st, Amblt	–	06	Very high
76–90	5.02	Ph, Dlmnt, Gnlis, Qtz, Lst, St, Amblt, Grt	–	–	Extremely high
Zone V					
0–15	22.67	Qtz, Ph, St, Sl, Sle, Clmrt, Gnlis, Lst, Dlmnt, Lcgrt, Snst	18	112	Low
16–30	46.42	Qtz, Ph, St, Sl, Lst, Clmrt, Gnlis, Grt, Amblt, Migt, Dlmnt, Lcgrt	63	731	Moderate
31–45	53.83	Qtz, Ph, St, Sl, Lst, Clmrt, Gnlis, Lcgrt, Grt, Amblt, Migt, Dlmnt, Dlmnt	53	906	High
46–60	71.95	Qtz, Ph, St, Sl, Lst, Clmrt, Gnlis, Lcgrt, Grt, Amblt, Migt, Dlmnt	20	175	Moderately high
61–75	85.30	Qtz, Ph, St, Sl, Lst, Dlmnt, Gnlis, Migt Amblt, Lcgrt, Grt, Dlmnt	03	10	Very high
76–90	94.98	Qtz, Ph, St, Sl, Lst, Gnlis, Lcgrt, Grt, Amblt, Migt	–	–	Extremely high

The realized landslide slope values in the literature

Author	A	B	C	D	E	F	G
Authors (1)	0–12	13–25	26–38	39–51	52–64	65–77	>77
Authors (2)	0–15	15–30	30–45	45–60	60–75	75–90	
Authors (3)	<15	16–25	26–35	36–45	46–65	>65	
Authors (4)	0–15	15–25	26–35	35–50	>50		
Authors (5)	<15	16–25	26–35	36–45	>46		
Authors (6)	0–8.5	8.5–35	>35				

Note: Broad-defined metamorphic/meta-sedimentary rocks—Gnlis: Gneisses; Ph: Phyllite; St: Schist; Sl: Slate; Qtz: Quartzite; Sle: Shale; Lcgrt: Leucogranite; grt: Granite; Migt: Migmatites; Sedimentary rocks—Snst: Sandstone; Lst: Limestone, Claystone; Clmrt: Conglomerate and Mudstone; DnGrvl: Doon Gravels; Uncslst st.: Unconsolidated Sediment; Dlmnt: Dolomite; Amblt: Amphibolite.

(1) (Gupta and Satyam 2022); (2) (Batar and Watanabe 2021); (3) Kainthura and Sharma 2022); (4) (Bhattacharyya et al. 2020); (5) (Tiwar et al. 2020); (6) (Jain et al. 2022).

Table 5. Characteristics of slope failure.

Different characteristics of landslides and rapid slope failures according to Watari (1986)					
		Landslide	Rapid slope failures		
Geology (structure and lithology)		Frequently affected by geology and geologic structures	Geology and geologic structure have little to no influence.		
Soils (top-soil and regolith)		Movement take places along slip surfaces (consists of highly plastic clay)	Generally, participates topsoil, residual soil, and regolith.		
Topographic slope		Occur on gentle to moderate slopes (5–45°) The upper slopes supports flat-plateau-like topography	Usually occurs on slopes steeper than 30°		
Nature of act		Continual; recurring (repetitive occurrence) The average episode lasts a long time.	Occur quickly and unexpectedly		
Movement rate		Typically very slow to slow (0.01–10 mm/day) most common	Exceptionally quick 10 m/s or quicker		
Moving mass nature		Hardly any movement within a sliding. The block frequently shifts while retaining the original shape and characteristics.	Erratic movement as a very disturbed mass		
Mechanism for triggering		Elevated groundwater table and excess groundwater are the main factors.	Likely influenced by rainfall intensity		
Size of slope failure		Surface area is often large (1–100 ha).	surface area is generally small (an average volume of about 440 m ³)		
Precursors or surface warning signs		Before sliding, surfaces frequently develop cracks, depressions, upheavals, groundwater fluctuations, etc.	A sudden failure, always occurs without warning		
Gradient support to slope failure (in degree)		10–25	35–65		
Classification of slope morphometry defining the terrain					
Morphometry-type as slope		Slope categories (in degree)	Probable type of failure (Table 2)		
Escarpment or cliff		GT 65	Falls and topples		
Very steep		46–65	Falls and topples		
Steep		36–45	Slides		
Moderately steep		26–35	Slides		
Gentle		16–25	Slides with creep movement		
Very gentle		LT 15	Slides with creep movement		
Landslide movement scale (Varnes 1978)					
		Movement type and rate		Mass velocity (mm/s)	Typical velocity
Falls	Topples	Slides	spread		
Extremely rapid					
Very rapid				5*10 ³	5 m/s
Rapid				5*10 ¹	3 m/min
Moderate				5*10 ⁻¹	1.8 m/h
Slow				5*10 ⁻³	13 m/month
Very slow				5*10 ⁻⁵	1.6 m/year
Extremely slow				5*10 ⁻⁷	16 mm/year

Their classification, and rate of movement as per literatures.

deformation) and shear stress (Force/area) of the slope material, it is possible to classify the slope movement into three stages stable, marginal, or meta-stable and unstable and can be represented by the probability distribution curve representing time dependency in creating slope failure (Figure 9).

4.2. Landslide inventory

The first step in assessing susceptibility is to compile a list of an inventory. Historically, inventory data have been used to trace the landslide and their patterns more likely in any area. It can be used for a variety of perceptions and goals that can be implemented for a variety of purposes. These could be local or regional landslide documentation and/or for the susceptibility, vulnerability, and risk analysis. Most inventories are created manually using visual image interpretation based on various sources, such as aerial photographs, unspecified satellite images, Google Earth (GE) images, or pixel-based records of previous inventories. To identify a landslide, land features special characteristics commonly used, such as terrain signature, spectral reflectance, appearance, morphological expression, DN (digital number) values, color, tone, texture, and indices, among others. To construct a landslide inventory, there are no standard guidelines.

Review assessment: While going through the regional database, 15.2% of articles did not mention any kind of inventory information in their LSZ process. In the majority of the articles, the inventory was described as large-small and cross-checked with field visits. The comprehensive evaluation of the technique used by the authors is summarized as the velocity and depth of the scar illustrated in Figure 10(A). Technically, field and domain supervision as an expertise will be very beneficial in such an analysis otherwise, the degree of reliability and ambiguity in the records will continue to exist. According to (Sarkar and Kanungo 2004; Guzzetti et al. (2012)), In addition to field work and other database-the quality of the landslide inventory can be improved by including additional information, such as the depth and type of slide, the material involved, the number of losses, and so on. Records say the number of activities in terms of landslide and associated subsidence has increased in the region. Fall, creeping, and shallow focus slope movements are found to be very common in literature whereas, the reporting on the earlier exposed scars can be figured out as most of the deep-seated slope failures with their space and time distribution as shown by Figure 10(B). It also depicts the trend in terms of increase, decrease, and no change of the slope failure categories in the major districts representing Uttarakhand.

RS and GIS limitations can be attributed to the researcher's ability to identify landslides from RS data, which requires high-resolution cloud-free images for better interpretation. Concerning challenges the adjacency effect also makes it difficult to delineate the exact boundary of landslides in hilly terrain due to different slope heights and aspects A significant number of articles on susceptibility, or zonation were found to be used in unique databases for an inventory. The illustration in Figure 11 is entirely based on existing work. Selection of the factor theme is one of the most difficult aspects of assessing landslide susceptibility determining the best combination of themes and representative factors. However, their association with the

study area should be usually locally established along with data availability. With the literature, we have examined important sixty-five factors under the abovementioned six broad categories displayed in Figure 11 below.

These themes have been observed as the initial important factor for susceptibility mapping. The role of individual themes in the percent was graphed, extending in Figure 11. There were ~91.5% of publications that use slope, followed by Lithology (62.7%), aspect (50.8%), elevation (43%), curvature (37.2%), lineament, fault (38 and 23%), and others. Future perspectives on conducting such studies can eliminate and replace these factors with terrain sense ideas.

4.3. Dataset selection for LSM and thematic modelling

Figure 12 depicts the outcome of this analysis, which depicts widely used globally accessible paid/free datasets for mapping and monitoring of such natural hazards by the scientific, research, and communities’/level authorities periodically to encompass the potential threat. Existing available information shows the categories to which one can use it by the spatial information, their revisit over the study area, and reliability while focusing the scar identification. The quality and effectiveness of the map can be further increased with the subcategories demanding local, regional, and wide perspectives of the map using high (1–10 m), moderate (10–30 m), and coarse (>30 m) datasets. Landslide mapping scales as; Large (1:5k–1:15k), Medium (1:25k–1:100k), Regional (1:100k–1:500k), and National (<1:500k) Functionalities sometime change with the datasets like DEM (DTM/DSM/) which differs sometimes and quite important when dealing with changes in topographic undulations from sudden terrain flatness to sudden rising ridges alongside or their combined integration. Similarly, dependency upon the resolution of the satellite dataset sometimes results in a long spatial revisit which further results in the lack of updation in the calamities frequency over the region and plays a significant role in configuring finer mapping units (In

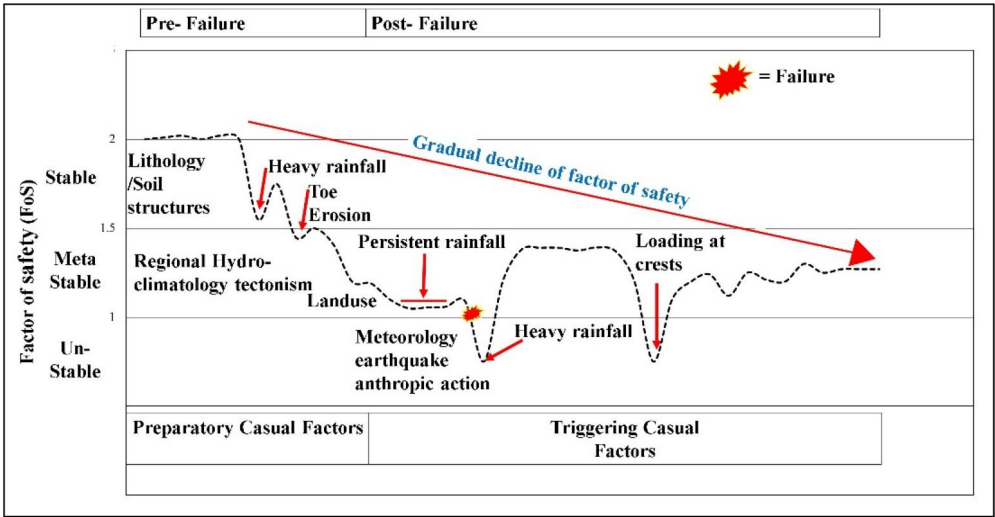


Figure 9. Factor of safety of the region representing slope failure condition.

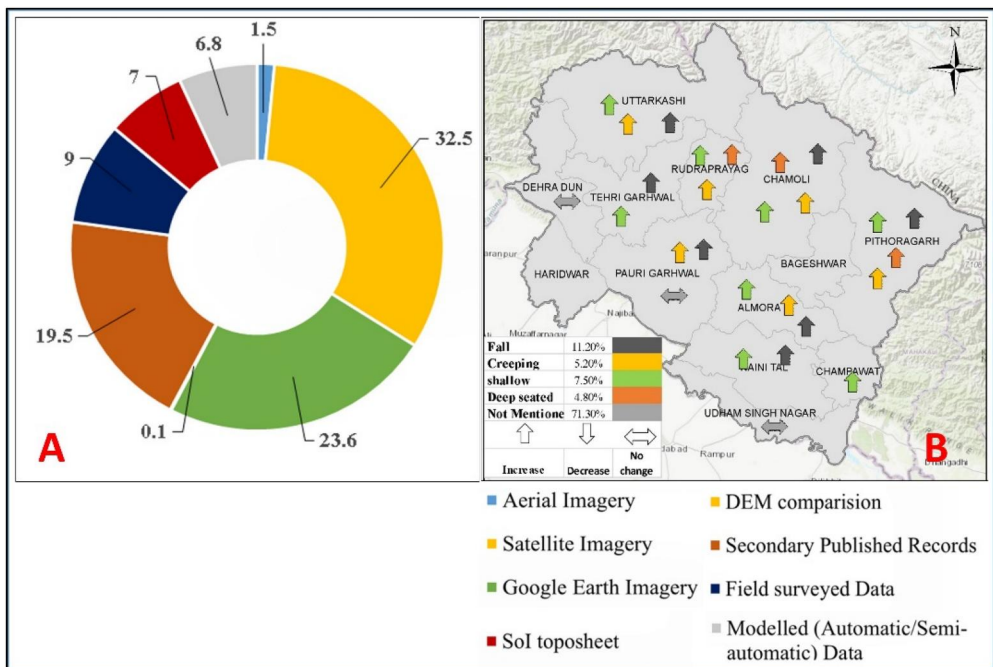


Figure 10. (A) Technique and data source used widely in LSM/LSA inventory as reviewed and (B) space-time distribution of slope failure in the region.

terms of the type of landslide, and its failure mechanisms). Because the mapping unit, which can be either regular or irregular primitives, is the smallest indivisible unit of space used in the landslide susceptibility analysis. When analyzing susceptibility, it is essential to select meaningful mapping units. The most appropriate mapping unit is determined by several factors, including the type of landslide phenomenon, the scale of investigation, quality, resolution, thematic information scale and type, and adequate information management with analysis tools (Calvella et al. 2013). All units in this study are divided into five categories: Grid units, Terrain units, unique condition units, Slope units, and Topographic units (Guzzetti et al. 1999), as illustrated in Figure 13.

5. Model/approach and validation methods

Model and various approaches used for the validation of landslide risk assessments are essential elements in mapping like LSA/LSM/LSZ, as the estimation of risk is usually subject to substantial uncertainty. However, very few studies have addressed this issue specifically. To maximize investment for landslide risk mitigation, management authority, and decision-makers should be aware of the limitations of risk analysis results. The majority of the modeling approaches have been discussed in the introductory part of the article.

The elementary framework of any hazard model and its validation should centre around the basic pattern of investigation (1) detailed area analysis and hazard modelling, (2) topographic support reliable slope failure modelling, (3) damage modelling

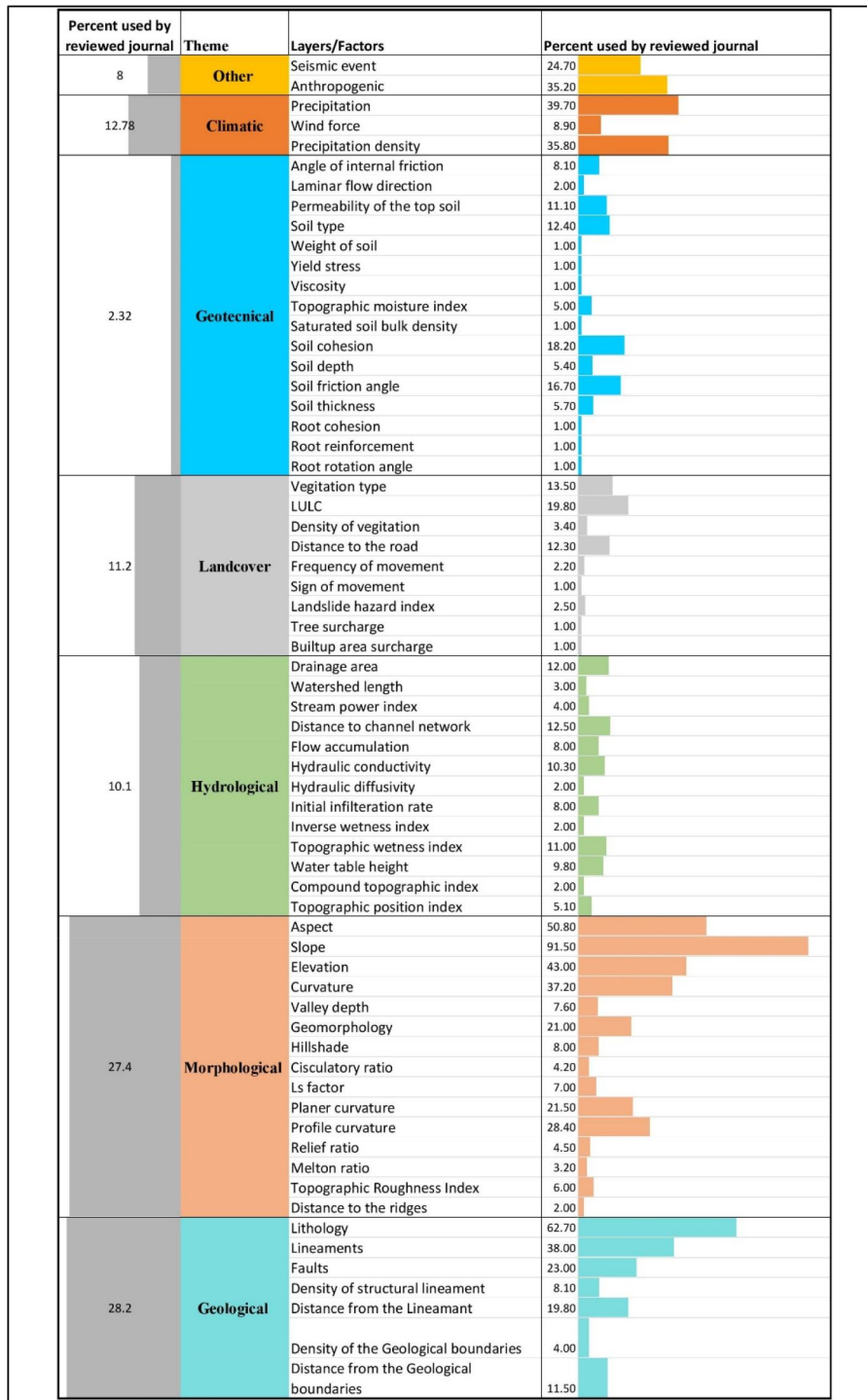


Figure 11. Causative factor used for the LSM/LSA and used by the articles acquired from the records.

(probability of affecting area accumulates), and (4) integration of hazards-associated failures-produced damage to compute and evaluate risk, failure and reliable modelling. The session summarized perspectives from various records on effective model validation and their practices on accuracy statements. A total of twelve validation practices were listed addressing the key challenges. By these recommendations, we may ultimately improve the potential reliability and usability of slope failure analyses (Figures 14(A–D)).

With these twelve important validation methods, we found that 80.50% of articles/Publications choice with these validation methods, such as AUC/ROC/SR/PRC, Event data (inventoried frequency and density) method, Expert opinion, RMSE, R-index techniques, and quality sum index methods for validation. Where, Specifically, AUC/ROC/SR/PRC is found to be used by 33%, inventoried frequency, and density have been used by 19.5%, Indexes (LDI) by 5%, RMSE, and R-index techniques were used by 3.5 and 1.5%, respectively and so on. A total of 19.5% were found to perform no validation for the model evaluation. For the performance of any model calibration, an initial training dataset is required. After calibration and execution of the model, the resultant map can be checked for their prediction accuracy of landslides over an area scientifically. The compatibility of models should be checked in any scientific studies using these Qualitative/Quantitative validation techniques.

6. Discussion

In this literature review and analysis, the author identified the different methods and variety of input data, etc. commonly used to map landslide susceptibility. Various aspects were analyzed and examined to better understand disparities in the worldwide study, especially for Uttarakhand. A considerable heterogeneity was observed in the methods, thematic variables, origins of the inventories, and validation practices to compose the final susceptibility map. This could be due to the user space and dependency of potential drivers (participatory and triggering) acting separately and applied on a different part of the region.

This investigation included an evaluation of 360 articles from 2010 to 2022 on landslide susceptibility mapping (LSM/LSA) and its fundamentals. The articles targeted for the analysis on the current subject covering year-by-year changes, used techniques, type of landslides, movement, number of landslides and their frequency, their periodic causes, and finding their close association with climatic or Geo-disturbances, etc. Moreover, to observe the temporal trend, we segmented the articles into four phases. Based on it, we observed that the number of articles published in the study period since 2010 has increased annually, with new introductory techniques but also with advanced scale analysis. Such a development could be attributed to increased public awareness of certain disasters, as well as rapid advancements in related application and model development. To map and monitor landslide hazards across an area, it is critical to check the ease of access of digital datasets, including RS data, for the execution and evolution of new models (machine learning models) (Devoli et al. 2007). Recent reports indicate that investigators becoming increasingly interested in the sensitivity of mapping-monitoring landslides due to their global prevalence and

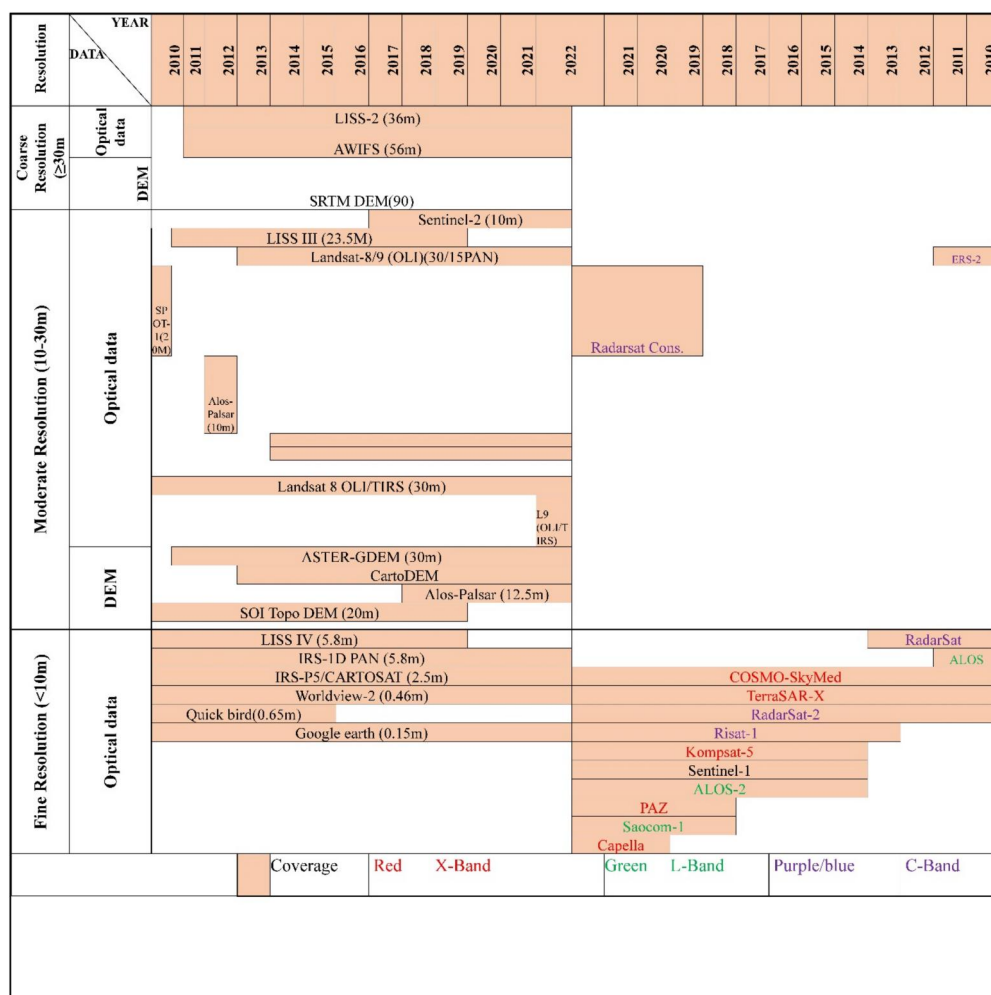


Figure 12. Globally open access/paid datasets for the natural hazard application (LSM/LSZ) model/approach.

ability to inflict irreparable harm to people their property and at the same time their prosperity. The present capabilities of scientific dealing coupled with the present Synthetic Aperture Radar (SAR) environment gives accurate and near possible prone areas delineation using such analysis (Ciampalini et al. 2016; Li et al. 2019). The regions investigated using the articles cover large parts of the state of Uttarakhand. However, Nainital, Tehri Garhwal, Rudraprayag, Chamoli, Pithoragarh, Almora and Uttarkashi were particularly targeted due to the frequency of movement that happened in the region from time to time in a long history. Such incidence contains region-specific characteristics. For instance, the likelihood of landslides is greater in areas with hills and affects when events impact, such as rainfall or earthquakes, which leads to more data being available and supporting more studies.

The examined papers included thousands of landslides, although some appeared to be duplicated. Many Individual studies have found that landslides occur frequently,

Grid Unit (a) (divide the territory into regular squares with same size)	Terrain Unit (b) (Based on the geological and geomorphological boundary)	Condition unit (c)	Slope unit (d) (Dividing the individual territory into independent slope by ridge line and valley.	Topographic unit (e)
Advantage		Limitation		
Small sampling limit and easy gridding, easily obtained and their matrix format is convenient for calculation		Natural slope is separated, connection with geological and geomorphic information are lacking		
Relationship among landslide and land surface is easy to analysis		It needs a lot of topographic/geology/information		
Covering different factor attribute for statistical analysis		Regional environmental differences are not considered		
Defined by ridge lines and valley lines based on hydrological theory, definite geological integration		Poor automation		
Suitable for predicting shallow landslide under the control of surface saturation and topography		Not closely related to deep or complex landslides		

Figure 13. Summary of the mapping units in LSM/LSA.

regardless of how frequently they occur. Refinement in the datasets can be used in future studies for further analysis in terms of new and more accurate models. Additionally, a concerted academic effort should be made to better understand landslides. Hence, landslide information and modeling must be improved through further case studies. It is recommended to ensure instrumental-based academic collaboration in which new models and merging of applied data can be used for better development for the site selection base study.

Pictorial and tabulated representation in Table 5, Figures 8, 9, 11, and 14 show the role of different observation and their affection in such studies which was considered 1000s times in the GIS-based LSM/LSA. All of the individuals, such as effect of role angles on stability, the association of slope parameters with others, the association of soil parameters with slope angle, the association of hydrology and slope angle, the association of lithology and slope angle, the association of climate and slope angle, the association of aspect and slope angle, the association of vegetation and slope angle, the association of erosion and slope angle, the association of seismicity and slope angle, the association of slope length elevation and slope angle, the association of landslides according to the slope values was majorly discussed. Because slope plays an intrinsic and governing major factor in defining movement so it is valued more with all the associated combinations. Several of these factors were considered frequently, suggesting that they are closely related to the occurrence of landslides. Despite this, the likely causes for landslides have not significantly changed over the study period. In account, of this microwave space-borne data can add movement,

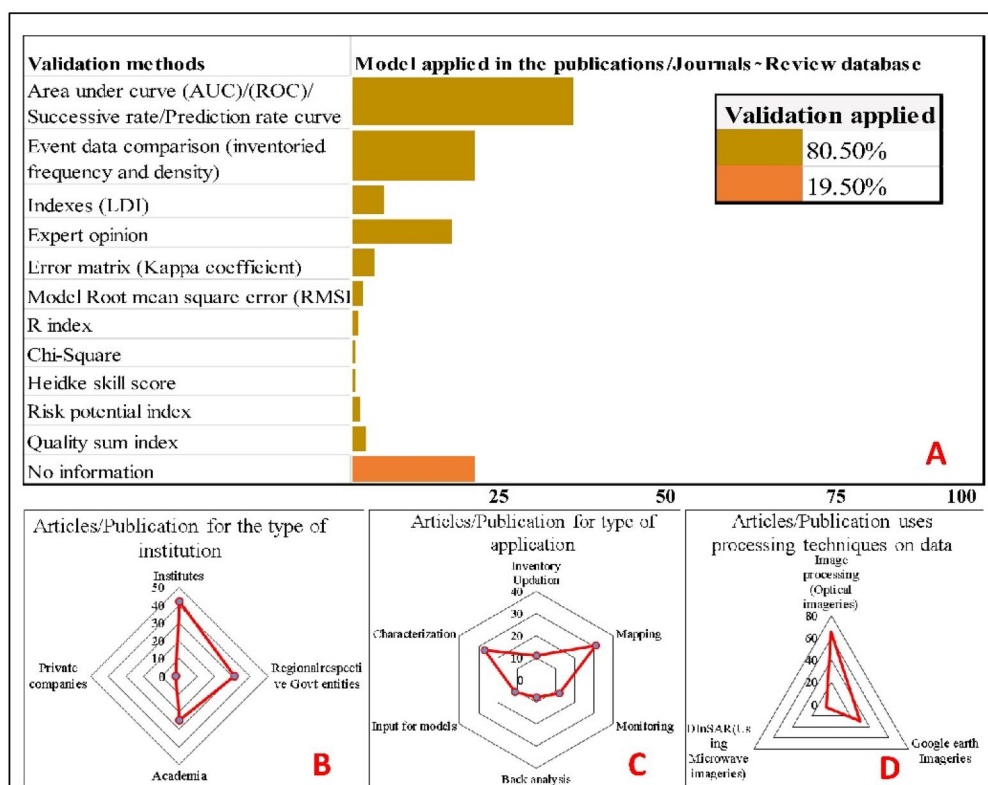


Figure 14. (A) Validation methods of LSM/LSA. (B) Radar diagram of articles published by the type of institution (C) for different applications, and (D) Processing technique on data collection.

their rate over the period, weights of causes, and other important add-ins for further research dimensions.

In terms of the employed models, several types were introduced by various authors as listed at the beginning of Table 2. Logistic regression, Frequency ratio, artificial neural network, fuzzy logic, support vector machine, AHP, and weight of evidence models were applied in most of the cases in the articles. Machine learning models, such as support vector machine, random forest, decision tree, and naïve Bayes models, have been applied more recently.

The first three steps of the analysis of landslides are susceptibility, hazards, and risk mapping. Susceptibility has been examined in numerous studies, including the current literature review. The hazard and risk steps, however, are covered in fewer articles. Therefore, more research should be done on the hazards and risk management techniques to lessen landslide damage, save lives, and prevent property.

For initial planning and cost-effective analysis, these issues at the catchment scale require additional information. Still, there is a lot of work to do in the integration of such models to improve zonation maps, which initially can be expensive (real-time data order) for real-time growth but cost-effective with the archival resources.

7. Conclusion

A large part of the review on landslide susceptibility mapping was devoted to Uttarakhand, as the state experienced ever so often landslide activities in its active territories. However, the central part (LH) that encompasses the region is where activities are more likely to occur. This could be the effect of the proximity of the dense identified major-minor fault system, localized lineaments, well-established urbanized colonies/developing projects and their load, and the presence of natural/artificial DAM impoundment, Lakes in the nearby region. Slope stability problem and their presence also explain their vast occurrences to the proximity of these sites likely to be mentioned above.

Various publications in the international/national community repeatedly and time-to-time have covered their changing status using advanced and comparatives techniques, which rely on the slope-movements defining models. It is further accomplished using different validation curves and accuracy methods. Current observation from the review figured out that, there is a lack of validation when it comes to decision-makers and stakeholders to assess the practical applicability of the generated LSM/LSZ. It is important and to be very precise when dealing with regional analyses, especially if the country/federal or state depends on terrain for its economic population, tourism, and revenue.

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Authors' contributions

HK conceptualized and compiled this manuscript from different sources; Original and technical articles, Books, conference papers, thesis's, proceedings, and state government/agencies of respective domain reports. HK thoroughly reviewed the contents, as material, technical processing, analyzed and prepared all structural data for this manuscript. KSR and RSC provided required/necessary input in the general organization of this manuscript significantly. The manuscript was read and approved by the author (s) and the datasets prepared/generated during and/or analyzed in this doctoral research are available from the corresponding author on reasonable request.

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Data availability statement

All materials used for the review article compilation are properly cited. The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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