



Geospatial assessment of urban sprawl and landslide susceptibility around the Nainital lake, Uttarakhand, India

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Abstract

Landslide is one of the challenges faced by mountainous regions due to natural phenomena and human activity. Nainital district in the state of Uttarakhand is one of the popular tourist spots in India. It is situated in a lesser Himalayan belt facing experiences number of landslides every year. This region comes under the Main Boundary Thrust and Main Central Thrust which are considered to be very sensitive for landslides. Landslide susceptibility mapping is a proficient tool to identify vulnerable zones for landslides. Remote sensing and geographic information system are very effective tools for collecting, analysing and interpreting land use data, and on the other hand, multi-criteria valuation (MCE) allows users for decision-making by considering various factors affecting the process of the landslide. The MCE technique was applied considering present land use/land cover, slope, drainage, lithology, geomorphology, and type of soil. Overlay analysis and land susceptibility mapping was carried out for the area around the Nainital lake. The study concludes with hot spot analysis and recommends mitigation measures like geotextiles, retaining walls and strict building by-laws for preventing landslides.

Keywords Landslide · Overlay analysis · Landslide susceptibility mapping · GIS · Nainital

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1 Introduction

The locomotion of rocks or rock debris along the downslope in a hilly region is known as landslide (Pasang et al. 2018). This geological phenomenon governed by the movement type, speed and existed materials into the rock (Hungur et al. 2014). Landslides are one of the major threats that significantly occur in the hilly terrain. It dangerously affects human lives, properties and has a very severe effect on natural resources. There are several factors which are responsible for the occurrence of a landslide and can broadly be classified into two categories viz. natural and anthropogenic. Natural factors entail earthquakes, heavy rainfall, floods and volcanic eruption, etc., while anthropogenic activity contains haphazard and un-effective infrastructure planning which alters the land environment and supports triggering of landslide (Turner and Schuster 1996; Ayalew et al. 2005; Erginal et al. 2008). Slope modification activity is one of the reasons which make the urban area more vulnerable to landslides (Borgatti and Soldati 2005; Lee and Hancher 2009; Fanyu et al. 2009; Martire et al. 2012). Last two decades of the ecosphere has subjected to tremendous urbanisation effects of which can also be seen in mountainous regions (Mukherjee et al. 2019). The developmental activity, especially in steep slopes, is tremendously susceptible to landslides (Hukku et al. 1977; Uniyal 2018). Due to the rapid growth of population, plain lands are facing massive pressure in terms of accommodation facilities. In a hilly region already there are inadequate plain lands are present but demand is increasing day by day. In view of that urbanisation is taking place on the slopy terrain and sprawling unscientifically over the year. Increasing Population density, improper land use, unplanned tourism activity, deforestation due to human activities (Vijay et al. 2016; Dey et al. 2018) is working as a trigger to haphazard expansion of urban area and other construction activities on the strong to steep slope area without any concern about urban sustainability (Ahmed 2015).

Nainital district is a tourist spot situated in Kumaun Himalaya, Uttarakhand, India. Several landslides have been reported in Nainital district (Pande 1974; Hukku et al. 1977; Anbalagan and Singh 1996; Pande et al. 2008; Puniya et al. 2013). It is reported by Disaster Mitigation and Management Centre (DMMR 2017) that there are almost 529, 155 and 150 landslide-prone areas along the Chardham Yatra route, Rishikesh–Gangotri route and Rishikesh–Badrinath route, respectively, which costs many lives and loss of property in the area. It is reported in recent year (2018) that the historic lower mall road collapsed near about 25 m section and fell into the Naini lake, and a high alert has been issued for upper mall road also for the public interest (Web-1). It is also reported that the place is facing many more landslides, road damages and other threats.

Landslide susceptibility mapping (LSM) is an effective and adequate way to identify and categorised the vulnerable sites, which have a great contribution to planning for developmental activity. Use of LSM is flourishing nowadays for effective land-use planning as it depicts the areas which are prone to a landslide (Wold et al. 1989). LSM can provide different degrees of vulnerability to a landslide which enables an urban planner to choose the development activity based on the degree of susceptibility and intensity of the project (Gorsevski et al. 2006; Bathrellos et al. 2009). Thus, LSM is a pioneering and sensible perspective and realistic minimisation of landslide threats. (Guzzetti et al. 2000; Sterlacchini et al. 2007). To carry out the LSM study, multi-criteria evaluation (MCE) is a statistical application used to estimate and predict the risk zone (Ahmed 2015). MCE analysis considers different physical conditions like slope, relief, drainage, terrain aspect, land use, etc., to get a comprehensive idea about the study area. MCE is strongly related with information value index (IVI) method that applied on several

thematic layers and after combining these raster thematic layers, the susceptibility map is prepared (Shahabi and Hashim 2015; Salcedo et al. 2018).

Remote sensing and geographic information system (GIS) are very effective tools for spatial analysis as it provides a platform for data analysis, interpretation, alternate scenario analysis and mapping. It is a proven and efficient technology for landslide research and evaluation (Sarkar et al. 1995). In the present scenario, several researchers used this technology for landslide hazard classification mapping (Gupta and Joshi 1990; Carrara et al. 1999; Westen 1994; Chung et al. 1995; Nagrajan et al. 1998; Dhakal et al. 2000; Saha et al. 2002; Sarkar and Kanungo 2004). Therefore, the objective of the study is to perform LSM and hotspot analysis around the Nainital region using remote sensing and GIS technology.

2 Study area

Nainital is one of the glorious hill town situated in Nainital district, Uttarakhand, India. Nainital is the most attractive tourist spot because of its picturesque beauty and healthy atmosphere. As per the physiographic settings, it is located at the outer lesser Himalayan range which is also known as Siwalik range (Sah et al. 2018). Other important ridges like Sher-Ka-Danda ridge are situated in the north-east side, Ayarpatta in the south-west and China peaks in the north-west side. This region is also coming under the main boundary thrust (Valdiya 1988). The geological activity like dissection is found to occur in Nainital lake region due to Nainital lake fault (NLF) which passes through the centre of the lake (Middlemiss 1890). Nainital lake is situated at an altitude of 1940 m above mean sea level. The maximum length of the lake is 1423 m with an average depth of 18.52 m (NIH 1998–99). The present study area considered is 2 km buffer from the periphery of the lake as shown in Fig. 1. The geographical settings of the location are 79°26' E to 79°29' E and 29°21' N to 29°25' N with an area 19.45 km². As far as the climate of the study area is concerned, it comes under tropical climate with a mean temperature of summer at 25 °C and 0 °C in winter. The average annual rainfall of the study area is 3500 mm, and it is influenced by south-west monsoon (Gupta et al. 2016).

3 Methodology

LSM technology requires detailed data so that it can be used for decision-making. As mentioned earlier, there are various factors which affect the incident of a landslide. As manual data collection is tedious, geospatial technology has been used in the present study (Carrara et al. 1999; Van Westen 1994).

The methodology adopted to carry out the study is explained in five sections. Section I explains the acquisition of satellite data; Section II deals with the spatial analysis for generation of different thematic layers like LULC, slope, aspect, drainage, lithology, geomorphology, hillshed, etc; Section III is about field verification/ground-truthing; Section IV throws light on overlay analysis performed in the study, and Section V describes the generation of final landslide susceptibility maps. The flow chart of the research methodology is represented in Fig. 2.

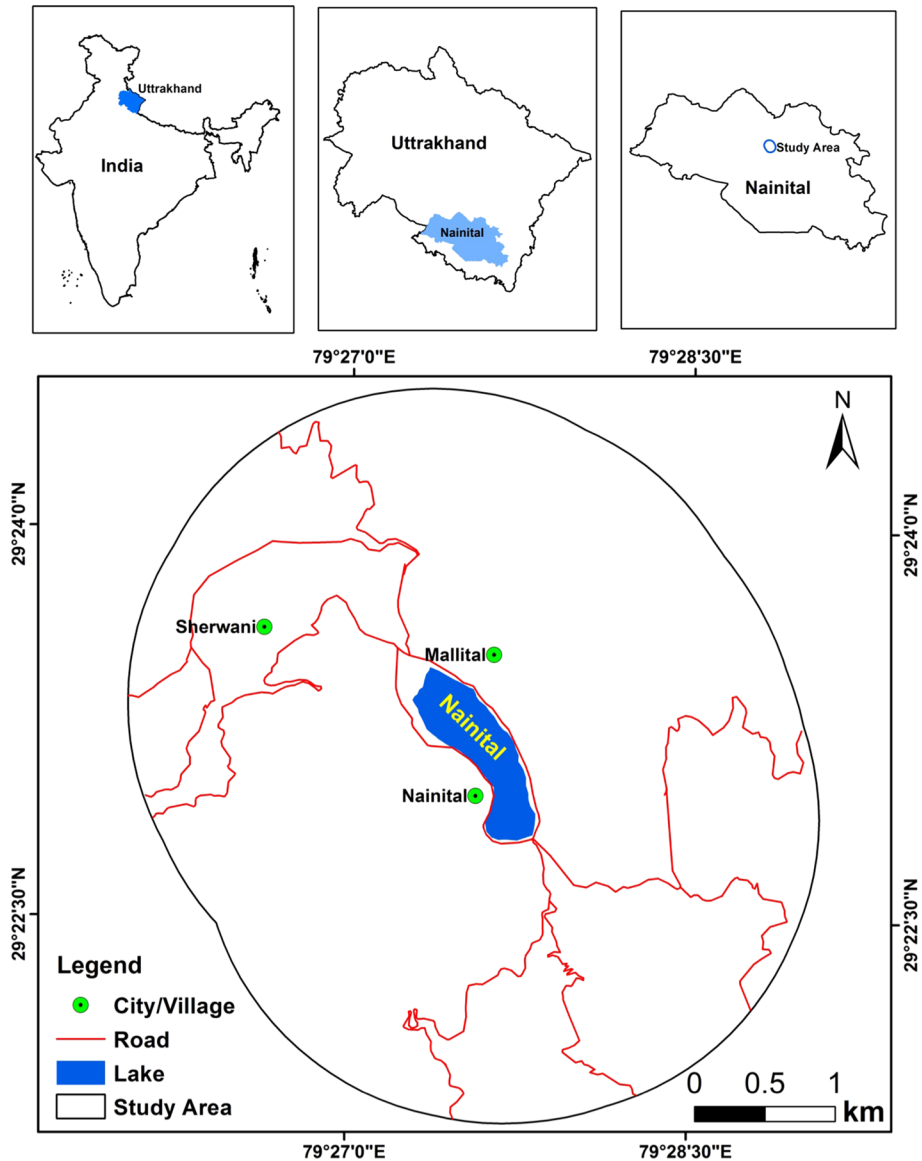
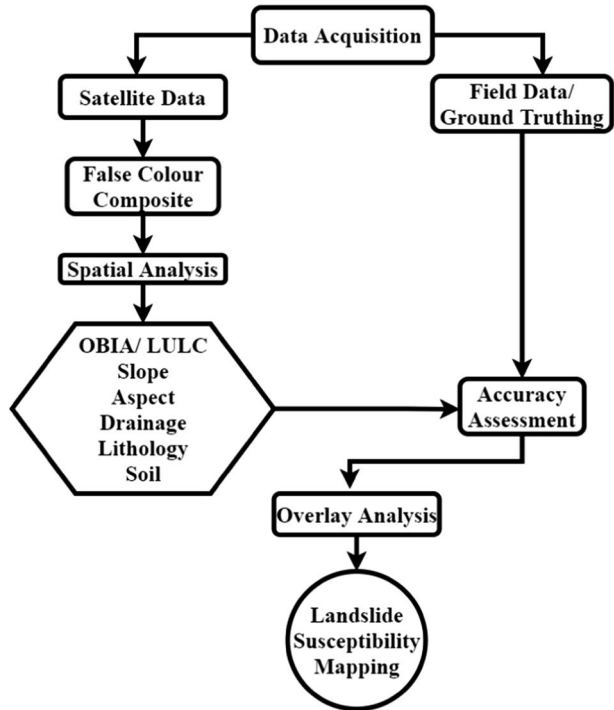


Fig. 1 Base map of the study area

3.1 Section I acquisition of data

In the present study, satellite images of three different years were considered to perform the LULC analysis. Landsat, Indian Remote Sensing (IRS)-P6 and IRS-Resourcessat-2 (R-2) satellite images were assimilated to assess the effect the anthropogenic activities on natural Earth. To understand the topography of the area, Airborne Space Thermal

Fig. 2 Flow chart of the methodology



Emission Reflection and Radiometer (ASTER)–Digital elevation model (DEM) was used. The details of the satellite are depicted in Table 1.

Apart from the satellite data, field data were also collected in terms of ground control points (GCPs) that are represented in Fig. 3c.

3.1.1 False colour composites (FCC)

FCC is a combination of near infra-red, red and green spectral bands. This FCC image was further used for LULC analysis. In the FCC image, the forest appears red, built-up appears in light blue and cyan, vegetation appears reddish, agriculture including cropland and fallow land appears greyish to pinkish and waterbody appears black, blue and sky blue in colour and sand or river bed in whitish colour. Attributes such as colour, tone, texture, shape and size are used for visual image interpretation. Based on the visual interpretation of the FCC images, the study area is majorly occupied by evergreen forest followed by built-up,

Table 1 Satellite data and use

S. no.	Satellite	Sensor	Resolution (m)	Date of acquisition	Use
1	Landsat	TM	30	30/04/1997	LULC
2	IRS P6	LISS IV	5.8	05/04/2005	LULC
3	IRS, R2	LISS IV	5.8	24/02/2017	LULC
4	Terra Stellite	ASTER	30	Feb, 2000	DEM/Slope

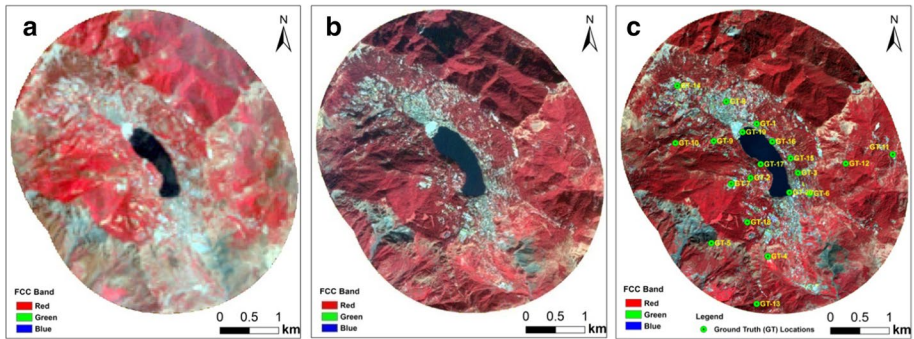


Fig. 3 FCC of the study area. **a** 30th April 1997, **b** 5th April 2005, **c** 24th Feb 2017

deciduous forest, barren land, barren rocky, waterbody and agriculture. FCC of the study area is shown in Fig. 3a–c for the year of 1997, the year 2005 and year 2017, respectively.

3.2 Section II spatial analysis

This section deals with the generation of various thematic layers using remote sensing and GIS for MCE analysis to derive the LSM. Thematic layers, which were used to perform the MCE, are described in the following paragraphs.

3.2.1 LULC analysis

In order to perform the LULC analysis, object-based image analysis (OBIA) which is an advance robust technique was applied. OBIA groups similar pixels in a satellite image to a single object using multi-resolution segmentation. It is a very efficient and sophisticated algorithm technique that considered spatial, spectral resolution and tonal variation of every pixel, which used to classify the satellite images (Kindu et al. 2013) as objects are more meaningful (Baatz et al. 2000; Weih et al. 2010) as compared to pixels-based technique. The OBIA has performed on e-cognition® software because of its higher accuracy and precision level of classification as compared to pixel-based classification (Kavzoglu et al. 2016; Dey et al. 2018; Vijay et al. 2020). In order to generate segmentation, several parameters like scale factor, shape compactness were incorporated, because these parameters have a great impact on classification (Lemenkova 2015). The scale factor plays a key role to identify and interpret the minute details from an image. Similarly, the shape is allied with the homogeneity of pixel, and compactness factor is necessary for the grouping of similar kind of pixels (Laliberte et al. 2009; Lemenkova 2015). Due to the significance on classification, setup of every parameter was tested for several times and the appropriate criteria were considered as scale 5, compactness 0.8 and shape 0.3. Based on the visual interpretation, the LULC classes adopted in the study are agriculture, barren land, barren rocky, built-up, deciduous forest, evergreen forest and waterbody. The classification was carried out using the mean value of different spectral band and several spectral indices like normalised difference built-up index (NDBI), normalised difference vegetation index (NDVI), normalised difference water index (NDWI). Spectral indices play a key role to make the threshold to outline differentiation between different LULC classes (Jawak et al. 2019); sensor-specific indices are

potential to extract maximum information about a particular class (Casey et al. 2012). These indexes make the classification relatively easy as differentiation deployed on arithmetical values is simple as compared to visual interpretation (Jensen 2007; Lucas et al. 2008; Jones and Vaughan 2010). The expressions for spectral indices are given below

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \tag{2}$$

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{3}$$

where NIR = near-infrared spectral band, R = red spectral band, MIR = mid-infrared spectral band and Green denotes green spectral band (Zha et al. 2003). The NIR and Red bands were considered to calculate the NDVI as it is reported by researchers (Yin et al. 2012; Ozyavuz et al. 2015; Serrano et al. 2019) Similarly NIR and MIR bands for NDBI (Xu 2008) and Green and NIR bands for NDWI (Xu 2006; McFeeters 2013; Hennig 2014; Gautam et al. 2015; Rasul et al. 2018; Vijay et al. 2020). Apart from these indices, brightness value was also used as a parameter of identification in LULC analysis. Brightness refers to the shiny reflectance of a surface in the visible light spectrum. The range of spectral indices used in the present study is given in Table 2.

3.2.2 Slope analysis

Slope inclination is a measure of the relationship between changes in vertical distance corresponding to a horizontal distance. The slope is one the important factor for developmental decision-making in hilly and mountainous terrains (Ben-Joseph et al. 2002). In the present work, spatial analysis of slope has been carried out using Arc GIS® spatial analyst tool. The slope categories considered are gentle (0°–5°), moderate (5°–15°), strong (15°–26.5°) and steep (26.5°–62.6°) (Sikdar et al. 2004).

Table 2 Class wise range of spectral indices used in the present study

LULC Class	Year					
	1997		2005		2017	
	Spectral index	Range	Spectral index	Range	Spectral index	Range
Agriculture	NDVI	0.05–0.12	NDVI	0.08–0.17	NDVI	0.2–0.38
Built-up	NDBI	0.08–0.77	Brightness	52–70	Brightness	40–83
Barren land	Red	68–69	Red	36–37	Red	44–56
Barren Rocky	Brightness	72–81	Brightness	76–84	Brightness	86–92
Forest Deciduous	NDVI	0.3–0.72	NIR	33–49	NIR	24–46
Forest Evergreen	Green	40–56	Green	29–55	Green	33–67

3.2.3 Aspect

Aspect or aspect of slope indicates the direction of slope and is derived using DEM of the study area. It is calculated clockwise in degrees from north. Aspect enables the user to trace the direction of slope through every cell or pixel of the image (Pal and Samanta 2012).

3.2.4 Drainage

ASTER Digital Elevation Model (DEM) having 30 m resolution was used to derive different order's drainage in the study area. Drainage networks were derived from ASTER DEM using Arc GIS® spatial analyst tool and stream ordering was done using the derived streamlines (Sarkar et al. 2012). Maximum fourth-order drainage was found in Nainital area. First- and second-order streams are the most vulnerable to landslides.

3.2.5 Lithology

Geologically, the study area is much diversified. It is classified into three geotechnical divisions namely the lesser Himalayans, the sub-Himalayas and the piedmont alluvial plain (Jamloki 2010). The study area is very fragile (Rawat 2016) in terms of its geology which consists of black shale of the lower Permian period, conglomerate, sandy, oolitic and shelly limestone, upper Permian fossils and Upper Carboniferous formation (Valdiya 1975).

3.2.6 Geomorphology

Geomorphology of the study area has been generated using DEM, lithology, slope, aspect, drainage and contours of the study area. The main geomorphic features consist of a highly dissected hill, moderately dissected hill, escarpment, piedmont, and narrow valley (Web-2).

3.2.7 Soil

Around 70–80% of the land in the study area is under the sandy and 20% clayey soil. The major soil group is sandy loam, sandy skeletal and loamy skeletal (Rawat 2016). Majority of the soil is neutral to acidic in nature.

3.3 Section III Field verification/ground truthing

Field verification depicts the present scenario of the real world that enhanced the quality of the research work. Ground truth information is very useful to the validation of the laboratory-based work. In this study, Garmin global positioning system (GPS) receiver was used to collect the coordinates and real earth information, which were further used for accuracy assessment.

3.4 Section IV overlay analysis

This section explains the overlay analysis performed to generate various thematic layers to better identify and understand the relationship between features. As worked out in LULC analysis, the built-up area of three different years 1997, 2005 and 2017 was overlaid on the slope map to understand the sprawl on different slope categories over the years. This overlay analysis was then used as an input in the landslide susceptibility mapping.

3.5 Section V landslide susceptibility mapping

It is reported that there is no worldwide methodology available to prepare a landslide susceptibility map (Ayalew et al. 2005; Yalcin 2008). In view of that criteria for deriving the landslide susceptibility depend on the physical settings and data availability of the study area (Magliulo et al. 2008). The landslide potential index (LPI) is as described as severity (Web-3) and repetivity of the landslide in a particular area. To perfectly categorise the landslide-prone area LPI is one of the key components that depend on multiple physical settings and significant criteria. Therefore, the MCE technique that considers various terrain condition was adopted to identify the landslide-prone area using the IVI method. The MCE works on analytical hierarchy process (Yalcin 2008; Althuwaynee et al. 2014) that predicts the vulnerable zones (Ahmed 2015) and IVI event spatially forecasts the incident using the parameters and event relationship (Jade and Sarkar 1993; Yin and Yan 1988). IVI model is a simple procedure based on the statistical application that affects every regular factor on the incidents of the landslide in an area (Pasang et al. 2018). The information values derived from individual thematic raster layers were integrated at the GIS domain. After the integration procedure, a single raster layer was produced as a map of landslide susceptibility index (Pasang et al. 2018). All the necessary thematic layers like LULC, lithology, geomorphology, slope, aspect, elevation, drainage network and soil type were integrated through IVI method (Dey et al. 2018). The final landslide susceptibility maps were then generated using spatial analysis of IVI method. IVI method enables the analyst to correlate dominant factors responsible for the triggering of the landslide (Jade and Sarkar 1993).

4 Results and discussion

This section discusses the results of the research work carried out in the present study. LULC, overlay analysis and landslide susceptibility mapping have been explained in the following section.

4.1 LULC analysis

The LULC analysis in the present study was performed using OBIA. LULC classes considered in the study are evergreen forest, built-up, deciduous forest, barren land, barren rocky, waterbody and agriculture. The LULC maps of the study area are shown in Fig. 4a–c for the year 1997, the year 2005 and year 2017, respectively, and its graphical representation is presented in Fig. 5. LULC statistics shows that highest spatial extent is observed with evergreen forest (56%) followed by built-up (16.3%), deciduous forest (13.1%), barren land (7.2%), barren rocky (3.6%), waterbody (2.6%) and agriculture (1.2%) for the present

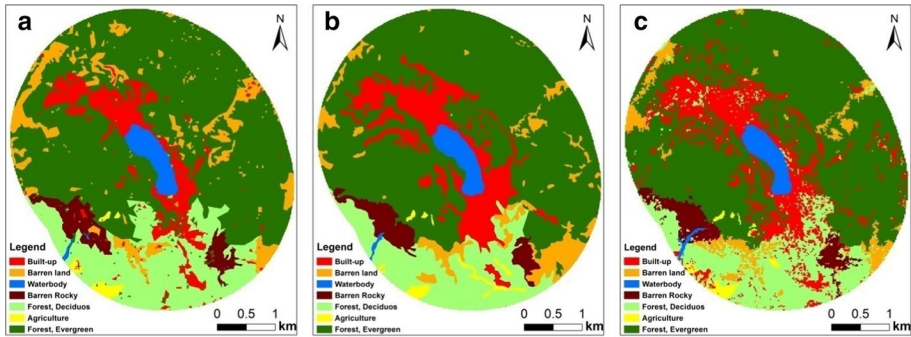


Fig. 4 LULC of the study area. a 30th April 1997, b 5th April 2005, c 24th Feb 2017

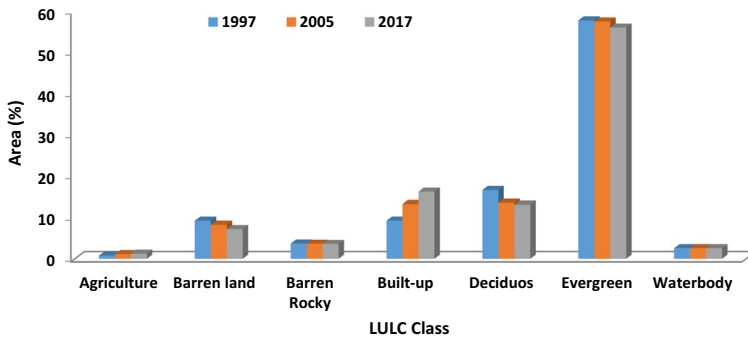


Fig. 5 Inventory of LULC of the study area

year of 2017. The total spatial area of the Nainital lake and its 2 km buffer zone from the periphery is 19.45 km².

According to LULC analysis, the exponential growth in built-up is seen from 9.3% (km²) in 1997 to 16.3% in 2017. The spatial extents of evergreen forest cover gradually showed a decrease from 57.8% in 1997, 57.7% in 2005 and 56% in 2017. As far as the deciduous forest is concerned, it showed a considerable decrease in from 16.7% in 1997 to 13.6% in 2005 and a slight decrease from 13.6% to 13.1% during 2005 to 2017, respectively. The decrease in the evergreen forest may be attributed to the increase in built-up of the area. Clearing of the forest for development activity is not a good practice especially in hilly terrain, because the roots of the tree bind the pockets of the land and make it less vulnerable for landslides. Such activities make the area more prone to landslides. There is increase in agricultural activity from 0.8% to 1.1% during 1997 to 2005, respectively, and 1.1% to 1.2% during 2005 to 2017, respectively. The barren land in the study area is gradually decreased from 9.3% to 8.3% during 1997 to 2005, respectively, and 8.3% and 7.2% during 2005 to 2017, respectively, whereas barren rocky showed a decrease of 3.7% to 3.7% during 1997 to 2005, respectively, and 3.7% to 3.6% during 2005 to 2017, respectively. The spatial extent of the water body is found to be constant as 2.6% throughout the study span.

The classified image of 2017 that depicts the present scenario has been taken to perform the accuracy assessment that can check the consistency of the analysis as it is important to

check the satellite data analysis with the real-world information (Anderson 1976). A total of 20 ground truth points were collected for accuracy assessment and a confusion matrix was created. The overall accuracy was found out to be 84.4% along with a kappa coefficient of 0.79. Field photographs are presented in Fig. 6.

4.2 DEM and slope analysis

DEM of the study area is represented in Fig. 7a, obtaining the range of the elevation is 1402–2575 m with the reference of mean sea level. With the help of ArcGIS 10.5, spatial analysis toolbox was used for deriving the slope (Fig. 7b) and slopes were categorised as gentle (0° – 5°), moderate (5° – 15°), strong (15° – 26.5°) and steep (26.5° – 62.6°). The areal distributions of different slope classes are as follows: gentle 2.4%, moderate 15.4%, strong 48.8% and steep 33.4%.



Fig. 6 Field photographs

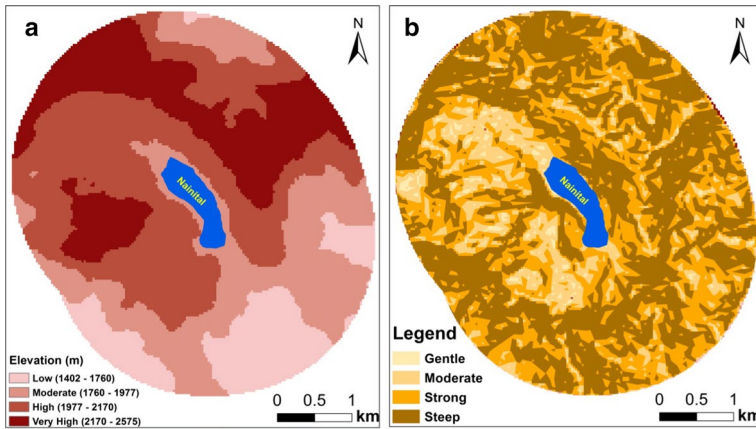
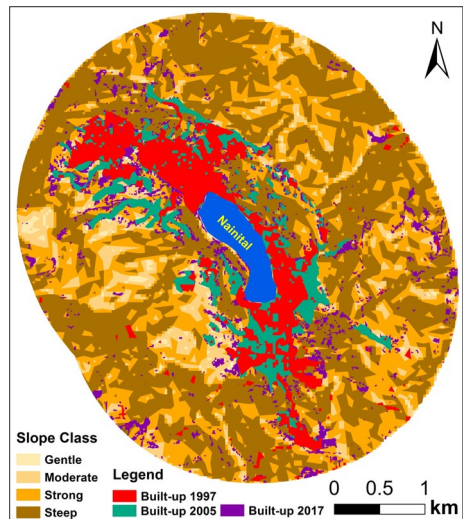


Fig. 7 a DEM of the study area b slope of the study area

Fig. 8 Impact of built-up sprawling on slope classes



4.3 Overlay analysis

To quantify the spread of urban growth on a natural slope, the built-up area of three different years were superimposed on different slope classes and their spatial extent on a particular slope was determined. The overlay analysis helps in assessing the periodical disparity in urban growth. The overlay analysis is shown in Fig. 8. It is observed that the built-up has increased significantly in all direction and it is a serious issue of concern in such mountainous environs.

The space occupied by man-made development activities on various slope categories was determined using the ArcGIS spatial analyst toolbox and is displayed in Fig. 9. It is observed that built-up is increased from 1997 to 2017 in all slope categories. It is found out that built-up occupied the predominant area of a gentle slope and it is increased from 0.4% to 0.6% during the year 1997 to 2017, respectively. There is an increase from 3.1% to 4.7% in the moderate class during the year 1997 to 2017, respectively. There is an increase from 3.5% to 6.1%

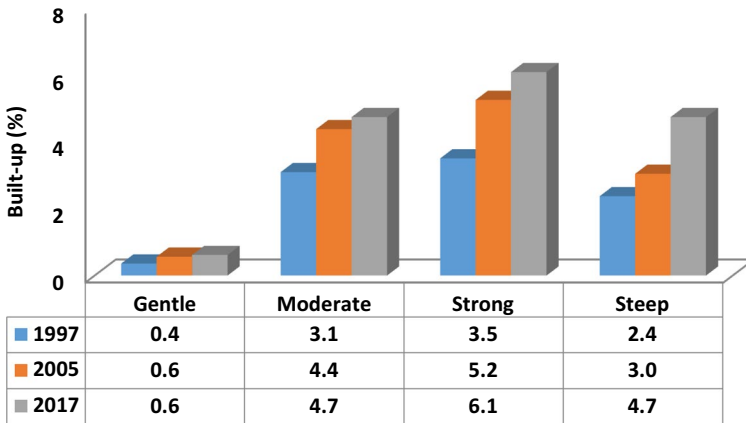


Fig. 9 Occupancy of built-up on different slope class

and 2.4% to 4.7% on the strong and steep slope during the years 1997 to 2017, respectively. It is observed that there is a small increase on gentle slope class as it was previously occupied with the considerable spatial extent of built-up. It is also observed that maximum increase occurs on strong and steep slope classes which are more vulnerable to landslides as compared to gentle and moderate slope classes (Vijay et al. 2016; Dey et al. 2018).

This heterogeneous sprawling of built-up area on various slope categories indicates the use of haphazard land use ratio which ultimately leads to geophysical calamities and is a peril to the human being (Kuniyal et al. 2004). It is also worth mentioning here the flood disasters of Badrinath and Kedarnath situated in Uttarakhand, India. It created more havoc to structures which were built on the natural slopes of the area. Therefore it is a matter immediate concern for competent authorities and local municipalities to frame and implement such laws which prevent haphazard construction in hilly areas (Vijay et al. 2016).

4.4 Landslide susceptibility mapping

Landslide susceptibility mapping has enormous advantages on urban management because this map shows the landslide-prone area so that the urban planner can avoid those areas for developmental activities (Reichenbach et al. 2018). The susceptibility map should be helpful to minimise the loss of natural resources as well as human beings, property, economical damages, etc. Generation of landslides susceptibility zones requires primarily two things viz. potency of slope and propagation area of landslides debris (Brabb 1984). The susceptibility map is presented in Fig. 10. The LPI in the present study ranges from 4.3 to 7.7. Table 3 shows the landslide susceptibility classes of the LPI calculated and the spatial extent falling under related class. The higher value of the LPI, the higher will be the susceptibility of the landslide. The landslide susceptibility of the study area is categorised as low, moderate, high and very high. Majority of percentage is monitored in the category, pursued by moderate (48.7%), high (40.5%), very high (8.2%), low (2.6%). In view of that, sprawling of the urban area on extreme to the steep slope is seriously risky and it increases the rate of the landslide. To minimise the landslide and effective urban management it is necessary to avoid the development activities on extreme to very steep slope area.

Fig. 10 Landslide susceptibility map

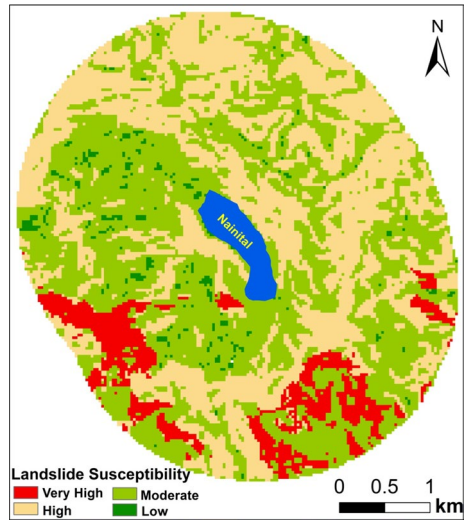


Table 3 Inventory of susceptibility class

S. no.	LPI	Susceptibility Class	Area	
			Sq km	(%)
2	4.3–5.1	Low	0.5	2.6
3	5.1–5.9	Moderate	9.5	48.7
4	5.9–6.7	High	7.9	40.5
5	6.7–7.7	Very High	1.6	8.2

4.5 Urban management

Landslide susceptibility map offers an adequate way to retrieve the information about landslide types, spatial probability and intensity of landslide of the mapped area (Hartlén and Viberg 1988). The map of the vulnerable zone can be helpful to decide where development activity can take place or not, which might be helpful to reduce the damage of human and natural resources (Cascini et al. 2005). Future urban planning, expansion of the city, especially construction activities on the hilly region must be comparable with the zonation of hazard area (Fell et al. 2005). In this way, development work should be authoritative in terms of cost–benefit investigation and protection of natural slope (Cascini et al. 2005). Landslide map has some controlling factor for urban development (Garry and Grasz 1997; Besson et al. 1999). One of the significant aims of susceptibility mapping at an urban scale is to regulate land use planning (Cascini et al. 2005). Proper planning is required for development activities in the mountainous region, because haphazard urban development may change the reaction of the slopes (Cascini et al. 2005). It is true that landslide mapping is helpful to reduce the rate of hazard (Fell et al. 2005), and such relevant outcome can direct the urban planning and development and the countermeasure planning (Cascini et al. 2005). Landslide susceptibility mapping is scrutinised as an important useful appliance for province land cover planning and disaster supervision to decrease the negative impact on human lives and development work (Cascini et al. 2005; Fell et al. 2005; Bell et al. 2015).

Landslide susceptibility map is the evidence of instability of land, and it provides inclusive clarification in the intricate kinetics of the various laws and rules which, both at the local and national level, should have directed and managed the urbanisation over the years (Cascini et al. 2005). Building regulation activity should be applied to controlled disaster management (Jayaweera 2007). With the help of the hazard zonation map, local government body or/and special mountain development/urban development board can implement some restriction and laws for land management in an efficient way (UMDMP Sri Lanka 2003). Disaster management in most of the Asian countries is under of central government but local government body is responsible for land management, town planning; so both the government can take an observation about illegal construction on the steep slope and that can create some strategy for transparent urban planning and management (UMDMP Sri Lanka 2003). UNISDR has taken an agenda for 2030 for sustainable development and disaster management across the world (Web-4). Short-term and long-term activities are helpful to manage landslide hazard (Guedjeo et al. 2017). NGOs and Community organisation can also monitor the landslide-prone area to reduce the risk. (National Disaster Management Guidelines, Govt. of India 2009).

5 Conclusion

A geospatial assessment has been carried out to assess the impact of urban sprawl around the Nainital lake. During the study span, it was observed that urbanisation is increasing drastically over the years. As a critical observation, the existing gentle slope area is already occupied by the dense built-up and overpopulated from the past, and similarly, moderate slope area is majorly influenced by human activities. In view of this, haphazard and unscientific urban sprawling is taking place on the strong and steep slope. Due to the high inclination angle with the horizontal plane, those slopes are prone to landslide hazard that might be a serious concern about urban sustainability. A GIS-based activity involving MCE, IVI, overlay analysis along with the physical status of the site is assimilated to identify and ranked the landslide susceptible zone around the Nainital Lake. There is an interesting fact that depicts by the susceptibility map, which is around 50% of the area is highly susceptible that belongs to the steep slope. Some significant pockets on the steep slope are identified as the very high sensitive zone that might be considered as a hotspot area.

In this context, there is a need for immediate control and regulation on unscientific urbanisation on steep slope area. Implementation of laws against improper urbanisation and frequent monitoring should be helpful to minimise the rate of landslides. It is strongly recommended that avoiding the new construction activity on the steep slope area. The urban area on the strong and steep slope which has been identified and mapped can be protected through geotextiles. Retaining walls along the road, fencing, thick vegetation cover on the escarpment and barren land are strongly recommended. The susceptibility map is again very helpful for an urban planner to identify the suitable zone for future planning and sophisticated urban management. Thus, the study is very helpful to overcome the landslide hazard on mountainous region and sustainable urban management. The study also recommended strict compliance of building by-laws for preventing landslide hazard.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

- Althuwaynee, O. F., Pradhan, B., Park, H., & Hyun, J. (2014). A novel ensemble bivariate statistical evidential belief function with knowledge-based analytical hierarchy process and multivariate statistical logistic regression for landslide susceptibility mapping. *CATENA*, *114*, 21–36.
- Anbalagan, R., & Singh, B. (1996). Landslide hazard and risk assessment mapping of mountainous terrains: A case study from Kumaun Himalaya, India. *Engineering Geology*, pp. 237–246.
- Anderson, J.R. (1976) *A land use and land cover classification system for use with remote sensor data* (vol. 964). US Government Printing Office.
- Ahmed, B. (2015). Landslide susceptibility mapping using multi-criteria evaluation techniques in Chittagong Metropolitan Area. *Bangladesh. Landslides*, *12*(6), 1077–1095.
- Ayalew, L., & Yamagishi, H. (2005). The application of GISbased logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. *Geomorphology*, *65*, 15–31.
- Baatz, M., & Schape, A., (2000). Multiresolution segmentation: An optimization approach for high-quality multi-scale image. In *Angewandte Geographische information*.
- Bathrellos, G. D., Kalivas, D. P., & Skilodimou, H. D. (2009). GIS-based landslide susceptibility mapping models applied to natural and urban planning in Trikala, Central Greece. *Estud Geol*, *65*(1), 49–65.
- Bell, J., & Morrison, T. (2015). Land use planning for flood risk: A comparative case of adaptive and precautionary governance systems. *Journal of Environmental Policy and Planning*.
- Ben-Joseph, E., Ishii, H., & Ratti, C. (2002). 11.304 J Site and Urban Systems Planning, Department of Urban Studies and Planning Department of Architecture, Massachusetts Institute of Technology, Spring 2002.
- Besson, L., Durville, J. L., Garry, G., Graszak, E., Hubert, T. & Toulemon, M., (1999). Plans de prévention des risques naturels (PPR): Risques de mouvements de terrain. Guide méthodologique. La Documentation Française, Paris.
- Borgatti L., & Soldati M. (2005). Geomorphological hazard and human impact in mountain environments: an introduction. *Geomorphology*, pp. 1–390
- Brabb, E. E. (1985). Innovative approaches to landslide hazard and risk mapping. In *International landslide symposium proceedings*, Toronto, Canada (vol. 1, pp. 17–22).
- Carrara, A., Guzzetti, F., Cardinali, M., & Reichenbach, P. (1999). Use of GIS technology in the prediction and monitoring of landslide hazard. *Natural Hazards*, *20*(2–3), 117–135.
- Cascini, L., Bonnard, C., Corominas, J., Jibson, R., & Montero-Olarte, J. (2005). Landslide hazard and risk zoning for urban planning and development. In *Landslide risk management* (pp. 209–246). CRC Press.
- Casey, K. A., Käab, A., & Benn, D. I. (2012). Geochemical characterization of supraglacial debris via in situ and optical remote sensing methods: a case study in Khumbu Himalaya, Nepal. *The Cryosphere*, *6*(1), 85–100.
- Chung, C. J. F., Fabbri, A. G., & Van Westen, C. J. (1995). Multivariate regression analysis for landslide hazard zonation. In *Geographical information systems in assessing natural hazards* (pp. 107–133). Springer, Dordrecht.
- Dhakal, A. S., Amada, T., & Aniya, M. (2000). Landslide hazard mapping and its evaluation using GIS: An investigation of sampling schemes for a grid-cell based quantitative method. *Photogrammetric Engineering and Remote Sensing*, *66*(8), 981–989.
- Dey, J., Sakhre, S., Gupta, V., Vijay, R., Pathak, S., Biniwale, R., et al. (2018). Geospatial assessment of tourism impact on land environment of Dehradun, Uttarakhand, India. *Environmental Monitoring and Assessment*, *190*(4), 181.
- Erginal, A. E., Türkeş, M., Ertek, T. A., Baba, A., & Bayrakdar, C. (2008). Geomorphological investigation of the excavation-induced dündar landslide, bursa—turkey. *Geografiska Annaler: Series A, Physical Geography*, *90*(2), 109–123.

- Fanyu, Z., Gao, L., Wenwu, C., Wenfeng, H., & Shouyun, L. (2009). The evolution mechanism of the Yuanjiawan landslide in the process of cutting slope and excavation. *Chinese Journal of Geotechnical Engineering*, 31(8), 1.
- Fell, R., Ho, K. K., Lacasse, S., & Leroy, E. (2005). A framework for landslide risk assessment and management. In *Landslide risk management* (pp. 13–36). CRC Press.
- Garry, G. & Graszak, E. (Ed.) (1997). Plans de prévention des risques naturels (PPR) – Guide général. La Documentation Fran- çaise, Paris.
- Gautam, V. K., Gaurav, P. K., Murugan, P., & Annadurai, M. (2015). Assessment of surface water Dynamics in Bangalore using WRI, NDWI, MNDWI, supervised classification and KT transformation. *Aquatic Procedia*, 4, 739–746.
- Gorsevski, P. V., Gessler, P. E., Foltz, R. B., & Elliot, W. J. (2006). Spatial prediction of landslide hazard using logistic regression and ROC analysis. *Transactions in GIS*, 10(3), 395–415.
- Guedjeo, C. S., Kagou, Dongmo A., Wotchoko, P., Nkouathio, D. G., Chenyi, M. L., Wilson Buma, G., et al. (2017). Landslide susceptibility mapping and risk assessment on the bamenda mountain (cameroon volcanic line). *Journal of Geosciences and Geomatics*, 5(4), 173–185.
- Gupta, R. P., & Joshi, B. C. (1990). Landslide hazard zoning using the GIS approach: A case study from the Ramganga catchment. *Himalayas. Engineering Geology*, 28(1–2), 119–131.
- Gupta, V., Bhasin, R. K., Kaynia, A. M., Tandon, R. S., & Venkateshwarlu, B. (2016). Landslide hazard in the Nainital township, Kumaun Himalaya, India: the case of September 2014 Balia Nala landslide. *Natural Hazards*, 80(2), 863–877.
- Guzzetti, F., Cardinali, M., Reichenbach, P., & Carrara, A. (2000). Comparing landslide maps: A case study in the Upper Tiber River Basin, Central Italy. *Environmental Management*, 25(3).
- Hartlen, J., & Viberg, L. (1988). General report: Evaluation of landslide hazard. In International symposium on landslides. 5 (pp. 1037–1057).
- Hennig, H. (2014) Multi-temporal and multi-sensor thermal analyses for submarine groundwater discharge detection over large spatial scales. Available on https://www.hydrology.uni-freiburg.de/abschluss/Hennig_H_2014_MA.pdf
- Hukku, B. M. , Srivastava, A. K. , Jaitly, G. N. (1997). Measurement of slope movements in Nainital area Engineering Geology.
- Hung, O., Leroueil, S., & Picarelli, L. (2014). The Varnes classification of landslide types, an update. *Landslides*, 11(2), 167–194.
- Jade, S., & Sarkar, S. (1993). Statistical models for slope instability classification. *Engineering Geology*, 36(1–2), 91–98.
- Jamloki D., (2010). District groundwater brochure of Nainital district, Uttarakhand. Available on https://cgwb.gov.in/District_Profile/Uttarakhand/Nainital.pdf
- Jawak, S. D., Wankhede, S. F., & Luis, A. J. (2019). Explorative study on mapping surface facies of selected glaciers from Chandra Basin, Himalaya using WorldView-2 data. *Remote Sensing*, 11(10), 1207.
- Jayaweera, S., (2007). Importance of planning guidelines in landslide disaster risk reduction. Available on https://www.nbro.gov.lk/images/content_image/publications/symposia/importance_of_planning_guidelines.pdf
- Jensen, J. R. (2007). *Remote sensing of the environment: an earth resource perspective: Pearson Prentice Hall*. NJ: Upper Saddle River.
- Jones, H. G., & Vaughan, R. A. (2010). *Remote sensing of vegetation: Principles, techniques, and applications*. Oxford: Oxford University Press.
- Kavzoglu, T., Yildiz, M., & Tonbul, H. (2016). Evaluating performances of spectral indices for burned area mapping using object-based image analysis. In *12th International symposium on spatial accuracy assessment in natural resources and environmental sciences* (pp. 5–8).
- Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2013). Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene landscape of the Ethiopian highlands. *Remote Sensing*, 5(5), 2411–2435.
- Kuniyal, J. C., Vishvakarma, S. C. R., Badola, H. K., & Jain, A. P. (2004). *Tourism in Kullu valley: An environmental assessment*. Dehradun, India: Bishen Singh & Mohindra Pal Singh.
- Laliberte, A. S., & Rango, A. (2009). Texture and scale in object-based analysis of sub decimeter resolution unmanned aerial vehicle (UAV) imagery. *IEEE Transactions on Geoscience and Remote Sensing*, 47(3), 761–770.
- Lee, S. G., & Hencher, S. R. (2009). The repeated failure of a cut-slope despite continuous reassessment and remedial works. *Engineering Geology*, 107(1–2), 16–41.

- Lemenkova, P. (2015). Topology, homogeneity and scale factors for object detection: application of eCognition software for urban mapping using multispectral satellite image. In *Proceedings of 7th international scientific and practical conference*. INSO2015 (Akaki Tsereteli State University ATSU (pp. 80–85).
- Lucas, R., Mitchell, A., & Bunting, P. (2008). *Hyperspectral data for assessing carbon dynamics and biodiversity of forests* (pp. 47–86). New York, NY: Taylor & Francis Group.
- Magliulo, P., Lisio, A. D., Russo, F., & Zelano, A. (2008). Geomorphology and landslide susceptibility assessment using GIS and bivariate statistics: a case study in southern Italy. *Natural Hazards*, *47*, 411–435.
- Martire, D., De Rosa, M., Pesce, V., Santangelo, M. A., & Calcaterra, D. (2012). Landslide hazard and land management in high-density urban areas of Campania region, Italy. *Natural Hazards & Earth System Sciences*, *12*(4).
- McFeeters, S. K. (2013). Using the normalized difference water index (NDWI) within a geographic information system to detect swimming pools for mosquito abatement: A practical approach. *Remote Sensing*, *5*(7), 3544–3561.
- Middlemiss, C. S. (1890). Geological sketch of Nainital with some remarks on the natural conditions governing mountain slopes. *India*, *23*(4), 213–234. Survey
- Mukherji, A., Sinisalo, A., Nüsser, M., Garrard, R., & Eriksson, M. (2019). Contributions of the cryosphere to mountain communities in the Hindu Kush Himalaya: A review. *Regional Environmental Change*, *19*(5), 1311–1326.
- Nagarajan, R., Mukherjee, A., Roy, A., & Khire, M. V. (1998). Technical note temporal remote sensing data and GIS application in landslide hazard zonation of part of Western Ghat, India.
- National Disaster Management Guidelines, Govt. of India (2009) available on <https://nidm.gov.in/pdf/guidelines/new/landslidessnowavalanches.pdf>
- Ozayavuz, M., Bilgili, B. C., & Salici, A. (2015). Determination of vegetation changes with NDVI method. *Journal of Environmental Protection and Ecology*, *16*(1), 264–273.
- Pal, B., & Samanta, S., (2012). Topography and land temperature investigation
- Pande, I. C., (1974). Tectonic interpretation of the geology of the Nainital area Himalayan Geology, pp. 532–546
- Pande, R. K., & Pande, N. (2008). Nainital: A landslide town of Uttarakhand (India). *Disaster Prevention and Management: An International Journal*.
- Puniya M. K., Joshi P., Pant P. D. (2013). Geological investigation of Nainital Bypass: a special emphasis on slope stability analysis, Kumaun Lesser Himalaya, Himalayan vulnerability, Uttarakhand, 2013: learning for planning and action, Xpressions Print & Graphics Pvt. Ltd, pp. 65–72
- Pasang, S., & Kubiček, P. (2018). Information value model based landslide susceptibility mapping at Phuentsholing, Bhutan. AGILE 2018–Lund, June 12–15.
- Rasul, A., Balzter, H., Ibrahim, G. R. F., Hameed, H. M., Wheeler, J., Adamu, B., et al. (2018). Applying built-up and bare-soil indices from landsat 8 to cities in dry climates. *Land*, *7*(3), 81.
- Rawat A. S. (2016). Geology of Nainital and History of Nainital.
- Reichenbach, P., Rossi, M., Malamud, B. D., Mihir, M., & Guzzetti, F. (2018). A review of statistically-based landslide susceptibility models. *Earth-Science Reviews*, *80*, 60–91.
- Saha, A. K., Gupta, R. P., & Arora, M. K. (2002). GIS-based landslide hazard zonation in the Bhagirathi (Ganga) valley, Himalayas. *International Journal of Remote Sensing*, *23*(2), 357–369.
- Sah, N., Kumar, M., Upadhyay, R., & Dutt, S. (2018). Hill slope instability of Nainital City, Kumaun Lesser Himalaya, Uttarakhand, India. *Journal of Rock Mechanics and Geotechnical Engineering*, *10*(2), 280–289.
- Shahabi, H., & Hashim, M. (2015). Landslide susceptibility mapping using GIS-based statistical models and Remote sensing data in tropical environment. *Scientific reports*, *5*(1), 1–15.
- Sarkar, S., Kanungo, D. P., Patra, A. K., & Kumar, P. (2012). GIS based landslide susceptibility mapping: A case study in Indian Himalaya.
- Sarkar, S., & Kanungo, D. P. (2004). An integrated approach for landslide susceptibility mapping using remote sensing and GIS. *Photogrammetric Engineering & Remote Sensing*, *70*(5), 617–625.
- Sarkar, S., Kanungo, D. P., & Mehrotra, G. S. (1995). Landslide hazard zonation: A case study in Garhwal Himalaya, India. *Mountain Research and Development*, pp. 301–309.
- Salcedo, D., Almeida, O. P., & Toulkeridis, B. M. T. (2018) Landslide susceptibility mapping using fuzzy logic and multi-criteria evaluation 1 techniques in the city of Quito, Ecuador 2.
- Serrano, J., Shahidian, S., & Marques da Silva, J. (2019). Evaluation of normalized difference water index as a tool for monitoring pasture seasonal and inter-annual variability in a Mediterranean agro-silvo-pastoral system. *Water*, *11*(1), 62.
- Sikdar, P. K., Chakraborty, S., Adhya, E., & Paul, P. K. (2004). Land use/land cover changes and groundwater potential zoning in and around Raniganj coal mining area, Bardhaman District, West Bengal - a GIS and remote sensing approach. *Journal of Spatial Hydrology*, *4*(2), 1–24.

- Sri Lanka Urban Multi-hazard Disaster Mitigation Project, Guidelines for Construction in Landslide Prone Areas (2003).
- Sterlacchini, S., Frigerio, S., Giacomelli, P., Brambilla M., (2007). Landslide risk analysis: A multi-disciplinary methodological approach.
- Turner, A. K., & Schuster, R. L. (1996). Landslides-Investigation and mitigation: Transportation Research Board. *National Research Council, Special Report*, 247, 672.
- United Nations Environment Programme (UNEP). Year Book. (2011). Emerging issues in our global environment; UNEP/Earthprint: Nairobi, Kenya.
- Uniyal, R., (2018). Nainital at risk of major landslides Study. Available on <https://timesofindia.indiatimes.com/city/dehradun/nainital-at-risk-of-major-landslidesstudy/articleshow/63124942.cms>
- Urban Development in the Lake Region: A historical perspective. (2017). Available on <https://shodhganga.inflibnet.ac.in/bitstream/10603/44102/2/chapter%202.pdf>
- Van Westen, C. J. (1994). GIS in landslide hazard zonation: A review, with examples from the Andes of Colombia. In *Mountain environments & geographic information systems* (pp. 135–166). Taylor & Francis.
- Valdiya, K. S. (1988). *Geology and natural environment of Nainital Hills, Kumaun Himalaya*. Nainital: Gyandaya Prakashan.
- Valdiya, K. S. (1975). Lithology and age of the Tal Formation in Garhwal, and implication on stratigraphic scheme of Krol Belt in Kumaun Himalaya
- Vijay, R., Kushwaha, V. K., Chaudhury, A. S., Naik, K., Gupta, I., Kumar, R., et al. (2016). Assessment of tourism impact on land use/land cover and natural slope in Manali, India: A geospatial analysis. *Environmental Earth Sciences*, 75(1), 20.
- Vijay, R., Dey, J., Sakhre, S., & Kumar, R. (2020). Impact of urbanization on creeks of Mumbai, India: A geospatial assessment approach. *Journal of Coastal Conservation*, 24(1), 1–16.
- Web-1: Nainital mall road collapsing, falling into Naini lake, daily hunt news. <https://m.dailyhunt.in/news/india/english/newsroom+post-e-paper-newspost/watch+here+nainital+mall+road+collapsing+falling+into+naini+lake-newsid-94976936>; <https://www.amarujala.com/photo-gallery/dehradun/nainital-mall-road-collapse-in-naini-lake>.
- Web-2: Indian Geo-platform of ISRO, Thematic Services, Geomorphology. <https://bhuvan.nrsc.gov.in>.
- Web-3: Landslide Potential Index, Information Note 8/2014, June 2014, Hong Kong Slope Safety, Geotechnical Engineering Office, Civil Engineering and Development Department. https://hkss.cedd.gov.hk/hkss/eng/landslipwarn/IN_2014_08E.pdf.
- Web-4: Disaster Risk Reduction and Resilience in The 2030 Agenda for Sustainable Development, United Nations Office for Disaster Risk Reduction. https://www.unisdr.org/files/46052_disasterriskreductioninthe2030agenda.pdf.
- Weih, R. C., & Riggan, N. D. (2010). Object-based classification vs. pixel-based classification: Comparative importance of multi-resolution imagery. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 38(4), 7.
- Wold, R. L., & Jochim, C. L. (1989). Landslide loss reduction: A guide for state and local government planning. In *Earthquake Hazards reduction series* (vol. 52). US Federal Emergency Management Agency (FEMA).
- Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*, 27(14), 3025–3033.
- Xu, H. (2008). A new index for delineating built-up land features in satellite imagery. *International Journal of Remote Sensing*, 29(14), 4269–4276.
- Yalcin, A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): comparison of results and confirmations. *CATENA*, 72, 1–12.
- Yin, K. L. & Yan, T. Z. (1988). Statistical prediction models for slope instability of metamorphosed rocks. In Bonnard, C. (Ed.), *Landslides, proceedings of the fifth international symposium on landslides*, (vol. 2, pp. 1269–1272). Balkema, Rotterdam.
- Yin, H., Udelhoven, T., Fensholt, R., Pflugmacher, D., & Hostert, P. (2012). How normalized difference vegetation index (ndvi) trends from advanced very high resolution radiometer (AVHRR) and système probatoire d'observation de la terre vegetation (spot vgt) time series differ in agricultural areas: An inner mongolian case study. *Remote Sensing*, 4(11), 3364–3389.
- Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, 24(3), 583–594.