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Research Article

A Remote Sensing-Based Approach for Debris-Flow Susceptibility Assessment Using Artificial Neural Network in Uttarkashi, India.

Raju Sarkar[1], P. Shalini[2]

Abstract

This study aims at identifying, mapping the distribution of vulnerable debris flow sites, and generating a corresponding susceptible map of the study area using Remote Sensing, Geographic Information system (GIS), and Artificial Neural Network (ANN). The above sites are identified using visualization technique in Google Earth to be later utilized in ANN-based model setup. The model is constructed, optimized, and validated using identified sites. The controlling factors of debris flow: Topographic Position Index (TPI), Normalized Vegetation Index (NDVI), Slope, Aspect, Topographic Wetness Index (TWI), Stream Power Index (SPI), Distance to Drainage and Digital Elevation Model (DEM) derived from Remote Sensing and observed datasets are utilized for generation of a best-fit model (Area Under Curve (AUC) - 0.77). The observations analyzed from generated susceptibility map include 1) area along the river with less vegetation, high slopes, barren land are more susceptible 2) consistent field validation results made this technique potentially reliable.

Keywords: *Debris Flow, GIS, Digital Elevation Model (DEM), Artificial Neural Network (ANN), Susceptibility*

[1] Professor , Department of Civil Engineering, Delhi Technological University, Delhi, India, Email: rajusarkar@dce.ac.in

[2] Student , Department of Civil Engineering, Delhi Technological University, Delhi, India, Email: deeshalu@gmail.com

Introduction

The mapping and identification of any susceptible natural hazard in a given study area is always a challenge to the research community due to shortcomings in the availability of the historical database, limitation of accessibility for data collection, and lack of proper monitoring systems. The present study aims to identify, map the distribution of the susceptible debris flows of the study area i.e., Uttarkashi District of the Uttarakhand state in India. This region was selected as it has shown a high number of incidents of debris flow. During the last few years, there has been a significant increase in the reports of natural disasters (Gupta, Bhatt, et al., 2020; Sharma et al., 2020; Thakur et al., 2020). In addition to the global warming threats which has sparked a stream of literature analyzing what the effects may be, the reality is that we are experiencing a high number of natural disasters, and hence this is also a research gap that still needs to develop(Michael ides& Wainwright, 2002). Mountain regions are susceptibly at higher risk exposure to various natural hazards and it is quite challenging to predict and identify the probable hazardous sites(Michael ides& Chappell, 2009). Among the various mountain hazards, the debris flow is considered as one of the most destructive occurrences after the avalanche as far as the loss of lives is considered(Prochaska et al., 2008; Santi et al., 2011). This hugely affects the local economy in several ways: reducing firm productivity by destroying productive capital or disrupting supply chains, creating unanticipated disamenities for consumers, or demolishing a part of the housing stock causing serious out-migration of the major population from any area. Extensive research is being conducted to assess debris-flow susceptibility (DFS) for mitigating and preventing debris flow risks. In recent years, several studies have focused on analyzing channel processes about hydrological, geomorphological, and ecological systems to model the hydrological response of catchments and sediment dynamics (Berti & Simoni, 2005; Glade, 2005). Debris susceptible maps are very useful and necessary for disaster management, planning, and development activities (Su & Cui, 2009).

The current study mainly focuses on the debris flow susceptibility of the study area using remote sensing and an ANN-based approach. The ANN model is considered very intelligent to solve complicated problems which include prediction, clustering, optimization, modelling, pattern recognition, and simulations, and many more (Amrouche & Le Pivert, 2014; Çelik et al., 2016; Hasni et al., 2012; Litta et al., 2013; Mohamed, 2019). Remote sensing and GIS are utilized to obtain datasets of topography, vegetation, soil factors, and local/human activities in the region. The datasets are then utilized in setting up the controlling factors for the ANN-based model(Elkadiri et al., 2014; Zhang et al., 2019). An ANN-based model was set up to find susceptibility towards debris flow at a specific location using the statistical inter-relationships between various physical parameters. The rationale behind this step was to find out if a data mining method such as ANN can find out if a particular area is susceptible to debris flow or not considering the physical parameters of the said location without considering the possible physical reasons of debris flow. ANN can be summarized as an approximation method where inter-relationships between different input and output variables are approximated in terms of neurons. The same approximation can be further used for new unseen input variables and the output can be predicted. Like any other approximation function, ANN contains many coefficients assigned to neurons such as weight and bias. These coefficients are fitted to the given datasets during model training using backpropagation. The coefficients are further optimized so that the model performs with the least possible error. ANN has been widely used for such regression and classification operations in every field possible with satisfactory accuracy. However, the accuracy of the model depends on various factors such as the quality of input datasets, tuning of hyper-parameters, computational power, etc. The current effort to find out if a location is susceptible to debris flow or not can be regarded as a classification problem as there are two possible outputs, i.e., susceptible and not susceptible. The entire process of structuring and implementing an ANN model can be divided into different parts which are described in the methodology section.

Study Area and Datasets Used

Study Area

The Uttarkashi district is located in the Garhwal region of the Uttarakhand state (Figure.1). It lies in the lower and higher Himalayas between 30°43' North to 30°73' North Latitude and 78°27' East to 78°45' East Longitude. Natural disasters like cloudbursts, landslides, flash floods often result in frequent debris flow in this area, especially in the rainy season. According to the census 2011, the district occupies an area of 8,016 sq. km. with a population of 0.3 million. The climate of the district is subtropical in the foothills, humid-subtropical at mid altitudes, temperate at the higher part of the altitudes and cold at the very high altitudes. The topographical representation of the study region is characterized by mountain ranges having narrow and deep valleys.

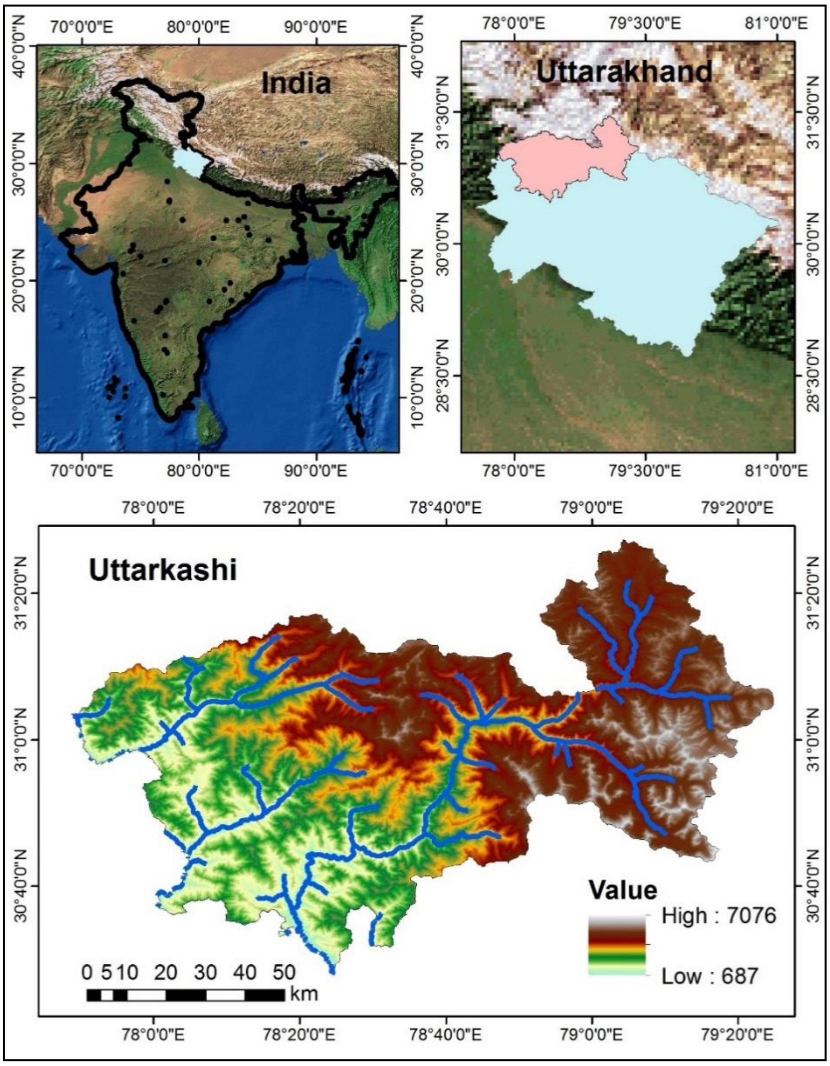


Figure 1. Study area

Geomorphologically, the whole area represents a highly fragile elevation; it is marked by high relief and active erosion processes on slopes of the hills and valleys. Three rivers namely Yamuna, Bhagirathi, Rupin, and their tributaries flow in this region. The fluvial phase has played a significant role in the development of the present topography. Uttarkashi experiences landslides and debris flow of various magnitudes and dimensions almost every year, therefore it has been selected as the study area. These debris-flows are caused due to various agents like earthquakes and rainfall and result in loss of lives and properties. Geologically, the region is complex and structurally impaired and lies in Zone IV and Zone V of the Seismic Zonation Map of India. In the monsoon season, the ground is more vulnerable to collapse when the water is percolating in the ground, not only decreasing the cohesion of the rock content but exerting pore water pressure on the discontinuity planes.

Datasets Used

The current study requires extensive data collection and data processing before the Artificial Neural Network (ANN) based model setup. The data collection requires 1. Acquiring data from remote sensing, 2. Generate certain data using the visualization technique in Google Earth and 3. Collection of data from field survey. Data collected from the field survey is used for inventory creation and testing of the result obtained from model simulations.

Table 1. Datasets Used

S.No	Datasets	Resolution	Source
1	Sentinel 2	10m X 10m	European Space Agency (ESA) - Sentinel
2	Digital Elevation Model	30m X 30m	Aster - Digital Elevation Model
3	Soil	1:500000	Food and Agriculture Organization (FAO)- Harmonized World Soil Database (HWSD)
4	Land Use Land Cover	250 m X 250 m	European Space Agency (ESA) - Land Use Land Cover

Debris-flow Inventory

Recently, numerous incidents of debris flow and landslides have been reported in the area. Most of them occurred alongside the embankment, cut-slopes and roads, highways in mountainous regions. Detailed mapping of landslide areas and effectively discovering past debris flow is critical for landslide risk assessment and mitigation. But identifying the location of landslide scarring is difficult and time-consuming. In this regard, remote sensing techniques utilize aerial photographs and satellite images for gathering valuable information regarding landslides. Debris-flows are mapped by identifying typical geomorphological irregularities such as breaks in the forest canopy, bare soil, and other typical surface deformations. In addition, all significant debris-flows from the historical past have been collected for the period under study. Based on the description of the site, the database, and the satellite imagery analysis, the locations of the individual landslides &debris flow were mapped and plotted.

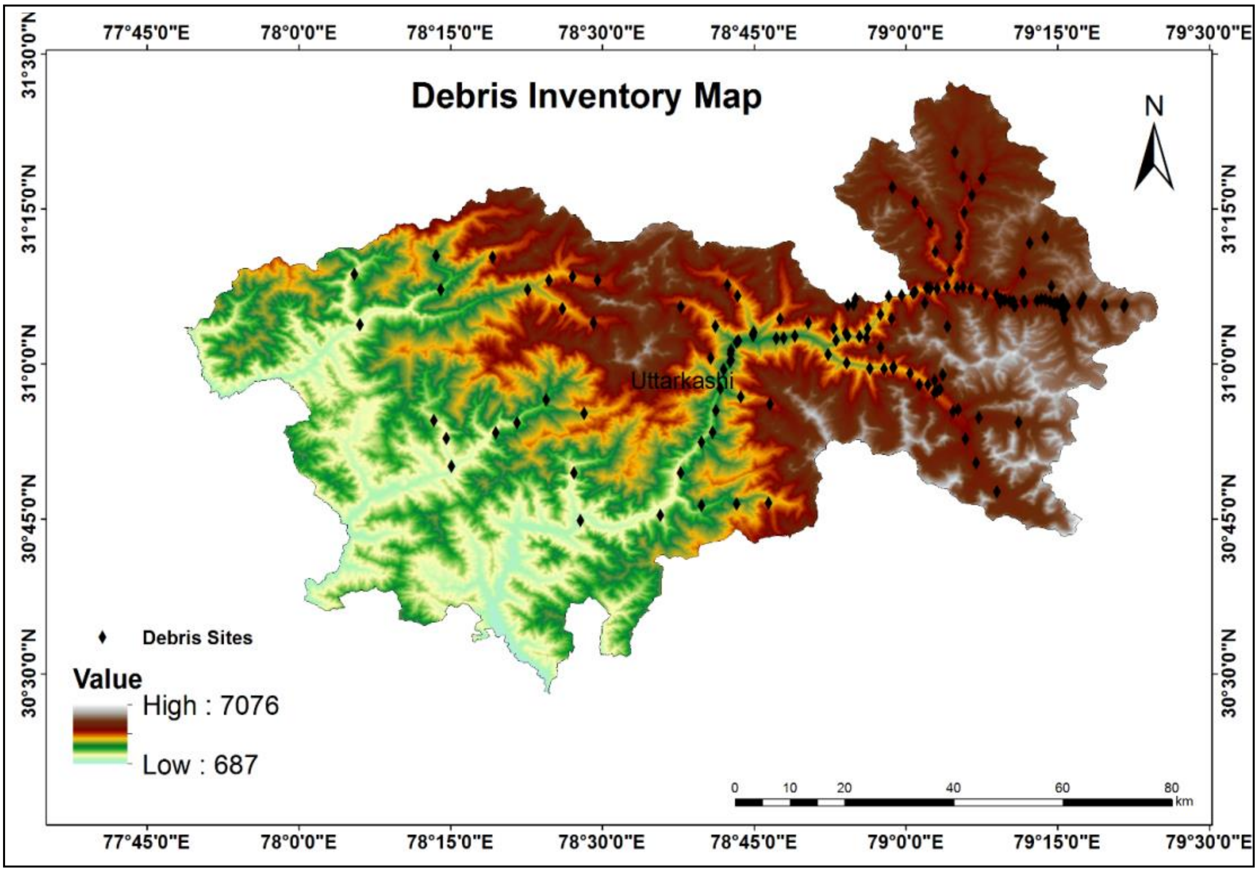


Figure 2.Debris Flow inventory map

Spatial data of conditioning factors

Identification of a set of applicable instability factors requires a complete understanding of the causes of debris-flow failures. A total of eight factors is selected to assess the debris-flow susceptibility for the Uttarkashi region namely - Slope, Aspect, Flow Accumulation, Elevation, Topographic Position Index (TPI), Distance to Drainage, Topographic Wetness Index (TWI), Normalized Difference Vegetation Index (NDVI). Depending on the type, scale, and method of data acquisition, the availability of thematic data differs. However, it is often intriguing to collect an ideal debris database to an appropriate level. For this study, a spatial database was developed and installed to implement the ANN model, which takes account of landslide and debris flow conditions. Approximately 22% of the total area in Uttarkashi is under permafrost or glaciated region and 68% of the total area is higher than 3000m altitude. It is observed that the valley regions are higher than 1750m in this region. This exceptional rugged terrain has a varying slope of 0 to 81degrees. Approximately 16% of the total area has a slope of more than 75degrees which is often associated with cliff area. Of the total area in this district, 47% has Aspect of south-west, south, and south-east. This southward slope often experiences higher rainfall from June to September each year which accelerates the possibility of high mass movement from the higher altitude. Aspect plays a key role both in witnessing heavy precipitation during a western disturbance at the north and north-western facing slopes and the southern facing slopes experiencing heavy rainfall during the monsoon season. NDVI depicts the vegetation condition, areas with higher NDVI will be less vulnerable to debris flow. On other hand, Distance from Drainage is proportionately related to debris damage. Area with higher stream power causes debris to flow down along the slope, thus higher Stream Power Index (SPI) directly proportionate with debris susceptibility. Similarly, the Topographic Position Index (TPI) and the Topographic Wetness Index (TWI) are proportionately related to the occurrence of debris flow. The controlling factors obtained after preprocessing the data are shown below in Figure 3.

Methodology

Overview of Methodology

The methodology includes the pre-processing of the data to generate the controlling factors, development of training and testing data, and then ANN-based model setup.

The overall methodology of the current study is as shown below in Figure 3.

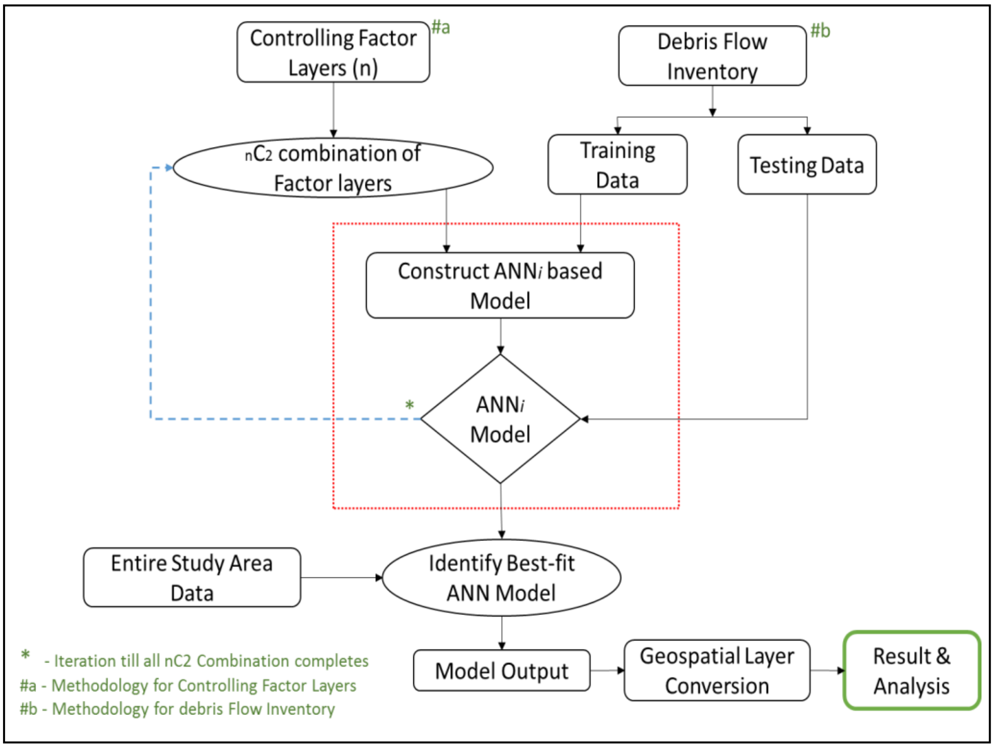
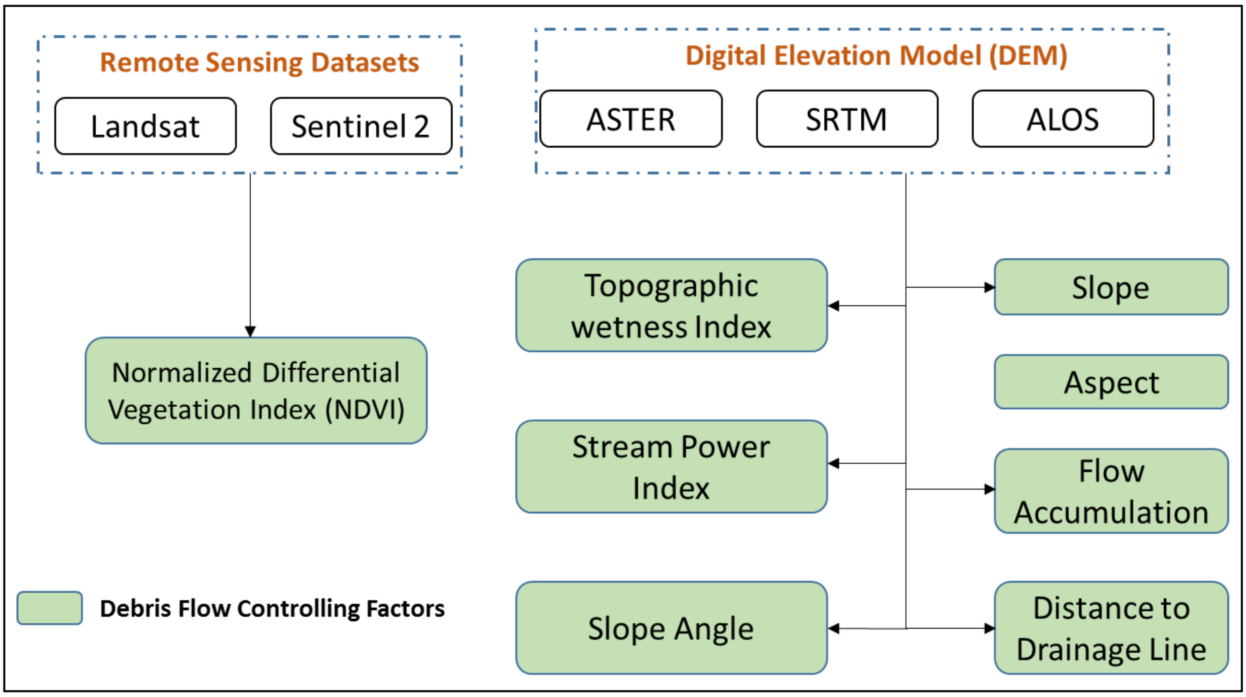


Figure 3.Methodology

Controlling factors Inventory

Each of the controlling factors are generated using datasets as provided in layers shown in figure 4. The Digital Elevation Model (DEM) is the major input for most of the layers as shown. The Topographic Wetness Index (TWI), Topographic Position Index (TPI), Stream Power Index (SPI), Flow Accumulation, Slope, Aspect, and Distance to Drainage require DEM as input. The Normalized Differential Vegetation Index (NDVI) is generated using the satellite data of Near-Infrared (NIR) and Red bands.

Figure 4. Controlling factors inventory



Then the controlling factors are normalized to the 0-1 range to fit the layers in the ANN-based model. The training and testing points are segregated from the inventory in a ratio of 70:30 respectively for this study area. Simultaneously, non-debris points are also being identified from satellite imageries. The data for each layer has been extracted over the testing points and put into the ANN model to setup the input layer over which the debris and non-debris events are remarked as 1 and 0 respectively. The model is then tested as per the testing points obtained to get the model's accuracy. The training and testing point inventory is generated as per the methodology given in **Error! Reference source not found.**5.

Training and Testing Points Methodology:
The controlling factors are generated as per the given data inventory in **Error! Reference source not found.**

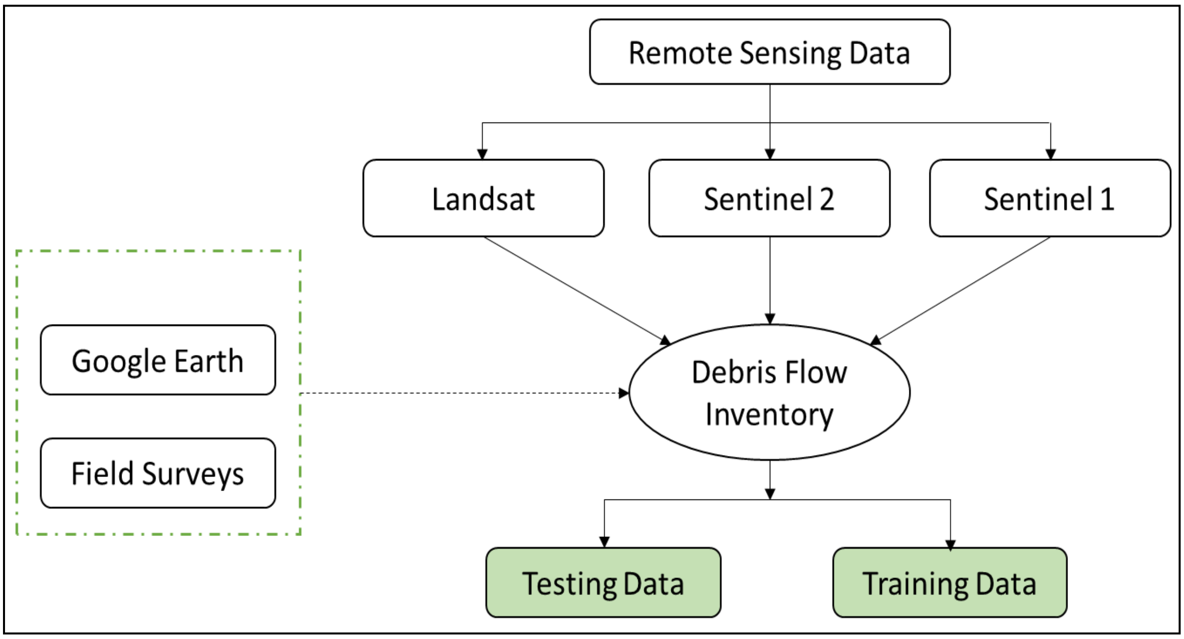


Figure 5. Training and testing points methodology

The training and testing points are generated using the Visualization techniques using the Remote Sensing datasets. The testing and training points contain both the debris and non-debris locations. The debris flows inventory of the training and testing points is verified using the Google Earth and Field Surveys. The total number of training and testing points considered in the model built up are ~70% and ~30% of the total points identified. The points generated using Google Earth are shown in the below images.

Artificial Neural Network

Input Data Processing

To implement an ANN, the training data needs to be constructed. In the current study, debris flow susceptible points were found out by ground survey. Some other points with no debris flow were also considered. Values of different input parameters such as Elevation, Slope, NDVI, Aspect, Flow, Distance to Drainage, TWI, TPI for the training points were generated. The values in the input dataset were normalized between 0 to 1 using a standard scaler function. 70% of the input dataset was set to be the training set using which the model is to be trained. The rest of the dataset was set to be the test set using which the trained model is to be tested. Naturally, the model has to be run successively so that with each iteration, the model accuracy increases. However, the model accuracy tends to hit a plateau after a certain iteration and the model does not improve at all. To find the plateau point, multiple hits and trials are to be performed.

The input data layers are generated using the Arc GIS and QGIS tools. The specified plugins are present in the QGIS to generate Distance to Drainage, Stream Power Index, Topographic Position Index, Topographic wetness Index. The Slope, Aspect, and Flow Accumulation are generated using the Digital Elevation Model. The Normalized Differential Vegetation Index is generated using the Sentinel 2 Satellite Imagery.

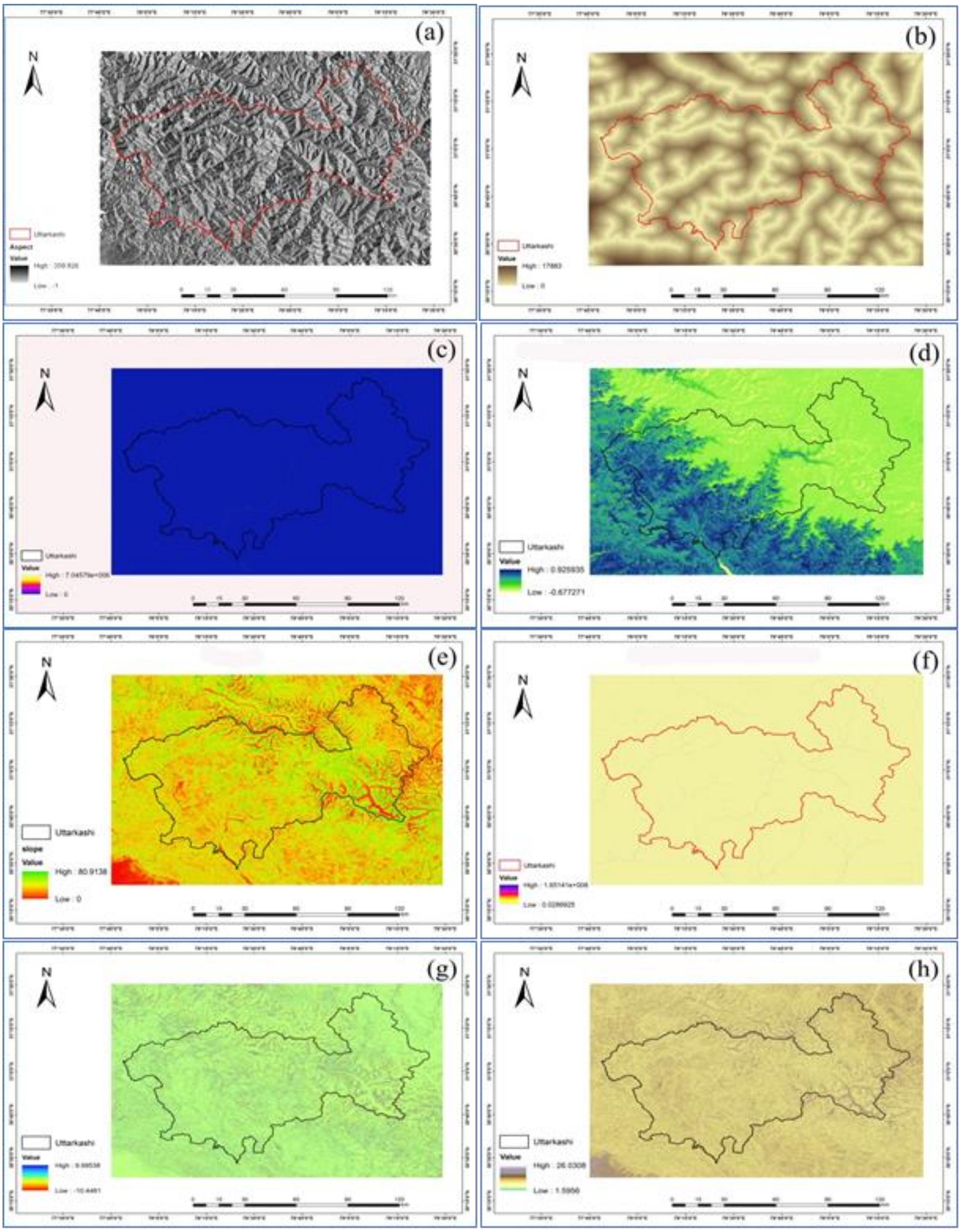


Figure 6.(a)Aspect, (b) Distance to Drainage, (c)Flow Accumulation (FAC), (d) Normalized Differential Vegetation index (NDVI), (e) The Slope, (f)Stream Power Index (SPI, (g)Topographic Position Index (TPI), (h) Topographic Wetness Index (TWI).

Model Construction and Implementation

The Artificial Neural Network (ANN) makes use of nonlinear and complex learning and prediction algorithms to extract the complex relationships among the various factors controlling debris-flow occurrences. The model contained 5 layers in total. The first and last layers were the input layer and output layers respectively. The rest of the 3 layers are hidden layers with 32 neurons each. Rectified Linear unit (ReLU) activation function was used for each of the layers as it has been found to work well with simple classification problems. Activation layers associated with each neuron act as switches that activate or deactivate a neuron. To optimize the model, an Adam optimizer was used and binary cross-entropy was used as the loss index. The schematic diagram for the ANN model is shown in **Error! Reference source not found.**7.

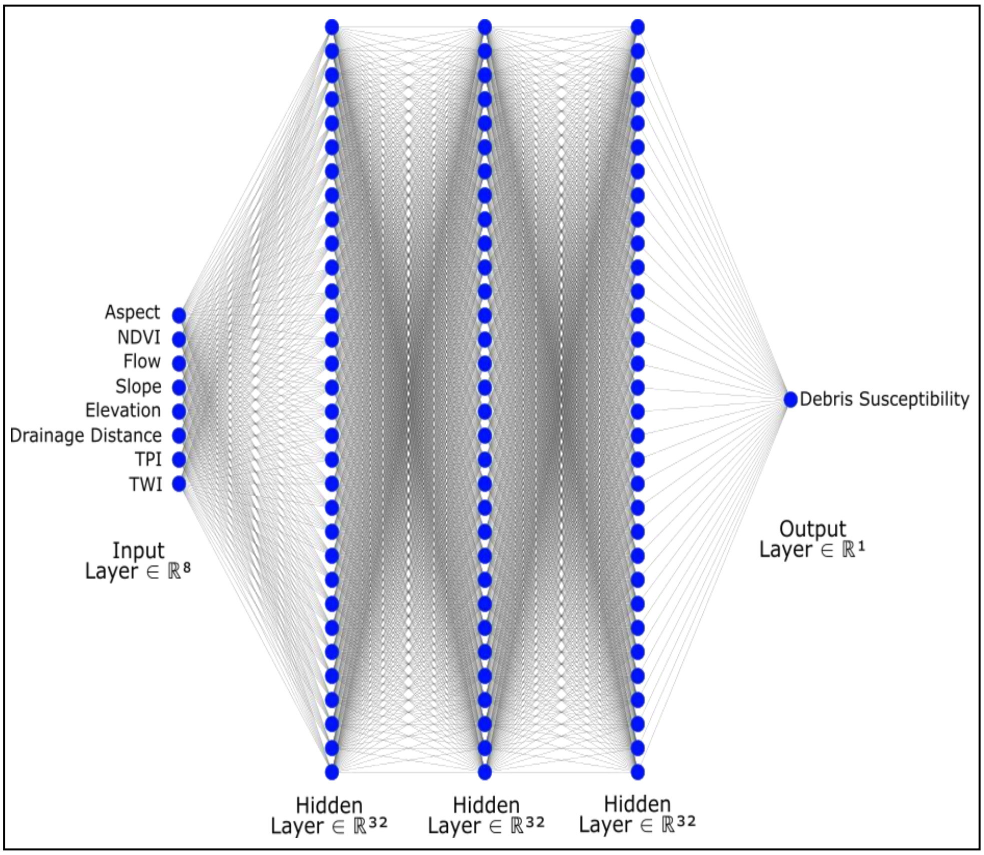


Figure 7. Artificial Neural Network (ANN) model structure

To train the model, iterative backpropagation is performed in multiple time executions called epochs. One epoch is the time taken by the model to go through the entire input dataset once.

A forward stepwise approach was adopted to implement the ANN model to understand the relatively important factors which control the occurrence of debris flow and their order of importance. The procedure was also followed to find out the optimal combination of inputs which led to the best predictive model. Initially, the model was trained 8 times by using only one factor as input to the model. The model was then used to perform predictions on the test data and the accuracy was calculated. Considering the accuracies provided by the 8 input factors, the factor which provided the highest accuracy was selected. Next, 7 models were run using two variables: the factor which was chosen from the previous step and one of the remaining 7 variables at a time. Then the variable whose addition produced the largest increment in model prediction performance was selected. This process of adding controlling variables was repeated until it was found that the addition of remaining variables no longer improved or decreased the overall model performance. Finally, the optimum and validated ANN model was used to derive a susceptibility measure for each pixel in the study area. The final raster was exported which served as the debris flow susceptibility map.

Results and discussions

The current section involves data processing and ANN model simulations as the outcomes. The data processing was performed to obtain the controlling factors utilized in the ANN-based debris flow model. Altogether, the data layers depict Uttarkashi district as a region with highly rugged terrain, a drainage network with higher stream erosion capacity, and lesser vegetation in the semi-alpine altitudes. Therefore due to highly rugged terrain with a higher slope, there is a higher chance of slide-events significantly. In the upper slope region, the area with comparatively higher topographic wetness could have resulted in massive rockfall which may lead to debris flow at very high risk.

Artificial Neural Network (ANN) Model Simulations

Our findings as obtained from the ANN model setup for the debris flow susceptibility can be grouped in the form of a table as shown below. The Area Under Curve (AUC) of the model considering the different variables is shown below in **Error! Reference source not found.**.

Table 2. Area Under Curve (AUC) of ANN-based model generated

	1-variable	2-variable	3-variable	4-variable	5-variable	6-variable
Distance to Drainage	0.701					
NDVI	0.495	0.727				
Aspect	0.5	0.723	0.745			
Slope (degree)	0.519	0.617	0.627	0.77		
Flow Accumulation	0.498	0.708	0.649	0.649	0.724	
Elevation	0.5	0.67	0.637	0.744	0.69	0.746
Topographic Position Index (TPI)	0.5	0.632	0.69	0.63	0.689	0.685
Topographic Wetness Index (TWI)	0.497	0.689	0.644	0.697	0.701	0.67

The AUC obtained for most of the model lie between 0.7 and 0.8 and hence, this model is acceptable. The area of this district is nearly 8000 sq. km and the model accuracy obtained for such a large area is satisfactory. The best fit model from the above table selected is utilized and is set to simulate for the entire district pixels. The Receiver Operating Characteristic (ROC) curve obtained during the simulations is shown in Figure 8. It depicts significant accuracy of the ANN-based model at 95% for the 25 epochs. For the epoch at a range of 100 – 200, the model accuracy ticks at its best i.e. more than 99%.

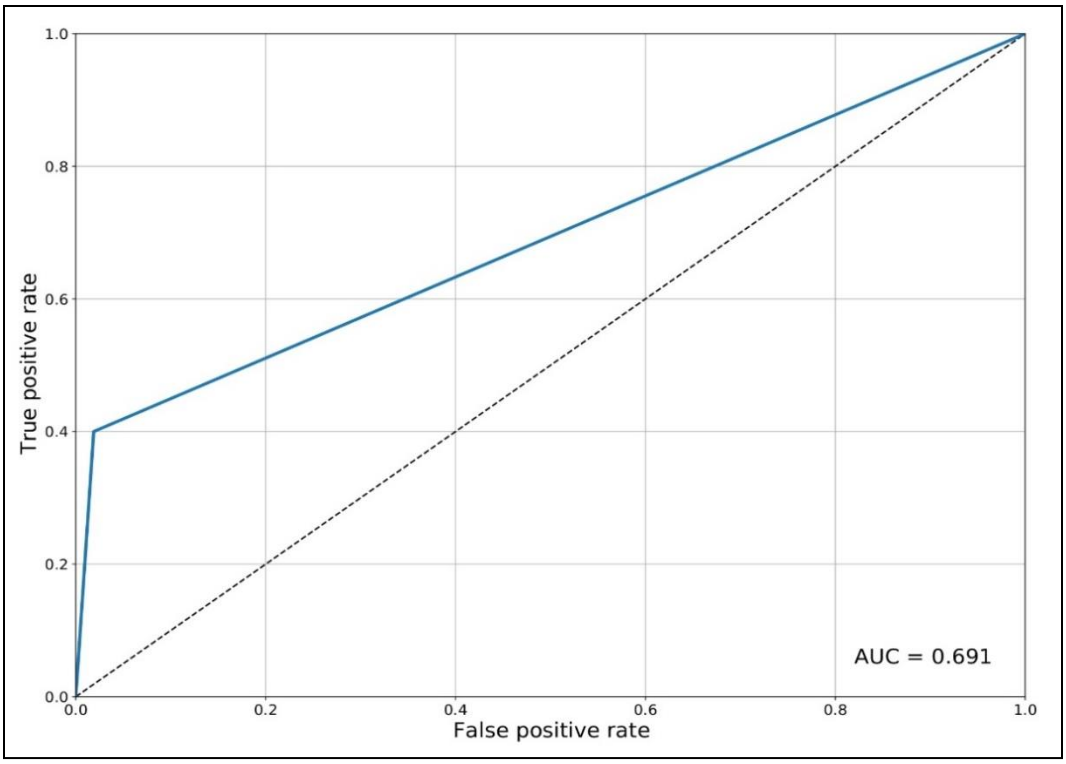


Figure 8. Receiver Operating Characteristic (ROC)curve of the model

The model is simulated on various epochs, the obtained metrics of the model behaviour are shown in Figure 9. The figure depicts, with an increase in epochs of the model simulations, the model accuracy has shown improvement in the prediction.

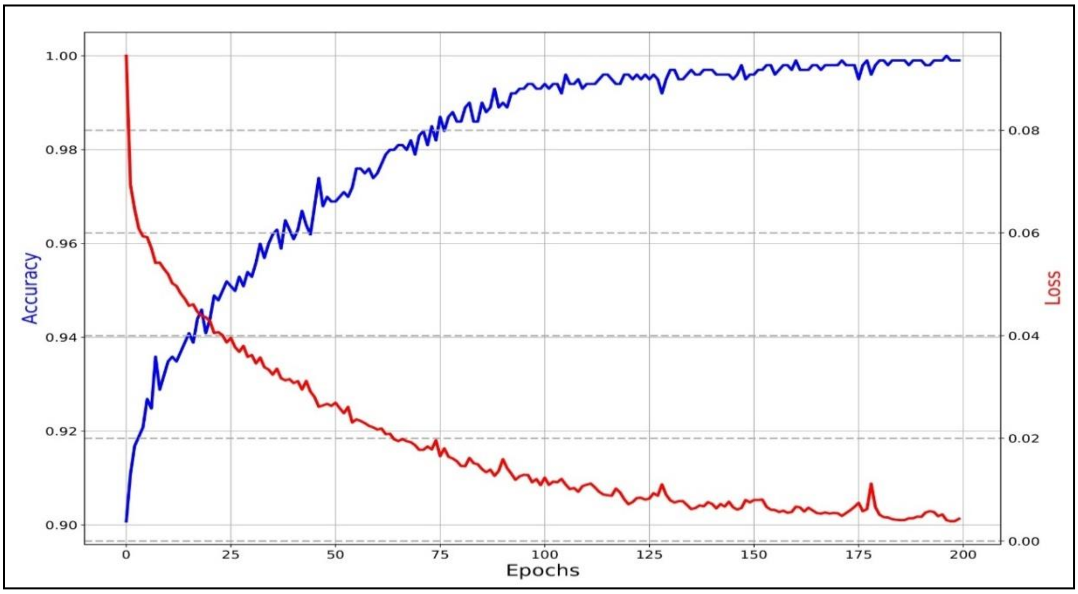


Figure 9.Metrics of the model epochs

The susceptibility map is generated in five zones based upon the probability obtained from the ANN model simulations. The various zones classified are very low, low, moderate, high, and very high the debris flow susceptibility map obtained for the district is shown below in Figure 10.

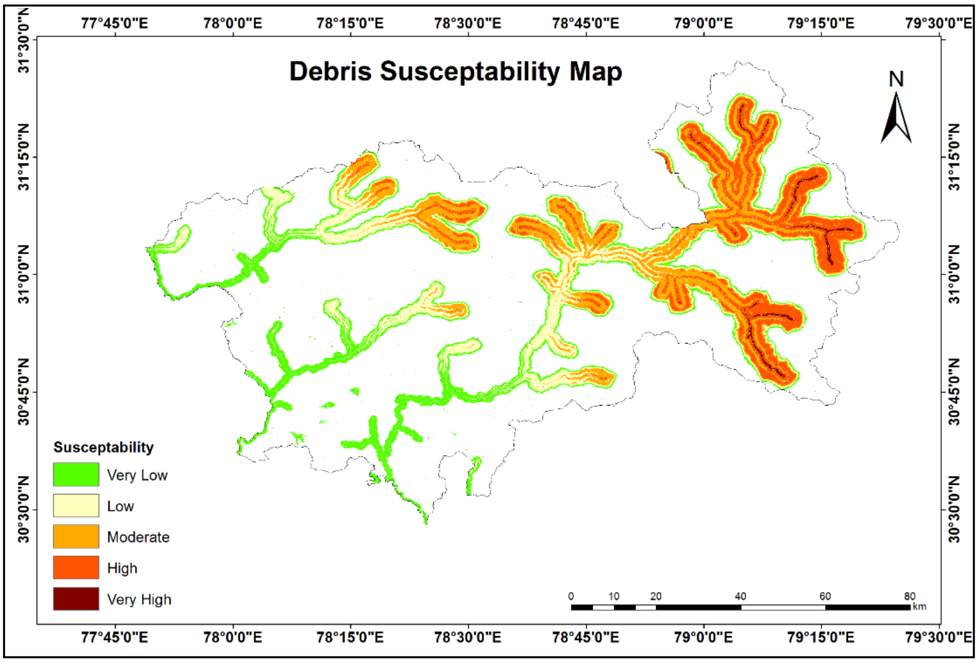


Figure 10.Debris Susceptibility map of the Uttarkashi district

It has also been obtained from the above map that most of the high and very high debris susceptible region lies in and along the drainage lines in the eastern part of the district. Also, the debris susceptibility is higher in the region which has a higher slope and also with very less or no vegetation. The region with a high NDVI value or the forested area will have low debris susceptibility. It can be shown from the land cover map in **Error! Reference source not found.**11.

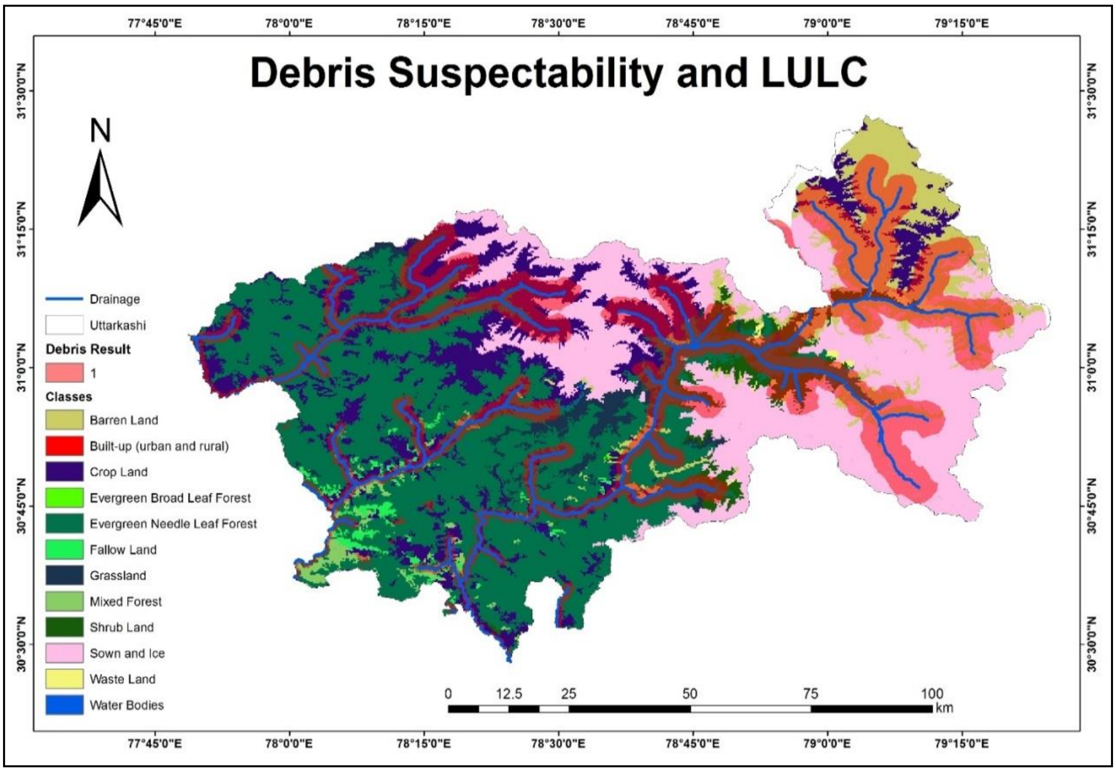


Figure 11. Debris Susceptibility and Land use Land cover (LULC)

Therefore the area with better vegetation cover would have been less susceptible to such occurrence. In the central part of the district, some fallow land can be observed through the land-use and land cover map, which also comes under a moderately susceptible zone. Such an area with a comparatively lesser slope could be afforested to restrict the chances of debris flow. In the northeastern part of the district, approx. 60% of the very high and high category of debris susceptible zones comes under barren land while more than 90% of low and very low category debris susceptible zones come under high vegetation density zone of more than 0.5 value in NDVI. In the northern part of the district, approx. 80% of the moderate to high susceptible zones are near the cropland area, where the soil could lose its strength due to ploughing and harvesting while practising agricultural activities. In the eastern part, the stream power index was also noticed to be high which could cause severe erosion through the river banks, therefore slope stabilization and embankment could be fruitful to restrict the damage due to debris flow.

Conclusions

To resolve the various uncertainties in the numerical modelling of debris flow (Bertolo & Bottino, 2008), the machine learning techniques could be a suitable alternative as it is flexible to incorporate all the input parameters with its non-linear dependency to resolve a multi-complex process (Gupta, Pradhan, et al., 2020). Debris flow causes enormous loss to life and property if not analyzed beforehand. Remote sensing and GIS technology have always been very useful in data acquisition, processing, analysis, and data management. The remote sensing data becomes very useful when it becomes the input for the Artificial Neural Network (ANN) for estimation. The susceptibility map obtained using remote sensing and ANN-based approach is validated and is found acceptable as verified from satellite images and field visits. This study indicates that Artificial Neural Network (ANN) along with the remote sensing data is apt for ascertaining susceptibility map for debris-flows. The debris flow susceptibility study can be performed at any part using the controlling factors and the Artificial Neural Network (ANN). In the present study, multiple spatial dataset for various input layers have been prepared using different satellite data. It helped to assess the broader coverage of land use land cover parameters along with various physiographic parameter and drainage parameters to estimate the susceptibility of debris in Uttarkashi district. However, all this input layers are static; the changes in physical aspects of this region due to land use land cover change could produce slight changes in susceptible zonation. Howsoever, the high and very high-risk zones contain almost 75% of debris identified locations depicted in the inventory map. Hence, this study could be very helpful for the disaster mitigation purpose of the Uttarkashi district.

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