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# DATA DRIVEN BASED SPATIO-TEMPORAL QUANTIFICATION AND PREDICTION OF LANDSLIDE SUSCEPTIBILITY FOR THE HIMALAYAN REGION

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Landslides are the most common natural hazard in the hilly regions of the world. In India, high landslide susceptibility zones are mainly found in the Himalayas, the Western Ghats, and North-east India. The use of landslide susceptibility and hazard maps for land use planning has increased significantly during the last few decades. Landslide Susceptibility (LS) mapping is an essential step in mitigation measures for planning and recognising the regions needing protective measurements. Many studies have performed these mapping measures; however, they all lack consistency in selecting landslide-causing factors for the susceptibility analysis and mapping. The variability in choosing factors for the same region by different researchers has made it challenging to compare the models' prediction accuracies. In the present study, a scientific method was adopted for identification of significant landslide causing factors for LS analysis. The chosen combination was also tested on two test sites with similar terrain conditions. Further, dynamic factors such as land use land cover and climate variables were adopted to predict future projections of LS analysis. The result shows that chosen 11 significant factor model has highest prediction accuracy of 0.93 area under curve (AUC) value. The Analytical Hierarchy Process (AHP) based LS mapping for Chamba, Bhuntar, and Tehri regions achieved a prediction accuracy of 0.86, 0.82, and 0.89 AUC values. Also, the results show a promising increment in the built-up area and agriculture field and reduced forest area in LULC projection of 2050. Further, the results also indicate that the zones of very high landslide susceptibility class will increase by 2%, 4%, 7%, and 9% under projected LULC and climate scenarios of Shared Socioeconomic Pathway (SSP) 1–2.6, SSP 2–4.5, SSP 3–7.0, and SSP 5–8.5 respectively.

*Keywords*: Future landslide susceptibility mapping, Land use land cover projections, Climate projections.

## 1. Introduction

Landslides are fragile and unstable landscape where habitation or other engineering structures cannot be developed or constructed. The increase in human population and urban growth in the mountains such as infrastructure constructions has led to deforestation, cutting vertical slope and has resulted in frequent landslides at such places. In many developing countries, this problem is remarkable, mainly due to the rapid non-sustainable development of natural resources. Climate change and associated extreme weather conditions result in a surge of natural hazards such as floods, landslides, and avalanches worldwide. With the present land use scenarios and changing climate, these natural hazards will likely increase in the future on habitat areas. The Himalayan region in India faces severe challenges due to landslide activities. Landslide susceptibility (LS) mapping is the most important tool for reducing the damage caused by landslides. Hence, LS mapping is an essential step for identifying dangerous areas and a piece of crucial evidence for encouraging people to inhabitant on safe ground. Identifying the location of future landslides, even if we are unaware of when they will occur, can resist urbanization and development in the direction of high landslide-risk zones. Researchers have concluded that urbanisation and climate changes will significantly impact landslide frequency in future (Persichillo et al. 2017).LS mapping is a primary step in mitigation measures for planning and recognizing the regions needing protective measurements and vital tools for the reduction of landslide hazard losses (Tyagi et al., 2023). Though, studies have investigated the impact of Land Use Land Cover (LULC) change (Pisano et al. 2017) and climate change (Hürlimann et al. 2022) on landslide occurrence. However, the LS prediction using significant landslide causing factors and projecting it to future using dynamic factors has not been quantified. Hence, this study attempts to accurately predict future 2050 LS map for the Tehri region incorporating 2050 LULC and climate projections. To achieve this, following work task were performed.

1. Identification of significant landslide causing factors for the study area using multicollinearity analysis and sensitivity analysis.
2. The significant factors derived for the study region were tested on two landslide prone sites of Chamba and Bhuntar having similar terrain condition using Analytical Hierarchy Process (AHP) model.

3. Generation of the LS maps for the year 2010, 2015 and 2020 of the Tehri regionusing derived significant factors.
4. Derivation of future LULC projection using Artificial-neural-network-based cellular automaton(ANN-CA) model and future climate variables using CMIP6 Climate Projections.
5. Generation of future LS map for the Tehri region by projecting the predicted LS maps using projected dynamic factors.

## 2. Study Area

The Himalayas has a conspicuous landscape consisting of tall ridges, steep slopes, large streams, and deep valleys. After carrying out the literature review, the area where the landslide problem dominated was selected. The site should also have the availability of historical landslide data and good-resolution satellite imagery. The Tehri region of Uttarakhand, the Chamba and the Bhuntar regions of Himachal Pradesh are some of the landslide-prone sites chosen in this study (Fig. 1). These three study regions have an almost similar types of terrain and climatic conditions. Apart from heavy rainfall and high seismic factors, these study areas also have a high stream network that adds to the hill’s instability. The two test sites from the Himalayas were selected from the state of Himachal Pradesh with similar terrain conditions and data availability of historical landslide events and landslide causative factors.

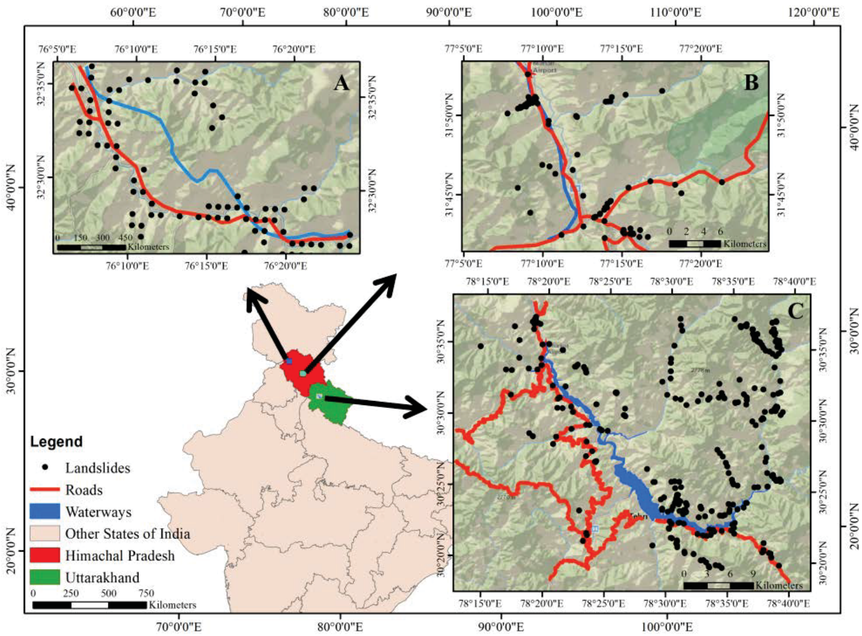


Fig. 1 Location of (A) Chamba test site 1, (B) Bhuntar test site 2, and (C) Tehri study area.

## 3. Methodology

In the present study, we adopted following methodology as shown in flow chart (Fig. 2). First, the landslide causing factors were derived using satellite, field and ancillary data sources. Second, two optimizing techniques were adopted to identify the significant factors.Multicollinearity analysis was first applied to remove the high inter-correlations factors. Further, sensitivity analysis was performed to achieve the highest accuracy by identifying the suitable combination of significant factors. Sensitivity analysis in an ANN identifies the significant factors based on the prediction accuracy. Third, the derived significant factors were tested on two landslide prone sites using AHP model. Forth, the LS maps for the study area were derived for the year 2010, 2015 and 2020 using significant factors and ANN model. Fifth, future 2050 projected map of LULC was generated using ANN-CA model for the study area. Sixth, climate projections for 2050 were used to derive future projected data for four Shared Socioeconomic Pathways (SSPs) scenarios. The climate projections in this study includes mean precipitation flux and surface temperature projections, which were obtained from the CMIP6 climate projections. We have adopted the Indian Institute of Tropical Meteorology earth system model (IITM ESM) for climate projections, and they were further used to derive the future LS maps for the study region.

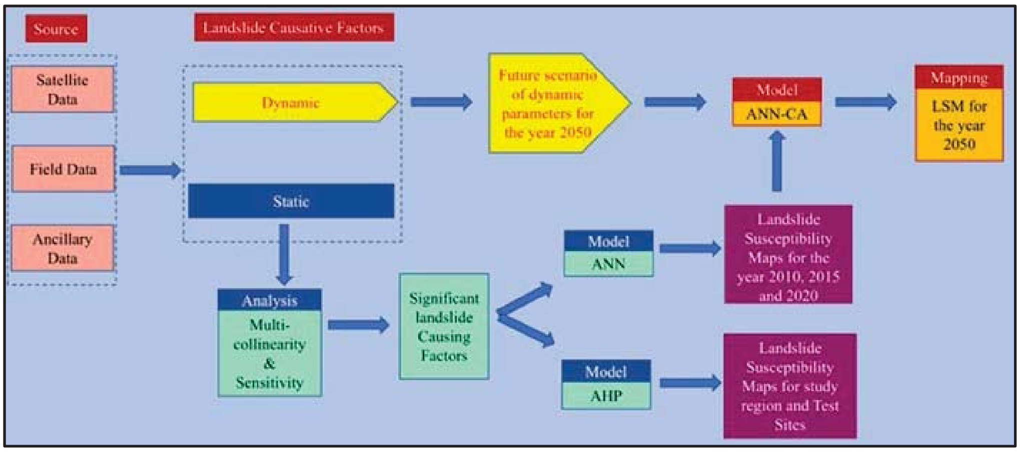


Fig. 2. Methodology adopted in the present study in a flow chart form

## 4. Results

### 4.1.*Optimization of landslide causing factor*

The Pearson's correlation values of all the factors are less than 0.7, they all are taken forward for sensitivity analysis. For sensitivity analysis, all the factors were considered for analysis, and to identify the significant factors, one by one, the least significant factors were removed, and LS analysis was performed. The top 11 significant factors gave the maximum precision with an AUC value of 0.93.

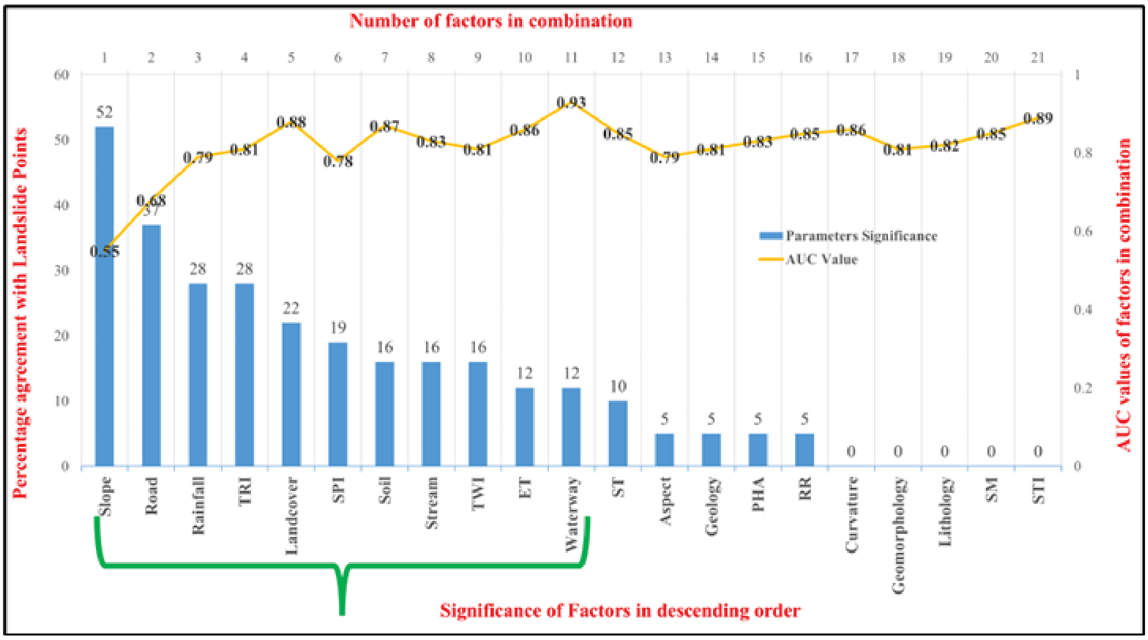


Fig. 3. Significant factors showing percentage agreement with landslide points. (TWI is topographic wetness index, TRI is topographic ruggedness index, ET is evapotranspiration, PHA is peak horizontal acceleration, RR is relative relief, SPI is stream power index, SM is soil moisture, and STI is sediment transport index).

### 4.2.*Validating the significant factors using AHP Model at Chamba and Bhuntar test sites.*

The derived significant factors can be adopted for LS mapping using the AHP model and maps of the Tehri region, Chamba test site, and Bhuntar test site are prepared as follows (Fig.4.).Here, we have compared the eleven factors subjectively by adopting AHP technique and weights were derived. After calculating the weights of all the factors and their class, landslide susceptibility index (LHI) is calculated. The LSI maps were then classified into five classes using the Jenks natural break classifier. As AHP is subjective, we have not incorporated historical landslide data of test sites for generating these susceptibility maps. However, the historical landslide data of these regions were used to check the accuracy of the predicted maps. The derived maps for the three regions have 0.86, 0.82, and 0.89 AUC values.

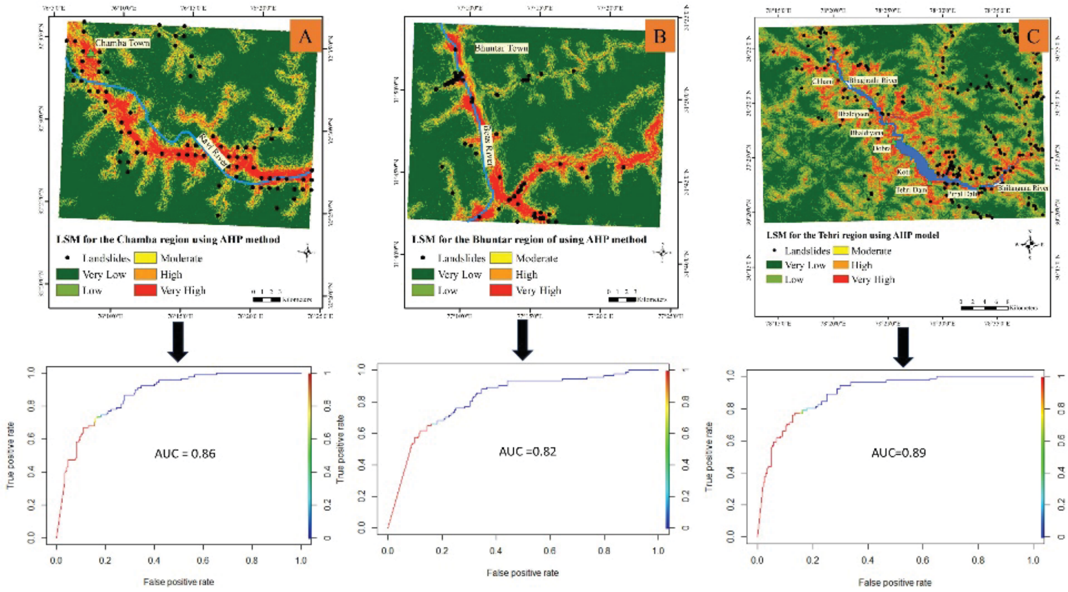


Fig. 4. LS maps for (A) Chamba test site 1, (B) Bhuntar test site 2, and (C) Tehri study area using AHP Model.

### 4.3.*Future Predicted Landslide Susceptibility Maps for Tehri Region.*

The LS maps were predicted for the year 2050 (Fig.5), considering dynamic factors. These maps show how the future LS maps will look like based on the four climate scenarios and LULC projections. Red pixels are the covering zones which will be highly susceptible to landsliding whereas, dark and light green pixels are safer place. The zoom images highlight the increase in the very high LS class for an area close to the river. The map of SSP 1-2.6 scenario has least percentage of very high susceptibility pixels whereas the SSP 5-8.5 scenario has the highest.

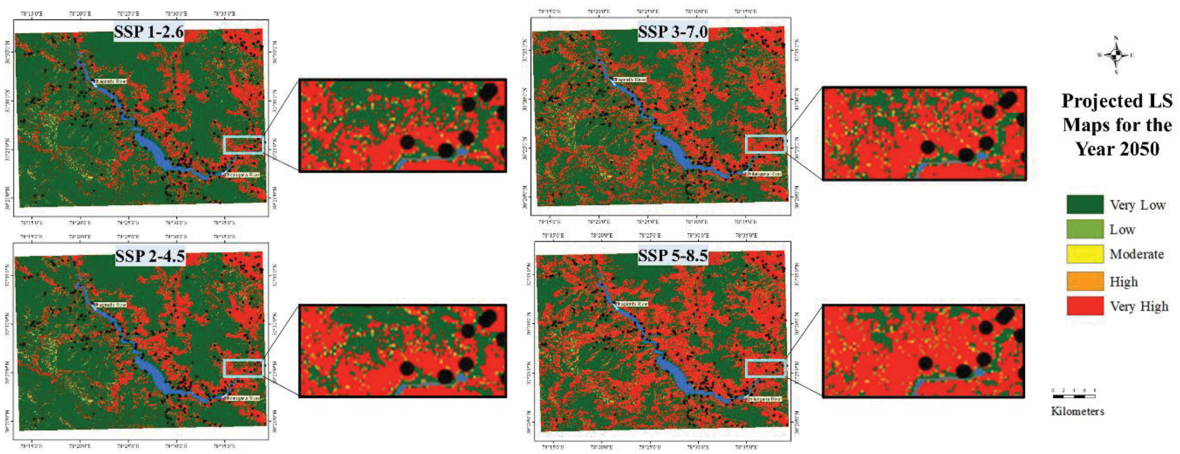


Fig. 5. Projected 2050 LS maps of Tehri region for SSP 1-2.6, SSP 2-4.5, SSP 3-7.0 and SSP 5-8.5 Scenarios.

### 5. Conclusion

In this research, we have scientifically obtained the most significant landslide-causing factors for the Tehri region. The results reveal that out of 21 parameters considered for the Tehri region, 11 were found to be significant for LS mapping and achieved the prediction accuracy of 0.93 AUC value. Earlier research on this study area using multiple models also couldn't achieve this high accuracy. This may be because the selected factors in earlier studies were not all that significant for the LS analysis. Incorporating less significant factors in the analysis can act as noise in the ANN model and hence can negatively impact the model's ability to learn patterns effectively. Thus, this study recommends using the derived 11 landslide parameters and their hierarchy for carrying out LS mapping in the Himalayan region.

The dynamic factors such as LULC and climate change can be used for future predictions by examining the trends in change detection. This LULC change and change in climate variable under four climate forcing scenarios of SSP 1-2.6, SSP 2-4.5, SSP 3-7.0 and SSP 5-8.5 has resulted in an increase of very high LS class by 2%, 4%, 7%, and 9% respectively. Based on the results, urbanization or construction activities are not recommended on these zones. Safer zones in dark green and light green should be given priority for such development.

The results also concludes that the scale of landslide-susceptible areas is estimated to increase in the future as the forcing scenarios change from SSP 1-2.6 to SSP 5-8.5. This shows more restrictions zones will develop in the future as the climate changes. The present study results may benefit LULC and mitigation strategies planning for the Tehri region and other similar terrain conditions. Future prediction of LS mapping can help in the proper management and sustainable distribution of environmental resources. Hence, this methodology can also be adopted by other national and international government agencies to derive future maps for such landslide prone areas. The target audiences can be land use policymakers who must decide which direction urbanization takes and which direction to restrict.

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