ISSN: 2469-4134
Journal of Remote Sensing & GIS

OPEN ACCESS Freely available online

Research Article

# Landslide Susceptibility Mapping Using Shannon's Entropy Methods Using Hybrid Technique: A Case Study of Kinnaur District, Himachal Pradesh, India

**Vicky Anand[1*], Aastha Sharma[2], Amit Kumar Sahni[3], Sahnoor Bano[4], Sunil Kumar Jangra[5]**

*[1]GIS, Professional, Saritha Vihar, Delhi, India;[2]Ph.D. Scholar, Department of Geography, Faculty of Natural Sciences, Jamia Millia Islamia University, New Delhi, India;[3]GIS, Professional, Faridabad, Haryana, India;[4]GIS, Professional, Chandigarh, India;[5]GIS, Professional, Hisar, Haryana, India*

## ABSTRACT

Global climate change has developed into one of the most complex problems facing mankind in the current scenario. This change has an irrefutable disturbance on the stability of natural and engineered slopes, including landslides. In mountainous terrain such as the Himalayas, landslides are among the most harmful hazards. Most landslides occur under the influence of earthquakes or rainfall, and they are often among the most devastating natural hazards. Increasing awareness of landslides' socioeconomic impacts has attracted global attention to landslide studies. A landslide risk assessment in Himachal Pradesh's Kinnaur region was conducted using remote sensing and Geographic Information Systems (GIS). For the Landslide Susceptibility Mapping, a hybrid approach is used. Using a hybrid approach, weighted overlay is combined with Shannon's entropy, an eminent technique based on evidence. To prepare a susceptibility map, eight landslide-related criteria are used in conjunction with the inventory of landslides that contained recent and historical landslides. The validation results show that the models derived using the following approach have the highest prediction capability.

**Keywords:** Landslides; Susceptibility; Shannon entropy; Weighted overlay; Remote sensing

**Abbreviations:** RS: Remote Sensing; GIS: Geographical Information System; LSM: Landslide Susceptibility Mapping; IMO: Indian Meteorological Organization; ETM: Enhance Thematic Mapper; DEM: Digital Elevation Model; SRTM-Shuttle Radar Topography Mission; LULC: Land Use/Land Cover; ROC: Receiver Operating Characteristics.

## INTRODUCTION

In geophysics and climate science, landslides are defined as an earth's surface movement due to a geophysical phenomenon or a climatic change. Typically, it involves soil and rock mass displacement along one or more slip surfaces. Among Asian countries, South Asian nations suffer the greatest fatalities, and even among South Asian countries, India is one of the worst devastated by landslides [1]. Impacts from extreme-weather events hit the least developed countries most vigorously, as they are susceptible to the damaging repercussions of a hazard, have a lower coping capacity, and may need more time to rebuild and recover. The Indian Himalayan belt has been persistently threatened by landslides of varying intensities throughout history [2-4]. Human, material, and environmental losses have been caused by landslides when they occur in proximity to human habitation because of the high exposure to landslide risk. Unsustainable construction activities in vulnerable zones, deforestation for urban boundary expansion, and inadequate slope management will accentuate the number of people exposed to the risk of landslides. In view of escalating climate risk, it is imperative to adopt suitable adaptation strategies for landslides. In understanding and forecasting probable future landslides, Landslide Susceptibility Maps (LSMs) can be an effective tool [5-7]. Landslides frequently occur concurrently with other natural disasters such as wildfires and floods, rendering them a significant concern in hazard mitigation and comprehensive planning. LSMs depict areas prone to landslides event in the future

**Correspondence to:** Vicky Anand, GIS, Professional, Saritha Vihar, Delhi, India, E-mail: vickyanand198@ gmail.com

**Received:** 26-Sep-2022, Manuscript No.JGRS-22-18161; **Editor assigned:** 29-Sep-2022, PreQC No. JGRS-22-18161 (PQ); **Reviewed:** 13-Oct-2022, QC No JGRS-22-18161; **Revised:** 19-Oct-2022, Manuscript No. JGRS-22-18161 (R); **Published:** 28-Oct-2022, DOI: 10.35248/2469-4134.22.11.261

**Citation**: Anand V, Sharma A, Sahni AK, Bano S, Jangra SK (2022) Landslide Susceptibility Mapping Using Shannon's Entropy Methods Using Hybrid Technique: A Case Study of Kinnaur District, Himachal Pradesh, India. J Remote Sens GIS. 11:261.

through associating some of the major aspects that cause landslides by historical slope failure distributions, making it possible to predict where they will occur in the future [8-12]. For these reasons, the production of LSM early in the landslide assessment process plays a crucial role in the safe planning of economic activities, such as urbanization and building structures.

In contrast, no standard procedures for producing maps showing landslide susceptibility exist. Landslide risk management can thus be achieved through providing risk executives with timely and precise information about landslides [13-19]. Because of the complex nature of landslides, predicting their location in advance is challenging. In addition to providing information regarding landslide hazards, LSM also indicates whether landslides will occur within a particular period.

This study aims to determine a universal degree measure of inconclusiveness associated with fuzzy sets in the defined circumstances [20-26]. A new functional defined of the class of generalized characteristic functions (fuzzy sets) is introduced, called “entropy”, which does not use probabilistic concepts. This quantity has a very different meaning than classical entropy because it doesn’t require a probabilistic picture to be defined [27-34]. This measure gives a symbol of the “indefiniteness” of the situation. The definition of probability isn’t agreed upon, even though there is a mathematically defined theory of probability. Understanding susceptible regions would be possible with effective LSMs [35-40]. GIS-based tools are developed and used to create susceptibility maps to help planners in understanding of landslide hazards. There are three general types of approaches: subjective, objective, and Shannon entropy.

### Study area

Kinnaur district is one of Himachal Pradesh’s 12 administrative districts that have been given the special status of a tribal district under Schedule 5 of the Indian constitution. Kinnaur can be found between 77°45’ and 79°00’35” East longitudes and between 31°05’50” and 32°05’15” north latitudes. This area is surrounded by Tibet and Uttaranchal in the east, Shimla district in the southwest, Kullu district in the northwest, and Lahaul-Spiti district in the northeast [41-47]. This district has three high mountain ranges, namely the Greater Himalayas, Zanskar, and Dhauladhar, which encompasses the valleys of Baspa, Sutlej, Spiti and their tributaries. Kinnaur’s topography ranges in altitude from 1600 meters to 6816 meters. Forests, orchards, fields, and picturesque hamlets are scattered along the mountainsides. Shivlinga is located at Kinner Kailash’s peak, an extremely religious place for Hinduism. 1989 was the year that this beautiful district was opened to outsiders [48-53]. A portion of the old Hindustan-Tibet Road runs along the banks of the Sutlej River through the Kinnaur valley until it arrives at the Shipki La Pass, which leads to Tibet.

## MATERIALS AND METHODS

The susceptibility map of the Kinnaur region was determined by utilizing the landslide-related criteria outlined in the table above. Input maps of the roads, rivers, and drainage systems were obtained from the study area’s topographic maps (1:50,000), while geology maps were obtained from geological survey of India. Additionally, the aspect and slope criteria derived using the Shuttle Radar Topography Mission (SRTM) 30 m Digital Elevation Model (DEM) using ArcGIS version 10.4. Images with 30 m spatial resolution of Landsat ETM+ satellites were used to create land use/cover maps [54-59]. A mean annual rainfall map was created in ArcGIS using kriging interpolation techniques and data from the Indian Meteorological Organization (IMO). Additionally, the inventory of landslides polygons obtained from the Geological Survey of India containing 1190 recent and historical landslide polygons (Table 1 and Figures 1-7).

**Table 1:** Description of criteria and data source.

| Criteria | Data source |
|---|---|
| Slope | 30 m, SRTM DEM |
| Aspect | 30 m, SRTM DEM |
| Rivers | 1:50,000 Topo-map |
| Altitude | SRTM |
| Rainfall | 30 years, IMO data |
| Transport network | 1:50,000, Topo-map |
| Geology | 1:100,000, Geo-map |
| Land use | 30 m, Landsat Images |

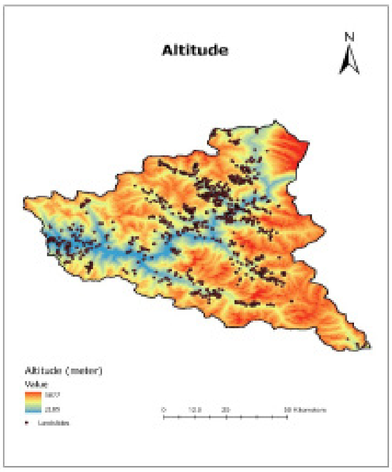


**Figure 1:** Altitude of the Kinnaur region.

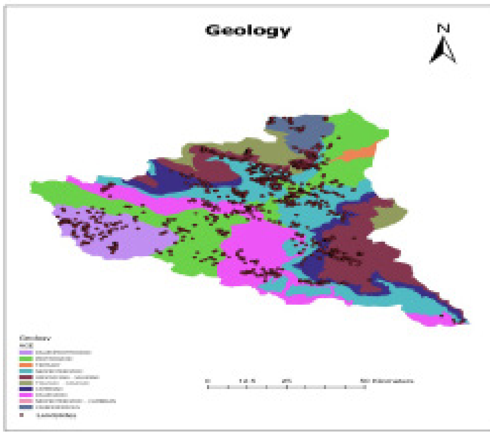


**Figure 2:** Geology of the Kinnaur region. **Note:** (▬) Palaeoproterozoic, (▬) Proterozoic, (▬) Tertiary, (▬) Neoproterozoic, (▬) Ordovician-Silurian, (▬) Triassic-Jurassic, (▬) Cambrian, (▬) Palaeozoic, (▬) Neoproterozoic-Cambrian, (▬) Carboniferrous.

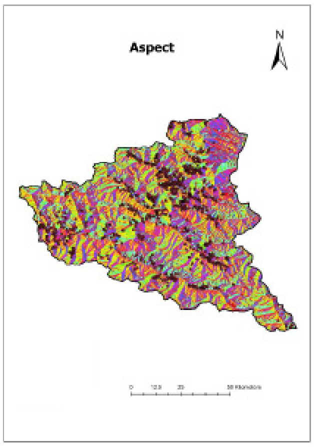


Figure 3: Aspect of the Kinnaur region. Note: (▬) North (-1), (▬) North (-1), (▬) Northeast (0-22.5), (▬) East (67.5-112.5), (▬) Southeast (112.5-157.5), (▬) South (157.5-202.5), (▬) Southwest (202.5-247.5), (▬) West (247.5-292.5), (▬) Northwest (292.5-337.5), (▬) North (337.5-360).

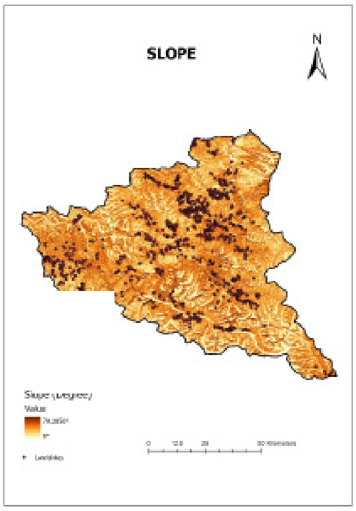


**Figure 4:** Slope degree value of the Kinnaur region.

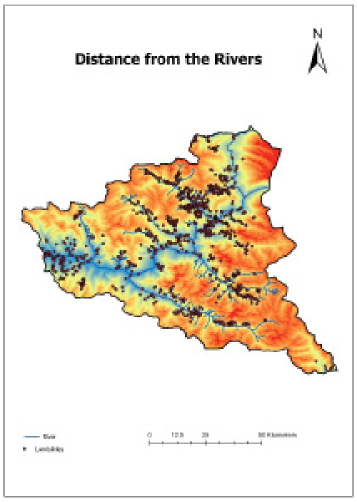


**Figure 5:** Distance from rivers. **Note:** (—) River, ( ▪ ) Landslides.

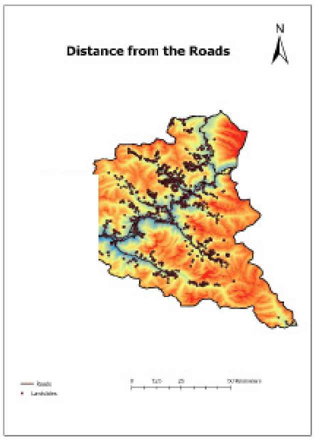


**Figure 6:** Distance from roads. **Note:** (▬) Roads, ( ▪ ) Landslides.

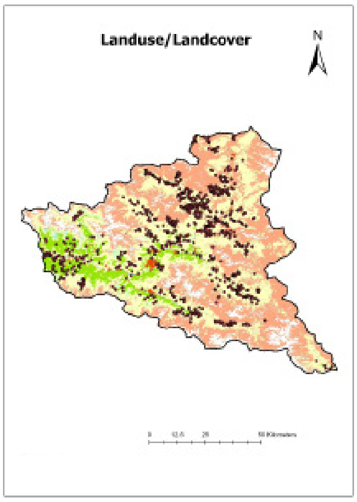


**Figure 7:** Landuse/Landcover of the Kinnaur region. **Note:** (▬) Water, (▬) Trees, (▬) Grass, (▬) Flooded vegetation, (▬) Crops, (▬) Scrub/shrub, (▬) Built Area, (▬) Bare ground, ( ) Snow.

## Shannon's entropy approach

A system's entropy can be described as disorder, instability, imbalance or uncertainty. According to Boltzmann's principle, entropy in a system is proportional to its condition [60-64]. As a thermodynamic measure, this correspondence describes the status of a system.

Using this method, the dissimilarity or diversity of each factor in the environment determines whether it has the potential to cause a landslide.

The entropy of landslides measures the extent to which different factors cause landslides; the higher the entropy index, the stronger the influence of the factor.

This approach indicates the extent of each factors causing the landslide; the greater the entropy index, the stronger the influence, and the lower the entropy index, the weaker the landslide effect.

The index system provides additional entropy through several important factors. Therefore, objectives weights can be calculated based on entropy.

$$Positive\,effect = \left\{ \begin{array}{l} 1 \\ 0.5\left(1-\cos\left(\pi\dfrac{x-X_{\min}}{X_{mac}-X_{\min}}\right)\right) \\ 0 \end{array} \right. \begin{array}{ccc} X & = & X_{\max} \\ X_{\min} & \prec & X \prec X_{\max} \\ X & = & X_{\min} \end{array}$$

$$Negative\ effect=\left\{\begin{matrix} 1 & X = X_{min}\\ 0.5\left(1+\cos\left(\pi\frac{X_{mac}-X}{X_{mac}-X_{min}}\right)\right) & X_{min} \prec X \prec X_{max} \\ 0 & X = X_{max}\end{matrix}\right\}$$

A positive effect of mean annual rainfall and drainage density on the probability of landslide occurrence is predicted by equation (1).

There is a positive relationship between the mean annual rainfall and drainage density and the probability of landslides occurring and this relationship is predicted by the equation (1).

In other words, the higher the criterion value, the bigger the probability of a landslides. Alternatively, some other criteria, such as the proximity to roads, proximity to the rivers, etc. apply reverse conditions, and the equation 2 is best representation of it [65-69].

In the next step, the landslide shanon's entropy matrix (R) is created by combining (m) landslide events sample with (n) geo-data layers:

$$R=\left\{\begin{matrix} r1,1 & r1,2 & \ldots & r1,n \\ r2,1 & r2,2 & \ldots & r2,n \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ r_m,1 & r_m,2 & \ldots & r_{m,n}\end{matrix}\right\}$$

The next step is to prepare the entropy matrix by combining the previously landslide samples with the n geo-data layers.

Therefore, Shannon entropy can be defined as follows:

$$E_j=-k\sum_{i=1}^{m} Pi,j\ In\ pi,j$$

In this equation, Ej is the entropy value of the jth landslide, pi,j is its value in the jth criteria, and k is a positive constant,

Units of measure are determined essentially by the following:

$$K=(In\ m)^{-1}$$

Taking m as the number of landslides that have occurred, we can define a normalized decision matrix pi,j for each landslide criteria as follows:

$$P_{i,j}=\frac{r_{i,j}}{\sum_{i=1}^{m} r_{i,j}}$$

In this index system, weights indicate the role the factors play in the synthesis assessment, and higher values indicate a greater importance for that factor.

$$W_j=\frac{v,j}{\sum_{i=1}^{m} v,j}$$

Taking Wj as the weight of the jth geo-data layer and Vj as the value of the jth layer, Vj is defined as:

$$v_j=1-E_j$$

## Hybrid Landslide Susceptibility Mapping Model

T In terms of landslide susceptibility mapping, the proposed hybrid model is as follows:

$$S=\sum_{i=1}^{n} w_i \otimes X_i$$

Assume that S is a measure of the susceptibility to landslides, Wi is the weight of each criterion, and Xi is the standardized criteria for landslides.

# RESULTS AND DISCUSSSION

## Landslide susceptibility mapping

To analyze the landslides susceptibility, Shannon entropy method was used. In the present study, the susceptibility of landslides was assessed by calculating the relationship between landslides occurrence and these eight conditioning factors using Shannon entropy method (Supplementary Table 1).

Supplementary Table 1, Shannon's entropy has an aspect weight of 0.158148 that is calculated based on the equation no.6. Similarly, Aspect weight of Shannon's entropy is 0.158148 which is higher than the slope angle indicates that, the direction of slope is one of the major factors for landslide susceptibility mapping in the Kinnaur district [70-73]. For Geology, Altitude, Proximity to river, Proximity to roads, Landuse/Land Cover and Rainfall weights are 0.153516855, 0.126592428, 0.149489064, 0.148656291, 0.127152285, and 0.122543344 respectively (Figure 8).

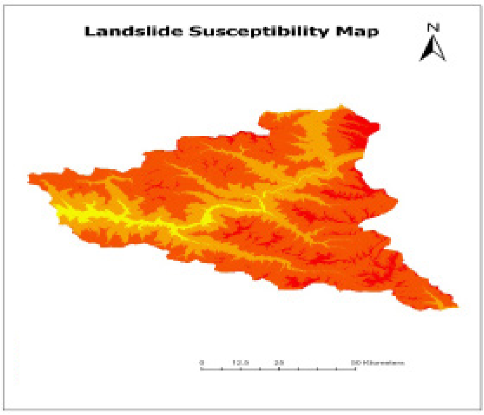


**Figure 8:** Landslide susceptibility of the Kinnaur region. **Note:** (▬) Unlikely, (▬) Moderate to low, (▬) High, (▬) Severe to very high.

Based on the weighted average, it can be concluded that factors such as geology, aspect, proximity to the river and proximity to the roads are the major factors in landslide susceptibility mapping. It is difficult for locals to access water because of the debris slipping down the slopes and blocking the river channel [74-76]. Subsequently, with the aim of prepare the final map of landslide susceptibility, On the basis of natural breaks, we combined weighted products of secondarily parametric maps.

## Validation of landslide susceptibility models

In statistical theory, the Receiver operating characteristics curve is a classic method for evaluating performance to examine susceptibility maps. As the classifier threshold changes, the ROC curve, which has a value range of [0,1], describes the process of classifier performance. As seen in ROC curve, the model's sensitivity is plotted against 1−specificity.

Based on these values, negative and positive observations in the validation sample are correctly differentiated by the model. Signal sensitivity is represented by every point on the curve [76-79]. This graph shows a horizontal axis indicating False Positive Rate (FPR) specifity compared to a vertical axis showing True Positive Rate (TPR) sensitivity. The prediction rate could be used to assess the prediction capability of the landslide models [8]. The ROC shows an accuracy of 88.23%. In analyzing the AUC results, we observed that the produced map exhibits a high level of accuracy (Figure 9).

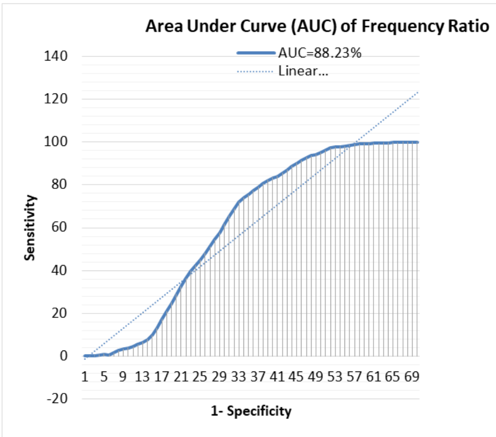


**Figure 9:** Area under curve of frequency ratio.

Human life and property are at risk from landslides, so mapping landslides' susceptibility is an important and preliminary step to preventing them. A landslide susceptibility map and an evaluation of contributing factors that trigger the landslides were produced using Shannon's entropy model. In this study, Shannon entropy model was applied to develop a map of landslides susceptibility, and cause-effect relationships were analyzed in order to determine the cause of the landslides. In the modelling, eight landslide conditioning factors were taken into account in this modelling. Landslide conditioning factors are added with geographic information systems. A ROC curve was developed using the landslide inventory datasets acquired from geological survey of India to calculate Shannon's entropy for the block entry. Based on the AUC curve, the result showed 88.23% accuracy. It has been divided into four classes: moderate to low, high, severe and very high. The area of each class falls under 252.20799 square kilometers, 1810.1757 square kilometers, 3826.0683 square kilometers, and 513.4724 square kilometers, respectively. The susceptibility map shows that Nichar tehsil falls within the unlikely and moderate landslide risk categories. Tehsil Sangla is most vulnerable to landslides and has a significant risk. Management of disasters through forecasting and monitoring may help in lessening the vulnerability of the communities.

## CONCLUSION

There is an urgent exigency for landslide risk management at various spatio-temporal scales to map the landslide hazard to deal with its future occurrences. Human losses can be reduced by taking timely precautions and detecting early warning signs. It enables planners to make better decisions regarding further mitigation of landslide effects. A better understanding of the results of this study will provide engineers and planners with better methods for managing and mitigating landslides in the study area.

## REFERENCES

1. Sivakumar MV, Stefanski R. Climate change in South Asia. InClimate change and food security in South Asia. 2010. 13-30.
2. Martha TR, van Westen CJ, Kerle N, Jetten V, Kumar KV. Landslide hazard and risk assessment using semi-automatically created landslide inventories. Geomorphology. 2013;184:139-150.
3. Wang WD, Guo J, Fang LG, Chang XS. A subjective and objective integrated weighting method for landslides susceptibility mapping based on GIS. Environ Earth Sci. 2012;65(6):1705-1714.
4. Mondal S, Mandal S. Landslide susceptibility mapping of Darjeeling Himalaya, India using index of entropy (IOE) model. Appl Geomat. 2019;11(2):129-146.
5. Hanifinia A, Abghari H. Investigation of affecting factors landslide occurrence in shannon entropy model with two WOE and LNRF approaches in order to zoning sensitivity landslide in Ziveh watershed of Urmia. GMPJ. 2022.
6. Kerekes AH, Poszet SL, Andrea GÁ. Landslide susceptibility assessment using the maximum entropy model in a sector of the Cluj–Napoca Municipality, Romania. Rev geomorfol. 2018;20(1):130-146.
7. Bhutia SL, Borah S, Pradhan R. Landslide susceptibility mapping: Development towards a machine learning-based model. Trends in Communication, Cloud and Big Data. 2020:129-139.
8. Shirani K, Pasandi M, Arabameri A. Landslide susceptibility assessment by dempster–shafer and index of entropy models, Sarkhoun basin, southwestern Iran. Nat Hazards. 2018; 93(3):1379-1418.
9. Agrawal N, Dixit J. Assessment of landslide susceptibility for Meghalaya (India) using bivariate (frequency ratio and Shannon entropy) and multi-criteria decision analysis (AHP and fuzzy-AHP) models. All Earth. 2022;34(1):179-201.
10. Akter S, Javed SA. GIS-Based assessment of landslide susceptibility and inventory mapping using different Bivariate Models. Geocarto Int. 2022:1-31.
11. Arabameri A, Pradhan B, Rezaei K, Lee S, Sohrabi M. An ensemble model for landslide susceptibility mapping in a forested area. Geocarto Int. 2020;35(15):1680-1705.
12. Aram A, Dalalian MR, Saedi S, Rafieyan O, Darbandi S. An assessment of data mining and bivariate statistical methods for landslide susceptibility mapping. Sci Iran. 2022;29(3):1077-1094.
13. Bhardwaj D. Landslide susceptibility mapping using GIS-based frequency ratio and shannon entropy, in part of chamoli district, Uttarakhand, India.
14. Chen W, Pourghasemi HR, Kornejady A, Xie X. GIS-based landslide susceptibility evaluation using certainty factor and index of entropy ensembled with alternating decision tree models. InNatural hazards GIS-based spatial modeling using data mining techniques. 2019; 225-251.
15. Chooreshwarsingh SB. Landslide susceptibility mapping using gis-based frequency ratio, shannon entropy, information value and weight-of-evidence approaches in part of kullu district, Himachal pradesh, India.
16. Dam ND, Amiri M, Al-Ansari N, Prakash I, Le HV, Nguyen HB, et al. Evaluation of Shannon Entropy and weights of evidence models in landslide susceptibility mapping for the Pithoragarh District of Uttarakhand State, India. Adv Civ Eng. 2022.
17. Deng X, Sun G, He N, Yu Y. Integration of information theory, fractal theory and statistical analyses for landslide susceptibility mapping at Regional Scales.

18. Deng X, Sun G, He N, Yu Y. Landslide susceptibility mapping with the integration of information theory, fractal theory, and statistical analyses at a regional scale: a case study of Altay Prefecture, China. Environ Earth Sci. 2022;81(13):1-7.

19. El Jazouli A, Barakat A, Khellouk R. GIS-multicriteria evaluation using AHP for landslide susceptibility mapping in Oum Er Rbia high basin (Morocco). Geoenvironmental Disasters. 2019;6(1):1-2.

20. Es-smairi A, Elmoutchou B, Mir RA, Touhami AE, Namous M. Spatial prediction of landslide susceptibility using Frequency Ration (FR) and Shannon Entropy (SE) models: A case study from northern Rif, Morocco.

21. Fallah Zazuli M, Vafaei Nezhad A, Alesheikh AA, Modiri M, Aghamohammadi H. Landslide hazard zoning using shannon entropy and information value models in GIS environment-Case study: East Rudbar-e Alamut District-Qazvin Province. Sci Res Q Geogr Data. 2020;28(112):123-136.

22. Follador M, Viezzer J, Egler M, Becher M, Hach L, Pereira V, et al. Modelling potential biophysical impacts of climate change in the Atlantic Forest: Closing the gap to identify vulnerabilities in Brazil. InClimate Change Adaptation in Latin America 2018; 33-64.

23. Haghizadeh A, Siahkamari S, Haghiabi AH, Rahmati O. Forecasting flood-prone areas using Shannon's entropy model. J Earth Syst Sci. 2017;126(3):1-1.

24. Hanifinia A, Nazarnejad H, Najafi S, Kornejady A. Prioritization of effective factors on landslide occurrence and mapping of its sensitivity in CherikAbad Watershed, Urmia Using Shannon Entropy Model. J Watershed Manag Res. 2020;33(4):30-46.

25. Hanifinia A, Nazarnejad H, Najafi S, Kornejady A, Pourghasemi HR. Landslide susceptibility assessment and mapping using statistical and data mining models in Iran.

26. He Y, Beighley RE. GIS-based regional landslide susceptibility mapping: A case study in southern California. ESPLDB. 2008;33(3):380-393.

27. Hong H, Chen W, Xu C, Youssef AM, Pradhan B, Tien Bui D. Rainfall-induced landslide susceptibility assessment at the Chongren area (China) using frequency ratio, certainty factor, and index of entropy. Geocarto Int. 2017;32(2):139-154.

28. Hong H, Pradhan B, Sameen MI, Kalantar B, Zhu A, Chen W. Improving the accuracy of landslide susceptibility model using a novel region-partitioning approach. Landslides. 2018;15(4):753-772.

29. Hong H, Tsangaratos P, Ilia I, Loupasakis C, Wang Y. Introducing a novel multi-layer perceptron network based on stochastic gradient descent optimized by a meta-heuristic algorithm for landslide susceptibility mapping. Sci Total Environ. 2020;742:140549.

30. Hoseinpoor Milaghardan A, Abbaspoor RA. Improving landslide prediction results using Shannon entropy theory. Environ Hazards. 2014;1(2):253-268.

31. Jaafari A, Najafi A, Pourghasemi HR, Rezaeian J, Sattarian A. GIS-based frequency ratio and index of entropy models for landslide susceptibility assessment in the Caspian forest, northern Iran. Int J Environ Sci Tech. 2014;11(4):909-926.

32. Kaur H, Gupta S, Parkash S, Thapa R, Gupta A, Khanal GC. Evaluation of landslide susceptibility in a hill city of Sikkim Himalaya with the perspective of hybrid modelling techniques. Ann GIS. 2019; 25(2):113-132.

33. Khosravi K, Pourghasemi HR, Chapi K, Bahri M. Flash flood susceptibility analysis and its mapping using different bivariate models in Iran: A comparison between Shannon's entropy, statistical index, and weighting factor models. Environ Monit Assess. 2016;188(12):1-21.

34. Kincal C, Kayhan H. A combined method for preparation of landslide susceptibility map in Izmir (Türkiye). Appl Sci. 2022;12(18):9029.

35. Kornejady A, Pourghasemi HR. Producing a spatially focused landslide susceptibility map using an ensemble of Shannon's entropy and fractal dimension (Case Study: Ziarat Watershed, Iran). InSpatial Modeling in GIS and R for Earth and Environmental Sciences. 2019; 689-732.

36. Kornejady A, Ownegh M, Bahremand A. Landslide susceptibility assessment using maximum entropy model with two different data sampling methods. Catena. 2017;152:144-162.

37. Liu C, Li W, Lu P, Sang K, Hong Y, Li R. Susceptibility evaluation and mapping of China's landslide disaster based on multi-temporal ground and remote sensing satellite data. Int. Arch. Photogramm. Remote Sens. Spat Inf Sci. 2012;39:45-50.

38. Liu Y, Zhao L, Bao A, Li J, Yan X. Chinese high resolution satellite data and GIS-based assessment of landslide susceptibility along highway G30 in guozigou valley using logistic regression and MaxEnt Model. Remote Sens. 2022;14(15):3620.

39. Melese T, Belay T, Andemo A. Application of analytical hierarchal process, frequency ratio, and Shannon entropy approaches for landslide susceptibility mapping using geospatial technology: The case of Dejen district, Ethiopia. Arab J Geosci. 2022;15(5):1-21.

40. Mokhtari M, Abedian S. Spatial prediction of landslide susceptibility in Taleghan basin, Iran. Stoch Environ Res Risk Assess. 2019;33(7):1297-1325.

41. Moradi H, Avand MT, Janizadeh S. Landslide susceptibility survey using modeling methods. InSpatial modeling in GIS and R for earth and environmental sciences. 2019; 259-275.

42. Naghibi SA, Pourghasemi HR, Pourtaghi ZS, Rezaei A. Ground water qanat potential mapping using frequency ratio and Shannon's entropy models in the Moghan watershed, Iran. Earth Sci Inform. 2015;8(1):171-186.

43. Nanehkaran YA, Mao Y, Azarafza M, Kockar MK, Zhu HH. Fuzzy-based multiple decision method for landslide susceptibility and hazard assessment: A case study of Tabriz, Iran. Geomech Eng. 2021;24(5):407-418.

44. Nohani E, Moharrami M, Sharafi S, Khosravi K, Pradhan B, Pham BT, et al. Landslide susceptibility mapping using different GIS-based bivariate models. Water. 2019; 11(7):1402.

45. Pal SC, Chowdhuri I. GIS-based spatial prediction of landslide susceptibility using frequency ratio model of Lachung River basin, North Sikkim, India. SN Appl Sci. 2019;1(5):1-25.

46. Panchal S, Shrivastava AK. A comparative study of frequency ratio, Shannon's entropy and analytic hierarchy process (AHP) models for landslide susceptibility assessment. ISPRS Int J Geoinf. 2021;10(9):603.

47. Pandey VK, Pourghasemi HR, Sharma MC. Landslide susceptibility mapping using maximum entropy and support vector machine models along the Highway Corridor, Garhwal Himalaya. Geocarto Int. 2020;35(2):168-187.

48. Pourghasemi HR, Mohammady M, Pradhan B. Landslide susceptibility mapping using index of entropy and conditional probability models in GIS: Safarood Basin, Iran. Catena. 2012; 97:71-84.

49. Pourghasemi HR, Moradi HR, Fatemi Aghda SM. Prioritizing effective factors in landslide occurrence and its susceptibility mapping using shannon's entropy index. JWSS-Isfahan University of Technology. 2015;18(70):181-192.

50. Pourghasemi HR, Pradhan B, Gokceoglu C. Remote sensing data derived parameters and its use in landslide susceptibility assessment using Shannon's entropy and GIS. Appl Mech Mater. 2012; 225:486-491.

51. Rahaman A, Venkatesan MS, Ayyamperumal R. GIS-based landslide susceptibility mapping method and Shannon entropy model: A case study on Sakaleshapur Taluk, Western Ghats, Karnataka, India. Arab J Geosci. 2021;14(20):1-2.

52. Razavi-Termeh SV, Shirani K, Pasandi M. Mapping of landslide susceptibility using the combination of neuro-fuzzy inference system (ANFIS), ant colony (ANFIS-ACOR), and differential evolution (ANFIS-DE) models. Bull Eng Geol Environ. 2021;80(3):2045-2067.

53. Roodposhti MS, Aryal J, Pradhan B. A novel rule-based approach in mapping landslide susceptibility. Sensors. 2019;19(10):2274.

54. Sayyad D, Omidvar E, Naserianasl Z. Comparative evaluation of the use of statistical models of frequency ratio and Shannon entropy in order to zone landslide-sensitive areas. GMPJ. 2022.

55. Shadman Roodposhti M, Aryal J, Shahabi H, Safarrad T. Fuzzy shannon entropy: A hybrid gis-based landslide susceptibility mapping method. Entropy. 2016;18(10):343.

56. Sharma A, Prakash C, Manivasagam VS. Entropy-based hybrid integration of random forest and support vector machine for landslide susceptibility analysis. Geomatics. 2021;1(4):399-416.

57. Sharma LP, Patel N, Ghose MK, Debnath P. Influence of Shannon's entropy on landslide-causing parameters for vulnerability study and zonation-a case study in Sikkim, India. Arab J Geosci. 2012;5(3):421-431.

58. Sharma LP, Patel N, Ghose MK, Debnath P. Development and application of Shannon's entropy integrated information value model for landslide susceptibility assessment and zonation in Sikkim Himalayas in India. Nat Hazards. 2015;75(2):1555-1576.

59. Shen L, Liu L, Wang J, Xu C. Earthquake-induced landslide susceptibility evaluation based on fuzzy logic and Shannon's entropy integrated information value models in the 2013 Minxian, China earthquake-affected area.

60. Shen l, Liu l, Xu C, Wang J. Multi-models based landslide susceptibility evaluation illustrated with landslides triggered by minxian earthquake. J Eng Geol. 2016;24(1):19-28.

61. Shirani K. Modelling of landslide susceptibility zonation using Shannon's entropy index and weight of evidence model (case study: Sarkhoon's Karoon). J Soils Water Conserv. 2017;21(1).

62. Khaidem S, Singh K. Landslide susceptibility mapping along Manipur-Assam NH-37. InIOP Conference Series: Earth and Environmental Science 2021. 889(1); 012002.

63. Singh P, Sharma A, Sur U, Rai PK. Comparative landslide susceptibility assessment using statistical information value and index of entropy model in Bhanupali-Beri region, Himachal Pradesh, India. Liu Environ Dev Sustain. 2021;23(4):5233-5250.

64. Sterlacchini S, Ballabio C, Blahut J, Masetti M, Sorichetta A. Spatial agreement of predicted patterns in landslide susceptibility maps. Geomorphology. 2011;125(1):51-61.

65. Ta□o□lu E, Abujayyab SK. Comparison of the frequency ratio, index of entropy, and artificial neural networks methods for landslide susceptibility mapping: A case study in Pınarba□ı/Kastamonu (North of Turkey). Environ Earth Sci. 2022. 491-508.

66. Teimoori Yansari Z, Hosseinzadeh SR, Kavian A, Pourghasemi HR. Determination of sensitive areas to landslide occurrence using shannon entropy model (CaseStudy: Chahardangeh Basin, Mazandaran Province). J Geog Environ Hazards. 2017;6(2):183-204.

67. Tien Bui D, Pradhan B, Lofman O, Revhaug I. Landslide susceptibility assessment in vietnam using support vector machines, decision tree, and Naive Bayes Models. Math Probl Eng. 2012.

68. Tsangaratos P, Ilia I. Combining fuzzy logic and information theory for producing a landslide susceptibility model. Geol Soc Am Bull. 2016;50(3):1737-1746.

69. Tsangaratos P, Ilia I. Landslide susceptibility mapping using a modified decision tree classifier in the Xanthi Perfection, Greece. Landslides. 2016;13(2):305-320.

70. Tsangaratos P, Ilia I, Hong H, Chen W, Xu C. Applying information theory and GIS-based quantitative methods to produce landslide susceptibility maps in Nancheng County, China. Landslides. 2017;14(3):1091-1111.

71. Wan S. A spatial decision support system for extracting the core factors and thresholds for landslide susceptibility map. Eng Geol. 2009;108(3-4):237-251.

72. Wan S. Entropy-based particle swarm optimization with clustering analysis on landslide susceptibility mapping. Environ Earth Sci. 2013;68(5):1349-1366.

73. Wang Q, Wang Y, Niu R, Peng L. Integration of information theory, K-means cluster analysis and the logistic regression model for landslide susceptibility mapping in the Three Gorges Area, China. Remote Sens. 2017;9(9):938.

74. Wang Y, Fang Z, Wang M, Peng L, Hong H. Comparative study of landslide susceptibility mapping with different recurrent neural networks. Comput and Geosci. 2020;138:104445.

75. Xu S, Liu J, Wang X, Zhang Y, Lin R, Zhang M, et al. Landslide susceptibility assessment method incorporating index of entropy based on support vector machine: A case study of Shaanxi Province. J. Wuhan Univ. 2020;45(8):1214-1222.

76. Yan F, Zhang Q, Ye S, Ren B. A novel hybrid approach for landslide susceptibility mapping integrating analytical hierarchy process and normalized frequency ratio methods with the cloud model. Geomorphology. 2019;327:170-187.

77. Youssef AM, Pourghasemi HR, El-Haddad BA, Dhahry BK. Landslide susceptibility maps using different probabilistic and bivariate statistical models and comparison of their performance at Wadi Itwad Basin, Asir Region, Saudi Arabia. Bull Eng Geol Environ. 2016;75(1):63-87.

78. Zabihi M, Pourghasemi HR, Behzadfar M. Groundwater potential mapping using shannon's entropy and random forest models in the bojnourd township. Iranian Journal of Ecohydrology. 2015;2(2):221-232.

79. Zhao H, Yao L, Mei G, Liu T, Ning Y. A fuzzy comprehensive evaluation method based on AHP and entropy for a landslide susceptibility map. Entropy. 2017;19(8):396.