Comparative Exploration of Statistical Techniques for Landslide Identification and Zonation Mapping and Assessment: A Critical Review

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Abstract. Landslides are found to be one of the most dangerous and critical natural hazards, and these are nature's primary ways of slope stability adjustment. For the assessment of landslides, the study of landslide susceptibility, identification of landslides and mapping for the hazardous areas are crucial tasks for the same and it is necessary for the safety of human life and the economic losses that happen each time the natural geo-hazard like landslide occurs in any area throughout the country. There are several methodologies for landslide hazard zonation viz. probabilistic, semi-quantitative, quantitative, and heuristic. However, no method is universally accepted for the effective assessment and management of the same. In recent years, the methodologies have been comprehensively shifted from the heuristic techniques to the data-driven techniques. This paper is aimed to present the review of different statistical techniques for the same. The statistical techniques are found to be more objective and result-oriented as these techniques involve subjectivity in the assignment of weights to the potential factors. The collaboration of statistical and machine-learning techniques with the RS-GIS methods has shown new perspectives for detailed and accurate assessment of landslide hazard mapping and identification.

Keywords: Landslide susceptibility mapping · Hazard zonation · Statistical techniques · Bi-variate statistical analysis · Multivariate statistical analysis · Landslide evaluation

1 Introduction

Landslides are one of the most critical and life-threatening natural disasters having the potential of causing huge economic breakdown especially for the hilly terrains in North-Eastern India. These areas as a consequence, face terrible challenges due to landslide occurrences in the rainy season. Hence the formulation of adequate methodologies to identify the occurrences of landslides is a critical task. Several researches have been carried out that illuminate different ML techniques for landslide identification. For instance, a high-resolution digital elevation model was constructed and its derivatives are exploited

for the identification of bedrock landslides [36]. Advanced remote sensing, visual interpretation, and perception are collaborated to evaluate remotely sensed images along with topographic surfaces [22]. Researches yield that spectral, shape and contextual information can be combined together in the OO approaches for the landslide identification and using the multi-temporal images, further exploration can be done in order to identify the historical landslides [33, 35], on which the digital terrain model is used very often [20]. An object-based approach for landslide inventory mapping has been proposed which is optimized by the Taguchi method [40]. The method of data segmentation and SVM can be used to identify the forested landslides with the association of the DTM [60]. Again, the DTM derivatives can be associated with RF along with the SVM to identify the forested landslides [31]. In the field of landslide identification along with many geo-morphological, geotechnical applications, ML and DL methods are found to be efficient and propitious. An integrated method for identifying landslides using ML and DL techniques has been proposed [63], in which the DCNN-11 model and RecLD landslide database were found to be the most promising procedures. An adaptive neural-fuzzy inference system has been proposed for landslide-susceptibility mapping using a geographic information system (GIS) environment [3, 42]. A GIS based SVM model has been proposed for susceptibility mapping of landslides triggered by earthquakes [64]. Studies using DT, ANN, GAM model, CART, LR model, ME model have been carried out [5, 6, 32, 51, 56, 57]. Although the ML techniques are getting importance, each method has its advantages and disadvantages regarding the factors depending on which, the selection of ML methods are carried out [61]. Consequently no one technique or method is universally approved accepted or preferred for landslide hazard and zonation mapping satisfactorily or sufficiently, which results that landslide susceptibility mapping and zonation remain a convoluted and perplexing area of study.

2   Causative Factors for the Occurrence of Landslide

The causative factors for the landslide's occurrences in hilly terrains may be divided into two categories, internal and external. The internal factors such as heavy rainfall, stream erosion, snow melting, ground water-level change, volcanic eruption [9, 16, 26] and the external factors such as expansion of the agricultural area and built-up area, deforestation, clear-cutting, shifting agriculture, poorly planned construction of roadways play an important role in the happening of the landslides and its increase to a fair extent. Undoubtedly, the external factors are mostly human activities. Previous studies indicate that the frequency as well as the magnitude of the landslides occurrence has been on the increasing side due to elevation, slope gradient, slope aspect, slope curvature, rainfall, fault distance, distance to drainage, distance to road, LULC, NDVI, TWI, STI, SPI [17, 45, 58, 59]. Moreover, to the accumulation of the internal and external factors, the climatic extremities in hilly or mountainous regions are also to be considered. In the Indian Himachal Region, the internal factors such as lithology, altitude, slope steepness, fragility of soil, heavy rainfall and many anthropogenic activities like rapid deforestation, agricultural shifting and expansion act as emphatic reasons behind the increased landslides in many of the potentially unstable areas [50]. Consequently, the increment in the landslide occurrence is becoming causative factors for tree losses,

forest fragmentation, changes in LULC, slope-instability [1, 38], eventually the natural landscape is vastly affected by the impact of the landslides [14, 52]. Hence, mitigation of frequent landslides occurrence on unstable slopes and assessment of the adverse effects on natural landscapes is one context of this paper.

3 Statistical Approaches for Landslide Susceptibility and Zonation Mapping

For the evaluation of landslide susceptibility and hazard zonation, several techniques have been proposed, including landslide inventories design, statistical modeling techniques, probabilistic methodologies, deterministic methodologies etc. [8, 45, 46, 48]. In the past few years, the landslide susceptibility and zonation mapping approaches have been shifted from heuristic approaches to statistical (data-driven) approaches. The statistical methods can be broadly classified into two categories, namely, bi-variate and multivariate statistical analysis.

3.1 Bi-variate Statistical Methodologies

The bi-variate statistical technique illuminates that if a situation holds in all observed cases, then the situation holds in all cases. There is a general assumption on which the bi-variate statistical techniques depend, "past and present are the key to the future". The common techniques falling under the bi-variate statistical approach are; Weight-of-Evidence (WoE) model [39] and Information Value (IV) model [37]. Apart from these, Frequency Analysis method, known as likelihood ratio method has also been proposed [30]; Fuzzy Logic approach and Weighted Overlay method are proposed respectively [28].

Weight-of-Evidence (WoE) Approach
A quantitative and data-driven approach, used to calculate the causative factors after avoiding the weight's subjectivity. Originally developed for the identification and exploration of mineral deposits, this method came to the application area for the study of landslide susceptibility and with this method, the prior probability, conditional probability, and the positive and negative weights of landslide susceptibility can be determined [11, 54]. The positive and negative weights are:

$$W^{-ve} = ln\frac{\{B|D\}}{\{B|\overline{D}\}} \tag{1}$$

$$W^{-ve} = ln\frac{\{\overline{B}|D\}}{\{\overline{B}|\overline{D}\}} \tag{2}$$

With 'P' denoting the probability, 'B' and '$\overline{B}$' denote the presence and absence of potentially desired landslide causative factors respectively, 'D' and '$\overline{D}$' respectively denote the presence and absence of landslides.

Information Value (IV) Method
Alternatively known as landslide index method, this method is used to compute the

weighted class value through the landslide density with respect to each and every landslide causative factors [37, 66]. The mathematical representation of information value follows:

$$W = ln \frac{Landslide\ density\ with\ a\ potential\ class\ of\ causative\ factors}{Landslide\ density\ in\ the\ area} \quad (3)$$

$$W = ln \frac{N_{pix}(S_i)/N_{pix}(x_i)}{\sum N_{pix}(S_i)/N_{pix}(x_i)} \quad (4)$$

Frequency Ratio Analysis Method

Popularly known as likelihood ratio method, FR is one of the very widely used bi-variate statistical technique, which uses the correlation between the classes of potential causative factors and the spatial distribution of occurred landslides in the area of study [7, 30]. So, $FR > 1$ shows more significant correlation to the landslide occurrence, while $FR < 1$ shows less significant correlation to the same. It can be represented as

$$FR = \frac{Percentage\ of\ landslide\ in\ a\ class}{Area\ of\ the\ factor\ class\ as\ a\ percentage\ of\ the\ entire\ area} \quad (5)$$

The landslide susceptibility index can be thus represented as follows:

$$LSI = \sum_{i=1}^{n} FR_i \quad (6)$$

Weighted Overlay Method

In this method, the landslide hazard can be calculated by assigning the weights based on the correlation of landslide frequency with its causative factors [12]. It is assumed in this method, that if the factors for which landslides occurred in the past, if reoccur in some other area in the future, can again result in the occurrence of landslides. Higher the weight to a potential causative factor or to its class, represents greater significance for the occurrence of landslides [25, 29]. The mathematical representation for the same follows:

$$S = \frac{\sum W * SP}{\sum W} \quad (7)$$

'W' denotes the weight assigned to the respective factor, 'SP' represents the weight to the spatial class and 'S' is the spatial value of the output map.

3.2 Multivariate Statistical Analysis and Methodologies

Multivariate statistical analysis approach for landslide hazard zonation and susceptibility mapping is based on the relative contribution of each potential instability factors to the entire landslide susceptibility of the study area [41]. The multivariate statistical methodologies, determine the percentage of landslide for each and every pixel, and data

layer on the presence and absence of landslides is produced and calculated, then the reclassification of hazard is followed with the help of the said methodologies. Logistic regression (LR) analysis, Discriminant analysis are the methodologies that fall under the category of multivariate statistical analysis.

Logistic Regression (LR) Analysis
Using LR method, the occurrence of landslides and the dependability factors can be represented by the following equation:

$$P = \frac{1}{1 + e^{-z}} \qquad (8)$$

where, P is the probability of the occurrence of landslide, and z represents a linear combinatorial equation as follows:

$$z = c_0 + c_1 x_1 + c_2 x_2 + \ldots + c_n x_n \qquad (9)$$

where x_i (i = 1,2,3,…,n), represents the environmental factors for landslides, c_0 represents the model intercept, c_i (i = 1,2,3,…,n), represents the regression coefficient. Extensive application has been done with this methodology for landslide susceptibility for the Umbria region in central Italy [19]. The LR technique has been used for landslide hazard zonation mapping model for Hong Kong, based on the use of DEM in the GIS perspective [49]. A comparative analysis of different ML techniques along with the heuristic model for predicting landslides has been carried out [23].

Discriminant Analysis Methodology
A frequently used multivariate statistical modeling technique, facilitating to compute the maximum difference for each potential causes segregated in two groups as landslide and non-landslide group. This method assumes all dependent variables to be categorical rather than being continuous [17]. Thus, the weights can be calculated on the basis of the maximum difference. This method can be classified in two categories, (a) Quadratic Discriminant Analysis (QDA), (b) Linear Discriminant Analysis (LDA) [62]. By the use of this method, the Standardized Discriminant Function Coefficient (SDFC) can be calculated and further the relative significance can be represented in terms of discriminant function, acting as a predictor of the instability of slope, eventually considered as one of the most potential factors for landslides occurrence. Using SDFC, the variables having maximized coefficients are correlated strongly to presence or absence of landslide in the study area [21, 44].

4 Pros and Cons of Different Statistical Methodologies for Landslide Susceptibility and Zonation Mapping

Previous studies have suggested that the advantages and disadvantages depend on the application of the technique to the relative context, procurement and/or collection of data and scale of their application [4, 19]. The statistical methodologies are developed based on the correlation between occurred landslides and their causative factors, to which

weights are assigned for the measurement of the same, and these weights for the factors are statistically determined. The analysis of the functional relationship between the thematic factors or variables and the distribution of slope deterioration, also termed as the landslide inventory. The statistical techniques are advantageous as these methodologies can be applied over a large area and the past landslide data can extensively be used in the determination, stratification and calculation of the weights for various causative factors for landslides, as it can be witnessed in the WoE model [2]. However, there are some limitations associated with these data-driven techniques. The collection of the past landslide inventory data over large area is considered to be the fundamental disadvantage for the statistical techniques, as the general regulations for landslides susceptibility are formulated based on the past landslides in the area. Consequently, the requirement of a well-defined and distributed landslide inventory data as an input becomes essential for ensuring prompt result. However, there are no fully accepted techniques for the same, which acts as the motivation for the study of landslide susceptibility and hazard zonation mapping in a more extensive way [53].

In addition, to ensure effective and promptness, the collection and validation of the necessary input data are also required, however, the data are rarely available. As a result, large efforts are required to accomplish the same, provided extensive interaction is also a requirement, between the geo-morphologists and statisticians to execute and assess the collected geo-environmental, geo-morphological and landslide data. Apart from these, the study area plays a crucial role as the statistical models are negatively impacted by the study area, which makes it an uneasy task to compute the comparison between the classes of landslide susceptibility from different locations. Moreover, studies are extensively required in the hilly terrains for the future geo-morphological and environmental planning, but very often the mapping techniques based on statistical methodologies happen to be non-understandable by non-specialists which include planners and stakeholders [13, 43, 46, 64]. Research yields that the statistical techniques can extensively be applied for medium scale study in a data scarce environment, however small-scale study for the same can also be done, but the result may not be prompt enough as the data collection in a large geographical area is less feasible, making the statistical methodologies less or practically not feasible for the same.

5 Landslide Susceptibility Assessment and Zonation Mapping Techniques: Literature Survey in Indian Context

The following section contains a summarized literature study about landslide susceptibility and zonation mapping techniques in the Indian Context. An in-depth study along the national highway (NH-39), Manipur has been given about the landslides along with the involvement of various landslides triggering mechanisms and also revealing the fact that the landslides are caused by wedge failure for the slope instability [27]. It is also observed that the terrain comprising soil and rock with a high factor of safety (0.62–1.82) are landslide-prone. The landslide risk and hazard assessment technique using an index value, landslide nominal risk factor (LNRF) and GIS techniques have been proposed [18] from the Ramganga catchment, Himalayas. The heuristic techniques have been proposed, a quantitative methodology has been developed for landslide hazard zonation

based on a factor in a numerical rating scheme, called landslide hazard evaluation factor (LHEF). For the Indian mountains, a comparison between BIS and WoE has been drawn [15], which shows that the latter produces enhanced and improved results. A comparative exploration among the BIS, MCA and FR methods was carried out [24] which have shown that FR method is more establishing in nature. Studies were also carried out for establishing the impact of landslides on human lives in the Himalayan region in India [10]. Considering all types of studies altogether, it becomes very clear that the database or inventory related to landslide is insufficient, which may be eradicated by a universally accepted procedure through extensive study.

6 Recent Gaps and Future Directives in the Study of Landslide Susceptibility Mapping and Hazard Zonation

Indian Himalayan Region is highly susceptible to natural disasters, and landslides are one of the same. For the study in landslides, the landslides susceptibility mapping and hazard assessment become very crucial in order to pick out the susceptible areas and assess the risk. This way, the disaster and economic loss may be optimized. The national level organizations and institutions associated with the disaster mitigation and analysis in India include NRSC, IIRS, NIDM, ISRO, GSI, and BMTPC. To obtain landslide susceptibility maps, GSI applies AHP for computing the rating of factors of the classes and assignment of weights to the potential factors with the help of knowledge driven approaches, provided that AHP is a semi-quantitative method which assigns weights through the pair wise relative comparison in the decision process without any inconsistencies. However, AHP does not provide any certainty regarding the selection in ranking of the geo-factors as it may differ from expert to expert. Hence, other quantitative techniques are required to be compared with AHP in order to prepare useful landslide susceptibility maps. The NRSC has a significant role to play with the preparation of landslide inventory using the earth observation data. It has prepared historical landslide inventories using a semi-automatic image analysis algorithmic approach [34]. The historical landslide inventories and landslide susceptibility maps are limited as these are event based such as earthquakes, rainfall. Consequently, the multi-spatial temporal and non-event-based landslide inventories and landslide susceptibility mapping are crucial as these acts as an existing gap in the disaster mitigation.

7 Conclusion

Landslide identification, susceptibility mapping and hazard zonation are comprehensive, crucial and at the same time very critical task in nature as the historical landslide inventories, datasets associated to the existing statistical and knowledge-driven methodologies are very much on the limited side and there are limitations in order to acquire them. The statistical techniques and quantitative methodologies are found to be reliable as these are promising in nature and the landslide identification, prediction and hazard mitigation present the comprehensibility as these are based on the realistic and interpreted data, however the limitations in the availability of credible data makes it effort-worthy

techniques. Furthermore, the purpose of investigation, the extent of the study area to be covered, type of landslide, resource availability is to be considered as the potential factors for the same. In the current scenario, the collaboration of quantitative and data-driven techniques has made the landslide susceptibility and zonation mapping a more objective and promising procedure. However, the study for the same is a never-ending process; so good understanding and governing factors are required for the study. The ML techniques are to be collaborated with the remote sensing and GIS methodologies in order to produce comprehensive susceptible maps for the complex natural geo-hazard so that the hazard mitigation and management may be apprehended at local/state/national level.

The following Table 1 gives a comparison among Weight-of-Evidence, Frequency Ratio, Information Value, Logistic Regression for regions in Darjeeling Himalayas

Table 1. Comparison of WoE, FR, IV, LR

Landslide susceptibility classes	WoE		FR		IV		LR	
	Area (in sq. km)	% of Area	Area (in sq. km)	% of Area	Area (in sq. km)	% of Area	Area (in sq. km)	% of Area
Very low	692	21.9	674	21.3	697	22.0	685	21.6
Low	379	12.0	397	12.5	376	11.8	388	12.2
Moderate	813	25.8	811	25.7	820	26.0	828	26.2
High	635	20.2	646	20.5	616	19.6	611	19.2
Very high	630	19.9	621	19.6	640	20.2	637	20.2

References

1. Batar, A., et al.: Assessment of land-use/land-cover change and forest fragmentation in the Garhwal Himalayan region of India. Environments **4**(2), 34–44 (2017). https://doi.org/10.3390/environments4020034
2. Batar, A.K., Watanabe, T.: Landslide susceptibility mapping and assessment using geospatial platforms and weights of evidence (woe) method in the Indian Himalayan Region: recent developments, gaps, and future directions. ISPRS Int. J. Geo-Inf. **10**(3), 114 (2021). https://doi.org/10.3390/ijgi10030114
3. Can, T., et al.: Susceptibility assessments of shallow earthflows triggered by heavy rainfall at three catchments by logistic regression analyses. Geomorphology **72**(1–4), 250–271 (2005). https://doi.org/10.1016/j.geomorph.2005.05.011
4. Casagli, N.: An inventory-based approach to landslide susceptibility assessment and its application to the Virginio River Basin, Italy. Environ. Eng. Geosci. **10**(3), 203–216 (2004). https://doi.org/10.2113/10.3.203
5. Chen, B., et al.: Structural safety evaluation of in-service tunnels using an adaptive neuro-fuzzy inference system. J. Aerospace Eng. **31**(5), 04018073 (2018). https://doi.org/10.1061/(asce)as.1943-5525.0000883

6. Chen, W., et al.: Landslide susceptibility modeling using integrated ensemble weights of evidence with logistic regression and random forest models. Appl. Sci. **9**(1), 171 (2019). https://doi.org/10.3390/app9010171

7. Chimidi, G., et al.: Landslide hazard evaluation and zonation in and around Gimbi town, western Ethiopia – a GIS-based statistical approach. Appl. Geomat. **9**(4), 219–236 (2017). https://doi.org/10.1007/s12518-017-0195-x

8. Corominas, J., et al.: Recommendations for the quantitative analysis of landslide risk. Bull. Eng. Geol. Environ. **73**(2), 209–263 (2013). https://doi.org/10.1007/s10064-013-0538-8

9. Dai, F.C., et al.: Landslide risk assessment and management: an overview. Eng. Geol. **64**(1), 65–87 (2002). https://doi.org/10.1016/s0013-7952(01)00093-x

10. Sunil Kumar, D.E.: Landslides and human interference in Darjiling Himalayas, India. Revista de Geomorfologie **19**(1), 44–57 (2017). https://doi.org/10.21094/rg.2017.014

11. Ding, Q., et al.: Application of frequency ratio, weights of evidence and evidential belief function models in landslide susceptibility mapping. Geocarto Int. **1**, 1–21 (2016). https://doi.org/10.1080/10106049.2016.1165294

12. Erener, A., Düzgün, H.S.B.: Landslide susceptibility assessment: what are the effects of mapping unit and mapping method? Environ. Earth Sci. **66**(3), 859–877 (2011). https://doi.org/10.1007/s12665-011-1297-0

13. Fall, M., et al.: A multi-method approach to study the stability of natural slopes and landslide susceptibility mapping. Eng. Geol. **82**(4), 241–263 (2006). https://doi.org/10.1016/j.enggeo.2005.11.007

14. Geertsema, M., Pojar, J.J.: Influence of landslides on biophysical spanersity – a perspective from British Columbia. Geomorphology **89**(1–2), 55–69 (2007). https://doi.org/10.1016/j.geomorph.2006.07.019

15. Ghosh, S., et al.: A quantitative approach for improving the BIS (Indian) method of medium-scale landslide susceptibility. J. Geol. Soc. India **74**(5), 625–638 (2009). https://doi.org/10.1007/s12594-009-0167-9

16. Glade, T.: Landslide occurrence as a response to land use change: a review of evidence from New Zealand. CATENA **51**(3–4), 297–314 (2003). https://doi.org/10.1016/s0341-8162(02)00170-4

17. Gorsevski, P.V., et al.: Spatial prediction of landslide hazard using logistic regression and ROC analysis. Trans. GIS **10**(3), 395–415 (2006). https://doi.org/10.1111/j.1467-9671.2006.01004.x

18. Gupta, R.P., Joshi, B.C.: Landslide hazard zoning using the GIS approach – a case study from the Ramganga catchment, Himalayas. Eng. Geol. **28**(1–2), 119–131 (1990). https://doi.org/10.1016/0013-7952(90)90037-2

19. Guzzetti, F., et al.: Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. Geomorphology **31**(1–4), 181–216 (1999). https://doi.org/10.1016/s0169-555x(99)00078-1

20. Guzzetti, F., et al.: Landslide inventory maps: new tools for an old problem. Earth Sci. Rev. **112**(1–2), 42–66 (2012). https://doi.org/10.1016/j.earscirev.2012.02.001

21. Guzzetti, F., et al.: Probabilistic landslide hazard assessment at the basin scale. Geomorphology **72**(1–4), 272–299 (2005). https://doi.org/10.1016/j.geomorph.2005.06.002

22. Haneberg, W.C., et al.: High-resolution LIDAR-based landslide hazard mapping and modeling, UCSF Parnassus Campus, San Francisco, USA. Bull. Eng. Geol. Environ. **68**(2), 263–276 (2009). https://doi.org/10.1007/s10064-009-0204-3

23. Huang, F., et al.: Comparisons of heuristic, general statistical and machine learning models for landslide susceptibility prediction and mapping. CATENA **191**, 104580 (2020). https://doi.org/10.1016/j.catena.2020.104580

24. Kannan, M., et al.: Comparative analysis in GIS-based landslide hazard zonation – a case study in Bodi-Bodimettu Ghat section, Theni District, Tamil Nadu, India. Arab. J. Geosci. **8**(2), 691–699 (2014). https://doi.org/10.1007/s12517-013-1259-9

25. Kanungo, D.P., et al.: A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas. Eng. Geol. **85**(3–4), 347–366 (2006). https://doi.org/10.1016/j.eng geo.2006.03.004

26. Keefer, D.K.: Landslides caused by earthquakes. Geol. Soc. Am. Bull. **95**(4), 406 (1984)

27. Kumar, A., Sanoujam, M.: Landslide studies along the national highway (NH 39) in Manipur. Nat. Hazards **40**(3), 603–614 (2006). https://doi.org/10.1007/s11069-006-9024-y

28. Lee, S.: Application and verification of fuzzy algebraic operators to landslide susceptibility mapping. Environ. Geol. **52**(4), 615–623 (2006). https://doi.org/10.1007/s00254-006-0491-y

29. Lee, S., et al.: Determination and application of the weights for landslide susceptibility mapping using an artificial neural network. Eng. Geol. **71**(3–4), 289–302 (2004). https://doi.org/10.1016/s0013-7952(03)00142-x

30. Lee, S., Min, K.: Statistical analysis of landslide susceptibility at Yongin, Korea. Environ. Geol. **40**(9), 1095–1113 (2001). https://doi.org/10.1007/s002540100310

31. Li, X., et al.: Identification of forested landslides using lidar data, object-based image analysis, and machine learning algorithms. Remote Sens. **7**(8), 9705–9726 (2015). https://doi.org/10.3390/rs70809705

32. Li, X., Wang, Y.: Applying various algorithms for species distribution modelling. Integr. Zool. **8**(2), 124–135 (2013). https://doi.org/10.1111/1749-4877.12000

33. Martha, T.R., et al.: Characterizing spectral, spatial and morphometric properties of landslides for semi-automatic detection using object-oriented methods. Geomorphology **116**(1–2), 24–36 (2010). https://doi.org/10.1016/j.geomorph.2009.10.004

34. Martha, T.R., et al.: Landslide hazard and risk assessment using semi-automatically created landslide inventories. Geomorphology **184**, 139–150 (2013). https://doi.org/10.1016/j.geo morph.2012.12.001

35. Martha, T.R., et al.: Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories. ISPRS J. Photogram. Remote. Sens. **67**, 105–119 (2012). https://doi.org/10.1016/j.isprsjprs.2011.11.004

36. McKean, J., Roering, J.: Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. Geomorphology **57**(3–4), 331–351 (2004). https://doi.org/10.1016/s0169-555x(03)00164-8

37. Filagot Mengistu, K.V., et al.: Landslide hazard zonation and slope instability assessment using optical and InSAR data: a case study from Gidole Town and its surrounding areas, Southern Ethiopia. Remote Sens. Land **3**(1), 1–14 (2019). https://doi.org/10.21523/gcj1.190 30101

38. Meusburger, K., Alewell, C.: Impacts of anthropogenic and environmental factors on the occurrence of shallow landslides in an alpine catchment (Urseren Valley, Switzerland). Nat. Hazards **8**(3), 509–520 (2008). https://doi.org/10.5194/nhess-8-509-2008

39. Mohammady, M., et al.: Landslide susceptibility mapping at Golestan Province, Iran: a comparison between frequency ratio, Dempster-Shafer, and weights-of-evidence models. J. Asian Earth Sci. **61**, 221–236 (2012). https://doi.org/10.1016/j.jseaes.2012.10.005

40. Moosavi, V., et al.: Producing a landslide inventory map using pixel-based and object-oriented approaches optimized by Taguchi method. Geomorphology **204**, 646–656 (2014). https://doi.org/10.1016/j.geomorph.2013.09.012

41. Nandi, A., Shakoor, A.: A GIS-based landslide susceptibility evaluation using bivariate and multivariate statistical analyses. Eng. Geol. **110**(1–2), 11–20 (2010). https://doi.org/10.1016/j.enggeo.2009.10.001

42. Oh, H.-J., Pradhan, B.: Application of a neuro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area. Comput. Geosci. **37**(9), 1264–1276 (2011). https://doi.org/10.1016/j.cageo.2010.10.012

43. Pachauri, A.K., et al.: Landslide zoning in a part of the Garhwal Himalayas. Environ. Geol. **36**(3–4), 325–334 (1998). https://doi.org/10.1007/s002540050348

44. Pardeshi, S.D., et al.: Landslide hazard assessment: recent trends and techniques. Springerplus **2**(1), 1–11 (2013). https://doi.org/10.1186/2193-1801-2-523

45. Raghuvanshi, T.K., et al.: GIS based grid overlay method versus modeling approach – a comparative study for landslide hazard zonation (LHZ) in Meta Robi District of West Showa Zone in Ethiopia. Egypt. J. Remote Sens. Space Sci. **18**(2), 235–250 (2015). https://doi.org/10.1016/j.ejrs.2015.08.001

46. Raghuvanshi, T.K., et al.: Slope stability susceptibility evaluation parameter (SSEP) rating scheme – an approach for landslide hazard zonation. J. Afr. Earth Sci. **99**, 595–612 (2014). https://doi.org/10.1016/j.jafrearsci.2014.05.004

47. Reichenbach, P., et al.: A review of statistically-based landslide susceptibility models. Earth Sci. Rev. **180**, 60–91 (2018). https://doi.org/10.1016/j.earscirev.2018.03.001

48. Reichenbach, P., Busca, C., Mondini, A.C., Rossi, M.: Land use change scenarios and landslide susceptibility zonation: the briga catchment test area (Messina, Italy). In: Lollino, G., Manconi, A., Clague, J., Shan, W., Chiarle, M. (eds.) Engineering Geology for Society and Territory – Volume 1, pp. 557–561. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-09300-0_104

49. Rowbotham, D.N., Dudycha, D.: GIS modelling of slope stability in Phewa Tal watershed, Nepal. Geomorphology **26**(1–3), 151–170 (1998). https://doi.org/10.1016/s0169-555x(98)00056-7

50. Saha, A.K., et al.: GIS-based landslide hazard zonation in the Bhagirathi (Ganga) valley, Himalayas. Int. J. Remote Sens. **23**(2), 357–369 (2002). https://doi.org/10.1080/01431160010014260

51. Saito, H., et al.: Comparison of landslide susceptibility based on a decision-tree model and actual landslide occurrence: the Akaishi Mountains, Japan. Geomorphology **109**(3–4), 108–121 (2009). https://doi.org/10.1016/j.geomorph.2009.02.026

52. Schuster, R.L., Highland, L.M.: Urban landslides: Socioeconomic impacts and overview of mitigative strategies. Bull. Eng. Geol. Environ. **66**(1), 1–27 (2006). https://doi.org/10.1007/s10064-006-0080-z

53. Shano, L., et al.: Landslide susceptibility evaluation and hazard zonation techniques – a review. Geoenviron. Disast. **7**(1), 1–19 (2020). https://doi.org/10.1186/s40677-020-00152-0

54. Sifa, S.F., et al.: Event-based landslide susceptibility mapping using weights of evidence (WoE) and modified frequency ratio (MFR) model: a case study of Rangamati district in Bangladesh. Geol. Ecol. Landsc. **4**(3), 222–235 (2019). https://doi.org/10.1080/24749508.2019.1619222

55. Sun, D., et al.: Assessment of landslide susceptibility mapping based on Bayesian hyperparameter optimization: a comparison between logistic regression and random forest. Eng. Geol. **281**, 105972 (2021). https://doi.org/10.1016/j.enggeo.2020.105972

56. Tian, Y., et al.: Mapping earthquake-triggered landslide susceptibility by use of artificial neural network (ANN) models: an example of the 2013 Minxian (China) Mw 5.9 event. Geomat. Nat. Hazards Risk **10**(1), 1–25 (2018). https://doi.org/10.1080/19475705.2018.1487471

57. Tien Bui, D., et al.: Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. Landslides **13**(2), 361–378 (2015). https://doi.org/10.1007/s10346-015-0557-6

58. Tropeano, D., Turconi, L.: Using historical documents for landslide, debris flow and stream flood prevention. Applications in Northern Italy. Nat. Hazards **31**(3), 663–679 (2004). https://doi.org/10.1023/b:nhaz.0000024897.71471.f2

59. Van Beek, L.P.H., Van Asch, T.: Regional assessment of the effects of land-use change on landslide hazard by means of physically based modelling. Nat. Hazards **31**(1), 289–304 (2004). https://doi.org/10.1023/b:nhaz.0000020267.39691.39

60. Van Den Eeckhaut, M., et al.: Object-oriented identification of forested landslides with derivatives of single pulse LiDAR data. Geomorphology **173–174**, 30–42 (2012). https://doi.org/10.1016/j.geomorph.2012.05.024

61. van Westen, C.J., et al.: Landslide hazard and risk zonation – why is it still so difficult? Bull. Eng. Geol. Environ. **65**(2), 167–184 (2005). https://doi.org/10.1007/s10064-005-0023-0

62. Wang, G., et al.: Spatial prediction of landslide susceptibility based on GIS and discriminant functions. ISPRS Int. J. Geo-Inf. **9**(3), 144 (2020). https://doi.org/10.3390/ijgi9030144

63. Wang, H., et al.: Landslide identification using machine learning. Geosci. Front. **12**(1), 351–364 (2021). https://doi.org/10.1016/j.gsf.2020.02.012

64. Xu, C., et al.: GIS-based support vector machine modeling of earthquake-triggered landslide susceptibility in the Jianjiang River watershed, China. Geomorphology **145–146**, 70–80 (2012). https://doi.org/10.1016/j.geomorph.2011.12.040