

Environmental Science and Engineering

Sijing Wang
Runqiu Huang
Rafiq Azzam
Vassilis P. Marinos *Editors*

Engineering Geology for a Habitable Earth: IAEG XIV Congress 2023 Proceedings, Chengdu, China

Volume 2: Geohazard Mechanisms, Risk
Assessment and Control, Monitoring
and Early Warning

 Springer

Environmental Science and Engineering

Series Editors

Ulrich Förstner, Buchholz, Germany

Wim H. Rulkens, Department of Environmental Technology, Wageningen,
The Netherlands

The ultimate goal of this series is to contribute to the protection of our environment, which calls for both profound research and the ongoing development of solutions and measurements by experts in the field. Accordingly, the series promotes not only a deeper understanding of environmental processes and the evaluation of management strategies, but also design and technology aimed at improving environmental quality. Books focusing on the former are published in the subseries Environmental Science, those focusing on the latter in the subseries Environmental Engineering.

Sijing Wang · Runqiu Huang · Rafiq Azzam ·
Vassilis P. Marinos
Editors

Engineering Geology for a Habitable Earth: IAEG XIV Congress 2023 Proceedings, Chengdu, China

Volume 2: Geohazard Mechanisms, Risk
Assessment and Control, Monitoring
and Early Warning

Editors

Sijing Wang
Department of Hydraulic Engineering
Tsinghua University
Beijing, China

Rafiq Azzam
Department of Engineering Geology
and Hydrogeology
RWTH Aachen University
Aachen, Germany

Runqiu Huang
Chengdu University of Technology
Chengdu, Sichuan, China

Vassilis P. Marinos
School of Civil Engineering
National Technical University of Athens
Zografou, Greece

ISSN 1863-5520 ISSN 1863-5539 (electronic)
Environmental Science and Engineering
ISBN 978-981-99-9060-3 ISBN 978-981-99-9061-0 (eBook)
<https://doi.org/10.1007/978-981-99-9061-0>

© The Editor(s) (if applicable) and The Author(s), under exclusive license to Springer Nature Singapore Pte Ltd. 2024

This work is subject to copyright. All rights are solely and exclusively licensed by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.

The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

The publisher, the authors and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd. The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

If disposing of this product, please recycle the paper.

Preface

The XIV Congress of the International Association for Engineering Geology and the Environment (XIV IAEG Congress 2023) was successfully held in Chengdu, China, from September 21 to 27, 2023. Focusing on the main theme “Engineering Geology for a Habitable Earth,” researchers and practitioners worldwide from academia, industry, and government have joined us in this prestigious event. Based on the topics discussed at the congress, the proceedings are organized into six volumes as follows:

- Volume 1: Engineering Geomechanics of Rock and Soil Masses
- Volume 2: Geohazard Mechanisms, Risk Assessment and Control, Monitoring and Early Warning
- Volume 3: Active Tectonics, Geomorphology, Climate and Geoenvironmental Engineering Geology
- Volume 4: Technological Innovation and Applied for Engineering Geology
- Volume 5: Megacity Development and Preservation of Cultural Heritage Engineering Geology
- Volume 6: Marine and Deep Earth Engineering Geology.

Meanwhile, on behalf of the organizing committee, we would also like to express our deepest appreciation to the technical program committee members, reviewers, session chairs, and volunteers for their strong support for congress.

Last but not least, our gratitude also goes to the editors and press for their great support to the congress.

September 2023

IAEG XIV Congress 2023 Organizing Committee

Contents

1	Rock Avalanches’ Morphological Classification: Important Tool for Risk Assessment	1
	Alexander Strom	
2	Enhancing Spectral Clustering Performance Using Self-Supervised Support Vector Machines for Regional Landslide Risk Assessment Visualization: A Case Study in Han-Yuan County, Ya’an City	13
	Yuting Ma, Mei Han, Shiyuan Zeng, Huijing Li, and Zihao Gao	
3	A Comprehensive Landslide Hazard Assessment Around Transmission Lines After the 2022 Ms6.8 Luding Earthquake, China	29
	Xiao Ling, Jianao Cai, Liang Zhang, and Dongping Ming	
4	Research on Intelligent Recognition Algorithms for Common Subgrade Diseases Based on Radar Images	39
	Mingzhou Bai, Yanli Qi, Jiazhi Li, Zelin Li, Linlin Song, Lingkang Dai, and Gang Tian	
5	Stability Prediction of Rock Slope Based on Fuzzy Clustering GA-FNN Model	55
	Wenlian Zhang, Yudong Li, and Xiaoyun Sun	
6	Landslide Hazard Assessment in Trung Chai Commune, Sapa, Vietnam Using Frequency Ratio Method and Scoops3D	69
	Binh Van Duong, Igor Konstantinovich Fomenko, Dang Hong Vu, Kien Trung Nguyen, and Oleg Vladimirovich Zerkal	
7	Research on Prediction and Prevention of Nonuniform Deformation in Unsymmetrical Loading Tunnel	85
	Qiushi Liu, Bin Shao, Bo Wang, Wenqing Zhang, Zhanying Ju, Xinmin Ma, and Peng Wang	

8	Investigation of Dynamic Fragmentation Mechanism of Granular Column Collapse Via Discrete Element Analyses	99
	Wenbin Chang, Aiguo Xing, and Kaiping Jin	
9	An Improved Bond-Based Smoothed Particle Hydrodynamics for Simulating Progressive Failure of Rock Slope Under Seismic Conditions	117
	Chengzhi Xia, Zhenming Shi, and Huanjia Kou	
10	Numerical Investigation of Influence of Low Ice Friction on Mobility of Rock-Ice Avalanches	131
	Yuhao Ren, Qingqing Yang, Fei Cai, and Zhiman Su	
11	Research on Radar Forward Modeling for Detecting Urban Road Subgrade Disease Based on Radar	143
	Dayong Wang, Yanli Qi, Mingzhou Bai, Zelin Li, Linlin Song, and Gang Tian	
12	Causes and Damage of the 2020 Periglacial Debris Flows at Zelunglung Catchment in the Eastern Syntaxis of Himalaya	161
	Hao Li, Kaiheng Hu, Xiaopeng Zhang, Shuang Liu, and Li Wei	
13	Energy Dissipation Effect of Different Structures on Debris Flow	173
	Bingtao Han, Zhankui Liu, Yuxin Jie, and Jianbo Fei	
14	Numerical Simulation of a Rainfall-Induced Debris Flow: A Case Study in Tianquan County, Southwest China	183
	Ruichen Zhou, Xiewen Hu, Bo Liu, Kun He, Chuanjie Xi, and Guanglin Huang	
15	Investigation and Analysis of “6.21” Debris Flow in Jiuzhaigou County, Sichuan Province	199
	Li Ning, Zhao Boju, Chang Ming, Shu Zhile, and Bu Xianghang	
16	A Study on the Relationship Between Building Damage and Shallow Subsurface Ground in the 2015 Nepal Gorkha Earthquake	217
	Nobusuke Hasegawa, Pradhan Om, Atsushi Yatagai, and Nobuhiko Toyama	
17	Study on Rockfall Simulation Method Using Discontinuous Deformation Analysis	229
	Guichen Ma	
18	Investigating Challenges and Countermeasures for the Yoshinogawa River Environment in Japan	239
	Qinxue Wang, Tomohiro Okadera, and Satoshi Kameyama	

19	Estimation of Slip Surfaces Using the Results of Groundwater Logging in Fracture Zone Landslides	253
	Tsunataka Furuya and Jingcai Jiang	
20	Detection of Deep-Seated Gravitational Slope Deformations by Aerial Photo Interpretation and Statistical Analysis in an Accretionary Complex in Japan	263
	Teruyuki Kikuchi and Satoshi Nishiyama	
21	Response of Groundwater to Rainfall and the Recession Constant of Antecedent Precipitation in a Slope with Residual Soil	279
	Yukai Fu, Chunli Chen, Chenxing Wang, Tonglu Li, Zhongjie Fan, and He Liu	
22	A New Simulation Tool on Rockfall Fragmentation-Movement-Deposition Process	301
	Huang Jian, Wang Hao, Huang Xiang, Yuan Jingqing, and He Zicheng	
23	Comparison Study of Typical Landslides in Hong Kong and Shenzhen	319
	Aiguo Li, Weiqiang Feng, Zhongqi Yue, George Tham, and C. F. Lee	
24	Design and Application of a Flexible Enclosure for Seasonally Saline Frozen Areas in Airports	335
	Shuang Wang, Rui Wang, Hong Qin, Fumin Shu, and Biao Yang	
25	Mechanism and Structural Evidence of Interlayered Rock Slope Failures	349
	Mian Sohail Akram and Luqman Ahmed	
26	Engineering Geo-mechanics System for Coal and Gas Outbursts	359
	Xubiao Deng, Yanjie Hou, and Huaichang Yu	
27	Insights into a Large-Prone Area in the Eastern Margin of the Tibetan Plateau, China—A Case Study Along the Danba Reach of the Dadu River	383
	Yunsheng Wang, Liang Song, Ruibin Kou, Shicheng Liu, Tao Tang, Zhuo Feng, and Mingbin Zhan	
28	Critical Physical and Hydraulic Condition for Fine Grains Migration, Deposition and Self-dredging in Seepage Erosion of Gravel Soil	397
	Jiazhan Ren, Hui Dong, Fengming Tan, and Lei Wen	

29	Stability of Coal Pillars and Backfill Due to Intermittent Cut-and-Fill Mining Under Loose Aquifer	413
	Jiawei Liu, Zhenyu Yin, and Yingzhi Xia	
30	Geological Hazard Risk Assessment of Landslide Geological Hazards in the Gushan Navigation and Hydropower Hub Reservoir Area	429
	Minhao Hu, Kunsheng Hu, Qiguo Wang, and Yi Hu	
31	Integration of Passive Seismic Techniques to Investigate the Landslide Dam Generated by the Yang Jia Gou Rock Avalanche (Sichuan–China)	445
	Paola Capone, Vincenzo Del Gaudio, Janusz Wasowski, and Wei Hu	
32	Identifying the Potential Landslides Along Duba Highway (Guangxi, China) in Dense Vegetation Environment by Time Series InSAR	457
	Xianlin Liu, Tao Yin, Youdong Chen, Yu Shao, and Keren Dai	
33	Early Identification, Monitoring and Warning of Landslide Hazard in Northeast Sichuan Based on Integrated Remote Sensing Technology	465
	Peng He, Zhaocheng Guo, Hong Chen, Genhou Wang, and Haochen Wang	
34	Real-Time Intelligent Monitoring of Rockfall in the Complex Environment	477
	Juan Liu, Hui Chen, and Ying Hu	
35	Research on the Application of InSAR Technology for the Recognition of the Potential Danger of Suspected Geological Hazards	489
	Zhimin Feng, Haiqiang Xin, Yong Wang, Hairong Liu, and Shanqing Zhang	
36	Potential Geohazards Identification and Deformation Monitoring by Time-Series InSAR Along Anhui Ningwu Expressway	505
	Dongsheng Qian, Hongxiang Wang, Xuewen Huang, Xiaoyong Li, Xiangsheng Liu, Lei Zhang, Yu Wang, Fanfan Li, and Jiahong Zhong	
37	Failure Mode of Steep Bedding Slopes Undergoing Strong Earthquake	515
	Longqi Li, Kang Xie, and Nengpan Ju	

38 Permanent Displacement of Slopes Considering Horizontal and Vertical Ground Motions Based on the Tensile-Shear Sliding Mode	527
Xiao Cheng, Lianheng Zhao, Xinyan Peng, Dejian Li, Baofeng Di, and Yingbin Zhang	
39 System Reliability Analysis of Geosynthetic-Reinforced Soil Slopes Under Seismic Conditions	545
Rui Sun, Jianfeng Chen, Ming Peng, Ning Bao, and Hui Qi	
40 Study on Development Stage and Evolution of Landslide in Wide Fracture Zone of Anninghe Active Fault	557
Bin Liu, HongFu Zhou, Ming Liu, Su Zhang, Min You, and XiaoBo Ma	
41 Monitoring Spatial-temporal Seismic Velocity Changes and Microstructural Changes on Rock Slope Associated with the M 6.8 Luding Earthquake	571
Zhengran He, Li Zhao, and Fan Xie	
42 Determination of Crucial Shear Parameters in Highly Landslide Prone Tropical Soils in Bello Oriente, Medellín, Colombia	583
Tamara Breuninger, Bettina Menschik, Moritz Gamperl, and Kuroschi Thuro	
43 Post-wildfire Landslide Engineering: Hazard Assessment to Mitigation in the Cameron Peak Wildfire, Colorado, USA	593
Thad Wasklewicz, Richard Guthrie, Paul Eickenberg, and Benjamin Kramka	
44 Landslide Susceptibility in the Turkish Northwesternmost Sector: Distinctive Patterns of Inactive and Active Landslides	613
Marco Loche, Hakan Tanyas, Gianvito Scaringi, Tolga Gorum, and Luigi Lombardo	
45 Movement Process Analysis of Long-Runout Guanling Landslide in Guizhou, China	629
Shunbo Zhang, Wenbing Shi, Xiongwu Peng, and Xiaoming Wang	
46 Reinforced Slope with Micropiles Based on Centrifugal Simulation Test	649
Yulin Xu, Dongdong Wu, and Dongpo Wang	
47 Evaluating Dark Fiber Distributed Acoustic and Strain Sensing for Shallow Ground Movement Monitoring: A Field Trial	665
Cheng-Cheng Zhang and Bin Shi	

48	A Case Study of Automatically Monitoring System Experiment for Landslide Within Tianfu New District in Chengdu	675
	Hu Depan, Wang Xuben, Luo Yongkang, Shi Lily, and Yang Huajin	
49	A Practical Method to Predict the Occurrence Time of Storm-Induced Shallow Landslide Considering the Underlying Impermeable Bedrock	683
	Li-Ming Zhang, Qing Lü, Jun-Yu Wu, Chang-Gui Xiao, Zheng-Hua Liu, and Xing-Hua Xu	
50	Estimation of Seismic Earth Pressure Acting on Stabilizing Piles in Sandy Slopes Considering Soil Arching Effect	699
	Ning Bao, Jianfeng Chen, and Rui Sun	
51	Experimental Investigation on Impact Force of Dry Granular Flows on a Rigid Retaining Wall	713
	Xiaoyi Fan, Yuanjun Jiang, Haonan Liu, and Huan Liu	
52	Sliding Tbilisi: Why Georgia's Capital is Haunted by Multiple Landslides	729
	Klaus Keilig, Peter Neumann, Markus Bauer, Kurosch Thuro, and Zurab Menabde	
53	Experimental Investigation and Numerical Simulation on Progressive Failure of Landslide Under Different Rainfall Conditions	743
	Ni Jiji, Huang Yongliang, Sha Peng, and Liu Dongyan	
54	The Occurrence of a Rainfall-Induced Catastrophic Landslide in a Soil and Rock-Like Stratum in Southwest China	761
	Leilei Jin, Zhengfeng Chen, Wenxi Fu, Cheng Zhou, Bingshuang Ye, and Rui Qian	
55	Various Applications of Developed DDA-SPH Method to Coupling Problems Involved in Geological Disasters	785
	Xinyan Peng, Xiao Cheng, Pengcheng Yu, Baofeng Di, Yingbin Zhang, and Lu Zheng	
56	Numerical Simulation of Crack Propagation in Jointed Rock Mass Based on an Enhanced SPH Method	799
	Guangyin Lu, Chuanyi Tao, and Chengzhi Xia	
57	Strength Characteristics of Ili Loess and Its Landslide Numerical Simulation	817
	Boyue Gao, Zhijun Zhou, Yubo Ren, Jiayan Yi, and Zhongtong Sui	

58 Mechanisms of Reservoir Impoundment-Induced Large Deformation of the Guobu Slope at the Laxiwa Hydropower Station, China: Preliminary Insights from Remote Sensing and Numerical Modelling 835
Moritz Lesche, Liang Wang, Andrea Manconi, Simon Loew, Qiang Yang, Yaoru Liu, and Qinghua Lei

Chapter 6

Landslide Hazard Assessment in Trung Chai Commune, Sapa, Vietnam Using Frequency Ratio Method and Scoops3D



Binh Van Duong, Igor Konstantinovich Fomenko, Dang Hong Vu,
Kien Trung Nguyen, and Oleg Vladimirovich Zerkal

Abstract In the mountainous urban areas of Vietnam, including Sapa, minimizing damage from natural disasters is a critical aspect of the sustainable development strategy. Along with natural elements, tourism development and construction have led to landslide occurrences that threaten the sustainability of residential areas in Sapa, particularly in mountainous zones. Therefore, a landslide susceptibility analysis for the Trung Chai area was conducted in this study using the frequency ratio method. A set of landslide causative factors was selected and analyzed in the FR model for establishing the landslide susceptibility zonation (LSZ) map and categorizing the Trung Chai area into five zones. The results show that the very high susceptibility zone covers 9.93% of the study area. The FR model shows high performance in predicting landslide susceptibility in the study area, with success and prediction rates of 83.90% and 85.75%, respectively. Subsequently, the rainfall-induced landslide stability at a site in the Trung Chai area was simulated using the 3D limit equilibrium analysis in Scoops3D. Because of the high model efficiency, the study results can help identify areas with a high landslide risk for long-term planning and reduce damage caused by landslides.

B. Van Duong (✉)
Hanoi University of Mining and Geology, Hanoi, Vietnam
e-mail: duongvanbinh@humg.edu.vn

B. Van Duong · I. K. Fomenko
Sergo Ordzhonikidze Russian State University for Geological Prospecting (MGRI), Moscow, Russia

D. H. Vu
Vietnam Institute of Geosciences and Mineral Resources, Hanoi, Vietnam

K. T. Nguyen
Institute of Geological Sciences, Vietnam Academy of Science and Technology, Hanoi, Vietnam

O. V. Zerkal
Moscow State University, Moscow, Russia

Keywords Landslide hazard · Landslide susceptibility · Frequency ratio · Limit equilibrium method · Scoops3D · Trung Chai · Vietnam

6.1 Introduction

Frequent natural disasters, such as landslides, threaten mountainous regions. Along with other natural disasters, landslides cause serious environmental problems and devastate residential areas, highways, agricultural areas, gardens, and grasslands (Roy et al. 2019). Landslides in Vietnam have become more frequent and severe, with most events recorded in the Northern mountainous regions, particularly in Lao Cai province. Landslide inventories have provided evidence of a correlation between landslide occurrences and human activities (road construction), climate conditions (heavy precipitation), and terrain characteristics (many narrow, small valleys) within this region (Tien Bui et al. 2017). Therefore, managers can benefit from a tool based on accurate data on the distribution of landslide-prone areas and knowledge of landslide mechanisms for land use planning (Tien Bui et al. 2016). Mapping landslide susceptibility/hazard for a specific region is a critical initial step in assessing and managing landslide disasters, urban development, land use planning, and risk mitigation strategies (Pradhan and Lee 2010). It is possible to categorize the approaches employed in landslide susceptibility mapping (LSM) as qualitative or quantitative, direct or indirect (Guzzetti et al. 1999). Yalcin et al. (2011) concluded that subjectivity is a characteristic of qualitative methods since they depend on expert judgment to estimate landslide hazards by evaluating the connection between relevant variables and landslide occurrences. Quantitative methods are classified as deterministic and statistical (Aleotti and Chowdhury 1999). Deterministic methods have been frequently employed in landslide studies on local and site-specific scales. This method develops and calibrates a physically-based model for LSM using surveys and laboratory test results (Ciurleo et al. 2017; Park et al. 2013a, b). Statistical methods, meanwhile, are extensively utilized in the study of LSM at various scales by drawing a picture of the relationship between landslide conditioning factors, triggering factors, and landslide events that have been triggered within a specified period (Chacón et al. 2006; Ciurleo et al. 2017; Guzzetti et al. 1999). The fundamental assumption of a statistical model is that future landslides will be caused by the same factors that contributed to slope instability in a given area (Guzzetti et al. 1999). In this paper, landslide hazards in the study area were assessed using two different models: a physical-based model (Scoops3D) and a statistical model (Frequency ratio). The landslide susceptibility maps were prepared using eight causative factor maps. For model validation, the landslide susceptibility index (LSI) and landslide susceptibility zonation (LSZ) maps were compared to the landslide inventory map using the area (AUC) under the ROC curve, the seed cell area index (SCAI), and the precision of predicted results (P) values. Scoops3D (Reid et al. 2015) has been effectively used in various landslide stability studies worldwide, including in Vietnam (Rashid et al. 2020; Tran et al. 2020; Zhang and Wang 2019). Using survey data (UAV photos,

geotechnical properties, rainfall) and the Scoops3D model, we produced a rainfall-induced landslide assessment at a landslide site on the road connecting Sapa district and Laocai city.

6.2 Study Area

Sediment-related natural disasters, including landslides, have been increasingly influencing the expansion and development of communities in the Northwest region of Lao Cai province, particularly in the “hot spots” of Sapa (Dang et al. 2018). Landslides in Lao Cai, especially those in Sapa, have drawn considerable attention in the past decade because of the high number of deaths, damage to infrastructure, and environmental destruction they have caused (Tien Bui et al. 2017). Trung Chai (Fig. 6.1) is a mountainous commune in northwest Sapa, covering an area of about 38.6 km² and an average annual rainfall of over 2500 mm. The seasonal distribution of precipitation in Trung Chai is uneven, with the summer months accounting for a significant concentration of more than 80% of the total annual rainfall (Tien Bui et al. 2017). Trung Chai is one of the communes with the highest landslide hazard in Sapa. The Mong Sen event (Fig. 6.2a) is located on national road 4D, connecting Laocai City with the Sapa district. This landslide, which was first triggered in 1998 and subsequently reactivated in 2000, 2002, and 2009, provides compelling proof of landslide activity in Vietnam’s Northwest region. The landslide site (Fig. 6.2b) is located in Trung Chai commune, on the road connecting the Sapa district to the Hanoi-Laocai expressway and about 500 m from the Mong Sen bridge. At the time of the survey, the body of the landslide mass had cracks and displacements. Geologically, rocks of the Posen complex with relatively high strength (i.e., granodiorite, granite, and granite migmatite) are widely distributed in the study area. The weathering process of the bedrock has resulted in the formation of a thick cover layer with high permeability, increasing the landslide hazard. Previous studies revealed that heavy, high-intensity rainfall is the main trigger of various-scale landslides in the Trung Chai area (Tien Bui et al. 2017; Tran et al. 2020).

6.3 Materials and Methods

6.3.1 Frequency Ratio Method (FR)

In numerous landslide studies, the FR method, which is based on statistical analysis, has been selected to build effective models for LSM (Kose and Turk 2019; Lee and Pradhan 2007; Vakhshoori and Zare 2016). By analyzing the correlation between recorded landslides and causative variables, this well-known method quantifies the

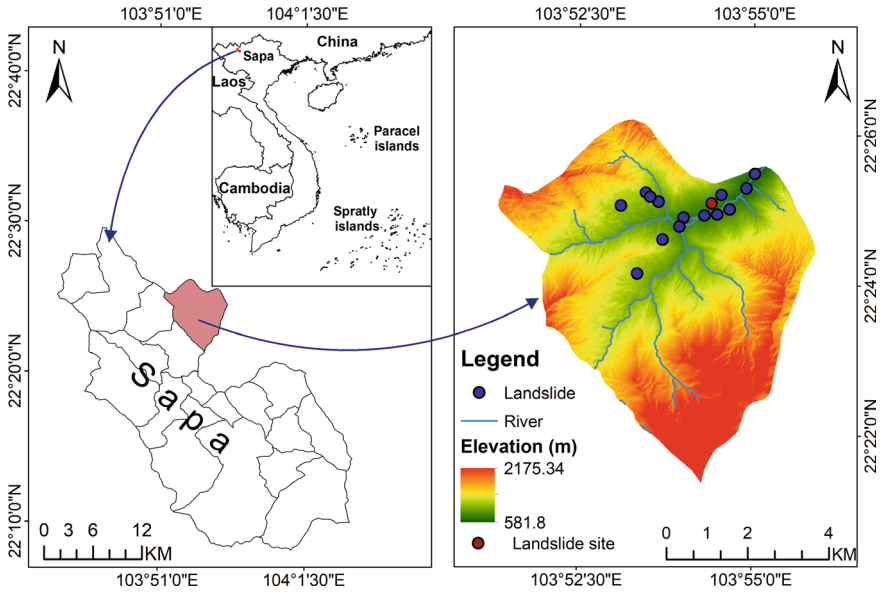


Fig. 6.1 Location of study area



Fig. 6.2 Photo of the Mong Sen landslide (a) and the landslide site (b) in Trung Chai area

influence of factors contributing to the landslide process to predict the future distribution of landslides in a given area. Hence, classifying an area as a potential or non-potential landslide zone correlates directly with the accuracy of historical landslide data. Landslide occurrence and factor class are strongly correlated when the $FR > 1$, whereas the $FR < 1$ represents a weak relationship (Lee and Talib 2005). The FR value is calculated as follows:

$$FR = \left(\frac{N_{LSi}}{N_{LS}} \right) / \left(\frac{N_{pxi}}{N_{px}} \right) \quad (6.1)$$

where: N_{LSi} and N_{pxi} represent the number of landslides and pixels in class i , while N_{LS} and N_{px} represent the total number of landslides and pixels in the study area, respectively.

Finally, Eq. (6.2) (Kose and Turk 2019) was employed to calculate the LSI value to establish a susceptibility zonation map for the Trung Chai area:

$$LSI = \sum FR \quad (6.2)$$

6.3.2 Three-Dimensional (3D) Column Analysis Method in Scoops3D

Reid et al. (2015) developed Scoops3D to search for slope landslides on digitized terrain surfaces, with the digital elevation model (DEM) serving as the most crucial input data. A considerable number of three-dimensional stability analyses are subsequently performed following a systematic investigation of the terrain surface by Scoops3D (Reid et al. 2000). The model for evaluating slope behavior can be built using 3D limit equilibrium analysis based on the “column method” with a spherical potential sliding surface. By conducting analyses using limit equilibrium, Scoops3D users, therefore, have to accept the existence of drawbacks related to this method (Duncan et al. 2014; Krahn 2003). Scoops3D computes stability by extending the Ordinary (Fellenius) or Bishop simplified methods in three dimensions. However, the 3D analysis based on the Bishop approach usually produces factor-of-safety values comparable to those obtained using more rigorous limit equilibrium methods (Reid et al. 2015).

Scoops3D uses moment equilibrium to calculate the factor-of-safety (Fs) value for the stability of an examined terrain surface. In limit equilibrium methods, the Fs value determines the equilibrium condition of the potential failure surface based on the relationship between the shear stress and soil strength (Reid et al. 2015). A Fs value of less than one is regarded as an indicator of a slope failure.

The simplified method developed by Bishop (1955) has been frequently used in Scoops3D to evaluate the stability of spherical potential slip surfaces because it produces more accurate results in Fs. The 3D extensions of this method determined the Fs value using the following equation (Reid et al. 2015):

$$FS = \frac{\sum R_{i,j} [c_{i,j} A_{h_{i,j}} + (W_{i,j} - u_{i,j} A_{h_{i,j}}) \tan \varphi_{i,j}] / m_{\alpha_{i,j}}}{\sum W_{i,j} (R_{i,j} \sin \alpha_{i,j} + k_{eq} e_{i,j})} \quad (6.3)$$

The symbols utilized in Eq. (6.3) are described in detail in the Scoop3D document by Reid et al. (2015)

6.3.3 Data Preparation

In landslide hazard and susceptibility assessment, it is widely accepted that the distribution of potential landslides is closely related to the occurrence of past landslides. Therefore, input data for predicting future landslides must include past landslides and a set of landslide-related factors (van Westen et al. 2008). However, to get the most accurate assessment results, it is necessary to consider the change in these factors or the appearance of new factors that increase the likelihood of landslides.

6.3.3.1 Landslide Inventory Map

Landslide inventory maps (LIM) need to represent the spatial distribution, morphological attributes, and characteristics of landslide events, according to Guzzetti et al. (1999). Landslide inventory maps are established for a variety of purposes: (1) identifying landslide distribution in an examined area; (2) indicating the magnitude of the damage produced by a single landslide; (3) illustrating the abundance of mass movements; (4) determining the landslide frequency in an area; and (5) supplying input data for developing landslide prediction models (Galli et al. 2008). A LIM of the study area was prepared utilizing field investigations, local information, and the analysis of aerial photos. Finally, 14 landslides ranging in size from 1297.5 to 25,596.4 m² were identified and mapped. Landslide locations were randomly categorized into training (70%) and testing data (30%).

6.3.3.2 Landslide Causative Factors

Eight causative factors were considered for preparing LSI and LSZ maps, including elevation, relative relief, slope, aspect, distance to road and drainage, rainfall, and land use/land cover (LULC) (Figs. 6.3 and 6.4).

Topographic maps (aspect map, elevation map, slope map, and relative relief map) were extracted from a 10-m DEM using spatial analyst tools in ArcGIS 10.5. The maps of distance to drainage and roads were prepared using the Euclidean

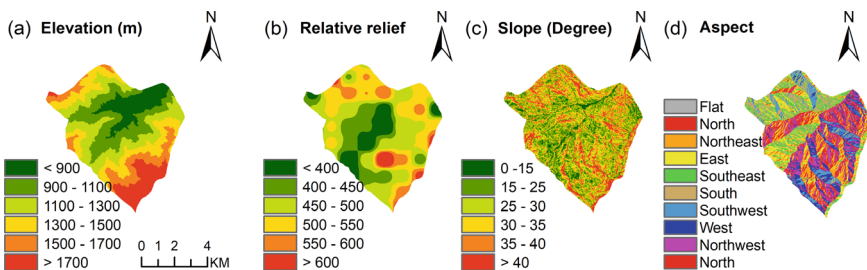


Fig. 6.3 Landslide causative factor maps: **a** Elevation, **b** Relative relief, **c** Slope, **d** Aspect

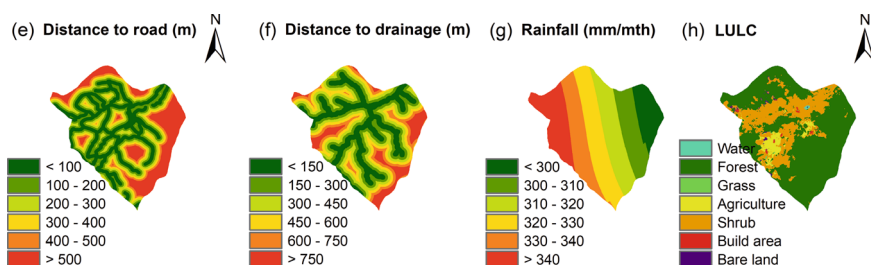


Fig. 6.4 Landslide causative factor maps: **e** Distance to road, **f** Distance to drainage, **g** Rainfall, **h** LULC

distance tool in ArcGIS. The rainfall map was produced by interpolating rainfall data from the weather stations in Laocai province. The land use map was prepared using data from the project ĐTĐL.CN-81/21. After that, we converted all factor maps to a raster format (10 m $\times$ 10 m pixels), and each factor was divided into several classes for calculating class and factor weights (Table 6.1). “Accountability” (A) and “Reliability” (R) (Abella 2008; Greenbaum et al. 1995a, b) are two estimated indicators that quantify the role of landslide causative factors in the Trung Chai area.

6.3.3.3 Data for Modeling Slope Stability in Scoops3D

The survey results were used to prepare DEM, determine the variation in soil depth and groundwater, and determine the parameters of the soil layer to evaluate slope failure conditions for the landslide site. To identify and analyze slope instability events, Scoops3D performs a systematic analysis of the DEM of a specified area determined by the analyst and a set of search-grid layers containing the sphere centers (Reid et al. 2015). Resolution—a critical parameter of the DEM, should be selected carefully and related to the object, research purpose, landslide characteristics, and analytical data response (Chang et al. 2019). Therefore, the 1.0 m DEM was used in this study for slope stability analysis. The thickness of the weathering cover on a slope, which correlates to the depth of the sliding surface, is a critical variable to consider when performing a slope stability analysis. Several models, such as GIST (Catani et al. 2010), U model (Park et al. 2013a, b), GAM and RF (Tesfa et al. 2009), and S1 model (Tran et al. 2018, 2017), may be used to assess the distribution of soil thickness. In this study, we assumed a uniform soil thickness of 5 m for the study site. For modeling pore water pressure (PWP), five options simulating PWP distribution are integrated into Scoops3D (Reid et al. 2015). The PWP simulation was conducted in this study using the pore water pressure ratio (Ru). We utilized the SLIDE model (Liao et al. 2010) to calculate the Ru value variation caused by recorded rainfall triggering slope failure. In Scoops3D, to analyze slope stability, it is necessary to define the properties of all earth materials underlying the DEM (Reid et al. 2015). Based on the actual condition of the examined slope, the layered material model

Table 6.1 Spatial relationship between landslide causative factors and landslides for the FR model

Factor	Class	% Class area	% Landslide	A	R	FR
Elevation (m)	< 900	12.70	60	100	42.58	4.72
	900–1100	21.34	40			1.87
	1100–1300	23.31	0			0
	1300–1500	19.48	0			0
	1500–1700	12.25	0			0
	> 1700	10.92	0			0
Relative relief (m/ Km ²)	< 400	12.05	10	80.36	19.92	0.83
	400–450	17.81	10			0.56
	450–500	30.62	40			1.31
	500–550	27.87	40			1.44
	550–600	8.89	0			0
	> 600	2.76	0			0
Slope (degree)	0–15	6.60	10	88.39	17.27	1.52
	15–25	25.47	30			1.18
	25–30	21.18	30			1.42
	30–35	20.93	20			0.96
	35–40	14.96	10			0.67
	> 40	10.86	0			0
Aspect	Flat	0.002	0	77.32	23.18	0
	North	8.016	10			1.25
	Northeast	14.226	20			1.41
	East	13.534	20			1.48
	Southeast	11.343	40			3.53
	South	9.661	0			0
	Southwest	8.717	0			0
	West	10.829	10			0.92
	Northwest	15.461	0			0
	North	8.211	0			0
Distance to road (m)	0–100	27.92	50	73.57	28.55	1.79
	100–200	20.63	10			0.48
	200–300	13.78	20			1.45
	300–400	9.44	10			1.06
	400–500	6.95	10			1.44
	> 500	21.28	0			0
Distance to drainage (m)	0–150	24.07	30	76.25	24.09	1.25
	150–300	21.81	40			1.83
	300–450	18.95	20			1.06

(continued)

Table 6.1 (continued)

Factor	Class	% Class area	% Landslide	A	R	FR
	450–600	14.8	10			0.68
	600–750	9.84	0			0
	> 750	10.53	0			0
Rainfall (mm/mth)	< 300	11.00	10	83.57	32.66	0.91
	300–310	14.86	30			2.02
	310–320	18.67	0			0
	320–330	22.24	50			2.25
	330–340	17.19	10			0.58
	> 340	16.04	0			0
LULC	Water	0.13	0	63.03	33.96	0
	Forest	67.21	50			0.74
	Grass	0.11	0			0
	Agriculture	4.62	0			0
	Shrub	26.91	50			1.86
	Build area	0.47	0			0
	Bare land	0.55	0			0

Table 6.2 Soil parameters used for slope stability assessment using Scoops3D

Parameters	Symbol	Unit	Value
Unit weight	γ	kN/m ³	19.3
Internal friction angle	φ	(°)	12.2
Cohesion	c	kN/m ²	15.2

was used to build an analysis model using the strength parameters of soil, including internal friction angle (φ), cohesion (c), and unit weight (γ) (Table 6.2).

6.3.4 Model Validation

The evaluation of the FR model’s performance was conducted in this study using the AUC, SCAI, and P values. The AUC value, which varies from 0.5 to 1.0 (Cantarino et al. 2019), has been widely employed to evaluate the accuracy of landslide susceptibility maps and can be divided into six categories (Šimundić 2009). The SCAI, which represents the density of landslides throughout each susceptibility class, is computed by dividing the percentage of the class area by the landslide percentage in each class (Süzen and Doyuran 2004). The *P*-value is calculated by dividing the landslide area in the upper-moderate susceptibility class (K_S) by the entire area covered by landslides (S) (Mokhtari and Abedian 2019). The efficacy assessment of the Scoops3D model

was conducted utilizing the Modified Success Rate (MSR) proposed by Huang and Kao (2006):

$$MSR = 0.5 \frac{AUU}{TAU} + 0.5 \frac{ASS}{TAS} = 0.5SR + 0.5 \frac{ASS}{TAS} \quad (6.4)$$

The SR value is calculated by dividing the number of accurately predicted landslide pixels (AUU) by the total number of actual landslide pixels (TAU). The remaining ratio is determined by dividing the accurately predicted stable pixels (ASS) by the total number of actual stable pixels (TAS).

6.4 Results and Discussion

The LSI (Fig. 6.5a) and LSZ (Fig. 6.5b) maps were generated using a bivariate statistical model to study the landslide hazards in the Trung Chai area. The “Accountability” and “Reliability” values indicated that elevation, LULC, rainfall, and distance to road are the four most influential factors in landslide occurrences. Based on the LSZ map, the Trung Chai area was categorized into five zones, including very low (25.4%), low (32.12%), medium (18.86%), high (13.69%), and very high (9.93%). Finally, the performance evaluation of the FR model was conducted using LSI and LSZ maps and historical landslides. As a result, the AUC = 83.90% (success rate), 85.75% (prediction rate), and $P = 88.69\%$ indicated the high performance of the FR model for LSM in the study area (Table 6.3). It has been determined that the SCAI value tends to decrease from moderate to very high landslide susceptibility classes. SCAI analysis results, therefore, revealed a high relationship between the prediction map and the actual landslide locations, showing that the FR model had high efficiency for LSM in the study area. In this study, the P -value also demonstrated the FR model’s high precision in LSM. Because of the limited number of landslides, the accuracy of the maps produced by the FR model may be affected. However, this model performed well in this study. The results indicated that 74.83% of the landslide area is within the very high susceptibility zones. In addition, the zone with very high landslide susceptibility contains a newly formed slope failure in the study territory. The most significant factors influencing landslide occurrences are consistent with actual landslides in the Trung Chai commune. In addition, most of the recorded landslides were identified along the main roads based on the field survey results. Landslides in the Trung Chai area were caused by an increase in slope angle (from 15° to 30°), road excavation, inadequate slope construction, or limited land-use planning, such as deforestation and building activity.

The F_s map for the landslide site is shown in Fig. 6.6, and the F_s value was divided into four categories (Mandal and Maiti 2015): stable ($F_s \geq 1.5$), moderately stable ($1.25 \leq F_s < 1.5$), quasi-stable ($1 \leq F_s < 1.25$), and unstable ($F_s < 1$). The SR and MSR values are shown in Table 6.4. The slope stability analysis by Scoops3D showed that the sliding area simulated by the model does not entirely

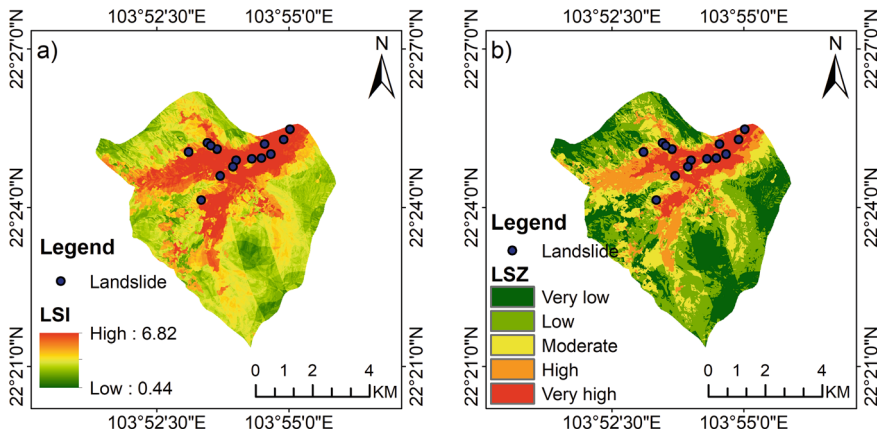


Fig. 6.5 LSI map (a) and LSZ map (b) using FR method

Table 6.3 Evaluation of model performance using SCAI and P

Class	% Area	% Landslide area	SCAI	K_S (km ²)	S (km ²)	P (%)	Success rate (%)	Prediction rate (%)
Very low	25.4	0	–	0	9.02	88.69	83.90	85.75
Low	32.12	0	–	0				
Moderate	18.86	11.31	1.67	1.02				
High	13.69	13.86	0.99	1.25				
Very high	9.93	74.83	0.13	6.75				

match the actual landslide scar. As shown in Fig. 6.6, about 51% of the cells inside the landslide scar were correctly predicted, whereas the MSR value in Table 6.4 indicates an under-predicted outcome. It’s reasonable since the Scoops3D model relies on several simplified assumptions, such as the distribution of soil depth, hydrogeological conditions, and mechanical properties of soil.

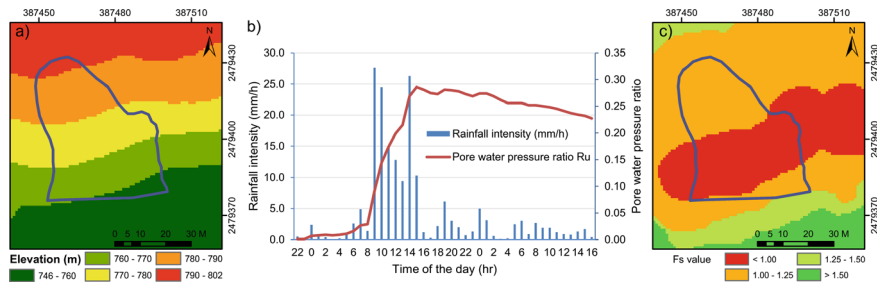


Fig. 6.6 DEM of the slope failure site (a), graph illustrating the change of Ru (b) and Fs map (c)

Table 6.4 Simulation of SR and MSR

Parameters	TAU	TAS	AUU	ASS	SR	MSR
Value	1972	6989	1002	5830	0.51	0.67

6.5 Conclusions

One approach to assessing landslide hazards and risks is to improve landslide knowledge and establish LSZ maps. Based on this idea, we conducted a landslide hazard assessment in this study using the FR and Scoops3D models. For preparing LSI and LSZ maps, eight landslide-related factors were selected and analyzed in ArcGIS. The factor selection is based on their relevance to historical landslides in the examined area and data availability. As a result, the LSZ map was established, and the study area was divided into five zones. Our classification showed that the zones related to very low and very high landslide susceptibility accounted for 9.93 and 25.4% of the entire area, respectively. Finally, we compared the prediction maps with the landslide inventory map to validate the analysis model using AUC, SCAI, and P values. These values showed the high performance of the FR model for LSM in the study area. The Scoops3D model was used for analyzing slope stability at a landslide site. The outcomes suggested that the Scoops3D model represented moderate effectiveness in predicting landslide areas. However, when the input data is trustworthy, the Scoops3D model may be a relatively effective predictor in slope stability analysis. The results of this study can be used for land-use management and long-term territorial planning. The LSZ map provides critical information, especially for the very high landslide susceptibility zone, which directly influences infrastructure development, residential area development, disaster management, landslide prevention, and natural disaster early warning.

Acknowledgements This study was sponsored by the Institute of Geological Sciences, Vietnam Academy of Science and Technology, as part of the national science and technology project under grant number ĐTĐL.CN-81/21. Additionally, the authors would like to thank the Vietnam Institute of Geosciences and Mineral Resources and Dr. Lan Chau Nguyen, University of Transport and Communications, Vietnam, for assisting with data collection.

References

- Abella EAC (2008) Multi-scale landslide risk assessment in Cuba. (Doctoral ITC dissertation), University of Utrecht, Enschede, The Netherlands, p 273
- Aleotti P, Chowdhury R (1999) Landslide hazard assessment: summary review and new perspectives. *Bull Eng Geol Environ* 58(1):21–44. <https://doi.org/10.1007/s100640050066>
- Bishop AW (1955) The use of the slip circle in the stability analysis of slopes. *Geotechnique* 5(1):7–17. <https://doi.org/10.1680/geot.1955.5.1.7>

- Cantarino I, Carrion MA, Goerlich F, Martinez Ibañez V (2019) A ROC analysis-based classification method for landslide susceptibility maps. *Landslides* 16(2):265–282. <https://doi.org/10.1007/s10346-018-1063-4>
- Catani F, Segoni S, Falorni G (2010) An empirical geomorphology-based approach to the spatial prediction of soil thickness at catchment scale. *Water Resour Res* 46(5):7450. <https://doi.org/10.1029/2008WR007450>
- Chacón J, Irigaray C, Castillo T, Hamdouni R (2006) Engineering geology maps: landslides and geographical information systems. *Bull Eng Geol Environ* 65:341–411. <https://doi.org/10.1007/s10064-006-0064-z>
- Chang K-T, Merghadi A, Yunus AP, Pham BT, Dou J (2019) Evaluating scale effects of topographic variables in landslide susceptibility models using GIS-based machine learning techniques. *Sci Rep* 9(1):12296. <https://doi.org/10.1038/s41598-019-48773-2>
- Ciurleo M, Cascini L, Calvello M (2017) A comparison of statistical and deterministic methods for shallow landslide susceptibility zoning in clayey soils. *Eng Geol* 223:71–81. <https://doi.org/10.1016/j.enggeo.2017.04.023>
- Dang KB, Burkhard B, Müller F, Dang VB (2018) Modelling and mapping natural hazard regulating ecosystem services in Sapa, Lao Cai province, Vietnam. *Paddy Water Environ* 16(4):767–781. <https://doi.org/10.1007/s10333-018-0667-6>
- Duncan JM, Wright Stephen G, Brandon Thomas L (2014) Soil strength and slope stability, 2nd edn. Wiley, Hoboken, p 336
- Galli M, Ardizzone F, Cardinali M, Guzzetti F, Reichenbach P (2008) Comparing landslide inventory maps. *Geomorphology* 94(3):268–289. <https://doi.org/10.1016/j.geomorph.2006.09.023>
- Greenbaum D, Bowker M, Dau I, Dropsy H, Greally K, McDonald AJW et al (1995a) Rapid methods of landslide hazard mapping: Fiji case study. <http://core.ac.uk/download/pdf/58059.pdf>
- Greenbaum D, Tutton M, Bowker M, Browne T, Buleka J, Greally K et al (1995b) Rapid methods of landslide hazard mapping: Papua New Guinea case study. <https://core.ac.uk/download/pdf/57306.pdf>
- Guzzetti F, Carrara A, Cardinali M, Reichenbach P (1999) Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. *Geomorphology* 31(1):181–216. [https://doi.org/10.1016/S0169-555X\(99\)00078-1](https://doi.org/10.1016/S0169-555X(99)00078-1)
- Huang JC, Kao SJ (2006) Optimal estimator for assessing landslide model performance. *Hydrol Earth Syst Sci* 10(6):957–965. <https://doi.org/10.5194/hess-10-957-2006>
- Kose DD, Turk T (2019) GIS-based fully automatic landslide susceptibility analysis by weight-of-evidence and frequency ratio methods. *Phys Geogr* 40(5):481–501. <https://doi.org/10.1080/02723646.2018.1559583>
- Krahn J (2003) The 2001 R. M. Hardy lecture: the limits of limit equilibrium analyses. *Can Geotech J* 40(3):643–660
- Lee S, Pradhan B (2007) Landslide hazard mapping at Selangor, Malaysia using frequency ratio and logistic regression models. *Landslides* 4(1):33–41. <https://doi.org/10.1007/s10346-006-0047-y>
- Lee S, Talib JA (2005) Probabilistic landslide susceptibility and factor effect analysis. *Environ Geol* 47(7):982–990. <https://doi.org/10.1007/s00254-005-1228-z>
- Liao Z, Hong Y, Wang J, Fukuoka H, Sassa K, Karnawati D, Fathani F (2010) Prototyping an experimental early warning system for rainfall-induced landslides in Indonesia using satellite remote sensing and geospatial datasets. *Landslides* 7(3):317–324. <https://doi.org/10.1007/s10346-010-0219-7>
- Mandal S, Maiti R (2015) Semi-quantitative approaches for landslide assessment and prediction. Springer, Singapore, p 292
- Mokhtari M, Abedian S (2019) Spatial prediction of landslide susceptibility in Taleghan basin, Iran. *Stochast Environ Res Risk Assess* 33(7):1297–1325. <https://doi.org/10.1007/s00477-019-01696-w>
- Park DW, Nikhil NV, Lee SR (2013a) Landslide and debris flow susceptibility zonation using TRIGRS for the 2011 Seoul landslide event. *Natl Hazards Earth Syst Sci* 13(11):2833–2849. <https://doi.org/10.5194/nhess-13-2833-2013>

- Park HJ, Lee JH, Woo I (2013b) Assessment of rainfall-induced shallow landslide susceptibility using a GIS-based probabilistic approach. *Eng Geol* 161:1–15. <https://doi.org/10.1016/j.enggeo.2013.04.011>
- Pradhan B, Lee S (2010) Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia. *Landslides* 7(1):13–30. <https://doi.org/10.1007/s10346-009-0183-2>
- Rashid B, Iqbal J, Su L-J (2020) Landslide susceptibility analysis of Karakoram highway using analytical hierarchy process and scoops 3D. *J Mount Sci* 17(7):1596–1612. <https://doi.org/10.1007/s11629-018-5195-8>
- Reid ME, Christian SB, Brien DL (2000) Gravitational stability of three-dimensional stratovolcano edifices. *J Geophys Res Solid Earth* 105(B3):6043–6056. <https://doi.org/10.1029/1999JB900310>
- Reid E, Christian SB, Brien DL, Henderson ST (2015) Scoops3D: software to analyze 3D slope stability throughout a digital landscape. <https://doi.org/10.3133/tm14A1>
- Roy J, Saha S, Arabameri A, Blaschke T, Bui DT (2019) A novel ensemble approach for landslide susceptibility mapping (LSM) in Darjeeling and Kalimpong Districts, West Bengal, India. *Remote Sens* 11(23):2866. <https://doi.org/10.3390/rs11232866>
- Šimunčić A-M (2009) Measures of diagnostic accuracy: basic definitions. *EJIFCC* 19(4):203–211
- Süzen ML, Doyuran V (2004) A comparison of the GIS based landslide susceptibility assessment methods: multivariate versus bivariate. *Environ Geol* 45(5):665–679. <https://doi.org/10.1007/s00254-003-0917-8>
- Tesfa TK, Tarboton DG, Chandler DG, McNamara JP (2009) Modeling soil depth from topographic and land cover attributes. *Water Resour Res* 45(10):1–16. <https://doi.org/10.1029/2008WR007474>
- Tien Bui D, Tuan TA, Klempe H, Pradhan B, Revhaug I (2016) 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. <https://doi.org/10.1007/s10346-015-0557-6>
- Tien Bui D, Tuan TA, Hoang N-D, Thanh NQ, Nguyen DB, Van Liem N, Pradhan B (2017) Spatial prediction of rainfall-induced landslides for the Lao Cai area (Vietnam) using a hybrid intelligent approach of least squares support vector machines inference model and artificial bee colony optimization. *Landslides* 14(2):447–458. <https://doi.org/10.1007/s10346-016-0711-9>
- Tran TV, Lee G, Trinh MT, An H (2017) Effect of digital elevation model resolution on shallow landslide modeling using TRIGRS. *Natl Hazards Rev* 18(2):1–12. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000233](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000233)
- Tran TV, Alvioli M, Lee G, An HU (2018) Three-dimensional, time-dependent modeling of rainfall-induced landslides over a digital landscape: a case study. *Landslides* 15(6):1071–1084. <https://doi.org/10.1007/s10346-017-0931-7>
- Tran TV, Hoang VH, Pham HD, Sato G (2020) Use of Scoops3D and GIS for the assessment of slope stability in three-dimensional: a case study in Sapa, Vietnam. In: Paper presented at the proceedings of the international conference on innovations for sustainable and responsible mining (ISRM 2020), Hanoi
- Vakhshoori V, Zare M (2016) Landslide susceptibility mapping by comparing weight of evidence, fuzzy logic, and frequency ratio methods. *Geomat Natl Hazards Risk* 7(5):1731–1752. <https://doi.org/10.1080/19475705.2016.1144655>
- van Westen CJ, Castellanos E, Kuriakose SL (2008) Spatial data for landslide susceptibility, hazard, and vulnerability assessment: an overview. *Eng Geol* 102(3):112–131. <https://doi.org/10.1016/j.enggeo.2008.03.010>
- Yalcin A, Reis S, Aydinoglu AC, Yomralioglu T (2011) A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey. *CATENA* 85(3):274–287. <https://doi.org/10.1016/j.catena.2011.01.014>

Zhang S, Wang F (2019) Three-dimensional seismic slope stability assessment with the application of Scoops3D and GIS: a case study in Atsuma, Hokkaido. *Geoenviron Disast* 6(1):9. <https://doi.org/10.1186/s40677-019-0125-9>