Influence of the landslide inventory sampling on the accuracy of the susceptibility modelling using Random Forests: A case study from the NW Croatia

Marko Sinčić[(1)*], Sanja Bernat Gazibara[(1)], Mauro Rossi[(2)], Martin Krkač[(1)], Hrvoje Lukačić[(1)], Snježana Mihalić Arbanas[(1)]

1) University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Pierottijeva 6, 10000 Zagreb, Croatia (msincic@rgn.hr)

2) Research Institute for Geo-Hydrological Protection, Italian National Research Council (CNR IRPI), Via della Madonna Alta 126, 06128 Perugia, Italy

Abstract The quality of landslide susceptibility maps depends on the quality of the input data, i.e. the spatial resolution and accuracy of the landslide conditioning factor maps and the completeness and accuracy of the landslide inventory map. For the pilot areas (40 km^2) in NW Croatia, a detailed landslide mapping was done based on visual interpretation of high-resolution LiDAR DTM. This study aims to test the relevance of landslide inventory completeness and sampling on the landslide susceptibility model. Moreover, by analysing different scenarios, i.e. different ratios of landslides for model training and validation and sampling of landslide location and morphological conditions, we aim to provide new insight into the need for detailed landslide mapping for large-scale susceptibility modelling, as well as the impact on the landslide susceptibility map. Landslide susceptibility modelling was performed based on 5 m pixel-based analysis and Random Forests machine learning method. The landslide susceptibility analysis consists of nine scenarios that were defined considering the percentage of landslide polygons in the inventory for model training (S1 = 90%, S2 = 80 %, S3 = 70%, etc.). Furthermore, three more scenarios were defined based on sampling strategy, i.e. original terrain inside landslide polygon, smooth terrain inside landslide polygon and original buffer around landslide boundary. Landslide susceptibility performance was measured with the Area Under the ROC Curve (AUC) metric. The results are part of the scientific research project “Methodology development for landslide susceptibility assessment for land-use planning based on LiDAR technology” (LandSlidePlan, HRZZ IP-2019-04-9900). The purpose of comparing landslide susceptibility models is to define the most suitable methodology for application in the Croatian spatial planning system at the local level.

Keywords landslide susceptibility modelling, sampling strategy, landslide inventory, large-scale, random forests

Introduction

Landslide susceptibility presents the spatial element of a landslide occurrence (Guzzetti et al. 2005), further resulting in zonation maps which depict homogenous areas of an equal degree of susceptibility (Fell et al. 2008), whose applicability is welcomed in spatial and urban planning (Mihalić Arbanas et al. 2023). As identified in a recent and most comprehensive review paper Reichenbach et al. 2018, researchers in statistically-based susceptibility modelling are eager to experiment with parameters, leading to certain conclusions about each of the suggested steps for developing landslide susceptibility assessments. Namely, mapping units (Jacobs et al. 2020), statistical models, (Chen et al. 2017), inventory types (Guzzetti et al. 2012) and landslide conditioning factors (LCFs) (Gaidzik and Ramírez 2021) are some of the topics of interest. Considering sampling strategies (i.e. the scope of this research), stable areas are often discussed in recent years (Fu et al. 2023), but the most common approach is still random sampling. Similarly, polygon sampling (Farooq and Akram 2021) and point sampling (Hemasinghe et al. 2018) remain the two most common landslide sampling strategies. Süzen and Doyuran, 2004 introduced seed cells as areas which sample undisturbed terrain, i.e. settings prior to the landslide occurrence, whereas several comprehensive comparisons of landslide sampling strategies are given in Hussin et al. 2016. Most researchers opt for a larger training over validation landslide dataset, e.g. Lucchese et al. 2021, whereas an equal amount of stable and unstable areas is usually ensured (Xi et al. 2022).

The objective of this research is to provide preliminary information about the influence of landslide sampling strategies using a representative and LiDAR (Light Detection and Ranging) based landslide inventory. Two approaches are defined in a large scale 5 m pixel analysis using Random Forests (RF) to model small and shallow landslides. Namely, the amount of training landslides is tested in Podsljeme zone pilot area, varying from 10 to 90% with a 10% increment resulting in nine scenarios. On the other hand, in Hrvatsko Zagorje pilot area, two scenarios based on capturing undisturbed terrain approach are defined alongside one regular polygon sampling scenario as a reference point. For each of the 12 models, Area Under the Curve (AUC) is calculated, followed by a discussion and drawing out conclusions about the two approaches in the two pilot areas in NW Croatia.

Study area

For large-scale landslide susceptibility modelling, two pilot areas approximately 20 km² in size each were selected to investigate the landslide inventory completeness and sampling strategies of unstable areas. Namely, Podsljeme zone and Hrvatsko Zagorje are located in NW Croatia (Fig. 1), being a part of the Pannonian basin where small and shallow landslides commonly occur in soil and soft rock. Both pilot areas are predominantly hilly with steep slopes (Sinčić et al. 2022a; Bernat Gazibara et al. 2023a) where intensive rainfall and snowmelt are considered the main triggering factors for landslide occurrence, recorded as Multiple-Occurrence Regional Landslide Events (MORLE) (Bernat et al. 2014a,b). Administratively, the Podsljeme zone is an urbanized part of the City of Zagreb, unlike the Hrvatsko Zagorje pilot area, which belongs to the rural parts of the City of Lepoglava and the Bednja Municipality in the Varaždin County. Previous landslide susceptibility assessments conducted in the pilot areas include Bernat Gazibara et al. 2023a in Podsljeme zone and Krkač et al. 2023 and Bernat Gazibara et al. 2023b in Hrvatsko Zagorje.

Figure 1 Podsljeme zone and Hrvatsko Zagorje pilot areas, located in NW Croatia (modified after Bernat Gazibara et al. 2022)

Material

Landslide and thematic data represent the two necessary input datasets for statistically-based landslide susceptibility modelling and should be acquired according to the scope of the analysis (Reichenbach et al. 2018). Acquiring a representative landslide inventory map for large-scale landslide susceptibility modelling of small and shallow landslides commonly located in vegetated areas is challenging, leaving LiDAR as the optimal remote sensing approach (Razak et al. 2011). Namely, for both pilot areas airborne laser scanning was performed, resulting in approximately 30 cm average point spacing of bare earth ground points (Bernat Gazibara et al. 2022). After thorough mapping of the high-resolution digital terrain model (DTM) derivatives followed by field verification, representative polygon based landslide inventory maps are presented in Bernat Gazibara et al. 2019 and Krkač et al. 2022 for Podsljeme zone and Hrvatsko Zagorje, respectively. With an approximate landslide density of 33 per square kilometre in the Podsljeme area and 45 in Hrvatsko Zagorje, landslide management in terms of a landslide susceptibility assessment is imperative (Mihalić Arbanas et al. 2023).

Considering the scale of the analysis, great attention was given to developing LCFs of appropriate spatial accuracy. Namely, a variety of different data sources were considered, leading to specific procedures in preparing certain LCFs, e.g. improving geological and anthropogenic LCFs (Sinčić et al. 2022a). Scarce of thematic data can often be the case for undeveloped regions, leaving remote sensing data such as LiDAR point cloud and orthophoto imagery as an affordable and appropriate solution. On the other hand, free and available datasets are often used in small-scale and can be of good use for regional landslide susceptibility assessments (Sinčić et al. 2022b). Driven by experience and preliminary research, a final list of LCFs used for two pilot areas is given in Table 1, grouped as geomorphological, hydrological, geological or anthropogenic.

Table 1 List of used LCFs in Podsljeme zone and Hrvatsko Zagorje pilot areas.

LCF group	Landslide conditioning factor (LCF)	Podsljeme zone	Hrvatsko Zagorje
Geomor-phological	Elevation*	YES	YES
	Slope*	YES	YES
	Aspect*	YES	YES
	Landform curvature*	NO	YES
Hydrological	Proximity to drainage network	YES	YES
	Site exposure index*	NO	YES
	Integrated moisture index*	NO	YES
	Compound Topographic index	YES	NO
	Proximity to streams	YES	NO
Geolo-gical	Soil/rock type	YES	YES
	Proximity to geological contact	YES	YES
	Proximity to faults	YES	NO
Antropo-genic	Land use	YES	YES
	Proximity to land use contact	NO	YES
	Proximity to traffic infrastructure	NO	YES

*DTM based LCFs, smoothened for S_S scenario

Methodology

General susceptibility modelling workflow

After acquiring relevant landslide and thematic data, landslide susceptibility modelling requires certain parameters to be selected in each of the modelling steps. Namely, a 5 m pixel is selected as a mapping unit (Bernat Gazibara et al. 2023b) for Random Forests (RF) machine learning algorithm. A pixel based analysis is commonly used in landslide susceptibility assessments (Reichenbach et al. 2018), whereas RF as a method was introduced in Breiman 2001, followed by numerous applications in susceptibility modelling (e.g. Catani et al. 2013 and Sandić et al. 2023), and nowadays often analysed in algorithm review papers as a successful method choice (Merghadi et al. 2020). As most of the data processing and evaluation metrics were conducted jointly in ArcMap 10.8 and Microsoft Excel, the "*Statistics and Machine Learning Toolbox*" (The MathWorks, Inc., 2021) in MATLAB software was used to perform the RF method. Moreover, it should be stated that LCF collinearity was tested prior to the susceptibility modelling by using a Pearson's R absolute value of 0.5 as the cut-off threshold to ensure no collinearity presence. The latter was performed in R software, using an open-source software LAND-SUITE (Rossi et al. 2022). As we experiment with different sampling strategies, we opted for an equal comparison strategy as commonly used fitting and predictive performance would not result in objective conclusions. Namely, for each landslide susceptibility model, a curve is plotted by defining cumulative landslide area against cumulative susceptibility area with a 0.01 interval of probabilistic value to calculate AUC. As defined in Chung and Fabbri 1999 and Chung and Fabbri 2003, this is used to measure success and prediction rate (e.g. in bivariate analysis Moazzam et al. 2020 and Sinčić et al. 2022b) by examining training and validation landslides, respectively. In our case, all landslides will be examined to emphasize applicability on a local scale, i.e. measuring classification capabilities of the models for all mapped landslides only. Moreover, this metric is the basis for the zonation method applicable in the Croatian local scale spatial planning system (Bernat Gazibara et al. 2023a). In both pilot areas, the equal procedure to define stable pixels is as follows. By removing training landslides from the pilot area, an extent where stable pixels can be generated is defined, ensuring unbiased sampling. Namely, the stable pixels are generated randomly and as single units, in an equal amount as there are unstable pixels in the training landslide dataset. On the other hand, unstable pixel sampling differs greatly from model to model and is explained in detail separately for each pilot area.

Podsljeme zone pilot area

All landslide polygons in the Podsljeme zone are firstly split randomly into ten equal-in-size sets. Then, scenario S1 is defined by using nine sets for training (i.e. 90%), followed by using eight sets (i.e. 80%) for training in scenario S2, etc., up to scenario S9 which uses only one set (i.e. 10%) for training the model. Scenarios S1 to S9 define the nine models derived in the Podsljeme zone with the purpose of testing landslide inventory representatives and its possibility to yield satisfactory results with a limited training landslide.

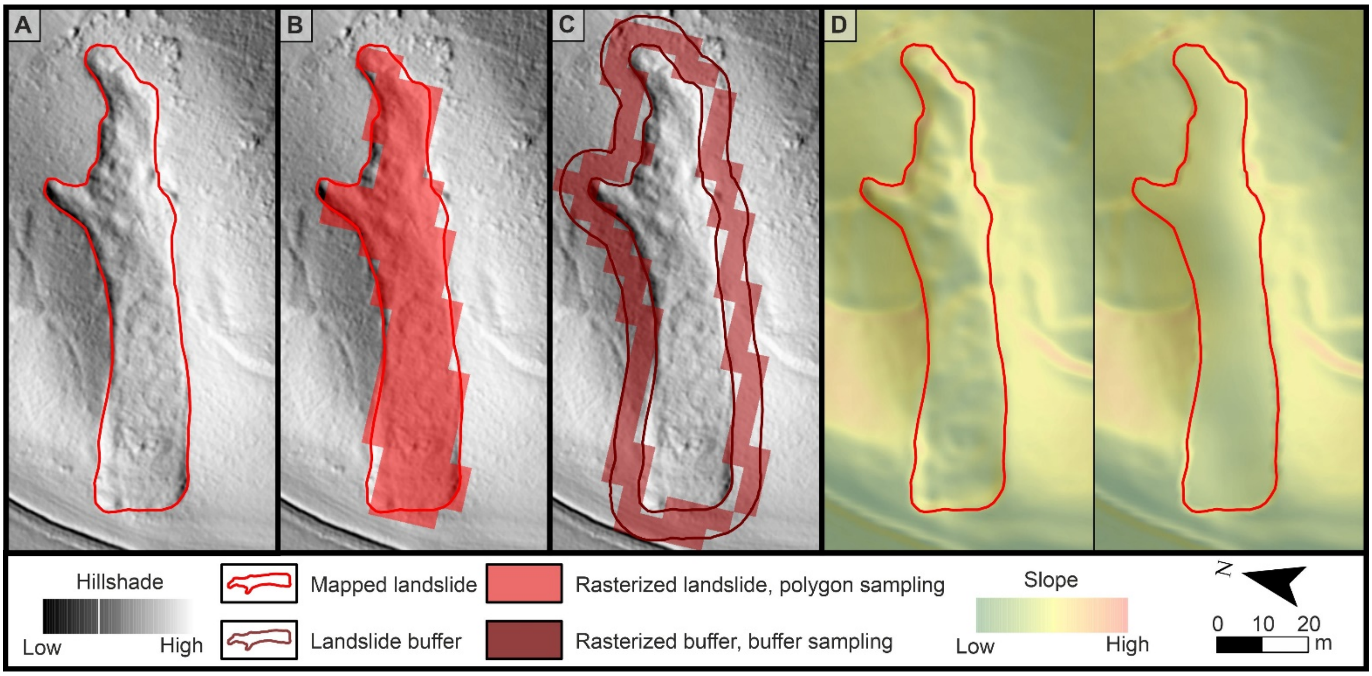

Figure 2 An example of mapped landslide (A) and sampling methodologies for scenarios S_P (B), S_B (C) and S_S (D) in the Hrvatsko Zagorje pilot area.

Hrvatsko Zagorje pilot area

The landslide inventory is split into two equal sets, using one half differently to train the model in each of the three scenarios in Hrvatsko Zagorje. The first scenario S_P samples rasterized polygons ("P"), as does the second scenario S_S. However, in the S_S scenario, DTM based LCFs are smoothened ("S") at all landslide locations prior to the modelling. By buffering ("B") a 6.25m zone around the landslides, a sampling zone for scenario S_B is defined, using exclusively the rasterized pixels from the buffered zone. Smoothened LCFs for S_S scenario are noted with an asterisk (*) in Table 1, whereas Fig. 2 illustrates the described sampling methodology. Commonly used strategy as in scenario S_P serves for comparison (a reference point), whereas scenarios S_S and S_B aim to capture the geomorphologically undistributed terrain conditions, i.e. prior to landslide occurrence.

Results and discussion

Testing nine different amounts of landslides included in training the model ranging from 10 to 90% was tested in the Podsljeme zone. Namely, the AUC results are as follows: S1-0.98, S2-0.97, S3-0.96, S4-0.95, S5-0.94, S6-0.92, S7-0.91, S8-0.89 and S9-0.86 (Fig. 3). Surprisingly, results indicate excellent performance in all scenarios when measuring the classification capabilities for all landslides. A general declining trend in AUC values is evident as the amount of training landslides decreases, i.e. from 90% (S1) to 10% (S9). As this is not surprising, however, even a rigorous S9 scenario managed to yield high AUC, indirectly pointing to very high predictive performance of the model. We argue that the presented results are due to the systematic and complete mapping which resulted in a representative landslide inventory. Thus, we highlight the benefits and emphasize the capabilities of such a landslide inventory map even in rigorous landslide susceptibility modelling. Moreover, compared to approximately 0.86 AUC values for fitting and predictive performance in Bernat Gazibara et al. 2023a where 50% of the landslide were used for training, an evident increase in performance is noted. Namely, scenario S5 using 50% of training landslides in this study resulted in 0.94 AUC values, likely due to the use of machine learning instead of bivariate methodology. Different findings are found in the Hrvatsko Zagorje where S_P, S_S and S_B scenarios resulted in 0.88, 0.89 and 0.80 AUC values, respectively (Fig. 3). The minimal change in scenario S_s is not surprising as a small portion of the study area was altered, whereas a significant decrease to 0.80 in scenario S_B is undoubtedly a drastic decrease in model performance. Compared to previous landslide susceptibility assessments, i.e. Krkač et al. 2023 and Bernat Gazibara et al. 2023b, a significant increase is seen in S_P and S_S scenarios, likely due to the application of the RF method. In both cases, we reckon that a more detailed analysis is necessary to deliver a complete and comprehensive conclusion about the sampling scenarios, whereas in this research, we identified preliminary model behaviour for the given settings. For instance, measuring the variability, fitting and predictive performance (individually), as well as zoning the model (and analysing it qualitatively) into an applicable map for local scale application remains a task out of the scope of this research.

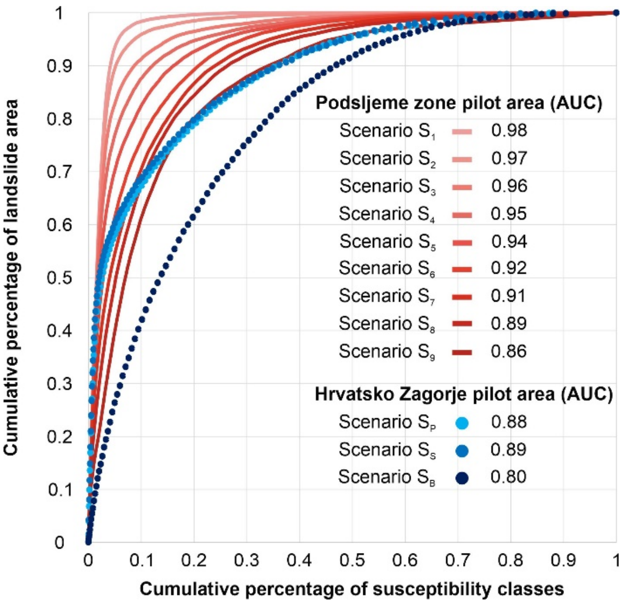

Figure 3 Calculated AUC values for scenarios in Podsljeme zone and Hrvatsko Zagorje pilot areas.

Conclusions

This study aimed to preliminary investigate the landslide inventory sampling in landslide susceptibility modelling of small and shallow landslides present in NW Croatia. One approach was tested in the Podsljeme zone where landslide training amount was reduced from 90 to 10% in nine equal steps. In the Hrvatsko Zagorje we opted for common polygon sampling, smoothing the DTM derived LCFs at landslide locations and buffering the landslides as two scenarios simulating undistributed terrain conditions, i.e. prior to landslide occurrence. In both pilot areas, used landslide inventories are representative and mapped based on high resolution DTM derivatives, used in combination with reliable LCFs for a 5 m pixel based analysis by applying the RF algorithm. Furthermore, AUC which considered all landslides was calculated, serving as a metric unifying fitting and predictive performance.

Generally, satisfactory results were achieved in both pilot areas for all defined scenarios, with generally better results in the Podsljeme zone. Scenario S_B is the only scenario which yielded significantly lower AUC values, i.e. 0.80 and can be considered as a less favorable strategy. On the other hand, using smoothened DTM derived LCFs led to an insignificantly AUC increase compared to the S_P scenario. The most interesting finding in Podsljeme zone is that using only 10% of landslides for training can yield an AUC of 0.86. For both cases, using additional metrics and assessing the models qualitatively considering possible zoning methods is likely to unveil more significant differences in the sampling strategies. Compared to previous landslide susceptibility assessments in the study area, a general increase in AUC is noted, likely due to the RF method.

A further approach considering the experiment in the Podsljeme zone could be splitting the pilot area spatially, unlike randomly as in this research. Similarly, simultaneously experimenting with stable and unstable area sampling in the Hrvatsko Zagorje pilot area is likely to yield new insight into the sampling strategies, as it is uncommon in the literature.

Acknowledgements

This research has been fully supported by the Croatian Science Foundation under the project 'Methodology development for landslide susceptibility assessment for land-use planning based on LiDAR technology', LandSlidePlan (HRZZ IP-2019-04-9900, HRZZ DOK-2020-01-2432) and by Institutional project 311980036 ModKLIZ, co-funded by the Faculty of Mining, Geology and Petroleum Engineering.

References

Bernat S, Mihalić Arbanas S, Krkač M (2014a) Inventory of precipitation triggered landslides in the winter of 2013 in Zagreb (Croatia, Europe). Proceedings of World Landslide Forum 3, 2-6 June 2014. Springer, Cham. pp. 829-836.

Bernat S, Mihalić Arbanas S, Krkač M (2014b) Landslides triggered in the continental part of Croatia by extreme precipitation in 2013. Proceedings of the XII IAEG Congress, 15-19 September 2014. Springer, Heidelberg. pp. 1599–1603.

Bernat Gazibara S, Krkač M, Mihalić Arbanas S (2019) Landslide inventory mapping using LiDAR data in the City of Zagreb (Croatia). Journal of Maps 15:773–779. https://doi.org/10.1080/17445647.2019.1671906.

Bernat Gazibara S, Sinčić M, Krkač M, Lukačić H, Mihalić Arbanas S (2023a) Landslide susceptibility assessment on a large scale in the Podsljeme area, City of Zagreb (Croatia). Journal of Maps 19:1. https://doi.org/10.1080/17445647.2022.2163197.

Bernat Gazibara S, Mihalić Arbanas S, Sinčić M, Krkač M, Lukačić H, Jagodnik P, Arbanas Ž (2022) LandSlidePlan -Scientific research project on landslide susceptibility assessment in large scale. Proceedings of the 5th regional symposium on landslides in Adriatic-Balkan Region, 23-26 March 2022. University of Rijeka, Faculty of Civil Engineering, Rijeka, Croatia and University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Zagreb, Croatia. pp. 99–106.

Bernat Gazibara S, Sinčić M, Rossi M, Reichenbach P, Krkač M, Lukačić H, Jagodnik P, Šarić G, Mihalić Arbanas S (2023b) Application of LAND-SUITE for Landslide Susceptibility Modelling Using Different Mapping Units: A Case Study in Croatia. Progress in Landslide Research and Technology, Volume 2 Issue 2. Alcántara-Ayala I, Arbanas Ž, Huntley D, Konagai K, Mihalić Arbanas M, Mikoš M, Ramesh MV, Sassa K, Sassa S, Tang H, Tiwari B (eds.). Springer, Cham, Fullerton, CA, USA. (ISBN 978-3-031-44295-7). 503p.

Breiman L (2001) Random Forests. Machine Learning 45:5–32. https://doi.org/10.1023/A:1010933404324.

Catani F, Lagomarsino D, Segoni S, Tofani V (2013) Landslide susceptibility estimation by random forests technique: sensitivity and scaling issues. Natural Hazards and Earth System Sciences 13:2815–2831. https://doi.org/10.5194/nhess-13-2815-2013.

Chen W, Xie X, Wang J, Pradhan B, Hong H, Bui DT, Duan Z, Ma J (2017) A comparative study of logistic model tree, random forest, and classification and regression tree models for spatial prediction of landslide susceptibility. Catena 151:147–160. https://doi.org/10.1016/j.catena.2016.11.032.

Chung CJF, Fabbri AG (1999) Probabilistic Prediction Models for Landslide Hazard Mapping. Photogrammetric Engineering and Remote Sensing 65:1389–1399.

Chung CJF, Fabbri AG (2003) Validation of Spatial Prediction Models for Landslide Hazard Mapping. Natural Hazards 30:451–472. https://doi.org/10.1023/B:NHAZ.0000007172.62651.2b.

Farooq S, Akram MS (2021) Landslide susceptibility mapping using information value method in Jhelum Valley of the Himalayas. Arabian Journal of Geosciences 14:824. https://doi.org/10.1007/s12517-021-07147-7.

Fell R, Corominas J, Bonnard C, Cascini L, Leroi E, Savage WZ (2008) Guidelines for landslide susceptibility, hazard and risk zoning for land use planning. Engineering Geology 102:85–98. https://doi.org/10.1016/j.enggeo.2008.03.022.

Fu Z, Wang F, Dou J, Nam K, Ma H. (2023) Enhanced Absence Sampling Technique for Data-Driven Landslide Susceptibility Mapping: A Case Study in Songyang County, China. Remote Sensing 15, 3345. https://doi.org/10.3390/rs15133345.

Gaidzik K, Ramírez-Herrera MT (2021) The importance of input data on landslide susceptibility mapping. Scientific Reports 11:19334. https://doi.org/10.1038/s41598-021-98830-y.

Guzzetti F, Reichenbach P, Cardinali M, Galli M, Ardizzone F (2005) Probabilistic landslide hazard assessment at the basin scale. Geomorphology 72, 272–299. http://dx.doi.org/10.1016/j.geomorph.2005.06.002.

Guzzetti F, Mondini AC, Cardinali M, Fiorucci F, Santangelo M, Chang K-T (2012) Landslide inventory maps: New tools for an old problem. Earth- Science Reviews 112:42–66. https://doi.org/10.1016/j.earscirev.2012.02.001.

Hemasinghe H, Rangali RSS, Deshapriya NL, Samarakoon L (2018) Landslide susceptibility mapping using logistic regression model (a case study in Badulla District, Sri Lanka). Procedia Engineering 212:1046–1053. https://doi.org/10.1016/j.proeng.2018.01.135.

Hussin HY, Zumpano V, Reichenbach P, Sterlacchini S, Micu M, van Westen C, Bălteanu D (2016) Different landslide sampling strategies in a grid-based bi-variate statistical susceptibility model. Geomorphology, 253, 508–523. https://doi.org/10.1016/j.geomorph.2015.10.030.

Jacobs L, Kervyn M, Reichenbach P, Rossi M, Marchesini I, Alvioli M, Dewitte O (2020) Regional susceptibility assessments with heterogeneous landslide information: Slope unit- vs. pixel-based approach. Geomorphology 356:107084. https://doi.org/10.1016/j.geomorph.2020.107084.

Krkač M, Bernat Gazibara S, Sinčić M, Lukačić, H, Mihalić Arbanas S (2022) Landslide inventory mapping based on LiDAR data: A case study from Hrvatsko Zagorje (Croatia) Proceedings of the 5th regional symposium on landslides in Adriatic-Balkan Region, 23-26 March 2022. University of Rijeka, Faculty of Civil Engineering, Rijeka, Croatia and University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Zagreb, Croatia. pp. 81–86.

Krkač M, Bernat Gazibara S, Sinčić M, Lukačić H, Šarić G, Mihalić Arbanas S (2023) Impact of input data on the quality of the landslide susceptibility large-scale maps: A case study from NW Croatia. Progress in Landslide Research and Technology, Volume 2 Issue 1. Alcántara-Ayala I, Arbanas Ž, Cuomo S, Huntley D., Konagai K, Mihalić Arbanas S, Mikoš M, Sassa K, Tang H, Tiwari B (eds). Springer, Cham, Fullerton, CA, USA. (ISBN 978-3-031-39011-1). 482p.

Lucchese LV, de Oliviera GG, Pedrollo OC (2021) Investigation of the influence of nonoccurrence sampling on landslide susceptibility assessment using Artificial Neural Networks. Catena 198, 105067 https://doi.org/10.1016/j.catena.2020.105067.

Mihalić Arbanas S, Bernat Gazibara S, Krkač M, Sinčić M, Lukačić H, Jagodnik P, Arbanas Ž (2023) Landslide Detection and Spatial Prediction: Application of Data and Information from Landslide Maps. Progress in Landslide Research and Technology, Volume 1 Issue 2. Alcantara-Ayala I, Arbanas Ž, Huntley D, Konagai K, Mikoš M, Sassa K, Sassa S, Tang H, Tiwari B (eds.). Springer, Cham, Fullerton, CA, USA. (ISBN 978-3-031-18470-3). 475p.

Merghadi A, Yunus AP, Dou J, Whiteley J, ThaiPham B, Bui DT, Avtar R, Abderrahmane B (2020) Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. Earth- Science Reviews 207:103225. https://doi.org/10.1016/j.earscirev.2020.103225.

Moazzam MFU, Vansarochana A, Boonyanuphap J, Choosumrong S, Rahman G, Djueyep GP (2020) Spatio-statistical comparative approaches for landslide susceptibility modeling: case of Mae Phun, Uttaradit Province, Thailand. SN Applied Sciences, 2(3). https://doi.org/10.1007/s42452-020-2106-8.

Razak KA, Straatsma MW, van Westen CJ, Malet JP, de Jong SM (2011) Airborne laser scanning of forested landslides characterization: terrain model quality and visualization. Geomorphology 126, 186–200.

Reichenbach P, Rossi M, Malamud BD, Mihir M, Guzzetti F (2018) A review of statistically-based landslide susceptibility models. Earth-Science Reviews 180:60–91. https://doi.org/10.1016/j.earscirev.2018.03.001.

Rossi M, Bornaetxea T, Reichenbach P (2022) LAND-SUITE V1.0: a suite of tools for statistically based landslide susceptibility zonation. Geoscientific Model Development 15:5651–5666. https://doi.org/10.5194/gmd-15-5651-2022.

Sandić C, Marjanović M, Abolmasov B, Tošić R (2023) Integrating landslide magnitude in the susceptibility assessment of the City of Doboj, using machine learning and heuristic approach. Journal of Maps 19:1. https://doi.org/10.1080/17445647.2022.2163199.

Sinčić M, Bernat Gazibara S, Krkač M, Lukačić H, Mihalić Arbanas S (2022a) The Use of High-Resolution Remote Sensing Data in Preparation of Input Data for Large-Scale Landslide Hazard Assessments. Land (Basel) 11:1360. https://doi.org/10.3390/land11081360.

Sinčić M, Bernat Gazibara S, Krkač M, Mihalić Arbanas S (2022b) Landslide susceptibility assessment of the City of Karlovac using the bivariate statistical analysis. Rudarsko-geološko-naftni zbornik 37:149–170. https://doi.org/10.17794/rgn.2022.2.13.

Süzen ML, Doyuran V (2004) Data driven bivariate landslide susceptibility assessment using geographical information systems: a method and application to Asarsuyu catchment, Turkey. Engineering Geology 71(3-4):303-321 https://doi.org/10.1016/S0013-7952(03)00143-1.

The MathWorks Inc. (2021) Statistics and Machine Learning Toolbox: 12.1 (R2021), Natick, Massachusetts: The MathWorks Inc. https://www.mathworks.com [Last accessed: 29.2.2024.].

Xi C, Han M, Hu X, Liu B, He K, Luo G, Cao X (2002) Effectiveness of Newmark-based sampling strategy for coseismic landslide susceptibility mapping using deep learning, support vector machine, and logistic regression. Bulletin of Engineering Geology and the Environment 81, 174. https://doi.org/10.1007/s10064-022-02664-5.