https://doi.org/10.18485/resylab.2024.6.ch20

Large-scale landslide susceptibility models: Examples and conclusions from the modelling of small and shallow landslides in the continental part of Croatia

Sanja Bernat Gazibara[(1)*], Marko Sinčić[(1)], Mauro Rossi[(2)], Martin Krkač[(1)], Hrvoje Lukačić[(1)], Petra Jagodnik[(3)], Snježana Mihalić Arbanas[(1)]

1) University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering, Pierottijeva 6, 10000 Zagreb, Croatia, +38515535760 (sbernat @rgn.unizg.hr)

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

3) Faculty of Civil Engineering, University of Rijeka, Radmile Matejčić 3, 51000 Rijeka, Croatia

Abstract Large-scale landslide susceptibility modelling is carried out in the frame of the scientific project *Methodology development for landslide susceptibility assessment for land-use planning based on LiDAR technology* (LandSlidePlan, HRZZ IP-2019-04-9900) on two pilot areas in the City of Zagreb and Hrvatsko Zagorje. The methodology includes defining input data quality, landslide sampling strategies, mapping units, applied statistical method, and zonation method for providing final landslide susceptibility maps. Finally, all landslide susceptibility models were evaluated based on model fitting performance, model prediction performance, and model uncertainty. The purpose of comparing landslide susceptibility models was to define the most suitable methodology for modelling small and shallow landslides in the continental part of Croatia and application in spatial planning systems at a local level. The main results and conclusions were compiled in guidelines for large-scale landslide inventory and susceptibility map production based on high-resolution remote sensing data.

Keywords landslide susceptibility modelling, large-scale, spatial planning system

Introduction

The main motivation to research the large-scale landslide susceptibility modelling for application in spatial planning systems arises from the national landslide risk assessment (Bernat Gazibara et al. 2019), which recognised landslides as a second natural risk in Croatia. The scientific project *Methodology development for landslide susceptibility assessment for land-use planning based on LiDAR technology* (LandSlidePlan, HRZZ IP-2019-04-9900) has three main scientific goals (Bernat Gazibara et al. 2022): (i) to create the optimal digital model of the bare-earth terrain that shows realistic landslide footprints and differences between landslide and non-landslide area that may influence land use; (ii) to create the most reliable large-scale landslide susceptibility map with the optimal differentiation of landslide-prone and non-susceptible areas using scientific methods customised to specific engineering geological conditions of Croatian environments, and (iii) to create maps depicting information about landslides for the application in land-use planning. The research was based on innovative technologies, limitations related to the availability of spatial data in Croatia (limited amount of geological data), and urgent needs for efficient solutions applicable in the Croatian spatial planning system in line with European and global requirements related to sustainable development, human and environmental protection. This paper presents an overview of the several research papers published in the frame of the LandSlidePlan project. Furthermore, main project results and conclusions regarding input data quality, landslide sampling strategies, mapping units, statistical methods, and zonation for providing accurate and reliable landslide susceptibility maps are given.

Study areas were selected based on similar geological settings and geomorphological conditions but different degrees of urbanisation in the NW part of Croatia (Fig.1): the pilot area (20 km^2) in the urbanised part of the Podsljeme area, City of Zagreb and the pilot area (20 km^2) in a rural part of Hrvatsko Zagorje. Part of the Podsljeme area of the City of Zagreb was selected as a pilot area because of hilly relief, a high degree of urbanisation, and Neogene and Quaternary deposits extremely susceptible to landslides. The pilot area in Hrvatsko Zagorje is composed of Miocene, Quaternary and Triassic sediments. Landslides in this area mainly occur in weathered clastic rocks and soils of Miocene age. Precipitations and human activity are the primary triggers of landslides in NW Croatia (Bernat et al. 2014). Landslides can be classified as shallow to moderately shallow (1 – 20 m) and small (10^1 - 10^3 m^2), based on abundant landslide size, which is approx. 500 m^2.

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

Landslide susceptibility modelling

Input data

Airborne laser scanning (ALS) was undertaken during the leaf-off period in March 2020, resulting in a point cloud for the Hrvatsko Zagorje pilot area with a surface point horizontal accuracy of 3 cm and vertical accuracy of 4 cm, point density of 16.09 pt./m², and average point spacing of 0.28 cm. The bare-earth digital terrain model (DTM) with a 30 cm resolution using the kriging interpolation method was created for visual landslide identification and mapping, while 5 m LiDAR DTM was created for large-scale landslide susceptibility modelling.

The input data for landslide susceptibility assessment (LSA) on a large scale were analysed for the study area in Hrvatsko Zagorje. The result of the visual interpretation of LiDAR DTM morphometric derivatives is the landslide inventory map, which consists of 912 identified and mapped landslides, ranging in size from 3.3 to 13,779 m² and with an average landslide density of 45.1 landslides/km² (Krkač et al. 2022). Sinčić et al. (2022a) compared the geographic and thematic consistency of different geoenvironmental input data sets to address the adequate scale of input data to minimise deviations from actual environmental conditions. The spatial distribution of the classes in landslide conditioning factors was compared using a LiDAR-based landslide inventory map, pointing out the influence of small-scale input data sets on a large-scale LSA. Fig. 2 shows the comparison of slope classes and landslide area distributions for different DTM resolutions available for the study area. Geological data are often available only on a small scale, e.g. in the Republic of Croatia, only The Basic Geological Map on a scale of 1:100,000 is available for most of the territory, which is inadequate for large-scale LSA. Using a combination of geological data from small-scale geological maps to get acquainted with geological settings and terrain information from high-resolution LiDAR data enables distinguishing the geological settings in more detail, improving geological contacts, and aggregating chronostratigraphic units into engineering formation units, which are more suitable for LSA (Sinčić et al. 2022a). However, the limitations of this approach could be the presence of different geological settings across the study area, in which engineering units cannot be distinguished from the LiDAR DTM derivatives. Sinčić et al. (2022a) concluded that the high-resolution remote sensing data, LiDAR DTM, and orthophoto images are optimal input data sets for large-scale LSA because they enable the following: (i) derivation of geomorphological, geological, hydrological, and anthropogenic input data layers on a large scale, except geological structures and spring data; (ii) verification of input data layers; (iii) derivation of input data layers with the best fit to the actual environmental conditions (spatial accuracy testing); and (iv) efficient derivation of input data layers considering both price and time.

Furthermore, Krkač et al. (2023) compared two different input data sets to derive landslide causal factor maps for landslide susceptibility analysis, i.e. scenarios: (i) Scenario 1 included free-available input data sets with a lower resolution and lower spatial accuracy, such as EU-DEM or Corine Land Cover; and (ii) Scenario 2 included a more detailed input data set, such as high-resolution remote sensing data, i.e. LiDAR point cloud and digital orthophoto imagery in resolution 0.5 m. The landslide data used for susceptibility analysis was LiDAR-based inventory (Krkač et al. 2022). The success and prediction rates for Scenario 1 were approximately 10 % lower than the values for Scenario 2. Moreover, landslide susceptibility maps looked relatively similar based on visual comparison, although the most significant difference between the two scenarios is the percentage of low landslide susceptibility values in valleys. Considering the stated, the landslide susceptibility map based on causal factors derived from high-resolution remote sensing data (Scenario 2) has minor deviations from actual environmental conditions. i.e., the spatial accuracy of the resulting LSA is significantly higher, which is not sufficiently emphasized by the obtained AUC values Krkač et al. (2023).

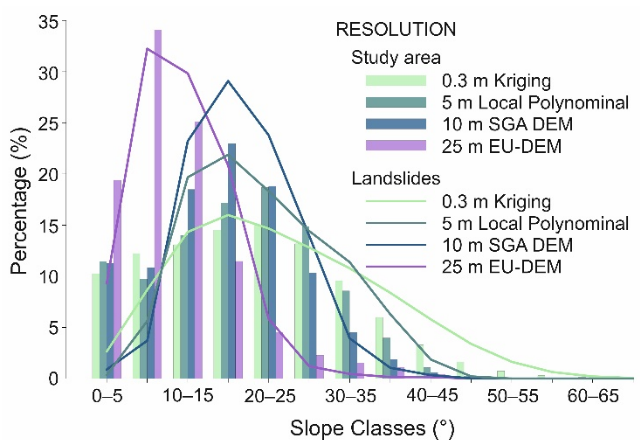

Figure 2 Comparison of slope class area and landslide area distribution on the slope maps derived from 0.3 and 5 m LiDAR DTMs, 10 m DEM, and 25 m EU-DEM (modified after Sinčić et al. 2022a).

Defining the most significant landslide causal factors (LCF) in a study area is one of the most important steps in susceptibility modelling. Bernat Gazibara et al. (2023a) evaluated a large number of geomorphological, geological, hydrological and anthropogenic data as variables for the study area in Hrvatsko Zagorje since general criteria or guidelines for the selection of causal factors for susceptibility modelling are not available. In this work, appropriate LCFs were selected based on the pairwise correlation test and Leave One Out test in LAND-SUITE developed by Rossi et al. (2022). Only six were selected from the 22 original factor maps, considering the lack of variable relevance on the susceptibility model and following the rule "less is more", avoiding over-parameterisation issues. LAND-SUITE proved to be a helpful tool for landslide susceptibility variable analysis and allows the preparation of susceptibility maps of the highest Susceptibility Quality Level, i.e., SQL index, as illustrated in Reichenbach et al. (2018).

Landslide sampling strategy

Bernat Gazibara et al. (2023b) and Sinčić et al. (2024a) analysed different ratios of landslides for model training and validation for the Podsljeme zone pilot area, to provide new insight into the need for detailed landslide mapping for large-scale susceptibility modelling, as well as the impact on the final landslide susceptibility map. The landslide susceptibility analysis consists of ten scenarios that were defined considering the percentage of landslide polygons in the inventory for model training (S100 = 100% of landslides in the LiDAR-based inventory, S90 = 90 % of landslides, S70 = 70% of landslides, etc.), while the rest of the landslides were used for model validation (S90 = 10% of landslides in the LiDAR-based inventory, S70 = 30 % of landslides, etc.). The presented analyses showed that using 70% of inventory landslides for model training (S70) resulted in the model having a training AUC value of 98.1 %. Using half of the landslide inventory for training (S50) keeps the training AUC value higher than 98 %, and the model trained with only 10 % of inventory landslides (S10) resulted in training AUC value higher than 99 %. Using the same 30 % of landslides in the inventory for model validation in scenarios S70, S50, S30, and S10 showed variability of AUC value from 89,4 %, 89 %, 89,2 %, to 87 %. Fig 3. shows the spatial distribution of the absolute difference in probabilistic values of landslide susceptibility models (LSM) regarding scenario S100 and scenarios S90, S70, S50 and S10. Lastly, comparing ten derived susceptibility models, more than 10% of the study area showed a standard deviation of probability values of more than 0.1. The question of minimising the influence of the landslide data sampling on the final large-scale landslide susceptibility zonation maps remains open. However, the research highlights the importance of qualitative assessment, alongside commonly used quantitative metrics, to verify spatial accuracy and to test the applicability of derived LSM in the spatial planning system.

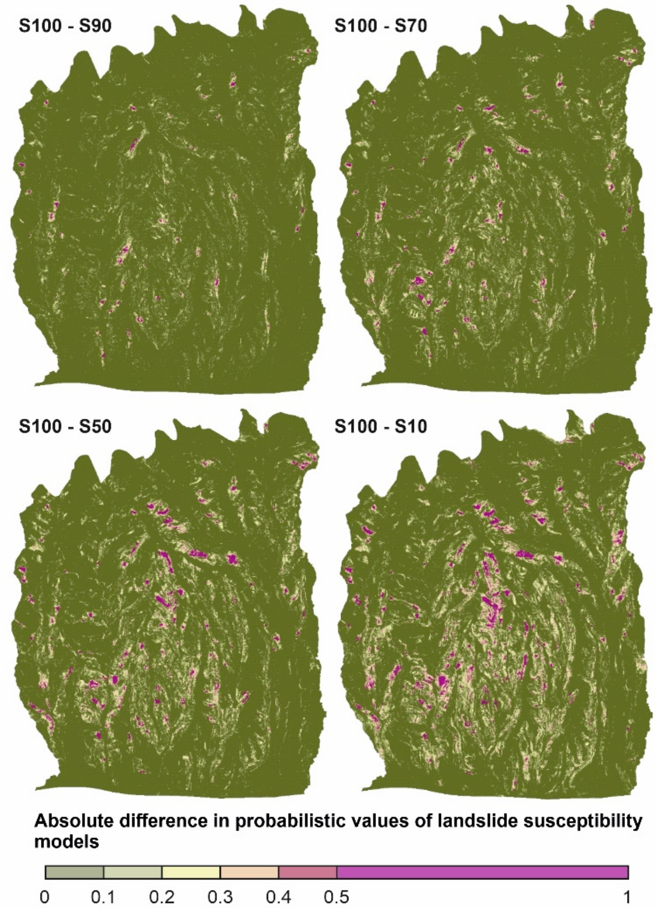

Figure 3 Absolute difference in probabilistic values of landslides susceptibility models regarding scenario S100 (using 100% of landslides in the inventory) and scenarios S90 (using 90 % of landslides), S70, S50 and S10.

Statistical methods

The selection of an appropriate mapping unit and statistical method is a critical phase in landslide susceptibility modelling (Reichenbach et al. 2018). Bernat Gazibara et al. (2023a) considered 5 m x 5 m regular grid cells and slope units (Alvioli et al. 2016) for the Podsljeme pilot area to analyse the effect of different statistical methods on training LSM for application on a local level, i.e. scale 1:5,000. LAND-SUITE was used to prepare landslide susceptibility maps, i.e., four single statistical models (Logistic regression, Linear and Quadratic discriminant analysis, and Neural network analysis) and one combined model for the two mapping units. All model evaluation tests indicate pixel-based models have better model fitting and predictive performance than slope-unit based models, regardless of the statistical method. The probability of landslide occurrence for each of the ten models was classified into five susceptibility classes, based on threshold values 0.2, 0.45, 0.55, 0.8 (Bernat Gazibara et al. 2023a). The pixel and slope unit-based maps displayed differences in the information detail, indicating that pixel-based models are more appropriate for the local-level spatial planning system. However, pixel-based maps require "post-processing" of the susceptibility zones to produce more clustered and homogeneous information for the final purpose.

Sinčić et al. (2024b) focused their work on the crucial step of classifying continuous landslide conditioning factors for susceptibility modelling in the Podsljeme pilot area by presenting an innovative, comprehensive analysis that resulted in 54 landslide susceptibility models to test 11 classification criteria (scenarios which vary from stretched values, partially stretched classes, heuristic approach, classification based on studentized contrast and landslide presence, and commonly used classification criteria, such as Natural Neighbor, Quantiles and Geometrical intervals) in combination with five statistical methods (Information Value (IV), Logistic Regression (LR), Neural Network (NN), Random Forests (RF) and Support Vector Machine (SVM)). The main conclusions and novelties derived from the comprehensive large-scale landslide susceptibility analysis that Sinčić et al. (2024b) performed are the following: (i) applying input data layers as stretched rasters and line vectors as buffers with >10 buffer zones prove more reliable simplifies the susceptibility modelling process and provides a uniform solution to preparing LCFs; (ii) optimal method selection remains an open question and generally should be considered regarding the final applicability of the LSA, whereas LR method presents the most stable and representative option, and the RF method offers optimal performance when appropriately applied, achieving far better performance. Fig. 4 shows a close-up view comparison of the landslide susceptibility maps derived using four statistical methods, while input data in all four scenarios are the same. Overall, the SVM method (Fig. 4d) on a close-up view shows minimal pixelization, i.e. depicting zones rather than pixel shaped transfer from class to class. RF method (Fig. 4c) proves its poorest predictive performance, with a substantial amount of visible validation landslides in low or very low susceptibility zones.

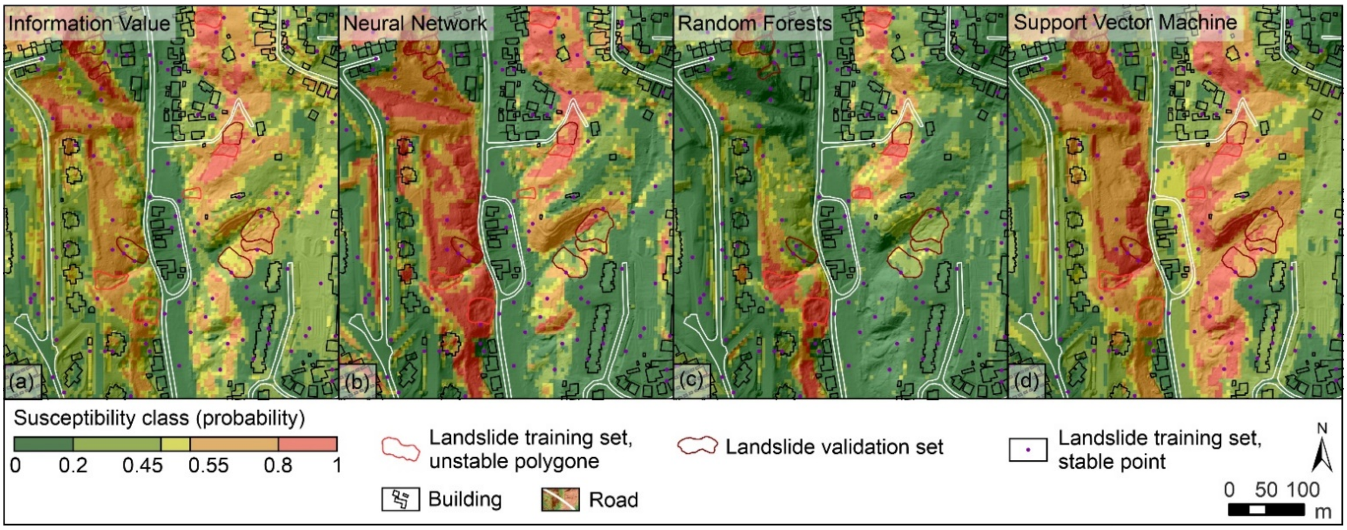

Figure 4 Close-up views of landslide susceptibility maps derived using four statistical methods: (a) Information Value; (b) Neural Network; (c) Random Forests; (d) Support Vector Machine (modified after Sinčić et al. 2024b).

Landslide susceptibility zoning

The landslide susceptibility models obtained through statistical analyses need to be interpreted; that is, a probability classification must be carried out that results in a landslide susceptibility zonation map. By reviewing the world literature, there are no uniform recommendations for landslide susceptibility zonation, and different authors apply different methods. For the application of landslide susceptibility zonation maps in the spatial planning system of the Republic of Croatia, it is recommended to use three zonation classes, i.e. low, medium and high landslide susceptibility zones (Mihalić Arbanas et al. 2023). Threshold values of landslide susceptibility zones are defined by the ROC curve (Fig. 5), i.e., all landslides in the inventory are observed for zonation purposes, and the probabilistic LSM ranging from 0.0 to 1.0 is split into 100 classes with a 0.01 interval to construct the ROC curve.

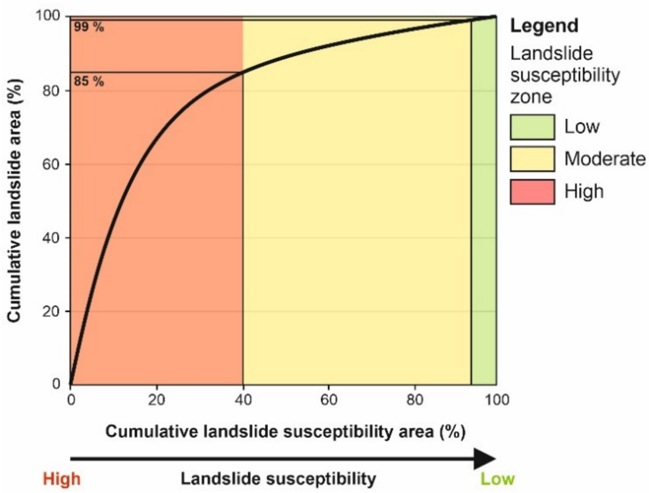

Figure 5 Landslide susceptibility zoning using the ROC curve and threshold values based on cumulative landslide area.

Furthermore, cut-off values for zonation are set to 85% and 99% of cumulative landslide area presence, similar to the approach introduced by Bernat Gazibara, 2019 and applied in Sinčić et al. 2022b and Bernat Gazibara et al. 2023c. As a result, high, medium and low susceptibility zones are defined: (i) low susceptibility zone is defined with only 1 % landslide presence, (ii) medium susceptibility zone is defined with 14 % landslide presence, and (iii) high susceptibility zone is defined with 85 % landslide presence. The proposed zonation method defines distinct landslide density in a particular landslide susceptibility zone and thus enables the regulation of preventative measures for landslide mitigation through the spatial planning system.

After landslide susceptibility zonation, it is necessary to generalize the final map so that the susceptibility zones are relatively homogeneous, which enables simple and unambiguous practical use in the spatial planning system. Generalization involves averaging and filtering the landslide susceptibility zone values obtained for each pixel by applying focal statistics. A close-up view of the susceptibility model, susceptibility zonation map, and a final, generalized landslide susceptibility map is shown in Fig. 6. Generalization of the landslide susceptibility zonation map must preserve the model's spatial accuracy and differences in the susceptibility zone areas should be minimal after processing with focal statistics.

.

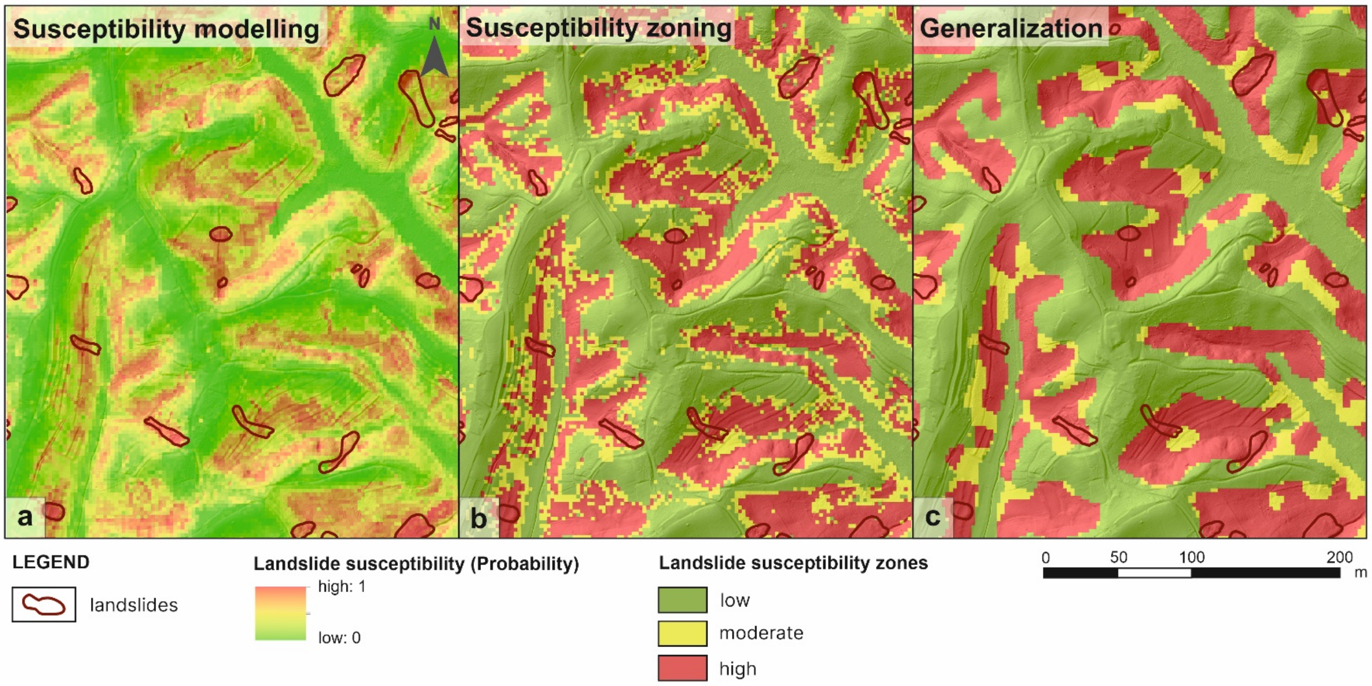

Figure 6 Production of final landslide susceptibility zonation map through three steps: (a) landslide probability after susceptibility modelling; (b) landslide susceptibility map after zonation; (c) final landslide susceptibility map after generalization.

Conclusion

In the framework of the LandSlidePlan project, more than 500 landslide susceptibility models were derived for two pilot areas in NW Croatia regarding differences in resolution and quality of input data, variations of causal factors, geometrical type of LiDAR-based inventory, landslide sampling strategies, mapping units, statistical methods, and zonation methods for providing final landslide susceptibility maps. The main conclusions from the derived comprehensive large-scale landslide susceptibility analysis are:

(i) relevant and high-resolution input data with sufficient spatial accuracy will result in highly reliable LSM (Krkač et al. 2023) performed by any statistical method or any LCF classification scenario (Sinčić et al. 2024b);

(ii) landslide sampling significantly influences the spatial accuracy of derived LSM (Bernat Gazibara et al. 2023b, Sinčić et al. 2024a);

(iii) pixel-based models are more appropriate mapping units for the local-level spatial planning system than slope unit-based models, resulting in more detailed susceptibility information, but also require "post-processing" of the susceptibility zones to produce more clustered and homogeneous information for the final purpose;

(iv) optimal method selection remains an open question and generally should be considered regarding the final applicability of the LSA, whereas in the study Sinčić et al. 2024b, the LR method presents the most stable and representative option, and the RF method offers optimal performance when appropriately applied, achieving far better performance;

(v) qualitative assessment, alongside commonly used quantitative metrics, is mandatory to verify spatial accuracy and to test the applicability of derived LSM (Sinčić et al. 2024b).

In landslide science, a large number of published works deal with different aspects of landslide mapping or susceptibility modelling; however, very few of these works focus on the development of landslide susceptibility methodologies that can be applied in spatial planning, construction or civil protection systems. One of the most significant results of the LandSlidePlan project is the guidelines for the compilation and application of large-scale landslide maps in Croatia's spatial planning system (Bernat Gazibara et al. 2023d). Guidelines are designed to introduce future landslide map makers with recommendations based on a review of existing literature and conclusions from scientific research on the LandSlidePlan project. The guidelines contain definitions of basic terms and terminology related to landslides, descriptions of landslide map types and landslide hazard zoning levels, recommendations for creating large-scale landslide inventory and susceptibility zoning maps, and recommendations on the application of landslide maps for sustainable spatial management, with a focus on spatial planning and construction system.

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

Alvioli M, Marchesini I, Reichenbach P, Rossi M, Ardizzone F, Fiorucci F, Guzzetti F (2016) Automatic delineation of geomorphological slope units with r.slopeunits v1.0 and their optimisation for landslide susceptibility modelling. Geoscientific Model Development 9:3975–3991. https://doi.org/10.5194/gmd-9-3975-2016

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 Gazibara S (2019) Methodology for landslide mapping using high resolution digital elevation model in the Podsljeme area (City of Zagreb). Doctoral thesis, Faculty of Mining, Geology and Petroleum Engineering, University of Zagreb. (in Croatian)

Bernat Gazibara S, Cindrić Kalin, K, Erak M, Krkač M, Đomlija P, Arbanas Ž, Mihalić Arbanas S (2019) Landslide hazard analysis in national-scale for landslide risk assessment in Croatia. Proceedings of the 4th Regional Symposium on Landslides in the Adriatic-Balkan Region,23-25 October 2019. Geotechnical Society of Bosnia and Herzegovina, Sarajevo, Bosnia and Herzegovina. pp. 175-182.

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 (2023a) 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.

Bernat Gazibara S, Sinčić M, Krkač M, Jagodnik P, Lukačić H, Mihalić Arbanas S (2023b) Influence of the landslide inventory completeness on the accuracy of the landslide susceptibility modelling: A case study from the City of Zagreb (Croatia). Abstract book of the 6th World Landslide Forum "Landslide science for sustainable development", 14-17 November 2023. OIC S.r.l., Firenze, Italy. pp. 644-644.

Bernat Gazibara S, Sinčić M, Krkač M, Lukačić H, Mihalić Arbanas S (2023c) 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, Sinčić M, Krkač M, Jagodnik P, Mihalić Arbanas S (2023d) Guidelines for the development of landslide maps in Croatia. Faculty of Mining, Geology and Petroleum Engineering, University of Zagreb, Zagreb, Croatia, 56p. (in Croatian)

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.

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.

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.

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.

Sinčić M, Bernat Gazibara S, Rossi M, Krkač M, Lukačić H, Mihalić Arbanas A (2024a) Influence of the landslide inventory sampling on the accuracy of the susceptibility modelling using Random Forests: A case study from the NW Croatia. Proceedings of the 6th regional symposium on landslides in Adriatic – Balkan Region, 15-18 May 2024. (under review)

Sinčić M, Bernat Gazibara S, Rossi M, Mihalić Arbanas S (2024b), Comparison of conditioning factors classification criteria in large scale statistically based landslide susceptibility models. Natural Hazards and Earth System Sciences (under review). https://doi.org/10.5194/nhess-2024-29