Retrospective evaluation of landslides susceptibility maps for selected area of the Stará Ľubovňa district

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Abstract: Landslide research has long been a primary focus for engineering geologists. In recent years, the occurrence of significant slope deformations has garnered attention due to climate change and abrupt weather fluctuations. As a result, there is a growing need for accurate prediction of landslide events that is both cost-effective and technically feasible. Quantitative statistical analyses and modelling within a Geographical Information System (GIS) have emerged as valuable methods for this purpose. Despite their widespread use, there is limited evidence regarding the effectiveness of susceptibility maps in predicting landslide locations. Most studies primarily assess the success of the prediction model itself, without evaluating whether newly occurring landslides align with the predicted areas. To address this gap, we propose a retrospective evaluation using real data. We compiled landslide hazard susceptibility maps using a dataset of registered landslides up to 2010. We then verified the accuracy of these maps using a dataset of newly registered landslides that occurred between 2010 and 2014. This approach allows for a more comprehensive assessment of the success of the compiled maps in predicting actual landslide occurrences.

Keywords: landslides, susceptibility maps, multivariate analysis, retrospective evaluation, Stará Ľubovňa

1. INTRODUCTION

The overarching objective in slope deformation research is to develop an accurate forecast that can reliably predict future landslide occurrences (Tornyai & Dunčko, 2013). The utilization of Geographical Information Systems (GIS) has proven to be highly suitable in conjunction with interdisciplinary studies on factors contributing to landslide risk. GIS has significantly advanced the development of landslide hazard forecasting. In recent years, numerous scientific papers have been published on the statistical analysis of landslide hazards using GIS (Chang et al., 2008; Shahabi & Hashim, 2015; Tornyai et al., 2016; Anis et al., 2019; Buša et al., 2019; Azeze, 2021; Mersha & Meten, 2020; Roccati et al., 2021; Ye et al., 2022; Zhao et al., 2022; Das et al., 2023).

Statistical methods for predicting landslide hazards rely on an accurate comparison of the spatial distribution of existing landslides in a given area with the spatial distribution of various parameters that serve as independent input variables (Tornyai & Dunčko, 2013). The processing of landslide hazards and predictions is based on the principle of geological actualization, which suggests that landslides will occur in areas where they have previously occurred or under similar activation conditions (Pauditš et al., 2014). Selected factors that influence the initiation and progression of slope movements are represented as parametric maps, which are then integrated into the statistical evaluation process within the GIS environment.

The investigated area is situated in northeast Slovakia in the Prešov region (Fig. 1). It extends through the center of the Stará Ľubovňa district and covers the territory of 17 communes. Namely Pilhov, Mníšek nad Popradom, Hraničné, Kremná, Veľký Sulín, Malý Sulín, Matysová, Malý Lipník, Stará Ľubovňa, Chmeľnica, Hajtovka, Hniezdne, Nová Ľubovňa, Plavnica, Kolačkov, Jakubany and Šambron.

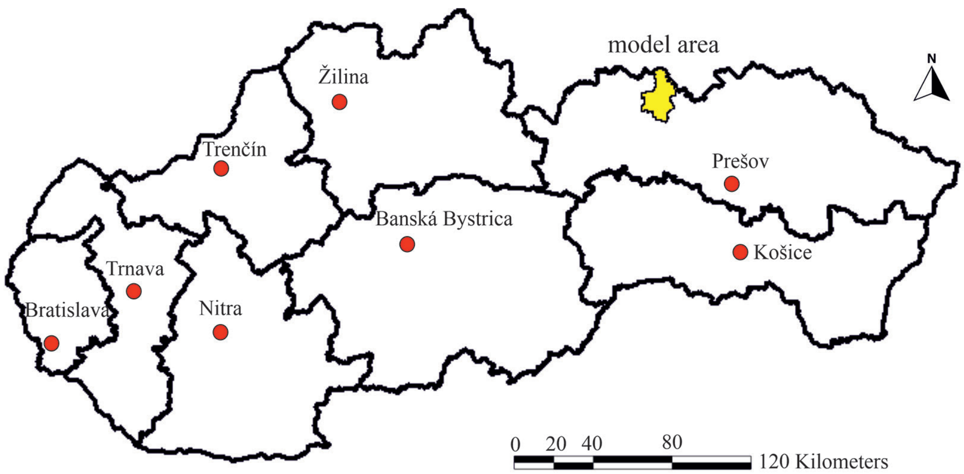

Fig. 1 Geographic location of the investigated area of the Stará Ľubovňa district

2. METHODS

The outcomes of the statistical evaluation of landslide

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hazard in GIS are typically presented in the form of landslide susceptibility maps (LSMs). These maps divide the area into three or five spatial zones, each representing a specific level of susceptibility to slope deformation. The construction of LSMs can incorporate various parameters and can be achieved through different methodologies. Among the commonly used statistical techniques for LSM modelling are bivariate analysis (BA) and multivariate analysis (MA). In the traditional approach of bivariate analysis, the relationship between landslide occurrence and individual parameters is examined. However, this method may require certain adjustments and can be influenced by the subjective judgment and expertise of the researcher. On the other hand, multivariate analysis is considered more suitable for landslide assessment. It accounts for multiple parameters simultaneously and provides a more comprehensive evaluation. Multivariate analysis is also less computationally and time-intensive compared to bivariate analysis, making it a preferred approach (Pauditš et al., 2014).

2.1. Multivariate statistical analysis for prognosing landslide hazard in GIS

Multivariate analysis (MA) in the context of GIS involves the simultaneous utilization of all input parameters. In the GIS environment, both vector and raster graphics are employed for MA. The vector form is utilized to process individual input parameters as parametric maps. These vector parametric maps are then converted into raster form for statistical analysis using map algebra. It is crucial to accurately define the geometry of the raster grid when converting from vector to raster format. Specifically, each input parametric map must have the same number of cells with identical sizes. Failure to ensure this consistency can lead to unreliable and unusable results. For this study, a grid size of 10 x 10 meters was selected as the baseline.

The MA process generates a table that includes all combinations of categories from the overlapping input maps (Bednarik et al., 2014). This is achieved by simultaneously combining the input parametric maps, resulting in new areal features represented as quasi-homogeneous unique conditional units (UCUs) (Clerici, 2002). The subsequent step in MA involves comparing the UCU map with the evaluation data (in this case, the slope deformation map). The resulting combinations of the UCU map and the evaluated data are assigned values of 1 (indicating true, i.e., the occurrence of slope deformation) or 0 (indicating false, i.e., no slope deformation). These combinations are then ranked based on the calculated intensity of occurrence and extrapolated.

The final step entails reclassifying the map into 3 or 5 categories based on the statistical distribution. This classification represents the different levels of landslide hazard within the study area. For this study, two statistical distributions—natural breaks (NB) and quantile (Q)—were chosen and modelled using ArcGIS.

2.2. Retrospective evaluation based on comparison of LSMs with newly registered landslide inventory

Once the landslide susceptibility map (LSM) has been generated, evaluating its predictive value becomes crucial. The primary criterion used to assess the quality of the LSM is the construction of a success model that examines the relationship between the forecast and the map of recorded slope deformations. The success model typically compares the density of landslides in the recorded slope deformation map with the different susceptibility grades in the prognosis landslide susceptibility map (Bednarik et al., 2014). The precision or accuracy of the model is commonly evaluated using ROC curves (Receiver Operating Characteristic) and PR (Prediction Rate) curves.

While many susceptibility maps achieve high validation scores in ROC and PRC evaluations, often around 80% (Fleuchaus et al., 2021), it is important to note that these validations only test the landslides used to create the map or the landslides extracted from the dataset before processing the susceptibility map as a test dataset. As a result, these evaluations may be misleading, as they only demonstrate the success of the prediction model and not whether newly formed landslides occur in the predicted areas.

In contrast, retrospective evaluation involves validating the success of susceptibility maps using a dataset of newly formed landslides. In this study, we verified the degree of success of the constructed LSMs through a simple yet effective and sufficient method of retrospective validation. The LSMs were overlaid with a raster map of newly registered slope deformations recorded between 2010 and 2014. A total of 102 newly registered landslides were used for retrospective validation. Most of them occurred in 2010 due to extreme amounts of precipitation, especially in the east of Slovakia. Initially, statistical verification in ArcGIS compared the spatial distribution of landslides from the raster map of registered slope deformations with the areas classified as medium, high, and very high landslide hazard (corresponding to classes 3, 4, and 5) in the selected susceptibility map. The resulting analysis produced a table where each category of landslide hazard indicated the percentage representation of the landslide area within its territory. Additionally, a qualitative approach based on knowledge-based judgment was employed to evaluate the entire map in terms of the occurrence of new landslides, without providing a percentage representation of the map's success.

3. INPUT PARAMETERS

The stability of slopes is influenced by various factors, including geography, geomorphology, geology, climate, hydrogeology, vegetation, and human activities. When conducting statistical analysis for landslide hazard assessment, the selection of input parameters is crucial. These parameters represent the factors that influence the occurrence of slope movements. In this particular study, nine parameters were chosen to enter the multivariate analysis (MA).

The selected parameters include:

Lithology: The type of rock or soil material present in the slope.

Elevation: The height of the land surface above sea level.

Slope orientation: The compass direction towards which the slope faces.

Slope gradient: The steepness of the slope, typically expressed as a percentage or angle.

Slope length: The horizontal distance of the slope.

Contributing areas: The areas that contribute water and sediment to the slope.

Relief curvature: The curvature of the land surface.

Landscape cover: The type and extent of vegetation or land cover on the slope.

Past slope deformations: Historical records or data of previous slope movements.

By incorporating these nine parameters into the multivariate analysis, the study aims to assess their collective influence on slope stability and landslide hazard. ArcGIS version 10.2 software was used to process all parametric maps (Fig. 2).

3.1. Parametric map of lithological units

The lithology parameter is considered essential because the physical and mechanical properties resulting from the composition of rocks play a significant role in slope stability. To obtain information about the geological structure of the study area in the Stará Ľubovňa district, a digital geological map at a scale of 1:50,000 was utilized (Káčer et al., 2005). The original digital geological map was available in vector format and based on the S-JTSK coordinate system. To align the geological map with the topographic base at a scale of 1:10,000, modifications and adjustments were made.

The original geological map consisted of 34 lithological units, representing different rock types. However, for the purpose of multivariate statistical analysis, it is necessary to reduce the number of lithological units into a smaller number of classes while retaining important geological information. Through an initial reclassification process, the number of lithological classes was reduced to 13, allowing for a more manageable dataset. The modified geological map in vector format was subsequently converted to raster format, which is suitable for statistical processing and integration with other parameters in the multivariate analysis.

3.2. Digital elevation model (DEM)

A Digital Elevation Model (DEM) is a dataset that represents the spatial distribution of elevation values across a given area. It consists of a set of numbers stored in computer memory, where each number represents the elevation of a specific area or pixel. DEMs provide a discrete representation of the relief in a continuous manner.

To derive morphometric parameters and analyse the terrain, the DEM needs to be processed using raster analysis tools in a Geographical Information System (GIS) (Hofierka, 2003). In this study, the input data for creating and calculating the DEM were contour lines from a vector topographic map at a scale of 1:10,000, obtained from the Geodetic and Cartographic Institute (GKÚ) in Bratislava (https://www.geoportal.sk/).

The contour lines were used to create the raster DEM, where each cell in the raster represents a specific elevation value. To simplify the DEM and make it more manageable for analysis, the raster model was reclassified into integer values based on hypsographic degrees. In the Stará Ľubovňa district, a height step of 100 meters was chosen, meaning that the elevation values in the DEM were grouped into discrete categories based on intervals of 100 meters. This reclassification allows for easier interpretation and analysis of the terrain characteristics within the study area.

3.3. Parametric map of slope gradient

The slope gradient grid, in digital form, is a matrix that represents the magnitudes of the gradients of the scalar field of elevations derived from the Digital Elevation Model (DEM) (Hofierka, 2003). The slope gradient refers to the steepness or inclination of the terrain at each location and is typically measured in degrees ranging from 0° (horizontal) to 90° (vertical). To calculate the slope gradient in degrees, the DEM data is used. By analysing the elevation values of neighbouring cells in the DEM, the change in elevation over a given distance is determined, which corresponds to the slope gradient. The result is a grid or matrix where each cell contains the slope gradient value at that particular location. This information allows for the characterization of the terrain's steepness and identifies areas with varying degrees of slope inclination.

The slope gradient is an important parameter used in various geospatial analyses, such as terrain classification, hydrological modelling, and slope stability assessments. It provides valuable information for understanding the terrain morphology and identifying areas that may be prone to erosion, landslides, or other slope-related processes.

3.4. Parametric map of slope orientation

The orientation of slopes in relation to cardinal directions is an important factor to consider when assessing the impact of weather and meteorological conditions on landslide-prone areas. The parametric map of slope orientation represents the angles between the slopes and a specific cardinal direction, typically measured in a clockwise direction from the north. The resulting map is expressed in degrees, indicating the orientation of each slope with respect to the cardinal direction.

To classify the slope orientation, the map is reclassified into categories. In this particular case, the reclassification divides the slope orientations into 9 categories. Category 1 represents planes or slopes that do not have a significant relationship to any particular cardinal direction. The remaining categories classify the slopes based on their orientation relative to the cardinal directions, allowing for a more detailed characterization of the slope orientations within the study area.

By analysing the slope orientation, researchers and experts can better understand how slopes interact with weather and meteorological conditions, such as prevailing winds or rainfall patterns. This information is valuable in assessing the potential impact of these conditions on slope stability and landslide occurrence.

3.5. Parametric map of slope length

The slope length is a hydrological parameter that describes the total length of the gradient line from the highest point on a slope. It provides information on the length of the flow path from the top of the slope to the bottom, which is important in understanding the hydrological characteristics and potential water flow patterns within a given area.

To derive the slope length parameter, a hydrologically correct Digital Elevation Model (DEM) is required. The DEM represents the elevation values of the terrain and serves as the basis for calculating the flow direction of water across the landscape. By analysing the DEM, the direction of water flow can be determined, considering the topography and the natural flow pathways.

3.6. Parametric map of micro-watersheds

The density of gradient curves, when expressed against the direction of water flow, is commonly referred to as the contributing area. The contributing area represents the total area of the micro-watershed that contributes flow downslope to a specific point. To calculate the contributing area, the raster of the direction of water flow, derived from the hydrologically correct Digital Elevation Model (DEM), is utilized. The direction of water flow determines the flow pathways across the terrain. By analysing the flow direction grid, it is possible to identify the contributing areas for each point in the landscape. The contributing area is measured in square meters (m^2) and provides valuable information on the catchment characteristics and hydrological connectivity within the study area.

3.7. Parametric map of relief curvature

The parameter known as relief curvature captures the dynamics of surface water flow over the terrain, including the deceleration, acceleration, convergence, and divergence of water flow patterns (Mitasova et al., 1995). Relief curvatures are derived from the DEM data. In the context of the model area, Stará Ľubovňa district, the relief curvatures were reclassified into three categories: convex, concave, and linear. Convex forms have positive relief curvature values, indicating outward curvature or bulging surfaces. Concave forms have negative relief curvature values, indicating inward curvature or basin-like depressions. Linear forms have relief curvature values close to 0, suggesting relatively flat or straight sections of the terrain. The junction points where the relief curvature values are equal to zero represent isolines that separate the convex and concave forms. These inflection points indicate areas of transition from convex to concave or vice versa, highlighting significant changes in the curvature of the terrain.

3.8. Parametric map of landslide cover

The parametric map of landscape cover plays a crucial role in assessing the susceptibility to slope movements, as it reflects the influence of vegetation on various aspects of slope stability. Vegetation cover affects the terrain's ability to undergo evapotranspiration, retain rainfall, and resist erosion, all of which are important factors in determining the geological environment's stability.

In the construction of the parametric map of landscape cover, certain areas have been excluded to focus on specific land cover types. Forested areas, which provide significant vegetation cover and contribute to slope stability, are likely to be included in the map. Similarly, areas without permanent forest cover, such as grasslands or bare soil, may be excluded as they may have lower vegetation density and less effective erosion control.

Human settlements, including urban areas or infrastructure, are typically excluded from the landscape cover map since they are not directly related to natural vegetation cover and may have different characteristics influencing slope stability.

Water areas, such as lakes, rivers, or reservoirs, are also excluded from the landscape cover map. While they may have their own specific vegetation or aquatic ecosystems, they are typically not considered in the context of slope stability assessment, as they do not directly influence the terrestrial vegetation cover or erosion processes.

By focusing on specific land cover types that are relevant to slope stability assessment, the parametric map of landscape cover provides valuable information about the distribution and density of vegetation within the study area. This information helps in understanding the potential role of vegetation in mitigating or exacerbating slope movements and aids in the overall assessment of landslide susceptibility.

3.9. Register of slope deformations

The slope deformation map plays a significant role as the binary dependent variable in the statistical evaluation of landslide susceptibility. It serves as the reference or baseline against which all the input parametric maps are compared simultaneously during the statistical analysis process. In the case of the model area of the Stará Ľubovňa district, the slope deformation map represents a binary grid or raster. Each cell in the grid contains either a value of 0 or 1, representing the absence or presence of a landslide, respectively. This binary representation simplifies the analysis, allowing for a clear distinction between areas with and without recorded slope deformations. The slope deformation map was derived from a vector map of slope deformations that were registered up to the year 2010 (Geofond – Register of landslides, 2023). In the vector map, individual slope deformations were represented by polygons, which provide spatial information about the locations and extents of the recorded slope deformations.

4 RESULTS AND DISCUSSION

The creation of landslide susceptibility maps (LSMs) using multivariate analysis (MA) with 9 input parameters is an important step in assessing landslide hazard. After generating the LSMs, they are typically reclassified into different landslide hazard classes to provide a clear representation of the susceptibility levels in the area. In this case, the LSMs for the investigated area were reclassified into 5 landslide hazard classes ranging from very low to very high susceptibility. The reclassification was performed using two different statistical distributions: natural breaks (NB) and quantile (Q). The resulting hazard maps showed significant differences between the two classification methods. The map created by the NB classification (Fig. 3a) exhibited a more optimistic outlook, with a larger portion of the area falling into the

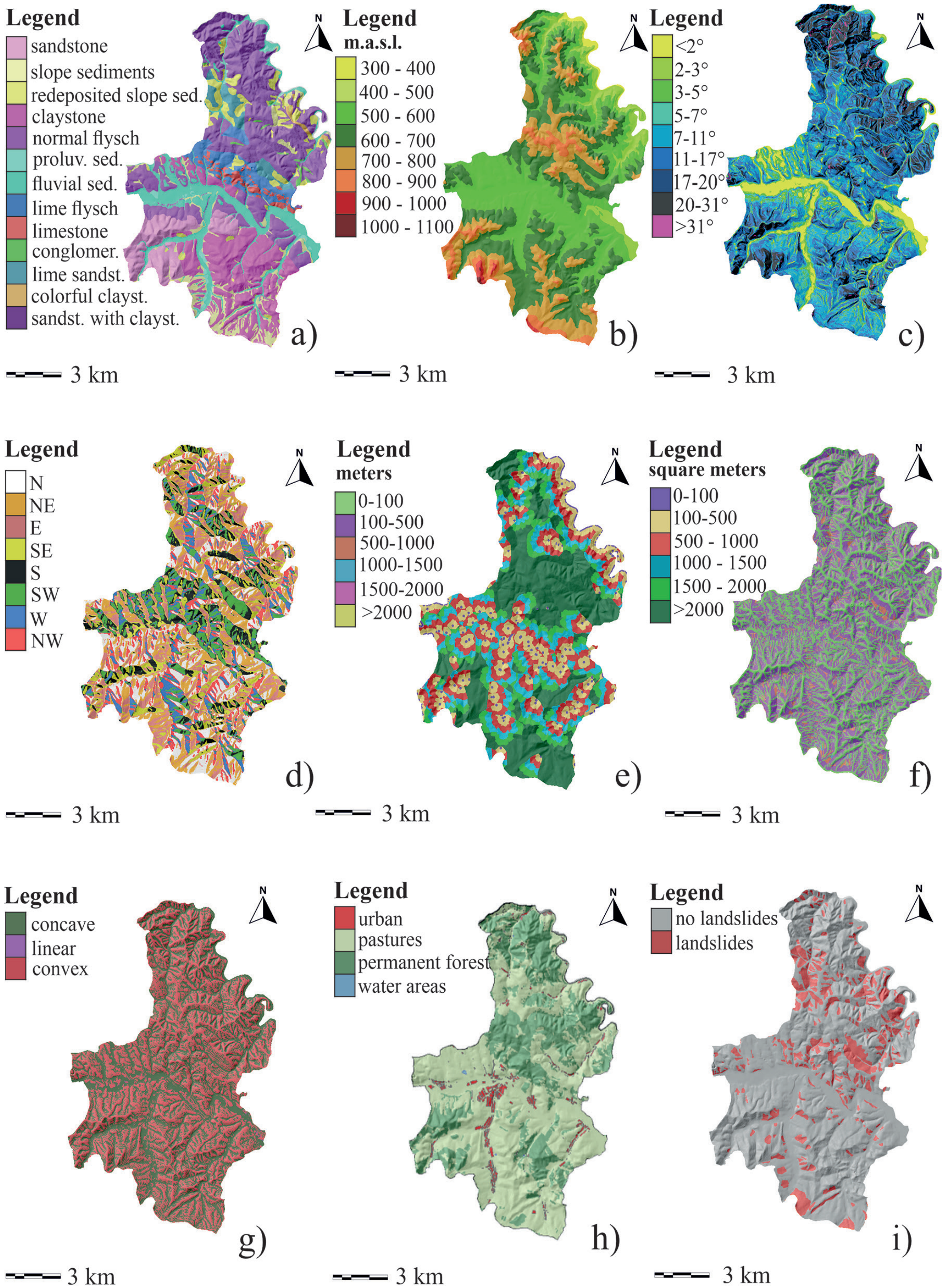

Fig. 2 Parametric maps as they have entered multivariate analysis (a - lithology; b - elevation; c - slope gradient; d - slope orientation; e - slope length; f - contributing areas; g - relief curvature; h - landscape cover; i - slope deformations)

landslide-resistant categories (very low and low). On the other hand, the map created using the quantile classification (Fig. 3b) showed a higher proportion of the area falling into moderate to high landslide hazard categories. Both hazard maps indicated specific areas with a higher susceptibility to landslides. These areas included the Klippen Belt, along the Poprad river and its creeks, and regions with a history of large past slope deformations. These findings suggest that these locations are more prone to slope instability and should be given increased attention in terms of landslide risk management. To assess the predictive value of the landslide hazard maps, a retrospective evaluation was conducted using data on 102 newly formed landslides. The success rate of the prediction maps was calculated based on the percentage of landslides that occurred within categories 3, 4, and 5 of the landslide hazard classification. For the map constructed using the NB classification, the success rate was determined to be 55 % (Fig. 4a). This means that 55 % of the newly formed landslides fell within the areas classified as having a moderate to very high landslide hazard. On the other hand, the map created using the quantile classification showed a higher success rate of 72 % (Fig. 4b). A closer look at LSMs reveals that newly formed landslides that fell into categories 1 and 2 in statistical assessment are located at the edges of areas with a high or very high degree of susceptibility to landslide hazard. We attribute this fact to the quality and accuracy of the input data. We note that the susceptibility maps for the land in the Stará Ľubovňa district identified areas prone to landslides, while the quantile distribution was more accurate. The lower values of the percentage success rate were more caused by the accuracy of the input data than by the susceptibility maps themselves. We used a standard procedure and input parameters for multivariate analysis. However, as the maps contain up to 9 parameters and the distribution into 5 classes was used, the maps appear to be too precise in areal delimitation for this scale.

Overall, the retrospective assessment and success rates provide valuable insights into the performance of the landslide hazard

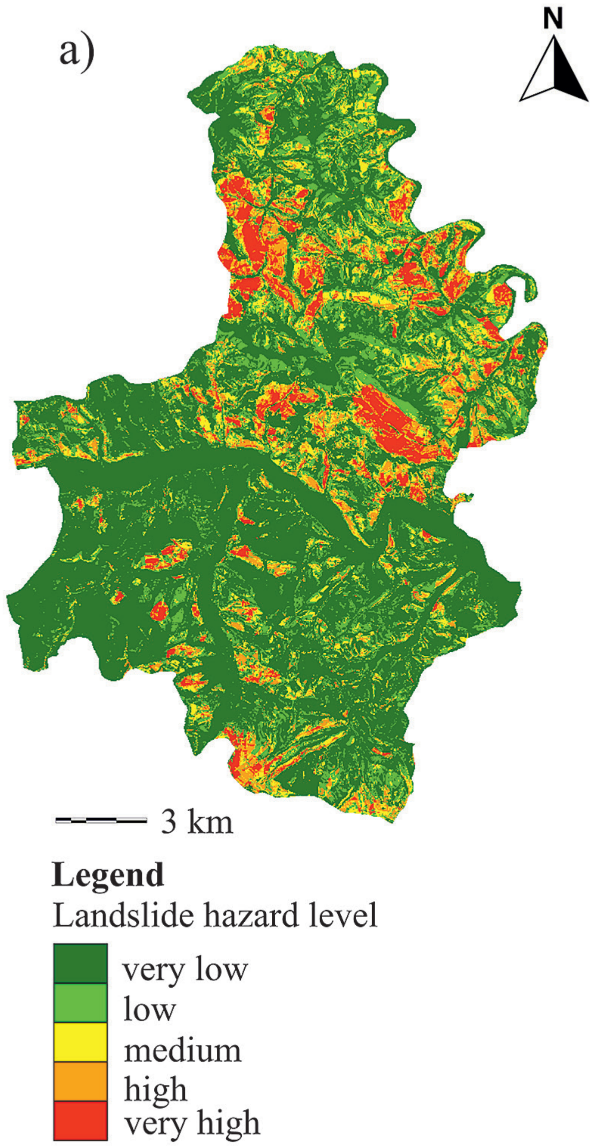

Fig 3. LSMs for the selected region (a – natural breaks; b – quantile)

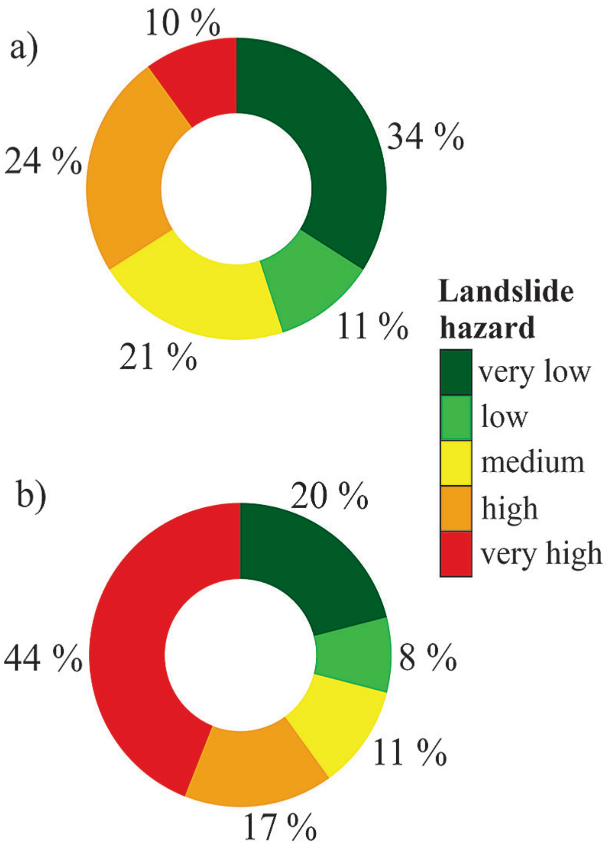

Fig 4. Percentage of landslide area that falls within certain landslide hazard levels (a – natural breaks; b – quantile)

maps and can guide future mitigation and risk management efforts in the investigated area.

5 CONCLUSION

The continuous advancement of computer technology, including software and hardware, has significantly contributed to the growing popularity and stability of GIS in scientific research. As a result, quantitative methods, particularly for landslide hazard analysis, have become increasingly prevalent. However, retrospective validation of susceptibility maps, although a simple and transparent method, has not been widely utilized thus far.

In the case of the Stará Ľubovňa district, the retrospective evaluation of landslide susceptibility maps yielded positive results in both statistical and knowledge-based validation. This indicates that the susceptibility maps are valuable tools for identifying potential landslide areas and providing accurate predictions that can serve multiple purposes.

To further enhance our understanding of the success and reliability of such models, it is essential to conduct retrospective validation on other susceptibility maps. By accumulating a larger dataset and establishing correlations, we can gain a clearer and more comprehensive perspective on the predictive capabilities of these models.

In conclusion, it is important to note that even areas classified as having a low risk of landslides can still experience slope deformations if subjected to irresponsible human activities. This highlights the need for responsible land management practices and awareness of potential risks, regardless of the perceived level of landslide hazard in a given area.

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