Landslide susceptibility assessment using Frequency Ratio model for the Polog region, Macedonia

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Abstract The aim of this study is to assess the landslide susceptibility in the Polog region, which is considered as one of the most landslide prone-areas in Macedonia due to the combination of complex geological setting, an articulate morphology and specific climate conditions. Geographic Information Systems (GIS) and Frequency Ratio (FR) model were implemented in this study to assess the contribution of conditioning factors to landslides, and to produce a landslide susceptibility map of the Polog region. The landslide inventory map for the study area was prepared by applying three approaches: (1) collecting archive landslide data, (2) analysis of DInSAR (Differential Interferometric Synthetic Aperture Radar) indicated zones with registered displacements, and (3) detecting landslides by visual analysis of a digital terrain model (DTM) obtained by LiDAR (Light Detection And Ranging) terrain scanning. Twelve landslide conditioning factors were considered in the landslide susceptibility modeling, which include slope, elevation, aspect, plane curvature, profile curvature, roughness, distance to roads, lithology, distance to faults, rainfalls, distance to rivers and land use/land cover. The relationship between landslides and conditioning factors was statistically calculated with FR analysis. FR values were used to produce the Landslide Susceptibility Index (LSI), based on which the study area was divided into five zones of relative landslide susceptibility, being very low, low, medium, high and very high. The results of the analysis have been validated by estimating the relative density of landslides, that is, calculation of the so-called R-index. The statistical results show that the R-index value increases as the landslide susceptibility level increases from very low to very high, which indicates a high-quality landslide susceptibility map obtained by using the FR model. The results also showed that the FR is simple method for landslide susceptibility assessment since the input, output, and calculation process are readily understood.

Keywords landslide, susceptibility, frequency ratio (FR), inventory, validation, Geographic Information System (GIS)

Introduction

All over the world, people face the challenge of establishing a balance between the risk of natural hazards (geohazards) and the need for space urbanization. Landslides are among the most significant and widespread geohazards, causing enormous social and economic losses worldwide (Herrera et al. 2018). A recent study by Haque et al. (2016) shows that in 27 analyzed European countries, during the 20 years, from 1995 to 2014, 1370 deaths and 784 injuries were recorded within 476 landslides events. As a result of landslides, economic losses were also significant in many of the analyzed European countries.

Every year in Macedonia, various unstable phenomena in the terrain cause significant losses, measured in millions of euros, and unfortunately, a loss of human lives. The history of landslide mapping in Macedonia, is briefly presented in Peshevski et al. 2024 (in print).

Polog region is considered as one of the most landslide prone-areas in Macedonia, comprising almost 2/3 of registered landslides in the country. The first landslide susceptibility study of Polog was done by Peshevski et al. in 2015, and later by Peshevski et al. in 2019. Since landslide susceptibility can change over time due to various factors such as land use changes, climate change, or geological processes, it is important to periodically update the landslide susceptibility maps. In this study landslide susceptibility assessment in Polog region is done, implementing the Geographic Information Systems (GIS) and the Frequency Ratio (FR) model. Delimiting the potential landslide areas through susceptibility assessment, can be used by the decision makers for developing and implementing appropriate landslide mitigation strategies.

Study area

The Polog region is located in the northwestern part of Macedonia (Fig.1) and covers an area of 2416 km². The relief of the study area is complex and diverse. The region consists of the Polog Valley, the mountains of Shar Mountain, Zeden, Suva Gora, Bistra, Mavrovo Plateau, and the valley of the river Radika. In the Polog region geological formations can be found from almost all geological periods, from the Cambrian to the Quaternary period, with different types of igneous, sedimentary and metamorphic rocks. The region belongs to seismic zones where the maximum expected seismic intensities of 7, 8 and 9 are likely (according to the MSK scale) for return periods of 100 and 500 years. It is characterized by the highest annual rainfall in the country (Ilijovski 2013), from 600 mm/year to more than 1250 mm/year.

In the Polog region, which occupies almost 10% of the territory of Macedonia, the combined presence of a complex geological setting, an articulate morphology, and particular climatic conditions contribute to it being one of the most landslide-prone regions in the country.

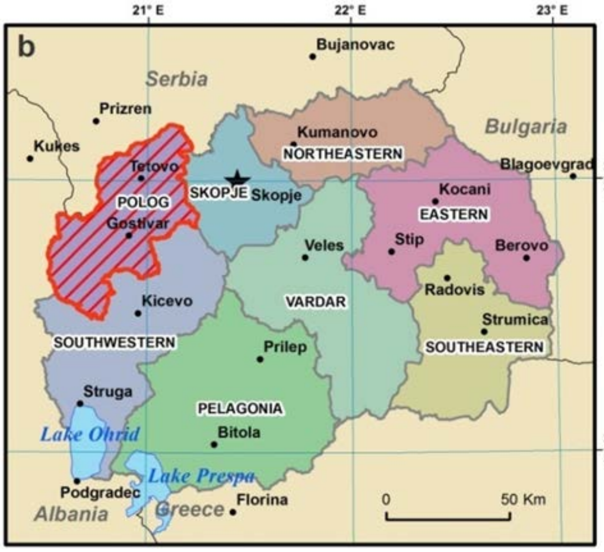

Figure 1 Location of Polog region (red outline).

Materials and methods

Landslide inventory

In order to predict the future potential zones for landslide occurrence, it is necessary to know the zones previously affected by landslides. The inventory map is the easiest and most direct method for mapping landslides (Guzzetti et al. 2012). The inventory map is the basis for susceptibility assessment. The landslide inventory map for the study area was prepared by applying three approaches: (1) collecting archive landslide data, (2) detecting landslides by visual analysis of a digital terrain model (DTM) obtained by LiDAR (Light Detection And Ranging) terrain scanning, and (3) analysis of DInSAR (Differential Interferometric Synthetic Aperture Radar) indicated zones with registered displacements.

The process of collecting archive landslide data consisted of several activities (Nedelkovska et al. 2020) and a landslide database of 136 occurrences was established. The number of landslides in the region was thought to be much higher, but they have not been appropriately recorded in the past. Therefore, it was proceeded with upgrading the landslide inventory by detection of landslides using another two methods that were applied for the first time in Macedonia for such purposes.

The first method was use of images acquired by satellite Synthetic Aperture Radar (SAR) sensors and processed using the Differential Interferometry (DInSAR) technique. Details for application of this remote sensing technology over the Polog region can be found in Jovanovski et al. (2021). By this method, total of 26 already inventoried landslides were found to be moving. Additioanlly, 38 “hotspots” were identified where a concentration of moving coherent pixels was identified out of the mapped landslides. The indicated 38 zones, jointly with geomorphological/geological criteria and photo-interpretation were exploited to map undetected landslides. The second method was detection of landslides by visual analysis of Digital Terrain Model obtained from data from LiDAR scanning of the terrain. In this way total of 46 new landslides were identified (Nedelkovska 2023).

Landslide causative factors

Landslide susceptibility is the probability of landslide occurrence in a given area based on the terrain conditions (Brabb 1984). Accordingly, to achieve high accuracy of landslide susceptibility models, selecting the landslide causative factors is a very significant step.

The landslide causative factors for the study area are selected based on literature inspection and detailed analysis of regional field conditions. 12 factors were selected, which can be broadly categorized into four groups: topographic (slope, elevation, aspect, plane curvature, profile curvature, roughness, distance to roads), geological (lithology, distance to faults), hydrological (rainfalls, distance to rivers) and land use/cover.

The slope is considered a critical topographic factor that directly influences landslide occurrence. Generally, the slope influences the water infiltration process and stresses distribution, closely related to the slope stability. **The elevation** is a factor used in almost all landslide susceptibility assessment analyses. The elevation is controlled by various geological, geomorphological, and meteorological factors, including lithological units, weathering, wind action, and precipitations (Pourghasemi et al. 2013). **Aspect** refers to slope orientation. This factor affects the exposure to sunlight, wind, and precipitation, which indirectly affect other factors that contribute to landslide occurrence, such as soil moisture, vegetation cover, and soil thickness (Clerici et al. 2006). **Plane curvature** and **profile curvature** are topographic factors that reflect the geometrical characteristics of the slopes (Ohlamacher 2007). Profile curvature affects the driving and resisting stresses within a landslide in the direction of motion. Plane curvature controls the convergence or divergence of landslide material and water in the direction of landslide motion. **Terrain roughness** expressed through a roughness index is an indicator of terrain topography. It refers to the flatness or undulation of the terrain, that is, the variability of the topographic surface of the terrain. **Distance to roads** can be a potential indicator of landslide occurrence. The construction of roads in mountainous areas requires engineering activities such as cutting and excavation. This leads to a change in the initial geological conditions of the terrain, that is, the equilibrium slope state is disturbed, and conditions for slope instabilities are being created. **Lithology** plays a vital role in landslide occurrence and is a significant internal controlling factor used in all landslide susceptibility analyses performed. Lithological units vary in physical and mechanical characteristics, including type, strength, degree of weathering, fracturing, permeability, etc. **Distance to faults** is an important predisposing factor for landslide susceptibility assessment. Structural discontinuities such as faults lead to joints and fissures in the surrounding rock mass (decreasing the rock strength) and causing instability. **Rainfall** affecting the groundwater level is one of the main landslide-triggering factors. When rainfall exceeds the infiltration capacity of the ground, it becomes saturated, which reduces its strength and makes it susceptible to sliding. Rainfall also affects the erosion process, leading to the slopes' destabilization. **Distance to a river** affects in the way the water erodes and saturates the slope toe and thus adversely affects stability. Therefore this factor is often included in the landslide susceptibility assessment. **Land use/cover** is another of several factors used in almost all landslide susceptibility assessment analyses. This factor is considered dynamic and associated with human activities (Rabby et al. 2022).

These 12 landslide causative factors were generated using Geographical Information System (GIS), so 12 thematic layers (maps) with a 1 m × 1 m spatial resolution pixel size were prepared. Table 1 provides a summary of the factors, the source from which the adopted factors were derived/calculated, the defined classes, and the method according to which the classes were defined.

Landslide susceptibility mapping

Landslide susceptibility (LS) is the measure of how prone an area is to landsliding. It measures the degree to which the terrain may be affected by future instabilities, or in other words, it predicts "where" landslides are likely to occur (Guzzetti 2006). The methods used for LS assessment have evolved over the years, and can be grouped into two general groups: qualitative and quantitative. More about the LS assessment methods can be found in Reichenbach et al. 2018. Quantitative methods are based on establishing a function between the conditioning factors and the distribution of past landslides. The way the classifier explicitly works is to measure each conditioning factor's contribution to landslides' occurrence based on the spatial correlation between the landslide occurrences and the factors. Past landslides represent dependent variables in these models, while conditioning factors are explanatory/independent variables.

The "*Frequency Ratio*" method which was proposed by Lee and Talib (2005) is a quantitative method that is used for statistical analysis of landslides. This method is based on the relationship between the distribution of landslides and each predisposing factor (Eq. 1):

$$FR_{ij} = \frac{N_{ij}/N_{total}}{A_{ij}/A_{total}} \qquad [1]$$

where: N_{ij} is the number of landslides in the *j*th class of factor *i*, N_{total} is the total number of landslides in the study area, A_{ij} is the area of the *j*th class of factor *i,* and A_{total} is the total area of the study area. Table 1 shows the results obtained from the analysis.

The "*Frequency Ratio*" method obeys the principle of conditional probability where the greater the ratio is, the stronger the relationship between landslides and predisposing factor classes, and vice versa. Actually, FR value greater than 1 indicates a strong relationship between landslide occurrence and the factor class, a value less than 1 indicates a weak relationship. The correlation is average if the frequency ratio is 1 (Lee and Sambath 2006).

Table 1 Analysis of the relationship between selected predisposing factors and past landslides using the "frequency ratio" method.

Factor	Class *j*	Landslides [%]	Class area [%]	FR$_{ji}$
Slope [°] Source: DTM Class. method: Custom interval	**1.**< 5	3.31	4.15	**0.797**
	2. 5 - 10	4.96	8.30	**0.597**
	3. 10 - 15	9.09	11.96	**0.760**
	4. 15 - 20	5.79	14.25	**0.406**
	5. 20 - 25	9.92	15.05	**0.659**
	6. 25 - 30	15.70	14.68	**1.069**
	7. 30 - 35	12.40	13.24	**0.937**
	8. 35 - 40	16.53	9.84	**1.680**
	9. > 40	22.31	8.54	**2.614**
Elevation [m] Source: DTM Class. method: Custom interval Natural breaks	**1.** 447 - 744	20.66	9.45	**2.187**
	2. 744 - 1031	15.70	11.54	**1.361**
	3. 1031 - 1292	18.18	13.77	**1.320**
	4. 1292 - 1544	26.45	15.23	**1.736**
	5. 1544 - 1786	6.61	15.78	**0.419**
	6. 1786 - 2029	4.96	12.96	**0.383**
	7. 2029 - 2272	6.61	12.48	**0.530**
	8. 2272 - 2749	0.83	8.80	**0.094**
Aspect	**1.** Flat (-1)	0.00	0.03	**0.000**

Factor	Class *j*	Landslides [%]	Class area [%]	FR$_{ji}$
Source: DTM Class. method: /	**2.** North (0 - 22.5; 337.5 - 360)	4.13	9.13	**0.453**
	3. Northeast (22.5 - 67.5)	9.92	14.44	**0.687**
	4. East (67.5 - 112.5)	18.18	19.35	**0.940**
	5. Southeast (112.5 - 157.5)	19.01	21.00	**0.905**
	6. South (157.5 - 202.5)	34.71	15.85	**2.189**
	7. Southwest (202.5 - 247.5)	11.57	8.68	**1.333**
	8. West (247.5 - 292.5)	0.00	5.26	**0.000**
	9. Northwest (292.5 – 337.5)	2.48	6.27	**0.395**
Plane curvature Source: DTM Class. method: /	**1.** Concave	6.61	3.37	**1.964**
	2. Linear	85.12	93.57	**0.910**
	3. Convex	8.26	3.06	**2.701**
Profile curvature Source: DTM Class. method: /	**1.** Convex	13.22	3.89	**3.399**
	2. Linear	78.51	92.36	**0.850**
	3. Concave	8.26	3.75	**2.205**
Terrain roughness Source: DTM Class. method: Natural breaks	**1.** 0.1 - 0.389	2.48	2.58	**0.962**
	2. 0.389 - 0.458	10.74	12.29	**0.874**
	3. 0.458 - 0.498	38.02	32.75	**1.161**
	4. 0.498 - 0.539	28.10	36.35	**0.773**
	5. 0.539 - 0.605	18.18	13.25	**1.373**
	6. 0.605 – 0.9	2.48	2.79	**0.889**
Distance to roads [m] Source: DTM Class. method: Natural breaks	**1.**< 407	83.47	55.81	**1.496**
	2. 407 - 1118	12.40	19.46	**0.637**
	3. 1118 - 2058	3.31	10.19	**0.325**
	4. 2058 - 3151	0.83	6.72	**0.123**
	5. 3151 - 4221	0.00	4.69	**0.000**
	6. 4221 - 6479	0.00	3.14	**0.000**
Lithology Source: Basic geological map 1:100000 Class. method: /	**1.** Quaternary deposits	9.09	11.83	**0.769**
	2. Albite chlorite sericite schists	4.13	6.38	**0.647**
	3. Albite chlorite epidote sericite schists	3.31	3.20	**1.033**
	4. Gabbro	0.00	0.03	**0.000**
	5.Granitoid rock masses	16.53	8.89	**1.860**
	6.Diabases and spilites	0.00	0.39	**0.000**
	7. Epidote actinolite schists	37.19	35.26	**1.055**
	8. Carbonate schists	0.00	0.04	**0.000**
	9. Quartz carbonate sericite schists and phyllites	7.44	9.15	**0.813**
	10. Quartz-porphyry	0.00	0.21	**0.000**
	11. Quartzite and quartz sandstones	2.48	1.77	**1.403**
	12. Crystalline limestones with cherts	4.96	8.26	**0.600**
	13. Marbles and marble limestones	6.61	8.83	**0.749**
	14. Metasandstones	0.00	0.19	**0.000**
	15. Serpentinite	0.00	0.10	**0.000**
	16. Phyllite metamorphosed sandstones & schists	0.00	0.63	**0.000**
	17. Phyllitoid	7.44	4.32	**1.722**
	18. Harzburgite	0.00	0.01	**0.000**
	19. Chlorite sericite schists	0.83	0.52	**1.600**
Distance to faults [m] Source: Basic geological map 1:100000 Class. method: Natural breaks	**1.**< 134	42.98	34.23	**1.256**
	2. 134 - 308	26.45	28.45	**0.930**
	3. 308 - 513	19.01	18.05	**1.053**
	4. 513 - 765	5.79	10.58	**0.547**
	5. 765 - 1097	4.13	5.95	**0.694**
	6. 1097 - 2012	1.65	2.75	**0.600**
Rainfalls [mm/year] Source: Rainfalls map 1:100000 Class. method: /	**1.** 600 – 700	0.00	1.53	**0.000**
	2. 700 – 800	20.66	19.26	**1.073**
	3. 800 – 900	20.66	32.14	**0.643**
	4. 900 – 1050	58.68	47.07	**1.247**
Distance to rivers [m] Source: DTM Class. method: Natural breaks	**1.**< 291	31.40	27.91	**1.125**
	2. 291 - 617	29.75	26.14	**1.138**
	3. 617 - 964	21.49	20.62	**1.042**
	4. 964 - 1368	14.88	13.68	**1.088**

Factor	Class *j*	Landslides [%]	Class area [%]	FR$_{ji}$
	5. 1368 - 1906	1.65	8.06	**0.205**
	6. 1906 - 2859	0.83	3.59	**0.230**
Land use / land cover Source: CLC2018 Class. method: /	**1.** Broad-leaved forest	38.84	27.63	**1.406**
	2. Complex cultivation patterns	4.13	2.60	**1.592**
	3. Coniferous forest	0.00	1.15	**0.000**
	4. Discontinuous urban fabric	2.48	2.04	**1.214**
	5. Land principally occupied by agriculture, with significant areas of natural vegetation	19.83	11.84	**1.675**
	6. Mixed forest	1.65	4.02	**0.411**
	7. Moors and heathland	0.83	4.94	**0.167**
	8. Natural grasslands	15.70	33.35	**0.471**
	9. Non-irrigated arable land	0.00	0.05	**0.000**
	10. Pastures	1.65	1.38	**1.195**
	11. Sparsely vegetated areas	0.00	1.89	**0.000**
	12. Transitional woodland-shrub	14.88	9.11	**1.633**

Results and discussion

Once the “frequency ratio” value of each landslide factor's class was found, which represents a weighting coefficient that quantitatively measures the contribution of each value of the factor to the occurrence of landslides, an overlaying of the thematic weight maps is performed in ArcGIS. Summation of each factor’s frequency ratio value in each pixel is done in order to obtain the landslide susceptibility index (LSI). A higher LSI means a higher susceptibility to landsliding. The prepared landslide susceptibility map for the Polog region is presented in Fig. 2. The Natural Breaks (Jenks) classification method was used to classify the landslide susceptibility of the study area into five categories (very low, low, moderate, high, and very high). This method is considered the most appropriate one, because the different classes are generated based on the inherent characteristics of the dataset without any subjective consideration.

The percentage of landslides in each susceptibility class was calculated to check the validity of the final susceptibility map. For this, all the landslides have been overlaid over the landslide susceptibility map. Table 2 presents the obtained results. Namely, the low and very low landslide susceptibility classes occupy 43% of the study area with only 9% of the landslides in these zones. Conversely, the high and very high susceptibility classes occupy 26% of the study area, but all have 52% of the landslides.

Table 2 Results obtained from the landslide susceptibility map.

Landslide susceptibility class	Area [%]	Landslides [%]
Very low	19.0	2.2
Low	23.8	6.5
Medium	31.0	39.1
High	21.1	32.6
Very high	5.1	19.6

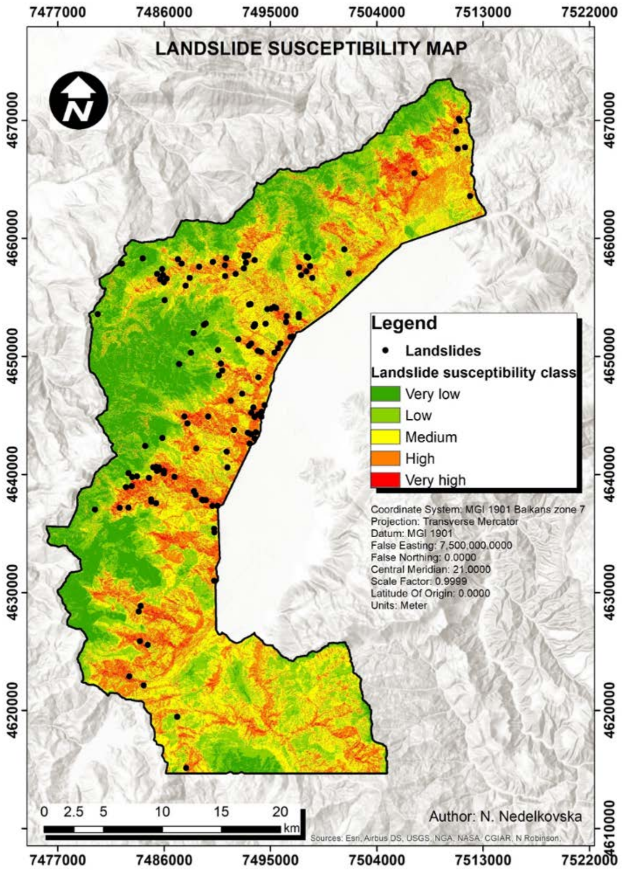

Figure 2 Landslide susceptibility map for the Polog region.

Validation of the landslide susceptibility model is also done by estimating the relative density of landslides by calculation the R-index, using the following equation:

$$R = (n_i/N_i)/\sum(n_i/N_i) \quad [2]$$

where n_i is the number of landslides in each landslide susceptibility class, and N_i is the area of the susceptibility classes. The statistical results show that the R-index value gradually increases as the landslide susceptibility level increases from very low to very high (Tab. 3). Considering this, it can be concluded that the landslide susceptibility map is reasonable and reliable.

Table 3 R-index value per landslide susceptibility class.

Landslide susceptibility class	R-index
Very low	0.114
Low	0.274
Medium	1.260
High	1.547
Very high	3.870

Conclusions

In this study “Frequency ratio” model was used to identify the landslides susceptible areas in the Polog region, Macedonia. Twelve landslide conditioning factors and the landslide inventory map for the study area were used to calculate FR values. Furthermore, the Landslide Susceptibility Index (LSI) was obtained based on which the study area was divided into five zones of relative landslide susceptibility. Validation of the landslide susceptibility map was done by estimating the relative density of landslides through calculation of the statistical R-index value, which gradually increases as the landslide susceptibility level increases from very low to very high.

This case study confirmed that the FR model was found to be simple and effective model for landslide susceptibility assessment of the study area. Its main advantage is the simplicity, i.e. inputs, output, and calculation process are readily understood, and even a large amount of data can be processed quickly, easily and efficiently in GIS environment.

Systematic data collection is crucial in order to make more detailed analyzes related to this topic. This can be achieved by continuous and timely updating of the inventory with new landslides. In such way also a “retrospective validation” of the susceptibility models would be feasible, which implies overlapping the newly invenotired landslides with the susceptibility map, so it can be concluded whether the zones where the new landslides occurred are really zoned as susceptible to landslides.

The final output of landslide susceptibility map can help the decision makers as basic information for district and zonal level of land use planning to formulate and implement proper actions in order to prevent and mitigate the existing landslides occurrence and future once.

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