

Landslide Hazard Maps of Georgia Using Machine Learning Approach

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Abstract. Georgia belongs to one of the most vulnerable regions in the world, as it is prone to hazardous geological processes such as landslides (LS). As the statistical data on LS in Georgia are of relatively low quality, a three-stage methodology was applied for assessing LS probability. First, an initial statistical assessment of LS hazard was performed using 11 weighted objective factors. Second, the initial statistical model was compared with the map of observed LS on the territory of Georgia. Third, machine learning (ML) methods were applied to assess LS probability for obtaining the final LS hazard map. The obtained results indicate a good correlation between the model predictions and the observed data, which confirms the reliability and robustness of the proposed model, even in the case of unbalanced data. © 2026 *Bull. Natl. Acad. Sci. Georg.*

Keywords: landslides, machine learning, climatic factors, hazard maps

Introduction

The fatality count of landslides over the past 20 years worldwide is estimated to be on the order of 60 000. Thus, it is important to create stationary and dynamic (precipitation sensitive) LS models as well as reliable and cost-effective early warning systems for monitoring mass-movements in potentially hazardous areas. The Sendai Framework calls for enhanced scientific and technical work on disaster risk reduction (DRR) and its mobilization through the coordination of existing arrays and scientific research institutions at all levels and all regions (Sendai Framework for Disaster Risk Reduction 2015-2030, 2015; Appliance of science key to disaster risk reduction. UNISDR, 2015) Publi-

cations, related to LS hazard prediction, indicate that in addition to time-independent spatial factors (slope steepness, lithology, land cover, etc.) one should take into consideration strong triggering impact of intensive rainfall (Froude and Petley, 2018). Thus, there are two main directions in the research of LS risk reduction: (i) stationary LS risk assessment, including also long-term precipitation data, and (ii) dynamic models of LS formation, taking into account occurrence of intensive rainfalls (RF). According to Kirschbaum et al. (2012), there is a strong correlation between the number of landslides and monthly RF values in various regions of the world.

Review of Landslide Risk Assessment Studies

At the global scale, three main directions have developed in recent years in the mass-movement prediction theory: 1. Statistical mathematical methods for temporal LS prediction founded on the strong correlation of LS events with rainfall intensity I / duration D thresholds (Helmstetter and Garambois, 2004) achieving prediction accuracies of approximately 80% (Guzzetti et. al., 2019); 2. Machine learning (ML) approach, integrating statistical spatial and seasonal temporal characteristics of LS in order to create stationary of map landslide susceptibility (Merghadi et. al., 2020; Sharma et. al., 2023); 3. Spatio-temporal prediction of LS risk: machine learning assessed probability of LS occurrence for a given precipitation intensity and duration at a given location (Liu et. al., 2024). For example, Sharma et. al. (2024) present a stationary ML – based assessment of LS hazard for India. The stationary precipitation-accounting maps are important for optimal planning of infrastructural objects. The dynamic maps in future can predict the probability of the LS damaging results due to intensive RFs and help in issuing corresponding alarm signal.

Review of Landslide Risk in the Study Area: Georgia

Georgia belongs to one of the most vulnerable regions in the world, as it is prone to a large-scale hazardous geological processes (Gaprindashvili and Van Westen, 2015). The Duruji River basin in Eastern Georgia is an example of mass-movements intensity. Over the past 115 years, 37 large LS/DF were registered in the Kakheti area with the damage estimated at approximately 200 million USD. In 2014, catastrophic DF occurred in Dariali Canyon. In 2015, the big LS/DF in Tbilisi region led to 20 fatalities. Accordingly, it is important to add at least the long-term precipitation data to time-independent spatial factors (slope steepness, lithology, land co-

ver, etc.) in order to create stationary LS/DF hazard map of Georgia, including the factor of precipitation. In 2015, the stationary LS hazard and risk maps of the country was published (Chelidze et. al., 2022), which used spatial multi-criteria evaluation. The map was validated using the available landslide inventory, as well as stationary precipitation map, namely, the maximum 5-day precipitation data recorded for a century on the territory of Georgia.

LS Hazards Maps

LS hazard maps compiled by fuzzy logic system.

A wide variety of factors is significant in influencing LS susceptibility and they have been extensively studied (Guzzetti et. al., 2006). In LS susceptibility studies, these parameters are required to model the shear strength of soil, soil–water interaction, soil vegetation interaction, and the impact of anthropogenic activities. In the paper (Chelidze et. al., 2022), we used one of ML methods, namely Fuzzy Logic System (FLS) to assess perennial precipitation factor. The resulting map shows large LS risk in the Western Georgia.

Classification Rules

Based on the entire dataset, each parameter (Table) was normalized and classified on a [0, 1] scale. The following built-in logic was applied for individual factors.

Table. Parameters used for LS analysis and their dimensions: features used. Resolution 20x20 m, total by 175 million values for each unit

Parameters	Units
Elevation	meters
Slope	degrees
Aspect	degrees
Curvature	–
Forest	binary
Precipitation	mm/year
RiverDist	meters
FaultDist	meters
Soil type	categorical
Lithology	categorical
Topographic Wetness Index (TWI)	-

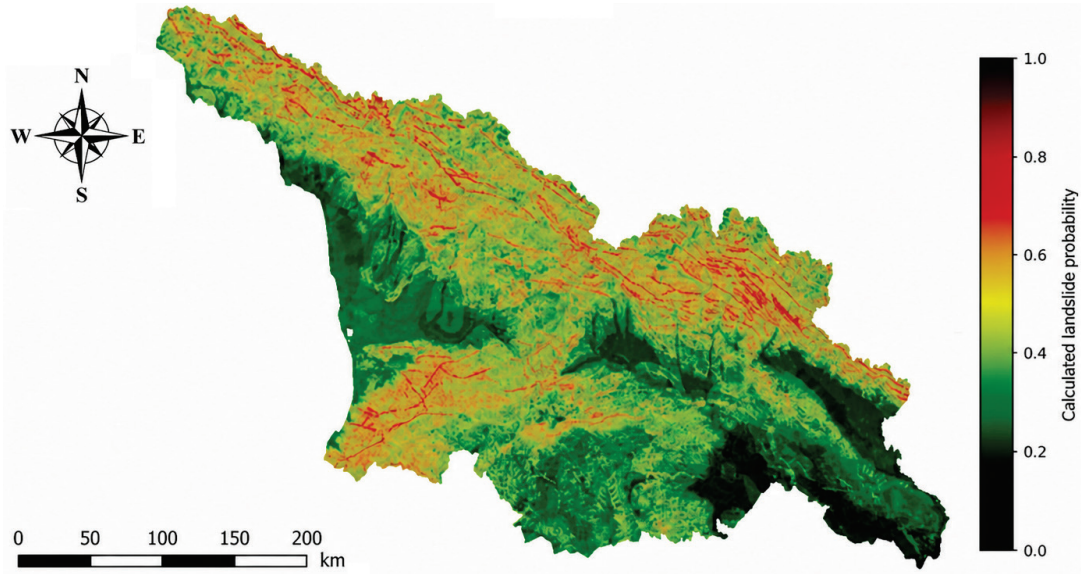


Fig. 1. Corrected and refined. The spatial distribution map of LS risk probabilities in Georgia.

Slope. In mountainous regions, the probability of LS occurrence increases sharply with slope steepness. The following rule is applied:

$$S_{slope}(x) = \begin{cases} 0.1 & \text{if } x \leq 2^\circ \\ 0.3 & \text{if } 2^\circ < x \leq 15^\circ \\ 0.5 & \text{if } 15^\circ < x \leq 25^\circ \\ 0.7 & \text{if } 25^\circ < x \leq 40^\circ \\ 0.9 & \text{if } x > 40^\circ \end{cases} \quad (1)$$

Elevation. Elevation influences precipitation, temperature and soil moisture, all of which significantly affect LS occurrence.

$$S_{elev}(x) = \begin{cases} 0.1 & \text{if } x \leq 500 \\ 0.3 & \text{if } 500 < x \leq 1500 \\ 0.5 & \text{if } 1500 < x \leq 3000 \\ 0.7 & \text{if } 3000 < x \leq 4000 \\ 0.9 & \text{if } x > 4000 \end{cases} \quad (2)$$

Distance to River (RiverDist) and Slope

$$S_{river}(d, s) = \begin{cases} 0.2 & \text{if } s \leq 5^\circ \\ 0.9 & \text{if } d \leq 100 \\ 0.5 & \text{if } d \leq 500 \\ 0.1 & \text{otherwise} \end{cases} \quad (3)$$

Distance to Fault (FaultDist)

$$S_{fault}(d) = \begin{cases} 0.9 & \text{if } d \leq 100 \\ 0.5 & \text{if } 100 < d \leq 500 \\ 0.1, & d > 500 \end{cases} \quad (4)$$

Precipitation

$$S_{precip}(p) = \begin{cases} 0.2 & \text{if } p \leq 500 \\ 0.3 & \text{if } 500 < p \leq 1000 \\ 0.5 & \text{if } 1000 < p \leq 1500 \\ 0.7 & \text{if } p > 1500 \end{cases} \quad (5)$$

Forest

$$S_{forest}(f) = \begin{cases} 0.7 & \text{if } f = 1 \\ 0.3 & \text{if } f = 0 \end{cases} \quad (6)$$

The final statistical theoretical model of LS probability P is expressed as:

$$P = \frac{\sum_{i=1}^{11} \omega_i \cdot S_i(x_i)}{\sum_{i=1}^{11} \omega_i} \quad (7)$$

where ω_i denotes the predefined weight (e.g., slope = 2.0, fault = 1.5, ...); $S_i(x_i)$ is the scoring function for each parameter.

The weights accepted are based on the published data on the LS risk (Lee & Pradhan, 2007). The obtained Georgia's landslides theoretical probabilistic susceptibility map is presented in Fig. 1. At this stage, the first phase of the study was completed, during which a probabilistic LS hazard map of Georgia was developed using 11 geophysical, geological, and hydrological parameters within a theoretical framework (see Table). Modern appra-

zones available in our database. The analysis revealed potential for improving model accuracy, suggesting that further refinement could be achieved through the application of machine learning techniques.

Refined Machine Learning Models Training Steps and Comparative Results

At the third stage, the theoretical probability map derived from the initial model (Fig. 1) was refined using ML algorithms. The objective was to develop a predictive model that would more accurately reflect actual LS occurrences and reduce the errors inherent in the purely theoretical calculations.

Figure 3 presents the corrected and refined by ML approach, namely, the Multi-Layer Perceptron (MLP) model, LS susceptibility map, generated using the results of the first stage calculations and a real LS data for learning. The application of MLP improved the results of the first stage assessment (weighted factor analysis) by approximately 10%. The computed probabilities were transformed into a color-coded visualization, where red and yellow tones represent high-risk zones, while green areas indicate relatively stable regions. A shaded relief background provides additional topographic context, enhancing the visual interpretation of spatial risk patterns.

Conclusions

The developed theoretical LS susceptibility map serves as a powerful initial tool for this geohazard assessment, effectively identifying areas with a high probability of LS occurrence, especially in the regions lacking a well-developed meteorological

monitoring network. A three-stage methodology was applied to assess LS probability: (1) Initial statistical assessment of LS hazard using weighted factors analysis; (2) Comparison of the initial statistical model with the map of observed LSs on the territory of Georgia; (3) Application of machine learning method to the results of the first-stage assessment of LS probability for obtaining the final map of LS hazard.

The obtained map of LS hazard can be used in several practical contexts. It may serve as a preliminary LS hazard assessment map, to determine which regions require further detailed risk investigation and act as a supporting instrument for geological monitoring, either in real time or through periodic updates; as well as a training foundation for advanced models, enabling integration of additional environmental and remote sensing data.

Future work will focus on several directions including the integration of dynamic climatic factors such as precipitation and temperature; incorporation of temporal dynamics to allow prediction of LS risk variations across seasons or years; use of higher-resolution dynamical and spatial data to enhance model precision. Integration of the model outputs into national geoinformation system (GIS) infrastructures, improving accessibility and decision-making for hazard management and spatial planning.

Acknowledgements

This work was supported by Shota Rustaveli National Science Foundation of Georgia (SRNSFG), Grant number FR-23-5466, "Machine Learning Approach to the Landslide Activation Prediction in Georgia".

გეოფიზიკა

საქართველოს მეწყრების საშიშროების რუკები მანქანური სწავლების მიდგომის გამოყენებით

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საქართველო მსოფლიოში ერთ-ერთ ყველაზე დაუცველ რეგიონს მიეკუთვნება, რადგან ის მიდრეკილია საშიში გეოლოგიური პროცესებისკენ, როგორცაა მეწყერი. ვინაიდან საქართველოს მეწყრების შესახებ სტატისტიკური მონაცემები დაბალი ხარისხისაა, მეწყრის ალბათობის შესაფასებლად გამოყენებულ იქნა სამსაფეხურიანი მეთოდოლოგია. პირველ ეტაპზე შეფასდა: მეწყრის საწყისი სტატისტიკური საფრთხე, 11 შეწონილი ობიექტური ფაქტორის ანალიზის გამოყენებით; საწყისი სტატისტიკური მოდელის შედარება საქართველოს ტერიტორიაზე დაკვირვებული მეწყრების რუკასთან; მანქანური სწავლების მეთოდების გამოყენება მეწყრული საფრთხის საბოლოო რუკის მისაღებად. ნაშრომში წარმოდგენილი, ჩატარებული კვლევების შედეგები მიუთითებს მოდელის პროგნოზებსა და დაკვირვებულ შედეგებს შორის კარგ კორელაციაზე, რაც ადასტურებს მოდელის სანდოობას და მდგრადობას არაბალანსირებული მონაცემების შემთხვევაშიც კი.

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Received March, 2026