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### From Concept to Implementation: An Integrated Geoinformation Framework for Landslide Susceptibility and Geocological Risk Assessment with Quantitative Forest Cover Parameterization

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#### SUMMARY

Reliable assessment of landslide susceptibility and geocological risk requires an integrated workflow that moves coherently from a conceptual factor system to a reproducible, scalable implementation. This study presents an integrated geoinformation framework that unifies five sequential stages - data preparation, factor processing, landslide susceptibility (LSA) modelling, validation, and risk modelling - within a single pipeline on the Google Earth Engine cloud platform. Within this framework, forest cover is parameterized as a self-contained structural block of six quantitative indicators rather than a binary attribute. Each factor is calibrated by the frequency ratio method, and weight coefficients are determined by Random Forest Feature Importance; the calibrated layers are integrated into a logistically transformed susceptibility index and classified into five classes. The framework was implemented and validated at two independent test sites in the Ukrainian Carpathians - a base site on the Tereblia River (236 landslide occurrences) and a control site in the Verkhovyna district (190 occurrences). In the resulting ten-factor model the thematic-block contributions are morphometric  $\approx 49.7\%$ , forest  $\approx 25.9\%$ , geological  $\approx 14.2\%$ , and hydrological  $\approx 10.3\%$ ; under spatial-block validation 88.1% of independent test landslides fell into the medium-to-very-high classes (AUC 0.72). At the output stage the framework yields two parallel risk indicators — a nature-conservation priority index based on the Nature Protection Status (NPS) and risk to population and infrastructure. The proposed framework is fully interpretable, reproducible, and scalable to other landslide-prone regions.

**Keywords:** Landslide Susceptibility; Forest cover; Geocological risk; Frequency ratio; Random Forest; Google Earth Engine; Ukrainian Carpathians; Remote sensing.

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## Introduction

Landslide processes are among the major exogenous geological processes of the Ukrainian Carpathians: more than 20,000 landslide occurrences have been documented in the mountainous and foothill parts of the Zakarpattia, Ivano-Frankivsk, Lviv and Chernivtsi regions. The most widespread are shallow translational landslides in flysch formations, activated during intense precipitation. The flysch structure with characteristic lithological heterogeneities, mid-mountain relief with slope gradients of 20–40°, high annual precipitation (over 1200 mm at the base study site), and substantial anthropogenic transformation of forests during 2000–2010 together create favourable conditions for hazardous slope processes (Günther et al., 2014).

Forest cover is traditionally regarded as a stabilizing factor: root systems reinforce the near-surface layer, while forest stands regulate infiltration and runoff. At the same time, landslides occur on both forested and deforested slopes, with transition zones along forest boundaries being particularly vulnerable (Gariano & Guzzetti, 2016). Existing regional susceptibility assessments are often implemented as fragmented, hard-to-reproduce workflows, whereas forest cover is typically represented as a binary “forest/non-forest” variable (Reichenbach et al., 2018), neglecting its structure and temporal dynamics. For the Carpathian region, where forests cover 50–70% of the territory, these limitations highlight the need for an integrated and reproducible modelling framework.

To address these challenges, an integrated geoinformation framework for landslide susceptibility and geocological risk assessment was developed. The framework combines conceptual factor selection, quantitative parameterization, susceptibility modelling, validation, and risk assessment within a unified workflow.

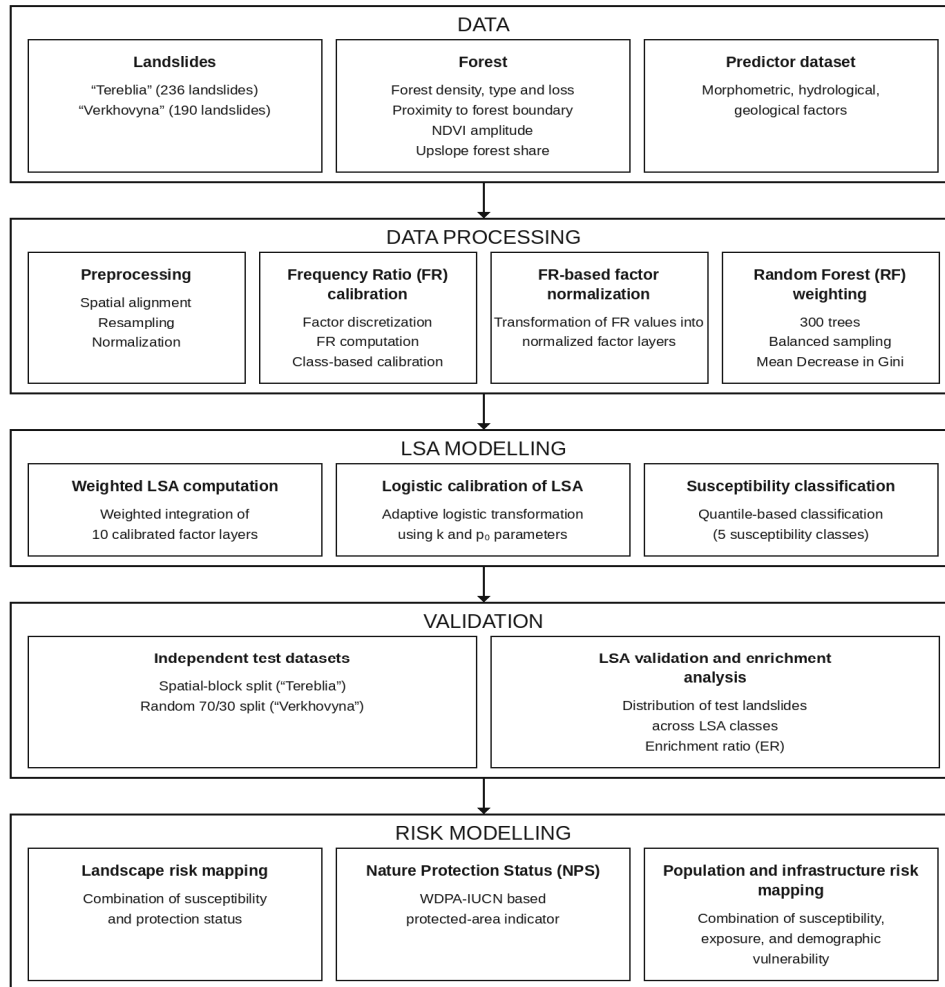
The aim of this study is to develop and implement this framework on the Google Earth Engine cloud platform (Gorelick et al., 2017). Unlike previous regional approaches, forest cover is represented as a dedicated factor block comprising quantitative indicators of forest structure and dynamics rather than a binary land-cover attribute (Reichenbach et al., 2018; Chepurna et al., 2022), providing a reproducible basis for landslide susceptibility and geocological risk assessment in the Ukrainian Carpathians.

## Method and Theory

The proposed methodology is organized as an integrated geoinformation framework comprising five sequential stages, from data preparation to geocological risk assessment (Figure 1). The framework integrates heterogeneous geospatial data, factor calibration, machine-learning-based weighting, landslide susceptibility modelling, validation, and risk mapping into a single reproducible workflow implemented in Google Earth Engine. Its modular architecture enables consistent model implementation and transferability between study areas.

The study was carried out at two independent test sites in the Ukrainian Carpathians: a base site of 25 × 25 km in the upper reaches of the Tereblia River (236 landslide occurrences) and a control site in the Verkhovyna district (190 occurrences). The dataset was compiled from cadastral data of the State Research and Production Enterprise “Geoinform of Ukraine” and open Earth remote-sensing products: the ALOS AW3D30 digital elevation model, the MERIT Hydro hydrographic dataset, ESA WorldCover 2021, Copernicus Global Land Cover (CGLS-LC100) with forest type, Hansen Global Forest Change, Landsat and Sentinel-2, as well as population and built-up layers (WorldPop, JRC GHSL) and the WDPA/IUCN protected-areas database.

Methodologically, the assessment is organized as an integrated framework of five sequential stages (Figure 1): data preparation (spatial alignment, resampling, and normalization of heterogeneous inputs); factor processing (frequency ratio calibration of each factor and Random Forest weighting); LSA modelling (weighted integration of the calibrated layers, logistic calibration, and quantile classification); validation (independent-sample testing and enrichment analysis); and risk modelling (derivation of landscape and population-and-infrastructure risk). All stages are executed within a single reproducible workflow in Google Earth Engine, which links the conceptual factor system directly to its computational realization and supports the transfer of the model between study areas.



**Figure 1.** Architecture of the integrated geoinformation framework for landslide susceptibility and geocological risk assessment: five sequential stages — data preparation, factor processing (FR calibration and RF weighting), LSA modelling, validation, and risk modelling

The factor system of the index-based landslide-susceptibility model (LSA) is grouped into five thematic blocks — morphometric, hydrological, forest, geological, and climatic. The central element is the forest block of six quantitative indicators: forest density, forest type, proximity to the forest boundary, NDVI amplitude, forest loss over 2001–2023, and the upslope forest share. Each indicator describes a particular aspect of the state or dynamics of the forest derived from satellite data.

Each continuous factor is calibrated using the frequency ratio method, which objectively estimates the probability of landslide occurrence within the factor classes from the spatial coincidence of documented occurrences with these classes (Lee & Pradhan, 2007):

$$FR_i = P_i(\text{train}) / P_i(\text{area}) \quad (1)$$

where  $P_i(\text{train})$  is the share of training landslides in class  $i$  and  $P_i(\text{area})$  is the share of the area of that class. The weight coefficients of the ten final factors are determined by Random Forest Feature Importance through the mean decrease in the Gini index over an ensemble of 300 trees (Breiman, 2001; Merghadi et al., 2020), and the intermediate index is computed as the weighted sum of the FR-calibrated layers:

$$LSA(\text{proxy}) = \sum w_i \cdot F_i(FR), \quad i = 1 \dots n \quad (2)$$

After logistic calibration, the LSA index is classified into five susceptibility classes. The dataset was split into training (57%) and test (43%) subsets using a spatial-block approach (3 × 3 km). Two risk indicators

were derived: a nature-conservation priority index ( $LSA \times NPS$ ), where NPS values range from 0.20 (outside protected areas) to 1.00 (World Heritage sites and biosphere reserves), and a population-and-infrastructure risk index combining susceptibility with spatial exposure and demographic vulnerability.

## Results

The proposed geoinformation framework successfully integrated multi-source geospatial data, factor calibration, susceptibility modelling, validation, and risk assessment into a unified workflow. FR calibration revealed physically consistent patterns: maximum FR values occurred at slope gradients of 25–40°, 31% of landslides were located within 250 m of watercourses, and the highest FR values were observed near forest boundaries. Landsat data showed forest cover declined from 71% to 62% during 1990–2010, followed by recovery to 70% by 2020 (Rushchak & Chepurnyi, 2025). Buffer analysis confirmed a strong association with forest disturbances: 61% of landslides at the base site and 84% at the control site occurred within 100 m of disturbed forests (Chepurnyi, Rushchak, & Chepurna, 2024). After excluding precipitation because of its high correlation with elevation ( $r = 0.96$ ), the maximum VIF decreased from  $>15$  to  $<3$ . Random Forest weighting assigned 49.7% of the total importance to morphometric factors, 25.9% to forest, 14.2% to geological, and 10.3% to hydrological factors, with proximity to the forest boundary, forest density, and forest type being the most influential forest variables. At the base site, 40.2% of the area was classified as highly or very highly susceptible, containing 74.6% of documented landslides. Independent validation showed that 88.1% of test landslides fell within the medium-to-very-high susceptibility classes ( $AUC = 0.72$ ), while successful application to the control site confirmed the framework's transferability. The resulting framework produced both nature-conservation priority and population-and-infrastructure risk maps, identifying 28 WDPA protected areas, including the Carpathian Biosphere Reserve and Synevir National Nature Park.

## Discussion

The proposed geoinformation framework demonstrates that the forest block (25.9%) contributes nearly as much as the geological and hydrological blocks, confirming that forest cover should be treated as a first-order factor in landslide susceptibility modelling rather than a binary land-cover attribute. Elevated FR values near forest boundaries support the importance of edge effects, while forest degradation during 2000–2010 links landslide activity to anthropogenic pressure and climate change (Gariano & Guzzetti, 2016; Trevoho et al., 2021). The stable weighting structure across geologically contrasting study areas demonstrates the framework's transferability, whereas the combination of Frequency Ratio and Random Forest provides both interpretability and objective weighting (Merghadi et al., 2020). Compared with conventional regional models using a binary forest variable (Reichenbach et al., 2018), the proposed framework better represents forest structure and dynamics, improving susceptibility assessment and supporting hazard monitoring, forest management, and spatial planning. Its implementation in Google Earth Engine ensures reproducibility and facilitates application to other landslide-prone regions (Gorelick et al., 2017; Hrushko et al., 2025). The main limitations are the absence of a temporal triggering component, dependence on the completeness of the landslide inventory, limited representation of anthropogenic factors, and validation at only two study sites.

## Conclusions

An integrated geoinformation framework for landslide susceptibility and geocological risk assessment has been developed and implemented, spanning the entire workflow from a conceptual factor system to a validated cloud-based implementation through five integrated stages (Figure 1). Within this framework, the role of forest cover as a key ecosystem factor controlling landslide susceptibility has been quantitatively demonstrated for the first time in the Ukrainian Carpathians: indicators of forest condition, structure, and spatial configuration were identified as statistically significant predictors, and the forest block accounted for approximately one quarter ( $\approx 25.9\%$ ) of the total factor importance.

The framework integrates Frequency Ratio calibration with Random Forest Feature Importance weighting within Google Earth Engine, providing an interpretable, reproducible, and transferable workflow for regional susceptibility assessment. Under spatial-block validation, 88.1% of independent test landslides fell within the elevated-susceptibility classes ( $AUC = 0.72$ ). The integrated risk-assessment component,

comprising a nature-conservation priority index (NPS-based) and a population-and-infrastructure risk index, supports landslide monitoring, forest management, spatial planning, climate-change adaptation, and biodiversity conservation. Future work should incorporate the temporal dynamics of triggering precipitation, climate-change scenarios, and higher-resolution geospatial datasets.

## References

- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
- Hrushko, O. & Zhytar, D. & Ilkiv, E. & Hrynishak, M. & Kukhtar, Denys. (2025). Geospatial Analysis of War-Affected Areas in Ukraine Based on SAR and GIS Technologies. *International Conference of Young Professionals Geoterrace 2025*. 1-5. 10.3997/2214-4609.2025510159.
- Chepurna, T., Salyha, V., & Chepurnyi, I. (2022, October). To the issue of monitoring of mudflows within Carpathian region using modern web GIS technology. In *International Conference of Young Professionals «GeoTerrace-2022»*, Vol. 2022, No. 1, pp. 1–5. <https://doi.org/10.3997/2214-4609.2022590024>.
- Chepurnyi, I., Rushchak, V., & Chepurna, T. (2024). Spatial analysis of the relationship between the distribution of landslide areas and forest cover. *GeoTerrace-2024: International Conference of Young Professionals*, 2024(1), 1–5. <https://doi.org/10.3997/2214-4609.2024510017>
- Gariano, S. L., & Guzzetti, F. (2016). Landslides in a changing climate. *Earth-Science Reviews*, 162, 227–252. <https://doi.org/10.1016/j.earscirev.2016.08.011>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Günther, A., Van Den Eeckhaut, M., Malet, J.-P., Reichenbach, P., & Hervás, J. (2014). Climate-physiographically differentiated Pan-European landslide susceptibility assessment using spatial multi-criteria evaluation and transnational landslide information. *Geomorphology*, 224, 69–85. <https://doi.org/10.1016/j.geomorph.2014.07.011>
- Lee, S., & Pradhan, B. (2007). Landslide hazard mapping at Selangor, Malaysia using frequency ratio and logistic regression models. *Landslides*, 4(1), 33–41. <https://doi.org/10.1007/s10346-006-0047-y>
- Merghadi, A., Yunus, A. P., Dou, J., Whiteley, J., ThaiPham, B., Bui, D. T., Avtar, R., & Abderrahmane, B. (2020). Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Science Reviews*, 207, 103225. <https://doi.org/10.1016/j.earscirev.2020.103225>
- Reichenbach, P., Rossi, M., Malamud, B. D., 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>
- Rushchak, V., & Chepurnyi, I. (2025). Assessment of forest cover dynamics in landslide-prone areas of the Ukrainian Carpathians using remote sensing data. *18th International Conference Monitoring of Geological Processes and Ecological Condition of the Environment*, 2025(1), 1–5. <https://doi.org/10.3997/2214-4609.2025510172>
- Trevoho, Ihor & Prykhodko, Mykola & Ilkiv, E. & Halyarnyk, M. & Yershov, Maksym. (2021). Scientific fundamentals of agricultural landscapes optimization and planning with the use of GIS technologies. *International Conference of Young Professionals Geoterrace 2021*. 1-5. 10.3997/2214-4609.20215K3036.