Landslide25_18

Remote sensing and Google Earth Engine for regional landslide assessment in the Carpathians

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SUMMARY

Landslides are among the most frequent and destructive natural hazards in mountainous regions, posing serious risks to human life, infrastructure, and ecosystems. The Carpathian Mountains, spanning Central and Eastern Europe, are particularly susceptible due to their complex geomorphology, steep topography, and increasing anthropogenic pressures. Comparing traditional field-based assessments, advancements in remote sensing and cloud-based platforms such as Google Earth Engine (GEE) enable scalable, high-frequency, and cost-efficient analysis of landslide-prone terrain. This study utilizes GEE to integrate multi-source satellite and environmental data for regional-scale landslide susceptibility mapping across the Carpathians. A weighted overlay model combining factors such as elevation, slope, aspect, curvature, vegetation (NDVI), and precipitation was used to compute a Landslide Susceptibility Index (LSI). The resulting map, validated using the NASA Global Landslide Catalog, identifies low to very high susceptibility zones.

Introduction

Landslides are a major natural hazard in mountainous regions, leading to significant environmental damage, economic losses, and community risks. In the Carpathian Mountains – which stretch across parts of Ukraine, Poland, Slovakia, Romania, and Hungary – landslides occur frequently due to the region's complex geology, steep terrain, and increasing pressure from human activity and climate variability (Ivanik et al., 2019; Shtohryn, & Kasiynchuk, 2024). Effective monitoring and assessment of these processes are essential for land-use planning and disaster risk management.
Remote sensing data play a critical role in landslide research, providing dynamic and large-scale observations (Fossi et al., 2025) often inaccessible through conventional field methods (Heruk et al., 2017; Kuzmenko et al., 2018). Their integration into geospatial analysis significantly enhances the ability to detect, monitor, and model hazardous processes in hard-to-access terrains, including mountainous areas.
This study aims to evaluate the potential of Google Earth Engine (GEE) (Laghari et al., 2025) for regional-scale landslide susceptibility mapping across the Carpathians. The main objectives include identifying key natural and anthropogenic factors influencing landslides, processing open-access satellite and terrain data, and producing a spatial model of hazard distribution. The research demonstrates the usefulness of remote sensing and the power of cloud-based geospatial analysis for supporting sustainable land management in vulnerable mountain landscapes.

Method and/or Theory

The methodology integrates multiple geospatial datasets representing topographic, climatic, vegetation, and landslide event information to generate a Landslide Susceptibility Index (LSI) (Lee, & Talib, 2005). A weighted overlay model was applied, incorporating such characteristics as geomorphological factor values, NDVI, and precipitation (Liang et al., 2021; Ostapenko et al., 2023). Table 1 provides general information about the datasets used in the assessment.

Table 1 *Datasets used in the landslide susceptibility assessment*

Dataset	Source	Temporal Coverage	Spatial Resolution	Purpose
SRTM DEM	USGS/SRTMGL1_003	N/A	~30 m	Derivation of elevation, slope, aspect, curvature
Sentinel-2 Surface Reflectance	COPERNICUS/S2_SR	Summer 2022	10 m	NDVI calculation for vegetation coverage
CHIRPS Daily Precipitation	UCSB-CHG/CHIRPS/DAILY	Year 2023	~5 km	Annual precipitation estimation
NASA Global Landslide Catalog	NASA (GLC, 1970-2019)	1970-2019	Point data	Validation of the Landslide Susceptibility Index

The area of interest (AOI) is the Carpathian Mountains, defined by a shapefile containing the vector boundary of the region (approximate geographic extent between 17.5° – 26.5°E longitude and 45.5° – 50.5°N latitude). All raster datasets were clipped to this AOI and resampled to a uniform spatial resolution. The landslide inventory points were also filtered to fall within the AOI. Each layer was normalised to a 0–1 scale to standardise input variables. NDVI was inverted to reflect increased landslide susceptibility with lower vegetation. Curvature was normalised assuming a range from -1 to 1. The Landslide Susceptibility Index (LSI) was computed using a weighted linear combination of six factors, each representing a key

environmental variable influencing landslide occurrence: altitude (w = 0.2), slope (w = 0.25), aspect (w = 0.2), curvature (w = 0.15), NDVI (w = 0.1), and precipitation (w = 0.1).
LSI values were divided into four susceptibility zones using the 25th, 50th, and 75th percentiles of the LSI distribution across the study area:

- Low susceptibility;
- Moderate susceptibility;
- High susceptibility;
- Very high susceptibility.

The resulting LSI was validated using historical landslide data from the NASA Global Landslide Catalog (NASA GLC) (Kirschbaum et al., 2010).

Results

The resulting Landslide Susceptibility Index (LSI) map for the Carpathian region (Figure 1) effectively highlights spatial patterns of landslide risk across mountainous areas. Areas of very high susceptibility are predominantly found along steep slopes in the northern and south-eastern Carpathians, particularly in Romania, Slovakia, western Ukraine, and southern Poland. High susceptibility zones follow a similar pattern, extending across ridgelines and escarpments. Moderate susceptibility areas are distributed across mid-elevation zones and transitional terrains, whereas low susceptibility is associated with flatter terrain, usually found outside mountainous regions.

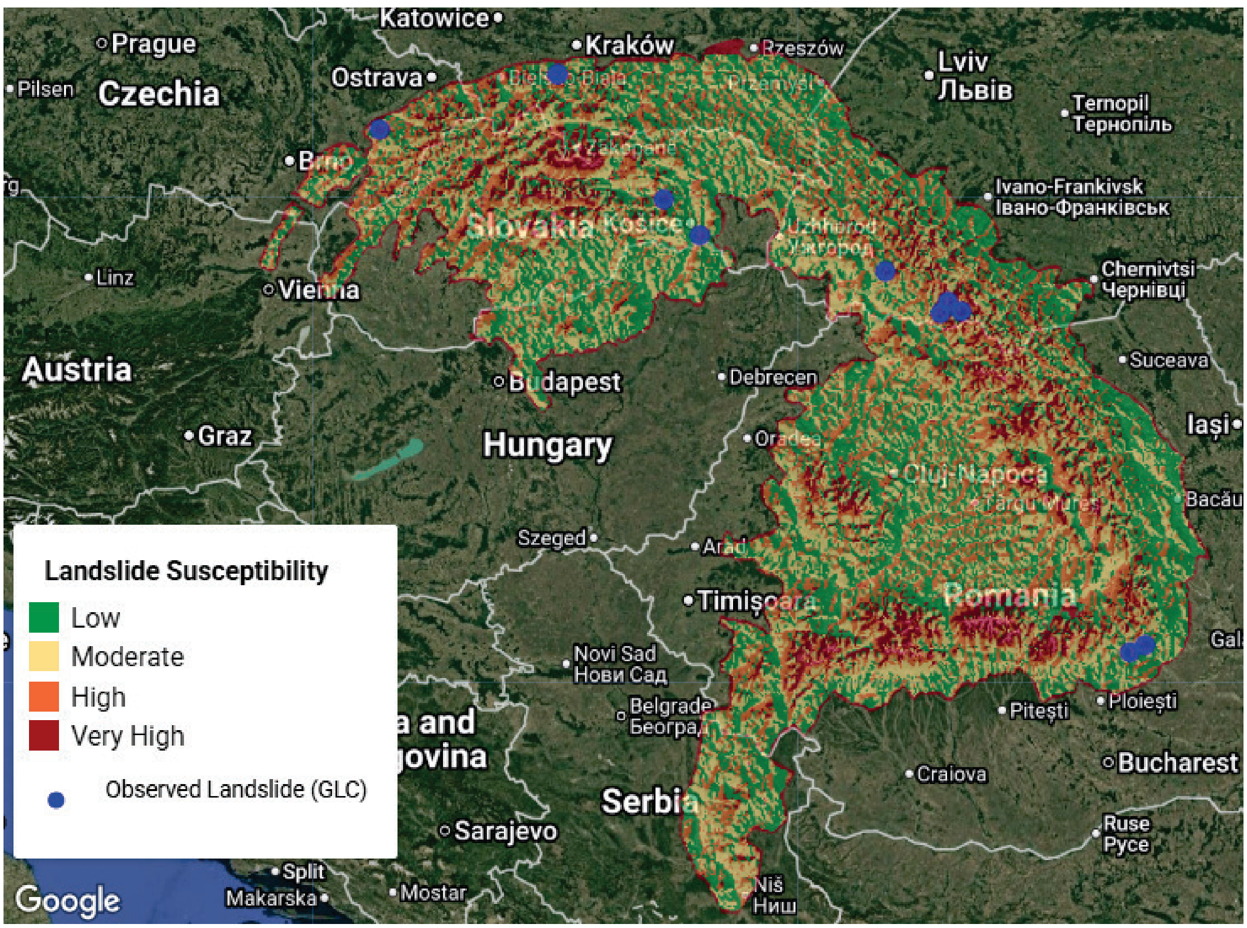

***Figure 1** Map of landslide susceptibility in the researched region*

The landslide events observed in the NASA GLC are predominantly concentrated within the high and very high susceptibility zones. This spatial overlap provides a compelling indication of the model's validity and suggests a general agreement between the predicted risk levels and the actual landslide occurrences (Figure 2). The correlation of historical landslides with modelled zones of higher susceptibility serves to demonstrate the efficacy of the weighted overlay approach in identifying vulnerable areas across the Carpathians.

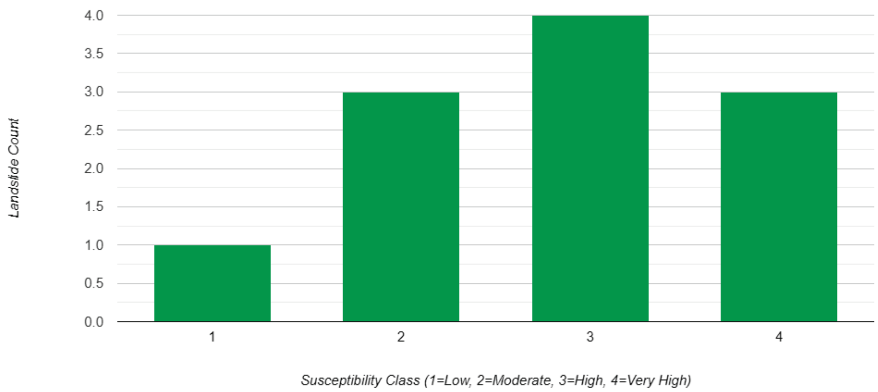

Figure 2 *Landslide counts per susceptibility class*

Conclusions

This study successfully demonstrates the application of a multi-criteria weighted overlay approach for assessing landslide susceptibility in the Carpathian region with open source data and cloud geoinformation platform Google Earth Engine. LSI values allow for highlighting priority areas for risk mitigation and support regional planning initiatives by identifying zones of low to very high susceptibility across the mountain range.

The approach integrates topographic, vegetative, and climatic indicators from global remote sensing datasets. While effective for regional-scale assessments, several limitations must be acknowledged. The model assumes static environmental conditions and does not account for dynamic processes such as deforestation, urban development, or land use change, which can significantly alter landslide risk over time. The precipitation data used from the CHIRPS dataset, although globally accessible, has relatively coarse spatial resolution, which may not adequately capture localised rainfall events critical to triggering landslides. Using NDVI as a proxy for vegetation stability is a simplification that does not fully represent land cover, forest structure, and vegetation type. Additionally, the assignment of weights for the contributing factors was based on expert judgment and literature review rather than statistical optimisation, potentially introducing bias into the model.

Another important constraint is the limited number of observed landslide events in the study area's NASA GLC. The spatial coverage of the catalog is sparse in the Carpathians, reducing the robustness of the validation step and underrepresenting actual landslide occurrences. Incorporating national or regional landslide inventories – such as those maintained by Polish, Ukrainian, Romanian, or Slovak geological institutes – would be highly beneficial to enhance the accuracy of susceptibility mapping and validation. Higher spatial resolution datasets would improve the model's sensitivity and would strengthen the model's reliability and operational utility.

Future research should consider integrating more detailed and dynamic variables such as land cover and land use variability, lithology, hydrology, tectonic, and seismic data. Statistical methods or machine learning techniques (e.g., logistic regression, random forests, or AHP) could be applied to refine the selection and weighting of input factors. Advancements in these directions would support the development of more accurate and responsive landslide susceptibility models, ultimately contributing to more effective early warning systems, sustainable land management, and climate resilience planning in mountainous regions like the Carpathians.

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