GeoTerrace-2026-060

A Geoinformation Framework for Automated Geomorphological Mapping of Periglacial Landforms in the Volhynian Upland

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SUMMARY

Automation of geomorphological mapping has become an important direction in the development of modern geoinformation technologies. Despite recent advances in deep learning, the automated detection of relict periglacial landforms remains challenging because of their subdued morphology and the influence of contemporary land use. This paper proposes a geoinformation framework for automated geomorphological mapping that integrates semantic segmentation, spatial post-processing, and automated generation of vector geospatial data. The framework was evaluated in the Volhynian Upland, a region characterised by diverse relict periglacial landforms. The results indicate that the proposed approach enables automated production of GIS-ready spatial datasets suitable for subsequent expert interpretation and geomorphological mapping.

Keywords: Geoinformation framework; Automated geomorphological mapping; Periglacial landforms; Deep learning; Semantic segmentation; Volhynian Upland.

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Introduction

Relict periglacial landforms record past permafrost conditions and subsequent landscape evolution. This study focuses on relict post-cryogenic patterned ground (large-polygon microrelief) formed through degradation of permafrost associated with the last palaeocryogenic (Krasyliv, late MIS 2) stage. These features are important components of the relief of the Volhynian Upland, but their subdued morphology, vegetation cover, and fragmentation by contemporary land use complicate both visual interpretation and automated recognition. Their spectral characteristics may also resemble the surrounding background (Bogucki et al., 2007, 2021).

Traditional mapping relies on expert interpretation of topographic maps, digital elevation models, aerial photographs, and satellite imagery. It is labour-intensive and difficult to reproduce consistently among researchers (van der Meij et al., 2022). Deep learning has enabled automated mapping of glacial, volcanic, and other landforms (Garajeh et al., 2022; Nodjoumi et al., 2023; Rocamora et al., 2024; Maslov et al., 2025), although many studies concern well-defined relief or use elevation data as their principal input.

Most studies emphasise individual model performance, while fewer integrate all stages from reference-data preparation to GIS-ready vector outputs (Nodjoumi et al., 2023; Rocamora et al., 2024). The aim of this study is to develop and test such a geoinformation framework for the Volhynian Upland, combining satellite-image semantic segmentation, spatial post-processing, vectorisation, and regional analysis of periglacial landforms.
Method and Theory

The study area is the Volhynian Loess Upland, a subregion of the Volhynian-Podolian Upland bounded by Volhynian Polissia to the north and Male Polissia to the south (Bogucki et al., 2021). Its relief reflects the interaction of continental glaciation and periglacial processes. The western part was affected by the Oka (MIS 12) Glaciation, which produced glacial and glaciofluvial landforms. Subsequent loess accumulation and erosion obscured many relict features (Bogucki et al., 2007). This history, together with contemporary land-use transformation, makes the area a challenging test site for automated mapping.

Materials

The input data comprised Google Satellite imagery with a spatial resolution of 2 m covering the Volhynian Upland. The source raster was automatically divided into equal-sized tiles for model training and inference. Reference polygons were delineated manually through expert interpretation of satellite imagery, informed by the geomorphology of the region (Bogucki et al., 2021), and used for training and validation.

The framework was implemented in Python using Rasterio, GeoPandas, Shapely, NumPy, SciPy, scikit-learn, PyTorch, and Torchvision. All spatial data were transformed to a common coordinate reference system. No digital elevation models or auxiliary data were used, allowing recognition to be assessed exclusively from high-resolution satellite imagery.

Proposed Geoinformation Framework

The proposed geoinformation framework is designed for the automated mapping of periglacial landforms from satellite imagery. Unlike most existing approaches, which focus primarily on improving individual machine-learning models, the proposed framework covers the complete geospatial-processing cycle, from preparation of the source data to the production of ready-to-use vector layers suitable for geographic information systems (Nodjoumi et al., 2023; Rocamora et al., 2024).

The framework consists of five consecutive stages (Figure 1).

The first stage (Input Data) prepares equal-sized GeoTIFF tiles, expert-created reference polygons, and coordinate reference system metadata for consistent spatial processing.

The second stage (Feature Extraction) combines normalised RGB channels with gradient magnitude and local texture features to enhance the image characteristics of periglacial landforms.

The third stage (Model Training) trains a U-Net semantic segmentation model with a ResNet18 encoder using a combined BCE + Dice loss function. Reference polygons are split 80:20 into training and validation samples.

The fourth stage (Inference) applies the trained model across the study area using 512 × 512-pixel tiles with a 64-pixel-wide context area to support recognition at tile boundaries and produce a continuous prediction map.

The fifth stage (GIS Output) includes morphological mask cleaning, automated vectorisation, polygon filtering by area, and generation of the final layer in the appropriate coordinate reference system.

Quality-control procedures include a fixed random seed for reproducibility, evaluation using Dice, IoU, Precision, and Recall, and early stopping. Vector post-processing includes boundary smoothing, topology-preserving geometry simplification, and removal of small objects.

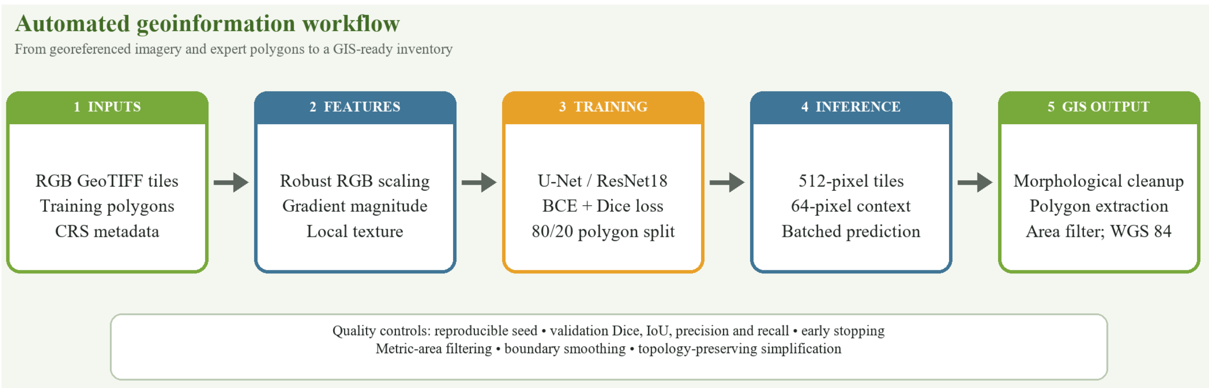

Figure 1. *Structure of the automated geoinformation workflow from raster and vector inputs to a GIS-ready candidate inventory*

Results

Application of the framework to 2 m satellite imagery produced a continuous polygon layer of candidate periglacial landforms in the Volhynian Upland. Once trained on manually interpreted reference polygons, the model delineated features automatically across the study area. In the example shown in Figure 2, the polygons generally correspond to visually identifiable landforms and represent both compact and elongated forms, with continuous boundaries suitable for subsequent spatial analysis.

A regular hexagonal grid was used to assess regional distribution (Figure 3). Coverage was calculated as the area of recognised landform polygons within each cell divided by the total cell area, expressed as a percentage. This generalisation reduces the influence of individual feature geometry on regional comparisons.

The distribution is uneven: cells with 20-50% coverage predominate, while local concentrations of 50-70% occur mainly in the central and central-western parts of the upland and near Rivne. Coverage generally decreases to 0-20% at the periphery, particularly in the north-western and partly southern parts of the upland. The resulting mosaic identifies zones of greatest concentration of the recognised landforms.

Figure 2. *Sample output of the proposed geoinformation framework showing automatically extracted periglacial landform polygons over high-resolution satellite imagery*

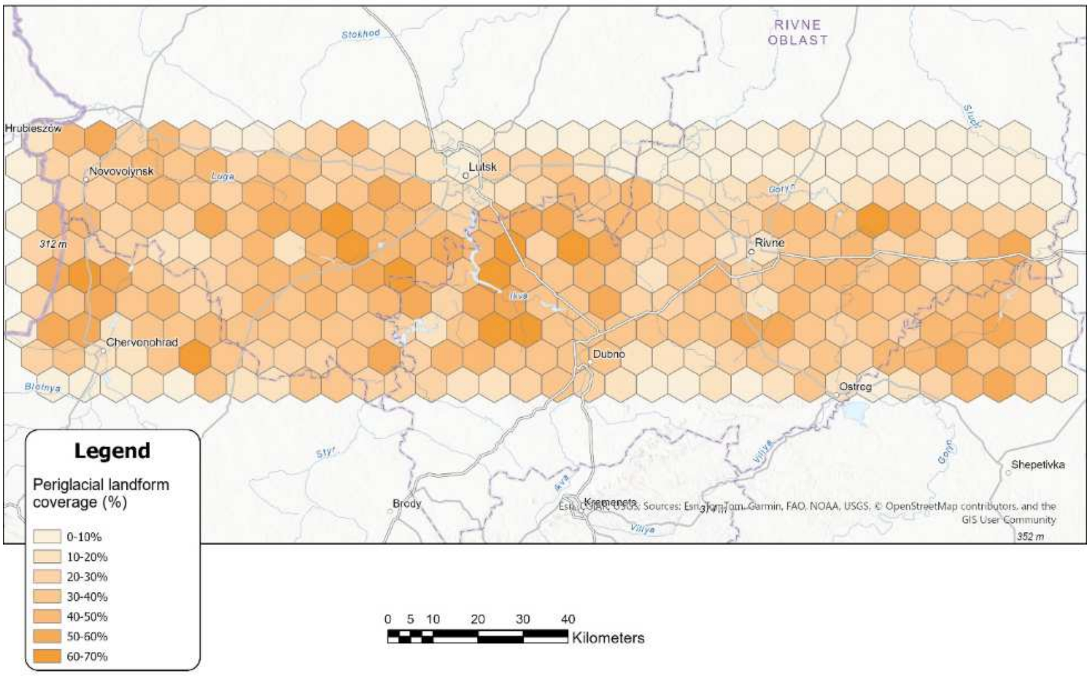

Figure 3. *Hexagonal representation of the relative coverage (%) of automatically extracted periglacial landforms within the Volhynian Upland*

Discussion

The framework provides a spatially consistent candidate inventory for preliminary geomorphological mapping. Hexagonal generalisation complements individual polygons by showing regional patterns of landform concentration. The mapped distribution represents the present-day expression of relict post-cryogenic landforms in satellite imagery; differences in concentration may reflect both primary periglacial morphogenesis and subsequent transformation and preservation.

Further work should expand the training sample, evaluate model accuracy against independent test data, and verify the delineated features using morphometric data and field observations. These steps are also needed when adapting the method to other areas and landform types.

Conclusions

The developed framework integrates reference-data preparation, U-Net segmentation, spatial post-processing, and vectorisation to map periglacial landforms from 2 m satellite imagery without elevation data. Its application in the Volhynian Upland produced GIS-ready candidate polygons and enabled quantitative analysis of their territorial distribution.

Hexagonal analysis revealed a mosaic pattern, with predominant coverage of 20-50%, local concentrations of 50-70%, and lower values at the periphery. The approach connects automated detection of individual features with regional geomorphological analysis and provides a basis for subsequent expert and field verification.

Acknowledgements

This research was funded by the National Research Foundation of Ukraine, project no. 2025.07/0260.

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