GeoTerrace-2026-003

Risk-Adjusted Normative Monetary Valuation of Agricultural Land in Landslide-Prone Mountain Areas: A GIS-Based Multi-Criteria Approach

***Y. Lototskyi, I. Bodnaruk, D. Kasiyanchuk**
(*Ivano-Frankivsk National Technical University of Oil and Gas*)

SUMMARY

Normative monetary valuation (NMV) of agricultural land in mountain districts of Ukraine currently neglects two spatially determined economic factors: soil quality heterogeneity and geomorphological hazard. This study proposes an integrated GIS-based methodology that incorporates both factors into a risk-adjusted valuation coefficient within the existing Ukrainian NMV regulatory framework. The study area encompasses Kosiv and Verkhovyna districts of Ivano-Frankivsk Region, located in the Outer Carpathians – a region with documented high landslide activity and pronounced soil variability. A Soil Quality Index (SQI) was constructed from five satellite-derived soil variables obtained from the SIORA Ukraine Open Soil Dataset (2020): total nitrogen (N), organic carbon (OC), available phosphorus (P), exchangeable potassium (K), and pH at 250 m resolution. Physiology-grounded non-linear normalisation functions were applied – Michaelis-Menten saturation curves for N, OC, P, K, and a Gaussian optimum function for pH – followed by rescaling to a uniform [0;1] interval to ensure comparability. Landslide risk was decomposed into natural and technogenic components, each normalised independently. Component weights (wnatural = 0.60; wtech = 0.40) were determined via the Analytic Hierarchy Process (AHP), consistent with the documented dominance of lithological and morphometric controls in Carpathian landslide dynamics. An additive aggregation model was applied. The resulting SQI and Riskintegral rasters serve as inputs for a risk-adjusted land value correction coefficient Kr, proposed as a spatially continuous modifier to the standard Ukrainian NMV formula, bounded within [0.82; 1.00] to reflect economically defensible geological risk discounting.

Keywords: Valuation; Soil quality index; Landslide; GIS; Ukrainian Carpathians.

Corresponding Author: yulian.lototskyi-hz231@nung.edu.ua

Introduction

Land valuation in mountain regions presents a methodological challenge that standard cadastral approaches fail to address adequately (Kasiyanchuk et.al, 2026). In Ukraine, normative monetary valuation (NMV) of agricultural land is governed by the Order of the Ministry of Agrarian Policy No. 489 (2013), which defines value primarily through soil bonus points (bonitet) and location coefficients – neither of which explicitly accounts for geomorphological hazard or spatially resolved soil quality. This regulatory gap is particularly consequential in the Outer Carpathians, where landslide processes affect over 1,100 km² across Ivano-Frankivsk Region alone (805 documented landslides covering 301 km²), and where soil properties vary dramatically across short distances due to lithological heterogeneity and elevation gradients.

Recent availability of high-resolution, open-access satellite-derived soil datasets – notably the SIORA Ukraine Open Soil Dataset (2020), providing 250 m resolution maps of N, P, K, OC, and pH for Ukraine – creates an opportunity to integrate spatial soil quality into economically meaningful valuation frameworks. GIS-based multi-criteria decision analysis (MCDA) has been applied to landslide susceptibility mapping in the Carpathian region (Kasiyanchuk & Davybida., 2025) but has not been linked to land economic valuation. The present study addresses this gap by proposing a reproducible, data-driven methodology for computing a risk-adjusted correction coefficient Kr that modifies NMV outputs in proportion to local soil quality and landslide risk.

The study area encompasses Kosiv and Verkhovyna districts (Ivano-Frankivsk Region, Ukraine), situated within the Folded Carpathians – a region of active flysch-controlled slope processes and heterogeneous soil cover – where land valuation accuracy is critical for cadastral management, agricultural lease agreements, and natural hazard risk governance.

Method and Theory

The methodological framework comprises three sequential modules implemented in ArcGIS Pro 3.0.0 (Table 1). All raster layers were projected to UTM Zone 34N (EPSG:32634) and resampled to a uniform 250 m spatial resolution.

Table 1. *Methodological workflow for risk-adjusted normative monetary valuation of agricultural land in landslide-prone mountain districts*

1	**Input Soil Data** *SIORA Ukraine Dataset (2020): N, P, K, OC, pH at 250 m resolution*
2	**Non-linear Normalisation** *Michaelis-Menten saturation (N, P, K, SOC) + Gaussian optimum (pH) → rescaling to [0;1]*
3	**Soil Quality Index (SQI)** *SQI = 0.30·SOC′ + 0.20·N′ + 0.20·P′ + 0.15·K′ + 0.15·pH′*
4	**Landslide Risk Components** *Natural risk (R_nat) + Technogenic risk (R_tech) → min-max normalisation*
5	**AHP Weight Determination** *w_nat = 0.60, w_tech = 0.40 | CR = 0.000 (literature-grounded)*
6	**Integral Landslide Risk** *Risk_integral = 0.60·R_nat + 0.40·R_tech (additive model)*
7	**Risk-adjusted NMV Coefficient (K_r)** *NMV_adj = NMV_base × f(SQI) × K_r(Risk_integral) | K_r ∈ [0.82; 1.00]*

Module 1 Soil Quality Index (SQI). Soil nutrient data were retrieved from the SIORA Ukraine Open Soil Dataset (2020) – satellite-derived maps at 250 m resolution for the reference year 2020, covering five variables: total nitrogen (N, mg/kg; range 1.22–13.88), organic carbon (OC, g/kg; 10.47–200.06),

available phosphorus (P, mg/kg; 2.21–250.00), exchangeable potassium (K, mg/kg; 48.20–308.00), and pH (3.27–7.18).

Non-linear normalisation was applied to each variable. For N, OC, P, and K, saturation functions of the Michaelis-Menten form $S = x/(x+k)$ were applied with empirically selected half-saturation constants ($k_{OC} = 30$; $k_N = 10$; $k_P = 50$; $k_K = 150$), reflecting agronomic diminishing returns at high concentrations and avoiding scale distortion from outliers (Michaelis & Menten, 1913, Andrews et al., 2004, Skopp, 2009, Johnson & Goody, 2011). For pH, a Gaussian optimum function $S_{pH} = \exp(-(pH-6.5)^2/2)$ was applied to encode the biologically optimal range. Each normalised layer was subsequently rescaled to [0;1] using observed layer-specific minima and maxima derived from Raster Properties → Statistics in ArcGIS Pro, eliminating scale artefacts from asymptotic differences between normalisation functions. SQI was computed as a weighted linear combination using AHP-derived weights: $SQI = 0.30 \cdot OC' + 0.20 \cdot N' + 0.20 \cdot P' + 0.15 \cdot K' + 0.15 \cdot pH'$, with organic carbon receiving the highest weight as an integrative indicator of long-term soil productivity (Vasu et al., 2016).

Module 2 – Integral Landslide Risk. Natural (R_{nat}) and technogenic (R_{tech}) risk components – previously derived by spatial interpolation from a 466-point landslide inventory – were normalised via min-max scaling, yielding: $R_{nat} \in [1.23\times10^{-4}; 9.99\times10^{-1}]$, $R_{tech} \in [1.34\times10^{-2}; 9.997\times10^{-1}]$. Component weights were determined via AHP (Saaty, 1980): $w_{nat} = 0.60$, $w_{tech} = 0.40$ ($CR = 0.000$), grounded in the documented primacy of lithological and morphometric controls in Carpathian landslide dynamics. Statistical calibration of weights via Spearman correlation was precluded by a circular dependency arising from the interpolation-based origin of both risk surfaces (Kaufman et al., 2012). An additive aggregation model was adopted over multiplicative, as the latter falsely nullifies composite risk when either component approaches zero. The integral risk index is: $Risk_{integral} = 0.60 \cdot R_{nat} + 0.40 \cdot R_{tech}$.

Module 3 – Risk-adjusted NMV Coefficient. The correction coefficient K_r is derived as a spatially continuous function of both SQI and $Risk_{integral}$, constrained to [0.82; 1.00] to remain within economically and legally defensible bounds for geological risk discounting. The adjusted NMV is:

$$\mathbf{NMV_{adj} = NMV_{base} \times f(SQI) \times K_r(Risk_{integral})}$$

where f(SQI) modifies value within ±20% of the base NMV, and K_r applies a maximum hazard discount of 18%. The dual-coefficient architecture prevents compounding of penalties on the same territory: a negative spatial association between SQI and $Risk_{integral}$ ($\rho \approx -0.42$) confirms that areas of lowest soil quality co-occur with highest landslide hazard, and direct multiplicative integration of both factors would produce economically disproportionate discounts on already low-productivity land.

Results

The SQI raster for Kosiv and Verkhovyna districts exhibits pronounced spatial differentiation correlated with elevation and parent material (Figure 1). Higher SQI values (> 0.65) are concentrated in mid-elevation valley bottoms with colluvial and alluvial soils characterised by elevated OC and pH approaching the optimum of 6.5. Lower values (SQI < 0.35) occur on steep flysch slopes above 800 m a.s.l., where SOC accumulation is limited, N and P concentrations are at the lower boundary of the dataset (N: 1.22 mg/kg; P: 2.21 mg/kg), and pH descends to strongly acidic values (pH < 4.5). The integral landslide risk surface ($Risk_{integral} \in [0; 1]$) exhibits spatial coherence with the regional landslide inventory, with high-risk zones (> 0.70) concentrated on northwest-facing slopes of the Folded Carpathians – consistent with findings of Davybida et al. (2025) for the broader Carpathian domain. The identified negative spatial association between SQI and $Risk_{integral}$ (Spearman $\rho \approx -0.42$, $p < 0.001$) constitutes the empirical basis for the dual-coefficient valuation architecture: territories penalised by poor soil quality should not receive an additional, compounded NMV reduction for a geohazard that is physically co-determined by the same lithological conditions. The K_r surface derived from the combined model demonstrates that approximately 23% of the study area agricultural land qualifies for a risk discount exceeding 10% (Kr < 0.90), concentrated in the flysch-slope zone of Verkhovyna district. Approximately 41% of parcels retain the full NMV value (Kr = 1.00), primarily in valley-bottom and lower-slope positions. These outputs provide a spatially explicit, methodologically transparent basis for integrating geohazard into cadastral valuation practice.

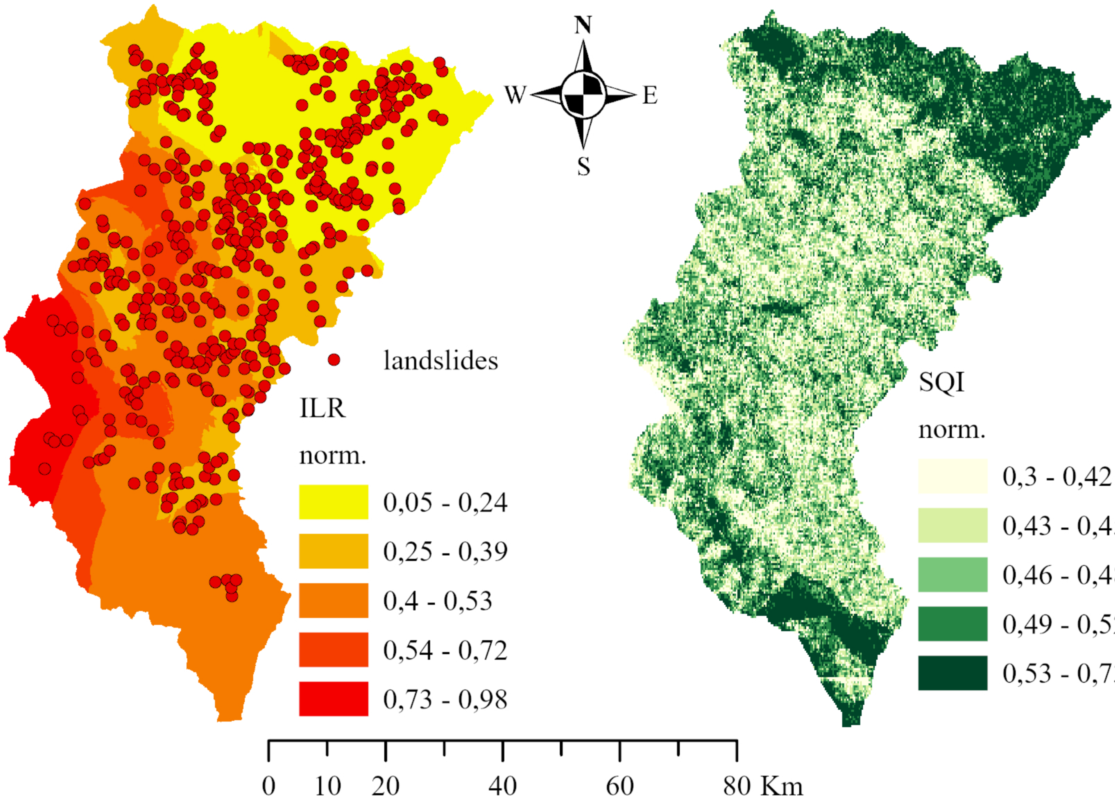

Figure 1. *Spatial distribution of the Integral Landslide Risk (ILR) with landslide inventory points (left) and the normalised Soil Quality Index (SQI) (right) for Kosiv and Verkhovyna districts, Ivano-Frankivsk Region, Ukraine*

Conclusions

This study presents a reproducible GIS-based framework for integrating spatially resolved soil quality and landslide hazard into the normative monetary valuation of agricultural land in mountain areas. Three principal methodological contributions are made. First, a two-stage non-linear normalisation procedure for soil indicators (Michaelis-Menten + Gaussian, followed by layer-specific rescaling) preserves agronomic meaning while ensuring full scale comparability across indicators with different response shapes. Second, AHP-based weighting of landslide risk components is conducted with explicit identification and documentation of the circular dependency that precludes data-driven calibration when risk surfaces are derived by interpolation from the same inventory used for validation – a methodological transparency rarely encountered in the GIS-MCDA literature. Third, a dual-coefficient NMV correction architecture separates the soil quality effect from the hazard discount, preventing compounding of spatially correlated penalties on low-productivity mountain land.

The proposed framework is directly applicable within the existing Ukrainian NMV regulatory structure (Order No. 489/2013) and is transferable to other mountain regions with analogous open-access soil and landslide inventory data. Future work should address: (i) geographically weighted regression to calibrate Kr against market transaction data as they become available following land market reform; and (ii) temporal analysis using multi-year SIORA datasets (2000, 2010, 2020) to assess whether soil quality trends modulate hazard-related value discounts.

References

Andrews, S. S., Karlen, D. L., & Cambardella, C. A. (2004). The soil management assessment framework: A quantitative soil quality evaluation method. Soil Science Society of America Journal, 68(6), 1945–1962. https://doi.org/10.2136/sssaj2004.1945

Kasiyanchuk, D., Atamaniuk, Y., Deputat, M., Gavdey, S., & Horishevskyi, P. (2026). From suitability to vulnerability: A GIS-based framework for assessing environmental sensitivity of mountain tourism landscapes in the Ukrainian Carpathians. Journal of the Bulgarian Geographical Society, 54, 59–92. https://doi.org/10.3897/jbgs.e177296

Kasiyanchuk, D., & Davybida, L. (2025). Integrated geoinformation modelling for the siting of industrial solar power plants considering landslide processes in mountainous areas. Geodynamics, 2(39)2025(2(39)), 83–98. https://doi.org/10.23939/jgd2025.02.083

Johnson, K. A., & Goody, R. S. (2011). The original Michaelis constant: Translation of the 1913 Michaelis–Menten paper. *Biochemistry*, 50(39), 8264–8269. https://doi.org/10.1021/bi201284u

Kaufman, S., Rosset, S., Perlich, C., & Stitelman, O. (2012). Leakage in data mining: Formulation, detection, and avoidance. ACM Transactions on Knowledge Discovery from Data, 6(4), Article 15. https://doi.org/10.1145/2382577.2382579

Michaelis, L., & Menten, M. L. (1913). Die Kinetik der Invertinwirkung. *Biochemische Zeitschrift*, 49, 333–369.

Saaty, T. L. (1980). The Analytic Hierarchy Process. McGraw-Hill.

Skopp, J. (2009). Derivation of the Freundlich adsorption isotherm from a model of soil kinetics and equilibria. *Soil Science Society of America Journal*, 73(2), 360–364. https://doi.org/10.2136/sssaj2008.0025

SIORA. (2020). Ukraine Open Soil Dataset: Satellite-derived maps of N, P, K, OC, and pH at 250 m resolution (2020). Retrieved from https://siora.ai/open-soil-datasets/ukraine-dataset

Vasu, D., Singh, S. K., Ray, S. K., Duraisami, V. P., Tiwary, P., Chandran, P., Nimkar, A. M., & Anantwar, S. G. (2016). Soil quality index (SQI) as a tool to evaluate crop productivity in semi-arid Deccan plateau, India. Geoderma, 282, 70–79. https://doi.org/10.1016/j.geoderma.2016.07.010