

Loss of Agricultural Land in Slovakia: Evidence from LPIS and Sentinel-2 Data

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Abstract

Agricultural land in Slovakia has undergone a significant transformation over the past two decades, but the extent and direction of this change remain insufficiently quantified at the national level. This study provides the first spatially explicit assessment of agricultural land loss using Land Parcel Identification System (LPIS) records (2004–2022) in combination with Sentinel-2-based land cover classification. By differentiating the LPIS, we identified polygons that were lost from the agricultural land register; these polygons could represent abandoned agricultural land as well as areas converted to other uses. These polygons were classified into four land cover classes using a Random Forest model trained on Sentinel-2 spectro-temporal metrics and cleaned LUCAS 2022 samples ($F1 = 0.867$), with additional filtering applied to separate grasslands from shrubs based on vegetation height. The results show that more than 1,000 km² of originally suitable agricultural land has been converted to other land cover types. Forest expansion accounts for 834 km², while 298 km² has been converted to shrubland and 553 km² remains as grassland. Non-forested areas, including buildings and infrastructure, cover an area of 258 km². Only 17 km² of formerly agricultural land remained as actively utilised arable land. These findings indicate that agricultural land abandonment, ecological succession, and urbanisation are the primary causes of agricultural land loss in Slovakia. The research presented provides important data confirming that the loss of agricultural land is extensive and largely threatens habitats with high biodiversity, highlighting the urgent need to harmonise strategies across agriculture, the environment, and land-use planning.

1. Introduction

Agricultural landscapes across Europe have undergone profound transformations over the past two decades, driven by a combination of socio-economic, demographic, and environmental factors. In Central and Eastern Europe, the transition from state-controlled to market-oriented economies following 1990 resulted in extensive restructuring of agricultural production systems and ownership patterns (Szatmári et al., 2021). These structural changes, accompanied by declining livestock numbers, shifts in rural population dynamics, and the expansion of urban and infrastructural development, have led to the widespread abandonment of agricultural land and its conversion to alternative land-cover types, such as forest, shrubland, or built-up areas (Bezák and Mitchley, 2014; Šveda et al., 2018). In particular, the changes were pronounced in traditional agricultural landscapes (Lieskovský et al., 2015) and in areas of high biodiversity value (Hegedúšová and Senko, 2011), where abandonment leads to a rapid decline in grassland species richness (Galváněk and Lepš, 2008).

In Slovakia, these processes have been particularly pronounced since the country acceded to the European Union in 2004, when agricultural policy reforms and CAP subsidy mechanisms further reshaped land-use patterns (Pazúr et al., 2014). The ownership fragmentation of former co-operative farms, low profitability of grassland management, and increasing land competition from construction and industrial activities have contributed to the loss of productive farmland and to significant spatial heterogeneity in land-use trajectories (Sklénicka et al., 2017). Monitoring these changes is essential for understanding the long-term sustainability of agricultural systems, assessing compliance with CAP regulations, and ensuring the effective management of agricultural land resources.

The accuracy of assessing changes in the agricultural landscape largely depends on the quality and accuracy of the input data used in this process, whether farm census statistics, cadastre records, aerial/satellite maps, or Copernicus land-cover layers, such as CORINE Land Cover or the emerging CLCplus product for Slovakia (Hudcovič et al., 2025). Because land cover changes rapidly, operational monitoring demands modern data collection

and processing methods that serve both landscape tracking and EU support schemes. The primary administrative instrument is the Integrated Administration and Control System (IACS), which manages applications, checks (administrative and on-the-spot), payments, and sanctions (Sagris and Devos, 2009). A key component of the IACS system for agricultural land is the Land Parcel Identification System (LPIS), legislatively defined in Regulation (EU) No. 1306/2013 of the European Parliament. The LPIS enables the unambiguous identification and localisation of declared parcels, serving as a reference database for verifying support applications. It draws on a wide range of data (orthophotomaps, field inspections, farmer-reported changes, and other departmental sources), so consistency with the legal status and current land use in IACS/LPIS is essential (Efthimiou et al., 2022).

The LPIS has also been a valuable source of information on local landscape dynamics since the early 1990s. These data can serve as a basis for analysing High Nature Value farmland (Lomba et al., 2017; Šatalová et al., 2021), assessing grassland dynamics (Nitsch et al., 2012; Zimmermann et al., 2016), or examining the dynamics of farm areas (Barbottin et al., 2018). The potential of LPIS as an input for advanced land-cover products has recently been demonstrated in the creation of the CLCplus Legacy 2018 map for Slovakia, where LPIS formed a key component of the national data stack (Hudcovič et al., 2025). Kopecká et al. (2019) analysed LPIS-based changes in agricultural land use from 2004 to 2018 in the Pezinok and Senec districts of Slovakia, focusing on the share of abandoned and construction-intended land within agricultural land losses. LPIS also serves as an alternative source of land-use information, complementing statistical data derived from cadastral records. However, it is essential to be aware of the differences from the cadastre (Kocur-Bera, 2020). Unlike the real estate cadastre, LPIS is typically based on physical blocks, defined by natural boundaries, and on user relations (rather than ownership relations); thus, significant differences in the extent of landscape changes are often described when comparing data from these two major databases (Vachuda, 2016).

The LPIS system in the Slovak Republic was launched in 2004. With updates, it enables the monitoring of land-cover changes, including managed agricultural land, which is quantified into

categories such as arable land, hop fields, vineyards, gardens, orchards, and permanent grassland, while also recording agricultural land without a registered support applicant. It is based on digital orthophotomaps (not older than five years). It is continuously and cyclically updated using support applications, on-the-spot checks, and remote sensing, gradually removing unauthorised elements such as buildings, roads, invasive trees, and expanding forest edges from eligible areas (Kopecká et al., 2019). Because LPIS evolves (through changes in parcel delineation, eligibility rules, update cadence, and attribute schemas), long-term comparability is not guaranteed and requires explicit harmonisation (Şimşek and Durduran, 2022; Kocur-Bera, 2020). Since July 2018, LPIS data has been available to the public, in addition to applicants for support and control institutions.

Although LPIS serves as a key administrative tool for tracking agricultural land use, its updates are often limited by the frequency of field inspections and manual revisions. Recent advances in Earth observation technologies, particularly the availability of high-resolution, multi-temporal Sentinel-2 data, provide new opportunities for automated, large-scale assessment of land-cover dynamics. Machine learning approaches, such as the Random Forest classifier, have proven highly effective at capturing spectral and temporal variability across diverse land-cover types (Belgiu and Drăguţ, 2016). When combined with reliable reference datasets such as LUCAS (Land Use and Coverage Area Frame Survey) (d'Andrimont et al., 2024), these methods enable robust mapping of land-cover transitions at national and regional scales.

Two specific goals of this contribution are

1. To delineate and quantify agricultural land that dropped out of the Slovak LPIS between 2004 and 2022.
2. To map and analyse the post-LPIS land-cover classes and transformation pathways within these LPIS dropout polygons using Sentinel-2-based classification.

Based on these goals, the study addresses the following research questions:

- What proportion of agricultural land removed from LPIS between 2004 and 2022 has transitioned to different land-cover types?
- What are the dominant land-cover trajectories (e.g., succession, urbanisation, persistence of agricultural use) within LPIS dropout areas?
- To what extent can Sentinel-2 spectral-temporal metrics combined with LPIS-derived dropout polygons reliably classify post-agricultural land cover across different climatic regions of Slovakia?

2. Data and Methods

2.1 Identification of LPIS Dropout Polygons for EO-Based Attribution

The Land Parcel Identification System (LPIS) serves as the spatial core for locating and monitoring agricultural land in support of the implementation of the Common Agricultural Policy.

During the data preparation phase, the exact locations where agricultural parcels were removed from LPIS after 2004 were identified. A parcel-level geometric difference between LPIS 2004 and 2022 was computed to obtain "difference polygons" representing areas that exited the LPIS register relative to the 2004 baseline. To avoid slice artefacts and ensure compatibility with Sentinel-2, polygons that could not fit into a 10 m Sentinel-2 pixel were removed (i.e., features with an effective width below

~10 m or an area smaller than the single-pixel footprint). We discarded micro-gaps along parcel borders introduced by topology updates.

The resulting dropout polygons (Figure 1) define the analysis domain for EO-based attribution. Only within these polygons, Sentinel-2 surface reflectance time series were extracted, and spectral-temporal metrics (indices and seasonal descriptors) were calculated.

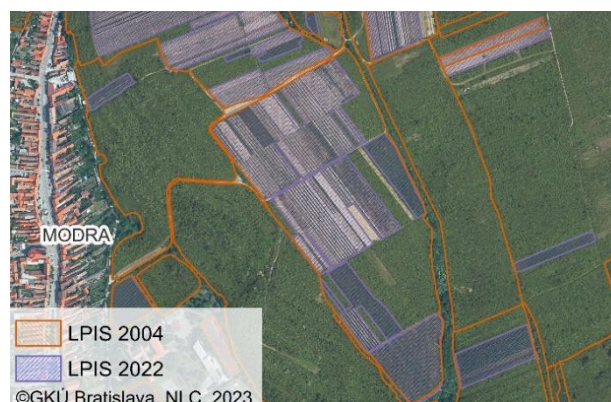


Figure 1. Example of LPIS dropout polygons between 2004 and 2022 in the Modra area.

2.2 Distribution of Training Data

Reference samples for model training were taken from the point and polygon layers of the LUCAS 2022 survey (d'Andrimont et al., 2024). The original eight LUCAS land-cover categories were reclassified into four target classes (Table 1):

- No Vegetation,
- Arable land,
- Woodland,
- Grassland/Shrubland.

The aggregation was necessary because several of the original classes cannot be reliably distinguished in Sentinel-2 data due to their similar reflectance characteristics. Built-up areas, bare soil, and water were merged into a single class. Grasslands and shrublands exhibit nearly identical spectral–seasonal trajectories, and attempts to model shrubland independently produced unstable, non-generalizable predictions. The aggregation was guided by both spectral separability and class representation. Preliminary experiments using the full set of LUCAS classes resulted in unstable class boundaries and reduced classification accuracy, particularly for spectrally similar classes such as shrubland and grassland. By merging overlapping classes with spectral-temporal signatures, model robustness improved.

In addition, class aggregation ensured a sufficient number of training samples per class, reducing the risk of model bias caused by class imbalance and improving the stability of cross-validation results.

Despite LUCAS being field-verified, several subclasses contained inconsistencies with the spectral signature (Figure 2/A). Class F40 – Other bare soil included recently ploughed arable land that the field survey confirmed as bareland rather than active agricultural plots. Because this condition produces reflectance patterns that are easily confused with those of actively managed fields, the class was removed to prevent systematic misclassification. Similarly, class A – Artificial surfaces often included narrow field or forest roads between active agricultural plots, or samples under tree crowns where the satellite signal did not reflect a homogeneous artificial cover. Such ambiguous observations were removed during model training, as described in detail in Section 2.4. Training.

Class Name	LUCAS Class Name
No Vegetation	A - Artificial Land, F - Bare Land, G - Water
Arable land	B - Cropland
Woodland	C- Woodland
Grassland/Shrubland	D - Shrubland, E - Grassland, H - Wetlands

Table 1. Reclassification of LUCAS 2022 land-cover classes.

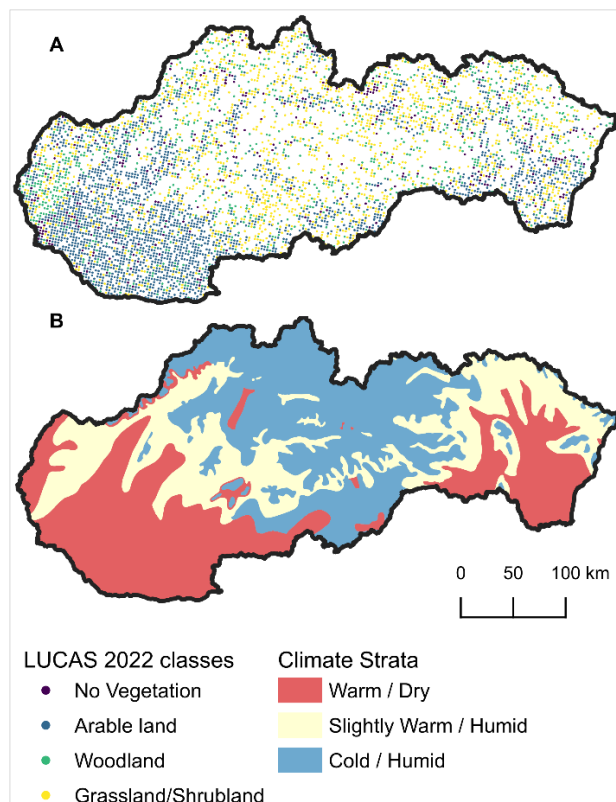


Figure 2. Spatial distribution of LUCAS 2022 reference samples and climate strata in Slovakia.

2.3 Satellite Data

Sentinel-2 surface reflectance was processed in Google Earth Engine. Clouds were removed using CloudScore+ (Pasquarella, 2024) with a 75% mask confidence and tile-level cloud filter $\leq 80\%$. All 20 m bands were upsampled to 10 m via nearest-neighbour to maintain band alignment before index computation. Subsequently, several vegetation indices were computed (Table 2), and the resulting time series was converted into spectro-temporal metrics. For each index, we computed median, standard deviation, and percentiles (P5, P25, P75, P95) and for NDVI, seasonal medians (spring: March–April; summer: May–August; autumn: September–November; winter: December–February), skewness, kurtosis, and amplitude (P95–P5). Textural heterogeneity was captured as the standard deviation of the median NDVI, computed using a 3×3 moving window. These metrics were spatially reduced to the LUCAS reference-area geometry and used as predictor variables in the classification model.

Vegetation Index	Equation
Normalised Difference Vegetation Index (NDVI)	$\frac{\text{NIR [B8]} - \text{RED [B4]}}{\text{NIR [B8]} + \text{RED [B4]}}$
Two-band Enhanced Vegetation Index (EVI2)	$2.5 \left(\frac{\text{NIR [B8]} - \text{RED [B4]}}{\text{NIR [B8]} + (2.4 \text{ RED [B4]}) + 1} \right)$
Normalised Difference Moisture Index (NDMI)	$\frac{\text{NIR [B8]} - \text{SWIR[B11]}}{\text{NIR [B8]} + \text{SWIR[B11]}}$
Normalised Burn Ratio (NBR)	$\frac{\text{NIR [B8]} - \text{SWIR[B12]}}{\text{NIR [B8]} + \text{SWIR[B12]}}$
Normalised Difference Red-Edge Index (NDREI)	$\frac{\text{NIR [B8]} - \text{RED EDGE [B5]}}{\text{NIR [B8]} + \text{RED EDGE [B5]}}$
Chlorophyll Index – Red Edge (CI-RE)	$\frac{\text{NIR [B8]}}{\text{RED EDGE [B5]}} - 1$
Plant Senescence Reflectance Index (PSRI)	$\frac{\text{RED [B4]} - \text{BLUE [B2]}}{\text{RED EDGE 2 [B6]}}$

Table 2. The vegetation indices used for classification were calculated from Sentinel-2 imagery.

2.4 Training

LUCAS outlier samples were removed using a two-stage procedure combining robust Mahalanobis distance with an Isolation Forest (contamination = 0.25), which eliminated observations exhibiting anomalous spectral behaviour within their assigned land-cover classes. This filtering step removed 1899 points, resulting in a final training set of 4043 samples. Because no independent, field-verified validation dataset was available, the cleaned dataset was stratified by climatic zones for spatial cross-validation (Figure 2/B). In each iteration, one climatic zone served as the test fold. At the same time, the remaining zones formed the training set, enabling an evaluation of the classifier's ability to generalise beyond the environmental conditions present in the training data.

The Random Forest algorithm was selected due to its robustness to high-dimensional data, ability to model non-linear relationships, and strong performance in remote sensing classification tasks. These properties are particularly advantageous in our case, where spectral-temporal metrics derived from Sentinel-2 exhibit varying distributions across climatic regions and land-cover types. The Random Forest model was trained with 300 trees, using the Google Earth Engine Random Forest classifier with default settings and class-balanced weights to reduce the influence of uneven class representation. Performance was evaluated separately for each climatic zone using precision, recall, and F1-score for individual classes.

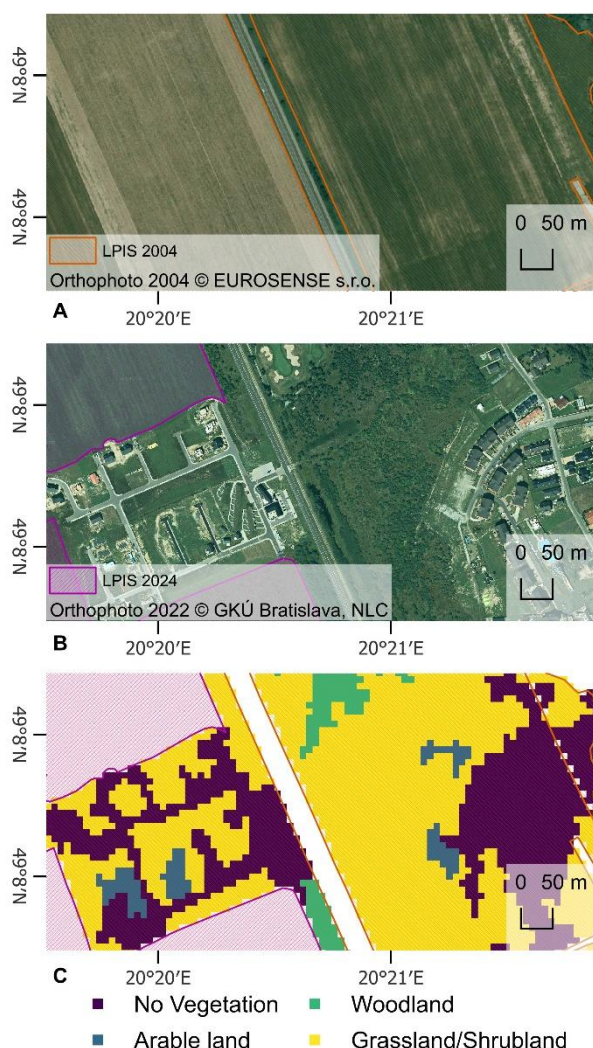


Figure 3. Example of LPIS dropout area and subsequent land-cover transition. Orthophoto from 2004 (A) and 2022 (B) with LPIS boundaries, classified land cover derived from Sentinel-2 (C). The figure illustrates how areas removed from LPIS correspond to actual land-cover changes in the landscape.

2.5 Postprocessing

To improve spatial coherence, the classified map was sieved using a minimum patch size threshold of 10 pixels to remove isolated or spurious predictions. Additionally, we applied the canopy height model (CHM) developed by Liu et al. (2023) to refine the classification of Grassland and Shrubland. This canopy height model is computed based on 3.5-meter PlanetScope data. Therefore, the data were aggregated to the 10-meter grid using Google Earth Engine's `reduceResolution` function. Resulting pixels with canopy height < 1 m were labelled as grassland, while pixels ≥ 1 m were labelled as shrubland. This postprocessing step introduces a structural constraint that compensates for the inherent spectral ambiguity between these two vegetation types.

3. Results

3.1 Accuracy Assessment

The model demonstrated high stability and accuracy (Table 3) across various climatic zones, with an average weighted F1 score of 0.867, precision of 0.871, and recall of 0.867. The Arable land class was classified most accurately ($F1 = 0.924$), followed by

Forest (0.859) and Grassland/Shrubland (0.823). The lowest accuracy was achieved for No Vegetation ($F1 = 0.688$), which was often misclassified as Grassland/Shrubland. Results across the individual strata were balanced, with weighted F1 ranging from 0.853 to 0.886. Overall, the model demonstrated good generalisation capability and stable performance across varying climatic conditions.

Reference class →	No Vegetation	Arable land	Forest	Grassland/Shrubland
Prediction ↓				
No Vegetation	62	2	1	12
Arable land	2	516	0	14
Forest	6	1	218	30
Grassland/Shrubland	32	39	35	378
Precision	0.804	0.928	0.857	0.784
Recall	0.602	0.921	0.861	0.870
F1-score	0.688	0.924	0.859	0.823

Table 3. Error matrix with evaluation of Precision, Recall and F1-score. The error matrix, along with other metrics, corresponds to the weighted average across zones.

3.2 Agricultural Land Transformation (2004–2022)

To illustrate the characteristics of LPIS dropout areas and their subsequent land-cover transitions, Figure 3 presents an example of a selected location. This example demonstrates how areas removed from LPIS correspond to real landscape changes, such as vegetation succession and urban development.

Our results indicate that 834 km² of originally agricultural land was converted to forest, and 258 km² was converted to non-vegetated areas. Only a small portion (17 km²) of the regions that dropped out between 2004 and 2022 remained arable land (Figure 4). The pixel-level labelling of grassland and shrubland from the canopy height model indicates that 298 km² of former agricultural land have become overgrown by successional vegetation. In comparison, more than 553 km² remain classified as grassland.

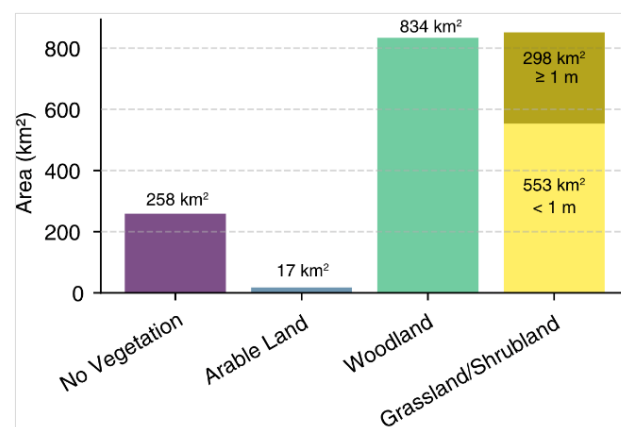


Figure 4. Post-LPIS land-cover classification of areas that dropped out between 2004 and 2022. The split bar for Grassland/Shrubland separates pixels with canopy heights of ≥ 1 m and < 1 m. Areas are derived from pixel counts within LPIS dropout polygons and are not corrected for classification or LPIS input errors.

4. Discussion

4.1 Drivers of Agricultural Land Loss

Figure 4 shows that most land where LPIS dropouts now appear as woodland or shrub-dominated vegetation, while direct conversion to non-vegetated surfaces is substantial. This pattern is consistent with widespread abandonment of marginal farmland and a decline in grazing, with only a minimal share of dropouts remaining in active arable land (Prishchepov et al., 2025). The dominant processes in the agricultural abandoned land landscape are: (i) suburbanization and construction, (ii) succession following the abandonment of agricultural use, and (iii) afforestation as a form of revitalisation or spontaneous overgrowth. Similar trends have been observed across Central and Eastern Europe since 1990, when structural changes in agriculture and a decline in livestock production led to the widespread abandonment of grasslands and the conversion of agricultural land to forest and shrub formations (Pazúr et al., 2024).

The LPIS conversion to a no-vegetation class (Figure 4) likely represents construction sites, infrastructure, and temporarily exposed soils, which aligns with the expansion of built-up areas. These activities focus on fast-growing commuter belts where residential and logistics development have replaced farmland. For instance, suburbanization is one of the primary explanations for the decline in agricultural land near Bratislava (Figure 5/A) and in other cities (Šuška and Šveda, 2023; Halás and Klapka, 2024). District-level LPIS change audits around Bratislava document the same mechanism: in the Senec district, construction accounted for 78.5 % of agricultural land loss (with a large share of single-family housing and logistics along the D1 highway); the Pezinok district also shows intense construction pressures and mapping of losses by cadastral unit (Kopecká et al., 2019). The expansion of tourism infrastructure with high environmental impact in highly protected biodiverse areas is also an extremely negative driving force (Masný et al., 2023; Kaim et al., 2022). Both abandonment and the repurposing of farmland for construction and development also threaten High Nature Value agricultural mosaics. Part of the apparent loss is reinforced by LPIS updates that exclude woody elements (Šatalová et al., 2021).

In Slovakia, long-term LPIS trends repeatedly confirm that the loss of agricultural land is driven by a combination of economic pressures, EU policies, and demographic processes (Pazúr et al., 2020). Driving forces, such as depopulation, urbanisation, and the intensification of production, are contributing to the decline of traditional low-intensity systems that rely on livestock (Figure 5/B), with the abandonment of semi-natural grasslands a frequent outcome (Šatalová et al., 2021). The transformation of land from agricultural use to forest or shrub vegetation (834 km²) indicates ongoing ecological succession in abandoned areas. This process has been well documented, for example, in regions such as Poland (Kopeć and Ślawik, 2020) and Serbia, where abandoned pastures have regenerated into young forests over 10–20 years (Janišová et al., 2024). In Slovak conditions, this trend is linked to the low economic profitability of agricultural production in mountainous areas (Figure 5/C) and a decline in livestock numbers (Mihina et al., 2003).

From a forest biodiversity perspective, these secondary forests and shrub successional stages serve as temporary habitats that can enhance forest ecological connectivity. However, the other side of the same coin is the grasslands, which in Slovakia belong to habitats with the highest species richness per area in the world (Chytrý et al., 2015). The spread of forests and shrubs leads to the fragmentation of grasslands and the loss of their biodiversity

value. From a landscape-management viewpoint, they entail a loss of agricultural function and increased fuel loads during drier seasons (Pazúr et al., 2021).

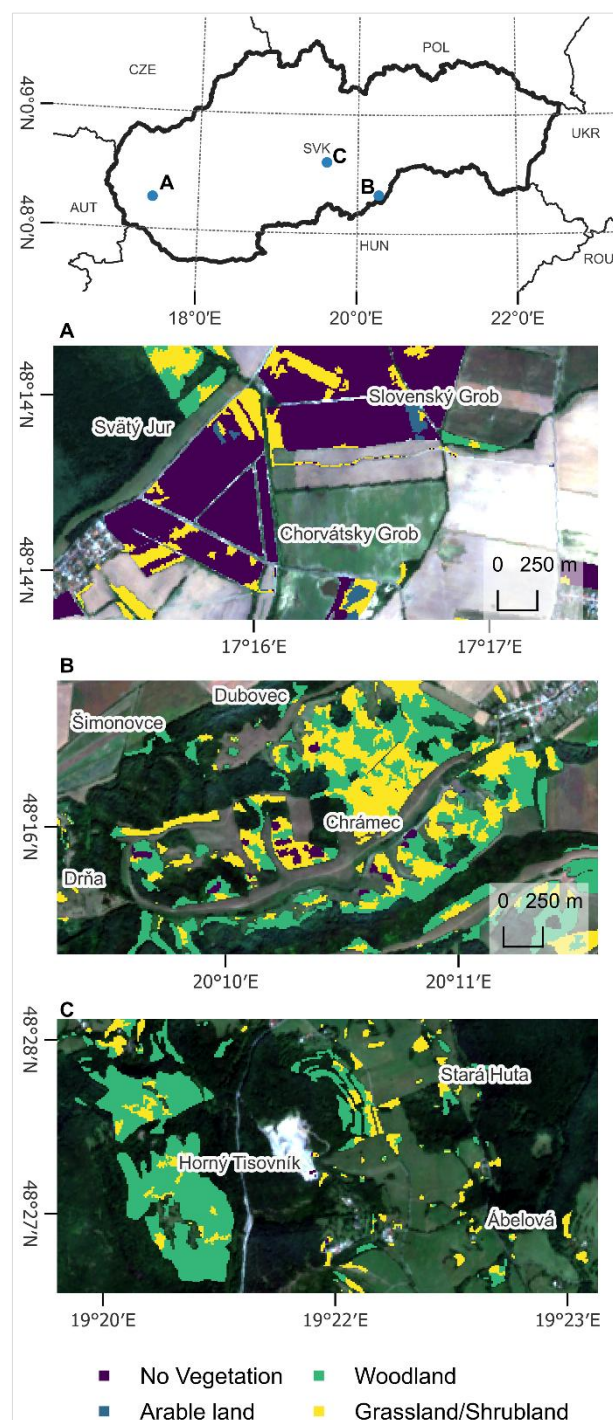


Figure 5. Spatial examples of post-LPIS land-cover trajectories in Slovakia. Polygons represent areas that dropped out of LPIS between 2004 and 2022, classified into four classes.

4.2 Classification Performance and Methodological Reliability

The Random Forest model achieved a weighted F1 score of 0.867, with “Arable land” and “Woodland” classes being mapped most reliably. This performance is consistent with findings from other Sentinel-2 land-cover studies, which report overall accuracies ranging from 0.85 to 0.91 for similar multi-class

RF classifications (Venter and Sydenham, 2021; Malinowski et al., 2020). Our model struggled with the more heterogeneous "No Vegetation" class ($F1 = 0.688$), where we grouped spectrally diverse surfaces as artificial land, water, and bare land. This pattern aligns with results from other Sentinel-based land-use/land-cover (LULC) products, where mixed non-vegetated categories often show reduced class separability, and with findings from CLCplus Legacy mapping in Slovakia, where complex classes at the third hierarchical level similarly exhibited lower conformity and modelling difficulties (Hudcovič et al., 2025).

We used LUCAS 2022 as reference data, aligning with current European-scale mapping approaches that integrate LUCAS with Sentinel-1/2 data to produce operational land-cover products (Venter and Sydenham, 2021; Mirmazloumi et al., 2022). These methods typically report Random Forest accuracies around 0.88–0.90. As in previous LUCAS-based studies, we found it necessary to filter or relabel ambiguous and mixed points (e.g., transitional land-cover types) due to well-known issues with class ambiguity and boundary effects in the LUCAS database.

To handle outliers, we employed a combination of the Mahalanobis distance and the Isolation Forest, providing a principled approach to removing spectrally inconsistent samples. This aligns with recent recommendations advocating the use of ensemble-based anomaly detection methods for identifying non-representative training data in satellite-based LULC classification tasks (Alonso-Sarria et al., 2019).

Spatially stratified cross-validation by climatic zones provided an objective test of generalisation, which is crucial for mapping at the national scale (Beigaitė et al., 2022). Although no fully independent validation dataset was available, spatial cross-validation across climatic zones provides a robust proxy for assessing model generalisation. The high consistency of results across strata indicates that the model effectively captured the spectral characteristics of land cover classes across different climatic regions. Nevertheless, the absence of an independent validation dataset remains a limitation, and future studies should incorporate field-verified datasets or high-resolution reference data to further validate classification performance.

The canopy height-based postprocessing imposes a mechanistic height cutoff to separate grassland from shrubland; however, this constraint cannot be independently verified in our case. Aggregating the 3.5 m PlanetScope canopy height model to a coarser resolution and enforcing a strict 1 m threshold inevitably produces classification artefacts, meaning the grassland–shrubland split should be interpreted as an indicative pattern rather than a categorical boundary.

4.3 Implications for Land Management and Policy

The identification of more than 1,000 km² of permanently lost agricultural land (including forest, non-vegetated areas, and urbanised land) represents a significant indicator of landscape transformation. It highlights the need for integrated management of the LPIS database.

The conversion of grasslands to shrublands or forests also has a very negative impact on biodiversity and compliance with EU nature conservation objectives, as a significant portion of habitat types protected under the EU Habitats Directive relies on regular agricultural use (Halada et al., 2011).

In the context of the European Union's Common Agricultural Policy, these results are critical, as such lost areas reduce the effective agricultural base and may lead to inaccuracies in administrative monitoring. For future analyses, it would be beneficial to differentiate between permanent loss (in built-up areas) and temporary succession (due to abandonment).

Furthermore, reinstatements (parcels that re-enter eligibility after a period out of the register), which reflect management recovery/recultivation, should be better monitored (Kerselaers and Levin, 2018). Robust mapping must distinguish between long-term abandonment and fallowing, as well as policy-driven ecological recovery (Liu et al., 2025), and should be supported by multi-source evidence and reporting of uncertainty (Prishchepov et al., 2025).

4.4 Limitations and Future Research

Frequent methodological updates to LPIS (changes in unit delineation, eligibility rules, and orthophoto base) can lead to misinterpretations of land-use dynamics. In addition to methodological errors in the LPIS, a limiting factor for detecting agricultural land is the geometry of gaps, which is influenced by farming methods and accessibility. This means that farmers often abandon land from its edges, where succession begins. At the same time, this creates relatively narrow, long slice polygons, which are problematic for distinguishing between this gradual succession and topological errors during LPIS database updates. Therefore, alignment between the time series with a policy/method change log and a stable schema cross-walk must be further analysed to explain the uncertainty in both net and gross flows. The future direction aims to combine satellite detection with 3D scanning based on LiDAR technologies to increase the resolution and detail of understanding biological traits and the complex effects of biodiversity transformation. Available satellite data, combined with a detailed point cloud model of vegetation geometry from 3D scanning, reflect tree species composition and can be used for precise estimation of above-ground biomass stocks and related GHG emissions and removals, and for understanding the mutual interaction between natural ecological succession and human activities in the landscape.

5. Conclusions

Analyses of the LPIS database between 2004 and 2022 pointed to more than 1,000 km² of formerly eligible agricultural land that has transitioned to other LCLU classes. Attributing their post-LPIS classification using an accuracy-validated Random Forest model, we demonstrate that agricultural land loss is extensive and dominated by ecological succession (forest, shrubland, grassland, or non-vegetated surfaces), with woodland and shrub encroachment representing the most common trajectory. Direct conversion to built-up or other non-vegetated areas is also substantial and reflects ongoing urbanisation pressures. The high classification accuracy across climatic zones confirms the reliability of combining LPIS dropout polygons with Sentinel-2 spectral-temporal metrics and LUCAS reference data. Although some uncertainty remains due to methodological updates in the LPIS and mixed land-cover categories, the approach offers a robust framework for monitoring long-term landscape change at the national scale.

The results underscore the need for enhanced coordination among agricultural, environmental, and spatial planning policies. The ongoing loss of permanent grasslands and their replacement by shrub and forest vegetation poses a threat to biodiversity-rich habitats protected under EU legislation. At the same time, urban expansion continues to reduce the country's productive agricultural base. At the same time, distinguishing between temporary succession and irreversible conversion is essential for designing targeted management and restoration measures. Future research should prioritise quantifying uncertainty in LPIS-derived change trajectories, distinguishing between abandonment, fallowing, and permanent loss, and integrating

emerging 3D remote-sensing data (including LiDAR-based canopy models) to improve the detection of structural vegetation changes. Together, these efforts will support more accurate monitoring of agricultural land resources and inform evidence-based land-use policies in Slovakia.

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During the preparation of this work, the authors utilised Grammarly and ChatGPT to verify grammar and correct misspellings, as well as to restructure sentences. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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