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THE ALTGORITHMIC LANDSCAPE OF AI BASED LAND USE INTERPRETATION

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Abstract

This study investigates the application of Artificial Intelligence (AI) techniques in land cover classification based on satellite imagery, with the objective of improving the accuracy and efficiency of traditional geospatial workflows. The research evaluates how conventional Geographic Information System (GIS) procedures can be enhanced through the integration of machine learning algorithms, particularly those designed for raster segmentation and automated image classification. A comparative analysis between classical supervised methods and AI-based approaches was conducted to detect land use and land cover (LULC) changes in the city of Satu Mare using multitemporal satellite data. Results show that AI-driven models offer improved classification consistency and reduced manual processing efforts. The results underline the relevance of AI-assisted image interpretation for land monitoring and its potential contribution to sustainable spatial planning. The proposed approach can be transferred to similar LULC studies.

Key words*: Artificial Intelligence, automated classification, land use and land cover (LULC), satellite imagery, urban expansion.*

INTRODUCTION

Land use and land cover (LULC) dynamics are the indicator of human pressure on land resources and a major driver of environmental change with direct implications for agriculture, soil functions, and ecosystem services. Sustainable land management requires accurate and timely monitoring of land cover (LC), especially in rapidly evolving urban areas (Vitale & Lamonaca, 2026).

Urban expansion and peri-urban development often compete with agricultural land through land take, fragmentation, and the conversion of open or cultivated areas into sealed surfaces. These processes can alter infiltration and runoff regimes, reduce soil water storage capacity, and constrain the long-term productivity and resilience of agroecosystems. Recent European assessments underline soil sealing and land occupation as persistent and relevant pressures linked to spatial development, reinforcing the need for robust monitoring tools that can support sustainable land management and evidence-based planning (Arias-Navarro et al., 2024).

Earth observation (EO) provides an operational framework for consistent and repeatable LULC monitoring across large areas and multi-annual time spans. Among currently available EO missions, Sentinel-2 multispectral imagery offers a well-balanced combination of spatial resolution (10-20 m), revisit frequency, and spectral capability, enabling the detection and mapping of heterogeneous land-cover patterns.

Multitemporal analyses derived from such imagery can capture trajectories of change (e.g., densification, conversion of open land into built-up areas, or shifts between vegetated and non-vegetated surfaces) when acquisition dates are chosen to minimize seasonal bias. In the underlying study that informs this paper, Sentinel-2 imagery acquired in July 2017, July 2019, and July 2024 was selected to improve cross-year comparability and reduce confounding seasonal effects.

Conventional GIS LULC mapping typically relies on supervised classification algorithms (e.g., Random Forest/Random Trees, Support Vector Machines), supported training samples

and post-classification refinement. While these approaches remain widely used and can provide reliable outputs under appropriate conditions, their performance is often sensitive to training-sample representativeness and to class separability. This limitation becomes particularly pronounced in urban and peri-urban settings where spectral mixing, shadowing, and material heterogeneity increase confusion between classes (e.g., bare soil vs. construction surfaces; bright roofs vs. exposed ground).

In the Satu Mare case study, the baseline workflow required iterative training-sample refinement to mitigate overlaps between "bare soil" and "construction zones" and to address localized reflectance anomalies (e.g., highly reflective surfaces) that can propagate classification noise.

In recent years, Artificial Intelligence (AI), and especially deep learning (DL), has advanced LULC mapping by enabling models to learn complex spectral and spatial reform imagery. Unlike pixel-wise classifiers that often treat observations independently, DL methods can exploit contextual information (texture, morphology, neighbourhood structure), which tends to improve thematic consistency and reduce the characteristic "salt-and-pepper" effect in heterogeneous landscapes (Hurskainen et al., 2019).

A comprehensive review in Remote Sensing of Environment highlights how DL has accelerated urban land use mapping in scale, automation, and accuracy, particularly when integrated with modern geospatial data ecosystems (Li et al., 2024). Within DL, semantic segmentation has become a particularly relevant paradigm for EO-based LULC mapping because it produces dense, pixel-level predictions while implicitly capturing spatial structure. Recent empirical comparisons of segmentation architectures (e.g., U-Net, DeepLabV3+) demonstrate strong performance for multi-class land-cover tasks and suggest meaningful gains in both accuracy and robustness across diverse geographic contexts (Deressu et al., 2025). Furthermore, methodological work emphasizes that careful use of spectral information (including band-selection strategies) can strengthen segmentation outputs in applications relevant to urban planning and land-use management (Jia et al., 2024). Despite these advances, the practical adoption of AI in applied LULC monitoring still raises questions regarding labelling requirements, generalization across years and acquisition conditions, and integration into established GIS workflows.

This paper investigates how traditional Geographic Information System (GIS) LULC workflows can be enhanced through Artificial Intelligence approaches for raster segmentation and automated image classification. A comparative analysis is conducted between a classical supervised method implemented in a GIS environment and AI based approaches using multitemporal Sentinel-2 imagery for the municipality of Satu Mare, Romania. To ensure cross-temporal comparability, we employed a consistent four-class LULC classification scheme represented in Figure 1, for all acquisition years.

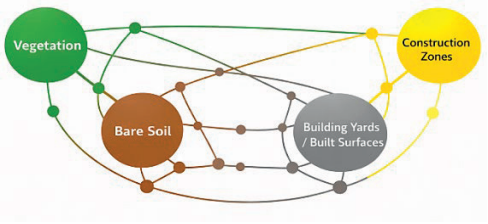


Figure 1. Land Cover classes

The study aims to evaluate improvements in classification consistency, quantify the reduction of manual effort linked to iterative training and correction, and to propose a transferable workflow for comparable LULC monitoring tasks at the urban and agricultural interface.

MATERIALS AND METHODS

Study Area

The selected case study is the municipality of Satu Mare, located in north-western Romania, in Satu Mare County, near the national borders with Hungary and Ukraine. The city is situated along the Someș River, mainly on its right bank, at approximately 47°47′24″ N latitude and 22°53′24″ E longitude. Positioned at an average altitude of about 126 m, Satu Mare lies within the lower floodplain of the Someș River, in a predominantly lowland area characterized by flat terrain.

Covering an area of approximately 120 km², Satu Mare represents an important administrative, economic, and cultural centre in the

north-western part of the country. Its geographical location, about 13 km from the border with Hungary and around 27 km from the border with Ukraine, provides the city with a strategic role as a connection point between different regions and cultural influences.
Therefore, understanding the spatial and urban evolution of Satu Mare is important for supporting future development strategies and planning, as illustrated in Figure 2.

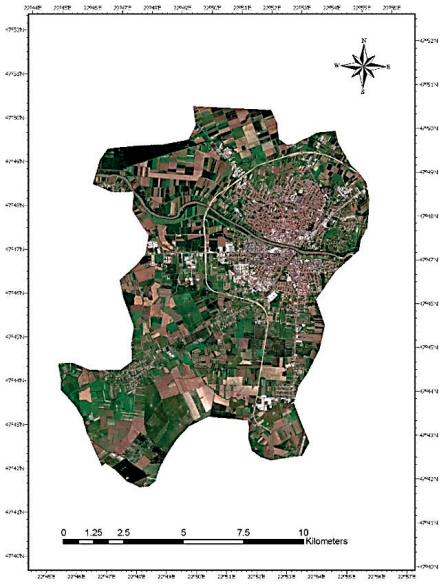


Figure 2. Localization of study area

Evolution of AI in land cover mapping

The methodological evolution of land use and land cover classification reflects a broader transformation in remote sensing, from conventional GIS image interpretation toward automated and data driven geospatial workflows. This transition is particularly relevant for multitemporal urban studies, where the objective is not limited to producing thematic maps, but also involves the consistent detection of spatial changes across different time periods. In the present study, focused on the city of Satu Mare, A.I is therefore approached as a complementary component of the GIS workflow, supporting the improvement of classification consistency, processing efficiency, and methodological transferability.
Classical supervised classification methods continue to provide an important basis for satellite image interpretation because they are relatively transparent, operational, and widely implemented in GIS environments. However, their performance may decrease in heterogeneous areas, where built-up surfaces, vegetation, agricultural land, bare soil, and water bodies can present overlapping spectral responses.
Recent comparative research confirms that urban LULC classification remains challenging because landscape heterogeneity directly influences feature extraction and model reliability. For this reason, comparative evaluations between traditional classifiers, machine learning algorithms, and deep-learning approaches are increasingly used to identify robust classification strategies for urban environments (Chowdhury, 2024).
The first major stage in the transition toward AI and LULC is represented by machine learning methods such as Random Forest, Support Vector Machine, and Artificial Neural Networks. These approaches are able to model nonlinear relationships between satellite-derived predictors and land cover categories more effectively than many conventional statistical methods. Their relevance is especially important in multitemporal studies, where the classification model must maintain stable performance across images acquired in different years. In this sense, machine learning contributes not only to classification accuracy, but also to the reproducibility of the change-detection workflow.
A further methodological development is represented by segmentation and object classification. Unlike the pixel methods, which classify each pixel independently, segmentation approaches group neighbouring pixels into spatially meaningful units before classification (Ma et al., 2020). This is particularly useful in urban and mixed landscapes, where land cover categories are often better represented as objects or patches rather than isolated pixels. More recently, deep learning has introduced a significant shift in classifications, by enabling automated feature extraction directly from remote sensing data. Instead of relying mainly on manually selected bands, indices, or predefined rules, deep-learning models can learn hierarchical spatial and spectral patterns from the imagery itself. This capacity is particularly

relevant for heterogeneous urban and peri-urban environments such as Satu Mare, where land-cover classes may vary in shape, texture, density, and spectral behaviour.

Recent reviews emphasize the growing role of deep learning in LULC classification using multispectral and hyperspectral Earth-observation data, while also noting persistent challenges related to training data availability, ground-truth quality, spatial resolution, and sensor-specific characteristics (Vali et al., 2020). Within this context, semantic segmentation is particularly important because it links classification with the spatial delineation of land-cover units. For raster LULC mapping, the objective is not only to assign thematic labels, but also to represent the spatial extent and configuration of land cover classes in a form suitable for change detection (Deressu et al., 2025). At a broader operational scale, AI has also evolved toward large area and frequently updated monitoring systems. Dynamic World is a relevant example of this development, providing near-real-time global LULC predictions at 10 m spatial resolution from Sentinel-2 imagery through a deep-learning workflow. Such products illustrate the movement from isolated map production toward continuous land-monitoring systems capable of supporting flexible temporal analysis and rapid interpretation of landscape change (Brown et al., 2022).

For the present research, this evolution provides the methodological foundation for comparing classical supervised GIS classification with AI assisted approaches in the multitemporal analysis of LULC change in Satu Mare. The purpose is not to replace GIS, but to enhance the geospatial workflow through greater automation, reproducibility, and classification stability. This is particularly important in urban and peri-urban change detection, where errors in individual classified maps may propagate into the final change analysis if the outputs are not produced and validated through a consistent methodological framework.

Therefore, AI classification must be supported by rigorous accuracy assessment. In LULC studies, the reliability of the final interpretation depends on the classification model, but also on the quality of reference data, sampling strategy, validation design, and the interpretation of accuracy indicators derived from the error matrix (Stehman & Foody, 2019). Consequently, the transition from classical GIS classification to AI can be understood as a progression toward more automated and reliable land monitoring workflows. In the case of Satu Mare, this approach supports the evaluation of how AI raster segmentation and automated image classification can improve the detection of land cover transformations.

Data acquisition

Nowadays, remote sensing applications rely on a wide range of satellite systems and observation platforms, each providing specific spatial, spectral and temporal perspectives of the Earth's surface. These multisource satellite observations, characterized by different levels of spectral and spatial detail, play an essential role in understanding landscape dynamics and monitoring land use and land cover transformations over time (Dong et al., 2020).

The methodological workflow presented in this study supports the analysis of AI land use interpretation by using Sentinel-2 satellite imagery acquired for three reference years: 2017, 2019 and 2024. The proposed approach highlights how artificial intelligence models can improve classification consistency and reduce the limitations of conventional manual geospatial procedures. By integrating multitemporal Sentinel-2 data with GIS preprocessing and AI assisted classification, the methodology provides a structured framework presented in the following Figure 3, for detecting and comparing land use and land cover changes across the selected study area.

Sentinel-2

The Sentinel-2 satellite constellation provides multispectral imagery composed of 13 spectral bands covering the visible, near-infrared and shortwave-infrared regions of the electromagnetic spectrum. With spatial resolutions of 10 m, 20 m and 60 m, depending on the spectral band, and a high temporal revisit frequency, Sentinel-2 data represent a valuable compromise between spatial detail, spectral information and temporal availability.

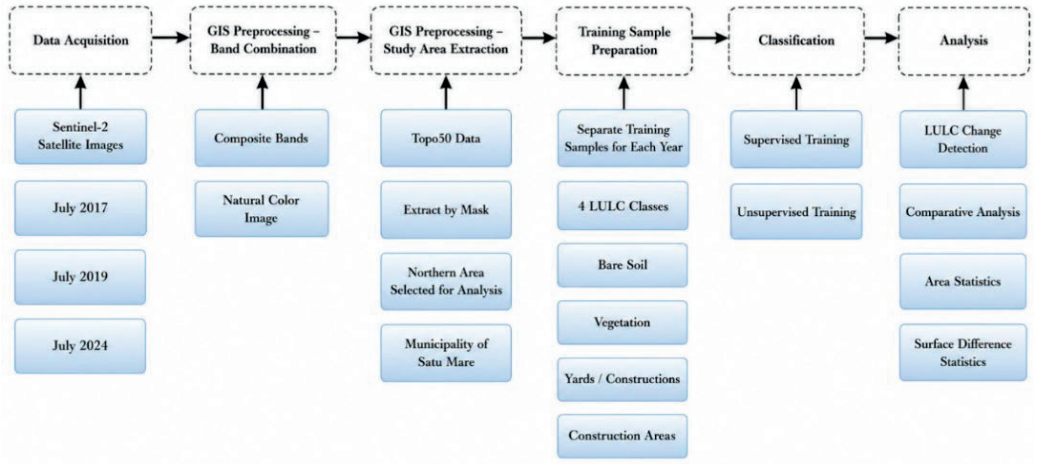


Figure 3. Worflow for AI land use interpretetion using multitemporal Sentinel-2 data in GIS

These characteristics make Sentinel-2 particularly suitable for land use and land cover mapping, especially in studies based on multitemporal image classification and comparative analysis (Vrieling et al., 2018; Rapinel et al., 2019; Le Dez et al., 2021).

In this context, remote sensing provides an efficient and reliable tool for identifying, mapping and monitoring landscape features, as well as areas affected by spatial transformation.

The analysis focuses on three reference years: 2017, 2019 and 2024 and evaluates different classification approaches in order to compare the resulting spatial patterns and highlight the main changes identified within the study area.

The satellite images used in this study were downloaded from the Copernicus platform. For the multitemporal comparative analysis, Sentinel-2 datasets were selected from dates as close as possible within the same month, but from different years, in order to minimize seasonal variations and ensure a more reliable comparison between the analysed periods. The selected images correspond to July and were chosen with 0% cloud cover so that the land surface features would not be obstructed. This selection criterion was important for improving the visual and spectral distinction between the land use and land cover classes used in the supervised classification process.

The Sentinel-2 products were downloaded in *. *safe* format, as this structure preserves the original satellite data and provides access to the complete set of spectral bands available at different spatial resolutions. Therefore, the extension format offered the necessary data quality and completeness for the subsequent preprocessing stages.

GIS Preprocessing

As presented in the Data Acquisition subsection in Figure 3, the GIS preprocessing stage was structured into two main components:

1. ***Band combination***;
2. ***Study area extraction*** - which involves the extraction of the study area based on official administrative boundary data.

These preprocessing steps were necessary to prepare the Sentinel-2 imagery for visual interpretation, supervised classification and subsequent comparative land use analysis.

For the first component, the Sentinel-2 datasets were imported into ArcGIS Pro, where the satellite information was available as separate multispectral bands. In order to obtain a visual representation that approximates the natural appearance of the Earth's surface, the Sentinel-2 spectral bands were combined using remote sensing processing techniques. The Natural Color composite was generated by assigning the red, green and blue spectral channels to Band 4, Band 3 and Band 2, respectively. Maintaining this band order is essential, as it ensures a correct RGB representation of the terrain. The band combination was performed in ArcGIS Pro using the Composite Bands function, which allowed the individual Sentinel-2 bands to be merged into a single multiband raster dataset.

The resulting natural color images provided a suitable basis for visual interpretation, further GIS preprocessing and subsequent land use and land cover classification.

Following the generation of the natural color composites, the study area was defined and extracted for the analysis. For this purpose, official administrative boundary data were obtained from the Geoportal ANCPI platform. The TopRo50 dataset was selected because it contains vector data representing administrative limits, including municipality boundaries. This dataset was imported into ArcGIS Pro and processed as a separate vector layer in order to identify and isolate the administrative boundary of Satu Mare Municipality, which represents the area of interest for this study.

Once the area of interest was defined, the boundary layer was used to extract the relevant portion from each Sentinel-2 natural color composite. This step ensured that the analysis was spatially limited to the selected study area and that all multitemporal datasets were processed using the same geographic extent, as illustrated in Figure 4.

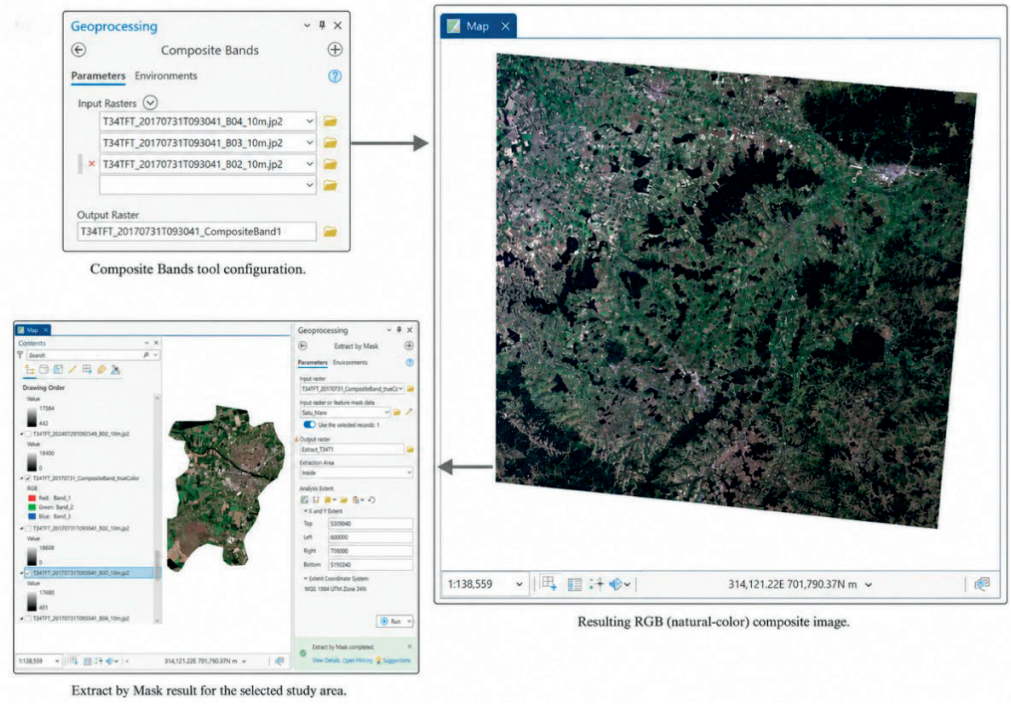


Figure 4. Band composition and study area extraction

Training data preparation

Training data preparation represents an essential stage in supervised land use and land cover classification, as this approach relies on labelled samples from the land cover classes of interest to train the classification algorithm (Moraes et al., 2024).

In remote sensing workflows, these samples consist of representative pixels or areas selected for each thematic category, enabling the classifier to associate the spectral characteristics of the satellite image with predefined land use and land cover classes. Their quality, spatial distribution and thematic consistency are important factors, as training sample selection and sample size can influence classification accuracy (Zhang et al., 2023).

In this study, separate training samples were created for each analysed year, namely 2017, 2019 and 2024. This approach was adopted to account for the specific spectral and spatial characteristics of each Sentinel-2 image, while maintaining a consistent classification scheme across the multitemporal analysis. Sentinel-2

imagery is widely used in land cover/use mapping due to its spectral characteristics, spatial resolution and temporal availability, which make it suitable for monitoring different types of land surface features (Phiri et al., 2020). For the differentiation of land use and land cover categories, four thematic classes were defined: *Bare Soil, Vegetation, Yards and Constructions, and Construction Areas.* These classes were selected according to the objective of the study, which focuses on identifying and comparing spatial changes. The prepared training samples were then used as reference data for the supervised classification process.

This step was carried out in ArcGIS Pro, using the Classify function available in the Imagery tab. The selected supervised classification method was Random Trees, which was applied to assign the Sentinel-2 pixels to one of the four predefined land use and land cover classes. This procedure allowed the generation of comparable thematic maps for 2017, 2019 and 2024, supporting the subsequent spatial and statistical analysis of land cover changes. The methodological approach is consistent with machine learning LULC classification, where satellite derived spectral information and predefined land cover classes are used to produce thematic maps for spatial interpretation (Talukdar et al., 2020).

Supervised Pixel Based Classification

Following the preparation of the training samples, the supervised classification stage was applied to transform the pre-processed Sentinel-2 imagery into thematic land use and land cover maps. This step represents the operational continuation of the training data stage, since the classifier uses the previously defined reference samples to associate the spectral characteristics of the raster pixels with the selected thematic classes. Supervised pixel-based classification is based on user defined classes within the raster dataset. The training samples are used to create spectral information that guides the classification process and supports the assignment of image pixels to the appropriate land use and land cover categories. Therefore, the reliability of this method depends on the quality of the training samples and on their capacity to represent the spectral variability of the surfaces present in the study area. According to the methodological guidelines, supervised classification relies on user-defined training samples, which are incorporated into a spectral signature file used for raster classification. The same perspective also highlights that training samples should represent the surfaces present in the study area through spectrally pure pixel samples.

In this study, the supervised classification was carried out in ArcGIS Pro using the classification tools available in the Imagery tab. The Random Trees algorithm was selected as the supervised classification method and was applied separately to the Sentinel-2 datasets corresponding to 2017, 2019 and 2024.

The classification was based on the four predefined land use and land cover categories, and a classified thematic raster was generated for each analysed year, providing the basis for the subsequent spatial comparison and statistical evaluation of land cover differences.

Unsupervised Pixel Based Classification

In parallel with the supervised approach, an unsupervised pixel-based classification was applied as a complementary method for interpreting the datasets. Unlike supervised classification, this method does not depend on predefined training samples. Instead, it automatically groups pixels into spectral clusters according to the similarity of their values. This makes the method useful for exploratory analysis, especially when the objective is to observe how the raster data are naturally organized based on their spectral characteristics.

The unsupervised classification process is automated, but the resulting clusters require interpretation after the classification has been completed. The methodology explains that the algorithm groups pixels according to similar spectral values, while the user must subsequently label the resulting clusters using additional raster information or visual interpretation. It also notes that the number of initial classes is often higher than the final number of visible land cover categories, because several spectral clusters may correspond to the same thematic class and may need to be merged during interpretation.

The purpose of this step was to provide an additional perspective on the spectral structure

of the images and to support the comparison between classification approaches. After processing, the spectral clusters were interpreted in relation to the main land use and land cover categories considered in the study.

The role of AI in land use interpretation

Artificial Intelligence techniques have become increasingly relevant in land use and land cover classification, particularly in studies based on satellite imagery and multitemporal geospatial datasets. The continuous development of remote sensing platforms, including satellite, UAV and airborne systems, has led to the generation of large volumes of spatial, spectral and temporal data. These datasets provide relevant information for understanding land surface dynamics, but their complexity requires analytical methods capable of supporting consistent and reproducible interpretation.

In this context, Geospatial Artificial Intelligence, or GeoAI, represents a methodological framework that integrates artificial intelligence, remote sensing and spatial data science. By combining machine learning and deep learning models with geospatial analysis principles, GeoAI can support the identification of spectral patterns, spatial structures and contextual relationships within heterogeneous landscapes (Dritsas & Trigka, 2026). This is particularly important in land use interpretation, as land cover classes are not defined only by individual pixel values, but also by their spatial distribution, neighbourhood relationships and variability across the landscape.

In the present study, AI is considered an algorithm implemented in the process of image. GIS methods provided the operational framework for Sentinel-2 data preparation and spatial analysis, including band composition, study area extraction, visualization, training sample preparation, map production and surface statistics. These procedures ensured that the classified rasters corresponding to 2017, 2019 and 2024 were spatially comparable and suitable for multitemporal analysis. The AI component is represented by a machine-learning classification algorithm that automatically assigns pixels to predefined LULC classes based on the characteristics learned from the training data.

Based on the training samples, the classifier learns the spectral characteristics associated with each class and applies this information to the entire raster image. In this way, AI assisted classification contributes to a more systematic interpretation of the Sentinel-2 imagery and reduces part of the repetitive manual effort involved in conventional image classification.

The use of Sentinel-2 imagery is appropriate for this type of analysis due to its multispectral characteristics and its balance between spatial, spectral and temporal resolution. Multispectral datasets such as Sentinel-2 and Landsat 8 are widely used for vegetation monitoring, land use classification and environmental assessment (Dritsas & Trigka, 2026). Within this research, Sentinel-2 data supported the supervised and unsupervised classification of the selected land cover classes and enabled the comparison of their spatial evolution over time.

Nevertheless, AI classification remains dependent on the quality of the input data, the representativeness of the training samples and the spectral separability of the selected classes. Therefore, the methodological approach adopted in this study can be understood as a GIS based land cover analysis enhanced by AI assisted classification.

RESULTS AND DISCUSSIONS

Multitemporal distribution of training samples

The first stage of the results focuses on the spatial distribution of the training samples created for each analysed year as presented in the Material and Methods chapter. These samples were used to support the supervised classification process and to define the main land use categories considered in this study. Presenting the training samples separately it will allow to understand the importance of each classification and how the spectral characteristics of the study area varied across the analyses.

For the year 2017, the training samples were created according to the predefined classes. During this stage, an important classification issue was observed in relation to the Someș River, which crosses the selected study area as presented in Figure 5.

In the processed image, the river displayed a visual and spectral response similar to that of

vegetation, which generated ambiguity during the interpretation process.

As a result, parts of the river were associated with the vegetation class, highlighting one of the limitations of the pixel-based classification, when different land cover elements present similar spectral characteristics. A similar issue was also observed in other parts of the classified image, where the initial result was affected by the spectral resemblance between several classes. In particular, confusion occurred between the Bare Soil and Construction Areas classes, as exposed soil, construction surfaces and some building rooftops presented comparable pixel values. This led to partial class overlap and reduced the separability of these categories within the classification output.



Figure 5. River classification result for 2017 in ArcGIS Pro

For this reason, the workflow was returned to the previous stage, where the training samples were revised in the areas affected by classification errors. The first category that required correction was the Bare Soil class, for which additional training samples were created in order to better represent its spectral variability. These samples were adjusted and extended in the problematic areas, rather than being limited only to small and isolated polygons, because the Bare Soil class included surfaces with different tones, textures and pixel values. By incorporating a wider range of representative pixels, the revised training samples aimed to improve the separability of this class from spectrally similar categories, especially Construction Areas and certain built-up surfaces, and to obtain a more accurate supervised classification result, represented in Figure 6.

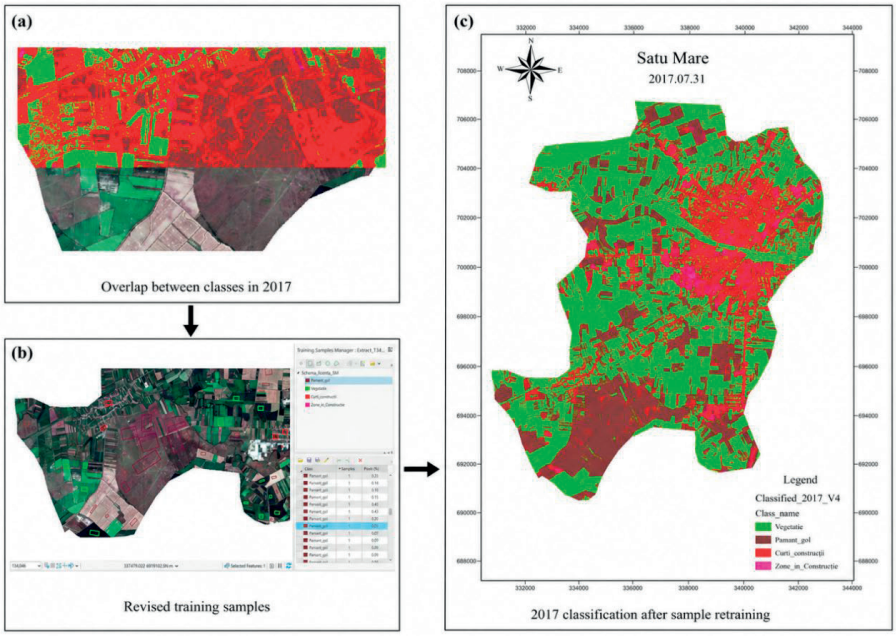


Figure 6. Overlap identification (a), training sample revision (b) and reclassified 2017 result (c)

2019 training results

Following the methodological approach applied to the 2017 dataset, a separate set of training samples was also created for the subsequent analysed image, using the same classification scheme and the same predefined land use and land cover classes. After the initial classification, a detailed visual assessment of the output revealed several limitations similar to those observed in the 2017 classification. The main issue was represented by the partial overlap between certain classes, which reduced the clarity and reliability of the thematic result. These inaccuracies indicated the need to refine the training samples in the areas where spectral confusion occurred, in order to improve class separability and obtain a more accurate classification output. Consequently, the workflow was returned to the training sample preparation stage. Additional samples were introduced in the problematic areas, with the purpose of better representing the local spectral variability and reducing the confusion between classes. This iterative correction process was necessary because some surface elements presented similar spectral responses, leading to misclassification in the initial result.

A particular anomaly was again observed in relation to the Yards and Constructions class as shown in Figure 7, similar to the situation identified in the 2017 dataset. In this case, the distortion may be associated with highly reflective surfaces, possibly solar panels, whose spectral response can influence the classification result and generate local errors.



Figure 7. a) Singularities identified for 2019; b) Training sample details

After revising the training samples and repeating the classification, the final output showed a visible improvement, with most of the previous class overlaps and impurities being reduced. Therefore, the corrected result provides a more reliable representation for 2019, demonstrated in Figure 8.

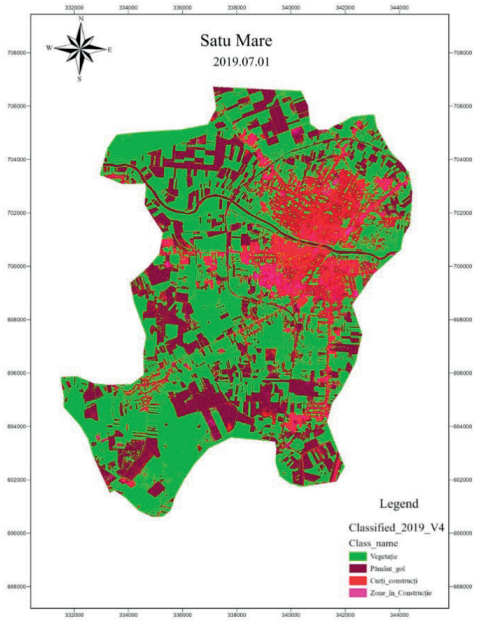


Figure 8. Final classified map for 2019

2024 training results

Consistent with the approach used for the previous two analysed years, the same methodological procedure was applied. The training sample preparation followed the same classification scheme used to maintain consistency across the multitemporal analysis.

However, although the images correspond to different years, the classification process revealed similar challenges related to the spectral overlap between certain land use and land cover classes. A recurrent issue identified in all three analysed datasets was the confusion between Construction Areas and Bare Soil. This overlap can be explained by the similar spectral response of exposed soil, construction surfaces and unfinished built-up areas, which makes their separation difficult in pixel-based classification. To reduce this problem, the Bare Soil class required larger and more representative training samples, capable of capturing a wider range of tones and pixel values associated with exposed soil surfaces. In contrast, for the Yards and Constructions class, smaller and more precise samples were necessary, especially in areas corresponding to rooftops and compact built-up elements. This adjustment allowed the classifier to better distinguish between surfaces that initially presented similar spectral characteristics. Therefore, as in the previous years, the 2024 classification required an iterative refinement of the training samples. The correction process was essential for reducing class overlap and improving the thematic clarity of the final classification result.

The final classified map for 2024, presented in Figure 9, illustrates the result obtained after the refinement of the training samples and the correction of the main classification inconsistencies.

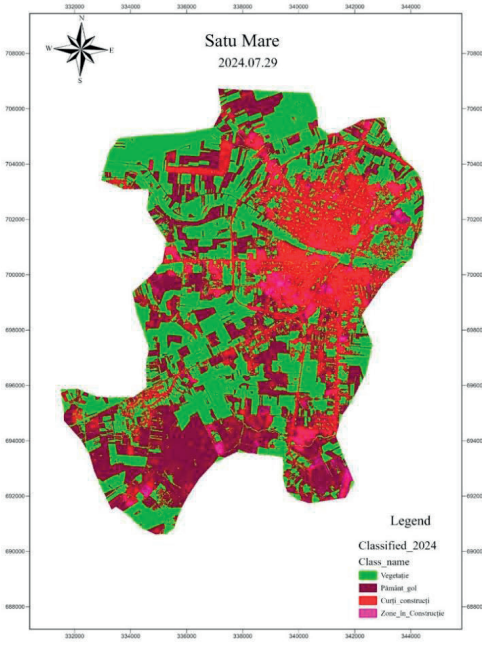


Figure 9. Classified map for 2024

Comparative analysis based on land use classification results

The analysis was conducted to evaluate the spatial dynamics of the selected land cover classes and to highlight the main changes

identified within the study area. The surface area of each land cover class was calculated using the raster attribute table generated after the classification process. In the classified raster, the count field represents the number of pixels assigned to each class. Since the Sentinel-2 raster used in this study has a spatial resolution of 10 m × 10 m, each pixel corresponds to an area of 100 m². Therefore, the surface area of each class was obtained by multiplying the number of pixels by 100 m² and then converting the result into hectares and square kilometres. This calculation was applied consistently to the classified rasters from 2017, 2019 and 2024, as presented in the following tables Table 1 for 2017, Table 2 for 2019 and Table 3 for 2024.

Table 1. Surfaces calculated for 2017

Surface area of land cover classes in 2017		
Land cover class	Pixel count	Area (km²)
Vegetation	598536	59.85
Bare Soil	414969	41.50
Yards and Constructions	174523	17.45
Construction Areas	52743	5.27
Total	1240771	124.08

Table 2. Surfaces calculated for 2019

Surface area of land cover classes in 2019		
Land cover class	Pixel count	Area (km²)
Vegetation	639505	63.95
Bare Soil	408773	40.88
Yards and Constructions	125082	12.51
Construction Areas	67411	6.74
Total	1240771	124.08

Table 3. Surfaces calculated for 2024

Surface area of land cover classes in 2024		
Land cover class	Pixel count	Area (km²)
Vegetation	496421	49.64
Bare Soil	483470	48.35
Yards and Constructions	209900	20.99
Construction Areas	50980	5.10
Total	1240771	124.08

The calculated surfaces show that vegetation represented the dominant class in 2017 and 2019, reaching its highest value in 2019 with 63.95 km². In 2024, vegetation decreased to 49.64 km², while bare soil increased to 48.35 km². The Yards and Constructions class also increased in 2024, reaching 20.99 km², compared with 12.51 km² in 2019 and 17.45 km² in 2017. Construction Areas remained the smallest class throughout the analysed period, with values ranging between 5.10 km² and 6.74 km².

The accuracy assessment was generated in ArcGIS Pro using the accuracy assessment points and the confusion matrix tool, resulting Figure 10.

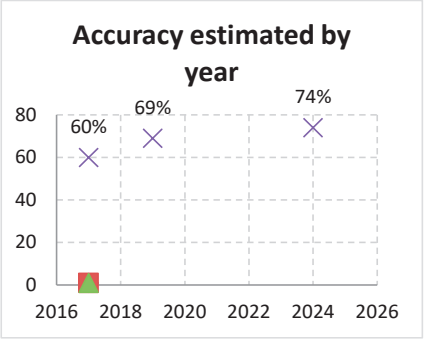


Figure 10. Accuracy estimation for each year classification

The overall accuracy increased from approximately 60% in 2017 to 74% in 2024, indicating a moderate improvement in classification performance. Given that all Sentinel-2 images were acquired using the same sensor and processed with the same classification methodology and algorithm, this improvement is associated with enhanced spectral separability among the land cover classes and the representativeness of the training samples used for each image. The accuracy assessment was performed using an independent set of validation samples, distinct from the training samples employed for model development, ensuring an unbiased evaluation of the classification performance.

In addition to these methodological aspects, the differences in accuracy may also be influenced by the climatic and phenological conditions recorded during the acquisition period. Although all Sentinel-2 images were selected from July, the spectral response of vegetation can vary from one year to another depending on precipitation, soil moisture, temperature and drought intensity. In drier years, vegetation may

show lower vigor and reduced spectral contrast, which can increase confusion with bare soil or transitional construction surfaces.

The lower accuracy obtained may therefore be partly related to the older temporal reference of the image and to possible vegetation stress during the summer period, which can reduce the spectral separability. For 2017, drought monitoring reports indicate a significant precipitation deficit in northern Romania, which may explain the lower spectral separability of vegetation. Under drought conditions, vegetation shows reduced vigor and can be more easily confused with bare soil or surfaces undergoing transformation. The year 2019 appears to have had more stable hydrological conditions for south-eastern Europe, which may support a clearer interpretation of the classes. In contrast, 2024 was characterized by very high temperatures and regional drought, factors that may introduce errors in the vegetation class, even though the image is the most recent and has better temporal relevance.

The results obtained from the classified maps were further analysed through class surface statistics, allowing the differences between the three years to be examined more clearly. The comparative Figure 11 illustrates the evolution of the identified classes.

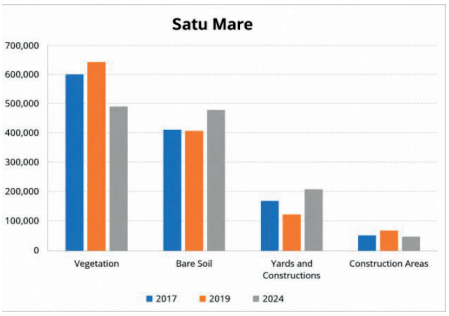


Figure 11. Surface area differences between the identified land cover classes across the analysed years

Vegetation represents the dominant class in all three analysed years, with the highest value recorded in 2019. However, a noticeable decrease can be observed in 2024, suggesting a reduction of vegetated surfaces compared to the previous two reference years. The bare soil class shows a relatively stable evolution between 2017 and 2019, followed by a clear increase in 2024. This may indicate the expansion of exposed or temporarily unused land surfaces, possibly related to land clearing, agricultural activity or areas prepared for future development.

As for the yards and constructions class, they fluctuated, decreasing in 2019 and increasing again in 2024, presented a more fluctuating evolution. A decrease was observed in 2019 compared to 2017, followed by an increase in 2024. This pattern may reflect changes in the built-up structure of the municipality, including residential, industrial or mixed-use developments.

In contrast, the areas classified as construction areas remained relatively limited in extent. The highest value was identified in 2019, while a decrease was observed in 2024. This may suggest that some of the construction sites detected in 2019 were completed by 2024 and were subsequently integrated into other classes, particularly yards and constructions. This evolution highlights the transitional character of construction areas, which often represent temporary land cover conditions rather than stable long-term classes.

CONCLUSIONS

This study assessed the evolution of land use and land cover in Satu Mare Municipality between 2017, 2019 and 2024 through the integration of Sentinel-2 satellite imagery, GIS preprocessing and AI assisted classification methods.

The results indicate measurable variations in the spatial distribution of the analysed land cover classes. Changes were observed in the extent of Vegetation, Bare Soil, Yards and Constructions, and Construction Areas across the three reference years. These variations describe changes in the classified land cover structure of the study area, but they should not be interpreted as direct evidence of specific urban development processes, land reorganization or socio-economic transformations without additional field observations, cadastral data or planning documents.

A relevant example was identified in the southern part of the study area, where an area classified mainly as Bare Soil in 2017 was predominantly associated with Vegetation in 2019. By 2024, the same sector presented a more heterogeneous classification pattern, including Construction Areas, Bare Soil and smaller

vegetated surfaces. This research illustrates the capacity of multitemporal classification to detect changes in land cover patterns, while the causes of these changes require further validation through complementary data sources. The main contribution of the study is represented by the capacity of the proposed methodology to support a consistent multitemporal comparison. By applying the same classification scheme to the 2017, 2019 and 2024 datasets, the analysis provided both visual and quantitative information regarding land cover distribution and surface changes. This confirms the usefulness of integrating GIS preprocessing and AI assisted classification for territorial monitoring and comparative land cover analysis.

At the same time, several limitations were identified. The most important limitation is related to the spectral similarity between certain land cover classes. Confusion occurred especially between Bare Soil, Construction Areas and some built-up surfaces, while parts of the Someș River were associated with Vegetation due to similar spectral responses. These situations show that pixel classification can generate class overlap when different surface types present comparable pixel values. Another limitation is connected to the 10 m spatial resolution of Sentinel-2 imagery, which may not fully capture small or mixed urban features such as rooftops, courtyards, roads and construction materials.

Despite these limitations, the proposed workflow proved suitable for supporting multitemporal land cover analysis through the consistent processing and comparison of classified satellite imagery.

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