

Article

Evaluation of LULC Use Classification for the Municipality of Deva, Hunedoara County, Romania Using Sentinel 2A Multispectral Satellite Imagery—A Comparative Study of GIS Software Analysis and Accuracy Assessment

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Abstract

The degree of urbanization and the uncontrolled expansion of the built environment play a defining role in shaping contemporary society, contributing significantly to abrupt temperature fluctuations and a declining quality of life. This study aims to analyze land use and land cover (LULC) patterns in the municipality of Deva, located in the central part of Hunedoara County, Romania (45°52' N, 22°54' E). The analysis covers the period from March 2022 to March 2023 and is based on open-source datasets. Supervised classification of LULC was performed using two GIS software platforms: ArcGIS Pro and QGIS. Sentinel-2A satellite imagery, with spatial resolutions of 10 m, 20 m, and 60 m, was processed using two different classification algorithms—the Minimum Distance classifier (via the Semi-Automatic Classification Plugin in QGIS) and the k-Nearest Neighbor (k-NN) algorithm in ArcGIS Pro. The comparative accuracy assessment indicated that the k-NN classifier in ArcGIS Pro performed better, achieving an overall accuracy of 89.7% and a Kappa coefficient of 0.86, while the Minimum Distance classifier in QGIS obtained an overall accuracy of 81.2% and a Kappa coefficient of 0.78. The outputs of both classification workflows were compared, and an accuracy assessment was conducted during the post-processing stage. The best results were obtained using the k-NN algorithm. The classification maps generated in this study can serve as a valuable foundation for local authorities to monitor environmental changes and support urban planning initiatives in Deva.

Keywords: Sentinel-2A; minimum distance; k-Near Neighbor; land use/cover; LULC; GIS



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1. Introduction

Rapid urban expansion has accelerated the degradation of natural ecosystems worldwide, with the urban population projected to increase from 55% today to about 68% by 2050 [1]. Accurate land use and land cover (LULC) datasets are indispensable for detecting and assessing land surface changes arising from complex interactions between human activities and environmental processes [2] and socio-economic events [3]. Urbanization, defined by the expansion of built-up areas, is a major anthropogenic driver of environmental change and the key cause of land use and land cover (LULC) transformations [4].

The increasing availability of satellite sensors and the regular acquisition of geospatial data over large areas have significantly improved the accessibility of land surface moni-

toring for research purposes [5]. However, several challenges associated with large-scale monitoring still remain and require further attention [6].

Remote Sensing (RS) is a very key field of geospatial data acquisition (both satellite and aerial photogrammetry), playing a key role in analyzing land use, vegetation and land use change monitoring [4,7]. Satellite remote sensing imagery relies on GIS for visualization and processing. This data is freely available from satellites such as Landsat [8] and Sentinel-2 [9–12]. The most widely used methods for extracting time-series features and handling data gaps are: time-series composition, spectral-temporal metrics and phenological metrics [13].

In recent years, Sentinel-2A provides data with improved resolution compared to Landsat imagery, which is why Sentinel-2A is being used in many land use and land cover surveys [14]. Copernicus [15] is the European Union's Earth observation program. It provides services based on satellite imagery based on both satellite imagery and in situ data. However, the tools for processing, analyzing and visualizing the quality of this data are under continuous research [16,17].

A study conducted in East Kalimantan employed machine learning algorithms including Random Forest, K-Nearest Neighbors (k-NN), XGBoost, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) to analyze LULC changes, revealing that the Random Forest model achieved the highest accuracy of 97.59% [18]. Also, a recent study [19] evaluated multiple machine learning algorithms—Random Forest (RF), k-NN, SVM, ANN, Maximum Likelihood Classification (MLC) and Regression Tree (CART)—for LULC classification. The results demonstrated that RF provided the highest overall accuracy, while incorporating remote sensing indices and DEM data further enhanced classification performance and kappa statistics.

Recent research [13,20–23] demonstrates that for monitoring changes over time in land use patterns, high spatial resolution satellite imagery, processed through a GIS-based workflow, provides conclusive results. A number of papers integrate GIS software such as ArcGIS Pro, QGIS, ENVI ERDAS IMAGINE in the analysis of satellite imagery [4,24,25].

At the national level in Romania, Stoica et al. compared the Corine Land Cover and Landsat datasets to evaluate built-up area expansion in Bucharest and Ilfov County between 1990 and 2018. The research examined both datasets against ground truth data, highlighting discrepancies in spatial detail and accuracy. While both datasets effectively captured the overall urban growth pattern, Landsat imagery provided finer spatial resolution, whereas Corine Land Cover offered broader territorial consistency [26]. A recent study compared four open-source satellite datasets—Corine Land Cover Backbone, High Resolution Layers Imperviousness, Esri Land Cover, and Dynamic World—for mapping built-up areas across twelve metropolitan regions, revealing that Corine Land Cover Backbone 2018 achieved the highest accuracy (overall accuracy = 0.85) and proved to be the most reliable dataset for both urban and rural land use and land cover assessment.

Traditional methods such as visual interpretation and basic statistical analysis are no longer adequate or practical for handling large-scale data required for reliable Land Use and Land Cover (LULC) classification. Contemporary tools (e.g., ArcGIS Pro, Google Earth Engine, QGIS), along with advanced software and cutting-edge algorithms, enable the production of accurate classification maps [27].

Recent studies indicate that nearly 62% of the global terrestrial surface has been transformed from natural vegetation into croplands and urban areas, mainly due to agricultural expansion, deforestation, and rapid urbanization. These land use and land cover (LULC) changes represent one of the most significant human impacts on the environment, affecting approximately 37% of the Earth's surface and influencing biodiversity, food security, and ecosystem services [28].

Satellite observations play a crucial role in setting indicators for the Sustainable Development Goals (SDGs). At its 46th session in March 2015, the United Nations Statistical Commission established the Inter-Agency and Expert Group on SDG Indicators (IAEG-SDGs), which includes Member States, as well as regional and international agencies as observers. The IAEG-SDGs' report to the Committee on Statistics in March 2016 highlighted that integrating statistical data with geospatial information will be essential for producing additional indicators [29].

SDG Indicator 11.3.1 is defined as the ratio between the land consumption rate and the population growth rate, calculated through spatial analysis using land use or built-up land cover data in conjunction with demographic information for the urban area under study. The purpose of this indicator is to assess the extent to which undeveloped land is being converted into urban areas and to compare this process with the rate of population growth within the same region. In cases where detailed local data are unavailable, global geospatial datasets may serve as substitutes; however, their lower spatial resolution can influence the accuracy of assessments [30]. Given the role of LULC datasets in calculating SDG Indicator 11.3.1, the classified maps generated in this study using Sentinel-2 imagery can contribute to assessing urban expansion dynamics and support local-level sustainable planning efforts.

Land use/land cover (LULC) provides essential spatial information that supports thematic mapping, analysis, and decision-making processes [31]. Hence, the objective of this study was to produce classification maps for the municipality of Deva using remote sensing (RS) and GIS. We applied supervised, semi-automated classification techniques using Sentinel-2A images acquired at one-year intervals (2022–2023) as input data in both ArcGIS and QGIS software. The goal was to analyze land cover and land use in Deva and to assess the precision and accuracy of each algorithm (MD and k-NN). Moreover, to the best of our knowledge, there are few studies comparing and evaluating the performance of two classification algorithms implemented in two different GIS platforms, using distinct training samples and Sentinel-2A input data, particularly in the context of Romania. The findings of this study offer valuable insights into parameter configuration, variable selection, and classifier choice for land cover classification in the municipality of Deva, as well as in other similar urban areas in Romania.

2. Data and Methods

2.1. Study Area

This study focuses on the municipality of Deva (Figure 1), located in Hunedoara County, western Romania, and intersected by Pan-European Corridor IV, both by rail and road. As the county seat and a strategic node in the Transylvania region, Deva is undergoing continuous development supported by national administrative initiatives.

The city (45°52' N 22°54' E) covers an area of approximately 34 km² and has a population of about 53,113 inhabitants, resulting in a density of 1700 inhabitants per km². Deva is encircled by mountains, forming a natural semicircle, and is situated on the left bank of the Mureş River. Deva is also a significant tourist destination, renowned for landmarks such as Deva Fortress, Fortress Hill, and various museums [32].

Vegetation in the area is mainly composed of deciduous forests, including oak (*Quercus robur* L.), hornbeam (*Carpinus betulus* L.), linden (*Tilia cordata* Mill.), beech (*Fagus sylvatica* L.), and walnut (*Juglans regia* L.) species. However, increasing anthropogenic pressure—particularly urban expansion and deforestation—has led to notable landscape changes, with many forested areas now being replaced by grasslands. The municipality includes three protected natural areas: Fortress Hill, Bejan Forest, and Colţ Hill–Zănoaga [33].

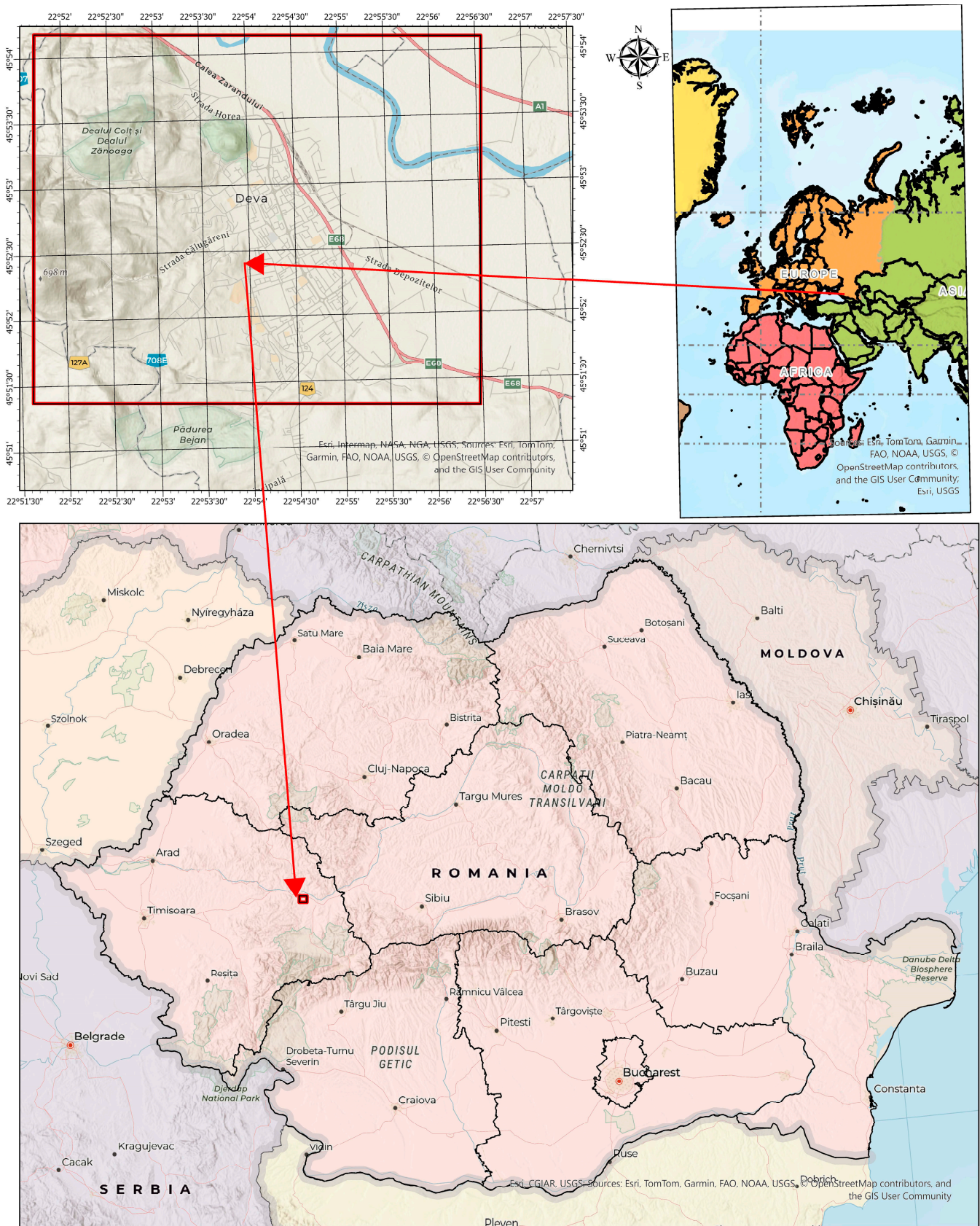


Figure 1. Map of the study area—Deva municipality (source: authors).

The region has a temperate continental climate, with average temperatures ranging from approximately 21 °C in summer to −1 °C in winter, and moderate precipitation patterns influenced by regional topography [34].

Given the ongoing land cover transformations and continuous urban growth, the area presents a suitable case for monitoring land use and land cover (LULC) dynamics using remote sensing techniques and machine learning-based classification methods.

2.2. Sentinel Data—2A

Copernicus Open Access Hub [35] provides both free and restricted data access, offering a wide range of products from Sentinel missions, including Sentinel-1, Sentinel-2, Sentinel-3, and Sentinel-5P. The images illustrated in Figure 2 were manually downloaded from the Copernicus Hub. The geospatial data used in this study consists of Sentinel-2A satellite imagery, provided by the European Space Agency (ESA, Paris, France), acquired over a 12-month period (21 March 2022–21 March 2023). The multispectral data from Sentinel-2A include 13 spectral bands, which are detailed in Table 1.

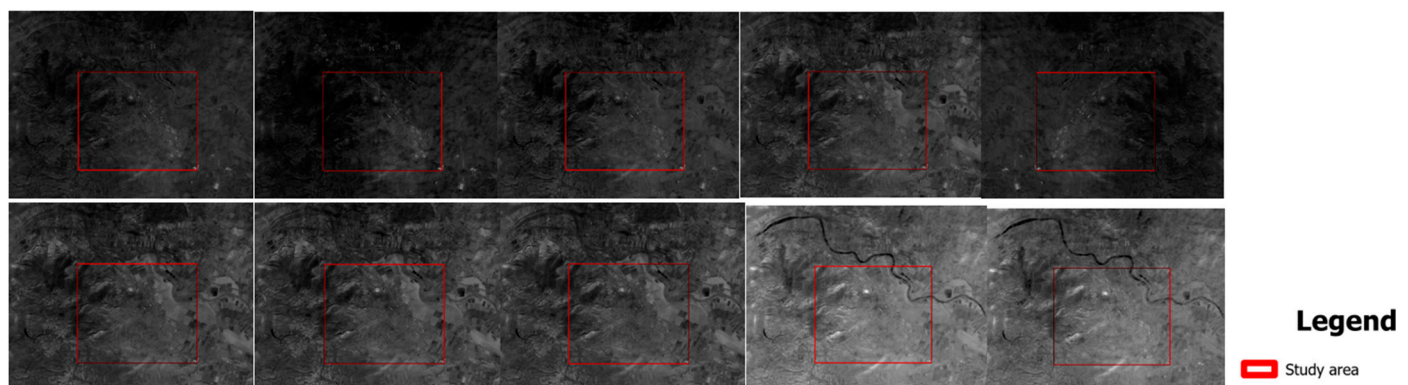


Figure 2. Sentinel-2 spectral bands used in the classification process. The figure illustrates ten gray scale images corresponding to spectral bands B2 (Blue), B3 (Green), B4 (Red), B5, B6, B7, B8 (Near-Infrared), B8A, B11 (Short-Wave Infrared 1), and B12 (Short-Wave Infrared 2). These bands were selected due to their relevance in distinguishing between various land cover types such as built-up areas, vegetation, and water bodies. Each image highlights specific reflectance characteristics that contribute to the spectral separability of surface features. (source: ESA, Paris, France).

The satellite images were obtained either directly from the ESA platform or via the Semi-Automatic Classification Plugin (SCP) in QGIS 7.10.11 (Open Source Geospatial Foundation, Beaverton, OR, USA). One of the advantages of using Sentinel-2A [36] is that its multispectral bands are atmospherically corrected [11]. During the pre-processing stage, bands 1, 8, 8A, 9, 10, and 11 were excluded to optimize data quality and reduce redundancy.

Table 1. Spectral bands of images captured by the Sentinel-2A satellite [37].

Spectral Bands	Center Wavelength (nm)	Band Width (nm)	Spatial Resolution (m)
Band 1	443	20	60
Band 2	490	65	10
Band 3	560	35	10
Band 4	665	30	10
Band 5	705	15	20
Band 6	740	15	20
Band 7	783	20	20
Band 8	842	115	10
Band 8a	865	20	20
Band 9	945	20	60
Band 10	1380	30	60
Band 11	1610	90	20
Band 12	2190	180	20

2.3. Methods

The study covers approximately 32 km², encompassing various types of land cover, including forest vegetation, water bodies, pastures, agricultural land, and urban areas, all subjects to continuous transformation. In this context, conducting a high-accuracy land cover analysis serves as a crucial first step toward achieving sustainable and efficient development. In this study, a land cover classification map of the area shown in Figure 1 was generated using satellite data. The objective was to compare two software platforms, ArcGIS Pro 2.9.2 (Esri, Redlands, CA, USA) and QGIS 7.10.11 (Open Source Geospatial Foundation, Beaverton, OR, USA) [38], by applying two supervised classification algorithms: k-NN (k-Nearest Neighbor) and the Minimum Distance classifier implemented through the Semi-Automatic Classification Plugin (SCP) in QGIS [38]. The study further aimed to analyze and compare the results obtained from these two classification approaches.

2.4. Image Classification

The main Land Use and Land Cover (LULC) categories in the study area include built-up areas, agricultural land (both cultivated and fallow), water bodies, and forests. The overall methodological workflow is illustrated in Figure 3. Precise identification of features such as roads, buildings, and vegetation is essential for accurate urban monitoring and natural hazard assessment. Complex and non-linear structures like urban settlements remain challenging to classify, where edge detection plays a key role in improving accuracy [39].

RGB composites (B4, B3, B2) were used for visual interpretation, enabling intuitive land cover identification. False Colour Composites were also generated to enhance vegetation detection.

The process of training sample identification and creation is a critical step, as it directly influences both the classification results and accuracy assessment [40]. The selection of appropriate samples has an even greater impact on classification accuracy than the choice of classification algorithm itself [5].

2.5. Image Pre-Processing

Image pre-processing is a crucial step that directly influences classification accuracy. It involves operations such as noise reduction, geometric correction, and radiometric normalization designed to ensure the quality and consistency of input data. The main pre-processing steps applied in this study are summarized below:

- Clipping maps—defining and extracting the area of interest (AOI) by cutting the satellite scenes to match the study boundaries;
- Image registration—aligning multiple image frames to ensure that corresponding elements can be accurately compared;
- Geo-referencing—a process in which locations are assigned to images, allowing a computer to identify the location of different objects covering the terrain;
- Radiometric correction—adjusting pixel values to normalize brightness and appearance;
- Composite band—a composite band is generated by merging several individual spectral bands captured by remote sensing sensors. Since each band captures distinct environmental characteristics—such as surface reflectance or vegetation health—they offer complementary insights. By integrating multiple bands into a single composite image, analysts can achieve a more comprehensive representation of the landscape. These composite images are particularly valuable for identifying and mapping land use and land cover (LULC) features with greater precision;
- Layout maps creation [41].

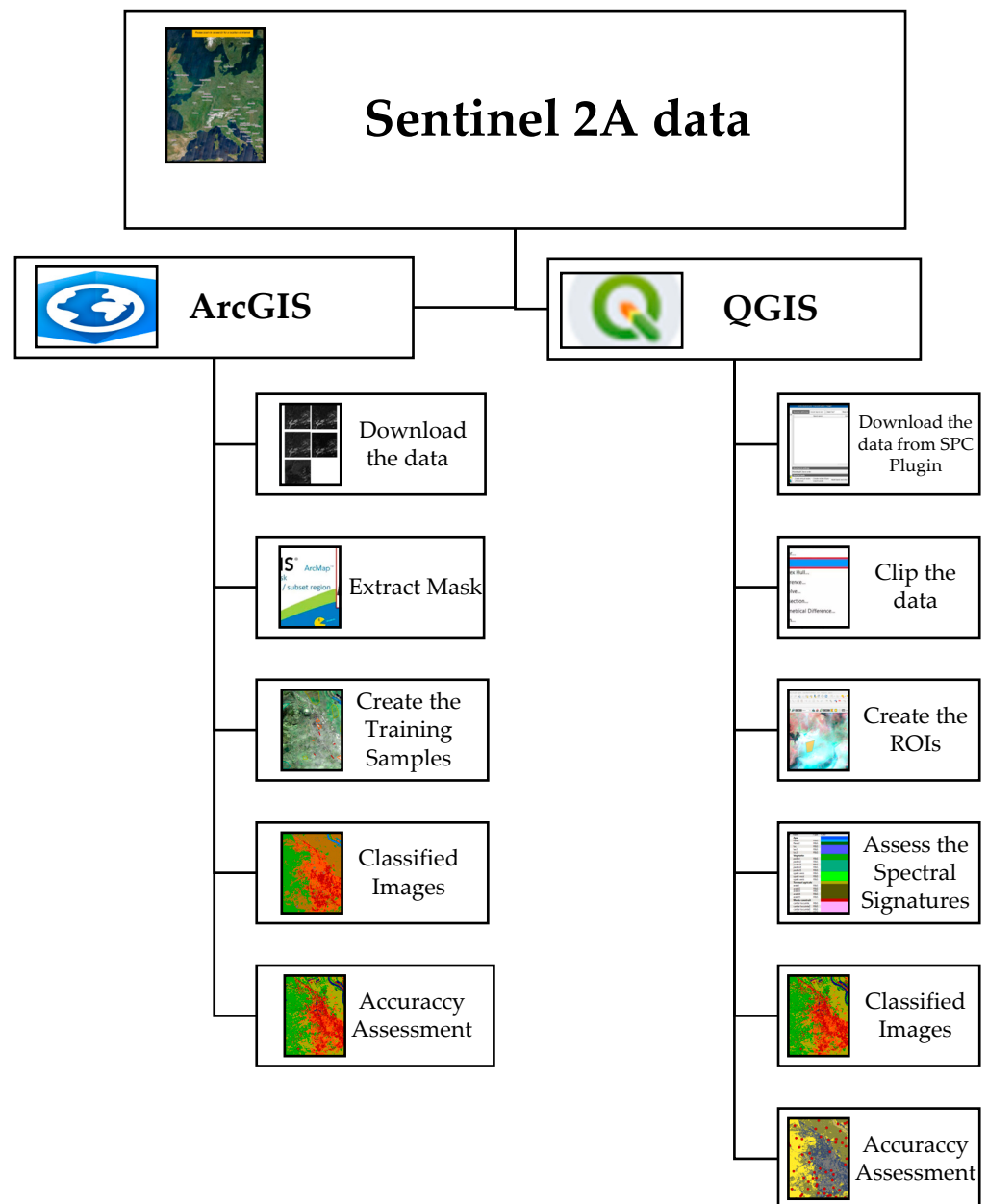


Figure 3. Workflow carried out using the software ArcGIS Pro and QGIS. Both ArcGIS Pro and QGIS support preparatory workflows for supervised classification. In ArcGIS Pro, training samples are digitized per class, while in QGIS, Spatial Point Clustering (SPC) applied to ROIs enables automatic identification of homogeneous training regions. (source: authors).

2.6. Satellite Image Processing

Supervised or semi-automatic classification is a technique for processing satellite imagery based on land cover categories by training an algorithm with samples containing the spectral signatures of surface features [38,42]. In essence, this method assumes prior knowledge of the study area, allowing the user to define specific land cover types and to select representative pixels corresponding to each class [43].

Figure 4 illustrates the main classification techniques. Although a wide range of satellite image classification algorithms is available, many of them exhibit limitations regarding result accuracy. These challenges often arise from the high heterogeneity within land cover classes, which makes it difficult to group pixels with diverse spectral characteristics into a single category. Furthermore, when images are affected by Gaussian or impulse

noise, numerous small and fragmented regions may appear, increasing the likelihood of misclassification [44].

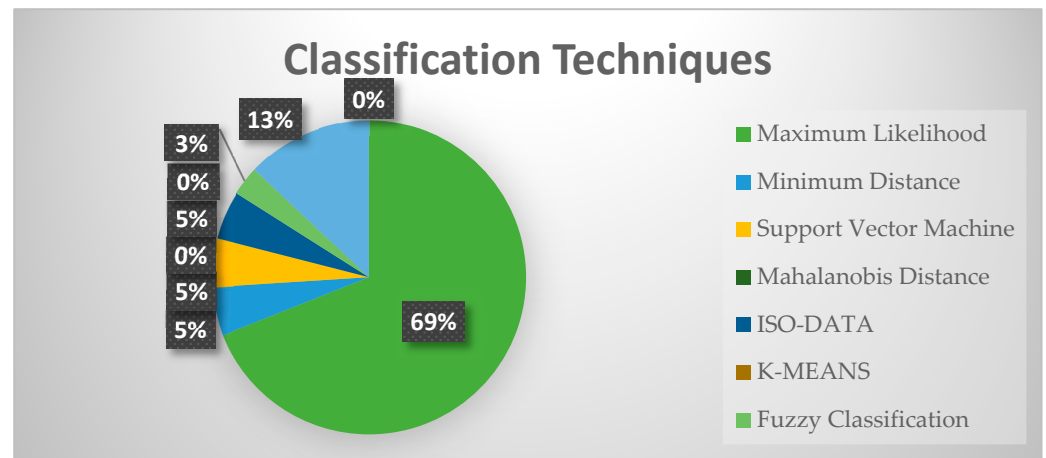


Figure 4. Types of the most used classification techniques, adapted from [45].

2.7. Algorithms Used

2.7.1. Minimum Distance Algorithm

The minimum distance (MINDIST) classifier operates under the assumption that classes that are geographically or spectrally similar should be grouped together as a single prototype. This method calculates the mean spectral vector for each class and assigns pixels to the class whose prototype is closest in terms of distance [14,27]. The approach can be visualized in Figure 5a).

The MINDIST algorithm each unclassified pixel to the class with the smallest Euclidean distance in a defined space, from the unclassified pixel to the known class average [46].

The minimum distance algorithm has the disadvantage of being prone to association errors (assigning a pixel to the wrong class), because it does not take into account the variance of each class during the classification process [47].

The Semi-Automatic Classification Plugin (SCP) is a Python-based tool integrated into QGIS that facilitates image classification and is widely used in applications such as urban planning, environmental monitoring, and agriculture. The plugin allows for rapid computation by encoding contextual image information using clustering and machine learning algorithms [11]. The satellite images were imported into QGIS and atmospherically corrected prior to processing.

Subsequently, a set of Regions of Interest (ROIs) corresponding to the predefined classes, each characterized by distinct spectral signatures, was delineated to generate the training datasets. These datasets were created using the SCP interface and further processed with the scikit-learn (Python Software Foundation, Wilmington, DE, USA), which employs the Spectral Angle Mapping (SAM) algorithm to generate the final classification maps [35].

2.7.2. k-Nearest Neighbor (k-NN) Algorithm

k-NN [48] is a supervised, non-parametric machine learning classification method, originally proposed in 1951. It is represented in Figure 5b). Unlike other algorithms, it does not build an explicit classification model during training; instead, it assigns a class to unknown samples based on the majority class among the k nearest training samples, determined using the Euclidean distance.

The value of the parameter k has a significant impact on the classifier's performance: high k values can lead to over-smoothing and reduced sensitivity to local patterns, while

very low k values may cause overfitting. The optimal value of k should be selected through cross-validation by testing different k values and choosing the one that provides the best classification accuracy [49].

k -NN is used for both classification and regression tasks [47]. This method is an effective option for small datasets, but in the case of large datasets, the curse of dimensionality may occur, and it is also time-consuming and resource-intensive.

Let

$$X = \{x_1, x_2, \dots, x_N\} \quad (1)$$

denote the training set, where each $x_i \in R^n$ represents a data point in the n -dimensional feature space, and let

$$Y = \{y_1, y_2, \dots, y_N\} \quad (2)$$

represent the corresponding class labels.

In the case of a given test point x' whose class is unknown, its class can be determined as follows: the similarities between the test sample and the training samples are determined using Euclidean distance, for example.

Euclidean distance (D)

$$D = \sqrt{\sum_{i=1}^d (s_i - x_i)^2} \quad (3)$$

Identify the k nearest neighbors of the test sample within the training dataset based on similarity, and determine the class label by majority voting among these neighbors [50].

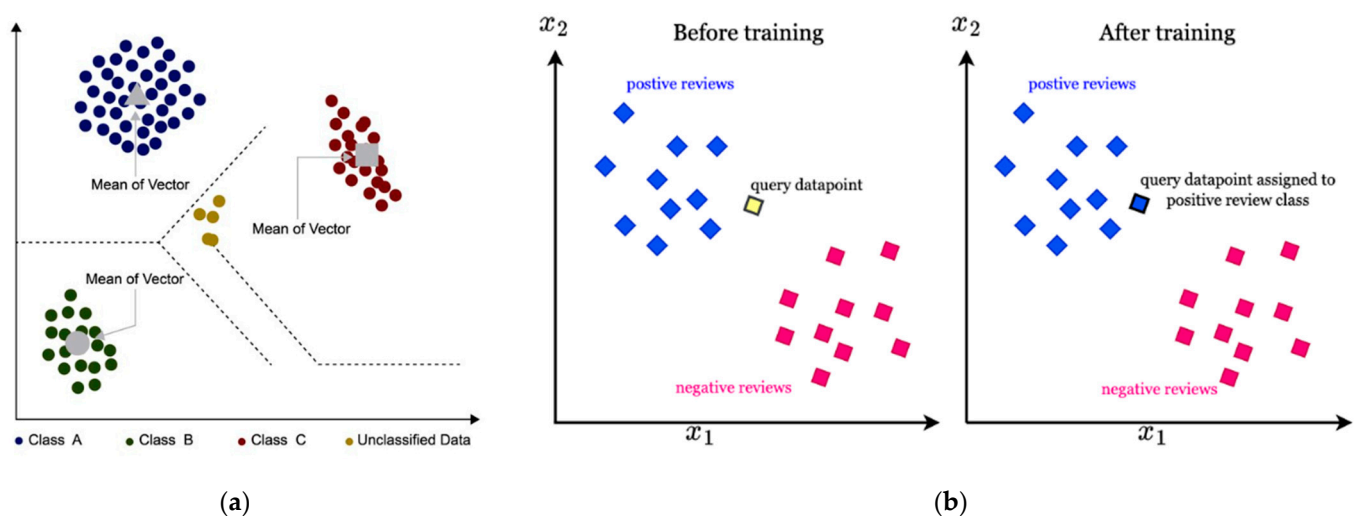


Figure 5. (a) Minimum distance classifier. Each class is represented by a mean spectral vector (centroid), and unclassified data points are assigned to the class with the shortest Euclidean distance to its centroid. This approach assumes that classes are statistically separable based on their mean vectors [51] and (b) k -NN classifies a new data point by identifying the k closest instances in the feature space and assigning the most frequent class among these neighbors [52].

2.8. Color Samples

In ArcGIS Pro, color samples are referred to as training samples, whereas in QGIS, they are referred to as ROIs.

Selecting color samples is a crucial step, as it involves defining a group of pixels with similar spectral characteristics corresponding to each class. It is essential that the color sample contains a sufficient number of correctly labeled pixels to ensure representative training data. The resulting distributions are typically close to normal distributions, often represented as a bell-shaped curve [53].

2.9. Classification of Land Cover and Assessment of Accuracy

Color samples were manually collected [51] through visual interpretation of images provided by Sentinel-2A (ESA, Paris, France) and Google Earth Pro (Google LLC, Mountain View, CA, USA). The classes defined in both software environments are presented in Table 2. To create the samples, polygons were uniformly distributed across the entire study area, with approximately 70 representative samples used in both case studies.

Table 2. Description of land classification in this study.

No.	Classes	Description
1	Water	Rivers, lakes, pools, ponds
2	Building	Residential, commercial, industrial, transportation
3	Vegetation	Forests, parks, green spaces
4	Agricultural Land	Arable land with less than 10% vegetation cover
5	Infrastructure	Streets, bridges, parking lots, platforms

Based on the initial imagery, five classes were defined: water, buildings, vegetation, agricultural land, and infrastructure (roads and parking lots).

Accuracy assessment methods are employed to validate LULC (Land Use/Land Cover) map classifications, determining the quality of the extracted information by evaluating whether image pixels have been correctly or incorrectly classified based on remotely sensed data. These assessments can be either qualitative, involving a comparison between the classified map and real-world conditions, or quantitative, involving a detailed comparison between classified cartographic data and reference data. Accuracy assessment is essential for evaluating classification performance and supporting decision-making processes. In this study, the performance of the minimum distance and k-NN algorithms was evaluated based on the classification accuracy achieved.

The literature presents several methods for evaluating accuracy to assess the reliability of image classification, and new approaches for accuracy assessment in change detection are continually being developed. The confusion matrix, also known as the error matrix, remains the most widely used method, relying on elements such as ground control points (GCPs), the classification scheme, sample type and size, and spatial autocorrelation [45]. However, studies indicate that factors such as the methods, procedures, temporal and spatial contexts, and the choice of classification algorithm can significantly influence classification accuracy [27].

Accuracy assessment is a crucial step for interpreting results and making predictions based on them [54]. Accuracy assessment was performed following the parameters illustrated in Figure 6. The application of the workflow shown in Figure 6 results in an error matrix, where pixel values represent the comparison between the classified data and the reference data. A detailed report summarizing these values was also generated automatically by the software.

The confusion matrix is one of the most commonly used methods for evaluating classification accuracy. After post-processing, a series of parameters were calculated: Producer Accuracy (*PA*), User Accuracy (*UA*), Overall Accuracy (*OA*), *F1 score*, and the Kappa coefficient. These parameters were computed according to Equations (4)–(9).

PA and *UA* represent the accuracy for individual categories, while *OA* reflects the accuracy of the entire classification. The *F1 score* combines *PA* and *UA* into a single metric. The indicators were calculated as follows:

$$OA = \frac{\sum_{i=1}^n X_{ii}}{X} \quad (4)$$

$$Kappa = \frac{X \sum_{i=1}^n X_{ii} - \sum_{i=1}^n X_i \times X_{*i}}{X^2 - \sum_{i=1}^n X_i \times X_{*i}} \quad (5)$$

$$PA = \frac{X_{ii}}{X_{i*}} \quad (6)$$

$$UA = \frac{X_{ii}}{X_{*i}} \quad (7)$$

$$F1score = \frac{2 \times PA \times UA}{PA + UA} \quad (8)$$

$$MacroF1 = \frac{\sum_{i=1}^n F1_i}{n} \quad (9)$$

where n represents the number of classes, X_{ii} —the column, respectively, row i in the confusion matrix, representing the number of pixels in a class that are classified correctly, X is the total number of samples, X_{i*} —the sum of the values in row i of the confusion matrix, representing the correct number of samples of class i and X_{*i} —the sum of the values in column i , representing the number of samples assumed to be in class i [55,56].

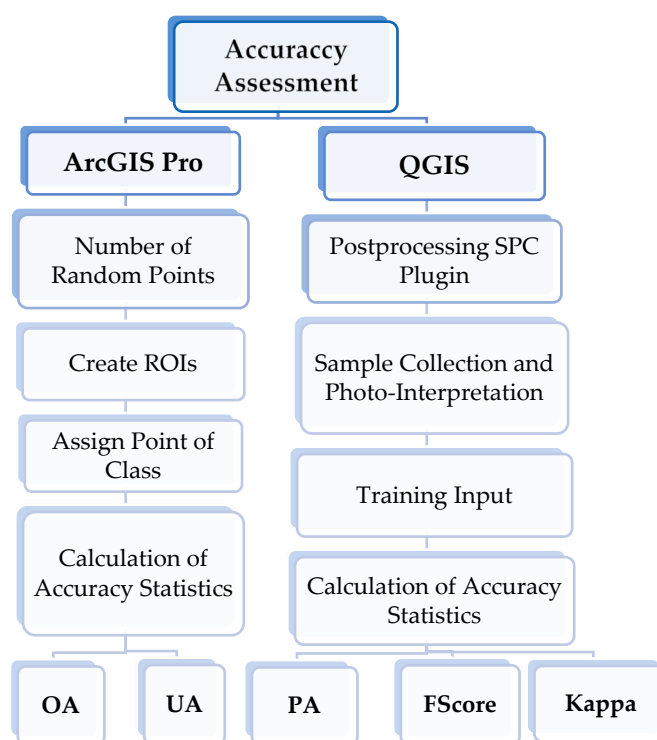


Figure 6. Workflow for accuracy assessment applied in ArcGIS Pro and QGIS. OA—Overall Accuracy; UA—User’s Accuracy; PA—Producer’s Accuracy; FScore—F1-score; Kappa—Cohen’s Kappa coefficient. The workflow shows the specific steps followed by the authors in each software environment to calculate classification accuracy metrics. (source: authors).

The Kappa coefficient measures the agreement between the classified map and the ground truth [55]. We tested both classifiers—MD in QGIS and k-NN in ArcGIS Pro—and obtained different Kappa values. For Kappa coefficient values between 0.80 and 1.00, the classification can be considered highly accurate.

3. Results and Discussion

3.1. Assessment of the Accuracy of LULC Classification

In this study, three key aspects were investigated: the use of satellite imagery for land cover analysis, the comparative performance of two supervised classification algorithms,

and the practical relevance of the results for enhancing urban planning and management strategies. Supervised classification was conducted in both ArcGIS Pro and QGIS environments, employing the k-Nearest Neighbor (k-NN) algorithm and the Minimum Distance (MD) classifier, respectively. To ensure methodological consistency, the same number of training samples—extracted from identical areas within Sentinel-2A imagery—was used for both classification processes.

Accuracy assessment in ArcGIS Pro was performed using 100 validation points randomly distributed across the study area by the software. These points were visually interpreted and manually labeled using Google Earth Pro. The classification accuracy results are presented in Figure 7.

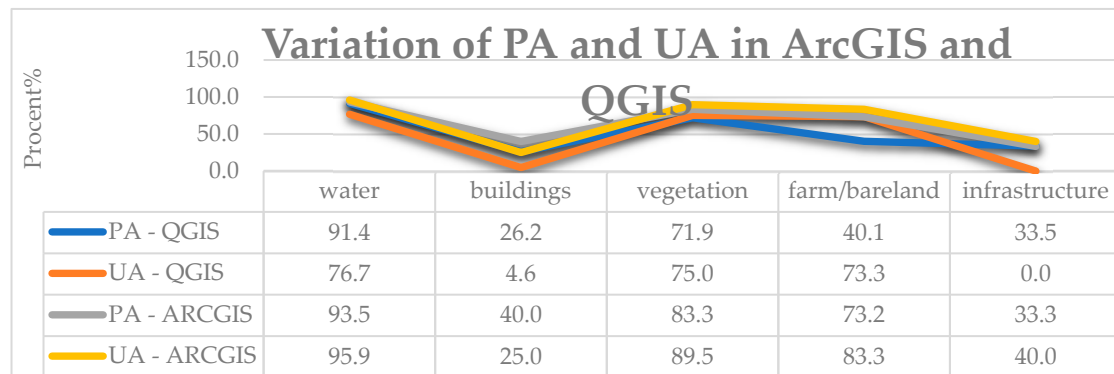


Figure 7. UA = user accuracy și PA = producer accuracy. They were obtained in both software programs. Comparison between the two analyses.

In QGIS, the validation was conducted using the same samples applied during classification. Visual interpretation was carried out using Google Satellite imagery, and the outcomes are summarized in Table 3. Although the Kappa coefficient indicated a satisfactory level of agreement in the QGIS classification, the k-NN algorithm in ArcGIS Pro produced superior accuracy when compared to the MD classifier. Additionally, the Overall Accuracy (OA) of the classified images was 53.53% in QGIS and 68% in ArcGIS Pro. Land Use/Land Cover (LULC) classification results following the accuracy assessment process in: (a) ArcGIS Pro using the k-NN algorithm; and (b) QGIS using the Minimum Distance classifier.

Table 3. Interpretation of the Kappa coefficient, adapted from [25].

Coefficient	Interval	Accuracy	QGIS (SPC)	ArcGIS Pro
Kappa	0.4–0.6	good	0.32	0.54
	0.6–0.8	very good	-	-
	0.8–1.00	excellent	-	-

3.2. LULC Classification

For the selected study area, five land cover types were defined for the city of Deva: water, buildings, vegetation, agricultural/open land, and infrastructure.

Figure 7 illustrates that, in ArcGIS Pro, the highest similarity based on the Producer Accuracy (PA) calculation was achieved for water bodies, while the lowest PA was recorded for infrastructure.

Figure 8 illustrates the increase in reflectance within the near-infrared spectrum, primarily due to the low absorption properties of vegetation. In this urban case study, where built-up areas are predominant, artificial surfaces demonstrate generally higher

reflectance across all wavelengths. In contrast, the lowest reflectance values are recorded for water bodies and infrastructure elements.

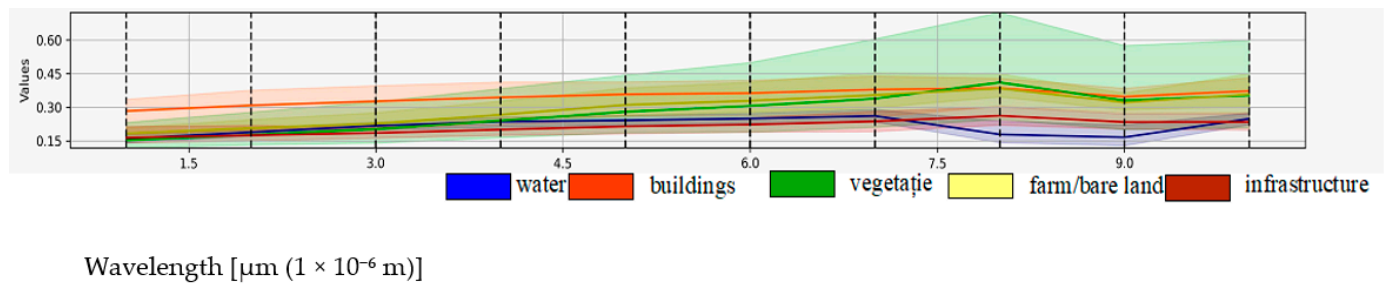


Figure 8. Signature reflectance in different land cover types. Spectral reflectance profiles of different land cover classes across multiple wavelength ranges. Vegetation exhibits a distinct increase in reflectance in the near-infrared region ($\sim 7.5 \mu\text{m}$), while water bodies show consistently low reflectance values. Built-up surfaces (infrastructure and buildings) display moderate, relatively uniform reflectance across all bands. These spectral differences support land cover classification based on supervised algorithms.

This lower accuracy is mainly due to the spectral similarity between roads, parking lots, and building rooftops, which can easily lead to classification confusion. Figure 8 also presents the spectral signature of images captured by Sentinel-2A, following classification using the SCP in QGIS and the Minimum Distance algorithm. The algorithm relies on spectral signatures, enabling the labeling of image pixels. Spectral signatures can also be used for classifying ground objects, depending on the sensor resolution and the type and extent of land cover [47].

These findings highlight the complexity of urban land cover classification due to the spectral similarity among anthropogenic surfaces. While water bodies and vegetation exhibited distinct spectral signatures that facilitated accurate classification, infrastructure elements posed challenges because of their spectral overlap with buildings and roads. Nonetheless, the comparative analysis between ArcGIS Pro and QGIS demonstrated that each platform, through its specific algorithm (k-NN and Minimum Distance, respectively), is capable of delivering valuable outputs when properly calibrated. These results support the practical applicability of open-source and proprietary GIS software in generating reliable LULC maps, especially in medium-resolution imagery contexts such as Sentinel-2A. The insights derived from this classification are essential for urban monitoring, environmental assessment, and decision-making processes related to sustainable development.

4. Discussion

The results obtained in this study indicate that the supervised classification of Sentinel-2A imagery provided a satisfactory representation of the land use and land cover (LULC) patterns in the municipality of Deva. Nevertheless, there remains potential for improvement, particularly in refining class definitions and mitigating the influence of local environmental conditions. Several factors contributed to the discrepancies observed between classification outputs. Among the most influential is the selection of land cover classes, which strongly affects the accuracy and interpretability of the final maps. For instance, the “buildings” class encompassed both apartment blocks and individual houses that differ in roofing materials, surface reflectance, and, notably, height.

Figure 9 illustrates the results obtained through the two classifications and how we chose the training samples. Pixel-based classification methods rely exclusively on the individual spectral information of each pixel, as illustrated in Figure 8. Water bodies are characterized by low reflectance in the near-infrared (NIR) band and are generally located in

low-lying and relatively flat areas (Figure 9). Consequently, the “water” class achieved the highest Producer Accuracy (PA) in both classification methods applied in this study. A similar result was also reported in the study conducted by Zhang et al. [57]. Conversely, tall buildings and roof structures generated shadows that reduced classification accuracy. The agricultural/open land category proved the most heterogeneous, encompassing a mixture of cultivated fields, grasslands, bare soil, and rocky areas. Introducing subclasses for these land types could significantly enhance classification precision. Moreover, the preprocessing of Sentinel-2A Level-2A products, which include the Scene Classification Layer (SCL), effectively mitigated common errors associated with cloud and cirrus contamination [58].

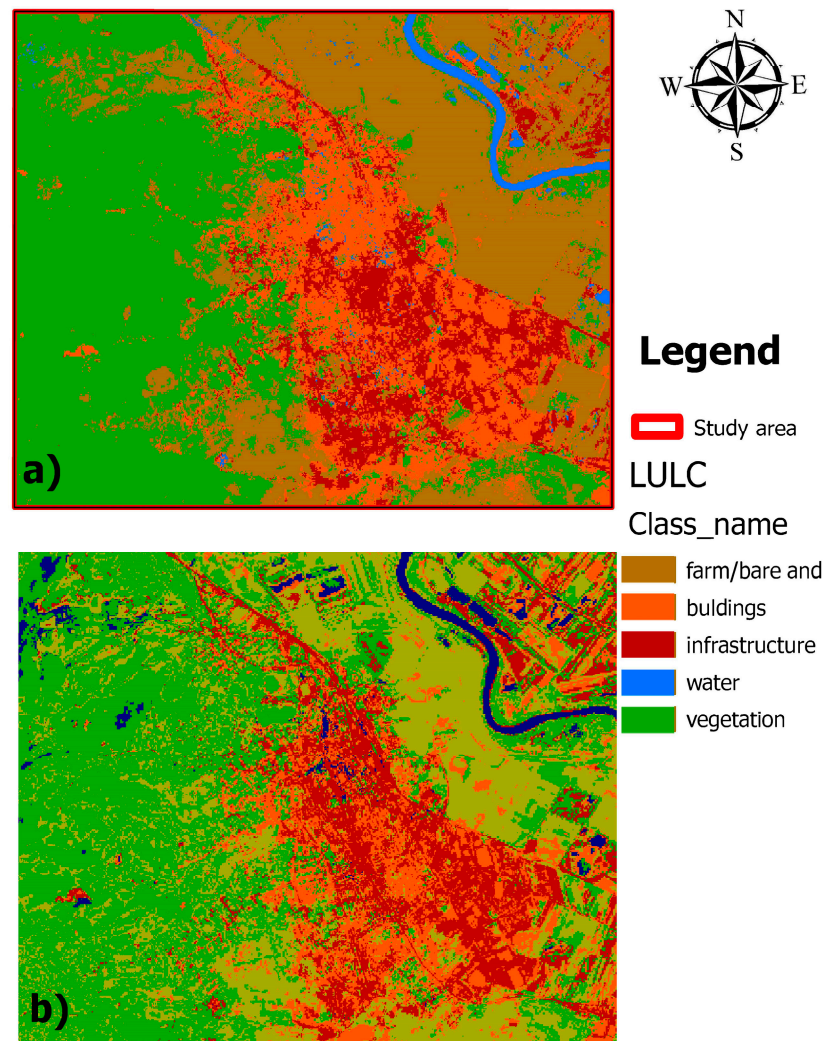


Figure 9. Land Use/Land Cover (LULC) classification results following the accuracy assessment process in: (a) ArcGIS Pro using the k-NN algorithm; and (b) QGIS using the Minimum Distance classifier.

Other uncertainties, more difficult to control, may also arise, including the timing of image acquisition, seasonal variations, data consistency, spatial resolution, and the chosen processing method. In our study, it is important to note that the selected area exhibits significant elevation differences, as it is a city surrounded by mountains. In this context, shadows cast by the mountainous terrain can lead to misclassification of objects with similar spectral signatures. Therefore, we believe that the considerable variation in altitude across the mountainous and transition areas has caused vertical changes, leading to classification errors. This factor is crucial for consideration in future research [59].

Standardizing a regional classification system, supported by field-validated geospatial data, would improve the robustness and comparability of future LULC analyses. The discrepancies identified—particularly within built-up and agricultural/open land categories—highlight the potential of combining multi-source data such as Landsat, MODIS, Sentinel, or UAV imagery to enhance classification reliability. Additionally, refining the selection of training samples, both in number and representativeness, remains critical to improving overall accuracy.

Accuracy assessment in image classification aims to determine the reliability of the results by comparing the classified output with an independent reference dataset. To ensure statistical robustness, previous research emphasizes the need for a sufficient and spatially balanced number of validation samples for each land cover type. Typically, around 50 samples per class are considered adequate for a representative evaluation [60]. In our research, the sample points were manually selected, with 100 points distributed randomly in ArcGIS Pro and chosen by us in QGIS [61]. The results obtained in this study are presented in Figures 10 and 11, which illustrate the land cover classification outputs generated in ArcGIS Pro and QGIS, respectively.

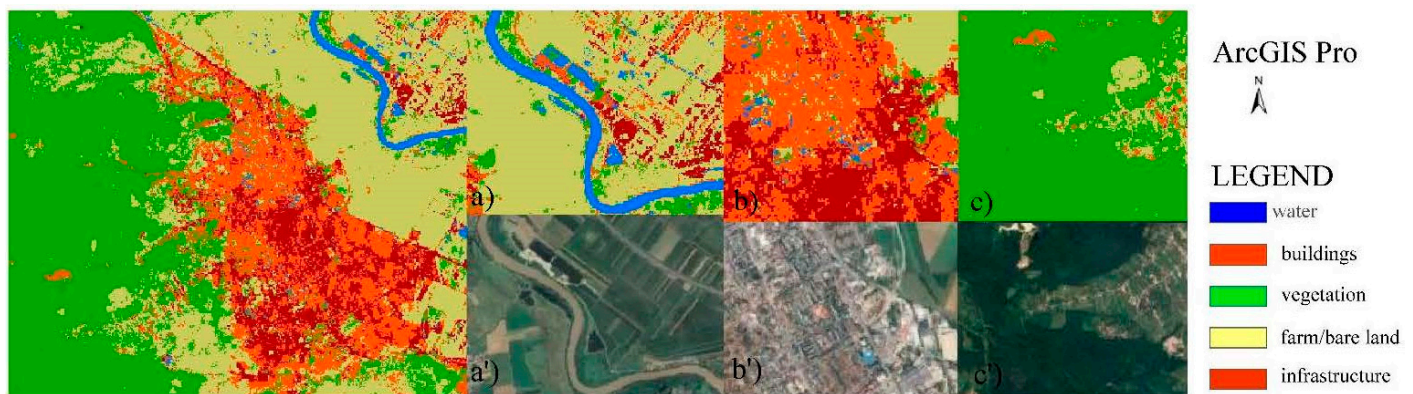


Figure 10. Classification map of the study area created in ArcGIS Pro: (a') Google Earth image highlighting the river and the corresponding classified area (a), (b') Urban area view from Google Earth and the classification result of the same classified area (b), (c') Forested area view from Google Earth and the classification result (c) of the same area.

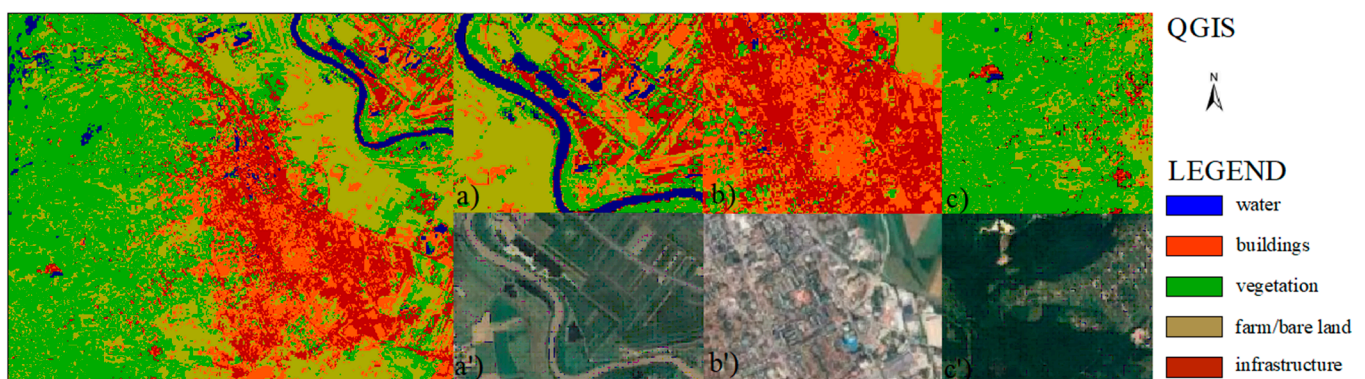


Figure 11. Classification map of the study area created in QGIS: (a') Google Earth image highlighting the river and the corresponding classified area (a), (b') Urban area view from Google Satellite and the classification result of the same classified area (b), (c') Forested area view from Google Satellite and the classification result (c) of the same area.

A previous study found that the Minimum Distance and K-Nearest Neighbors (k-NN) algorithms performed best in geomorphologically complex areas. This approach

helps address the current lack of standardized methods for overcoming remote sensing limitations in mountainous regions [62].

While this approach is practical, it is susceptible to errors due to the large volume and time constraints, compounded by the quality of images from Google Earth and Google Satellite, which do not offer sufficient predictability. Furthermore, defining subclasses for the main classes could improve accuracy; for instance, in the case of the vegetation class, subclasses such as coniferous forests, beech forests, lichens, shrubs, liverworts, and similar types could be defined.

Another perspective may be to integrate SDGs with information on land classification and livelihoods in order to identify informed and sustainable decisions for urban planning [21,63].

Future research could build upon the classification maps generated in this study by comparing them with global datasets such as WorldCover or GlobCover to assess consistency across spatial scales. The possibilities for classification are vast and can be further explored by developing specific algorithms tailored to the unique characteristics of the study area in both software platforms. Comparative analyses performed on identical datasets across multiple time intervals and atmospheric conditions are recommended, as the analytical capabilities of both platforms continue to expand.

5. Conclusions

Land classification represents a fundamental component of decision-making processes in local and regional governance. When integrated with geospatial data, it provides critical insights for spatial planning and environmental management. Satellite-based remote sensing offers a cost-effective and consistent source of geospatial data over extensive areas, forming a robust foundation for land cover analysis—particularly in rapidly evolving urban environments.

Image classification was carried out using two GIS software platforms with similar performance and capabilities. Two different classifiers were employed: k-NN in ArcGIS Pro, developed by Esri [64] and the SCP in QGIS, an open-source software developed by Luca Congedo [38], using the minimum distance classifier. These classifiers were used to create maps depicting the land cover of Deva municipality and to assess the accuracy with which they were produced. Our analysis aimed to explore image processing techniques and highlight the advantages and disadvantages they generate.

In this case study, better results were obtained in terms of Overall Accuracy (OA) using ArcGIS Pro. However, the study also revealed some errors, even after post-processing, related to the terrain and topography, particularly concerning the classification of dense vegetation (forests) and arable land (cultivated land and pastures) due to the similar spectral signatures of these two classes. Similar results were found for infrastructure and buildings, as both blocks and streets share similar spectral signatures (shades of gray). The best classification results were achieved for water bodies, where the Producer Accuracy (PA) was 91.36%, User Accuracy (UA) was 76.72% in QGIS, and PA was 73.17% and UA 83.33% in ArcGIS Pro. The weakest result was obtained for infrastructure.

Several limitations should be acknowledged when interpreting these results. Classification accuracy can be influenced by model parameters, input datasets, and acquisition timing. In general, Overall Accuracy (OA) is not significantly affected by the heterogeneity of the classes, although the accuracy of User Accuracy (UA) and Producer Accuracy (PA), especially for rare classes, can be significantly influenced [48]. To minimize class bias, all seven LULC classes were assigned an equal number of training and validation samples. While an imbalanced dataset might yield higher overall accuracy by favoring dominant

classes, this would compromise the reliability of individual class performance, especially for those less represented [65].

To address residual errors and improve classification accuracy, future analyses should incorporate a more detailed class hierarchy, including additional subclasses, and employ higher computational capacity to manage large datasets [48]. Another approach could involve integrating satellite images with ground control points collected for each defined class, combined with visual interpretation and classification algorithms, or higher-resolution datasets. Regarding the limitations of these methods, two aspects are particularly difficult to control: noise and clouds.

The potential of semi-automated supervised classification algorithms in the two software platforms is suitable for any geographical environment, and combining them with other types of geospatial data, such as 2D data, could increase the accuracy and reliability of the results. Therefore, maximizing the use of information obtained from remote sensing is essential, but in this study Sentinel-2 data were intentionally selected for their accessibility and cost-effectiveness compared to higher-resolution alternatives.

Future research could focus on analyzing the changes over time in the studied urban area, selecting a significant time period to study the socio-economic impact that the area has undergone. As future work, we plan to continue improving both the methods used and the exploitation of new modules, such as increasing the number of samples using augmented images, combining them with radar information, and exploring CNN architectures. Additionally, future analyses will be extended over longer time periods to better capture temporal dynamics and enhance the understanding of land use and land cover changes.

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