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EVALUATION OF URBAN EXPANSION IN CRAIOVA MUNICIPALITY USING REMOTE SENSING TECHNIQUES

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Abstract. *The paper entitled "Evaluation of Urban Expansion in Craiova Municipality Using Remote Sensing Techniques" aims to analyze the urbanization processes in Craiova between 2016 and 2025 through modern remote sensing and geospatial analysis methods. The main objective of the paper is to monitor and quantify the spatial expansion of built-up areas, identify land-use and land-cover changes (agricultural areas, green spaces, industrial and residential zones), and assess the environmental and territorial impacts of these transformations. The methodological framework involved the processing of Sentinel-2 satellite imagery obtained from the Copernicus Data Space Ecosystem and analyzed using ESA's SNAP software. Spectral indices such as NDVI and NDBI were applied, alongside supervised and unsupervised classification techniques, to detect and map urban growth patterns accurately. The processed data were integrated into GIS environments for generating comparative thematic maps and quantitative analyses.Results revealed significant expansion trends towards the northern and eastern sectors of Craiova, closely linked to infrastructure development and local urban policies. The study also emphasizes the ongoing densification of the urban core and the reduction of vegetated surfaces. This research supports sustainable urban planning and spatial management strategies, highlighting the efficiency of remote sensing as a reliable scientific tool for assessing urban transformation and guiding future development.*

Keywords: *remote sensing, urban expansion, Craiova, GIS, Sentinel-2, NDVI, NDBI, supervised classification, sustainable development, geospatial analysis.*

INTRODUCTION

The present paper, entitled "Evaluation of the Urban Expansion of Craiova Municipality through Remote Sensing Techniques," has as its main objective the analysis of the transformation processes of the urban space of Craiova Municipality over time, through the use of objective, quantifiable, and mappable methods. The study aims to provide a solid scientific foundation for understanding the dynamics of urbanization by employing modern tools of remote sensing and GIS analysis.

Craiova Municipality represents a complex spatial entity in which natural, economic, and social elements intertwine, constituting at the same time an important urban habitat. The research focuses on analyzing the urban expansion of Craiova Municipality between 2016 and 2025, using satellite imagery and remote sensing data. Through GIS and NDVI methods, changes in land use, directions and pace of urban development, as well as the impact on the environment and agricultural areas are identified.

The study provides databases and thematic maps useful to local authorities, academia, and investors, contributing to the foundation of sustainable urban policies. The research hypothesis supports the idea that Craiova's expansion occurred in a chaotic manner, mainly on the outskirts, under the influence of road infrastructure and uncontrolled urbanization.

The study analyzes the urban expansion of Craiova Municipality during 2015–2025, using Sentinel satellite imagery and data from the ESA Copernicus platform. The research seeks to identify land-use changes and urban development directions through indicators such as compactness, expansion rate, and the migration of the center of gravity.

The expected results highlight the increase in built-up areas and the reduction of agricultural and green lands, with urban zones expanding from the center toward the peripheries. The analysis correlates spatial data with socio-economic and infrastructural factors, providing scientific support for sustainable urban planning and territorial management.

Remote sensing is the process of obtaining information about the Earth's surface by measuring reflected or emitted radiation using sensors mounted on airborne or satellite platforms. It enables the analysis of the physical and biological properties of the terrain without direct contact.

The main fields of application include agriculture, forestry, meteorology, oceanography, geology, hydrology, environmental sciences, and geography. Through remote sensing, it is possible to monitor agricultural crops, forests, water resources, urban environments, natural hazards, and climate change, providing essential data for research, planning, and the sustainable management of resources.

The use of satellite imagery in the study of urban expansion

Why Use Satellite Imagery for Urban Expansion Analysis?

- Adequate spatial resolution: Sentinel-2 (10–20 m), Landsat (30 m), and for detailed studies <5 m (WorldView, PlanetScope, Pleiades).
- Long temporal coverage: enables multi-year comparisons (e.g., 1980/2000/2016/2025).
- Clear spectral indicators: high separability between built-up areas, vegetation, water, and soil.
- Low cost: many datasets are open-access (e.g., Sentinel, Landsat).

Main Methods

a) Supervised/Unsupervised Classification: algorithms such as Random Forest (RF), Support Vector Machine (SVM), and k-means are used to classify pixels into specific land-cover categories (built-up, vegetation, water, soil). Inter-annual comparison allows for quantifying the expansion of built-up surfaces.

b) Spectral Indices: NDBI (Normalized Difference Built-up Index) is used to detect built-up areas; UI (Urban Index) and IBI (Index-based Built-up Index) are applied for refinement, in combination with NDVI (Normalized Difference Vegetation Index) for vegetation and NDWI (Normalized Difference Water Index) for water, ensuring a robust separation of land-cover. classes.

$$NDVI = \frac{B8 - B4}{B8 + B4}$$

c) Multi-Temporal Analysis (Change Detection) Overlaying maps from different years (e.g., Craiova 2016 vs. 2025) allows the measurement of land-use conversions (in km²), especially agricultural → built-up.

d) High-Resolution Imagery Used for neighborhood-level analysis and identification of urbanization types (residential blocks, industrial areas, suburbs).

Image Classification

Supervised Classifications

- MLC (Maximum Likelihood Classifier) – a classical statistical approach (assuming a Gaussian distribution); simple but sensitive to noise and poorly separable classes.

- Random Forest – a robust machine learning method with high accuracy, making no assumptions about data distributions; requires training data and computational resources.

Unsupervised Classification (k-means): Grouping based on spectral similarity, followed by ex-post interpretation of clusters (water / vegetation / built-up / soil). Advantage: no need for training data. Limitation: lower accuracy.

LULC Categorization: Built-up (residential, industrial, commercial), agricultural land, natural vegetation/green spaces, water bodies, and non-productive surfaces (bare land, construction sites).

Change Detection (2016–2025)

- Comparison of multi-year maps;
- Calculation of converted areas (agricultural → built-up);
- Predominant growth directions: north (metropolitan area), west (new neighborhoods), south (industrial platform).

GIS Spatial Analysis

- Correlation of urban expansion with the transport network (Craiova ring road, national roads, highway connections);
- Assessment of the impact on agricultural lands and green spaces;
- Comparative thematic maps and diagrams of dominant growth directions.

Methodological Notes

- Random Forest was not adopted at this stage because built-up surfaces dominate the study area, and the main focus was on multi-year series and testing the spatial–temporal consistency of classifications; therefore, rigorous post-processing and visual validation were preferred.
- Expected results: comparative maps for 2016–2025, conversion statistics and annual urbanization rate, identification of green-space fragmentation, and predictive models of expansion trends.

Examples of Best Practices and Similar Studies in Romania and Abroad

- Romania (Established Studies / Datasets)
- Bucharest – 50 Years of Urban Transformations (CORONA 1968 → SPOT → Sentinel-1/2): multi-sensor, long-term time-series analysis [4].
- Craiova – Soil Sealing (NDBI): focused on the expansion of built-up surfaces over the last two decades; useful for calibrating local NDBI thresholds [5].
- Urban Atlas (Copernicus): FUA datasets for Romanian cities (Bucharest, Cluj, Craiova, Timișoara) – series 2006/2012/2018/2021; valuable as a cartographic “ground truth” reference [6].
- Dynamics of Urban Green Spaces (35 cities, 2006–2018): an example of multi-temporal analysis at a national scale [7].

International & Reference Resources

- GHSL (JRC): global layers for built-up areas, population, and settlement extent; open methodologies and tools – a standard reference for comparison [8].

- WSF / GUF (DLR): global built-up area maps (10–12 m), including 3D products (building height/elevation) for validation purposes [9].
- UN-Habitat: guidelines and indicator frameworks (SDG 11), Urban Observatories [10].
- USGS Landsat: case studies on urban change, replicable ML workflows (NDVI/NDBI, classification, heat mapping) [11].

General Overview

Craiova is located in the southwestern region of Romania, on the left bank of the Jiu River, within the Oltenia Plain. Typical elevation: 75–116 m; distances: approximately 227 km from Bucharest and 68 km from the Danube River.The city functions as the administrative, economic, and cultural center of the Oltenia region, hosting major universities, museums, theatres, and large public parks.

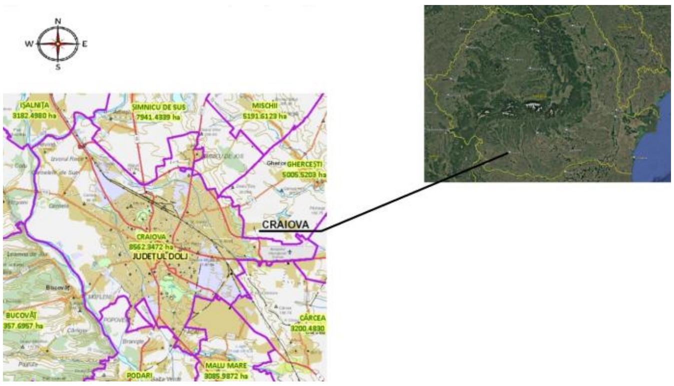

Figure 1. Craiova site plan (schematic)

After 1989, the industrial structure shifted from large integrated platforms (Electroputere, Oltcit/Daewoo, Doljchim, Aircraft Factory) to a peripheral, specialized model, characterized as follows: East (toward the airport / DN65): Ford and related companies, Industrial Park;

North (Ișalnița): heavy industry and construction materials (AdePlast, CET, partially the Doljchim platform); Southwest / West: reduced continuity and reconversions (Electroputere → commercial and office spaces; Softronic; Popeci).

Road Access: DN6/E70, DN65/E574, DN56/E79, and the Northern Ring Road (~14 km); ongoing projects include DX Craiova–Pitești (connection to the A1 motorway) and DX Craiova–Târgu Jiu.

Administrative Boundaries and Surface Area (Summary): the total area increased from 8,196 ha to approximately 8,581 ha through the inclusion of about 385 ha (Șimnicu de Sus ~250 ha, Podari ~135 ha), formally approved in 2023.

The coordinates, boundary extremes, and geometric indicators were obtained from geoportal.ancpi.ro.

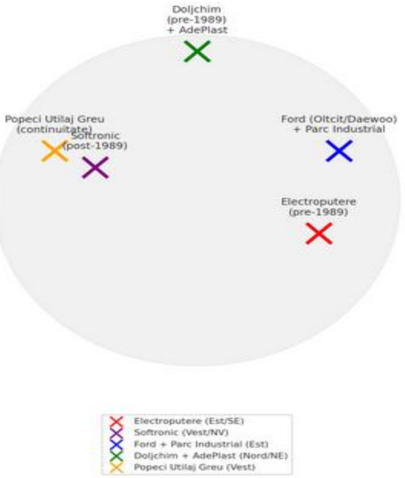

Figure 2. Industrial zones before and after 1989 (schematic)

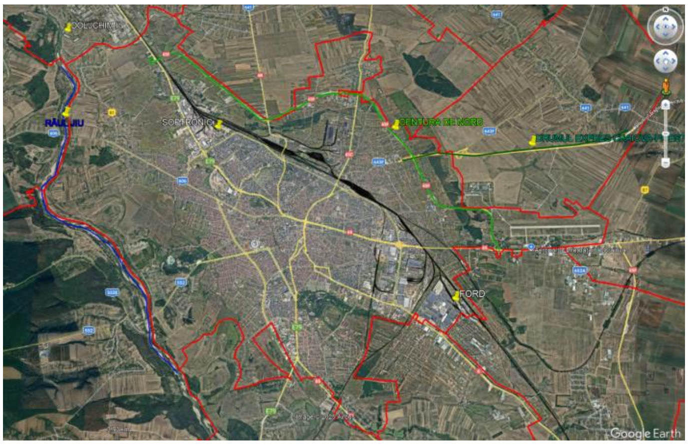

Figure 3. Relevant road network (scheme)

Table 1

Administrative-territorial unit (UAT) boundaries (summary parameters)

Shape_Length	73167,08754 m
Shape_Area	8565471,63286 mp
Limit south (maximum point)	406246,681 m and 308268,427 m
Limit east (point maxim)	412828,546 m and 313890,742 m
Limit north (point maxim)	399808,574 m and 320657,487 m
Limit west *Riverbed of the Jiu River* (maximum point)	397334,450 m and 314556,183 m

Source: geoportal.ancpi.ro

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Software and Data — SNAP & Sentinel-2

SNAP (ESA) is the software suite used for preprocessing (radiometric and geometric corrections, resampling), RGB/false-color compositions, spectral indices, and mosaicking, optimized for Sentinel-1/2/3 data.

Sentinel-2 (MSI) provides 13 spectral bands (visible, NIR, and SWIR) with spatial resolutions of 10 m (4 bands), 20 m (6 bands), and 60 m (3 bands).Common band combinations include:Natural RGB: B4–B3–B2, False-color vegetation: B8–B4–B3 Urban composite: B12–B11–B4.

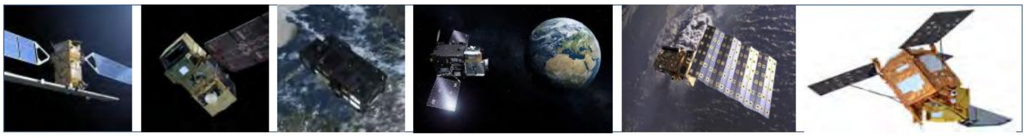

Figure 4. Sentinel Fleet (schematic representation)

Data and workflow:

1. Data acquisition from Copernicus Data Space Ecosystem (witch replaces the former Open Access Hub): AOI Craiova, time interval 2016–2025, processing level L2A, cloud coverage ≈ 0% (ex. 31.10.2016, 29.04.2025).

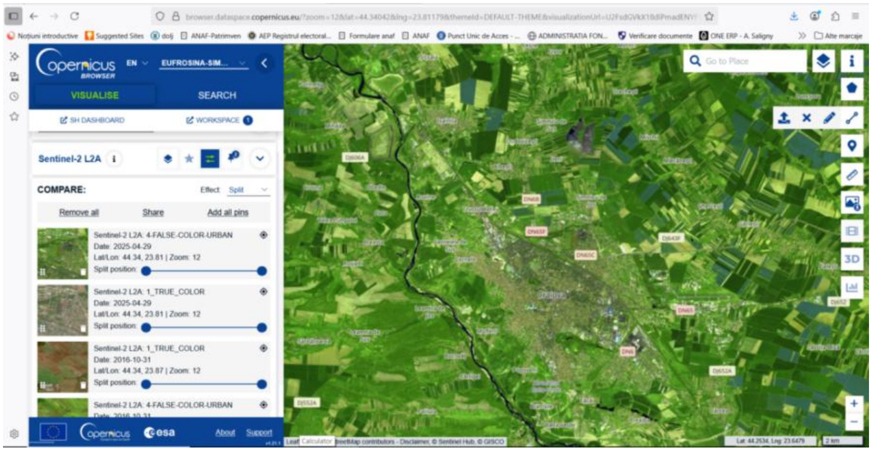

Figure 5. Browser-based color imagery viewing interface – Copernicus Urban Platform

2. Import into SNAP (manifest.safe), AOI subset, resampling to 10 m.
3. NDVI/NDBI/NDWI calculation using Band Maths; RGB/false color composites for interpretation.

Data structure: SAFE format (.zip archive), JP2 bands located in the *GRANULE* directory, XML metadata; pixels store DN values (linear transformation of at-sensor radiance).

File nomenclature (Fig. 6): S2A/S2B, L1C/L2A, YYYYMMDD, Thhmmss.

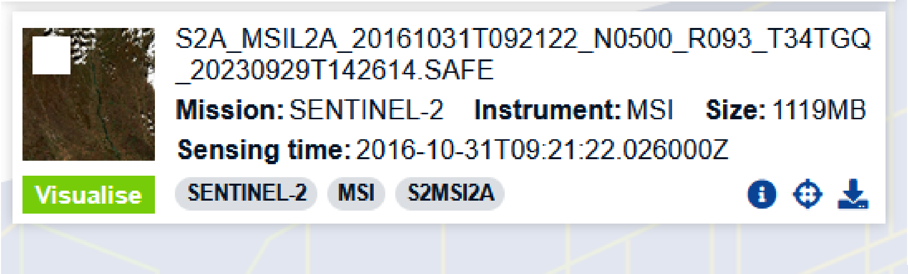

Figure 6. Copernicus image file name

Key Elements for Urban Expansion Analysis (Indicative)

- Methods: supervised classification (MLC, Random Forest, SVM) / unsupervised (k-means); multi-temporal Change Detection.
- Indices: NDBI (built-up), NDVI (vegetation), NDWI (water) — combined use ensures robust class separation.
- Spatial indicators: mean center of impervious surfaces, standard deviation ellipse, compactness, expansion intensity/rate, and migration of the center of gravity.
- Expected results: comparative maps for 2016–2025, agricultural → built-up conversion statistics, dominant expansion directions (N/NE/E; SW reconversions), and annual rate diagrams.

1) Algorithms & Data Fusion

Gouinaud (1996): segmentation algorithm based on histograms, using statistically defined thresholds in the neighborhood of isolated or bright pixels.

Data fusion: combining electro-optical and radar data to produce an integrated image with enhanced informational content compared to separate processing — “a group of methods that use multi-source / multi-nature data to improve information quality” [26].

Optical data: reflected solar energy, composition/color indices.

Microwave data: geometric and physical surface parameters (roughness, orientation, dielectric properties).

2) Band Combinations & Vegetation Interpretation (Fig. 7–8)

Tested combination: RGB = (B4_he, B8, B4), where B4_he = red band filtered with Horizontal Edge (base B4 + filter).

Practical meaning: RGB combinations reflect the spectral response of objects; interpretation relies on tone, shape, and context (Short, 1982) and is validated through field verification or auxiliary sources.

B8 (NIR, 842 nm, 10 m): Live vegetation → high reflectance; Soil / built-up / water → low reflectance.

Chromatic heuristics (B8 + B4):

- Conifers: dark green; Deciduous trees: bright green;Grasslands: light green.
- Pink/green contrasts distinguish areas with vs. without vegetation (role of B8/B4).

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Figure 7. False color composite (bands 8-4-3),2016   Figure 8. False color composite (bands 8-4-3), 2025) Sursa: Source: author's processing (band combination)

3) Observations for Craiova (2016 vs. 2025) – B8 & Thematic Maps

General trend: reduction of green areas within the built-up area in 2025, while public parks remain consistent landmarks.

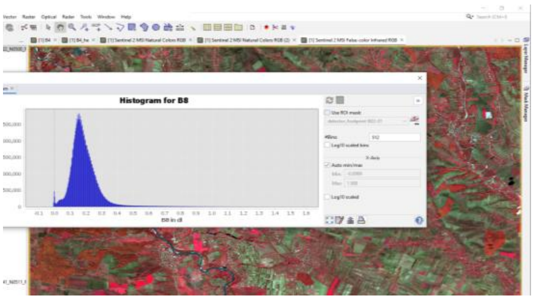
B8 Histograms:

- 2016: distribution concentrated between 0.10–0.30, with a peak around 0.17–0.19; overall higher frequency → indicates less vigorous vegetation / unfavorable season; negative or >1 values represent radiometric artifacts.
- 2025: mean ≈ 0.33, median ≈ 0.319, 90% < ≈ 0.48 → moderately healthy vegetation / mixed urban–agricultural landscape; few extreme values (>1) = artifacts.

Implication: the city–vegetation–water contrast is clearly separable in NDVI/NDBI; however, seasonal differences may influence vegetation extent perception, making temporal harmonization necessary.

4) Workflow SNAP

a) Download Sentinel-2 L2A (2016–2025) data from Copernicus Data Space; filter by AOI = Craiova; cloud coverage ≈ 0%.
b) Import SAFE → manifest.safe; subset AOI; resample to 10 m.
c) Band Maths: compute indices (NDVI, NDBI, NDWI), generate RGB/False Color composites.
d) Histograms / Statistics on B8; perform multi-temporal comparison and visual validation.



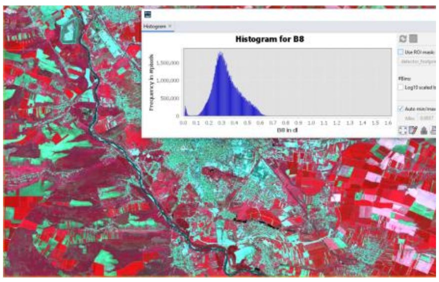


Figure 9. Histogram of the band combination 8-4-3,2016   Figure10. Histogram of the band combination 8-4-3, 2025

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The histogram for Band 8 in SNAP calculates, for each pixel, the digital number (DN) or reflectance value, and then displays their frequency distribution:

- X-axis: pixel values (reflectance or DN)
- Y-axis: number of pixels with that specific value (frequency)

5) Classification & Analysis

Table 2

Comparative histograms for the two images — 2016 vs. 2025

2016 (old image)	2025 (new image)	Interpretation:
Mean = 0.192 Median = 0.172 P90 = 0.281 Coef. Of variation = 0.57	Mean = 0.334 Median = 0.319 P90 = 0.482 Coef.of variation = 0.31	The mean NIR value has nearly doubled: from ~0.19 (2016) to ~0.33 (2025). Healthy vegetation has expanded and intensified → the acquisition period corresponds to the peak of the agricultural season (October 2016 vs. spring, April 2025) Considering that in recent years the summer months have been very dry, vegetation decreases significantly by autumn. The coefficient of variation was higher in 2016 (0.57 vs. 0.31 in 2025) → a more fragmented landscape, with strong contrast between barren areas and small patches of vegetation. In 2025, the landscape appears more uniformly green
NIR reflectance is relatively low → indicating that healthy vegetation was sparse at the time of acquisition (possibly autumn/winter, or fallow agricultural fields). The pixel distribution shows a landscape dominated by built-up areas, bare soils, and limited vegetation.	NIR reflectance is much higher → indicating that vegetation is more abundant and vigorous. A more compact distribution (lower coefficient of variation) indicates greater homogeneity → large areas are covered by active vegetation.	**2016:** Craiova and surroundings appear as an urban–agricultural landscape with sparse vegetation (low NIR reflectance). **2025:** The region shows much more vigorous vegetation (high NIR reflectance), suggesting either a different season (spring vs. autumn) or increased vegetation growth.

6) NDVI & synthetic results

$$NDVI = \frac{B8 - B4}{B8 + B4}$$

where:

- B8 (NIR, 842 nm) = Healthy vegetation exhibits high reflectance
- B4 (Red, 665 nm) = whereas less vigorous vegetation shows higher absorption

Indicative observations: In the 2016 vs. 2025 composites, red areas (vegetation in false-color) are more extensive/intense in 2016; in 2025, built-up areas have expanded and vegetation has receded outside parks (cf. Figs. 11–12).

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Figure 11. Vegetation changes in the Popoveni area Craiova 2016vs2025

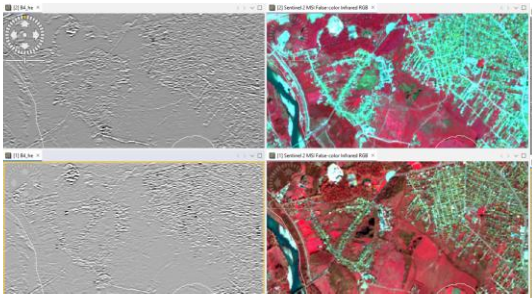
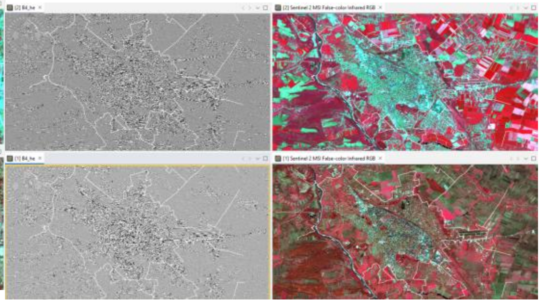


Figure 12Vegetation changes in the area Craiova 2016vs2025



7) Urban area expansion & green spaces

Table 3

Comparison (2015–2025, including urban area, green spaces, m² per inhabitant)

Year	*Urban area* (ha)	*Area of green spaces* (ha)	*Area of green spaces* (mp/inhabitans)	Observations
2015	Aprox 7.000 – 7.043 ha (PUG/PIDU)	Aprox 825 ha *local strategic reports*	Aprox 28–30 mp/inh. (estimativ)	Data sourced from strategy documents (Integrated Urban Development Plan).
2020	Aprox7.040 ha (stabil, serie INS)	Aprox 780 ha (estimates prior to RLSV)	Aprox 27 mp/inh. (alculated per population)Aprox 285.000)	The population is decreasing, but the green area per capita is also decreasing; the National Institute of Statistics (INS) maintains consistent statistical series.
2024	7.063 ha (Primary report)	1.044 ha (Official INS figure / Approximately 780 ha estimated by RLSV)	36,3 mp/inh. (raport INS)	There is a large difference between “official” and “actual” values (the RLSV cadastre could confirm lower figures).

CONCLUSIONS

Remote sensing, through the use of Sentinel-2 imagery processed in SNAP, enables the production of high-precision cartographic outputs for analyzing urban expansion. Multispectral and radar data fusion enhances the accuracy of classifications and improves the identification of built-up areas, vegetation, and water bodies.

In the case of Craiova (2016–2025), the NDVI and NDBI indices indicate an increase in built-up areas and a reduction in vegetation, while major green spaces have been preserved. Satellite data provide valuable support for urban planning, monitoring of PUG/PUZ policies, and assessment of environmental impacts.

The main limitations include the 10–20 m spatial resolution and the need for data preprocessing; however, remote sensing remains an essential tool for sustainable decision-making.

Future directions include multi-sensor data fusion, AI-based classification, and integration with socio-economic datasets to generate predictive maps of urban development.

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