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NEW CHALLENGES FOR CITIES IN THE TWENTY-FIRST CENTURY

Regenerative Design - Climate Adaptation & Mitigation
Circular Economy - Citizen Agency - Urban Livability

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Evaluating urban fabric transformations using GeoAI

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Abstract

Urban growth has reshaped land use patterns globally, demanding robust and scalable methodologies to monitor its long-term dynamics. This study proposes a GeoAI-based framework that integrates Random Forest (RF) classification with spatial indicators to analyze urban fabric transformations in Ravenna, northern Italy, from 2000 to 2024. Using Landsat 5 and Landsat 9 multispectral imagery processed in the Google Earth Engine (GEE) cloud computing platform, six Land Use and Land Cover (LULC) classes were mapped with high accuracy. The RF classifier achieved an overall accuracy of 86.2% in 2024, confirming its suitability for complex urban environments. The classified maps were imported into a GIS environment to extract built-up surfaces and compute spatial indicators, including Urban Density (UD), Urban Dispersion Index (UDI), Annual Growth Rate (AGR), and Urban Expansion Index (UEI). Results reveal a moderate densification in Ravenna's urban core alongside an increase in dispersed residential nuclei, confirming a dual trend of consolidation and sprawl. The indicator values align with northern Italian urbanization trends reported in the literature. This approach demonstrates how combining supervised classification with spatial metrics can provide deeper insights into urban growth, supporting more informed planning and policy-making. The framework is scalable, reproducible, and adaptable to different urban contexts.

Keywords

GeoAI; Remote sensing; Urban fabric transformation

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1. Introduction

The impact of human activities on environmental change is a central focus of land management and geomatics research, given the spatial complexity and heterogeneity of urban evolution. Although several monitoring approaches exist, capturing the temporal and spatial dynamics of urban landscapes remains a significant challenge due to limitations in traditional field-based techniques. While effective, conventional methods, such as field surveys and participatory mapping, are time-consuming, costly, and labor-intensive. Recent advancements in data acquisition technologies and the application of artificial intelligence (AI)-based algorithms to geospatial analysis (GeoAI) have offered innovative solutions to address these challenges, enabling more efficient and accurate analyses (Chaturvedi & de Vries, 2021; Fistola & La Rocca, 2024; Gaglione, 2023; Samardžić-Petrović et al., 2017). In particular, advancements in geomatics and remotely sensed imagery have revolutionized the ability to monitor and map changes in Land Use and Land Cover processes (LULC) (Khachoo et al., 2024; Partheepan et al., 2023). These technologies provide comprehensive temporal and synoptic insights, making them well-suited for capturing transformations in natural and built environments. Their integration with Geographic Information System (GIS) tools further enhances their utility, supporting large-scale analyses of LULC changes (Francini et al., 2023; Salvo & Vitale, 2024a; Salvo & Vitale, 2024b; Vitale, 2025; Wang et al., 2022; Zafar et al., 2024).

Machine Learning (ML) algorithms, a subset of AI-based methodologies, have played a pivotal role in advancing GeoAI capabilities, particularly in automated image classification. These algorithms have significantly enhanced the accuracy and scalability of analyzing large-scale geospatial datasets, especially when coupled with powerful computational infrastructures. Indeed, despite advancements in remote sensing and data acquisition technologies, large-scale geospatial data processing remains challenging due to significant computational demands, storage requirements, and the need for advanced technological resources (Song et al., 2022). Cloud-based platforms such as Google Earth Engine (GEE) have been developed to address these limitations (Gorelick et al., 2017). GEE is an open-access platform that hosts extensive geospatial datasets, including MODIS, Landsat, and Sentinel. It facilitates high-speed processing of planetary-scale remote sensing data, particularly for tasks such as image classification. By enabling the efficient integration of machine learning algorithms and providing integrated online storage, GEE has become a powerful tool for classifying multispectral satellite imagery and analyzing LULC (Benhammou et al., 2022; Velastegui-Montoya et al., 2023; Vitale et al., 2024; Vitale & Salvo, 2024).

Among ML models, Random Forest (RF) has demonstrated consistent reliability and robustness across LULC classification tasks. RF is particularly well-suited for multispectral image classification due to its resistance to overfitting, its ability to handle high-dimensional data, and its reduced sensitivity to parameter tuning. Several studies highlight its superiority over alternative algorithms such as SVM (Le et al., 2022). For instance, RF achieved 95.2% accuracy using Landsat 9 imagery, outperforming Support Vector Machine (SVM) in multiple class-specific evaluations (Zafar et al., 2024). Furthermore, the RF classifier was successfully integrated within a transfer learning framework to map built-up dynamics in southern Italy from 2006 to 2024, achieving an overall accuracy of 0.926 in 2024 and demonstrating the method's scalability, reproducibility, and high classification performance (Vitale & Lamonaca, 2025a; Vitale & Lamonaca, 2025b).

This paper proposes a GeoAI-driven methodology focused on classifying LULC changes and spatially characterizing urban fabric transformations using the RF classification algorithm. The study aims to provide an interpretation of urban evolution over a medium- to long-term period through a set of spatial indicators derived from classified maps. Four key indicators, Urban Density (UD), Urban Dispersion Index (UDI), Annual Growth Rate (AGR), and Urban Expansion Index (UEI), are employed to measure the intensity, direction, and fragmentation of urban growth over the 2000–2024 period (Romano et al., 2017a; Romano et al., 2017b)

Accordingly, the study addresses the following research question: Can a robust and scalable automatic GeoAI-based methodology be effectively integrated with urban spatial metrics to capture long-term urban transformations? How can these indicators help planners distinguish between sprawl and consolidation patterns in urban environments?

The rest of the paper is organized as follows: Section 2 describes the study area and the datasets employed. Section 3 outlines the methodological approach, detailing the RF-based classification process and the GIS-based measurement of urban transformation through spatial metrics. Section 4 presents the results of the land cover classification and the computed urban spatial metrics. Section 5 discusses the findings about the literature and planning implications. Section 6 concludes the paper with final considerations and future research directions.

2. Study area and dataset

The study area selected by the authors to test the proposed methodology is the city of Ravenna, a small-to-medium-sized municipality with a resident population of 157,277 inhabitants, located in the Emilia-Romagna region in northern Italy (Fig.1). This urban context, covering a surface area of about 630 km², is an ideal case for analyzing urban fabric transformations due to its historical significance and contemporary urban development. The city's core is defined by a well-preserved historical area featuring numerous UNESCO World Heritage Sites, which together form a dense, distinctive urban fabric. Surrounding the historic center, Ravenna has experienced significant urban transformations over the last two decades, particularly in its peripheral areas.

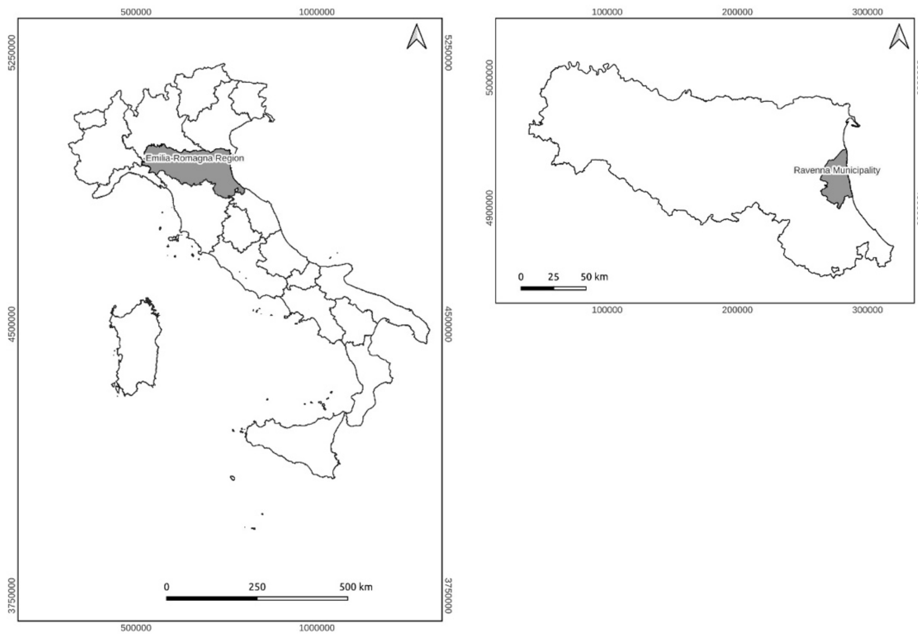

Fig.1 Study area key map

The industrial zones, in proximity to the Adriatic Sea and port facilities, have seen considerable growth, as have the adjacent residential neighborhoods. This development has resulted in a stark contrast between the compact historical urban core and the more fragmented modern urban textures elsewhere in the city.

The city’s urban fabric evolution is also influenced by environmental challenges such as flood risk and coastal erosion, further reinforcing the need for long-term monitoring using advanced geospatial tools.

Urban fabric transformations in Ravenna were determined by delineating several urban morphological zones, which were identified and characterized in consideration of the Municipal Structural Plan (PSM) documents. These zones include the historical core, suburban developments, peripheral industrial zones, and isolated residential structures. The delineation and temporal comparison of these zones were achieved by automatically classifying multitemporal multispectral satellite images using a supervised RF classifier.

Landsat 5 and Landsat 9 satellite images were used to capture and analyze urban fabric transformations in Ravenna over 24 years, from 2000 to 2024. The methodology, fully implemented in GEE, utilized Level 2, Collection 2, Tier 1 Landsat 5 imagery for the historical period (2000), which features atmospherically corrected surface reflectance and land surface temperature derived from the Landsat TM sensor. With a 30-meter spatial resolution, four Visible/Near-InfraRed (VNIR) bands and two Short-Wave InfraRed (SWIR) bands, these images were orthorectified to detect and map urban fabric and land use patterns at the start of the study period. For 2024, more advanced Landsat 9 imagery was used, characterized by improved radiometric resolution and spectral coverage, including 11 spectral bands across the visible, near-infrared, and short-wave infrared regions. The higher radiometric sensitivity of Landsat 9 allowed for more accurate classification of built-up and non-built-up areas, capturing even subtle urban development.

Ground-truth data were collected directly from the multispectral images to train and validate the RF classifier, ensuring the accuracy of automatic classification and subsequent measurement of urban fabric transformations. The integration of RF classification with a GIS-based framework enables a scalable, reproducible, and interpretable approach to monitor urban expansion and morphological change.

3. Methodology

3.1 Data preprocessing

To monitor LULC changes in Ravenna from 2000 to 2024, remote sensing data (Landsat 5 in 2000 and Landsat 9 in 2024) were processed using the GEE cloud computing platform. Following an open-source paradigm, this platform was designed and implemented to meet methodological requirements.

The platform is compatible with GIS, enabling the export of classified images and change-detection maps for further analysis and visualization within GIS environments.

The Landsat 5 and Landsat 9 satellite images were processed to temporally filter scenes, selecting the periods from 1 January to 31 December for 2000 and from 1 January to 30 September for 2024.

As a critical step for comparing the images from 2000 and 2024, the imagery from both datasets was geometrically aligned to ensure consistency in spatial resolution and coordinate systems.

Once the data were preprocessed, the RF classifier was applied in GEE to map the LULC classes for both periods. The resulting classified maps served as the basis for further GIS-based spatial analysis and for the computation of indicators in QGIS (QGIS, 2025).

3.2 Multispectral satellite images classification method

Land use and land cover Class	Description
Water	Areas covered by natural or artificial water bodies, such as rivers, lakes, ponds, and reservoirs.
Tree Cover	Areas dominated by trees, typically with continuous canopy cover, including forests and plantations.
Grassland and Shrubland	Open areas covered with grasses, shrubs, or sparse vegetation, often located in transitional zones between forests and barelands.
Agricultural	Lands used for agricultural purposes, including crop production, orchards, and managed fields.
Built-up	Urban areas characterized by human-made structures, including residential, commercial, industrial, and infrastructure developments.
Bareland	Exposed soils or rocky surfaces with little to no vegetation, often associated with deserts, rocky areas, or degraded lands.

Tab.1 A brief description of predicted LULC classes

The classification process relied on six LULC classes: tree cover, grassland and shrubland, agricultural, water bodies, built-up, and bareland (Tab.1). These classes were predicted using the RF classifier, trained on a labeled sample of 1,498 elements, of which 70% were used for training and 30% for validation.

The implementation of the RF classifier in GEE enabled the generation of consistent and accurate LULC maps for 2000 and 2024, which served as the foundation for the subsequent GIS-based evaluation of urban transformations and indicator computation.

3.3 Validation and accuracy assessment

The accuracy of the RF classifier depends on the input data dimensionality, the study area, and the satellite sensor used. Several studies in the scientific literature have evaluated different classifiers for LULC classification using Landsat 5 and Landsat 9 satellite images, reporting varying accuracies in validation (Basheer et al., 2022; Krivoguz et al., 2023; Puttinaovarat et al., 2023).

The confusion matrix was used to evaluate the classifiers' accuracy by comparing their predicted land use and land cover classifications against the actual ground-truth features. Indeed, the confusion matrix provides a detailed breakdown of the classification results, showing the number of correctly and incorrectly classified pixels for each LULC class. Moreover, two other accuracy indicators were used, particularly Overall Accuracy (OA) and Producer Accuracy (PA).

OA measures the proportion of correctly classified instances out of all instances and provides a general measure of the model's performance. The equation for OA determination is equation 1:

$$OA = \frac{Correct\ Classified\ Pixels}{Total\ Pixels} * 100 \tag{1}$$

PA or Recall is the ratio of correctly predicted positive observations to all actual positive observations (equation 2):

$$PA = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \tag{2}$$

True Positives (TP) correspond to the number of instances correctly predicted as the positive class.

False Positives (FP) refer to the number of instances incorrectly predicted as the positive class (when they are negative).

False Negatives (FN) represent the number of instances incorrectly predicted as the negative class (actually positive).

A higher PA value indicates the model correctly classified most of the class's pixels. A lower PA value indicates that many class pixels are misclassified into other classes (higher false negatives).

Based on the accuracy metrics described, the land use and land cover classification map generated by the RF classifier was selected for subsequent GIS-based evaluation and mapping of urban fabric transformation.

3.4 GIS-based urban fabric transformations evaluation and mapping

Following the classification of LULC for 2000 and 2024, the resulting maps were imported into the QGIS environment for post-processing and spatial analysis. A preliminary assessment was conducted to quantify changes in the areal extent of each LULC category over the 24-year observation window, with particular focus on the built-up class.

In addition to examining changes within specific morphological zones, the analysis included calculating the overall urban density and additional spatial indicators to characterize the intensity and nature of urban growth.

Four metrics were computed: UD, UDI, AGR, and UEI. These indicators are commonly used in spatial planning studies to quantify urban transformation dynamics.

The selected indicators provide complementary perspectives on growth intensity, spatial fragmentation, temporal trends, and urban expansion in relation to the total municipal area. Their application helps describe the structural transformation of the urban fabric beyond mere land consumption figures.

UD is calculated as in equation 3:

$$UD = \frac{BU}{TA} \tag{3}$$

BU is the total built-up area (in km²), and TA is the total area of the municipality (in km²). This indicator provides a normalized measure of the concentration of built-up land, allowing direct comparison between different periods or territories.

UDI is defined in equation 4:

$$UDI = \frac{N}{TA} \tag{4}$$

N is the number of distinct built-up nuclei, and TA is the total area of the municipality (in km²). UDI is particularly useful for assessing the degree of spatial fragmentation in urban settlements.

AGR is calculated using equation 5:

$$AGR = \left[\left(\frac{BU_{t2}}{BU_{t1}}\right)^{\frac{1}{t2-t1}} - 1\right] \tag{5}$$

BU_{t2} and BU_{t1} are the built-up areas at the final and initial years (2024 and 2000, respectively). This indicator quantifies the average yearly growth rate of urban fabric.

UEI is computed as in equation 6:

$$UEI = \left[\left(\frac{BU_{t2} - BU_{t1}}{TA}\right) \times 100\right] \tag{6}$$

As mentioned before, BU_{t2} and BU_{t1} are the built-up areas at the final and initial years, and TA is the total municipal area. UEI helps identify the portion of land converted to urban use as a proportion of the total municipal territory.

Together, these indicators provide a robust analytical framework for measuring urban growth and its morphological patterns. By associating spatial indicators with classified remote sensing data, the methodology ensures high comparability, transferability, and planning relevance. Their integration into GIS-based workflows allows planners and policymakers to assess the direction, rate, and sustainability of urban development processes. They support decision-making by revealing whether growth has occurred through compaction or dispersion, and how intensely the territory has been consumed over time.

The analysis was further refined by delineating specific urban morphological zones to evaluate the transformation of the urban fabric. These zones were defined using reference cartographic data provided by the Emilia-Romagna Region's geoportal and aligned with the city's PSM. The year 2000 served as the reference year for measuring spatial growth and transformation dynamics.

The city of Ravenna was subdivided into four morphological categories based on its structural and functional characteristics:

- Core Urban Zone The historical center and high-density residential and service areas;
- Suburban Zones Residential expansions developed outward from the urban core;
- Peripheral Areas Low-density, recent developments including industrial sectors, port-related infrastructure, and coastal residential settlements;
- Residential Isolated Structures Dispersed built-up forms in rural or semi-rural contexts, characterised by fragmentation and spatial discontinuity.

Built-up areas identified through classification were extracted for reference years and overlaid on these morphological zones. The spatial analysis thus provided a structured basis for evaluating how Ravenna's urban structure has evolved and identifying zones that experienced the most pronounced changes in built-up surface over the two-decade period.

4. Results

4.1 RF classification results

The classification results generated by the Random Forest (RF) model for the years 2000 and 2024 were evaluated using confusion matrices and standard accuracy metrics. In 2000, RF achieved an OA of 83.8%, indicating strong predictive reliability in distinguishing among the six LULC classes. PA values exceeded 0.90 for the water, built-up, and tree cover classes, confirming the classifier's effectiveness in detecting spectrally distinct and spatially coherent features (Tab.2).

	Water	**Tree Cover**	**Grassland and Shrubland**	**Agricultural**	**Built-up**	**Bareland**
Water	55	0	0	2	1	0
Tree Cover	0	37	0	0	3	1
Grass./Shrub.	0	0	51	5	3	7
Agricultural	0	0	11	95	2	9
Built-up	0	0	2	6	108	1
Bareland	0	0	6	14	2	42

Tab.2 Validation process confusion matrix for RF 2000 LULC classification prediction

The agricultural class returned a PA of 0.81, slightly lower but still robust. Some confusion was observed between agricultural and adjacent categories, such as grassland and shrubland (11 pixels), and bareland (9 pixels), possibly due to seasonal effects or spectral similarity. Grassland and shrubland recorded a PA of 0.77, with misclassification primarily involving agricultural (5 pixels) and bareland (7 pixels). The bareland class exhibited a moderate PA of 0.65, with significant confusion with agricultural (14 pixels) and grassland/shrubland (6 pixels) areas, typical of transitional or degraded land surfaces. By 2024, the RF classifier demonstrated enhanced performance, achieving an OA of 86.2%. Nearly all land cover classes experienced improvements in PA (Tab.3). Water and built-up areas retained high accuracy (PA = 0.95 and 0.92, respectively). Grassland and shrubland notably improved, with PA values of 0.94 and 0.90, respectively, and tree cover reached a PA of 0.90. Agricultural areas reached a PA of 0.88, although some confusion persisted with bareland (9 pixels) and grassland and shrubland (10 pixels). Bareland also improved, achieving a PA of 0.76, although it remained the least accurately predicted class. The RF classification outputs were selected as the definitive LULC maps for spatial analysis and the computation of urban growth indicators (Fig.2). These validated maps provided the analytical foundation for measuring the spatial distribution and temporal evolution of Ravenna's urban fabric from 2000 to 2024.

	Water	**Tree Cover**	**Grassland and Shrubland**	**Agricultural**	**Built-up**	**Bareland**
Water	55	2	1	0	0	0
Tree Cover	0	37	0	1	3	0
Grass./Shrub.	0	1	62	3	0	0
Agricultural	0	0	10	88	10	9
Built-up	0	2	0	4	108	3
Bareland	0	1	3	8	3	49

Tab.3 Validation process confusion matrix for RF 2024 LULC classification prediction

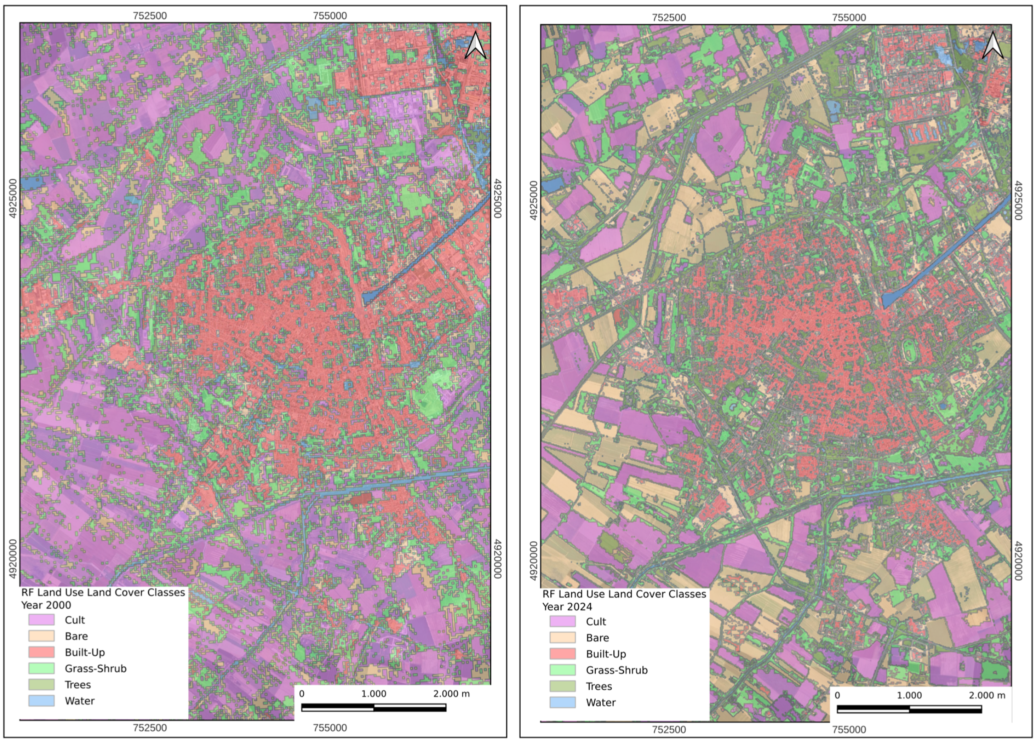

Fig.2 A sample of RF LULC classes predictions around Ravenna's historical center for 2000 and 2024

4.2 Urban fabric transformations analysis

The analysis of urban fabric transformations in Ravenna from 2000 to 2024 highlights significant changes in LULC. The spatial data and classification outputs, particularly those generated using the RF classifier, provide detailed insights into how Ravenna's urban structure has evolved.

The results reported in Tab.4, which present the surface area and percentage changes of the LULC classes from 2000 to 2024, show that the surface covered by water increased by 2.2 km² (+6.4 %), from 32.0 km² in 2000 to 34.2 km² in 2024. This increase is likely due to the expansion of water bodies and canals, or improved detection accuracy resulting from higher-resolution satellite imagery in 2024.

Tree cover decreased by 13.3 km² (-16.1 %), from 96.1 km² in 2000 to 82.8 km² in 2024. This decline indicates deforestation or urban expansion into forested areas, particularly in Ravenna's peripheral and suburban zones.

The area of grassland and shrubland increased significantly by 50.4 km² (+28.6 %), from 126.0 km² in 2000 to 176.4 km² in 2024. This increase might suggest land abandonment or a transition of agricultural land back into natural vegetation as agricultural activities decrease in some areas.

The Surface of agricultural land decreased by 12.1 km² (-4.9%), from 259.6 km² in 2000 to 247.5 km² in 2024. This reduction indicates urban encroachment on agricultural areas, particularly in the suburban and peripheral zones.

	Surface Covered in 2000 [Km²]	**Surface Covered in 2024 [Km²]**	**Surface Covered in 2000 [%]**	**Surface Covered in 2024 [%]**	**Difference 2000-2024 [Km²]**	**Difference 2000-2024 [%]**
Water	32.0	34.2	5.1	5.4	+2.2	+6.4
Tree Cover	96.1	82.8	15.2	13.1	-13.3	-16.1
Grass./Shrub.	126.0	176.4	20.0	28.0	+50.4	+28.6
Agricultural	259.6	247.5	41.2	39.4	-12.1	-4.9
Built-up	28.3	36.1	4.5	5.8	+7.8	+21.6
Bareland	87.8	52.8	14.0	8.4	-35.0	-66.3
Total	**629.8**	**629.8**	**100**	**100**	**0**	-

Tab.4 The surface of predicted LULC classes for 2000 and 2024

Bareland decreased considerably, losing 35.0 km² of surface area (-66.3 %), shrinking from 87.8 km² in 2000 to 52.8 km² in 2024. This may reflect urban development and the transformation of previously barren areas into built-up spaces or agricultural land.

Built-up areas experienced significant growth, increasing by 7.8 km² (+21.6 %), from 28.3 km² in 2000 to 36.1 km² in 2024. This reflects urban expansion, particularly in residential, commercial, and industrial developments in peripheral zones, as well as isolated residential structures.

Urban Density (UD) increased from 4.49% in 2000 to 5.73% in 2024. When compared to Romano et al. (2017a) and Romano et al. (2017b), this evolution places Ravenna above the 1950 value of 3.3% but still below the 2000 northern Italian average of 7.0%, suggesting a moderate level of urban compaction.

The Urban Dispersion Index (UDI), based on the number of built-up nuclei per square kilometer, increased from 0.0238 in 2000 to 0.0318 in 2024. These values align with the UDI range of 0.02–0.03 reported by Romano et al. for northern Italy in 2000, confirming a trend toward fragmentation consistent with that observed in the Emilia-Romagna region.

The Annual Growth Rate (AGR), which measures the average annual increase in built-up area, was calculated at +1.02%. This moderate rate reflects steady urban growth over the period.

Urban Expansion Index (UEI), which identifies the share of municipal territory converted to built-up use, aligns with the general expansion trends (1–2%) observed in Italian urban areas according to Romano et al.

In summary, Ravenna's urban transformation exhibits moderate densification, accompanied by increased dispersion. The UDI and AGR values suggest that while densification occurred within the core urban zone, growth also involved suburban and isolated areas, reinforcing the dual character of compaction and sprawl. The comparison with northern Italy further contextualizes Ravenna's evolution as a representative case of balanced urban expansion.

Considering the urban morphological zones described in the methodological section and focusing on the evolution of built-up areas, the connotation of urban fabric transformations can be outlined.

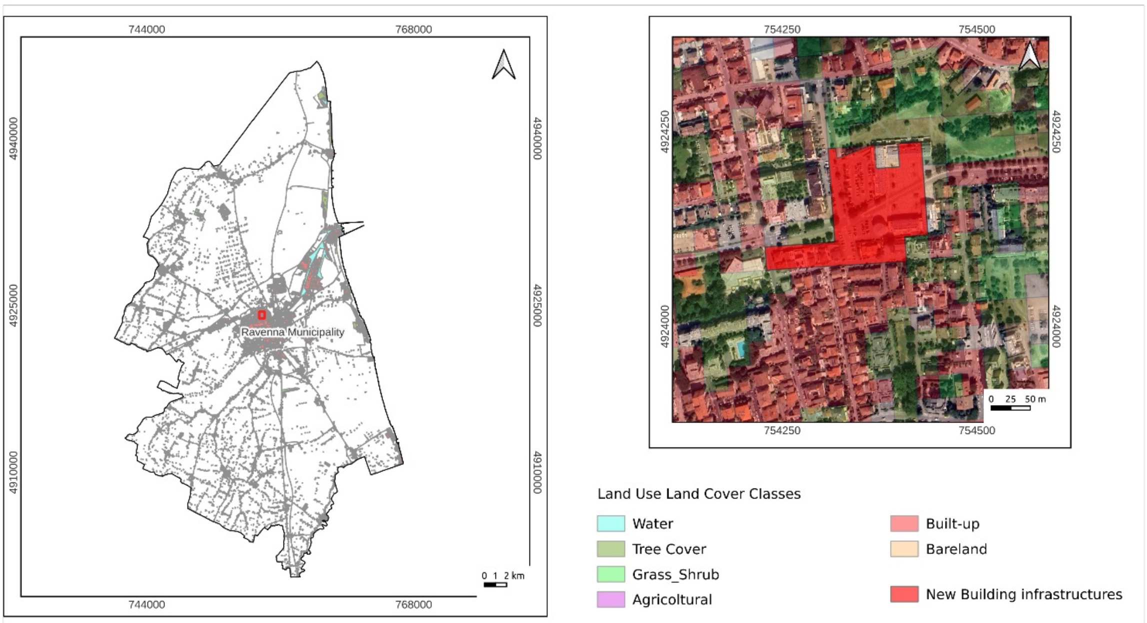

Fig.3 A sample of Built-up growth in the Core Urban Zone in the period 2000 - 2024

As can be seen from the image sample reported in Fig.3, the Core Urban Zone, which includes the historic center and the most densely populated areas, has been characterized by an increase in residential and private services. This growth has been concentrated primarily within the nucleus defined by the Municipal Structural Plan (PSM). Over the past two decades, significant urban mending has occurred within the core, focusing on intensifying the use of previously underutilized spaces. New residential buildings have replaced vacant lots and

have been infilled with medium-density housing and services, reflecting the city's policy of promoting urban densification. This policy not only supports sustainable urban growth but also preserves Ravenna's historic identity by limiting outward expansion and encouraging development within the existing urban footprint.
Beyond the core, suburban and peripheral zones have seen notable urban expansion, driven by demand for new housing and commercial facilities. These zones have experienced remarkable growth in built-up areas, particularly in the residential coastal settlement developments, often characterized by detached houses and low-density residential units (Fig.4). Also, in this case, the new residential buildings have replaced vacant areas with medium-low-density housing and services, mending the urban fabric and strengthening the densification policy undertaken in the last 24 years in Ravenna.

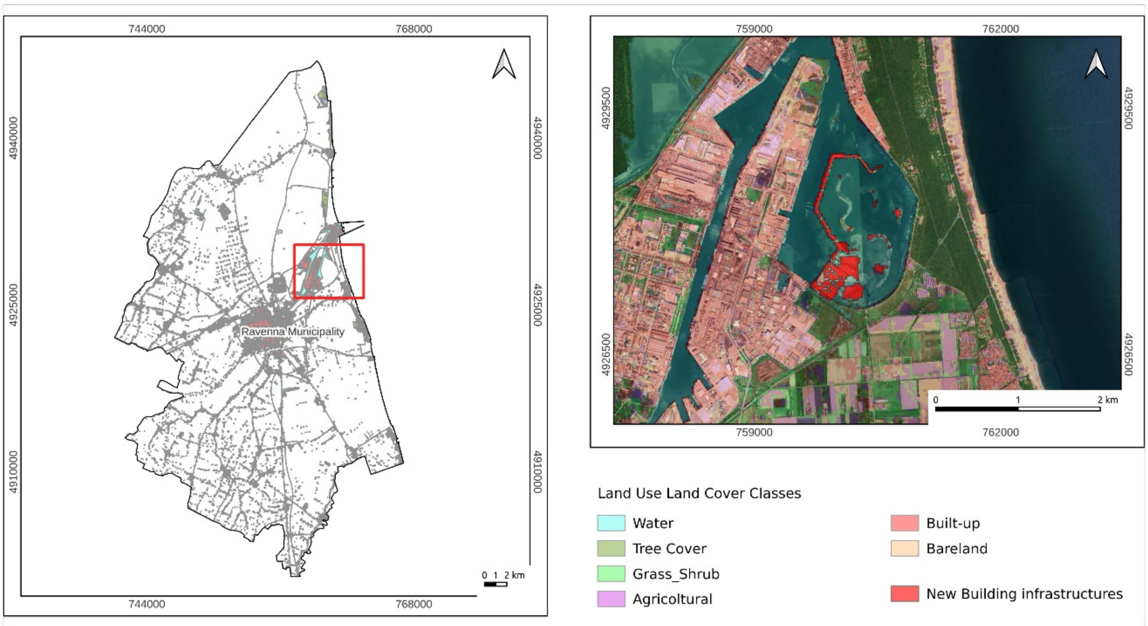

Fig.4 A sample of Built-up growth in the Suburban and Peripheral Areas in the period 2000 – 2024

The development of the commercial and industrial area near the Port of Ravenna, as depicted in Fig.4, consisted mainly of port and back-port infrastructures and services. The strategic development of these areas, hubs located near transport links and industrial hubs, within the region.

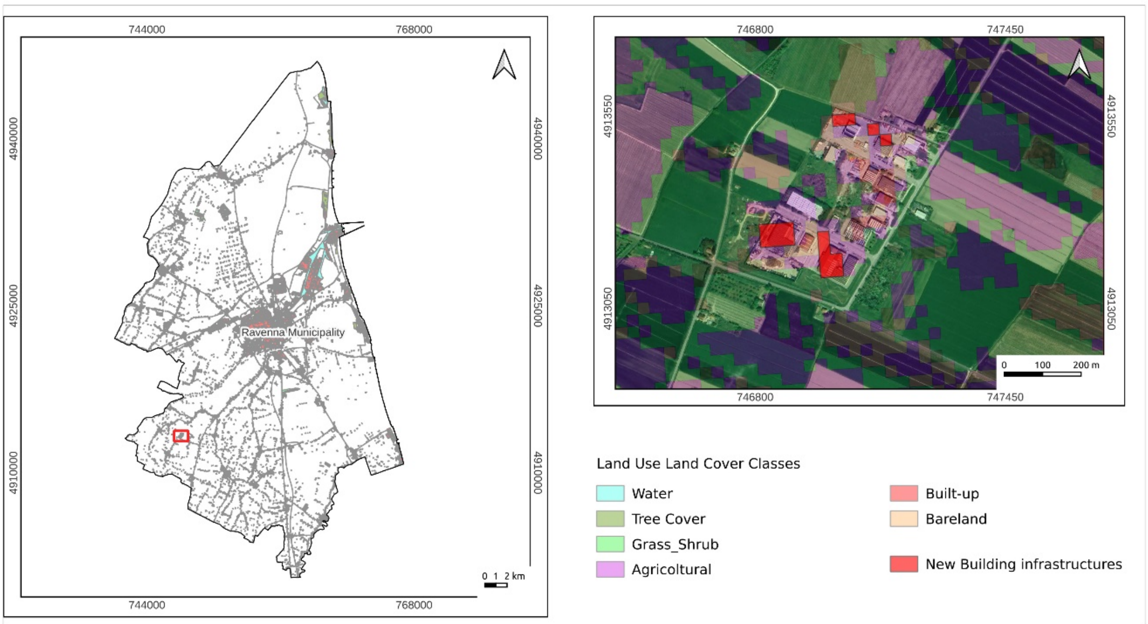

Fig.5 A sample of Built-up growth in the Isolated Residential Structures in the period 2000 – 2024

Growth in isolated residential structures has occurred primarily in the peripheral rural areas surrounding Ravenna, supporting agricultural activities. These isolated structures have contributed to a fragmented urban fabric, leading to less cohesive, more dispersed development. This development pattern is consistent with broader trends in urban sprawl, which can present challenges for infrastructure provision, transport planning, and environmental sustainability. However, these areas have become attractive for residents seeking a quieter, more suburban lifestyle while benefiting from proximity to the city center (Fig.5).

5. Discussion

The results of this study highlight the effectiveness and robustness of the proposed GeoAI-driven methodology for mapping urban fabric transformations. The RF classifier achieved an OA of 0.83 in 2000 and 0.86 in 2024, showing increased predictive performance over time. RF's ability to classify water, built-up, and tree cover classes with high accuracy (PA above 0.90) demonstrates its reliability in distinguishing these classes, especially in urban environments where rapid changes occur.

This reinforces the GeoAI-based approach as a reliable tool in geomatics for large-scale, long-term LULC monitoring, with high transferability and automation potential within GIS workflows.

The calculated spatial indicators provide strong empirical support for the classification output. Urban Density (UD) increased from 4.49% in 2000 to 5.73% in 2024, and Urban Dispersion Index (UDI) rose from 0.0238 to 0.0318, indicating a trend toward both densification and fragmentation. These results align with the spatial growth dynamics observed by Romano et al. (2017a) and Romano et al. (2017 b) in Northern Italy, confirming the relevance of the selected indicators. AGR and UEI values (1.02% and 1.24%, respectively) also align with the national trend of moderate urban expansion, validating the methodology's ability to quantify structural change.

The urban fabric transformations observed in Ravenna over the past 24 years suggest opportunities and challenges for urban and territorial planning. Consolidating the urban core, emphasizing redevelopment and densification, supports sustainable urban growth by reducing the need for outward expansion and preserving the city's historical identity. However, urban sprawl in peripheral areas poses challenges to infrastructure provision, transport planning, and environmental sustainability. This interpretation is consistent with the findings of Mazzeo and Russo (2016), who discuss land take and the territorial effects of urban expansion in Italian metropolitan contexts. The development of isolated residential structures in rural zones has contributed to a fragmented urban fabric, necessitating more strategic planning to manage growth effectively.

Methodologically, this research advances the field of geomatics by demonstrating that GeoAI-based LULC methodologies can yield multidimensional insights into urban morphology. The systematic inclusion of UD, UDI, AGR, and UEI metrics represents a significant enhancement over traditional pixel-based change detection, enabling the translation of satellite imagery into actionable urban knowledge.

While this study's results provide valuable insights into the transformations of Ravenna's urban fabric from 2000 to 2024, it is essential to highlight some limitations and potential areas for further research.

The present study relies on Landsat imagery, which, while freely accessible and valuable for long-term monitoring, has a spatial resolution of 30 meters. This resolution may not capture finer details in the urban landscape, such as small-scale residential or commercial developments. Higher-resolution imagery (e.g., from Sentinel-2 or commercial satellite providers) could provide more detailed insights into land use and cover changes in specific areas, particularly in dense urban cores or regions undergoing rapid, localized changes.

RF still encountered challenges in distinguishing between specific LULC classes, such as Bareland and Agricultural land. These challenges arise from spectral similarities between certain land cover types, which may necessitate more sophisticated classification techniques (e.g., deep learning models or object-based image analysis) to enhance accuracy, particularly in mixed-use or transition zones.

In addition, future applications could integrate ancillary data layers, such as cadastral boundaries, socio-economic indicators, or transport infrastructure datasets, to enrich the spatial interpretation of growth patterns. A multi-scalar or multi-temporal extension of this methodology would also enhance its analytical power. To overcome the limitations of traditional classifiers such as RF and SVM, deep learning models, such as Convolutional Neural Networks (CNNs), can improve land cover classification accuracy. These models are better suited to handle complex and nonlinear patterns in multispectral data. They can improve the differentiation between spectrally similar land cover types, such as Bareland and Agricultural areas.

Finally, while the methodology was validated on a single case study, its modular structure and use of open-access data and platforms make it easily replicable in other urban contexts. Future research should apply this framework to multiple cities across different regions to assess its generalizability and to contribute to a more comprehensive understanding of global urbanization processes.

6. Conclusions

This study demonstrated the effectiveness of a GeoAI-based methodology for detecting and quantifying long-term transformations in the urban fabric of Ravenna between 2000 and 2024. By integrating Random Forest (RF) classification with GIS-based spatial metrics, the approach enabled both high-accuracy land cover classification and a multi-dimensional analysis of urban growth patterns.

The RF classifier achieved an overall accuracy of 86.2% in 2024, confirming its suitability for complex land cover environments, particularly for detecting built-up areas, grassland/shrubland, and bare land. The adoption of spatial indicators, Urban Density (UD), Urban Dispersion Index (UDI), Annual Growth Rate (AGR), and Urban Expansion Index (UEI), provided a structured framework for evaluating the direction, intensity, and fragmentation of urban development.

These findings reinforce the value of geomatics-based methodologies that leverage AI and cloud computing for land monitoring. The results not only align with regional trends identified by Romano et al. (2017a) and Romano et al. (2017b) in northern Italy but also demonstrate the method's applicability to real-world urban planning challenges. Ravenna’s case illustrates how densification in the historic core coexists with a gradual increase in dispersed urban nuclei, reflecting a hybrid pattern of consolidation and sprawl.

The approach presented is scalable, reproducible, and adaptable to various urban contexts. By generating actionable, spatially explicit insights, this methodology supports more informed territorial governance, enabling policymakers to manage urban expansion while preserving environmental and cultural resources.

Future research should explore applying this framework to additional cities with different morphologies and integrating higher-resolution imagery or ancillary geospatial datasets to further enhance classification detail and planning relevance.

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