TeMA

Journal of Land Use, Mobility and Environment

print ISSN 1970-9889 e-ISSN 1970-9870
FedOA press - University of Naples Federico II

DOAJ Rivista scientifica di classe A - 08/F1 Scopus WEB OF SCIENCE

NEW CHALLENGES FOR CITIES IN THE TWENTY-FIRST CENTURY

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

Vol.19 n.1
April 2026

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Land Use, Mobility and Environment

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1 (2026)

Published by
Laboratory of Land Use, Mobility and Environment
DICEA - Department of Civil, Building and Environmental Engineering
University of Naples Federico II, Italy

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Editor-in-Chief: Rocco Papa
print ISSN 1970-9889 | online ISSN 1970-9870
Licence: Cancelleria del Tribunale di Napoli, n°6 of 29/01/2008

Editorial correspondence
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TeMA
Journal of
Land Use, Mobility and Environment

TeMA 1 (2026) 189-200
print ISSN 1970-9889, e-ISSN 1970-9870
DOI: 10.6093/1970-9870/11343
Received 10th December 2024, Accepted 28th February 2026, Available online 30th April 2026

Monitoring urban dynamics using Google Earth and GeoAI

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Abstract
Urban areas face mounting pressure from increased space demand, degrading key environmental services. Thus, understanding Land Use/Land Cover (LULC) changes is vital. In order to offer a robust decision-support framework for urban planning and environmental conservation, this study presents an innovative measurement method based on Google Earth Engine and Unsupervised K-means Clustering of multispectral satellite images to map urban and vegetation shifts. The proposed method was applied in 15 southern Italian cities and the results were validated with ESA Land Cover dataset. Results show 167 hectares consumed from 2005 to 2021. The proposed unsupervised classification achieved favorable F1-scores, with 0.64 for urban areas and 0.92 for vegetation, demonstrating strong performance despite the challenges of classifying diverse 30 m Landsat land cover types. For these reasons, these results show the potential to make the proposed method a useful tool for aiding policymakers and urban planners in making informed decisions to mitigate the adverse effects of urban growth on the environment.

Keywords
Built-up monitoring; Measurements; Artificial intelligence; Google earth engine; Unsupervised K-means clustering

How to cite item in APA format
Lamonaca, F. (2026). Monitoring urban dynamics using Google Earth and GeoAI. *TeMA - Journal of Land Use, Mobility and Environment*, *19* (1), 189-200. http://dx.doi.org/10.6093/1970-9870/11343

1. Introduction

Understanding the dynamics of Land Use and Land Cover (LULC) is crucial for guiding urban and territorial planning and management strategies aimed at conserving natural resources essential for sustainable development, as emphasized in both past and recent studies (Dwivedi et al., 2025; Fan et al., 2007; Esfandeh et al., 2022; Yao et al., 2022; Vitale et al., 2023; Salvo et al., 2023; Francini et al., 2023). In pursuit of this goal, researchers in recent years have extensively utilized RGB, multispectral (MSI), and hyperspectral (HSI) satellite imagery from major space agency programs, such as Landsat, Sentinel-2, and MODIS (Khachoo et al., 2022; Khachoo et al., 2023; Salvo & Vitale, 2024; Vitale & Salvo, 2024). Multispectral imaging (MSI) is a passive technique that is known to be an effective remote sensing technique for collecting earth observation (EO) data (Lim et al., 2023). MSI captures images in the visible, near-infrared (NIR), and short-wave infrared (SWIR) ranges in tens of bands. In contrast, HSI captures images in hundreds of narrow but contiguous spectral bands that extend from the visible range (0.4-0.5 μm) to the SWIR (Shaw & Burke, 2003). Although hyperspectral imaging (HSI) provides higher spectral resolution, multispectral imaging (MSI) and its enhanced versions remain widely preferred due to their balanced trade-off between spatial and spectral resolutions. This preference arises from the sensor complexity, which is determined by the product of the number of spectral bands and image resolution relative to spatial coverage. These MSI satellite images are readily accessible through cloud computing platforms, which enable efficient data storage, retrieval, and analysis on powerful servers that emulate the capabilities of supercomputers for users. Numerous cloud computing platforms have been established to date. For instance, Amazon Web Services (AWS) operates on a pay-as-you-go model, billing users for the services based on the duration of usage (Tamiminia et. al., 2020; Amani et al., 2020). This service provides access to open data from various satellites, including Landsat-8, Sentinel-1, Sentinel-2, the China–Brazil Earth Resources Satellite program, and datasets from the National Oceanographic and Atmospheric Administration (NOAA). Microsoft Azure is a cloud computing service that launched the AI for Earth initiative to tackle environmental issues in climate change, agriculture, biodiversity, and water management. Azure offers Landsat and Sentinel-2 datasets for North America from 2013 onwards, along with MODIS imagery, operating on a pay-as-you-go basis and providing virtual systems to users (Wilder, 2012). Launched in 2010, Google Earth Engine (GEE) leverages Google's advanced computing infrastructure to provide open-access remote sensing (RS) datasets (Gorelick et al., 2017). Renowned as a premier platform for large-scale geospatial data processing, GEE facilitates scientific research by offering free access to an extensive collection of remotely sensed data (Salvo & Vitale, 2024b; Vitale, 2025). It can be accessed through an internet-based Application Programming Interface (API) that requires HTML expertise.

Remote sensing data is invaluable for mapping LULC and detecting changes (Partheepan et al., 2023), offering unmatched spatial and temporal resolution. Nonetheless, accurately identifying urban and territorial features presents significant challenges due to the complex interactions and variability in spectral, spatial, and textural characteristics (Blaschke et al., 2014). A thematic LULC map featuring classified categories is a crucial instrument for visualizing changes in land use and land cover within a study area. Mapping land use and land cover (LULC) at medium spatial resolution requires a comprehensive dataset encompassing modern and historical remote sensing data. Progress in LULC mapping has been realized by integrating machine learning (ML) and artificial intelligence (AI) classifiers (Fistola & La Rocca, 2024; Gaglione, 2023). This advancement is part of a broader field known as GeoAI, Artificial Intelligence for Geospatial Data, which combines geospatial science with artificial intelligence technologies to analyze and interpret vast amounts of geographical data. GeoAI leverages the capabilities of ML and AI to automate and enhance the accuracy of spatial analysis, including the critical task of LULC mapping, by efficiently processing and learning from multi-temporal and multi-source remote sensing datasets. Numerous approaches, including unsupervised algorithms, parametric supervised techniques, and machine learning (ML) methods, have been widely applied for Land Use and Land Cover (LULC) mapping (Halder et al., 2011; Li et al., 2016; Orieschnig et al., 2021). Supervised classification techniques include methods such as the maximum likelihood classifier, Mahalanobis distance, k-nearest neighbors (kNN), support vector machine (SVM), random forest (RF), decision trees (DT), spectral angle mapper (SAM), fuzzy logic, fuzzy adaptive resonance theory-supervised predictive mapping (Fuzzy-ARTMAP), radial basis function (RBF), artificial neural networks (ANN), and naive Bayes (NB) (Ma et al., 2019; Shih et al., 2019, Vitale & Lamonaca, 2025a; Vitale & Lamonaca, 2025b). Unsupervised classification techniques encompass fuzzy c-means, the k-means algorithm, the affinity propagation clustering algorithm, and ISODATA methods (Maxwell et al., 2018).

Among these methods, ML algorithms for LULC mapping have gained considerable attention (Wang et al., 2022) due to their ability to handle input data without assuming specific distributions and their superior performance compared to traditional parametric classifiers (Jozdani et al., 2018). ML algorithms have been extensively applied to urban LULC mapping and modeling (e.g., Zhang et al., 2019; Mao et al., 2020) and evaluated in comparative studies (Camargo et al., 2019; Ouma et al., 2023). However, the accuracy of ML algorithms varies across different datasets and case studies. Among these, the unsupervised K-means classifier stands out for its computational efficiency, enabling the processing of large datasets quickly. This capability is especially valuable for analyzing the extensive remote sensing datasets used in LULC mapping. As an unsupervised algorithm, K-means does not require retraining and can be easily applied to new datasets, making it particularly useful for monitoring temporal LULC changes where new land cover classes may emerge (Lemenkova & Debeir, 2022).

This study proposes an innovative methodology that integrates advanced geospatial techniques with artificial intelligence to analyze and map LULC changes. It focuses on built-up and vegetation cover dynamics over 16 years (2005-2021) in a territorial-scale case study. The analysis emphasizes built-up area dynamics due to their significant social, economic, and environmental impacts, including increased resource demand and alterations to natural landscapes. Expanding built-up areas often results in vegetation loss, with ecological consequences such as reduced biodiversity, carbon cycle disruptions, and regional climate shifts.

Using the Google Earth Engine (GEE) cloud computing platform, implemented with JavaScript code, the study utilized a multitemporal series of multispectral satellite images from the Landsat 5 (1984-2012) and Landsat 8 (2013–present) datasets. These images were pre-processed and classified using the unsupervised K-means algorithm to assess built-up area dynamics over time. The classification accuracy for 2021 was evaluated by comparing the algorithm’s results with the European Space Agency's (ESA) WorldCover 10 m product derived from Sentinel-1 and Sentinel-2 data, using the F1-Score as the accuracy metric. Following the validation of the classification process, changes in built-up and vegetation cover were analyzed in the QGIS environment by comparing the K-means algorithm outputs for 2005 and 2015 with those for 2022.

The structure of this paper is organized in the following manner: Section 2 provides a comprehensive overview of the study area and the datasets used for the study. Moreover, in the same section, the authors introduce the proposed methodology to determine study area built-up and vegetation cover changes for 2005-2021. The research outcomes are thoroughly analyzed in Section 3, while Section 4 engages in a detailed discussion and presents the findings from the case study. The paper concludes with a Section summarizing the key conclusions drawn from the research.

2. Materials and methods

2.1 Study area

The study was conducted on a territorial-scale area encompassing 15 municipalities in the Calabria region of southern Italy (see Fig.1). These municipalities include Carolei, Castiglione Cosentino, Castrolibero, Cerisano, Cosenza, Dipignano, Lappano, Marano Marchesato, Marano Principato, Mendicino, Montalto Uffugo, Rende, San Pietro in Guarano, San Vincenzo la Costa, and Zumpano.

The study area covers approximately 8,685.68 hectares and has a resident population of about 70,550 people. Cosenza and Rende are the most prominent of these municipalities, serving as central hubs for regional activities. Calabria is largely characterized by small municipalities, with most having populations of no more than 5,000 inhabitants.

Including 15 municipalities provides a representative sample of the region's typical urban and rural landscapes, offering a comprehensive perspective on land use dynamics across communities of varying sizes and characteristics. In a region where urban growth and green space changes often occur subtly, especially in smaller municipalities, examining a broader geographical area is crucial to identifying significant transformations over time.

A study area of this scale enables the observation of meaningful development and transformation patterns that might not be evident in smaller, more homogeneous areas. This broader scope ensures a nuanced understanding of regional land use and land cover dynamics.

2.2 Datasets

Landsat multispectral images are among the most widely used datasets for time-series analysis in land use and land cover (LULC) classification, largely because of the extensive historical records available in their archives (Qu et al., 2021).

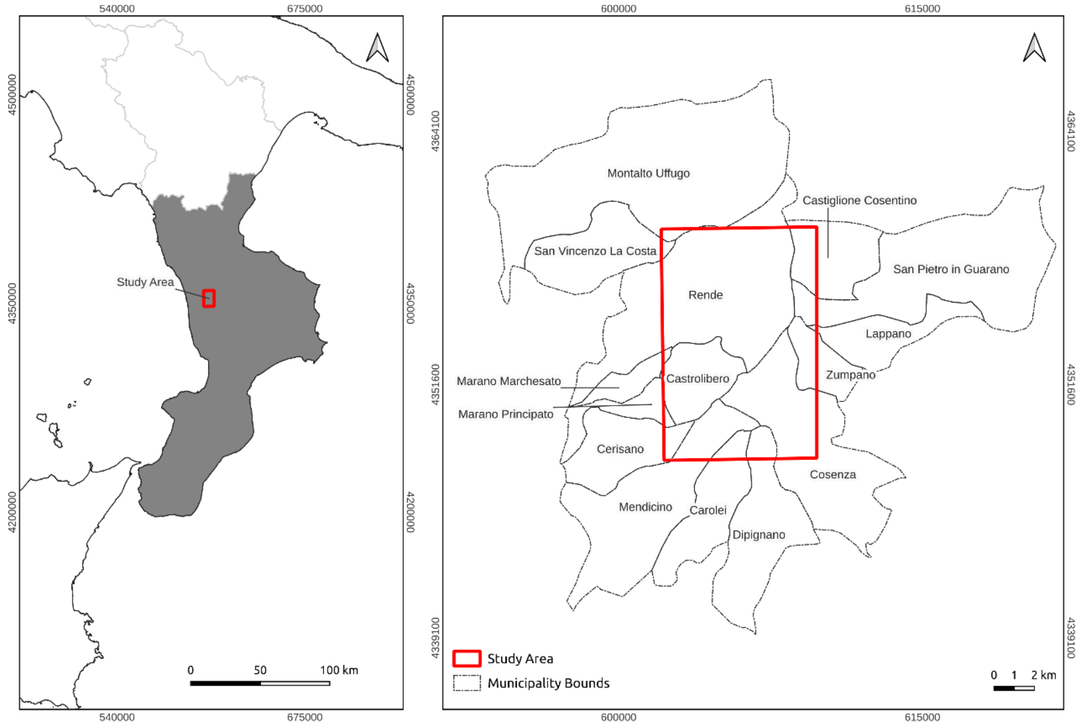

Fig.1 Study area Framework

For this analysis, Landsat imagery from multiple dates was utilized. Specifically, 2005, 2015, and 2021 satellite images were acquired from the Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) sensors. These images were obtained from the open-access Google Earth Engine (GEE) repository at a spatial resolution of 30 meters, using the World Geodetic System (WGS84) coordinate reference system.

Standard preprocessing steps were carried out within GEE prior to analysis. These steps included cloud cover removal, corrections for topographic, atmospheric, and geometric distortions, layer stacking, and image resizing. Additionally, histogram equalization was applied in ERDAS Imagine to enhance the multitemporal and multisensor Landsat imagery.

To evaluate the classification accuracy of the unsupervised k-means algorithm applied to the 2021 multispectral satellite image, the authors utilized the European Space Agency's (ESA) World Cover v200 map with a 10-meter resolution as ground truth. This map was obtained from GEE and is based on data from Sentinel-1 and Sentinel-2 satellites, part of the ESA's Earth Observation Envelope Programme. While Landsat imagery offers a longer temporal record, its operational bands have a coarser spatial resolution (30 meters). The finer resolution of the ESA map enhances accuracy by distinguishing land cover classes that might be blended in the Landsat data.

The World Cover v200 map classifies land into 11 distinct classes, including tree cover, shrubland, grassland, cropland, built-up areas, bare or sparse vegetation, snow and ice, permanent water bodies, herbaceous wetlands, mangroves, and moss and lichen. For this study, the authors focused on two layers: built-up areas and vegetation cover. The vegetation cover layer was created by merging the shrubland, grassland, cropland, bare or sparse vegetation, herbaceous wetlands, mangroves, and moss and lichen classes. This layer fusion was performed in QGIS by importing and processing the ESA World Cover map.

2.3 Landsat images classification

The authors used Landsat satellite imagery to analyze changes in built-up and vegetation cover from 2005 to 2021, and they classified the images using the unsupervised K-means clustering algorithm.

K-means clustering is a simple and widely adopted unsupervised learning method in data mining. This iterative algorithm partitions an unlabeled dataset into K predefined, distinct, and non-overlapping clusters based on similarity, ensuring that each data point is assigned to only one cluster. The main objective of K-means clustering is to minimize the distance between data points and their respective cluster centers. It is particularly effective for large datasets, ensuring the algorithm converges efficiently.

The number of clusters (K = 15) was established through an iterative process that combined visual inspection of the resulting classifications with domain knowledge of the study area, ensuring a clear separation between built-up and vegetation cover. The classification of Landsat images from the years 2005, 2015, and 2021 was carried out using ERDAS Imagine software.

2.4 Classification accuracy assessment

To assess the accuracy of the unsupervised K-means clustering algorithm's classification of built-up and vegetation cover areas, the authors used the 2021 Landsat satellite image and the 2021 ESA World Cover v200 Map as reference data. Both datasets were imported into QGIS software, enabling a direct comparison between the areas predicted by the algorithm and the ground truth provided by the ESA map.

The accuracy of the classification was assessed using Precision, Recall, and the F1-Score, which is the harmonic mean of Precision and Recall. Precision measures the proportion of correctly identified built-up and vegetation areas out of all regions predicted as such. In contrast, Recall measures the proportion of actual built-up and vegetation areas correctly identified by the model. The F1-Score provides a single balanced metric of classification performance, ranging from 0 (poor) to 1 (perfect).

These metrics can be calculated as follows:

$$Precision = \frac{TP}{TP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

The result is between 0 and 1, where 0 indicates the worst possible performance The F1-score ranges from 0 to 1, with 0 indicating poor performance, and 1 denotes perfect precision and recall. An F1-Score closer to 1 suggests that the model's predictions are accurate and reliable, indicating a high degree of agreement between the predicted mask and the ground truth data for built-up and vegetation cover areas.

Employing the F1-Score for comparing the model's predictions against the ground truth is particularly beneficial when there is an imbalance between the presence of built-up areas and vegetation or when the cost of false positives is different from the cost of false negatives. By considering both Precision and Recall, the F1-Score provides a more comprehensive evaluation of the model's performance than using either metric alone, offering insights into the model's overall effectiveness in classifying land cover types accurately.

Once the accuracy of the algorithm's classification using QGIS software is determined by considering Landsat satellite images from 2005, 2015, and 2021, it is possible to assess the changes in built-up and vegetation cover from 2005 to 2021. These changes were evaluated by comparing the areas occupied by built-up and vegetation over time.

3. Results

3.1 Built-up and vegetation cover mapping and classification accuracy estimation

Satellite images from the Landsat dataset for 2005, 2015, and 2021 were acquired using the Google Earth Engine platform. These images were classified using the unsupervised K-means clustering algorithm to identify built-up and vegetation cover areas. As outlined in Section 2, the study area encompasses 15 municipalities, covering a total surface area of approximately 8,685.68 ha, which was classified into built-up and vegetation areas using the K-means algorithm.

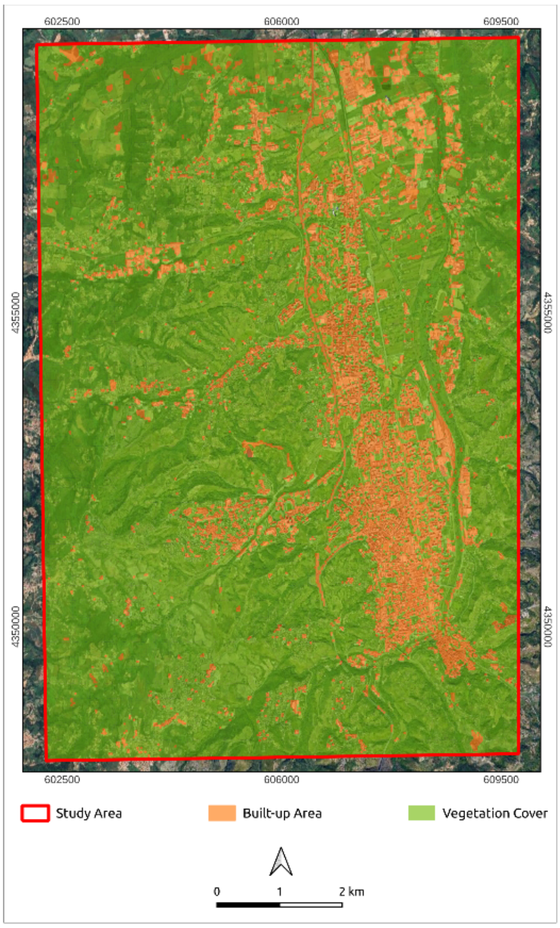

Fig.2 K-means classification algorithm prediction for 2021

To assess the accuracy of the classification, the algorithm's output for the study area in 2021 was compared to the ESA World Cover Map classification, which served as a benchmark. This comparison was performed in the QGIS environment. Fig.2 displays the classified built-up and green areas derived from the K-means clustering algorithm. The classification accuracy was evaluated using Precision, Recall, and F1-Score, with values of 0.63, 0.65, and 0.64 for built-up areas. The F1-Score of 0.64 indicates a moderate level of accuracy, suggesting that the algorithm achieves a reasonable balance between Precision (its ability to correctly identify positive instances) and Recall (its ability to capture all positive instances).

Land Cover Category	Areas [ha]	Changes [ha]	Changes [%]
2005	991.82	-	-
2015	1017.82	26.00	2.62
2021	1158.49	140.67	13.82

Tab.1 Built-Up changes from the k-means algorithm for 2005-2021

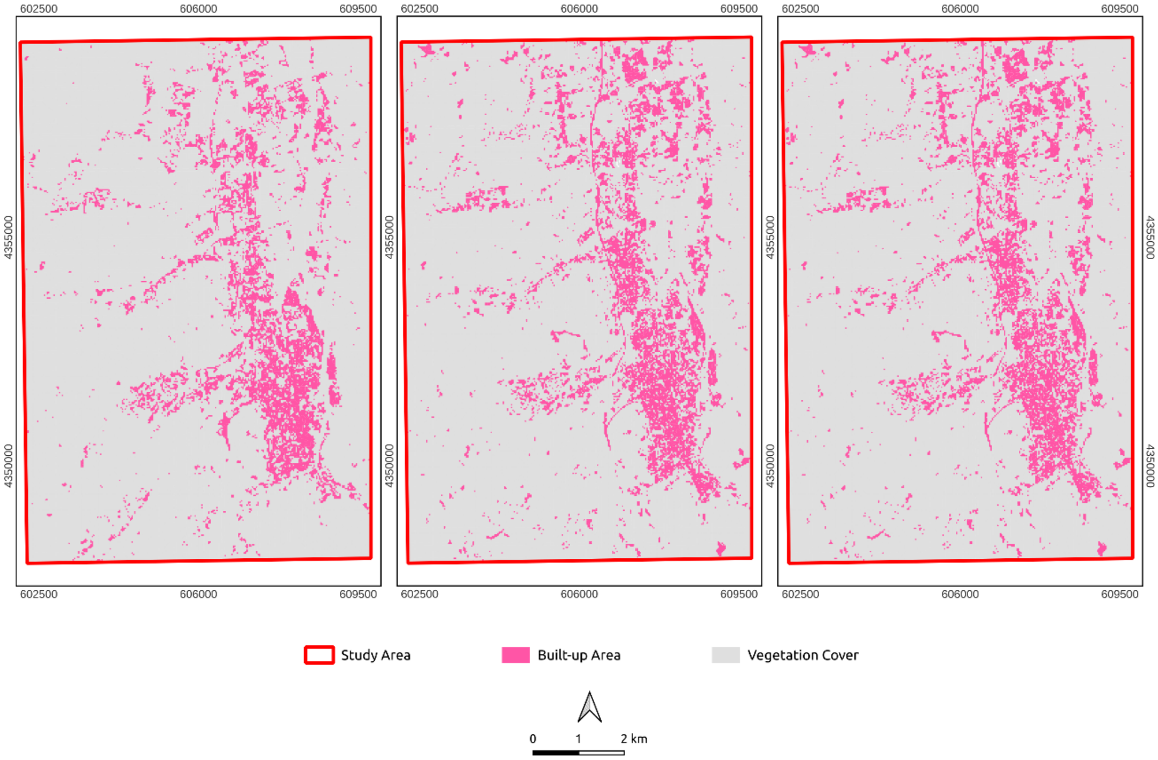

Fig.2 Built-up area evolution for the 2005-2021 period obtained from the K-means classification algorithm

Given that the classification was unsupervised, an F1-score of 0.64 can be considered a favorable result, particularly considering the challenges of accurately classifying the diverse land cover types present in Landsat imagery with a 30-meter resolution.

In contrast, the accuracy for vegetation cover is significantly higher, with Precision, Recall, and F1-Score values of 0.88, 0.95, and 0.92, respectively.

The F1-Score of 0.92 for vegetation cover indicates excellent classification performance. It should be noted that the vegetation cover class used for validation was obtained by merging several categories of the ESA WorldCover v200 dataset (shrubland, grassland, cropland, bare or sparse vegetation, herbaceous wetlands, mangroves, and moss/lichen).

This aggregation ensured consistency with the binary built-up/vegetation classification adopted in this study. Furthermore, vegetation is typically characterized by distinctive spectral properties in satellite images, which the K-means algorithm can readily identify and group into coherent clusters. This suggests that the spectral profiles of vegetation in the study area are well-differentiated from other land cover types, resulting in high Precision and Recall.

3.2 Built-up and vegetation cover classification and change detection

After assessing the accuracy of the K-means algorithm, the built-up and vegetation cover areas for 2005, 2015, and 2021 were determined, and the changes in built-up areas over the sixteen years were calculated (Tab.1 and Fig.3). This analysis was performed using the spatial analysis functions in QGIS software.

As shown in Tab. 1, the built-up areas in the study region experienced accelerated growth from 2005 to 2021. Between 2005 and 2015, the built-up areas across the 15 municipalities increased from 991.82 ha to 1017.82 ha, an increase of 26 ha, or 2.62%. Since the study only considers built-up and vegetation cover as LULC categories, any increase in built-up areas corresponds directly to a decrease in vegetation cover. Therefore, the 26 ha expansion in built-up areas equates to a 26 ha reduction in vegetation cover, assuming the total land area remains constant.

The period from 2015 to 2021 saw a significant acceleration in urban expansion compared to the earlier decade. During these six years, the built-up areas in the study region increased from 1017.82 ha to 1158.49 ha, an increase of approximately 140.67 ha, or 13.82%. This rapid urban growth can be attributed to regional socio-economic factors, notably the expansion of the University of Calabria campus in Rende, which currently serves around 70,000 students. This university has experienced remarkable growth, marking a 23% increase in student enrollment in 2022 compared to pre-pandemic levels. It is one of only three universities in Italy to see consistent increases in new enrollments each year. The expansion of educational infrastructure and related services has been a key driver of urbanization in the area.

In spatial terms, urban growth has been especially concentrated along the eastern and southern edges of the main municipalities, with new development radiating outward from consolidated centers. Expansion has tended to follow the existing transportation network, producing linear patterns of growth along major road corridors, while also including localized infill within already urbanized areas. This morphological mix of sprawl and densification reflects the dual influence of infrastructure accessibility and residential demand generated by the university expansion.

As with the previous decade, the rapid growth of built-up areas from 2015 to 2021 resulted in a corresponding decrease in vegetation cover. Overall, from 2005 to 2021, built-up areas in the study region increased by 166.67 ha, representing a 16.44% rise.

4. Discussion of results

The results presented in the previous section underscore the significance of a methodology that effectively maps and analyzes the relationship between urban growth and environmental changes within a specified study area. This methodology, applied to 15 municipalities in southern Italy, integrates advanced remote sensing techniques, artificial intelligence, and GIS technologies. Using Landsat imagery and an unsupervised K-means clustering algorithm offers a robust framework for quantifying and understanding land-use changes over a sixteen-year period, from 2005 to 2021.

The accuracy of the proposed methodology in classifying built-up and vegetation cover areas was evaluated on two levels. The classification of built-up areas showed a moderate level of accuracy, with an F1-Score of 0.64, revealing some challenges faced by the unsupervised K-means algorithm in differentiating built-up land from vegetation. These challenges may arise from the complexity of built-up areas, such as the diverse construction materials and varying spectral signatures of buildings. Additionally, the intricate nature of urban structures and the mixing of built-up pixels with other land cover types at the 30-meter resolution of Landsat imagery may lead to mixed pixels, further complicating classification. These factors likely contribute to lower Precision and Recall distinguishing built-up areas from other land cover classes.

The comparison of these results with the ESA World Cover map v200, which has a validation accuracy of 76.7%, provides a useful benchmark for evaluating the reliability of the K-means classification in this case study.

In contrast, the high F1-Score of 0.92 for vegetation cover suggests that the unsupervised classification performs well for this land cover type.

The rapid expansion of built-up areas, particularly between 2015 and 2021, is closely linked to broader socio-economic changes in the region. The establishment and growth of the University of Calabria in Rende has significantly contributed to local urbanization, illustrating how educational infrastructure can drive urban development. The university's expansion, which has attracted a large student population, has likely increased demand for housing, services, and amenities, thereby spurring the growth of built-up areas.

Beyond the quantitative increase, the results also reveal clear spatial and morphological patterns of expansion. Growth has predominantly occurred along the eastern and southern edges of urban centers, reflecting a directional tendency shaped by the availability of land and infrastructure connectivity.

Linear development along major road corridors highlights the guiding role of transportation networks, while simultaneous infill processes indicate consolidation within pre-existing built-up areas. Such a combination of sprawl and densification is typical of medium-sized Mediterranean cities, where accessibility and demographic drivers jointly shape urban form. The concurrent reduction in vegetation cover, directly tied to the growth of built-up areas, underscores the environmental consequences of urbanization. This reduction in green spaces affects biodiversity, disrupts ecosystem services, and has broader implications for urban sustainability, such as heightened vulnerability to urban heat islands and reduced recreational spaces for communities.

The high F1-Score for vegetation cover classification reflects the strength of the methodological framework in monitoring these changes, indicating that remote sensing and GIS technologies are effective tools for supporting environmental conservation initiatives.

5. Conclusions

This research highlights the potential of integrating advanced remote sensing, geospatial technologies, and artificial intelligence to monitor and analyze the spatiotemporal dynamics of urban growth and the loss of vegetation cover. Given the continued expansion of urban areas and land consumption in cities worldwide, leveraging these technologies is essential for developing strategies that promote sustainable development while safeguarding critical environmental services. While the study provides valuable insights, several limitations should be addressed. The use of 30-meter resolution Landsat imagery may limit the detection of finer-scale land cover changes. Future research could benefit from incorporating higher-resolution satellite data or combining datasets from multiple sources to capture more detailed spatial dynamics of land use and land cover (LULC) changes. Additionally, exploring supervised learning algorithms, such as Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNNs), could improve classification accuracy. These supervised algorithms, which rely on labeled training data, may offer more precise classifications of complex urban landscapes and diverse vegetation types. Comparative studies evaluating the performance of these algorithms against unsupervised K-means clustering could provide insights into the most effective methods for classifying specific LULC categories. While the study focuses on built-up areas and vegetation cover, which provides clear insights into urban and environmental changes, it may overlook other important land cover types and their dynamics. Expanding the scope of LULC categories in future research could offer a more comprehensive understanding of land cover transformations. Finally, the socio-economic drivers of urban expansion, exemplified by the growth of the University of Calabria, point to a promising direction for future research into the causal relationships between educational infrastructure, demographic changes, and urban development. Investigating these connections could inform more effective urban planning and policy strategies to balance development with environmental preservation.

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