From Natural Land to Built-Up Areas: Monitoring Residential Expansion Using Sentinel-2 and Support Vector Machine

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Keywords: Territorial planning, Urban expansion, Sentinel-2, Supervised classification, Multitemporal analysis, Land use monitoring

Abstract

Uncontrolled urban growth, known as urban sprawl, poses a significant challenge to territorial sustainability by affecting ecosystems, infrastructure, and urban quality of life. In this context, the present study aims to analyze residential expansion in Guayaquil between 2016 and 2024, identifying changes in land cover using Sentinel-2 imagery and an SVM classifier, to provide inputs for sustainable urban planning and growth management in peripheral areas. The study area corresponds to Guayaquil, a coastal city in the Guayas province, characterized by flat terrain, estuaries, and high environmental vulnerability. Methodologically, Sentinel-2 satellite images, the Built-up Area Extraction Index (BAEI), and the Support Vector Machine (SVM) supervised classification algorithm were used, along with a multitemporal analysis for the periods 2016–2020 and 2020–2024. The results revealed a considerable increase in residential areas, especially in the city's northern and southern peripheral zones, indicating expansion into natural and high-risk areas. The combination of SVM and BAEI achieved an overall accuracy of over 85% and a Kappa index of 0.84, confirming the effectiveness of the methodological approach. It is concluded that remote sensing is a useful, accurate, and low-cost tool for monitoring urban growth and supporting sustainable territorial planning.

1. Introduction

Accelerated urban growth represents a significant challenge for territorial sustainability. This phenomenon expands cities uncontrollably into agricultural and natural areas, affecting ecosystem services and sustainable planning (Concepción, 2022). Additionally, it generates adverse effects such as social segregation, loss of vegetation, and an increase in the ecological footprint (Castro-Rodas, Velastegui-Montoya, Carvalho Guimarães, et al., 2026; Kadhim et al., 2022a) reducing resilience to extreme climate events (Al-Shaar et al., 2025).

In recent years, monitoring land-use change through remote sensing has become increasingly relevant as a diagnostic and urban-planning tool (Freire-Granda et al., 2026; Phiri et al., 2020). The optical sensors of Sentinel-2, from the Copernicus program, provide accurate and up-to-date data on urban, vegetation, and aquatic covers, thanks to their high spatial resolution and frequent revisit times (Escandón-Panchana et al., 2025; Zhang et al., 2021a). This approach enables a detailed assessment of urban growth.

The Built-up Area Extraction Index (BAEI) is used to identify urban areas in satellite imagery and is effective at distinguishing built-up areas from vegetation and bare soil. Its combination with other spectral indices enhances the extraction of built-up areas, making it a valuable tool for analyzing urban expansion (Tabet et al., 2023). Algorithms such as SVM have demonstrated high performance in urban classification, achieving precise results even with limited data (Hosseiny et al., 2022).

The central problem of this research is land-use change towards urban development in Guayaquil, specifically between 2016–2020 and 2020–2024. It analyses how urban expansion has altered original cover types, including vegetation, bare soil, and water bodies, using Sentinel-2 images, the BAEI index, and an SVM classifier. This multitemporal approach allows for precise identification of transformed areas and helps to understand the magnitude, direction, and patterns of urban expansion in the city.

The main objective of this research is to analyze residential expansion in Guayaquil between 2016 and 2024, identifying changes in land cover using Sentinel-2 imagery and an SVM classifier, to provide inputs for sustainable urban planning and growth management in peripheral areas. The study aims to evaluate urban growth patterns within a 1 km environment and generate cartographic inputs to support sustainable planning. By applying the BAEI index and comparing covers across time, expansion areas are identified, proposing strategies for more balanced, environmentally respectful urban development.

2. Study Area

The study area corresponds to Guayaquil, located in the province of Guayas, Ecuador. This city is characterized by mostly flat terrain, with significant pressure on low-lying areas and estuaries, which directly influences its residential expansion (Ulloa-Espindola & Martín-Fernández, 2024). Proximity to the coastal strip and the Guayas River increases the city's vulnerability to flooding risks and sea-level rise, factors of great relevance when analyzing expansion into peripheral areas (Abadie et al., 2020). These geographical aspects, along with the region's humid tropical climate, favor heat island effects in densely urbanized areas, affecting the quality of life and urban planning processes (Litardo et al., 2021) (figure 1).

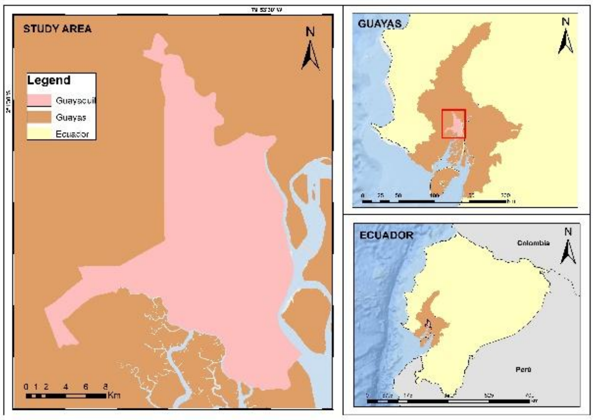

Figure 1. Map of the urban area in the Gulf of Guayaquil

The city of Guayaquil is located in an ecologically vulnerable area, where the interaction between urban growth and aquatic ecosystems, such as estuaries and surrounding water bodies, requires special attention for environmental risk management (Grijalva-Endara et al., 2024). This study area, with its complex territorial dynamics, is key to understanding urban expansion patterns and their impact on environmental sustainability and the quality of life of its inhabitants (Castro-Rodas, Velastegui-Montoya, Guimarães, et al., 2026).

3. Methodology

The methodology consists of five phases information acquisition, spatial processing, training data generation, supervised classification, and validation and change analysis (figure 2).

PHASE I: Information Acquisition

The initial phase of the study involved acquiring Sentinel-2 satellite images for 2016, 2020, and 2024 (Gao et al., 2021). The images were obtained through the Copernicus portal, which provided access to high-resolution, high-temporal-resolution data (Grijalva-Endara et al., 2024). Additionally, shapefile files of Guayaquil's urban boundary were downloaded, facilitating precise delineation of the study area (Anaya et al., 2023). This step was crucial to ensure that the images used were representative and aligned with the study's objectives, as Sentinel-2 satellite images are particularly useful for efficiently monitoring land cover changes at low cost (Maslukah et al., 2024).

PHASE II: Spatial Preprocessing

In the second phase of the process, image preprocessing was performed (Rawat & Singh, 2018). This step included verifying the coordinates to ensure consistent spatial representation of the data (Anaya et al., 2023). The images were clipped to a specific area of interest using a rectangular polygon that encompassed only the urban area of Guayaquil (Abunnasr & Mhawej, 2023). Natural color (RGB) and false-color compositions were also generated using Sentinel-2 bands (B4, B3, and B2) to facilitate the visualization of land cover (Zhang et al., 2021b). Additionally, the BAEI index (1) was calculated, which enabled highlighting built-up areas and differentiating them from vegetation and water zones, thereby enabling more precise identification of urbanized areas (Kebede et al., 2022).

$$BAEI = \frac{Red\ Band + L}{Green\ Band + SWIR\ Band}$$

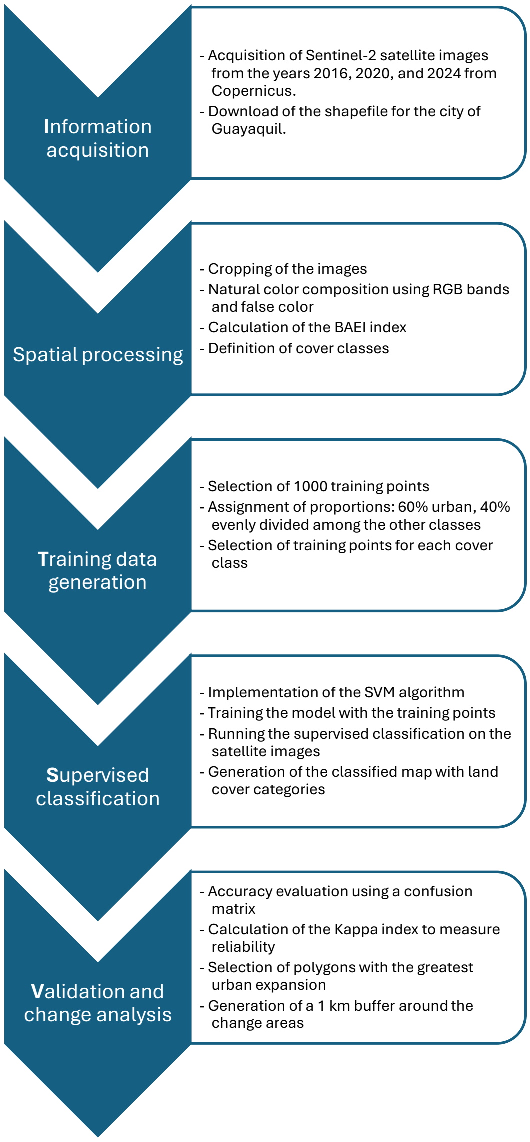

Figure 2. Methodological framework.

PHASE III: Generation of Training Data

For the training data generation phase, 1000 representative points were selected and evenly distributed across the urban area of Guayaquil, ensuring diversity in land cover classes (Noi Phan et al., 2020). The training points were classified into four main categories: urban areas, vegetation, bare soil, and water bodies (Maslukah et al., 2024). To achieve a balanced and representative dataset, specific proportions were assigned to each category: 60% of the points were allocated to urban areas, while the remaining 40% was evenly distributed among the other classes (Gao et al., 2021). This distribution ensures the model's accuracy and its ability to generalize the classification across the entire study area.

PHASE IV: Supervised Classification

In the supervised classification phase, the Support Vector Machine (SVM) algorithm was implemented to train the model using the previously selected training points. This algorithm is highly effective for satellite image classification due to its ability to handle large volumes of data and obtain accurate results in areas with clear boundaries (Zhang et al., 2021b). Once the model was trained, supervised classification was run on the processed images, generating a map that classified the areas into the defined land cover categories (Abunnasr & Mhawej, 2023). This map provided an accurate spatial representation of land cover in the city of Guayaquil, enabling analysis of the distribution of land cover classes across the city.

PHASE V: Validation and Change Analysis

The final phase of the study focused on validating the results and analyzing changes in land cover over time. To assess the accuracy of the SVM classification model, a confusion matrix was constructed, and the Kappa index was calculated to measure the reliability of the classifications (Foody, 2020). Subsequently, the polygons with the greatest urban expansion during the study periods, between 2016-2020 and 2020-2024, were selected (Castro-Rodas, Velastegui-Montoya, Guimarães, et al., 2026). Buffers of 1 km were generated around the change areas to assess the effects of urban expansion on the surrounding areas, providing relevant information on the environmental impacts of urbanization (Al-Shaar et al., 2025). This analysis facilitated the identification of the city's main residential growth areas, providing key information for territorial planning and the sustainable management of the urban environment (Abunnasr & Mhawej, 2023).

4. Results and Discussion

The multitemporal analysis using Sentinel-2 images and the supervised classification with the SVM algorithm revealed clear patterns of urban expansion in Guayaquil during the periods 2016-2020 and 2020-2024. The confusion matrices (Tables 1, 2, and 3) demonstrate the high accuracy of the model in classifying urban areas, vegetation, bare soil, and water bodies. The results obtained for each period show an overall accuracy greater than 89%, with a Kappa index close to 1.0, indicating almost perfect agreement between the classified classes and the reference areas. The fields C1, C2, C3, and C4 represent the urban, bare soil, and water classes, respectively (Zhang et al., 2021c; Zhao et al., 2024a).

Table 1. Confusion matrix of the supervised classification with SVM (2016)

Class Value	C1	C2	C3	C4	Total	Accuracy	Kappa
C1	33	9	9	1	52	0,63	0
C2	1	90	0	0	91	0,98	0
C3	0	1	39	0	40	0,97	0
C4	0	0	0	17	17	1	0
Total	34	100	48	18	200	0	0
Accuracy	0,97	0,9	0,81	0,94	0	0,89	0
Kappa	0	0	0	0	0	0	0,84

In Table 1, the confusion matrix for the 2016 period shows that the SVM correctly classifies urban areas (C1) with an accuracy of 63%, reinforcing its effectiveness in distinguishing built-up areas from other covers, such as vegetation and bare soil. Additionally, the classification of water zones achieved 95% accuracy, confirming the SVM's ability to effectively differentiate urban areas from water bodies in the study area.

Table 2. Confusion matrix of the supervised classification with SVM (2020)

Class Value	C1	C2	C3	C4	Total	Accuracy	Kappa
C1	36	12	3	0	51	0,7	0
C2	2	65	1	0	68	0,95	0
C3	0	3	56	0	59	0,94	0
C4	0	0	1	21	22	0,95	0
Total	38	80	61	21	200	0	0
Accuracy	0,94	0,8	0,9	1	0	0,89	0
Kappa	0	0	0	0	0	0	0,84

In Table 2, corresponding to the 2020 period, a slight improvement in the classification of urban areas is observed, with an accuracy exceeding 70%. The SVM algorithm continues to demonstrate its efficiency in classifying residential and natural areas, allowing for accurate tracking of land cover changes. Additionally, vegetation and water areas maintained high accuracy values, further reinforcing the model's reliability in identifying land cover changes (Kingma & Ba, 2015).

Table 3. Confusion matrix of the supervised classification with SVM (2024)

Class Value	C1	C2	C3	C4	Total	Accuracy	Kappa
C1	37	13	1	0	51	0,72	0
C2	1	62	0	0	63	0,98	0
C3	0	1	51	0	52	0,98	0
C4	0	5	0	29	34	0,95	0
Total	38	80	61	21	200	0	0
Accuracy	0,98	0,7	0,9	1	0	0,89	0
Kappa	0	0	0	0	0	0	0,85

Finally, Table 3 for the 2024 period shows that the model has achieved a reasonable accuracy, with a Kappa index of 0.85 across all analyzed categories. This suggests that urban expansion areas are being effectively differentiated from other covers, highlighting the robustness of the methodological approach (Al-Shaar et al., 2025).

The spatial and temporal analysis of the areas with the most significant land-use change, detailed in Table 4, confirms that the sectors with the highest residential growth are primarily located in the city's peripheral areas. Areas such as Mucho Lote 2, Mi Lote, and Ciudad Santiago experienced significant change from bare soil to urban between 2016 and 2020, indicating accelerated expansion into previously non-urbanized land. This pattern continued during the 2020-2024 period, especially in sectors such as Puerto Marítimo de Guayaquil and Pradera, where expansion continues to affect areas near water bodies and agricultural land (Diego et al., 2022).

Table 4. Zones of greatest land use change

Zone	Area (m^2)	Years	Change
Trinipuerto	18.561,07	2016-2020	Water → urban
Pradera	2.875,59	2016-2020	Vegetation → urban
Urb. Ciudad Santiago	96.284,65	2016-2020	Bare soil → urban
Urb. Ciudad Santiago	10.520,22	2016-2020	Vegetation → urban
Mi lote	62.473,07	2016-2020	Bare soil → urban
Puerto Marítimo de Gye	4.066,95	2020-2024	Water → urban
Mucho Lote 2	63.333,43	2020-2024	Bare soil → urban
Urb. Bonavila (vía Daule)	117.382,25	2020-2024	Bare soil → urban
Urb. Paseo del sol 1	39.498,2	2020-2024	Vegetation → urban
PTAR Los Merinos (Av. Narcisa de Jesús)	35.645,82	2020-2024	Vegetation → urbano

Figures (3-4-5-6-7-8-9-10-11) below highlight the focal points of residential expansion around major avenues and peripheral areas, reinforcing the interpretation of the results. The spatial analysis reveals that the expansion follows a linear pattern, with new developments located near urbanized areas, thereby favoring the consolidation of housing clusters on the city's outskirts (Kadhim et al., 2022b).

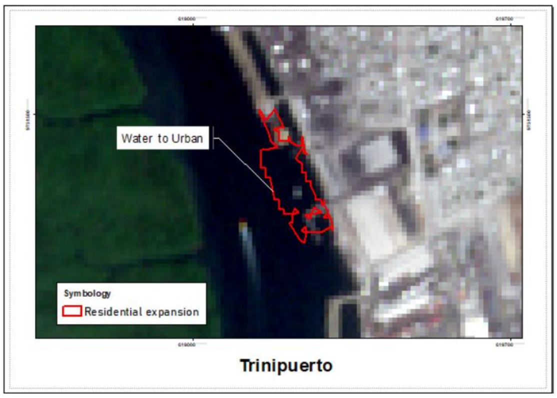

Figure 3. Map of residential expansion in the Trinipuerto area between the years 2016 and 2020.

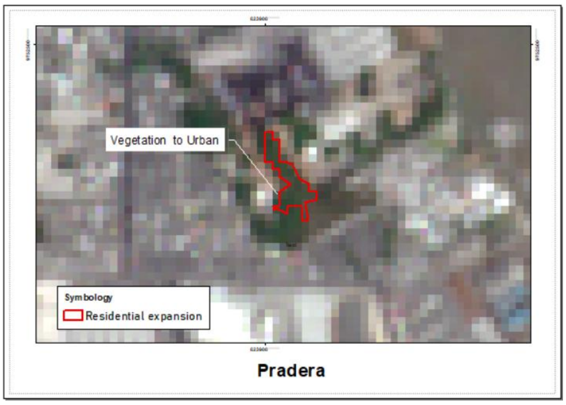

Figure 4. Map of residential expansion in the Pradera area between the years 2016 and 2020.

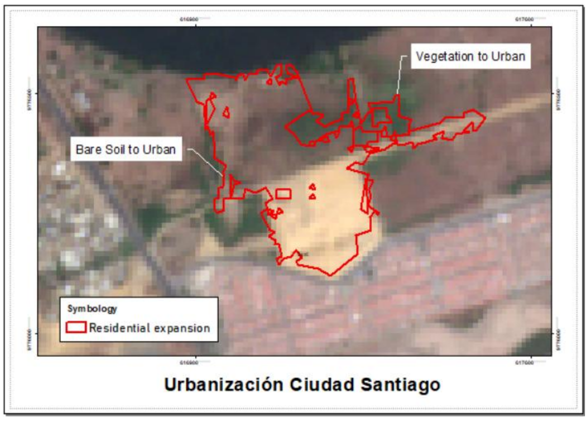

Figure 5. Map of residential expansion in Urb. Ciudad Santiago between the years 2016 and 2020.

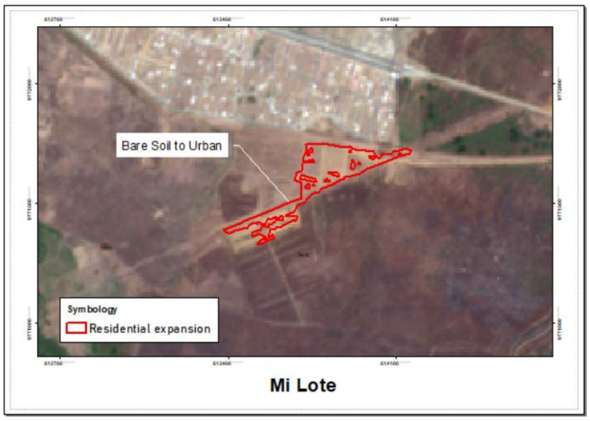

Figure 6. Map of residential expansion in the Mi Lote area between the years 2016 and 2020.

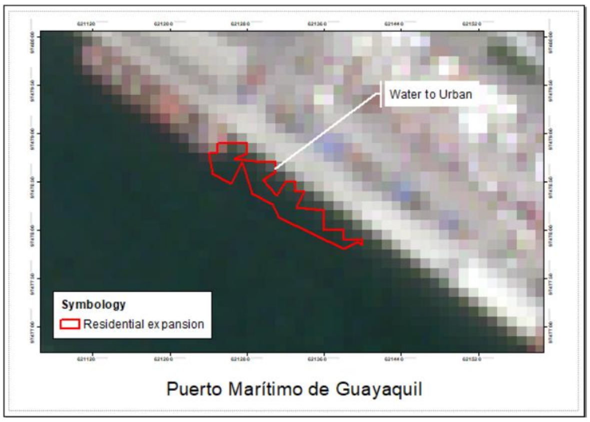

Figure 7. Map of residential expansion in the Puerto Marítimo de Guayaquil area between the years 2020 and 2024.

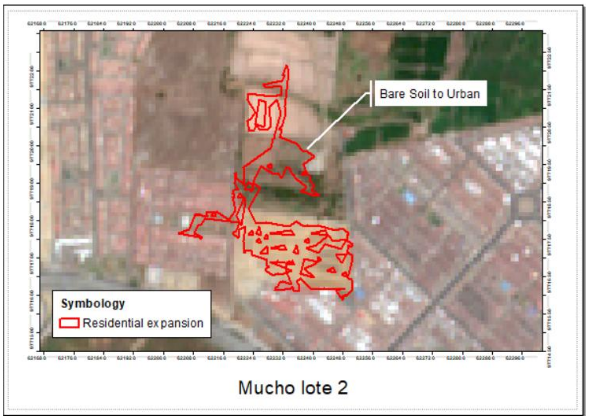

Figure 8. Map of residential expansion in the Mucho Lote 2 area between the years 2020 and 2024.

Figure 9. Map of residential expansion in the Urb. Bonavila area between the years 2020 and 2024.

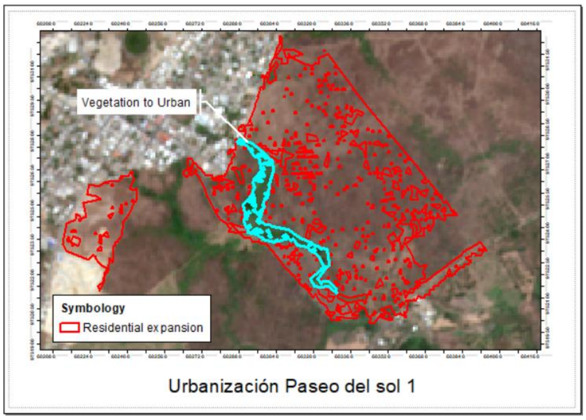

Figure 10. Map of residential expansion in the Urb. Paseo del Sol 1 area between the years 2020 and 2024.

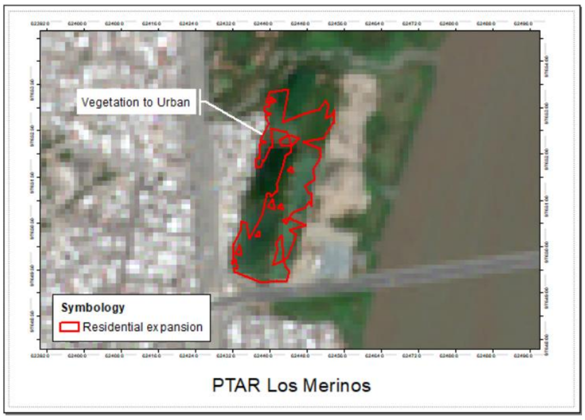

Figure 11. Map of residential expansion in the PTAR Los Merinos area between the years 2020 and 2024.

The results suggest that urban expansion in Guayaquil is moving towards peripheral and vulnerable areas, creating pressure on basic services and natural resources. This phenomenon, which affects areas such as Trinipuerto, Pradera, and Mi Lote, presents significant challenges for urban planning and environmental management (Hamud et al., 2021).

The dynamics of residential growth in Guayaquil show an expansion towards the northern and northwestern peripheral sectors, driven by the availability of land and improved road connectivity, which consolidates new residential clusters. In contrast, the southern areas experience linear development, linked to the proximity of transportation corridors and water bodies, which fosters unplanned occupation, increasing environmental vulnerability and pressure on urban infrastructure.

The integration of the BAEI index with the SVM classifier was key to improving spectral discrimination between built-up areas, vegetation, and bare soil, surpassing traditional classification methods (Zhao et al., 2024b). This approach proved effective in detecting land cover changes associated with residential expansion, establishing a replicable methodology for monitoring and managing housing growth in tropical and coastal contexts.

5. Conclusions

Between 2016 and 2024, residential expansion in Guayaquil has been sustained and accelerated, with sectors such as Mucho Lote 2, Mi Lote, Ciudad Santiago, and areas near Av. Narcisa de Jesús, Trinipuerto, Puerto Marítimo, and Pradera standing out as the main growth hotspots. This phenomenon has been driven by high housing demand and the availability of peripheral land, although in many cases, it has occurred on vulnerable land or without proper planning. The combined use of Sentinel-2 imagery, the BAEI index, and an SVM classifier has proven effective for identifying built-up areas and tracking their temporal evolution, validating remote sensing as a strategic tool for monitoring urban growth. This methodology is replicable in other cities with similar characteristics due to its high accuracy, low cost, and scalability. Finally, expansion into peripheral areas requires territorial planning policies based on geospatial evidence, aimed at ensuring more balanced, resilient, and sustainable urban development.

6. Limitations

This study presents limitations inherent to the use of optical remote sensing for analyzing residential expansion. The spatial resolution of Sentinel-2 (10–20 m) limits the detection of small-scale housing and generates mixed pixels, affecting accuracy in heterogeneous urban areas. Additionally, atmospheric correction and band resampling may introduce radiometric uncertainties that affect temporal consistency and the interpretation of the BAEI index.

The SVM algorithm's performance depends on the quality and representativeness of the training sample. This may lead to overfitting or class confusion. Using only the Kappa index can overestimate reliability if not supported by class-specific metrics.

Future research could integrate higher-resolution images (e.g., PlanetScope or UAV imagery) and deep learning approaches to improve the detection of urban structures at finer scales.

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