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Multitemporal analysis of urban built-up growth and its impact on land cover and land use dynamics Análisis multitemporal del crecimiento edificado y su impacto en la cobertura y uso de suelo

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ABSTRACT Intermediate Latin American cities are facing accelerated urban expansion processes that reshape land cover and land use. This study analyzes the spatio-temporal dynamics of built-up growth in Portoviejo, Ecuador, during the 1998–2024 period. For this purpose, Landsat Collection 2 Surface Reflectance satellite imagery was processed using the Maximum Likelihood classification algorithm. Post-classification comparison, transition matrices, and accuracy assessment based on confusion matrices were applied. The results show that the built-up/impervious class increased from 1,012.05 ha in 1998 to 2,027.34 ha in 2024, while vegetation and bare/transitional soil decreased. The classifications reached Overall Accuracy values between 84.50% and 87.00%, with Kappa coefficients ranging from 0.773 to 0.823. The SDG 11.3.1 indicator showed that land consumption was proportionally higher than urban population growth. These findings provide empirical support for understanding territorial transition processes. This information is relevant for defining territorial planning strategies, enabling more precise regulation of urban expansion limits and promoting land use under sustainability criteria.

RESUMEN Las ciudades intermedias latinoamericanas enfrentan procesos acelerados de expansión urbana que transforman la cobertura y uso del suelo. Este estudio analiza la dinámica espacio-temporal del crecimiento edificado en (Ecuador) durante el periodo 1998-2024. Para ello, se procesaron imágenes de satélite (Landsat Collection 2 Surface Reflectance) aplicando el algoritmo de Máxima Verosimilitud (*Maximum Likelihood*). Se aplicó comparación posclasificación, matrices de transición y evaluación de exactitud mediante matrices de confusión. Los resultados muestran que la clase edificado/impermeable aumentó de 1012,05 ha en 1998 a 2027,34 ha en 2024, mientras que la vegetación y el suelo desnudo/transición disminuyeron. Las clasificaciones alcanzaron exactitudes globales entre 84,50 % y 87,00 %, con coeficientes Kappa de 0,773 a 0,823. El indicador ODS 11.3.1 mostró que el consumo de suelo fue proporcionalmente superior al crecimiento poblacional urbano. Estos descubrimientos suministran sustento empírico para comprender la transición del territorio. Dicha información resulta fundamental en la definición de estrategias para la planeación del territorio, permitiendo una regulación más precisa de los límites de expansión, promoviendo el aprovechamiento del suelo bajo criterios de sostenibilidad.

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1. Introduction

Urban growth is one of the most significant territorial processes today, due to its impact on the organization of space and the transformation of the Earth's surface. On a global scale, it has been documented that cities continue to expand, with nearly 32% of the planet's surface having undergone transformations that result in significant changes in land cover and land use, posing challenges for sustainable land planning and management (Winkler et al., 2021). In this context, urban expansion does not always occur in direct proportion to population growth. Scientific evidence highlights that the expansion of urbanized areas tends to significantly outpace population growth. This phenomenon, analyzed using indicators that link land consumption to population dynamics, results in inefficient land-use patterns that challenge urban sustainability at the global and regional levels (Estoque et al., 2021; Zhou et al., 2021).

Latin America is currently one of the most urbanized regions in the world, with an urbanization rate of nearly 81%; the population distribution reflects the consolidation of the urban environment as the predominant space. While migratory dynamics and rapid physical growth have reshaped the regional landscape, this expansion has come at the expense of a shortage of basic services. Given this scenario, land management can no longer be reactive; it requires models that prioritize equity and the adaptive capacity of communities (UN-Habitat, 2022). In light of this reality, intermediate cities have taken on an increasingly important role in the urban structure. Not only do they concentrate growth dynamics, but they also fulfill territorial coordination functions that were previously attributed mainly to large metropolitan areas (Bolay and Kern, 2019; Cattaneo et al., 2024). Regional evidence shows that urban expansion tends to move toward peripheral edges and urban-rural fringes. In Chile, this growth has been linked to processes of socio-spatial segregation and residential projects in sparsely developed peripheral areas (Schuster-Olbrich et al., 2024).



Figure 1: Geographic location of the city of Portoviejo in South America, Ecuador, and the province of Manabí. (2025)

In Brazil, metropolitan expansion is seen to respond to a logic of real estate development in peripheral areas, driven by the symbiosis between financial capital and the construction sector (Cruz, 2016). Similarly, in Argentina, the conversion of agricultural land to urban uses has been documented, with direct effects on local territorial systems (Cahe and Prada, 2022). This background helps us understand that urban expansion is not merely an increase in built-up area but a form of territorial reorganization.

Portoviejo, as the provincial capital of Manabí (Figure 1), offers a relevant case for analyzing these dynamics in a mid-sized Ecuadorian city, as it concentrates administrative, commercial, financial, and service functions, thereby strengthening its role within the provincial structure (Valencia, 2022). Portoviejo's urban configuration has shifted from a compact model to a diffuse one, driven by weak land management and planning that has historically equated territorial expansion with progress. This process was drastically accelerated by the 2016 earthquake, which, by rendering the central district uninhabitable, forced the relocation of administrative and commercial functions to the peripheries, consolidating new centers along strategic road corridors (Cedeño Zambrano et al., 2020). As a result, the city exerts persistent pressure on land of high agricultural value and natural protection areas, blurring the urban-rural boundary and intensifying territorial vulnerability due to the lack of technical tools to regulate this spontaneous expansion (Reyna et al., 2017).

Locally, Cedeño Zambrano et al. (2020) documented that between 2001 and 2010, Portoviejo lost 2,083.5 ha due to deforestation, pollution, and the conversion of agricultural land into urban developments. Meanwhile, Saavedra (2020) identified processes of unregulated land subdivision and the occupation of agricultural land in Riochico, a rural parish within the canton, which are progressively transforming the territory. These findings show that Portoviejo's urban growth is not solely driven by population increase but also by economic, institutional, and territorial conditions that have shaped land use.

As a result of these processes, the urban area is undergoing transformations that involve the replacement of natural and agricultural land cover with built-up areas. These types of changes have been extensively studied through land use and land cover (LULC) analysis, which identifies and quantifies spatial transformations over time (Chughtai et al., 2021). The development of remote sensing techniques has strengthened this type of analysis, facilitating multitemporal monitoring of the Earth's surface through the use of satellite imagery. In particular, Landsat sensors have been widely used due to the availability of extensive and consistent time series, which allow for the analysis of changes over extended periods (Cheng et al., 2024). Although the literature acknowledges the limitations associated with spatial resolution and the quality of available data, various studies agree that the use of geospatial and Earth observation information is a fundamental tool for analyzing urban expansion and evaluating land-use efficiency. This approach is particularly relevant in intermediate and secondary cities in developing countries, where gaps in territorial information systems limit the systematic monitoring of urban dynamics (Laituri et al., 2021; Mudau et al., 2020; Sondou et al., 2024).

An analysis of studies related to urban growth and land use in Portoviejo reveals that these have addressed only partial aspects, such as simulations or sectoral analyses, without incorporating a multitemporal approach that evaluates the evolution of built-up growth over extended periods (Chun et al., 2023; Farías et al., 2025; Reyna et al., 2017). This study focuses on the official area defined by the Decentralized Autonomous Municipal Government (GAD), which delimits the urban zone of Portoviejo, covering an approximate area of 5,084 hectares—a jurisdiction that reflects Portoviejo's role as the administrative, economic, and social center of Manabí.

Although previous studies on Portoviejo have provided a current overview of urban expansion and territorial transformation, their approaches have focused on sectoral analyses, simulations, or localized case studies, without integrating a multitemporal analysis of land-use changes, persistent areas, and their relationship to the population. Given the above, this study asks: How did built-up land in Portoviejo evolve between 1998 and 2024, which land cover types were transformed, and how does this expansion relate to urban growth? The hypothesis is that this growth was not driven solely by population increase, but also by the conversion of undeveloped land cover, the consolidation of urban areas, and land consumption that was not proportional to population growth (Figure 2). The objective is to analyze this process using remote sensing to identify transitions and persistent features, thereby providing criteria for local planning.

2. Methodology

2.1. Methodological design and study area

The research adopted a quantitative and multitemporal approach aimed at identifying changes in land cover and land use associated with the built-up growth of Portoviejo between 1998 and 2024. The analysis was based on the official urban polygon of Portoviejo, provided by the Municipal GAD in shapefile format current as of 2025. This delineation allowed us to work with an institutionally recognized spatial scope and to consistently compare the territorial transformations that occurred during the study period. All spatial processing was performed in ArcGIS Pro 3.4.0, using the WGS 1984 UTM Zone

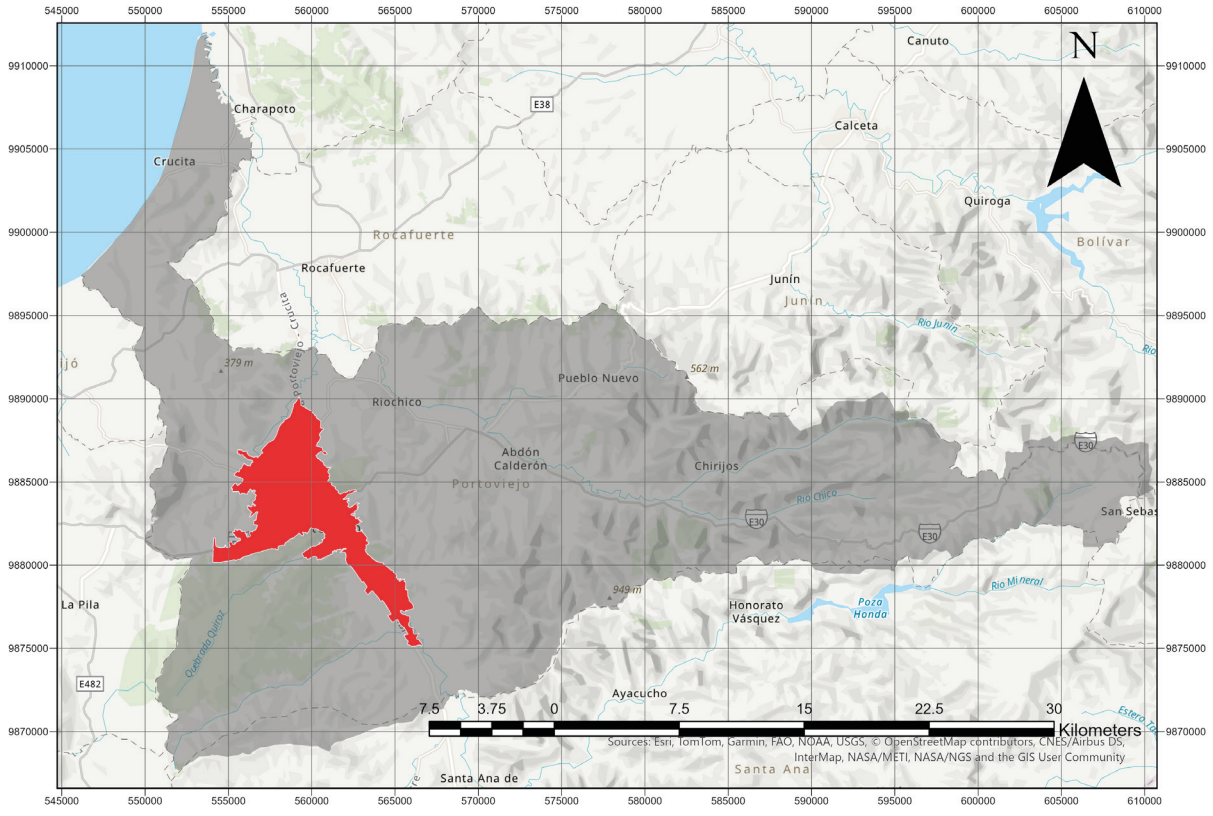


Figure 2: Delimitation of the Portoviejo urban area. (2025)

17S (EPSG:32717) reference system, with units in meters. This system was maintained across images, vector layers, and derived products to ensure geometric consistency during the classification, validation, and change analysis stages.

2.2. Selection and preprocessing of landsat images

Landsat Collection 2 Level-2 Surface Reflectance (L2SP) images, downloaded from USGS Earth Explorer, were used. The L2SP products were selected because they meet specific geometric and radiometric requirements (U.S. Geological Survey, 2025). The scenes corresponded to Path/Row 011/061 and were acquired on the following dates: March 15, 1998 (Landsat 5 TM), August 2, 2014 (Landsat 8 OLI/TIRS), and August 29, 2024 (Landsat 8 OLI/TIRS). The metadata reports cloud cover for the entire scene; however, since the study area represents only a fraction of the Path/Row, it was visually verified that the urban polygon of Portoviejo did not have cloud cover that would affect the classification.

Spectral bands 1–5 and 7 were used for Landsat 5 TM, and bands 2–7 for Landsat 8 OLI. Prior to classification, the multispectral composites were visually reviewed to verify the absence of local cloud cover and relevant radiometric artifacts, such as banding or *striping*, within the study area. Since no anomalies were identified that would compromise the analysis, the scenes were cropped using the official urban polygon (Hua et al., 2017; Pesta et al., 2014).

Although the 30-meter spatial resolution provided by Landsat sensors is optimal for reconstructing long-term evolutionary patterns, its accuracy is limited in fringe zones or peri-urban areas. In these highly heterogeneous regions, the coexistence of vegetation cover and paved surfaces within a single pixel unit prevents accurate discrimination of individual architectural units. Consequently, the results presented should be regarded as

approximations of development trends at the macro-urban level, and should not be considered precise at the parcel level. This methodology facilitates the assessment of extended time intervals, although it limits the identification of micro-densifications, segregated buildings, or transition zones with combined spectral signatures (Guan et al., 2022; Nie et al., 2019).

2.3. Land cover and land use classification

LULC classification was performed using Maximum Likelihood Classification (MLC), a method widely used in multitemporal studies due to its robustness in scenarios with relatively homogeneous spectral response (Chughtai et al., 2021). Given the nature of the research, four classes were defined: vegetation, built-up/impervious, bare soil/transition, and dark surfaces. The latter category included bodies of water, shadows, and other low-reflectance surfaces. Although an attempt was made to separate these elements into distinct classes, spectral similarity did not allow for a stable differentiation between scenes. Therefore, it was retained as an operational spectral control category, useful for organizing the classification, but not as a central territorial indicator of urban expansion.

The training areas were constructed by digitizing polygons in ArcGIS Pro's Training Sample Manager, based on rigorous visual photointerpretation for each period. The source inventory included a historical aerial photograph from the Military Geographic Institute (IGM), provided by the Portoviejo Municipal Government (GAD), for the 1998 scenario; an institutional orthophoto for 2014; and high-resolution base images from ArcGIS Pro itself for the year 2024. This effort resulted in a robust dataset comprising 228, 230, and 240 records, respectively, ensuring balanced representation across the four thematic categories analyzed.

2.4. Thematic accuracy assessment

The accuracy of the classifications was evaluated using confusion matrices and independent validation points, in accordance with the recommendations of Congalton and Green (2019) and Olofsson et al. (2014). Class-stratified sampling was applied, with 200 validation points per year. In 1998 and 2024, 50 points were allocated per class; in 2014, 51 points were used for vegetation, 50 for built-up/impervious areas, 49 for bare soil/transition areas, and 50 for dark surfaces.

The evaluation of LULC classification performance was based on parameters derived from confusion matrices, specifically overall accuracy, the kappa coefficient, as well as Producer Accuracy (PA) and User Accuracy (UA). In order to maintain the lexical consistency throughout the manuscript, the term "Accuracy" was deliberately chosen over "Precision." Under this approach, the reliability and consistency of the resulting categories are primarily assessed using the User Accuracy (UA) and Producer Accuracy (PA) metrics.

2.5. Analysis of changes, persistence, and spectral support

Change detection was performed through post-classification comparison of the 1998, 2014, and 2024 maps. This procedure allows for the identification of transitions between classes based on independent thematic maps (Lu et al., 2004). Change matrices were calculated using the Tabulate Area tool in ArcGIS Pro for the periods 1998–2014, 2014–2024, and 1998–2024.

By examining persistence, it was possible to distinguish transition processes from those areas that maintained their original state during the study period. In the spatial assessment, priority was given to changes in vegetation and bare soil/transition to built-up/impervious areas, as these trajectories constitute direct indicators of urban growth. On the other hand, although changes related to dark surfaces were documented for the sake of methodological rigor, their interpretation was considered secondary due to the intrinsic spectral complexity and variability of that category. Complementarily, the NDBI index was calculated as a visual aid for identifying urbanized areas (Ghosh et al., 2018; Prasomsup et al., 2020), without incorporating it as a primary variable or an independent outcome; therefore, it was not projected as an autonomous outcome in the model.

2.6. Demographic integration and SDG 11.3.1

To link urban growth with demographic trends, census data from INEC (2001, 2010, and 2022) were used. This empirical source was prioritized to mitigate biases in mathematical models that overlook local realities. According to GHSL and SDG 11.3.1 criteria, a three-year time discrepancy is acceptable in regional analyses. This approach ensures official statistical support, providing the study with transparency, reproducibility, and scientific rigor (Melchiorri et al., 2019).

The SDG 11.3.1 indicator was calculated as a comparative ratio between the land consumption rate and the population growth rate. The consumption rate was estimated based on the built-up/impervious land class derived from the LULC classification, while the population growth rate was calculated using the most recent available urban censuses. Since the satellite images correspond to 1998, 2014, and 2024, there is a time lag relative to the census years. For this reason, the indicator is not interpreted as a definitive measure of urban efficiency, but rather as an approximate assessment of the relationship between physical growth and population, in line with recent approaches to land consumption and urban expansion (Cardenas-Ritzert et al., 2024; Cimini et al., 2023).

3. Results

3.1. Thematic accuracy of the classifications

The thematic accuracy of the classifications was evaluated using confusion matrices, considering Overall Accuracy, User Accuracy, Producer Accuracy, and the Kappa Coefficient—metrics widely used in the validation of land cover and land use classifications derived from remote sensing (Congalton and Green, 2019; Olofsson et al., 2014; Stehman, 1997). In Table 1, the classifications for 1998, 2014, and 2024 show Overall Accuracy values above 84%, indicating adequate performance for the multitemporal analysis of urban expansion in Portoviejo.

In the 1998 analysis, the classification achieved an Overall Accuracy of 84.50% (Kappa = 0.773). As detailed in Table 2, the vegetation class was accurately identified, recording a UA of 92.59% and a PA of 91.46%. In contrast, the built-up/impervious category showed an asymmetric performance, with a UA of 65.00% compared to a PA of 92.86%. This discrepancy suggests that, although the algorithm captured most of the urban areas, the spectral similarity between bare soil and built surfaces—typical of 30-meter Landsat sensors—led to false positives at the peri-urban edges.

The 2014 results demonstrated the cycle's peak overall performance (Kappa = 0.823), highlighting the consistency of the built-up/impervious category (UA: 79.69%; PA: 94.44%). This trend of improvement was consolidated in 2024, reaching optimal levels of UA (93.75%) and PA (94.94%), which confirms the mapping accuracy for analyzing current urban expansion. Finally, dark areas recorded a UA of 67.74% in 2024; this modest performance is due to the spectral complexity of the class, which includes shadows and bodies of water, thereby increasing the risk of confusion.

3.2. Changes in land cover and land use

The multitemporal analysis revealed a significant transformation in land cover and land use within the Portoviejo urban area during the period 1998–2024. As shown in Table 3 and illustrated in Figure 3, the built-up/impervious class recorded the most significant change, increasing from 1,012.05 ha in 1998 to 2,027.34 ha in 2024, representing a net increase of 1,015.29 ha. Vegetation showed a reduction of 939.51 ha over the entire period, decreasing from 2,050.74 ha in 1998 to 1,111.23 ha in 2024. Similarly, bare soil/transition areas decreased from 1,682.19 ha to 1,135.71 ha, representing a net loss of 546.48 ha. In contrast, dark-colored areas increased from 342.27 ha in 1998 to 812.97 ha in 2024; however, this result should be interpreted with caution due to the heterogeneity of this class.

The largest increase in built-up land occurred between 1998 and 2014, a period during which it increased by 610.11 ha. Between 2014 and 2024, growth continued, albeit at a slower rate, adding an additional 405.18 ha. The results show a sustained expansion of the built-up area throughout the study period (Figure 3).

Year	Validation points	Overall accuracy	Kappa coefficient
1998	200	84.50%	0.773
2014	200	87.00%	0.823
2024	200	86.50%	0.811

Table 1: Overall Accuracy and Kappa Coefficient of LULC Classifications. (2025)

Year	Class	User accuracy (UA)	Producer accuracy (PA)
1998	Vegetation	92.59%	91.46%
1998	Built-up/impervious	65.00%	92.86%
1998	Floor bare/transition	84.85%	80.00%
1998	Dark Areas	92.31%	60.00%
2014	Vegetation	95.12%	88.64%
2014	Built-up/impervious	79.69%	94.44%
2014	Floor bare/transition	91.94%	82.61%
2014	Dark surfaces	81.82%	81.82%
2024	Vegetation	97.73%	79.63%
2024	Built-up/impervious	93.75%	94.94%
2024	Floor bare/transition	75.56%	77.27%
2024	Dark surfaces	67.74%	91.30%

Table 2: User Accuracy and Producer Accuracy by LULC Class. (2025)

LULC Class	1998 (ha)	2014 (ha)	2024 (ha)	Change 1998– 2024 (ha)
Vegetation	2,050.74	1,054.53	1,111.23	−939.51
Built-up/impervious	1,012.05	1,622.16	2,027.34	+1,015.29
Floor bare/transition	1,682.19	1,609.11	1,135.71	−546.48
Dark surfaces	342.27	801.45	812.97	+470.70

Table 3: Area by LULC class and net change, 1998–2024. (2025)

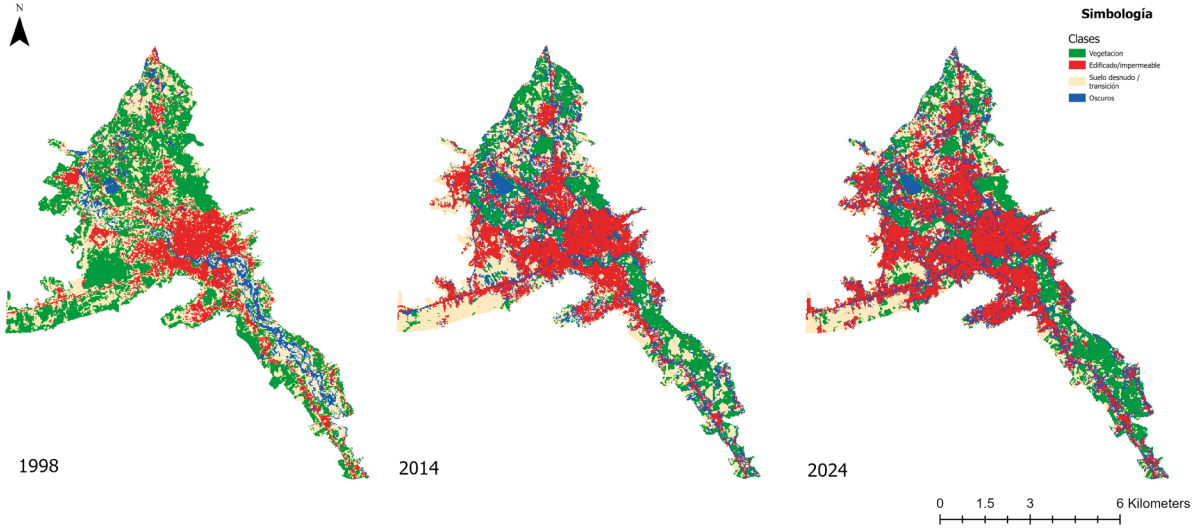


Figure 3: LULC Maps (1998, 2014, and 2024). (2025)

3.3. Transitions to built-up land

Transition matrices made it possible to identify the land cover types that contributed to the growth of the built-up/impervious land class. As shown in Table 4, between 1998 and 2014 (Figure 4), the main conversions to built-up land came from bare land/transition areas, accounting for 486.00 ha, and from vegetation, accounting for 308.25 ha. Together, these transitions represented 815.58 ha added to the built-up land class.

During the 2014–2024 period, the conversion to built-up areas continued to be greatest from bare land/transition areas, totaling 402.84 ha (Figure 4). During this period, a transition from dark surfaces to built-up areas of 203.94 ha was also recorded; however, this finding should be interpreted with caution given the spectral ambiguity of that category. When evaluating the entire period (1998–2024), the largest cumulative contributions to built-up growth came from bare land/transition areas, at 649.89 ha, and from vegetation, at 539.37 ha.

Overall, the transitions show that Portoviejo's built-up growth occurred primarily through the conversion of bare/transitional land and vegetation into impervious surfaces (Figure 4). This interpretation frames the expansion as a gradual incorporation of areas undergoing change, associated with urban edges and peri-urban spaces. Transitions from dark surfaces are retained for methodological transparency but do not support the central interpretation due to their heterogeneity. Furthermore, the total number of transitions to built-up areas does not equal the net change, because some built-up areas shifted to other categories.

3.4. Stability and urban consolidation

In addition to the transitions, the change matrices identified areas that remained stable between periods. This analysis is relevant because it allows us to distinguish the expansion of new built-up areas from previously existing stable areas. As shown in Table 5, between 1998 and 2014, the built-up/impervious land class exhibited a persistence of 806.58 ha. Between 2014 and 2024, this persistence increased to 1,380.78 ha, indicating a process of progressive consolidation of urbanized land.

During the 1998–2024 cycle, a stable core of 801.99 ha was identified within the built-up/impervious land class, defining the persistent urban footprint in the area.

Transition to Built-up/impervious	1998–2014 (ha)	2014–2024 (ha)	1998–2024 (ha)
Vegetation → Built-up	308.25	39.78	539.37
Bare ground/transition → Built-up	486.00	402.84	649.89
Dark areas → Built-up	21.33	203.94	36.18
Total	815.58	646.56	1,225.44

Table 4: Transitions to the built/impervious class. (2025)

Period	Persistent Vegetation (ha)	Persistent built-up area (ha)	Bare soil/persistent transition (ha)	Persistent dark areas (ha)
1998–2014	500.49	806.58	550.17	80.82
2014–2024	677.43	1,380.78	730.44	329.40
1998–2024	522.18	801.99	350.55	71.46

Table 5: Persistence by LULC class across periods. (2025)

Year census	Urban	Population rural	Total population county
2001	171,847	66583	238,430
2010	206,682	73,347	280,029
2022	252,248	70,677	322,925

Table 6: Urban, rural, and total cantonal population of Portoviejo. (2025)

Spatial Period	Census Census period	Land land consumption	Rate of population growth rate	SDG 11.3.1
1998–2014	2001–2010	0.02949	0.02051	1.44
2014–2024	2010–2022	0.02230	0.01660	1.34
1998–2024	2001–2022	0.02672	0.01828	1.46

Table 7: SDG 11.3.1 indicator by analysis period. (2025)

By cross-referencing these stability data with transition dynamics, it becomes apparent that Portoviejo's expansion goes beyond simple horizontal sprawl toward new peripheries. In reality, the city is experiencing a dual phenomenon that combines edge growth with the strengthening and densification of its original urban structure.

3.5. Relationship between built-up area growth and population dynamics

The expansion of built-up land was compared with urban population dynamics, based on official censuses from the National Institute of Statistics and Censuses (INEC) for 2001, 2010, and 2022 (INEC, 2001, 2010, 2022). According to the data in Table 6, Portoviejo experienced a population increase of 80,401 residents between 2001 (171,847 inhabitants) and 2022 (252,248 inhabitants). At the same time, the built-up area expanded by 1,015.29 ha, rising from 1,012.05 ha in 1998 to 2,027.34 ha recorded in 2024.

Additionally, the SDG 11.3.1 indicator was calculated as a comparative approximation of land use and population growth. Logarithmic rates, the built-up area derived from the LULC classification, and the most recent available urban censuses were used for this purpose. Because the census years do not exactly coincide with the dates of the satellite images, this result should be interpreted with caution.

As shown in Table 7, the rate of land consumption (0.02672) exceeded the rate of population growth (0.01828) during the period analyzed, yielding an approximate value of 1.46. This figure indicates that the physical expansion of the built-up area exceeded urban population growth proportionally. However, this indicator should be interpreted with caution and not as an absolute measure of land-use efficiency.

4. Discussion

Based on the results, Portoviejo's built-up expansion is interpreted as a process of territorial reorganization, rather than merely an increase in impervious surface area. The main transitions to built-up/impervious areas originated from bare soil/transition zones and vegetation, suggesting that urban growth relied on unconsolidated land cover, much of which was located on urban fringes, in peri-urban areas, or in sectors undergoing transformation.

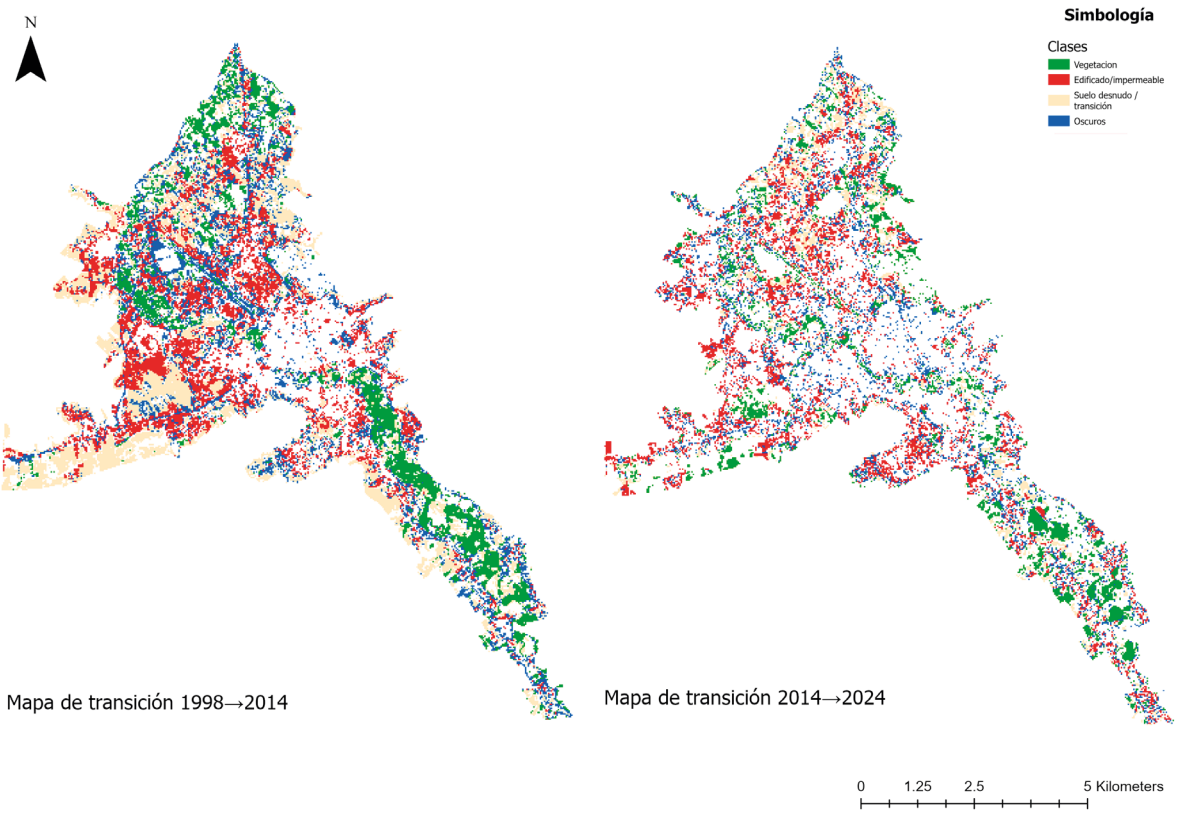


Figure 4: Transition maps for 1998→2014 and 2014→2024. (2025)

This pattern is consistent with Latin American studies that have linked urban expansion to the occupation of peripheral, peri-urban, or agricultural areas, as well as to pressures on lands with environmental or productive functions (Cahe and Prada, 2022; Cruz-Muñoz, 2021; de Lima et al., 2023; Duque et al., 2019; Salamanca-Fonseca et al., 2023).

Through an analysis of persistence, we observe more than just the net change in area. In Portoviejo, persistent built-up areas show that part of the urban fabric remained intact during the periods evaluated, while other areas were incorporated into the urbanization process. Consequently, the analysis is not limited to showing how much the city grew, but also how that growth occurred (Fenta et al., 2017; Stoica et al., 2021). Although this study does not incorporate specific metrics of urban form, recognizing persistencies and transitions helps distinguish relatively consolidated areas from sectors of recent growth. For local planning, this distinction is useful because not all areas require the same response; urban edges function as transitional spaces where landscape fragmentation and environmental degradation demand urgent intervention (Aguilar et al., 2022), whereas persistent areas require maintenance, infrastructure, mobility, and services.

From a methodological standpoint, the Global Accuracies obtained—ranging from 84.50% to 87.00%—support the use of these classifications to analyze multitemporal trends in land cover and land use. It should be noted that the use of confusion matrices, User Accuracy, Producer Accuracy, and the Kappa coefficient follows widely accepted procedures for evaluating the thematic quality of LULC classifications (Congalton and Green, 2019; Olofsson et al., 2014). Nevertheless, Landsat's 30-meter resolution requires that the findings be interpreted with caution, given the spectral overlap between bare areas and the urban fabric. This phenomenon remains a recurring technical challenge even with multispectral sensors (Delaney et al., 2025; Osgouei et al., 2019).

Compounding this issue is the fact that the 1998 aerial photograph, despite having a higher spatial resolution than Landsat sensors, was panchromatic in nature. This characteristic may have led to greater optical uncertainty when distinguishing urban fabric from bare land or shaded areas. This technical limitation explains the decline in User Accuracy for the built-up/impervious class in that year, as well as the discrepancies in dark surfaces. Consequently, the information generated should be interpreted as a trend in territorial growth rather than as a high-precision cartographic survey.

For this study, the category of dark surfaces served as an auxiliary element; its variability may stem from both anthropogenic changes and factors such as lighting or spectral mix. Therefore, the analysis focused on transitions from vegetation and bare soil/transition areas to built-up/impervious areas. Likewise, the link between physical expansion and population requires a cautious interpretation given the time lag between satellite imagery and census data. Although SDG 11.3.1 suggests that urban land area grew faster than the population, this indicator serves as a trend indicator rather than a definitive verdict on efficiency in Portoviejo.

From a territorial perspective, Portoviejo's evolution goes beyond mere demographic pressure; this suggests urban development processes governed by variables unrelated to migration or birth rates. Mahtta et al. (2022) argue that the expansion of the built environment typically responds to real estate dynamics and institutional frameworks that value land as a financial asset. Such a mismatch—with urban sprawl outpacing population growth—poses severe challenges for local planning, as it requires substantial investments to extend service networks to dispersed outlying areas.

In intermediate urban settings, land management faces critical obstacles stemming from institutional weakness and limited technical capacity to deploy large-scale infrastructure. Budget constraints and difficulties with interdepartmental coordination hinder the adoption of *smart growth* strategies that balance density with the protection of ecosystem services (Artmann et al., 2019). However, in these cities, implementing efficient land-use models and diversifying municipal revenue streams are vital for ensuring financial sustainability and access to basic services (Tan and Taeihagh, 2020).

From the perspective of local planning, the findings suggest three strategic priorities. First, it is imperative to rigorously monitor expansion fronts, particularly where the loss of agricultural land reveals the fragility of transition zones in the face of uncontrolled sprawl and real estate pressure (Aguilar et al., 2022). At the same time, urban policy should focus on strengthening sectors already equipped with basic infrastructure, thereby preventing the formation of dispersed peripheries that increase the costs of maintenance and the provision of basic services (Daunt et al., 2021). Finally, the systematic adoption of multitemporal land-cover studies is recommended as a key input for updating land-use planning instruments.

Looking ahead to future research, this analysis could be enhanced through the use of sensors with higher spatial resolution, capable of refining the detail of the categories and reducing spectral signature uncertainties (Qin and Liu, 2022; Xu et al., 2024). Similarly, the integration of cadastral records, urban morphology parameters, and *on-site* verifications would provide a more nuanced view of land use. This approach would allow for the capture of phenomena that exceed the capabilities of Landsat sensors, such as internal densification processes, the development of vacant lots, and microspatial transformations in the immediate periphery.

5. Conclusions

The multitemporal assessment conducted shows that, during the 1998–2024 period, Portoviejo experienced a substantial expansion of its urban footprint. This evolution is closely linked to the decline in vegetation and uncovered areas, confirming a progressive shift toward impervious surfaces. The results derived from the persistence matrices indicate a complex evolution: simultaneously with the incorporation of new land into the urban area, there was a consolidation of pre-existing sectors. This analytical methodology facilitates the differentiation between growth at the margins and internal compaction processes, overcoming the limitation of net balance calculations.

Regarding SDG 11.3.1, the figures indicate that the rate of land use exceeded the rate of population growth, although this data should be considered an approximation given the time lag between satellite imagery and census records. Although the Landsat system allowed for a homogeneous historical reconstruction, its detection capability is limited by its 30-meter resolution. Ultimately, the results emphasize the need to monitor expansion boundaries and protect productive land, suggesting that future studies should integrate cadastral data and high-resolution sensors.

Conflict of Interests. The author declare no conflict of interests.

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