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Article

Development of a Methodology for Detecting Changes in Vegetation Cover Using NDVI in Google Earth Engine: A Case Study in Maricá, RJ

Diego Ramos Inácio[1], **Douglas Vieira Barboza**[2], **Dácio de Castro Vivas Neto**[3], **Sávio Freire Bruno**[4]

[1] Master's degree in Biosystems Engineering. Professor in the Software Engineering Undergraduate Program at the University of Vassouras. ORCID: 0000-0003-2002-2154. E-mail: diego.inacio@univassouras.edu.br
[2] Ph.D. in Sustainable Management Systems. Iguaçu University and Federal University of the State of Rio de Janeiro. ORCID: 0000-0002-2653-8541. E-mail: douglas.barboza@campus1.unig.br
[3] Ph.D. in Civil Engineering. Fluminense Federal University. ORCID: 0009-0006-6787-9533. E-mail: daciovivas@id.uff.br
[4] Doctor of Veterinary Medicine. Faculty member in the Graduate Program in Biosystems Engineering at Fluminense Federal University. ORCID: 0000-0002-7267-9310. E-mail: saviobruno@id.uff.br

ABSTRACT
This study aims to analyze changes in vegetation cover in the municipality of Maricá (RJ) that occurred between 1984 and 2024, organized into eight five-year intervals, and analyzed using Landsat imagery from Landsat 5, 8, and 9 satellites, processed in Google Earth Engine (GEE). The Normalized Difference Vegetation Index (NDVI) was applied to detect significant changes in vegetation across different periods, with thresholds adjusted to better reflect local conditions (loss: $\Delta NDVI \leq -0.07$; gain: $\Delta NDVI \geq 0.25$). Image classification was performed in GEE, while subsequent steps—including vectorization, spatial intersection with neighborhood boundaries, and temporal difference analysis—were conducted in a local Python environment using the geopandas, pandas, and matplotlib libraries. The data indicated significant urban expansion between 1989 and 1993, with substantial vegetation loss in neighborhoods such as Silvado, Espraiado, and Lagarto, while areas like Ponta Negra and Cajueiros showed gains in the most re -evaluated periods. The analysis also revealed resilient neighborhoods and distinct dynamics of vegetation loss and gain over the years. These results were discussed in connection with Maricá's Master Plan and Law No. 2,272/2008, which addresses land use and occupation, highlighting the importance of integrating geospatial monitoring into public policies and sustainable urban planning.
Keywords: Atlantic Forest; remote sensing; environmental monitoring; Maricá; urban expansion.

Introduction

Change detection is an essential technique in environmental, urban, and natural resource monitoring studies. In the municipality of Maricá (RJ), a population growth of approximately 130% was observed between 1991 and 2022—rising from about 60,000 to over 138,000 inhabitants (IBGE 2023)—accompanied by intense pressure on sensitive ecosystems such as restinga vegetations, hillsides, and mangroves. Urban expansion encroaches on these fragile ecosystems, making the monitoring of changes in vegetation cover urgent, since remote sensing techniques, such as the application of NDVI, are fundamental for identifying patterns of vegetation degradation and regeneration in areas subject to intense anthropogenic pressure. This scenario highlights the importance of tools capable of continuously monitoring changes in vegetation cover and land use.

Landscape dynamics and changes in land use and vegetation cover are complex processes that reflect the interaction between natural and anthropogenic factors. Understanding these changes is essential for the sustainable management of natural resources, land-use planning, and ecosystem conservation (Turner & Meyer

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1994). In this context, change detection emerges as a fundamental tool, enabling the monitoring and analysis of landscape changes over time. One of the most widely used techniques for this purpose is the Normalized Difference Vegetation Index (NDVI), which allows for the efficient and accurate assessment of vegetation health and cover (Rouse et al. 1974).

Programming plays a fundamental role in the analysis of large volumes of geospatial data. Python, in particular, has emerged as one of the most popular languages for data science and environmental analysis due to its simplicity, vast library of tools, and active community support (Virtanen et al. 2020). Libraries such as NumPy, Pandas, Matplotlib, and Geopandas facilitate the processing, visualization, and analysis of geospatial data, while frameworks such as Rasterio and GDAL expand their capabilities for working with satellite imagery (Rasterio Developers 2020).

Google Earth Engine (GEE) is a cloud computing platform that offers access to a vast catalog of satellite images and tools for geospatial analysis. It enables the processing of large volumes of data in real time, eliminating the need for downloading and local storage (Gorelick et al. 2017). GEE is widely used in change detection studies due to its ability to process time series of satellite images, such as those from Landsat, Sentinel, and MODIS (Tamiminia et al. 2020). Its integration with Python, via the Earth Engine API, enables the creation of custom workflows and the application of advanced geospatial analysis techniques, such as the calculation of vegetation indices, including the NDVI (Gorelick et al. 2017).

Inácio et al. (2025) highlight the need to expand the practical application of methodologies based on NDVI and the Google Earth Engine (GEE) platform in tropical and subtropical contexts, also noting the lack of research focused on under-explored geographic areas in Latin America. In this context, the development of a robust methodology for detecting and classifying changes in vegetation cover over time, as proposed in this study, represents a significant step forward in addressing these gaps. It is worth noting that, although Maricá is located in a tropical context, the presence of different phytophysiognomies of the Atlantic Forest—such as restinga vegetation, mangrove, and rainforest — poses specific challenges in defining NDVI thresholds, since each of these formations exhibits distinct spectral responses, making it difficult to adopt a single, universal value, an aspect also highlighted by Inácio et al. (2025) when pointing out the need for methodologies adapted to tropical and subtropical contexts.

The literature highlights the consolidation of NDVI as an effective indicator in vegetation analysis, especially when integrated with cloud-based processing platforms such as GEE, which, combined with the Python language—even though GEE is native to JavaScript—enables the automation of analytical processes and the efficient handling of large volumes of multitemporal data (Nursaputra et al. 2021). The adoption of this approach allows for the monitoring of vegetation changes at different spatial and temporal scales, with resolution dependent on the characteristics of the sensor used, employing accessible and replicable technologies with strong potential to inform public policies and environmental conservation actions in vulnerable regions. Thus, this study not only addresses current guidelines in the literature but also contributes to the refinement of methodologies aimed at understanding vegetation dynamics in sensitive Atlantic Forest ecosystems—such as restinga vegetations, mangroves, and ombrophilous forests—undergoing rapid transformation.

Given the need for continuous monitoring of environmental changes in Maricá (RJ), a municipality located within the Atlantic Forest region and subject to intense urban pressure resulting from population growth of approximately 130% between 1991 and 2022 (IBGE 2023), the main objective of this study is to develop a systematic methodology to identify and classify areas affected by changes in vegetation cover for the period from 1984 to 2024. The proposed approach is based on the application of the Normalized Difference Vegetation Index (NDVI) using images from the Landsat series, processed on the Google Earth Engine (GEE) platform—whose native language is JavaScript—with workflow automation performed via the Earth Engine API in Python. The research encompasses the stages of selecting and filtering images available in the GEE catalog, analyzing multitemporal data, and applying algorithms to calculate the index and detect changes. By delineating spatial and temporal patterns of change in a specific geographic region, the methodology aims to provide robust insights for assessing environmental trends and impacts. In addition to prioritizing the reproducibility and scalability of the approach, the goal is to ensure its applicability in identifying patterns of vegetation degradation and regeneration, with an emphasis on protected areas and zones subject to urban expansion. The use of multitemporal data enables a more sensitive analysis of vegetation cover dynamics, especially in heterogeneous landscapes, highlighting the importance of approaches that recognize the complexity of ecological systems.

Materials and Methods

Study Area

The municipality of Maricá (Figure 1), located in the Metropolitan Region of the State of Rio de Janeiro, has undergone an intense process of urbanization in recent decades, driven by its proximity to the capital, investments in infrastructure, and the appreciation of the real estate market. The paving of the Amaral Peixoto Highway (RJ-106) in 1952 marked the beginning of the occupation of coastal and lagoon areas, with the development of more than 2,400 hectares into subdivisions. The widening of the highway accelerated this process, encouraging the settlement of both seasonal and permanent residents (Maricá 2022).

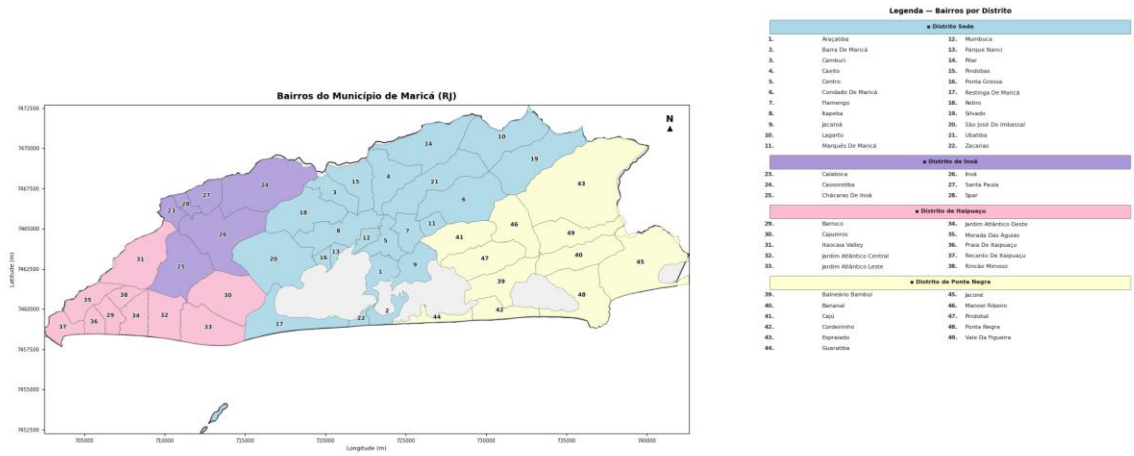


Figure 1 Map showing the location of neighborhoods in the Municipality of Maricá - RJ. Source: the authors

Land appreciation has intensified with the arrival of large-scale developments. A 2023 appraisal valued a property in Ponta Grossa at R$ 682,000.00, with a unit price exceeding R$ 2,300 per square meter (Dexter Engenharia 2023). In addition, the City Government has been addressing the rise in irregular construction and sales by implementing enforcement measures to curb unregulated occupation (Maricá 2022).

Regional factors also influence territorial dynamics. The construction of COMPERJ in Itaboraí has increased speculation in the region (Silva 2009). The MARAEY project, a large-scale tourism and real estate development planned for an Environmental Protection Area (APA), raises concerns about environmental degradation and the displacement of the traditional community of Zacarias (Duarte & Garcia 2024). The Jaconé Port project (Ponta Negra Terminal) has also been the target of criticism, particularly due to risks to local geodiversity—such as "beachrocks"—and impacts on wave patterns (Melo 2018).

Maricá is home to a rich diversity of phytophysiognomies belonging to the Atlantic Forest biome, notably the restinga vegetation vegetation, composed of halophilic communities, scrubs, herbaceous marshes, dry forest, and slack wetlands (Santos et al. 2017). Other relevant phytophysiognomies include the Dense Rainforest, secondary regenerating vegetation (with species such as *Mimosa bimucronata* and *Gochnatia polymorpha*), hygrophilous vegetation in wetland areas, and forest fragments on slopes (Maricá 2022).

These ecosystems play a fundamental role in biodiversity conservation, including endemic and threatened species, as well as serving as habitat for migratory birds and mammals (Barbier et al. 2011; Mitsch & Gosselink 2015). However, they face growing threats from urbanization, intensive agriculture, sand mining, and forest fires (Duarte & Garcia 2024; Silva et al. 2016; Maricá 2022). Climate change intensifies these risks through rising temperatures, changes in precipitation patterns, and sea-level rise, compromising local ecological stability (IPCC 2022).

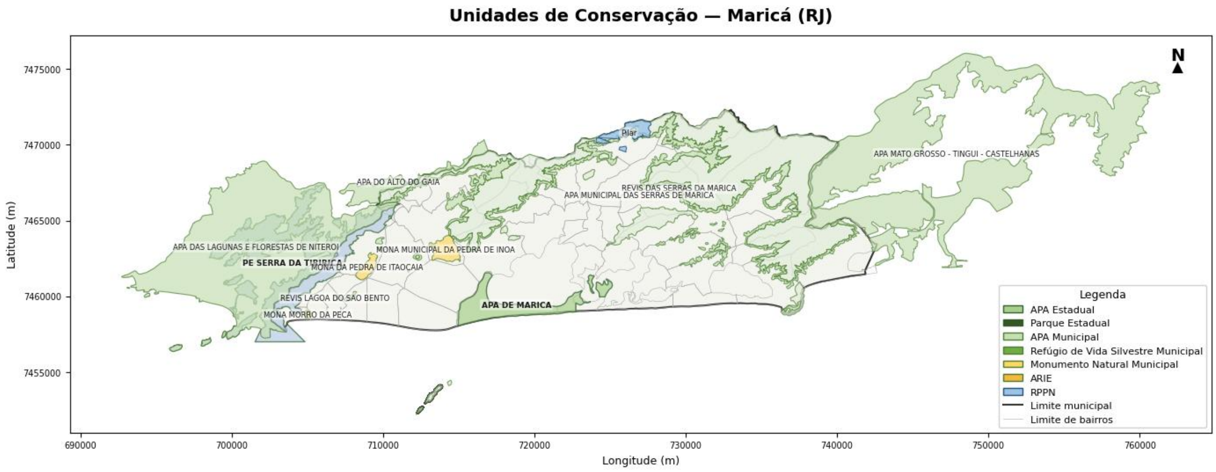


Figure 2 Map showing the location of conservation units in the municipality of Maricá and neighboring municipalities. Source: the authors

In this context, as shown in Figure 2, the municipality has a significant number of Conservation Units (UCs), which play a strategic role in preserving its ecosystems. Among the state-level UCs, the Maricá Environmental Protection Area (APA), created in 1984 to protect the lagoon system and restinga vegetation areas, and the Serra da Tiririca State Park, established in 1991, covering areas of Maricá, Niterói, and São Gonçalo, with a focus on the conservation of the Atlantic Forest and the promotion of environmental education.

At the municipal level, notable areas include the Maricá Mountains Municipal Wildlife Refuge (REVISSERMAR) and the Maricá Mountains Municipal Environmental Protection Area (APASERMAR), both created by municipal decrees in 2011, as well as the Morro da Peça Municipal Natural Monument, established by municipal decree in 2017, and the Lagoa do São Bento Wildlife Refuge, created in 2023 (Maricá 2011, 2017, 2022). The Cachoeira do Espraiado Area of Significant Ecological Interest (ARIE), created in 2005, protects areas of significant ecological and landscape importance (Maricá 2005). There are also private conservation initiatives, such as the Pilar Private Natural Heritage Reserve (RPPN) and the MARAEY RPPN, the latter currently in the process of formalization with the State Environmental Institute – INEA (INEA 2021).

These units protect areas of restinga vegetations, lagoons, mountain ranges, and forest fragments, contributing to biodiversity conservation, the protection of water resources, and the promotion of sustainable activities. Academic studies reinforce their relevance, such as that by Maciel (2017), which analyzes the effectiveness of municipal conservation unit management and highlights the importance of adequate environmental planning to ensure their ecological function.

Given this scenario, it is essential to strengthen local environmental governance, implement effective conservation measures, and encourage sustainable practices. Community involvement and environmental education are fundamental to ensuring the protection of vegetation types and ecosystem services in Maricá.

GEE Processing

The choice of data and processing techniques adopted in this study was based on technical and operational criteria that ensured efficiency, reproducibility, and suitability for the environmental context of the municipality of Maricá (Pande et al. 2024).

The Google Earth Engine (GEE) platform was selected for this study due to its cloud-based computing infrastructure, which enables the efficient processing of large volumes of geospatial data and imagery without the need for local storage (Gorelick et al. 2017). GEE[1] also offers direct access to historical collections of satellite imagery, such as the Landsat series, covering different sensors over time.

[1] Access to Google Earth Engine used in this study was obtained through a non-commercial account (academic research) between January and June 2025. It is worth noting that the platform has undergone gradual changes to its free-use policy, with a reduction in the processing power available to users without a commercial account. It is

Images from the Landsat 5 TM, Landsat 8 OLI, and Landsat 9 OLI-2 sensors were used, all with a spatial resolution of 30 meters, covering the period from 1984 to 2024. Image selection considered scenes with cloud cover of less than 30%, using the CLOUD_COVER field available in the metadata. In addition, a quality mask based on the QA_PIXEL band was applied, which identifies and excludes pixels affected by clouds, cloud shadows, snow, or other artifacts (USGS 2021). This filtering aims to ensure greater accuracy in the analysis of spectral changes in vegetation.

The Python programming language was used due to its broad compatibility with data science and geoprocessing libraries, such as geemap, ee, numpy, pandas, and matplotlib, enabling integrated vector and raster analysis workflows. Access to the GEE platform was achieved entirely via the Earth Engine (ee) API, which allows the cloud processing environment to be operated directly from Python, without the need to use GEE's native JavaScript interface.

The process of detecting changes in vegetation cover was divided into 8 main steps, described below:

Data Loading and Preprocessing

The shapefile for the municipality of Maricá was loaded and manipulated using the geopandas library (GeoPandas Developers 2020), with reprojection to EPSG:4326 (WGS84) to ensure compatibility with Google Earth Engine, which uses geographic coordinates as the standard. The coordinates were then converted into an ee.Geometry.MultiPolygon object for use on the platform, and API authentication and initialization were performed according to the official GEE documentation.

NDVI Calculation

The Normalized Difference Vegetation Index (NDVI) was calculated for each satellite image using the formula (Equation 1):

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Equation 1: NDVI calculation.

Where:

- **NIR** is the reflectance in the near-infrared band.
- **RED** is the reflectance in the red band.

The NDVI ranges from -1 to 1, where values close to 1 indicate healthy and dense vegetation, values close to 0 indicate exposed soil or urban areas, and negative values are associated with water bodies (Pettorelli et al. 2005).

Change Detection

NDVI Difference: The NDVI difference between two years was calculated to identify changes in vegetation cover. The formula used was (Equation 2):

$$\Delta NDVI = NDVI_{ano2} - NDVI_{ano1}$$

Equation2 NDVI Difference.

Where:

- $NDVI_{year1}$ is the NDVI for the initial year.
- $NDVI_{year2}$ is the NDVI for the final year.

recommended to check the current access conditions at https://earthengine.google.com before replicating the methodology described here.

Export and Vectorization

The results were visualized using the geemap library. The classified images were exported in GeoTIFF format directly to Google Drive. Subsequently, the areas identified as vegetation loss and gain were converted into vector polygons using the rasterio and geopandas libraries, enabling overlay with territorial units, ecological zones, and environmental protection areas.

The methodological process is schematically represented in Figure 3, covering the stages of data input, preprocessing, index calculation, classification, export, and spatial analysis.

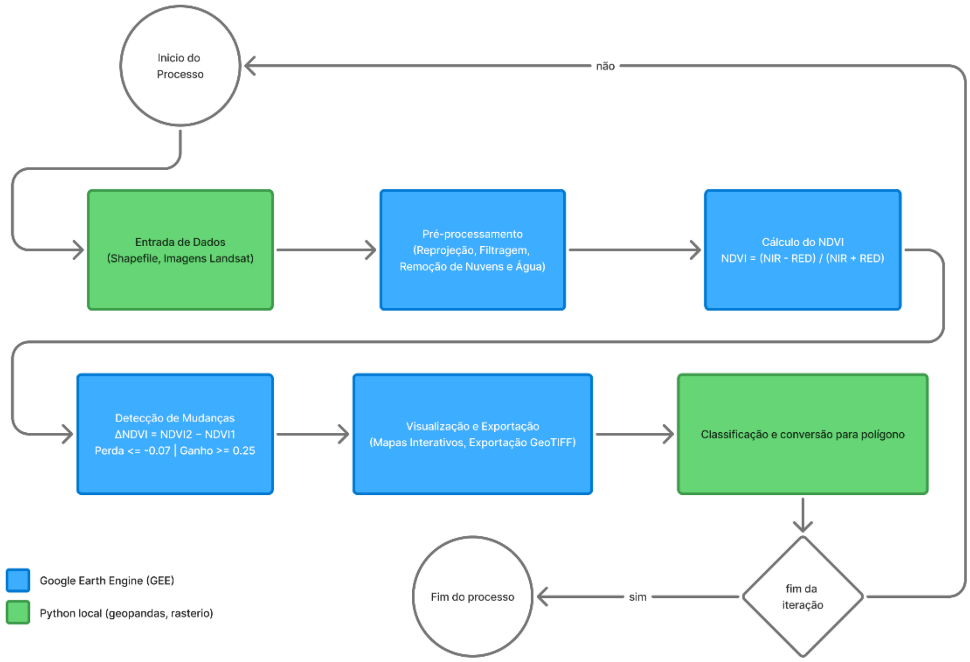


Figure 3 Flowchart of change detection. Source: the authors

Validation of Thresholds

The validation of the thresholds adopted for classifying NDVI changes was performed through comparative visual inspection, a procedure recognized as an essential step in remote sensing change detection projects (Kennedy et al. 2009; Hemati et al. 2021). Twenty random samples of the classified results—10 representing vegetation loss and 10 representing vegetation gain—were collected and distributed across different periods and regions of the municipality. These samples were overlaid onto Landsat images from the corresponding period to verify the spatial correspondence between the detected areas and the observed reality.

For periods where data availability permitted, images from sensors with higher spatial resolution, such as Sentinel-2 and CBERS, were used, always prioritizing publicly available and free sensors. For the remaining periods, validation was performed using images from the same Landsat sensor used in the analysis, ensuring radiometric consistency between the compared scenes (Zhu & Woodcock 2014).

Validation by sampling resulted in an Overall Accuracy of 85%, with 100% accuracy for the vegetation loss class and 70% for the gain class. The incorrect cases were concentrated in areas of vegetation gain, possibly associated with phenological variations or short-term natural regeneration, which reinforces the need for more restrictive thresholds for this class in ecosystems such as those in Maricá (Kennedy et al. 2009; Zhu & Woodcock 2014; Hemati et al. 2021).

Classification of Changes

The definition of thresholds for vegetation loss ($\Delta NDVI \leq -0.07$) and gain ($\Delta NDVI \geq 0.25$) was based on exploratory analyses and empirical tests conducted using time series of Landsat images. Initially, the values widely used in the literature ($\Delta NDVI \leq -0.05$ and $\Delta NDVI \geq 0.05$) were considered, as suggested by Singh (1989) and Kennedy et al. (2009). However, it was observed that these thresholds resulted in high sensitivity to seasonal variations, especially in areas of herbaceous or transitional vegetation, such as restinga vegetation formations and mangroves (Zhu & Woodcock 2014).

Maricá's vegetation cover consists of diverse Atlantic Forest ecosystems—including restinga vegetation forests, mangroves, and rainforests—each with distinct spectral responses and marked seasonal variations, which pose specific challenges in defining single NDVI thresholds (Silva & Oliveira 1989; Maricá 2013). Given this complexity, the adoption of more restrictive values aimed to improve the accuracy of detecting actual changes, minimizing false positives caused by natural phenological variations or residual atmospheric interference—an aspect also highlighted by Inácio et al. (2025) when they pointed out the need for methodologies adapted to tropical and subtropical contexts.

Furthermore, recent studies highlight the importance of calibrating ΔNDVI thresholds according to the specific characteristics of the vegetation and the local environment. Hemati et al. (2021) emphasized the need for contextual adjustments to the thresholds to improve the accuracy of analyses in studies using Landsat data.

The thresholds adopted were validated through comparative visual validation, using images with higher spatial resolution when available and, in other periods, by comparison with images from the same Landsat mission, ensuring radiometric consistency among the analyzed scenes (Rouse et al. 1974; Tucker 1979; Pettorelli et al. 2005; Inácio et al. 2025).

Results and Discussion

Urban expansion in coastal municipalities such as Maricá has intensified in recent decades, leading to significant changes in vegetation cover. A recent study by Duarte and Garcia (2024) demonstrates how real estate developments and unplanned land use are encroaching on sensitive ecosystems — such as restinga vegetation and mangrove areas, intensifying environmental conflicts. In this context, understanding the spatiotemporal dynamics of these changes is essential to inform sustainable public policies and land-use planning actions.

The environmental impacts associated with urbanization are exacerbated by extreme weather events, such as the prolonged drought recorded in 2023, which contributed to the intensification of forest fires in areas of native vegetation—making Maricá the municipality with the highest number of hotspots in the state of Rio de Janeiro that year (INPE 2023).

Validation of classification thresholds

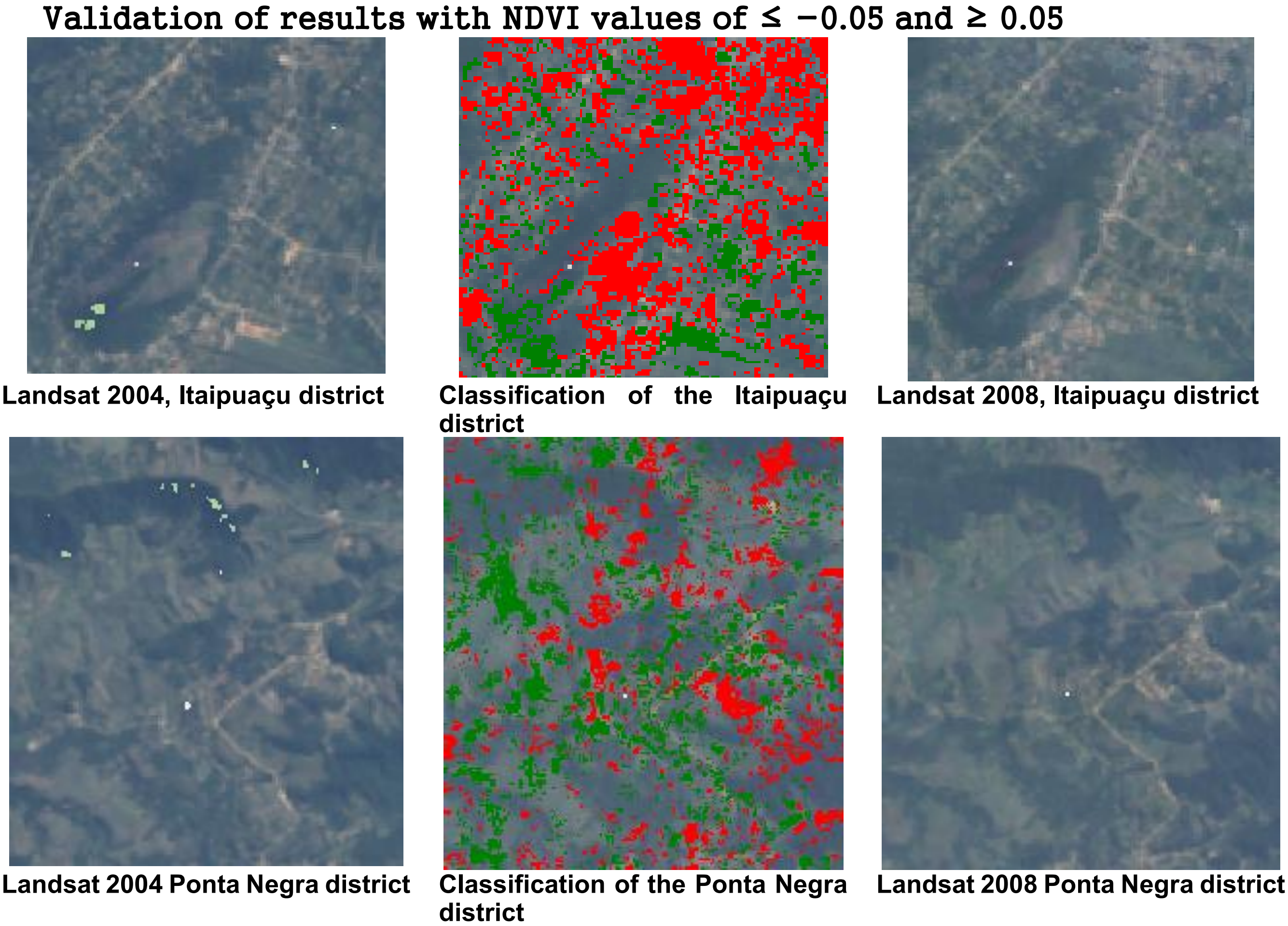
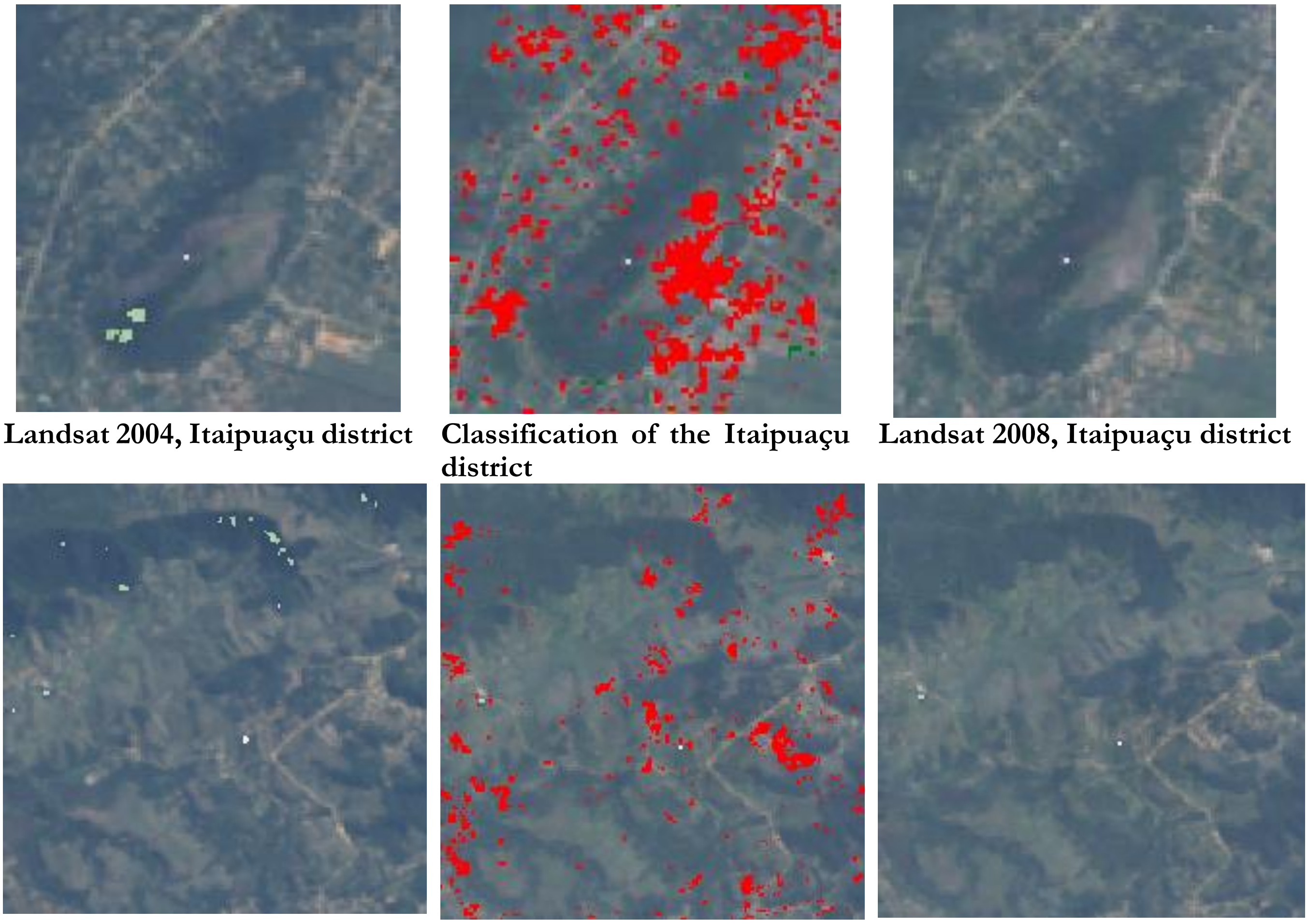


Figure 4. Detection of changes between 2004 and 2008 for the districts of Itaipuaçu and Ponta Negra, based on ΔNDVI. The conventional thresholds of ΔNDVI ≤ −0.05 for vegetation loss and ≥ 0.05 for vegetation gain were used. Red: vegetation loss; Green: vegetation gain. Source: the authors

Validation of the results using two distinct sets of thresholds for the normalized difference vegetation index (NDVI)—ΔNDVI ≤ −0.05 and ≥ 0.05, and ΔNDVI ≤ −0.07 and ≥ 0.25—revealed significant differences in the accuracy of vegetation loss and gain classifications, as shown in Figure 4. The application of the wider thresholds (±0.05) resulted in a clear overestimation of areas of change, for both losses and gains, as illustrated in the classifications of the districts of Itaipuaçu and Ponta Negra for the years 2004 and 2008. In this approach, a large number of pixels classified as changes which were observed, even in areas that, visually, did not show significant changes in vegetation cover, suggesting the interference of spectral noise and seasonal variations.

Validation of results with NDVI values of ≤ −0.07 and ≥ 0.25



Landsat 2004, Itaipuaçu district | **Classification of the Itaipuaçu district** | **Landsat 2008, Itaipuaçu district**

Landsat 2004 Ponta Negra district | **Classification of the Ponta Negra district** | **Landsat 2008 Ponta Negra district**

Figure 5. Detection of changes between 2004 and 2008 for the districts of Itaipuaçu and Ponta Negra, based on ΔNDVI. The conventional thresholds of ΔNDVI ≤ −0.07 for vegetation loss and ≥ 0.25 for vegetation gain were used. Red: vegetation loss; Green: vegetation gain. Source: the authors

In contrast, Figure 4 demonstrates that the adoption of more restrictive thresholds (ΔNDVI ≤ −0.07 for loss and ΔNDVI ≥ 0.25 for gain) proved more effective in detecting actual changes in vegetation, especially in sensitive ecosystems such as restinga vegetations, mangroves, and fragments of Atlantic Forest. Validation by sampling confirmed this effectiveness, resulting in an Overall Accuracy of 85%, with 100% accuracy for the loss class and 70% for the gain class (see section 2.4). The results obtained showed greater visual consistency with the original Landsat sensor images, restricting detection to areas with more significant changes consistent with expected environmental dynamics. This approach contributed to a significant reduction in false positives, lending greater robustness to the final classification. Furthermore, this trend persisted across all analyzed time series, justifying the adoption of the new thresholds for data processing throughout the study.

Despite the effectiveness of the methodology adopted to detect changes in vegetation cover in the municipality of Maricá, some limitations must be considered to contextualize the results and guide future studies. One of the main limitations relates to the spatial resolution of Landsat images, which is 30 meters. This resolution may not be sufficient to identify small-scale changes, such as selective deforestation or natural regeneration in fragmented areas, since subtle changes tend to be diluted in the spectral average of the pixel (Pontius & Millones 2011).

Another relevant factor is the influence of seasonal variations and atmospheric conditions, even when care is taken to select images that are close in terms of phenology. Natural phenomena such as flowering, leaf fall, and atmospheric disturbances (cloud cover, fog, or shadows) can directly affect NDVI values, influencing the detection of changes (Jensen 2007).

The choice of classification thresholds (ΔNDVI ≤ −0.07 and ΔNDVI ≥ 0.25), although intended to reduce false positives and increase the accuracy of results, may lead to the exclusion of actual changes in ecosystems with more subtle spectral responses, such as the restinga vegetation and mangrove vegetation in Maricá (Okoduwa & Amaechi 2024). This behavior can be observed in the comparison between the conventional thresholds (ΔNDVI ≤ −0.05 and ≥ 0.05) and the restrictive thresholds adopted in this study (ΔNDVI ≤ −0.07 and ≥ 0.25), illustrated in Figures 4 and 5, which highlight the reduction in false positives and the greater spatial consistency of the detected changes.

Furthermore, it is important to note that the NDVI, although widely used, has limitations. It tends to saturate in areas of dense vegetation and may have low sensitivity in humid environments or those with sparse vegetation. As an alternative, the use of complementary indices such as the EVI (Enhanced Vegetation Index), the SAVI (Soil-Adjusted Vegetation Index), or the NBR (Normalized Burn Ratio) could enrich the analyses and improve the interpretation of the results (Pettorelli et al. 2005).

Another critical issue concerns the conversion of raster data to vector format, a necessary step for detailed spatial analysis. However, this process can introduce geometric distortions, especially at edges or in transition areas, affecting the accuracy of delineating areas of loss and gain (Fisher & Comber 2005).

Finally, it is worth noting the technological dependence on the Google Earth Engine (GEE) platform, whose infrastructure and libraries (such as geemap, rasterio, and geopandas) are essential for implementing the proposed method. Future changes to the GEE API, the libraries used, or the platform's usage policies may compromise the reproducibility and continuity of the process (Gorelick et al. 2017).

These limitations do not invalidate the results obtained, but they underscore the importance of critical interpretation and the possibility of methodological refinements in future studies, particularly through field validation and the use of multiple spectral indicators.

Analysis by Period

The analysis was organized into eight five-year periods (1984–1988, 1989–1993, 1994–1998, 1999–2003, 2004–2008, 2009–2013, 2014–2018, and 2019–2024), a criterion detailed in the methodology (section 2.2). The definition of these time periods was based on the availability and compatibility of Landsat sensor images over time — Landsat 5 TM (1984–2012), Landsat 8 OLI (2013–2020), and Landsat 9 OLI-2 (2021–present) — ensuring continuous coverage of the municipality of Maricá over four decades, with regular intervals that allow for consistent temporal comparisons.

1984–1988: Mixed Pattern

This period (1984–1988) exhibited a mixed pattern of land-use changes, with a relatively balanced distribution between areas of vegetation gain and loss. As illustrated in Figure 6, significant gains in vegetation were recorded in all neighborhoods analyzed, notably in Pilar (41.87 ha), which showed the largest gain for the period, followed by Inoã, Flamengo, and Itaocaia Valley. In contrast, significant losses were recorded in neighborhoods such as Itapeba (86.26 ha), Jardim Atlântico, and Cordeirinho, evidencing the first signs of advancing urban occupation, especially over areas of remaining vegetation. The high concentration of losses in Itapeba, as shown in the graph on the right, underscores its vulnerability to the real estate development observed throughout the 1980s.

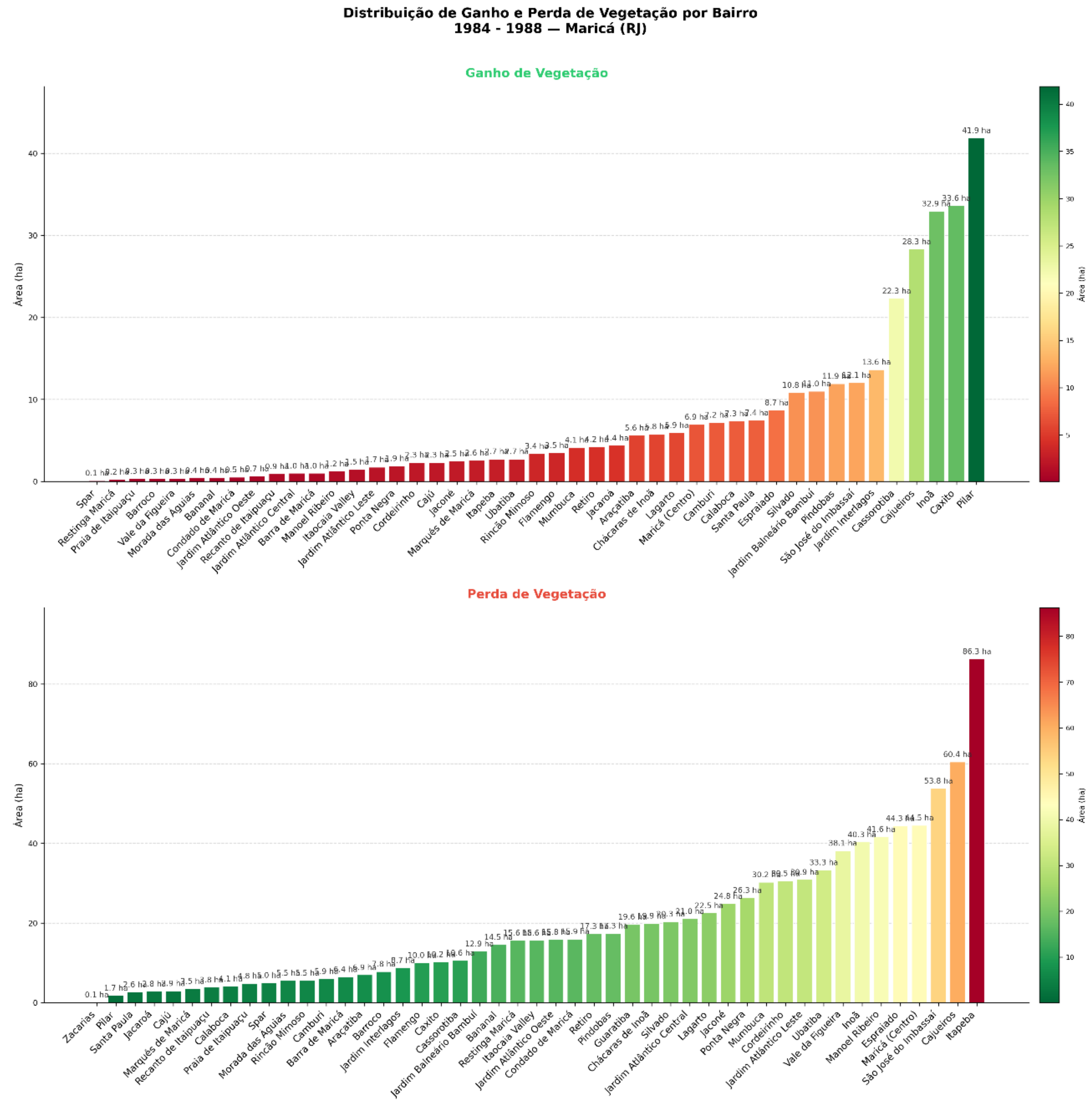


Figure 6. Charts of Gains and Losses from 1984 to 1988 in Maricá – RJ. Source: the authors

Analysis of the graphs in Figure 6 reveals that, between 1984 and 1988, the distribution of territorial gains was relatively dispersed among neighborhoods, with Pilar standing out as the leader in growth with an increase of approximately 41.87 hectares. Other neighborhoods such as São José de Imbassaí and Condado also recorded smaller increases, suggesting a process of controlled expansion in certain areas. This pattern may indicate a period of stabilization or localized investments in urban infrastructure and planned development, albeit sporadic.

On the other hand, the graph of territorial losses shows a significant concentration in neighborhoods such as Itapeba, which alone lost 86.26 hectares, followed by other regions with significant losses, such as Flamengo, and Caxito. These losses may be associated with the encroachment of urbanization on natural or rural areas, reflecting an urban growth dynamic that is still in its early stages but already having a significant impact. The severity of these losses in central and peri-urban neighborhoods suggests the need for stronger land-use planning policies that balance urban expansion with environmental conservation.

1989–1993: Environmental Crisis

Characterized by severe losses, this period highlights the impact of unplanned expansion, as shown in Table 1, which highlights the neighborhoods of Silvado and Espraiado, which recorded significant losses between 1989 and 1993:

Table 1: Neighborhoods with the Greatest Losses.

Neighborhood	Area Loss (ha)	%
Espraiado	-1,065.58	39.56
Silvado	-786.99	70.85

Source (Authors).

Figure 7 below illustrates a critical scenario of land loss between 1989 and 1993, marked by a significant decline in vegetated areas, particularly in the neighborhoods of Espraiado and Silvado, which lost 1,065.58 ha and 786.99 ha, respectively, as shown in Table 1. This magnitude of loss, exceeding 1,000 hectares, represents approximately 39.56% of the Espraiado neighborhood's area and 70.85% of the Silvado neighborhood's area, reflecting a process of unplanned urban expansion, likely driven by real estate pressure, a lack of oversight, and the occupation of environmentally sensitive areas. The most affected neighborhoods are located in areas that traditionally contained large expanses of native vegetation, which exacerbates the severity of the situation.

On the other hand, gains in area during this period were sporadic and insignificant when compared to the losses. Neighborhoods such as Lagarto, Espraiado, and Silvado showed the highest gain values, although these were much lower than the areas lost. The gains graph shows significantly lower bars than the losses graph, reinforcing the asymmetry of this historical moment. This discrepancy between gains and losses illustrates not only the fragility of environmental restoration processes but also the absence of effective policies for the preservation and recovery of vegetation cover during this interval, establishing the period as one of the most impactful for the analyzed territory.

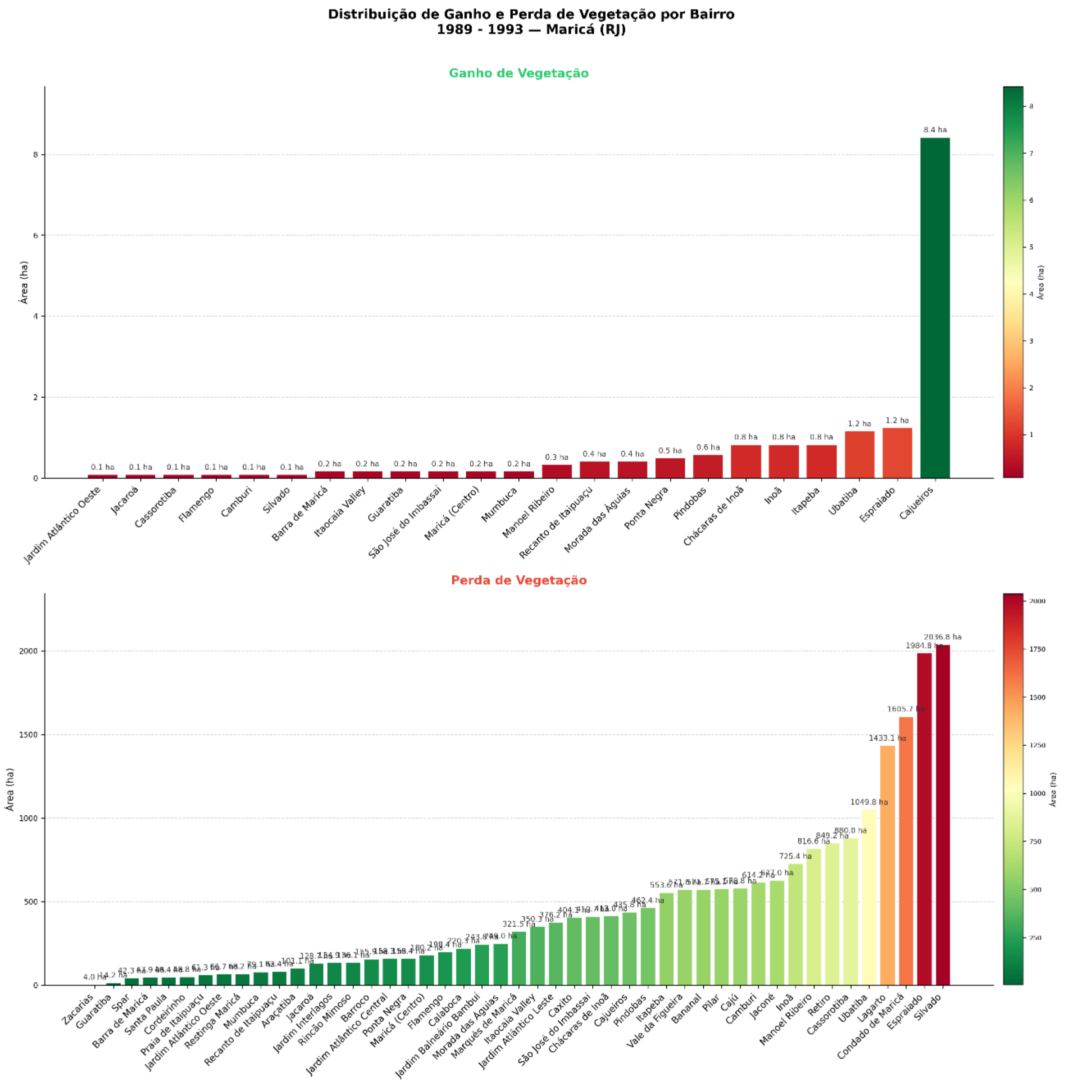


Figure 7. Gains and Losses Graphs from 1989 to 1993 in Maricá – RJ. Source: the authors

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1994–1998: Partial Recovery

As shown in Figure 8, there was a reduction in the intensity of losses and the first signs of recovery in neighborhoods such as Ponta Negra (+2.31 ha).

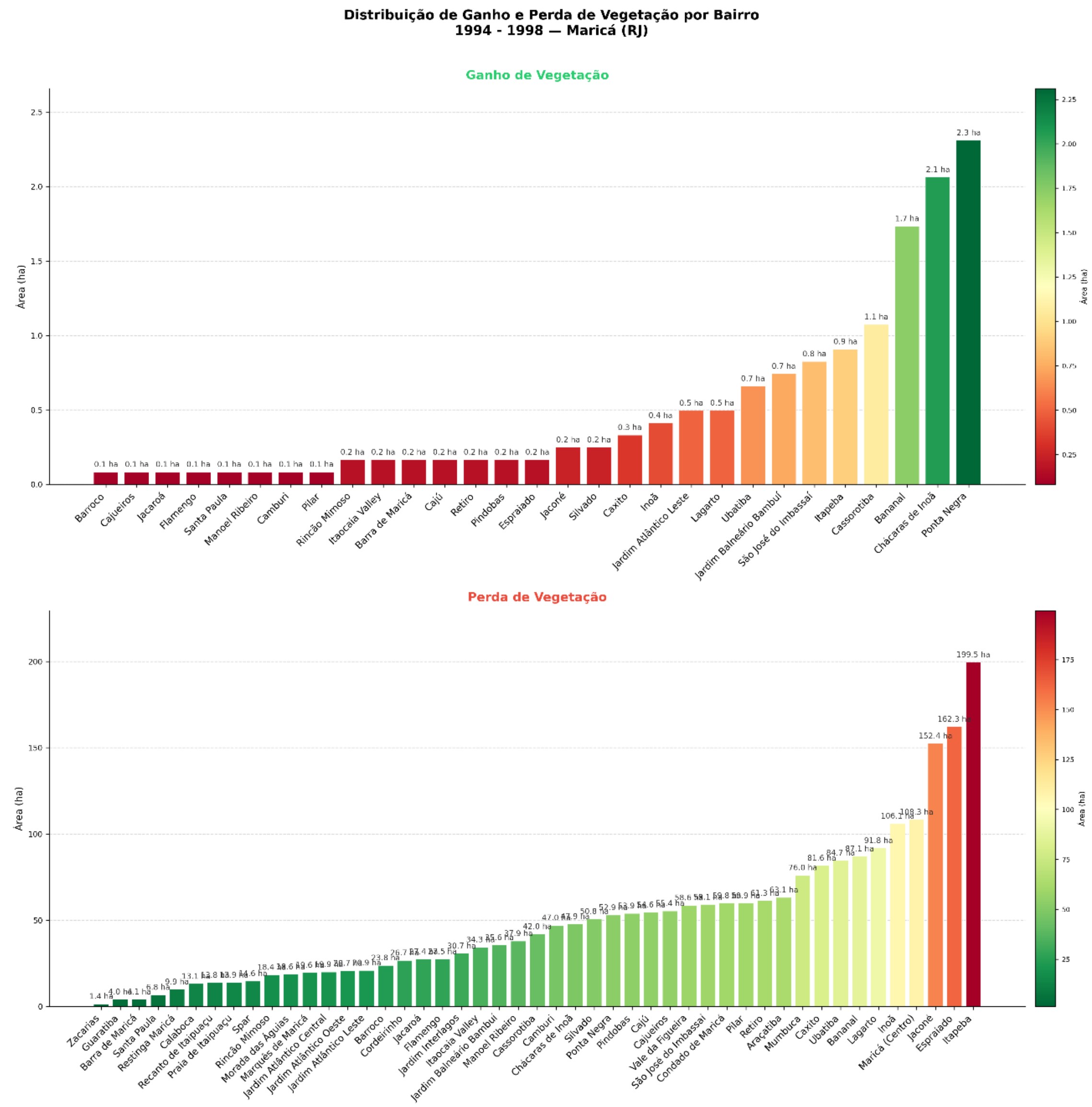

Figure 8. Gains and Losses Charts for 1994–1998 in Maricá, RJ. Source: the authors

During the period from 1994 to 1998, a reduction in the intensity of territorial losses is observed when compared to the previous interval (1989–1993), marked as the "Environmental Crisis." The graphs show that, although there were still significant losses, the distribution of these losses is more balanced and less pronounced in the most affected neighborhoods. The greatest individual loss still occurs in neighborhoods such as Silvado, Espraiado, and Cordeirinho, but at values noticeably lower than those recorded in the previous period. This indicates the beginning of a stabilization process, possibly the result of actions to curb urban expansion or a depletion of natural areas available for occupation in the most vulnerable neighborhoods.

At the same time, there has been a slight improvement in environmental recovery, particularly in the Ponta Negra neighborhood, which recorded a gain of +2.31 hectares—a small but symbolic figure given the previous context of massive losses. Neighborhoods such as Lagarto, Espraiado, and Silvado remain among those gaining the most area, although the figures are low and insufficient to offset accumulated losses. This pattern reflects what can be interpreted as a partial recovery, where urban dynamics remain active but with a lesser impact on the natural environment, and where the first signs of native vegetation regeneration are beginning to emerge in certain locations.

2019–2024: Extreme Losses

The most recent period has brought significant new losses, particularly in neighborhoods undergoing urban expansion, as shown in Table 2:

Table 2: Largest losses from 2019 to 2024.

Neighborhood	Area loss (ha)	%
Ubatiba	-677.33	68.83
Caxito	-636.04	92.81
Pilar	-607.03	58.06

Source (Authors).

Table 2 highlights the neighborhoods with the greatest losses of area from 2019 to 2024, revealing an intensifying process of urban and environmental pressure in certain locations. The neighborhoods of Ubatiba (-677.33 ha), accounting for approximately 68% of the neighborhood, Caxito (-636.04 ha) (about 92.81% of the neighborhood), and Itaocaia Valley (-607.03 ha) (about 56.06% of the neighborhood) top the list, revealing a critical scenario of vegetation cover loss and possible poorly planned urban or rural expansion, as illustrated in Figure 9.

This pattern is confirmed by the graphs shown in Figure 9 on Loss Distribution by Area, where these neighborhoods stand out with high values and wide error bars, indicating significant variations in local losses, which may be related to specific actions such as land subdivisions, expansion of agricultural areas, or informal settlements.

The graph showing gains by area reveals that, although there are regeneration or recovery efforts underway in several neighborhoods—such as Lagarto, Espraiado, and Silvado—the gains are far smaller than the losses. This discrepancy indicates that the pace of regeneration is insufficient to offset the increasing losses, creating a situation of growing ecological imbalance.

The spatial distribution of these processes suggests that, while gains are concentrated in historically rural or peripheral neighborhoods, losses are more pronounced in areas with high potential for urbanization, especially in the eastern part of the city, where Caxito, Pilar, and Itaocaia Valley are located.

Therefore, the 2019–2024 period is marked by environmental regression, with a significant net loss of native vegetation and signs of unplanned urban expansion, reinforcing the need for public policies on land use control and incentives for environmental recovery in critical areas.

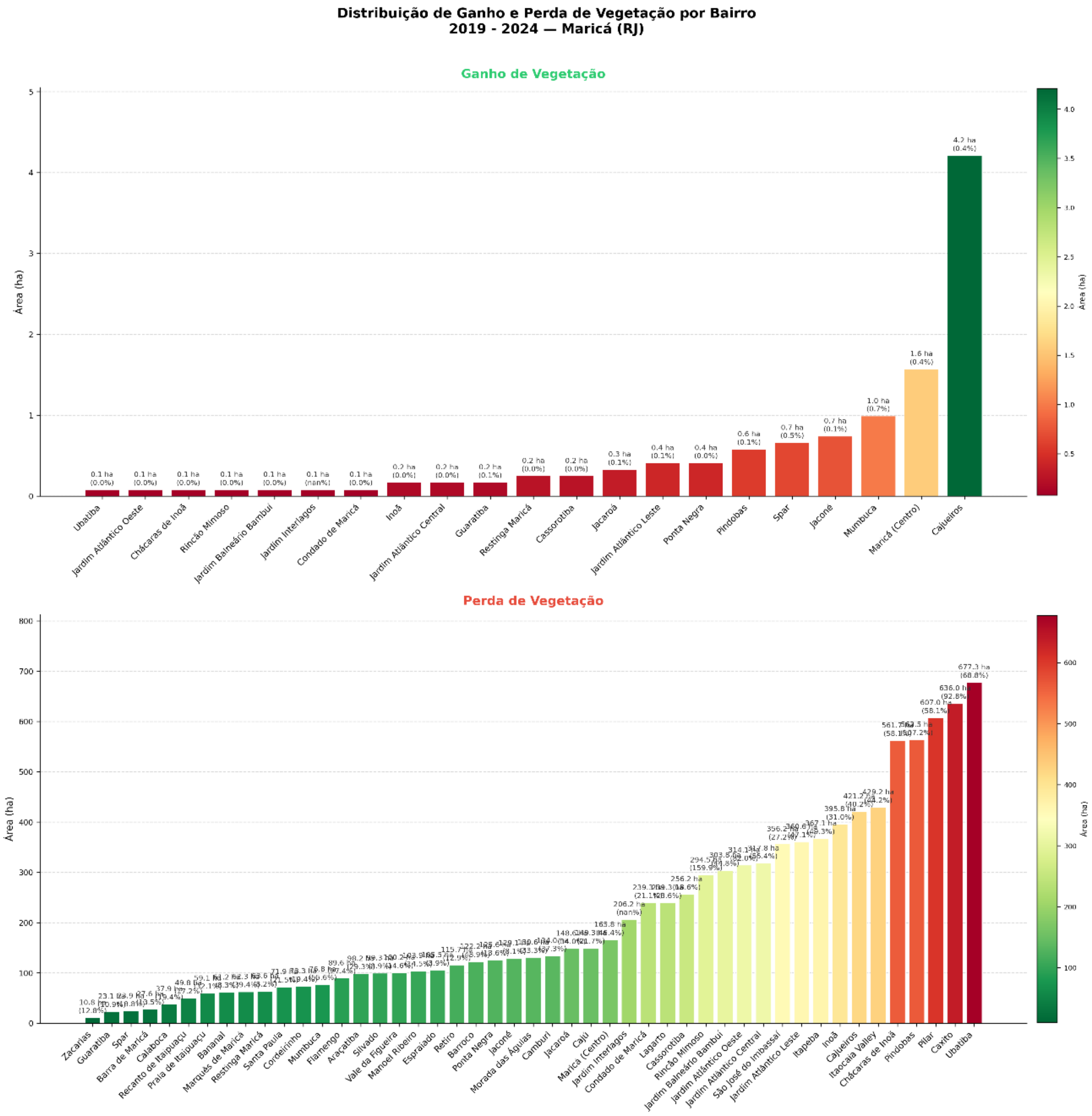

Figure 9. Gains and Losses Charts for 2019–2024 in Maricá – RJ. Source: the authors

Spatial Transformations in Maricá: Dynamics of Vegetation Gains and Losses between 1984 and 2024.

Figure 8 below presents a series of maps illustrating the distribution of losses and gains in the ecosystem of the municipality of Maricá over eight five-year periods, between 1984 and 2024. Each map highlights the expansion and contraction of vegetation cover, predominantly marked by the color red (losses), with some isolated areas of gain (in green).

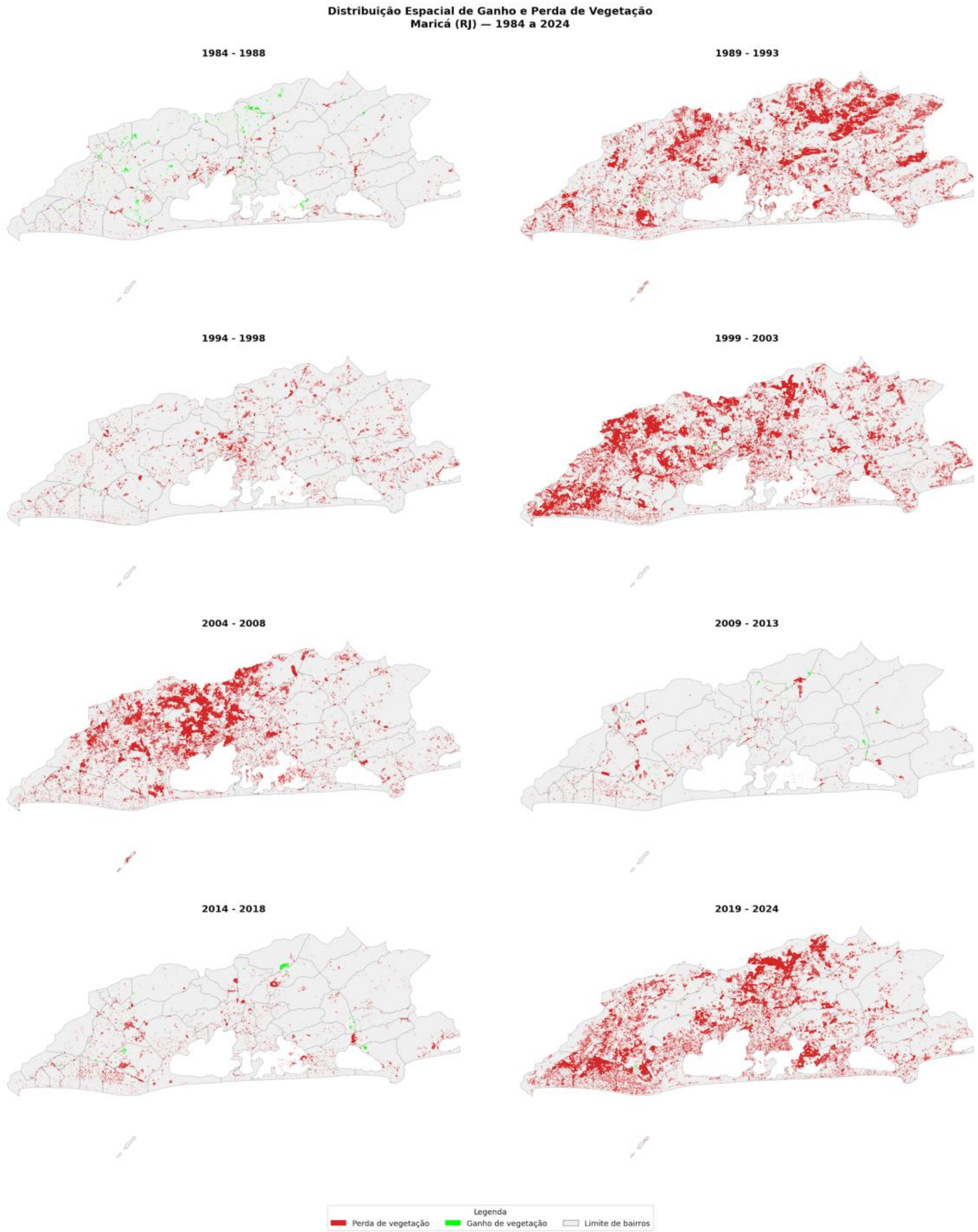

Figure 10. Maps of the Distribution of Gains and Losses from 1984 to 2024 in Maricá – RJ. Source: the authors

It can be observed that territorial transformations in Maricá do not follow a linear pattern, but rather a cyclical dynamic, marked by periods of intense urban expansion followed by moments of relative stabilization. Between the periods of 1989–1993, 1999–2003, and 2004–2008, losses intensified significantly, indicating an aggressive process of land occupation, possibly driven by rising property values, land speculation, and the absence of effective urban planning.

In contrast, during the 2009–2013 period, there was a significant reduction in losses, suggesting a period of containment or deceleration of urban expansion, which may be related to regulatory policies, economic crises, or greater environmental control. However, this stability is disrupted in subsequent cycles, particularly in 2019–2024, when loss levels rise again, mainly in regions such as the east and southeast of the municipality, aligning with the data previously presented in the graphs and tables.

This pattern demonstrates a structural vulnerability in land use and vegetation cover in the municipality, with cycles that alternate between periods of anthropogenic pressure and brief pauses, without, in fact, a significant reversal of the environmental degradation process. Temporal mapping, therefore, reveals the need for consistent public interventions, integrated territorial planning, and environmental recovery policies, especially in areas that have historically suffered the most from the loss of natural cover.

The Maricá Master Plan (Maricá 2025) recognizes these vulnerabilities and establishes guidelines to address them. Among the proposed measures, the adoption of bioclimatic guidelines for land subdivision, land use, and land occupation stands out, aiming to improve urban environmental quality, as well as the expansion of green areas to contribute to urban environmental comfort. In addition, the plan provides for the development of programs and projects aimed at the restoration of degraded areas and riparian forests along rivers, streams, and canals, as well as the maintenance of soil permeability.

Regarding conservation units within the Maricá territory, based on the detailed analysis shown in Table 3 below, which indicates which Conservation Units (UCs) suffered the most losses in Maricá, it is possible to identify relevant temporal patterns regarding the effectiveness of establishing these areas. Below are the main cases, considering the management level, the type of CU, the period of greatest recorded loss, and whether this loss occurred before, after, or around the time of the CU's creation.

Table 3: Largest losses from 2019 to 2024.

Name	Management Authority	Year of creation	Area	Type	Largest Loss	Area of Greatest Loss	Before or after creation
MARICA ENVIRONMENTAL PROTECTION AREA	State (Inea)	1984	6,052,546.20	Undefined	2004 to 2008	3,260,989	After
MARICA MOUNTAINS MUNICIPAL ENVIRONMENTAL PROTECTION AREA	Municipality (Maricá)	2011	395,679,851.90	Undefined	1999 to 2003	140,412,367.39	Before
ITAOCAIA ROCK NATURAL MONUMENT	Municipality (Maricá)	2017	44,234,696.80	Full Protection	2019 to 2024	41,094,905	After
MORRO DA PECA MUNICIPAL NATURAL MONUMENT	Municipality (Maricá)	2017	10,215,267.33	Full Protection	1999 to 2003	10,031,295	Before
PEDRA DE INOA MUNICIPAL NATURAL MONUMENT	Municipality (Maricá)	2017	24,282,618.63	Full Protection	1999 to 2003	9,995,135	Before
SERRA DA TIRIRICA STATE PARK	State (Inea)	1991	91,364,247.06	Full Protection	1999 to 2003	82,817,925	After
RPPN Pilar	Private	2021	53,805,457.05	Undefined	2019 through 2024	29,659,576	After
SAO BENTO LAGOON WILDLIFE REFUGE	Municipality (Maricá)	2023	1,423,204.76	Full Protection	1999 to 2003	1,395,978	Before
MARICA MOUNTAINS WILDLIFE REFUGE	Municipality (Maricá)	2011	427,540,173.10	Full Protection	1989 to 1993	137,456,209.90	Before

Source (Authors).

An analysis of the Conservation Units (UCs) located in Maricá reveals a recurring trend of significant losses in vegetation cover prior to the legal formalization of these protected areas. Units such as the Serras da Maricá Wildlife Refuge and the Serr , Maricá Municipal Environmental Protection Area recorded their greatest losses during the periods from 1989 to 1993 and 1999 to 2003, respectively—that is, before their official establishment in 2011. The same pattern is observed in other municipal conservation units, such as the Pedra de Inoã and Morro da Peça Natural Monuments, where the greatest impacts also occurred prior to their establishment dates. This pattern suggests a reactive institutional response to environmental degradation that was already underway, which compromised, in some cases, the full conservation of the original ecological attributes.

However, significant environmental losses were also observed even after the creation of some Conservation Units, which had already been duly established. The Serras da Maricá Wildlife Refuge, the Pedra de Itaocaia Natural Monument, the Pilar Private Nature Reserve (RPPN), and the Maricá Environmental Protection Area experienced considerable losses even while their legal protection instruments were in effect. The Serra da Tiririca State Park, despite having been created in 1991, recorded its greatest impact in Maricá between 1999 and 2003, revealing weaknesses in the state management model in the face of anthropogenic pressures. A similar situation is observed at the Lagoa do São Bento Wildlife Refuge, established only in 2023, but which already exhibits accumulated environmental liabilities from previous periods.

These results demonstrate that, although the legal establishment of protected areas represents an important step toward conservation, it does not, by itself, guarantee the effective protection of ecosystems. The persistence of losses after the creation of these units highlights gaps in management, enforcement, and territorial planning, as well as challenges in integrating actions between the municipal and state levels. The case of Maricá illustrates the need to strengthen environmental public policies with preventive mechanisms, environmental restoration actions, and greater social participation, aiming to increase the effectiveness of conservation in legally protected areas.

Main Trends

Spatial analysis of vegetation cover in Maricá between 1984 and 2024 reveals territorial trends marked by distinct patterns of loss and gain, reflecting the impact of urban expansion and land-use and land-occupation policies at different historical moments. One of the most critical periods occurred between 1989 and 1993, when the municipality experienced a sharp acceleration in the urbanization process. As shown in Table 4, the neighborhoods of Silvado, Lagarto, and Espraiado experienced the greatest territorial losses during this period, with reductions of 786.99 ha (70.85% of the neighborhood's area), 676.36 ha (66.82%), and 1,065.58 ha (39.56%), respectively. Also notable were Condado de Maricá (552.22 ha; 48.70%), Camburi (288.13 ha; 80.20%), and Marquês de Maricá (128.37 ha; 81.07%). This trend is associated with the absence of effective urban planning and the haphazard conversion of natural areas into subdivisions and real estate developments, within a context of poorly regulated urbanization policies (Seabra et al. 2024).

Table 4: Losses due to urban expansion

Neighborhood	Area loss (ha)
Espraiado	-1,065.58
Silvado	-786.99
Lagarto	-676.36

Source (Authors).

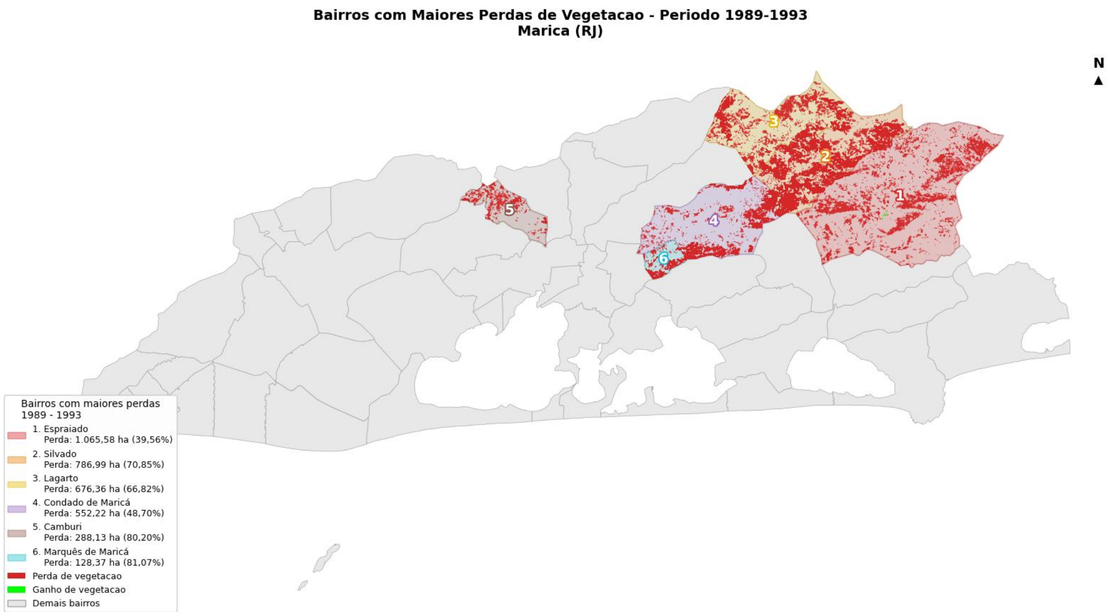

Figure 11. Map showing the location and distribution of losses and gains in the most affected neighborhoods during the period 1989–1993. Source: the authors

In the recent period from 2019 to 2024, the dynamics of territorial transformation remained intense, although with a focus on areas different from those of previous decades. As shown in Table 5, the neighborhoods of Pilar (368.49 ha; 35.24% of the neighborhood's area), Cajueiros (333.61 ha; 31.85%), Chácaras de Inoã (309.00 ha; 31.94%), and Ubatiba (277.78 ha; 28.23%) were among those that lost the most vegetation cover during the period. The intensification of these losses is directly related to the pressure exerted by new urban developments and the accelerated conversion of rural areas into residential zones, reinforcing the challenges of unplanned urban expansion in previously less populated regions (Lopes et al. 2024).

Table 5: Neighborhoods with the greatest dynamics of change.

Neighborhood	Area loss (ha)
Pilar	-368.49
Cajueiros	-333.61
Inoã smallholdings	-309.00
Ubatiba	-277.78

Source (Authors).

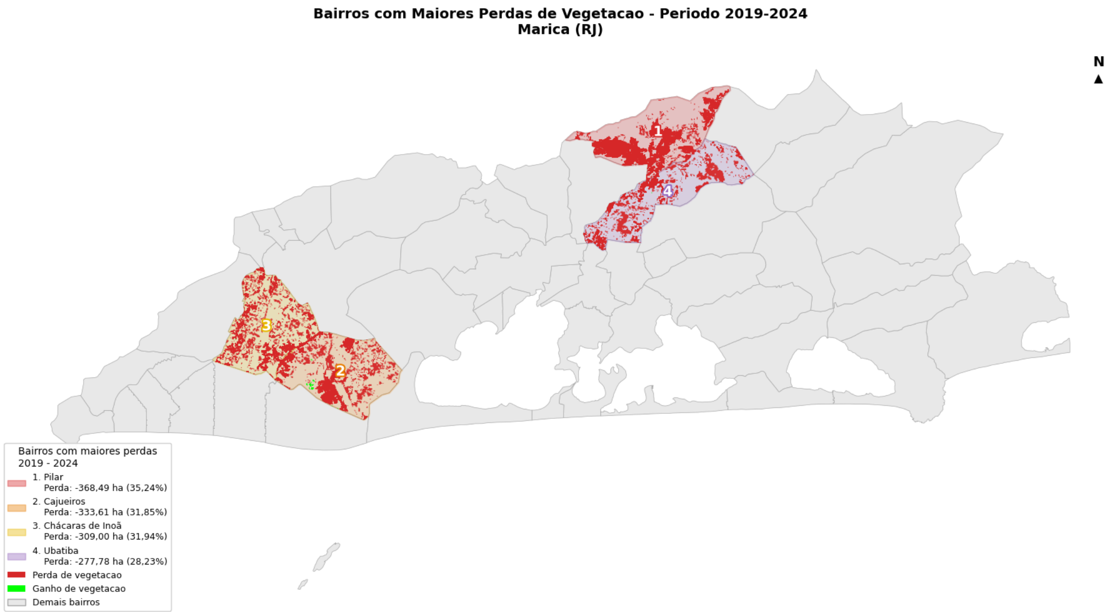

Figure 12. Map showing the location and distribution of losses and gains in the most affected neighborhoods during the 2019–2024 period. Source: the authors

In contrast, the period between 2014 and 2018 showed signs of territorial stabilization in some neighborhoods, notably Pilar, Cajueiros, and Ponta Negra. According to Table 6, these neighborhoods recorded the largest territorial gains during the period, with increases of 17.01 ha (1.63% of the neighborhood's area), 13.37 ha (1.28%), and 9.34 ha (1.01%), respectively. It is worth noting, however, that these same neighborhoods also recorded losses during the period—Cajueiros lost 74.04 ha and Ponta Negra 25.48 ha—evidencing a simultaneous dynamic of vegetation degradation and regeneration. These results can be attributed to the adoption of effective urban and environmental planning tools, such as the establishment of protected zones, the implementation of master plans, and urban renewal programs. The presence of conservation units and areas of ecological interest, combined with community awareness and policy integration between the municipal and state levels, contributed to curbing degradation and, in some cases, to the recovery of vegetated areas.

Table 6: Neighborhoods with consistent gains.

Neighborhood	Area gain (ha)
Pilar	+17.01 (2014–2018)
Cajueiros	+13.37 (2014–2018)
Ponta Negra	+9.34 (2014–2018)

Source (Authors).

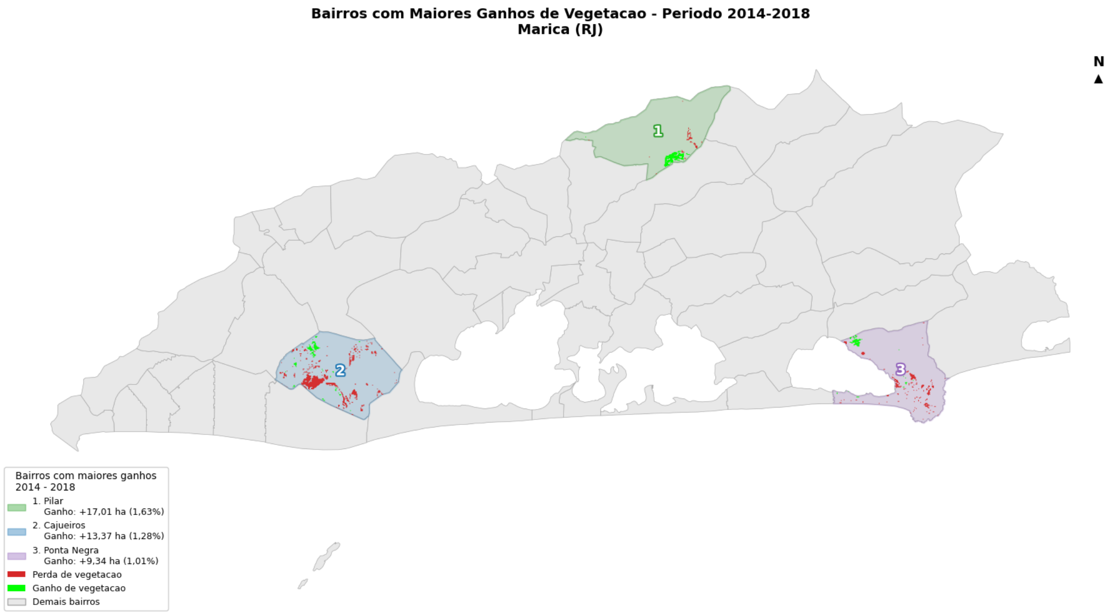

Figure 13. Map showing the location and distribution of population losses and gains in the most affected neighborhoods during the 2014–2018 period. Source: the authors

These areas demonstrate that, even in contexts of rapid urbanization, it is possible to achieve positive results when public policies are coordinated with rigorous land-use planning, social engagement, and the strategic use of monitoring technologies. In the case of Maricá (Downtown), the implementation of the Municipal Master Plan may have played a decisive role in organizing land use. In Ponta Negra and Cajueiros, however, policies focused on urban renewal and environmental preservation, combined with community mobilization, contributed to the preservation of vegetation. Replicating these experiences in more vulnerable neighborhoods can be made feasible through the dissemination of best practices, technical training for public managers, and the adoption of geotechnology tools, promoting more balanced and sustainable territorial management (Araújo et al. 2024).

Final Considerations

The results obtained demonstrate that the municipality of Maricá underwent intense changes in vegetation cover between 1984 and 2024, with a notable predominance of losses in regions with high real estate value and sensitive ecosystems. Neighborhoods such as Silvado, Espraiado, Caxito, Pilar, and Itaocaia Valley were among the most impacted, accumulating losses exceeding 1,500 hectares in some periods. Multitemporal analysis using ΔNDVI revealed that the main changes occurred between the 1989–1993 and 2019–2024 cycles, both marked by strong urban pressure and unplanned expansion. In contrast, isolated territorial gains were observed in neighborhoods such as Cajueiros, Ponta Negra, and Maricá (Centro), suggesting a heterogeneous dynamic of land use and vegetation cover and highlighting the resilience of certain areas in the face of anthropogenic pressure.

The application of more restrictive thresholds ($\Delta NDVI \leq -0.07$ and $\Delta NDVI \geq 0.25$) proved more consistent in reducing spurious detections and in delineating more significant changes in vegetation cover, especially in areas with sand dune vegetation and mangroves, whose spectral response tends to be more subtle. This adaptation was observed through visual comparison with original Landsat images and historical land use and vegetation cover records. However, it should be noted that future evaluations may incorporate formal quantitative validation procedures, such as confusion matrix analyses and accuracy estimates, in order to enhance the statistical robustness of the classifications obtained.

The research fulfilled its main objective by developing and applying a systematic methodology based on remote sensing and geospatial analysis, integrating Landsat data with Google Earth Engine and Python libraries (Geemap, Rasterio, Geopandas), to identify and classify changes in vegetation cover over a 40-year period. This approach allowed not only for mapping cycles of degradation and regeneration but also for generating useful technical inputs for environmental management and local urban planning.

The application of remote sensing in this context proved fundamental for the continuous monitoring of territorial transformations in Maricá, enabling the precise identification of spatial patterns of vegetation cover change. The combination of image time series and modern computational tools proved effective in clearly identifying the most vulnerable areas, such as the neighborhoods of Pilar, Caxito, and Itaocaia Valley—true hotspots of environmental degradation.

Despite the consistent results, some methodological limitations must be considered when interpreting the data. The 30-meter spatial resolution of the Landsat series images may limit the detection of small-scale changes, such as selective deforestation or initial processes of vegetation regeneration in fragmented areas. Furthermore, the use of the NDVI index, although widely established in the literature, has limitations in environments with very dense vegetation or in wetlands, where spectral saturation or reduced sensitivity to structural variations in vegetation may occur. Another aspect concerns the adoption of more restrictive ΔNDVI thresholds, which, although they reduced the incidence of false positives, may have excluded actual changes with a more subtle spectral response. Finally, factors such as natural phenological variations and residual atmospheric interference may also partially influence the results obtained. These limitations do not invalidate the research findings but highlight the importance of complementing future analyses with additional spectral indices, field validation, and data with higher spatial resolution.

The results provide concrete insights for the reassessment of the municipality's environmental zoning, including the delineation of priority zones for the conservation and restoration of native vegetation. Incorporating this evidence can strengthen the management of existing Environmental Protection Areas (APAs) and conservation units, as well as guide the creation of new territorial control instruments. Periodic monitoring of the most impacted neighborhoods is recommended, as well as the replication of strategies observed in resilient areas, such as Maricá (Downtown) and Cajueiros, where urban planning and environmental preservation policies have proven effective.

These actions align with key Sustainable Development Goals (SDGs), such as SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land), reinforcing the need for integrated public policies that reconcile urban growth with environmental protection.

For future research, it is recommended to deepen the analysis of the relationship between real estate dynamics and environmental degradation processes, especially in areas subject to intense land speculation. The importance of developing an interactive geospatial platform that makes the data produced in this study available to public managers and civil society is also highlighted. The incorporation of artificial intelligence techniques for the automatic detection of changes and the prioritization of critical areas can enhance the effectiveness of evidence-based environmental monitoring strategies.

In terms of scientific implications, this study opens the door to various lines of research. It is recommended, for example, to conduct a more in-depth analysis of the correlation between real estate dynamics and environmental degradation processes, especially in areas subject to intense land speculation. This aspect can be explored in future studies focusing on socioeconomic variables, urban spatial production, and territorial conflicts.

Another promising avenue is the continuous monitoring of areas classified as resilient, in order to assess the effectiveness of public policies already implemented and identify potential natural regeneration processes. Furthermore, we propose the development of an interactive geospatial platform or cartographic portal that enables public access to the data produced, thereby broadening the dialogue between science, environmental management, and social participation.

As a methodological advance, the potential of applying artificial intelligence (AI) techniques for the automatic detection of changes and the prioritization of critical areas stands out. The incorporation of supervised or unsupervised models could represent a significant evolution in the speed and accuracy of territorial monitoring, strengthening evidence-based environmental management strategies.

These proposals constitute a future research agenda that may result in new scientific articles with analytical, methodological, and applied focuses, contributing both to theoretical deepening and to the improvement of territorial planning and environmental conservation practices.

Based on the identified spatial patterns, it is recommended that practical measures be adopted to improve environmental management and territorial planning in Maricá. Continuous monitoring of resilient areas—such as Ponta Negra, Maricá (Center), and Cajueiros—can help assess the effectiveness of conservation actions already implemented and reinforce successful initiatives. We also highlight the importance of developing an interactive graphical interface or geospatial portal that makes the data and maps generated by this study available, promoting transparency, environmental education, and informed decision-making by public officials and civil society. Such strategies can be incorporated into municipal planning tools, such as environmental zoning and the updating of master plans, especially in neighborhoods with high concentrations of degradation hotspots.

From a scientific perspective, this study paves the way for complementary research. We suggest further analysis of the correlation between real estate dynamics and environmental degradation in areas subject to intense land speculation, taking into account socioeconomic and legal variables. We also propose the application of artificial intelligence techniques to improve the automatic detection of changes and the prioritization of critical areas, as a way to advance monitoring processes methodologically. The integration of spectral analysis and machine learning can be explored in future work, with the potential to generate articles dedicated to predictive models or the evaluation of environmental policies. Thus, the present study offers not only a robust diagnosis but also a foundation for applied and academic developments that contribute to the territorial sustainability of Maricá.

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