Integrating Remote Sensing and MOLUSCE to Map and Predict Land Degradation in Baton Rouge

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Abstract

Land degradation, driven primarily by deforestation and urbanization, presents a growing threat to ecological integrity and sustainable development, particularly in rapidly urbanizing regions. This study analyzes historical land use and land cover (LULC) changes from 1994 to 2024 in East Baton Rouge Parish, Louisiana, and projects future trends up to 2054 using the Modules for Land Use Change Simulations (MOLUSCE) plugin in QGIS. Utilizing Landsat satellite imagery, Random Forest classification, and neural network-based predictive modeling, the study categorizes LULC into closed forest, open forest, built-up areas, and water bodies. Key findings reveal significant land degradation (~19%) between 1994 and 2024, primarily driven by forest conversion to urban areas. However, the projection for 2024–2054 indicates a trend toward stabilization, with a slight increase in closed forest cover (+12.45 million m²) and minimal urban expansion (+0.3%). The research highlights the urgency of proactive land-use planning, reforestation policies, and improved modeling techniques to mitigate long-term degradation. These insights provide vital guidance for policymakers, urban planners, and environmental stakeholders aiming to balance development and conservation in the Baton Rouge metropolitan region.

1. Introduction

Land degradation is increasingly framed as a negative, long-term trend in land condition**,** expressed as a reduction in biological productivity, ecological integrity, or value to humans, driven by human activities and, in many settings, compounded by climate-related pressures (IPCC, 2019). In policy terms, the United Nations Convention to Combat Desertification similarly emphasizes land degradation as the reduction or loss of biological or economic productivity of land systems linked to land uses and habitation patterns (UNCCD, 1994). Together, these definitions underscore that land degradation is not limited to “dryland desertification” but can also occur in humid, metropolitan landscapes, where development alters vegetation cover, soils, and hydrologic function over time.

One prominent pathway of degradation in rapidly urbanizing regions is urban expansion, in which forested and other permeable land cover is converted to built environments. This conversion typically increases surface sealing, fragments habitats, and reduces ecosystem functions that support environmental quality and resilience. From a monitoring perspective, these changes are well-suited to remote sensing because they leave strong, spatially explicit signatures in land cover composition and configuration. The multi-decadal Landsat program archive is especially valuable for metropolitan-scale analysis because it provides a consistent record of medium-resolution Earth observation extending back to 1972, enabling standardized land-cover mapping and change detection over long periods (Wulder et al., 2022; USGS, 2008).

Within East Baton Rouge Parish, the Baton Rouge metropolitan region continues to experience land-use transitions that can manifest as land degradation when vegetation loss and landscape conversion outpace conservation, restoration, and sustainable planning efforts. While historical land-cover mapping is essential for documenting these transitions, decision-making also requires forward-looking evidence**:** planners and environmental stakeholders need to understand not only where degradation has occurred, but where it is likely to intensify if current transition dynamics continue. This has motivated the growing use of land-change simulation models that combine observed transitions with spatial drivers to generate plausible future land-cover scenarios.

To address this need, this study integrates multi-temporal remote sensing with spatially explicit land-change modeling to map and predict land degradation from 1994 to 2054. Historical land use/land cover (LULC) maps (1994–2024) were produced from Landsat imagery using a Random Forest classifier, an ensemble machine-learning approach that is widely used in remote sensing because of its strong performance, ability to handle nonlinear relationships, and robustness to noisy inputs (Breiman, 2001; Belgiu & Drăguţ, 2016). The resulting LULC products were then used in the MOLUSCE (Modules for Land Use Change Simulations) framework for transition analysis and simulation, which supports transition-potential modeling (including artificial neural networks) and validation options appropriate for land-change forecasting (QGIS MOLUSCE plugin documentation; Muhammad et al., 2022). Because this workflow is built on widely accessible tools and standardized Earth observation products, it is designed to be reproducible and extensible for future monitoring updates.

The objectives of this research are to: (1) map and quantify historical LULC change in East Baton Rouge Parish from 1994 to 2024 using Landsat imagery; (2) estimate the magnitude and spatial distribution of land degradation, operationalized as conversion of forest/vegetated classes to built-up land; (3) model transition dynamics and transition potentials using MOLUSCE; and (4) simulate future LULC patterns from 2024 to 2054 to support proactive planning, conservation, and restoration strategies. By coupling long-term remote sensing with scenario-oriented simulation, the study provides an evidence base for anticipating land degradation risks and aligning land-use policy with sustainable development goals.

2. Study Area

East Baton Rouge Parish (EBRP) is located in southeastern Louisiana and forms the core of the Baton Rouge metropolitan area. The parish has a land area of 455.493 mi² and a water area of 14.852 mi² (total ≈ 470.345 mi²**)** based on the U.S. Census Bureau's county file for Louisiana. (U.S. Census Bureau, 2025). Baton Rouge, the parish's principal city, is also the state capital of Louisiana**,** making EBRP a central administrative and economic hub with a diverse mix of residential, commercial, industrial, and transportation land uses. (City of Baton Rouge–Parish of East Baton Rouge, n.d.).

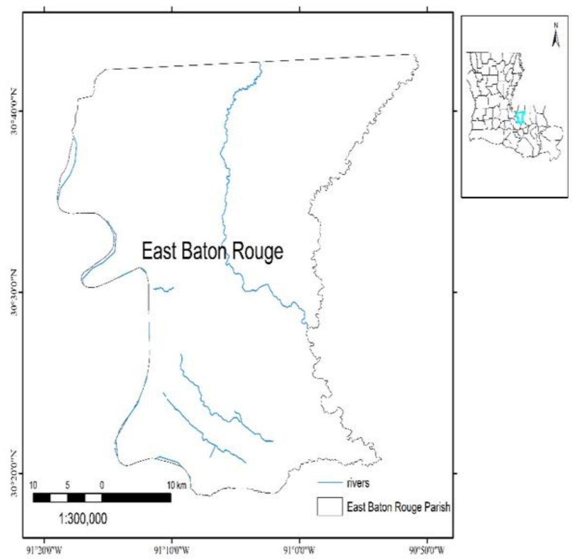

Fig 1 Study area map

Demographically, EBRP had an estimated population of 453,022, indicating sustained development pressure and continued demand for land conversion along urban and suburban growth fronts. (U.S. Census Bureau, 2024). Ecologically, the parish includes and is influenced by Louisiana's broader wetland–forest systems, which are widely recognized as highly valuable and sensitive landscapes that support biodiversity, provide critical functions (e.g., water and habitat resources), and are vulnerable to human-driven stressors and land conversion. (U.S. Geological Survey, 2014; Williams, n.d.).

3. Methods

3.1 Data sources and inputs

This study integrates multi-temporal satellite remote sensing and land-change simulation to map and predict land degradation in East Baton Rouge Parish (EBRP). Two primary Landsat epochs were used to represent historical and contemporary land-cover conditions: Landsat 5 TM (1994) and Landsat 8 OLI (2024)**.** These epochs were selected to capture long-term land-cover transitions across 30 years using consistent medium-resolution imagery suitable for parish-scale analysis. In addition to spectral imagery, auxiliary spatial drivers commonly associated with land conversion were compiled for land-change modeling, including digital elevation model (DEM)**,** slope (derived from DEM), and transport accessibility proxies (e.g., roads). These drivers were used within MOLUSCE to support transition potential modeling and spatial allocation of future land-cover change.

3.2 Image preprocessing and harmonized LULC legend

Landsat images were prepared for supervised classification using standard preprocessing steps appropriate for LULC mapping, including selecting images to minimize cloud contamination, masking invalid pixels as needed, and preparing band stacks. A consistent LULC classification scheme was applied across epochs to ensure comparability during change detection and simulation. Four classes were mapped:

1. Closed forest
2. Open forest
3. Built-up
4. Water

Training samples were digitized to represent the spectral variability of each class across the study area. To reduce class bias and improve model generalization, training data were distributed across both urban and peri-urban landscapes and included representative examples of each class.

3.3 LULC classification using Random Forest

LULC maps for 1994 and 2024 were produced using a Random Forest (RF) classifier. RF is an ensemble learning method that constructs multiple decision trees using bootstrapped samples and aggregates predictions by majority vote. For a pixel with feature vector x, the RF class prediction can be expressed as:

$$y(x) = mode\ \{h_b(x)\}_{b=1}^{B}, \qquad 1$$

where h_b is the class predicted by the b-th tree, and B is the total number of trees. RF was used because it is robust to noise, handles non-linear class boundaries, and performs well with multispectral remote sensing predictors.

3.4 Change detection and land degradation metric

Land-cover change was quantified using post-classification comparison**,** which identifies transitions by cross-tabulating the categorical LULC maps from two periods. Let C_{t1} and C_{t2}be the classified maps at times t_1 and t_2. The transition from class i to class j is represented by the set of pixels satisfying C_{t1}=I and C_{t2}=j

Land degradation was operationalized as forest conversion to built-up areas, reflecting deforestation-driven urban expansion. The degradation area A_{deg} was computed as:

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$$A_{deg} = A_{ClosedForest \rightarrow BuiltUp} + A_{OpenForest \rightarrow BuiltUp}, \quad 2$$

Moreover, the percent degradation over the historical period was computed as:

$$\%Deg = \frac{A_{deg}}{A_{total}} \times 100, \quad 3$$

where A_{total} is the total mapped land area (excluding masked pixels and permanent water if treated separately)

3.5 LULC prediction using MOLUSCE (Markov + MLP + Cellular Automata)

Future land-cover patterns for 2024–2054 were simulated using the MOLUSCE plugin in QGIS, which combines (i) transition probability estimation, (ii) transition potential modeling, and (iii) spatial allocation using a Cellular Automata (CA) framework.

3.5.1 Transition probability estimation (Markov structure)

Observed transitions between 1994 and 2024 were summarized into a transition count matrix $N=[n_{ij}]$where n_{ij} is the number of pixels that changed from class i to class j. Transition probabilities were then computed as:

$$p_{ij} = \frac{n_{ij}}{\sum_{j=1}^{m} n_{ij}} \qquad \text{for } i = 1, \ldots, m, \quad 4$$

where m is the number of classes and $\sum_j p_{ij} =1$for each origin class i. This yields a Markov transition matrix P, which is used to estimate the amount of future change.

3.5.2 Transition potential modeling (MLP neural network)

To model where transitions are likely to occur, MOLUSCE uses driver variables (e.g., roads, slope, elevation) and learns a transition potential surface using a multilayer perceptron (MLP) neural network. In general form:

$$h = f(Wx + b), \;\; \hat{p} = \sigma(Vh + c), \quad 5$$

where x is the vector of drivers at a pixel, h is the hidden-layer representation, f is a non-linear activation function, σ maps outputs to probabilities, and $\hat{p}$ represents the predicted transition potential (probability) for one or more transitions.

3.5.3 Spatial allocation (Cellular Automata simulation)

MOLUSCE allocates predicted change spatially using Cellular Automata, which represent neighborhood effects. Conceptually, the state of pixel i at time t +1 is assigned based on the transition probability/potential and neighborhood influence:

$$C_i^{t+1} = {}^{\arg}\underset{j}{max} \left[T_{ij} \times S_{ij} \times N_{ij}\right], \quad 6$$

where T_{ij} represents Markov-type transition likelihood from class i to j, S_{ij} represents suitability/transition potential from the MLP, and N_{ij} represents neighborhood influence promoting spatial contiguity. The output is a simulated LULC map for 2054.

3.6 Accuracy assessment and validation

Classification accuracy was assessed using a confusion matrix comparing classified outputs to reference samples. Overall accuracy (OA) was computed as:

$$OA = \frac{\sum_{k=1}^{m} n_{kk}}{N}, \quad 7$$

where n_{kk} are diagonal elements (correct classifications), m is the number of classes, and N is total validation samples.

Agreement beyond chance was quantified using the Kappa coefficient:

$$k = \frac{P_o - P_e}{1 - P_e}, \quad 8$$

where P_o = OA and the chance agreement P_e is:

$$P_e = \sum_{k=1}^{m} \left(\frac{n_{k+}}{N} . \frac{n{+k}}{N}\right), \quad 9$$

with $n_{k+}$the total of row k and n+k the total of column k in the confusion matrix. In addition to these metrics, simulated outputs were evaluated by comparing the spatial distribution of modeled classes with observed patterns where applicable

4. Results and Discussion

4.1 Classified LULC maps (1994 and 2024)

Figure 2 presents the Random Forest–classified LULC maps for 1994 (Landsat 5 TM) and 2024 (Landsat 8 OLI) using four classes: closed forest, open forest, built-up, and water. Across both periods, vegetated classes dominate the parish landscape. At the same time, built-up land is concentrated in and around the Baton Rouge urban core and extends outward along major transportation corridors and growth fronts. Water bodies remain spatially consistent and are primarily associated with major river and channel features.

Comparison of the 1994 and 2024 maps indicates a clear, spatially structured change signal driven by urban expansion**.** Built-up cover increases visibly from the central urban area and spreads outward, reflecting corridor-based development and edge growth. This expansion is accompanied by a corresponding reduction and fragmentation in forested land, particularly where closed/open forest transitions to built-up **areas** occur. The observed pattern is consistent with typical metropolitan growth processes, where development infills near existing built-up areas and then diffuses along arterial routes and into peri-urban zones.

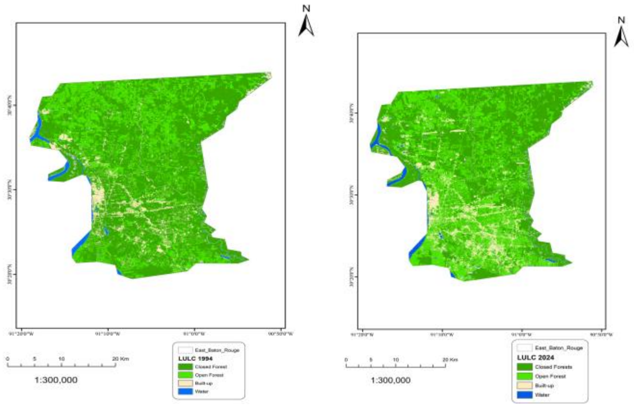

Figure 2. Random Forest–classified LULC maps for 1994 and 2024

4.2 LULC transitions and land degradation pathways (1994–2024)

Change detection between the 1994 and 2024 Random Forest LULC maps reveals that land-cover transitions in East Baton Rouge Parish are dominated by forest-to-built conversion, consistent with urban expansion as the primary degradation pathway (Figure 3). The transition map shows widespread conversion patches concentrated in and around the Baton Rouge urban core and extending along major corridors and peri-urban development fronts, indicating both infill and outward growth dynamics.

Quantitatively, closed forest loss to built-up accounted for approximately 61,164,000 m² (≈ 6.12 km²; 5.07%), while open forest loss to built-up contributed an additional 25,175,700 m² (≈ 2.52 km²; 2.09%). These transitions indicate that both dense and more fragmented forest/wooded cover types have been converted to developed land uses over the past 30 years, with closed forest conversion accounting for the greater share of forest loss.

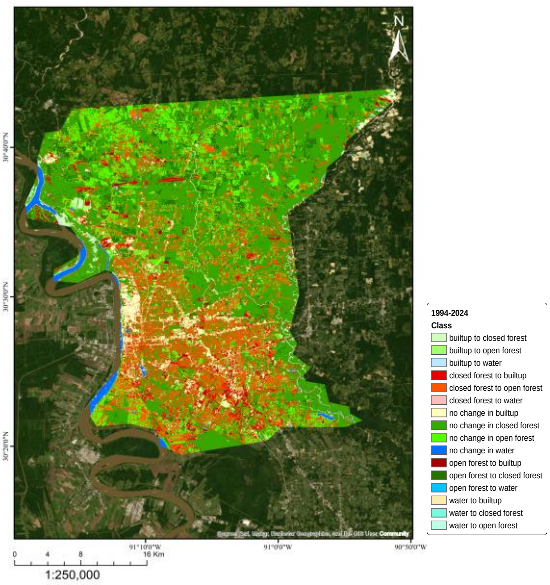

Fig 3. LULC change detection map

4.3 Forest cover trends and urban expansion magnitude

The forest cover trend plots show a clear downward trajectory from 1994 to 2024 for both closed and open forest classes, consistent with net vegetation removal associated with development. In contrast, built-up area increases substantially during the same period. The results indicate that the total built-up area increased by approximately 141,068,700 m² (141.07 km²), representing a 11.7% increase from the 1994 baseline (Figure 4). This expansion magnitude reinforces the spatial evidence of outward development and corridor-driven growth across the parish.

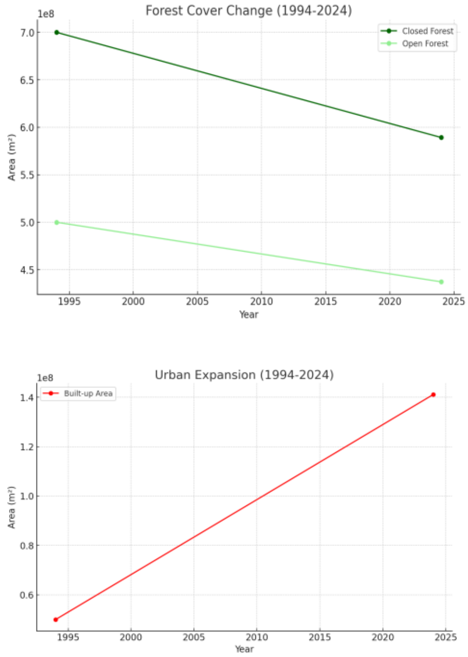

Fig 4. Forest cover trends and urban expansion magnitude

Aggregating transitions consistent with degradation (i.e., vegetated classes converted to built-up), the analysis indicates an overall degradation impact of approximately 19% of the total area over 1994–2024 (Figure 4). This finding confirms that long-term landscape change in EBRP is characterized by a substantial shift from vegetated land covers toward built surfaces, with implications for ecosystem service loss, increased surface sealing, and reduced landscape ecological function.

4.4 Predicted LULC patterns and spatial allocation (2024–2054)

The MOLUSCE simulation outputs indicate that the overall spatial configuration of land cover in East Baton Rouge Parish remains broadly similar (stabilization trend) between 2024 and the predicted 2054 map (Figure 5). Built-up land remains concentrated in the Baton Rouge urban core and along established development corridors, while forest classes continue to dominate the broader parish landscape. The predicted changes are expressed primarily as incremental adjustments near existing built-up edges and along corridor networks, patterns consistent with the neighborhood-contiguity logic embedded in cellular automata allocation.

Quantitative summaries from the 2024–2054 simulation suggest a stabilization trend relative to the stronger historical conversion observed during 1994–2024. Specifically, the model projects a closed forest increase of approximately +12,453,300 m² and a near-stable open forest change of approximately +533,700 m² over the projection period. In contrast, built-up area is projected to increase only slightly, by approximately +0.3%, indicating limited additional expansion under the transition dynamics learned from the historical period and the driver configuration used in MOLUSCE.

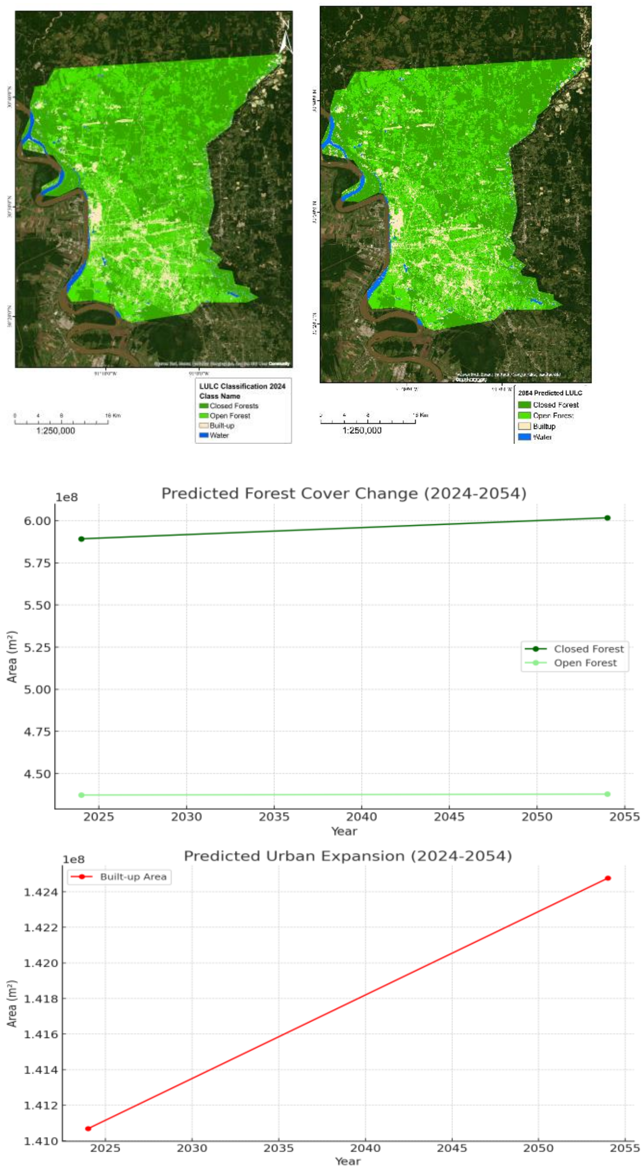

Fig 5. LULC patterns (2024-2054)

The simulated changes imply that, under the modeled transition probabilities and suitability surfaces, future land degradation may be slower than in the historical period. The modest built-up growth, combined with small net gains in closed forest, suggests a scenario in which continued development occurs but does not accelerate at the same pace as observed during 1994–2024. This stabilization signal may reflect saturation effects around existing built-up areas, constraints captured by the driver layers (e.g., terrain and accessibility), and/or the transition structure learned from the two historical snapshots. Practically, the projected pattern indicates that targeted land-use planning and reforestation efforts could maintain or improve vegetation cover if implemented proactively, particularly along development fronts where incremental conversion is most likely.

4.5 Discussion

Land degradation in East Baton Rouge Parish (EBRP) is expressed in this study as a sustained decline in land condition driven by land-cover conversion, especially forest loss to built-up land, consistent with widely used definitions that frame degradation as a reduction in the productivity/complexity of land systems caused by human activities (UNCCD, 1994; IPCC, 2019). The 1994–2024 change detection shows a strong, spatially structured urbanization signal, with conversions clustered around the Baton Rouge core and extending along corridors and peri-urban edges. Quantitatively, closed forest → built-up accounted for 61,164,000 m² (5.07%) and open forest → built-up for 25,175,700 m² (2.09%), alongside a net built-up increase of 141,068,700 m² (~141.07 km²; ~11.7%), supporting an overall degradation impact of roughly 19% of the mapped area.

Confidence in these transition estimates is strengthened by the high thematic accuracy of the LULC maps used for post-classification comparison. The Random Forest approach is widely recognized as a robust classifier for remote-sensing applications because it models nonlinear class boundaries and reduces overfitting through ensemble learning (Breiman, 2001; Belgiu & Drăguţ, 2016). In addition, the use of confusion-matrix metrics (overall accuracy) and chance-corrected agreement (Kappa) follows established guidance for assessing classified remote-sensing products and ensuring suitability for change detection (Congalton, 1991; Cohen, 1960). With overall accuracies near the mid-90% range and Kappa values >0.94 for both epochs, the mapped patterns of forest conversion and built-up expansion are unlikely to be artifacts of classification noise. They are appropriate for informing the simulation phase.

The MOLUSCE projections for 2024–2054 indicate a stabilization trend compared to the strong historical conversion signal, with only 0.3% additional built-up growth and small net gains in forest classes (closed forest 12,453,300 m²; open forest 533,700 m²). MOLUSCE implements a standard land-change modeling structure, transition analysis/probabilities, transition potential modeling (including neural networks), and cellular automata allocation that encourages contiguity and edge expansion near existing development. The spatial placement of predicted change near existing urban edges is consistent with established CA-based urban growth concepts (Clarke et al., 1997), and recent applied studies demonstrate that MOLUSCE CA–ANN/MLP frameworks can produce plausible land-change simulations when appropriately parameterized and validated. Interpreted as a scenario (rather than a guarantee), the projection suggests an opportunity window for proactive planning, focusing on conservation, corridor management, and reforestation/forest-protection measures along active growth fronts, which could help prevent a repeat of the higher historical degradation rates.

This contribution has been peer-reviewed.
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5.0 Conclusion

This study integrated multi-temporal satellite remote sensing and land-change simulation to map and forecast land degradation in East Baton Rouge Parish (EBRP). Using Random Forest classified Landsat LULC maps for 1994 and 2024, results show that degradation over the historical period is dominated by forest-to-built conversion, consistent with land degradation definitions that emphasize declining land condition and productivity due to human land-use change (UNCCD, 1994; IPCC, 2019). From 1994–2024, closed forest → built-up accounted for 61,164,000 m² (5.07%) and open forest → built-up for 25,175,700 m² (2.09%), while built-up land expanded by 141,068,700 m² (141.07 km²; 11.7%), contributing to an overall degradation impact of approximately 19% of the mapped area.

The reliability of these findings is supported by strong classification performance (OA ~94–95%; Kappa > 0.94), which is important because post-classification change detection depends directly on the quality of the thematic map (Congalton, 1991). The results, therefore, provide a defensible baseline for understanding where and how land degradation has progressed in EBRP, highlighting corridor- and edge-growth patterns that are most associated with forest loss and landscape transformation.

Projections using MOLUSCE (Markov transition structure, MLP transition potential, and CA spatial allocation) suggest a stabilization tendency for 2024–2054, with only 0.3% additional built-up growth and small net gains in forest cover (closed forest +12,453,300 m²; open forest +533,700 m²) (Clarke et al., 1997; QGIS MOLUSCE, n.d.). Interpreted as a scenario conditioned on the observed transition dynamics and selected drivers, this outcome indicates that proactive planning—especially along identified growth fronts and corridors—could meaningfully reduce future forest loss and support restoration or protection strategies. Overall, the workflow provides a transparent, reproducible approach for long-term monitoring and forecasting of land degradation at metropolitan scale, supporting evidence-based land-use decisions that balance development and conservation.

6. Acknowlegment

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