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Comparative Assessment of Machine Learning Algorithms in Characterizing Urban Sprawl in Benin City

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Abstract- Urban growth across Sub-Saharan Africa is occurring at an unprecedented pace, often without adequate planning control. In cities such as Benin City, Nigeria, this expansion is reshaping landscapes, accelerating forest loss, and increasing environmental vulnerability. This study comparatively assesses two widely used machine learning algorithms: Support Vector Machine (SVM) and Random Forest (RF), in mapping and characterizing urban sprawl using multi-temporal Landsat imagery from 2014, 2019, and 2024.Supervised classifications were performed to generate land use/land cover (LULC) maps, and classification accuracy was evaluated using confusion matrices, Overall Accuracy (OA), Kappa statistics, and class-level accuracies. Post-classification change detection, land cover transition analysis, transportation corridor buffering, and Digital Elevation Model (DEM) assessment were employed to examine spatial growth patterns and their environmental implications. The results show that built up land increased dramatically from approximately 13% to 18% in 2014 to about 35% to 36% in 2024. Conversely, forest cover declined from over 47% to 56% to less than 12% to 16% during the same period. Nearly 79% of new urban development occurred within 1 km of major road corridors, while about 68% took place in medium elevation zones. Although both algorithms performed strongly, SVM demonstrated more consistent and stable classification accuracy across years. The findings highlight that the scale of urban transformation in Benin City and underscore the value of machine learning based monitoring in supporting sustainable urban planning and environmental management.

I. INTRODUCTION

Urbanization has become one of the most powerful forces reshaping land surfaces in the Global South. In Nigeria, urban expansion is frequently characterized by limited regulatory enforcement, infrastructure led growth, and conversion of ecologically sensitive land (Odjugo et al., 2015; Odeyale, 2023). Benin City provides a clear example of this transformation. Once dominated by dense tropical forest, the city has rapidly evolved into a complex urban and peri-urban landscape (Iduseri et al., 2024).

Monitoring this transition is essential for effective planning. However, traditional approaches such as field surveys and manual GIS interpretation are often time-consuming and struggle to keep pace with rapid change (Alsharif and Pradhan, 2014; Krishnaveni and Anilkumar, 2020). The integration of machine learning (ML) with satellite remote sensing has therefore emerged as a practical and efficient alternative (Mao et al., 2020; Wang et al., 2024).

Among the ML algorithms, Support Vector Machine (SVM) and Random Forest (RF) are particularly popular due to their ability to model nonlinear relationships and handle high-dimensional data (Belgiu and Drăguţ, 2016). Nevertheless, the comparative effectiveness of these models in tropical, heterogeneous urban environments such as Benin City remains insufficiently explored. This study addresses that gap.

II. METHODOLOGY

Study Area

Benin City lies between latitudes 6°12'38.36" N to 6°27'25.00" N, and longitudes 5°29'46.03" E to 5°45'00.41" E within Nigeria’s humid tropical rainforest belt. The area experiences annual rainfall of about 2,000 mm and mean temperatures of 27°C to 28°C (Okhakhu, 2018). The terrain is gently undulating and drained by the Ikpoba and Ogba Rivers. These environmental characteristics make the area both ecologically rich and vulnerable to land conversion pressures.

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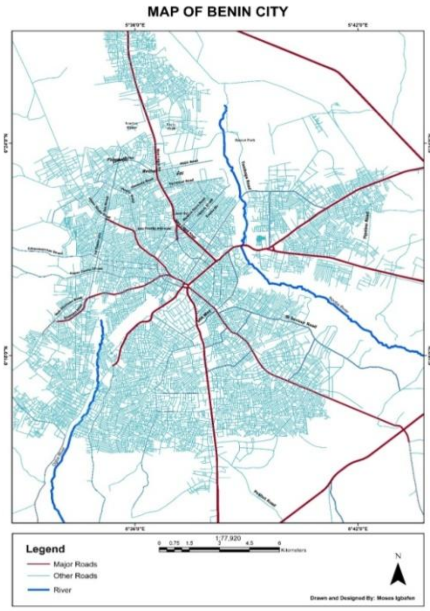

Figure 1: Map Showing Benin City as the Study Area

Data and Image Processing

Landsat OLI/TIRS imagery for 2014, 2019, and 2024 (30 m resolution) was used. Images were preprocessed through radiometric and geometric correction, cloud masking, and clipping to the study boundary.

Four land use/land cover classes were identified: Built-up, Forest, Grassland, and Bare land. A stratified random sampling approach generated 70% training and 30% validation datasets. SVM utilized a nonlinear kernel to maximize class separability, while RF applied bootstrap aggregation and random feature selection to construct multiple decision trees.

Classification accuracy was evaluated using Overall Accuracy, Kappa coefficient, User's Accuracy, and Producer's Accuracy.

III. RESULTS AND FINDINGS

A. Spatial and Temporal Patterns of Urban Sprawl (2014–2024)

SVM Classification Results

Table 1

SVM LULC Classification of Benin City (2014, 2019 and 2024)

Land Cover	Area (km²) 2014	% 2014	Area (km²) 2019	% 2019	Area (km²) 2024	% 2024
Grassland	402.94	29.93	598.66	44.48	643.20	47.79
Bare-land	6.85	0.51	9.94	0.74	4.69	0.35
Forest	749.87	55.71	361.41	26.85	213.63	15.87
Built up	186.38	13.85	376.03	27.94	484.48	35.99

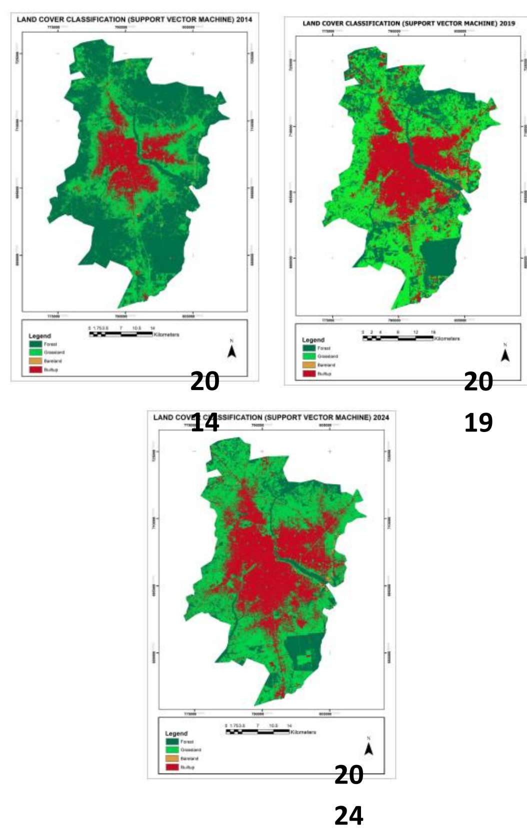

Figure 2: LULC Classification of Benin City Using Support Vector Machine (2014, 2019 and 2024)

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In 2014, forest dominated the landscape at 55.71% (749.87 km²), followed by grassland (29.93%) and built up areas (13.85%). By 2019, built up areas had nearly doubled to 27.94%, while forest cover declined sharply to 26.85%. Grassland increased to 44.48%, suggesting vegetation disturbance and transitional land conversion.

By 2024, built up land further expanded to 35.99% (484.48 km²), while forest reduced drastically to 15.87%. Over the ten-year period, built-up increased by 298.09 km², while forest declined by 536.24 km². These results clearly demonstrate rapid outward urban growth primarily at the expense of forest ecosystems.

Random Forest Classification Results

Table 2
Random Forest LULC Classification of Benin City (2014, 2019 and 2024)

Land cover	Area (km²) 2014	% 2014	Area (km²) 2019	% 2019	Area (km²) 2024	% 2024
Grassland	437.62	32.51	659.66	49.01	707.11	52.54
Bare-land	24.89	1.85	6.82	0.51	3.77	0.28
Forest	638.54	47.44	365.41	27.15	161.16	11.97
Built up	244.97	18.20	314.16	23.34	473.97	35.21

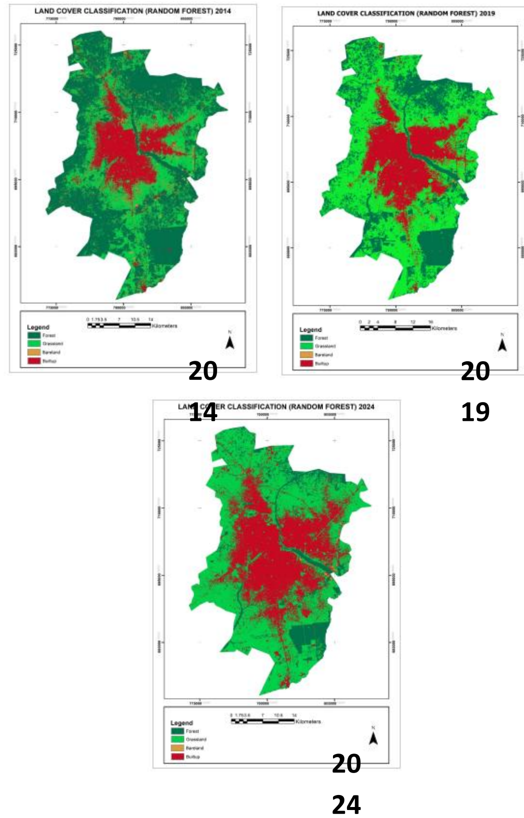

Figure 3: LULC Classification of Benin City Using Random Forest (2014, 2019 and 2024)

The RF model revealed similar trends. In 2014, forest accounted for 47.44% and built-up 18.20%. By 2024, built up had reached 35.21%, while forest declined to 11.97%. Although percentage distributions differ slightly between models, both confirm accelerated urban expansion and substantial ecological loss.

B Land Cover Transition Dynamics
Transition analysis reveals a consistent two stage transformation process:
Forest → Grassland → Built-up
Large areas of forest were first degraded into grassland before eventual urban conversion. Grassland therefore serves as an intermediate transitional class, reflecting progressive environmental degradation prior to permanent urban sealing.

C Factors Influencing Urban Sprawl
Corridor Influence

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Table 3
Major Corridor Impact on Urban Sprawling in Benin City

Feature	Area (Square Kilometer)	Percentage (%)
Area within Major Corridor 1km Buffer	384.529 km²	79.38%
Area outside Major 1km Buffer	99.947 km²	20.62%

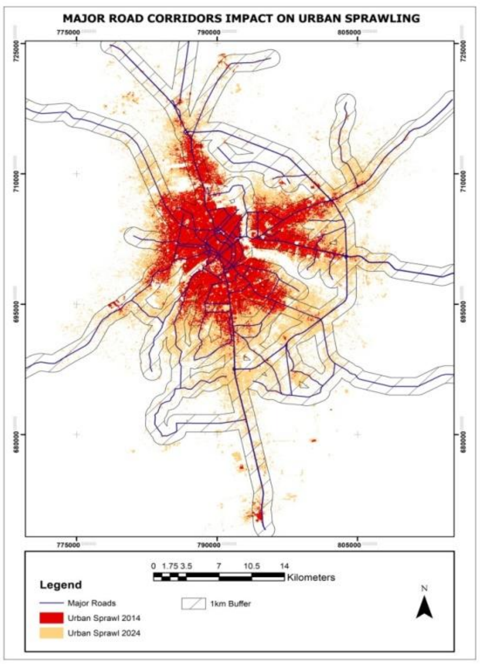

Figure 4: Major Corridor Impact on Urban Sprawling in Benin City

Approximately 79.38% of new urban development occurred within a 1 km buffer of major transportation corridors. This confirms that accessibility strongly shapes urban growth patterns, resulting in linear and ribbon-like expansion.

Elevation Influence

Table 4
Effect of Digital Elevation Model (DEM) on Urban Sprawling in Benin City

Feature	Area (km²)	Percentage (%)
Low	74.816 km²	24.24%
Med	211.225 km²	68.43%
High	22.612 km²	7.33%

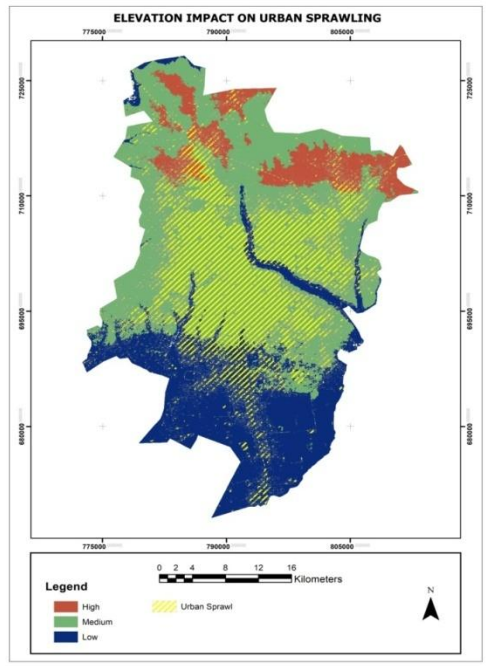

Figure 5: Effect of DEM on Urban Sprawling in Benin City

DEM analysis shows that 68.43% of sprawl occurred in medium-elevation zones. Moderately elevated terrain provides improved drainage and reduced flood risk, making it more attractive for development.

D Comparative Performance of SVM and RF

SVM maintained Overall Accuracy above 80% across all years, showing greater stability. RF demonstrated strong performance but exhibited noticeable fluctuation in 2019.

SVM achieved exceptionally high User Accuracy for built up areas in 2024, indicating minimal commission errors. Producer Accuracy results further suggests that

SVM offered stronger long term consistency in detecting complex urban vegetation boundaries.

Both models performed well; however, SVM demonstrated slightly greater reliability in heterogeneous tropical urban landscapes.

IV. CONCLUSION

This study confirms that Benin City is undergoing rapid and predominantly corridor driven urban expansion over the past decade. This growth has come at a significant environmental cost, particularly in the form of widespread forest loss and noticeable landscape transformation between 2014 and 2024. The extent of these changes raises important concerns about biodiversity conservation, surface runoff patterns, flood vulnerability, and the broader sustainability of the urban environment.

Both Support Vector Machine (SVM) and Random Forest (RF) algorithms performed well in mapping and monitoring these changes. However, SVM demonstrated slightly greater consistency and precision in distinguishing complex urban and vegetation classes within the study area, making it particularly suitable for similar heterogeneous tropical environments.

Considering the speed and environmental implications of the observed urban growth, there is a clear need for more proactive and data-informed planning interventions. Establishing machine learning based urban monitoring systems within state planning agencies would allow for continuous tracking of land transformation and support evidence-based decision-making. Strengthening corridor-sensitive zoning regulations could help reduce uncontrolled ribbon development, while incorporating ecological buffer zones into urban master plans would contribute to protecting remaining forest areas. Furthermore, integrating higher-resolution satellite imagery and relevant socio-economic data in future studies would improve predictive modeling and enhance long-term sustainable urban planning strategies.

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