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MAPPING URBAN EXPANSION IN BENIN CITY, NIGERIA (2000–2024) USING LANDSAT TIME SERIES AND MACHINE LEARNING

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Abstract

Rapid urban expansion poses significant challenges for sustainable land management in many cities across sub-Saharan Africa. This study assesses the spatial and temporal patterns of urban expansion in Benin City, Nigeria, between 2000 and 2024 using multi-temporal Landsat imagery and machine-learning classification. Landsat 5, 7, 8, and 9 surface reflectance data were processed and classified using a Random Forest algorithm into four land use/land cover classes: built-up, vegetation, water, and bare land. Classification accuracy was evaluated using independent validation samples, yielding an overall accuracy of approximately 71%. To reduce spectral ambiguity between built-up and bare surfaces and to address temporal inconsistencies common in pixel-based classification, built-up and bare land were aggregated into a single urban class, and urban expansion was analyzed using a cumulative urban footprint approach. Results show that cumulative urban area increased from approximately 1,584 km² in 2000 to 1,914 km² in 2024, representing a net increase of about 331 km² (20.9%). Urban expansion was spatially concentrated around the city core and along major transportation corridors, with notable outward growth between 2000 and 2020, followed by a slower expansion rate in recent years. The findings demonstrate the effectiveness of combining Landsat time-series data with machine-learning techniques for long-term urban expansion analysis and provide valuable insights for urban planning and sustainable development in rapidly growing Nigerian cities.

Keywords: *Urban expansion, LULC classification, Landsat imagery, Random Forest classifier, Machine learning, Benin City, Nigeria*

Introduction

Urban expansion and land use/land cover (LULC) change are among the most pervasive landscape transformations associated with population growth, economic development, and rural-to-urban migration, particularly in rapidly urbanizing regions of sub-Saharan Africa (Gyile *et al*., 2025). Remote sensing and geographic information systems (GIS) have become indispensable tools for monitoring these changes over time, offering consistent, spatially explicit observations at decadal or multi-decadal scales (Sharma *et al*., 2024; Tharik *et al*., 2025. Satellite time series, especially from the Landsat program, provide high-quality, long-term data that enable robust assessment of urban growth patterns, impervious surface expansion, and vegetation dynamics (Vohra *et al*., 2024).

Machine learning algorithms, such as Random Forest, have gained prominence in LULC classification because of their ability to handle high-dimensional data and to improve classification accuracy compared with traditional methods (Kasahun and Legesse, 2024; Shandu *et al*., 2026). Random Forest classifiers have been widely applied to map urban and non-urban land use categories from Landsat imagery, yielding reliable results across diverse geographic contexts (Bogale *et al*., 2025). Such approaches support evidence-based planning and enable quantification of spatio-temporal patterns of urban expansion (Ahouandjinou *et al*., 2025; Ioannidis *et al*., 2025). Evaluation of classification accuracy, typically through confusion matrices and metrics such as overall accuracy and Kappa statistics, is crucial for validating the reliability of LULC maps derived from remote sensing data (Gülci *et al*., 2025; Zhang *et al*., 2024).

Benin City, one of Nigeria's major urban centers, has experienced rapid expansion in recent decades as the population and built environment have grown (Fabolude and Aighewi, 2022). Historical analyses of Benin City have highlighted trends of increasing built-up area at the expense of vegetation and agricultural lands, with implications for local climate, ecosystem services, and planning frameworks (Fabolude and Aighewi, 2022). Such transformation is emblematic of broader trends across many medium-sized cities in West Africa, where urban sprawl, informal settlement growth, and infrastructure development have altered land cover patterns substantially.

Despite the clear value of remote sensing for urban studies, challenges remain in producing temporally consistent and physically interpretable LULC change products, particularly when integrating data across multiple satellite sensors and classification methods. Differences in sensor characteristics, spectral responses, and classification uncertainty can lead to noise and temporal instability in per-pixel change estimates, complicating interpretation of long-term urban dynamics. Addressing these issues requires careful preprocessing, accuracy assessment, and analytical frameworks that account for temporal consistency (Baidoo and Obeng, 2023; Yin *et al*., 2021).

This study employed multi-temporal Landsat imagery and a Random Forest classification framework to map and quantify urban expansion in Benin City, Nigeria, from 2000 to 2024. By aggregating built-up and bare land into a unified urban class and applying a cumulative-footprint approach, the research provides robust estimates of spatial and temporal trends in urban area change. The findings contribute to understanding long-term urbanization patterns in a rapidly growing African city and offer insights for sustainable land management and urban planning efforts.

Methodology

Study Area

Benin City is located in southern Nigeria at approximately 6.34° N latitude and 5.60° E longitude (WGS 84) and serves as a major administrative, commercial, and cultural center in Edo State. The city lies within the tropical rainforest zone and has experienced sustained population growth and spatial expansion over recent decades. Rapid urban development, infrastructure expansion, and land conversion have transformed large portions of the surrounding landscape, making Benin City a suitable case study for long-term urban expansion analysis using satellite remote sensing. (Fabolude and Aighewi, 2022).

Data Sources

Multi-temporal Landsat surface reflectance imagery was used to analyze urban expansion between 2000 and 2024. Landsat scenes were obtained for four representative epochs: 2000 (Landsat 5 TM), 2010 (Landsat 7 ETM+), 2020 (Landsat 8 OLI), and 2024 (Landsat 9 OLI-2). All images were accessed and processed using Google Earth Engine (GEE), which provides cloud-based access to harmonized Landsat Collection 2 Level-2 surface reflectance products.

The Landsat Collection 2 dataset includes radiometrically and atmospherically corrected imagery, ensuring consistency across sensors and acquisition dates. Images were selected within comparable seasonal windows to minimize phenological variation and were clipped to the administrative boundary of Benin City, derived from the FAO Global Administrative Unit Layers (GAUL).

Image Pre-Processing

Pre-processing steps were carried out in Google Earth Engine to ensure consistency across the multi-temporal dataset. For each epoch, available Landsat scenes covering the study area were filtered by date and spatial extent and composited to produce a representative image for that year. Optical bands were scaled to surface reflectance values using the scaling coefficients provided with the Landsat Collection 2 products.

To enhance land cover separability, several spectral indices commonly used in urban and vegetation studies were computed, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), Modified Normalized Difference Water Index (MNDWI), and Bare Soil Index (BSI). These indices were combined with the original spectral bands to form the predictor variables used in classification.

Land Use/Land Cover Classification

Land use/land cover classification was performed using the Random Forest (RF) algorithm, a non-parametric ensemble machine-learning method widely applied in remote sensing due to its robustness, ability to handle high-dimensional data, and strong classification performance (Frimpong and Molkenthin, 2021) RF classification was implemented using training samples derived from reference land cover data and visual interpretation of high-resolution imagery.

Four LULC classes were defined: built-up, vegetation, water, and bare land. Training samples were generated using a stratified sampling approach to ensure balanced representation of each class. The classifier was trained using spectral bands and derived indices as input features. Classification accuracy was evaluated using independent validation samples, and standard accuracy metrics including confusion matrices, overall accuracy, and Kappa statistics were computed.

Urban Class Aggregation and Change Analysis

Pixel-based classification of multi-temporal Landsat imagery is often affected by spectral confusion between built-up surfaces and bare land, as well as temporal inconsistencies caused by mixed pixels and sensor differences. To reduce these effects and improve the interpretability of long-term urban change, built-up and bare land classes were aggregated into a single urban category for change analysis, following common practice in urban remote sensing studies (Yin *et al*., 2021).

Urban expansion was analyzed using a cumulative urban footprint approach. For each epoch, pixels classified as urban were identified, and a cumulative map was generated by retaining pixels that were classified as urban in any previous or subsequent year. This approach assumes that once land is converted to urban use, it does not revert to non-urban land cover at the city scale, thereby reducing spurious urban loss caused by classification noise.

Area Estimation and Temporal Analysis

Urban area for each epoch was calculated by counting the number of urban pixels and converting pixel counts to area (km²) based on the Landsat spatial resolution. Net and percentage changes in urban area were computed between 2000 and 2024 using the cumulative urban footprint results. Spatial patterns of urban expansion were further examined through urban expansion maps highlighting areas that transitioned from non-urban to urban land during the study period.

Visualization and Post-Processing

Final classified maps and urban expansion results were exported for visualization and analysis in Python and GIS environments. Map layouts were standardized across epochs to ensure consistent visual comparison. Figures were designed to emphasize spatial patterns of urban expansion while minimizing visual clutter, using uniform color schemes, shared legends, and clear map annotations.

Results

Land Use/Land Cover Classification Accuracy

The Random Forest classifier produced land use/land cover (LULC) maps for Benin City for the years 2000, 2010, 2020, and 2024. Four LULC classes were identified: built-up, vegetation, water, and bare land. Accuracy assessment using independent validation samples yielded an overall classification accuracy of approximately 71%, with class-specific accuracies varying across categories. Vegetation and water classes exhibited higher classification reliability, while some confusion was observed between built-up and bare land, reflecting known spectral similarities between these surfaces at Landsat spatial resolution. Despite these limitations, the classification results were spatially coherent and consistent across epochs, providing a suitable basis for analyzing long-term urban expansion patterns.

Spatial Patterns of Land Use/Land Cover Change

The LULC maps (Figure 1) reveal clear spatial differences in land cover distribution across the four study years. In 2000, built-up areas were largely concentrated within the urban core of Benin City, with extensive vegetation and bare land dominating the surrounding landscape. By 2010 and 2020, built-up areas had expanded outward from the city center, with noticeable growth along major transportation corridors and peri-urban zones. In 2024, urban land was more spatially extensive, reflecting continued outward expansion and densification. The maps illustrate the spatial distribution of built-up areas, vegetation, water bodies, and bare land, using a consistent color scheme to facilitate visual comparison across years. Vegetation cover showed a gradual reduction in proximity to expanding urban areas, while water bodies remained relatively stable in spatial extent throughout the study period.

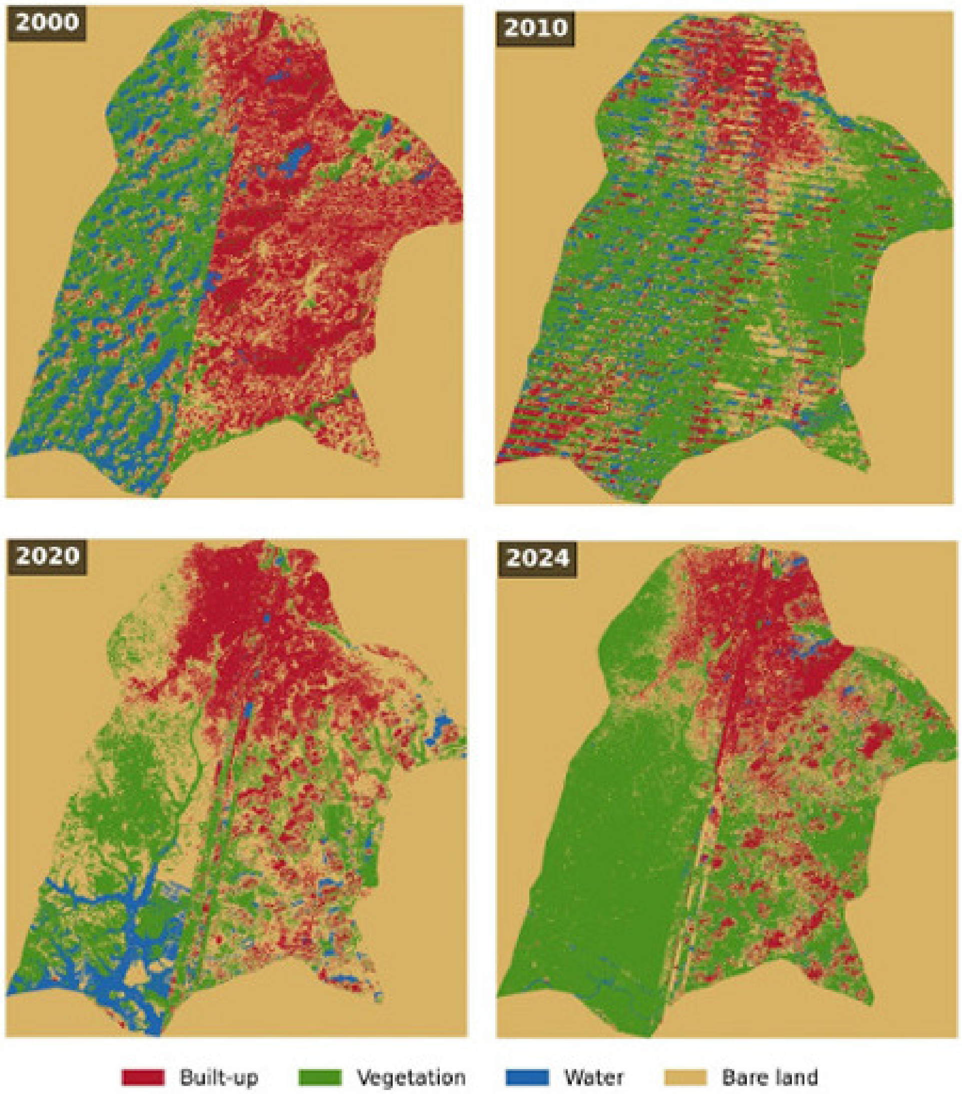

Fig. 1: Land use/land cover maps of Benin City for 2000, 2010, 2020, and 2024 derived from multi-temporal Landsat imagery using a Random Forest classifier.

Spatial Distribution of Urban Expansion

The spatial distribution of urban expansion between 2000 and 2024 is shown in Figure 2. Newly urbanized areas are primarily concentrated at the periphery of the existing urban core, indicating outward expansion rather than infill alone. Expansion is particularly evident along major road networks and in peri-urban zones, suggesting the influence of transportation infrastructure on urban growth patterns. Urban expansion was most pronounced between 2000 and 2020, while the period from 2020 to 2024 shows a relatively smaller increase in cumulative urban area, indicating a possible slowing of expansion in recent years.

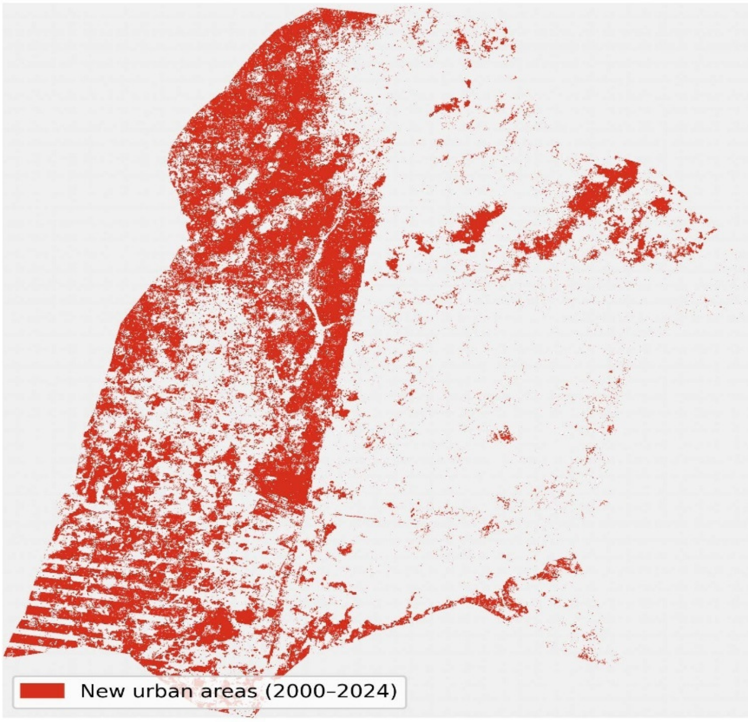

Fig. 2. Spatial distribution of urban expansion in Benin City between 2000 and 2024. Highlighted areas represent locations that transitioned from non-urban to urban land (built-up or bare land) during the study period, illustrating the dominant directions and peripheral patterns of long-term urban growth.

Urban Expansion Based on Cumulative Urban Footprint

To reduce the effects of spectral ambiguity and temporal instability inherent in pixel-based classification, built-up and bare land classes were aggregated into a single urban category, and urban expansion was quantified using a cumulative urban footprint approach. This method identifies areas that transitioned to urban land at any point during the study period and provides a robust representation of long-term urban growth.

The cumulative urban area increased steadily from 1,583.52 km² in 2000 to 1,731.53 km² in 2010, 1,905.33 km² in 2020, and 1,914.17 km² in 2024 (Figure 3). Overall, this represents a net increase of approximately 330.65 km², corresponding to a 20.88% increase in urban area between 2000 and 2024.

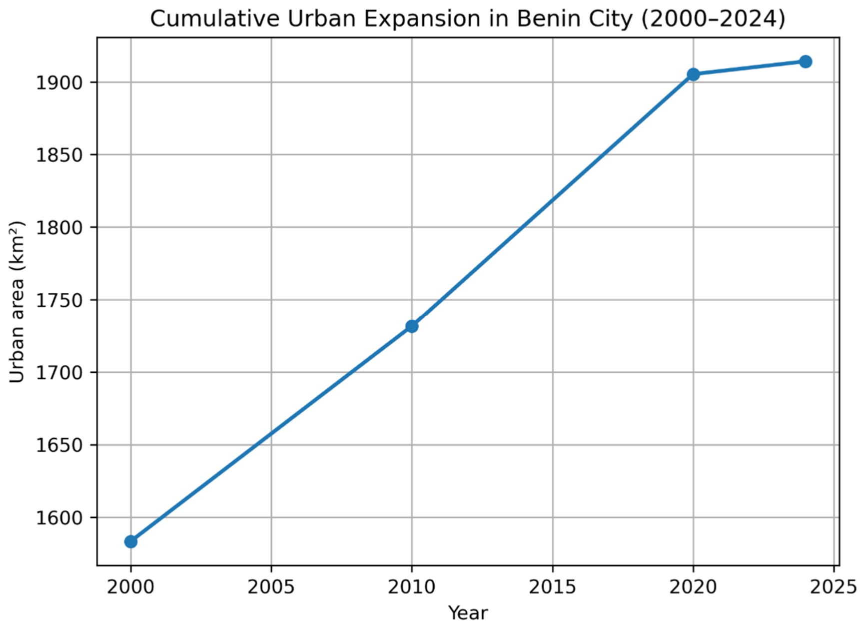

Fig. 3: Temporal trend of cumulative urban area in Benin City from 2000 to 2024 based on a cumulative urban footprint approach. Urban area increased steadily over the study period, reflecting sustained urban expansion.

Discussion

Urban Expansion Trends in Benin City

The results of this study reveal sustained urban expansion in Benin City between 2000 and 2024, with a cumulative increase of approximately 331 km², representing a 20.9% rise in urban area. This finding is consistent with broader urbanization trends observed in many medium-sized cities across sub-Saharan Africa, where population growth, economic development, and infrastructure expansion have driven outward urban growth (Koranteng *et al*., 2023; Yin *et al*., 2021). The spatial patterns observed; characterized by expansion from the urban core toward peripheral areas and along major transportation corridors, reflect typical modes of urban growth reported in similar urban contexts (Barman *et al*., 2024; Soltani *et al*., 2025).

The temporal trajectory of urban expansion indicates that growth was more pronounced between 2000 and 2020, followed by a relatively slower increase between 2020 and 2024. Comparable temporal patterns have been reported in other African cities, where rapid early expansion is often followed by periods of slower spatial growth or densification (Frimpong and Molkenthin, 2021). Although the specific drivers of these temporal variations were not examined in this study, the observed trends underscore the dynamic nature of urban growth and highlight the importance of long-term satellite monitoring for understanding urbanization processes (Yin *et al*., 2021).

Implications of the Cumulative Urban Footprint Approach

A key methodological contribution of this study is the application of a cumulative urban footprint approach to quantify long-term urban expansion. Traditional year-to-year comparisons of pixel-based land cover classifications can produce unrealistic patterns of urban loss due to spectral confusion, mixed pixels, and temporal inconsistencies, particularly when using moderate-resolution imagery such as Landsat (Barman *et al*., 2024; Soltani *et al*., 2025). By aggregating built-up and bare land into a unified urban category and assuming persistence of urban land once established, the cumulative approach reduces the influence of classification noise and yields physically interpretable urban growth trajectories.

The increase in urban area observed across the study period aligns with established urban land-use theory and empirical evidence from rapidly growing cities, where long-term reversal from urban to non-urban land cover is rare at the city scale Yin *et al*., 2021). Similar cumulative or persistence-based approaches have been adopted, either explicitly or implicitly, in previous urban remote sensing studies to improve the robustness of long-term urban change analysis (Frimpong and Molkenthin, 2021). These results demonstrate that cumulative metrics provide a reliable alternative for urban expansion studies when high-resolution temporal data are unavailable.

Classification Performance and Uncertainty

The overall classification accuracy of approximately 71% is comparable to values reported in other Landsat-based urban studies conducted in heterogeneous urban environments (Frimpong and Molkenthin, 2021; Koranteng *et al*., 2023). Higher classification accuracy was achieved for vegetation and water classes, while confusion between built-up and bare land persisted across epochs. This confusion reflects inherent spectral similarities between impervious surfaces and exposed soil at Landsat spatial resolution and is a well-documented limitation in urban remote sensing (Barman *et al*., 2024; Soltani *et al*., 2025).

Rather than attempting to eliminate this uncertainty through increasingly complex classification schemes, this study addressed it through class aggregation and analytical design. By explicitly acknowledging and accommodating classification uncertainty, the analysis prioritizes interpretability and temporal consistency over pixel-level precision. Similar methodological choices have been recommended in previous studies to strengthen confidence in long-term urban change estimates derived from moderate-resolution imagery (Yin *et al*., 2021).

Comparison with Previous Studies

The magnitude and spatial patterns of urban expansion observed in this study are broadly consistent with findings from other West African cities analyzed using Landsat imagery and machine-learning techniques. Studies conducted in cities such as Kumasi and other rapidly urbanizing regions have reported outward expansion patterns, vegetation loss at urban fringes, and the influence of transportation corridors on growth direction (Frimpong and Molkenthin, 2021; Koranteng *et al*., 2023). While direct numerical comparison is constrained by differences in study periods, spatial extents, and classification schemes, the overall urbanization trends observed in Benin City align with regional urban growth dynamics documented in the literature (Yin *et al*., 2021).

Notably, the cumulative urban footprint approach adopted in this study distinguishes it from many previous analyses that rely on direct inter-annual area comparisons. This methodological choice enhances the physical realism of long-term urban change estimates and contributes to the growing body of research advocating for temporally robust urban expansion metrics in data-scarce environments (Barman *et al*., 2024; Soltani *et al*., 2025; Yin *et al*., 2021).

Implications for Urban Planning and Land Management

The observed expansion of urban land in Benin City has important implications for land management and sustainable urban planning. Continued outward growth into peri-urban areas may increase pressure on remaining vegetation, agricultural land, and ecosystem services, a pattern commonly reported in rapidly expanding African cities (Koranteng *et al*., 2023). The concentration of expansion along transportation corridors suggests opportunities for targeted planning interventions aimed at promoting compact development and efficient infrastructure use.

By providing spatially explicit and temporally consistent estimates of urban expansion, this study offers valuable information for planners and policymakers seeking to manage future growth. Similar studies have demonstrated the utility of remote sensing–based urban growth assessments for supporting land-use planning and sustainability initiatives (Frimpong and Molkenthin, 2021; Koranteng *et al*., 2023; Yin *et al*., 2021).

Limitations and Future Research

Despite its contributions, this study has several limitations. The use of moderate-resolution Landsat imagery constrains the ability to resolve fine-scale urban features and contributes to spectral confusion between certain land cover classes, particularly built-up and bare land (Dou *et al*., 2024; Shandu *et al*., 2026). Additionally, the cumulative urban footprint approach, while effective for long-term trend analysis, does not capture short-term land-use reversals or detailed intra-urban dynamics.

Future research could address these limitations by incorporating higher-resolution satellite data, such as Sentinel-2 or commercial imagery, to improve class separability and spatial detail. Integrating socio-economic data and urban infrastructure information would also enable more detailed analysis of the drivers and impacts of urban expansion. Furthermore, extending cumulative approaches to probabilistic or multi-resolution frameworks may enhance their applicability across diverse urban contexts (Yin *et al*., 2021).

Conclusion

This study examined long-term urban expansion in Benin City, Nigeria, from 2000 to 2024 using multi-temporal Landsat imagery and a Random Forest classification framework. By integrating Landsat time-series data with a cumulative urban footprint approach, the analysis provides a robust and physically interpretable assessment of urban growth in a rapidly developing African city.

Urban land expanded steadily during the study period, increasing from approximately 1,583 km² in 2000 to 1,914 km² in 2024, representing a net gain of about 331 km² (20.9%). Expansion was concentrated around the existing urban core and along major transportation corridors, with more rapid growth between 2000 and 2020 and a slower increase in recent years.

Methodologically, aggregating built-up and bare land into a single urban class and applying a cumulative framework reduced spectral ambiguity and temporal instability associated with moderate-resolution imagery. This approach improves the reliability of long-term urban expansion estimates derived from Landsat data.

Overall, the findings confirm sustained urban growth in Benin City and provide spatially explicit evidence to support urban planning and sustainable land-use management. Future research could incorporate higher-resolution imagery and socio-economic data to further refine understanding of urban growth drivers and impacts.

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