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Integrating Multi-Temporal Land Use Dynamics and GIS-Based Green Infrastructure Priority Mapping for Climate-Responsive Urban Planning in Ilorin Metropolis, Nigeria

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Abstract

Rapid urbanization in African cities increasingly drives vegetation loss, ecological fragmentation, thermal stress, and declining environmental resilience. This study examined the spatio-temporal dynamics of Land Use Land Cover (LULC) change and developed a Green Infrastructure (GI) priority framework for climate-responsive urban ecological planning in Ilorin Metropolis, Nigeria. Multi-temporal Landsat imagery for 2005, 2015, and 2025 was analyzed using Remote Sensing, GIS, Google Earth Engine (GEE), and Random Forest classification. Post-classification change detection revealed significant outward expansion of built-up land from 7,007.87 ha (3.57%) in 2005 to 28,981.44 ha (14.76%) in 2025, accompanied by substantial vegetation decline and increasing peri-urban fragmentation. Urban growth occurred mainly along major transportation and institutional corridors, including Ajase-Ipo road, Tanke, Ganmo, Airport road, and Eiyenkorin, with vegetation-to-built-up conversion emerging as the dominant transformation pathway. To support ecological planning, Land Surface Temperature (LST), NDVI, NDBI, slope, distance to roads, and distance to water bodies were integrated within a GIS-based Multi-Criteria Decision Analysis (MCDA) and Analytical Hierarchy Process (AHP) framework to identify GI priority zones. Very high-priority intervention areas were concentrated within densely urbanized districts, while high-priority peri-urban corridors were identified around rapidly expanding urban fringes. The study demonstrated the value of integrating multi-temporal urban growth assessment with ecological prioritization to support climate-responsive urban planning and sustainable metropolitan governance in rapidly urbanizing African cities.

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1.0 INTRODUCTION

Rapid urbanization has become one of the most significant drivers of environmental transformation in the twenty-first century, reshaping ecological systems, land-use patterns, and urban sustainability trajectories globally (Ellis, 2021; McGee & Mori, 2021). The accelerated expansion of built-up environments has intensified the conversion of vegetation, wetlands, and agricultural landscapes into impervious surfaces, resulting in ecological fragmentation, biodiversity decline, hydrological instability, and urban heat island effects (Ullah *et al*., 2023; Duan *et al*., 2025). These environmental pressures are particularly severe in rapidly urbanizing cities of the Global South, where population growth, infrastructural expansion, and weak land-use governance frequently exceed the capacity of metropolitan planning systems (Mohamed *et al*., 2020; Mashi *et al*., 2025). Consequently, balancing urban growth with ecological sustainability has become a major challenge within contemporary urban planning and climate adaptation discourse.

Sub-Saharan African cities increasingly exemplify these challenges due to rapid peri-urbanization, informal settlement growth, and uncontrolled land conversion processes. Although urbanization contributes significantly to economic growth and infrastructural development, it simultaneously accelerates vegetation loss, ecological fragmentation, and environmental degradation through continuous expansion into peri-urban landscapes (Asogwa *et al*., 2022; Sulaiman *et al*., 2025). Nigerian metropolitan regions, particularly secondary cities, have experienced substantial transformation of natural and agricultural landscapes into residential, commercial, and transportation infrastructure, thereby increasing environmental vulnerability and reducing ecological resilience (Njoku & Tenenbaum, 2022; Koko *et al*., 2022). These trends increasingly undermine broader sustainability objectives associated with climate adaptation, resilient urban development, and the Sustainable Development Goals (SDGs).

Specifically, the environmental consequences of uncontrolled urban growth directly threaten the realization of Sustainable Development Goal 11 (Sustainable Cities and Communities) and Sustainable Development Goal 13 (Climate Action), particularly in relation to urban resilience, inclusive ecological planning, climate adaptation, and sustainable land-use management. Consequently, climate-responsive spatial planning strategies capable of balancing urban expansion with ecological conservation are increasingly required within rapidly urbanizing African metropolitan regions.

Recent advances in Remote Sensing and Geographic Information Systems (GIS) have substantially enhanced the ability to monitor and model urban ecological transformation. Multi-temporal satellite imagery enables long-term assessment of Land Use Land Cover (LULC) dynamics, vegetation decline, thermal stress, and urban expansion processes (Limaye *et al*., 2025). In addition, cloud-based geospatial platforms such as Google Earth Engine (GEE) now facilitate efficient processing of large satellite datasets and reproducible metropolitan-scale environmental analysis (Essa & Lhissou, 2023). These developments have strengthened the role of integrated geospatial approaches within urban ecological planning and sustainability assessment.

Simultaneously, Green Infrastructure (GI) has emerged as a key climate-responsive planning strategy for enhancing ecological resilience in rapidly urbanizing metropolitan environments. GI comprises interconnected natural and semi-natural ecological systems, including urban forests, wetlands, parks, riparian corridors, and permeable landscapes, which provide critical ecosystem services such as thermal regulation, stormwater management, biodiversity conservation, and carbon sequestration (Korkou *et al*., 2023; Wang *et al*., 2024). Unlike conventional gray infrastructure, GI supports ecological connectivity and environmental resilience while enhancing urban climate adaptation capacity. Consequently, integrating Green Infrastructure into metropolitan planning frameworks has become increasingly important for addressing the environmental impacts of rapid urbanization and strengthening long-term urban sustainability (Waheeb *et al*., 2023; Wu *et al*., 2025).

The relationship between urban expansion and ecological degradation can be understood through Landscape Ecology and Urban Ecological Resilience theories. Landscape Ecology emphasizes the importance of spatial structure, ecological connectivity, and landscape configuration in sustaining ecosystem functionality within human-dominated environments (Hersperger *et al*., 2021). Rapid urbanization frequently disrupts ecological corridors through vegetation fragmentation and impervious surface expansion, thereby reducing ecological continuity and environmental stability. Similarly, Urban Ecological Resilience theory conceptualizes cities as socio-ecological systems whose sustainability depends on their ability to absorb environmental disturbances while maintaining ecological functionality (Sharifi, 2023). Within rapidly urbanizing cities, declining ecological infrastructure reduces adaptive capacity and increases vulnerability to flooding, heat stress, and environmental degradation.

Despite growing advances in urban geospatial analysis, important conceptual and methodological gaps remain within existing scholarship. Many LULC studies in African cities primarily focus on retrospective land-cover assessment without integrating predictive ecological intervention planning or Green Infrastructure prioritization frameworks (Enoh *et al*., 2023; Negesse *et al*., 2024). Existing studies also pay limited attention to ecological fragmentation, environmental stress prioritization, and climate-responsive urban ecological planning. Furthermore, relatively few studies within rapidly urbanizing African secondary cities have integrated multi-temporal LULC dynamics with GIS-based Multi-Criteria Decision Analysis (MCDA) for Green Infrastructure priority mapping within a unified analytical framework.

In Ilorin Metropolis, rapid urban expansion has increasingly transformed peri-urban and environmentally sensitive landscapes into built-up environments, particularly along major transportation and institutional growth corridors, including Ajase-Ipo Road, Airport Road, Tanke, Ganmo, Oke-Oyi, and Eiyenkorin (Orire *et al*., 2022; Aduloju *et al.,* 2025). These transformations have intensified vegetation decline, ecological fragmentation, and thermal stress across the metropolitan region. However, limited research has examined how these urban transformation processes influence the priority of ecological interventions, Green Infrastructure planning, and long-term urban resilience within the metropolis.

In addition, limited attention has been given to how Green Infrastructure prioritization can support the implementation of the Kwara State Master Plan, urban development control regulations, climate-responsive land-use management policies, and metropolitan environmental governance frameworks. The absence of integrated ecological prioritization in planning practice may further undermine long-term sustainability and resilience outcomes across rapidly urbanizing districts of the Ilorin Metropolis.

Therefore, the present study develops an integrated geospatial framework combining multi-temporal LULC analysis, Remote Sensing, GIS-based Multi-Criteria Decision Analysis (MCDA), and Analytical Hierarchy Process (AHP) modelling for Green Infrastructure priority mapping in Ilorin Metropolis, Nigeria. Unlike previous studies that primarily emphasize retrospective land-cover assessment, the study integrates historical urban transformation analysis with predictive ecological intervention prioritization within a unified and scalable framework. Methodologically, the study advances urban ecological planning by integrating Google Earth Engine-based cloud processing, Random Forest classification, GIS-MCDA modelling, and spatial prioritization analysis for climate-responsive metropolitan planning.

Although uncertainty modelling, AHP sensitivity analysis, machine learning-based predictive simulation, and deep learning approaches were not implemented within the present study, their potential relevance for improving ecological prioritization robustness, predictive urban growth assessment, and future climate-risk modelling is acknowledged. Future studies may therefore integrate sensitivity analysis techniques, Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and explainable artificial intelligence frameworks to further strengthen metropolitan ecological assessment and predictive urban sustainability planning.

The study aims to examine the spatio-temporal dynamics of Land Use Land Cover (LULC) change in Ilorin Metropolis between 2005 and 2025, evaluate major urban expansion corridors and land transformation pathways, assess the ecological implications of vegetation decline and landscape fragmentation, and develop a Green Infrastructure priority framework for identifying major ecological intervention zones within the metropolis. The findings are expected to support climate-responsive urban planning, ecological restoration prioritization, and sustainable metropolitan governance in rapidly urbanizing African cities facing similar environmental pressures.

2.0 MATERIALS AND METHODS

2.1 Study Area

The study was conducted in Ilorin Metropolis, the capital city of Kwara State, North-Central Nigeria. The metropolis comprises the three principal Local Government Areas (LGAs). These are Ilorin West, Ilorin East, and Ilorin South, including rapidly urbanizing peripheral settlements extending toward Asa, Moro, Ifelodun, and Oyun LGAs. Following the delineation adopted by the Kwara State Geographic Information Service (Kwara State Geographic Information Service, the study area was defined using a 25 km radius from the central business district around the Post Office axis, covering approximately 196,298.91 ha.

Geographically, Ilorin Metropolis lies within latitudes 8°24′00″N to 8°45′00″N and longitudes 4°29′00″E to 4°58′00″E within the Guinea Savannah ecological zone of Nigeria. The area experiences a tropical savanna climate characterized by distinct wet and dry seasons, with annual rainfall ranging between 1,000 mm and 1,500 mm as well as mean annual temperatures varying between 25°C and 34°C (Fashae *et al*., 2017).

Rapid urbanization, transportation expansion, institutional growth, and increasing peri-urban land conversion have substantially transformed the metropolitan landscape over recent decades. Major growth corridors extending toward Tanke, Ganmo, Oke-Oyi, Ajase-Ipo, Airport Road, and Eiyenkorin increasingly exhibit extensive vegetation loss and built-up expansion, making Ilorin Metropolis suitable for evaluating the interaction between Land Use Land Cover (LULC) dynamics and Green Infrastructure (GI) priority planning within rapidly urbanizing African cities.

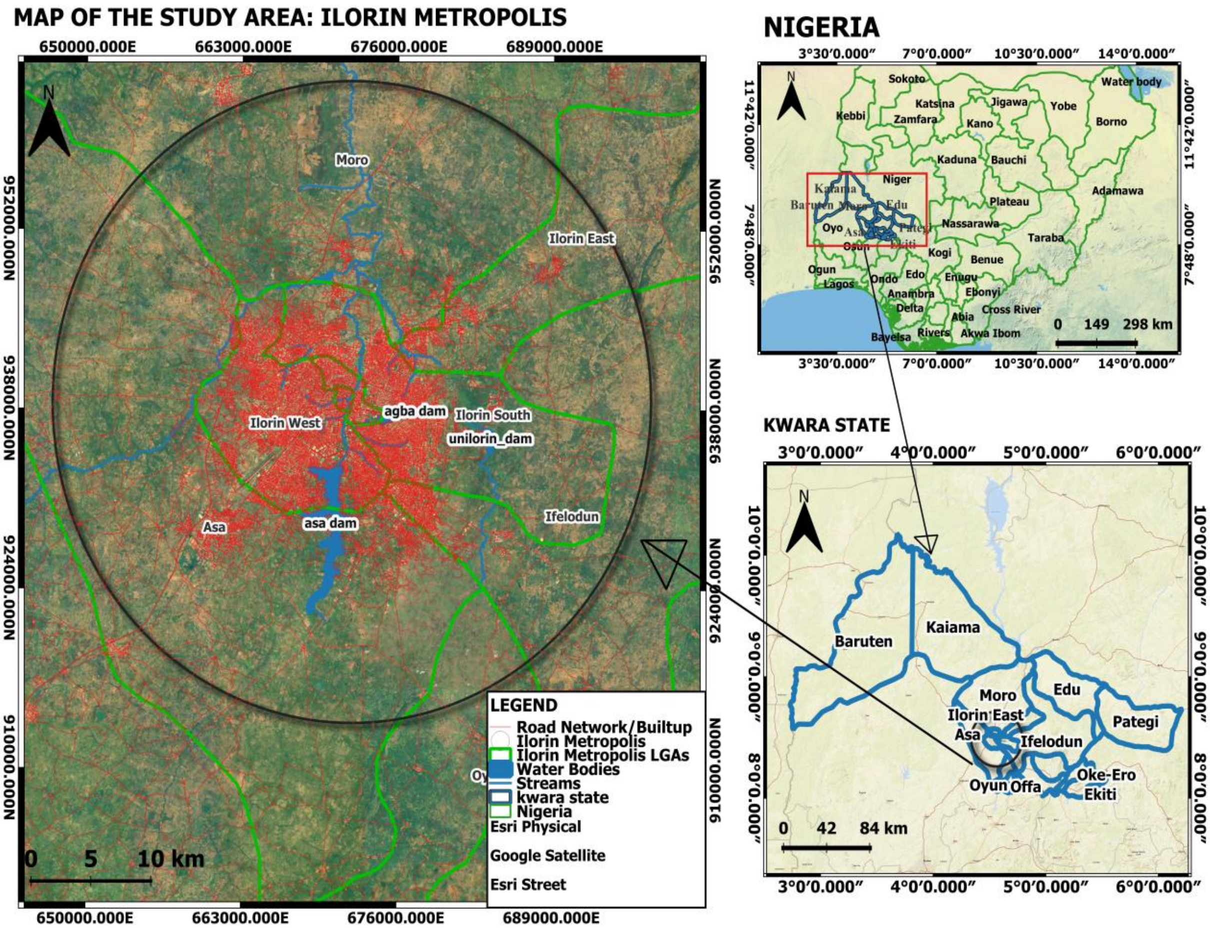

Figure 1. Location map of Ilorin Metropolis
Source: Authors' GIS analysis using administrative boundary data and Google Satellite imagery (2025).

2.2 Data Sources and Acquisition

Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8/9 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) datasets for 2005, 2015, and 2025, respectively, were acquired from the United States Geological Survey (USGS) archive through the Google Earth Engine (GEE) platform. In addition, ancillary datasets including a Digital Elevation Model (DEM), road network layers, hydrological data, and administrative boundaries were utilized to support ecological analysis, spatial overlay modelling, and Green Infrastructure priority classification. A summary of the datasets employed in the study is presented in Table 1.

Table 1. Summary of Datasets Used

Dataset	Sensor/Source	Year	Spatial Resolution	Purpose
Landsat 5 TM	USGS/GEE	2005	30 m	LULC classification and change detection
Landsat 7 ETM+	USGS/GEE	2015	30 m	LULC classification and change detection
Landsat 8/9 OLI/TIRS	USGS/GEE	2025	30 m	LULC classification, NDVI, NDBI, and LST analysis
DEM	SRTM	2025	30 m	Slope derivation
Road Network	OpenStreetMap	2025	Vector	Accessibility analysis
Hydrological Data	GEE/OpenStreetMap	2025	Vector	Distance-to-water analysis

2.3 Image Pre-Processing

Image pre-processing was conducted within the Google Earth Engine environment to improve spectral consistency and ensure temporal comparability among datasets. Landsat Level-2 surface reflectance products were utilized to minimize atmospheric distortion and improve radiometric reliability (Nazeer *et al*., 2021).

Cloud and cloud-shadow contamination were removed using Quality Assessment (QA) bands and cloud masking algorithms available within GEE. Images with cloud cover exceeding 10% were excluded from analysis to minimize spectral inconsistencies associated with tropical atmospheric conditions. Median compositing techniques were subsequently applied to generate cloud-free composite imagery for each study year.

All datasets were reprojected to the Universal Transverse Mercator (UTM) Zone 31N coordinate system referenced to the WGS 84 datum. Image normalization and resampling procedures were additionally conducted to maintain uniform spatial resolution and spatial consistency during overlay analysis.

The cloud-based geospatial workflow significantly improved computational efficiency, analytical reproducibility, and scalability for long-term metropolitan ecological assessment.

2.4 Land Use Land Cover Classification

LULC classification was performed using a supervised Random Forest (RF) classifier implemented within Google Earth Engine. The Random Forest algorithm was selected because of its robustness to spectral variability, resistance to overfitting, and high classification performance in heterogeneous urban environments (Durowoju *et al*., 2025). The study area was classified into four major Land Use/Land Cover (LULC) categories: built-up areas, vegetation, bare land, and water bodies. Training samples were generated through visual interpretation of high-resolution Google Earth imagery, historical satellite datasets, and field knowledge of the study area. Approximately 300 stratified random training samples were collected for each study year to ensure balanced representation across all land-cover classes. Seventy percent (70%) of the samples were used for classification training, while the remaining 30% were reserved for validation. The Random Forest classifier was implemented using 500 decision trees with default bagging parameters to improve classification stability and reduce prediction uncertainty. Vegetation distribution was evaluated using the Normalized Difference Vegetation Index (NDVI) (equation 1):

$$NDVI = \frac{NIR-RED}{NIR+RED} \tag{1}$$

Built-up intensity was assessed using the Normalized Difference Built-up Index (NDBI) (equation 2):

$$NDBI = \frac{SWIR-NIR}{SWIR+NIR} \tag{2}$$

For Landsat 5 TM and Landsat 7 ETM+, the NIR, Red, and SWIR bands correspond to Bands 4, 3, and 5, respectively, while Landsat 8/9 OLI utilizes Bands 5, 4, and 6.

Post-classification refinement, including majority filtering and isolated pixel removal, was conducted to improve thematic consistency and reduce classification noise.

2.5 Land Surface Temperature Estimation
Land Surface Temperature (LST) was derived from Landsat thermal infrared bands using radiative transfer and emissivity correction procedures following standard USGS protocols (Weng *et al*., 2004).
Thermal bands were converted from digital numbers to spectral radiance and subsequently transformed into brightness temperature using (equation 3):

$$T_B = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda}+1\right)} \qquad (3)$$

where: T_B) = Brightness Temperature, (L_λ) = Spectral radiance, (K_1) and (K_2) = thermal calibration constants.

Land surface emissivity was estimated using the NDVI-based emissivity approach (equation 4):

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \qquad (4)$$

Final Land Surface Temperature was computed as (equation 5):

$$LST = \frac{BT}{1+\left(\frac{\lambda BT}{\rho}\right)\ln\varepsilon} - 273.15 \qquad (5)$$

where: LST = Land Surface Temperature (°C), λ= wavelength of emitted radiance, ρ = thermal constant, ε= land surface emissivity.

In this study, Land Surface Temperature (LST) was incorporated as an environmental stress indicator within the Green Infrastructure prioritization framework rather than as a standalone urban heat hotspot analysis. The inclusion of LST was important for identifying spatial variations in thermal conditions associated with vegetation depletion, impervious surface concentration, and increasing urban development intensity across the metropolitan landscape.

2.6 Accuracy Assessment and Validation
Classification accuracy assessment was conducted using confusion matrices derived from independent validation samples. Statistical indicators computed included the Producer's Accuracy (PA), User's Accuracy (UA), Overall Accuracy, and the Kappa Coefficient.

The Kappa coefficient (κ) was computed as (equation 6):

$$\kappa = \frac{P_o - P_e}{1 - P_e} \qquad (6)$$

where: P_o = observed agreement, P_e= expected agreement by random chance.

Overall classification accuracies exceeded the minimum 85% threshold recommended for reliable LULC classification, while Kappa values indicated strong thematic consistency across all study years.
For Green Infrastructure priority analysis, the consistency of the Analytical Hierarchy Process (AHP) was evaluated using the Consistency Ratio (CR). CR values below 0.10 confirm acceptable consistency within the pairwise comparison matrix (Saaty, 1980).

Although AHP consistency validation was conducted to ensure acceptable reliability of the weighting structure, uncertainty propagation analysis and AHP weight sensitivity analysis were not implemented within the present study. The authors acknowledge that sensitivity analysis could further improve understanding of the influence of criterion weighting variations on Green Infrastructure prioritization outcomes.

Future studies may therefore incorporate sensitivity-based validation techniques, Monte Carlo simulation, uncertainty propagation modelling, and scenario-based weighting approaches to further strengthen the robustness and reproducibility of GIS-MCDA ecological prioritization frameworks.

2.7 Spatio-Temporal Change Detection

Post-classification change detection was employed to evaluate the magnitude, direction, and spatial distribution of LULC transitions between 2005 and 2025. This approach enabled direct comparison of independently classified imagery while minimizing spectral inconsistencies among sensors and acquisition periods (Khan & Khan, 2025).

Spatial overlay analysis and transition matrices were generated to quantify pixel-level conversions among land cover classes and identify dominant transformation pathways. Percentage change analysis was additionally applied to assess urban growth intensity and peri-urban expansion patterns across major metropolitan development corridors. The transition analysis facilitated the identification of major vegetation-to-built-up conversion corridors associated with transportation accessibility, institutional expansion, and peri-urban land transformation. The findings are particularly relevant for supporting development control, climate-responsive planning, and sustainable metropolitan management within the context of the Kwara State urban development framework and broader Sustainable Development Goals (SDGs 11 and 13).

2.8 Green Infrastructure Priority Mapping

Green Infrastructure Priority Mapping was conducted using a GIS-based Multi-Criteria Decision Analysis (MCDA) framework integrated with the Analytical Hierarchy Process (AHP). Unlike conventional suitability assessment approaches that primarily identify environmentally favorable locations, the adopted framework emphasized ecological intervention priority based on environmental stress, urban pressure, restoration opportunity, and climate adaptation relevance.

The prioritization framework was developed to identify areas requiring urgent ecological intervention to enhance thermal regulation, ecological connectivity, stormwater management, and environmental resilience within rapidly urbanizing metropolitan landscapes. The framework incorporated multiple prioritization criteria, including Land Use Land Cover (LULC), Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), slope, distance to roads, and distance to water bodies.

LULC was incorporated as a primary ecological prioritization criterion because it directly reflects the spatial distribution of built-up intensity, vegetation decline, ecological disturbance, and land transformation pressure within the metropolitan landscape. Areas characterized by dense built-up development and declining vegetation were assigned higher ecological intervention priority due to their increased susceptibility to thermal stress, environmental degradation, and ecological fragmentation.
These variables were selected because they collectively capture ecological condition, urban development intensity, environmental stress, accessibility, and restoration opportunity within rapidly urbanizing metropolitan environments.

Pairwise comparison matrices were subsequently developed to determine criterion importance based on expert judgement and literature-supported ecological significance. Criterion weights derived from the AHP process were integrated using weighted linear combination analysis.

The priority index was computed as (equation 7):

$$\boldsymbol{PI} = \sum_{i=1}^{n} \boldsymbol{W_i} \times \boldsymbol{X_i} \tag{7}$$

where $\boldsymbol{PI}$ is the Priority index, $\boldsymbol{W_i}$ represents the weight of each criterion, and $\boldsymbol{X_i}$ represents the standardized criterion value.

The final priority map classified the study area into very high, high, moderate, and low ecological intervention priority zones for Green Infrastructure development. Figure 2 illustrates the Methodological workflow for GIS-MCDA Green Infrastructure priority analysis.

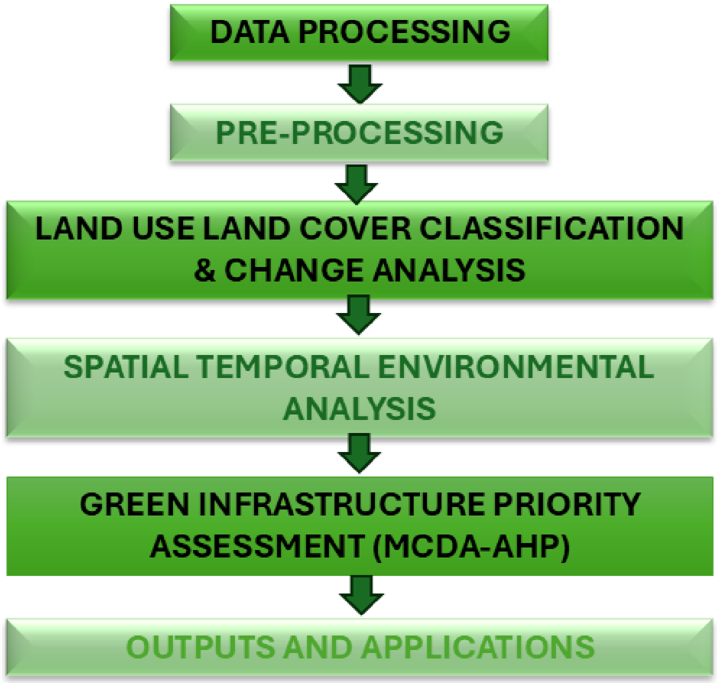

Figure 2. Methodological workflow for Green Infrastructure priority mapping.
Source: Researcher's Conceptualisation (2026)

2.8.1 Selection of Green Infrastructure Prioritization Criteria

The selection of criteria for Green Infrastructure (GI) priority mapping was guided by their relevance to urban ecological resilience, environmental quality, climate adaptation, and restoration potential. Seven criteria were incorporated into the GIS-based Multi-Criteria Decision Analysis (MCDA) framework, namely Land Surface Temperature (LST), Land Use/Land Cover (LULC), Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), distance to roads, distance to water bodies, and slope.

LST was included to represent thermal stress and urban heat island intensity because elevated surface temperatures are commonly associated with vegetation loss and increasing impervious surface cover (Weng *et al*., 2004; Duan *et al*., 2025). LULC was incorporated to capture patterns of urbanization, ecological disturbance, and land transformation that influence ecosystem functionality and resilience (Hersperger *et al*., 2021; Liu *et al*., 2025). NDBI was selected as an indicator of built-up intensity and urban development pressure, while NDVI was used to assess vegetation condition and ecological quality (Ullah *et al*., 2023; Jamalfaisal *et al*., 2025; Nawar *et al*., 2022).

Distance to roads was included because transportation corridors often stimulate urban expansion and ecological fragmentation (Mohamed *et al*., 2020; Waheeb *et al*., 2023). Distance to water bodies was incorporated to account for hydrological sensitivity, flood regulation functions, and ecological connectivity within riparian environments (Wang *et al*., 2024; Wu *et al*., 2025). Slope was considered because terrain characteristics influence runoff generation, erosion susceptibility, and the suitability of ecological restoration interventions (Feizizadeh *et al*., 2014). Collectively, these criteria provide a comprehensive representation of environmental stress, ecological condition, and restoration opportunity within the study area.

2.8.2 Criteria Standardization and Suitability Ranking

Following criterion selection, all spatial layers were standardized to a common suitability scale to enable integration within the GIS-MCDA framework. The standardization process transformed the original datasets into comparable raster layers representing relative Green Infrastructure priority levels. Higher suitability scores were assigned to areas exhibiting greater ecological stress, restoration need, or strategic importance for climate adaptation and ecological connectivity.

2.8.3 Analytical Hierarchy Process (AHP) Weighting and Priority Mapping

The relative importance of the selected criteria was determined using the Analytical Hierarchy Process (AHP) developed by Saaty (1980). Pairwise comparisons were conducted to evaluate the contribution of each criterion to Green Infrastructure prioritization based on ecological restoration urgency, climate adaptation relevance, and urban environmental pressures. The resulting weights were subsequently applied within a weighted overlay framework to generate the final Green Infrastructure Priority Map.

2.8.4 Sensitivity Analysis of the GI Prioritization Model

To evaluate the robustness of the AHP weighting scheme and assess the influence of individual criteria on Green Infrastructure (GI) priority allocation, a One-at-a-Time (OAT) sensitivity analysis was conducted following established GIS-MCDA procedures (Chen *et al*., 2010; Feizizadeh *et al*., 2014). Each criterion weight was systematically adjusted by ±10% relative to its baseline value, while the remaining criterion weights were proportionally recalculated to maintain a normalized total weight of 1.00 in accordance with AHP requirements (Saaty, 1980). For each simulation scenario, the weighted overlay analysis was repeated, and the resulting spatial extent of High Priority and Very High Priority GI zones was compared with the baseline model. This procedure enabled assessment of model stability, evaluation of uncertainty associated with criterion weighting, and identification of the most influential factors governing ecological intervention priorities within the study area.

2.9 Methodological Limitations

Despite the robustness of the integrated analytical framework, certain limitations should be acknowledged. First, the 30 m spatial resolution of Landsat imagery may not fully capture fine-scale urban heterogeneity within densely built-up districts. Second, spectral confusion between bare land and built-up surfaces may introduce classification uncertainty within transitional peri-urban landscapes. Third, the AHP weighting procedure involves a degree of expert subjectivity despite consistency validation measures.

Nevertheless, the integration of Random Forest classification, cloud-based geospatial processing, multi-temporal analysis, GIS-MCDA, and spatial overlay modelling substantially improved analytical reliability, reproducibility, and scalability for long-term metropolitan ecological assessment and climate-responsive urban planning.

Despite the robustness of the integrated analytical framework, certain limitations are acknowledged. First, the 30 m spatial resolution of Landsat imagery may not fully capture fine-scale urban heterogeneity within densely built-up districts. Second, spectral confusion between bare land and built-up surfaces may introduce classification uncertainty within transitional peri-urban landscapes. Third, the AHP weighting procedure involves a degree of expert subjectivity despite consistency validation measures.

Although an AHP-based sensitivity analysis was conducted to evaluate model robustness, more advanced uncertainty assessment approaches such as Monte Carlo simulation, probabilistic uncertainty propagation, and spatial error modelling were beyond the scope of the present study. Future studies may integrate these techniques to provide a more comprehensive evaluation of uncertainty within Green Infrastructure prioritization frameworks. This would further strengthen the reproducibility and transferability of GIS-MCDA-based ecological planning models.

In addition, while the Random Forest classifier provided strong classification performance and computational efficiency for metropolitan-scale analysis, emerging machine learning and deep learning approaches such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and hybrid geospatial-AI models may further improve fine-scale classification accuracy, predictive urban growth simulation, and ecological forecasting capabilities in future studies.

Furthermore, although stakeholder relevance was conceptually acknowledged within the Green Infrastructure planning framework, direct participatory engagement involving urban planners, environmental agencies, local communities, NGOs, and development control institutions was beyond the scope of the present study. Future research may therefore integrate participatory GIS approaches and stakeholder-driven ecological prioritization to strengthen policy applicability, implementation feasibility, and climate-responsive urban governance outcomes.

Nevertheless, the integration of Random Forest classification, cloud-based geospatial processing, multi-temporal analysis, GIS-MCDA, and spatial overlay modelling substantially improved analytical reliability, reproducibility, and scalability for long-term metropolitan ecological assessment and climate-responsive urban planning.

3.0 RESULTS AND DISCUSSION

3.1 Spatio-Temporal Dynamics of Urban Expansion and Land Transformation

The multi-temporal Land Use Land Cover (LULC) analysis revealed substantial spatial transformation within Ilorin Metropolis between 2005 and 2025, characterized primarily by rapid urban expansion, peri-urbanization, vegetation decline, and increasing ecological fragmentation (Figure 3). Built-up land increased from 7,007.87 ha (3.57%) in 2005 to 28,981.44 ha (14.76%) in 2025, representing a net increase of 21,973.57 ha over the study period (Table 2). In contrast, vegetation cover declined from 112,361.49 ha (57.24%) to 101,616.75 ha (51.77%), indicating sustained anthropogenic pressure on ecological landscapes. Bare land exhibited transitional dynamics, increasing between 2005 and 2015 before declining by 2025 due to progressive conversion into urban infrastructure, while water bodies remained relatively stable. The classified LULC maps presented in Figure 3(a-c) indicate a significant increase in built-up surfaces accompanied by declining vegetation cover and increasing fragmentation of peri-urban ecological landscapes.

Table 2. Land Use Land Cover statistics and change analysis for Ilorin Metropolis (2005–2025).

LULC Class	2005 Area (Ha)	2005 (%)	2015 Area (Ha)	2015 (%)	2025 Area (Ha)	2025 (%)	Net Change 2005–2025 (Ha)	Total Change (%)
Built-up	7,007.87	3.57	14,899.09	7.59	28,981.44	14.76	+21,973.57	+11.19
Vegetation	112,361.49	57.24	92,653.09	47.20	101,616.75	51.77	−10,744.74	−5.47
Bare Land	76,163.98	38.80	87,922.28	44.79	64,916.73	33.07	−11,247.25	−5.73
Water	765.57	0.39	824.45	0.42	783.99	0.40	+18.42	+0.01
Total	196,298.91	100.00	196,298.91	100.00	196,298.91	100.00	0.00	0.00

Spatially, urban expansion occurred through pronounced outward growth from the traditional monocentric core around Oja-Oba toward surrounding peri-urban and rural landscapes. The expansion pattern followed major transportation and institutional corridors, particularly along Ajase-Ipo Road, Airport Road, Tanke, Ganmo, Oke-Oyi, Eiyenkorin, and the University of Ilorin axis (Figure 4). The southeastern corridor extending toward UITH, Idofian, Jimba-Oja, and Oke-Oyi experienced some of the most intense peri-urban transformations, while rapid residential and commercial expansion also intensified around Tanke, Sanrab, Oke-Odo, and Airport Road. Northern expansion became increasingly evident by 2025 through ribbon development toward Shao and Moro along the Sango–Jebba corridor.

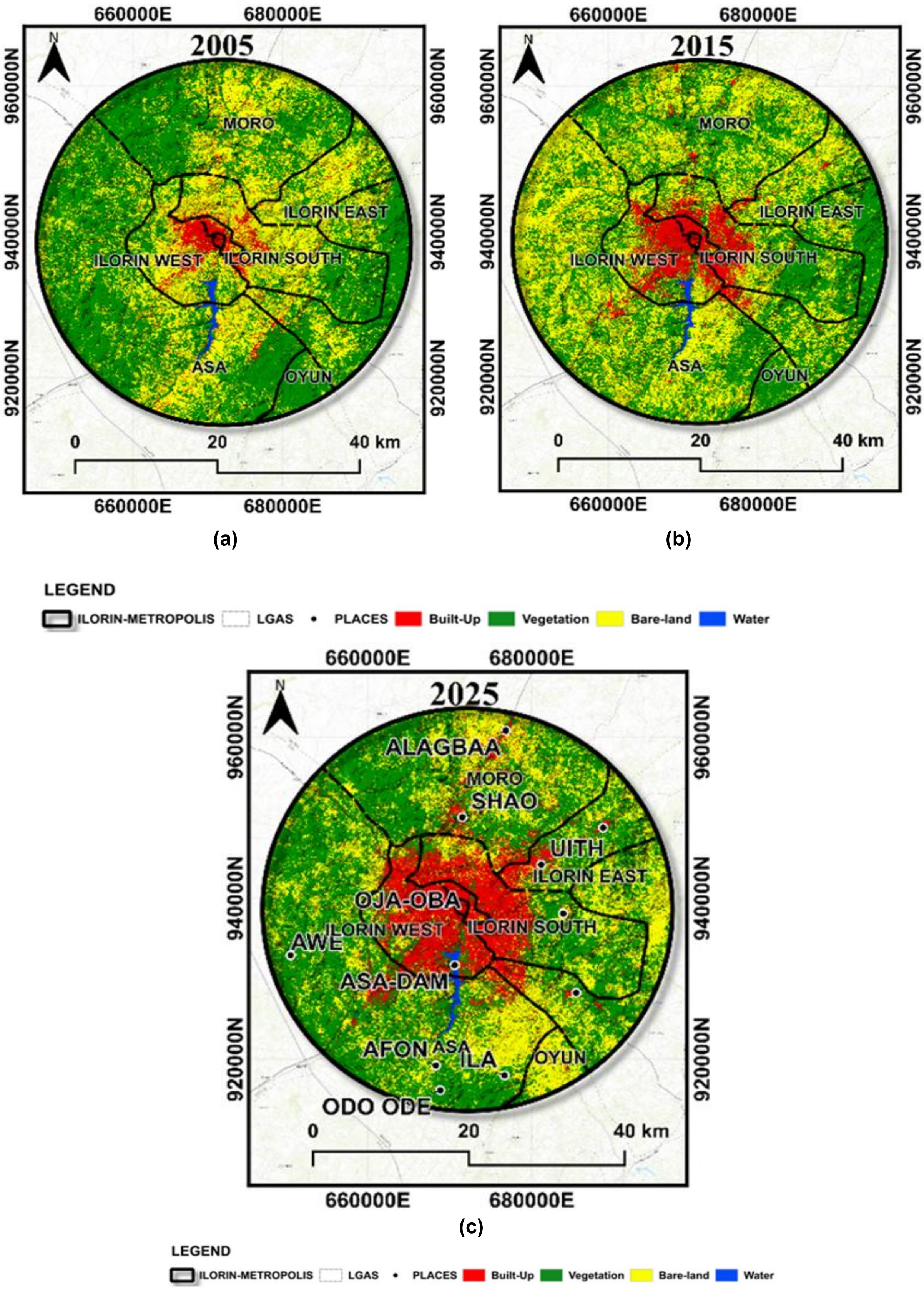

Figure 3. Multi-temporal LULC maps of Ilorin Metropolis for 2005, 2015, and 2025

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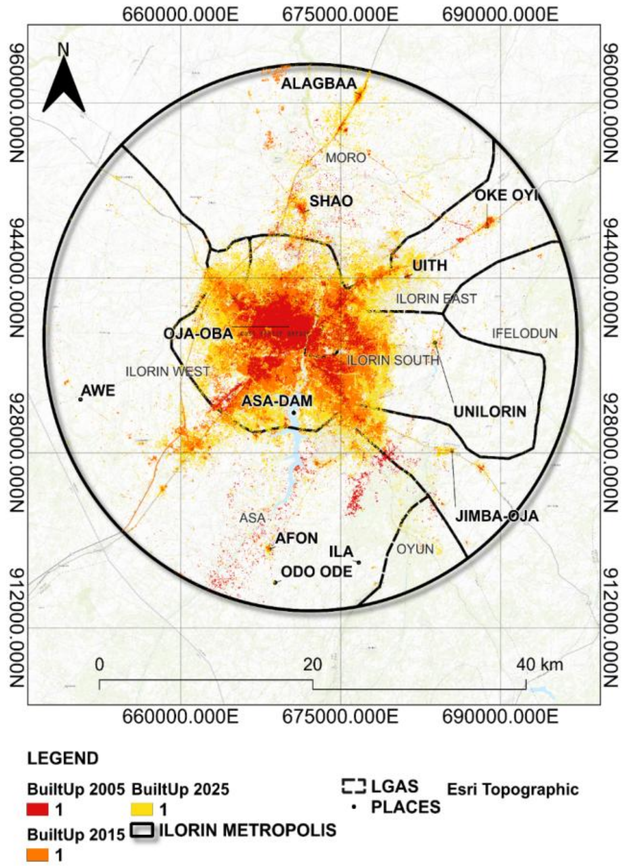


Figure 4. Spatial distribution and directional urban growth trajectories in Ilorin Metropolis between 2005 and 2025.

The observed transformation reflects broader urbanization dynamics occurring across rapidly expanding African cities where infrastructural development, transportation accessibility, institutional concentration, and weak spatial governance increasingly reshape metropolitan landscapes (Ablo *et al*., 2020; Mashi *et al*., 2025). The transition from a relatively monocentric structure toward a fragmented polycentric metropolitan system further indicates increasing dependence on peri-urban accessibility and speculative land conversion rather than compact urban redevelopment. Similar urbanization trajectories have been documented in Accra, Nairobi, Addis Ababa, and Lagos, where transportation-driven peri-urbanization increasingly threatens ecological sustainability and agricultural land preservation (Enoh *et al*., 2023; Gebre Egziabher *et al*., 2025).

The observed peri-urban expansion pattern additionally suggests limitations in existing development control mechanisms within Ilorin Metropolis. Continuous outward growth into vegetated landscapes indicates increasing fragmentation of ecological corridors associated with weak planning enforcement and unregulated land conversion processes. Consequently, urban growth within the metropolis increasingly reflects reactive spatial expansion rather than coordinated ecological planning.
These findings further highlight the importance of integrating ecological prioritization and Green Infrastructure planning within the broader framework of metropolitan land-use regulation, development control, and climate-responsive urban governance. Aligning urban expansion management with the objectives of the Kwara State Master Plan and sustainable urban development strategies may help reduce uncontrolled peri-urban encroachment, ecological degradation, and long-term environmental vulnerability.

From a sustainability perspective, the observed urban transformation patterns have important implications for the achievement of Sustainable Development Goals 11 and 13, particularly regarding sustainable urbanization, climate adaptation, ecological resilience, and environmentally responsive metropolitan planning. Continued outward expansion without integrated ecological safeguards may progressively weaken urban environmental sustainability and climate resilience across the metropolis.

3.2 Land Transformation Pathways and Ecological Fragmentation

Transition matrix analysis revealed that vegetation-to-built-up conversion constituted the dominant land transformation pathway within Ilorin Metropolis between 2005 and 2025 (Table 3). Approximately 18,964.25 ha of vegetation were converted into built-up surfaces, while 3,587.91 ha of bare land transitioned into urban infrastructure. Conversely, 20,945.74 ha of bare land transitioned into vegetation, indicating localized ecological recovery within some peripheral landscapes.

Table 3 presents the most significant transitions that occurred from vegetation-to-built-up and bare land-to-built-up categories, indicating substantial encroachment of urban development into ecologically functional landscapes. The interpretation of major transitions is presented in Table 4.

Table 3. Land Use Land Cover (LULC) Transition Matrix for Ilorin Metropolis (2005–2025)

2005 / 2025	Built-up (Ha)	Vegetation (Ha)	Bare Land (Ha)	Water Bodies (Ha)	Total (Ha)
Built-up	6,215.43	312.18	451.77	28.49	7,007.87
Vegetation	18,964.25	79,845.62	12,944.38	607.24	112,361.49
Bare Land	3,587.91	20,945.74	51,228.06	402.27	76,163.98
Water Bodies	213.85	513.21	292.52	511.56	765.57
Total (Ha)	28,981.44	101,616.75	64,916.73	783.99	196,298.91

Table 4. Major LULC transition pathways and ecological interpretation.

Major Transition	Area (Ha)	Interpretation
Vegetation → Built-up	18,964.25	Urban encroachment into vegetated landscapes
Bare Land → Built-up	3,587.91	Infill and peri-urban development
Vegetation → Bare Land	12,944.38	Deforestation and vegetation degradation
Bare Land → Vegetation	20,945.74	Ecological recovery and revegetation
Built-up → Built-up	6,215.43	Stable urban core persistence
Water → Built-up	213.85	Land reclamation and urban intrusion

The transition dynamics demonstrate that urban growth occurred primarily through the conversion of ecologically sensitive landscapes rather than compact urban redevelopment. Vegetation-to-built-up conversion was heavily concentrated along peri-urban growth corridors extending toward Ganmo, Tanke, Sanrab, Oke-Oyi, Eiyenkorin, Shao, and the Ajase-Ipo axis, where transportation accessibility and institutional expansion intensified land conversion pressure.

Rapid peri-urban consolidation transformed formerly vegetated and agricultural landscapes around Ganmo, Amoyo, Jimba-Oja, and Idofian into dense residential and mixed-use developments. Similarly, the University of Ilorin corridor significantly altered land-use dynamics within Tanke, Oke-Odo, and Sanrab through accelerated residential and commercial development. The western axis toward Eiyenkorin and Airport Road also experienced substantial bare land-to-built-up conversion associated with industrial growth and peri-urban commercial expansion. These dynamics reflect increasing integration of formerly isolated satellite communities into the broader metropolitan structure.

The findings therefore suggest that urban expansion within Ilorin is increasingly driven by peri-urban land accessibility, speculative land conversion, and weak development control mechanisms, resulting in fragmented polycentric expansion and inefficient land consumption patterns.

From a Landscape Ecology perspective, the extensive conversion of vegetation into impervious surfaces substantially disrupts ecological connectivity and weakens ecosystem functionality (Hersperger *et al.*, 2021). Fragmented ecological systems become progressively less capable of supporting hydrological regulation, biodiversity conservation, thermal buffering, and climate adaptation functions. Consequently, the observed vegetation decline indicates declining ecological resilience and increasing environmental vulnerability across the metropolitan landscape. Figure 5 presents the vegetation cover change map showing the spatial distribution of vegetation loss, persistence, and transformation patterns in Ilorin Metropolis between 2005 and 2025.

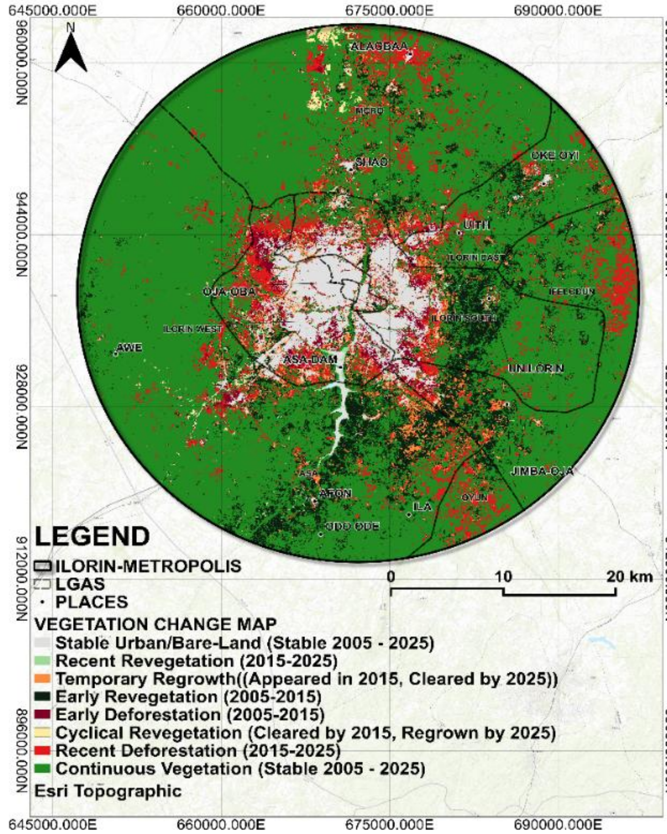


Figure 5. Vegetation cover change and fragmentation patterns in Ilorin Metropolis between 2005 and 2025.

Spatial analysis further revealed increasing fragmentation of ecological landscapes across rapidly urbanizing peri-urban corridors extending toward Ganmo, Tanke, Oke-Oyi, Eiyenkorin, and the Ajase-Ipo development axis. Continuous residential expansion, transportation infrastructure development, and mixed-use peri-urban growth substantially disrupted formerly connected vegetation networks, particularly within the southeastern and southern development corridors associated with the University of Ilorin and Ajase-Ipo highway axes.

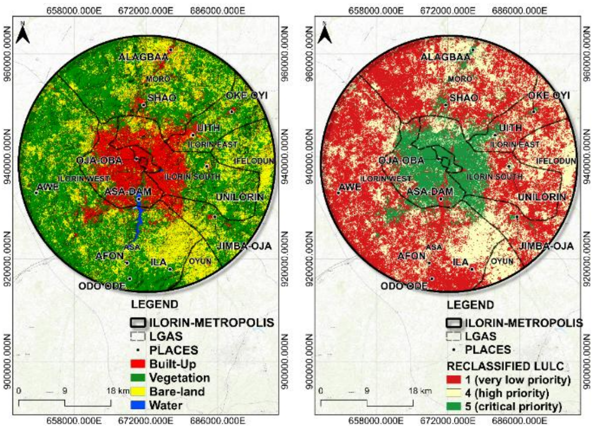
The ecological implications of these transformations extend beyond land-cover change alone to broader concerns regarding urban sustainability and climate resilience. Areas characterized by substantial vegetation loss and increasing built-up intensity corresponded strongly with elevated Land Surface Temperature (LST) conditions, particularly within Tanke, Fate, Basin, Airport Road, and the Ajase-Ipo corridor. This relationship indicates increasing urban heat island intensity associated with impervious surface expansion, consistent with findings from other rapidly urbanizing tropical cities (Waheeb *et al*., 2023; Liu *et al*., 2025).

The increasing dominance of impervious surfaces additionally reduces infiltration capacity and increases surface runoff generation, thereby elevating urban flood vulnerability within densely urbanized districts. Consequently, continued vegetation decline may progressively weaken the capacity of the metropolitan landscape to regulate stormwater dynamics and mitigate climate-related environmental hazards.

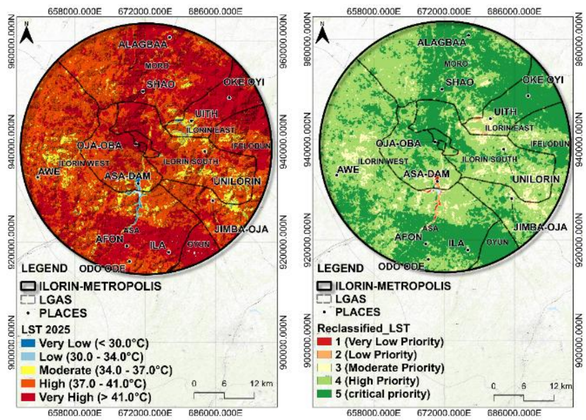
The findings further reinforce the need for stronger integration of ecological restoration priorities within metropolitan development control frameworks, land-use regulation policies, and urban planning strategies in Ilorin Metropolis. Without coordinated ecological planning and Green Infrastructure integration, continued peri-urban expansion may progressively constrain future environmental sustainability and climate adaptation capacity within the metropolis. These outcomes also have important implications for achieving Sustainable Development Goals 11 and 13, particularly regarding resilient urbanization, climate adaptation, ecological sustainability, and environmentally responsive metropolitan governance

3.3 Green Infrastructure Priority Mapping and Spatial Ecological Prioritization

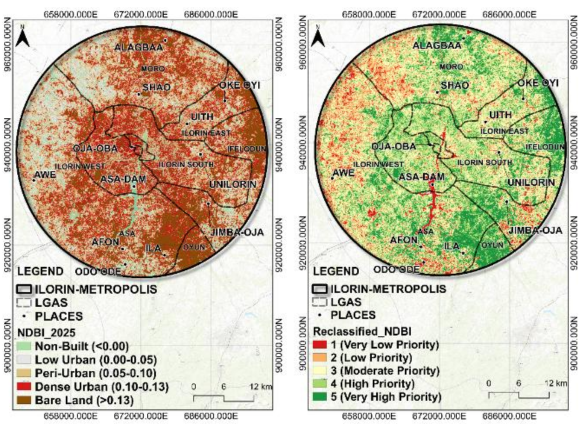
The GIS-based Multi-Criteria Decision Analysis (MCDA) and Analytical Hierarchy Process (AHP) revealed considerable spatial variation in Green Infrastructure (GI) priority levels across Ilorin Metropolis. The prioritization framework classified the metropolitan landscape into very high, high, moderate, and low priority intervention zones based on ecological sensitivity, urban pressure, thermal conditions, vegetation condition, accessibility, and restoration urgency. Figure 6(a-g) presents the standardized criteria maps used in the Green Infrastructure (GI) suitability analysis, including land use and land cover, land surface temperature, NDBI, NDVI, proximity to water bodies, distance to road, and slope.



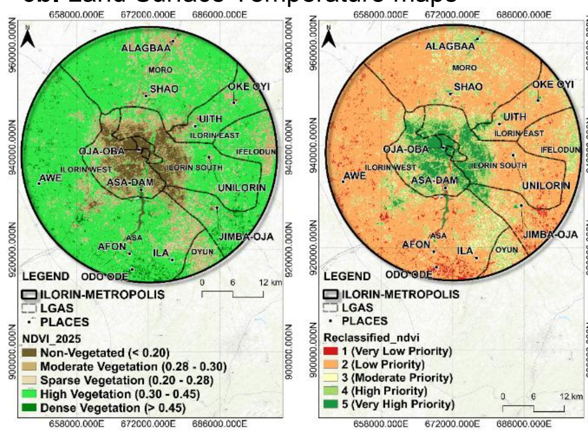
6a. Land Use Land Cover Maps



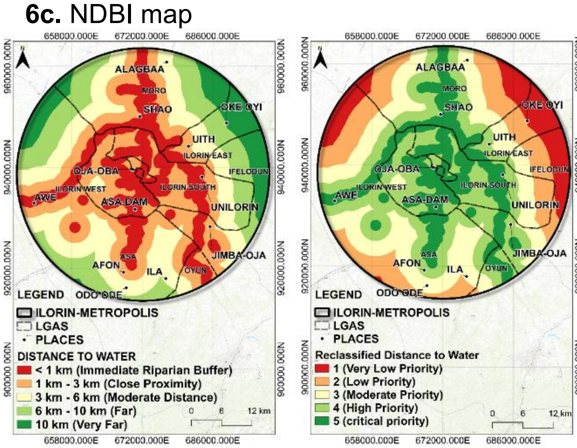
6b. Land Surface Temperature maps



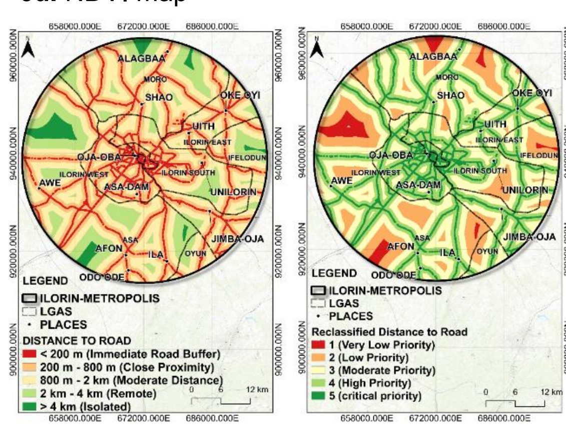
6c. NDBI map



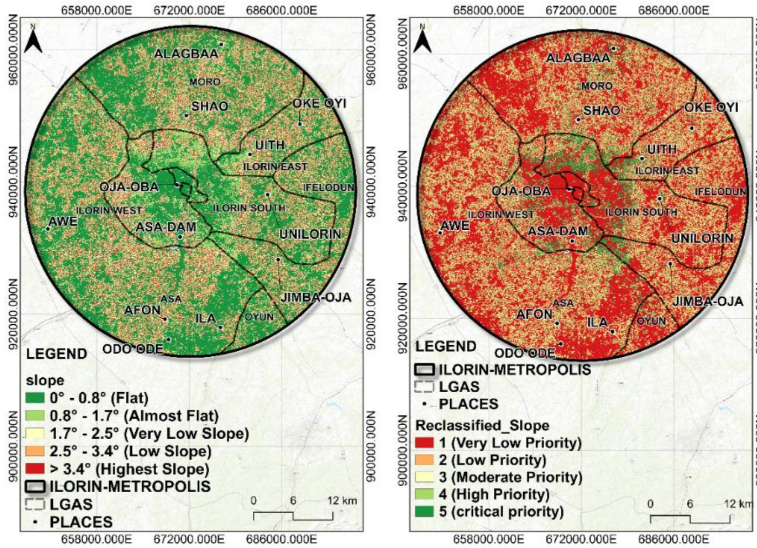
6d. NDVI map



6e. Distance to Water map



6**f.** Distance to Road map



6g. Slope map

Figure 6(a–g). Standardized criteria layers used for Green Infrastructure priority mapping, including NDVI, NDBI, LST, slope, distance to roads, and distance to water bodies.

The AHP weighting results indicate that Land Surface Temperature (35.4%) constituted the most influential prioritization criterion, followed by LULC (23.4%) and NDBI (15.4%) (Table 5). This weighting structure demonstrates the dominant influence of thermal stress, urban intensity, and vegetation depletion in determining ecological intervention priority.

Table 5. Analytical Hierarchy Process (AHP) criteria weights for Green Infrastructure priority mapping

Criteria	LST	LULC	NDBI	NDVI	Dist. Roads	Dist. Water	Slope	Normalized Weight	Percentage (%)
LST	0.381	0.441	0.405	0.353	0.303	0.303	0.292	**0.354**	**35.4**
LULC	0.191	0.221	0.270	0.265	0.242	0.242	0.208	**0.234**	**23.4**
NDBI	0.126	0.110	0.135	0.176	0.182	0.182	0.167	**0.154**	**15.4**
NDVI	0.095	0.073	0.067	0.088	0.121	0.121	0.125	**0.099**	**9.9**
Dist. Roads	0.076	0.055	0.044	0.044	0.061	0.061	0.083	**0.061**	**6.1**
Dist. Water	0.076	0.055	0.044	0.044	0.061	0.061	0.083	**0.061**	**6.1**
Slope	0.053	0.044	0.034	0.029	0.030	0.030	0.042	**0.038**	**3.8**
TOTAL								**1.000**	**100**

The final Green Infrastructure Priority Map identified 27,470.97ha (13.99%) of the metropolis as very high priority intervention zones, 68,590.51ha (34.95%) were classified as high priority areas, while low and Very Low Priority make a combined total of 20,490.53ha (10.44%) (Table 6). Moderate-priority zones occupied extensive peri-urban transitional landscapes, whereas low-priority zones were predominantly associated with environmentally stable or less development-pressured areas.

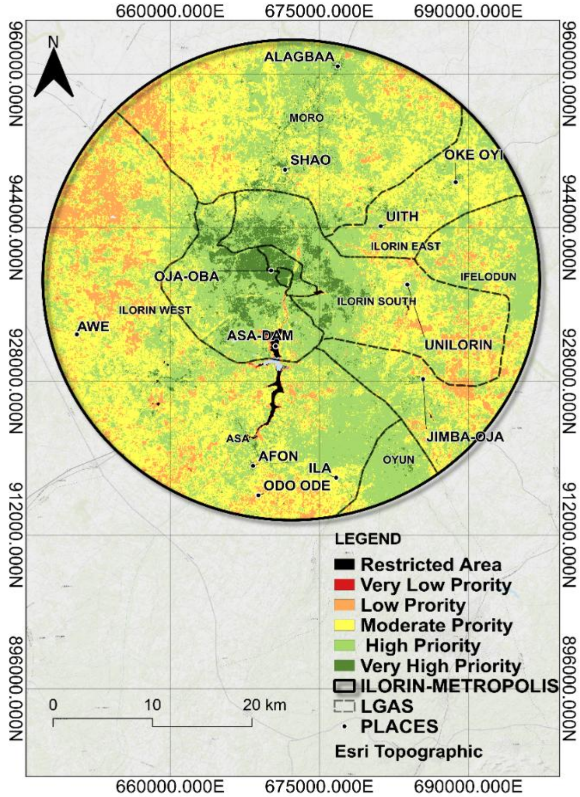


Figure 7. Green Infrastructure Priority Map of Ilorin Metropolis.

Table 6. Physical Land Priority areas for Green Infrastructure in Ilorin Metropolis

GIP Value	Priority Level	Total Area (Hectares)	Percentage (%)
0	No Deployment/Restricted area	684.46	0.35%
1	Very Low Priority	395.26	0.20%
2	Low Priority	28,762.91	14.65%
3	Moderate Priority	70,394.80	35.86%
4	High Priority	68,590.51	34.95%
5	Very High Priority	27,470.97	13.99%
	Total Usable Area:	**196,298.91**	**100.00%**

Source: Authors' GIS-based Multi-Criteria Evaluation (MCE) and Analytical Hierarchy Process (AHP) analysis (2025).

Very high priority zones were concentrated within densely urbanized metropolitan districts characterized by elevated thermal stress, fragmented vegetation, and high impervious surface concentration. Major commercial and administrative districts, including Challenge, Post Office, Taiwo Road, Geri Alimi, Murtala Mohammed Way, and Oja-Oba, as well as densely populated residential districts such as Surulere, Adewole Estate, Maraba, and Gaa Akanbi, emerged as critical ecological intervention zones.
High-priority zones formed extensive peri-urban buffers extending toward Ganmo, Amoyo, Jimba-Oja, Tanke, Sanrab, Oke-Odo, Fate, Basin, Airport Road, Kulende, Zango, Odota, and Eiyenkorin. These landscapes currently retain moderate ecological functionality but are increasingly threatened by accelerated development pressure and vegetation fragmentation.

The prioritization pattern demonstrates that areas experiencing rapid urban expansion frequently correspond spatially with environmentally stressed landscapes requiring urgent ecological intervention. Unlike conventional suitability mapping approaches that primarily identify environmentally favorable locations, the present framework emphasizes ecological restoration urgency and climate adaptation relevance. Consequently, Green Infrastructure intervention within Ilorin Metropolis should focus not only on preserving stable ecological landscapes but also on restoring environmentally degraded urban districts characterized by elevated thermal conditions, fragmented vegetation networks, and declining environmental quality. The findings further demonstrate the importance of integrating Green Infrastructure prioritization into metropolitan land-use governance, development control mechanisms, and climate-responsive planning frameworks within Ilorin Metropolis. Incorporating ecological intervention priorities into the broader implementation framework of the Kwara State Master Plan may substantially improve urban resilience, environmental sustainability, and coordinated metropolitan growth management.

From a climate adaptation perspective, the identified very high and high priority zones represent major intervention areas for mitigating urban heat island effects, improving stormwater infiltration, enhancing ecological connectivity, and strengthening environmental resilience. Similar GI prioritization patterns have been documented in rapidly urbanizing metropolitan environments where ecological intervention strategies increasingly focus on balancing urban development with climate-responsive planning objectives (Waheeb *et al*., 2023; Liu *et al*., 2025).

The study also recognizes that effective implementation of Green Infrastructure strategies requires collaboration among urban planners, environmental agencies, local communities, NGOs, and development control authorities. Stakeholder-oriented ecological planning is essential for ensuring the long-term sustainability, implementation feasibility, and governance effectiveness of metropolitan ecological restoration initiatives.

3.4 Sensitivity Analysis of the Green Infrastructure Prioritization Model

To assess the reliability of the GIS-MCDA framework, a sensitivity analysis was performed using the OAT approach by systematically varying criterion weights by ±10% while maintaining the normalized AHP structure (Table 7). The baseline model produced a combined High and Very High Priority area of 95,693.58 ha. Variations generated through the sensitivity analysis were subsequently evaluated relative to this baseline.

Table 7. Sensitivity Analysis Results for Green Infrastructure Priority Allocation

Scenario	Total Priority Area (ha)	Change from Baseline (%)
Baseline	95,693.58	0.00
LST +10%	99,629.53	+4.11
LST −10%	92,908.03	−2.91
LULC +10%	94,196.71	−1.56
LULC −10%	98,472.65	+2.90
NDBI +10%	101,594.42	+6.17
NDBI −10%	95,285.35	−0.43
NDVI +10%	95,004.81	−0.72
NDVI −10%	97,072.97	+1.44
Distance to Roads +10%	95,939.14	+0.26
Distance to Roads −10%	95,927.61	+0.24
Distance to Water +10%	95,745.40	+0.05
Distance to Water −10%	96,126.04	+0.45
Slope +10%	94,196.71	−1.56
Slope −10%	95,973.62	+0.29

Source: Authors' sensitivity analysis based on OAT (±10%) criterion weight perturbation within the GIS-MCDA-AHP framework. Adapted from the sensitivity analysis results

The maximum observed variation was associated with NDBI (+6.17%) and LST (+4.11%), whereas slope, distance to roads, and distance to water bodies produced changes below ±0.5%, indicating that urban intensity and thermal conditions are the primary drivers of Green Infrastructure prioritization in Ilorin Metropolis.

The results demonstrate that the prioritization model is generally stable and robust to moderate variations in criterion weighting. Most criteria produced relatively small changes in the total priority area, indicating limited sensitivity of the overall model structure. However, notable differences were observed for NDBI and

LST. Increasing the weight assigned to NDBI by 10% resulted in the largest expansion of priority zones (+6.17%), while increasing the weight of LST generated a 4.11% increase. Conversely, reductions in LST weight produced the largest decrease in total priority area (-2.91%). These findings indicate that built-up intensity and thermal stress exert the strongest influence on ecological intervention prioritization within the study area.

Land Use/Land Cover (LULC) produced a moderate effect on spatial distribution. Increasing its weight reduced the total high-priority area by 1.56%, while decreasing its weight caused a clear increase of 2.90%. This inverse relationship shows that LULC acts mostly as a restricting factor in the model, while it is important for spatial allocation, its overall effect is smaller than NDBI and LST (Jamalfaisal *et al.,* 2020). The model also showed low to moderate sensitivity to the Normalized Difference Vegetation Index (NDVI). Spatial changes ranged from −0.72% to +1.44%, which suggests that current vegetation conditions help refine the priority zones but do not greatly change their total size (Nawar *et al.*, 2022).

In contrast, slope, distance to roads, and distance to water bodies exhibited minimal influence on priority allocation, with most changes remaining below ±0.5% relative to the baseline scenario. This suggests that these variables function primarily as supporting criteria rather than principal determinants of Green Infrastructure priority distribution.

The sensitivity analysis confirms that the spatial model is highly reliable. A ±10% adjustment is a widely established threshold in spatial MCDA literature because it introduces enough variation to observe meaningful spatial dynamics without completely invalidating the original expert judgments established in the AHP weighting matrix (Amrutha *et al*., 2022; Huang *et al*., 2023). Except for the extreme positive scenarios of NDBI (+6.17%) and LST (+4.11%), the weight adjustments resulted in total area changes well below ±3.5%. These results validate the AHP weighting matrix and confirm that urban development intensity and land surface temperatures are the dominant factors determining the final Green Infrastructure priority zones. The relatively limited variation observed across most simulation scenarios confirms the stability of the AHP weighting structure and supports the reliability of the resulting Green Infrastructure priority map for climate-responsive urban planning applications. Figure 8 presents the Spatial distribution of Green Infrastructure priority areas under baseline and extreme sensitivity scenarios.

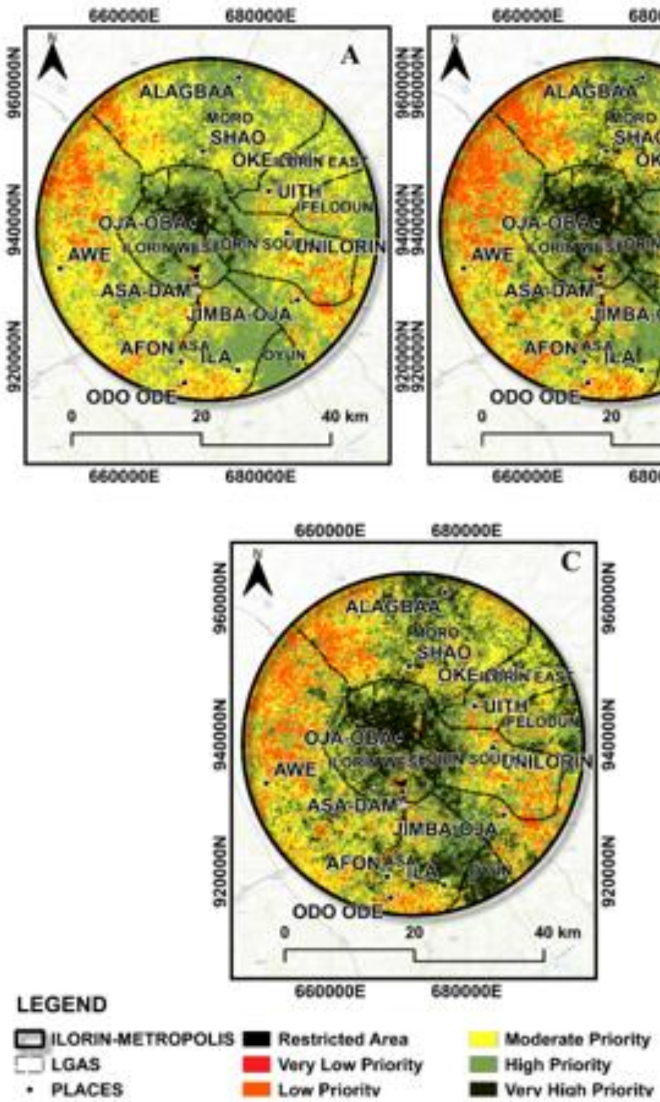


Figure 8. Spatial distribution of Green Infrastructure priority areas under baseline and extreme sensitivity scenarios. (A) The baseline constrained priority model; (B) Maximum reduction scenario (LST −10%); (C) Maximum expansion scenario (NDBI +10%).

3.5 Integration of Urban Expansion Dynamics with Green Infrastructure Priority Zones

Overlay analysis of LULC dynamics and Green Infrastructure priority zones revealed substantial spatial interaction between rapid urban expansion corridors and environmentally stressed landscapes requiring ecological intervention (Figure 9). Major growth corridors extending toward Ganmo, Tanke, Oke-Oyi, Eiyenkorin, Airport Road, Fate, Basin, and the Ajase-Ipo axis increasingly overlapped with areas characterized by declining vegetation cover, elevated thermal conditions, and increasing impervious surface concentration.

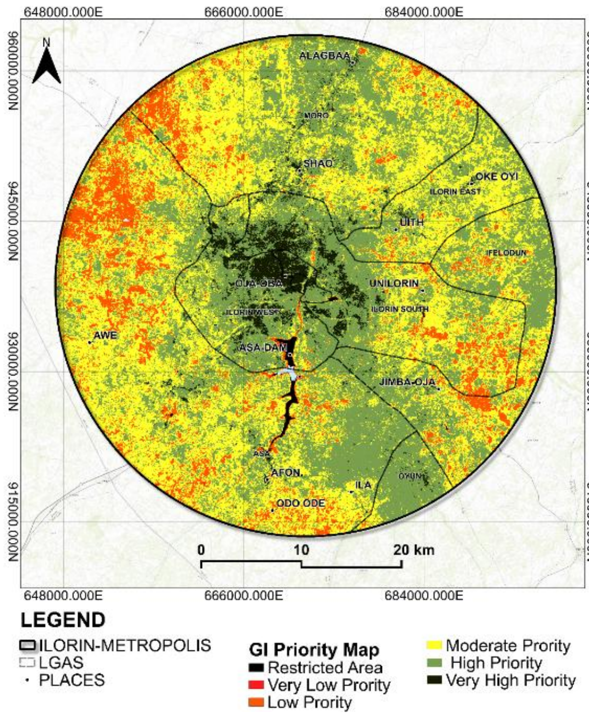


Figure 9. Overlay analysis of urban expansion dynamics and Green Infrastructure priority zones in Ilorin Metropolis

The southeastern corridor exhibited particularly strong interaction between rapid urban expansion and high-priority ecological intervention zones, where continuous residential and commercial development along the Ajase-Ipo highway transformed formerly vegetated landscapes into dense peri-urban settlements. Similar fragmentation patterns were observed around Tanke, Sanrab, and Oke-Odo within the University of Ilorin growth corridor. The western axis toward Eiyenkorin and Airport Road also demonstrated significant vegetation depletion associated with rapid industrial and residential development.

The concentration of very high priority zones within densely urbanized districts such as Challenge, Taiwo Road, Geri Alimi, Post Office, Adewole Estate, and Surulere further indicates that environmental degradation increasingly affects both peri-urban and metropolitan core areas through thermal accumulation, ecological fragmentation, and declining urban green-space availability.
The observed interaction between urban expansion and GI priority zones reinforces the conceptual relationship between land transformation processes and urban ecological resilience. As vegetated landscapes are progressively replaced by impervious infrastructure, ecosystem services, including thermal regulation, hydrological buffering, biodiversity support, and carbon sequestration, become increasingly disrupted. Consequently, urban vulnerability to flooding, thermal stress, and environmental degradation intensifies across rapidly urbanizing districts.

The findings, therefore, highlight the importance of integrating predictive ecological prioritization within metropolitan planning frameworks. Conventional urban planning approaches frequently prioritize infrastructural expansion without adequately incorporating ecological sensitivity and environmental resilience considerations. By integrating multi-temporal LULC dynamics with Green Infrastructure priority mapping, the present study advances a more strategic and climate-responsive framework for sustainable metropolitan management within rapidly urbanizing African cities.

The findings also demonstrate the need for stronger alignment between ecological prioritization outcomes and metropolitan development control mechanisms, land-use regulations, and implementation strategies within the Kwara State Master Plan framework. Integrating Green Infrastructure priorities into urban planning policy may substantially improve ecological sustainability, climate adaptation capacity, and long-term metropolitan resilience.

The sensitivity analysis further strengthens confidence in the ecological prioritization framework by demonstrating that the spatial allocation of Green Infrastructure priority zones remains largely stable under moderate weight perturbations. The dominance of NDBI and LST across simulation scenarios is consistent with the observed urbanization dynamics of Ilorin Metropolis, where increasing built-up intensity and thermal stress constitute the primary manifestations of environmental degradation. The findings therefore provide additional empirical support for prioritizing ecological interventions in rapidly urbanizing districts characterized by extensive impervious surface development and elevated thermal conditions.

Methodologically, the integration of Google Earth Engine-based cloud processing, Random Forest classification, GIS-MCDA modelling, and spatial overlay analysis provide a scalable and transferable framework for ecological restoration prioritization and climate adaptation planning. Despite limitations associated with the 30 m spatial resolution of Landsat imagery and potential subjectivity within AHP weighting procedures, the integrated analytical framework substantially improves reproducibility, scalability, and long-term urban ecological assessment capability. Furthermore, effective implementation of Green Infrastructure interventions will require active collaboration among urban planners, environmental agencies, local communities, NGOs, and development control authorities. Stakeholder-oriented ecological governance is essential for translating spatial prioritization outputs into practical and sustainable metropolitan environmental management strategies.

The findings demonstrate that continued uncontrolled urban expansion may progressively constrain future ecological restoration opportunities and weaken metropolitan environmental resilience unless Green Infrastructure priority planning is integrated into urban land management systems.

4.0 CONCLUSION

This study integrated multi-temporal Land Use Land Cover (LULC) analysis, Remote Sensing, Geographic Information Systems (GIS), and Multi-Criteria Decision Analysis (MCDA) to investigate urban expansion dynamics and develop a Green Infrastructure (GI) priority framework for Ilorin Metropolis, Nigeria. The results revealed substantial outward growth of built-up land between 2005 and 2025, accompanied by pronounced vegetation decline, increasing ecological fragmentation, and intensified peri-urban transformation. Urban expansion occurred predominantly along major transportation and institutional corridors, including Ajase-Ipo Road, Airport Road, Tanke, Ganmo, Oke-Oyi, and Eiyenkorin, reflecting infrastructure-driven metropolitan growth and escalating pressure on ecological landscapes.

Land transition analysis identified vegetation-to-built-up conversion as the dominant transformation pathway, indicating significant disruption of ecological connectivity and declining urban environmental resilience. Spatial analysis further demonstrated a strong relationship between rapid urbanization, fragmented vegetation networks, and increasing thermal stress, particularly within densely urbanized districts and expanding peri-urban zones.

The developed Green Infrastructure priority framework identified critical ecological intervention areas requiring urgent restoration and climate-responsive planning. Methodologically, the integration of Google Earth Engine cloud processing, Random Forest classification, GIS-based MCDA, and spatial overlay modelling provided a scalable, reproducible, and transferable framework for predictive ecological prioritization in rapidly urbanizing metropolitan environments.

The sensitivity analysis further demonstrated that the GIS-MCDA framework is robust to moderate variations in criterion weights. While NDBI and LST emerged as the dominant determinants of Green Infrastructure priority allocation, most criteria produced relatively minor changes in the distribution of priority areas, confirming the stability and reliability of the AHP weighting structure. These findings increase confidence in the applicability of the developed prioritization framework for climate-responsive urban planning and ecological interventions in rapidly urbanizing metropolitan environments.

The findings underscore the urgent need to mainstream Green Infrastructure planning within metropolitan land-use governance systems to enhance ecological connectivity, thermal regulation, stormwater management, and long-term urban climate resilience across rapidly urbanizing African cities.

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Author Contributions
Conceptualization: O.A.I; Methodology: O.A.I.; Data curation: O.A.I. and I.A.A.; Formal analysis: O.A.I. and I.A.A.; Writing—original draft: O.A.I; Writing—review and editing: O.A.I., A.B., and O.O.A..; Supervision: A.B. and O.O.A.

Disclosure Statement
The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted solely for academic and scientific purposes as part of the doctoral research activities of the first author within the Department of Surveying and Geoinformatics.

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