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ORIGINAL RESEARCH ARTICLE

SPATIO-TEMPORAL DYNAMICS AND FORECASTING OF URBAN LAND USE AND LAND COVER CHANGE IN MAIDUGURI USING GOOGLE EARTH ENGINE AND MACHINE LEARNING

M. Shettima[1,2*], M. Hasnat[2], G.H. Sambo[1], A.G. Bukar [3], A.M. Boyoma[2], and M. A. Mohammed[4]

[1]Department of Geography, University of Maiduguri, Borno State
[2]Department of Environmental Science, Integral University Lucknow, India
[3]Department of Civil and Water Resources Engineering, University of Maiduguri
[4]Department of Computer Science and Engineering, Integral University Lucknow, India
**Corresponding author's email address:* mswulgo@gmail.com

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ABSTRACT

Urbanization is one of the defining processes of the 21st century, particularly in the rapidly developing country like Nigeria. Google Earth Engine (GEE) and machine Learning techniques were utilized in this study to quantify spatio-temporal Landuse and Landcover (LULC) dynamics for 2000, 2010, 2020, and 2025 and to forecast the future trends to 2035 in Maiduguri Metropolis. A decadal classification framework was adopted to facilitate long-term LULC analysis, while the inclusion of 2025 enables the capture of emergent post-conflict land transformations and the spatial impacts of the 2024 flood event, which significantly altered land cover configurations. The projection to 2035 maintains a 10-year forecasting interval, ensuring consistency with established temporal benchmarks. Landsat imagery of the selected years was acquired and processed in GEE using the Classification and Regression Tree (CART) algorithm to classify major LULC categories, including built-up areas, cropland, vegetation, wetlands, bare surface, and water body. The overall accuracy for all the assessed years was 80% which indicates high classification reliability. The generated LULC was used to carryout Regression models (linear for five classes and polynomial for cropland) were fitted in Python's scikit-learn to project 2035 distributions. The results revealed that built-up area expanded from 324.8 km² (19.0%) in 2000 to 464.9 km² (27.2%) in 2025, cropland plummeted from 966.9 km² (56.7%) to 103.6 km² (6.1%) and bare land surged from 33.6 km² (1.9%) to 834.1 km² (48.9%). The wetlands and water bodies exhibited fluctuating trends linked to insurgency-driven land abandonment and the 2024 flood event. Forecasts for 2035 indicate bare land will dominate nearly 72% of the study area, built-up will reach 517.4 km², and cropland will shrink to 75.3 km². Given these findings, the study strongly recommends integrated sustainable land-use planning and conflict-sensitive restoration strategies to mitigate escalating environmental and socio-economic risks in rapidly urbanizing conflict zones like Maiduguri.

1.0 Introduction

Urbanization has emerged as one of the most significant transformations of landscapes, socio-economic structures, and environmental systems in 21st century, particularly in the developing nations (Haddad, 2024). The world's urban population is projected to rise to more than 60% of the global population by 2050, up from just over 50% in 2018 (Wang and Kintrea, 2021). This trend is part of a broader shift in human settlement patterns, driven by economic opportunities, technological advancements, and the concentration of services and infrastructure in urban areas (Yasin *et al.*, 2024). The epicenter of urbanization has shifted from the Northern Hemisphere to the Southern Hemisphere with cities in Asia and Africa experiencing the fastest growth rates (Huang and Xu, 2022). By 2050, Asia and Africa are expected to account for nearly 90% of the world's urban population growth, with countries like India, China, and Nigeria (Ekeh and Jegede, 2024)

Rapid urbanization in Nigerian cities is driven by employment opportunities, socio-economic, trading activities as well as insecurity in the rural areas, leading to significant population growth and spatial expansion, environmental degradation and unsustainable practices, impacting landscape design and sustainability (Oladunmoye, 2024) The environmental impacts of rapid urbanization are a major concern. The conversion of agricultural land and forests to urban uses has significant implications for food security and biodiversity (Ogunbode *et al.,* 2025) therefore, monitoring urban expansion is crucial for effective urban planning, management and spatial development models (Ding *et al.,* 2022).

Recent advancements in geospatial technology and machine learning have significantly enhanced the ability to monitor urban land use and land cover (LULC) changes. These technologies enable the analysis of land use and land cover (LULC) changes providing insights into urban growth patterns and facilitating urban planning. Several Studies have shown that combining these technologies enhances the accuracy of urban area assessments (Prasetyadi *et al.,* 2024; Al Mazroa *et al.,* 2024; Farooqi, *et al* 2024; Raj *et al.,* 2024). However, despite the increasing number of LULC studies in Maiduguri, most previous research (Dami *et al.* 2011; Ikusemoran and Mohammed, 2014; Babagana, *et al* 2019; Bello 2019; Umar, *et al.* 2023; Danung *et al*., 2025) have been limited to retrospective analysis using conventional geospatial techniques and they generally lack predictive modeling capabilities to forecast the future urban land use which are critical for proactive planning and sustainability. Therefore, this study integrates Google Earth Engine and Machine Learning Technology to assess the spatiotemporal Dynamics and Forecasting of Urban Land Use and Land Cover Changes in Maiduguri Metropolis between 2000 to 2025. This approach offers a robust framework to support sustainable urban development and spatial policy formulation in urban environments.

2. The Study Area and Methodology

2.1 Study Area

Maiduguri Metropolis is the capital and largest city in Borno State, North-Eastern Nigeria (Figure 1c) and is the second largest State in Nigeria after Niger State. Borno State is bounded in North-East by Chad, East by Cameroon, North by Niger, West by Yobe State and South by Gombe and Adamawa States. It is located between latitudes 11°N and 13°N and longitudes 10°E and 14°E. Spanning 65,868 square kilometers. It comprises of 27 local government areas. Maiduguri Metropolis is located between latitudes 11° 42’00”N and 12° 00’ 00” N and from longitudes 12° 54’ 00” to 13°20’ 00” E. It covered about 648 km^2. Maiduguri Metropolis encompasses approximately four Local Government Areas (LGAs), including Maiduguri Metropolitan Council and parts of Konduga, Jere, and Mafa LGAs (Figure 1d). The Metropolis typically receives rainfall from June to September. However, during rainy years, precipitation may begin earlier than June and extend beyond September. In some cases, rainfall has been recorded as early as April and lasting into October (Ikusemoran & Jimme, 2014). The rainfall pattern in the area generally shows spatial and temporal variability and has been characterized by a single maximum, with a peak around August. In the dry period, the temperature over the area may go up to 42°C. During harmattan, it may be as low as 15°C. It has a mean annual maximum temperature of 35°C with a mean temperature ranging between 30° and 40°C. The months of March and April are usually the hottest months, while November and January are the cold and dry periods of harmattan. Maiduguri is drained by the Rivers Ngadda and Ngaddabul which acts as a tributary to the Ngadda and the vegetation is similar to Sahel Savannah which is surrounded by shrubby vegetation interspersed with tall tree woodland (Bukar *et al.* 2025).

2.2 Methodology

This study systematically applied remote sensing and geospatial analysis techniques to detect LULC changes in Maiduguri Metropolis for the years 2000, 2010, 2020, and 2025. A decadal interval (2000–2020) align with standard remote sensing practices and ensure consistency in Landsat imagery quality and coverage. The inclusion of 2025 introduces a mid-decade snapshot to reflect recent urban acceleration and post-conflict land transformations. For forecasting, a 10-year projection to 2035 was adopted to maintain methodological continuity with earlier intervals. GEE was utilized to acquire and preprocess satellite imagery. It provides access to a multi-petabyte catalog of satellite imagery, including MODIS, Landsat, and Sentinel data, facilitating extensive environmental analyses (Wilson *et al.,* 2025). The Classification and Regression Tree (CART) algorithm was used for supervised classification, while regression modeling using Python's scikit-learn library was used to project future LULC trends. This combined approach facilitated the production and projection of accurate LULC.

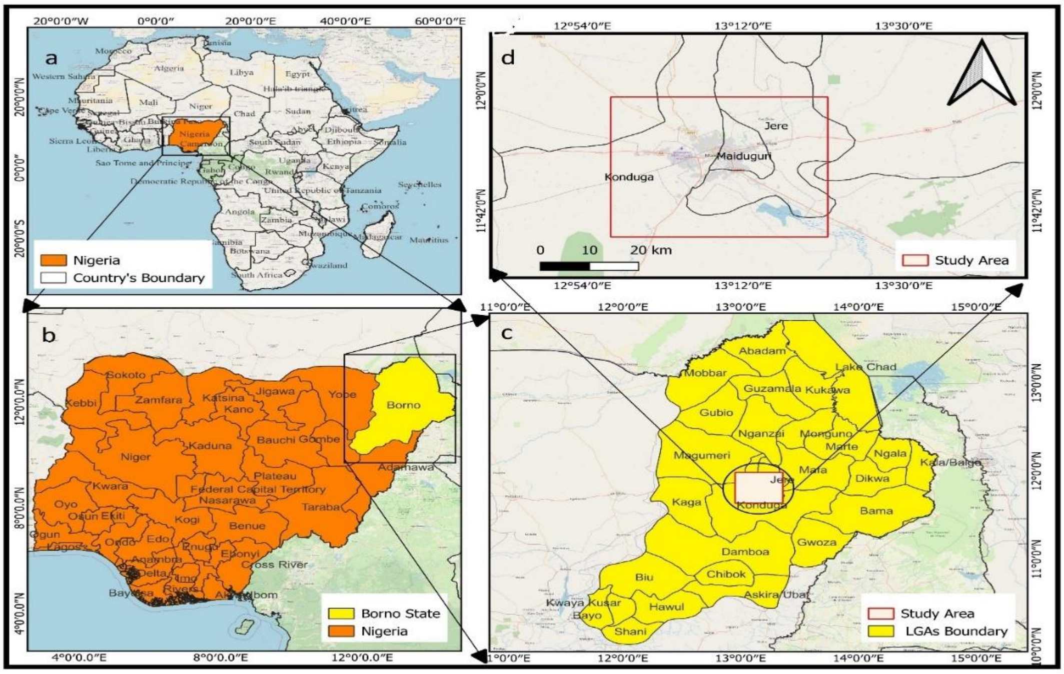

Figure 1: Study Area Description:(a) Africa showing Nigeria (b) Nigeria showing Borno State (c) Borno State showing Maiduguri Metropolis (d) Maiduguri Metropolis

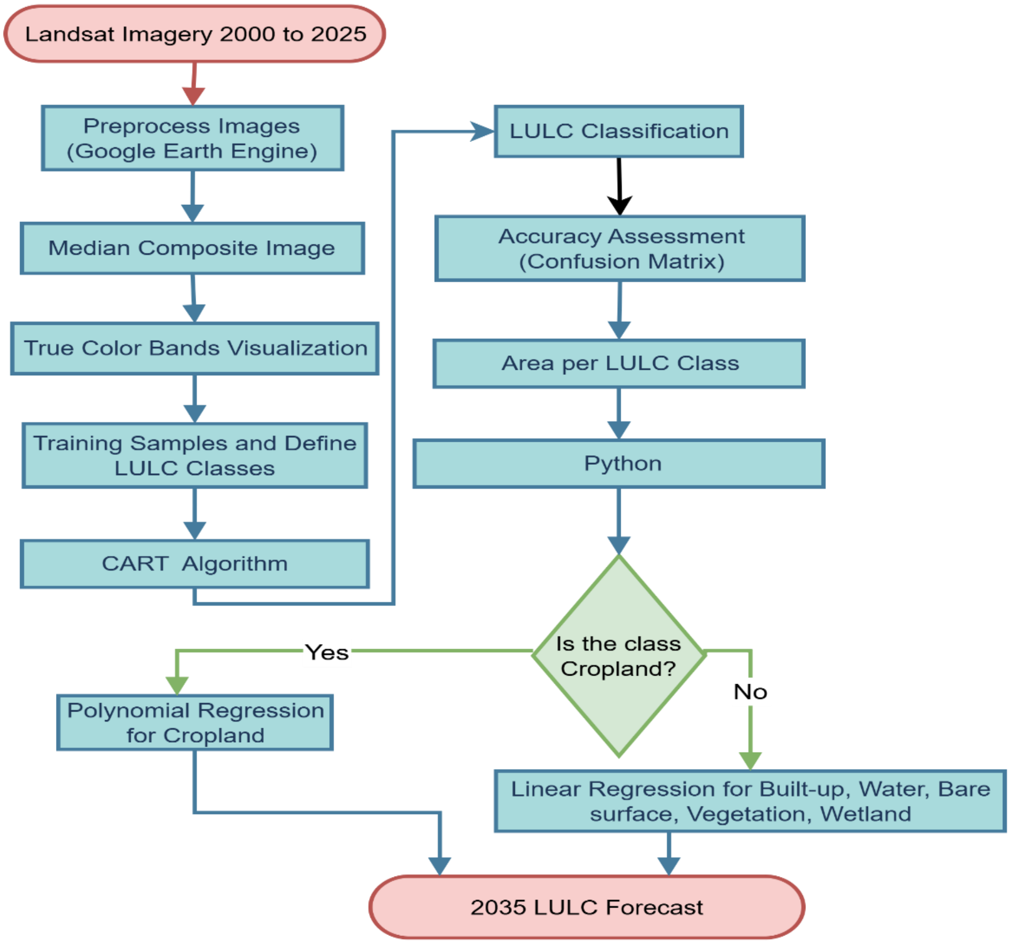

Figure 2: Methodology Flow Chart

Table 1: Tools and Software Environment

Software/Platform	Purpose
Google Earth Engine	Satellite image processing, classification (CART), LULC mapping
Python (scikit-learn)	Regression modeling and forecasting
QGIS	Map layout design, spatial validation, additional visualization

2.2.1 Dataset acquired

Landsat imagery from four time periods was used to generate LULC maps.

Table 2: Dataset Details

Year	Band Description	Sensor	Dataset ID	Reflectance Scaling	Spatial Resolution
2000	Visible spectrum (true color)	Landsat 5	LANDSAT/LT05/C02/T1_L2	0.0 – 0.3	30m
2010	Visible spectrum (true color)	Landsat 5	LANDSAT/LT05/C02/T1_L2	0.0 – 0.3	30m
2020	Surface Reflectance (true color)	Landsat 8	LANDSAT/LC08/C02/T1_L2	0.0 – 0.3	30m
2025	Surface Reflectance (true color)	Landsat 9	LANDSAT/LC09/C02/T1_L2	0.0 – 0.3	30m

Source: USGS Earth Explorer, 2025

2.3 Data Processing and Analysis

2.3.1 Image Preprocessing and compositing

The selected images were filtered by acquisition date (January to December), cloud cover (less than 20%), and the geographic bounds of Maiduguri Metropolis. Each year's imagery was processed to create a median composite and clipped to the study area. True color band combinations were used for visual inspection, and reflectance values were scaled appropriately for visualization (Xie *et al.,* 2021). For Landsat 5, B3 (Red), B2 (Green), B1 (Blue) were used, while for Landsat 8/9, bands SR_B4 (Red), SR_B3 (Green), SR_B2 (Blue) were employed. Reflectance values were scaled between 0.0 and 0.3 for visual interpretation (Table 2).

2.3.2 Supervised classification using CART

The LULC classification was categorized into six major classes: Water, Built-up, Vegetation, Cropland, Wetland, and Bare Surface. Representative training samples for each class were manually digitized through visual interpretation of high-resolution satellite imagery, complemented by local knowledge to improve accuracy (Barnoaiea *et al.,* 2024). Supervised classification was carried out using the Classification and Regression Tree (CART) algorithm within the GEE environment. The trained CART model was then applied to annual image composites to generate LULC maps for the selected reference years.

2.3.3 Accuracy assessment

To ensure the reliability and validity of the land use/land cover (LULC) classification results, accuracy assessment was conducted using the confusion matrix approach and matrix and the overall accuracy metric, calculated as:

$$\text{Overall Accuracy (OA)} = \frac{\text{Correctly Classified Pixels}}{\text{Total Pixels}} \times 100 \qquad 1$$

This method evaluates how well the classifier (CART algorithm) was able to assign the correct land cover labels by comparing the predicted classes against ground truth data (test samples). For all the years assessed

(2000, 2010, 2020, and 2025) the classification achieved the overall accuracy 80% and above (Table 3) suggesting good spectral separability and quality training data (Helmud *et al.,* 2024).

Table 3. Accuracy Assessment

Year	Overall Accuracy (%)
2000	89.1
2010	81.9
2020	87.5
2025	80.6

Source: Author's analysis, 2025.

2.3.4 Regression-based forecasting of LULC for 2035

To project future LULC (for 2035), regression models were built using LULC area data from 2000 to 2025. Python's scikit-learn library was used for this purpose. The approach involved fitting trend lines for each land cover class (Water, Built-up, Vegetation, Cropland, Wetland, and Bare Surface) based on historical area data. These models then predicted the expected area coverage of each class in the year 2035.

(i) Linear Regression Model

Linear regression is a statistical technique used to analyze the linear relationship between a dependent variable and one or more independent variables, forming the basis of statistical learning theory (Jacobs, 2023).

For classes with linear trends (built-up, bare surface, wetland, vegetation, water), simple linear regression was used, expressed as:

$$\gamma = \beta 0 + \beta 1x + \varepsilon \qquad 2$$

Where γ = Projected LULC area (in km²), χ = year (e.g., 2000, 2010, etc.), β_0 = intercept, β_1 = slope (rate of change), ε = random error term

(ii) Polynomial Regression Model

Polynomial Regression Models (PRM) estimate a dependent variable's parameters using independent variables with polynomial relationships, including interactions up to third order. Model selection involves minimizing multicollinearity and applying eight selection criteria to identify the best-fitting model (Abdullah *et al.*, 2011). The Model used for cropland, which exhibited nonlinear trends:

$$\gamma = \beta 0 + \beta 1x + \beta 2x + 2\,\varepsilon \qquad 3$$

$\beta 2$ = coefficient of the squared term, accounting for curvature in the trend

Model performance was evaluated using R^2 scores and Mean Squared Error (MSE) to assess goodness of fit. Once validated, the models were used to estimate the area of each LULC class for the year 2035 by substituting χ=2035 in the respective regression equations. These Models were also applied to forecast rainfall (Sittichok *et al*., 2024).

3. Results and Discussion

The analysis of land use and land cover (LULC) changes in Maiduguri between 2000 and 2025 revealed a distinct trend (Table 4). One of the most notable shifts is the dramatic expansion of built-up areas which increased from 324.80 km² (19.03%) in 2000 to 464.89 km² (27.24%) presently in 2025 (Table 4). The built-up area expanded consistently, with a net gain of 4.997 km² between 2000 and 2010, a much sharper increase of 104.189 km² from 2010 to 2020, and an additional 30.903 km² between 2020 and 2025 (Figure 3). These totals approximately 140 km² gained over 25 years. This finding is consistent with similar studies conducted in Maiduguri previously (Babagana, *et al* 2019; Bello 2019). The consistent increase particularly the spike during the 2010–2020 demonstrates urban growth driven by population growth, rural-to-urban migration, and the influx of internally displaced persons (IDPs) resulting from the Boko Haram crisis which intensified after the year 2009 (Egbuta, 2024). The shorter five-year period (2020-2025) also shows significant growth indicating the continued demand for residential and commercial land (Figure 3).

Table 4: Changes in LULC Area Between 2000 and 2025 (in km²)

Class	2000		2010		2020		2025	
	(km²)	(%)	(km²)	(%)	(km²)	(%)	(km²)	(%)
Water	68.634	4.02	73.243	4.29	19.243	1.13	36.984	2.17
Built-up	324.802	19.03	329.799	19.33	433.988	25.4	464.891	27.24
Wetland	302.539	17.72	265.401	15.55	122.708	7.19	253.105	14.83
Vegetation	10.394	0.61	13.976	0.82	34.699	2.03	14.22	0.83
Cropland	966.9	56.65	977.334	57.27	284.646	16.6	103.558	6.07
Bare Surface	33.63	1.97	47.145	2.76	811.614	47.5	834.141	48.89
Total	1706.89	100	1706.898	100	1706.89	100	1706.89	100

Source: Author's analysis, 2025.

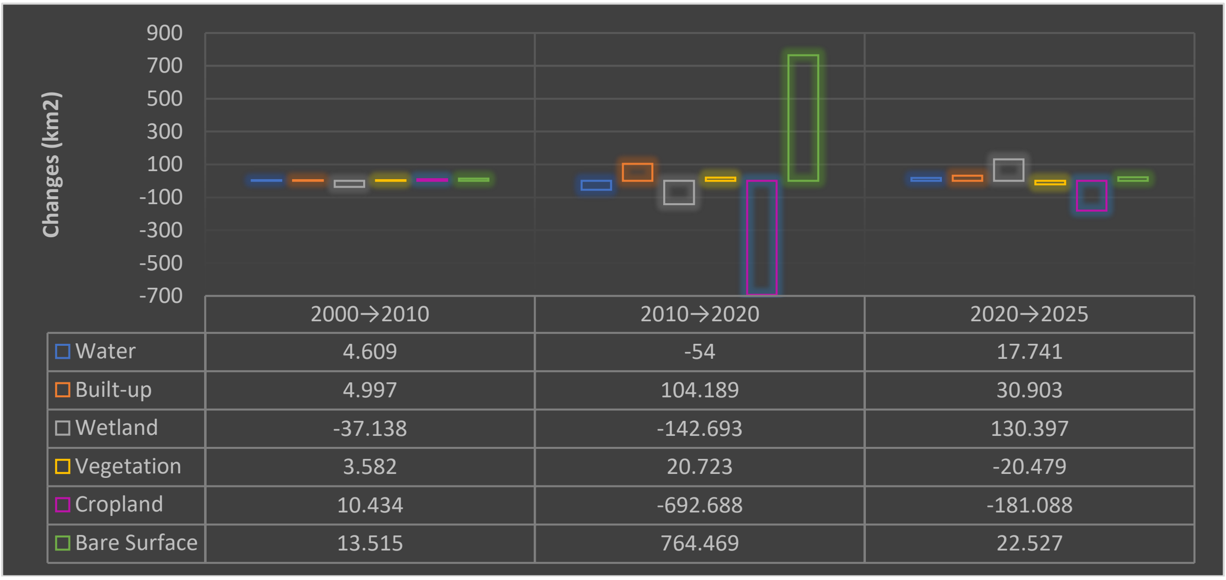

Figure 3: Net Changes of LULC Classes

While cropland the dominant land use in 2000, covering 966.90 km² (56.65%) has experienced a severe and sustained decline, decreasing to 103.56 km² (6.07%) today in 2025 (Table 4) and clearly depicted in Figure 3. After a slight increase of 10.434 km² between 2000 and 2010, cropland suffered massive declines of 692.688 km² from 2010 to 2020 and a further 181.088 km² from 2020 to 2025 (Figure 3). This finding corroborates with study by Bello, *et al.* (2023) and similar study conducted by Guo *et al.,* (2024) in Hainan Island, China. The cumulative net loss of approximately 863 km² represents a significant conversion of agricultural land to other uses. This change is largely attributed to the prolonged inaccessibility of farmlands due to ongoing insurgency which has led to widespread land abandonment (Ya'u, 2024). This land abandonment has severely impacted food security, disrupted local economies, and triggered widespread rural–urban migration (Okeleye *et al.,* 2023). Agriculture, being the backbone of rural livelihoods, has suffered a major setback, leading to increased poverty, market instability, and dependence on humanitarian aid (FAO, 2021; OCHA, 2023).

Bare Surface revealed a reverse trend from cropland, increasing steadily across all periods. 13.515 km² (2000–2010), 764.469 km² (2010–2020), and 22.527 km² (2020–2025) (Figure 3). In 2000, bare surface constituted a mere 33.63 km² (1.97%) of the total area and today in 2025, it is rose to 834.14 km², accounting for a staggering 48.89% of the total land area (Table 4). The net gain of over 800 km² highlights ongoing land degradation, likely resulting from vegetation loss, overgrazing, drought, and erosion sharp spike during the 2010–2020 period which coincides with the most significant loss of cropland (Abdulmalik and Zewide, 2021). Thus, suggesting that croplands are left as barren land due to insurgency (Ya'u, 2024). Moreover, the satellite images used for classification were captured predominantly during the dry season, when vegetation cover is naturally reduced, allowing the extent of bare surfaces to be more accurately detected. This seasonal timing strengthens the interpretation that the observed expansion of bare surface is not merely a short-term seasonal effect but reflects a long-term and structural shift in land use.

Wetlands also experienced significant fluctuation. Initially covering 302.54 km² (17.72%) in 2000, their extent fell drastically to 122.71 km² (7.19%) in 2020. However, the trend reversed between 2020 and 2025, with a gain of 130.397 km² (Figure 3) and it is not surprising, considering the flood that occurred in Maiduguri in 2024, which submerged more than 40% of the metropolis UNICEF, (2024) and left behind extensive wetland areas. Similarly, water bodies decrease from 68.63 km² (4.02%) in 2000 to a low of 19.24 km² (1.13%) in 2020, before slightly recovering to 36.98 km² (2.17%) in 2025 (Table 4). A modest recovery of 17.741 km² in the last five years (Figure 3) aligns with Mokhtarisabet and Okoduwa's (2025) observation in Maiduguri Metropolis, where NDWI analysis revealed a long-term decline in surface water and high-moisture areas driven by climate variability, vegetation loss, and urban expansion, followed by a slight recovery in 2024 linked to record-high rainfall of 863 mm and possible seasonal hydrological recharge.

Vegetation showed modest fluctuations, increasing from 10.39 km² (0.61%) in 2000 to 34.70 km² (2.03%) in 2020, before dropping again to 14.22 km² (0.83%) in 2025 (Table 4). This near balance in gains and losses over the 25 years indicates that vegetation has remained relatively static in net terms (Figure 3). This indicate that vegetation gains prior to the peak insurgency years were gradual, while a sharp increase during peak insurgency likely resulted from farmland abandonment and reduced anthropogenic disturbance. The post-insurgency decline coincides with population resettlement, agricultural expansion, and renewed urban growth, which accelerated vegetation clearance. Climatic variability, particularly the statistically significant upward rainfall trend of 3.33 mm/year from 1987 to 2024 and extreme precipitation events such as the 863 mm recorded in 2024 (Mokhtarisabet, and Okoduwa, 2025), likely amplified seasonal greening in wetter years and influenced regeneration rates, indicating the combined roles of socio-political instability and climate-driven hydrological changes in shaping vegetation dynamics.

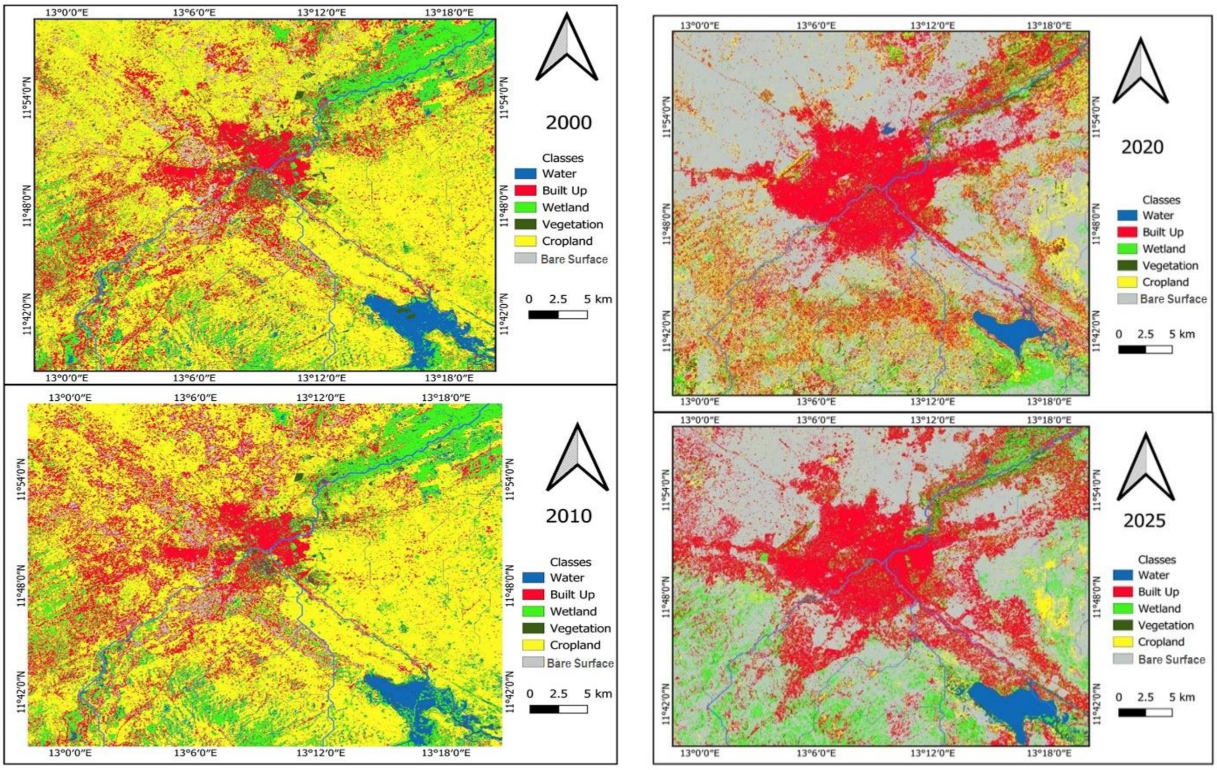

Figure 4: Land use and Land Cover dynamic of Maiduguri Metropolis

3.1 Forecasted Land Use/Land Cover Areas for 2035 in Maiduguri Metropolis

Based on regression analyses of LULC results from 2000 to 2025, future projections for the LULC distribution of Maiduguri Metropolis in 2035 indicate substantial landscape transformations (Figure 5). The most striking outcome of the projection is the anticipated dominance of bare land, which is expected to expand significantly to approximately 1,227.89 km², accounting for nearly 72% of Maiduguri's total land area. This finding aligns with that of Bedada (2024), who also reported a substantial increase in barren land alongside built-up areas. However, some other studies contradict this result, highlighting instead an increase in built-up areas (Paudel *et al.,* 2024; Ban, 2024). The scale of this expansion is alarming, indicating that if current trends persist, most of the productive and vegetated land in Maiduguri will transition into bare surface by 2035 posing serious ecological threats and undermining land sustainability. In the same vein, the built-up area is forecasted to reach approximately 517.44 km² (Figure 5), further validating the persistent and aggressive nature of urban. The expansion of urban land use, although indicative of economic growth and modernization, poses considerable challenges for spatial planning, waste management, traffic congestion, and provision of urban services in a rapidly evolving landscape (Hu *et al.,* 2023; Kanav *et al.,* 2024). Conversely, cropland projected to decline drastically to just 75.32 km² (Guo *et al.,* 2024). This forecast modeled using polynomial regression due to its observed non-linear fluctuations over the past decades. The wetland area is predicted to expand modestly to about 147.15 km² (Figure 5). Vegetation cover is expected to occupy 28.78 km² by 2035 an increase from current values but still a marginal share of the total area while water bodies are forecasted to shrink to 10.22 km² (Figure 5) showing ongoing hydrological stress. The continued reduction in surface water availability poses risks to domestic supply, irrigation, and ecosystem health, particularly in a semi-arid environment where water scarcity is already a pressing issue (Hassan *et al.,* 2024)

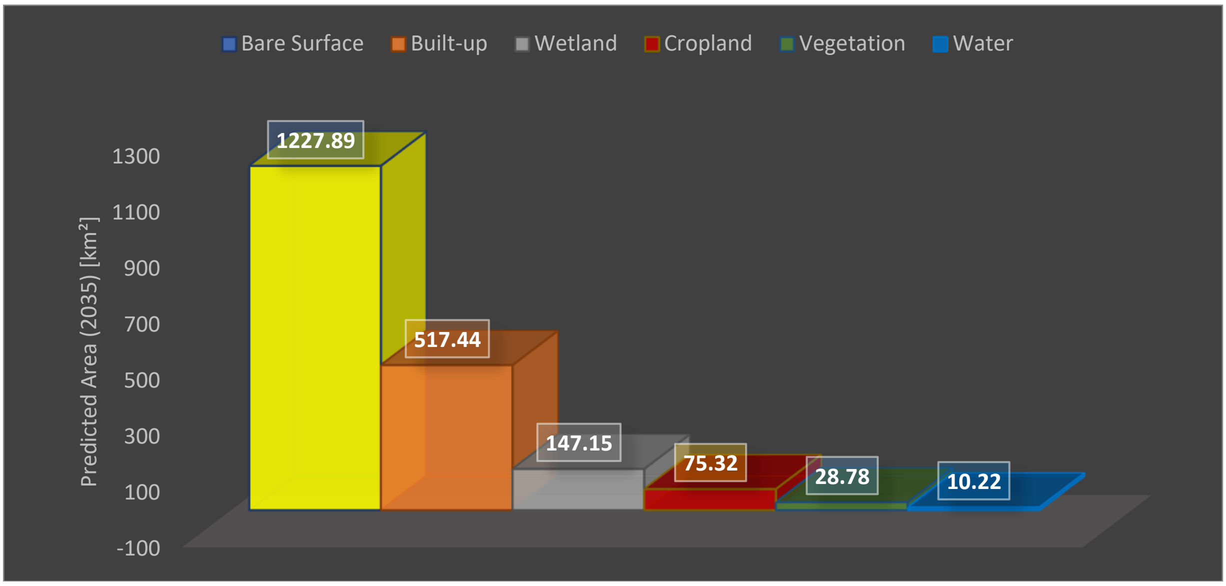

Figure 5: Forecasted Land Use/Land Cover Areas for 2035 in Maiduguri Metropolis

4. Conclusion

The spatio-temporal analysis of land use and land cover (LULC) changes in Maiduguri Metropolis reveals a significant spatial transformation over the past 25 years, marked by rapid urban expansion, severe cropland decline, and increasing Bare Surface. Built-up areas grew steadily driven by population pressures and socio-political instability (Boko Haram insurgency) while cropland once the dominant land use experienced a drastic reduction of over 860 km². Concurrently, Bare Surface expanded from just 1.97% in 2000 to nearly 49% in 2025 indicating an extensive land degradation likely influenced by insurgency, deforestation and poor land management. While waterbody, wetlands and vegetation exhibited fluctuations the 2024 flood notably contributed to a temporary rise in wetland and water bodies coverage showcasing the role of extreme weather events in shaping land cover patterns. Projections for 2035 indicate even more critical shifts, with bare land expected to dominate up to 72% of Maiduguri's total area and cropland shrinking further to just 75.32 km². Built-up areas are expected to continue expanding reaching over 517 km² this growth poses serious challenges to sustainable urban development. Although slight improvements are predicted for wetlands and vegetation, they remain marginal. These findings revealed that Integrating cloud-based platforms like GEE and machine learning not only enables real-time monitoring but also offers a scalable approach for evidence-based interventions in urban environments undergoing rapid and unregulated transformation. In view of these findings, this study recommended an integrated sustainable land use planning, conflict-sensitive land restoration programs and water resource management to mitigate the severe environmental and socio-economic constraints.

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