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Assessment and Monitoring of Land Use Land Cover Dynamics in Edo State Over a Designated Temporal Interval Utilizing Remote Sensing and GIS Techniques

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Abstract

The demand for accurate and timely information regarding land resources and their temporal evolution is increasingly critical, especially in rapidly expanding urban areas. In this study, Landsat satellite imagery spanning eleven time points; 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019, and 2022 was utilized to assess changes in land use and land cover (LULC) in Edo State and its environs over a 21-year period. Employing ArcGIS 10.6.1 and ERDAS Imagine software, false-color composites (FCCs) were generated, and supervised classification using the maximum likelihood technique was conducted to categorize the study area into thirteen secondary classes including forest (evergreen broadleaf forest, deciduous broadleaf forest, and mixed forest), woodland (closed shrublands, woody savanna, and savanna), grasslands, permanent wetlands, croplands, urban/built-up areas, cropland/vegetation, barren land, and water bodies. Results revealed a notable increase in water bodies, with increments of 5.852% from 2001 to 2009, 5.932% from 2009 to 2015, and 4.936% from 2015 to 2022. Additionally, closed shrublands, urban/built-up areas, and water bodies exhibited considerable growth over the entire period, while croplands, grasslands, permanent wetlands, cropland/vegetation, evergreen broadleaf forest, and deciduous broadleaf forest experienced declining growth rates. In 2001, the urban/built-up area measured approximately 317.873 km^2, with gradual increases observed in subsequent years. For instance, from 2003 to 2007, the urban/built-up area expanded from 319.127 km^2 in 2003 to 323.780 km^2 in 2005 and 329.320 km^2 in 2007. These results highlight significant changes in land use and land cover patterns over the study period.

1.0. Introduction

Land use and land cover change (LULCC) represent critical components of environmental dynamics, with far-reaching implications for ecosystem health, natural resource management, and sustainable development. Extensive research in this field has underscored the importance of understanding the drivers, patterns, and consequences of LULCC, particularly in rapidly urbanizing regions. Previous studies have demonstrated the utility of remote sensing and GIS techniques in quantifying LULCC dynamics, providing valuable insights into landscape transformations over time. While existing literature has contributed significantly to our understanding of LULCC processes, there remains a need for comprehensive assessments in specific geographic contexts to address regional variations and emerging challenges.

Land is a vital natural resource for human life. Land use/land cover (LULC) is a cross-cutting environmental variable with significant applications in hydrological modeling, watershed management, natural disaster management, climate change studies, and land management [1, 2, 3]. Land use and land cover change (LULCC) has become a central component in current strategies for managing natural resources and monitoring environmental changes [4, 5]. The ability to forecast land use and land cover changes and to ultimately predict the consequence of change will depend on the ability to understand the past, present and future state of the land use and land cover condition. This ability is enabled through the use of multi temporal data which provide valuable information on the state of the natural resources like land, water, forests, infrastructure, road network etc [6, 7, 8].

The land use/land cover pattern of a region is an outcome of natural and socio – economic factors and their utilization by man in time and space [9, 10]. Land is becoming a scarce resource due to immense agricultural and demographic pressure. Hence, information on land use / land cover and possibilities for their optimal use is essential for the selection, planning and implementation of land use schemes to meet the increasing demands for basic human needs and welfare [8, 5]. This information also assists in monitoring the dynamics of land use resulting out of changing demands of increasing population [11, 5].

Land use land cover (LULC) changes are mostly influenced by increase and decrease in population growth in the system [12], economic growth, and physical factors including topography, slope condition, soil type, and climate [13, 14]. LULC change analysis is usually required by planners and decision-makers for effective planning and management interventions on local, national, regional, and even global scales [15, 3]. Change detection has emerged as a significant process in managing and monitoring natural resources and urban development mainly due to provision of quantitative analysis of the spatial distribution of the population of interest [16]. There are a lot of available techniques that serve purpose of detecting and recording differences and might also be attributable to change [17, 18]. Though, simple change detection is seldom adequate in itself: there is a requirement of information regarding initial and final land cover/types/uses, the ‘‘from-to’’ analysis. It is necessary to have accurate and up-to-date land cover change information for understanding and assessment of the environmental consequences of such changes [19].

Satellite Remote Sensing and GIS are prominent methods for evaluating, mapping, and identifying trends in LULCC owing to their precise spatial referencing, digital data format conducive to computerized analysis, and repetitive data capture [20, 21, 22]. The process of digital change detection, widely utilized in analyzing multi-temporal remotely sensed data, facilitates the determination and description of prevailing changes in LULC characteristics. Numerous scholars have tackled the issue of precisely monitoring alterations in Land Utilization and Cover Transformation (LUCT) across diverse landscapes [17, 23, 24]. A variety of methodologies, encompassing image differentiation, pre-and post-assessment comparison (PPC), variation in vegetation indices, and principal component examination (PCA), have been devised and applied for detecting changes utilizing remotely captured data [25]. The technique of pre-and post-assessment comparison has emerged as a widely employed method across different studies due to its capacity to illustrate the nature of occurring modifications. Employing the PPC method aids in alleviating issues linked with; multi-temporal images captured under varying atmospheric and environmental conditions [17, 26, 27, 28]. Remote Sensing (RS) stands out as the primary tool for Land Utilization and Cover Dynamics (LUCD), facilitating the examination of shifts in land use traits and processes by utilizing datasets spanning different periods and extensive geographical areas. RS imagery presents various advantages, including widespread coverage, extended temporal spans, and relatively straightforward data processing, solidifying its status as a fundamental data resource for identifying alterations in land utilization over recent epochs [29, 30].

Previous research has emphasized the importance of understanding the socio-economic and environmental drivers of LULCC to develop effective land use policies and management strategies. Studies have shown how factors such as agricultural intensification, urbanization, deforestation, and climate change influence land cover changes and ecosystem services provision. By elucidating the complex interactions between human activities and natural processes, previous research has contributed to advancing our understanding of LULCC dynamics and their implications for sustainable development and environmental conservation. By building upon these foundations and employing advanced geospatial analysis techniques, the present study aims to contribute new insights into LULCC patterns and processes in Edo State and its environs, thereby informing land management decisions and promoting sustainable development practices in the region.

2. Methodology

2.1 Description of Study Area

Edo State, situated in southern Nigeria, is characterized by its capital city, Benin City, known for its historical significance and vibrant cultural heritage. Positioned at approximately 6.34° N latitude and 5.62° E longitude with an elevation of 88 meters above sea level, the state is endowed with a diverse population that contributes to its cultural richness. Home to various ethnic groups, Edo State boasts a population 1.15 million persons according to the last national census in 2006. The projected population of the state using the National Population Commission’s growth rate of 3.5% per annum for urban centers is estimated to reach 5.5 million by the year 2050. The region's geology is marked by a mix of sedimentary and metamorphic formations, while its mineral resources include limestone, granite, and crude oil. Edo State experiences distinct wet and dry seasons typical of the West African climate. The local culture is deeply rooted in traditions and festivals, with the renowned Benin Kingdom historically contributing to the artistic and cultural tapestry of the region. Figure 1 shows the 3D map of the study area.

2.2 Data Requirement

Data used for the study are Landsat images (Landsat 8 OLI/TIRS) for 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019 and 2022 which were obtained freely from the United States Geological Survey (USGS) archive. This was with a view to obtaining useful information on the changes in land use patterns within the study area for adequate monitoring and planning. Landsat datasets were selected for this study, since they are highly suitable for studies on land use/land cover change detection. They can also give a time series of data on an area and also have good spatial resolution [31, 32]. The characteristics of the datasets employed in this study is presented in Table 1.

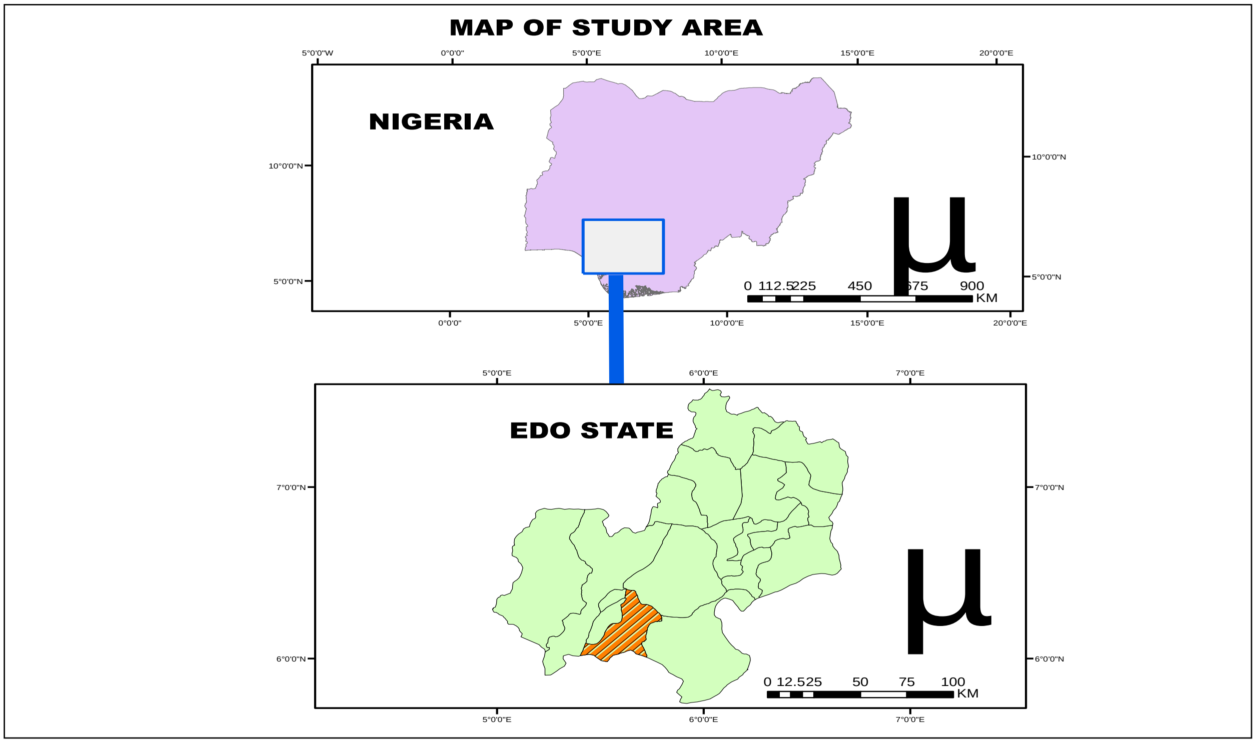

Figure 1: 2D study area map

Table 1: Characteristics of dataset for Edo State

Data Type	Date of Capture	Spatial Resolution	Landsat Scene	Source
Landsat Imagery	Oct. 2001	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2003	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2005	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2005	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2007	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2009	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2011	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2013	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2015	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2017	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2019	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2021	30m	Landsat 8	USGS
Landsat Imagery	Oct. 2022	30m	Landsat 8	USGS

2.3 Processing and Analysis of Satellite Imagery

The initial step in processing satellite imagery involved the creation of a digital topographic database. This process began with the acquisition of hardcopy topographic maps of the study area, which were then, digitized using ArcGIS 10.6.1 and ERDAS Imagine 9.0. Within ArcGIS 10.6.1, the conversion process included scanning the maps, geo-referencing, and raster-vector conversion, resulting in a vectorized land use/land cover map. The vectorized map was then rasterized to obtain data for estimating the actual area (in square kilometers) covered by different land use classes.

Additionally, cross operations were performed on the land use land cover maps to analyze temporal changes. Using the raster database, the area coverage of each land use land cover class was calculated for different time periods. Geometric correction was applied to rectify distortions from earth curvature, atmospheric refraction, and relief displacement. Finally, false color composites were evaluated by assigning three bands of color composite (Red, Green, and Blue) to one of the basic colors, including Natural Color Composite (NCC) and false color composite (FCC) configurations, as documented in previous studies [33, 34, 35].

2.4 Accuracy Assessment of LULC Maps

To conduct a comprehensive accuracy assessment of the land use and land cover (LULC) classification process, several steps were undertaken. Initially, ground truth data were collected through high-resolution imagery, with representative sample points selected across the study area covering different land cover types. These samples were visually identified and classified into corresponding land cover classes, forming the reference dataset. Subsequently, a pixel-based accuracy assessment was performed and a confusion matrix was generated, comparing the classified land cover classes with the reference dataset. Producer's accuracy (PA) and user's accuracy (UA) metrics were calculated using the following equations:

$$PA_i = \frac{C_{ii}}{r_i} \times 100\% \tag{1}$$

$$UA_i = \frac{C_{ii}}{C_i} \times 100\% \tag{2}$$

Where; c_{ii} represents the number of correctly classified samples in class ii, r_i is the total number of reference samples in class ii, and c_i is the total number of classified samples in class ii. The overall accuracy (OA) was then computed as the proportion of correctly classified pixels or objects relative to the total number of samples, using the equation:

$$\text{OA} = \frac{\sum C_{ii}}{N} \times 100\% \tag{3}$$

Additionally, the kappa coefficient (K_C) was calculated to assess the agreement between the classified land cover and the reference dataset by using the equation:

$$K_C = \frac{\left(N \times \sum C_{ii} - \sum r_i \times C_i\right)}{N^2 - \sum r_i \times C_i} \tag{4}$$

Interpretation of results involved evaluating the overall accuracy and kappa coefficient values, aiming for values close to 1 for high agreement, and considering producer's and user's accuracy values for individual land cover classes to identify areas of improvement in the classification process. By following this methodology, the reliability and validity of the LULC classification results were strengthened, providing more robust evidence for land cover change analysis and informing decision-making processes in land management and environmental planning.

3. Results and Discussion

3.1. LULC Classification

The LULC classification maps of years 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019 and 2022 produced in the study are displayed in Figures 2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12, respectively. Each of these maps includes thirteen (13) secondary classes in the study area.

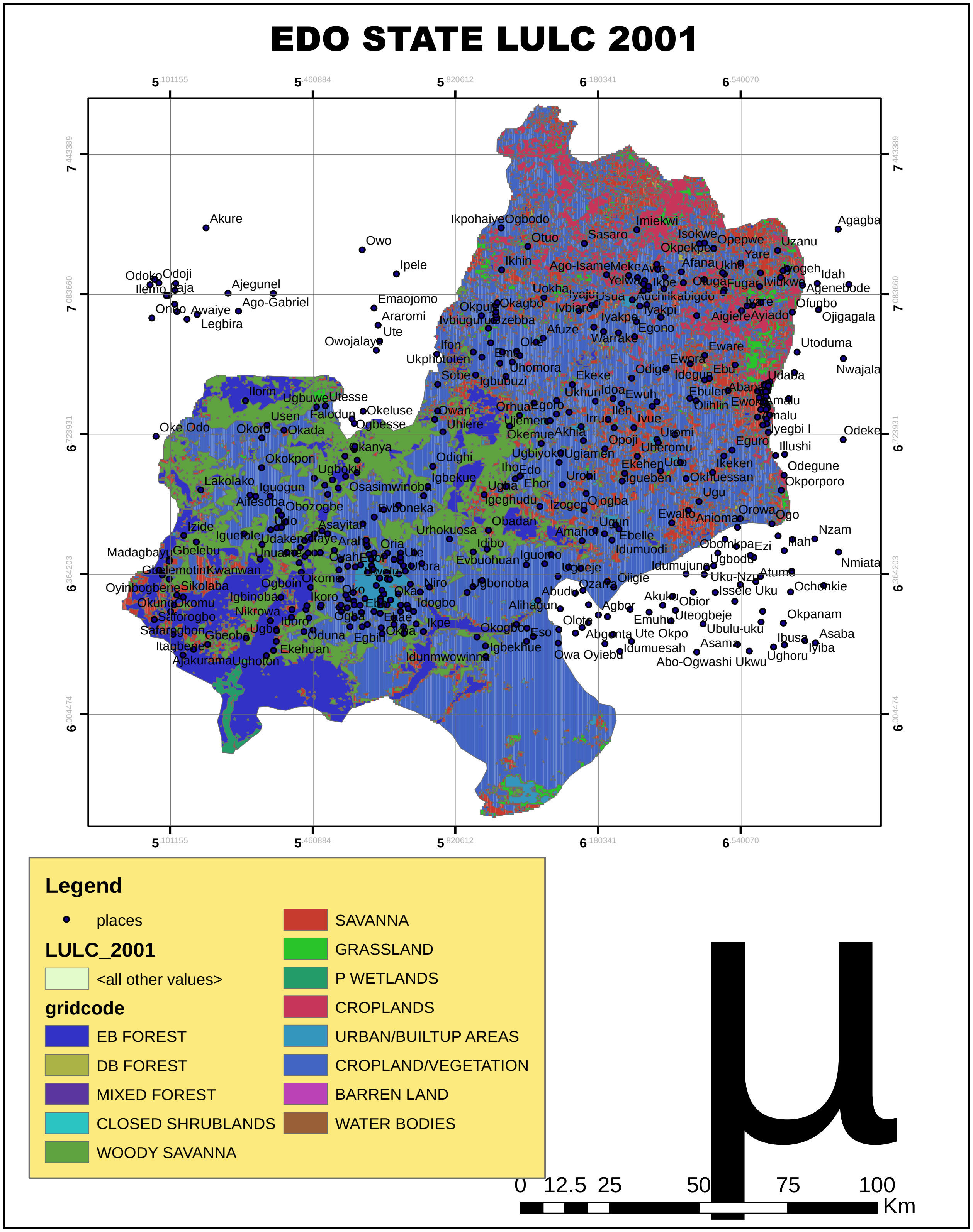

Figure 2: Edo State LULC map for 2001

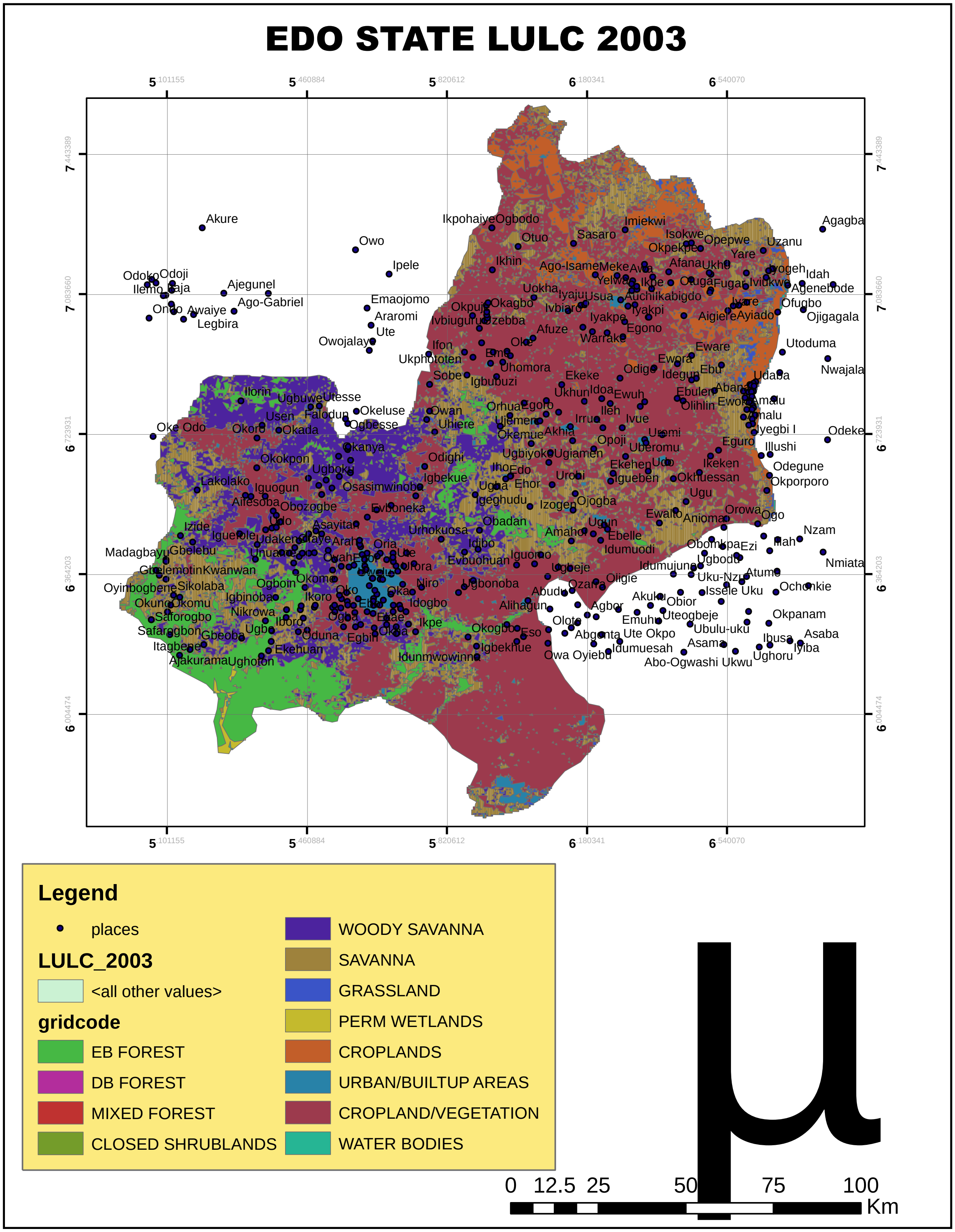

Figure 3: Edo State LULC map for 2003

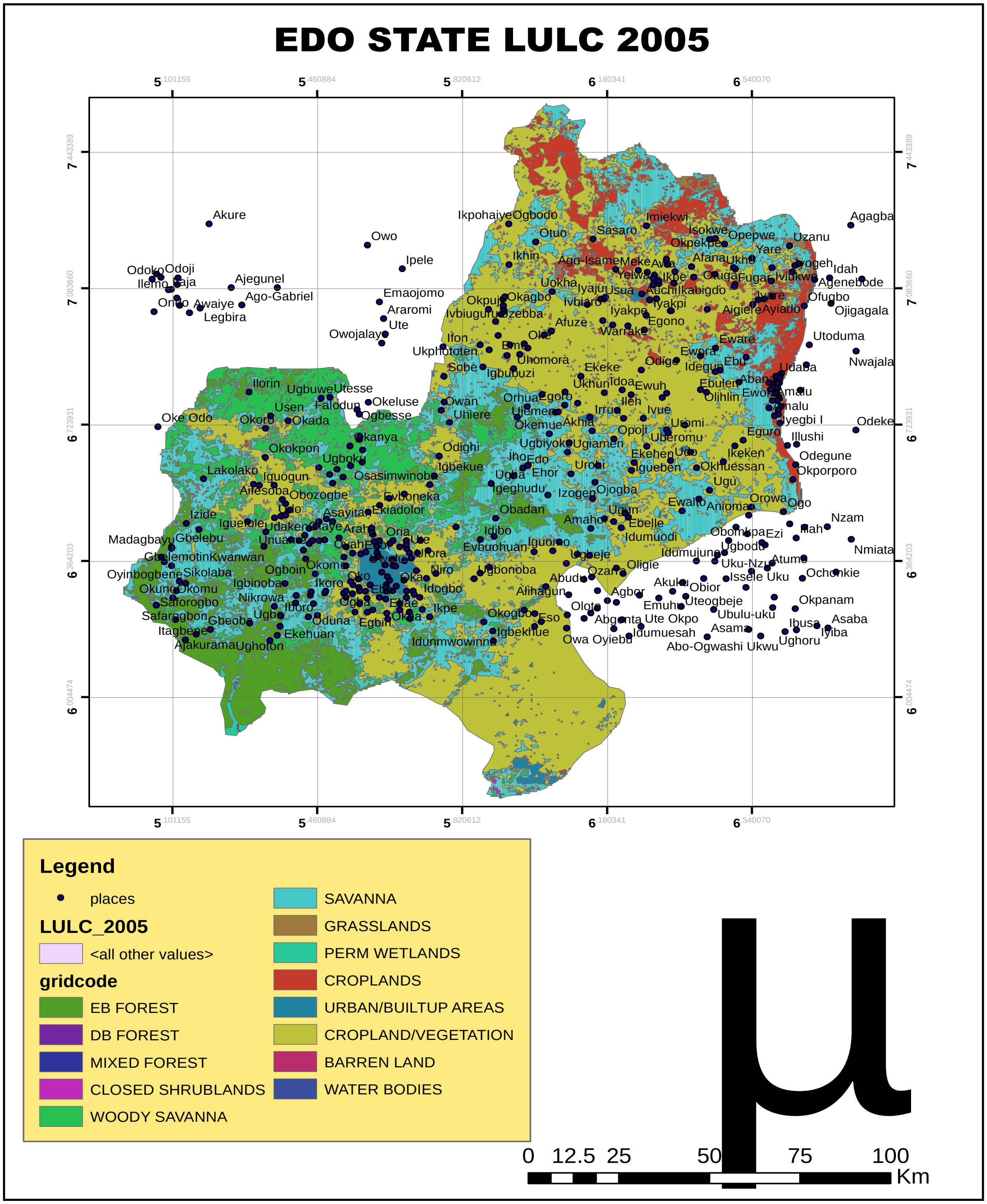

Figure 4: Edo State LULC map for 2005

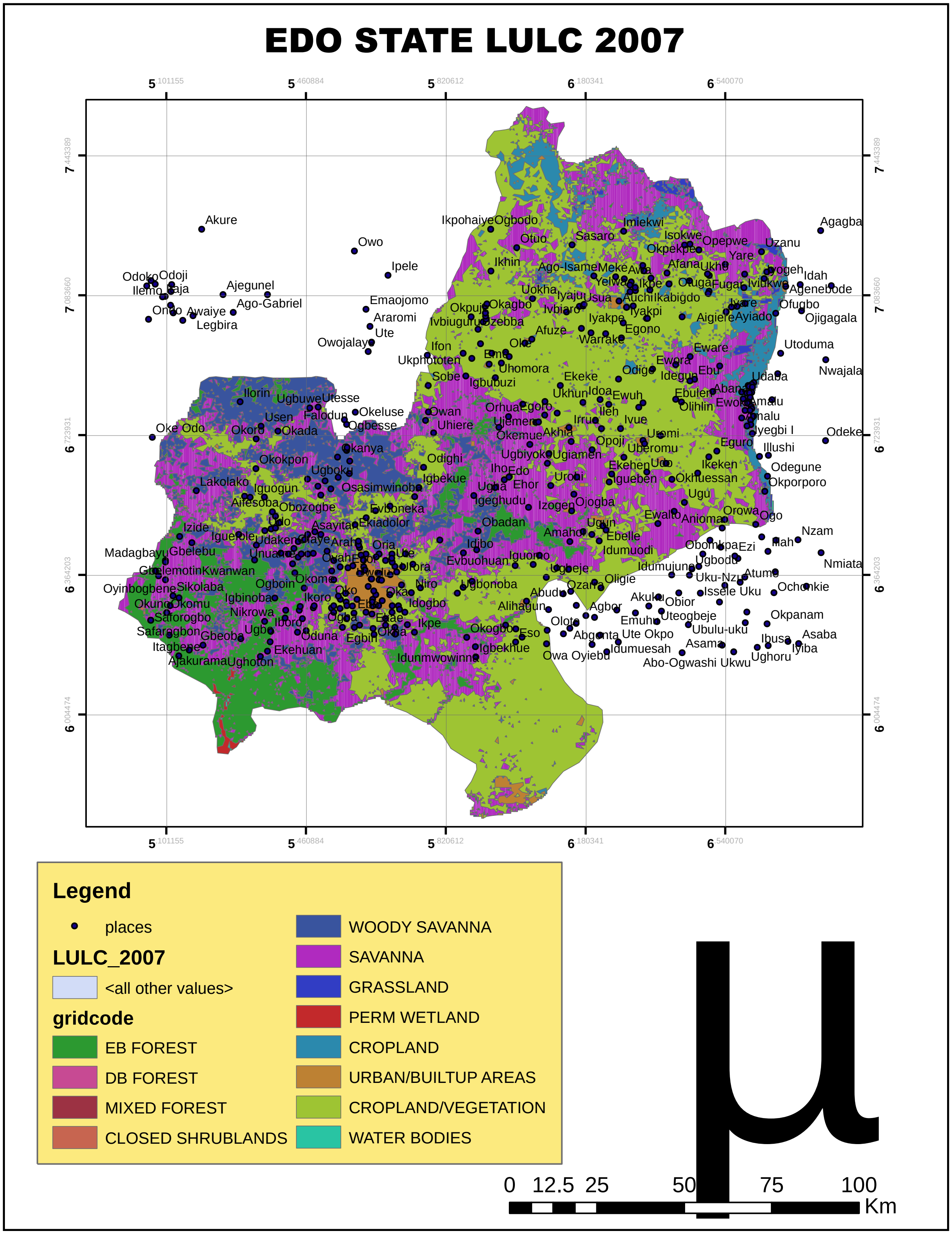

Figure 5: Edo State LULC map for 2007

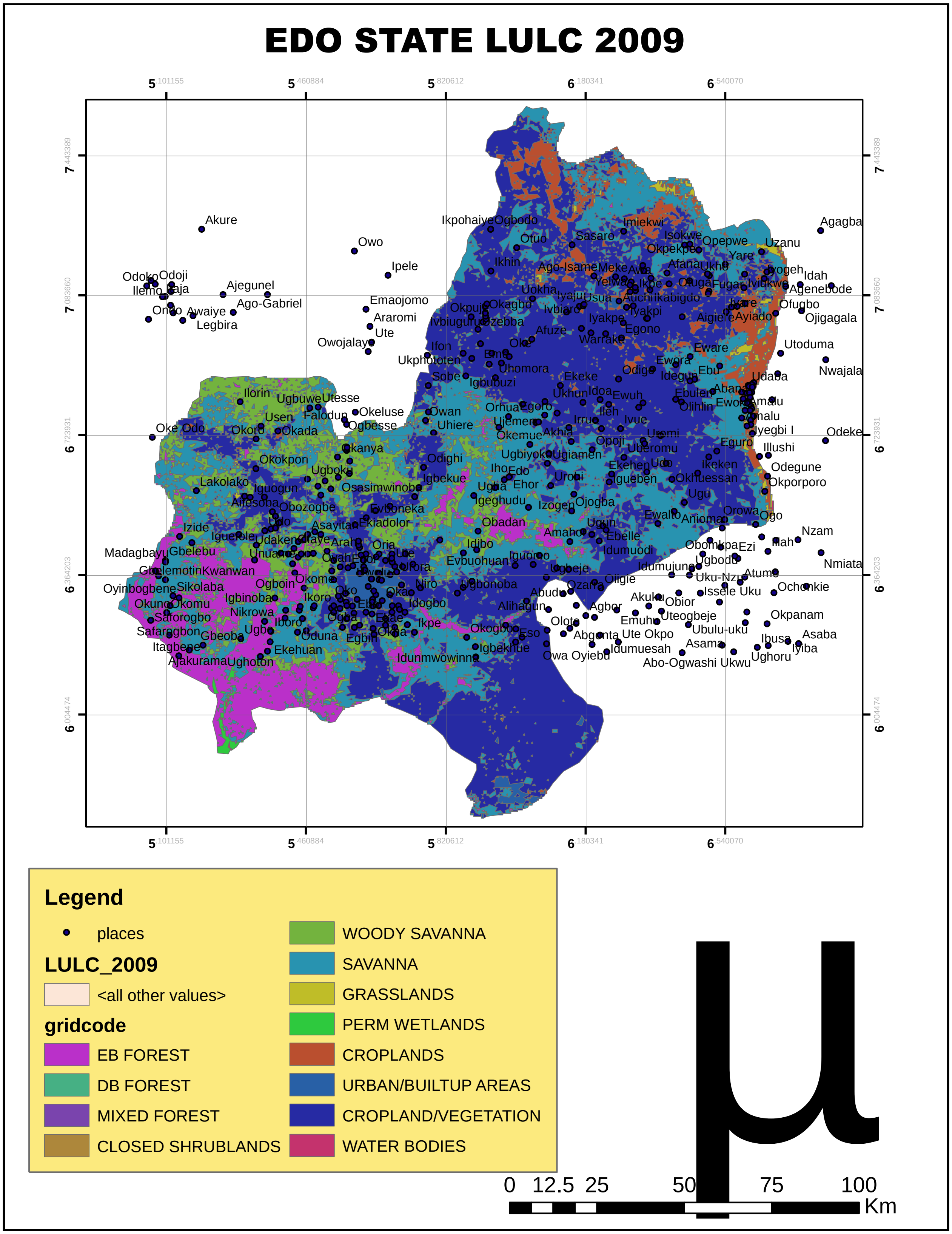

Figure 6: Edo State LULC map for 2009

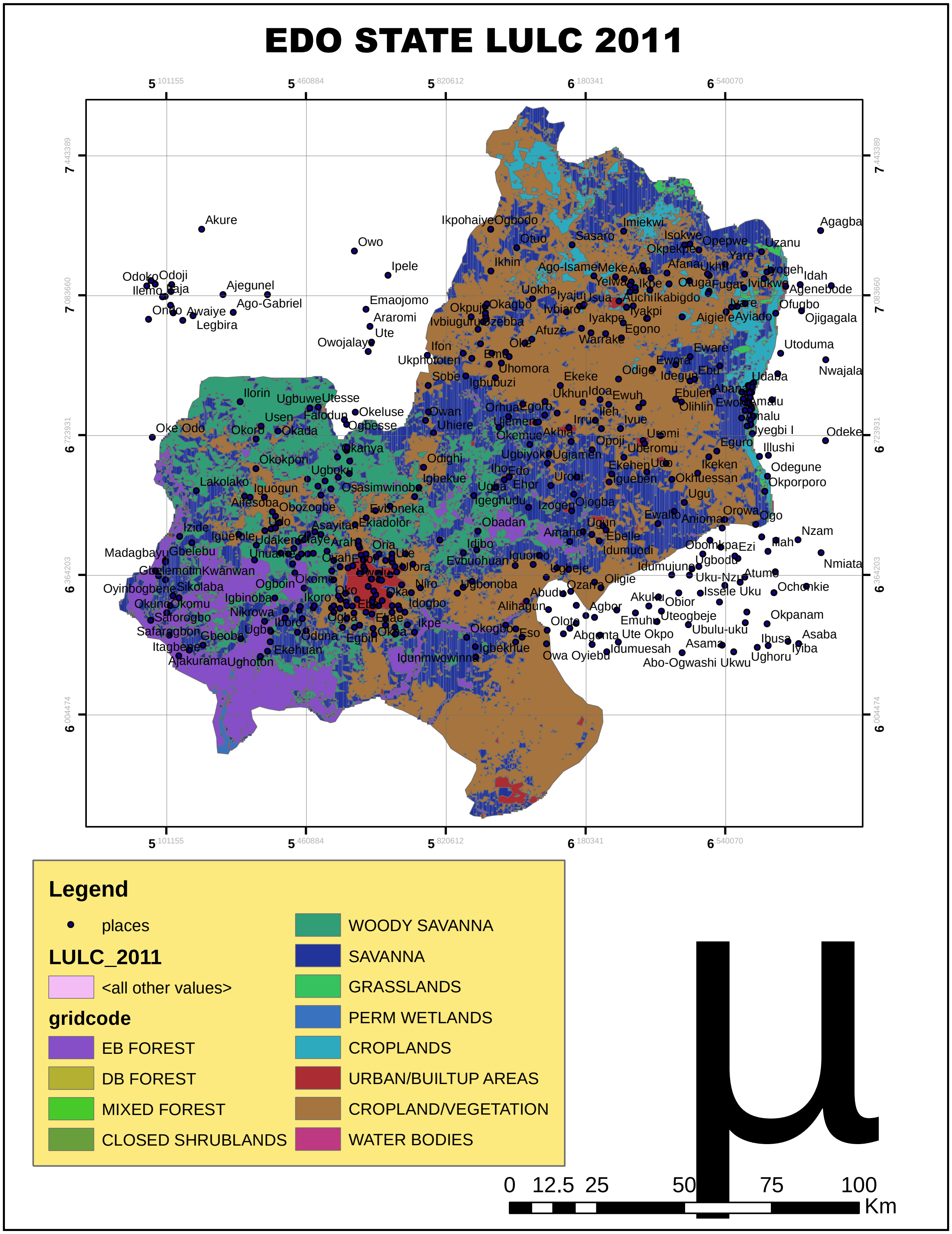

Figure 7: Edo State LULC map for 2011

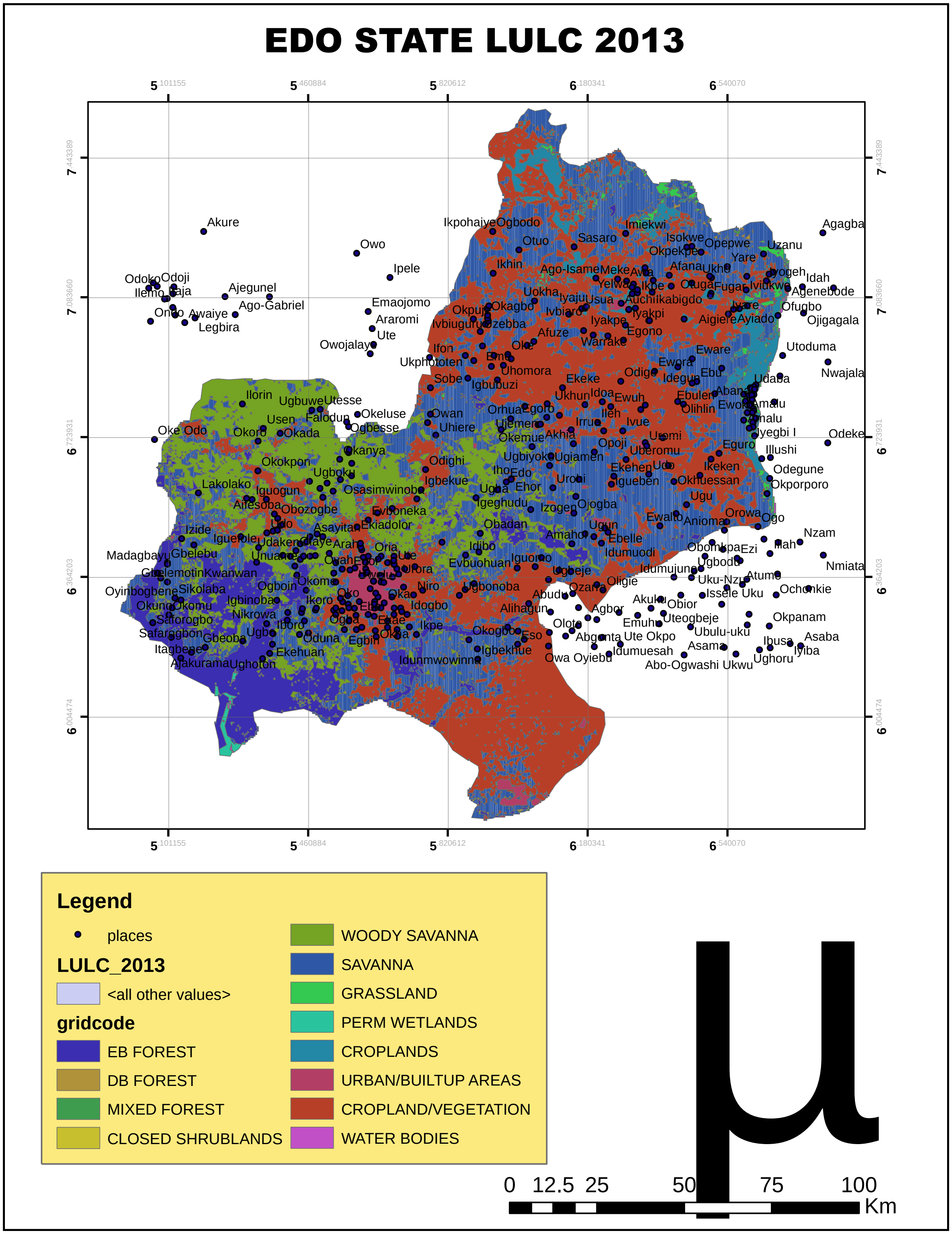

Figure 8: Edo State LULC map for 2013

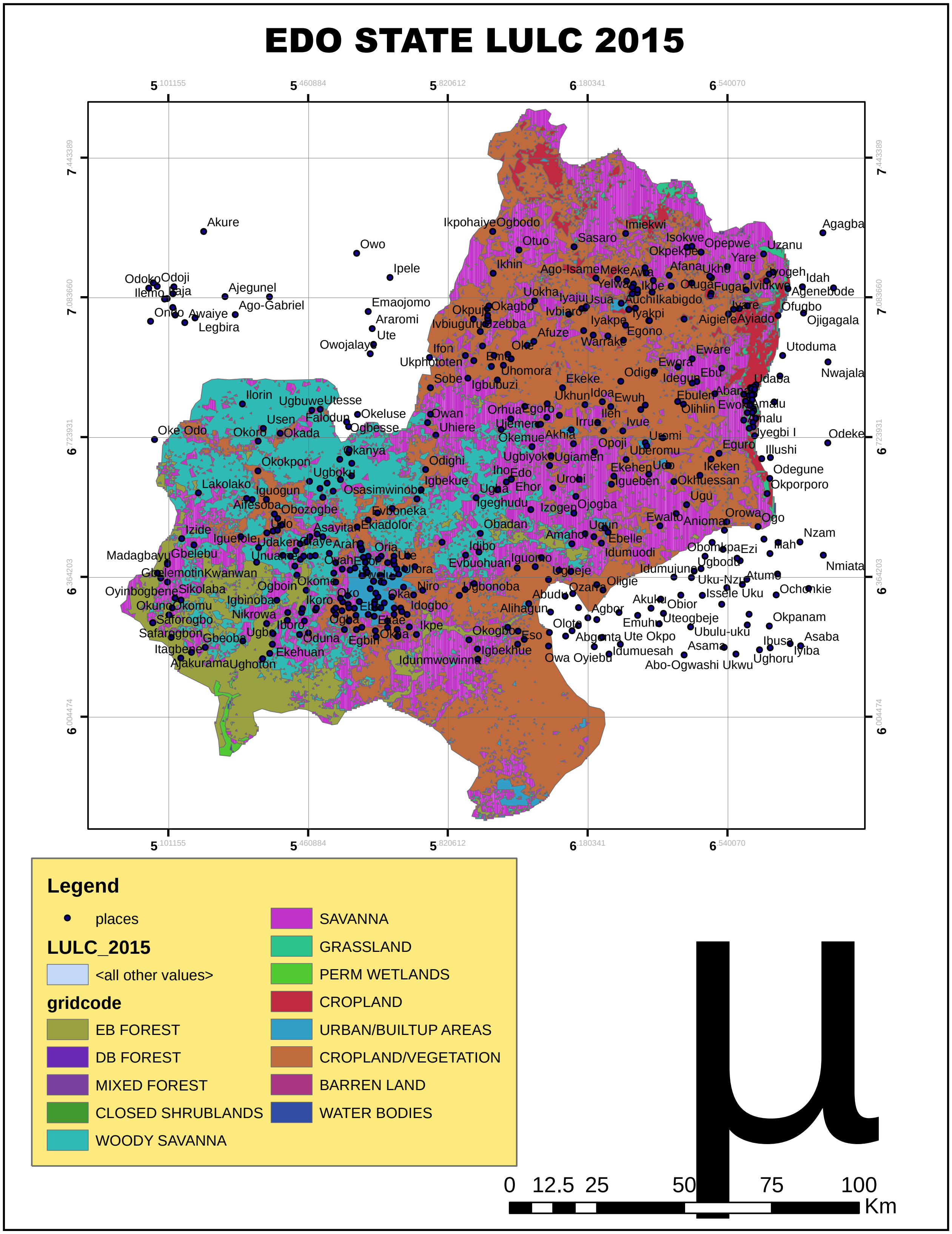

Figure 9: Edo State LULC map for 2015

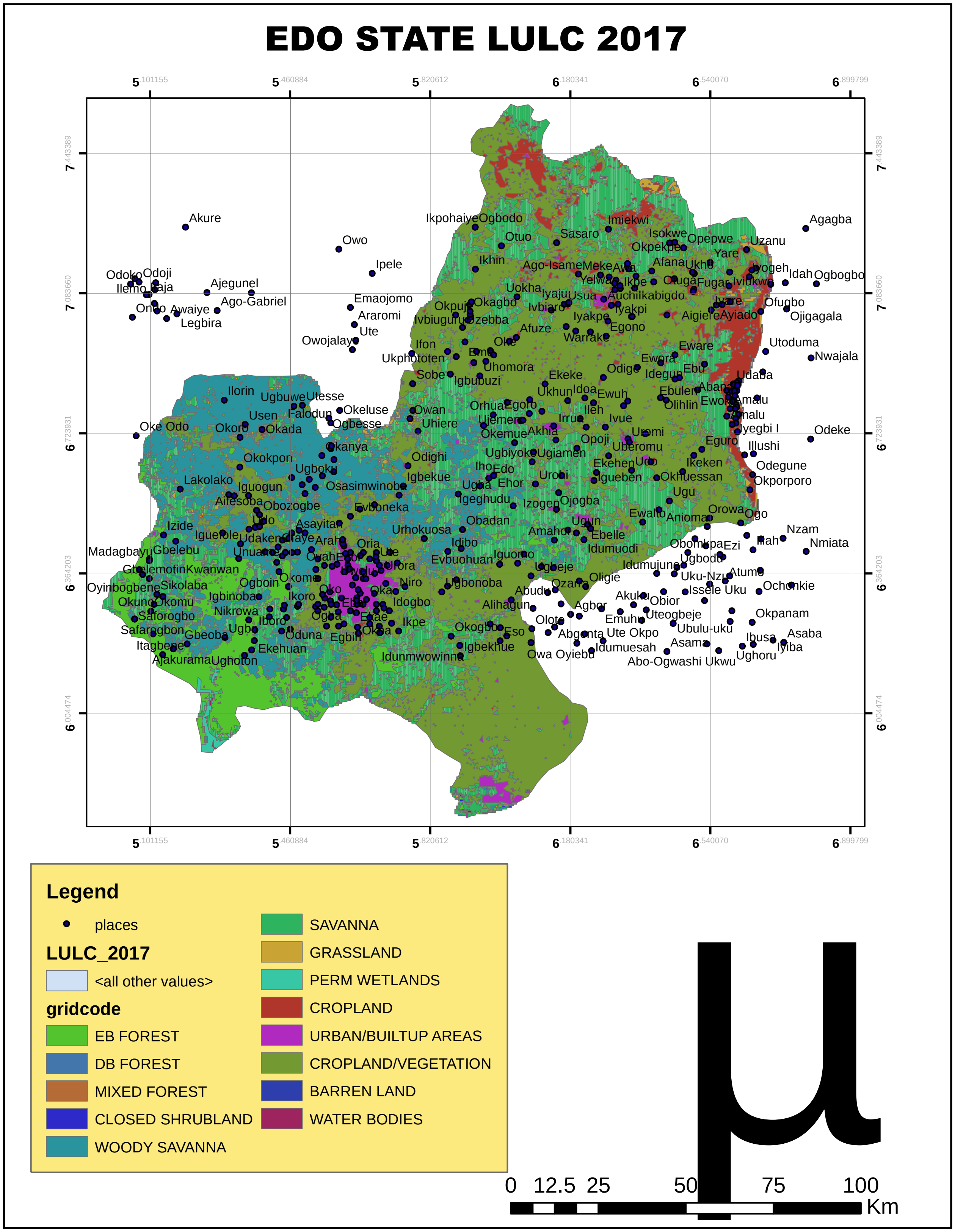

Figure 10: Edo State LULC map for 2017

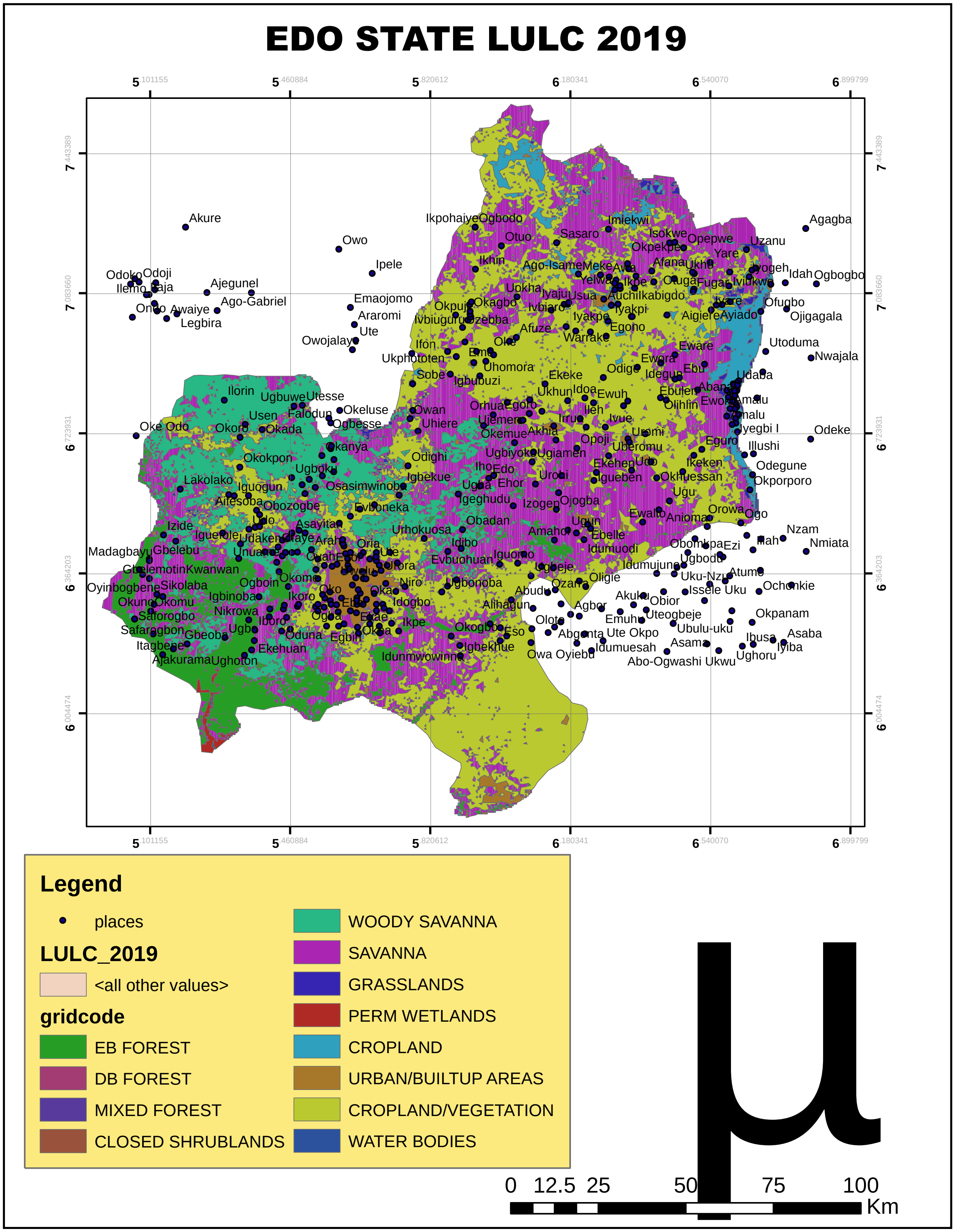

Figure 11: Edo State LULC map for 2019

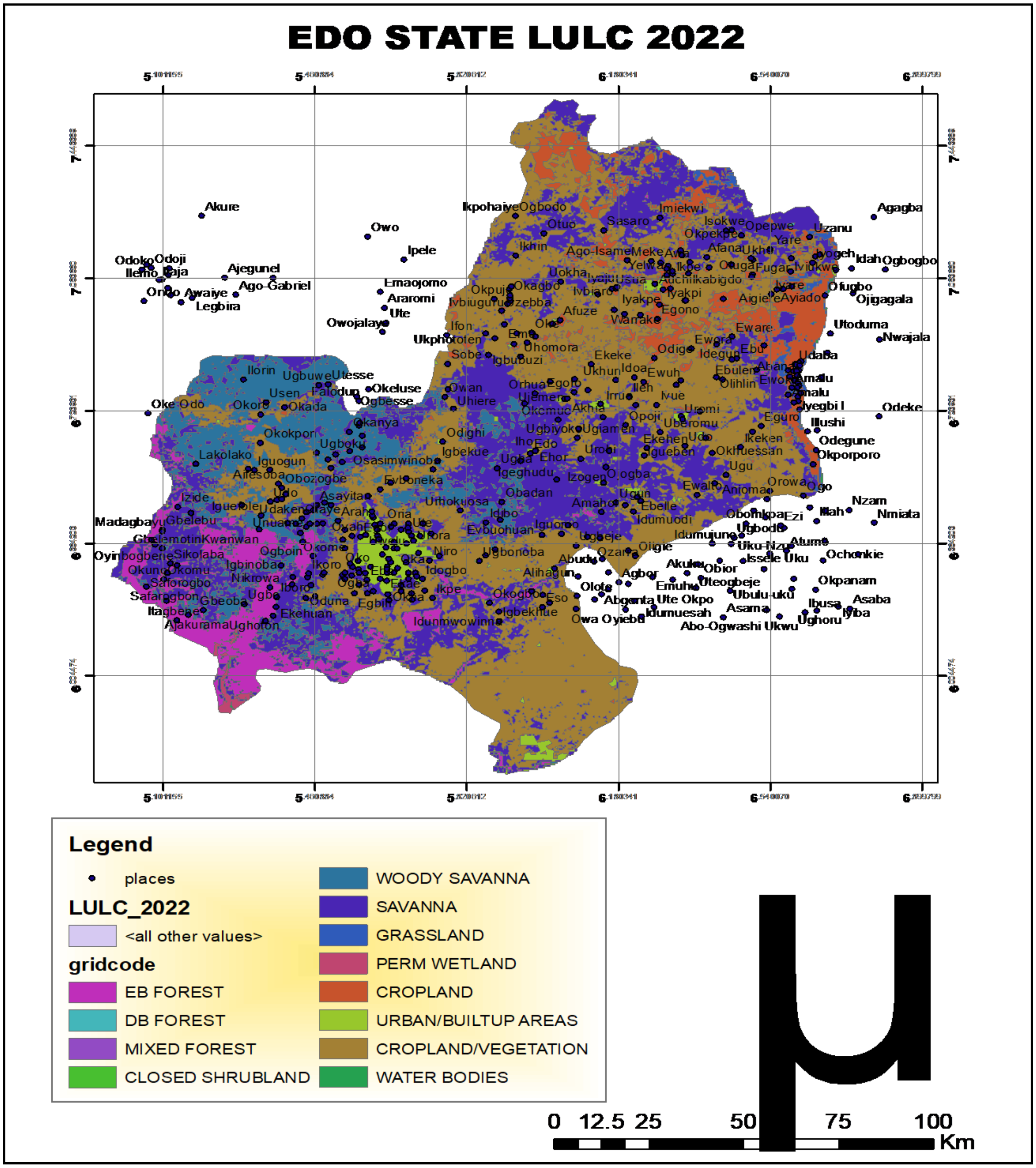

Figure 12: Edo State LULC map for 2022

The main LULC classes of the study area in the year 2001 to 2022 were found to be forest (evergreen broadleaf forest (EB), deciduous broadleaf forest (DB) and mixed forest), woodland (closed shrublands, woody savanna, and savanna) including grasslands. Others are; permanent wetlands, croplands, urban/built-up areas, cropland/vegetation, barren land and water bodies.

3.2. Spatiotemporal Change Analysis.

The annual rates of change (%) of the 13 LULC secondary classes during the years 2001–2009, 2001– 2015 and 2001–2022 are presented in Tables 2, 3 and 4.

Table 2: Percentage Change Analysis for 2001 and 2009

Landuse Code	Landuse Class	Area_Sq_Km 2001	Area_Sq_Km 2009	Percentage Change (%)
2	Evergreen Broadleaf Forest (EB)	2220.623	1600.310	27.93419
4	Deciduous Broadleaf Forest (DB)	57.514	1.660	97.11375
5	Mixed Forest	12.755	1.262	90.10584
6	Closed Shrublands	0.147	2.425	-1549.66
8	Woody Savanna	2977.387	1863.297	37.41838
9	Savanna	2212.801	6252.570	-182.564
10	Grasslands	425.042	185.241	56.41819
11	Permanent Wetlands	93.719	35.924	61.66839
12	Croplands	1437.127	884.583	38.44782
13	Urban / Built-up Areas	317.873	332.629	-4.64211
14	Cropland / Vegetation	9852.761	8446.892	14.26878
16	Barren Land	0.429	0.000	100
17	Water Bodies	8.732	9.243	-5.85204

Table 3: Percentage Change Analysis for 2001 and 2015

Landuse Code	Landuse Class	Area_Sq_Km 2001	Area_Sq_Km 2015	Percentage Change (%)
2	Evergreen Broadleaf Forest (EB)	2220.623	1524.441	31.35075
4	Deciduous Broadleaf Forest (DB)	57.514	8.255	85.64697
5	Mixed Forest	12.755	1.670	86.9071
6	Closed Shrublands	0.147	1.783	-1112.93
8	Woody Savanna	2977.387	3256.427	-9.37198
9	Savanna	2212.801	6403.760	-189.396
10	Grasslands	425.042	191.498	54.9461
11	Permanent Wetlands	93.719	49.705	46.9638
12	Croplands	1437.127	635.335	55.79131
13	Urban / Built-up Areas	317.873	372.525	-17.193
14	Cropland / Vegetation	9852.761	7161.143	27.31841
16	Barren Land	0.429	0.214	50.11655
17	Water Bodies	8.732	9.250	-5.9322

Table 4: Percentage Change Analysis for 2001 and 2022

Landuse Code	Landuse Class	Area_Sq_Km 2001	Area_Sq_Km 2022	Percentage Change (%)
2	Evergreen Broadleaf Forest (EB)	2220.623	1161.373	47.70058
4	Deciduous Broadleaf Forest (DB)	57.514	4.185	92.72351
5	Mixed Forest	12.755	0.147	98.84751
6	Closed Shrublands	0.147	1.850	-1158.5
8	Woody Savanna	2977.387	2070.812	30.44868
9	Savanna	2212.801	5928.982	-167.94
10	Grasslands	425.042	170.204	59.95596

11	Permanent Wetlands	93.719	46.535	50.34625
12	Croplands	1437.127	1329.928	7.459257
13	Urban / Built-up Areas	317.873	423.898	-33.3545
14	Cropland / Vegetation	9852.761	8468.144	14.05309
16	Barren Land	0.429	0.000	100
17	Water Bodies	8.732	9.163	-4.93587

From the result of Tables 2, 3 and 4, it was observed that water body increase by 5.852% from 2001 to 2009. Between 2009 and 2015, 5.932% increment was observed while from 2015 to 2022, there was a 4.936% increment. The overall summary of the percentage changes in land use land class from 2001 to 2022 is presented in Table 4.

Table 5: Percentage Change in LULC Class between 2001 - 2022

	Area_Sq_Km 2001	**Estimated Percentage Change**			
		2009	**2015**	**2022**	**Remark**
Evergreen Broadleaf Forest	2220.623	27.934	31.351	47.701	Decrease
Deciduous Broadleaf Forest	57.514	97.114	85.647	92.724	Decrease
Mixed Forest	12.755	90.106	86.907	98.848	Decrease
Closed Shrublands	0.147	-1549.66	-1112.93	-1158.50	Increase
Woody Savanna	2977.387	37.418	-9.372	30.449	Fluctuates
Savanna	2212.801	-182.564	-189.396	-167.940	Increase
Grasslands	425.042	56.418	54.946	59.956	Decrease
Permanent Wetlands	93.719	61.668	46.964	50.346	Decrease
Croplands	1437.127	38.448	55.791	7.459	Decrease
Urban / Built-up Areas	317.873	-4.642	-17.193	-33.355	Increase
Cropland / Vegetation	9852.761	14.269	27.318	14.053	Decrease
Barren Land	0.429	100.000	50.117	100.000	Fluctuates
Water Bodies	8.732	-5.852	-5.932	-4.936	Increase

As shown in Table 5, significant changes in the LULC secondary classes over the past 22 years (2001–2022) have been detected in the study area. Over this period (2001– 2022), closed shrublands, urban/built-up area and water bodies have increased considerably while croplands, grasslands permanent wetland, cropland/vegetation, Evergreen Broadleaf Forest and Deciduous Broadleaf Forest have all shown a decreasing growth rate.

The baseline year was taken as 2001 and the observable changes in land use land cover from 2001 to 2022 is presented in Table 6, 7, and 8 respectively.

Table 6: Comparison of land use land cover class estimate

Landuse Code	**Landuse Class**	**Area_Sq_Km 2001**	**Area_Sq_Km 2003**	**Area_Sq_Km 2005**	**Area_Sq_Km 2007**
2	Evergreen Broadleaf Forest (EB)	2220.623	1730.591	1664.006	1652.495
4	Deciduous Broadleaf Forest (DB)	57.514	1.576	1.236	1.601
5	Mixed Forest	12.755	0.852	0.436	0.309

6	Closed Shrublands	0.147	12.204	9.964	3.901
8	Woody Savanna	2977.387	2551.301	2197.011	2059.976
9	Savanna	2212.801	4314.893	5442.697	6271.442
10	Grasslands	425.042	180.075	143.319	177.705
11	Permanent Wetlands	93.719	39.881	33.559	33.074
12	Croplands	1437.127	1387.486	1156.064	803.237
13	Urban / Built-up Areas	317.873	319.127	323.780	329.320
14	Cropland / Vegetation	9852.761	9071.533	8635.984	8275.675
16	Barren Land	0.429	0.000	0.214	0.000
17	Water Bodies	8.732	9.025	9.580	9.320

Table 7: Comparison of land use land cover class estimate

Landuse Code	Landuse Class	Area_Sq_Km 2001	Area_Sq_Km 2009	Area_Sq_Km 2011	Area_Sq_Km 2013
2	Evergreen Broadleaf Forest (EB)	2220.623	1600.310	1711.752	1629.673
4	Deciduous Broadleaf Forest (DB)	57.514	1.660	3.619	9.495
5	Mixed Forest	12.755	1.262	0.997	1.785
6	Closed Shrublands	0.147	2.425	3.507	1.555
8	Woody Savanna	2977.387	1863.297	2778.235	3133.607
9	Savanna	2212.801	6252.570	5906.276	6891.641
10	Grasslands	425.042	185.241	154.637	163.001
11	Permanent Wetlands	93.719	35.924	35.687	40.566
12	Croplands	1437.127	884.583	808.319	643.613
13	Urban / Built-up Areas	317.873	332.629	337.085	345.937
14	Cropland / Vegetation	9852.761	8446.892	7867.393	6746.288
16	Barren Land	0.429	0.000	0.000	0.000
17	Water Bodies	8.732	9.243	9.240	9.182

Table 8: Comparison of land use land cover class estimate

Landuse Code	Landuse Class	Area_Sq_Km 2001	Area_Sq_Km 2017	Area_Sq_Km 2019	Area_Sq_Km 2022
2	Evergreen Broadleaf Forest (EB)	2220.623	1318.785	1385.941	1161.373
4	Deciduous Broadleaf Forest (DB)	57.514	1.625	20.956	4.185
5	Mixed Forest	12.755	0.868	2.879	0.147
6	Closed Shrublands	0.147	3.349	1.927	1.850
8	Woody Savanna	2977.387	3010.089	2808.427	2070.812
9	Savanna	2212.801	5740.569	6559.744	5928.982
10	Grasslands	425.042	205.801	171.955	170.204
11	Permanent Wetlands	93.719	47.303	42.935	46.535

12	Croplands	1437.127	813.818	688.317	1329.928
13	Urban / Built-up Areas	317.873	388.474	400.343	423.898
14	Cropland / Vegetation	9852.761	8076.237	7522.476	8468.144
16	Barren Land	0.429	0.214	0.000	0.000
17	Water Bodies	8.732	9.317	9.317	9.163

The observable changes in land use land cover class from the basline year of 2001 to the year 2022 is discussed as follows;

3.2.1 Water Bodies

In the baseline year of 2001, the area occupied by water body was 8.732km^2 . For subsequent years, a fluctuation in the area occupied by water was observed. In 2003, the area increased to 9.025km^2 while in 2005 it was 9.580km^2 . A decrease in the area occupied by water was observed in 2007 as the estimate area became 9.320km^2 as against 9.580 km^2 in 2005. In 2009 to 2013 the area further decrease to 9.243km^2, 9.240km^2 and 9.182km^2. A further increase in the area was obserbed 2017 as the estimated area became 9.317km^2 before decreasing to 9.163 km^2 in 2022.

3.2.2 Urban/Built-up Areas

In the baseline year of 2001, the urban/built-up area was about 317.873km^2. For subsequent years, a gradual increament in urban/built-up area was observed. For example, in 2003 to 2007, urban/built-up area increased from 319.127km^2 in 2003 to 323.780km^2 in 2005 and 329.320km^2 in 2007. There was a further increse in urban/built-up area from 2009 to 2013 and from 2017 to 2022. By the year 2017, urban/built-up area was estimated as 388.474km^2 while in 2022 it was 423.898km^2. The observable increase in urban/built-up area can be trace to the concept of urbanization occassioned by rural-urban migration.

3.2.3 Barren Land

With an increasing urban/built-up area, a decreasing level of the barren land was observed. For example in the baseline year of 2001, the barren land area was 0.429km^2. This area decreased to 0.214km^2 by 2005 and 2017 respectively. Fluctuation in the area occupied by water was observed. In 2003, the area increased to 9.025km^2 while in 2005 it was 9.580km^2 . A decrease in the area occupied by water was observed in 2007 as the estimate area became 9.320km^2 as against 9.580km^2 in 2005. In 2009 to 2013 the area further decrease to 9.243km^2, 9.240km^2 and 9.182km^2. A further increase in the area was obserbed 2017 as the estimated area became 9.317 km^2 before decreasing to 9.163km^2 in 2022.

3.2.4 Mixed Forest

With increasing urban/built up area, the mixed forest decreases proportionately. For example, in the baseline year of 2001, the area occupied by mixed forest was observed to be 12.755km^2, with increasing urban/built up area, the mixed forest area decreased to 0.852km^2 in 2003 and further decreases to 0.309km^2 in 2007. By the year 2022 the area occupied by mixed forest had decreased to 0.147km^2.

3.2.5 Grassland

The land use land cover change analysis reveals a notable decline in the area covered by grassland from 2001 to 2022, with measurements decreasing from 425.042km^2 to 170.204km^2. Within this timeframe, fluctuations occur, indicating periods of both increase and decrease in grassland area.

These findings suggest dynamic changes influenced by various factors such as natural processes, human activities, and management practices. Comparing these results with previous work underscores the importance of understanding the study area, data sources, and methodology, while implications may include habitat loss, land degradation, and shifts in agricultural practices. Further analysis is warranted to explore the drivers behind these changes and their broader implications for environmental conservation and land management policies.

3.3 Change Detection Analysis

The land use land cover changes for (2001-2003), (2001-2005), (2001-2007), (2001-2009), (2001-2011), (2001-2013), (2001-2015), (2001-2017), (2001-2019) and (2001-2022) is presented in Figures 13, 14, 15, 16, 17, 18, 19, 20, 21, 22 and 23 respectively

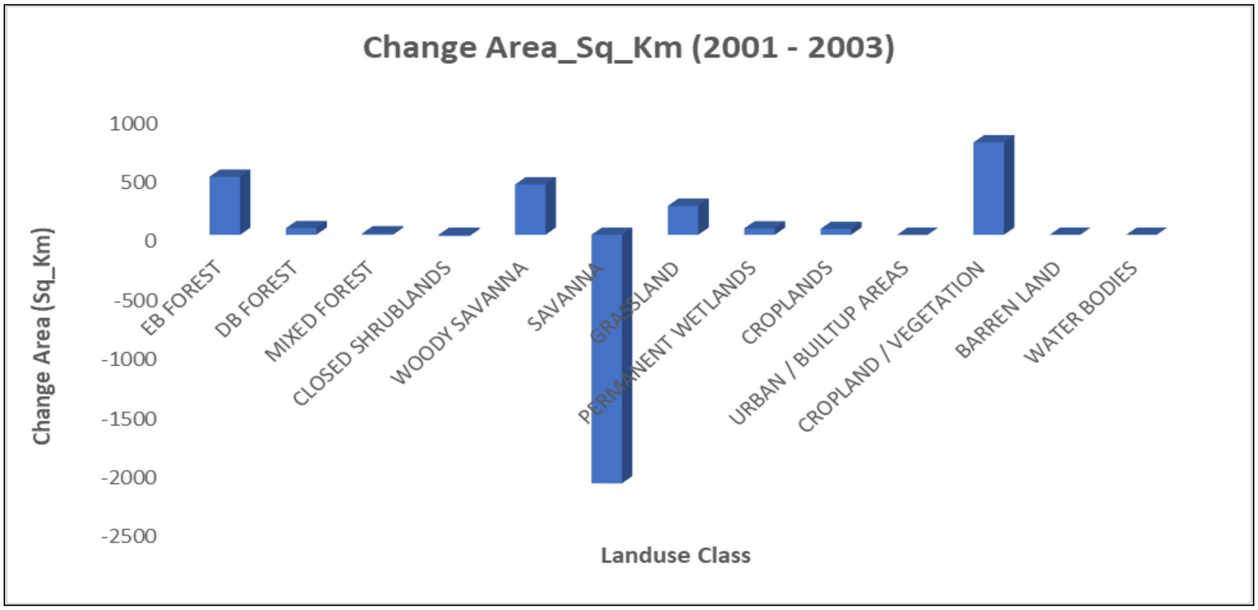

Figure 13: Edo State land use land cover change from 2001 – 2003

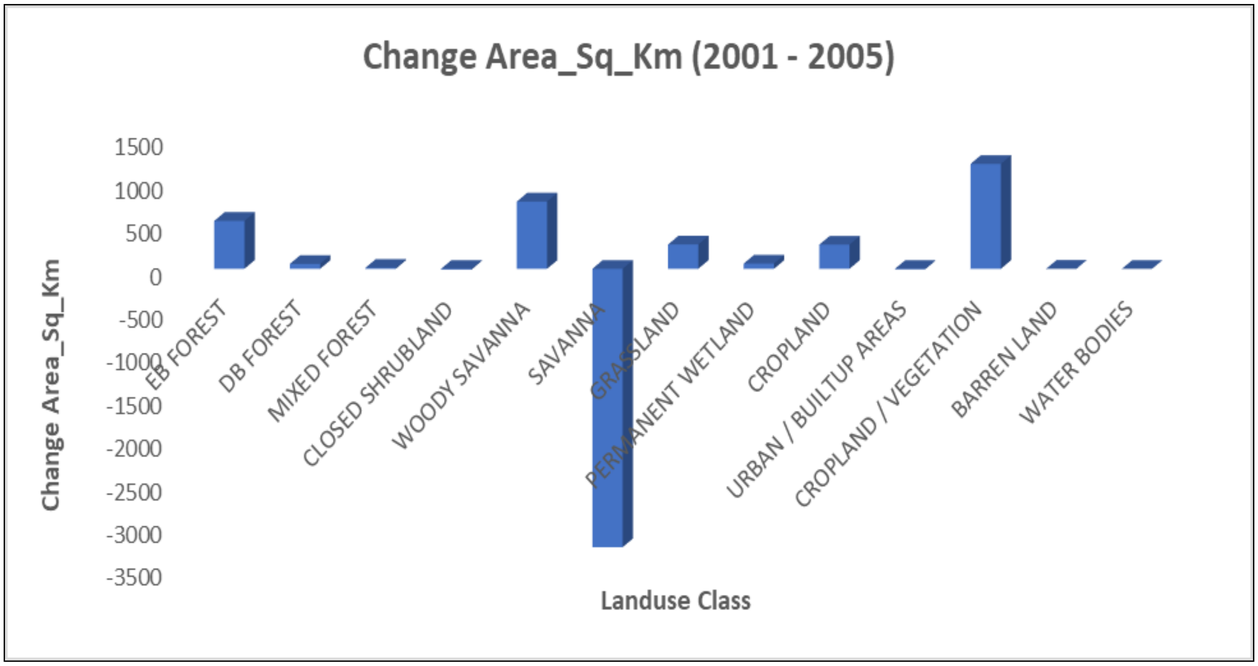

Figure 14: Edo State land use land cover change from 2001 – 2005

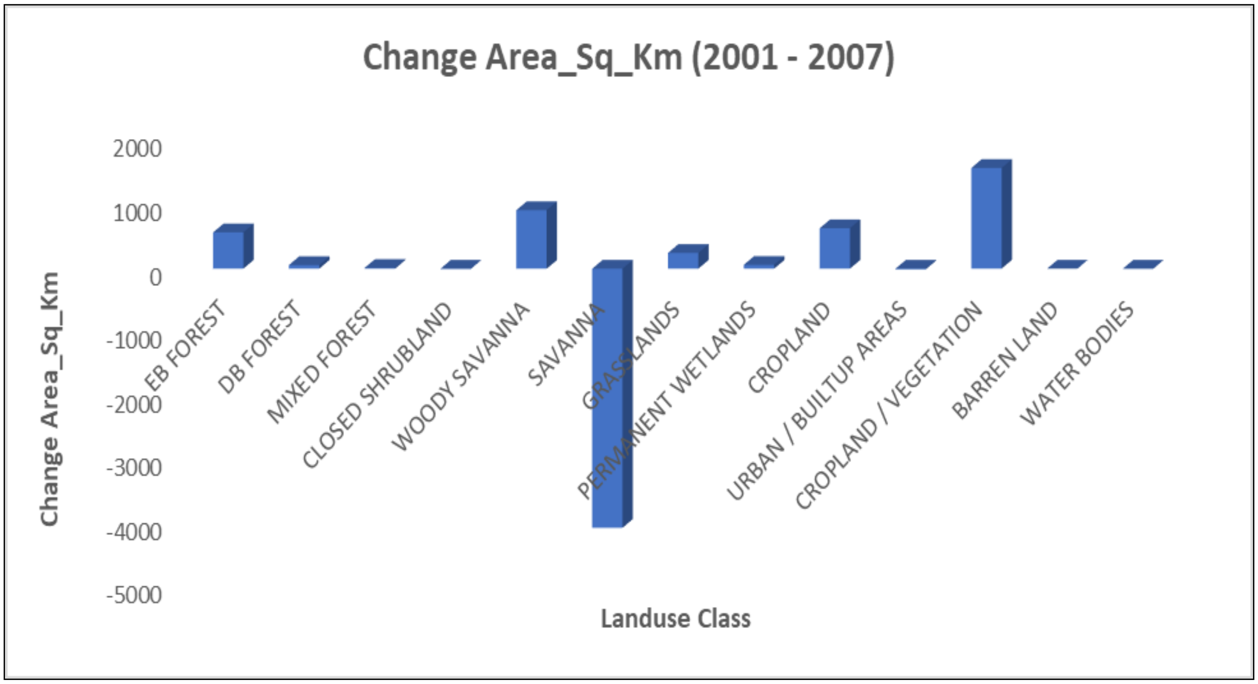

Figure 15: Edo State land use land cover change from 2001 – 2007

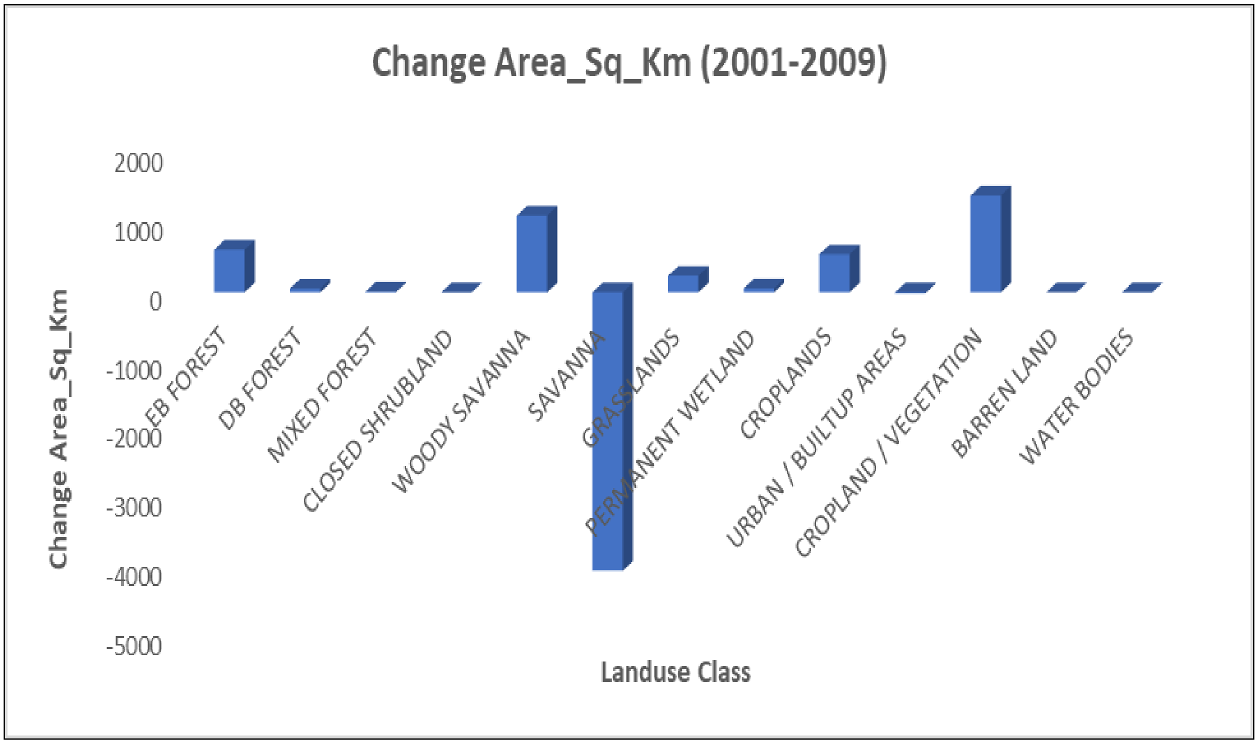

Figure 16: Edo State land use land cover change from 2001 – 2009

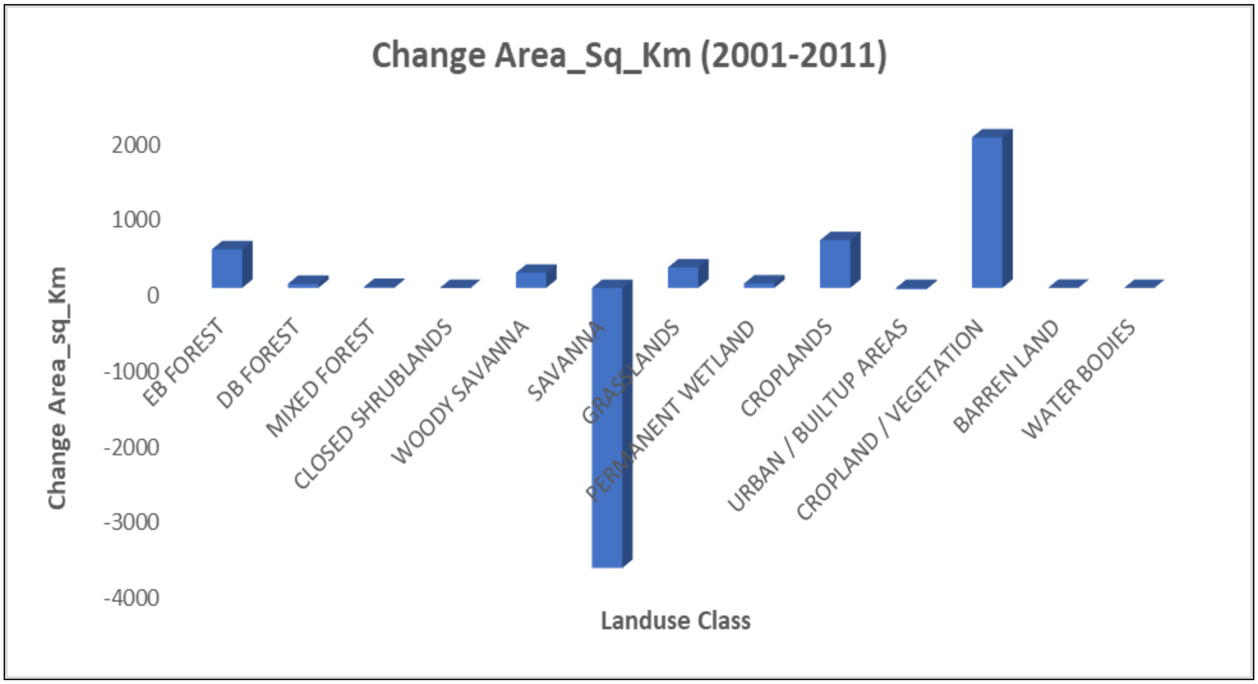

Figure 17: Edo State land use land cover change from 2001 – 2011

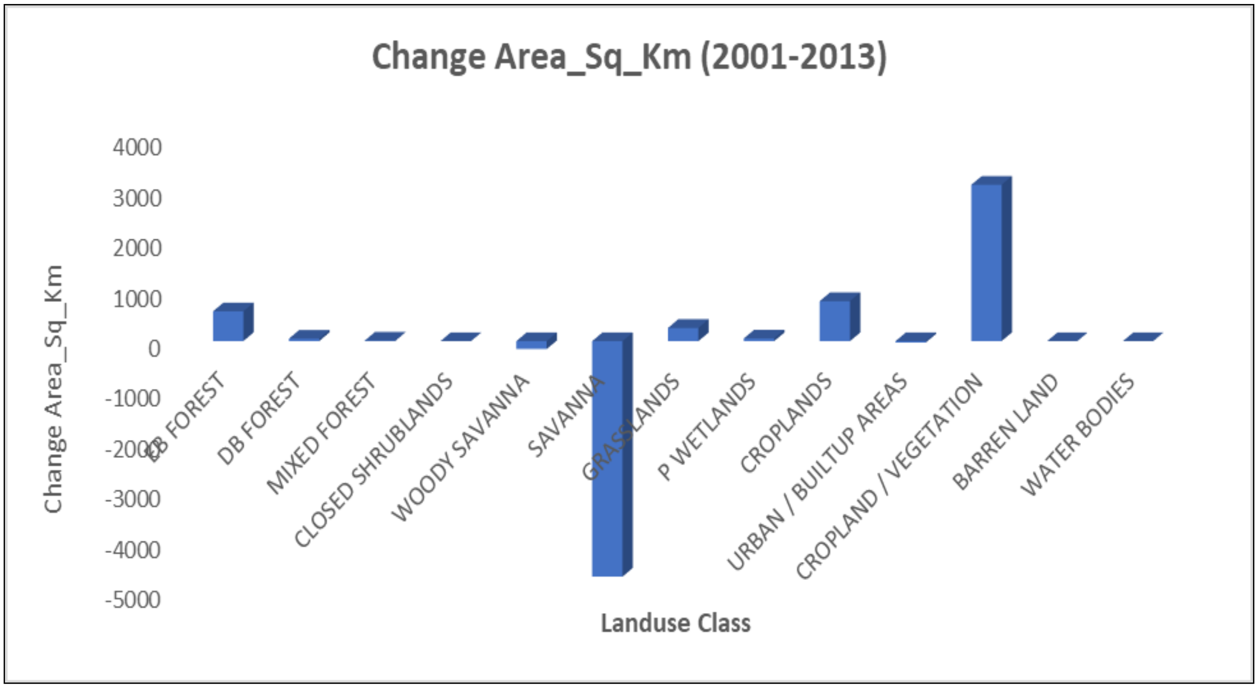

Figure 18: Edo State land use land cover change from 2001 – 2013

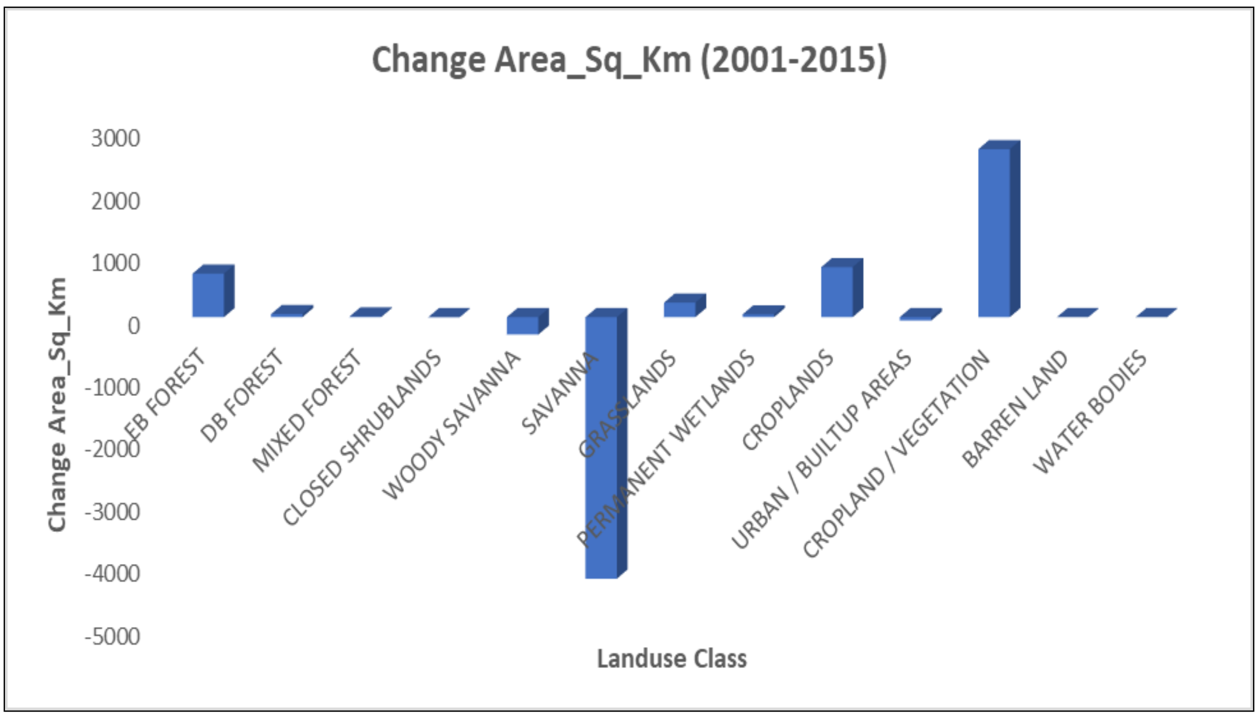

Figure 19: Edo State land use land cover change from 2001 – 2015

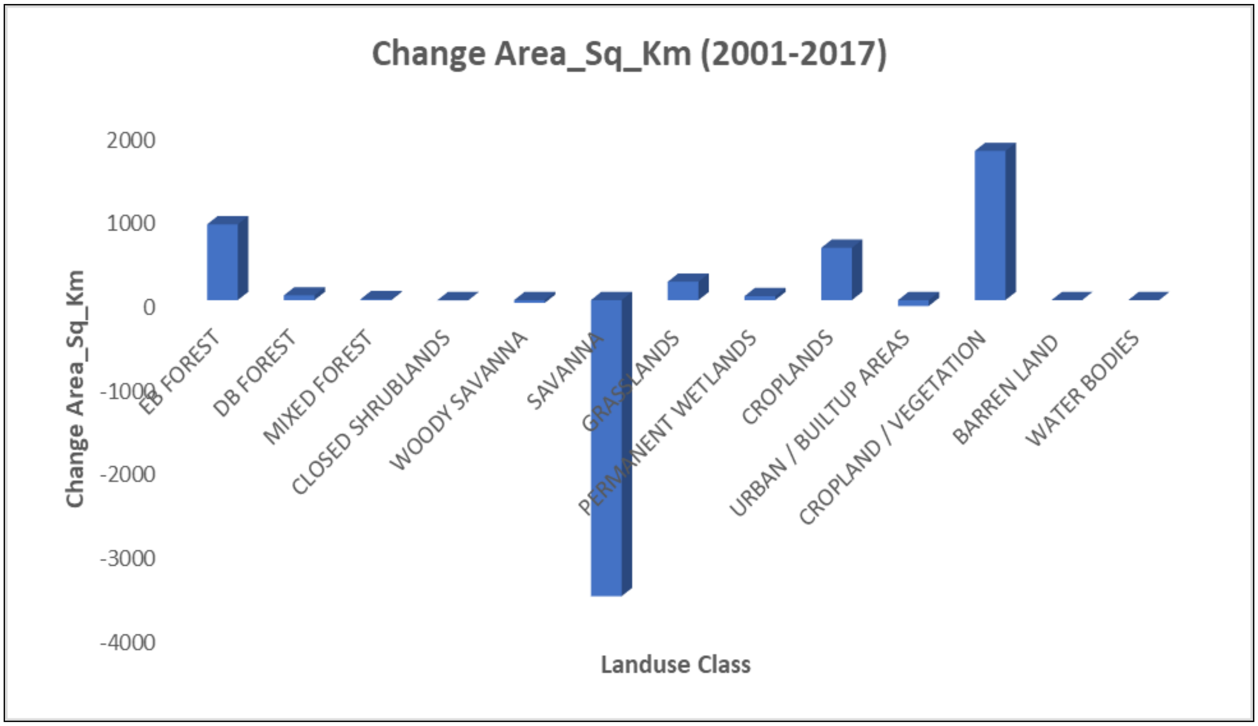

Figure 20: Edo State land use land cover change from 2001 – 2017

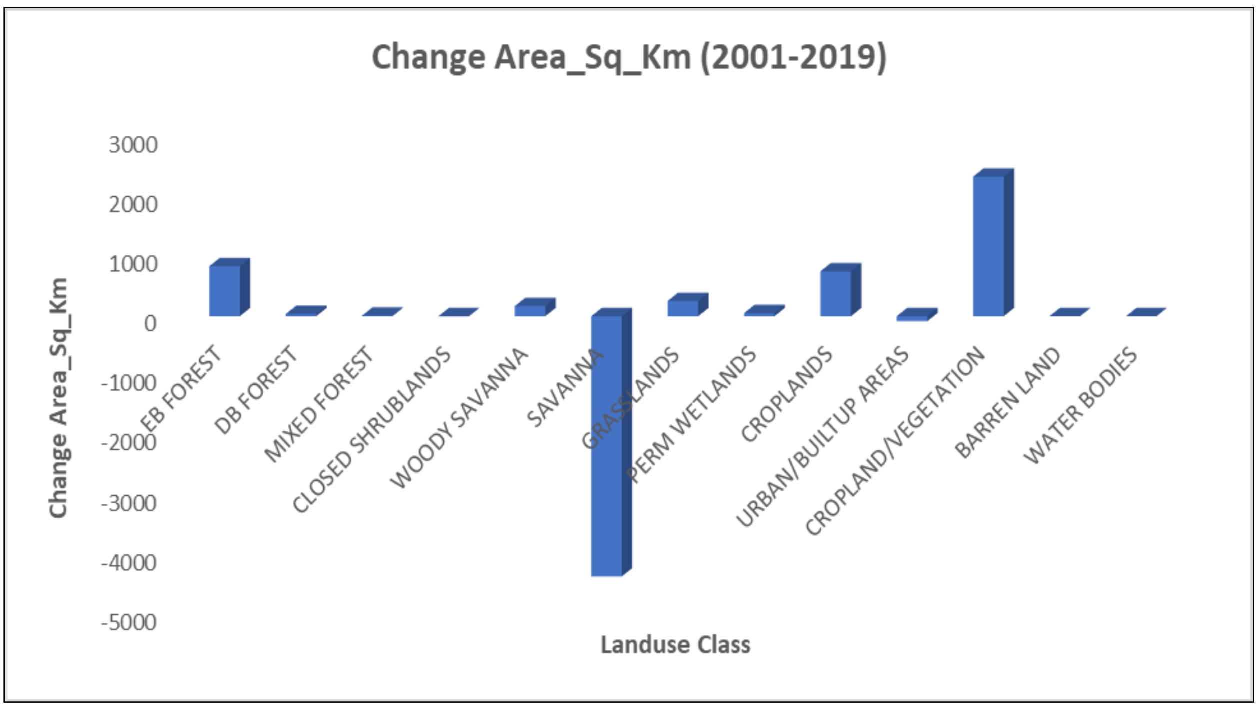

Figure 21: Edo State land use land cover change from 2001 – 2019

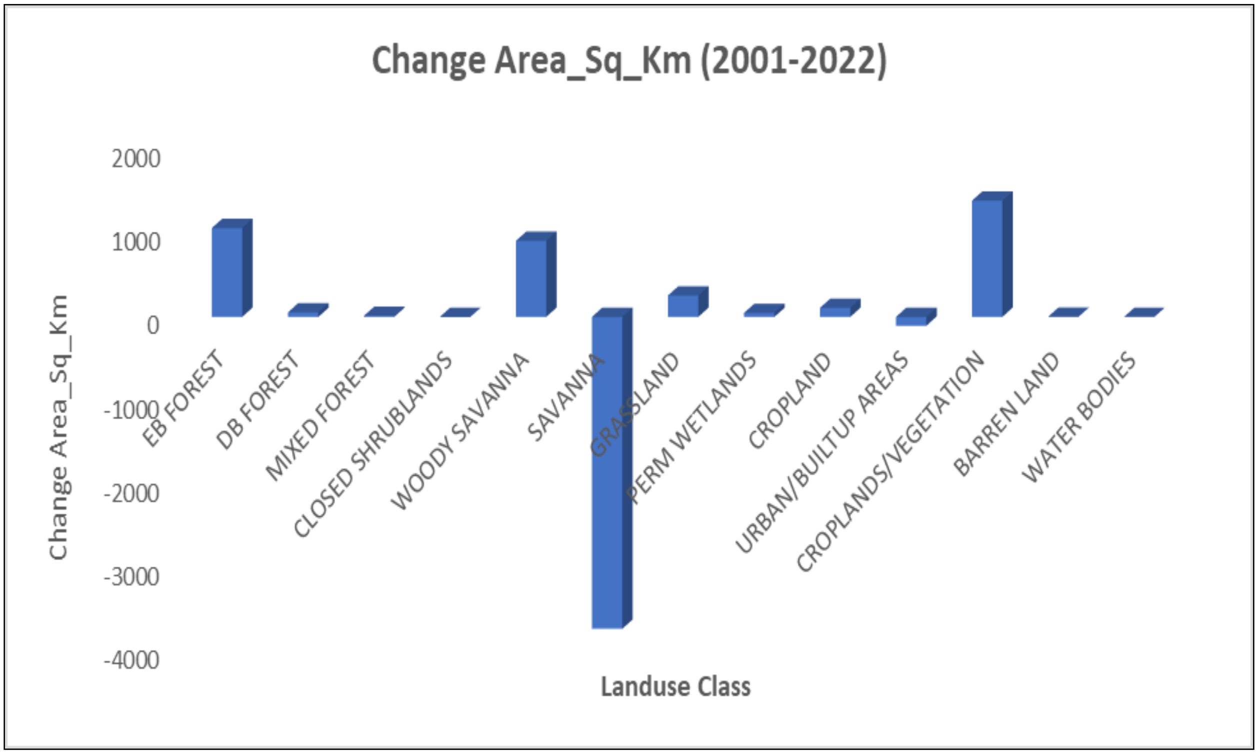

Figure 22: Edo State land use land cover change from 2001 – 2022

3.3 Accuracy Assessment of LULC Maps

The accuracy assessment of Land Use/Land Cover (LULC) maps was crucial for validating mapping methods, ensuring quality control, and supporting decision-making processes. It provided a baseline for monitoring changes over time and facilitated comparisons with ground truth data collected through high-resolution imagery. By establishing standards for accuracy assessment, it allowed for benchmarking across different studies and regions, enhancing the credibility of mapping efforts and building trust among stakeholders. Ultimately, accurate LULC mapping supported informed decision-making in areas such as urban planning, natural resource management, environmental monitoring, and disaster response, contributing to more sustainable land management practices. The summary result of the accuracy assessment of LULC covering the period 2005 to 2022 is presented in Table 9.

The accuracy assessment of the land use/land cover (LULC) classification yielded promising results across the years 2005, 2010, 2015, and 2020. The overall accuracy ranged from 82.2% to 86.2%, indicating a consistently high level of agreement between the classified LULC maps and ground truth data. Additionally, the Kappa statistics, ranging from 78.6% to 89.7%, further affirm the reliability of the classification, considering the influence of chance agreements. These results suggest that the classification method effectively captured the spatial distribution and changes in land use and land cover over the specified time periods, providing valuable insights for monitoring and management purposes.

Table 9: Summary result of accuracy assessment of LULC maps

LULC Class	2005		2010		2015		2022	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Mixed Forest	78.9	81.2	88.7	82.3	80.9	78.8	88.2	87.3
Grasslands	88.5	79.8	81.2	78.9	83.5	79.4	89.7	84.5
Croplands	77.5	83.3	87.6	80.3	87.7	85.7	93.2	88.3
Urban / Built-up Areas	87.9	86.5	85.4	81.6	84.5	88.6	88.7	89.1
Cropland / Vegetation	76.5	78.9	89.3	82.2	88.6	89.4	89.4	83.3
Barren Land	77.3	81.2	86.1	85.5	84.2	89.1	82.2	81.7
Water Bodies	88.3	84.4	79.4	86.6	87.6	88.8	81.7	80.0
Overall Accuracy	82.2		84.8		85.3		86.2	
Kappa Statistics	78.6		82.1		85.4		89.7	

4. Conclusion

The study addresses the pressing need for accurate and timely information on land use and land cover (LULC) dynamics, particularly in rapidly urbanizing regions like Edo State and its environs. Utilizing Landsat satellite imagery spanning eleven time points from 2001 to 2022, the research assesses changes in LULC patterns over a 21-year period. Through advanced geospatial analysis techniques using ArcGIS and ERDAS Imagine software, false-color composites (FCCs) were generated, and supervised classification employing the maximum likelihood technique was conducted to categorize the study area into thirteen secondary classes. The findings reveal significant transformations, notably an increase in water bodies and urban/built-up areas, while croplands and grasslands experienced declines. The study highlights the importance of understanding LULC changes for effective natural resource management and environmental monitoring, emphasizing the role of multi-temporal satellite data and advanced remote sensing techniques in facilitating such assessments. By focusing on Edo State, the research contributes valuable insights into the dynamics of land use and land cover, aiding informed decision-making for sustainable development and resource allocation.

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