World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

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Mapping Land Use and Land Cover Change Detection Using Supervised Maximum Likelihood Classification of Multi-Temporal Landsat Imagery: A Case Study of Nakuru County

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World Journal of Advanced Research and Reviews, 2025, 28(03), 706-716

Publication history: Received 27 October 2025; revised on 06 December 2025; accepted on 08 December 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.28.3.4092

Abstract

Monitoring land use and land cover (LULC) change is crucial for analyzing the socio-economic and environmental effects of land development and management. This research aims to explore the dynamics of urban growth and LULC changes in Nakuru County, Kenya, over a decade from 2014 to 2024. Supervised Maximum Likelihood Classification (MLC), a popular remote-sensing technique, was utilized for the multi-temporal analysis of Landsat 8 Operational Land Imager (OLI) data acquired from the United States Geological Survey (USGS) Earth Explorer website. Five dominant land-cover classes were distinguished, including built-up areas, bare land, sparse vegetation, dense vegetation, and water bodies. The findings reveal that rapid urbanization and agricultural expansion are the primary forces behind LULC changes, resulting in significant loss of green spaces, forest cover, and water resources. These alterations have led to ecosystem disruption and increased environmental stress throughout Nakuru County. The results underscore the urgent need for sustainable land-use planning and management practices that consider the implications of urban growth. Integrating remote-sensing data into decision-making processes is crucial for formulating policies that effectively mitigate land degradation and promote environmentally sustainable urban development in rapidly expanding regions. The findings provide spatially explicit evidence to guide sustainable land management policies under Kenya's Vision 2030 and United Nations Sustainable Development Goals (SDGs 11 and 15).

Keywords: Remote sensing; Landsat OLI; Maximum Likelihood Classification; Land use/land cover; Urban expansion; Sustainable land management

1. Introduction

Land use and land cover (LULC) change is the result of complex interactions between various natural and anthropogenic drivers. Rapid urbanization, population growth, and agricultural intensification are some of the main factors driving land transformation processes such as deforestation, biodiversity loss, and soil and water degradation [1-3]. These cumulative impacts can lead to a decline in the resilience of natural and human systems and a reduction in the sustainability of livelihoods. Monitoring how land cover types change over time is critical to the conservation of natural resources, environmental management, and sustainable development planning.

Remote sensing is a useful tool for detecting and monitoring LULC changes since it provides accurate, repeatable, and large-scale coverage over long time periods [4]. Thanks to improvements in spatial and spectral resolution, satellite imagery is increasingly used for mapping the spatial extent and dynamics of human-induced landscape change. Landsat data have been playing a critical role in environmental monitoring and research since the 1970s, providing free,

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continuous, and multi-temporal coverage of the earth's surface. These datasets allow comparative analyses across different time periods and have been used extensively to document and analyze land-cover change and its drivers across diverse ecosystems and socio-economic contexts [5,6].

Supervised Maximum Likelihood Classification (MLC) is one of the most widely used techniques for digital image classification [7]. MLC is a statistical method that assigns each pixel in an image to the class to which it belongs based on the pixel's spectral values. The approach assumes that the training data used to create each land-cover class follows a normal distribution and uses these training data to calculate the likelihood of a pixel belonging to each class. MLC is considered to be a more robust method than unsupervised approaches such as K-Means or ISODATA and can achieve higher classification accuracies when provided with good training data [8]. As a result, MLC has been widely used in various land-change studies involving urban expansion, agricultural conversion, and habitat loss when multi-temporal Landsat data is available [9].

Many authors have used remote sensing and MLC to monitor spatial changes in both developed and developing contexts. Herold et al. [10] combined remote sensing with spatial modeling to assess the extent and drivers of urban expansion and its environmental impacts. Mohan et al. [11] found that economic and population growth in the Mangalore region in India between 1972 and 1999 resulted in a 145 % increase in built-up areas and a concomitant decrease in vegetation cover. Pérez et al. [12] used SPOT images to detect and map urban sprawl in Tunis and found the conversion of agricultural and forested areas into residential and industrial areas. In East Africa, Mwaniki et al. [13] used Landsat data to analyze deforestation in the Mau Forest Complex in Kenya and identified settlement and agricultural expansion as the main drivers of change in land cover. These and many other studies have shown the ability of MLC and Landsat imagery to provide the data and information necessary for detecting, quantifying, and understanding land-cover change over time.

Nakuru County in Kenya's Great Rift Valley is one such context. The region has experienced significant urban growth and agricultural intensification during the last decade, resulting in environmental challenges such as deforestation and loss of water quality. The built-up area around Nakuru City and other towns such as Njoro and Naivasha has increased, putting pressure on forests, wetlands, and water resources in the region. A key gap in the literature on Nakuru and many other similar Kenyan contexts, however, is the lack of spatially explicit research using rigorous statistical methods to quantify and characterize land-use and land-cover change.

This study aims to use supervised Maximum Likelihood Classification on multi-temporal Landsat 8 Operational Land Imager (OLI) data for 2014, 2019, and 2024 to quantify and analyze land-use and land-cover change in Nakuru County, Kenya. The hypothesis to be tested is that LULC change in the region has been characterized by the continued expansion of built-up areas at the expense of vegetated and water-covered areas. The project will provide valuable insights into the dominant patterns and drivers of landscape change in rapidly growing urban centers in Kenya and other similar contexts in sub-Saharan Africa. The findings of this research will be of particular use to urban planners, environmental managers, and policy makers who are responsible for developing and implementing strategies for sustainable land-use planning and environmentally responsible urban growth.

Objectives of the study:

- Map and classify major LULC types in Nakuru County, Kenya, for the years 2014, 2019, and 2024.
- Quantify the magnitude and direction of LULC change over the study period.
- Identify the main drivers of the observed changes, with a particular focus on urban expansion and agricultural intensification.
- Evaluate the environmental impacts of the observed changes on vegetation and water resources.
- Recommend evidence-based strategies for sustainable land-use management and planning in Nakuru County.

2. Materials and Methods

2.1. Study Area: Nakuru County

In the Great Rift Valley, Nakuru lies between latitudes 00^0 13'N and 00^0 10'N and longitudes 35^0 28'E and 35^0 36' E. Nakuru County is Kenya's 19th largest county, with an area of 7,496.5 square kilometers. All spatial datasets were projected to the Universal Transverse Mercator (UTM) Zone 37S coordinate system (EPSG: 32737) based on the WGS84 datum. The county's diverse landscape includes forests, urban areas, water bodies, wetlands, and agricultural land. Nakuru experiences a temperate tropical highland climate with notable rainy seasons in March and April and the dry seasons start in January and ends in February. It exhibits a double rainfall maxima pattern. Daytime temperature ranges from a high of 28°C to a low of 23°C i.e. 82°F and 73°F depending on the month. The temperature is moderated by its elevation of about 6,070 feet above sea level. This variation has influenced the types of land cover present in the county. According to the KNBS 2019 census, the county has experienced rapid urbanization, the population of Nakuru County, Kenya was 2,162,202(2019 census). The rapid population growth in the area has resulted to heightened demand for land and the clearing of the forest to create room for agricultural activities mainly growing maize, wheat, and potatoes. This has led to a significant change in LULC patterns over the years.

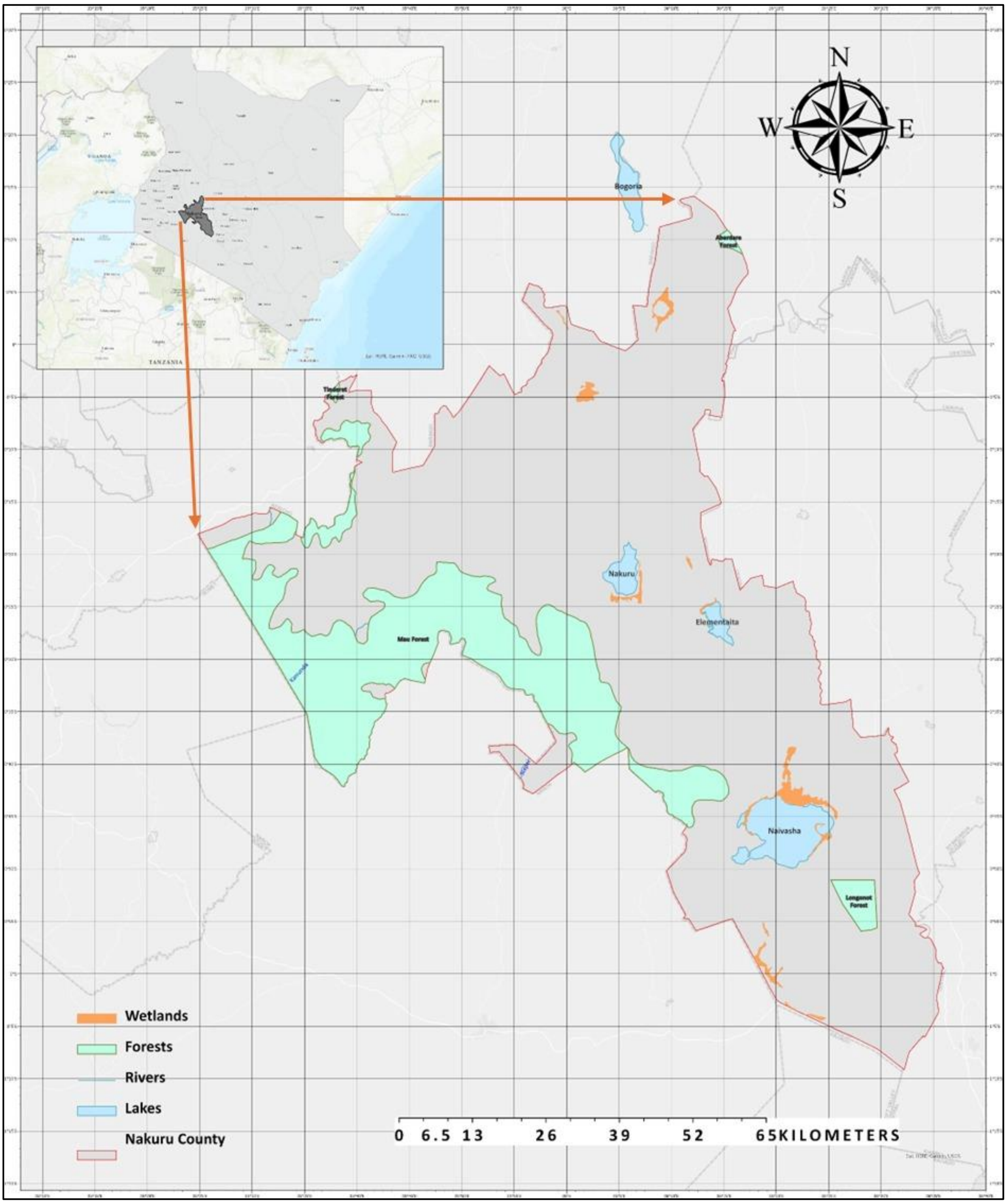


Figure 1 The study area of Nakuru County, Kenya

2.2. Flow Chart of Methodology

The flow chart below depicts the methodology used to achieve the results. This structured workflow provides a systematic approach to Land Use Land Cover classification.

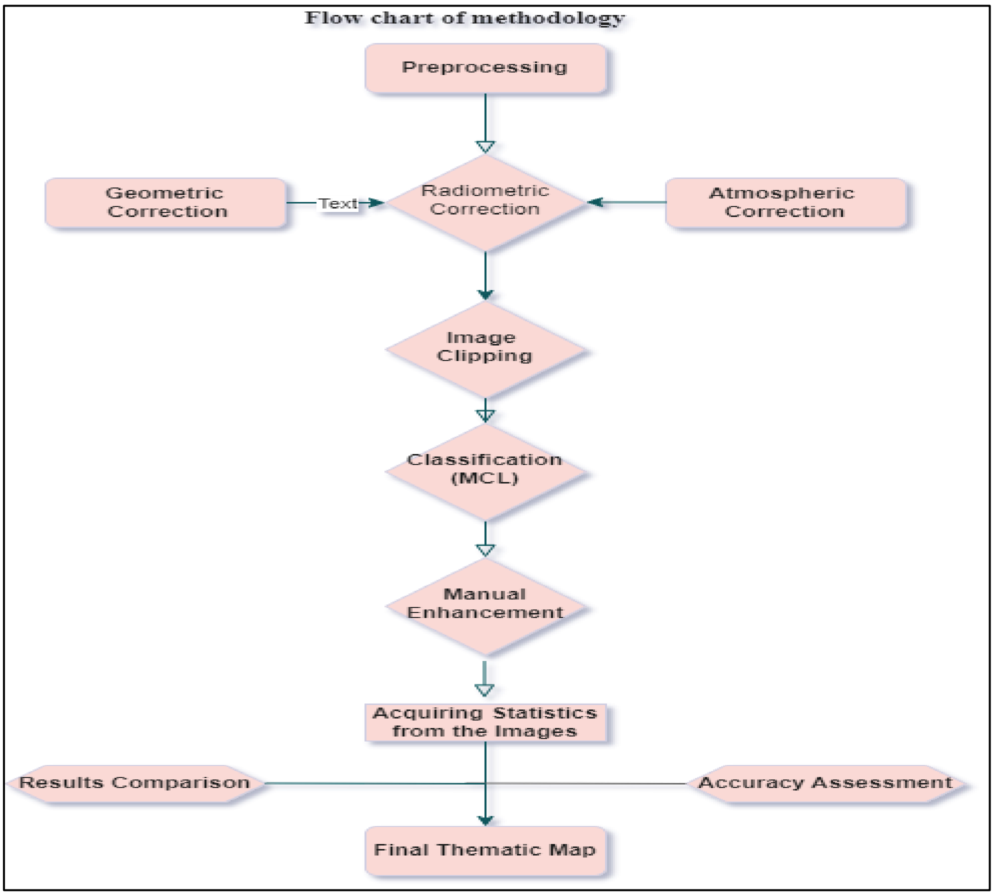


Figure 2 Flow Chart of Methodology. Source: Author (2024)

2.3. Data Acquisition

For this study, multi-temporal satellite data was used. In particular, from Landsat 8 Operational Land Imager (OLI) sensor for both 2014, 2019, and 2024, sourced from the United States Geological Survey (USGS) Earth Explorer platform. All data were acquired for Path 169/Row 060, and covered the entire extent of Nakuru County. The imagery consists of Landsat 8 OLI Level-2 Surface Reflectance products that have been atmospherically and radiometrically corrected by the USGS to be temporally consistent. The data were Level-2 products, referenced to the WGS84 datum. Both images offered a spatial resolution of 30 meters. The Landsat Imagery was preferred because of its high resolution, accessibility, and consistent data quality. Google Earth Pro will also be used to provide ground-truthing which will guide in selecting regions of interest (ROI) for model training. To minimize the effects of cloud cover and avoid difficulties in vegetation growth variations (e.g. forest and crops) on classification accuracy, the images were acquired during a dry season (January). Land sat8 images cover a larger area than required, to save on processing time a shape file of Nakuru County will be used to subset the image.

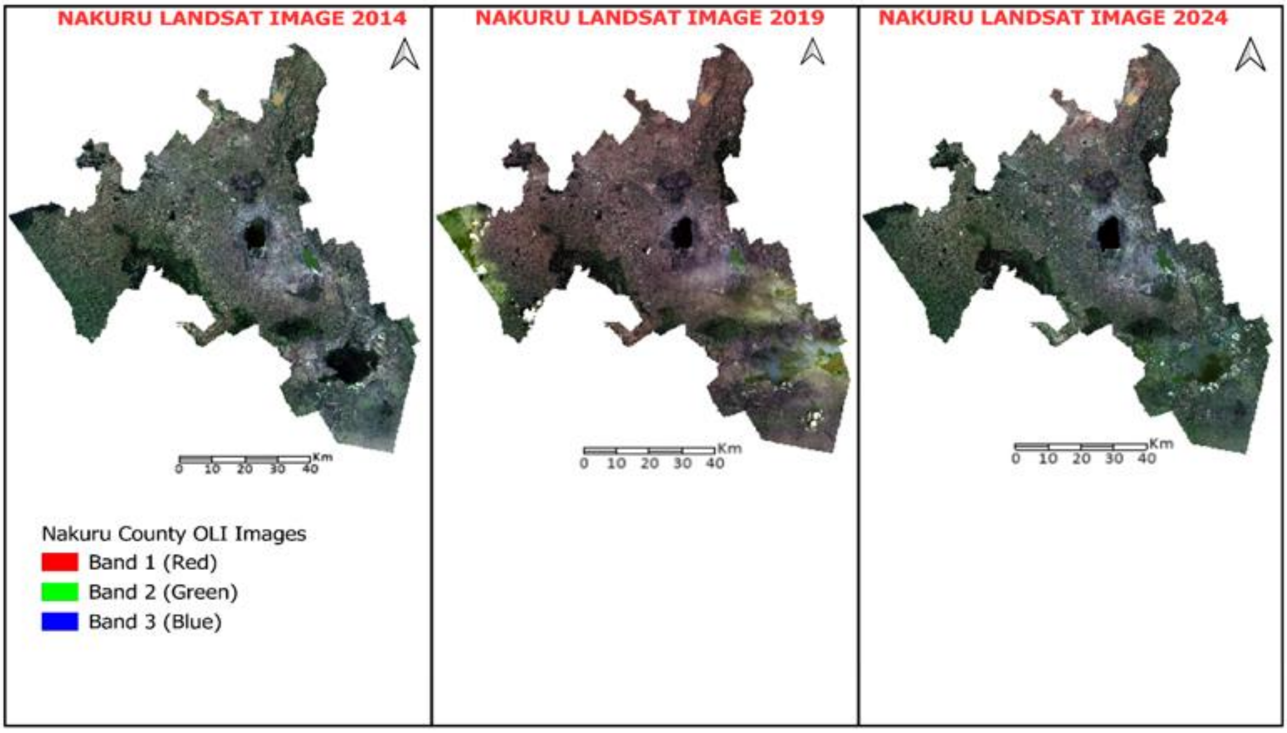


Figure 3 Landsat 8 images of Nakuru County from 2014, 2019, and 2024 used to assess LULC Changes over time. Source: USGS Earth Explorer (2024)

2.4. Preprocessing

For comparable and consistent imagery, the following operations were performed for finer precision otherwise Level 2 products offer pre-corrected for

- **Geometrical Correction** to have a common coordinate system (UTM Zone 37S) using GCPs.
- **Radiometric Calibration** uses calibration coefficients stored in the metadata file to convert DN values into radiance or top-of-atmosphere reflectance.
- **Atmospheric Correction:** Quick Atmospheric Correction was conducted to remove atmospheric effects, also called path radiance(noise).

All preprocessed scenes were visually inspected and coregistered with sub-pixel accuracy (< 0.5 pixels) prior to classification.

2.5. Classification Technique

Maximum Likelihood Classification (MLC) algorithm was used to classify the Landsat 8 images. The land cover classes include five classes, i.e., Built-up Area, Bare Land, Sparse Vegetation, Dense Vegetation, and Water Surface. MLC is a supervised probabilistic classification algorithm, which determines the probability of the pixel belonging to the class with the closest spectral signature. MLC is selected as the most accurate and appropriate algorithm for multi-temporal classification in a heterogeneous area. All the classification was conducted using ENVI 5.6 software with preprocessed Level-2 Surface Reflectance images.

2.6. Training Data Selection and Testing Sites Collection

2.6.1. Training sites

Training data were created in ENVI 5.6 by digitizing Regions of Interest (ROIs) representing the five LULC classes: Built-up Area, Bare Land, Sparse Vegetation, Dense Vegetation and Water Surface. About 30 ROIs per class were collected from the 2014 imagery and applied consistently to the 2019 and 2024 images to maintain temporal uniformity. Training polygons were selected from spectrally homogeneous areas distributed across the county.**2.6.2. Testing sites** independent testing samples were obtained from high-resolution Google Earth images for accuracy assessment of the classification. Approximately 30 testing points per class, randomly distributed over the entire study area, were used to prepare the error matrix for accuracy assessment.

2.7. Classification Process

Classification was executed in ENVI 5.6 through Maximum Likelihood Classification (MLC) algorithm. Pixels were attributed to the land-cover class with the highest probability, according to spectral statistics of the training data. Classified maps for the years 2014, 2019, and 2024 were generated and visually checked for class consistency and to remove clear misclassifications, and then used for post-classification change detection.

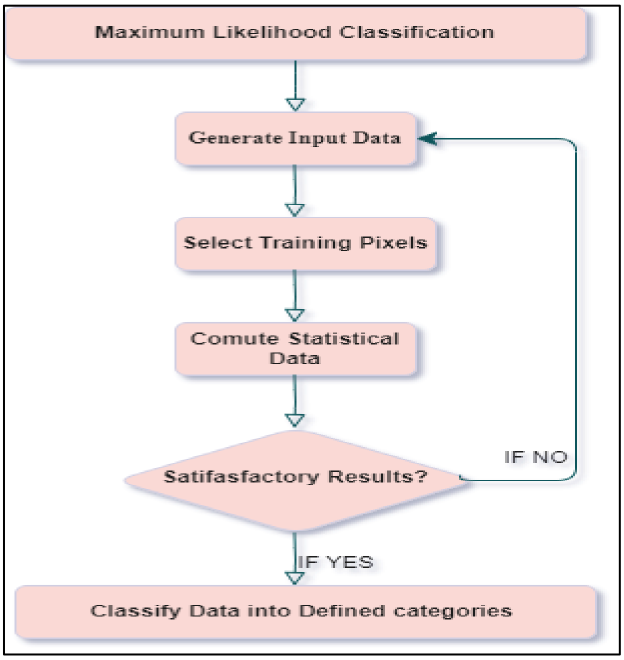


Figure 4 Classification Process Flowchart. Source: Author (2024)

2.8. Accuracy Assessment

Accuracy is termed as the level of similarity between the produced and the original reference map. Accuracy assessment evaluates the reliability of LULC classifications by comparing produced maps to reference data using a confusion matrix, generating metrics like Overall Accuracy, Kappa Coefficient, Producer's and User's Accuracy, and omission/commission errors. High-resolution Google Earth imagery was used for validation. The classified maps achieved Overall Accuracies of 89% (2014), 90% (2019), and 92% (2024), with corresponding Kappa Coefficients of 0.81, 0.83, and 0.85, as detailed in Appendix A.

3. Results

This chapter contains the classified LULC maps for the years 2014, 2019, and 2024. This also includes the calculated change between the classes, and the associated environmental interpretations. The results are discussed in terms of urban expansion, vegetation changes, and water-resource alterations in Nakuru County.

3.1. Classification of the Land Cover / Land Use

The Land Cover Land Use Classification in Nakuru County is divided into five classes based on Maximum Likelihood: Built-up Area, Bareland, Sparse Vegetation, Dense Vegetation, and Water Surfaces. The classification was conducted with Envi software. About 30 training sites were collected for each class.

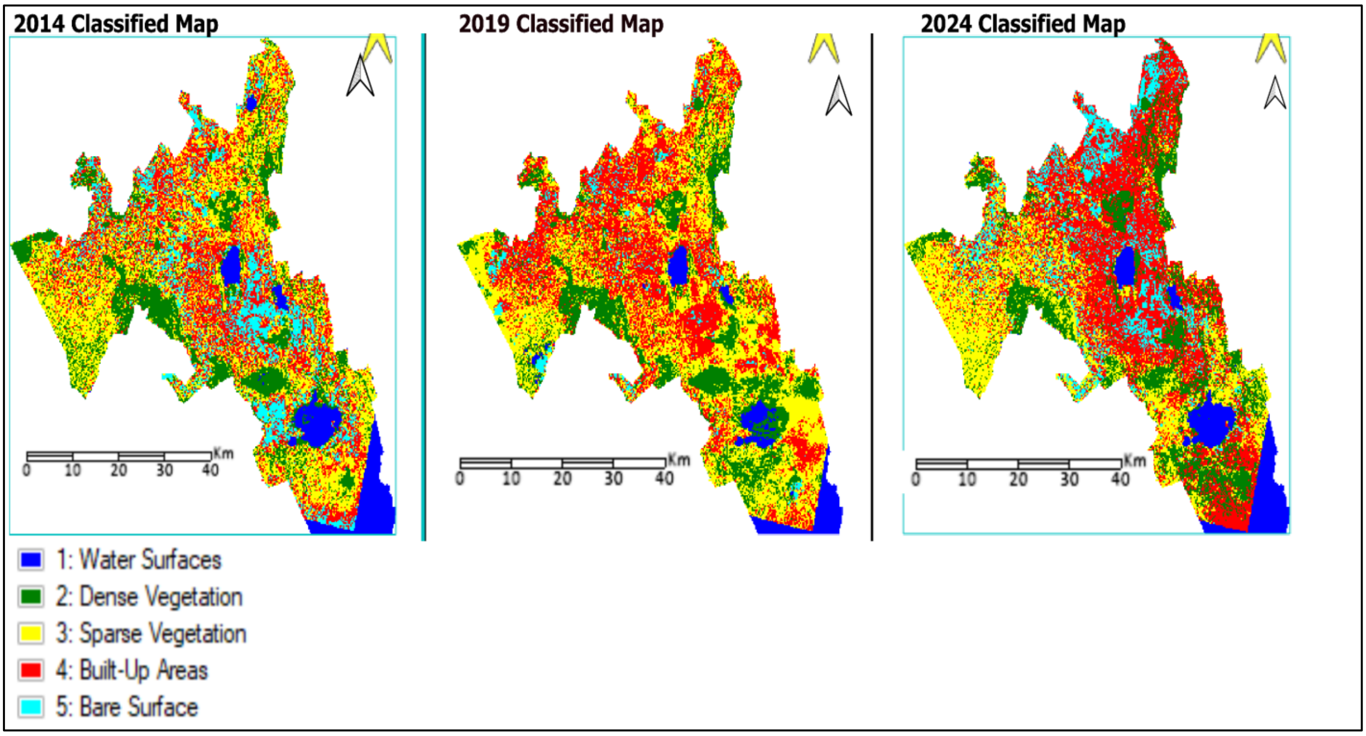


Figure 5 Land Use Land Cover Maps for 2014, 2019 and 2024. Source: Author (2024)

3.2. Change Detection

Post-classification change detection was conducted by cross-examining the classified images in the 2014-2019 and 2019-2024 study periods. A change matrix was generated to quantify the transitions between different LULC categories. The tables below show transition matrices extracted from the thematic maps for the two study periods 2014-2019 and 2019-2024. It reveals the changes across the land uses. These changes pinpoint transformations in urban areas, vegetated areas, bare land, and water bodies as indicated below:

3.3. 2014-2019 PERIOD

Table 1 Change Detection Statistics between 2014 and 2019 Classified Images (Landsat 8 OLI)

Final State	Water Surfaces	Dense Vegetation	Sparse Vegetation	Built-up Areas	Bare Surface	Row Total	Class Total
Unclassified	0.000	0.000	0.000	0.276	0.000	0.000	100.000
Water Surfaces	60.052	1.375	0.731	0.274	1.052	100.000	100.000
Dense Vegetation	17.542	70.941	12.742	3.464	1.827	100.000	100.000
Sparse Vegetation	13.712	22.557	60.463	33.589	23.312	100.000	100.000
Built-up Areas	6.069	3.302	24.426	59.149	11.687	100.000	100.000
Bare Surface	7.105	1.820	1.639	3.248	60.122	100.000	100.000
Class Total	100.000	100.000	100.000	100.000	100.000	-	-
Class Changes	39.948	29.059	39.537	40.081	39.878	-	-
Image Difference	-30.347	6.556	11.154	22.052	-72.116	-	-

3.4. 2019-2024 PERIOD

Table 2 Change Detection Statistics between 2019 and 2024 Classified Images (Landsat 8 OLI, MLC Method)

Final State	Water Surfaces	Dense Vegetation	Sparse Vegetation	Built-up Areas	Bare Surface	Row Total	Class Total
Unclassified	0.000	0.000	0.000	0.000	0.000	0.000	100.000
Water Surfaces	89.692	6.024	2.779	1.817	0.124	100.000	100.000
Dense Vegetation	2.154	63.196	14.734	5.256	4.770	100.000	100.000
Sparse Vegetation	3.147	22.508	52.133	23.126	26.140	100.000	100.000
Built-up Areas	4.874	7.106	24.839	53.930	25.389	100.000	100.000
Bare Surface	0.133	1.167	5.514	15.871	43.577	100.000	100.000
Class Total	100.000	100.000	100.000	100.000	100.000	-	-
Class Changes	10.308	36.804	47.867	46.070	56.423	-	-
Image Difference	48.131	-5.391	-34.823	12.436	230.870	-	-

3.5. Net Land-Use Percentage Changes (2014-2019 and 2019-2024)

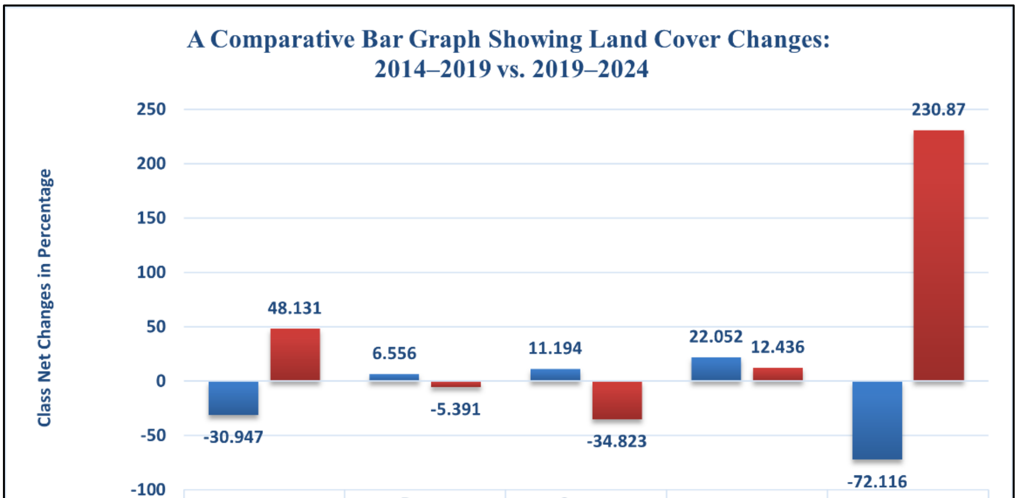
The table below reveals overall LULC shifts in percentage for the two study periods 2014-2019 and 2019-2024.

Table 3 Net Land-Use Percentage Changes (2014–2019 and 2019–2024)

Class	2014-2019 (%)	2019-2024(%)
Water Surfaces	-30.947	48.131
Dense Vegetation	6.556	-5.391
Sparse Vegetation	11.194	-34.823
Built-Up Areas	22.052	12.436
Bare Surface	-72.116	230.87

3.6. Graphical Comparison of LULC Changes Across the Two Periods

The clustered comparative bar graph below highlights changes in land-use categories across two periods based on the net Land-Use Percentage Changes. It shows notable increases in Bare and Water Surfaces in the second period, contrasting with earlier declines. Built-up areas consistently increase in both periods, while Dense and Sparse Vegetation declines in the latter period contrasting with increases in the former.



	Water Surfaces	Dense Vegetation	Sparse Vegetation	Built-Up Areas	Bare Surface
2014-2019 (%)	-30.947	6.556	11.194	22.052	-72.116
2019-2024(%)	48.131	-5.391	-34.823	12.436	230.87

Figure 6 Comparative Class Changes by Category (2014–2019 vs. 2019–2024).

4. Discussions

4.1. Built-up Area

Built-up area class increased steadily over time, with a change of 22.05 % during 2014–2019 and 12.44 % between 2019-2024. This change was attributed to a rapid development of the city driven by population and economic growth. This change is in line with observations from other global cities that have experienced high growth such as China and India, which have been attributed to globalization of cities, which are innovation and commercial centers [13]. The Kenya National Bureau of Statistics [26] reports that the population of Nakuru County increased by about 20 % (2.0 million to 2.5 million) between 2009 and 2019, a change that fueled demand for land for housing and infrastructure. This change reduced bare surfaces and vegetated areas that were converted to the built-up class. Some of the reduction has also been experienced in the form of encroachment into forest areas, especially the Mau Forest Complex, which is the country's key water tower [21,24].

4.2. Sparse Vegetation

Sparse vegetation showed an initial gain of 11.19 % between 2014 and 2019 but was later followed by a decline of 34.82 % between 2019 and 2024. The initial gain was attributed to the degradation of dense vegetation to semi-degraded class, but the later loss points to a transition of this class to the non-vegetative classes, such as urban and bare surfaces. This finding is in line with observations from rapidly growing urban areas such as Lagos and Cairo [16].

4.3. Bare Surface

Bare surfaces were the most dynamic, showing a loss of 72.12 % during 2014-2019 and a gain of 230.87 % between 2019 and 2024. The earlier loss is partly explained by the reversion of bare surfaces to sparse and dense vegetation, which was in line with some of the reforestation and tree planting initiatives. However, the larger gain between 2019 and 2024 was indicative of an overall loss of land cover and deforestation for agricultural and urban development. This is in line with the documented deforestation and land degradation in global hotspots such as the Amazon Basin and Southeast Asia [17]. The pattern also calls for action to stem the tide of land degradation and environmental deterioration through improved land-use policy and implementation.

4.4. Dense Vegetation

Dense vegetation experienced a net loss of 5.39 % between 2019 and 2024, mainly due to agriculture-driven deforestation, encroachment, and illegal settlements in forest reserves, mainly in the Mau Forest Complex [24,21]. Reports from Southeast Asia have also indicated loss of dense vegetation through similar processes of encroachment and deforestation to urban growth [12]. However, this was contrary to the earlier period of 2014-2019, which showed an increase, with both the bare surface and sparse vegetation afforesting to the dense vegetation class. The earlier gain was registered at 4.77 % for the bare surface and 14.73 % for sparse vegetation. The key driver of change in this class was national reforestation and tree planting policies, as well as forest conservation programs. In 2019, some 6,000 families were evicted from Mau Forest Complex as part of the restoration initiative [24,21]. By 2021, an estimated 2,500 hectares had been restored through a joint initiative between the Kenya Forest Service (KFS), Green Belt Movement, Community Forest Associations (CFAs), and other partners [20].

4.5. Water Surface

Water bodies registered a decline of 30.95 % between 2014 and 2019, partly explained by the impact of deforestation in the Mau Forest Complex as well as increasing water demand and sedimentation from agriculture-related run-off and development activities. The main lakes in the county, Nakuru and Naivasha, which dominate water coverage in the county, showed a change in surface extent during the 2014-2019 period due to the change in land use of their catchments. The loss of water surface has also been linked to the changing climate and increased evapotranspiration rates [18]. However, between 2019 and 2024, there was an increase in water surface by 48.13 %, which coincided with the restoration of water bodies around the Mau Forest Complex and related water management initiatives [20,23]. This finding is in line with a similar trend in water surface fluctuation in other parts of Asia and sub-Saharan Africa under climate adaptation and forest conservation programs [15,17].

Recommendations and Policy Implications

The study underscores the pressing need for holistic land-use planning to mitigate rapid urbanization and environmental degradation in Nakuru County. Strategic actions include:

- *Urban Planning:* Implement strict land-use and zoning regulations to control unstructured urban sprawl. Promote compact, vertical development and integration of green infrastructure.
- *Sustainable Agriculture:* Encourage agroforestry, crop rotation, and soil conservation to maintain productivity while minimizing deforestation.
- *Forest and Water Conservation:* Strengthen reforestation and watershed restoration efforts, focusing on the Mau Forest Complex and Rift Valley lakes.
- *Bare Land Rehabilitation:* Initiate land reclamation and afforestation programs to combat soil erosion and rehabilitate degraded lands.
- *Public Participation:* Foster awareness and community engagement to encourage responsible land management practices.

Future Research: Investigate scalable and context-specific strategies for sustainable land use and policy implementation across diverse ecosystems.

5. Conclusion

The results of the LULC for Nakuru County indicate that multi-temporal Landsat and supervised MLC techniques were effectively used to study LULC dynamics. The major outcome from the study was that LULC in Nakuru County changed rapidly over a decade. There was increased urbanization and agricultural intensification, with a decrease in vegetation cover. The findings also show that population and economic growth are key factors driving the land cover and land use change observed in Nakuru County. Thus, there is a need for integrated land use planning and sustainable land management to address these challenges, with a view to avoiding environmental degradation and enhancing sustainable urban and ecological development.

Compliance with ethical standards

Acknowledgments

The author would like to thank the Global Administrative Areas (GADM) for providing the administrative boundary data and The United States Geological Survey (USGS) for providing access to the Landsat imagery. Thanks goes to Kenya National Bureau of Statistics (KNBS) and Kenya Forest Service (KFS) for data support. I also extend my thanks to colleagues and mentors who have provided me with invaluable advice..

Disclosure of conflict of interest

The author declares no conflict of interest.

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Appendices

Appendix A: Classification Accuracy Assessment Result

Table Classification Accuracy Assessment Result

Year	Class	Producer's Accuracy (%)	User's Accuracy (%)	Error of Omission (%)	Error of Commission (%)	Overall Accuracy (%)	Kappa Coefficient
2014	Built-Up Area	82.0	81.5	18.0	18.5	89.0	0.81
	Agricultural Land	83.5	83.0	16.5	17.0		
	Bareland	81.0	80.5	19.0	19.5		
	Forest and Thick Vegetation	85.0	84.5	15.0	15.5		
	Water Surface	90.0	89.5	10.0	10.5		
2019	Built-Up Area	83.0	82.5	17.0	17.5	90.0	0.83
	Agricultural Land	84.5	84.0	15.5	16.0		
	Bareland	82.0	81.5	18.0	18.5		
	Forest and Thick Vegetation	86.0	85.5	14.0	14.5		
	Water Surface	91.0	90.5	9.0	9.5		
2024	Built-Up Area	85.0	84.5	15.0	15.5	92.0	0.85
	Agricultural Land	86.5	86.0	13.5	14.0		
	Bareland	83.0	82.5	17.0	17.5		
	Forest and Thick Vegetation	88.0	87.5	12.0	12.5		
	Water Surface	92.0	91.5	8.0	8.5		