

Assessing Forest Degradation and Encroachment Patterns in Kafue National Park Using Remote Sensing and GIS (2014-2024)

Bwalya Mutale^{1*}, Jonas Pule¹, Samson Nyoni¹, Joseph Mphande^{1,2}, Emmanuel Nkweto¹

¹Department of Agriculture and Aquatic Sciences, Kapasa Makasa University, Chinsali, Zambia

²Department of Fisheries, Ministry of Fisheries and Livestock, Ndola, Zambia

Email: *bwalya.mutale.writer@gmail.com

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Abstract

Change-detection analysis highlighted significant declines in sparse forest (−72.88%) and wetlands (−73.49%), alongside a substantial increase in bare land (+55.26%). These trends underscore the impact of human activities such as agricultural expansion, logging, and infrastructure development, exacerbated by climate variability. This study investigated forest degradation and encroachment patterns in Kafue National Park, Zambia, over a decade (2014-2024), using remote sensing and Geographic Information Systems (GIS). By analyzing land-use and land-cover (LULC) changes, it identified key drivers of landscape transformation and their consequences for biodiversity conservation and sustainable management. High-resolution Landsat imagery and supervised classification methods were used to map five primary LULC classes—dense forest, sparse forest, water bodies, bare land, and wetland—achieving an overall accuracy of 84%. The findings highlight the need for targeted conservation strategies, community engagement, and policy interventions to curb forest loss and enhance ecosystem resilience. This study provides data-driven recommendations to help policymakers integrate conservation efforts with sustainable land-use planning in the region.

Keywords

Kafue National Park, Forest Degradation, Land-Use and Land-Cover (LULC) Changes, Landscape Transformation, Spatial Analysis

1. Introduction

Land use and land cover (LULC) are critical components of terrestrial ecosystems,

influencing biodiversity, climate, and human livelihoods. Over the past century, anthropogenic pressures have dramatically altered these landscapes, leading to unprecedented rates of change that threaten ecological stability and human well-being (Millennium Ecosystem Assessment, 2005; Ojima, Galvin, & Turner, 1994). In Zambia, particularly in Kafue National Park, these dynamics have significant implications for biodiversity conservation and resource management. The park is not only a vital ecological zone but also an area experiencing pressures from agricultural expansion, urbanization, and other human activities that pose risks to its ecological integrity. The transformation of LULC is a double-edged sword; while it can contribute to economic development and human well-being, it often results in biodiversity loss and ecosystem degradation (Foley et al., 2005; Lambin & Geist, 2008).

Accurate LULC mapping is essential for addressing challenges such as biodiversity loss and urban sprawl. Recent studies emphasize the need for advanced techniques, like machine learning and cellular automata models, to predict and manage LULC changes effectively (Mutale et al., 2024; Mutale & Qiang, 2024). Consequently, it is crucial to assess LULC changes and their trajectories to inform sustainable land management practices. Such assessments are essential for monitoring environmental changes and developing policies that can mitigate the impacts of climate change and promote biodiversity conservation (Singh, 2023). The integration of remote sensing and Geographic Information Systems (GIS) has revolutionized the way LULC changes are studied. These technologies allow researchers to analyze landscape dynamics over extensive temporal and spatial scales (Lambin, Geist, & Lepers, 2003; Li et al., 2015; Ojima, Galvin, & Turner, 1994).

The availability of high-resolution satellite imagery, such as Landsat, has enabled the creation of comprehensive databases that facilitate the monitoring of LULC changes and their implications for ecosystems (Boyle et al., 2014; Majerovičová et al., 2022). Furthermore, methodologies, like intensity analysis and land cover change trajectory analysis, have emerged as effective tools for evaluating the complexities of LULC dynamics (Baral, Wen, & Urriola, 2018; Badjana et al., 2015). Intensity analysis quantifies the magnitude of changes, while trajectory analysis traces historical patterns at the pixel level, offering insights into the drivers and consequences of LULC changes (Li et al., 2015). In Kafue National Park, understanding LULC dynamics is critical for addressing the challenges posed by human activities such as poaching, land clearing for agriculture, and infrastructure development. These activities not only threaten the park's biodiversity but also undermine its role in providing essential ecosystem services. As in other regions of Africa, Kafue has seen significant alterations in its landscape, driven by socio-economic factors and demographic pressures (Awoke & Bewket, 2014; Lambin & Geist, 2006). The conversion of natural habitats into agricultural land and settlements has far-reaching consequences for both ecological stability and community livelihoods. Notably, previous studies have highlighted the dire consequences of LULC changes across Africa. Between 1975 and 2000, approximately 5% of wood-

lands and grasslands and 16% of natural forest cover disappeared, equating to a loss of over 50,000 km² of natural vegetation each year (Eva et al., 2006). These trends are not isolated to specific regions but represent a broader pattern of land degradation that is evident in many parts of the continent. In Zambia, agricultural expansion and encroachment into protected areas exacerbate the decline of natural habitats, leading to biodiversity loss and increasing the vulnerability of ecosystems to climate change (Ahialey et al., 2024). Therefore, this study aims to investigate the historical dynamics of land use and land cover in Kafue National Park from 2014 to 2024. The study adopts a synergistic approach that combines remote sensing and GIS to comprehensively analyze LULC changes and their spatial-temporal dynamics. The specific objectives include: 1) identifying and mapping the major LULC categories for the years 2014 and 2024, 2) determining the types and processes of LULC dynamics and their rates of occurrence, and 3) analyzing land change trajectories. Through these objectives, this research seeks to contribute to the existing body of knowledge on LULC dynamics and their implications for biodiversity conservation and sustainable land management. The findings will not only enhance our understanding of land use changes in Kafue National Park but will also provide insights for policymakers and land managers seeking to balance conservation efforts with the needs of local communities.

2. Materials and Methods

2.1. Study Area

Kafue National Park, Zambia's largest and oldest national park, spans approximately 22,400 square kilometers across North-Western, Central, and Southern provinces (see Figure 1). Established in 1950, Kafue is known for its rich biodiversity and housing ecosystems such as miombo woodlands, savannas, and floodplains (Mwima, 2001). The Kafue River flows through the park, creating seasonal wetlands such as the Busanga Plains, which support diverse wildlife, including elephants, buffalo, and rare species such as the roan antelope. The park faces pressures from surrounding human activities, including agriculture, illegal logging, and poaching, leading to habitat degradation, especially along its boundaries (Mutti et al., 2023). Road infrastructure has increased access, further heightening human-wildlife conflicts and land-use shifts (Mkanda & Chansa, 2011). This study focuses on analyzing land-use and land-cover (LULC) changes within Kafue National Park from 2014 to 2024 using remote sensing and GIS, providing crucial insights into landscape change drivers that will aid in developing sustainable management strategies.

2.2. Methodology

To analyze land-use and land-cover (LULC) changes in Kafue National Park, satellite imagery for 2014 and 2024 was obtained from the United States Geological Survey (USGS) Earth Explorer (<https://earthexplorer.usgs.gov/>) as shown in Figure 2. Landsat 8 Level-2 data were used for 2014, and Landsat 9 Level-2 data for 2024, each

providing a spatial resolution of 30 meters, ideal for medium-resolution LULC mapping. The selection of Level-2 data ensures that the images have been atmospherically corrected to surface reflectance, improving data accuracy and facilitating reliable inter-year comparisons. The chosen imagery dates correspond to the early dry season, reducing cloud cover interference and allowing for consistent seasonal analysis across the two time points (Macarringue et al., 2022). This temporal consistency is critical in examining landscape dynamics, such as transitions between woodland, grassland, and wetland environments within the park. The years 2014 and 2024 were selected to represent a decadal window of change, allowing the assessment of long-term landscape transformations while minimizing seasonal variability. These dates correspond to the availability of cloud-free, atmospherically corrected imagery during the early dry season, which enhances classification consistency. Intermediate years were reviewed during initial image screening; however, most lacked sufficient quality due to cloud contamination, temporal mismatch, or incomplete coverage of the study area. Furthermore, this study prioritized detecting major directional shifts in LULC over a decade rather than short-term fluctuations. Nonetheless, future research could incorporate multi-temporal series to capture intra-decadal dynamics and seasonal variability in greater detail.

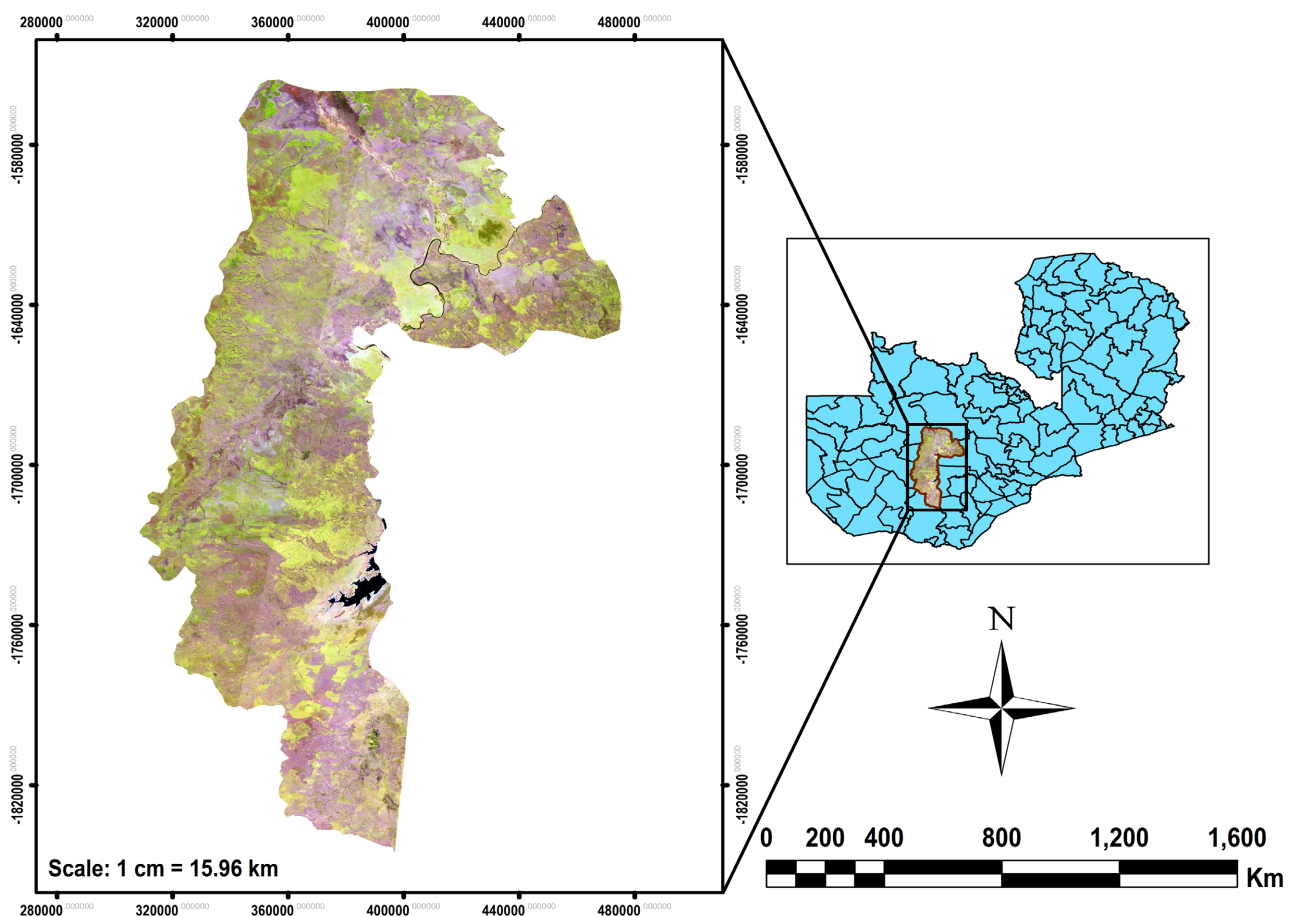


Figure 1. Map showing the geographical location of the study area.

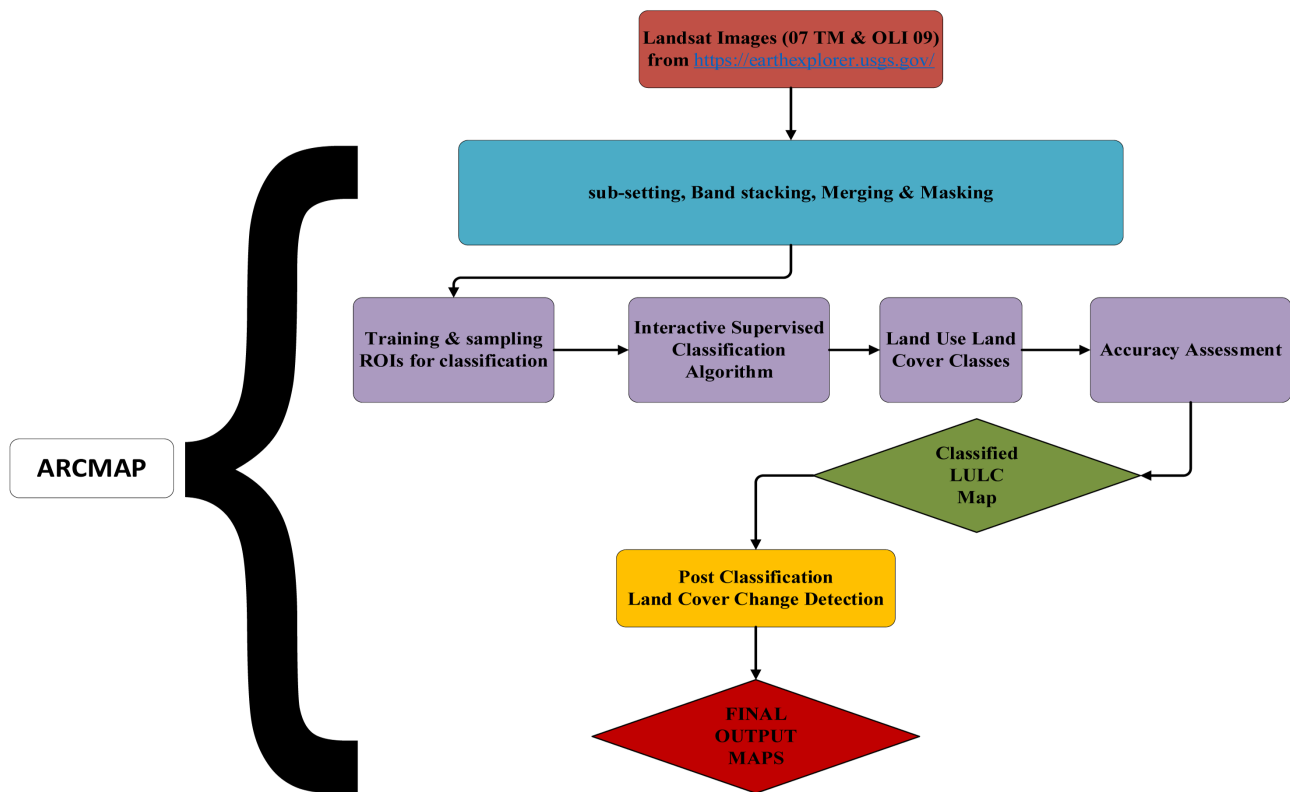


Figure 2. Flowchart depicting the outline of the general methodology.

2.3. Data Source and Preprocessing

This study utilized ArcMap 10.8 for spatial analysis and Excel for organizing and tabulating data outputs. Landsat 9 Level 2 data for 2024 and Landsat 8 Level 2 data for 2014 and 2024 were used in the analysis of land-cover changes over time. Both datasets, with a spatial resolution of 30 meters, included Bands 1 - 7 (Table 1), which were used to capture diverse spectral characteristics essential for accurate classification. The preprocessing of the imagery involved stacking Bands 1 - 7 using ArcMap's band composition feature, which allows for the integration of spectral information to enhance class separability. Following band stacking, a mosaic operation was performed to merge multiple scenes, ensuring complete spatial coverage of Kafue National Park. The extent of the park was then defined by applying a mask to the mosaicked images, limiting analysis strictly to park boundaries.

2.4. Image classification

The supervised classification of Landsat imagery was performed using the Random Forest (RF) algorithm. This ensemble learning method builds multiple decision trees during training and outputs the mode of the classes. RF is particularly well-suited for high-dimensional data and has demonstrated superior performance in Land Use and Land Cover (LULC) classification compared to other machine learning algorithms, such as Support Vector Machines (SVM) and Artificial Neu-

ral Networks (ANN) (Mutale et al., 2024). Its robustness and ability to handle spectral variability in satellite imagery made it the ideal choice for this study.

Table 1. Band numbers and specifications of Landsat 8 OLI and Landsat 9 OLI.

Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)			Operational Land Imager 2 (OLI-2) and Thermal Infrared Sensor 2 (TIRS-2)		
Bands	μm	Res(meters)	Bands	μm	Res(meters)
Band 1	0.433 - 0.453	30	Band 1	0.435 - 0.45	30
Band 2	0.450 - 0.515	30	Band 2	0.452 - 0.512	30
Band 3	0.525 - 0.600	30	Band 3	0.533 - 0.590	30
Band 4	0.630 - 0.680	30	Band 4	0.636 - 0.673	30
Band 5	0.845 - 0.885	30	Band 5	0.851 - 0.879	30
Band 6	1.560 - 1.660	30	Band 6	1.566 - 1.651	30
Band 7	2.100 - 2.300	30	Band 7	2.107 - 2.294	30

Table 2. LULC classification scheme/description of LULC types in the study area.

LULC Type	Definition
Dense Forest	Areas with high canopy cover consist predominantly of mature trees and rich biodiversity.
Sparse Forest	Regions with lower canopy density comprise scattered trees and minimal undergrowth.
Water Bodies	Natural or man-made accumulations of water, including rivers, lakes, and ponds.
Bare Land	Exposed areas devoid of significant vegetation cover, including rocky outcrops and sandy surfaces.
Wetland	Saturated land areas with distinct vegetation adapted to high water tables, providing critical habitats for various species.

Training samples for key land cover classes—dense forest, sparse forest, wetlands, bare land, and water bodies—were derived from high-resolution Google Earth imagery. The Random Forest (RF) classification was performed using the “Random Trees” algorithm in ArcMap 10.8 via the Image Classification toolbar using the Spatial Analyst and Image Analyst extensions. A total of 100 trees were specified for the ensemble, with the Gini index used as the splitting criterion. Variable sampling was based on the square root of the number of predictor variables at each split, a standard practice for improving model generalization. ArcMap’s implementation uses all supplied training samples for model development without manual parameter tuning or internal validation controls. As such, post-classification accuracy assessment was conducted independently using reference points derived from Google Earth. This configuration aligns with established practices in LULC mapping using RF in desktop GIS environments (Macarringue et al., 2022). Five primary LULC classes were established: dense forest, sparse forest, wetlands, bare land, and water bodies (Table 2). These classes represent distinct land cover

types, each playing a unique ecological role in the study area. The classification provides a detailed understanding of LULC dynamics, offering valuable insights for conservation and land management strategies.

2.5. Accuracy Assessment

To evaluate the classification accuracy of the Land Use and Land Cover (LULC) map for Kafue National Park, a rigorous validation process was conducted. Random sampling generated 420 accuracy assessment points over the 2024 classified map using ArcMap (Figure 3). These points were exported to KML format and visualized in Google Earth to confirm their locations and corresponding ground-truth data. Each point was verified by comparing the classified map with high-resolution reference data, ensuring consistency between the land cover class assigned in the classification and the ground truth observed on Google Earth. This ground-truth verification approach aligns with best practices in remote sensing, providing a robust foundation for accuracy assessment (Macar-ringue et al., 2022).

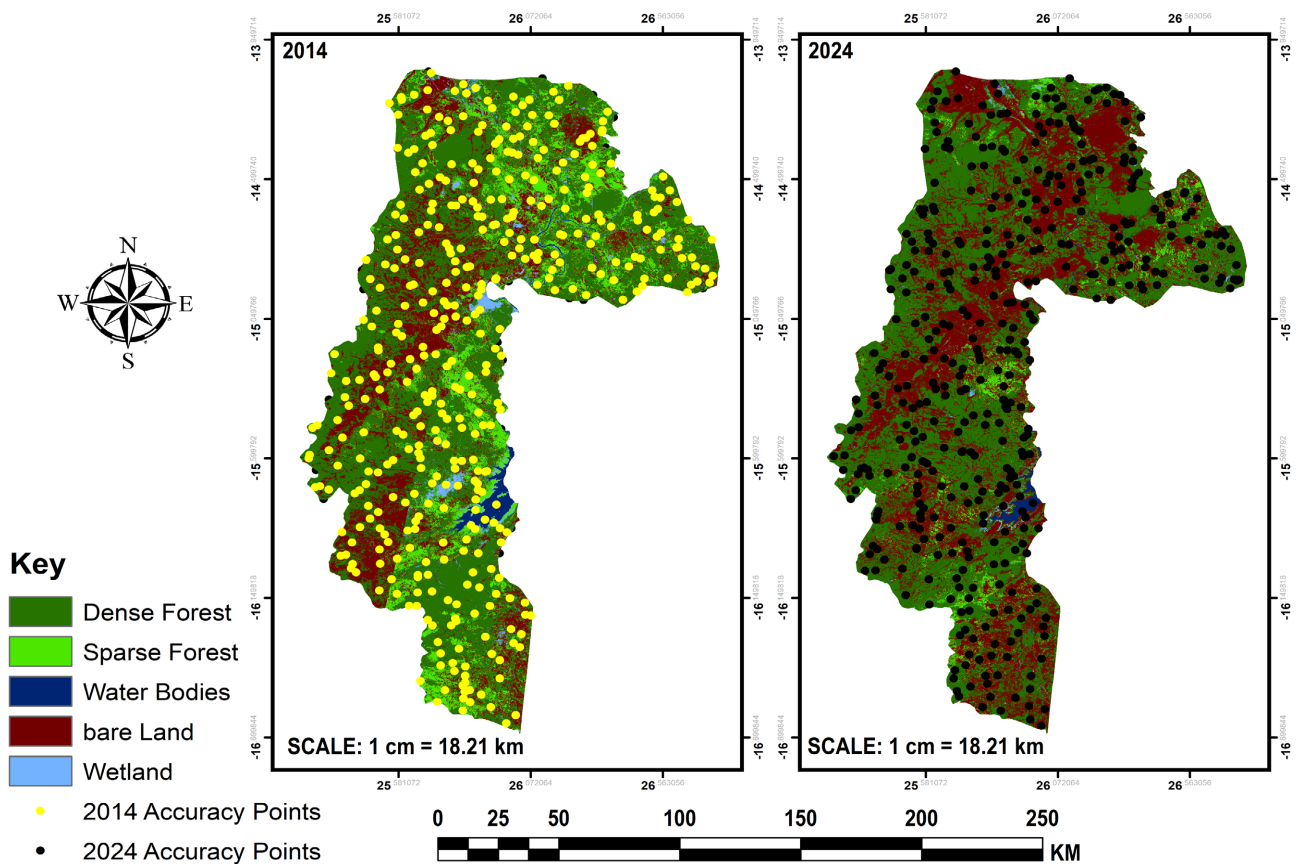


Figure 3. Accuracy assessment points overlaid on the 2014 and 2024 classified maps.

A confusion matrix was generated using the classified and ground truth data, with classification accuracy assessed through metrics such as Overall Accuracy (OA) and other relevant indicators (Table 3). These metrics quantify classification

errors and provide a comprehensive evaluation of the model's performance, offering valuable insights into its reliability (Vatitsi et al., 2023). The high accuracy and robustness of the Random Forest (RF) algorithm further emphasize its reliability for LULC classification, consistent with findings from previous studies validating RF and other machine learning models, such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs), in similar contexts (Mutale et al., 2024). The accuracy assessment results not only validate the quality of the classified map but also highlight areas for improvement, guiding future mapping and analysis efforts.

2.6. Change Detection

To detect changes in land use and land cover (LULC) within Kafue National Park over the study period, a series of analytical steps was performed to transform and analyze the classified imagery data for 2014 and 2024. The raster images from both years were transformed into polygon format to facilitate spatial analysis using vector data. This approach improves the precision of detecting distinct LULC types across different periods (Ahialey et al., 2024; Gupta et al., 2023). Subsequently, the polygons were dissolved to merge adjacent areas with the same LULC classification, simplifying the dataset and ensuring that each land cover class was uniquely represented (Ullah et al., 2024; Patel et al., 2024). Following the dissolving process, an intersection analysis was conducted. This step allowed for direct comparison of spatial overlaps and distinctions between the two years. By intersecting the polygons, changes in each LULC class across the two time periods were identified, providing detailed insights into the extent and distribution of land cover transformations within the park.

3. Results

3.1. LULC Classification Results for 2014 and 2024

The supervised classification of Landsat imagery for 2014 and 2024 yielded insights into land-use and land-cover (LULC) dynamics within Kafue National Park over the past decade. The analysis categorized five primary LULC types: dense forest, sparse forest, water bodies, bare land, and wetland, as shown in **Figure 4**, allowing for the assessment of changes in land cover.

3.2. Accuracy Assessment

To evaluate and verify the accuracy of our generated Land Use and Land Cover (LULC) maps, ground-truthing was conducted using high-resolution imagery available from Google Earth. Three commonly employed accuracy assessment metrics were calculated: Overall Accuracy (OA), Producer's Accuracy (PA), and User's Accuracy (UA). OA, which reflects the overall proportion of correctly classified LULC categories, is determined by dividing the number of correctly classified land cover pixels by the total number of pixels in the dataset, as expressed in the following Equation (1) (Olofsson, 2018; Mutale & Qiang, 2024).

$$OA = \frac{1}{N} \sum_{ii=1}^n P_{ii} \quad (1)$$

where OA is the overall accuracy; N is the total number of samples; n is the total number of categories; and P_{ii} is the number of correct classifications of the i -th sample in the confusion matrix.

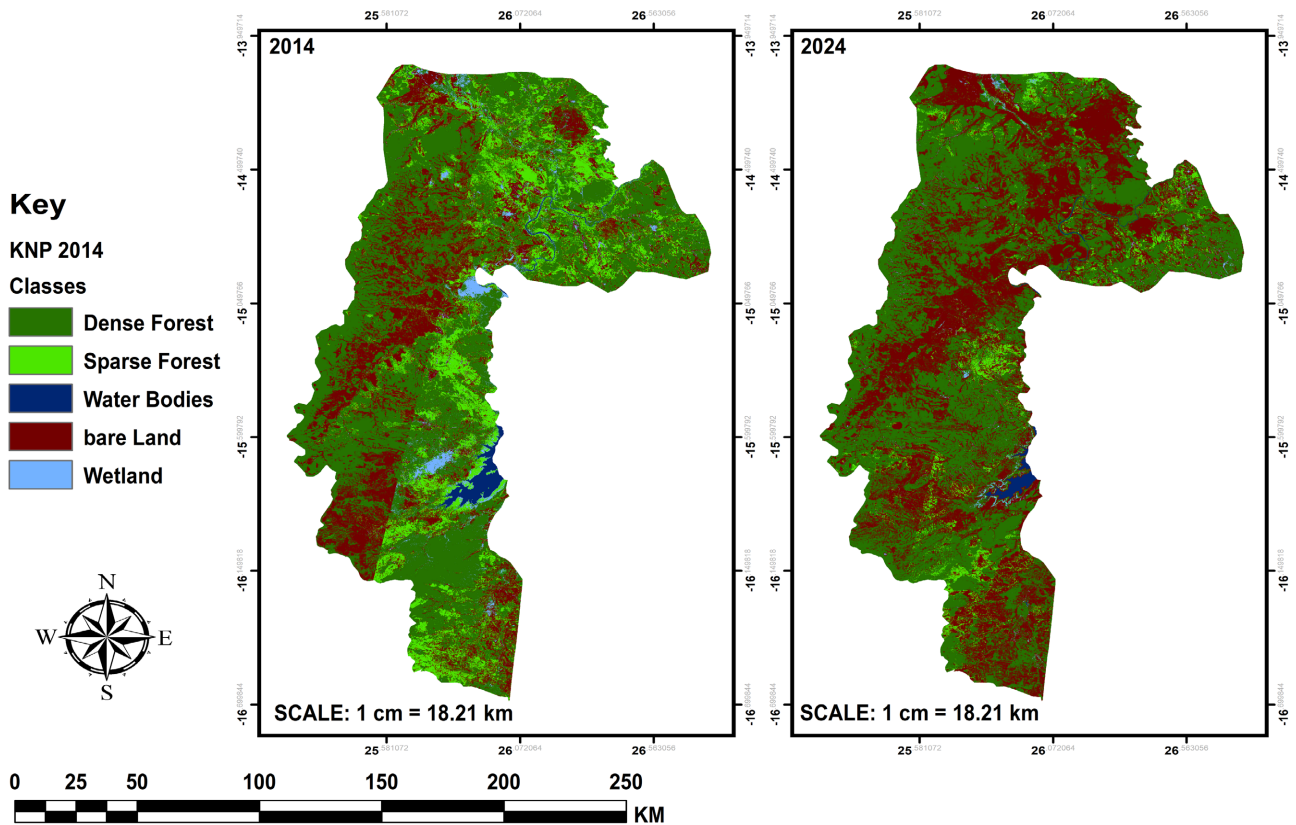


Figure 4. LULC classification maps of Kafue National Park for 2014 and 2024.

PA quantifies the classification accuracy of individual LULC classes within a map. It is computed by dividing the number of correctly classified pixels for a given land cover class by the total number of pixels for that class in the reference dataset. Pixels that were misclassified under this metric, referred to as errors of omission, were calculated using the following Equation (2):

$$PA = \frac{n_{ii}}{n_{i+}} \quad (2)$$

where n_{ii} is the number of correctly classified pixels in each category; n_{i+} is the total number of correctly classified pixels in that category (column total).

UA assesses the reliability of a land cover map by measuring its consistency with ground observations. It is determined by dividing the number of correctly classified pixels in a specific land cover class by the total number of pixels assigned to that class in the classification. Misclassified pixels under this metric are known as errors of omission. The calculation follows Equation (3) below.

$$UA = \frac{n_{ii}}{n_{i+}} \quad (3)$$

where n_{ii} is the number of correctly classified pixels in each category; n_{i+} is the total number of correctly classified pixels in that category (row total).

The tables (Tables 3(a)-(c)) summarize the accuracy assessment of the land-use and land cover (LULC) classification for 2014 and 2024. In Table 3(a), each row represents the actual LULC class (verified by reference points), while each column represents the corresponding predicted class from the classification model. The diagonal values (e.g., 163 for Dense Forest) indicate correctly classified points, while the off-diagonal values represent misclassifications.

Table 3. (a) Confusion matrix for LULC classification (2024); (b) Summary of accuracy metrics for 2024 LULC classification; (c) Summary of accuracy metrics for 2014 LULC classification.

(a)							
Class Value	Dense Forest	Sparse Forest	Wet Land	Water Bodies	Bare Land	Total	User's Accuracy
Dense Forest	163	23	7	1	24	218	0.75 (75%)
Sparse Forest	8	11	0	0	1	20	0.55 (55%)
Wet Land	0	0	3	0	0	3	1.00 (100%)
Water Bodies	0	0	0	4	0	4	1.00 (100%)
Bare Land	3	4	0	0	168	175	0.96 (96%)
Total	174	38	10	5	193	420	0.00
P_Accuracy	0.94	0.29	0.30	0.80	0.87	0.00	0.83

(b)	
Overall Metrics	Value
Overall Accuracy	83.1%

(c)							
Class Value	Dense Forest	Sparse Forest	Wet Land	Water Bodies	Bare Land	Total	User's Accuracy
Dense Forest	168	31	2	0	18	219	0.77 (77%)
Sparse Forest	0	55	1	0	11	67	0.82 (82%)
Wet Land	0	0	14	0	0	14	1 (100%)
Water Bodies	0	0	0	3	0	3	1 (100%)
Bare Land	5	7	0	0	105	117	0.90 (90%)
Total	173	93	17	3	134	420	0.00
P_Accuracy	0.97	0.59	0.82	1	0.78	0	0.821 429

3.3. Change Detection

This section provides an in-depth analysis of land use and land-cover (LULC) changes over the period 2014 to 2024. **Table 4** presents a detailed summary of area changes across various LULC classes, while **Figure 5** offers a visual representation of the change trends, highlighting the magnitude and direction of these transformations.

Table 4. LULC area and changes in Kafue National Park (2014-2024).

LULC Type	Area (2014, ha)	Area (2024, ha)	Change (2014-2024) (ha)	(%) Change
Dense Forest	1,162,376.90	1,165,036.94	2660.04	0.23
Sparse Forest	359,200.49	97,405.71	-261,794.78	-72.88
Wetland	48,747.44	12,923.54	-35,823.90	-73.49
Water Bodies	26,868.81	14,626.74	-12,242.07	-45.56
Bare Land	555,892.59	863,103.37	307,210.78	55.26

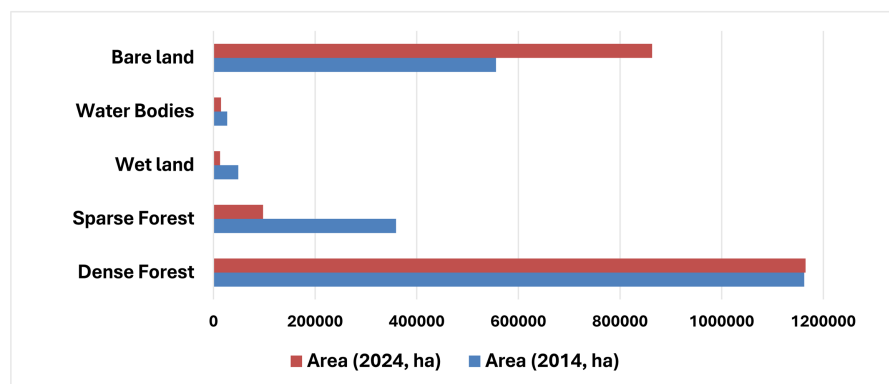


Figure 5. Changes in LULC classes from 2014 to 2024.

4. Discussion

Land Use and Land Cover (LULC) dynamics are integral to understanding human–environment interactions, particularly in ecologically sensitive areas like Kafue National Park, Zambia. Over the decade between 2014 and 2024, the park’s landscape has undergone significant transformations due to a combination of human activities and natural factors. These changes have profound implications for biodiversity conservation, ecosystem stability, and sustainable land management. This discussion evaluates the study’s findings on LULC changes, focusing on classification accuracy and observed trends, while contextualizing the results with existing literature.

The LULC classification achieved an overall accuracy of 84.1%, reflecting substantial agreement between classified data and reference points, thus underscoring the reliability of the process. Despite achieving an overall classification accuracy of 83.1%, the Sparse Forest class exhibited a notably low Producer’s Accuracy (29%),

indicating substantial omission errors. This suggests that a significant portion of actual sparse forest areas were misclassified, primarily as dense forest or bare land. Such confusion is common in remote sensing, especially in landscapes with gradual transitions between closed and open canopy or in areas affected by selective logging, regrowth, or fire, where spectral overlap and pixel heterogeneity often lead to misclassification (Foody, 2002; Lu & Weng, 2007). The moderate spatial resolution (30 m) of Landsat imagery further compounds this challenge, as it may not adequately capture fine-scale heterogeneity within transitional forest zones. Although efforts were made to refine training samples, the spectral similarity among vegetation classes likely contributed to classification uncertainty. Future research could benefit from integrating higher-resolution imagery (e.g., Sentinel-2), texture analysis, or object-based classification approaches to improve the discrimination of sparse vegetation types. For this study, the classification still captures the overall trend of degradation affecting sparse forest areas, though results should be interpreted with caution in this specific class. In contrast, Wetland and Water Bodies achieved 100% User's Accuracy, attributed to their distinct spectral signatures that enhance classification precision. However, the small sample size for Wetland (three reference points) likely inflated the accuracy metric, a limitation discussed by Pontius and Millones (2011). Bare Land performed well with a User's Accuracy of 96%, consistent with Fritz et al. (2011), who emphasized the high reliability of classifying open, non-vegetated areas due to their unique spectral properties.

Change detection analysis revealed significant LULC transformations between 2014 and 2024, as depicted in maps and trend analysis. Sparse Forest and Wetland experienced drastic declines of 72.88% and 73.49%, respectively, while Bare Land expanded by 55.26%. Dense Forests demonstrated relative stability, with a slight increase of 0.23%, and Water Bodies decreased by 45.56%. Although settlements and agriculture are prohibited in national parks like Kafue due to strict preservation policies, their impacts are indirectly evident in the increased Bare Land and decreased Sparse Forest. These changes likely result from illegal activities or external pressures near park boundaries. Factors such as agricultural expansion and charcoal production by nearby communities are plausible drivers, aligning with Chidumayo (2013), who documented similar drivers of forest loss in Zambia. Geist and Lambin (2002) similarly highlighted the role of population pressures in exacerbating forest degradation. These findings are consistent with Eva et al. (2006), who reported widespread vegetation loss across Africa due to agricultural expansion and urbanization. To investigate the drivers of land cover change further, we conducted a proximity analysis (see Figure) using the Near Analysis tool in ArcGIS. Summary statistics showed that all land cover types lie within a narrow range, between 896.85 m and 1285.75 m from major roads. Water bodies were the closest (896.85 m), followed by dense forest (1054.80 m), bare land (1062.62 m), wetlands (1166.46 m), and sparse forest (1285.75 m). Although the sparse forest had the greatest mean distance, the margin is relatively small (less than 400 m), suggesting

that all LULC classes are situated within zones of potential human influence. The presence of degraded classes such as bare land and reduced sparse forest close to roads supports the assertion that infrastructure increases exposure to logging, burning, and informal agricultural expansion. Moreover, sparse forests, being more open and easier to clear, may be particularly targeted in these fringe zones. These findings underscore the importance of accessibility in driving LULC changes within protected areas and align with global observations that road networks, including unofficial routes, act as catalysts for deforestation and land degradation in protected and indigenous areas (da Silva et al., 2023). The decline in Wetlands is particularly alarming, with their area decreasing from 48747.44 hectares in 2014 to 12923.54 hectares in 2024, representing a 73.49% reduction. Wetlands are critical for biodiversity, water filtration, and carbon storage. The change detection analysis indicates that Wetlands were predominantly replaced by Bare Land and Sparse Forest. This reduction aligns with Davidson's estimate that over 64% of global wetlands have been lost since 1900 (Davidson, 2014). Factors such as agricultural drainage, sedimentation, and water abstraction likely contributed to wetland loss in Kafue. Wulder et al. (2008) and Gao (1996) emphasized that wetlands are especially vulnerable during dry seasons when lower water levels heighten their susceptibility to misclassification and degradation. Additionally, climate change-induced alterations in rainfall patterns and evaporation rates, as discussed by the Intergovernmental Panel on Climate Change (IPCC) (2014), may have compounded these losses.

The expansion of Bare Land reflects intensified human activity, including land clearing for cultivation and infrastructure development. Similar trends were observed by Awoke and Bewket (2014) in Ethiopia, where population growth and agricultural expansion drove land degradation. In Kafue, bushfires, often set for agricultural purposes or poaching, may further contribute to the expansion of degraded landscapes. Chidumayo and Gumbo (2010) noted that fire plays a significant role in transforming forested areas into Bare Land, a dynamic likely at play in this region.

The slight increase in Dense Forests contrasts with regional deforestation trends reported by Hansen et al. (2013), who documented extensive forest loss in tropical regions. This anomaly may reflect localized factors such as effective park management, natural regeneration, or reduced human activity in certain forested areas. Rozario et al. (2017) observed similar patterns of forest stability in protected areas, attributing these trends to conservation efforts that mitigate large-scale deforestation. However, localized degradation within Dense Forests may not have been fully captured due to the spatial resolution of Landsat imagery, a limitation highlighted by Zhang and Lu (2008). The reduction in Water Bodies, by 45.56%, from 26,868.81 hectares in 2014 to 14,626.74 hectares in 2024, underscores the pressures of human activities and environmental factors on aquatic ecosystems. Upstream deforestation and land clearing likely increased sediment loads in rivers and lakes, reducing their capacity to retain water, as discussed by Kondolf et al. (2014). Dam-

ming, water abstraction, and sedimentation may have further contributed to these losses. Pekel et al. (2016) reported similar global trends in surface water reduction, linking them to a combination of human activities and climate variability. When compared with regional and global studies, the findings reveal both consistencies and anomalies. The decline in Sparse Forests and wetlands aligns with broader patterns of vegetation loss across Africa, as reported by Lambin and Geist (2006). However, the slight increase in Dense Forests deviates from widespread deforestation trends observed in Zambia and other tropical regions. This discrepancy underscores the importance of localized analyses to capture unique dynamics in protected areas. Similarly, the expansion of Bare Land aligns with Lambin et al. (2003), who identified land degradation as a consequence of weak governance and socio-economic pressures. This finding contrasts with Turner et al. (2007), who observed reforestation trends in areas experiencing rural-to-urban migration and land

5. Conclusion and Recommendations

The LULC dynamics in Kafue National Park between 2014 and 2024 highlight the complex interplay of human activities, environmental factors, and conservation efforts. The dramatic declines in Sparse Forests and wetlands emphasize the urgent need for targeted interventions to mitigate land degradation and biodiversity loss. The slight stability of Dense Forest and the expansion of Bare Land reflect the contrasting impacts of conservation and socio-economic pressures. These findings provide critical insights for policymakers and land managers aiming to balance biodiversity conservation with sustainable development objectives, contributing to broader efforts to address land use challenges in Zambia and beyond. Furthermore, similar studies should be carried out in other National Parks in order to identify the key drivers of forest degradation and encroachment patterns.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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