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COMPREHENSIVE ANALYSIS AND QUANTITATIVE ASSESSMENT OF LAND USE/LAND COVER DYNAMICS IN WAKISO AND KAMPALA, UGANDA: A MULTIDECADAL REMOTE SENSING STUDY

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ABSTRACT

Aim of the study

This study analyses LULC changes in Wakiso and Kampala districts from 1995 to 2024. Objectives include mapping LULC types, assessing changes, evaluating transitions among categories (agriculture, water, built-up areas, forests), and examining trends and drivers. It provides insights into the impacts of urbanization and agricultural expansion, offering practical implications for sustainable land management.

Material and methods

Landsat images from 1995, 2010, and 2024 were used, sourced from NASA's Earth Explorer. January images minimized seasonal variation, and data were reprojected to UTM Zone 36N with WGS84. Pre-processing included corrections and haze reduction in ArcMap 10.4. Supervised classification used a False Colour Composite of blue, green, and red bands, with 2,500–3,000 pixels per LULC category sampled. Accuracy was assessed with Kappa statistics and overall accuracy, and NDVI and NDBI were calculated for vegetation and urban growth analysis.

Results and conclusions

The analysis showed significant land use changes: built-up areas increased by 163%, reducing vegetation cover by 30.7%. Agricultural land grew by 112.4%, while forest cover rose by 29.2%. NDVI trends revealed a vegetation density increase until 2010, then a slight decline by 2024 due to urban sprawl. NDBI showed substantial urban growth, stabilizing between 2010 and 2024. The study highlights the impact of urbanization and agricultural expansion in Wakiso and Kampala, emphasizing the need for sustainable land management to balance development and conservation.

Keywords: climate, LULC, NDBI, NDVI, remote sensing

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INTRODUCTION

Land Use Land Cover (LULC) changes have been recognized globally as critical indicators of environmental and socio-economic dynamics(X. Li et al., 2016). These changes are driven by a complex interplay of factors, including urbanization, agricultural expansion, deforestation, and infrastructure development. The ongoing and rapid transformations in LULC are reshaping natural landscapes across the globe, leading to a cascade of environmental consequences (Mutale and Qiang, 2024). These include biodiversity loss, climate change, and the degradation of essential ecosystem services that sustain human life and economic activities(Afuye et al., 2024). As such, the global discourse on LULC changes underscores the intricate interconnections between land use, environmental sustainability (Din & Yamamoto, 2024), and socio-economic development, making it a critical area of study in the quest for sustainable development (Y. Li et al., 2024).

Africa's rapid urbanization, one of the fastest globally, presents both opportunities and challenges (Assede et al., 2023; Sarfo et al., 2024). The continent's population, projected to reach 2.5 billion by 2050 (You et al., 2015), is expected to concentrate over 80% of growth in urban areas (Shah Heydari et al., 2024). While urban expansion drives economic development, it also causes environmental degradation, including soil erosion, biodiversity loss, and increased greenhouse gas emissions (De Vos et al., 2024; Tewabe and Adametie, 2020). East Africa, particularly Kampala and Wakiso in Uganda, is experiencing significant land use and land cover (LULC) changes driven by population growth, agriculture, and infrastructure development (Haileslassie et al., 2024; Kitole et al., 2024). These pressures lead to deforestation, conversion of agricultural land, and depletion of natural resources (Bullock et al., 2021; Ortiz et al., 2021; Chisika and Yeom, 2023; Pokhariya et al., 2024).

Within Africa, East Africa stands out as a particularly dynamic region experiencing rapid and profound LULC changes(Haileslassie et al., 2024). In the region, LULC changes are often driven by a combination of factors, including population growth, agricultural practices, and infrastructure development (Kitole et al., 2024). This region, characterized by a mix of urban and rural landscapes, is facing significant pressures from population growth (Frigerio, 2016), economic development, and inadequate infrastructure leading to significant LULC changes (Kiribou et al., 2024). These pressures are leading to unsustainable exploitation of natural resources and substantial alterations in land cover patterns (Ngounou et al., 2024).Researchers (Bullock et al., 2021; Chisika and Yeom, 2023) in this region have shown that the conversion of natural landscapes into urban and agricultural areas has led to a decline in forest cover and vegetation, with significant impacts on the region's ecosystems (Bullock et al., 2021). These changes are particularly pronounced in rapidly urbanizing areas like Kampala and Wakiso in Uganda, where the pressures of urban expansion are leading to significant alterations in land cover.

Uganda, particularly in the central regions like Wakiso and Kampala, is facing accelerated urbanization driven by internal migration and population growth Click or tap here to enter text.(Onyutha et al., 2021; Bwambale et al., 2022). This rapid urban expansion has led to significant land use and cover (LULC) changes, with natural landscapes such as forests and vegetation being converted into built-up and agricultural areas (Mutesi et al., 2021; Muchelo et al., 2024). These changes threaten biodiversity, alter water resources, and disrupt climate regulation (Wolde et al., 2024). While several studies have explored these impacts (Nuwagira et al., 2023; Wolde et al., 2024), more research is needed to integrate high-resolution spatial data and examine the socio-economic drivers behind these changes.

This study focuses on the Wakiso and Kampala districts in Uganda, which are among the most rapidly urbanizing areas in East Africa. We employed a combination of remote sensing, Geographic Information Systems (GIS), and advanced statistical analysis to examine LULC changes from 1995 to 2024. Landsat satellite imagery was used to classify and analyze land cover changes over the study period. The images were processed and classified into different LULC categories, including vegetation, water bodies, built-up areas, forests, and agriculture. Descriptive statistics were used to quantify the extent of land cover changes, while normality tests and regression analysis were employed to understand the relationships between different LULC classes. Sen's slope estimation was used to quantify the rate and direction of change for each LULC class throughout the study period. The classification accuracy was evaluated using Kappa statistics along with overall accuracy measures.

The primary objective of this study is to analyze the LULC changes in the Wakiso and Kampala districts from 1995 to 2024 and to understand the socio-economic and environmental drivers of these changes. Specifically, this study aims to (a) map and analyze the spatial distribution and extent of different land use and land cover types over the study period, identifying areas of significant change, (b) assess the transitions between different land use and land cover types in Wakiso and Kampala districts, (c) to analyze the temporal changes and trends in landcover types over the study period. The study seeks to enhance both academic knowledge of climate-land dynamics (Song et al., 2024) and practical insights essential for effective environmental management in the region. This study is significant in that it provides a comprehensive analysis of LULC changes in one of Uganda's most rapidly urbanizing regions. The findings offer valuable insights into the environmental and socio-economic impacts of urbanization and agricultural expansion, highlighting the need for sustainable land management strategies. The study also contributes to the broader understanding of LULC dynamics in East Africa, where rapid population growth and economic development are driving significant changes in land use. The use of high-resolution spatial data and advanced statistical methods ensures that the study's findings are robust (Gebrechorkos et al., 2023) and can inform policy and planning decisions. By identifying the key drivers of land cover changes and assessing their impacts on the environment, the study provides a basis for developing interventions that balance development with environmental sustainability.

MATERIALS AND METHODOLOGY

Study area

Kampala and Wakiso districts are located in the central part of Uganda (Fig. 1), forming a contiguous and dynamic region around the northern shores of Lake Victoria. Kampala, the capital city of Uganda, covers an area of approximately 189 km^2 and is divided into five administrative divisions: Central, Kawempe, Makindye, Nakawa, and Rubaga.

Wakiso District surrounds Kampala, covering approximately 2,704 km^2, making it one of the largest districts in the region. It borders Kampala to the south and east, Mpigi to the west, and Luwero to the north, and features a mix of urban, semi-urban, and rural areas. Both Wakiso and Kampala experience a tropical rainforest climate with two main rainy seasons: from March to May and September to November (Atube et al., 2022). The average annual rainfall is about 1,200 mm. Temperatures in the region are relatively stable throughout the year, ranging between 20°C and 27°C, providing a favourable climate for both urban living and agricultural activities(Umer et al., 2023).

Kampala is the most populous city in Uganda (Vermeiren et al., 2012) with an estimated population of over 1.5 million residents. Wakiso District is one of the most populous in the country, with an estimated population exceeding 2 million people (Vermeiren et al., 2012). The population in both districts is diverse, with the Baganda people being the predominant ethnic group. The area also hosts a significant number of expatriates and refugees, contributing to its multicultural dynamic.

Kampala and Wakiso are undergoing rapid urbanization driven by population growth and economic development (Kahangirwe, 2012). This has led to the expansion of residential, commercial, and industrial zones. Urban sprawl from Kampala into Wakiso has transformed the latter into a peri-urban area with increasing real estate development. However, this urbanization has brought challenges such as traffic congestion, inadequate housing, land use conflicts, and environmental degradation (Richmond et al., 2018). Sustainable urban planning is crucial to address these issues and support the region's growth.

Data source and acquisition

Landsat imagery serves as the primary data source for analysing changes in land use/land cover (LULC) and land surface temperature (LST) (Pratim Gogoi et al., n.d.). For this study, data from the month of January were acquired through the NASA Earth Explorer

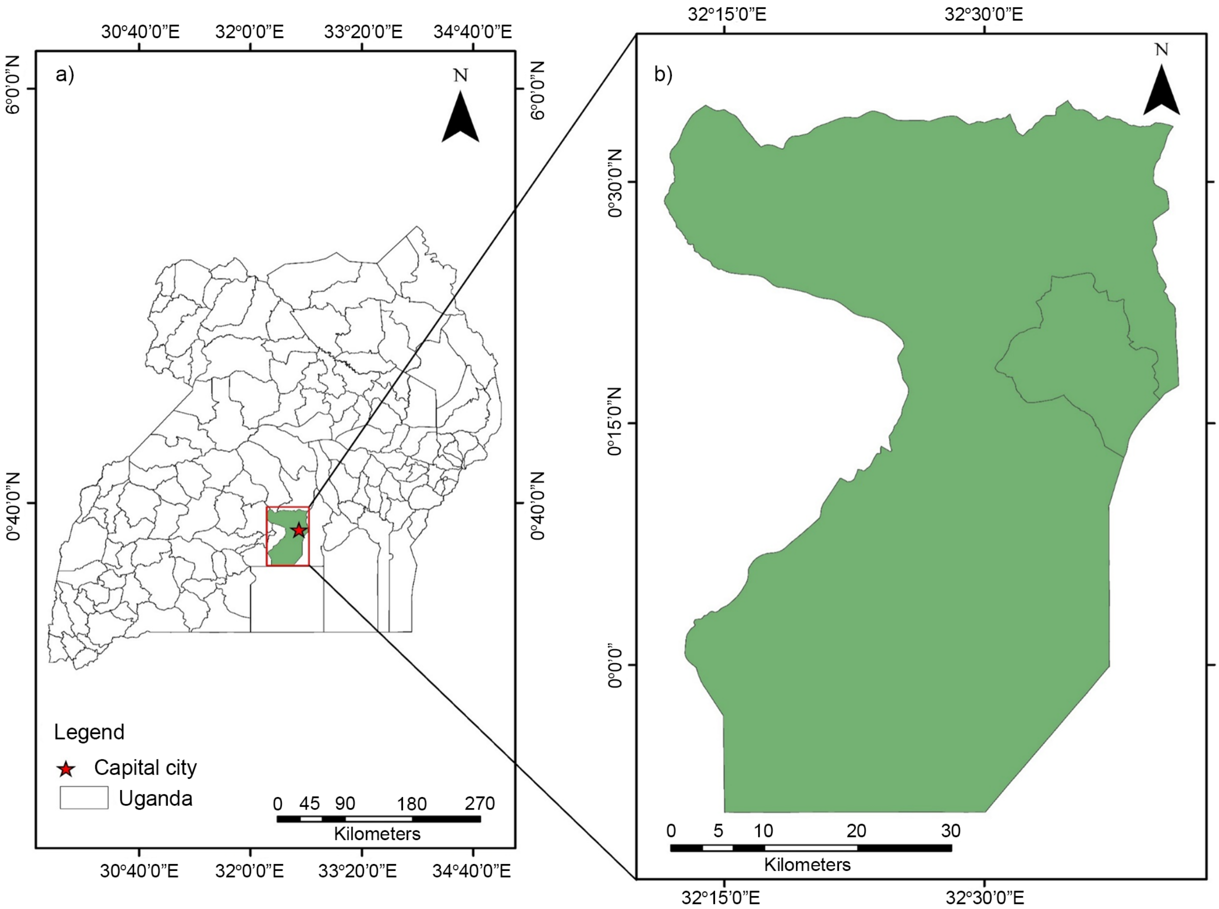

Fig. 1. Map of a) Uganda indicating b) the study area Wakiso and Kampala (source: generated by Authors using ArcGIS with administrative boundary data from GADM, Version 4.0)

(USGS) data portal. The dataset includes scenes from Landsat's Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) and Thematic Mapper (TM) for the years 1995, 2010, and 2024. A summary of the Landsat images utilized in the study is presented (Table 1). By selecting satellite images from January of 1995, 2010, and 2024, the study aimed to minimize the influence of seasonal variations on classification results. The data were reprojected to the 36N zone of the Universal Transverse Mercator (UTM) projection system and aligned with the World Geodetic System 84 (WGS84) datum to ensure consistency across datasets during analysis. Pre-processing steps, including radiometric, atmospheric, and geometric corrections, as well as haze reduction, were conducted using ArcMap 10.4.

Data analysis

Computation of land use / land cover change

LULC classification is a complex process influenced by various factors (Alshari and Gawali, 2021), leading to differing perspectives on the classification system (İnalpulat et al., 2023). While quantitative approaches like machine learning algorithms can enhance objectivity in classification (Choudhury et al., 2023), subjectivity may still persist due to evolving land use patterns and environmental changes. The dynamic nature of LULC necessitates continuous monitoring and updates to classification systems to ensure relevance and accuracy over time (Puttinaovarat et al., 2023). Despite advancements in technology and methodologies, achieving a flawless and everlasting LULC classifica-

Table 1. Summary of Landsat data source and acquisition (source: Earth-explorer, USGS)

Satellite	WRS row	Acquisition date	Resolution	Bands	Scene centre time
4/5 TM	171 per 060	1995-01-19	30 m	4,3,2	7:13:45
4/5 TM	171 per 060	1995-01-19	30 m	6	7:13:45
4/5 TM	171 per 060	2010-01-28	30 m	4,3,2	7:52:10
8 OLI	171 per 060	2024-01-19	30 m	5,4,3	8:01:25
8 TIRS	171 per 060	2024-01-19	30 m	10,11	8:01:25

tion system remains improbable (Alshari and Gawali, 2021), highlighting the need for ongoing research and adaptation to capture the intricate and evolving nature of land use and cover patterns.

In this current investigation, the supervised maximum likelihood classification method was employed to analyze alterations in LULC (Nooni et al., 2014). The supervised classification process involves using the False Colour Composite (FCC), which combines blue, green, and red bands to delineate areas of interest, including features such as agriculture, water bodies, built-up areas, forests, and vegetation. For this classification, approximately 2,500 to 3,000 pixels were selected from each category to represent the five key attributes necessary for image classification. These selected pixels, known as spectral signatures in remote sensing, were derived from reference data to characterize each land use and land cover (LULC) type. These spectral signatures are crucial in image enhancement, enabling the identification of specific areas based on colour coding and spectral uniformity within those regions. To streamline the analysis and facilitate change detection, the various LULC types were grouped into five classes. This approach was selected due to the limitation of the 30-meter resolution of the satellite imagery, which restricts the ability to achieve more than five LULC classifications. A detailed summary of the LULC categories is provided in Table 2.

Computation of NDVI and NDBI

Normalized Difference Vegetation Index (*NDVI*) was computed by using Near-Infrared (*NIR*) and *RED* Sensor (*RED*)(Rouse et al., 1973).

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

Normalized Difference Built-up Index (*NDBI*) is computed by using the Near-Infrared (*NIR*) and Shortwave Infrared (*SWIR*) bands;

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

Table 2. Description of Land Use/Land Cover types (source: Authors' classification based on geospatial analysis, 2024)

LULC	General description
Agriculture	Crop lands, fallow land
Water body	Lakes and rivers
Built-up	Residential areas, commercial areas, industrial area, transport infrastructure, etc.
Forest	Natural and planted forests
Vegetation	Shrubs, playgrounds, and grassland

Accuracy assessment

A satellite image classification is not deemed complete until its accuracy has been validated and the classification's quality has been thoroughly evaluated (Yogesh and Devi, 2024). The evaluation of the accuracy of LULC maps was conducted using ground truth data obtained from accessible Google Earth images for 1995, 2010 and 2024 (Google LLC, 2024). One of the crucial stages in categorizing Landsat images into different classes is known as the "accuracy assessment". The main objective of this evaluation is to assess how effectively the pixels in Landsat images are assigned to the correct LULC classes in a quantitative way. To assess the accuracy of the classified images, both the confusion matrix and the Kappa coefficient were utilized. To assess the accuracy of the classified images, an error matrix and confusion matrix techniques were utilized. The error matrix is particularly effective in demonstrating precision (Olofsson et al., 2013) by clearly detailing the accuracy of each category and identifying both inclusion (commission) and omission errors within the classification. The kappa coefficient measures the improvement brought by the classifier over what would be expected from a purely random assignment to classes. Kappa accuracy was calculated using the following equation.

$$Q^X = \frac{(XP - T)}{(X^2 - T)} \tag{3}$$

where:
X: Total number of pixels
P: Sum of correctly classified pixels
T: Sum of the products of the row totals and column

Test for normality and trend analysis

Normality test

The normality of the LULCC data was assessed using both the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (W) tests. These tests were chosen for their suitability and broad acceptance in evaluating normality (Avram and Mărușteri, 2022), and they complement each other in their application. The purpose of these tests was to determine how well the sample data aligned with a normal distribution. The null hypothesis in these tests asserts that the sample distribution is normal, and the test results are compared against those from a normally distributed sample with the same mean and standard deviation. The equation utilized for the Shapiro-Wilk test is provided below:

$$\frac{\sum_{i=1}^{n} a_i \, x_{(i)^2}}{\sum_{i=1}^{n} (x_i - \sigma)^2} \tag{4}$$

The equation above shows that x_i denotes the ordered sample values, a is a constant derived from the means, variances, and covariances of the ordered statistics, n is the number of observations, and σ represents the sample mean. In addition to the statistical tests, a graphical analysis was conducted to display the long-term variability of the annual LULCC. The slope coefficient was examined to determine whether the data reveals a positive or negative trend.

Trend analysis

The Mann–Kendall test is a non-parametric approach used to identify trends in time series data. Rather than depending on the actual data values, it compares their relative magnitudes (Kendall, 1975; Mann, 1945). The test considers two hypotheses: the null hypothesis (H_0) asserts that there is no trend, implying that the data are independent and randomly distributed, while the alternative hypothesis (H_1) suggests the presence of a trend. The Mann–Kendall test statistic (S) was calculated using the following formula:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1} sign(x_j - x_k) \tag{5}$$

$$sign(x_j - x_k) = \begin{cases} 1 \; if \; x_j - x_k > 0 \\ 0 \; if \; x_j - x_k = 0 \\ -1 \; if \; x_j - x_k < 0 \end{cases} \tag{6}$$

A significantly high positive value of S indicates an upward trend, whereas a significantly low negative value suggests a downward trend. The Mann-Kendall test was conducted using Python packages, with the trend's statistical significance assessed by examining the Z value. The variance was computed using the following equation:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{m} t_i (t_i - 1)(2t_i + 5)}{18} \quad (7)$$

Estimation of Sen's slope

The non-parametric method for estimating the trend slope in a sample of N data pairs was developed by Sen (1968).

$$Q = M\left(\frac{X_j - X_k}{j - k}\right) j > k \quad (8)$$

Here, x_j and x_k represent the data values at times j and k ($j > k$), respectively. If there is only one data point for each time period, then $N = n(n–1)/2$, where n is the number of time periods. However, if there are multiple observations in one or more time periods, then $N < n(n–1)/2$ is the total number of observations. The N values of Qi are then ranked from smallest to largest, and the median of these slopes, known as Sen's slope estimator, is computed as follows.

$$Q_{med} = \begin{cases} Q_{[(N+1)/2]}, \\ \frac{Q_{[N/2]} + Q_{[N+2]/2}}{2} \end{cases} \quad (9)$$

The Q_{med} reflects the direction of the data trend, while its magnitude indicates the trend's steepness. To assess whether the median slope is statistically different from zero, the confidence interval for Q_{med} at a specific probability level should be determined. In this study, Sen's slope, a non-parametric method, was employed to estimate the slope and trend of LULC classes. This analysis was conducted using Python packages. A positive Sen's slope value indicates an increasing trend, while a negative value signifies a decreasing trend in the time series.

RESULTS AND DISCUSSION

Accuracy assessment

The Kappa coefficient and overall accuracy for the classified images from 1995, 2010, and 2024 (Tables 3–5) all exceeded standard accuracy thresholds (> 0.85 for Kappa and > 85% for overall accuracy). Specifically, Kappa values were 0.88 (1995), 0.89 (2010), and 0.91 (2024), with corresponding overall accuracies of 91.08%, 91.65%, and 91.45%. Producer and user accuracy were also calculated for key land cover classes agriculture, water bodies, built-up areas, forests, and vegetation all demonstrating high precision. Commission and omission errors were likewise computed and showed reliable classification performance.

Table 3. Error matrix of classified image, 1995 (source: Authors' own elaboration)

Classified data	Agriculture	Water body	Built-up	Forest	Vegetation	Total	Use accuracy (%)	Commission error (%)
Agriculture	115	0	0	2	10	127	90.55	9.45
Water body	0	100	0	0	5	105	95.24	4.76
Built up	0	0	104	0	5	109	95.41	4.59
Forests	5	0	0	112	0	117	95.73	4.27
Vegetation	10	8	5	2	100	125	80.00	20.00
Total	130	108	109	116	120	583	–	–
Producer accuracy (%)	88.46	92.59	95.41	96.55	83.33	–	–	–
Omission error (%)	11.54	7.41	4.59	3.45	16.67	–	–	–

Overall accuracy = 91.08%. Kappa accuracy = 0.88

Table 4. Error matrix of classified image, 2010 (source: Author's own elaboration)

Classified data	Agriculture	Water body	Built-up	Forests	Vegetation	Total	User accuracy (%)	Commission error (%)
Agriculture	125	0	0	10	8	143	87.41	12.59
Water body	0	110	0	2	2	114	96.49	3.51
Built-up	0	0	106	0	4	110	96.36	3.64
Forests	10	1	2	104	1	118	88.14	11.86
Vegetation	5	0	1	5	115	126	91.27	8.73
Total	140	111	109	121	130	611	–	–
Producer accuracy (%)	89.29	99.10	97.25	85.95	88.46	–	–	–
Omission error (%)	10.71	0.91	2.75	14.05	11.54	–	–	–

Overall accuracy = 91.65%. Kappa accuracy = 0.89

Table 5. Error matrix of classified image, 2024 (source: Authors' own elaboration)

Classified data	Agriculture	Water body	Built-up	Forests	Vegetation	Total	User accuracy (%)	Commission error (%)
Agriculture	108	0	0	6	5	119	91.47	8.53
Water body	0	112	0	2	2	116	96.55	3.45
Built-up	0	2	110	0	4	116	94.83	5.17
Forests	8	0	2	90	1	101	91.41	8.59
Vegetation	5	1	1	5	102	114	89.47	10.53
Total	121	115	113	103	114	566	–	–
Producer accuracy (%)	90.08	97.39	97.35	90.00	89.47	–	–	–
Omission error (%)	9.92	2.61	2.65	10.00	10.53	–	–	–

Overall accuracy = 92.70%. Kappa accuracy = 0.90

Land use land cover dynamics

Land Use and Land Cover (LULC) are often discussed together (Alshari and Gawali, 2021), although they represent distinct concepts. Land cover refers to the natural features of the Earth's surface, while land use involves how these features are utilized by nature and human activities (Tumwine et al., 2018). For this study, LULC in the area was categorized into five major types to facilitate analysis. The results show that vegetation and water bodies are the predominant LULC types in the study area, with vegetation occupying the largest area and water bodies being the second most extensive.

The observed land cover changes (Fig. 2) in Wakiso and Kampala from 1995 to 2024 reveal significant environmental pressures, primarily driven by urbanization, agricultural expansion, and population growthClick or tap here to enter text. (Onyutha et al., 2021; Bwambale et al., 2022). Vegetation cover experienced a notable decline from 1,623.0 km² in 1995 to 1,084.5 km² in 2010 (Table 6), with only a modest recovery to 1,125.0 km² by 2024. This fluctuation suggests that while some temporary interventions may have been implemented, ongoing urban expansion continues to hinder full restoration efforts (Muchelo

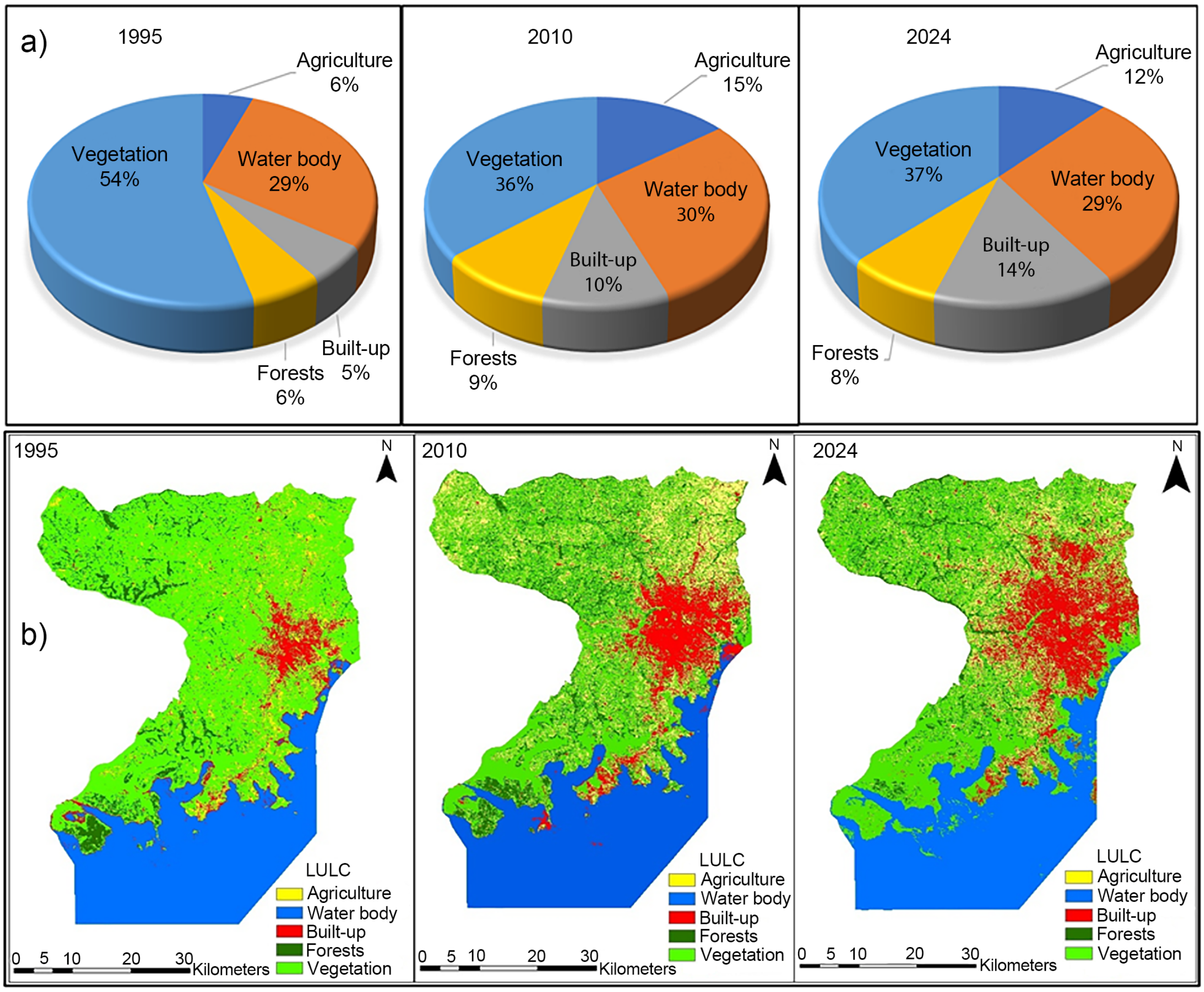

Fig. 2. State of Land Use/Land Cover Wakiso and Kampala districts in Uganda for the periods, 1995, 2010, and 2024 (source: generated by Authors using Landsat 5 (1995 and 2010) and Landsat 8 (2024) satellite imagery, classified using supervised classification in ArcGIS 10.4)

Table 6. States of Land/Use Land Cover (km²) as calculated from Landsat imageries (source: Authors' own elaboration)

LULC class	1995		2010		2024	
	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)
Total area	3002.0		3002.0		3002.0	
Agriculture	165.2	5.50	440.7	14.68	350.8	11.69
Water body	877.4	29.23	884.3	29.46	873.7	29.10
Built-up	162.6	5.42	308.9	10.29	427.7	14.25
Forests	173.9	5.79	283.5	9.45	224.7	7.49
Vegetation	1623.0	54.06	1084.5	36.13	1125.0	37.47

et al., 2024). The loss of vegetation not only affects biodiversity but also undermines carbon storage and essential ecosystem services vital for climate regulation(Mutesi et al., 2021; Wolde et al., 2024).

The dynamics of water body coverage further illustrate the impacts of human activity. Water bodies slightly increased from 877.4 km² in 1995 to 884.3 km² in 2010, but declined to 873.7 km² by 2024. This decline may reflect alterations in water management practices or land reclamation efforts around Lake Victoria (Tumwine et al., 2018). Such shifts have critical implications for local hydrology, which is crucial for agriculture, domestic consumption, and wildlife habitats. The encroachment on natural vegetation types like shrubs, grazing lands, and grasslands, exacerbates risks such as soil erosion and disrupted water cyclesClick or tap here to enter text.(Tewabe and Adametie, 2020).

From a socio-economic perspective, the rapid urban expansion necessitates careful management to mitigate long-term environmental degradation. Risks include diminished agricultural productivity, increased water scarcity, and biodiversity loss (Nuwagira et al., 2023). Therefore, implementing sustainable land use strategies, reforestation initiatives, and wetland protection becomes imperative to reconcile development with environmental conservation (Bullock et al., 2021; Kitole et al., 2024). The results indicate that, while vegetation loss continues, the slight recovery by 2024 may signal the potential for effective management practices if implemented comprehensively.

In terms of specific land use categories, forest cover initially represented a significant component of land use in 1995, covering 173.9 km², but fluctuated over the years peaking at 283.5 km² in 2010 before decreasing to 224.7 km² by 2024. Agricultural land expanded dramatically from 165.2 km² in 1995 to 440.7 km² in 2010 but decreased to 350.8 km² by 2024, indicating the complexity of land use dynamics amid urban pressures. Notably, built-up areas surged from 162.6 km² in 1995 to 427.7 km² in 2024, highlighting the region's rapid urbanization and its significant transformation over the study period (Table 6).

Overall, the analysis of LULCC in Wakiso and Kampala underscores the urgent need for integrated planning strategies that address urban growth while prioritizing environmental sustainability. This approach is crucial not only for preserving biodiversity and ecosystem functions but also for ensuring the long-term viability of local communities and their livelihoods. The detailed insights provided by Landsat imagery demonstrate the critical need for ongoing monitoring and adaptive management to support sustainable development in these rapidly changing landscapes.

Change detection

The Agricultural LULC category saw a dramatic rise, growing by 112.4%, which translates to an addition of 185.6 km² (Table 7). This expansion reflects the intensification of agricultural activities to meet the demands of the growing population(Nyapendi et al., 2004). In contrast, the forest area experienced a more modest increase of 29.2%, corresponding to a gain of 50.8 km² over the same period. This growth could be indicative of reforestation efforts or natural forest regeneration (Obua et al., 2010). On the other hand, the study documented a significant decline in the vegetation LULC, which decreased by 30.7%, amounting to a loss of 498.0 km².

Table 7. LULC change detection (1995–2024) (source: Authors' own elaboration)

LULC types	1995–2024	
	Area (km²)	Area (%)
Agriculture	185.6	112.4
Water body	–3.7	–0.4
Built-up	265.1	163.0
Forests	50.8	29.2
Vegetation	–498.0	–30.7

This reduction may be due to the conversion of vegetative land to urban or agricultural uses. The construction of roads, highways, and other infrastructure projects significantly reduced vegetative cover over the area (Richmond et al., 2018). As individuals migrate from rural regions to urban areas in pursuit of enhanced opportunities (Vermeiren et al., 2012; Patra et al., 2018), the urban land demand escalates, resulting in the transformation of these vegetated areas. Additionally, a minor decrease was noted in the water body LULC category, which saw

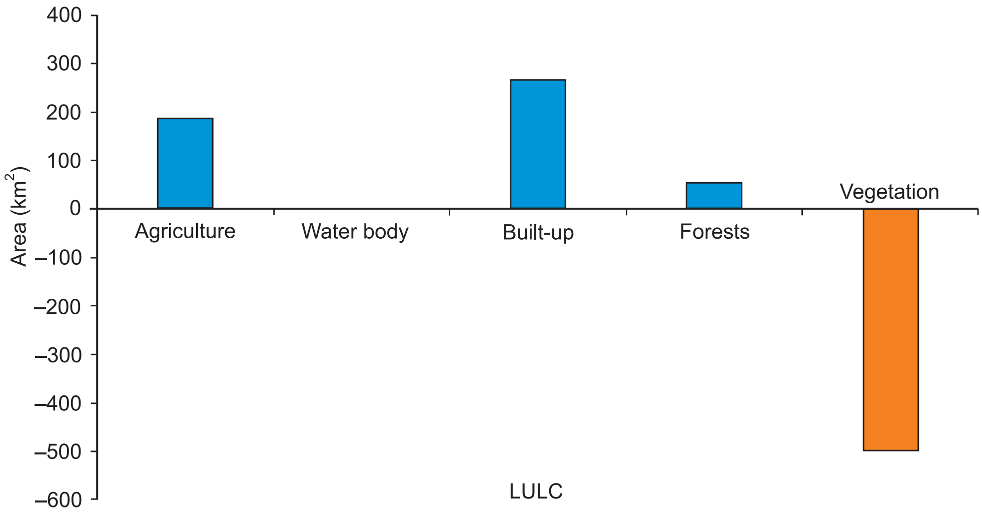

Fig. 3. Area changes in km^2 (1995–2024) (source: Authors' own elaboration)

a slight reduction of 0.4%, or 3.7 km². This reduction can be attributed to the conversion of water bodies to land for agricultural, urban development, or industrial purposes (Patra et al., 2018), as the expansion of urban areas may encroach upon these water bodies, diminishing their size, while the construction of roads and other infrastructure can disrupt water flow and further contribute to the decrease in water body size. These findings underscore the dynamic nature of land use changes in the region and highlight the diverse factors driving these changes.

Land cover transition assessment

During the study period, the most significant land cover transition observed was the conversion from vegetation land use/land cover (LULC) type to agriculture (Figure 4). This transition affected a substantial area of 388.6 km² converted in the first period (1995–2010) and 171.1 km² in the second period (2010–2024). This large-scale transformation suggests a notable shift in land use, potentially driven by changes in agricultural practices, land management policies, or natural processes (Ministry of Agriculture, 2011). Conversely, there was also a dynamic shift in the opposite direction. A total of 45.96 km² and 208.36 km² of agricultural land was converted into vegetation during the two respective periods. This indicates a bidirectional and complex pattern of land use change, reflecting the interplay between agricultural demands and natural vegetation growth or restoration efforts (Winkler et al., 2021).

The study also identified a significant conversion of forests to vegetation, with 70.5 km² and 161.3 km² of forested areas transitioning into vegetation during the two respective periods. This shift may be attributed to deforestation activities, natural events, or other land management practices affecting forested regions. In contrast to the loss of forest cover, there was a transition of 194 km² and 118.35 km² of vegetation into forested areas during the same periods. This suggests efforts towards reforestation or natural forest regeneration processes, contributing to the dynamic changes observed in the landscape.

Another significant transition observed in the study area was the conversion of various LULC types into built-up areas, illustrating the pronounced impact of urbanization. Between 1995 and 2010, approximately 142.84 km² of vegetation was transformed into built-up areas (Figure 5a), followed by an additional 94.32 km² converted between 2010 and 2024 (Figure 5b). This trend underscores the ongoing urban expansion and development activities in the region. Similarly, the conversion of agricultural land into built-up areas was notable, with 44.75 km² transformed during the first period and 91.38 km² during the second, indicating substantial pressures on agricultural landscapes that could adversely affect food production and rural livelihoods (Richmond et al., 2018).

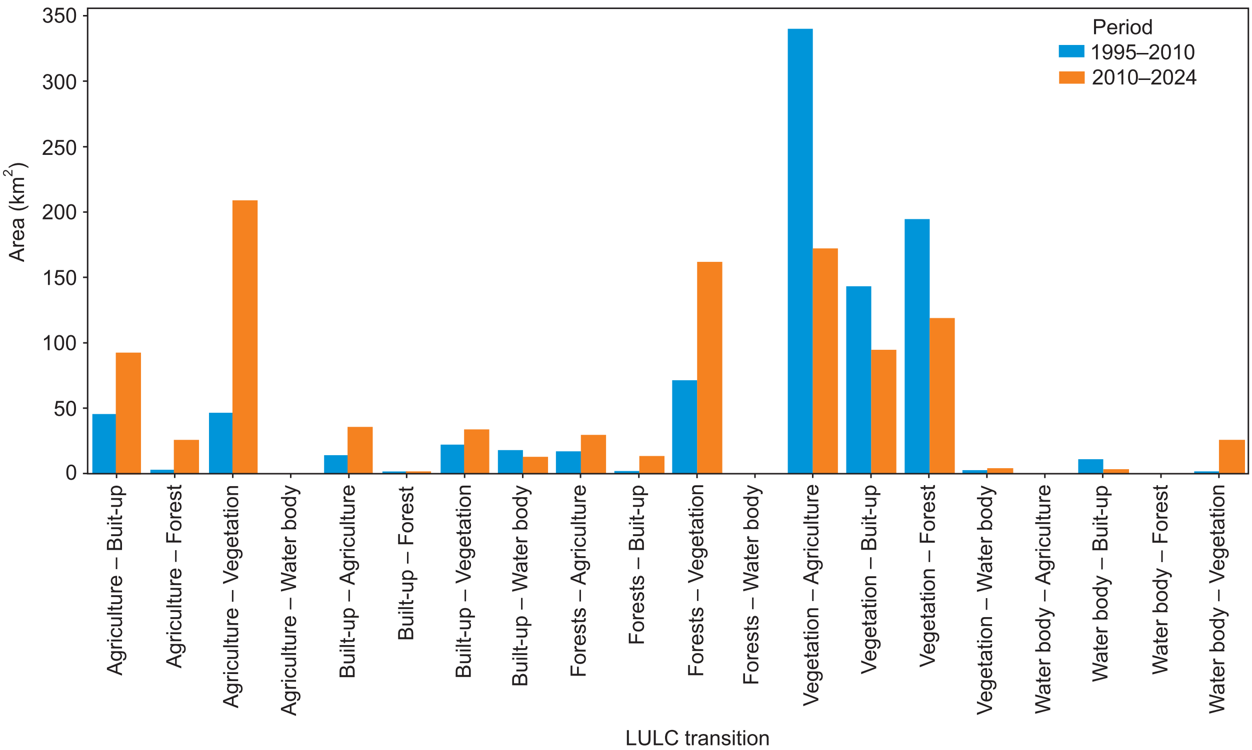

Fig. 4. Land cover transition for Wakiso and Kampala districts, Uganda for the two period of 1995 to 2010 and 2010 to 2024 (source: Authors' own elaboration)

The encroachment of urban development into forested regions was also significant, with 12.9 km² of forest cover converted to built-up areas. This transition raises important ecological and environmental concerns, as forests play a critical role in biodiversity conservation, carbon sequestration, and the maintenance of local climate regulation. The loss of forested areas not only diminishes habitat availability for various species but also exacerbates issues such as soil erosion and water cycle disruption, which can further threaten agricultural productivity and water resources in the region (Mutesi et al., 2021).

These conversions highlight the urgent need for strategic land use planning and management to balance urban growth with environmental preservation. Implementing sustainable development practices that prioritize the protection of agricultural and forested lands is essential for mitigating the adverse impacts of urbanization. Furthermore, fostering community engagement in land management decisions can help ensure that local populations are considered in the planning process, ultimately contributing to sustainable livelihoods and enhanced resilience against environmental changes. The findings stress the importance of integrated approaches that recognize the interconnectedness of urban and rural landscapes and promote policies that support sustainable development while safeguarding vital ecosystems.

Lastly, the transformation of 10.6 km² and 2.9 km² of water bodies into built-up areas during the two periods further underscores the extensive impact of urbanization, significantly affecting aquatic ecosystems and potentially altering hydrological dynamics. The conversion of water bodies to urban areas raises critical concerns regarding the availability of freshwater resources, essential for both human consumption and agricultural irrigation. Such changes can disrupt local hydrology, leading to issues like increased flooding, reduced water quality, and habitat loss for aquatic species (Tumwine et al., 2018).

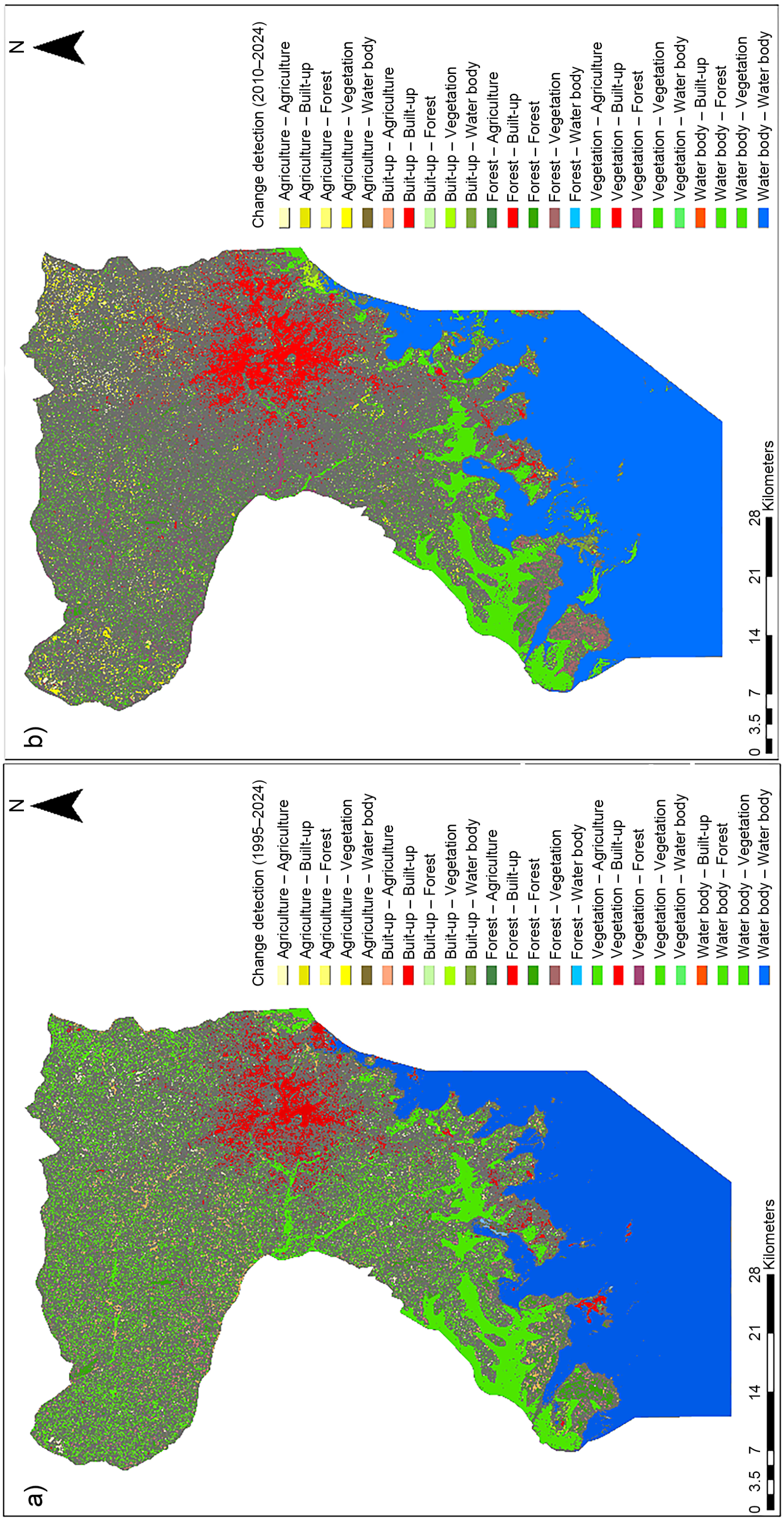

Fig. 5. LULC conversion maps for a) 1995–2010 and b) 2010–2024 (source: generated by Authors using Landsat 5 (1995 and 2010) and Landsat 8 (2024) satellite imagery. Supervised classification was performed in ArcGIS 10.4)

These alterations in land cover types highlight the complex interplay between various land use categories and emphasize the evolving landscape dynamics within the study area. The observed transitions are indicative of a multifaceted process driven by a combination of human activities, including rapid population growth, urban sprawl, and agricultural expansion, as well as natural processes and policy interventions aimed at land management. The push for economic development often leads to prioritizing built-up areas at the expense of natural habitats, which can have long-term repercussions for biodiversity and ecosystem services.

Furthermore, the degradation of aquatic ecosystems due to urban encroachment can impair the ability of these systems to provide essential services, such as water filtration, flood regulation, and habitat for wildlife. This underscores the necessity for integrated land use planning that recognizes the value of preserving natural water bodies and the ecosystems they support. Implementing sustainable practices that protect these vital resources is crucial for maintaining ecological balance and ensuring the resilience of both urban and rural environments. These findings highlight the urgent need for comprehensive policies that promote sustainable land management and protect aquatic ecosystems amid ongoing urban pressures.

Vegetation and urbanization trends in Wakiso and Kampala: NDVI and NDBI analysis

Between 1995 and 2010, there was an overall increase in the maximum NDVI values from 0.49 to 0.51 (Fig. 6), indicating enhanced vegetation density possibly due to conservation efforts, afforestation, or favorable climatic conditions. The rise in the minimum NDVI value from –0.46 to –0.04 highlighted a substantial decrease in non-vegetated areas, reflecting urban greening initiatives or improved land use practices (Zhong and Li, 2024). From 2010 to 2024, there was a slight decline in the maximum NDVI value (Fig. 6) to 0.47, suggesting a minor reduction in dense vegetation, possibly due to urban expansion, deforestation, or climate-related factors. The minimum NDVI value remained stable, indicating no significant increase in non-vegetated areas.

In Wakiso and Kampala regions, the NDVI trend from 1995 to 2024 initially showed increased vegetation density and reduced barren areas until 2010. However, from 2010 to 2024, there was a slight decline in dense vegetation areas while non-vegetated land extent remained stable, possibly influenced by urbanization or environmental stressors. The NDBI trends observed in the Wakiso and Kampala regions from 1995 to 2024 reveal a distinct pattern characterized by initial urban expansion followed by a potential phase of stabilization or reclassification. The substantial urban growth experienced between 1995 and 2010 is believed to be a response to the escalating demands of population growth and economic advancements (Richmond et al., 2018).

Conversely, the period spanning from 2010 to 2024, marked by a decline in maximum NDBI values, suggests a shift towards more regulated urban development practices or alterations in land-use classification methodologies.

Statistical analysis of land use classes: Insights into trends and predictive modelling

The statistical tables (Table 8) provided a detailed overview of various land use classes, including Agriculture, Waterbodies, Built-up areas, Forests, and Vegetation. The descriptive statistics reveal that Vegetation has the highest average value (1111.94) among the classes, indicating its prevalence, while Forests have the lowest mean (296.15). The standard deviation for Vegetation is also the highest, suggesting significant variability in this class, whereas Waterbodies show the least variability, indicating more consistency across observations. Skewness values indicate that most distributions are nearly symmetrical, except for Vvegetation and Waterbodies, which are positively skewed, suggesting a tail on the right. Kurtosis values indicate that Vegetation and Waterbodies have a more peaked distribution, while Built-up areas are flatter, as reflected by their negative kurtosis.

The tests of normality, specifically the Kolmogorov-Smirnov and Shapiro-Wilk tests (Table 8a), show that most variables, including Agriculture, Waterbodies, Built-up areas, and Forests, adhere to a normal distribution, making them suitable for parametric analysis. However, Vegetation deviates from normality, which might require transformation or alternative statistical methods for accurate analysis (Patra et al., 2018). In the regression analysis, the unstandardized

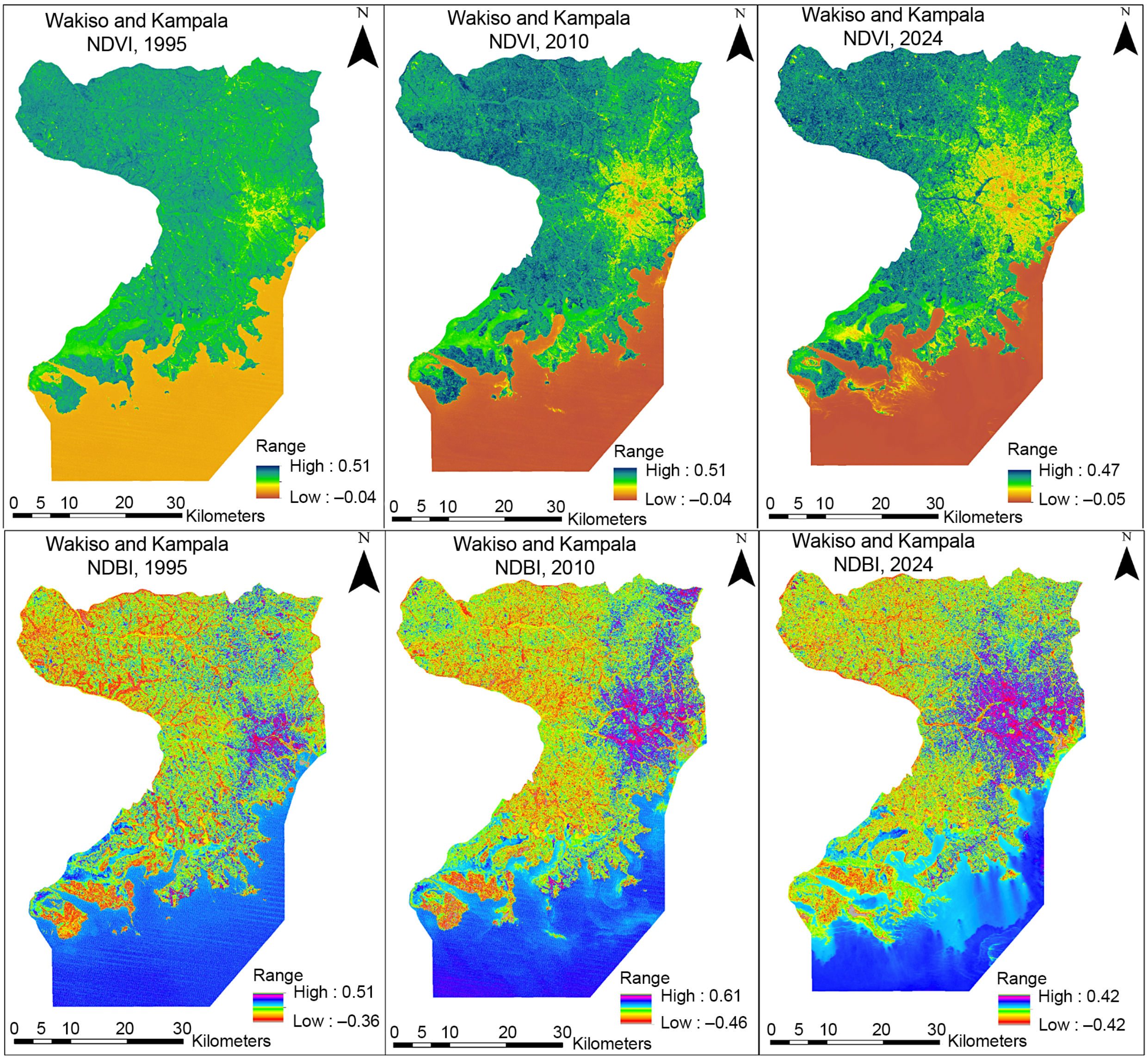

Fig. 6. LULC conversion patterns based on NDVI and NDBI (source: generated by Authors' using Landsat 5 imagery for 1995 and 2010, and Landsat 8 imagery for 2024)

coefficients (Table 8b) reveal that Built-up areas have the most substantial positive impact on the dependent variable, as indicated by a significant coefficient (B = 0.111).

Vegetation and forests also contribute positively, though to a lesser extent, while waterbodies have a negligible and non-significant effect. The standardized coefficients reinforce this finding, with built-up areas showing the highest influence (Beta = 1.091) (Table 8c). The collinearity statistics (Table 8d) indicate that multicollinearity is not a major concern, as the VIF values are within acceptable limits. However, the collinearity diagnostics suggest some potential issues with redundancy, particularly between Built-up areas and Forests, which might affect the stability of the regression coefficients.

Table 8. Results for statistical analysis (source: Authors' own elaboration)

a) Tests of normality

	Kolmogorov–Smirnov				Shapiro–Wilk		
	Statistic	Df	Q	Sig	Statistic	Df	Sig.
Agriculture	0.123	30	3.60	0.200*	0.956	30	0.245
Water bodies	0.116	30	–0.01	0.200*	0.967	30	0.460
Built-up	0.130	30	9.16	0.200*	0.941	30	0.100
Forests	0.091	30	2.34	0.200*	0.967	30	0.467
Vegetation	0.169	30	–12.4	0.029	0.929	30	0.045

b)

Model		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.	Collinearity statistics	
							Tolerance	VIF
1	(Constant)	2011.706	84.453		23.82	0		
	Water bodies	–0.073	0.094	–0.07	–0.78	0.443	0.971	1.03
	Built-up	0.111	0.016	1.091	7.092	0.000	0.328	3.051
	Forest	0.034	0.015	0.377	2.339	0.028	0.298	3.354
	Vegetation	0.016	0.009	0.38	1.786	0.086	0.171	5.837

c) Excluded variable

Model		Beta in	t	Sig.	Partial correlation	Collinearity statistics tolerance	VIF	Minimum tolerance
1	Agriculture	83.849	1.102	0.281	0.22	1.33E-06	752532.17	3.19E-07

d) Collinearity diagnostics

Model	Dimension	Eigenvalue	Condition index	(Constant)	Variance proportion			
					Water bodies	Built-up	Forest	Vegetation
1	1	4.816	1.0000	0.00	0.00	0.00	0.00	0.00
	2	0.113	6.5370	0.00	0.00	0.01	0.12	0.02
	3	0.069	8.3670	0.00	0.00	0.22	0.11	0.00
	4	0.002	48.7940	0.01	0.01	0.77	0.76	0.96
	5	4.20E-05	338.6840	0.99	0.99	0.00	0.00	0.02

e) Model summary

Model	R	R square	Adjusted R square	Std. error of the estimate	Change statistics				
					R square change	F change	df1	df2	Sig. F change
1	0.898a	0.806	0.775	4.175	0.806	25.983	4	25	0

The model summary underscores the strength of the regression model, with an R-Square value of 0.806, indicating that 80.6% of the variance in the dependent variable is explained by the independent variables. The Adjusted R-Square of 0.775 confirms that the model remains robust even after adjusting for the number of predictors. The standard error of the estimate (4.175) is relatively low, suggesting that the model's predictions are close to the observed data. Overall, these results provide valuable insights into land use trends, highlighting the significant impact of built-up areas on the dependent variable, while also noting the contributions of vegetation and forests. The findings are essential for guiding decisions in urban planning, conservation, and resource management, with considerations for normality and multicollinearity informing the refinement of predictive models (Ettinger et al., 2021;Winkler et al.; 2021;Simkin et al., 2022).

Assessing land use trends through Sen's slope and normality analysis

The inclusion of Sen's slope (represented by Q) in the normality test table provides a critical insight into the trends and direction of change for each land use class over time (Kagabo et al., 2024), complementing the normality tests. Sen's slope is a non-parametric measure that quantifies the rate of change, offering a clear indication of whether the values within each class are increasing, decreasing, or remaining stable. For instance, the positive slope for Agriculture (Q = 3.60) (Figure 7a) suggests a steady increase in agricultural land, indicating potential expansion or intensification of farming activities. Similarly, the Built-up areas (Fig. 7b) show a significant positive trend (Q = 9.16), reflecting rapid urbanization or infrastructure development. Conversely, Vegetation exhibits a substantial negative slope (Q = –12.4) (Figure 7e), highlighting a concerning decline in vegetation cover over time, which may be due to deforestation or land conversion for other uses. Waterbodies (Figure 7f), with a negligible slope (Q = –0.01), indicate stability in water coverage, while Forests show a modest positive trend (Figure 7d) (Q = 2.34), suggesting slight improvements in forest cover, possibly due to conservation efforts.

These trends are crucial as they provide context to the normality tests, such as the Shapiro-Wilk and Kolmogorov-Smirnov tests, which assess whether the distribution of each variable deviates from normality. For example, the significant Shapiro-Wilk value for Vegetation (Sig. = 0.045) suggests a deviation from normality, which may be linked to the strong negative trend indicated by its Sen's slope. This negative trend could be contributing to the skewness in the distribution, leading to the rejection of the null hypothesis of normality.

Incorporating Sen's slope into the study enhances the understanding of how these land use classes are evolving over time, providing essential insights for policy-making, resource management, and environmental planning. The identified trends, such as the decline in vegetation or the increase in built-up areas, can inform targeted interventions to address environmental challenges and promote sustainable development (Ettinger et al., 2021; Assede et al., 2023; Kagabo et al., 2024). Additionally, the slopes offer supplementary evidence that enriches the interpretation of the normality tests, helping to create a more comprehensive understanding of the data's behaviour and guiding the selection of appropriate analytical methods for further investigation (Avram and Mărușteri, 2022).

Comprehensive analysis of LULC dynamics in Wakiso and Kampala: Implications and future directions

This study provides a comprehensive analysis of LULC dynamics in the rapidly urbanizing districts of Wakiso and Kampala, Uganda, over three decades. By employing Landsat imagery and various statistical methods, the research offers crucial insights into the patterns and trends of urban expansion, agricultural intensification, and environmental degradation. These findings are particularly valuable for policymakers, urban planners, and conservationists, as they provide data-driven evidence to inform sustainable land management strategies and urban development policies. The study highlights the significant impact of urbanization on natural landscapes, especially the decline in vegetation and forest cover, with important implications for biodiversity, ecosystem services, and climate regulation.

However, the study also has some limitations that need to be addressed in future research. One major setback is the reliance on medium-resolution Landsat imagery, which, while effective for capturing broad

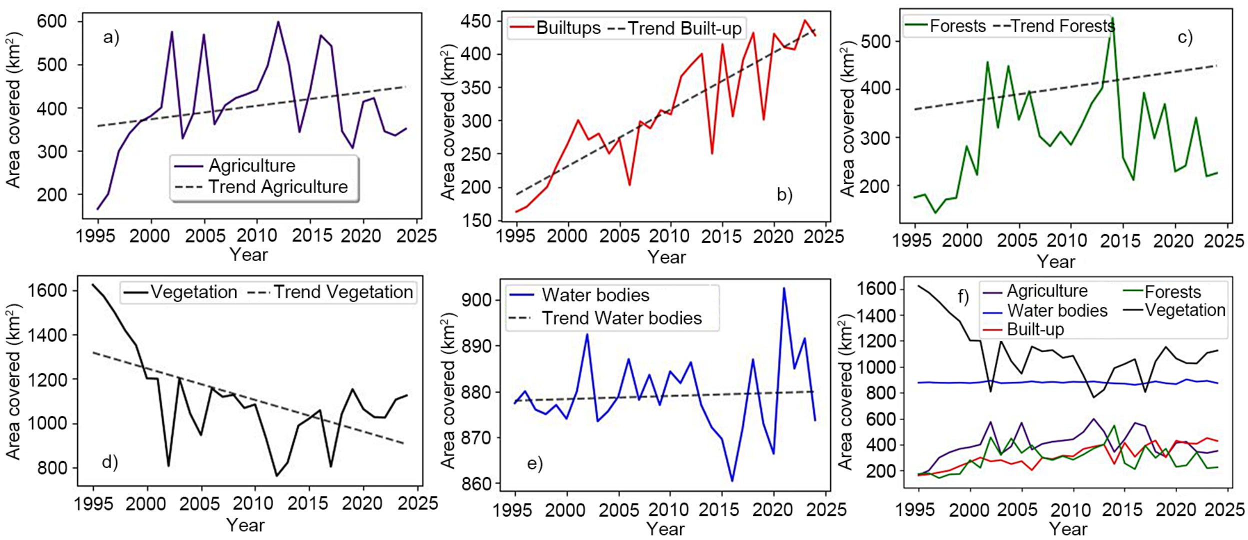

Fig. 7. Inter-decadal changes of a) agriculture; b) built-ups; c) forest; d) vegetation; e) water bodies and f) all LULC observed with trend lines conversion patterns (source: Authors' own elaboration)

trends, may not adequately capture finer details of land cover changes or small-scale variations. Additionally, the study's geographical focus on Wakiso and Kampala may limit the generalizability of the findings to other regions with different socio-economic and environmental contexts. Furthermore, the analysis primarily focuses on the physical changes in land use and cover, without deeply exploring the socio-economic drivers behind these changes or the long-term ecological impacts.

Given these limitations, further studies are crucial to fully understand the socio-economic drivers behind the LULC changes observed in these districts, particularly the rapid urbanization and agricultural expansion. Future research should delve into specific factors such as population growth, economic pressures, and policy decisions that are accelerating these transformations. There is also a pressing need to investigate the ecological consequences of the significant decline in vegetation and forest cover, including impacts on local biodiversity, ecosystem services, and climate regulation. In order to enhance the precision of monitoring LULC changes, future studies should incorporate higher-resolution spatial data, such as LiDAR or drone-based imagery, to capture more detailed and accurate observations. Additionally, exploring sustainable urban growth models that incorporate green infrastructure and low-impact development practices could offer practical solutions for balancing urban expansion with environmental preservation. Expanding the research scope to include neighbouring regions or other rapidly urbanizing areas across Africa would provide valuable comparative insights and help formulate broader strategies for sustainable land management in similar contexts.

CONCLUSION AND RECOMMENDATION

Key findings:

1. *Land Use Changes*: The study revealed substantial shifts in land use patterns, with a significant increase in built-up areas and a concerning decline in both vegetation and forest cover.
2. *Environmental Implications*: These changes have critical consequences for biodiversity, ecosystem services, and climate regulation, underscoring the environmental costs associated with unchecked urban growth.

Statistical analysis results:

1. Vegetation coverage was the highest among land use types, while forest cover was the lowest, with vegetation showing significant variability over time.

2. Normality tests indicated that most land use and land cover (LULC) variables conformed to a normal distribution, thus suitable for parametric analysis, although vegetation exhibited slight deviations.
3. Built-up areas exhibited the most pronounced positive impact on land use changes, illustrating the dynamics of urban expansion.
4. Directional Trends: Sen's slope analysis demonstrated a consistent increase in agricultural land and built-up areas, contrasted by a significant decline in vegetation over the study period.

BRIDGING THEORY AND PRACTICE

This study effectively bridges the gap between theoretical frameworks and practical applications by providing empirical data on land use changes in Wakiso and Kampala. The findings serve as a critical resource for urban planning and conservation strategies, highlighting the necessity for sustainable resource management. By combining statistical analyses with land cover observations, the research delivers actionable insights for policymakers and urban planners. This evidence-based approach not only enhances understanding of the ecological impacts of urbanization but also fosters the development of strategies that reconcile urban growth with environmental sustainability. As a result, this study contributes to informed decision-making and more effective land use planning in rapidly urbanizing regions.

RECOMMENDATIONS

1. *Sustainable urban planning*: Policymakers should prioritize sustainable urban growth models that incorporate green infrastructure and low-impact development practices to mitigate ecological degradation.
2. *Enhanced data collection*: Future research should utilize higher-resolution spatial data, such as LiDAR or drone imagery, to capture more detailed observations of land cover changes.
3. *Broader regional analysis*: Expanding the research scope to include adjacent regions or other rapidly urbanizing areas across Africa could yield valuable comparative insights, facilitating the development of more generalized sustainable land management strategies.
4. *Socio-economic factors investigation*: It is crucial to delve deeper into the socio-economic drivers behind LULC changes and assess their long-term ecological impacts, especially concerning biodiversity and ecosystem services.
5. *Integrated resource management*: A collaborative approach that engages stakeholders at various levels will be essential for developing and implementing effective land use policies that balance urban expansion with environmental health.

By addressing these recommendations, future research can enhance the understanding of land use dynamics and contribute to sustainable planning efforts in rapidly urbanizing contexts.

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KOMPLEKSOWA ANALIZA I ILOŚCIOWA OCENA DYNAMIKI UŻYTKOWANIA GRUNTÓW/POKRYCIA TERENU W WAKISO I KAMPALI W UGANDZIE: KILKUDZIESIĘCIOLETNIE BADANIA TELEDETEKCYJNE

ABSTRAKT

Cel pracy

Niniejsze badania stanowią analizę zmian w zakresie użytkowania gruntów/pokrycia terenu (LULC) w regionach Wakiso i Kampala od 1995 do 2024 roku. Miało na celu mapowanie typów LULC, ewaluację zmian, m.in. pomiędzy kategoriami (rolnictwo, woda, obszary zabudowane, lasy), a także badanie trendów i czynników, które na te zmiany wpływają. Pozwoliło ono ukazać skutki urbanizacji i ekspansji rolnictwa, a jednocześnie dostarczyć praktycznych wskazówek w zakresie zrównoważonego zarządzania gruntami.

Materiał i metody

Podczas badań wykorzystano zdjęcia satelitarne Landsat z lat 1995, 2010 i 2024, pochodzące z Earth Explorer NASA. Dzięki zastosowaniu obrazów ze stycznia, zminimalizowano wahania sezonowe, a dane zostały ponownie odwzorowane w strefie UTM 36N z WGS84. Wstępne przetwarzanie obejmowało korekty i redukcję zamglenia w ArcMap 10.4. Nadzorowana klasyfikacja wykorzystywała narzędzie False Colour Composite (prezentację w kolorach nierzeczywistych) pasm niebieskich, zielonych i czerwonych, z rozdzielczością 2500–3000 pikseli na każdą kategorię LULC. Dokładność oceniano za pomocą statystyk Kappa i wskaźnika ogólnej dokładności, a na potrzeby analizy stref roślinności i wzrostu powierzchni obszarów miejskich obliczono wskaźniki NDVI i NDBI.

Wyniki i wnioski

Analiza wykazała znaczące zmiany w użytkowaniu gruntów: udział obszarów zabudowanych wzrósł o 163%, zmniejszając udział pokrywy roślinnej o 30,7%. Obszar gruntów rolnych wzrósł o 112,4%, podczas gdy udział pokrywy leśnej o 29,2%. Trend wskaźnika NDVI ujawnił wzrost gęstości pokrywy roślinnej do 2010 roku, a następnie niewielki spadek do 2024 roku z powodu rozrostu obszarów miejskich. Wskaźnik NDBI świadczy o znacznym powiększeniu się obszarów miejskich, stabilizującym się między 2010 a 2024 rokiem. Wyniki badań uwidaczniają wpływ urbanizacji i ekspansji rolniczej w regionach Wakiso i Kampali, podkreślając potrzebę zrównoważonego zarządzania gruntami w celu zbalansowania ich rozwoju i ochrony.

Słowa kluczowe: klimat, użytkowanie gruntów/pokrycie terenu LULC, NDBI, NDVI, teledetekcja