

# Mapping Vegetation Types and Land Use Dynamics in Kanyabaha Wetland from 1990 to 2021

## ABSTRACT

Wetlands are crucial ecosystems providing essential ecological services, yet they face increasing threats from human activities. This study focuses on Kanyabaha Wetland in Uganda, examining its vegetation dynamics over three decades (1990-2021) using Landsat satellite imagery. The research characterizes land use and cover types including papyrus, grasslands, farmlands, tree plantations, built-up areas, and woodlands. Remote sensing data was processed and classified using ArcMap software, validated through field verification, resulting in high overall accuracy (>75%) across all study years. The images were analyzed using a hybrid of unsupervised (ISO data) and supervised (Maximum Likelihood) classification techniques. Findings reveal significant shifts in vegetation cover, with papyrus dominating initially but declining over time due to expansion in farmlands and settlements. Grasslands also decreased, while areas under farming and built-up structures expanded. Transition matrices illustrate these changes, highlighting stable and shifting landscape dynamics. Statistical analyses indicate a decrease in papyrus cover from 51.5% in 1990 to 39.1% in 2021, while farmland and built-up areas increased from 3.0% to 31.6% and 3.2% to 5.1%, respectively. This study highlights the vulnerability of Kanyabaha Wetland to anthropogenic impacts, necessitating targeted conservation strategies to sustain its ecological integrity amid ongoing land use changes.

**Key Words:** *Vegetation Coverage, Vegetation Types, Kanyabaha Wetland, Wetland resources*

## 1. INTRODUCTION

Wetlands are among the most productive and biologically diverse ecosystems on Earth, providing crucial services such as water filtration, flood control, and habitat for numerous species [1, 2, 3]. Despite their importance, these ecosystems are increasingly threatened by anthropogenic pressures that drive significant land use changes, potentially altering their ecological functions and biodiversity.

Kanyabaha Wetland, located in the Rukiga District of Uganda, exemplifies the ecological and economic significance of wetlands. This wetland supports a variety of land use and cover types, including papyrus, small-scale farmlands, tree plantations, built-up areas, grasslands, and woodlands [4,5]. These diverse land use types are critical for maintaining the wetland's biodiversity and ecological balance. However, while it is recognized that land use changes in wetlands can significantly impact their ecological functions[6], there is a notable gap in comprehensive data and analysis specific to Kanyabaha Wetland. Previous studies[7, 8, 9, 10] have largely focused on general assessments of wetland ecosystems or have provided fragmented insights into specific vegetation types without a thorough temporal analysis. Consequently, there is limited understanding of how different land use types and their transitions over time affect the overall health and biodiversity of this particular wetland. This study aims to address this gap by providing a detailed characterization of the vegetation types in Kanyabaha Wetland and analyzing the spatial and temporal changes in land use and cover over a 30-year period (1990-2021). By leveraging remote sensing data and land cover classification techniques, this research seeks to elucidate the trends and transitions in vegetation cover types and to assess their implications for the wetland's ecological health and biodiversity. The findings are expected

to contribute to more informed conservation and management strategies for Kanyabaha Wetland and similar ecosystems, emphasizing the need for targeted interventions to mitigate the impacts of land use changes. *Additionally, policymakers at the local and national levels can use the findings of this study to inform the development of policies and regulations aimed at protecting and conserving wetland ecosystems.* This research not only fills a critical gap in the understanding of land use dynamics and their ecological impacts in Kanyabaha Wetland but also provides a framework for future studies aiming to enhance the sustainability of wetland ecosystems amid growing anthropogenic pressures.

## **2. METHODOLOGY**

### **2.1 Study Site Description**

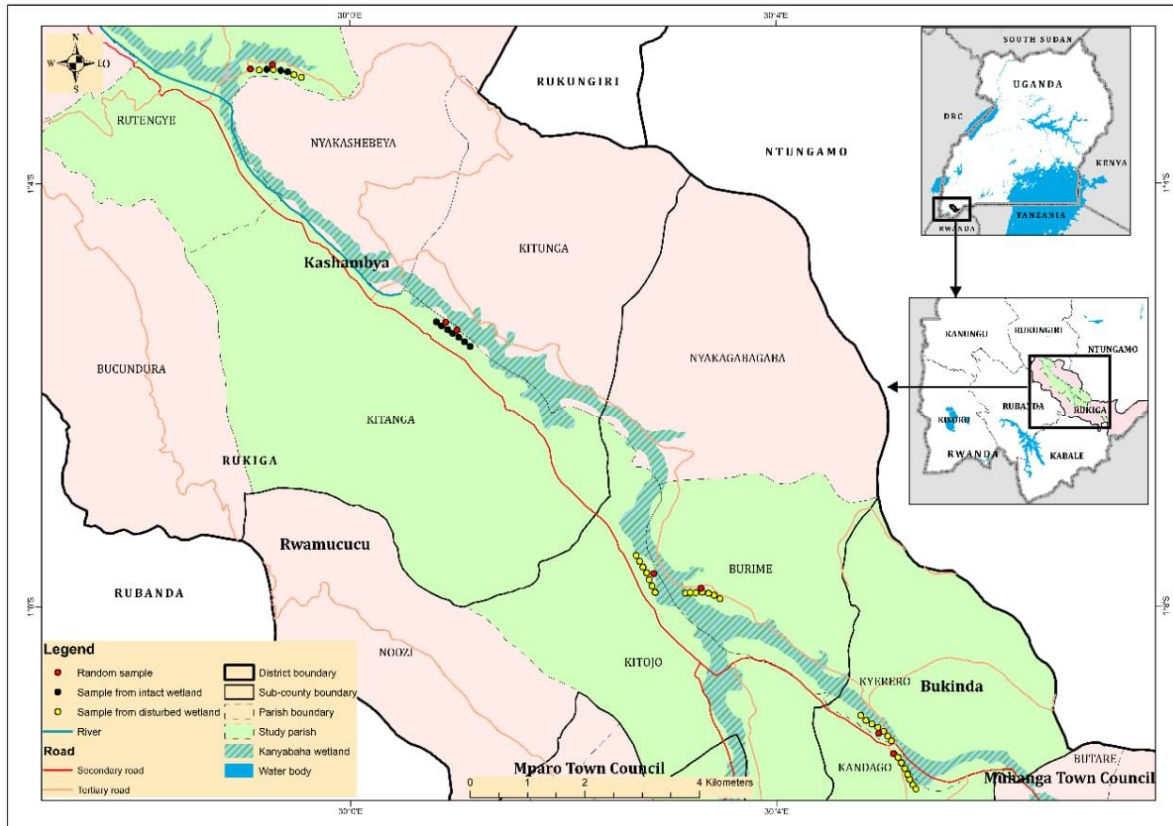
The study was conducted in Kanyabaha Wetland. The details of the study site were as followed.

### **2.2 Location**

The study was undertaken around Kanyabaha wetland in Rukiga District, which is located in southwestern Uganda (Figure1). Kanyabaha wetland covers an area of 33 km<sup>2</sup> and is located between latitude 1.1326° S and longitude 30.0434° E in Kigezi Sub region. The wetland lies in a river valley and the average elevation of the surrounding landscape is about 2000 meters above sea level. This wetland supported a diverse range of land use and cover types, including papyrus, grasslands, small-scale farmlands, tree plantations, built-up areas, and woodlands, making it an ecologically significant area.

### **2.3 Climate**

Kanyabaha wetland experiences a humid subtropical climate, typical of the southwestern region of Uganda. This climate is characterized by relatively consistent temperatures throughout the year, with moderate to high levels of precipitation.



**Figure 1: Map of the Study Area**

### 3. METHODS

#### 3.2 Data Sources

This study utilized two satellite multi-temporal datasets to characterize the vegetation changes in the Kanyabaha Wetland between 1990 and 2021. Landsat 4-5 TM (30m resolution) datasets were selected for the years 1990, 2001, and 2011, while Landsat 8 OLI/TIRS (30m resolution) imagery was used for 2021. The images were downloaded from the USGS Global Visualization geoportal (<https://glovis.usgs.gov/>) and captured during the dry season months of December to January, ensuring similar spectral reflectance. The selected images had less than 5% cloud cover to maintain data quality. The specifications of the satellite images used are detailed in 1.

**Table 1: Satellite specifications of the spatial data imagery used in the study areas**

Year	Sensor	Imagery Id	Resolution	Source
1990	Landsat 4-5 TM	LT04_L1TP_173061_19900604_20170129_01_T1	30m	<a href="https://glovis.usgs.gov">https://glovis.usgs.gov</a>
2001	Landsat 4-5 TM	LT05_L1GS_173061_20011029_20161213_01_T2	30m	<a href="https://glovis.usgs.gov">https://glovis.usgs.gov</a>
2011	Landsat 4-5 TM	LT05_L1TP_173061_20110708_20161008_01_T1	30m	<a href="https://glovis.usgs.gov">https://glovis.usgs.gov</a>
2021	Landsat 8 OLI/TIRS	LC08_L1TP_173061_20210719_20210729_01_T1	30m	<a href="https://glovis.usgs.gov">https://glovis.usgs.gov</a>

### 3.2.1 Image Processing

The downloaded images were pre-processed and interpreted using ArcMap 10.x remote sensing software. Initially, image bands were enhanced to improve visualization and distinction of spectral features. The images underwent atmospheric correction using the dark object subtraction method to remove haze, followed by geometric correction and co-registration to align the images accurately with geographical coordinates. *Image enhancement can be accomplished by employing methods such as contrast manipulation, histogram equalization, and filtering [11]. The objective of image enhancement is to enhance the visual interpretability of an image by enhancing the clear differentiation between its features. The objective of visually comprehending digitally manipulated images is to optimize the synergistic capabilities of the human intellect and computer technology [12]. The 1990, 2001, 2011 images were then atmospherically corrected using the dark object subtraction method to remove haze. In addition, the images were also geometrically corrected and enhanced. The objective of these procedures is to guarantee the precision, uniformity, and completeness of the satellite data for image classification.* Image composites of the different years were developed to facilitate interpretation, and areas of interest were masked out for faster rendering.

The images were analyzed using a hybrid of unsupervised (ISO data) and supervised (Maximum Likelihood) classification techniques due to the heterogeneity of vegetation types within the study area. The definition and description of land use/cover classes were based on field knowledge and observations. Table 2 provides the descriptions of the different land use/land cover (LULC) categories identified.

**Table 2: Description of different Land use / Land cover (LULC) categories**

LULC Category	General Description
Built-up areas	Areas characterized by settlements, roads, and bare ground
Grassland	Vegetation type dominated by large, rolling terrains of grasses, flowers, and herbs
Farmland	Land covered with crops on small plots for household use without advanced and expensive technologies
Papyrus	Tall aquatic sedge plants (Cyperus papyrus) with small green-stalked flowers in swampy areas
Woodland	Land covered with densely scattered trees, with or without grassland underneath

Tree Plantation	Large-scale plantations of a single tree species (e.g., Eucalyptus, Coniferous trees) for timber
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### 3.2.2 Field Verification

To validate the classified images, field verification was conducted using randomly generated points in the area of interest. An area frame sampling methodology was used to generate these points, which were visited to confirm if the classified classes matched the ground information. A Garmin handheld GPS was used to locate the points. For the years 1990, 2001, and 2011, random points were extracted from each classified map and overlaid on Google Earth for validation using the time slider feature to move between the time series of each year.

### 3.2.3 Image Accuracy Assessment

*To assess the vegetation types accuracy of 2021 classification, 500 GPS points were picked from the different vegetation types and compared with the classification outputs. However, the earlier years (1990, 2001, 2011), as used in the study Google earth platform was used as to assess the accuracy of their classification. Google earth platform was preferred because of its historical imagery slider*

The accuracy of the classified images was assessed using a confusion matrix to define producer and user accuracies for each class. The overall Kappa statistics and overall accuracy for each classified image were calculated from the corresponding error matrix, with a total of 500 points collected from different vegetation cover types between 1990, 2001, 2011, and 2021. The confusion matrix compared error values for each classified class with their respective values in the ground truth data. The Kappa statistic, a measure of overall statistical agreement of an error matrix considering non-diagonal elements, was used to analyze the accuracy of the classifications. Kappa analysis is recognized as a powerful method for analyzing single error matrices and comparing differences between various error matrices [13].

### 3.3 Data Analysis

To understand the changes in land cover over time, change detection analysis was performed. This involved comparing the classified images from different years (1990, 2001, 2011, and 2021) to identify trends and transitions in land cover types. The Land Change Modeler (LCM) in TerrSet software was used to analyze these trends and transitions. Additionally, land use/cover transition matrices were created to quantify the changes between different land cover types over time, providing a detailed understanding of the stability and transition probabilities for each land cover type.

### 3.4 Reporting

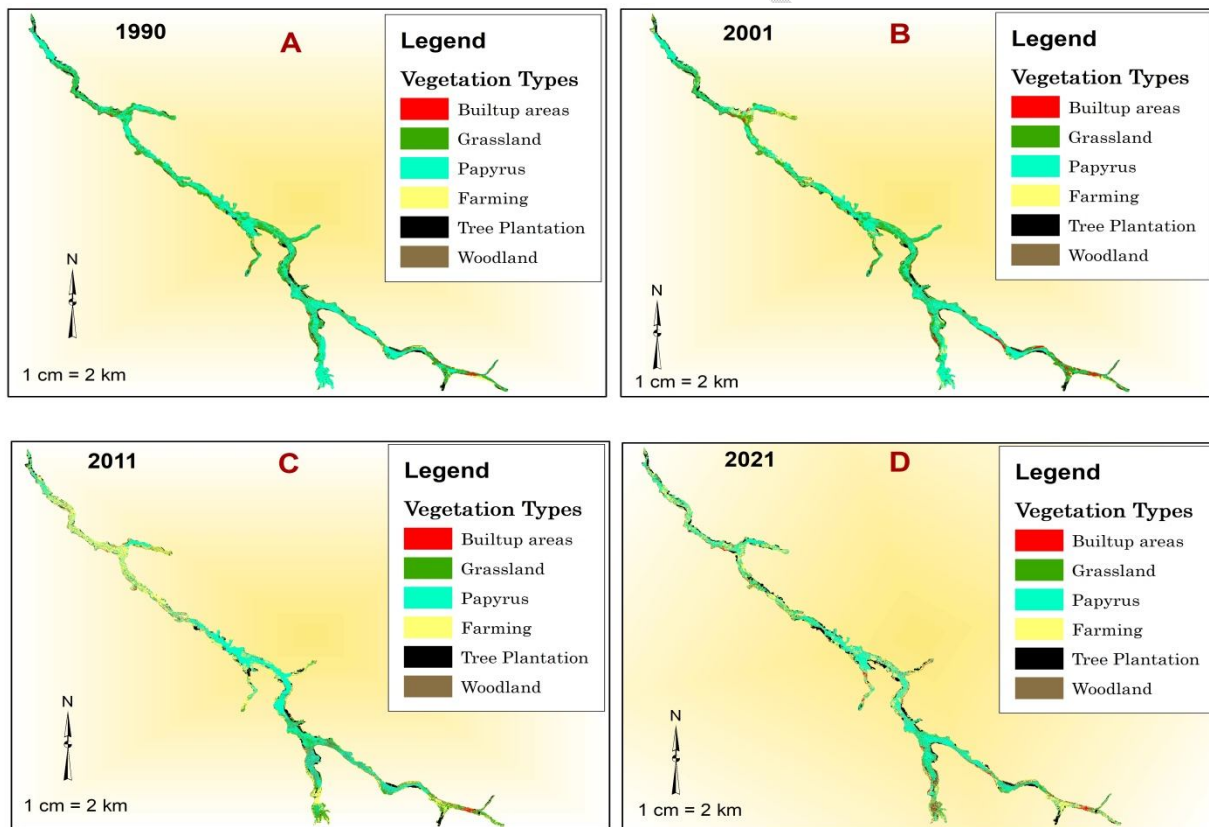
The results of the analysis were presented through maps illustrating the spatial distribution of vegetation cover types for each year, tables summarizing the areas and percentages of different land cover types, and graphs depicting trends in land cover changes over the study period. The results were interpreted in the context of anthropogenic impacts, natural processes, and

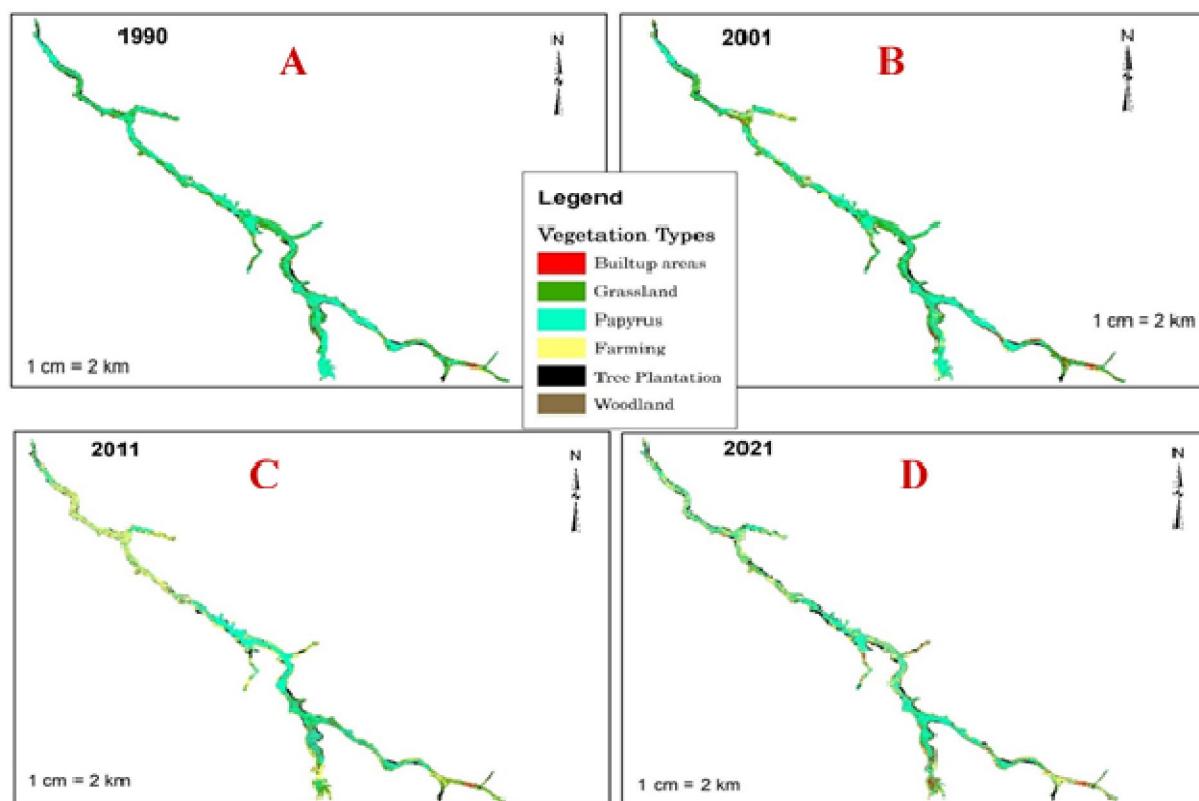
ecological significance, and were compared with previous studies to contextualize the findings and highlight the uniqueness of Kanyabaha Wetland.

## 4, RESULTS AND DISCUSSION

### 4.1Vegetation characterization of Kanyabaha Wetland

Wetlands are diverse ecosystems in their spatial patterning, hydrological conditions and species of plant communities [14]. This section addresses the vegetation types found in Kanyabaha wetland and the surrounding landscape. The types of vegetation in the wetland and the surrounding watershed is important because it contributes to the amount of organic carbon in the soil. It also constitutes an important resource base and is therefore exploited by local residents in different ways. Figure 2 shows the vegetation cover maps from the classification of Landsat images for a ten-year interval period (1990-2001, 2001-2011, 2011-2020). It shows the distribution of cover types in the study area during the period between 1990 and 2021. The main cover types comprised built-up areas, grasslands, papyrus reeds, farm land, tree plantation and woodland. The results confirmed that the total land area covered by this study was 15.4 km<sup>2</sup> (Table 4).Over these years, the most dominant vegetation cover was papyrus followed by grassland especially in 1990 and 2001. Papyrus vegetation types was continuously distributed throughout the study area with patches of other vegetation types within the wetland area.





**Figure 2: Spatial and Temporal coverage of Vegetation cover types change 1990, 2001, 2011 and 2021**

#### 4.2 Accuracy assessment for land cover classifications

During the study period spanning from 1990 to 2020, the assessment of land use and land cover (LULC) within the Kanyabaha wetland yielded an overall accuracy (OA) of 75% for the images captured in 1990, 2001, 2011, and 2020. Following the criteria established by [15], which categorized the agreement of Kappa statistics (K) as poor when  $K < 0.4$ , good when  $K$  ranged from 0.4 to 0.7, and excellent when  $K > 0.75$ , the results indicated a high level of accuracy in LULC classifications for each studied year. Specifically, the Kappa statistics for 1990, 2001, 2011, and 2020 were determined to be 0.85, 0.81, 0.86, and 0.78, respectively, signifying excellent agreement between the classified images and reference data (Table 3).

Comparatively, the overall accuracy of this LULC assessment aligns with findings reported by [16], who achieved a satisfactory overall accuracy of 86.6%. The robustness of the Kappa statistics in this study demonstrates a strong agreement across all classified images, meeting the recommended standards for further analysis of vegetation changes, as advocated by [17].

**Table 3** summarizes the producer accuracy, user accuracy, overall accuracy (OA), and Kappa statistics for land cover classifications conducted in the Kanyabaha Wetland across four different years: 1990, 2001, 2011, and 2021. Producer accuracy refers to the probability that a specific land cover type identified by the classifier is indeed present on the ground. On the other hand, user accuracy represents the likelihood that a land cover type identified on the map corresponds

to the actual land cover present in the field. Overall accuracy (OA) provides a general measure of the correctness of the classification results across all land cover types.

In 1990, the overall accuracy of the land cover classification was 87.8%, with a Kappa statistic of 0.85, indicating excellent agreement between the classified images and reference data. The producer and user accuracies ranged from 78.8% to 92.2%, demonstrating high reliability in identifying various land cover types. In 2001, the overall accuracy slightly decreased to 83.8%, with a Kappa statistic of 0.81. Although still considered good, there was a slight decline compared to 1990. However, producer and user accuracies remained relatively consistent across different land cover types.

By 2011, there was a notable improvement in the overall accuracy, reaching 88.6%, with a Kappa statistic of 0.86, indicating excellent agreement. This improvement suggests a refinement in classification techniques or better image quality, resulting in more accurate land cover mapping. Producer and user accuracies also showed improvements, particularly for some land cover types like papyrus and farming. In 2021, there was a slight decrease in overall accuracy to 82%, with a Kappa statistic of 0.78, still indicating good agreement but slightly lower compared to previous years. This decline may be attributed to changes in land cover patterns over time or potential challenges in image interpretation. However, producer and user accuracies remained relatively consistent across different land cover types.

Overall, the results suggest that the classification accuracy varied slightly over the study period, with some fluctuations observed in overall accuracy and Kappa statistics. However, the producer and user accuracies generally remained high, indicating the reliability of the land cover classification methodology used in mapping the Kanyabaha Wetland across different years.

**Table 3: Summary of producer, user, overall accuracy and kappa statistics taken between 1990, 2001, 2011 and 2021 in Kanyabaha Wetland, Uganda**

<b>1990</b>	<i>Built-up areas</i>	<i>Grassland</i>	<i>Papyrus</i>	<i>Farmland</i>	<i>Tree Plantation</i>	<i>Woodland</i>
Producer accuracy (%)	89.9	92.2	86.5	90.7	89.2	78.8
User accuracy	81.3	89.9	91.7	87.6	83.5	80.7
Overall accuracy (OA) (%)	87.8					
Kappa statistics	0.85					
<b>2001</b>	<i>Built-up areas</i>	<i>Grassland</i>	<i>Papyrus</i>	<i>Farmland</i>	<i>Tree Plantation</i>	<i>Woodland</i>
Producer accuracy (%)	81.5	84.9	82.1	85.1	84.5	85.0
User accuracy	81.3	81.6	82.1	88.1	84.5	94.4
Overall accuracy (OA) (%)	83.8					
Kappa statistics	0.81					
<b>2011</b>	<i>Built-up areas</i>	<i>Grassland</i>	<i>Papyrus</i>	<i>Farmland</i>	<i>Tree Plantation</i>	<i>Woodland</i>
Producer accuracy (%)	85.0	87.0	96.0	82.6	88.2	94.8
User accuracy	81.3	81.1	91.1	94.7	90.1	84.9
Overall accuracy (OA) (%)	88.6					
Kappa statistics	0.86					

<b>2021</b>	<i>Built-up areas</i>	<i>Grassland</i>	<i>Papyrus</i>	<i>Farmland</i>	<i>Tree Plantation</i>	<i>Woodland</i>
Producer accuracy (%)	81.3	88.2	82.9	87.8	77.2	76.9
User accuracy	81.3	82.2	90.0	80.0	92.2	79.5
Overall accuracy (OA)- (%)	82					
Kapa statistics	0.78					

### 4.3 Vegetation cover types in Kanyabaha Wetland

During the last thirty-year period, there has been considerable change in vegetation of Kanyabaha wetland. The LULC image analysis indicated that in the year 1990, 2001, 2011 and 2021 shown (Figure 2-A, B, C, D), papyrus was the dominant vegetation cover type, which occupied 51.5%, 46.5%, 35.9%, and 39.1% of the wetland respectively. Grassland cover was also extensive, covering 34.2% in 1990 and 32.1% in 2001 respectively. In 1990 (Figure 2(A)), other cover types occupied relatively small areas of Kanyabaha wetland with woodland covering 2.5%, farmland 3% and built-up areas covering 3.2%. Tree plantations covered 5.6% of wetland margins from the year 2011 to 2021 (Figure 2 C, D). These cover types that occupied small areas of the wetland in the 1990s expanded continuously at the expense of Papyrus cover in 2011 and, grassland cover in 2011 and 2021. However, in 2021, Papyrus cover increased to 39.1% and appeared to have been regenerated faster than in all the other years, (Table 4).

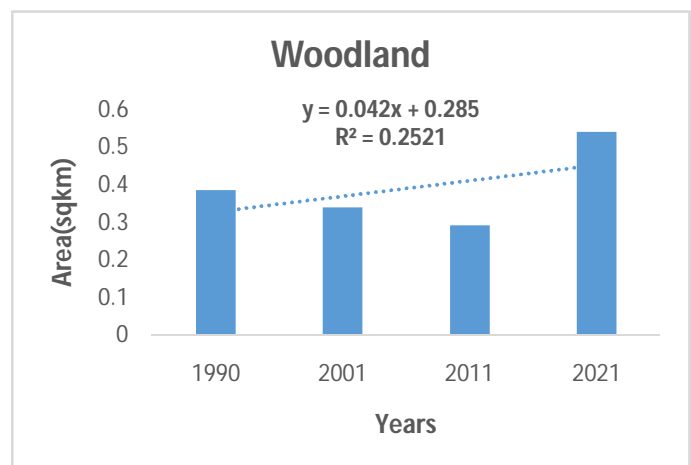
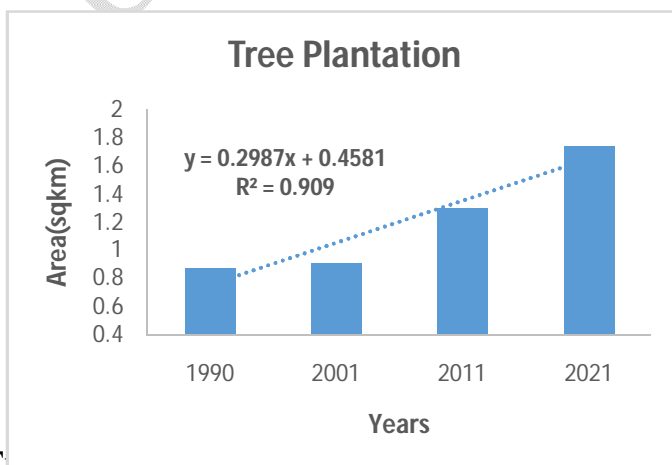
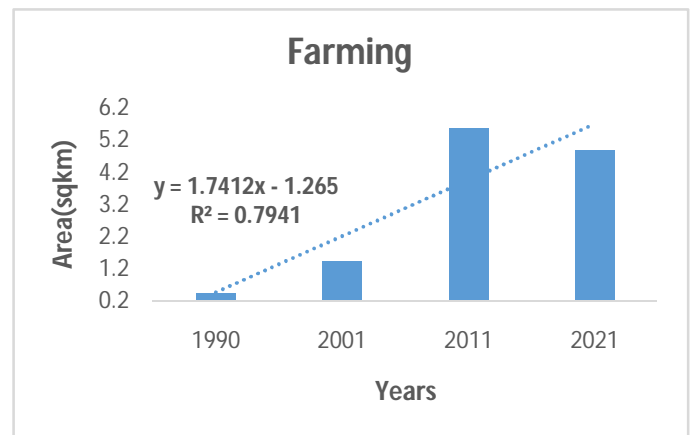
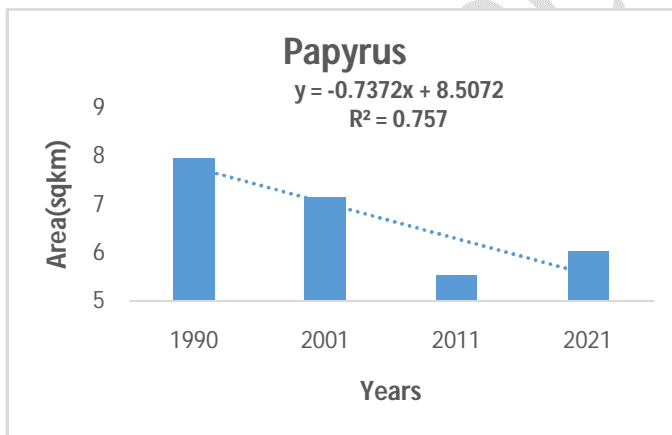
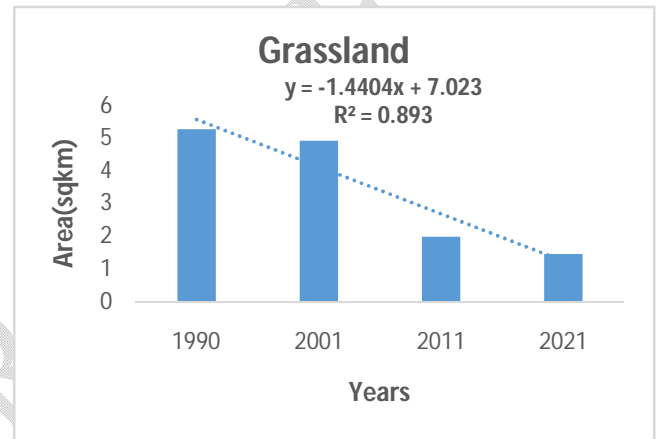
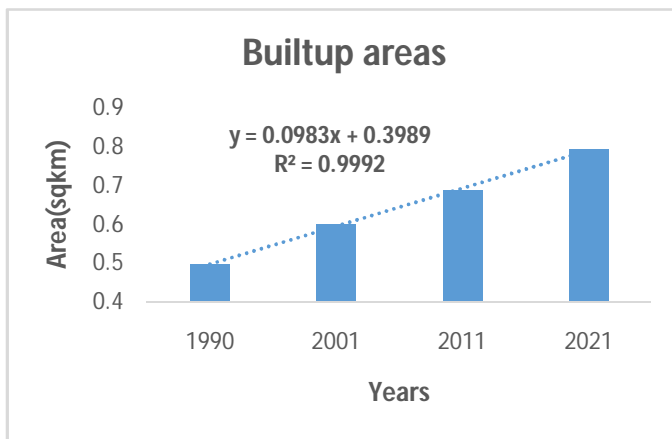
**Table 4: Vegetation cover types in Kanyabaha Wetland during the period between 1990 and 2021**

Vegetation Types	1990		2001		2011		2021	
	Area (Km <sup>2</sup> )	%	Area (Km <sup>2</sup> )	%	Area (Km <sup>2</sup> )	%	Area (Km <sup>2</sup> )	%
Build up areas	0.50	3.2	0.60	3.9	0.69	4.5	0.79	5.1
Grassland	5.29	34.2	4.93	32.1	2.00	13.0	1.46	9.5
Papyrus	7.95	51.5	7.15	46.5	5.52	35.9	6.03	39.1
Farmland	0.46	3.0	1.43	9.3	5.58	36.3	4.88	31.6
Tree Plantation	0.87	5.6	0.91	5.9	1.30	8.5	1.74	11.2
Woodland	0.39	2.5	0.34	2.2	0.29	1.9	0.54	3.5

### 4.4 Trends in cover types over the period between 1990 and 2021 in Kanyabaha Wetland

Trend data correlations was performed to examine the quantitative relationship between a particular vegetation type with changes in years as shown in Figure 3below. In

correlation analysis, the magnitude of the correlation coefficient indicates the strength of the relationship. Built up area increased steadily during the 30-year period, indicating increase in settlements and reflecting population growth and expanded business opportunities. This strong positive trend was found in areas under tree plantation (reflecting growing demand for wood for fuel and construction), and crop cultivation. A weak positive trend was also detected in the area under woodland, implying a steady expansion of woody vegetation into the wetland. This could be attributed to reduced water levels in the wetland due to siltation from the farmland and built-up areas. However, there a strong negative trend in areas occupied by papyrus swamp and grassland. The gradual loss of these cover types was attributed to expansion of farmland and built-up areas.



#### 4.5 Dynamics of land use/cover overtime (Land use/cover Transition Matrix)

The transition matrix plays an essential role in analyzing temporal changes within a set of LULC categories. The rows of the matrix table represent the categories in the initial year, while the columns show the same order of LULC categories in the final year. The diagonal entries show the size of class stability, and each off-diagonal entry represents the size of the transition from one class to different classes. To show how each LULC type was projected to change in our study area, we calculated the transition potential matrix with the help of the Terra Sat Land modeler v17 during the periods of 1990-2001, 2001-2011 and 2011-2021 based on the existing LULC conditions and explanatory variables. Table 5 below shows the transition potential matrix during 1990–2001, in which Papyrus, and grassland were the most stable landscapes with probabilities of 7.1, and 4.7, respectively, while farming, woodland and built-up areas increased with a transition probability of 0.36, 0.37 and 0.48 respectively, which contributed nothing to the papyrus vegetation. The stable papyrus and grassland showed no serious encroachment by the years 1990-2001.

**Table 5: Transition Matrix of LULC change (Km<sup>2</sup>) from 1990 to 2011 in Kanyabaha wetland**

Year	Landuse/cover	2001						
		Builtup areas	Farming	Grassland	Papyrus	Tree Plantation	Woodland	Grand Total
1990	Builtup areas	0.48	0.02	0.00				0.50
	Farming	0.10	0.36	0.00			0.00	0.46
	Grassland	0.10	0.47	4.65	0.01	0.06	0.00	5.29
	Papyrus	0.05	0.57	0.28	7.05	0.00	0.00	7.95
	Tree Plantation	0.00	0.02	0.00	0.00	0.85	0.00	0.87
	Woodland	0.00	0.01	0.00	0.00	0.00	0.37	0.39
	<b>Grand Total</b>	0.74	1.43	4.93	7.05	0.91	0.38	<b>15.4</b>

Table 6 shows the transition potential matrix during 2001–2011, in which Papyrus, Farming and grassland were the most stable landscapes with probabilities of 3.49, 0.78 and 0.69, respectively, while woodland, Built-up areas and Tree plantation decreased with a transition probability of 0.03, 0.18 and 0.42 respectively, and woodland and Tree plantation contributed 0.52 and 0.39 respectively to papyrus.

**Table 6: Transition Matrix of LULC change (Km<sup>2</sup>) from 2001 to 2011**

Year	Land covers	2011						
		Built-up areas	Farming	Grassland	Papyrus	Tree Plantation	Woodland	Grand Total
2001	Built-up areas	0.18	0.40	0.08	0.05	0.03	0.01	0.74
	Farming	0.04	0.78	0.22	0.25	0.11	0.03	1.43
	Grassland	0.08	2.36	0.69	1.40	0.32	0.08	4.93
	Papyrus	0.02	1.79	0.85	3.49	0.39	0.52	7.05
	Tree	0.01	0.20	0.09	0.16	0.42	0.04	0.91

	Plantation							
	Woodland	0.00	0.05	0.08	0.18	0.03	0.03	0.38
	<b>Grand Total</b>	0.32	5.58	2.00	5.52	1.30	0.71	<b>15.4</b>

During 2011–2021 (Table 7 below), the probability of built-up area and farming were 0.2 and 2.7, respectively, those of grassland and papyrus were 0.4 and 3.1, respectively, and that of Tree plantation and woodland was 0.6 and 0.1, respectively. Farming and grassland again contributed 1.5 and 0.7 to the papyrus, respectively. Accordingly, during 1990-2001, 2001-2011 and, 2011–2021, papyrus (7.1, 3.49 and 3.1) and Farming (0.36, 0.78 and 2.7) had higher stable transition respectively while grassland, tree plantation and woodland had fragmentation values during 1990-2001, 2001-2011 and, 2011–2021, respectively.

**Table 7: Transition Matrix of LULC change(Km<sup>2</sup>) from 2011 to 2022**

Year	Landuse/cover	2021						
		Builtup areas	Farming	Grassland	Papyrus	Tree Plantation	Woodland	Grand Total
2011	Builtup areas	0.2	0.1	0.0	0.0	0.0	0.0	0.3
	Farming	0.4	2.7	0.5	1.5	0.5	0.1	5.6
	Grassland	0.1	0.7	0.4	0.7	0.1	0.1	2.0
	Papyrus	0.1	1.2	0.5	3.1	0.4	0.3	5.5
	Tree Plantation	0.0	0.2	0.1	0.3	0.6	0.0	1.3
	Woodland	0.0	0.0	0.1	0.5	0.1	0.0	0.7
	<b>Grand Total</b>	<b>0.79</b>	<b>4.88</b>	<b>1.46</b>	<b>6.03</b>	<b>1.74</b>	<b>0.54</b>	<b>15.4</b>

## 4.6 Discussion

### 4.6.1 Vegetation Characterization of Kanyabaha Wetland

The primary objective of this study was to characterize the different types of vegetation in the Kanyabaha wetland, a task critical for understanding the wetland's ecological dynamics and its role as a resource base for local communities. Wetlands are known for their diverse ecosystems, marked by varying spatial patterns, hydrological conditions, and plant communities [14]. The analysis of Landsat images from 1990, 2001, 2011, and 2021 provided a comprehensive view of the distribution and changes in vegetation cover types over three decades.

The dominant vegetation types identified included built-up areas, grasslands, papyrus reeds, farmland, tree plantations, and woodlands. Papyrus was the most prevalent vegetation cover, particularly in the earlier years (1990 and 2001), covering 51.5% and 46.5% of the wetland area, respectively. Grasslands were also significant, covering 34.2% in 1990 and 32.1% in 2001. However, over the years, the areas occupied by papyrus and grasslands decreased, with notable expansions in farmland and built-up areas, reflecting increased human activities and land use

changes. The continuous decline in the wetland vegetation coverage could be attributed to anthropogenic activities like crop growing, clay mining, grazing, papyrus harvesting and grass cutting carried out in the area, which greatly contributed to the gradual diminishing of the Kanyabaha wetland. Reclamation of wetlands for agriculture and settlements leads to the loss of biodiversity and exposes sedimentary carbon stock to degradation resulting into Greenhouse gas emissions. The dominance of papyrus in the Kanyabaha wetland aligns with previous studies emphasizing the ecological significance of wetland vegetation, especially in biodiversity conservation and carbon sequestration [8, 6]. The gradual decline observed highlights broader concerns about the vulnerability of wetland ecosystems to anthropogenic pressures and land use changes globally.

#### **4.6.2 Accuracy Assessment for Land Cover Classifications**

The accuracy of land use and land cover (LULC) classifications for the study period (1990-2020) was robust, with overall accuracies (OA) of 75% and Kappa statistics indicating excellent agreement between classified images and reference data. The Kappa statistics for the years 1990, 2001, 2011, and 2021 were 0.85, 0.81, 0.86, and 0.78, respectively, signifying strong agreement and reliability of the classification methodology used. These findings are consistent with other studies, such as [16], which reported an overall accuracy of 86.6%, and [17], which highlighted the robustness of Kappa statistics for LULC analysis.

#### **4.6.3 Vegetation Cover Changes (1990-2021)**

Over the 30-year period, there were significant changes in the vegetation cover of the Kanyabaha wetland. In 1990, papyrus and grasslands were the dominant cover types. However, by 2021, these areas had decreased significantly, with papyrus covering only 39.1% and grasslands 9.5% of the wetland. Concurrently, farmland increased dramatically from 3% in 1990 to 31.6% in 2021, and built-up areas expanded from 3.2% to 5.1%. Tree plantations also grew, particularly from 2011 onwards, reflecting increased demand for timber and fuel wood. This shift in vegetation cover is indicative of significant land use changes driven by human activities, such as agriculture and urbanization. These changes have implications for the ecological health of the wetland, affecting biodiversity, hydrology, and carbon storage.

The observed vegetation cover changes align with global trends in wetland degradation and land use conversion [8, 10]. Studies have consistently shown that agricultural expansion and urban growth lead to habitat loss and fragmentation, impacting biodiversity and ecosystem services provided by wetlands [1]. The findings stress the urgent need for sustainable land use planning and conservation strategies to mitigate these impacts.

#### **4.6.4 Trends in Vegetation Cover Types**

Trend analysis of the vegetation cover types revealed several patterns. Built-up areas and farmlands showed a strong positive trend, indicating ongoing urbanization and agricultural expansion. Tree plantations also increased, reflecting growing demand for wood products. Conversely, there was a strong negative trend for papyrus and grasslands, indicating a loss of these critical habitats due to land conversion for agriculture and urban development. Similar trends in vegetation cover changes have been documented globally, emphasizing the role of

human activities in reshaping landscapes and altering ecological processes [18, 19]. The study contributes to understanding these dynamics by providing localized evidence of how land use changes impact wetland vegetation and biodiversity.

#### **4.6.5 Dynamics of Land Use/Cover over Time (Land Use/Cover Transition Matrix)**

The transition matrices for the periods 1990-2001, 2001-2011, and 2011-2021 provide insights into the stability and transitions of different LULC categories. Papyrus and grasslands were relatively stable in the early period (1990-2001), but later periods saw significant transitions, particularly towards farmland and built-up areas. The increasing instability of these natural vegetation types highlights the pressures from expanding human activities. The matrices show that during 1990-2001, papyrus and grasslands were the most stable with transition probabilities of 7.1 and 4.7, respectively. However, in subsequent periods, these probabilities decreased, indicating higher rates of transition to other land uses such as farming and urban areas. For instance, during 2011-2021, papyrus stability was lower at 3.1, reflecting increased encroachment and conversion to other land uses. Transition matrices are valuable tools for assessing land cover dynamics and understanding the drivers of change in ecosystems [20]. Previous studies have shown that transitions from natural to anthropogenic land cover types are common in areas undergoing rapid development and urbanization [21, 22, 23]. The findings underscore the need for integrated land management approaches that balance socio-economic development with environmental conservation.

#### **1. Conclusion**

Over the past three decades, the Kanyabaha Wetland has experienced significant shifts in vegetation cover and land use, characterized by declines in natural habitats like papyrus reeds and grasslands, alongside expansions in agricultural lands and built-up areas. These changes underscore the ongoing pressures from human activities such as agriculture and urbanization, highlighting the urgent need for integrated conservation and management strategies to sustain the ecological health and biodiversity of the wetland ecosystem. **The study highlights the need to promote sustainable land management practices to maximize land productivity without encroaching on wetlands. Additionally, there is a need to support research initiatives focused on understanding the interplay between change in land use/cover types and carbon dynamics in Kanyabaha wetland ecosystem.**

#### **Disclaimer (Artificial intelligence)**

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