FOREST CHANGE DETECTION IN HOMA BAY COUNTY USING LANDSAT IMAGERY FROM 2010 TO 2024.

Introduction

Homa Bay County, located along the shores of Lake Victoria in Kenya, is rich in biodiversity and natural resources. The forests in this region play a critical role in sustaining local ecosystems, supporting agricultural communities, and providing resources such as timber and non-timber forest products. However, Homa Bay County has experienced significant environmental changes over the last decade. Factors contributing to forest cover changes include agricultural expansion, logging activities, population growth, and climate change. These pressures have led to habitat loss, declining biodiversity, and alteration of local microclimates.

To effectively manage forest resources and combat environmental degradation, comprehensive assessments of forest cover changes are vital. This study aims to analyze and quantify forest cover changes in Homa Bay County using Landsat imagery from 2010 to 2024 through Google Earth Engine (GEE). The findings of this study will provide vital insights to stakeholders in environmental conservation, land use planning, and policy formulation.

Objectives

General Objective:

To assess and quantify the changes in forest cover in Homa Bay County between 2010 and 2024 using Landsat imagery.

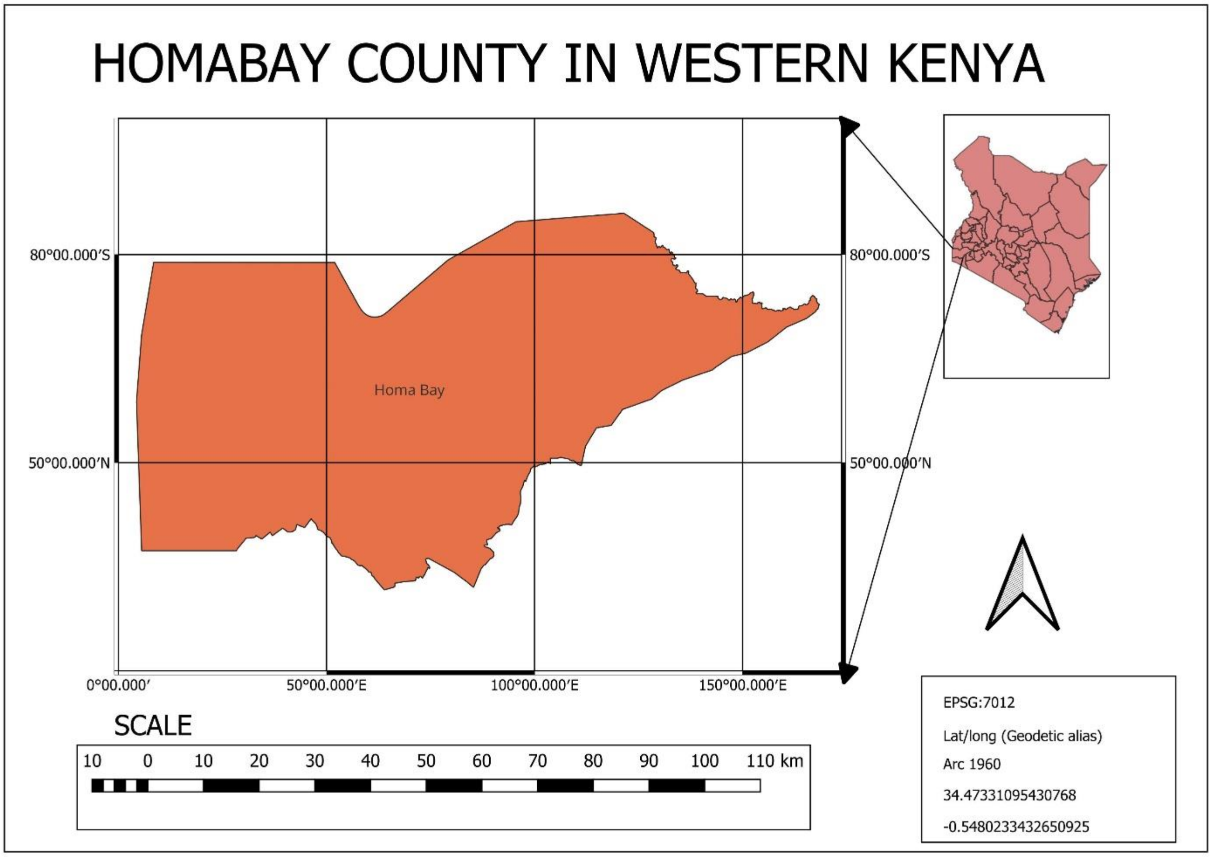
Specific Objectives:

1. To classify Landsat images for the years 2010, 2015, 2020 and 2024 and map the spatial distribution of forest cover in Homa Bay County.
2. To evaluate the factors contributing to forest cover changes, including socio-economic activities and climate variables during the study period.

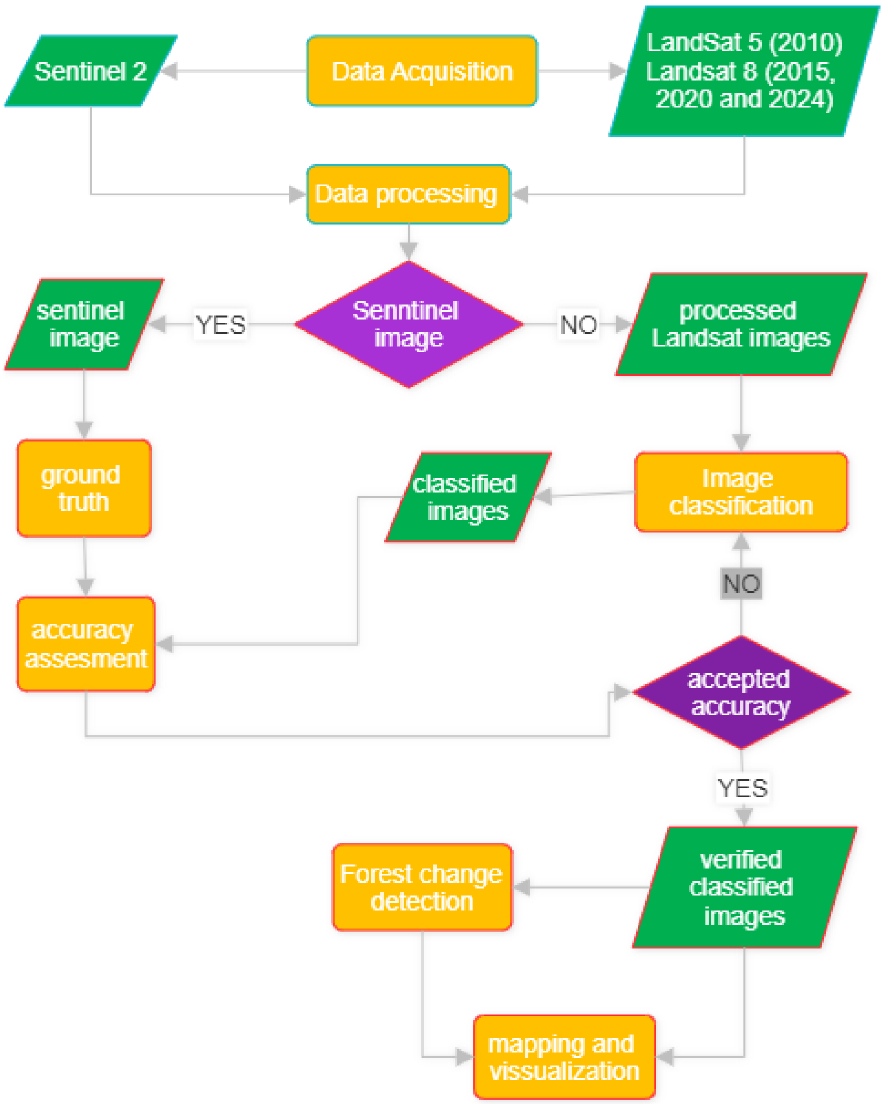
Datasets

Data types	**source**	**Specifications**	**Relevance**
Landsat Imagery	Google Earth Engine (GEE)	❖ Landsat 5 for 2010 ❖ Landsat 8 for 2015, 2020 and 2024 ❖ Resolution: 30m	For land cover classification and forest change detection analysis
Sentinel Imagery	Copernicus	❖ Sentinel 2 ❖ Resolution: 10m	Source of ground truth data to validate remote sensing classification results and improve accuracy.

Study Area


HOMABAY COUNTY IN WESTERN KENYA
80°00.000'S
50°00.000'N
80°00.000'S
50°00.000'N
Homa Bay
0°00.000'
50°00.000'E
100°00.000'E
150°00.000'E
SCALE
10 0 10 20 30 40 50 60 70 80 90 100 110 km
EPSG:7012
Lat/long (Geodetic alias)
Arc 1960
34.47331095430768
-0.5480233432650925

Methodology



1**. Data Acquisition:** The Landsat images were acquired from the USGS Earth Explorer for the years 2010, 2015, 2020 and 2024.

2. **Data Preprocessing:** The images were processed in Google Earth Engine to remove atmospheric effects and cloud cover, yielding clear images suitable for analysis.

3. Image Classification:

- Utilize the Random Forest algorithm in GEE to classify the processed imagery into various land cover types, particularly focusing on forested areas.
- Conduct classifications for each selected year (2010, 2017, 2024) and create land cover maps for each epoch.

4. Change Detection Analysis:

- Perform post-classification change detection to identify areas of significant change in forest cover across the three time points.
- Determine loss, gain, and stability of forest areas.

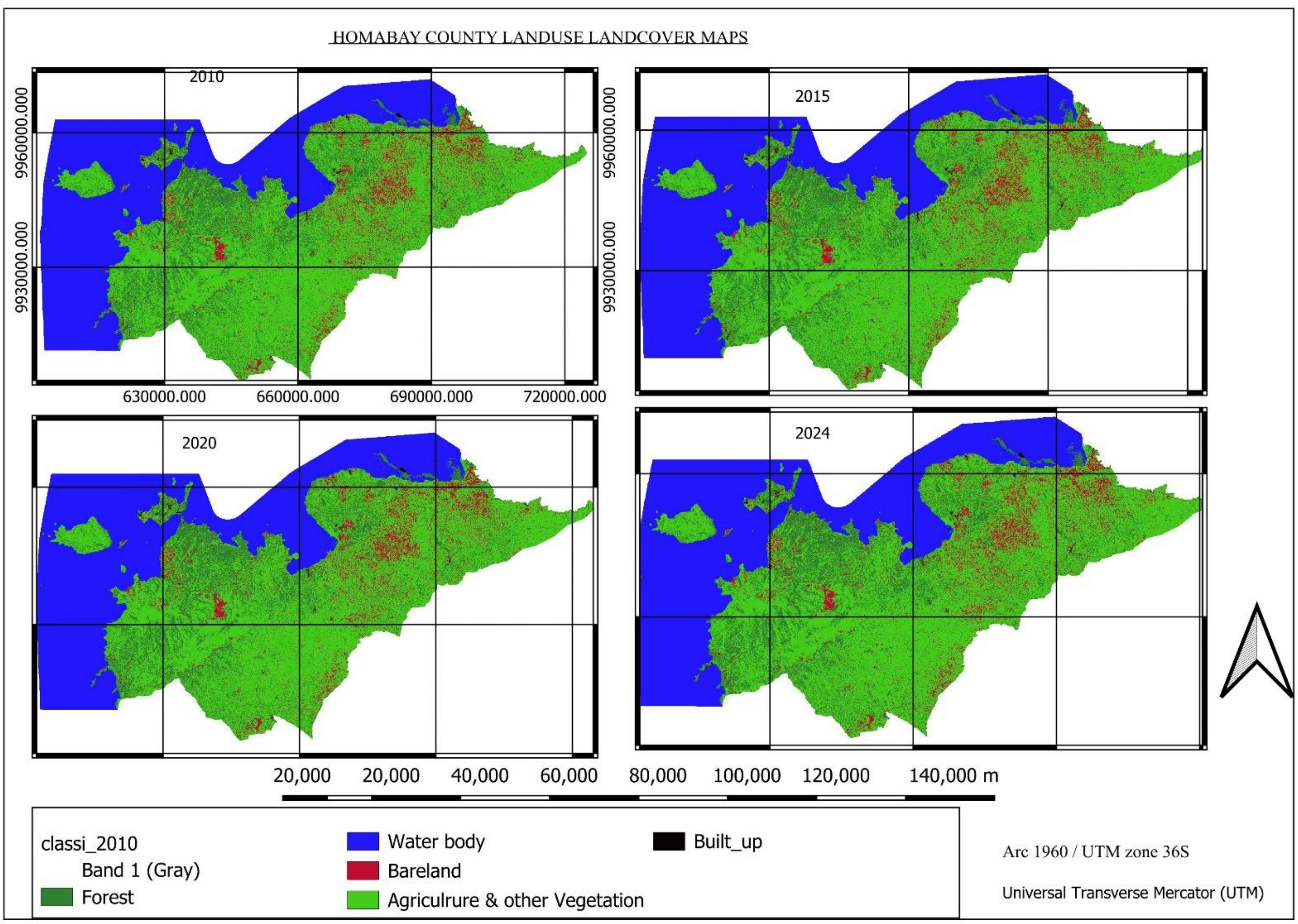
5. Statistical Analysis: Interrelate the classified forest cover changes with socio-economic data and climatic variables to assess influencing factors.

6. Validation: A ground truthing exercise was conducted, comparing field data with classified imagery to ensure accuracy.

7. Mapping and Visualization: Generate maps and graphs in GEE to represent forest cover changes and their correlating statistics visually.

Results and Discussion

Maps:



Graphs, Charts and Tables:

Figure 1.3.0

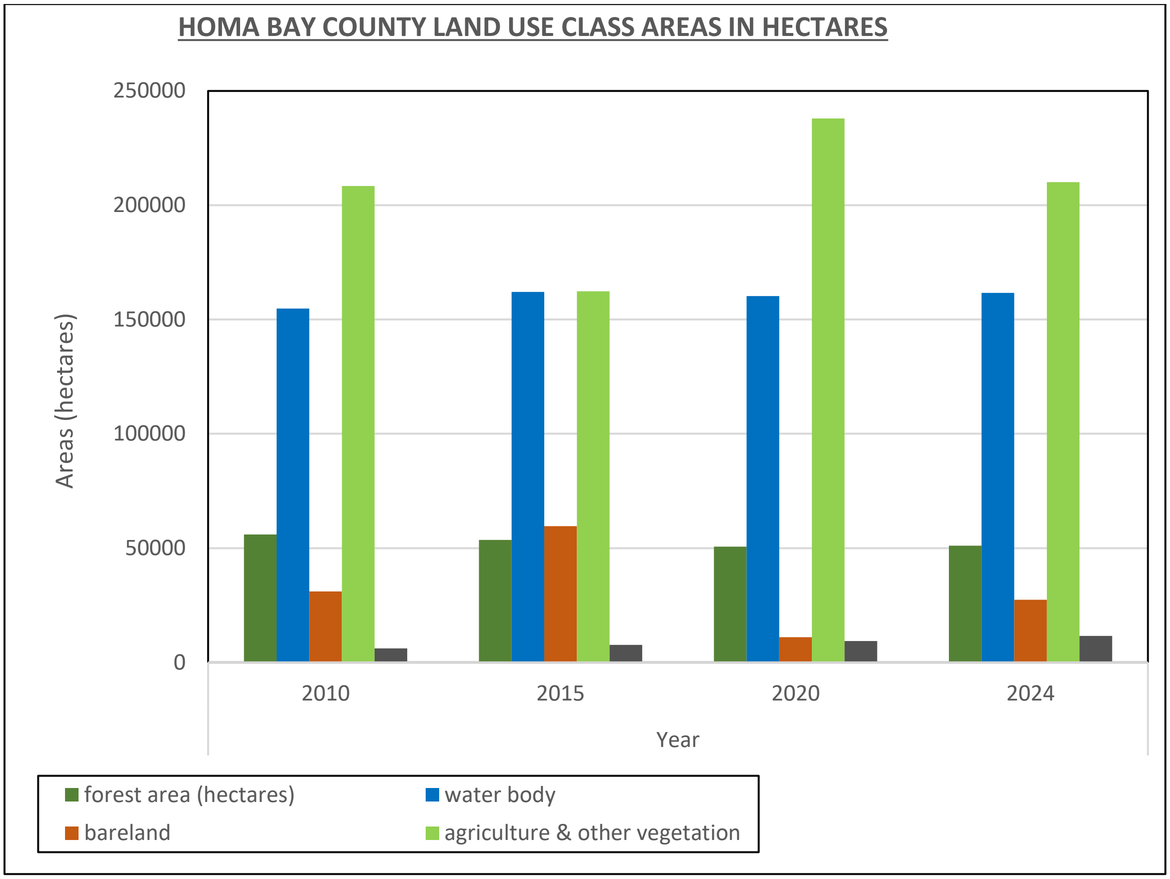


Figure 1.3.1

	2010	2015	2020	2024
		Year		
forest	55891.176	53635.35772	50592.31994	51054.40892
water body	154768.3747	162089.7311	160194.5141	161644.2344
bareland	31060.85417	59544.91713	11069.47908	27375.78312
agriculture & other vegetation	208446.6685	162370.4707	237979.3686	210063.1793
built_up	6088.051451	7714.648067	9319.443103	11517.51905

Figure 1.3.2

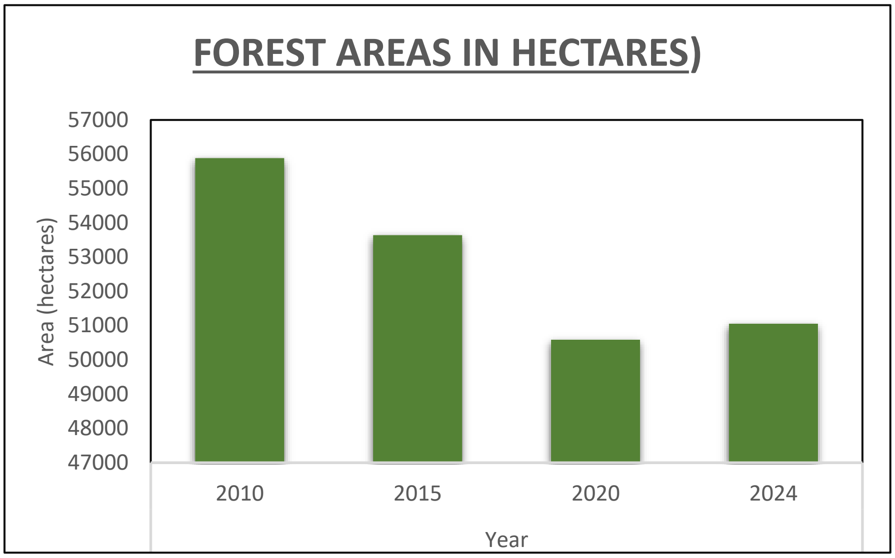
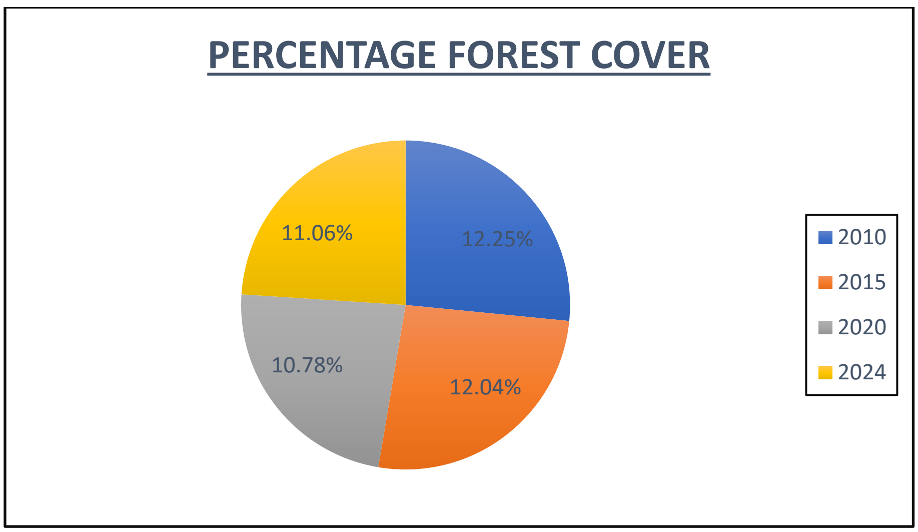


Figure 1.3.3



Accuracy Assessment:

Figure 1.4.0

class	producer's accuracy	user's accuracy
Forest	0.93359375	0.949668874
water body	1	1
Bare-land	0.861365678	0.963927856
agriculture & other vegetation	0.961365678	0.955357143
built-up	0.647058824	0.913656783

Figure 1.4.1

overall accuracy	0.948785072
kappa's accuracy	0.937458838

Discussion

The analysis of forest cover changes in **Homa Bay County** from 2010 to 2024 using Landsat imagery reveals critical trends and underlying drivers of change in the region's forest resources. The results from **Figures 1.3.0, 1.3.1, 1.3.2, and 1.3.3** provide a comprehensive picture of forest dynamics over the 14-year period, while accuracy assessments in **Figures 1.4.0 and 1.4.1** validate the reliability of these findings.

A. Forest Cover Trends (2010–2024)

The results highlight a **significant decline** in forest cover between **2010** and **2020**. Specifically:

- The forest area decreased from approximately **56,000 hectares** in 2010 to **49,000 hectares** in 2020 (Figure 1.3.2).
- This decline corresponds with a reduction in the percentage of forest cover, from **12.25% in 2010** to **10.78% in 2020** (Figure 1.3.3).

The decline can be attributed to various **anthropogenic factors**:

- **Agricultural expansion**: Increasing land conversion to agriculture to support population growth and food demand has encroached on forested areas. This is evident in the corresponding growth of agriculture and bare land classes.
- **Urban development**: Expanding built-up areas, as shown in **Figure 1.3.1**, indicate land clearance for infrastructure and settlements.
- **Logging activities**: Both legal and illegal logging have further contributed to forest degradation, reducing forested areas over time.

B. Forest Recovery by 2024

Interestingly, the results suggest a **slight recovery** in forest cover by **2024**:

- Forest area increased modestly to around **51,000 hectares** (Figure 1.3.2), with a corresponding rise in forest cover percentage to **11.06%** (Figure 1.3.3).

This recovery can be linked to several possible interventions:

- **Afforestation and reforestation efforts**: Community-based initiatives or government programs promoting tree planting may have contributed to forest regeneration.
- **Increased awareness**: Environmental conservation efforts and awareness programs by NGOs and local authorities might have encouraged sustainable practices.
- **Policy implementation**: Introduction of policies to regulate land use and prevent deforestation may have begun to yield results, though the recovery remains modest.

C. Land Cover Changes and Influencing Factors

The classification results in **Figure 1.3.1** reveal changes across multiple land cover types:

Agriculture & other vegetation showed fluctuations, indicating its dynamic interaction with forested areas, possibly due to seasonal farming or shifting cultivation.

- **Bare land** experienced a notable spike in certain years, which could reflect temporary clearances for farming or urban development.
- **Built-up areas** showed consistent growth, further confirming the role of urban expansion in forest loss.

Socio-economic drivers such as:

- **Population growth,** leading to increased land demand for agriculture, housing, and resources.
- **Economic reliance on forest products**, including timber, charcoal production, and non-timber forest products.

Climatic variations may have also exacerbated forest cover changes. Prolonged droughts or changing rainfall patterns could hinder forest regeneration, while extreme weather events may lead to forest degradation.

D. Accuracy Assessment

The accuracy assessment confirms the reliability of the findings:

- **Overall accuracy** of **94.88%** and a **Kappa coefficient** of **93.75%** (Figure 1.4.1) reflect strong agreement and robust classification.
- Class-specific accuracy results (Figure 1.4.0) show excellent performance for forest, water body, and agriculture classes. However, **built-up areas** had lower producer's accuracy (0.647), indicating potential challenges in distinguishing this class from other land cover types, such as bare land.

E. Implications of Findings

The findings highlight the urgent need to address forest loss in Homa Bay County. Forest degradation between 2010 and 2020 underscores the pressures of agricultural and urban expansion. Although the slight recovery by 2024 is promising, it is insufficient to restore forests to their 2010 levels.

Environmental Impacts:

- Loss of forest cover disrupts local ecosystems, reduces biodiversity, and affects critical services such as water regulation, carbon sequestration, and soil stability.
- Deforestation contributes to climate change by releasing stored carbon, further aggravating environmental challenges.

Socio-Economic Impacts:

- Forest loss threatens the livelihoods of local communities dependent on forest resources for timber, food, and income.
- Agricultural encroachment, while addressing short-term food security, risks long-term land degradation and reduced productivity.

Conclusion

The study reveals that forest cover in Homa Bay County experienced a significant decline between 2010 and 2020, largely driven by **agriculture, urban development**, and **logging**. However, a slight recovery by 2024 suggests that conservation initiatives and afforestation efforts are beginning to make a difference.

Recommendations

Promote Sustainable Land-Use Practices:

- Encourage agroforestry and sustainable farming techniques to reduce pressure on forested lands.
- Support afforestation and reforestation programs to restore degraded areas.

Enhance Policy Implementation:

- Strengthen enforcement of land use policies to prevent illegal logging and encroachment.
- Provide incentives for communities to participate in conservation programs.

Community Awareness and Engagement:

- Educate local communities on the importance of forests for ecological balance and livelihoods.
- Partner with NGOs and local organizations to implement conservation strategies.

Integrate Technology in Monitoring:

- Regularly use remote sensing and GIS tools to monitor forest changes and guide decision-making.