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Spatio-Temporal Patterns of Urban Agriculture from Landsat Data in Eldoret City, Kenya

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Abstract
Urban agriculture plays a key role in enhancing food and nutrition security while supporting the sustainability and resilience of rapidly growing cities such as Eldoret. Despite a population of approximately 500,000, Eldoret's agricultural activities remain fragmented and poorly integrated into urban planning. Evidence from field observations suggest that the existing urban development plans are rarely implemented fully. This study aimed to map urban agricultural patterns and assess changes in land use and land cover over for the past two decades using Landsat imagery from 2003, 2015 and 2024. Four major land use/land cover types were identified: forest land, built-up land, bare land and cropland. Between 2003 and 2024, forest land declined from 3,757 to 1,294 hectares, bare land decreased from 8,621 to 4,171 hectares, while built-up land increased from 594 to 1,554 hectares and cropland expanded significantly from 1,989 to 7,929 hectares. During the 2003–2015 period, forest and bare land reduced to 1,353 and 5,187 hectares respectively, while built-up land and cropland grew to 948 and 7,440 hectares respectively. These spatial changes are distributed across the city, reflecting a growing role for urban agriculture. The findings provide a foundation for policymakers and planners to develop more inclusive, resilient, and food-secure urban strategies.

Keywords: Urban Agriculture; Classification; Change Detection; Land Use/Land Cover
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1. Introduction

It has been estimated that about 60% of the world's population will be living in urban centres by the year 2050. Asia and Africa are urbanizing faster than any other region (UN-Habitat, 2016; UN, 2018). Huho & Muriuki (2021) and Republic of Kenya (2008) note that Kenya is rapidly urbanizing at an annual rate of about 4.3% with an estimated 63% of the population expected to be living in urban areas by 2030, and one of the consequences being the problem of food and nutrition security. The UN Food and Agriculture Organization [FAO] (2003) defines food security thus: 'Food security, at the individual, household, national, regional and global levels [is achieved] when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life'. The rising urban population will continue putting pressure on urban resources, especially in cities of low and middle-income countries, leading to pressure on urban food security (Korir, Rotich & Mining, 2015; Swanepoel, Niekerk & Tirivanhu, 2021). In order to mitigate against this challenge, proper planning and finding alternatives to the conventional food security measures in urban centres is needed. Furthermore, as Omali et al. (2022) note, urban agriculture is not given enough recognition in developing nations especially at policy level and monitoring agronomic activities in space and time is necessary to improve it. In many cities and urban areas in developing world, urban agriculture is outlawed by by-laws and ordinances thereby leaving cities and urban areas to rely on food supplies from other regions. When food is transported to urban areas from elsewhere, environment is seriously placed at risk because of emissions arising from transporting vehicles and energy usage which exacerbate global warming and attendant climate change. Localized food production in urban areas can be used to mitigate against negative environmental impacts associated with importation of food supplies from areas away from the cities.

As a step towards understanding the dynamics of urban agriculture within Eldoret city and its contribution to food and nutrition security, this study aimed at mapping urban agricultural patterns from Landsat images showing the major land use types associated with urban agriculture and how they have been changing for the period between 2003 and 2024. Knowledge on spatial dynamics of urban and peri urban agriculture provides important lens to understand future scenarios for urbanization patterns and the social and economic implications (Willcomm, Follmann & Dannenberg, 2019). Remote sensing is an important tool for providing information about land use and its development over time. It is used to investigate urban environments and in particular urban land cover changes and city growth (Eckert, 2011) and offers an efficient tool to collect land cover/land use (LCLU) data for decision-making (Forster, Buehler & Kellenbergerd, 2009).

LCLU mapping from satellite imagery has been carried out for different applications since the emergence of satellite image data collection in the early seventies when Landsat program started. Spectral, radiometric and spatial resolution together with temporal aspects of image data are important issues to consider when selecting image data for a given application (Asokan et al., 2020; USGS, 2022). The objective of this study was to map the spatial distribution of urban agricultural zones in Eldoret city from remotely sensed satellite imagery focusing on crop land and evaluate the changes for the past two decades.

2. Material and Methods

2.1 Study Area

The study area lies between longitudes 35^{o} 20’ 33” East and 35^{o} 12’ 33” East and latitudes 0^{o} 26’ 39” North and 0^{o} 35’ 37” North (Figure 1). It is within Uasin Gishu county, has an approximate area of 150 km^2 and comprises of Huruma, Kamukunji, Kapsoya and Langas sub locations. According to the 2019 Kenya Population and Housing Census (KPHC), the population of Eldoret city stood at 257,360 with 129,843 males, 127,506 females and 84,316 households. The inter-censual population growth rate for the County is 3.8 per cent which is higher than the national rate of 2.2 per cent. The high population growth rate is mainly due to a high fertility rate of 3.0 per cent and immigration from other regions in search of employment and business opportunities (Republic of Kenya, 2019; UG, 2023).

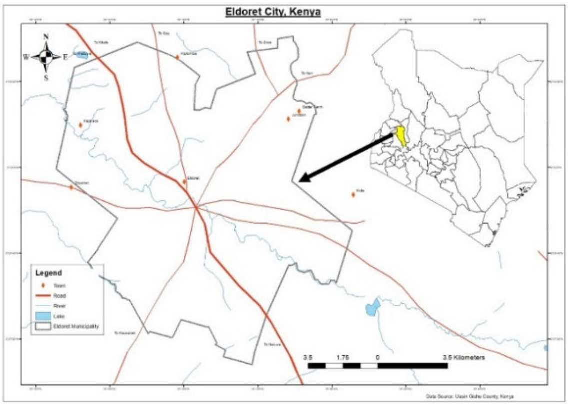


Figure 1: Location of Study Area

The county has a mild and temperate climate favorable for large-scale production of maize and wheat, which along with neighbouring Trans-Nzoia, is often referred to as the country’s breadbasket. It also produces sizable quantities of milk, horticultural produce, and a wide variety of other crops and animals in smaller amounts. It experiences much cooler temperatures ranging between 18°C to 21°C and receives an annual average rainfall of 1500 mm per year. The county is characterized by four distinct seasons, dominated by two rainfall periods: January to March, which is generally considered the ‘warm dry season’, April to June known as the ‘long wet season’, July to September the ‘cool dry season’, and October to December as the ‘short wet season’ (UG, 2023).

2.2 Data Acquisition

Landsat images were downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/) ensuring less than 1% cloud cover and for the months between April and July when crops are in the fields. The datasets downloaded were for May 2003 (Landsat 7 ETM+), July 2015 (Landsat 8 OLI/TIRS) and May 2024 (Landsat 9 OLI/TIRS) with a spatial resolution of 30m. Table 1 and figure 2 show the characteristics of the data downloaded.

Table 1: Landsat Data Characteristics

Band Name	**Landsat 8/9 OLI/TIRS**		**Landsat 7 ETM+**		**Applications**
	Band No.	**Wavelength**	**Band No.**	**Wavelength**	
Coastal Aerosol	Band 1	0.43–0.45	-	-	Coastal areas and shallow water observations; aerosol, dust, smoke detection studies.
Blue	Band 2	0.45–0.51	Band 1	0.45–0.52	Bathymetric mapping; soil/vegetation discrimination, forest type mapping, and identifying man made features.
Green	Band 3	0.53–0.59	Band 2	0.52–0.60	Peak vegetation; plant vigor assessments.
Red	Band 4	0.64–0.67	Band 3	0.63–0.69	Vegetation type identification; soils and urban features.
Near IR	Band 5	0.85–0.88	Band 4	0.77–0.90	Vegetation detection and analysis; shoreline mapping and biomass content
Shortwave IR-1	Band 6	1.57–1.65	Band 5	1.55–1.75	Vegetation moisture content/drought analysis; burned and fire affected areas; detection of active fires.
Shortwave IR-2	Band 7	2.11–2.29	Band 7	2.09–2.35	Additional detection of active fires (especially at night); plant moisture/drought analysis.
Panchromatic	Band 8	0.50–0.68	Band 8	0.52–0.90	Sharpening multispectral imagery to higher resolution.
Cirrus	Band 9	1.36–1.38	-	-	Cirrus cloud detection.
Thermal	Band 10 T1	10.60–11.19	Band 6	10.40–12.50	Ground temperature mapping and soil moisture estimations.
Thermal	Band 11 T1	11.50–12.51			Ground temperature mapping and soil moisture estimations.

Source: USGS, 2022

(a) (b) (c)

Figure 2: True Color Composite Images for (a) May, 2003 (b) July, 2015 and (c) May, 2024

2.3 Image Processing

There are three kinds of remotely sensed image classification methods: pixel based, object based and scene based (Forster et al., 2009; Asokan et al., 2020; Mehmood et al., 2022). Hybrid methods which combine two or more of these methods also exist. In this study, because of the coarse spatial resolution of Landsat data, the conventional pixel based classification technique was used. The minimum distance parametric algorithm (Minu & Bindhu, 2016) of supervised classification within ERDAS IMAGINE 2022 remote sensing software was employed and four major classes identified-forest land, built up land, bare land and crop land. Figure 3 shows the image processing methodology.

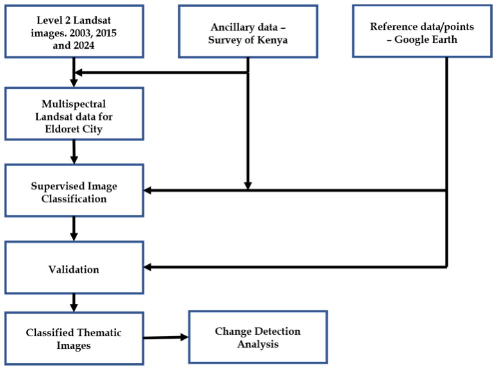
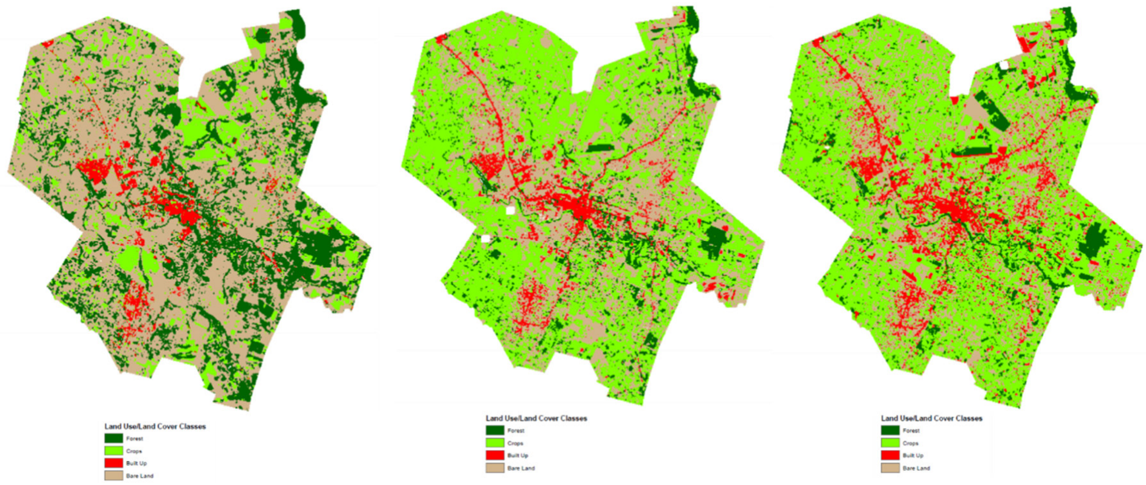


Figure 3: Image Analysis

The quality assurance (QA) band downloaded alongside the other image bands was used to identify cloud/shadow areas within the images and subsequently masking these areas. The images had a cloud/shadow cover of 0.5% for 2015 and 0.3% for 2003 and 2024. In order to utilize all the information in the bands and improve classification accuracy, bands 1-7 were stacked together for Landsat 7 ETM+ and bands 2-7 were stacked together for Landsat 8 OLI/TIRS and Landsat 9 OLI/TIRS.

3. Results

Four major land use/land cover types were identified from analysis of Landsat imagery of 2003, 2015 and 2024: forest land; built up land; bare land; and crop land. Between 2003 and 2024, forest land reduced from 3,757 Ha to 1,294 Ha, built up area increased from 594 Ha to 1,554 Ha, bare land decreased from 8,621 Ha to 4,171 Ha, while there was an increase of crop land from 1,989 Ha to 7,929 Ha. The period between 2003 and 2015 saw a decrease in forest and bare land to 1,353 Ha and 5,187 Ha respectively. Built up land and crop land increased to 948 Ha and 7,440 Ha respectively. Figure 4 shows the classified images while figure 5 and table 2 depict the area in hectares for the four-land use/land cover classes between 2003 and 2024.



(a) (b) (c)

Figure 4: Classified Images (a) 2003; (b) 2015; (c) 2024

Table 2: Land Use/Land Cover Classes

Area (Ha) of Land Use/Land Cover			
	2003	2015	2024
Forest	3757.00	1353.00	1294.00
Built Up	594.00	948.00	1554.00
Bare Land	8621.00	5187.00	4171.00
Crops	1989.00	7440.00	7929.00

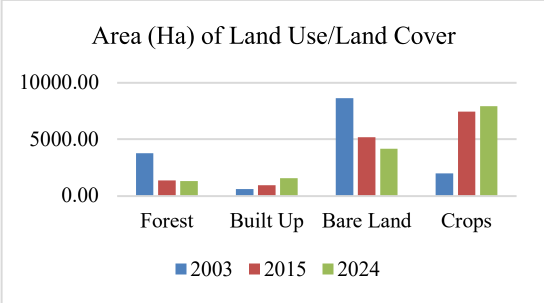


Figure 5: Area (Ha) of Land Use/Land Cover Classes

Table 3: LULC Change Matrix 2003-2015

Change Matrix (Ha) 2003-2015				
From/To	Forest	Built Up	Bare Land	Crops
Forest	920.97	122.67	815.67	1888.92
Built Up	13.14	415.53	144.90	19.62
Bare Land	312.30	312.84	3664.98	4313.43
Crops	104.31	96.84	562.05	1218.51

Table 4: LULC Change Matrix 2015-2024

Change Matrix (Ha) 2015-2024				
From/To	Forest	Built Up	Bare Land	Crops
Forest	679.59	47.61	75.60	548.55
Built Up	27.00	645.48	175.77	99.54
Bare Land	108.90	599.67	2542.23	1934.64
Crops	471.78	255.69	1363.68	5338.98

Table 5: LULC Change Matrix 2003-2024

Change Matrix (Ha) 2003-2024				
From/To	Forest	Built Up	Bare Land	Crops
Forest	778.77	199.26	520.29	2254.77
Built Up	14.31	394.02	145.62	40.59
Bare Land	360.72	746.55	2886.30	4618.71
Crops	137.97	214.56	619.20	1015.11

Table 6: Accuracy Assessment

Accuracy Assessment			
	2003	2015	2024
Overal Accuracy	0.9643	0.7857	0.9286
Kappa Statistics	0.9524	0.7176	0.9048

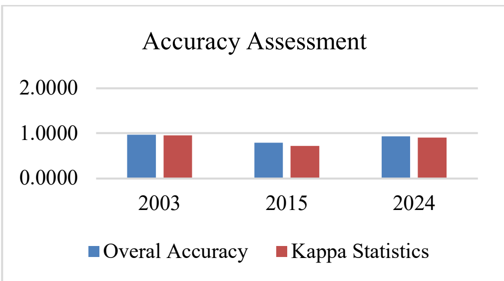


Figure 6: Accuracy Assessment

Tables 3, 4 and 5 capture the change matrices for the periods 2003-2015, 2015-2024 and 2003-2024 respectively. The overall classification accuracy for the three images was over 78% while the kappa indices were above 0.71. These statistics are shown in table 6 and figure 6. The kappa indices achieved indicate very good classification quality (Mangabeira et al. in Duarte et al. 2016) while the average overall accuracy is within the widely used target overall accuracy of 85% (Foody, 2008).

4. Discussion

Four land use/ land cover types were identified from the classified images. These are forest land, built up area, bare land and crop land. The classification could not distinguish among the different crop types and therefore all vegetation other than forest were classified as crop land. Crop land and bare land are LULC types associated with urban agriculture in Eldoret city. This is so because in some instances, the parcels of land are not planted while others are planted late and at the time of image acquisition, the plots are depicted as bare land.

The population of Eldoret has been growing fast from 197,449 people in 1999 (Republic of Kenya, 1999) to 475,716 people in 2019 (Republic of Kenya, 2019). On the other hand, forest land and bare land have been reducing from 3,757 Ha and 8,621 Ha in 2003 to 1,294 Ha and 4,171 Ha in 2024 respectively. This could be attributed to people clearing forests and utilizing empty spaces for settlement and agriculture as shown in the increase of built up and crop land between the years 2003 and 2024. This is also in line with the argument in NCC, 2015 that urban agriculture is neither a relic of the past that will fade away (urban agriculture increases when the city grows) nor brought to the city by rural immigrants that will lose their rural habits over time. It is an integral part of the urban system. A study by Odhiambo et al. (2024) in the Chepkoilel/Sergoit river catchment area of Eldoret city reveal that between the years 1995 and 2020, there was a 69% forest cover loss, 44% increase in farmland and 261% increase in settlement area, results consistent with findings in this study.

The pattern depicted by the LULC classes is of importance given that development in urban areas are guided by urban development plans. From the classified images, it is evident that development is linear and taking place along transport corridors. The other LULC types are distributed throughout the city.

Table 5 shows the change matrix between the years 2003 and 2024. Between this period, a lot of forest and bare land was lost to crop land at 2,255 Ha and 4,618 Ha respectively. The increase in built up land was majorly from bare land at 2,886 Ha. These results paint a picture of an urban populace that is actively involved in urban agriculture within a city that is rapidly developing. It is necessary that a policy on urban agriculture in Eldoret city is crafted so as to have a framework within which this important land use can operate.

5. Conclusions

"What are the dominant land use types associated with urban agriculture and how have they changed over time in Eldoret city?" This study aimed at answering this research question. Four LULC types were identified from classification of three images for 2003, 2015 and 2024 with crop land and bare land as the dominant land use types associated with urban agriculture. The other classes were forest land and built up land. Between the year 2003 and 2024, bare land reduced from 8,621 Ha to 4,171 Ha while crop land increased from 1,989 Ha to 7,929 Ha.

Crop land was the focus of this research as an urban agriculture activity. Other activities associated with urban agriculture could not be identified from the satellite imagery. Furthermore, the 30m spatial resolution of the Landsat images analysed and the pixel-based classification method employed could not distinguish finer details and differentiate plant species. As revealed from the results, Eldoret city is growing at a high rate and the population is actively involved in urban agriculture. It is anticipated that this research will form a starting point from which the dynamics of urban agriculture within the city can be understood in order to guide in the formulation of relevant policies and instruments to guide this important land use that is an integral part of the urban system.

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