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Spatial Temporal Trends of Land Use Land Cover and its Relation with Milk Production in Baringo County, Kenya

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Abstract

Land degradation caused by land use land cover (LULC) changes has become a great threat to agriculture, impacting rural livelihoods and food security. Dairy farming is a key livelihood and income source for households in Eldama Ravine and Mogotio Sub-counties, Baringo County. The relationship between LULC changes and dairy production has remained poorly understood. The objective of the study was to assess the relationship between LULC changes and milk yield in the study area. Satellite images from 2013 to 2025 were sourced via the Google Earth Engine and analyzed using supervised classification and change detection. Milk yield records from 2013 to 2025 were obtained from the dairy farmers cooperative societies in the study area. Focused Group Discussions and Key Informant Interviews were the qualitative data collection methods. Data was analyzed using both descriptive and inferential statistics. In Mogotio Ward, there were expansions in Built-up area (20.45 km²), Cropland (26.30km²), Water (26.77km²) and reductions in Forest (52.62 km²), Bareland (11.16 km²) and Grassland (9.73 km²). In Mumberes Ward, there were expansions in Forest (17.08 km²), Cropland (5.448 km²), Built-up (4.29 km²), Bareland (1.670 km²) and reductions in Water (8.71 km²) and Grassland (19.77 km²). Milk yield data revealed an increasing trend in Mumberes and a fairly constant trend in Mogotio. In Mogotio Ward, LULC variables did not have any significant association with milk yields ($p > 0.05$). In Mumberes ward, there was a strong positive correlation with built-up ($r = 0.813$, $p = 0.001$), cropland ($r = 0.781$, $p = 0.001$), forest ($r = 0.791$, $p = 0.001$) and a strong negative relationship with grassland ($r = -0.812$, $p = 0.002$). The study reveals that LULC changes are correlated with milk production. The study recommends intensification of dairy farming systems to increase milk production in the face of LULC constraints.

Keywords: Land Use Land Cover Changes, Dairy Farming, Milk Yields, Google Earth Engine, Baringo County

INTRODUCTION

Land use land cover (LULC) changes is driven by human activities and it drives changes in the environment that limit the accessibility of services and products for livestock and humans worldwide (Gessese, 2018; Raza *et al.*, 2024). LULC changes have resulted to habitat loss, soil deterioration, water scarcity thus lowering the value of ecological ecosystems. Additionally, LULC changes has negatively impacted rural livelihoods that rely on the environment for socioeconomic well-being (Baffour-Ata *et al.*, 2021).

Kenya is one of Sub-Saharan Africa's biggest producers of dairy products with an estimated herd of over 3.5 million exotic dairy cattle, 2.97 million dairy camels, 270,400 dairy goats and 14.1 million native cattle (Ministry of Investments, Trade and Industry, 2023). An estimated 5.7 billion liters of milk are produced annually, with the dairy industry contributing 12% of the agricultural gross domestic product (GDP), 3% to 4% of the national GDP and supporting almost 1.8 million rural households (Ministry of Investments, Trade and Industry, 2023).

In dairy farming systems, LULC relate with milk production through reduction of fodder, alteration of water availability and reduction of pasturelands. In the Atlantic forest areas in Brazil, conversion of pasturelands to forest areas reduced pasture for grazing dairy cattle, resulting to low milk production (Silveira *et al.*, 2022). Conversion of grasslands, wetlands and shrublands to cropland and built-up regions have reduced the availability of grazing feed resources in Africa, resulting to decline in milk yields (Gessese, 2018; Habte *et al.*, 2020). Land fragmentation has impacted dairy farming in Kiambu County, Kenya, by reduction of land for growing pasture (Wanjala, 2021). Conversion of grasslands to farmlands causes soil erosion thus lowering soil fertility, pasture yields and consequently milk production (Kogo *et al.*, 2020).

The reliance on natural forage and rain-fed pastures for grazing makes milk production extremely vulnerable to changes in rainfall patterns (Kirui, 2022). Agro-pastoral systems yield less milk compared to mixed crop-livestock farms, due to inefficient land management practices (Notenbaert *et al.*, 2020). However, intensification of dairy farming systems and adoption of sustainable land management practices including fodder production, preservation, use of concentrates and improved breeds can increase milk production despite LULC dynamics and land constraints (Bosire *et al.*, 2016; Brandt *et al.*, 2018).

Successful dairy farming and increased milk production is dependent on enough drinking water according to Miglierina *et al.* (2018), enough pastures for grazing as reported by Practical Dairy Training Centre, (2024) and good land conditions and land size (Otieno *et al.*, 2020). Scarcity of land caused by growing human and cattle populations, urbanization, pastureland conversion to cropland is the main restriction on dairy farming (Otieno and Gicheha, 2021).

LULC change detection is crucial for understanding how landscape dynamics relate with dairy production which informs decision on sustainable land management (SLM) practices (Olweny, 2022; Teka *et al.*, 2018; Winkler *et al.*, 2021; Zafar *et al.*, 2021). There is evidence of the potential of livestock farming as an opportunistic business venture Baringo in that may be pursued with great success, and appropriate connections can give young farmers a path to success in such an economy (Yatich, 2024).

Previous studies in Baringo County have looked at the dynamics of LULC changes (Boitt *et al.*, 2022; Greiner *et al.*, 2021; Jebiwott *et al.*, 2019; Kipkulei *et al.*, 2025; Ochuka *et al.*, 2019), but there are no studies that have linked spatiotemporal LULC trends and milk yields dynamics despite Baringo County being a high potential area for dairy farming. Additionally, these studies on LULC have focused on other Sub-counties in Baringo, but there is a lack of study in Mogotio and Eldama Ravine. It is against this background that this study was conducted in order to (i) Determine the trends of LULC changes between 2013 to 2025 in Mumberes ward in Eldama Ravine Sub-county and Mogotio ward in Mogotio Sub-county and (ii) To assess the relationship between the LULC changes and milk yield in the study area.

We hypothesized that grassland cover would be positively associated with milk yields as it represents increased forage for dairy cows.

Secondly, an increase in built-up, driven by population growth at the expense of other classes including grassland, was expected to be negatively associated with milk yields as it reduces the availability of grazing land. Similarly, an increase in cropland was hypothesized to be negatively associated with milk yields, as it reduces the land available for grazing dairy cattle. We expected that increase in bareland would be negatively associated with milk yield as it reflects reduced vegetation production caused by land degradation. Additionally, an increase in water cover was expected to be positively associated with milk yields due to improved water availability for livestock and pasture production. Lastly, we hypothesized that an increase in forest cover would be positively associated with milk yields due to its role in microclimate regulation which supports pasture production.

METHODS

Study Area

The study was conducted in two regions of Baringo County. Mogotio Ward located in Mogotio Sub-County Figure 1, at latitude and longitude 0.02°S, 35.97°E. The ward has a total of 41,261 people, out of which 20,882 are male and 20,378 are female.

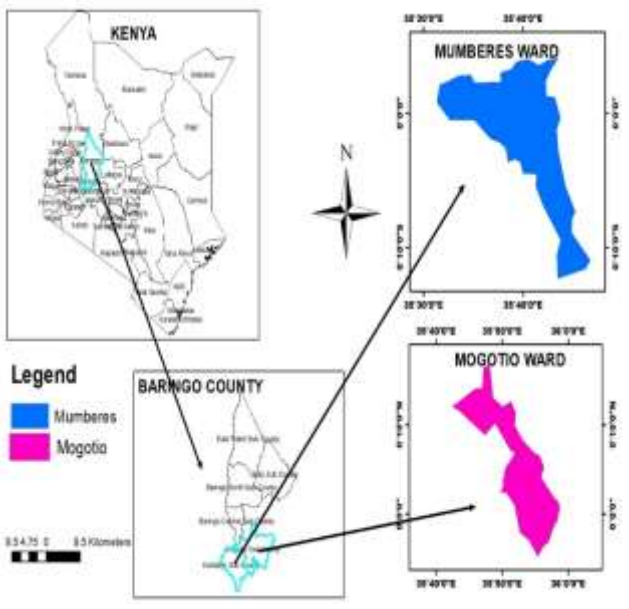


Figure 1: Map of Mogotio and Mumberes wards
Source: Author modified from Environmental Systems Research Institute (ESRI) website

The total number of households is 8,786 and it covers an area of 564.1 square kilometers (Kenya National Bureau of Statistics, 2019). The second study area was Mumberes ward located along the C55 (Makutano-Ravine-Kampi Ya Moto) Route in Eldama Ravine Sub-County in Baringo County, Kenya

Figure **1**. It is located at geographical coordinates, latitude -0.01168 and longitude, 35.60793. Mumberes ward has a total of 13,233 people, out of which 6,620 are men and 6,613 are female. It has a total of 3,091 households and a total land area of 306 square kilometers (Kenya National Bureau of Statistics, 2019).

Data Acquisition Method and Data Sources

LULC Data: LULC change was detected using satellite data comprised of multispectral data that was obtained from Landsat 8 (Operational Land Imager/Thermal Infrared Sensor, OLI/TIRS) for 2013 and Sentinel-2 for 2019 and 2025. The Google Earth Engine (GEE) platform provided access to the surface reflectance products of these sensors, which were atmospheric and radiometrically corrected. Through a cloud computing platform, the GEE platform stores temporal satellite data series from several sensors. These data may be filtered and accessed through an online interactive development environment and application programming interface (API) (Amani *et al.*, 2020). The satellite images were processed and the final LULCC product was exported to Google drive for download and subsequent analysis. It has been shown that using automated processes in GEE can greatly improve satellite image processing while also making the best use of available storage space (Gorelick *et al.*, 2017). Reference/ground truth data for verifying the classification results and validating the LULCC categories of the study areas was conducted using a hand-held GPS device. This helped in land cover classification to improve accuracy.

Milk Yield Data: The milk yield data used in this study represent total annual milk deliveries in liters recorded at the cooperative level. Data on number of milking cows, herd size, individual dairy cow productivity and cooperative membership from 2013 to 2025 were not available. Milk yield in Mogotio was obtained from Mogotio Dairy Farmers Cooperative Society and milk yield in Mumberes was obtained from Mumberes Dairy Farmers Cooperative Society. These two

cooperatives were purposively chosen as they are the main cooperatives in the study area.

Qualitative Data: Key informant interviews (KII) and focused group discussions (FGDs) were conducted to gain deep insights into the trends of LULC changes and milk yields in both study areas. The KII was conducted with individuals who had expertise on land use dynamics and dairy farming and who had resided in the area for more than 20 years. They were purposively selected and they included, a representative from Agricultural extension office, veterinary officers, dairy co-operative extension officer, the managers for the dairy cooperative societies, the village elder and the Chief in both study areas. Each KII lasted for 45 minutes. FGDs consisted of eight members in each ward. The participants of the FGD were identified with the assistance of local leaders. Only dairy farmers with more than 20 years-experience in dairy farming and who resided in the area for more than 20 years were selected for the study.

Data Analysis

Classification of the Satellite Images: Surface reflectance format was used to obtain the Landsat images. The cloud cover threshold of the three satellite images was set to less than 10% during acquisition and filtering procedure. The selected images were taken within the same season of the year, between March and August to eliminate uncertainties and also due to low cloud cover.

Random forest (RF) technique created by (Breiman, 2001) was used to do the LULC change classification on GEE. Random Forest is based on the bagging and ID3 principles (Kulkarni & Lowe, 2016). The number of trees (ntree) and the variable number (mtry), which impact the accuracy of the land cover classification, are the two very important parameters in the RF method classification (Ming *et al.*, 2016). Ming further suggests the RF algorithm because it is resilient, swiftly learning and uses bootstrap samples for random selection to avoid overfitting (Ming *et al.*, 2016).

This study analysed spatial properties from the sample training data using supervised classification. The classifier uses a random split of the training data to generate independent and unrelated decision trees (Pal, 2005). After that, each decision tree assesses the pixel's potential class. The number of decision trees constructed (ntrees) and the number of predictors considered at each tree fork (mtry) are the parameters needed for the RF method. 'e.Classifier.smile' function was used to implement the RF classification since it is inbuilt within the GEE platform. The green, blue, near-infrared and red bands were used as inputs for the classification procedure.

A total of 150 training samples per class were used for each LULC category. 2025 LULC image was classified using GPS points, while 2013 and 2019 were classified using high resolution Google Earth Images, County land use plans and historical information on LULC that was provided by the local residents. The local residents who had lived in the area for more than 20 years provided these information on LULC types (Asante-Yeboah *et al.*, 2022). The training datasets were separated in the ratio of 70% training and 30% validation samples using randomization approach in GEE. Landsat 8 with a spatial resolution of 30 m was used for 2013 as it was the most reliable dataset for 2013. Landsat 7 could have been used but it had data gaps due to failure of the Scan Line Corrector (SLC) which could have resulted to lower classification accuracy. Sentinel-2 was used for 2019 and 2025 due to its higher spatial resolution and improved spectral capabilities. Sentinel-2 was launched in 2015 therefore it could not be used for 2013 analysis. Both Sentinel-2 and Landsat 8 imageries were resampled to a common spatial resolution of 30m prior to classification to ensure consistency and comparability.

Cloud masking of the satellite images was applied using the QA_PIXEL band for landsat imagery and the QA60 band for Sentinel-2 in order to reduce atmospheric and cloud contamination. The ntree was set at 500, while the square root of the number of overall variables was used as the mtry parameter. Post classification smoothing was not applied in order to preserve spatial details. Higher classification training was ensured using robust training and validation procedure.

Accuracy Assessment and Change Detection: Accuracy evaluation procedure was enhanced by the ground truthing data that was digitalized using topographical maps and past land use information that dairy farmers provided. Whereas the user accuracy (Eq. (2)) indicates how frequently the

class in the classification map will be present on the ground, the producer accuracy (Eq. (1)) shows how frequently actual features in the study area are accurately displayed on the classification map. The percentage of correctly mapped class types is provided by the overall accuracy (Eq. (3)), which indicates how closely the classified map matches the real ground features. When the classification accurately matches real ground features, the overall accuracy should be closer to 1. The performance of the actual classification utilizing the reference data is shown by the kappa coefficient (Eq. (4)) in comparison to an agreement predicted by chance or by randomly allocating values. According to Congalton (1991), a classification that is near to 1 is superior to a random class assignment.

$$\text{Producer accuracy} = \frac{X_{ig}}{\text{R}} * 100 \quad \text{(1)}$$

$$\text{User accuracy} = \frac{X_{ic}}{\text{P}} * 100 \quad \text{(2)}$$

$$\text{Overall accuracy} = \frac{X_{ii}}{N} * 100 \quad \text{(3)}$$

$$\text{Kappa coefficient} = \frac{\text{N}\sum_{\text{i=1}}^{\text{r}} X_{ii} - \sum_{\text{i=1}}^{\text{r}} (X_{ic} * X_{ig})}{\text{C}^2 - \sum_{\text{i=1}}^{\text{r}} (X_{ic} * X_{ig})} \quad \text{(4)}$$

where each class's total number of points that match the classified map is denoted by P, while the reference class category's total number of points is denoted by R., C is the total number of pixels that have been classified correctly, and N is the total number of samples. Xic shows how many points the user successfully classified in each class. The sum of the accurate classifications for samples is denoted by Xii, and the total number of expected correct classifications for samples is denoted by Xic.

Patterns and Trends of LULC: Subsequent analysis and post-classification procedures, such as change detection, were used to determine LULC trends and dynamics. ArcGIS and R statistical software were used to implement the post-classification analysis. To visualize the patterns and trends of LULC, maps and graphs were used.

Milk Yield Analysis: Annual milk yield in liters was computed per ward using linear regression analysis, from 2013 to 2025.

Qualitative Data Analysis: Qualitative data was analysed using thematic analysis. Audio recordings were transcribed verbatim and reviewed for accuracy. The transcripts were then coded to identify recurring patterns. The findings obtained were used to discuss and triangulate the quantitative results on LULC changes and milk yield trends.

Relationship between Land Use Land Cover and Milk Yields: Pearson correlation analysis test was used to assess the relationship between LULC changes and milk yields. The annual milk yields data from 2013 to 2025 was correlated with interpolated LULC variables across the same time period, from 2013 to 2025. These values were used as unit of analysis and resulted to a sample size of n = 26 observations.

Ethical Consideration

Egerton University's Institutional Scientific and Review Committee provided ethical approval of the study instruments prior to commencing data collection [Approval No: EUISERC/APP/503/2025]. A research permit was obtained from the National Commission for Science, Technology, and Innovation (NACOSTI) [License No: NACOSTI/P/25/4177546], and finally, additional permits were sought from the local authorities in Baringo County and the managers for the dairy co-operatives. The respondents' identities were kept private and confidential.

RESULTS

Accuracy Assessment

The Producer, User and Overall accuracies and kappa coefficient for the land cover classes for both study areas were determined. In 2013, the producer and user accuracies for Mumberes ranged from 80% to 100%. In 2019, they ranged from 75% to 100%, while in 2025, they ranged from 64% to 100% (Table 1), demonstrating a satisfactory level of classification reliability across all the study years. In addition, the Producer and User accuracies for all the classes in Mogotio ward was also calculated and it ranged 76% to 98% in 2013, 78% to 100% in 2019, and 75% to 95% in 2025 Table 2. These results show that the classification for all years was generally reliable, with strong agreement between the classified and reference data across most land cover classes.

Table 1: Mumberes Ward Classification Accuracy for 2013, 2019 and 2025

Mumberes	2013		2019		2025	
Land Cover Class	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**
Forest	100	98	100	100	100	97
Water	100	94	100	100	82	100
Grassland	95	97	93	97	83	95
Cropland	100	89	97	81	82	70
Built-up	85	93	88	95	90	84
Bareland	80	80	25	75	41	64
Overall Accuracy	**95**		**92**		**88**	
Kappa Coefficient	**94**		**88**		**81**	

Table 2: Mogotio Ward Classification Accuracy for 2013, 2019 and 2025

Mogotio	2013		2019		2025	
Land Cover Class	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (%)**	**User Accuracy (%)**
Forest	95	89	90	93	81	76
Water	98	97	100	100	88	86
Grassland	95	90	85	78	94	80
Cropland	86	91	95	85	88	95
Built-up	76	94	81	88	80	90
Bareland	96	94	81	87	75	86
Overall Accuracy	**92**		**86**		**85**	
Kappa Coefficient	**91**		**84**		**81**	

For Mumberes ward the Kappa coefficients were 94%, 88%, and 81%, while the corresponding overall accuracies were 95%, 92%, and 88%, for 2013, 2019 and 2025 respectively (Table 1). In Mogotio ward, the kappa coefficient was 91%, 84% and 81% for 2013, 2019 and 2025 respectively and overall accuracy was 92%, 86% and 85% for 2013, 2019 and 2025, respectively (Table 2).

Land Use and Land Cover Distribution

Supervised classification using random forest algorithm revealed six land cover classes for years 2013, 2019 and 2025 for both study areas. The land cover classes included Bareland, Built-up, Cropland, Forest, Grassland and Water. Figure 1 shows the trends in LULC change for Mogotio while Figure 2 shows trends in LULC change for Mumberes.

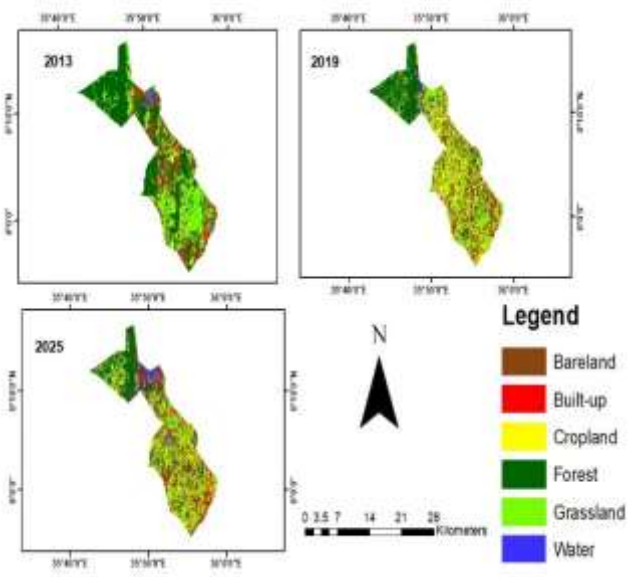


Figure 1: Mogotio LULC Maps from 2013 to 2025

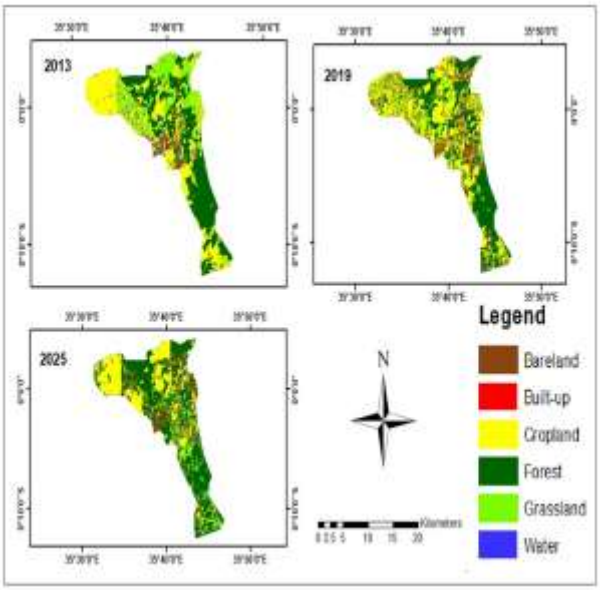


Figure 2: Mumberes LULC Maps from 2013 to 2025

LULC Area Statistics

The area of the LULC classes statistics is summarised in Table 3 and Table 4 below, for the two study areas. Forest was the dominant land cover in Mogotio while water bodies had the lowest coverage as depicted in Table 3. In Mumberes, forest cover dominated the area, while water and built up had the lowest coverage as depicted in Table 4.

Change Detection

The results in Table 5 indicate that over the full period from 2013 to 2025, forest and grassland areas decreased steadily, while cropland, built-up areas, and water bodies expanded considerably. This indicates that agricultural expansion, urban growth, and water body increase were the main land cover changes in Mogotio Ward during this period.

Table 6 shows that over the full period from 2013 to 2025, forest, cropland, and built-up areas increased, while grassland and water bodies reduced greatly. This shows that Mumberes Ward experienced major land cover changes likely linked to farming expansion, settlement growth, and vegetation recovery.

Annual Milk Yield Trends in Mogotio and Mumberes Ward

Linear regression analysis showed contrasting trends in milk production between the two wards. Separate regressions were fitted for each ward to account for ward-specific trends. These results also reflect total milk production and not productivity per cow or per hectare. In Mumberes, the baseline milk yield was 2,805,648 litres, with an annual increase of approximately 124,867 litres. The regression equation is as follows:

Milk = 2,805,648 + 124,867 x Year_Centred

With a sample size of n =13 years (2013-2025), Mumberes Ward showed a statistically significant trend ($p = 0.001$, $R^2 = 0.62$ and Adjusted $R^2 = 0.58$), revealing a substantial increase in milk production over the study period.

In Mogotio Ward, the baseline milk yield was 1,395,643 litres, with a slight annual increase of approximately 3,115 litres. The regression equation is as follows:

Milk = 1,395,643 + 3,115 x Year_Centred

With a sample size of n =13 years (2013-2025), the trend in Mogotio Ward is however not statistically significant ($p = 0.92$, $R^2 = 0.001$ and Adjusted $R^2 = -0.09$) revealing that milk production in is fairly constant from 2013 to 2025.

Relationship between LULC Changes and Milk Yields

The annual milk yields data from 2013 to 2025 was correlated with interpolated LULC variables across the same time period, from 2013 to 2025 as depicted in Table 7. The correlation was based on a small number of observations n = 26, which may limit statistical reliability. These findings are therefore exploratory and do not imply causation.

In Mogotio Ward, LULC variables did not have any significant association with milk yields. All the correlations were weak and non-significant ($p > 0.05$). In Mumberes ward, several LULC variables were significantly correlated with milk yields. There was a strong positive correlation with built-up (r= 0.813, p = 0.001), cropland (r = 0.781, $p = 0.001$), forest (r = 0.791, $p = 0.001$) and a strong negative relationship with grassland (r = -0.812, $p = 0.002$).

Table 3: Land cover class Areas for Mogotio Ward, Baringo County

Class	2013 Area km2	2013 %	2019 Area km2	2019 %	2025 Area km2	2025 %
Forest	151.81	45.09	130.18	38.66	99.18	29.46
Water	8.210	2.44	2.510	0.77	34.99	10.39
Grassland	87.03	25.85	81.99	24.35	77.30	22.96
Cropland	16.53	4.91	53.19	15.80	42.82	12.72
Built-up	14.92	4.43	22.44	6.67	35.37	10.51
Bareland	58.18	17.28	46.28	13.75	47.02	13.97
Total	**336.69**	**100**	**336.69**	**100**	**336.69**	**100**

Table 4: Land cover class Areas for Mumberes Ward, Baringo County

Class	2013 Area km2	2013 %	2019 Area km2	2019%	2025 Area km2	2025 %
Forest	128.03	45.32	135.95	48.12	145.11	51.37
Water	9.02	3.19	1.02	0.36	0.32	0.11
Grassland	40.29	14.26	36.77	13.02	20.52	7.26
Cropland	82.64	29.25	80.88	28.63	88.08	31.18
Built-up	4.27	1.51	4.94	1.74	8.56	3.03
Bareland	18.24	6.46	22.92	8.12	19.91	7.05
Total	**282.48**	**100**	**282.48**	**100**	**282.48**	**100**

Table 5: LULC Change Detection Table for Mogotio

LULC Classes	2013-2019			2019-2025			2013-2025		
	Km²	%	Rate (Km² /yr)	Km²	%	Rate (Km² /yr)	Km²	%	Rate (Km² /yr)
Forest	-21.63	-14.25	-3.61	-30.99	-23.81	-5.17	-52.62	-34.67	-4.39
Water	-5.61	-68.38	-0.94	32.39	1247.7	5.4	26.77	326.18	2.23
Grassland	-5.04	-5.79	-0.84	-4.70	-5.72	-0.78	-9.73	-11.18	-0.81
Cropland	36.66	221.86	6.11	-10.37	-19.49	-1.79	26.30	159.17	2.19
Built-up	7.51	50.38	1.25	12.93	57.59	2.15	20.45	136.99	1.70
Bareland	-11.90	-20.45	-1.98	0.74	1.59	0.12	-11.16	-19.19	-0.93

Table 6: LULC Change Detection Table for Mumberes

LULC Classes	2013-2019			2019-2025			2013-2025		
	Km²	%	Rate (Km² /yr)	Area Km²	%	Rate (Km² /yr)	Km²	%	Rate (Km² /yr)
Forest	7.92	6.19	1.32	9.16	6.74	1.53	17.08	13.34	1.42
Water	-8.00	-88.65	-1.33	-0.71	-69.02	-0.12	-8.71	-96.48	-0.73
Grassland	-3.52	-8.73	-0.59	-16.25	-44.21	-2.71	-19.77	-49.08	-1.65
Cropland	-1.76	-2.13	-0.29	7.20	8.90	1.20	5.448	6.58	0.45
Built-up	0.67	15.69	0.11	3.62	73.35	0.60	4.29	100.53	0.36
Bareland	4.69	25.71	0.78	-3.02	-13.17	-0.50	1.670	9.16	0.14

Table 7: Pearson correlation analysis between LULC changes and milk yields changes in the study areas (n = 26)

Dependent variable	Independent variables	Mogotio r	Mogotio *p*	Mumberes r	Mumberes *P*
Milk yields	Forest	-0.028	0.928	0.791	0.001*
	Cropland	0.052	0.865	0.781	0.001*
	Grassland	-0.032	0.918	-0.812	0.002*
	Bareland	-0.047	0.879	0.225	0.459
	Built-up	0.026	0.932	0.813	0.001*
	Water	0.006	0.986	-0.692	0.009

** Correlation is significant at the 0.05 level.*

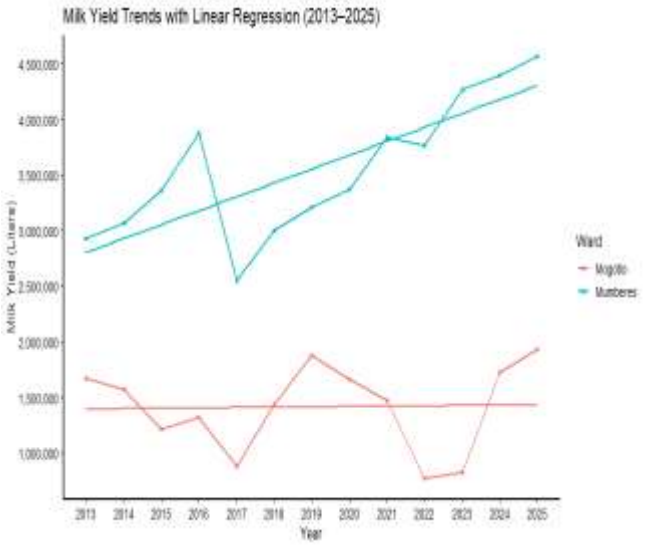


Figure 3: Annual milk yield trends in Mogotio and Mumberes ward from 2013 to 2025

DISCUSSION

Accuracy Assessment

Anderson (1976) states that an accuracy of 85% is required for a land cover categorisation to be considered reliable. Previous studies on LULC analysis also found an accuracy of 85 and above (Kipkulei, *et al.*, 2025; Obura *et al.*, 2025). Bareland class had lower producer accuracy (25% in 2019 and 41% in 2025) in Mumberes possibly due to confusion with built up class. Previous study on remote sensing have also highlighted low bareland accuracy due to spectral confusion with built-up area as the colour of their pixel might be nearly related (As-Syakur *et al.*, 2012; Haque & Uddin, 2025; He *et al.*, 2024; Ologunde *et al.*, 2025)**.**

Land Use Land Cover Change Trends

Vegetation and Pasture Dynamics: The decline in forest cover in Mogotio is as a result of deforestation for charcoal production which is highly practiced in the area. One key informant reported that "*the cost of charcoal has increased thus encouraging deforestation in the area*". FGD reported an increase in the sale of indigenous trees including '*emityot'* whose scientific name is *Olea europaea*, and '*Torokwee*' whose scientific name is *Juniperus procera*. KII reported that exotic trees such as *Pinus radiata* commonly known as '*paini'*, *Cupressus lusitanica* commonly known as '*Saipresit'* and *Grevillia robusta* commonly known as *'Graveliat'* are increasingly attacked by ants which discourages residents from planting such trees. Decline in forest cover in the study area is also attributed to conversion of forestlands to grasslands, especially the Boma Rhodes grass used for hay production and conversion to agricultural lands for the cultivation of tomatoes according to the KII and FGDs in the study area. Kimutai & Watanabe (2016) reported that Lembus forest cover decreased in Baringo County from 1985 to 2015. A study by Karaya *et al.*, (2020) in Njemps Flats in Baringo county also reported a decline in forest cover.

The increase in forest cover in Mumberes is as a result of afforestation by local residents, particularly the establishment of exotic timber species *Cupressus lusitanica* (cypress), *Eucalyptus saligna* (Eucalyptus) and *Juniperus procera* (cedar) which are viewed as a source of income, as reported by the FGD and KII. However, they reported that the indigenous trees in the area have increasingly declined. The KII reported that the Mumberes Dairy Cooperative Society located in the area issues tree seedlings to the residents at affordable prices thus encouraging afforestation. These findings are in line with Ochuka *et al.* (2019) who reported an increase in forest cover from 1988 to 2018 in Baringo County due to afforestation. These results are contrasting with a study on other parts of Baringo that indicate a decline of forest cover due to deforestation for charcoal production, firewood and timber for construction of buildings (Kipkulei *et al.*, 2025). A similar study in the Miombo woodlands of Tanzania from 1992 to 2022 indicated an initial decrease in forest cover from 1992 to 2006 followed by an increase in forest cover from 2006 to 2022. The author further explains that the increase was due to strategic conservation efforts including afforestation (Baltazary *et al.*, 2025).

The increase in forest cover in Mumberes and the decline in Mogotio are driven by local differences in land-use and institutional support for tree planting: Mumberes benefits from cooperative-led afforestation and residents planting exotic timber for income, whereas Mogotio experiences forest loss due to charcoal production, agricultural expansion, and pest attacks on exotic trees.

The reduction of grassland in Mogotio is due to increased settlements and population growth as reported by KII. Previous studies in different parts in Baringo revealed that grassland decreased from

1980 to 2019 thus supporting these findings (Boitt *et al.*, 2022; Karaya *et al.*, 2021). A study in the Ethiopians Lake Tana basin also reported an increase in grassland due to conversion to agricultural land (Obura *et al.*, 2025). A study in Malewa River basin similarly reported a decline in grassland by 19.2% due to increased population growth (Cheruiyot *et al.*, 2019). Similar global findings on LULC are reported by FAO and are attributed to conversion of pasturelands to agricultural lands (FAO, 2025).

The decrease in grassland in Mumberes is attributed to conversion to croplands as a result of agricultural expansion as reported by the FGD and KII. They reported that more farmers have resorted to sustainable agriculture. One key informant observed that "*grazing lands have decreased because more farmers are embracing fodder establishment such as the super nappier grass and only a few farmers who reside close to the forest are still grazing their cattle.*" These findings are supported by a related study by Ochuka *et al.* (2019). Similarly, a study in Nakuru County, an area with similar climatic conditions as Mumberes reported a decrease in grasslands from 2003 to 2023 (Cherotich *et al.*, 2025). A study in the Ethiopians Lake Tana basin also reported an decrease in grassland due to conversion to agricultural land (Obura *et al.*, 2025). Another study on LULC in Central Uganda reported a reduction in grassland due to conversion to farmlands (Kuule *et al.*, 2022).

Cropland Conversion and Dairy Trade-offs: The initial expansion of cropland in Mogotio was due to agricultural intensification and especially cultivation of tomatoes along river Molo as reported by FGDs with dairy farmers. The slight reduction from 2019 to 2025 was due to land sub-division and increased settlements. These findings on overall increase in cropland is supported by Mercy *et al.* (2025) in Moiben that show similar trend and a research in Malewa River basin in Kenya (Cheruiyot *et al.*, 2019). Global studies on cropland dynamics indicated an increase in cropland coverage in Africa and North America caused by agricultural intensification (Potapov *et al.*, 2022). The findings are in line with a report by FAO on the trends of LULC which states that cropland covers one third of global land area and it has expanded globally by 5% due to increased demand for food for the growing population (FAO, 2025). Another study by Liu *et al.* (2021) also reported increased cropland areas globally due to urban expansion.

The decline in cropland in Mumberes Ward from 2013 to 2019 was as a result of reduced cultivation due to unfavourable climatic conditions as reported by the KII and FGD. They further reported that cropland area increased from 2019 to 2025 as most farmers in the study area started to cultivate potatoes, cowpeas and vegetables due to favourable climatic conditions. Additionally, the increase is attributed to population growth which has in turn resulted to increased cultivation of lands in order to provide more food for sustaining the growing population in the area. These findings on overall increase in cropland are supported by similar studies in Baringo *(*Boitt *et al.*, 2022; Kipkulei *et al.*, 2025). Economic activities like agriculture and pastoralism are the main sources of income for households in Baringo (Baringo County, 2014). Additionally, the findings are supported by studies in other parts of Kenya (Rotich & Ojwang, 2021).

Settlement and Water Changes: KII in Mogotio reported that in 2013 river Molo had dried up due to over-abstraction of water for irrigation. Water pans have been established in the area thus resulting to increased water cover from 2019 to 2025. Water in Mogotio represent the open water sources including seasonal man-made water pans. The reason for the sharp increase is as a result of establishment of water pans in the area to alleviate water shortages, given that Mogotio is an ASAL area. A similar study on LULC changes in Baringo catchment found out similar variations in water cover in Baringo County (Ochuka *et al.*, 2019). Peer reviewed analysis report that several Kenyan Rift valley lakes experienced increases in water levels during the 2010s–2020s, driven primarily by increased rainfall and basin-scale hydrological change. These studies support the observation that increase in water area coverage over a few years is plausible in this region (Byrne *et al.*, 2024).

The KII and FGD in Mumberes revealed that water bodies have declined due to sedimentation resulting from unsustainable farming practices in the area, such as crop cultivation near the water sources, excessive abstraction of water for irrigation and livestock use, and deforestation of indigenous trees along the riparian zones. A study in China also

reported a decline of water levels in small water bodies due to agricultural intensification in Central and Eastern China (Shen *et al.*, 2025). A study in Pakistan reported reduced water levels due to conversion from vegetated areas to bareland and built-up areas resulting to reduced moisture levels and water stress (Khan & Chen, 2025).

The steady increase in Mogotio built-up reflects rapid settlement growth, infrastructural development as a result of population expansion within Mogotio Ward. This is consistent with national trends of rural urbanization (Kipkulei *et al.*, 2025; Rotich *et al.*, 2024; Sang *et al.*, 2022), regional trends (Masiza *et al.*, 2023; Obura *et al.*, 2025) and globally such as in a Bangladesh study by Haque & Uddin (2025) and Iraq study by Khwarahm (2021) due to increased population growth rate.

The increase in settlements in Mumberes is as a result of population expansion in the area as revealed by interviews with key informants and group discussions with lead farmers. This findings is supported by similar studies in the highlands of Kenya which indicated that built-up areas increased over the study period (Cherotich *et al.*, 2025; Kimtai *et al.*, 2023; Mbuba *et al.*, 2025). A study in Katimok forest reserve also revealed expansion of settlements (Jebiwott *et al.*, 2019). Similar studies in East Africa also indicate an increase in built-up areas (Kuule *et al.*, 2022; Obura *et al.*, 2025). Global studies including a study in Nigeria reported increased urban areas due to population growth (Ologunde *et al.*, 2025). Similar observation was reported in a study in Pakistan (Khan & Chen, 2025).

Bareland Dynamics: Interviews with key informants indicated that there was a reduction in bareland as a result of conversion to agricultural lands. According to them, the human population has increased over time thus everyone is making use of the available lands. An overall reduction in bareland from 2013 to 2025 (13.97%) was observed which is supported by a research in Baringo that involved LULC dynamics in the county's catchment (Ochuka *et al.*, 2019). The findings are further consistent with a study on LULC in Cherangany hills from 1985 to 2022 that reported a decline in bareland by 24.15% (Rotich *et al.*, 2024). A similar study in semi -arid areas of Makueni from 2000 to 2016 reported a decline in barelands due to conversion to grasslands (Cheruto *et al.*, 2016). A study on LULC trends in Morocco in two decades up to 2023 reported an decrease in bareland due to expansion of agriculture (Ben-Said *et al.*, 2025).

The rise in bareland in Mumberes from 2013 up to 2019 was possibly as a result of overgrazing according to KII and FGDs. Although an increase in bareland was observed, the trends are less reliable due to a lower producer accuracy. The subsequent reduction from 2019 to 2025 is attributed to increased population growth in the area as reported by KII and FGDs, which has in turn resulted to agricultural expansion in Mumberes. The overall decrease in bareland from 2013 to 2025 is supported by similar studies in Baringo (Ochuka *et al.*, 2019). Similar study in East Africa indicate a decline in bareland due to expansion of agricultural lands (Abera *et al.*, 2020). Similar study in Pakistan reported a decrease in bareland caused by expansion of cultivated lands (Ali *et al.*, 2025).

Annual Milk Yields in Mumberes and Mogotio Wards

These findings suggest that total annual milk production from 2013 to 2025 for Mumberes and Mogotio differ according to wards. The increasing trend in Mumberes is due to increased adoption of fodder preservation methods, superior cattle breeds and strong extension support services as suggested by the key informant interviews and focused group discussions. The relatively constant trends in Mogotio is due to low adoption of practices that increase total milk production such as fodder preservation, low adoption of improved cattle breeds and reduced pasture production due to reduced rainfall as suggested by the key informant interviews and focused group discussions.

Relationship between LULC Changes and Milk Yields

The results revealed that increase in croplands is associated with increase in milk yields in Mumberes Ward which was contrary to the study hypothesis. This is because dairy farmers in Mumberes Ward do not heavily rely on natural pastures for grazing their livestock which would be prone to seasonal fluctuations and reduction due to conversion to other land cover classes. The key informants' interviews reports stated that cultivation of supper nappier grass, cultivation of

maize for silage making and oats for cover cropping are the highly adopted fodder crops in Mumberes Ward which significantly increase milk production. Similar studies indicate that conversion of grazing lands to croplands for production of feeds with higher nutritional content increases milk production. A study in Nandi County on smallholder milk production found that fodder availability is associated with increased milk production (Kirui *et al.*, 2021). Similar findings on increased milk production due to cultivation of improved forages were reported in Tanzania (Nyawira *et al.*, 2025). A study in Colombia stated that converting a portion of farmland into pasture growth greatly increases milk production (Gonzalez Quintero *et al.*, 2024).

Positive associations between forests and milk yields was observed in Mumberes. The relationship supports our hypothesis. The increase is as a result of improved microclimate in the study area which may support productive livestock landscapes. The KII and FGDs suggested that dairy farmers in Mumberes only cultivate exotic tree species for sale and have not embraced cultivation of fodder trees. This is consistent with findings by Brandt *et al.* (2020) who reported that intensification of fodder systems preserves natural ecosystems including forest lands from degradation and is linked to increased milk production.

Strong negative associations between grasslands and milk yields was observed which contradicts the study hypothesis. The unexpected results are explained by dairy farmers shift from extensive grazing (free-range) to more intensive zero grazing systems and cultivation of fodder crops, reducing over reliance on natural pastures that are prone to seasonal fluctuations and also have low nutritional content. This is consistent with similar studies in Africa which reports that improved feeding methods are more productive than traditional pasture based systems (Smit *et al.*, 2021).

Strong positive relationship between built-up and milk yields was reported which contradicts the initial hypothesis. This may suggest that more built up areas in Mumberes may be associated with higher milk yields. This may be linked to improved infrastructure including roads, cooling plants, improved market access, dairy cooperative buildings which house extension officers who provide advisory services on modern dairy farming practices including fodder preservation methods, veterinary officers who offer treatment of dairy animals with improve their health and milk production. These findings are consistent with a study by Migose *et al.* (2018) and van der Lee *et al.* (2020) who reported that dairy systems that were closer to urban markets show higher productivity made possible by better access to inputs and services.

Bareland showed non-significant correlation with milk yields. This finding does not support the hypothesized negative relationship likely because bareland areas are neither used for grazing nor for production of fodder in Mumberes. Water was negatively associated with milk yields, also contrary to the initial hypothesized positive relationship. This is possibly due to the fact that dairy farmers rely on alternative water sources including shallow wells therefore the reduction in open water sources does not limit milk production.

In Mumberes Ward, the largest proportion of dairy farmers have adopted intensification systems where milk yield is enhanced by cropland expansion, improved infrastructure and ecosystem services from forested landscapes while over reliance on natural grasslands constraints productivity, which is why LULC is associated with milk yields. In Mogotio, dairy farmers have practiced extensive system, a reason as to why LULC do not show any correlation with milk yields. However, these relationships indicate associations rather that causal effects due to strong multicollinearity among LULC variables.

CONCLUSION

This study revealed distinct spatial variations in the relationship between LULC changes and milk yields in Baringo County. In Mogotio Ward, forest, bareland and grassland declined while cropland, built-up areas, and water bodies expanded, yet these changes showed no significant correlation with milk yields, which remained fairly constant. In contrast, Mumberes Ward experienced increases in forest, cropland, and built-up areas alongside reductions in bareland, grassland and water cover. Here, milk yields displayed a strong positive correlation with forest, cropland, and built-up areas, and a strong negative correlation with

grassland. Bareland and water had no significant correlation. These findings demonstrate that LULC changes correlate with milk production differently across wards, underscoring the need for localized and context- specific analysis.

The study recommends the State Department for Livestock, the County government and dairy cooperatives to promote integrated land management to reduce degradation and also encourage mixed farming whereby farmers can put aside portions of cropland to grow fodder crops which will contribute to increased milk production. Extension services should be conducted to advise farmers to adopt modern dairy farming practices without heavily relying on natural pastures that are prone to seasonal fluctuations, degradation and conversion to other land cover classes.

Credit Authorship Contribution Statement

Sarah M. Kabaya: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration, Funding acquisition. **George M. Ogendi:** Conceptualization, Writing - Review & Editing, Supervision, Project administration. **Oscar O. Donde:** Conceptualization, Writing - Review & Editing, Supervision, Project administration

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