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Assessment of Land Use and Land Cover Change Dynamics and Drivers in Mbagathi River Catchment in Kajiado County, Kenya

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Abstract

Land use and land cover change through human modifications has brought great changes at global, regional and local levels part of which poses a threat to human and environmental systems. Monitoring of these changes is necessary to ensure the sustainability of terrestrial ecosystems such as the Mbagathi River catchment. The study sought to determine the land use and land cover changes and drivers in the Mbagathi River catchment for the period 1990-2020. This was achieved by the classification of multitemporal Landsat imageries of 1990, 2000, 2010 and 2020 using the Google Earth Engine web platform. The study established four main land use/cover classes including forest, grassland, urban and bare ground. The results of the classification and analysis process established that forest cover reduced from 32% to 14%, grassland reduced from 53% to 30%, bare ground increased from 10% to 38% and urban land cover increased from 4% to 17%. This revealed that urban and bare ground land covers increased at the expense of forest and grassland covers. Multitemporal and spatial assessment of settlement observed that more settlements emerged around the key urban centres namely Kiserian, Ongata Rongai, Ngong, Mlolongo and Tuala. Further analysis within a 3 Km radius of the towns revealed that urban area increased by 11% and 19% for Tuala and Kiserian respectively while in Ongata Rongai and Ngong, the urban area increased by 20% and 23% respectively.

Subject Areas

Land Use and Land Cover Changes

Keywords

Land Use, Land Cover, Google Earth Engine

1. Introduction

Land cover (LC) refers to how the earth appears physically, which may include farmland, urban developments, shrubland, grassland, forests and bare or barren ground. LUC, which includes land modification from its initial usage to another and LC through land use (LU) management, has brought a great change in many regions globally with a major goal of meeting the basic essentials of human beings from the available naturally occurring resources (Meyer and Turner, 1992 [1]; Vitousek *et al.*, 1997 [2]). LC is affected by how the land is used mainly due to anthropogenic activities and LC changes may have an effect on LU. Despite limitations by conditions that are physical, different activities alter rural and urban land.

Growing human population, urban development, agriculture and environmental challenges have greatly contributed to detrimental changes in land use and land cover with major consequences on water and forest cover among other natural resources. Before the start of this millennium, more than a quarter of all forests had been cleared (Steffen *et al.*, 2002) [3]. In the year 2000, it was estimated that 28% of agricultural land resulted from forests. Even with the efforts to reduce the decline in forest cover, it is estimated that losses of more than 15 million hectares have been reported annually. By the end of the 1990s, Africa was estimated to have lost approximately 4.8% in forest cover (Masayi *et al.*, 2021) [4].

Kebrom Tekle and Hedlund (2000) [5] in a study in Kalu District, Southern Wello in Ethiopia observed that there were increased open areas and settlements resulting from anthropogenic activities which also contributed to the reduction of shrublands and forests. The majority of the LULC change studies have made a conclusion that unsustainable anthropogenic activities are the key threats to natural resources. In order to avert permanent and irreversible changes such as forest extinction and deterioration of water quality in the Mbagathi catchment, proper land use and land cover monitoring were necessary. This study focused on the Mbagathi River catchment with an aim of understanding the extents, magnitudes and dynamics of LULC changes so as to form bases for sustainable land use practices.

2. Materials and Methods

2.1. Site Description

The study was conducted on Mbagathi river catchment which covers Kandisi, Keraraponi, Kisembe, Mokoyeti, Mbagathi and Kiserian streams as major tributaries of the main river, (Krhoda, 2002) [6] forms part of the upper and wider Athi basin. It cuts across three counties namely; Kajiado, Nairobi and Machakos. It is situated between grid 240,000 m S - 985,000 E and 269,000 m S - 984,300 m E (WGS84-UTM37S) (**Figure 1**) and covers an area of 166 square kilometre. The catchment has an altitude ranging from 1493 m to 1883 m above sea level. It is sub-divided into three parts based on the topography: the upper part that has rolling topography, the middle part with moderate slopes comprising of urban settlements and the lower part with gentle slope to flatland.

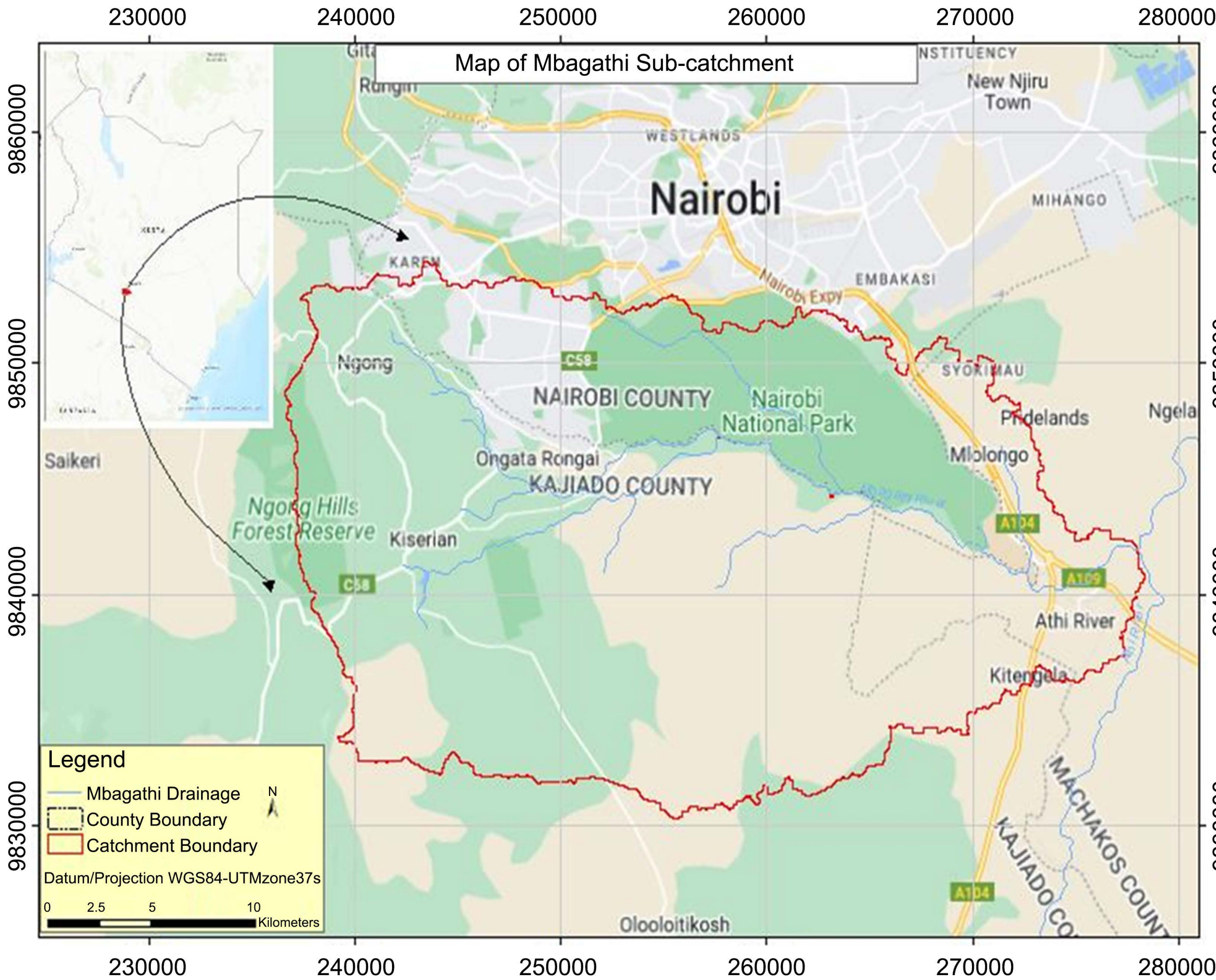

Figure 1. Map of Mbagathi catchment. Source: Author.

Mbagathi catchment falls in agro-climatic zones IV to V that is classified as semi-humid to semi-arid land. Rainfall in the catchment exhibits bimodal distribution. Long rains are experienced between mid-March and end of May while short rains occur between mid-October and end of December. Mean annual rainfall ranges between 800 - 1400 mm. A minimum temperature of 100˚C and maximum 240˚C is experienced in the catchment in July and January, respectively (Krhoda, 2002) [6].

The main river in the catchment is River Mbagathi which is currently seasonal. Its source is at Ngong hills at an altitude of 1980 meters and flows through Nairobi National Park before joining Stony Athi River. During wet seasons, Mbagathi streamflow is estimated to be 0.6 m^3/s while the river dries up during the dry seasons (Krhoda, 2002) [6]. The geology in the study area consists of basanites and Mbagathi trachytes. These rocks have fluviatile and lacustrine deposits that supply Nairobi Aquifer Suite with groundwater and have pores that permeate salts, which determine the mineral composition of groundwater. The catchment's middle and upper parts have Nitisols that are friable, dark brown and well drained clay while the downstream area has Vertisols that swell when wet and crack and shrink when dry.

Mbagathi River snakes through the edge of Nairobi, which borders Kajiado. It forms the boundary between these two counties. Its importance is paramount to the surrounding ecosystem as it passes through the Nairobi National Park, serving all the wild animals and many lives downstream. It has diversified LU types with the upstream area being used for subsistence farming while the area downstream is mostly used for commercial farming with growing of flowers and horticultural crops as the main activities. The area in middle of the study area has the Nairobi National Park. Domestic and urban settlements cover the rest of the area since the catchment is part of the larger Nairobi metropolitan.

2.2. Research Methodology

The theory of land use changes explores the conceptual framework and principles that underlie shifts in how land is utilized over time. This field of study delves into the various factors, drivers, and dynamics contributing to alterations in land utilization, including urbanization, agricultural expansion, and conservation initiatives. It encompasses a comprehensive understanding of the socio-economic, environmental, and policy-driven influences shaping patterns of land use change. This theoretical foundation aids in comprehending and predicting transformations across diverse landscapes. Land use and cover change (LUCC) involves the analysis of modifications to the Earth's surface. Changes in land use can impact land cover, and alterations in land cover can reciprocally influence land use. This interplay highlights the intricate relationship between human activities and the Earth's surface characteristics in the context of land use dynamics.

Quantitative research investigating the land use and land cover changes and drivers in Mbagathi catchment was applied. In the detection and monitoring of the LULC types, Landsat series remote sensing imageries were used owing to their longer period of earth observation monitoring and consistency. The study utilized Landsat 5 Enhanced Thematic Plus (ETM+) and Landsat 8. Landsat 5 (ETM+) had been in use from 1984 to 2012. Landsat 8 series imageries were available from year 2013 onwards. Towards this, Landsat 5 (ETM+) was applied in assessment of LULC images of 1990, 2000 and 2010. Landsat 8 was used in the analysis and determination of LULC types for year 2020.

2.2.1. Image Classification

The entire LULC change process started with retrieval and clipping of Landsat images of 1990, 2000, 2010 and 2020 using the imported Mbagathi River catchment shapefile. For a supervised classification to be carried out, training sites were developed for the four land cover types (forest, grassland, urban and bare ground). In order to ensure proper classification, a minimum of 60 training sites was ensured for each of the four classes. Classification of images was done using supervised classification method where maximum likelihood algorithm was applied with training sites developed for the various land cover types (Muriuki *et al.*, 2023) [7].

Maximum likelihood is a parametric classifier which is very popular in LULC classification and is extensively used across the world over time. This classic algorithm is chosen to compare the accuracy of other algorithms by many researchers. The classifier measures the Gaussian distribution of each of the spectral classes based on input data by using a covariance matrix. The covariance matrix is used to weight the gaps between spectral clusters and the image pixels (Karan and Samadder, 2018 [8]). Maximum likelihood calculates the probability distribution of classes which is related to Bayes' theorem. Class probability distributions in this method are assumed to have the form of multivariate normal models (Richards and Jia, 2006) [9].

Google earth images formed an important reference in the process of developing training sites and validation of classified image outputs. The validation process also involved ground truthing for the forest, grassland, urban and bare ground land covers.

2.2.2. Accuracy Assessment

To ensure that pixels were as accurately classified, an accuracy assessment was carried out. The assessment aimed at attaining the correct thresholds of: overall accuracy, producer's accuracy, user's accuracy and Kappa coefficient in an error matrix. Overall accuracy was computed by dividing the sum of all correct values in the diagonal of the error matrix by the total number of values in the matrix. The producer's accuracy was computed by dividing the correct number of pixels in the class by the total number of pixels in the reference data. On the other hand, Users' accuracy was computed by diving the correctly classified pixel values in a class by the total number of pixel values in the classification data. The Kappa coefficient which measures the agreement between the classified and reference map was computed based on the Equation (1) (Yesuph and Dagnew, 2019) [10].

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}\left(x_{i+}\right)\left(x_{+i}\right)}{N^2 - \sum_{i=1}^{r}\left(x_{i+}\right)\left(x_{+i}\right)} \tag{1}$$

where K is the Kappa coefficient, N is the total number of values, r is the rows in the matrix, i is the column, x_{ii} is the number of values in the row i and column i, x_{i+} is the total of row i, and x_{+i} is the total values in column i (Yesuph and Dagnew, 2019) [10]. After attaining acceptable users and producer's accuracies, the areas of each of the four land covers (forest, grassland, urban, bare ground) were computed and changes were assessed by imagery and area subtraction between two subsequent years.

2.2.3. Change Detection

LULC change detection followed a successful classification process. This was carried out in online GEE platform with the help of appropriate java codes and algorithms. This involved computation of the sum of pixels/area for each class in each of the 1990, 2000, 2010 and 2020 classified image. Resulting areas and corresponding percent coverage were tabulated and checked against errors from the sum totals. The temporal changes for each LULC were determined by subtracting the previous from subsequent areas/percent coverage (2000-1990, 2010-2000 and 2020-2010). Spatial changes were assessed by subtracting two classified images. The change detection results from GEE were validated using similar approach and ground truthing.

The GEE codes and algorithms were used in computing the areas under each LULC classification in the entire catchment. Change in land covers between two subsequent years was determined by subtraction of areas for the corresponding land covers. Further changes were assessed by computing the areas of the four LULC types within 3 Km radius from the epicentre of an urban development. This was aimed at detecting the changes due to the rapid urban development.

3. Results and Discussion

3.1. Determination of LULC in Mbagathi Catchment for the Period 1990-2020

3.1.1. Accuracy Assessment

A multivariate error matrix criterion was applied in the assessment of accuracy for the classification process. The accuracies included producer's accuracy (PA), user's accuracy (UA) and overall accuracy (OA) in addition to Kappa coefficient. Table 1 gives summary results of error matrix while the detailed individual confusion matrices are given in **Appendices**.

From the analysis of error matrix, the classifications gave overall accuracies of 92.16%, 90.77%, 92.0% and 80.67% with kappa coefficient values of 0.856, 0.776, 0.856 and 0.733 for 1990, 2000, 2010, and 2020 classifications respectively. The high values of overall accuracies and Kappa Coefficient indicated good classification and agreement between the classification and validation classes (Islami *et al.*, 2022) [11]. The results also revealed that forest cover largely covering Ngong Hill Forest, Ngong Lenana Forest, Dagoretti Forest, Oloolua forest and Nairobi National Park was the best classified among all the four LULC.

Table 1. Accuracy assessment for the classification process.

Land cover/use type	1990		2000		2010		2020	
	UA	PA	UA	PA	UA	PA	UA	PA
Forest	98.24	93.08	99.44	93.37	96.41	89.44	91.67	95.65
Bare-ground	68.42	61.90	56.52	58.43	91.86	98.91	72.00	67.00
Urban	85.48	56.99	61.54	99.80	91.89	75.14	87.76	93.48
Grassland	90.01	97.45	72.26	88.75	60.00	75.00	61.90	65.00
OA	92.16		90.77		92.00		80.67	
Kappa	0.8564		0.7761		0.8559		0.7313	

UA = User's Accuracy, PA = Producer's Accuracy and OA = Overall Accuracy.

3.1.2. LULC Changes in Mbagathi Catchment

Figure 2 shows the results of the percent area changes in the catchment between year 1990 and 2020. The total area for the catchment was estimated at approximately 510 Km^2. An analysis of percentage change revealed that forest and grass land cover decreased between 1990 and 2020 while urban and bare-ground cover increased over the same period. Forest cover decreased from 32.2% to 14.4% while grassland reduced from 53.5% to 30.2%. On the other hand, urban and bare ground land covers increased from 4.1% to 17.5% and 10.1% to 37.9% respectively.

The increase in urban LULC would be attributed to the growing population and low land prices within the satellite towns (Ongata Rongai, Kiserian, Ngong and Tuala). The rapid urban development could also be related to good roads and connectivity between the satellite towns along with closeness to Nairobi town which attracts high labour force but has minimal provision for residential services. Most of the people work in Nairobi but live in these satellite towns.

3.2. Drivers of LULC in the Catchment

3.2.1. Urban Development within the Catchment

Figure 3 shows the areas under urban development based on LULC analysis.

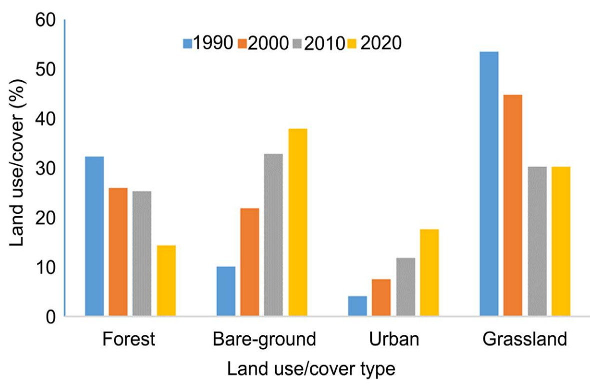

Figure 2. Percentage changes for the four LULC types. Source: Author (2023).

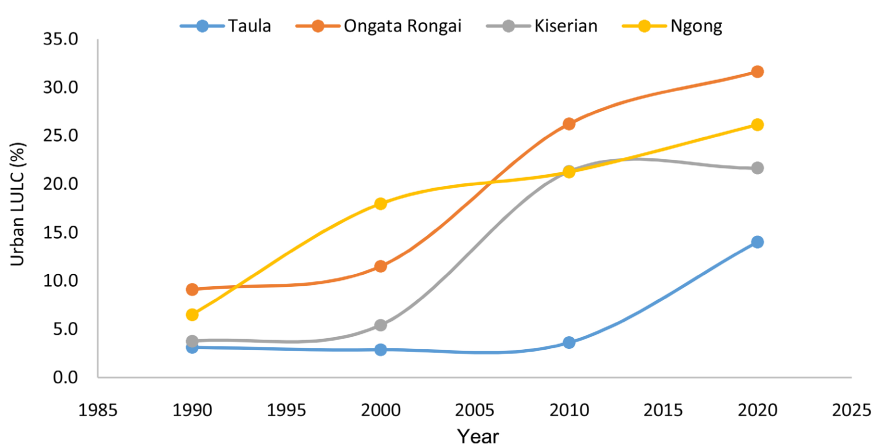

Figure 3. Urban development in the catchment.

The LULC analysis established that urban development was on the increase at each of the four selected sites namely Ongata Rongai, Kiserian, Ngong and Tuala alongside Langata suburbs. The urban area under 3 Km radius increased from as low as 3% in Kiserian and Taula to a high of 14% and 22% in Tuala and Kiserian respectively. In Ngong town, urban area under 3 Km radius increased from 6.5% to 26% while Ongata Rongai recorded an increase in urban area from 9% to 32% for the 3 km radius coverage. Shawul *et al.*, (2019) [12] reported similar findings in Awash basin where vegetation changes were highly occasioned by social developments and population growth. Additionally, Muriuki *et al.*, (2023) [7] also recorded related findings in Lagha-Bor catchment in Wajir County, Kenya.

Similar spatial and temporal patterns and trend were reflected in the GHSL multi-temporal built-up information layer derived from Landsat image collections GLS1975, GLS1990, GLS2000, and Landsat 8 2015. **Figure 4** shows the spatial-temporal patterns of built-up area. Visual inspection of the multi-temporal changes in built-up area re-affirmed changes occurred around Ongata Rongai, Kiserian, Ngong, Tuala and Mlolongo.

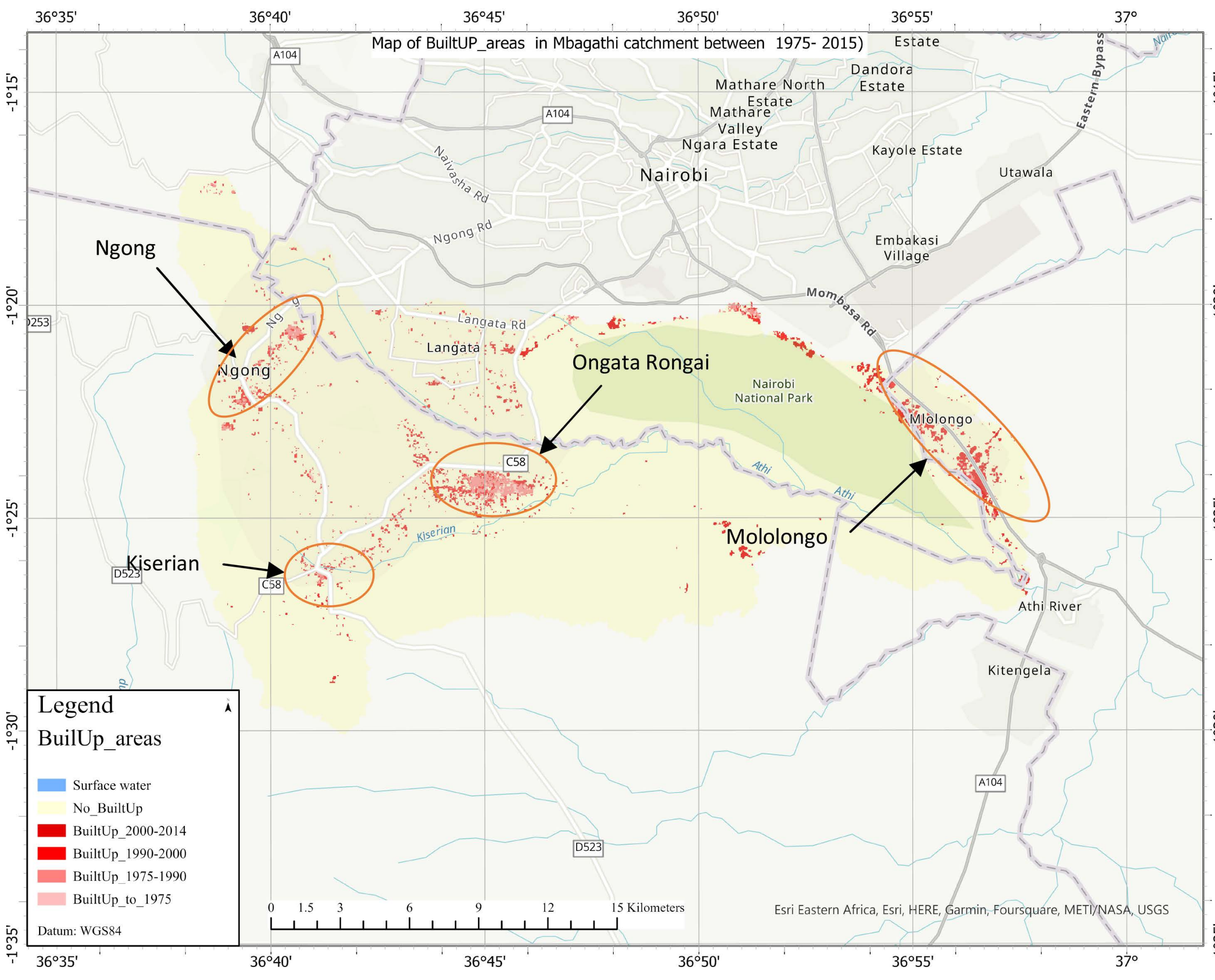

Figure 4. Rate of change in built-up area based on GHSL.

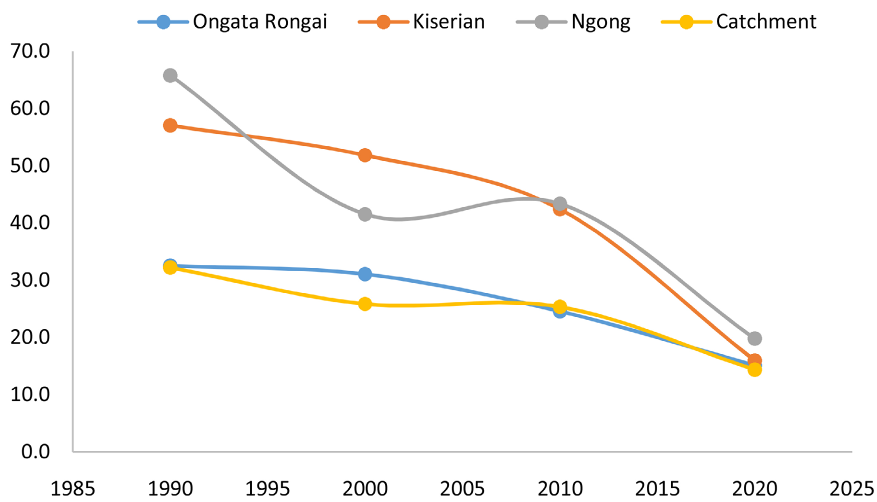

Figure 5. Reduction in forest cover within Mbagathi catchment.

3.2.2. Catchment Encroachment and Destruction

Results from the LULC change were used in assessing the level of catchment destruction within Mbagathi catchment. From Figure 5, the study observed that forest cover in the whole catchment reduced from 32.2% to 14.4%. Forest cover was also observed to reduce within the surroundings of Kiserian, Ngong and Ongata Rongai towns. The findings were confirmed by a forest officer at Ngong.

4. Recommendations

1) Owing to the rapid changes in the catchment, it is important that policymakers, practitioners and other stakeholders especially the three county governments take into consideration the land use change patterns in their action plans. The LULC changes were most likely associated with rapid urbanisation which in turn caused a rise in bare ground following clearance of forest and grass cover.

2) Based on the observed LULC changes in the catchment, we recommend the preparation of a land use plan map aimed at protecting the forest loss, and sprawling of bare ground and urban land uses.

Conflicts of Interest

The authors declare no conflicts of interest.

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Appendices: Confusion/Error Matrix

Table A1. Confusion matrix for land clover classification in year 1990.

Prediction	Dense shrubs	Bare ground	Sparse shrubs	Grassland	Sum	PA
Dense shrubs	303	45	72	19	439	69.02
Bare ground	19	1840	67	0	1926	95.53
Sparse shrubs	7	201	4542	36	4786	94.90
Grassland	0	10	18	252	280	90.00
Sum	329	2096	4699	307	7431	86.32
Users accuracy (%)	92.10	87.79	96.66	82.08		

Overall accuracy = 0.9335 and Kappa = 0.8710.

Table A2. Confusion matrix for land clover classification in year 2000.

Prediction	Dense shrubs	Bare ground	Sparse shrubs	Grassland	Sum	Producers accuracy (%)
Dense shrubs	281	45	110	3	439	64.01
Bare ground	1	1892	28	5	1926	98.23
Sparse shrubs	14	119	4619	34	4786	96.51
Grassland	14	6	54	206	280	73.57
Sum	310	2062	4811	248	7183	
Users accuracy (%)	90.65	91.76	96.01	83.06		

Overall accuracy = 94.17% and Kappa = 0.8852.

Table A3. Confusion matrix for land clover classification in year 2010.

Prediction	Dense shrubs	Bare ground	Sparse shrubs	Grassland	Sum	PA
Dense shrubs	347	20	70	2	439	79.04
Bare ground	5	1862	59	0	1926	96.68
Sparse shrubs	7	156	4506	117	4786	94.15
Grassland	2	15	35	228	280	81.43
Sum	361	2053	4670	347	7084	
UA	96.12	90.70	96.49	65.71		

Overall accuracy = 93.43% and Kappa = 0.8735.

Table A4. Confusion matrix for land clover classification in year 2020.

Prediction	Dense shrubs	Bare ground	Sparse Shrubs	Grassland	Sum	PA
Dense shrubs	285	40	107	7	439	64.92
Bare ground	2	1895	24	5	1926	98.39

Continued

Sparse Shrubs	29	175	4556	26	4786	95.19
Grassland	18	5	51	206	280	73.57
Sum	334	2115	4738	244	7431	
UA	85.33	89.6	96.16	84.43		

Overall accuracy = 93.45% and Kappa = 0.8714.