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Land use and land cover changes using Orfeo tool box open-source classifier within an urban river riparian reserve of Nairobi River, Kenya

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Urban riparian reserves are a vital source of ecosystem services for urban dwellers. These zones support urban food production, environmental quality, and are home to rich biodiversity of flora and fauna. Even though urban riparian zones offer many benefits to the urban dwellers, the same zones are under tremendous threats from increased anthropogenic activities resulting from Land Use Land Cover (LULC) changes. Nairobi River is a perfect example where urban pressure emanating from the expansion of Nairobi City has undergone immense LULC changes for the past 20 years. Therefore, remotely sensed data could be used to provide detailed information for changes caused by human activities especially within riverine environment using open-source classifiers such as Orfeo Tool Box (OTB). OTB is an essential open-source Remote Sensing tool in assessing the impacts of changes in urban LULC on the environment. High resolution aerial imagery epoched at 2000, 2010 and 2020 was used to detect and assess information about the predominant LULC, their changes over the years and their potential causes. Four LULC classes of bare-land, vegetation, built up and water were identified and analyzed over a 28 km stretch of Nairobi River segmented at the lower, middle and upper based on the topography. The lower section had the most drastic land use changes especially for the built up and vegetation which both increased steadily at 1 and 1.5% annually, respectively eating up both bare land and water which declined at the rate of 1.7 and 0.8% respectively. Likewise, the middle section was equally found to be invaded by double increase of both built up and vegetation at 2 and 3% for the same 20-year period. On the contrary, the upper section of the Nairobi River area was dominated by urban agriculture which covered almost 50% and increased further to 62% over the period registering a growth of approximately 12% translating into 1.2% per annum. This signifies rapid depletion of the riparian reserves which needed an enforcement mechanism and harmonization of various laws and policies for riparian conservation.

Key words: Remote sensing, land use land cover, random forest, urban rivers, digital terrain model, geographical information system.

INTRODUCTION

The root word “riparian‟ comes from the Latin word “ripa‟ which means bank (Webster Dictionary, 1976). This suggests that, riparian lands are found along the edge of water bodies including rivers, streams, lakes, wetlands,

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springs, and ponds. Karisa (2010) outlines a classical definition of riparian lands to mean woody vegetation cover associated only with surface flowing water. This definition identifies a riparian reserve to be the interface between land and a flowing surface water body. The 2030 Agenda for Sustainable Development comprises 17 Sustainable Development Goals (SDGs) and 169 targets aimed to eradicate hunger, poverty, and oppression globally. The agenda seeks to protect and preserve the planet through international cooperation. Specifically, SDGs 6 (Clean Water and Sanitation), 11 (Sustainable Cities and Communities), and 12 (Responsible Consumption) focus on conserving urban riparian zones (Agenda 2030). However, riparian zones worldwide, such as those along Japan's Shonai River and Miya River, face human-induced pressures, including the construction of recreation spaces and footpaths, leading to riparian degradation (Cao and Natuhara, 2019).

Both urban and rural riparian zones experience human impacts, with studies showing that 73% of Mexico's aquatic systems are degraded due to adjacent land use influences, resulting in riparian modification and vegetation loss, as observed along the Sabinal River in Chiapas, Mexico (Diaz-Pascacio et al., 2018).

In cities worldwide, including Nairobi, vegetated riparian corridors are highly valued for their ecological, environmental, social, economic, and aesthetic benefits, representing the last remnants of natural bushland (Findlay and Taylor, 2006).

These corridors provide essential physical benefits, including improved water quality through buffering against sediments and pollutants, and geomorphic stabilization of stream beds and banks (McBride and Booth, 2005; Schiff and Benoit, 2007; Sweeney et al., 2007).

The ecological benefits of riparian corridors include providing energy and organic matter inputs (Benson and Pearson, 1993; Keller and MacDonald, 1995; Tabacchi et al., 1998), maintaining local and regional biodiversity (Naiman et al., 1993; Pollock et al., 1998; Sabo et al., 2005; Ward et al., 2002), and facilitating organism movement. Additionally, urban riparian corridors offer significant aesthetic, recreational, and psychological benefits to city residents. However, riparian zones are highly sensitive to human impacts, as they comprise riverine vegetation and rivers threatened by settlement development (Koskey et al., 2021).

The expansion of human activities, including increasing demand for water resources and land-use changes in riparian zones, has a detrimental impact on riverine ecosystem processes (Koskey et al., 2021). Consequently, human settlement development has an adverse effect on riparian zones, prompting the need for land use/land cover change detection. This study aimed to inform stakeholders, including government agencies, riparian users, NGOs, CBOs, and private investors, to take appropriate measures to mitigate these impacts.

LITERATURE REVIEW

A study conducted by Al-Dousari et al. (2023) along the midstream of River Ciliwung in Jakarta, Indonesia, examined compliance with established riparian reserve guidelines as a strategy for flood control and water catchment conservation. The study classified riparian landscapes into developed and undeveloped areas, revealing that developments occupied 37% of the riparian reserves, leading to ecological damage and frequent flooding. Furthermore, a study by War et al. (2014) in the Narmada Basin, India, found that 80% of the riparian buffer zone along the River Chandni Nall was dominated by illegal agricultural practices, leading to degradation of the stream ecosystem. These findings are consistent with those of Olokeogun et al. (2020), who observed and confirmed through in-depth interviews that incompatible land uses, such as fuel pumps, solid waste disposal, car washing, and sand harvesting, were prevalent on the riparian reserves of rivers Omidu and Okomayan in Okun-Ijebu, Nigeria. To address this issue, the researchers recommended the gazettement of a 240-foot riparian buffer zone as a strategy to protect the affected areas.

Numerous studies have demonstrated that compliance with recommended riparian reserves can be effectively assessed through spatial analysis using Geographic Information Systems (GIS) and Remote Sensing (RS). For instance, Pu et al. (2021) utilized remote sensing to quantify a 17% loss of riparian vegetation along the Genesee River in New York between 2006 and 2015. Similarly, Olokeogun et al. (2020) employed Landsat 7 imagery to investigate the Eleyele area of Ibadan, Nigeria, and found that despite the ecological importance of riparian reserves in flood mitigation, 19% of built-up areas were located within these reserves between 1999 and 2019. Recent studies have corroborated these findings, highlighting the widespread degradation of riparian ecosystems. Olatidoye et al. (2021) reported a 31% destruction of original forest land cover along the 150 m Omo Biosphere Reserve between 1986 and 2016. Similarly, Nsor et al. (2021) found that grazing, bush fires, farming, and logging led to a 54% loss of plant species in the riparian zones of Kamawu district in Ghana. Furthermore, Xu et al. (2020) observed a high rate of conversion of riparian forestland to arable land around Lake Tanganyika between 2001 and 2011, with the rate of conversion fluctuating with increasing distance from settlements.

Riparian zones in Kenya face similar human settlement interference, leading to biodiversity loss and disturbances. Human activities such as agriculture and water abstraction for domestic use have resulted in the loss of canopy cover in rivers like Njoro and Kamweti (Koskey et al., 2021). The development of built-up areas within and around these riparian zones is linked to various human activities that compromise biological integrity and affect riparian vegetation (Koskey et al., 2021). Additionally, urban rivers in Kenya, such as the Sosiani River in Eldoret town, Uasin Gishu County, experience vegetation loss in riparian zones, which compromises the filtering mechanism (Nyakora, 2016). Furthermore, Nyakora (2016) establishes a link between human settlement development along urban rivers and land use changes that alter the natural aquatic ecosystem, highlighting the impact of grazing on the Sosiani River. Informal settlements are a primary driver of land use changes that adversely affect riparian zones in Nairobi's main rivers, including Ngong, Mathare, and Nairobi River (Muketha, 2020). Despite their numerous benefits, urban riparian reserves are increasingly encroached upon by anthropogenic activities, which continue to erode the ecological spaces they were intended to preserve, with Nairobi River being no exception to these land use and land cover changes.

Rapid urbanisation is characterised by an increased number of residential buildings, industrial, commercial and transportation routes; however, there is a drastic decrease of vacant land, while in other cases land use is changed. A typical example would be agricultural land being transformed to residential; this affects food security as less land is available to produce food (Rana and Marwasta, 2015). LULC changes are accelerated by several factors and activities taking place on the earth’s surface. These factors include livestock farming, forest management and harvesting and agriculture (Owoeye and Ibitoye, 2016). Due to the nature of developing countries, it is expected that rapid changes will occur in LULC as a result of the growth of cities resulting from rural- urban migration and high birth rate, as compared to developed countries (Lefulebe et al., 2023).

LULC terms are often confused, and their meaning is different. Land use is defined as how humans use land, both in terms of economic and cultural activities (Jansen and Di Gregorio, 1998), this includes residential, agricultural, mining, etc. Land cover specifies the physical land type, an illustration of the amount of land region covered by forests, agriculture, wetlands, waterbodies and other lands (Jansen and Di Gregorio, 1998).

Additionally, different types of land cover are used differently, for instance; forests are used to produce wood while agricultural land is used to produce food. Land cover is determined by remotely sensed data such as satellite or aerial images, acquired at different periods (Lefulebe et al., 2023). Comparison and analysis of land cover maps assist in understanding changes that occurred in the period in question, therefore informed decisions can be made. The impact of rural-to-urban migration and high birth rate on LULC is the rapid growth of informal settlements, growth of built-up areas, and a decrease of vacant land, wetlands and the occupation of flood-prone areas (Rahman et al., 2018).

Growing cities such as Nairobi, such impact is felt and it’s on this basis that land use land cover classes of bare-land, vegetation, built up and water played a critical role in understanding the change dynamics within the riparian reserves which ideally should be maintained with riparian vegetation.

MATERIALS AND METHODS

An open-source classifier known as Orfeo tool box (OTB) was adopted as the software environment for classification of the aerial images at different epochs. Change detection in terms of areas were computed similarly using open source QGIS and trends were then analyzed using graphs and charts.

Figure 2 illustrates the summarized methodology diagram, which was created using the Unified Modeling Language (UML) tools in Dia software, providing a visual representation of the methodology flow chart.

OTB classifier

OTB is an open-source, supervised classifier developed by CNES, a French space agency, for earth observation image processing (Christophe et al., 2008). It can operate as either an object-based classifier (OBIA) or a pixel-based classifier, with the former recommended for low-resolution imagery and the latter suitable for high-resolution images, as used in this study (Christophe et al., 2008). Supervised classification relies on human guidance, where the user selects sample pixels representing specific classes, such as built-up areas, vegetation, water, and bare land, using a polygon tool. The accuracy of the classification depends on the quality of the training samples. The user then directs the software to use the created training samples as references for classifying the remaining pixels in the image (Madariya and Sharma, 2022).

The supervised classification process involves three key steps: training sample selection, extraction of spectral signatures, and image classification. User knowledge plays a crucial role in determining the input classes. Additionally, the user sets boundaries to determine the similarity threshold for grouping pixels together. When setting these boundaries, the following factors are considered: the spectral characteristics of the training area, increment based on brightness, and reflection from image spectral bands. Furthermore, the user determines the number of output classes, allowing for tailored classification results. Supervised classification technique requires the user to have prior knowledge of land cover in the study area. This is essential because hyperspectral data generated by pixels is required to train the classification algorithm before OTB algorithm is run.

OTB comes with a set of application to perform supervised or unsupervised pixel-based image classification. The framework allows learning from multiple images, and using several machine learning methods such as SVM, Bayes, KNN, Random Forests, Artificial Neural Network, and others. The following processes were followed:

1) Compute samples statistics for each image
2) Select samples positions for each image
3) Extract samples measurements for each image
4) Compute images statistics
5) Train machine learning model from samples

Randon Forest (RF) machine learning algorithm was used as the modeler.

Description of the study area

Nairobi, situated at the southeastern edge of Kenya's agricultural hub, covers an area of approximately 700 km². With an elevation of

1,600 to 1,850 m above sea level, the city enjoys relatively mild temperatures throughout the year (Mitullah, 2003). The western part of Nairobi features a rugged topography, with higher elevations, while the eastern side is generally flatter and lower-lying. The city is traversed by the Nairobi, Ngong, and Mathare rivers, which flow through numerous neighborhoods, and the indigenous Karura forest still covers parts of northern Nairobi. The Ngong Hills are situated nearby to the west, while Mount Kenya rises in the distance to the north, and Mount Kilimanjaro emerges from the plains in Tanzania to the southeast. As Nairobi is located adjacent to the Rift Valley, a region of ongoing tectonic activity, the city occasionally experiences minor earthquakes and tremors. The rapid growth and urbanization of Nairobi have exerted immense pressure on the Nairobi River, which traverses the county from west to east, flowing from the upper reaches in the west, through the central business district (CBD), to the lower reaches in the eastern part of the county.

Nairobi river riparian reserve as the case study with three segments purposively selected to represent the upper, middle and lowland of the river. This was due to diversity and uniqueness of the land uses prevalent in those sections, differences on the terrain and water volumes. The area of study map is shown in Figure 1. A 28 km section of the Nairobi River was segmented into upper, middle, and lower sections based on distinct dominant land uses and varying elevations above mean sea level (MSL). For the purpose of this research, a specific section of the Nairobi River was selected, stretching from GPS coordinates 36° 41' 0.1" E, 1° 16' 30.2" S to 36° 54' 6.54" E, 1º 14' 7.36" S, due to its diverse range of land uses.

Research design

A case study design was employed, a technique suitable for gaining an in-depth understanding of complex issues within their natural and real-time settings (Rashid et al., 2019). This approach enabled a detailed examination of the specified segments of the Nairobi River, where extensive land use and land cover analysis were conducted. Due to the variety of geospatial analysis tools adopted, this design can be replicated to study other urban river riparian reserves, which are similarly affected by anthropogenic land uses.

Data collection and analysis

High-resolution aerial images of the study sites were obtained for the years 2000, 2010, and 2020, and were used to conduct LULC classification and change detection. Change detection is the process of identifying differences on the Earth's surface over time using remote sensing data, such as satellite or aerial images acquired at different periods, to monitor changes in LULC (Théau, 2008). The availability of up-to-date information on the Earth's surface has increased significantly, forming the basis of various applications, including LULC change monitoring and resource monitoring at local, regional, and global scales (Hussain et al., 2013). The change detection analysis along the Nairobi River riparian zone at the epochs of 2000, 2010, and 2020 is part of a local-scale study, driven by the urbanization of the city, as well as natural and climatic factors, with anthropogenic activities being the primary contributor.

Remote sensing data has played a crucial role in change detection studies, and significant advancements in satellite and aerial imagery resolution have improved the quality of change detection results. The availability of high-resolution aerial imagery for the targeted sections provided an excellent depiction of changes over a 20-year period. A study by Abijith and Saravanan (2022) demonstrated the effectiveness of remote sensing data (Landsat images) in detecting and predicting LULC changes in the northern coastal districts of Tamil Nadu, India, using CA Markov, Google Earth Engine (GEE), Terrset, and GIS tools. The results showed a decline in waterbodies and an increase in built-up areas between 2009 and 2019. Additionally, bare land and vegetation were found to be under stress, with many areas being converted into buildings. The study achieved a kappa coefficient of 87% and an overall accuracy of 89%, validating the map.

Remotely sensed data from high-resolution aerial photographs taken over time can provide detailed information on changes caused by human activities. Digital change detection involves quantifying multi-temporal phenomena from multi-date imagery, typically acquired by satellite-based multi-spectral sensors (Vakalopoulou and Argialas, 2012). With the increasing availability of high-resolution satellite data, automating the change detection process has become crucial to assist human analysts in quickly identifying significant changes. The OTB is a significant innovation in automating land use/land cover classification. The primary purpose of OTB is to leverage methodological expertise and adopt an incremental development approach to efficiently exploit the results obtained through the classification process.

The OTB is a valuable resource for the remote sensing imagery community. By releasing OTB under an open-source license, CNES aims to leverage contributions from specialists to enhance the practical applications of satellite and aerial imagery (Christophe and Inglada, 2009). OTB is an indispensable tool for assessing the environmental impacts of changes in urban LULC. Aerial and satellite imagery can be utilized to detect and assess information about predominant LULC classes, their changes, and potential impacts (Netzband et al., 2007). Given the dynamic nature of urban areas, a reliable and effective remote sensing tool is essential. OTB technology has been successfully applied in detecting encroachment and land conversion, making it a valuable asset for monitoring LULC changes (Netzband et al., 2007).

Data sources

Aerial Imagery data set

Aerial imagery for the years 2000, 2010, and 2020 was sourced from the Survey of Kenya (SOK) and Ramani Geosystems, respectively. The imagery had a spatial resolution of 15 cm, with a 60% forward overlap and 30% side overlap, enabling the creation of a seamless mosaic covering the targeted sites. The project sites, measuring 2 km by 200 m from the centerline of the river, were divided into lower, middle, and upper segments. The coordinate system of the photo-mosaic is based on the UTM Zone 37 WGS 1984 projection.

DTM

The river morphology was derived from a 5m resolution Digital Elevation Model (DEM) which was processed to generate the DTM for the lower, middle and upper segments. These were sourced from Ramani Geosystems for the year 2020.

GIS

Raster images were prepared and processed in QGIS, vectorization and other GIS spatial and statistical analysis were done using the QGIS toolbox. Output and extraction such as clipping were conducted in QGIS.

OTB

OTB was utilized to run the classification, input the training dataset,

Figure 1. Study area map.

Table 1. Four distinct land use classes.

Land use type	Description
Built up area	Areas having residential, commercial, industrial and other infrastructural uses
Vegetation	Land used for cultivating crops, for example, bananas, napier grass, maize, vegetables or tea bushes (Urban Agriculture)
Bare-land	Land which is temporarily barren
Water	Areas with presence of river water surface

and establish the ratios for the testing set, with RF serving as the classification model.

Adopted land classification scheme

Land use refers to the description of the features and extent of human activities in a specific location. Land use classification provides the foundation for monitoring and forecasting urban growth patterns, managing natural resources, and spatial planning, ultimately contributing to a better understanding of the environment and its dynamics (Liping et al., 2018). Although various land use classification systems have been developed, a universally accepted scheme remains elusive (Jansen and Di Gregorio, 1998). Therefore, this study identified four distinct land use classes, as outlined in Table 1.

Raster layer processing

Open-source GIS software, QGIS, and the OTB plug-in were utilized to prepare and load the aerial imageries of the targeted sites along the Nairobi River for the years 2000, 2010, and 2020. The analysis was conducted segment-wise, as each river segment exhibited distinct predominant land use/land cover characteristics. The segments were categorized into lower, middle, and upper

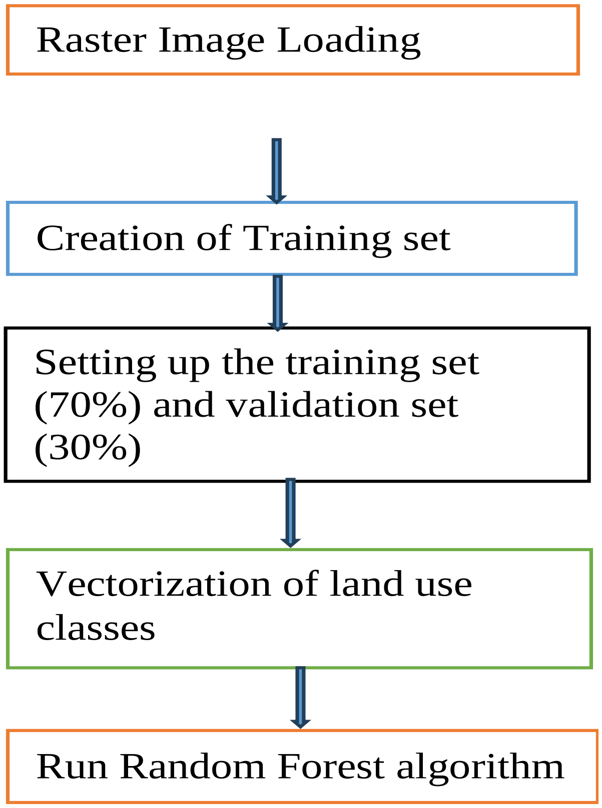

Figure 2. Work flow diagram.

areas based on elevation and topography.

Creation of training set

Shapefiles for the training set of various land use/land cover types were digitized using the vectorization tool in QGIS and subsequently coded. The integer values 1, 2, 3, and 4 were assigned to represent bare land, built-up areas, vegetation, and water bodies, respectively. The toggle editing tool was then employed to digitize all corresponding land uses according to the developed code.

Setting the test and validation samples in OTB

The OTB plugin was launched within QGIS, and the Train Image Classifier algorithm was run to activate its libraries. The input datasets, comprising the image and training sites, were entered into the Input Image List and Input Vector Data List, respectively. The training data was set to 70%, while the validation set was set to 30%, and RF was selected as the model for extending the trained datasets to the entire imagery. Additionally, the output model and confusion matrix locations were specified for displaying the model and confusion matrix, respectively. The image classifier was then utilized to load the different images from 2000, 2010, and 2020, and the selected model was run.

Vectorization of the raster classified images

The classified raster was vectorized to facilitate automated area computations. The generated vector layer was loaded, and its attribute table was opened to convert the digital numbers to land use/land cover classes. The area of each class was then computed using the built-in function for area computation, as well as the $Area function, to obtain accurate and reliable results.

Land use land cover changes

Utilizing the Statistical Analyst toolbox, all classes were consolidated using the calculate statistics function. The resulting output was an excel file containing the total areas per class for each classified image, corresponding to the epochs of 2000, 2010, and 2020. Subsequently, change detection analysis was performed using the change detection analysis algorithm within the OTB plug-in.

RESULTS AND DISCUSSION

This study aimed to analyze LULC changes along a 28 km stretch of the Nairobi River, divided into lower, middle, and upper segments due to distinct predominant land use characterizations. Using the Orfeo Tool Box open-source tool, the study employed Random Forest classification algorithms to achieve this objective. This section presents and discusses the results emanating from the research findings.

Table 2. Land use land cover areas at epoch 2000.

Land use/cover type	Area(m²)	% Area
Bareland	247.946.08	58.328
Built_up	45.299.38	10.65644
Vegetation	93.298.87	21.94806
Water	38.544.98	9.067502
Total Area	425.089.31	100

Lower segment

As shown in Table 2, the riparian reserve in the lower segment was predominantly characterized by bare land (58%), followed by vegetation (22%), while built-up areas accounted for only 11%, and the river channel and associated wet areas comprised 9%. This suggests that the riparian reserve was in a near-natural state, likely due to the relatively small population of Nairobi at the time (approximately 3 million). The city's expansion had not yet reached the fringes, where the lower segment is currently located, and which is now predominantly occupied by informal settlements. Figure 3 illustrates the LULC map of the Lower Segment of Nairobi River Riparian neighborhood in 2000.

Over a 10-year period, it was observed that the bare land area decreased by approximately 10%, translating to a depletion rate of 1% per year. Conversely, built-up areas increased by 6%, while water bodies and wet areas expanded by 4%. This transformation can be attributed to the proliferation of informal settlements and the increase in floodwaters due to climate change and urbanization, which led to the construction of impervious surfaces and, consequently, increased runoff. Table 3 presents the LULC areas for the year 2010, while Figure 4 illustrates the LULC map of the lower segment of Nairobi River Riparian neighborhood in 2010.

Over the subsequent 10-year period, the reduction in bare land almost doubled, decreasing by 18%. Built-up areas accounted for approximately 10% of this decrease, while vegetation claimed another 8%, likely due to the emergence of urban agriculture along the riverbanks.

This agricultural expansion further depleted water resources, as it relied on irrigation. Consequently, water and wet areas declined to 3%, down from 11% in the previous 10-year period. The graph in Figure 5 illustrates the 20-year trend, revealing a sharp decline in bare land area, initially at a rate of 1% per year, increasing to 2% per annum in the second epoch. In contrast, vegetation remained stagnant in the first epoch before increasing significantly in the second epoch at a rate of 1.5% per annum, attributed to the rise of urban agriculture. This, in turn, led to a sharp decline in water availability, decreasing at a rate of 0.8% per annum, primarily due to irrigation for urban farms.

Table 4 presents the land use/land cover areas for the year 2020. Figure 6 shows the graph of the land use land change at the lower segment trend in 20-year period.

Middle segment

The middle segment of the Nairobi River neighborhood, located within the CBD, was found to be predominantly characterized by bare land and vegetation in 2000, accounting for 33 and 37%, respectively. Water bodies and associated wetlands covered 17% of the area, while built-up areas accounted for 11%. Historically, Nairobi's CBD has been known for its natural beauty, featuring aseries of wetlands and being a place of "cool waters" since colonial times. This legacy could explain the relatively high percentages of vegetation, bare land, and water in this segment compared to the lower segment of the Nairobi River riparian areas. Figure 7 illustrates the Land Use/Land Cover Map of the Middle Segment of Nairobi River Riparian neighborhood in 2000, while Table 5 presents the land use/land cover areas for the year 2000.

Over the 10-year period, vegetation in the middle segment of the Nairobi River neighborhood decreased significantly by 8%, while built-up areas increased substantially by 10%. This transformation can be attributed to rapid urbanization within the city, likely driven by the clearance of vegetation for business premises. In contrast, bare land and water surfaces remained relatively stable, with a marginal 1% decrease and increase, respectively. Figure 8 illustrates the land use/land cover map of the middle segment of Nairobi River Riparian neighborhood in 2010, while Table 6 presents the land use/land cover areas for the year 2010.

The second phase of this epoch witnessed fundamental changes, particularly a significant increase in vegetation coverage, likely attributed to conservation interventions, such as tree-planting initiatives led by the late Minister John Michuki, and the establishment of Michuki Park. This conservation effort led to a substantial reduction in bare land, as areas were rehabilitated and reforested. Conversely, built-up areas experienced tremendous growth, driven by the proliferation of commercial premises and temporary makeshift structures in the

Table 3. Land use land cover areas at epoch 2010.

Land use/cover type	Area (m²)	%Area
Bareland	210519.1	49.52047
Built_up	71137.23	16.73363
Vegetation	94309.27	22.1844
Water	49149.71	11.5615
Total	425115.3	100

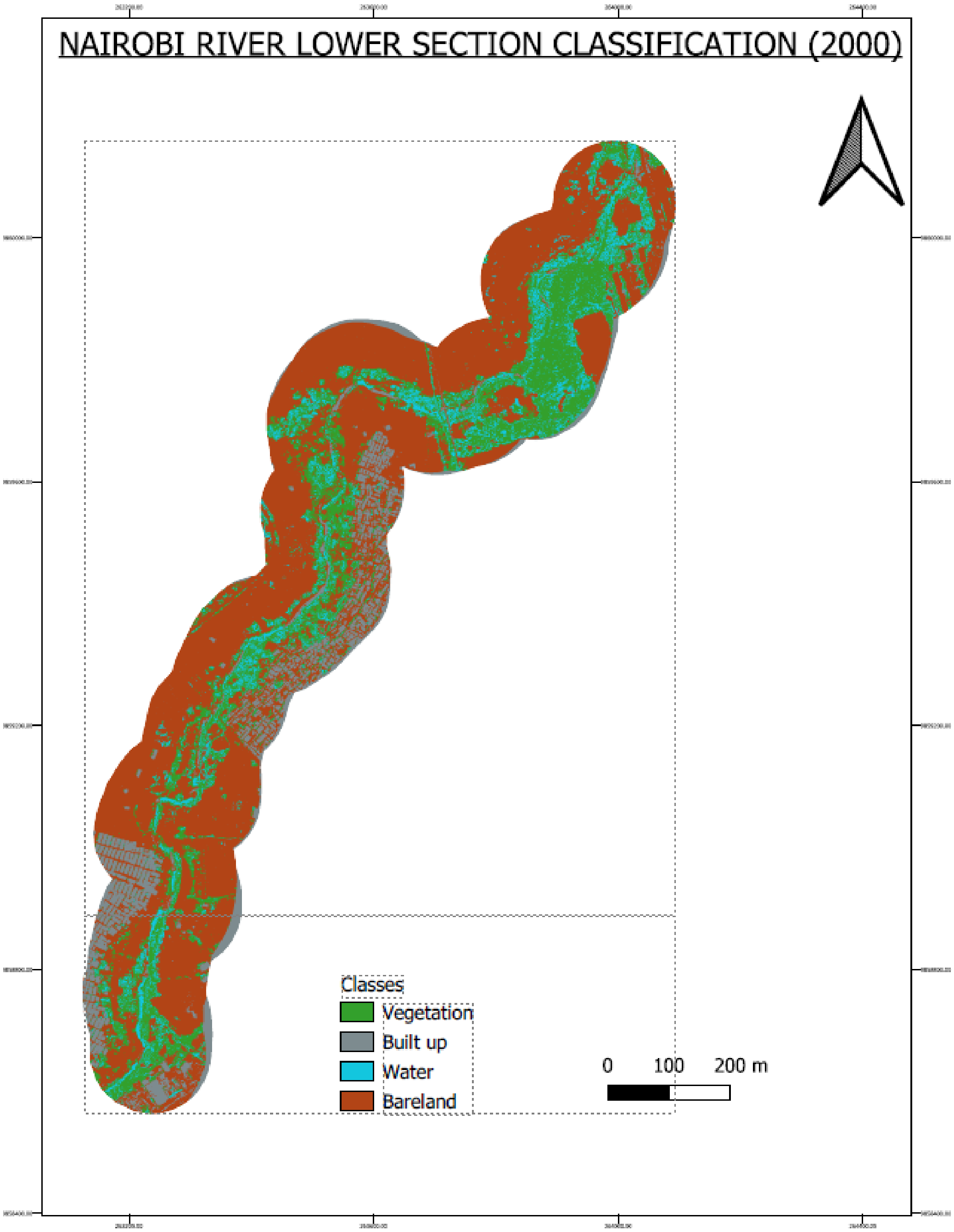

Figure 3. Land use land cover map of the lower segment of Nairobi River Riparian neighborhood in 2000.

Table 4. Land use land cover areas at epoch 2020.

Land use/cover type	Area (m²)	%Area
Bareland	136876.1	32.19707
Built up	117300.9	27.59243
Vegetation	158573.2	37.30082
Water	12369.63	2.909681
Total	425119.7	100

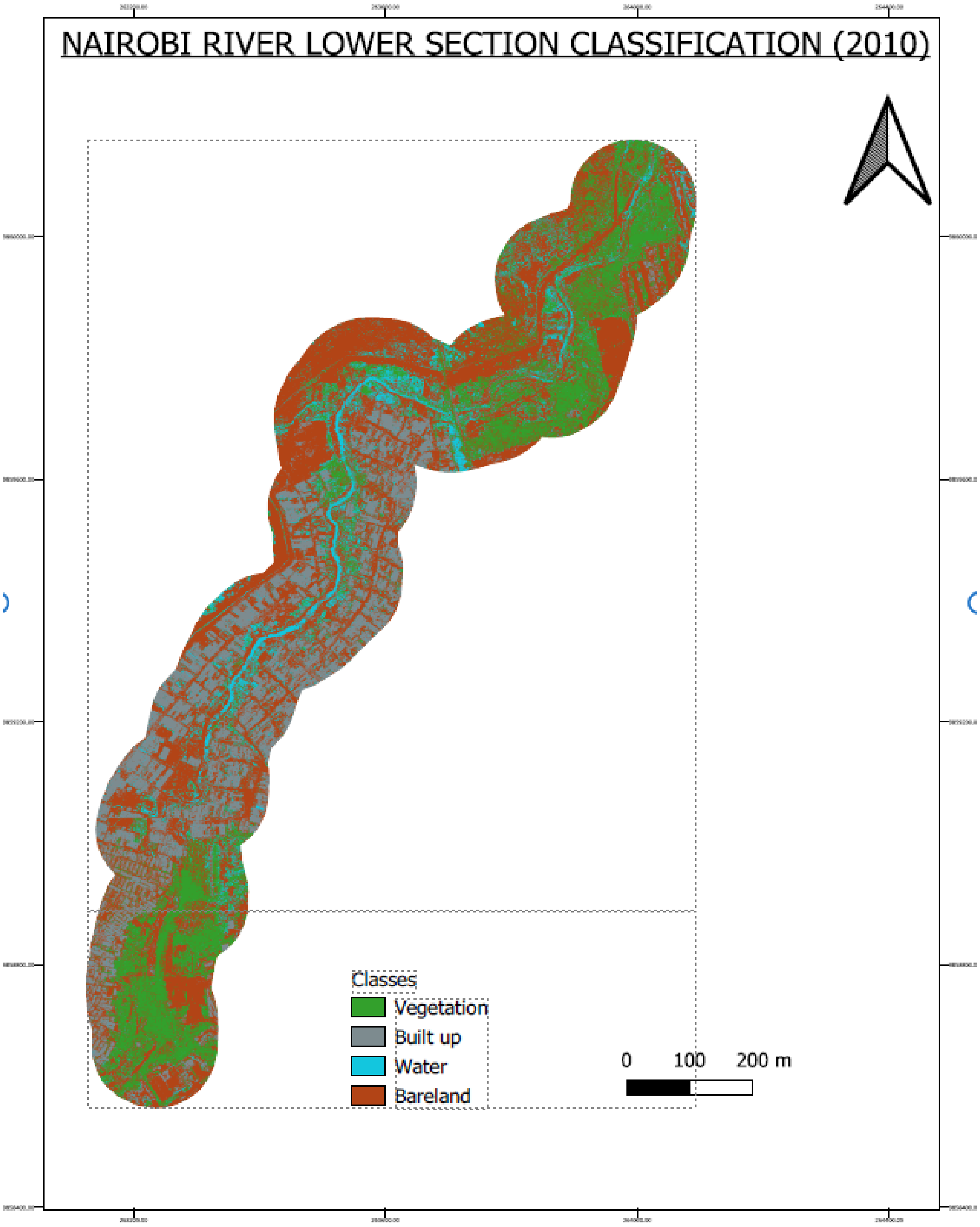

Figure 4. Land use land cover map of the lower segment of Nairobi River Riparian neighborhood in 2010.

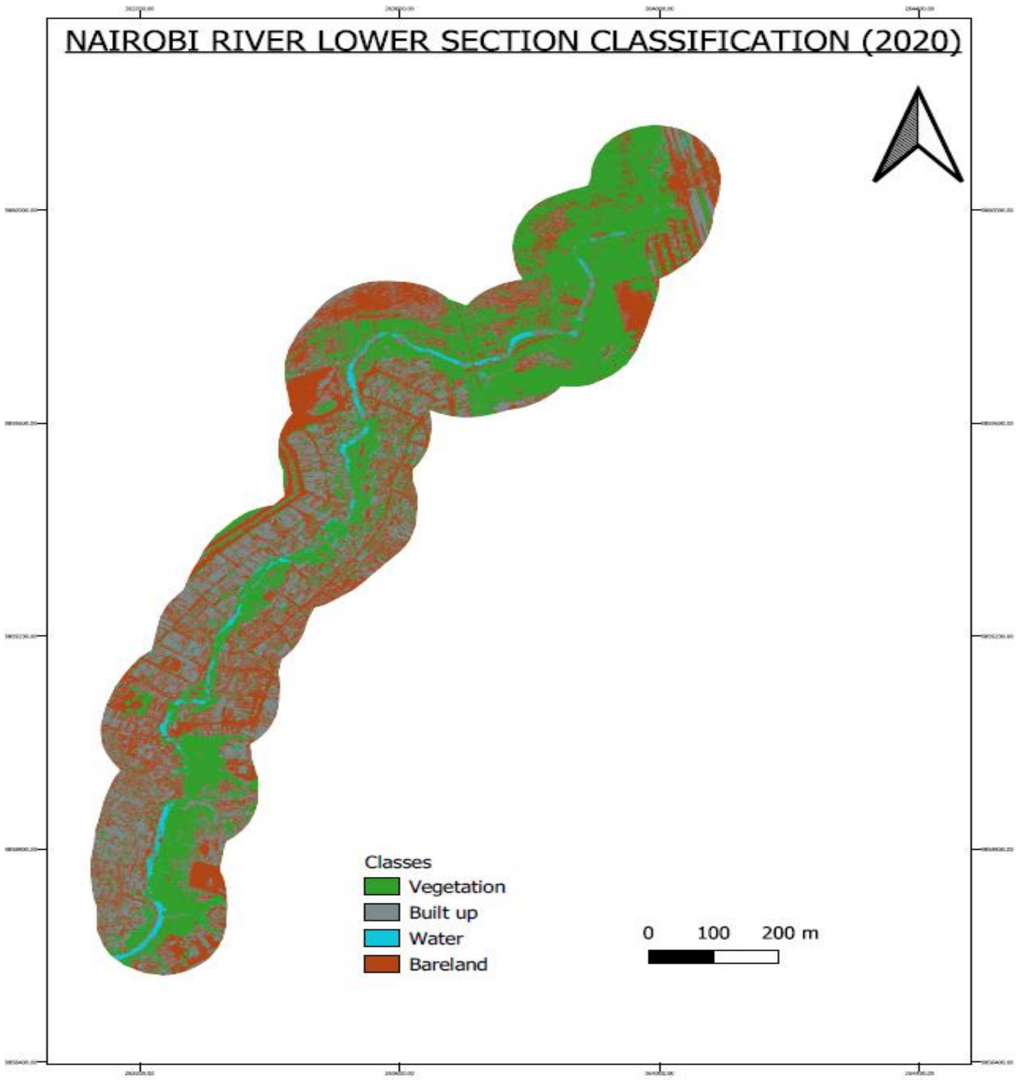

Figure 5. Land use land cover map of the lower segment of Nairobi River Riparian neighborhood in 2020.

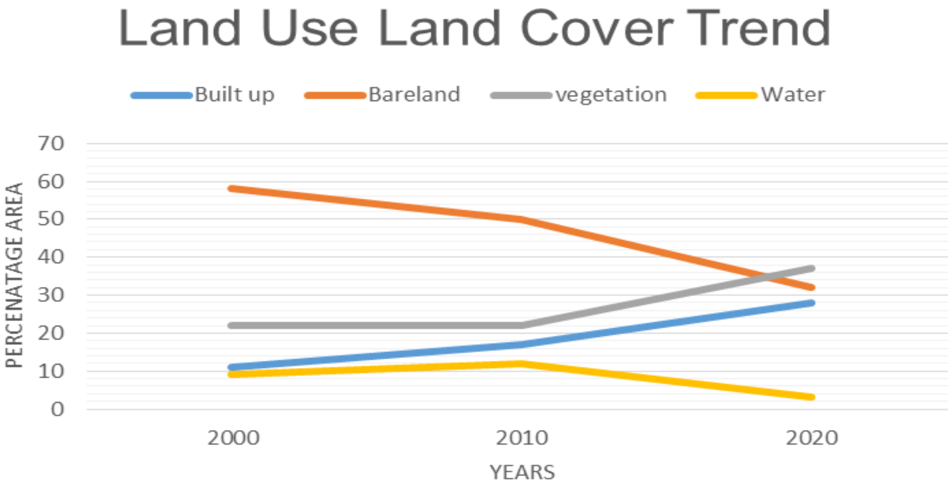

Figure 6. Graph of the land use land change at the lower segment trend in 20-year period.

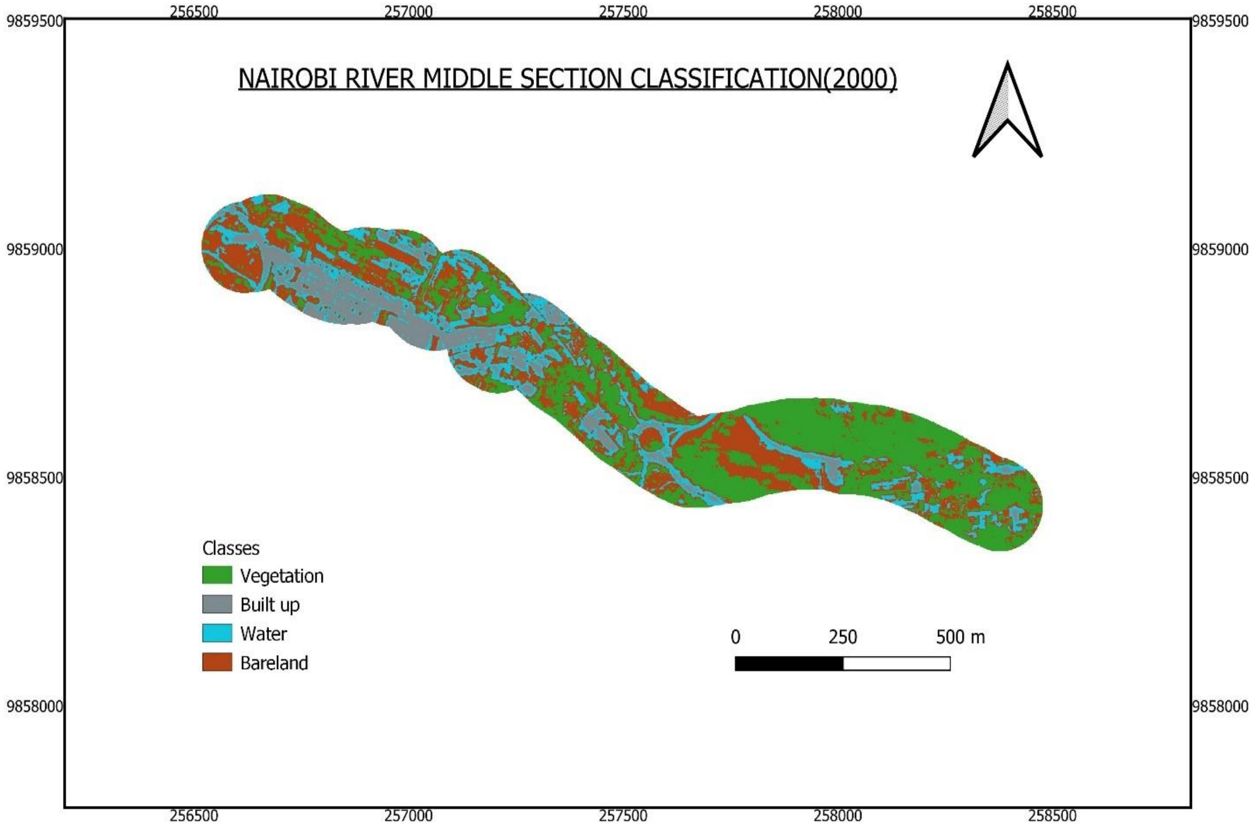

Figure 7. Land use land cover map of the middle segment of Nairobi River Riparian neighborhood in 2000.

Table 5. Land use land cover areas at epoch 2000.

Land use/cover type	Area (m²)	%Area
Bareland	141697.17	33.04342
Built_up	49601.41	11.56692
Vegetation	160610.92	37.45406
Water	76911.58	17.93559
Total Area	428,821.08	100

Table 6. Land Use Land Cover areas at epoch 2010.

Land use/cover type	Area(m²)	%Area
Bareland	136700.7	31.87434
Built_up	93533.62	21.80912
Vegetation	128126.4	29.87507
Water	70513.21	16.44148
Total Area	428873.9	100

Ngara area. Despite these conservation efforts, water surfaces decreased substantially to 5%. The cumulative results for the 20-year period are illustrated in Figure 9, while Table 7 presents the Land Use/Land Cover areas for the year 2020. Figure 10 shows the graph of the land use land change at the middle segment trend in 20 year

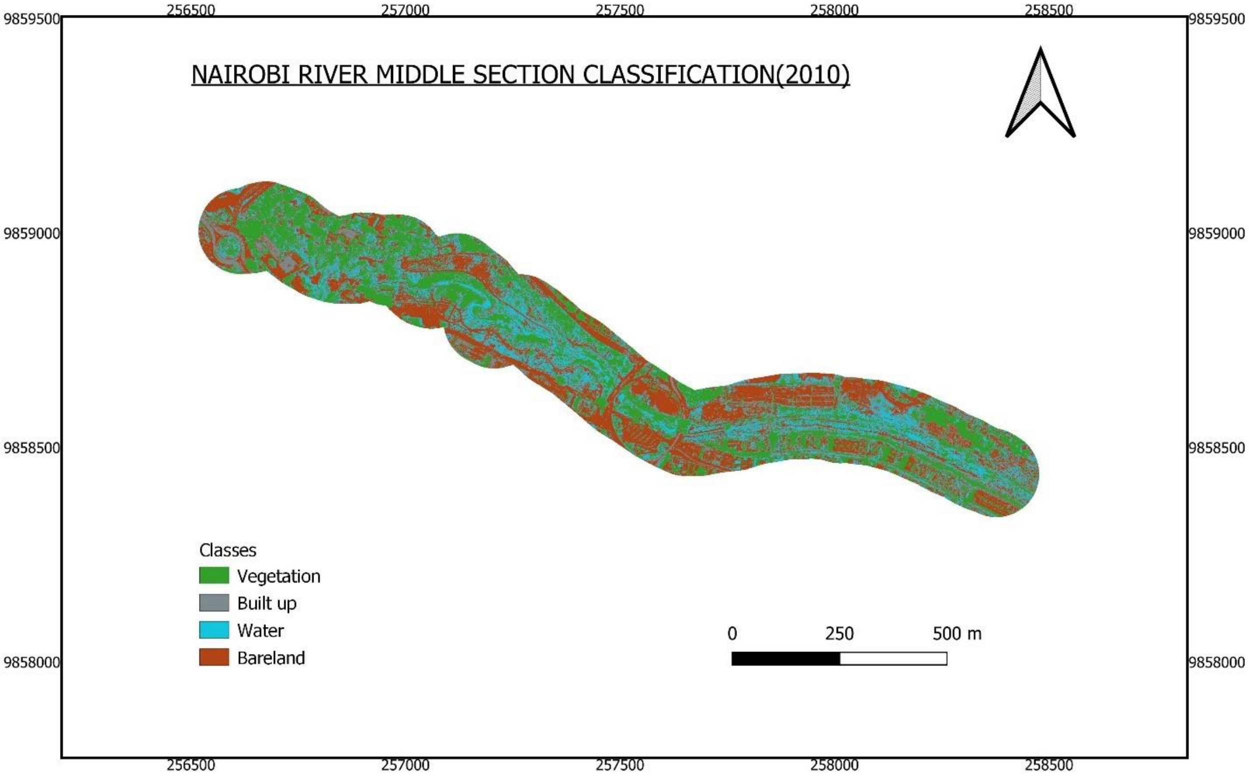

Figure 8. Land use land cover map of the middle segment of Nairobi River Riparian neighborhood in 2010.

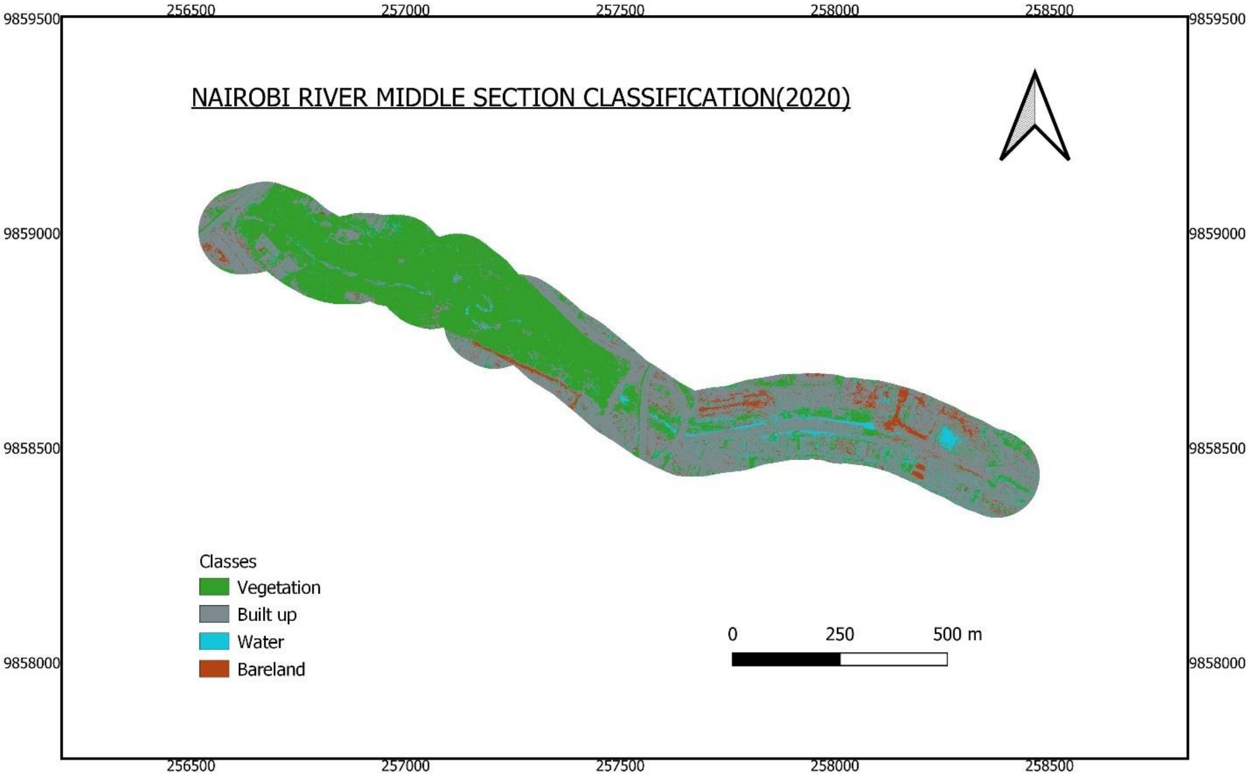

Figure 9. Land use land cover map of the middle segment of Nairobi River Riparian neighborhood in 2020.

Table 7. Land use land cover areas at epoch 2020.

Land use/cover type	Area (m²)	%Area
Bareland	18180.39	4.239526
Built_up	198294.5	46.24073
Vegetation	192161	44.81044
Water	20194.96	4.709308
Total Area	428830.8	100

Table 8. Land Use Land Cover areas at epoch 2010.

Land use/cover type	Area (m²)	%Area
Bareland	101294.832	23.12219
Built_up	6166.597	1.407626
Vegetation	221467.535	50.55356
Water	109155.972	24.91662
Total Area	438,084.94	100

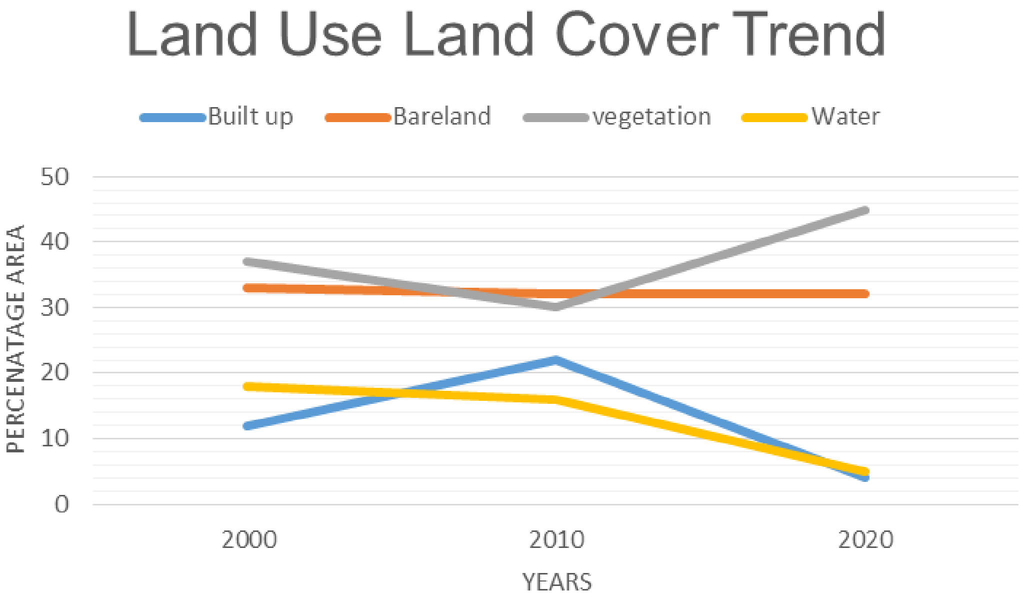

Figure 10. Graph of the land use land change at the middle segment trend in 20 year period.

period.

Upper segment

The upper segment of the Nairobi River riparian section was characterized by a predominance of vegetation, accounting for 50% of the area, followed by water surfaces and bare land, which comprised 25 and 23%, respectively. Built-up areas were relatively scarce, accounting for only 1%. This segment was found to be a peri-urban area, with extensive urban agricultural activities and limited drivers of urbanization. Figure 11 illustrates the land use/land cover map of the upper segment of Nairobi River Riparian neighborhood in 2010, while Table 8 presents the land use/land cover areas for the year 2010.

Over the last decade, the Upper segment of the Nairobi River riparian section underwent significant transformations, characterized by an increase in agricultural activities, which led to a 12% growth in

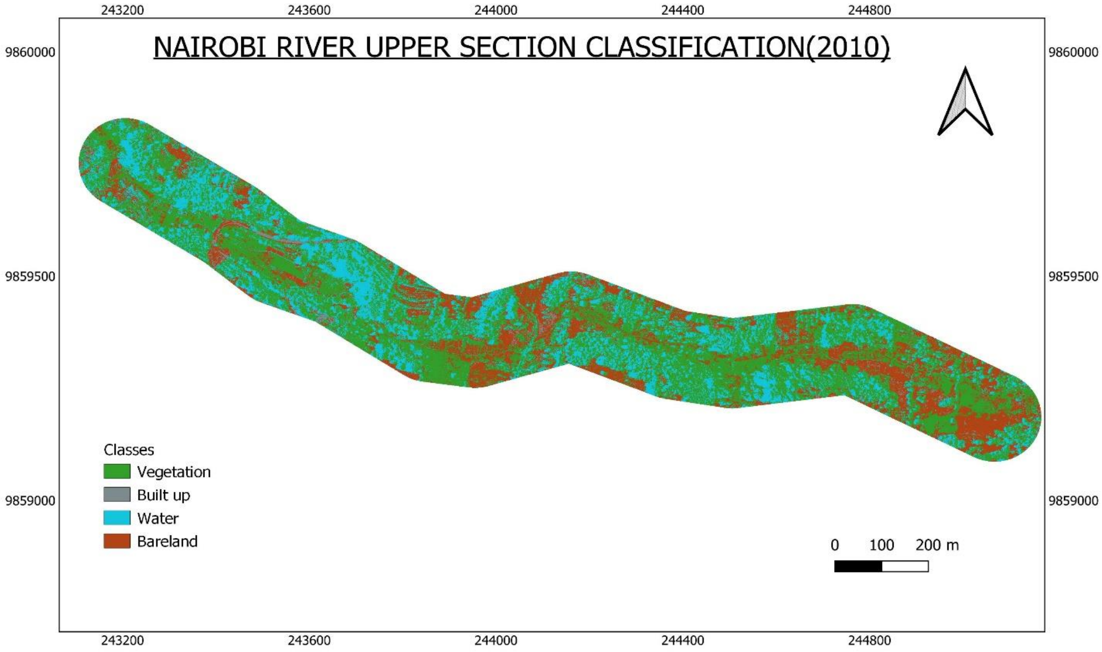

Figure 11. Land use land cover map of the upper segment of Nairobi River Riparian neighborhood in 2010.

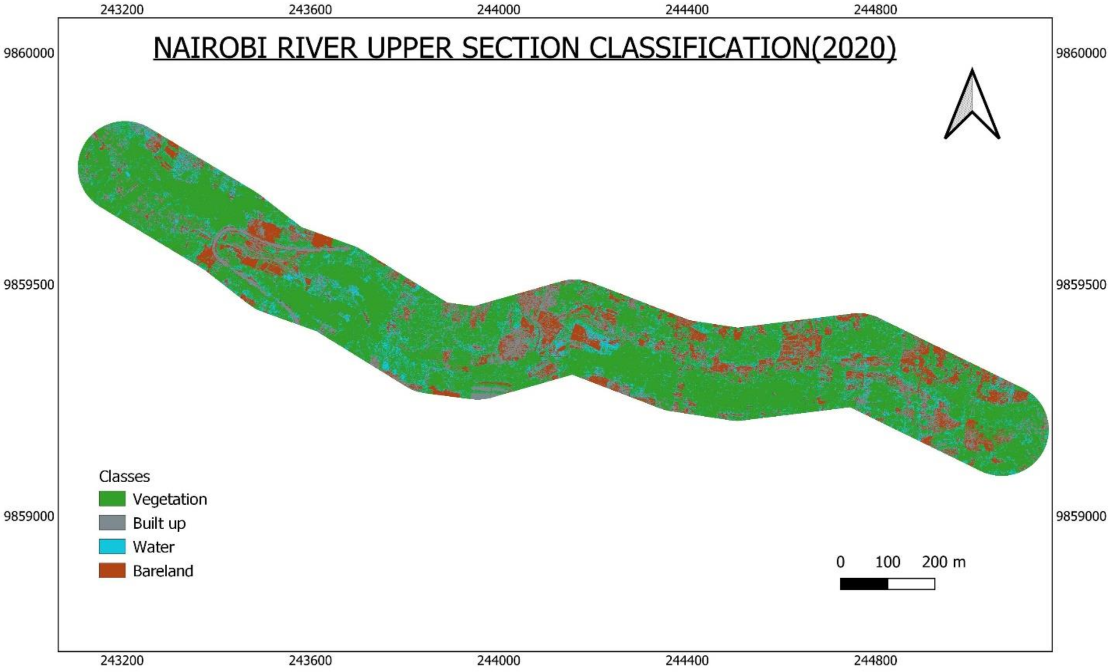

Figure 12. Land use land cover map of the upper segment of Nairobi River Riparian neighborhood in 2020.

vegetation cover. Concurrently, built-up areas expanded by 10% due to the outward growth of Nairobi City into the former rural areas of Dagoretti. Conversely, bare land and water surfaces decreased by an equal measure of 10% each, attributed to the intensified urban agriculture and increased water abstraction. Due to the unavailability of aerial imagery for the year 2000, trend analysis for the upper segment was limited to the period between 2010 and 2020, as illustrated in Figure 12. Table 9 presents the land use/land cover areas for the year 2020. Figure 13

Table 9. Land use land cover areas at epoch 2020.

Land use/cover type	Area (m²)	%Area
Bareland	60183.146	13.73704
Built_up	50444.04	11.51405
Vegetation	274274.051	62.60412
Water	53207.395	12.14479
Total Area	438,108.63	100

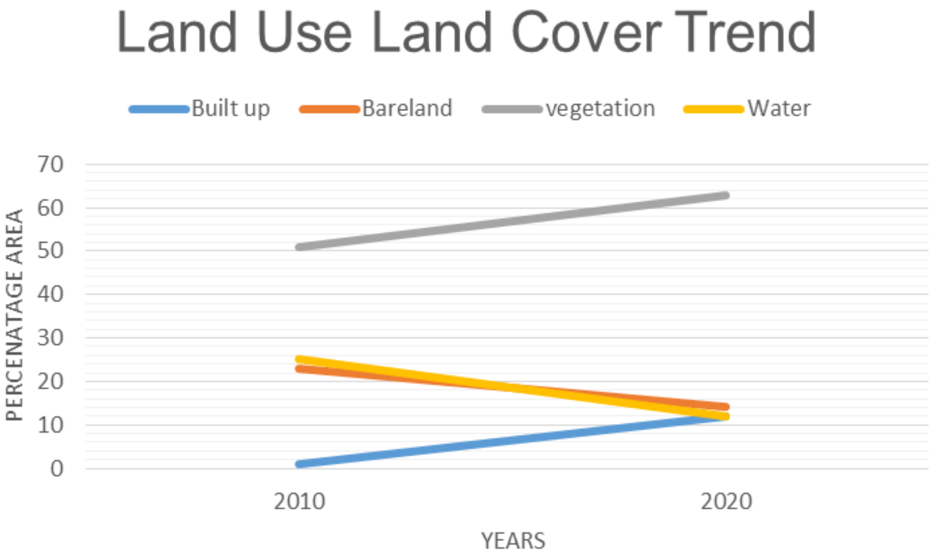

Figure 13. Graph of the land use land change at the upper segment trend in 10 year period.

shows the graph of the land use land change at the upper segment trend in 10-year period.

Conclusion

This study demonstrates the effectiveness of using the OTB open-source classifier to analyze land use/land cover changes in the Nairobi River riparian areas, achieving overall accuracies of 98, 91, and 95% for the lower, middle, and upper parts, respectively. The lower part of the study exhibited the most drastic land use changes, with built-up areas and vegetation increasing steadily at rates of 1 and 1.5% per annum, respectively, while bare land and water declined at rates of 1.7 and 0.8% per annum, respectively. These changes can be attributed to the rapid expansion of the city into fragile and sensitive areas, such as riparian reserves, which were initially characterized by inactivity, bare land, and riparian vegetation. Notably, the expansion of informal settlements, such as Kyambiu, and associated urban agricultural activities, has encroached upon more than half of the riparian space in the lower segment of the Nairobi River riparian reserve.

Similarly, the middle section underwent significant transformations, with built-up areas and vegetation increasing by 2 and 3%, respectively, over the same 20-year period. This can be attributed to its location within the Central Business District (CBD), where numerous business premises emerged, particularly in the Ngara area. The growth in vegetation can be linked to the conservation efforts initiated by the late Environment Minister, Hon. John Michuki, and the greening of Michuki Park. Conversely, bare land and water declined by 2 and 1%, respectively. Notably, the middle section serves as a positive example of successful rehabilitation and restoration, with vegetation covering 45% of the total area. In contrast, the Upper section of the Nairobi River area was predominantly characterized by urban agriculture, which initially covered almost 50% of the area and increased further to 62% over the period, registering a growth of approximately 12 or 1.2% per annum. Conversely, the built-up area expanded at a relatively slow rate of 1.4%, which is negligible compared to the changes in bare land and water, which accounted for 23 and 25% of the area, respectively.

This represents a significant availability of open spaces and water surfaces, likely due to the proximity of the river's origin at the Ondiri swamp, located near the Upper section, resulting in an abundance of water and wetlands, covering 25% of the total riparian area.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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