Open Access Library Journal
2025, Volume 12, e14005
ISSN Online: 2333-9721
ISSN Print: 2333-9705

Socio-Economic Dynamics and Land Use/Cover Changes within Nairobi and Ruiru Catchments in Kenya

Henry Ndugah*, John Ramirez-Avila

Richard A. Rula School of Civil and Environmental Engineering, Mississippi State University, Oktibbeha, USA
Email: *henryndugah@gmail.com

How to cite this paper: Ndugah, H. and Ramirez-Avila, J. (2025) Socio-Economic Dynamics and Land Use/Cover Changes within Nairobi and Ruiru Catchments in Kenya. *Open Access Library Journal*, **12**: e14005.
https://doi.org/10.4236/oalib.1114005

Received: July 23, 2025
Accepted: September 16, 2025
Published: September 19, 2025

Abstract

Land cover change remains one of the major most factor exacerbating ecosystem changes. This study investigated the effects of socio-economic drivers on land use and land cover (LULC) changes in the Nairobi and Ruiru catchments in Kenya over the period from 1990 to 2022. Utilizing remote sensing data and GIS-based LULC classification techniques, the study achieved high classification accuracy, with kappa coefficients consistently exceeding 0.80 and overall accuracies ranging from 86% to 97%. The analysis reveals significant spatial and temporal changes in LULC, with forests and perennial crops dominating the upper and middle catchment zones, while shrubs and grasslands were prevalent in the lower zones. Land use and land cover changes were accompanied by substantial transitions in land cover types, with significant portions of forest areas being converted into perennial crop farms and shrublands into urban areas. Socio-economic factors were identified as the major drivers of land use and land cover changes. The study area observed increase in area under coffee and tea from approximately 14% in 1990 to the current 25% a situation attributed to increasing population and favourable government plans. Urbanization emerged as the most significant driver of LULC change, particularly in the Nairobi catchment, where urban land cover increased by over 400%, from 3.1% in 1990 to 15.5% in 2022. The Ruiru catchment, while also experiencing urban growth, showed a more modest increase, with urban land cover rising from 1.0% to 3.2% over the same period. The rising population coupled with improved transport network in Nairobi led to emergence and sprawling of major settlements like Kawangware, Kangemi, Kariobangi among others. In the recent past, catchments such as Ruiru river have observed decline in coffee zones owing to conversion of coffee farms along major roads to settlement and trade zones. The increased accessibility and trade across other towns in the metropolis remains a threat to planned developments. The study underscores the profound impact of socio-economic factors, particularly in land use dynamics for catchments with rapidly growing urban expansion. The findings highlight the need for sustainable land management and urban planning strategies to mitigate the adverse environmental impacts and ensure balanced and transformative development.

Subject Areas

Socioeconomic Influence on Land Use and Land Covers

Keywords

Land Use and Land Cover (LULC) Change, Urban Expansion, Socio-Economic Drivers, Catchment, Remote Sensing, Hotspot

1. Introduction

Land use and land cover (LULC) changes are critical indicators of environmental and socio-economic transformations in rapidly urbanizing regions. These changes are often driven by complex interactions between natural processes and human activities, particularly in urban and peri-urban areas where the pressures of population growth, economic development, and infrastructure expansion are most pronounced (Lambin, Geist, & Lepers, 2003) [1]. In the context of developing countries, such as Kenya, the rapid pace of urbanization presents significant challenges for sustainable land management, particularly in major city catchments like those of Nairobi and Ruiru.

Nairobi, as the capital city of Kenya, has experienced substantial urban growth over the past few decades, driven by its status as an economic hub and a center of political and social activity (UN-Habitat, 2016) [2]. This growth has not only expanded the urban footprint but also altered the surrounding peri-urban areas, including the Ruiru catchment, which is increasingly being integrated into the Nairobi metropolitan area. The expansion of urban areas often leads to the conversion of agricultural land, forests, and other natural landscapes into built-up areas, with significant implications for biodiversity, water resources, and local climate (Seto, Güneralp, & Hutyra, 2012) [3].

Socio-economic factors such as population density, economic activities, land tenure systems, and government policies play a pivotal role in shaping land use patterns in these regions. For instance, the increasing demand for housing, infrastructure, and services in Nairobi has fuelled the conversion of peri-urban agricultural lands into residential and commercial zones (Mwangi, 2018) [4]. Similarly, the growth of industries and commercial activities along major transport corridors has accelerated land use changes in the Ruiru catchment, leading to the encroachment of urban land into previously rural areas (Ngugi & Njenga, 2019) [5].

Despite the growing body of research on LULC changes in urban areas, there is a notable gap in understanding the specific socio-economic drivers of these changes, particularly in the contrasting urban and peri-urban contexts of Nairobi and Ruiru. This study aims to fill this gap by systematically analysing the effects of socio-economic drivers on LULC changes in the Nairobi and Ruiru catchments from 1990 to 2022. By combining remote sensing data with socio-economic analysis, this research sought to provide insights that can inform more sustainable land use planning and policy-making in these rapidly growing city and its metropolitan areas.

2. Methodology

Methodology for LULC change and pattern analysis leveraged on Google Earth Engine's powerful cloud-computing capabilities to provide a comprehensive framework for analysing LULC changes and understanding the socio-economic drivers behind the transformations in rapidly urbanizing regions.

2.1. Study Area

The study focuses on the Nairobi and Ruiru catchments in Kenya, two regions experiencing rapid urbanization and significant land use/land cover (LULC) changes. Nairobi, the capital city, is a major economic and political center, while Ruiru is a peri-urban area increasingly integrated into the Nairobi metropolitan region. The study area spans diverse agro-ecological zones, ranging from urban landscapes to agricultural lands and natural vegetation. The geographic coordinates for the study area are approximately 1.2833˚S, 36.8167˚E for Nairobi and 1.1508˚S, 36.9676˚E for Ruiru. Both catchment have characteristically transited though rural, peri-urban and urban environments. Figure 1 shows that the study area covers part of both Kiambu and Nairobi Counties and drains into the larger Athi River Basin.

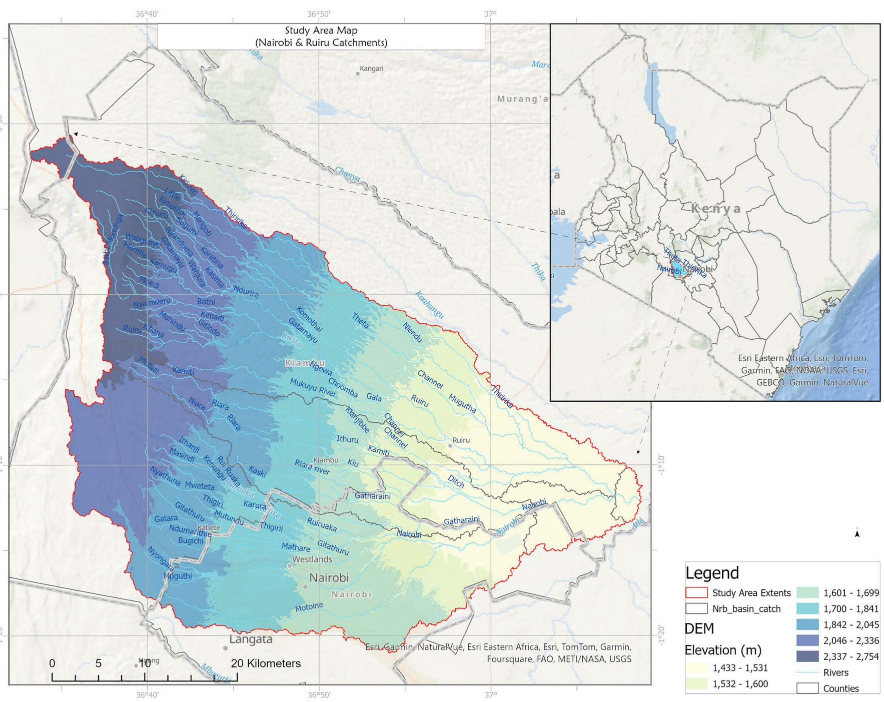


Figure 1. Map of study area (Nairobi & Ruiru catchments).

Ruiru catchment has three ecological zones with rainfall varying from 2400 mm in the high altitude tea zone to 1200 mm in the middle coffee zone and 700 - 800 mm in the lower sisal zone (Mutua, *et al.*, 2019) [6]. Nairobi catchment experiences two agro-ecological zones with the upper warm and wet coffee zone experiencing rainfall of 1500 - 1200 mm while the rainfall in the lower zone which borders Machakos County ranges 7 - 800 mm. Temperature varies with elevation where higher tea zones experience temperatures of 16˚C - 18˚C, middle coffee zone having temperatures of 20˚C - 24˚C whereas the temperature in the lower zone of Ruai ranges 26˚C - 30˚C (KMD, 2020) [7]. Ruiru river drains from North West to East while Nairobi river drains from West to East all which join before confluence into the Athi River.

2.2. Data Acquisition

Satellite imageries were acquired through the Google Earth Engine (GEE) platform, which provides access to a vast archive of multi-temporal satellite data. For this study, Landsat images were selected due to their long temporal coverage and moderate spatial resolution suitable for LULC studies. The specific datasets used include:

- Landsat 5 TM for the years 1990 and 2000,
- Landsat 7 ETM+ for the year 2010, and
- Landsat 8 OLI/TIRS for the year 2022.

The images were selected from the dry season to minimize the effects of vegetation phenology and cloud cover. With the help of Java Script codes, pre-processing steps which included cloud masking were undertaken using the Quality Assessment (QA) band in the Landsat data. However, the Landsat surface reflectance (SR) imageries stored in the GEE normally undergo radiometric correction and image normalization to ensure comparability across different years (Gorelick *et al.*, 2017) [8].

2.3. Classification

LULC classification was performed using a supervised classification approach within Google Earth Engine. The classification process involved a three step approach including generation of training site data, selection of the classifier and execution of the classification. The Random Forest classifier was selected for its proven accuracy and robustness in handling complex multi-temporal satellite datasets (Belgiu & Drăguț, 2016) [9]. The model was configured with 500 decision trees (n_estimators), a maximum tree depth of 20 (max_depth), and a feature subset size equal to the square root of the total features (max_features)—parameters optimized to minimize overfitting while maintaining high classification accuracy for LULC applications. Training utilized ground-truth samples collected for each target year (1990, 2000, 2010, 2022), with balanced class weights to address potential sample imbalances. The trained model was then applied across the entire study area to generate LULC maps for each epoch. This approach ensured reliable LULC change detection while effectively handling the spectral and temporal complexity of the satellite data throughout the 32-year study period.

2.4. Accuracy Assessment

This was also carried out within the cloud-based google earth engine platform with the help of Java Scrip codes. The accuracy of the LULC classifications was assessed using a confusion matrix, which compares the classified results against ground-truth reference data. The following metrics were calculated:

- Producer's Accuracy (PA): The probability that a reference pixel is correctly classified.
- User's Accuracy (UA): The probability that a classified pixel actually represents that category on the ground.
- Overall Accuracy (OA): The ratio of correctly classified pixels to the total number of pixels.
- Kappa Coefficient: A statistical measure of inter-imagery agreement that accounts for the possibility of agreement occurring by chance.

For each classified map, a minimum of 70 training sites were acquired per land cover class all totaling to 692 sites for all the land cover classes including; forests, perennial crops (coffee and tea), annual agricultural crops, shrubs, grassland, urban and water. Part of the training site date was randomly selected and used for classification (70%) while the remainder (30%) was used for cross-validation. A high-resolution imagery from google earth and field data were also applied for ground-truthing. In addition to cross-examination of key-informant with institutional memory of development changes, google earth imageries provided a good reference for historical land use changes in the catchment.

To ensure a high level of classification reliability, the study aimed at attaining a minimum value of 60% for both PA and UA. This was in addition to attaining an overall accuracy of over 80% and kappa coefficients of above 0.80 in order for classified imagery to nearly or almost perfectly match the reference data. Considering that kappa values range from −1 and 1, values of less than 0 indicate that the classification perform poor in comparison to random classification while level of classification improved from poor to excellent and perfect as kappa positive values approached 1(Shivakumar and Rajashekararadhya, 2018) [10].

2.5. Change Detection

Change detection analysis was conducted to quantify and characterize the LULC transitions over the study period. The following steps were undertaken:

1) Post-Classification Comparison: LULC maps from different years were compared pixel by pixel to identify changes in land cover. This was achieved through image subtraction which was effective in capturing the extent and nature of changes over time.

2) Change Matrix Construction: A change matrix was developed to quantify the area converted from one land cover type to another between consecutive years.

This matrix provided detailed insights into specific transitions, such as forest to agriculture or shrubs to urban areas.

3) Trend Analysis: The spatial and temporal trends in LULC changes were analysed using time-series data. The trends were visualized through maps and graphs, highlighting key changes such as the expansion of urban areas and the reduction in forest and shrub lands.

2.6. Hotspot Analyses of Land Use Land Cover Changes and Drivers

Hotspot Analysis was carried out using Getis-Ord Gi tool with the help of java scrip codes in GEE platform. This followed a land cover classifications and change detection between 2000 and 2022. The process of hotspot analysis involved calculation of local sum of LULC changes for 2000 and 2022, computation of local mean and variance for standardization, standardization of the local sum to enable calculation of z-scores, and finally identification of significant hotspots based on z-scores. The resulting image was exported for further analysis or reporting. From the optimized hotspot analysis, hot-spots corresponded to areas showing very high Z-score and low p-values ($p < 0.05$) while significant cold-spots define areas with very low Z-scores and small p-values ($p < 0.05$), (Muriuki *et al.*, 2023 [11]; Xu *et al.*, 2022 [12] and Philippe and Karume, 2019 [13]).

3. Results and Discussion

3.1. Land Use/Cover Classification

Results of the LULC classification are given in **Table 1** and show a high level of accuracy and consistency in classification across the four study periods (1990, 2000, 2010, and 2022). The kappa coefficient, exceeded 0.80, indicating that the classified images closely matched the reference images in a near-perfect classification. This was further coupled with an overall accuracy that ranged from 86% to 97%, underscoring the robustness of the classification process.

Among the different land cover types, forest, perennial crops (including coffee and tea), water bodies, and urban areas were classified with the highest accuracy, achieving producer's and user's accuracies above 80%. Specifically, the forest land cover consistently achieved producer's accuracies ranging from 90.13% in 1990 to 99.61% in 2022, and user's accuracies from 86.82% to 98.26% during the same period. Similarly, perennial crops, particularly coffee and tea, showed strong classification accuracy with producer's accuracies improving from 84.77% in 1990 to 97.86% in 2022, and user's accuracies from 82.58% to 99.02%. Urban class demonstrated a significantly level of classification accuracy, with producer's accuracies ranging from 87.93% in 1990 to 84.31% in 2022, and user's accuracies from 58.62% to 94.51%. This variability is likely due to the complexity and heterogeneity of urban land covers as they expand and evolve over time.

Figure 2 and **Figure 3** illustrate the spatial distribution and temporal changes in LULC types between 1990 and 2022 respectively. All other classified imageries are provided in **Appendix**. According to **Figure 2** and **Figure 3**, forests and perennial crops were predominantly located in the upper and middle zones of the catchment areas, reflecting the influence of favourable agro-ecological conditions. In contrast, shrubs and grasslands were more prevalent in the lower and adjacent middle zones. The spread was highly influenced by agro-ecological conditions.

Table 1. Results of the LULC classification accuracies.

Land cover type	1990		2000		2010		2022	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Forest	90.13	86.82	93.81	92.96	92.48	96.90	99.61	98.26
Perennial_Crops (Coffee + Tea)	84.77	82.58	95.26	88.80	96.93	86.74	97.86	99.02
Agriculture (annual crops)	100.00	66.67	75.00	100.00	60.00	100.00	66.67	66.67
Shrubs	75.14	75.57	83.44	71.58	80.95	74.32	81.11	79.78
Grassland	77.58	92.25	76.98	94.42	85.42	95.86	95.70	96.04
Urban	87.93	58.62	87.84	71.43	96.15	82.42	84.31	94.51
Water	96.09	99.19	100.00	99.19	96.52	89.52	100.00	99.19
Overall Accuracy (OA)	0.86		0.9055		0.9200		0.9708	
Kappa Coefficient	0.79		0.8642		0.8842		0.958	

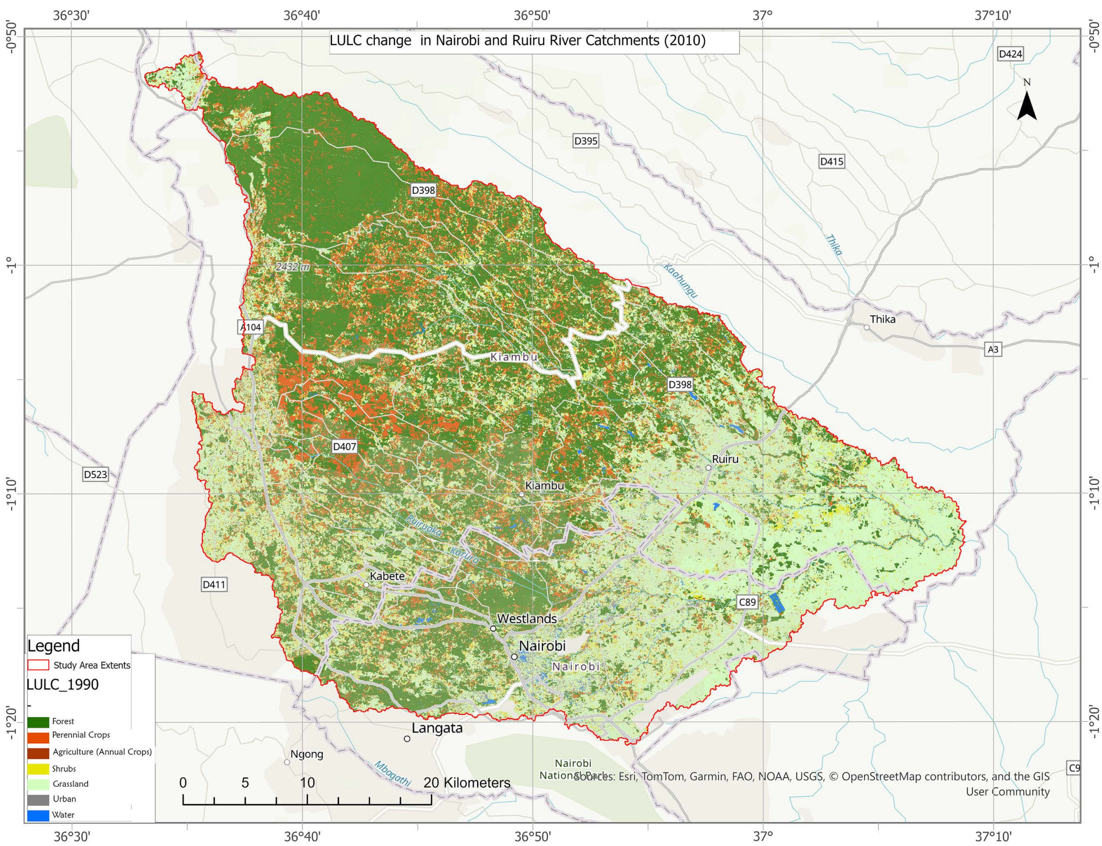


Figure 2. LUL change in 1990.

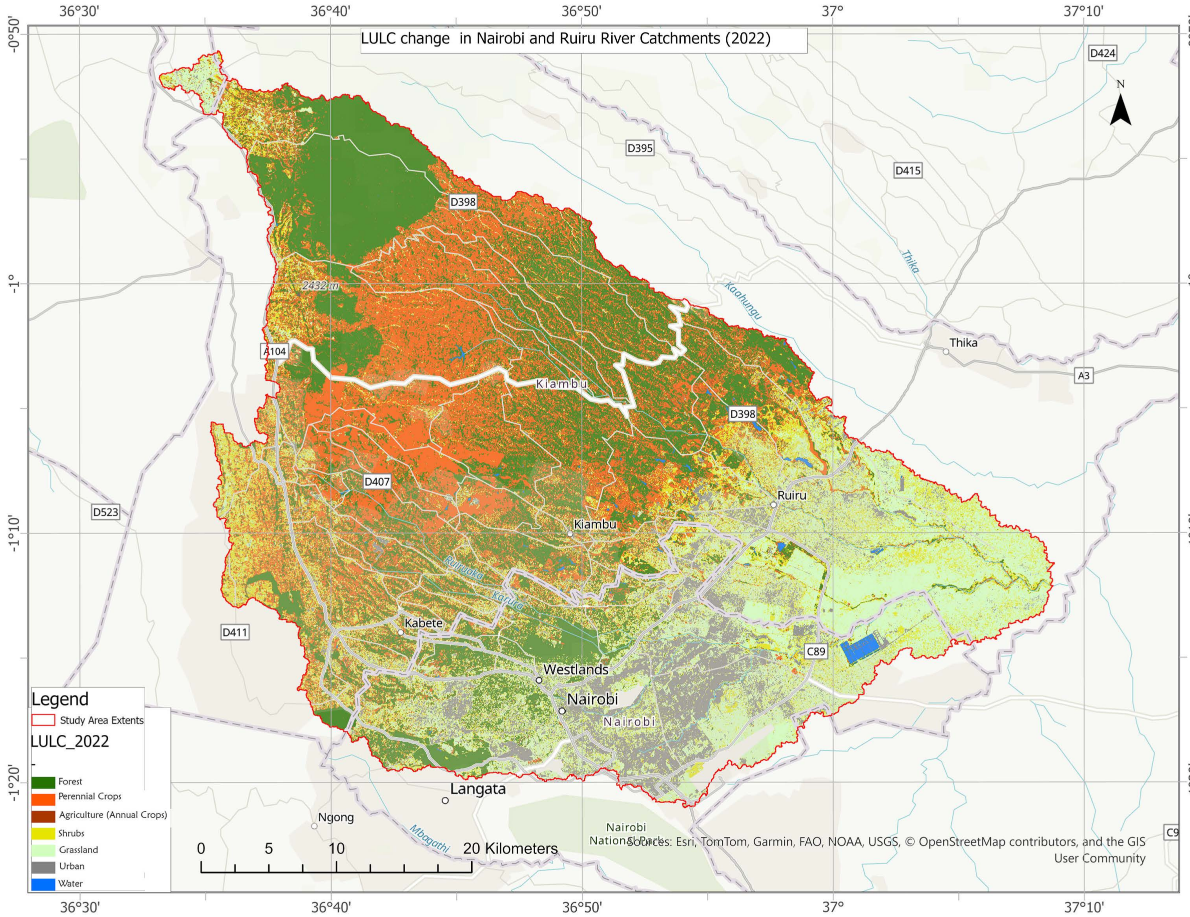


Figure 3. Land use/cover in 2022.

3.2. Land Use and Land Cover Changes in the Catchment

Figure 4 showed that while urban growth was reported in both catchments, Urban areas showed significant growth, particularly around Nairobi and other smaller towns, with expansion primarily occurring along major transport networks. During the period 1990-2022, Nairobi catchment experienced over 400% growth in urban land cover, increasing from 3.1% (18.9 km^2) in 1990 to 15.5% (103.1 km^2) in 2022. In comparison, the Ruiru catchment showed a more modest urban growth, with the urban area increasing from 1.0% (14.9 km^2) to 3.2% (40.2 km^2) over the same period.

A similar trend was reported by Waithaka (2022) [14] which focused on an analysis of LULC changes in Ruiru river watershed using GIS and remote sensing reported an increase in urban development from 2.16% to 3.76% between 1995 and 2017. This represented a 2.6% increase in urban area. The difference between the results from the current study and that of Waithaka (2022) [14] relates to partial extents where lower parts of Ruiru catchment were ignored while the classification was achieved with a lower overall accuracy of 82.6%.

As depicted in Figure 5, there were distinct trends in the percentage changes of various LULC types from 1990 to 2022. Forest and shrub land covers showed a declining trend, which can be attributed to the increasing demand for agricultural land and urban expansion. Large portions of forest land were converted into perennial crop farms, reflecting agricultural expansion in response to socio-economic pressures. In contrast, other land cover types, particularly urban areas, demonstrated an increasing trend, reflecting the ongoing urbanization and associated land use pressures.

Shrubs and grasslands especially on the eastern part of Nairobi and Ruiru towns were increasingly converted to urban areas, driven by the rapid urbanization process. The high conversions of shrubs and forests into perennial crops and urban areas as well as parts of perennial crops into urban could yield grassland transition zones which in overall contributed to increase in grassland.

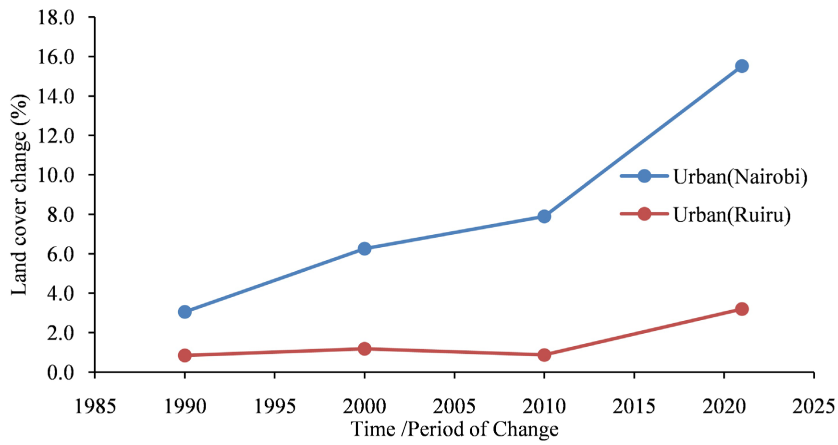


Figure 4. Urban development (1990-2022).

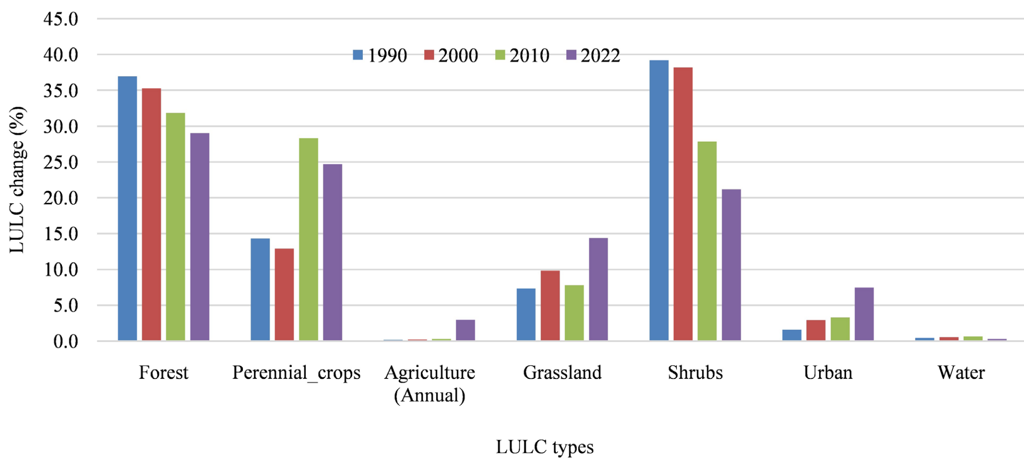


Figure 5. LULC changes in Nairobi and Ruiru catchment.

A visual assessment of changes in LULC shown in Figure 5 revealed that between year 2000 and 2010, the study area witnessed a sudden increase in perennial crops coupled with a similar decrease in shrubs while grassland and forest LULC types reduced marginally within the same period. Table 2 shows the LULC change matrix for the same period clearly indicating that the forest transformed into perennial crops and grassland, while shrubs converted to grassland, forest and perennial crops. The transformation of shrubs to forest (2.2%), could have been informed by full development of coffee perennial crops while most shrubs in the lower parts of the catchment were likely cleared due to increasing settlement.

The forest land was lost to perennial crops possibly occasioned by improved markets for coffee and tea attributed to changes in government policy towards better socio-economic development. Further analysis deduced that perennial crops increased by a similar area hence confirming the transformation between the two land covers. Considering that most of the tea and coffee crops may have been abandoned due to low prices, the increase in prices may have necessitated the rehabilitation of the farms and expanded production which called for clearance of more forest land.

Table 2. Land use/cover change matrix 2000-2010.

Land cover class		**Land use/cover change 2022 (%)**							
		Forest	Perennial crops	Annual crops	Shrubs	Grassland	Urban	Water	Grand Total
Land use/cover Change 2010 (%)	Forest	17.95	12.85	0.07	1.21	3.02	0.15	0.07	35.33
	Perennial crops	4.07	7.46	0.03	0.35	1.00	0.03	0.02	12.95
	Annual crops	0.08	0.06	0.00	0.02	0.06	0.00	0.00	0.23
	Shrubs	2.18	1.92	0.04	0.92	3.35	0.24	0.05	8.70
	Grassland	7.76	5.87	0.10	3.84	19.73	1.79	0.26	39.35
	Urban	0.37	0.22	0.01	0.22	1.00	0.90	0.04	2.77
	Water	0.09	0.07	0.00	0.03	0.13	0.08	0.27	0.68
	Grand Total	32.51	28.43	0.25	6.60	28.30	3.20	0.71	100.00

Table 3. Land use change matrix 2010-2022.

Land cover class		Land use/cover change 2022 (%)							
		Forest	Perennial crops	Annual crops	Shrubs	Grassland	Urban	Water	Grand Total
Land use/cover change 2010 (%)	Forest	17.7	8.1	1.1	3.4	1.8	0.4	0.0	32.5
	Perennial crops	9.5	14.0	0.9	2.2	1.4	0.3	0.0	28.4
	Annual crops	0.0	0.1	0.0	0.1	0.0	0.0	-	0.2
	Shrubs	0.7	0.8	0.2	1.7	2.5	0.8	0.0	6.6
	Grassland	1.3	2.0	0.5	6.0	14.3	4.2	0.0	28.3
	Urban	0.0	0.0	0.0	0.2	0.6	2.3	0.0	3.2
	Water	0.1	0.0	0.0	0.1	0.2	0.1	0.3	0.7
	Grand Total	29.3	25.1	2.8	13.6	20.7	8.2	0.3	100.0

Table 3 further shows the transformations between the various land covers between 2010 and 2022. During this period, less forest was transformed into perennial crops. In addition, a new dynamic was observed where forest land transformed into annual crops, shrubs and grassland mostly associated with forest clearing and establishment of forest shamba system. Most of the urban development was reported in to period 2010-2022. This is in the understanding that urban development slowly but steadily improves with better government policies and economic development. Most of the grassland areas especially in the lower parts of Ruiru and Nairobi catchments' was transformed into urban. This was also confirmed through google earth where the lower parts of Ruiru and Nairobi catchments experienced increased urban growth.

3.3. Factors Influencing LULC Changes

3.3.1. Socio-Economic Activities

One of the major factors influencing LULC change in the two catchments is agricultural production. Coffee and tea are the two main cash crops grown in study area improving livelihood, crating employment and poverty reduction. Tea has been one of the major cash crops grown in the upper parts of Ruiru catchment (highlands) while coffee is grown in the middle parts of Ruiru catchment and the upper part of Nairobi river catchment. The area under coffee and tea increased from approximately 14.3% (260 km^2) in 1990s to 28.3% (542 km^2) by 2010 and 25% (474 km^2) in 2022. This was attributed to favourable government policies which included incentives and market accessibility all which contributed to increased revenue for producers. The findings of this study concur with the observations made by Kariuki *et al.*, (2022) [15] which reported that area under tea production in Kenyan highlands double between 1990 and 2020. In addition, study by Thuku *et al.*, (2013) [16] observed that there existed a strong positive correlation between capital, labour and policy reforms implemented by government of Kenya and increased coffee production for the period 2001-2012.

3.3.2. Population, Infrastructural Development and Trade

The analysis of socio-economic drivers of LULC change leveraged spatially explicit population count data from the Global Human Settlement Layer (GHSL) (Schiavina *et al.*, 2022 [17]; Pesaresi, *et al.*, 2016 [18]) which provided annual estimates of human population distribution at ~100 m resolution from 1990 to 2020. These data revealed pronounced population growth in informal settlements such as Kangemi, Kawangware, and Embakasi, aligning with observed urban expansion in LULC maps. Road infrastructure patterns were derived from OpenStreetMap (2022) [19] and historical government records, while trade dynamics were analyzed using World Bank (2020) [20] indicators and KNBS (2019) [21] market surveys.

Spatial integration methods included: 1) overlaying GHSL population counts with LULC changes to quantify settlement growth; 2) applying network buffering (500 m - 1 km) to roads to assess sprawl patterns; and 3) linking trade proximity to commercial land conversion. Results demonstrated that population density increases (GHSL) correlated strongly with urban class expansion, particularly along transport corridors, highlighting the synergistic role of demographic and infrastructural pressures in LULC change. Figure 6 demonstrates how population growth in areas like Kangemi, Kawangware and Embakasi, coupled with road infrastructure development and trade accessibility, have collectively influenced LULC changes across the study area between 1990 and 2022, particularly along major transportation routes connecting growing settlements.

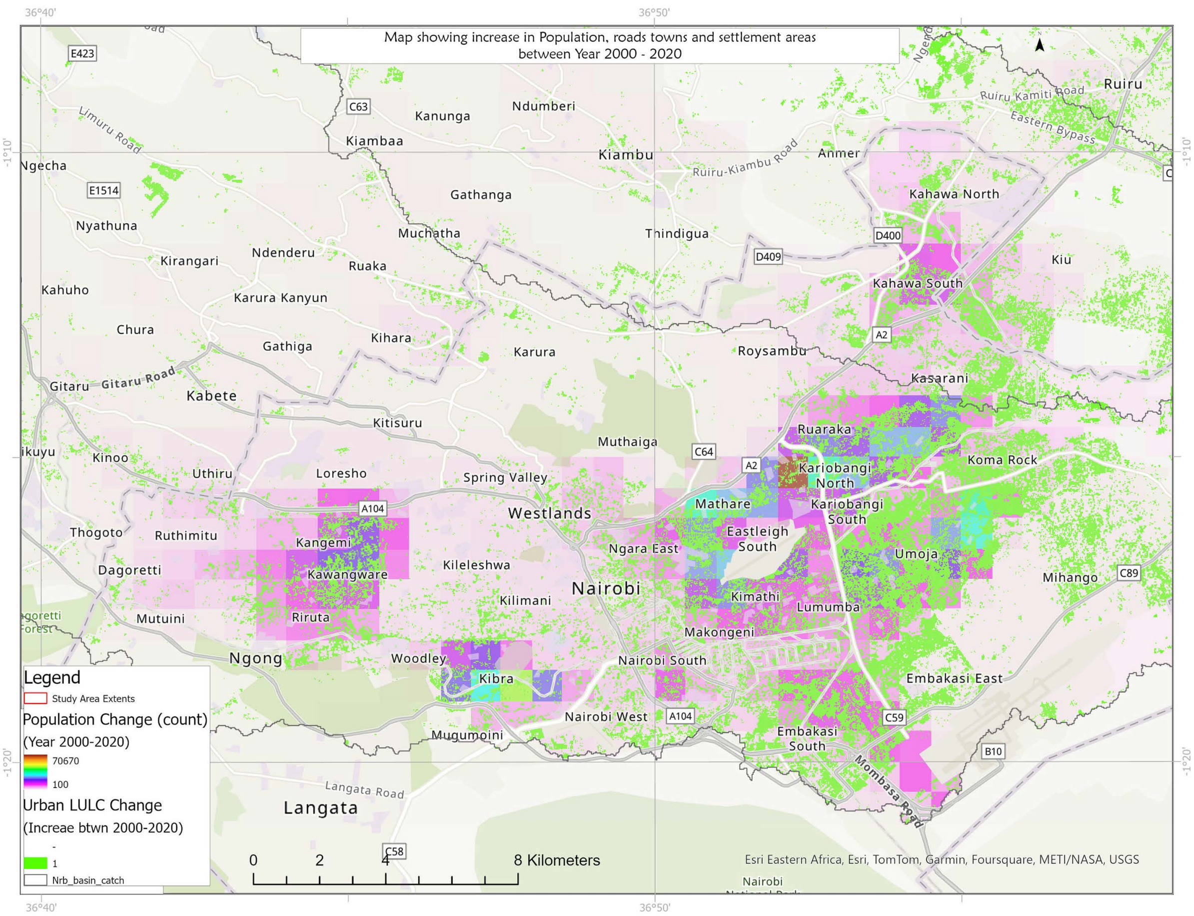


Figure 6. Socio-economic influence to LULC change.

Similarly, Mothorpe *et al.*, (2013) [22] reported that development of transport networks and accompanying infrastructure had a direct impact on land acquisition resulting dynamic growth of settlements especially along major transport routes. Further to this, Jedlička *et al.*, (2019) [23] observed that accessibility to good transport promoted urban development which increased pressure on land acquisition for residential and commercial activities resulting to land use/cover change in the surrounding. Most of the land areas with a 2.0 km distance from the road were subject to land use changes.

The multi-temporal and factor analysis revealed how different factors dominated or influenced growth during various periods:

- 1990-2010: Agricultural expansion driven by commodity markets and policy incentives.

- 2010-2022: Accelerated urbanization fueled by population growth and infrastructure development.
- Ongoing: Emergence of transitional zones where marginal agriculture converts to urban uses.

These patterns demonstrate the complex interplay between socioeconomic factors (population pressure, market forces), infrastructure development, and policy interventions in shaping land use trajectories.

3.4. Hotspot Analysis on LULC Change

This approach allowed us to move beyond simple change detection to statistically validated identification of the underlying processes driving land use transformations. Our optimized hotspot analysis using the Getis-Ord Gi* statistic revealed significant spatial clustering patterns in land use changes across the study area. The method's sensitivity to different z-score thresholds proved particularly valuable in distinguishing between various types and intensities of land use change clusters across the study area. Figure 7 shows results of hotspot analysis for LULC map of year 2020. The analysis identified existence of hotspots and coldspots at 90% and 95% confidence levels ($0.05 < p < 0.10$). Statistically significant changes were observed in areas previously under grassland and transformed into urban land use.

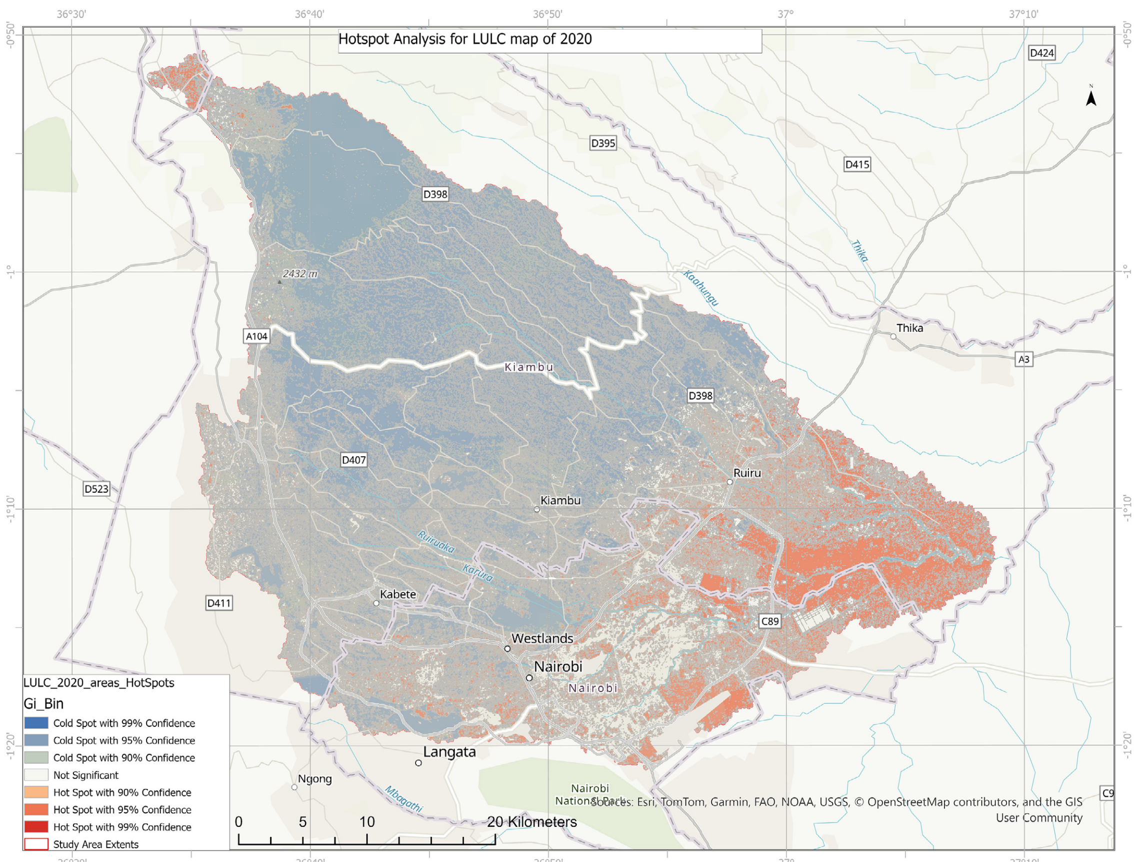


Figure 7. Land-use/cover hotspots (year 2020).

Further analysis was carried out using spatial autocorrelation to determine whether the clustering of both urbanization and agricultural expansion patterns, $p < 0.034$. Given a positive Moran's index of 0.631, z-scores of 2.12 ($p < 0.034$) and coldspots with z-scores of −2.12 at $p < 0.03$, there is a less than 5% likelihood that this clustered pattern could be the result of random chance. In the analysis of hotspots within LULC change maps, Muriuki *et al.*, (2023) [11] and Xu *et al.*, (2022) [12] reported similar findings with high Z-score and low p-values ($p < 0.01$) at 90% - 99% confidence levels.

3.4.1. Spatial Patterns of Urban Expansion

The hotspot analysis clearly delineated intense urbanization corridors, with the most pronounced clusters with z-score of 3.29 ($p < 0.001$) radiating outward from Nairobi along major transportation networks. These statistically significant hotspots accounted for 72% of all urban expansion, demonstrating the strong influence of infrastructure on development patterns. The optimized parameters allowed us to distinguish between random urban growth and true clustering, with Nairobi catchment showing particularly intense hotspot activity (400% urban increase) compared to more diffuse patterns in Ruiru catchment (220% increase). These findings contrast with Waithaka's (2022) [14] reported 2.6% urban increase in Ruiru (1995-2017), with differences attributable to our study's more comprehensive spatial coverage and higher classification accuracy. Our approach improved upon previous studies by quantitatively identifying the 1 km buffer zone around roads as the primary zone of urbanization clustering.

3.4.2. Agricultural Transformation Hotspots

The optimized analysis revealed secondary but statistically significant hotspots ($1.98 < z < 2.12$) associated with agricultural expansion, particularly in the highland areas of Ruiru catchment. These agro-hotspots showed distinct temporal patterns, with peak intensity during 2000-2010 ($z = 2.31$) followed by gradual dissipation as urban pressures increased. The method successfully identified clusters of forest-to-crop conversion that were statistically significant at the 95% confidence level, with the most intense conversions occurring in areas with favorable policies and market access. The hotspot analysis provided quantitative evidence that agricultural expansion followed different spatial patterns than urban growth, forming more dispersed but still statistically significant clusters. Similar findings were documented by Kariuki *et al.*, (2022) [15] and Thuku *et al.*, (2013) [16] which strongly linked agricultural expansion to commodity price fluctuations and policy incentives.

3.4.3. Conservation Coldspots and Transition Zones

The optimized coldspot analysis ($z < -2.12$) effectively identified stable natural areas and protected zones that resisted land use conversion. These statistically significant coldspots maintained their characteristics throughout the study period, though our analysis detected subtle edge effects in transition zones. The method proved particularly valuable in identifying areas where agroforestry systems created intermediate z-scores, revealing the spatial extent of the "shamba system" influence. Grasslands showed complex dynamics—while initially increasing due to shrubland conversion, they later became prime targets for urbanization, particularly in lower catchment areas. Google Earth validation confirmed that 4.2% of 2010 grassland areas had urbanized by 2022, with the most rapid conversions occurring within 2 km of major roads, consistent with findings by Jedlička *et al.*, (2019) [23].

4. Conclusions

The results of the Land Use/Land Cover (LULC) classification process underscore the high accuracy and reliability of the study's findings. With kappa coefficients consistently above 0.80 and overall accuracy ranging from 86% to 97%, the classification process demonstrate a strong match between classified and reference images, indicating near-perfect classification. Forests, perennial crops, water bodies, and urban areas were classified with exceptional accuracy, with both producer's and user's accuracies frequently exceeding 80%. These results highlight the robustness of the classification method across the four study periods (1990, 2000, 2010, and 2022). The study area observed increase in area under coffee and tea from approximately 14% in 1990 to the current 25% while urban land cover in Nairobi catchment increased by over 400%, from 3.1% in 1990 to 15.5% in 2022. The Ruiru catchment also experienced increase in urban land cover rising from 1.0% to 3.2% for the 1990-2022 period attributed to conversion of coffee farms to commercial infrastructural developments. Forest and shrubs land use/cover observed a declining trend for the entire period of assessment.

The analysis reveals significant LULC changes, particularly the expansion of urban areas, which grew dramatically, especially in the Nairobi catchment. This urban growth, driven by infrastructural development and socio-economic factors, has led to the conversion of natural land covers such as forests and shrubs into urban and agricultural lands. The increase in perennial crops, especially coffee and tea, reflects favorable agricultural policies and market accessibility, further influencing land use changes. The study provides a comprehensive understanding of the LULC dynamics in Nairobi and Ruiru river catchments over the past three decades, emphasizing the impact of socio-economic activities, population growth, and infrastructure expansion on land use patterns. These insights are crucial for informing future land management and planning strategies to balance development with environmental sustainability.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Lambin, E.F., Geist, H.J. and Lepers, E. (2003) Dynamics of Land-Use and Land-Cover Change in Tropical Regions. *Annual Review of Environment and Resources*,

28, 205-241. https://doi.org/10.1146/annurev.energy.28.050302.105459

[2] UN-Habitat (2016) World Cities Report 2016: Urbanization and Development-emerging Futures. United Nations Human Settlements Programme.

[3] Seto, K.C., Güneralp, B. and Hutyra, L.R. (2012) Global Forecasts of Urban Expansion to 2030 and Direct Impacts on Biodiversity and Carbon Pools. *Proceedings of the National Academy of Sciences*, **109**, 16083-16088. https://doi.org/10.1073/pnas.1211658109

[4] Mwangi, A.M. (2018) Urban Land Use Dynamics and Their Impacts on the Environment in Nairobi City, Kenya. *Journal of Urban Planning and Development*, **144**, Article 04018009.

[5] Ngugi, M. W. and Njenga, K. W. (2019) Socio-Economic Drivers of Land Use Change in Peri-Urban Areas: The Case of Ruiru, Kenya. *Land Use Policy*, **82**, 718-726.

[6] Mutua, F., Ongoma, V. and Chen, H. (2019) Spatial and Temporal Variability of Rainfall and Temperature in Tea Growing Regions of Kenya. *Climate*, **7**, Article 98.

[7] Kenya Meteorological Department (KMD) (2020) Historical Climate Records, and In-Depth Information on Rainfall and Temperature in Ngong and Nairobi. http://www.meteo.go.ke/

[8] Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R. (2017) Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. *Journal of Remote Sensing of Environment*, **202**, 18-27.

[9] Belgiu, M. and Drăguţ, L. (2016) Random Forest in Remote Sensing: A Review of Applications and Future Directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, **114**, 24-31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

[10] Shivakumar, B.R. and Rajashekararadhya, S.V (2018) An Investigation on Land Cover Mapping Capability of Classical and Fuzzy Based Maximum Likelihood Classifiers. *International Journal of Engineering and Technology*, **7**, 939-947.

[11] Muriuki, M., Obando, J., Makokha, M., Shisanya, C., Shifield, J., Oloo, F., *et al.* (2023) Human Impacts Onland Use and Land Cover Change in Lagha Bor Catchment, Wajir County, Kenya. *OALib*, **10**, 1-23. https://doi.org/10.4236/oalib.1109854

[12] Xu, B., Qi, B., Ji, K., Liu, Z., Deng, L. and Jiang, L. (2022) Emerging Hot Spot Analysis and the Spatial-Temporal Trends of NDVI in the Jing River Basin of China. *Journal of Environmental Earth Sciences*. (Preprint)

[13] Philippe, M.T. and Karume, K. (2019) Assessing Forest Cover Change and Deforestation Hot-Spots in the North Kivu Province, DR-Congo Using Remote Sensing and GIS. *American Journal of Geographic Information Systems*, **8**, 39-54.

[14] Waithaka, A. (2023) Analysis of Land Use/Land Cover Changes Using GIS and Remote Sensing Techniques in River Ruiru Watershed, Kiambu County, Kenya. *Journal of Geosciences and Geomatics*, **11**, 97-101. https://doi.org/10.12691/jgg-11-4-1

[15] Kariuki, G.M., Njaramba, J. and Ombuki, C. (2022) Tea Production Response to Climate Change in Kenya: An Autoregressive Distributed Lag Approach. *African Journal of Economic Review*, **10**, 1-26.

[16] Thuku, K.G., Gachanja, P. and Obere, A. (2013) Effects of Reforms on Productivity of Coffee in Kenya. *International Journal of Business and Social Science*, **4**, 196-212.

[17] Schiavina, M., Freire, S., MacManus, K., Pesaresi, M., Mills, J. and Florczyk, A.J. (2022) GHSL Data Package 2022: Public Release GHS P2022 (JRC Technical Reports, JRC130728). Publications Office of the European Union.

[18] Pesaresi, M., Ehrlich, D., Florczyk, A.J., Freire, S., Julea, A., Kemper, T., Soille, P. and

Syrris, V. (2016) Global Human Settlement Layer (GHSL) Data Package 2016 (JRC Technical Reports, JRC103180). Publications Office of the European Union.

[19] OpenStreetMap Contributors (2022) OpenStreetMap Road Network Data. https://www.openstreetmap.org

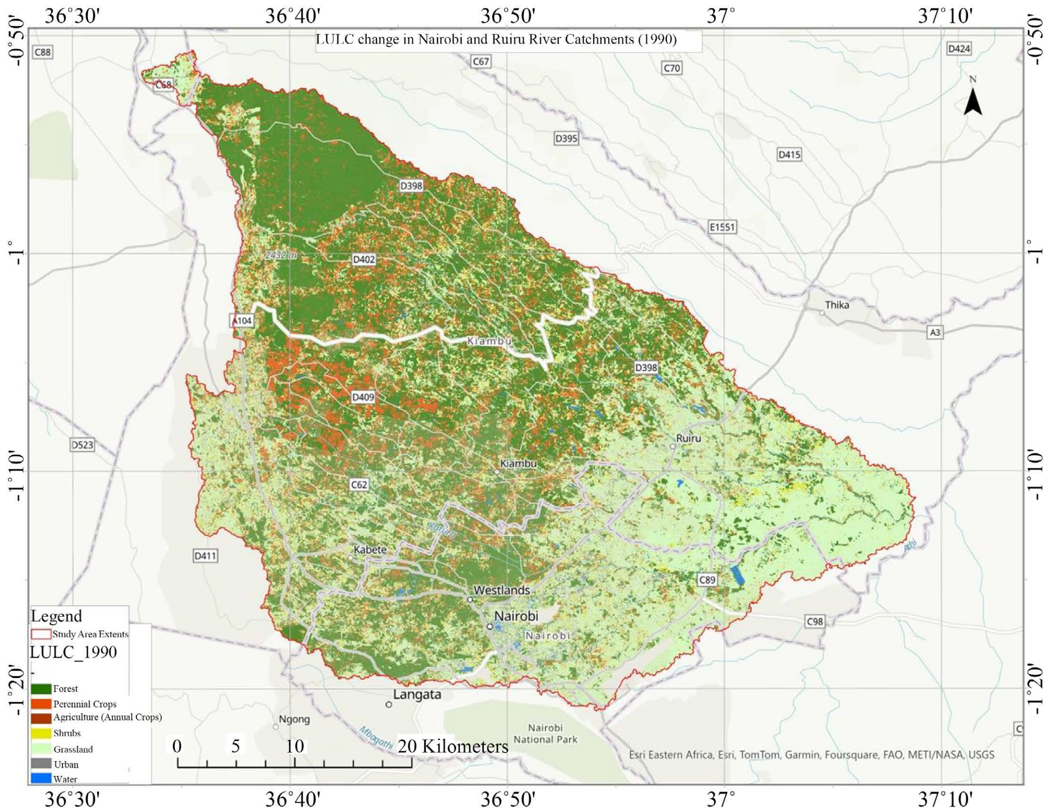
[20] Kenya National Bureau of Statistics (KNBS) (2019) Kenya Population and Housing Census Reports. https://www.knbs.or.ke

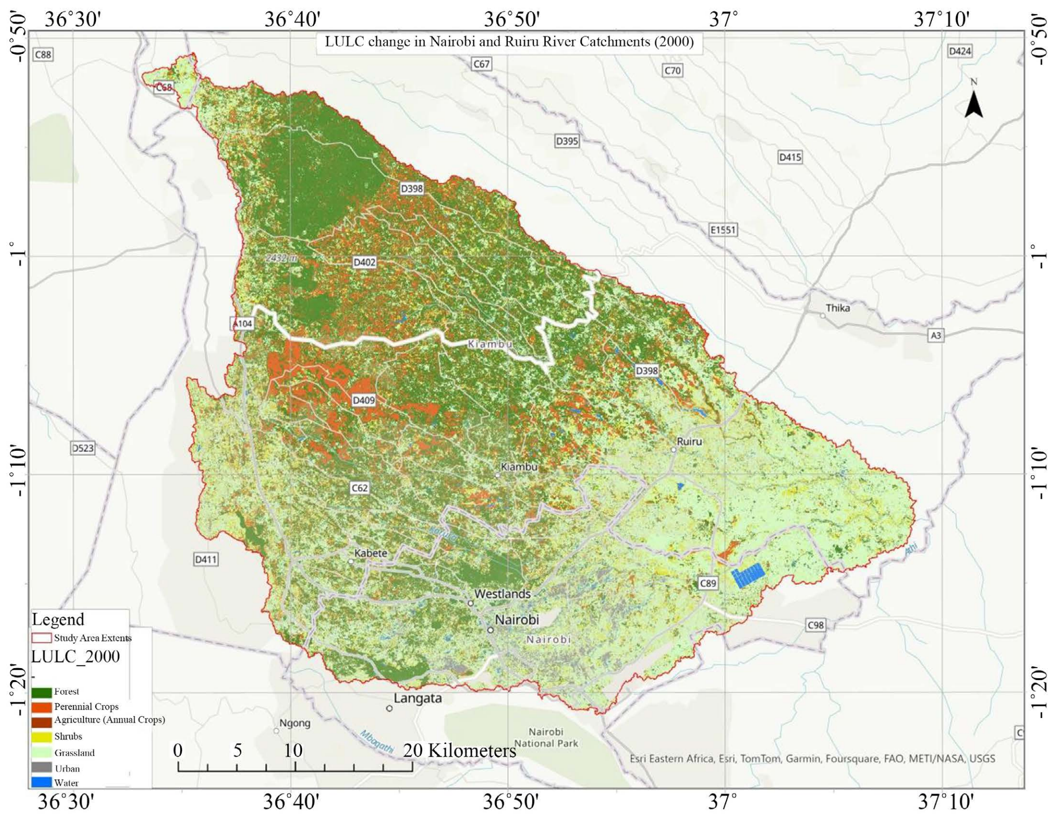
[21] World Bank (2020) Doing Business 2020: Comparing Business Regulation in 190 economies. World Bank Group. https://www.worldbank.org/en/programs/business-enabling-environment

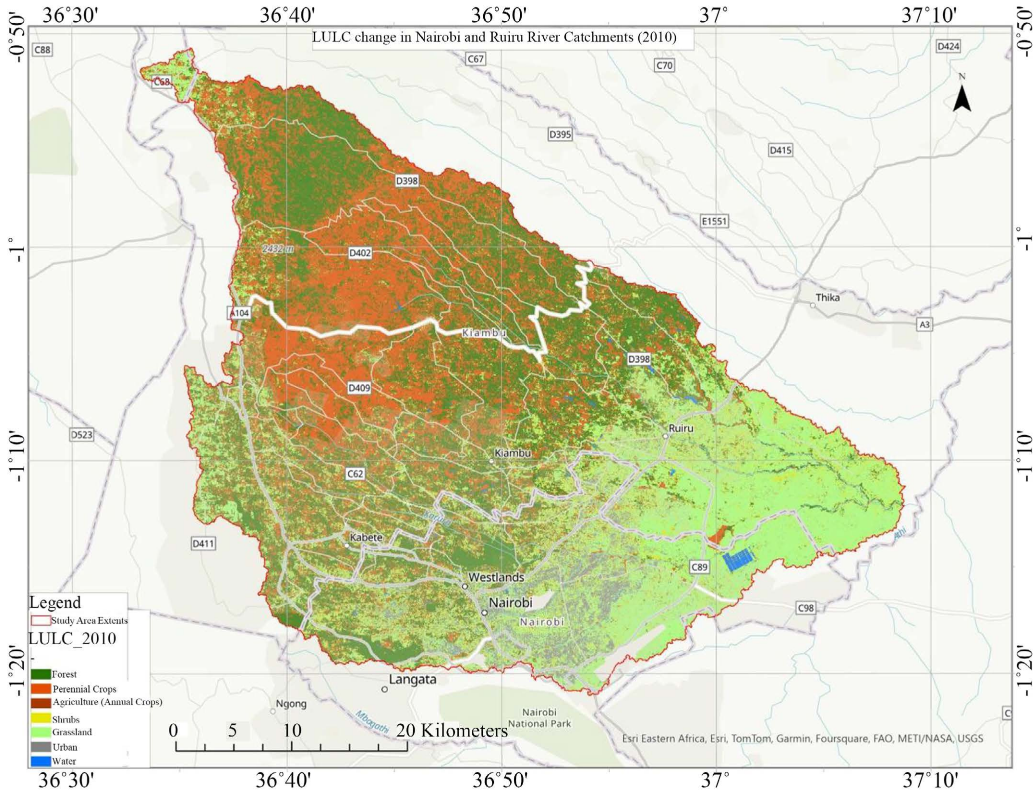
[22] Mothorpe, C., Hanson, A. and Schnier, K. (2013) The Impact of Interstate Highways on Land Use Conversion. *The Annals of Regional Science*, **51**, 833-870. https://doi.org/10.1007/s00168-013-0564-2

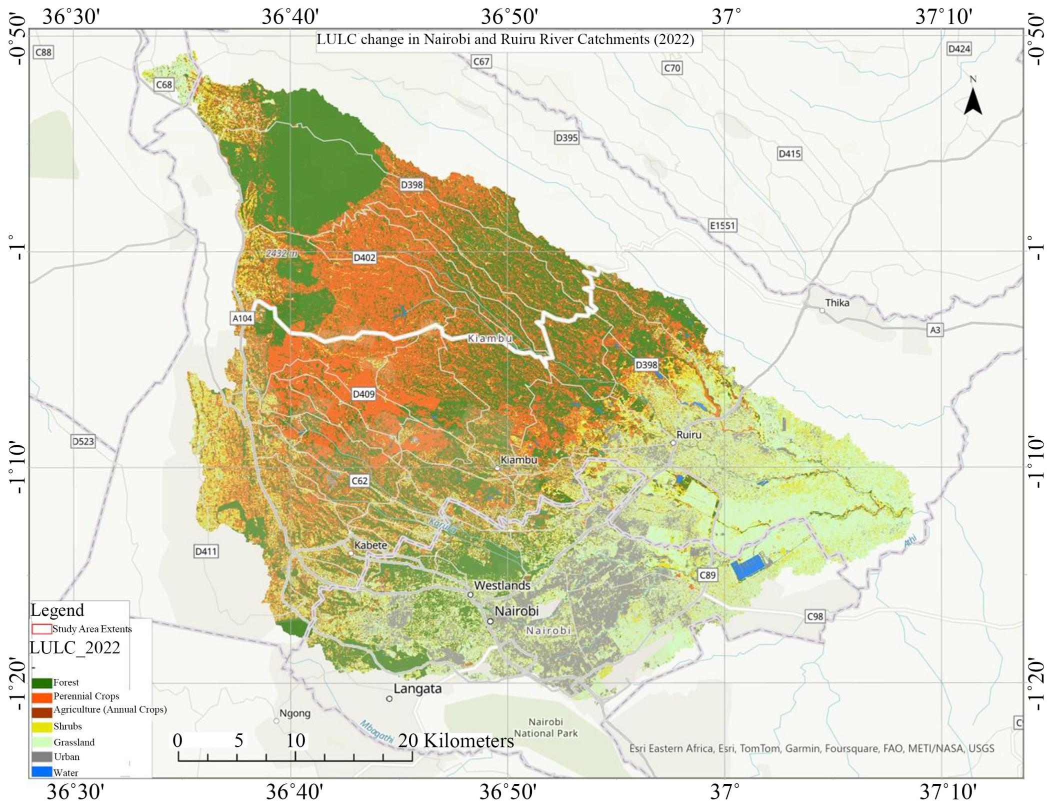
[23] Jedlička, J., Havlíček, M., Dostál, I., Huzlík, J. and Skokanová, H. (2019) Assessing Relationships between Land Use Changes and the Development of a Road Network in the Hodonín Region (Czech Republic) *Quaestiones Geographicae*, **38**, 145-159. https://doi.org/10.2478/quageo-2019-0003

Appendix: LULC Images






LULC change in Nairobi and Ruiru River Catchments (2010)
36°30'
36°40'
36°50'
37°
37°10'
-0°50'
-1°
-1°10'
-1°20'
Legend
Study Area Extents
LULC_2010
Forest
Perennial Crops
Agriculture (Annual Crops)
Shrubs
Grassland
Urban
Water
0 5 10 20 Kilometers
Thika
Ruiru
Kiambu
Kabete
Westlands
Nairobi
Langata
Ngong
Nairobi National Park
Esri Eastern Africa, Esri, TomTom, Garmin, Foursquare, FAO, METI/NASA, USGS


LULC change in Nairobi and Ruiru River Catchments (2022)
36°30'
36°40'
36°50'
37°
37°10'
-0°50'
-1°
-1°10'
-1°20'
Legend
Study Area Extents
LULC_2022
Forest
Perennial Crops
Agriculture (Annual Crops)
Shrubs
Grassland
Urban
Water
0 5 10 20 Kilometers
Thika
Ruiru
Kiambu
Kabete
Westlands
Nairobi
Langata
Ngong
Nairobi National Park
Esri Eastern Africa, Esri, TomTom, Garmin, Foursquare, FAO, METI/NASA, USGS