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RESEARCH

LULC Assessment and Green Infrastructure Conservation in residential neighborhoods: a case of FESTAC Town, Lagos, Nigeria

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Abstract In addressing environmental challenges and ecosystem resilience, green networks are preserved, repaired, and rebuilt by green infrastructure. However, urbanization effects have seen urban land form undergo significant modifications over time due to different anthropogenic activities. The objective of this study is to evaluate the land use and land cover (LULC) change in FESTAC Town, a government-owned residential neighborhood in Lagos, with the goal of recommending interventions for conserving green infrastructure. The study mainly focuses on employing remote sensing and geographic information system (GIS) techniques to detect alterations in land use in FESTAC Town from 1984 to 2022. The ERDAS Imagine software was utilized, employing a supervised classification-maximum likelihood algorithm, to identify changes in LULC. Additionally, an accuracy assessment was conducted using ground truth data. Findings from this study show significant increase in built-up areas at the cost of loss in dense vegetation over a 38-year period thereby, putting pressure on available green spaces. In terms of the area under each LULC category, most significant changes have been observed in built-up area (410.86%), bare surface (−79.79%), sparse vegetation (−53.42%), and dense vegetation (−31.83%). Effective conservation strategies should focus on promoting connectivity between green spaces, engaging stakeholders in the planning and implementation of green infrastructure projects.

Keywords Land use · Land cover · Green infrastructure · Lagos state · FESTAC Town

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Introduction

Land use and land cover change (LULC) are key indicators of environmental change and have significant impacts on ecosystem services in cities (Belay et al., 2022; Tolessa et al., 2017). From identifying areas with high potential for development, understanding the distribution and density of various land use types to detecting changes in land use over time, LULC assessment has become valuable for providing information for urban planning and is one of the main determinants of most landscape structures and functions globally (Liu et al., 2020).

LULC change is one of the contributing factors in both the development and intensity of urban heat island (UHI) effects (Kafy et al, 2021). Mitigating UHI involves urban planning strategies that prioritize green infrastructure. The intersections between LULC change and green infrastructure conservation provide an effective method to evaluate future land use change and landscape connectivity (Sun et al., 2022). With increasing urbanization and population growth, several natural spaces have been reclaimed for diverse socioeconomic activities ranging from residential, industrial, agricultural, and commercial land uses (Xu et al., 2019; Zhang et al, 2021). Reduction in vegetation cover through housing and infrastructural development in course of urban expansion (Wu et al., 2016), leading to increase in impervious surfaces (Rizvi et al, 2020), alters surface reflectivity (Fu & Weng, 2016) and increases energy consumption (Kumari et al., 2021) and atmospheric changes (Shahrin et al, 2019) in addition to other corollaries of change LULC.

Green infrastructure (GI) remains an integral component of sustainable, livable, and healthy places (Calvert et al., 2018), because it entails using nature-based approaches to address environmental challenges and ecosystem resilience (Hansen et al., 2019; Norton et al., 2015). Similarly, green networks are preserved, repaired, and rebuilt by green infrastructure (Apostolopoulou & Adams, 2015; Ying et al., 2011; Zhai, 2012). Although GI operates across different spatial scales, at the urban scale, where human activities are prevalent, GI connects public spaces like streets and parks with surrounding landscapes and ecological resources. Other features, which include street trees, shrubs, vertical green systems (VGSs), permeable pavers, and other forms of land cover, perform other important ecological functions.

Urban green infrastructure provides diverse opportunities by making connections between people and nature for sustainable cities (Herzog et al., 2019). Similarly, for residential neighborhoods, GI is crucial to improving quality of life as it provides a range of benefits such as protecting and enhancing urban biodiversity (Sinnett, 2015), supporting well-being and overall health (Frumkin et al., 2017), increasing the thermal performance of buildings, reducing urban heat island effect (Zölch et al., 2016), increasing aesthetic quality of the built environment (Swanwick, 2009), climate change adaptation (Demuzere et al., 2014), temperature regulation, manage rainfall discharge and pollutant sources (Lovell & Taylor, 2013), and improving air and water quality (Salmond et al., 2016).

Many studies have explored the use of remote sensing technology for LULC assessment and green infrastructure conservation in urban centers within developing countries (see for example Sam & Balasubramanian, 2023; Abebe et al., 2022; Hassan et al., 2016). Even in extremely varied and complicated urban contexts, remote sensing offers a beneficial array of technologies that can reduce the need for field investigations. Modern advancements like enhanced spatial resolution imaging and free data access regulations make it more suitable (Shahtahmassebi et al., 2021). Similarly, remote sensing assists in mapping street trees and plants effectively (Chance, 2016; Parmehr et al., 2016), improving air quality in urban spaces (Wang et al., 2021), measuring urban heat island (UHI) effects (Ngie et al., 2014), and GI conservation in urban areas (Abebe et al., 2022; Sam & Balasubramanian, 2023). It is relevant in the context of cities in developing countries where land uses are changing rapidly and the ensuing land cover patterns should be tracked.

Lagos, the largest and thriving city in Nigeria, is a typical example of an urban center re undergoing accelerated urbanization, which is significantly impacting the quantity of vegetative cover as strong contradictions and conflicts are currently being experienced between socioeconomic development and natural ecosystems. Evidence on land use and land cover analysis in Lagos, for example, indicates the vanishing at a fast rate of the available soft green infrastructure in exchange for more construction (Okorie, 2012, Olaleye et al., 2009). In FESTAC Town, for example, a total of 128,880.73 m^2 in land area was earmarked as open spaces during its creation, which represents a total of 64% (Fasona & Omojola, 2004; Anyakora et al., 2013). The current situation reveals that a significant portion of the green spaces provided in the original plan has since been encroached upon and converted into other commercial land uses.

In summary, decline in nature systems affects green infrastructure as land use and land cover change in context of urbanisation. Also, there is knowledge gap on actual extent of this change which precludes appropriate information that can guide initiatives for green space planning and development. Literature suggests that geospatial analysis forms an important tool for assessing LULC changes in cities and identifying opportunities to conserve and enhance green infrastructure (Shahfahad et al., 2022; Uddin et al, 2023). Similarly, in promoting a sustainable and resilient residential neighborhood, geospatial analysis provides strong potential such as monitoring micro-climate parameters, urban growth resulting from rapid urbanization and areas with risk of disaster (Mourshed et al., 2015, Kadhim et al., 2016).

The goal of this study is therefore to assess the LULC changes and change detection within a residential neighborhood in Lagos, Nigeria, between 1984 and 2022, using remote sensing technology, with a view to recommending GI conservation approaches. Using remote sensing and geospatial tools is not new, but its application to a residential setting in Lagos is novel. The available studies on housing transformation in Nigeria have mainly engaged changes in the dwellings that is, the physical structure (See for example Aduwo & Ibem, 2017; Maina, 2023), often poorly considering spaces between the buildings. This study's originality lies is the focus on land use and land cover (landscape) transformations over time in the largest formally planned public housing estate in Lagos, Nigeria.

Research methods and materials

Study area

Geographically, FESTAC Town is located along the Badagry Expressway, Lagos, Nigeria with a latitude of 6°27′59.2″N and a longitude of 3°17′0.65″E, respectively (Fig. 1). It is a government-owned housing estate that is managed by the Federal Housing Authority (FHA). The original acquisition of FESTAC Town encompasses roughly 17 km^2 and has a

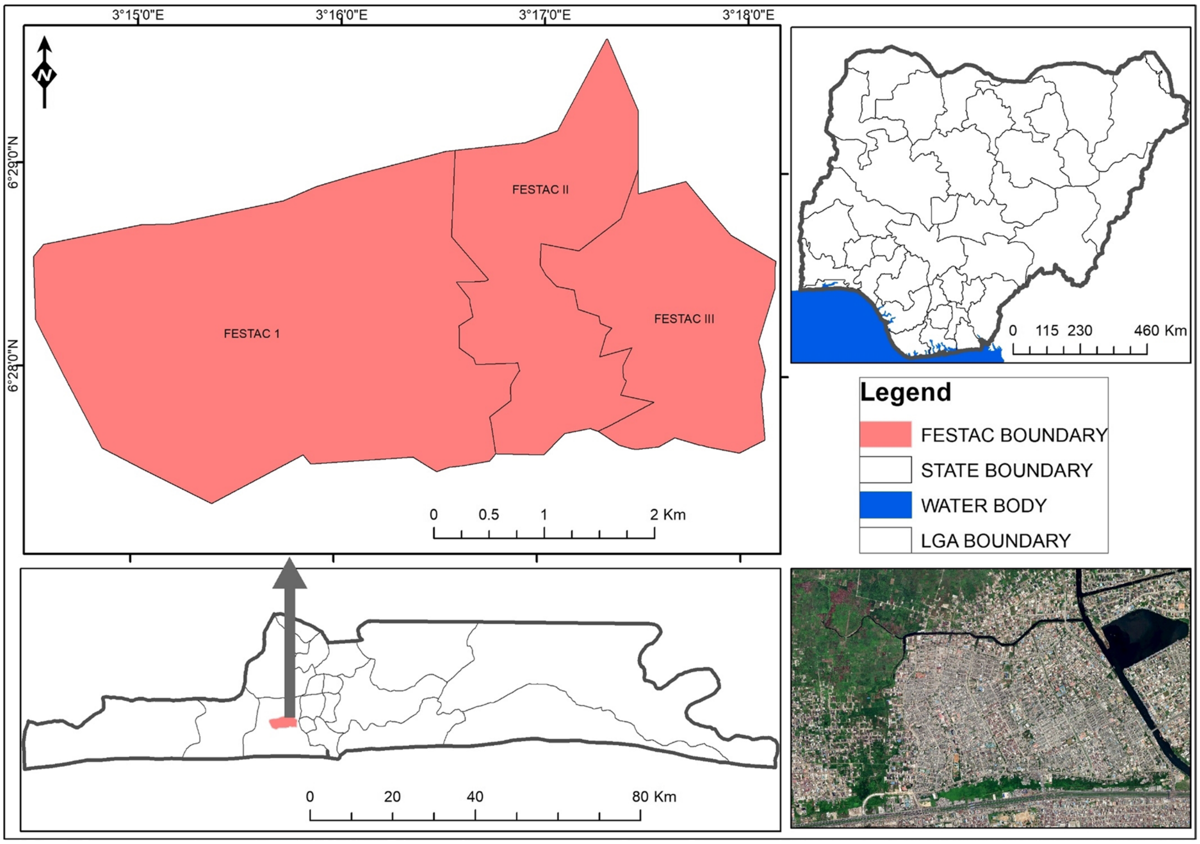


Fig. 1 Map of study area

perimeter of about 220 km. It is situated about 10 km southwest of central Lagos, between Amuwo Odofin and Alimosho LGAs of the metropolitan area (Fig. 1).

In terms of both land size and resident population, the FESTAC Town housing estate is the largest public residential housing estate in Nigeria (Ibiyemi et al., 2013). It includes every income class, dwelling units of various sorts, and floor heights. FESTAC town features building structures with a variety of typologies.

Evaluating changes in land use and land cover using satellite images was the main focus in this study. The GIS procedure was undertaken by mapping out the study area to highlight the quantity of greenery present at the site/neighborhood scale. Two remote sensing-based indices, namely normalized difference vegetative index (NDVI) and the normalized difference built-up index (NDBI), which both benefit from the distinctive spectral outcomes of built-up areas and other land cover types, were adopted for the study.

The amount and quality of green areas were measured using the NDVI and the NDBI. LULC assessment of various years between 1984 and 2022 was carried out to look into the various patterns of land changes over time. The green space ratio (GSR) and vegetation cover area (VGA) are two examples.

Vegetation indices on one hand provide relevant statistics from the multispectral data. The most recent estimates of an area's density, quality, and distribution of urban green space are made using the normalized difference vegetative index. NDVI is calculated as the difference between near-infrared (NIR) and red (R) reflectance divided by their sum. NDVI values range from $+1$ to -1, wherein -1 is generally area with no vegetative cover such as bare earth, deserts and water bodies and $+1$ is generally area with available vegetation cover (Gessesse & Melesse, 2019; Gupta et al, 2021).

It has the following formula:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - R}{\mathrm{NIR} + R}$$

Values between 0.6 and 0.8 reveal agricultural fields and parks, while values between 0.2 and 0.6 show shrub and grassland. Values below 0.2 indicate a lack of green space (Lotfata, 2021).

NDBI analysis measures built-up cover because it has a relatively low measuring value for vegetation (Ettehadi et al, 2019; Lotfata, 2021). To highlight man-made built-up regions, it uses the near-infrared (NIR) and short-wave infrared (SWIR) bands. The formula for measuring NDBI is shown below:

$$\mathrm{NDBI} = \frac{\mathrm{SWIR1} - \mathrm{NIR}}{\mathrm{SWIR1} + \mathrm{NIR}}$$

SWIR 1 (Band 11) and NIR (Band 8) are two abbreviations for short wave near-infrared and near-infrared reflectance, respectively. The range of the NDBI value is -1 to $+1$. NDBI has a negative value for water bodies and a positive value for built-up areas.

In order to create the NDVI and NDBI maps for the year 2022, Sentinel-2A imagery was chosen over Landsat due to its superior spatial resolution and the significantly smaller land of the study area. While Landsat has a wider resolution, Sentinel-2A has a smaller resolution. This made gathering the required information simpler. Due of its temporal characteristics and longer year duration, Landsat was preferred to Sentinel-2A for the LULC maps. Sentinel does have limitations in that sense because it was only launched in 2014, taking into account the length of time (1984–2022) needed for the LULC data.

Satellite data represent the principal information source for detecting LULC changes in any geographical region (Chughtai et al, 2021). The selection of Landsat imagery has been driven by the desire for cost-effectiveness and the availability of suitable data with a 30-m spatial resolution, enabling a broad spectrum of applications. To analyze land use and land cover changes in FESTAC, we obtained cloud-free satellite images (Table 1) from the United States Geological Survey (USGS) on the following dates: Landsat-5 Thematic Mapper on December 11, 1984, Landsat-7 Enhanced Thematic Mapper Plus on December 28, 2002, and Landsat-8 Operational Land Imager on December 27, 2022.

Band combination of 543 (Landsat 8 OLI) and 432 (Landsat ETM + and TM) color composites were processed using the maximum likelihood algorithm for supervised classification in Erdas Imagine 2015. The accuracy assessment was carried out using ground truth data obtained from selected points during the fieldwork, coupled with high-resolution Google Earth images and visual interpretation. Error matrices were applied in the statistical comparison of reference data and classification

Table 1 Landsat data information

Sensor ID	Landsat path and row	Acquisition date	Resolution (m)	Source
LT05_L1TP_191055_19841218_20200918_02_T1	p191/r055 (Landsat 5 TM)	11/12/1984	30	USGS
LE07_L1TP_191055_20021228_20200916_02_T1	p191/r055 (Landsat 7 ETM+)	28/12/2002	30	USGS
LC08_L1TP_191055_20221227_20230104_02_T1	p191/r055 (Landsat 8 OLI)	27/12/2022	30	USGS

results. The error matrices were generated to assess the user's accuracy, producer's accuracy, and overall classification accuracy.

The post-classification comparison (PCC) method was utilized to detect the LULC change dynamics of the study area, between 1984 and 2022 to produce a land use change matrix using independently classified imageries of two different time nodes. The study performed the post-classification comparison in ArcGIS 10.7.1 using a thematic classified map overlay and various geospatial operations. The result indicates the numerous land use transformations that occurred during the period between 1984 and 2022.

Results

Green infrastructure quality and quantity

The quantity of green space within the boundary of the study area for the year 2022 is shown in the resulting NDVI image (Fig. 2). The difference

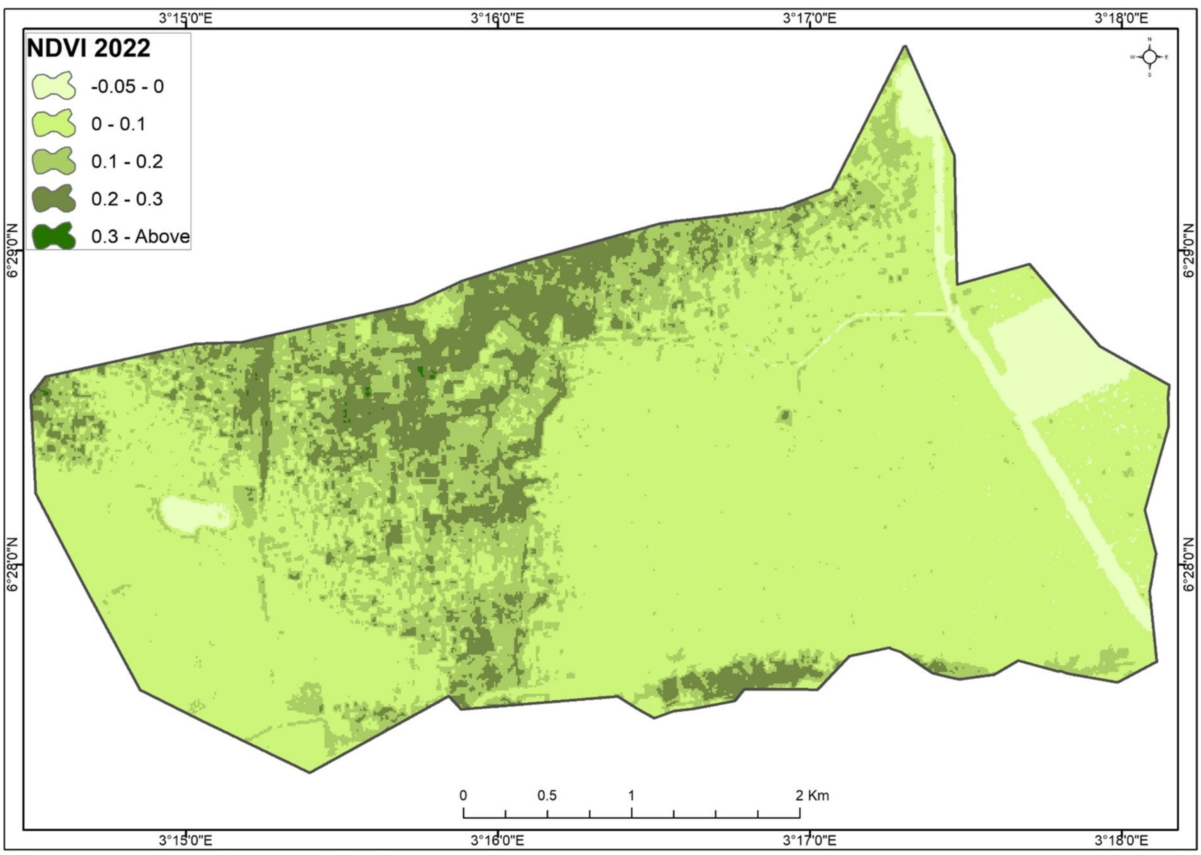


Fig. 2 NDVI analysis result 2022

in shade of color green (light and dark) on a color scale represents how much green space is arranged in the study area. The areas indicated by light green exhibit a low green space, while the areas indicated by dark green show a large green space. FESTAC Town has a low percentage of green space, as seen by the NDVI range of − 0.05 to 0.2. The lack of greenness is indicated by values of green space cover in the 0.1 and below range.

The graphic representation of the NDBI of the study area demonstrates the degree of built-up urban density. The difference in color between blue, yellow, and orange (Fig. 3) depicts the organization of built-up areas at various levels within the study region. In contrast to places with orange, which have the most built-up densities, the blue area exhibits no built-up areas. On the NDBI map, Fig. 3 indicates a pattern of built-up areas expanding towards the east and west limits, with some scatted built-up areas in the middle.

Multi-index land use and land cover pattern of study area

The Anderson classification system used in USGS LULC Level 1 class datasets was used in this study. Five general categories were used to classify the study area. Table 2 contains details of the classes, with each class developed based on texture, tone, and color (Radhakrishnan et al., 2014).

Kappa coefficient and overall accuracy for the classified images

The study focused on two types of correctness within the confusion matrix: user accuracy and producer accuracy (Table 3). Total image classification correctness and overall kappa statistics were then determined based on these classification types. The accuracy assessment was conducted for the LULC maps of 1984, 2002, and 2022. Classifiers were employed

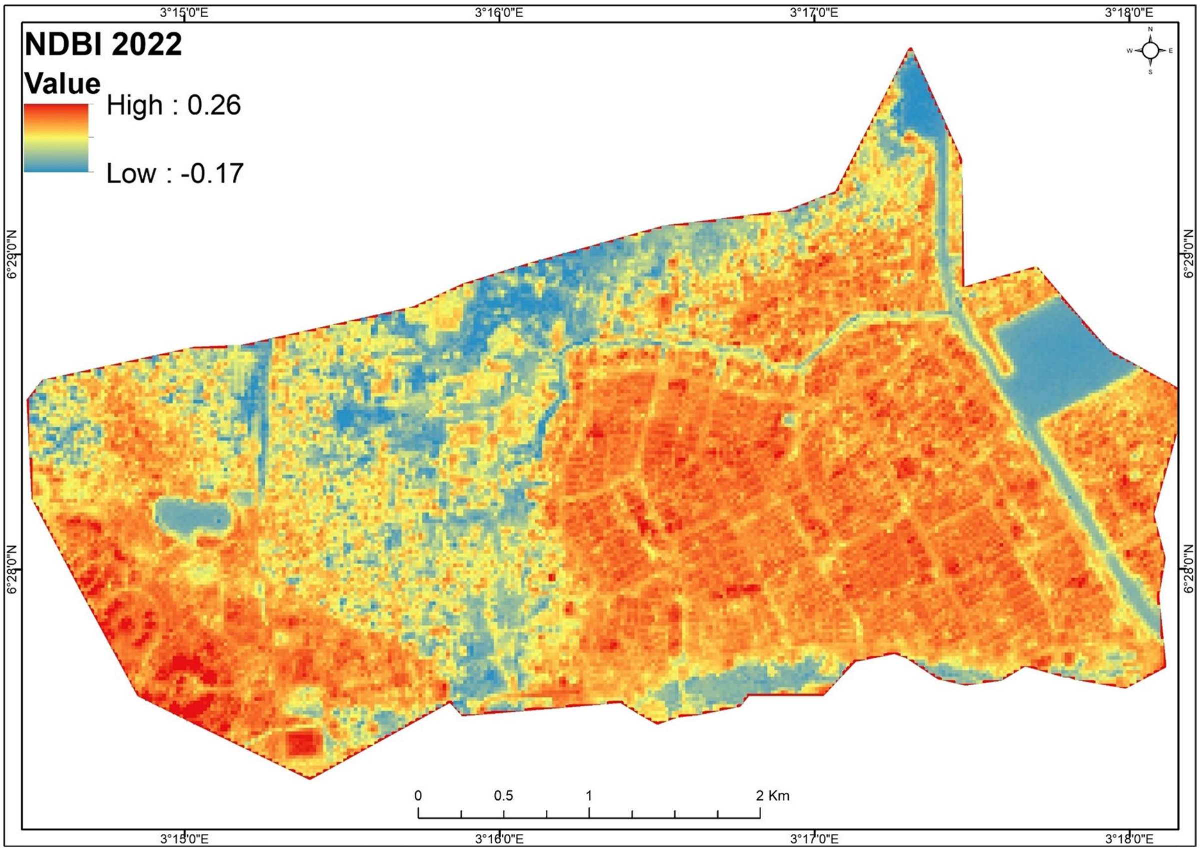


Fig. 3 NDBI analysis result 2022

Table 2 Image classification details adopted for this study

s/n	Class	Description
1	Water bodies	Areas submerged in water, such as rivers, reservoirs, ponds, lakes, and streams
2	Sparse vegetation (forest)	A region with a generally sparse amount of forest vegetation
3	Dense vegetation (agricultural land)	Areas with a high concentration of grasses, plants, and crops, such as parks and consistently cultivated, cultivated croplands
4	Built-up area	Concrete-covered ground, comprising low-, medium-, and high-density road networks, houses, businesses, and other structures constructed by humans, as well as landfills for solid waste, educational facilities, and transportation
5	Bare surface	Areas with minimal vegetation, whether present or absent, that could change or accommodate new users in the future. This group comprises lands devoid of crops, rocky terrain, and sandy shorelines near rivers and streams

Source: Anderson et al. (1976)

Table 3 Matrix indicating the overall accuracy and kappa statistics for 1984, 2002, and 2022 LULC map of the study area

Year 1984								
Data	Water body	Densed veg	Sparse veg	Bare surface	Built-up area	Row total	Producer's (%)	User's (%)
Water body	98.64	0.34	0.07	0	0	29,055	91.3	90.8
Densed veg	1.35	91.68	31.69	2.41	0.28	1,760,869	83.2	85.5
Sparse veg	0.01	7.2	40.53	1.72	1.21	267,381	72	70.1
Bare surface	0	0.72	8.57	75	22.94	583,481	82.1	80
Built-up area	0	0.05	19.14	20.88	75.57	229,871	74.7	72.1
Column total	22,975	1,794,345	309,711	717,395	26,231	2,870,657		
Overall kappa coefficient = 85.6%								
Year 2002								
Data	**Densed veg**	**Sparse veg**	**Water body**	**Built-up area**	**Bare surface**	**Row total**	**Producer's (%)**	**User's (%)**
Densed veg	97.37	1.51	1.64	0.01	0.1	790,612	93.2	90.2
Sparse veg	1.67	93.98	0.19	3.9	3.23	76,849	91.5	93.1
Water body	0.19	0	97.36	0	0.01	38,043	93	88.9
Built-up area	0	2.81	0.03	82.66	24.07	118,776	79.6	80.3
Bare surface	0.77	1.7	0.77	13.42	72.59	325,121	74.8	70.5
Column total	810,115	51,720	37,410	15,263	434,893	1,349,401		
Overall kappa coefficient = 89.1%								
Year 2022								
Data	**Water body**	**Densed veg**	**Sparse veg**	**Bare surface**	**Built-up area**	**Row total**	**Producer's (%)**	**User's (%)**
Densed veg	98.81	0.23	0.23	0.25	0	680,883	95.6	93.2
Sparse veg	0.5	99.15	0.19	0	0.11	51,777	97.1	95.5
Bare surface	0.69	0.61	87.79	0.15	11.5	56,093	85.1	84.1
Water body	0	0	3.09	99.58	0	31,633	96.4	98.7
Built-up area	0.01	8.69	0.02	0.02	88.39	33,716	85.6	87.5
Column total	688,776	48,626	53,755	30,097	32,848	854,102		
Overall kappa coefficient = 89.9%								
Overall classification accuracy = 86.4%				**Overall kappa coefficient = 88.2%**				

to validate the accuracy calculation of the various land use maps produced. The outcomes revealed different accuracy measures, including overall accuracy, user accuracy, producer accuracy, and the kappa coefficient for the land use maps.

The overall accuracy results for the classified imageries in the years 1984, 2002, and 2022 were 86.4%, with overall kappa coefficient as 88.2%. The water body category had a minimum producer accuracy of 91.3%, while the correctness for the other four land use and land cover classes (dense vegetation, sparse vegetation, bare surface, and built-up area) was below 90% in the year 1984. User accuracy results for dense vegetation in 1984, 2002, and 2022 were 85.5%, 90.2%, and 93.2%, respectively, compared to the other land use classes.

According to the 2002 results, the land area mainly comprised of built-up area (7.28 km^2, 44.83% of total area) followed by dense vegetation (4.47 km^2, 27.52%). The other land use categories were water bodies (0.79 km^2, 4.86%), sparse vegetation (1.97 km^2, 12.13%), and bare surface (1.73 km^2, 10.65%). The year 2022 shows that the largest category was the built-up area (8.94 km^2, 55.05%), followed by dense vegetation (4.54 km^2, 27.96%). Others include water bodies (0.8 km^2, 4.93%), sparse vegetation (1.02 km^2, 6.28%), and bare surface (1.73 km^2, 5.79%). Histogram of LULC change of the study area (Fig. 7) reveals the changes over the 38-year period.

The LULC map layout is displayed in Fig. 4, 5, and 6, respectively. It includes vegetative cover area (VCA) and green space ratio (GSR) categories for the years 1984, 2002, and 2022 and their statistics, respectively.

Change detection from 1984 to 2022

The area covered by LULC classes and how it changed between 1984 and 2022 is displayed in Table 4. In 1984, there was minimal built-up area, and there was a substantial amount of dense vegetation and bare surface.

Over the course of 38 years, both good and negative developments were seen in the area covered by the LULC categories. In contrast to the built-up area, which showed an increase in land area, water bodies, sparse and dense vegetation, and bare surfaces all showed considerable decreases in respective areas.

The following equation was used to calculate the percentages of change observed in LULC:

$$\Delta = \frac{A2 - A1}{A1} \times 100$$

where A1 and A2 are beginning and final, and Δ is the proportion of land use/land cover change. Negative values denote loss while positive values suggest gain.

Water bodies

The area occupied by water bodies decreased by 0.19 km^2 (−19.19%), from 0.99 km^2 in 1984 to 0.80 km^2 in 2022. One factor contributing to this reduction is the alteration of water bodies into other land uses.

Sparse vegetation/forest

The area under sparse vegetation decreased from 2.19 km^2 (−53.42%) in 1984 to 1.02 km^2 in 2022, representing a net decrease of 1.17 km^2. The transformation of forest lands into developed areas, such as parks, highways, and other development initiatives, is responsible for this loss.

Dense vegetation

The area occupied by dense vegetation decreased by 2.12 km^2 (−31.83%), from 6.66 km^2 in 1984 to 4.54 km^2 in 2022. This decline is due to the ongoing demand for urban housing and other socioeconomic growth. Another factor contributing to the fall is a decrease in farming activities for other enterprises.

Built-up area

Residential, industrial, and commercial areas make up an urban built-up area. The outcome demonstrates that as the area covered by built-up land increased, the development of built-up areas has surpassed other land uses from 1.75 to 8.94 km^2 between 1984 and 2022. This represents an increase of 7.19 km^2 (+410.86%). Continuous rise in urban population leading to increased demand for housing is responsible for the increase. The locational attribute of the study area is also a significant factor.

Bare surface

The area occupied by bare land reduced from 4.65 to 0.94 km^2 from 1984 to 2022, representing a decrease of 3.71 km^2 (−79.79%). The conversion of bare land into other uses is attributed to the observed decrease.

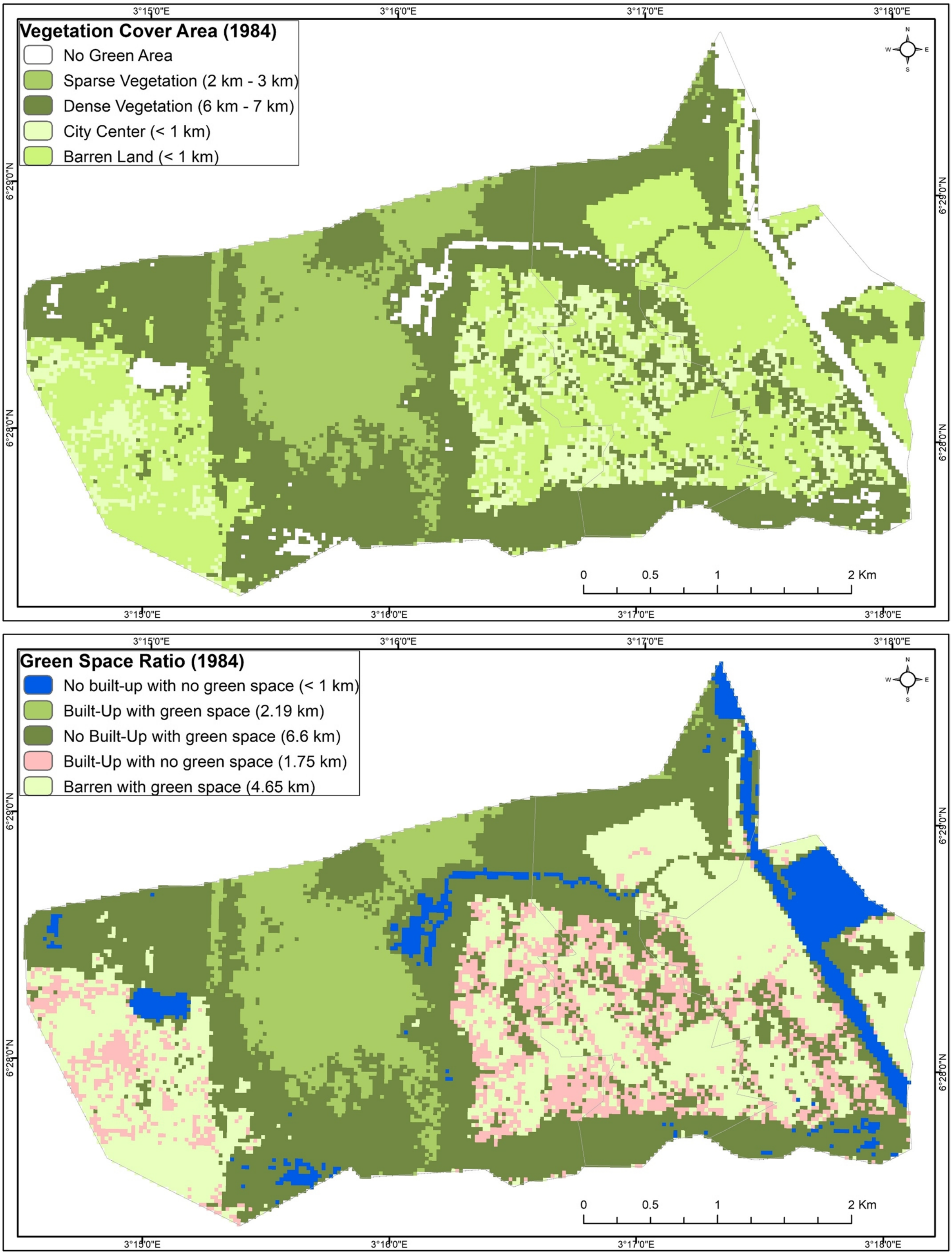


Fig. 4 LULC map of study area indicating both the vegetation cover area (VCA) and green space ratio (GSR) in 1984

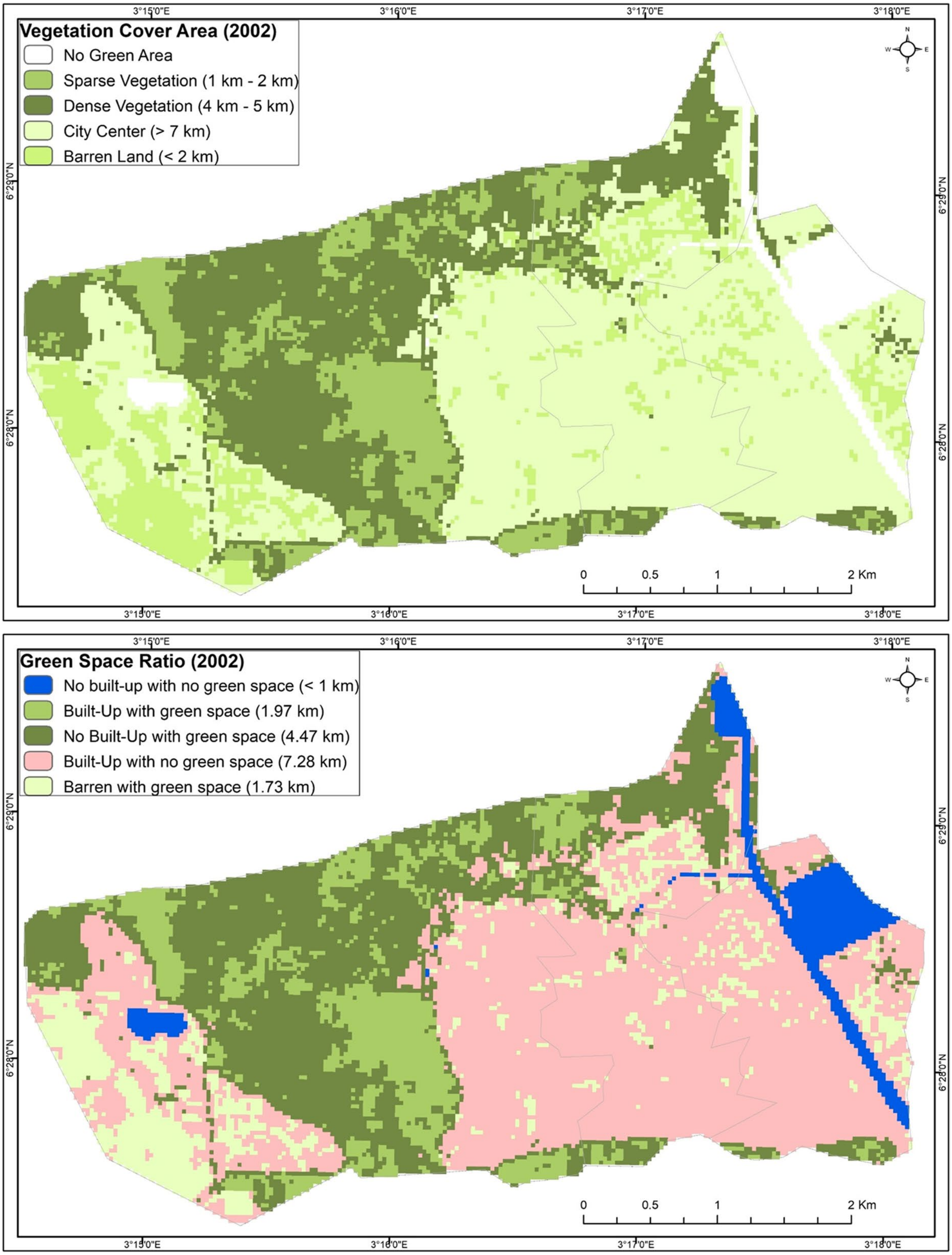
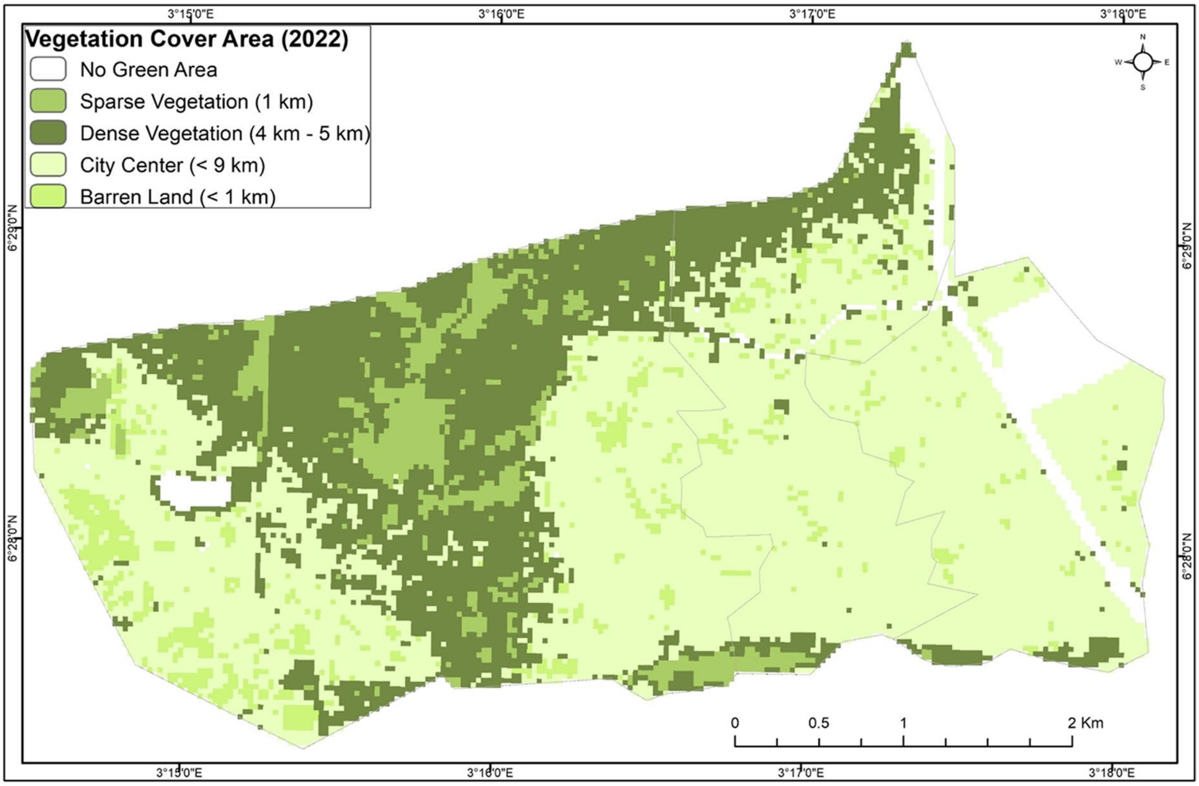


Fig. 5 LULC map of study area indicating both the vegetation cover area (VCA) and green space ratio (GSR) in 2002



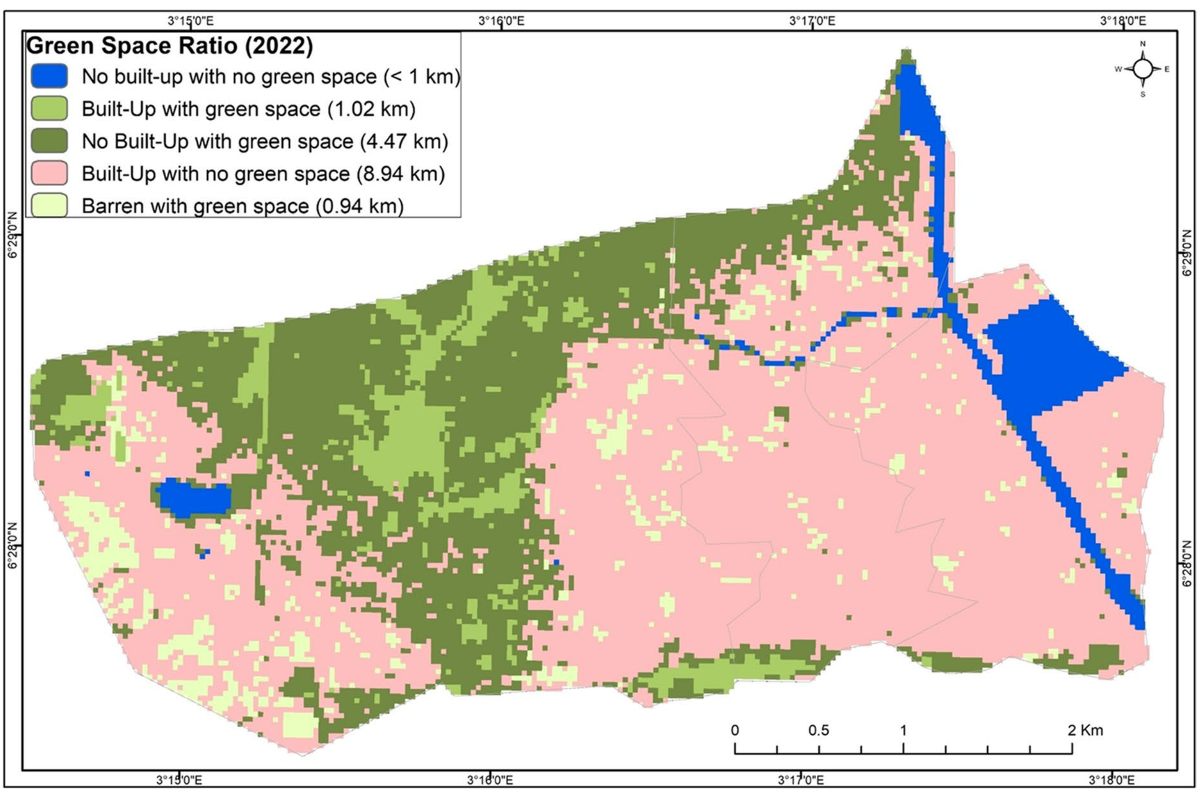


Fig. 6 LULC map of study area indicating both the vegetation cover area (VCA) and green space ratio (GSR) in 2022

Discussion

In this research, we have shown through both NDVI and NDBI analysis the pattern of green space fragmentation within FESTAC Town for a 38-year period (1984–2022). During this period, green infrastructure quantity has experienced decimation (see Fig. 7). The change detection statistics (Table 5) agrees with trends observed in related previous studies outside Nigeria (Alam et al, 2020; Nanda et al, 2014; Vivekananda et al, 2021). The rate of change observed in FESTAC also aligns with changes reported from other cities in Nigeria. Adegun et al.'s (2021) review shows consistent decline in vegetation cover across 10 Nigeria cities on which meso-scale land cover analysis was conducted. For example, in Dutse city (Jigawa

Table 4 LULC statistics of the 1984, 2002, and 2022 map of the study area

s/n	Class	1984 (km^2)	%	2002 (km^2)	%	2022 (km^2)	%
1	Water bodies	0.99	6.10	0.79	4.86	0.80	4.93
2	Sparse vegetation (forest)	2.19	13.49	1.97	12.13	1.02	6.28
3	Dense vegetation (agricultural land)	6.66	41.01	4.47	27.52	4.54	27.96
4	Built-up area	1.75	10.77	7.28	44.83	8.94	55.04
5	Bare surface	4.65	28.63	1.73	10.65	0.94	5.79
	Total	**16.24**		**16.24**		**16.24**	

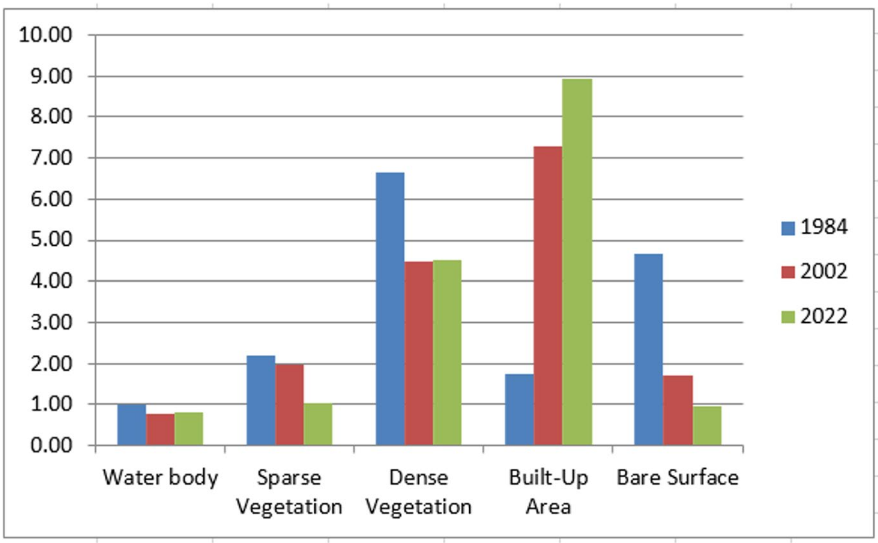


Fig. 7 Histogram of LULC change of study area between 1984, 2002 to 2022

Table 5 The total land area comprising each LULC class in the datasets from 1984 and 2022 and change in the area over a 38-year period

s/n	Classified data	1984	2022	Area changed (km^2) 2022–1984	Percent change (%)
1	Water bodies	0.99	0.80	−0.19	−19.19
2	Sparse vegetation	2.19	1.02	−1.17	−53.42
3	Dense vegetation	6.66	4.54	−2.12	−31.83
4	Built-up area	1.75	8.94	+7.19	410.86
5	Bare surface	4.65	0.94	−3.71	−79.79
	Total	**16.24**	**16.24**		

Over 38 years (1984–2022), (+) represents an increase and (−) represents a decline in the area under the LULC class

State), 19.3% of cultivated land and vegetation cover was transformed to built-up areas between 1986 and 2014 (Zangina et al., 2019). The 19.19% reduction in water bodies (blue spaces) also follows the same decline trend for vegetation loss.

The ongoing convergence due to socioeconomic development and population expansion has resulted in the diminishing availability of green areas in the study area. This loss of green spaces is replaced by more socioeconomically inclined activities. This is one of the characteristics of urbanization which has led to green space fragmentation worldwide (Xu et al., 2019; Zhang et al, 2021).

Urbanization and industrialization represent essential phases in the progression of social and economic systems (Hu et al, 2019). LULC matrix as an intrinsic component of the landscape exhibits both direct and indirect connections with diverse geophysical and socioeconomic processes (Alam et al, 2020). The LULC pattern in FESTAC Town indicates that both urbanization and industrialization pose a significant challenge, contributing to the reduction of green infrastructure.

The decline also has implication for human comfort. Decline in quantity and quality of green infrastructure and blue spaces usually leads to higher temperatures due to urban heat island that ensues in such neighborhoods. In their analysis of a part of Akure—Ondo state's capital city—Daramola and Balogun (2019) shows that parts of urban areas with the highest land surface temperature were notably with the least or lower vegetation cover.

Results build on existing evidence that green infrastructure actively supports the preservation, restoring, construction, and even renovation of ecological networks (Ying et al, 2011; Zhai, 2012). To attain sustainable urban development and curtail the unplanned growth associated with rapid urbanization, it is necessary that relevant authorities formulate planning models that ensure rational and optimal utilization of every available piece of land in FESTAC Town.

Conclusion and future work

This study demonstrates the pattern of LULC change between 1984 and 2002, and 2022 in FESTAC Town using remote sensing technology. It firstly reiterates the potential of geospatial analysis to inform planning and management decisions that conserve and enhance green infrastructure. More importantly, the study shows pattern of change in this formally planned and developed housing estate. The decline in coverage of green and blue spaces is evident. Majority of these changes in LULC are primarily driven by human activities, leading to a variety of adverse environmental consequences. The loss of natural systems affects green infrastructure and ecosystem services derivable. There is need to conserve what is remaining and re(green) lost areas. This would demand effective site-scale GI strategies given that less land is and will be available. Vertical greening systems (VGSs) and green roofs which demand no or little land hold potentials in greening the housing estate. There is need to emphasize fostering connectivity between green spaces, as well as engaging stakeholders in the planning and execution of green infrastructure projects, to ensure that all residents have equitable access to green spaces.

Further research could explore the effectiveness of different green infrastructure conservation measures implemented or possible and their impact on reversing current LULC patterns in the FESTAC case study and other similar residential neighborhoods within African cities. Additionally, research could also investigate the relationship between socioeconomic factors, LULC, and green infrastructure conservation in the areas. The further impact of the decline in green space on micro-climate and environmental factors, such as land surface temperature and air quality, can be also established in future studies.

Data availability

The corresponding author will provide the datasets analyzed during the current investigation upon request.

Authors' contributions Conceptualization: Olawale Oreoluwa Olusoga. Methodology: Olawale Oreoluwa Olusoga and Samuel Olumide Akande. Formal analysis and investigation: Olawale Oreoluwa Olusoga. Writing—original draft preparation: Olawale Oreoluwa Olusoga. Writing—review and editing: Olawale Oreoluwa Olusoga, Yomi Michael Daisiowa Adedeji, and Olumuyiwa Bayode Adegun.

Declarations All authors have read, understood, and have complied as applicable with the statement on "Ethical Responsibilities of Authors" as found in the instructions for Authors.

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