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GEOSPATIAL ASSESSMENT OF LAND USE/ LAND COVER OF THE FEDERAL CAPITAL TERRITORY: A CASE STUDY FOR THE YEAR 2050

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Abstract

The increased rate of urbanization has led to the transformation of landscapes at a higher rate, making the accurate assessment of land use and land cover changes (LULCC) imperative for sustainable urban planning and environmental management. This study presents the geospatial assessment of LULCC in the FCT (Federal Capital Territory) of Nigeria over a 35-year period, selecting the following years: 1987, 2002, 2011, and 2022, based on low cloud cover using remote sensing imagery and GIS techniques. By incorporating integrated cellular automata (CA)-Markov module from IDRISI-TerrSet software, the year 2050 was predicted. The overall accuracy for the four years (1987, 2002, 2011, and 2022) was 89.76%, 88.93%, 87.97%, and 86.54%, respectively. The Kappa coefficients were 0.88, 0.85, 0.86, and 0.83, respectively, which is considered acceptable. From 1987–2022, built-up land gained 881.74 km^2 in area, barren land gained 73.93 km^2 in area, forest lost 1,761.85 km^2 in area, wetland lost 97.44 km^2 in area, water body gained 1.75 km^2, shrub land lost 905.77 km^2, and grassland gained 1,806.47 km^2. The results of the predicted year (2050) showed that from 2022–2050, built-up land will gain 182.93 km^2 in area, barren land will gain 119.20 km^2 in area, forest will lose 39.78 km^2 in area, wetland will lose 99.94 km^2 in area, water bodies will gain 1.75 km^2, shrub land will lose 499.51 km^2, and grassland will gain 237.91 km^2. Results from the study will provide insight for urban planners, policymakers, and environmentalists in making decisions geared towards sustainable development and resilient urban growth in the FCT.

Key Words: *Geospatial, Remote sensing, CA-Markov, Land use land cover change, Future projection*

Introduction

According to Xu *et al*. (2023), Land Use and Land Cover Change (LULCC) refers to the alteration of the Earth's land surface, which is primarily due to human activity. It is also referred to as a widespread, accelerating, and significant process that is driven by natural and/or anthropogenic agents, and, in many cases, it also drives changes that affect humans (Hailu *et al*., 2020). Many factors lead to changes in land use (Yuan *et al*., 2005; Sivakumar, 2014). Such factors include population growth and urbanization (Seto and Reenberg, 2014), cultural and social factors (Briassoulis, 2009), natural disturbances, market forces, and economic drivers (Geist and Lambin, 2002), climate change (IPCC, 2019), agricultural expansion, infrastructure development (Laurance *et al*., 2009), and deforestation (Amaechi *et al*., 2023).

LULCC can affect the functioning of natural eco-system services (Niu *et al*., 2021), drainage (Sugianto *et al*., 2022), the richness of biodiversity (Mosisa and Asefa, 2020), and loss in vegetative cover (Amaechi *et al*., 2023), which can result in higher surface temperatures (Nzoiwu *et al*., 2017) and habitat destruction (Sodango *et al*., 2017). Abuja Federal Capital Territory (FCT) is the capital city of the most populous black nation in Africa (Sodango *et al*., 2017). It is thus a national hub for business, commerce, and tourism in the country, making it one of the first choices for many individuals in terms of economic opportunities, investment, and leisure. This attribute makes the FCT prone to rapid urbanization and growth; therefore, it is necessary to track the use and change of its natural and existing land cover to ensure the city develops in a sustainable pattern while maintaining commitment to the sustainable development goals (SDGs) to which its country is signatory (Ikutal *et al*., 2018).

Projections have placed more than half the world population, by the year 2050, within urban areas (United Nations, 2018), and as urban populations rapidly increase, so does the need for space in varying quantities and sizes. This would result in unplanned urban development, which can lead to increased paved surfaces, the loss of agricultural land and natural areas, and a decrease in vegetation cover. Such rapid population growth and unplanned urban development raises concerns about the sustainability of urban settlements (Rana, 2011), which poses a direct threat to the achievement of the Sustainable Development Goals (SDGs) 11 (Sustainable Cities and Communities), 13 (Climate Action), and 15 (Life on Land).

The mapping and analysis of LULCC is a good indicator of urban growth, sprawl, and deforestation (Hassan et al., 2016; Olorunfemi et al., 2020). Hence, this study aims to estimate the change in the LULC of FCT for the year 2050. This analysis affords stakeholders within the public and private sectors of urban development the opportunity to monitor and track current and potential changes that might occur within landscapes to make comprehensive plans for future interventions and design effective land management policies that would protect and preserve environmental stability and integrity alongside man's societal development.

Materials and Method

Study Area

The selected study location was Abuja, the Federal Capital Territory of Nigeria. The FCT is located in the heart of Nigeria at an average altitude of about 760 metres above sea level (Ujoh and Ifatimehin, 2010). It is situated within latitudes $9^{o}25'$N and $9^{o}30'$N and longitudes $7^{o}26'$E and $7^{o}30'$E (Olla et al., 2020). It is bordered by the state of Niger to the west, Kaduna State to the north, Nasarawa State to the east, and Kogi State to the southwest. The FCT covers approximately 7,350 km^2 and is made up of six local government areas, namely: Abuja Municipal (AMAC), Abaji, Bwari, Gwagwalada, Kuje, and Kwali. Figure 1 shows FCT (Adeiza *et al*., 2023).

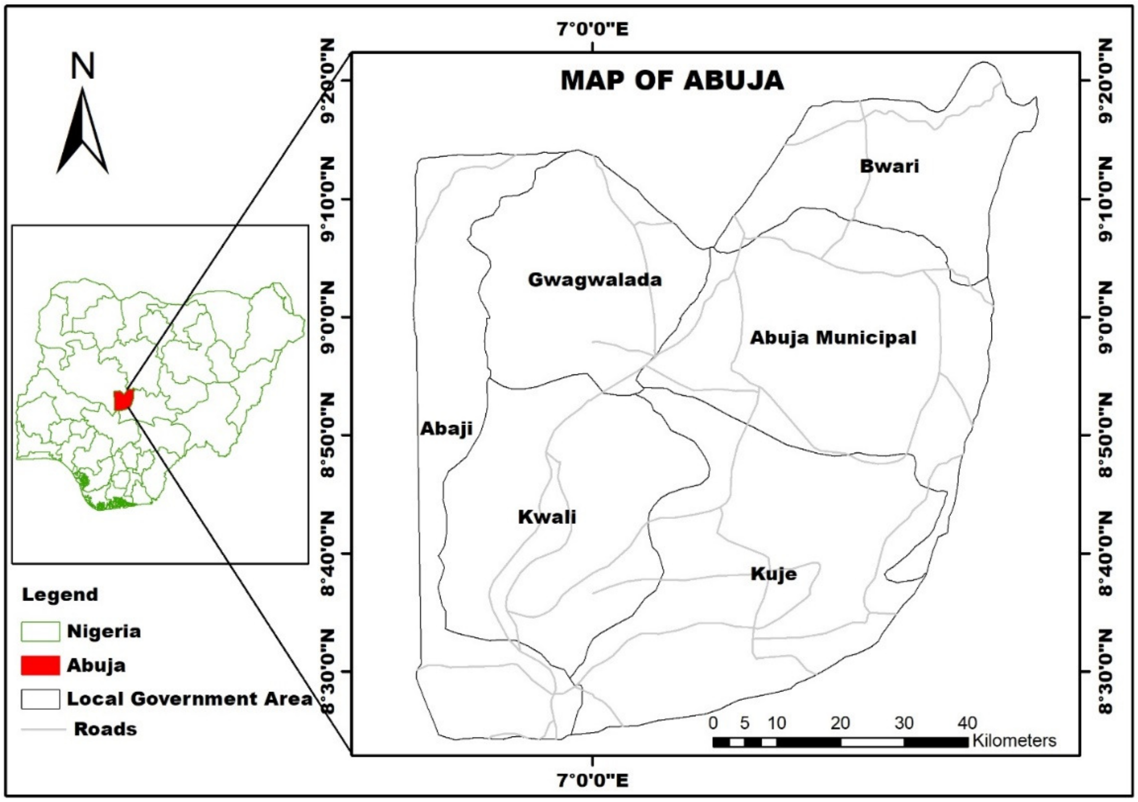

Fig. 1: Map showing the Federal Capital Territory, Abuja

Data Acquisition

Landsat 4 TM (Thematic Mapper), Landsat 7 ETM+ (Enhanced Thematic Mapper Plus), and Landsat 8 OLI/TRIS (Operational Land Imager/Thermal Infrared Sensor) data (path and row 189/054) dated 1987, 2002, 2011, and 2022 were utilized in this study. Images were sourced from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). To ensure quality and improve the validity of analyses performed, only images with less than 1% land and scene cloud cover were downloaded (Table 1).

Table 1: Data type and data source

Data	Source	Resolution	Land/Scene Cloud Cover	Year
Landsat 4 TM	USGS Earth Explorer	30	0.00	1987
Landsat 7 ETM+	USGS Earth Explorer	30	0.00	2002
Landsat 7 ETM+	USGS Earth Explorer	30	0.00	2011
Landsat 8 OLI/TRIS	USGS Earth Explorer	30	0.02	2022

Software Utilized

In the investigation of LULCC detection, ENVI software version 5.3 was utilized for image pre-processing, image classification, accuracy assessment, thematic change detection, and generating statistical results. ArcGIS desktop version 10.3 was used for editing the study area's boundary, post-classification processes, map layout design, and visualizations. IdirisiSelva software package (version 17.0) was used in carrying out prediction to fulfil the study's aim. Figure 2 shows the research methodology flowchart.

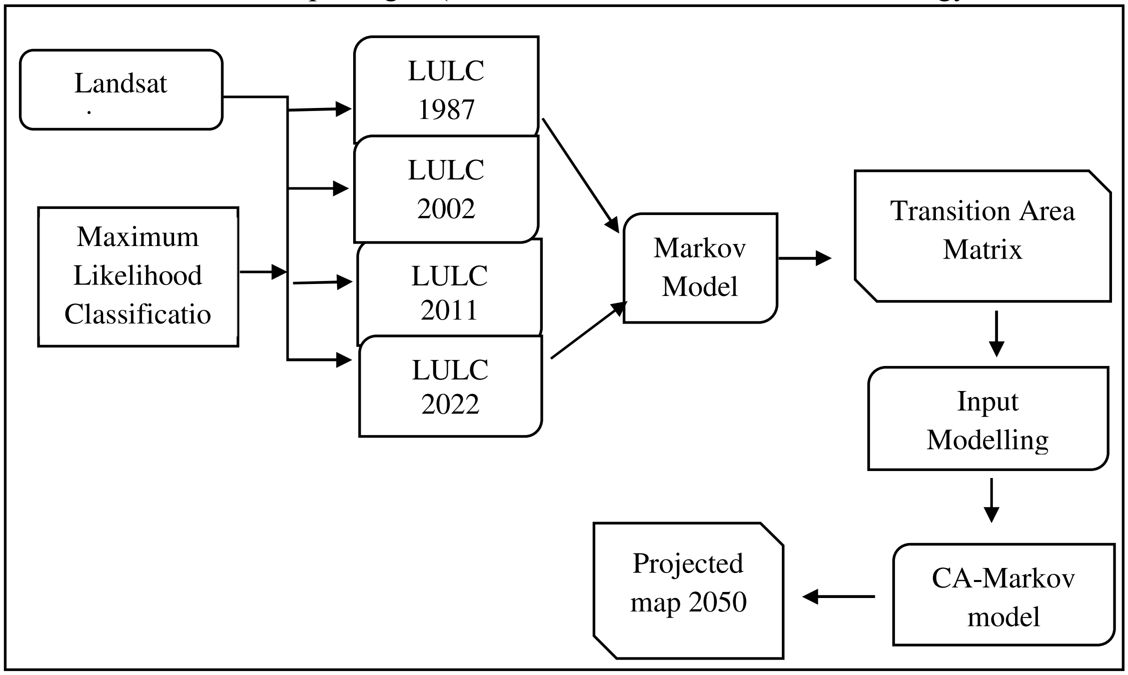

Fig. 2: Flow chat for LULCC assessment

Image Pre-Processing

In this study, pre-processing operations were adopted, which included radiometric and atmospheric correction, as well as image enhancement and masking of the study area. These operations were conducted using ENVI 5.3 FLASH tool.

Image Processing for LULC Analysis

The study employed the Maximum likelihood supervised classification approach to categorize the LULC of Landsat images. The application of this method on Landsat images involved the adoption of six classes from the Anderson level 1 classification, which comprised built-up areas, barren land, water bodies, wetlands, grassland, and forest land covers with an extra class added during the course of classification: shrub land.

Classification of Image

Carefully gathered training signature samples were utilized for the supervised classification process. These training samples were chosen based on the identification of LULC categories found within the Landsat images. Additionally, various band combinations from Landsat images were employed to facilitate the visual interpretation of LULC classes depicted in the images. Table 2 shows the various LULC classification names, description and number of trained samples for each class of Landsat datasets.

Table 2: Land-use/cover classification names, description and number of trained samples for each class of Landsat datasets

LULC Type	Class	Description	No. of samples (1987)	No. of samples (2002)	No. of samples (2011)	No. of samples (2022)
Built-up Area	1	Areas occupied by buildings and factories (commercial and industrial), including paved road and parking lots.	75	67	61	56
Barren land	2	Places devoid of any vegetation and exposed rocks.	53	45	56	38
Wetland	3	Land regions with a consistent high moisture content.	63	54	62	65
Forest	4	Forested areas of conifers and oak, both continuous and discontinuous.	66	53	64	67
Grassland	5	Grass-covered spaces used for grazing.	51	39	45	43
Shrub land	6	Area covered in little trees, bushes, and shrubs; occasionally combined with less dense grasslands than forests.	49	51	53	47
Water	7	Surface water bodies	53	65	53	59

Assessment of Accuracy

Conducting accuracy assessment on classified images from 1987, 2002, 2011 and 2022, involved utilizing the ENVI software's confusion matrix and ground truth image tool. This assessment method employs reference data to establish a connection between the classified images and the ground truth data, yielding comprehensive results such as overall accuracy, producers and user accuracy, and a multivariate Kappa coefficient representing connectivity accuracy on a scale of 0 to 1. The ground truth data used in this study were collected from high-resolution images obtained from Google Earth for each respective year.

Results and Discussion

Accuracy Assessment

Table 3 present the classification accuracy for the four years; 1987, 2002, 2011, and 2022. The overall accuracy for the four years (1987, 2002, 2011, and 2022) was 89.76%, 88.93%, 87.97%, and 86.54%, respectively. The Kappa coefficients were 0.88, 0.85, 0.86, and 0.83, respectively, which is considered acceptable. This study's overall accuracy is similar with the findings of Tadese *et al*. (2020) and Reis (2008), who reported satisfactory overall accuracy of 86.6% and 87.1%, respectively. Furthermore, the Kappa statistics of this investigation revealed a high level of agreement for the classified images, and the accuracy was within the acceptable range for subsequent LULC change detection assessment (Kindu *et al*., 2013).

Table 3: Accuracy assessment showing the Kappa coefficient, producer, user and overall accuracy

Class	UA	PA	UA	PA	UA	PA	UA	PA
	1987		2002		2011		2022	
Built-up	91.37	93.29	93.15	96.90	89.87	92.79	91.14	93.74
Barren land	94.10	96.20	85.65	90.38	85.43	89.98	84.57	85.79
Grassland	86.32	89.22	89.61	91.30	87.87	90.42	86.98	87.85
Forest	92.30	95.87	88.82	89.89	89.21	93.32	87.98	91.05
Shrub land	92.36	95.67	89.78	92.76	84.45	88.90	88.22	93.27
Wetland	89.23	92.56	87.32	88.22	90.12	94.34	85.67	89.43
Water	87.23	89.34	89.32	90.99	89.32	91.21	85.98	86.87
Overall Accuracy (%)	89.76		88.93		87.97		86.54	
Kappa Coefficient	0.88		0.85		0.86		0.83	

Where UA = User accuracy and PA = producer accuracy

LULC Classification

Seven major LULC types (Table 2) were classified for the years 1987, 2002, 2011, and 2022. The area of these classes was measured using the ArcGIS software, as shown in Table 4. In the year 1987, built-up area covered 76.18 km^2. In 2002, built-up area occupied an area of 228.48 km^2. In 2011, built-up area occupied an area of 706.93 km^2, which increased to 957.92 km^{2}in 2022. Barren land, in the year 1987, covered an area of 85.69 km^2. In 2002, barren land occupied an area of 99.95 km^2 which slightly reduced to 99.46 km^2 in 2011 and then increased to 159.62 km^2 in 2022. Forestland, in the year 1987, covered an area of 2841.22 km^2. In 2002, forestland occupied an area of 2206.53 km^2. In 2011, forestland occupied an area of 1935.68 km^2, which further decreased to 1079.37 km^2 in 2022. Furthermore, Wetland in the year 1987, covered an area of 110.16 km^2. In 2002, wetland occupied an area of 53.09 km^2. In 2011, wetland occupied an area of 20.03 km^2, which decreased to 12.72 km^2 in 2022.

Waterbody, in the year 1987, covered an area of 16.9 km^2. In 2002, water occupied an area of 11.41 km^2. In 2011, water occupied an area of 10.47 km^2, which increased to 19.82 km^2 in 2022. Shrub land, in the year 1987, covered an area of 3016.77 km^2. In 2002, shrub land occupied an area of 2374.86 km^2. In 2011, shrub land occupied an area of 2298.84 km^2, which decreased to 2111 km^2 in 2022. Grassland, in the year 1987, covered an area of 1175.67 km^2. In 2002, grassland occupied an area of 2348.27 km^2. In 2011, grassland occupied an area of 2251.18 km^2, which increased to 2982.14 km^2 in 2022.

Table 4: Quantitative LULC distribution for 1987, 2002, 2012 and 2022

LULC Class	Class	1987		2002		2011		2022	
		Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
Built-up	1	76.18	1.04	228.48	3.12	706.93	9.65	957.92	13.08
Barren land	2	85.69	1.17	99.95	1.36	99.46	1.36	159.62	2.18
Forest	3	2841.22	38.80	2206.53	30.13	1935.68	26.43	1079.37	14.74
Wetland	4	110.16	1.50	53.09	0.73	20.03	0.27	12.72	0.17
Water	5	16.9	0.23	11.41	0.16	10.47	0.14	19.82	0.27
Shrub land	6	3016.77	41.20	2374.86	32.43	2298.84	31.39	2111	28.83
Grassland	7	1175.67	16.06	2348.27	32.07	2251.18	30.74	2982.14	40.73
TOTAL		7322.59	100	7322.59	100	7322.59	100	7322.59	100

Table 5 presents a comprehensive LULC change from 1987-2022. The results show that built-up class increased by 11.99% from 1987-2022. Barren land increased by 1.01%. Forest decreased by 23.96%, wetland deceased by 1.33%, water increased by 0.04%, shrub land decreased by 12.32%, and grass land increased by 24.57%. Figure 3 (a–g) shows the trends in land class changes. From the trend, the land cover classes that are increasing include built-up, barren land, water bodies, and grass land. While forest, wetland and shrubland are decreasing.

Table 5: Quantitative changes of LULC in the FCT from 1987 to 2022

LULC Class	1987-2002		2002-2011		2011-2022		1987-2022	
	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)	Area (Km^2)	Area (%)
Built-up	152.3	2.07	478.45	6.51	250.99	3.41	881.74	11.99
Barren land	14.26	0.19	-0.49	-0.01	60.16	0.82	73.93	1.01
Forest	-634.69	-8.63	-270.85	-3.68	-856.31	-11.65	-1761.85	-23.96
Wetland	-57.07	-0.78	-33.07	-0.45	-7.3	-0.1	-97.44	-1.33
Water	-5.49	-0.07	-0.94	-0.01	9.35	0.13	2.92	0.04
Shrub land	-611.91	-8.32	-106.02	-1.44	-187.84	-2.55	-905.77	-12.32
Grassland	1172.6	15.95	-97.09	-1.32	730.96	9.94	1806.47	24.57

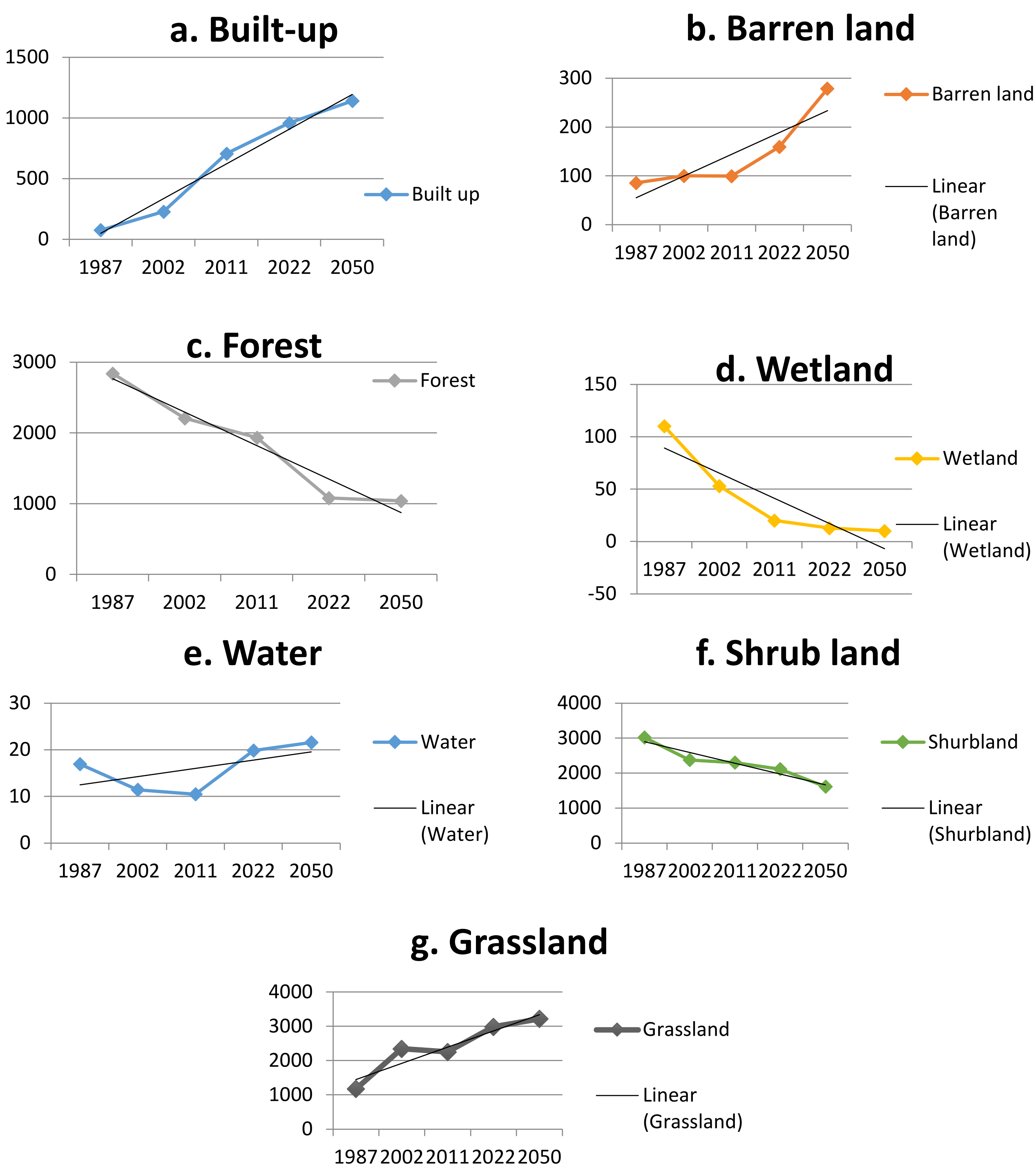

Fig. 3 (a-g): Trends in land class changes

The result of the geospatial assessment for the year 1987 (Figure 4) reveals a landscape that has yet to undergo rigorous alteration through the action of anthropogenic activities, as shown by the abundance of forest cover. The assessment results for years 2002, 2011, and 2022 are presented in figures 5 and 6, respectively. Graphical representation (Figure 4-6) shows that forest is gradually lost over time and replaced with other classes such as built-up, barren land, or shrub land within Bwari, AMAC, Kuje, Gwagwalada, and Abaji local government areas. This may be the outcome of urban expansion and development; such a decline affects the attainment of SDGs 13 and 15. A similar study conducted in Abuja by Ameachi *et al*. (2023) shows an increasing trend in the built-up area, grassland, and water body, with a massive decline in forestland, indicating massive deforestation in Abuja. Factors that must have led to the reduction in forest cover between 1987 and 2022 include population growth and urbanization (Musetsho *et al*., 2021), agricultural expansion (Lambin and Meyfroidt, 2011), infrastructure development (Laurance *et al*., 2009), deforestation, and forest degradation (Amaechi *et al*., 2023).

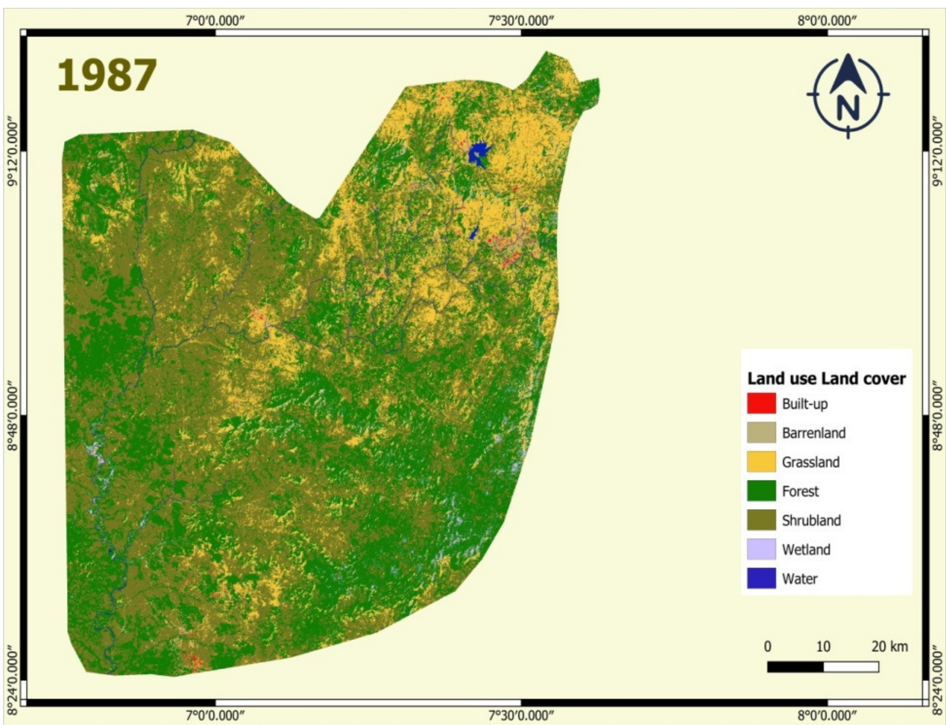

Fig. 4: LULC of the FCT for the year 1987

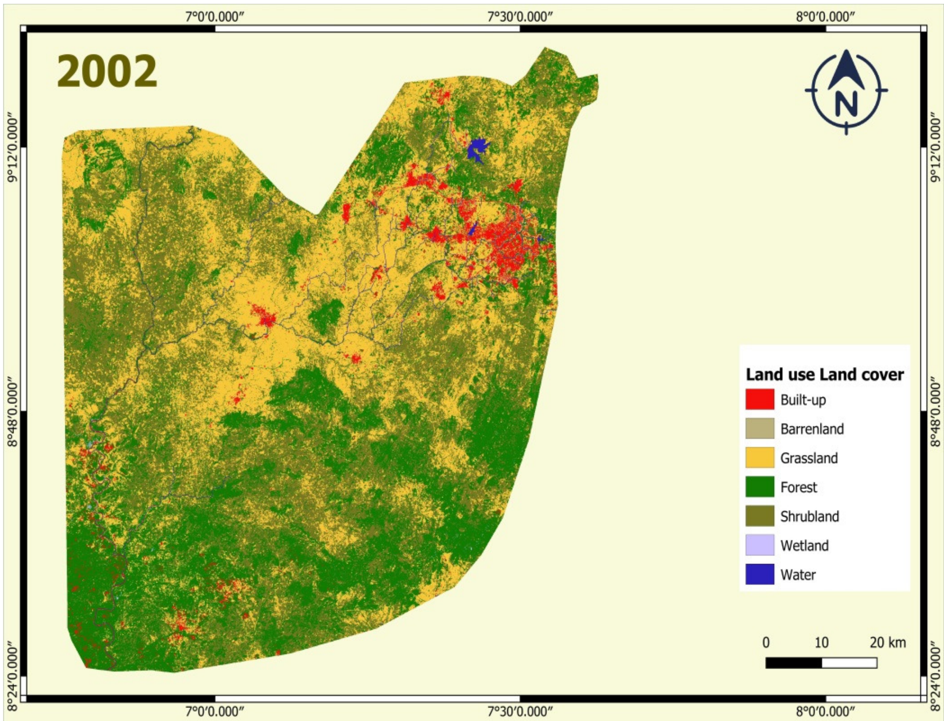

Fig. 5**:** LULC of the FCT for the year 2002.

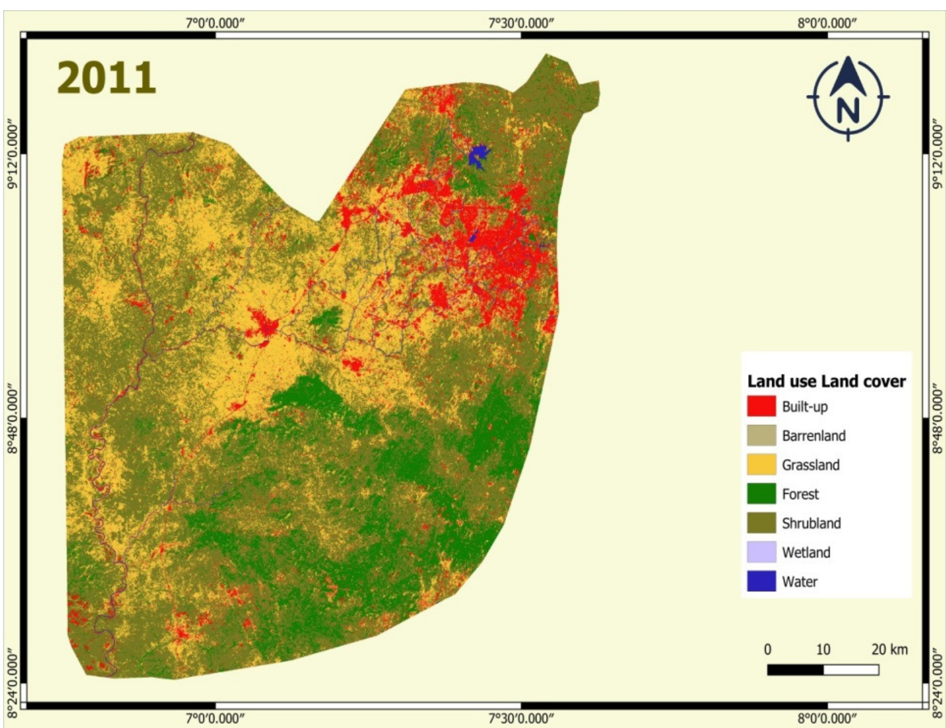

Fig. 6: LULC of the FCT for the year 2002

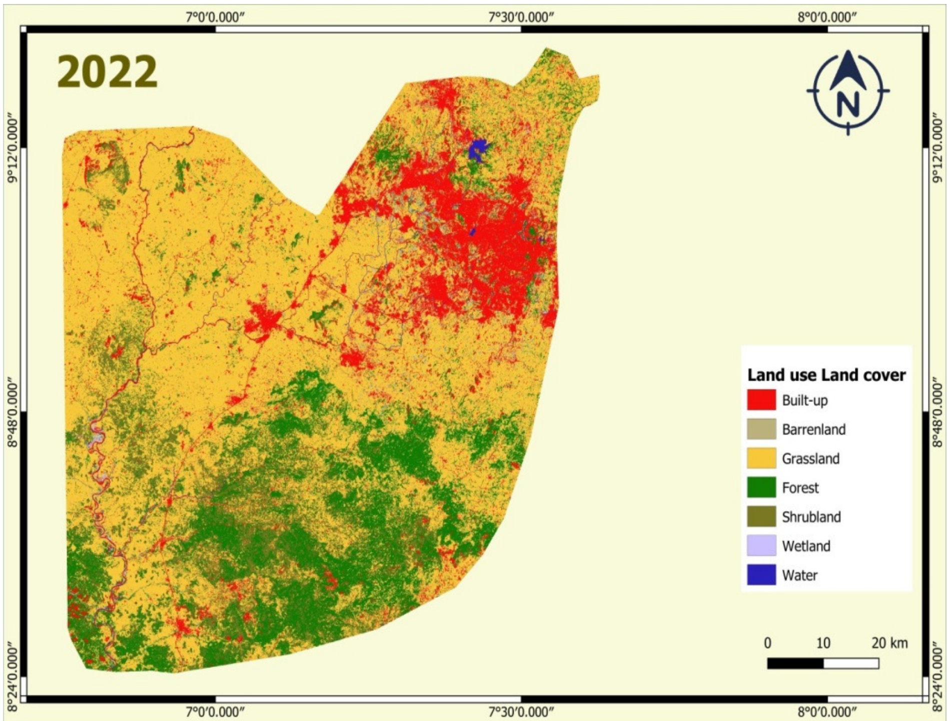

Fig. 7: LULC of the FCT for the year 2022.

For the predicted year, the results (Table 6) show that in 2050, the built-up area will occupy an area of 1,140.85 km^2, barren land will occupy an area of 278.82 km^2, forest will occupy an area of 1,039.59 km^2, wetland will occupy an area of 10.22 km^2, water bodies will occupy an area of 21.57 km^2, shrub land will occupy an area of 1,611.49 km^2, and finally grassland will occupy an area of 3,220 km^2. This means that from 2022–2050, built-up area is projected to increase by 2.50%, barren land will increase by 1.63%, forest land will decrease by 0.54%, wetland will decrease by 1.36%, waterbody will increase by 0.02%, scrubland will decrease by 6.72%, and grassland will increase by 3.25%. A study conducted by Koko et al. (2020) employed the CA-Markov model to predict LULC within Zaria City, Nigeria. The projected LULC maps for 2050 showed that, as a result of urbanization, deforestation, and the expansion of agricultural activities (Demissie, 2022), these patterns of barren land turning into built up will persist for the next 30 years.

Research conducted in the Irbid governorate by Khawaldah *et al*. (2020) projects a continued built-up increase from 2015 to 2030 and 2050, respectively. Another study conducted in Bathinda by Rani *et al*. (2023) suggests that barren land is anticipated to decrease in 2050. In contrast, vegetative expanses are anticipated to increase in 2050, showing a balance between urbanization and ecological conservation. Water bodies were also projected to diminish by 2050, posing potential water resource challenges. Wetland areas were projected to shrink, making irrigation and groundwater reservoir sustainability more difficult. Debnath *et al*. (2023) found that the amount of agricultural land in the Koch Bihar urban agglomeration will decline significantly in 2050 while the built-up area would grow dramatically. If the government doesn't reduce unsustainable urban development, this development will limit the nation's forest cover in the future and make it harder for the state to achieve SDGs 11, 13, and 15. Therefore, rapid urban growth and expansion must be controlled in order to balance urban expansion and conservation of the natural environment in FCT.

Table 6: Summary table for the projected year 2050

LULC Class	2050 (Km^2)	Area (%)	1987-2050 (Km^2)	Area (%)	2022-2050 (Km^2)	Area (%)
Built-up	1140.85	15.58	1064.67	14.54	182.93	2.5
Barren land	278.82	3.81	193.13	2.64	119.2	1.63
Forest	1039.59	14.2	-1801.63	-24.6	-39.78	-0.54
Wetland	10.22	0.14	-99.94	-1.36	-99.94	-1.36
Water	21.57	0.29	4.67	0.06	1.75	0.02
Shrub land	1611.49	22.01	-1405.28	-19.19	-499.51	-6.82
Grassland	3220.05	43.97	2044.38	27.92	237.91	3.25

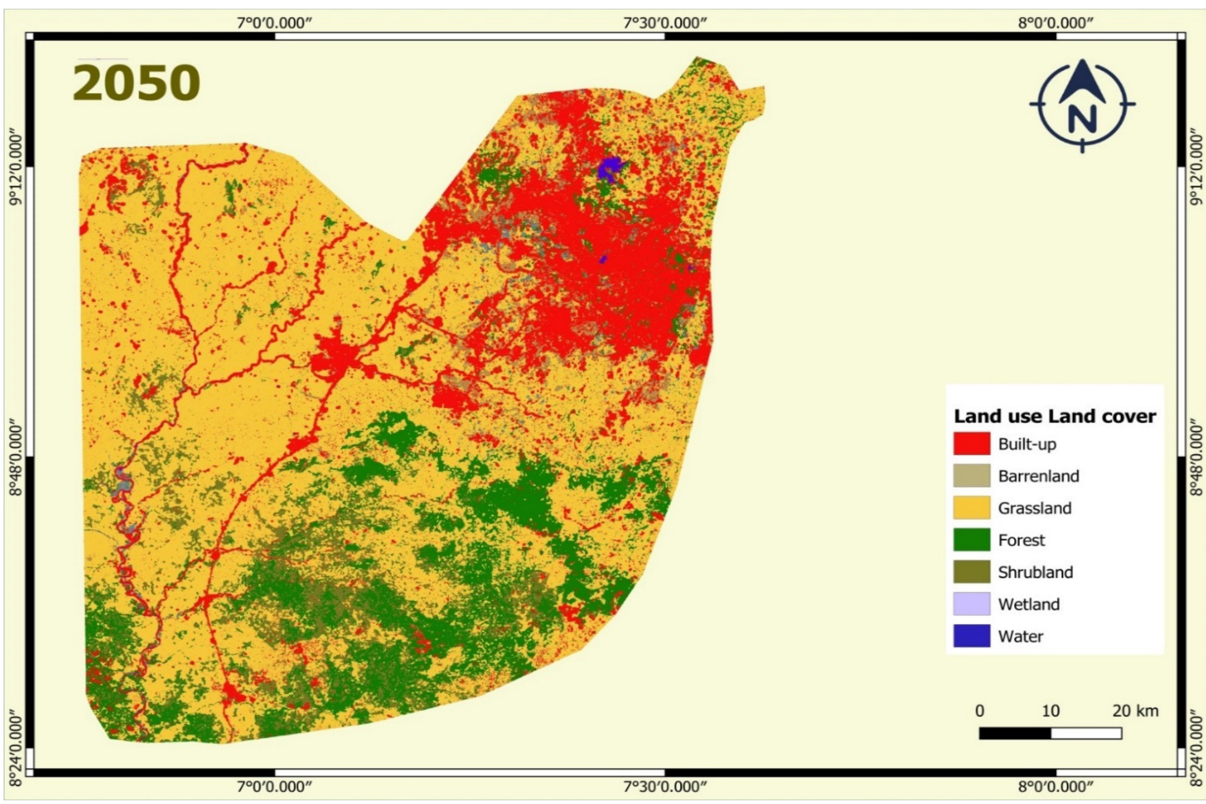

Fig. 8: Predicted Land use/ land cover of the FCT for the year 2050

Conclusion

The observed LULCC in the FCT indicate rapid urbanization at the expense of forest cover, projected to continue until 2050. Without proper planning, the city risks losing green spaces, impacting SDGs 13 and 15. To promote sustainable development (SDG 11), authorities should adopt strategies like constructing tall buildings to curb urban sprawl. Encouraging the FCT as a green city with allocated parks and preserving natural forest reserves is vital for ecological conservation, contributing to SDG 15.

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