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Assessment of Urban Development Expansion Using Object-Based Image Classification Technique. A Case Study of Asokoro City, Federal Capital Territory, Abuja, Nigeria.

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Abstract

Urban development expansion is critical to urban planning and management, particularly in rapidly growing cities. This study uses object-based image classification techniques to assess the urban development expansion of Asokoro, a prominent city in the Federal C capital Territory, Abuja. Satellite multi-spectral image data was employed to capture spatial changes over time, providing valuable insights into the dynamics of urban growth. The methodology involves collecting multi-temporal satellite image data covering various periods of three epochs (2003, 2013 and 2023) to analyses the trend expansion patterns of the study area. The Google image was pre-processed using a dehazing and shadow extraction algorithm. The segmentation process was carefully carried out, after which the features were extracted. Object-based image classification technique was utilized to accurately delineate urban features and monitor dynamics in land use and land cover of the study area. This approach allows for a more detailed and precise analysis than pixel-based classification methods. The outcome recorded about 14.42% of built-up areas in the year 2003. In the year 2013 and 2023, it recorded an increasing trend of about 5.21% and 7.03% respectively. Simple least square regression analyses technique was used to projection the built-up areas to the next ten years (2033). At 95% significant level, the built-up area is expected to record an increasing trend of about 7.24% which translate to be about 34.34% of the total area of Asokoro. The results reveal significant urban development expansion within the study area, characterized by increased built-up areas, infrastructure development, and changes in land use patterns. The findings provide valuable information for urban planners and policymakers to understand the spatial dynamics of Asokoro's growth and formulate sustainable development strategies.

Keywords: **Object-Based Classification, Built-Up Patches, Urban Planning and Features Segmentation**

1. Introduction

Humans have relied on land for food production and other economic development since the beginning, resulting in constant changes in the local environment. The quest for Development has increased stress on Earth's surface and is driven by the constant push to meet the needs of an ever-increasing population demand (Weinzettel *et al.,* 2013). Under these circumstances, human activity and the resulting dynamics of land use and land cover (LULC) have emerged as a pressing concern for the modern era, highlighting the threats of environmental degradation on a global scale (Li *et al.,* 2020). Since ancient times, many natural resources have been extensively exploited or completely depleted in the worst situations. Human activity have affected or created almost half of the world's terrain (Goldewijk *et al.*, 2011). Numerous factors, such as altered hydrological cycles, increased water extraction, deteriorated soil nutrients, increased surface erosion, loss of biodiversity, and altered climate, are all consequences of this widespread LULC change on the environment (Paiboonvorachat, 2008). As a result, data on land use/land cover, evolving trends, and the best use of available resources have evolved into predetermined standards for area-wide land use planning and efficient management of natural resources. The development brings about expansion, improvement, and positive change or adds components to the social, demographic, environmental, economic, and physical domains (Hazarika *et al.,* 2015). Development aims to raise the standard of living for the public while protecting the environment's resources and generating or increasing local, regional, and employment possibilities (Baba *et al.,* 2023). A development component is the creation of conditions necessary for the continuation of the qualitative change. Although it doesn't always happen immediately, it is transparent and beneficial. Remote sensing and GIS techniques provide more reliable and cost-effective data assessments than conventional methods and surveys.. Scientists and researchers can detect large-scale changes in land use patterns with the knowledge acquired on a temporal and spatial level, allowing regional politicians and authorities to make future decisions (Robert *et al.,* 2000).

It is crucial to monitor the evolution of development as towns and cities expand, facilitating efficient planning, organization, and utilization of a community's resources (lopez *et al.,* 2020). In this context, "development" refers to structures and their various purposes, such as residential and commercial, government initiatives, executing a government-mandated maintenance plan for a city, and many more. Land use managers require access to up-to-date, spatially precise time series data on land resources and changing patterns to plan for the future (Ayele *et al.,* 2018). As a result, it is critical to assess how urbanization and population growth have affected development. Before implementing any further conservation measures, it is imperative to understand the state of development in a specific area. A comprehensive analysis of time series fine-scale satellite images is required to monitor the pattern and development change (Yang and Zeng, 2023) since satellite images are the most often utilized data source for change detection, quantification, and mapping of change trends since they can be precisely geo-referenced and give repeated data (Liu and Madhavan, 2019). One of the world's most planned and fastest-growing modern cities is the capital of Nigeria. After Maitama District in the federal capital city of Abuja, Asokoro is arguably the cutest residential habitant (dwelling) (Unah, 2019). The type of infrastructure development has changed, disregarding the master plan as more and more residential, commercial, and social activity structures are constructed. Asokoro is a residential area where the population has gradually been taking over, leading to increased commerce due to the growing need for public buildings. However, given Asokoro's situation, the development's aspect categories, and the requirement to ascertain the extent of the city's coverage as of the year 2023, it is necessary to checkmate the rate of its growth. This study aims to portray Asokoro City's urban growth trend pattern in Abuja's Federal Capital Territory (FCT).

2.0 Study Area

Abuja is a young city that began on 3rd February 1976 when the federal military government established the FCT (Falola, 2008). Located in the north-central part of Nigeria, Confluence of the Niger and Benue Rivers. The city is Nigeria Federal Capital Territory (FCT), whose land area is about 8000 km2. The area's geography is defined by two renowned rock formations: The Zuma Rock, from whose base the FCT begins, and the Aso Rock, located east of the city. Abuja lies at latitude 9.07_N and longitude 7.48_E and at an elevation of 840 m (2760 ft.) above mean sea level, which is located on the shores of the Atlantic Ocean at 35 m (11 ft.) above sea level. Figure 1, show the map of the study area.

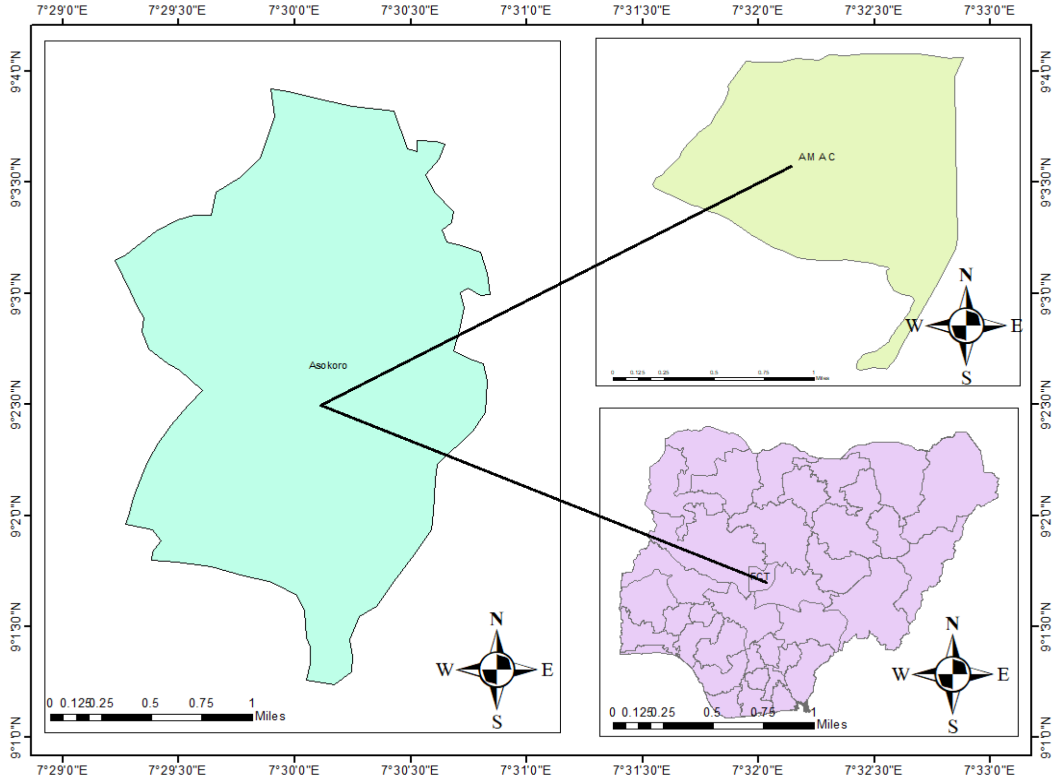

Figure 1: Map of Nigeria to the right down, map of Amac (FCT Municipal Area) of Abuja to the right up and map of the study area Asokoro to the left.

3.0 METHOD

3.1 Data Acquisition

The satellite image data was sourced from Google Earth Pro from the year 2003, 2013 and 2023. The characteristics of the data used are depicted in Table 3.1

Table 3.1 Data Characteristics

S/N	Data	Type	Epoch	Format	Resolution	Source	Relevance
1	Administrative boundary	Secondary		Shapefile		OSGOF	To define the spatial boundary
2	Google earth aerial imagery	Secondary	2003,2013 and 2023	TIFF	30m	USGS	For image classification analysis

Google Earth Pro was launched, the location of interest was navigated, and the north arrow toggle was manipulated to be aligned to meet the satellite images that needed to be retrieved. The four points were indicated on the four cardinal points of the images using the point tool, and their ground coordinates were generated to enable geo-referencing. The coordinate points were used to geo-reference the satellite imagery using "Add control Points" in the geo-referencing toolbar. The image was corrected from the distortion caused by the sensor, haze, terrain displacement, and sun angle. The haze in the image was removed using image processing techniques called dehazing algorithms. These algorithms work by estimating the transmission and atmospheric light in the scene and then removing the effects of haze from the image (Jian and Xiaoou, 2011).

$$I_{dehazed} = \frac{I_{raw} - A}{t} + A \qquad 1$$

Where

$I_{dehazed}$: Dehazed image, I_{raw}: Raw image, A: atmospheric light, which is assumed to be constant throughout the image, t : the transmission map, indicating the proportion of light transmitted through the haze at each pixel.

The Terrain displacement, where buildings appear skewed due to perspective distortion, was corrected by geometric corrections. The correction is aimed to remove the effects of terrain displacement and restore the correct proportions and geometry to objects in the scene. Correction for sun angle effects involves adjusting the image's brightness, contrast, and color balance to compensate for these variations. Figure 3.1 depicts the conceptual workflow of the research

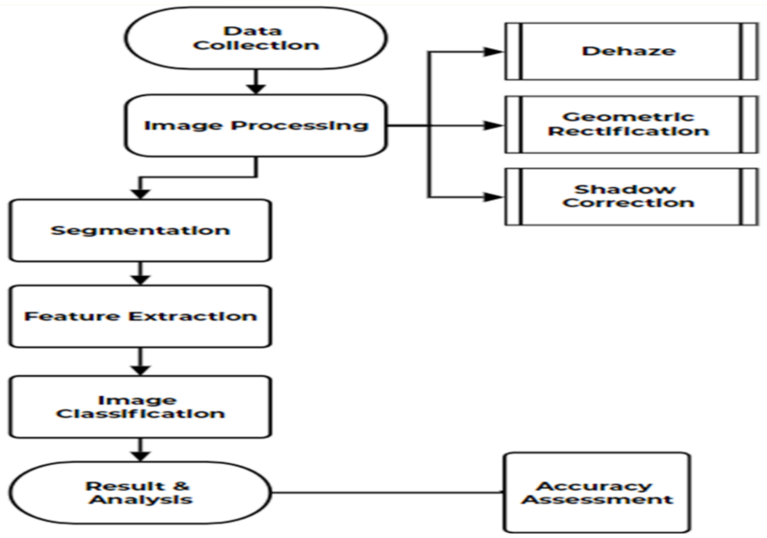

Figure 3.1. Conceptual Work Flow of the Research

3.2 Segmentation

In object-based classification, segmentation is the primary stage that determines accuracy outcomes; nevertheless, multiresolution segmentation algorithms are widely used and have been used in numerous research (Ma *et al.,* 2015). Because the scale, shape, and compactness parameters are crucial in determining how the algorithm behaves and can be adjusted by the analyst, this algorithm may be intricate and user-dependent. To get the ideal values for the segmentation's associated parameters presumably based on the analyst's experience. The multi-resolution algorithm typically requires trial and error, mainly when employed for the first time (Laliberte and Rango, 2009). According to Hussain et al. (2013), the scale parameter is a crucial component of the object-based classification strategy since it establishes the permissible size of the picture objects, which governs all other steps in the classification process. According to Blaschke *et al.* (2014), semantically meaningful regions exist at different scales. Identifying all the objects required for the classification may be necessary to experiment with changing the scale parameter during the segmentation step. Since the trial-and-error method introduces subjectivity into scientific research, it is undesirable. Various techniques have been developed to identify the ideal scale parameter value (Johnson and Wichern 2011), but none of them have been able to identify a value that is suitable for all types of imagery. High feature counts can often complicate the structure of any algorithm and, consequently, the research process, making them less useful for classification because they are time-consuming to analyses (Pal and Foody, 2010). However, feature extraction is essential in creating a more compelling image classification considering context, spectral, and spatial information.

3.3 Image Classification

Spatial maps can be several types that change based on the research scale, which can be local, global, or any other scale depending on it goal (Forghani *et al.,* 2008). Pixel-based classification is the earliest and, as a result, most popular method for classifying imagery in remote sensing. It treats each pixel in an image as a separate component of the scene based on its spectral information, independent of its geographical context. When creating classified maps using a pixel-based method, the primary problem is typically the lack of precise and comprehensive spatial context and potential class confusion caused by spectral responses from major geographic features in urban areas being similar to one another. The development of object-based classification makes spatial classification of features on map easier and accurate (Hussein *et al.,* 2013). The object-based classes' correctness is evaluated using an error matrix. The patches of the classification are shown in Table 3.3. The research's aims guided the determination of the categories.

Table 3.3 Patches used for the land used land cover change.

s/n	Patches	Description
I	Vegetation	Lands covered with natural vegetation
Ii	Agricultural Land	Rangeland, cultivated land
Iii	Built-Up area	Lands are used for residential, commercial, industrial, roan networks, etc.
Iv	Bare surface	Sparse vegetation; lands with exposed soil, rocks

The process involves categorizing pixel values from multi-raster images to create a thematic layer, and the process uses a maximum likelihood classifier, which assumes the statistics of each class in each band that are usually distributed and calculates the probability of a given pixel belonging to a specific class. Based on the model, a training set of pixels was selected for a supervised classification using a Maximum Likelihood (ML) classification algorithm for four categories (agricultural land, built-up, bare land, vegetation) classes, after which the LULC classification was derived.

The projection was executed using a simple least square regression method to find the line (or curve) that best fits a set of data points. It works by minimizing the sum of the squared differences between the observed (y) values and the values predicted by the regression line for each corresponding (x) value. In simpler terms, the principle involves finding the line closest to all the data points.. According to Montgomery and vining (2012), the relationship between (y) and (X)

$$y = mx + b \qquad 2$$

Where

(m); slope of the line (coefficient of x),(b): y-intercept (the point where the line crosses the y-axis). To compute the values of (m) and (b) That best fits the data; you can use the following.

$$m = \frac{n(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2} \qquad 3$$

$$b = \frac{\sum y - m(\sum x)}{n} \qquad 4$$

Where

n:The number of data points, $\sum x$: the sum of all (x) values, $\sum y$:The sum of all (y) values, $\sum xy$: The sum of the products of each (x) and (y) pair, $\sum(x)^2$ Is the sum of the squares of each (x)

4.0 Results and Discussion

The results of the object-based image classification for the years 2003, 2013 and 2023 are presented in Figure 4.1. Table 4.1 shows the vector statistical data for the object-based LULC of Asokoro City of the Federal Capital Territory Abuja for 2003, 2013 and 2023. Table 4.1 depicts the accuracy assessment of the map.

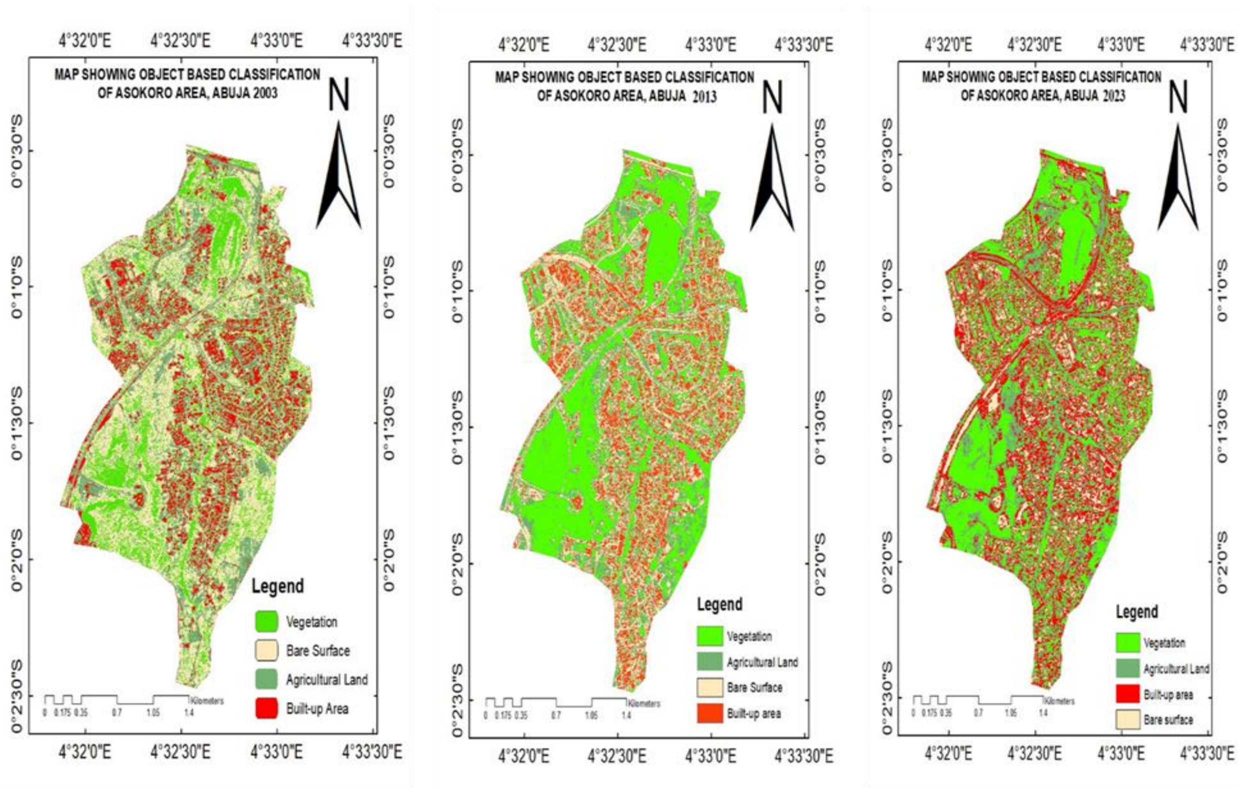

Figure 4.1. LULC change map of Asokoro city for the years 2003, 2013 and 2023

Table 4.1: Vector Statistics Data for Asokoro City for 2003, 2013 And 2023.

Patches	2003	User	Producer	2013	User	Producer	2023	User	Producer
Agricultural land	28.181	81.11	81.53	25.065	77.57	71.29	32.688	82.85	79.25
Bare Land	39.034	86.41	83.03	26.176	81.81	71.29	13.227	66.15	66.25
Built up Area	14.442	75.34	82.04	18.790	71.14	74.43	27.945	85.84	78.44
Vegetation	18.344	71.11	89.69	29.969	71.14	61.05	27.140	65.24	64.28
Overall Accuracy	89.4%			87.5%			83.4%		
Kappa Coefficient	0.768			0.731			0.724		

4.1 Discussion

From Table 4 above, in 2003, agricultural patches constituted around (28.18%), the bare land surface recorded about 39.034%, and vegetation covered about 18. 344%, while built-up areas recorded about 14.442% of the total area. The outcome indicates the land used as of the year 2003. The accuracy assessment was done by deploying 200 stratified random samples on the classified image and critically comparing the classified image with ground reference information (Bing Map). The accuracy of the classification falls within the acceptable threshold; the producer accuracy, which depicts the classification on the map, while the user accuracy depicts the level of accuracy attained of features on the ground, all fall above the acceptable threshold(citation) (see table 4.2) and of kappa coefficient obtained was (0.881)

The year 2013 recorded a decreasing trend of about 3.12% for agricultural patches, indicating that agricultural practices decreased compared to the previous epoch. Bare land surfaces also recorded a downward trend of about 12.23% compared to the previous epoch. Built-up patches recorded an increasing trend of about 4.35% compared with the previous epochs, and it also shows how other patches compensated for the built-up areas, which signifies that a portion of other reducing patches are compensating for built-up areas. The vegetation area also experienced an increasing trend of about 11.36%. The vegetation area was intentionally preserved for beautification and landscaping of the environment.

In 2023, the agricultural patch decreased by about 4.72% because Asokoro is mainly for residential structures. Bare land surface recorded a slight decrease of about 3.01%. The built-up area recorded an increasing trend of about 07.03%, indicating many structural developments (estate and other structural infrastructure) from 2013 to 2023. The vegetation area also indicated a slight increase in vegetation area. It recorded a 0.37% increase for 2023 compared to the previous epoch. (Figure 4.2) indicate the trend pattern of built-up patches from the year 2003 to 2023. For the accuracy assessment for both years (2013 and 2023), see Table 4.2, which shows the error matrix for the LULCC map for 2013 and 2023. In Figure 4.2, bar chat represented the LULCC data, depicting the trend pattern for the built-up categories.

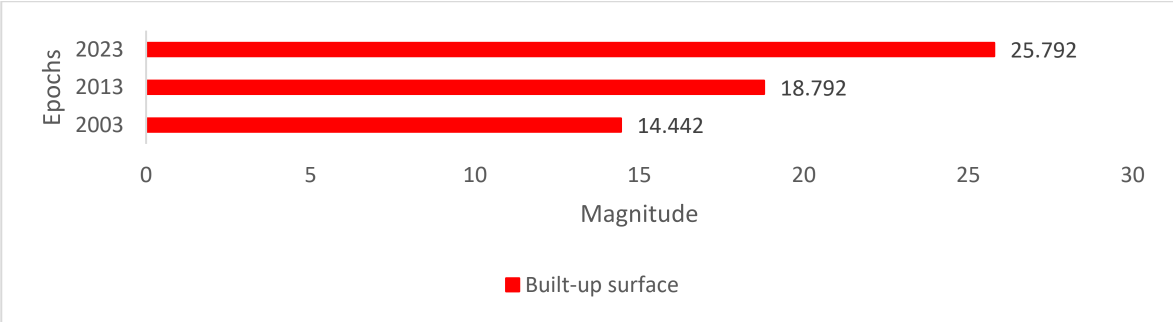

Figure 4.2: Magnitude of Built-up Areas from the years 2003, 2013 and 2023

Figure 4.2 shows the trend pattern of the built-up areas in Asokoro city of Abuja for twenty years. It has shown the city's growth rate over the years. Other patches, such as agriculture and bare land surfaces, compensated for the growth of built-up patches. Over time, part of the agricultural and bare land surfaces was converted to built-up areas for infrastructural development. However, it was also observed that the vegetation patches recorded a significant growth from the epochs. These could be the number of reserved areas and landscaping aesthetics from the city's master plan. It used a simple least square regression technique to project the growth of the built area in the next ten years. Figure 4.3 shows a bar chart of the projection rate for the next year

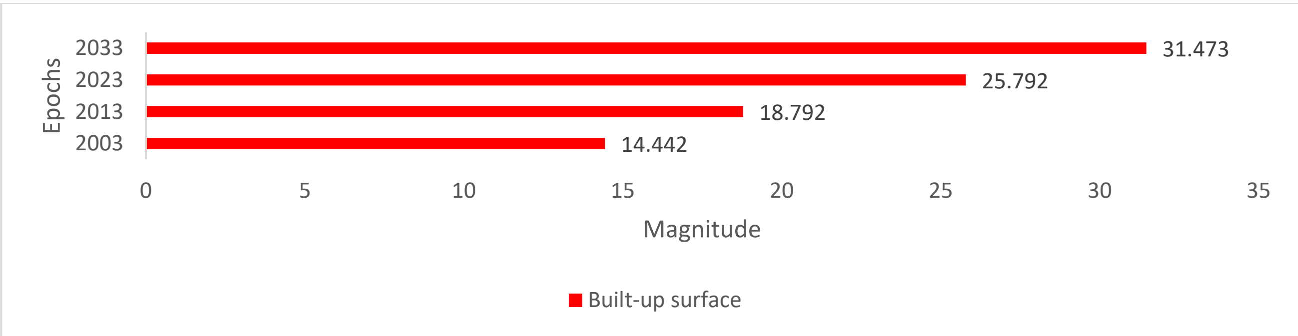

Figure 4.3: LULCC projection for the year 2033

5.0 Conclusion

Accurately mapping LULC change using object-based classification is extremely helpful for many environmental applications such as urban planning, land rehabilitation, land management, and risk analysis. This research aimed to assess the rate of land use and land cover change dynamics (built-up expansion) in Asokoro, the city of the federal capital FCT, Abuja. The method used in this research has proved to be more reliable and accurate, judging from the results. The growth rate of Asokoro city, Abuja, is not scary as it is the second most recognized city from Maitama, Abuja. The residential city showed a sharp change from 2003 to 2023. It recorded a gross change of about 13.503% from the year in view (2003-2023) and an additional projection change of about 7.2% to 2033. The generated error matrix justified the results' outcomes based on the user, personal accuracy and the overall and kappa coefficient obtained. There is a need to measure the land use rate, especially in Abuja, the country's capital. It will go a long way in checking the master plan of the smart city and also guide administrators on policies to be made regarding the protection of the master plan and the avoidance of people going against it.

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