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Geospatial Assessment of the Physical Expansion in Urban Development in Bwari Area Council, Federal Capital Territory, Abuja, Nigeria

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Abstract:
Globally, urbanization has become an inevitable occurrence increasing at a faster rate in developing countries, especially in Nigeria. This has called for the present strategies in the monitoring and management of its limited environmental resources. The research is aimed at monitoring the spatial extent of physical expansion in urban development of Bwari Area Council, Abuja using satellite imageries of Landsat TM (1986), Landsat ETM+ (2003) and Landsat OLI (2020) a period of 34 years and predict the future change in the next 30 years (2050) using an integrated Cellular Automata and Markov Chain Model. The Maximum Likelihood Algorithm was applied for the image classification in which five feature classes of Built-up, Vegetation, Bare surface, Rock outcrop and Water body were extracted. Future growth prediction was carried out by applying the Cellular Automata and Markov Chain Model analysis. The result reveals an observable land cover changes of the study area for the three epoch years. It shows a continuous increase in Built up areas between the years 1986, 2003 and 2020. Further analysis also reveals the trends in the urban expansion. In addition, the classification accuracy for the three periods of 1986, 2003 and 2020 of the classified imageries showed an overall accuracy of 95.8%, 99.9% and 99% respectively while the kappa statistics for the selected images were given as 0.89, 0.99 and 0.98 respectively. The information retrieved from this research will serve as a veritable tool for decision makers such as the government, city planners, and relevant authorities to effectively plan towards the formulation of sustainable future urban development.

Keywords: Urban development, Supervised classification, cellular automata and Markov chain

INTRODUCTION

In many parts of the world, urbanization has been viewed as one of the major change indicators which directly impacts on the increasing rate in the growth of the population (China, 2006). Hussain and Imtiyaz (2016) define urbanization as an increase in the proportional increase of the population size living in the urban settlement. Urbanization is also a form of land transformation caused by the alterations spatially as regards the dynamics in population and socio-economic activities (Jokar, Helbich, and Noronha, 2013). Wei Sun et al., (2020) described urbanization as a major socioeconomic indicator with far-reaching impacts on the development of a region or country, social progress-wise and economically. The proportion of urbanization is induced by living and property costs, physical geography, demand for more living space, and lack of proper planning policies (Bhatta, 2010).

Globally, urbanization is an inevitable occurrence that has led to the continued transformation and alteration of the natural landscapes and how these further impacts on the function and development of the societal framework (Griffith, 2009). In most metropolitan of the world, there has been occurrences of rapid rate of spatial urbanization, particularly in developing countries (Ogunleye, 2013). This is largely attributed to economic development, infrastructure initiatives and rapid population (Jat, Garg and Khare, 2008). According to Angel, Sheppard, Civco, et al. (2005), the urban built up area occupied over 400,00 square kilometers which would amount to about 0.3% of the world's land mass in the year 2000, of which its projection by the year 2030 is to consume 1,100,000km^2 (about 0.85%) if the growth rate is being sustained. Other statistics as reported by China (2006) projected of the world's population, over more than half would have occupied the urbanized areas by 2050, attributed to rural-urban migration with an average growth at the rate of 55.2% (United Nations, 2021; China, 2006).

Unprecedented urban growth often results in poor conditions of the environment, destroys natural resources, disrupts the ecosystem which would invariably lead to various forms of hazards with its adverse effects on both the natural and human environment, increased pressure on the current urban infrastructure and afterward results in resource limitations (Institute for Sustainable Communities, 2013; Akpu et al, 2017). Although urban development adds to socio-economic growth and improves the quality of life, it is the most prevalent and noticeable factor that has led to the changes in the natural environment (Herold, Goldstein and Clarke, 2003). According to Schlein, De Capua, and Kruger (2007), the most endangered of them would be the vegetation.

In Nigeria, urban centers are identified on the basis of population, legal or administrative criteria and adopts a threshold population of 20,000 people or more for defining an urban center compared to many other countries (Ofem, 2012). The population increase in the urban centres of Nigeria could be attributed to the expansion of existing built-up areas, the development of new and noticeably urban settlements (Bloch, Fox, Monroy, and Ojo, 2015). In addition to this, all states like the Federal Capital Territory, Abuja and Area council headquarters (Bwari Area council inclusive) have historically, legally or administratively been regarded as urban centers (National Urban Development Policy, 2006).

The Draft of the National Urban Policy Development (2004), also notes that Nigerian towns are grows without appropriate planning procedures and permits. The relocation of the nation's administrative capital to Abuja in 1991 was considered the fastest growing cities in the western sub region (Aliyu and Bashiru, 2015) and the proximity of settlements around the administrative capital led to the prosperity and economic transformation of the area, particularly of the satellite towns (Bwari and its Environs inclusive) from a remote rural settlement to a vibrant urban area (Olujimi, 2009). Since the creation of Bwari Area council (BAC), Nigeria law school, Jamb office, and other institutions influences her growth rate in terms of population and development within the town. Also, due to the problem of housing affordability, high rent and policy in land acquisition within the Federal Capital City, these have force development towards the satellite towns leading to haphazard and uncontrolled development. These changes in development need to be monitored and evaluated at regular intervals in ensuring environmental sustainability (Mohan, 2006). This will enable that instituted policies and planning strategies are adequately evaluated in addition to its accountability and effectiveness in urban governance.

Remote Sensing and Geographic Information System (GIS) is conceived a veritable tool pivotal to the monitoring and modelling urban expansion rates to aimed towards achieving sustainable development. As cited in Ufuah, (2003); Bello and Ojigi, (2003), the effective planning and infrastructural development of any country is fundamentally hinged upon its ability to provide up to date and reliable spatial data from various outlets such as satellite Remote sensing, ground surveying, and crowd sourced mapping. According to Zhang and Cao (2019), a geographic information system (GIS) is an integrated operating system of hardware, software, and a GIS database that is controlled by qualified personnel and is able to thoroughly and methodically gather, store, search for, and analyze complicated spatial information.

Modeling urban growth appears to play a significant part in urban planning to assist in decisions that are related to sustainable urban development as a result of the increasing development of urbanization and the attendant environmental repercussions (Esch et al., 2009). Khoshgoftar and Mohammad (2010), analyzed and modeled Tehran's urban development over the past two decades in a report entitled "Tehran's urban growth modeling, using CA-Markov". In this work, the simulation was extended to 2025, and the mechanism of urban growth was examined using historical data from Landsat satellite photos taken in 1988, 2000, and 2006. Urban areas grew by around 11% between 1988 and 2006, according to a comparison of changes. The findings demonstrated how well the hybrid CA-Markov model predicted urban growth for the upcoming years based on the growth pattern of the preceding years. Balogun et al. (2011) employed field surveys, multitemporal remote sensing data, and GIS approaches to identify changes in land use and land cover in Akure, a city in southwest Nigeria, between 1986 and 2007. Their investigation revealed considerable alterations in Akure's land usage and land cover between 1986 and 2007. They also found that the pattern of change will continue along the same path through the year 2020. Aishwarya et al., (2019) attempted to compare Urban Growth Modeling using Neural Network- Cellular Automata and Deep Belief-Cellular Automata. The data they adopted was Landsat 7 and 8 of 2010 and 2013, and 2017. Support Vector Machine (SVM) was used for the preparation of land cover maps of all the epochs. The different land covers were converted into binary types as built up and non-built up. Hotspots of urbanization using buffer of 500m was determined. The prediction was done using agents of urbanization such as the Landsat datasets whereby 2013 referred to as existing while restricted areas for development labeled constraints.

This research is geared towards using Remote Sensing and GIS approach in monitoring the physical expansion of urban development in Bwari Area Council, Abuja and future prediction using Cellular Automata and Markov Chain Model. The specific objectives of this research are to:

i. examine the land cover map of the study area between 1986, 2003 and 2020,
ii. evaluate the changes in the Land cover classes of the study area,
iii. examine the pattern and direction of physical expansion of Built up in the study area,
iv. predict the future urban expansion for the next 30 years.

MATERIALS AND METHODS

Study Area

Bwari is located in the North-Eastern part of Federal Capital Territory, Abuja. It is located between latitude 9°5'00''N to 9°25'0''N and longitude 7°10'0''E to 7°35' 0''E as shown in the figure below. Bwari is approximately 15 kilometer north of Abuja city and 25 kilometers north east of suleja, in Niger state. It covers a total of about 2,300 square kilometers, and lies in the north – eastern part of the Federal Capital Territory (FCDA, 2004). The northern expressway of Abuja is the boundary between Abuja Municipal Area council and the Bwari Area Council. Sub-regionally, the area is surrounded by over twenty (20) minor settlements: Sabongari, Zango, Kuchiko, Kuduru, Zuma, Kogo and Ushafaare the immediate settlements of the urban area while others are farther away from the township.

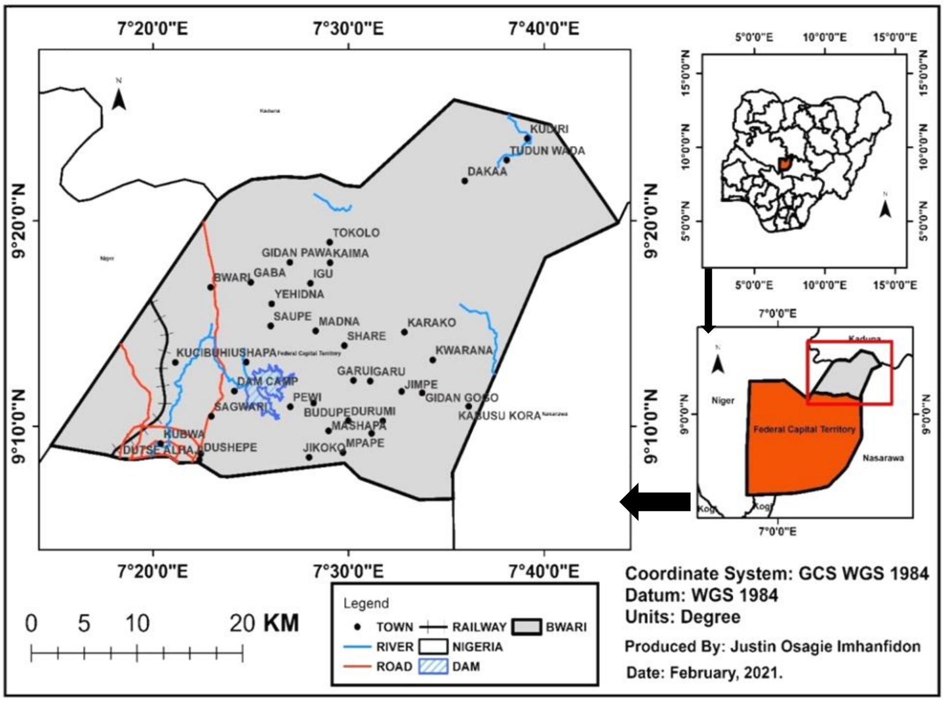


Figure 1: Location of the Study Area

Source: Author, 2021

Data Requirement

In this study, both the primary and secondary data were used. The table below shows the specific dataset used.

Table 1: Specifications of Dataset

SN	DATA	PATH/ROW	YEAR	FORMAT	SCALE/ RESOLUTION	SOURCE
1.	GPS coordinates point of geographic features		2020	Table	±3m accuracy	Field Work
2.	Landsat Satellite TM	189/053 189/054	1986	Raster	30m	https://glovis.usgs.gov
3	Landsat Satellite ETM+	189/053 189/054	2003	Raster	30m	https://glovis.usgs.gov
4.	Landsat Satellite OLI	189/053 189/054	2020	Raster	30m	https://glovis.usgs.gov

Source: Author, 2021

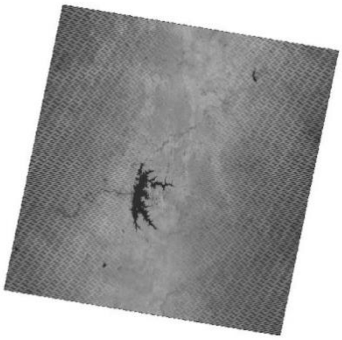
METHOD OF DATA ANALYSIS

Pre-Processing of Dataset

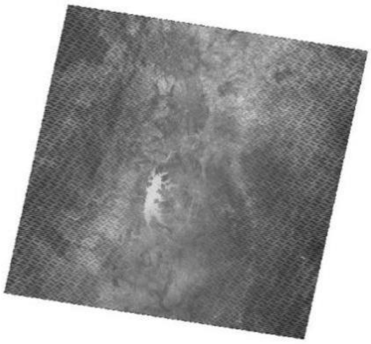
These include radiometric correction and geometric correction. It involves the correction of Landsat images through Lines tripping removal, Cloud removal, Geo-registered to the Universal Transverse Mercator, mosaicking of images scenes and clipping the images using the shapefile of Bwari Area Council. The shapefile of the study area was used to clip from the mosaicked images.

This is because the mosaicked area is larger than the Area of interest (AOI) and it helps in defining accurately the study area.

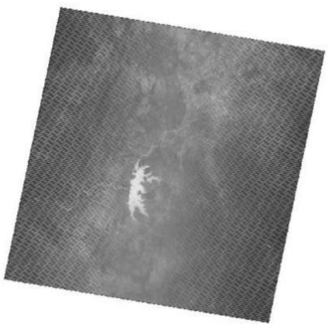
Lines tripping Removal:
For the removal of the lines tripping on the Landsat images each Band of 4, 3, and 2 of the different Landsat images of 189/053 and 189/054 were subjected to several processes using the Focal analysis tool on Erdas Imagine 2015.



a. BAND 4



b. BAND 3



c. BAND 2

Figure 2: Landsat 2003 (189/053) band 432 with Lines tripping

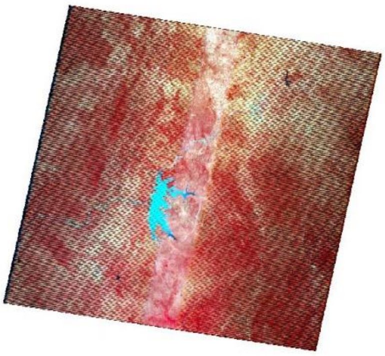
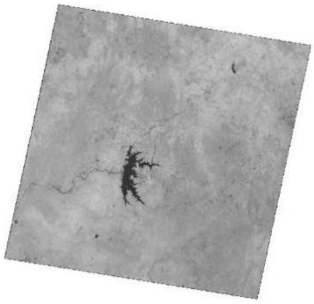
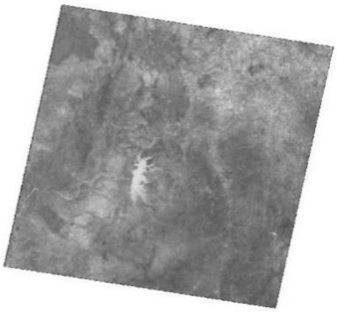


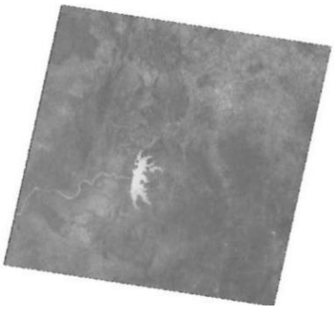
Figure 3: Landsat 2003 (189/053) False colour Composite images with Lines tripping



Band 4



Band 3



Band 2

Figure 4: Corrected Landsat 2003 (189/053) band 432

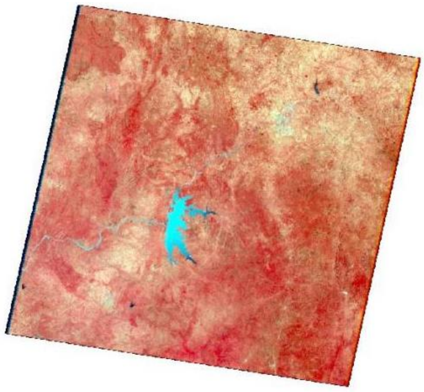
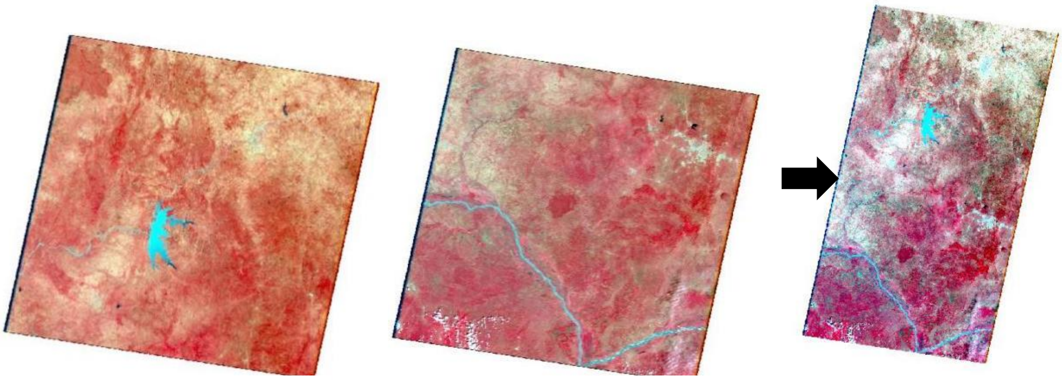


Figure 5: Corrected Landsat 2003(189/053) False colour Composite images

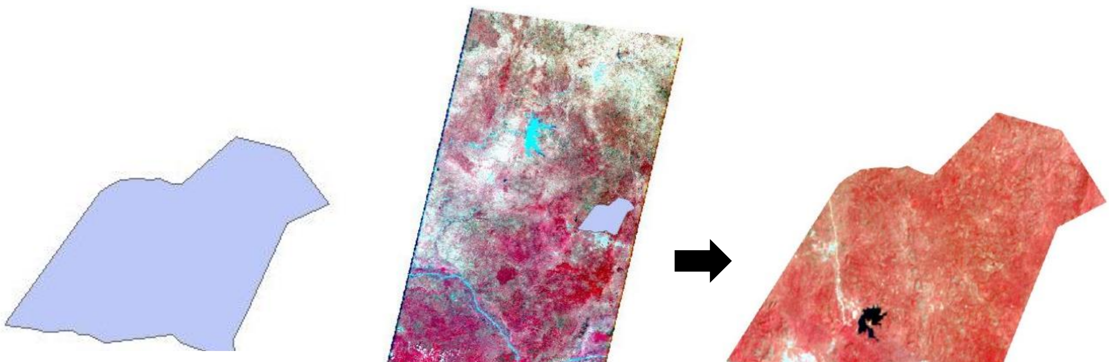
Mosaicking:
This is the combination or merging of two or more images together. The process was achieved using Mosaic Pro on Erdas imagine 2015.



a. **Landsat 2003 (189/053)** b. **Landsat 2003 (189/054)** c. **Mosaicked Landsat Image**

Figure 6: Mosaicked image of two different scenes

Subset of the Study Area:
This procedure is used to only get the portions of huge files that are relevant for a given task. Additionally, Erdas Imagine 2015 was used to execute the subset of the study region.



a. **Bwari Shapefile**

b. Landsat 2003 overlaid with Bwari **c. Clipped images of Bwari, Abuja**

Figure 7: Subset of the Study a

Image Enhancement
Image enhancement is done to improve the contrast between various features, making it easier to identify features and then classify them. For good visual interpretation, Histogram Equalization on Erdas Imagine 2015 Software was performed on the satellite imageries. In order to achieve the best results, a band combination of 4,3,2 (for Red, Green, and Blue) was chosen for the Landsat TM and ETM images and 5,4,3 for OLI photos. It is appropriate for urban use for defining vegetation, water, and land boundaries.

Image Classification
According to Campbell and Wynn (2011), image classification is the process of categorizing pixels into relevant informative classes. In order for pixels in the same class to have similar qualities, remote sensing classification entails grouping the pixels of an image into a manageable number of classes. There are two different kinds of classification techniques: supervised classification and unsupervised classification.

The supervised classification technique was used in this study. The supervised classification system uses "training" sites of known targets to detect spectrally comparable regions on an image, and it then applies those spectral signatures to other areas of unknown targets (Mather and Koch, 2011).

Accuracy Assessment
In order to evaluate various image processing techniques for picture classification, accuracy assessment is thought to be a crucial step (Foody, 2002; Lu and Weng, 2005). To determine the degree of agreement or disagreement, the classification's final result is compared to the real world or other trustworthy sources. To evaluate the classification's accuracy, Erdas Imagine 2015 employed the Error Matrix Approaches. The Kappa Index of Agreement (KIA), user accuracy, producer accuracy, and overall accuracy are the four factors used by the error matrix to evaluate accuracy.

Change Detection
The following variables were computed on ArcGIS 10.8 to assess the degree of growth and rate of change in the Land cover classes in the study area.

Built-up Extraction
The thematic map of Built-up was retrieved, layered, and examined using ArcGIS 10.8 in order to determine the pattern and direction of expansion within the study area.

Prediction Model
To predict the future expansion for the next 30 years, the hybrid of Cellular Automata and Markov Chain (Ca-Markov) models was adopted.

Markov Chain Model:
The Markov model process describes the likelihood that one state will change into another. It describes the state of a system at time 2 that can be anticipated from the state of the system at time 1. This would then provide a transition probability to describe the possibility of a pixel of a given class changing to any other class in the ensuing state. This distinction enables it to function in the process of changing land cover, but the model is unable to generate a two-dimensional spatial surface (Guan et al. 2011). The Markov module in the Idrisi Terrset software was used to

implement the Markov Chain analysis. In a unique stochastic process known as a Markov Chain, the result of each experiment depends only on the result of the experiment that came before it. As a result, the system's subsequent state depends only on its current state and not on its past states (a system at time 2 can be predicted by the state of the system at time 1). A transition likelihood matrix and a file for transition areas were created using the changes in land cover patterns between the two known dates. According to Eastman (2009), a transition probability is the possibility that a land cover will either change or stay the same in the future.

To create two transition matrices for all of the LC categories, time series LC maps from 1986, 2003, and 2020 were divided into two time periods (1986-2003 and 2003-2020). According to Weng (2002), the Markov approach is used to forecast changes in stochastic processes that depend on their past states at time t and are expressed as conditional probabilities, such as state S at time t + 1. Any future state Xt+1, given the past states X0, X1..., Xt-1and the present state Xt, is only dependent on its prior state, according to the conditional distribution of a Markov chain. A transition probability matrix from state i to j is represented by a Markov chain with n states (S1, S2..., Sn) and Pij. Consequently, the matrix can solve the prediction.

$$S^{(t+1)} = S^{(t)} * P_{ij} \qquad (1)$$

Where, $S^{(t+1)}$, $S^{(t)}$are the states at times t and t+1, respectively, and P_{ij} is the transition probability matrix.

Cellular Automata:

To produce a spatial distribution, the cellular automata (CA) method develops a "spatially-explicit weighting factor." The fundamental components of a cellular automaton are state, cell, neighborhood, transition rule, and discrete time (White and Engelen 1997). The transition rule uses the conventional neighbor function; the cell is a land cover category cell, where land cover category is a state. Unless it is 0, the neighborhood filter returns a value of 1 when it entirely fits the existing class. The suitability pixel adjacent to the contiguous region of the same categories is then reweighted by multiplying the neighborhood filter by the final suitability potential maps (Guan, Inohae, Su, Nagaie, and Hokao, 2011). In this case, the neighborhood designates the cell that is affected by the possible change, and the transition rule aids in moving the cell.

Cellular Automata analysis in Idrisi Terrset is carried out via the CA-Markov module. A cellular automata method that is especially tailored to the setting of predictive land cover change modeling is provided in this module (Eastman, 2009). The land cover map (y) from which changes should be projected, the transitions areas file created by Markov from analysis of that image (y) and an earlier one (x), and a collection of suitability images are all inputs to the CA-Markov module. These images express how suitable a pixel is for each of the land cover types under consideration. The land cover is then redistributed iteratively until it reaches the Markov module's projected area totals. An expression for a cellular automaton as expressed by Liu (2015), a discrete dynamic function, is

$$t{+}1_{DPij} = f(t_{sij}, t_{Nij}) \qquad (2)$$

where the probability surface is represented by t + 1Dpij, the development suitability surface is represented by tSij, and the neighborhood effect is represented by tNij.

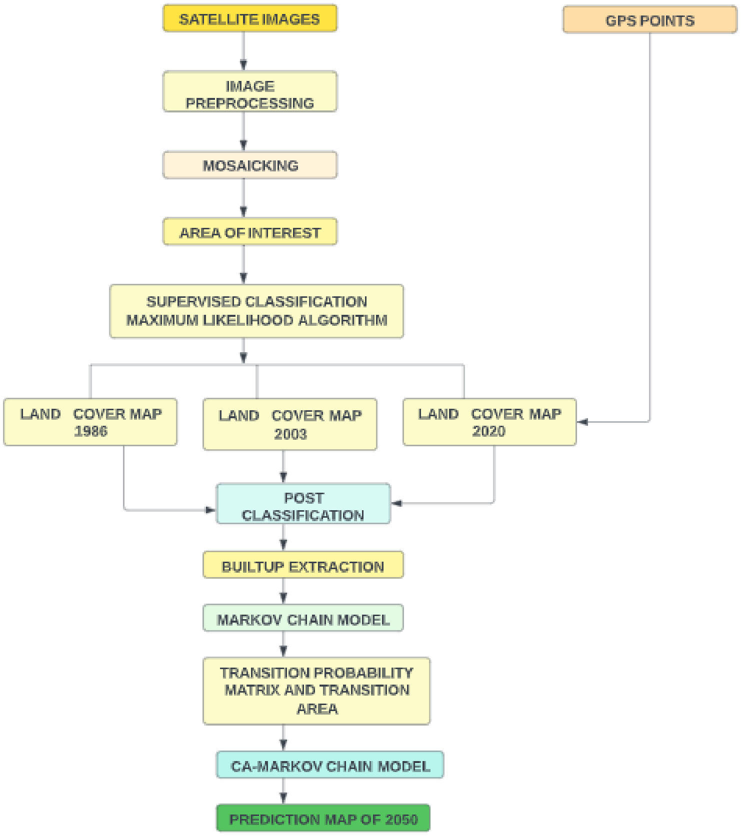


Figure 8: Flow chart Methodology.

RESULTS AND DISCUSSION

OBJECTIVE 1. Land Cover Map of the Study Area between 1986, 2003 and 2020.

Figure 9 to 11 below shows the land cover map of Bwari Area Council, Abuja for the year 1986, 2003 and 2020 respectively. From the classified satellites imageries, five land cover classes were extracted and these include Vegetation, Built-up, Bare surface, Water body and Rock outcrop. The classification revealed the area coverage for each of the Land cover classes (Table 2). In 1986, Built-up area covers 6.73km^2 (0.64%) in the study area and this shows that early settlement started in Bwari town as shown in Figure 9. Vegetation occupies 511.34km^2 (48.80%), Rock outcrop occupies 464.70km^2 (44.35%), Bare surface covers 58.8km^2 (5.61%) and Waterbody covers 6.12km^2 (0.58%) which is the least land cover coverage in the study area. In 2003, Built-up area covers 17.20km^2 (1.64%) which shows more rise in Built-up as shown in Figure 10. Vegetation occupies 646.19km^2 (61.67%), Rock outcrop occupies 362.18km^2 (34.56%), Bare surface covers 15.42km^2 (1.47%) and Water body covers 6.70km^2 (0.63%). In 2020, Built-up area covers 63.91km^2 (6.10%) and this shows a significant rise in urban expansion from the earliest years. Vegetation occupies 310.01km^2(29.58%), Rock outcrop occupies 452.62km^2 (43.20%), Bare surface covers 213.38km^2 (20.36%) and Water body covers 7.77km^2 (0.74%).

Where the probability surface is represented by t + 1Dpij, the development suitability surface is represented by tSij, and the neighborhood effect is represented by tNij.Table 3 lists the land cover classes of the research area's overall accuracy, kappa statistics, producer accuracy, and user accuracy for 1986, 2003, and 2020, respectively. For the three time periods of 1986, 2003, and 2020, the categorization accuracy indicated an overall accuracy of 95.8%, 99.9%, and 99%, respectively. The subsequent analysis and change detection were likewise thought to have a respectable overall accuracy from this. The accuracy of different land cover classes among users varied from 68.9% to 100%, and that of producers varied from 95.1% to 100%. For each classed map, the aggregate Kappa index was generated in order to assess the precision of the findings. The Kappa statistics for the three time periods of 1986, 2003, and 2020 were 0.89, 0.99, and 0.98, respectively. The three periods' Kappa coefficients exhibit nearly complete agreement on the kappa scale.

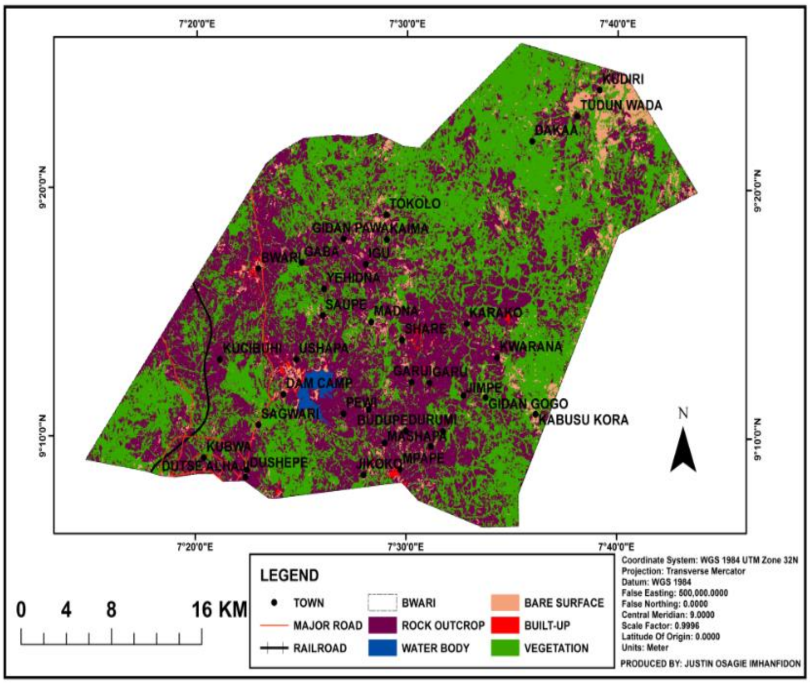


Figure 9: Land Cover Map of Bwari Area Council, Abuja (Landsat TM 1986)

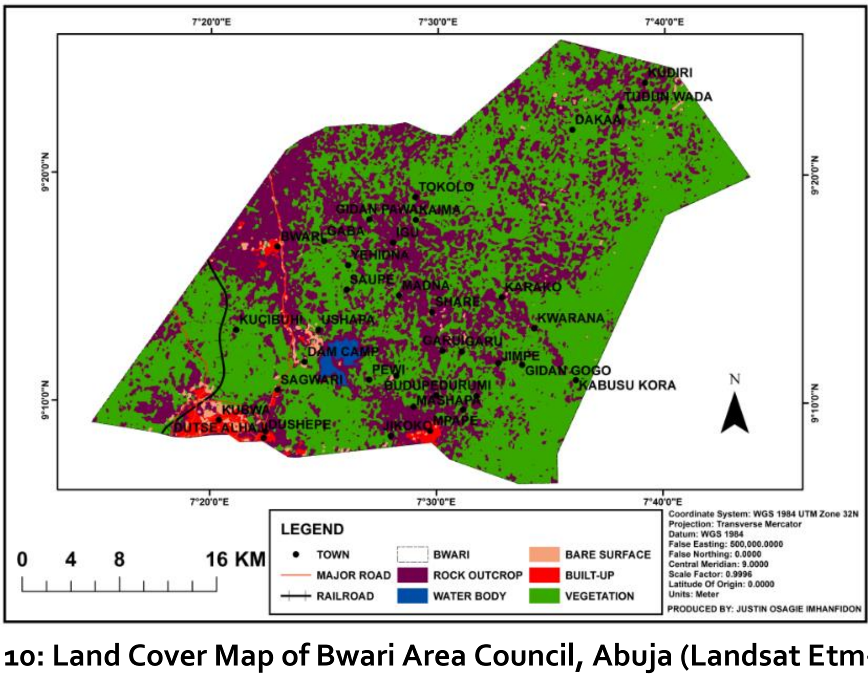


Figure 10: Land Cover Map of Bwari Area Council, Abuja (Landsat Etm+ 2003)

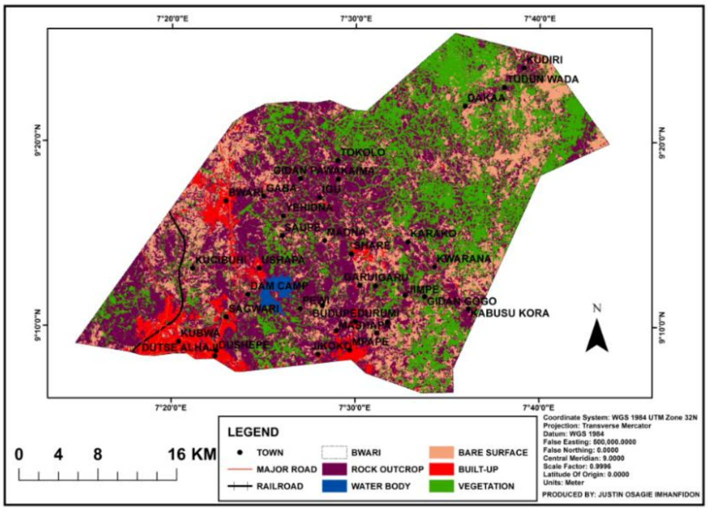


Figure 11: Land Cover Map of Bwari Area Council, Abuja (Landsat OLI, 2020)

Table 2: Area covered by the Land cover classes from 1986, 2003 and 2020

Land Cover Classes	1986		2003		2020	
	Area Covered (Km²)	Area Covered%	Area Covered (Km²)	Area Covered %	Area Covered (Km²)	Area Covered %
Built-Up	6.73	0.64	17.20	1.64	63.91	6.10
Vegetation	511.34	48.80	646.19	61.67	310.01	29.58
Rock Outcrop	464.70	44.35	362.18	34.56	452.62	43.20
Water Body	6.12	0.58	6.70	0.63	7.77	0.74
Bare Surface	58.8	5.61	15.42	1.47	213.38	20.36
Total	1047.69	100	1047.69	100	1047.69	100

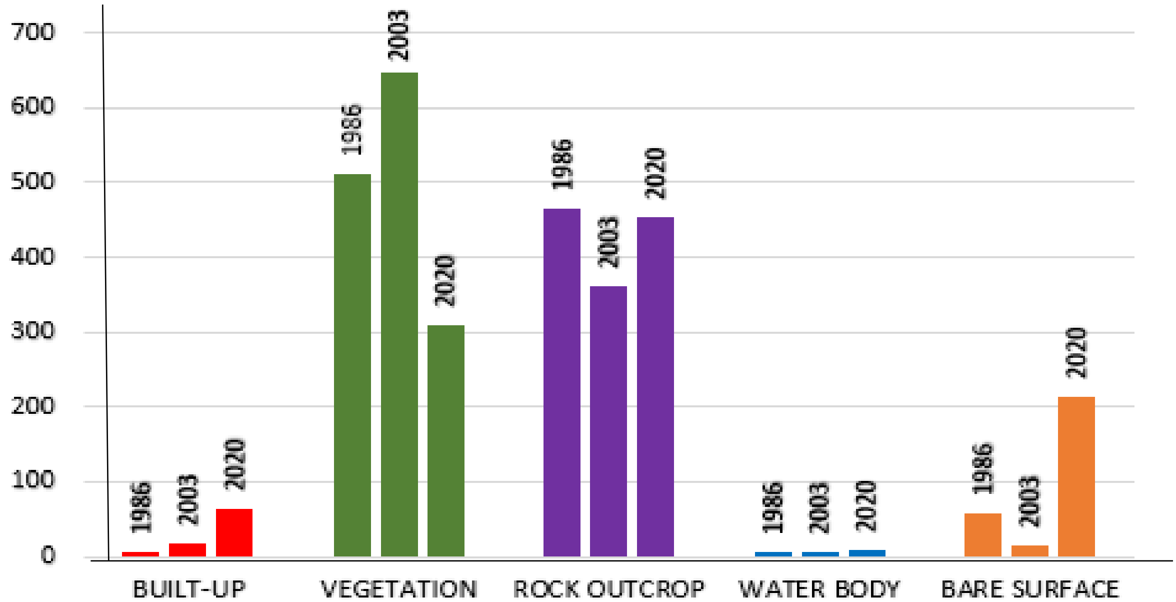


Chart 1: Comparison of Land cover Classes in Bwari and Its Environs (1986, 2003 and 2020)

Table 3: The Overall Accuracy, Kappa Statistics, Producer and User Accuracy of Land cover classes in Bwari Area Council, Abuja (1986, 2003, and 2020).

Land Cover Classes	1986		2003		2020	
	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy	Producer Accuracy	User Accuracy
Built-Up	100	100	100	100	99.6	98.5
Vegetation	95.1	99.8	99.9	99.9	100	100
Rock Outcrop	97.2	77.9	99.9	100	99.5	97.0
Bare Surface	99.1	68.9	100	99.4	98.5	99.9
Water Body	99.7	77.3	100	100	98.3	100
Overall Accuracy	95.8%		99.9%		99.0	
Kappa Statistics	0.89		0.99		0.98	

OBJECTIVE 2. The Extent of Changes in Land Cover between 1986, 2003 and 2020.

Table 4 displays the change detection analysis of the land cover classes in Bwari Area Council, Abuja (1986, 2003, and 2020) during a 34-year period. Chart 2 displays the percentage trend in the study area's land cover change. The outcome showed a considerable shift in built-up from +10.47Km2 (+3.58%) to +46.71Km2 (+6.94%) and climbs to +57.18Km2 (+13.3%) accordingly between the years 1986 and 2003, 2003 and 2020, 1986 and 2020. The steady increase in built-up could be as a result of numerous factors such as population increase due to migration, and socio-economic status (such as creation of the Bwari Area Council, Proximity to the Central Area, General Hospital, Joint Admission and Matriculation Board Office, Usman Dam, Law School, Dorben Polytechnic and Veritas Catholic University). As Vegetation increases between 1986 and 2003 by +134.85Km² (+46.21%), there was also a reduction in both Rock outcrop and Bare surface to -102.52Km² (-35.13%) and -43.38Km² (-14.86%) respectively as shown in Table 4. Between 2003 and 2020, Vegetation reduces to -336.18Km² (-50%) while Rock outcrop and Bare surface increases to +90.44Km² (+13.45%) and +197.96Km² (+29.44) respectively. From the earlier year to the later year (1986 and 2020), Vegetation also reduces to -201.33 (-47.16%), Rock outcrop had a slight reduction to -12.02Km² (-2.83%) while Bare surface increases to +154.58Km² (+36.21%). Water body had a slight increase throughout the period of years (1986, 2003, and 2020) from +0.58Km² (+0.19%) to +1.07Km² (+0.1%) and 1.65Km² (+0.38%) respectively. The dredging at the Usman Dam to meet the portable water demand of the Federal Capital Territory may have led to a minor rise in the size of the water body.

Table 4: Specific Land cover changes for Bwari Area Council, Abuja in 1986, 2003 and 2020

Land Cover Classes	1986 and 2003		2003 and 2020		1986 and 2020	
	Area Covered (Km²)	Area Covered%	Area Covered (Km²)	Area Covered %	Area Covered (Km²)	Area Covered %
Built-Up	+10.47	+3.58	+46.71	+6.94	+57.18	+13.3
Vegetation	+134.85	+46.21	-336.18	-50	-201.33	-47.16
Rock Outcrop	-102.52	-35.13	+90.44	+13.45	-12.08	-2.83
Water Body	+0.58	+0.19	+1.07	+0.1	+1.65	+0.38
Bare Surface	-43.38	-14.86	+197.96	+29.44	+154.58	+36.21

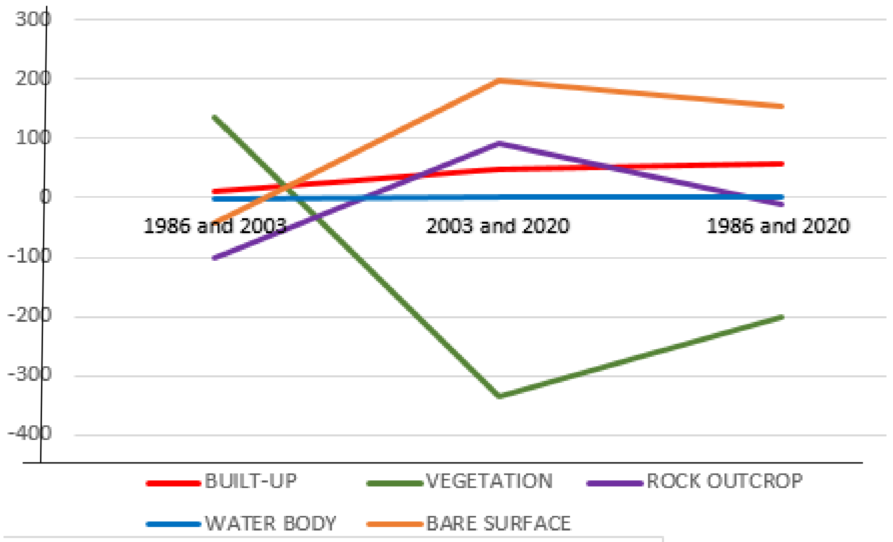


Chart 2: Percentage Trend in Land cover change of Bwari Area Council, Abuja (1986, 2003 and 2020)

OBJECTIVES 3. Built-up Extraction Showing the Pattern and Direction of Expansion

To easily visualize the amount of urban expansion within the research area, the built-up areas from each of the epochs were extracted from the identified imageries and superimposed (Figure 12 and chart 3). Table 5 displays the area occupied by buildings in 1986, 2003, and 2020, accordingly. It shows that the area occupied by buildings was 6.73 km2, 17.20 km2, and 63.91 km2 in 1986, 2003, and 2020, respectively. This graph demonstrates major alterations in populated areas over time. The outcome shows linear development of built-up along the road and adjacent to the rail track, as well as a leap frog kind of development within the research area. The research region has also seen a significant rate of urban expansion heading out from Bwari town and towards the southern and southern-eastern axes (Kubwa, Dutse Alhaji, and Ushepe, etc.).

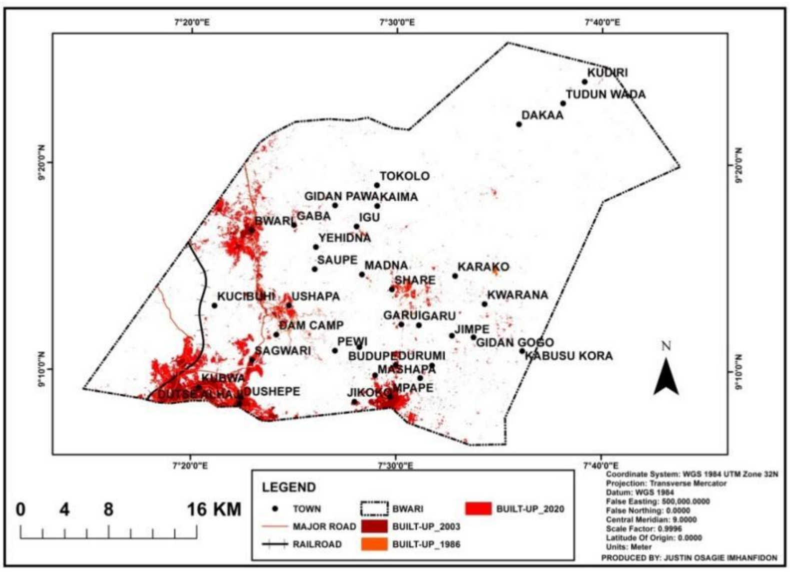


Figure 12: The Growth Extent in Built-up Between 1986, 2003 and 2020.

Table 5: Area Covered by Built-up between 1986, 2003 and 2020.

YEAR	AREA COVERED KM^2
BUILT-UP_ 1986	6.73
BUILT-UP_ 2003	17.20
BUILT-UP_ 2020	63.91

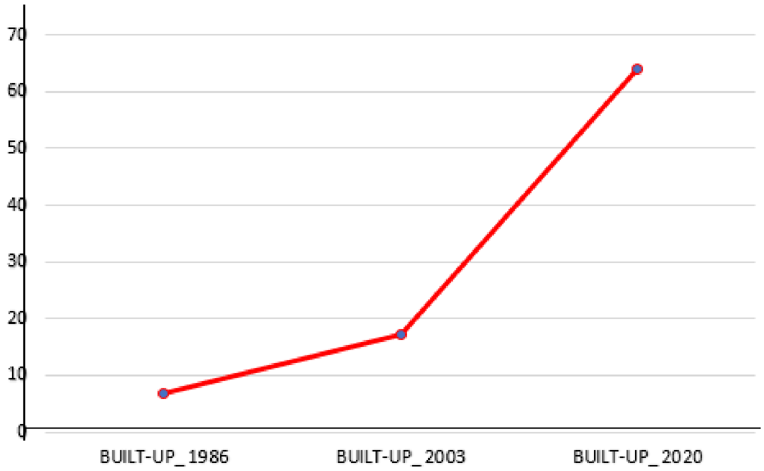


Chart 3: The Growth Extent in Built-up Between 1986, 2003 and 2020.

OBJECTIVE 4. To Predict the Future Urban Expansion for the Next 30 years.

The CA-Markov prediction model is really built upon the transition probability matrix that was produced by the Markov model that was run using the Idrisi Terrset software. Through pairwise analysis of the images of the land cover, the Markov chain model generates the transition probability matrix as a stochastic model (Table 6). Figure 13 shows the predicted 2050 land cover distribution map of 30 years period and chart 4 presents the comparison of Land cover Changes in Bwari Area Council, Abuja (1986, 2003, 2020 and 2050). The result revealed that built-up will increase to 97.25km (9.28%) which also showed more of infill development within Bwari town, Kubwa, Mpape and Dutse Alhaji as shown in Figure 13. Vegetation and Rock outcrop will reduce to 247.70Km^2 (23.64%) and 446.31Km^2 (42.60%) respectively while Bare surface increases to 247.99Km^2 (23.67%). Water body will maintain a steady increase to 8.44Km^2 (0.81%).

Table 6: The transition probability matrix of Bwari, 2050

Land cover classes	Vegetation	Built-up	Bare surface	Water body	Rock outcrop
Vegetation	0.4642	0.0203	0.1614	0.0000	0.3541
Built-up	0.0325	0.5076	0.1793	0.0140	0.2667
Bare surface	0.1339	0.0945	0.4228	0.0005	0.3483
Water body	0.0002	0.0010	0.0000	0.9952	0.0036
Rock outcrop	0.1616	0.0842	0.2125	0.0028	0.5389

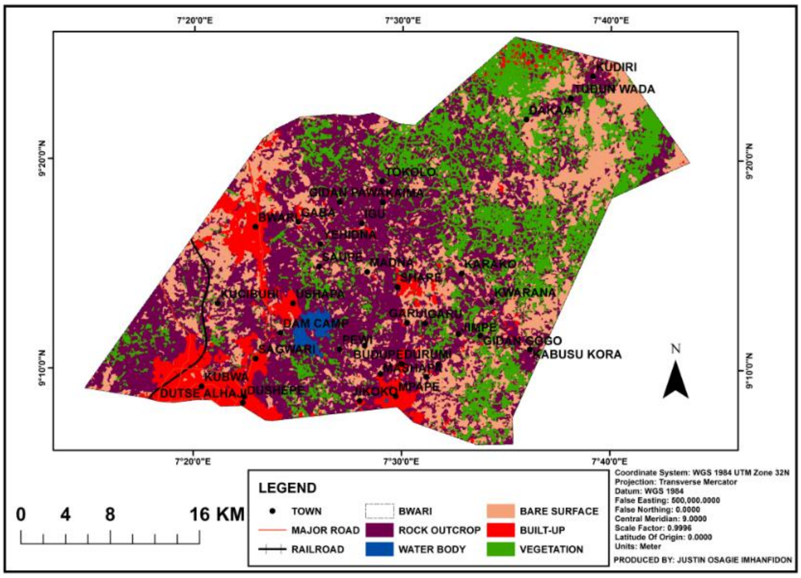


Figure 13: Predicted 2050 Land Cover Distribution in Bwari Area Council, Abuja

Table 7: Area covered by the Land cover classes from 1986, 2003, 2020 and 2050.

Land Cover Classes	1986		2003		2020		2050	
	Area Covered (Km²)	Area Covered%	Area Covered (Km²)	Area Covered %	Area Covered (Km²)	Area Covered %	Area Covered (Km²)	Area Covered %
Built-Up	6.73	0.64	17.20	1.64	63.91	6.10	97.25	9.28
Vegetation	511.34	48.80	646.19	61.67	310.01	29.58	247.70	23.64
Rock Outcrop	464.70	44.35	362.18	34.56	452.62	43.20	446.31	42.60
Water Body	6.12	0.58	6.70	0.63	7.77	0.74	8.44	0.81
Bare Surface	58.8	5.61	15.42	1.47	213.38	20.36	247.99	23.67
Total	1047.69	100	1047.69	100	1047.69	100	1047.69	100

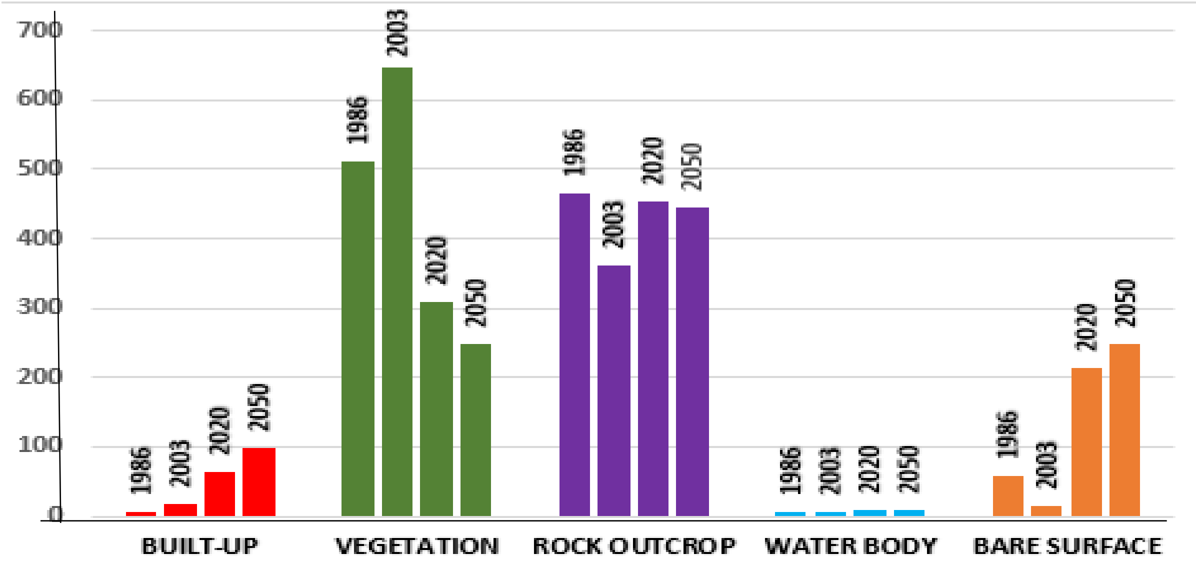


Chart 4: Comparison of Land Cover Changes in Bwari and Its Environs (1986, 2003, 2020 `and 2050)

CONCLUSION

Based on the aforementioned findings, the study has demonstrated the value of using space-based technology in place of the conventional approach to monitor and predict changes in the physical expansion of urban growth through time. Additionally, it has shown a map of the research area's land cover during a 34-year period, evaluated changes to the study area's land cover classes, looked at the pattern and direction of built-up area growth, and forecasted future urban growth for the following 30 years. It is stated that for efficient land management and sustainable urban planning, it is crucial to comprehend how an area's spatial pattern of urban expansion has changed over time. Urban dynamics modeling is an important method for estimating growth rates and understanding the implications that growth may have in the future.

RECOMMENDATIONS

From the following findings discovered in this study, it is therefore recommended that

1. There is need to create more awareness in acquiring the needed and necessary information and knowledge about the use of Geospatial technologies in spatial planning which should be of great value to Decision makers, Town Planners and managers of the urban environment.
2. The local planning authority in the study area has to strengthen its local government monitoring efforts in regard to the rates of change found in this research, particularly development near the Usman Dam and on the periphery.
3. To better their development planning, city planners and the Developmental Control Agency should adapt their usage of GIS and remote sensing data with good spatial resolution.
4. The study has given decision-makers data from various eras within the study period to aid in future planning and implementations for the expanding town in order to avoid unanticipated developments and to provide reliable data for monitoring and assessments of the environment's ability to sustain development.
5. This study has identified land cover changes that occurred over the study periods that require urgent management attention in order to execute the necessary environmental policies for development and the sustainability of land resources.

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