LANDUSE AND LANDCOVER CHANGE DETECTION ANALYSIS IN UDU L.G.A., DELTA STATE

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Abstract: The ecosystems of many cities in emerging nations are changing and being modified. Approximately 10 million hectares of the global forest cover are being used for various purposes. Between 1995 and 2025, agriculture in Nigeria is expected to rise by 10 million hectares, while forest cover is expected to decline by 1.9 million hectares. This shows that Nigeria has been through a wide range of changes to its land use and land cover. This study examines the patterns and trends of land use and land cover changes in Udu Local Government Area, Southern (Niger Delta area) Nigeria from 2000 to 2020 with the goal of providing appropriate information for accurate monitoring and efficient planning. The research made use of Landsat 8 satellite imagery of 2000, 2010 and 2020. Remote sensing and Geographical Information System techniques as well as supervised image classification method were used to assess the magnitude of changes in the city over the study period.

Keywords: Land use, Land cover, Remote sensing, Geographic Information System, Supervised classification

1.Introduction

1.1 Background of Study

The term "land use" encompasses the management and alteration of natural environments, transforming them into developed spaces, semi-natural habitats, agricultural lands, pastures, and managed forests. It also delves into the impact of various activities on ecosystem health, environmental population, deforestation, erosion, and stream flow, among other factors. The increasing global demand for food, shelter, fiber, and water for over seven billion people is driving changes in land use, particularly in forests, agricultural areas, and regions near water bodies (Foley et al., 2005).

Urbanization, as indicated by studies (Orimoogunje, 2014; Nath et al., 2020), has significantly altered land use and land cover due to population growth, urban development, and expansions. Throughout history, humans have utilized various forms of land use to modify different types of land cover, especially since the inception of organized human settlements, to harness biosphere resources. Prior to the 1970s, ecologists primarily focused on studying interactions between organisms and environmental elements such as soil, light, and temperature. Notable research by McIntosh (1974) explored interactions between flora and fauna within their habitats. While numerous studies investigated how plants and animals adapted to specific environments, attention towards changes in land use and land cover was limited. It's estimated by the UN that around 55% of the global population resides in urban areas, and this is projected to increase to 68% by 2050 (United Nations, 2019). Given this trend, ecological research has increasingly centered on human activities in urban settings.

The continuous reduction of natural vegetation, forests, and water bodies in urban areas is a concerning global trend. These shifts in land use patterns worldwide have resulted in ecological imbalances, environmental challenges such as floods and loss of biodiversity, and localized climate alterations. The significance of this research stems from addressing the ecological imbalances and environmental problems brought about by the ongoing conversion of natural land cover into various man-made ecosystems, particularly in urban centers. Therefore, accurately monit ring and assessing the extent of human impact on ecosystems and their resources relies on detecting changes in land use, land cover, and climate. Consequently, this study investigates the changes in land use and land cover in Udu Local Government Area (LGA), Delta State, from 2000 to 2020. The objective is to gather comprehensive data on the pattern and trajectory of land use and land cover changes over a thirty-year period, facilitating precise monitoring and effective planning.

2. Aim and Objectives of the Study

Aim

The aim of this project is to carry out land use land cover changes detection analysis from the year 2000 to 2020 using a geographic information system and satellite images of Udu L.G.A., Delta State, Nigeria.

Objectives

a. Identify and quantify land cover changes in UDU LGA
b. Assess the rate and magnitude of land cover change in UDU LGA
c. Monitor environmental impacts in UDU LGA
d. Support land management and planning in UDU LGA
e. Provide baseline data for future analysis in UDU LGA

3. METHODOLOGY

3.1 Description of the Study Area

UDU Local Government Area, South Southern (Niger Delta area), Nigeria. UDU LGA lies approximately between latitude 5 ° 24'33.44", 5 ° 32'13.50" and longitude 5 ° 52'48", 5 ° 44'57" Udu is the name of a Kingdom, local government, and a town in Delta State Nigeria. Udu represents the ancestral homeland of the Udu people, an ethnic group within the Urhobo community residing in the western region of the Niger delta. They primarily communicate in the Urhobo language. The Udu territory, known as Udu Clan, is situated on level terrain between the Warri River in the west and the Okpare Creek to the east. Encompassing approximately 138 square kilometers (53 sq mi), it is geographically defined by its borders: Warri to the north, Effurun to the northeast, Otu Jeremi to the southeast, and Ohwahwa, Esaba, and Ogbe Ijaw to the south. OtorUdu serves as the administrative hub for the Udu Local Government area in Delta State, Nigeria, situated approximately 7 km (4.3 mi) away from the city of Warri.

She has a population of one hundred and forty-three thousand, three hundred and sixty-one (143,361) with male seventy-one thousand, two hundred and forty-two (71,242) and female to be seventy-two thousand, one hundred and nineteen (72,119) through the recent census conducted in Udu.
Figure 3.1 below shows the location map of Udu local government area:

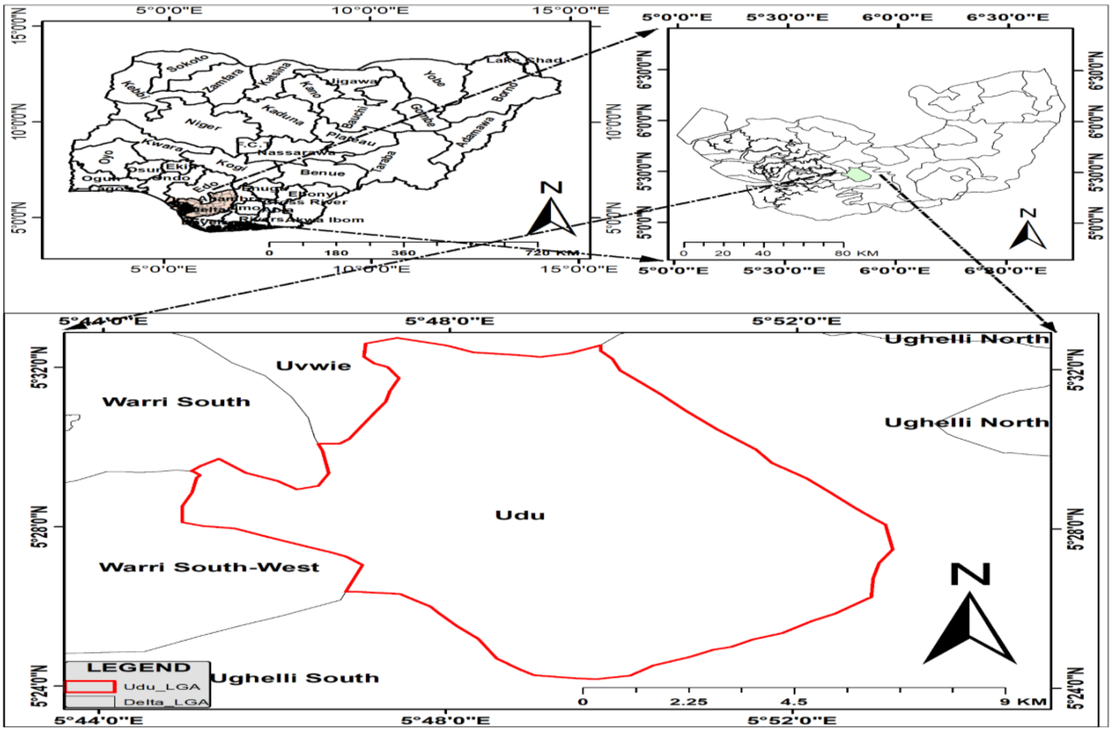


Figure 3.1: ShowingStudy Area Map

3.2 Materials

The material adopted for the study are classified as primary and secondary materials as well as hardware and software

Primary Material

The primary sources are original materials on which research is based. Low resolution imageries were obtained from USGS website, which table 3.1 shows the sources and data type used in achieving the aim and objective of the study area

Table 3.1: Source – Researcher

S/N	Data Type	Date of Acquisition	Path	Row	Resolution	Source
1	Landsat 7 ETM+	20-04-2000	189	056	30 meters	USGS
2	Landsat 7 ETM+	17-12-2010	189	056	30 meters	USGS
3	Landsat 8 OTI/LIRS	19-12-2020	189	056	30 meters	USGS

The data are multispectral Landsat imageries which are acquired in 2000, 2010, 2020 respectively. These imageries (7 ETM+ and 8 OTI/LIRS) were acquired from USGS, it has 30m resolution and it is classified as a low-resolution image.

Secondary Material

Secondary material are relevant literature materials were obtained from textbooks, Journals, UNEC Geoinformatics and Surveying Department Thesis Library and other existing literatures that are related to the research problem.

Hardware and Software

The term hardware are the physical components of the computer system, for this research work HP elite ProBook 450 G2 laptop computer system, HP Officejet 7500 W809 color printer. All hardware is personal and belongs to me.

The software used for this study is ArcGIS 10.8, Microsoft word, Microsoft Excel.

3.3 Reconnaissance Survey

It was carried out on the study area which is aimed at getting the general knowledge of the area which was done on USGS website and Using Google earth Pro. The methodology flow chart below explains the procedure of this research on change detection in Udu, Delta State, Nigeria.

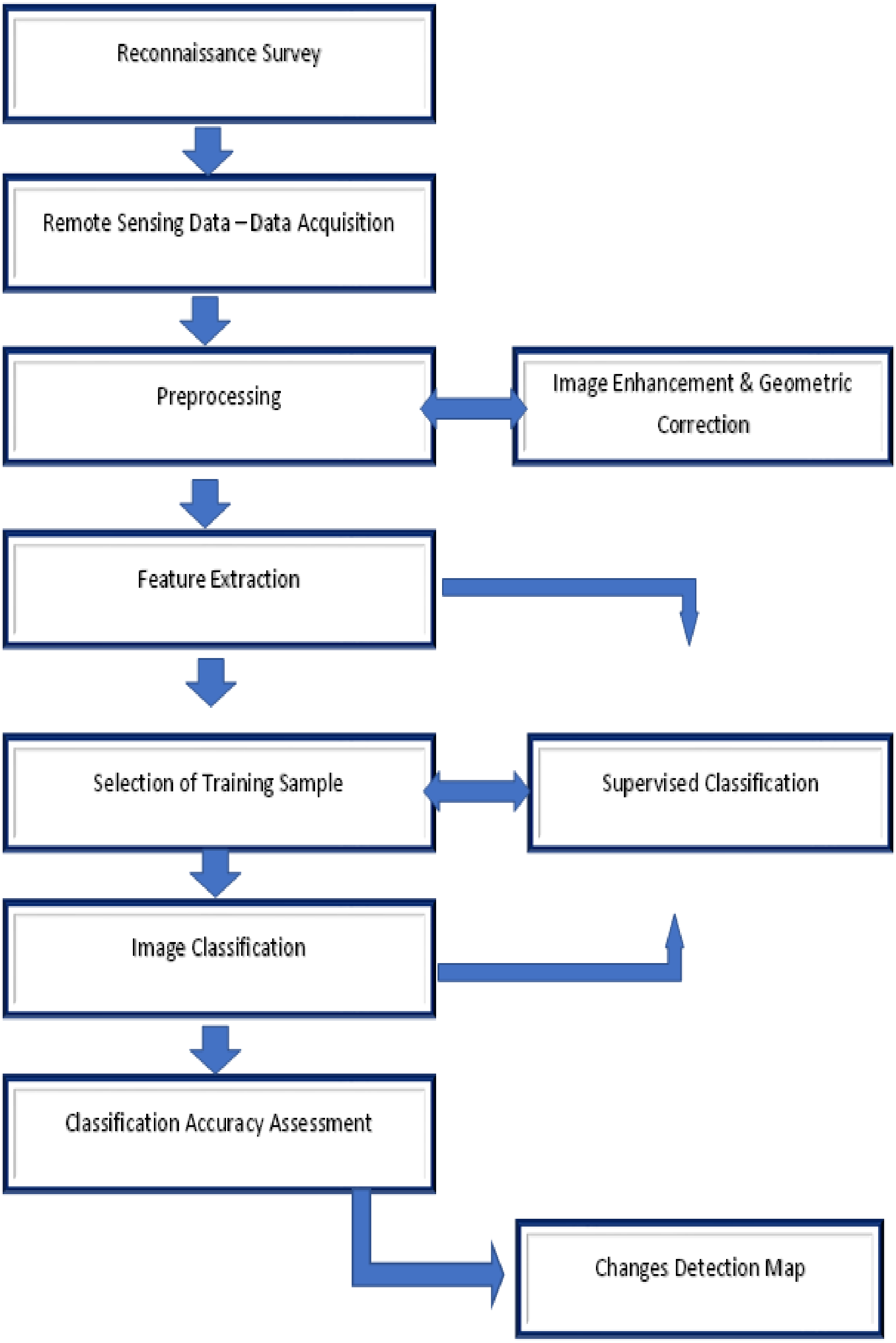


Figure 3.2: Methodology Flow Map

3.4 Data Acquisition and Preprocessing

The image was gotten from USGS that's 2000, 2010 and 2020 image by using the following steps;

Entering Search Criteria, to narrow your search area, I imported the .kml data of the boundary to define your search area then choose a date range and cloud cover.

In dataset, the Landsat was checked and other additional information was also checked, the result was loaded and preferred image was downloaded after checking the data metadata.

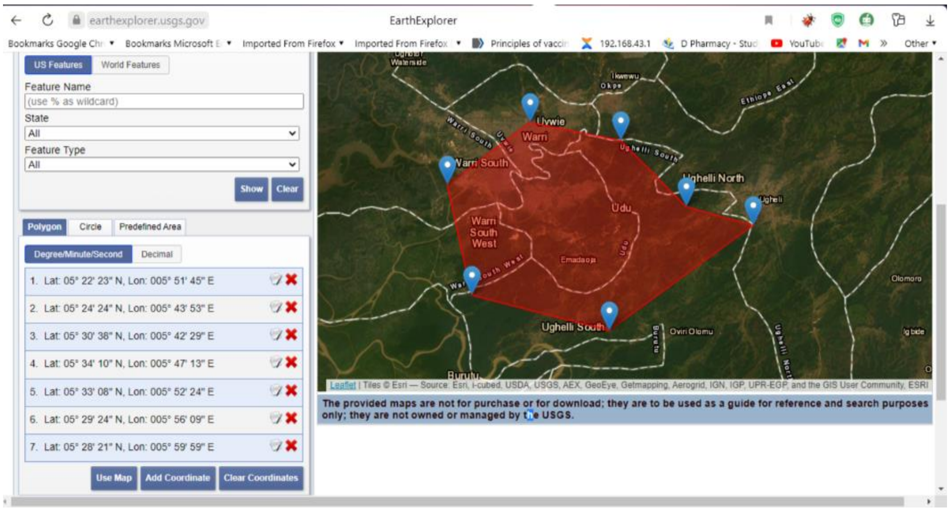


Figure 3.3 Launch ArcMap and define the Coordinate system to work

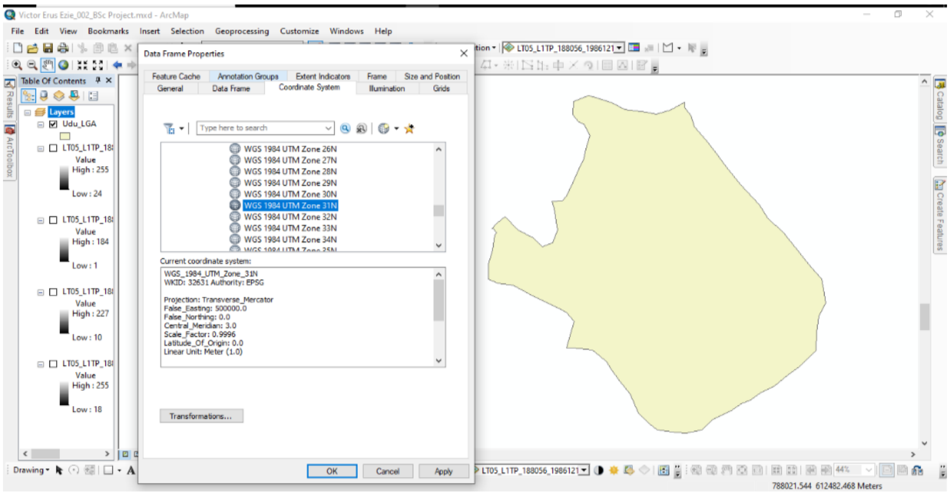


Figure 3.4 Unzip the imagery and import to ArcMap environment

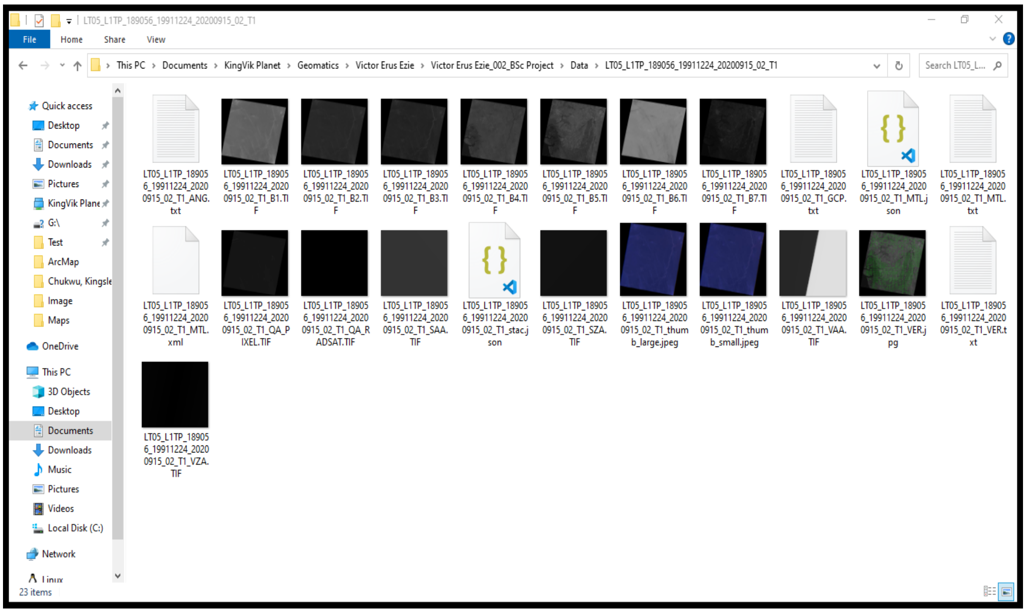


Figure 3.5 Importing the bands to ArcMa

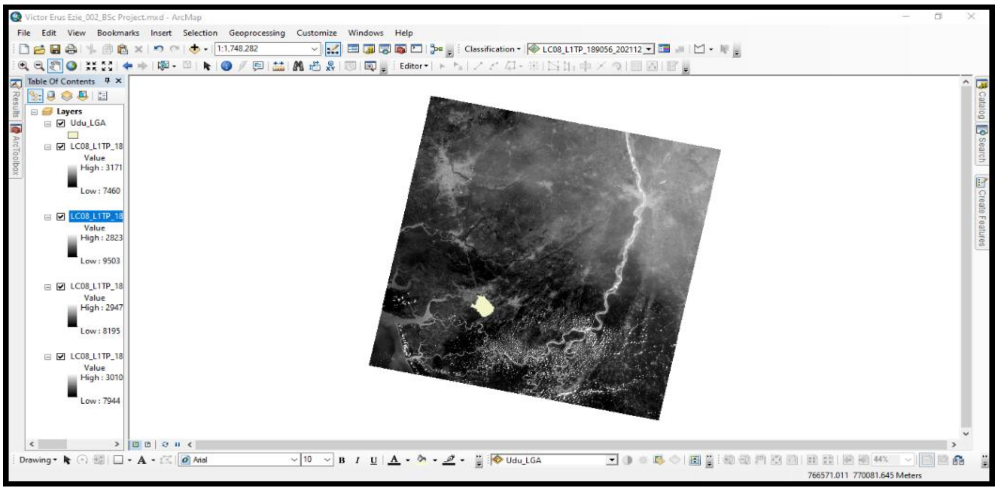


Figure 3.6: Band Composite Carried Out

From Arc toolbox, carry out band composite: The bands were combined using ArcGIS Data management extension which created composite image and from the output of the bands combination the area of interest was extracted by masking using the boundary layer.

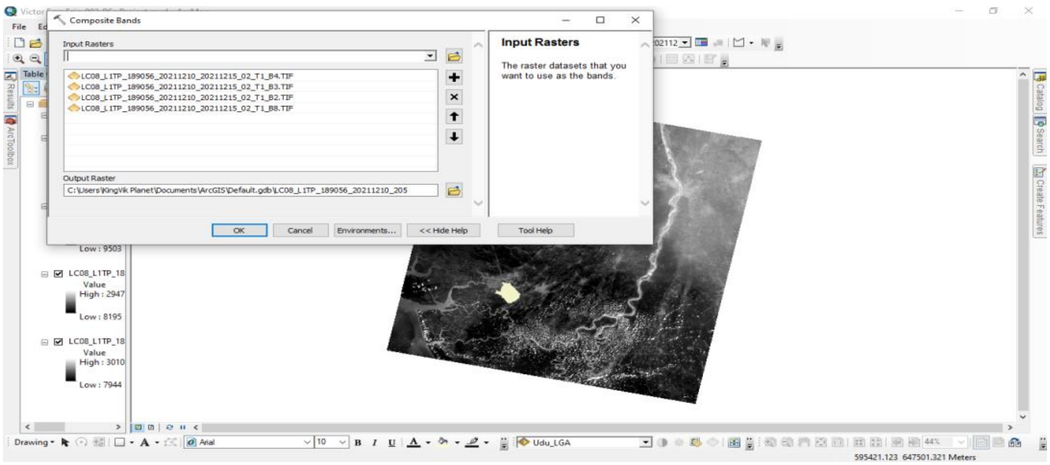


Figure 3.7: After bands composite

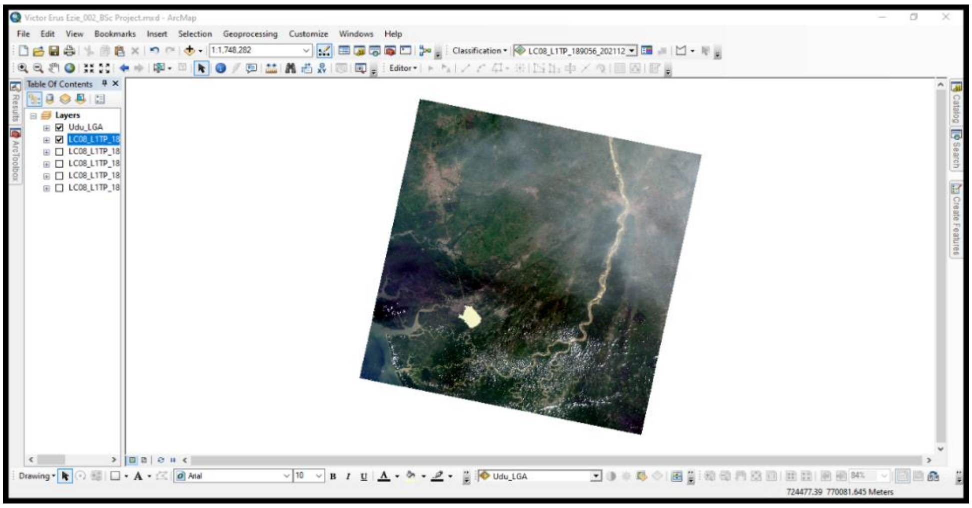


Figure 3.8: Area of interest

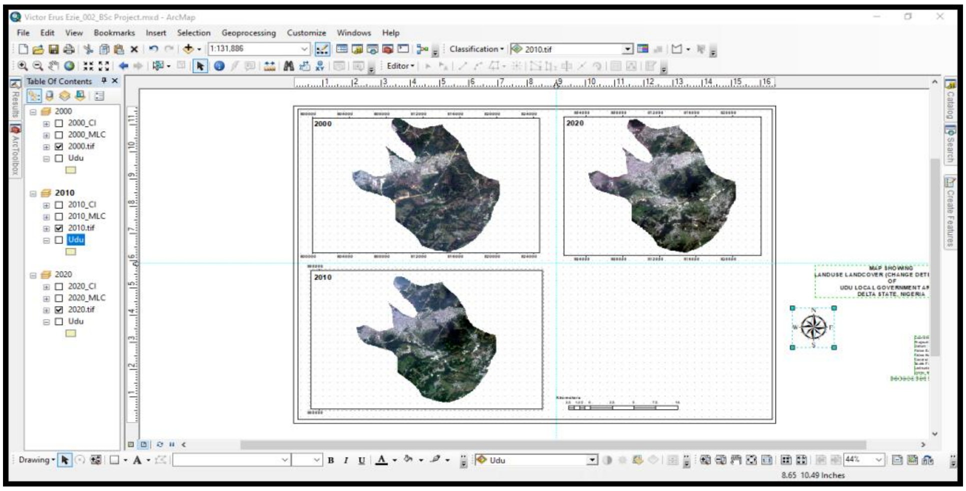


Figure 3.9: Clipped Raster of 2010, 2000 and 2020

Data Exploration and Pre-Processing

ArcGIS version 10.8 was utilized to conduct the analysis. The Multivariate toolset within the ArcGIS Spatial Analyst extension offers tools for supervised analysis. Within this context, the Image Classification toolbar serves as an accessible platform for generating training samples and signature files, crucial components in supervised classification. The primary method of classification employed was the Maximum Likelihood Classification tool. A critical input for this method is the signature file, detailing class identifications and their respective statistics. To facilitate supervised classification, the signature file is formulated by utilizing training samples via the Image Classification toolbar.

Collecting Training Samples

In supervised classification, training instances were employed to delineate categories and compute their distinctive features. These training instances were generated interactively through the utilization of training sample drawing tools available on the Image Classification toolbar.

To generate a training instance, the polygon tool on the Image Classification toolbar was utilized to mark regions on the input image layer. Care was taken to ensure that the size of each training instance was optimal—neither excessively small nor overly large. If a training instance is too small, it might lack sufficient information to effectively construct the characteristic features of the class. Conversely, an excessively large training instance could encompass pixels that do not belong to the intended class.

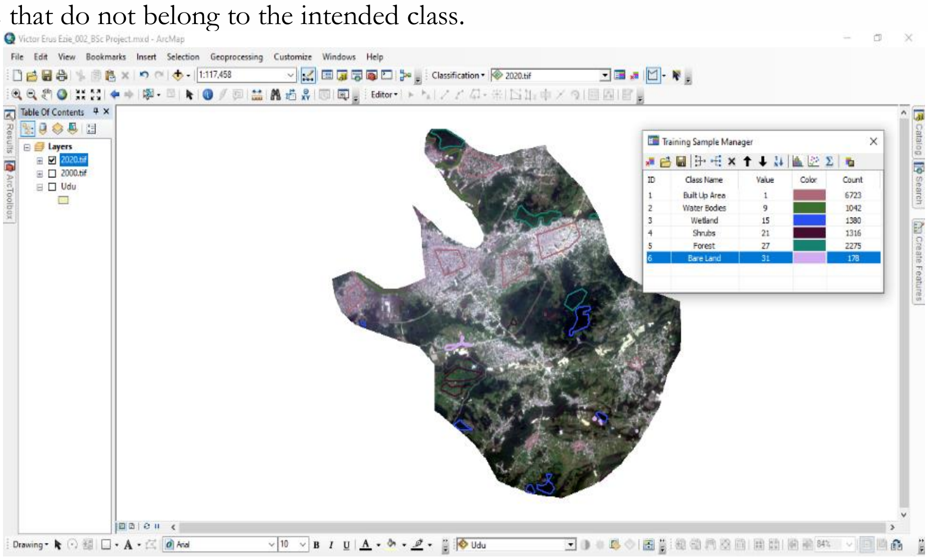


Figure 3.10: Evaluating Training Samples

When samples are selected in the display during training, the training sampling manager generates new classes automatically.

Editing Classes

Depending on the results of the training sample evaluation, I took several actions to streamline the classes with overlapping attributes. In certain instances, I used the Merge tool found in the manager window to combine overlapping classes into a single class. Additionally, I made modifications such as renaming or renumbering classes, adjusting their display colors, splitting classes when necessary, deleting redundant classes, and saving and loading training samples at appropriate intervals.

Creating the Signature File

Upon verifying that the training samples accurately depict the intended classes and possess clear distinctions from each other, a signature file was generated utilizing the Create Signature File tool found within the manager window.

Examining the Signature File

The Dendrogram utility was employed to analyze the dissimilarities in attributes among progressively combined classes within a signature file. The result is a text-based file presenting a hierarchical tree diagram illustrating the division of these classes. Using the dendrogram, I assessed whether it is possible to discern distinctiveness between two or more classes or clusters. This tool, known as the Dendrogram tool, can be accessed through the Spatial Analyst Multivariate toolset.

Editing the Signature File

The signature file wasn't directly modified using a text editor. Instead, I utilized the Edit Signatures tool within the Multivariate toolset. This feature enabled me to combine, renumber, and remove class signatures as needed.

Applying Classification

The process of image classification involved the utilization of the Maximum Likelihood Classification tool, which is grounded in the theory of maximum likelihood probability. This tool categorizes individual pixels into specific classes by considering the means and variances of the class signatures, which are stored in a signature file. Accessible through the Image Classification toolbar, this tool efficiently assigns pixels to respective classes based on statistical parameters.

An alternative approach for image classification is the Interactive Supervised Classification tool. This tool expedites the maximum likelihood classification procedure, enabling a quick preview of the classification outcome without executing the Maximum Likelihood Classification tool.

Post-Classification Processing

The image produced through the Maximum Likelihood Classification tool might inaccurately label specific cells (referred to as random noise) and generate minor erroneous regions. To enhance the accuracy of classification, my objective is to reclassify these erroneously labeled cells into a neighboring class or cluster. The strategies employed to refine the classified image encompass filtering, smoothing the boundaries between classes, and eliminating small isolated areas. The outcome of employing these data refinement methods is a visually enhanced map.

Layout and Production

When the classification was down, the layout view was turned on, title, north arrow, scale text and bar, legend and other marginal information

The map was exported as .PDF and JPEG file format.

Analysis was done using the information on the raster created and the attribute data

4. DISCUSSION

4.1 Data Analysis, Result and Discussion

This chapter is concerned with the presentation and discussion of the result obtained from the analysis. It is presented in the changes in Udu local government area from 2010 through 2020 using 2010, 2000 and 2020 Landsat imageries.

Spatial Extent of Land use/Landcover Classes (Classification Result) Distribution The spatial extent of land use/landcover classes of the study area in 2010,2000 and 2020 is represented in Table4.1. The land uses/land covers identified by this study were of five categories:

i. Bare soil: Bare soil refers to soil or sand lacking coverage by grass, turf, live ground vegetation, wood chips, gravel, artificial turf, or similar materials.
ii. Urban Zone: An urban zone, developed area, or urban cluster is a human habitation characterized by a high concentration of people and a developed built environment infrastructure. These areas emerge through urbanization and are classified by urban structure as cities, towns, conurbations, or suburban regions.
iii. Forst: Vegetation constitutes a gathering of plant species along with the ground cover they supply.
iv. Wetlands/Water Features: A wetland is a unique ecosystem that undergoes flooding or saturation by water, either on a permanent or seasonal basis. Flooding leads to the prevalence of oxygen-free processes, especially in the soils, while water pathways comprise continuous surface water flowing within the bed and borders of a watercourse.
v. Shrubs: A shrub is a perennial woody plant of small to medium size. Unlike herbaceous plants, shrubs possess enduring woody stems above the surface. Shrubs can either be deciduous or evergreen, and they are differentiated from trees by their multitude of stems and reduced height, typically less than 6–10 m in stature.

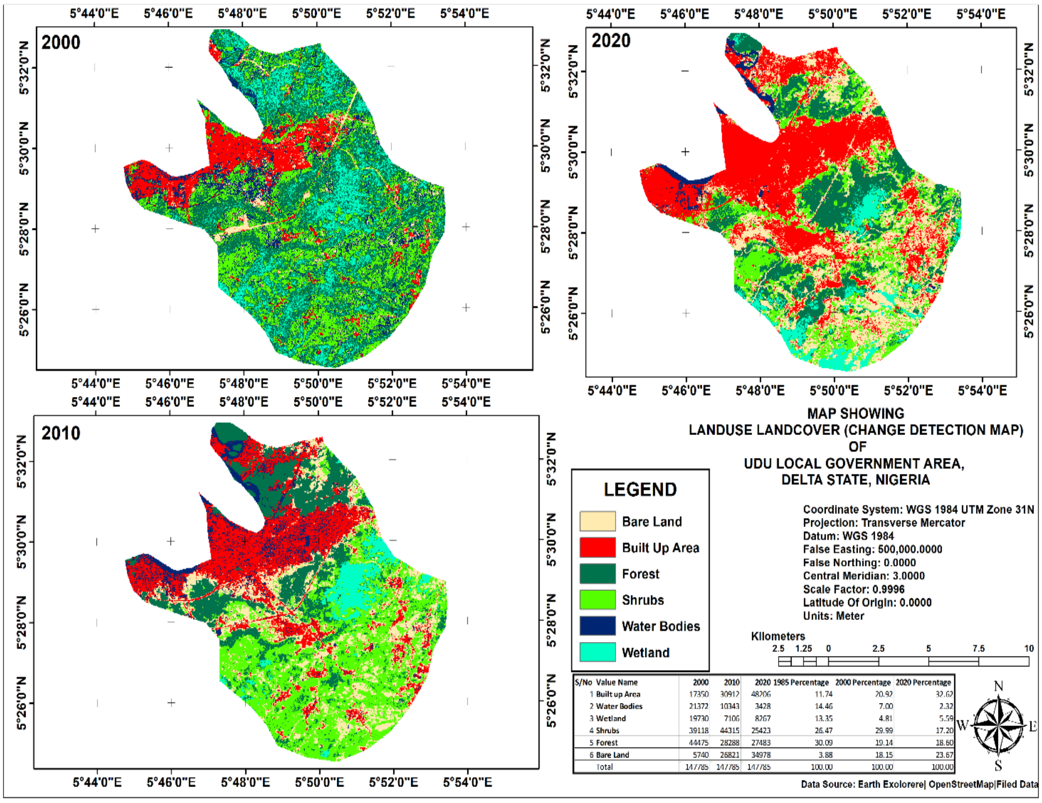


Figure 4.1: Map showing classification result from 2000, 2010 and 2020

Table 4.1: Result from map

S/No	Value Name	2000	2010	2020	2000 Percentage	2010 Percentage	2020 Percentage
1	**Built up Area**	17350	30912	48206	11.74	20.92	32.62
2	**Water Bodies**	21372	10343	3428	14.46	7.00	2.32
3	**Wetland**	19730	7106	8267	13.35	4.81	5.59
4	**Shrubs**	39118	44315	25423	26.47	29.99	17.20
5	**Forest**	44475	28288	27483	30.09	19.14	18.60
6	**Bare Land**	5740	26821	34978	3.88	18.15	23.67
	Total	147785	147785	147785	100.00	100.00	100.00

Bare Soil: Bare soil refers to exposed soil or sand that lacks any coverage by grass, sod, living ground covers, wood chips, gravel, artificial turf, or comparable coverings. The bare soil has a variation from 2000 through 2000 where it has 21.264% in 2000 to 22.447% in 2010 (+1.183) then to 29.458% (+7.011) which might be as result of development taking places like people building, construction and other human and natural activities taking place in Udu.

Shrubs: A shrub refers to a perennial woody plant of modest to medium size. In contrast to herbaceous plants, shrubs possess enduring woody stems that extend above the soil's surface. These plants can fall into the categories of deciduous or evergreen. What sets shrubs apart from trees is their characteristic of having multiple stems and a stature that is typically shorter, generally measuring less than 6–10 meters in height.

The Shrubs makes up part of Enugu around 36% of the Udu as at 2010, the increase and decrease of grassland in Udu are due to Natural and manmade effect, it was 36.991% in 2000 then to 32.436% in 2010 (-4.555) to 16.663% in 2020 (-15.773). The decrease of Shrubs in Udu which can be attributed to the growth and urban expansion in Udu.

Urban Area: An urban locality, built-up locality, or urban cluster refers to a human habitation characterized by a dense population and a developed built environment infrastructure. These areas result from the process of urbanization and can be classified based on their urban structure as cities, towns, conurbations, or suburbs.

These urban activities attributes to road construction, industry building, house construction, schools and other activities that comes is associated with population increases. From https://www.citypopulation.de/en/nigeria/admin/delta/NGA010018__udu/;
The current metro area population of Udu in 2020 is 820,000, a 3.14% increase from 2021.The metro area population of Udu in 2021 was 795,000, a 2.85% increase from 2020. The metro area population of Udu in 2020 was 773,000, a 2.79% increase from 2019.The metro area population of Udu in 2019 was 752,000, a 2.59% increase from 2018. This trend continued which means that they have been increase of population which changes the pattern and growth/expansion of urban area in Udu which greatly affected Udu.

These changes in population are the result of changes in all aspect of Udu Local government Area, the urban area changed from 9.047% in 1985 to 13.026% in 2000 (+3.979) to 25.010% in 2020(+11.984) and +15.963 increase from 1985.

Forest: Forest is an assemblage of plant species and the ground cover they provide, human activities lead to deforestation which lead to cutting down and uprooting of trees, shrubs etc. They have been rapid decrease of vegetation in Udu from 19.506% in 1985 to 17.358% in 2000(-2.148) and 12.952% (-4.406) in 2020.

Wetland/Water Path: A wetland is a unique ecological system characterized by being inundated or saturated with water, either permanently or during specific seasons. This inundation leads to predominant anaerobic processes, particularly in the soil, while the water flows continuously within the channel's bed and banks. Urban activities can cause changes in wetland and natural water path as percentage of wetland will be filed to build houses or construct roads, and some water path or channels will be close, modified or created in the course to trying to channel water paths.

The wetland and water bodies in Udu have changed from 13.191% in 1985 to 14.824% in 2010 and 15.917% in 2020 which means that there is modification and closing of wetland and water bodies which all depend of Deforestation which led to opening of river path under the trees, construction which change the path of waterbodies and other activities which lead to the increase of the waterways, water path and water bodies around Udu

4.2 Accuracy Assessment/Confusion Matrix

The assessment of accuracy involves utilizing a reference dataset to evaluate the precision of your classified outcome. It's essential that the data in your reference dataset aligns with the prescribed schema. One common approach to ascertain the accuracy of a classified map is generating a set of random points based on the ground truth data, then comparing this set with the classified data using a confusion matrix. While this process involves two steps, it is crucial when comparing results across various classification methods or training sites. In cases where ground truth data is unavailable, and reliance is solely on the same imagery used for the classification, this approach remains applicable.

4.3 Accuracy Assessment Formula

Users Accuracy= (Number of Correctly Classified Pixels in each Category)/ (Total number of Classified Pixels in that Category (The Row Total)) ×100
Producer Accuracy= (Number of Correctly Classified Pixels in each Category)/ (Total Number of Reference Pixels in that Category (The Column Total)) ×100
Overall Accuracy= (Total Number of Correctly Classified Pixels (Diagonal))/ (Total Number of Reference Pixels) ×100
Kappa Coefficient (T)=((TS×TCS)-∑ (Column Total Row Total))/ (TS^2-∑ (Column Total Row Total)) ×100

Table 4.2: Accuracy assessment/Confusion Matrix on Year 2000 data.
Accuracy assessment/Confusion Matrix on Year 2000 data was done using the training sample with the Imagery and the Maximum likelihood Supervised classification.

Year 2000	**Sample Training and Imagery and the MLC**						**Number of Classified Pixels**
	Built Up Area	Water Bodies	Wetland	Shrubs	Forest	Bare Land	
Built Up Area	47	1	2	0	0	**0**	**50**
Water Bodies	1	45	0	3	1	**0**	**50**
Wetland	4	1	43	1	1	**0**	**50**
Shrubs	0	2	0	48	0	**0**	**50**
Forest	1	1	0	1	47	**0**	**50**
Bare Land	0	1	0	1	48	**48**	**50**
No of Sample points pixel	**53**	**50**	**45**	**53**	**49**	**48**	**300**

Overall Accuracy= (Total Number of Correctly Classified Pixels (Diagonal))/ (Total Number of Reference Pixels) ×100
Overall Accuracy = 47+45+43+48+47=230
Total Number of samples = 230
Overall Accuracy = 230/250 =0.9200 (or 92%)

Table 4.3: Accuracy assessment/Confusion Matrix on Year 2010 data.

Accuracy assessment/Confusion Matrix on Year 2010 data was done using the training sample with the Imagery and the Maximum likelihood Supervised classification.

Year 2010	**Sample Training and Imagery and the MLC**						**Number of Classified Pixels**
	Bare soil	**Forest**	**Urban Area**	**Shrubs**	**Wetland/Water bodies**		
Bare soil	44	1	2	0	2	**1**	**50**
Forest	3	42	0	3	1	**1**	**50**
Urban Area	1	1	46	1	1	**0**	**50**
Shrubs	3	2	0	45	0	**0**	**50**
Wetland/Water bodies	1	1	0	1	47	**0**	**50**
	0	1	0	1	2	**46**	**50**
No of Sample points pixel	**52**	**47**	**49**	**50**	**52**		**250**

Overall Accuracy= (Total Number of Correctly Classified Pixels (Diagonal))/ (Total Number of Reference Pixels) ×100

Overall Accuracy = 44+42+46+45+47=224

Total Number of samples = 224

Overall Accuracy = 224/250 =0.896(or 89.6%)

Table 4.4: Accuracy assessment/Confusion Matrix on Year 2020 data.

Accuracy assessment/Confusion Matrix on Year 2020 data was done using Google Earth Pro and the Maximum likelihood Supervised classification.

Year 2020	**Google Earth Pro and Imagery and the MLC**						**Number of Classified Pixels**
	Bare soil	**Forest**	**Urban Area**	**Shrubs**	**Wetland/Water bodies**		
Bare soil	46	1	1	0	1	**0**	**50**
Forest	3	45	0	1	1	**0**	**50**
Urban Area	1	1	47	0	1	**0**	**50**
Shrubs	2	2	0	46	0	**0**	**50**
Wetland/Water bodies	2	1	0	1	46	**1**	**50**
	0	1	0	0	1	**48**	
No of Sample points pixel	**54**	**50**	**48**	**48**	**49**		**250**

Overall Accuracy= (Total Number of Correctly Classified Pixels (Diagonal))/ (Total Number of Reference Pixels) ×100

Overall Accuracy = 46+45+47+46+46=230

Total Number of samples = 230

Overall Accuracy = 230/250 =0.92(or 92%)

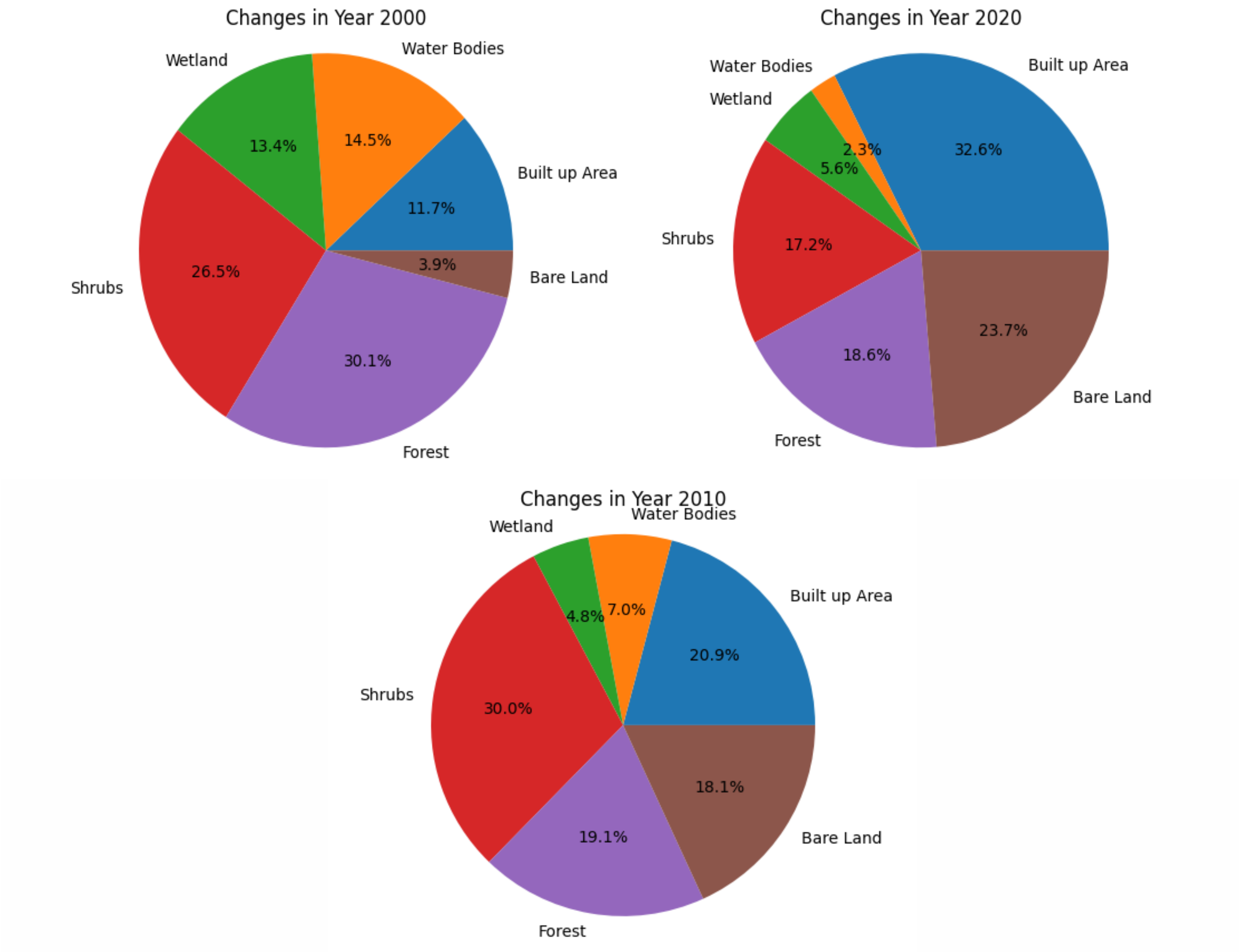
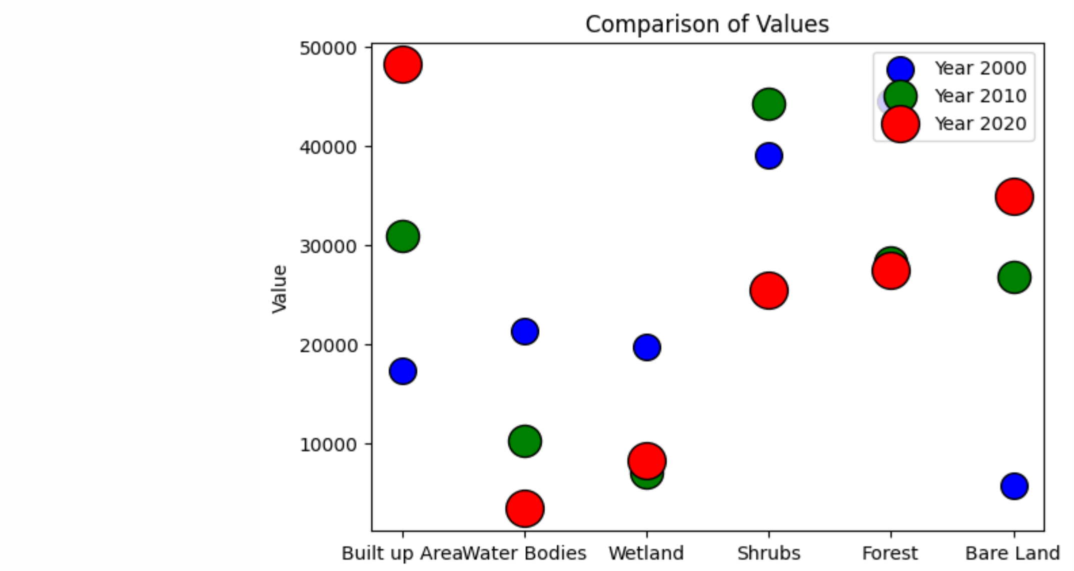


Figure 4.2: Pie chart showing change detection from 2000, 2010 to 2020



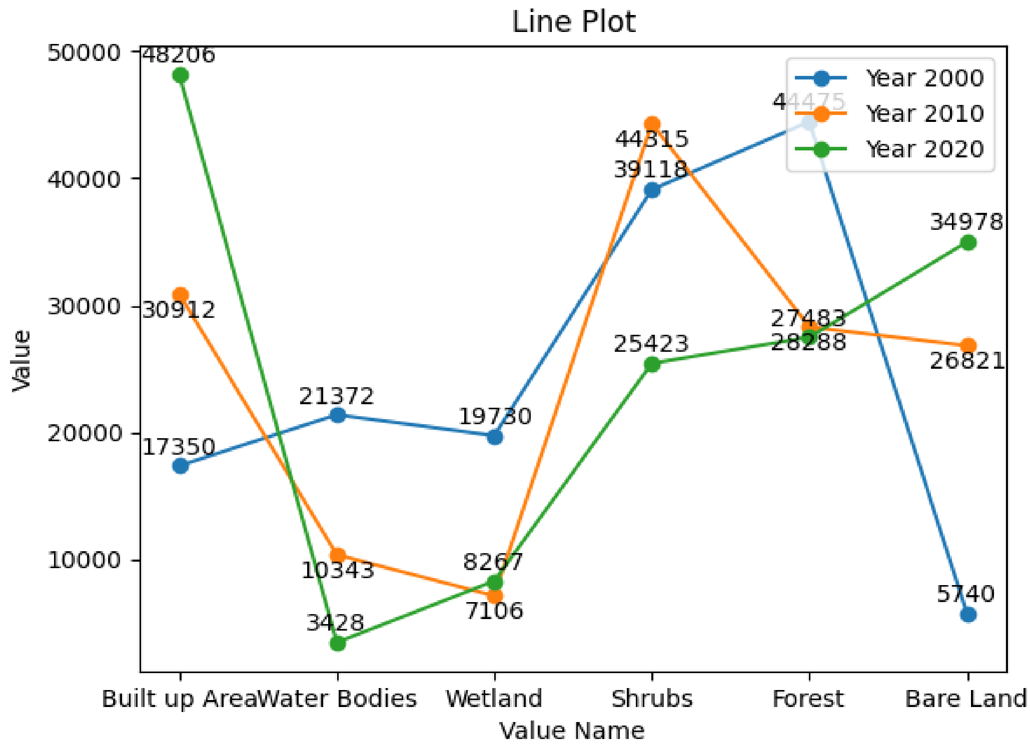


Figure 4.3: Graph showing change detection from 2000, 2010 to 2020

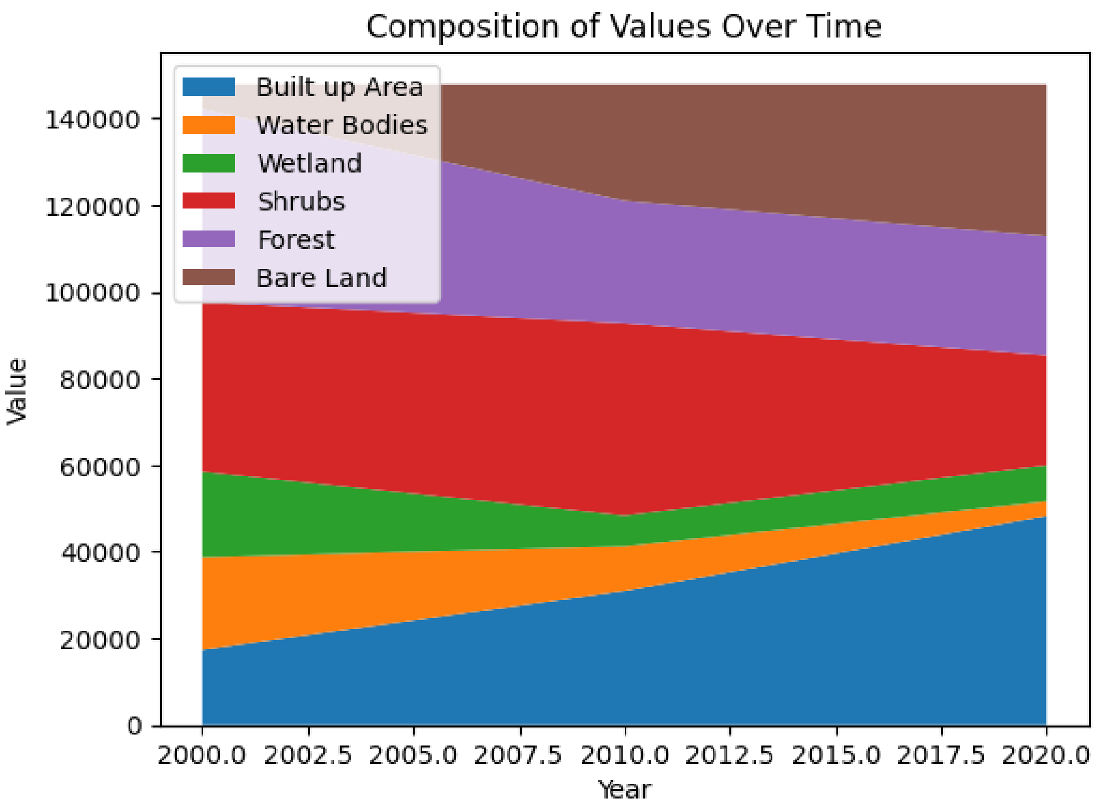


Figure 4.4 Chart Showing Change Detection between 2000, 2010 And 2020

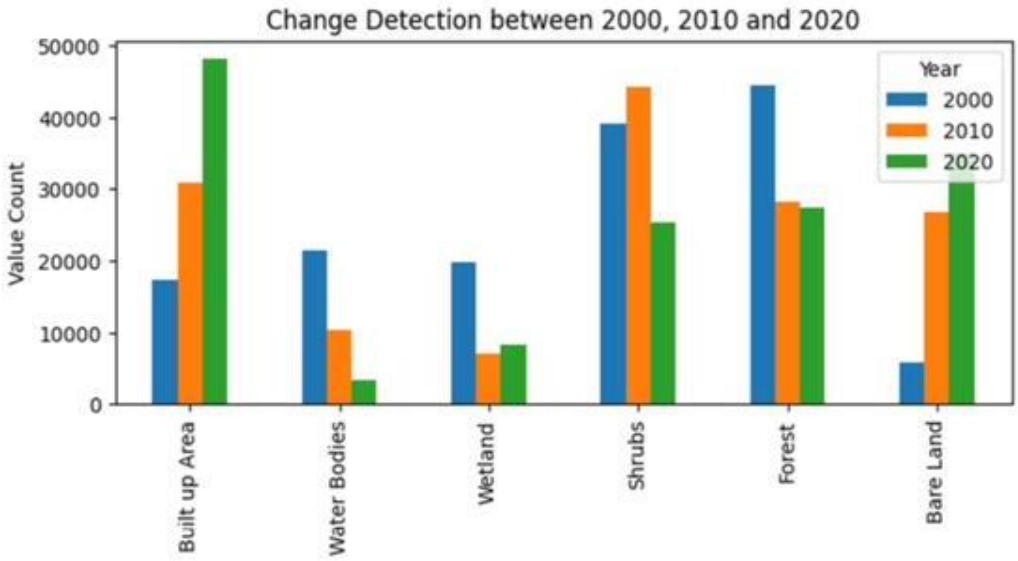


Figure 4.5: Histogram showing changes between classified feature from 2000, 2010 and 2020

Table 4.5: Showing changes between classified feature from 2000, 2010 and 2020

Changes Count Table

	2000	2010	2020
Built up Area	17350	30912	48206
Water Bodies	21372	10343	3428
Wetland	19730	7106	8267
Shrubs	39118	44315	25423
Forest	44475	28288	27483
Bare Land	5740	26821	34978

SUMMARY, CONCLUSION AND RECOMMENDATIONS

This chapter described the summary of findings of the study, conclusions derived from the findings as well as recommendations for effective changes within study area.

5.1 Summary of Findings

The research delved into urban expansion concerning the geographical reach of urban land usage, the spatial expansion of urban sprawl, and the velocity and configuration of urban sprawl within the specified study zone from 2000 to 2020. The findings revealed a substantial rise in the urban area, notwithstanding Udu's topographical features. Swift developmental activities were observed, resulting in deforestation and disruptions to the ecosystem.

Moreover, with the escalating population in Enugu, an impending challenge might emerge in maintaining ecosystem equilibrium.

5.2 Conclusion

This research illustrates the effectiveness of GIS and Remote Sensing in analyzing land cover and land use. The findings of this investigation indicate a consistent decline in forest and shrub cover, underscoring a significant impact on Udu's land cover. The ecosystem is not being adequately preserved, particularly with the rise in urban land use and alterations in hydrological patterns, as evidenced by increased bare soil. Notably, there is a continual and notable expansion of urban development, both in terms of spatial coverage and annual growth rates over the study period. In summary, this study concludes that satellite imagery offers a rapid and efficient means to monitor changes in urban growth and land cover. Moreover, it underscores that remote sensing and GIS serve as contemporary tools for mapping and analyzing land cover and land use at varying planning levels, from local to regional. Furthermore, these tools offer repetitive coverage, critical for monitoring urban development and historical land use activities over time.

5.3 Recommendations

Due to the persistent rise in urban expansion both in scale and pace within the studied region, the researcher provides the subsequent recommendations:

i. Regular monitoring of urban expansion and development within the study locale by the state Government utilizing GIS and remote sensing methodologies is imperative to enhance decision-making.
ii. It is essential for all stakeholders, including the Ministry of Land and Survey, Ministry of Environment, State Development Board, and urban land use management NGOs, to enforce strict compliance with urban land use regulations.
iii. Regular evaluation by the state government through the analysis of urban dynamics and development using GIS and remote sensing is necessary to swiftly identify swiftly growing areas in need of attention within the study region.
iv. The government should incentivize and financially support researchers to conduct extensive studies related to urban growth and its socio-economic impacts within the study area, promoting a deeper comprehension of the dynamics of urban expansion.
v. Encouraging and expanding agricultural production and investment within the study area is vital to enhance agricultural output.
vi. There is a pressing need to enhance rural infrastructure development to mitigate the high rate of rural-urban migration.

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