Spatio-Temporal Classification and Prediction of Land Use and Land Cover Change in Finima Nature Park Bonny Island, Nigeria

ABSTRACT

Land Use Land Cover (LULC) is naturally dynamic, thus change is inevitable. However, its changes have greatly increased to a frightening proportion as a result high rate of anthropogenic and natural processes. Consequently, land use and land cover classes of Finima Nature Park were classified and changes observed within the last 33 years (1987 - 2021) and predicted for the next 33 years (2021 – 2054).

Remote sensing and Geographic Information System (GIS) were used to achieve the goal. Coordinate points were collected from the various land use and land cover classes as a reference data for accuracy assessment of the classification. Landsat imageries of 1987, 1999, 2010 and 2021 were acquired from The United States Geological Survey (USGS). The imageries were pre-processed, processed and classified into various LULC classes using Maximum Likelihood Classification in Idrisi and ArcGis10.5. Confusion matrix and Cellular Automata (CA) Markov Chain algorithm were used for accuracy assessment and prediction of LULC.

Results showed that dense vegetation, sparse vegetation, bare land, and water body were the main LULC class in 1987 and 1999, while built up area was only observed in the years 2010, 2021 and 2054. The Kappa Coefficient values were 93%, 81%, 83% and 90% for 1987, 1999, 2010 and 2021 respectively; an indication of strong accuracy of the classification. Generally, there were changes in land use and land cover within the study periods. However, changes were mostly observed in the areas of water body and bare lands closer to the sea coast. Hence, the sea was implicated as the major driver of land use and land cover change in the park. The slight decrease in dense vegetation and sparse vegetation from 1999 to 2021, and 2021 to 2054 underscores the importance and benefit of conservation.

Keywords: Land use land cover, change detection, mapping, modelling, remote sensing, GIS

INTRODUCTION

Land use and land cover change is a natural phenomenon often triggered by natural and anthropogenic forces. It results to various physical and biological alterations in the forest environment and is often times seen as the main factor of forest degradation, fragmentation and subsequent dynamics of natural processes. Historically, land use and land cover change (LULCC) has been a tradition especially in the developing countries, but the rate and pattern has increased due to the increase in human population, industrialization and urbanization (Ubaekwe *et al*., 2021). Briassoullis (1999) rightly exposed that in the last 300 years, LULCC has been on a rapid increase especially in developing countries as a result of increase in human population growth rate and the subsequent resource over-exploitation; hence, its impacts on human-environment has greatly increased to frightening proportion. Álvarez-Cabria *et al*. (2016) and Krishnaraj & Deka (2020) revealed that Changes in LULC can considerably alter the water quality as the increase in urbanisation and agriculture results in nitrates and phosphates in the freshwater. In other words, it results to increase in air and water pollution, climate change related problems, urban floods, Urban Heat Island (UHI) impacts and biodiversity loss (Saxena *et al*., 2021). In the same vein, the loss of biodiversity and its associated ecosystem instability has been recognised globally as the chief consequences of rapid land use and land cover change. And biodiversity loss results to general ecosystem degradation often measured using the Natural Capital Index (NCI) framework, which involves calculating the extent of natural area assessed from land-use maps. Thus, research on land use dynamics will aid examination of various ecological and developmental consequences of land use change over a space of time. This makes land use classification and change detection and prediction pertinent in decision-making for effective execution of appropriate policy responses (Fasona *et al*., 2011).

LULCC detection and classification according to Singh (1989) involve the process of identifying the variations in the status of an object at different times. It involves identifying the changes that have taken place; classifying the nature of the change; evaluating the area coverage of the change and assessing the spatial pattern of the change. It provides quantitative analysis of the tempo-spatial distribution of the population of interest, and hence, it is a significant course of action in monitoring and managing natural resources and urban expansion (Macleod & Congation, 1998). Many approaches have been deployed in detecting and mapping LULCC such as conventional and modern approaches (Ayanlade, 2015). Conventional ground techniques are time and labour intensive, and are limited to small area of land. However modern techniques such as remote sensing are often used because of its accuracy and ability to cover a large expanse of land within a short period of time. Remote sensing and Geographic Information System (GIS) have been reported by several authors (Lu *et. al*., 2004; Mundia & Aniya, 2005; Yang & Lo, 2002) as perfect tools for detecting, mapping and predicting LULCC. Thus, remotely sensed imageries offer an efficient means of acquiring information on spatio-temporal trends and spatial distribution of metropolitan areas needed for understanding, modeling and predicting land changes (Elvidge *et al*., 2004a). Hence, remote sensing and GIS techniques were employed in this study.

For efficient use of land, it is crucial to have the basic information on the existing land use and land cover of an area and also have the ability to monitor the dynamics over time; this will promote sustainable land use management and reduce the risk associated with increasing LULCC. Unfortunately, there is no known literature on the status of land use and land cover in Finima Nature Park and the changes over time since it was delineated as a Nature Park. There is no known literature on the major determinants of the LULCC and the impacts of anthropogenic and natural forces on the original status of the park; hence, the need for this study. This study therefore, attempts to provide baseline information on the different land use and land cover of the park, evaluate the changes for the past 33 years (1987 - 2021) at 11 years intervals and predict the status of the LULC of the park in the next 33 years (2021-2054). This will review the trends of LULCC and thus provide first hand information that will promote sustainable land use management, enhance management decision and improve policy implementation in the Park; thereby, reducing the risk associated with random LULCC.

MATERIALS AND METHODS

Study Area

The study was carried out in Finima Nature Park (FNP) Bonny Island, Rivers State. It is located within the latitude 4°22'49" and 4°23'53" and longitude7°8'40" and 7°12'17" (figure 1). FNP was established in the year 1999 by the Nigerian Liquefied Natural Gas (NLNG) Limited and handed to Nigeria Conservation Foundation (NCF) to manage and safeguard the forest for its integrity and rich biodiversity. The park covered 1000 hectares, and cuts across mangrove and fresh water habitats, and is recorded to be home to many wildlife and plant species of conservation value (Nigeria Conservation Foundation, 2016).

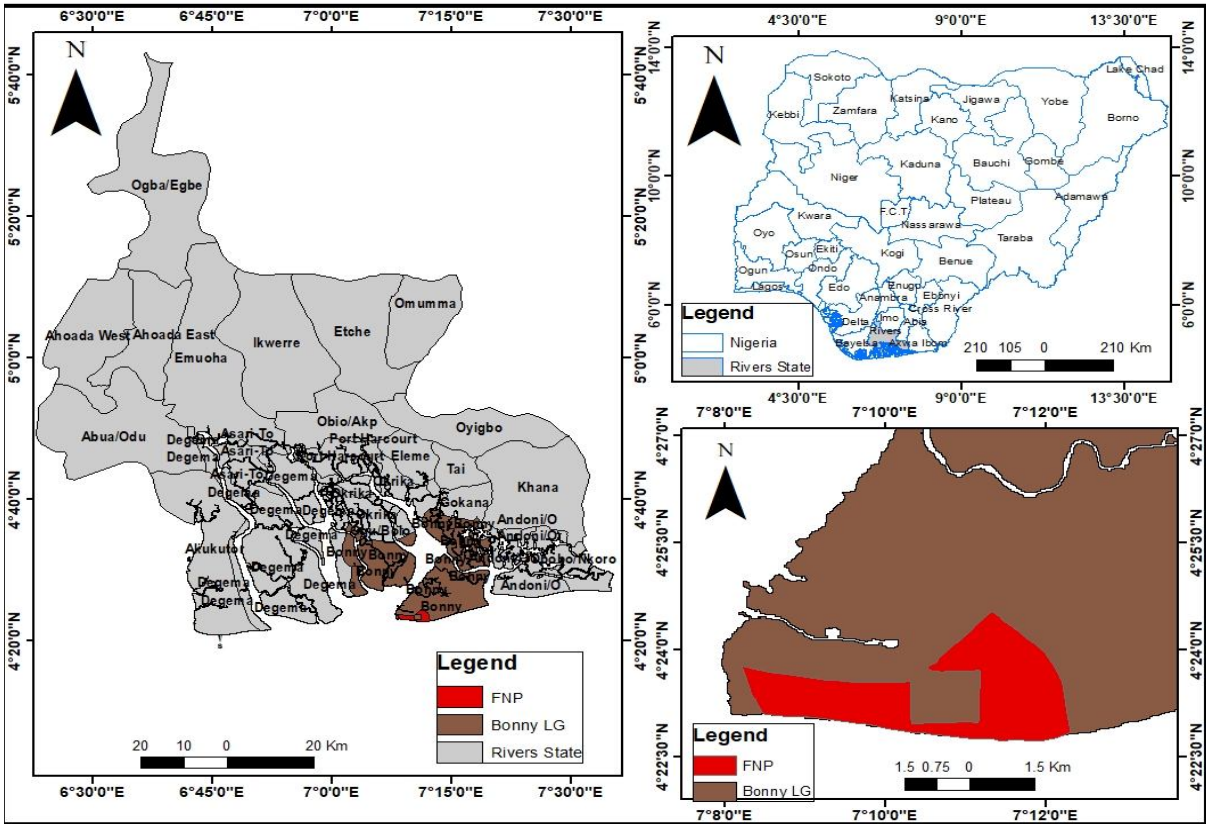


Figure 1: Map showing Finima Nature Park

Data Collection

Twenty (20) Ground Truth Points were collected from each five (5) different land uses and land covers identified in the field using Geographic Positioning System (GPS). Less than 10% cloud cover Landsat Imageries of one season (path 188 and row 56) were acquired from United States Geological Survey (USGS) in time series of 1987 Thematic Mapper (TM), 1999 TM, 2010 Enhanced Thematic Mapper (ETM) and 2021 Operational Land Imager (OLI) as shown in the Table 1 below.

Table 1: Properties of Landsat Imageries used for the study

	1987	1999	2010	2021
Scene ID	"LM51880571987052AAA03"	"LE71880571999333AGS00"	LE71880572010347ASN00	"LC81880572021353LGN00"
Path	188	188	188	188
Row	057	057	057	57
SpaceCraft ID	Landsat 5	Landsat 7	Landsat 7	Landsat 8
Sensor ID	"TM"	"L7_ETM"	"L7_ETM"	"OLI_TIRS
Spatial Resolution	30m	30m	30m	30m
Acquisition Date	1987-02-21	1999-11-29	2010-12-13	2021-12-19
Datum	"WGS84"	"WGS84"	"WGS84"	"WGS84"
UTM	32	32	32	32

Data Analysis

The acquired landsat imageries were pre-processed for geometric and radiometric corrections, geo-referenced to the World Geodetic System (WGS) 1984 ellipsoid using Ground Control Points (GCP) gotten with GPS and then projected to zone 32N coordinate system of the Universal Transverse Mercator (UTM). Bands 2, 3, 4 for Landsat TM and ETM+ and bands 3, 4, 5 for Landsat OLI/TIRS were employed for false colour composite operation in the IDRISI software (Abegunde and Adedeji, 2015). Supervised classification was further carried out on the false colour composite using the Maximum Likelihood Classification Technique. Area of interest was extracted using extract by mask tool in ArcGis software. Five land use and land cover classes (dense vegetation, sparse vegetation, bare land, water and built-up) were identified and classified. Confusion Matrix using the training samples, ground truth points and Google Earth were used to determine the accuracy of the LULCC classification; Cellular Automata and Markov Chain algorithm were employed in Idrisi Software for the prediction of LULC (Souidi *et al*, 2019). Post-classification approach was used to evaluate the spatio-temporal changes from 1988-2021; and those that would take place between 2021 -2054. The area coverage of each LULC class and differences were calculated in ArcGis software (Suratman and Surayahana 2012; Ubaekwe *et al.,* 2021). The results are presented in maps, charts and tables. Below (figure 2) is the flow chart of the methodology used.

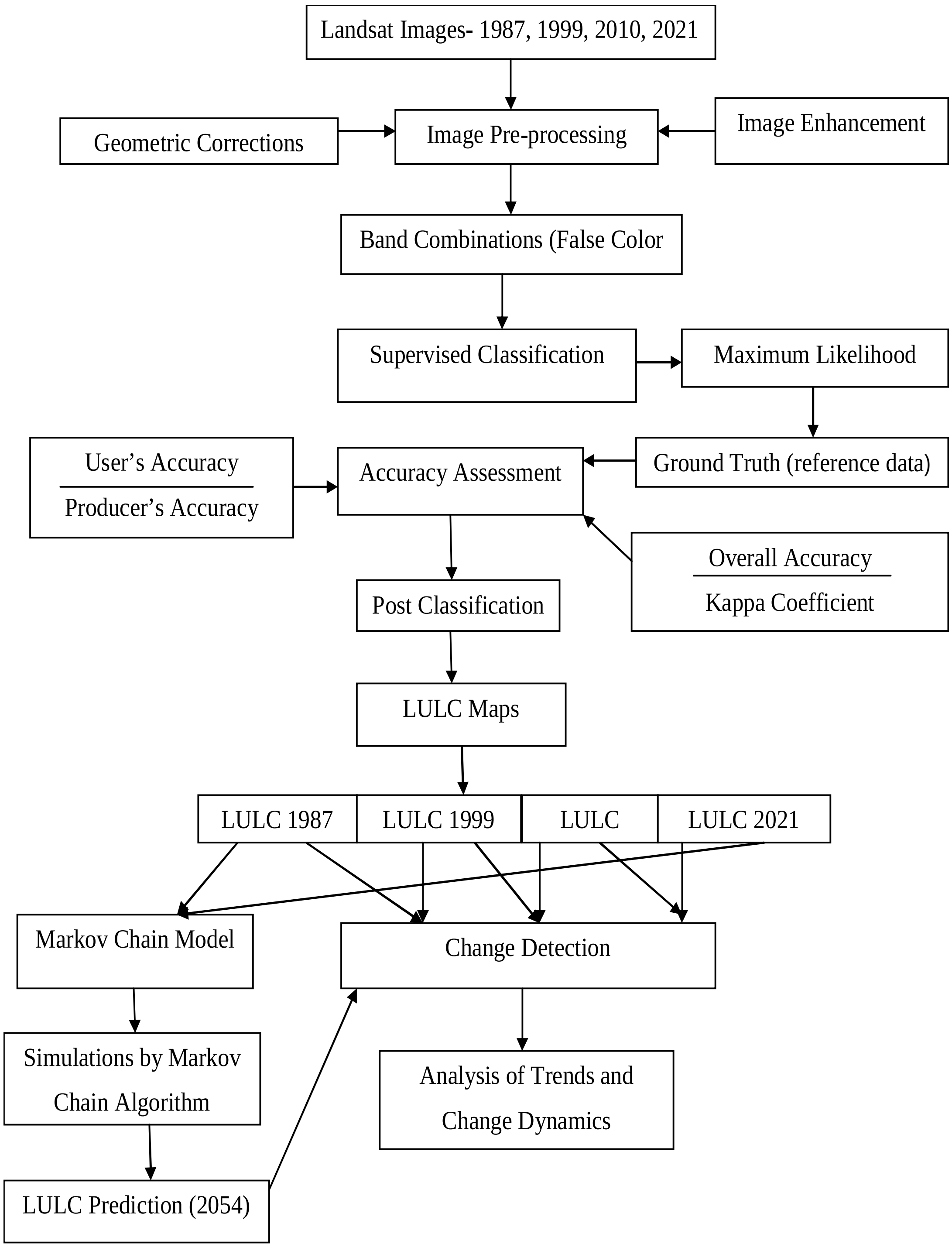


Figure 2: Flow chart of LULC Classification, Prediction and Change Detection

RESULTS

This study identified four land use and land cover classes in the year 1987 and 1999, and five land use and land cover classes in the years 2010, 2021 and 2054 prediction. Figure 3, shows the land use and land cover of the park in the year 1987. It reveals that the entire Finima Nature Park (FNP) comprises of dense vegetation, sparse vegetation, bare lands and water body in 1987 with dense vegetation in abundance. The same pattern was observed in 1999 classification (Figure 4) with observable increase in bare land and decrease in water body. LULC of the years 2010, 2021 and the 2054 prediction (Figures 5, 6 & 7) recorded five land use and land cover classes: dense vegetation, sparse vegetation, bare land, water body and built up. Dense vegetation dominated the area within the study periods. Bare lands and water body were on a high increase, with subsequent decrease in dense and sparse vegetation. Built up area was minimal at first in 2010 but slightly increased in 2021 and more in 2054 prediction. An indication of encroachment was generally observed.

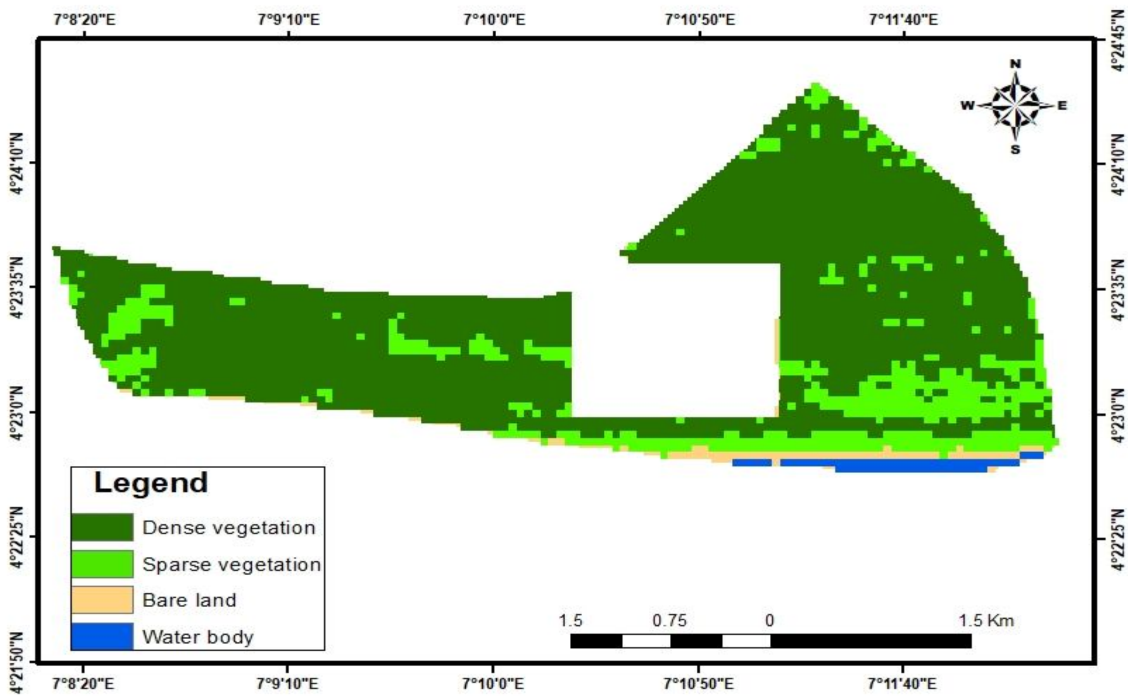


Figure 3: Land use and land cover of FNP in 1987

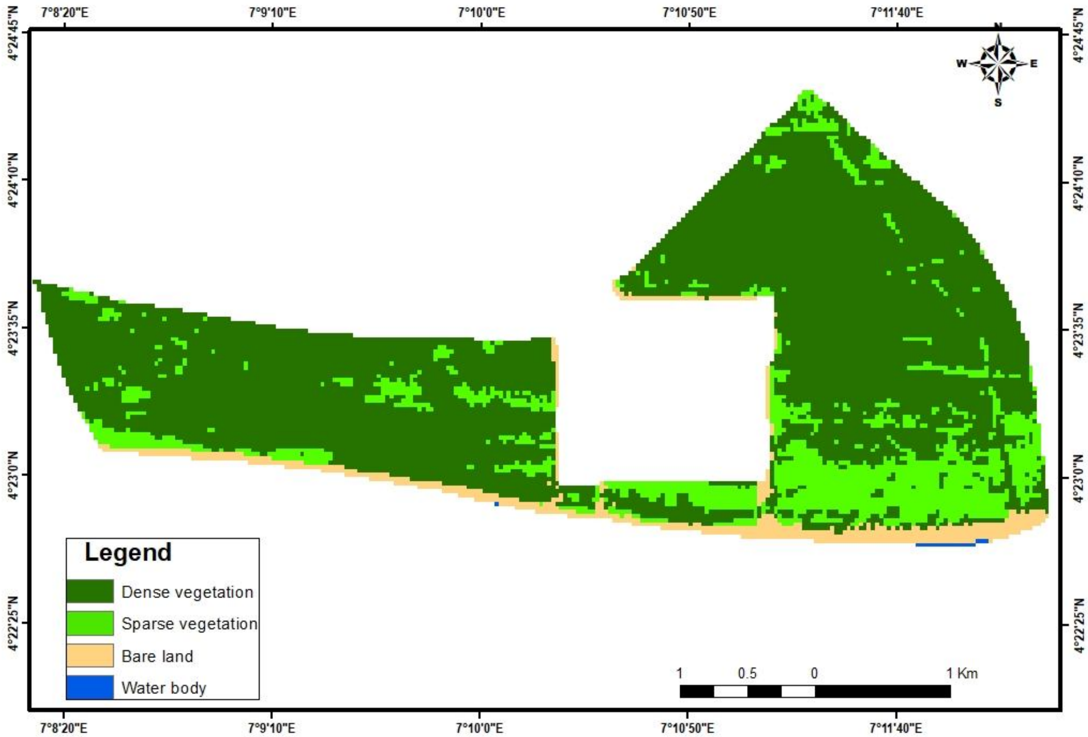


Figure 4: Land use and land cover of FNP in 1999

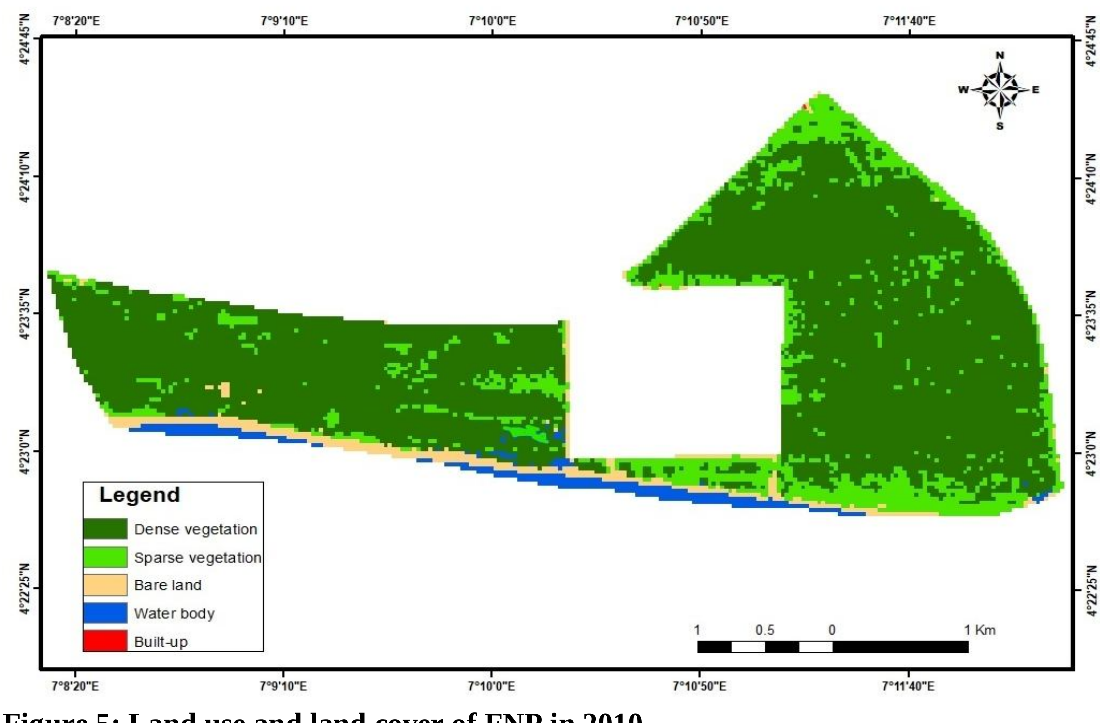


Figure 5: Land use and land cover of FNP in 2010

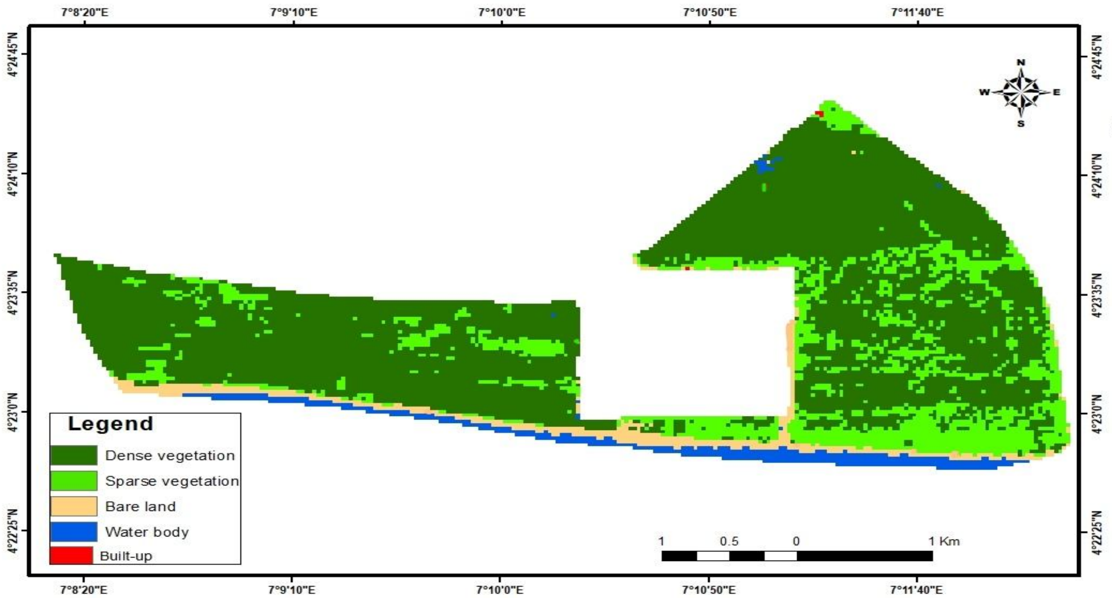


Figure 6: Land use and land cover of FNP in 2021

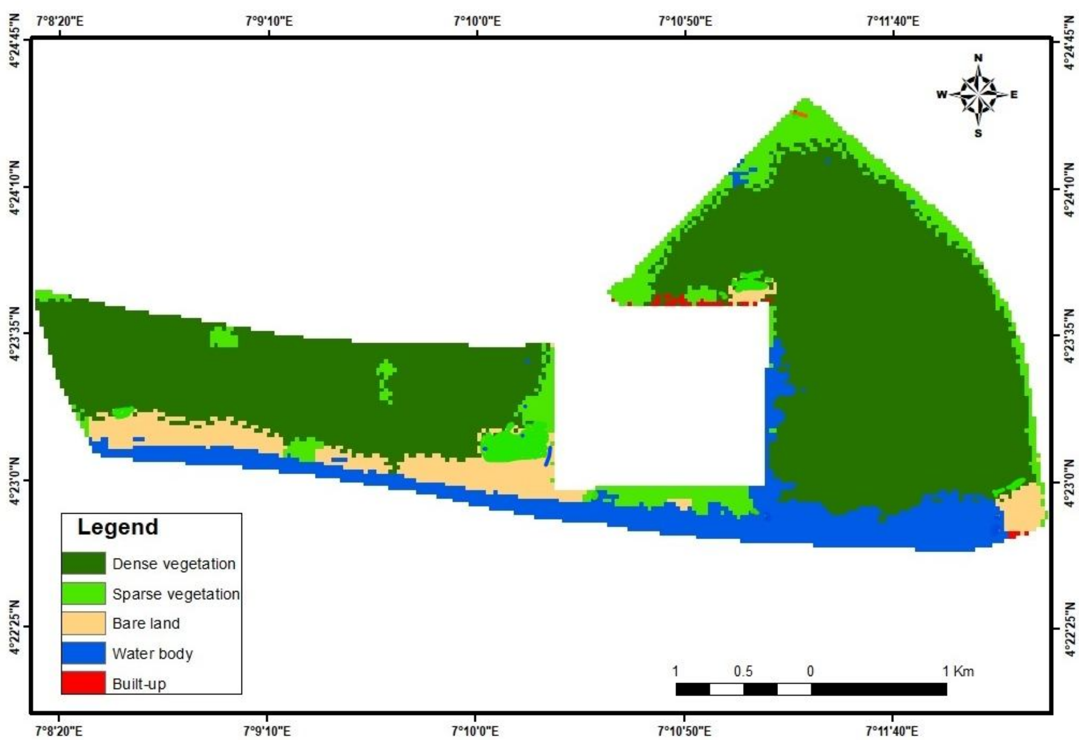


Figure 7: Predicted Land use and land cover of FNP by 2054

Confusion Matrix tables for accuracy of the LULC classification assessment are presented in Tables 2 to 5. The overall accuracy were 0.95, 0.86, 0.86, and 0.92 and the Kappa Coefficient Values were 93%, 81%, 83% and 90% for 1987, 1999, 2010 and 2021 respectively.

Table 2: Accuracy of 1987 LULC Classification

LULC Classes	**Dense Veg.**	**Sparse Veg**	**Water**	**Bare Land**	**Ground points**	**Commission Error**	**User's Accuracy**
Dense Veg	44	0	1	2	47	0.06	0.94
Sparse Veg	0	49	1	1	51	0.04	0.96
Water	3	0	49	0	52	0.06	0.94
Bare land	1	1	0	48	50	0.04	0.96
Total	48	50	51	51	200		
Omission Error	0.08	0.02	0.04	0.06			
Producer's Accuracy	0.92	0.98	0.96	0.94			
Overall Accuracy	**0.95**						
p(r)	**0.25**						
Kappa Coefficient	**0.93**						
Kappa (%)	**93**						

Table 3: Accuracy of 1999 LULC Classification

LULC classes	**Dense Veg.**	**Sparse Veg**	**Water**	**Bare Land**	**Ground points**	**Commission Error**	**User's Accuracy**
Dense Veg	42	4	0	3	49	0.14	0.86
Sparse Veg	2	41	0	6	49	0.16	0.84
Water	3	2	42	3	50	0.16	0.84
Bare land	4	1	0	44	49	0.10	0.90
Total	51	48	42	56	197		
Omission Error	0.18	0.15	0	0.21			
Producer's Accuracy	0.82	0.85	1	0.79			
Over all accuracy	**0.86**						
P(r)	**0.25**						
KappaCoefficient	**0.81**						
Kappa (%)	**81**						

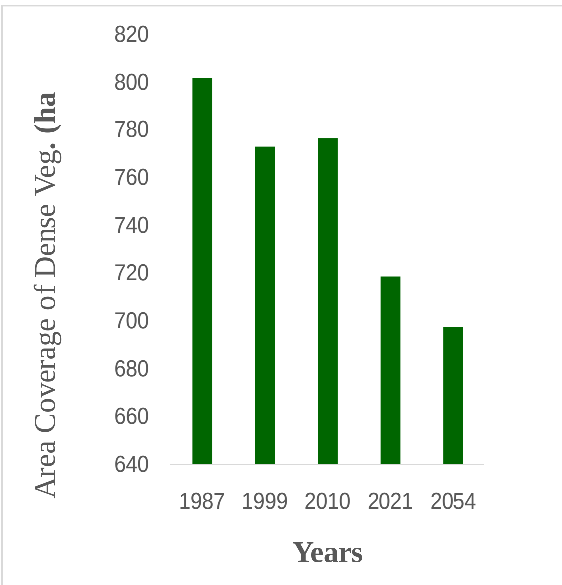
Table 4: Accuracy of 2010 LULC Classification

LULC Classes	Dense Veg	Sparse Veg	Water	Built - up	Bare land	Ground Points	Commission Error	User's Accuracy
Dense Veg	40	4	0	5	1	50	0.20	0.80
Sparse Veg	2	41	0	0	6	49	0.16	0.84
Water	1	2	42	4	3	52	0.19	0.81
Built up	0	0	0	48	1	49	0.02	0.98
Bare land	6	0	0		44	50	0.12	0.88
Total	49	47	42	57	55	250		
Omission Error	0.18	0.13	0	0.16	0.2			
Producer's Accuracy	0.82	0.87	1	0.84	0.8			
Over all Accuracy	**0.86**							
P(r)	**0.20**							
Kappa Coefficient	**0.83**							
Kappa (%)	**83**							

Table 5: Accuracy of 2021 LULC Classification

LULC Classes	Dense Veg	Sparse Veg	Water	Built - up	Bare land	Ground Points	Commission Error	User's Accuracy
Dense Veg	41	4	0	0	1	46	0.11	0.89
Sparse Veg	0	45	0	1	0	46	0.02	0.98
Water	0	0	50	4	1	55	0.09	0.91
Built up	0	0	0	48	1	49	0.02	0.98
Bare land	6	1	0	1	42	50	0.16	0.84
Total	47	50	50	54	45	246		
Omission Error	0.13	0.1	0	0.11	0.07			
Producer's Accuracy	0.87	0.9	1	0.89	0.93			
Over all Accuracy	**0.92**							
P(r)	**0.20**							
Kappa Coefficient	**0.90**							
Kappa (%)	**90**							

The area coverage of different land use and land cover classes within the study periods were presented in figures 8a to 8g.It was observed that out of 1000ha of the entire FNP, dense vegetation covered 801.76 ha, sparse vegetation 167.92ha, water body 15.52 haand bare land 14.8 ha, no traces of built up observed in 1987. In the year 1999, dense vegetation decreased to 773.14ha, sparse vegetation increased to 170.98 ha, water body greatly reduced to 1.71ha while bare land significantly increased to 54.17ha, no traces of built up observed. In 2010, there was slight increase in dense vegetation (776.65ha), decrease in sparse vegetation (147.34ha), significant increase in water body (31.81ha), decrease in bare land (43.15ha) and traces of built up (1.05ha) was observed. The trend continued in 2021, dense vegetation reduced to 718.87ha, sparse vegetation increased to 189.70ha, water body increased to 42.16ha, bare land increased to 47.65ha while built up slightly increased to 1.62ha. The 2054 prediction has it that dense vegetation will decrease to 697.71ha, sparse vegetation will reduce to 90.22ha, water body will severely increase to 122.74ha, bare land and built up will also increase significantly to 85.45ha and 3.88ha respectively.



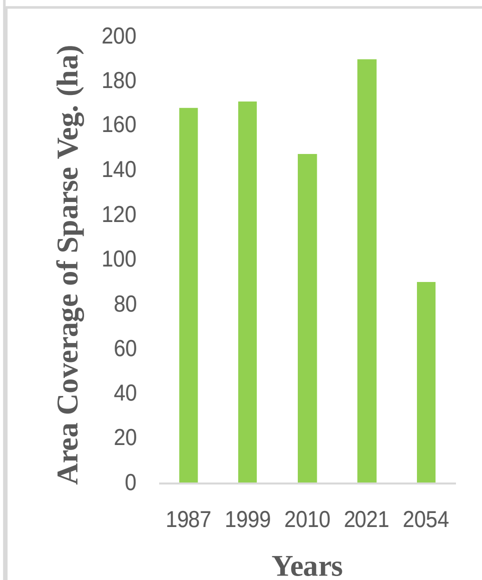


Figure 8a: Area Coverage of Dense Veg. (ha) Figure8b: Area Coverage of Sparse Veg. (ha)

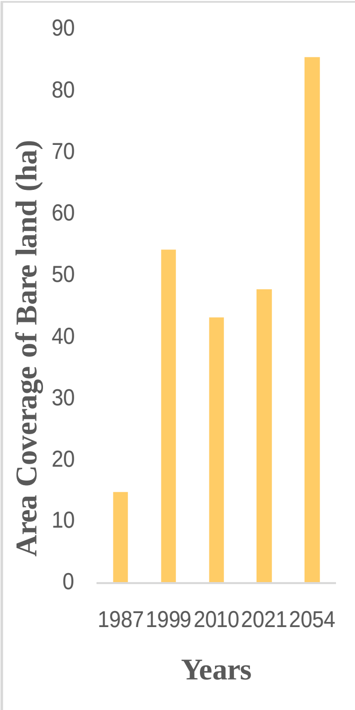


Figure 8c: Area of bare land

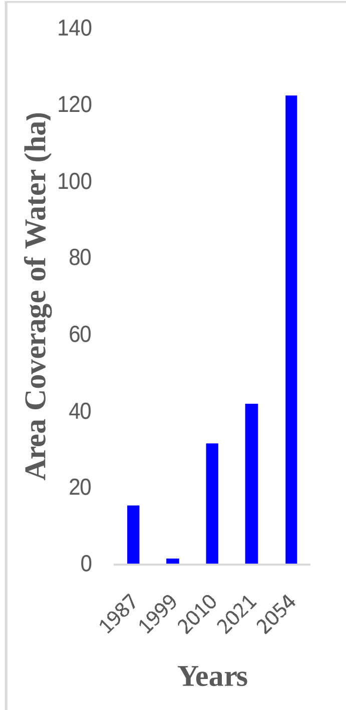


Figure 8d: Area of water body

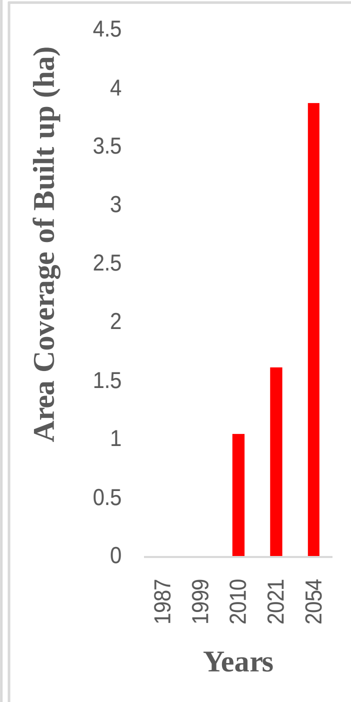


Figure 8e: Area of Built-up

Observed Changes in the Area Coverage of different LULC Categories within the study periods

The observed changes were presented in table 6. From 1987 to 1999, 28.62ha of dense vegetation and 13.81ha of water body at the decreasing rate of -2.39ha/yr and -1.15ha/yr were lost to sparse vegetation and bare lands respectively. Sparse vegetation and bare lands gained 3.06ha (3.61%) and 39.37ha (46.39%) at the increasing rate of 0.26ha/yr and 3.38ha/yr respectively. In other words, sparse vegetation and bare lands increased with decrease in dense vegetation and water body from 1987 to 1999. Between 1999 to 2010, total area of dense vegetation, water body and built up gained 3.51ha, 30.1ha and 1.05ha at the increasing rate of 0.32ha/yr, 2.74ha/yr and 0.10ha/yr respectively; Sparse vegetation and bare lands lost 23.64ha and 11.02ha at the of 2.15ha/yr and 1.00ha/yr respectively. Between 2010 and 2021, dense vegetation lost 57.78ha at the decreasing rate of 5.25ha/yr while sparse vegetation, water body, bare land and built up gained 42.36ha; 10.35ha; 4.5ha and 0.57ha at the increasing rate of 3.85ha/yr, 0.94ha/yr, 0.41ha/yr, and 0.05ha/yr respectively. In other words, 57.78ha of dense vegetation were converted to other land classes within the period.

The predicted changes between 2021 to 2055 reveals that 99.48ha and 21.16ha of sparse and dense vegetation would be converted or lost to water body (80.58ha), bare lands 37.8ha and built up 2.26ha respectively. The net lost in the sparse and dense vegetation at the annual decrease of 2.93ha/yr and 0.62ha/yr will result to annual increase of 2.37ha/yr water, 1.11ha/yr bare lands and 0.07ha/yr built up respectively. In other words, effect of water body will be enormous in the park in the next 34 years.

Table 6: Change Detection from 1987 to 1999; 1999-2010; 2010 – 2021 and 2021 -2054

Land Classes	1987 (ha)	1999 (ha)	Change observed (ha)	Rate of Change ha/Yr	% Change Observed	Remark
Dense Veg.	801.76	773.14	-28.62	-2.39	33.73	Loss
Sparse Veg.	167.92	170.98	3.06	0.26	3.61	Gain
Water	15.52	1.71	-13.81	-1.15	16.27	Loss
Bare Land	14.8	54.17	39.37	3.28	46.39	Gain
Built up	0	0	0	0	0.00	None
	1999	**2010**				
Dense Veg.	773.14	776.65	3.51	0.32	5.06	Gain
Sparse Veg.	170.98	147.34	-23.64	-2.15	34.10	Loss
Water	1.71	31.81	30.1	2.74	43.42	Gain
Bare Land	54.17	43.15	-11.02	-1.00	15.90	Loss
Built up	0	1.05	1.05	0.10	1.51	Gain
	2010	**2021**				
Dense Veg.	776.65	718.87	-57.78	-5.25	50.00	Loss
Sparse Veg.	147.34	189.7	42.36	3.85	36.66	Gain
Water	31.81	42.16	10.35	0.94	8.96	Gain
Bare Land	43.15	47.65	4.5	0.41	3.89	Gain
Built up	1.05	1.62	0.57	0.05	0.49	Gain
	2021	**2054**				
Dense Veg.	718.87	697.71	-21.16	-0.62	8.77	Loss
Sparse Veg.	189.7	90.22	-99.48	-2.93	41.23	Loss
Water	42.16	122.74	80.58	2.37	33.40	Gain
Bare Land	47.65	85.45	37.8	1.11	15.67	Gain
Built up	1.62	3.88	2.26	0.07	0.94	Gain

DISCUSSION

The study mapped out different land uses and land covers observed in the park for the period of 33 years and predicted the status of the park in terms of land use land cover change for the next 33 years. Four LULC classes (dense vegetation, sparse vegetation, bare lands, water body) were observed in 1987 and 1999; while five (5) LULC classes (dense vegetation, sparse vegetation, bare lands, water body and built up) classes were observed in 2010, 2021 and were also predicted in the year 1954. There was no built up area in the land use and land cover of the park as at 1987 – 1999; however, the emergence of built up area in the later years (2010, 2021 and 2054) could be as a result of developing community market that was sighted in the park and other structures within FNP Resource Centre. This is an indication of encroachment and anthropogenic activities in the park.

The accuracy of the classification was high using Kappa coefficient values; according to Jensen (2005) and Lilles *et al*. (2004) Kappa values greater than 80% indicate strong classification performance, Kappa values between 40 and 80% indicate good classification performance and Kappa values of less than 40%indicate poor classification performance. However, the kappa coefficient values obtained in this study were all above 80% hence, the accuracy of the classification were high, indicating strong LULC classification performance.

Generally, the results showed that land use and land cover of the park have been on continuous state of transformation as a result of various anthropogenic and natural processes. Areas of dense vegetation decreased between 1987 and 1999 and increased slightly between 1999 and 2010. This could be as a result of conservation success, as it was reported that FNP was gazetted in 1999 by NLNG and handed to Nigeria Conservation Foundation (NCF) in the same 1999, for effective management to safeguard the integrity and rich biodiversity of the Park (NCF 2016). Hence, the observed increase in dense vegetation areas could be attributed to the management strategy of the NCF. In a similar vein, a sharp increase in areas of bare lands and sparse vegetation was observed between 1987 and 1999; this indicated high rate of anthropogenic activities in the area before the time NCF took over its management. Consequently, between 1999 – 2010, the areas covered by bare lands and sparse vegetation decreased as a result of their management strategy given that some areas that were bare prior to the time they took over the management of the Park were reclaimed and vegetated within the first decade of their existence; more so anthropogenic activities (deforestation) that often open up closed canopies leading to increase in sparse vegetation areas were controlled.

It was also recorded that the areas of water body were more in 1987, but drastically reduced in 1999. In 2010 and 2021, the areas of water body greatly increased, and it is expected to continue to the year 2054. This could be as a result of rise in sea level as IPCC (1996) predicted rise in sea level between 0.3 and 1.0 meter by the year 2100. Arokoyu and Ogoro (2014) expressed that the impact of the rise in sea level will result to submergence of several settlements in the coastal area including Bonny Island. Oyegun (2007) also reported that at a 1m rise in sea level, over 482.9km^2 of land is susceptible to inundation. However, there was an indication of rise and fall in the sea level on the border with the Park, which sometimes wipes out vegetations within that area during the rise but eventually flows back to its course or even beyond during the fall in sea level, leaving some areas bare. This was the situation in 1987 LULC and 1999 LULC. It was observed that some areas of bare lands in the park closer to the sea coast in 1999 were originally water body in 1987, an indication of fall in sea level in 1999. However, in 2010 and beyond, water body took over its course and even beyond due to persistence rise in sea level. Furthermore, other anthropogenic activities such as fishing, tree harvesting especially in the mangrove areas could also increase the water encroachment. In the same vein, Griffiths (1988) opined that coastal zone is progressively under pressure from anthropogenic activities such as seaweed farming, fishing, coral sand mining, mangrove removal and sewage disposal. According to him, the above-mentioned activities especially dynamite fishing and mangrove harvesting have great negative impacts on coastal stability and could lead to coastal erosion and shoreline.

Between 2010 and 2021, it was observed that areas of dense vegetation gradually decreased while areas of sparse vegetation, bare lands, water body and built up moderately increased. This could be as a result of increase in anthropogenic and natural forces which are often beyond the management control. The industrial activities such as extraction and export of petroleum products often affect land use and land cover of the park as trees along the pipelines are being removed. This creates routes for encroachers to thrive in their mission. Also the construction of walkways as observed in the park could encourage the activities of encroachers as it offers them easy accessibility into the park. Given that Ayanlade (2014) explained that road network contributes to deforestation in Delta regions, given that road networks offers local people easy access to log the forest.

The prediction analysis reveals that by the year 2054, dense vegetation will be slightly reduced with significant decrease in sparse vegetation, whereas water body and bare land will be greatly increased with moderate increase in built up area. However, the changes are mostly observed in the areas of water body and bare lands closer to the coast. In other words, the sea coast is the major driver of land use and land cover change in the park and the slight decrease in dense vegetation and sparse vegetation from 1999 to 2021 is an indication of conservation success. Consequently, the Park will be more stable if a rise in sea level which is the major cause of inundation is controlled.

CONCLUSSION AND RECOMMENDATIONS

This study has successfully classified the various land use and land cover of Finima Nature Park and also predicted what would be the status of the park in the next 33 years using Landsat imageries of 1987, 1999, 2010 and 2021. Dense vegetation, sparse vegetation, bare land and water body were observed in 1987 and 1999, whereas built up, dense vegetation, sparse vegetation, bare land and water body were observed in 2010, 2021 and 2054. Generally, there were changes in land use and land cover within the study periods. However, changes were mostly observed in the areas of water body and bare lands closer to the coast. In other words, the sea is the major driver of land use and land cover change in the park and the slight decrease in dense vegetation and sparse vegetation from 1999 to 2021 is an indication of conservation success. Remote sensing and GIS techniques are efficient tools for land use land cover classification and prediction.

REFERENCES

Álvarez-Cabria, M., Barquín, J. and Peñas, F. J. Modelling the spatial and seasonal variability of water quality for entire river networks: Relationships with natural and anthropogenic factors." Science of the Total Environment, 2016:545-546, 152-162. DOI: 10.1016/j.scitotenv.2015.12.109.

Arokoyu and Ogoro. Vulnerability of Bonny Coastal Communities to Sea Level Changes. Journal of Research in Environmental and Earth Sciences. 2014:1(3):32-43.

Ayanlade, A. Remote Sensing of Environmental Change in the Niger Delta, Nigeria. Doctoral thesis retrieved from the King's Research Portal at https://kclpure.kcl.ac.uk/portal/, 2015.

Briassoullis H. Analysis of Land Use Change: Theoretical and Modelling Approaches – The Web Book of Regional Science, Regional Research Institute, West Virginia University, USA. 1999.

Elvidge, C.D., Safran, J., Nelson, I.L., Tuttle, B.T., Hobson, V.R., et al. Area and position accuracy of DMSP nighttime lights data. Remote Sensing and GIS Accuracy Assessment, CRC Press. 2004a;281- 292

Fasona, M., Omojola, A. and Soneye, A. A Study of Land Degradation Pattern in the Mahin Mud-beach Coast of Southwest Nigeria with Spatial-statistical Modelling Geostatistics. Journal of Geography and Geology. 2011:3(1):141-159.

Griffith, D.A. Advanced Spatial Statistics: Special Topics in the Exploration of Quantitative Spatial Data Series. Kluwer, Dordrecht. 1988.

IPCC. The Science of Climate Change in Oyegun C. U.; Climate Change and Nigeria Coastal Resources, 1996. UPPL, 2007.

Krishnaraj, A., and Deka, P. C. "Spatial and temporal variations in river water quality of the Middle Ganga Basin using unsupervised machine learning techniques." Environmental Monitoring and Assessment, Springer Science and Business Media Deutschland GmbH. 2020:192(12).

Macleod & Congalton. A Quantitative Comparison of Change Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data. Photogrammetric Engineering & Remote Sensing. 1998:64(3)207-216.

Mundia, C.N. and Aniya, M. Analysis of land use/cover changes and urban expansion in

Nairobi city using remote sensing and GIS. International Journal of Remote Sensing. 2005:26:2831–2849.
Nigerian Conservation Foundation (NCF) Report for Nigeria Liquefied Natural Gas (NLNG) Limited. Finima, Bonny Island, Rivers State, Nigeria. 2016.
Ojo, L.O. The fate of a tropical rainforest in Nigeria: Abeku sector of Omo Forest Reserve. The International Journal. 2004:6(2):116-130
Oyegun C. U. Climate Change and Nigeria Coasstal Resources UPPL Nigeria. 2007.
Saxena, A., Jat, M. K., and Clarke, K. C. "Development of SLEUTH-Density for the simulation of built-up land density." Computers, Environment and Urban Systems, Elsevier Ltd, 86(November 2020).2021:101586.
Singh, A. Review article digital change detection techniques using remotely-sensed data. International journal of remote sensing. 1989:10(6): 989-1003.
Lu, D., Mausel, P., Brondízio, E. and Moran, E. Change detection techniques. International Journal of Remote Sensing. 2004:25(12):2365-2407.
Ubaekwe, R. E., Chima, U.D and Okonkwo, N.O. Geospatial Assessment Of Land Use/Land Cover Change And Its Impact On Forest Cover In Owerri, Imo State, Nigeria. Nat Sci. 2021:19(10):30-38. ISSN1545-0740 (print); ISSN 2375-7167 (online). http://www.sciencepub.net/nature. 5. doi:10.7537/marsnsj191021.05.
Souidi, H., Ouadif, L. Bahi, L. and Habitou N. Spatiotemporal Monitoring and Prediction of Land Use Integrating the Markov Chain and Cellular Automata in the Coastal Chaouia. International Journal of Recent Technology and Engineering (IJRTE). 2019:8(4):1704 – 1711. DOI:10.35940/ijrte.C5760.118419.
Suratman, M., & Surayahana, A. Multi temporal Landsat TM for monitoring mangrove changes in Pulau Indah, Malaysia. IEEE Symposium on Business, Engineering and Industrial Applications. 2012.
Jensen, J. R. Introductory digital image processing: a remote sensing perspective. John R. Jensen. 3rd ed., Pearson Education Inc., Upper Saddle River. 2005.
Lillesand, T.M, Kiefer, R.W. and Chipman, J.W. Remote Sensing and Image Interpretation (5th_edn.), John Wiley and sons, Inc.: Hoboken, New. 2004.
Ayanlade A. Remote Sensing of Environmental Change in the Niger Delta, Nigeria. PhD thesis submitted to Department of Geography, School of Social Sciences and Public Policy, King's College London, University of London. 2014.
Yang, X. and Lo, C.P. Using a time series of satellite imagery to detect land use and cover changes in the Atlanta, Georgia. International Journal of Remote Sensing. 2002:23(9):1775–1798