Extent of Forest Depletion from 1986-2015 as a Consequence of Land use in Andoni Local Government Areas of Rivers State, Nigeria

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ABSTRACT: The study investigated the extent of forest depletion between 1986 and 2015 in Andoni LGA, Rivers State, Nigeria. Landsat images of 1986, 2000 and 2015 were employed for the study. Image classifications were done in Erdas Imagine using supervised classification with maximum likelihood module whereby six major classes of landuse were identified namely forest, built up area, waterbodies, mangrove, cultivated land, and bareground/sand. The area in square kilometers of each land use type in each year was computed in ArcGIS 10.0 and simple calculations were used to compute the change and percentage change of each landuse from one period to the other. Landuse probability of change to other landuse in 2025, 2035 and 2045 were done Idrisi Selva 17.0. Findings showed that forest coverage was 125.95 km^2 (39.56%) in 1986 and 74.14 km^2 (23.29%) in 2015. Forest, cultivated land, and waterbodies decreased by 41.14%, 80.8% and 76.52% while built up area, mangrove and bareground/sand increased by 303.64%, 18.67% and 3.64% from 1986 to 2015. Bareground/sand and built-up areas replaced forest with 21.23 km^2 (38.40%) and 20.26km^2 (3.64%) respectively. The study predicted that 3.68% of bareground/sand, 0.47% of mangrove and 3.51% of built up area had probability of replacing forest by 2025 while 5.09%, 2.1% and 7.32% of bareground/sand, mangrove and built up area had the probability of changing to forest by 2045. The study recommended that strict legislation, policies and strategies should be put in place to protect the forests from undue exploitation.

Deforestation is becoming a global problem in recent time, periodic monitoring of the spatial coverage of forest is inevitable. Overall, there was a net decrease in global forest area of 3% between 1990 and 2015, from 4128 M ha to 3999 M ha, with natural and human-induced deforestation being offset by increases in forest area that had both natural and human causes (Keenan *et al*., 2015). At the present time, the forest loss has decreased to approximately 13million hectares per year (Forkuo and Frimpong, 2012). The largest net loss of forest occurs in South America and Africa and reports showed that about 4.0 million hectares per year were lost between 2000 and 2010. The net loss of forests has been significantly reduced, mainly because of several projects including forest planting, restoration of landscape and natural expansion of forests (FAO, 2012). It was reported in Lambin *et al* (2003) that forest degradation was most extensive in Southeast Asia (0.42% per year), lowest in Latin America (0.13% per year), and intermediate in Africa (0.21% per year). Forest area has declined in Central America, South America, South and Southeast Asia and all three regions in Africa between 2010 and 2015 (Keenan *et al*. 2015). For instance, net loss of forest area between 2010 and 2015 in South America

was dominated by Brazil (984 K ha y^{-1}), also significant net losses were recorded in Paraguay (325 K ha y^{-1}), Argentina (297 K ha y^{-1}), Bolivia (289 K ha y^{-1}) and Peru (187 K ha y^{-1}) (Keenan *et al*., 2015). In South and Southeast Asia, the rate of net forest loss was greatest in Indonesia (684 K ha y^{-1}), followed by Myanmar, where the loss rate of 546 K ha y1 between 2010 and 2015 was 25% higher than in the 1990s (Keenan *et al*, 2015). In Africa, the greatest net losses in forest area between 2010 and 2015 were in Nigeria (410 K ha y^{-1}), Tanzania (372 K ha y^{-1}), Zimbabwe (312 K ha y^{-1}) and Democratic Republic of Congo (311 K ha y^{-1}) (Keenan *et al*, 2015). Having seen the rate of forest degradation in Africa in which Andoni LGA is inclusive and some parts of the world, it is important to monitor and quantify the spatio-temporal changes of forest cover and other landuse types. Technological progress allows a comprehensive understanding of any region of the earth's surface from satellite images (Chuvieco *et al*., 2012). These images of the earth have been widely used for change detection, specifically to the mapping and monitoring deforestation and forest degradation. Forest resource maps were traditionally prepared from forest inventories, involving aerial photography and

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fieldwork (Fabiyi, 2001). Remote sensing and geographical information system have been proven to be excellent techniques for studying the environment, offering facilities for combining different maps, variables and data for diverse sources as well as predictive analysis and trend assessment of events (Lambin and Geist, 2006). Hacke (2012) used geo-information technologies in detecting oil spill; and Mahesk (2008) monitored and modelled urban sprawl using geo-information technologies. However, several studies had been done with the use of geo-information technologies to assess landuse change especially monitoring deforestation over time. These included Hansen *et al* (2003) which reported that 1.6 billion hectares tropical forest globally has reduced over time due to urbanization and settlement using geo-information technologies. Adia and Rabiu (2007) investigated the spatio-temporal change detection of vegetation cover of Jos and its surrounding areas while Eludoyin *et al*. (2009) used GIS and remote sensing to assess the landuse change of Obio/Akpor LGA of Rivers State, revealing that farmland, mangrove, primary forest and sparse vegetation had reduced over time. Ochege *et al*. (2014) assessed forest degradation in Sagbama, Bayelsa State using landsat images between 1987 and 2013 with the study showing that there was a reduction in the spatial extent of vegetation cover. None of these studies was done to assess forest depletion over time in Andoni LGA suggesting that studies on deforestation monitoring in Andoni LGA is rare in the literature. The present study therefore investigated the landuse change between 1986 and 2015 with a view to monitoring deforestation in Andoni LGA, Rivers State, Nigeria.

MATERIALS AND METHODS

Study Area: The study area was Andoni LGA, Rivers State, Nigeria. Andoni Local Government Area is located between latitudes 4° 27' 30"N and 4° 35' 30"N and longitudes 7° 17' 30''E and 7° 32' 30''E (Figure 1). Andoni LGA is bounded in the north by Khana LGA, in the south by Atlantic Ocean, in the east by Opobo/Nkoro LGA and west by Bonny LGA. Andoni LGA is situated in sub-equatorial region. The study area has a mean annual temperature of 28°C with the lowest month of not less than 25°C and the hottest of about 31°C. The annual range of temperature is 3.8°C. Andoni LGA enjoys monsoon climate with high rainfall of about 2500 mm annually and relative humidity of about 85%. The moist south east air blows over the region between February and November and the region receives its rain while the north east trade wind blows over the region in the months of November through February which ushers in the dry season (Eludoyin *et al*, 2015). The study area is endowed with high forest and mangrove. Rainforest tree species include Mahogany, *Militia excelsa*, and *Triplochiton scleroxylon*. The mangrove swamp forests included *Rhizophora sp.* and *Nypa fruticans.* The topography of the area is flat terrain with very gentle slopes with an elevation less than 15m above mean sea level. The soil of Andoni LGA is predominantly sandy and also endowed with sandy beach-ridges which cause alternating lower and higher lands. The ecological zone of Andoni area is salt water swamp and the major occupation in Andoni LGA was fishing and farming.
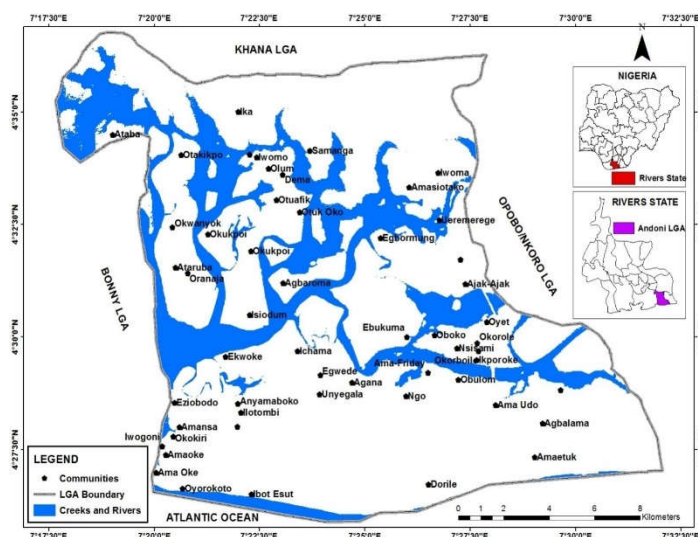

Fig 1. Andoni Local Government Area

Image geo-processing, Landuse change and Percentage change: The study made use multi-

spectral satellite images of Landsat TM 5, ETM 7 and ETM 7; all having some characteristics presented in

Table 1. Landsat images were used because of their ability to have valuable and continuous records of the earth's surface for identifying and monitoring changes in man-made and physical environments (El Bastawesy, 2014; USGS, 2014; Ramat and Kumar, 2017). The images were enhanced by combining all the image bands using layer stack module in Erdas Imagine 9.2 and a false colour composite image of 7, 4, and 2 was selected for each year for further studies. Band sequence 7, 4, 2 RGB is good to be used for classifying the land cover (Cummings, 2007) and moreso the band combination has the capabilities to clearly define different vegetation types (Geospatial Innovation Facility, 2008). Furthermore, Enaruvbe and Atafo (2014) confirmed that a combination of channel 5 (red), channel 4 (green) and channel 2 (blue) is effective in discriminating different vegetal cover types. Cohen and Goward (2004) also showed the importance of the shortwave infrared channels in characterizing vegetation. Information from each land cover classes was collected from extensive field survey before the classification of satellite imageries (Balogun *et al*., 2011; Enaruvbe and Atedhor, 2015). The field survey was performed throughout Andoni LGA of Rivers State using global positioning system (GPS). The GPS has developed into an efficient GIS data collection technology which in order to acquire datasets directly from the field which forms part of ground truthing (Balogun *et al*., 2011). The field work was conducted in between December, 2015 and January, 2016; to tally with the season during which the imageries were obtained. A total of one hundred and ninety three sample locations were determined within all the categories.

In this study, accuracy assessment was performed for the classified maps of 1986, 2000, and 2015. The accuracy assessment is the most often used statistical measure of classification accuracy of satellite imageries (Enavrube and Atafo, 2014) and it is essentially a measure of how many ground truth pixels were classified correctly (Gessesse, 2007). Overall accuracy, user's and producer's accuracies and the Kappa statistics were derived from the error matrices to find the reliability and accuracy of the maps produced (Manandhar *et al*., 2009). The error matrix is described as the starting point for a variety of descriptive and analytical statistical techniques for accuracy assessment (Congalton, 1991); and this was generated in Idrisi Selva software. Thus, overall accuracy was computed by dividing the total correctly classified pixels by the total number of pixels in the error matrix (Congalton, 1991; Enavrube and Atedhor, 2015).

The Kappa coefficient lies typically on a scale between 0 (no reduction in error) and 1 (complete reduction of error) (Forkuo and Frimpong, 2012). Kappa values are characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement (Congalton, 1991; Forkuo and Frimpong, 2012).

Supervised classification using maximum likelihood algorithm classifiers in Erdas Imagine 9.2 (Lillesand and Kiefer, 1994) was used to classify similar spectral signatures into various classes which included forest, mangrove, water bodies, built-up area, cultivated land and bare soil/sand. Maximum likelihood classifier was chosen because it is the most widely adopted parametric classification algorithm (Manandhar *et al*., 2009). The area of each landuse class was calculated in ArcGIS 10.0 which was used to compute the landuse change and percentage change in squared kilometers. The percentage change was computed using equation (1) as given in Enaruvbe and Atedhor (2015).

$$\frac{\left(\frac{d}{t_1}\right)*100}{y2-y1} \quad \ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where, d is the difference in the value of area covered by a land cover category at the initial time point and final time point, t_1 is the value of the area covered by a land cover category in the initial time point, y1 and y2 are base year and final year respectively.

The probability of landuse changing to another in the next 10 years (2025), 20 years (2035) and 30 years (2045) was done using Markov's Transition Estimator in Idrisi Selva 17.0. The extent at which other landuse types have reduced the forest landuse in 2000 and 2015 was computed in ArcGIS 10.0 using overlay method with INTERSECT operator. The INTERSECT-based overlay method gives room for the landuse of a year to be overlaid on the landuse of another year.

Table 1. Characteristics of Landsat Images

Year	Date Acquired	Sensor	Cloud Cover (%)	Path	Row	Resolution
1986	19/12/1986	Landsat 5 MSS	0	188	57	30m x 30m
2000	17/12/2000	Landsat 7 ETM	0	188	57	30m x 30m
2015	09/01/2015	Landsat 7 ETM	0	188	57	30m x 30m

Source: US Geological Survey, 2015

Table 2. Landuse/Landcover Classification Scheme

S/N	Landuse Types	Description
1	Forest	Thick forest, Derived forest, mixed forest lands, palms, shrubs, herbs
2	Built Up Area	Residential, commercial and services, industrial, transportation, roads
3	Mangrove	Trees in the swamps and along the creeks or marshy lands
4	Waterbodies	Rivers, permanent open water, lakes, ponds, reservoirs, etc
5	Cultivated land	Agricultural area, crop fields, fallow lands and vegetable lands
6	Bare ground /Sand	Land areas of exposed soil, barren area and open soil without vegetation

*Sources: Adapted from Anderson et al. (2001); Butt et al., (2015)*

RESULTS AND DISCUSSION

Landuse patterns of Andoni LGA between 1986 and 2015: The landuse pattern in 1986, 2000, and 2015 presented in Table 3, Figure 2, Figure 3 and Figure 4 show that in 1986, forest had spatial extent of 125.95km^2 (39.56%) of the total land area, built-up area had 14.01km^2 (4.41%), cultivated land occupied 22.92km^2 (7.21%), mangrove occupied 58.13 km^2 (18.26%) while bare ground/sand and water body occupied 25.55km^2 (8.03%) and 71.71km^2 (22.53%) respectively. In 2000, forest had spatial extent of 100.47km^2 (31.56%) of the total land area, built-up area had 16.28km^2 (5.15%), cultivated land occupied 22.17km^2 (6.96%), mangrove occupied 78.23 km^2 (24%) while bare ground/sand and water body occupied 29.78km^2 (9.35%)and 71.34km^2 (22.41%) respectively. While in 2015, forest had spatial extent of 74.14km^2 (23.29%) of the total land area, built-up area had 56.55km^2 (17.77%), cultivated land occupied 4.4km^2 (1.38%), mangrove occupied 68.98 km^2 (21.67%) while bare ground/sand and waterbodies occupied 45.1km^2 (14.17%) and 69.1km^2 (22.72%) respectively.

Table 3. Spatial extent of landuse in Andoni between 1986 and 2015

Landuse	1986		2000		2015	
	Areal Extent	Percentage (%)	Areal Extent	Percentage (%)	Areal Extent	Percentage (%)
Forest	125.95	39.56	100.47	31.56	74.14	23.29
Built up Area	14.01	4.41	16.28	5.15	56.55	17.77
Cultivated land	22.92	7.21	22.17	6.96	4.4	1.38
Mangrove	58.13	18.26	78.23	24.57	68.98	21.67
Bare ground/sand	25.55	8.03	29.78	9.35	45.1	14.17
Water bodies	71.71	22.53	71.34	22.41	69.1	21.72
Total	318.27	100.0	318.27	100.0	318.27	100.0
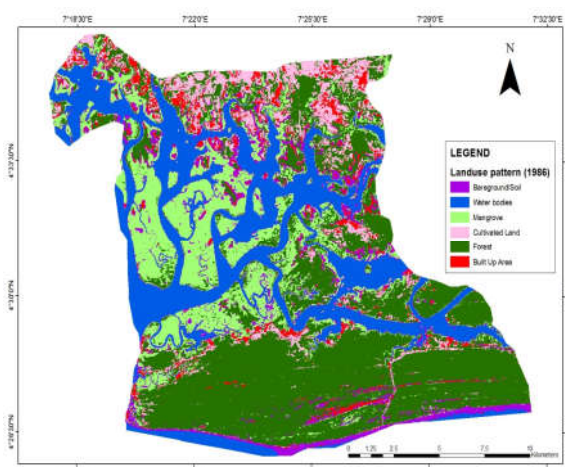
Fig 2. Landuse pattern of Andoni LGA in 1986
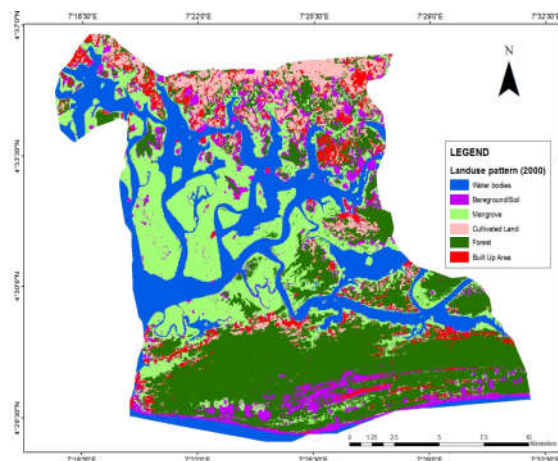
Fig 3. Landuse pattern of Andoni LGA in 2000

Trend and magnitude of landuse change and percentage change of landuse in Andoni LGA between 1986 and 2015: Considering the result of the analysis in Table 4, it is clearly observed that forest, cultivated land, bare soil/sand landuse types reduced by 20.23%, 3.27%, and 0.57% respectively while built-up area, mangrove and water bodies increased by 16.2%, 16.56%, and 34.58% respectively between 1986 and 2000.

The result also shows that forest, built up area, cultivated land, mangrove and water bodies landuse types reduces by 26.21%, 247.36%, 80.15%, 50.77% and 3.14% respectively between 2000 and 2015. The trend analysis shows that forest cover, cultivated land, mangrove and water bodies had reduced between 2000 and 2015. Furthermore, between 1986 and 2015, forest, cultivated land and waterbodies landuse types reduced by 41.14%, 80.8%, and 3.64% respectively.

On the other hand, built-up area, mangrove and bare ground/sand landuse type increased by 303.64%, 18.67%, and 76.52% respectively.

Error of Matrix and Accuracy Assessment for Landuse Types: Post-classification accuracy assessment of the data shows an overall accuracy of 91.7% in 1986, 91.5% in 2000 and 87.6% in 2015 (Table 6). Similarly, the Kappa statistics in 1986, 2000 and 2015 are 0.84 (84%), 0.85 (85%) and 0.86 (86%) respectively (Table 6). The results of overall accuracy assessment and Kappa statistics indicated a strong agreement or accuracy between the classified maps and the ground reference information ((Manandhar *et al*., 2009).
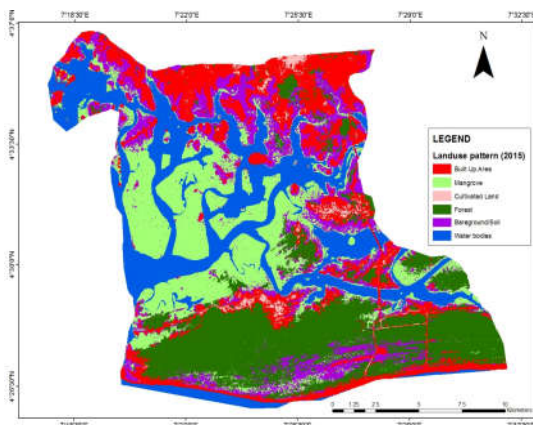

Fig 4. Landuse pattern of Andoni LGA in 2015

Table 4. Trend and magnitude of landuse change and percentage change in Andoni LGA between 1986 and 2015

Landuse	(1986-2000)		(2000-2015)		(1986-2015)	
	Trend/Magnitude of landuse change (km^2)	Percentage change (%)	Trend/Magnitude of landuse change (km^2)	Percentage change (%)	Trend/Magnitude of landuse change (km^2)	Percentage change (%)
Forest	-25.48	20.23	-26.33	26.21	-51.81	41.14
Built Up Area	+2.25	16.2	+40.27	247.36	+42.54	303.64
Cultivated	-0.75	3.27	-17.77	80.15	-18.52	80.8
Mangrove	+4.23	16.56	-9.25	11.82	+10.85	18.67
Bare ground/sand	-0.37	0.56	+15.12	50.77	+19.55	76.52
Waterbodies	+20.1	34.58	-2.24	3.14	-2.61	3.64

Table 5. Error of Matrix of Landuse/Land cover Classes

Year	Landuse	Built-Up Area	Mangrove	Cultivated	Forest	Bare ground/ Sand	Water bodies	Total
1986	Built Up Area	109	12	0	0	0	0	121
	Mangrove	0	15	5	0	0	0	20
	Cultivated	0	0	35	7	0	0	42
	Forest	0	0	0	28	3	0	31
	Bare ground/Sand	0	0	0	0	22	2	24
	Waterbodies	0	0	0	0	0	21	21
	Total	109	27	40	35	25	23	259
2000	Built Up Area	86	10	0	0	0	0	96
	Mangrove	0	11	5	0	0	0	16
	Cultivated	0	0	27	6	0	0	33
	Forest	0	0	0	22	2	0	24
	Bare ground/Sand	0	0	0	0	18	1	19
	Waterbodies	0	0	0	0	0	17	17
	Total	86	21	32	28	20	18	205
2015	Built-Up Area	81	9	0	0	0	0	90
	Mangrove	0	11	4	0	0	0	15
	Cultivated	0	0	26	5	0	0	31
	Forest	0	0	0	21	2	0	23
	Bare ground/Sand	0	0	0	0	17	1	18
	Waterbodies	0	0	0	0	0	16	16
	Total	81	20	30	26	19	17	193

Spatial Extent of Other Landuse into Forest Landuse between 1986 and 2015: The spatial extent of forest landuse captured by water bodies, bareground/sand, mangrove, cultivated land and built up area in Andoni LGA between 1986 and 2015 is presented in Table 5. It was shown that between 1986 and 2000, water bodies captured 0.02 km^2 (0.06%), bareground/sand captured 9.15 km^2 (26.72%), mangrove 13.7 km^2 (40%), cultivated land 6.77 km^2 (19.77%) while built

up area captured 4.61 km^2 (13.46%). Furthermore, between 2000 and 2015, water bodies captured 0.001 km^2 (0.003%), bare ground/sand captured 13.94 km^2 (41.11%), mangrove 4.63 km^2 (13.65%), cultivated land 1.13 km^2 (3.33%) while built up area captured 14.21 km^2 (41.91%). From 1986 to 2015, water bodies captured 0.15 km^2 (0.27%), bare ground/sand captured 21.23 km^2 (38.40%), mangrove 11.90 km^2 (21.52%), cultivated land 1.75 km^2 (3.17%) while built up area

captured 20.26 km² (36.64 %). Thus, the total spatial extent of forest landuse lost to other landuse types between 1986 and 2000 was 34.25 km² while it was 33.91 km² between 2000 and 2015.

Table 6. Accuracy assessment for the supervised classified image

Year	Class name	Reference total	Classified total	Number correct	Producer's Accuracy (%)	User's Accuracy (%)
1986	Built-up	86	96	83	96.51	86.46
	Mangrove	21	16	16	76.19	100.00
	Cultivated	32	33	31	96.88	93.94
	Forest	28	24	23	82.14	95.83
	Bare soil/sand	20	19	18	90.00	94.74
	Waterbodies	18	17	17	94.44	100.00
	Total	205	205	188		
2000	Built-up	109	121	107	98.17	88.42
	Mangrove	27	20	20	74.07	100.00
	Cultivated	40	42	39	97.50	92.86
	Forest	35	31	30	85.71	96.77
	Bare soil/sand	25	24	20	80.00	83.33
	Waterbodies	23	21	21	91.30	100.00
	Total	259	259	237		
2015	Built-up	81	90	78	96.30	86.67
	Mangrove	20	15	14	75.00	93.33
	Cultivated	30	31	26	86.67	83.87
	Forest	26	23	22	88.46	95.65
	Bare soil/sand	19	18	15	94.74	83.33
	Waterbodies	17	16	14	94.12	87.50
	Total	193	193	169		

Overall classification accuracy for 1986 = 91.7%; Kappa statistics = 0.84 = 84%; Overall classification accuracy for 2000 = 91.5%; Kappa statistics = 0.85 = 85%; Overall classification accuracy for 2015 = 87.6%; Kappa statistics = 0.86 = 86%

Table 7. Extent of Other Landuse into Forest Landuse between 1986 and 2015

Landuse	1986-2000		2000-2015		2000-2015	
	Spatial Coverage (km²)	Percentage (%)	Spatial Coverage (km²)	Percentage (%)	Spatial Coverage (km²)	Percentage (%)
Waterbodies	0.02	0.06	0.001	0.003	0.15	0.27
Bareground/sand	9.15	26.72	13.94	41.11	21.23	38.40
Mangrove	13.7	40.00	4.63	13.65	11.9	21.52
Cultivated Land	6.77	19.77	1.13	3.33	1.75	3.17
Built Up Area	4.61	13.46	14.21	41.91	20.26	36.64
Total	34.25	100.0	33.91	100.0	55.29	100.0

*Probability of forest landuse changing to other landuse in 2025, 2035 and 2045***:** The probabilities of forest landuse changing to other landuse types in 2025, 2035 and 2045 in Andoni LGA shown in Table 6 shows that 3.68%, 0.47%, 6.62% and 3.51% of bare ground/sand, mangrove, cultivated land and built up area respectively had a chance of changing to forest landuse while water bodies did not have any chance of capturing forest landuse in 2025. In 2035, findings reveals that water bodies had a chance of 0.03% of changing to forest landuse, bare ground/sand had 4.72%, mangrove had 1.33%, and cultivated land had 8.06% while built up area had 6.08%. In 2045, water bodies had a chance of 0.17% of changing to forest landuse, bare ground/sand had a chance of 5.09%, and mangrove had 2.10% while cultivated land and built up area had a chance of 8.75% and 7.32% respectively of changing to forest landuse. Findings show that spatial coverage of forest decreased between 1986 and 2015 and this shows that forest land is often tampered with over the years by other landuse. The findings are in agreement with Gessesse (2007) and Egwuogu *et al.* (2016) whose studies revealed that forest cover changes from time to time because of population growth, urbanization, industrialization, and other form of exploitation. Fabiyi (2011) believed that human actions especially those involving biomass fuel consumption, land-use change, and agricultural activities have direct interaction with the land surface and negative consequences on vegetation and environmental qualities (Fabiyi, 2011). Similarly, Johnson *et al*. (2002) further stated that overall changes in the landscape show an increased trend for urban development with non-forested vegetation and coastal wetlands suffering the consequences. Adoki (2013) also noted that several forces especially settlement developments and oil prospecting over the years have imprinted indelibly on the Niger Delta which is found in the fragile ecosystem. The reduction in forest cover reduces the significant role that it plays in maintaining the ecosystem.

Table 8. Probability of forest landuse changing to another landuse in 2025, 2035 and 2045

Landuse classes	Water	Bare soil/sand	Mangrove	Cultivated	Forest	Built-up
2025						
Waterbodies	0.9335	0.0000	0.0488	0.0000	0.0000	0.0167
Bare soil/sand	0.0782	0.3661	0.2847	0.0000	0.0368	0.2340
Mangrove	0.0166	0.1749	0.8033	0.0000	0.0047	0.0000
Cultivated	0.0000	0.0175	0.0000	0.1163	0.0662	0.7982
Forest	0.0000	0.1556	0.0666	0.0140	0.6430	0.1204
Built Up Area	0.0000	0.1779	0.0000	0.0337	0.0351	0.7503
2035						
Waterbodies	0.8720	0.0100	0.0871	0.0004	0.0003	0.0283
Bare soil/sand	0.1057	0.2320	0.3391	0.0081	0.0472	0.2664
Mangrove	0.0429	0.2065	0.6959	0.0000	0.0133	0.0404
Cultivated	0.0000	0.1691	0.0000	0.0422	0.0806	0.7035
Forest	0.0073	0.1938	0.1420	0.0148	0.4217	0.2193
Built Up Area	0.0076	0.2132	0.0437	0.0307	0.0608	0.6384
2045						
Waterbodies	0.8160	0.0230	0.1168	0.0008	0.0017	0.0387
Bare soil/sand	0.1215	0.2010	0.3452	0.0106	0.0509	0.2681
Mangrove	0.0680	0.2078	0.6198	0.0012	0.0210	0.0807
Cultivated	0.0078	0.2077	0.0477	0.0305	0.0875	0.6119
Forest	0.0219	0.2036	0.1977	0.0151	0.2842	0.2753
Built Up Area	0.0217	0.2147	0.0961	0.0265	0.0732	0.5599

Efiong (2011) reported that forest removal is a factor that enhances global warming that is threatening the environment as the role of plants to reduce the concentration of carbon dioxide in the atmosphere has been defeated. The decrease of forest cover in this study area is an epitome of regional or global forest cover change over a period of time amidst varying reasons which was also reported in Keenan *et al.* (2015). The reduction in the waterbody and increase in the bareground/sand is similar to the work of Suleiman *et al.* (2014) which reported that vegetation and water bodies have been greatly tampered with, as a result of human activities through exploitation and development of built up areas. The increase in the bareground/sand over time may be attributed to the reduction in forest cover and infrastructural development in the built up area. Ejaro and Abdullahi (2013) had similar findings with respect to the spatial coverage of bare ground increase between 1987 and 2011 in Suleja LGA, Federal Capital Territory, Nigeria.

Conclusion: The study has demonstrated the roles of geo-information technologies at monitoring forest depletion in Andoni LGA, Rivers State, Nigeria between 1986 and 2015 and it can be concluded that forest landuse had reduced with time and had been replaced mostly by built-up areas. The study therefore recommended that re-afforestation projects should be established to replenish the forests; strict legislation, policies and strategies should be put in place to protect the forests from undue exploitation; and finally, establishment of forest reserve should be encouraged.

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