

VEGETATIVE INDEX ASSESSMENT AND MONITORING OF OLUWA FOREST RESERVE ONDO STATE, NIGERIA

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ABSTRACT

In recent time climate change mitigation has become a global challenge, and it is imperative to monitor one of the important forest reserves in Ondo State using three vegetative indices to determine its greenness, the depleting category, and forecast the future condition of the forest reserve area. This study aims to carry out vegetative index assessment and monitoring of Oluwa forest reserve. Especially, the study investigates vegetation cover that is conspicuous and responsible for the greenness of the forest reserve or otherwise and to also show the trend in vegetation indices changes in about three decades. Landsat imagery was downloaded for 1991, 2002, and 2018 while the Differential Global Positioning System (DGPS) in static mode was used to obtain the ground coordinate of some selected points in the study area to test the quality of the Landsat data. The shapefile of the study area was used in ArcGIS 10.4 environment for clipping and sub-setting while supervised classification and Maximum Likelihood algorithm were employed for vegetation classification. The Vegetative index method was employed to calculate and determine vegetation cover greenness for each year. Specifically, three different models of the vegetative index were used in the research which is Normalized Difference Vegetative Index (NDVI), Soil Adjusted Vegetative Index (SAVI), and Green Normalized Difference Vegetative Index (GNDVI). From the analysis carried out, this research reveals that the results obtained from SAVI was the most reliable as it has the highest accuracy when compared to NDVI and GNDVI. Furthermore, results from SAVI also showed that it represented the true condition of the study area and more realistic than the other two vegetation indices. Notably, the results of NDVI, SAVI, and GNDVI showed that the moderate Vegetation Index class (0.2 – 0.4) has the highest coverage area in Oluwa Forest Reserve, signifying that it contains more Shrub (bush) and grassland hence the greenness. The analysis also showed that the trend of dense vegetation (> 0.4) class (i.e. the class containing trees) showed a declining order as seen from SAVI result. This signifies that the rate at which dense vegetation (tress) is depleting without replacement is greater in Oluwa forest reserve area. The projection results for the three models showed that Dense vegetation will also be declining by the year 2030 and it is advised that Government should introduce stringent measures to protect the remnants of vegetation in Oluwa forest reserve for posterity sake.

INTRODUCTION

Forests all over the world embrace a broad range of multiple-use and management. Forest usages include the provision of timber, fuelwood, wildlife habitat, natural water supply, recreation, landscape, and community protection while others are employment generation [4], aesthetically appealing landscapes, biodiversity management, watershed management, erosion control [13]. Forest ecosystems are the most important feature of the earth according to [19] and it has emerged as a science embraced by the majority of industrialized countries. Generally, intensive and effective forest management requires reliable field data, maps, and plans indicating the current state of the forest [6], and over some decades, Remote Sensing (RS) has been consistently employed for forest resources monitoring and management, because it provides real-time information about the state and conditions of forests [7]. One very important life-supporting system that is available to man naturally is the forest ecosystems services that are essential to human well-being such as; soaking of dangerous greenhouse gasses that

bring about climate change which affect environmental conditions for people and wildlife species both directly and indirectly, reduces the amount of rainfall, and unfavorable weather condition among other things [18]. Forests everywhere are undergoing systemic changes through the intentional threat pose by forest speculators and other factors. It is significant to have the basic intrinsic understanding and the configuration of the change and extent of the forest as a vital aspect of monitoring. Remote sensing is essentially appropriate in studying Spatio-temporal changes in forest locations around the world [14]. The advent of computer technology has equipped forest managers with ubiquitous new tools for data capture, data visualization in three Dimension (3-D), and robust management planning applications.

This research aimed at assessing the vegetative indices and monitoring of Oluwa forest reserve Ondo State to determining the vegetation greenness which is a measure of the forest healthiness using NDVI, SAVI, and GNDVI in the years 1991, 2002, and 2018 respectively. The research will also attempt to solve the following problem which is common to forest reserves nationwide: (i.) the expected benefit from Oluwa forest reserves are vague, (ii.) the quality and status of forest resources is difficult to ascertain when required; (iii.) vegetation cover that is prominent in the forest reserve are indistinct leading to deforestation due to over-grazing by Fulani herdsmen as well as uncontrolled illegal logging activities. To attain the aim of the research and also proffer solution to these problems, the following objectives were set; (i.) assess and monitor the condition of Oluwa forest reserve area using different vegetation indices and imageries of different epochs (ii.) analyze the performances of the vegetation indices used and (iii.) forecast the future condition of the forest reserve area.

From the previewed journals such as [24]; [16]; [15] used different vegetation indices separately to monitor forest reserves while [10] applied different vegetation indices to assess the healthiness of forest and compared their results. The major research gap in this study is the application of normalized difference vegetation index (NDVI), Soil-adjusted vegetation index (SAVI), Green Normalized Difference Vegetative Index(GNDVI) at the same time to assess and monitor the healthiness of the Oluwa forest reserve area using Landsat imageries. In this research, Oluwa forest reserve was monitored and vegetative indices assessment was carried out and information about the greenness which is the attribute of the forest health as well as the future status of Oluwa forest reserve among other things were predicted in line with [12] and [8].

STUDY AREA

Oluwa forest reserve area is one of 14 forest reserves that is scattered in the three ecological zones of Ondo State. Other forest reserves as listed by [22] are Akure Aponmu (Akure forest), Akure Ofosu, Ala, Eba Island, Idanre, Ifon game reserves, Ipele / Idoani, Irele, Ojigbobini, Okeluse, Onisere/Otu, Owo and Oyinmo. It has an area of 1,186 square kilometers and approximately lies within latitudes and longitudes (7°00'n, 4°36'e), (6°59'n, 4°50'e), (6°35'n, 4°49'e), and (6°42'n, 4°28'e) respectively. Majority of the forest landmass lies in Odigbo LGA while a very small fraction is found in Okitipupa LGA of Ondo State (Fig. I). the climate of the study area is characterized by rainy (wet) season (April and October) and dry season (November to March) and the annual rainfall varies from 1,900mm – 2,700 mm. also, the mean annual temperature ranges from 22.3°c (minimum) to 31.4°c (maximum) while the elevation ranges between 3m to 402m above mean sea level.

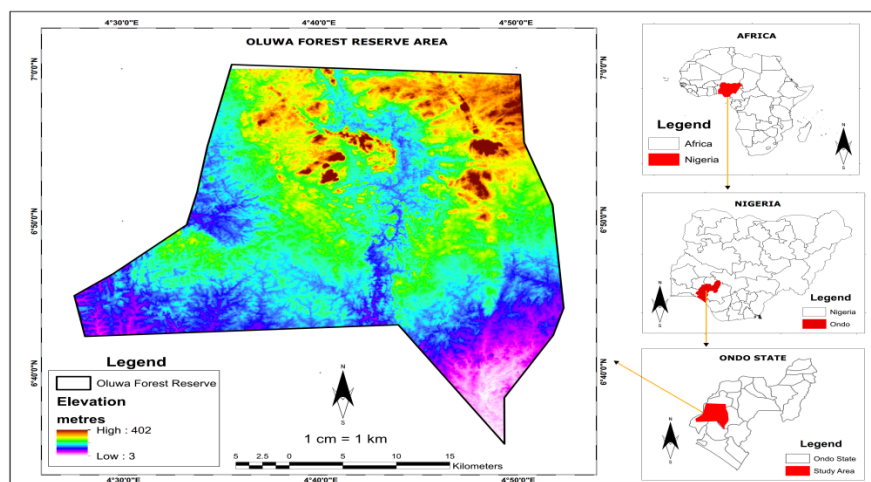


Fig.I Study Area Map

METHODOLOGY

In this research data was acquired from primary and secondary data sources. The primary data was the ground coordinate which was gotten with the use of Differential Global Positioning System (DGPS) in static mode within the study area and the secondary source was the Landsat imageries of 1991, 2002, and 2018 respectively. The imageries that were downloaded from the United State Geological Survey (USGS) include Operational Land Imager (OLI)/ Thermal Infrared Sensor (TIRS); Enhanced Thematic Mapper (ETM+), and Thematic Mapper (TM) as shown in Table I while detailed information about the LANDSAT imageries is shown in table II.

Table-I The Adopted Data and their Attributes

S/N	Data	Source	Year	Resolution/Scale
1	LANDSAT OLI/TIRS, ETM+, and TM	United State Geological Survey (USGS)	2018, 2002, & 1991	30 m
2	Administrative map	Office of the Surveyor General of the Federation (OSGOF)		1:1,300,000
3	GPS coordinates	Field Survey	2019	

Source (Author)

Table-II Information of the Landsat 8 Image of the study area.

Year	Sensor	Scene ID #	Path / Row	Date Acquired	Resolution
2018	OLI / TIRS (Operational Land Imager / Thermal Infrared Sensor)	LC81900552018004LGN00.tar	190 / 055	2018-03-14	30m
2002	Enhanced Thematic Mapper	LE71900552002003SGS00	190 / 055	2002-03-01	30m
1991	Landsat Thematic Mapper	LT41900551991005XXX04	190 / 055	1991-01-05	30m

Source [21]

All Landsat standard data products are processed using the Level 1 Product Generation System (LPGS) by applying Geostationary Earth Orbit Tagged Image File Format (GeoTIFF) output format, Cubic Convolution (CC) resampling method, 30-meter (TM, ETM+), Universal Transverse Mercator (UTM) map projection World Geodetic System (WGS) 84 datum and MAP (North-up) image orientation in line with USGS Landsat Processing Details (2014). The shapefile of the study area was used in ArcGIS 10.4 for clipping and sub-setting while supervised classification and Maximum Likelihood algorithm was used to determine land use and land cover classes that were peculiar to the study area and these were non-vegetation, sparse vegetation, Moderate Vegetation, and dense

vegetation. The accuracy assessment was done using 50 points. The point was acquired by choosing the random stratified method to represent different vegetation classes of the area. Also, trend analysis was carried out to assess the course of the area coverage by the vegetation index classes at the Oluwa forest reserve. The area of the vegetation index classes in each epoch was calculated using ArcGIS 10.4 software.

Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Green Normalized Difference Vegetation Index (GNDVI) was used as a model in conjunction with equations I, II, and III to determine the healthiness of the Oluwa forest reserve. The RED, Near Infrared (NIR) and GREEN present in the equations of the various vegetation indices correspond to bands 1, 3, and 4 of Landsat Thematic Mapper (LTM) and Landsat Enhanced Thematic Mapper (ETM+) while they are bands 2, 4, and 5 in Landsat Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) also known as Landsat 8. Equations I, II, and III were inputted into the raster calculator tool in the ArcGIS environment to determine NDVI, SAVI, and GNDVI as a measure of healthiness for each year under consideration. Specifically, it was calculated on the filtered sub-map Landsat imageries of 1991, 2002, and 2018 classifications respectively. The results obtained for each model were compared to [5] [11], [17] and [20] NDVI values for different vegetation cover types. These classes are also applicable to other types of vegetation index.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \dots \dots \dots (I) [2]$$

$$SAVI = \frac{(1 + L)(NIR - RED)}{(NIR + RED + L)} \dots \dots \dots (II) [3]$$

$$GNDVI = \frac{(NIR - GREEN)}{(NIR + GREEN)} \dots \dots \dots (III) [1].$$

Projection of forest changes in the next 12 years (2030) was achieved using projection formula (IV) given by [12] and [8]

$$\text{Changes} = \frac{\text{Changes between base year and recent year}}{\text{Time differences between base year and recent year}} \times \text{predicted number of years} \dots \dots (IV)$$

RESULTS AND DISCUSSION

Vegetation index in the years 1991, 2002, and 2018 was assessed using Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Green Normalized Difference Vegetation Index (GNDVI). The level of healthiness for each model per year were determined and indicated in terms of hectares (Ha) and percentages coverage of the total area. Figures II, III, and IV show the pseudo color map of the study area using NDVI for the study years respectively.

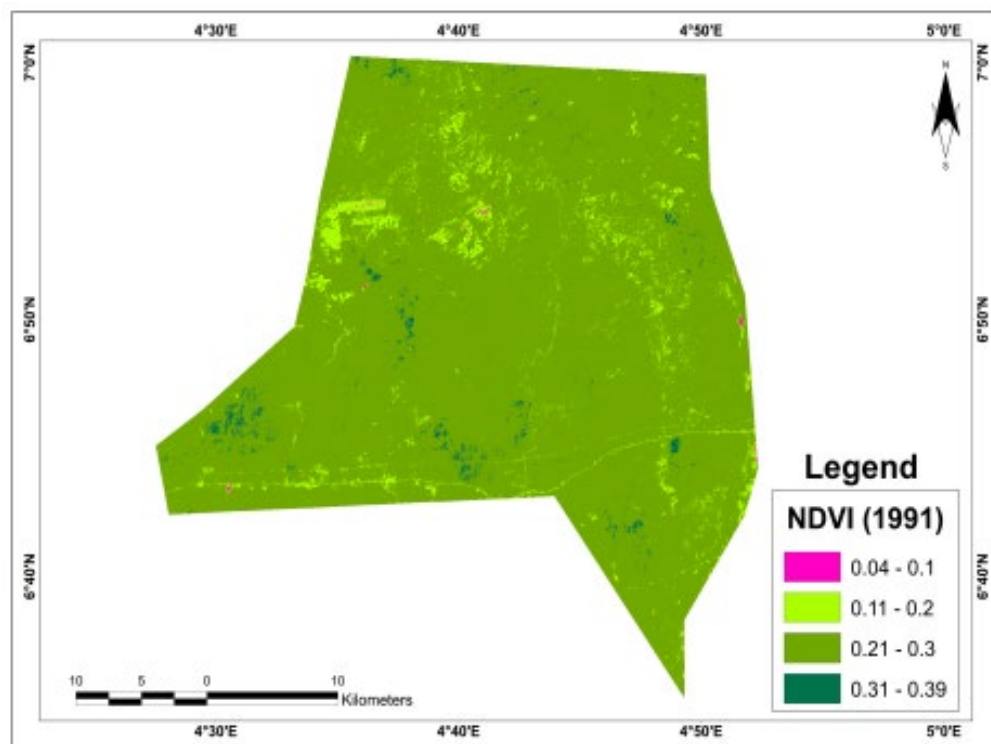


Fig. II 1991 NDVI classes for Oluwa forest reserve.

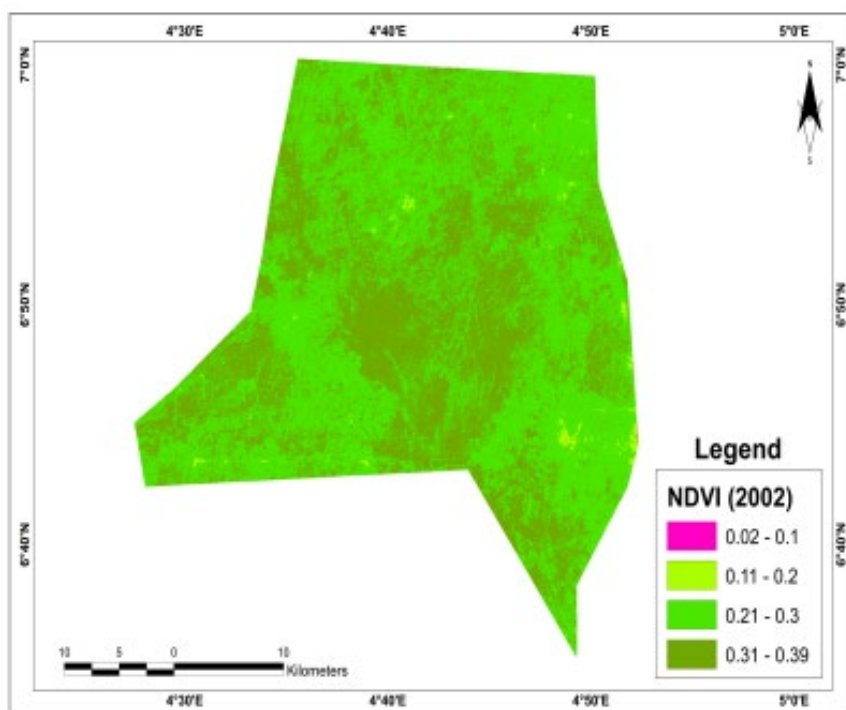


Fig.III 2002 NDVI classes for Oluwa forest reserve

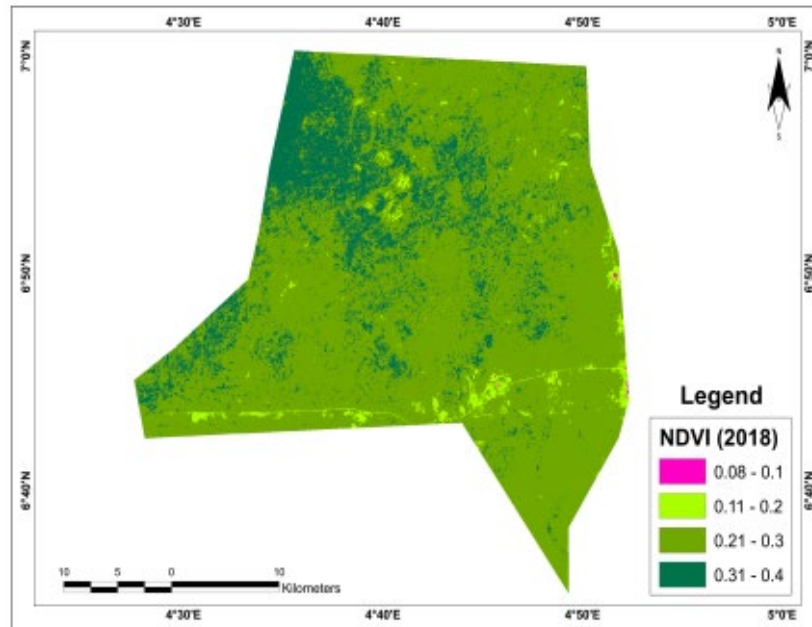


Fig.IV 2018 NDVI classes for Oluwa forest reserve

The NDVI result shows that the Oluwa forest reserve contains all cover types. The vegetative index class ranges between < 0.1 to 0.39 which indicates that the forest reserves contain barren rock, sand, water and a lot of moderate vegetation in form of shrub and grassland while tropical forest and dense vegetation was absent. The NDVI result for 2002 shows a similar trend with 1991 while NDVI result for 2018 indicates that the shrub and grassland in the Oluwa forest were more pronounced. It can be remarked that vegetative index class of $0.2 - 0.4$ (shrub and grassland) are healthy.

Similarly, the results of Vegetation greenness/healthiness using SAVI in the years 1991, 2002, and 2018 are shown in figures V, VI, and VII.

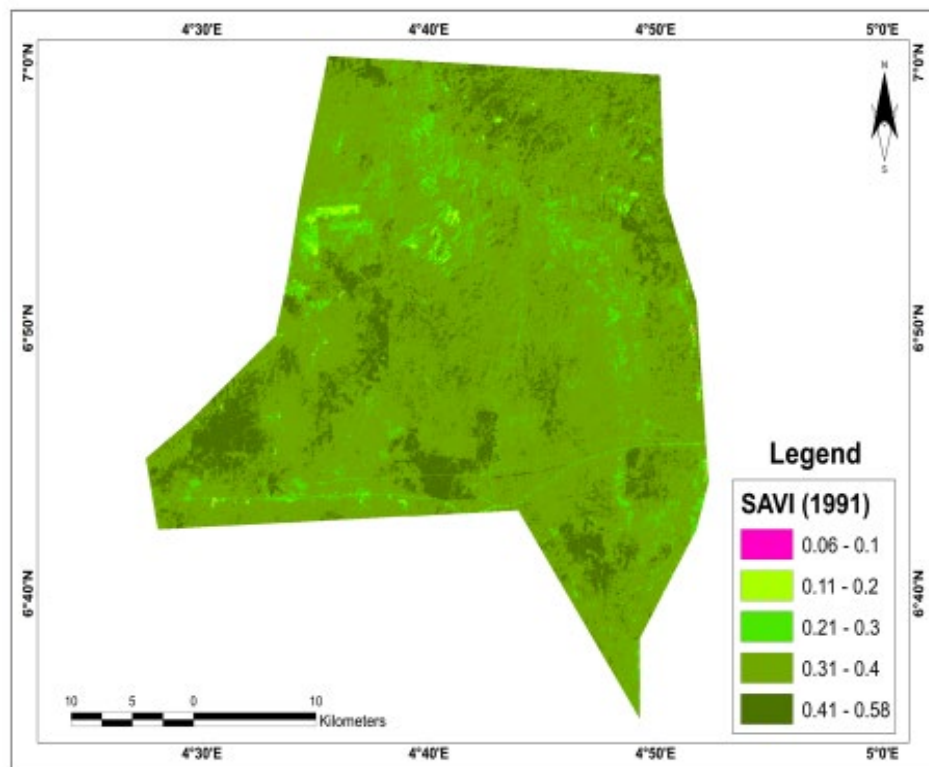


Fig.V 2002 SAVI classes for Oluwa forest reserve.

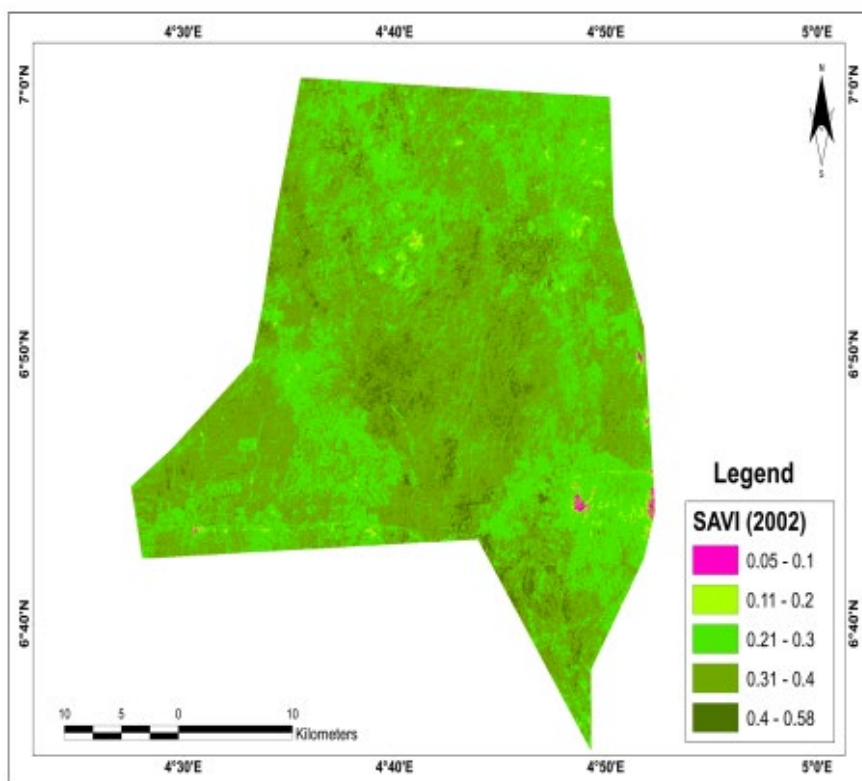


Fig.VI: 1991 SAVI classes for Oluwa forest reserve

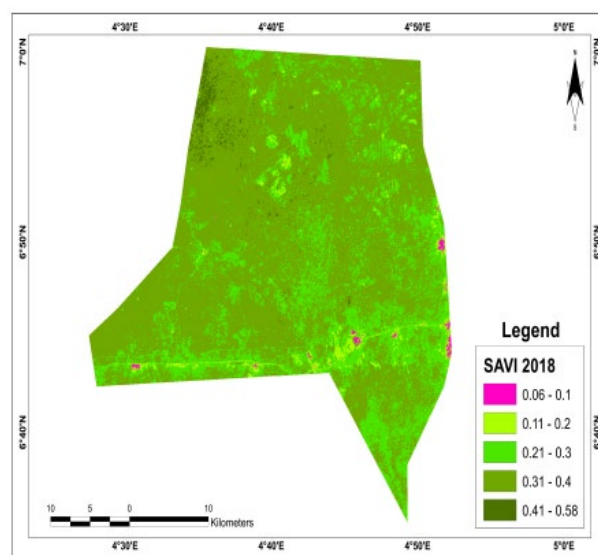


Fig.VII 2018 SAVI classes for Oluwa forest reserve.

The SAVI result for 1991 indicates that the forest reserve was healthy due to the abundance of shrub and grassland as well as a little dense vegetation notwithstanding, barren rock, and sand that were typically absent. However, in 2002 the forest reserve contains barren rock, sand, water, moderate vegetation and a little dense vegetation as the vegetative index class ranges between 0.05- 0.1 and 0.4- 0.58. However, the result for 2018 was similar to the 2002 SAVI result. Specifically, the forest reserve contains barren rock, moderate vegetation and a little dense vegetation in 2018 which revealed that the health of the forest reserve further declined culminating in unhealthy forest conditions. Also, the GNDVI result showed that the Oluwa forest contains moderate vegetation, and a little dense vegetation as well as an insignificant amount of barren rock, sand, and water in 1991 as displayed in (figure VIII). During this period, the forest reserve could be adjudged to be healthy, nevertheless, in 2002 the health of the forest reserve deteriorated due to more pronounced barren rock, sand, water, and mostly moderate vegetation (figure IX) notwithstanding the 2018 result which was partially similar to 1991 result with the attendant of healthy forest reserves (figure X).

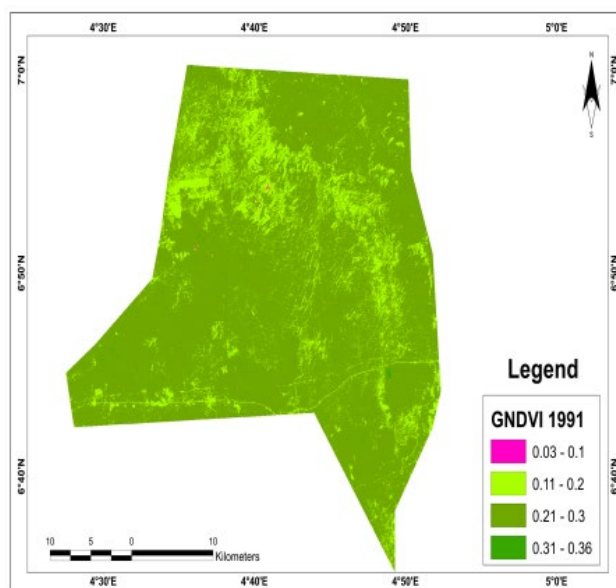


Fig.VIII: 1991 GNDVI classes for Oluwa forest reserve

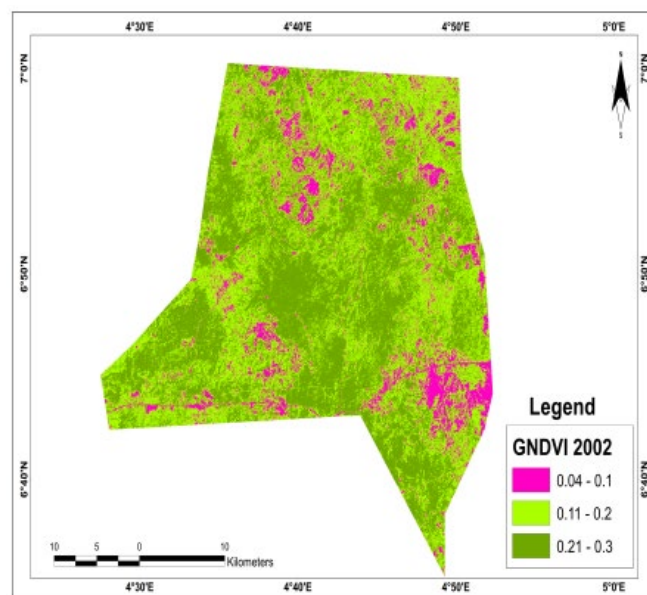


Fig.IX 2002 GNDVI classes for Oluwa forest reserve

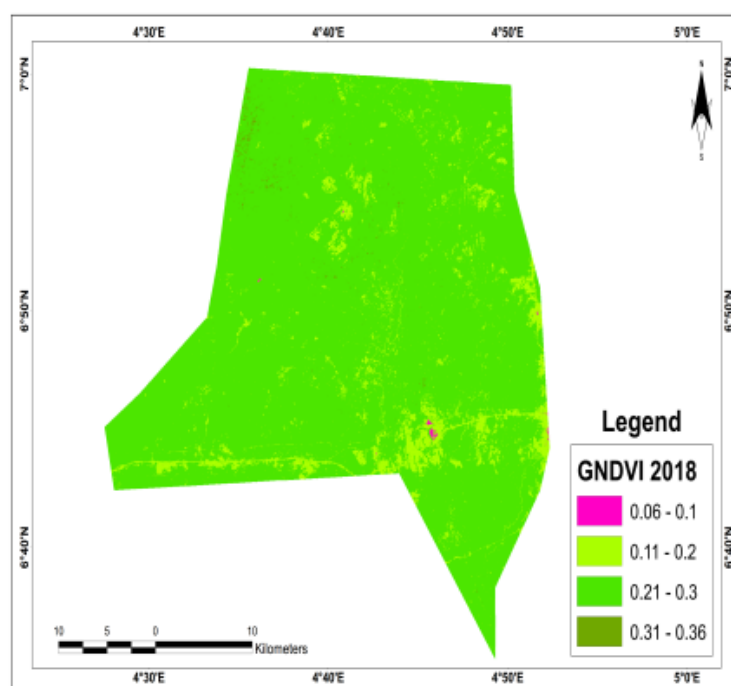


Fig.X 2018 GNDVI classes for Oluwa forest reserve

The vegetation index class of NDVI in Square Kilometers (Km^2) coverage and percentages (%) as derived from time-series images of years 1991, 2002, and 2018 respectively in the Oluwa forest reserve were exhibited in table III.

Table-III NDVI classes for time-series images of 1991, 2002, and 2018

Vegetation Level	NDVI						Percentage (%)
	Vegetation Index Class	1991 (Km ²)	Percentage (%)	2002 (Km ²)	Percentage (%)	2018 (Km ²)	
Non Vegetation	<0.1	0.813	0.07	0.672	0.11	0.468	0.04
Sparse Vegetation	0.1 - 0.2	55.210	4.65	43.864	3.70	27.360	2.31
Moderate Vegetation	0.2 - 0.4	1130.313	95.28	1141.800	96.25	1158.508	97.65
Dense Vegetation	>0.4	0.000	0.00	0.000	0.00	0.000	0.00
	TOTAL	1186.336	100.00	1186.336	100.00	1186.336	100.00

Source: Author's field work

Specifically, the table explicates the vegetative index classes of NDVI and it also reveals that the classes of 0.1-0.2 (sparse vegetation) and 0.2-0.4 (moderate vegetation) occupies 4.65% and 95.28% in 1991 while in 2002 and 2018 for the same vegetation index class, sparse vegetation decreased from 3.70% to 2.31% while shrub and grassland increased from 96.25% to 97.65%. the table also reveals a 2.37% increase in moderate vegetation for about three decades.

Essentially, the vegetative index classes of SAVI rendered in table 4 reveals that the non-vegetation, sparse vegetation, and moderate vegetation were on the increase while dense vegetation were on a declining trend from 1991 to 2018. The decrease in dense vegetation was a result of multi-various human activities ranging from slashes and burn agriculture to non-stop logging ongoing in the forest reserve all year round. These activities were noticed during data collection for this research.

Table-IV Vegetation index of SAVI from time-series images of years; 1991, 2002, and 2018

SAVI							
Vegetation Level	Vegetation Index Class	1991 (Km ²)	Percentage (%)	2002 (Km ²)	Percentage (%)	2018 (Km ²)	Percentage (%)
Non Vegetation	<0.1	0.174	0.01	1.479	0.12	3.376	0.28
Sparse Vegetation	0.1 - 0.2	4.967	0.42	12.945	1.09	24.549	2.07
Moderate Vegetation	0.2 - 0.4	1008.029	84.97	1062.727	89.58	1142.287	96.29
Dense Vegetation	>0.4	173.166	14.60	109.186	9.20	16.125	1.36
	TOTAL	1186.336	100.00	1186.336	100.00	1186.336	100.00

Source: Author's field work

Notably, table V describes the vegetative index classes of GNDVI and reveals a similar trend with SAVI for all the years under study for the non-vegetation, sparse vegetation, and shrub and grassland while dense vegetation exhibits a similar trend with NDVI result for the same vegetative class.

Table-V vegetation index classes of GNDVI from time-series images of years; 1991, 2002, and 2018

GNDVI							
Vegetation Level	Vegetation Index Class	1991 (Km ²)	Percentage (%)	2002 (Km ²)	Percentage (%)	2018 (Km ²)	Percentage (%)
Non Vegetation	<0.1	0.286	0.02	0.433	0.04	0.646	0.05
Sparse Vegetation	0.1 - 0.2	1.157	0.10	34.656	2.92	83.383	7.03
Moderate Vegetation	0.2 - 0.4	1184.894	99.88	1151.247	97.04	1102.307	92.92
Dense Vegetation	>0.4	0.000	0.00	0.000	0.00	0.000	0.00
	TOTAL	1186.336	100.00	1186.336	100.00	1186.336	100.00

Source: Author's field work

The ground data and also data from high-resolution image (Digital Globe Image) of the study area for different vegetation classes were compared with the generated vegetation index maps from NDVI, SAVI, and GNDVI respectively. It was discovered that the moderate vegetation class has the highest producer's accuracy (73.1%) while the sparse vegetation also has the highest User Accuracy (74.5%) and kappa statistic (0.74) for accuracy assessment result for NDVI. This implies that spatial features are represented correctly while the vegetative index classes of the study area were adjudged to be classified accurately and that the various instances classified by the machine learning classifier matched closely the data labelled as ground truth as at the time of this research. Also, the accuracy assessment result for SAVI shows that the producer's accuracy of dense vegetation was 90.1% which was the highest among other land use and land cover classes while non-vegetation class also has the highest user accuracy and kappa statistics of 91.2 % and 0.90 respectively. Similarly, it was also revealed that in the GNDVI accuracy assessment, 69.3% Producer's Accuracy garners by dense vegetation was the highest as well as the User's accuracy of 71.1% for Non-Vegetation which was also the highest, notwithstanding the 0.68kappa statistic accuracies recorded for both Non vegetation and moderate vegetation respectively. The accuracy of SAVI was the highest out of the three vegetative indices considered in this research and it showed that it holistically represented the true condition of the study area and more realistic than the other two vegetation indices in terms of producer's accuracy and user's accuracy.

The result obtained from trend analysis during the 'years' under investigation was used to predict the size of future vegetation classes in square kilometers (Km²) as well as the corresponding vegetation index class for the projected year 2030. This was estimated for NDVI, SAVI, and GNDVI using the projection formula given by [12] and [8] Figure XI reveals that vegetation index classes 0.2 -0.4 (moderate vegetation) for NDVI will increase by 2030 while the projection for other vegetation classes would tend towards negative.

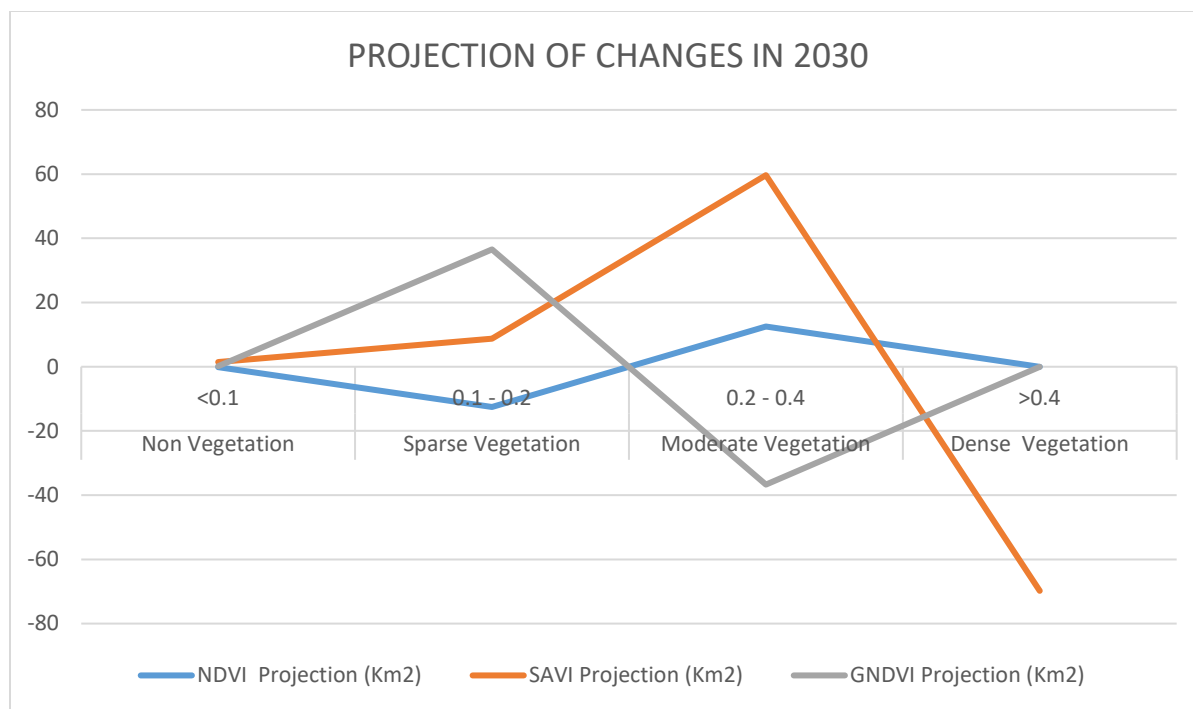


Fig.XI Vegetative indices Projections for 2030

Furthermore, the SAVI projection results also exhibit similar traits to the projection result of NDVI projections on the moderate vegetation class with a little difference that existed in sparse vegetation (positive change) and the dense forest (negative change) which may likely be extinct in 2030. This was due to the high rate of degradation and deforestation in form of farming and logging which was evident during the fieldwork and this confirms the result of [9] research work. The moderate vegetation in form of shrubs and grassland discovered in this research for both NDVI and SAVI that dominated the study area could only have occurred when the forest reserve area has been degraded due to Ecoterrorism over the years such that areas left to regenerate tend to grow grasses that are easily affected by the seasonal fire. In a nutshell, the degraded areas were fast-changing to grasses and this validates the outcome of [23] research that there is the possibility of total degradation of portions of the forest reserves revert to grassland ecosystem.

Also, the projection result for GNDVI shows that vegetation index classes <0.1 and 0.1 - 0.2 will tend to appreciate by 2030, while class 0.2 – 0.4 (moderate vegetation) will decrease and class >0.4 (dense forest) will remain stagnant at zero allowing the natural regeneration tendencies of the forest reserve to be at its best.

CONCLUSION AND RECOMMENDATIONS

The results obtained from SAVI was the most reliable as it had the highest accuracy in term of producer's accuracy and user's accuracy when compared to NDVI and GNDVI. The results showed that it represented the true condition of the study area and more dependable than the other two vegetation indices. The results of NDVI, SAVI, and GNDVI showed that the moderate vegetation in form of Shrub and grassland Index class (0.2 – 0.4) has the highest area coverage in Oluwa Forest Reserve, signifying that it contains more bush than forest trees. Also, the SAVI result reveals that the class containing trees showed a declining order, as it decreased from 14.6% (173.166 Km²), to 9.2% (109.186 Km²) between 1991 and 2002, further decreased to 1.36% (16.25 Km²) in 2018. This signifies that the dense vegetation

(Tress) is declining in Oluwa Forest Reserve Area. The results of SAVI also showed that dense vegetation (>0.4) will decline by 69.80Km^2 by 2030. The study recommends that:

- i. SAVI vegetative index assessment should be used in future for monitoring the greenness of forest reserves in Ondo State and beyond;
- ii. The area covered by sparse vegetation and moderate vegetation revealed in this study should be re-forested through the planting of new trees;
- iii. Any erring Farmers practicing slash and burn agriculture that was evident during data collection for this research should be chased away from the forest environment or prosecuted; and
- iv. Sensitization program in form of an awareness campaign about the importance of forest trees to humanity vis-a-vis climate change mitigation and carbon sequestration should be re-echoed times without number both on social media and advert placement on Radio and televisions.

ACKNOWLEDGMENTS

Dr. Victor A. Ijaware wish to thank Akande Babatunde Abulazeez of Geomatics and Remote Sensing Research Group, Surveying and Geoinformatics Department Federal University of Technology, Akure, Ondo State Nigeria, West Africa for making the data for the research available. Credit also goes to Nnamani Onyemaechi John for reading and editing the manuscripts.

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