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Time-series Analysis of Vegetation Cover in the Southwest Nigeria using Remote Sensing and GIS

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Abstract— Dependable mapping and assessment of vegetation cover are essential for planning a sustainable ecosystem in the face of current global change. Satellite-based analysis of vegetation cover is an effective alternative to the costly ground-based surveys. Thus, this study is focused on monitoring the long–term modification in the vegetation cover of Southwest Nigeria from 2000 to 2020 using Time-series MODIS–NDVI datasets. The major plus for using MODIS–NDVI is its sufficient spatial, spectral, and temporal resolutions to identify distinct multi-temporal signatures for vegetation to distinguish vegetation from other land covers. For this study, MODIS–NDVI datasets covering Southwest Nigeria were acquired for 2000, 2010, and 2020. This was followed by image reprojection to WGS 84 and clipping of Southwest Nigeria. Also, the clipped images were classified and subjected to accuracy assessment using field-verified referenced data. Also, the change detection was conducted on the classified images. The result is a map of Southwest Nigeria showing non–vegetation, savanna, and forest areas. Furthermore, the overall image classification accuracies are 80 %, 82 %, and 83 %, for 2000, 2010, and 2020, respectively, while the kappa coefficients are 0.696, 0.728, and 0.731 for 2000, 2010, and 2020, respectively.

Keywords— Ecosystem, forest, global change, mapping, satellite imageries, savanna

I. INTRODUCTION

Vegetation broadly expresses the plant ecosystems on the biosphere, especially forest and rangeland resources. The forest ecosystem primarily comprises trees that buffer the Earth and sustain numerous life forms. Forest is a land area covering above 10 per cent tree crown cover and a spatial extent of above half a hectare [1] while rangeland vegetation covers native vegetation that is mainly grasses, grass-like plants, herbs and shrubs.

Investigating the condition of terrestrial vegetation is vital as it has demonstrated to be one of the most significant components of the Earth. For instance, the terrestrial vegetation plays a vital function in the process of energy interchange, and thus serves as an "indicator" for the assessment of global changes [2].

Nigeria is characterized by a wealth of vegetation cover due to its flexible climatic condition and physical features. Likewise, the Southwest Nigeria is well known for its dense forest resources. However, loss of vegetation in the form of deforestation and forest degradation is apparent in the zone due to both natural and anthropogenic factors. Generally, the loss of forests in Nigeria is at a yearly rate of 3.5 per cent [3]. Of course, the fast expansion in population, farming, fuel wood and logging is a major factor of deforestation [4] in the Southwest Nigeria. This is affecting the ecosystem [5] negatively as it contributes to the release of more greenhouse gases (especially carbon dioxide) into the atmosphere, which in turn results in many climatic variations and concomitant consequences. Of course, about 70 % of the total emissions in Africa come from deforestation [6]. Furthermore, the comprehensive representation of vegetation cover is lacking in most studies. There is more focus on the forest plantations through commercial inventories while rangelands, with little or no commercial value have not received adequate attention [7]. It is therefore vital to conduct a comprehensive estimation and mapping of vegetation encompassing forest and rangeland in the Southwest Nigeria.

Mapping vegetation with precision is a crucial task for managing nature, and it also plays an imperative role in different protection and restoration programs. Vegetation mapping offers a clue for understanding the environments [8,9], which is essential for sustainable management of critical ecosystem services. Currently, various approaches frequently used for mapping and evaluating vegetation exist. For example, the most accurate spatial extent of vegetation can be known through in-depth field surveys [10] and aerial photography. However, these techniques are not sufficient on an operational basis. Their applications are time–consuming, data lag, and costly. In contrast, satellite remote sensing affords an improved way of small– and large–scale assessment of vegetation changes [11,12]. The remote sensing is based on continuous and repeated observations of the Earth [13] and it is important for mapping and monitoring vegetation cover. Of course, the surface biophysical parameters retrieved from satellite imageries based on the unique spectral and textural properties [14] are fundamental for investigating and monitoring vegetation cover [15,16]. This is proven by the plethora of research in the literature (e.g., [17-23]). The present study is concerned with the application of satellite data in monitoring vegetation in the Southwest Nigeria from 2000 to 2020 by producing the map and estimate of vegetation and also detecting the alterations in the vegetation of the study area

Rest of the paper is organized as follows, Section I contains the introduction, Section II contain the related work, Section III explain the methodology, Section VI describes results and discussion, Section V concludes the research work with future directions.

II. LITERATURE REVIEW

Vegetation plays a significant ecological role in the global ecosystem. Plants are the major site for the interchange of water, energy, and momentum between the land and atmosphere, as such, they are essential in the climate system. Regrettably, the continuous population growth has resulted in the increase in unsustainable exploitation of vegetation particularly in the Tropics. Thus, several studies have been conducted using various approaches such as geospatial technology. For instance, Schucknecht, Erasmi, Niemeyer, and Matschullat [24] analyzed the variability of vegetation in north-eastern Brazil from 1982 to 2006 using satellite time-series data. It was shown that nearly 10 per cent of the study area is negatively affected while almost 28 per cent is positively affected.

Brandt, Hiernaux, Rasmussen, Mbow, Kergoat, Tagesson …, and Fensholt [25] used MODIS-based seasonal metrics to study woody vegetation in the Sahelian dry lands from 2000 to 2014. A fair accuracy with RMSE of 4.3 (woody cover percent) and $r^2 = 0.74$ was achieved.

Nwaogu, Okeke, Fadipe, Bashiru, and Pechanec [26] used Geoinformation technology to investigate the LULC change trajectories and how they influence the vegetation and landscape of Onitsha metropolis. It was discovered that all the vegetation types in the study area reduced in extent throughout the study period while the non-vegetation covers increased in 2015 when compared with the total in 1987.

Fashae, Olusola, and Adedeji [27] conducted a spatiotemporal assessment of vegetation over Nigeria from 1981 to 2010 using satellite images. The results revealed that dense vegetation declined from 358,534.2 km^2 in 1981 to 207,812 km^2 in 2010 while non-vegetation increased from 312,640.8 km^2 in 1981 to 474,436.4 km^2 in 2010. Also, the study predicts an increase in the non-vegetal areas to 501,504.9 km^2 by 2030.

III. METHODOLOGY

3.1 *LOCATION OF STUDY*

The area under investigation is Southwest Nigeria which lies nearly between longitudes 2° 59’ and 6° 00’ East, and Latitudes 5° 45’and 9° 15’ North (see Figure 1). It is a typical tropical environment. Its primary vegetation comprises freshwater swamps and mangrove forests. Also, the low land forest extends inland while secondary forest can be observed around the northern fringe where the derived southern savanna predominate [28].

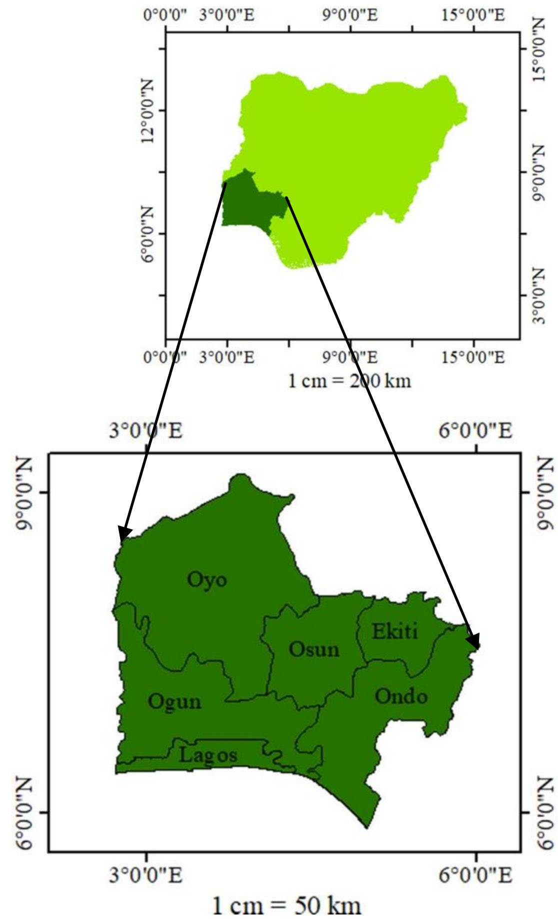


Figure 1. Inset map of Nigeria showing Southwest Nigeria

3.2 *MODIS–NDVI DATASETS*

Time-series data offers valuable information about what occurs after a disturbance [29]. Thus, investigating and monitoring LULC or vegetation requires the use of time-series data such as remotely sensed images of different epochs.

Normally, finer details on LULC information is afforded by satellite data with higher spatial resolution. Yet, high-resolution data call for laborious computations and extensive time for processing. Also, their utilizations are restricted to smaller study areas as they are expensive [30]. On the other hand, satellite data with coarser spatial resolution need less time for computation [31]. Thus, a time series of 16–day composite MODIS 500 m spatial resolution NDVI datasets (MOD 13A1) was acquired and used in this study. The acquired datasets covers the location of the study (h18v08) for the December period of 20 years between 2000 and 2020 at ten years intervals. The choice of MODIS data is because it represents the best trade-off among remote sensing data since they have (i) a high temporal resolution, (ii) a decadal acquisition period and (iii) a spatial resolution similar to parcel sizes [32].

3.3 *Field Verification Data*

To ensure that the information derived from an image is correct and truly represents the features as they are on the ground, field verification (ground-truthing) is required. In other words, ground data collection helps in building the link between the image and the ground reality. Reference data (that were used in the present study) are generally acquired from sources assumed to be more accurate than the data to be classified or by using a GPS-based approach. Area frame sampling with the aid of high resolution Google map that shows the observed site and surrounding area was used for field verification. A total of 200 points were collected with consideration to each land cover category in the classification scheme designed for this study.

3.4 *Processing*

MODIS datasets are delivered as HDF 10 by 10 arc degree– tiles in a Sinusoidal coordinate system. But the HDF and Sinusoidal projected data require further processing for them to be compatible with GIS and other processing environments. Hence the downloaded MODIS data were pre-processed to coerce them into a more usable format. Then, the subset images covering the location of the study were extracted to restrict the subsequent analysis to the area of interest (AOI). Furthermore, MODIS–NDVI values provided by NASA data are multiplied by 10000. These values were converted to index values (–0.2 to 1.0) by multiplying the datasets by a scale factor of 0.0001. Additionally, the NDVI threshold values used to recognize land cover classes were determined based on the ground truth information.

3.5 *Classification of MODIS datasets*

A proper classification scheme and an adequate number of training samples are requirements for effective image classification [33]. Developing a classification scheme involves selecting the criteria for defining and differentiating the classes. This depends on certain factors, including the purpose of classification and the number of attributes used to assign an object to a group, etc. The classification scheme adopted in this research employed the physiognomic categories. It includes non–vegetation, Savanna, and forest classes.

The land cover classification aims to categorize every pixel in an image into one of many land cover categories [34]. Based on their spectral signatures, the MODIS image pixels were classified into a finite set of groups that distinguished the unique surface types using the ISODATA unsupervised classification technique.

3.6 *Accuracy Assessment*

Accuracy assessment of image classification is essential for classification products to be used efficiently [35] as remote sensing data classification are frequently affected by errors from various sources. The confusion matrix was used in this study to show the accuracy assessment information in an error matrix (contingency table) [36]. Here, the tables used consist of arrays of numbers in rows and columns. Of course, the number of pixels ascribed to a certain land cover group relative to the real class on the ground was shown [37].

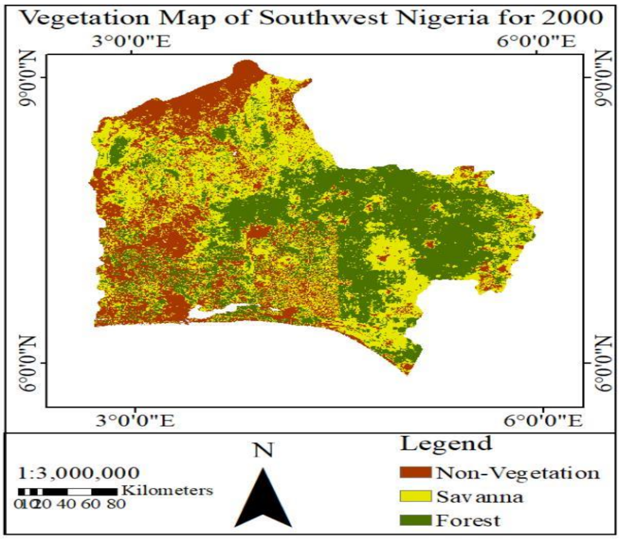
3.7 *Change Detection*

After classifying the MODIS datasets and the accuracy assessment was conducted, two independent layers were overlaid, and through the pixel–by–pixel comparison algorithm, those pixels that indicate changes between the images were determined [38]. In this way, changes were derived with regard to the groups rather than on the differences in Digital Number values.

IV. RESULTS AND DISCUSSION

The result presented here is a time-series of LULC of Southwest Nigeria for the period between 2000 and 2020 at ten-year interval. However, the main emphasis is on the vegetation land cover. The LULC classification maps for 2000, 2010, and 2020 are shown in figure 2. Similarly, the areal extent estimates of each LULC for the same epochs are presented in table 1. Also, the bar chart (figure 3) depicts the classification results for more clarity.

Figure 2 shows that for all the epochs of the study, the non–vegetation in the study region is predominant around the west and central areas. This covers all the other classes that are not of interest in this study, including built-up wetland, cropland, and other lands. Also, the savanna is virtually present all over the study location in all the epochs. It encompasses rangelands, meadows, herbs and brushes, grassland, and agricultural and Silvi–pastoral systems. Equally, the forest cover is more apparent in the eastern axis of the study area throughout the study epoch.



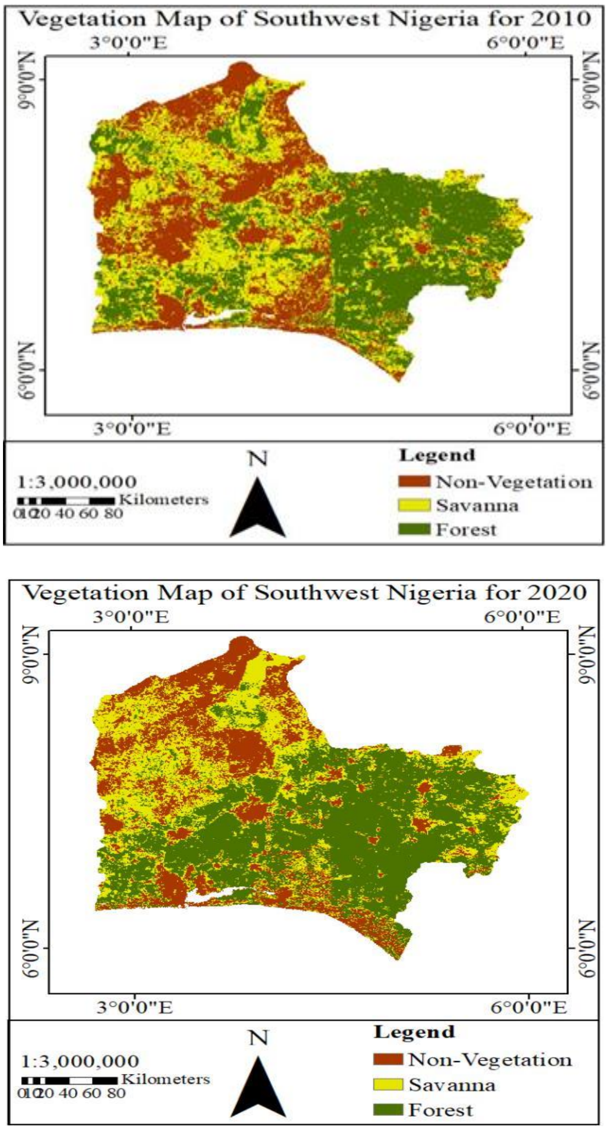


Figure 2. Land cover map of Southwest Nigeria: Top (2000), Middle (2010), Down (2020).

Table 1 revealed a fluctuating trend in non-vegetation. It occupied 26.46 % of the total land area in 2000, increased to 29.69 % in 2010 and decreased to 26.05 % in 2020. Savanna vegetation had a continuous decrease from 37.01 % of the total land area in 2000 to 34.10 % in 2010 and 29.86 % in 2020. The trend in forest cover is similar to that of non-vegetation. It reduced from 36.53 % in 2000 to 36.21 % in 2010 and increased to 44.10 % in 2020.

Furthermore, the dominant land cover type for each epoch is savanna with a spatial extent of 28,442 square kilometres in 2000, forest covering an area of 33,891 square kilometres in 2010, and forest with an areal coverage of 33,891 square kilometres in 2020. On the other hand, the non-vegetation is shown to have the list coverage throughout the three epochs.

Table 1. Areal extent (in sqm) and percentage coverage of LULC classes

Year		Non–Vegetation	Savanna	Forest	Total
2000	Area	20332	28442	28078	76852
	%	26.46	37.01	36.53	100
2010	Area	22821	26210	27821	76852
	%	29.69	34.10	36.21	100
2020	Area	20017	22945	33891	76852
	%	26.05	29.86	44.10	100

The following bar chart (figure 3) presents the classification results to support a better visualization of the vegetation cover in the study area, and its spatiotemporal behaviour.

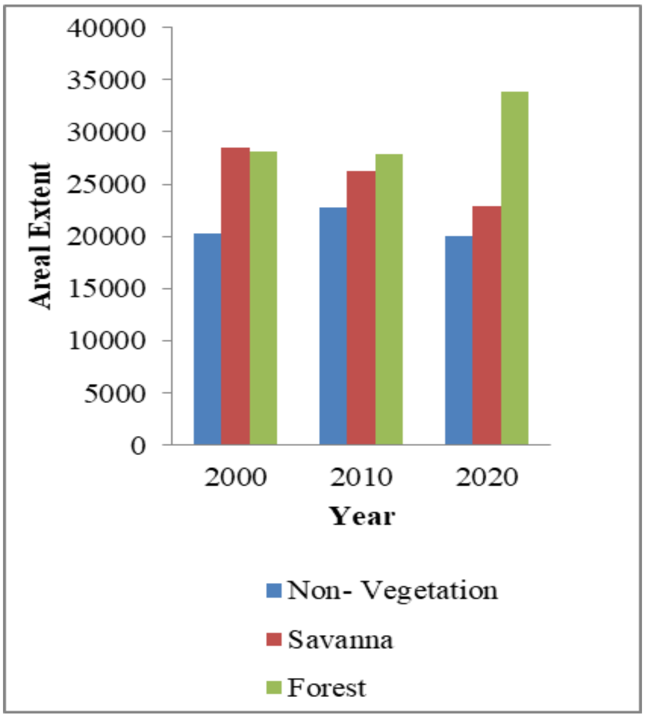


Figure 3. Bar chart showing the areal extent of the classified land covers

Furthermore, the statistical information regarding the accuracy assessment is presented in the contingency table (table 2). The ground verification data were utilized as the independent datasets from which the classification accuracies and the kappa coefficients were computed. The error matrix generated by using 200 reference data shows overall accuracies of 80 %, 83 %, and 83 % for 2000, 2010, and 2020, respectively. Also, the Kappa (K) coefficients indicate a good agreement measure with Kappa values of 0.696, 0.728, and 0.731 for 2000, 2010, and 2020, respectively. Of course, this level of kappa coefficient is highly acceptable because the agreement can only be said to be poor when $K < 0.4$ and good when $0.4 < K < 0.7$.

Table 2: Error matrices for 2000, 2010, and 2020 LULC classifications

	2000						
	Reference Data						
	Class	Non–Vegetation	Savanna	Forest	Total	U_Accuracy	Kappa
Classified Data	Non–Vegetation	48	4	1	53	0.906	0.000
	Savanna	2	58	14	74	0.784	0.000
	Forest	0	19	54	73	0.740	0.000
	Total	50	81	69	200	0.000	0.000
	P_Accuracy	0.960	0.716	0.783	0.000	0.800	0.000
	Kappa	0.000	0.000	0.000	0.000	0.000	0.696

	2010						
	Reference Data						
	Class	Non–Vegetation	Savanna	Forest	Total	U_Accuracy	Kappa
Classified Data	Non–Vegetation	58	1	0	59	0.983	0.000
	Savanna	0	49	19	68	0.721	0.000
	Forest	0	16	56	72	0.778	0.000
	Total	58	66	75	199	0.000	0.000
	P_Accuracy	1.000	0.742	0.747	0.000	0.819	0.000
	Kappa	0.000	0.000	0.000	0.000	0.000	0.728

	2020						
	Reference Data						
	Class	Non–Vegetation	Savanna	Forest	Total	U_Accuracy	Kappa
Classified Data	Non–Vegetation	52	0	0	52	1.000	0.000
	Savanna	0	44	16	60	0.733	0.000
	Forest	0	19	69	88	0.784	0.000
	Total	52	63	85	200	0.000	0.000
	P_Accuracy	1.000	0.698	0.812	0.000	0.825	0.000
	Kappa	0.000	0.000	0.000	0.000	0.000	0.731

Also, the post-classification comparison technique used in this study involves the digital grouping of the multi-temporal image of the same area. It resulted in the matrices that offered ‘from-to’ information (see table 3). Land cover changes were computed between 2000 and 2010, and between 2010 and 2020 for the three land cover types’ classification.

Furthermore, table 4 demonstrates a rising tendency with a magnitude of 2482.10 km^2 (124.45 %) for the non–vegetation between 2000 and 2010. However, the result shows a decrease of 2791.85 km^2 (124.43 %) between 2010 and 2020. Similarly, the savanna vegetation shows a reduction in spatial extent throughout the epochs. The decrease is about 2230.95 km^2 or 79.30 % between 2000 and 2010, and 3271.40 km^2 or 126.30 % between 2010 and 2020. Also, the forest land cover class decreased by 251.151 km^2 (9.04 %) from 2000 to 2010, and increased by 6063.25 km^2 (220.31 %) from 2010 to 2020.

Table 3: Change matrices for 2000 to 2010 and 2010 to 2020 classifications.

2000 to 2010				
Class	***Non–Vegetation***	***Savanna***	***Forest***	***Total***
Non–Vegetation	11931802355	6026756911	1986236704	19944795971
Savanna	8045192416	12042136913	8048626955	28135956285
Forest	2449899438	7836114869	17488242113	27774256420
Total	22426894210	25905008693	27523105773	

2010 to 2020				
Class	***Non–Vegetation***	***Savanna***	***Forest***	***Total***
Non–Vegetation	12675165341	7348195704	2413836781	22437197826
Savanna	5630282342	10492086633	9780707790	25903076765
Forest	1339899439	4791396247	21389663501	27520959186
Total	19645347121	22631678584	33584208072	

Table 4: Change magnitude (km^2) and percentage change from 2000 to 2020

	2000 – 2010		**2010 – 2020**	
	Change Mag.	**% Change**	**Change Mag.**	**% Change**
Non–Vegetation	2482.10	124.45	–2791.85	–124.43
Savanna	–2230.95	–79.30	–3271.40	–126.30
Forest	–251.151	–9.04	6063.25	220.31

V. CONCLUSION AND FUTURE SCOPE

The preceding sections have demonstrated a technique of studying vegetation land cover using satellite remote sensing and GIS technologies. Generally, this paper indicates how time-series satellite data is suitable for land cover change analysis.

The remote sensing vegetation indices have been a primary factor in vegetation monitoring. The MODIS NDVI–based vegetation mapping and monitoring implemented in this study allows for the acquisition of information about the rapid LULC change such as vegetation alterations, which has been a dominant scenario in the tropical region.

The result of this research, which is, for the most part, vegetation–based land cover map and estimate for Southwest Nigeria, would find applicability in a far-reaching spectrum of fields, especially in ecological applications. In addition, the result shows the importance of the satellite datasets for estimating vegetation, even in the regions that, historically, researchers were unable to reach. It is also hoped that this research would stimulate similar studies in other parts of Nigeria experiencing a shortage in the supply of accurate vegetation cover maps.

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