SPATIO-TEMPORAL MAPPING OF WETLAND ECOSYSTEM IN ABEOKUTA NORTH LOCAL GOVERNMENT AREA, NIGERIA

BY

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ABSTRACT

The environmental benefits accruable to mankind through wetland ecosystems are unquantifiable. The wetland ecosystem services principally include the gradual recharge of groundwater and provision of habitat for fauna and flora. The increase in human population over the years has accelerated growth in anthropogenic activities, which, have led to the conversion of wetlands to other land uses. In the sequel, it has become imperative for researchers to focus on the mapping of wetlands through time-efficient, automated and low-cost methods to preserve the existing wetlands. In pursuance of this, geospatial technology was deployed in this study to assess the spatial characteristics of the wetland ecosystem in Abeokuta North Local Government Area (LGA). Landsat imagery and Shuttle Radar Topography Mission (SRTM) were the major data used. Object-based classification, Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), Elevation and Topographic Wetness Index (TWI) algorithms in ArcGIS 10.4 software were deployed in data generation and analysis. The Land use land cover (LULC) showed that the Forest area was 20338 ha (26%), 13440 ha (17%), and 10427 ha (13%) in the years 2001, 2011 and 2021 respectively. The results of the mapped wetland showed that in 2001, about 10803 ha of the study area was occupied by wetlands and water bodies. In 2011, it decreased to 10443 ha, with a difference of about 360 ha. It further decreased to 8598 ha in 2021. Government and private organizations should establish policies aimed at minimizing the growing dangers to wetland ecosystems, as a recommendation. This might be accomplished by preventing farmers and other land developers from encroaching into wetlands.

Key words: Geospatial techniques, MNDWI, NDVI, SRTM, TWI, Wetland

INTRODUCTION

Wetlands are among the most significant, multi-functional, and productive ecosystems on the earth (Mengesha, 2017; Davidson et al., 2019). Places that have shallow water or lands that are permanently saturated with temporarily inundated floodplains are classified as wetlands (Ralph et al., 2015). Freshwater aquatic systems that are greater than 2.5 m deep in America are considered "deep-water habitats". They are not considered wetlands unless they support persistent self-supporting vegetation (Wetlands Subcommittee, 2013). Many indigenous peoples and rural residents still rely on local wetlands and water sources for survival. Most countries now recognize wetlands as one of the world's most valuable natural resources (Schuyt, 2005). Approximately 8% of the world's land surface area is covered by wetland and contain 20% of the global terrestrial carbon (Dixon et al., 2021). However, despite the environmental degradation faced by wetlands, there is an increasing demand for wetland ecosystem services they provide (Suding, 2011). By 2050, global water demand is projected to increase by 55% (Terefe, 2017).

One of the uniqueness of wetland is that it serves as a transitional belt between terrestrial and aquatic systems where the water table is at or near the surface (Ollis et al., 2013). Some of the essential environmental services attributable to a wetland ecosystem, include storing floodwater, reducing peak runoff, recharging groundwater, filtering impurities in water, carbon storage, and critical habitat for several species of plant communities, invertebrates, fish, and wildlife (Wu, 2018; Chouari, 2021). According to Russi et al. (2013), about 50 % of the world's wetlands may have been lost. It is also pertinent to state according to Polidoro et al. (2010) that, sixteen of the world's 70 known species of mangroves are now on the verge of extinction. As a result of rising sea levels, wetlands are becoming increasingly common in coastal lowland areas (Tiner, 2013).

Comprehenvive monitoring of the dynamics of wetland and its resources are very imperative (Kaplan and Avdan, 2019; Wu, 2018). The deployment of Remote Sensing and Geographic Information System (GIS) in the mapping and inventory of wetlands have been further enhanced (Suryabhagavan, 2017). Image interpretation and feature extraction are very germane in Remote Sensing-based wetland mapping, especially concerning accuracy. According to Ozesmi et al. (2002), achieving high accuracy in wetland mapping is quite a herculean task with regards to pixel-based classification. Another mapping constraint of the wetland is the spatial resolution of commonly used image datasets (such as 30-m Landsat) which are often frequently insufficient to detect fine-scale wetland features at sub-pixel scales (Dronova et al., 2011). Given the aforementioned drawbacks, object-based image analysis (OBIA) offers a better classification approach to address these constraints in heterogeneous wetland landscapes. The key benefits of OBIA relative to pixel-based methods include the possibility of incorporating object-level shape, texture and relevant contextual variables into classification (Blaschke, 2010).

In Nigeria, population explosion, urban migration, and poor management of urban growth have led to encroachment into the wetland areas (Wali et al., 2018a). Obiefuna et al. (2013) determined the spatial changes in the wetlands of Lagos/Lekki Lagoons of Lagos, Nigeria. They employed the parallelepiped classification technique which uses a simple decision rule to classify multispectral data. Field and ancillary data were also used for validation. Results showed that there was a significant reduction in the wetland ecosystems during the study period. Li et al., 2022 deployed Random Forest and K-Nearest Neighbour classifiers for classification. Four vegetation indices (Normalized Difference Vegetation Index, Difference Vegetation Index, Enhanced Vegetation Index and Ratio Vegetation Index) were also used to extract data from Sentinel-2 image. The results showed that Random Forest and K-Nearest Neighbour classifiers performed very well in wetland delineation. Conversely, the use of four vegetation indices for wetland mapping was not satisfactory. These studies though quite robust, did not emphasize the contributions of elevation and by extension the Topographic Wetness Index (TWI) in their studies. Therefore, the objective of this study is to assess the spatio-temporal dynamics in wetland distribution in Abeokuta North, Ogun State, Nigeria.

THE STUDY AREA

This research was carried out in Abeokuta North Local Government Area of Ogun State, southwest Nigeria. The study area falls within Latitudes 7°4'3"N and 7°25'8"N and Longitudes 3°0'2"N and 3°21'12"E (Fig. 1). The basement complex rocks that underlain the topography of the study area, is characterized by a general rising elevation ranging from 30m to 40m above sea level (Akinyemi and Souley, 2014). The study area has two distinctive seasons, namely, the dry (from November to February) and the rainy season (from March to October). The average annual rainfall varies from about 1200 mm to 1472 mm (Ogun-Oshun River Basin Development Authority (OORBDA), 1996). The average minimum and maximum air temperatures are 23°C and 32°C. Relative humidity varies from 76% to 85% coinciding with the dry and wet seasons respectively (Akinyemi and Souley, 2014).

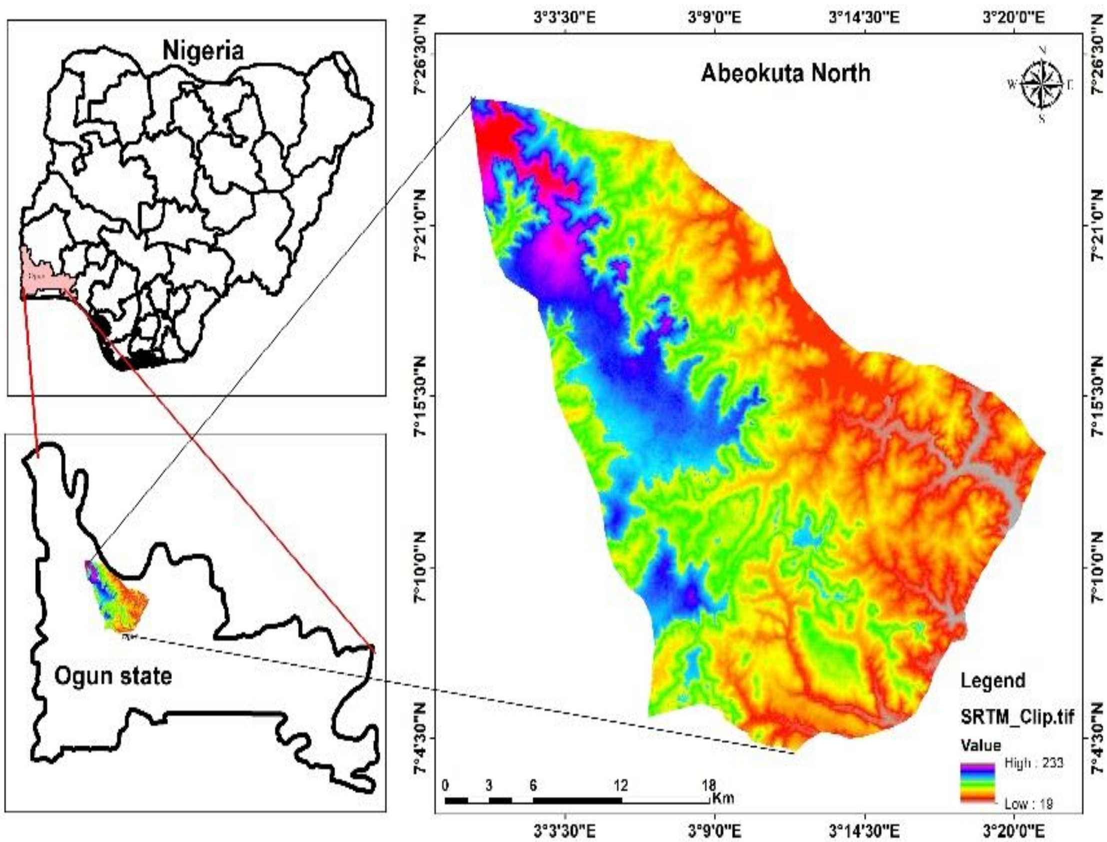

Figure 1: The Study Area

MATERIALS AND METHODS

The flow chart of the methodology is shown in Figure 2. The Landsat imagery for this study from path 191 and row 55, was downloaded from the United States Geological Survey (USGS) Global Visualization Viewer (GLOVIS) website (http://glovis.usgs.gov). The specifications of the Landsat images are shown in Table 1. Atmospheric correction was applied to all images using the Dark Object Subtraction 1 (DOS1) as contained in the Semi-Automatic Classification Plugin of QGIS 3.16 software. The algorithm used all the required information contained in the Landsat header MTL metadata file to carry out the required image preprocessing.

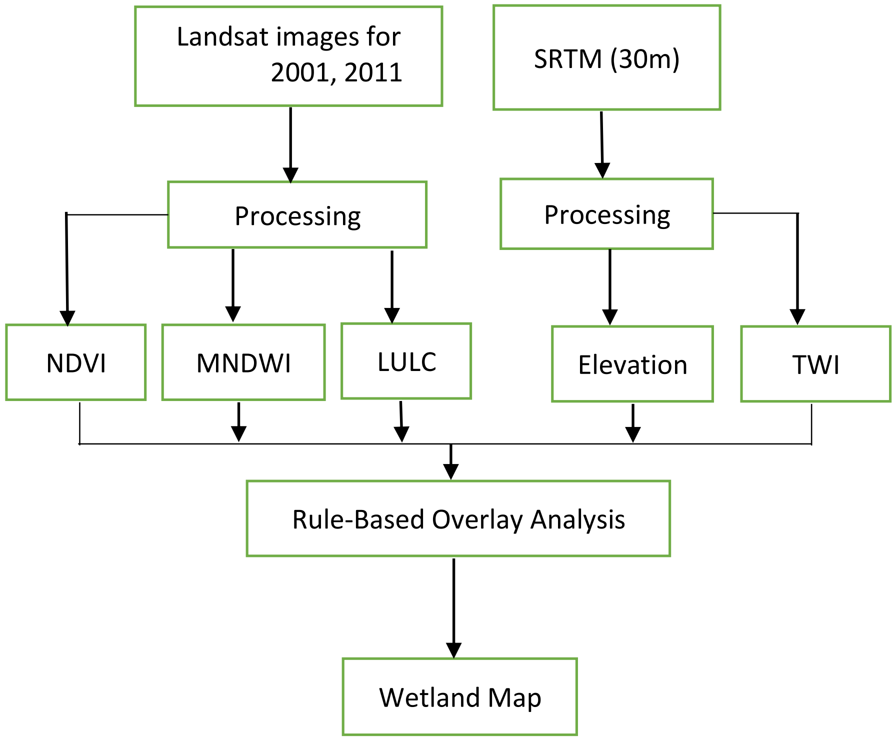

Figure 2: The Flow Chart of the Methodology

Table 1: Characteristics of Landsat Satellite Images

Acquisition date	Sensor Type	Path	Row	Spatial resolution
12/3/2001	Landsat 5 TM	191	55	30m x 30m
16/2/2011	Landsat 7 ETM+	191	55	30m x 30m
26/3/2021	Landsat 8 OLI	191	55	30m x 30m
2014	SRTM	-	-	30m x 30m

The generated map was projected to World Geodetic System (WGS) 1984 Universal Transverse Mercator (UTM) zone 31 N. The subset of the study area from the Nigeria shapefile was carried out using QGIS 3.16. The images were imported to ArcGIS 10.4 where bands of the images were composited for further analysis. An object-based classification method was adopted because it achieves better accuracy than pixel-based classification. Maximum likelihood supervised classifications were performed in ArcGIS 10.4 on the Landsat imagery. Five thematic classes were identified namely Bare land, Shrubs, Forest, Wetland and Waterbodies.

For the extraction of elevation and the Topographic Wetness Index (TWI), the Shuttle Radar Topography Mission (SRTM) Global Digital Elevation Model (DEM) of 30 m (Farr et al., 2007) was obtained from the Open Topography website (http://opentopo.sdsc.edu). Hilly areas are best represented when compared to high-resolution data with SRTM (Acharya et al., 2018). Basic Terrain Analysis Tools in SAGA 6.4.0 software were deployed to generate all the necessary data outputs (maps) for this study (Table 2).

Table 2: Multiband Indices used for Water Feature Extraction

Multiband	Equation	Water	Reference
Normalized Difference Vegetation Index	NDVI = (NIR - Red)/ (NIR + Red)	Negative	Rouse et al., (1973) Jones, (2015)
Modified Normalized Difference Water Index	MNDWI1 = (Green - SWIR1)/ (Green + SWIR	Positive	McFeeters (1996) Lane et al., (2014)
Topographic Wetness Index	$TWI = \ln\left(\frac{\sigma}{Tan\beta}\right)$	Positive	(Beven & Kirkby, 1979).

The Normalized Difference Vegetation Index (NDVI) and Wetland

The NDVI measures the vigour or health of a plant leaf by picking the frequency that the plant leaf releases (Xue and Su 2017; Onyia et al. 2018). Several researchers have used NDVI for wetlands change detection mapping (Nsubuga et al., 2017; Das, 2017; Li et al., 2019; Dehm et al., 2019) and they all concluded that NDVI is significantly useful in wetland mapping. The Red and NIR bands help to discriminate plant from non-plant and water from other surface features. The NDVI values range from -1 to 1, where negative values close to -1 correspond to water, and positive values indicate vegetation cover (Zhao et al. 2017). The derived values from NDVI were then reclassified into three classes (non-vegetation, water, and vegetation) using information from Remote Sensing literature (Wilson and Norman 2018). In the study, NDVI thresholds were set between -0.21 and 0.19 for non-vegetation, NDVI ≥ 0.2 for vegetation and NDVI ≤ -02 for water. The formula for calculating NDVI is contained in Equation 1.

$$NDVI = \left(\frac{NIR - Red}{NIR - Red}\right) \qquad (1)$$

Where NIR represents the Near-Infrared Band and Red represents the Red band.

Modified Normalized Difference Water Index (MNDWI) and Wetland

One of the weaknesses of NDWI in extracting water information is that it often mixes with built-up spectral noise. Therefore, if a MIR band is used instead of the NIR band in the calculation of NDWI, the built-up areas would have negative values (HANQIU, 2006). In the sequel, the NDWI was modified by substituting the MIR band for the NIR band to produce the Modified Normalized Difference Water Index (MNDWI) **(**Lane et al., (2014). The use of MNDWI will result in a more accurate extraction of open water features. The Normalized Difference Vegetation Index (NDVI) and the Modified Normalized Water Index were both used to also extract wetland using different threshold values. This was premised on the previous work by Das (2017) and Dehm et al. (2019).

$$MNDWI = \left(\frac{Green - MIR}{Green - MIR}\right) \qquad (2)$$

Where;

Green represents band two in ETM+ and band three in OLI
MIR represents the Mid Near-Infrared Band.

Topography Wetness Index

This tool calculates the topographic wetness index (TWI) to be subsequently used as a predictor of wetland areas. The TWI relates the tendency of an area to receive water to its tendency to drain water and is defined in Equation 3

$$TWI = \ln\left(\frac{\sigma}{Tan\beta}\right) \tag{3}$$

Where;
α is the specific catchment area (contributing area per unit contour length) and
tan(β) is the local slope (Beven & Kirkby, 1979).

Generally, TWI is calculated based on a hydrologically-corrected DEM, implying that all sinks (including real depressions) are filled before TWI computations. Due to the sink-filling pre-processing, flow directions, flow accumulations, and slopes of all the grids associated with depressions are altered (Habtezion et al., 2016). In this study, the Topographic Wetness Index (TWI) was derived from Shuttle Radar Topography Mission (SRTM) 30 DEM using The System for Automated Geo-Scientific Analyses (SAGA) software (Mattivi et al., 2019). SAGA 6.4.0 is an open-source GIS, that since its first release in 2004 has rapidly developed from a specialized tool for digital terrain analysis to a comprehensive and globally established GIS platform for scientific analysis and modelling (Mattivi et al., 2019).

Object-based classification of wetland

Given the complexities involved in the mapping of wetlands, this study deployed the Object-Based classification algorithm against the pixel-based classification. This is because the OBIA technique has now replaced the traditional pixel-based method as the new standard method of land-cover classification from remote sensing imagery (Blaschke et al., 2014. This assertion, however, appeared to have been supported by numerous researchers (Cleve et al., 2008; Myint et al., 2011; Duro et al., 2012a; Tehrany et al., 2014). This study deployed an OBIA algorithm to extract wetlands. It first and foremost segmented an image into “objects” that are groups of pixels representing ground features that can subsequently be classified of interest by unsupervised, supervised or rule-based algorithms (Blaschke, 2010).

RESULTS AND DISCUSSION

Wetland delineation using spectral indices

As shown in Figures 3 and 4, the results demonstrated that using spectral indices like NDVI and MNDWI to identify changes in the wetland environment did not provide a good delineation of the wetland. The coarse nature of Landsat photos could be to blame for this. Jones (2015) validated my findings in his paper titled "Efficient Wetland Surface Water Detection and Monitoring through Landsat: Comparison with in situ Data from the Everglades Depth Estimation Network." The subjective character of threshold selection was one of the recognized limitations in the use of MNDWI for wetland delineation (Thomas, 2015; Gordana and Ugur, 2018).

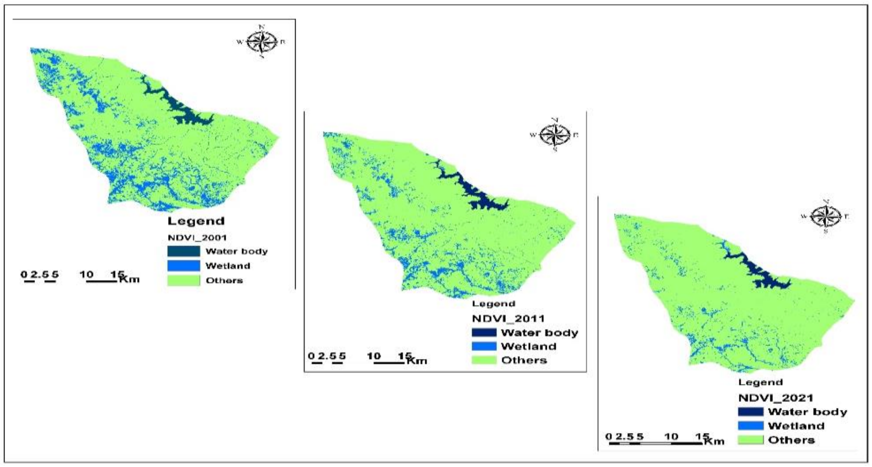

Figure 3: Normalized Difference Vegetation Index (NDVI) for 2001, 2011 and 2021

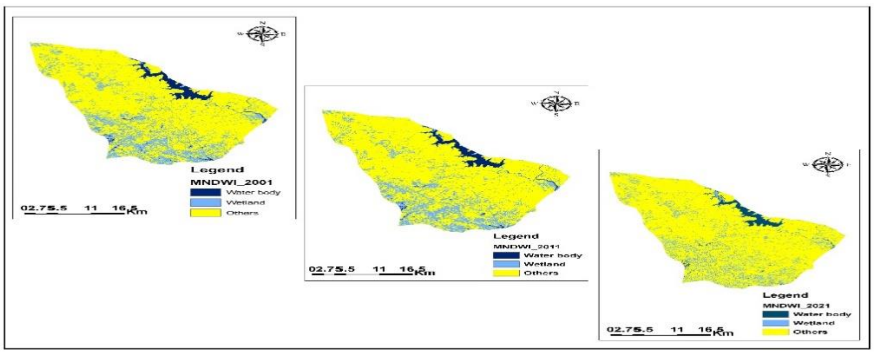

Figure 4: Modified Normalized Difference Water Index (MNDWI) for 2001, 2011 and 2021.

To further delineate the wetland areas, an elevation map (Fig. 5) was used to identify places that were susceptible to the wetland concerning the surrounding pixels. The pie chart in Figure 5 showed that about 16% of the study area was occupied by a very high elevation. About 22%, 31% and 31% were High, Low and Very low areas respectively. Water bodies and wetland ecosystems were situated within the Very low the Low areas of the elevation map.

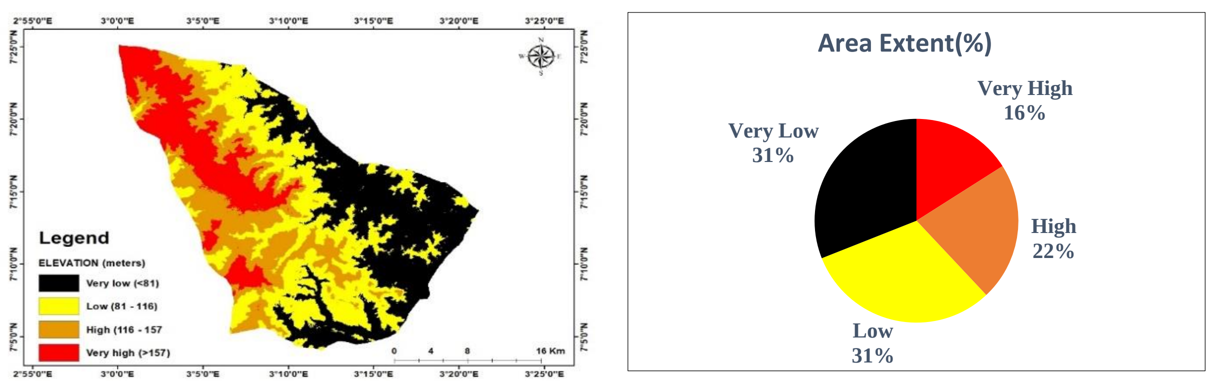

Figure 5: Elevation map and the pie-chart of the study area

Land use land cover classification in relation to wetland mapping

The results of the OBIA classification algorithms (Fig. 6) showed that in the year 2001, wetland occupied a total area of about 12415 ha (16%). This drastically reduced to 9283 ha (12%) in 2011. In 2021, there was a further reduction in the area extent of wetland cover which reduced to 5366 ha (7%). The study area is very reputable as one of the agrarian Local Government Areas in Ogun State, Southwest Nigeria (Adamu, 2018). By extension, therefore, most of the farmers are heavily dependent on the wetland ecosystem for their dry season farming. One of the environmental impacts of this and other anthropogenic activities is the systematic depletion of the wetland within the study area as depicted in Table 3. There is a symbiotic relationship between forest land cover and wetland conservation. A reduction in forest abundance exposes the hitherto protected wetland areas to water loss due to evapotranspiration among other factors. This study revealed that forests covered about 20338 ha (26%), 13440 ha (17%) and 10427 ha (13%) in the years 2001, 2011 and 2021 respectively. Table 4 revealed that between 2001 and 2021, Bare land increased by about 7%.

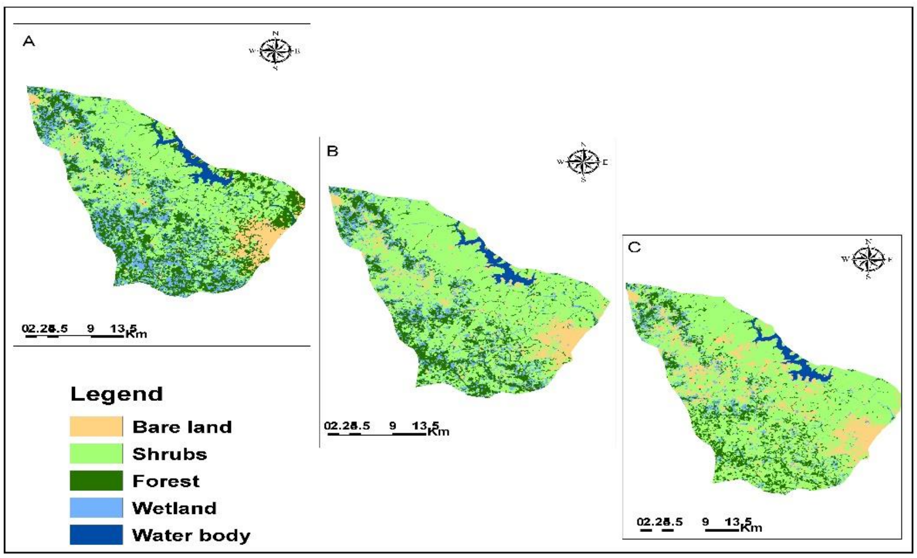

Figure 6: LULC for 2001(A), 2011(B) and 2021(C)

Table 3: LULC statistics extracted from the classified images

	2001		2011		2021	
Class	Area (ha)	%	Area (ha)	%	Area (ha)	%
Bare land	5773	7	82887	9	11506	14
Shrubs	38042	48	47611	60	50495	63
Forest	20338	26	13440	17	10427	13
Wetland	12415	16	9283	12	5366	7
water body	3173	4	1947	2	1947	2

Shrubs also increased by about 15%, that is from 38042 ha in 2001 to 50495 ha in 2021. Forest, Wetland and Water decreased by about 13%, 9% and 2% respectively. The decrease in Forest, Wetland and Water bodies attested to the fact that anthropogenic activities especially farming, had contributed to the changes noticed during the study.

Table 4: Changes in LULC between 2001 and 2021

	Change (2001-2011)		Change (2011-2021)		Change (2001-2021)	
Class	Area (ha)	%	Area (ha)	%	Area (ha)	%
Bare land	77114	2	71381	5	5733	7
Shrubs	9569	12	2884	3	12453	15
Forest	-6898	9	-3013	4	-9911	13
Wetland	-3132	4	-917	5	-7049	9
Waterbody	-1226	2	0	0	-1226	2

Table 4 and Figure 7 showed the LULC changes between 2001and 2011, 2011 and 2021, and finally between 2001 and 2021. Bare land increased with a total area of about 5733 ha (7%) between 2001 and 2021. Shrubs, which includes farmlands, also witnessed an astronomical increase in area extent. It had increased by about 12453 ha (15%). This could be attributable to the increase in the number of people going into farming activities. Conversely, changes in Forest, Wetland and Waterbody were on a downward trend with 13%, 9% and 2% respectively. Deforestation, as a result of farming, causes a reduction in the wetland ecosystem and water bodies.

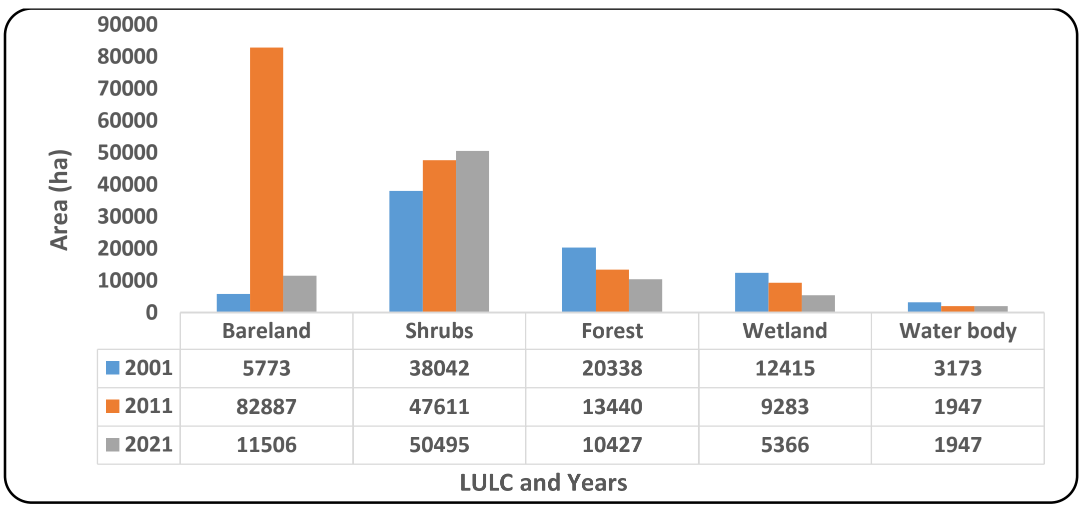

Figure 7: A chart showing the LULC statistics of the study area

The topographic wetness index (TWI) from the study, depicted the stream network in the study area. However, it was unable to correctly outline the wetlands (Fig. 8). Some places with high elevation were misclassified as wetlands when in reality, they were up streams of the drainage system. This drawback was also noticed in the wetland land cover change detection using multitemporal Landsat data in Saudi Arabia by Chouari (2021). The TWI ranged between -12.19 to 8.58. Using the symbology stretched colour rump, the blue colour represents places with high TWI (threshold >6), while the magenta and yellow colours represent places with low TWI (threshold <6)

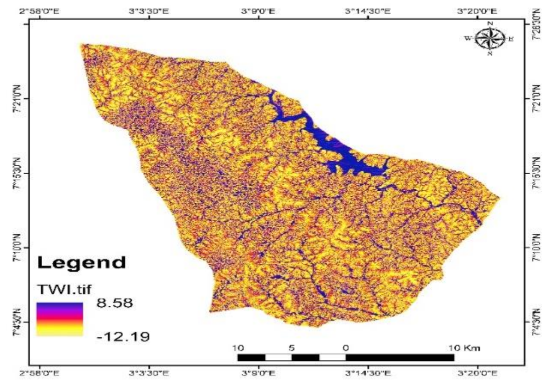

Figure 8: TWI map showing rivers and wetlands

Figure 9 revealed that most of the wetlands are located at the southern axis of the study area. Table 5 showed that in 2001, about 10803 ha of the study area was occupied by wetland and water bodies. In 2011, it decreased to 10443 ha, with a difference of about 360 ha.

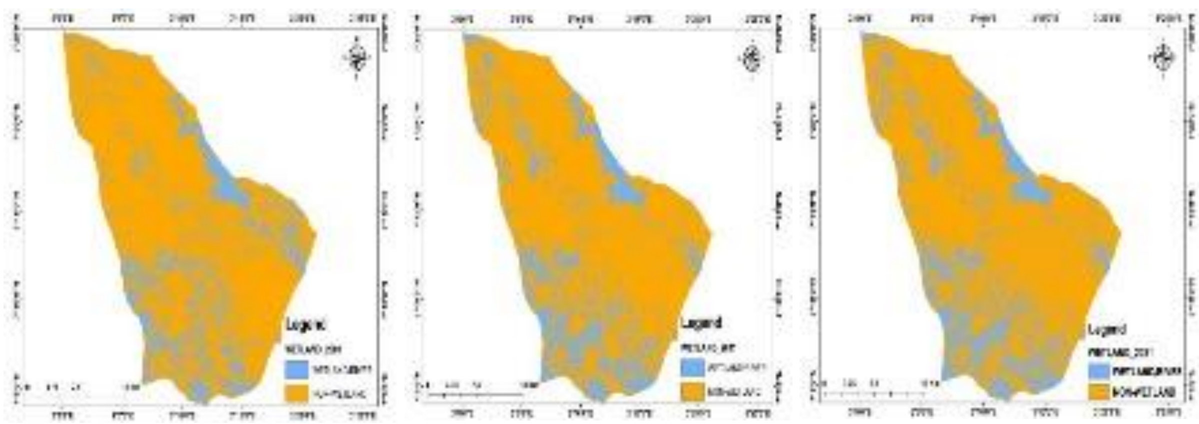

Figure 9: Map of wetlands in 2001, 2011 and 2021

The wetlands decreased from 10443 ha (13%) in 2011 to 8598 ha (11%) in 2021. While the wetlands were decreasing, the none wetlands were increasing from 65347 ha in 2021, 65707 ha in 2011 to 67452 ha in 2021. This aligns with similar studies on wetland dynamics (Taiwo and Areola, 2009; Odunuga and Oyebande, 2007; Orimoogunje et al., 2009; Ollis et al., 2013; Amsalu et al., 2014 Chouari, 2021). The environmental implications of these findings are that the wetland ecosystem is rapidly being depleted, and consequently, all the ecosystem services provided by the wetlands are diminishing.

Table 5: Wetland statistics for 2001, 2011 and 2021

CLASS	2001		2011			2021		
	Area(ha)	**%**	**Area(ha)**	**%**	**Diff. (%) 2001-2011**	**Area(ha)**	**%**	**Diff. (%) 2011-2021**
WETLAND/RIVER	**10803**	**14**	**10443**	**13**	**1**	**8598**	**11**	**2**
NON-WETLAND	**65347**	**84**	**65707**	**87**	**1**	**67452**	**89**	**2**

Table 5 shows that in the periods under consideration, wetlands consistently decreased with increasing expansion in non-wetland areas of the study areas. Hence wetland decreased from 10803 ha in 2001 to 8598 ha in 2021, whereas non-wetland increased from 65347 ha in 2001 to 67452 ha in 2021. These findings are in concert with the studies conducted by McDonald et al., (2014) and Wali (2018), that built-up area has negative implication on wetland loss. Hence an inverse relationship exists between non-wetland and wetland loss.

CONCLUSION

Wetlands render numerous environmental services which are of socio-economic benefits to communities. The pressure on wetlands is attributable to the increase in anthropogenic activities. It, therefore, behooves all stakeholders to work assiduously towards more comprehensive monitoring of the changes occurring in the wetland area. The present study was therefore carried out to underscore the spatial and temporal changes occurring in the wetland areas in Abeokuta North Local Government Area. It was revealed that about between 2001 and 2021, about 2205 ha of hitherto wetlands have been converted to other land uses. Government and private organizations should establish policies aimed at minimizing the growing dangers to wetland ecosystems, as a recommendation. This might be accomplished by preventing farmers and other land developers from encroaching into wetlands.

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