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Relating the Land-Use Changes to the Invasion of *Pneumatopteris afra* in Nigeria Using Remote Sensing

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ABSTRACT

The study aimed at using satellite remote sensing in identifying the land-use changes that have occurred in Lafia, Nigeria within the past 35 years, especially in relation to the current and the predicted future invasion of a fern (*Pneumatopteris afra*). Landsat satellite images OLI/TIRS, ETM+ and TM within the interval of 15 years from 1985 to 2020 were used for the extraction of land-use. Six broad classification systems were used to classify the land-use changes by employing a supervised classification technique. In 1985, the bare land dominated the land-use having an area of 69156 ha while the wetland was the least having an area of 3412 ha. However, in 2020, the built-up area has dominated the land-use of Lafia with an area of 144645 ha (52.21%) while the wetland still remained the least with area of 1477 ha. This is obviously due to the geometric increase in the urbanization of this city. There was a consistent loss of the forests from 1985 to 2020 with an annual rate of loss of 0.46%. This resulted in a loss of 44329 ha of forests in 2020 out of the 47643 ha in 1985. This approximately leads to a total loss of 172,732,045 USD of forest products. The current invasion of *Pneumatopteris afra* in Lafia was found to fall within the shrub and grasses land-use class. This indicates that the landsat satellite could not detect the wetlands where the plant dominated due to its massive covering. This study calls for immediate conservation of the remaining forests and wetlands in Lafia to prevent further encroachments and invasion by plants.

Keywords: Forests, GIS, invasion, Lafia, *Pneumatopteris afra,* remote sensing

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INTRODUCTION

Land-use change may be regarded as the changes that have occurred in the environment over a long period of time which can be measured by comparing the past and current land-use or vegetation data (Kapfer et al., 2017; Vellend et al., 2013). One of the main consequences of land-use change is the habitat fragmentation and loss, reduction in species diversity, changes in species composition and vegetation structure (Rodríguez-Echeverry et al., 2018; Savilaakso et al., 2014). These are mostly caused by the alteration in processes of community assemblages, for instance habitat filtering and limitation of dispersal (Bergeron et al., 2019). Land-use change may also result in changes in ecosystem functions (Laliberté & Tylianakis, 2012) and making the area susceptible to invasion by either plants or animals (Rembold et al., 2017).

Land-use types coupled with other factors such as soil functioning, ecosystem disturbances, community structure, species composition and diversity are known to determine the vulnerability of an ecosystem to biological invasions (Dimitrakopoulos et al., 2017; Menzel et al., 2017; Rembold et al., 2017; Schrama & Bardgett, 2016). This is regarded as the invasibility of such ecosystems (Catford et al., 2012; Milbau et al., 2009). One other thing that contributes to the high diversity of invasive species in an area is the broad environmental conditions of such area (Wilson et al., 2020). The climatic conditions most importantly influence the establishments of invasive plant species at larger scales while the local land-use activities mostly enhance the spread of invasive plants at habitat scales (Terzano et al., 2018).

In addition, several researches have revealed that the past land-use systems do influence the present distribution of species due to the alteration in the soil physic-chemical properties and disturbance regimes of the ecosystems (Flinn & Vellend, 2005; Johnson et al., 2015). Knowledge of land-use pattern of an area is important for the understanding of the vegetation cover changes of such area over a long period of time (Brůna, 2018). In actual form, land-use type of an area is a function of the degree of intensity and types of human disturbances in the ecosystems (Bart et al., 2015; Chytrý et al., 2012; Clotet et al., 2016; Csecserits et al., 2016). Therefore, there is a direct relationship between the land-use type and the environmental factors (mostly anthropogenic) of the ecosystem (Zhou et al., 2019). In addition, areas with high rate of disturbances in the land-use, for example urban areas are found to be more susceptible to the survival and spread of invasive plants (Portgieter et al., 2020). The construction of roads and railways in some cities in South Africa, which is a major disturbance, has been reported to have served as gateway for the rapid spread of many invasive plants (Faulkner et al., 2020).

Before the advent of remotely sensed data, researchers have utilized old maps such as topographic maps, military survey maps and economic maps for their studies on land-use changes (Fuchs et al., 2015; Godet & Thomas, 2013). However, the recent advances in remote sensing and aerial photography have made it easier to map and understand the patterns of land cover changes of an area (Wachiye et al., 2013). The remote sensing approach has been widely used in urban planning, hydrological studies, prediction of drought and erosion and mapping of forest cover (Adamu, 2019; Sajjad et al., 2015). The advantages of using remote sensing techniques include data consistency, wide coverage, maximum data precision and accuracy (Adamu, 2019). Remote sensing can classify land-use features of an area based on their distinguish characteristics which can then be used for making specific land-use and land cover maps of the areas (Homer et al., 2004).

The most widely used satellite data for monitoring and classifying land-use in many countries is the Landsat TM image which is a medium-resolution data (Potapov et al. 2012; Zhuravleva et al. 2013). Several methods were already developed by researchers in classifying land-use of areas using the specific satellite image data (Saadat et al., 2011; Sivanpillai et al., 2007; Wardlow et al., 2007). Methods such as the supervised classification, unsupervised classification, image segmentation and the normalized differential vegetation index (NDVI) have been widely used for classifying land-use and land cover in remote sensing (Saadat et al., 2011). Other remote sensing methods of classifying images such as the non-parametric or knowledge-based and sub-pixel classification methods have also been used in many studies mostly in arid and semi-arid regions (Dawelbait & Morari, 2012; Salih et al., 2017). The only limitation to these methods is their unsuitability for limited resources and the specificity for spectrally distinctive components (Salih, 2018).

Therefore, combining GIS and remote sensing approaches can provide unswerving information on the land-use change of an area (Akingbogun et al., 2012). This study will reveal long-term changes in the vegetation and land-use pattern of Lafia, Nigeria which could not have been adequately covered by field work. It also aimed at using remote sensing and GIS approach to relate the current land-use and land cover type with the colonization of *Pneumatopteris afra* (Christ.) Holttum on several wetlands in Lafia, Nigeria. This plant has been reported as a colonizer of wetlands in many parts of Nigeria (Akomolafe & Rahmad, 2018).

MATERIALS AND METHOD

Study Area

Lafia is the capital city of Nasarawa State of Nigeria. It has a geographical extent of latitude 08^{o} 33' N and longitude 08^{o} 32' E (Figure 1). This is categorized to be within the north-central geopolitical zone of the country. Ecologically, it is also known to have the southern guinea savanna vegetation having an annual precipitation range of 1000 to 1500 mm and mean annual temperature range of 24^{o}C to 33^{o}C. This type of vegetation comprises mainly few trees, abundant woody shrubs and grasses. The soil of Lafia is predominantly sandy loam. Lafia, Nigeria is known to have two main seasons which are the wet and dry seasons. Wet season occurs between May to September while the dry season falls between October and April. The major occupations of the indigenes of this area include fishing, mining and farming. The most widely cultivated crops include the maize, rice, cowpea, guinea corn, sesame and sugar cane. The use of wetlands for irrigation farming during the dry season is also very paramount in this study area. The methodological flowchart of the study is shown in Figure 2.

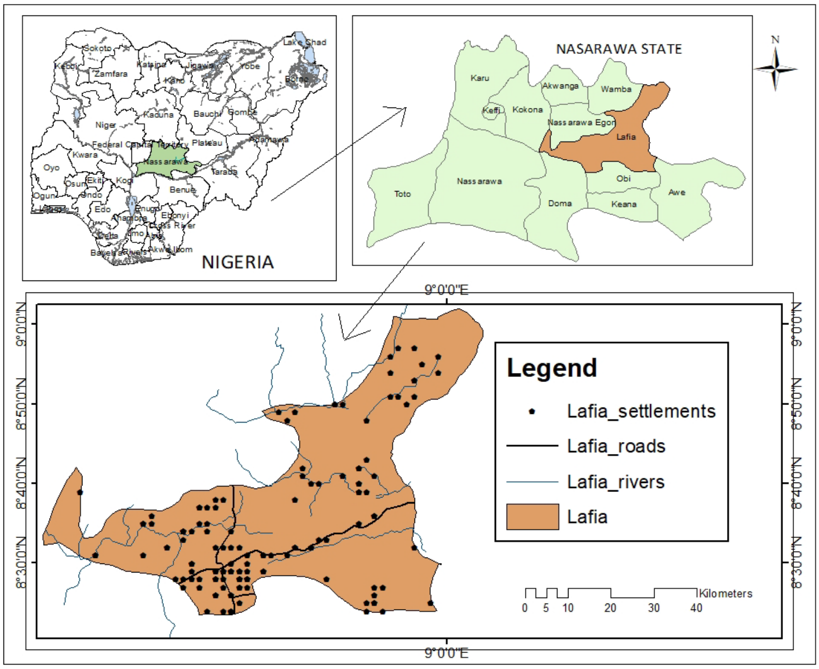

Figure 1. Study area map of Lafia, Nasarawa State, Nigeria (Source: author).

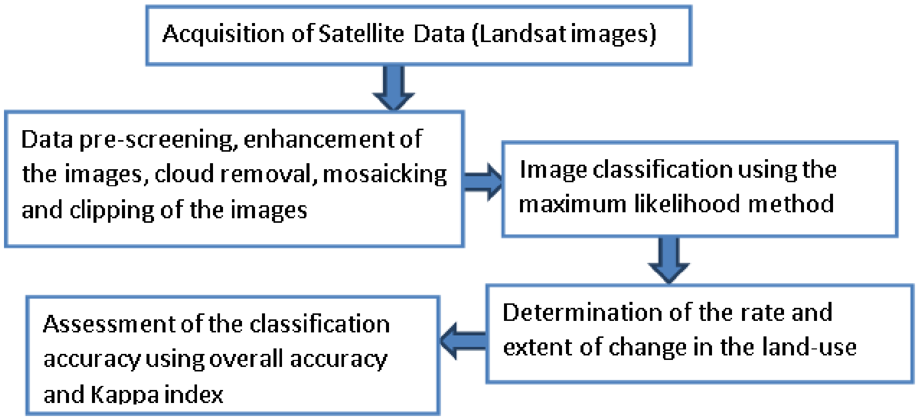

Figure 2. Methodological flowchart of the study

Spatial Data Acquisition

In order for the assessment of the changes in the land-use over the period of 1985 to 2020, Landsat satellite images were downloaded from the website of United State Geological Survey (https://earthexplorer.usgs.gov). The Landsat images include the Landsat 8 OLI / TIRS (operational land imager / thermal infrared sensor), Landsat 7 ETM+ (enhanced thematic mapper) and Landsat 4-5 TM (thematic mapper). These Landsat images were downloaded at Landsat level 1 dataset (Table 1). In order to reduce the cloud cover which is a major challenge of remote sensing of tropical countries (Hansen et al., 2008; Kim, 2016; Margono et al., 2012), additional criteria of land and scene cloud covers less than 10 were selected before downloading the Landsat images.

Table 1

The specifications of the satellite images used

Satellite	Path/Row	Sensor	Number of bands	Period covered	Date captured by sensor	Spatial resolution
Landsat 8	188/54	OLI/TIRS	11	2013 till date	31st January, 2020	30 m
Landsat 7	188/54	ETM+	8	2000 – 2012	2nd March, 2005	30 m
Landsat 5	188/54	TM	7	1984-1999	3rd March 1985	30 m

Georeferencing Techniques

These acquired Landsat raster files were loaded into the ArcMap 10.2.1 software for further georeferencing and analysis. The Landsat images were subjected to several techniques including the data pre-screening, enhancement of the images by cloud removal, correction of radiometric errors, mosaic and clipping of the images and image classification. All the Landsat 7 images acquired since 30th May 2003 till present were reported to have data gaps due to the scan line corrector (SLC) failure. In this study, the scan line stripping errors in the Landsat 7 bands were corrected using the QGIS 2.14.7 software package. The bands were loaded into the software and the "fill nodata" option was chosen from the "raster" tab. After this, the respective bands were chosen as input bands. The gap masks of the respective band which were initially downloaded with the Landsat images were then chosen as the "validity mask". By doing all these, the stripping effects were corrected. The image enhancement was done in order to ensure easier detection and classification of the land-use types (Jande et al., 2019). The boundary shape file of Lafia was used to clip out the area of study from the larger mosaic area.

Image Classification

The satellite image classification in this study involved both unsupervised random selection of sample training points and supervised classifications of the land-use types. The combination of these methods of image classifications has been advocated as more advantageous in ensuring a high level of accuracy (Saadat et al., 2011). For the Landsat 8 satellite image, bands 5, 4 and 3 were used for the analysis while for Landsat 5 and Landsat 7 images, bands 4, 3 and 2 were used (Table 2). The extraction by mask method in the spatial analyst tool was used to extract the Lafia from the selected bands. Each band served as the input while Lafia boundary map served as the feature mask. This extraction process was repeated for the remaining Landsat satellite images. The supervised image classification which had been widely used in remote sensing was employed in this study to classify the Landsat bands (Adamu, 2019; ILWIS, 2001; Jande et al., 2019). This method of image classification works on the principle of identifying training points of known targets and then using these to categorize other unknown sites with similar spectral signatures (Mather & Koch, 2011). In the data management tool, the raster processing was selected, and the three monochromatic bands were joined together using the composite band tool to form the false colour composite (FCC). The FCC was classified through selection of training sites by drawing polygons on the respective land cover type (built up, shrubs and grasses, rocks, forests, wetlands and bare surfaces). These land-use and land cover categories were modified from IPOC Good Practice Guidance (Change, 2003). Not less than 40 sample points were randomly selected for each land cover type. The prior knowledge of the study area was helpful in the selection of training sites as symbolized by different colours (Sinha et al., 2015). The signature file was hereafter created.

For the image transformation, we used the multivariate maximum likelihood classification (MLC) method. Besides MLC, there are other methods of image classification used by researchers. They include the extraction and classification of homogenous objects

Table 2

Characteristics of the satellite bands used for the classification

Spectral characteristics	Landsat 5 and Landsat 7			Landsat 8		
Types of bands used	4	3	2	5	4	3
Colour of bands	Near Infrared (NIR)	Red	Green	Near Infrared (NIR)	Red	Green
Wavelength range (μm)	0.772 – 0.898	0.631 – 0.692	0.519 – 0.601	0.851 – 0.879	0.636 – 0.673	0.533 – 0.590

(ECHO) classifier, fuzzy set classifier, neural networks (NN) classifier, sub-pixel classifier, per-field classifier, minimum distance classifier (MDC) (Lu et al., 2004), decision trees (DTs), support vector machines (SVMs) (Otukei & Blaschke, 2010) and so-on. The analyst choice and the efficiency of any of these classifiers are dependent on several factors such as the band selection, knowledge of the study area, complexity of landscape, accessibility of remote sensing data, the proficiency of the analyst on the classifier used and the classification algorithm (Otukei & Blaschke, 2010). In this study, MLC was preferred to other methods because it has been reported suitable for classification of land-use and land cover with high accuracy in northern Nigeria by recent studies (Adamu, 2019; Jande et al., 2019). MLC enabled the utilization of the prior knowledge of the area where we had already collected the ground-truth data of the respective land-use types (Kim, 2016). In addition, MLC was chosen over others because it was mostly available in many popular image processing and GIS software packages. The maximum likelihood algorithm has the principle of allocating pixels to the class of highest probability and then using it to ascertain the class ownership of that pixel. It is a parametric classifier which operates on the basis that the data follows a normal or near-normal distribution and that the featured classes have equal probability (Otukei & Blaschke, 2010). It has also been reported to perform better than the other parametric classifiers (Richards & Richards, 1999). Accuracy of the performance of MLC was ensured by selecting large number of training samples based on the knowledge of the area of interest.

Description of the Land-use Categories

The built-up is the portion of the land that has been fully developed into roads, railways, houses, industries, and other developed areas. It may also be referred to as settlement in other literature (Kim, 2016). Shrubs and Grasses is the portion of the land dominated by short woody plants called shrubs and other herbaceous plants including grasses (more than 90% cover). The shrubs are short trees usually less than 5m in height. They are generally products of forests degradation. Lafia is expected to have larger portion of land with shrubs and grasses because it falls within the southern guinea savanna zone of Nigeria. Rocks is the part of the land dominated by solid mineral material projecting out of the earth surface (rocks). Bare land is also regarded as bare soil and it falls within the areas of the land that are either made open by natural or anthropogenic activities. Some of these bare lands are lands cleared for agricultural activities particularly farming of rice, sugar cane, sorghum, millet and sesame in the study area. Forests comprises both primary and secondary forests. They are areas of the land occupied by trees. Forest has been defined as an area of land with more than 0.5 ha vegetation comprising trees of 5 m above in height with canopy greater than 10% (FAO, 2010). The forests in Lafia are generally secondary forests which have already experienced disturbances in the past. Some of them are also products of agroforestry.

Wetlands are land areas covered by water seasonally or permanently. They include rivers, streams, lakes or reservoirs which may either be man-made or natural (Kim, 2016).

Determination of Change in the Land-use

The determination of the rate and extent of change in the land-use and land cover of Lafia, Nigeria within the studied periods was done using the following Equation 1, 2 and 3 (Yesserie, 2009):

$$\text{Changed area } (C_a) = T_a(2^{nd} \text{ year}) - T_a(1^{st} \text{ year}) \qquad [1]$$

$$\text{Changed extent } (C_e) = C_a \,/\, T_a(1^{st} \text{ year}) \qquad [2]$$

$$\text{Percentage of change} = C_e \text{ x } 100 \qquad [3]$$

Where T_a means total area

Classification Accuracy Assessment

The accuracy of the classification was assessed following the ideal method of taking ground truth data of the land-use and land cover of Lafia with the aid of a Garmin Etrex 10 device. These ground truth data (GPS coordinates) were then compared with the already classified land-use and land cover map (Jande et al., 2019). The ground truth assessment was done to also be familiar with the land-use features on the satellite. Areas that could not be accessible by field work were confirmed with the use of google earth images. An error matrix which generally explains the accuracy of the classified remotely sensed data by linking it with the ground truth data was produced. This error matrix utilizes the producer's accuracy, user's accuracy, overall accuracy and Kappa index (Jande et al., 2019). The producer's accuracy also known as omission error is the probability of the reference pixel correctly classified. The user's accuracy also known as commission error is the probability that the classified pixel on the map is exactly that on the ground. The Kappa coefficient was then calculated from this error matrix to give the entire statistical accuracy of the error matrix (Foody, 2004). The Kappa coefficient determines the agreement between the classified images and the ground truth data. The Kappa values ranges from -1 to +1 in increasing order of agreement (Borana & Yadav, 2017). The overall accuracy of the classification of the land-use was calculated by dividing the total number of pixels correctly classified by the total number of sampled ground data (Kim, 2016).

Relating the Invasion of *Pneumatopteris afra* to the Land-use of Lafia

This was done in order to relate the land-use classification map of Lafia, Nigeria to the incidence of the invasion of *Pneumatopteris afra* earlier reported from our previous study (Akomolafe et al., 2019). Ninety-five occurrence points of invasion of *P. afra* were identified through ground validation in the previous study. These points were obtained at 20m intervals using 200 m transect laid at the three sites already invaded by *P. afra* in Lafia, Nigeria. This was done by superimposing the georeferenced points of present occurrence of *P. afra* on the land-use classification map of Lafia, Nigeria. By so doing, the portion of the land cover occupied by the invasion of this plant was identified. In addition, to identify the land-use classes that are affected by the predicted species distribution model of *P. afra,* the species distribution map that was generated from our previous study was laid side by side with the land-use map of Lafia, Nigeria. This species distribution model of *P. afra* was done using the Maxent algorithm to predict areas of future invasion of *P. afra* in Lafia, Nigeria (Akomolafe et al., 2019).

RESULTS AND DISCUSSION

The land-use and land cover of Lafia, Nigeria from 1985 to 2020 are presented in Table 3. These results were products of the land-use and land cover classification of Landsat images used. In 1985, bare lands (comprising unused land and farmlands) and rocks dominated the land cover of Lafia with areas of 69,156 ha (24.96% of the whole land cover area) and 58,573 ha (21.14%) respectively. The wetland was the least of all having an area of 3,412 ha (1.23% of the whole land cover area). The classification map of the land-use of Lafia in 1985 is shown in Figure 3. In 2005, the built up dominated the land cover with an area of 122,196 ha (44.11% of the total area) while the wetland still remained the least having an area of 2293 ha (0.83% of the total area). Also in 2020, the built up areas (comprising the roads and settlements) became the dominant land cover with an area of 144,645 ha (52.21% of the total land area) while the wetland still remained the least land cover with an area of 1477 ha (0.53% of the total land area). In 2020, the built-up areas (urbanized) have spread almost uniformly across the entire land in Lafia. This is a consistent increase in built up land-use class from 1985 to 2020. The land-use classification maps of Lafia in 2005 and 2020 are presented in Figures 4 and 5 respectively.

Table 3
Area of land use and land cover of Lafia, Nigeria (1985-2020)

Land-use class	1985		2005		2020	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Built up	48764	17.60	122196	44.11	144645	52.21
Shrubs and Grasses	49477	17.86	38629	13.94	54997	19.85
Rocks	58573	21.14	95666	34.53	28091	10.14
Bare land	69156	24.96	13417	4.84	44501	16.06
Forests	47643	17.19	4824	1.74	3314	1.19
Wetlands	3412	1.23	2293	0.83	1477	0.53
Total Area	277025	100	277025	100	277025	100

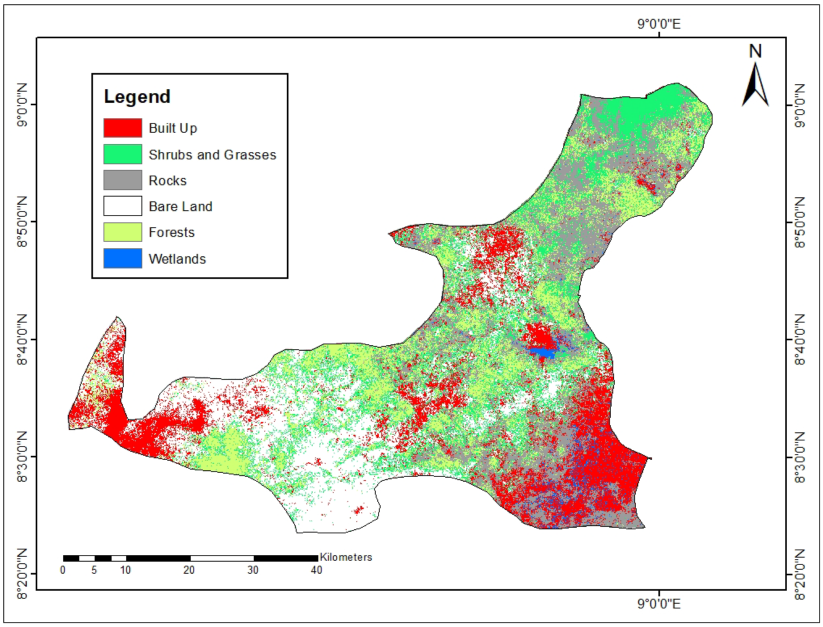

Figure 3. Land use and land cover map of Lafia (1985)

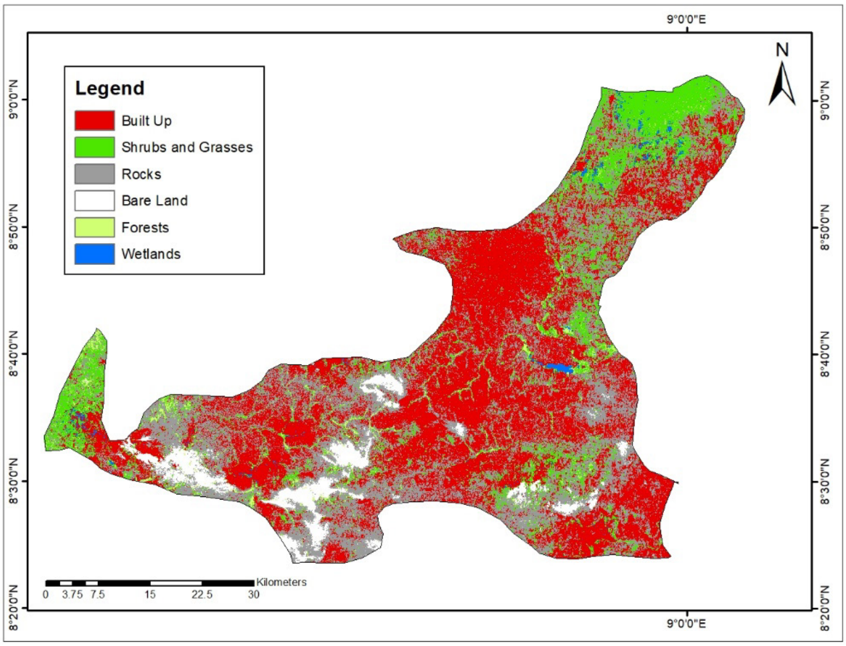

Figure 4. Land use and land cover map of Lafia (2005)

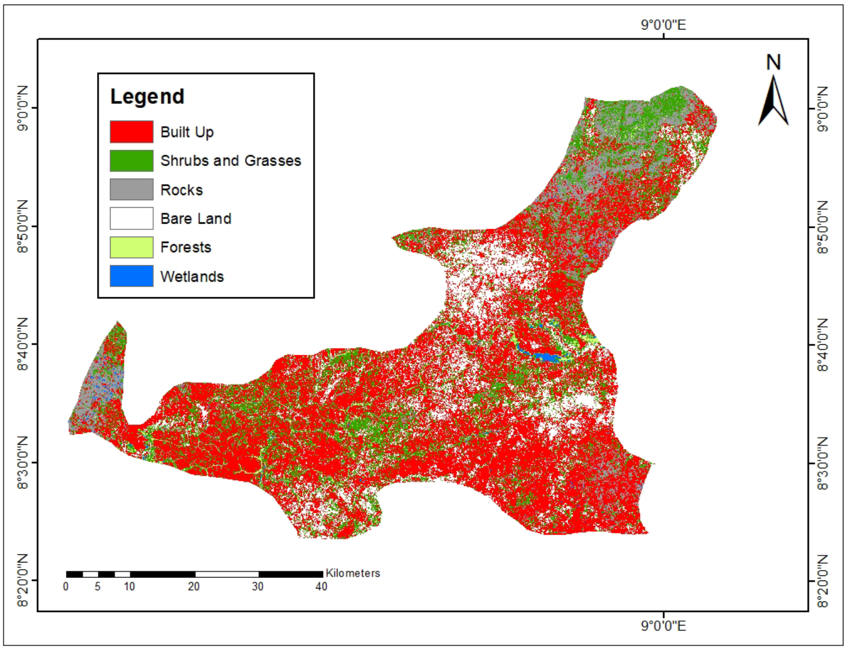

Figure 5. Land use and land cover map of Lafia (2020)

The analysis of the percentage change at interval of not less than 15 years and the annual rate of change in the land-use and land cover of Lafia, Nigeria from 1985 to 2020 are presented in Table 4 and Figure 6. In this result, there is a persistent decrease of forest land from 1985 to 2020 with an annual decrease rate of -4.49 (1985 – 2005), -2.09% (2005 – 2020) and -0.46% (1985 – 2020). This means that 42,819 ha of forests were lost to other land-use types between 1985 and 2005 while 1510 ha were lost between 2005 and 2020. The annual rate of loss of forest is lesser between 2005 and 2020 (2.09%) as compared to between 1985 and 2005 (4.49%). The loss of forest land in any land-use classifications has been attributed to several anthropogenic activities such as logging, clearing of land for farming, urbanization, and inefficiency of government agencies involved in the protection of forests (Curran et al., 2004; Kim, 2016). This could be the case in Lafia, Nigeria whereby the built-up and shrubs and grasses land-use gained from the other land-use classes and increased from 1985 to 2020. This loss in forest land from 1985 to 2020 can be equated to a total loss of 3.38 metric tons of CO_2 (Saka-rasaq, 2019). This resulted in a total loss of 172,732,045 USD of forest products in Lafia, Nigeria within 35 years. Lafia which is found within the guinea savanna vegetation zone of Nigeria was expected to have been dominated more by woody shrubs and grasses. The reverse was the case in this study whereby the shrubs and grasses were almost approximately having the same percentage area with the forests in 1985 (17.86% and 17.19% respectively). However, in 2020, the shrubs and grasses were observed to have expanded in area of coverage than the forests, thereby justifying its classification as a guinea savanna zone of Nigeria. This result agrees with a similar analysis of land-use of Gboko town (a neighbouring State within the same guinea savanna) whereby the grassland was the dominant land cover increasing from 35.97% in 1987 to 67.54% in 2017 (Jande et al., 2019). The consistent loss of forests and increase in bare lands in the land-use and land cover maps of some parts of Pakistan was also reported (Qamer et al., 2012; Sajjad et al., 2015). It has been established that increase in human population is a major driver of forest loss in an area (Adamu, 2019). This same trend of persistent increased in urbanization and reduction of forest lands was also reported in Accra, Ghana (Addae & Oppelt, 2019) and Adamawa, Nigeria (Adamu, 2019).

Table 4

The annual rate of change in the land use and land cover of Lafia, Nigeria (1985-2020)

Land-use class	1985 - 2005		2005 - 2020	
	Change in area (ha)	% change	Change in area (ha)	% change
Built up	73432	150.59	22449	18.37
Shrubs and Grasses	-10848	-21.93	16368	42.37
Rocks	37093	63.32	-67575	-70.63
Bare land	-55739	-80.59	31084	231.68
Forests	-42819	-89.88	-1510	-31.30
Wetlands	-1119	-32.79	-816	-35.59

Land-use class	1985 - 2020		Annual rate of change (%)		
	Change in area (ha)	% change	1985-2005	2005-2020	1985-2020
Built up	95881	34.61	7.53	1.22	0.99
Shrubs and Grasses	5520	1.99	-1.09	2.83	0.06
Rocks	-30482	-11	3.16	-4.71	-0.31
Bare land	-24655	-8.89	-4.03	15.45	-0.25
Forests	-44329	-16	-4.49	-2.09	-0.46
Wetlands	-1935	-0.69	-1.64	-2.37	-0.02

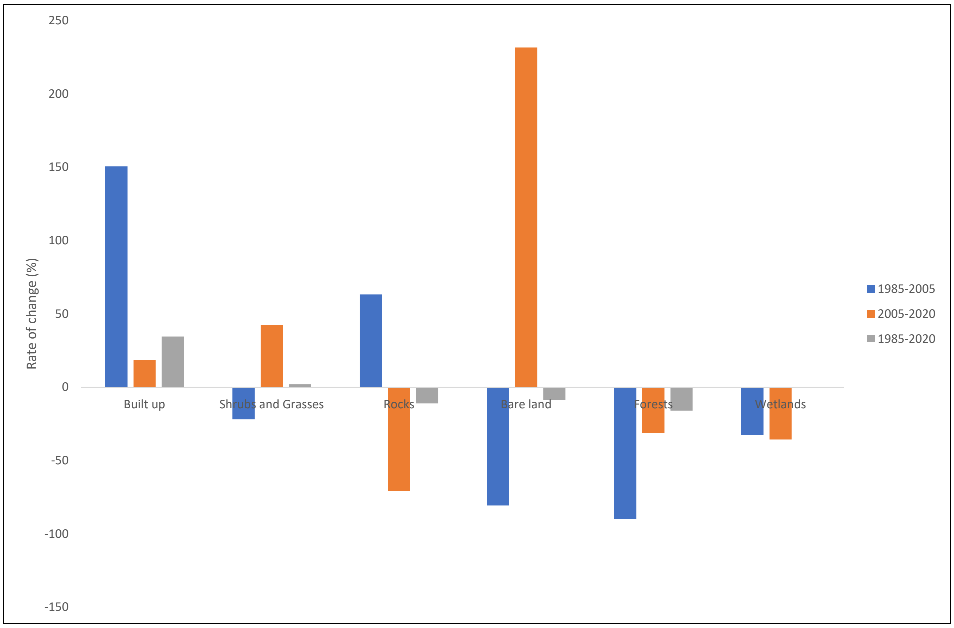

Figure 6. Rate of change in the land-use classes from 1985-2020

The wetlands and bare land also experienced decrease annual rate of change with -0.02% and - 0.25% (1985 – 2020) respectively. It was only the built-up areas that experienced an increase in the annual rate of change from 1985 to 2020. The built-up areas have 7.53% annual increase from 1985 – 2005, 1.22% from 2005 – 2020 and 0.99% from 1985 – 2020. The increased annual rate of change in the built-up areas of Lafia from 1985 to 2020 shows that there has been a steady rate of urbanization and human population of the city. The bulk of this urbanization might have occurred between 1985 and 2005 due to the higher annual rate of change. The shrub and grasses also had increase in the annual rate of change except from 1985 – 2005 where there was a slight loss of 10,843 ha of the area thereby giving rise to an annual rate of change of -1.09% during that period. Also, the decrease in the annual rate of change of the bare lands which are mostly farmlands is an indication that there is a reduction in the farming activities due to the non-involvement of youths in agriculture (Jande et al., 2019). It is very common in recent times that youths are mostly interested in ready-made jobs rather than engaging in farming activities. The elderly ones who have been practicing agriculture are reduced in number due to retirement or death.

The overall accuracy for the land-use classifications of 1985, 2005 and 2020 are 71.36%, 78.93% and 87.47% respectively (Table 5). These indicate that the analysis for the land-use and change detections within the period under consideration were fair enough.

Table 5
Accuracy assessment of land-use classification of Lafia, Nigeria

Land-use class	1985		2005		2020	
	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Producer's accuracy (%)	User's accuracy (%)
Built up	74.61	78.95	80.31	82.33	89.92	94.53
Shrubs and Grasses	81.23	80.34	81.34	83.45	86.54	87.89
Rocks	60.56	76.81	70.87	80.21	70.54	76.12
Bare land	69.76	80.21	79.01	84.32	86.75	89.90
Forests	78.32	80.43	81.09	83.23	98.54	99.01
Wetlands	60.54	77.33	75.34	81.32	80.21	84.32
Overall Accuracy	**71.36%**		**78.93%**		**87.47%**	
Kappa	**0.71**		**0.83**		**0.89**	

The Kappa coefficients for the period of 1985 to 2020 also ranged between 0.71 – 0.89. This means that the agreement between the classified land-use and the observed ground data in Lafia, Nigeria ranged from substantial agreement to almost perfect agreement (Borana & Yadav, 2017). This is also an indication that the selected land-use classification method in this study is feasible and appropriate for the area under consideration. Other researchers have also used similar land-use classification methods in Northern Nigeria, and they reported higher degrees of classification accuracy (Adamu, 2019; Jande et al., 2019).

With respect to the invasion of the fern, *Pneumatopteris afra* in Lafia, Nigeria, the superimposition of its current invaded georeferenced points on the land-use classification map of Lafia in 2020 revealed that the plant was found within the shrub and grasses land-use class (Figure 7A). The area covered by *P. afra* within the land-use of Lafia is 75 ha. However, in the land-use and land cover maps of 1985 and 2005, the same areas invaded by *P. afra* fall within the bare lands and seasonally flooded wetlands. The landsat image was able to identify the current land-use category where *P. afra* invaded as shrubs and grasses. This could be probably due to the herbaceous growth form of this plant. The massive growth of this plant could have covered those wetlands so that the landsat satellite images could not detect the wetlands but see it rather as shrubs and grasslands.

However, comparing the predicted Maxent species distribution model of future invasion of *P. afra* in Lafia with the year 2020 land-use map revealed that the areas of high probability (0.8 – 1) of invasion of *P. afra* fall within shrubs and grasses, built-up, bare land, and wetlands (Figure 7B). This shows that the areas predicted to be susceptible to the future invasion of this plant in Lafia, Nigeria affect more land-use classes than the current areas of invasion. This also indicates that *P. afra* is a plant that has the potential to invade diverse land-use and land cover types in the future. This is buttressed by Oloyede et al., (2011) who reported that this plant could adapt to different types of habitats in Nigeria. The predicted areas of land affected was approximately 178407 ha (Akomolafe et al., 2019). Several researches have reported that the change in the land-use type of an area has direct influence on the success of invasive plants across the world (Bart et al., 2015; Chytrý et al., 2012; Clotet et al., 2016; Csecserits et al., 2016). This might be the case in this study whereby the land-use type of the areas currently invaded by *P. afra* changed from bare land and seasonally flooded wetlands in 1985 and 2005 respectively to shrub and grasslands in 2020. The changes in the land-use and land cover of Lafia from 1985 to 2020 as a result of environmental disturbances could have served as the gateway for the successful invasion of *P. afra* as confirmed by other studies whereby land-use change due to disturbances were promoters of invasion (Faulkner et al., 2020; Portgieter et al., 2020). If the spread of this plant is not controlled early, it poses serious threats on the large areas already predicted by the Maxent model to be affected which fall within the productive parts of the land-use in Lafia, Nigeria.

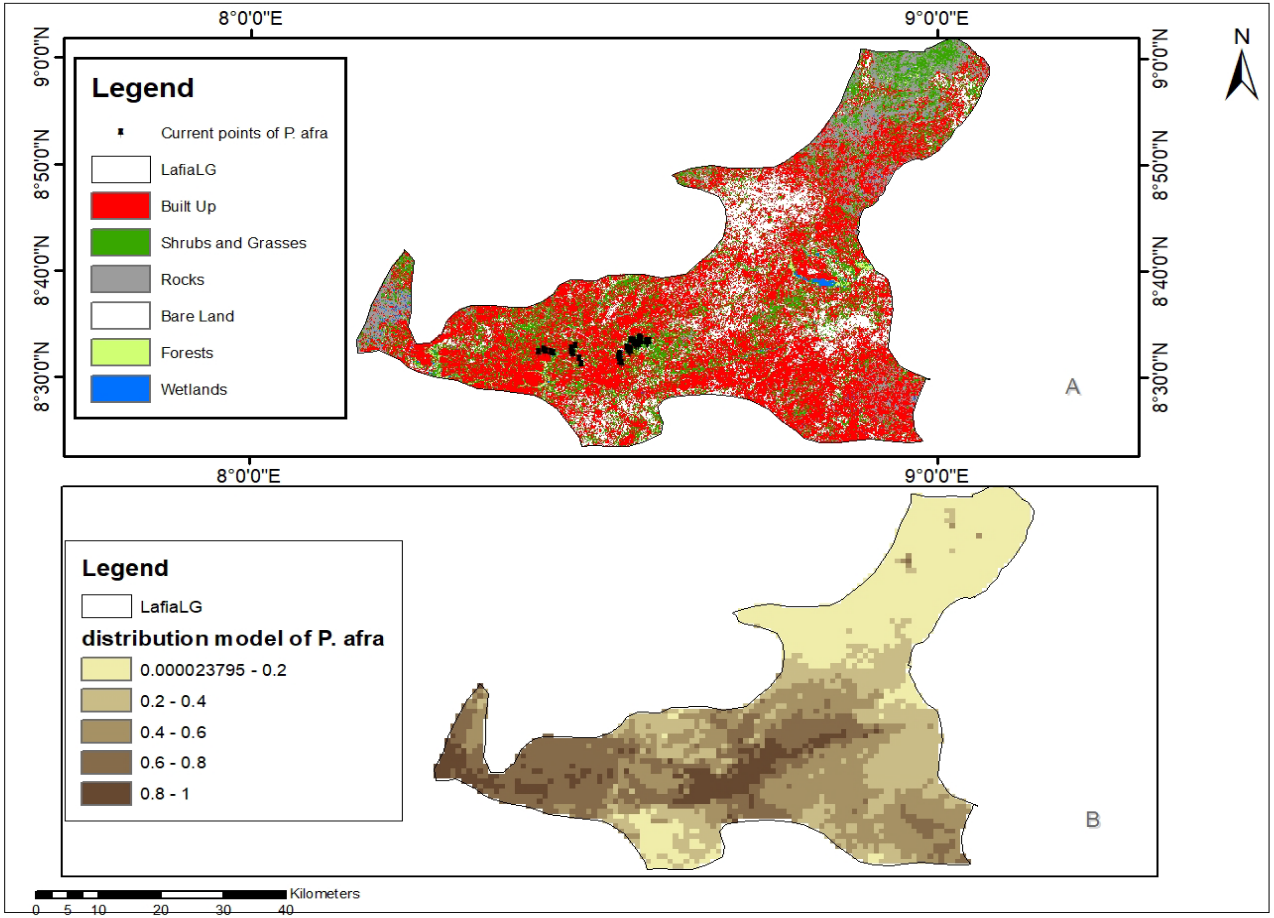

Figure 7A and 7B. Land use and land cover map of Lafia (2020) in relation with the invasion of *P. afra*

CONCLUSION

This study has been able to use the remote sensed data and GIS techniques to simulate the land-use and land cover changes in Lafia from 1985 to 2020 and relates it with the recent invasion of *Pneumatopteris afra* there. This is very critical in decision making by policy makers particularly as it reveals the rapid loss of forest lands and wetlands whereas built up areas have increased geometrically. The rapid increase in the built-up areas could be directly linked with increase in human population and its associated demand for several social amenities. It is so disturbing that the forest lands and wetlands are being depleted continuously for urbanization and invasion of plants. This has serious implication for increase in greenhouse gases in the environment and loss of native biodiversity. It is therefore highly imperative for relevant government agencies to prioritize the conservation of the remaining forests and wetlands in Lafia, Nigeria. The current and the predicted future invasion of *P. afra* which was observed to occupy large areas of the land-use classes in Lafia, Nigeria should be regarded as a major environmental threat which needs immediate attention by the policy makers.

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