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Geospatial Assessment of Human-induced Land cover Changes and its Environmental Implications along the Coastal Areas of Ibeju-Lekki LGA, Lagos State, Nigeria

Adegboyega A. Suleiman[1]; Adedamola Baderinwa[1] and Olajuyigbe, A. Emmanuel[2]

[1]*Department of Remote Sensing & GIS, Federal University of Technology, Akure, Nigeria*

[2]*Department of Urban and Regional Planning, Federal University of Technology, Akure, Nigeria*

Corresponding Author: Adegboyega, S.A.: saadegboyega@futa.edu.ng

ABSTRACT: The rapid growth of population and infrastructure around the coastal areas of Lagos State has given rise to multifaceted environmental challenges. For this reason, it becomes imperative to study the major drivers that reduce the quality of coastal environments through a valid framework. The study aims to utilize GIS and remote sensing for assessing the level of human-induced changes in land cover along the coastal areas of Ibeju-Lekki and examining the drivers that are responsible for the observed changes with a view to developing an environmental degradation index framework for the monitoring of the observed changes. To this end, a temporal analysis of the land use/land cover types was carried out using Landsat images of Ibeju-Lekki for years 1984, 2000 and 2017. The elevation model of the study area was also used to analyze the nature of the terrain and its behavior in response to climatic conditions. GIS techniques of change detection for the temporal analysis and an analytical Hierarchical procedure (AHP) were used to establish the relationship among the parameters of assessment. Through the relationship, it was observed that urbanization occurred in the coastal areas gaining 66 km^2 between 1984 and 2017, depleting the area extent of vegetation with 65.92 km^2 in Ibeju-Lekki and the extent covered by water body reduced by 1.78 km^2. By implication, the areas are going to be more prone to surface runoff and large-scale flooding. The study advocates tree planting and evolvement of land use policy that will curtail sprawling development in these areas.

Keywords: GIS; Environmental Challenges; Analytical Hierarchical Procedure; Flooding; Urbanization

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INTRODUCTION

Coastal zones occupy less than 15% of the earth's land surface, yet they accommodate more than 60% of the world's population (Cleveland, 2007). It is predicted that by 2025 there could be up to 75% of humanity residing in coastal areas and most of the world coastal ecosystems potentially threatened by unsustainable development (EEA, 2018). It could trigger a systemic destruction and depletion of the earth's ecological systems such as water resources, mangroves, plants, and the natural soil and air, which are the source of life (Jimoh et al., 2011). This could culminate in water pollution, air pollution, unsustainable agricultural and fishing practices, overconsumption, deforestation, over-population, among others (Tyagi et al., 2014). It is, therefore, necessary to understand that environmental changes tend to be connected with the process of development that culminates in local, regional and global effects arising from human activities, which may have devastating consequences on the environment, human beings, animals and plants and can be passed on to future generations (Ogboru, 2015).

The use of satellite remote sensing techniques and geographic information systems (GIS) for the identification, mapping and analyses of coastal changes have gained prominence in recent years as high-resolution satellite data have become more readily available. Previous works in this direction include Moore (2000), El-Raey et al (1997), El-Amsar (2002) and Liu et al (2011). These studies showed that remote sensing techniques when combined with geomorphologic and sedimentary data can be effectively used to assess coastal environment changes over time. Thus, Omenai and Ayodele (2014) used the distance to the water body and elevation as the primary parameters to determine environmental degradation vulnerability. For a more detailed study, it is necessary to explore more environmental parameters such as slope, rainfall, flow accumulation, land use/land cover, flow direction and soil using remote sensing and GIS, and hence, this study. In addition to this, the study focuses on the generation of a multi-temporal environmental degradation vulnerability index map that provides reliable baseline information for the monitoring of environmental change indicators, which has been given little or no attention by the previous studies.

MATERIALS AND METHODS

Research Locale

Ibeju-Lekki covers about 445 km^2 which equals 25% of the total landmass of Lagos State. It has a coordinate of Latitude $6^0$29'36" N, Longitude $3^0$43'14" E and Latitude $6^0$23'21" N, Longitude $4^0$21'31" E and falls in the creek zone of tropical South-western Nigeria. The area is relatively flat with an altitude of about 6.40 m. Ibeju-Lekki has tropical wet and dry seasons that borders on a tropical monsoon climate. Thus, it experiences two rainy seasons, with the heaviest rains falling from April to July and a weaker rainy season in October and November. However, a brief relatively dry spell is prevalent in August and September and a longer dry season from December to March (Adebisi, 2016).

Data Types, Image Processing and Classification

In the study, both primary and secondary data were used. The primary data used include Landsat 5 TM 1984, Landsat 7 ETM+ 2000, and Landsat 8 2017. The secondary data such as ASTER DEM (30m resolution), soil map and Rainfall data were also utilized. The shapefile of the study area was extracted from the Nigeria Administrative Map. This was clipped on the Landsat series images and ASTER DEM image to generate Ibeju-Lekki multidate Landsat images and ASTER DEM. The Landsat series images (30m resolution) were preprocessed and used for land use/ land cover classification. The band combinations used for the study were 432 for 1984 and 2000 while 543 were used for 2017. Topographic correction: the metadata of the imageries was utilized for this pre-processing. The sun elevation data was copied and subjected to mathematical operations. The 'sin' of the sun elevation was used as a divider for individual bands. A brighter and more accurate image was produced which was used for the analysis. All the images were georeferenced and projected into UTM and WGS-84 Datum.

The land use/ land cover classification was based on predefined classes; vegetated areas, Built-up areas (such as settlement, roads), Bare surfaces and water bodies. The images were subjected to supervised classification using a maximum likelihood algorithm.

Topographical Analysis

The ASTER DEM image was used as the input raster. Sink and fill operations were initiated on the DEM imagery to eliminate all forms of sinks. Flow direction, flow accumulation, elevation and slope were derived from the ASTER DEM using the spatial analyst toolbox. Soil distribution data was gotten from the National Space Research and Development Agency (NASRDA). Different soil types have different permeability, porosity and infiltration capacities and therefore differing influences on land degradation.

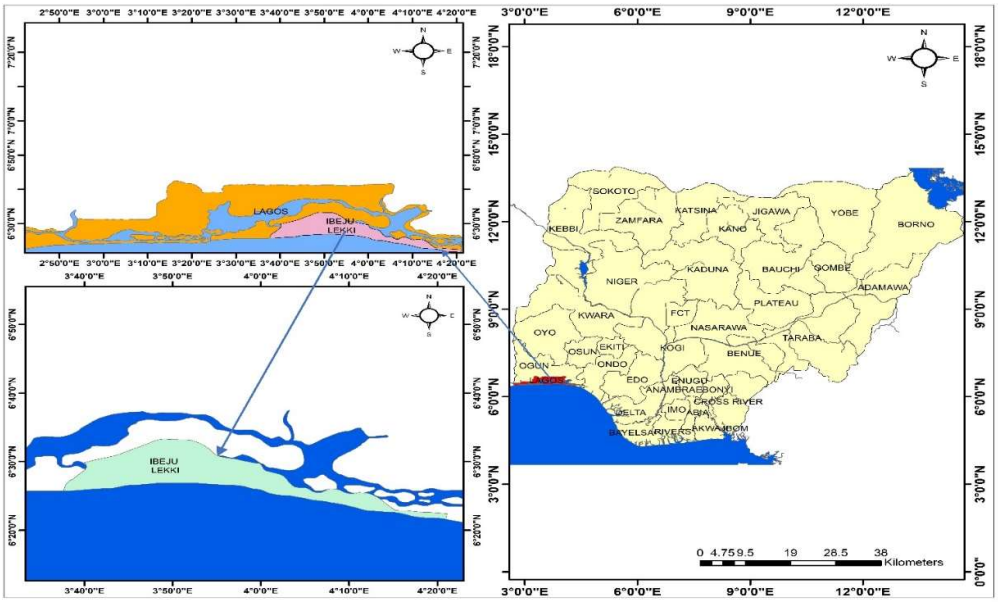


Figure 1: Map showing the Study Area and its surrounding Water Body

The rainfall data of the study area was obtained from the Nigeria Meteorological Agency (NiMET) and it is represented originally on an excel spreadsheet with a table of the longitude and latitude with the mean annual rainfall of the study area. This was imported into the GIS environment as point data. The points were extracted into raster features; the extracted point was then subjected to an extraction with values analysis using the area extent of Ibeju-Lekki as a boundary using ArcMap 10.3 software. The spatial interpolation process was initiated to efficiently distribute the rainfall data based on their coordinates.

NDVI, NDBI and Change Detection Analysis

Normalised difference vegetation index (NDVI) and normalized difference built-up index (NDBI) were carried out on the Landsat images for 1984 and 2016 using the equations below:

NDVI: (NIR - R) / (NIR + R) 1

NDBI: (SWIR – NIR) / (SWIR + NIR) 2

Change detection of land cover in the study area was done in three stages which include the land use/land cover changes of 1984-2000, 2000-2017 and 1984-2017 using Idrissi Taiga Software. An accuracy assessment of the LULC maps was conducted using the theoretical error matrix method in ArcGIS.

For accuracy, a post-classification change detection method was used. This method avoids problems encountered at the pixel level (such as shadows and reflections) and requires both images to be individually rectified and classified before they can be compared pixel by pixel (Jensen, 1996). This pixel-by-pixel comparison is accomplished using a change detection matrix; hence, a specific number was assigned to all classes to achieve uniformity. The involved images were reclassified using the same matrix. This helps to ensure that both classifications are as accurate as possible since any errors that occur in the classification could be carried over into the change detection.

AHP Process Description

All criteria/factors which are considered relevant for a decision are compared against each other in a pair-wise comparison matrix which is a measure to express the relative preference among the factors. Therefore, numerical values expressing a judgment of the relative importance (or preference) of one factor against another have to be assigned to each factor. Since it is known from psychological studies that an individual cannot simultaneously

compare more than 7 ± 2 elements, (Nwilo, Olayinka, & Adzandeh, 2012), suggested a scale for comparison consisting of values ranging from 1 to 9 which describe the intensity of importance.

A value of 1 express "equal importance" and a value of 9 were given for those factors having an "extreme importance" over another. The pairwise comparison matrix was accepted as the Consistency ratio (CR) was less than 0.1 (CR< 0.1 (Tables 1, 2 & 3). Overlay analysis was carried out on the factors to generate the multi-temporal degradation index map as a baseline for the monitoring of the environmental change indicators in the rapidly urbanizing environment.

Table 1: Pairwise Comparison

	Rainfall	Land Use	Flow Accumulation	Flow Direction	Soil	Slope	Total
Rainfall	1	3	3	3	7	5	22.00
Land Use	1/3	1	3	3	5	5	17.333
Flow Accumulation	1/3	1/3	1	1	3	5	10.667
Flow Direction	1/3	1/3	1	1	5	5	12.667
Soil	1/7	1/5	1/3	1/5	1	3	4.876
Slope	1/5	1/5	1/5	1/5	1/3	1	2.133
Total	2.343	5.067	8.533	8.400	21.333	24.000	69.676

Table 2: Consistency Ratio

	Rain-fall	Land Use	Flow Accumulation	Flow Direction	Soil	Slope	Sum	Average	Weight	Weight (%)
Rainfall	0.427	0.592	0.352	0.357	0.328	0.208	2.264	0.377	0.883	13.4
Land Use	0.142	0.197	0.352	0.234	0.208	1.481	1.491	0.249	1.262	18.9
Flow Accumulation	0.142	0.066	0.117	0.119	0.141	0.208	0.793	0.132	1.166	17.5
Flow Direction	0.142	0.066	0.117	0.119	0.234	0.208	0.887	0.148	1.243	18.6
Soil	0.061	0.039	0.039	0.024	0.047	0.125	0.335	0.056	1.195	17.9
Slope	0.061	0.039	0.023	0.024	0.016	0.042	0.229	0.038	0.912	13.7
Total	1	1	1	1	1	1	6.000	1	6.661	100

Consistency Ratio=0.067

Table 3: Criteria Levels used in the AHP

Intensity of importance	Description
1	Equal importance
3	Moderate importance of one factor over another
5	Strong or essential importance
7	Very strong importance
9	Extreme importance
Reciprocal	Values for inverse comparison

Source: Authors' Data Analysis, 2020

Procedures of Analysis on the Parameters

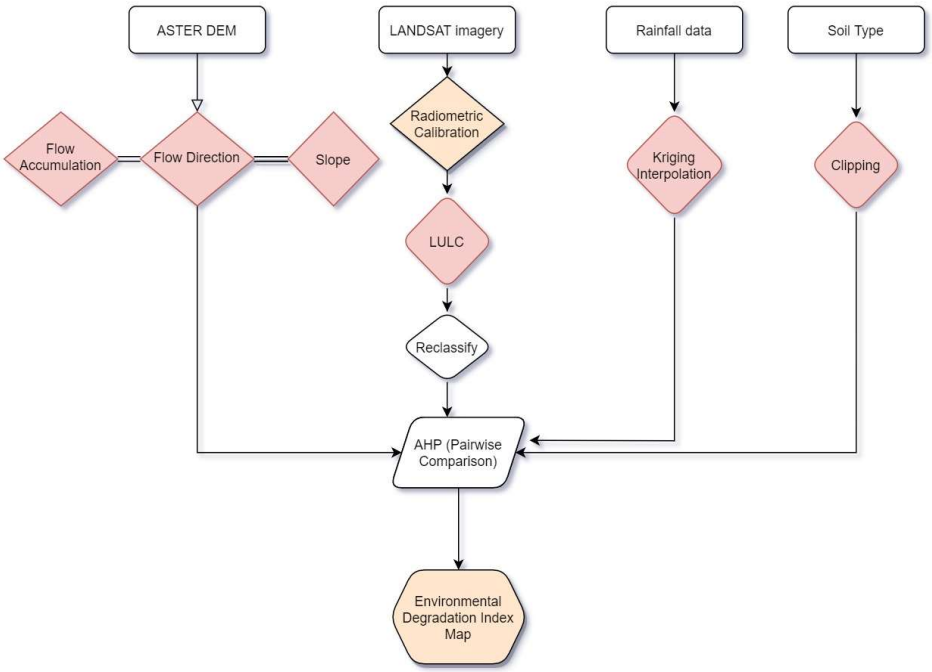


Figure 2: Methodology Flowchart

RESULTS AND DISCUSSION

Accuracy assessment

For the accuracy assessment, sample references were obtained for each year in the field to verify the land cover type. In 1984, 140 samples were obtained (Table 4); 2000, 211 samples were taken (Table 5); and in 2017, 140 samples were obtained (Table 6). The sample references were then compared to the result of the maximum likelihood classification to obtain an error matrix. A confusion matrix (or error matrix) is usually used as the quantitative method of characterizing image classification accuracy (Ukrainski, 2016). The >75% value obtained for the accuracy assessment of 1984 (80.7%), 2000 (89.1%) and 2017 (95%) depicts an accurate level of assessment with a negligible amount of errors.

Land Use/Land Cover Change Detection

The land use/land cover change detection analysis was used to assess the extent to which urbanization and vegetation degradation has contributed to and also its potentials to the degradation index of Ibeju-Lekki. The map results (Figures 2, 4 and 5) depict the west wing of Ibeju-Lekki as the most urbanized area in terms of change.

Table 4: Accuracy Assessment for LULC 1984

Class	Water body	Vegetation	Built-up	Bare Surface	Total	Correct Sampled
Water body	22	3	0	4	29	22
Vegetation	4	14	0	5	23	14
Built-up	0	5	64	3	72	64
Bare Surface	1	0	2	13	16	13
Total	27	22	66	25	140	113

Overall classification accuracy= (113/140) * 100 = 80.7%

Table 5: Accuracy Assessment for 2000

Class	Water body	Vegetation	Built-up	Bare Surface	Total	Correct Sampled
Water body	20	3	3	0	26	20
Vegetation	2	55	0	4	61	55
Built-up	2	0	79	0	81	79
Bare Surface	4	0	5	34	43	34
Total	28	58	87	38	211	188

Overall accuracy classification= (188/211) * 100 = 89.1%

Table 6: Accuracy Assessment 2017

Class	Water body	Vegetation	Built-up	Bare Surface	Total	Correct Sampled
Water body	40	1	1	0	42	40
Vegetation	3	26	0	0	29	26
Built-up	0	0	45	1	46	45
Bare Surface	0	0	1	22	23	22
Total	43	27	47	23	140	133

Overall accuracy assessment: (133/140) * 100 = 95%

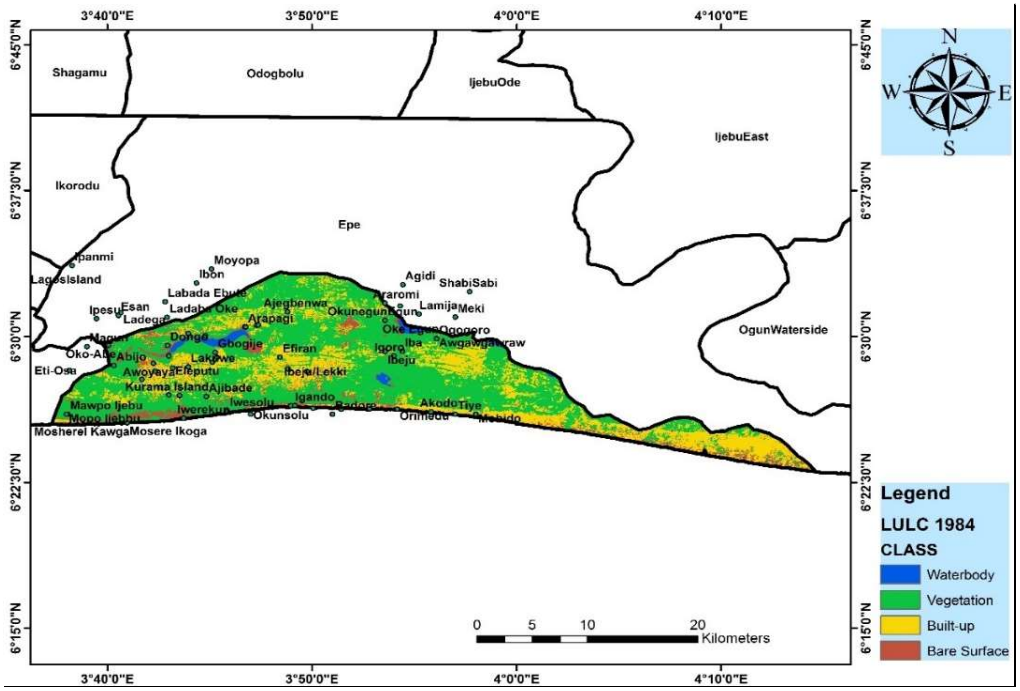


Figure 3: Land use/Land cover Map of Ibeju-Lekki in 1984

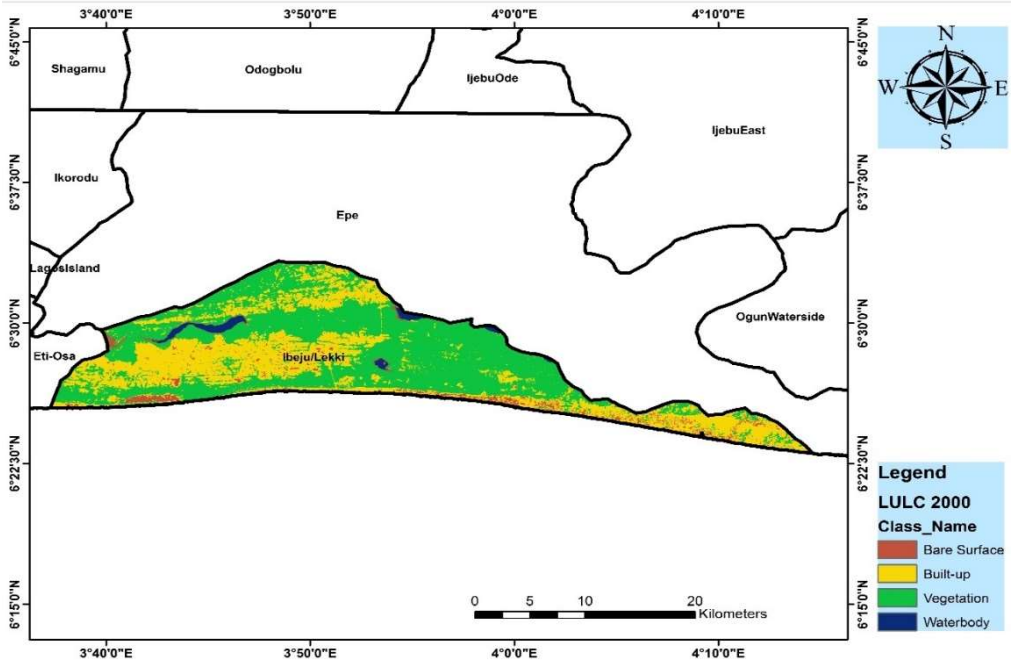


Figure 4: Land use/Land cover Map of Ibeju-Lekki in 2000

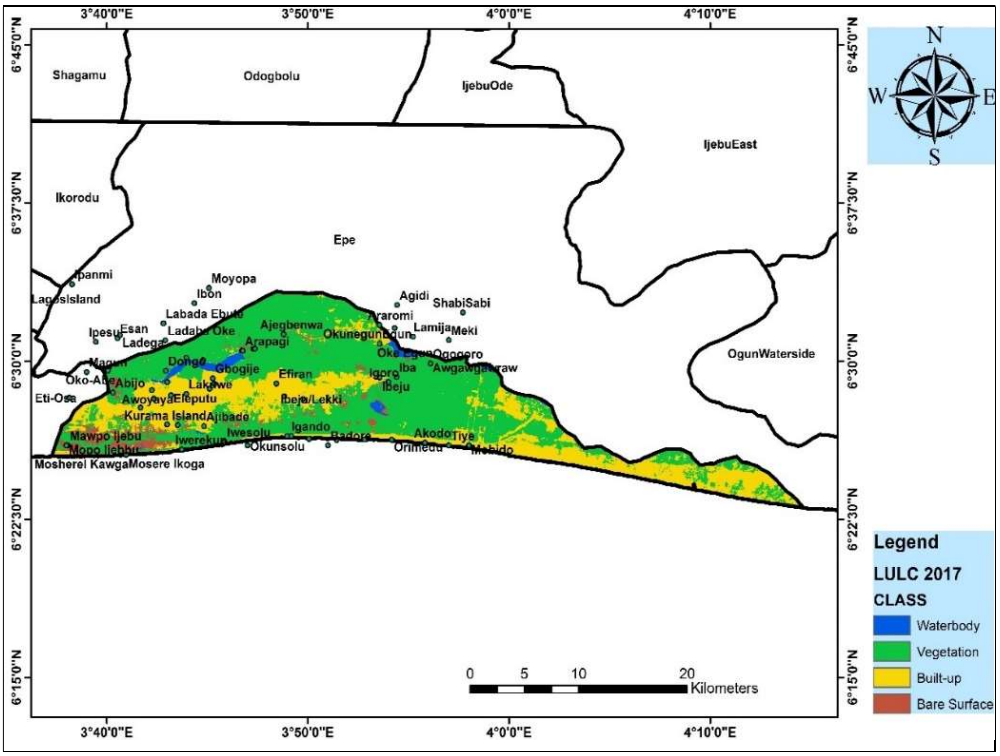


Figure 5: Land use/Land cover Map of Ibeju-Lekki in 2017

Urbanization Assessment

The extent of exchange between bare surface, vegetation, water body and built-up in Ibeju-Lekki for years 1984, 2000, 2017 was assessed to obtain the degradation inland. Fig 5 shows the land cover classes that have contributed to the changes in the area occupied by the water body in km^2. It indicates that vegetation has lost a noticeable amount to the water body through riparian vegetation degradation while the water body has lost about 66.07 km2 to the built-up area. This may be attributed to land reclamation activities that are prominent in the coastal area as bare surface area predominates (Fig 6) between 1984 and 2017. From the field survey, the major driver of land reclamation identified in Ibeju-Lekki is residential and industrial development due to the establishment of Lekki Free Trade Zone in the area. More land in square kilometres is required to fit in structures and built-ups, this accounts for the sand-filling activity that led to the loss of 1.3 km2. Vegetation and bare surface have contributed 52.67% and 13.05% to built-ups respectively (Fig. 7). This has translated into an increase of approximately 66.0% in built-up areas in 2017 as reflected in Figure 8. This is corroborated by the influx of population to the area as reflected in Table 7. The population of Ibeju-Lekki as shown in the Table has grown by 10.96% per annum between 1991 and 2006, and 3.44% between 2006 and 2017. This implies further encroachment of built-ups on the coastal environment that would aggravate land reclamation and sandfilling activities as preconditions for building construction in the area, resulting in loss of marine vegetation and aquatic habitats.

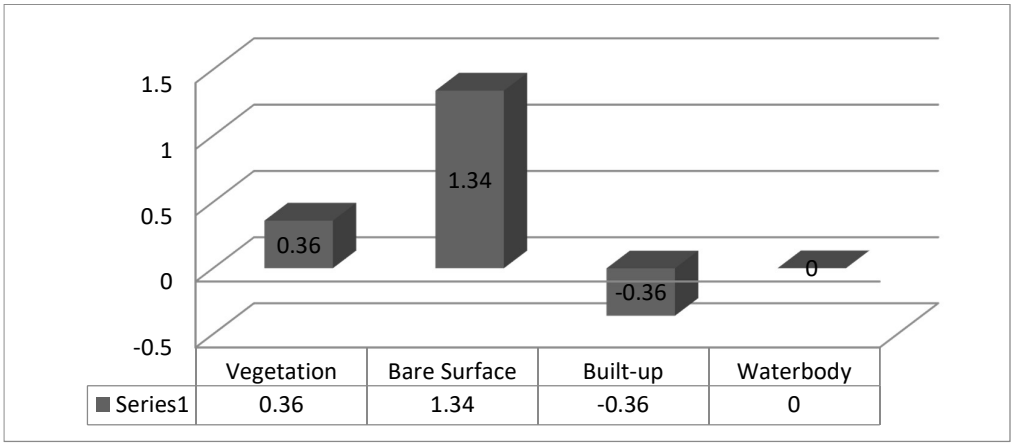


Figure 6: Contributors to Net Change in Water body between 1984-2017

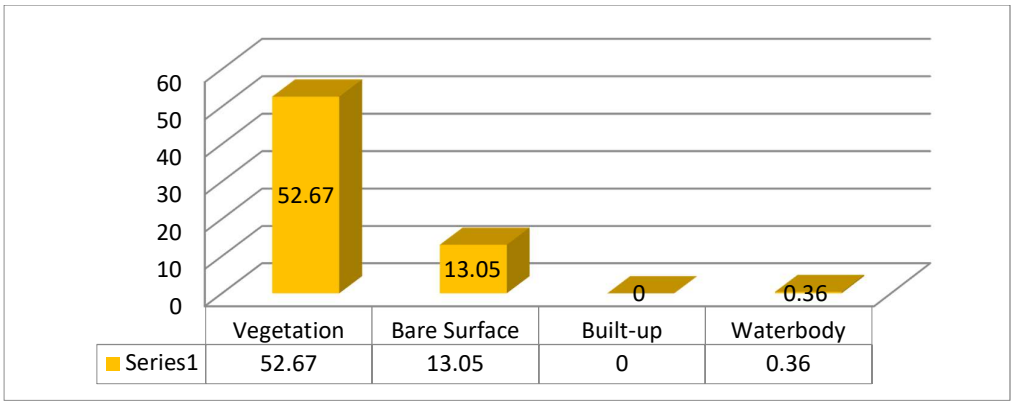
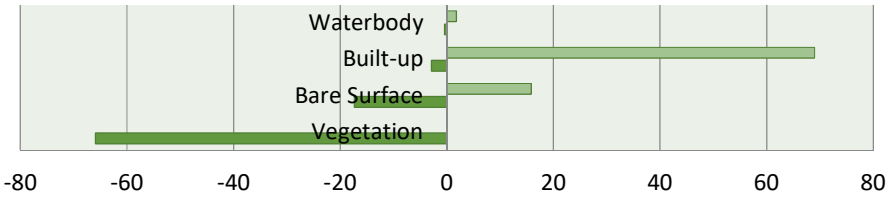


Figure 7: Contributors to Net Change in Built-up between 1984-2017



	Vegetation	Bare Surface	Built-up	Waterbody
Series2	0	15.88	68.99	1.78
Series1	-65.92	-17.38	-2.92	-0.43

Figure 8: Gains and Losses by Category between 1984 and 2017

Table 7: Population of Ibeju-Lekki

Name	Population (Census) 1991-11-26	Population (Census) 2006-03-21	Population (Projection) 2017-03-21
Ibeju/Lekki	24,937	117,793	171,200
Population growth rate per annum	.....	10.96%	3.44%

Source: National population commission through the National Bureau of Statistics, 2017

The reddish patches in the southeastern wing of Figure 9 show areas with high NDBI values between 0 and 0.38 representing a high concentration of buildings. Areas with low NDBI values between 0 and -0.286 are locations with high vegetation concentration or water bodies. Notably, most of these areas coincide with the locations with a high increase in built-up and vegetation concentration in the LULC map for 1984.

The Normalized Difference Built-up Index map of Ibeju-Lekki 2017 depicts a more evenly distributed built-up occurrence in Ibeju-Lekki. Areas with high index values (High built-up concentration) ranging between 0 and 0.5402 occupy more landmass as opposed to early years represented in Figure 9. Location with values between 0 and -0.2747 with vegetation or bare surface land cover corroborates the rapid urbanization that has occurred within the years of study. More so, the rate of built-up index is alarming and rapid, hence, an obvious fact is that the coastal areas of Ibeju-Lekki are under the immense pressure of human activities.

Table 8: LULC exchange description

Category	Area (km^2) (1984-2017)	Exchange Description
1	7.5563128	Bare Surface to Vegetation
2	7.4710473	Built-up to Vegetation
3	0.1534778	Waterbody to Vegetation
4	2.1810001	Vegetation to Bare Surface
5	1.1111433	Built-up to Bare Surface
6	0.7988025	Waterbody to Bare Surface
7	130.4848397	Vegetation to Built-up
8	17.0225714	Bare Surface to Built-up
9	1.597605	Waterbody to Built-up
10	0.0053852	Vegetation to Waterbody
11	0.6273741	Bare Surface to Waterbody
12	0.0224383	Built-up to Waterbody

Source: Author Data Analysis

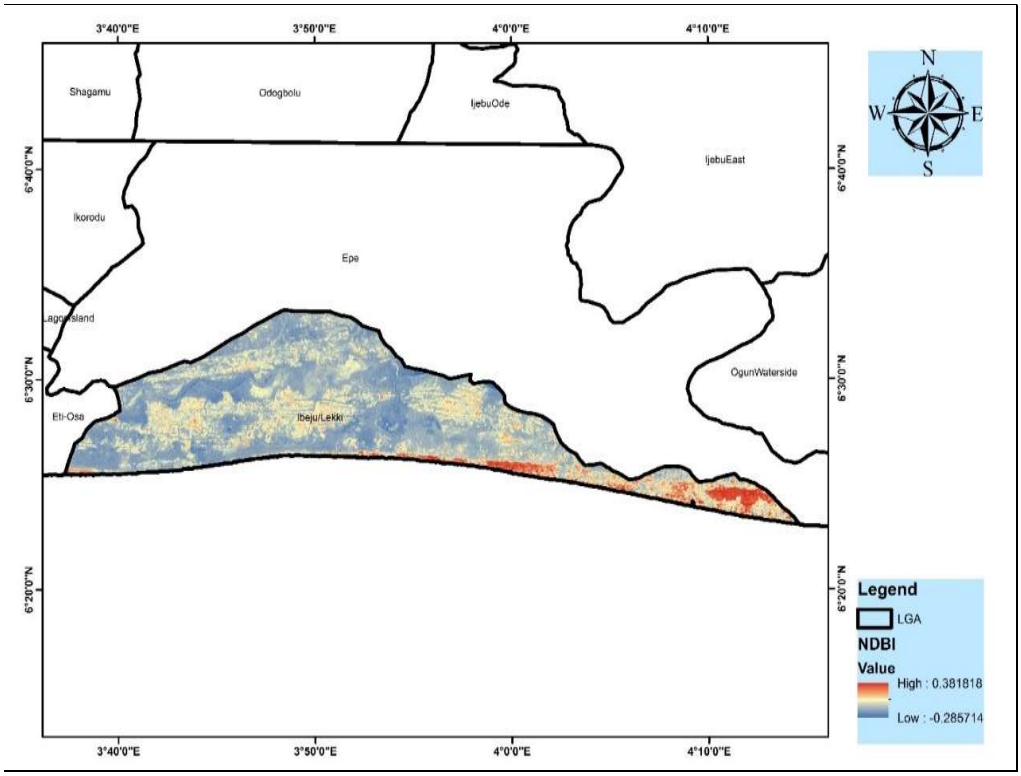


Figure 9: NDBI of Ibeju-Lekki in 1984

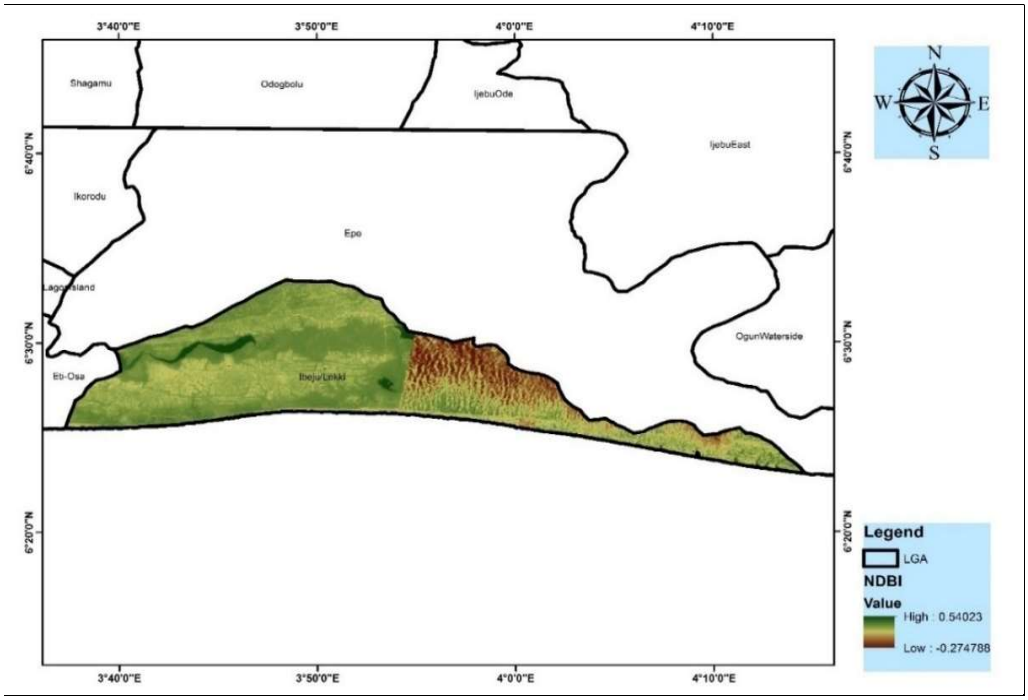


Figure 10: NDBI of Ibeju-Lekki 2017

Vegetation Degradation in Ibeju-Lekki

Areas within the range of 0 and 0.311475 represented by green patches in Figure 11 below shows the vegetated areas of the study area. The figure revealed that a large portion of the coastal areas was still occupied by marine shrub and grassland with scanty locations within 0 and -0.105263, suggesting bare surface and sand in 1984. This is in agreement with (Crippen, 1990; Earth observation.nasa.gov., 2014) that an NDVI value of zero means no green vegetation and close to +1 (0.8 – 0.9) indicates the highest possible density of green leaves. In general terms, (values approaching -1) correspond to water. Values close to zero (-0.1 to 0.1) correspond to barren areas of rock, sand, or snow. Low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate tropical rainforests (values approaching 1). It suggests that in 1984, there was a predominance of shrub and grassland due to the age-long urbanization process in the area.

In 2017 as shown in Figure 12, the NDVI values between 0 and 0.427083 were represented by green patches, suggesting further degrading shrub and grassland over 33 years. As reflected in Figure 13, increasing built-up and bare surface areas have been responsible for vegetation depletion. The NDVI values range from 0 to -0.07216 lend credence to rapid urbanization in the area. The built-ups and bare surface have taken 52.67% and 12.9% of areas initially covered by vegetation while 0.36% of water body has been encroached by both within the spate of 33 years. The Vegetation loss experienced through the temporal years of study is quite alarming. Notably, 95% of the loss was gained by built-up areas, indicating a high level of urbanization as well as rapid deforestation. The ripple effect of the deforestation activity is evident in the environmental quality of Ibeju-Lekki, considering its low altitude, vegetation is expected to serve as a repellant to surface runoff, erosion and large-scale flooding but the reverse is the case.

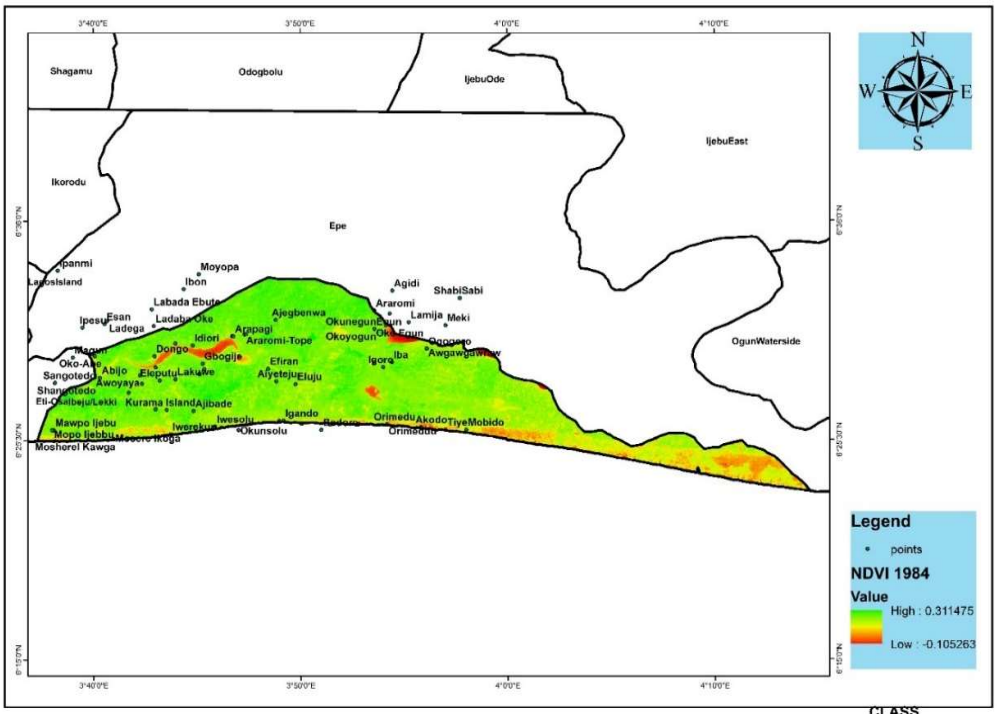


Figure11: NDVI map of Ibeju-Lekki 1984

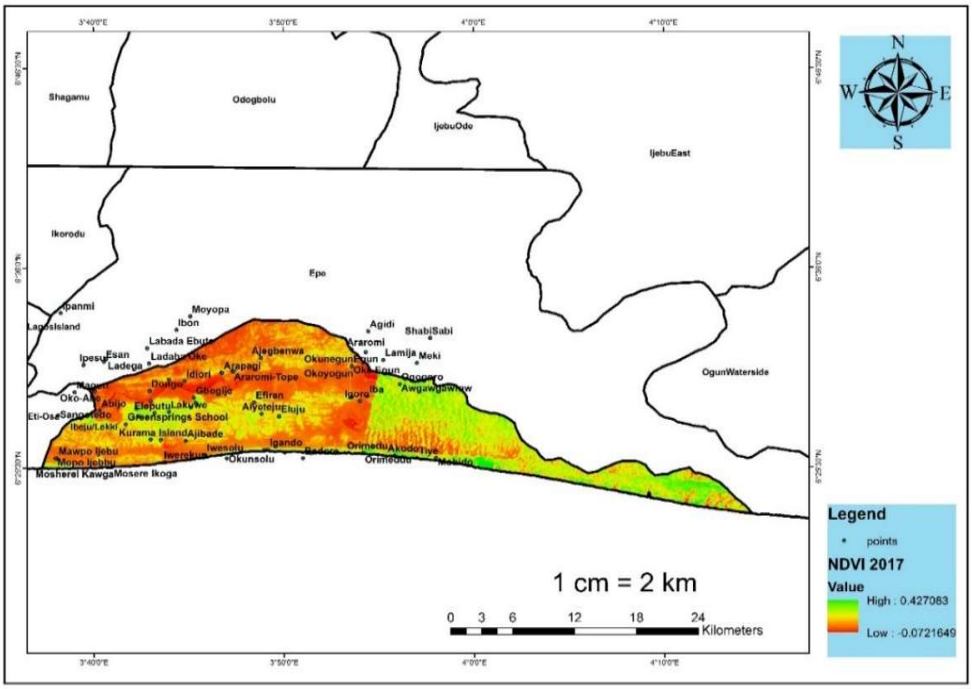


Figure12: NDVI map of Ibeju-Lekki 2017

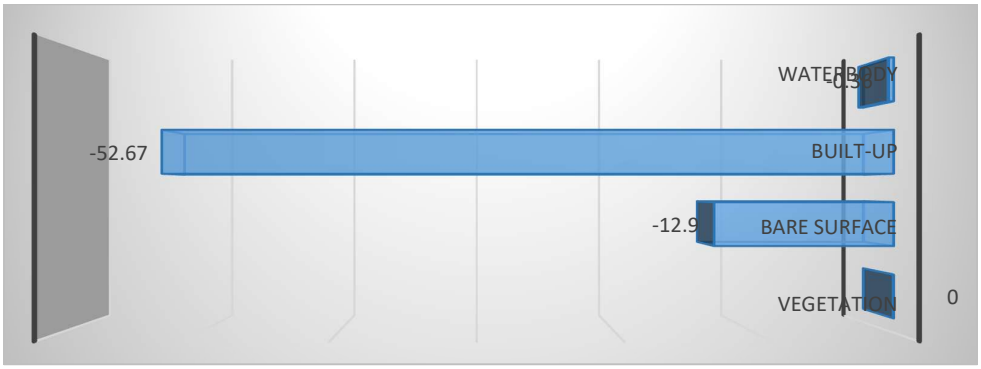


Figure 13: Contributors to Net Change in Vegetation between 1984 and 2017

Environmental Change Indices

This was achieved through the Analytical Hierarchical Process (AHP) using different criteria that are peculiar to the study area to deduce the vulnerability zones and their extent of importance. The degradation vulnerability zones were based on Land use, Rainfall distribution, Slope, Flow accumulation, flow direction and soil type.

Land Use Index

The four classes obtained from the supervised classification of the study area imagery: bare surfaces, vegetation, waterbody and built-up were reclassified and assigned the range "1 – 4" which depicts the index of degradation. The criteria of land use were used in the pair-wise comparison to obtaining vulnerability. The water body class was assigned to range 1 which shows it is the least vulnerable, the vegetation to range 2, the bare surface to range 3 and the built-up to range 4, which shows it is the most vulnerable to environmental degradation.

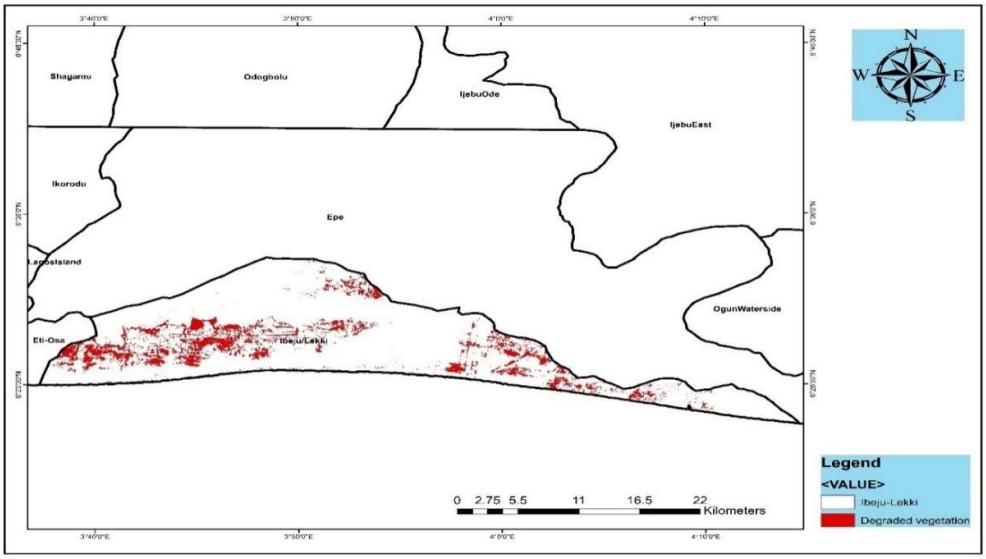


Figure 14: Degraded vegetation due to Built-up in Ibeju Lekki

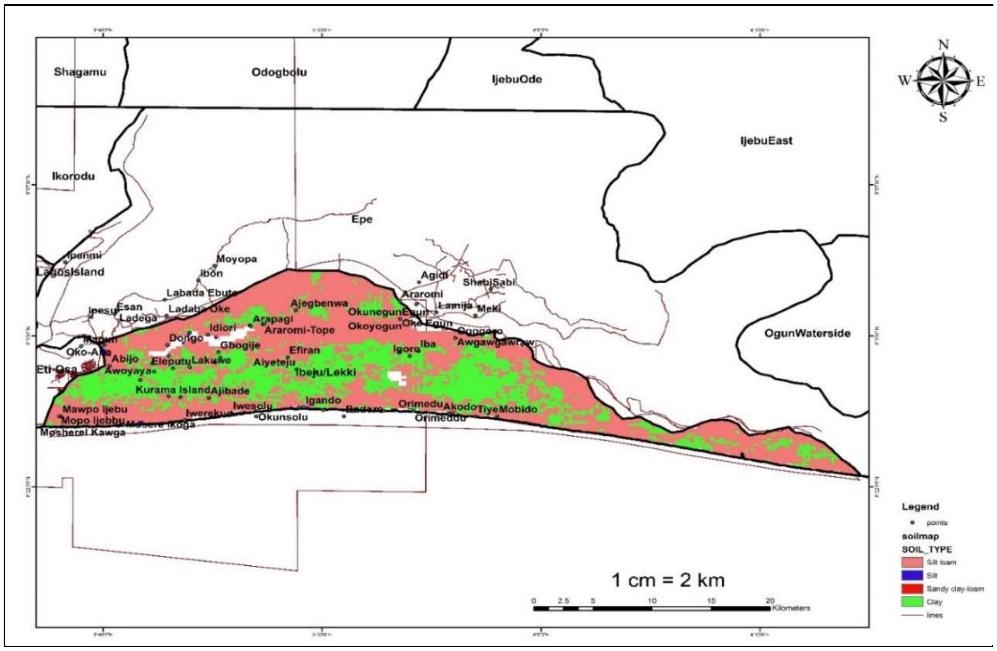


Figure 15: Map showing the soil type distribution

Soil Type Index

The grouping of soils in the case of this study was based on type (Figure 15). Soils in Lagos State were categorized into four; Silt loam, Silt, Loam and Clay. The classes were then reclassified into three major classes and ranking was done and the soil type with the capacity to generate high flood rates was assigned "4" while the soil type with the least likelihood of generating into a flood was assigned rank "1". Soil texture impacts heavily on flooding. Sandy soils allow water to pass through them faster compared to other soil types due to their large soil particles and thus little runoff is experienced. Clay soils have fine particles, are less permeable and allow the buildup of runoff

for a longer period compared to other soil types. The implication of this is that areas with clay soils are more prone and more likely affected by flooding.

Rainfall amount Index

Heavy rainfall is a primary driver of environmental degradation particularly in the absence or thin vegetation cover. For instance, floods occur mainly in areas of heavy rainfall when available drainage systems are unable to convey excess water to the flood plains or water bodies or when the soil cannot absorb excess water; mainly because they have reached the saturation point. Five classes were generated from the rainfall data. The generated rainfall classes were then reclassified and ranked based on their influence on flood risk. Areas with the highest mean annual rainfall are considered to be more at risk of flooding than areas with the least rainfall. High rainfall areas were assigned rank "4" while the areas with the least rainfall were assigned rank "1". From the rainfall map, areas near the coastline receive the highest rainfall amounts (Figure 16).

Slope Index

Different areas in the study area fall under different slope categories; low, medium or steep. The slope map in this study was prepared from the ASTER DEM. The classes of the slope with lesser values were allocated higher ranks as their angles are not steep. Classes with the highest slope values were assigned lower ranks for degradation index values. Such areas do not permit the accumulation of water that eventually causes flooding as a form of environmental degradation. Thus, areas falling at the lowest point of the elevation have the highest likelihood of inundation in the event of precipitation (Figure 17).

Flow Configuration Index

Flow configuration is related to the nature of the soil and rock structure and properties. Areas with high drainage density are highly susceptible to erosion and result in massive sedimentation on the lower grounds. A watershed adequately served with stream channels should have a density greater than or equal to five. Moderately and poorly drained areas have densities ranging between 1 and 5 and less than 1 respectively. The study area is characterized by first, second and third-order streams. For this study, poorly drained areas were allocated the highest ranks while the well-drained areas were assigned lower ranks (Figure 18).

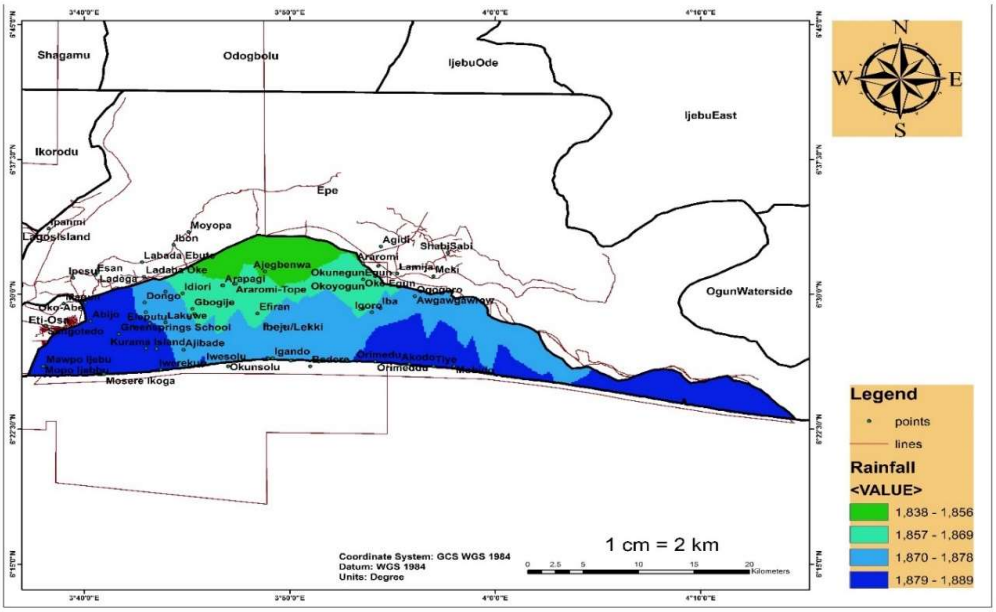


Figure 16: Map showing the rainfall distribution

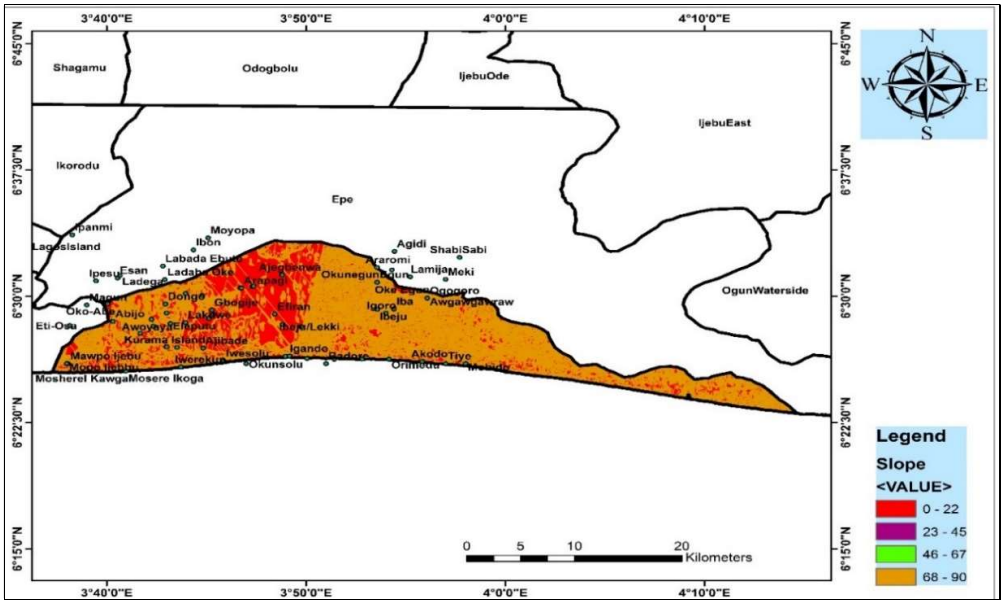


Figure 17: Map showing the Slope of the study area

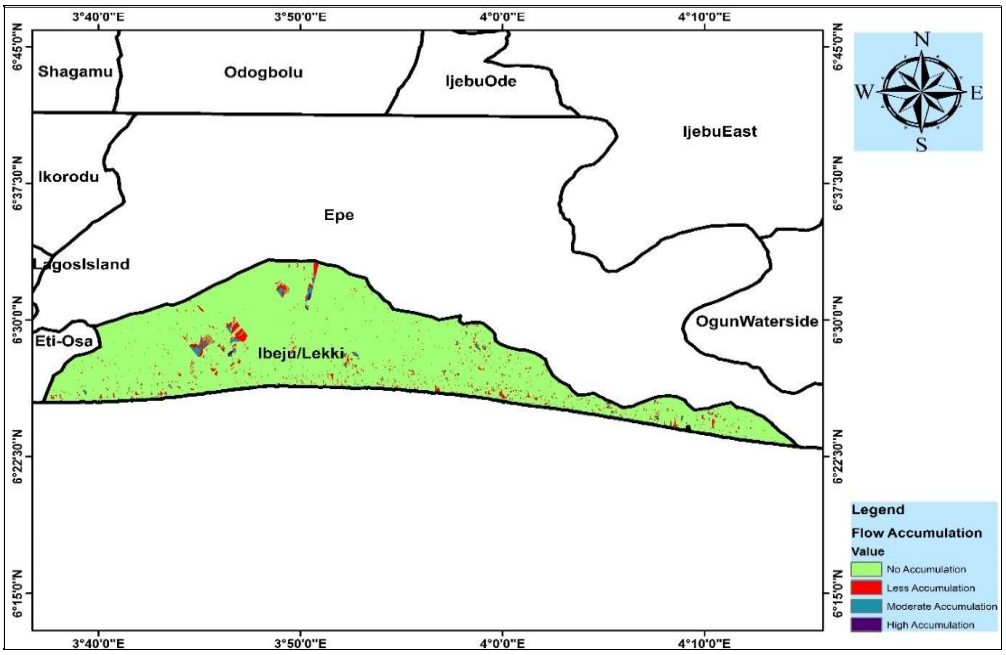


Figure 18: Map showing the Flow accumulation of the study area

The brown shade represents the lowest areas. DEM was used to generate the flow direction, flow accumulation and the stream network of the area. The flow direction map (Figure 19) shows the cells to which water is more likely to accumulate as it flows downslope. Cells with the greatest values are located at the lowest points and as such form accumulation points thus defining the flow direction. Water will flow towards the areas with the highest values.

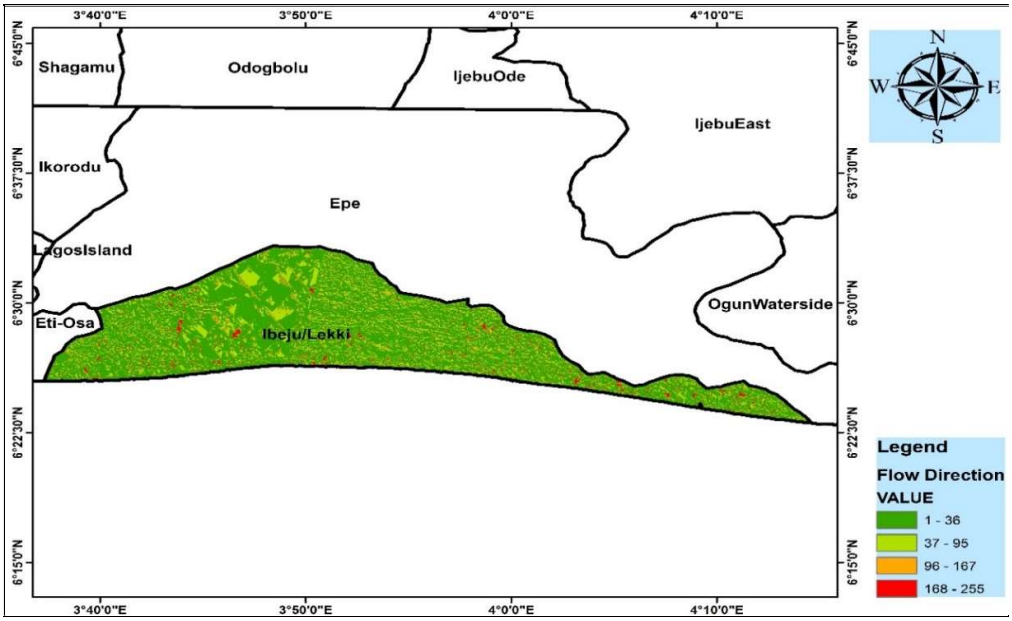


Figure 19: Map showing the Flow direction of the study area

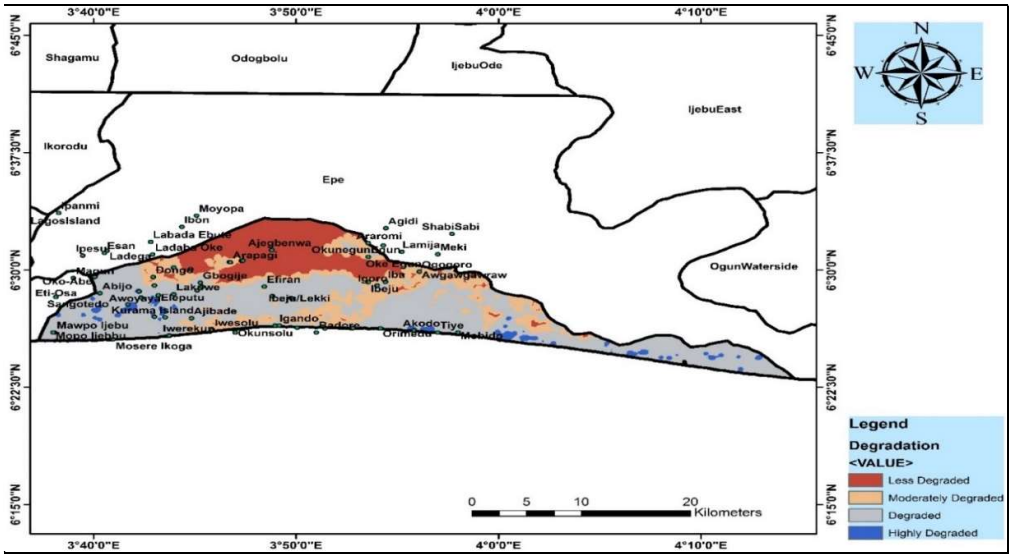


Figure 20: Degradation Vulnerability map of Study area

Figure 20 shows the degradation vulnerability index of Ibeju-Lekki which ranges between four classes; less vulnerable, moderately vulnerable, vulnerable and highly vulnerable. The vulnerable places cover the highest extent in the area and it can also be observed that places that have experienced a high level of urbanization tend to be the vulnerable portions of the area with some parts also being highly vulnerable inside the vulnerable areas. Areas originally covered by vegetation got removed to create space for buildings that serve various purposes like economic and residential. Consequently, the areas with degraded classes of vegetation and bare surface show a trend of high vulnerability to environmental degradation. More so, due to the generally low altitude of Ibeju-Lekki, areas along the coastal line such as

Mapo Ijebu, Iwerekun, Badore, MapoAkinlade are shown to be vulnerable to environmental degradation.

According to (Barbara Neumann, 2008), the drivers that create pressure on coastal zones are population or demographic change, socio-economic development and land use policy or regulation; among those, population growth and economic development are indicated as the most influential causes of pressure on coastal regions. This agrees with the findings of the current study, as the areas that have experienced the highest depletion in vegetation were discovered to be the most vulnerable to environmental degradation. This also aligns with Adegboyega et al. (2019) who observes degrading vegetation due to unstainable land use/land cover change in the coastal areas of Lagos State, Nigeria. Notably, urbanization and population growth have a direct relationship. Areas such as Kuramo, Eleputu, Efiran have lost a lot in km^2 to the consistent urbanization activity in Ibeju-Lekki. They also belong to the class of locations with large tendencies of high vulnerability to degradation in Ibeju-Lekki. This aligns with the submission made by Joyce Omenai (2014) that MopoOnijebu, Iwerekun, Maroko, Mopoakinlade and other areas close to the water body as areas with the highest environmental degradation vulnerability index. The extent of built-up in Ibeju-Lekki was always on the increase in the successive years considered at geometric progression which signifies an increase in population as a result of the consequent human activities. The areas that experienced the increase in built-up were then subjected as a criterion for the vulnerability of degradation and then discovered to be of high risk. This is consequent of the high extent of land reclamation that has occurred in the area which has caused the high rise in sea level.

CONCLUSION

The study has demonstrated the capability of geospatial technologies to generate environmental degradation vulnerability indices for monitoring and sustainable controlling of human-induced environmental changes around the coastal areas of Ibeju-Lekki LGA, Lagos State, Nigeria. The indices include swift urbanization rate, high population growth rate, high rate of deforestation, high rate of land reclamation, rapid land use change, soil degradation and heavy rainfall. These indices have been coalesced to generate environmental degradation index map to guide the State Government and other stakeholders in arriving at well-informed decisions regarding the sustainable development of coastal areas for industrial and urban developments as is the case in Ibeju-Lekki LGA and other coastal areas of cities in developing countries. The study advocates tree planting around these areas and evolvement of land use policy that will curtail sprawling and unauthorized developments in these areas.

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