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GEOSPATIAL ASSESSMENT OF THE COASTAL REGION OF SOUTHWEST NIGERIA

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Abstract

Land use/cover change is one of the main driving forces for global climate change, the change from vegetation to urban land causes not only interruptions of carbon and water cycles but also energy fluxes between the land and the atmosphere. The spatial distribution of the LST varies depending on the land cover type. The southwestern coastal region of Nigeria consist of towns experiencing rapid urbanization most especially towns located on Lagos coastal land. The land use land cover change of the region has produced remarkable influences on the land surface temperature. The land surface temperature influences the micro climate and social-economic development on a regional scale. The vegetation health, Land Surface Temperature (LST) and Land Use Land Cover of 1986, 2001 and 2016 were analyzed for the spatial distribution of changes in temperature, vegetation cover and land cover using Landsat images. A quantitative approach was used to explore the relationships among land surface temperature, land cover areas and Normalized Difference Vegetation Index (NDVI). Results showed that the vegetation cover has decreased rapidly over the 30 years' period from 72.45% to 54.00% and built-ups (urban areas) increased from 4.14% to 20.57%; and this changes has contributed to the variations in the microclimate and affected the land surface temperature. Furthermore, the NDVI correlated negatively with high land surface temperatures for the considered study years with 2001 showing the strongest negative correlation.

Keywords: Land surface temperature, land use, land cover, vegetation index.

Introduction

The coast is a unique environment in which atmosphere, hydrosphere and lithosphere contact each other (Alesheikh, 2007). The coast is home to three-quarters of the world's population and being an interaction area between the land and the ocean support many of the world's most productive and biologically diverse ecosystems, produce most of the world's fish catch, and support significant portions of the world's agriculture, industry and tourism (Sorensen *et al*., 1992). The coastal region is increasingly under pressure from human activities such as fishing, coral and sand mining, mangrove harvesting, seaweed farming, sewage disposal, urban expansion and tourism (Makota, 2004). These various human activities pose harmful threat to the coastal environment and are generally considered as environmental issues. The main drivers of the environmental pressures, effects and impacts include the climate change, economic growth and increasing coastal population change.

Land use and land cover change has become a central component in current strategies for managing natural resources and monitoring environmental changes. The advancement in the concept of vegetation mapping has greatly increased research on land use land cover change thus providing an accurate evaluation of the spread and health of the world’s forest, grassland, and agricultural resources has become an important priority. Land use-land cover (LULC) has become increasingly important as Nigeria plans to overcome the problems of haphazard, uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands and loss of fish and wildlife habitat. One of the prime prerequisites for better use of land is information on existing land use -land cover patterns and changes in land use through time. Since land use-land cover change is not an event but a process, it can be understood and hence forecasted quite well before time.

Land use/cover change is one of the main driving forces for global climate change. For example, the change from vegetation to urban land causes not only interruptions of carbon and water cycles but also energy fluxes between the land and the atmosphere (Lejeune *et al*., 2015). The spatial distribution of the LST varies depending on the land cover type (Voogt and Oke, 2003). The research carried out by Hereher (2017) demonstrated that the anthropogenic activities in the Nile Delta not only change the land use in the region but also its land surface temperature. Surface temperature is a major prediction variable for air temperature, and with the current issues concerning climate change across the globe, it has become imperative that researches such as this and carried out from time to time to monitor the activities going on in the climate environment, all contributing factors must be monitored and their rate of influence checked so that solutions will be easily reached (Joy, 2004).

Vegetation dynamics, especially over large scales, can be monitored using remote sensing (Barbosa et al., 2006; Gaughan *et al*., 2012; McGrath *et al*., 2012; Wang *et al*., 2003). Of the spectral indices derived from remote sensing which identify vegetated areas and their condition, the Normalised Difference Vegetation Index (NDVI) is still the most well-known and frequently used (Bulcock and Jewitt, 2010; Sims and Colloff, 2012). The relationship between NDVI and surface radiance temperature was studied for each land-cover type by Ewis Omran (2012). The studies showed that the strong negative correlation between surface radiance temperature and NDVI implies that the higher biomass land-cover has the lower surface temperature. Because of this relationship between surface radiance temperature and NDVI, land use/land cover change has an indirect impact on surface temperatures through NDVI.

Remote sensing is an essential tool of land-change science because it facilitates observations across larger extents of Earth‘s surface than is possible by ground-based observations. This is accomplished by the use of cameras, multi-spectral scanners, RADAR and LiDAR sensors mounted on air- and space-borne platforms, yielding aerial photographs, satellite imagery, RADAR and LiDAR datasets. Data available from remote sensing vary from the very high resolution datasets produced irregularly over extents no larger than a single state or province (by aerial photography, imaging, LiDAR, and by high resolution satellite sensors such as IKONOS and Quickbird), to regional datasets produced at regular intervals from satellites (e.g., Nigeriasat1, Landsat, SPOT), to the lower-resolution (> 250 m) datasets now produced across the entire Earth on a daily basis (e.g., MODIS). Therefore, for the measurement of land cover change and its surface attributes, remote sensing has been the best. This study therefore utilizes satellite data to analyze the change in the LULC, LST and NDVI of the coastal region of southwest Nigeria.

Nigeria is currently undergoing rapid and wide-range changes in its land due to climate change, the practice of slash-and-burn or shifting cultivation and rapid infrastructural development. Urbanization, being the main driver of land cover changes, is considered as one of the most significant factors in this regard. The study area has witnessed remarkable expansion, growth and developmental activities such as building, road construction, deforestation and many other anthropogenic activities without any detailed and comprehensive attempt (as provided by a Remote Sensing data and GIS) to evaluate this status as it changes over time. Land use changes and anthropogenic activities are affecting the environment and land surface temperature (Dehua *et al*., 2012; Weng and Schubring, 2004). There are lots of environmental challenges in the coastal region of Southwest Nigeria which have in recent time contributed immensely to the economic and social wellbeing of her inhabitants and quite a high percentage of these challenges have resulted from inadequate management of land use/land cover.

The dynamics of land use land cover and particularly settlement expansion in the study area requires a more powerful and sophisticated system such as GIS and Remote Sensing data which provides a general extensive synoptic coverage of large areas than area photography. The information produced from the land surface temperature analysis of this research will go a long way in adding value to the database of the coastal region planners when issues regarding human comfort, health and city geometry need to be addressed and if adequately updated, the result may be a baseline data to the planners for monitoring temperature variation, pollution and impact of development. The information produced from the vegetation health dynamics would help experts to tackle the issue of deforestation and land degradation in the study area.

Data and Methodology

Figure 1 shows the map of the study area. The study area comprises of the coastal regions in Southwest Nigeria which falls into Lagos, Ogun and Ondo State. Lagos lagoon cuts across the southern part of the metropolis, linking the Atlantic Ocean (in the west and south) and Lekki lagoon (in the east). It is about 6354.708 sq.km in area and 285km in perimeter. Some of the important areas or towns on the Lagos coast include: Ikeja, Surulere, Ipokia, Alimosho, Badagry etc. The marine coastal water in the western coast of the Gulf of Guinea in Ogun state is geographically situated between 06.29^{o}N, 04.24^{o}E and 06.48^{o}N, 04.42^{o}E. It is also the only area of the State with a coastline on the Bight of Benin and also borders Lagos Lagoon (Odebiyi, 2013). Ondo State coastline is along the 75 km eastern boundary mud beaches which terminate at the Molume at the boundary with Delta State of the western flank of the Niger Delta. The town that dominates the Ondo coast is the Ilaje town.

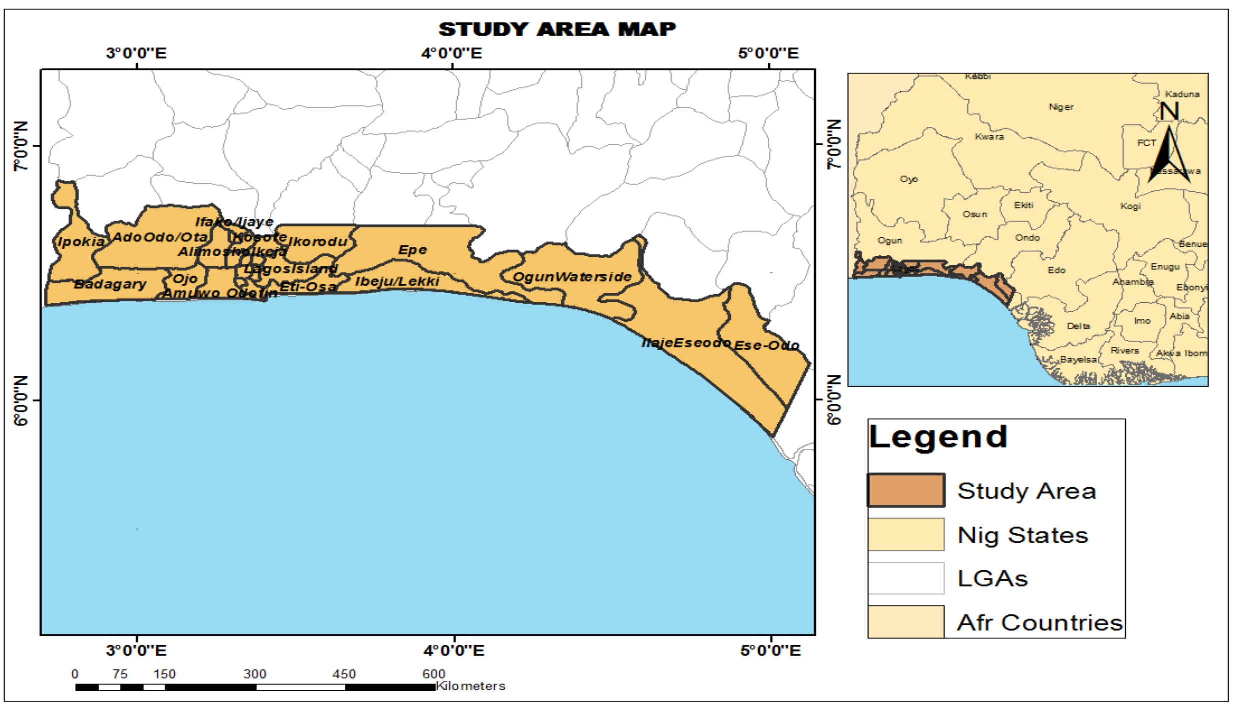

Figure 1: Study area map showing the coastal communities of South Western Nigeria.

The main data used in this work were Landsat images gotten from the United State Geological Survey (USGS) site. The data collection of interest were chosen, in which case it is imagery for this purpose, and then the Landsat header was selected from the archives of Earth Science Data

Interface (ESDI). All data were downloaded with projection from UTM-32 and they include the thermal band 6. Table 1 lists the data obtained for the work.

Table 1: List of data acquired, the sources and the resolutions.

S/N	Data sensor	Date acquired	Sources	Resolution
1	Landsat 5TM	15-Jan-1986	USGS (Earth Explorer)	30m
2.	Landsat 7ETM+	15-feb-2001	USGS (Earth Explorer)	30m
3.	Landsat8 OLI	21-nov-2016	USGS (Earth Explorer)	30m

Development of a Classification Scheme

Based on information from previous research in the study area, a classification scheme was developed for the study area after Anderson *et al*. (1967). The classification scheme developed gives a rather broad classification where the land use land cover was identified by a single digit. The classification classes used were listed in Table 2. The definition of bare lands as used in this research work denotes land without scrub, sandy areas, dry grasses, rocky areas and other human induced barren lands.

Table 2: Land use and land cover classes (after Anderson et al. 2016).

Code	Land use/ land cover categories
1	Barelands
2	Built-ups
3	Vegetation
4	Water Bodies

Methods of Data Analysis for Land Use/Land Cover Change

The stepwise methods of data analysis adopted for land use/land cover change are: calculation of the area in hectares of the resulting land use/land cover types for each study year and subsequently comparing the results; overlay operations; image thinning and maximum likelihood classification.

The first three methods above were used for identifying change in the land use types. Therefore, they have been combined in this study. The comparison of the land use land cover statistics assisted in identifying the percentage change, trend and rate of change between consecutive periods. A table was developed showing the area in hectares and the percentage change for each year measured against each land use land cover type. Percentage change to determine the trend of change can then be calculated by dividing observed change by sum of changes multiplied by 100%.

$$Q = O/S * 100\% \quad (1)$$

where; Q is percentage change; O is observed change; and S is sum of change and surface temperature methods. The data will be converted from digital number to spectral radiance (L_λ) using the following equation (Landsat 7 Handbook, 2003):

$$L\lambda = LMIN_\lambda + \frac{(\mathrm{LMAX\lambda - LMIN\lambda})}{\mathrm{QCALMAX}} QCAL \quad (2)$$

where, QCALMIN = 1, QCALMAX = 255 and QCAL = Digital Number, $LMIN_\lambda$ and $LMAX_\lambda$ are the spectral radiances for band 6 at digital numbers 1 and 255 respectively.

Normalized difference vegetation index (NDVI) image was computed for the years from 1986 to 2016 from visible (0.63 - 0.69 mm) and near-infrared (0.76 - 0.90 mm) data of the Landsat TM, and ETM+ using the following formula:

$$NDVI = (Band4 - Band3)/(Band4 + Band3) \quad (3)$$

where; Band 3 is Red Band and Band 4 is the Near-Infrared Band

NDVI has been found to be a good indicator of surface radiant temperature (Gallo, et al., 1993). The ETM+ thermal band data can be converted from spectral radiance temperature, which assumes surface emissivity = 1

$$TB = K2/\ln(\frac{K1}{L_\lambda} + 1) \quad (4)$$

where, TB = Effective at-satellite temperature in Kelvin, K1 = Calibration constant 1 (watts/meter squared*ster*µm) (666.09), K2 = Calibration 2 (Kelvin) (1282.71), and Lλ = Spectral radiance (watts/meter squared*ster*µm).

The brightness values obtained was then converted into land surface temperature. Since brightness temperature from equation (4) refers to black body with emissivity ε equal 1, the temperature of real surface would be different. LST in degree kelvin was calculated using the following equation by (Cartalis and Stathopoulou, 2007)

$$LST = \frac{TB}{1 + \left(\lambda \times \frac{TB}{\rho}\right) \times ln(\varepsilon)} \quad (5)$$

where, λ is the wavelength, ρ is h×c/σ (1.438×10−2 m K); and ε is emissivity and

Emissivity $\boldsymbol{\varepsilon}$ = 0.004PV + 0.986 and $PV = \left[\frac{NDVI - NDVI_{MIN}}{NDVI_{MAX} - NDVI_{MIN}}\right]^2$

The zonal statistical method is used to extract statistical information from satellite images on the GIS interface. The zonal statistics method (Situse, 2009) is used to compute the relationship between the land cover changes, LST changes and NDVI changes including their statistics.

Results and Discussion

Land Use Land Cover Classes

Figures 2(a-c) present the LULC of the study area during the study period. The static land use land cover distribution for each year as derived from the imageries is presented in Table 2. This characterizes the area covered by each land use and land cover class of the study area over thirty years in Square Kilometers and percentage. The values presented in Table 2 represent the static area of each land use land cover category for each year. Built-up in 1986 occupies the least class with just 4.14% of the total land area. On the other hand, vegetation occupies the highest portion with 72.45% in 1986 and decreased to 53.53% in 2001. It subsequently increased to 54% in 2016. Bare lands occupied 14% of the total area in 1986 was increased to 31.25% in 2001 and drastically reduced to 16.56% in 2016. The spatial extent in area of each land cover is shown in figure 2. Vegetation is the most dominant land cover type in 1986 as it occupied the largest area. Bare land was also the second most dominant land cover type. Built-ups covered the least area of the land of the study area. Figure 3 showed also that the 1986 built-ups had the least spatial extent in area compared to other study years. Vegetation and bare lands were the most dominant land cover types in year 2001. In year 2016, built-ups and vegetation were the most dominant land cover types. Built-up for 2016 had the largest spatial extent in area. Bare lands considerably increased to 2590.03Km^2 in 2001 and subsequently decreased to 1373 Km^2 in 2016.

The study further revealed that since the study area consists of coastal towns, the water body had almost consistent proportions across the study years. It occupied 9.41% in 1986, 9.47% in 2001 and 8.87% in 2016. The spatial growth of the other land cover types took place directly on vegetation between 1986 and 2001. This, therefore marked decrease in the vegetation cover between 1986 and 2001. The spatial growth and expansion of other land cover types took place on bare lands between 2001 and 2016. Figure 2 shows the Land use/Land cover maps derived from the satellite imageries of 1986, 2001 and 2016 respectively that showed different land use classes of the study area as they appeared in these years. Figure 2a showed that the various areas that were urbanized in year 1986. The areas include Agege, Ikeja, Alimosho, Ifako, Apapa, Shomolu, Kosofe e.t.c. By 2001, the rate of urbanization was already increasing most importantly in Alimosho and Amuwo Odofin as shown in figure 2b. By 2016, a lot of the coastal areas in Lagos State had become highly urbanized with built-ups occupying the land. Areas like Ojo, Adoodo/Ota, Amuwo Odofin, Agege, Ikeja, Kosofe, Surulere, Shomolu, Kosofe had become highly urbanized centers as shown in figure 2c. Therefore, it is quite obvious that the rate of urbanization grew from 1986 to 2016 in coastal areas that fell within Lagos State compared to the Ondo and Ogun coast. Population growth may therefore be referred to as the greatest driving force in the observed land use and land cover dynamics. There has been intense migration to the study area most especially to the Lagos coastal towns since it is the commercial hub of Nigeria. The demands for land for development of settlement, forest for fuel and construction of infrastructures have become great. From the land use land cover dynamics, it is discovered that urbanization has been a driving force towards a particular land use or land cover changes over time. Migration of people from the other states and indeed rural areas is also causing rapid land use land cover changes. This implies greater demand for food, housing and other basic amenities thus resulting to alteration of the land resources such as vegetation, bare lands, and water bodies so as to meet the needs of the ever growing population of the study area.

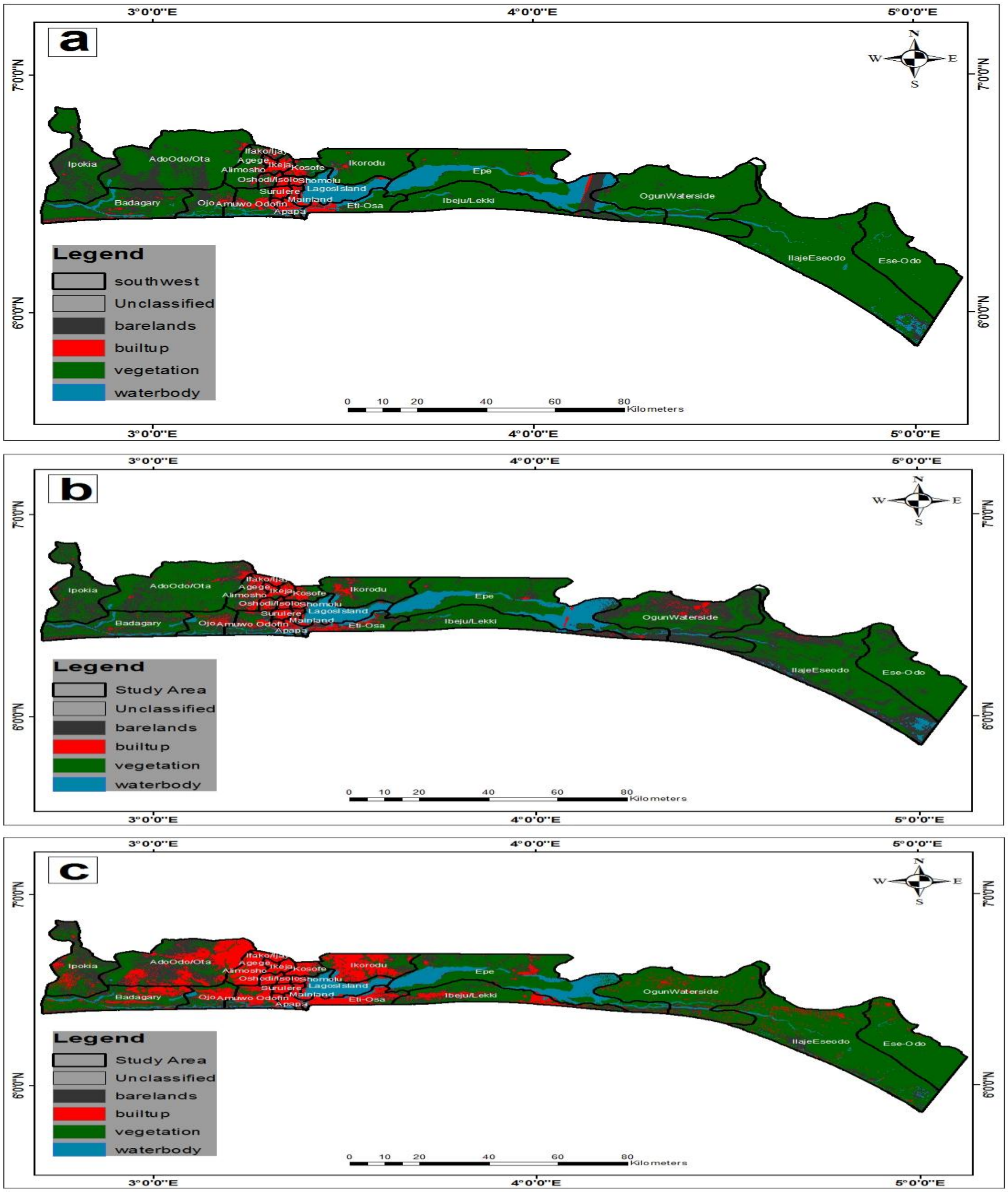

Figure 2: Spatial distribution of Land Use and Land Cover for (a) 1986; (b) 2001 and (c) 2016.

Table 3: Area covered by each LULC class.

Years	1986		2001		2016	
LULC	Area (SqKm)	Area (%)	Area (SqKm)	Area (%)	Area (SqKm)	Ar (%
Built-ups	343.24	4.14	476.50	5.75	1704.65	20
Vegetation	6005.59	72.45	4437.04	53.53	4475.99	54
Barelands	1160.06	14.00	2590.03	31.25	1373.00	16
Waterbodies	780.19	9.41	785.14	9.47	735.59	8
Total	8289	100	8289	100	8289	

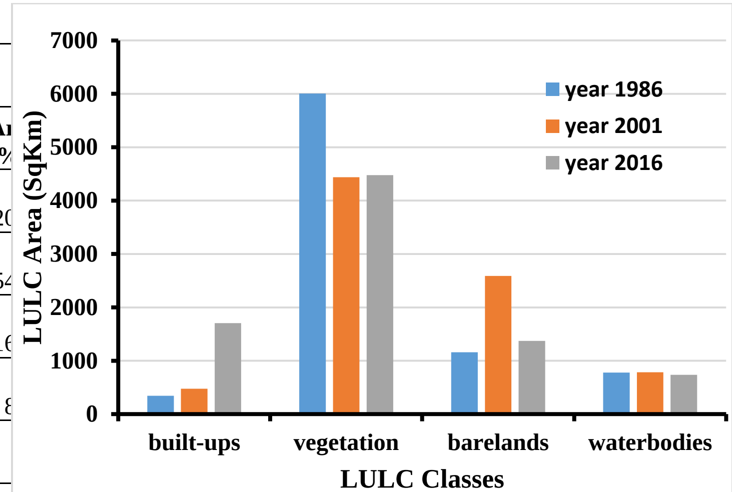

Figure 3: The spatial extent of each LULC class for 1986, 2001 and 2016

Land Surface Temperature Dynamics

The results of the land surface temperature (LST) analysis are presented. The land surface temperature map displayed in figures 4(a-c) are derived using the thermal bands and the of the Landsat satellite image of each study year. Maps showing the spatial patterns of LST across the study area are shown in figures 4(a-c). The minimum, maximum and mean land surface temperature for the three years considered are further illustrated in table and graphs. Land surface temperature of an area is an indicator of its climate change and radiation exchange with the atmosphere and its environment. The LST can best be described by analyzing the daily min, max and mean values. In figure 4a, Most of the study area had LST values of over 26.34^{o}C and the LST value ranged from 18.7^{o}C to 30.43^{o}C. Although the LST value ranged from 20.26^{o}C to 33.8^{o}C in 2001, it was very much observed in Figure 4a that the coastal towns of the study area dominantly had LST values of above 27.97^{o}C. In Figure 4b, the LST value ranged from 22.83^{o}C to 34.63^{o}C. Most places especially Ondo State coastal areas and Epe had low LST values. In Figure 5, for the year 1986, the area with lowest minimum LST is Ogun waterside (18.71^{o}C) and Agege, Ajeromi/ Ifelodun, Mainland, Mushin all with close values had the higher minimum land surface temperature. In 2001, Epe had the lowest value of 20.76^{o}C and Agege had the highest value of 29.75^{o}C. In 2016, Ese-Odo had the lowest value of 22.83^{o}C while Agege had the highest value of 25.65^{o}C. It was observed from Figure 5 that Ogun waterside grew to become one of the areas with higher minimum land surface temperature in 2001 with a value of 29.19^{o}C from 18.71^{o}C in 1986. In 2016, there was reduction again in the value of Ogun waterside. Minimum land surface temperature information is used as a proxy for monitoring minimum air temperature. Minimum air temperature is a factor of mosquito development time as well as an indicator of plasmodium parasite development within the mosquito vectors.

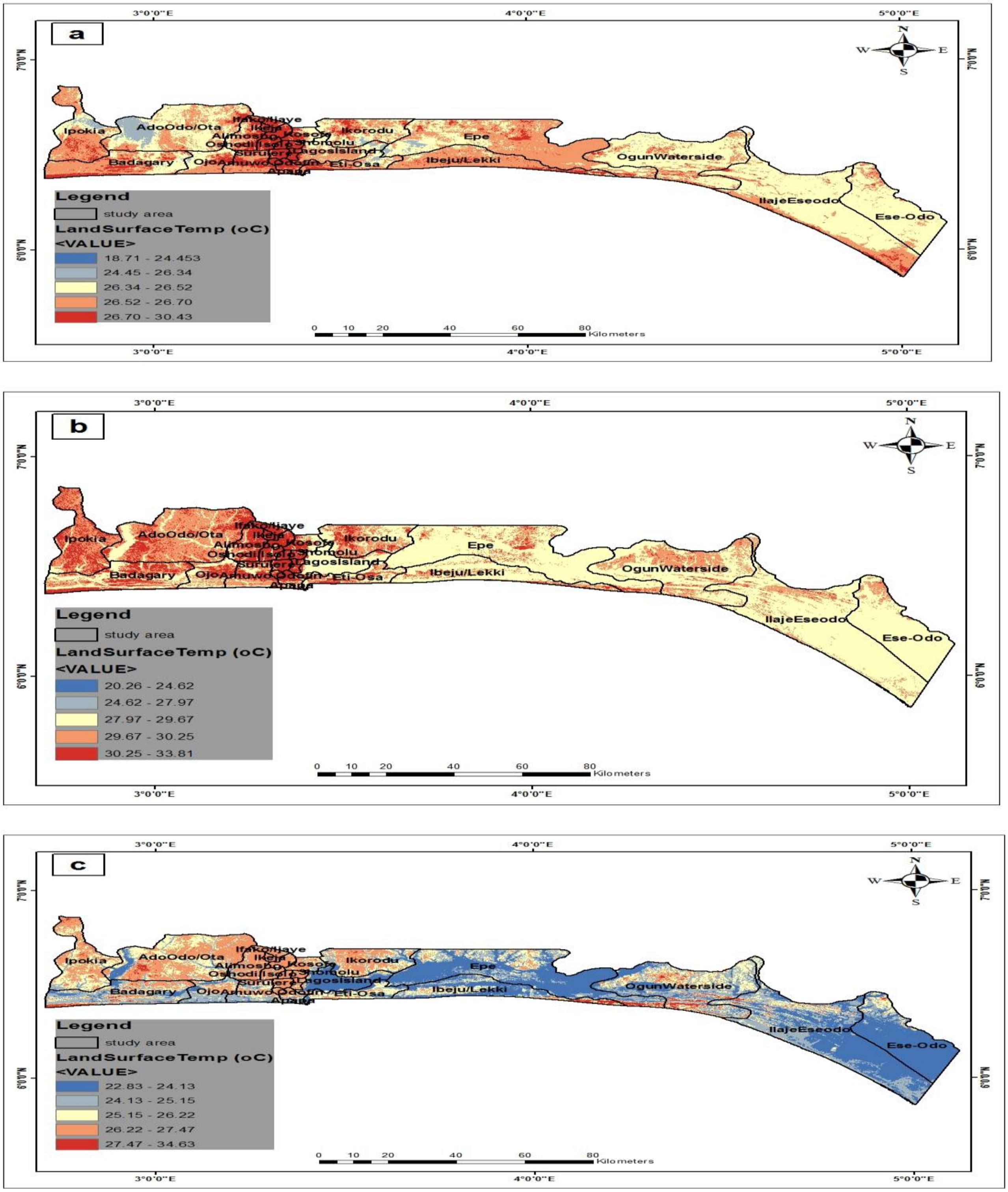

Figure 4: Map showing the spatial Pattern of LST across the study area in (a) 1986; (b) 2001 and (c) 2016

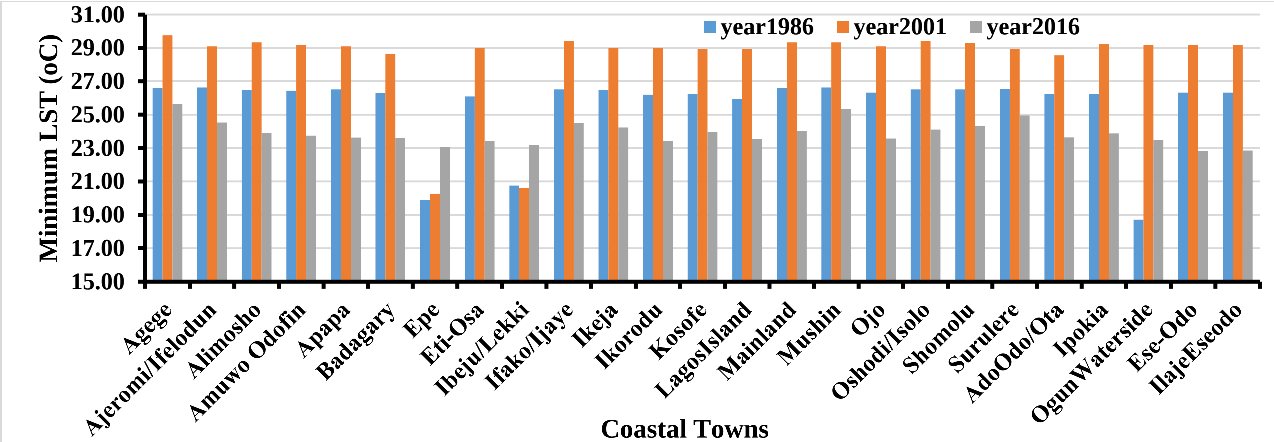

Figure 5: Minimum land surface temperature of the coastal towns for years 1986, 2001 and 2016

As depicted in Figure 6, the area with lowest maximum LST in 1986 was Ipokia (27.00°C) and Epe had the highest maximum land surface temperature. In 2001, Ese-Odo had the lowest value of 30.70°C and Ibeju/ Lekki had the highest value of 33.81°C. In 2016, Ifako/ Ijaye had the lowest value of 27.50°C while Ikorodu had the highest value of 34.68°C. As noticed in the figure, there was a decrease in the Maximum LST values for areas like Epe and Ogun waterside experienced very obvious decrease between 1986 and 2001 and gradual increase is noticed in both areas in 2016. Areas like Ibeju/Lekki and Ikorodu on the other hand experienced increase in their maximum LST values- Ibeju/Lekki experienced a very obvious increase between 1986 and 2001 and IKorodu experienced an increase between 2001 and 2016. From figure 7, in 1986, the area with lowest mean LST is Ese-Odo (26.48°C) and Mushin had the highest mean land surface temperature. Epe had the lowest value of 29.43°C in 2001 and Agege had the highest value of 30.79°C consecutively. In 2016, Ese-Odo had the lowest value of 23.86°C while Agege had the highest value of 27.64°C. Therefore, areas with the high minimum temperatures are areas that are continuously increasing in urban spatial extent. Vegetation is being cleared out in these areas and buildings are constructed. Areas dominated by bare lands also tend to have high maximum and minimum LST values.

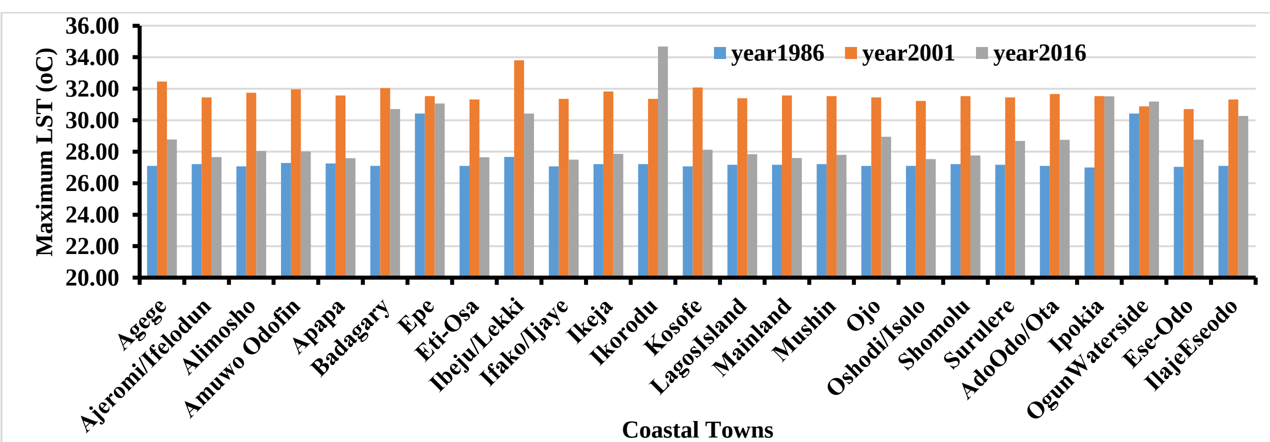

Figure 6: Maximum land surface temperature of the coastal towns for years 1986, 2001 and 2016

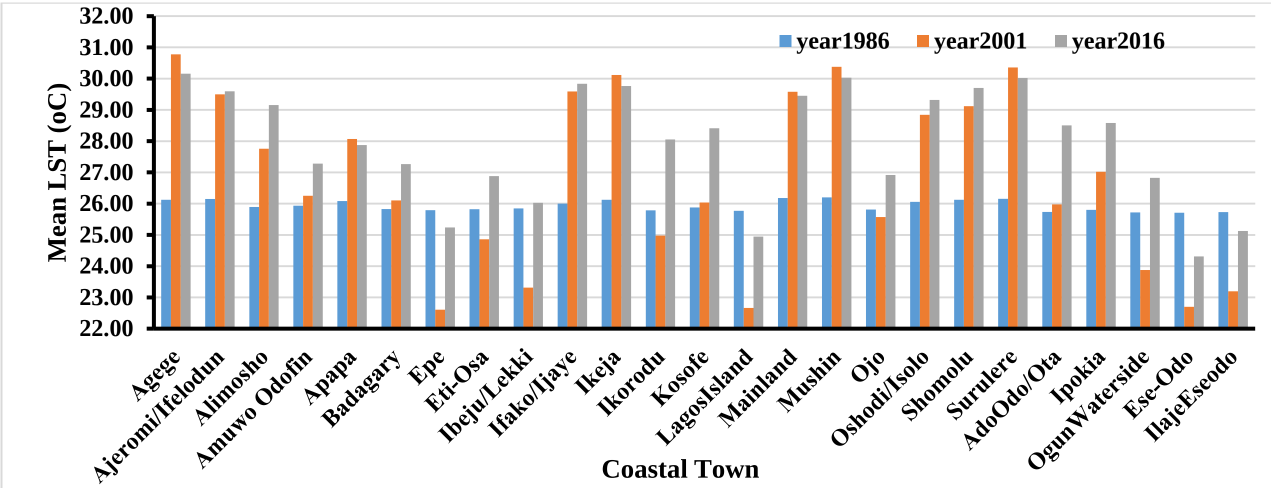

Figure 7: Mean land surface temperature of the coastal towns for years 1986, 2001 and 2016.

Relationship between Land Use Land Cover and Land Surface Temperature

Zonal statistics analysis was carried out in order to investigate the relationship between land use land cover and land surface temperature of the study area. Therefore, the mean LST of each land use land cover class was used in order to know the impact of each LULC class on the LST of the study area for each study year. Table 3 shows the various minimum, maximum and mean LST value for each LULC class. As presented in Table 3, built-ups had the highest minimum LST value of 26.25°C for 1986 which increased greatly to 28.55°C in 2001. The minimum LST then reduced drastically to 23.13°C in 2016. The minimum LST value of the bare land increased from 20.51°C to 22.98°C from 1986 to 2016. The vegetation's minimum LST value increased from 18.71°C to 22.83oC from 1986 to 2016. The bare lands had the highest maximum LST maximum values from 1986 to 2016. The values ranged from 28.94°C to 34.68°C. The built-ups had high maximum LST values too which ranged from 26.25°C to 32.45°C. The maximum LST value of the vegetation increased between 1986 and 2001 and decreased in 2016 to 29.78°C. The maximum value of the waterbody's LST also decreased to 27.06°C in 2016.

Built-ups consecutively showed the highest LST value as depicted in figure 8a. It has the value of 26.90°C. Bare lands also showed a very high LST value of 26.63°C. Vegetation and waterbody had the lowest LST value of 26.51°C and 26.55°C respectively. In figure 8b, built-ups and bare lands also had the highest value of 30.58°C and 29.98°C. Vegetation and waterbody invariably had the least LST values of 29.56°C and 29.33°C respectively. In figure 8c, built-ups and bare lands were found to have the highest LST values of 25.94°C and 26.48°C respectively. The vegetation and waterbody classes were also found to have the least LST values of 24.36°C and 23.76°C respectively.

The graphs therefore generally showed lower mean land surface temperatures over the vegetation and waterbody. Built-ups and bare lands exhibited high land surface temperature values. The high surface temperature even over vegetation cover was as a result of more surface modifications, anthropogenic activities, little vegetation, and consequently little/no evapotranspiration. Therefore it can be deduced from the results in Figures 8(a, b and c) that high LST values are associated with built-ups which constitute urban centers and low LST values are associated with natural vegetative surfaces.

Table 3: Minimum, maximum and mean LST values for each land use land cover class

Years	1986			2001			2016		
Class name	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Bare lands	20.51	28.94	26.63	20.60	33.81	29.98	22.98	34.68	25.94
Built-ups	26.25	27.29	26.90	28.55	32.45	30.58	23.13	30.71	26.48
Vegetation	18.71	30.43	26.51	21.87	31.40	29.56	22.83	29.78	24.36
Waterbody	19.89	30.43	26.55	20.26	31.06	29.33	23.00	27.06	23.76

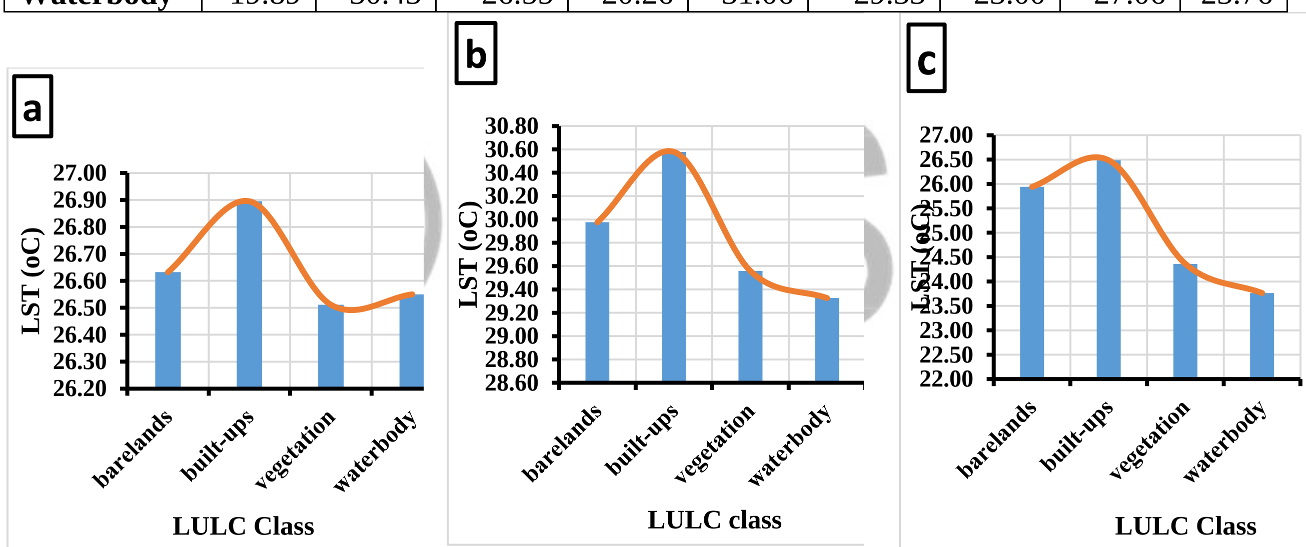

Figure 8: The relationship between LST and LULC for (a) 1986; (b) 2001; and (c) 2016.

Vegetation Health Dynamics

The Normalized difference vegetation index (NDVI) was computed in order to evaluate the health and abundance of the vegetation of the study area. The NDVI maps of the study area for the study years (1986, 2001 and 2016) are shown in figures 9(a-c). The minimum, maximum and mean land surface temperature for the three considered years are illustrated in table and graphs. The normalized difference vegetation index (NDVI) which is a numerical indicator that uses the visible and near-infrared bands of the electromagnetic spectrum was computed for each of the study year. Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1 but in practice, extreme negative values represent water, values around zero represent bare soil and values close to one represent dense green vegetation. The Figure 9 show the NDVI maps for the coastal towns in southwestern Nigeria highlighting the spatial distributions of vegetation based on the images of 1986, 2001 and 2016. It is to be noted that the spatial variation of NDVI is not only subjected to the influence of vegetation amount, but also to topography, slope, and solar radiation availability and other factors (Liu et al., 2004).

The minimum NDVI values for the year 1986 was -0.694 while the maximum for the NDVI was 0.947 as seen in Figure 9a. Areas like Lagos Island, Odofin, Isolo, Surulere, Somolu have low NDVI values. Ibeju-lekki, Ikorodu and Lekki have fairly high NDVI values. The Ilaje and Ese-odo towns have high NDVI values. In Figure 9b, The NDVI value ranges from -0.694 as the minimum to 0.041 as the maximum in 2001. Areas like lagos island, Odofin, Isolo, Ikeja, Somolu, Ifako/Ijaye have very low values of NDVI. Ilaje, Ese-Odo, Ogun waterside, Ipokia have the highest values of NDVI. The NDVI values ranges from -0.280 to 0.620 in year 2016 as seen in Figure 9c. Areas like Epe, Ipokia have the highest NDVI values, Ogun waterside, Ilaje, Ese-odo have fairly high NDVI values and lagos island, somolu, ikeja, ifako/ ijaye, Oshodi, Surulere have the least NDVI values.

The highest degree of difference was observed in 2001, with the majority of NDVI values appearing to be below 0. The dominance of negative NDVI values in areas like Lagos Island, Surulere, Ikeja, Oshodi, Isolo may be attributed to increasing urbanization leading to more built-up areas and bare-surfaces. Generally, healthy vegetation will absorb most of the visible light that falls on it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum. Therefore, the observed negative value is because the reflectance value in the red band is higher than reflectance value in Near Infra-red band. Comparing the NDVIs of 1986 and 2016, changes were identified. The two years both have majority of the region under study exhibiting positive values of NDVI except core urban centers e.g. the Lagos Island, Ikeja, Oshodi etc which indicate expanse of wide coverage of healthy vegetation.

Minimum NDVI values indicate the minimum photosynthetic capacity of the study area which is under consideration. Figure 10 shows chart shows the values of minimum NDVI across the coastal towns in the study area for the considered years. In 1986, Ese-odo had the highest value of NDVI of 0.121 while Lagos Island had the lowest value of NDVI of -0.203. Epe had the highest value of minimum NDVI in 2001 with Agege having the lowest value of NDVI with value of -0.595 respectively. In 2016, Ese-Ode had the highest minimum value of 0.167 and Lagos Island had the lowest minimum value of -0.183. It is observed that Lagos Island and some corresponding areas (Lagos coastal areas) had lowest minimum NDVI. This means the photosynthetic capacity of these areas is pretty low basically due to the urban nature hence decreased vegetal cover of the areas.

Maximum NDVI values indicate the maximum photosynthetic capacity of the study area which is under consideration.

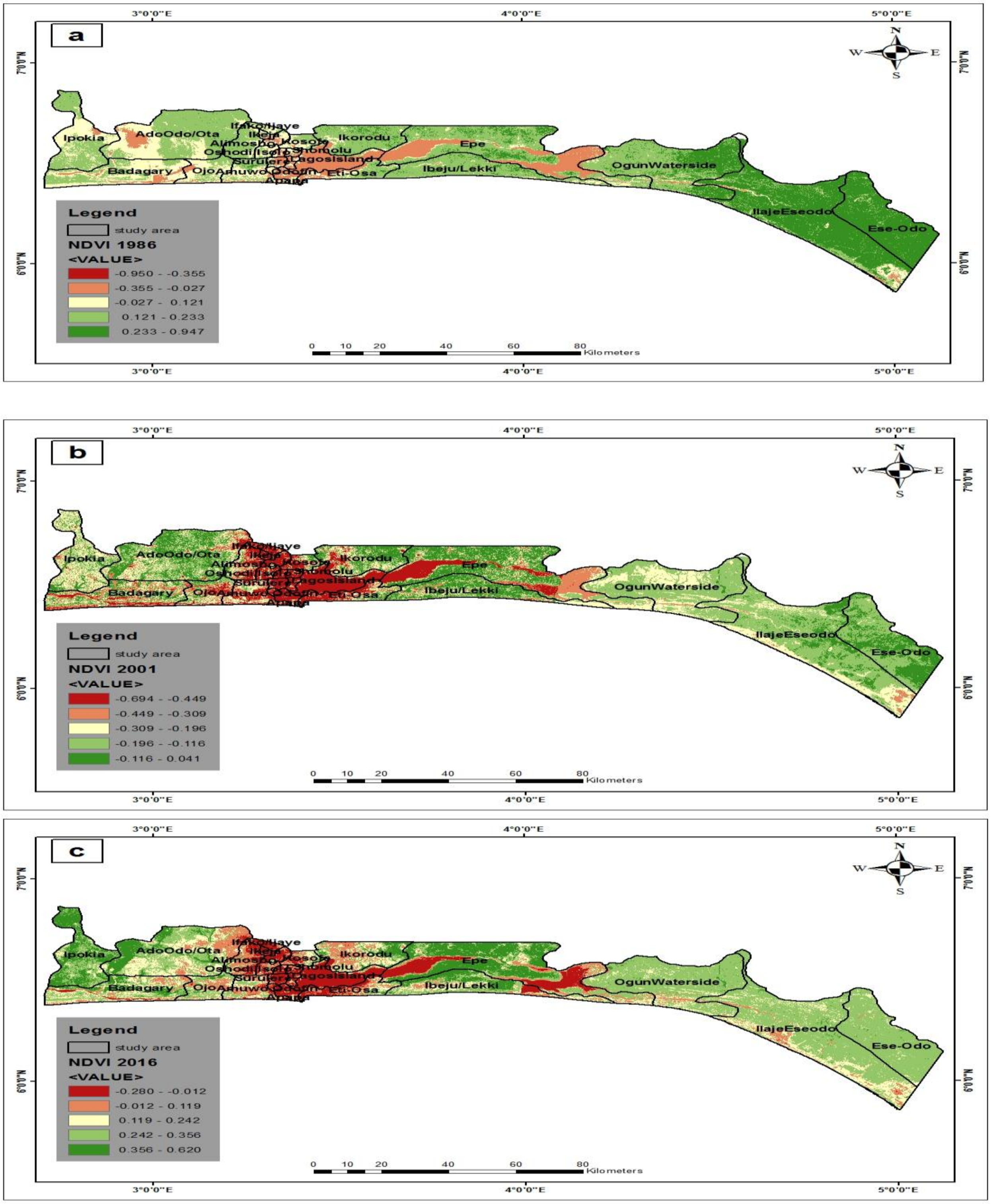

Figure 9: The spatial pattern of NDVI across the study area in (a) 1986; (b) 2001 and (c) 2016

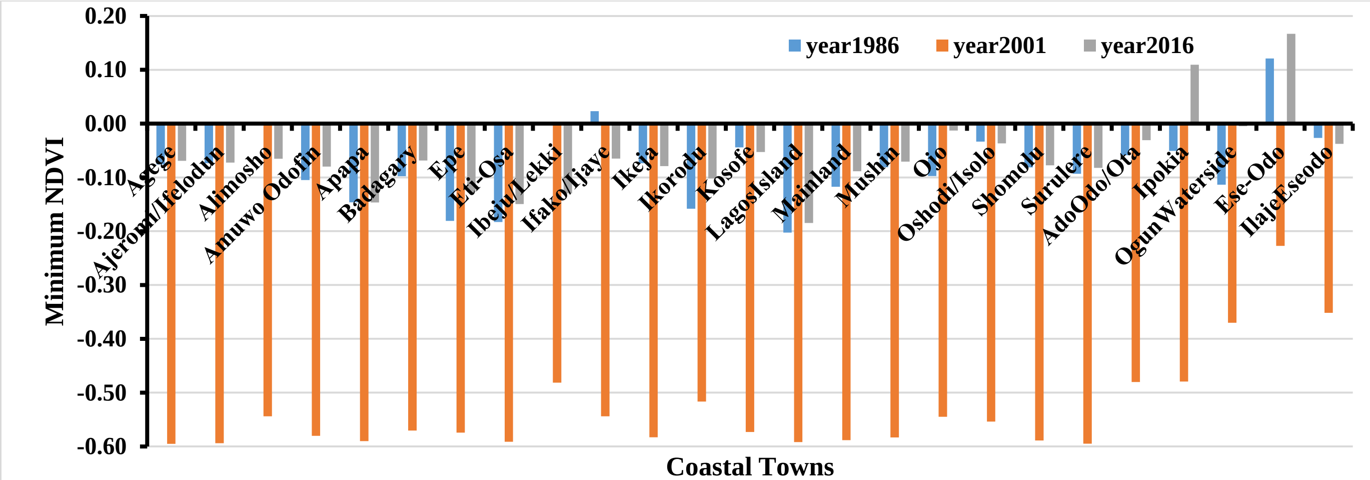

Fig 10: Minimum NDVI value over the coastal towns for 1986, 2001 and 2016.

Figure 11 presents the values of maximum NDVI across the coastal towns in the study area for the considered years. In 1986, Ese-odo had the highest value of NDVI of 0.370 while Mainland had the lowest value of NDVI of 0.054. In 2001, Epe had the highest value of maximum NDVI in figure. With Adoodo/Ota having the lowest value of maximum NDVI with value of -0.002. In 2016, Adoodo/Ota had the highest maximum value of 0.537 while Mushin had the lowest maximum value of 0.084. It was therefore observed that Adoodo/Ota drastically moved from having the lowest Maximum NDVI value in 2001 to having the highest maximum in 2016. This therefore implies that vegetation cover considerably increased in Adoodo/Ota from 2001 to 2016. It was also observed from figures that areas with the lowest maximum NDVI values were found in the Lagos coastal region. Areas like Mainland, Mushin, Ikorodu, Ojo all have low maximum NDVI values and they are all in Lagos state and are referred to as urban centers. Epe, Ilaje and Ese-Odo tend to have high maximum NDVI values because they are yet to fully develop into urban centers and there is no rapidness in the conversion of their vegetal covers to urban infrastructures.

Mean NDVI values indicate the primary productivity proxy for the period when the NDVI values are averaged. Figure 12 shows the chart showing the values of mean NDVI across the coastal towns in the study area for the considered years. In 1986, Ese-odo had the highest value of mean NDVI of 0.29 while Lagos Island had the lowest value of mean NDVI of -0.11. Epe had the highest value of mean NDVI in 2001 with Surulere having the lowest mean value of NDVI with value of -0.53. In 2016, Ipokia had the highest mean value of 0.36 and Lagos Island had the lowest mean value of -0.08. It is also observed here that Lagos Island and some corresponding areas (Lagos coastal areas) had lowest mean NDVI.

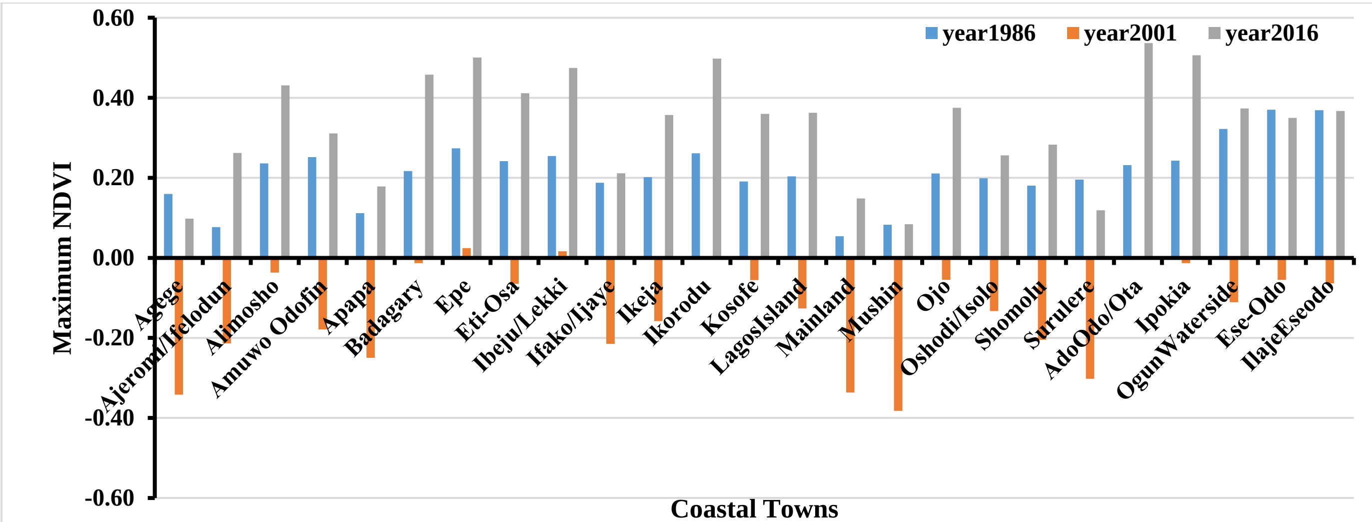

Figure 11: Maximum NDVI over the coastal towns for 1986, 2001 and 2016

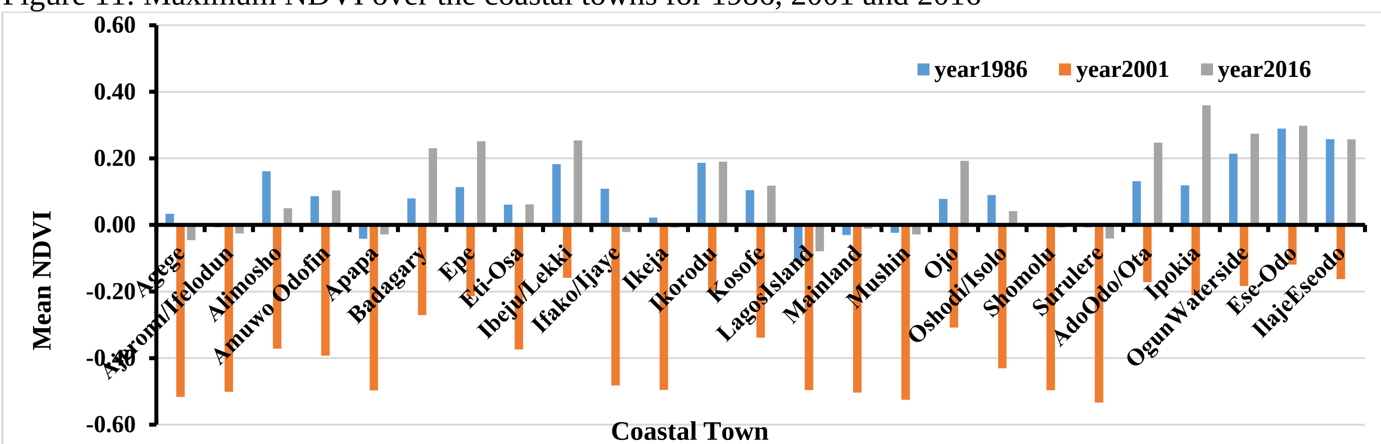

Figure 12: Mean NDVI over the coastal towns for 1986, 2001 and 2016.

Relationship between Land Surface Temperature and NDVI

A regression analysis between mean LST and mean NDVI for all the towns in the study area was conducted (the NDVI is an indicator of vegetation health). The results of the regression analysis are depicted in Figure 16 where each point represents the mean LST and mean NDVI value associated with each town within the study area. The results shown in figure 13(a-c) indicated a significant correlation between LST and NDVI for the study area. The results indicated a significant inverse correlation between LST and NDVI for the study area. In other words, coastal towns with high LSTs will register low NDVI readings whereas towns with high LSTs will register high NDVI readings. Therefore, NDVI information can be used to invariably relate and assess land use temperature of any area.

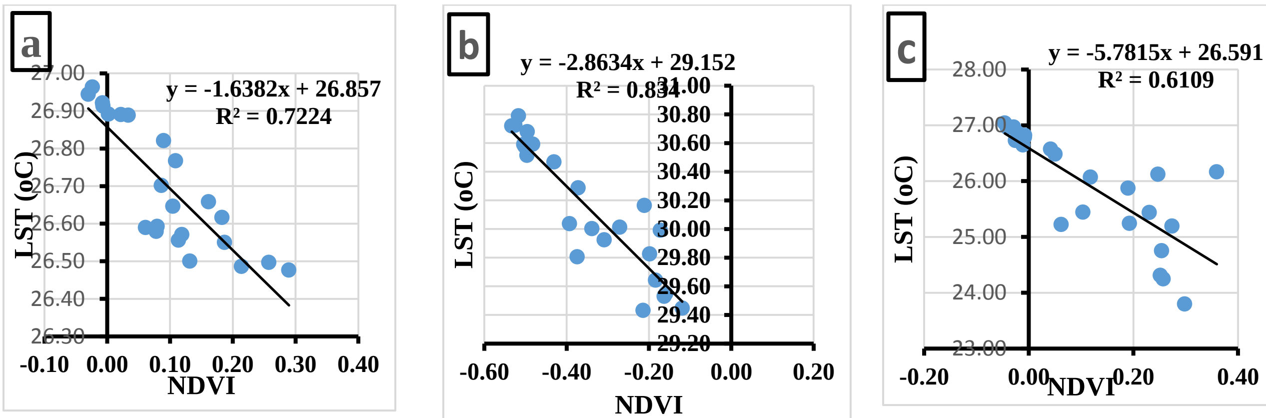

Figure 13: Relationship between LST and NDVI for (a) 1986; (b) 2001; and (c) 2016.

Conclusion

Summarily, this research has successfully explored the use of satellite remote sensing and GIS techniques in comprehensively assessing the various environmental phenomenon of the coastal region of Southwest Nigeria for the last three decades (1986 to 2016). The spatial and temporal analysis of the LULC change trends indicated that from 1986 to 2016, the land use/ land cover of the study area has been significantly altered from its initial state. Also, the result raises concern over the magnitude of alteration of the land cover particularly the depletion of vegetation covers and conversions of bare lands to urban settlements. The results of the land surface temperature showed that as at 1986, the lowest LST was 18.71^{o}C while the highest LST was 30.43^{o}C but in 2001, the LST increased to a minimum of 20.26^{o}C while the maximum temperature rose to 33.81^{o}C and in 2016, the LST ranges further increased to lowest of 22.83^{o}C and maximum of 34.63^{o}C. Through this analysis, the relationship of different land use land cover change pattern and land surface temperature was revealed. The spatial and temporal variation of the surface temperature followed the pattern of LULC changes over time and LST is very high over built-ups (urban settlements) and bare lands while vegetation and water bodies consistently had low LSTs.

The in-depth analysis of spatial and temporal results from NDVI has revealed very valuable information about the general conditions of vegetation cover and health over the study area. 1986 happened to be the most vegetated year among the considered years. The NDVI ranged from -0.950 to 0.947. There was a very obvious decrease in the vegetation cover of 2001. The NDVI ranged from -0.694 to 0.041. The NDVI for 2016 ranged from -0.280 to 0.620. The relationship between the LST and NDVI was established. It was observed that a strong negative correlation existed between them and the LST increased as a result of decrease in the NDVI values of the area. Therefore, conclusion is being made that relationships exist between LULC, LST and NDVI.

Recommendation

It is recommended that the relevant research institutes should advocate for frequent assessment and simulation of the state of LULC in our environment using high resolution images at shorter intervals of 3 years minimum so as to timely depict changes early enough and raise concerns to appropriate authority even if they will not respond but for record purposes. Because if the rate of alteration of the natural environment particularly the depletion of vegetation and conversions of bare lands and vegetation to settlements is continued unabated, urban heat intensity will increase leading to rise in temperatures and this will further worsen the present climate change situation.

It is also recommended that researches on land surface temperature be carried out using high resolution satellite images in the same study area and relationship with Land use land cover changes be evaluated most especially over the Lagos coast. High resolution satellite images should also be used to assess the spatial and temporal vegetation health dynamics at shorter interval across the study area so as to compare results with this research. Finally, it is recommended that all the results in this research be used as a veritable guide to stakeholders and policy makers of the Southwest coastal region and by extension the other relevant ministries in charge of our environment in Nigeria.

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