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Change Detection in the Land Surface Temperature and NDVI of Okomu National Park and Adjoining Communities, Edo State, Nigeria

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ABSTRACT

The purpose of this study was to establish the influence of temperature on the forest resource and estimate the extent of changes in the environment of Okomu National Park for the years 2000, 2010, and 2020 using satellite imagery analysis. The study used normalized difference vegetation index (NDVI), land cover, and land surface temperature (LST) data acquired from Landsat. The acquired data were analyzed using descriptive statistics, and correlations were investigated using regression analysis and Pearson's correlation. For correlation analysis, LST and NDVI were both divided into five classes. Fron the results obtained, the NDVI map provided that the high category of the forest cover classes had degraded to medium and low classes, and the values of 2000, 2010 and 2020 indicates that the land cover had experienced an evident degradation over the study periods. The NDVI high class of 184.24 km^2 of 2000 was reduced to 38.07 km^2 in 2020. The values of the 2000 LST ranged of the from 19.1632 (low) – 34.4896 (high) degrees; value for 2010 was low: 31.1872 – high: 43.0681°C and 2020 was 18.1622 – high: 25.061°C. The correlation analysis reveals that the R^2 = 0.981, 0.7198, 0.9835 for years 2000, 2010 and 2020 respectively. The study showed that year 2010 had the highest LST over the area, with LST reducing by 2020. The LST map also revealed that high temperature was obtained in the north eastern section of the map where there the percentage of built-up areas was highest. The conversion of the forests to other land use/landcover classes will lead to increased temperature and cause decline in forest biodiversity.

Keywords: Temperature, Vegetation Index, Forest Cover, Correlation, Okomu

1.0. Introduction

Climate Change is now widely recognized as a major environmental problem facing the globe (United Nations Environment Programme, 2013). According to Ishaya and Abaje (2008), climate change in the dynamics of nature has an effect on balance of nature and natural resources, and these effects are already visible in Nigeria. The visible effect may relate to variations in temperature, precipitation, and climatic patterns, which in turn affect nutrient cycles and the physiological activities of plants as well as microbial activity. The risks associated with Climate Change are real but highly uncertain (Ogbo *et al.*, 2013). Recent studies point out that reduced or increased precipitation is considered to be the vital limiting factor in vegetation growth (Zhang *et al.*, 2019). Furthermore, some studies have also suggested that temperature decrease could also limit vegetation growth (Kong *et al.*, 2017).

Vegetation indices have been reported reliable in monitoring vegetation change. One of the most widely used indices for vegetation monitoring is the Normalized Difference Vegetation Index (NDVI) (Nath and Acharjee, 2013). Red to NIR band ratios of a sensor system can be used to determine NDVI. The NDVI threshold value, according to Furkuo and Frimpong (2012), varies from -1 to +1; observed values vary from -0.35 (water), through zero (soil), to +0.6 (dense green vegetation). This has a pixel digital number of 135 or higher based on grey scale. The researchers came to the conclusion that the more positive the NDVI the greener vegetation there is within a pixel.

Okomu National Park (ONP), which is one of the few remaining rich tropical dense forests, is the only protected area of Okomu Forest Reserve (OFR). The protected forests of Okomu National Park (ONP), Nigeria is currently under threat due to pressure from illegal logging and encroachments, and these activities directly impact ecosystem functions. Osadolor and Chenge (2023) reported that between 2000 and 2020, ONP and the surrounding forest patches experienced high level degradation, where 10% of the forest was lost annually. However, the responses of different vegetation types to climate change show great disparity, which undoubtedly increases the difficulty of quantitative analysis (Haoche *et al*., 2020). It becomes necessary to provide information on the relationship between the vegetation changes observed in the study area and the change in climate respectively. The purpose of this study was therefore to analyze satellite imagery using Landsat-derived data on land cover, land surface temperature (LST), and normalized difference vegetation index (NDVI) in order to estimate the extent of changes in the environment of Okomu National Park for the time periods of 2000, 2010, and 2020; and to assess the relationship between these variables.

2.0 Methodology

2.1. Study Area

Okomu National Park (ONP), formerly known as Okomu Wildlife Sanctuary, is depicted in Figure 1. forest block within Okomu Forest Reserve (OFR), The Rivers Okomu and Osse form the west and east boundaries of the reserve, which is located between latitudes 6°10´0´´N - 6°30´0´´N and longitudes 5°8´0´´E - 5°26´28´´E. According to Okomu National Park (2010), the park, which was formed by Decree 46 of 1999, has a total size of 202.24 km^2. The Nigerian Conservation Foundation expanded the National Park from a 66 km^2 sanctuary to 114 km^2, adding a 1.6 km wide buffer zone. Okomu National Park (ONP) was established from Okomu Forest Reserve (OFR), principally for the preservation of the reserve's already-existing endangered fauna.

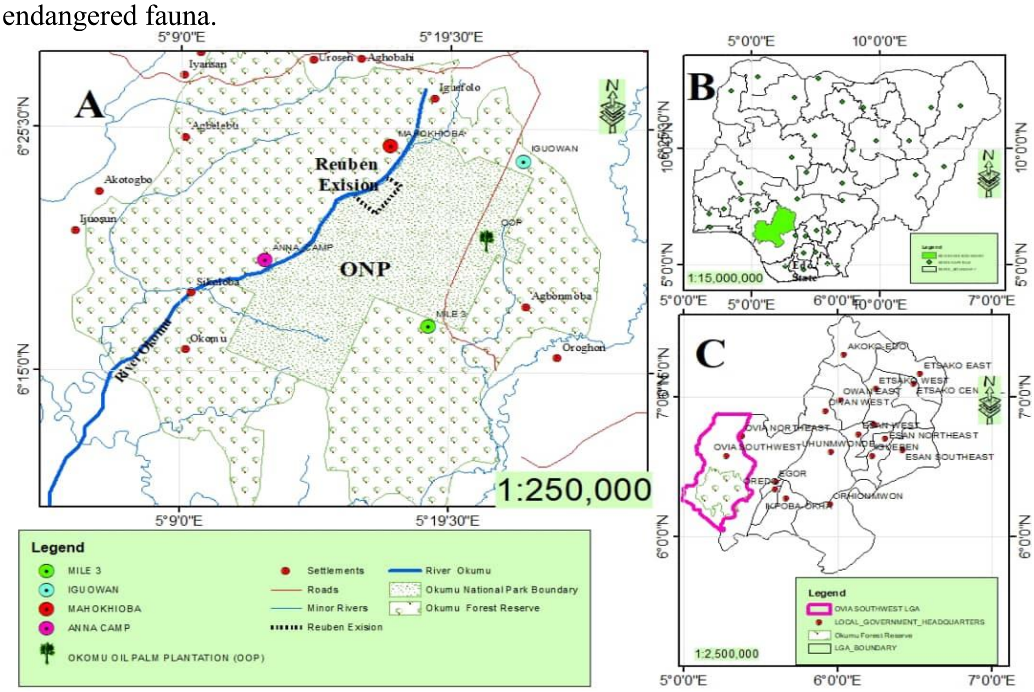

Figure 1. Okomu Forest Reserve (OFR) showing the study areas (Field Work, 2020)

2.2 Study Procedure

2.2.1 Assessment of the impact of temperature on the study area for the study period (2000, 2010 and 2020)

The impact of temperature on Okomu National Park was assessed using the spatial analysis tool of the ArcGIS tool box. The distribution of temperature over the research region was calculated using the raster calculator technique. This was accomplished by processing data in the order listed below, which is highlighted:

Step 1: Conversion to Top of Atmospheric Radiance (ToAR)

$$L\lambda = M_L Q_{CAL} + A_L \quad (1)$$

where:

$L\lambda$ is Top of Atmospheric Radiance ToAR
M_L is the radiance multiplier
Q_{CAL} is the pixel value in DN (DN)
A_L = is the radiance additive scaling factor for the bands obtained from the metadata

Step 2: Conversion to Top of Atmosphere Brightness Temperature

$$TB = \frac{K2}{\left({}^{k1}/_{L\lambda}+1\right)} - 273.15 \quad (2)$$

Where:

TB = is the satellite brightness temperature (K)
$L\lambda$ = TOA spectral radiance (watts/(m2*srad*mm))
K1 = is the band specific-thermal conversation constant 1 (W/m2 sr μm)
K2 = is a calibration constant 2 in Kelvin

Step 3: Calculating Emissivity

The formula below was used to calculate land surface emissivity (LSE)

e = 0.004*Pv+0.986

$$Pv = \left(\frac{NDVI - NDVImin}{NDVImax - NDVImin}\right)^2$$

Where:
e = emissivity (3)

Pv = proportion of vegetation

Step 4: conversion from At-Satellite Temperature to Land Surface Temperature

$$LST = \frac{TB}{1+\left(\lambda*\frac{TB}{c2}\right)*\ln(e)} \quad (4)$$

TB= is the satellite brightness temperature
c2 = h*c/s = $1.4388*10^{-2}$ m.K = 14388 mK
h = Planck's constant = $6.626*10^{-34}$ J.s
s = Boltzman constant = $1.38*10^{-23}$J/K
c = velocity of light = $2.998*10^{8}$ m/s
e = emissivity

2.2.2 Normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a numerical representation of vegetation based on the red and near-infrared spectral bands. Regions with high NDVI values tend to reflect more near-infrared light. Higher near-infrared reflectance is associated with denser and healthier vegetation (Voiland, 2009). The Normalized Difference Vegetation Index (NDVI) general equation was utilized to compute this. It is represented by

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \quad (5)$$

Where: Normalized Difference Vegetation Index, or NDVI.
NIR = near-infrared = an abbreviation for visible red reflectance (spectral band 0.6–0.7 m).
NIR stands for near-infrared reflectance, and RED for reflectance in the visible red band.
The NDVI algorithm makes use of the fact that dense or less green vegetation reflects more visible light and less near-IR, whereas green vegetation reflects less visible light and more NIR.

2.3 Relationship Between LST and NDVI within the study area

The analysis of relationship between LST and NDVI was carried out using the correlation tool of excel sheet. This was done to determine the strength of the relationship. Similarly, correlation analysis was carried out to establish the influence of temperature on the forest resource. Both LST and NDVI were categorized into five classes for correlation analysis. The classes are low, secondary low, medium, secondary high and high. The Pearson product moment correlation coefficient formula is represented mathematically as:

$$rxy = \left(\frac{N\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{(N\Sigma x^2 - (\Sigma x)^2)\,(N\Sigma y^2 - (\Sigma y)^2)}} \right)$$

3.0. Results and Discussion

3.1. Land Surface Temperature of the Study Area for 2000, 2010 and 2020

Based on the LST retrieval technique, three (3) LST maps were made with a ten-year interval (2000, 2010, 2020) to assess the quantity and quantify LST throughout the whole research region in a spatially explicit way. The spatial analysis feature of ArcGIS was used to differentiate the LST zones using different colors in order to clearly depict the LST map. In order to improve understanding of the regional variations in the research area's temperature distribution, land surface temperature (LST) data were classified into five groups: low, secondary low, medium, secondary high, and high. The LST image findings were sorted and shown in degrees Celsius. The LST for 2000, 2010, and 2020 is displayed in Figures 2 through 4.

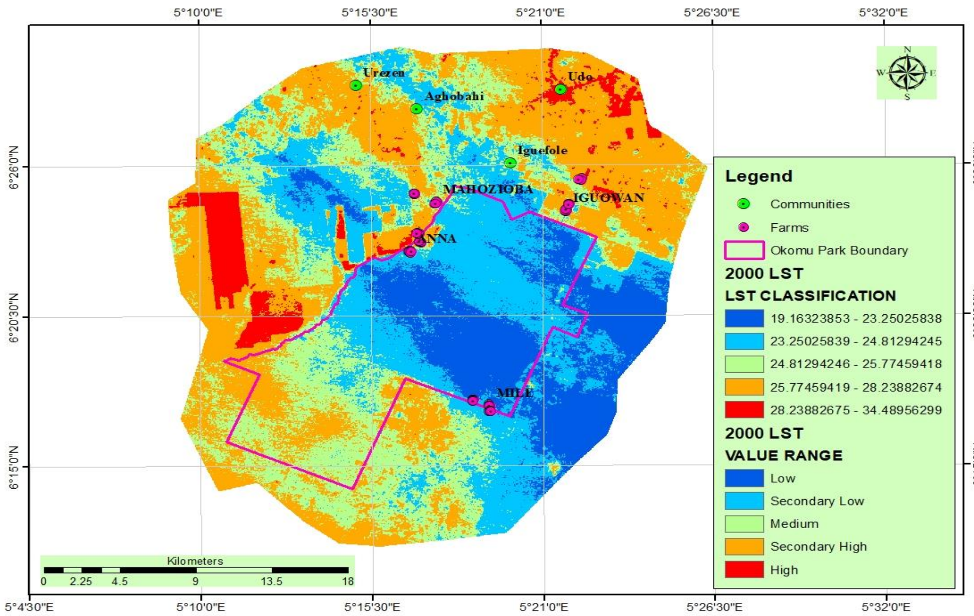

Figure 2: Classified 2000 LST for the Study Area

Figure 2 shows the readings obtained for LST in 2000 which varied from 19.1632 to 34.4896 degrees. For the year 2000, the blue color denotes low temperature zones, while the red color denotes high temperature areas. The legends also show the distribution of temperature fluctuation. The low class covered approximately 191.90 km^2 (23.35%), followed by secondary low (215 km^2), medium (294.91 km^2), secondary high (91 km^2), and high (28.94 km^2) (3.52%). When compared to the western, north eastern, and other sections of the map where the temperature is high, the Okomu National Park and the eastern portion of the map have lower temperatures. 821.78 km^2 of land are covered in all.

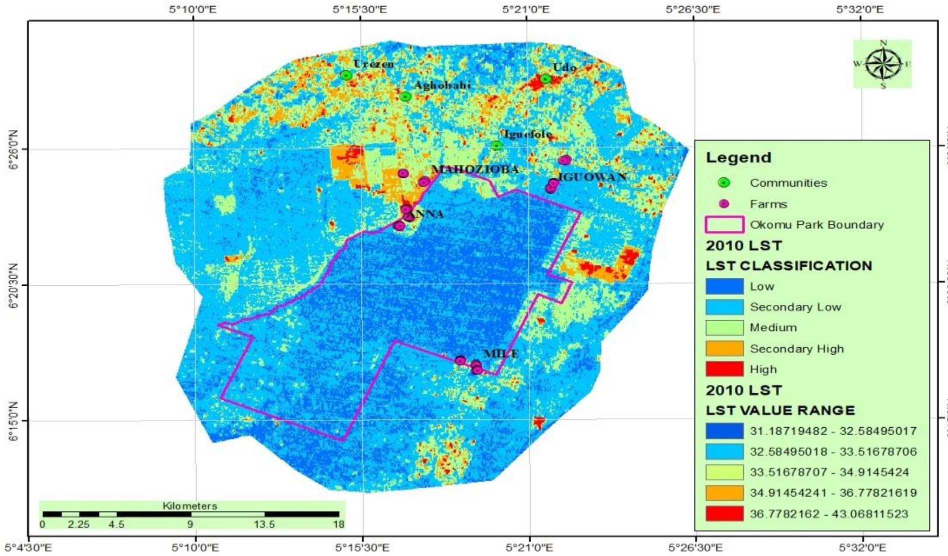

Figure 3. Classified 2010 LST for the Study Area

Figure 3 represents the 2010 LST and the value obtained varied from 31.1872 degrees at the low to 43.0681 degrees at the high. For the year 2010, the blue color denotes low temperature zones, while the red color denotes high temperature areas. The low class takes approximately 424.00 km^2 (51.60%) of the land, followed by secondary low (262.27 km^2 (31.92%), medium (98.08 km2), secondary high (30.37 km^2), and high (7.06 km^2) (0.86%). When compared to the eastern region, notably the oil palm plantation and the northern half of the map, including Udo, Urezen, Aghobahi, and Iguowan town, where the temperature was high, Okomu National Park and the southern part of the map had lower temperatures. This can be linked to community activities that have led to deforestation, which exposes the surface to solar radiation and causes fluctuations in local temperature.

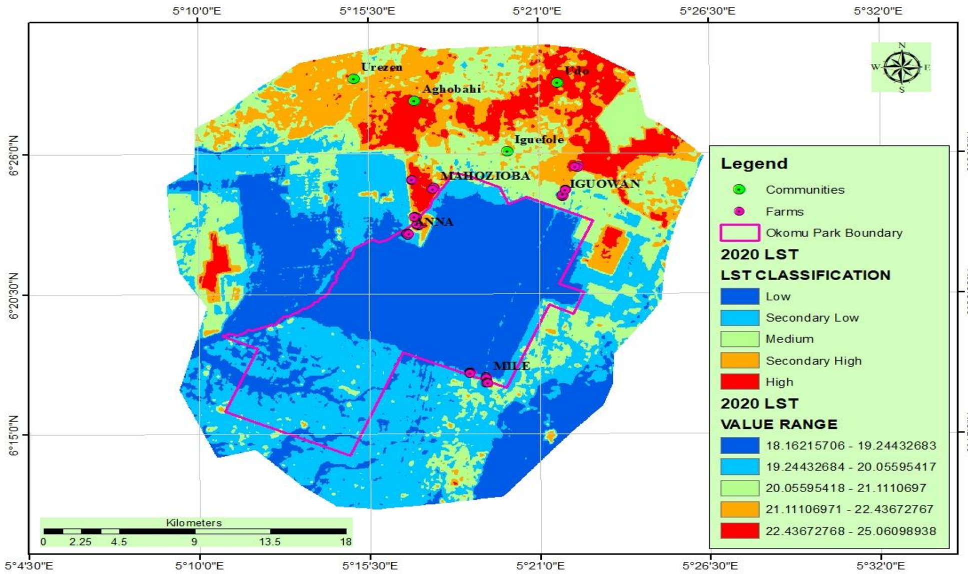

Figure 4 Classified 2020 LST for the Study Area

Figure 4 reveals the values of LST obtained for 2020. The value ranged from Low: 18.1622 – high: 25.061 degrees. The low class occupies an area of 249.50 km^2 (30.36%), secondary low 247.92 km^2 (30.17%), medium 163.24 km^2 (19.86%), secondary high 102.45 km^2 (12.47%) and high 58.67km^2 (7.14%). Within the Okomu national park and towards the southern section of the map temperature was low when compared to the eastern particularly the oil palm plantation and northern section of the map such as udo, Uezen, Aghobahi, Anna Camp and Iguowan settlements where the temperature is high.

The findings showed that between 2000 and 2020, the LST over the region dramatically rose. With 2010 being the year with the highest land surface temperatures in the region, a progressive trend is clearly evident. There was a little cooling in 2020 compared to 2010. It was observed that the temperatures are substantially lower in places with vegetation and water bodies that function as heat sinks. The increase in evapotranspiration caused by the vegetation's densification decreases the temperature while preserving the heat flow. On the north-eastern part of the map, where there are many populated regions, the temperature is high. The LST is accelerated by the huge volume of logging and wood transport operations as well as other activities. This outcome is consistent with the work of Subhanil *et al*. (2018), who used Landsat 8 OLI and TIRS data to conduct an analysis of land surface temperature using NDVI and NDBI in Florence and Naples, Italy. The results show that rising human activity in the area is causing rise in temperature.

3.2. Normalized Difference Vegetation Index (NDVI) for 2000, 2010, 2020

The NDVI values were classified into five groups, which may alternatively be described as non-vegetated land and vegetated land: low, secondary low, medium, secondary high, and high classes. The gradations show the state of the degraded forest. Figures 5 to 7 represents the NDVI maps of the three epochs considered.

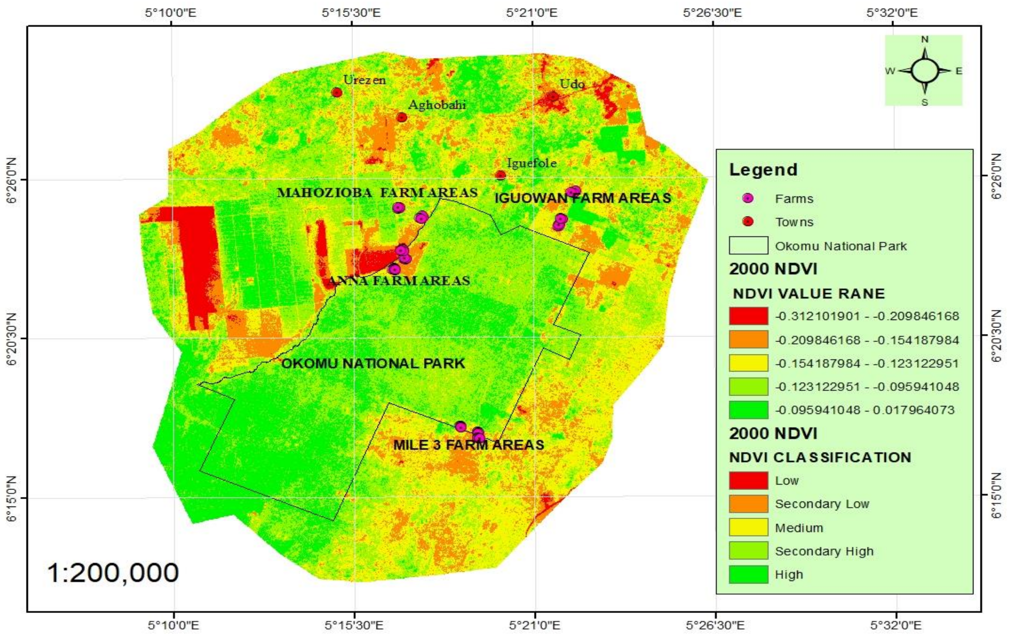

Figure 5. Classified 2000 NDVI between vegetated land and non-vegetated land

Figure 5 represents the NDVI value for the year 2000 and the value obtained was between -0.312102 to 0.0179641, with negative values denoting non-vegetated land and positive values denoting vegetated area. The graphic shows the NDVI findings, which indicate the distribution of NDVI values showing classes of vegetation and areas without vegetation. The area used by the low class is 23.41 km^2 (2.85%), followed by secondary low at 93.75 km^2 (11.41%), medium at 226.54 km^2 (27.57%), secondary high at 293.85 km^2 (35.76%), and high at 184 km^2 (22.42%).

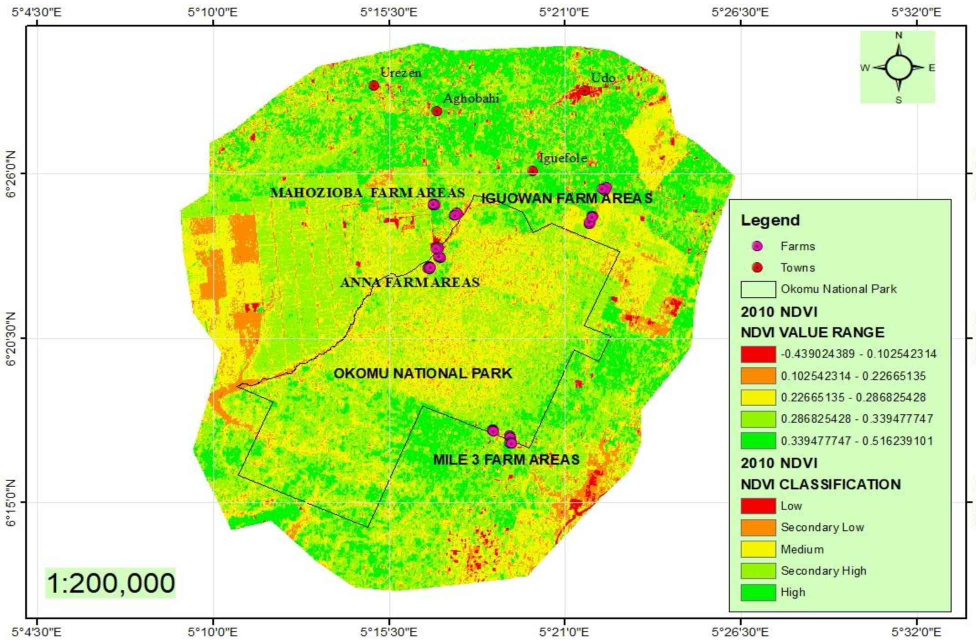

Figure 6. Classified 2010 NDVI between vegetated land and non-vegetated land

Similarly, the NDVI value for Year 2010 shown in (Figure 6) varied from Low: Low class area is 8.54 km^2 (1.04%), secondary low is 61.18 km^2 (7.45%), medium is 248.02 km^2 (30.18%), secondary high is 333.98 km^2 (40.64%), and high is 170.06 km2 (20.69%), according to the categorization.

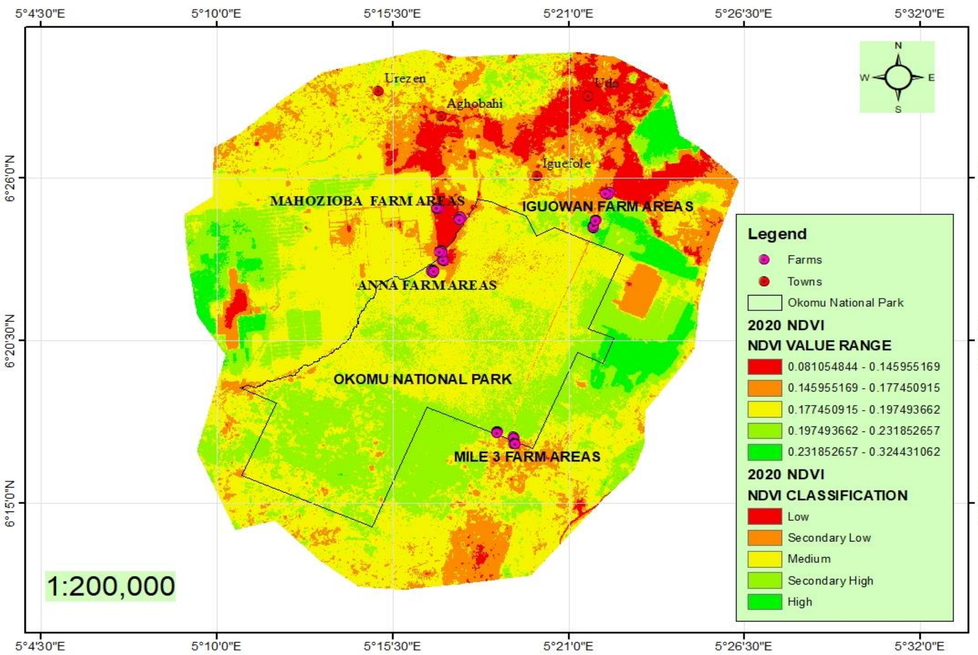

Figure 7. Classified 2020 NDVI between vegetated land and non-vegetated land

Figure 7 depicts the NDVI map for the year 2020, which reveals that there has been an increase in the degradation of the forest in the reserve and the national park. From Low (0.0810548) to High (0.32443), the value varies. According to the categorization, the low class took up 51.09 km^2 (6.22%), followed by secondary low (122.85 km^2), medium (399.62 km2), secondary high (210.17 km^2), and high (38.07 km^2) areas.

In remote sensing, vegetation indices have long been employed to track the temporal changes in vegetation. Little over zero NDVI values signify the presence of vegetation classes. Moderate and high values indicate stressed vegetation and healthy vegetation respectively; whereas near zero and negative values indicate non-vegetation class such as water, snow, built up areas and barren land (Nath and Archarjee, 2013). The findings showed that in the year 2000, the area covered by vegetated land had a positive value in green and was significantly larger than the area covered by non-vegetated, land which had a negative value and zero value in light red. The following figures demonstrate that over the previous 20 years, there has been a clear decrease in the land cover. The NDVI classification values of 2020 indicate that the increase in medium (399.62 km^2) and secondary high (210.17 km^2) vegetation classes which drastically reduced the size of the high (38.07km^2) vegetation class. This shows that between the years 2000 and 2010; between 2010 and 2020, the area's land cover changed rapidly, with more and more vegetation being replaced by other non-vegetation.

The relationship between NDVI and LST for the respective epochs are presented in the following sub-sections in form of charts which are represented in Figures 8 to 10.

3.3. Relationship Between LST and NDVI of the study area for the year 2000

The link between LST and NDVI was examined to see whether variable has a greater influence than the other. To assess the link between the different research years, the map was split into five groups. Usually, there is an inverse connection between NDVI and LST. Examined was a negative correlation between NDVI and vegetation percentages estimated from LST.

Figure 8 shows the relationship between NDVI and LST for the year 2000. Green vegetation is typically indicated by high NDVI readings, indicating a negative correlation between NDVI and LST. The correlation value (R^2 = 0.981) between the variables in the 2000 chart shows a high positive linear link.

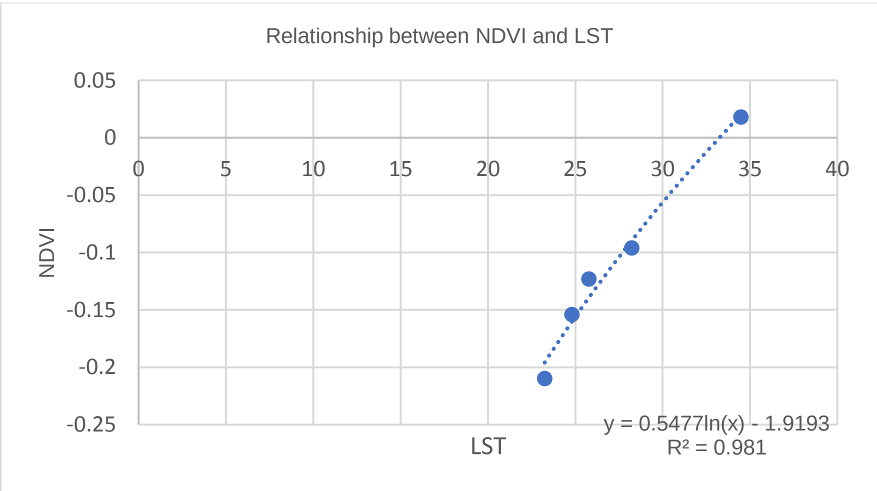

Figure 8. Relationship between NDVI and LST for year 2000

3.4. Relationship between the study area's LST and NDVI in 2010

LST essentially rises with an increase in bare land and built-up areas while falling with an increase in forest, farmland, wetland, and water bodies. A positive linear association with the correlation coefficient R^2 = 0.7198 was also observed in the 2010 image. This is explained by the fact that there was a lot of greenery in the research location.

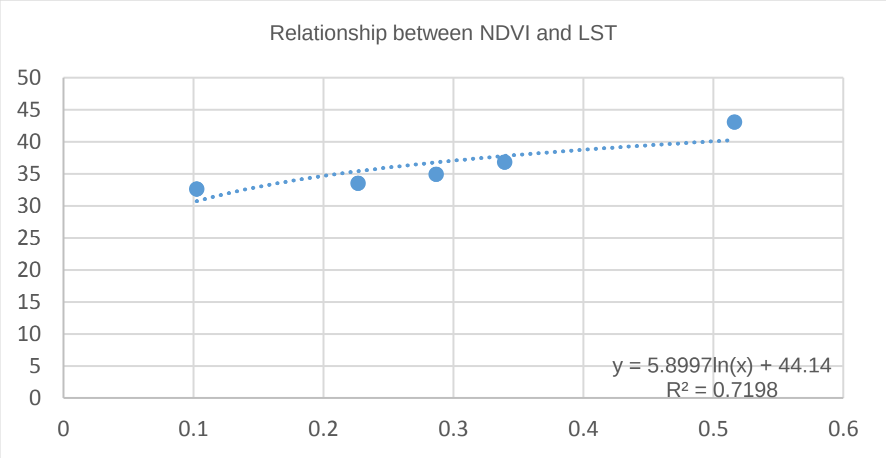

Figure 9. Relationship between NDVI and LST for year 2010

3.5. Relationship between LST and NDVI for the year 2020 for the study area

Figure 10 refers to the relationship between NDVI and LST in year 2020 ($R^2 = 0.9835$) for the study area. There was a positive association with respect to the intensification of anthropogenic activities in the research region, such as the use of water bodies, farmland, or agricultural land, which in turn increases the land's emissivity, albedo, and abundance of flora, among other things. Together, these elements cause the NDVI and LST to have a positive association. In a study by Igun and William (2018), the authors observed a strong positive correlation between the mean LST and percentage proportion of non-vegetated areas such that as the percentage proportion of non-vegetated areas increases, the mean LST increases. According to research by Subhanil *et al*. (2018) and Orhan & Yakar (2016), LST builds a high association with NDVI (negative) and NDBI (positive), which are both environmental indices.

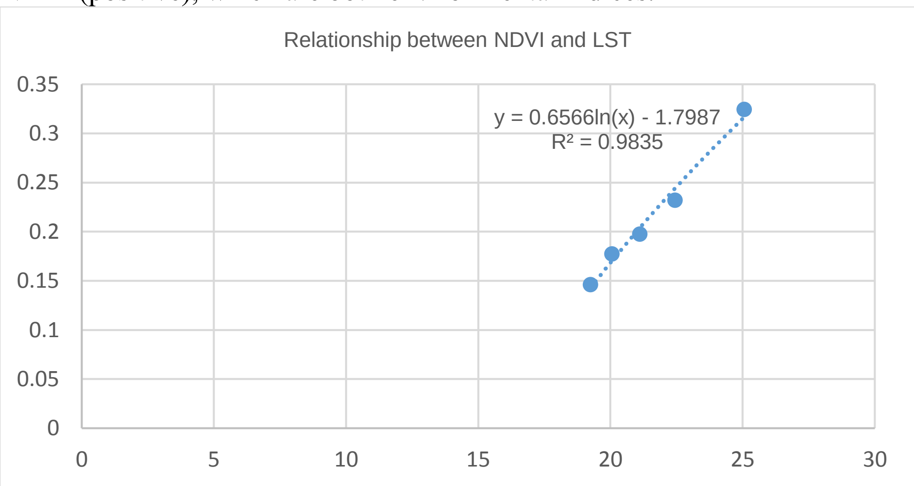

Figure 10. Relationship between NDVI and LST for year 2020

4.0. Conclusion

The study reveals that change in the land use and land cover significantly affected that NDVI and LST of the study area. The highest LST was recorded in the year 2010 as a result of massive degradation of the forest area. The temperature was evidently higher in built up areas and other areas where human activities were identified. The study reveals that the high class of the LST was more prominent in the built-up areas, indicating that conversion of forests to other land use/landcover classes will always lead to increased temperature, decline in biodiversity and increased soil erosion and degradation. The NDVI results provide that in year 2020 medium (399.62 km^2) and secondary high (210.17 km^2) vegetation classes drastically reduced the size of the high (38.07km^2) vegetation class, indicating a stressed vegetation. The NDVI values of this study indicate that the forest ecosystem experienced a significant degradation, and as a result an increase in the land surface temperature in areas with degraded vegetation. Restoration of trees in forests gaps, vegetation covers around built-up areas will go a long way in regulating the NDVI and subsequently, LST.

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