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# ANALYSING THE EFFECT OF HYDROCARBON SEEPAGE ON VEGETATION IN UGWUEME TOWN, AWGU LOCAL GOVERNMENT AREA OF ENUGU STATE USING NORMALIZED DIFFERENCING VEGETATION INDEX (NDVI) THRESHOLD CLASSIFICATION METHOD

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**Abstract:**

*The aim of this study is to perform threshold NDVI classification over a period of time to determine the condition of the vegetation in Ugwueme town which is influence by natural hydrocarbon seepage. To achieve this objective, three Landsat images, Landsat 7 TM+ 1996, Landsat 7 ETM+ 2006 and Landsat 8 OLI/TIRS 2016 were used to map the Landcover and monitor NDVI over the investigated areas. The classification analysis shows three vegetation cover classes which include Low class cover, Moderate class cover and High class cover, which were in increasing order of vegetation vigor. The result of the study shows that the category of high NDVI density reduces progressively from 36.81% in 1996 to 29.89% in 2006 and then to 23.12% in 2016. Similarly, the category of moderately NDVI density was also observed to reduce from 36.56% in 1996 to 28.25% in 2006 and then increase to 28.70% in 2016. In contrast to the high and moderate NDVI density category which were decreasing, the category of low NDVI density were visualize to increase from 26.63% in 1996 to 41.86% in 2006 and then to 48.18% in 2016. The study shows that sequel to natural hydrocarbon seepages in Ugwueme town, there was a general decrease in vegetation land cover indicating a trend of degradation of the ecosystem. Thus, afforestation and good land practices is recommended in the study area.*

**Key Words:** Hydrocarbon Seepage, Land Cover, NDVI, Remote Sensing, Vegetation Change Detection & Mapping

## 1. Introduction:

Underground hydrocarbon reservoir often leak. The leak due to abundance of oil and gas at the earth's subsurface and as the pass through impermeable seals, along faults zones and fractures in rocks and planes of weakness between geological layers at high pressure, the form seepages at the earth's surface. Hydrocarbon seepage is one of the world environmental problems, which comes with negative impact on soil and vegetation (Ebele et al. 2013). The negative impact of hydrocarbon seepages in our environment includes destruction of wild life, loss of fertile soil, pollution of air and water and damage to the ecosystem (Aghalino, 2000). Hydrocarbon seepage in an area often give rise to brownish and stressed vegetation and make fertilie soil to become barren (Roberts, 1997).

Vegetation is very important in our daily lives and we depend upon it to satisfy our basic needs which include food, clothing, shelter and health care etc. On a daily day, our basic need is increasing and this is attributed to increase in world population, income and urbanization (Ebele et al. 2013). Unfortunately, under field condition, vegetation is continuously vulnerable to a wide range of biotic, abiotic and anthropogenic changes owing to hydrocarbon seepage. Hydrocarbon seepage often influences the soil chemistry, spectral reflectance, soil air composition and makes growing vegetation deficient in water and minerals intake, thus affecting their optimum growth (Schumacher, 2001). Hydrocarbon seepage also affects the health status of vegetation and makes them to be stressed. Crawford (1996) stated that when hydrocarbon seeps into the environment and into the roots of growing plants, it leads to stress as well as chlorosis. According to Silvestre et al (2006), significant harm is caused to vegetation growing within and around hydrocarbon seepage zone owing to lack of oxygen in the root environment, which affects their spectral reflectance and their biochemistry.

Remote sensing is considered as one of the most valuable tools to obtain information about the earth's land cover. The conventional methods which include geochemical and geophysical analyses for mapping hydrocarbon seepage zones on land have been widely studied by several researchers (Zirnig et al. 2002). These methods are expensive, destructive and time consuming and are only applicable to some observations collected in the field mainly around drilling areas in petroleum fields. When compared to the conventional traditional methods, remote sensing has proven to be an important tool for mapping hydrocarbon seepage areas within a limited time interval and at a reduce cost (Abrams et al 1984; Yang et al 1998; Schumacher et al 2001).

Remote sensing has been found suitable to have a wide range of applications. Among these applications include detecting vegetation changes. Detecting vegetation changes can be done by remote sensing data through a process known as change detection. Change detection is simply the process of identifying differences in vegetation or land cover over a period of time. Possessing great knowledge about vegetation changes is a fundamental step towards understanding the earth as a system as well as identifying why and where the changes have occurred. Several methods exit to detect, monitor and quantify vegetation changes. They include but are not limited to image differencing, image ratioing, image classification techniques and so on. Vegetation index differencing is the most widely used method to detect vegetation changes. Vegetation indices which are calculated from satellite images can be used for monitoring temporal changes associated with vegetation. Several number of vegetation indices have been used by researchers to detect vegetation changes. Lyon et al (1998) compared seven vegetation indices from three different dates of Landsat for vegetation change detection and concluded that NDVI differencing techniques demonstrate the best vegetation change detection. Normalized Differencing Vegetation Index (NDVI) is the most commonly used vegetation indices to study vegetation Landover changes over a period of time (Schnumacger, 2001). It is a vegetation index that is adopted to distinguish between stressed and healthy vegetation, bare surfaces and most other surfaces with the aid of red and near – infrared reflectance values. Normalized Difference Vegetation Index (NDVI) derived from satellite image data have become one of the key information source for monitoring vegetation conditions and mapping land cover changes in recent times (Teillet et al, 1998). It has been found to have a wide application in vegetation studies as it has been used to estimate plants and vegetation yields, pasture performance and rangeland carrying capacities. NDVI is effective in highlighting stressed vegetation. When vegetation is stressed owed to seepages, the absorption of light by photosynthesis pigment in its leaves decreases and the infrared reflectance also decreases sequel to changes in the cell structure of the vegetation. This reduces the reflectance in the NIR and the increase reflectance in the red edge (Oyundari, 2008).

**2. Study Area:**

The study was conducted in Ugwueme town in the present Awgu Local Government Area of Enugu State in the South - Eastern geo – political zone of Nigeria. It is bound by Latitude $6^0$ 0' 00"$N$ and $6^0$ 03' 00"$N$ and Longitude $7^0$ 24' 00"$E$ and $7^0$ 28'

00"$E$ of geographical co - ordinates. According to the National Population Commission (2006), Ugwueme town has an estimated population of 13,000 people. The town is accessible through a network of un – tarred road, laterite graded roads and several footpaths through Awgu, Awgu Market, Nkwe and Onoli etc. It also comprises of mixed farming zones where food crops (including yam, cassava, cocoyam and maize) and cash crops (cashew, oil palm and banana) are produced and livestock for complementary purpose to meet farmer's cash need during food shortage (Onyeabor, 2013). The soil in the study area is mainly Ferralitic soils known as called Red Earth. It is poorly drained and is particularly suitable for the cultivation of cash crops. The study area often experiences heavy rainfall during the raining season and has a rainfall record of 1,800 mm. This heavy rainfall often promote high infiltration rate and is believed to cause the oil bitumen to be flushed out from the tar sand as heavy tarry and sticky crude in the study area. This assertion is supported by the frequency reports of oil and gas which is associated with seepage in the study area during and immediately after each rainy season (Okeke, H. C., 2006).


Figure 1: Hydrocarbon Seepage observed in the study area

## 2. Materials and Methods:

### 2.1 Data Collection:

The study was conducted using Landsat 7 TM 1996, Landsat 7 ETM+ 2006 and Landsat 8 OLI/TIRS 2016 imageries which were acquired freely online from the site www.http://earthexplorer.usgs.gov. They were retrieved from path 188 and row 55, path 188 and row 56 and path 189 and row 55 at a scale resolution of 30m. The imageries are cloud free and were considered to be obtained during dry season. Topographic sheet of part of the study was acquired from OSGOF (Office of the surveyor General of the federation) at a scale resolution of 1:100,000. It was used with the global positioning system (GPS) during field studies for ground verification.

### 2.2 NDVI Remote Sensing Processes:

Landsat Thematic mapper (TM) and Enhanced Thematic mapper Plus (ETM+) sensors often capture reflected solar energy. It converts these data to radiance and then rescales it into an 8 – bits digital number (DN) which ranges between 0 and 255. DNs can be manually converted to reflectance using two steps – process. The first step involves converting the DNs to radiance values using the bias and gain values specific to the individual scene the researcher is working with. The second step has to do with converting the radiance data to a reflectance. Landsat 8 OLI/TIRS sensor is more sensitive, so these data are rescale into 16 – bit DNs with a range from 0 and 65536. Erdas Imagine was adopted for processing in the study. This software easily converts Ladsat data from the USGS in the "USGS GeoTiff with Metadata" format in a single step.

**2.3 Data Analysis:**

**2.3.1 NDVI Calculations:**

NDVI is an empirical formula which is designed to separate green vegetation from other surfaces based on the vegetation reflectance properties of the area. It is a function of two bands: The red band and the near – infrared spectral band. By using the NDVI results of 1996, 2006 and 2016 imageries, vegetation changes were detected which is calculated (Temesgen et al., 2014) as NDVI = (NIR – RED) / (NIR + RED) Where NIR is the near infrared band response for a given pixel and RED is the red response. To measure biomass change in the study, the NDVI differences (DVDVI) was observed. This technique involves comparing and computing the NDVI values between images acquired on different dates. The result of NDVI value, by definition is between -1 and +1. Increasing positive NDVI values indicate increasing green vegetation and negative values indicate non-vegetated surface features such as water, barren land, ice, snow, or clouds. According to Gross (2005), very low values (0.1 and lower) represents barren areas of rock, sand and snow; moderate values (0.2 to 0.3) corresponds to shrub and grassland and (0.6 to 0.8) represents green and tropical rainforest. The higher the vegetation index value, the higher the probability that the corresponding region on the ground surface has a dense coverage of green vegetation, while negative values indicate absence of vegetation and corresponds to water bodies (Kiage et al., 2007). The final NDVI maps were categorized into four aspects. The water bodies (NDVI value $< 0$), highly stressed ($0 <$ NDVI value $\leq 0.2$), moderately stressed (NDVI value $0.2 <$ NDVI value $\leq 0.4$) and low stressed areas (NDVI value $> 0.4$). To do so, ARCGIS 10.3 for satellite image processing and NDVI mapping and ERDAS imagine 9.1 for calculating NDVI values were used.

**2.3.2 Change Rate Analysis:**

(i) Change area: To obtain the change area in the study, the NDVI 1996 image was subtracted from the NDVI 2006 image. Similarly, the NDVI 2006 image was subtracted from the NDVI 2016 image and the NDVI 1996 image was subtracted from the NDVI 2016 image. This arithmetic which is the change area is all shown in the equations below:

$$DNDVI = NDVI\ (2006) - NDVI\ (1996)$$
$$DNDVI = NDVI\ (2016) - NDVI\ (2006)$$
$$DNDVI = NDVI\ (2016) - NDVI\ (1996)$$

(ii) Percentage change (Tread) = (magnitude of change area/sum of change area) x 100;
(iii) Annual rate of change ($km^2$/year) = (percentage change area/Ti), where Ti is the number of years between the beginning and the end of the study period;

**3. Experimental Results and Discussion of the Study:**

Table 1 shows the statistics and visual observation of the NDVI images over the subsequent periods. The observations show those decrements in vegetation biomass. As it can be visually compared, the amount of green vegetation is decreasing. Considering the maximum value, the NDVI decreases dramatically from 0.390 in 1996 to 0.320 in 2006 and to 0.310 in 2016. To this effect, the standard deviation value decreases in certain amount in 2016 image as compared to 2006 image and as compared to 1996.

Table 1: Descriptive statistics for NDVI values for selected epoch Periods

| Year | Min | Max | Mean | Standard Deviation |
|---|---|---|---|---|
| **1996** | -0.15 | 0.390 | 0.120 | 0.07 |
| **2006** | -0.18 | 0.320 | -0.07 | 0.05 |
| **2016** | -0.01 | 0.310 | 0.15 | 0.04 |

Figure 2 and 3 shows the NDVI maps of the study area for years 1996, 2006 and 2016.

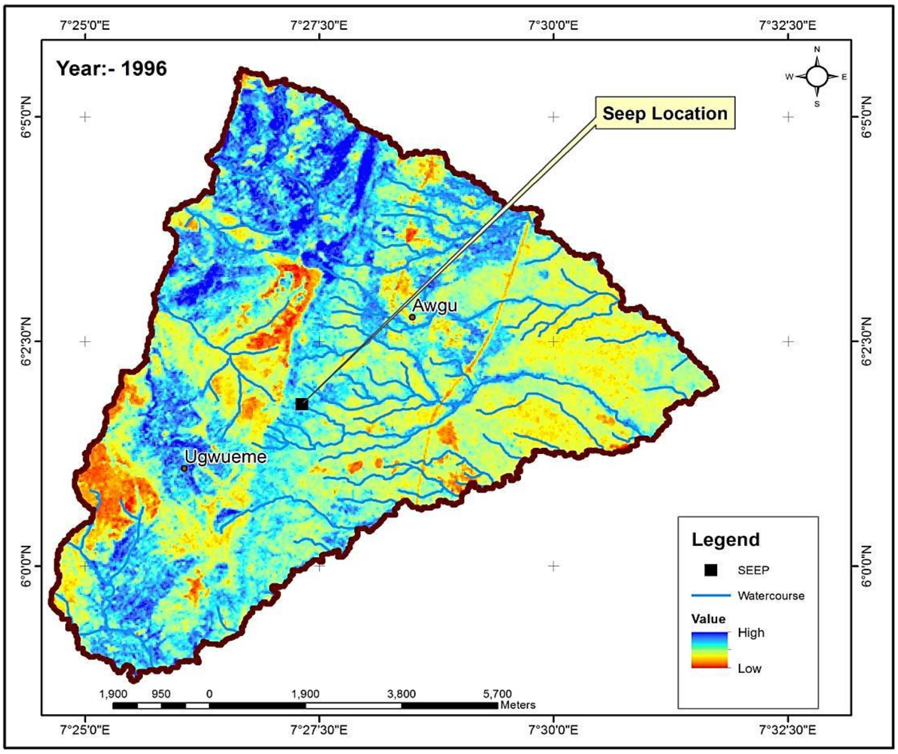


Figure 2: NDVI map of the study area (1996)

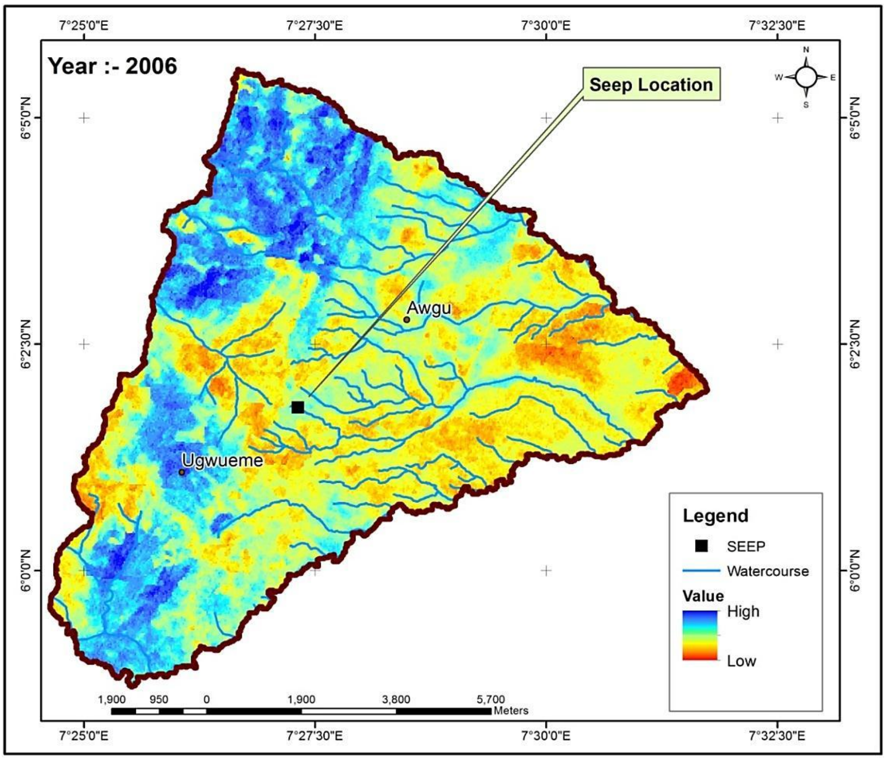


Figure 3: NDVI map of the study area (2006)

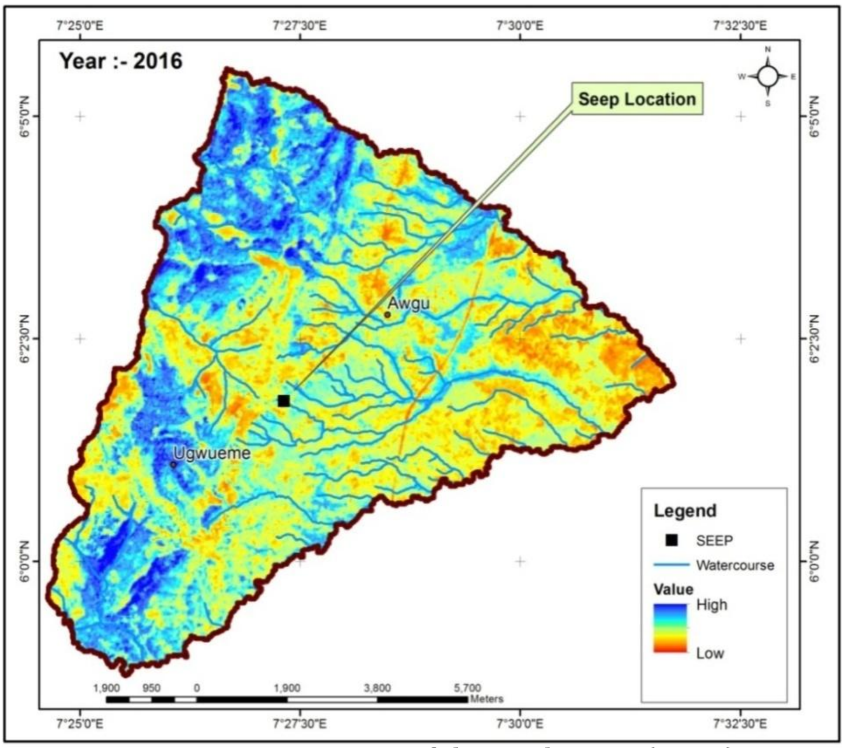


Figure 4: NDVI map of the study area (2016)

### 3.1 NDVI image Classification for the Study Area:

Table 2 shows the NDVI density classes for the years 1996, 2006 and 2016. The values were classified into low, moderate and high vegetation areas, which show the threshold and the distribution of vegetation cover classes across the different images. The vegetation classification maps in figures 6, 7 and 8 clearly illustrated the spatial patterns of vegetation cover distribution within the study area. As we can visualize in table 2, important changes have occurred in the vegetation image cover classes. The category of high NDVI density was observed to reduce progressively from 36.81% in 1996 to 29.89% in 2006 and then to 23.12% in 2016. Similarly, the category of moderately NDVI density was also observed to reduce from 36.56% in 1996 to 28.25% in 2006 and then increase to 28.70% in 2016. In contrast to the high and moderate NDVI density category which were decreasing, the category of low NDVI density were visualize to increase from 26.63% in 1996 to 41.86% in 2006 and then to 48.18% in 2016.

Table 2: NDVI density Classification on the vegetation condition of the study area from the year 1996 – 2016

| Classes Cover | 1996 | | 2006 | | 2016 | |
|---|---|---|---|---|---|---|
| | Area ($Km^2$) | (%) | Area ($Km^2$) | (%) | Area ($Km^2$) | (%) |
| Low | 126.606 | 26.63 | 199.014 | 41.86 | 229.048 | 48.18 |
| Moderately | 173.823 | 36.56 | 134.306 | 28.25 | 136.438 | 28.70 |
| High | 175.000 | 36.81 | 142.109 | 29.89 | 109.942 | 23.12 |
| **Total** | **475.429** | **100** | **475.429** | **100** | **475.428** | **100** |

Table 3: Area and rate of change of the density image classification of the study from 1996 to 2006

| Types of Cover | Change in Area ($km^2$) | % Change in area | Annual rate of change ($km^2$/year) |
|---|---|---|---|
| Low cover | 72.408 | 22.24 | 2.22 |
| Moderately cover | - 39.517 | - 12.82 | - 1.28 |
| High cover | - 32.891 | - 10.37 | - 1.04 |

Table 4: Area and rate of change of the density image classification of the study from 2006 to 2016

| Types of Cover | Change in area ($km^2$) | % Change in area | Annual rate of change ($km^2$/year) |
|---|---|---|---|
| Low cover | 30.034 | 7.02 | 0.70 |
| Moderately cover | 2.132 | 0.79 | 0.08 |
| High cover | - 32.167 | - 12.76 | - 1.28 |

Table 5: Area and rate of change of the density image classification of the study from 1996 to 2016

| Types of Cover | Change in area ($km^2$) | % Change in area | Annual rate of change ($km^2$/year) |
|---|---|---|---|
| Low cover | 102.442 | 28.80 | 5.76 |
| Moderately cover | - 37.385 | - 12.05 | - 2.41 |
| High cover | - 65.058 | - 22.83 | - 4.57 |

The statistical chart in figure 5 and the vegetation classification maps in figures 6, 7 and 8 clearly illustrated the spatial patterns of vegetation cover distribution within the study area.

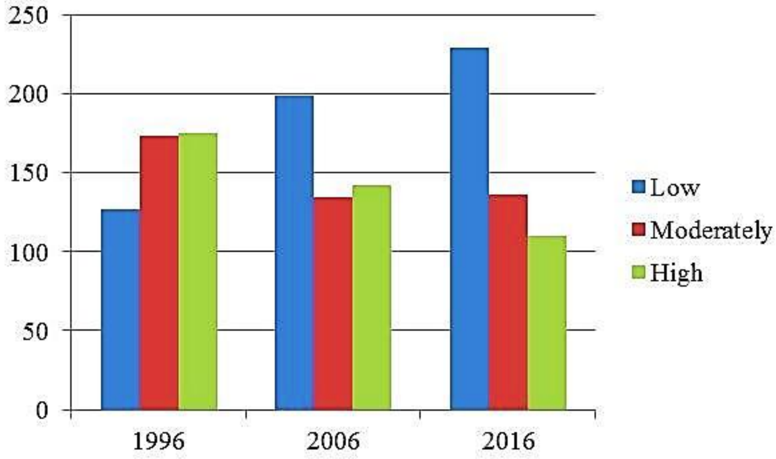


Figure 5: Statistical chart showing the NDVI density image classification of the study from 1996 to 2016

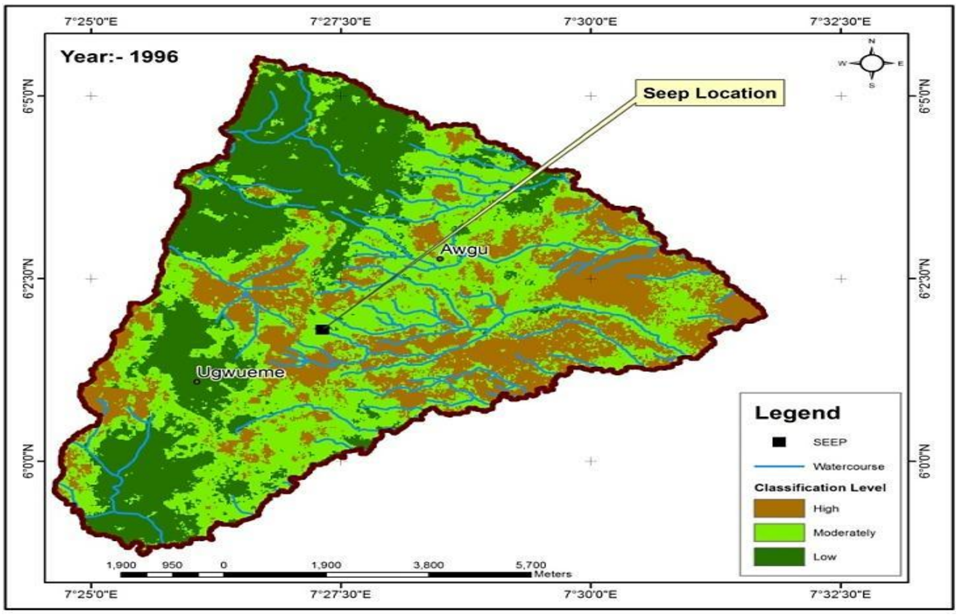


Figure 6: NDVI density classification cover class for 1996

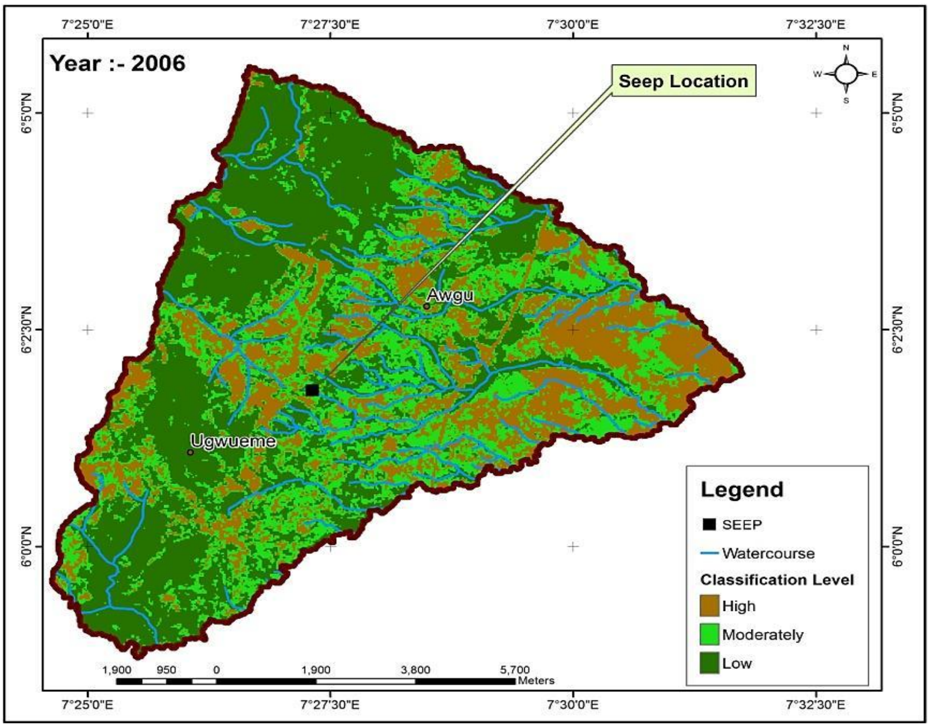


Figure 7: NDVI density classification cover class for 2006

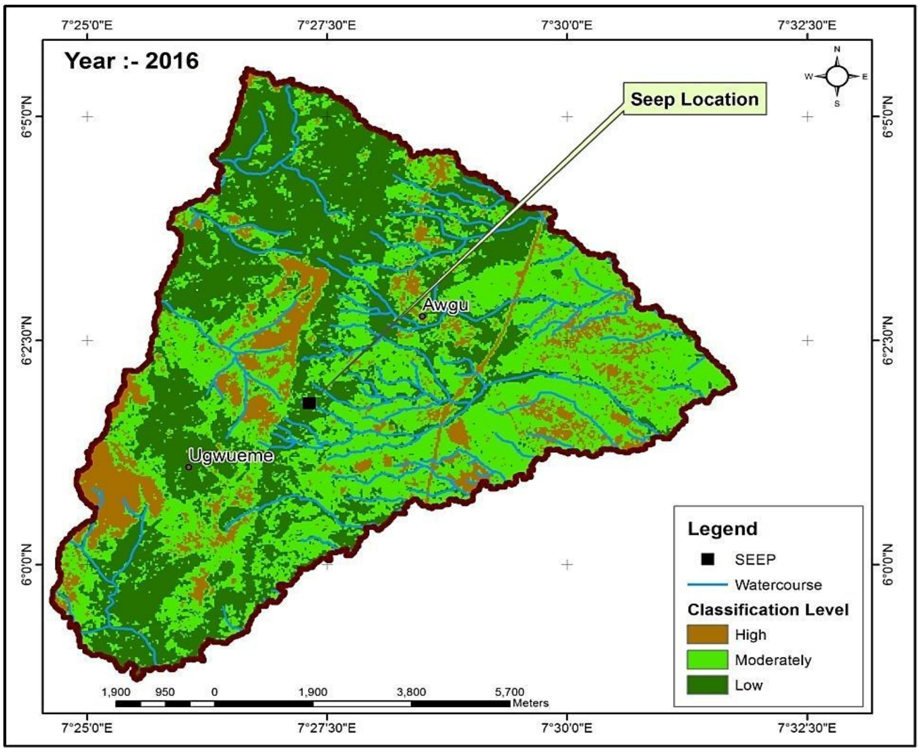


Figure 8: NDVI density classification cover class for 2016

## 4. Conclusion:

The study shows that Remote Sensing and GIS is an important tool to detect vegetation stress changes over a period of time. Using this tool, the result of the study shows that there was an overall increase in the size of Landover class which was identified as high cover class. Owing to this finding, afforestation, re – afforestation and good land practices is recommended in the study area. The finding of the study further shows that the study area possesses good site for oil and gas exploration

## 5. References:

1. Abrams, M. (2005): The significant of hydrocarbon seepage relative to petroleum generation and entrapment; Marine Petroleum Geology: pp 22, 457 – 477.
2. Blackburn, G. A. and Steele C. M. (1999): Mapping the effect of natural oil and gas on plants using remote sensing: International Journal of Remote Sensing.
3. Clarke, R. H. and Cleverly R. W. (1991): Petroleum seepage and Post accumulations migration: Geological Society Special Publication of London.
4. Hoeks, J. (1972): The effect of leaking natural oil and gas on soil and vegetation in urban areas; Agricultural Research Reports, Wageningen.
5. Horivitz, L. (1972): Vegetation and geochemical prospecting for petroleum: American Association of Petroleum Geologists Bulletin, Volume 56.
6. Hugh, C. (2012): The effect of leaking petroleum on soil and vegetation: Encyclopedia Britannica.
7. Lichtenthaler, H. K. (1996): Vegetation Stress: An introduction to stress concept in plants: Journal of Plant Physiology, volume 158.
8. Kadafa, M. and Adati, A. (2012): The Environmental Impacts of Oil Exploration and Exploitation in the Niger Delta region of Nigeria: The Global Journal of Science Frontier Research Environment & Earth Sciences: Volume 12: Issue 3, Version 10.
9. Miller, L. R. and Carter, A. G. (1994): Early detection of vegetation stress by digital imaging within narrow stress – sensitive wavebands: Remote sensing of Environment.
10. Noomen, M. F. and Van der Werff (2007): Remote Sensing of onshore hydrocarbon seepage, problems and solutions: Geological Society London Special Publications.
11. Noomen, M. F., Skidmore, A. K. and Meer, F. D. (2007): Detecting the Influence of Gas Seepage of vegetation using Hyper – Spectral Remote Sensing, ITC, Enschede.