## Article

# **Remote Sensing for Detection and Monitoring of Vegetation Affected by Oil Spills**

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Abstract: This study is aimed at demonstrating application of vegetation spectral techniques for detection and monitoring of impact of oil spills on vegetation. Vegetation spectral reflectance from Landsat 8 data were used in the calculation of five vegetation indices (normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), adjusted resistant vegetation index 2 (ARVI2), green-infrared index (G/NIR) and green-shortwave infrared (G/SWIR) from the spill sites (SS) and non-spill (NSS) sites in 2013 (pre-oil spill), 2014 (oil spill date) and 2015 (post-oil spill) for statistical comparison. The result shows that NDVI, SAVI, ARVI2, G/NIR and G/SWIR indicated certain level difference between vegetation condition at the SS and the NSS were significant with *p*value <0.5 in December 2013. In December 2014 vegetation conditions indicated higher level of significant difference between the vegetation at the SS and NSS as follows where NDVI, SAVI and ARVI2 with *p-value 0.005*, G/NIR - *p-value 0.01* and GSWIR *p-value 0.05*. Similarly, in January 2015 a very significant difference with p-value <0.005. Three indices NDVI, ARVI2 and G/NIR indicated highly significant difference in vegetation conditions with *p-value <0.005* between December 2013 and December 2014 at the same sites. Post-spill analysis show that NDVI and ARVI2 indicated low level of significance difference p-value <0.05 suggesting subtle change in vegetation conditions between December 2014 and January 2015. This technique is essential for real time detection, response and monitoring of oil spills from pipelines for mitigation of pollution at the affected sites in the mangrove forest.

**Keywords:** spectral reflectance; vegetation indices; vegetation; remote sensing; oil spill; mangrove forest; oil pollution; Landsat 8

## 1.0 Introduction

One of the critical global environmental problems is human and ecological exposure to hazardous wastes from agriculture, industrial, military, oil and mining activities. These wastes often include heavy metals, hydrocarbons and other organic chemicals [1]. According to the European Environmental Agency [2], about 242,000 contaminated sites in European Economic Area (EEA) countries are in need of clean-up or remediation. The main source of contamination are municipal and industrial waste disposals, mining and military sites no longer in operation, present and past industrial plants such as metallurgical, chemical, oil and wood industries [3]. This amount of wastes has been predicted to increase by up to 50% by 2025. The EEA also reported in 2007 that heavy metals and mineral oil caused 37.3% and 33.7% of soil contamination respectively. The application of remote sensing for oil or hydrocarbon leaks detection, monitoring and remediation of contaminated sites dates back to the 1970s, initially through the use of aerial photographs [4]. In recent studies, ultraviolet (UV), Thermal Infrared and microwave sensors have been shown to have the potential for detecting oil pollution [5,6]. Recent developments in geospatial sensors, data analysis and communication technologies has presented new opportunities. There are a number of remote sensing images that can be used for monitoring oil pipeline and spills. These include airborne and satellite

radar, LIDAR, hyperspectral and multispectral sensors [7]. Information on oil-contaminated sites during remediation process is important to policy makers and environmental observers on regular basis. Satellite sensors repeatedly and simultaneously observe wide areas of Earth's surface, and continually acquire spatial information of ground features and any environmental changes. Satellite sensors detect and record electro-magnetic radiation reflected or emitted by features on the earth surface over a wide range of spectrum within visible and infrared wavelengths. Remote sensing images has been used for detection of stressed vegetation from hazardous liquid leakage, quantification of pollution/stress level and monitoring polluted sites after remediation [8]. These studies have shown the capability of remote sensing for detection of environmental stress resulting from oil leaks from pipelines without direct contact [9]. An increasingly common application of remotely sensed data is change detection where the state of an object or phenomenon over different period of time can be assessed [10]. Oil spill on the immediate natural environment can induce stress on the surrounding natural vegetation [11,12]. The natural vegetation serves as a medium for water and gas atmospheric exchange, source and sink in biogeochemical cycles [13-15]. Thus, any alterations in the plant biogeochemical cycle due to impact of oil, the vegetation can be used as a proxy to detect presence of pollution. Changes in vegetation spectral reflectance could be associated with stress from oil pollution [16]. The detection, site characterization and remediation of polluted sites is typically a long and costly endeavor [1,8]. As a result of expenses and time involved in the traditional methods of investigating environmental contamination or pollution. Remote sensing offers an alternative efficient tool that is time saving, cost effective and non-destructive for detection of vegetation affected by oil spill [17-19].

The absence of full utilization of space technology legislation and enforcement of policies on using remote sensing had contributed negatively in tackling environmental/oil pollution in mangrove forest in Nigeria's Niger Delta region. For example, timely identification, detection and restoration of widespread ecological damages as a results of oil activities could reduce scale of impact from oil spills. Oil spills from operational activities in the region has remained in the environment for many years without been noticed at early stage. The natural vegetation affected by these oil spills in some areas were never clean-up and yet to recover (e.g. Ogoniland, Nigeria) [20]. Following the UNEP investigation report in 2011 it was recommended that the affected sites be cleaned-up and restored. The government of Nigeria in June 2016 adopted the UNEP recommendation to begin the remediation and recovery process of the areas affected by oil pollution. Oil production and transportation traverse across the mangrove forests and difficult to access areas that are affected by oil spills resulting in pollution. The response of polluted mangroves forest communities can lead to leaf defoliation and deformation, changes in vegetation density and distribution of plants [21,22]. This change in mangrove canopy properties from oil spills can be diagnosed through the change in leaf spectral reflectance [8]. Remote sensing is an important tool for monitoring oil affected mangroves using leaf spectral changes as an indicator for mapping polluted sites [17,23]. Thus, vegetation condition in the Niger delta can be detected by analysing the leaf spectral reflectance and the vegetation indices derived from these spectral bands [24,25]. In previous work we evaluated the capabilities of twenty vegetation indices derived from optical data (Landsat 5 and 7), only five (NDVI, SAVI, ARVI2, G/NIR and G/SWIR) have shown potential for detection and monitoring of vegetation affected by oil spills [26]. This study builds on the findings of [26,27] to demonstrate and test the potential replication of this method in different study site using the five indices derived from Landsat 8 data. A broader implication of this study is the production of a method or technique based on satellite broadband optical data that is needed for detection, response and monitoring of pipelines and related oil spills in mangrove forest of the Niger Delta Nigeria and other similar environments.

#### 1.1 Effects of oil spill on vegetation

Oil-impacted mangroves may suffer yellowed leaves, defoliation, and tree death [28]. It has also been observed that mangroves suffer from very harmful to less harmful effects from oil exposure [29].

Vegetation health and vigour can be affected by hydrocarbons through spillage onto roots, stems, leaves and soil [20,30]. The uptake through roots and direct contact between soil and plants tissues are also a medium by which organic contaminants enter the plants [31]. [32], explained that settling down of hydrocarbon particulates and it gaseous contents on leaves and intake via leaf stomata may affect the vegetation. [33] have shown that hydrocarbons may have a negative effect on plants and that lack of oxygen in soil environment coupled with increase in CO<sub>2</sub> [34] are some of the factors that are responsible for the stress in plants. In response to oil spill concentration, the colour of plant leaves change with a loss of photosynthesis pigments. Photosynthesis in plants reduces due to restrictions of entry of carbon dioxide CO<sub>2</sub> into leaf when oil is spilled and coated on plants [35]. Leaf spectral reflectance can be measured to determine whether leaf reflectance responses to plant stress may differ according to the agent of stress and species [36]. The mineral alteration that occurs in the soil and geobotanical anomaly (e.g. abnormal behaviour of vegetation) that reflected in the portion of the electromagnetic spectrum has become evidence for detecting hydrocarbon leakage [16] from the oil facilities. The presence of hydrocarbons seems to produce a change in the internal structure of the plant that results in low reflectance values and gas affected areas may also be responsible for low vegetation density in the area [37]. However, it is important to note that not every stress vegetation may be related with oil spill. For example environmental conditions can be an agent of stress that may lead to dehydration in vegetation [36]. Droughts lower water potentials in plants and subsequently decrease transpiration [38]. Stress conditions that induced damage in vegetation could be from biotic, abiotic and anthropogenic stressors [39]. Biotic stress in vegetation includes disease infection, competition and herbivory and the abiotic includes temperature, water, chemical and mechanical stress [14]. Stress in vegetation from anthropogenic activities, for example in the Niger Delta region are related to the process of exploration and exploitation of oil and gas resources [20]. The exploration process includes removal of vegetation for site selection, facility construction and operations [40,41]. Vegetation can be affected by chemical substances and other wastes that are released into the soil during operation activities [42]. Identifying and monitoring of anthropogenic stress on vegetation such as oil spills can be validated using a priori knowledge of the oil facility sites, oil spill record and GPS location of the affected sites [18,43].

#### 1.2 Remote sensing approach to vegetation stress

Various remote sensing techniques have been used for detection of oil spill impacts on vegetation including vegetation indices [12]. Relationship between plant vitality and oil/gas pollution can be assessed using spectral indicators [44,45]. Khanna, *et al.* [46], used vegetation indices including NDVI from AVIRIS data to detect vegetation stress and recovery from oil spills in wetland areas of Louisiana, USA. Hyperspectral AVIRIS data sets were used to investigate vegetation stress due to the oil spill at the Jornada LTER, New Mexico [12]. These studies demonstrated the potential capability of vegetation indices in determining the variation in vegetation spectra affected by oil pollution. It has also been shown that vegetation indices such as mNDVI (modified NDVI) and NDII (Normalized Difference Infrared Index) were effective in conjunction with biogeochemical data to analyse changes in Gulf Coast wetlands affected by oil spills [47]. Importantly, most of the vegetation indices demonstrated in these studies were derived from hyperspectral data for detection of vegetation affected by oil spills. However, only few focused on indices derived from broadband multispectral data, thus, study will focus on the application of five vegetation indices derived from Landsat 8 sensor discussed below:

Spectral bands (Red and NIR) combination used in the calculation of NDVI has unique spectral characteristics for detection of stress vegetation. For example red band is sensitive to changes in chlorophyll contents in the visible spectrum and NIR has a capacity to characterise vegetation varieties and conditions. The index has been successfully used for characterising vegetation cover and it is still considered a great potential for application in environmental monitoring because of it low cost compared to hyperspectral data [48,49].

$$NDVI = (NIR - Red)/(NIR + Red)$$

SAVI developed by [50,51] incorporated adjustment factor of canopy background and atmospheric conditions to address noise found in NDVI. This index could be useful for addressing effects the soil and atmospheric effects [52].

$$SAVI = ((NIR - Red)/(NIR + Red + 0.5))^*(1+0.5)$$

ARVI2 was designed to be resistant to atmospheric effects and more sensitive to a wide range of Chl-concentrations. Both NDVI and ARVI2 are sensitive to vegetation fraction and to rate of absorption of photosynthetic solar radiation [53,54].

$$ARVI2 = -0.18 + 1.17^* (NIR - Red/NIR + Red)$$

G/NIR is based on simple combinations of green and near-infrared reflectance. The green band has a capacity for assessing plant vigour while the NIR characterise vegetation internal structure [55]. It has also shown potential to discriminate between vegetation affected by oil spill and unaffected both spatially and temporally [26].

GRN/NIR = (Green-NIR)/ (Green+NIR)

The GRN/SWIR-based) indices have a capacity to predict and sense nitrogen in plants [56]. SWIR is also capable of discriminating moisture content of soil and vegetation[57] therefore G/SWIR could be useful in detecting changes in vegetation affected by oil spill.

*GRN/SWIR* = (*Green-SWIR*)/(*Green+SWIR*)

#### 2. Study area

The study site is located in Warri, South West in the Nigeria's Niger Delta within (4°33'27.77"N, 6°52'34.43"E) with ground area of 1,722 km<sup>2</sup> (Figure 1). The region experiences moderate rainfall and humidity for most of the year. The climate is equatorial marked by two distinct seasons: the dry season and the rainy season. The physical environment of the Niger Delta region generally harbours a wide variety of trees and plants including mangrove trees of all kinds, grasses, herbs and climbers which is attributed to the depositional nature of the shoreline [58]. The *rhizophora racemosa* also known as red mangrove occupies more than 90% of the saline swamps and dominates the main vegetation of the mangrove swamps in the region [59]. The *Avicennia Africana* also known as White mangrove is found sparsely distributed amongst the red mangrove and survives in less water-logged areas. There are other common vegetation where salt water content is not too high includes ferns (*acrostichum aureum*), Nympa Palm (*Nympa fruticans*), and herbs (*paspalum vaginatum*) [20,60]. The mangrove swamp in the eastern flank of the Niger Delta is the conspicuous presence Nympa palm, an exotic species. In the saltwater zone (*Rhizophora Mangle*) vegetation type is restricted to the coastal strip, which varies in width.





Figure 1: Image of the study area (subset) (image data false colour composite (bands 5, 4 and 3)), pipeline and oil spill sites.

## 3. Data and method

Cloud cover in the Niger Delta persists for most of the year due to the wet season (from March to October). Therefore it is appropriate to obtain a cloud free data that fall in dry season in the months of December and January. For this study, images from December 2013, December 2014 and January 2015 were used. Table 1 are the nine oil sample spill sites showing the difference in time (number of days) between the oil spill and image acquisition date, spill location and quantity of oil spill in barrels (bbl).

Sample SS	Latitude	Longitude	Date	Date of	Time	Quantity of Oil
			of Spill	Image	(Days)	Spill in Barrels
						(bbl)
SP1	6.0945278	5.5345830	13/12/2014	23/12/2014	10	108
SP2	5.5632500	5.5948056	25/11/2014	23/12/2014	28	5000
SP3	5.5191111	5.9779444	08/09/2014	23/12/2014	106	Na
SP4	5.5633056	5.5948333	06/09/2014	23/12/2014	108	60
SP5	5.9433889	5.9090556	01/09/2014	23/12/2014	113	1000
SP6	5.5009722	5.9501667	20/08/2014	23/12/2014	125	3
SP7	5.5482500	5.8749722	n/a	23/12/2014	na	na
SP8	5.5464722	6.3670833	05/08/2014	23/12/2014	140	7.7
SP9	5.5908889	5.6496667	18/07/2014	23/12/2014	158	60

Table 1: Information on oil spill data for the study site

## 3.1 Image Data

Landsat 8 images (path 189 and row 57) Level 1 terrain corrected products for 20/12/2013 (prespill), 23/12/2014 (oil spill date) and 08/01/2015 (post spill) were used in the study. The images were acquired with minimal cloud cover <26% at the scenes centre. The images used in the study were atmospherically corrected in order to obtain a surface reflectance image free from noise. The processed Landsat 8 images for the study is shown Figure 3 (bands 5, 4 and 3) and oil spill data. The method was used to convert the data from digital numbers (DN) to surface reflectance using the calibration parameters provided in the product metadata file (MTL file). In this study full atmospheric correction using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) routine available on the Exelis Environment Visual Information (ENVI) software was used to change the radiance values into surface reflectance.

## 3.3 Data analysis

The reflectance data from the three L8 images were used in the calculation of the five vegetation indices for 18 sample sites (i.e. 9 oil spill sites (SS) identified along the oil pipeline route and 9 stratified randomly selected non-spill sites (NSS) for the years 2013, 2014 and 2015. The vegetation type (mangrove forest) where this samples were collected have similar biophysical characteristics. Samples at the NSS were chosen where there are no oil facilities and used as control points. At each of the oil spill point nine pixels around the polluted pixel (in a 3 x 3 window pixels) were sampled for extracting vegetation spectra and used for calculation of the vegetation indices. This is because oil spill may migrate from point of source thereby affecting neighbouring surroundings. For example in Nigeria by law oil pipeline routes (right-of-way) of pipelines shall be 30 meters wide from each side [20,61,62]. Therefore the nine pixels from Landsat data is buffered at around 100 meters within the pipeline corridor. The reflectance spectra for each pixel were calculated and then averaged the computed indices from the nine pixels to represent each spill sites for analysis. This technique was replicated in the selection and computation of samples at the non-spill sites (i.e. vegetation not affected by pollution) away from oil facilities. Vegetation conditions in December 2013 (pre-spill), December 2014 (spill date) and January 2015 (post-spill) were assessed and statistically tested and compared. Thus, the following assumptions were tested using a paired t-test statistics: i) that spatially, vegetation affected by oil spills at the SS will spectrally respond differently with the ones at the NSS in 2014 (spill-date), ii) vegetation at the SS will spectrally respond indifferently with the ones at the NSS in 2013 (pre-spill) and 2015 (post-spill), and iii) temporally, spectral response of vegetation affected by oil spills in 2014 at the SS will differ with ones obtained in 2013/2014 and 2014/2015. Meanwhile it is expected that vegetation conditions may remain relatively invariant at the NSS in 2013, 2014 and 2015. Note that both SS in 2013 and NSS (2013, 2014 and 2015) were used as a control points in this analysis.





Figure 2: Reflectance data for 2014 in false colour composite (bands 5, 4 and 3) showing date of spills, spill and non-spill sites and pipelines location in the study area.

#### 4. Results

In this section, we first analysed difference in vegetation at the SS and the ones at the NSS in 2014 in section 4.1. We also show the significant difference in vegetation between the two sites in 2013, 2014 and 2015. In section 4.2 change in vegetation conditions at the SS and NSS from pre-spill, spill date and post-spill were analysed.

## 4.1 Impact of oil spill on vegetation

To determine whether vegetation affected by oil spills at the SS respond spectrally different with the ones at the NSS, vegetation indices obtained from December 2014 was used. The calculated indices are expected to show low values at the SS and high values at the NSS in the December 2014 (i.e. oil spill date). Figure 3 shows the difference between vegetation indices obtained at SS and NSS in during oil spill events in 2014.





Figure 3: Box plot for the calculated mean of the 5 vegetation indices from (SS) and (NSS) sites for the 18 sample points each in December 2014.

Table 2 demonstrates the result of the t-test was computed to determine if there are significant differences between the vegetation indices at the SS and NSS in 2014. The results show that four vegetation indices (NDVI, SAVI, ARVI2 and G/NIR) indicated higher level of significant difference between the ones obtained at the SS and NSS, only G/SWIR indicated low level of significant difference at *p*-value 0.05.

Table 2: A comparison of p-values from paired t-test analysis for the study sites (SS and NSS sites) in December 2014

	Indices	NDVI	SAVI	ARVI2	G/NIR	G/SWIR
	Developer	***	***	***	**	*
55 VS IN55 sites	P-values					

\*\*\*\*p-value <0.0001, \*\*\* p-value <0.005, \*\* p-value <0.01, \* p-value <0.05, ™ p-value ≥ 0.05 Key: \*\*\*\*Highly significant, \*\*\*Highly significant, \*\*Very significant, \*Significant, ™Not significant

#### 4.2 Change detection of vegetation conditions at the SS and NSS

In Table 3 vegetation indices calculated from the December 2013 image at the both SS and NSS were statistically compared. The results show that the five vegetation indices indicated a low level of significant difference with *p*-value <0.05. In December 2014 three indices (NDVI, SAVI and ARVI2) indicated higher level of significant difference between the vegetation at SS and NSS with *p*-value <0.005. In the post spill image in January 2015 which has a small time difference with the image in December 2014 showed almost the similar results with that of 2014. For example NDVI and ARVI2 indicated a highly significant difference with *p*-value <0.005 between SS and NSS while SAVI and NIR level of significant difference with *p*-value <0.01. G/SWIR remain relatively the same (no change) in 2013, 2014 and 2015. The similarity in the results found in December 2014 image used for the observation of the oil spill impact and the post-spill in January 2015 have only 16 days difference in acquisition. This could be argued that the time difference at the SS. The purpose of 2015 image was

used to examine the changes in vegetation as a recovery from an oil spill that took place in 2014. Unfortunately, it did not indicate any significant change which could be due to a slower recovery of the vegetation.

	December 2013 (Pre- Spill Not Polluted)		December 2014 (Spill Date -Polluted)		January 2015 (Post-Spill- Not Polluted)	
SS vs NSS			SS vs NSS		SS vs NSS	
Indices	Difference	P-values	Difference	P-values	Difference	P-values
NDVI	0.00	*	-0.08	***	-0.08	***
SAVI	0.05	*	-0.04	***	-0.05	**
ARVI2	-0.02	*	-0.09	***	-0.10	***
G/NIR	-0.02	*	-0.06	**	-0.06	**
G/SWIR	0.03	*	-0.09	*	-0.11	*

Table 3: Analysis of change detection using paired t-test statistics of means of vegetation indices at the SS and NSS.

\*\*\*\*p-value <0.0001, \*\*\* p-value <0.005, \*\* p-value <0.01, \* p-value <0.05, ™ p-value ≥ 0.05 Key: \*\*\*\*Highly significant, \*\*\*Highly significant, \*\*Very significant, \*Significant, ™Not significant

In Table 4: shows the t	-test analysis of the mea	n values for indices o	of vegetation af	fected by oil spill	at the SS.
	2		0	<b>y 1</b>	

T. diana	2013 vs 20	14	2014 vs 2015	
Indices	Change ( $\Delta$ )	p-values	Change ( $\Delta$ )	p-values
NDVI	-0.03	***	-0.03	*
SAVI	0.06	ns	-0.03	***
ARVI2	-0.04	***	0.04	*
G/NIR	-0.05	***	-0.02	**
G/SWIR	0.06	ns	-0.04	****

\*\*\*\*p-value <0.0001, \*\*\* p-value <0.005, \*\* p-value <0.01, \* p-value <0.05, ™ p-value ≥ 0.05 Key: \*\*\*\*Highly significant, \*\*\*Highly significant, \*\*Very significant, \*Significant, ™Not significant

To further explain the vegetation status at the SS before and after oil spill, the vegetation conditions at the SS before oil spill in December 2013 and December 2014 show that NDVI, ARVI2 and G/NIR indicated higher level of significant difference with *p-value 0.005* in Table 4. This is because in 2013 vegetation at these spill sites did not experience oil spill. In Table 3 vegetation condition at presupposed SS and NSS in 2013 exhibited low level of significant difference compared to 2014. Thus, spectral changes exhibited by vegetation at these sites in 2013 (pre-spill) may not be related to oil spill. SAVI and G/SWIR indicated no significance. Similarly, at the same sites vegetation response to oil spill in December 2014 and after spill in January 2015, NDVI, SAVI and G/NIR indicated level of significant difference with *p-value* <0.05. Vegetation indices e.g. SAVI indicated very significant level with (p-value <0.005) and G/SWIR (p-value <0.0001) between December 2014 and January 2015. The three indices (NDVI, ARVI2 and G/NIR) suggests some evidence of plant spectral alterations/changes in vegetation affected by oil pollution between December 2013 and December 2014 at the same sites. The December 2014/January 2015 show that vegetation conditions between the periods did not change significantly compare to the ones observed in December 2013 and December 2014. The level of significant difference between SS and NSS in 2014 depends on the volume of the oil and severity on vegetation at SS. Also, since there was no oil spill incident at the SS in 2013 it would be expected

that vegetation at the NSS may not differ at high significant level as in 2014. However, a noticeable difference between the two sites could be due to other stressors (anthropogenic and natural) which may not be related to oil spill. Thus, the mean significant difference between SS and NSS in 2013 may be small compare with the ones in 2014 and 2015 in Table 3. Note: in this study, the lowest p-value or significant difference found is <0.05 (low level of confidence) with single asterisk (\*) and the highest is <0.0001 (\*\*\*\*) (a high level of confidence).

## 5. Discussion

The study focused on demonstrating the potential application of remote sensing techniques such as vegetation indices to detect and monitor vegetation affected by oil spills in the Niger Delta region. In Figure 4 the box plot show that the 5 indices (NDVI, SAVI, ARVI2, G/NIR and G/SWIR) indicated a capacity to detect changes in vegetation chlorophyll content, leaf internal structure and water contents in leaf that relates to stress. Researches have attributed these biochemical alterations in forest areas where oil facilities are located [23,45,63,64]. As observed in Table 2 there is a higher level of significant difference between vegetation at the SS and NSS (NDVI, SAVI, ARVI2 and G/NIR), this might suggest that vegetation at the SS responded spectrally different with the ones at the NSS. The performance of these indices e.g. NDVI could be related to their sensitivity to changes in leaf chlorophyll content and internal structure as demonstrated in [26,64]. ARVI2 performance can also be attributed to its ability to resist atmospheric effect while SAVI is designed to address the background noise present in NDVI. These characteristics have made them potentially capable to detect changes in spectral properties of vegetation affected by oil spills and ability to discriminate them from the ones at the NSS as found in [26]. The low levels of chlorophyll recorded by these spectral bands can be as a result of vegetation stress as it may reduce photosynthetic activity in vegetation affected by oil spills at the investigated sites (SS) in December 2014. Therefore, the differences in the vegetation spectral properties at the SS and NSS could be used to suggest the basis on the result in Table 2 that vegetation at SS may have been exhibiting symptoms of stress due to oil spills compare to the ones at NSS in December 2014. These results show that some vegetation indices were able to spatially discriminate between vegetation conditions at the areas oil spills were recorded (SS) and where no spills (NSS). It is equally important to assess the general vegetation conditions in the study area before and after oil spill to determine if they differ with ones found at the SS and NSS over time (2013, 2014 and 2015). The results in Table 3 show that vegetation conditions in December 2013 between the SS and the NSS sites were at low level of significant different with *p*-value <0.05 for all the five indices. Similarly, for December 2014 (year of oil spill) the results of three indices (NDVI, SAVI and ARVI2) indicated higher level of significant difference with *p-value* <0.005 between vegetation conditions at the SS and NSS. G/SWIR indicated a low level of significance with a *p*-value <0.05 between the two SS and NSS. In 2015, which was used as the post-spill year, significant difference was observed between vegetation at the SS and NSS and only G/SWIR maintaining consistency over the period (2013, 2014 and 2015). The Green (G) and SWIR band may have influenced the result as it is sensitive on peak of vegetation and useful for assessing plant vigour and water contents in plants but appear less sensitive in this study. In previous work [26] combination of spectral bands from R and NIR indicated consistent sensitivity. It is expected that this index will provide contrasting information on plant vigour and water contents at SS and NSS. Notwithstanding evidence from this result may suggest that vegetation spectral difference 2013 between SS and NSS were relatively similar. In 2014 vegetation status at the SS and NSS appears to differ with the ones at NSS which could be as a result of spectral changes in vegetation affected by oil spill. The post-spill analysis which did not presented much difference with the ones in December 2014 suggest that vegetation conditions between SS and NSS in January 2015 may still be under stress due influence of oil residues at the spill sites.

The assumption that the vegetation condition at the same spill site in January 2013 (pre-spill) and December 2014 (spill-date) could differ. Two indices SAVI and G/SWIR did not detect any

significant difference between vegetation at the SS in January 2013 and January 2014. But NDVI, ARVI2 and G/NIR indicated a significant difference during the same period and sample points. In contrast, the post spill scenario there are highly significant differences between vegetation condition in December 2014 and January 2015 indicated by G/SWIR with *p-value* <0.0001, NDVI and SAVI with *p-value* <0.005 and least significance from ARVI2 and G/NIR with *p-value* <0.05. In Figure 6 and 7 below are two sample sites 2 and 4 where oil spill events took place twice at different dates and same place.

## 5.1 Visual interpretation of detected oil spill sites

A visual interpretation of the spill sites detected by Landsat using NDVI in 2013 and 2014 is shown in Figure 4 (*a*, *b*, *c* and *d*). The image (*a* and *b*) and NDVI (*c* and *d*) of 2013 showing vegetation at the spill site before the oil spill in Figures 4*a* and 4*c* compared with Figures 4*b* and 4*c*. The vegetation cover in NDVI map of 2013 (Figures 4*c*) appeared educed in 2014 (Figure 4*d*).



Figure 4: Oil spill sites (SS2 and SS4) detected by Landsat data (a & b) and NDVI (c & d) for 2013 and 2014



Figure 5: Oil spill sites (SS2 and SS4) detected in (b)Landsat data shown in Google Earth image of (a) February 2010, (c) June 2015 and (d) NDVI overlaid on 2015 Google image.

Figure 5, SS 2 and SS 4 were detected by these indices derived from 2014 data. In the figure a pre-spill image from Google Earth for February 2010 (Figure 5*a*) was used as the 2013 was not available. As observed in the image (Figure 5*a*) the vegetation appearance changed compare with the one in post-spill image 2015 (Figure 5*c*). The Landsat data for December 2014 used for the detection (Figure 5*c*) and the NDVI overlaid on the post-spill image 2015 (Figure 5*d*). The events at these sites for example SS2 occurred on the 25/11/2014 and about 5000 bbl volume of oil spilt in to the environment. Four weeks (28 days) after the oil spill the image was acquired on the 23/12/2014 which the sensor was able to record the spectral changes in vegetation affected. Other spill sites appear to show a subtle changes in the vegetation due to oil spill size and gap in number of days between the oil spill event and image acquisition dates. The subtle spectral changes in vegetation at other SS were not effectively detected using 30m resolution compared to SS 2 & SS4. From these analyses, it can be stated that the NDVI, SAVI, ARVI2 and G/NIR could be used to characterise the impacts of oil spill on vegetation health. The G/SWIR seemed inconsistent in showing the impacts of oil spills on vegetation which contradicts it performance in [26].

#### 5.2 Implication of the result for oil spill response and mitigation

The development of effective strategies to plan for and respond to oil spills is predicated on a suitable methodology to accurately classify remotely sensed information. Previous workers outlining suggested strategies applied to mangrove forest e.g. Hoff [29] have been confined to utilising methodologies that in many cases are expensive, time consuming, limited in spatial and temporal coverage or unsuitable in detecting oil spills under canopy cover [6,17,29]. These advised techniques are therefore considered as inappropriate for the purpose of the accurate detection of oil spills and the advisement of suitable containment and clean-up models in regions where mangrove forests are ecologically important and need to be carefully managed. This has prompted the introduction of an alternative methodology, as developed in this study, which maintains the effectiveness of detecting oil spills while reducing costs and increasing the spatio-temporal resolution of post-event monitoring [26]. The technique prescribed here is demonstrated as an effective tool in the early detection of oil spills in regions of poor accessibility (e.g. 28 days post-event; Figures 4-5) and hence enhances the

ability to quickly respond to spill events. Other studies e.g. [65] have similarly observed oil spillinduced stress on plants within this short time scale of detection, a feature which may be dependent on the volume of the oil spill [27,35]. For comparatively larger oil spills a 30m resolution sensor was found to be sufficient in detecting changes in the spectral reflectance of affected plant material. Oil spills of a lesser volume, meanwhile, appear to have a subtle impact on vegetation with mapping limited by the resolution of the sensor. The ability to monitor the recovery of vegetation post-spill was also assessed through the use of Google Earth imagery collected on an annual basis from 2014 to 2016. Previous workers have shown the residue from oil spills may remain in the environment several months post event [66]. Thus, this work demonstrated how oil spill detection will provide information to local authorities on how this technique can be useful for to oil spill response in mangrove areas. First, we investigated in pre-spill (2013) image to assess the vegetation health before oil spill while the 2014 image was used to detect vegetation affected by oil spill. This will provide like areas where response may be needed for mitigating the impact at early stage. The post-spill (2015) data assessed and monitor the remediation/clean-up process of the affected sites. Secondly, vegetation at the SS and NSS were used to discriminate between vegetation affected by oil spill and unaffected ones.

### 6. Conclusions

The performance of these indices in this study could have been influenced by variation between individual pigments between the same vegetation type, physical environment, climatic conditions, volume of oil spill, image and spill date. For instance number of days between the oil spill and image is one day minimum and the maximum is six months. Thus, in this study it might be possible that sensor may have not recorded subtle spectral changes in vegetation properties due to low volume of oil spill at some spill sites and due to sensor spatial characteristics. However, as observed at some spill sites (SS2 and SS4) where there were large oil spill, the sensor resolution was able to detect the spectral changes in vegetation resulting from oil spill (Figures 4 and 5) after 28 days of oil spill. In overall these findings has shown a great potential of using spectral techniques for detection and monitoring of oil spill in oil producing environments. The technique could potentially be used for monitoring environmental compliance in oil producing areas like Nigeria where polluted sites may require remediation or clean-up. For example the clean-up process of contaminated sites in Ogoniland Nigeria which has been recommended by UNEP report in 2011 has started in June 2016. The results in this study, that builds on previous works, is essential not only to the oil industry but to government and non-governmental environmental agencies who are responsible for safe guarding natural environment. Local authorities could benefit from the effective and low cost of monitoring oil facilities using space technologies. With the recent launch of Sentinel 2 offering free data with high spatial resolution of 10m and temporal resolution of 12 days could also be useful. Since oil spill impact on vegetation takes some time to fully manifest on vegetation. Also current Landsat 7 and 8 systems offer an alternative of 7 days temporal acquisition between two the images for real time monitoring of forest areas where oil facilities are located. Thus use of this techniques could be apply for early mitigation response to reduce the impact on the environment before it cause a large scale damage. Further study will require considering other factors such as how variations in local physical environment, vegetation plant species type (as the respond differently to oil spill), oil type (as different types of oil vary in severity to plants), satellite sensor characteristics (e.g. spectral and spatial resolution), time gap between spill and image date and volume of oil that could be influential.

#### Acknowledgement

This work is supported and funded by the Petroleum Technology Development Fund (PTDF) under the Federal Government of Nigeria [PTDF/E/OSS/PHD/AB/347/11] and Modibbo Adama University of Technology (MAUTECH) Yola, Nigeria [MAUTECH/R/SP1132/Vol.1].

## **Disclosure statement**

No potential conflict of interest was reported by the authors.

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