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An investigation into the factors influencing the detectability of oil spills using spectral indices in an oil-polluted environment

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ABSTRACT

The aim of this article is to investigate and test the influence of oil spill volume and time gap (number of days between oil spill events and image acquisition date) on normalized difference vegetation index (NDVI) and normalized difference water index (NDWI). This was carried out to determine the effect of these factors on vegetation condition affected by the oil spill. Based on regression analysis, it was shown that increase in the volume of oil spill resulted in increased deterioration of vegetation condition (estimated using NDVI and NDWI) in the study site. The study also tested how the length of time gap between the oil spill and image acquisition date influences the detectability of impacts of oil spill on vegetation. The results showed that the length of time between image acquisition and oil spill influenced the detectability of impacts of oil spill on vegetation condition. The longer the time between the date of image acquisition and the oil spill event, the lower the detectability of impacts of oil spill on vegetation condition. The NDVI seemed to produce better results than the NDWI. In conclusion, time and volume of oil spill can be important factors influencing the detection of pollution using vegetation indices (VIs) in an oil-polluted environment.

1. Introduction

Oil has become a vital commodity for the government as a source of revenue and national economic growth (Bridge 2008). It also serves as a source of energy for the maintenance of industrial civilization, which has become a critical concern for many countries (Smil 2010). Globally, energy consumption in almost all regions of the world has increased from 1965 to 2010 and likewise the crude oil production (IEA 2011; BP 2011). The increase in oil production has undoubtedly continued to add pressure on the natural and human environment. The consequences for oil production and pollution from the oil operation have been documented around the world. Oil spills occurring during the exploration, production, and distribution/transportation of crude oil can have a disastrous impact on the environment. When oil spill occurs, it degrades the air quality

due to emission, and leads to loss of vegetation and soil productivity (Obire and Nwaubeta 2002). Frequent incidences of oil spills have had wide-ranging impacts, including the contamination of streams and rivers, forest destruction, and loss of biodiversity. There have been several incidents of oil spills in places such as the Gulf of Mexico in 2010, Canadian marine waters (Serra-Sogas et al. 2008) and Prince Williams Sound, off the coast of Alaska in March 1989. According to Exxon Mobil the total volume of hydrocarbons spilled on soil and water was 9,100 barrels (bbl) in 2014 from different incidences. In another incident, in 1989 the Exxon Valdez reported by Exxon Mobil in 2003 that a super-tanker ran aground at Alaska's Prince William Sound and discharged more than 250,000 bbl of oil into the environment (Short 2003). The European Economic Community (EEA) also reported in 2007 that primary pollutants such as heavy metals and mineral oil caused 37.3% and 33.7% soil contamination, respectively. In other parts of the world, for instance, Nigeria, Colombia, Peru, Ecuador, and Bolivia, substantial oil operations are located in the rain forest. As such, oil extraction and transportation can be destructive to the natural environment. Oil spills from burst pipelines and toxic drilling by-products may be dumped directly into local channels and rivers (CIA 2005). Oil spills in water may severely affect the marine environment, causing a decline in phytoplankton and other aquatic organisms (Jha, Levy, and Gao 2008). The multiplier effect of this environmental destruction will result in the deterioration of the environment through the depletion of resources such as air, water, vegetation and soils, the loss of ecosystems, and the extinction of wildlife. Oil spill site characterization traditionally requires extensive field sampling and laboratory analysis (Slonecker et al. 2010). Field data collection is expensive and time-consuming, making this approach unsustainable. Remote sensing offers an efficient, time-saving, cost-effective, and non-destructive method of characterizing oil spills and their impacts on the environment.

Remote sensing has an advantage of covering large oil-polluted areas and can access information on environmental variables affected by pollution through their spatial and spectral characteristics. Furthermore, remote sensing offers the capacity to acquire data in remote areas that are difficult to access. The use of remote sensing for oil or hydrocarbon pollution monitoring dates back to the 1970s, where aerial photographs were used for the first time (Casciello et al. 2007). There are a number of studies that demonstrate the use of remote sensing for the detection of oil pipelines and vegetation stress from oil pollution, quantification of pollution/stress level, and monitoring after remediation (van der Werff et al. 2008). Remote-sensing sensors that record information in the ultraviolet (UV), thermal infrared, and microwave sections of the electromagnetic spectrum have been used to detect oil spills (Brekke and Solberg 2005; Zhao and Li 2007). Studies have shown that hyperspectral sensors, e.g. Airborne Visible/Infrared Imaging Spectrometer (AVARIS) and Airborne Imaging Spectrometer for Application (AISA), have capabilities to detect oil spill (Jha, Levy, and Gao 2008; Landgrebe 2005). Data from active sensors that collect data in radio wavelength have also been used to detect the presence of oil in offshores areas mainly through the reduction of ocean reflectance (Brown and Fingas 2003). Microwave sensors have been used to detect oil spill and their thickness (Jha, Levy, and Gao 2008), whereas laser-acoustic oil thickness sensors have been used to detect oil mechanical properties instead of its optical and electromagnetic properties (Goodman 1994). Onshore oil pollution monitoring in forested areas using remote-sensing data has been limited, especially in developing

countries such as Nigeria, mainly due to the lack of readily available data. The recent release of all Landsat archive of images has made it possible to explore the use of these images to monitor the impacts of onshore oil spills on vegetation condition in developing countries such as Nigeria.

Monitoring the impacts of oil spills on vegetation using remote-sensing data requires an understanding of the spectral reflectance characteristics of vegetation. Vegetation has a unique spectral signature that enables it to be distinguishable from other types of land cover in an optical/near-infrared (NIR) image. Vegetation has reflectance in both blue and red regions of the spectrum because of the absorption of chlorophyll for photosynthesis and the relatively high reflectance at the green region (Sims 2002). Furthermore, in the NIR region, vegetation has a high reflectance mostly due to the cellular structure in the leaves (Purkis and Klemas 2011). Therefore, vegetation and its condition can be characterized using reflectance information form the NIR and the visible bands. The common approach of carrying this out is to calculate the band ratios often referred to as vegetation indices (VIs) and monitor their dynamics. Healthy plants have diagnostic high reflectance in the NIR region and low reflectance in the visible bands and hence the high values of VIs indicate healthy vegetation and vice versa. It has been suggested that the presence of hydrocarbons seems to produce a change in the internal structure of the plant that results in low reflectance values and oil pollution may also lead to low density of vegetation in the affected areas (Oliveira, Crosta, and Goncalves 1997). In addition, vegetation growing near leaking gas pipelines has been shown to have changes in their geobotany and reflectance (van der Meer et al. 2002; Arellano et al. 2015). The geobotanical anomalies were associated with the effects of oil spills and pollution on the growth of the vegetation (Noomen et al. 2008). Furthermore, changes in the colour of leaves, stems, and trunks are an extremely good indication of plants' response to stress from oil pollution (Guyot, Baret, and Jacquemoud 1992). All these changes due to oil spills and pollution manifest themselves in the VIs; hence, the impacts of oil pollution on vegetation condition can be assessed using VIs. VIs (e.g. normalized difference vegetation index, NDVI) have shown a great potential for detecting the impacts of oil pollution on vegetation in oil-polluted environments (Zhu et al. 2013; Adamu, Tansey, and Ogutu 2015). In an earlier study, Adamu, Tansey, and Ogutu (2015) showed that oil spills resulted in the reduction of values of VIs (especially the NDVI and the normalized difference water index, NDWI), implying these indices can be used to detect the impacts of oil pollution on vegetation condition. However, in that study, factors that influence the detectability of impacts of oil pollution on vegetation using the spectral indices (e.g. volume of oil spill and time difference between spill and image acquisition) were not investigated.

A number of factors can influence the detectability of impacts of oil spill on vegetation condition. One such factor is the toxicity of the oil spilled, i.e. the higher the toxicity, the higher the impacts on vegetation (Reed et al. 1999; Lehr 2001; Mendelssohn et al. 2012). A second factor that influences the impacts of oil spill on vegetation is the volume of oil spill. Noomen et al. (2012) suggested that high volumes of oil spill in vegetated areas might result in shortage of oxygen supply to plants and consequently retard their growth. Furthermore, Pezeshki et al. (2000) demonstrated how a large volume of oil spills can impact vegetation more than the small spills. Therefore, it is expected that high-volume spills would lead to higher impacts on the vegetation condition as it will

take time for larger-volume spills to degrade and evaporate (Mendelssohn et al. 2012). Finally, the length of time between the spill event and the image acquisition may affect the detectability of oils spills from remote-sensing data. As mentioned previously, oil spills degrade and evaporate with time and hence if the imagery is acquired at a longer length of time from the spill date, the vegetation in the area may already have recovered, making it difficult to detect the impacts of the oil spill. A study by Yim et al. (2011) showed that samples of oil residue collected 90–120 days after pollution already had the molecular weight of their alkanes depleted or biodegraded. Duke et al. (2000) observed that obvious signs of stress of mangrove plants were noticed within the first two weeks of oil spill, causing chlorosis to defoliation to death of the affected plants. This study aims to investigate the influence of volume and time of image acquisition in the detectability of oil spill impacts of vegetation in the Niger Delta, Nigeria, using two indices (i.e. the NDVI and NDWI). The indices (NDVI and NDWI) used in the study are products derived from atmospherically corrected and temporarily processed Landsat images to further reduce noise. In brief the NDWI uses infrared channels (NIR and MIR) centred approximately at 0.86 and 1.24 μm, and primarily sensitive to the liquid content of vegetation from space (Gao 1996). NDVI uses a formula based on the fact that chlorophyll absorbs RED, whereas the mesophyll leaf structure scatters NIR (Myneni et al. 2002).
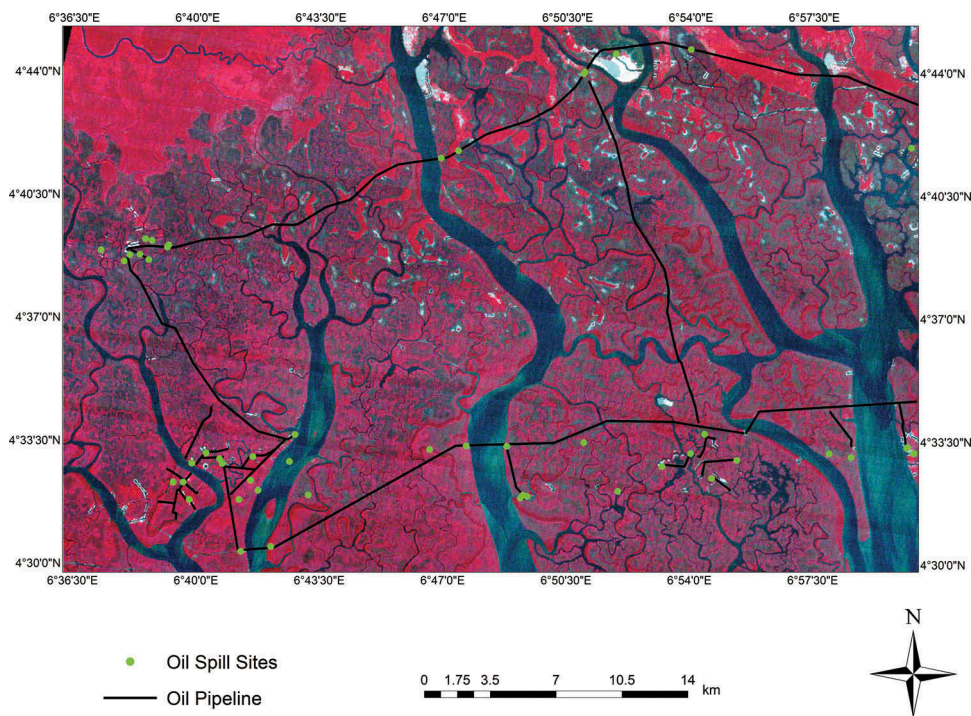
2. Study area

2.1. *Physical environment*

The study area is located in the Niger Delta region of southern Nigeria shown in Figure 1 in green colour within the map of Nigeria. The area extent is within Longitude 5.05°E and 7.35°E and Latitude 4.15°N and 6.01°N, and it covers approximately 1294 km^2 (Figure 2) in a red box. The study area in the red box fitted in a single Landsat 5 and 7 data frame from Path 188 Row 57. The study site contains a wide variety of trees and plants including mangrove trees of all kinds, grasses, herbs, and climbers. 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. The region is characterized by rain-fed deltaic vegetation in places, with high elevation, and the majority of the region is dominated by low-lying landforms (Avbovbo 1978). The area is formed of both fluvial and marine sediments built up over the past 50 million years (since the upper Cretaceous period) (Short and Stauble 1967; Burke, Dessauvagie, and Whiteman 1971). These sediments form a shallow marine and deltaic characterized mainly by River Niger and its tributaries. The Niger delta coastal mangroves ecosystem is supported by saline soil with a pH value of between 0 and 4 for the freshly deposited soft silt low tides and 7 for transitional swamps at high tides. An intermediate soil type such as peat clay is about 90% of the soil formation in the ecosystem (Fagbami, Udo, and Odu 1988). The oil spill sites identified were all located in the mangrove swamp areas (Figure 2), where there is the presence of both underground and surface water. The hydrological characteristics of the area could influence the detection of oil pollution. The region is also drained by the river systems, which are mostly associated with channels and
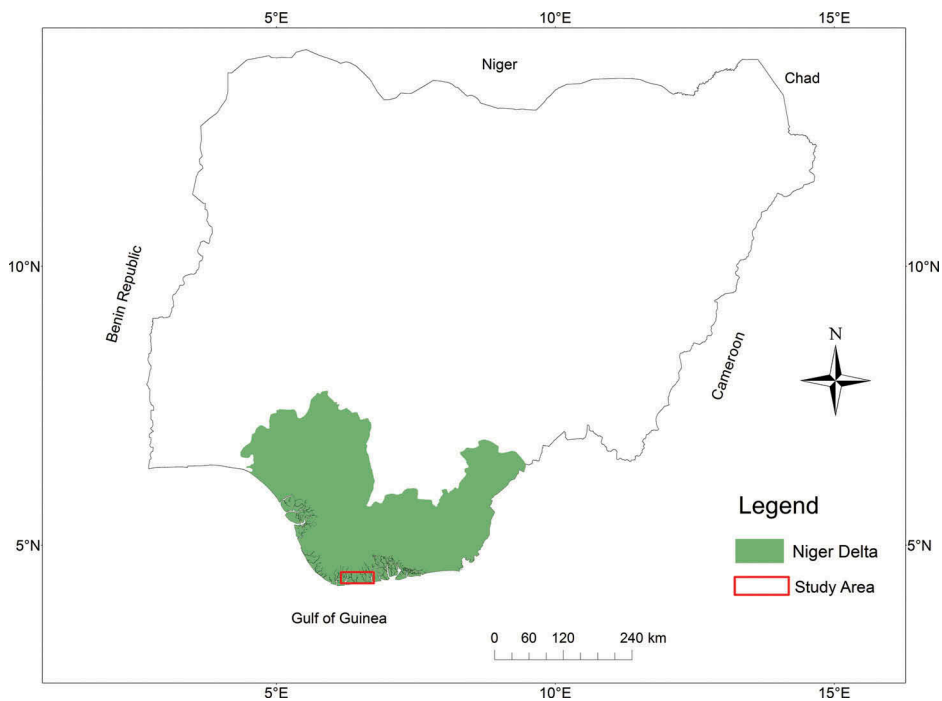
Figure 1. The Niger Delta is shown in green colour within the map of Nigeria.

Figure 2. Landsat data in false colour composite (bands 4, 3, and 2) showing oil spill points and pipelines in the study area.

streams. The surface water, freshwater, and deltaic estuaries (an area of interaction between freshwater and seawater) cover approximately 2,370 km^2 and stagnant swamp 8600 km^2 spanning an area of 1900 km^2, and other sources of inflow during the rainy season, which is also influenced by tidal variations. The width and velocity of freshwater channels increase downstream to meandering or braided channels in the delta.

2.2. *Climate*

Nigeria's climate is tropical, characterized by high temperatures and humidity as well as marked wet and dry seasons, although there are variations from South to North. The total rainfall decreases from the coast northwards (Oguntunde, Abiodun, and Lischeid 2011). The long wet season starts in March and lasts to the end of July, with a peak period in June over most parts of Niger Delta similar to other parts of southern Nigeria. It is a period of thick clouds and is excessively wet particularly in the Niger Delta and the coastal lowlands. The long dry season period starts from late October and lasts to early March with peak dry conditions between early December and late February (Adejuwon 2012). The annual temperature in the Niger Delta ranges between 26°C and 34°C, with the highest during the dry season (November–March) and the lowest between 24.5^{o}C and 26.9^{o}C in June, July, and August. The topography of the Niger Delta or Nigerian coastal areas is generally low-lying at about 2–4 m above the sea level (Allen 1965; Ajao, Oyewo, and Unyimadu 1996), which is also a factor that could influence the flow direction of the oil spilt in the study.

2.3. *Land use and land cover*

The coast of Nigeria's Niger Delta region where the study area is located is characterized by a high concentration of oil exploration and local farming activities. This has led to continuous changes in both land-cover and land-use patterns of the region. It has also been shown that expansion in the oil exploration and exploitation activities had increased pressure with heavy impact on the natural ecosystems as a result of oil spill incidences (Abbas 2012). Records have shown that most of the oil pollution from oil operations in the regions has remained in the environment for many years without clean-up and yet to recover the lost natural vegetation (UNEP 2011).

3. Data analysis

The oil spill events for 56 oil spill sites were recorded in 1985, 1986, 1998, 1999, 2000, 2004, 2006, and 2007 with the volume of oil spill ranging between 3 and 3500 bbl (Table 1). The 56 sample spill sites analysed in the study were all located within the same vegetation type (swamp mangrove forest) to ensure that there are no significant variations in the vegetation spectral reflectance. Note in this study, the volume of oil spill is quantified in bbl and interpreted using SI units as 1 bbl approximately 160 litres (l).

The ancillary data used include oil pipeline maps, spill records from 1985 to 2006 containing information on the date of events, vegetation land-cover type, causes of spill, and GPS locations of spill points (showing where the oil spill events occurred) obtained

Table 1. Year of oil spills, sample points, and available image data.

Year of Spill	Sample Points	Acquisition Date
1985	2	17 January 1986
1986	9	19 December 1986
1998	7	21 February 1987
1999	11	29 November 1999
2000	10	17 December 2000
2002	6	8 January 2003
2004	4	26 November 2004
2006	5	19 January 2007
2007	1	19 January 2007
Total	56	

from Shell Nigeria through the Department of Petroleum Resources, Nigeria (DPRN, Nigeria's oil and gas regulatory agency).

3.1. Data preprocessing

In this article Landsat TM and ETM data obtained as digital number (DN) were converted to comparable measures of radiance and reflectance as a starting point for data processing. Thus, the images were processed by converting top-of-atmosphere radiance values to surface reflectance following a method proposed by Chander, Markham, and Helder (2009). 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. Atmospheric correction was then performed on the reflectance values derived using the FLAASH routine. The input file was converted to radiance image in a band-interleaved-by-line (BIL) format with a scale factor of 1.0 (μW cm^{-2} sr^{-1} nm^{-1}) before applying the FLAASH module. The FLAASH module input information (such as flight date and time, sensor altitude, and sensor location) needed for the processing of these images was contained in the Landsat image metadata file downloaded from the USGS archive. Sensor altitude (km) is automatically set according to sensor type and the average study area elevation (0.4 km) was used as an input for ground elevation. Some multispectral sensors such as Landsat data do not have appropriate bands to perform water retrieval; hence, this was not undertaken in this work. Figure 3 shows the preprocessed Landsat 5 and 7 images used for the analysis.

3.2. Method of analysis

From the database, the range of volume of oil spill that occurred in the study is from a minimum of 3 to a maximum of 3500 bbl and the number of days computed between the oil spill event and image acquisition date ranges from 2 to 844 days. The relationship between oil spill volume and the level of impact on the vegetation health has been demonstrated in Mackay and Matsugu (1973) and Mackay and Mohtadi (1975) in Canada. Hypothetically, a small volume of oil spill over land may occupy little space in a pixel of 30 m resolution. In contrast, the large volume of oil spill could occupy a large space in a 30 m pixel over land. Thus, it is expected that a smaller volume of oil spill may have little impact on vegetation, thereby limiting the detectability of these effects using
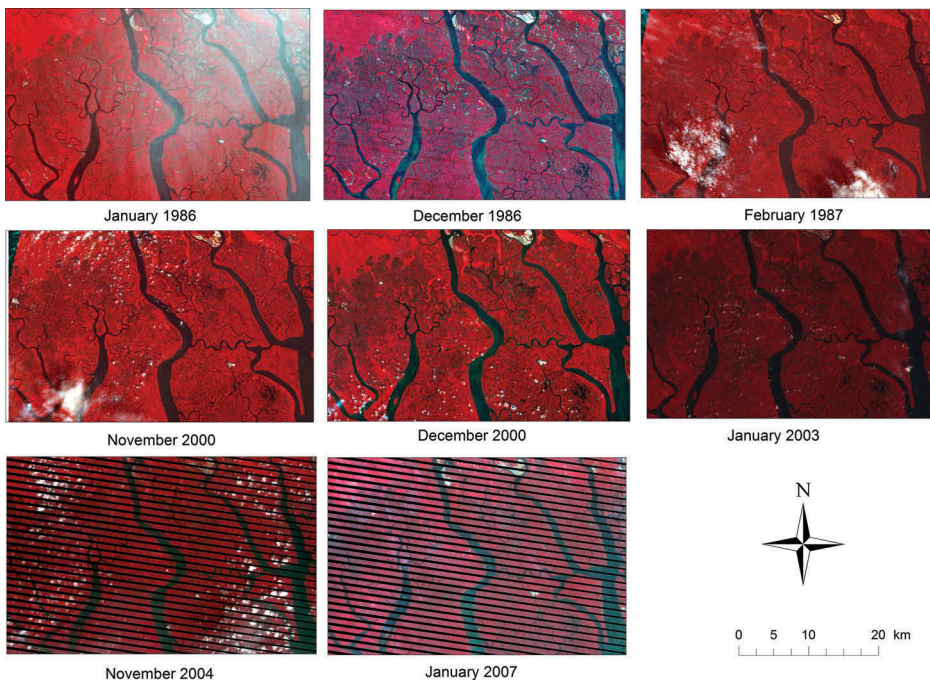
Figure 3. Landsat-5 and -7 images in false colour composite (bands 4, 3, and 2) of the study area.

a 30 m spatial resolution sensor such as Landsat. Factors such as land-cover types (where the spill occurred), volume of oil spill, and time of image acquisition were taken into consideration in this study. To determine whether the volume of oil spill and the number of days between oil spill events and image acquisition date can affect the detection of oil spill over vegetated areas using NDVI and NDWI, a number of assumptions were made. We assumed that index (NDVI and NDWI) values could drop as the volume oil spill increases and they may remain relatively unchanged or go up at the affected sites as the volume of oil spill decreases. Similarly, it is also assumed that as the number of days increases between the oil spill event and the image date, there are high chances of vegetation recovery and that NDVI and NDWI values will go up. Statistical regression was used to determine which volume of oil spill could lead to detectable impacts on vegetation through the use of two indices (NDVI and NDWI). This was done by plotting all the 56 oil spill data at the first stage of analysis to see how a change in volume of oil spill affects the two indices. The second stage of analysis involved determining the minimum amount of oils spill that can effectively fill a 30 m by 30 m pixel and hence would lead to detectable change in vegetation condition in a single Landsat pixel.

Environmental conditions, e.g. water-saturated soil, increase the surface pool of oil spill and limit the penetration of oil into the ground (Grimaz et al. 2008). When oil spill occurs on a surface, the force balance between the downward pull of gravity caused by density and internal tension of the liquid may allow the oil pool to form a final spill size. A pool is considered to be a large drop of oil with a defined amount of oil held to a certain penetration depth in a surface area (Grimaz et al. 2008; Simmons and Keller 2003). It also depends on the

property of the oil (in the case for this study, heavy oils are used as no specific oil type is considered); the spilled oil will eventually stand a certain height or depth above the surface (Simmons, Keller, and Hylden 2004). For example this model (Simmons, Keller, and Hylden 2004) presumed that the volume of oil-spilled partition over an area is given by

$$V = A\delta\varphi + Ah, \tag{1}$$

where h is the height of liquid standing above the surface. Liquid below penetrated to a certain depth, δ, in the substrate porosity, φ. Thus the height is given by

$$(1 - cos\theta) \times \sigma = \rho \times g \times h^2, \tag{2}$$

where h = spill height (cm)

ρ = density (gm/ml)

g = gravity acceleration

σ = surface tension (dyne/cm)

θ = contact angle (angle between spill height of liquid and surface)

Oil spill height can be determined by surface tension divided by the weight density of liquid for adhesion quantified by contact angle. In Simmons, Keller, and Hylden (2004) the model used different types of oil liquid properties to produce different heights of oil spill based on various scenarios ranging from 0.01 to 0.5 cm. Since the oil found in the Niger Delta could be assumed to behave similar to the ones demonstrated, the height of oil spill is presumed at 0.04 m for this study based on the calculation in Simmons, Keller, and Hylden (2004). The following calculation was used to predict the expected volume of oil spill to fill a 30 m pixel:

$$1m^3 = 1000 \text{ l}$$
$$1 \text{ bbl of oil} = 160 \text{ l}$$
$$\text{Volume of oil spill} (V_{Spill}) = (l \times b) \times (h \times 1000)/160 \text{ l}$$
$$V_{Spill} = A \times (h \times 1000)/160$$

where

V_{spill} = volume of oil expected to fill an area corresponding to one pixel A
(Pixel area) : Length (l) = 30 m, breadth (b) = 30 m
A(pixel area) = $l \times b$, where $l = b$ = 30 m
h = Assumed height of oil spill = 0.04 m

Therefore:

$$V_{Spill}(\text{bbl}) = (l \times b) \times (h \times 1000)/160 \text{ l}$$
$$V_{Spill}(\text{bbl}) = (30 \times 30) \times (0.04 \times 1000)/160 \text{ l} = 225 \text{ bbl}.$$

Consequently, in further analysis, 225 bbl was used as the minimum value where impacts of oil pollution on vegetation can be detected.

In the second part of the analysis, the influence of the number of days between oil spill and date of image acquisition on the detectability of pollution impacts on vegetation was determined. In the first stage of this analysis, all the date data was used to derive the regression statistics between time and the VIs. Next, the data was divided into two dates (i.e. 0–1 year and 1–2 years) to determine any variations in vegetation response.

4. Results

The data in Table 2 shows that some spill sites have high values of NDVI and NDWI despite a large volume of spills; others appear to have a low volume of spill but with high values of NDVI and NDWI.
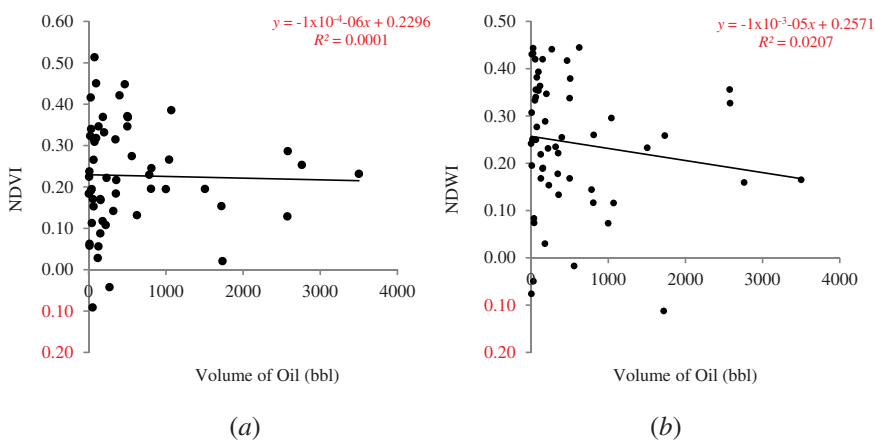
4.1. *Influence of volume of oil spill on NDVI and NDWI*

The computed NDVI and NDWI from all the 56 sample sites in Table 2 were used to determine the relationship between the indices and the volume of oil spill using all the data in Table 2. All the oil spill data (volume of oil spill) were plotted against NDVI and NDWI in Figure 4.

 The relationship between the two indices and the volume of oil spill between 3 and 3500 bbl indicated was weak, with the coefficient of determination ($R^2 = 0.0001$ and $R^2 = 0.02$) for NDVI and NDWI, respectively (Figures 4(a) and 4(b), respectively). The reason for this analysis is to determine whether there is any relationship at all between all the volume of oil spill data and the spectral indices without considering the influence of the number of days between the oil spill events and the image acquisition date. Generally, considering the regression analysis shows that the volume of oil spill indicated a poor relationship with the NDVI and NDWI at this stage. The next stage of analysis used a minimum volume of 225 bbl calculated in the methods section to

Table 2. Number of sample points, volume of oil spill, and time gap between oil spill and image dates.

| Sample Points	Volume Of oil (bbl)	Time (Days)	NDVI	NDWI	Sample Points	Volume	Time (Days)	NDVI	NDWI
SP1	558	2	0.27	0.02	SP29	346	135	0.2	0.44
SP2	813	3	0.25	0.19	SP30	62	144	0.32	0.34
SP3	150	5	0.17	0.42	SP31	1042	158	0.24	0.22
SP4	352	11	0.18	0.22	SP32	200	161	0.33	0.35
SP5	28	12	0.19	0.44	SP33	1720	163	0.18	0.07
SP6	50	14	−0.09	0.33	SP34	150	169	0.09	0.19
SP7	2761	20	0.26	0.1	SP35	97	184	0.45	0.39
SP8	2	32	0.18	0.24	SP36	3500	198	0.17	0.38
SP9	54	33	0.17	0.42	SP37	269	206	0.13	0.35
SP10	318	35	0.45	0.34	SP38	96	221	0.32	0.35
SP11	1069	37	0.2	0.4	SP39	2578	234	0.04	0.44
SP12	63	45	0.15	0.25	SP40	232	237	0.34	0.43
SP13	400	46	0.42	0.26	SP41	126	254	0.06	0.22
SP14	40	47	0.11	0.07	SP42	2573	270	0.13	0.36
SP15	117	48	0.03	0.36	SP43	75	281	0.31	0.28
SP16	180	52	0.12	1.03	SP44	625	300	0.13	0.44
SP17	39	69	0.2	0.08	SP45	128	306	0.35	0.17
SP18	155	70	0.17	0.19	SP46	10	363	0.06	0.20
SP19	75	75	0.51	0.38	SP47	507	370	0.47	0.39
SP20	10	80	0.06	0.43	SP48	27	378	0.42	0.43
SP21	500	89	0.35	0.17	SP49	20	378	0.32	0.25
SP22	5	96	0.22	−0.08	SP50	785	474	0.23	0.14
SP23	184	97	0.37	0.29	SP51	468	560	0.40	0.31
SP24	32	99	0.34	−0.05	SP52	500	650	0.37	0.34
SP25	63	116	0.27	0.36	SP53	1000	707	0.48	0.40
SP26	9	118	0.24	0.31	SP54	807	708	0.48	0.41
SP27	221	127	0.31	0.32	SP55	358	819	0.38	0.39
SP28	1734	134	0.2	0.22	SP56	1505	844	0.33	0.34

Figure 4. Relationship between NDVI and NDWI and all volumes of oil spill.

determine whether there would be any improvement in the detection of the influence of volume of oil spill on the VIs. This amount of oil spill was assumed capable of covering a single Landsat pixel and hence would result in detectable changes in vegetation condition.

Figure 5 shows the relationship between oil spill and the two VIs when the minimum volume of 225 bbl is used. In this figure the relationship between the volume of oil spill (> 225 bbl) and the two indices (NDVI and NDWI) was better than the one shown in Figure 4. Figure 5 shows that as the volume increases, the VIs value decrease. This was more pronounced in the NDVI than in the NDWI.

To further analyse the relationship between the oil spill volume and the VIs, the oil spill volumes were divided into different categories (i.e. 225–400 bbl, 401–1000 bbl, and
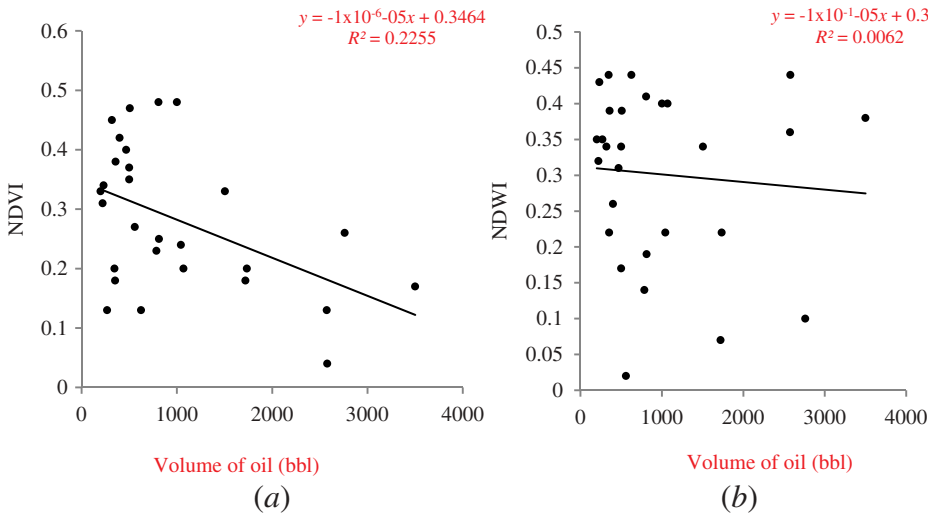
Figure 5. Relationship between (*a*) NDVI and (*b*) NDWI and volume of oil spill where the volume was greater than 225 bbl.
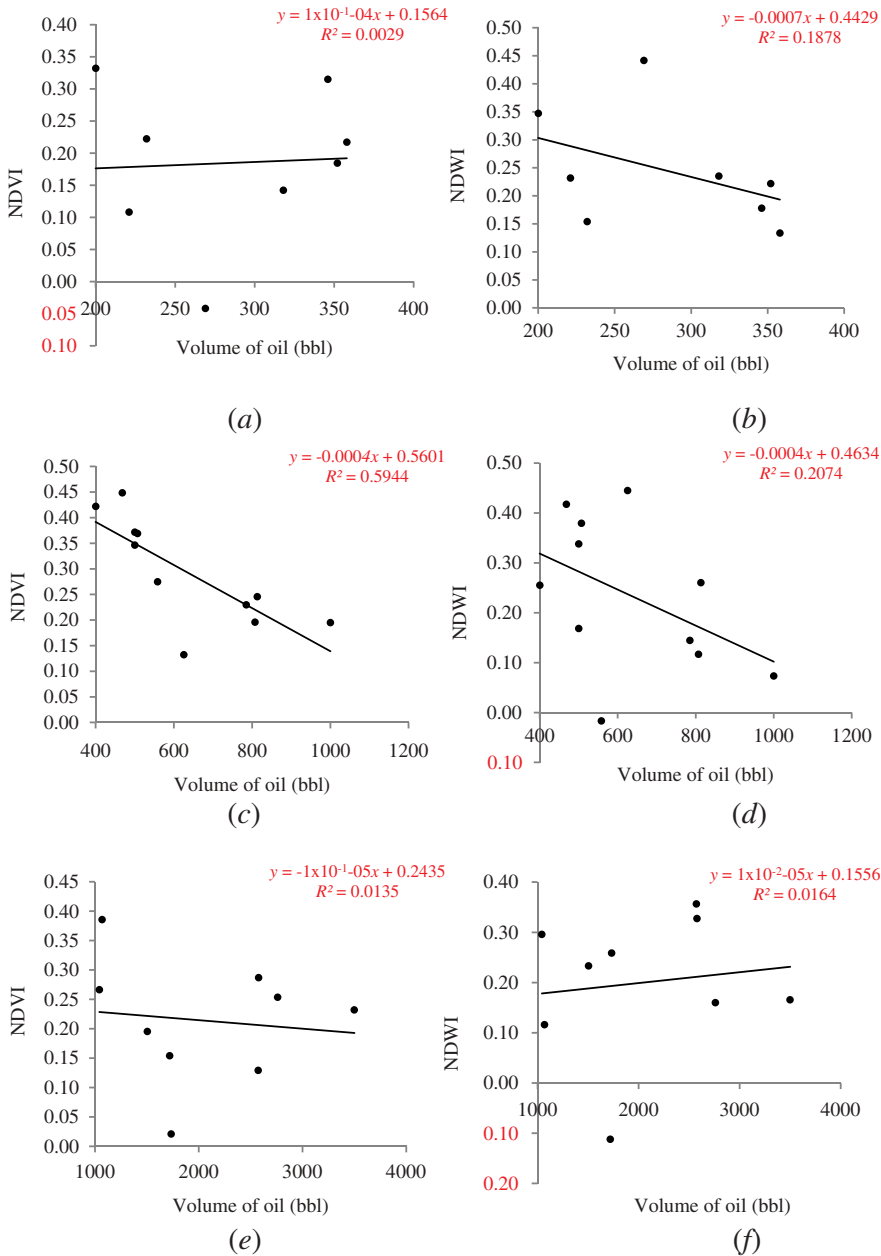
Figure 6. Variation in relationship between NDVI and NDWI and volume of oil for different oil spill volume ranges: 6(*a*) and 6(*b*), 225–400 bbl; 6(*c*) and 6(*d*), 401–1000 bbl; and 6(*e*) and 6(*f*), 1001 bbl and above.

>1001 bbl) and each category related to the VIs. The results from this analysis are shown in Figure 6. The results from this analysis showed that the volume from 400 bbl to 1000 bbl [Figure 6(c) and 6(d)] seemed to result in the greatest detectable reduction in both indices ($R^2 = 0.59$ for NDVI and $R^2 = 0.21$ for NDWI). This could be because this volume range is not too small to adequately cover the pixels (hence result in response from

plants) and not too large to contaminate the reflectance of vegetation recorded by satellite sensor (which would reduce the sensitivity of the VIs).

4.2. Analysis of influence of time on NDVI and NDWI

From the analysis provided in section 4.1 the influence of volume appears to be clear in the category between 400 and 1000 bbl. In this section, the results from the influence of time gap (i.e. oil spill and image date) on the detection of changes in vegetation spectral values at the polluted sites are presented. Table 2 shows the NDVI and NDWI values for all oil spill volumes. In this table, the trend seems to be that the oil spill sites with less number of days between the oil spill and imagery dates have low NDVI and NDWI values, and those with a high number of days have high index values. However, to obtain a clear picture of the influence of time on the effects of oil spill on vegetation, only sites where the volume of oil spill was greater than 225 bbl are analysed further. Table 3 lists the NDWI and NDVI for sites with oil spills greater than 225 bbl.
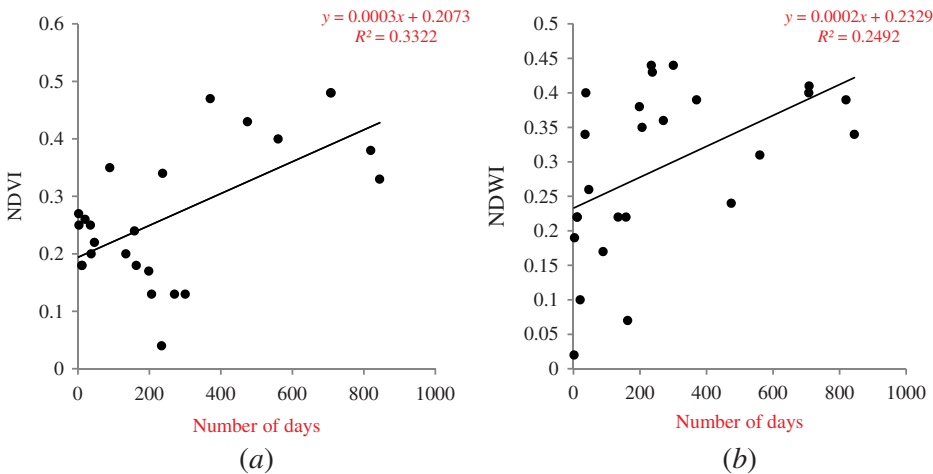
The relationship between the number of days and the VIs for all of the sites with oil spill greater than 225 bbl is presented in Figure 7. This figure shows that as the number of days increases, so do the values of the VIs. This implies that with time, vegetation seems to recover from the effects of oil pollution. However, further analysis was performed by splitting the length of time into categories (0–1 year) and (1–2) year to determine whether initially the vegetation would get affected and then recover after a specific time. Results from this analysis are presented in Figure 8.

Figure 8(a) shows that the NDVI decreased in the first year, which could be attributed to the effects of oil spill, and started to increase in the second year (Figure 8(c), which

Table 3. Time gap between oil spill and image dates and NDVI and NDWI for 25 spill sites with volume of oil spill volumes of more than > 225 bbl.

| Sample Points	Oil Spill Volume (bbl)	Time Gap (Days)	NDVI	NDWI
SP1	558	2	0.27	0.02
SP2	813	3	0.25	0.19
SP3	352	11	0.18	0.22
SP5	2761	20	0.26	0.10
SP6	318	35	0.25	0.34
SP7	1069	37	0.2	0.40
SP8	400	46	0.22	0.26
SP9	500	89	0.35	0.17
SP11	1734	134	0.2	0.22
SP12	1042	158	0.24	0.22
SP15	1720	163	0.18	0.07
SP16	3500	198	0.17	0.38
SP17	269	206	0.13	0.35
SP18	2578	234	0.04	0.44
SP19	232	237	0.34	0.43
SP20	2573	270	0.13	0.36
SP21	625	300	0.13	0.44
SP22	507	370	0.47	0.39
SP28	785	474	0.43	0.24
SP23	468	560	0.4	0.31
SP24	1000	707	0.48	0.40
SP25	807	708	0.48	0.41
SP26	358	819	0.38	0.39
SP27	1505	844	0.33	0.34

Figure 7. Relationship between time gap (number of days between oil spill and image date) and (a) NDVI and (b) NDWI in polluted sites.

could be linked to the recovery of the vegetation in the study site. The NDWI does not seem to respond to the effects of oils spill, as depicted by Figure 8(b) and 8(d).

5. Discussion

### 5.1. Influence of volume of oil spill on NDVI and NDWI

This study examined the relationship between the volume of oil spill and spill effects on vegetation health using VIs. VIs have been shown to be good indicators of the effects of oil pollution on vegetation (Zhu et al. 2013, Noomen et al. 2015, Adamu, Tansey, and Ogutu 2015). First, we plotted and analysed all the oil spill data to determine at which volume the impacts of oil spill on vegetation could be detectable using two indices (i.e. NDVI and NDWI). From Figure 4 the regression analysis computed showed that all volumes of oil spill at the first stage (where all the 56 spill data were plotted against the indices) had poor or no relationship with NDVI (R^2 = 0.0001) and with NDWI (R^2 = 0.02). This relationship suggests that there is less or no influence of the volume of oil spill on vegetation. However, it is known that low-volume oil spills would not cover the entire Landsat pixel (i.e. 30 m by 30 m) and hence the impact of oil spill on vegetation cannot be detected through VIs. This result could have influenced the strength of the relationship between the volume of oil and NDVI and NDWI in the regression analysis in Figure 4. To make the analysis more realistic, a minimum volume of oil, which would ideally cover a single Landsat pixel, was calculated and only oils spills above this volume (225 bbl) were used in subsequent analysis. Using this minimum volume, the negative relationship between the increase in the volume of oil spill and the VIs improved (i.e. R^2 = 0.2 for NDVI and R^2 = 0.01 for NDWI) (Figure 5). To determine the ideal volume where clear impacts of pollution on vegetation can be detected, this study divided the volumes further into various categories (Figure 6). Results from these categories showed that there was a strong negative relationship between the NDVI
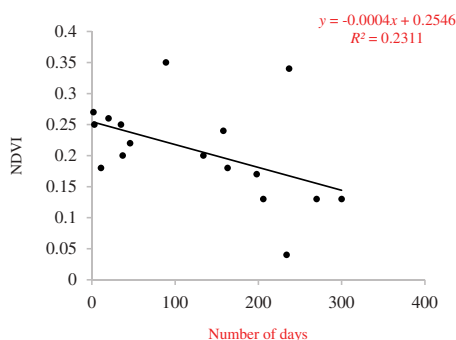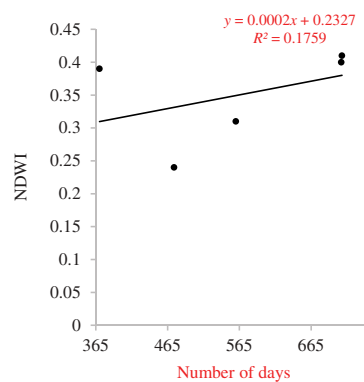
(*a*) NDVI vs time between oil spill and image
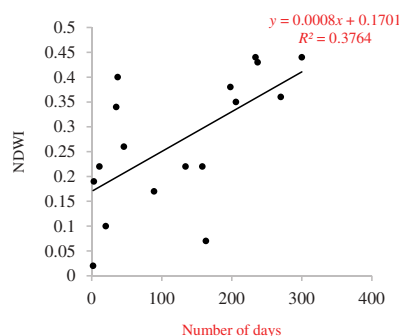
(*b*) NDWI vs time between oil spill and image
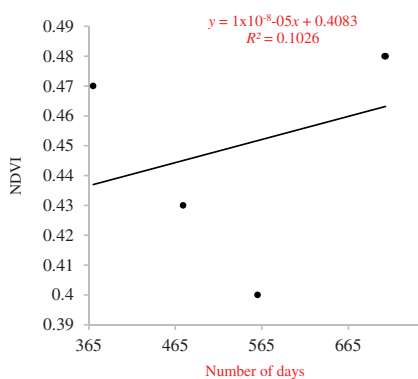
(*c*) NDVI vs time between oil spill and image

(*d*) NDWI vs time between oil spill and image

Figure 8. The relationship between time [< 1 year 8(*a*) and 8(*b*) and 1–2 years 8(*c*) and 8(*d*)] and the two vegetation indices (NDVI and NDWI).

(R^2 = 0.59) and the oil spill category between 400 and 1000 bbl. The relationship between NDWI and this volume category was also better than in the other categories (R^2 = 0.21). One possible explanation for this increased sensitivity could be that this volume is probably not too small to adequately cover the pixels (hence result in impacts on plants) and not too large to contaminate the reflectance of vegetation recorded by satellite sensor (which would reduce the sensitivity of the VIs). Therefore, this category seems to be the ideal volume where the impacts of oil spill on vegetation condition could be detected. From this result, it can be stated that the volume of oil spill is an important variable to consider when determining the impacts of oil spill on vegetation condition from remote-sensing data. This result is supported by Wardrop et al. (1998) that the degree of oil spill impact on vegetation and (Lewis Iii 1983) vegetation recovery is correlated to the extent of the spill.

5.2. *Influence of time factor on NDVI and NDWI*

In Figures 7(a) and 7(b), the regression line indicates a relatively weak but positive relationship between the number of days and the two VIs with R^2 = 0.3322 and

R^2 = 0.2224 for both NDVI and NDWI, respectively. This suggests that the time of image acquisition can be a factor that influences the detectability of impacts of oil spills on vegetation. The VI values increase with increasing time between the image acquisition and oil spill date, implying some form of vegetation recovery with time. To obtain a clear picture of the impacts of time on the detectability of impacts of oil spill on vegetation, the data was divided into two categories (i.e. 0–1 year and 1–2 years) (Figure 8). Results from the NDVI showed that in the first year, there was a general decrease in its values (Figure 8(a)), implying the impacts of oil pollution on vegetation. After the first year, the NDVI values started to increase (Figure 8(c)), which implies that the impacted vegetation started to recover. The NDWI results did not show a similar pattern. Other researchers have shown that the impact of oil spills on vegetation can start to show within the first two weeks of a spill event, and these can range from chlorosis to defoliation to tree death (Duke and Burns 1999). However, these impacts can vary depending on the vegetation type, persistence of the oil spill (level of degradability), and the physical factors in the affected area (Hoff et al. 2002). A study in a mangrove reported that the amount of oil reaching the mangroves and the length of time spilled oil remains near the mangroves are key variables in determining the severity of effect (Garrity, Levings, and Burns 1993; Burns et al. 2002). The results from the NDVI in the current study showed that the impacts of oil spill on the mangrove forests were visible within the first year and the forests started to recover after the first year. Thus, it can be stated that the time of image acquisition is an important factor to consider when studying the impacts of oil spills on vegetation using remote-sensing data.

6. Conclusion

The aim of this study was to test the influence of volume of oil spill and time gap between the image acquisition dates on the detectability of changes in vegetation status using VIs. First, all oil spills were used to test the influence of volume on the detectability of pollution on vegetation condition using two VIs (i.e. NDVI and NDWI). Results from this showed a weak negative relationship between an increase in volume and impacts on vegetation condition (i.e. reduction in NDVI and NDWI values). A minimum volume (225 bbl), which was considered adequate to cover a single Landsat pixel, was calculated and used in subsequent analysis. The use of this minimum volume improved the relationship between the VIs and oil spill volume. Further analysis showed that the oil spill volume between 400 bbl and 1000 bbl resulted in the most detectable influence of pollution on vegetation as shown by the strong negative relationships between the VIs (especially NDVI) and this volume category. The analysis on the influence of time on the detectability of impacts of oil pollution on vegetation showed that, in general, the longer the time between image acquisition and oil spill, the lower the detectability of the impacts of pollution on the vegetation (showed by the positive relationship between NDVI/NDWI and time). However, further analysis showed that the NDVI was able to detect the effects on vegetation condition (indicated by the reduction in NDVI values) within the first year of oil spill. In addition, the NDVI showed that the vegetation began to recover (increase in NDVI values) after the first year. Overall, as time increased between the date of oil spill and image acquisition, the chances of detecting the impacts of oil

pollution on vegetation seem to diminish. However, it is worth noting that these relationships can be influenced by other factors such as the vegetation type, physical condition in the area, sensor characteristics, and type and persistence (degradability) of the oil (Pezeshki et al. 2000, Mendelssohn et al. 2012). The sensitivity of the indices has also contributed in the detection of oil spill. In conclusion, this study showed that both the volume of oil spill, and the time between image acquisition and spill date are important factors to consider when using multispectral data to study the impacts of oil pollution on vegetation.

Disclosure statement

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