# Long-Term Monitoring of Oil Spill Impacted Vegetation in the Niger Delta Region of Nigeria:aGoogle Earth Engine Derived Vegetation Indices Approach


## Abstract

New and emerging cases of oil spill incidents are reported almost on a weekly basis in the Niger Delta region of Nigeria with accusations and counter-accusations as to the claims made by interested parties on perceived impacts of the spills on the environment and its associated constituents.This study applied the capabilities offered by the Google Earth Engine (GEE) platform to monitor long-termvegetation dynamics as a result of exposure to pollution emanating from crude oil spills in the Niger Delta region of Nigeria. The capabilities offered by GEE provide a platform for rapid access to big data for the assessment of environmental change, especially in the Niger Delta with its difficult terrain and security concerns. This study considered oil spill incidents in vegetated terrestrial locationsin the Niger Delta acrossten years. Fifteen locations spread across the region with oil spill incidents identified as large incidents being selected (>50 <5000bbl). Results of the statistical analysis performed on the vegetation indices data generated from GEE suggest that the analysis of long-term vegetation indices using GEE can provide a broad view of the impact of oil spills on vegetation over time if the spills are relatively large or the spills are repetitive. However, when the spills were relatively small, there was no statistically significant variation in the spectral signatures of the vegetation over time. This suggests that for large spills, GEE-derived vegetation indices can be a very useful synoptic tool in monitoring oil spill occurrence and impact on vegetated terrestrial environments in the Niger Delta and elsewhere where environmental accessibility is a challenge.



Key Words: GEEP, Environmental Monitoring, NDVI, Oil Spill Pollution, Vegetation Indices.

## 1. Introduction

Oil spills describe the inadvertent or deliberate introduction or discharge of petroleum hydrocarbon products and their byproducts into any environment (Guo &Zhang, 2014; Durango-Cordero et al., 2018; Ndimele et al., 2018; Carpenter, 2019; Ozigis et al., 2019; Wait, 2021). These environments comprise the air, water, or land. The occurrence of oil spills has generally increased in frequency in the last decades, due to increased international transportation of cargo and consumption, energy generation and industrial usage (Berenshtein et al., 2019. For the Niger Delta Region of Nigeria, the case is worse as incidences of oil spills are reported almost every week (Mba et al, 2019; Akpokodje et al., 2020; Ugwu et al., 2021; Wekpe et al., 2022).

Oil spills can emanate from a combination of several factors, which can be human-induced or naturally occurring. The due to human-induced factors that lead to oil spills include, but arenot limited to activities such as willful theft or interdiction, terrorism, accidents, and operational expulsions of petroleum hydrocarbon into the environment (Alpers et al., 2017; Bayramove&Butchroithner, 2018; Amnesty International, 2018; Mba et al., 2019; Ugwu et al., 2021).

Accusations and counter-accusations are very rampant in the reportage of oil spill incidents in the Niger Delta. These accusations range from under-reporting to over-reporting of spill incidents which are often dependent on the specific bias of people involved in the reporting efforts. The oil-producing communities would always insist that the spill volume and number are underreported, while the multinational oil companies would argue that the values reported by the communities and NGOs are significantly over-bloated (Eziukwu et al., 2015; Anyawu&Lein; 2019; Elekwachi et al., 2019). This lack of trust in the spill data reported has continually bred mistrust amongst stakeholders in the oil spill control and management quarters in Nigeria. This mutual distrust effectively sabotages and negates meaningful progress as valuable time is spent first trying to validate and harmonize the available oil spill information (Watts & Zalik, 2020); this mistrust stems from the people of the Niger Delta beingquite suspicious of outsiders and their intentions (Oviasuyi&Uwadiae, 2010). These suspicions can be attributed to the years of deliberate neglect and marginalization of the people and environment of the Niger Delta (UNEP, 2011, Wekpe, 2018; Bodo &Gimah, 2019).

An increasingly alarming quantity of spills in the Niger Delta is being attributed to activities of *kpofire* (artisanal and illegal refineries), with significant losses of crude oil to the environment (Badejo &Nwilo, 2004; Naanen& Tolani; 2014; Yeeles, &Akporiaye, 2016; Mba et al., 2019; Ugwu et al., 2021; Zabbey et al., 2021). These significant losses of crude to the natural environment given the right conditions can significantly impair the functioning and viability of various ecological systems (de la Huz et al., 2019). Petroleum based pollutants resulting from oil spills are a serious threat to human health and the environment due to their toxicity, mutagenicity, and carcinogenicity related properties (Mohammadi, et al., 2020).

## 2.0 Materials and Methods

### 2.1 Study area description

The Niger Delta Region (NDR) describes an area in the South of Nigeria where the main river channel of the River Niger attains base level and bifurcates into multiple distributaries, disposing of discharge and sediment load into the Atlantic Ocean (James et al., 2007). The Niger Delta of Nigeria hosts the oil industry of the country as well as serves as a home to the largest mangrove forest in Africa, the third largest in the world, and occupies about 10,000 square kilometers (Nwilo, 2013). The NDR covers an area of about 70,000 km$^2$ (Mmom &Arokoyu, 2010; Ocholi, 2017; Izah, 2018;Anyadiegwu&Uwaezuoke, 2015). It is the largest river delta in Africa and the third largest in the world (Wetlands International, 2016). The NDR has been described as mostly a flat swampy basin, crisscrossed by an intricate and dense network of rivers, creeks and streams. It is home to diverse species of mangroves forests, rainforests and freshwater swamps (Abam, 2001; Abam & Ngah, 2016; Olufemi et al., 2020). Its topography, geology and soil properties, hydrodynamics and heavy rainfalls make the region highly vulnerable to incidences of annual flooding and erosion; throw in a mix of people of who are deeply suspicious of outsiders and any attempt to research the region becomes quite challenging (Oviasuyi, &Uwadiae 2010; Akpokodje, 2020).

It is estimated that worldwide, for a period covering the last 35 years; energy use has doubled, contributing to a 7-fold increase in gross domestic product (GDP) in that time. During this period, crude oil dominated the world's energy supply, constituting34 percent of total primary energy supply in 2017 (Byrne, 2019). The implication of this assertion by Byrne (2019), is that the foundations and maintenance of modern economies are significantly dependent on the continued production of fossil fuels of which crude oil is the most sought-after (Nwozor et al., 2018; Graham & Ovadia, 2019). Even as attempts are continuously made by the advanced economies to shift their energy uses away from fossil fuels to renewable sources of energy (Adesipo et al., 2020), the developing economies of the world are far behind in this regard and will depend on the energy sources supplied by fossil fuels for the foreseeable future to meet up with their energy demands. This can be seen in the continuous prospecting for new and more productive offshore and onshore oil blocks (Graham &Ovadia, 2019). In addition to the energy importance of crude oil, it is also important because a lot of industries (existing and emerging) depend on the base material from crude for the production of cosmetics, synthetic fabrics, plastics, lubricants, fertilizers and medical drugs (Wu & Chen, 2019: de Moura et al., 2022).

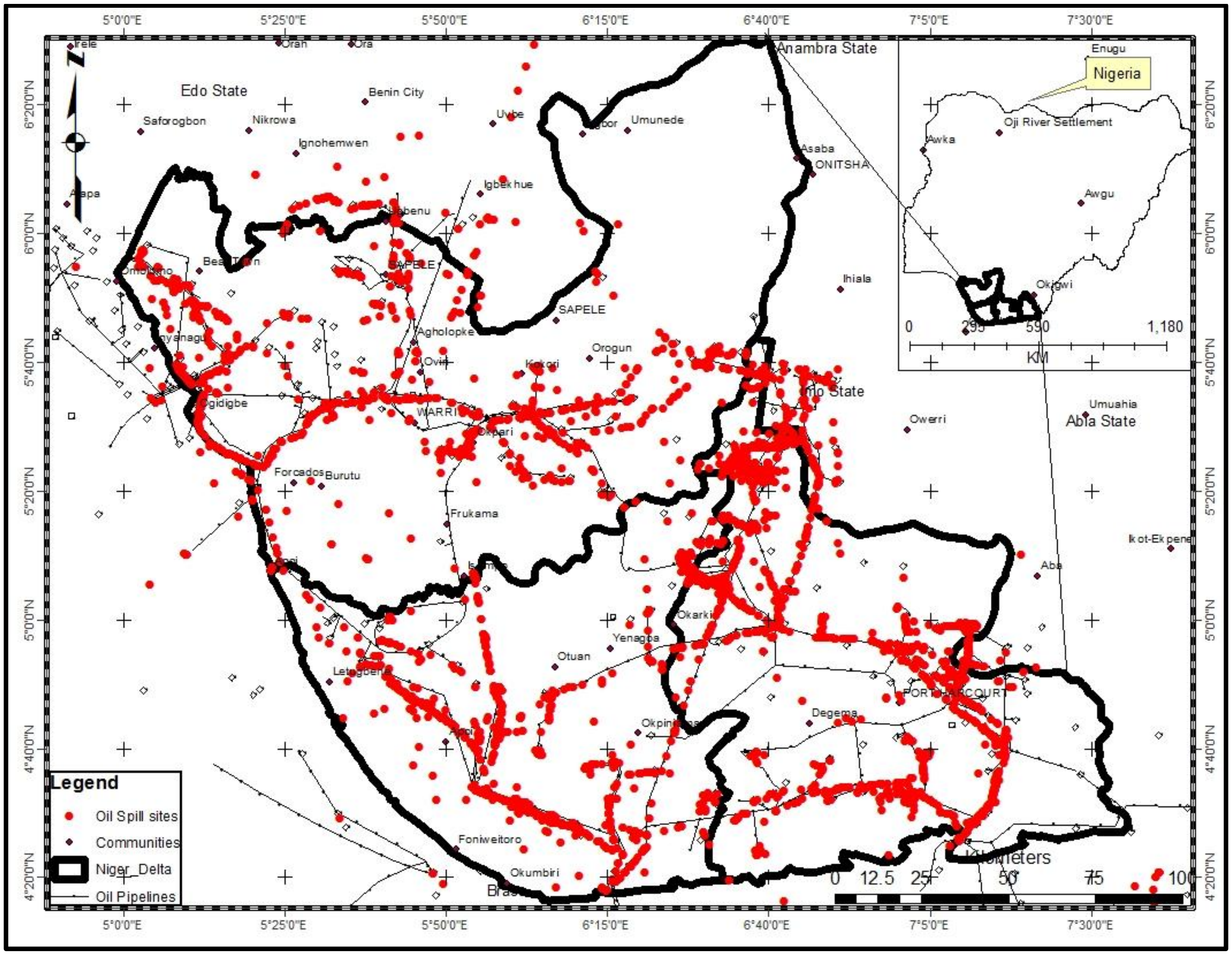


**Figure 1: The Niger Delta Region showing oil spill locations and pipeline network**

## 2.2 Google Earth Engine Platform (GEEP)

Conventional methods of collecting information about vegetation changes can be very difficult, costly, and time-consuming. Remote sensing applications, however, are very useful in proving a synoptic, reliable, and efficient view of a large area (Kirkos et al., 2018; Amiri &Pourghasemi, 2022). The GEEP is described as an online web portal that can provide global time series satellite imagery and vector data (Gorelick et al., 2017; Kennedy et al., 2018; Kumar & Mutanga, 2018). Google Earth Engine is a planetary-scale cloud-based geospatial analysis platform; the platform aids in the rapid processing of large-scale satellite-derived datasets and visualization of processed results (Robinson et al., 2017).

The GEE portal provides increased opportunities and capabilities for undertaking Earth observation studies using large-scale planetary data that is freely available. The platform/portal was created towards the end of 2010 as a cloud (web) based platform that provides free access to over 500 types of satellite and other ancillary data (demography and temperature) and contains algorithms that can process large amounts of data with relative ease (Kennedy et al., 2018; Kumar & Mutanga, 2018; Lee et al., 2020). The GEE platform has introduced a contemporary paradigm for big data that involves the storage and analysis of remotely sensed data at a scale that is otherwise not possible using desktop conventional processing machines (Kennedy et al., 2018; Kumar & Mutanga, 2018; Lee et al., 2020).

### 2.3 Vegetation Indices for oil spill detection and monitoring

Satellite-derivedvegetation indices (VIs) are generally employed and adapted in ecological based research, ecosystem modeling, and land surface monitoring (Balogun, 2015; Esau et al., 2016; Dutsenwai et al., 2017; Adamu et al., 2018; Onyia, et al., 2018; Onyia, et al., 2019; Ozigis et al., 2020). Vegetation indices (VIs), are defined as “the arithmetic combination of two or more bands related to the spectral characteristics of vegetation” (Martín-Ortega et al., 2020; Kumari et al., 2021). Vegetation indices are used to describe vegetation structure and functioning (Robinson et al., 2017; Martín-Ortega et al., 2020; Kumari et al., 2021). However, they are affected by illumination conditions (Martín-Ortega et al., 2020).

The index utilizes the optical properties of the cellular structure of leaves; as well as the photosynthetic pigments which include; chlorophyll and the other associated light-harvesting pigments, and accessory pigments. These efficiently absorb radiation in the visible range of the spectrum (to power photosynthesis) and reflect radiation in the near-infrared (NIR) range (Robinson et al., 2017).

VIs can be calculated or estimated from airborne or satellite imagery and have been successfully adopted to assess a variety of plant characteristics (Huete et al., 2002; Jarchow et al., 2018).For example, the widely adopted and frequently utilized normalized difference vegetation index (NDVI) captures and responds to activelyphotosynthesizing plant tissues (Jarchow et al., 2018).

#### 2.3.1 Application of NDVI in oil spill incidents validation using GEE (time series analysis)

It has been observed that vegetation reflects light in the near-infrared (NIR) part of the electromagnetic spectrum and absorbs light in the red part. It is this simple but effective observation that NDVI uses to create a single value roughly reflecting and estimating the photosynthetic activity occurring at a pixel point. This results in a number between 1 and -1, where pixels with high photosynthetic activity have a high NDVI value (close to +1) and pixels associated with low photosynthetic activity have a lower value closer to -1 (Ahmad et al., 2017; Adamu et al., 2019). For this study, the Google Earth Engine Platform (GEEP) is adopted for use in creating the NDVI statistics. GEEP is an online web platform that can provide incredibly massive global time series satellite imagery and vector data (Gorelick et al., 2017; Kennedy et al., 2018; Kumar & Mutanga, 2018).
Several studies have adopted the use of GEE in in vegetation mapping and monitoring (Robinson et al., 2017; Campos-Taberner et al., 2018; Poortinga et al., 2018; Tsai et al., 2018; Amiri, &Pourghasemi, 2022). Campos-Taberner et al., (2018), carried out a global estimation of key biodiversity variables such as "Leaf Area Index (LAI), Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), Fraction Vegetation Cover (FVC), and Canopy water content (CWC) using MODIS historical data".

A planetary-scale vegetation mapping project using MODIS-derived EVI products and the GEE web-based application was carried out in Vietnam by Poortinga et al., (2018). A relatively more refined and accurate thirty-meter (30m) NDVI composite, covering a period of 30 years, was developed for the United States using the Google Engine cloud-based planetary processing platform (Robinson et al., 2017).Satellite images contain several layers known as bands that are stacked on top of each other. Each of these bands or layers captures different wavelength of electromagnetic energy. Due to the spectral signature of different types of land cover, some features are easier to detect using certain bands or layers than others. A typical example is green vegetation, which tends to reflect more light in the green, red and near-infrared (NIR) sections of the electromagnetic spectrum (Ahmad et al., 2017), (Figure 2). This makes it easier to detect vegetation using bands 2 (green), 3 (red) and 4 (NIR) of the Landsat satellite imagery. Dutsenwai et al., (2017), applied the use of NDVI in spatial and temporal analysis of vegetation and oil spill intensity in Ogoniland in the southern part of Nigeria.

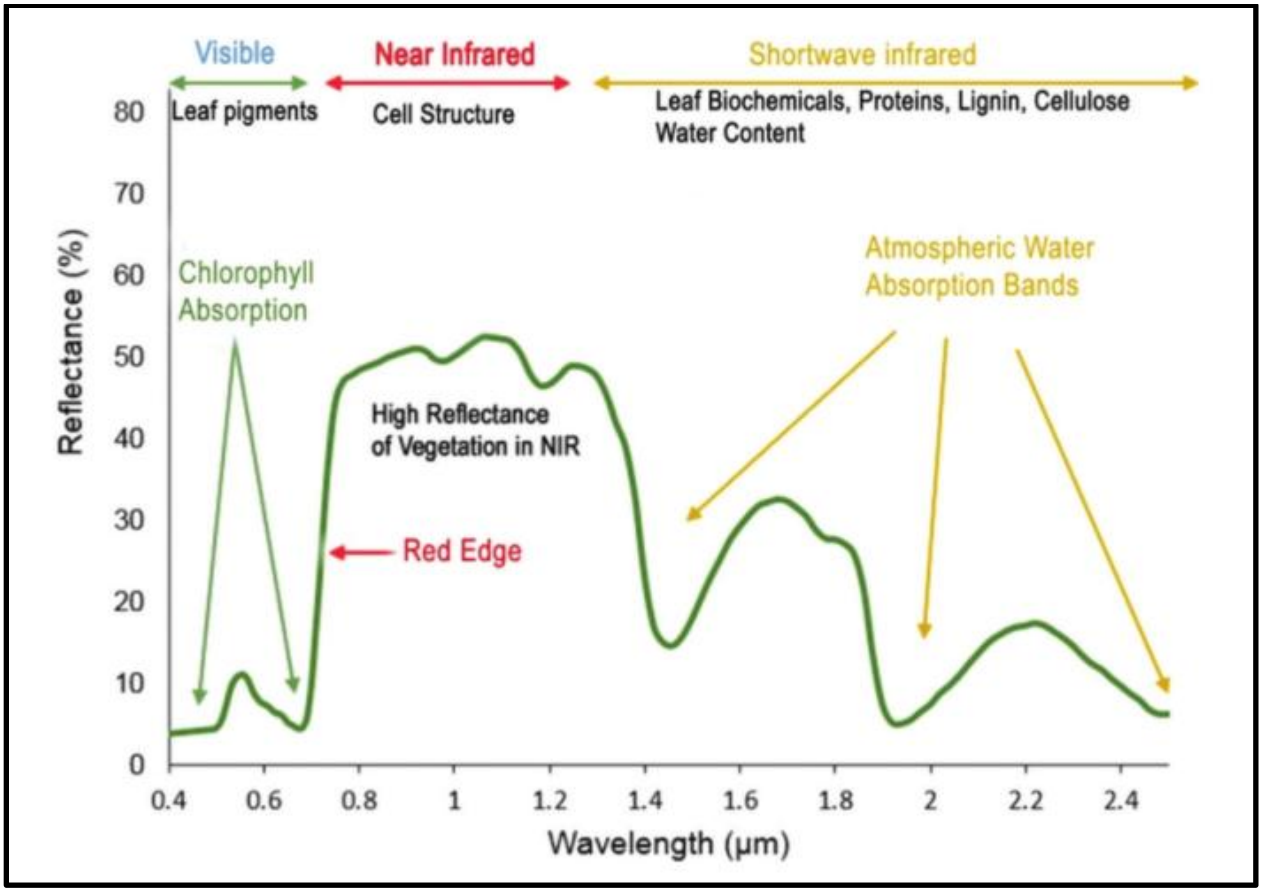


**Figure 2: Spectral response curve of vegetation (Adapted after: Ahmad et al., 2017).**

Healthy vegetation tends to absorb most of the incoming visible light, and reflects a large portion (about 25%) of the near infra-red (NIR) light (Ahmad et al., 2017). However, a lower portion of light is reflected inthe red band (RED) (Figure 4.1). Unhealthy or sparse vegetation reflects more visible light and less NIR light (Adamu et al., 2013; Ahmad et al., 2017;). It is this contrasting nature in the ability of both healthy and unhealthy (stressed) vegetation, that makes it particularly useful in detecting areas of stress in a continuously vegetated area. The NDVI is calculated by a simple but effective formula given by equation 1.

NDVI = (NIR – RED) / (NIR + RED) …………………………… ***equation 1***

NDVI analysis typically generates a new image based on the vegetation cover characteristics and reflectance values from an original input image. Calculations for a given pixel always result in a value that ranges between minus one (-1) to plus one (+1) (Ahmad et al., 2017; Adamu et al., 2019; Nursaputra et al., 2021). An NDVI is a proxy for vegetation greenness. As such, it is expected that it possesses a relatively smooth and continuous temporal profile except ifthere are outside perturbations or land cover change events. An unanticipated drop in NDVI values can then be attributed to atmospheric contamination or a quality issue not identified in the image reflectance product (Robinson et al., 2017; Nursaputra et al., 2021).

## 2.4 Data Analysis

This study leveraged the inherent advantages available on the Google Earth Engine platform. The portal offers petabytes of archived satellite imagery which can be retrieved and manipulated with the appropriate computer language script. A mosaic of sixty (60) MODIS and Sentinel images was compiled and manipulated to generate the vegetation index (NDVI) for specific locations within the study area. These specific locations represent major oil spill points captured at different times. The NDVI values were generated for two time periods. These periods captured periods before the spills occurred and periods after the spill occurred in order to distinguish if significant variations exist in NDVI values across the spill locations in the study area. The justification for this is to see the trend of vegetation health changes within the period under consideration.

The data derived from vegetation indices (NDVI) analysis generated from the GEE platform was subjected to further statistical analysis using the analysis of variance technique to identify if there was any statistical variation in the spectral signatures of the vegetation pre and post-the oil spill incident.

# 3.0 Results and Discussion

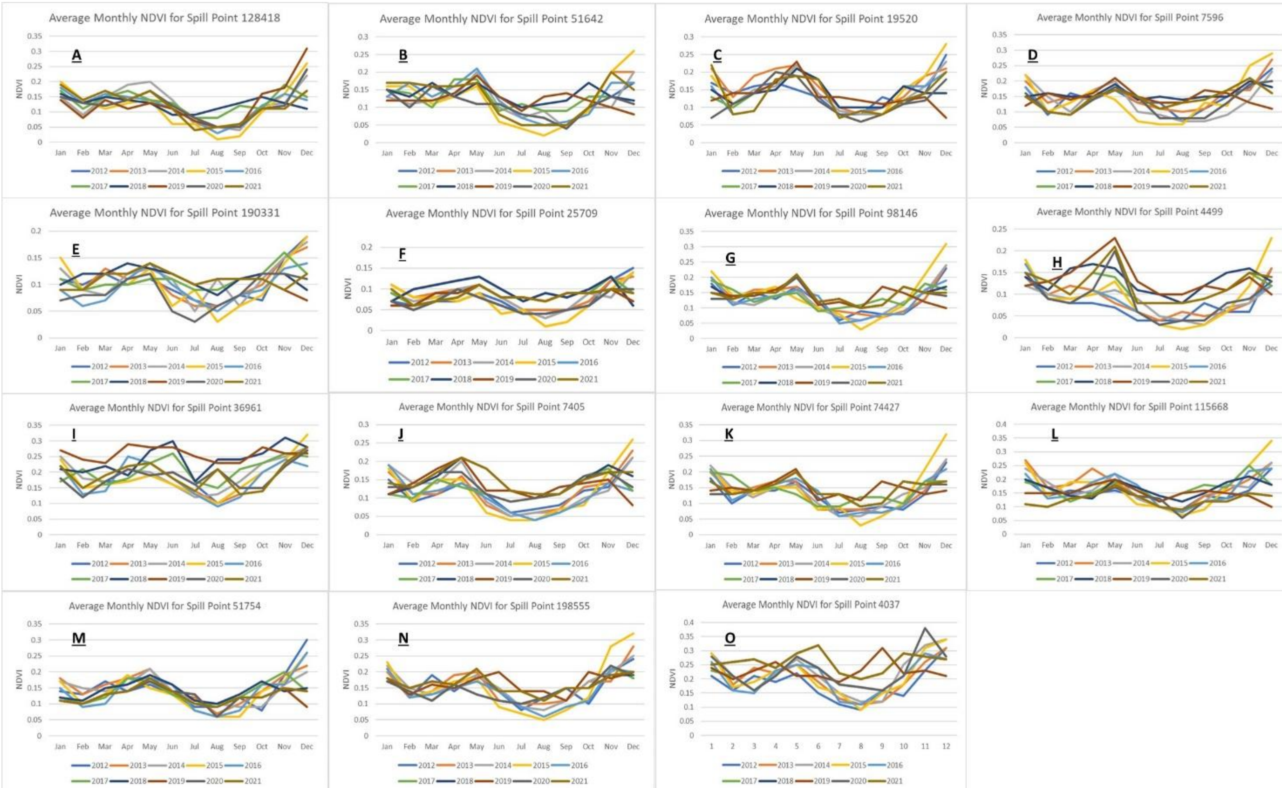


**Figure 3: This figure shows split figures A to Ocorresponding to the GEE-generated NDVI spectral signatures for 15 oil spill locations in the Niger Delta between January 2012 and December 2021.**

The data was generated by running the appropriate Java Scripts in the code editor environment of the GEE platform.

In this section, we present the results of the data generated from the cloud computing enabled on the GEE platform. An ample demonstration is put forward to show the capability of the GEE platform to generate long-term data to monitor the impacts of oil spills using vegetative indices as aproxy for environmental quality.

**Table 1: Summary table showing statistical significance in variation in NDVI values at various spill points across the study Area.**

| S/N | Spill Point | Spill Volume | Recovered | Statistical variation in NDVI |
|---|---|---|---|---|
| **1** | 128418 | 1000 | 0 | Not significant |
| **2** | 51642 | 417 | 187 | Not significant |
| **3** | 19520 | 1370 | 1300 | Not significant |
| **4** | 190331 | 1403.6 | 1387.6 | Significant |
| **5** | 25709 | 5000 | 0 | Not significant |
| **6** | 98146 | 2026 | 0 | Not significant |
| **7** | 36961 | 17,386 | 0 | Significant |
| **8** | 7405 | 4688.12 | 3675 | Not significant |
| **9** | 74427 | 1127 | 600 | Not significant |
| **10** | 7596 | 1070 | 187 | Not significant |
| **11** | 4499 | 400 | 300 | Significant |
| **12** | 115668 | 1669 | 825 | Not significant |
| **13** | 51754 | 16,720 | 7,391 | Significant |
| **14** | 198555 | 390 | 0 | Not significant |
| **15** | 4037 | 529 | 0 | Not significant |

**Variance significant at 0.05 alpha level**

Table 1 shows the results summary of theanalysis of variance (ANOVA) performed for the GEE-derived NDVI for locations (Table 1) locations and one control site across the study area. From the table, it shows that four locations, (spill point190331, 36961, 4499 and 51754) present statistically significant variations in the average monthly NDVI values across the months for a ten (10) year period (2012 – 2021). These locations have relatively large spill volumes with the exception of spill point 4499, which had a spill volume of 400bbl, while 300bbl was successfully recovered from the environment. The remaining three locations had spill volumes of 1403.6bbl, 17,386bbl and 16,720bbl respectively. The significant variation in the NDVI values for spill point 4499 even though it is arelatively small spill is explained by the area being described as a stressed region. The area has previously experienced oil spill and had been cleaned up previously by the responsible oil company. However, with the reintroduction of 400bbl of crude oil into the environment the tolerance threshold of the vegetation was exceeded hence the significant variation in the NDVI values for the region. This accounts for why the relatively small spill of 400bbls could result in significant variation in NDVI values for that particular spill location.

The statistically significant variation in average monthly NDVI values in those locations suggest that vegetation is affected by relatively large oil spills (Adamu et al., 2018), while the relatively smaller spills do not have such a profound physiological impact on the vegetative health.

### 3.1 Validation of Oil Spill Data in the Niger Delta Using GEE derived Vegetation Indices and Statistics

A major point of contention in oil spill management discourse is the verification of the occurrence of a spill (Amnesty International, 2012; Amnesty International, 2015; Eziukwu, 2015; Elekwachi, 2019). There is usually a battle of wits, arguments and counter arguments between multinational oil companies (MOCs), and in recent times indigenous oil companies (IOCs) who mostly operate in the marginal terrestrial oil fields about the veracity of claims about oil spill incidents within the Niger Delta. This study has proposed and tested the possibility of using google earth engine derived vegetation indices (NDVI) as proxy for validating oil spill events within the vegetated zones of the Niger Delta coastal areas. Figure 3(A to N) and Table 1 shows the results of the analysis of the NDVI data generated from the GEE platform. The data and subsequent results cover fifteen (15) oil spill locations located in vegetated areas over a ten-year period (January 2012- December 2021).

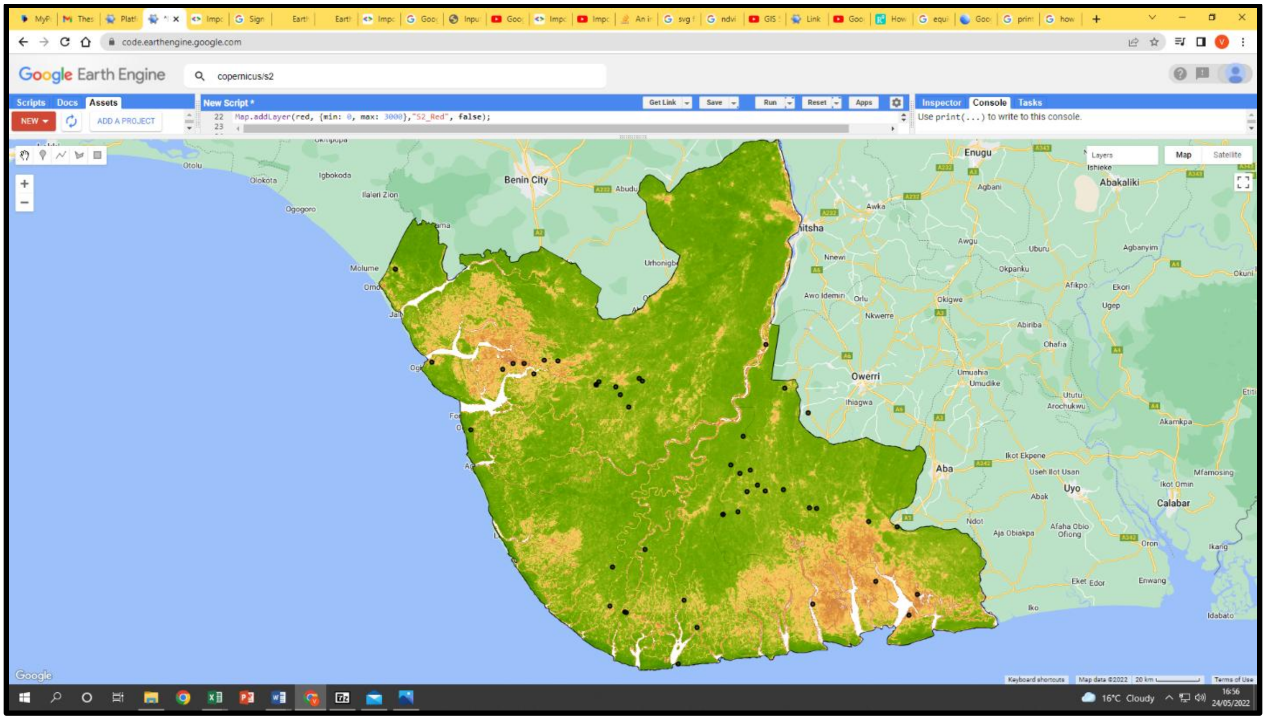


**Figure 4.: Google Earth Engine Generated NDVI Map with the points identifying oil spill locations.**

### Impact of Oil Spills on Vegetation in the Niger Delta

Hydrocarbon or crude oil contamination of soils affects plants by impeding the physiological processes that occur in plants owing to their interaction with soil and soil nutrients (Lassalle et al., 2019). Thesephysiological constrains experienced by the plants are engendered by the interference of hydrocarbons with the chemical and ecological balance of the soil and soil nutrients. This often results in stressed plants which manifests through the alteration of the spectral signatures of impacted vegetation (Adamu et al., 2015; Ozigis et al., 2019).

Several studies such as (Adamu et al., 2015; Lassalle et al., 2019; Ozigis et al., 2019), have suggested with evidence that crude oils in soils bring on alterations in several soil parameters such as available nutrients, temperature, microorganism activity, soil pH and soil temperature.These changes in soil chemistry and physiologyinduce stress in vegetation growing on soils polluted by crude oil bychanging their suboptimal adaptation capabilities to a unique environment. This interference and associated plant stress are manifested by the alteration of chlorophyll production and other related photosynthetic pigments that absorb solar radiation, thereby affecting the normal reflectance values of vegetation (Onyia et al., 2018; Li et al., 2018; Onyia et al., 2019).

In this study, there is a significant alteration in the reflectance values proxied by NDVI values extracted from oil-impacted vegetation locations within the study area when the spills are relatively large or reoccurring. Table 1 presents the statistically significant variations in vegetation reflectance (vegetative health) with volume of oil spilled into the soil, vegetation interface. From the significance of associations presented in Table 1, a marked difference in vegetation reflectance is significant with anincrease in the quantity of crude oil introduced into the environment. The relatively smaller spills did not induce statistically significant stress in the vegetation as there was no statistically significant difference between the average monthly NDVI values before and after the spill.

However, with increasing volume in the quantity of oil spilled or repeat pollution, a statistically significant difference was observed in average monthly NDVI values before and after a spill event, suggesting that significantly large spills or repeat spill events in the same location induce stress in vegetation within the study area.This finding agrees with the results of Li et al., (2005), who reported changes in reflectance values of vegetation subjected to crude oil pollution-induced stress. The implication is the marked reduction in the available chlorophyll content of polluted vegetation since these pigments usually absorb light for photosynthetic purposes in the visible wavelength regions of the spectrum (Mishra et al. 2012; Adamu et al., 2018).

The scientific relevance of the findings in this study lies in the application of the Google Earth Engine (GEE) platform to monitor long-term vegetation dynamics in response to crude oil spills in the Niger Delta region of Nigeria. With the region experiencing frequent oil spill incidents and ongoing debates regarding their environmental impacts, the utilization of GEE provides a valuable approach for assessing these impacts efficiently and comprehensively.

By analyzing vegetation indices data generated from GEE over ten years in fifteen selected locations affected by oil spills, this study identifies significant patterns in vegetation dynamics associated with the magnitude and frequency of spills. The results of the statistical analysis indicate that GEE-derived vegetation indices offer a robust means of monitoring the impact of large or repetitive oil spills on vegetated terrestrial environments over time. This finding underscores the utility of GEE as a synoptic tool for assessing oil spill occurrence and its subsequent effects on vegetation (López et al. 2019; Olivares and Lopez, 2019), particularly in regions with challenging environmental accessibility such as the Niger Delta (Ozigis et al., 2019).).

Moreover, the comparison with studies of environmental factors in tropical agricultural areas in Latin America adds scientific depth to the findings by highlighting the broader applicability of the GEE approach. By demonstrating its effectiveness in addressing challenges related to terrain and accessibility in both the Niger Delta and similar regions in Latin America, this study underscores the versatility and relevance of GEE as a platform for monitoring environmental change in complex landscapes affected by anthropogenic activities (Olivares, 2016; Olivares and Franco, 2015; Zingaretti et al. 2017).

## 4.0 Conclusion

This study contributes to filling the knowledge gap that exists in the monitoring of crude oil impacted vegetation in the Niger Delta, through its contribution to the understanding of long-term vegetation dynamics in response to oil spill incidents within the region. facilitated by the innovative use of GEE. The findings emphasize the importance of considering the magnitude and frequency of spills in assessing their impact on vegetated terrestrial environments and highlight the potential of GEE-derived vegetation indices as a valuable tool for environmental monitoring in regions facing similar challenges globally.

This research has amply demonstrated that GEE-derived vegetation statistics can be used to monitor long-term changes in vegetation induced by large or repeat oil spill events. However, the effectiveness of the NDVI in detecting subtle changes is not very explicit. Arising from this deficiency, it is recommended that other more sensitive indices should be used in conjunction with the NDVI as well as the use of drones to capture high-resolution images of areas that are suspected to be negatively impacted by oil spills. This study investigated the use of GEE-derived vegetation indices in validating oil spill data reported in the NDR of Nigeria, in order to improve the confidence of stakeholders in the oil spill data reported for the region. This study has been able to demonstrate that the GEE derived vegetation indices can indeed be a useful tool in monitoring the long-term changes in the vegetation impacted by oil spills. Key findings show that for relatively large oil spills in the Niger Delta, GEE derived NDVI statistics can help in putting to bed some uncertainty about the verification of oil spill incidents across the Niger Delta especially as it relates to relatively large oil spills. It has also been successfully demonstrated that GEE derived vegetation indices can be used to identify, detect and monitor vegetation impacted by oil spills within the study area as it can be used to detect cases of spill, especially the relatively large or repetitive spills. This method proposed in this study can provide an easy to use technique to provide rapid assessment of oil spill incidents within the study area.

**Data Availability Statement**

The data sources that support the findings of this study have been provided in the body of the study.

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