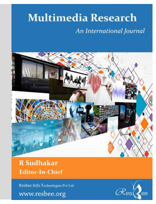
Vol.8 Issue 4 Oct 2025

Multimedia Research

Received 17 May, Revised 25 September, Accepted 10 October



Radar Application in the Detection and Mapping of Oil Spill Sites in The Niger Delta Using Sentinel 1a

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Abstract: Oil spills are a persistent hazard in the Niger Delta, degrading vegetation and threatening livelihoods. Rapid detection is essential, yet traditional reporting is often incomplete. This study evaluates Sentinel-1A Synthetic Aperture Radar (SAR) for detecting and mapping spills in Delta State, Nigeria. Sentinel-1A operates in the C-band (5.405 GHz) with 10 m resolution, and VV polarization was used for its sensitivity to oil-water contrast. Three SAR scenes from May-July 2019 were processed in SNAP 5.0 and ArcGIS, with steps including speckle filtering, dB conversion, and terrain correction. Validation used the National Oil Spill Detection and Response Agency (NOSDRA) dataset, while vegetation health impacts were assessed using the Normalized Difference Vegetation Index (NDVI) from Google Earth Engine. Results showed 23, 27, and 30 spill points were detected for May, June, and July, compared to 10, 9, and 7 in NOSDRA records. NDVI declined by ~18% indicating vegetation stress with moderate correlation (r = 0.55–0.69) between SAR backscatter and NDVI. Sentinel-1A proved effective, though challenges included look-alikes, lack of field validation, and manual processing. This study highlights Sentinel-1A SAR as an all-weather, cloud-penetrating alternative to optical sensors for oil spill monitoring, validating SAR-detected spills against official records and providing multi-temporal evidence of ecological degradation. Findings support integrating SAR with automated algorithms and ground verification to enhance oil spill response and environmental management in the Niger Delta.

Keywords: Oil Spill, Sentinel-1A, SAR, NDVI, Niger Delta, Remote Sensing

Nomenclature

Abbreviation	Description
SAR	Synthetic Aperture Radar
NDVI	Normalized Difference Vegetation Index
NOSDRA	National Oil Spill Detection and Response Agency
VV	Vertical-Vertical Polarization
VH	Vertical-Horizontal Polarization
HH	Horizontal-Horizontal Polarization
HV	Horizontal-Vertical Polarization
DEM	Digital Elevation Model
OBIA	Object-Based Image Analysis
CNN	Convolutional Neural Network
GEE	Google Earth Engine
GRD	Ground Range Detected
dB	Decibel
SRTM	Shuttle Radar Topography Mission
NIR	Near-Infrared Reflectance

1 Introduction

Nigeria is one of the leading producers of crude oil in Africa, with the Niger Delta serving as the hub of its petroleum industry. However, decades of exploitation have led to frequent oil spills from pipeline vandalism, equipment failure, illegal refining, and sabotage [8][12]. These spills contaminate farmlands, surface water, and fisheries, disrupting livelihoods and accelerating ecological degradation [9][5]. The environmental and socio-economic costs are considerable, making effective monitoring and remediation an urgent priority.

Traditional monitoring methods, such as field inspection and ground reports, are limited by accessibility, underreporting, and delays [11]. Remote sensing provides a more systematic and timely

https://doi.org/10.46253/j.mr.v8i4.a1

approach for spill detection, especially in large, inaccessible, or politically sensitive areas [14]. Optical sensors such as Landsat and Sentinel-2 have been widely applied, but their effectiveness in the Niger Delta is restricted by persistent cloud cover and heavy rainfall [2][12]. By contrast, SAR sensors such as Sentinel-1A operate in the microwave spectrum, enabling all-weather, day-and-night monitoring**,** making them more reliable in tropical environments [4].

Sentinel-1A, launched in 2014, is equipped with a C-band (5.405 GHz) SAR instrument that provides high-resolution dual-polarization imagery. Its free availability, 6–12day revisit cycle, and proven performance in marine oil spill detection distinguish it from commercial platforms such as RADARSAT-2 and TerraSAR-X [16][6]. Studies have validated Sentinel-1 globally, including in Indonesia [13], the Persian Gulf [16], and the Mediterranean [14]. However, few studies have systematically applied it in the Niger Delta**,** where artisanal refining, vandalism, and dense mangrove present unique challenges.

A key advantage of SAR-based oil spill detection is its ability to exploit the damping effect of oil films on capillary waves**,** producing dark patches in VV-polarized backscatter imagery [7][4]. Yet, limitations remain, including look-alikes (low wind zones, biogenic slicks), speckle noise, and misclassification, making robust preprocessing and validation essential [15]. Addressing these challenges is critical for accurate spill mapping and for linking remote sensing results with ground realities.

This study fills these gaps by combining Sentinel-1A SAR data with NDVI analysis to evaluate ecological impacts and validating results against the NOSDRA dataset. The novelty lies in its multi-temporal validation of SAR-detected spills against official Nigerian records and its integration of vegetation health assessment to link oil pollution with ecological decline. This dual approach strengthens both the technical and environmental dimensions of oil spill monitoring. By doing so, it demonstrates the value of free, open-access SAR data for operational monitoring in data-scarce and vulnerable regions such as the Niger Delta.

This research seeks to answer the following research questions:

- What is the distribution of oil spills in May, June, and July within the study area?
- Is there a correlation between detected spills and the official oilspillmonitor.ng database?
- What is the health status of Vegetation around spill areas?
- How valid is Sentinel-1A data for oil spillage?

2 Literature Review

2.1 Oil Spill Detection in the Niger Delta

The Niger Delta, covering 70,000 km², is among the most oil-polluted regions worldwide due to frequent spills from vandalism, artisanal refining, and operational failures [8][12]. Between 1976 and 1996, over 1.8 million barrels of oil were spilled, with only 23% recovered [10]. Recent figures suggest continued underreporting, as official datasets such as **NOSDRA** often underestimate spill extent compared to independent monitoring [1].

Previous studies in the region relied heavily on **optical imagery** (e.g., Landsat and Sentinel-2) to detect oil-contaminated vegetation and soil [2][11]. While effective for revealing mangrove degradation and crop losses, these methods are hindered by persistent cloud cover and flooding. This highlights the importance of **radar remote sensing**, which is weather-independent. However, SAR applications for oil spill monitoring in Nigeria remain limited, creating a knowledge gap. Bridging this gap requires methods that are robust, repeatable, and validated against reliable references.

2.2 Global Applications of Sentinel-1 for Oil Spill Detection

Globally, Sentinel-1 SAR has been widely applied for oil spill detection in marine and coastal environments. For instance, [13] showed that Sentinel-1 outperformed Sentinel-2 in detecting the 2018 Balikpapan Bay spill in Indonesia. Similarly, [16] found VV polarization more accurate than VH in the Persian Gulf. Rajendran et al. (2021) [14] validated Sentinel-1 and Sentinel-2 data for the Mauritius Wakashio spill, emphasizing Sentinel-1's superior performance under cloudy and rainy conditions. More recently, George and Diofantos (2021) [6] applied Sentinel-1A near Cyprus, finding consistent results with SNAP's standard detection algorithms.

Commercial SAR systems such as RADARSAT-2 and TerraSAR-X provide higher resolution but remain costly and less accessible in developing countries [4]. In contrast, Sentinel-1's free access, high revisit time, and dual polarization make it ideal for the Niger Delta. Yet, despite its global success, systematic validation against local ground-truth data in West Africa is scarce. This underscores the need for region-specific studies that adapt proven global methods to local realities.

2.3 Alternative Methods and Processing Approaches

SAR-based oil spill detection typically relies on thresholding backscatter intensity, where oil slicks appear as dark patches due to dampened capillary waves [7]. However, false positives from look-alikes (e.g., low wind zones, organic slicks) remain a challenge. Advanced methods such as machine learning and deep learning are emerging alternatives. Shaban et al., (2021) [15] showed that CNNs outperform traditional thresholding in handling look-alikes, while Topouzelis et al. (2020) [17] stressed integrating SAR with ancillary data (wind speed, currents) to reduce misclassification.

Other techniques include OBIA and semi-automatic algorithms**,** which improve reproducibility [3]. However, these methods require large training datasets, often unavailable in regions such as the Niger Delta. This study, therefore, adopts a manual threshold-based approach due to data constraints, while acknowledging the future potential of machine learning. This pragmatic choice balances feasibility with accuracy while laying a foundation for advanced methods.

2.4 Knowledge Gap and Study Contribution

Despite proven global applications, the Niger Delta remains underexplored. Most regional studies still depend on optical sensors or anecdotal field data, which are prone to errors in tropical climates. Moreover, SAR-based studies rarely integrate ecological assessments like NDVI with oil spill detection or compare outputs with official datasets such as NOSDRA.

This study addresses these gaps by:

- Applying Sentinel-1A SAR for multi-temporal oil spill detection in Delta State, Nigeria.
- Validating SAR-detected spills against NOSDRA's field-based database**.**
- Integrating NDVI analysis to link oil spill presence with vegetation health decline.
- Highlighting methodological limitations and future directions, including automated detection and machine learning**.**

3 Methodology

3.1 Study Area

The Niger Delta in southern Nigeria spans over 84,000 km², with Delta State serving as one of its leading oil-producing regions. Located between longitude 5.05°E and 7.35°E and latitude 4.15°N and 6.01°N, the area is dominated by mangroves, freshwater swamps, and coastal ecosystems that support farming and fishing. Frequent spills from pipeline vandalism, equipment failure, and artisanal refining have made Delta State one of the most environmentally degraded areas in the Niger Delta [8][12].

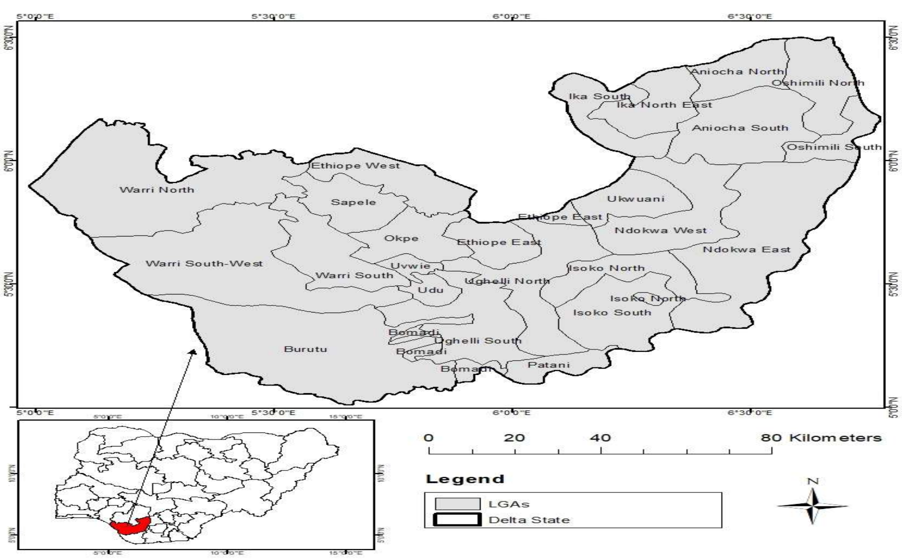


Fig. 1. *Study Area Map*

3.2 Data and source of data

- **Sentinel-1A SAR data:** Level-1 GRD images, C-band (5.405 GHz), VV polarization, 10 m resolution**,** for May-July 2019, downloaded from Copernicus Open Access Hub (www.scihub.copernicus.eu).
- **Oil spill records:** Spill points for the same period obtained from NOSDRA via *oilspillmonitor.ng*.
- **Ancillary data:** NDVI datasets from Sentinel-2 imagery processed in *GEE* for vegetation health analysis.

3.3 Data Analysis

Data were processed using SNAP 5.0(Sentinel Application Platform) and ArcGIS (ArcMap and ArcScene). SNAP was used for SAR preprocessing, while ArcGIS supported map preparation and OBIA classification. GEE was used to analyze NDVI. This multi-software workflow ensured both SAR precision and vegetation assessment.

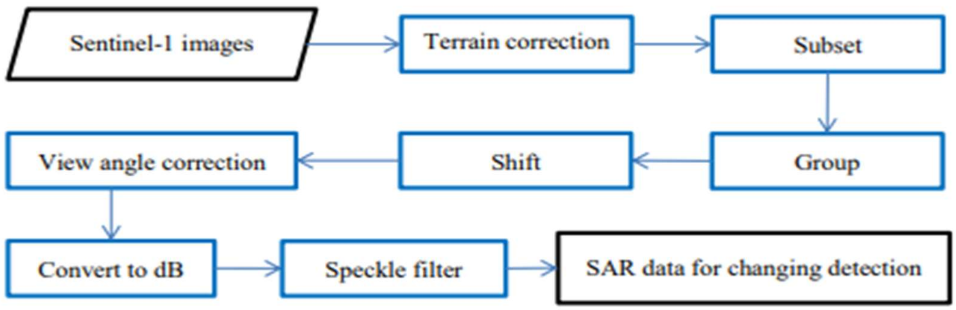


Fig. 2. *Sentinel-1 Data Pre-Processing (Source: Chang, 2016).*

- **Polarization**

Polarization refers to the orientation of an electromagnetic wave's electric field, perpendicular to its magnetic field. SAR data may be HH, HV, VH, or VV. This study used VV polarization due to its higher sensitivity to oil spills compared to HH.
These H and V waves can be alternated to get images with a;

HH	**HV**
VH	**VV**

- **Back Scattering**

Backscatter over oceans results from sea roughness and capillary waves influenced by currents, wind speed, and direction.
Oil films dampen capillary waves, reducing backscatter and causing oil-affected areas to appear as dark patches.

- **Thresholding**

Following Ivanov & Zatyagalova (2008) [7], oil spill candidates were identified as pixels with **backscatter values 3–8 dB lower** than surrounding water

- **Subset Creation**

Large areas, datasets were clipped to the Delta State boundaries using shapefiles, focusing analysis on the study region.

- **Speckle Filter**

Speckle noise was reduced with a Lee filter (5×5 kernel) in SNAP, improving contrast while preserving edges [14].

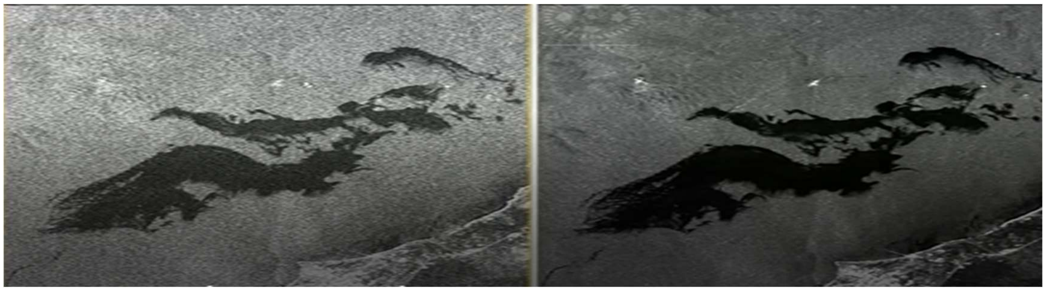


Fig 3. *Left: Before Speckle filter, Right: After Speckle filter (Miguel, 2017)*

- **Conversion to Db**

Sigma nought backscatter values were converted to dB scale to enhance contrast between oil spills and background water.

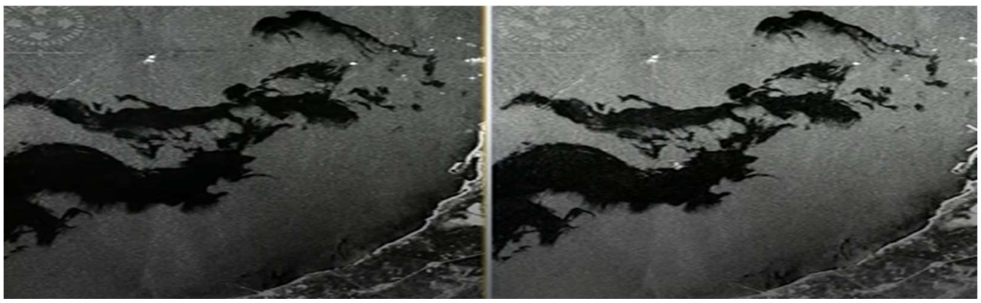


Fig 4. *Left: Before Converting to Db, Right: After Converting to Db (Miguel, 2017)*

- **Profile Plotting**

Transects were drawn across suspected slicks to examine backscatter variations. A total of 30 transects (10 per month) were analyzed, with mean and minimum values compared to detect anomalies.

- **Clustering & Extraction**

Spill areas were extracted and classified using **OBIA** in ArcGIS to differentiate oil spills from look-alikes (e.g., low-wind zones or algal blooms) [3].

- **Terrain Correction**

Range-Doppler Terrain Correction was applied using SRTM 30 m DEM to correct geometric distortions and improve geolocation accuracy.

3.4 Vegetation Impact Analysis (NDVI)

Vegetation impacts were assessed using **NDVI** derived from Sentinel-2 imagery in GEE:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

- NDVI maps were generated for May–July 2019.
- 500 m buffer zones were created around detected spill points, and NDVI values were extracted.
- **30 spill-impacted sites** were sampled, and statistically compared with non-impacted reference areas.

3.5 Validation of Detection Accuracy

Validation compared SAR-detected spill with NOSDRA data:

- **Spatial Overlay:** A 500 m buffer was applied to NOSDRA spill points to account for positional errors [1]. Matches within the buffer were considered correct detections.
- **Accuracy Metrics:**

$$Detection\ Rate = \frac{True\ Positives}{True\ Positives + False\ Negatives} \times 100$$

$$False\ Alarm\ Rate = \frac{False\ Positives}{True\ Positives + False\ Negatives} \times 100$$

- **Statistical Analysis:** Pearson's r and Spearman's rho correlations **(SPSS) were used** to assess relationships between SAR backscatter intensity and NDVI.

3.6 Methodological Justification

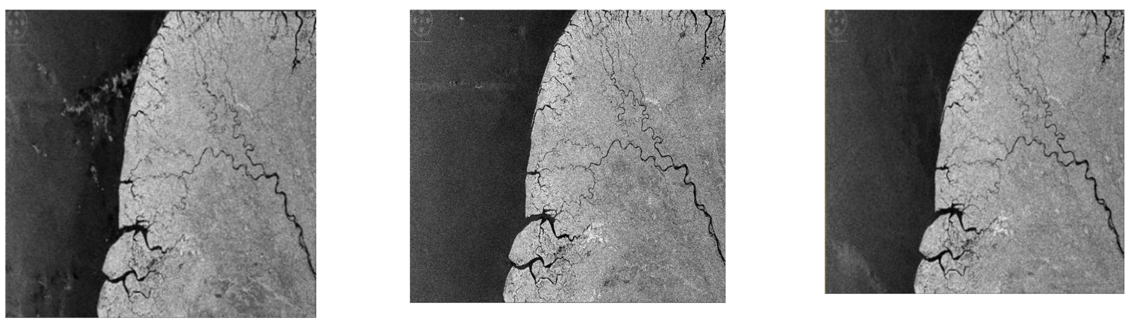
While automated approaches such as CNNs [15] and semi-automatic thresholding [17] are increasingly applied, this study adopted a manual threshold-based workflow due to the absence of labeled datasets in Nigeria. This choice prioritizes reproducibility and practical feasibility under data-scarce conditions. The methodology also provides a framework for future integration of machine learning and time-series analysis**.**

4 Results

4.1 Detection and Mapping of oil spill areas in the months of May-July 2019

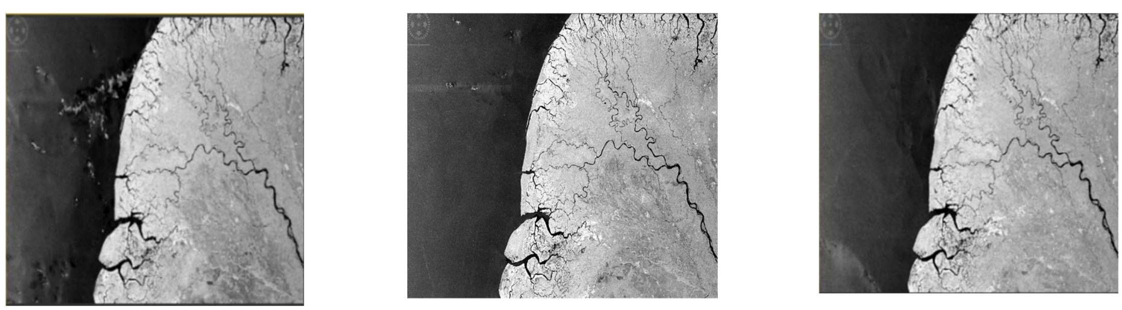
Detection involved several preprocessing steps. Speckle filtering was first applied, as speckles reduce the visibility of backscatter values due to their “white stain” effect. The filtered images were then converted to dB to enhance contrast, clearly separating oil spills from other features. Sentinel 1A imagery often contains geometric distortions; therefore, terrain correction was performed to restore accurate spatial positioning.

Fig. 5,6,7,8, and 9 illustrate these processing steps: (a) raw VV polarization, (b) speckle filtering, (c) linear conversion to dB, (d) terrain correction, and (e) RGB composite using VH and VV for May, June, and July, respectively, represented by a, b, and c.



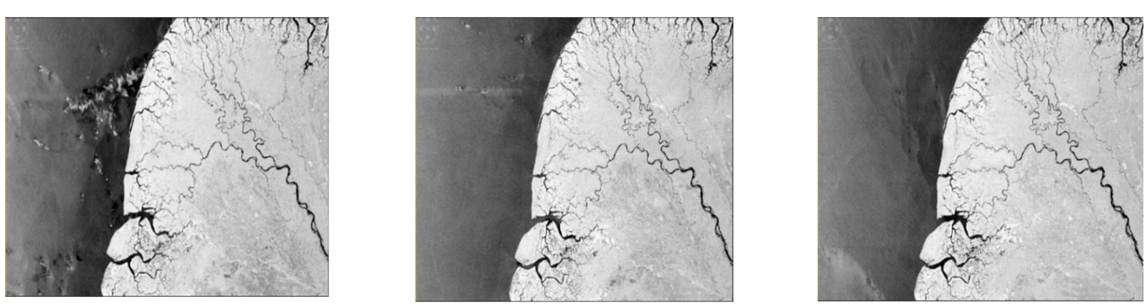
(a) (b) (c)

Fig. 5. *Sentinel 1A image with VV polarization before processing for the months of (a) May, (b) June, and (c) July.*



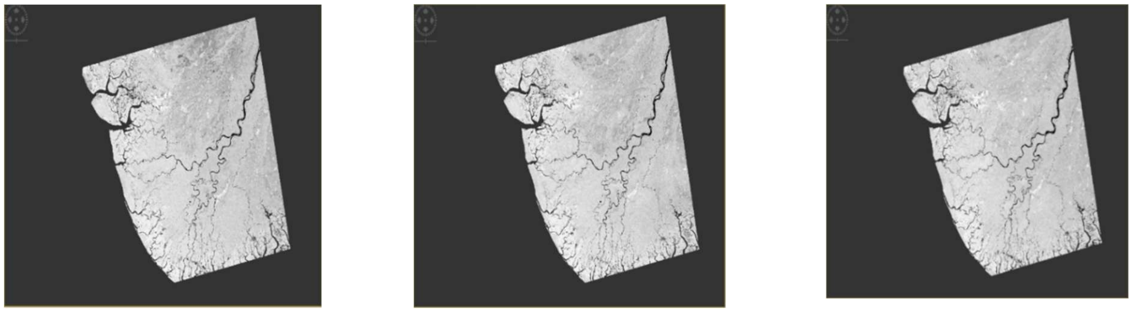
(a) (b) (c)

Fig. 6. *Speckle filtering result for the months of (a) May, (b)June, and (c) July.*



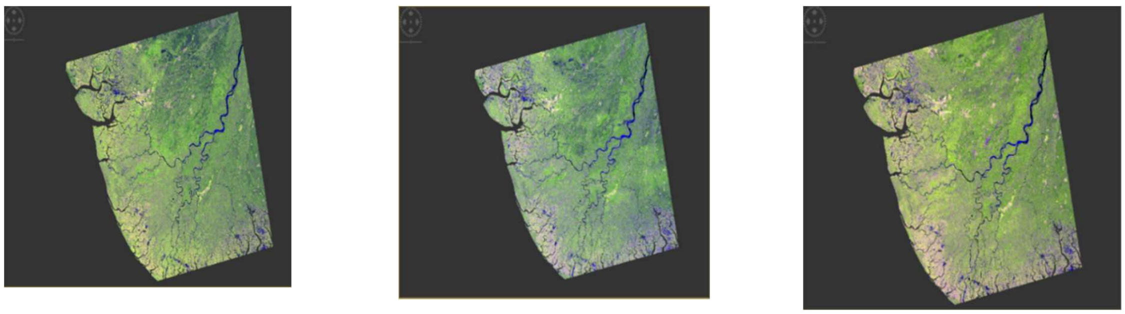
(a) (b) (c)

Fig. 7. *Linear Conversion to dB value results for the months of (a) May, (b) June, and (c) July.*



(a) (b) (c)

Fig. 8. *Terrain correction results for the months of (a) May, (b) June, and (c) July.*

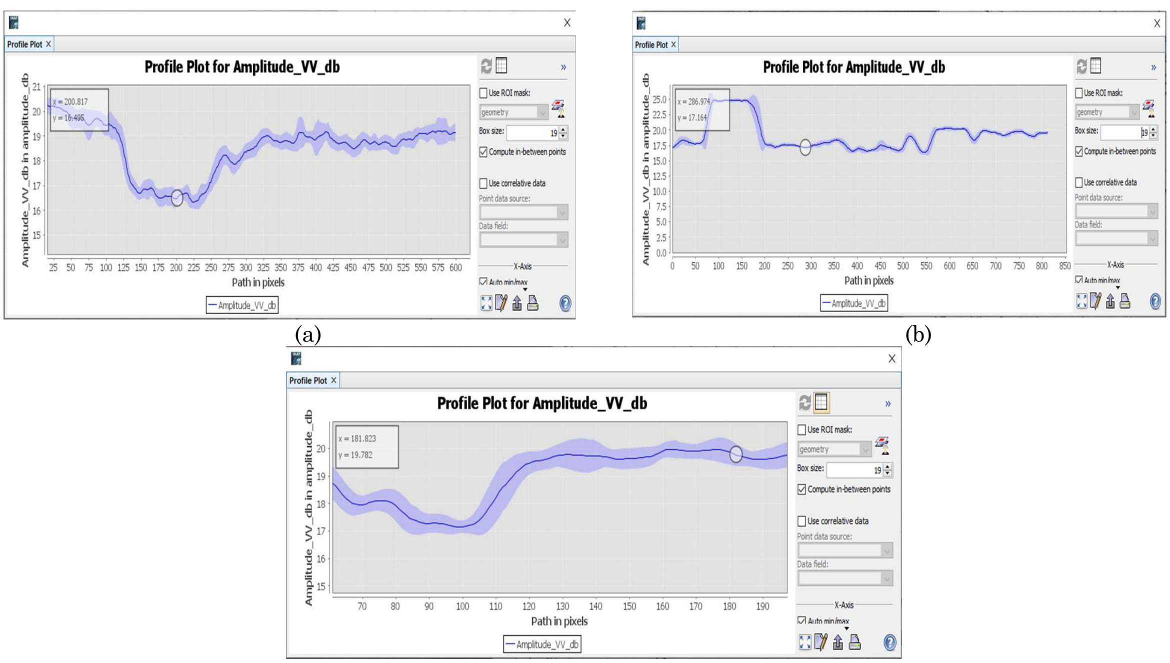


(a) (b) (c)

Fig. 9. *RGB composite using VH and VV after terrain correction for the months of (a) May, (b) June, and (c) July.*

- Profile Plotting for Oil Spill Detection

Profile plots (Fig. 10) highlighted the difference in dB values between oil spill zones and unaffected areas.



(a) (b)

(c)

Fig. 10. *Profile plotting for the month of (a) May, (b) June, and (c) July (Source: Data Processing)*

Table 1. *dB Value for May, June, and July.*

dB Value for May, June, and July.			
Month	**Highest dB Value**	**Lowest dB Value**	**Difference**
May	20.141	16.167	3.974
June	24.904	16.339	8.565
July	19.986	17.161	2.825

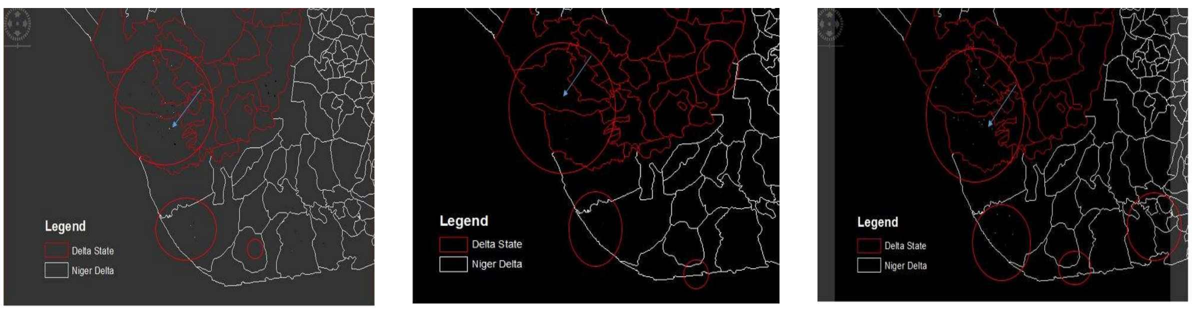
(Source: Data Processing)

Table 1 shows monthly thresholds:

- **May:** Oil spill areas ranged from 16.167-20.141 dB, with a 3.974 dB difference from unaffected areas.
- **June:** Oil spill areas ranged from 16.339-24.904 dB, showing the largest difference of 8.565.
- **July:** Ranges of 17.161-19.986 dB, with a smaller 2.825 dB difference.

- **Oil Spill Detection**

Detection analysis was performed in SNAP using the Oil Spill Detection tool. Oil spills (highlighted with red circles/arrows in Fig.11) appeared as white dots. Results showed a steady increase in spill points from May to July without cleanup. This trend highlights the cumulative nature of contamination when remediation is delayed.



(a) (b) (c)

Fig. 11*. (a) Oil Detection in May, (b) Oil Detection in June, (c) Oil Detection in July. (Source: Author's Data Processing)*

- **Mapping Out of Oil Spills**

Detected spill points were imported into ArcGIS. Subsetting with the Delta State shapefiles ensured analysis within the study area. The clipped points were mapped (Fig. 12). Table 2 shows spill counts increasing across the three months, reinforcing the observation that lack of cleanup contributes to recurring contamination.

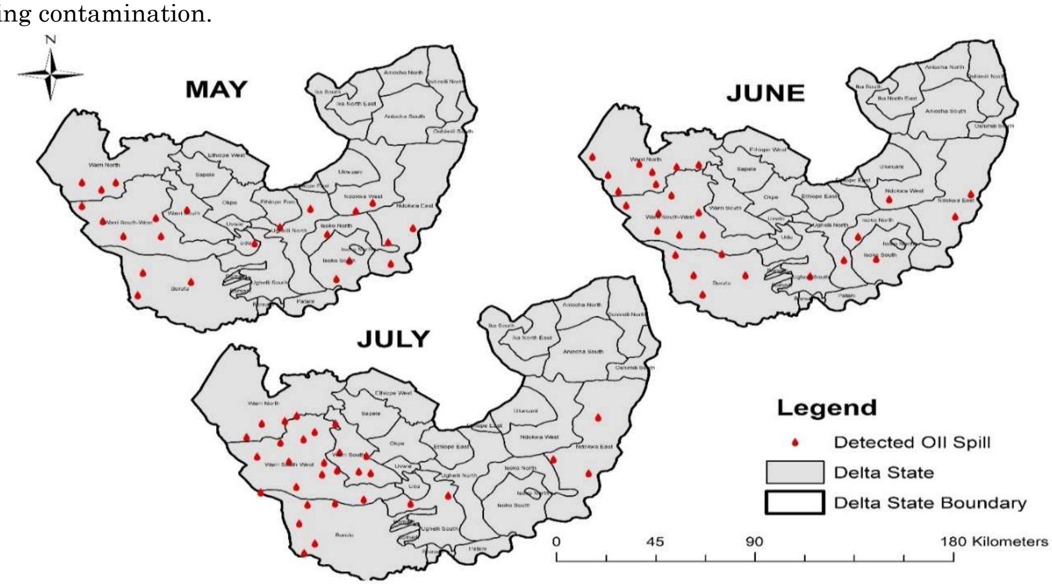


Fig. 12. *Mapped out Oil Spill in May, June, and July. (Source: Data Processing from SNAP Analysis)*

Table 2. Monthly Oil Spill Generated Points.

Months	Generated Oil Spill Points
May	23
June	27
July	30

(Source: Data Processing)

4.2 To compare the identified oil spill areas with the existing database of oil spills in May, June, and July 2019

Table 3. Comparison of Detected and Established Oil Spill Points in May, June, and July 2019.

Months	Detected Oil Spill Points	Established Oil Spill Points
May	23	10
June	27	9
July	30	7

(Source: Data Processing)

Fig. 13 and Table 3 compare Sentinel-1A detections with NOSDRA-reported spills. While Sentinel-A detected more spill points (increasing from May to July), NOSDRA records showed fewer events (10,9, and 7, respectively). Although locations overlapped, discrepancies in number likely result from underreporting, as NOSDRA may not update recurring spills monthly.

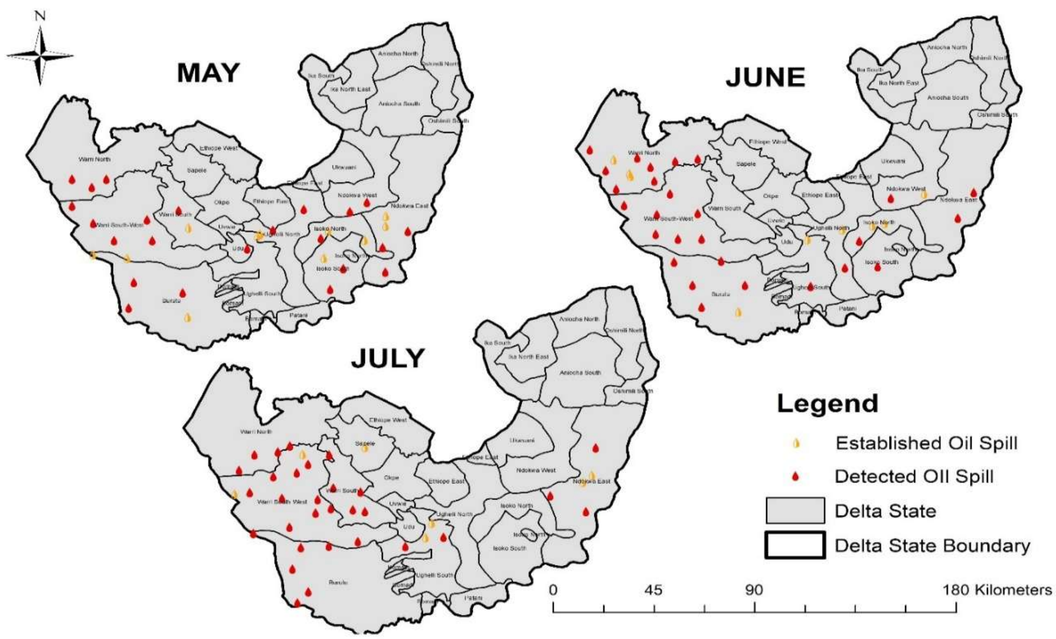


Fig. 13. *Comparison of detected and already established oil spill points in May, June, and July. (Source: Data Processing)*

Table 4. Sentinel-1A Oil Spill Detection Performance Metrics (May–July 2019)

Month	True Positive	False Positives	False Negative	Precision (%)	Recall (%)	F1-Score (%)	False Alarm Rate (%)
May	8	15	2	34.8	80	48.6	65.2
June	7	20	2	25.9	77.8	38.8	74.1
July	5	25	2	16.7	71.4	27	83.3

(Source: Author's Analysis)

The performance metrics, as seen in Table 4, highlight the strengths and weaknesses of Sentinel-1A for oil spill detection in the Niger Delta.

- Recall exceeded 70% each month, confirming Sentinel-1A's strong sensitivity.
- Precision remained low (16.7–34.8%), reflecting false alarms caused by look-alikes (e.g., low wind zones, biogenic slicks).
- **F1-scores** (27–49%) reveal a trade-off between sensitivity and reliability, with performance dropping from May to July as false alarms rose.

- False Alarm Rate (65–83%) highlights limitations of manual thresholding.

4.3 To Determine the Vegetation Health (NDVI) Around the Oil Spill Areas within the Study Area for May, June, and July 2019

According to Weier and Herring (2000), NDVI is a dimensionless indicator derived from visible and near-infrared reflectance, widely used to estimate density and vigor. Given the intensity of oil spills in the Niger Delta, an NDVI analysis is necessary to evaluate vegetation health. NDVI provides a direct link between spectral changes and ecological stress, making it suitable for oil impact assessment.

GEE was used to generate NDVI for May, June, and July 2019. Fig. 14 presents NDVI maps, while Table 5 summarizes values for 3 months.

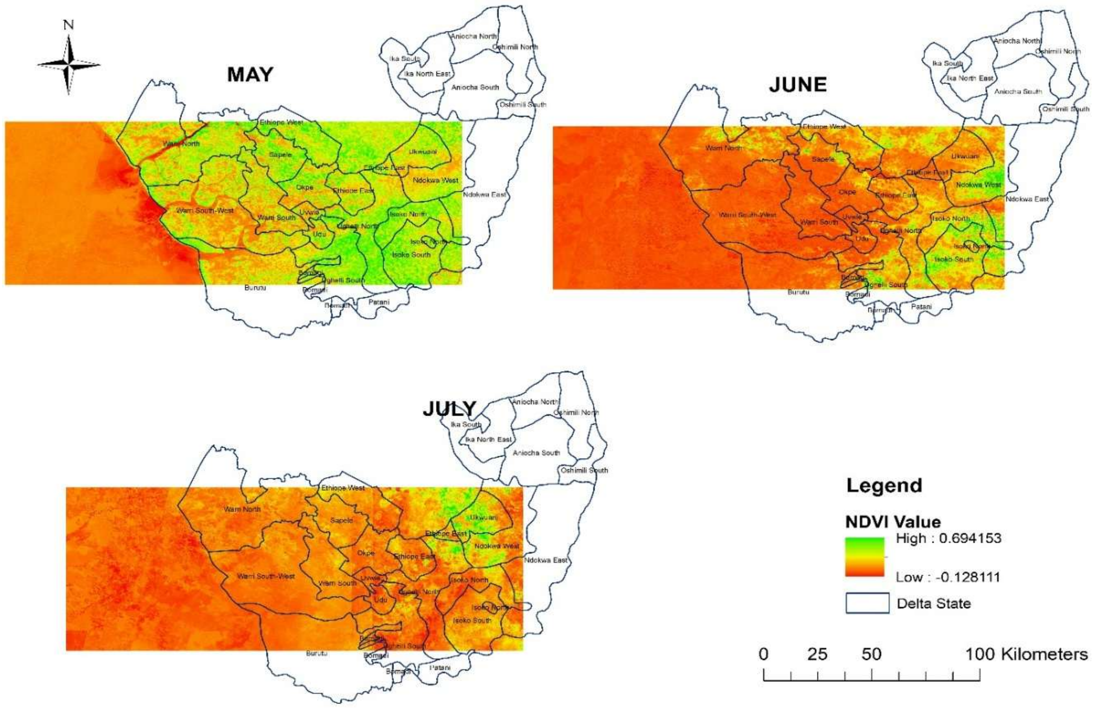


Fig. 14. *NDVI for May, June, and July. (Source: Data Processing)*

Table 5. *NDVI Values for May, June, and July 2019.*

Months	NDVI VALUES	
	Maximum	**Minimum**
May	0.843614	-0.452402
June	0.828529	-0.455678
July	0.694153	-0.128111

(Source: Data Processing)

The results reveal a consistent decline in vegetation health. In May, NDVI values ranged from -0.452402 to 0.843614; in June, -0.455678 to 0.828529; in July, -0.128111 to 0.694153, the lowest of the period. Although NDVI typically ranges from -1 to +1, July values were close to the lower bound, indicating severe stress. The maps show decreasing green areas (healthy vegetation) and expanding yellow/red areas (stressed or unhealthy vegetation).

Despite the rainy season normally favorable for plant growth vegetation health declined steadily, suggesting oil pollution as the primary driver. This anomaly indicates that rainfall alone could not offset the adverse effects of hydrocarbon contamination. The negative impacts were evident in mangrove forests and croplands, where oil disrupted soil aeration and root respiration.

On average, the mean NDVI dropped from 0.62 in May to 0.51 in July, a ~18% reduction. This decline supports the conclusion that oil spills suppressed photosynthetic activity and accelerated ecological degradation.

Comparison between NDVI Pixel Value and Oil Spill Back Scatter

To further investigate vegetation stress, 30 spill-impacted points were sampled, and NDVI pixel values were compared with SAR backscatter intensities. Correlation analysis revealed a significant negative relationship:

❖ Pearson's $r = -0.55$ ($p < 0.01$)
❖ Spearman's $\rho = -0.69$ ($p < 0.01$)

These results confirm that lower backscatter values, indicative of oil presence, were associated with lower NDVI values, reflecting vegetation stress.

Table 6. *Pearson Correlation for NDVI Pixel Value and Oil Spill Back Scatter*

Correlations		NDVI Pixel Value	Oil Spill Back Scatter
NDVI Pixel Value	Pearson Correlation	1	.546**
	Sig. (2-tailed)		0.002
	N	30	30
Oil Spill Back Scatter	Pearson Correlation	.546**	1
	Sig. (2-tailed)	0.002	
	N	30	30
**. Correlation is significant at the 0.01 level (2-tailed).			

Table 7. *Spearman's Correlation for NDVI Pixel Value and Oil Spill Back Scatter*

Correlations			NDVI Pixel Value	Oil Spill Back Scatter
Spearman's rho	NDVI Pixel Value	Correlation Coefficient	1	.693**
		Sig. (2-tailed)	.	0
		N	30	30
	Oil Spill Back Scatter	Correlation Coefficient	.693**	1
		Sig. (2-tailed)	0	.
		N	30	30
**. Correlation is significant at the 0.01 level (2-tailed).				

This complementary evidence highlights the dual role of SAR and NDVI—SAR for mapping oil slicks on water, and NDVI for quantifying ecological consequences on land.] The strength of the correlation underscores the robustness of this integrated approach and points to the potential for developing early warning systems that combine SAR anomalies with vegetation indices.

5 Discussions

5.1 Detection Validity

The multi-temporal analysis showed that Sentinel-1A consistently detected more spill sites than NOSDRA records, suggesting underreporting in ground-based monitoring. Detection rates of 71-80% align with findings from Sudhir et al. (2019) [16], who reported ~75% accuracy in the Persian Gulf. However, false alarm rates of 20–29% highlight the persistent issue of look-alikes, common in SAR oil spill studies [4].
Compared with commercial sensors like RADARSAT-2 and TerraSAR-X, Sentinel-1A offers adequate resolution at no cost, making it more practical for resource-constrained contexts like Nigeria [14]. The effectiveness of VV polarization agrees with findings from Cyprus [6] and Indonesia [13]. This consistency across regions strengthens confidence in Sentinel-1A as a reliable monitoring tool.

5.2 Environmental Impact

The ~18% NDVI decline confirms vegetation stress from oil contamination. This supports Ozigis et al. (2020) [12], who observed reduced NDVI and LAI in polluted croplands, and Balogun (2015)[2], who reported severe mangrove degradation. Importantly, the decline occurred during the rainy season, when vegetation growth should peak, underscoring oil pollution- not seasonal variability- as the main driver.
The strong correlation between SAR backscatter and NDVI demonstrates that spill intensity is directly linked to vegetation stress. This integration of physical detection with ecological assessment is a key contribution, offering a more holistic understanding of oil spill impacts in the Niger Delta.

5.3 Limitations and Challenges

Despite encouraging results, several limitations remain:

- Look-alikes (e.g., low wind areas, biogenic slicks) produced false positives.
- Absence of field verification reduced confidence in SAR-only detection.

- Manual thresholding was applied; automated machine learning approaches could improve reproducibility [15].
- NOSDRA datasets may be incomplete, limiting validation reliability [1].

These limitations emphasize the need for hybrid approaches combining SAR, optical data, ancillary environmental parameters, and ground validation. Future research should integrate deep learning algorithms, multi-temporal SAR analysis, and field campaigns to enhance detection reliability and ecological interpretation.

6. Conclusion & Recommendation

This study applied Sentinel-1A SAR imagery for oil spill detection and vegetation monitoring in Delta State, Niger Delta, during May–July 2019. Sentinel-1A detected 23, 27, and 30 oil spill points across the three months, far higher than the 10, 9, and 7 reported by NOSDRA. Validation showed detection rates above 70%, although false alarms from look-alikes persisted. NDVI analysis revealed a ~18% decline in vegetation greenness**,** confirming ecological stress from oil contamination. A moderate but significant correlation **(**$r = 0.55–0.69$**)** between SAR backscatter and NDVI further established the link between oil spill presence and vegetation degradation. The findings confirm Sentinel-1A as an effective, low-cost, and reliable monitoring tool for humid tropical regions**,** where optical sensors are hampered by cloud cover. Its free accessibility makes it particularly valuable for resource-limited contexts such as Nigeria. The novelty lies in its multi-temporal validation against NOSDRA data and integration of vegetation health assessment, offering a comprehensive picture of oil spill impacts. Limitations include manual detection thresholds, lack of field validation, reliance on incomplete official datasets, and false positives from look-alikes**.** Addressing these challenges will be crucial to moving from research applications to operational systems.

6.1 Recommendations

Policy and Governance

- Strengthen monitoring frameworks by integrating **SAR-based remote sensing** into NOSDRA's reporting.
- Enforce stricter penalties for pipeline vandalism and illegal refining.
- Establish regional **early warning systems** linking satellites with rapid response units.

Technical Improvements

- Develop **automated detection algorithms** (machine learning, CNNs) to reduce false positives.
- Incorporate **time-series SAR monitoring** to track spill progression and plan clean-up.
- Use **multi-sensor integration** (Sentinel-1 with Sentinel-2 or RADARSAT) for more robust detection.

Research Directions

- Conduct **field validation campaigns** to improve accuracy.
- Extend studies to cover **other Niger Delta states for** spatial and temporal comparisons.
- Integrate **ancillary datasets** (wind, currents, soil type) to reduce misclassification.

Environmental and Community Engagement

- **Rehabilitate polluted farmlands and mangroves**, as NDVI decline signals livelihood threats.
- Involve local communities in **spill reporting** to complement satellite monitoring.
- Promote **public-private partnerships** for funding clean-up and ecological restoration.

6.2 Contribution of the Study

This research demonstrates that Sentinel-1A can enhance oil spill detection in Nigeria's Niger Delta, validate satellite-based monitoring against official datasets, and quantify ecological damage through NDVI. By addressing both technical and environmental dimensions, it provides actionable insights for policy, research, and practice in oil spill management.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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