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# Assessing the Impact of Anthropogenic Stressors on Ecosystem Dynamics in the Niger Delta Coastal Area, Nigeria

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**ABSTRACT**
Anthropogenic stressors, particularly oil pollution, forest fires, and urbanization, are major drivers of ecosystem degradation in the Niger Delta coastal region of Nigeria. This study assessed their impacts on vegetation health by integrating oil spill records from the National Oil Spill Detection and Response Agency (NOSDRA) with Sentinel-2 MSI Level-2A imagery. Vegetation condition and disturbance were evaluated using the Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), and Normalized Difference Building Index (NDBI), alongside biophysical variables including Leaf Area Index (LAI), Leaf Chlorophyll Content (LCC), Fraction of Vegetation Cover (FCOVER), and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR). Maximum Likelihood Supervised Classification (MLSC) was applied to map land cover and quantify its spatial distribution. Results revealed that oil spills, predominantly caused by sabotage (85%), substantially reduced vegetation greenness, density, and productivity. Fire outbreaks associated with illegal refining further intensified vegetation loss and landscape degradation. Land cover analysis showed that grasslands occupied 33% of the study area, canopy vegetation 30%, non-vegetated and burned land 21%, built-up areas 12%, and freshwater bodies 5%. The integration of Sentinel-2 imagery, biophysical variables, and oil spill records provided a robust framework for monitoring the cumulative effects of multiple anthropogenic stressors on ecosystem dynamics. The findings underscore the need for strengthened environmental governance, sustainable vegetation management, and improved oil spill prevention strategies to enhance ecosystem resilience and support environmental restoration in the Niger Delta.

**Keywords**:
Oil spillage,
Fire Outbreaks,
Urbanization,
Sentinel-2 MSI Level-2A,
Land Cover Classification,
Vegetation Indices.

## INTRODUCTION

Human activity has introduced several threats to the Earth. The most significant are climate change, environmental pollution, and forest fires. While climate change is the foremost challenge, pollution and forest fires are closely followed as the major anthropogenic activities, threatening the existence of plants and animals. Freshwater bodies, the ocean, and the open sea have become reservoirs for many non-biodegradable wastes that are poorly disposed of by humans. The land also carries the imprint of these solid wastes, many of which make their way into water bodies (Bentsi-Enchill et al., 2022; Fan et al., 2023). In addition to solid un-decay wastes, crude oil spills, forest fires, and unregulated land use contribute greatly to the annual forest loss. Sustainable management of the ecosystem, particularly the wetlands, is required due to their roles in food storage, water quality maintenance, and habitat for various wildlife species. Over 75% of commercial fish species depend on them to complete a portion of their life cycle, and many local and migratory birds use coastal wetlands for breeding and perching (Clere et al., 2022). They are also important storehouses for large quantities of terrestrial carbon (Dai et al., 2023; Nahlik & Fennessy, 2016). Their destruction, therefore, can release carbon in the form of carbon dioxide and methane into the atmosphere, thereby, accelerating climate change. Understanding the dynamic interplay between human activities and natural ecosystems is crucial for sustainable environmental management. Earth observation technologies, such as multispectral satellite imaging, have emerged as powerful tools to monitor and analyze these complex interactions at continental and national scales (Barbache et al., 2018).

Recent studies have highlighted the increasing demand for comprehensive environmental assessments, driven by the growing interest of government and international agencies, as well as the rapid advancements in remote sensing applications and the availability of high-speed computational resources (Mashala et al., 2023). These technological developments have enabled the scientific community to characterize land use and land cover changes at an unprecedented scale and frequency, providing valuable insights into the signs of ecosystem distress and the underlying processes driving environmental transformations (Zhu et al., 2022).

A study compared Fuzzy Forest and Random Forest classifiers to detect and map oil-spill impacted vegetation using a post-spill multispectral optical Sentinel-2 image alongside multifrequency C and X band SAR data (Sentinel-1, COSMO SkyMed, TanDEM-X) in the Niger Delta. The study demonstrated that combining Sentinel-2 optical data with SAR significantly improved discrimination between oil-polluted and oil-free vegetation classes (Ozigis et al., 2019).

The use of diachronic analysis, or the study of changes over time, on multi-date satellite imagery has proven to be a robust approach for monitoring the state of forest cover and other land cover types, and for identifying the signs of environmental degradation. This method allows for objective, exhaustive, and continuous monitoring of environmental phenomena, enabling the establishment of early warning systems and informing decision-makers on appropriate strategies for sustainable development (Barbache et al., 2018).

Sentinel-2 satellite imagery has proven valuable in detecting and monitoring environmental change in the Niger Delta region. Notably, a study employed synergistic approach by combining Sentinel-2-derived spectral reflectance and vegetation health indices with Sentinel-1 backscatter, alpha, and entropy scatter parameters to detect and spatially delineate oil spill impacts on terrestrial vegetation. Their findings further established the blue wavelength region as a reliable stress indicator, given that non-photo synthetic or physiologically compromised vegetation exhibits diminished absorption of blue and green energy within the visible spectrum (Adamu et al., 2018).

The previous studies primarily employed the synergistic application of Sentinel-1 SAR and Sentinel-2 multispectral derivatives to map the spatial extent and severity of terrestrial oil spill impacts in the Niger Delta. Their focus was largely limited to the detection, classification and mapping of oil spill-affected areas, thereby addressing only a single anthropogenic stressor. However, these studies did not investigate the cumulative or interactive effects of multiple anthropogenic stressors on ecosystem dynamics across the Niger Delta coastal region.

In contrast, the present study utilizes Sentinel-2 multispectral imagery to evaluate the combined impacts of multiple anthropogenic stressors, including oil spills, forest fires, deforestation, urban expansion, agricultural activities, and other land-use changes, on ecosystem dynamics. Rather than concentrating exclusively on oil spill mapping, this study investigates how these interacting human-induced disturbances collectively influence vegetation health, land cover dynamics, and ecosystem sustainability in the Niger Delta coastal area. By adopting a multi-stressor ecosystem assessment, this research provides a more comprehensive understanding of environmental degradation and ecosystem responses than previous oil spill-focused studies.

This paper aims to utilize Sentinel-2 Multispectral Instrument Level-2A satellite imagery to assess the impacts of anthropogenic disturbances on ecosystem dynamics. The objectives include assessing vegetation health, coverage, and biophysical conditions associated with oil pollution, fire outbreaks and urbanization. These include correlational and spatial assessments of the land cover degradation due to human activities.

## MATERIALS AND METHODS

### Description of the Study Area

The study area is the Niger Delta in southern Nigeria. It is a coastal area located northwest of Equatorial Guinea in West Africa (Figure 1). The Niger Delta is one of the world's most prolific petroleum-producing tertiary deltas, accounting for approximately 2.5% of the present-day basin areas (Haack et al., 2000). It is among the world's largest regressive sequences with a sedimentary thickness of over 12 km and occupies an area of approximately 75,000 km$^2$ (Kuye & Hampson, 2023). Several pipelines and abandoned oil wells are scattered throughout the area, particularly the western segment. Pressure sometimes builds up in these wells, causing crude oil to sprout. The Niger Delta sabotage. The region is undoubtedly one of the most polluted coastal areas in the world (Echendu et al., 2022). Freshwater bodies are covered by oil, stretching as far as the eyes can see. Vast areas of land originally covered by lush vegetation have been transformed into non-vegetated landmass or marshlands contaminated by mixtures of oils and water. This condition has significantly impacted the lives of the people in the region, rendering many agricultural lands unusable. Similarly, oil spillage has continually degraded wetlands, raising concerns for coastal erosion, loss of biodiversity, and climate change. The Niger Delta is home to significant biodiversity, encompassing plants and animals. The climate in the region readily supports and sustains biodiversity. Warm and humid tropical oceanic air masses from February to November are associated with the rainy season, while dry tropical continental air masses from December to January are linked to a short period of dryness (Ozigis et al., 2019). The annual average precipitation ranges from 4500 mm along the coast to 2000 mm away from the coastline. The temperature in the region is invariably low amounting to an average yearly value of $27^{o}C$ (Ozigis et al., 2019).

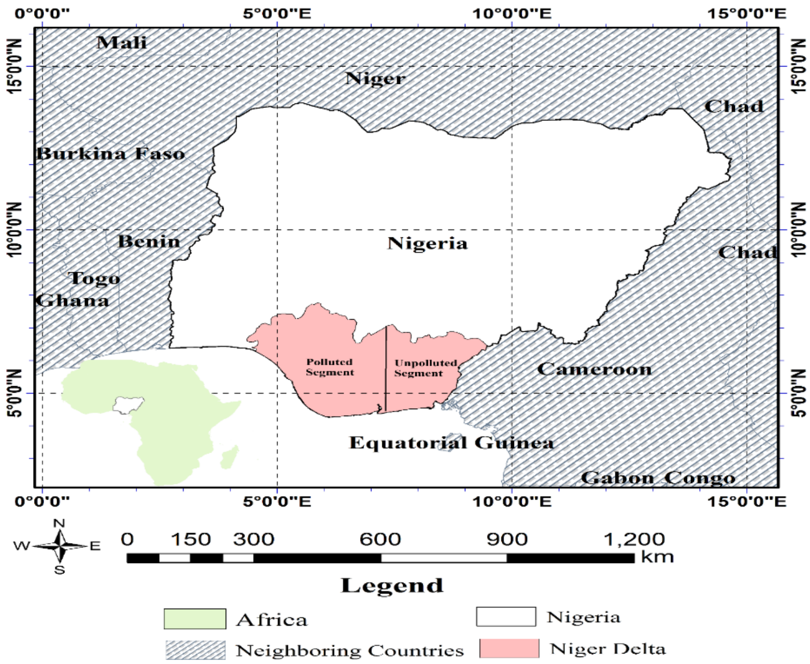


Figure 1: Map of Nigeria showing the oil-rich Niger Delta in West Africa. The western part has a record high spillage incidence while the eastern segment has few or no incidences of oil spillage

## Data and Analysis

### *Oil Spillage Monitoring Data*

The oil spillage data in this study were obtained from the National Oil Spillage Detection and Response Agency's (NOSDRA) website. The data consists of the spill point's coordinates, spillage causes, and facility involved, spill products, habitat affected, estimated quantity, and spill area affected. Other spill data on the website are gas, drill mud, chemicals, condensate, and refined products. Figure 2 is the map of the Niger Delta area showing the oil spill sites between January 2020 and August 2024. The map shows spill sites caused by oil firms and those resulting from sabotage. It equally shows the latest clean-up areas that indicate the governments and other stakeholders' concerted efforts to restore the vegetation to its natural state. The affected States are Rivers, Bayelsa, Delta, and parts of Imo and Abia. Consequently, Rivers State has the highest incidences of oil spillage, followed by Delta and Bayelsa States. The primary cause of oil spillage is sabotage/theft, accounting for 85% while equipment failure, pipeline corrosion, and operational/maintenance error only account for 8% (Figure 3). A few other causes have remained unknown to date. The bulk of the oil spillage occurred on land, followed by seasonal swamps and mangroves (Figure 4). The data, however, do not cover all the known pollution sites in the Niger Delta. Factors such as the security of the operating environment and the logistical challenges have been responsible for the observed limitations. The Niger Delta also encompasses an extensive area of land degraded by oil-related fire incidents, many of which have been inadequately documented (Ozigis et al., 2020). These limitations underscore the need for monitoring the ecosystem, particularly through the use of geospatial data like Sentinel-2 (MSI) Level-2A imagery or other accessible satellite imagery.

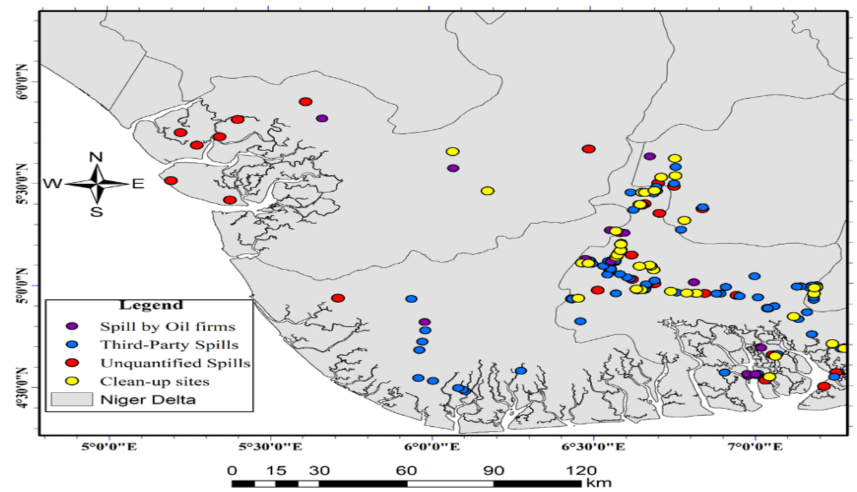


Figure 2: Map of Niger Delta Showing Crude Oil Spillage Locations between January 2020 and January 2024 according to NOSDRA

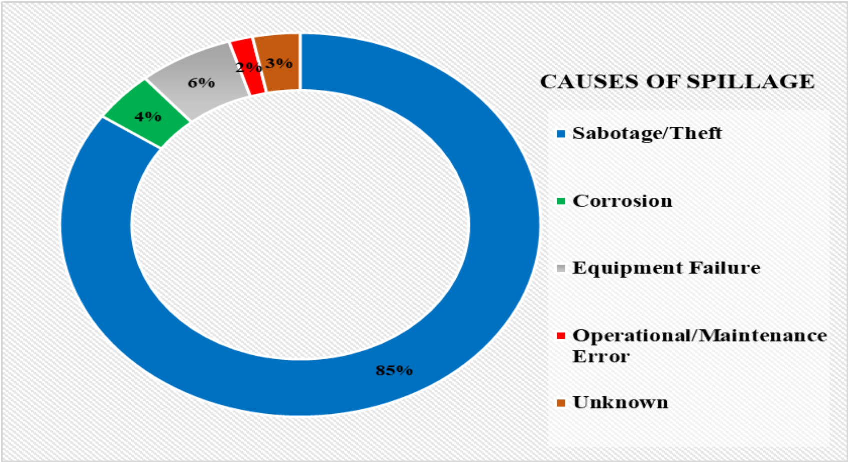


Figure 3: A Chart showing Causes of Spillage in the Niger Delta area between January 2020 and January 2024 (NOSDRA)

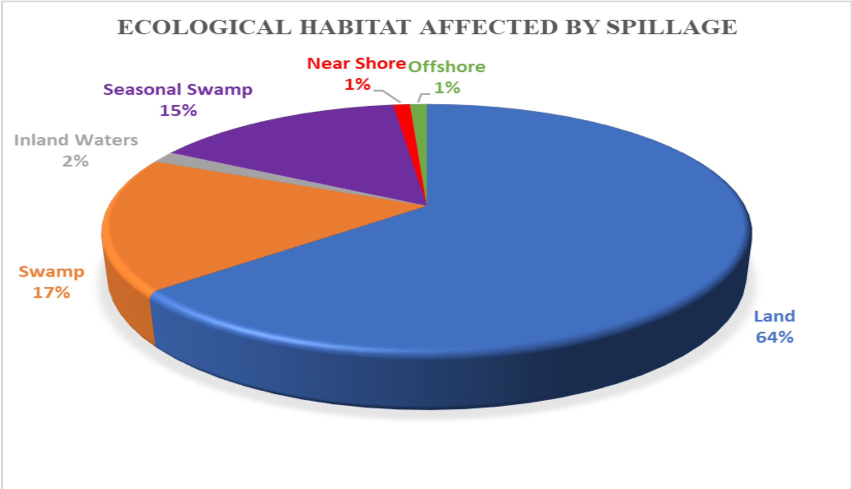


Figure 4: A Chart Showing the Ecological Habitats Affected By Spillage in the Niger Delta between January 2020 and January 2024 (NOSDRA)

**Sentinel-2 Multispectral Data**

The oil spillage monitoring data from NOSDRA are extremely valuable, however, they do not have significant coverage to be suitable for a complete assessment of the vegetation health regarding oil pollution, fire outbreaks and urbanization in the Niger Delta area. To fill this gap, Sentinel-2 (MSI) Level-2A satellite imagery across the Niger Delta area was utilized. The Sentinel-2 (MSI) Level-2A satellite imagery was used because it offers both high spatial resolution and unlimited coverage, unlike other satellite imagery, which lacks both features simultaneously (Afgatiani et al., 2020; Lassalle et al., 2019). The Sentinel-2 MSI Level-2A satellite mission is part of the European Space Agency Copernicus Program. It carries a multispectral optical sensor capturing high-resolution imagery of the Earth's surface in the visible, near-infrared (NIR), and short-wave infrared (SWIR) bands with a 10-day single-satellite and 5-day dual-satellite revisits around the equator (Liu et al., 2023). The Sentinel-2 mission provides satellite imagery in thirteen spectral bands with a spatial resolution ranging from 10 to 60 meters (Table 1). The image acquired is a Surface Reflectance (SR) product with additional data improvements such as radiometric calibration, geometric correction, orthorectification, image registration, and atmospheric correction, necessitating no further data improvements (Liu et al., 2023). Due to the lack of Sentinel-2 MSI level-2A imagery spanning the entire Niger Delta for each year, data from December and January of 2021, 2023 and 2024 were combined for the study. The images were downloaded with a cloud coverage of 2%, while cloud masking was performed using a quality assessment band (QA60) to remove the cloud effects. Figure 5 shows the wavelengths and the amplitudes of the various bands B1, B2, B3, B4, B8, B10, B11 and B12 in the study area.

**Table 1: Sentinel-2A MSI Level-2 Bands, Wavelength and Resolution**

| Band | Band Name | Central Wavelength (nm) | | Resolution (m) |
|---|---|---|---|---|
| | | S2A | S2B | |
| B1 | Coastal Aerosol | 443.9 | 442.3 | 60 |
| B2 | Blue | 496.6 | 492.1 | 10 |
| B3 | Green | 560.0 | 559.0 | 10 |
| B4 | Red | 66 4.5 | 665.0 | 10 |
| B5 | Red Edge 1 | 703.9 | 703.8 | 20 |
| B6 | Red Edge 2 | 740.3 | 739.1 | 20 |
| B7 | Red Edge 3 | 782.5 | 779.7 | 20 |
| B8 | Near Infrared | 835.1 | 833.0 | 10 |
| B8A | Narrow Near Infrared | 864.8 | 864.0 | 20 |
| B9 | Water Vapor | 945.0 | 943.2 | 60 |
| B10 | Shortwave Infrared Cirrus | 1373.5 | 1376.9 | 60 |
| B11 | Shortwave Infrared | 1613.7 | 1610.4 | 20 |
| B12 | Shortwave Infrared | 2202.4 | 2185.7 | 20 |

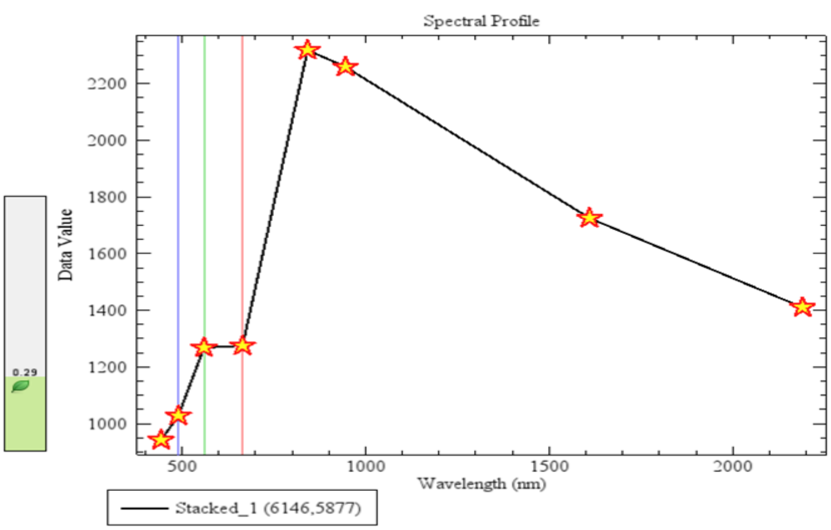


Figure 5: Sentinel-2A MSI Level-2 Band Features in the Study Area

**Methods of Analysis**

The Sentinel-2 MSI Level-2A imagery was analyzed using Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), Normalized Difference Building Index (NDBI) and a few Biophysical Variables namely Leave Area Index (LAI), Leaf Chlorophyll Content (LCC), Fraction of Vegetation Cover (FCOVER), and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR).

***Normalized Difference Vegetation Index***

The NDVI offers a modest, but effective index for discriminating vegetative areas. It produces discrete components of a vegetative area based on the reflectivity of the near-infrared spectrum of the electromagnetic radiation by plants (Priya et al., 2023). The NDVI was chosen for its effectiveness in discriminating between vegetated and non-vegetated landmasses (Huang et al., 2021). Usually, the NDVI values range from -1 to 1, with negative values close to -1 representing water. The values near zero, usually from -0.1 to 0.1, mostly correspond to infertile sand, rock, or snow areas (Huang et al., 2021). Low, positive values indicate shrubs and grasslands (roughly 0.2 to 0.4), while high values represent temperate and tropical rainforests (close to 1). To compute NDVI, the expression in equation (1) was employed (Huang et al., 2021).

$$NDVI = \frac{(NIR\ band) - (R\ band)}{(NIR\ band) + (R\ band)} \qquad (1)$$

The near-infra-red (NIR) band corresponds to band eight (B8) while the red (R) band corresponds to band four (B4) of the Sentinel-2 MSI Level-2A (equation 2).

$$NDVI = \frac{B8 - B4}{B8 + B4} \qquad (2)$$

***Biophysical Variables***

The Biophysical Variables LAI, LCC, FCOVER, and FAPAR were computed using the Biophysical Processor S2 of the ESA SNAP and R. The processor utilized 8 bands at 20 meters resolution to derive the variables (Djamai et al., 2019). The Biophysical Variables in this study provide means to measure important biophysical properties of vegetation such as leave area, chlorophyll content, and photosynthetic activities of plants. The Biophysical variable LAI is a dimensionless vegetation health indicator often defined as the total surface area of leaves per unit of the ground surface. The variable gives information regarding the amount of leaf material present in a given area, effectively distinguishing vegetation based on density (Akbari et al., 2023). The Biophysical variable LCC measures the chlorophyll content in vegetation and represents an important indicator of plant physiological function (Waldner et al., 2015). FCOVER reveals the portion of the ground surface which is covered by lush vegetation, helping to distinguish non-vegetated areas, built-up areas and forest cover (Akbari et al., 2023). FAPAR measures the effectiveness of vegetation in converting sunlight into biomass, providing insight into vegetation health and productivity (Djamai et al., 2019). These variables are important because they provide insights for understanding vegetation health, particularly for vegetation affected by intense climate change and anthropogenic disturbances such as pollution, forest fires, and deforestation due to urbanization. The relationship between the Biophysical Variables and the NDVI was evaluated to optimize the reliability and robustness of the analysis.

***Normalized Burn Ratio***

The Normalized Burn Ratio (NBR) is used primarily to identify burnt vegetation but can also detect oil spills because the spectral signatures of burnt vegetation are similar to oil slicks in the infrared spectrum (Liu et al., 2023). This index was used to characterize the vegetation because, in addition to oil-induced stressed vegetation, the study area also has several burned vegetation areas caused by fire outbreaks from illegal refineries and sabotage. NBR is calculated from the near-infrared (NIR) and shortwave infrared (SWIR) bands using equation (3) (Liu et al., 2023).

$$NBR = \frac{(NIR\ band) - (SWIR\ band)}{(NIR\ band) + (SWIR\ band)} \qquad (3)$$

In the case of the Sentinel-2 MSI Level-2A data, the near infra-red (NIR) band corresponds to band eight (B8) while the shortwave infrared (SWIR) band corresponds to band eleven (B11) (equation 4)

$$NBR = \frac{B8 - B11}{B8 + B11} \qquad (4)$$

The effectiveness of the NBR is owed to the fact that healthy vegetation strongly reflects the NIR and absorbs SWIR spectra of the electromagnet radiation, whereas burned vegetation reflects less NIR and more SWIR. This results in burnt vegetation areas being characterized by low NBR compared to healthy vegetation areas (Alcaras et al., 2022).

***Normalized Difference Building Index***

The Normalized Difference Building Index (NDBI) is useful for identifying built-up areas (Liang et al., 2023). This index is important because it helps measure the urbanization rate in a given ecological habitat. The assessment of the built-up area and, perhaps, the urbanization is very crucial since they play important roles in monitoring changes in the ecosystem (Yang et al., 2022). The expression in equation (5) is used to compute the NDBI to identify parts of the study area characterized by buildings and related infrastructures (Yang et al., 2022).

$$NDBI = \frac{(SWIR\ band) - (R\ band)}{(SWIR\ band) + (R\ band)} \qquad (5)$$

This is equivalent to equation (6) for Sentinel-2 MSI Level-2A data used in this study.

$$NDBI = \frac{B12 - B4}{B12 + B4} \qquad (6)$$

***Training and Reclassification of Images***

The reclassification of the vegetation into various forest covers namely built-up, inland waters, oil-impacted vegetation, burned area, and healthy vegetation was implemented with machine learning using Maximum Likelihood Supervised Classification (MLSC) (Asad & Bais, 2020; Hagner & Reese, 2007; S. Liang et al., 2020). The reclassification was implemented with NDVI, NDBI, NBR, and the Biophysical Variables. While NDVI, NDBI, and NBR provide spectral information regarding vegetation condition, built-up, and burned areas, the Biophysical Variables offer deeper insights into plant structure and physiological condition. The combination of LAI and NDVI assisted in making confident decisions for distinguishing dense and healthy vegetation from sparse and stressed vegetation. FCOVER and NDBI helped to distinguish sparse vegetation from built-up areas that may look similar in certain spectral bands. LCC and NBR provided improved differentiation of oil spill areas and burned vegetation from healthy vegetation. As such, integrating LAI, LCC, FCOVER, and FAPAR with NDVI, NDBI, and NBR reduced the overlap between classes, assisting the classifier to make more confident decisions regarding the class of each pixel. To train and classify the raster, a training set was created from each raster, based on oil spill areas, burned vegetation, built-up areas, healthy vegetation, and inland waters.

## RESULTS AND DISCUSSION

### Vegetation Health Indicators

The NDVI and the Biophysical Variables namely LAI, LCC, FCOVER, and FAPAR enable the assessment of vegetation health regarding environmental stress and anthropogenic interferences such as oil pollution, oil spill fires, and man-made infrastructures. Figures 6(a), 6(b), 6(c), and 6(d) show the scatter plots of the NDVI against Biophysical Variables. These plots show the relationship between each variable, providing important information regarding vegetation vitality. The NDVI from −0.50 to 0.47 corresponds to low and constant LAI and LCC (Figures 6a and 6b), and beyond 0.47, the NDVI increases, as LAI, and LCC increase. The fact that the NDVI exhibits similar correlation strengths with LAI and LCC indicates that the vegetation's greenness is responding the same way to the leaf area and chlorophyll content. This suggests a change in structural and physiological features such as thinning of the canopy and reduction in chlorophyll production at places. Similarly, Figures 6(c) and 6(d) show scatter plots of the NDVI against FCOVER and FAPAR. The relationship shows a fairly linear change in NDVI as FCOVER and FAPAR changed. The stronger correlation between NDVI, FCOVER and FAPAR emphasizes the extreme sensitivity of the vegetation's greenness to vegetation cover and its ability to absorb sunlight. The low NDVI in specific areas indicates a decline in vegetation density and its ability to absorb sunlight. These further highlight acute stresses on the vegetation that impacted its ability to carry out photosynthesis, leading to a decline in ecosystem efficiency. Figure 7 shows the graph of correlation coefficients between NDVI and each of the LAI, LCC, FCOVER and FAPAR. The graph shows that the NDVI, as an indicator of vegetation health in the study area, is more sensitive to the vegetation density and fraction of light absorbed than the leaf area and chlorophyll content. The result helps highlight the rapid disappearing of vast areas of land originally covered by green vegetation. Table 3 provides statistical analysis for the regression model between NDVI and each of the Biophysical Variables, highlighting the significance of the NDVI and the Biophysical Variables for monitoring the ecosystem in the study area.

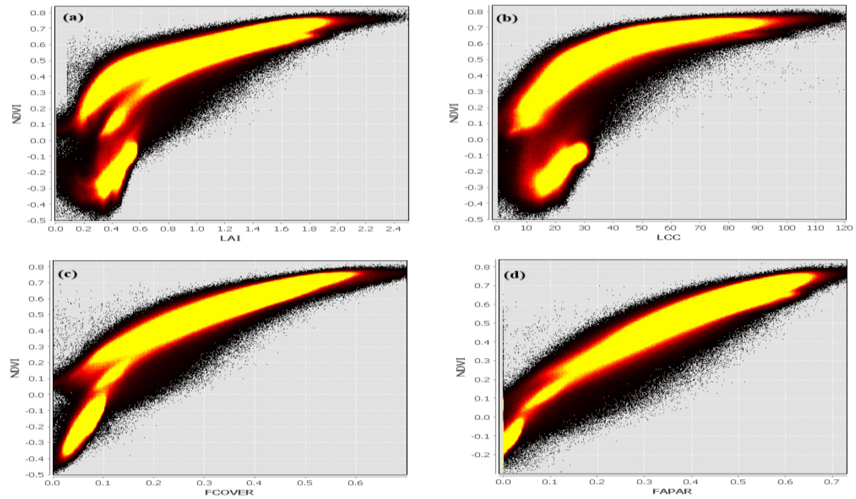


Figure 6: Sentinel-2 MSILevel-2A data of the Niger Delta area showing Scatter plot of NDVI against (a) LAI (b) LCC (c) FCOVER (d) FAPAR

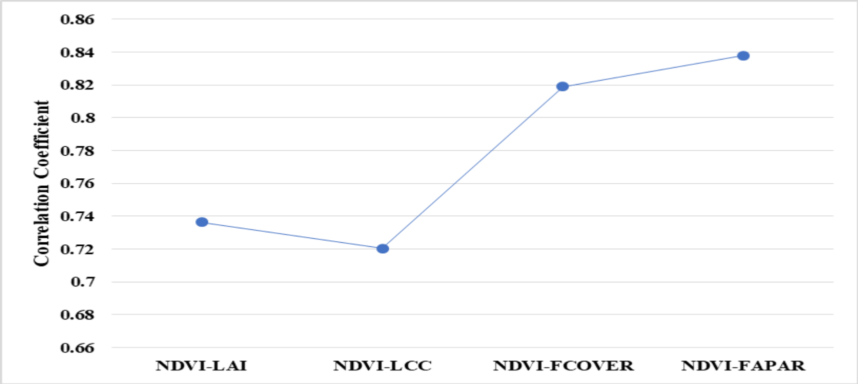


Figure 7: A Graph showing the Correlation Coefficients between NDVI and each of LAI, LCC, FCOVER and FAPAR

**Table 3: Statistical Parameters for the Regression Model between NDVI and the Biophysical Variables**

| Statistical Analysis | NDVI VS LAI | NDVI VS LCC | NDVI VS FCOVER | NDVI VS FAPAR |
|---|---|---|---|---|
| Corr. Coef. | 0.7365 | 0.7205 | 0.8191 | 0.8380 |
| Gradient | 0.4342 | 0.0081 | 1.4474 | 1.1864 |
| Intercept | -0.0627 | -0.0253 | -0.0578 | -0.0160 |
| Multiple R | 0.7365 | 0.7205 | 0.8191 | 0.8380 |
| $R^2$ | 0.5425 | 0.5191 | 0.6710 | 0.7023 |
| Adjusted $R^2$ | 0.5425 | 0.5190 | 0.6710 | 0.7023 |
| Stand. Error | 0.2197 | 0.2377 | 0.1731 | 0.1525 |
| P-Value | 0 | 0 | 0 | 0 |
| Significance F | 0 | 0 | 0 | 0 |

Correlation coefficient (r), multiple regression (R), coefficient of determination ($R^2$), adjusted$R^2$, standard error (S.E), probability value (P-value), and significance-F

**Vegetation Health Assessment**

The NDVI satellite imagery in this study provides original insights into the vegetation health distribution across the Niger Delta coastal area (Figure 8). The canopy areas exhibit NDVI values between 0.62 and 0.72, grasslands between 0.47 and 0.61, and non-vegetated land, including burned areas have values ranging from 0.06 to 0.46. On the other hand, freshwater bodies exhibit negative values of the NDVI. Notably, high NDVI values indicate healthy vegetation, whereas, lower values signify stressed and non-vegetated areas. The machine learning MLSC shows different land covers and the area occupied by each in percentage (Figure 9). Built-up areas, consisting of all man-made structures occupy approximately 12% of the total area. Non-vegetated land, including burned areas, covers 21%. Grasslands occupy 33%, encompassing both healthy and stressed grasslands. Canopy, including tall trees and shrubs, covers 30% of the area, while freshwater bodies constitute about 5% of the study area. The geolocation of the oil spillage data on the NDVI image shows that the cleanup and remediation effort in the Niger Delta is yielding positive results in certain areas, while also highlighting little or no improvement in other areas. The mangroves, in particular, have shown no improvement in vegetation regeneration. This may be attributed to the incessant fire outbreaks resulting from the illegal refineries that are prevalent in the mangroves. Although the NDVI successfully identified different vegetation types such as grassland and canopy, it was incapable of distinguishing stressed vegetation. Additionally, there is the possibility of overlap between built-up and non-vegetated areas, which may have contributed to misclassification.

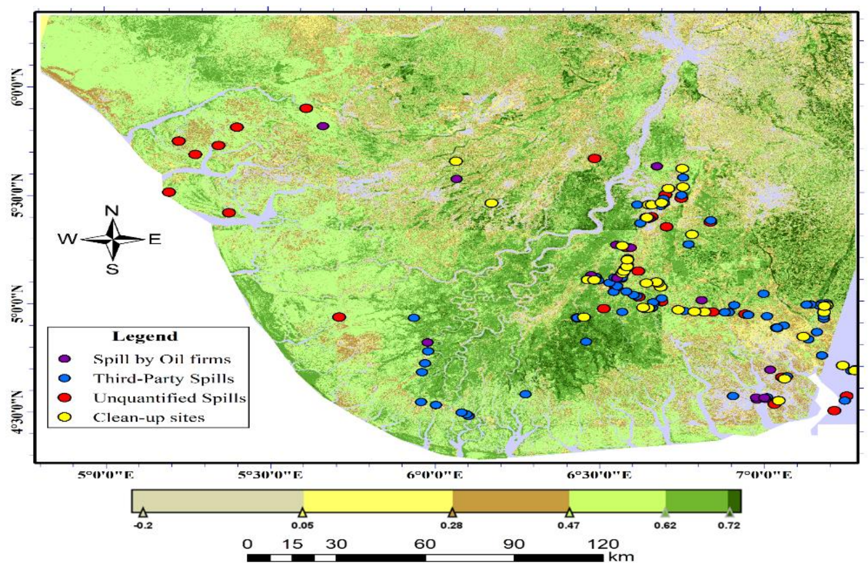


Figure 8: NDVI map derived from Sentinel-2 MSI Level-2A across the Niger Delta. The map shows the locations of all the spill sites including cleaned-up areas between January 2020 and January 2024

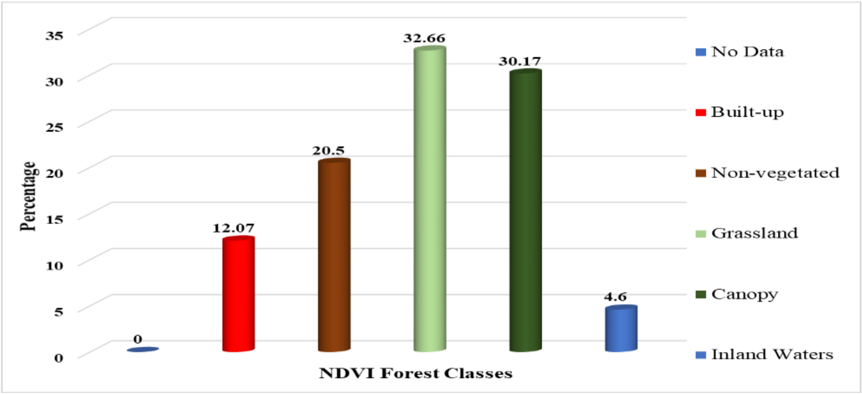


Figure 9: NDVI reclassification derived from Sentinel-2 MSI Level-2A across the Niger Delta

**Multi-Raster Land Cover Reclassification**

To address misclassification resulting from insufficient training samples, the NDVI was complemented with NDBI, NBR, LAI, LCC, FCOVER, and FAPAR to classify the land cover accurately. Figures 10(a), 10(b), 10(c) and 10(d) show evenly tiled images of a location within the northern study area highlighting distinct land cover classes, namely freshwater, vegetated, stressed vegetation resulting from oil pollution, and non-vegetated including built-up and burned vegetation. The images include Normalized Burn Ratio (NBR) (Figure 10a), True Color Composite (TCC) (Figure 10b), Normalized Difference Vegetation Index (NDVI) (Figure 10c) and a Multi-Raster Reclassified Image (MRRI) (Figure 10d). The results of the machine learning reclassification, in this case, provide more reliable land cover categories. Built-up areas account for approximately 19% of the total area. The oil-induced stressed vegetation and the non-vegetated areas including burned areas amount to 31% of the study area. Healthy vegetation, including grasslands and canopy, occupy 45%, while freshwater bodies constitute about 6% of the study area (Figure 11). The land cover reclassification from the integration of the aforementioned raster, therefore, provides the basis for quantifying the damage to the natural ecosystem by human activities.

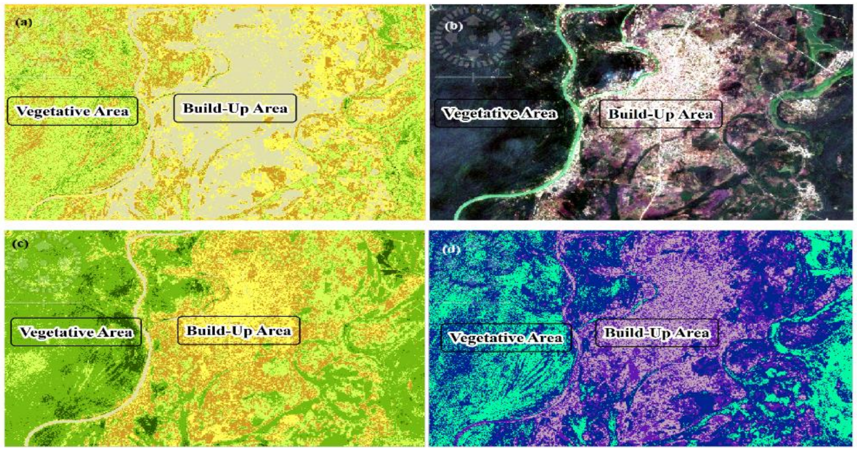


Figure 10: An evenly-tiled map of a small location in the northern study area showing different landcover classes notably built-up and vegetative areas with (a) NBR (b) TCC (c) NDVI (d) MRRI

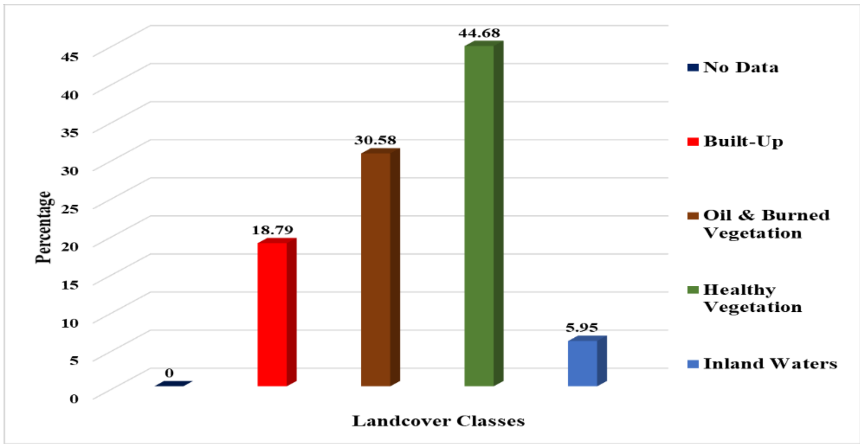


Figure 11: Multi-raster reclassification derived from Sentinel-2 MSI Level-2A across the Niger Delta.

**Discussion**

The assessment of the Niger Delta Coastal area using oil spillage incident data and Sentinel-2 MSI Level-2A imagery has provided critical insights into the state of the vegetation, land cover, and environmental degradation. Although the lack of Sentinel-2 MSI level-2A imagery spanning the entire Niger Delta for each year did restrict the ability to measure year-by-year time series vegetation variability, the results, nevertheless, highlighted the profound impact of human activities, particularly, oil pollution, oil-induced fires, and urbanization on the ecosystem in the region. The oil-spillage data from NOSDRA (Figure 3) confirmed the prevalence of oil spillage in the Niger Delta area with sabotage and theft accounting for 85% of the total spillage incidences (Figures 3 and 4). This correlates with the extensive areas of non-vegetated and stressed vegetation observed in the Sentinel-2 MSI Level-2A imageries within the mangroves, indicating a strong association between oil pollution and loss of vitality in the area. The NDVI and the Biophysical Variables consistently reveal impacted vegetation areas including stressed vegetation and non-vegetated landmasses (Figures 6a, 6b, 6c, 6d,). The reduction in NDVI and FCOVER values in specific areas reflects the diminished photosynthetic activity of the stressed vegetation, which corresponds to low LAI, LCC, and FAPAR values (Figure 7). The results show that oil spills have degraded the natural habitat in the Niger Delta area, reducing the ability of the vegetation to regenerate and support biodiversity despite the clean-up and remediation efforts in the area (Figure 8).

In addition to oil spills, the region has experienced many fire outbreaks, caused mainly by illegal oil refineries and pipeline sabotage. The NBR used to detect burned vegetation revealed significant areas of the vegetation destroyed by oil-related fires (about 31% together with oil spill areas), further worsening the environmental crisis in the Niger Delta area (Figure 9). The spectral similarity between burnt vegetation and oil slicks allows the detection of burnt vegetation and oil spill areas with NBR.

The integration of the NDVI, LAI, LCC, FCOVER, and FAPAR with NBR further facilitated a distinct classification of the vegetation into healthy (45%) and stressed vegetation (about 31% together with burned areas) (Figures 10 and 11). The fires not only destroy the vegetation but may equally have released carbon stored in plants into the atmosphere, contributing to climate change.

Finally, the NDBI provides a complementary standpoint on the impact of urbanization in the Niger Delta area, aiding the reclassification of the land cover into the built-up areas that account for 19% of the total area (Figures 10 and 11). This indicates possible expansion of the urban areas, often at the expense of the natural ecosystems. The increasing built-up which also signifies an increase in these number of industries such as oil firms encourages the release of greenhouse agents such as carbon dioxide into the atmosphere.

## CONCLUSION

The increasing occurrence of oil spills, forest fires, and expansion of built-up areas has resulted in significant degradation of the lush canopy, grasslands, and wetland ecosystems of the Niger Delta coastal area. This study demonstrates the effectiveness of integrating oil spill inventory data with Sentinel-2 MSI Level-2A imagery to assess vegetation health and quantify the impacts of multiple anthropogenic stressors using vegetation biophysical indicators. Unlike studies that focus primarily on mapping oil spill extent, this research provides a comprehensive ecosystem-based assessment by evaluating the cumulative effects of oil spills, fire, and urban expansion on vegetation condition. This represents a valuable contribution to environmental monitoring in the Niger Delta by establishing a remote sensing framework for detecting and assessing multiple anthropogenic disturbances simultaneously.

The findings reveal widespread vegetation degradation, declining ecosystem health, and extensive areas with little or no vegetation cover, highlighting the growing threat to the ecological sustainability of the Niger Delta coastal environment. These results underscore the urgent need for stronger environmental regulations, improved oil spill prevention and response strategies, effective fire management, and sustainable land-use planning. Ecosystem restoration through reforestation, wetland conservation, carbon sequestration initiatives, and continuous vegetation monitoring should be prioritized to enhance ecosystem resilience.

Future research should integrate multi-temporal Sentinel-1 and Sentinel-2 datasets with advanced machine learning and artificial intelligence techniques to improve the detection, monitoring, and prediction of anthropogenic stressors. Further studies should also incorporate climate variables, field-based validation, biodiversity assessments, and socioeconomic data to better understand the long-term ecological consequences of human activities and support evidence-based environmental management and policy development in the Niger Delta.

## REFERENCES


Adamu, B., Tansey, K., & Ogutu, B. (2018). Synergistic application of Sentinel-1 and Sentinel-2 derivatives for terrestrial oil spill impact mapping. ResearchGate/Remote Sensing Letters. https://www.researchgate.net/publication/32908007

Afgatiani, P. M., Putri, F. A., Suhadha, A. G., & Ibrahim, A. (2020). Determination of Sentinel-2 spectral reflectance to detect oil spill on the sea surface. Sustinere: Journal of Environment and Sustainability, 4(3), 144–154. https://doi.org/10.22515/sustinere.jes.v4i3.115

Akbari, E., Boloorani, A. D., Verrelst, J., Pignatti, S., Neysani Samany, N., Soufizadeh, S., & Hamzeh, S. (2023). Biophysical Variable Retrieval of Silage Maize with Gaussian Process Regression and Hyperparameter Optimization Algorithms. Remote Sensing, 15(14). https://doi.org/10.3390/rs15143690

Alcaras, E., Costantino, D., Guastaferro, F., Parente, C., & Pepe, M. (2022). Normalized Burn Ratio plus (NBR+): A New Index for Sentinel-2 Imagery. Remote Sensing, 14(7). https://doi.org/10.3390/rs14071727

Asad, M. H., & Bais, A. (2020). Weed detection in canola fields using maximum likelihood classification and deep convolutional neural network. Information Processing in Agriculture, 7(4). https://doi.org/10.1016/j.inpa.2019.12.002

Barbache, A., Beghami, Y., & Benmessaoud, H. (2018). Study and diachronic analysis of forest cover changes of Belezma-Algeria. Geographica Pannonica, 22(4). https://doi.org/10.5937/gp22-18806

Bentsi-Enchill, F., Damptey, F. G., Pappoe, A. N. M., Ekumah, B., & Akotoye, H. K. (2022). Impact of anthropogenic disturbance on tree species diversity, vegetation structure and carbon storage potential in an upland evergreen forest of Ghana, West Africa. Trees, Forests and People, 8. https://doi.org/10.1016/j.tfp.2022.100238

Clere, I. K., Ahmmed, F., Remoto, P. I. J. G., Fraser-Miller, S. J., Gordon, K. C., Komyakova, V., & Allan, B. J. M. (2022). Quantification and characterization of microplastics in commercial fish from southern New Zealand. Marine Pollution Bulletin, 184. https://doi.org/10.1016/j.marpolbul.2022.114121

Dai, X., Wang, Y., Li, X., Wang, K., Zhou, J., & Ni, H. (2023). Effects of Temporal and Spatial Changes in Wetlands on Regional Carbon Storage in the Naoli River Basin, Sanjiang Plain, China. Land, 12(7). https://doi.org/10.3390/land12071300

Djamai, N., Zhong, D., Fernandes, R., & Zhou, F. (2019). Evaluation of vegetation biophysical variables time series derived from synthetic Sentinel-2 images. Remote Sensing, 11(13). https://doi.org/10.3390/rs11131547

Echendu, A. J., Okafor, H. F., & Iyiola, O. (2022). Air Pollution, Climate Change and Ecosystem Health in the Niger Delta. In Social Sciences (Vol. 11, Issue 11). https://doi.org/10.3390/socsci11110525

Fan, C., Hou, X., Zheng, Q., Xu, H., Li, D., Donnici, S., & Tang, C. (2023). Emerging signals of coastal system changes under rapid anthropogenic disturbance in Hangzhou Bay, China. Ecological Indicators, 146. https://doi.org/10.1016/j.ecolind.2022.109816

Haack, R. C., Sundararaman, P., Diedjomahor, J. O., Xiao, H., Gant, N. J., May, E. D., & Kelsch, K. (2000). Niger delta petroleum systems, Nigeria. AAPG Memoir, 73. https://doi.org/10.1306/m73705c16

Hagner, O., & Reese, H. (2007). A method for calibrated maximum likelihood classification of forest types. Remote Sensing of Environment, 110(4). https://doi.org/10.1016/j.rse.2006.08.017

Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. In Journal of Forestry Research (Vol. 32, Issue 1). https://doi.org/10.1007/s11676-020-01155-1

Kuye, D. A., & Hampson, G. J. (2023). Sedimentological and tectono-stratigraphic characterisation of a shallow-marine reservoir, 'Dona' field, offshore Niger Delta. Marine and Petroleum Geology, 158. https://doi.org/10.1016/j.marpetgeo.2023.106517

Lassalle, G., Credoz, A., Hédacq, R., Bertoni, G., Dubucq, D., Fabre, S., & Elger, A. (2019). Estimating persistent oil contamination in tropical region using vegetation indices and random forest regression. Ecotoxicology and Environmental Safety, 184. https://doi.org/10.1016/j.ecoenv.2019.109654

Liang, M., Zhang, L., Wu, S., Zhu, Y., Dai, Z., Wang, Y., Qi, J., Chen, Y., & Du, Z. (2023). A High-Resolution Land Surface Temperature Downscaling Method Based on Geographically Weighted Neural Network Regression. Remote Sensing, 15(7). https://doi.org/10.3390/rs15071740

Liang, S., Cheng, J., & Zhang, J. (2020). Maximum likelihood classification of soil remote sensing image based on deep learning. Earth Sciences Research Journal, 24(3). https://doi.org/10.15446/esrj.v24n3.89750

Liu, P., Liu, Y., Guo, X., Zhao, W., Wu, H., & Xu, W. (2023). Burned area detection and mapping using time series Sentinel-2 multispectral images. Remote Sensing of Environment, 296. https://doi.org/10.1016/j.rse.2023.113753

Mashala, M. J., Dube, T., Mudereri, B. T., Ayisi, K. K., & Ramudzuli, M. R. (2023). A Systematic Review on Advancements in Remote Sensing for Assessing and Monitoring Land Use and Land Cover Changes Impacts on Surface Water Resources in Semi-Arid Tropical Environments. In Remote Sensing (Vol. 15, Issue 16). https://doi.org/10.3390/rs15163926

Nahlik, A. M., & Fennessy, M. S. (2016). Carbon storage in US wetlands. Nature Communications, 7. https://doi.org/10.1038/ncomms13835

Ozigis, M. S., Kaduk, J. D., & Jarvis, C. H. (2019). Mapping terrestrial oil spill impact using machine learning random forest and Landsat 8 OLI imagery: a case site within the Niger Delta region of Nigeria. Environmental Science and Pollution Research, 26(4), 3621–3635. https://doi.org/10.1007/s11356-018-3824-y

Ozigis, M. S., Kaduk, J. D., Jarvis, C. H., da Conceição Bispo, P., & Balzter, H. (2020). Detection of oil pollution impacts on vegetation using multifrequency SAR, multispectral images with fuzzy forest and random forest methods. Environmental Pollution, 256. https://doi.org/10.1016/j.envpol.2019.113360

Priya, M. V., Kalpana, R., Pazhanivelan, S., Kumaraperumal, R., Ragunath, K. P., Vanitha, G., Nihar, A., Prajesh, P. J., & Vasumathi, V. (2023). Monitoring vegetation dynamics using mulsti-temporal Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) images of Tamil Nadu. Journal of Applied and Natural Science, 15(3). https://doi.org/10.31018/jans.v15i3.4803

Waldner, F., Lambert, M. J., Li, W., Weiss, M., Demarez, V., Morin, D., Marais-Sicre, C., Hagolle, O., Baret, F., & Defourny, P. (2015). Land cover and crop type classification along the season based on biophysical variables retrieved from multi-sensor high-resolution time series. Remote Sensing, 7(8). https://doi.org/10.3390/rs70810400

Yang, J., Alahmadi, K. M., & Shirowzhan, S. (2022). The impact of urban expansion in Beijing and Metropolitan Area urban heat Island from 1999 to 2019. Applied Mathematics and Nonlinear Sciences, 7(2). https://doi.org/10.2478/amns.2021.1.00104

Zhu, Z., Qiu, S., & Ye, S. (2022). Remote sensing of land change: A multifaceted perspective. In Remote Sensing of Environment s(Vol. 282). https://doi.org/10.1016/j.rse.2022