Monitoring and Managing Oil Spillage and Environmental Degradation through Geoinformation

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Abstract

The Niger Delta region of Nigeria is a major oil-producing area which experiences frequent oil spills which severely impacts the local environment and communities. Effective environmental monitoring and management remain inadequate in this area due to negligence, slow response times following oil spills, and difficulties regarding access and safety. This thesis investigates the pervasive issue of oil spills in the Niger Delta region, employing a multidisciplinary approach to provide insight into their spatiotemporal patterns, environmental impacts, and socio-economic consequences on local communities. The research integrates advanced geospatial techniques, remote sensing analysis, and community-based participatory methods to provide a framework for oil spill impact assessment and quantification. Utilising the spNetwork package in R, Network Kernel Density Estimates (NKDE) and Temporal Network Kernel Density Estimates (TNKDE) were employed to analyse oil spill patterns along the pipeline network. By transforming pipeline data into 500-metre lixels (linear pixels), this network-based approach uncovered chronically high-risk oil spill hotspots zones and tracked their temporal evolution, thereby offering a vital evidence base for targeted intervention and remediation. This method surpasses traditional spatial analyses by incorporating network constraints and revealing critical spatiotemporal patterns where spills recur over time.

Furthermore**,** a remote sensing approach was developed, leveraging geospatial cloud computing and machine learning to evaluate vegetation health indices (SR1, SR2, NDVI, EVI2, GRNDVI, GNDVI). These indices were analysed using Slow Moving Average (SMA) regression, which revealed significant declines in vegetation health following oil spill events. The contaminated landcovers exhibit a Spearman's correlation coefficient *(ρ)* ranging from -0.68 to -0.82, $p < 0.005$ and P-values below 0.05 in most landcover categories, suggesting a clear and consistent downward trend in the indices' values, reflecting a decrease in vegetation health in contaminated areas between 2016 and 2023. A Random Forest (RF) classifier further quantified the extent of contaminated land cover, demonstrating the effectiveness of this method for monitoring environmental damage in this challenging terrain. The classifier revealed that landcovers, including contaminated vegetation, wetland, farmland, and grassland cover approximately 4% (1,180 hectares) of the total area. Conversely, the non-contaminated prioritised landcovers (non-contaminated vegetation, wetland, farmland, and grassland) account for 96% (32,215 hectares) of the total landcover area.

Qualitative methods, specifically structured Focus Group Discussions (FGDs) and Community Participatory Mapping Exercises (CPME), were conducted in six affected communities. This analysis revealed the lived realities of oil spill-impacted communities. Participants highlighted severe health consequences (including cancer, respiratory issues, and heightened infant mortality), declines in agricultural productivity, and the depletion of critical fisheries, compounding socio-economic hardships and undermining food security. These findings align with broader assessments of hydrocarbon exposure risks and underscore the immediate need for enhanced cleanup measures and sustainable restoration policies. The research also navigated significant logistical and ethical challenges. Initially designed for in-person data collection, the study adapted to a "distanciated" approach due to the UK Foreign, Commonwealth, and Development Office's "essential travel only" designation for the Niger Delta. Collaboration with experienced data collectors from the National Bureau of Statistics (NBS) in Nigeria was established, highlighting ethical considerations in research design and practice under challenging circumstances.

Overall, this thesis contributes to the understanding of oil spill impacts in the Niger Delta through its methodological approach and findings. It offers a framework for improved environmental monitoring and management, emphasising the need for targeted interventions and highlighting the importance of integrating local knowledge and community participation in addressing environmental crises. Furthermore, it contributes to broader discussions on ethical research practices and the adaptation of research designs in challenging field settings.

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Dedication

This work is dedicated to God. For without Him, I am nothing and can do nothing.

Authors Declaration

I declare that this thesis is my own work, unless otherwise cited or recognised. This thesis has not been submitted for any degree at the University of Glasgow or any other Institution. Unless otherwise noted, the views, ideas and opinions stated here are mine.

Seyi Adewale Adebangbe

2025

List of Acronyms

ARVI2: Adjusted Resistant Vegetation Index 2

BMVIs: Broadband Multispectral Vegetation Indices

CDV: Contaminated Dense Vegetation

CFL: Contaminated Farmland

CGL: Contaminated Grassland

CPME: Community Participatory Mapping Exercises

CVI: Chlorophyll Vegetation Index

CWL: Contaminated Wetland

EVI: Enhanced Vegetation Index

EVI2: Enhanced Vegetation Index 2

FGDs: Focus Group Discussions

G/NIR: Green/Near-Infrared Ratio

G/SWIR: Green/Shortwave Infrared Ratio

GCVI: Green Chlorophyll Vegetation Index

GEE: Google Earth Engine

GNDVI: Green Normalized Difference Vegetation Index

GOSAVI: Green Optimized Soil Adjusted Vegetation Index

GRNDVI: Green-Red Normalized Difference Vegetation Index

HTML: HyperText Markup Language

JM: Jeffries-Matusita Distance

KDE: Kernel Density Estimation

LAI: Leaf Area Index

LAD: Leaf Area Density

LGA: Local Government Area

LSTM: Long Short-Term Memory

LULC: Land Use and Land Cover

MDWI: Modified Difference Water Index

NBS: National Bureau of Statistics

NDV: Non-Contaminated Dense Vegetation

NDVI: Normalized Difference Vegetation Index

NDWI: Normalized Difference Water Index

NEITI: Nigeria Extractive Industries Transparency Initiative

NFL: Non-Contaminated Farmland
NGL: Non-Contaminated Grassland
NIR: Near-Infrared
NKDE: Network Kernel Density Estimates
NNPC: Nigerian National Petroleum Corporation
NOSDRA: National Oil Spill Detection and Response Agency
NUPRC: Nigerian Upstream Petroleum Regulatory Commission
NWL: Non-Contaminated Wetland
OPEC: Organization of the Petroleum Exporting Countries
RF: Random Forest
SAR: Synthetic Aperture Radar
SAVI: Soil-Adjusted Vegetation Index
SMA: Slow Moving Average
SR: Simple Ratio
SR2: Simple Ratio (800 and 550 nm)
SWI: Snow Water Index
TNKDE: Temporal Network Kernel Density Estimates
UAVs: Unmanned Aerial Vehicles
UNEP: United Nations Environment Programme
UN/ISDR: United Nations International Strategy for Disaster Reduction
UTM: Universal Transverse Mercator
VHIs: Vegetation Health Indices
VIs: Vegetation Indices
WHO: World Health Organization

Chapter One

1. Introduction

Oil spills are complex disasters globally with far-reaching impacts on the environment, human health, and economies. Oil spill, characterized by the release of liquid petroleum hydrocarbons into the environment, present significant ecological and societal challenges predominantly caused by human activities within the oil industry's infrastructure(UNDRR, n.d.; United Nation, n.d.).These incidents, affecting marine, freshwater, and terrestrial ecosystems, have both immediate and long-term consequences for natural environments and human populations (NASA, n.d.; United Nation, n.d.). The increasing scale of offshore oil drilling and the extensive global transport of oil have unfortunately contributed to a rise in the frequency and severity of human-induced oil spills, underscoring the urgency of addressing this complex issue (Albert et al., 2019; Dong & Lu, 2022). It is important to note that approximately 90% of oil spills are attributable to human actions rather than natural phenomena (Dong & Lu, 2022).

The global history of oil exploration is unfortunately punctuated by numerous significant oil spill disasters that have left lasting environmental and social consequences (UNDRR, n.d.). This is exemplified by the severe and recurring oil pollution in the Niger Delta region, largely stemming from pipeline problems (6). Notable historical incidents such as the 1969 Santa Barbara Channel blowout (Morgan et al., 2014), the 1977 Ekofisk Bravo spill (Oil Rig Disasters, n.d.), the 1983 Persian Gulf releases (Morgan et al., 2014), the 1979 IXTOC blowout (Morgan et al., 2014), the massive 1991 Persian Gulf Oil Spill (Mclean Jessica, 2024), and the 2010 Deepwater Horizon disaster (Morgan et al., 2014; NASA, n.d.; Ritchie et al., 2022), alongside major spills off the coasts of South Africa (Castillo de Bellver, 1983) and Angola (ABT Summer, 1991), and a significant land-based spill in Russia (Kovla River Pipeline Leak, 1994), underscore the potential for catastrophic environmental degradation. The Niger Delta's ongoing struggle with oil pollution thus reflects a global pattern of environmental devastation caused by oil spills, highlighting the urgent need for effective prevention and remediation strategies worldwide.

The Niger Delta region of Nigeria, situated in the southern part of the country, is home to Africa's largest reserves of oil and gas. Spanning approximately 70,000 square kilometres, the Delta covers nine states and is one of the world's most ecologically diverse wetland areas. Rich in resources, it includes dense forests, freshwater swamps, and extensive mangrove ecosystems that support a wealth of biodiversity. The region has become synonymous with environmental degradation, socioeconomic hardship, and political instability. The Niger Delta’s wealth of oil and gas has turned it into a critical area for the Nigerian economy, while paradoxically creating extensive environmental and social challenges for its residents. Nigeria's oil and gas resources are essential to its economy, accounting for about two-thirds of government revenue and around 90% of foreign exchange earnings (Bala-Gbogbo, 2024; Okoli, 2016). As the primary export commodity, oil significantly shapes the nation's development trajectory. The Niger Delta, therefore, is not just a regional asset but a national one, vital to the nation's economy and energy security. However, the vast benefits derived from this natural wealth are not equally distributed, and communities within the Delta often bear the burden of the industry's adverse effects while receiving few of its benefits. This has created a paradox where the region that fuels Nigeria's prosperity also faces severe poverty, with limited access to quality healthcare, education, and infrastructure. Oil production in the Niger Delta began in the colonial era, and since then, the industry has introduced complex layers of inequality and environmental degradation. Oil exploration and extraction have resulted in a litany of environmental challenges for communities, including frequent oil spills, loss of biodiversity, erosion, flooding, gas flaring, air and noise pollution, contamination of water sources, soil fertility depletion, and deforestation (Kpae, 2020; Lindén & Pålsson, 2013; Obida et al., 2021; Ukhurebor et al., 2021). These challenges have compounded over the decades, impacting local agriculture, fishing, and overall quality of life. Oil spills, in particular, have become emblematic of the environmental degradation that the Delta has suffered. As a result, local communities have raised concerns about the industry, expressing awareness, resistance, and at times fear of speaking out due to potential repercussions (Nwajiaku, 2005).

Oil spills in the Niger Delta are not merely environmental incidents; they reflect broader socio-political tensions and inequities. Studies have shown that the majority of oil spills in the Delta result from pipeline vandalism, where pipelines are deliberately damaged to steal oil, a practice known locally as "oil bunkering" (Sanusi et al., 2016; Tukur & Hajj, 2017). Beyond the immediate economic loss, these spills have long-lasting impacts on the environment. Oil spills can poison water bodies, disrupt food supplies, contaminate soil, destroy vegetation, and diminish the quality of air. Moreover, the environmental impact of spills is compounded by inadequate cleanup efforts, which leaves communities with polluted land and waterways for years, if not decades.

The relationship between oil companies and the communities in the Niger Delta is complicated by unequal power dynamics. Oil companies often work closely with government agencies and security forces to protect their interests, a collaboration that has sometimes led to the suppression of local dissent (Nwajiaku, 2005). Community dissatisfaction with state governance has prompted many affected communities to seek justice through legal avenues. Recent cases, such as those brought by the Ogale and Bille communities, highlight the determination of local groups to hold oil companies accountable. In one landmark case, the Court of Appeals in The Hague ruled that Shell could be held liable for the environmental damage caused by its Nigerian subsidiary, setting an important precedent for corporate accountability (Aljazeera, 2023; Business & Human Right Resources Centre, 2021; Laville, 2023).

Despite the Nigerian government's heavy reliance on petroleum, the economic and environmental costs of oil production are immense. Pipeline vandalism alone costs Nigeria billions in lost revenue. According to the Nigeria Extractive Industries Transparency Initiative (NEITI), oil theft, pipeline vandalism, and operational lapses lead to daily losses of approximately $11 million, amounting to around $4.2 billion annually (Okafor, 2019). The cumulative impact of these issues on the Nigerian economy is staggering, affecting both national finances and the livelihoods of those in oil-producing regions. Environmental degradation, in particular, imposes significant costs on local communities, often creating conflicts between local groups, governmental authorities, and oil companies.

The toll on the environment is severe and ongoing. From 2010 to 2018, nearly 170,000 barrels of oil were spilled in the Niger Delta (Ikporukpo, 2020a). Akinpelu (2021) further stated that a total of 1,161 pipeline points were vandalized across Nigeria during the 21 months from January 2019 to September 2020. Elaborating on the impacts on the environment and people; Ipingbemi (2009) and Lindén & Pålsson (2013) indicate that pipelines in the Niger Delta are often situated near farmland and sometimes even cross water bodies that supply drinking water to rural communities. Consequently, these spills have directly polluted essential water sources and crops, leading to illness among many residents of the Niger Delta and contributing to rising infant mortality rates (Onuoha, 2007, 2009). These spills are detrimental to the Delta's ecosystems, which are essential for the subsistence of local communities. Contaminated water and soil make it difficult for residents to engage in traditional economic activities, such as fishing and farming, and lead to health issues like respiratory problems and skin diseases. In many cases, spills also reduce the availability of potable water, directly impacting the health and well-being of the population. Additionally, the destruction of habitats from oil spills leads to a loss of biodiversity, affecting both terrestrial and aquatic species. (Amnesty International, 2015; Aroh et al., 2010; Obi, 2023; Ogeleka et al., 2017).

The environmental damage resulting from these spills is often long-lasting and challenging to remediate (Amnesty International, 2013; Eke, 2016; UNEP, 2011). Ultimately, oil spills have been linked to numerous detrimental effects on the environment (Onyango, 2021; Sanusi et al., 2016; Umar et al., 2021). The Niger Delta's history of oil spills has also contributed to social unrest. The activities of militant groups, local activists, and criminal networks have often centered around resource control and economic justice. Militant groups in the region have emerged as significant actors, with some engaging in acts of sabotage against oil infrastructure as a form of protest (Nwajiaku, 2005). These groups claim to represent the interests of local communities, although some authors argue that their actions are often motivated by personal gain rather than communal benefit (Albert et al., 2019; Koos & Pierskalla, 2016; Okoli, 2019; Uchechukwu et al., 2017). Nonetheless, the persistence of violence in the region underscores the deep-seated grievances among the local populace regarding their marginalisation from the wealth generated by oil extraction.

The increasing frequency and severity of oil spills in the Niger Delta have drawn considerable attention from academics, policymakers, and international organizations (Babatunde, 2020; Muhammad et al., 2024; Olukaejire et al., 2024; Wekpe et al., 2024). Despite this attention, there remains a significant gap in understanding the nexus between oil spills, environmental degradation, and community perspectives. While numerous studies have examined the environmental impact of oil spills, fewer have delved into the role of community intelligence and local experiences in understanding and addressing these challenges. This gap highlights the need for a more situated approach that incorporates local perspectives and geospatial technology to monitor, manage, and mitigate the impacts of oil spills. This study seeks to bridge this gap by examining the relationship between oil spills and environmental degradation in the Niger Delta, with a particular focus on community perspectives. Using geoinformation systems, the research quantifies the effects of oil spills and explores sustainable strategies for managing and monitoring these incidents. In doing so, it addresses not only the environmental implications of oil spills but also the broader social, economic, and political issues that frame this ongoing crisis. Furthermore, by focusing on community voices, this study seeks to amplify the experiences of those most affected by oil production, offering a holistic understanding of the challenges and potential solutions.

In what follows, an overview of Nigeria's longstanding challenges is presented, focusing on the interconnected issues of security, the environment, politics, and economics in relation to oil production in the Niger Delta. This overview is followed by a presentation of the thesis's aim, objectives, and research questions. The discussion then shifts to the Niger Delta region, examining its constituent states and demographic and geographical characteristics. The scope of the study and the rationale for selecting specific areas are also addressed, including details on the three prioritized states and the chosen fieldwork locations. Finally, the chapter concludes by outlining the thesis structure, thereby establishing the framework for the entire study.

1.1 Problem Statement

A 'Problematic' Region

Nigeria as a federation grapples with long-standing political challenges, giving rise to a complex interweaving of security, political, environmental and economic crises. Factors such as land grabs and exploitative labour, governance issues, corruption, poverty, and unemployment all feed into social and political conflict (Koos & Pierskalla, 2016). Communities are faced with escalating insecurity on multiple fronts, including banditry in the north-west, the presence of jihadist groups such as Boko Haram in the north-east, violent conflicts between farmers and pastoralists in the expansive "middle belt," secession agitations in the Southeast, gang wars in the Southwest, and environmental justice protests met with violence in the South-south (Niger Delta) where the oil and gas industries operate (Albert et al., 2018; Beaumont, 2021; Nextier, 2022).

The history of oil production in Nigeria is marked by conflicting accounts and multiple initiation dates. Steyn (2009) notes that formal exploration began in 1903 by Nigeria Properties (Limited) and Nigeria and West African Development Syndicate (Limited) for bitumen, coal, and oil. The Nigerian National Petroleum Corporation (NNPC, n.d.) asserts that the search for oil commenced in 1908 through the Nigerian Bitumen Corporation and British Colonial Petroleum. According to Steyn (2009), in 1930 D'Arcy Exploration and Anglo-Saxon Petroleum (later Shell) began exploration, discovering oil in Oloibiri (Niger Delta) in 1956.

Steyn (2009) reports further discoveries in Afam and Bomu (both in the Niger Delta) by 1958. Nigeria joined the oil-producing nations in 1958, with the first field producing 5,100 barrel per day (bpd), and joined the Organization of the Petroleum Exporting Countries (OPEC) in 1971. As of 2023, Nigeria's oil industry has seen a significant decline in production by 37% compared to 2012, attributed to various factors including reduced international investor interest, challenges with oil theft, aging infrastructure, and security-related disruptions, despite its status as the world's ninth-largest holder of natural gas reserves and tenth-largest for crude oil (Eboh, 2023; EIA, 2023).

Niger Delta communities thus bear the brunt of the impact of oil exploration and production (Ikporukpo, 2020; Okotie et al., 2018). Historical records from the 1970s reveal extensive oil spills and environmental damage caused by oil production, notably the incident at Shell's Bomu oil well in Boobanabe; forty-five years later observations by Amnesty International researchers depict lingering environmental degradation (Amnesty International, 2015; Saint, 2022). Ikporukpo (1983) revealed the awareness among petroleum-producing communities regarding pollution and underscored the significance of displacement without resettlement and property destruction without compensation. In 1987, the use of the Mobile Police Force to suppress a demonstration in Iko against Shell resulted in fatalities (Rowell, 1995). The 1990s marked a significant escalation in struggles, as Ken Saro-Wiwa emerged as a prominent figure leading the Movement for the Survival of the Ogoni People (MOSOP) and advocating for environmental protection and justice (Amnesty International, 2018). The decade also saw the emergence of various movements, such as the Kaiama Declaration in 1998, that articulated a growing resistance and demands for autonomy and environmental justice (Nwajiaku, 2005). During this period, protests, military backlash, and environmental crises unfolded in Ogoniland (Rowell, 1995). Moving into the late 1990s, protesters in Ogbia LGA (Local Government Areas) and the Kaiama Declaration demanded social investment and autonomy (Nwajiaku, 2005). The ELIMOTU (EL-ebele, IM-iringi, and OTU-asega) uprising in 1998, born out of unsuccessful negotiations with Shell, further demonstrated resistance against the exploitation and environmental degradation in the Niger Delta (Nwajiaku, 2005). Reports from the early 2000s to the 2010s, including studies by Amnesty International (2018, 2020) and from UNEP (2011) underscored the severe and ongoing environmental impact of petroleum in the Niger Delta, with ineffective cleanup efforts exacerbating the situation.

The oil industry's impacts on livelihoods, health, and well-being are extensively documented, with various research methodologies shedding light on these issues. Kpae (2020) utilised questionnaires, oral interviews, and focus groups to argue that delayed responses to oil spills by companies contribute significantly to conflict in communities like B-Dere and Bomu (Rivers state). Studies by Oghenetega et al. (2020), Alemzero et al. (2021), and Nriagu et al.

(2016) examined factors influencing perceptions of oil pollution, its impacts on coastal communities, and health risks for pregnant women in polluted areas, respectively. Environmental reports from UNEP (2011) and Amnesty International (2018, 2020) underscore the severe and ongoing impact of the oil industry in Ogoniland (Rivers state), including underreported oil spills.

Together, what these and similar studies indicate is the issue of environmental justice and precarious safety of communities in the Niger Delta. A useful concept to draw on here is 'slow violence', which refers to often slow, often anonymous work of policies from states, and practices from businesses and organisations, that expose people to risk and exacerbate their physical/mental suffering. Nixon (2011) explains, this is "a violence of delayed destruction that is dispersed across time and space, an attritional violence that is typically not viewed as violence at all... but rather incremental and accretive, its calamitous repercussions playing out across a range of temporal scales". What they also provide glimpses of, however, is how the problematising of this region has been understood as posing a safety issue for researchers.

The growing intensity of oil exploration and exploitation in Nigeria has resulted in poverty, violence, and socioeconomic and sociocultural neglect in the country's oil-producing areas (Achi, 2003; Adeola et al., 2022; O. N. Albert et al., 2018; Elum et al., 2016; Mohammed, 2021). Human activities, including oil exploration and exploitation, cause a number of issues such as biodiversity loss, coastal and riverbank erosion, flooding, oil spillage, gas flaring, noise pollution, sewage and wastewater pollution, land degradation, soil fertility loss, and deforestation, all of which are major environmental issues affecting Nigeria's Niger Delta region (Kadafa et al., 2012). According to Albert et al. (2019), vandalisation, sabotage, and oil theft has a negative impact on the environment, the local economy, and the socio-cultural dimensions of the people in the affected areas. However, due to a lack of efficient monitoring and slow response, the rate and magnitude of oil spillage caused by pipeline vandalisation cannot be adequately accounted for (Ikporukpo, 2020). Furthermore, there have been few studies that show how oil spillage are related to environmental degradation in the region as well as the socioeconomic situation of the people who live there, (Obida et al., 2018a; Sanusi et al., 2016; Ukhurebor et al., 2021). Previous studies have assessed the environmental and socioeconomic impacts of pipeline vandalisation in the Niger Delta region of Nigeria; however, they either conducted environmental studies or socio-economic studies, but not both, or they did not use sufficient area samples to derive robust evidence of the impact of oil spillage on the socioeconomic situation of the citizens of Niger Delta. Moreover, oil spillage in the context of the Niger Delta continues to be a fluid, developing, and dynamic problem requiring a timely analysis.

Monitoring, according to Kadafa et al. (2012), is crucial in places where oil exploration is taking place, but it is lacking in the Niger Delta region. Despite the fact that the government has regulations and acts in place to monitor and guide oil production in Nigeria, such as the National Oil Spill Detection and Response Agency (NOSDRA) and the Nigerian Upstream Petroleum Regulatory Commission (NUPRC), the organizational structure for monitoring and controlling oil spills is lacking. Rim-Rukeh (2015) and Ikporukpo (2020) list the following inadequacies of these agencies: lack of independence and oversight, a lack of technical competence on the part of regulatory bodies, a lack of technical competence on the part of community representatives, a lack of transparency on the part of oil companies, a lack of general procedure for determining the actual cause of a spill, a lack of general procedure for determining the actual volume of oil spilled, a lack of determination on the size of the impacted area; these shortcomings have rendered the agencies ineffective. As stated by Ozigis et al. (2019), oil contamination damages terrestrial ecosystems and there is an immediate need to enhance traditional procedures for detecting, mapping, and establishing the precise amount of contaminated and unaffected vegetation. GIS and remote sensing hold great potential for the prompt management of oil spills and the reduction of pipeline vandalism through early detection of wrongdoing. From initial prospect analysis and exploration to appraisal, production, and abandonment, spatial data is a crucial component of every petroleum operation. Over 80% of the data used in the petroleum sector is expected to have a geographical component, implying that it might be accessed via a map or linked to something with a location Exprodat (2015). This means that proactive solutions for preventing and managing oil spills must be developed in order to protect the environment. Proactive intervention can be aided by combining geo-information techniques and environmental variables with spill characterisation (Owens et al., 2016).

Despite the existence of a National Oil Spill Contingency Plan and NOSDRA's legislative role (UNEP, 2011), on-the-ground realities in the Niger Delta reveal persistent issues with inadequate and untimely oil spill response, a fact corroborated by Ikporukpo (2020). This is further highlighted by studies suggesting greater social, economic, and political peace in non-oil producing areas compared to oil-producing regions (Elum et al., 2016). Moreover, oil spill aftermaths often leave affected communities to manage the consequences with limited external support. Consequently, numerous studies have examined the environmental and human impacts of oil spillage in the Niger Delta, utilizing both physical (Adamu et al., 2018; Bankole et al., 2024; Muhammad et al., 2024; Obida et al., 2018, 2021) and qualitative (Aduloju & Okwechime, 2016; O. Albert et al., 2019; Bayelsa commission, n.d.; Bello, 2017; Emelu et al., 2021) methodologies. However, these studies have often analysed the impacts on the ecosystem and affected populations separately. Recognising the interconnectedness of this environmental challenge, this research employs a mixed-methods approach, integrating geostatistical and spatial analysis of oil spill patterns, remote sensing to quantify affected areas, and qualitative insights from impacted communities. This integrated approach allows for a more nuanced understanding of oil spill impacts, moving beyond isolated analyses to encompass the lived experiences of those most affected.

Elum et al. (2016)(Adamu et al., 2018a; Bankole et al., 2024; Muhammad et al., 2024; Obida et al., 2018a, 2021)(Aduloju & Okwechime, 2016; O. Albert et al., 2019; Bayelsa commission, n.d.; Bello, 2017; V. O. Emelu et al., 2021)A critical reference point for understanding the scale of pollution in the region is the comprehensive scientific assessment of Ogoniland conducted by the UNEP, concluded fourteen years ago in 2011. This landmark study provided authoritative, science-backed evidence of the profound environmental contamination resulting from over five decades of oil operations, establishing an essential, though now dated, baseline for pollution and biodiversity impacts.

Therefore, this study seeks to provide an updated assessment of environmental conditions in specific Niger Delta communities, using the 2011 UNEP study as a temporal benchmark to evaluate changes over the past fourteen years. Crucially, the study will integrate spatial and remote sensing analysis with community-derived data (including local knowledge and testimonials) to elucidate the direct, geographically specific impacts of oil spillage on both the environment and the resident population. By doing so, this research anticipates making several key contributions. It endeavours to broaden and deepen the theoretical and empirical understanding of the long-term dynamics of oil pollution, environmental degradation, and community impacts within the Niger Delta context. The findings are expected to inform more evidence-based interventions and policies for environmental management, and resource preservation, providing current, spatially explicit data valuable to government agencies, oil companies, and environmental bodies. Ultimately, by documenting environmental changes, degradation and community concerns within a spatial framework.

1.2 Aim and Objectives

This research aims to explore the use of geospatial, remote sensing, and community intelligence in developing an appropriate approach for assessing and quantifying the impact of oil spills in the Niger Delta region of Nigeria.

The specific objectives of the research are to:

1. Analyse the spatio-temporal patterns of oil spillage along the pipeline network.
2. Develop a remote sensing-based approach for evaluating contaminated land and the environmental impact of oil spills in the Niger Delta region.
3. Understand community concerns around oil spillage and their environmental impacts.

To date, there is an absence of comprehensive data that examines the historical and contextual issues related to oil spillage and the direct implications on the Niger Delta region. Through the objectives listed above, this research will address the following specific research questions:

I. What are the emerging spatio-temporal patterns of oil spillages recorded along the pipeline network in the Niger Delta? (Objective 1)

II. How effective are remote sensing based approaches for evaluating contaminated areas and the environmental impact of oil spills? (Objective 2)

III. What are the perceived dangers and challenges posed by oil spillages for the Niger Delta communities? (Objective 3)

1.3 Study Area

The Niger Delta of Nigeria (5°33′49″N latitude and 6°31′38″E longitude) is one of the world's largest Deltas. The Niger Delta region is made up of nine states namely, Cross River, Edo, Delta, Abia, Imo, Bayelsa, River, Akwa-Ibom and Ondo (see figure 1.1). The Niger Delta covers more than 70,000 km^2 and makes up 7.5% of Nigeria's land mass (923,770km^2) (Clinton & Chinago, 2019; Ukhurebor et al., 2021).

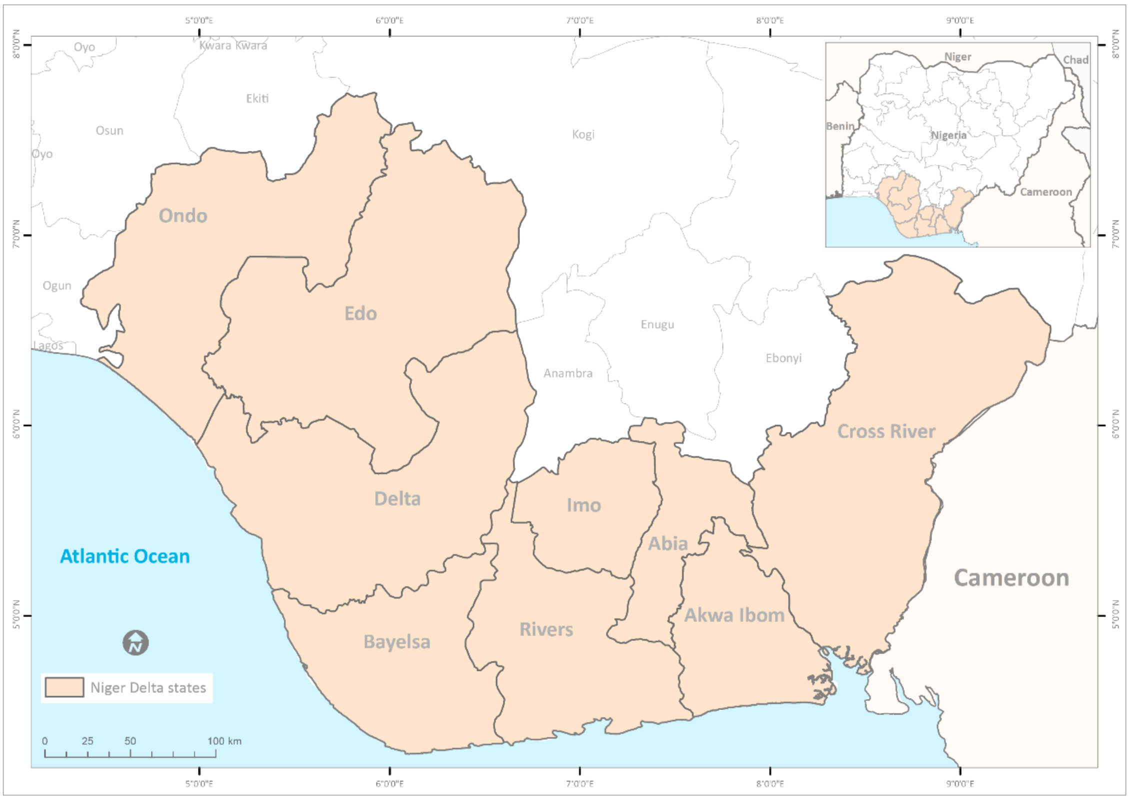


Figure 0.1. Location of the Niger Delta study area, Nigeria.

According to Alagoa (2005), the Niger Delta has the largest wetland in Africa and the third largest in the world, with rivers, streams, and estuaries covering around 2,370 square kilometres, 8,600 square kilometres of swamp forest and around 1,900 square kilometres of mangrove forests. The primary types of vegetation in the Niger Delta region are mangrove, freshwater swamp and low land rainforest. This illustration indicates that the extensive habitats and ecosystems in the Niger Delta are particularly vulnerable to oil spill pollution, making it imperative to consider how spills affect not only the physical environment but also the livelihoods of local communities dependent on these wetland resources.

Nigeria has the second largest oil reserve and largest gas reserves in Africa (OPEC, 2024), with the majority of these resources located in the Niger Delta (Lindén & Pålsson, 2013b). The Niger, Benue, and Cross rivers have supplied the delta for centuries, draining 106 km^2 of lowland savannah (Doust, 1990). The delta sequence includes Tertiary clastics up to 12 km thick that coarsen upward. It is separated into three main lithofacies: (i) marine claystones and shales of unknown thickness at the base; (ii) alternating sandstones, silstones, and claystones with increasing sand percentage; (iii) alluvial sands at the top. The Niger Delta has six primary geomorphic units: beaches and barrier islands, mangrove swamp forests, coastal plain sands, Warri-Sombreiro Deltaic plain, Lower Niger Flood plain, and Niger flood (Abam, 2016; Akpokodje, 1987; Allen, 1965).

According to the most recent census in 2006, the population of the Niger Delta was 31,277,901 (NBS, n.d.-b); however, the National Population Commission (NPC) estimates that the population reached 44,732,022 by 2022 (see Table 1.1). Of these 44,732,022 individuals, 22,373,248 (50.02%) are women, 22,358,774 (49.98%) are men, 17,244,694 (39%) are children (ages 0 to 14), 14,949,027 (33%) are youth or young adults (ages 15 to 35), 11,063,595 (25%) are adults (ages 36 to 65), and 1,474,706 (3%) are elderly (64 and above) (see Figures 1.2). The Niger Delta is a fascinating mosaic of over 40 ethnic groups, including Ijaw, Urhobo, Itsekiri, Isoko, Efik, Etche, Ibibio, Igbo, Andoni, Ikwere, Ogoni, Edo, and Kwale-Igbo, who speak roughly 250 distinct languages (Douglas & Okonta, 2018; Ndebumog, n.d.).

The inhabitants of the Niger Delta rely heavily on the environment for their livelihoods (NDDC, n.d.). In coastal areas, fishing and trading are the main vocations, while inland residents cultivate food and cash crops such as cocoa, rubber, rice, sweet potato, maize, yam, cassava, and vegetables. Seventy to ninety percent of the region's annual revenue is derived from artisan fisheries resources, including boat building, fish merchandising, outboard engine maintenance, fishing, and fish processing. Additionally, rural residents engage in small-scale activities like baking, tailoring, masonry, and carpentry (Persson, 2018). Except for the oil sector, the industrial base in the region is virtually nonexistent (NDDC, n.d.).

This demographic and economic overview is crucial for understanding the profound impacts of oil spills in the Niger Delta. With a large and growing population of over 44 million people, the region's diverse ethnic groups and their reliance on environmental resources make them highly vulnerable to environmental degradation caused by oil spills. The heavy dependence on fishing, agriculture, and small-scale industries means that oil pollution directly threatens the livelihoods and economic stability of the population. Furthermore, the demographic breakdown highlights that a significant portion of the population consists of children and young adults, who are particularly vulnerable to the health and socio-economic repercussions of environmental pollution.

Table 1.1. The Population of Niger Delta (Data source: National Population Commission (NPC)))

States	Land area (km^2)	Population				
		2006	**2010**	**2015**	**2020**	**2022**
Abia	4,877	2,845,380	3,098,063	3,466,125	3,941,279	4,143,093
Akwa Ibom	6,806	3,902,051	4,159,871	4,507,044	4,847,542	4,979,418
Bayelsa	11,007	1,704,515	1,929,864	2,183,880	2,444,028	2,537,375
Cross River	21,930	2,892,988	3,289,317	3,828,099	4,253,698	4,406,204
Delta	17,163	4,112,445	4,443,441	4,885,710	5,416,738	5,636,145
Edo	19,698	3,233,366	3,595,335	4,040,178	4,567,512	4,777,042
Imo	5,165	3,927,563	4,279,489	4,773,738	5,265,082	5,459,337
Ondo	15,086	3,460,877	3,888,324	4,507,463	5,084,330	5,316,603
Rivers	10,378	5,198,716	5,736,180	6,439,012	7,183,473	7,476,805
Total	112,110	31,277,901	34,419,884	38,631,249	43,003,682	44,732,022

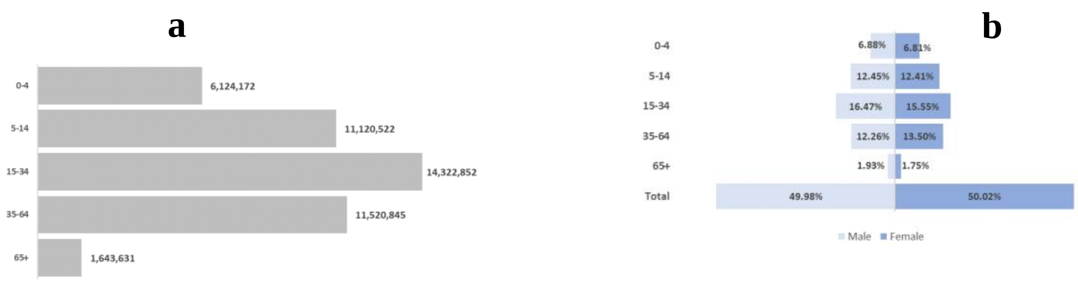
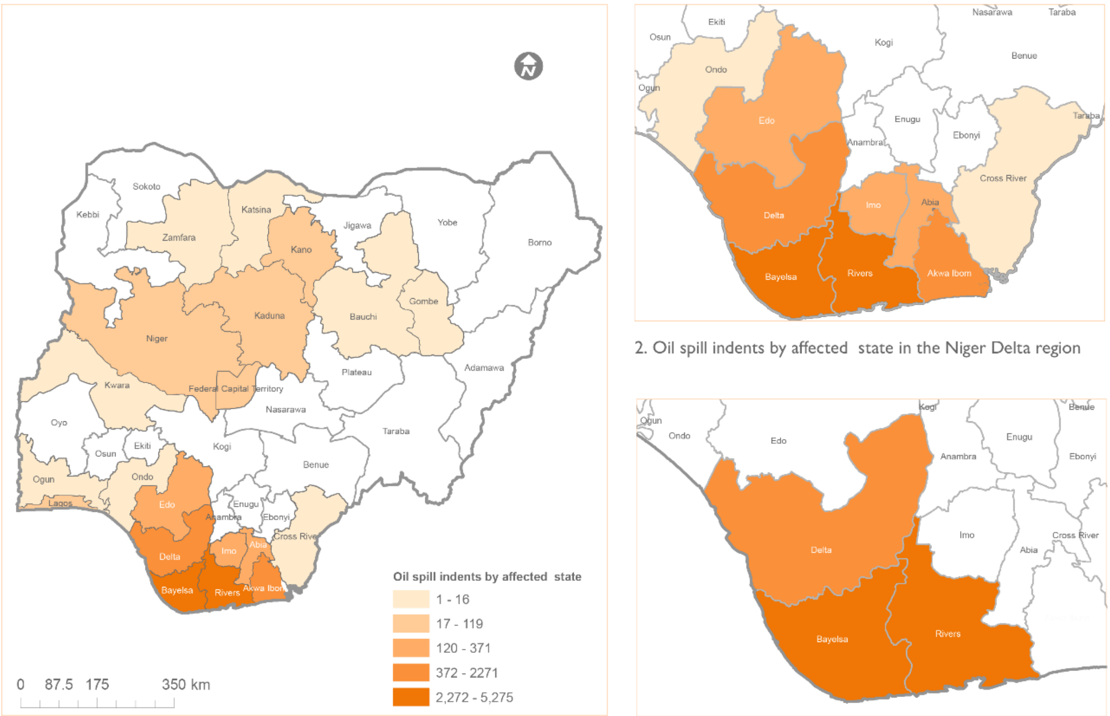


Figure 0.2. Niger Delta Demographic Breakdown (Figure 1.2a and 1.2b were adapted from NPC 2022 population projection)

1.3.1 Scope of Study

While oil extraction occurs across all nine states of the Niger Delta, this study focuses specifically on the three states most significantly affected by pipeline oil spills. These states collectively account for over 85% of oil spills recorded by NOSDRA (see Figure 1.3). This focused approach allows for a more in-depth analysis of the environmental and social consequences of oil spills in these particularly impacted areas.



1. Oil spill indents by affected state in Nigeria

2. Oil spill indents by affected state in the Niger Delta region

3. Oil spill indents in Rivers, Bayelsa and Delta states

Figure 1.3. Map showing states affected by oil spills and the three study states.

Bayelsa: Located in the Niger Delta, was formed from three initial Local Government Areas (LGAs): Brass, Yenagoa, and Sagbama, which together form the acronym "Bayelsa." Originally comprising eight LGAs, the state expanded to include 24 more in December 1999. Geographically, Bayelsa lies between 4°15′ north and 5°23′ south latitude, and 5°22' W and 6°45' E longitude (Bayelsa commission, n.d.). It shares borders with Delta and Rivers states and is bounded to the south by the Atlantic Ocean. The state's geology is characterized by sedimentary alluvium, with young, shallow, and poorly drained soils, including inceptisol Aquepts and acid sulphate Sulphaquepts (Abam, 2016; Ndebumog, n.d.). Bayelsa experiences considerable rainfall throughout the year and maintains a mean monthly temperature ranging from 25°C to 31°C, with the warmest months occurring between December and April. Like other Niger Delta states, Bayelsa encompasses four distinct ecological zones: barrier islands, mangroves, freshwater swamps, and lowland rainforests. This diverse environment supports a rich variety of plant life, including tropical species in both the mangrove and freshwater marshes. In the drier northern regions, rubber cultivation is a significant economic activity (Gbadegesin et al., 2023; Ndebumog, n.d.)..

The Ijaw ethnic group constitutes the majority in Bayelsa, and their language, Ijaw, is widely spoken. However, the state also boasts a diverse linguistic landscape, with other languages such as Tamu, Mein, Jobu, Oyariri, Tarakiri, Urhobo, and Isoko, as well as various dialects, contributing to its cultural richness. Epie, Atisa, Nembe, and Ogbia are also spoken in certain areas (Bayelsa commission, n.d.; NDDC, n.d.; Oyegun et al., 2023). Christianity and traditional belief systems are the predominant faiths practiced in Bayelsa State. Despite the challenges posed by its marshy terrain, agriculture plays a role in Bayelsa's economy. Crops such as yam, cocoyam, banana, pineapple, and plantain are cultivated, while coconut, pears, oil palm, and raffia palm are important cash crops (Ndebumog, n.d.). The abundant waterways, including streams, lagoons, rivers, and wetlands, provide ample opportunities for fishing, a vital source of livelihood for many residents. Bayelsa State holds significant economic importance for Nigeria as it contains the country's largest crude oil reserves. Administratively, the state is divided into eight LGAs: Brass, Ekeremor, Kolokuma, Nembe, Ogbia, Sagbama, Southern Ijaw, and Yenagoa. (Ndebumog, n.d.).

Delta state: Established on August 27, 1991, has a rich history, having been part of the former Midwestern State and Bendel State. Initially comprised of 12 Local Government Divisions (LGDs), it was reorganized into 19 Local Government Areas (LGAs) in 1991 and further expanded to 25 LGAs in 1997 (Oyegun et al., 2023). Asaba, the state capital, is undergoing a transformation into a modern city through a comprehensive master plan for the Asaba Capital Territory (NDDC, n.d.). Geographically, Delta State is situated between 5°00' and 6°45' east longitude, and 5°00' and 6°30' north latitude, encompassing an area of 16,842 square kilometers. It shares borders with Edo, Ondo, Anambra, Bayelsa, and Rivers states (Ndebumog, n.d.).

Delta State's climate is tropical, with variations across the region. The southern part experiences a humid tropical climate, while the northeast is characterized by a sub-humid climate. Rainfall also varies, with coastal regions receiving an average of 266.5mm and the northern areas experiencing 1905mm annually (Oyegun et al., 2023). July is typically the wettest month. The state's diverse landscape includes mangrove swamps along the coast, evergreen forests in the central region, and savannah in the northeast (NDDC, n.d.; Oyegun et al., 2023). Three main soil types are found in Delta State: alluvial soil along the coast, alluvial and hydromorphic soils in the Niger and Benin river areas, and ferralitic soils in the north and northeast (Abam, 2016; Douglas & Okonta, 2018; Ndebumog, n.d.).

Delta State is home to a variety of ethnic groups, with the Urhobo, Igbo, Izon, Isoko, and Itsekiri being the most prominent (Alagoa, 2005; Douglas & Okonta, 2018). Religious practices in the state are diverse, encompassing Christianity, Islam, and indigenous religions such as Igbe and Ebura. In terms of natural resources, Delta State possesses significant deposits of petroleum, natural gas, lignite, silica sand, and clay, contributing to its economic potential. (Ndebumog, n.d.).

Rivers state was established by military decree on May 27, 1967, predates the creation of Bayelsa State in 1996. The agitation for the creation of Rivers State began even before Nigeria's independence in 1960, rooted in the unique identity and interests of the region (NDDC, n.d.; Oyegun et al., 2023). . During the colonial era, the British government entered into protective treaties with coastal leaders, recognizing the distinct character of the area (Alagoa, 2005). Situated in the Niger Delta's coastal plain, Rivers State is characterized by a land surface formed from fluvial deposits, primarily sediments from the Andoni, Bonny, and New Calabar rivers. These deposits, comprising clays, peat, silts, sands, and gravels, form a regolith overburden reaching up to 30 meters deep (Douglas & Okonta, 2018; NDDC, n.d.).

The state's landscape features a diverse mix of freshwater swamps, mangrove swamps, and coastal sand ridges. Low-lying areas with heavy rainfall (ranging from 3,420 to 7,300 mm annually) and inadequate drainage often experience poor water runoff (Oyegun et al., 2023). Rivers State exhibits three main soil types: coastal and riverine sediments, alluvial soils in the mangrove swamps, and brown and sandy loams in freshwater areas (Abam, 2016). Rainfall in Rivers State is substantial and seasonal, with a clear pattern of decreasing precipitation from south to north. The coast experiences an average annual rainfall of 4,700 mm, while the northern parts accumulate around 1,700 mm. Temperatures are generally high, with mean monthly highs ranging from 28°C to 33°C and lows from 17°C to 24°C. The hottest period typically occurs between February and May. Rivers State holds significant economic importance for Nigeria due to its rich oil reserves. (Ndebumog, n.d.).

1.3.1.1 Fieldwork Locations

Focus Group Discussions (FGDs) and Community Participatory Mapping Exercises (CPMEs) were conducted in two communities within each state: Rivers (Bodo and Ogale), Bayelsa (Aghoro and Okpoama), and Delta (Benikrukru and Ubeji). These locations were prioritized based on a cross-tabulation of areas with the highest incidence of oil spills, as indicated by

NOSDRA data, and those most frequently mentioned in social media searches for oil spill impacts. See Figure 1.4 for the prioritised fieldwork locations.

Figure 1.4. The fieldwork locations and core oil-producing states (Rivers, Delta, Bayelsa, Akwa Ibom, Imo, Lagos, Edo, Ondo, Cross River, and Abia states) in Nigeria.

1.4 Thesis Outline

The thesis consists of seven chapters, and a brief description of each is presented below:

Chapter 1 provides an introduction to the thesis, emphasising the Niger Delta as the main hub for crude oil production, highlighting its vital role in the national economy. It also highlights the region's significant environmental degradation, socioeconomic challenges, and political instability resulting from oil extraction activities. The chapter outlines the historical context of oil production in the Niger Delta and discusses the adverse effects of oil spills on local ecosystems and communities. It identifies key research gaps, particularly the need for comprehensive data on the interplay between oil spills, environmental harm, and community impacts. The chapter also presents the study's aims, objectives, and scope, providing an overview of the region's geography, demographics, and socioeconomic conditions. Additionally, it explains the rationale for selecting specific states and fieldwork locations. Finally, Chapter 1 concludes by outlining the overall structure of the thesis, establishing the foundation for the detailed analysis in subsequent chapters.

Chapter 2 examines the historical development and evolution of oil production in Nigeria, highlighting its critical role in the national economy and the significant challenges the industry faces today. It discusses Nigeria's current oil production capabilities and the ongoing issues of oil theft, sabotage, vandalism, and technical difficulties that have hindered the country from meeting its OPEC quotas. The chapter then delves into the phenomenon of pipeline vandalisation in the Niger Delta, categorising the motivations behind these acts into need, greed, and grievance. It defines crude oil pipeline vandalism and explores the socio-economic and political factors driving individuals to engage in such activities. Additionally, the environmental impacts of oil spills are thoroughly reviewed, detailing both immediate and long-term effects on ecosystems, fisheries, and agricultural productivity.

Furthermore, Chapter 2 evaluates the latest approaches for monitoring and managing oil spills, integrating both quantitative and qualitative methodologies. It discusses remote sensing techniques, including optical satellite and Synthetic Aperture Radar (SAR) Remote Sensing, for detecting and monitoring oil spills. The importance of qualitative methods, such as Focus Group Discussions (FGDs) and Community Participatory Mapping Exercises (CPME), is also highlighted for capturing community perspectives and experiences related to oil spills.

Chapter 3 investigates the spatiotemporal patterns of oil spills along the pipeline network from 2013 to 2021 using geo-computation techniques. Utilising the spNetwork package in R, Network Kernel Density Estimates (NKDE) and its temporal extension, Temporal Network Kernel Density Estimates (TNKDE) were carried out. Pipeline data were transformed into 500-metre lixels (linear pixels) to compute network distances and generate density estimates. NKDE identified oil spill hotspots, while TNKDE illustrated the temporal transitions of spills. These methods surpass traditional approaches (e.g. KDE, cluster analysis, point pattern analysis) by incorporating network constraints and uncovering critical spatial–temporal patterns. The findings offer valuable insights for targeted interventions to reduce future spills and mitigate past impacts.

Chapter 4 develops remote sensing-based approach to evaluate oil-contaminated areas using geospatial cloud computing and machine learning techniques. The analysis of vegetation health trends revealed significant declines in vegetation health index values following oil spills. Key indices, including the NDVI, EVI2, GRNDVI, and GNDVI, were prioritised for their high accuracy in distinguishing between oil-affected and non-affected land cover. A Slow-Moving Average (SMA) regression analysis revealed significant declines in all indices within contaminated dense vegetation areas from 2016 to 2023. Specifically, NDVI exhibited a strong negative correlation with time (Spearman's $\rho = -0.77$, $p = 0.0005$), indicating a progressive decline in vegetation health following oil contamination. Similar trends were observed for EVI2 ($\rho = -0.77$, $p = 0.0005$), GRNDVI ($\rho = -0.82$, $p = 0.0001$), and GNDVI ($\rho = -0.68$, $p = 0.004$), further confirming the detrimental effects of oil spills on vegetation. The random forest (RF) classifier effectively quantified the extent of contamination, classifying 22.81% of the total land cover as non-contaminated dense vegetation (8,390 hectares) and 1.39% (513 hectares) as contaminated. Non-contaminated farmland accounted for 9.04% (3,326 hectares), with only 0.07% (26 hectares) contaminated. Grasslands and wetlands also exhibited significant differences in contamination levels.

Chapter 5 explores the perceived dangers and challenges posed by oil spills to Niger Delta communities through qualitative methods, specifically structured Focus Group Discussions (FGDs) and Community Participatory Mapping Exercises (CPME). These methods were chosen to reveal the nuanced layers of meaning behind the lived experiences of the region’s residents. It details how due to safety and travel restrictions, the study adopted a distanced methodology by partnering with NBS data collectors, ensuring safety and data integrity while addressing ethical considerations.

The chapter details the research design, including the development of research questions, selection of fieldwork locations, and the protocols established to ensure the safety of data collectors and participants. It also describes the process of annotating maps during CPMEs and the steps taken to analyse and interpret data from FGDs and CPMEs. Furthermore, Chapter 5 presents the results of the FGDs and CPMEs on a location-by-location basis, integrating qualitative and spatial data to provide a nuanced understanding of the concerns of the affected communities. This integrated approach highlights the complex interplay between environmental degradation and socio-economic challenges, offering valuable insights for developing effective monitoring and management strategies to mitigate the impacts of oil spills in the Niger Delta.

Chapter 6 serves as the synthesis chapter, interrelating the findings and results from Chapters 3 to 5 while formulating a robust conceptual framework for assessing and quantifying the impact of oil spills in affected areas.

Chapter 7 highlights the contributions from the empirical chapters (3–5), emphasizing their significance within the broader context of this thesis. It discusses the limitations encountered during the research and provides thoughtful recommendations for future studies. Additionally, the chapter presents conclusions drawn from the research, highlighting their implications for oil spill management, policy development, and sustainable practices in the Niger Delta.

Chapter Two

2. Literature Review

This chapter provides a review of the historical development and evolution of oil production in Nigeria, highlighting key milestones and significant changes over time. Additionally, the chapter discusses oil spill from pipelines and the resulting environmental degradation. Furthermore, it evaluates the latest approaches for monitoring and managing oil spills, integrating both quantitative and qualitative methodologies to present a nuanced understanding of effective strategies for mitigating environmental impacts. By synthesising existing research and identifying critical gaps, this literature review sets the foundation for the subsequent analysis and discussions within the thesis.

2.1 Oil Spills from Pipeline Vandalisation and Oil Theft: Global Trends

While global oil theft represents a significant financial loss, estimated at US$133 billion annually (Romsom, 2022) its environmental impact is far more devastating. This section focuses on the connection between oil spills from pipeline vandalism, oil theft, and the resulting environmental damage. Oil theft often leads to undetected spills, particularly in countries like Russia where incidents go unreported and regulatory enforcement is lax (Romsom, 2022). These spills contaminate the soil and water, harming ecosystems and local communities. The problem is exacerbated by the fact that thieves may repeatedly tap the same pipeline, causing further leaks and delaying any potential cleanup efforts. This issue is not unique to Russia. In Mexico, over 12,500 illegal taps in 2018 resulted in the loss of 81,000 barrels per day and significant environmental damage (Semple, 2019). The problem extends beyond physical tampering; cyberattacks, like the ransomware attack on the US Colonial Pipeline in 2021, also disrupt operations and can potentially lead to spills (Eaton & Volz, 2021). This review will delve deeper into case studies from countries with substantial oil reserves, including Mexico, Russia, Libya, Venezuela, and Nigeria, looking at the causes of oil spills and their environmental consequences. By examining the challenges and responses in these nations, we can gain valuable insights into mitigating the environmental consequences of oil theft.

2.1.1 Mexico

Mexico, a major oil producer with reserves nearing 10 billion barrels, faces a significant challenge with oil theft and its devastating environmental consequences. While the financial losses are substantial, with Pemex, the state-owned oil company, losing billions of dollars annually (Mexico News Daily, 2019), the environmental impact is far more profound. The widespread practice of "milking" pipelines— illegally tapping into them to steal oil—often results in spills that contaminate soil and water. These spills pose a serious threat to ecosystems and the health of communities living near pipelines. Mexico is notorious for the magnitude and frequency of its gasoline theft, to the point where it has its own term for it: 'huachicolero: someone who steals and sells fuel or adulterated alcohol illegally ' (Yucatan Times, 2019). The problem is exacerbated by the sophisticated methods used by thieves, often involving former or current Pemex employees, highlighting the difficulty in detection and prevention (Ralby, 2017).

Despite efforts to monitor the vast pipeline network using SCADA systems, their effectiveness is hampered by poor management and maintenance (Mexico News Daily, 2019). This lack of oversight creates opportunities for illegal tapping and increases the risk of undetected leaks and spills. The Federal Auditor's Office has criticised Pemex for its inadequate pipeline monitoring and security, further emphasising the need for improved practices to mitigate the environmental damage associated with oil theft. The high frequency of illegal taps, reaching over 12,500 in 2018 alone (Semple, 2019), underscores the urgency of addressing this issue. Mexico's experience serves as a stark reminder of the environmental costs of oil theft and the need for robust preventative measures and effective pipeline management to protect vulnerable ecosystems.

2.1.2 Russia

Russia, as the world's third-largest oil producer, faces significant environmental challenges stemming from oil theft and pipeline vandalism. While the financial losses are substantial, reaching billions of dollars annually (Khazov-Cassia, 2021), the ecological impact is of even greater concern. Organised crime groups, often with the complicity of corrupt officials, engage in widespread illegal tapping of pipelines, leading to numerous oil spills. These spills contaminate vast areas, damaging fragile ecosystems and posing risks to the health of communities. The remoteness of many pipelines and the lack of regulatory enforcement exacerbate the problem, as spills often go unreported and unremediated (Transneft, 2021)

Despite efforts to crack down on illegal refineries and storage facilities, the number of illicit pipeline taps remains high, with Transneft identifying 566 between 2018 and 2020 alone (Transneft, 2021). This highlights the ongoing challenge of securing Russia's vast pipeline network. The complexity of the issue is further compounded by the involvement of corrupt officials who protect oil thieves and intimidate those who investigate these crimes (Khazov-Cassia, 2021). This creates a climate of fear and impunity, hindering efforts to address the environmental damage caused by oil theft. Russia's experience demonstrates the urgent need for stronger environmental regulations, improved pipeline security, and a crackdown on corruption to effectively combat the ecological damage associated with oil theft and pipeline vandalism.

2.1.3 Libya

Libya, a nation with significant oil reserves (holding 3% of the world's total), faces a critical challenge in protecting its environment from the impacts of oil spills from oil theft and pipeline vandalism. The instability following the 2011 revolution has exacerbated this problem, leading to frequent attacks on pipelines and significant oil spills (Adusei, 2015; EIA, 2022; Emadi, 2012). These spills have devastating consequences for Libya's fragile desert ecosystems and coastal areas. Oil contamination pollutes water sources, harms wildlife, and threatens the health of communities that depend on these resources. The incident in 2018, where an armed group set fire to a pipeline connecting the Waha oilfield to the Sidra port, exemplifies the vulnerability of Libya's oil infrastructure and the environmental risks involved (Alharathy, 2018).

While the financial cost of fuel smuggling is estimated at $750 million annually (Africa News, 2018; Arab News, 2018; Zaptia, 2018), the environmental costs are immeasurable. Oil spills not only cause immediate damage but also have long-term effects on soil and water quality, impacting biodiversity and the livelihoods of local populations. Libya's situation highlights the urgent need for greater security and stability to protect its oil infrastructure and prevent environmental disasters. Investing in pipeline protection, strengthening environmental regulations, and promoting sustainable practices in the oil industry are crucial steps towards mitigating the ecological damage and ensuring the long-term health of Libya's environment.

2.1.4 Venezuela

Venezuela, a country with the world's largest proven oil reserves, faces a growing environmental crisis due to oil spills, despite a decline in production in recent years (OPEC, 2021). While the nation has experienced fewer spills compared to countries like Nigeria (Amnesty International, 2013; Chinedu & Chukwuemeka, 2018; Ikporukpo, 2020; Mba et al., 2019), the impact on its delicate ecosystems remains significant. The decline in Venezuela's oil production, largely due to US sanctions, has led to the neglect of critical infrastructure. Abandoned underwater wells and pipelines are leaking oil into the environment, with reports of at least nine spills in 2020 and 2021 alone (Buitrago, 2022). These spills threaten marine life, contaminate water sources, and damage coastal ecosystems. The lack of transparency and reporting on the causes of these spills further exacerbates the problem. Without proper investigation and accountability, it becomes difficult to address the root causes and implement effective preventative measures.

While the focus has often been on the economic impact of Venezuela's declining oil industry, the environmental consequences are equally dire. Oil spills pose a serious threat to the country's biodiversity, the health of its citizens, and the long-term sustainability of its natural resources(Berg, 2021; Burelli, 2021; Radwin, 2021).

2.1.5 Nigeria

Nigeria, Africa's largest oil producer, faces a severe environmental crisis due to the rampant oil theft and pipeline vandalism plaguing the Niger Delta (Otanocha, 2015) While the financial losses are substantial, the ecological damage is far more devastating and has long-term consequences for the region's fragile ecosystems and the health of its communities. Oil theft, often involving sophisticated operations with complicity from various actors, leads to frequent pipeline breaches and spills (Campbell, 2015; Otanocha, 2015). These spills contaminate vast areas of land and water, destroying mangroves, polluting soil and groundwater, and decimating fish populations (UNEP, 2011). The UNEP report on Ogoniland, which found that oil pollution posed a serious threat to public health and could take decades to remediate, serves as a stark reminder of the environmental devastation caused by oil theft (UNEP, 2011).

The problem is further compounded by the prevalence of illegal artisanal refineries, which is locally referred to as "cooking" - refining the crude oil into various products using a makeshift local refinery, discarding the waste into the environment (Campbell, 2015). This practice contributes significantly to water pollution and soil degradation, further harming the livelihoods of communities that depend on fishing and farming. While various estimates highlight the significant amount of oil lost to theft, the environmental cost remains incalculable. Oil spills not only cause immediate damage but also have long-term effects on biodiversity, water quality, and public health. The degradation of the environment further exacerbates poverty and social unrest in the Niger Delta.

Addressing this crisis requires a multi-faceted approach, including strengthening law enforcement, improving pipeline security, and holding perpetrators accountable. Furthermore, investing in sustainable development and alternative livelihood opportunities for local communities can help reduce their dependence on oil-related activities and promote environmental stewardship. Nigeria must prioritise environmental protection and implement effective measures to combat oil theft and mitigate its devastating ecological impact.

The global review presented in this section highlights the extensive environmental impact caused by oil spills stemming from pipeline vandalism and oil theft. Across diverse geographical contexts—from Mexico and Russia to Libya, Venezuela, and Nigeria—common themes emerge, including regulatory inadequacies, corruption, inadequate pipeline security, and insufficient transparency in incident reporting. While economic losses are significant, the environmental consequences are often more severe and enduring, threatening biodiversity, community health, and sustainable development. Effective mitigation of these environmental harms demands strategies incorporating robust regulatory frameworks, enhanced security and surveillance of pipelines, improved accountability mechanisms, and greater investment in sustainable economic alternatives.

2.2 History of Oil Production in Nigeria

Several authors have recorded different accounts (in terms of year of commencement and locations) about the history of oil production in Nigeria. According to Steyn (2009), exploration of crude oil in Nigeria was formally launched in 1903 by the Nigeria Properties (Limited) and Nigeria and West African Development Syndicate (Limited). These two corporations began exploration for bitumen, coal, and oil in Nigeria, however their activities were limited and put to a halt after 1905. On the other hand, the apex petroleum agency of the Federal Government of Nigeria, Nigerian National Petroleum Corporation (NNPC, n.d.) stated that the search began in 1908 through a company named the Nigerian Bitumen Corporation and the British Colonial Petroleum. They drilled about 14 wells in the Okitipupa area of Ondo State and had found no oil from the areas. Later, the beginning of World War 1 disrupted the continuity of the exploration in those areas (Okorobia & Olali, (2018)). However, Steyn (2009) strongly argued against this, debunking and calling it a myth, stating that the Nigeria Bitumen Corporation was established in November 1905 by a British businessman called John Simon Bergheim, and by 1906, the firm had begun operations. Between 1908 and 1912, 15 wells were dug in the then-Lekki Concession. These operations were reportedly a failure because the explorers found the Nigerian terrain to be very difficult and challenging (Steyn, 2009).

According to Steyn (2009), in 1930, the D'Arcy Exploration Company partnered with Anglo-Saxon Petroleum Company, a wholly-owned subsidiary of the Royal Dutch/Shell group of companies whose name was changed to Shell Overseas Exploration Company Limited in December 1937 and subsequently Shell. Shell/D'Arcy suspended exploration in 1941 and resumed it in 1946. In 1955, the first non-Shell/D’Arcy oil exploration license was granted to the Mobil Exploration Company of Nigeria Limited (a locally incorporated subsidiary of the Socony-Mobil Oil Company). Mobil’s concession covered most of the areas in Northern Nigeria. In January 1956, Shell/D'Arcy found commercial oil 72 kilometres west of Port Harcourt in Oloibiri (at 12,008 feet). Then oil was discovered in Afam (40 km east of Port Harcourt). Shell/D'Arcy discovered oil in twelve places by 1958, including Oloibiri, Afam, and Bomu (Steyn, 2009). Afterwards in 1958, Nigeria joined the ranks of oil producing countries when its first oil field came on stream producing 5,100 barrels per day (bdp). On March 8 of that same year, the first shipment of Nigerian crude oil exports (8,500 tonnes) landed in Rotterdam (Steyn, 2009). A summary of important events in the history of oil production in Nigeria is shown in the Figure 2.1.

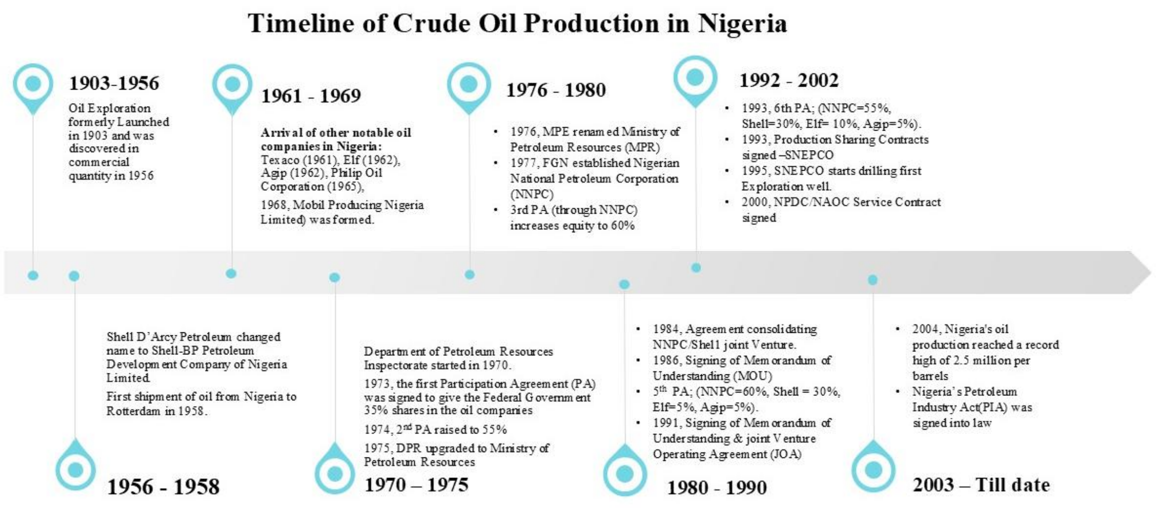


Figure 2.1. Timeline of Crude Oil Production in Nigeria (adapted from (NNPC; Steyn , 2009; Okorobia 2018).

According to the NNPC now Nigerian Upstream Petroleum Regulatory Commission (NUPRC), Nigeria's crude oil output exceeded 2 million barrels per day in the late 1960s and early 1970s. In 2004, Nigeria's oil production reached a record high of 2.5 million barrels per day, even though production statistics had declined in the 1980s due to the economic downturn (Addeh, 2022). Over the years and still currently, petroleum production and export play a dominant role in Nigeria's economy and account for about 90 percent of the country's gross earnings (NBS, 2021). This dominant role has pushed agriculture, the traditional mainstay of the economy, from the early fifties and sixties to the background. However, the oil industry's contribution to employment has been surprisingly limited. In 2018, the Nigeria Extractive Industries Transparency Initiative (NEITI) reported that only 0.03% of Nigeria's 69.54 million workers were employed in the oil sector (Okafor, 2020).

According to the NUPRC, Nigeria has been failing to meet its OPEC quota, losing millions of barrels in 2021. The Chief Executive of the commission stated that "with OPEC production quotas of 1.683 million bpd in January and 1.701 million bpd in February, the commission is only allowed to pump 1.396 million bpd, equating to a loss of at least 115,926 million bpd daily, or $300 million monthly". He ascribed the underachievement on oil theft, sabotage, vandalism, and technical difficulties, including ruptures in the country's oil assets (Addeh, 2022). According to NNPC, as of 2022, Nigeria has 61 oil production and lifting companies (both foreign and indigenous) presently operating (NNPC, n.d.). Figure 2.2 shows Nigerian oil production from 2002 to 2022.

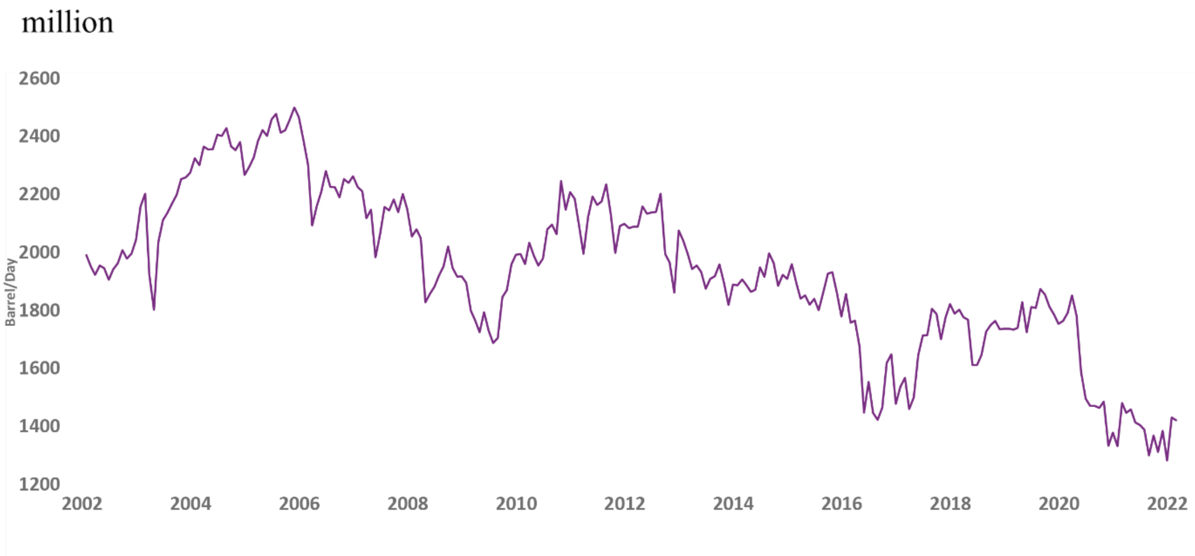


Figure 2.2. Nigeria's crude oil production from January 2002 to April 2022 (Source: https://www.ceicdata.com/)

The following sections examine how pipeline vandalism, and irresponsible practices by oil companies contribute to environmental degradation. The analysis draws on diverse literature to illustrate the various ways spills occur and their devastating impact on the environment and communities located near production sites and oil pipeline networks.

2.2.1 Oil spills from Pipelines in the Niger Delta

Shaikh et al. (2017) notes pipelines as the important parts of the infrastructure for moving oil and natural gas. They connect the places where oil and gas are made to refineries, chemical plants, homes, and businesses. Over the years, the Nigerian oil industry has had to deal with two challenges that have threatened it. The challenges relate to the prevalence of militancy and oil pipeline vandalism in the Niger Delta (Okoli, 2013). According to Okoli (2019), crude oil pipeline vandalism is defined as the violation of the safety and functional integrity of a petroleum pipeline for political, economic, or other reasons. (Okogwu & Ba, 2021) also defined it as an unlawful activity carried out by certain individuals in Nigeria's Niger Delta region who extract petroleum products for personal gain or as a form of protest, regardless of the repercussions to themselves, others, or the environment.

Studies have found several factors to influence pipeline vandalization in Nigeria. Okoli (2019) categorised the factors influencing pipeline vandalization into three, namely, i) the need, ii) greed and iii) grievance factors. Under the need factors, he argued that the Niger Delta's societal problems provide a background and excuse for oil-related crimes, including petroleum vandalism. The Niger Delta region is poor and lacks basic amenities, and environmental degradation from oil contamination has made it challenging for rural residents to participate in sustainable farming and fishing. Other need factors include unemployment, illiteracy, poverty and livelihood failures (Okoli, 2019). Among the nine states which formed the Niger Delta region in Nigeria, the unemployment rate in Rivers state is 42%, followed by Bayelsa at 37% and Delta at 31% respectively (NESG, 2021). This predicament forces a desperate survival fight and some turn to crime to survive. Further, under the greed factor, crude materialism and extravagant lifestyle promote this and some Nigerians commit crimes, such as oil pipeline vandalism, to increase their fortune. Finally, the grievance factor explains pipeline vandalism prompted by collective agitation in militancy. Oil pipeline sabotage is a way to protest the unfair and unresponsive Nigerian government and oil corporations.

Tukur and Hajj (2017) suggests that poor management, legal factors, and poor governance are the major factors that influence crude oil pipeline vandalism in the Niger Delta region of Nigeria. Olu-Adeyemi (2020) listed pervasive poverty due to unfulfilled expectations/promises by oil producing companies and the government, corrupt leadership and sabotage in the oil sector, activities of militant group, youth unemployment, fatigued pipelines, activities of illegal refineries and international involvement of pipeline vandalisation as factors that influence pipeline vandalism in Niger Delta. Their study identified critical socioeconomic and social well-being factors as influencing factors, yet stopped short of considering if livelihood factors, such as income or financial level influences the cessation or continuation of pipeline vandalism in the Niger Delta region.

Various studies have identified several issues that arise due to oil spills from pipeline vandalism in Nigeria. Massive economic losses from pipeline and plant shutdowns, environmental degradation, fire outbreaks typically ending in loss of life, displacement of populations, and disturbance of the ecosystem are among the most significant repercussions of pipeline vandalism in the Niger Delta region (Okoli, 2013). In addition, there is a lack of petroleum products and a decline in the gas supply for electricity generation in the area due to the pipeline vandalism (Okoli, 2013; Olu-Adeyemi, 2020). An assessment study carried out by the United Nations Environment Programme (2011) in Ogoni, Niger Delta showed that air pollution resulting from oil sector operations is prevalent and impairs the quality of life of around one million individuals in the area. Their findings also showed that there is contamination of drinking water with amounts of benzene, carcinogen, and a multitude of other pollutants that exceed the World Health Organization's (WHO) recommendations by more than 900 times.

The environmental problem is further compounded by the prevalence of illegal artisanal refineries, which is locally referred to as "cooking" - refining the crude oil tapped from pipelines into various products using makeshift local refineries, discarding the waste into the environment (Campbell, 2015). This practice contributes significantly to air and water pollution, and soil degradation, further harming the livelihoods of communities that depend on fishing and farming. While various estimates highlight the significant amount of oil lost to theft, the environmental cost remains incalculable. Oil spills not only cause immediate damage but also have long-term effects on biodiversity, water quality, and public health. The degradation of the environment further exacerbates poverty and social unrest in the Niger Delta. In addition, their other investigations showed that, soil contamination extend beyond five metres in their findings. They concluded that even when oil corporations claimed to have cleaned up affected spill locations, the areas remained extremely polluted. The oil sector failed to fulfil even the basic Nigerian standards, let alone worldwide oil industry standards. This research aims to comprehensively evaluate the environmental impact of oil spills in Nigeria, providing valuable data to develop effective mitigation and remediation strategies. By analysing the extent of pollution and its effects, this study will contribute to a deeper understanding of the environmental challenges in the Niger Delta and inform efforts to protect the health and livelihoods of its people. The following sections will discuss the impact of oil spills on the Niger Delta environment.

2.3 Effect of Oil Spills on the Environment

Oil spills include any release of crude oil or oil-derived products (such as gasoline, diesel fuels, jet fuels, kerosene, Stoddard solvent, hydraulic oils, and lubricating oils) that can harm the land, air, and water habitats (Environmental Pollution Centers, 2017). Rim-Rukeh (2015) detailed what typically happens immediately after an oil spill: spreading, evaporation and dissolving of the components, some components dissolved in water and even oxidising, while others undergo bacterial transformations and finally sink to the bottom due to gravity. The resulting contamination of the soil has a severe impact on terrestrial life. As the evaporation of volatile components with low molecular weight impacts aerial life, so does the dissolution of less volatile components in the ensuing emulsified water influence aquatic life. In addition, they illustrated the direct effects of an oil spill on the marine environment, which include direct lethal toxicity, sub-lethal disruption of physiological and behavioural activities, and death due to interference with feeding and reproduction, direct coating or painting, entry of hydrocarbons into the food web, and modification of biological habitats.

Due to the influence of oil spills, Osuagwu & Olaifa (2018) confirmed that there is a trade-off between oil extraction and fish productivity. They demonstrated in their study how growing levels of oil leakage and oil production have a detrimental impact on fish output in Nigeria's Niger Delta area. Further, Nwilo & Badejo (2005) elaborated on the scope of the problem by explaining that between 1976 and 1996, roughly 2,369,470 barrels of oil were released into the environment because of 4,647 accidents. In addition, Nigeria documented a total of 2,097 oil spilled occurrences between 1997 and 2001 (Iyasara et al., 2013). In 1998, 40,000 barrels of oil were spilled from the Mobil platform off the coast of Akwa Ibom, inflicting catastrophic harm to the coastal ecology. Primarily located in the Niger Delta, the oil industry has wreaked havoc on farmlands, supplies of drinking water, mangrove forests, fishing grounds, and the populations of fish, crabs, molluscs, periwinkles, and birds. Widespread destruction of mangrove forests has had a negative impact on both terrestrial and marine ecosystems. Some previous spills have necessitated the complete relocation of some communities, the loss of ancestral homes, the contamination of freshwater, the loss of forest and agricultural land, the destruction of fishing grounds, and the reduction of the fish population, which is the primary source of income for the people of the Niger Delta (Tolulope, 2004; CAB, 2009). Andrews (2015) attributed oil spills in the Niger Delta region to a lack of maintenance of exploration and exploitation infrastructure and equipment. According to Akujuru (2014) and Okoli (2013), the epidemic of oil spillage in the Niger Delta region of Nigeria could be directly attributed to the illegal bunkering and refining of petroleum products by residents who claim to be making ends meet at the expense of environmental and public health.

2.3.1 Environmental Degradation

Environmental degradation is described as the degradation of the natural environment resulting from natural disasters and human activity (UN/ISDR, 2004). According to the International Strategy for Disaster Loss (ISDR, 2004), environmental degradation is the reduction in the value of the environment to satisfy its ecological and socio-economic demands. It encompasses land degradation, deforestation, desertification, biodiversity loss, land, water, and air pollution, climate change, sea level rise, and ozone depletion. The UNEP (2011) asserts that in a substantial number of areas, major hazards to human health stem from polluted drinking water and concerns regarding the sustainability and productivity of ecosystems pose grave dangers. In addition, pollution may have spread further and permeated deeper than it did in the past. In the Niger Delta, the degradation stemming from oil exploration and exploitation is particularly severe, jeopardising the livelihoods and survival of local communities (Chukwuka et al., 2018; Obi, 2023; Ochei, 2024; Yakubu, 2017).

The link between environmental degradation and poverty is undeniable, as unsustainable practices and resource depletion often drive vulnerable populations further into poverty (Adeola et al., 2022; Elum et al., 2016; Mohammed, 2021). In the Niger Delta, the environmental injustices faced by communities highlight the concept of "slow violence," where the gradual and often invisible effects of pollution and ecological damage cause long-term suffering and undermine human rights (Nixon, 2011). This study aims to shed light on the long-term impact of oil spills in the Niger Delta by utilising temporal satellite imagery and community testimonials for damage assessment. By analysing the extent and persistence of environmental degradation, this research will contribute valuable data and insights for developing effective strategies to mitigate the impacts of oil spills, promote environmental justice, and protect the well-being of communities in the region.

2.4 Approaches for Monitoring and Managing Oil Spills

Research into the practices and power relations surrounding oil spill monitoring and management in the Niger Delta is crucial, albeit challenging. This research can expose the disproportionate risks faced by communities and how their safety is compromised. Employing qualitative methods like focus group discussions and participatory mapping can effectively capture community perspectives on oil spill risks, their impacts on livelihoods, and the environment (Calheiros et al., 2000; Cochrane & Corbett, 2018; Corbett et al., 2016; IFAD, 2009; Ralls & Pottinger, 2021).

Quantitative approaches, particularly those leveraging geo-information and community intelligence, are also vital for effective oil spill management. These methods allow for spatial analysis of oil spill patterns, risk assessment, and hazard identification (Mohamadi et al., 2015). For instance, Sani et al. (2016) used hotspot analysis and kernel density estimation to map vandalism incidents in Oviri, Nigeria. They created 50-meter buffers around vandalism points and pipelines (corresponding to the Nigerian petroleum pipeline right-of-way) to analyse spatial patterns, identify hotspots, and assess the proximity of settlements to incidents. This approach provides valuable insights for controlling pipeline vandalism in the region. Gómez and Green (2017) highlight the vulnerability of pipelines to degradation, failure, and vandalism, emphasizing the potential of small Unmanned Aerial Vehicles (UAVs) to enhance existing monitoring systems. While UAVs offer advantages through multispectral and hyperspectral analysis for vegetation change detection and infrastructure inspection, the authors note that they are not yet fully equipped for comprehensive oil and gas pipeline monitoring.

Epuh et al. (2017) developed digital maps integrating pipeline infrastructure with terrain, vegetation, and settlement data, coupled with a relational database for managing pipeline attributes. This approach facilitates visualization and monitoring but provides limited information on oil spills and their environmental impact. (Ngada & Bowers, 2018) utilized geoinformation to map crude oil theft incidents in the Niger Delta, aggregating data to Local Government Areas (LGAs) and employing spatial autocorrelation and kernel density estimation to identify hotspots and theft patterns. While valuable for understanding past incidents, this study does not offer specific recommendations for pipeline monitoring, prevention, or environmental impact assessment. Similarly, Ojiako and Duru (2017) employed GIS and remote sensing to classify and analyse oil spill images and growth trends. This method effectively identifies and maps spills, but it does not address mitigation strategies for environmental impacts.

2.4.1 Remote Sensing Techniques for Detecting and Monitoring Oil Spills

Remote sensing (RS) collects, extracts, and analyses information about objects on the earth surface without physical interaction (Wong et al., 2021). This information is communicated by electromagnetic radiation (EMR), which may come from the sun or the Earth (or artificially generated as in radar). Remote sensing uses the interaction between the source signal or irradiance interacting with the surface and the reflected, received signal at the sensor to describe the Earth's surface (Huete, 2004).

Traditional oil spill monitoring approaches, such as airborne or field inquiry, are costly and fail to locate oil leak regions quickly. Due to its vast coverage, synoptic perspectives, and regularity of obtaining multisensory data, satellite-based RS has been frequently utilised to identify and monitor oil spills (Al-Ruzouq et al., 2020). Fingers and Brown (2014) identified the relevance of oil spill remote sensing as mapping spills, surveillance and general slick detection, providing evidence for prosecution, enforcing ship discharge rules, directing oil spill countermeasures, and determining slick trajectories (Topouzelis, 2008). Passive and active devices collect remotely sensed data to identify oil spills. Passive sensors record naturally reflected and/or released solar energy from the seen object, producing optical pictures based on weather and light. Both optical and microwave airborne and satellite remote sensors are used for oil spill monitoring, with microwave sensors being more widely used due to their ability to operate in any weather condition (Al-Ruzouq et al., 2020; Yekeen & Balogun, 2020).

2.4.1.1 Optical Satellite Remote Sensing

The use of satellite-based multispectral data is increasing, owing to its growing availability, synoptic coverage, and unique spectral characteristics. In addition, their optical features assist in the differentiation between oil spills and lookalikes (Al-Ruzouq et al., 2020). Different studies use different resolutions of multispectral satellite data to find oil spills (see table 2.2).

Table 2.1. Optical satellites used in oil spill studies (Adapted from Al-Ruzouq et al., 2020; M. S. Wong et al. 2021).

Satellite	**Spectral Region (Bands)**	**Spatial Resolution (m)**	**Revisit Time (Days)**	**References**
MODIS (Terra, Aqua)	VIS, NIR, MIR, SWIR,55 LWIR (36 spectral bands)	250,500, 1000 m	1–2	(Bulgarelli & Djavidnia, 2012; Chen & Hu, 2014; Cococcioni et al., 2012; Corucci et al., 2010; Lacava et al., 2017
Landsat-8	VIS, NIR, SWIR, TIR (12 spectral bands)	15, 30, 100 m	16	(Arslan, 2018; Bayramov, Kada, et al., 2018; Bayramov, Knee, et al., 2018)
Landsat-7	VIS, NIR, MIR, TIR (8 spectral bands)	15, 30, 60 m	16	(Lavrova & Mityagina, 2013; Polychronis & Vassilia, 2013; Taravat & del Frate, 2012)
Landsat-5	VIS, NIR, MIR, TIR (8 spectral bands)	30, 120 m	16	(Bayramov, Knee, et al., 2018a; Polychronis & Vassilia, 2013; Svejkovsky et al., 2016)
Sentinel-2	VIS, NIR, SWIR (12 spectral bands)	10, 20, 60 m	5	(Althawadi & Hashim, 2019; Kolokoussis & Karathanassi, 2018; Nezhad et al., 2018)
KOMPSAT-2	VIS, NIR (5 bands)	1(pan), 4 m (MS)	14	(Park et al., 2020)
Gaofen-1	VIS, NIR (5 bands)	2 (pan), 8 m (MS)	4	(Y. Li et al., 2017; J. Yang et al., 2019)
ASTER	VIS, NIR, SWIR, TIR (14 bands)	15, 30, 90 m	4–16	(Cai et al., 2010; G. Guo et al., 2020; Guoyin Cai et al., 2007)
Quickbird	VIS, NIR (5 bands)	0.61(pan), 2.4(MS)	1–3.5	(Hese & Schmullius, n.d.; Kolokoussis & Karathanassi, 2018)
Dubaisat-2	Visible, NIR (5 bands)	1(pan), 4 (MS)	<8	(M.-S. Lee et al., 2016b)
Huan Jing-1	VIS, NIR (4 bands)	30 m	4	(Y. Li et al., 2017; S. Liu et al., 2017; Q. Xu et al., 2013)
RapidEye	VIS, NIR (4 bands)	5 m	4	(Polychronis & Vassilia, 2013)
WorldView-2	VIS, NIR (8 bands)	0.52(pan), 2.4(MS)	1–5.5	(Svejkovsky et al., 2016)
IKONOS	VIS, NIR (4 bands)	0.82(pan), 3.28(MS)	1–14	(Polychronis & Vassilia, 2013)
AVHRR (NOAA)	VIS, MIR, TIR(6 bands)	1.1 km	0.5	(Casciello et al., 2011; Grimaldi et al., 2011; G. Guo et al., 2020)
SeaWiFS	VIS, NIR (8 bands)	1.1–4.5 km	1	(Mihoub & Hassini, 2019)
MERIS	VIS, NIR (15 bands)	300	3	(S. Chen & Hu, 2014; de Carolis et al., 2012)
SPOT-5	VIS, NIR, SWIR (4 bands)	2.5 or 5 m(Pan), 10(MS), 20(SWIR)	2–3	(Svejkovsky et al., 2016)

In their studies, Althawadi & Hashim (2019); Kolokoussis & Karathanassi, (2018), used the region-expanding segmentation method to find oil spill pixels in a processed Sentinel MSI image, while Argamosa et al. (2022) used principal component analysis on Sentinel 2 level 1C image to detect oil spills and, possibly, surfactants in their area of study. Rajendran et al. (2021)

also used Sentinel-2 satellite data, to examine snow, ice, water, vegetation, and wetlands in their study area after an oil spill. They looked at Sentinel-2 data from before, during, and after the event. They made true and false-colour composites (FCC), decorrelated spectral bands, and used the Snow Water Index (SWI), Normalized Difference Water Index (NDWI), and Normalized Difference Vegetation Index (NDVI).

Ozigis et al. (2019) distinguished between oil-free and oil-spill-affected landcovers using a machine-learning random forest classifier. They accomplished this by integrating spectral wavelengths and health indices from the visible, near-infrared, and shortwave infrared bands. Abbas & George (2022) used the temperature data from the Landsat-8 satellite images to determine the locations of hydrocarbon surface spills. The study utilised spatial interpolation and gradient approaches to calculate the size of the oil spill.

2.4.1.2 Synthetic Aperture Radar (SAR) Satellite Remote Sensing

Spaceborne SAR data (see Table 2.4) provides a great deal of promise for mapping oil-polluted areas, monitoring oil and gas transport systems for spills, and determining hydrocarbons are spilling and harming surrounding plants (Ozigis et al., 2019). SAR (Topouzelis, 2008) is an active sensor that detects the microwaves backscattered from a surface or objects upon the surface. Satellite-deployed SAR is a crucial monitoring tool for oil spills owing to its vast area coverage and day/night, all-weather capabilities. A SAR sensor can be characterised by its frequency band, polarisation, which refers to the geometry of the tip of the electric vector, incidence angle, which is the angular relationship between the radar beam and the ground target, swath width, which is the width of the imaged scene, and image resolution, which is the size of the smallest detail discernible on an image, see Table 2.3. A trade-off exists between image resolution and swath coverage. Typically, broad swath widths are utilised at the price of precision for oil spill detection. Widespread usage of spaceborne SAR sensors for the detection of oil spills in the maritime environment (Ozigis et al., 2019; Topouzelis, 2008).

Table 2.2. Characteristics of commonly used SAR bands (Adapted from (Fingas & Brown, 2017))

SAR Band	Key Features	Advantages	Limitations	Applications
C-Band	Wavelength: 4–8 GHz (~5.6 cm).	High sensitivity to surface roughness changes.	None specified.	Ideal for monitoring oil slicks as oil reduces backscatter by damping capillary waves.
	Sensors: Sentinel-1, RADARSAT.	Effective in moderate sea conditions.		
	Balance between resolution and penetration depth.			
X-Band	Wavelength: 8–12 GHz (~3 cm).	Suitable for high-precision monitoring of smaller oil spills or spills near coastlines.	Limited penetration depth.	High-resolution monitoring of localized oil spills.
	Sensors: TerraSAR-X, COSMO-SkyMed.	Better in low sea states.	Less effective in rough sea conditions compared to longer wavelengths.	
	Provides higher resolution imagery.			
L-Band	Wavelength: 1–2 GHz (~23 cm).	Effective in challenging environments, such as vegetated areas or turbid water near coastlines.	Lower resolution compared to X- and C-bands.	Suitable for detecting spills in complex environments, such as coastal zones or areas with natural surface phenomena.
	Sensor: ALOS PALSAR.	Differentiates oil slicks from algae blooms or grease ice.		
	Longer wavelength allows deeper penetration and reduced sensitivity to surface roughness.			

Oil smooths the water surface, reducing surface roughness and leading to lower backscatter in SAR imagery. This appears as dark patches against the brighter background of undisturbed water, particularly in VV-polarized images. Cross-polarized channels (e.g., VH) can help confirm oil spills by minimizing ambiguities caused by environmental factors like waves or wind (Bonnington et al., 2021; SU et al., 2012; L. Xu et al., 2014). Different wavelengths offer distinct advantages. Shorter wavelengths (X-band) provide higher resolution imagery suitable for detecting localized spills, while longer wavelengths (L-band) are more effective in challenging conditions or complex environments like coastal zones (Bonnington et al., 2021; Fingas & Brown, 2018; SU et al., 2012). By combining these parameters, SAR sensors can effectively detect, monitor, and differentiate oil spills, contributing to rapid response and mitigation efforts

Table 2.3. List of SAR-equipped satellites used in the oil spill detection community (adapted from Al-Ruzouq et al., 2020).

Satellite Name	**Operational Period**	**Spatial Resolution (m)**	**Revisit Time (Days)**	**References**
ERS-1, ERS-2	1991–2000, 1995–2011 / SAR	10 - 30 m	3-35	(Bayramov, Knee, et al., 2018a; Gambardella et al., 2010; Y. Guo & Zhang, 2014; P. Liu et al., 2010)
RADARSAT-1	1995–2013 / SAR	8 - 100 m	24	(Bayramov, Knee, et al., 2018a; Cao et al., 2017; T.-S. Kim et al., 2015; Raeisi et al., 2018)
RADARSAT-2	2007 /SAR	3 - 100 m	24	(Marghany, 2015; Ozkan et al., 2012; Tong et al., 2019)
Huan Jing-1C	2012 / SAR	30 - 300 m	4-5	(Y. Lin et al., 2016; Tian et al., 2015)
Kompsat-5	2013 / SAR	1 - 20 m	28	(Harahsheh, 2016; D.-J. Kim, 2011)
Sentinel-1	2014 / SAR	5, 20 m	6, 12	(Abou El-Magd et al., 2020; Arslan, 2018; Bayramov, Knee, et al., 2018)

2.4.2 Remote sensing of vegetation and their response to oil spills

Conventional field-based monitoring approaches, although providing precise localized data, are often constrained by factors like cost, time requirements, labour demands, and limited spatial reach, making them unsuitable for extensive or ongoing assessments, particularly in areas that are remote or hazardous (Adamu et al., 2018a; Noomen et al., 2008). Remote sensing technology offers a vital solution, enabling the acquisition of information about the Earth's surface from afar (Emery & Camps, 2017; Wong et al., 2021). Key benefits include the capacity for repeated observation of large areas, cost-efficient data gathering, non-invasive analysis, and the ability to monitor locations that are difficult to access, such as the oil-affected Niger Delta (Adamu et al., 2018a; Arellano et al., 2015; Fingas & Brown, 2014, 2017, 2018). As a result, remote sensing has become integral to numerous environmental tasks, notably including oil spill response efforts (Fingas & Brown, 2018).

2.4.2.1 Oil Contamination Impacts on Vegetation Physiology and Spectral Responses

Activities related to oil production, especially spills, have the potential to severely damage or eliminate vegetation (Adamu et al., 2015; Arellano et al., 2015). Plants exposed to oil pollution experience considerable stress, which adversely affects their overall health and vitality (Adamu et al., 2018; Arellano et al., 2015). The underlying causes of this stress are complex. Oil contamination within the soil can impede the flow of air and water, potentially causing oxygen deprivation and reducing the plant's ability to absorb nutrients and water, which can indirectly lead to water stress (Arellano et al., 2015)). From a physiological standpoint, oil exposure can cause changes in leaf coloration resulting from the degradation of photosynthetic pigments like chlorophyll (Noomen et al., 2008). Significantly, these physiological changes alter how vegetation interacts with electromagnetic energy, especially within the optical (visible, near-infrared, shortwave infrared) and thermal parts of the spectrum (Arellano et al., 2015). Variations in chlorophyll levels influence reflectance in the visible range (particularly red light), whereas changes in leaf internal structure and moisture content affect reflectance in the near-infrared (NIR) and shortwave infrared (SWIR) bands (Arellano et al., 2015; Adamu et al., 2018). Furthermore, stress-induced alterations in transpiration, often associated with the closing of stomata, can cause variations in leaf and canopy temperatures that thermal sensors can detect (Noomen, 2008; Arellano et al., 2015). The capacity of remote sensing to identify these subtle spectral and thermal variations allows for the detection of stress before it becomes visually apparent, providing a significant benefit for timely intervention and mitigation actions (Noomen, 2008). Additionally, the consequences of oil spills can be enduring. Ecosystems continuously subjected to pollution may display sublethal effects even decades after an initial spill, affecting their long-term vitality, growth (Adamu et al., 2018; Arellano et al., 2015).

Selecting the appropriate sensor technology is vital for effectively identifying and assessing vegetation stress resulting from oil contamination, as different sensors gather information related to distinct plant biophysical characteristics. Multispectral sensors are frequently employed for vegetation monitoring and are mounted on diverse platforms including satellites (like Landsat ETM+, MODIS, Sentinel-2, WorldView2, RapidEye, see Table 2.1) (Fingas & Brown, 2018). Their prevalence is due to factors like data accessibility, comparatively lower costs, and well-developed analytical methods (Adamu et al., 2018a; Arellano et al., 2015; Mishra & Mishra, 2012). Multispectral instruments collect data across a few broad spectral bands, commonly including Blue, Green, Red, Near-Infrared (NIR), and occasionally

Shortwave Infrared (SWIR) (Arellano et al., 2015; Mishra et al., 2012). These specific bands are responsive to important vegetation attributes: the red band detects chlorophyll absorption, while the NIR band is strongly reflected by healthy leaf structures (Arellano et al., 2015). Various vegetation indices (VIs), calculated using combinations of these bands, are used to monitor changes in pigment levels, leaf area, and overall plant health (Arellano et al., 2015; (Mishra & Mishra, 2012)).

Another vital sensor for detecting oil spills is hyperspectral Sensors, also referred to as imaging spectrometers, gather data in hundreds of closely spaced, narrow spectral bands spanning the visible, NIR, and SWIR ranges (Mishra et al., 2012; Noomen, 2008). This high spectral detail yields a comprehensive spectral signature for every pixel, facilitating the detection of slight modifications in plant biochemistry (like pigment levels, water content, lignin, cellulose) and biophysical structure, which often signal stress before visual symptoms emerge (Mishra et al., 2012; Noomen, 2008; Arellano et al., 2015).

Hyperspectral data offers considerable potential for differentiating among various stress sources, like oil contamination versus waterlogging, which might produce similar signals in broader multispectral bands (Noomen, 2008; Fingas & Brown, 2018). Thermal infrared sensors quantify the heat radiated from surfaces. For vegetation, this temperature relates to physiological conditions, especially transpiration rates and stomatal activity (Fingas & Brown, 2018; Lillesand et al., 2015; Noomen et al., 2008). Plant stress, such as that caused by oil contamination hindering water absorption, can interfere with normal transpiration, resulting in elevated leaf or canopy temperatures (Noomen, 2008). Consequently, thermal imaging can indicate developing stress (Noomen, 2008; Fingas & Brown, 2018). Radar systems, especially Synthetic Aperture Radar (SAR), function in the microwave spectrum and are mainly employed to detect oil slicks on water (Fingas & Brown, 2018). They operate by identifying how oil suppresses small surface waves, causing the oiled region to appear smoother (darker) in radar images under suitable wind conditions (Fingas & Brown, 2018). SAR provides notable benefits for extensive surveillance due to its capability to function regardless of daylight or weather conditions like clouds and rain, see Table 2.3 (Fingas, 2000; Fingas & Brown, 2018). Light Detection and Ranging (LiDAR) employs laser pulses as an active sensing method to measure distances, enabling the creation of detailed 3D surface maps. Although noted as a potential instrument for monitoring oil infrastructure and spills (Asadzadeh et al., 2022; Chemisky et al., 2021; Leifer et al., 2012), its specific application concerning vegetation impact involves quantifying structural alterations. A significant challenge arising from comparing different sensor capabilities is the issue of specificity. Various environmental stressors can trigger similar physiological reactions in plants, leading to comparable spectral signatures (Fingas & Brown, 2018; Noomen et al., 2008).

Remote sensing has significantly advanced, becoming an essential tool for environmental surveillance, providing robust methods for evaluating oil spill effects on vegetation and tracking land cover dynamics. Progress in sensor technologies across various platforms (satellite, airborne, UAV) yields complementary datasets. Concurrently, the refinement of analytical methods, including sophisticated machine learning and deep learning algorithms, allows for the extraction of increasingly precise and detailed information. Remote sensing presents benefits such as extensive area coverage, cost savings compared to ground surveys, the capability to monitor inaccessible regions, and, importantly, the potential for detecting vegetation stress before it is visually evident.

2.4.2.2 Vegetation Indices and Spectral Techniques for Monitoring Oil Spill Impacts

Remote sensing offers powerful tools for environmental monitoring, particularly using vegetation indices (VIs). These indices, derived from satellite data, have been widely employed to assess vegetation health across various landscapes (Adamu et al., 2018a; Adamu, Ogutu, et al., 2016; Adamu, Tansey, et al., 2016; Amiri & Pourghasemi, 2022; Kovalev & Tokareva, 2016). VIs are quantitative metrics calculated from mathematical combinations or transformations of spectral reflectance measurements across multiple wavelength bands (H. Huang & Roy, 2021; Qi et al., 1994; Vélez et al., 2023). Their design aims to amplify the signal from green vegetation while minimizing distortions from factors like soil background variability, atmospheric conditions (e.g., aerosols, haze), and illumination differences (A. R. Huete, 1988; Prudnikova et al., 2019; Qi et al., 1994; Rondeaux et al., 1996). By condensing complex spectral data from multispectral or hyperspectral imagery, VIs serve as effective proxies for estimating key biophysical characteristics of vegetation canopies (Huang et al., 2021).

The effectiveness of VIs stems from the unique spectral signature of healthy green vegetation (H. Huang & Roy, 2021; Jiang et al., 2008; Tucker, 1979). Plant leaves absorb strongly in the visible spectrum, particularly red wavelengths (approx. 600–700 nm) due to chlorophyll pigments used in photosynthesis, while strongly reflecting near-infrared (NIR) light (approx.

700–1300 nm) because of their internal cellular structure (Kior et al., 2021; Rouse et al., 1974; Tucker, 1979). The magnitude of this contrast between red absorption and NIR reflectance acts as a direct indicator of vegetation density, health, and overall vigour (Huete, 2004; Y. Kim, 2010; Rondeaux et al., 1996).

Oil spills and chronic hydrocarbon pollution pose severe threats to terrestrial and aquatic ecosystems. Vegetation can suffer direct impacts from contamination through various pathways, including root uptake from polluted soil or water, direct coating of plant tissues, and exposure to volatile organic compounds (Adamu et al., 2018; Adamu, Ogutu, et al., 2016; Yekeen & Balogun, 2020). Such exposure induces physiological stress, altering fundamental biophysical and biochemical properties like chlorophyll content, water levels, leaf structure, and photosynthetic efficiency (A. R. Huete, 1988, 2004a). These stress responses manifest as changes in the plant's spectral reflectance signature (Arellano et al., 2015; Kim, 2010). Consequently, remote sensing methods, especially those utilizing VIs, provide a critical and efficient means for identifying, monitoring, and evaluating the repercussions of oil pollution on vegetation (Adamu et al., 2016, 2018; Balogun et al., 2020). This approach is particularly valuable for surveying large geographical areas, tracking the temporal progression of environmental damage, and assessing conditions in locations that are difficult or hazardous to access for ground-based fieldwork (Huang et al., 2021; Vélez et al., 2023).

Over recent decades, numerous VIs have been developed, initially leveraging the red/NIR contrast. Later indices incorporated additional spectral bands (e.g., green, blue) or adjustment factors to reduce sensitivity to soil background and atmospheric interference. Several key VIs relevant to vegetation stress monitoring, including their application to oil spill contexts, are discussed below.

4.4.2.3 Key Vegetation Indices for Environmental Assessment and Oil Spill Monitoring

Normalised Difference Vegetation Index (NDVI): Perhaps the most widely recognized VI, the NDVI (Rouse et al., 1974; Tucker, 1979) is calculated as:

$$NDVI = (NIR - Red) / (NIR + Red) \qquad \textit{eq 2.1}$$

This normalization confines values theoretically between -1 and +1 (Tucker, 1979). High positive values (0.6-0.9) typically indicate dense, healthy vegetation, moderate values (0.2-0.5) suggest sparse vegetation, values near zero represent non-vegetated surfaces like bare soil, and negative values usually correspond to water, clouds, or snow (Amiri & Pourghasemi, 2022;

Kovalev & Tokareva, 2016; Tucker, 1979). NDVI serves as a general indicator of vegetation presence, density, and "greenness" (S. Huang et al., 2021). It is applied broadly in assessing vegetation cover (Rouse et al., 1974), condition (Tucker, 1979), biophysical parameters (e.g., LAI, biomass, chlorophyll) (S. Huang et al., 2021), productivity (Adamu et al., 2018; S.Huang et al., 2021), crop mapping (Kumar et al., 2023), drought monitoring (Chang et al., 2021), irrigation assessment (Dingre et al., 2021; Lykhovyd et al., 2024; Poudel et al., 2021), land degradation (Yengoh, 2015), forest dynamics (Li et al., 2021; Zhang et al., 2022), plant stress/disease detection (Lei et al., 2021; Shin et al., 2022), and phenology analysis (Li et al., 2021; Zhang et al., 2022).

Crucially for this research, studies have demonstrated NDVI's sensitivity to oil pollution impacts on various vegetation types, including mangroves and different densities of vegetation within regions like the Niger Delta (Adamu et al., 2016, 2018; Balogun et al., 2020). It is frequently used to assess changes in vegetation health following spills, comparing pre- and post-spill conditions or contrasting affected sites with control areas (Adamu et al., 2015). Statistically significant reductions in NDVI values have been observed in polluted areas compared to unpolluted ones (Kuta et al., 2025; Yekeen & Balogun, 2020). Despite its utility, NDVI is susceptible to atmospheric interference (e.g., aerosol scattering) and soil background brightness, especially in sparsely vegetated areas (S.Huang et al., 2021; Qi et al., 1994). It also tends to saturate in very dense vegetation, limiting its ability to differentiate subtle changes in high-biomass environments (S.Huang et al., 2021; Qi et al., 1994). Sensor differences can also introduce inconsistencies (S. Huang et al., 2021).

Soil-Adjusted Vegetation Index (SAVI): Developed by Huete (1988), SAVI aims to minimize the influence of soil background reflectance on vegetation signals (Huete, 1988; Qi et al., 1994). It incorporates a soil adjustment factor (L):

$$SAVI = [(NIR - Red) / (NIR + Red + L)] * (1 + L) \qquad eq.\ 2.2$$

An *L* value of 0.5 is commonly used, aiming to reduce soil noise across various vegetation densities (Huete, 1988; Qi et al., 1994).

SAVI is particularly useful in environments with significant soil visibility, such as arid/semi-arid regions, areas with sparse vegetation, or during early/late crop growth stages (Huete, 1988; Qi et al., 1994). Applications include analysing spatio-temporal vegetation patterns (Qi et al., 1994), crop monitoring and yield prediction (Qi et al., 1994; Yengoh et al., 2015), differentiating soil from vegetation (Fadl et al., 2024; Msadek et al., 2025), and land assessment (Ebrahimi et al., 2024; Kocur-Bera & Małek, 2024). Like NDVI, SAVI has shown sensitivity to oil pollution effects on vegetation (Adamu et al., 2016). Comparative studies in oil-impacted areas report significantly lower SAVI values at polluted sites versus controls, indicating reduced vegetation health even after accounting for soil influence (Adamu et al., 2016).

A limitation is that a fixed L factor (e.g., 0.5) may not be optimal for all conditions. Additionally, more complex indices like SAVI might potentially amplify measurement errors compared to simpler ratios (Chen et al., 1996).

Green Optimised Soil Adjusted Vegetation Index (GOSAVI): GOSAVI is identified as a soil-adjusted index optimized for vegetation monitoring, specifically utilizing the green spectral band (Loaiza, 2023; Mulla, 2013; Sripada et al., 2005).

$$GOSAVI = (NIR - Red) / (NIR - Green + 0.16) \qquad \text{eq. 2.3}$$

It's often referenced in studies aiming for enhanced vegetation assessment (Mulla, 2013; Sripada et al., 2006). GOSAVI has been used as a feature in machine learning models for vegetation mapping (Z. Zhang et al., 2024) and mentioned in studies estimating maize nitrogen content alongside other green-band or soil-adjusted indices (Sripada et al., 2005). It falls within the category of indices designed to mitigate soil background effects (Mulla, 2013).

Green Normalised Difference Vegetation Index (GNDVI): GNDVI substitutes the red band in the NDVI formula with the green band (Gitelson et al., 1996a; Mulla, 2013; Sripada et al., 2005):

$$GNDVI = (NIR - Green) / (NIR + Green) \qquad \textit{eq. 2.4}$$

GNDVI is recognized for being more sensitive than NDVI to variations in chlorophyll concentration, particularly in moderate-to-high biomass conditions where NDVI may saturate (Gitelson et al., 1996a; Mulla, 2013; Sripada et al., 2005, 2008). This makes it valuable for monitoring crop health (Daliman et al., 2024; Pengphorm et al., 2024), photosynthetic activity (Pengphorm et al., 2024), estimating LAI/biomass (Sripada et al., 2005, 2008), assessing plant stress and nitrogen status (Daliman et al., 2024; Gitelson et al., 1996; Pengphorm et al., 2024; Sripada et al., 2008), and potentially inferring soil moisture via vegetation vigor (Sripada et al., 2006). It has been used in forest classification (Daliman et al., 2024; Pengphorm et al., 2024; Sripada et al., 2008) and shown superior performance in predicting leaf chlorophyll content in some crops (Pengphorm et al., 2024; Sripada et al., 2008). Its heightened sensitivity to chlorophyll could make it useful for detecting certain types of oil-induced stress.

Green-Red Normalised Difference Vegetation Index (GRNDVI): GRNDVI incorporates green, red, and NIR bands to assess plant health (Wang et al., 2007):

GRNDVI = [NIR - (Green + Red)] / [NIR + (Green + Red)] *eq.2.5*

This index is sensitive to chlorophyll content and photosynthetic activity, potentially effective for detecting early vegetation stress (Gitelson et al., 2002). It can be useful where NIR band quality is limited (Gitelson et al., 2002). GRNDVI is used in agriculture and remote sensing for vegetation health assessment, change detection, and crop monitoring, potentially offering advantages over NDVI in saturation conditions (Gitelson et al., 1996b; Kvande et al., 2024; Loaiza, 2023). Its sensitivity to subtle changes could be relevant for monitoring oil spill impacts.

Simple Ratio (SR): One of the earliest VIs (Jordan, 1969; Rouse et al., 1974; Tucker, 1979), SR (or RVI) is calculated as the direct ratio of NIR to Red reflectance:

SR = NIR / Red *eq. 2.6*

SR correlates with biophysical parameters like LAI and FPAR (Fraction of Photosynthetically Active Radiation) (J. M. Chen & Cihlar, 1996) and has been used in yield prediction (Sripada et al., 2006). A variation using NIR (approx. 800nm) and Green (approx. 550nm) bands (SR 800/550) has been specifically linked to biomass estimation (Sripada et al., 2006). As a fundamental measure of the red/NIR contrast, changes in SR can indicate vegetation stress potentially caused by oil contamination.

Simple Ratio 2 (SR2): SR2 modifies the SR concept by incorporating SWIR (Shortwave Infrared) bands to enhance sensitivity to vegetation moisture (D. Chen et al., 2005):

SR2 = NIR / SWIR eq. 2.7

SR2 is particularly sensitive to plant water stress and is useful for identifying drought conditions. Applications include drought assessment, vegetation moisture monitoring, and forest health/fire risk assessment (D. Chen et al., 2005). Since oil contamination can affect plant water relations, SR2 may offer insights into this aspect of oil spill impacts.

Enhanced Vegetation Index (EVI): EVI was developed to improve upon NDVI, especially in high biomass regions, by reducing sensitivity to atmospheric and soil background effects (A. Huete et al., 2002; UP42, n.d.). It incorporates the blue band for atmospheric correction and includes coefficients for canopy background and atmospheric resistance:

$$EVI = G * (NIR - Red) / (NIR + C1 * Red - C2 * Blue + L) \qquad eq.\ 2.8$$

(Common MODIS coefficients: G=2.5, C1=6, C2=7.5, L=1) (Huete et al., 2002)

EVI avoids saturation better than NDVI in dense vegetation and shows improved linearity with parameters like LAI (Huete et al., 2002). It is more responsive to canopy structure variations compared to NDVI's primary sensitivity to chlorophyll (Huete et al., 2002). Applications include assessing LAI, monitoring crop development, quantifying evapotranspiration, and detecting forest disturbances (Huete et al., 2002; UP42, n.d.).

Enhanced Vegetation Index 2 (EVI2): EVI2 is a simplified version of EVI, designed for situations where the blue band is unavailable or unreliable (Jiang et al., 2008). It uses only red and NIR bands:

$$EVI2 = 2.5 * (NIR - Red) / (NIR + 2.4 * Red + L) \qquad eq.2.9$$

EVI2 aims to retain EVI's reduced sensitivity to atmospheric and soil effects while requiring fewer input bands, providing results similar to EVI (Jiang et al., 2008). It is widely used with sensors like MODIS, Sentinel-2, and Landsat (Jiang et al., 2008). Applications include crop monitoring, vegetation health assessment, drought analysis, and forest monitoring (Jiang et al., 2008). Its utility similar to EVI suggests potential for monitoring oil spill impacts, especially when blue band data is absent.

In the context of environmental monitoring within the Niger Delta, the application of satellite-derived spectral indices and remote sensing techniques has proven invaluable. These methods have significantly enhanced the accuracy of identifying contaminated land, monitoring the spatial and temporal extent of oil spill impacts, and assessing the progress of ecological recovery (Adamu et al., 2015; Arellano et al., 2015). Remote sensing has emerged as an essential tool for environmental assessment and management in regions chronically affected by oil pollution, enabling stakeholders to formulate targeted remediation strategies and evidence-based policy responses (Ayanlade & Drake, 2016; Obida et al., 2018a)

In summary, the suite of vegetation indices derived from remote sensing data provides critical capabilities for assessing the environmental consequences of oil spills. By quantifying changes in vegetation health and stress levels reflected in spectral signatures, these techniques allow for the identification of contaminated areas, monitoring of degradation extent, and evaluation of recovery processes. As demonstrated by research, particularly within the Niger Delta, remote sensing approaches utilizing VIs are fundamental tools for ongoing environmental surveillance and the effective management of oil spill incidents and their aftermath.

2.4.3. Remote Sensing-Based Land Cover Mapping

Land cover describes the physical materials present on the Earth's surface, including elements like vegetation (such as forests, grasslands, agricultural areas), water bodies, bare ground, ice, and man-made structures (Kamalu & Wokocha, 2019; Talukdar et al., 2020). As a primary characteristic of the terrestrial environment, land cover is inherently changeable, constantly modified by natural forces and, increasingly, by human actions (Junaid et al., 2023; Talukdar et al., 2020a; Yuh et al., 2023a).

Consequently, precise and current Land Use/Land Cover (LULC) maps serve as critical inputs for numerous applications. These include environmental surveillance and evaluation, managing and conserving natural resources, urban and regional development planning, agricultural oversight, climate change simulation and impact assessment, valuation of ecosystem services, and guiding policy formulation (Al-Najjar et al., 2025; Talukdar et al., 2020a; Wang et al., 2022a). Remote sensing technology, frequently combined with Geographic Information Systems (GIS), offers the main data sources and analytical capabilities for producing LULC maps efficiently and uniformly over extensive regions, thereby overcoming the constraints of conventional ground-based surveys and census methods (Abdi, 2020; Talukdar et al., 2020a).

Initial LULC classification techniques primarily focused on individual pixels, assigning each pixel to a land cover category largely based on its spectral characteristics (i.e., the reflectance values measured in various spectral bands).

Unsupervised Classification: These methods group pixels into spectral clusters according to statistical similarity, without needing prior information about the existing land cover types. Algorithms such as ISODATA, K-Means (implied through clustering), and more recently, spectral clustering techniques, belong to this group (Wu et al., 2025). The analyst subsequently assigns meaningful LULC labels to these generated clusters. While relatively straightforward to apply, these methods depend significantly on the spectral distinctiveness of the target classes (Wu et al., 2025).

Supervised Classification: These approaches necessitate the analyst providing training samples—pixels with known land cover identities—which are used to "train" the classification algorithm. The algorithm then categorizes unknown pixels based on their spectral resemblance to the known classes. The Maximum Likelihood Classifier (MLC) is a traditional and frequently utilized supervised algorithm (Sumangala & Kini, 2022); Maxwell et al., 2019). Generally, supervised techniques yield more accurate outcomes than unsupervised ones, provided that representative training data is accessible.

To mitigate the shortcomings of pixel-based methods when dealing with high-resolution data, Object-Based Image Analysis (OBIA), also termed Geographic Object-Based Image Analysis (GEOBIA), emerged as a major paradigm advancement (Hughes & Kennedy, 2019; Maxwell et al., 2015). OBIA initially divides the image into spatially connected and spectrally somewhat uniform areas, or "objects," which ideally represent meaningful real-world items (like individual fields, building outlines, or forest patches). Classification is subsequently carried out on these objects instead of individual pixels. A significant benefit is that classification decisions can integrate not just the object's spectral data (e.g., average reflectance) but also its spatial attributes (shape, size, geometry) and contextual details (texture, relationship to adjacent objects) (Hughes & Kennedy, 2019). This inclusion of spatial context typically enhances classification accuracy, especially for high-resolution images in complex environments such as urban areas.

The challenge presented by "Big Data" in remote sensing—stemming from immense data quantities, diversity across sensors and time, and high-speed acquisition from many satellite and airborne sources—has created a demand for enhanced and automated analysis techniques (Khilar et al., 2019; Lazzeri, 2021; Löw et al., 2021; Yekeen & Balogun, 2020b; Yuh et al., 2023a). Consequently, Artificial Intelligence (AI), including Machine Learning (ML) and its specialized form, Deep Learning (DL), is now heavily utilized for LULC classification tasks (Al-Najjar et al., 2025; Corucci et al., 2010; Gokool et al., 2024; Talukdar et al., 2020, 2020b; Wang et al., 2022a; Yuh et al., 2023a).

2.4.3.1 Machine Learning Algorithms

ML includes algorithms capable of learning patterns and relationships from data to make predictions or decisions without explicit programming for the specific task (Abhishek Jha, 2023; Yekeen & Balogun, 2020b). Several ML algorithms have become standard instruments in remote sensing LULC classification, frequently surpassing traditional supervised classifiers (Lazzeri, 2021; Löw et al., 2021; Yekeen & Balogun, 2020b).

Random Forests (RF): RF is an ensemble learning approach that builds numerous decision trees during its training phase and determines the final class based on the most frequent output among the individual trees (Breiman, 2001; (Hughes & Kennedy, 2019; Maxwell et al., 2018)). It functions by constructing each tree using a random bootstrap sample of the training data and considering only a random subset of features at each decision point (Breiman, 2001; (Hughes & Kennedy, 2019)). This methodology renders RF resistant to overfitting and adept at handling high-dimensional data with intricate interactions (Maxwell et al., 2019). RF is broadly utilized and often attains high classification accuracies, frequently comparable to or slightly less than SVM, yet sometimes significantly better than traditional methods (Maxwell et al., 2019; Al-Najjar et al., 2025).

Support Vector Machines (SVM): SVM is a supervised learning technique that seeks to identify an optimal dividing hyperplane (decision boundary) to distinguish classes within a high-dimensional feature space (Choubin et al., 2019; Cococcioni et al., 2012; Cortes & Vapnik, 1995; Maxwell et al., 2018; Mountrakis et al., 2011). It is recognized for its proficiency in managing high-dimensional data (like multispectral or hyperspectral images) and often achieves good results even with comparatively small training datasets (Hughes & Kennedy, 2019; Mountrakis et al., 2011). The application of kernel functions (e.g., Radial Basis Function - RBF) enables SVM to address data that is not linearly separable (Cortes & Vapnik, 1995; Mountrakis et al., 2011). SVM consistently yields high accuracy in LULC classification across numerous studies ((Hughes & Kennedy, 2019); Al-Najjar et al., 2025 (Choubin et al., 2019;).

Artificial Neural Networks (ANN): ANNs, drawing inspiration from biological neural systems, represented early ML methods applied to LULC classification, occasionally integrating supplementary data (Al-Najjar et al., 2025; Maxwell et al., 2018). They serve as the foundation for contemporary deep learning models.

2.4.3.2 Deep Learning Architectures

DL signifies a major progression within ML, defined by the utilization of Artificial Neural Networks comprising multiple layers (Southworth et al., 2024; X. Zhang et al., 2024). These networks can autonomously learn hierarchical feature representations directly from the input data (Rewhel et al., 2023; Southworth et al., 2024; Vali et al., 2020; X. Zhang et al., 2024). This capacity for automatic feature extraction obviates the need for the manual feature engineering often necessary in conventional ML processes and permits DL models to discern highly complex spatial and spectral patterns (Southworth et al., 2024). DL has achieved notable success in diverse image analysis applications and is increasingly employed for LULC classification using remote sensing data, frequently delivering state-of-the-art outcomes, especially when dealing with large datasets (Praticò et al., 2021; Rewhel et al., 2023; Southworth et al., 2024; X. Zhang et al., 2024; S. Zhao et al., 2023).

Convolutional Neural Networks (CNNs): CNNs are the primary tool in DL for image analysis. Their structure, usually comprising convolutional layers, pooling layers, and fully connected layers, is tailored for processing grid-like data (images) and effectively learning spatial feature hierarchies, progressing from basic edges and textures in initial layers to intricate object components in deeper layers (Hughes & Kennedy, 2019; Nigar et al., 2024). CNNs have been effectively utilized for LULC classification (Al-Najjar et al., 2025; Praticò et al., 2021) and related applications such as detecting oil spills from hyperspectral imagery (J.-F. Yang et al., 2019). They frequently produce very high levels of accuracy (Praticò et al., 2021; Al-Najjar et al., 2025).

Recurrent Neural Networks (RNNs): While CNNs are adept at recognizing spatial patterns, RNNs are tailored for sequential data. They have also been applied to LULC classification, showing strong results, possibly by identifying sequential patterns in multi-temporal data or specific spatial arrangements (Praticò et al., 2021).

Despite the often-remarkable performance attributed to DL models (Al-Najjar et al., 2025; Praticò et al., 2021; J.-F. Yang et al., 2019), selecting between ML and DL is not invariably straightforward. Certain comparative analyses show instances where established ML algorithms like SVM or RF attain accuracies similar to, or occasionally even surpassing, DL models in particular situations (Maxwell et al., 2018; Southworth et al., 2024). This observed variability implies that the best algorithm selection depends on the specific context. Factors influencing performance include the volume and quality of available training data (DL typically needs more data) (Maxwell et al., 2021; Ramezan et al., 2021), the intricacy of the landscape being mapped (Maxwell et al., 2018), the particular spectral and spatial properties of the remote sensing data employed, the computational resources accessible for training (DL is generally more resource-intensive) (Al-Najjar et al., 2025; Southworth et al., 2024; Vali et al., 2020), and the specific architecture and hyperparameter adjustments applied to the DL model (Maxwell et al., 2015, 2021; Ramezan et al., 2021). Thus, although DL provides potent capabilities for automatic feature learning and potentially superior peak accuracy, robust ML algorithms continue to be highly pertinent and might be more suitable in scenarios with restricted data, computational limitations, or where interpretability is a primary concern. Thorough evaluation and comparison within the specific application framework are essential.

Despite this progress, significant hurdles persist. Reliably distinguishing specific stressors (like oil) from other interfering factors, the reliance on high-quality data and ground verification for training and validation, the intricacy and "black box" characteristics of advanced algorithms, and the divide between research advancements and operational implementation remain ongoing challenges. Future progress is anticipated through synergistic sensor fusion, the creation of more resilient, data-efficient, and interpretable AI models customized for remote sensing data, the ongoing utilization of big data platforms, and the increased operational incorporation of adaptable platforms like UAVs. Continuous innovation in these domains offers substantial potential for overcoming existing limitations and further strengthening the vital role of remote sensing in comprehending, managing, and addressing environmental issues worldwide.

2.4.4 Oil Spill Monitoring Using Qualitative Approach

Several authors have already shown the value of qualitative inquiry for understanding how oil-spill related hazards unfold in the Niger Delta. Babatunde (2023), using key-informant interviews and focus-group discussions across Bayelsa, Delta and Rivers States, links oil extraction to soil, water and livelihood degradation that has steadily undermined households' ability to obtain adequate, safe and culturally appropriate food. Isidiho et al. (2023) interviewed fishers, farmers, traders and community leaders in Imo State and the wider Delta, revealing how five decades of chronic spills have forced people to adopt ad-hoc coping strategies while contending with job loss, ill-health and environmental decline. Drawing on questionnaire surveys and clinic records, Oghenetega et al. (2022) exposed the heightened obstetric risks faced by women chronically exposed to hydrocarbons. Johnson et al. (2022), through semi-structured, open-ended interviews, found that residents, industry personnel and regulators possess a keen awareness of both the immediate and systemic drivers of pipeline accidents. Emelu et al. (2021) used survey designs to show, first, that sabotage is propelled by unemployment, perceived injustice and weak policing, and second, that community preparedness and mitigation efforts are hampered by limited resources and inadequate institutional support.

Collectively, these studies showcase the strength of qualitative tools such as focus-group discussions and interviews in unpacking the experiences of communities affected by of oil spills.

To address the fundamental questions surrounding community experiences of oil spills in the Niger Delta, it is essential to embed qualitative methods (focus group discussion and community participatory mapping) within a theoretical framework drawn from social and human geography (Austin & Sutton, 2014; Marshall & Rossman, 2014; Mohajan, 2018). This study uses the integration of two interconnected concepts—slow violence and infrastructural violence—as critical analytical lenses. By applying these frameworks with the qualitative tools, I intend to strategically unpack the nuanced nature of harm stemming from decades of oil extraction in the Niger Delta.

Slow Violence: The concept of "slow violence," developed by Rob Nixon, offers a critical lens for understanding environmental degradation that unfolds gradually and often escapes immediate attention (Nixon, 2011, 2). Nixon defines slow violence as "a violence that occurs gradually and out of sight, a violence of delayed destruction that is dispersed across time and space, an attritional violence that is typically not viewed as violence at all (Nixon, 2011).

Several key characteristics define slow violence. Its temporal dispersion is central; the harm is incremental, accretive, and unfolds over extended periods – years, decades, or even generations. This delay between cause and effect, between actions and consequences, obscures the origins of the harm and makes it difficult to perceive and respond effectively. Slow violence is also characterised by geographical dispersion, spreading across space, potentially affecting locations far removed from the initial polluting activity or decision (Nixon, 2011).

The concept is particularly pertinent to understanding environmental degradation, including the effects of toxic waste disposal, deforestation, climate change impacts, the environmental aftermath of war (T. Davies, 2022; Finch-Race, 2025; Nixon, 2011), and, crucially for this study's context, that is, the Niger Delta oil spills.

Infrastructural Violence: Complementing the temporal focus of slow violence, the concept of "infrastructural violence," notably articulated by Rodgers and O'Neill (2012), directs attention to the ways physical infrastructures – or their absence – can inflict harm, exclude populations, perpetuate inequality, and mediate power relations. This perspective challenges the notion of infrastructure as merely neutral or benign technical systems, instead positioning it as a key site where social, economic, and political forces converge and where violence can be enacted, often systemically (Graham, 2004; Kallianos et al., 2023). The concept builds on earlier ideas like Mann's "infrastructural power" (the state's capacity to penetrate society through logistics (Mann, 1984)) and Graham's "infrastructural warfare" (targeting infrastructure for military/political ends (Graham, 2004, 2006)) .

Infrastructural violence manifests in two primary forms: active and passive. Active infrastructural violence involves the intentional design or deployment of infrastructure to control, harm, or exclude specific populations (Rodgers & O'Neill, 2012). Passive infrastructural violence, conversely, arises from the absence, failure, neglect, or inherent limitations of infrastructure (Rodgers & O'Neill, 2012).

This framework is highly relevant to resource extraction contexts, where large-scale infrastructures like pipelines, processing plants, refineries, power stations, roads, and waste disposal sites are central to operations (Enns & Sneyd, 2021). These systems often become conduits of infrastructural violence by facilitating the removal of resources for external benefit while imposing risks and negative externalities on local populations (Enns & Sneyd, 2021), reinforcing historical patterns of colonial or neocolonial exploitation, enabling dispossession, and prioritizing corporate interests over community well-being and environmental health (Enns & Sneyd, 2021; Grabowski et al., 2022; Kallianos et al., 2023; Otsuki, 2024).

In resource extraction zones like the Niger Delta, the interplay between active and passive infrastructural violence is particularly pronounced. Active decisions regarding the placement of pipelines, the construction of facilities, and the deployment of security infrastructure or personnel often occur alongside, and are compounded by, passive neglect. This neglect manifests as the failure to adequately maintain aging infrastructure (leading to spills and accidents) (Chijioke, 2009; Everest, 2021; John, 2012; Shittu, 2014), the slow or inadequate response to environmental emergencies (Aduloju & Okwechime, 2016; Okonkwo & Etemire, 2017), the chronic underinvestment in basic services for host communities (Elum et al., 2016; Kpae, 2020; Oladipupo et al., 2016; Oluwaniyi, 2018), and the lack of enforcement of safety and environmental regulations (Emelu et al., 2021; Omotola, 2009; Oteh & Eze, 2012). This combination means communities often experience harm both directly from the presence and operation of extractive infrastructure and indirectly from the systemic failure to manage risks and invest in local well-being, creating a situation of compounded vulnerability.

2.4.4.1 Oil Spills and Environmental Degradation as Slow Violence

The chronic and cumulative effects of oil spills, gas flaring, and associated pollution in the Niger Delta serve as a powerful illustration of Rob Nixon's concept of slow violence. The harm manifests in multiple, interwoven ways:

Rather than a single, contained event, the environmental damage is attritional. Frequent oil spills – numbering over 10,000 between 2011 and 2022 alone (Ikporukpo, 2020a; NOSDRA, n.d.; Saint, 2022) – and continuous gas flaring have led to the progressive contamination of vast areas of land, rivers, creeks, and groundwater (Amnesty International, 2018; Bruederle & Hodler, 2019; Saint, 2022). This poisons farmlands, decimates fish populations, destroys ecologically vital mangrove forests, and diminishes biodiversity over extended periods(Babatunde, 2020; John, 2012; Umar et al., 2021). The UNEP assessment of Ogoniland, for instance, documented severe contamination impacting over 1,000 km^2, rendering water undrinkable and land unusable (UNEP, 2011).

The slow violence extends to human health. Communities are chronically exposed to a cocktail of toxins released through spills and flaring, including hydrocarbons like benzene (a known carcinogen), polycyclic aromatic hydrocarbons (PAHs), heavy metals, and potentially naturally occurring radioactive materials (Chinedu & Chukwuemeka, 2018; Obida et al., 2021; Ordinioha & Brisibe, 2013). These exposures contribute to long-term health problems such as respiratory illnesses, cancers, skin diseases, and other ailments that may take years or decades to fully manifest, making the direct link to pollution difficult to prove definitively in individual cases (Nriagu et al., 2016; O. B. Oghenetega et al., 2022; Ordinioha & Brisibe, 2013; Zheng, 2022). The UNEP report's finding of benzene in drinking water at levels 900 times above WHO guidelines underscore the severity of this hidden health threat (UNEP, 2011).

The gradual poisoning of the environment directly undermines the traditional livelihoods of Niger Delta communities, primarily farming and fishing. As land becomes infertile and waters polluted, the ability to produce food and generate income slowly erodes, leading to deepening poverty, food insecurity, and a form of "displacement without moving" – the loss of the productive capacity of the land and resources communities depend upon.

A significant danger arising from the chronic, attritional character of oil pollution in the Niger Delta is the potential for its normalization(Ekhator et al., 2023; Okonkwo & Etemire, 2017). When environmental degradation becomes a constant backdrop to daily life, endured over decades (Ansah et al., 2022; Clinton & Chinago, 2019; Little et al., 2018), there is a risk that both affected communities and external observers begin to perceive it as an unavoidable, almost 'normal' situation. This normalisation reinforces the very 'invisibility' that characterises slow violence (Nixon, 2011). Consequently, qualitative methods such as focus group discussions and community participatory mapping that delve into lived experiences become essential tools not just for documenting harm, but for actively disrupting this normalisation by highlighting the ongoing, unacceptable costs borne by communities due to oil spills.

2.4.4.2 Oil Pipeline as Infrastructural Violence

The physical infrastructure associated with oil extraction in the Niger Delta – the vast network of pipelines, flow stations, export terminals, refineries, gas flares, and waste pits – is not merely a passive backdrop to environmental harm but actively constitutes a form of infrastructural violence.

- **Pipelines as Sites of Harm:** This infrastructure is a direct source of risk and harm (Iyasara et al., 2013; Mahmoud, 2021; Ofualagba & Ejofodomi, 2017). Aging, poorly maintained pipelines are prone to leaks and ruptures, causing devastating spills (Iyasara et al., 2013). This represents a failure of maintenance (passive violence) that directly leads to active harm. The very construction of this infrastructure fragments landscapes and disrupts ecosystems (Agbagwa & Ndukwu, 2014). Furthermore, the failure to adhere to safety standards, the slow response times to reported leaks or spills (Ikporukpo, 2020), and inadequate remediation practices (Ndimele et al., 2018; Nuhu et al., 2021; Sam & Zabbey, 2018) represent forms of passive violence through systemic neglect.

- **Exclusion and Dispossession:** Oil infrastructure facilitates the extraction and export of wealth, primarily benefiting the Nigerian state and multinational corporations, while largely bypassing the communities whose lands and waters are exploited (Achunike, 2020). Land acquisition for pipelines and facilities can lead to the displacement of communities or the loss of access to traditional farmlands and fishing grounds (Enns & Sneyd, 2021).

- **Infrastructure as Conflict Driver:** The presence of valuable oil infrastructure in impoverished and environmentally degraded areas inevitably makes it a focal point for conflict (Kpae, 2020; Nextier, 2022; Nwajiaku, 2005; Udoh, 2020). Pipelines become targets for sabotage by aggrieved groups seeking compensation or political attention (Albert et al., 2019; Ejoh, 2021; Umar et al., 2019), or for theft ('bunkering') by criminal networks (Campbell, 2015; Osuntokun, 2014; Romsom, 2022; This Day Newspaper, 2022). This, in turn, leads to increased militarization and securitization of the region by state forces and private security hired by oil companies, often resulting in human rights abuses and further instability. Furthermore, access to infrastructure-related benefits (contracts, compensation, jobs) often becomes a source of intense intra-community conflict, exacerbated by 'divide-and-rule' tactics employed by companies (Nwajiaku, 2005).

The oil pipelines traversing the Niger Delta landscape embody a deep paradox. They are conduits carrying billions of dollars of oil wealth out of the region, fuelling the national economy and global markets (Abayomi et al., 2015; Odularu, 2008; Soremi, 2020). Simultaneously, these same pipelines are sources of chronic pollution through leaks and spills, contaminating the very environment local communities depend on (Amnesty International, 2020; E. Ite et al., 2018; Elum et al., 2016). They represent both the immense potential of the region's resources and the devastating reality of its exploitation. As sites of sabotage, theft, and conflict, they further symbolize the social breakdown and instability engendered by the oil economy (Eboh, 2022; Osuntokun, 2014; Ralby, 2017; Romsom, 2022). Thus, the pipeline itself serves as a potent material symbol of the core contradiction defining the Niger Delta experience: the coexistence of vast resource wealth with profound local impoverishment, environmental destruction, and social unrest.

Environmental justice (EJ) offers a framework for interpreting these ethical and political dimensions (Hoover et al., 2021; Wang et al., 2023; Ziaja, 2020). Originating in civil-rights struggles, EJ foregrounds the injustice that arises when marginalized communities disproportionately suffer environmental harms—pollution, hazardous waste, resource extraction—while enjoying fewer environmental benefits (Grabowski et al., 2022; Samanlangi, 2024; Wang et al., 2023; Ziaja, 2020). The US Environmental Protection Agency (EPA) defines EJ as "the fair treatment and meaningful involvement of all people regardless of race, colour, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (Van Horne et al., 2023). Two core principles arise:

> **Fair Treatment (Distributive Justice):** No group should bear a disproportionate share of environmental “bads” (pollution, risk exposure) or be denied environmental “goods” (clean air, water, green space) (Oluwatomilola Olunusi & Emmanuel Adeboye, 2025; Van Horne et al., 2023).
>
> **Meaningful Involvement (Procedural Justice):** All affected people must have the opportunity to participate in decisions that affect their environment or health, with genuine access to information and influence over outcomes (Oluwatomilola Olunusi & Emmanuel Adeboye, 2025; Van Horne et al., 2023).

Crucially, EJ requires access to effective remedies and accountability mechanisms for state and corporate actors (Grabowski et al., 2022; Schlosberg, 2013; Van Horne et al., 2023; Wang et al., 2023; Ziaja, 2020). Focusing solely on unequal outcomes overlooks the decision-making processes and power dynamics that produce them (Hoover et al., 2021; Rodgers & O’Neill, 2012; Schlosberg, 2013). In the Niger Delta, persistent exclusion of local voices and dismissal of indigenous knowledge demonstrate that justice demands not only redistribution of environmental goods and harms but also transformation of governance: whose voices count, whose values guide policy, and how decisions are made (Adomokai & Sheate, 2004; Oluwatomilola Olunusi & Emmanuel Adeboye, 2025).

Consequently, the pursuit of environmental justice is rarely a passive state but an active political struggle (Adomokai & Sheate, 2004; Van Horne et al., 2023). Communities impacted by harmful or inequitable environmental conditions or infrastructure often mobilise to contest dominant development paradigms, challenge state and corporate power, demand accountability, and advocate for alternative, more just and sustainable futures. (Adomokai & Sheate, 2004; T. Davies, 2022; Nwajiaku, 2005). The Niger Delta's history of protest, legal action, and grassroots activism exemplifies this ongoing contestation over resource control, environmental protection, and the very meaning of development (Adomokai & Sheate, 2004; Nwajiaku, 2005).

2.4.5 Qualitative Information Capture Approaches for Monitoring and Managing Oil Spills

Understanding community perspectives and experiences related to oil spills in the Niger Delta necessitates moving beyond technical monitoring to engage with the profound social, political, and experiential dimensions of environmental harm that have characterised the region for decades. Critical theoretical lenses from social and human geography, particularly the concepts of slow violence (Nixon, 2011) , infrastructural violence (Rodgers & O'Neill, 2012) , and environmental justice, are essential for analysing the gradual, often hidden, and structurally embedded nature of harm caused by oil extraction and its associated infrastructure. Slow violence, as conceptualized by Nixon (2011), draws attention to the delayed, attritional, and often invisible destruction dispersed across time and space. Infrastructural violence (Rodgers & O'Neill, 2012) highlights how physical infrastructure itself—or its absence—can inflict harm and perpetuate inequality. Environmental justice provides the overarching framework demanding fair treatment and meaningful involvement for all communities, scrutinizing the inequitable distribution of environmental burdens and benefits and the fairness of decision-making processes (Hoover et al., 2021; Schlosberg, 2013; Wang et al., 2023). This section explores how qualitative information capture approaches, specifically Focus Group Discussions (FGDs) and Community Participatory Mapping (CPM), can be utilized not merely as descriptive tools, but as analytical methods to investigate community perspectives on oil spills through these interconnected theoretical frameworks. Employing these methods in a theoretically informed manner allows research to address critical gaps concerning the lived experience of long-term environmental degradation, the tangible impacts of oil infrastructure, and ongoing community struggles for environmental and infrastructural justice

2.4.5.1 Focus Group Discussions (FGDs)

Focus Group Discussions (FGDs) provide a crucial methodology for investigating the lived realities of slow violence associated with oil spills. Through facilitated group discussions, researchers can gain insights into shared experiences, diverse perspectives, and complex social dynamics within affected communities (Calheiros et al., 2000; Cochrane & Corbett, 2018, 2020; Corbett et al., 2016). Moreover, researchers can garner collective memories of gradual environmental degradation (e.g., declining soil fertility, water contamination), chronic health concerns potentially linked to long-term exposure, and the attritional loss of traditional livelihoods like farming and fishing – impacts often rendered invisible in official assessments or short-term surveys (Babatunde, 2023; Nixon, 2011).

Furthermore, FGDs are vital for understanding community experiences of infrastructural violence and broader environmental injustice. They allow for exploration of how communities interact with and are affected by the physical presence of oil infrastructure (e.g., proximity to pipelines, noise and pollution from flares, land disruption from construction), their perceptions of risk associated with this infrastructure, and their experiences of exclusion from decision-making processes or from the economic benefits derived from resource extraction (Rodgers & O'Neill, 2012). Discussions can illuminate local understandings of fairness, responsibility, and the pursuit of environmental and infrastructural justice, revealing community demands for meaningful participation, adequate remedy for harms suffered, and accountability from corporate and state actors (Babatunde, 2023; Rodgers & O'Neill, 2012; Samanlangi, 2024).

The COVID-19 pandemic has undeniably reshaped the landscape of research, particularly fieldwork. This has led to a growing emphasis on reimagining traditional methods and embracing remote data collection approaches (Bruun & Guasco, 2023; Dinko & Nyantakyi-Frimpong, 2023; Luh Sin, 2015; Monnier-Reyna, 2024; Rogers et al., 2022). This shift is particularly relevant in contexts like the Niger Delta, where in-person data collection can be challenging due to safety concerns, or travel restrictions. While remote FGDs offer possibilities, researchers must carefully consider strategies to build rapport, ensure equitable participation across potential digital divides, maintain data quality, and address the ethical complexities of discussing sensitive experiences of violence and injustice in a virtual setting, particularly within marginalized Niger Delta communities where trust and access can be significant challenges (Davis & Ramírez-Andreotta, 2021; Udoh, 2020).

FGDs can also be facilitated virtually, offering a valuable platform to explore how communities perceive the risks and challenges associated with oil spills, particularly their impacts on livelihoods, the environment, and way of life. Through these online group discussions, researchers can gain insights into shared experiences, diverse perspectives, and complex social dynamics within affected communities (Calheiros et al., 2000; Cochrane & Corbett, 2018; Corbett et al., 2016). While offering valuable opportunities, remote FGDs also introduce new complexities. Researchers must carefully consider strategies to ensure participant engagement, maintain data quality, and address ethical considerations in a virtual setting.

Beyond FGDs, other qualitative methods include audio-diary methods, where participants document their experiences and reflections over time; photovoice, which empowers individuals to capture and communicate their lived experiences through photography; video documenting, allowing for visual records of events or phenomena; and documentary analysis of social media content (e.g., Facebook, WhatsApp, YouTube) to glean insights into online discourse and community perspectives. Auto-ethnography, where researchers reflect on their personal experiences and observations, can also generate valuable insights. Quantitative approaches in remote settings include mobile phone surveys using interactive voice response (IVR), short messaging service (SMS), or computer-assisted telephone interviews (CATI) to gather structured data from a wider population. Researchers can also distribute self-completed online questionnaires through email or social media platforms.

Furthermore, the environmental impacts of oil spills can be assessed remotely using satellite imagery. This approach aligns with the broader shift towards remote data collection and offers valuable opportunities for monitoring environmental change and assessing the effectiveness of mitigation strategies.

2.4.5.2 Participatory Mapping

Community Participatory Mapping (CPM) offers a spatially explicit approach to documenting and analysing slow violence, infrastructural violence, and environmental injustice in the Niger Delta. By engaging communities in mapping their own environments and recalling historical changes, CPM can visually represent the dispersed and cumulative nature of slow violence (Nixon, 2011), such as the spatial extent of recurring oil spills over decades, the locations of chronically contaminated sites, and the gradual loss of access to vital resources like specific farmlands, fishing grounds, or clean water sources(Babatunde, 2023). In addition, researchers can gain a deeper understanding of local realities and contribute to more inclusive and equitable decision-making (Calheiros et al., 2000; Cochrane & Corbett, 2018; Corbett et al., 2016; IFAD, 2009; Ralls & Pottinger, 2021).

CPM is also uniquely suited to investigating infrastructural violence 1 and mapping patterns of environmental injustice (Wang et al., 2023) by enabling communities to map the precise location and perceived impacts of oil infrastructure (pipelines, flares, waste pits, flow stations) relative to their homes, schools, health facilities, agricultural lands, water bodies, and sacred sites. This process can highlight spatial patterns of risk exposure, vulnerability hotspots, unequal distribution of environmental 'bads', and zones of exclusion associated with this infrastructure (Hoover et al., 2021; Wang et al., 2023).1 Furthermore, CPM serves as a tool for pursuing environmental and infrastructural justice (Hoover et al., 2021), empowering communities to document their spatial knowledge, identify areas suffering from neglect or lack of essential services potentially challenge the accuracy or completeness of official maps and data, and develop community-led plans or advocacy materials demanding equitable resource distribution, safer infrastructure, and targeted remediation (L. F. Davis & Ramírez-Andreotta, 2021; Hoover et al., 2021; Wang et al., 2023).

Key strength of CPM lies in its ability to centre and validate local, embodied spatial knowledge – the deep understanding residents possess of their environment derived from lived experience and intergenerational transmission – which is often overlooked in top-down assessments but is crucial for understanding the nuanced realities of environmental harm and injustice on the ground (L. F. Davis & Ramírez-Andreotta, 2021; IFAD, 2009; Ralls & Pottinger, 2021)

Adapting CPM methods for remote or hybrid settings presents considerable challenges in ensuring accessibility, fostering genuine collaboration and participation in the mapping process, and verifying spatial information, requiring careful planning and innovative approaches to maintain the method's integrity and participatory ethos." By actively engaging communities in mapping their experiences through these theoretical lenses, CPM can contribute to more inclusive research processes and potentially empower marginalized groups in their advocacy for environmental and infrastructural justice.

This review highlights that while technological approaches like remote sensing offer valuable large-scale data for monitoring oil spills, qualitative methods such as Focus Group Discussions and Community Participatory Mapping, when explicitly framed by theories of slow violence, infrastructural violence, and environmental justice, provide indispensable insights into the crucial human dimensions of oil extraction's impact in the Niger Delta. These methods function not merely as descriptive tools for gathering community perspectives, but as powerful analytical approaches capable of uncovering the hidden temporalities of gradual harm (slow violence), the complex spatialities of infrastructural risk and exclusion (infrastructural violence), and the profound inequities in burden distribution and participation (environmental justice) inherent in these environmental conflicts. Integrating these theoretically informed qualitative approaches is essential for developing monitoring and management strategies that are not only technically sound but also socially just, ethically grounded, and responsive to the lived realities and articulated needs of affected communities. Ultimately, employing FGDs and CPM through these critical lenses contributes to the vital task of making invisible violence visible and supporting communities in their protracted struggles for environmental and infrastructural justice

This literature review has explored a range of approaches for monitoring and managing oil spills, with a particular focus on remote sensing techniques and community intelligence. Satellite-based remote sensing, utilising both optical and microwave sensors, offers significant advantages for detecting, monitoring, and assessing the impacts of oil spills. SAR technology, with its all-weather capability and wide area coverage, is particularly valuable for mapping oil-polluted areas and guiding response efforts.

Complementing these technological approaches, qualitative methods like FGDs and participatory mapping provide crucial insights into community perspectives on oil spill risks, impacts, and mitigation strategies. These methods offer possibility to assess and quantify the impact of environmental degradation in hard-to-reach areas and empower marginalised communities and contribute to more inclusive and equitable decision-making in oil spill management.

2.5 Conclusion

The preceding review underscores the critical challenge posed by oil spills in the Niger Delta and highlights the evolution of scientific approaches aimed at understanding, monitoring and mitigating their impacts. The literature demonstrates significant progress in utilizing remote sensing technologies as powerful tools for environmental monitoring specifically in the Niger Delta region. Both optical satellite imagery (leveraging spectral characteristics to differentiate oil and assess environmental features) and Synthetic Aperture Radar (SAR) (offering all-weather detection capabilities) have proven valuable for identifying spills and monitoring affected areas (Al-Ruzouq et al., 2020; Ozigis et al., 2019; Wong et al., 2021). Furthermore, specific remote sensing techniques, particularly the application of vegetation indices derived from satellite data, are well-established for assessing vegetation health and quantifying the detrimental effects of oil pollution on plant life, overcoming the spatial and logistical limitations of traditional field methods (Adamu et al., 2015, 2018; Amiri & Pourghasemi, 2022). Advanced computational methods, including machine learning and deep learning algorithms, are increasingly integrated with remote sensing data, enhancing the accuracy and sophistication of analyses such as oil spill detection and assessment, and land cover mapping, thereby providing deeper insights into environmental changes driven by oil spills (Junaid et al., 2023; Southworth et al., 2024; Yekeen & Balogun, 2020b; X. Zhang et al., 2024).

Concurrently, the literature recognises the indispensable value of qualitative research methodologies for capturing the profound human experiences of oil spills in the Niger Delta. Studies employing focus groups, interviews, and participatory approaches have been crucial in documenting the lived experiences, social disruptions, and perceived injustices faced by affected communities. Concepts drawn from social and human geography, such as slow violence and infrastructural violence, provide critical analytical lenses to interpret the nuanced nature of harm stemming from prolonged oil extraction activities.

Despite these advancements, a critical gap persists in the integration of advanced geospatial and remote sensing analysis with rich, community-derived qualitative data. While remote sensing can map environmental degradation and qualitative studies can explore social impacts, there is a need for research that systematically connects the spatio-temporal patterns of environmental degradation directly with the long-term, lived experiences and testimonials of affected communities.

This study aims to address this integration gap. By integrating geospatial and remote sensing analysis with community testimonials and participatory mapping, this research seeks to unpack the long-term impacts of oil spillage on both the environment and the resident population in the affected communities.

Chapter Three

Adebangbe, S. A., Dixon, D., & Barrett, B. (2025). Geo-computation techniques for identifying spatio-temporal patterns of reported oil spills along crude oil pipeline networks. *International Journal of Digital Earth*, 18(1). https://doi.org/10.1080/17538947.2024.2448218

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3. Geo-computation techniques for identifying spatio-temporal patterns of reported oil spills along crude oil pipeline networks

3.1 Introduction

The Niger Delta region of Nigeria (see Figure 3.1) is a crucial oil-producing area with substantial oil reserves and gas deposits (Omotola, 2009; Tukur & Hajj, 2017) , yet faces a devastating environmental crisis due to frequent oil spills (Oteh & Eze, 2012) Between 2010 and 2022, there have been 11,863 incidents resulting in the spillage of approximately 563,206 barrels (i.e. 90 million litres) of crude oil (NOSDRA, n.d.). These spills have severe environmental and socioeconomic consequences, impacting local livelihoods and ecosystems (Umar et al. 2021; UNEP 2011; Wakil et al. 2021) . Several factors contribute to oil spills from the pipelines in the Niger Delta region, including aging infrastructure, vandalisation, a lack of community-based security, inadequate maintenance, mechanical failures, and human error (O. N. Albert et al., 2018; Everest, 2021; Johnson et al., 2022). It is increasingly important to understand the impacts of human activities on the environment for effective ecological protection (Che et al., 2023). Benke et al. (2015) argue that processing and visualising information can reveal data clusters and trends that are difficult to discern from traditional data tables and matrices. Similarly, Whanda et al. (2016) stress that understanding the spatial distribution of oil spills is vital for effectively addressing the challenges they present. Spatial analysis serves as a key tool in assessing the long-term impact of these spills and aids in allocating limited resources for environ- mental protection and security (Obida et al., 2018a; Wang et al., 2024) .

In regions like the Niger Delta, oil spills predominantly occur along the pipeline network (Obida et al., 2018a). Spatial analysis techniques such as Kernel Density Estimation (KDE) have proven effec- tive in addressing network-related issues such as road traffic accidents and crime hotspots (Xie & Yan, 2008). Mohaymany, Shahri, and Mirbagheri (2013) introduced the Network Kernel Density Estimation method (NKDE) to visualise crash density along roadways, aiding resource allocation and Tang et al. (2016) subsequently introduced the NKDE method for linear features (NKDE-L) to analyse space–time distribution of linear features in networks, using it to study taxi pick-up events. The applicability of these methods for analysing oil spills along a pipeline network can offer several advantages over traditional KDE approaches, as suggested by Obida et al. (2018). Traditional KDE approaches overlook the temporal dimension (Hu et al., 2018) and the Spatial– Temporal Network Kernel Density Estimation (STNKDE), which incorporates both spatial and temporal dynamics for hotspot detection, can address this limitation (Romano & Jiang, 2017).

Figure 3.1. The three prioritised states in the Niger Delta region; Delta, Bayelsa, Rivers.

Milić et al. (2020) extended KDE to network-based KDE, enhancing hotspot accuracy, particularly for linear features while Karatzoglou (2022) explored NKDE for identifying safer routes in road net- works, demonstrating their effectiveness without significantly increasing travel distance or time. Lastly, Gelb (2021) introduced TNKDE, building upon NKDE and incorporating the temporal dimension, applying this method to study road crashes in Montreal from 2016 to 2019. The evolution of spatial analysis techniques, from KDE to NKDE and TNKDE, has played a crucial role in addressing various network-related spatial and temporal challenges in hotspot detection, including oil spills, traffic accidents, and crime. These methods offer valuable insights for resource allocation and safety enhancement in diverse network-based scenarios (Obida et al., 2018a).

The KDE method typically counts events in two dimensions, determining density at sample sites, often pixel centres dividing the area of interest into equal zones (Gelb, 2021). Notably, Serra-Sogas et al. (2008) employed KDE methods with fixed and adaptive bandwidths to identify hotspots of shipping-based oil pollution in the Pacific Region of Canada's Exclusive Economic Zone, concluding that Adaptive Kernel Estimation provided superior visualisation of areas with higher concentrations of oil spills. However, this study focused solely on a specific area without considering the network of shipping transportation or the temporal patterns of spills over the years. Lin et al. (2010) utilised KDE and geostatistical techniques to delineate hazardous zones and quantify the risk of multiple pollutants in a contaminated area. They found that, while various method- ologies showed generally consistent results, integrating KDE and geostatistical methods proved effective in determining sampling density for delineating heavy metal pollutions. Zhang et al. (2021) employed KDE and K-means clustering to create maps of global maritime accidents, identifying hotspots and subdividing accidents into classes. Similarly, Umar et al. (2019) used Kernel density and Getis-Ord G* statistic to map oil spill areas in the Niger Delta, revealing hotspot concentrations in specific states.

Obida et al. (2018) introduced a crucial shift in the exploration of oil spill hotspots by adopting an alternative approach along the crude oil pipelines in the Niger Delta of Nigeria. Acknowledging the linear distribution of oil spill points along the pipeline network, they departed from the traditional KDE method and adopted the NKDE approach. This method expands the KDE process by estimating neighbourhood bandwidth distance using the network rather than free space. Beckstrom (2014) argued that NKDE's strength lies in its ability to estimate neighbourhood bandwidth distance using the network, accounting for the unique challenges posed by linear structures such as pipelines. Traditional methods relying on Euclidean distance may underestimate network distances, as movement is constrained along the network's edges. In essence, NKDE provides a more accurate representation of the spatial distribution of oil spills along the intricate pipeline network, capturing the nuances of spill patterns in a way that conventional KDE approaches fall short. Given the dynamic nature of the oil spill situation due to the interplay of various factors, timely analyses of updated oil spills in spatial and temporal dimensions using accessible software like R can inform targeted interventions.

Therefore, this study aims to explore the spatio-temporal pattern of oil spills along the Niger Delta oil pipeline network by applying the NKDE and its temporal extension, the TNKDE. By leveraging the spNetwork package in R, developed by Gelb (2021), this study extends previous work by incorporating a temporal analysis on an extensive database of reported oil spill incidents spanning from 2013 to 2021. The choice of NKDE as a pivotal methodology underscore its capacity to adapt to the linear structures of pipeline networks, ensuring a comprehensive understanding of the spatial distribution of oil spills. The subsequent integration of TNKDE (see Appendix C.3 for the theory on NKDE and TNKDE) extends the analysis into the temporal dimension, capturing the evolving patterns of oil spills over time. This transition to advanced geo-computation techniques can provide a more nuanced and accurate portrayal of the spatiotemporal dynamics of oil spills along crude oil pipelines in the Niger Delta. The utilisation of NKDE and TNKDE, alongside the reproducibility and scalability afforded by R, positions this study at the forefront of network data analysis applications, aiming to offer valuable insights for spatially targeted interventions to reduce future spill incidents and mitigate the impacts of past spills.

3.2 Materials and methods

3.2.1 Study area

The Niger Delta region of Nigeria (5°33′49″N latitude, 6°31′38″E longitude) is one of the world's largest deltas, covering over 70,000 km2 and accounting for 7.5% of Nigeria's total land mass (923,770 km2). The region is made up of nine states namely; Cross River, Edo, Delta, Abia, Imo, Bayelsa, River, Akwa-Ibom and Ondo states. They were merged politically to the six South-South geopolitical zone in 2000 to form the Oil Mineral Producing Areas Development Commission (OMPADEC) (Clinton & Chinago, 2019; Ukhurebor et al., 2021).

The Niger Delta region has a wet equatorial climate, where considerable cloud cover and lower sunshine hours generate moist weather conditions for most of the year (Shittu, 2014). The monthly mean temperature is between 25°C and 29°C, and annual precipitation ranges between 2000 mm and 4000 mm, with relative humidity generally greater than 70%. The Niger Delta's rainy season runs from March to October, with a brief dry period in August caused by monsoon winds from the southwest that transport precipitation from the ocean into the interior. The dry season lasts from November to February, with harmattan occurring between December and February due to a mass of northern tropical continental air (Matemilola et al., 2018; Ohwo, 2018) . According to (Matemilola, Adedeji, and Enoguanbhor 2018; Ohwo 2018), the Niger Delta has the largest wetland in Africa and the third largest in the world, with rivers, streams, and estuaries covering around 2,370 square kilometres, swamp forest covering 8,600 square kilometres and around 1,900 square kilometres of man- grove forests. According to the most recent census in 2006, the population of the Niger Delta was 31,277,901 (NBS n.d.); however, the National Population Commission (NPC) estimated that the population reached 44,732,022 in 2022. The inhabitants of the Niger Delta rely largely on their local environment (NDDC n.d.). In coastal areas, fishing and trading are the main vocations, while inland inhabitants cultivate food and cash crops. Cocoa, rubber, rice, sweet potato, maize, yam, cassava, and vegetables are mostly farmed.

The region, however, has been grappling with recurrent oil spills, inflicting severe environmental damage and adverse consequences for local communities (Amnesty International 2018). Several factors contribute to these oil spills, including the aging and poor maintenance of infrastructure, accidents, vandalism, and incidents like oil theft, commonly referred to as bunkering (Albert et al., 2019; Everest, 2021; NOSDRA, n.d.) . Between 1958 and 2010, about 546 million gallons of oil (approx. 13.37 million barrels) were spilled (Ikporukpo 2020), with pipeline vandalisation and tanker accidents attributing to approximately 50% of these incidents, sabotage being responsible for roughly 28%, and the remaining oil production operations to 22% of the spills (Amnesty International, 2018; Aroh et al., 2010; Emelu et al., 2021; NOSDRA, n.d.; Ralby, 2017) .

The geographical distribution of these oil spills across the Niger Delta is not uniform. Coastal areas are particularly vulnerable due to their remoteness and limited security presence, making them hotspots for oil theft and pipeline sabotage (Obida et al. 2018). Although oil is exploited in the nine states of the Niger Delta, the scope of this study is limited to the three most affected states in terms of pipeline vandalisation incidents and oil spillages; Bayelsa, Delta and Rivers (see Figure 1), which together account for >85 percent of oil spillages recorded by Nigeria's National Oil Spill Detection and Response Entity (NOSDRA).

3.2.2. Oil spill data

This study relied on Niger Delta oil spill data provided by NOSDRA covering the period from 2013 to 2021. The data was acquired through a series of Joint Investigation Visits (JIVs). The JIV procedure involves several regulatory bodies: the Nigerian Upstream Petroleum Regulatory Commission, the National Oil Spill Detection and Response Agency (NOSDRA), and the State Ministry of Environment, with representatives from the oil firm, the affected community, and the security forces all comprising the joint investigative team. The team investigates the cause(s) of the oil spill and is required to agree on and sign a report that verifies the cause(s). The extensive database contains information such as the date, time, and position of the spill (GPS coordinates), the extent of the spill, the type of oil, the estimated volume of the spill, and the source of the spill (see Figure 3.2), though this information is not consistently recorded. From an initial dataset of 16,766 records, a total of 8,710 records were excluded due to the absence of critical information such as date of oil spill incidents and geographical coordinates of the oil spill's locations. Data was then streamlined to the three study states, all records lacking a year of incident (n = 1 288) and all records dated 2012 or earlier (n = 6 532) were first removed to focus the spatio-temporal analysis on 2013–2022. Next, records missing latitude/longitude coordinates (n = 1 095 total, e.g., 588 in 2013, 592 in 2014, …, 297 in 2021, See Appendix E) were excluded. This left yearly sample sizes of 1 140 (2013), 1 131 (2014), 688 (2015), 489 (2016), 372 (2017), 498 (2018), 564 (2019), 373 (2020), and 274 (2021). Annual exclusion rates for missing coordinates ranged from 33.4 % (2020) to 52% (2021), a final dataset of 5,530 records remained for analysis. All density estimations and comparative analyses were performed using these retained counts, ensuring that spill-density outputs are normalized by the actual number of incidents analysed each year.

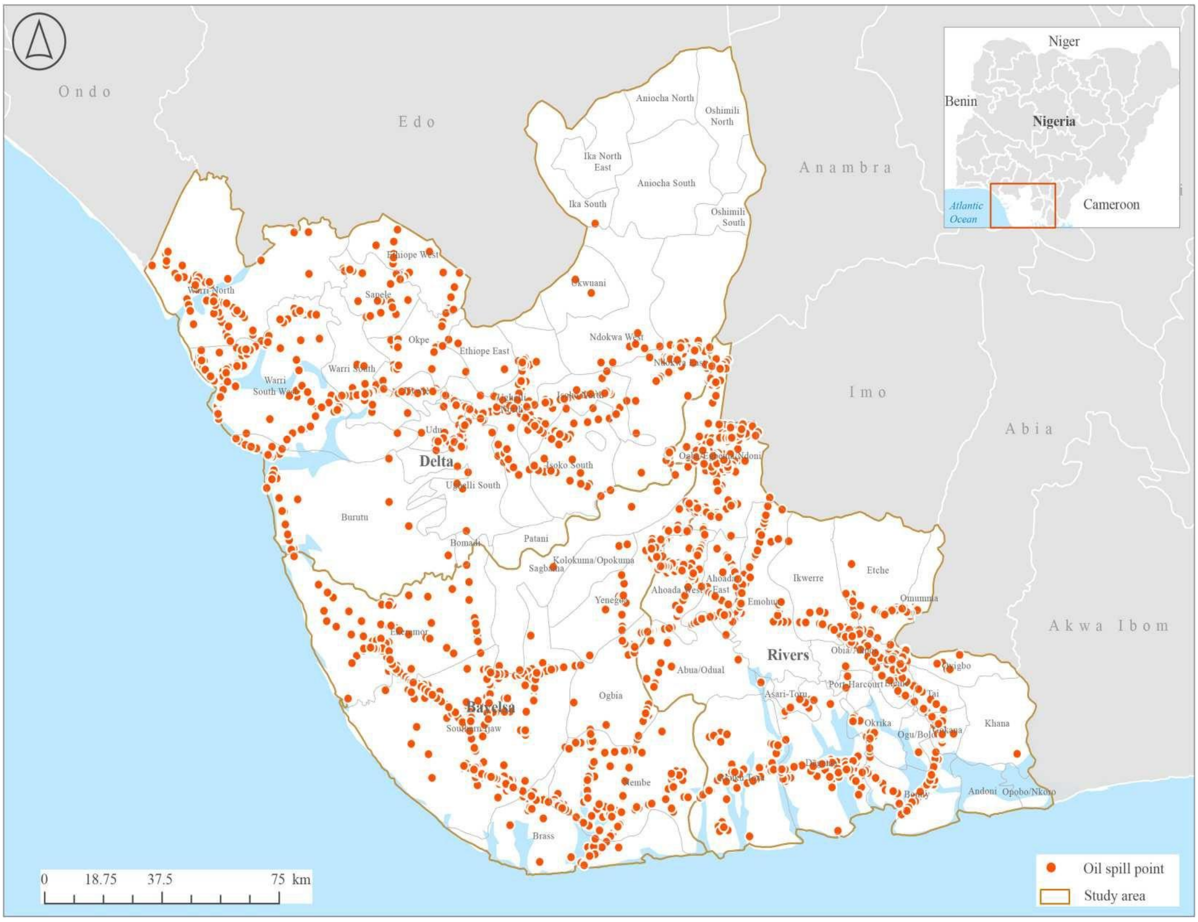

Figure 0.2. Oil spill locations from 2013 to 2021 across Delta, Bayelsa, and Rivers states (data source: NOSDRA).

3.2.3. Crude oil pipeline data

While the specific composition of spilled oil can vary in the Niger Delta, this study primarily focuses on crude oil spills from pipelines. Crude oil from this region generally falls into two categories: light and comparatively heavy (Thomas, 1995). The pipelines examined in this study are all onshore, primarily buried underground, but with some sections submerged underwater (see Figure 3.3). The data for the crude oil pipelines network in Nigeria was obtained from a private oil service company operating within Nigeria (Spinel Energy Solutions Limited). A total of 169 individual shapefiles, each containing coordinates for distinct sections of the pipeline network, were acquired. Subsequently, these datasets were imported into an ArcGIS Pro 3.0.0 environment which was used to perform the following data processing steps. The 'Points to Line' tool was used for the conversion of a set of individual points into a continuous polyline feature. The order of these points was determined based on their arrangement within the attribute table or, alternatively, based on a designated field that represents the sequential order of the points. The execution of the ‘Points to Line’ tool resulted in the generation of new polyline features, each corresponding to a distinct pipeline section (see Figure 3.3).

Figure 0.3.Crude oil pipelines in the Niger Delta region.

Subsequently, the dataset containing information about oil spill incidents was superimposed onto the newly created pipeline polylines. This overlay operation aimed to assess the visual alignment between the pipeline network and recorded oil spill incidents, as illustrated in Figure 3.4. The integration of these data sources and the visualisation of their spatial relationship provide valuable insights into the potential relationships between pipeline locations and incidents of oil spills. This analysis is central to this study’s investigation and forms a key aspect of the research methodology.

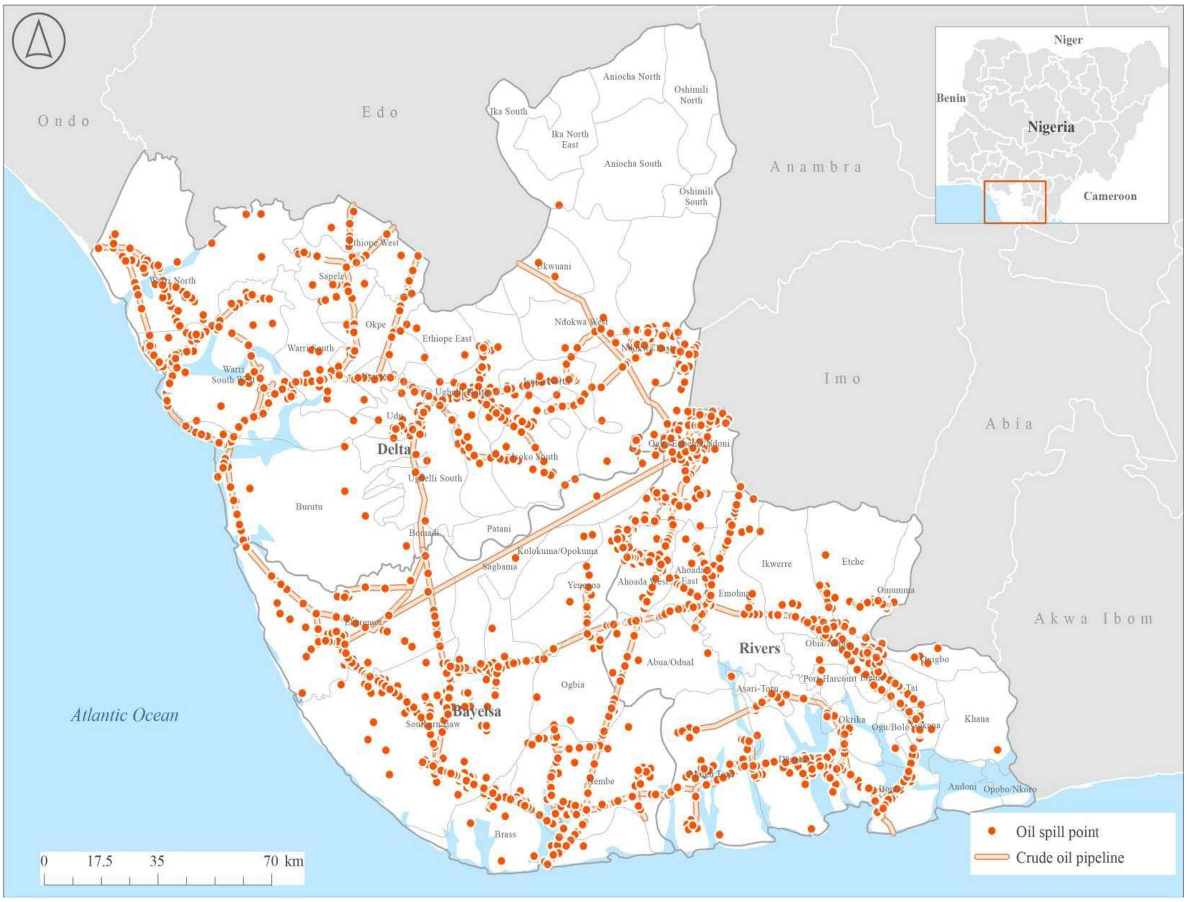

Figure 0.4. Overlay of oil spill points on the crude oil pipelines in Bayelsa, Delta and Rivers states.

3.2.4. Geo-computation of the network kernel density estimate (NKDE) and temporal network kernel density estimate (TNKDE)

The computation of the NKDE and TNKDE was performed using the spNetwork package (version 0.4.4) developed by Gelb (2021) in R (version 4.2.1) (R Core Team, 2023). The computation of NKDE and TNKDE followed the subsequent procedures: (i) data cleaning and preparation; (ii) loading cleaned data onto the R platform; (iii) generating lixels; (iv) calculating network distances between objects; and (v) computing lixel densities (see Figure 5). Full details of these steps have been previously discussed in Gelb (2021) and Romano and Jiang (2017). The TNKDE methodology necessitates the use of an event shapefile, which in this study pertains to the locations of oil spills. The dataset comprises various attributes, including but not limited to geographical location, date of oil spillage, street name, estimated quantity of spilled oil, estimated area impacted, and information regarding the oil company responsible for operating the pipeline. Additionally, a network shapefile, specifically the crude oil pipeline shapefile, is also required.

3.2.4.1. NKDE computation

During the data cleaning and preparation stage, a total of 8,710 records were excluded from our analysis out of the initial dataset of 16,766 records due to the absence of critical information. This missing information primarily included essential locational details such as geographic coordinates and addresses, as well as comprehensive descriptions of the contaminant involved. Consequently, our study was conducted using 5,530 records (to focus on 2013–2021 period) out of the remaining 8,056 records, which met the necessary criteria for inclusion (i.e. accurate geographic coordinates, the date of oil spillage, and the correct labelling of location names). Upon completion of the oil spill dataset cleaning process, it was subsequently imported into ArcGIS Pro and con- verted into a shapefile layer. The shapefile of the pipeline was also imported into ArcGIS Pro for re-vectorisation to streamline the topologies and address any topological issues that could potentially impede the spNetwork's functionality when applied to the data (Gelb 2021). Both the oil spill and pipeline network shapefiles underwent a reprojection process from geographic coordinates to Universal Transverse Mercator (UTM) coordinates. During the second stage, the shapefiles were imported into R by means of the st read function available in the sf package (version 4.0.2) in R. The network lines were partitioned into discrete units known as lixels, contingent upon the selected resolution. The lixel bears resemblance to the network pixel, albeit being composed of lines. The determination of density was conducted by means of the midpoints of the lixels' points, as per Gelb (2021) and Romano and Jiang (2017). The process of generating lixels from a pipeline network can be achieved through the utilisation of the 'lixelise lines' function provided by the spNetwork package in R. This function operates by dividing a given SpatialLinesDataFrame into lixels, as described by Gelb (2021). In order to accommodate the extensive scope of the research area, the lines were partitioned into segments of 500 m, with the lines of lesser length being consolidated into groupings of 50 m. The 500m segment provides sufficient granularity to resolve local variations in incident clustering without generating prohibitively large numbers of line segments. In preliminary trials, smaller segments (250 m) yielded very similar spatial patterns but increased computation time by over 60 %, whereas larger segments (1 000 m) smooth out sub-kilometre hotspots that are critical for identifying localized leak-prone reaches. Thus, 500 m represents a practical compromise: it is fine enough to detect neighbourhood-scale density anomalies yet coarse enough to allow rapid NKDE runs across the entire network. Subsequently, the 'line centre' function was employed to extract the central point of every line in a SpatialLinesDataFrame.

The nkde function from the spNetwork library was used to estimate the density of oil spills along the pipeline network. This estimation utilises a quartic kernel with a specified bandwidth and other relevant parameters. In order to restrict the total quantity of analogies, it is imperative to establish a suitable spatial search bandwidth. Increasing the spatial search bandwidth would result in a smoother visual representation and facilitate the observation of global patterns.

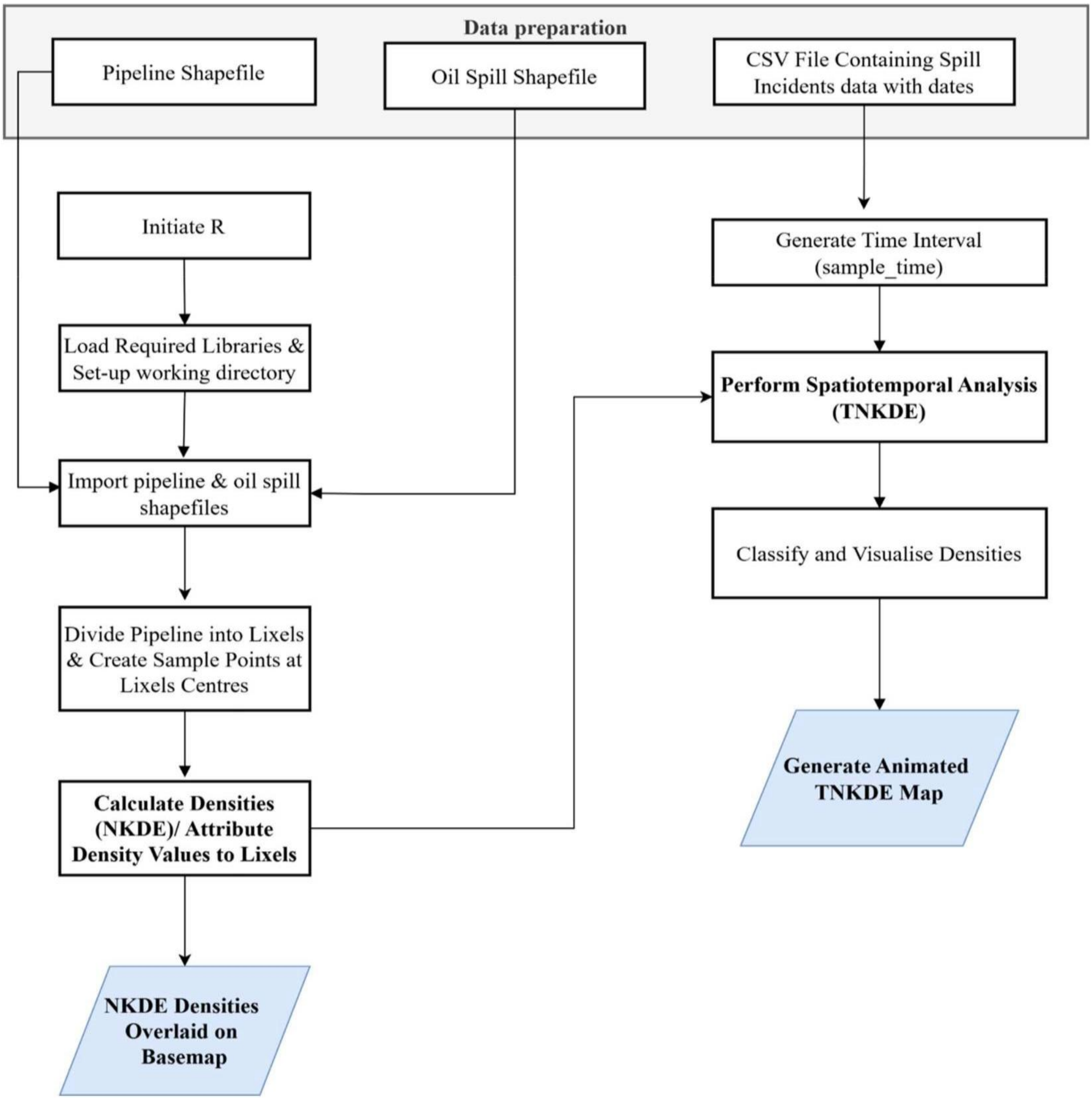

Figure 0.5. NKDE and TNKDE computation flowchart.

According to Romano and Jiang (2017), a reduced spatial search bandwidth facilitates the identification of local trends and enhances computational efficiency. As per the recommendation of Gelb (2021), using a quartic kernel, a lixel length of 500 m and a search bandwidth of 700 m were employed for NKDE due to the vast spatial expanse of the study area. The ‘st distance’ function from the sf package (version 1.0–15) in R was employed to compute the network distances among the objects. The calculated densities were multiplied by 1000 and incorporated into the lixels as an attribute. Visualisation was performed using the tmap library (version 3.3–4), which creates thematic maps based on the pipeline network’s density values. The visualisation employs a ‘plasma’ colour palette with five categories for better interpretation. Finally, the sample points generated during the analysis are saved as a new shapefile named ‘sample_points_line’ in the specified directory using the st_write function.

3.2.4.2 TNKDE computation

Understanding the distribution and temporal dynamics of spills is crucial for effective risk assessment, mitigation strategies, and emergency response planning. The TNKDE approach combines network analysis and kernel density estimation to capture both spatial and temporal patterns of oil spill incidents (see Figure 3.5). This study utilises two main datasets: (1) pipeline network data and (2) oil spill incident data. After data cleaning, coordinate transformation, and attribute format- ting to ensure data compatibility and consistency, the datasets were loaded into R using the appropriate libraries (rgdal, spNetwork, sf, tmap). To facilitate analysis at a finer scale, the pipeline network is lixelised into smaller segments using the lixelise_lines function, segmenting the pipelines into 500 m sections. This process divides the network into smaller spatial units, allowing for more accurate density estimation. Sample points are generated by calculating the centre points of the lix- els. The temporal information of the oil spill incidents is converted to a standardised format using the POSIXct function in R and numeric representation (time in days). This conversion enables meaningful temporal analysis and comparison. Additionally, missing or non-finite values were filtered out to ensure data quality.

The TNKDE method was implemented using the tnkde function in the spNetwork package. The function takes as input the pipeline network, oil spill incidents, sample points, and sample times. Other parameters such as kernel type, bandwidths (both spatial and temporal), and smoothing parameters (subset function to filter spills within 500 m of the pipeline and converts the date column to POSIXct format for time-based calculation) are specified. The network spatial bandwidths were set to 750 m and trimmed at 900 m, while the bandwidth for time was set to 90 and trimmed at 120 days (equivalent to approximately three to four months). The

TNKDE computation involves the estimation of oil spill densities at each sample point and sample time, considering the network struc- ture and temporal proximity. The computed kernel density estimates were reshaped into a matrix format to facilitate visualisation and analysis. A colour palette was created using classInt and viridis packages (‘plasma’ colour palette with five categories) to represent different density levels. The den- sities were then mapped onto the sample points using tmap functions (version 3.3–4), generating a series of maps at each sample time. These maps provide a visual representation of the spatio-tem- poral patterns of oil spill densities. Finally, the maps are compiled into an animated GIF using the tmap animation function. The animated map reveals the temporal evolution of oil spill densities and identifies areas of high density. The visualisation allows for the identification of temporal trends, hotspots, and potential risk areas.

3.2.4.3 Visualising the results

The classification scheme employed in visualising the results is based on the Jenks Natural Breaks algorithm. This algorithm identifies class intervals that optimise the grouping of similar values within each class while maximising the distinctions between classes (Lansley et al. 2019; O’Sullivan and Unwin 2014), thereby effectively categorising the data and facilitating a meaningful interpretation of the oil spill impact levels. The density values were systematically colour-coded and cate- gorised into five different classes, as presented in Table 1. Similar to the approach taken by Jayawardhana and Gorsevski (2019) to enhance the geovisualisation and interactivity of NKDE results, the tmap_mode(‘view’) function in the tmap package in R was used. This incorporates open street maps as a base map for the NKDE pipeline results and allows for overlay analysis, mak- ing it possible to visualise the areas impacted by oil spills based on the density attributed to the lixels. To make the results easily accessible, the generated NKDE with the open street map was published on RPubs by R studio (version 2023.09.0, (RStudio Team, 2023) in a simple format online. This online interactive NKDE can be accessed via: https://rpubs.com/Sheyih/1101517.

To illustrate the temporal evolution of the TNKDE results and facilitate the examination of each year alongside the respective hotspot regions identified along the pipelines, the R Markdown pack- age in R was employed to produce HTML output. Results were made readily accessible by embed- ding the generated TNKDE code snippet within the R Markdown document, which was then processed by knitr to execute the code chunks. Subsequently, the resulting HTML file was disseminated online in a straightforward format through RPubs by R

Studio (version 2023.09.0, (RStudio Team 2023)). The animated TNKDE can be accessed online via: https://rpubs.com/Sheyih/1169951.

Table 3.1. To facilitate interpretation, these density values were systematically color-coded and categorised into five different classes.

Colour	Value range	Description
`	0.000 - 0.022 (Very low)	Pipeline sections with minimal or no discernible impacts.
	0.0221 - 0.075 (Low)	Sections with relatively lower oil spill impacts.
	0.0752 - 0.151 (Medium)	Sections where oil spill occurrences are moderately concentrated.
	0.152 - 0.294 (High)	Sections with a substantial presence of oil spill incidents and consequently, elevated impact levels.
	0.294 - 0.768 (Very high)	Signalling sections with the most pronounced oil spill impacts.

3.3 Results

To calculate the TNKDE, the NKDE must first be calculated as a baseline. The NKDE analysis yielded a comprehensive visualisation of oil spill hotspots within the study area, identifying the specific pipeline sections and geographical regions most impacted by the oil spill incidents (see Figures 3.6 and 3.7). The NKDE analysis resulted in a range of density values spanning from 0.022 to 0.77. Notably, the analysis revealed that pipelines within Ekeremor, Brass and Southern Ijaw Local Government Areas (LGAs) in Bayelsa state exhibited the highest concentration of hotspots, suggesting that these areas were more susceptible to oil spills. Additionally, Gokana, Bonny, Tai, and Ogba/Egbemi/Ndoni LGAs in Rivers state also showed a high density of oil spills, indicating frequent occurrences in these pipeline sections. Figure 3.6(b) highlights the longest section of the pipeline impacted over a wide spatial extent, covering Southern Ijaw, Brass and Nembe LGAs of Bayelsa state. The oil spills primarily affected swamps and various creeks like Alabouturu, Diebu, Seibiri, Tebitada, and Isabatoru, as well as Sangana river. Moving slightly west of Figure 3.6(b) is 3.6a, depicting oil spill hotspots on pipelines within Ekeremor and Southern Ijaw LGAs. Here, the spills impacted the Apoi Creek Forest Reserve, Clough creek, and the mangrove forest in this part of the LGAs. Figure 3.6(c and d) are within Rivers state, with Figure 3.6(c) highlighting oil spills around Bodo community in Gokana LGA, and another notable community close to the oil spills hotspot is Ogale community, also situated in Gokana LGA.

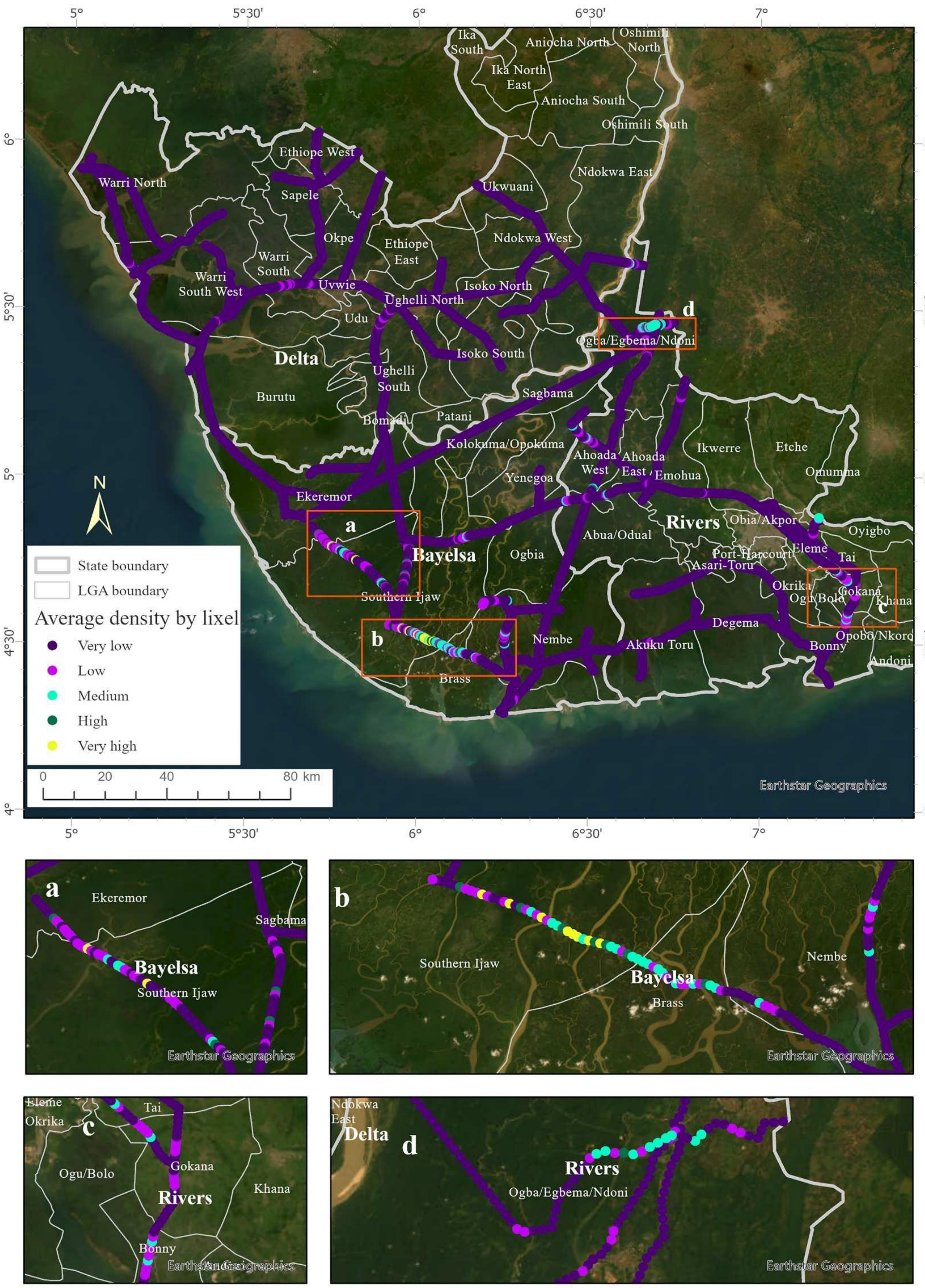

Figure 0.6. The average density of oil spill incidents by lixel. The densities were colour-coded for interpretation, with deep purple representing very low density (0.000–0.022), light purple indicating low density (0.0221–0.075),

light green indicating density (0.0752–0.151), deep green indicating high density (0.152–0.294), and yellow denoting very high density (0.294–0.768);(a) highlights the oil spill hotspots along the crude oil pipelines in Ekeremor, and Southern Ijaw LGAs of Bayelsa state; (b) high- lights the hotspot in Southern Ijaw, Brass and Nembe LGAs of Bayelsa state; (c) highlights the oil spill hotspots along the pipelines in Gokana, Bonny, and Tai LGAs of River state; and (d) highlights the hotspots along the pipelines in Ogba/Egbemi/Ndoni LGA in Rivers state.

The high concentration of spills also affected the swamp forest, Owokiri Creek in Bonny LGA, and section of the pipelines along Tai LGA. Figure 3.6(d), also in Rivers state, depicts oil spill hotspots in Ogba/Egbemi/Ndoni LGA, with impacts on the Ebocha community and the Orasi River. Nearby, the Obkron community is also situated in the affected LGA (see Figure 3.7).

Figure 3.7. Enhanced geo-visualisation of NKDE results using an OpenStreetMap basemap. This interactive approach allows for detailed examination of lixel properties and oil spill density along pipelines.

Various aspects can be observed and analysed concerning the temporal component, such as seasonality, periodicity, and frequency by month, day, weekend, time of day, among others (Karatzoglou, 2022). For this study, the particular interest lies in identifying the frequency pattern of oil spill incidents over the years. To address this, the TNKDE (see Figure 3.8(a–c)) was employed, which not only identified hotspots but also incorporated the temporal component of the oil spill data. By utilising the dates of occurrence, the TNKDE visualised the temporal transitioning of oil spill incidents alongside their spatial distribution. This feature provided a more nuanced understanding of the oil spill patterns over time. For a more focused analysis, Figure 3.8(a–c) illustrates different parts of the years. Each year is divided into three periods; P1 (January to April) or 1st 4-month period, P2 (May to August) or 2nd 4-month period, and P3 (September to December) or 3rd 4-month period, the images were extracted by period, making it three images per year. Comparing different images within the same time frame and bandwidth facilitates better comparison and understanding of the developments over the years (see Figure 3.8(a–c)).

The TNKDE analysis revealed persistent and evolving patterns of oil spill density along the pipe- lines from 2013 to 2021 (see Figure 3.9). Consistently clustered sections are highlighted in Figure 3.8(a– c). The 1st period (P1) of 2013 showed prominent high to medium-density oil spill clusters in Southern Ijaw LGA, Bayelsa State, particularly around Egbomatoro, Sangana River, Tebitada creek and community, and the Ikebiri Creek Forest Reserve and River (see link: htps://rpubs.- com/Sheyih/1101517 for detailed spatial exploration). Medium to low-density clusters were ident- ified in Alaboutoru Creek (Nembe LGA, Bayelsa) and near Ebocha (Ogba/Egbema/Ndoni LGA, Rivers State). Other pipeline sections exhibited low to no density hotspots during this period. The second period (P2) of 2013 displayed similar hotspots to P1 in Southern Ijaw LGA. However, new medium to low-density clusters emerged in the Apoi Creek reserve, further upstream from the P1 hotspots. In P3 of 2013, the hotspots persisted in similar locations to P2, with an increase in Clough Creek, extending up to Apoi Creek. Additionally, medium-density hotspots appeared in Brass and Nembe LGAs (Bayelsa State) (Figure 8(a)).

P1 of 2014 showed a more pronounced hotspot pattern compared to P3 of 2013. High and very high-density oil spill categories were observed in Southern Ijaw, Brass, and Nembe LGAs, marking an intensification compared to P1 of 2013. Furthermore, new low to medium-density clusters emerged around Ebocha. P2 of 2014 exhibited a similar hotspot distribution to P1, with increased prominence around Ebocha. In P3 of 2014, a reduction in hotspot intensity was observed around the Southern Ijaw pipeline stretch compared to P3 of 2013 and P2 of 2014. In P3 of 2014, a reduction in hotspot intensity was observed around the Southern Ijaw pipeline stretch compared to P3 of 2013 and P2 of 2014. P1 of 2015 showed a slight increase in medium to high-density clusters compared to P3 of 2014 in previously affected areas. The Southern Ijaw LGA continued to exhibit persistent medium to high-density hotspots. P2 of 2015 witnessed a reduction in oil spill clusters across all areas compared to P1 of 2015 and P2 of 2014. However, Ogba/Egbema/Ndoni LGA dis- played more pronounced medium to high-density hotspots, primarily in the Ebocha area. Similar to P2, P3 of 2015 showed a further reduction in oil spill clusters across all previously affected areas (Figure 8(a)).

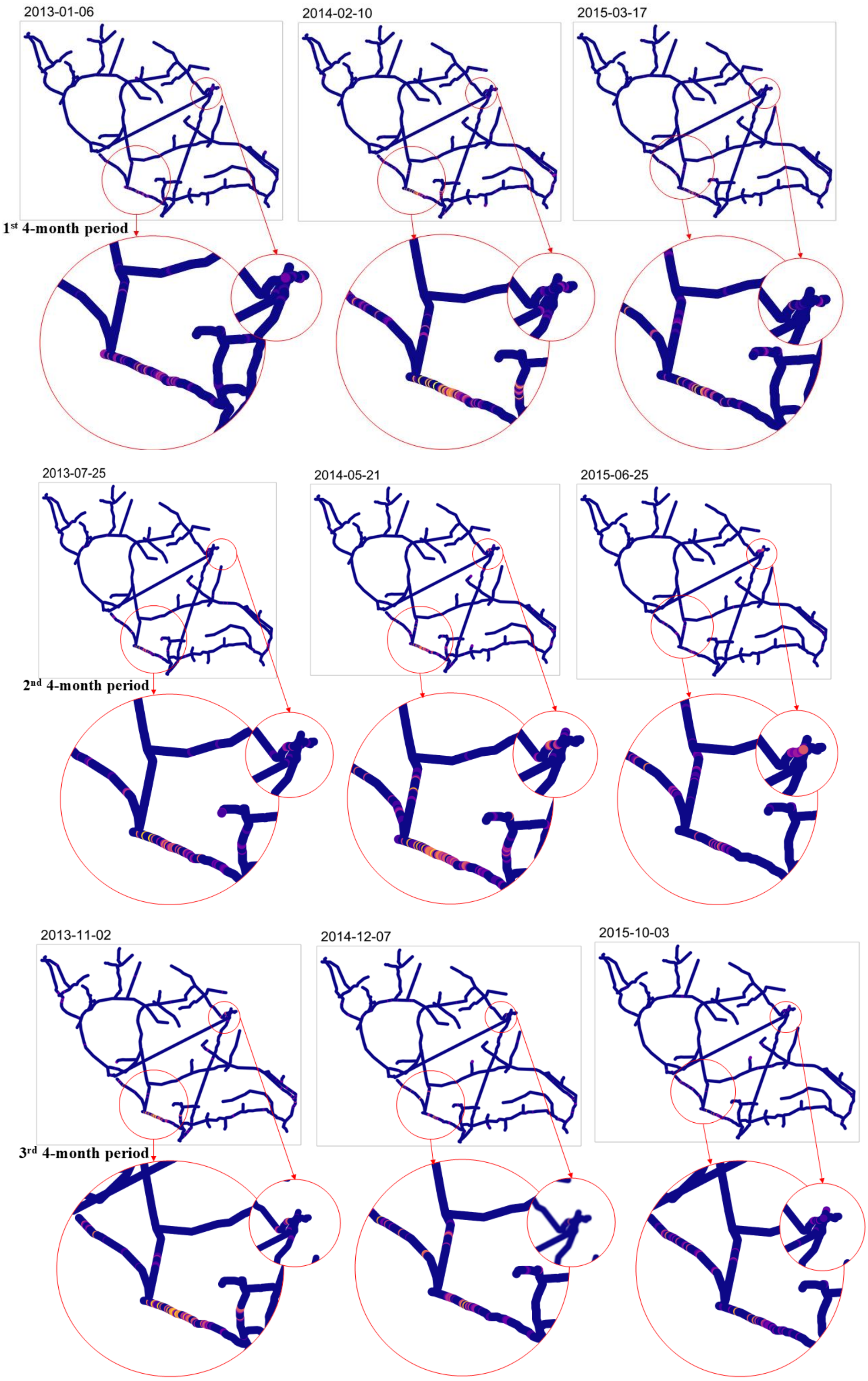

Figure 3.8a. TNKDE outputs highlighting the hotspot sections of the pipelines between 2013 to 2015; selecting images within the same time frame and bandwidth (4-month period) facilitates better comparison and understanding of the developments over the years. The red circles show the identified hotspot sections of the pipelines and their variation from year to year (to explore and zoom in on the hotspot areas see Figure 3.7)

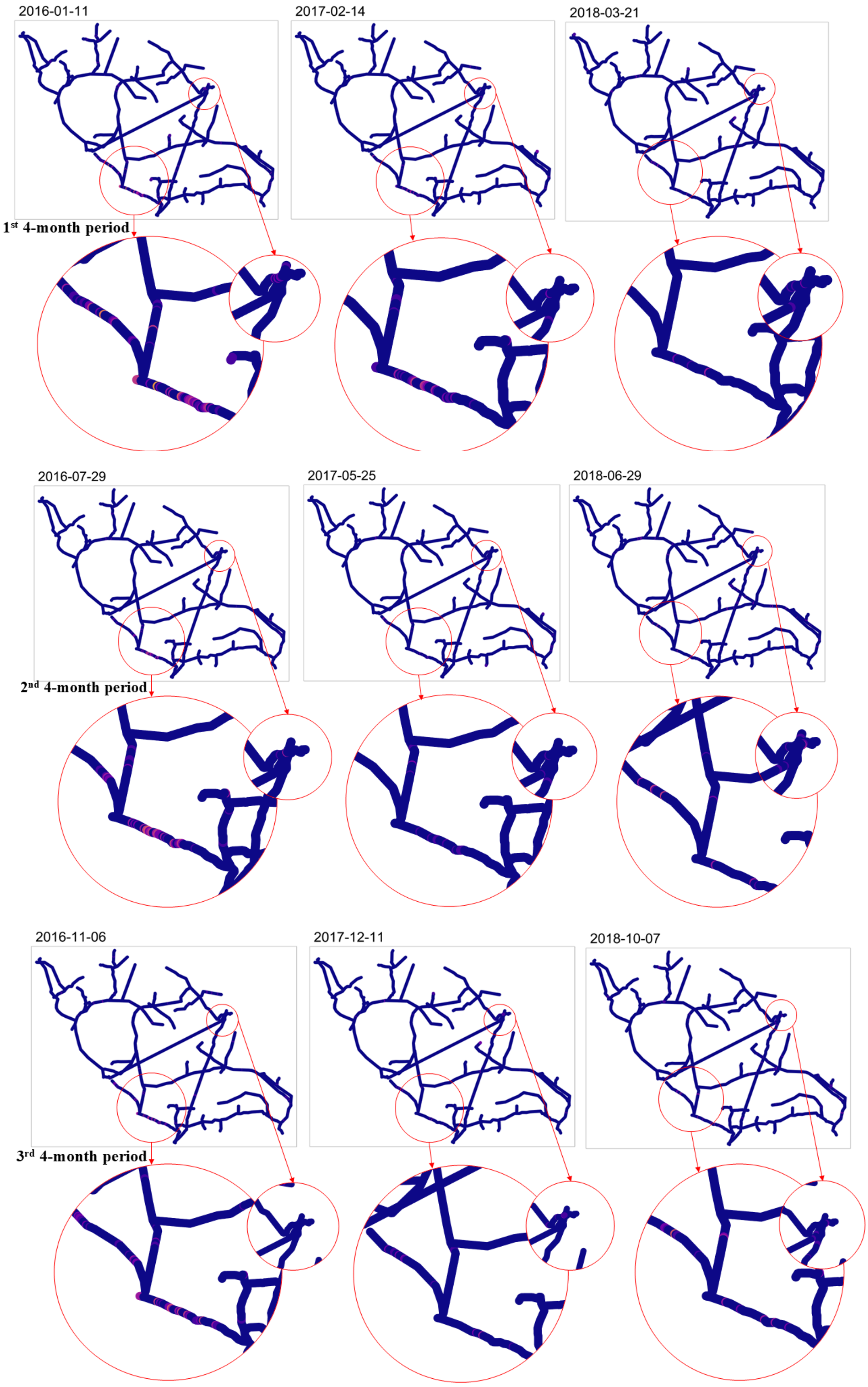

Figure 3.8b. TNKDE maps highlighting the hotspot sections of the pipelines between 2016 to 2018.

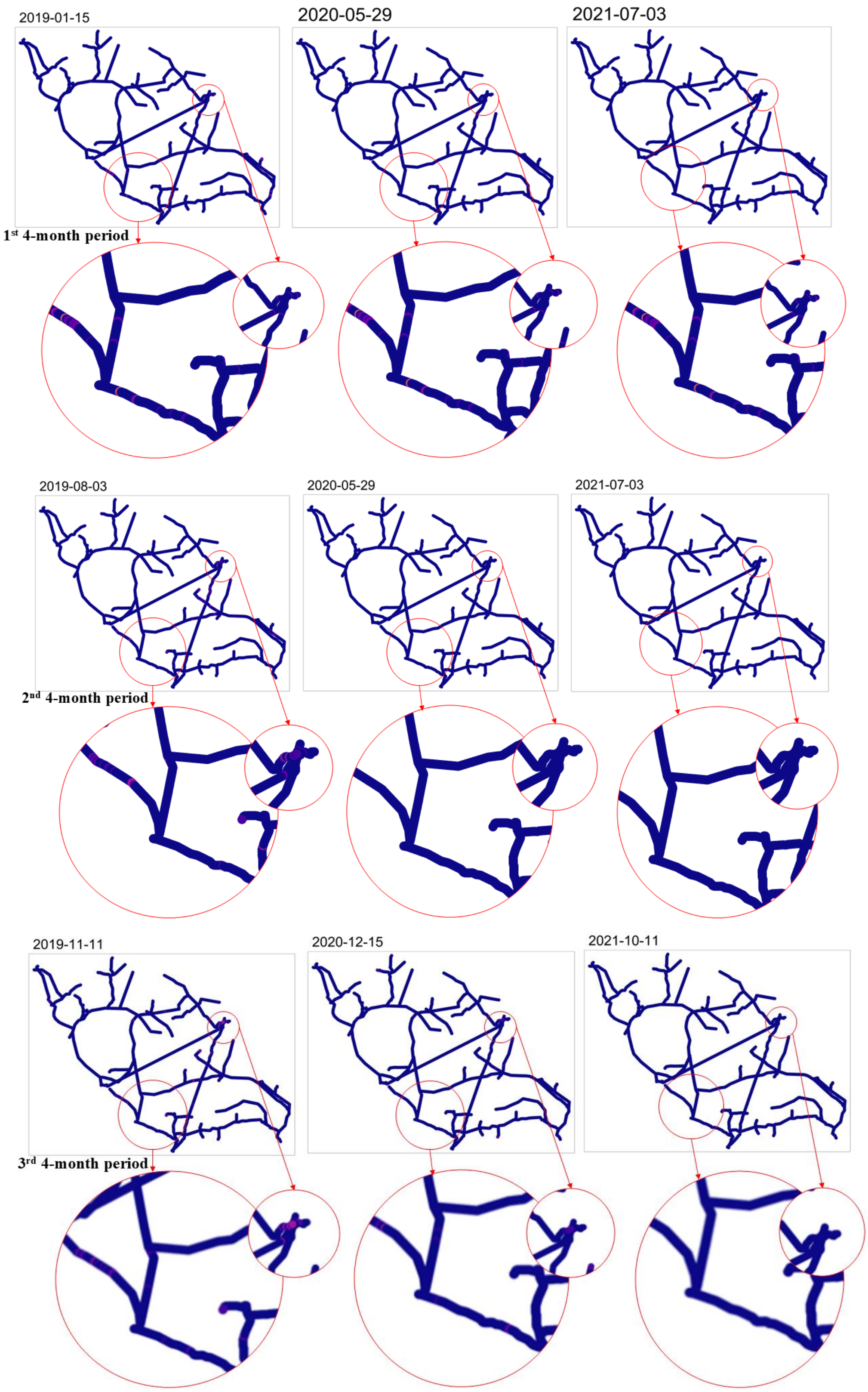

Figure 3.8c. TNKDE maps highlighting the hotspot sections of the pipelines between 2019 to 2021.

The year 2016 showed a decline in medium to high-density oil spill hotspots across the previously identified pipeline sections in Bayelsa State. Ogba/Egbema/Ndoni LGA in Rivers State exhibited few to no hotspots throughout the periods of 2016. Among the three periods in 2016, P3 displayed the lowest hotspot density across all pipeline sections (Figure 3.8(b)). In P1 of 2017, the pipeline sections with high oil spill cluster incidents were similar to those observed in P3 of 2016. However, P2 of 2017 showed minimal to no hotspots in all pipeline sections with a history of hotspots. This reduction in oil spill incidents persisted through P3 of 2017, indicating a wide-spread decrease in oil spill occurrences. This trend is also reflected in Figure 3.9, which shows 2017 having the lowest number of incidents since 2013.

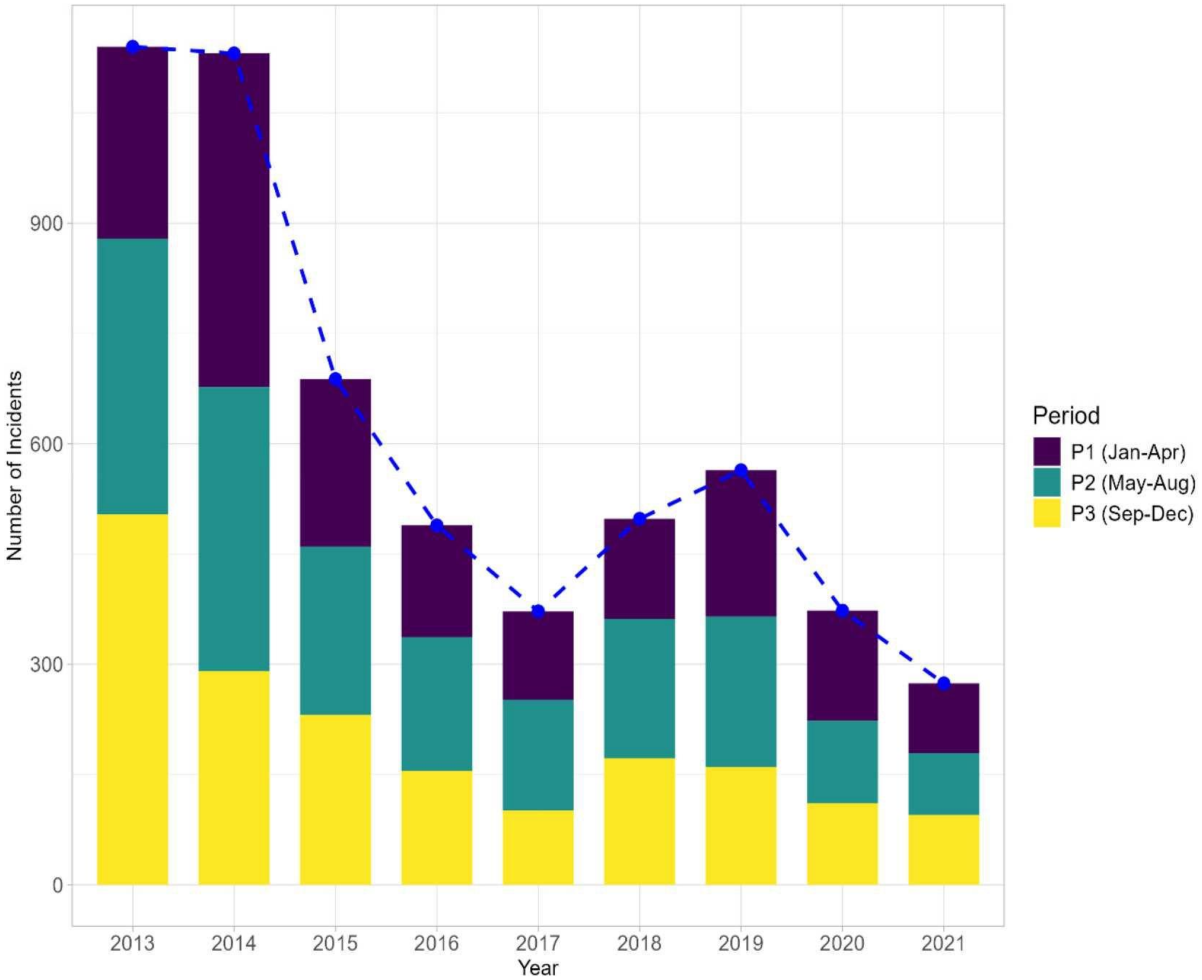

Figure 3.9. Distribution of oil spill incidents over time (Data source: Cleaned NOSDRA data), aggregated by year and 4-month periods. Each year is divided into three periods: P1 (January to April), P2 (May to August), and P3 (September to December). The bars represent the number of incidents within each period, while the blue dashed line indicates the total number of incidents per year.

P1 of 2018 showed a further reduction in clustered hotspots compared to P1 of 2017. However, in P2 of 2018, new medium to low-density hotspots emerged around the Ijaw South LGA pipelines, while other pipeline sections maintained low to very low-density hotspots. P3 of 2018 showed an extension of low to medium-density hotspots in Brass and Nembe LGAs in Bayelsa State. However, other pipeline sections experienced a significant reduction in hotspots (Figure 3.8(b)). P1 of 2019 exhibited similar characteristics to P3 of 2018. In contrast, P2 and P3 of 2019 showed new medium to low-density hotspot clusters in Rivers State, with a proliferation of new low-density hotspots in Ahoada West (around Ubeta and Owube communities in Ogba/Egbema/Ndoni LGA) and Ahoada East LGA (near Ihuama and Ihowo communities), see Figure 3.8(c). Throughout all periods in 2020 and 2021, minimal to no hotspots were observed across all pipeline sections from May to August (Figure 3.8(c)).

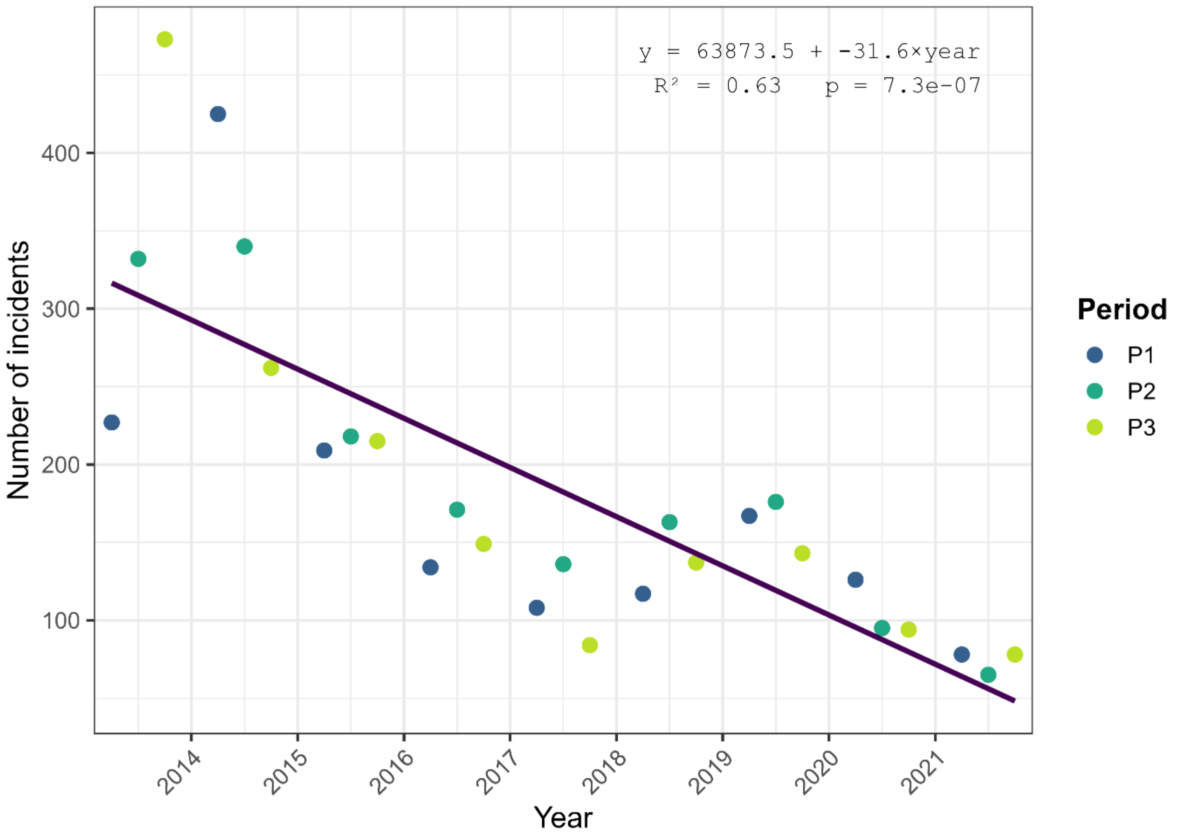

Figure 3.10. Statistical Trend in the Context of TNKDE Spatio-Temporal Patterns (Data source: Cleaned NOSDRA data). The combined year–period scatter and regression line (above) quantify the same declining spill-density pattern revealed by the TNKDE maps. The points (one per P1/P2/P3 each year) coloured by period aggregates spill counts for each year–period combination, yielding 27 data points (9 years × 3 periods). The single trend line summaries the overall direction in spill frequency across all periods.

As seen from Figure 3.9, the oil spills data in this study are dynamic and include a temporal dimension. This visualisation provides an insight into the evolving nature of oil spill incidents in the Niger Delta, highlighting periods of increased and decreased occurrences in specific areas. Furthermore, Figure 3.10 showcases the statistical trend analysis and corroborates the TNKDE's spatio-temporal pattern (see Figure 3.8a-c): oil-spill densities along the pipeline network have declined markedly from 2013 through 2021, and this reduction is evident in every 4-month period of the year. The NOSDRA oil monitoring platform also corroborates this pattern, see Table 3.2. Still from Figure 3.10, the regression of oil-spill counts against year confirms the same downward trajectory that the TNKDE maps make visible. The fitted line has a slope of –31.6 spills per year ($p=7.3\times10^{-7}$), meaning that each four-month period now sees, on average, about 32 fewer reported spills than the corresponding period one year earlier. The highly significant p-value ($< 10^{-6}$) gives statistical weight to the visual impression that spill counts are falling sharply. However, an R^2 of 0.63 tells us that nearly two-thirds of the variability in the 27 period-counts is explained by time alone, and residual scatter (37 % of variance unexplained) might suggest that local and seasonal factors still modulate spill occurrence. The TNKDE maps pinpoint those persistent pockets—e.g. Brass/Nembe in P3 2015–16 or Southern Ijaw in P1 2017—that merit continued targeted attention despite the overall downward momentum. Analysing various quarters of the years can provide a comprehensive understanding of temporal patterns, which is essential for policymakers and stakeholders to develop targeted strategies to mitigate and prevent future oil spill incidents in the region.

3.4 Discussion

This study employed NKDE and TNKDE to identify the spatio-temporal patterns of oil spill incidents along the Niger Delta pipeline network from 2013 to 2021. These methods allowed for the visualisation of both the spatial distribution and temporal progression of oil spills.

The analysis revealed significant spatio-temporal trends. Brass, Ekeremor and Southern Ijaw LGAs in Bayelsa State consistently exhibited the highest concentration of hotspots, particularly between 2013 and 2017. While these areas remained susceptible to spills in subsequent years, a reduction in hotspot intensity suggests potential positive impacts of mitigation efforts by government and oil companies. This observation underscores the importance of continuous monitoring and evaluation of interventions to ensure their long-term effectiveness. Delving deeper into the specific locations within Southern Ijaw LGA, the TNKDE analysis revealed that from 2013 to 2016, medium to high-density oil spill clusters were consistently evident around the Egbomatoro community, Sangana River, Tebitada creek and community, and the Ikebiri Creek Forest Reserve and River. These areas, however, started to see a reduction in incident clusters from 2017 onwards. Similarly, throughout 2014–2016, medium to low-density clusters were observed in Alaboutoru Creek (Nembe LGA), Brass LGA, and near the Ebocha community in Ogba/Egbema/Ndoni LGA (Rivers State). During this period, other sections of the pipeline in the Niger Delta recorded low to no density hotspots. Encouragingly, from 2017 onwards, the sections that previously experienced high incident clusters saw a substantial reduction, especially from 2019 to 2021.

The high concentration of hotspots in these LGAs can be attributed to several factors. Firstly, the intricate network of creeks, swamps, and rivers in these areas poses challenges for pipeline surveillance and maintenance, increasing vulnerability to spills. Secondly, the proximity to the Atlantic Ocean facilitates illegal bunkering and oil smuggling, as highlighted by Obida et al. (2018), further contributing to oil spill incidents. Specifically, the TNKDE analysis identified high-risk areas within these LGAs, including Alaboutoru, Diebu, Seibiri, Tebitada, and Isabatoru Creeks, Apoi Creek Forest Reserve, Clough Creek, mangrove forests, and the Sangana River. These areas experienced a reduction in clustered high-density oil spills from 2018 onwards, suggesting potential positive impacts of interventions. Nembe LGA, another area with a high concentration of hotspots, particularly from 2013 to 2016,

is home to OML 29, which contains Bayelsa's largest and most productive onshore oil fields. The presence of the active Nembe Creek Trunkline, coupled with the vulnerability factors mentioned earlier, makes this region particularly susceptible to oil bunkering and associated spills (Bayelsa commission, n.d.). This study's findings align with those of (Allison et al. 2018), who identified several locations within Nembe LGA as the most oil-polluted sites in the Niger Delta. The alarming number of spills reported by Eni (Agip) along the Tebidaba-Brass pipeline further emphasises the severity of the issue in this region (Amnesty International, 2018). The NKDE analysis also revealed a high concentration of hotspots in Gokana and Ogba/Egbema/Ndoni LGAs in Rivers State, corroborating previous findings by Obida et al. (2018). The Ogoniland area, particularly the Bodo and Ogale communities, has suffered significant environmental damage due to oil spills, highlighting the urgent need for remediation and preventative measures.

Table 3.2. Depicting the timeline of oil spills with spillage categories from 2012 to 2021 (extracted from NOSDRA oil spill monitoring platform).

Year	Number of spill incidents	Sites not visited	Major oil spills (over 250 barrels)	Medium oil spills (25-250 barrels)	Minor oil spills (up to 25 barrels)
2012	1,135	179	4	34	698
2013	1,667	450	1	29	823
2014	1,521	284	8	30	903
2015	921	159	4	27	582
2016	685	129	5	19	447
2017	604	72	6	15	384
2018	719	102	0	29	495
2019	710	70	5	28	453
2020	431	36	0	21	301
2021	400	32	2	5	250

A noticeable decline in the frequency of oil spills was observed from 2016 to 2021 when compared to the preceding years (Figures 3.10). This trend is supported by Ikporukpo (2020), who high- lighted that about 546 million gallons of oil, roughly equivalent to 13.37 million barrels, were spilled in Nigeria from 1958 to 2010. He stated the situation has improved; however the problem remains significant. Table 2, depicting the timeline of oil spills with corresponding spillage categories from 2012 to 2021 (extracted from NOSDRA oil spill monitoring platform), further illustrates this decline. From 2016 to 2021, there has been a sharp decrease in the number of oil spills. This decline can be attributed to various factors, with the most significant being the Nigerian government's crackdown on Niger Delta militants. In 2016, the President of Nigeria initiated an amnesty programme offering employment, training and educational opportunities to individuals formerly involved in causing disruption in the oil-rich Niger Delta region (Payne, 2016). Additionally, the crackdown on bush crude oil refineries Katsouris & Sayne (2013) has played a role in reducing spill incidents. Furthermore, the increasing sophistication of individuals involved in oil bunkering activities has evidently contributed to this decrease in the frequency of oil spills, exemplified by the recent discovery of an illegal connection pipeline from a major oil export terminal into the sea, which had been operating undetected for nine years (Eboh, 2023).

The environmental consequences of incessant oil spills in the Niger Delta are alarming. The region's freshwater resources, agricultural soils, and biodiversity are under significant threat. Native plant species are at risk of deterioration, paving the way for the influx of alien species. Moreover, the ongoing degradation of the Niger Delta's mangrove and riparian forests exacerbates coastal erosion and inundation of low-lying habitats (Adamu, Tansey, et al., 2016;

Afiesimama & Eludoyin, 2021; Duke, 2016; Kamalu & Wokocha, 2019). The oil spill problem in the Niger Delta stems from a multitude of factors, including sabotage, operational failures, and a lack of effective security measures. To mitigate these challenges, comprehensive strategies involving government, oil companies, and communities are essential. Furthermore, the use of advanced spatial analysis techniques provides a valuable tool for understanding and addressing the issue of oil spills in the region.

This study, while providing valuable insights into the spatio-temporal pattern along the Niger Delta oil pipeline network, acknowledges several limitations that stem from both the data and the methodological choices. First, out of the original 16,766 incident records only 5,530 incidents were utilised in the analysis—cases lacked either dates or geographic coordinates—before any spatial analysis commenced. Although the proportion of missing coordinates stabilised in later years, omissions in 2013–2014 and especially high attrition in 2021 (52 %) may have biased the apparent timing and intensity of TNKDE hotspots. Second, reported GPS coordinates vary in precision, with some spill sites recorded far from the actual pipeline breach—often reflecting the downstream extent or endpoint of a spill rather than its origin. To address this, each incident point was snapped to the nearest pipeline segment before segmentation. While this ensures all events lie on the network, it may smooth fine-scale clusters or shift the apparent location of hotspots along the pipeline.

Third, aggregation of each calendar year into three fixed four-month periods (P1 = January–April, P2 = May–August, P3 = September–December) aids visualization but may obscure shorter-term operational cycles—such as maintenance shutdowns or community reporting drives—and can split prolonged spill events across adjacent periods. Fourth, although a 500 m lixel length and 700 m search bandwidth align with published NKDE applications and sensitivity checks, these global parameters do not account for variation in terrain, pipeline age, or patrol frequency. As a result, kernel-density estimates may be over- or under-smoothed in different network segments. Finally, additional incident attributes—oil type, estimated volume, and operator identity—were recorded inconsistently and thus omitted. Future analyses that incorporate these factors could weight density surfaces by environmental impact or distinguish chronic leakage points from isolated catastrophic failures.

3.5 Conclusions

This study explored the application of Network Kernel Density Estimate (NKDE) as an extension of the classical Kernel Density Estimate (KDE) to analyse spatial phenomena constrained on a net- work, specifically focusing on oil spills along a pipeline network. As noted by McArdle et al. (2015) the challenge lies in extracting meaningful insights from the increasing volume of spatial data. Traditional KDE methods fall short when applied to network data, as they evaluate densities outside the network where events cannot occur. Moreover, the Euclidean distance underestimates distances between network objects, rendering it unsuitable for accurate analysis (Gelb & Apparicio, 2023; Karatzoglou, 2022; Okabe & Sugihara, 2012; Romano & Jiang, 2017). Acknowledging the limitations of standard 2-D planar KDE methods in network spaces, this study utilised a network KDE approach. The primary unit of the NKDE algorithm is a lixel, representing a defined network length along linear oil pipeline segments (Gelb & Apparicio, 2023; Xie & Yan, 2008, 2013a). Oil spills are associated with their nearest source lixels, and the density value at the lixel's centre point is computed using kernel-function derived densities from nearby source lixels measured by shortest-path network distance. This approach successfully identifies oil spill-prone pipelines and segments and offers a more condensed and detailed view of the data, highlighting particularly risky areas.

In this study, the spNetwork package in R was used, providing an open-source implementation of NKDE and TNKDE. By utilising this package, the study successfully identified hotspots of oil spills in the study area, which can serve as a crucial baseline for implementing future oil spill monitoring and prevention measures in the Niger Delta. Additionally, it serves as an indicative tool to predict possible oil spills in the future with the introduction of the TNKDE analysis. This development significantly supports decision-making processes for security operations, environmental protection, and the well-being of communities in the Niger Delta region. Furthermore, the study incorporated TNKDE, extending the NKDE to include spatiotemporal aspects of phenomena occurring on the pipelines network over time. TNKDE enables the estimation of spatiotemporal density, and animated maps provide intuitive visualisation and interpretation of results. The inclusion of comprehensive time-series data for each lixel further enhances analysis capabilities.

The analysis of the NKDE and TNKDE revealed oil-spill incidents along the Niger Delta pipeline network between 2013 and 2021 exhibited both persistent hotspots and a pronounced long-term decline. Spatially (NKDE), the highest concentrations of spills were consistently observed in the Bayelsa LGAs of Ekeremor, Brass and Southern Ijaw, and in the Rivers LGAs of Gokana, Bonny, Tai and Ogba/Egbema/Ndoni. These pipeline sections traversing swamp forests, mangrove creeks and riverine environments emerged as the most vulnerable, with repeated medium- to high-density clusters in the TNKDE maps—particularly in P2 (May–August) slices of 2014 and 2019.

Temporally, the TNKDE analysis revealed that, although seasonal peaks shifted location from year to year, each four-month period experienced a similar overall reduction in spill density. Division into P1 (January–April), P2 (May–August) and P3 (September–December) showed that hotspot intensity thinned out uniformly across all seasons, from dense, multi-LGA kernels in early years to sparse, low-intensity surfaces by 2021. Regression of 27 period-counts against decimal year confirmed this trajectory: a statistically significant slope of –31.6 spills per year ($p = 7.3 \times 10^{-7}$, $R^2 = 0.63$) indicates an average reduction of approximately 32 incidents in each period relative to its counterpart one year prior.These findings carry two critical implications. First, the decline in spill frequency likely reflects the impact of enhanced monitoring, maintenance and enforcement efforts deployed over the study decade. Second, the residual pockets of elevated density—such as Brass/Nembe in P3 2015–16 and Southern Ijaw in P1 2017—highlight pipeline segments that remain at elevated risk and warrant focused intervention. By pinpointing both where and when spills continue to concentrate, this combined TNKDE–trend framework offers a robust evidence base for targeted prevention strategies in the Niger Delta.

The NKDE and TNKDE approaches offer valuable insights into spatial and spatiotemporal patterns of oil spills and can be applied to various strategic network analyses, including pipelines, road net- works, rivers, and coastlines, in Nigeria and beyond. The underlying principles of these methods, which account for network constraints and spatiotemporal dynamics, are relevant to other linear features such as coastlines, shipping lanes and ocean currents. For instance, by conceptualising ocean currents or shipping lanes as a network with nodes and edges, oil spill locations as points for analysis and incorporating environmental factors like wind and temperature, these techniques could be adapted to model oil spill dispersal in marine environments. TNKDE can be particularly valuable in understanding how oil spills evolve over time in dynamic ocean environments, revealing patterns of dispersal and potential impacts on sensitive coastal areas. Future work will investigate adapting NKDE and TNKDE to model oil spill dispersal in onshore environments addressing the unique challenges of these dynamic systems. The findings from this research contribute to the advancement of network-based analysis techniques and can have practical implications for environ- mental management and disaster prevention strategies in the region and beyond.

Chapter Four

4. Evaluating contaminated land and the environmental impact of oil spills in the Niger Delta region: a remote sensing-based approach

4.1 Introduction

Nigeria's Niger Delta, a critical hub for the nation's oil industry, faces significant environmental challenges due to decades of crude oil exploration (Olukaejire et al., 2024; Steyn, 2009). Frequent oil spills, stemming from aging infrastructure, inadequate maintenance, and oil theft, have released vast quantities of hydrocarbons and heavy metals into the delicate ecosystem, severely impacting both the environment and human health (Muhammad et al., 2024; Olukaejire et al., 2024; Wekpe et al., 2024). Persistent contamination from oil spills has resulted in a cascade of environmental issues, including: soil degradation, vegetation deterioration, contamination of surface and groundwater resources, and air pollution (Ekhator et al., 2023; Obi, 2023).

Remote sensing technologies have emerged as powerful tools for monitoring and assessing environmental impacts, particularly in the context of oil spills (Fingas & Brown, 2014; Löw et al., 2021). Various sensors, including visible, infrared, and radar systems, have been used to detect and quantify the spatial extent of oil spills and their effects on vegetation (Asif et al., 2022; Obida et al., 2021). Biophysical and biochemical parameters affect the spectral reflectance of plants. Healthy green vegetation has a unique profile due to its reflectance peak in the visible range (400-700 nm), a plateau in the near-infrared range (700-1300 nm), and two substantial peaks in the short-wave-infrared range (1300-2500 nm)(Lassalle et al., 2020). The hydrocarbons influence the root structure and capacities of plants, causing them to undergo biophysical and metabolic alterations (Gholizadeh & Kopačková, 2019). Several studies have employed remote sensing and vegetation indices (VIs) to evaluate the impacts of oil spills on vegetation and monitor their recovery (Adamu et al., 2015; Adamu et al., 2018; Obida et al., 2018, 2021; Tucker, 1979; Wakil et al., 2021). Adamu et al. (2018) calculated five VIs, including Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Adjusted Resistant Vegetation Index 2 (ARVI2), Green/Near-Infrared Ratio (G/NIR) and, Green/Shortwave Infrared Ratio (G/SWIR), to differentiate between vegetation conditions at spill sites and non-spill sites. Egobueze et al. (2022) also used Landsat images and VIs to quantify vegetation stress at spill sites in different time periods. Balogun et al. (2020) used Landsat 8-OLI imagery and machine learning models to analyse oil spill impacts on coastal vegetation and wetlands, demonstrating the sensitivity of multiple VIs, such as NDVI, Chlorophyll Vegetation Index (CVI), Modified Difference Water Index (MDWI) and, Green Chlorophyll Vegetation Index (GCVI), in assessing vegetation and wetland stress.

Furthermore, Ansah et al. (2022) investigated the effects of oil spills on land cover and identified oil spill hotspots using VIs. They found that Enhanced Vegetation Index (EVI), NDVI, and SAVI were particularly sensitive to oil spill effects on vegetation cover. Similarly, Adamu et al. (2015) examined the variations in 12 Broadband Multispectral Vegetation Indices (BMVIs) between pre- and post-spill observations, showing substantial differences. A decline in NDVI values over time in the Niger Delta region due to oil spill impacts was observed by Wakil et al. (2021). They demonstrated a dynamic decrease in NDVI from the 1970s to 2010, with a slight recovery in 2020. Additionally, Adamu et al. (2016) found that the volume and timing of oil spills can impact VIs extracted from polluted environments. They observed that higher oil spill volumes and shorter time intervals between the spill and image acquisition were associated with lower VIs. Overall, the use of VIs, such as NDVI, SAVI, ARVI2, G/NIR, and G/SWIR, have been found effective in assessing the impacts of oil spills on vegetation and monitoring their recovery. These VIs provide valuable insights into vegetation stress caused by oil spills and can track the recovery trend of contaminated vegetation and wetlands. However, further research is needed to explore the long-term impacts of oil spills on different environments and improve the accuracy of detection and quantification using VIs.

Machine learning algorithms have further enhanced the capabilities of remote sensing analysis, enabling accurate land cover classification and change detection (e.g. Alshari et al., 2023; Loukika et al., 2021; Talukdar et al., 2020a; Yuh et al., 2023). Geospatial cloud platforms, such as Google Earth Engine (GEE), have significantly advanced environmental research by offering tools for analysing and visualising large datasets. GEE provides a cloud-based platform for planetary-scale geospatial analysis and has been instrumental in addressing societal challenges such as deforestation, drought, and climate change (Gorelick et al., 2017). The platform's ability to handle petabyte scale datasets and conduct large-scale computations quickly has made it an essential tool for researchers without access to high-performance computing resources. In recent years, studies have demonstrated the utility of GEE in diverse fields, including environmental monitoring and disaster prediction. For instance, Li et al. (2022) utilised GEE and long short-term memory (LSTM) modeling to forecast dengue outbreaks, highlighting the platform's ability to handle spatial data for epidemic prediction. Similarly, Ghorbanian et al., (2020) employed GEE to produce a high-resolution land cover map using Sentinel-1 and Sentinel-2 data, demonstrating the platform's efficacy in handling big satellite data.

Several studies have utilized remote sensing technologies, including optical and radar imagery, to evaluate the impacts of oil spills on vegetation in the Niger Delta. For instance, Kuta et al. (2025) employed Landsat imagery, analysing the Normalized Difference Vegetation Index (NDVI) to understand how vegetation response varied by spill volume, timing, and vegetation type. They found significant differences in NDVI responses across vegetation types, with sparse vegetation showing the strongest response, though these impacts diminished over time. Similarly, O'Farrell et al. (2025) specifically targeted mangrove ecosystems using Sentinel-1 Synthetic Aperture Radar (SAR) and machine learning methods, successfully identifying mangrove mortality and unreported spill sites despite inherent challenges in SAR interpretation.

Further work by Ozigis et al. (2019, 2020) tested multi-frequency SAR (L-, C-, X-bands), optical sensors (Sentinel-2, Landsat 8), and fusion of datasets, employing machine learning techniques. Their findings highlighted the effectiveness of SAR data, particularly during the wet season, but also acknowledged difficulties in differentiating oil pollution from waterlogging, noting that data fusion benefits were context specific. Complementary studies by this group demonstrated higher accuracy in classifying oil impacts in densely vegetated areas, although persistent cloud cover posed limitations to optical sensor performance. Likewise, studies by Egobueze et al. (2022) and Adamu et al. (2016, 2018) utilized multiple vegetation indices derived from optical sensors (NDVI, SAVI, ARVI2, G-NIR, G-SWIR, and NDWI) to differentiate spill from non-spill areas and explored temporal detection limitations, consistently identifying constraints linked to cloud cover and declining detectability over time. Balogun (2015) further underscored the limitations of radar and optical data, particularly in accurately distinguishing oil pollution from wet soil and coping with cloud-induced constraints.

Collectively, these studies underscore the utility of remote sensing in monitoring and quantifying oil spill impacts, while highlighting persistent methodological challenges, particularly regarding sensor-specific limitations, cloud interference, difficulties differentiating spill-induced vegetation stress from other environmental stressors, and insufficient integration of multiple data types to comprehensively assess all affected landcover categories.

This study addresses these gaps by proposing an integrated methodological approach that combines cloud free high spatial-resolution PlanetScope imagery, using machine learning, and cloud computing platform. Unlike previous research focusing on limited vegetation types or restricted spatial scales, and minimal coverage due to cloud cover challenge; this study aims to evaluate vegetation health impacts across all major land cover types (including, dense vegetation, grasslands, farmlands, and wetlands) in Bayelsa, Delta, and Rivers states. Specifically, this integrated approach aims to:

a) Analyse spatio-temporal trends in vegetation health across extensive oil spill-affected regions.

b) Map the detailed spatial extent and distribution of oil spill contamination across diverse landcover classes.

The integration of high-resolution optical data, advanced analytics, and cloud processing within this approach is designed to provide a robust approach for quantifying oil spill impacts on vegetation. The insights gained into spatial extent and vegetation health trends will ultimately enhance the environmental assessment capabilities available to decision-makers, facilitating the implementation of more targeted and effective mitigation and remediation strategies for oil spill-induced vegetation degradation in the Niger Delta.

4.2 Materials and Methods

4.2.1 Study area

The Niger Delta of Nigeria is one of the world's largest deltas, covering more than 70,000 km² and accounting for up to 7.5% of Nigeria's total landmass (923,770 km²). The region comprises nine states: Cross River, Edo, Delta, Abia, Imo, Bayelsa, Rivers, Akwa Ibom, and Ondo. Although oil is extracted in all nine states, this study focuses on the three most affected by pipeline vandalism and oil spills: Bayelsa, Delta, and Rivers. These states account for over 85% of oil spills recorded by the National Oil Spill Detection and Response Agency (NOSDRA) (see Figure 1.1). For further details on the study area, refer to section 1.3.

4.2.2 Data

Three datasets were used in this research: oil spill incident data, PlanetScope satellite imagery and landcover data.

4.2.2.1 Oil spill incident data

This study used oil spill data provided by Nigeria's National Oil Spill Detection and Response Entity (NOSDRA), the official government agency in charge of keeping such records. The data was acquired from 1994 to 2021 through a series of Joint Investigation Visits (JIV). Representatives from regulatory agencies, the oil firm, the affected community, and the security forces make up the joint investigative team. These include the Nigerian Upstream Petroleum Regulatory Commission, the National Oil Spill Detection and Response Agency (NOSDRA), and the State Ministry of Environment. The joint investigation team investigates the cause(s) of the oil spill and is required to agree on and sign a report that verifies the cause (s). The extensive dataset containing over 16,000 records of reported oil spills was initially acquired. After cleaning and filtering, this dataset was streamlined to approximately 5,530 usable records. Each record provided key information such as the date, time, GPS coordinates, estimated length, type, volume, and source of the spill. To utilize this data for vegetation impact analysis, the oil spill locations were spatially overlaid onto the landcover map (see Figure 4.1). This process allowed for the identification of areas within different land cover types that experienced oil spill impacts throughout the 2016-2022 study period. Areas subjected to repeated impacts across these years were specifically prioritized for selecting training sites for image classification and for conducting vegetation degradation trend assessment.

4.2.2.2 NICFI Satellite Data Program

The NICFI Satellite Data Program, a partnership between Norway's International Climate and Forests Initiative (NICFI), Planet, Kongsberg Satellite Services (KSAT), and Airbus (Collison & Curdoglo, 2025), provides free high-resolution satellite data covering tropical regions (Planet, 2025a). Its goal is to aid global efforts in reducing tropical forest loss, thus helping combat climate change, conserve biodiversity, foster sustainable development, and protect indigenous and local community rights (Collison & Curdoglo, 2025; Earthdata, n.d.; Planet, 2025), targeting non-commercial use.

The program includes historical data (Dec 2015 - Aug 2020, bi-annual basemaps) and ongoing monitoring (Sep 2020 - Jan 2025, monthly basemaps) (Earthdata, n.d.; Planet, 2025).

Satellite Data Specifications:

The dataset is the analysis-ready PlanetScope Tropical Normalized Analytic basemap (Planet, 2025a). Key specifications are:

- **Spatial Resolution:** The official specification for the NICFI basemap product indicates a Ground Sample Distance (GSD) of 4.77 meters per pixel at the Equator (Collison & Curdoglo, 2025; Planet, 2025a).
- **Spectral Bands:** The basemaps contain four spectral bands: Blue (B), Green (G), Red (R), Near-Infrared (NIR) (Collison & Curdoglo, 2025; Planet, 2025).
- **Radiometric Resolution**: The data is provided with a 16-bit radiometric resolution. This allows for the representation of 65,536 potential levels of reflectance intensity per pixel, offering a finer degree of distinction between surface features (Collison & Curdoglo, 2025; Planet, 2025a).
- **Temporal Cadence:** the basemaps are available bi-annually for the archive period (December 2015 – August 2020) and monthly for the monitoring period (September 2020 onwards) (Collison & Curdoglo, 2025; Planet, 2025a).

Format and Access: Basemaps are delivered as grids of GeoTIFF files ("quads"). Access within Google Earth Engine (GEE) is facilitated through regional Image Collections (Tropical Africa, Asia, Americas). Users must first register for the NICFI program via Planet's website and subsequently link their GEE-associated email address within their planet account settings (Earthdata, n.d.; Planet, 2025a).

Radiometric Calibration and Atmospheric Correction: The PlanetScope NICFI "Normalized Analytic" basemaps are confirmed as Surface Reflectance (SR) products (Collison & Curdoglo, 2025). SR quantifies the fraction of solar radiation reflected by the Earth's surface itself, derived by correcting satellite-measured Top-of-Atmosphere (TOA) data for atmospheric interference (absorption/scattering) (Planet, 2025b). Converting to SR is essential for quantitative analysis as it minimizes variations due to atmosphere, viewing geometry, and illumination, enabling more reliable comparisons over time and space (Collison & Curdoglo, 2025). SR values are scaled by 10,000 (actual SR = pixel value * 0.0001) and stored as 16-bit integers (Collison & Curdoglo, 2025; Planet, 2025b). This ensures data consistency by minimizing atmospheric and geometric variations (Collison & Curdoglo, 2025).

Standard PlanetScope Surface Reflectance Processing Pipeline: Planet's typical workflow for creating SR products (analytic_sr assets) involves several stages (Collison & Curdoglo, 2025). Initial sensor and radiometric calibration correct raw data for detector artifacts and ensures common radiometric response, often relying on vicarious methods like cross-calibration with Landsat 8/Sentinel-2 or using PICS (Collison & Curdoglo, 2025). Orthorectification then geometrically corrects images using RPCs and DEMs to produce map-accurate orthoimages (Collison & Curdoglo, 2025). Calibrated radiance is converted to TOA reflectance using solar/geometric metadata (Collison & Curdoglo, 2025; Pandey et al., 2023). Finally, atmospheric correction, commonly using the 6S radiative transfer model with inputs like Aerosol Optical Thickness (AOT) and water vapor (often from MODIS), converts TOA to SR using Look-Up Tables (LUTs) (Collison & Curdoglo, 2025; Frazier & Hemingway, 2021; H. Huang & Roy, 2021; Pandey et al., 2023; Roux et al., 2021).

NICFI-Specific Atmospheric Correction and Normalization: The NICFI basemap processing diverges significantly, especially in atmospheric correction, to address challenges in tropical zones. Persistent cloud cover often hinders reliable retrieval of atmospheric parameters (like AOT) from sources like MODIS, which are crucial for standard 6S correction (Frazier & Hemingway, 2021; Huang & Roy, 2021; Pandey et al., 2023). Rapid atmospheric changes also pose difficulties (Pandey et al., 2023). Consequently, instead of direct 6S application for the final SR, the NICFI method involves normalizing the PlanetScope TOA reflectance data to align with Surface Reflectance data derived from Landsat satellites, processed using the standard Landsat Surface Reflectance Code (LaSRC) (Huang & Roy, 2021; Pandey et al., 2023). Planet generates these Landsat SR mosaics as a stable radiometric target (Huang & Roy, 2021; Pandey et al., 2023).

This unique approach means NICFI SR values are radiometrically tied to the Landsat/LaSRC system, enhancing temporal consistency and cross-sensor usability (Pandey et al., 2023). However, a significant implication is the smoothing of natural seasonal vegetation dynamics; the normalization process averages phenological signals over approximately a 6-month timescale to ensure consistency across different input dates and mosaic cadences (Pandey et al., 2023).

NICFI Basemap Mosaicking Methodology:

To optimise quality and usability, NICFI selects input scenes based on:

- **Geometric Accuracy:** Prioritizes scenes orthorectified with more Ground Control Points (GCPs) for enhanced geometric fidelity and accurate change detection (Pandey et al., 2023).
- **Cloud Coverage Maximization:** Includes "test-quality" scenes (fewer GCPs) if necessary, to maximize coverage in cloudy regions, avoiding data gaps at the expense of slightly reduced quality (Pandey et al., 2023).

Mitigation of Inconsistencies during Mosaicking:

Creating seamless mosaics requires addressing inconsistencies from varying view angles (causing Bi-directional Reflectance Distribution Function - BRDF effects), differing solar illumination angles, and varied acquisition dates within the compositing period (Huang & Roy, 2021; Pandey et al., 2023).

- ***BRDF & Illumination:*** The primary mitigation is the normalization to Landsat SR. By adjusting PlanetScope pixels towards this consistent radiometric target (representing a standardized view), radiometric differences due to view angle and illumination variations are significantly reduced (Pandey et al., 2023). The conversion to SR itself inherently accounts for solar zenith angle effects (Pandey et al., 2023).

- ***Date Variations:*** Normalization to the seasonally representative Landsat target also smooths radiometric differences arising from different acquisition dates within the monthly or bi-annual compositing window (Pandey et al., 2023; Earthdata, n.d.; Frazier & Hemingway, 2021). The trade-off, again, is that these smoothing averages out finer intra-period surface changes and phenology (Pandey et al., 2023).

Cloud and Data Masking Strategy: The process uses Planet's Usable Data Mask 2 (UDM2) to identify pixels affected by cloud, heavy haze, or cloud shadow (Pandey et al., 2023), likely generated using advanced algorithms (Frazier & Hemingway, 2021; Huang & Roy, 2021). While these masked pixels are typically excluded, a specific NICFI rule applies in persistently obscured areas: if all available pixels for a location within the compositing period are flagged as unusable, the mosaicking selects the "best-ranked" unusable pixel to avoid 'nodata' gaps

(Pandey et al., 2023). This strategy prioritizes maximum spatial coverage, contrasting with standard Planet SR basemaps (which would have gaps) and standard visual basemaps (which may show clouds but lack rigorous masking) (Pandey et al., 2023).

Table 4.1. PlantScope acquisitions and composites

Period	Number of Acquisitions	Composite Date(s)	Key Characteristics
2016–2019	2 per year (8 total)	Two available dates each year	Consistent seasonal representation across years
2020–2023	2 per year (8 total)	July (annual peak greenness)	Captures maximum vs. minimum vegetation periods
		December (annual minimum greenness)	

This approach ensures data comparability and accounts for seasonal influences on vegetation dynamics.

Comparability between the bi-annual basemaps (used for 2015-August 2020) and the monthly basemaps (used from September 2020-2023) is fundamentally ensured by the standardized processing pipeline employed by Planet for the NICFI Satellite Data Program product accessed via Google Earth Engine(Planet, 2025b, 2025a). A key step in this pipeline is that all PlanetScope NICFI basemaps, regardless of whether they are bi-annual or monthly composites, are processed to Surface Reflectance (SR) and then **radiometrically normalized to the Landsat Surface Reflectance record** (Collison & Curdoglo, 2025; C. B. Lee et al., 2023; F. Yang & Zeng, 2023). This normalization process adjusts the PlanetScope SR values to align with the stable, long-term radiometric baseline provided by Landsat satellites (Collison & Curdoglo, 2025). By consistently applying this Landsat SR normalization across the entire time series (2015-2023), a uniform radiometric scale is established. This ensures that the SR values, and consequently derived indices like NDVI, GNDVI, GRNDVI etc., are directly comparable between the earlier bi-annual composites and the later monthly composites selected for analysis (July and December). This consistent normalization minimizes potential discrepancies arising from sensor differences, minor variations in illumination, or the change in the compositing window length, allowing for reliable time-series analysis focused on detecting changes in vegetation health attributable to factors like oil spills.

Vegetation phenology influence management was achieve through the inherent characteristics of the PlanetScope NICFI dataset and our specific temporal sampling strategy:

1. Inherent Temporal Smoothing in NICFI Basemaps: The PlanetScope NICFI basemaps are analysis-ready composites designed for large-area monitoring, particularly forest change detection. The process of creating these composites involves selecting representative pixels over the defined temporal window (bi-annually or monthly) and normalizing the data to the Landsat SR standard. This combination of temporal compositing and normalization inherently smooths out fine-scale seasonal variations in vegetation reflectance. The resulting SR values represent a more generalized, temporally averaged condition for the period, rather than capturing the instantaneous peaks and troughs of the phenological cycle. This characteristic makes the dataset less sensitive to short-term phenological fluctuations and more suitable for identifying persistent changes or anomalies, such as those potentially caused by oil spills.

2. Targeted Temporal Sampling Strategy: Recognizing the smoothed nature of the data, our methodology employed a specific temporal sampling strategy to further account for broad seasonal patterns. For the period with monthly composites (September 2020 onwards), we deliberately selected the July and December basemaps. In the Niger Delta region, these months generally correspond to periods of relatively peak vegetation greenness (around the height of the rainy season) and minimum greenness (during the drier season), respectively. By consistently sampling these two points within the smoothed annual cycle provided by the NICFI data, we aimed to establish a seasonally consistent baseline for each year. This allows us to compare, for example, the 'peak season' state in July 2021 with July 2022, and the 'minimal season' state in December 2021 with December 2022. This approach leverages the baseline radiometric consistency of the dataset while controlling for major seasonal influences, thereby enhancing our ability to attribute significant deviations in vegetation health indices (like NDVI) to external stressors such as oil spills, rather than to natural phenological variability

4.2.2.3 Landcover data

The Sentinel-2 10m Land Use/Land Cover map (Karra & Kontgis, 2021) was used for the landcover classification of the study area (see Figure 4.1). The 10m resolution land use/landcover map was created through a collaboration between Esri, Impact Observatory, and Microsoft. The map was produced using a deep learning model trained on over five billion hand-labelled Sentinel-2 pixels from 20,000 sites across the world's major biomes. The model uses six bands of Sentinel-2 L2A surface reflectance data (visible blue, green, red, near infrared, and two shortwave infrared bands) and contains nine classes for different landcover categories, including built-up areas, waterbody, and vegetation types. From the landcover map, water, vegetation, wetland, crops/farmland, built-up area, grassland, and cloud were identified. For the classification, the study included all the landcover classes identified and the map was imported into ArcGIS when the different classes were extracted and converted to polygons.

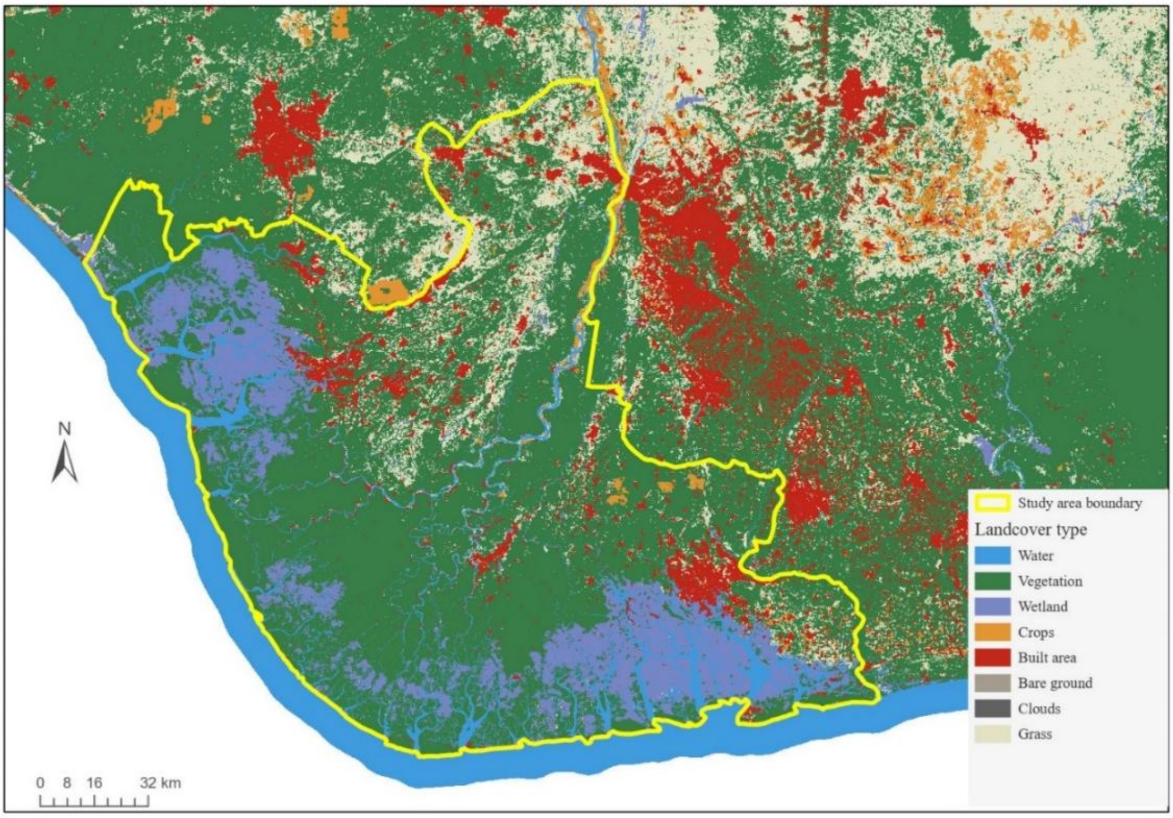

Figure 4.1. Landcover map of the study area (Delta, Bayelsa, and Rivers states). Data source: Sentinel-2 10m Land Use/Land Cover map (Karra & Kontgis, 2021).

To extract training data for the area of land contaminated by the local refinery, geospatial information obtained from online reports (Jone & Casserly, 2022; Owolabi, 2023; Taylor, 2013; The Cable, 2017). Names of local refinery locations were extracted from published news articles and technical reports. The names were search on Google Earth, where polygons delineating the contaminated zones were digitised and exported as shapefiles. The resulting training-area shapefiles were then ingested into GEE alongside the land-use/land-cover polygons derived from Sentinel imagery. It should be noted that these refinery-contamination polygons were used exclusively for classification, as no temporal sequence data were available.

4.3. Methodology

The study's methodology followed a structured, sequential approach, as illustrated in Figure 4.2. First, oil spill data was categorised and prioritised according to the landcover types affected and extent of spills. Subsequently, the corresponding landcover areas were extracted, along with the associated oil spill points. These points were then overlaid onto high-resolution Google Earth imagery, facilitating the generation of training site shapefiles.

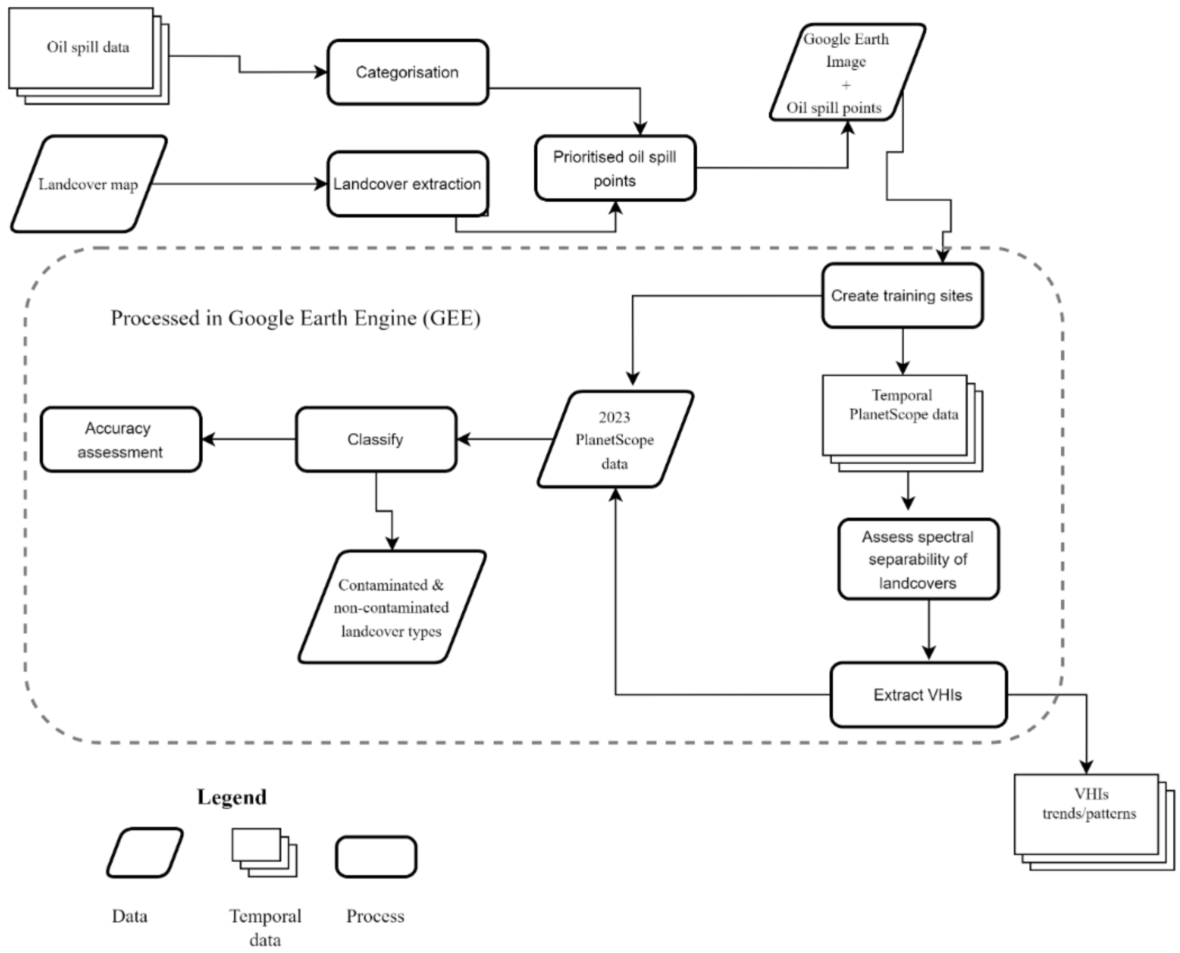

Figure 4.2. Methodology flowchart

These shapefiles were subsequently ingested into Google Earth Engine (GEE). Within GEE, a series of pre-processing steps were implemented to prepare the input data for the classifier algorithms. These pre-processing steps encompassed an assessment of the separability of the various landcover types, as well as the extraction of Vegetation Health Indices (VHIs). Following pre-processing, the different input datasets were classified, and the accuracy of the classification was assessed. Both the VHIs extraction and the classification sections of the workflow were executed within the GEE environment.

4.3.1 Oil Spill points sampling

The study examined information on oil spills, including their volume, size, and date, to track spill intensity across different types of landcover. To categorise the oil spill data, a histogram was used with a 100 bbl (barrel) bandwidth based on estimated spill volume. Training site selection prioritised areas significantly impacted by oil spills. Points with estimated spill quantities exceeding 1000 bbl were included, consistent with the methodology of Ozigis et al. (2019). This approach ensured that the spectral characteristics of the selected pixels were representative of typical oil pollution effects on vegetation, providing a strong basis for model training, testing, validation, and subsequent image classification. Complementing this, Adamu et al. (2016) found that spill volumes between 400 bbl and 1000 bbl yielded the most detectable influence on vegetation, evidenced by strong negative relationships with visible spectrum reflectance (Vis).

Assigning oil spill incidents to the appropriate land cover categories is a crucial aspect of the method. The classification process, which utilises a Random Forest classifier, depends heavily on the spectral signatures obtained from training sites to develop a reliable model. Specifically, spill incidents situated within each land cover class were identified, and these locations served as the training and validation sites for identifying polluted land cover classes impacted by oil spills.

4.3.2 Image Classification Approach

The image classification process involved three steps: establishing training datasets, classification, and accuracy assessment. The eight land use and land cover (LULC) classes in the study area were identified, including farmlands/croplands, dense vegetation, grassland, bare lands, built-up areas, water bodies, wetlands, and contaminated areas. To create the training datasets, the LULC classes were converted to polygons using ArcGIS Pro 3.3 and then exported to Google Earth. The contaminated areas were identified by overlaying prioritised oil spill points on the landcover polygons, and vectorised polygons were generated from the affected part of the landcover classes to create the training sites. As demonstrated in previous studies (e.g. Balogun et al., 2020; Obida et al., 2018b; Ozigis et al., 2019), non-polluted training sites were also selected for each landcover class, and proximity analysis was employed to ensure they were at least 2,000 metres away from polluted sites. Google Earth was also used to identify healthy vegetation for the non-contaminated training sites. At least 100 training sites were generated for each of the landcover types, including both contaminated and non-contaminated areas. These training datasets were then loaded into Google Earth Engine for image classification.

To evaluate the effectiveness of the training sites in classifying different pixel classes, GEE was used to generate spectral profiles. The shapefiles of the training sites were used as the area of interest and PlanetScope data was used as the image. A median reducer *(ee.Reducer.median)* was applied to get the median value for each of the over 100 polygons in the different classes. The results were exported as CSV, the average of the median spectral value of the polygons were calculated and visualised in Python with matplotlib package (version 3.8.4) and pandas (version 2.2.1). This helped to better understand the separability of the training sites and how well they could distinguish between different classes.

To assess the discriminative power between contaminated and non-contaminated landcover types, the Jeffries-Matusita (JM) Distance was calculated. The JM distance is a statistical measure of dissimilarity or separability between two probability distributions, particularly useful in classification tasks to evaluate class separability. It ranges from 0 (indicating maximum overlap or similarity) to 2 (indicating complete separation). This method is widely employed to assess the effectiveness of feature selection or dimensionality reduction techniques in enhancing class distinction (Aswin, 2024; Zhang et al., 2023).

The JM distance is given by:

$$JM = 2\left(1 - exp\left(\frac{-B}{8}\right)\right) \qquad (eq\ \ 4.1)($$

where B is the Bhattacharyya distance. The Bhattacharyya distance, in turn, is computed as:

$$B = \frac{1}{8}\left(\mu_i - \mu_j\right)^T \left(\frac{\Sigma_i+\Sigma_j}{2}\right)^{-1} \left(\mu_i - \mu_j\right) + \frac{1}{2}\ln\left(\frac{|\Sigma_i+\Sigma_j|}{2\sqrt{|\Sigma_i||\Sigma_j|}}\right) \qquad eq\ 4.2$$

where:

μ_i and μ_j are the mean reflectance values of two classes i and j,

Σ_i and Σ_j are the covariance matrices (based on standard deviations) for the spectral bands.

For each pair of contaminated and non-contaminated landcover classes, we extracted the i) mean reflectance values $(\mu_i - \mu_j)$ across the bands (Blue, Green, Red, and Near Infrared) and ii) the standard deviations for each band were used to construct diagonal covariance matrices (Σ_i, Σ_j) of both classes, assuming no correlation between bands.

The JM distance for the landcovers in this study was computed using Python (version 3.7.2). First, the data containing mean reflectance values and standard deviations for each landcover class across four spectral bands were organised into a DataFrame using the pandas package (version 2.2.3). This allowed for efficient extraction and manipulation of the spectral profiles for both contaminated and non-contaminated landcover classes. To compute the Bhattacharyya distance, which serves as the foundation for the JM distance, the NumPy package (version 2.1.1) was utilised. A function was created to calculate the Bhattacharyya distance by comparing the mean reflectance values and standard deviations between each pair of landcover classes.

To evaluate the separability between contaminated and non-contaminated landcover classes, the function was applied to pairs of contaminated and their respective non-contaminated counterparts. The calculated JM distances indicated the degree of spectral separability between each pair of classes. Higher JM distance values (approaching 2) indicated strong separability between contaminated and non-contaminated landcover types, while lower values (closer to 0) indicated poor separability, suggesting significant spectral overlap.

4.3.3 Retrieval of vegetation health indices from PlanetScope data

As demonstrated in previous studies (e.g. Balogun et al., 2020; Obida et al., 2018; Ozigis et al., 2019), this study utilised Vegetation Health Indices (VHIs) to examine the impact of pollutant stressors on vegetation. VHIs using the red, green, blue, and near-infrared (NIR) bands were generated (see Table 4.1). The VHIs employed in this study—EVI2, GNDVI, GOSAVI, GRNDVI, NDVI, SAVI, SR, and SR2—were selected based on their documented effectiveness in assessing vegetation stress, particularly in contexts involving oil spills and environmental disturbances. Previous studies have highlighted the efficacy of indices such as NDVI, which leverages the unique spectral characteristics of the Red and Near-Infrared (NIR) bands for detecting vegetation stress (Adamu, 2018). Balogun (2020) further supported the suitability of NDVI, EVI2, and SAVI, noting their sensitivity to vegetation greenness and biomass changes, key indicators of stress resulting from hydrocarbon contamination in wetlands. Specifically, EVI2 provides improved sensitivity in high biomass regions and minimizes background soil noise, enhancing detection capabilities in oil spill assessments (Balogun, 2020; Jiang et al., 2008). Similarly, GNDVI and GRNDVI, which integrate green band information, have shown superior performance in estimating Leaf area index (LAI; is an important characteristic of land surface vegetation system), detecting early-stage vegetation stress and chlorophyll content alterations, as reported by Wang et al. (2007). GOSAVI and SAVI have also been widely utilized in environmental impact studies due to their robustness in reducing soil background effects, thus providing accurate indications of vegetation conditions in disturbed ecosystems (Huete, 1988; Loaiza, 2023; Mulla, 2013; Sripada et al., 2005; Prudnikova et al., 2019; Rondeaux et al., 1996). Finally, SR and SR2 indices, which emphasize reflectance contrasts between NIR and visible wavelengths, have demonstrated effectiveness in monitoring vegetation stress and health deterioration due to oil-related pollution events (Chen et al., 2005; Chen et al., 1996; Sripada et al., 2006)). Thus, the selected indices collectively offer comprehensive sensitivity and accuracy for capturing the complex impacts of oil spills on vegetation. To generate multiple indices, the study utilized the Awesome Spectral Indices, a standardised, ready-to-use curated list of spectral indices that can be used as expressions for computing spectral indices in GEE (https://github.com/awesome-spectral-indices/awesome-spectral-indices). The training sites were used as an area of interest, and the Awesome Spectral Indices parameter was applied to generate the VHIs.

Table 4.2. Extracted vegetations health indices

Vegetation indices	Formula	Author
Green Optimised Soil Adjusted Vegetation Index (GOSAVI)	(N - G) / (N + G + 0.16)	(Sripada et al., 2005)
Green-Red Normalised Difference Vegetation Index (GRNDVI)	(N - (G + R))/(N + (G + R))	(Wang et al., 2007)
Green Normalised Difference Vegetation Index (GNDVI)	(N - G)/(N + G)	(Gitelson et al., 1996)
Normalised Difference Vegetation Index (NDVI)	(N - R)/(N + R)	(Tucker, 1979)
Soil-Adjusted Vegetation Index (SAVI)	(1.0 + L) * (N - R) / (N + R + L)	(Huete, 1988)
Simple Ratio (SR)	N/R	(Jordan, 1969)
Simple Ratio (800 and 550 nm) (SR2)	N/G	(Buschmann & Nagel, 1993)
Enhanced Vegetation Index (EVI)	g * (N - R) / (N + C1 *R - C2 *B + L)	(Huete et al, 2002)
Two-Band Enhanced Vegetation Index (EVI2)	g * (N - R) / (N + 2.4 * R + L)	(Jiang et al., 2008)

R = Red, G = Green, N = Near Infrared, B = Blue (bands)
g: Gain factor (e.g. Used for EVI)
L: Canopy background adjustment (e.g. Used for SAVI and EVI)

4.3.4 Simple Moving Average (SMA) regression

The regression trend analysis approach (Mancino et al., 2022) was adopted to understand the vegetation health in the study area. This approach is particularly useful when dealing with a large number of observations, such as long times series or data collected on a daily or weekly basis. By excluding outliers, the regression trend helps identify the slope of the line, which is crucial for assessing vegetation health trends. To implement this approach, VHIs values generated from 2016 to 2023 were exported from GEE and imported into Python 3.12.6. The code begins by importing necessary libraries and loading a CSV file containing the data.

The code begins with data preparation, where it extracts the year from the "Image Acquisition Date" column and identifies the VHIs columns along with their corresponding standard deviations in the imported CSV file. Moving to data visualisation, seaborn and matplotlib were used to create a 4 x 2 grid of scatter plots, each featuring error bars. These subplots display the VHIs values for different regions (e.g., "CDV NDVI", "NDV NDVI") over the years, with the error bars representing the standard deviation of the VHIs values. In the trend analysis phase, the code calculates a Simple Moving Average (SMA) regression line for each region, visually capturing the trend in VHIs values over time, which is overlaid onto the scatter plots. Finally, the code computes the Spearman correlation coefficient value which assesses the strength and direction of monotonic relationships between the VHIs values over time, and the p-value indicates the statistical significance of this correlation.

4.3.5 Machine learning supervised classification

Random forests (RF) are groups of decision trees that all use the same random vector to make predictions (Breiman, 2001). As a random forest grows, the error in its generalisation tends to get smaller. Generalisation error is based on how strong the trees are and how well they fit together. Random forests use uncertainty to make classifiers and regression models better. By measuring the strength and correlation of the predictors, the out-of-bag estimate can show how well the random forest can predict (Breiman, 2001). The RF classification was used to distinguish and effectively characterise parts of the landcovers impacted by oil pollution from oil-free parts. The analysis was carried out using the classifiers in Earth Engine API named, ee.Classifier.smileRandomForest(). The smile part refers to the Statistical Machine Intelligence and Learning Engine (SMILE) JAVA library which is used by Google Earth Engine (GEE) to implement these algorithms (Gandhi, 2021).

The selection of RF for classification is justified by its proven effectiveness in prior research on oil spill mapping, such as Ozigis et al. (2019), which demonstrated its reliability in mapping impacted and oil-free areas. Beyond this specific application, RF is favoured for large-scale land cover mapping due to its efficiency and lower computational demands (Southworth, 2024). Comparative studies, including Ramesan (2021), have shown RF to outperform other machine learning algorithms across various conditions. Furthermore, direct comparisons in remote sensing classification tasks, like Praticò (2021)'s work using Sentinel-2 imagery against SVM and CART, confirmed RF's superior accuracy.

Random Forest Classification Implementation Method: To classify the PlanetScope data pixels, the imagery was accessed and processed through Google Earth Engine (GEE). Training data consisting of over 100 sites per land cover class was loaded, excluding areas affected by cloud cover. A Random Forest classifier was trained on these training sites and subsequently applied to all image pixels to generate a classified image that included all pre-defined classes. The input features for the classifier comprised of the spectral bands and extracted vegetation health indices. As recommended by Low et al. (2021), the inclusion of vegetation indices can significantly improve the accuracy of oil spill detection. Table 4.2 expands on the classification schema used in this study by defining the various prioritised landcover types. These landcover types were derived from the Sentinel-2 10m Land Use/Land Cover map, and local refinery areas extracted using Google Earth image where polygons delineating the contaminated zones were digitised and exported as shapefiles. The resulting training-area shapefiles were then ingested into GEE alongside the land-use/land-cover polygons derived from Sentinel imagery. The analysis focused on the image acquired on January 1, 2023, which was deliberately selected to provide sufficient time for the environmental impacts of oil spills to become evident. This date aligns with the temporal scope of oil spill data acquired from the NOSDRA, which extends up to January 2022. By examining the choice of an image from one year later ensures that the dataset captures the full extent of the oil spills’ effects on the environment. This one-year gap provides sufficient time for the ecological consequences, particularly on vegetation and land cover, to manifest, offering a clear basis for classifying impacted areas in the study. The image was clipped to the study area boundary, and to ensure comparability of features for machine learning, all image bands were normalised to a 0-1 range. The RF algorithm available in GEE, specifically *ee.Classifier.smileRandomForest was utilised.*

Table 4.3. Classified landcover classes definition.

Class	Definitions
Contaminated Dense vegetation (CDV)	Dense vegetation, typically with a closed or dense canopy where oil spills have been recorded, when the oil spills data was overlayed on the high-resolution image, the NOSDRA oil spill oil spill points were found in this part of the landcover.
Non-Contaminated Dense Vegetation (NDV)	Dense vegetation, typically with a closed or dense canopy where there are no oil spills.
Contaminated Wetland vegetation (CWL)	Areas of vegetation showing evident intermixing with water, despite being contaminated with oil spills, are identified through the presence of recorded oil spill incidents when overlaying the NOSDRA oil spill data onto the landcover.
Non-Contaminated Wetland vegetation (NWL)	Areas of vegetation showing evident intermixing with water, lacking any observed oil spill points within them.
Contaminated Farmlands/crops (CFL)	Human planted/plotted land area with oil spills point observed within them.
Non-Contaminated Farmlands/crops (NFL)	Human planted/plotted land area with no oil spill points.
Local Refinery	Site utilised for local, rudimentary crude oil refining.
Contaminated Grasslands (CGL)	Open areas covered in homogenous grasses with little to no taller vegetation with oil spill points observed within them.
Non-Contaminated Grasslands (NGL)	Open areas covered in homogenous grasses with little to no taller vegetation with no oil spill points.
Water	An area with water.
Cloud	Cloudy section of the image.
Bare	An open area of land.

Input Features and Preparation: The classifier was trained using all available spectral bands present in the input image object. This included the original Near-Infrared (N), Red (R), Green (G), and Blue (B) bands from the NICFI basemap, supplemented with the calculated spectral indices (NDVI, EVI2, SAVI, etc.) calculated using the *users/dmlmont/spectral:spectral* GEE library module. This approach provided the model with a comprehensive set of spectral information. Prior to training, all input bands were normalized to a common 0-1 value range.

Training and Validation Data: Ground reference data were prepared by merging multiple GEE Feature Collections, each representing a distinct land cover class. From these merged geometries, pixel values corresponding to the normalized input bands were extracted along with their respective land cover labels. This dataset was then randomly partitioned into a training set (70% of the data) and a validation set (30% of the data) to allow for independent model assessment.

Random Forest Parameter Selection:

Number of Trees: To determine an appropriate number of trees, preliminary tests were conducted using values of 50, 100, 200, and 300. A final value of 300 decision trees was selected based on evaluating the trade-off between validation accuracy and computational cost.

Other Hyperparameters: For other RF algorithm hyperparameters, the standard GEE default values were adopted. These include:

- *variablesPerSplit:* Defaults to null, which uses the square root of the total number of input features (bands) at each split.
- *minLeafPopulation*: Defaults to 1, allowing terminal nodes (leaves) to be created even if they contain only a single training sample.
- *bagFraction:* Defaults to 0.5, meaning each tree is trained on a random 50% subset of the training data (bagging).
- *maxNodes:* Defaults to null, imposing no predefined limit on the maximum number of leaf nodes per tree.
- *seed:* Defaults to 0, ensuring reproducibility of the randomisation involved in the bagging and splitting process.

Training: Finally, the smileRandomForest classifier, configured with 300 trees and default settings for other parameters, was trained using the prepared 70% training dataset.

To evaluate the accuracy of the classification, an accuracy assessment was performed on the classified image using the *ee.Classifier.confusionMatrix()* method in GEE. The training samples were randomly divided into two parts: 70% for training and 30% for testing. The confusion matrix was used to estimate the accuracy of the classification. To further assess the accuracy of the classification, a 5-fold cross-validation was performed in GEE by partitioning the data into five stratified folds in a random manner using the utils package, with the objective of preserving a consistent ratio of all 13 classes in each fold. In each iteration of the classification, a single data fold is reserved for testing purposes while the remaining k-1 folds are utilised for training the classifier. The classifier's performance quality is evaluated on the excluded fold in each experiment, and subsequently, the overall performance metric is averaged across the k-folds. The results of the classification were exported to ArcGIS Pro 3.3 to calculate the spatial extent of the different classes and for visualisation.

4.3.6 Spectral profile of the training sites

In order to assess the separability of the training sites, the reflectance profiles of the sites were examined. The reflectance profile was calculated as the median reflectance value of the sampled polygons or pixels per band. Each class in the training data consisted of more than 100 polygons, and the median reflectance of each polygon was computed. The average reflectance across all polygons was then calculated to generate the reflectance profile (see Figure 4.3).

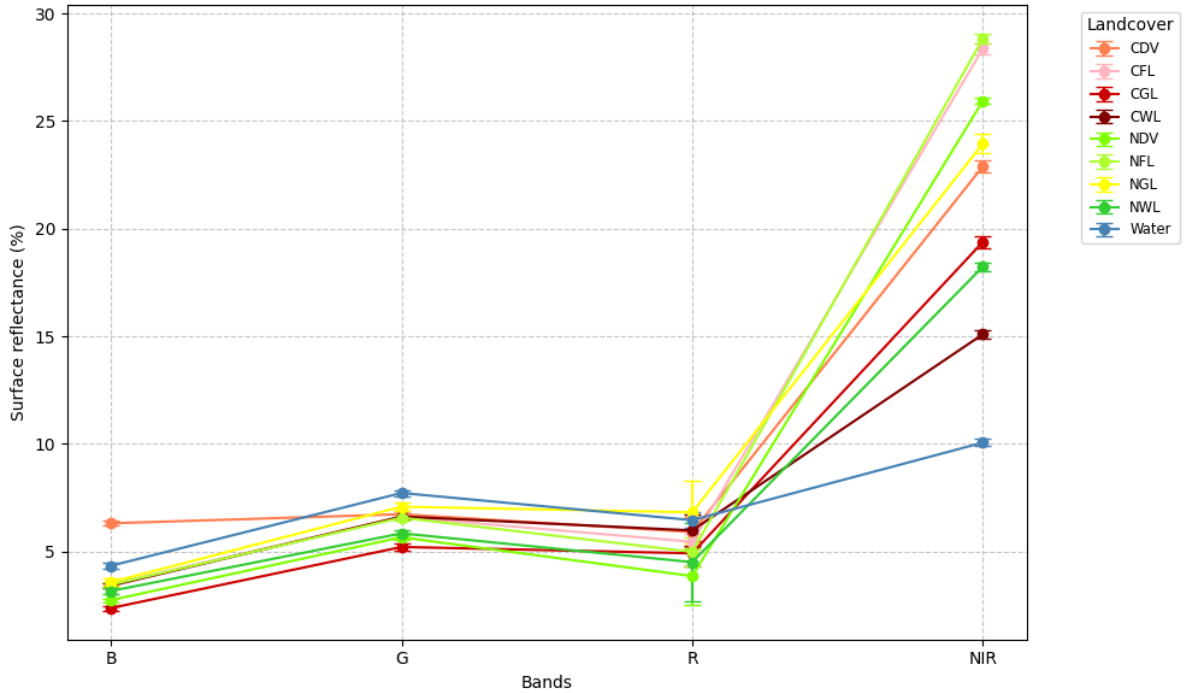

Figure 4.3. Training site spectral profile - *The average reflectance across all polygons was then calculated to generate the reflectance profile. CDV = Contaminated Dense Vegetation; NDV = Non-Contaminated Dense Vegetation; CFL = Contaminated Farmland; NFL = Non-Contaminated Farmland; CGL = Contaminated Grassland; NGL = Non-Contaminated Grassland; CWL =Contaminated Wetland; NWL = Non-Contaminated Wetland.*

The results of the reflectance profiles align with the expected characteristics of different land cover classes. Built-up areas displayed moderate to high reflectance across bands due to the presence of various building materials and surfaces, with near-infrared reflectance being notably high. Ultimately, waterbodies in the Niger Delta, known for their high turbidity exhibited very low reflectance across all bands due to high water absorption (Jain & Singh, 2003), as depicted in Figure 4.3.

The computed Jeffries-Matusita (JM) distances for the contaminated vs non-contaminated landcovers are presented in Table 4.3. For CDV vs NDV, CGL vs NGL, and CWL vs NWL, the JM distances are close to 2, indicating that these pairs are highly separable, meaning contaminated and non-contaminated versions of these landcover types are easily distinguishable based on their spectral profiles. CFL vs NFL has a much lower JM distance (0.17), indicating poor separability. The contaminated and non-contaminated farmlands have very similar spectral profiles, making it difficult to distinguish between them using these bands. Overall, the reflectance profiles demonstrate that the contaminated and non-contaminated landcover classes in the training dataset, except farmland, are easily distinguishable and highly separable in all bands of the PlanetScope data.

Table 4.4. Computed Jeffries-Matusita (JM) distances for spectral bands and landcover types

Landcover pair	Computed Jeffries-Matusita (JM) distances
CDV vs NDV	1.99
CFL vs NFL	0.17
CGL vs NGL	1.99
CWL vs NWL	1.97

4.3.7 Analysis of Contaminated Landcover against Non-Contaminated Landcover

To further understand and illustrate the separability of the contaminated landcover against the non-contaminated counterpart, the pair in each class was compared against each other. In comparing CDV to NDV, the spectral reflectance values across various bands showcase discernible differences, CDV consistently displays higher reflectance in all bands compared to NDV (see Table 4.3 for the computed JM distances between the landcovers pairs). Specifically, in the blue band CDV demonstrates a reflectance of 3.7% with a standard deviation of ±2.0%, contrasting with NDV's 2.7% with a standard deviation of ±. This trend persists across the other bands, indicating a consistent spectral distinction between the two landcover types (see Figure 4.4).

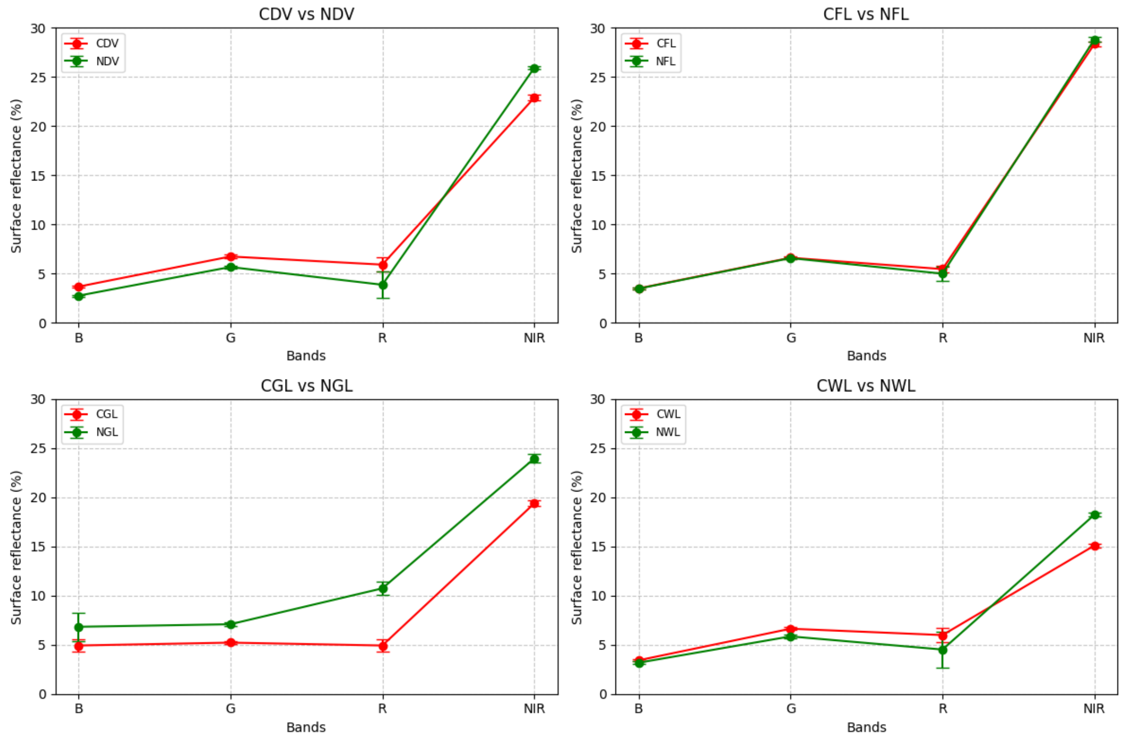

Figure 4.4. Cross-analysis of the contaminated landcover against non-contaminated landcover

When comparing CFL and NFL, the multispectral signatures of the two field types are virtually indistinguishable, with reflectance values showing more similarity across the bands. For instance, in band "B", both CFL and NFL exhibit values of around 3.5% ± 0.4%. This consistency is observed across other bands as well, with tight error bars confirming that this contaminant has no measurable effect on the average reflectance.

Contrasting CGL with NGL reveals a clear distinction in spectral reflectance, with NGL consistently exhibiting higher values across all bands compared to CGL. For instance, in the Blue band, NGL shows a reflectance of 6.8% with a standard deviation of ±1.9%, whereas CGL displays 4.9% with a standard deviation of ±1.9%. This trend persists across other bands, indicating a notable separation between the two landcover types.

Lastly, comparing CWL to NWL, CWL consistently displays higher reflectance values across all bands compared to NWL. For example, in Blue band, CWL exhibits a reflectance of 3.4% with a standard deviation of ±1.3%, while NWL shows 3.2% with a standard deviation of ±1.2%. This difference persists across other bands, indicating potential disparities in vegetation cover or surface properties between the two landcover types. Overall, these analyses demonstrate varying degrees of separability between different landcover pairs based on their spectral reflectance values.

4.3.8 Spectral separability of the Vegetation Health Indices

To enhance the classification of contaminated landcovers from the non-contaminated landcovers various vegetation indices were incorporated into the classifier. Figure 4.5 facilitates the visual comparison of vegetation health indices between the landcover types. The analysis reveals varying degrees of spectral separability between the landcover types, primarily based on their vegetation health indices. The calculated JM distances indicate varying degrees of separability between contaminated and non-contaminated land covers across different vegetation indices. The simple ratio indices (SR and SR2) emerged as the most powerful discriminators. For example, SR shows a strong separation of about 1.46 when separating CDV from NDV and maintains a robust 1.23 value for CWL landcover versus its NWL counterpart. SR2 performs closely, with values exceeding 1.0 for the most easily separated pairs and around 0.80 for those that are slightly tougher. Following these, EVI2 stands out as the next most reliable index, yielding a moderate separation (around 0.19) even in the toughest cases, such as CGL versus NGL, where other indices show very little distinction (barely past 0.15). At the lower end of the spectrum, GNDVI, GOSAVI, and GRNDVI offer only marginal discrimination, with JM distances typically between 0.12 and 0.27 across all pairs. NDVI and SAVI fall into a middle category; while useful, their separability does not exceed 0.40. The high JM distances in certain pairs underscore the potential utility of these vegetation indices for classifying landcover contamination, while the lower distances suggest that additional features or indices may be needed to improve separability in certain cases.

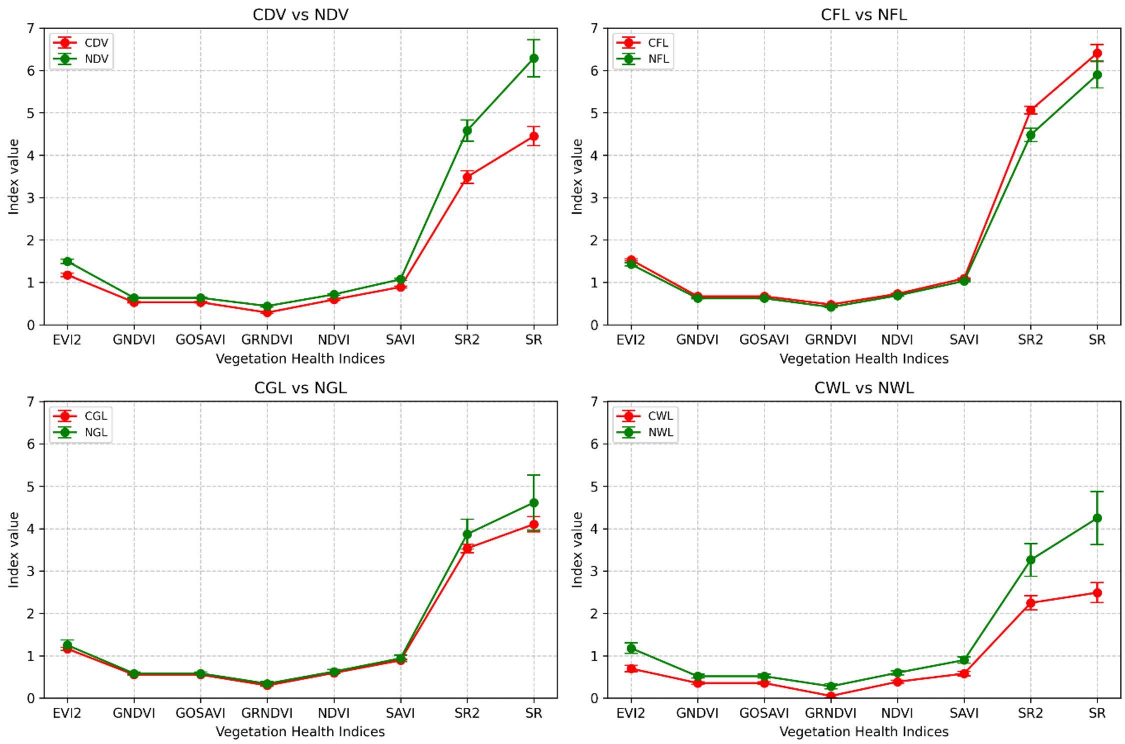

Figure 4.5. Spectral separability between different landcover types, primarily based on their vegetation health indices

Table 4.5. Computed Jeffries-Matusita (JM) distances for the VHIs and landcovers.

Index	**CDV vs NDV**	**CFL vs NFL**	**CGL vs NGL**	**CWL vs NWL**
SR2	1.46	0.26	0.33	1.23
SR2	1.07	0.60	0.29	0.80
EVI2	0.48	0.11	0.19	0.53
SAVI	0.30	0.08	0.18	0.38
GRNDVI	0.25	0.10	0.17	0.27
NDVI	0.20	0.06	0.18	0.26
GNDVI	0.16	0.12	0.15	0.18
GOSAVI	0.16	0.12	0.15	0.18

4.4 Results

4.4.1 Trend analysis

To assess the health trend of vegetation in areas affected by oil spills, the dense vegetation, wetland, grassland, and farmland (both contaminated and non-contaminated) were analysed using SR1, SR2, EVI2, NDVI, GRNDVI, GNDVI, and GOSAVI (see Table 4.5), Spearman's rank correlation (ρ) between each vegetation-health index and year (2016–2023) for contaminated vs. non-contaminated landcovers was computed, and the statistical significance ($p < 0.05$) was assessed. Table 4.5 (JM distances) orders the indices by their power to separate contaminated from non-contaminated areas.

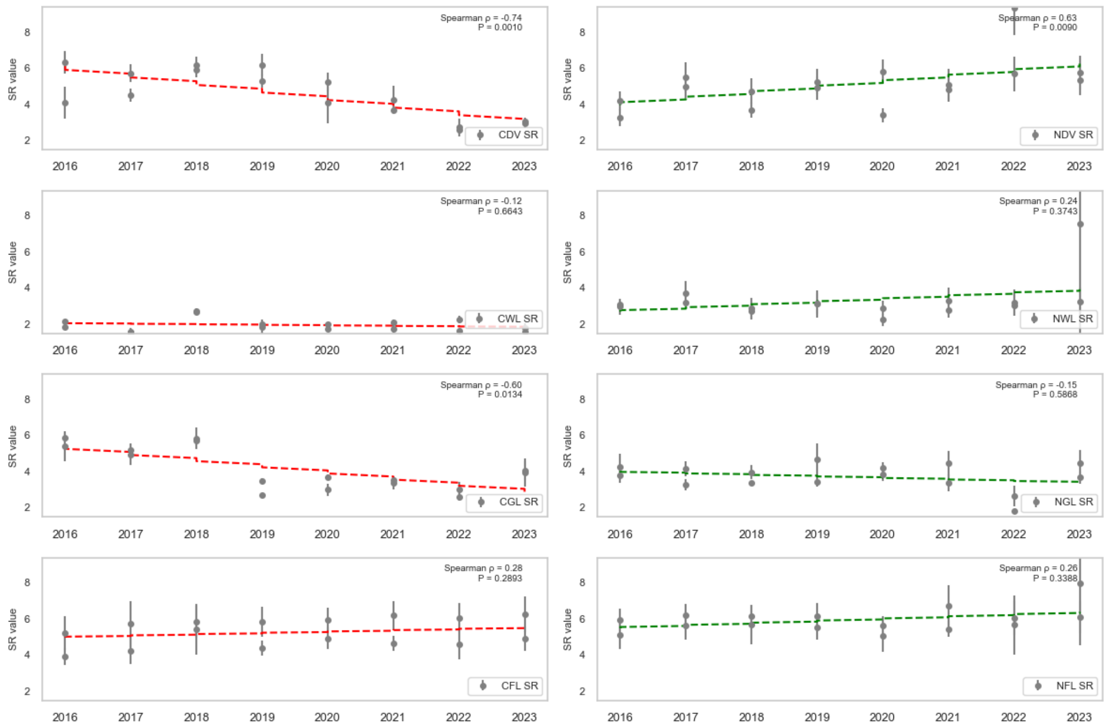

Figure 4.6. SR1 trends of contaminated and non-contaminated landcover types from 2016 to 2023 (the red lines represent the trends of contaminated landcovers while the green lines represent the non-contaminated counterparts).

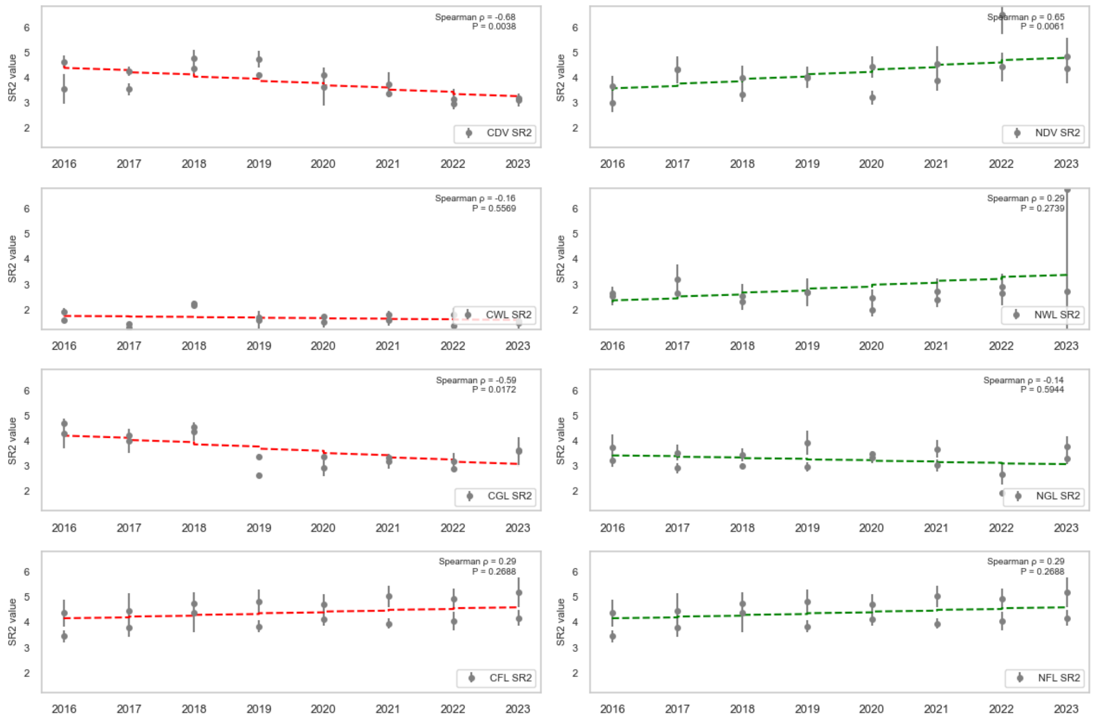

Figure 4.7. SR2 trends of contaminated and non-contaminated landcover types from 2016 to 2023 (the red lines represent the trends of contaminated landcovers while the green lines represent the non-contaminated counterparts).

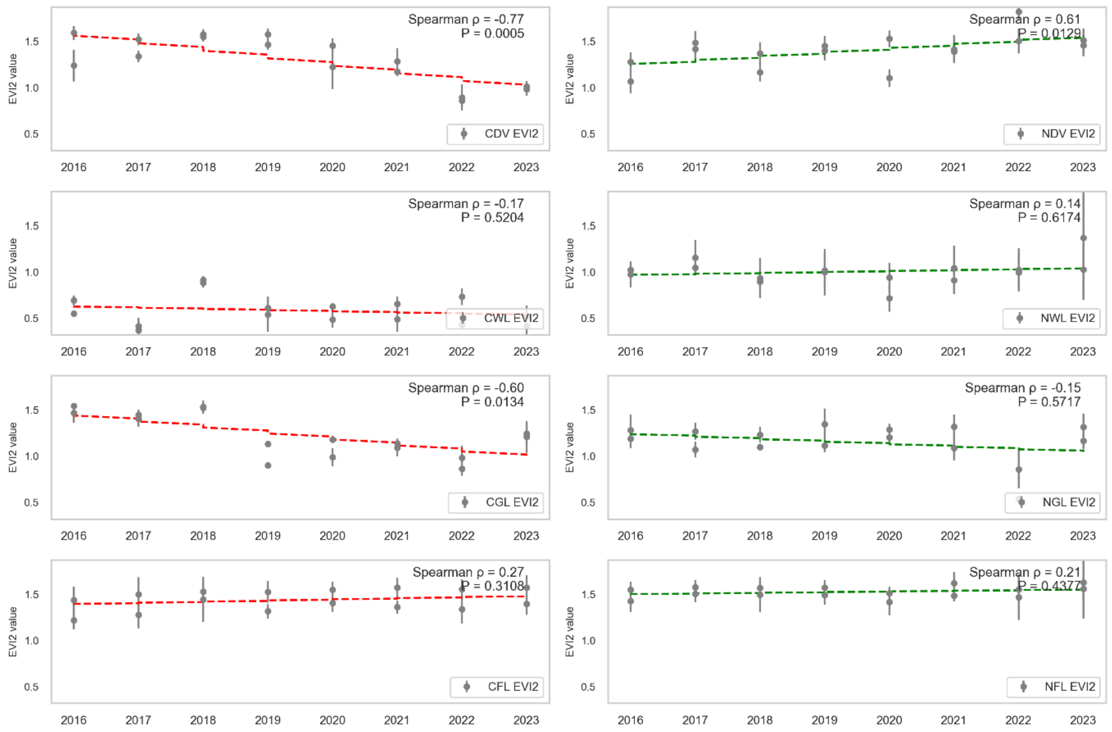

Figure 4.8. EVI2 trends of contaminated and non-contaminated landcover types from 2016 to 2023.

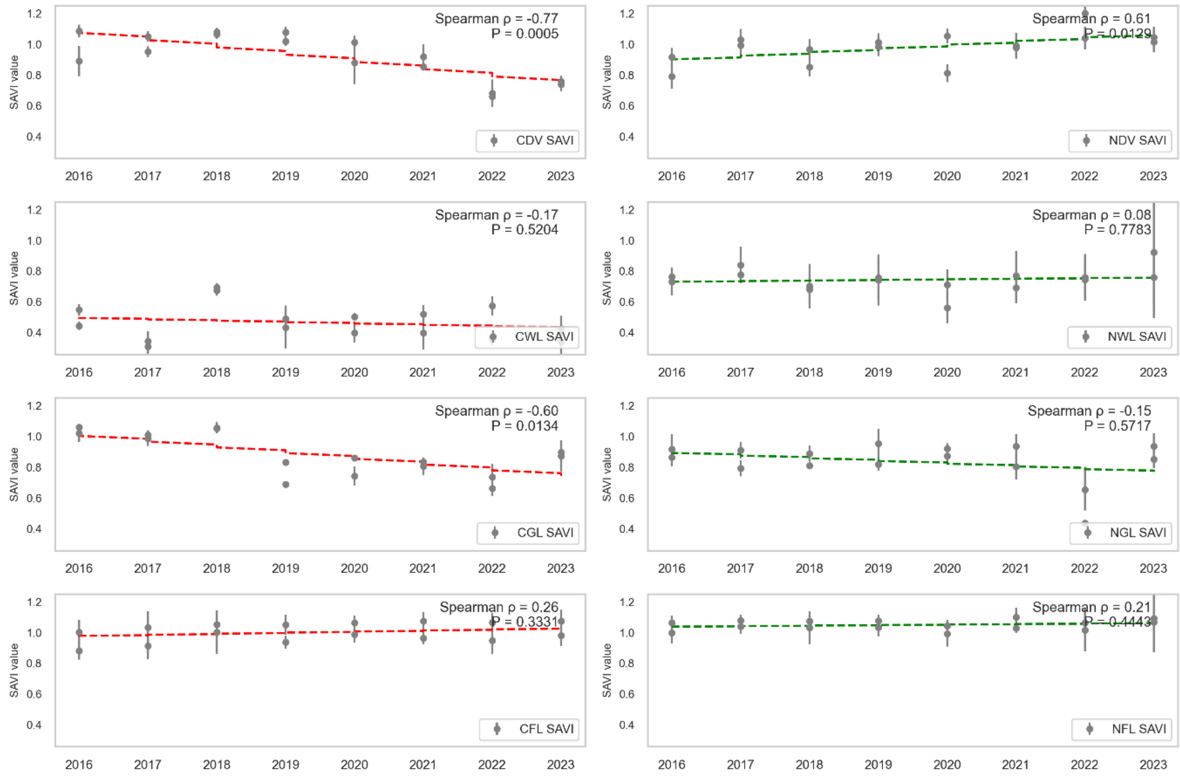

Figure 4.9. SAVI trends of contaminated and non-contaminated landcover types from 2016 to 2023.

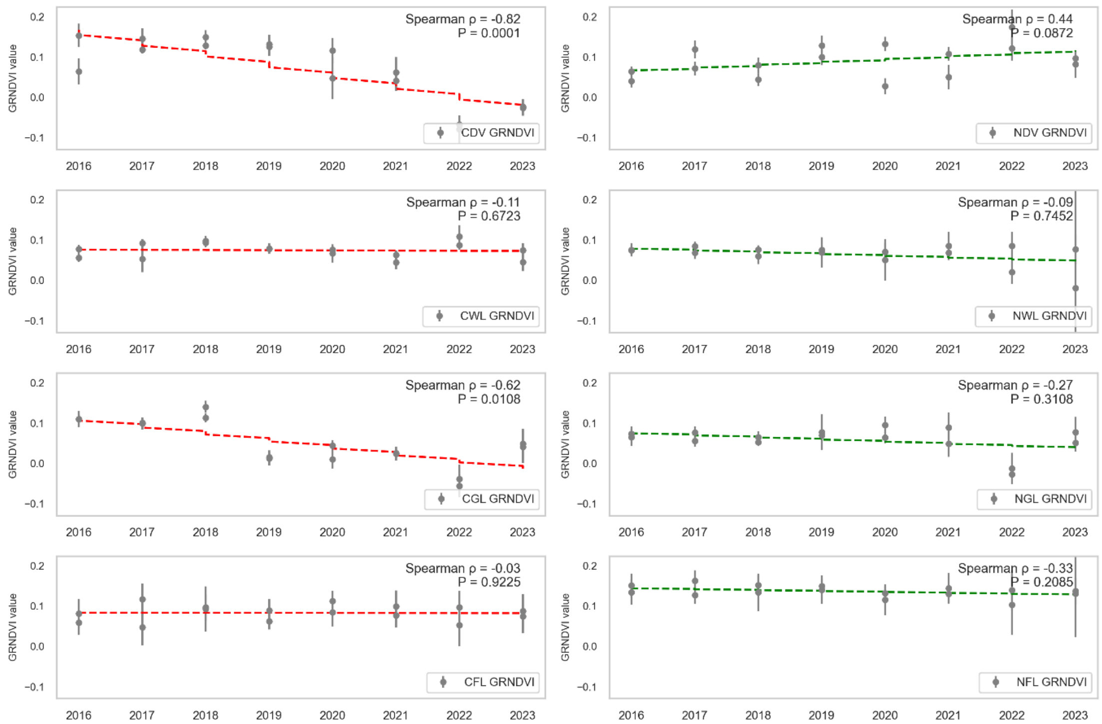

Figure 4.10. GRNDVI trends of contaminated and non-contaminated landcover types from 2016 to 2023.

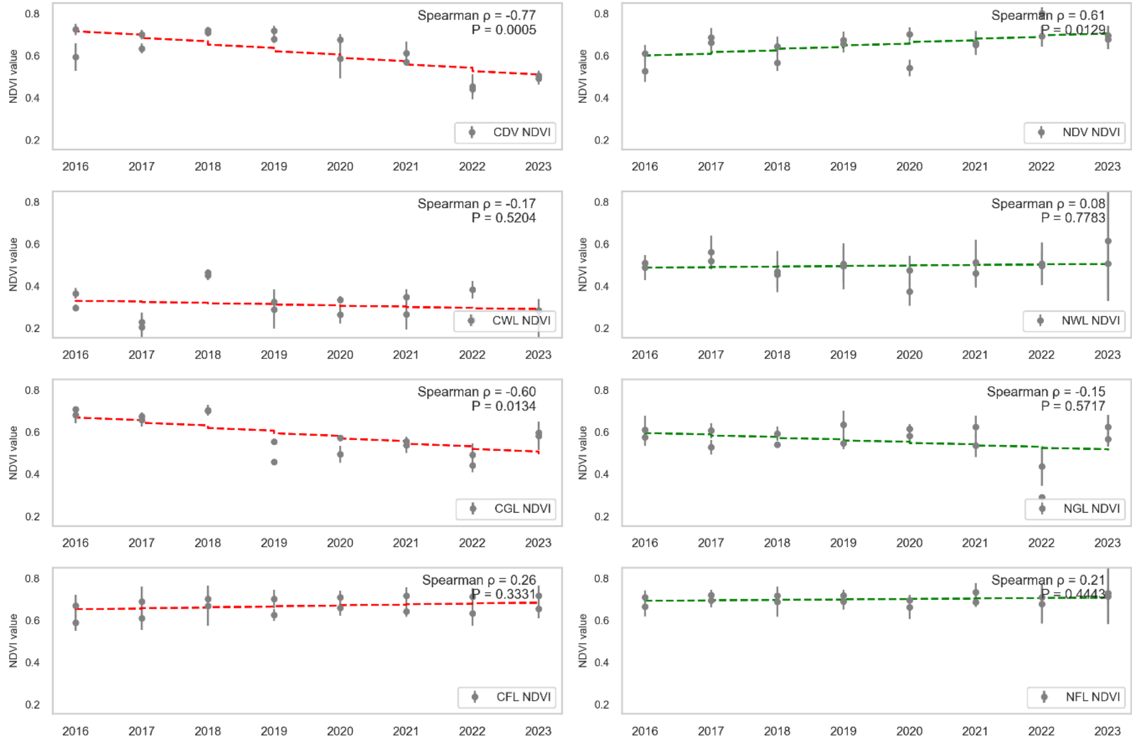

Figure 4.11. NDVI trends of contaminated and non-contaminated landcover types from 2016 to 2023 (the red lines represent the trends of contaminated landcovers while the green lines represent the non-contaminated counterparts).

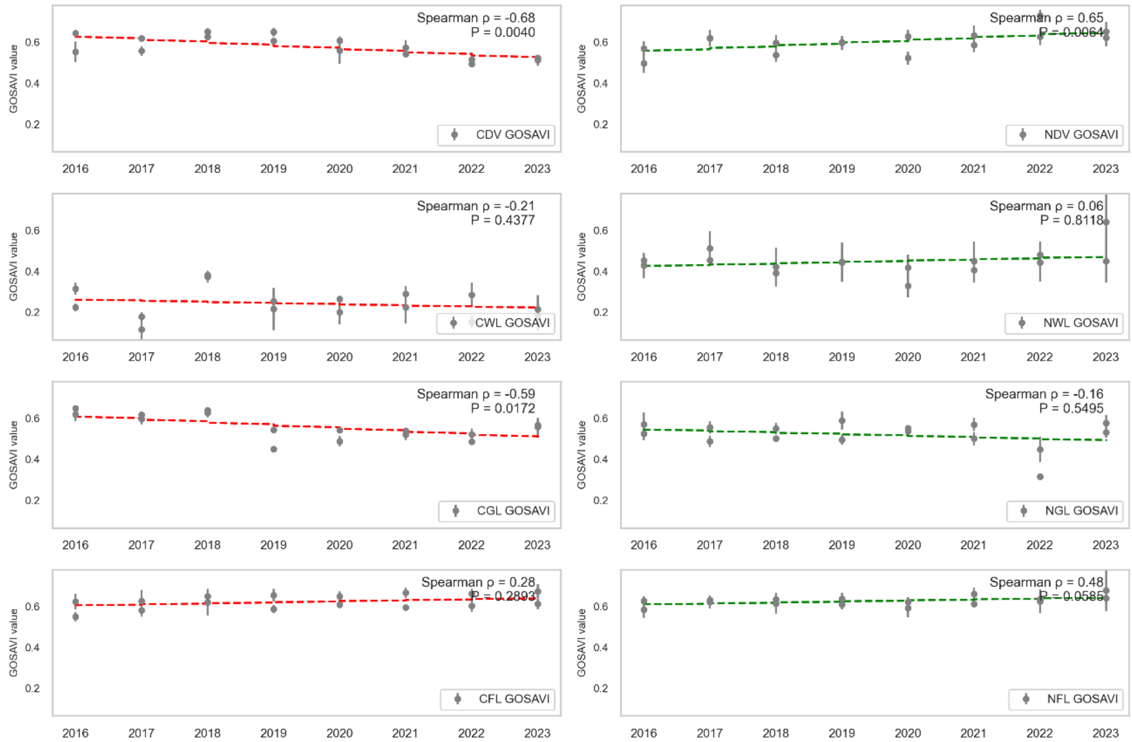

Figure 4.12. GOSAVI trends of contaminated and non-contaminated landcover types from 2016 to 2023.

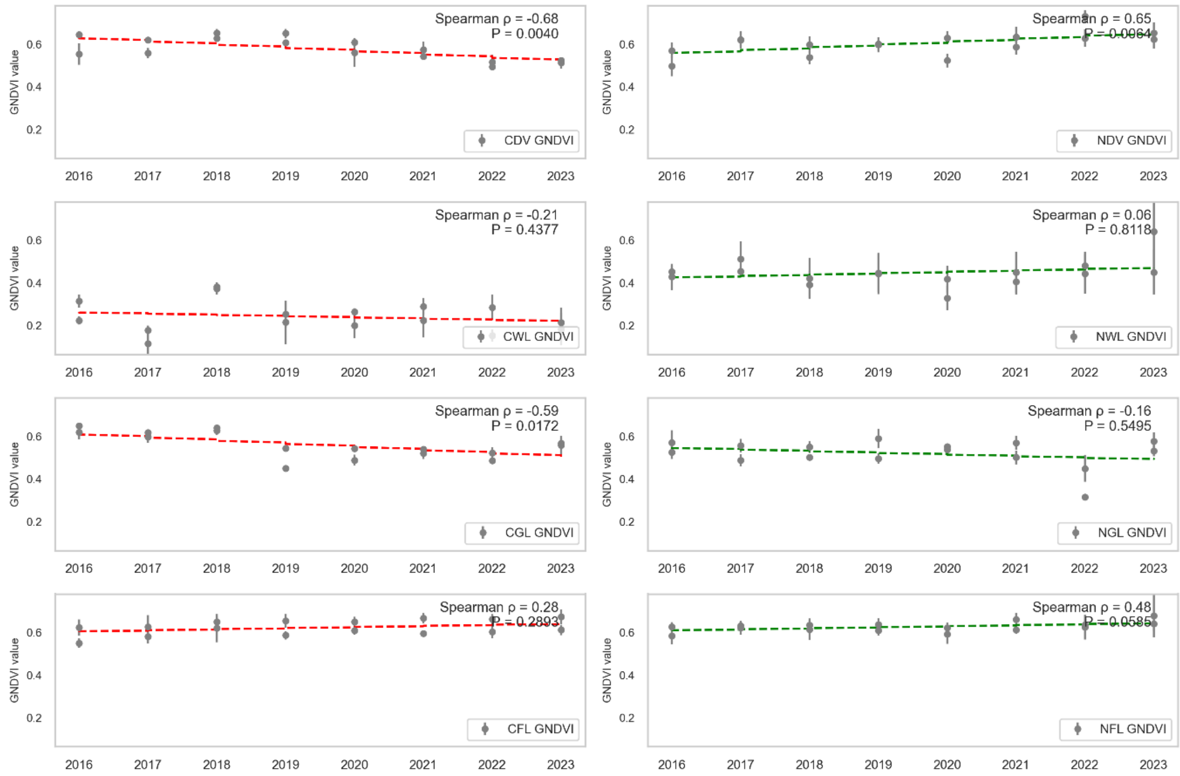

Figure 4.13. GNDVI trends of contaminated and non-contaminated landcover types from 2016 to 2023.

CDV landcover exhibited a strong, statistically significant decline across every vegetation index from 2016 to 2023, reflecting severe degradation under oil-spill impact. For example, CDV NDVI declines with a Spearman ρ = –0.77 and P-value = 0.0005 (Fig 4.10). Likewise, CDV SR1 (ρ = –0.74, P-value = 0.0010; Fig 4.5), SR2 (ρ = –0.68, P-value = 0.0038; Fig 4.6), EVI2 (ρ = –0.77, P-value = 0.0005; Fig 4.7), SAVI (ρ = –0.77, P-value = 0.0005; Fig 4.8), GRNDVI (ρ = –0.82, P-value = 0.0001; Fig 4.9), GOSAVI (ρ = –0.68, P-value = 0.0040; Fig 4.11) and GNDVI (ρ = –0.68, P-value = 0.0040; Fig 4.12) all show steep, significant downward trends. These consistent negative correlations confirm a pronounced, multi-index deterioration of vegetation health in CDV.

All the index trends clearly indicate a deterioration in vegetation health for the CDV region. By contrast, NDV landcover demonstrates significant positive trends in every index, indicating improving or stable vegetation in uncontaminated areas. NDV NDVI increases with ρ = +0.61 and P-value = 0.0129 (Fig 4.10). Similarly, SR1 (ρ = +0.63, P-value = 0.0090; Fig 4.5), SR2 (ρ = +0.65, P-value = 0.0061; Fig 4.6), EVI2 (ρ = +0.61, P-value = 0.0129; Fig 4.7), SAVI (ρ = +0.61, P-value = 0.0129; Fig 4.8), GRNDVI (ρ = +0.44, P-value = 0.0872; Fig 4.9), GOSAVI (ρ = +0.65, P-value = 0.0064; Fig 4.11) and GNDVI (ρ = +0.65, P-value = 0.0064; Fig 4.12) all trend upward. Together, these metrics highlight healthy and improving vegetation conditions in NDV, potentially due to better environmental conditions, in other words absence of oil contamination, or favourable climatic factors affecting this category, serving as a positive reference.

In CWL areas, no index shows a statistically significant trend, though all eight indices exhibit slight downward slopes. CWL SR1 (ρ = –0.12, P-value = 0.6643; Fig 4.5), SR2 (ρ = –0.16, P-value = 0.5569; Fig 4.6), EVI2 (ρ = –0.17, P-value = 0.5204; Fig 4.7), SAVI (ρ = –0.17, P-value = 0.5204; Fig 4.8), GRNDVI (ρ = –0.11, P-value = 0.6723; Fig 4.9), NDVI (ρ = –0.17, P-value = 0.5204; Fig 4.10), GOSAVI (ρ = –0.21, P-value = 0.4377; Fig 4.11) and GNDVI (ρ = –0.21, P-value = 0.4377; Fig 4.12) all trend gently downward but remain statistically indistinguishable from flat. This might suggest other factors influencing the decline, or that wetland vegetation is relatively resilient to the effects of oil spills, possibly due to the waterlogged environment. NWL landcover remains remarkably stable, with all indices showing weak, non-significant trends around zero. NWL SR1 (ρ = +0.24, P-value = 0.3743; Fig 4.5), SR2 (ρ = +0.29, P-value = 0.2739; Fig 4.6), EVI2 (ρ = +0.14, P-value = 0.6174; Fig 4.7), SAVI (ρ = +0.08, P-value = 0.7783; Fig 4.8), GRNDVI (ρ = –0.09, P-value = 0.7452; Fig 4.9), NDVI (ρ = +0.08, P-value = 0.7783; Fig 4.10), GOSAVI (ρ = +0.06, P-value = 0.8118; Fig 4.11) and GNDVI (ρ = +0.06, P-value = 0.8118; Fig 4.12). All the indices suggest that the NWL region remains relatively stable, with no strong evidence of vegetation stress, further serving as a baseline for the contaminated counterpart.

CGL landcover exhibited a strong downward trend, across all indices, mirroring the pattern in CDV but at moderate strength. CGL NDVI declines with ρ = –0.60 and P-value = 0.0134 (Fig 4.10). In parallel, SR1 (ρ = –0.60, P-value = 0.0134; Fig 4.5), SR2 (ρ = –0.59, P-value = 0.0172; Fig 4.6), EVI2 (ρ = –0.60, P-value = 0.0134; Fig 4.7), SAVI (ρ = –0.60, P-value = 0.0134; Fig 4.8), GRNDVI (ρ = –0.62, P-value = 0.0108; Fig 4.9), GOSAVI (ρ = –0.59, P-value = 0.0172; Fig 4.11) and GNDVI (ρ = –0.59, P-value = 0.0172; Fig 4.12) all show clear, statistically significant downward trends. NGL on the other hand shows no significant trends in any index, indicating stable but not improving vegetation health. NGL SR1 (ρ = –0.15, P-value = 0.5868; Fig 4.5), SR2 (ρ = –0.14, P-value = 0.5944; Fig 4.6), EVI2 (ρ = –0.15, P-value = 0.5717; Fig 4.7), SAVI (ρ = –0.15, P-value = 0.5717; Fig 4.8), GRNDVI (ρ = –0.27, P-value = 0.3108; Fig 4.9), NDVI (ρ = –0.15, P-value = 0.5868; Fig 4.10), GOSAVI (ρ = –0.16, P-value = 0.5495; Fig 4.11) and GNDVI (ρ = –0.16, P-value = 0.5495; Fig 4.12) all hover near zero, underscoring a lack of measurable change. All the indices indicate weak or no significant trends, implying that while the grassland is not heavily stressed, its recovery is slow and may be influenced by other factors.

Despite oil-spill presence, CFL indices remain flat to mildly positive, none reaching significance. CFL NDVI trends upward with $\rho = +0.26$ and P-value = 0.3331 (Fig 4.10). Similarly, SR1 ($\rho = +0.28$, P-value = 0.2893; Fig 4.5), SR2 ($\rho = +0.29$, P-value = 0.2688; Fig 4.6), EVI2 ($\rho = +0.27$, P-value = 0.3108; Fig 4.7), SAVI ($\rho = +0.26$, P-value = 0.3331; Fig 4.8), GRNDVI ($\rho = +0.03$, P-value = 0.9225; Fig 4.9), GOSAVI ($\rho = +0.28$, P-value = 0.2893; Fig 4.11) and GNDVI ($\rho = +0.28$, P-value = 0.2893; Fig 4.12). While all the indices indicate a weak relationship, the trends are statistically significant, highlighting that despite contamination, there has been no severe degradation in overall CFL's vegetation health, or that agricultural management or crop turnover may mitigate chronic decline. NFL likewise shows no significant declines, with modest upward tendencies in most indices. NFL NDVI rises with $\rho = +0.21$ and P-value = 0.4443 (Fig 4.10). SR1 ($\rho = +0.26$, P-value = 0.3388; Fig 4.5), SR2 ($\rho = +0.29$, P-value = 0.2688; Fig 4.6), EVI2 ($\rho = +0.21$, P-value = 0.4432; Fig 4.7), SAVI ($\rho = +0.21$, P-value = 0.4432; Fig 4.8), GRNDVI ($\rho = –0.33$, P-value = 0.2085; Fig 4.9), GOSAVI ($\rho = +0.48$, P-value = 0.0583; Fig 4.11) and GNDVI ($\rho = +0.48$, P-value = 0.0585; Fig 4.12), indicating vegetation improvement. All the indices suggest that NFL's vegetation remains relatively stable, with no significant decline, serving as a positive reference for non-contaminated farmland.

Comparing all the indices (SR1, SR2, EVI2, SAVI, GRNDVI, NDVI, GOSAVI and GNDVI) for both contaminated and non-contaminated regions reveal complementary insights into how oil spills contamination affects vegetation health. The statistical significance in both indices for contaminated areas highlights the negative impact of oil spills, particularly in regions like CDV and CGL, where significant downward trends in all indices indicate vegetation stress and degradation. On the other hand, non-contaminated regions like NDV, NWL, and NFL show stability or slight improvements in vegetation health, with NDVI and other VHIs trends generally reinforcing each other. This analysis underscores the importance of using multiple vegetation indices to provide a holistic understanding of environmental health and the effects of contamination.

4.4.2 Accuracy assessment

A confusion matrix was used to evaluate the performance of a classification model by comparing predicted and actual class labels, see Table 4.6. The test accuracy value, 0.98, indicates the overall accuracy of the classification model on the test dataset. It represents the proportion of correctly predicted instances out of the total number of instances in the test dataset.

Table 4.6. Confusion matrix results

Landcover type	NDV	CDV	NFL	CFL	NGL	CGL	Local refinery	NWL	CWL	Bare	Built	Water	Cloud
NDV	1365	1	3	0	7	0	0	74	0	0	0	0	0
CDV	6	55	0	0	16	0	0	9	0	0	1	0	0
NFL	7	0	1852	0	9	0	0	0	0	0	0	0	0
CFL	0	0	4	4	3	0	0	0	0	0	0	0	0
NGL	5	0	10	0	1357	0	0	14	3	0	0	0	0
CGL	0	1	0	0	7	1	1	2	0	0	0	0	0
Local refinery	0	0	1	0	2	0	0	1	0	0	0	0	0
NWL	58	0	2	0	4	0	0	3696	4	0	0	12	0
CWL	2	1	0	0	14	0	0	16	183	0	0	6	0
Bare	0	0	0	0	0	0	0	0	0	200	2	0	0
Built	0	0	0	0	5	0	0	1	1	3	65	1	0
Water	0	0	0	0	0	0	0	16	9	1	2	38709	0
Cloud	0	0	0	0	0	0	0	0	0	0	2	0	51

Looking across the matrix, the model shows considerable confidence and accuracy in delineating extensive areas of non-contaminated land cover types. These categories, along with features like open water, bare ground, and cloud cover, are largely well-distinguished from one another, forming a reliable foundation for our understanding of the general environment. The more intricate task, as highlighted by the matrix, lies in accurately identifying areas where contamination may be present. While the model does successfully pinpoint many instances of contaminated land cover types, this classification presents a more nuanced challenge compared to mapping the dominant uncontaminated land cover types. This might be because the contaminated counterparts are often represented with more specific or perhaps less extensive areas within the landscape. This relatively smaller number of examples for the model to learn from can subtly influence its ability to capture the full variability within these classes, contributing to the nuances seen in their classification performance.

To further verify the model, a k-fold cross-validation was conducted. Results from the cross-validation (k-fold) show that the training errors range from 0.9996 to 0.9995 in all the folds, see Table 4.7 indicating a high accuracy of the model on the training data. The validation errors (OOB) range from 0.9894 to 0.9877, suggesting a slightly lower accuracy on the validation data compared to the training data. The mean error is 0.9886, which is the average validation error across the different iterations. Overall, the model seems to perform well on both the training and validation data.

Table 4.7. K-fold results

Fold	Training error	Validation error
1	0.9996	0.9893
2	0.9995	0.9883
3	0.9997	0.9877
4	0.9996	0.9894
5	0.9995	0.9882

4.4.3 Spatial distribution of contaminated sites

The classification results presented in Figure 4.10 provide information on the spatial extent of different landcovers generated from the January 2023 PlanetScope data, while Table 4.6 provides the corresponding area of the different landcovers in hectares. Figure 4.10e and f specifically displays the spatial extent of non-contaminated dense vegetation and contaminated vegetation.

Table 4.8. Landcover area estimates.

Landcover	Area (hectares)	Area (%)
Non-contaminated dense vegetation	8,390	22.81%
Contaminated dense vegetation	513	1.39%
Non-contaminated farmland	3,326	9.04%
Contaminated farmland	26	0.07%
Non contaminated Grassland	7,475	20.32%
Contaminated grassland	13	0.04%
Local refinery	2	0.01%
Non-contaminated wetland	13,023	35.40%
Contaminated wetland	625	1.70%
Bare	365	0.99%
Built	532	1.45%
Water	2,471	6.72%
Clouds	24	0.07%

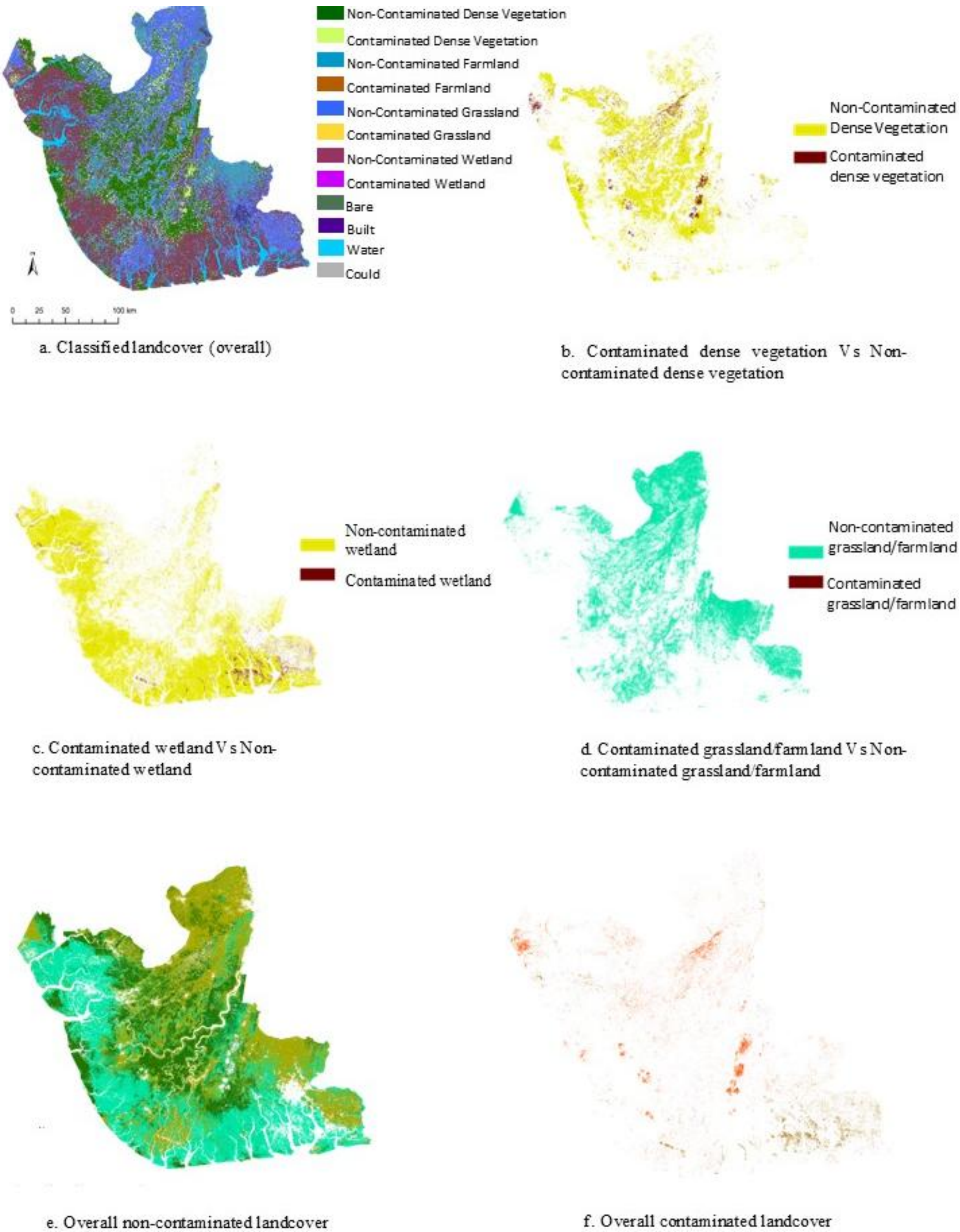

Figure 4.14. Thematic classification outputs displaying the spatial extent and corresponding area in hectares of different landcovers generated from January 2023 PlanetScope data.

Table 4.6 shows that the non-contaminated dense vegetation covers 22.8% of the total landcover area, which is equivalent to 8,390 hectares. On the other hand, the contaminated dense vegetation, affected by oil spills, constitutes 1.39% of the total landcover area, amounting to 513 hectares across the three states (Bayelsa, Delta, and Rivers). The non-contaminated wetland accounts for 35.4% of the total landcover area, encompassing 13,023 hectares. Conversely, the wetland area contaminated by oil spills represents 1.7% of the total landcover area, totalling 625 hectares. To enhance visual clarity on the map, the grassland and farmland classes were merged.

The results reveal that the non-contaminated grass/farmland covers 29.4% of the total landcover area, equivalent to 10,801 hectares. Meanwhile, the grass/farmland contaminated by oil spills occupies a minimal portion of the landcover, constituting only 0.11% or 39 hectares. Overall, the prioritised landcovers, including contaminated vegetation, wetland, farmland, grassland, and local refinery locations, cover approximately 4% (1,180 hectares) of the total area. Conversely, the non-contaminated prioritised landcovers (non-contaminated vegetation, wetland, farmland, and grassland) account for 96% (32,215 hectares) of the total landcover area.

4.5 Discussion

The Niger Delta, one of the world's largest deltas and home to a significant mangrove habitat, has been severely polluted due to recurring oil spills (NDDC, n.d.; Obi, 2023). This pollution has led to a depletion of soil oxygen, adversely affecting plant health and canopy reflectance. Vegetation indices derived from remote sensing data have become valuable tools for distinguishing between vegetation on hydrocarbon-contaminated soils and those on non-affected soils (Ansah et al., 2022; A. R. Huete, 2004a). Reliable information on land cover dynamics is crucial for the sustainable management of the Niger Delta. Traditional remote sensing mapping approaches have proven unreliable in the humid tropics due to issues such as cloud cover, data availability, and algorithm performance. This has resulted in conflicting estimates of land cover change for the Niger Delta and an inability to assess the extent of degradation of this endangered ecosystem (Adamu et al., 2018). This study developed a remote sensing-based approach to assess oil-contaminated areas and evaluate the environmental impact of oil spills in the Niger Delta region. To achieve this aim, the study investigated the impact of oil spills on vegetation in the Niger Delta by addressing three key objectives:

assessing spectral separability of contaminated and non-contaminated land, analysing spatio-temporal trends in vegetation health, and mapping the spatial extent of contamination.

4.5.1 Spectral Separability of Contaminated and Non-contaminated Land

Oil spills induce biophysical and biochemical changes in vegetation, altering their spectral reflectance (Ansah et al., 2022; A. R. Huete, 1988). This study utilised both reflectance values of the landcovers in different bands and vegetation health indices (VHIs) to assess the separability of contaminated and non-contaminated land covers. Analysis of reflectance profiles revealed distinct differences between contaminated and non-contaminated land covers, particularly in dense vegetation, grassland, and wetland areas. The high Jeffries-Matusita (JM) distances (close to 2) for these land cover pairs indicate that the spectral signatures of contaminated vegetation are significantly different from their healthy counterparts. This difference likely arises from the reduction in chlorophyll content and altered leaf structures caused by oil contamination, leading to increased reflectance in visible and near-infrared wavelengths (Fingas & Brown, 2014; A. R. Huete, 2004a).

The low JM distance (0.17) for farmland suggests that spectral reflectance alone may be insufficient for accurately discriminating between contaminated and non-contaminated farmland. This could be attributed to several factors, including the influence of soil background reflectance, variations in crop types and planting cycles, and potential mitigation measures employed in agricultural practices(Al-Shammary et al., 2024; Kooistra et al., 2003; Prudnikova et al., 2019). Further investigation is needed to understand the complex interactions between oil contamination and spectral response in farmland environments.

Incorporating VHIs further enhanced separability, particularly for EVI2, GNDVI, SAVI, SAVI2, GRNDVI and NDVI. These indices are designed to be more sensitive to variations in chlorophyll content and canopy structure, making them effective indicators of vegetation stress (Adamu et al., 2015, 2016, 2018). The consistently strong separation observed between contaminated and non-contaminated land covers using these indices (JM distances > 1.3) highlights their value in improving the classification accuracy of oil-contaminated areas. This finding aligns with previous research demonstrating the sensitivity of these indices to oil-induced stress in various vegetation types (e.g. Adamu et al., 2015; Ansah et al., 2022; Lassalle et al., 2020).

4.5.2 Spatio-temporal Trends in Vegetation Health

Analysing temporal trends in VHIs derived from PlanetScope data acquired between 2016 - 2023 revealed impacts of oil spills on vegetation health across different land cover types. Consistent with previous findings (e.g. Ansah et al., 2022), contaminated dense vegetation (CDV) exhibited the most pronounced decline in VHIs over time, indicating severe vegetation stress and degradation. The strong negative correlations observed between all VHIs and time (e.g., CDV SR1 ($\rho = -0.74$, P-value = 0.0010; Fig 4.5), SR2 ($\rho = -0.68$, P-value = 0.0038; Fig 4.6), EVI2 ($\rho = -0.77$, P-value = 0.0005; Fig 4.7), SAVI ($\rho = -0.77$, P-value = 0.0005; Fig 4.8), GRNDVI ($\rho = -0.82$, P-value = 0.0001; Fig 4.9), GOSAVI ($\rho = -0.68$, P-value = 0.0040; Fig 4.11) and GNDVI ($\rho = -0.68$, P-value = 0.0040; Fig 4.12)) suggest a progressive deterioration of vegetation health following oil contamination. This severe stress and degradation are likely attributed to the long-term effects of oil residues in the soil and water, disrupting nutrient uptake, root function, and overall plant physiological processes essential for survival and growth in these complex forest ecosystems. The persistence of oil hydrocarbons over time leads to cumulative toxicity, manifesting as a consistent downward trend in the spectral signature associated with healthy vegetation (Arellano et al., 2015). In contrast, the upward trend in VHIs for non-contaminated dense vegetation (NDV) (e.g., NDVI: $\rho = 0.61$, $p = 0.013$) indicates healthy and improving vegetation conditions in areas unaffected by oil spills. This serves as a vital baseline, highlighting the divergence in vegetation trajectories caused by contamination.

Contaminated grassland (CGL) also displayed a significant downward trend in VHIs, highlighting its vulnerability to oil contamination. The observed decline in VHIs (e.g., NDVI increases with $\rho = +0.61$ and P-value = 0.0129 (Fig 4.10). Similarly, SR_1 ($\rho = +0.63$, P-value = 0.0090; Fig 4.5), SR_2 ($\rho = +0.65$, P-value = 0.0061; Fig 4.6), EVI_2 ($\rho = +0.61$, P-value = 0.0129; Fig 4.7), SAVI ($\rho = +0.61$, P-value = 0.0129; Fig 4.8), GRNDVI ($\rho = +0.44$, P-value = 0.0872; Fig 4.9), GOSAVI ($\rho = +0.65$, P-value = 0.0064; Fig 4.11) and GNDVI ($\rho = +0.65$, P-value = 0.0064; Fig 4.12) suggests that grasslands may be less resilient to oil pollution compared to other vegetation types. This could be due to their shallower root systems which provide less access to uncontaminated soil layers and greater exposure of above-ground biomass and surface roots to spilled oil. The absence of a clear linear trend in non-contaminated grassland (NGL) further supports the interpretation that the decline observed in CGL is a direct consequence of oil impact rather than broader environmental factors.

Contaminated wetlands (CWL) exhibited a more complex and less pronounced response, showing only a slight overall decline in VHI values over the study period, see Figures 4.5 to 12. While this subtle downward trend suggests some degree of impact from oil spills, it is notably less severe than the degradation observed in CDV and CGL. This relative resilience of wetland vegetation to oil contamination could be attributed to several inherent characteristics of these ecosystems. The presence of standing water provides a diluting and buffering capacity, reducing the concentration of oil compounds directly interacting with plant tissues. Furthermore, many wetland plant species possess adaptations to waterlogged and anaerobic conditions, which may also confer some tolerance to hydrocarbon stress. The dynamic nature of wetlands, including tidal flushing or seasonal inundation, can facilitate the dispersion and natural degradation (bioremediation) of oil by microbial communities, as suggested by previous research (Breil et al., 2022; Dordio et al., 2008). However, even a slight observed decline warrants concern and further investigation to fully understand the long-term, cumulative effects of chronic oil pollution exposure on the delicate balance and biodiversity of wetland ecosystems.

This study also examined farmlands in the Niger Delta, an important land cover type frequently reported as severely affected by oil spills due to its adjacency to infrastructure and waterways (Ratcliffe, 2019; Chinedu & Chukwuemeka, 2018). Interestingly, results for Contaminated Farmland (CFL) showed a slightly flat to upward trend in VHIs over the study period, see Figures 4.5 to 12, indicating that across the areas classified as contaminated farmland, there was no widespread pattern of severe, progressive vegetation degradation detectable through overall VHI trends. This seemingly counterintuitive finding, given the well-documented devastating impacts of oil spills on soil fertility and crop yields at the local scale (Ratcliffe, 2019; Chinedu & Chukwuemeka, 2018), could be attributed to several factors influencing the remote sensing signal and the nature of agricultural land use. Agricultural practices such as regular tilling can mix contaminated soil layers, potentially reducing the immediate surface concentration of oil or promoting aeration conducive to some degradation. Irrigation and crop rotation might also play a role in mitigating visible stress signals in vegetation over time, depending on the crop cycle and management intensity. Crucially, the observed VHI trend in CFL must also be considered in light of the smaller spatial extent of land classified as contaminated farmland in this study (as highlighted in the spatial analysis results). As demonstrated by Ozigis et al. (2018) and Adamu et al. (2016), the detectability and mapping accuracy of oil spill impacts using satellite imagery are significantly influenced by the concentration and spatial size of the spill. Severely damaged agricultural areas might be misclassified as bare soil or non-vegetated land rather than "contaminated farmland" in the classification process, leading to an underrepresentation of the most degraded areas within the CFL category analysed for trends. Therefore, while the VHI trend for detected CFL areas does not show severe decline, this does not negate the known, severe, localized impact of oil spills on agricultural productivity and food security in the Niger Delta. Further targeted research, potentially using higher resolution data or field studies focusing on soil chemistry and crop health in known spill sites on farmland, is needed to fully assess the long-term impacts.

4.5.3 Mapping the Spatial Extent of Oil Spill Contamination

The Niger Delta, renowned for its exceptional biodiversity, hosts a wealth of terrestrial and aquatic flora and fauna, making it one of the world's most crucial wetland and tropical rainforest ecosystems (Chukwuka et al., 2018). However, this valuable ecosystem is under threat from recurring oil spills, which have devastating impacts on vegetation health and overall environmental integrity. To accurately assess and quantify the extent of oil contamination, this study developed a robust classification model. Recognising the sensitivity of various vegetation indices (VHIs) to oil-induced stress, the model incorporated a suite of indices known to be effective in detecting petroleum contamination (Ansah et al., 2022; Lassalle et al., 2019; Balogun et al., 2020; Onyia et al., 2018). These included EVI2, GNDVI, GOSAVI, NDVI, SAVI, GRNDVI, SR, and SR2, each capturing different aspects of vegetation health and response to stress. By integrating these indices with spectral bands, the model achieved high accuracy in discriminating between contaminated and non-contaminated land covers (test accuracy = 0.98).

The robustness of the model was further confirmed through k-fold cross-validation, which demonstrated its ability to generalise to unseen data and maintain high performance across different subsets of the data. This rigorous validation process ensures the reliability and generalisability of the contamination maps produced. The resulting map and area estimates provide valuable spatial information on the distribution of contaminated land covers across the Niger Delta. This information is crucial for prioritising areas for remediation and conservation efforts, enabling targeted interventions to mitigate the ecological damage caused by oil spills.

The spatial analysis revealed significant differences in the extent of contamination across different land cover types, providing insights into the varying vulnerability and impact pathways of oil spills in the Niger Delta. Specifically, contaminated dense vegetation constituted 1.39% of the total land area (513 hectares), significantly less than the 22.8% (8,390 hectares) occupied by non-contaminated dense vegetation. Similarly, contaminated wetlands comprised 1.7% of the total area (625 hectares), compared to 35.4% (13,023 hectares) for non-contaminated wetlands. The observed spatial pattern, showing notable contamination in dense vegetation and wetlands, is likely attributed to their proximity to waterways, which serve as primary conduits for oil spill dispersion. The physiochemical properties of oil cause it to accumulate in the water column, sediments, and the complex root systems characteristic of these environments, leading to prolonged exposure and difficulty in natural recovery. This finding aligns with numerous studies confirming the detrimental impact of oil spills on these sensitive ecosystems (Chukwuka et al., 2018; Duke, 2016; Obi, 2023; Onyena & Sam, 2020) and corroborates the general decline in dense vegetation cover highlighted by Wakil et al. (2021) in the region due to such contamination. The magnitudes observed emphasize that even relatively small percentages of total land area represent significant ecological damage within these critical biodiversity hotspots.

In contrast, non-contaminated grassland/farmland covered a much larger area (29.4%, 10,801 hectares), while contaminated grassland/farmland occupied a minimal 0.11% (39 hectares). Contaminated farmland specifically comprised only 0.07% of the total area (26 hectares). This stark contrast suggests that while oil spills are widespread, their direct physical impact on grassland and cultivated farmland is generally more localized compared to riparian or wetland areas. Contamination in these land cover types likely occurs due to specific events such as pipeline ruptures on land, leaks from flow stations, or spills occurring during transportation affecting adjacent agricultural plots. The localized nature of this impact, although covering a smaller area overall, underscores the devastating effect on soil fertility and crop viability where it occurs, corroborating findings by Babatunde (2020) on the severe impacts of oil pollution on agricultural productivity. Similarly, the impact of local refineries was evident, albeit highly localised, with contaminated areas covering approximately 0.01% of the total area (2 hectares). This concentrated contamination near refineries highlights them as specific point sources of pollution, aligning with research by Richard et al. (2022) documenting their detrimental effects on the immediate surrounding environment. Overall, the spatial analysis revealed that non-contaminated land covers dominated the study area (96%), while contaminated land covers accounted for approximately 4%. This spatial distribution underscores that oil spill impacts in the Niger Delta manifest as a mosaic of highly contaminated hotspots within a larger, but still vulnerable, landscape, emphasizing the need for spatially targeted monitoring and remediation efforts.

This study, while providing valuable insights into the impacts of oil spills, acknowledges several limitations stemming from the characteristics of the satellite data and the methodological approach.

Firstly, the study's reliance on PlanetScope NICFI data presented limitations due to its spectral resolution. The four spectral bands (blue, green, red, and near-infrared) inherent to this dataset resulted in reduced spectral dimensionality, potentially hindering the effective discrimination and detailed characterization of subtle vegetation degradation and contamination levels in affected landcovers like farmlands and wetlands. Higher spectral resolution imagery, encompassing a wider range of bands, could potentially enhance the accuracy of land cover classification and the detection of specific spectral signatures associated with oil spill impacts.

Secondly, the temporal resolution and compositing strategy of the NICFI data posed constraints on the analysis of short-term phenological changes and inter-annual variability. This study utilised the available bi-annual (6-month) composite basemaps (2016-2019) and then transitioned to monthly composites (from 2020 onwards), using the July and December composites—this introduced a significant level of temporal smoothing. This smoothing effect, while reducing cloud cover and atmospheric interference, limited the capacity to capture rapid ecological responses and accurately account for seasonal variations in vegetation health. Ideally, higher frequency data acquisitions (e.g., daily or weekly) without the need for extensive compositing would allow for a more precise temporal analysis and a better understanding of the phenological trajectory of the affected ecosystems.

Thirdly, these data characteristics, combined with the inherent complexity of defining and identifying subtle environmental impacts, led to challenges in the classification process itself. As highlighted by the confusion matrix (see Table 4.6), accurately distinguishing between contaminated and non-contaminated land cover types, such as dense vegetation, wetlands, farmlands, and grasslands, proved particularly nuanced. Subtle spectral or spatial differences between these states, potentially coupled with the relatively smaller variability due to the smaller sizes of the contaminated areas versus non-contaminated area, sometimes resulted in instances where contaminated areas were challenging to separate distinctly from their non-contaminated counterparts or even other land cover classes. This represents a key classification limitation influencing the precision of the contamination mapping.

Fourthly, the study's methodological choice of employing only the Random Forest machine learning algorithm represents a potential limitation. While Random Forest is a robust and widely used classifier due to its high accuracy (e.g. Junaid et al., 2023; Mohammadpour et al., 2022; Ozigis et al., 2020; Pande et al., 2024), exploring and comparing the performance of other algorithms, including deep learning approaches, could have provided a more comprehensive assessment of the classification accuracy and the robustness of the findings. Future research could benefit from a comparative analysis of different machine learning techniques to identify the most effective approach for this specific application.

Finally, the absence of in-situ ground-truthing data constitutes a limitation. While satellite imagery provides valuable spatial information, ground-based observations are crucial for validating the accuracy of the remote sensing-derived classifications and for gaining a deeper understanding of the on-the-ground conditions of the affected land cover, particularly regarding forest deterioration and vegetation health. Future studies could prioritise the collection of field data, including soil profiling, to assess the direct impacts of oil spills on soil properties and their subsequent effects on vegetation. Integrating ground-truthing efforts would significantly enhance the validation and interpretation of the remote sensing analysis. However, for locations such as the Niger Delta, safety and accessibility are key considerations and often represent barriers to data collection in the field.

Addressing these limitations in future research, through the utilisation of data with enhanced spectral and temporal resolution, the exploration of diverse analytical methodologies, and the incorporation of ground-based validation, could contribute to a more comprehensive and robust understanding of oil spill impacts and the development of effective mitigation and remediation strategies.

4.6 Conclusions

The efficacy of integrating cloud computing and machine learning classification algorithms for vegetation health trend analysis and to assess change dynamics across Bayelsa, Delta and River states in Niger Delta Region has been demonstrated in this study. Analysis of Vegetation Health Indices (VHIs) derived from PlanetScope data (2016-2023) revealed significant impacts of oil spills on vegetation health across different land cover types. The most pronounced decline in VHIs occurred in contaminated dense vegetation, indicating severe stress and degradation. Contaminated grassland also showed a significant downward trend, highlighting its vulnerability, while contaminated wetlands exhibited a more complex response with a slight VHI decrease, suggesting a less severe impact compared to the other contaminated types.

Spatial analysis quantified land cover, showing non-contaminated areas dominate (96%), while contaminated landcovers (wetlands, dense vegetation, farmland/grassland, and local refineries) constitute approximately 4%. The land cover estimates obtained have enabled a nuanced understanding of both contaminated and uncontaminated landcovers and reveal the extent of oil pollution within the studied landcovers. The study showcases the utility of these assessment and quantification techniques for disseminating information to local authorities and guiding response efforts, particularly for the heavily impacted landcovers like the dense vegetation and wetlands. By identifying regions requiring immediate attention for mitigating the impact of oil spills on vegetation, these techniques hold promise for enhancing environmental monitoring and compliance in oil-producing regions like Nigeria. The findings underscore the potential of spectral techniques for assessing and monitoring oil spills, thereby aiding in the identification and remediation of polluted sites. There is an urgent need for remote sensing-based approaches in assessing and managing contaminated areas in the Niger Delta. Through the integration of satellite imagery and advanced analytical tools, this study offers valuable insights into the environmental impacts of oil spills, thereby informing decision-making processes aimed at conserving and restoring the delicate ecosystems of the Niger Delta.

Chapter Five

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5. Exploring the Concerns of Oil Spill Impacted Communities in the Niger Delta

5.1 Introduction

The Niger Delta, a region of immense ecological significance and the economic engine of Nigeria due to vast oil reserves, simultaneously embodies a landscape scarred by profound environmental degradation (Chukwuka et al., 2018; Onyena & Sam, 2020). Decades of oil extraction have left a pervasive legacy of pollution, transforming the region into a critical site for examining the complex interplay between infrastructure, environment, and human well-being under conditions of persistent contamination (Laville, 2023). Oil spills are not isolated incidents but a persistent issue, resulting in widespread destruction of ecosystems, disruption of livelihoods, and significant health challenges for local communities (Laville, 2023; Amnesty International, 2013). The environmental toll is staggering, with hundreds of thousands of barrels of oil spilled over the years, impacting land and water bodies essential for sustenance and life (Ikporukpo, 2020; Akinpelu, 2021).

This chapter unveils the enduring crisis in the Niger Delta, particularly concerning oil spills and their impacts, through the lens of infrastructural violence and slow violence. Building on critical infrastructure studies (Enns & Sneyd, 2020), which view infrastructure as deeply entwined with economic, political, and social life (Enns, 2019; Lemanski, 2019; McFarlane & Rutherford, 2008; Wakefield, 2020), this chapter employs the concept of infrastructural violence. This concept highlights how built networks like oil pipelines are not merely technical systems but active agents in shaping precarious realities for marginalised populations (Rodgers and O'Neill, 2012). The presence of aging and poorly maintained oil pipelines, coupled with recurrent spills that degrade the environment and forcibly displace communities (Ikporukpo, 2020; Mahmoud, 2021), constitutes active infrastructural violence (Oluwatomilola Olunusi & Emmanuel Adeboye, 2025; Rodgers & O'Neill, 2012). This explicit form of harm stems directly from the function and failure of the infrastructure itself, leading to tangible destruction of farmlands, water sources, and homes (Ayanlade & Drake, 2016; Oghenetega et al., 2020; Wakil et al., 2021). Conversely, the persistent absence of adequate public amenities, essential services, and robust environmental protection mechanisms in this resource-rich region, despite the ongoing extraction, represents passive infrastructural violence (Oluwatomilola Olunusi &

Emmanuel Adeboye, 2025; Rodgers & O'Neill, 2012). This form of violence arises from the limitations and omissions of infrastructure, exacerbating community vulnerability and hindering their capacity to respond to and recover from the impacts of spills (Rodgers and O'Neill, 2012).

Furthermore, an exclusively anthropocentric view fails to capture the full scope of the harm. This chapter adopts a more-than-human infrastructural violence (Enns & Sneyd, 2021) perspective, recognising that the oil pipeline network and associated spills inflict violence not only upon human communities but also on nonhuman species, larger ecosystems, and the intricate web of more-than-human relations (Enns & Sneyd, 2020). Wetlands, forests, rivers, and soils function as vital natural and ecological infrastructure, providing essential ecosystem services and maintaining connections crucial for the flourishing of diverse life forms and cultural practices (Enns & Sneyd, 2021; Wakefield, 2020). The contamination and destruction of these socio-natural landscapes by oil spills represent a direct act of violence against this more-than-human infrastructure, disrupting ecological balance and undermining the very basis of life and livelihoods in the region.

The insidious nature of oil spill impacts in the Niger Delta also aligns with the concept of slow violence (Nixon, 2011). This is a violence of delayed destruction, dispersed across time and space, often incremental and attritional, whose catastrophic repercussions unfold over extended periods. The chronic health issues, the gradual decline in agricultural productivity, the slow erosion of traditional livelihoods, and the long-term environmental damage that can take decades to remediate (Amnesty International, 2013; Eke, 2016; UNEP, 2011; Lindén & Pålsson, 2013) are all manifestations of this slow violence. Unlike spectacular events, this form of violence often goes unnoticed or is normalized, yet its cumulative impact is devastating.

Existing literature has extensively documented the environmental consequences of oil spills, highlighting alarming levels of contaminants in water and soil (UNEP, 2011; Ordinioha and Brisibe, 2013), the disproportionate impact on critical ecosystems like mangroves (Mendoza-Cant et al., 2011; Ndidi et al., 2015; Obida et al., 2018), and the links between oil exposure and various health issues, including respiratory problems, skin diseases, and increased mortality rates (UNEP, 2011; Obida et al., 2018; Adekola and Fischbacher-Smith, 2016; Ordinioha and Brisibe, 2013; Bruederle and Hodler, 2019). Studies have also explored the severe disruption of livelihoods, particularly fishing and farming (Idowu & Lambo, 2018; Anifowose et al., 2014;

Elum et al., 2016), and the contribution of oil industry activities to social unrest and conflict (Nwajiaku, 2005; Albert et al., 2019).

Despite this body of work, there remains a significant gap in research that comprehensively integrates the lived experiences and community intelligence of those directly impacted by oil spills with spatial data to understand the complex nexus between pollution, environmental degradation, and the multi-scalar forms of violence inflicted upon communities and ecosystems. While some studies touch upon community perspectives or use mapping in isolation, fewer have combined these approaches within a robust theoretical framework like infrastructural and slow violence to provide a nuanced, situated understanding of the problem from the perspective of those at the sharp end of environmental pollution. The inadequacy of existing monitoring and response mechanisms (Ikporukpo, 2020; Kadafa et al., 2012; Rim-Rukeh, 2015), coupled with a lack of transparency and accountability, further underscores the need to centre community voices and knowledge in understanding the full scope of the issue.

This chapter seeks to bridge this gap by exploring the perceived dangers and challenges posed by oil spillages for six communities in the Niger Delta through a qualitative lens. By amplifying the voices of community members and integrating their narratives with spatial insights, this research aims to provide a more grounded understanding of how infrastructural violence, in its active, passive, and more-than-human dimensions, manifests as slow violence in the daily lives and environments of these communities. The guiding question addressed in this chapter is: What are the perceived dangers and challenges posed by oil spillages for the Niger Delta communities?

To capture the complexity of these experiences I utilised qualitative methods, specifically structured focus group discussions (FGDs) and community participatory mapping exercises (CPME). These approaches were chosen to reveal the nuanced layers of meaning behind the lived experiences of Niger Delta communities. As Secor (2010) highlights, FGDs allow for in-depth exploration of social phenomena without generalising findings to a broader population, thereby providing insights into community-specific perceptions. This method helped unpack local understandings of oil spills, perceived risks, and their broader implications for livelihoods, environmental integrity, and social well-being. FGDs as highlighted by Secor (2010), provide an opportunity for participants to collectively share and reflect on their experiences, generating deeper conversations around shared challenges and community-specific concerns. In the context of oil spills, FGDs allowed me to capture the community's diverse perceptions of risks, the emotional toll of environmental degradation, and their views on government and corporate responses to the crises. This method also enabled me to uncover localised knowledge that often goes unnoticed in broader surveys.

Community Participatory Mapping Exercises (CPME), on the other hand, played a critical role in translating these narratives into spatial data. Ralls and Pottinger (2021) emphasise that CPME allows communities to document their own spatial knowledge, bringing attention to areas that are of cultural, historical, or environmental importance. This approach, which has been widely used in environmental justice studies, provided a visual and geographic representation of the oil spill impacts on communities (Cochrane & Corbett, 2018, 2020; Ralls & Pottinger, 2021; Souto & Batalhão, 2022). By incorporating community intelligence into scientific inquiry, I was able to build a more comprehensive understanding of how oil spills affect not just the environment, but the very fabric of these communities' lives. Ralls and Pottinger (2021) note that CPME is valuable for understanding the diverse ways different groups perceive and interact with their environment. IFAD (2009) emphasises that participatory mapping might contribute to empowering marginalised communities, enabling them to articulate their needs and concerns within their territory.

The incorporation of individual and group narration of experiences is crucial to understanding the environmental and social challenges in the Niger Delta. At the heart of this research lies a broader socio-political issue: the widespread dissatisfaction of Niger Delta communities with the Nigerian government and oil companies (Amnesty International, 2018; Omotola, 2009). For decades, oil companies have been accused of exploiting the region's resources while contributing to environmental degradation (Nwajiaku, 2005). Meanwhile, government oversight has been criticised for its inefficiency, corruption, and failure to hold companies accountable (Amnesty International, 2020). Despite regulatory frameworks like those established by the National Oil Spill Detection and Response Agency (NOSDRA), communities continue to experience inadequate responses to spills, resulting in long-lasting damage to their ecosystems and livelihoods (Amnesty International, 2013; Ikporukpo, 2020).

5.2 Negotiating safety and ethics in an expanded "field"

The decision to employ a distanciated research design and collaborate with local experts was informed by literatures on distanciated research practice alongside literatures on the ethics of fieldwork (Guasco, 2022), particularly in marginalised and conflict-affected regions. Recent calls for reimagining fieldwork, and the potential of remote methods of data collection (Bruun & Guasco, 2023; Dinko & Nyantakyi-Frimpong, 2023; Luh Sin, 2015; Monnier-Reyna, 2024; Rogers et al., 2022) have highlighted the potential of remote methods for data collection, including online surveys, interviews, and focus group discussions. Several authors have extensively listed remote fieldwork methods, dividing them into remote qualitative and quantitative approaches (e.g. Copes et al., 2018; Hensen et al., 2021; Lau et al., 2019; Roy et al., 2020; Shaghaghi et al., 2011). While these methods are not new, the COVID-19 pandemic has underscored their importance for collecting data directly from individuals and populations (Guasco 2022). Contracting out fieldwork tasks to local research firms, or research assistants (RAs), has been utilised in research design. RAs are integral to field research, actively contributing to knowledge generation through data collection, analysis, and interpretation (Stevano & Deane, 2019).

Certainly, recognition of the potential of distanciated fieldwork – in part out of a concern of researcher safety, which has been made tangible in researcher-driven safety protocols and evidence-based risk assessments - is to be welcomed (Sluka, 2020; Williamson & Burns, 2014). There is also, however, the long-standing discussion on the need to recognise and negotiate power relations in fieldwork, particularly in the Global South (Caretta & Jokinen, 2017; Elwood & Martin, 2000; Fertaly & Fluri, 2019; Sultana, 2007; Van Ramshorst, 2020; Wickramasingha, 2023). Ethics-focused literature highlights the importance of considering issues such as researcher-RA relations, participant safety, data sovereignty, and various forms of power dynamics inherent in research relationships (Carroll et al., 2019, 2020; M. Davis, 2016). For instance, the relationship between researchers and RAs poses several methodological and ethical challenges. RAs often help bridge gaps when researchers are outsiders, yet being an insider has its own complexities, affecting how data is collected and interpreted (Stevano & Deane, 2019). Additionally, the employment relationship necessitates fair working conditions, clear contracts, and adequate compensation to maintain high scientific and ethical standards (Liamputtong, 2010; Molony & Hammett, 2007).

Furthermore, (Mena and Hilhorst (2022) emphasise the necessity of ensuring safety and security for all parties involved in fieldwork within conflict-affected areas. They argue that contemporary ethical standards predominantly focus on the safety of researchers, but this focus should extend to participants as well, as the presence of a researcher can have significant security repercussions for others. Their guidelines highlight that the safety of research participants, research assistants, and other stakeholders is a crucial ethical responsibility for researchers, which should be maintained throughout the entire research process. This approach marks a departure from the common practice of treating ethical considerations as merely preparatory steps leading to approval from an ethics review committee prior to data collection. Brigden and Hallett (2021) contend that interpersonal research on violence inherently complicates attempts to anticipate practical, ethical, or methodological challenges. Researchers must adapt and rethink their roles as they navigate violent terrains. To avoid methodological, ethical, and security pitfalls in such contexts, researchers must address three types of potential dangers, each with a distinct relationship to fieldwork: 1) risks, or the probability of danger to researchers or participants; 2) uncertainties, where past experiences do not necessarily inform future conditions, leaving researchers without adequate information to judge the probability of danger; and 3) certainties, situations where the presence of danger is guaranteed and must be managed accordingly.

On the issue of data sovereignty, the International Indigenous Data Sovereignty Interest Group within the Research Data Alliance developed the ‘CARE Principles for Indigenous Data Governance’ (Collective benefit, Authority to control, Responsibility, and Ethics) through consultations with indigenous peoples, scholars, non-profits, and governments. These principles address historical inequities by valuing indigenous data based on indigenous worldviews and creating opportunities within the knowledge economy (Carroll et al., 2020).

These studies collectively underscore the complexity of ensuring safety and ethical practice in fieldwork, emphasising the need for continuous ethical vigilance and adaptive strategies to navigate the volatile environments often encountered in conflict-affected areas. Such discussions have at times drawn on and also helped foreground the limits of institutional ethics review concerns and protocols (Fouché & Chubb, 2017; Guta et al., 2013; Mackenzie et al., 2007). By engaging with this literature, we were able to develop a more nuanced and ethical approach to data collection and analysis for this study.

Certainly, negotiating ethics in an expanded sense of 'the field' (Sultana, 2007) means carefully considering how a 'distanced' research project can be undertaken with the safety and well-being of all participants at the forefront of research design; and with the added, critical awareness of how this shapes what kinds of knowledge is created in the process. In the next section this process is expanded upon as research sought to address the risks facing communities in impacted regions of the Niger Delta, while negotiating what could be done where, how, and by whom 'safely'.

5.3 Research design

This study followed a structured approach encompassing data gathering, literature review, and adaptation to distanciated research and the contextual challenges of conducting field research in the Niger Delta.

5.3.1 Data Gathering

To begin, I collected data essential for constructing the research design. This phase involved gathering existing data from relevant agencies, conducting a literature review, and exploring social media content, as detailed below:

1. **Acquisition of In-situ Oil Spill Data from NOSDRA**

   I obtained oil spill data from the National Oil Spill Detection and Response Agency (NOSDRA), the Nigerian government agency responsible for documenting oil spills. This dataset, spanning from 1994 to 2021, includes detailed information from Joint Investigation Visits (JIVs), which involve representatives from regulatory agencies, oil companies, affected communities, and security forces. The data comprises essential attributes such as spill date, time, GPS coordinates, spill extent, oil type, volume, and source. Access to this data was granted following authorisation from NOSDRA's Director General.

2. **Utilisation of High-Resolution Satellite Imagery**

   To contextualise the spill data, I overlaid the obtained GPS coordinates onto high-resolution imagery from Google Earth. This overlay facilitated visual identification of impacted locations, allowing me to better understand the spatial relationship between spill sites and affected communities. This integration of satellite imagery with in-situ data provided a more comprehensive perspective on the affected regions.

3. **Literature Review**

   To gain an understanding of the history of oil production in the Niger Delta and its recorded impacts on the local population, I conducted an extensive literature review. This review informed the development of prompts and questions for the focus group discussions and participatory mapping exercises, ensuring that the study reflects both historical context and contemporary issues.

4. **Social Media Analysis**

   I conducted a social media search on platforms such as Twitter (now X) and Facebook to identify communities most frequently mentioned in relation to oil spills. This approach enabled me to prioritise areas with significant oil spill mentions, allowing the research to target communities with substantial, recent experiences of oil-related environmental issues.

5.3.2 Deciding on Research Questions and Selecting Material

To formulate the research questions and select materials for this study, I conducted a comprehensive review of the literature on the Niger Delta, focusing on oil production in the region and its environmental impacts on both the environment and local communities. Additionally, I actively searched social media platforms, particularly Twitter (now X) and Facebook, for keywords such as "oil spills in the Niger Delta" and "Niger Delta oil pollution." This exercise led to the generation of five prompts *(‘Knowledge of Oil Spillage’; ‘Impact of Oil Spills on the Environment’; ‘Impact of Oil Spills on the Everyday Lives of People’; ‘The Perceived Dangers and Challenges Posed by Oil Spills’; and ‘Responses to Oil Spills’)* for the Focus Group Discussions (FGD). These prompts were then used to structure the FGD questionnaire (see Appendix B.1), resulting in the creation of transcripts. In selecting sections of the transcripts for analysis, I prioritised responses under the impact of oil spills on the environment, livelihoods, and perceived dangers and challenges, as these directly address the aims and objectives of the study.

Given that the qualitative methods were now being carried out via the data collectors a key issue to acknowledge was that these people were now conduits through which knowledge was garnered, understood, translated and passed on in the form of data entries. The data collectors, being part of the local community, played a vital role in mediating questions and collecting responses. They were proficient in local languages (In Bayelsa state, i.e. Aghoro and Okpoama: Ijaw and Pidgin English; Delta state; Benikrukru: Ijaw and Pidgin English, Ubeji: Urhobo and Pidgin English; Bayelsa; and finally in Rivers state, Bodo and Ogale: Ogoni and Pidgin English languages) recording responses and later translating them for analysis. Data collectors thus played a crucial role in shaping responses to research prompts, such as compensation and community representation. They reported individual views and opinions, translating concerns into English. While some nuances were reduced, it is important to acknowledge that translation may have affected certain details, and the agency of data collectors in shaping responses should be recognised as an inherent aspect of the research process.

In addition to the FGDs, Community Participatory Mapping Exercise (CMPE) were also conducted in the prioritised communities to complement the FGDs. Similar to the FGD, pre-structured questionnaire (see Appendix B.2), asking participants to identify affected features such as, *impacted area, impacted water body, agricultural land & residential area that people have relocated from due to oil spills, oil spill flow pattern, pipelines, areas vulnerable to future oils* was created to guide the participants in using the CPME maps and in identifying the impacted areas/features based on the themes.

5.3.3 Adaptation to Research Challenges

As outlined in Chapter 1, the initial intent was to conduct in-person fieldwork using focus group discussions and community participatory mapping to explore the complex, layered experiences of communities affected by oil spills. However, due to safety concerns in a region designated as essential-travel-only by the UK's Foreign, Commonwealth, and Development Office, I had to adapt the research approach to ensure both my safety and that of the participants. To address this, I employed a distanced research approach, collaborating with experienced data collectors from the National Bureau of Statistics (NBS) in Nigeria. This adaptation allowed for continued data collection while reducing risk. Additionally, it introduced new ethical considerations, as some of the data collectors were part of the communities being studied.

5.4 Establishing a 'Safe' Research Process

5.4.1 Initiating a Collaboration

While some data could be gathered via pre-constructed datasets and satellite imagery, the designation of Nigeria – and especially the Niger Delta – as a problematic area meant that qualitative data collection on community experiences and understandings would need to be significantly revised. The decision to partner with the NBS to undertake research was deliberate and rooted both in their status as the apex statistical office for the Government of Nigeria (NBS, n.d.-b; UNSTAT, n.d.), and the fact that the work of particular personnel was known through prior connections. The NBS' extensive repository of economic, social, and geographical statistics covering the nation positions them as a vital resource for decision-making processes at various levels (Ogbuabor et al., 2018). Importantly, NBS personnel's everyday experience of research practice, especially regarding safety in the field, is noteworthy. Previous collaborations between the NBS and organisations such as the World Bank, as well as various local and international partners, focusing on studies related to the poverty index for Nigeria and livelihoods reports (NBS, n.d.-a; NBS et al., 2023; World Bank, 2022), underscore the Bureau's consideration of how to manage data collection.

Key to the collaboration was merging the NBS personnels' experience with the ethical protocols expected of focus group and community mapping methods, and the management of this online before, during and after the undertaking of these. To begin, I conducted an online meeting with a Principal Statistician at the National Bureau of Statistics (NBS) headquarters in Abuja, Nigeria. During the discussion I highlighted the safety concerns envisioned for research in the Niger Delta. Following this conversation, the contact facilitated connections with NBS coordinators in Bayelsa, Delta, and River states. Through subsequent, individual, online meetings with each state coordinator, the research aims, objectives, and security concerns were discussed. These coordinators, drawing from their teams, then identified data collectors with over six years' experience in oil-affected areas of their respective states of operation. These conversations were crucial to the selection of sites, noted below.

A significant concern arose regarding data ownership, particularly as the data collected during fieldwork was intended solely for academic purposes and might be archived in government repositories. This apprehension around 'where' the data would be located, and who might then have access to it – both issues that might well be of concern to participants – was communicated to the initial NBS contact and subsequently to state coordinators. Assurances were provided by NBS personnel that despite their role in collecting, compiling, analysing, interpreting, publishing, and disseminating statistical information, both independently and in collaboration with various agencies, governmental and non-governmental, they were willing for the Intellectual Property (IP) to remain with the primary academic researcher. An agreement was reached stipulating this ownership. Further negotiations with the state coordinators solidified the understanding that data collectors would carry ***Participant Information Sheets (See Appendix B.5-6)*** during fieldwork, outlining the research context and clarifying that the information collected from participants would be anonymised by NBS personnel on behalf of the researcher, and not the state. This delicate negotiation process underscored the challenge of reconciling the dual roles of NBS personnel as state agents and researchers with community apprehensions and the responsibilities of academics.

Negotiating ethics in an expanded sense of 'the field' (Sultana, 2007) means carefully considering how a 'distanced' research project can be undertaken with the safety and well-being of all participants at the forefront of research design; and with the added, critical awareness of how this shapes what kinds of knowledge is created in the process. In the next section this process is expanded upon as research sought to address the risks facing communities in impacted regions of the Niger Delta, while negotiating what could be done where, how and by whom 'safely'. Reading through these secondary literatures and engaging with the NBS staff in a new research design process, made clear a series of new methodological but also ethical issues. Boxes 5.1 and 5.2 below highlight the new methodological and ethical considerations.

5.4.2 Ethical Considerations

The conduct of this research was shaped by a complex interplay of ethical considerations, particularly given the sensitive nature of the topic and the challenging context of the Niger Delta region. More importantly, reading the existing literature and engaging with NBS staff during the new research design process made clear a series of new issues – both methodological and ethical, including:

i) Funding Source and Potential Bias:

A core ethical concern arose from the research funding provided by the Nigeria PTDF, a key player in Nigeria's oil industry. This industry is responsible for significant environmental problems and has contributed to the devastation and ongoing struggles of the communities from which the research participants were drawn. The lack of trust between oil-producing communities and both the oil companies and the government is well-documented (Koos & Pierskalla, 2016; Nwajiaku, 2005).

Given this context, there were significant concerns that the PTDF sponsorship might unduly influence both recruitment and participant responses. To mitigate this, the research team emphasised transparency, academic independence, and a commitment to meaningful consent and privacy through data anonymisation. Rigorous ethical protocols were implemented to ensure the integrity of the research and protect the interests of the participants (see Box 1). Methodological considerations, such as the selection of research sites and the training of data collectors, were also carefully planned (see Box 2).

ii) Co-authorship and Knowledge Sharing:

The collaboration with experienced data collectors from the NBS introduced ethical considerations related to authorship and knowledge sharing. While the NBS staff contributed valuable local knowledge and expertise, it was collectively decided that their contributions would not extend to co-authorship. This decision was based on the specific roles and responsibilities of each party involved in the research process.

iii) Indigenous Data Sovereignty and Ethical Research Practices:

The research adhered to principles of indigenous data sovereignty, recognising the rights of the Niger Delta communities to self-determination and control over their data. The researchers engaged in ethical research practices, including obtaining informed consent, ensuring participant confidentiality, and minimising potential harm (see Box 2). The study also considered the broader ethical implications of research in postcolonial contexts, particularly the power dynamics and potential for exploitation of vulnerable communities.

Box 1: Ethical considerations included

- **Informed Consent:** Ensuring that participants fully understand what remote fieldwork entails, including how their data will be collected, stored, and used.
- **Data Privacy and Security:** Protecting sensitive information, especially when data is transferred over the internet, and ensuring compliance with data protection regulations.
- **Selection Bias:** Remote fieldwork may limit access to certain populations, leading to a non-representative sample.
- **Digital Divide:** Communities with limited access to technology or internet may be excluded, introducing bias into the research findings.
- **Data Accuracy:** Verifying the reliability of data collected remotely, as there might be challenges in ensuring that the data accurately represents on-the-ground realities.
- **Power Imbalances:** The relationship between data collectors and the participants might introduce power dynamics that affect the objectivity and autonomy of the research.
- **Independence of Research:** Maintaining the independence of the research despite close collaboration with a governmental or national statistical body.

Box 2: Methodological considerations introduced

- **Conflicts of Interest:** the data collectors indigenous to the oil producing communities (in other words they are also from the affected communities, so they have stake in the matter) themselves, might introduce bias when interpreting participants responses as they are also concerned about the matters being discussed. Acceptance from the participants then becomes an issue because the data collectors who are seen as part of the communities are now being affiliated with a researcher being sponsor by an oil affiliated organisation (PTDF).

- **Meanings being lost during translation:** The loss of nuances during translation is a significant methodological challenge in the context of the Niger Delta area of Nigeria, where participants predominantly speak local dialects or broken English. Data collectors interpret interview questions in the participants' local languages and then translate the responses back into English. This dual translation process can alter the original meaning. To mitigate these issues, we utilised highly skilled data collectors familiar with both the local dialects and trained in the research context. We incorporated methods to cross-check and validate translations, ensuring the integrity of the original meanings. This included additional layers of data entry and validation, where data collectors transferred responses from notepads to Kobo Collect and cross-checked the responses during this process.

- Ensuring the data collectors understand the concept of the research.

- Safety of the data collectors, and the data collectors in turn ensuring safety of the participants.

- **Surveillance and Intrusion:** The data collectors having to conduct community participatory mapping in a terrain where land boundaries issues is a constant problem and data collectors affiliated oil organisation (an entity believed to be devastating their land and environment) facilitating this mapping exercise could raise concerns amongst participants.

- **Data colonialism:** Where the extraction and translation of local knowledge into a form suitable for external analysis risk perpetuating colonial power structures, potentially marginalising the voices of those within the community in favour of the researcher's narrative.

Box 2 outlines several key methodological considerations that were critical to navigate during this research to ensure the rigor, validity, and ethical conduct of the study, particularly given the sensitive context of the Niger Delta and the study's focus on vulnerable communities impacted by environmental degradation. Addressing these challenges upfront was essential for generating trustworthy findings that genuinely reflect the lived experiences of the participants.

One significant consideration was the **potential for conflicts of interest** and bias introduced by the data collectors' positionality. As members of the affected oil-producing communities themselves, the data collectors inherently held a stake in the matters being discussed, raising concerns about potential bias in interpreting participant responses. Furthermore, the research's affiliation with an oil-affiliated organization (PTDF sponsorship) presented a challenge regarding acceptance from the participants, who might view data collectors affiliated with a researcher receiving support from such an entity with suspicion. To address these interconnected issues, a multi-pronged approach was adopted. Data collectors underwent rigorous training that emphasized the importance of neutrality, active listening, and accurate, verbatim recording of responses. Reflexive practice was encouraged, where data collectors were prompted to reflect on their own perspectives and how these might influence data collection, with these reflections discussed during regular team meetings. Transparency with participants regarding the study's purpose and sponsorship, while carefully managed to avoid influencing responses, was a key ethical step to build trust and manage expectations regarding the research's independence and aims. While the sponsorship initially posed challenges for community entry and acceptance, consistent presence, clear communication of the study's focus on documenting community perspectives on impacts (rather than serving the sponsor's interests), and leveraging existing trust relationships built by the local data collectors helped to foster participant willingness to share their experiences.

The potential for **meanings being lost during translation** was another significant methodological challenge. In the Niger Delta, participants often communicate in local dialects or Nigerian Pidgin English, necessitating translation by the data collectors who are fluent in both local languages and English. This dual translation process from interview questions (originally in English) to local dialect for the participant, and back to English for recording, inherently risks altering the original meaning and losing nuances. Given that the qualitative methods were now being carried out via the data collectors a key issue to acknowledge was that these people were now conduits through which knowledge was garnered, understood, translated, and passed on in the form of data entries. The data collectors, being part of the local community, played a vital role in mediating questions and collecting responses. They were proficient in local languages, recording responses and later translating them for analysis. Data collectors thus played a crucial role in shaping responses to research prompts, such as compensation and community representation. They reported individual views and opinions, translating concerns into English. While some nuances were reduced, it is important to acknowledge that translation may have affected certain details, and the agency of data collectors in shaping responses should be recognised as an inherent aspect of the research process.

Ensuring that the **data collectors thoroughly understood the core concepts** of the research was paramount for consistent and relevant data collection. Comprehensive training sessions were conducted. These sessions involved detailed explanations of the context of the study, group discussions on this in the local context, and role-playing exercises to practice formulating and probing questions related to participants' experiences of environmental damage, infrastructure, and cumulative harm without leading participants. Regular debriefing sessions allowed for clarification of concepts and standardization of questioning approaches throughout the fieldwork period.

The safety of both the data collectors and the participants was a non-negotiable priority in the high-risk environment of the Niger Delta. Prior to fieldwork, a thorough risk assessment was conducted for each community. Detailed safety protocols were developed, including guidelines for daily check-ins, procedures for emergency situations, and maintaining a low profile. Participant safety was ensured through strict adherence to informed consent procedures, guaranteeing anonymity and confidentiality where requested, and avoiding any activities (such as mapping highly sensitive or disputed areas) that could potentially expose participants to risk of reprisal or conflict, more on this in section 5.4.

The process of community participatory mapping presented specific risks of surveillance and intrusion, particularly given the sensitivity of land boundaries and resource control issues in the Niger Delta, and the data collectors' unavoidable affiliation with a study sponsored by an oil-affiliated entity. Participants might naturally be wary of mapping exercises conducted by individuals perceived to be connected, however indirectly, to organizations believed to be responsible for devastating their land and environment. To address this, the purpose of the mapping exercise was framed clearly and consistently as a tool for participants to visually represent the environmental impacts of spills and the location of damaged natural/ecological infrastructure and affected livelihoods, rather than a land demarcation or ownership exercise. Participation was entirely voluntary, and community members were empowered to decide what information they were comfortable sharing and mapping. Emphasis was placed on the maps as being owned by the community participants as a way to tell their story of environmental harm, rather than data primarily for external analysis.

Finally, the research was acutely aware of the risks of data colonialism, defined here as the potential for the extraction and translation of local knowledge into a form suitable for external academic analysis to inadvertently perpetuate colonial power structures. This risk arises when the nuanced, place-based knowledge and experiences of marginalized communities are simplified, decontextualized, or instrumentalized to fit pre-existing academic frameworks or researchers' narratives, potentially marginalizing the voices and perspectives of those within the community (Spitz, 2024; Thatcher et al., 2016). The comparative analysis by (Couldry & Mejias, 2019) underscores that while the tools and territories have transformed, the underlying logic of appropriation, exploitation, and the establishment of unequal power relations shows striking and disturbing continuities. Addressing data colonialism required embedding principles of decolonizing methodologies and ethical research practices throughout the research design and implementation (e.g., (Chilisa, 2012; Smith, 1999; Tuck & Yang, 2012)). Key measures included:

- Centring Community Voices: In this study, I Prioritised participants' own words and narratives in the analysis and presentation of findings, I used extensive direct quotes to retain the richness and complexity of their experiences.
- Researcher Reflexivity: I Maintained critical self-awareness regarding my positionality, and that of the data collectors'. Potential biases stemming from academic training, sponsorship, the complexity introduced by collaborating with the NBS data collectors and the power dynamics inherent in the researcher-participant relationship were laid bared.
- Methodological Fit: I Chose qualitative and participatory methods (e.g., FGD and community mapping) specifically to capture the nuanced, situated knowledge, rather than imposing purely quantitative or extractive methods that might oversimplify complex realities.

By proactively addressing these methodological considerations, I aimed to navigate the complexities of the Niger Delta context responsibly and ethically, ensuring that the voices and experiences of those most affected by oil spills were central to the findings.

5.4.3 Selecting Sites

To gain an initial understanding of which communities might be impacted by oil spills, in-situ spill data spanning from 1994 to 2021 from NOSDRA, the official government agency responsible for recording spillages, was obtained. The acquired oil spill coordinates were overlaid on Google Earth high-resolution imagery (see Figure 5.1). Searches on platforms including Twitter (now X) and Facebook for comments on oil spills using keywords including oil spills, Niger Delta, oil pollution, environmental pollution, environmental degradation, Niger Delta communities and oil companies, and Niger Delta oil affected communities were undertaken, with the aim of identifying communities with the most mentions relating to the devastating impacts oil spills on them, and to draw out communities that fell within oil spill impacted areas as shown from the analysis and mapping of oil spills data acquired from NOSDRA. A prioritisation matrix (see Appendix 1) was created that highlighted areas with the highest incidents of oil spills and cross-tabulated locations mentioned most frequently in social media searches.

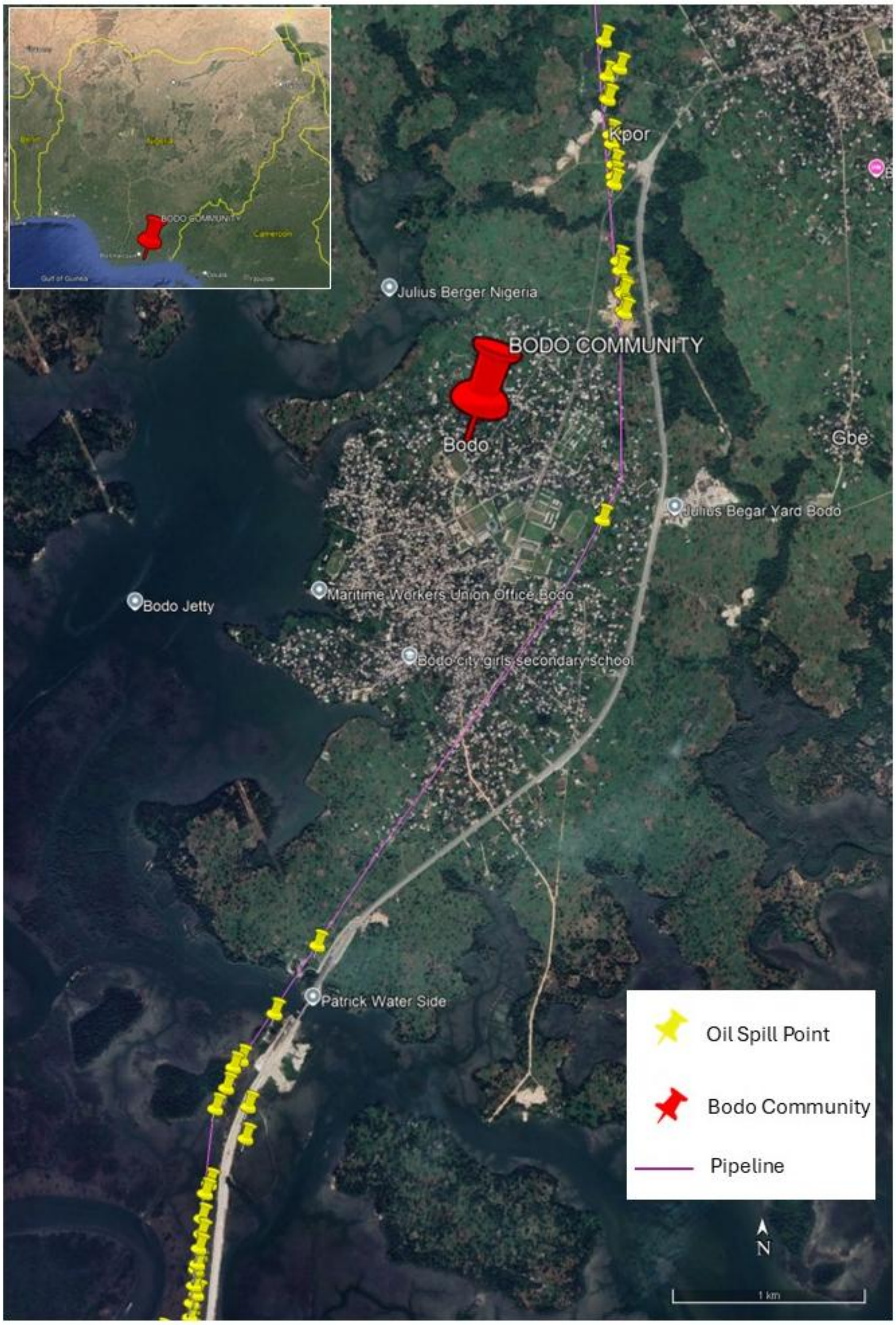


Figure 5.1. Example of location points of recorded oil spills in and around Bodo community (Data source: NOSDRA and Google Earth)

Crucially, 12 locations (see Appendix D) with both high incidents of oil spills and a high number of social media mentions were provided to the state coordinators and the data collectors. Leveraging their experiential knowledge gained from previous work within or in close proximity to these communities, the NBS data collectors and coordinators vetted the locations for both researcher safety and accessibility. Certain areas were known for makeshift oil refining activities and posing potential danger due to armed operators. Notably excluded were Rumuekpe in Emuoha Local Government Area (LGA) of Rivers State and Ekeremor in Ekeremor LGA of Bayelsa State. Ultimately, two communities in each of the three states were collectively prioritised: Bodo and Ogale communities in Rivers, Aghoro and Okpoama communities in Bayelsa, and Benikrukru and Ubeji communities in Delta (Figure 1.6).

5.3.4 Designing Safety-Facing Research Protocols

Recognition of researcher safety as an issue - tangible in researcher-driven safety protocols and evidence-based risk assessments - is to be welcomed (Sluka, 2020; Williamson & Burns, 2014). To ensure the safety and proper understanding of the research context and working protocol, online training sessions were organised and conducted for data collectors in Bayelsa, Delta, and Rivers states, integrating virtual discussions, interactive presentations, and virtual field activities, similar to the approach described by Gibbes & Skop (2022), to establish shared goals and practices. Safety protocols were central to the training, emphasising trust-building with local authority figures (such as the community leaders, local security guards and the youth leaders) and establishing procedures for potential hostility, such as ensuring access to sites and promptly leaving if unresolved issues arose.

It is important to highlight that what might initially be seen as conventional training – where the research manager determines what needs to be done and how - evolved here into a series of collaborative discussions. The expertise and guidance from the data collectors were actively sought and implemented. Indeed, prior to these sessions the state coordinators had cautioned that thoughtful questions from the data collectors, emphasising their extensive knowledge of data collection and their frequent work in the region, would be forthcoming. In practice, the training sessions transformed into interactive discussions. The data collectors not only shared their previous experiences in collecting data in the region but also expanded on their involvement in various socio-economic studies with agencies such as the World Bank and the United Nations, and their work with community leaders and the local populace. Insights into norms and usual practices, such as approaching community leaders and the significance of providing refreshments post-exercises, were invaluable. This collaborative exchange of information greatly influenced and was actively implemented throughout the exercises.

The initial point of contact for data collectors in the communities was these leaders. During this crucial encounter, data collectors narrated the context of the exercises to the leaders and sought their permission. They undertook a customary greeting and addressing of leaders, as well as the tradition of bearing gifts (traditional gins, koala nuts) to pay homage. These gifts were prepared and handed to community leaders when the data collectors made contact with them. Additionally, data collectors collaborated with community leaders to secure safe locations for the exercises. Community halls were generously offered, and when unavailable, safe open spaces were provided. Leaders were prepared to address any potential issues promptly, informing other security stakeholders to prevent interference during the exercises. In Bodo community, a brief interference was swiftly handled by the youth leader, who assured the group of proper approvals and engaged in dialogue to clarify the academic nature of the exercises, ensuring the safety of the researchers.

5.5 Undertaking Participant Safety

Mena and Hilhorst (2022) emphasise the necessity of ensuring safety and security for all parties involved in fieldwork within conflict-affected areas. They argue that contemporary ethical standards predominantly focus on the safety of researchers, but this focus should extend to participants as well, as the presence of a researcher can have significant security repercussions for others. Their guidelines highlight that the safety of research participants, research assistants, and other stakeholders is a crucial ethical responsibility for researchers, which should be maintained throughout the entire research process. This approach marks a departure from the common practice of treating ethical considerations as merely preparatory steps leading to approval from an ethics review committee prior to data collection.

The situation in the Niger Delta is highly sensitive due to political unrest and ongoing civilian agitation in the communities. Conducting open interviews becomes challenging in this region, given the prevailing lack of trust in the government and oil companies, and so research would require a sense of ‘safety’ to be offered and accepted by those participating. Data collectors were trained to emphasise the academic nature of the exercise and its independence from any oil company affiliation. Training sessions focused on effectively communicating the exercise's context and importance to community leaders and potential participants, reflected in the initial section of the data collector checklist. Simulation sessions addressed various scenarios, including potential questions about participatory mapping, with particular attention given to concerns arising from terminology like "mapping" and its implications, considering issues such as land grabbing and boundary disputes in Nigeria (Ukpong-Umo et al., 2019).

As a corollary to this focus on academic independence it was important for participants to feel a sense of safety in offering comments in front of other community members. Research has shown that women and youth tend to be hesitant to express their opinions or may not be adequately represented when men or community elders are present in local Niger Delta gatherings (Nwajiaku, 2005; Vite, 2018). To address this, participants were organised into different groups based on age and gender, aiming to create a comfortable environment for discussions. These groups were categorised as Women (above 35 years old), Men (above 35 years old), and Youths (18 to 34 years). This separation strategy was clearly outlined in the protocol guide provided to the data collectors (see Appendix B.4); the more practical 'how to' question was, however, discussed through the simulation sessions. Moreover, before the FGD sessions the criteria for participant selection were clearly communicated to village heads by the data collectors. Meetings were held with village heads a day in advance. Only after these preliminary discussions could group leaders, representing different demographics such as youth and women leaders, and other individuals be invited. The FGDs were held between July 4th to July 12th, 2023, across the six communities. In practice, the duration of FGDs varied amongst the groups in the communities, lasting from one to one and a half hours. The size of focus groups also varied, but typically, they consisted of 6 to 12 participants (e.g. see Figure 5.2 for participants photos and Appendix A for the participants composition chart).

Figure 5.2. Participants and data collectors during the FGDs (participants' faces have been obscured to protect their anonymity)

In addressing concerns about limited access to mental health or support services, proactive measures were taken. The deplorable conditions of health facilities in the Niger Delta, as acknowledged by several authors, were taken into consideration (Alemzero et al., 2021; Ering et al., 2013; Okonkwo & Etemire, 2017; Oladipupo et al., 2016), and the discussions with data collectors were held to foreground these issues. Participants were briefed on the research context before starting discussions, allowing them to willingly opt out if they felt emotionally uncomfortable or unprepared to participate. Additionally, data collectors were asked to immediately halt the exercise if a participant exhibited signs of distress. To ensure management of time and the FGD dynamics a guiding outline had been rehearsed during a refresher training session with the data collectors. The discussions followed a specific order, as outlined in Table 5.1.

Upon finalising the FGDs, the transcripts data was entered by the data collectors. These discussions were held in the local language, so the collectors had to translate the transcripts into English. They then manually entered the translated transcripts into KOBO, a specialised open access data collection and storing application designed for this study. After the data collectors entered and submitted the transcripts information to the KOBO platform, the data was extracted as a Comma Separated Values (CSV) file. This CSV file was then used for further analysis.

Table 5.1. Guiding Outline for the FGD

No	Item	Duration
1	Welcome the participants and express gratitude for their attendance.	5 minutes
2	Present the agenda.	5 minutes
3	Introduce the facilitation team and conduct participant introductions.	10 minutes
4	Provide information sheets to participants, considering varying literacy levels.	10 minutes
5	Address any questions or concerns.	5-10 minutes
6	Obtain meaningful consent and the signing of consent forms.	5 minutes
7	Proceed with the discussions.	50 - 60 minutes
8	Address any additional questions or concerns.	10 minutes
9	Conclude the session.	5 minutes

5.6 Annotating Maps

For the creation of Community Participatory Maps (CPMs) high-resolution satellite imagery of the study locations from Google Earth was acquired. Additionally, vector maps of the locations were generated using the Open Street Map (OSM) plugin on QGIS, allowing for layering and visualisation of roads, buildings, and other features.

The number of participants in the Community Participatory Mapping Exercise (CPME) for this study varied from 6 to 10 participants in different communities. Similar to the FGDs, individuals below the age of 18 were excluded. Participants in the CPME were not grouped by gender or age; all participants were 18 years of age or older. For the exercise, participants were able to annotate the map and identify ground features not depicted on the maps, such as pipelines. Different coloured markers were provided for annotations, with predetermined meanings; for instance, green markers with polygon symbols indicated areas affected by oil spills on the map, blue markers with polygon symbols denoted water bodies impacted by oil spills, and red markers with bold dot symbols signified infrastructure or public resources (e.g., schools, hospitals, markets) located near areas heavily affected by oil spills. The annotated maps were shipped from Nigeria to the United Kingdom by the data collectors. Upon arrival, the maps were scanned and georeferenced using QGIS. This process facilitated further analysis and allowed for the integration and overlay of other geographically referenced data with the maps.

The CPME emerged as a crucial tool in systematically uncovering and understanding safety concerns within the communities, shedding light on ongoing issues. For example, participants identified specific areas affected by oil spills. The CPME served not only to accumulate local knowledge but also to document past experiences through mapping. Participants marked farmlands, schools, rivers, markets, and community infrastructure impacted by oil spills. The identification of affected locations prompted memories of past oil spills among participants. They recounted the times and locations of spills, emphasising the adverse health effects on the community. Participants highlighted restrictions on swimming and drinking from polluted rivers due to health concerns. The CPME also provided a platform for discussing the broader impact on livelihoods. Participants delved into the diminished quality of farm produce, the negative effects on fishing due to polluted rivers, and the overall decline in environmental quality. Notably, some vulnerabilities identified during the CPME were echoed in the focus group discussions. In communities in Bodo and Ogale, the CPME discussion revealed a recurring challenge. Oil spill events impacting neighbouring communities often led to disputes. For example, the CPME map for Ogale explicitly highlighted flow patterns contributing to such disputes. Indeed, a key finding was the ‘gap’ between preconstructed datasets and community knowledge. Across the sites participants frequently complained about missing features on the map, referring to objects such as pipelines observed on the ground but not represented in the mapping (for example Figure 5.3). However, this challenge also presented an opportunity for participants to rectify the omission by incorporating the missing pipelines as well as oil spills into the map (Figure 5.3).

5.6.1 A Distanciated Moment

Data collectors were asked to obtain coordinates for areas affected by oil spills during the CPME. Unfortunately, some data collectors overlooked this aspect, resulting in missing coordinates for certain locations. To address this, data collectors had to revisit the affected communities, specifically Benikrukru and Ubeji (see Figure 1.6), to gather the coordinates. Although Okpoama (see Figure 1.6) was identified as another community requiring revisitation, security concerns prevented the data collectors from physically returning.

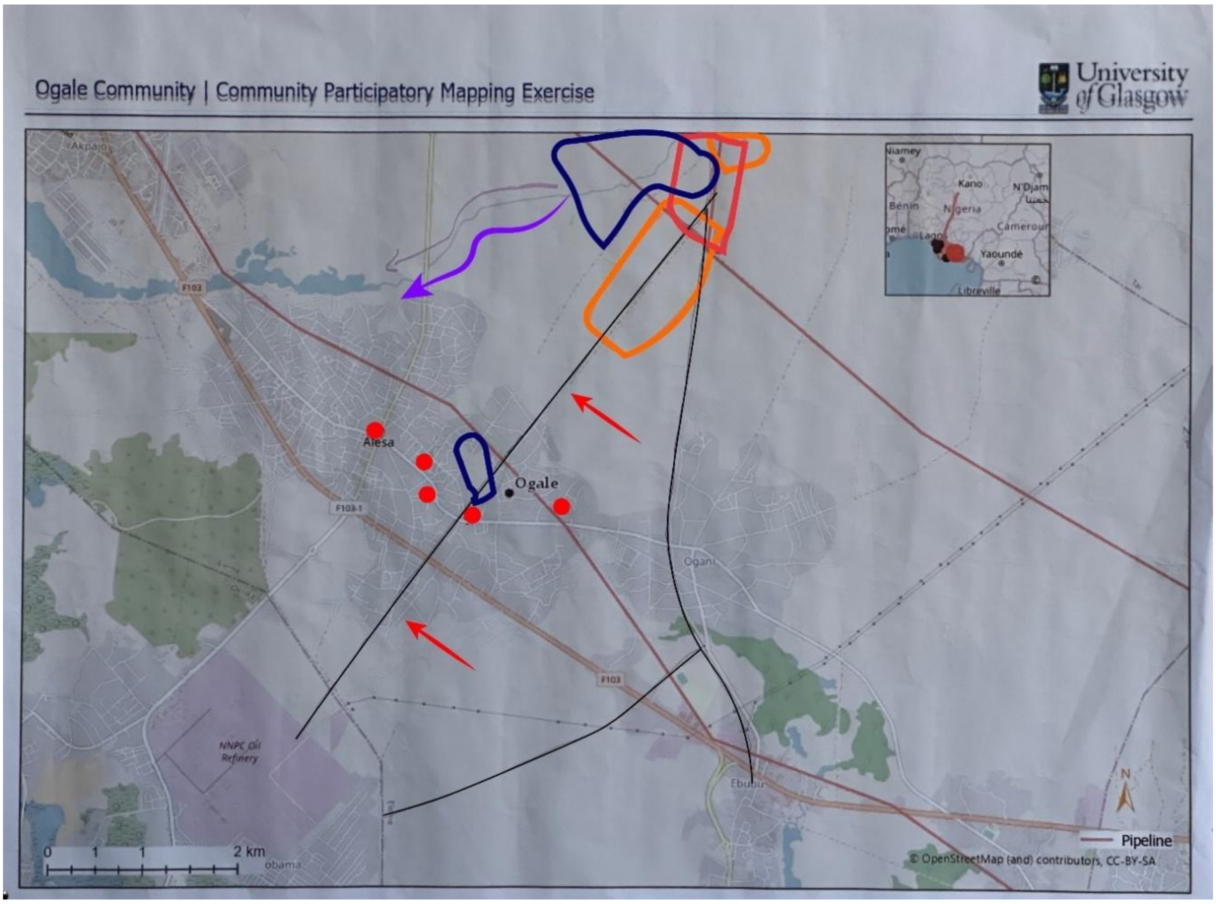


Figure 5.3. Ogale CPME output map: the arrows indicate the incorporated pipelines identified by the participants. Red lines represent existing pipelines, while red dots highlight affected infrastructure or public resources. The orange polygon delineates areas where cleanup efforts have been undertaken following oil spills. The purple arrow illustrates the patterns of oil spill dispersion within the community. The red polygon marks previous agricultural land and residential areas from which people have had to relocate due to oil spill impacts. Lastly, the dark blue polygons indicate wetlands impacted by the oil spill. Source: Fieldwork and Open Street Map.

In response to the security challenges in Okpoama, a strategy to remotely address the issue was designed. An online meeting was held with the data collectors during which a computer screen featuring the Google Earth Pro application was shared. By navigating through the Okpoama area using Google Earth Pro, the data collectors were able to identify and specify the exact locations of interest within the community. This virtual approach served as an effective alternative to physically revisiting Okpoama, ensuring researcher safety while capturing the missing coordinates.

5.6.2 Debriefing

Upon concluding the fieldwork activities, online debriefing sessions with the data collectors were held. These sessions served as a platform for data collectors to share their experiences and offer an overview of their observations during the exercises. In communities with good internet service, such as Ogale and Bodo, the sessions were held after each exercise. In the spirit of maintaining ongoing discussions, the WhatsApp group chat created for communication and logistical purposes during the exercise remained active after the exercises. During these sessions the data collectors actively engaged in discussions concerning safety and security. They delved into the strategies employed to effectively manage the proceedings, emphasising their vigilance in anticipating and addressing potential disruptions. For instance in Bodo, the data collectors recounted an incident where a particular group approached, inquiring about the ongoing discussions. Swift intervention by the community leader clarified the purpose of the exercises, securing permission for their continuation.

5.7 Methods

In the course of this research I encountered the complexities of presenting qualitative data, as discussed by Turner (2016). It is important to recognise that transcribing interviews and focus group discussions is not a straightforward process; it involves interpretation and translation. As explained by Turner (2016), transcripts are not merely reflections of the original interviews or focus group conversations; they represent new texts that have been shaped during these processes. The fieldwork was conducted with the assistance of data collectors from NBS, who translated the proceedings from the local language to English, serving as the initial step in the data analysis.

To analyse and contextualise the translated qualitative data I employed Content Analysis (CA). This method involves tracking and analysing themes, words, and phrases within and across transcripts, making it useful for identifying both commonalities and differences in content, as pointed out by Secor (2010). Mayring (2000) emphasise that content analysis is particularly useful for categorising large volumes of qualitative data such as transcripts from interviews, focus groups, and documents, allowing researchers to make inferences about patterns and themes. In line with Schreier (2014) recommendations, the analysis for this study was conducted in multiple stages:

1. **Downloading and Organising the Dataset:** The dataset for this study was downloaded from the *KOBO Toolbox platform*, where responses from data collection efforts were stored. The data, available as CSV files, offered an organised format that aligned prompts with responses, facilitating the initial visualisation of the dataset.
2. **Unit Identification in Content Analysis:** Schreier (2012) identifies three distinct units in CA: (1) the unit of analysis (e.g., each interview or article), (2) the coding units (segments of the material for analysis), and (3) the context units (material surrounding the coding units). This framework was important for my study, especially given the use of pre-structured themes derived from a review of literature and social media findings.
3. **Steps Followed for CA:** Schreier (2014) outlines an eight-step process for conducting CA: (1) deciding on a research question, (2) selecting material, (3) building a coding framework, (4) segmentation, (5) trial coding, (6) evaluating and modifying the coding frame, (7) main analysis, and (8) presenting and interpreting the findings.

5.7.1 Development of the Coding Framework

The coding frame serves as the core of CA and is essential for systematically analysing data. Schreier (2014) highlights that coding frames consist of main categories and subcategories. For this study coding framework, I systematically reviewed the data, assigning sections to existing categories or creating new subcategories where necessary, see Table 5.2 (Schreier, 2014; Marshall & Rossman, 2015).

Key thematic areas were Knowledge of Oil Spillage, Impact of Oil Spills on the Environment, Impact of Oil Spills on the Everyday Lives of People, Perceived Dangers and Challenges Posed by Oil Spills, and Responses to Oil Spills. Each prompt was divided into subcategories based on the issues that surfaced during the interviews. These subcategories were then further refined into smaller categories as new issues emerged. For example, under the prompt Impact of Oil Spills on the Environment, one of the primary categories was Pollution and Contamination. Within this category, Water and Air Contamination emerged as a subcategory, with indicators such as the impact on drinking water, recreational water use, and physical changes in water quality (e.g., colour and odour), as shown in Table 5.2. As previously mentioned, the themes that emerged from the data should not be interpreted with absolute certainty, given that nuances may have been lost during translation, and the meanings of participants' words would vary based on context. Therefore, the emerging themes shown below are community and participants specific, and meaning of words were not transferred or generalised across communities.

Table 5.2. Framework for the CA (showing examples of the coding process)

Main Category	**Description/When to use this category (Definition)**	**Indicator for Categorisation**	**Sub-category**	**Quotes from participants**
Pollution and Contamination	This category captures all the extent of environmental damage caused by oil spills, specifically focusing on the contamination of water sources, vegetation, soil degradation, and air pollution.	Mention of **water contamination** with crude oil	Water contamination	*"The water is so contaminated that it cannot be used for cooking due to the taste and smell of crude oil"* (BO_MEN_002)
		Visual or physical changes in water (colour, odour, particles)	Water contamination	*"Rainwater color and substances have changed due to pollution"* (OK_MEN_001)
		Physical signs of **air pollution** (black sediment, bad smell)	Air Pollution	*"Nostrils cleaning reveals black sediments due to polluted air"* (BO_MEN_004)
		Mention of **breathing difficulties** or suffocation	Air Pollution	*"Suffocation sensation due to polluted air"* (OK_WOMEN_006)
		Visual indicators of **air pollution** (cloudy, dark sky, smoke)	Air Pollution	"*The sky darkens due to pollution"* (OK_WOMEN_008)
Health Impacts	This category explores the health risks and challenges faced by the community due to exposure to oil and other pollutants.	Mention of **skin diseases** or **irritations** caused by pollution	Skin diseases	"*Bathing with the water causes skin irritation"* (BO_MEN_003)
		Respiratory issues due to air or water pollution	Respiratory issues	"*Gas release from the spillage has polluted the air, causing breathing difficulties"* (BO_WO_003)
		Health issues affecting children	Children health issues	*"Children experience eye issues due to water and air pollution"* (BO_YOUTH_005)
		Cancer or other **severe health risks** related to pollution	Severe health issues	"Contaminated water leads to skin diseases and even cancer" (BO_YOUTH_002)

Economic and Livelihood Impact	This category investigates the consequences of oil spills on the local economy and livelihoods, particularly the impact on farming, fishing, and traditional crafts.	Depletion or **disappearance of fish** due to oil spills	Fishing	“Constant pollution has depleted the Imo river's fish population" (OG_MEN_004)
		Contamination of fish and aquatic life (oil on fish, etc.)	Fishing	“Fish exhibit signs of crude oil contamination" (OK_MEN_009)
		Migration or **animals** due to environmental degradation	Wildlife	“…animals such monkeys and antilope normal walk in group, but due to the oil spillage the movement of this animals is long gone” (OK_MEN_008-).
		Mention of **damage to trading process**	Trading	“The oil spillage has destroyed the trading process between them and the nearby communities " (AG_WOMEN_009)
		Soil contamination affecting crop growth or **agriculture (Livelihood)**	Farming	“Groundwater is contaminated, making agriculture difficult" (OG_MEN_003)
		Environmental changes (rivers, creeks, streams polluted)	Fishing and farming	“Streams and rivers are filled with unknown substances" (AG_YOUTH_003)
		Pollution affecting **food sources or harvest**	Farming	“We cannot farm anymore,” (AG_YOUTH_001)

In line with Secor (2016), Schreier (2012; 2014) and Wheeler (2022) prescriptions, I categorised and summarised the content of the FGD transcripts using CA, revealing patterns and themes that emerge from the data. These emergent signifiers offer insights into the changes in the environment associated with both past and present oil spills. This approach complements traditional physical data analysis by delving into the nuanced narratives of the participants. However, the impact of translation on meaning is a notable consideration in this context. For instance, when working through this issue, I was aware that the translation of certain words or phrases from one language to another may introduce variations in interpretation. To navigate this uncertainty, I approached the interpretation of participants' words with a deep awareness of the influence of data collectors on translation and interpretation. Words were not assumed to carry absolute certainty, and their meanings were considered within the specific context of the conversation.

By using the CA approach, the common themes that emerged from the transcripts include the severe damage to the environment due to oil spills, echoing findings from organisations such as Amnesty International which have described the Niger Delta as one of the worst impacted zones globally. Participants consistently reported contamination of groundwater, rivers, and farmland, as well as harm to the aquatic ecosystem and wildlife. Health issues such as cancer, respiratory problems, and skin conditions were widely mentioned and linked to environmental pollution. Economic consequences, such as decreased crop yields, infertility of soil, and the inability to fish, were recurring concerns across all communities. Men, women, and youth from different locations shared similar concerns and experiences, although the specifics of the impacts varied. Box 3 highlights the theme of pollution and contamination, derived from the transcripts, providing valuable insights into the environmental pollution and contamination challenges posed by the occurrence of oil spills in the Niger Delta region.

5.7.2 Community Participatory Mapping Exercise (CPME)

The CPME was conducted in six oil spill-affected communities in Nigeria: Aghoro, Benikrukru, Bodo, Ogale, Okpoma, and Ubeji. Participants in each community identified the affected areas using CPME maps. Data collectors guided participants through the mapping process using a structured questionnaire developed with prompts from a literature review and social media sources. This approach enabled participants to systematically identify areas impacted by oil spills.

To analyse the generated maps, I mounted the A0-sized maps on the wall for better visibility, and scanned them using my phone camera. The scanned maps were then transferred and saved on my computer, where I was able to visualise both the original features and the additional features marked by participants. I conducted an external validation of the features added to the maps by importing the scanned maps into a GIS environment using QGIS (version 3.38.3). To enable spatial analysis, which involved examining the locations, attributes, and relationships of the added geographic features, and to facilitate the overlay of other spatially referenced data for this study (NOSDRA oil spills data and pipeline data), the maps were georeferenced and the features vectorised. Georeferencing is the process of aligning geographic data to a known coordinate system, enabling it to be viewed, queried, and analysed in conjunction with other geographic data (Lenahan, 2020). This process allows for the identification of spatial patterns, trends, and anomalies. Vectorisation is the conversion of raster data (an array of cell values) to vector data (a series of points, lines, and polygons).

Eight ground control points (GCPs) were established in QGIS Georeferencer by matching landmarks on the maps with a georeferenced base map (see Figure 5.4). A first-order polynomial transformation was applied. The resulting geotiffs were imported into ArcGIS Pro 3.2, where the added features were vectorised and organised into thematic layers based on the CPME questionnaire: impacted areas, affected water bodies, abandoned agricultural and residential land, oil spill flow patterns, participant-inserted pipelines, and areas vulnerable to future oil spills. Overlaying these layers produced the CPME output map.

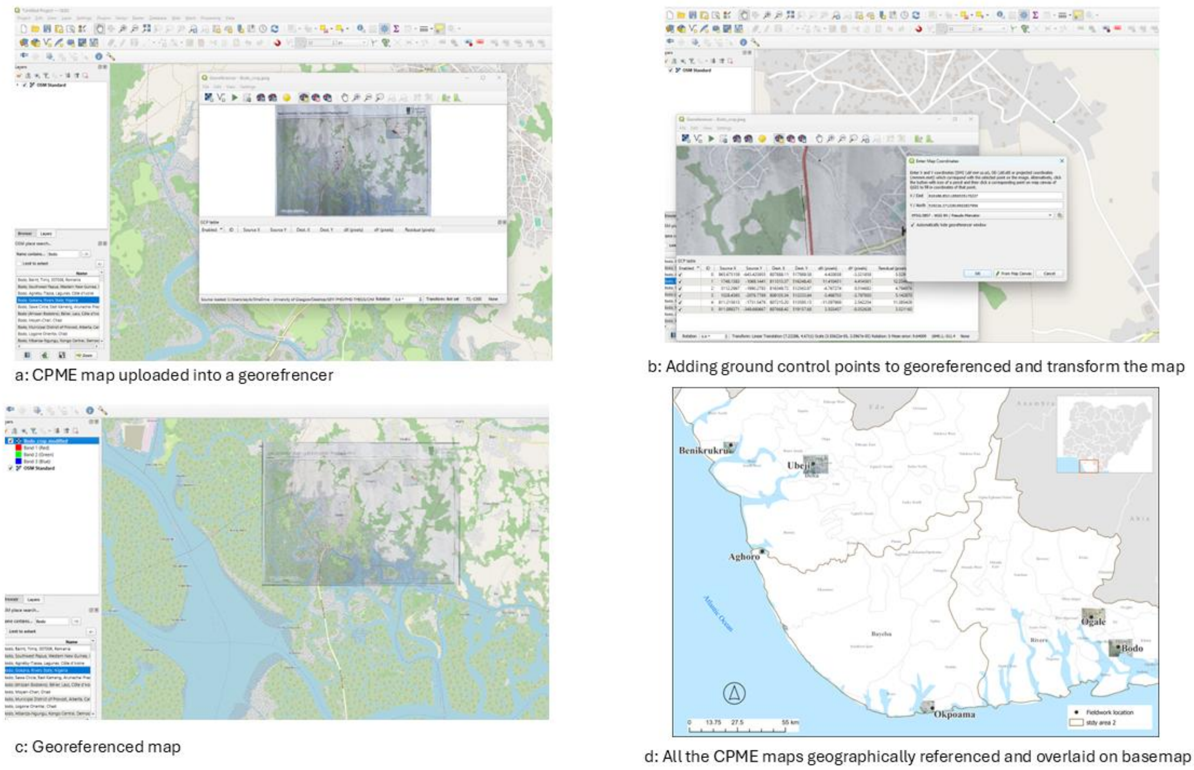


Figure 5.4. CPME maps preparation and processing for analysis, the original maps were imported into GIS environment where they were georeferenced and transformed.

This georeferenced and vectorised data facilitated visualisation and analysis of participant-added features in relation to their communities, oil spill impacts, and findings from the FGDs. Additionally, NOSDRA data was overlaid for further analysis of reported oil spill impacts.

In summary, by georeferencing and vectorising the hand-drawn maps, the information becomes spatially explicit, allowing for:

- **Integration with other data:** Comparison with official oil spill records (NOSDRA data) and insights from FGDs.

- **Spatial analysis:** Examination of the location, distribution, and patterns of participant-identified features. In addition, the process enables the connections between different impact types and their proximity to communities.

5.8 Results

The results are structured around three primary categories for each community: i) Pollution and Contamination, ii) Health Issues, and iii) Economic and Livelihood Impact. Each category is further explored through emerging sub-themes, providing a detailed picture of the multifaceted consequences of oil pollution in these communities. It should be noted that these emerging themes are community and participant specific, meaning of words were not transferred or generalised.

5.8.1 Aghoro Community

1. **Pollution and Contamination**

*a. **Farmlands and Vegetation***

Across all groups (Women, Men, Youth) in Aghoro, participants consistently reported destruction of vital vegetation, including mangroves and other flora essential for farming, fuel, and local biodiversity, (e.g. see **Quote 5.1**) Mangrove trees, once abundant, are now significantly diminished due to recurrent oil spills. This vegetation loss is not only ecological but deeply economic, as many community members rely on these resources for farming and firewood.

> **Quote 5.1**: AG_YOUTH_001 observed, *"We cannot farm anymore,"* while AG_YOUTH_009 noted, *"The mangrove trees meant for firewood have been reduced,"* underscoring the dual impact on both agricultural productivity and fuel sources.

*b. **Water Quality***

Participants reported severe water contamination, with rivers, creeks, and ponds heavily polluted by crude oil, making these water bodies unsuitable for fishing, drinking, and other essential uses, see **Quote 5.2**. The inability to fish has not only disrupted traditional livelihoods but also restricted access to clean water, further deepening the community's vulnerability.

Quote 5.2: AG_YOUTH_003 described, *"Even streams and ponds are filled with some unknown substances,"* and AG_YOUTH_008 emphasised, *"Fish ponds too have been contaminated by dangerous substances,"* illustrating the broad extent of water contamination and its impact on community health and sustenance.

c. ***Air Quality***

Oil spills have also affected air quality, with participants from Youth and Women groups reporting "cloudy air" and "black smoke," indicative of ongoing environmental contamination. As seen from **Quote 5.3**, poor air quality affects daily life and may contribute to respiratory issues within the community.

Quote 5.3: AG_YOUTH_001 observed, *"that the weather was very cloudy in nature"* while AG_YOUTH_004 reiterated this observation by noticing *"..something like white black smoke"*, suggesting potential combustion or other airborne pollutants arising from oil spills.

The CPME data corroborates these findings, highlighting specific areas within the community that have been marked as heavily affected by oil spills. Mapping results show the spread of contaminants, detailing how the flow of oil has reached residential areas, four water bodies, and other community spaces, amplifying the scope of these environmental impacts (See Figure 5.5 for visual reference.).

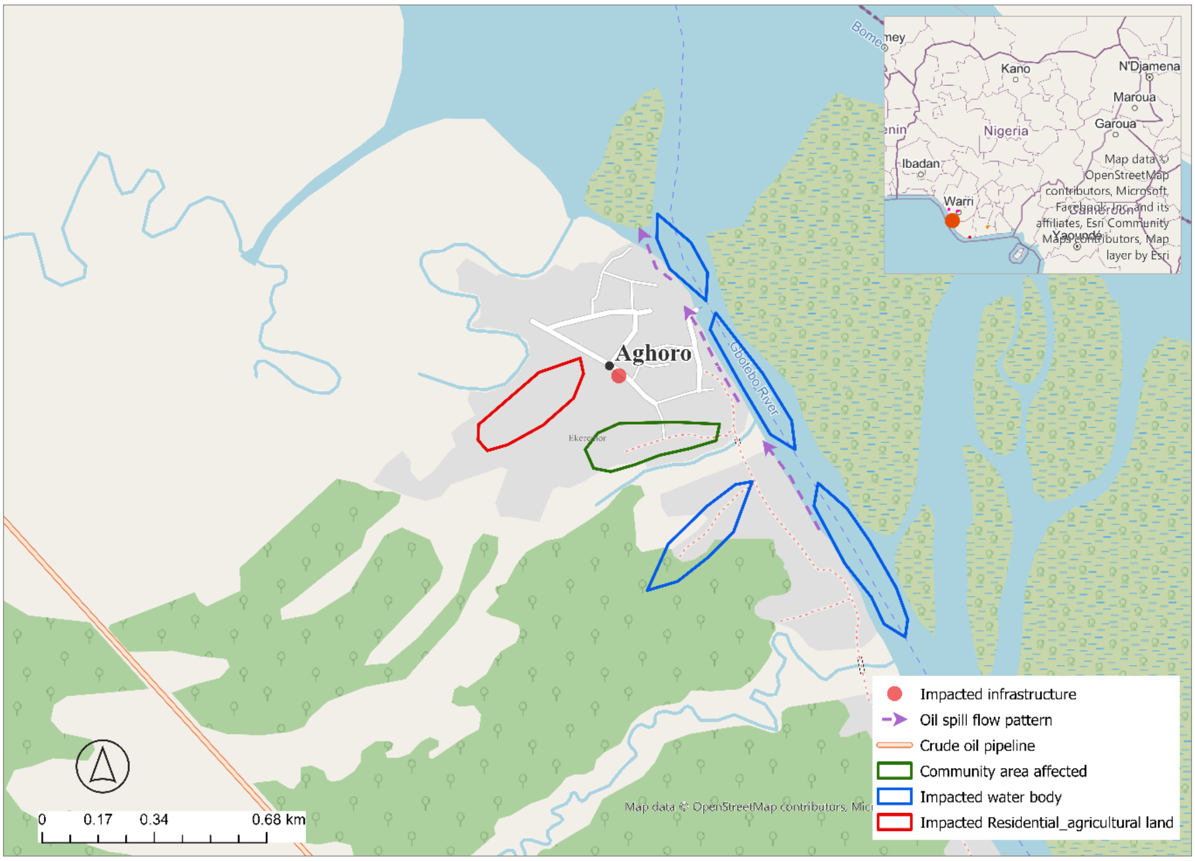


Figure 5.5. Aghoro CPME map output, showcasing the affected areas of the community corroborating the FGDs.

2. Health Issues

Participants across demographic groups reported various health impacts linked to environmental degradation. Notably, ***respiratory issues*** were cited by Youth participant (see **Quote 5.4**) who described difficulty in breathing, potentially linked to the contaminated air. Increased disease rates were also reported, with some participants expressing concern over rising illnesses since the spills.

> **Quote 5.4:** AG_MEN_010 observed, *"The rate of disease has increased among the people of Aghoro Community,"* also AG_YOUTH_006 attested to the fact that *"…… they find it very difficult to breathe."* indicating a correlation between the pollution and the prevalence of health issues.

This category underscores the urgent need for health interventions in Aghoro, as poor air and water quality present ongoing threats to community well-being.

3. Economic and Livelihood Impact

a. Fishing and Farming

Both fishing and farming, central to Aghoro's economy, have been severely impacted. Oil contamination in rivers has reduced fish populations, while oil-soaked soil has rendered farmland infertile, threatening food security and economic stability. As seen from **Quote 5.5,** participants mentioned decreased fishing yields, making it increasingly difficult for those reliant on fishing to sustain their livelihoods. The reduction in fish populations in Aghoro could have ripple effects, affecting dietary intake, income, and local trade. Additionally, farming has become nearly impossible due to soil contamination.

> **Quote 5.5:** AG_MEN_003 lamented, *"They no longer catch fish like before,"* while AG_MEN_008 noted, *"The oil spillage has affected their means of livelihood,"* showcasing the financial strain caused by environmental degradation.

b. Trading

The contamination has also hindered trade with nearby communities. Women participants shared that the degradation of natural resources has obstructed trade, limiting income sources and exacerbating economic hardship see **Quote 5.6**. The social impact of reduced trade has led to increased isolation, as the community can no longer effectively participate in regional markets.

> **Quote 5.6:** AG_WOMEN_009 expressed, *"The oil spillage has destroyed the trading process between them and the nearby communities,"* illustrating how this economic disruption has ripple effects beyond Aghoro.

c. Economic Hardship

The compounded effects of environmental destruction and livelihood disruption have driven the community into severe economic hardship, see **Quote 5.7**. Women reported that feeding their families has become a struggle, and Youth participants mentioned that previously reliable resources, such as ponds and creeks, are no longer safe or usable.

> **Quote 5.7:** AG_WOMEN_001 noted, *"Nearby communities are left in hardship caused by the oil spillage,"* highlighting the broader impact on the region and the challenges of securing essential resources.

The FGDs and CPME data analysis reveal the extensive impact of oil spills on Aghoro's environment, economy, and health. Pollution has destroyed local resources, particularly water bodies and farmlands, leading to severe livelihood disruptions. Economic hardship has escalated, driven by the inability to fish, farm, or trade, while poor air and water quality present persistent health risks. Finally, the oil spills have altered community dynamics, isolating the Aghoro community and affecting neighbouring areas, thereby indicating a need for comprehensive regional support and intervention. The spatial data from CPME further illustrates the spread and scope of these environmental issues, mapping the community's physical landscape and showcasing the interconnectedness of these challenges.

5.8.2 Benikrukru Community

1. Pollution and Contamination

a. Farmlands

The FGDs revealed extensive environmental degradation, with soil infertility being a major concern that has rendered farmlands unusable. This issue has directly affected local agricultural practices and productivity, impacting livelihoods, particularly for women who rely on farming for sustenance.

As described in:

> Quote 5.8: BE_YOUTH_001 explained, *"Our mothers can no longer farm because the soil is no longer fertile."* Similarly, BE_WOMEN_002 remarked, *"I can't farm anymore, the farmlands are damaged, even the river has no fish in it."*

These reflections underscore the community's dependency on farming and how environmental degradation threatens food security and economic stability.

b. Forest Resources

Community members also noted the contamination of forests, which traditionally provided resources such as wood for building and herbal plants. As seen from Quote 5.9, these resources have lost their utility due to pollution, impacting both cultural practices and local incomes.

> Quote 5.9: BE_MEN_005 mentioned, *"The wood we use for building is damaged and can't be used anymore,"* illustrating the financial and cultural losses resulting from the oil contamination of forest resources.

c. *Water Sources*

Participants expressed serious concerns regarding the pollution of rivers and streams, noting that these water sources were previously essential for drinking, fishing, and domestic use. However, oil slicks have made these activities nearly impossible, creating a severe strain on the community's access to clean water.

As reflected in;

> Quote 5.10: BE_MEN_003 stated, *"We can no longer drink rainwater, even our buckets we use for collecting water are filled with dark substances."* Meanwhile, BE_YOUTH_005 added, *"Our river is polluted, all the fishes are dead…you can't swim in the water without oil stains."* These quotes illustrate the far-reaching impacts of water pollution on daily life and livelihoods.

The CPME data reinforces these observations, mapping areas of contamination that align with the community's accounts. Specific zones identified as heavily polluted include abandoned farmlands and contaminated waterways, see Figure 5.6. The spatial data corroborates the community's reports, highlighting the extensive reach of the pollution.

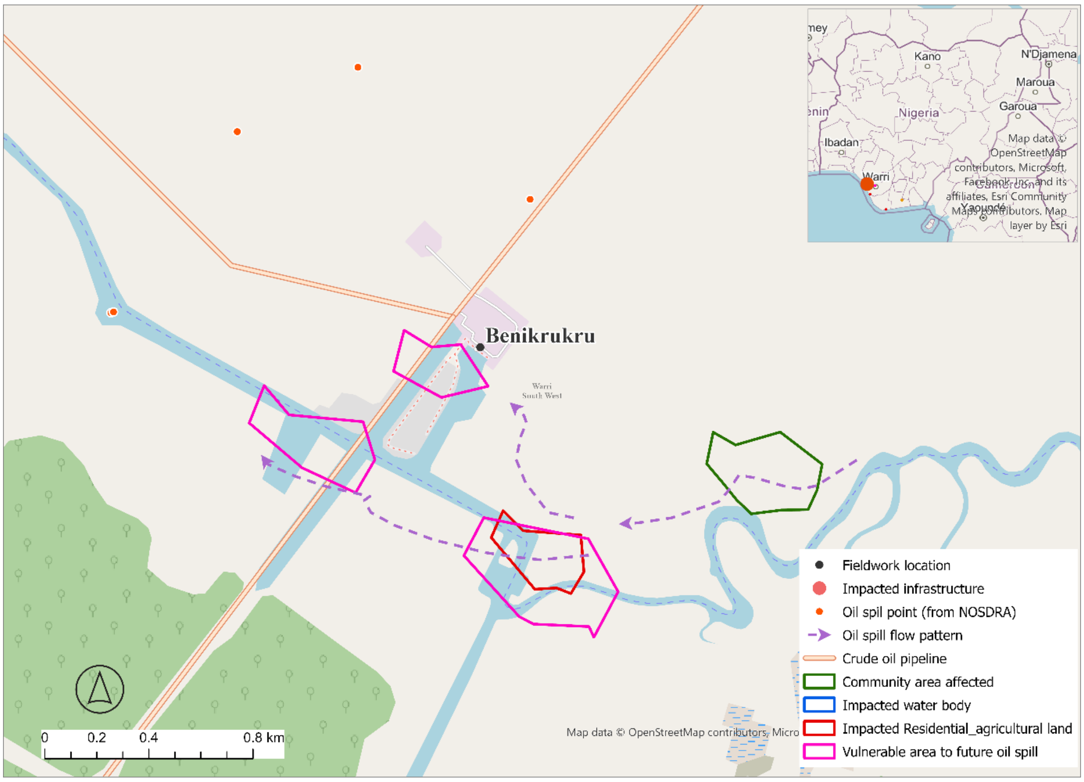


Figure 5.6. Benikrukru CPME map output, showcasing the affected areas of the community corroborating the FGDs.

d. Air Quality

Air pollution was another major issue, with participants describing particulate matter and sooths from oil spills that have affected their quality of life. The air contamination has led to stained clothing and reported respiratory issues, indicating a serious health hazard.

> Quote 5.11: BE_MEN_003 noted, *"The air is polluted, we can't put on a white shirt because it will become darker within a short time."* Likewise, BE_WOMEN_001 shared*, "The air is seriously polluted, even the water quality can't be useful, we now have coloured water."* These reflections point to the multifaceted impacts of oil-related pollution on the community's well-being.

e. Water Quality

FGD participants noted that rainwater, a traditional drinking water source, is now contaminated by oil residues. This pollution has rendered rainwater undrinkable, creating further water insecurity.

> Quote 5.12: BE_YOUTH_001 explained, *"When it rains, you can see the water instead of being colourless; it is gold in colour due to pollution,"* indicating that even rainwater is not exempt from the oil spill's effects.

CPME analysis confirms the extent of contamination, mapping oil spills flow pattern close to the waterways further support the community's verbal testimonies, reinforcing the urgent need for clean water access.

2. Health Issues

Health risks linked to oil pollution emerged as a significant theme. Participants described health conditions such as respiratory problems, skin irritations, and illnesses that they attributed to poor air and water quality.

a. Common Illnesses

Frequent conditions such as malaria, typhoid, and chronic headaches were widely reported, with participants connecting these illnesses to the toxic environment caused by oil spills.

Quote 5.13, BE_MEN_005 reported, "*Strange illnesses, malaria, and typhoid…the air we inhale is polluted,"* while BE_WOMEN_001 added, *"Constant sickness like malaria, chronic headaches, dizziness… the air we breathe is a problem."*

As indicated in Quote 5.13, these quotes from the FGDs emphasise the community's concerns about how the pollution has exacerbated health problems.

b. Children's Health

Participants expressed specific concerns for children, see Quote 5.14. Frequently participants expressed concerns over children's deteriorating health linked to contact with contaminated water.

Quote 5.14: BE_YOUTH_001 stated, *"If the water touches your body, it scratches and causes rashes all over"*, also BE_WOMEN_006 added that *"Children that died due to this spill has been the biggest challenge"* , and BE_MEN_01 *"even where we stay the rain water we drink is polluted, children normally fall sick"* highlighting the vulnerability of children to the adverse health effects of oil exposure.

The CPME data mapped the flow pattern of the oil spills across Benikrukru, see Figure 5.6. This mapping underscores the community's reports, and how different part of the community must have been impacted and contaminated, emphasising the need for health interventions in these zones.

4. Economic and Livelihood Impact

The FGDs highlighted the loss of income-generating activities as a direct consequence of environmental contamination. Fishing and farming, previously crucial to the Benikrukru economy, have been severely impacted.

a. Fishing and Farming

The community reported that oil pollution has devastated both fishing and farming activities, resulting in food scarcity and economic strain, see Quote 5.15. With agricultural lands and fishing areas rendered unusable, families face high costs for imported goods from neighbouring areas.

Quote 5.15, BE_MEN_002 explained, *"We can't fish or farm; the spill has obstructed many of our activities, which serve as a means of income."* Similarly, BE_WOMEN_005 remarked, *"The natural resources that served as a livelihood have been taken away, and we are left to starve."* These accounts underscore the profound economic disruption caused by the oil spill.

b. Resource Scarcity and Increased Poverty

As noted in Quote 5.16, participants described rising poverty due to resource scarcity, noting an increasing dependency on neighbouring communities as local resources become depleted.

Quote 5.16, BE_YOUTH_003 mentioned, *"Poverty has become the order of the day. We can't do the things we used to do to make a living,"* illustrating the pervasive impact of environmental degradation on economic well-being.

The CPME spatial data mapped areas where farming is no longer viable, see Figure 5.6, reinforcing the economic concerns voiced in the FGDs. Abandoned farmlands and polluted environment serve as stark reminders of the community's struggle to maintain their traditional livelihoods. This analysis illustrates the severe effects of oil spills on the Benikrukru community. Integrating CPME data with FGD findings offers a well-rounded view of both the spatial and human impacts, highlighting the need for immediate interventions. Community members advocated for improved monitoring and maintenance of pipelines to prevent future oil spills. Regular inspections, increased security, and governmental oversight were proposed as crucial strategies for reducing environmental harm. As articulated in Quote 5.17, These perspectives underscore the need for proactive measures to safeguard the community's environment and well-being.

Quote 5.17, BE_MEN_001 remarked, *"Monitoring and checking of pipelines is essential because the pipes have expiration dates,"* while BE_YOUTH_002 emphasised, *"The government should take security measures seriously to prevent future occurrences."*

5.8.3 Bodo Community

1. Pollution and Contamination

The Bodo community reported extensive environmental damage due to oil spills, impacting air, water, and soil quality.

a. Water Contamination:

Participants expressed severe concerns regarding the contamination of water sources, which were previously essential for drinking, cooking, and fishing. Many mentioned that even borehole water now carries a strong smell of crude oil, with substances like benzene affecting the water quality, see Quote 5.18.

Quote 5.18: BO_MEN_001 noted, *"Oil spillage damaged the environment…our people get sick, even the fish in the river are dying. It's hard to find fish anymore."* BO_MEN_002 added, *"Groundwater is contaminated with benzene; we don't have natural drinking water anymore, and even the mangroves and farmlands are destroyed."* BO_YOUTH_002 and BO_YOUTH_003 highlighted similar impacts: *"The spillages have killed off fish and other aquatic life,"* said BO_YOUTH_002, while BO_YOUTH_003 shared, *"Our drinking water is polluted…"*

b. Soil Contamination and Vegetation Degradation:

Participants described how fertile lands have become infertile, leading to significant declines in crop productivity.

Quote 5.19: BO_MEN_001 explained, "*Oil spills have severely damaged the environment...farmland isn't fertile anymore, and we rarely see fish."* BO_WO_001 noted, *"It's dangerous for us and our children…crops don't grow as they used to."* BO_YOUTH_004 added, *"We used to hunt in the surrounding forest, but the animals have migrated because their habitat is dying."*

They observed the mangrove forests dying, as seen from Quote 5.19. This phenomenon has disrupted the local ecosystem, affecting both vegetation and wildlife.

c. Air Quality:

Residents have noticed frequent occurrences of "black smoke" and persistent oily odours in the air. As described in Quote 5.20, some reported respiratory issues, nasal congestion, and even vision problems, attributing these to the oil spill's pollution.

Quote 5.20: BO_WO_003 remarked, *"The gas from the spillage doesn't just pollute the water; it also pollutes the air. I can't breathe well sometimes."* BO_MEN_003 noted, *"It's even caused violent clashes within the community."* BO_MEN_004 shared, *"When I clean my nostrils, I see black sediments."*

The CPME results further substantiate these observations, identifying multiple affected infrastructure points and abandoned farmlands. This illustrates the visible and widespread physical impacts of the oil spills on Bodo's environment (see Figure 5.7).

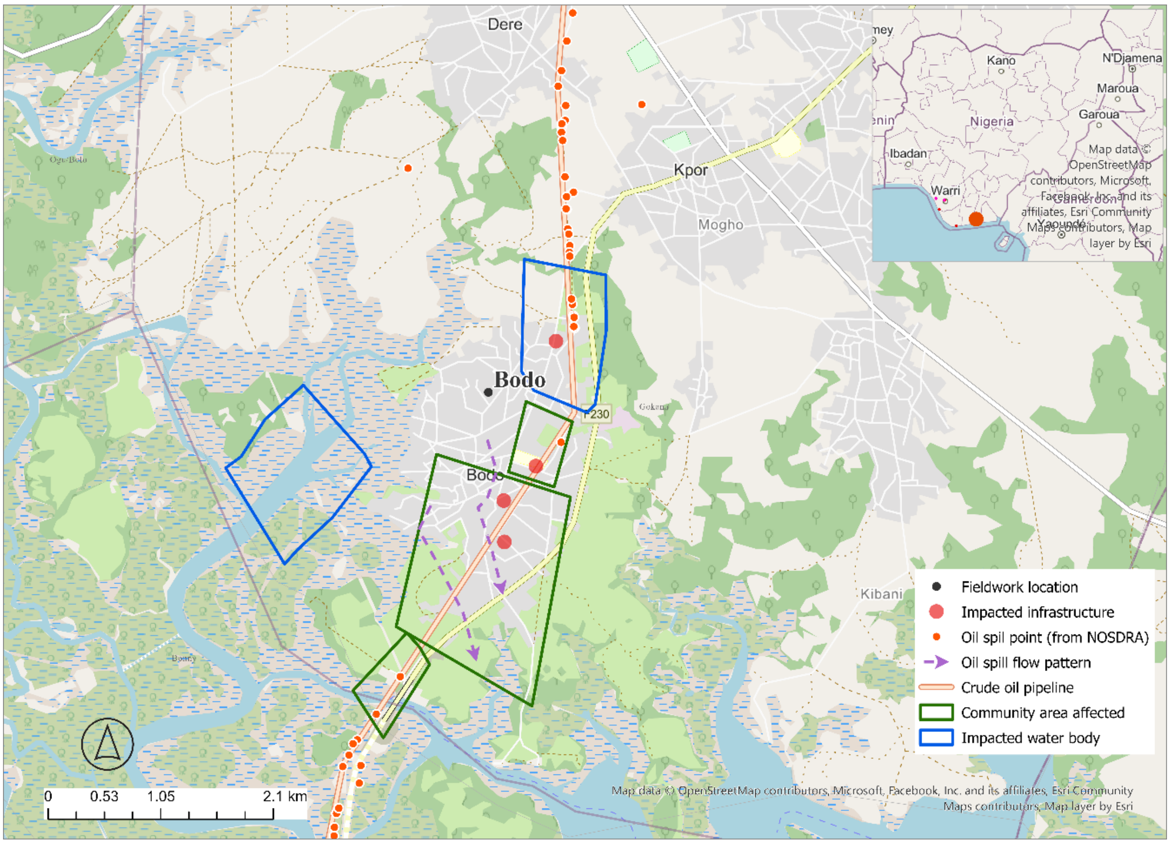


Figure 5.7. Bodo CPME map output, showcasing the affected areas of the community corroborating the FGDs.

2. Health Impacts

The community has experienced significant health issues, many of which they attribute to prolonged exposure to oil pollution.

a. Chronic Illnesses:

Men and youth participants reported increases in chronic illnesses, including cancer, see Quote 5.21. There were also concerns about reproductive health, with women mentioning frequent miscarriages and eye issues among children.

> Quote 5.21: BO_MEN_001 shared, *"Oil spills have caused serious health problems, like cancer."* BO_YOUTH_001 noted, *"The spills are dangerous, posing severe health risks to us."* BO_YOUTH_005 highlighted, *"Many children have eye issues now, which we think are due to the polluted water and air."* BO_YOUTH_004 shared, *"The*

air isn't fresh here anymore; pollution has made breathing difficult." BO_MEN_004 added, *"Every time we wipe our noses, we see black sediments on the handkerchiefs.*

b. Respiratory Issues:

Many participants reported respiratory symptoms such as coughing, shortness of breath, and lung infections.

As reflected in Quote 5.21, these issues were frequently linked to airborne pollutants from the oil spills.

c. Skin Diseases:

As seen from Quote 5.22, youth participants also noted skin irritations and rashes from bathing in contaminated water, which they fear may lead to more serious health issues.

> Quote 5.22: BO_YOUTH_002 said, *"Contaminated water has given many of us skin diseases, and it could lead to cancer."* BO_YOUTH_003 remarked, *"The water smells of crude oil and is very harmful."*

These health concerns align with CPME findings documenting widespread water and air contamination, confirming the likelihood of significant health impacts on the community.

3. Economic and Livelihood Impact

The oil spills have had a devastating effect on Bodo's economy, particularly its agriculture and fishing activities.

a. Farming:

Due to soil contamination, participants reported poor crop yields, leading to food shortages and financial strain on families. This is evidenced in Quote 5.23 below.

> Quote 5.23: BO_MEN_001 stated, *"The soil used to be fertile, but now crops don't grow well."* BO_WO_002 added, *"The soil is too hard to cultivate anything."*

b. Fishing:

As expressed in Quote 5.24, water pollution has drastically reduced fish populations, affecting local fishermen's primary source of income.

Quote 5.24: BO_YOUTH_001 explained, *"There aren't as many fish in the river anymore, and their quality has declined."* BO_WO_001 remarked, *"Fishing has almost stopped because of the oil in the water."*

c. Community Dynamics and Migration:

The disruption caused by the oil spills has led to increased migration as some community members seek safer living conditions. Due to oil spill contamination, the community's traditional land use practices have shifted. Movement within farming areas is restricted, as reflected in Quote 5.25, participants mentioned having to quickly harvest crops before the land becomes too contaminated and the crops destroyed. Additionally, strained relations with neighbouring communities have led to conflicts, as oil spills often affect areas beyond Bodo.

Quote 5.25: BO_YOUTH_001 noted, *"People are leaving the community and don't return for festivals."* BO_MEN_001 shared, *"The oil spread to our neighbours' land, and now there are disputes."* BO_WO_002 echoed, "I avoid certain communities now because of conflicts." BO_MEN_003 explained, "*Sometimes, we have to rush to harvest when spills happen."* BO_WO_003 noted, *"People no longer use the streams for domestic needs."*

The CPME map highlights abandoned lands and oil spills flow patterns indicating affected areas, see Figure 5.7, further supporting these observations of disrupted lives and fractured community relations.

d. Communal Tensions:

Participants in men and youth categories complained of how the oil spills have affected neighbouring communities, tensions and conflicts have arisen, disrupting previously cooperative relationships. This is evidenced in Quote 5.26.

Quote 5.26: BO_MEN_001 said, "*Oil flow from our land to others has caused disputes."* BO_YOUTH_005 shared, *"The spills have led to conflicts with our neighbours."*

The CA analysis reveals a picture of how oil spills have severely impacted Bodo's environment, economy, and health. The CPME data reinforces the analysis by highlighting affected areas and providing a spatial context for the community's experiences.

5.8.4 Ogale Community

1. Pollution and Contamination

a. Water Contamination:

Participants in Ogale community consistently reported severe water contamination, with rivers, streams, and lakes heavily polluted by crude oil, rendering them unsuitable for fishing and domestic use. As evidenced in Quote 5.27, this water contamination poses a significant threat to the community's health and disrupts essential activities like fishing and accessing clean drinking water.

> Quote 5.27: OG_YOUTH_004 stated, *"Due to oil spillages we no longer have fishing activities in the community, the lakes are highly contaminated,"* while OG_MEN_001 added, *"The effect of oil spillage has been very bad especially on the ground water and river that flow through the community as there are no longer fishing activities in the community,"* highlighting the severe impact on water bodies and fishing activities.

b. Soil Degradation:

As seen from Quote 5.28, soil degradation emerged as a major concern, with participants reporting that oil spills have contaminated the soil, making it hard and infertile, thus affecting crop growth and yield. This loss of fertile land threatens food security and disrupts traditional farming practices crucial for the community's sustenance.

> Quote 5.28: OG_YOUTH_002 explained, *"Though we have lost most of our farm locations, we still manage to farm with the remaining locations but soil is very hard,"* and OG_WOMEN_003 added, *"crude oil and petroleum products settle underneath the soil thereby causing the soil to be very infertile,"* further emphasising the detrimental impact of soil contamination on agricultural productivity.

The CPME results corroborate these observations, see Figure 5.8. The identification of two areas in Ogale with oil spill clean-up operations and a large vulnerable area on the northern outskirts due to oil spill impacts underscore the severity of land degradation.

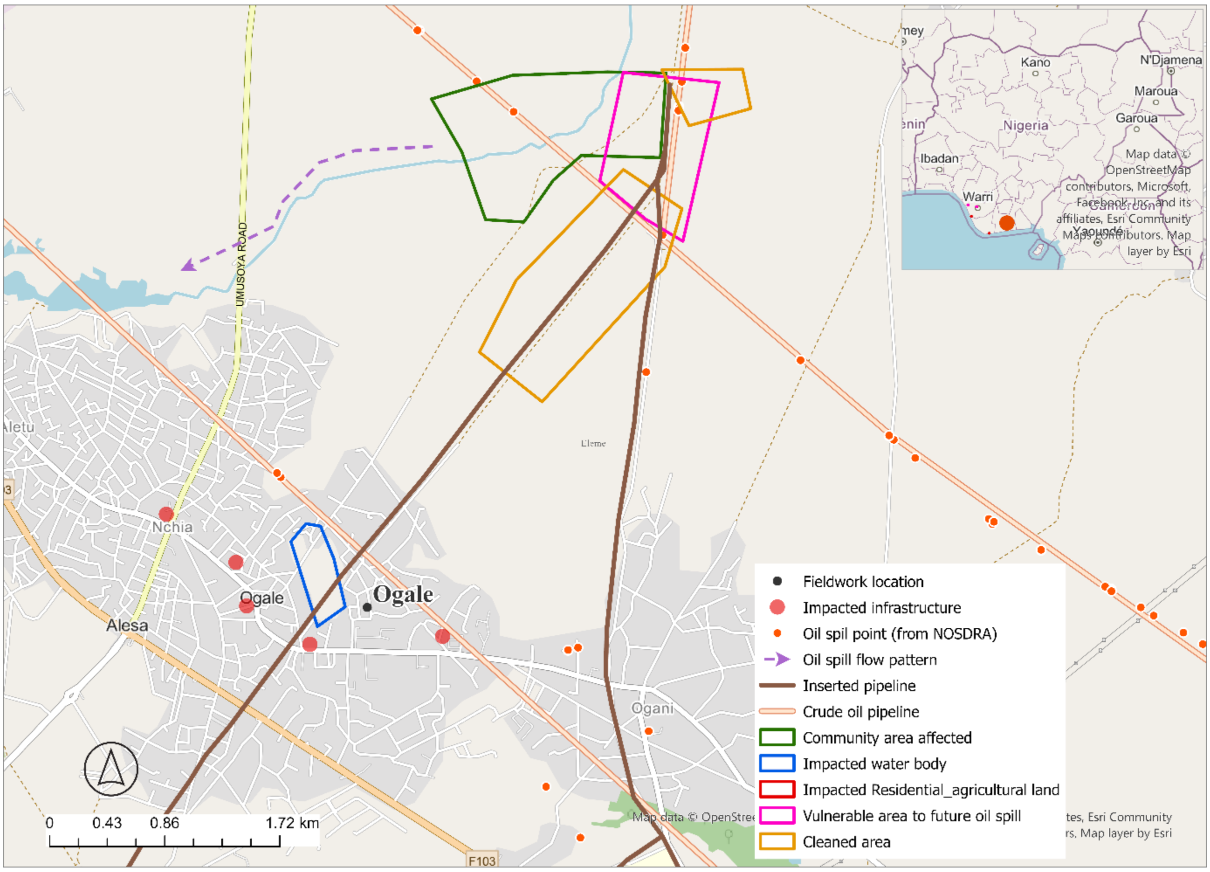


Figure 5.8. Ogale CPME map output, showcasing the affected areas of the community corroborating the FGDs.

c. *Vegetation Degradation:*

The impact on vegetation is also evident, with participants observing the death of mangroves and the overall decline in vegetation health and diversity, see Quote 5.29. This loss of vegetation disrupts the local ecosystem and affects the availability of resources traditionally used by the community.

> Quote 5.29: OG_YOUTH_001 noted, *"The forest are dyeing and the community finding it difficult to carry out agricultural activity,"* and OG_MEN_001 added, *"The mangroves are dying. Most farm land are highly contaminated with benzene,"* indicating the detrimental effects on vegetation and the loss of valuable plant resources.

d. *Air Pollution:*

Air pollution is another pressing issue, evidenced in Quote 5.30, participants in Ogale community reported polluted air and the presence of black stains in their nostrils, indicating the presence of harmful pollutants in the air. This compromised air quality raises concerns about respiratory health and the overall well-being of the community.

Quote 5.30: OG_YOUTH_005 shared, *".....even the air they breathe is highly contaminated, they have stains in their nostrils when they wipe their nose,"* while OG_MEN_001 stated, *"The air is polluted as they don't breathe clean air any more due to release of hydrocarbon in the air and also vandal refining crude oil illegally pollutes the air,"* emphasising the concerns regarding air pollution.

2. Health Issues

Participants expressed concerns about various health issues linked to oil pollution, including ***skin diseases, lung infections, intestinal and respiratory problems, cancer, and even death,*** see Quote 5.31. Concerns were also raised about the long-term effects of exposure to oil and other pollutants, such as infertility, stunted growth in children, and increased infant mortality. These health challenges underscore the direct impact of environmental contamination on the community's well-being.

Quote 5.31: OG_MEN_003 reported, *"..... the ground water being totally contaminated, people are having different skin diseases and other intestine infections from the water,"* highlighting the health risks associated with contaminated water.

The CPME map (Figure 5.8) effectively illustrates the widespread impact of oil spills on the community. While some areas have been cleaned or undergoing cleanup, others remain vulnerable to future contamination. The map also highlights the flow pattern of oil spills, even those originating from neighbouring community, which underscores the interconnectedness of environmental risks and the need for collaborative mitigation efforts. The mapping of the missing crude oil pipelines provides valuable information for identifying potential sources of contamination and prioritising infrastructure maintenance to prevent future spills.

3. Economic and Livelihood Impact

Oil spills have severely disrupted the local economy and livelihoods in Ogale. The contamination of water bodies and soil has affected ***fishing and farming activities*** (see Quote 5.32), leading to income loss and food insecurity. The loss of income and the disruption of traditional economic activities have far-reaching consequences for the overall well-being of the community.

Quote 5.32: OG_YOUTH_001 stated, *"The effect has been very bad to the community because we used to have nine (9) have farm sites that the rotate yearly for the Ogale* *community but spillage has destroyed five farm locations where remediation work is being carried out, we are left with just four farm locations currently,"* demonstrating the impact on agricultural practices and land availability.

The CPME results provide valuable spatial context to the qualitative data gathered from the FGDs. The identification of specific areas impacted by oil spills, including five infrastructure points, and areas undergoing cleanup, deserted areas, strengthens the findings from the FGDs and provides a visual representation of the extent of the damage. The content analysis of the FGD transcripts and the CPME results reveals the profound and multifaceted impact of oil spills on the Ogale community.

5.8.5 Okpoama Community

1. **Pollution and Contamination**

   a. ***Water Contamination:***

Participants reported severe water contamination, with rivers, creeks, and ponds heavily polluted by crude oil, making these water bodies unsuitable for fishing, drinking, and other essential uses, see Quote 5.33. The inability to fish has not only disrupted traditional livelihoods but also restricted access to clean water, further deepening the community's vulnerability.

> Quote 5.33: OK_YOUTHS_006 described, *"Our brothers and Sisters living in the fishing camp cannot stay there again because of oil spillage,"* and OK_YOUTH_003 emphasised, *"crude oil has taken over all our ponds and thereby make it difficult for us to drink water.,"* illustrating the broad extent of water contamination and its impact on community health and sustenance.

The CPME map (see Figure 5.9) effectively showcase the widespread impact of oil spills on the Okpoama community water bodies, the participants were able to identify the affected parts, buttressing the concerns.

   b. ***Soil Degradation:***

Soil degradation is another significant concern in Okpoama community. As depicted in Quote 5.34, participants reported that oil spills have contaminated the soil, making it unsuitable for farming and causing crops to die. This loss of arable land threatens food security and disrupts traditional farming practices, vital for the community's sustenance and economic stability. The was corroborated by the CPME data as two large areas of the community were identified to have been negatively affected by oil spills, see Figure 5.9.

> Quote 5.34: OK_WOMEN_001 lamented, *"we cannot plant again," while OK_WOMEN_006 added, "eventually if we plant all the crops will die,"* highlighting the devastating impact of soil contamination on agricultural productivity and food security.

c. Vegetation Degradation:

The impact on vegetation is also evident, with participants observing changes in the colour and health of trees, including mangroves, which are crucial to the local ecosystem, as illustrated in Quote 5.35. The loss of these vital trees not only disrupts the ecological balance but also removes a natural barrier against coastal erosion, leaving the community more vulnerable to the impacts of climate change.

> Quote 5.35: OK_YOUTHS_006 observed, *"the trees in forest has change colour and they can see the trees dieing,"* and OK_MEN_001 added, *"we discovered that all the mangrove tree's are all dead,"* emphasising the visible decline of vegetation and the ecological damage caused by oil spills.

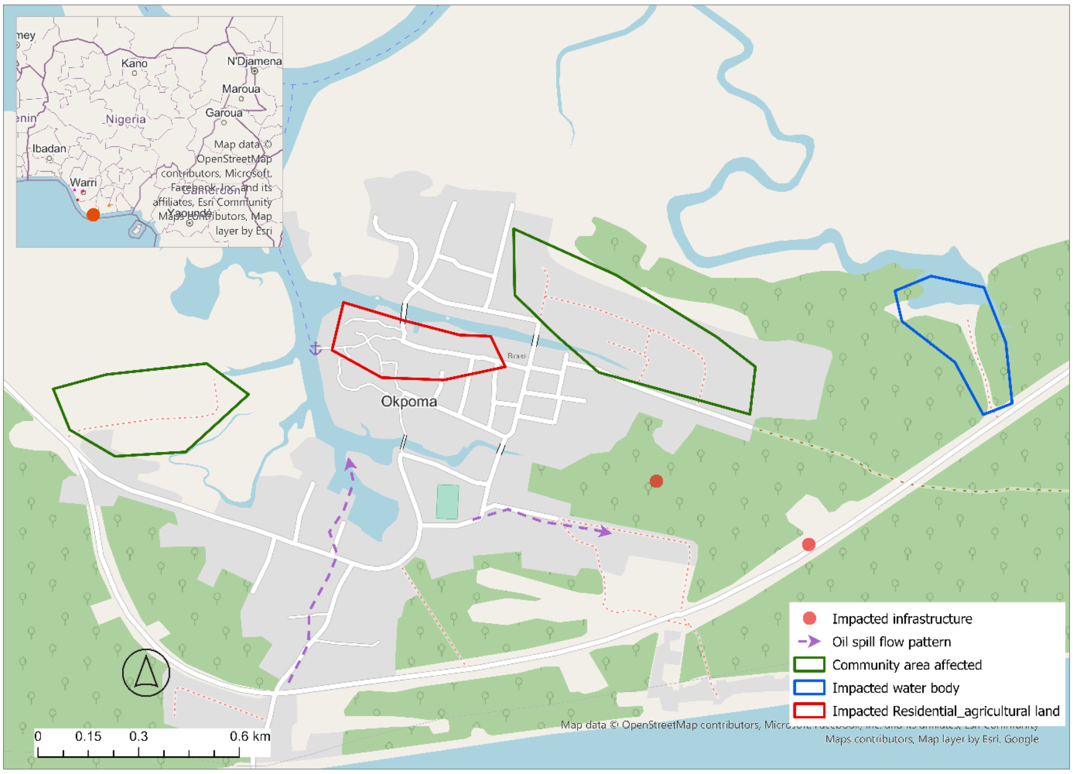


Figure 5.9. Okpoama CPME map output, showcasing the affected areas of the community corroborating the FGDs

d. Air Pollution

Air pollution is another pressing issue, with participants reporting a strong odor of crude oil in the air and experiencing respiratory difficulties. Quote 5.36 illustrates the community's concerns about air quality.

> Quote 5.36: OK_YOUTHS_002 shared, *"The participant said when you move inside your house you can smell the odour of the crude oil,"* while OK_WOMEN_007 described, *"The participant said the water surface is so black smelling and you cannot breath when inhaling your bresylralory system in siez -in,"* indicating the pervasive nature of air pollution and its potential health implications.

These accounts underscore the multi-faceted nature of pollution caused by oil spills, affecting not only water and soil but also the air quality, with potential implications for respiratory health.

2. Health Issues

The FGDs highlighted a range of health problems associated with exposure to oil and other pollutants. Quote 5.38 provides specific examples of the health challenges faced by the community.

> Quote 5.37: OK_YOUTHS_007 expressed concern about cholera, saying, *"The participant said it will cause Cholera,"* while OK_MEN_009 reported, *"The participant said they are exposed to Cough,"* and OK_WOMEN_001 added, *"The participant said to they have cholera,"* illustrating the diverse health risks associated with oil pollution.

These health issues are directly linked to the contaminated environment, with participants expressing concerns about the long-term effects of exposure to pollutants, this was evidenced in the CPME map, see Figure 5.9, where participants showcase oil spill flow patterns within the community. The fear of increased death rates and the prevalence of sickness underscore the serious health risks faced by the community, as captured in Quote 5.39.

> Quote 5.39: OK_YOUTHS_002 voiced their worry about rising mortality rates, stating, *"The participant said since the out break of the oil spillage the death rate in the will increase,"* and OK_WOMEN_005 added, *"The participant said every day and night people will become sick,"* highlighting the community's anxieties about the health consequences of oil spills.

3. Economic and Livelihood Impact

Oil spills have had a devastating impact on the local economy and livelihoods in Okpoama. Fishing, a primary source of income and sustenance for the community, has been severely affected due to the contamination of water bodies. Quote 5.40 reflects the community's concerns about the loss of livelihood and economic hardship.

> Quote 5.40: OK_YOUTHS_002 lamented, *"due to the oil spillage we cannot catch fish anymore,"* and OK_MEN_003 added, *".....due to increase rate of oil spillage they no fish in the river and streams anymore,"* demonstrating the severe impact on fishing activities and the resulting economic strain.

This loss of ***fishing activity*** has led to economic hardship and food insecurity, with participants expressing concerns about hunger and the inability to provide for their families, see Quote 5.41.

> Quote 5.41: OK_WOMEN_009 expressed the widespread concern about hunger, stating, *".... hunger has become the other of the day,"* and OK_WOMEN_008 added, *"... economic hardship is also on a high,"* emphasising the socio-economic challenges caused by the decline in fishing.

Furthermore, the impact on ***farming*** due to soil degradation further exacerbates the economic challenges faced by the community. The loss of income and the disruption of traditional economic activities have far-reaching consequences for the overall well-being of the community. The CPME results provide valuable spatial context to the qualitative data gathered from the FGDs, see Figure 5.9. The identification of specific areas impacted by oil spills, such as the residential area, community areas, infrastructure sites, and the water body, strengthens the findings from the FGDs and provides a visual representation of the extent of the damage. The mapping of oil spill flow patterns also helps to understand the spread of contamination and its impact on different parts of the community. The content analysis of the FGD transcripts and the CPME results reveals the profound and multifaceted impact of oil spills on the Okpoama community.

5.8.6 Ubeji Community

1. Pollution and Contamination

a. Water Contamination:

Participants in Ubeji community consistently highlighted severe water contamination, rendering rivers, streams, and even rainwater unusable due to oil pollution. As highlighted in Quote 5.42, this contamination poses a significant threat to the community's health and disrupts essential activities like fishing and obtaining clean drinking water.

> Quote 5.42: UB_YOUTH_001 stated, *"Farmlands has been unfertile due to oil saturated round the soil surface, water is polluted, the oil is just all over the water,"* while UB_MEN_004 added, *"the entire river even the streams are all conderm, you can't find good water anywhere,"* illustrating the widespread water contamination.

b. Soil Degradation:

Soil degradation emerged as a major concern, with participants reporting that oil spills have contaminated the soil, making it unsuitable for farming and affecting crop growth, see Quote 5.44.

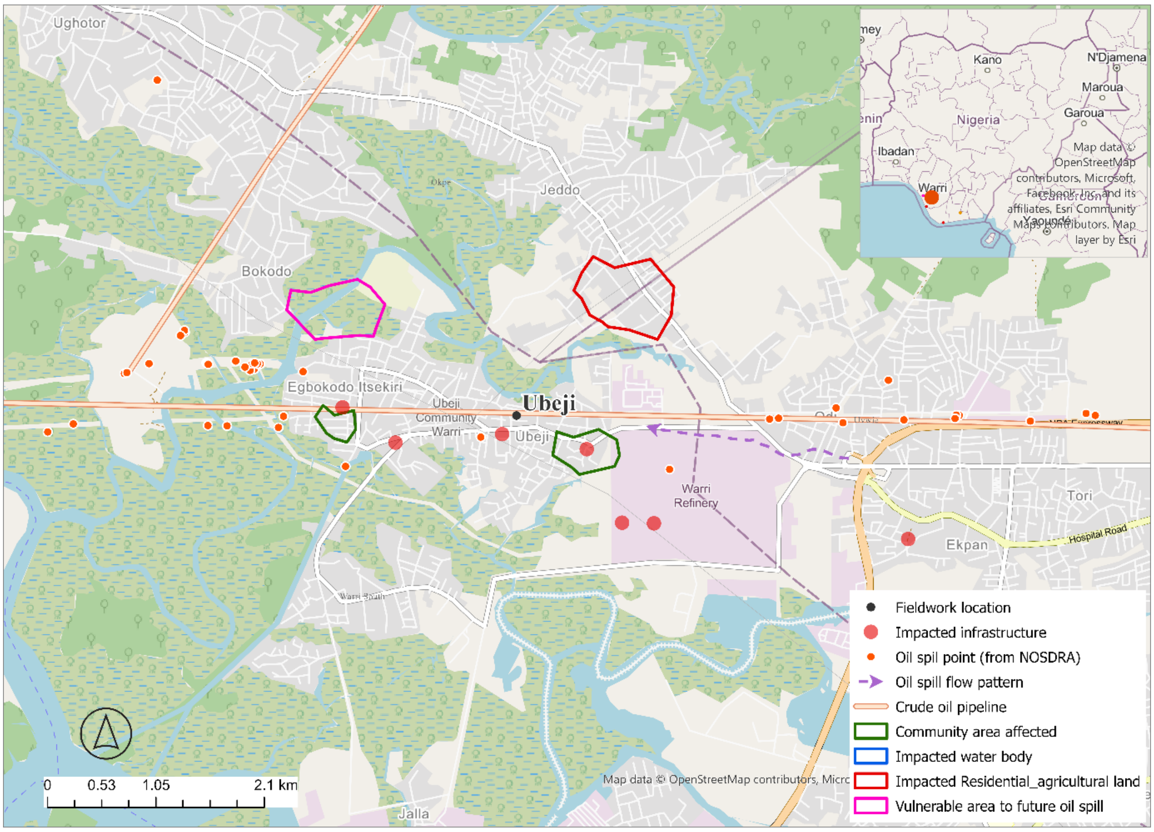


Figure 5.10. Ubeji CPME map output, showcasing the affected areas of the community corroborating the FGDs

This loss of fertile land threatens food security and disrupts traditional farming practices crucial for the community's sustenance. The CPME data substantiates this concern as different parts of the community were identified to have been affected by oil spills, see Figure 5.10.

> Quote 5.44: UB_WOMEN_001 lamented, *"Like I said the farmland can't produce what we wanted, the most lucrative part of the farmland is affected, the crops can't grow because of the bad soil,"* highlighting the detrimental impact of soil contamination on agricultural productivity.

c. Vegetation Degradation:

As illustrated in Quote 5.45, the impact on vegetation is also evident, with participants observing changes in the colour and health of plants and trees, the CPME map also corroborates this finding as different parts of the community were shown to have been affected including area designated as vulnerable to oil spills occurrence. The loss of important plant species used for medicine and other purposes further signifies the ecological damage caused by oil spills.

> Quote 5.45: UB_MEN_005 observed, *"Like when you see the plants, they've change colour and some of them we use for medicine are no longer available for use,"* indicating the detrimental effects on vegetation and the loss of valuable plant resources.

d. Air Pollution:

Air pollution is another pressing issue, with participants reporting polluted air and the inability to even collect clean rainwater due to contamination. This compromised air quality raises concerns about respiratory health and the overall well-being of the community, see Quote 5.46.

> Quote 5.46: UB_YOUTH_004 shared, *"The air is polluted, even rain water we can't drink because when it rain, we normally use bucket to fetch water flowing from the roof, but you see the roof is affected as well, so the water is 100 percent bad, even the air we inhale is contaminated,"* emphasising the pervasive nature of air pollution and its impact on water sources.

2. Health Issues

Participants expressed concerns about various health issues linked to oil pollution, including ***malaria, typhoid, dizziness, headaches, rashes, and breathing difficulties***. As illustrated in Quote 5.7, these health challenges underscore the direct impact of environmental contamination on the community's well-being.

Quote 5.47: UB_MEN_003 reported, *"People fall sick because we barely don't know what we inhale or mixed what we buy even what we drink, this particular malaria and typhoid is a constant thing, dizziness sometimes, headache, rashes in the body, most people faces difficulty in breath,"* highlighting the range of health problems associated with oil exposure.

3. **Economic and Livelihood Impact**

Oil spills have severely disrupted the local economy and livelihoods in Ubeji. Contamination of water bodies and soil has negatively impacted fishing and farming activities, resulting in income loss and food insecurity. The destruction of mangrove wood, essential for producing native salt and other traditional uses, has further compounded these economic challenges.

The CPME map (Figure 5.10) reveals that five infrastructure locations have been affected by oil spills, further exacerbating the economic strain on the community. Damage to infrastructure can disrupt transportation, trade, and access to essential services, hindering economic recovery and development.

Quote 5.48: UB_YOUTH_004 stated, *"both drinking water and other sanitary facilities are all affected, it has cut short many source of income by so doing cursing hardship,"* while UB_MEN_008 added, *"Life hasn't been fair to us here, it's been rough, hunger, sickness, pain, we are suffering and we need help,"* demonstrating the economic hardship and suffering caused by oil spills.

The loss of income and the disruption of traditional economic activities have far-reaching consequences for the overall well-being of the community.

The CPME results provide valuable spatial context to the qualitative data gathered from the FGDs. The identification of specific areas impacted by oil spills, including public resources, infrastructures, vulnerable areas, and residential areas, strengthens the findings from the FGDs and provides a visual representation of the extent of the damage. The mapping of oil spill flow patterns helps to understand the spread of contamination and its impact on different parts of the community. The content analysis of the FGD transcripts and the CPME results reveals the profound and multifaceted impact of oil spills on the Ubeji community.

5.9 Discussion

The findings reveal several key observations about the impacts of oil spills in Aghoro, Benikrukru, Bodo, Ogale, Okpoama, and Ubeji communities. Figure 5.11 shows the flow of primary themes from both methods (FGDs and CPMEs), with emerging sub-themes demonstrating overlaps. For example, "loss of farm locations" emerges from both "Economic and livelihood" and "Pollution and contamination" themes. Additionally, the figure highlights the connection between FGDs and CPMEs through the shared theme of "Pollution and contamination.

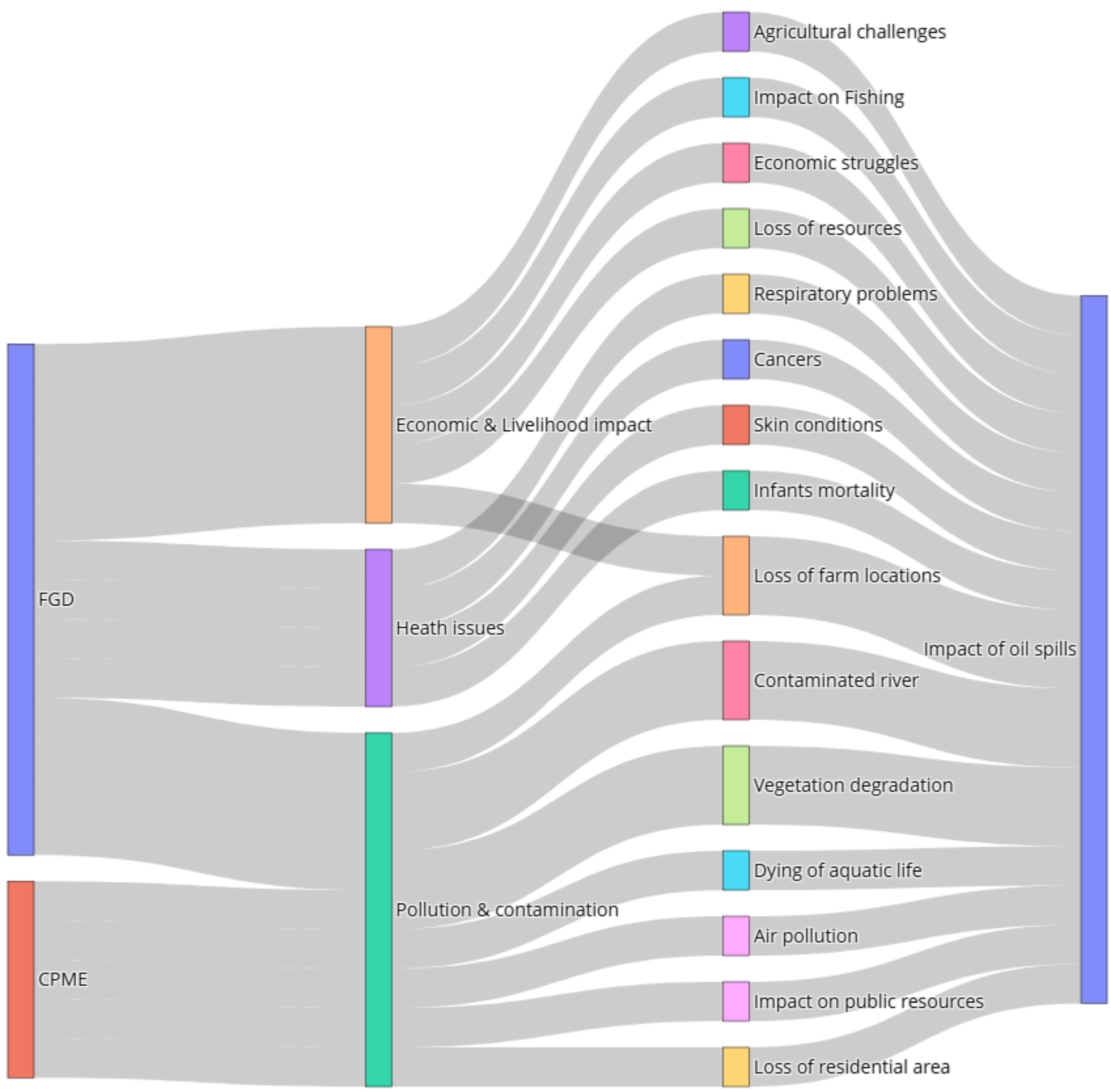


Figure 5.11. The substantive interconnectedness of the emerging themes and the integration of the FGD & CPME

The findings consistently highlight the devastating impact of oil spills on the environment, with water contamination, soil degradation, and air pollution as recurring themes. This aligns with existing literature documenting the extensive environmental damage caused by oil extraction in the Niger Delta. Amnesty International (2013) reports that hundreds of oil spills occur annually, damaging the environment and devastating lives. The UNEP (2011) investigation in Ogoniland revealed alarming levels of pollution, with extractable petroleum hydrocarbons (EPHs) in surface waters reaching 7420 µg/L and a staggering 42,200 µg/L in drinking water wells, exceeding WHO guidelines by over 900 times. Furthermore, unattended spills often escalate into fires, significantly altering biodiversity (UNEP, 2011). Research by Ordinioha and Brisibe (2013) found unusually high concentrations of ascorbic acid in vegetables grown on contaminated land and heavy metal concentrations in streams exceeding WHO standards. Mendoza-Cant et al. (2011), Ndidi et al. (2015), and Obida et al. (2018) emphasize the disproportionate impact of pollution on mangroves and rainforests, crucial carbon sinks vital for global climate change mitigation.

5.10 Niger Delta's Oil Pipelines and Spills through the Lens of Infrastructural Violence and Slow Violence

This section delves deeper into the devastating impacts of oil spills on the communities of Aghoro, Benikrukru, Bodo, Ogale, Okpoama, and Ubeji of Niger Delta region by employing the concept of infrastructural violence.

5.10.1 Oil Pipelines in the Niger Delta as Infrastructural Violence

As introduced, **infrastructural violence** highlights the detrimental ways in which infrastructure, such as oil pipelines, can converge in daily life to the detriment of marginalised actors (Rodgers and O'Neill, 2012). The experiences of these communities vividly illustrate both "active" and "passive" forms of this violence (Rodgers and O'Neill, 2012), as well as its "more-than-human" dimensions (Enns & Sneyd, 2020) and its manifestation as "slow violence (Nixon, 2011: 15)."

The oil pipeline network in the Niger Delta, a critical piece of infrastructure for crude oil extraction, stands as a paradoxical symbol. While intended for economic gain, its inherent failures and the resulting oil spills actively inflict harm on the environment and the communities dependent on it. This can be understood as **active infrastructural violence**. The direct contamination of land and water bodies, the destruction of vital ecosystems, and the immediate health impacts reported by residents are not merely unfortunate accidents but direct consequences of the presence and operation (or indeed, malfunction) of this infrastructure.

Conversely, the persistent lack of adequate public amenities, healthcare facilities, and alternative livelihood opportunities in these resource-rich areas, despite decades of oil extraction, exemplifies **passive infrastructural violence**. The vulnerability of the communities is exacerbated by this absence of supportive infrastructure, leaving them with limited capacity to cope with the impacts of the spills and hindering their ability to rebuild their lives and environments.

5.10.2 More-Than-Human Infrastructural Violence in the Niger Delta

Furthermore, focusing solely on the human experience risks overlooking the profound harm inflicted upon the nonhuman world. The concept of **more-than-human infrastructural violence** recognizes the violence enacted against ecosystems and the intricate relationships within them. The data from Section 5.7 provides compelling evidence of this:

> **Wetlands:** The reported severe water contamination and the death of fish populations in Aghoro (Quote 5.2), Benikrukru (Quote 5.10), Bodo (Quote 5.18), Ogale (Quote 5.27), Okpoama (Quote 5.33), and Ubeji (Quote 5.42) demonstrate the destruction of these vital ecosystems. Wetlands, serving as natural infrastructure for filtering water and supporting biodiversity, are actively degraded by the spills, disrupting ecological services and culturally significant fishing practices.
>
> **Forests and Vegetation:** The consistent reports of vegetation destruction, including mangroves (Quote 5.1, Aghoro; Quote 5.19, Bodo; Quote 5.29, Ogale; Quote 5.35, Okpoama) and other flora essential for various uses, highlight the more-than-human infrastructural violence against forest resources. The contamination of forests in Benikrukru (Quote 5.9) impacting wood for building further illustrates this. This loss affects not only the immediate resources but also the ecological infrastructure that provides essential ecosystem services and holds cultural value.
>
> **Farmlands:** The widespread soil contamination rendering farmlands infertile in Aghoro (Quote 5.1), Benikrukru (Quote 5.8), Bodo (Quote 5.19, 5.23), Ogale (Quote 5.28), Okpoama (Quote 5.34), and Ubeji (Quote 5.44) is a clear instance of more-than-human infrastructural violence against the land itself. This destruction of the soil's

capacity to support life directly impacts agricultural productivity and threatens food security, demonstrating the interconnectedness of human and environmental well-being. The CPME data, such as the identification of abandoned farmlands in Benikrukru (Figure 5.6) and Bodo (Figure 5.7), spatially corroborates this destruction.

Rivers and Water Bodies: Beyond the wetlands, the direct pollution of rivers, streams, and ponds across all communities (e.g., Quote 5.2, Aghoro; Quote 5.10, Benikrukru; Quote 5.18, Bodo; Quote 5.27, Ogale; Quote 5.33, Okpoama; Quote 5.42, Ubeji) constitutes a significant form of more-than-human infrastructural violence against these critical water sources. The CPME maps visually support the spread of contamination into these areas (e.g., Figure 5.5, Aghoro; Figure 5.9, Okpoama).

Soils: The reports of soil becoming hard and infertile due to oil contamination (Quote 5.28, Ogale; Quote 5.44, Ubeji) directly point to the violence inflicted upon the soil structure and composition, undermining its ecological function.

5.10.3 Oil Pipelines/Spills as Slow Violence in the Niger Delta

The cumulative and long-term effects of these repeated oil spills and the pervasive contamination they cause embody the concept of slow violence. Unlike sudden, visible acts of violence, slow violence unfolds gradually, often invisibly, accumulating over time and across space (Nixon, 2011). The chronic health issues reported by participants, such as respiratory problems, skin diseases, increased rates of malaria and typhoid, and concerns about long-term effects like cancer and reproductive issues (Quote 5.4, Aghoro; Quote 5.13, 5.14, Benikrukru; Quote 5.21, 5.22, Bodo; Quote 5.31, Ogale; Quote 5.37, 5.39, Okpoama; Quote 5.47, Ubeji), are manifestations of this slow violence. The persistent exposure to contaminated air and water leads to a gradual deterioration of health, the full extent of which may not be immediately apparent.

Similarly, the economic hardship experienced by the communities, including the decline in fishing yields (Quote 5.5, Aghoro; Quote 5.15, Bodo; Quote 5.40, Okpoama), the inability to farm (Quote 5.1, Aghoro; Quote 5.8, Benikrukru; Quote 5.23, Bodo; Quote 5.34, Okpoama; Quote 5.44, Ubeji), and the resulting food insecurity and poverty (Quote 5.7, Aghoro; Quote 5.16, Benikrukru; Quote 5.41, Okpoama; Quote 5.48, Ubeji), are not sudden events but the result of a prolonged process of environmental degradation undermining traditional livelihoods. The shift in land use practices, such as rushing to harvest crops before contamination worsens (Quote 5.25, Bodo), underscores the ongoing struggle against this creeping environmental violence.

Crucially, the communities in the Niger Delta are not simply passive victims of this slow violence. As Davies (2022) notes, people living with slow violence are often able to observe the incremental changes to their surroundings. The detailed testimonies and observations provided by the FGD participants in Section 5.7 serve as powerful acts of "bearing witness." Their ability to articulate the changes in their environment – the diminished mangroves, the altered water colour, the oily smell in the air, the reduced fish catches, the hardened soil – demonstrates their acute awareness of the slow violence unfolding around them. This informal knowledge, born from lived experience, is a critical form of recognizing and living with pollution (Davies, 2022).

The communal tensions and conflicts that arise from the spread of oil spills to neighbouring areas (Quote 5.25, 5.26, Bodo; Figure 5.8 showing flow from neighbouring communities in Ogale) also speak to the social dimensions of infrastructural violence and its potential to fracture relationships and exacerbate existing vulnerabilities.

In conclusion, the detailed data presented in Section 5.7, when interpreted through the theoretical lens of infrastructural violence and slow violence, reveals a complex picture of the multifaceted impacts of oil spills in the Niger Delta. The oil pipeline network, while a form of infrastructure, is deeply implicated in actively inflicting harm on the environment and livelihoods, passively contributing to vulnerability through the absence of essential services, enacting violence against the more-than-human world, and perpetrating a form of slow violence that erodes the health and well-being of communities over time. The voices of the community members, as captured in the FGDs and corroborated by the spatial data from the CPME, serve as crucial testimonies to this ongoing violence and highlight the urgent need for systemic change and environmental justice in the Niger Delta.

5.11 Study Limitation

While this study offers valuable insights into the lived experiences of communities affected by oil spills in the Niger Delta, it is important to acknowledge several limitations inherent in its design and execution. These limitations, primarily driven by the complex and challenging research environment, have shaped the nature of the data collected and the scope of the findings.

Firstly, the adaptation to a distanced research approach necessitated the involvement of local data collectors as intermediaries. This was a crucial safety measure given the security concerns in the region, which prevented direct, in-person fieldwork by the primary researcher. However, relying on data collectors meant that they became conduits through which community knowledge and concerns were garnered, understood, translated, and recorded. As highlighted in the research process, "the data collectors, being part of the local community, played a vital role in mediating questions and collecting responses." While their local proficiency and ability to translate were invaluable, it is essential to acknowledge that their agency inevitably played a role in shaping responses. The process of translating concerns into English may have led to a reduction in certain nuances present in the original local language accounts. Thus, while the data reflects the community's perspectives, it is mediated through the interpretation and recording of the data collectors, which is an inherent aspect of this research process that warrants recognition.

Secondly, the distanced nature of the research itself presents a limitation compared to traditional ethnographic or in-person qualitative studies. Direct immersion in the communities would likely have allowed for deeper rapport-building, more spontaneous interactions, and potentially richer, unprompted insights into the daily realities and subtle impacts of oil spills. While the chosen methods (FGDs and CPME conducted remotely through intermediaries) were effective in gathering structured information on perceived impacts, some of the tacit or less easily articulated aspects of living with ongoing environmental degradation might be less prominent than in a study involving prolonged researcher presence within the communities.

Thirdly, the collaboration with the National Bureau of Statistics (NBS) data collectors, while a pragmatic solution for data collection, introduced a layer of ethical and logistical complexity. As noted, "The complexities of this negotiation process became particularly evident with challenges related to data ownership... specifically between the primary researcher and the NBS." Furthermore, the dual role of NBS personnel as both state agents and researchers presented a delicate dynamic, potentially influencing community members' willingness to speak freely on sensitive issues related to government and corporate accountability. Navigating the ethical concerns stemming from this collaboration required careful consideration and highlights the difficulties in conducting independent research in contexts where state institutions are closely involved.

Finally, the study's focus on six specific communities, while allowing for in-depth exploration, means the findings may not be fully generalizable to the entire Niger Delta region. The Niger Delta is a vast and diverse area with varying levels of oil infrastructure density, ecological characteristics, and community socio-political dynamics. The experiences of the selected communities, while representative of significant impacts, may not capture the full spectrum of challenges faced across the entire region. Prioritizing only six communities, though necessary for manageability and depth within the scope of this research, limits the ability to make broader claims about the prevalence or severity of specific impacts across the entire Niger Delta.

Despite these limitations, the study provides a crucial account of the perceived dangers and challenges posed by oil spills from the perspective of affected communities, integrating their voices with spatial data. The chosen approach, while constrained by challenging circumstances, allowed for the collection of vital qualitative and spatial data that contributes to a more nuanced understanding of the multi-layered impacts of infrastructural and slow violence in the Niger Delta.

5.12 Conclusions

This chapter explored the multifaceted impacts of oil spills on six communities in the Niger Delta: Aghoro, Benikrukru, Bodo, Ogale, Okpoama, and Ubeji, by focusing on the concerns and lived experiences of the affected residents.

The findings consistently reveal a devastating environmental toll across all studied communities. Participants reported severe pollution and contamination of vital natural resources. Water bodies – rivers, creeks, streams, and ponds – are heavily polluted with crude oil, rendering them unusable for drinking, fishing, and domestic purposes, thereby eliminating essential resources and disrupting traditional practices (e.g., Aghoro, Quote 5.2; Benikrukru, Quote 5.10; Bodo, Quote 5.18; Ogale, Quote 5.27; Okpoama, Quote 5.33; Ubeji, Quote 5.42). Soil degradation is widespread, with contamination making land hard and infertile, severely impacting agricultural activities and threatening food security (e.g., Benikrukru, Quote 5.8; Bodo, Quote 5.23; Ogale, Quote 5.28; Okpoama, Quote 5.34; Ubeji, Quote 5.44). The reports of vegetation degradation, including the death of crucial mangroves and other plants, highlight the significant ecological damage and loss of resources essential for livelihoods and local biodiversity (e.g., Aghoro, Quote 5.1; Bodo, Quote 5.19; Okpoama, Quote 5.35; Ubeji, Quote

5.45). Furthermore, communities consistently reported issues with air quality, noting oily odours, black smoke, and particulate matter indicative of persistent contamination (e.g., Aghoro, Quote 5.3; Bodo, Quote 5.20; Ogale, Quote 5.30; Ubeji, Quote 5.46). The Community Participatory Mapping Exercises (CPME) visually corroborated these environmental impacts, illustrating the spatial extent of contamination, the flow patterns of spills, and the specific affected areas within each community, such as residential zones, water bodies, and farmlands (e.g., Figures 5.5, 5.6, 5.7, 5.8, 5.9, and 5.10).

The environmental degradation has direct and severe consequences for community health. Participants across all groups reported a range of health issues they attribute to the pollution, including respiratory problems, skin diseases, increased rates of illnesses like malaria and typhoid, and concerns about more serious long-term effects such as cancer, reproductive issues, and increased infant mortality (e.g., Aghoro, Quote 5.4; Benikrukru, Quote 5.13, 5.14; Bodo, Quote 5.21, 5.22; Ogale, Quote 5.31; Okpoama, Quote 5.37, 5.39; Ubeji, Quote 5.47). These health concerns underscore the profound human cost of persistent environmental contamination.

The economic and livelihood impacts of oil spills are equally devastating. Fishing and farming, the traditional mainstays of the local economy, have been severely disrupted or rendered impossible due to contaminated water and soil (e.g., Aghoro, Quote 5.5; Benikrukru, Quote 5.15; Bodo, Quote 5.24; Okpoama, Quote 5.40; Ubeji, Quote 5.48). This has led to substantial income loss, food insecurity, and widespread economic hardship, with participants describing struggles to feed their families and increased poverty (e.g., Aghoro, Quote 5.7; Benikrukru, Quote 5.16; Okpoama, Quote 5.41; Ubeji, Quote 5.48). Beyond fishing and farming, the degradation of natural resources has also hindered trade with neighboring communities and impacted the availability of resources used for traditional practices, further compounding economic challenges (e.g., Aghoro, Quote 5.6; Benikrukru, Quote 5.9; Ubeji, Quote 5.45).

The findings highlight that, over a decade after assessments like UNEP's (2011), the core issues of environmental degradation and associated health and livelihood impacts persist, with communities expressing skepticism about the effectiveness of current remediation efforts. Furthermore, the study revealed social consequences, including increased communal tensions stemming from the spread of spills to neighboring areas (e.g., Bodo, Quote 5.26).

In conclusion, the voices from Aghoro, Benikrukru, Bodo, Ogale, Okpoama, and Ubeji provide compelling evidence of the severe and ongoing environmental, health, and economic devastation wrought by oil spills in the Niger Delta. The consistency of these experiences across the studied communities, coupled with the spatial data confirming the extent of contamination, underscores the urgent need for effective interventions. These findings emphasize that addressing the crisis requires not only environmental remediation but also significant attention to the human cost, the restoration of livelihoods, and meaningful engagement with community concerns and knowledge.

Chapter Six

6. Synthesis

6.1 Introduction

This thesis developed a framework for understanding the impacts of oil spills in Nigeria's Niger Delta region by harnessing a mixed method approach – geospatial, remote sensing, and community knowledge. Recognising that the crisis of oil pollution in the Delta is a complex entanglement of environmental degradation, human suffering, and systemic failures, a multi-faceted approach was essential to move beyond siloed perspectives and capture the layered reality on the ground. Rather than treating environmental damage, its spatial patterns, and the human experience as separate phenomena, this study sought to weave them together into a coherent narrative.

Chapter 3 initiated this exploration by laying the groundwork: establishing the 'where' and 'when' of the oil spills. Utilising network geo-computation techniques - NKDE and TNKDE, this chapter analysed extensive oil spill data along the linear network of pipelines. By focusing on spatiotemporal patterns and identifying hotspots (as explored in Chapter 3), a crucial understanding of the physical geography of the hazard itself was gained – the locations and temporal dynamics where the failures of oil infrastructure most frequently manifest their destructive potential. This provided the essential spatial and temporal context for the subsequent analyses.

Building upon this spatial understanding, Chapter 4 then quantified the tangible environmental consequences of these spills. Employing remote sensing, machine learning, and cloud computing, this chapter assessed and mapped the impact on vegetation health across the extensive and diverse land covers of the Niger Delta. By demonstrating significant declines in vegetation indices following spills and quantifying the extent of contaminated land (as detailed in Chapter 4), this part of the thesis provided objective, empirical evidence of the ecological damage. This analysis speaks directly to the 'infrastructural violence and the more-than-human' dimensions of the crisis, illustrating how the physical presence and failures of infrastructure (the pipelines from Chapter 3) translate into measurable harm to the natural environment.

While Chapters 3 and 4 provided critical spatial and environmental data, a complete picture of the oil spill crisis in the Niger Delta is impossible without centring the human experience. Chapter 5 brought this essential perspective to the forefront, delving into the lived realities of communities residing in the shadow of oil infrastructure and pollution. Through qualitative methods, including focus group discussions and community participatory mapping (as presented in Chapter 5), the research captured the perceived dangers, challenges, health impacts, and livelihood disruptions articulated by those directly affected. The community-generated maps provided crucial spatial context from the ground, often validating the hotspots identified in Chapter 3 and illustrating how the environmental damage quantified in Chapter 4 translates into tangible impacts on homes, farmlands, and vital water sources within community space. This chapter illuminated the human scale of the problem and offered insights into how the environmental contamination constitutes a form of violence deeply embedded in the daily lives of residents.

Collectively, these chapters tell a story of how the infrastructure of oil extraction in the Niger Delta produces specific spatial and temporal patterns of spills (Chapter 3), resulting in quantifiable environmental degradation (Chapter 4), which in turn inflicts severe and interconnected harm on the health, livelihoods, and well-being of local communities (Chapter 5), see Figure 6.1. The real power of this research lies not in the individual chapters, but in the integration of these diverse forms of intelligence. Overlaying the spatial patterns of spills with the objective evidence of environmental damage and the subjective accounts and spatial knowledge of the communities allows for a triangulated understanding of the oil spill crisis – one that is both scientifically rigorous and deeply grounded in lived reality.

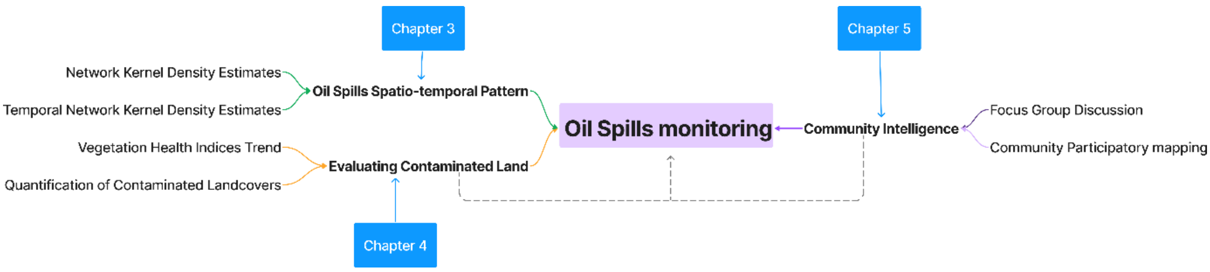


Figure 6.1. Synthesis of this study’s empirical chapters

This synthesis chapter brings together the findings from these preceding chapters to provide a holistic and nuanced overview of oil spill impacts in the Niger Delta. By integrating the geostatistical, remote sensing, and community-based data, a picture that speaks to the multi-scalar nature of the problem and underscores the critical connections between infrastructure, environment, and human well-being in this context was constructed. The experiences of the six studied communities were laid bare, analysing the convergence of quantitative evidence and qualitative accounts to provide a detailed synthesis of how oil spills shape the socio-environmental landscape of the Niger Delta. This integrated analysis serves to reinforce the key arguments woven throughout the thesis, particularly regarding the manifestation of infrastructural violence and slow violence in this heavily impacted region.

6.2 Oil Spills Contamination and Environmental Degradation along the Pipeline Network

The overarching goal of this thesis is to develop a comprehensive model integrating geospatial, remote sensing, and community intelligence to assess and quantify oil spill impacts on the Niger Delta environment. Chapter three delved into the NKDE and TNKDE analyses by identifying hotspots of oil spill incidents and provided insights into the temporal dynamics of these events. While Chapter three detailed the areas and pipeline segments most affected by oil spills, the strength of the study lies in its ability to link spatial hotspots to specific environmental deterioration levels.

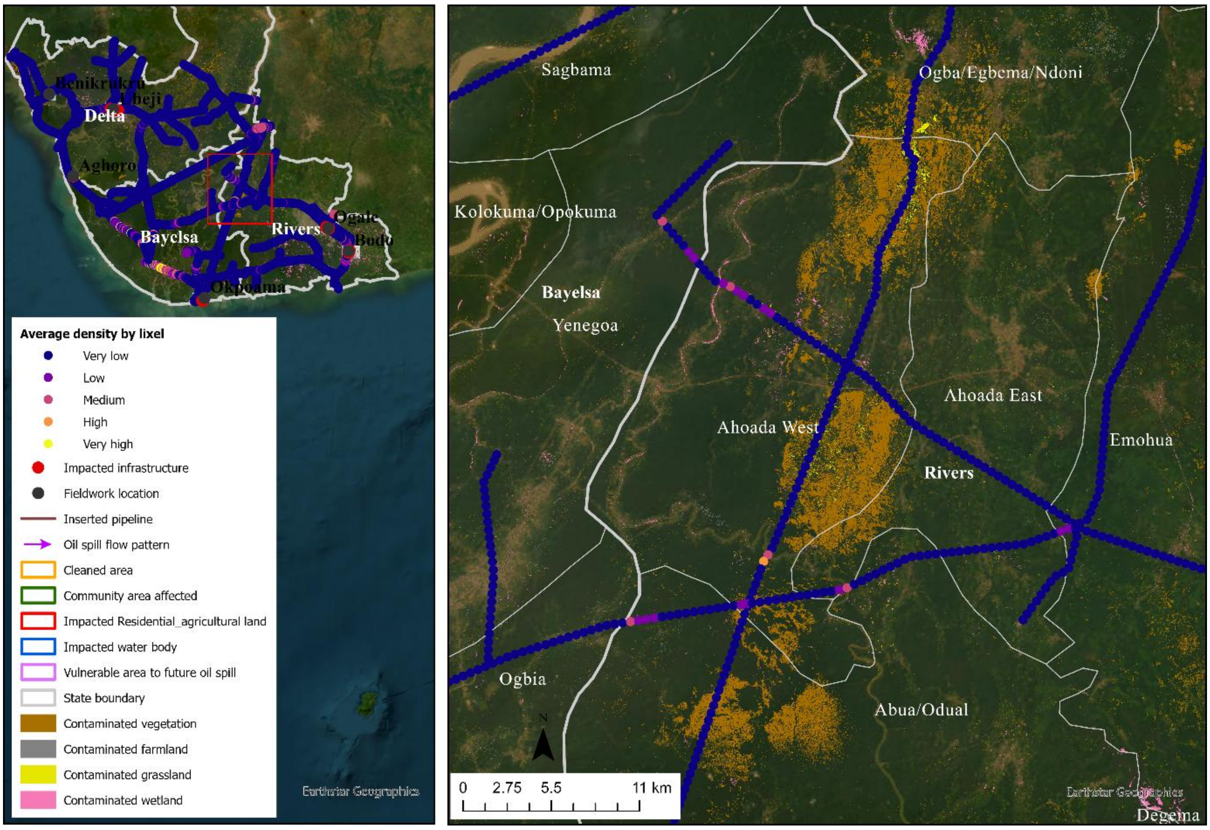


Figure 6.2. Showcases the section of pipeline with high concentrations of oil spills incidents but also the overlay analysis of the results of the classification analysis; areas in orange depict the oil spills impacting dense vegetation landcover while the yellow depict the impacted grassland.

For example, Figure 6.2 highlights pipeline sections with high oil spill concentrations and overlays these with classification results from Chapter Four, providing insights into the extent of environmental degradation. As previously established in Ikporupo (2020), NOSDRA faces challenges in accurately capturing oil spill incidents due to inadequate resources and enforcement capacity against oil companies. Consequently, some pipeline sections with low incident reports exhibit significant environmental damage, likely due to the volume of oil spilled or unreported incidents. The NKDE and TNKDE analyses, which measure incidents per 500-meter pipeline segments, illustrate this disconnect.

Integrating the NKDE/TNKDE and remote sensing classification results provides a more nuanced understanding of oil spill impacts. Beyond identifying affected regions, this approach reveals the specific land cover types impacted and quantifies the extent of the damage. For instance, the classification results highlight the direct correlation between pipeline oil spills and vegetation degradation, particularly along pipeline routes. Figure 6.2 vividly illustrates how the pervasive nature of spilled crude oil contributes to extensive environmental damage in areas adjacent to pipelines.

6.2.1 What are the Emerging Spatio-temporal Patterns of Oil Spillages Recorded along the Pipeline Network in the Niger Delta?

Addressing the first research question of this thesis, which aims to understand the emerging spatio-temporal patterns of oil spills along the pipeline network, this study employed NKDE and TNKDE analyses. These approaches facilitated the identification of oil spill hotspots and their evolution over time. The analysis revealed significant spatio-temporal trends. Brass, Ekeremor, and Southern Ijaw LGAs in Bayelsa State consistently exhibited high concentrations of oil spill incidents, particularly between 2013 and 2017. Further analysis within Southern Ijaw LGA identified persistent medium to high-density clusters around Egbomatoro community, Sangana River, Tebitada creek and community, and the Ikebiri Creek Forest Reserve and River from 2013 to 2016. However, these areas experienced a reduction in incident clusters from 2017 onwards.

Similarly, medium to low-density clusters were observed in Alaboutoru Creek (Nembe LGA), Brass LGA, and near the Ebocha community in Ogba/Egbema/Ndoni LGA (Rivers State) from 2014 to 2016. Other sections of the pipeline network recorded low to no density hotspots during this period. Encouragingly, a substantial reduction in oil spill incidents was observed in previously high-density areas from 2017 onwards, particularly between 2019 and 2021.

Overall, the analysis revealed a noticeable decline in oil spill frequency from 2016 to 2021 compared to previous years (Figure 3.8c). As explained in chapter three, this trend may be attributed to various factors, including increased surveillance, and improved operational practices. These findings emphasise the urgent need for proactive measures, including robust remediation and enhanced monitoring systems, to mitigate the environmental and socio-economic impacts of oil spills in the Niger Delta.

6.2.2 How effective are remote sensing based approaches for evaluating contaminated areas and the environmental impact of oil spills?

The second research question examines the efficacy of remote sensing-based approaches in evaluating oil spill contamination and its environmental impacts. This study demonstrates the power of integrating satellite imagery with advanced geospatial analysis and machine learning tools to assess the environmental implications of oil spills in the Niger Delta. Oil contamination disrupts vegetation by depleting soil oxygen necessary for plant respiration, leading to severe declines in plant health. Remote sensing emerges as a critical tool for distinguishing between oil-contaminated and unaffected areas, particularly in remote or unsafe regions. This capability is vital for managing and preserving the complex and expansive Niger Delta ecosystem.

Using geospatial cloud computing, remote sensing and machine learning techniques, this study developed an approach to evaluate oil-contaminated areas. The analysis of vegetation health trends on the prioritised training sites revealed significant declines in vegetation health index values after oil spill incidents. Key indices such as NDVI, EVI2, GRNDVI, and GNDVI were prioritised for their ability to accurately differentiate between oil-affected and unaffected land cover. An SMA regression analysis identified substantial declines in these indices across contaminated dense vegetation from 2016 to 2023.

NDVI exhibited a strong negative correlation with time (Spearman's $\rho = -0.77$, $p = 0.0005$), indicating progressive declines in vegetation health. EVI2 ($\rho = -0.77$, $p = 0.0005$), GRNDVI ($\rho = -0.82$, $p = 0.0001$), and GNDVI ($\rho = -0.68$, $p = 0.004$) showed similar trends, confirming the detrimental impacts of oil spills on vegetation. The Random Forest (RF) classifier effectively quantified land cover contamination, identifying 22.81% of the total land area as non-contaminated dense vegetation (8,390 hectares) and 1.39% (513 hectares) as contaminated. Grasslands and wetlands exhibited marked differences in contamination levels, further highlighting the localised impacts of oil spills.

Beyond assessing impact, this study demonstrates the value of remote sensing for timely information dissemination and response coordination. By identifying areas requiring immediate intervention, these techniques can enhance environmental monitoring and compliance in oil-producing regions. The findings emphasise the potential of spectral techniques for detecting, monitoring, and ultimately remediating oil-polluted sites.

6.2.3 What are the perceived dangers and challenges posed by oil spillages for the Niger Delta communities?

The third research question explored the perceived risks and challenges posed by oil spills to Niger Delta communities. To address this, qualitative methods, including Focus Group Discussions (FGDs) and Community Participatory Mapping Exercises (CPME), were employed in six communities: Aghoro, Benikrukru, Bodo, Ogale, Okpoama, and Ubeji. These methods provided a nuanced understanding of local experiences, capturing the socio-environmental, economic, and cultural dimensions of oil spill impacts. FGDs revealed widespread environmental degradation, including water contamination, soil infertility, and air pollution. Participants consistently reported health issues linked to oil pollution, such as respiratory illnesses, skin conditions, infant mortality, and cancer. Livelihoods based on fishing and farming have been severely disrupted, with significant declines in agricultural productivity, fish populations, and food security. Soil degradation has led to poor crop yields, while contaminated rivers have rendered traditional fishing practices unviable.

Beyond environmental and economic challenges, oil spills have deeply affected social and cultural dynamics. Participants described disruptions to traditional practices, restricted access to cultural sites, and escalating communal conflicts as oil spills spread from one community to another. Communities also reported premature crop harvesting to mitigate contamination risks, dependence on purchased sachet water due to polluted rivers and wells, and heightened insecurity.

The CPME complemented these narratives by translating them into spatial data, visualising the geographical extent of oil spill impacts and incorporating local knowledge. This spatial context enriched the qualitative findings, offering a more nuanced understanding of the challenges faced by these communities.

6.3 Integrating Geospatial, Remote Sensing, and Community Knowledge

Mahmoud (2021) rightly emphasizes the critical need for advanced environmental monitoring tools capable of geo-visualization and analysis to effectively identify, understand, and contextualize the spatial impacts of oil spills. While sophisticated quantitative methods are essential, they often fall short of capturing the full spectrum of impacts, particularly the nuanced socio-economic and health consequences experienced by affected communities. This thesis posits that a truly robust framework for understanding and addressing oil spill impacts in the Niger Delta requires integrating objective spatial and environmental data with the subjective experiences and spatial knowledge of those who live daily with the consequences. This integration moves beyond simply presenting different types of data; it is a methodological choice fundamental to achieving the thesis's aim of developing a holistic impact assessment framework.

The integration in this study was achieved through a deliberate process of spatially converging the quantitative and qualitative findings. Specifically, the research involved:

Overlaying Spatial Datasets: The geostatistical results from Chapter 3 (NKDE and TNKDE maps indicating oil spill hotspots and density along pipelines) and the remote sensing classification results from Chapter 4 (maps showing the spatial extent and type of contaminated land cover, particularly vegetation health) were digitally overlaid.

Integrating Community Spatial Knowledge: The georeferenced maps generated during the Community Participatory Mapping Exercises (CPME) in Chapter 5, which depicted community-identified affected areas (residential zones, water bodies, farmlands, infrastructure) and crucial spatial details like oil spill flow patterns, served as essential base layers and interpretive frameworks. The CPME maps provided the local spatial context, allowing the overlay of quantitative data to be understood within the community's own geographical understanding.

Contextualising Quantitative Patterns with Qualitative Narratives: The rich qualitative data from the Focus Group Discussions (FGDs) in Chapter 5 – the testimonies, concerns, and experiences regarding pollution, health, livelihoods, and social dynamics – were used to provide meaning and depth to the spatial patterns revealed by the quantitative analyses.

Analysing these different types of data together offers distinctive and significant benefits that would not be possible through a single-method approach:

Triangulation and Validation: The convergence of findings across different methods strengthens their validity. For instance, if NKDE analysis identifies a pipeline segment with a high density of spills (Chapter 3), remote sensing shows significant vegetation degradation in the adjacent area (Chapter 4), and community members consistently report the destruction of their farmlands in that exact location and link it to spills (Chapter 5 FGDs and CPME), this powerful triangulation provides robust evidence of a severe, localized impact. Conversely, discrepancies can prompt further investigation into the limitations or specific context of each data source.

Filling Knowledge Gaps: Quantitative data can show what is happening and where (e.g., the extent of contaminated wetlands), but qualitative data explains the human significance of this (e.g., how contaminated wetlands destroy fishing livelihoods and cultural practices). Similarly, community knowledge can highlight perceived problems or affected areas (e.g., a contaminated well), which quantitative methods can then be used to verify or quantify if not already apparent.

Providing Context and Meaning to Spatial Patterns: Geospatial hotspots or areas of vegetation stress are abstract data points until they are contextualized by the lived experiences of the people affected. Community narratives explain how the contamination impacts daily life, health, and economic well-being, providing the crucial 'so what?' to the spatial patterns.

Identifying Locally Relevant Issues: CPME allows communities to highlight areas and impacts that are most important to them, including intangible or culturally significant sites that might not be captured by standard environmental indicators used in remote sensing. This ensures the research addresses issues of local priority.

Understanding Complex Linkages: The integrated approach helps to illustrate and understand the complex causal chains between the hazard (spill location/frequency), the environmental consequences (type and extent of contamination), and the socio-economic and health impacts. By overlaying maps showing spills, contaminated land, and community areas, and interpreting these visually with narratives about lost livelihoods or health issues, the interconnectedness becomes clear.

Enhanced Communication and Actionability: Combining maps that show scientifically derived contamination data with community-drawn maps of affected areas creates powerful visualizations. These integrated maps, supported by compelling human testimonies, can be potent tools for communicating the severity and localized nature of the impacts to policymakers, oil companies, and the wider public, thereby supporting advocacy and the development of more targeted and effective interventions.

The following sections elaborate on this integrated analysis for the studied communities, presenting the overlaid spatial results and weaving in the qualitative insights to provide a detailed synthesis of the multifaceted impacts of oil spills in the Niger Delta, demonstrating the distinctive benefits of combining these diverse forms of intelligence.

6.3.1 Bodo and Ogale Communities (Rivers state)

The integration of geospatial and remote sensing results with community-based testimonials highlights the profound impacts of oil spills in Bodo and Ogale communities. Figure 6.3 presents the NKDE and the classification results, showing the density of oil spill incidents along pipelines running through the centres of these communities, with the CPME maps serving as basemaps.

In Ogale, the proximity of the community to crude oil pipelines renders the entire area highly vulnerable to oil spills. Participants consistently reported widespread water contamination, with rivers, streams, and lakes polluted to the extent that they are unsuitable for fishing or domestic use. The geospatial analysis corroborates these accounts, identifying water bodies already impacted by spills and facilities affected within the community (denoted with red dots). Additionally, the classification of land cover types reveals that wetlands in Ogale are predominantly contaminated, as depicted by the pink coloration in Figure 6.3. The death of mangroves and a general decline in vegetation health were noted, alongside economic and health challenges. Livelihoods reliant on fishing and agriculture have been severely disrupted, with participants reporting infertile lands and significant declines in crop productivity.

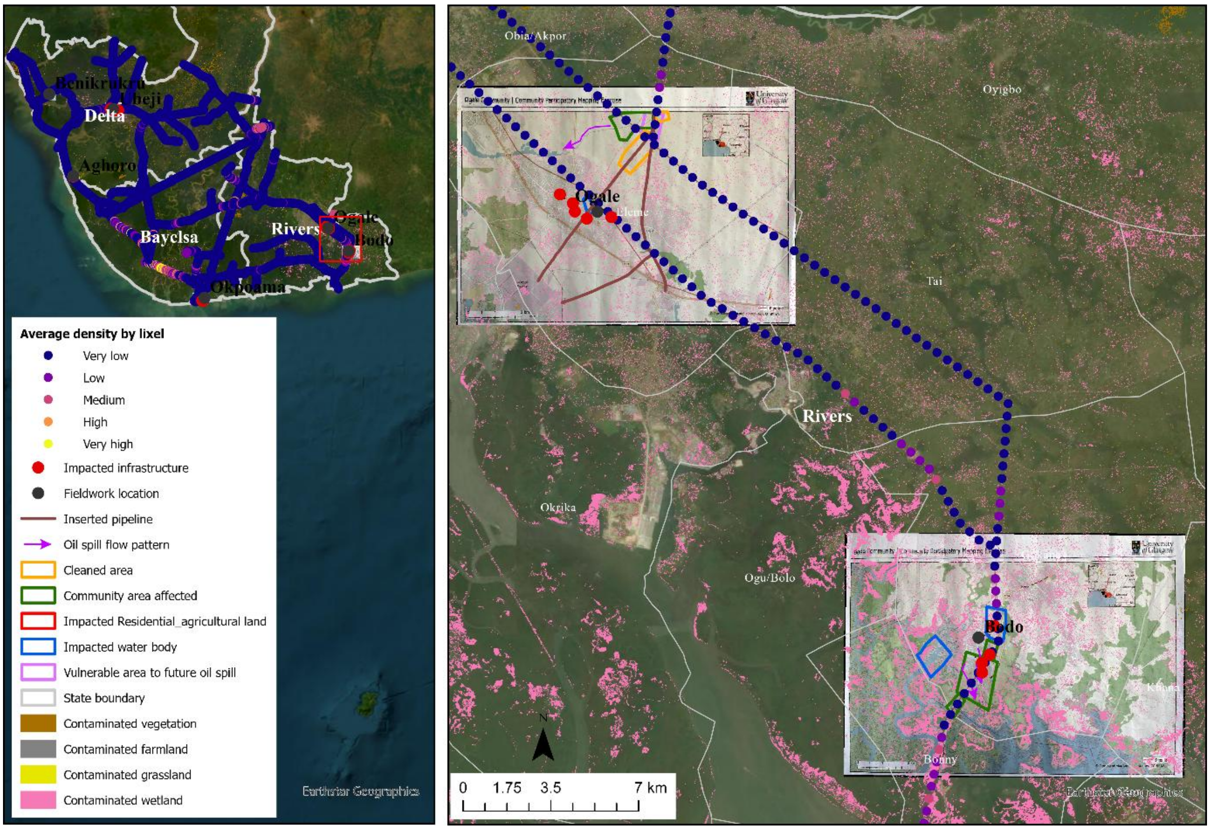


Figure 6.3. Integrating the NKDE and classification results with the georeferenced CPME maps of Ogale and Bodo communities.

Similarly, in Bodo, the NKDE analysis shows that crude oil pipelines run directly through the community, exposing residents to high spill vulnerability. The overlay of NKDE results with CPME maps highlights areas directly impacted by oil spills, including contaminated water bodies and facilities. Participants shared concerns about the contamination of essential water sources previously used for drinking, cooking, and fishing. Borehole water was reported to carry strong odours of crude oil, with chemical contaminants like benzene further degrading water quality. The classified land cover types also highlight widespread contamination of wetlands in Bodo, shown in pink in Figure 6.3. The effects on agriculture and fishing were severe, with declining fish populations and reduced crop fertility, leading to economic hardships for residents. Health issues, attributed to environmental contamination, were frequently mentioned by community members. Figure 6.3 underscores the precarious environmental conditions in the Niger Delta. By integrating NKDE results with remote sensing classifications and community testimonials, this analysis paints a nuanced picture of the multifaceted impacts of oil spills. This holistic approach reveals not only the spatial distribution of oil spills but also the underlying vulnerabilities of communities and ecosystems. The findings emphasise the urgent need for targeted remediation measures to mitigate the pervasive environmental and socio-economic damage caused by oil spills not only in Bodo and Ogale but in the region.

6.3.2 Aghoro Community (Bayelsa state)

In Aghoro Community, participants identified several critical areas affected by oil spills, including water bodies, residential zones, and agricultural lands. Testimonies consistently highlighted the destruction of essential vegetation, particularly mangroves and other flora critical for farming and environmental stability. These findings align with the results displayed in Figure 6.4, where classified contaminated land cover shows significant impacts on dense vegetation, depicted in orange.

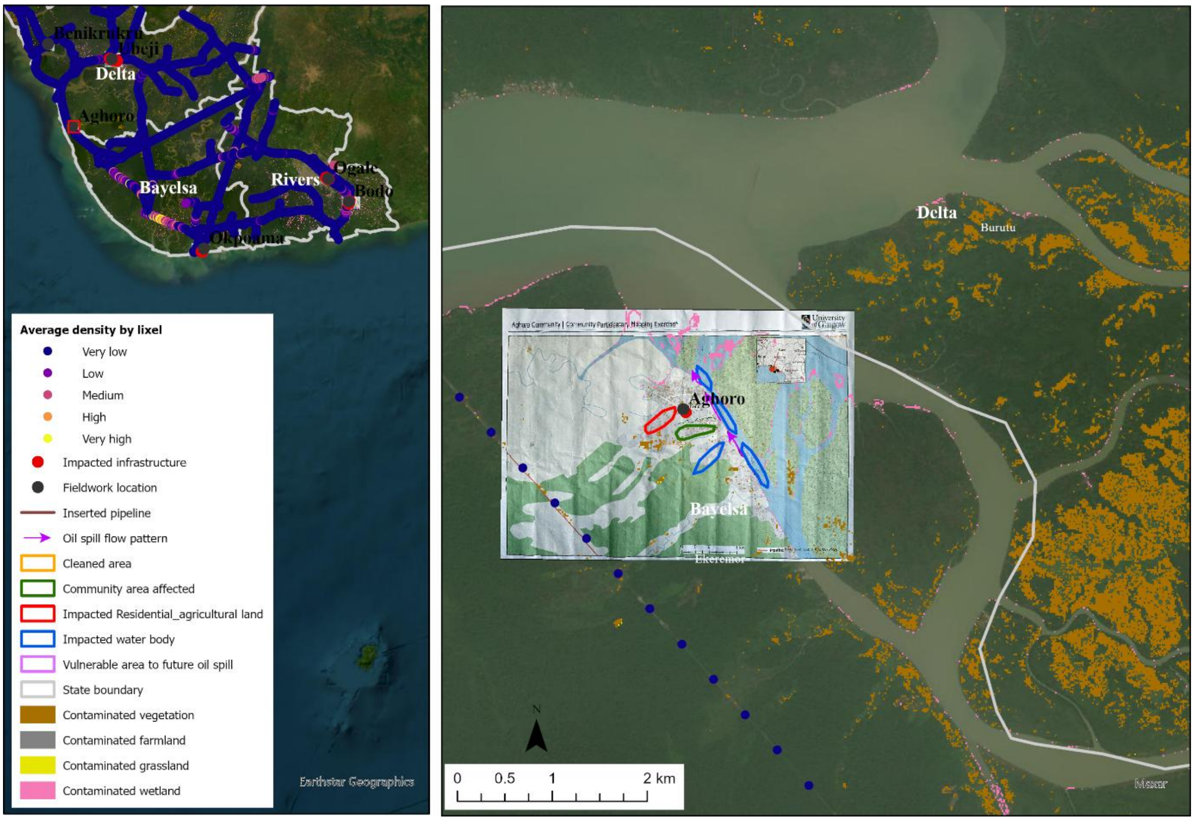


Figure 6.4. Integrating the NKDE and classification results with the georeferenced CPME maps of Aghoro community

The widespread environmental degradation has had severe socio-economic repercussions. Fishing and farming, which form the backbone of Aghoro's economy, have been severely disrupted. Oil contamination in rivers has drastically reduced fish populations, depriving local fishermen of their primary livelihood. Similarly, oil-saturated soil has rendered farmlands infertile, leading to diminished crop yields and threatening food security. Participants across various demographic groups also reported health issues, which they attributed to prolonged exposure to contaminated environments.

The spatial analysis corroborates these accounts, revealing dense contamination of vegetation around the community. A notable feature in Figure 6.4 is the presence of sporadic contaminated wetlands (depicted in pink), which appear along the riverbanks. The surrounding water bodies further highlight the vulnerability of Aghoro, given the community's dependence on aquatic ecosystems for sustenance and economic activities.

This integration of community narratives with geospatial results underscores the intricate linkages between oil spills, environmental degradation, and socio-economic decline. The findings emphasise the urgent need for targeted intervention measures to restore ecosystems and secure livelihoods in Aghoro.

6.3.3 Okpoama Community (Bayelsa state)

In Okpoama Community, the integration of geospatial analysis with community input highlights the severe socio-environmental consequences of oil spills. Using the CPME, participants identified several key areas affected by oil spills, including water bodies, residential zones, agricultural lands, community areas, and two pieces of critical infrastructure. These findings are reinforced by the discussions during the FGDs, where participants consistently reported severe water contamination. Rivers, creeks, and ponds were described as heavily polluted by crude oil, rendering them unsuitable for fishing, drinking, and other essential purposes. Soil degradation is another pressing issue in Okpoama, with participants observing changes in tree health and colour, including mangroves that are vital to the local ecosystem. The economic impact is equally devastating, as fishing—a primary source of income and sustenance—has been severely disrupted. Reduced fish populations due to oil contamination in rivers and infertile farmlands from oil-soaked soils have left many community members struggling to maintain their livelihoods. Participants also reported widespread health issues, attributing them to the ongoing environmental degradation.

These observations align with the results depicted in Figure 6.5, which shows the classified contaminated land cover types. Wetland vegetation, depicted in pink, is identified as the most heavily impacted. This is unsurprising, given the community’s proximity to rivers and wetlands, which exacerbate the spread of contamination. Although the pipeline does not run directly through the centre of the community, its close proximity means that oil spills are easily dispersed across the area due to the interconnected water bodies and wetlands.

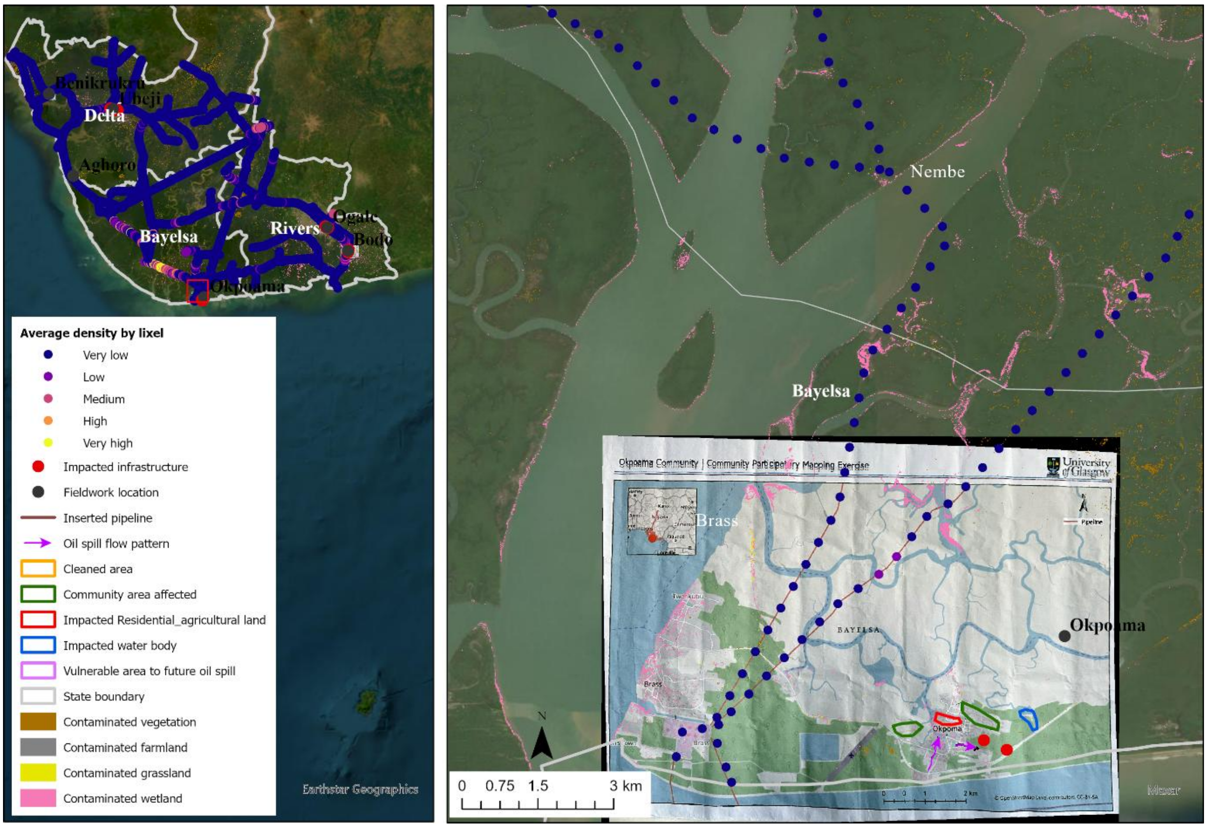


Figure 6.5. Integrating the NKDE and classification results with the georeferenced CPME maps of Okpoama community

Figure 6.5 illustrates the vulnerability of Okpoama, emphasising the role of its surrounding hydrological and ecological features in amplifying the effects of oil spills. The findings underscore the urgent need for targeted interventions to address the environmental degradation and restore the livelihoods of affected community members.

6.3.4 Benkrukru Community (Delta state)

In Benikrukru Community, the integration of CPME geospatial analysis and community testimonials highlights the extensive vulnerabilities and impacts of oil spills. As seen in Figure 6.6, the entire community area is highly vulnerable to future oil spills due to pipelines running directly through it. Participants identified specific zones already impacted, including community areas, abandoned farmlands, and heavily polluted waterways. They also mapped the flow patterns of previous oil spills, providing critical insights into the spatial dynamics of contamination across the community. The FGDs revealed that soil infertility is a significant concern in Benikrukru, with farmlands rendered unusable. Participants expressed distress over the contamination of forests, which traditionally supplied essential resources such as building materials and herbal plants. Rivers and streams, central to the community's sustenance, were reported as severely polluted, resulting in reduced fish populations and subsequent economic hardship for local fishermen. The mapping and testimonies also emphasised the need for targeted health interventions in zones most affected by pollution.

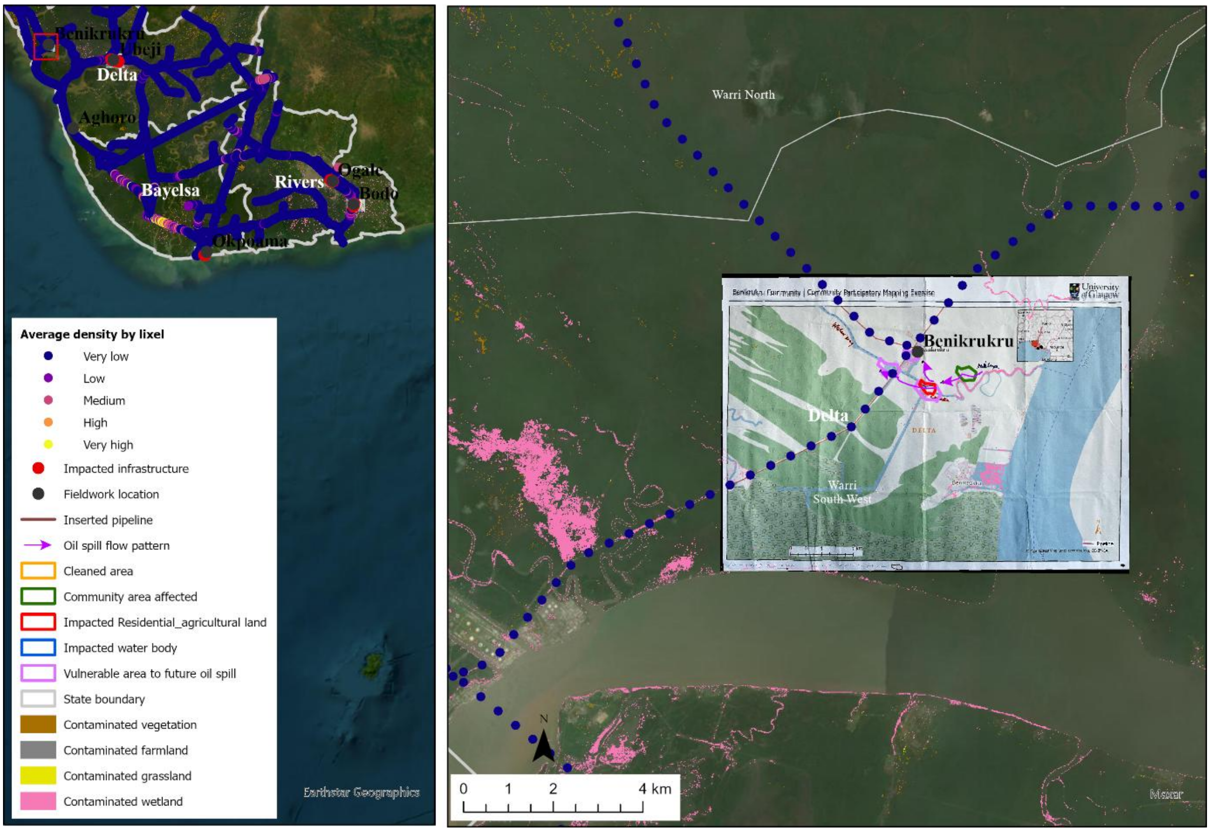


Figure 6.6. Integrating the NKDE and classification results with the georeferenced CPME maps of Benikrukru community

These observations align closely with the geospatial findings. The classified contaminated land cover types in Figure 6.6 show that wetland vegetation is the most impacted, depicted in pink. Contaminated wetlands are particularly noticeable along riverbanks and closely follow the oil spill flow patterns drawn by community members, emphasising the interconnectedness of environmental and community vulnerabilities. Benikrukru, like many other communities in the Niger Delta, is surrounded by water and wetlands, making it especially susceptible to the spread of oil spills. The integration of community knowledge with spatial analysis in this study underscores the need for urgent interventions to address both the environmental and socio-economic challenges faced by the community.

6.3.5 Ubeji Community (Delta state)

In Ubeji Community, the integration of geospatial analysis and community insights highlights extensive environmental degradation and its profound socio-economic consequences. Participants identified impacted infrastructure, residential zones, and agricultural areas, while consistently reporting severe water contamination. Rivers, streams, and even rainwater were described as unusable due to widespread oil pollution. Soil degradation also emerged as a significant concern, with participants linking these environmental changes to various health issues. Fishing and farming, which are central to Ubeji's economy, have been severely disrupted. Oil contamination in rivers has drastically reduced fish populations, depriving fishermen of their primary source of income. Similarly, oil-soaked soil has rendered farmlands infertile, leading to diminished agricultural productivity and threatening local livelihoods. Participants across demographic groups consistently reported the compounding health challenges posed by the degraded environment.

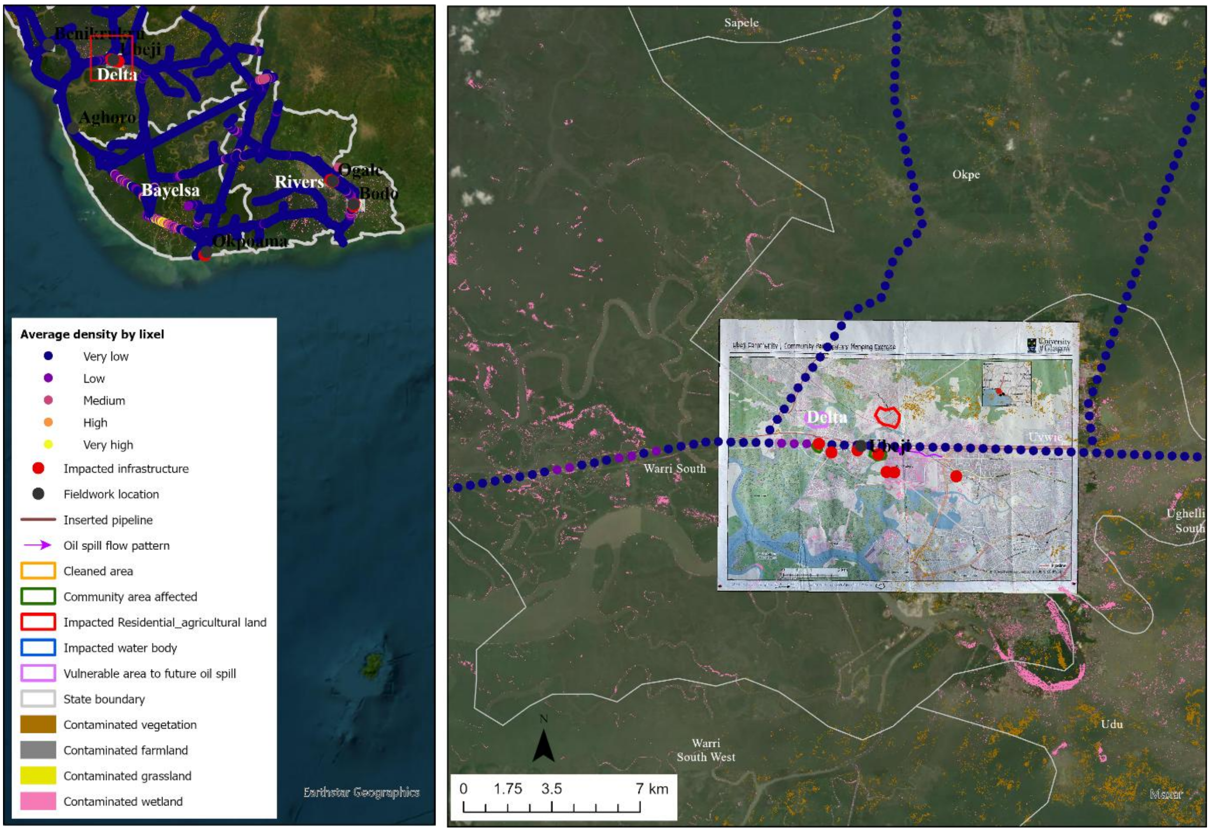


Figure 6.7. Integrating the NKDE and classification results with the georeferenced CPME maps of Ubeji community

The geospatial findings depicted in Figure 6.7 align with these community testimonies. The classified contaminated land cover types show that wetland vegetation, depicted in pink, is the most heavily impacted. Contamination is particularly evident around the rivers, wetlands, and along the pipeline network that runs through the community. This proximity to pipelines makes the entire community highly vulnerable to future oil spills. The results emphasise the interconnectedness of Ubeji's surrounding rivers, wetlands, and pipeline infrastructure, amplifying the scale of environmental degradation. The findings underscore the need for immediate intervention to address the environmental, economic, and health challenges faced by the community.

6.4 Conclusion

This synthesis chapter brought together the distinct, yet complementary, forms of intelligence gathered in the preceding chapters to construct a comprehensive understanding of oil spill impacts in the Niger Delta. By integrating the geospatial analysis of spill patterns (Chapter 3), the remote sensing assessment of environmental damage (Chapter 4), and the qualitative insights and spatial knowledge from affected communities (Chapter 5), this chapter achieved a triangulated view of the crisis that transcends the limitations of any single method.

The synthesis process, particularly through the spatial overlay of quantitative data with community-generated maps and the interpretation of these layers using qualitative narratives, yielded critical insights into the interconnectedness and severity of oil spill impacts. The convergence of evidence was striking areas identified as oil spill hotspots through network analysis (Chapter 3) consistently correlated with regions showing significant vegetation degradation in remote sensing imagery (Chapter 4), and these spatially defined environmental impacts were precisely where communities reported the most severe consequences for their health, livelihoods, and environment (Chapter 5).

This integrated picture powerfully demonstrates how the physical presence and failures of oil infrastructure translate into tangible environmental destruction and profound human suffering. The synthesis highlighted how community-identified affected areas, including residential zones, farmlands, and vital water bodies, directly overlap with areas of high spill density and environmental contamination revealed by the technical analyses. This not only validated the scientific findings with local realities but also provided essential context, revealing the lived experience behind the data points. The community maps, detailing spill flow patterns and specific impacted resources, offered an invaluable layer of local knowledge that enriched the interpretation of the broader spatial trends.

Ultimately, the synthesis confirms that the impacts of oil spills in the Niger Delta are severe, pervasive, and deeply interconnected across environmental and social domains. It provides empirical grounding for understanding the crisis through concepts such as infrastructural violence, highlighting how the infrastructure itself facilitates harm, and slow violence, illustrating the cumulative and insidious nature of living with persistent pollution.

In concluding this synthesis, the integrated findings underscore the urgent need for a holistic and spatially-informed approach to addressing oil spill impacts. Effective interventions must be guided not only by technical data on spill location and environmental damage but critically by the detailed, localized knowledge and experiences of the affected communities. The framework presented here, integrating diverse intelligence sources, offers a robust basis for more targeted monitoring, effective remediation planning, and the development of strategies that genuinely respond to the complex realities and vulnerabilities faced by communities in the Niger Delta.

Chapter Seven

7. Conclusions

7.1 Contribution to Knowledge

This thesis set out to develop a comprehensive framework for understanding and assessing the devastating impacts of oil spills in the Niger Delta by integrating geospatial, remote sensing, and community-based intelligence. By moving beyond single-method approaches, the research successfully produced novel insights into the complex interplay between oil infrastructure, environmental degradation, and human well-being, offering a more complete picture of the crisis faced by affected communities. The core contribution of this study lies in the new knowledge generated through the synthesis of diverse forms of intelligence, providing a spatially explicit, environmentally quantified, and human-centered understanding of oil spill impacts.

The integrated analysis confirmed and profoundly illustrated the severe, multifaceted, and interconnected nature of oil spill impacts in the Niger Delta. By combining spatial analysis of spill patterns, remote sensing of environmental contamination, and the lived experiences and spatial knowledge of six affected communities, the research provided compelling evidence that:

Oil infrastructure directly inflicts widespread environmental damage: The study's geospatial analysis (Chapter 3) precisely mapped the hotspots of oil spills along the pipeline network, revealing areas with persistently high occurrences. Complementing this, remote sensing (Chapter 4) quantified the tangible environmental consequences, showing significant, measurable damage to vital ecosystems like dense vegetation and wetlands in these spill-prone areas. This rigorous, spatially explicit evidence of contamination highlights how the physical presence and failures of oil infrastructure actively degrade the natural environment, a key empirical contribution grounding the concept of *active infrastructural violence* and *more-than-human infrastructural violence* in this context.

Environmental degradation translates directly into severe human impacts: The synthesis demonstrated a clear and validated link between the scientifically identified areas of contamination and the health, livelihood, and social challenges reported by community members (Chapter 5). Community participatory mapping visually overlaid perceived affected areas – homes, farms, water sources – onto maps showing spill hotspots and environmental damage, providing powerful spatial corroboration. Qualitative narratives added crucial depth, explaining how contaminated water and soil lead to specific health issues (respiratory problems, skin diseases, increased illness), destroy traditional livelihoods (fishing, farming), and precipitate severe economic hardship and food insecurity. This integrated finding is a central contribution, illustrating the human scale of the environmental crisis and the manifestation of *infrastructural violence* and *slow violence* in the daily lives of the affected population.

The interconnectedness of the socio-environmental system amplifies vulnerability: The study vividly illustrated how the Niger Delta's unique geography – its network of waterways, wetlands, and proximity of communities to infrastructure – facilitates the rapid spread of oil spills. The spatial integration showed how spills originating from pipelines quickly impact water bodies and adjacent lands, leading to widespread contamination that affects multiple aspects of community life simultaneously. This holistic view of interconnectedness, enabled by combining different data layers, is crucial for understanding the systemic nature of the vulnerability.

Beyond these key empirical findings regarding impacts, the research also produced valuable new knowledge in methodological and academic domains:

> **Demonstrating the practical applications of NKDE and TNKDE:** the study advances the field of network-based spatial analysis by providing open-source tools, incorporating temporal analysis, and demonstrating the practical applications of NKDE and TNKDE for understanding and mitigating risks associated with critical infrastructure networks.

> **Demonstrating the Power of Integrated Methods:** The study successfully implemented a mixed-methods approach that effectively combined geospatial techniques (NKDE/TNKDE in open-source software), remote sensing and cloud computing for contaminated land assessment and quantification, and community-based qualitative methods (FGD, CPME). This integrated methodological blueprint offers a robust framework for future research in complex socio-environmental settings, demonstrating how diverse forms of data can be synergistically combined to produce nuanced insights that single methods cannot achieve. The successful integration of community intelligence with technical spatial analysis, in particular, represents a

significant methodological contribution for environmental justice research and participatory mapping practices.

Navigating Research Challenges in High-Risk Contexts: The adaptation to a distanced research approach and the negotiation of ethical complexities in collaboration with local data collectors (Chapter 5) provide important lessons for conducting research in challenging and high-risk terrains within the Global South. The study's documented approach to prioritising safety while striving for ethical rigor contributes to academic knowledge on research methodologies in difficult contexts.

Methodological Blueprint: integration of qualitative insights (such as community intelligence) with quantitative spatial analyses (using tools like remote sensing and geospatial techniques) forms a robust methodological blueprint. This approach can be tailored to other environmental challenges or regions where similar data gaps exist.

Community Engagement: By demonstrating how to effectively involve local communities in the research process (through participatory mapping and focus group discussions), my work shows that meaningful engagement can lead to richer data and more actionable insights. This model can inspire similar practices in regions facing environmental or social challenges, ensuring that research is grounded in local realities.

Environmental Management: By identifying high-risk areas, resources can be allocated effectively for prevention and mitigation efforts. The TKNDE highlights the shifting nature of oil spill occurrences and underscores the importance of continuous monitoring and adaptive management strategies.

The new knowledge generated by this thesis holds significant implications. By providing validated, spatially explicit, and human-centred evidence of oil spill impacts, it offers crucial support for environmental justice advocacy in the Niger Delta. The detailed findings on hotspots, environmental damage types, and community-reported consequences can directly inform more effective and targeted policy and interventions by government agencies and oil companies, including improved monitoring strategies, prioritizing remediation efforts based on both environmental severity and community vulnerability, and developing locally responsive support programs. Furthermore, by framing the impacts through the lens of infrastructural and slow violence, the research challenges conventional understandings of oil spills as mere accidents, highlighting their systemic roots and insidious, long-term consequences.

In conclusion, this research has provided a critical, integrated perspective on the enduring crisis of oil spills in the Niger Delta. By synthesizing geospatial, environmental, and community intelligence, it offers a compelling narrative of environmental degradation and human suffering, revealing the profound and interconnected impacts of oil infrastructure failures. The new knowledge generated underscores the urgent need for action that is scientifically informed, environmentally responsible, and deeply rooted in the realities and resilience of the affected communities.

7.2 Limitations of the research

Despite the rigorous approach and the valuable insights generated, this research is subject to several limitations that have shaped its scope and the interpretation of its findings. These limitations arise from the nature of the available data, the constraints imposed by the research environment, and inherent aspects of the analytical methods employed.

7.2.1 Limitations of Chapter 3: Geo-Computation Techniques for Identifying Spatio-Temporal Patterns

While **Chapter three** provides valuable insights into the spatio-temporal pattern along the Niger Delta oil pipeline network, acknowledges several limitations that stem from both the data and the methodological choices. First, out of the original 16,766 incident records from the publicly available NOSDRA dataset, only 5,530 incidents were utilised in the analysis. This was because a significant number of cases lacked either dates or geographic coordinates, rendering them unusable before any spatial analysis commenced. Although the proportion of missing coordinates stabilised in later years, omissions in 2013–2014 and especially high attrition in 2021 (52%) may have biased the apparent timing and intensity of TNKDE hotspots. This significantly limits the comprehensiveness of the analysis, as a large number of reported incidents could not be included.

Second, reported GPS coordinates vary in precision, with some spill sites recorded far from the actual pipeline breach—often reflecting the downstream extent or endpoint of a spill rather than its origin. To address this and ensure all events were mappable to the network, each incident point was snapped to the nearest pipeline segment before segmentation. While this ensures all events lie on the network and enables network-based analysis, it may smooth fine-scale clusters or shift the apparent location of hotspots along the pipeline, potentially misrepresenting the precise origin of spills.

Third, aggregation of each calendar year into three fixed four-month periods (P1 = January–April, P2 = May–August, P3 = September–December) was employed to aid visualisation and analysis of temporal trends. However, this fixed temporal aggregation may obscure shorter-term operational cycles—such as maintenance shutdowns or community reporting drives—and can split prolonged spill events across adjacent periods, potentially masking the true duration or intensity of certain incidents.

Fourth, while Network Kernel Density Estimation (NKDE) and Temporal NKDE (TNKDE) offer significant advantages over traditional planar methods by accounting for network constraints, their application here is still subject to certain methodological considerations related to parameter selection. Although a 500 m lixel length and 700 m search bandwidth align with published NKDE applications and sensitivity checks, these global parameters do not account for potential variation in terrain, pipeline age, or patrol frequency across the entire network. As a result, kernel-density estimates may be over- or under-smoothed in different network segments, influencing the accuracy of hotspot identification and intensity.

Finally, additional incident attributes available in the raw data—such as oil type, estimated volume of spill, and operator identity—were recorded inconsistently across the dataset and were thus omitted from the quantitative spatio-temporal analysis. Future analyses that successfully incorporate these factors, perhaps through improved data collection or alternative data sources, could allow for weighting density surfaces by environmental impact or distinguishing chronic leakage points from isolated catastrophic failures, providing a more nuanced understanding of spill patterns and their consequences.

7.2.2 Limitations of Chapter 4: Remote Sensing-Based Evaluation of Contaminated Land

Chapter 4's remote sensing analysis, while leveraging high-resolution data and cloud computing, faced several limitations primarily related to the characteristics of the PlanetScope NICFI imagery and the methodological approach employed.

Firstly, the study's reliance on PlanetScope NICFI data presented limitations due to its spectral resolution. The four spectral bands (blue, green, red, and near-infrared) inherent to this dataset resulted in reduced spectral dimensionality. This limitation, compared to hyperspectral data, potentially hindered the effective discrimination and detailed characterization of subtle vegetation degradation and contamination levels in affected landcovers like farmlands and wetlands, especially in spectrally complex environments. Higher spectral resolution imagery, encompassing a wider range of bands, could potentially enhance the accuracy of land cover classification and the detection of specific spectral signatures associated with oil spill impacts.

Secondly, the temporal resolution and compositing strategy of the NICFI data posed constraints on the analysis of short-term phenological changes and inter-annual variability. This study utilised the available bi-annual (6-month) composite basemaps (2016-2019) and then transitioned to monthly composites (from 2020 onwards), using specifically the July and December composites. This introduced a significant level of temporal smoothing. While this smoothing effect helped in reducing cloud cover and atmospheric interference, it limited the capacity to capture rapid ecological responses and accurately account for seasonal variations in vegetation health. Ideally, higher frequency data acquisitions (e.g., daily or weekly) without the need for extensive compositing would allow for a more precise temporal analysis and a better understanding of the phenological trajectory of the affected ecosystems.

Thirdly, these data characteristics, combined with the inherent complexity of defining and identifying subtle environmental impacts, led to challenges in the classification process itself. As highlighted by the confusion matrix (see Table 4.6), accurately distinguishing between contaminated and non-contaminated land cover types, such as dense vegetation, wetlands, farmlands, and grasslands, proved particularly nuanced. Subtle spectral or spatial differences between these states, potentially coupled with the relatively smaller variability due to the smaller sizes of the contaminated areas versus non-contaminated area, sometimes resulted in instances where contaminated areas were challenging to separate distinctly from their non-contaminated counterparts or even other land cover classes. This represents a key classification limitation influencing the precision of the contamination mapping. Methodologically, while the selected Vegetation Health Indices (VHIs) proved effective in many cases, exploring a wider range of spectral indices or employing feature selection techniques could potentially enhance discrimination and improve classification accuracy.

Fourthly, the study's methodological choice of employing only the Random Forest machine learning algorithm represents a potential limitation. While Random Forest is a robust and widely used classifier due to its high accuracy, exploring and comparing the performance of other algorithms, including deep learning approaches, could have provided a more comprehensive assessment of the classification accuracy and the robustness of the findings. Future research could benefit from a comparative analysis of different machine learning techniques to identify the most effective approach for this specific application.

Finally, a significant methodological limitation for validating the remote sensing analysis was the absence of in-situ ground-truthing data. While satellite imagery provides valuable spatial information, ground-based observations are crucial for validating the accuracy of the remote sensing-derived classifications and for gaining a deeper understanding of the on-the-ground conditions of the affected land cover, particularly regarding forest deterioration and vegetation health. Due to safety and accessibility challenges in the Niger Delta, direct field validation of land cover classifications and vegetation health assessments was not feasible. While the remote sensing findings were corroborated by community accounts in Chapter 5, direct ground measurements, including soil profiling to assess the direct impacts of oil spills on soil properties and their subsequent effects on vegetation, would have provided a crucial layer of validation for the accuracy and interpretation of the satellite-derived environmental assessments. However, for locations such as the Niger Delta, safety and accessibility are key considerations and often represent barriers to data collection in the field.

Addressing these limitations in future research, through the utilisation of data with enhanced spectral and temporal resolution, the exploration of diverse analytical methodologies (including comparative algorithm analysis), and the incorporation of ground-based validation, could contribute to a more comprehensive and robust understanding of oil spill impacts and the development of effective mitigation and remediation strategies.

7.2.3 Limitations of Chapter 5: Exploring Community Concerns

Chapter 5's exploration of community concerns was shaped by limitations primarily related to data collection in a challenging environment. Security concerns significantly restricted direct access to certain communities, necessitating a distanced research approach. While essential for safety, this approach meant relying on local data collectors as intermediaries, which introduced potential challenges in ensuring precise translation of complex concepts and local dialects and acknowledging the inherent agency of the data collectors in mediating responses. The primary researcher's inability to directly participate in the Focus Group Discussions (FGDs) and Community Participatory Mapping Exercises (CPME) limited opportunities for immediate probing, clarification, and the building of deeper rapport that in-person fieldwork allows.

The collaboration with the National Bureau of Statistics (NBS) data collectors, though pragmatic, introduced ethical and logistical complexities, particularly concerning data ownership and navigating the potential for the data collectors' dual role as community members and state agents to influence participant responses on sensitive topics.

Finally, resource and time constraints limited the study's scope to six communities across three states. While these communities provided rich and consistent data, they represent only a small fraction of the vast and diverse Niger Delta. Therefore, the findings, while deeply insightful for the studied communities, may not be fully representative or generalizable to all affected areas within the entire region, potentially excluding valuable localized insights or variations in experiences.

Acknowledging these limitations is crucial for the proper interpretation of the study's findings and for guiding future research in the Niger Delta and other similar complex environments. Despite these constraints, the integration of multiple methods allowed for a degree of triangulation and mutual corroboration that strengthened the overall conclusions.

7.3 Recommendations

This research was conducted to assess and quantify the impact of oil spills in the Niger Delta. Based on findings on the deteriorating nature of the Niger Delta environment and impact of the spills on everyday lives of people in the affected areas; increased impacts of the spills, slow response from the oil companies and government, low adaptive capacity and the current management measures implemented in the region, the research recommendations have been divided into academic, community level and oil companies/government recommendations.

Table 7.1. Summary of proposed recommendations

Recommendations	Key Actors
1. Future research should prioritise the use of high-resolution (<3m) imagery with enhanced spectral and temporal detail to improve the accuracy of land cover classification and change detection analysis, particularly for wetlands and farmlands.	Researchers
2. Explore the potential of bioremediation processes and assess the effectiveness of different remediation strategies in mitigating the impacts of oil spills in the Niger Delta.	Researchers

3.	The development of early warning systems monitoring oil producing areas to facilitate timely response to oil spills and minimise environmental degradation from oil spills.	Researchers, Environmental Agencies
4.	Expanded research to include a wider range of affected communities across all nine states of the Niger Delta to gain a more comprehensive understanding of the impacts of oil spills and community concerns.	Researchers
5.	Local communities should be encouraged to actively participate in environmental monitoring and decision-making processes related to oil spill prevention and response.	Communities, Government, Oil Companies
6.	Community-based action groups and networks should be strengthened to enhance their capacity for advocacy and engagement on environmental issues.	Communities, Non-governmental Organisations (NGOs)
7.	Promote educational initiatives and awareness programs to increase community understanding of oil spill impacts, environmental risks, and sustainable practices.	Communities, Government, NGOs
8.	Support the development of alternative livelihood strategies and economic diversification to reduce community dependence on environment-related activities and enhance resilience.	Communities, Government, NGOs
9.	Oil companies should prioritise investment in infrastructure upgrades and maintenance to prevent oil spills and minimise environmental degradation.	Oil Companies
10.	Implement stricter environmental regulations and enforcement mechanisms to hold oil companies accountable for oil spills and ensure timely cleanup and remediation efforts.	Government, Environmental Agencies, NOSDRA
11.	Improve transparency and accountability in oil spill reporting and response mechanisms, ensuring community access to information and participation in decision-making.	Government, Oil Companies
12.	Foster collaboration between oil companies, government agencies, and local communities to develop and implement oil spill prevention and response plans.	Government, Oil Companies, Communities

Appendices

Appendix A: Participants Composition and Demography

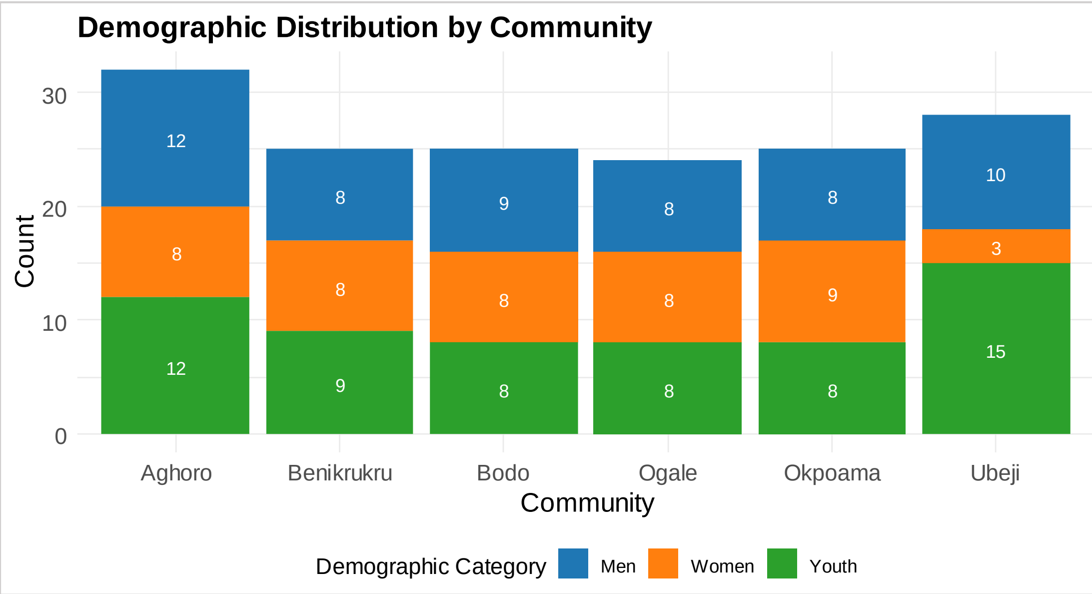


Figure A.0.1. Participants composition and demography by community

Appendix B: Fieldwork Material

B.1 Research Questionnaire

Research Title: Monitoring and Managing Oil Spillage and Environmental Degradation through Geoinformation.

Purpose: The goal of this research is to find out how the environmental impacts of oil spills can be assessed using information provided by satellites and the experiences of local communities.

Researcher: Seyi Adebangbe, a PhD research student from the University of Glasgow, United Kingdom.

Facilitator: My name is [Name], and I have been tasked with facilitating this survey/mapping exercise on behalf of Seyi Adebangbe. As a professional working with the National Bureau of Statistics (NBS) I take great pride in ensuring the highest standards of quality in all research activities that we undertake. My goal is to create a safe and welcoming environment that encourages participants to share their views and experiences on the topic at hand.

Thank you for considering this opportunity to contribute to our research efforts.

ETHICAL CONSIDERATION

This study is purely for academic purposes. Names and identities of participants will be duly protected and informed consent will be obtained from each participant.

Community Details (to be filled in by facilitator)

COMMUNITY:	**PRIMARY CONTACT PERSON NAME/EMAIL:**			
Date / time of FGD	Date		Time	
Facilitator or Team Member(s) Name and Title				
Location details	State	LGA	Ward	Community

	Longitude	Latitude
Community status	☐ Urban ☐ Peri-urban ☐ Rural	
Community population (if known)		
Total number of participants		
Group	☐ Men ☐ Women ☐ Youths	

Theme 1: Knowledge of Oil Spillage

QUESTION	RESPONSES / NOTES
1. Has there been an oil spill nearby recently? If so where was this and how did you learn of this event?	
2. Do oil spills happen often in this area?	

QUESTION	RESPONSES / NOTES
3. Have you noticed any changes in the community's knowledge or awareness of oil spills over time?	
4. Do you believe that the community has enough access to information about where oil spills occur, and what the environmental impacts of oil spills are?	

Theme 2: Impact of Oil Spills on the Environment

QUESTION	RESPONSES / NOTES
5. To what extent has oil spillage damaged the environment of this community? More specifically, how has oil spillage affected farmlands, rivers/streams, surrounding forest and any settlements?	
6. Have you noticed any changes in the vegetation associated with past and/or present oil spills?	
7. Have you noticed any changes in the air or water quality since the last oil spill?	

Theme 3: Impact of Oil Spills on the Everyday Lives of People

QUESTION	RESPONSES / NOTES
8. **How do you think oil spills have impacted local livelihoods?**	
9. **How have oil spills affected how people interact with the local environment?**	

Theme 4: The Perceived Dangers and Challenges Posed by Oil Spills

QUESTION	RESPONSES / NOTES
10. **What are the biggest dangers or challenges that you believe oil spills pose to your community?**	

QUESTION	RESPONSES / NOTES
11. In your opinion, what are some of the long-term effects of oil spills on the environment and your community?	
12. What are some of the health risks associated with exposure to oil and other pollutants after a spill?	
13. In your opinion, what can be done to prevent future oil spills from occurring?	

Theme 5: Responses to Oil Spills

QUESTION	RESPONSES / NOTES
14. How have community leaders responded to oil spills?	
15. How have local government officials responded to oil spills?	
16. Do you feel that your community has been adequately represented in discussions with the government and oil companies about compensation and recovery efforts?	
17. Have you received any compensation or assistance from the government or oil companies? If so, how has that process been for you?	

Final: Facilitators' observations, notes and additional comments

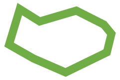
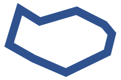
B.2 Community Participatory Companion Questionnaire

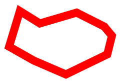
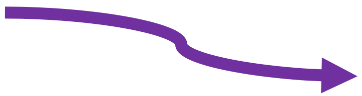
Research Title: Monitoring and Managing Oil Spillage and Environmental Degradation through Geoinformation. *(Participants are to be handed markers with different colours to annotate their observations on the map)*

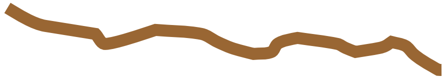
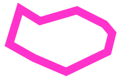
Community:

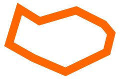
Date:

Name (s)of facilitator(s):

QUESTION	RESPONSES / NOTES
1. What areas of the community have been most impacted by the oil spills, based on the satellite map? *Guidance – please use green marker and a polygonoint symbol to illustrate this:* 	
2. Can you identify any bodies of water on the satellite map that have been impacted by the oil spill? *Guidance – please use blue marker and a polygon symbol to illustrate this:* 	Waterbodies seen on the map that have been affected by oil spills.

QUESTION	RESPONSES / NOTES
3. Based on the satellite map, can you identify previous agricultural land and residential areas that people have to relocate from due to the impact of oil spills? *Guidance – please use* ***red marker*** *and a polygon symbol to illustrate this:* 	Help them orientate the map so they can understand where they are located on the map.
4. Considering your responses to the previous questions, Are are there any patterns or trends in the way the oil spill has spread across the community, as seen on the satellite map? *Guidance – please use purple marker and an arrow symbol to illustrate this:* 	The way and pattern in which the oil usually flow whenever they spill

QUESTION	RESPONSES / NOTES
5. Based on the satellite map, can you identify areas with oil pipelines that are not shown on the map? *Guidance – please use brown marker and a line symbol to illustrate this:* 	Show them the pipeline on the map and ask if there are other areas with pipelines that are not shown on the map.
6. Based on the satellite map, can you identify any areas that are particularly vulnerable to future oil spills? *Guidance – please use pink marker and a polygon symbol to illustrate this:* 	Probe why they think this might be.e…
7. WhatAnnotate infrastructure or public resources (e.g. schools, hospitals, market etc.) that appear to be in close proximity to the areas most affected by the oil spill, based on the satellite map? *Guidance – please use* ***red marker*** *and a bold dot symbol to illustrate this:* 	Help them orientate the map so they can easily identify the facilities.

QUESTION	RESPONSES / NOTES
8. What, if any, cleanup efforts have been made in the areas affected by the oil spill, as seen on the satellite map? *Guidance – please use **orange marker** and a polygon symbol to illustrate this:* 	Remediated areas/ areas previously polluted by oil spills.
Are there any areas on the satellite map that appear to be less impacted by the oil spill than others, and if so, what distinguishes these areas?	
9. What are the potential long-term environmental effects of the oil spill on the areas seen on the satellite map?	Probe for their thoughts on the potential consequences are for the environment.

Final: Facilitators' observations, notes and additional comments

B.3 FIELDWORK CHECKLIST

Before you leave for the field, answer these questions

☐ Have you met with the community stakeholders to arrange the meeting time and venue (select a location that is convenient for participants and conducive to open discussion), and to agree on the modalities?

☐ Have you set-up the KOBO app on your phone?

☐ Have you downloaded the survey questionnaire to the app?

☐ Have you translated the questions into the local language?

☐ Have you printed the maps for the CPME?

☐ Do you have the jotter/note and pens for the exercise ready?

☐ Do you have the markers (in a variety of colours) for the CPME ready?

☐ Is your device (phone/tablet) fully charged?

☐ Have you printed the consent forms (for participants to sign, acknowledging their participation in the exercise)?

☐ Have you printed the participant information sheet?

Before you start the Focus Group Discussion

☐ Has the venue being set-up?

☐ Are there seats for all participants?

Before Starting the Community Participatory Mapping

☐ Satellite map

☐ Markers (in different colours)

☐ Gather the participants in a round table manner

After the Fieldwork Exercise

☐ Have you interpreted all the responses back to English?

☐ Have you key in the responses to KOBO?

☐ Have you scanned all the paper forms and send to Seyi?

☐ Have you scanned all the signed consent forms and send to Seyi?

☐ Have you scanned all the used CPME maps and send to Seyi?

☐ If you have scanned and sent the questionnaire forms, have you destroyed them?

☐ If you have scanned and sent the consent forms, have you destroyed them?

☐ If you have scanned and sent the all the used CPME maps, have you cargo them to Seyi?

B.4: Facilitators' Protocol Guide Document

RESEARCH TITLE: MONITORING AND MANAGING OIL SPILLAGE AND ENVIRONMENTAL DEGRADATION THROUGH GEOINFORMATION

Contact Details:

Seyi Adebangbe

Email: @student.gla.ac.uk

Contents

Introduction

You are one of the facilitators and this step-by-step guide document will guide you by outlining the procedures you should follow during the discussion sessions and community participatory mapping exercises to assess the impact of oil spills on the environment of the Niger Delta in Nigeria. The objective of this exercise is to understand community concerns around oil spills and their environmental impacts.

Seyi Adebangbe will conduct an online training sessions with you to ensure full understanding of the research, its approach, the details of the discussion sessions, community participatory mapping activity, ethical issues, protocols, and data management.

To make sure that you are fully proficient with the tools, a half-day preparation session is planned for you and other members of the team in the days leading up to the fieldwork exercise. In addition, a subsequent refresher training session is planned for the team a day before the exercise. A simulation of the exercise will be conducted with you and other members of the team before the actual exercise, to avoid confusion during the exercise.

People participating in the discussions and mapping exercise will be fully informed about the purpose, methods and intended possible uses of the research via a translated Participant Information sheet. Consent forms will also be translated and used.

2.0. Study area

Following a consultation process with staff at the National Bureau of Statistics, the proposed sites for surveys and mapping will be two communities in each state, namely Rivers (Bodo and Ogale communities), Bayelsa (Aghoro and Okpoama communities), and Delta (Benikrukru and Ubeji communities).

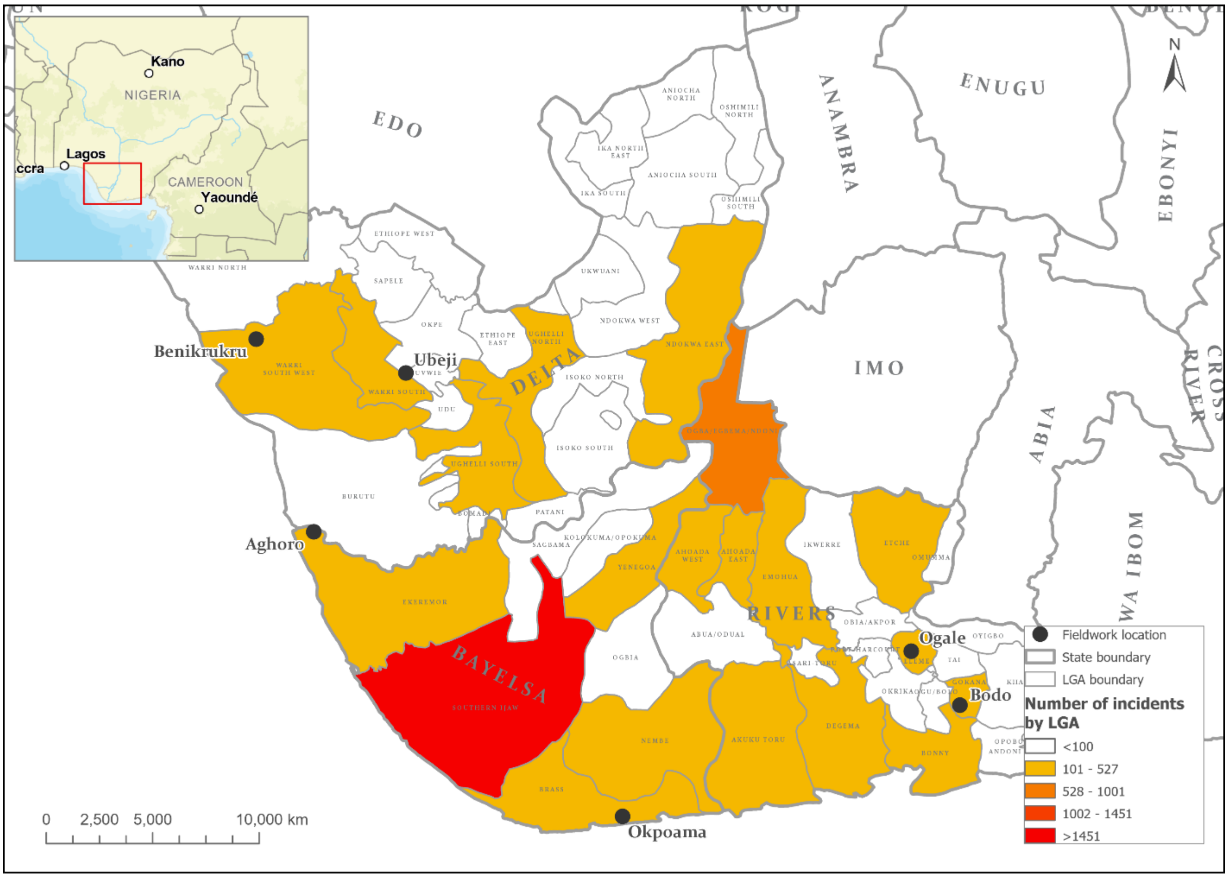


Figure 0.1: Prioritised communities (denoted with point) for the fieldwork exercise

3.0. Objectives of the Project

The main objectives of this field-work exercise are:

- To document the socio-economic impact of oil spills on local communities, including their livelihoods, and cultural practices.

- Identify areas that have been directly impacted with oil spills in the community with the aid of the mapping exercise.

4.0. Methodology

You will conduct the fieldwork exercise using the following two methods:

4.1. Focused Group Discussion (FGD): Open-ended questions are focused on the perceived environmental impacts of oil spills, the challenges posed by oil spills in the affected areas, and impacts on everyday life. FGD questions will be translated into local dialects by you to ensure clarity. The proposed interview questions are attached. In total 18 interviews are intended, 3 for each community, focusing on 3 groups (men – 35 years and above; women – 35 years and above; and youths – 18 to 34). All respondents must be over 18 years of age.

4.2. Community Participatory Mapping Exercise (CPME): In this exercise participants will be given satellite maps of their communities together with markers and asked if they could indicate on the maps areas that have been affected by oil spills, and previous agricultural land and residential areas that people had to relocate from due to the impact of oil spills etc. The group should be a mixture of the three groups mentioned above (men, women, and youths), and comprising between 8 to 12 people, and everyone in the group must be at least 18 years old4.3. Steps that must be followed in conducting the fieldwork exercise

Please check the box after each step if the step has been completed.

Initial Stakeholder Engagement

- Consultation with relevant community stakeholders to:
  - Present the exercise concept and scope;
  - Ensure buy-in and support from key stakeholders;
  - Determine the venue where the survey and the CPME will be conducted.

Focus Group Disscussion

- Arrive at the venue early and arrange the space in a way that facilitates communication; in other words, everyone should feel at ease as a member of the group.
- Introduce yourself and the topic of conversation.
- Participants should be given consent forms to fill out and approve.
- Participants will be allowed to speak freely without interruption.

Community Participatory Mapping Exercise

- Arrange the group and place the map in-betwwen in a roundtable format.
  - Presented the map to the participants.
  - Help them orient the maps by showing them important landmarks on them.
  - Participants use the maps to locate the identified affected areas.
  - Participants' answers to questions are noted on the maps/questionnaire/notepad.

Wrap-up

- Thank the participants.
- Ask the participants for questions.
- Acknowledgements.

Data Validation, Translation & Entry

- Crosscheck the responses with the themes and questions.
- If the answers were written down in the local language, you should translate them into English.
- For open-ended answers, type in the correct answers into Kobo.
- For CPME, the output maps from the mapping exercise will be scanned, uploaded to Google drive and the links sent to Seyi.
- The hardcopy map will be posted to Seyi.
- All consent signed consent forms will be scanned and send to Seyi, the scanned forms will be destroyed after confirmation that Seyi recieved the scannedd forms.

4.4. Groups to be consulted

The survey is committed to hearing from a diverse range of individuals about their unique experiences and perspectives. In carrying out the open-ended interview, the facilitator would ensure that each of the following groups are consulted from within the affected communities:

- Women (above 35 years old)
- Men (above 35 years old)
- Older people and people with disabilities (must be above 18 years of age)
- Individuals from minority groups (must be above 18 years of age)
- Any existing local leadership structures (must be above 18 years of age)
- Youths (18 to 34 years)

Where existing community consultation structures are in place (for example, women's committees or youth forums), I imagine these would be natural entry points.

4.4.1. Summary of the Exercises to be Conducted

No	Type of Survey	Interview Group	Number of Participants	Aim	Duration
1	Focus Group Discussion	Village leaders/representatives, community members.	6 - 12 persons per group (men, women, and youths)	Understand the perceived dangers and challenges posed by oil spills for the Niger Delta communities.	1-2 hours for the focus group discussions
2	Community Participatory Mapping Exercise	Village leaders/representatives, community members.	8 -12 persons per group	Participants mapping out the areas that has been affected by oil spills in their community	50 - 60 minutes this will be included in the FGD agenda

4.5. Conducting the Focused Group Discussion

Opening Session *(10 min)*

- Welcome the participants and thank them for their attendance.
- Emphasize the importance of the exercise to the community.
- Present the agenda.

- Introduce the facilitation team and conduct a roundtable of introductions for the participants

Below is a short introduction to be used to help frame the discussion.

Facilitator: My name is [Name], and I have been tasked with facilitating this survey exercise on behalf of Seyi Adebangbe a Nigerian student/researcher working on the impact of oil spills on Niger Delta region. As a professional working with the NBS I take great pride in ensuring the highest standards of quality in all research activities that we undertake. My goal is to create a safe and welcoming environment that encourages participants to share their views and experiences on the topic at hand.

Thank you for considering this opportunity to contribute to our research efforts.

Main Discussion *(1 to 2 hours)*

Refer to the open ended interview questionnaire for the questions.

- Verbally present the questions to the participants in their local language by reading them out loud.
- Give participants unique names***; refer to the following instructions for assigning unique names to participants:***
    - Each participant should be given a unique name.
    - The unique name should follow a specific format: the first two alphabets of the name should be the first two alphabets from the community name associated with the exercise, followed by a word that represents the group being focused on.

      For example:
    - If the community is **"Benikrukru "** and the group being focused on is "Men," the unique name would be "BE_MEN 001" (BE for Benikrukru and MEN for Men).
    - If the community is **"Aghoro"** and the group being focused on is "Women," the unique name would be "AG_WOMEN 002" (AG for Aghoro and WOMEN for Women).

- If the community is **"Bodo"** and the group being focused on is "Youths," the unique name would be "BO_YOUTHS 003" (BO for Bodo and YOUTHS for Youths).

- Reword the question without changing the meaning if the participants still do not understand it.
- Record all answers clearly and accurately at time of interview directly into the paper form or notepad in a legible manner. After the interview, facilitators should enter the responses (in English) into the KoboCollect app. This will allow for correction and an additional layer of verification by the facilitators, as some mistakes may have been made while taking notes.
- Do NOT assume you know the answer such as from previous interviews or questions – always remain neutral/impartial.
- Never lead the participants to a specific response.
- Listen actively to the interviewees and observe.
- It's important for facilitators to be extra careful when interpreting from the local language to English to avoid losing key messages during translation.
- Photograph of the FGD session and the environment must be taken.

4.6. Conducting the Community Participatory Mapping Exercise (CPME)

Opening Session *(10 min)*

- Welcome the participants and thank them for their attendance.
- Emphasize the importance of the exercise to the community.
- Present the agenda.
- Introduce the facilitation team and conduct a roundtable of introductions for the participants

Below is a short introduction to be used to help frame the discussion.

Facilitator: My name is [Name], and I have been tasked with facilitating this mapping exercise on behalf of Seyi Adebangbe a Nigerian student/researcher working on the impact of oil spills on Niger Delta region. As a professional working with the NBS I take great pride in ensuring the highest standards of quality in all research activities that we undertake. My

goal is to create a safe and welcoming environment that encourages participants to share their views and experiences on the topic at hand.

Thank you for considering this opportunity to contribute to our research efforts.

Method *(1 to 2 hours)*

Refer to the CPME companion questionnaire for the questions.

- The base map is presented to the participants to help orient them (show them important landmarks on the map).
- Participants are asked questions related to oil spills in the communities using the CPME companion questionnaire. They have the freedom to express their opinions on issues.
- Verbally present the questions to the participants in their local language by reading them out loud.

- Give participants unique names***; refer to the following instructions for assigning unique names to participants:***
  - ➢ Each participant should be given a unique name.
  - ➢ The unique name should follow a specific format: the first two alphabets of the name should be the first two alphabets from the community's name associated with the exercise

    For example:
  - ➢ If the community is **"Benikrukru "** and the group being focused on is "Men," the unique name would be "BE 001" (BE for Benikrukru).
  - ➢ If the community is **"Aghoro"** the unique name would be "AG 002" (AG for Aghoro).
  - ➢ If the community is **"Bodo"** the unique name would be "BO_YOUTHS 003" (BO for Bodo).

- Reword the question without changing the meaning if the participants still do not understand it.
- Participants use the base maps to locate the identified affected areas.
- Participants' answers to questions are noted on the base maps. All relevant additional information should also be noted on the questionnaire or notepad.

- Do NOT assume you know the answer such as from previous interviews or questions – always remain neutral/impartial.
- Never lead the participants to a specific response.
- Listen actively to the interviewees and observe.
- It's important for facilitators to be extra careful when interpreting from the local language to English to avoid losing key messages during translation.
- Photograph of the CPME session and the environment must be taken.

5.0. Tool

Form is available on KoboCollect app.

5.1. Kobo on Android

5.1.1. Installing KoBoCollect

Step 1: Install KoBoCollect Mobile App

- Go to **Google Play store** (in Applications).
- Search for 'KoBoCollect'.
- Download and Install application.

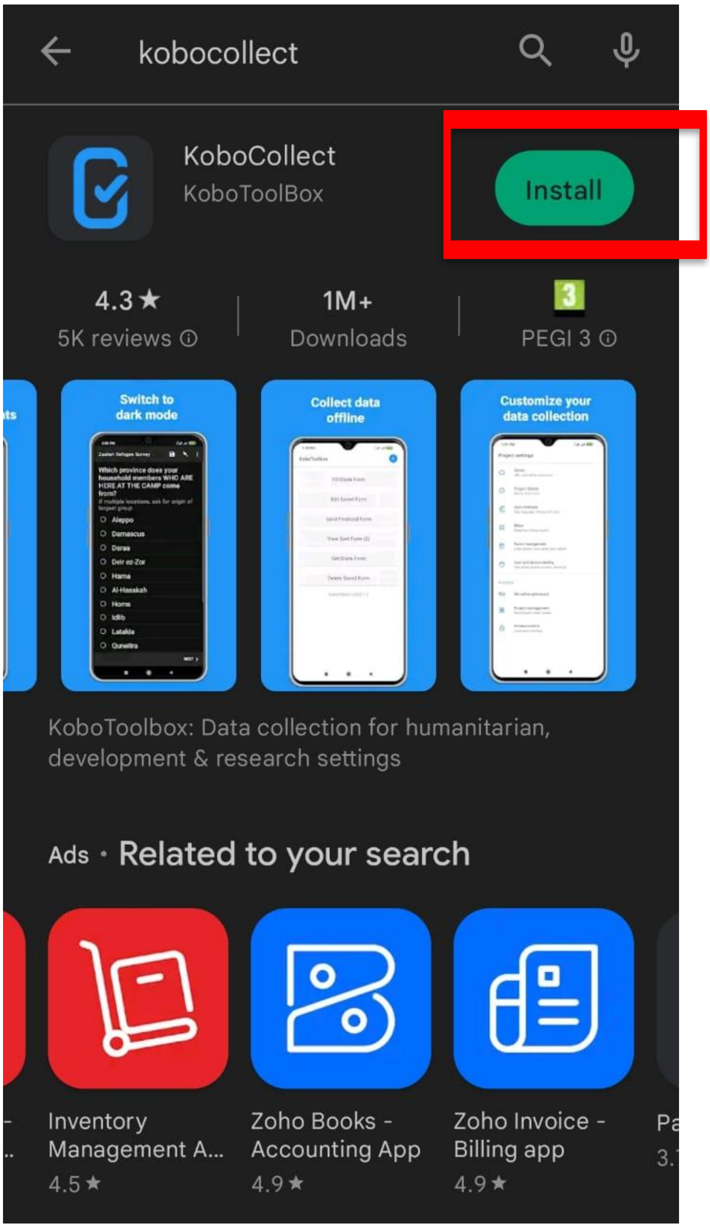


Figure 2

Step 2: Direct mobile application to Form

- Open KoboCollect
- Click manually enter project details *(Figure 3)*
- Under [URL], enter: https://kc.kobotoolbox.org *(Figure 4)*
- Username: **xxxxxxxxxx** *(Figure 4)*
- Password: **xxxxxxxx** *(Figure 4)*

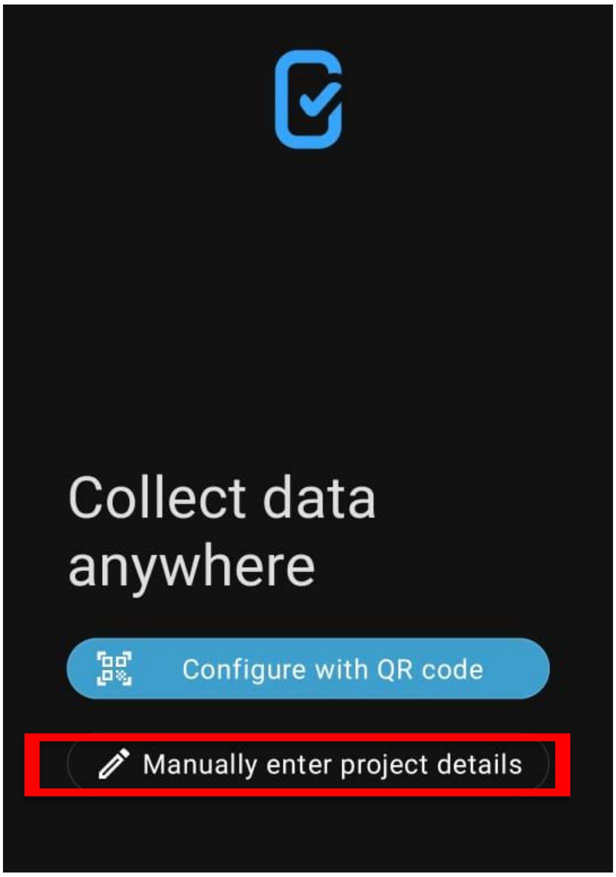


Figure 3

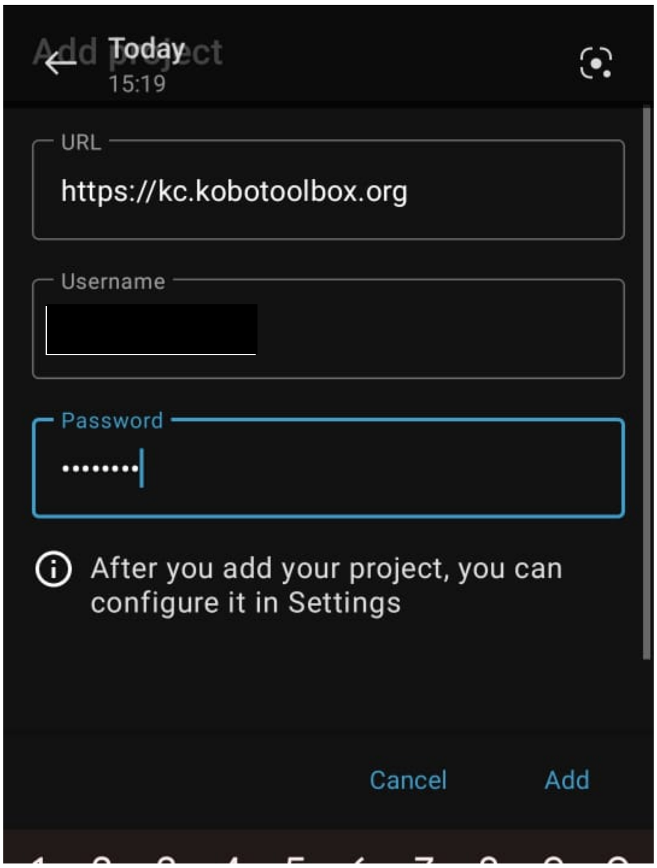


Figure 4

Step 3: Retrieve Blank Form (Figure 5)

- On the main menu, press the ***'Get Blank Form'*** button *(Figure 5)*
- Select / check the blank form(s) you would like to retrieve *(Figure 6)*
- Once selected, press ***'Get Selected'*** at bottom of screen *(Figure 6)*

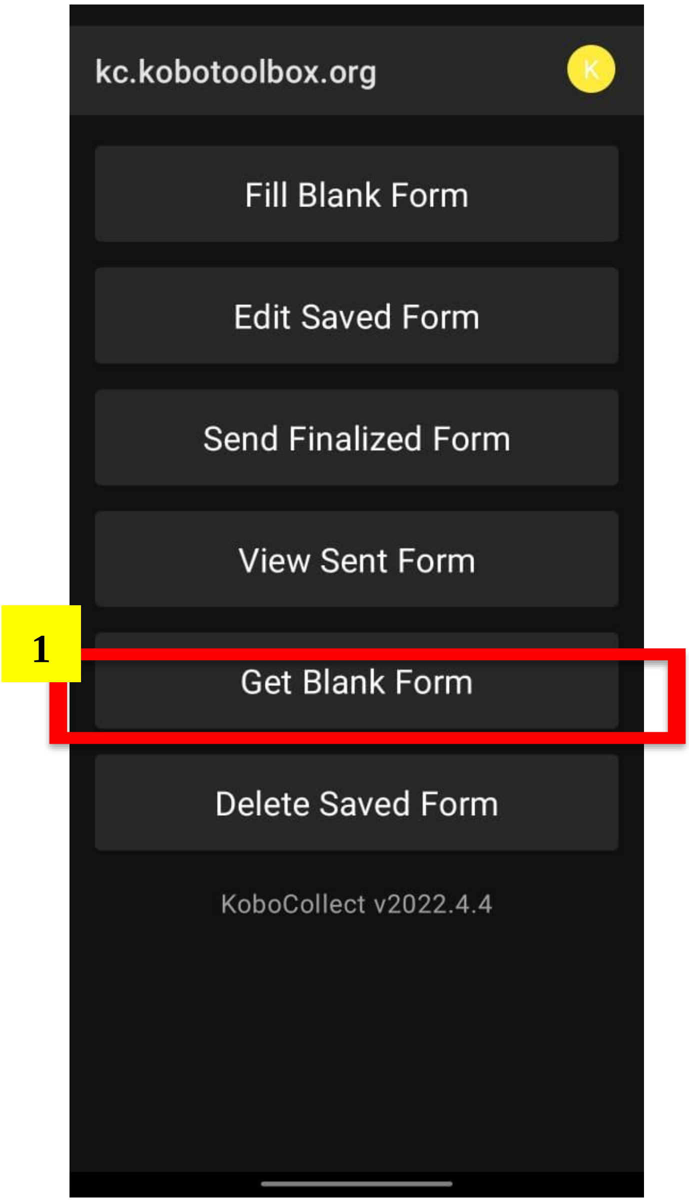


Figure 5

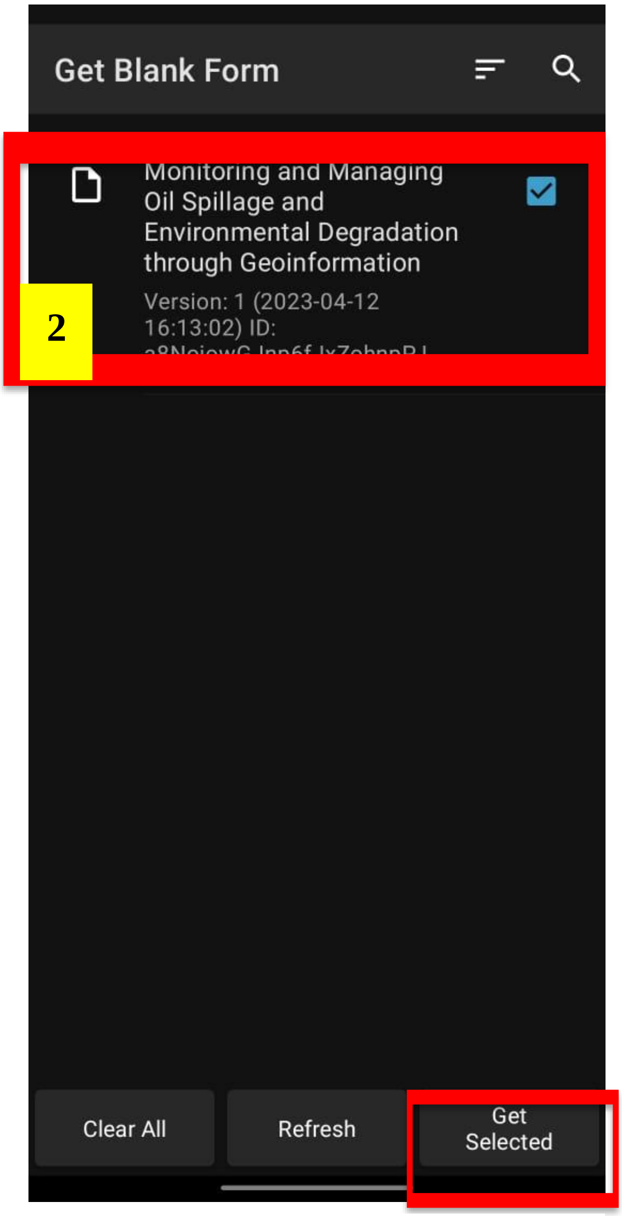


Figure 6

5.1.2. Filling the Mobile Forms

Step 1: Select Blank Form (Figure 7)

- On the main menu, press the ***'Fill Blank Form'*** button

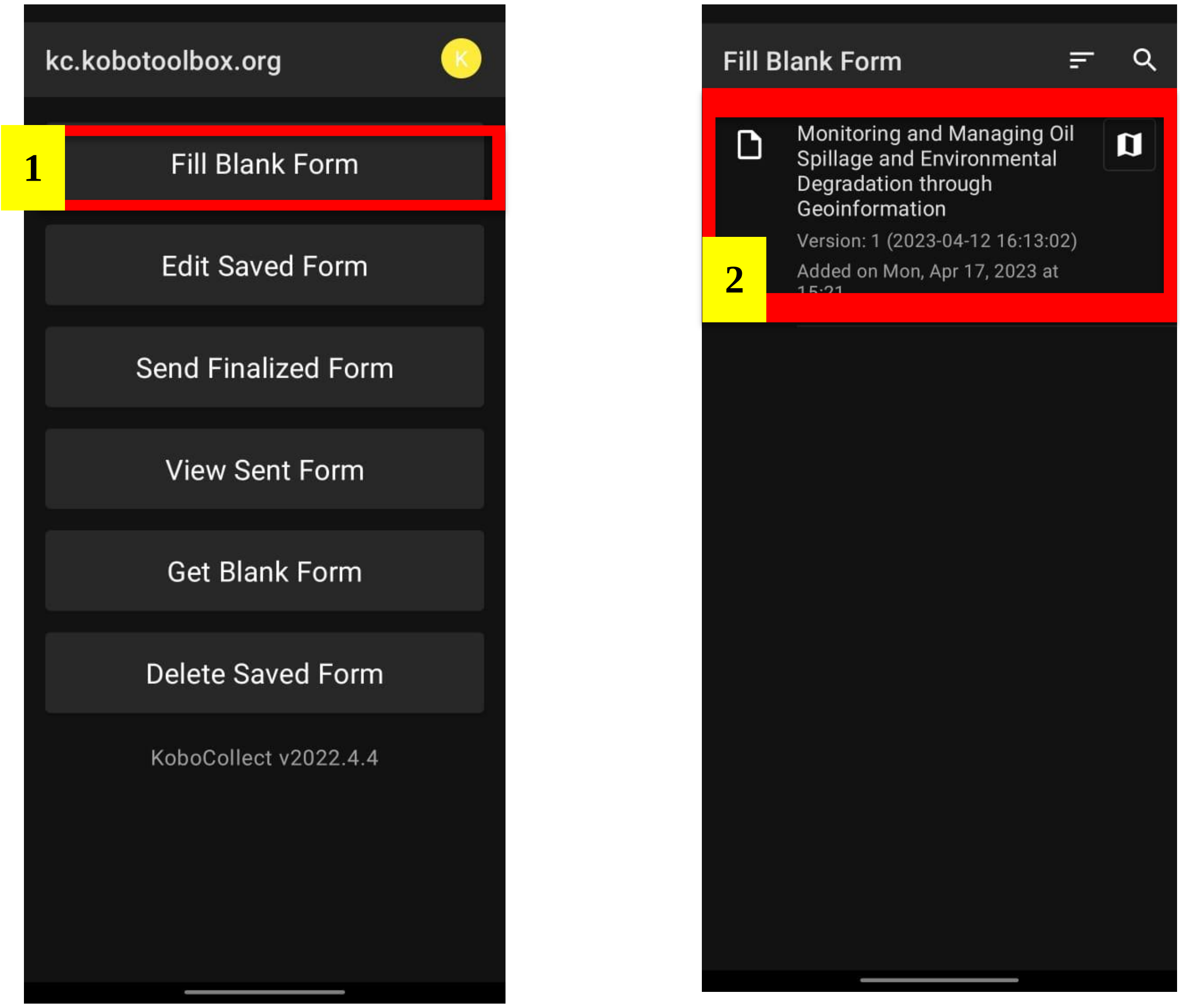


Figure 7

Step 2: Fill Out Mobile Form

- Once at end of form, make sure the box for ***'Mark form as finalized'*** is checked
- ***'Save Form and Exit'***

Step 3: Save Completed Mobile Form

- Once at end of form, make sure the box for ***'Mark form as finalized'*** is checked
- ***'Save Form and Exit'***
-

Step 4: Send Finalized Data to Server ('Data Synching')

- On the main menu, press ***'Send Finalised Form'***
- You should receive a confirmation if successful

Step 5: Complete New Form

Repeat Steps 1 & 4 for every form you complete

6.0. Ethics

It is imperative to prioritize ethical considerations in any research project to safeguard the rights and well-being of participants and maintain the integrity of the research. The field-work exercise will be conducted in an ethical manner, as this study is solely for academic purposes. The names and identities of participants will be duly protected, and informed consent will be obtained from each participant. Furthermore, the University of Glasgow's College of Science and Engineering Ethics Committee has reviewed and approved the ethical procedures of this field-work exercise.

7.0. Summary

This protocol document outlines the procedures to be followed during the field-work exercise to assess the impact of oil spills on the environment of the Niger Delta in Nigeria. By adhering to these procedures, the facilitation team will be able to conduct a thorough and ethical survey and community participatory mapping that will inform recommendations for mitigating the impact of oil spills on the environment and local communities.

University of Glasgow | College of Science & Engineering

B.5 Interviews

Plain Language Statement (or Participant Information Sheet)

Research Project: Monitoring and Managing Oil Spillage and Environmental Degradation through Geoinformation. Monitoring and Managing Pipeline Vandalisation, Oil Spillage and Environmental Degradation Through Geoinformation

Facilitator:

Researcher: Seyi Adebangbe

You are being invited to take part in a research study. Before you decide it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. Please do Aask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part. Thank you.

What is this project about.?

This research aims to explore the relationship between oil spills, environmental degradation, and ways of monitoring and managing these occurrences through the use of remote sensed data, industry data, and community knowledge testimony, and the use of Geographic Information Systems that can collate, integrate and display data**.:** The purpose of the study is to explore the use of geospatial and community intelligence in developing an appropriate framework for detecting and assessing oil spills in the Niger Delta region of Nigeria and to propose suitable management techniques for pipeline vandalisation. ***In other words,*** this study wants to bring to light the direct relationship between pipeline vandalisation, oil spills, environmental degradation, and ways of monitoring and managing these occurrences. In studying these issues, it can help offer solutions to the problem of ecological degradation and ways of preserving the environment for years to come.

What do I require from you?

We understand that living in a community impacted by oil spills can be a challenging and difficult experience. However, your knowledge and insights are critical to helping us understand the full impact of these events on your community. That's why we're reaching out to you today. You have been selected to participate in our surveys because we believe you have a unique perspective on the impact of oil spills in your area. I would like to hear from you about what causes these spills, how oil spills they have affected the your environment in the Niger Delta., property, and livelihood, and how you deal with the damages caused by these events. I expect this online interview to take around 50 minutes. Your participation in our surveys is entirely voluntary, and you. However, we strongly encourage you to participate in one or more of the following activities, from which you may withdraw at any time without explanation.:

What will happen to the information I provide? You have been selected to participate because you reside in one of the communities impacted by vandalisation and oil spills, and we feel you can provide us with information on the impact of this event on your community. We would want to hear what you know about vandalisation and oil spills, what causes them, and how they have impacted your environment, property, and livelihood in general. In addition, we would want to know how you deal with the damages caused by oil spills and your socioeconomic condition. To do this, we would really appreciate your participation in one or more of our surveys. You are not required to participate (it is voluntary), but if you do, you will be asked to take part in one or more of the following activities, from which you may withdraw at any time without explanation:

1) • Survey: questions are focused on the perceived dangers and challenges posed by oil spill in the affected areas, and impacts on everyday life. Survey questions will be translated into local dialects by the NBS staff to ensure clarity. The proposed survey questions are attached. In total 100 surveys are intended, 20 for each community. All respondents will be over 18 years of age.

• Community Participatory Mapping Exercise (CPME): In this exercise participants will be given satellite maps of their communities together with pencils and asked if they could indicate on the maps areas that have been affected by oil spillage, and previous agricultural land and residential areas that people have to relocate from due to the impact of oil spillage. At least 10–12 people from each community will take part, and all will be over 18 years of age.Focus group or questionnaire survey to discuss and answer questions on the impacts of oil spillages on the socio-economic situation of the communities. To the perceived dangers and challenges posed by oil spills. To understand the explanatory variables that pull theencourage or push citizens to engage in pipeline vandalisation and oil bunkering. The focus group discussion will include at least 10 - 12 members of the community and should not take us more than 45 minutes. This will take place in the village town hall or any official space designated to us by the village.

Your contribution will be invaluable in helping us develop effective strategies for preventing and responding to oil spills in the future. Plus, you will have the opportunity to connect with other members of your community who have experienced similar challenges.

Accompanying this information sheet is a consent form. Signed consent forms will be uploaded to a secure computer.

Interview notes, and a transcript (if consent is given for a recording) will be uploaded and kept securely on a password protected computer, only available to the PhD student Seyi Adebangbe and his supervisors at the University of Glasgow.

The collected data will be incorporated into Seyi Adebangde's PhD Project, and may also be used in an academic publication.

Final Details

If you would like your contribution to be anonymised then your personal details, along with any identifying information, can be deleted.

You have the right to withdraw at any time during and after the survey. If you would like your contribution to be removed after the survey this can be done by contacting **Seyi Adebangbe** using the contact details below. No further questions will be asked and any information collected from you prior to this will be destroyed.

Please do not hesitate to contact Seyi Adebangbe for further information regarding this project and the participation in it, or to ask any questions you may have.

2) Visit to affected sites/oil bunkering sites to show locations (if accessible and stable) that have been affected by oil spillages and oil bunkering activities. This exercise will involve just 1-2 Community volunteers and should not take more than 20 minutes and it will not require travel by vehicle. It involves walking to and showing the sites of nearby oil spills and bunkering activities while the researcher takes video (if consent is given) /audio recordings, pictures, coordinates and also take field notes at each location if more than one area.

For the government and company stakeholders: You will be required asked to partake in an open-endedsemi-structured question interview on government and company's roles in preventing and mitigating the effects of oil spillages through the policies in place and how effective that these have been has been in the Niger Delta area. where the study area is located. This interview should not take more than 15 minutes.

It is possible to remain anonymous if you choose to do so. Please indicate on the accompanying consent form if you are happy to be identified. If not, you will not be identified in the research, and any identifying statements will not be used. Please note that no personal data will be taken during this discussions.

All data will be stored on an encrypted on the field-work applaptop while in the field and subsequently stored on a password-protected data storage computer at the University of Glasgow.

Please note that assurances on confidentiality will be strictly adhered to unless evidence of wrongdoing or potential harm is uncovered. In such cases the University may be obliged to contact relevant statutory bodies/agencies.

The results of this research study will be used in scientific reports, the findings of this work may be presented at an academic conference, published in an academic journal and potentially as the basis for future research and maybe be used to help guide any future activities working with the local community, town committees and local government.

Petroleum Technology Development Fund (PTDF), Nigeria, funds this PhD research.

Contact for Further Information:

Researcher: Seyi Adebangbe; **@student.gla.ac.uk**

Lead Supervisors: Dr Brian Barrett; brian.barrett@glasgow.ac.ukProf

Deborah Dixon **;** Deborah.Dixon@glasgow.ac.uk

If you do wish to take part, you must sign a consent form which will also accompany this sheet. If you do decide to participate in this research Pplease keep hold of this information sheet for future reference.

You can also contact Professor **Hester Parr** at: **Hester.parr@glasgow.ac.uk** for further information if you have concerns about this project. If you wish to contact anyone beyond the immediate research team: please contact the **Chair of the CoSE Ethics Committee**: **Christoph.Scheepers@glasgow.ac.uk**.

University of Glasgow | College of Science & Engineering

B.6 Survey - Plain Language Statement (or Participant Information Sheet)

Research Project: Monitoring and Managing Oil Spillage and Environmental Degradation through Geoinformation. Monitoring and Managing Pipeline Vandalisation, Oil Spillage and Environmental Degradation Through Geoinformation

Facilitator: [Name]

Researcher: Seyi Adebangbe

You are being invited to take part in a research study. Before you decide it is important for you to understand why the research is being done and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. Please do Aask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part. Thank you.

What is this project about.?
This research aims to explore the relationship between oil spills, environmental degradation, and ways of monitoring and managing these occurrences through the use of remote sensed data, industry data, and community knowledgestestimony, and the use of Geographic Information Systems that can collate, integrate and display data**.:** The purpose of the study is to explore the use of geospatial and community intelligence in developing an appropriate framework for detecting and assessing oil spills in the Niger Delta region of Nigeria and to propose suitable management techniques for pipeline vandalizationvandalisation. ***In other words,*** this study wants to bring to light the direct relationship between pipeline vandalizationvandalisation, oil spills, environmental degradation, and ways of monitoring and managing these occurrences. SIn studying these issues, it can help offer solutions to the problem of ecological degradation and ways of preserving the environment for years to come.

What do we require from you?:

We understand that living in a community impacted by oil spills can be a challenging and difficult experience. However, your knowledge and insights are critical to helping us understand the full impact of these events on your community. That's why we're reaching out to you today. You have been selected to participate in our surveys because we believe you have a unique perspective on the impact of oil spills in your area. We would like to hear from you about what causes these spills, how oil spills they have affected your environment, property, and livelihood, and how you deal with the environmental impactsdamages caused by of these events. We expect this survey to take around 50 minutes. Your participation in our surveys is entirely voluntary, and you . However, we strongly encourage you to participate in one or more of the following activities, from which you may withdraw at any time without explanation.:

What will happen to the information I provide?You have been selected to participate because you reside in one of the communities impacted by vandalisation and oil spills, and we feel you can provide us with information on the impact of this event on your community. We would want to hear what you know about vandalisation and oil spills, what causes them, and how they have impacted your environment, property, and livelihood in general. In addition, we would want to know how you deal with the damages caused by oil spills and your socioeconomic condition. To do this, we would really appreciate your participation in one or more of our surveys. You are not required to participate (it is voluntary), but if you do, you will be asked to take part in one or more of the following activities, from which you may withdraw at any time without explanation:

1) • Survey: questions are focused on the perceived dangers and challenges posed by oil spill in the affected areas, and impacts on everyday life. Survey questions will be translated into local dialects by the NBS staff to ensure clarity. The proposed survey questions are attached. In total 100 surveys are intended, 20 for each community. All respondents will be over 18 years of age.

• Community Participatory Mapping Exercise (CPME): In this exercise participants will be given satellite maps of their communities together with pencils and asked if they could indicate on the maps areas that have been affected by oil spillage, and previous agricultural land and residential areas that people have to relocate from due to the impact of oil spillage. At least 10–12 people from each community will take part, and all will be over 18 years of age.Focus group or questionnaire survey to discuss and answer questions on the impacts of oil spillages on the socio-economic situation of the communities. To the perceived dangers and challenges posed by oil spills. To understand the explanatory variables that pull theencourage or push citizens to engage in pipeline vandalisation and oil bunkering. The focus group discussion will include at least 10 - 12 members of the community and should not take us more than 45 minutes. This will take place in the village town hall or any official space designated to us by the village.

Your contribution will be invaluable in helping us develop effective strategies for preventing and responding to oil spills in the future. Plus, you will have the opportunity to connect with other members of your community who have experienced similar challenges.

Accompanying this information sheet is a consent form. Signed consent forms will be uploaded to a secure computer and the hard copy will then be destroyed.

The information you provide on oil spills and the environment will be entered into a tablet by the facilitator and anonymised. This will include the removal of details that might allow you to be identified. The uploaded Information will be kept securely on a password protected computer, only available to the PhD student Seyi Adebangbe and his supervisors at the University of Glasgow.

The collected, anonymised data will be incorporated into Seyi Adebangde's PhD Project, and may also be used in an academic publication.

Final Details

Your participation in this research is entirely voluntary.

You have the right to withdraw at any time during and after the survey. If you would like your contribution to be removed after the survey this can be done by contacting **Seyi Adebangbe** using the contact details below. No further questions will be asked and any information collected from you prior to this will be destroyed.

Please do not hesitate to contact Seyi Adebangbe for further information regarding this project and the participation in it, or to ask any questions you may have.

2) Visit to affected sites/oil bunkering sites to show locations (if accessible and stable) that have been affected by oil spillages and oil bunkering activities. This exercise will involve just 1-2 Community volunteers and should not take more than 20 minutes and it will not require travel by vehicle. It involves walking to and showing the sites of nearby oil spills and bunkering activities while the researcher takes video (if consent is given) /audio recordings, pictures, coordinates and also take field notes at each location if more than one area.

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Contact for Further Information:

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B.7 Ethics Approval Letter

Confidential information removed from page 273

Appendix C: The Theory on NKDE and TNKDE

According to Gelb (2021), to conduct a NKDE, one can follow the following steps: Employ lixels as a substitute for pixels, where a lixel represents a linear replica of a pixel on a network. By dividing the network lines into lixels based on a set resolution, the centres of these lixels can be used to estimate the density. Use network distances instead of Euclidean distances to figure out how far apart things are on the network. This explains how the network is connected and how it is set up. Change the kernel function to fit the way the space isn't uniform. This change makes sure that the density estimate takes into account the directionality and differences in the network. By using these steps, the NKDE method can figure out a network's density while taking into account its unique features and connections.

In Figure C.1, a) and b) contains data points in red that signify events, while the lines within the dataset represent the network. Upon performing a Kernel Density Estimation (KDE) analysis on the given dataset, the resultant density plot would bear resemblance to the illustrated Figure C.1b. Nonetheless, this methodology is only partly adequate when our emphasis is on ascertaining the frequency of occurrences exclusively within the network (Gelb, 2021; Okabe et al., 2009).

b

a

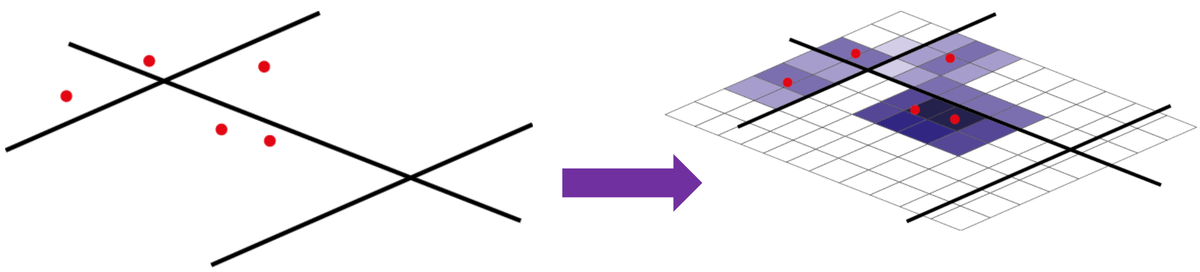

Figure C.1. Simple illustration of Kernel Density Estimate (KDE); a) contains data points in red that signify events, while the lines within the dataset represent the network, b) illustrates the resultant density plot (Source: Gelb, 2021).

Alignment of events with the network is a prerequisite for performing NKDE. Figure C.2 a) and b) highlights the events that have been aligned with the network, which are visually distinguished by the colour green.

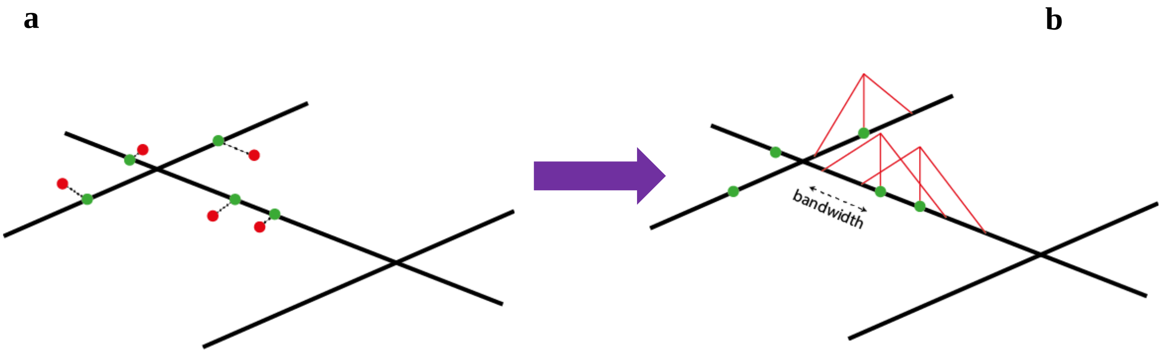

Figure C.2. Simple illustration of Network Kernel Density Estimate (NKDE); a) highlights the events being aligned with the network, while b) highlights the events that have been aligned with the network, which are visually distinguished by the colour.

The determination of the mass of each event can be regarded as an extra dimension that is ascertained through the utilisation of a selected kernel function (K) and a designated bandwidth. The kernel function is subject to the following criteria which must be satisfied.

$$k(x) \geq 0, if\ x < bandwith \qquad \textit{Eq.C.1}$$

$$k(x) = 0, if\ x\ > \ bandwith \qquad \textit{Eq.C.2}$$

$$\int k(x) = 1 \qquad \textit{Eq.C.3}$$

The entire event is assigned a total mass of 1, which is distributed based on the function K within a specific bandwidth. As shown in Figure 3.3b, the "influence" of each point is confined within this bandwidth and diminishes as the distance from the event increases.

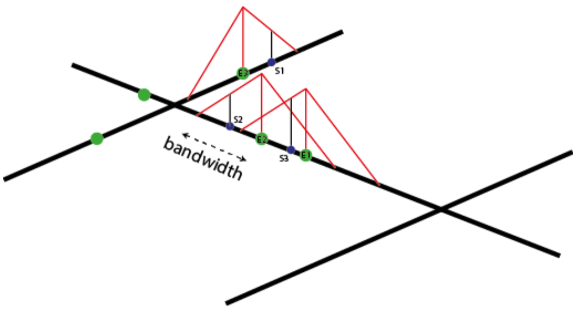

Figure C.3. NDKE calculation at identified three sampling points (s1, s2, and s3) are highlighted in blue. With NDKE it becomes possible to assess the density of the phenomenon under investigation at every location along the network (Gelb, 2021).

By employing this method, it becomes possible to assess the density of the phenomenon under investigation at every location along the network. In Figure C.3, three sampling points (s1, s2, and s3) are highlighted in blue.

$$ds1 = \frac{1}{bw^2} K(distance_{s1;e1)} \qquad Eq.C.4$$

$$ds2 = \frac{1}{bw^2} K(distance_{s2;e2)} \qquad Eq.C.5$$

$$ds3 = \frac{1}{bw^2} (K(distance_{s3;e2)} + K\left(distance_{s3;e3}\right)) \qquad Eq.C.6$$

In a broader sense:

$$dsi = \frac{1}{bw^2} \sum_j^n = 1\, K\left(distance_{si;ej}\right) \qquad Eq.C.7$$

Using the notation dsi to represent the density estimated at the sample point si, bw denote the bandwidth and ej to represent an event.

Different studies have proposed different methods of conducting the NDKE. Xie and Yan (2008) proposed an approach that has been termed the simple method for estimating the spatial process intensities on a network. This method differs from the traditional Kernel Density Estimation (KDE) in that it uses network distances instead of Euclidean distances and assigns event mass based on the count of edges at intersections. However, it has been criticized for its statistical imprecision as it does not integrate to 1 on its domain (Gelb, 2021; Okabe et al., 2009; Xie & Yan, 2008, 2013).

To summarize the key aspects of the simple method, the intensity estimation is performed exclusively on the network, with edges divided into lixels (one-dimensional pixels) used for intensity estimation. The distances between events and sampling points are calculated using shortest path distances on the network rather than Euclidean distances. The intensity function is adjusted slightly to account for the network configuration domain (Gelb, 2021; Okabe et al., 2009; Xie & Yan, 2008, 2013).

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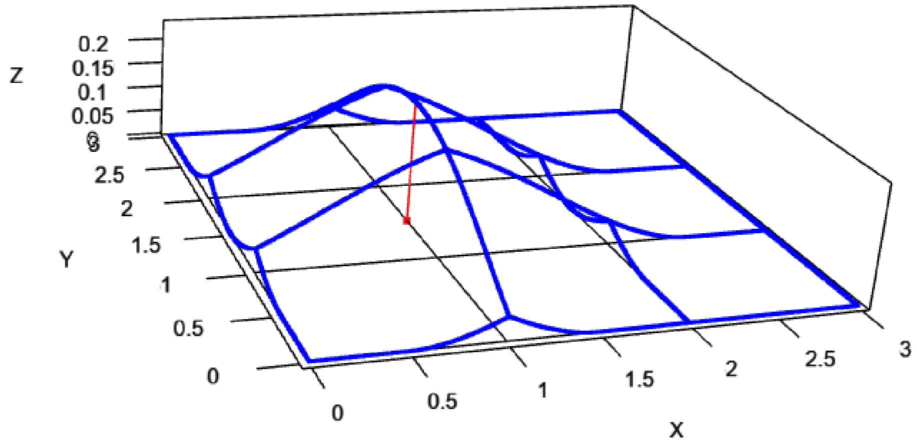

Figure C.4. Simple method showing NKDE is only determined by the distance between the sampling points and the event (Source: Gelb, 2021; Okabe & Sugihara, 2012)

The simple method (see Figure C.4) remains useful for preliminary inquiries and quick computations, particularly with extensive datasets (Gelb, 2021; Xie & Yan, 2008). From a geographical perspective, it has an intuitive appeal, especially in contexts such as crime analysis where the potency of an occurrence should not be affected by network intersections. However, it is important to note that the uncomplicated approach tends to overestimate densities, particularly in subregions with a high number of occurrences (Gelb, 2021).

To address this limitation, Okabe et al. (2009) introduced two impartial estimators, namely the discontinuous NKDE and the continuous NKDE, which aim to provide unbiased density estimates (Gelb, 2021; Okabe et al., 2009). In summary, the uncomplicated approach has the following characteristics: it offers rapid calculability, an intuitive nature, and continuity (Xie & Yan, 2008). However, it may be subject to bias due to its non-kernel nature, resulting in an overestimation of densities (Gelb, 2021; Okabe et al., 2009; Okabe & Sugihara, 2012; Xie & Yan, 2008, 2013b).

The Equal Split Discontinuous (ESD) Method

In order to address the limitations of the simple method, Okabe and Sugihara (2012) proposed a solution known as the ESD NKDE method (see Figure C.5). This method was further expanded upon by Sugihara, Satoh, and Okabe (2010) to account for scenarios where the network contains cycles that are shorter than the bandwidth. Unlike the simple method, the ESD NKDE method avoids multiplying the observed mass at intersections by splitting the values of the NKDE. However, it is worth noting that this NKDE approach exhibits a discontinuity, which goes against intuition and results in pronounced variations in density values within the network. This characteristic could pose challenges, especially in networks that have a substantial number of closely located intersections. Figure C.5 provides a visual representation of this phenomenon (Gelb, 2021; Okabe et al., 2009; Okabe & Sugihara, 2012; Xie & Yan, 2013).

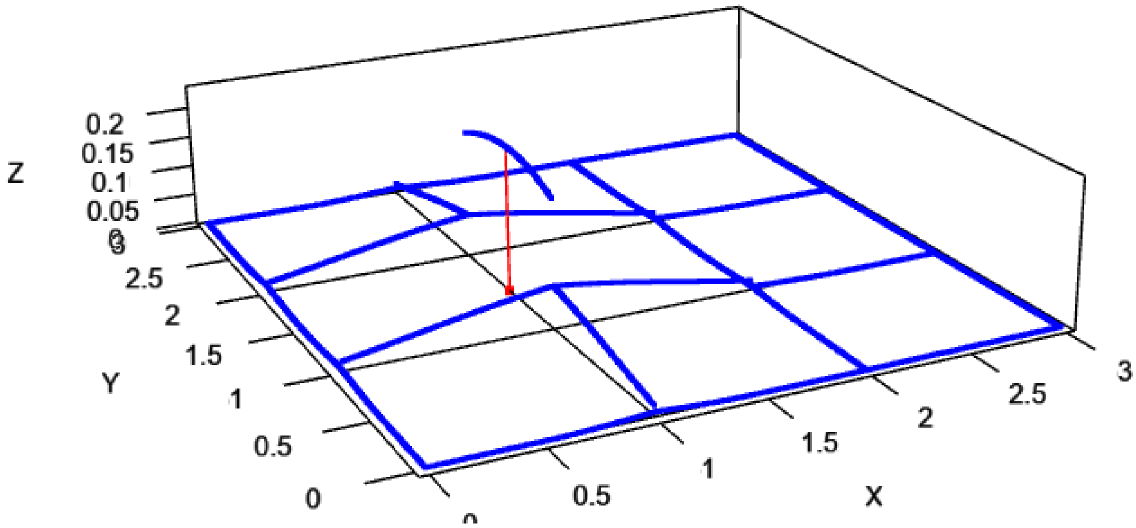

Figure C.5 . The ESD NKDE method avoids multiplying the observed mass at intersections by splitting the values of the NKDE (Gelb, 2021; Okabe & Sugihara, 2012)

The ESD method is unbiased and computationally simple, but its inherent discontinuity may not align with real-world applications. This can be particularly counter-intuitive in scenarios such as crime analysis on a network, where it is not intuitive for the "influence" of a crime to abruptly decrease from one street to another (Gelb, 2021).

The discontinuous NKDE can be succinctly described using Equation C.8.

$$K\big(distance(u, e_i)\big) = \frac{2k\big(distance(u,e_i)\big)}{n_{i1}\prod_{i=i}^{j}(n_{ij}-1)}, \qquad Eq.C.\ 8$$

Using the symbol K to represent the kernel function, n_{ij} refers to the count of edges connected at intersection j along the path that starts from the event location e_i and ends at the specific location u.

The Equal Split Continuous (ESC) Method

Finally, the ESC method takes the best of the two worlds: it adjusts the values of the NKDE at intersections to ensure that it integrates to one on its domain, and applies a backward correction to force the density values to be continuous. As seen from Figure C.6, the values of the NKDE are continuous, and the density values close to the events have been adjusted. The utilisation of this approach yields outcomes that exhibit a higher degree of smoothness in comparison to the ESD method (see Figure C.6).

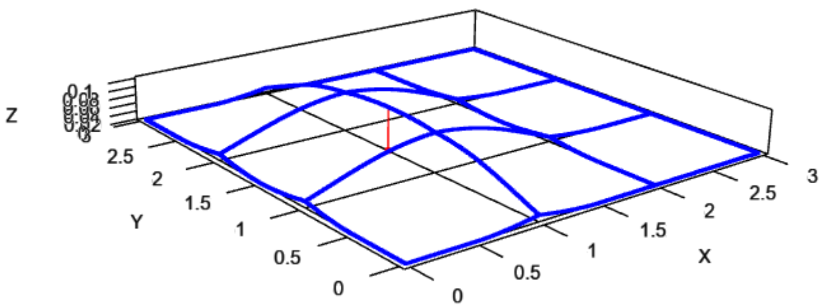

Figure C.6 . The ESC method; the values of the NKDE are continuous, and the density values close to the events have been adjusted leading to higher degree of smoothness. (Gelb, 2021; Okabe & Sugihara, 2012)

The ESC NKDE method is recursive in nature due to its backward correction process, making it challenging to express as a simple equation. Okabe and Sugihara (2012) explain this approach using a recursive function, see Equation C.9.

$$\coprod_{i=1}^{imax} \frac{bw-d}{d_{i+1} - d_i}, \qquad Eq.C.9$$

Using d_i to represent the distance between an event and the ith-nearest node, and $imax$ to denote the last node where d_i is less than the bandwidth (bw).

In this method, a correction factor needs to be applied to all previously traversed edges within the remaining bandwidth for each encountered node. The distribution of this correction factor is also required to be carried out among all nodes in the respective direction. By way of comparison, the two preceding techniques solely necessitate the algorithm to traverse the edges originating from the event in a singular direction. As a result, the iterative process for computing continuous NKDE is more time-consuming (Gelb, 2021; Okabe et al., 2009; Okabe & Sugihara, 2012).

Temporal Network Kernel Density Estimate (TNKDE)

The Temporal Network Kernel Density Estimate (TNKDE), see Figure C.7, an extension based on the three previous NKDEs and the generalized product of kernels. The NKDEs can be seen as unidimensional kernels as well as the temporal KDEs. Therefore, the TNKDE is a bi-dimensional kernel:

$$\hat{\boldsymbol{\lambda}}_{h_n h_t}\ (U_{nt}) = \frac{1}{h_n h_t}\ \sum_{i=1}^{N} k_{net}\ (\frac{dist_{net\ (U_{nt},e_i)}}{h_n}) \sum_{i=1}^{N} k_{net}\ (\frac{dist_{net\ (U_{nt},e_i)}}{h_t}) \qquad Eq.C.10$$

With h_n the bandwidth selected for the network part and h_t the bandwidth for the temporal part, where $knet$ is the network kernel as we had in NKDE u_{nt} point at the location n on the network and t in time, and e_i an event. Note that if the density of one of the two dimensions of this kernel is 0, the spatiotemporal density will also be 0. In other words, if an event is too far in time or on the network, its contribution to the density at u_{nt} will be 0. Geo-NKDE, ESC-NKDE and ESD-NKDE can be used in this framework. In this research work ESC-NKDE was used.

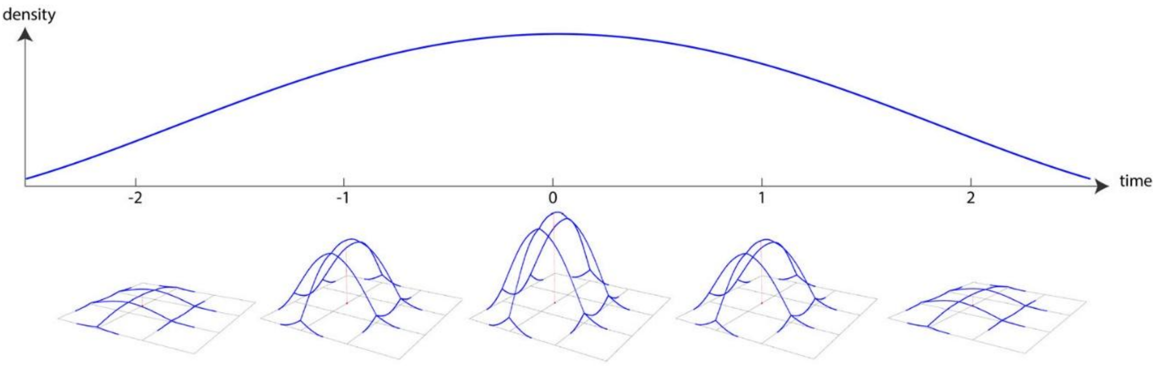

Figure C.7. ESC-TNKDE over time; product of the temporal and network kernel densities. TNKDE goes beyond NKDE's capabilities by offering a condensed view of accident-prone network (in the context of this research; pipelines). It identifies specific risky areas on

Bandwidth

The bandwidth is the most important parameter when applying a KDE (Gelb & Apparicio, 2023). Several methods have been proposed to select an optimal bandwidth and the leave-one-out maximum likelihood is probably the most popular. It is a data-driven method which can be easily adapted to multivariate kernels and thus to spatiotemporal KDE. The idea here is to maximize the sum of the log densities observed at each event location, if that event was missing (T. M. Davies & Lawson, 2019; Gelb & Apparicio, 2023; Turlach, 1993).

$$likelihood(h) = n^{-1} \sum_{i=1}^{n} \log \{\tilde{f}_{X^{[-i]}} (x_i|h)\} \qquad Eq.C.11$$

h = the bandwidth. $likelihood(h)$ represents the likelihood function, which is used to estimate the probability of observing the data given a certain set of parameters or model. In this case, it is the likelihood of observing the data "X" given the model "$h.$", n^{-1} is a fraction representing the reciprocal of the sample size "$n.$" It is used to normalize the likelihood function by dividing by the total number of data points in the sample. $\sum_{i=1}^{n}$ is the summation symbol, indicating that we are summing up the following expression for each data point "i" from 1 to "n," where "n" is the sample size, and $\log \{\tilde{f}_{X^{[-i]}}$ represents the conditional probability density function.

To assess the bandwidth for a spatiotemporal kernel, two bandwidths need to be chosen and evaluated concurrently, following the given procedure.

$$likelihood(h_{net,} h_{net}) = n^{-1} \sum_{i=1}^{n} \log \{\tilde{f}_{X^{[-i]}} (x_i|h_{net}, h_{net})\} \qquad Eq.C.12$$

$(h_{net,} h_{net})$ represents the likelihood function, while n^{-1} represent the reciprocal of the sample size "n."

Adaptive bandwidth

According to Gelb & Apparicio (2023), classical kernel density estimation employs a fixed bandwidth, but this rigidity can be problematic when the spatial process intensity varies over space or time. It may lead to biased density estimates by over smoothing areas with many events and undersmoothing areas with fewer events. Adaptive bandwidth refers to a variable smoothing method that adapts the bandwidth based on the spatial process density. This approach, proposed by Abramson (1982) involves varying the bandwidth inversely proportional to the square root of the target density. It offers several benefits, including decreased sensitivity to outliers, finer density estimation in areas with numerous events, and increased smoothing in regions with fewer events, yielding less precise results due to higher uncertainty(T. M. Davies & Lawson, 2019; Gelb & Apparicio, 2023).

To obtain the adaptive bandwidth, a three-step process is utilized, involving the selection of a fixed reference bandwidth, calculation of adaptive bandwidth for each event, and evaluation of densities at sampling points using the obtained vector of bandwidths (Gelb, 2021; Gelb & Apparicio, 2023).

$$h(u_{ei}) = h_0 \frac{1}{\sqrt{\tilde{f}(u_{ei})/y}} \quad \text{with } y = \left(\prod_{i=1}^{n} \frac{1}{\sqrt{\tilde{f}(e_i)}}\right)^{\frac{1}{n}} \qquad \textit{Eq.C.13}$$

with $h(u_{ei})$ the local bandwidth defined for the event ei located at u, h_0, the pilot bandwidth and $\widetilde{f}(u_{ei})$ the estimated density at point u.

According to Gelb & Apparicio (2023), it is recommended to include a trimming value in order to mitigate excessive bandwidth in regions characterised by infrequent occurrences. This approach can be readily implemented across different nonparametric kernel density estimators (NKDEs) without necessitating any modifications. However, in the case of TNKDE, two potential strategies are suggested: either independently modifying the network and time bandwidths, or simultaneously adjusting both.

The separated adjustment in TNKDE involves calculating the network kernel density for each event without considering the time dimension. Similarly, the temporal bandwidth is calculated based on isolated events in time. This approach is suitable when the analysed process lacks strong spatiotemporal autocorrelation and has a weak interaction between the network and temporal dimensions(T. M. Davies & Lawson, 2019; Gelb & Apparicio, 2023).

$$h_{net}(u_{ei}) = h_{net0} \frac{1}{\sqrt{\widetilde{f_{net}}(u_{ei})/y_{net}}};\ h_{time}(u_{ei}) = h_{time0} \frac{1}{\sqrt{\widetilde{f_{time}}(u_{ei})/y_{time}}} \qquad \textit{Eq.C.14}$$

The simultaneous adjustment of both bandwidths involves assessing the spatiotemporal density at each event using two initial pilot bandwidths. Afterward, both the network and temporal local bandwidths are modified by applying the same factor, which is determined based on this density. This approach facilitates the interaction between the temporal and network dimensions (T. M. Davies & Lawson, 2019; Gelb & Apparicio, 2023).

$$h_{net}(u_{ei}) = h_{net0} \frac{1}{\sqrt{\tilde{f}(u_{ei})/y}};\ h_{time}(u_{ei}) = h_{time0} \frac{1}{\sqrt{\tilde{f}(u_{ei})/y}} \qquad \textit{Eq.3.A.15}$$

Diggle’s correction

The classical spatial kernel density estimation (SKDE) assumes an unbounded spatial domain, but in reality, events are often confined to a finite sampling region, leading to less frequent occurrences at the periphery. This causes a loss of density beyond the boundary, resulting in biased density estimation for both network and time periods of study. To address this bias, Diggles' correction (Diggle, 1985) is commonly used, which involves increasing the weights of events near the study area boundary based on the reciprocal of their mass within the designated study area.(Diggle, 1985; Gelb & Apparicio, 2023)

When applying TNKDE, the Diggle's correction for an event e_{nt} can be computed as follows:

$$D(e_{nt}) = \left[1 - \left(\int_{Net'}^{w} k_{net}\left(\frac{dist_{net}\ (e_{nt},\ w)}{h_n}\right) \times \int_{Time'}^{v} k_{time}\left(\frac{dist_{time}\ (e_{nt},\ v)}{h_t}\right)\right)\right]^{-1} \quad Eq.C.16$$

With 'w' representing a point within the network Net, and 'v' denote a moment within the temporal window Time. Net' and Time' refer to the portions of the network and time that lie outside the defined study domain. The weight, represented as 1/(fraction of event density within space-time boundaries), serves as an inverse measure. For instance, if half of an event's mass lies beyond the studied network and a third of its mass extends beyond the studied period, the applicable weight is calculated as $\left(1 - \frac{1}{2} \times \frac{1}{3}\right)^{-1} = 1.2.$

Appendix D. Fieldwork Location Prioritisation Matrix

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
Rivers	Kana	Bodo community	Bodo is a community of around 49,000 people who rely on fishing and farming. In 2008 two massive oil spills from a Shell oil pipeline spilled at least 560,000 barrels of oil into the Community's land.	https://www.leighday.co.uk/latest-updates/cases-and-testimonials/cases/shell-bodo/	Shell	4.6335	7.2707	Equipment failure	2008, 08 - 09/ 2022. between August 2 and August 30, 2022, three separate spills were reported in Bodo community. 11/10/2022	High	Ekemini Isaiah @EkIsaiah Emeka @Emeka_oe · Jan 18 I went down to Ogoniland, Gokana LGA, Bodo town to observe an oil spill caused by a pipeline that had burst several years earlier. The River is biologically dead and the soil is degraded. The environment cannot sustain wildlife/farming thereby devastating the community. · Sep 3 Replying to @GodsonNweke @Obong_Ekpe and @blazeeyo I served in St Pius X College, Bodo Gokana, that community is an eyesore. Oil spill that affects their rivers and lands and			

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
											pollutes the whole community. I agree with you			
Rivers		Ogale	At least 40 oil spills from Shell's infrastructure in the Ogale community have made the land and waterways in the community very dirty, damaging the Ogale Stream, boreholes, and farmland.	https://www.leighday.co.uk/latest-updates/cases-and-testimonials/cases/shell-ogale-and-bille/		4.786759162	7.133299037	Equipment failure, sabotage		High				

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
Rivers	Emohua	Omoviri	(16/04/2021) oil started spilling into the community river three years ago without any efforts by government agencies and multinationals to identify the source of the leakage and remediate the environment.	https://punchng.com/residents-cry-out-as-oil-spill-ravages-rivers-community/ https://www.bbc.com/pidgin/tori-56605895		4.9312	6.6748			High	Now, we go and find fresh water to drink as this oil spill has spoilt our river water. Before, we use to bath, wash clothes and do other things in this river, but with this oil, we can't again." affect the farmland as what they planted is not doing well, but more importantly, they don't have any borehole water, school or hospital.			
Rivers		Rumuekpe												
Rivers	Ogba/Egbema/Ndoni	Ebocha (Ngbede, Okwuzi, Aggah)	The Nigeria Agip Oil Company (NAOC), the Itahani oil prospecting giant may have lost over 1.5million barrels of crude oil following successive explosions that lasted for three days that rocked its Ebocha oil centre located at Okwuzi/Mgbede axis in Ogba/Egbema/Ndoni Local Government Area of Rivers State. Ebocha Community in Ogba/Egbema/Ndoni	http://www.thetidenewsonline.com/2015/07/03/ebocha-explosions-agonies-of-host-communities/ https://twitter.com/i/status/1185268194098995200 https://www.facebook.com/publicpetitionsactivities/videos/investigative-hearing-ebocha-vs-agip-oil-company-	Agip	5.4621	6.6992		2015	High				

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
			Local Government Area of Rivers State is home to Agip's Ebocha, Obrikom and Obiafu Oil and Gas Facility. The people of Ebocha are from the Ogba speaking tribe in Onelga. The Ogba people are predominantly fishermen and farmers and depend on the little streams including the Orashi River as source of water for the community.	limited/204107901247158/ https://www.salvaleforeste.it/en/blog/72-news-en/eco-justice/2146-nigeria-agip-causes-oil-spill-at-the-abacheke-community.html										
Rivers	Ogba/Egbema/Ndoni											**Ngbede**, Okwuzi, Aggah	5.234722	6.7525
Rivers	Ahoada West											**Enito**, Ukpeliede, Idu-ekpeye, Akala-ola	5.093861404	6.488038099

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
Bayelsa	Nembe	Aghoro community	1,114 barrels of crude oil, impacted and polluted an estimated area of 113.03 hectares	https://earthjournalism.net/stories/in-niger-delta-oil-spill-is-impoverishing-residents-devastating-environment-dislocating https://twitter.com/NigeriaNRC/status/1093184439251845122?s=20&t=GRcA9wix9YgaFCPudbTsww https://phspectator.com/2021/03/30/rivers-community-cries-out-over-oil-spillage/	Shell	5.1243	5.4392	Equipment failure, sabotage	43237	High	Ibeh Genius @OfficialMGN ¤MGN-AFRICA» #OILSPILL: Our rivers contaminated, we can't fish anymore, Bayelsa community cries out: INDIGENES of the coastal fishing settlement of Aghoro, Ekeremor Local Government Area, Bayelsa State, have bemoaned the devastating	Santa Barbara, Okroba, Fantuo, **Okpoama,**	4.305732855	6.29337042
Bayelsa	Brass	Okpoama		https://www.vanguardngr.com/2020/11/oil-spill-again-pollutes-okpoama-communities-in-bayelsa/		4.319271	6.314245			High				
Bayelsa	Southern Ijaw											Oporoma, Obiloli, Okigbene, Tibidaba,	4.810893559	6.079343503

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
												Ologbobiri, Krokrose,		
Bayelsa	Ekeremore	Ekeremore												
Delta	Warri South	Benikrukru (Gbaramatu)		https://www.vanguardngr.com/2021/02/oil-spill-shuts-down-fishing-in-10-delta-communities/ https://thenationonlineng.net/delta-community-drags-chevron-for-abandoning-victims-of-oil-spill/	Chevron, Shell	5.6695	5.277	Equipment failure	13/04/2014, 16/02/2021	High	The crude oil discharged into the rivers and environs has since resulted in large scale devastation and degradation of the environment, disrupted fishing and farming activities and visited the people of the areas with untold hardship	Ogidigben	5.55394116	5.182200025
Delta	Ughelli South	Okpare-Olomu	Ravaged Okpare-Olomu community, destroying crude pipelines, farmlands, animals and other property	https://dailypost.ng/2018/03/06/tension-delta-oil-spill-ravages-okpare-community/ https://twitter.com/akughafelix/status/1111682501481848832?s=20&t=GRcA9wix9YgaFCPudbTsww		5.36	5.78	Sabotage/ illegal refinery		High	Destroyed crude pipelines, farmlands, animals and other property.			

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
Delta	Uvwie LGA											Ugbomrho, Ebrumede, Ekpan	5.570313628	5.833456575
Delta	Warri North	Opuama	Opuama was host to Shell for over 35 years before Nigerian Petroleum Development Company Ltd (NPDC); and Elcrest Exploration and Production Nigeria Ltd (NPDC/ELCREST, a joint venture between Starcrest Nigeria Energy and Seplat's Eland Oil and Gas) took over oil and gas operations in the community. Like many other communities in the Niger Delta playing hosts or neighbours to oil and gas companies, Opuama has lost more than it has gained from the operations.	https://homef.org/2021/04/23/unending-tragedies-following-oil-spill-in-opuamas-land-and-water/?utm_source=rss&utm_medium=rss&utm_campaign=unending-tragedies-following-oil-spill-in-opuamas-land-and-water https://twitter.com/NnimmoB/status/1371549804724113411?s=20&t=thbgT2hgJAQDsFWhVAB3NQ		5.9055	5.0682	Equipment failure	44269	3 times: The most recent occurred on March 14, 2021. The first incident happened in 2002, while the second occurred in 2009.	Affected the main river. There has been total lock down of economic activities here in our community, we had to shut down schools			

State	LGA	Community	Details	Reference	Operator	Lat	Lon	Cause	Date	Frequency	Impact	Locations Suggested by NBS	Lat-2	Lon-2
Delta	Warri South	Ubeji		https://ejatlas.org/conflict/crude-fire-ravages-ubeji-nigeria		5.5736	5.701	Equipment failure	39265	High	Outbreak of fire in the creeks which quickly spread all over consummating most of the vegetation in its path. It took fire fighters reportedly from several organisations about 3 hours to put out the inferno			

Appendix E. Oil Spill Data Cleaning Summary

Table E.1. Data breakdown by year of incident, missing coordinates and used data

Date	No date	2012 and below	2013	2014	2015	2016	2017	2018	2019	2020	2021
Overall data by year of incident	1288	6532	1728	1723	1087	802	706	817	928	560	571
Missing coordinates	1095	3494	588	592	399	313	334	319	364	187	296
Data used for analysis			1140	1131	688	489	372	498	564	373	275

Table E.2. Year-by-year breakdown of included and dropped data

Year	Original incidents	Missing coordinates (dropped)	Included for analysis	% removed
2013	1 728	588	1 140	34.0 %
2014	1 723	592	1 131	34.3 %
2015	1 087	399	688	36.7 %
2016	802	313	489	39.0 %
2017	706	334	372	47.3 %
2018	817	319	498	39.0 %
2019	928	364	564	39.2 %
2020	560	187	373	33.4 %
2021	571	296	275	52.0 %

Bibliography

Abam, T. K. S. (**2016**). Engineering Geology of the Niger Delta. In *Journal of Earth Sciences and Geotechnical Engineering*, 6(3). Scienpress Ltd.

Abayomi, A., **Adam, S.**, & **Alumbugu, A.** (**2015**). Oil Exportation and Economic Growth in Nigeria. *Journal of Economics and Sustainable Development*, 5(15). Retrieved from www.iiste.org

Abdi, A. M. (**2020**). Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. *GIScience & Remote Sensing*, 57(1), 1–20. https://doi.org/10.1080/15481603.2019.1650447

Abhishek Jha, V. L. (**2023**, April 26). Cross-Validation in Machine Learning: How to Do It Right. Retrieved from https://neptune.ai/blog/cross-validation-in-machine-learning-how-to-do-it-right

Abou El-Magd, I., **Zakzouk, M.**, **Abdulaziz, A. M.**, & **Ali, E. M.** (**2020**). The Potentiality of Operational Mapping of Oil Pollution in the Mediterranean Sea near the Entrance of the Suez Canal Using Sentinel-1 SAR Data. *Remote Sensing*, 12(8), 1352. https://doi.org/10.3390/rs12081352

Abramson, I. S. (**1982**). On Bandwidth Variation in Kernel Estimates—A Square Root Law. *The Annals of Statistics*, 10(4). https://doi.org/10.1214/aos/1176345986

Achi, C. (**2003**). Hydrocarbon Exploration, Environmental Degradation and Poverty: The Nigeria Delta Experience. In *Environmental Pollution Conference*. Retrieved from https://www.ucd.ie/dipcon/docs/theme02/theme02_07.PDF

Achunike, O. (**2020**). Social Impacts of Oil Extraction in the Niger Delta Region, Nigeria (Master’s thesis). University of Northern British Columbia.

Adamu, B., **Ogutu, B.**, & **Tansey, K.** (**2016**). Remote Sensing for Detection and Monitoring of Vegetation Affected by Oil Spills. *Preprints*, 201609.0081.v1. https://doi.org/10.20944/preprints201609.0081.v1

Adamu, B., **Tansey, K.**, & **Ogutu, B.** (**2015**). Using Vegetation Spectral Indices to Detect Oil Pollution in the Niger Delta. *Remote Sensing Letters*, 6(2), 145–154. https://doi.org/10.1080/2150704X.2015.1015656

Adamu, B., **Tansey, K.**, & **Ogutu, B.** (**2016**). An investigation into the factors influencing the detectability of oil spills using spectral indices in an oil-polluted environment. *International Journal of Remote Sensing*, 37(10), 2338–2357. https://doi.org/10.1080/01431161.2016.1176271

Adamu, B., **Tansey, K.**, & **Ogutu, B.** (**2018**). Remote Sensing for Detection and Monitoring of Vegetation Affected by Oil Spills. *International Journal of Remote Sensing*, 39(11), 3628–3645. https://doi.org/10.1080/01431161.2018.1448483

Addeh, E. (**2022**, January 23). Report: Nigeria's Oil & Gas Industry to Face Liquidity Challenges in 2022. *Thisday Newspaper*. Retrieved from https://www.thisdaylive.com/index.php/2022/01/23/report-nigerias-oil-gas-industry-to-face-liquidity-challenges-in-2022/

Adeola, A. O., **Akingboye, A. S.**, **Ore, O. T.**, **Oluwajana, O. A.**, **Adewole, A. H.**, **Olawade, D. B.**, & **Ogunyele, A. C.** (**2022**). Crude Oil Exploration in Africa: Socio-Economic Implications, Environmental Impacts, and Mitigation Strategies. *Environment Systems and Decisions*, 42(1), 26–50. https://doi.org/10.1007/s10669-021-09827-x

Adomokai, R., & **Sheate, W. R.** (**2004**). Community participation and environmental decision-making in the Niger Delta. *Environmental Impact Assessment Review*, 24(5), 495–518. https://doi.org/10.1016/j.eiar.2004.01.002

Aduloju, A. A., & **Okwechime, I.** (**2016**). Oil and Human Security Challenges in Nigeria's Niger Delta. *Critique*, 44(4), 505–525. https://doi.org/10.1080/03017605.2016.1236495

Adusei, L. A. (**2015**). Threats to the Exploration, Production and Supply of Africa's Energy Resources. *South African Journal of International Affairs*, 22(1), 43–65. https://doi.org/10.1080/10220461.2014.1001432

Afiesimama, S. E., & **Eludoyin, O. S.** (**2021**). Spatio-temporal Assessment of Mangrove Cover Change in Niger Delta, Nigeria. *International Journal of Innovative Science and Research Technology*, 6(7). Retrieved from www.ijisrt.com

Africa News. (**2018**, April 19). Fuel Smuggling Costing Libya $750 Million a Year—Oil Chief. *Africa News*. Retrieved from https://www.africanews.com/2018/04/19/fuel-smuggling-costing-libya-750-million-a-year-oil-chief//

Agbagwa, I. O., & **Ndukwu, B. C.** (**2014**). Oil and Gas Pipeline Construction-Induced Forest Fragmentation and Biodiversity Loss in the Niger Delta, Nigeria. *Natural Resources*, 5(12), 698–718. https://doi.org/10.4236/nr.2014.512061

Akinpelu, Y. (**2021**, April 11). Nigeria Spends Billions on Pipeline Maintenance as Hundreds are Vandalised Annually. *Premium Times*. Retrieved from https://www.premiumtimesng.com/news/headlines/454439-analysis-nigeria-spends-billions-on-pipeline-maintenance-as-hundreds-are-vandalised-annually.html

Akpokodje, E. G. (**1987**). The engineering-geological characteristics and classification of the major superficial soils of the Niger Delta. *Engineering Geology*, 23(3–4), 193–211. https://doi.org/10.1016/0013-7952(87)90090-1

Akujuru, V. A. (**2014**). A Framework for Determining the Compensable Value of Damages Due to Contamination to Wetlands in the Niger Delta of Nigeria (Master's thesis). University of Salford.

Alagoa, A. J. (**2005**). A History of the Niger Delta: An Historical Interpretation of Ijo Oral Tradition. Onyoma Research Publications.

Albert, O., **Amaratunga, D.**, & **Haigh, R.** (**2019**). An investigation into root causes of sabotage and vandalism of pipes: A major environmental hazard in Niger Delta, Nigeria. In N. Fernando & C. Siriwardana (Eds.), *International Conference on Capacity Building for Research and Innovation in Disaster Resilience* (pp. 22–37). National Science Foundation of Sri Lanka.

Albert, O. N., **Amaratunga, D.**, & **Haigh, R. P.** (**2018**). Evaluation of the Impacts of Oil Spill Disaster on Communities and Its Influence on Restiveness in Niger Delta, Nigeria. *Procedia Engineering*, 212, 1054–1061. https://doi.org/10.1016/J.PROENG.2018.01.136

Alemzero, D. A., **Iqbal, N.**, **Iqbal, S.**, **Mohsin, M.**, **Chukwuma, N. J.**, & **Shah, B. A.** (**2021**). Assessing the perceived impact of exploration and production of hydrocarbons on households' perspective of environmental regulation in Ghana. *Environmental Science and Pollution Research*, 28(5), 5359–5371. https://doi.org/10.1007/s11356-020-10880-3

Alharathy, S. (**2018**, April 22). Vandals Set Fire on Oil Pipeline in Marada, East of Libya. *The Libya Observer*. Retrieved from https://www.libyaobserver.ly/inbrief/vandals-set-fire-oil-pipeline-marada-east-libya

Aljazeera. (**2023**, February 2). Nigerian Communities File Damages Claim against Shell in UK Court. Retrieved from https://www.aljazeera.com/news/2023/2/2/nigerian-communities-file-damages-claim-against-shell-in-london-court

Allen, J. R. L. (**1965**). A review of the origin and characteristics of recent alluvial sediments. *Sedimentology*, 5(2), 89–191. https://doi.org/10.1111/j.1365-3091.1965.tb01561.x

Al-Najjar, H., **Kalantar, B.**, & **Abdul Halin, A.** (**2025**). Advancements in land cover classification and machine learning techniques for urban areas using remote sensing big data. *Frontiers in Environmental Science*, 13. https://doi.org/10.3389/fenvs.2025.1584485

Al-Ruzouq, R., **Gibril, M. B. A.**, **Shanableh, A.**, **Kais, A.**, **Hamed, O.**, **Al-Mansoori, S.**, & **Khalil, M. A.** (**2020**). Sensors, features, and machine learning for oil spill detection and monitoring: A review. *Remote Sensing*, 12(20), 1–42. https://doi.org/10.3390/rs12203338

Al-Shammary, A. A. G., **Al-Shihmani, L. S. S.**, **Fernández-Gálvez, J.**, & **Caballero-Calvo, A.** (**2024**). Optimizing sustainable agriculture: A comprehensive review of agronomic practices and their impacts on soil attributes. *Journal of Environmental Management*, 364, 121487. https://doi.org/10.1016/j.jenvman.2024.121487

Alshari, E. A., **Abdulkareem, M. B.**, & **Gawali, B. W.** (**2023**). Classification of land use/land cover using artificial intelligence (ANN–RF). *Frontiers in Artificial Intelligence*, 5. https://doi.org/10.3389/frai.2022.964279

Althawadi, J. J. A., & **Hashim, M.** (**2019**). An approach of vicarious calibration of Sentinel-2 satellite multispectral image based on spectral library for mapping oil spills. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-4/W16, 117–121. https://doi.org/10.5194/isprs-archives-XLII-4-W16-117-2019

Amiri, M., & **Pourghasemi, H. R.** (**2022**). Mapping the NDVI and monitoring of its changes using Google Earth Engine and Sentinel-2 images. In *Land Surface Monitoring* (pp. 1–xx). https://doi.org/10.1016/B978-0-323-89861-4.00044-0

Amnesty International. (**2013**). *Bad Information: Oil Spill Investigations in the Niger Delta.* Retrieved from www.amnesty.org

Amnesty International. (**2015**). *Clean It Up: Shell's False Claims about Oil Spill Response in the Niger Delta.* Retrieved from https://www.amnesty.ch/fr/pays/afrique/nigeria/docs/2015/pollution-petroliere-les-fausses-declarations-de-shell/clean-it-up-final.pdf

Amnesty International. (**2018**). *Negligence in the Niger Delta: Decoding Shell and Eni's Poor Record on Oil Spills.* Retrieved from https://www.amnesty.org/en/wp-content/uploads/2021/05/AFR4479702018ENGLISH.pdf

Amnesty International. (**2020**, June). *No Clean Up, No Justice: Shell's Oil Pollution in the Niger Delta.* Amnesty International.

Ansah, C. E., **Abu, I.-O.**, **Kleemann, J.**, **Mahmoud, M. I.**, & **Thiel, M.** (**2022**). Environmental contamination of a biodiversity hotspot—Action needed for nature conservation in the Niger Delta, Nigeria. *Sustainability*, 14(21), 14256. https://doi.org/10.3390/su142114256

Arab News. (**2018**, April 19). Oil Theft 'Costing Libya Over $750m Annually.' *Arab News*. Retrieved from https://www.arabnews.com/node/1287826/amp

Arellano, P., **Tansey, K.**, **Balzter, H.**, & **Boyd, D. S.** (**2015**). Detecting the effects of hydrocarbon pollution in the Amazon forest using hyperspectral satellite images. *Environmental Pollution*, 205, 225–239. https://doi.org/10.1016/j.envpol.2015.05.041

Argamosa, R. J. L., **Blanco, A. C.**, & **Reyes, R. B.** (**2022**). An approach of vicarious calibration of Sentinel-2 satellite multispectral image based on spectral library for mapping oil spills. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVI-4/W3-2021, 33–38. https://doi.org/10.5194/isprs-archives-XLVI-4-W3-2021-33-2022

Aroh, K. N., **Ubong, I. U.**, **Eze, C. L.**, **Harry, I. M.**, **Umo-Otong, J. C.**, & **Gobo, A. E.** (**2010**). Oil spill incidents and pipeline vandalization in Nigeria: Impact on public health and negation to attainment of Millennium Development Goal: The Ishiagu example. *Disaster Prevention and Management: An International Journal*, 19(1). https://doi.org/10.1108/09653561011022153

Arslan, N. (**2018**). Assessment of oil spills using Sentinel-1 C-band SAR and Landsat 8 multispectral sensors. *Environmental Monitoring and Assessment*, 190(11), 637. https://doi.org/10.1007/s10661-018-7017-4

Asadzadeh, S., **Oliveira, W. J.**, & **Souza Filho, C. R.** (**2022**). UAV-based remote sensing for the petroleum industry and environmental monitoring: State-of-the-art and perspectives. *Journal of Petroleum Science and Engineering*, 208, 109633. https://doi.org/10.1016/j.petrol.2021.109633

Asif, Z., **Chen, Z.**, **An, C.**, & **Dong, J.** (**2022**). Environmental impacts and challenges associated with oil spills on shorelines. *Journal of Marine Science and Engineering*, 10(6), 762. https://doi.org/10.3390/jmse10060762

Aswin, S. C. S. (**2024**). Jeffries-Matusita distance. MathWorks. Retrieved from https://www.mathworks.com/matlabcentral/fileexchange/159828-jeffries-matusita-distance

Austin, Z., & **Sutton, J.** (**2014**). Qualitative research: Getting started. *Canadian Journal of Hospital Pharmacy*, 67(6). https://doi.org/10.4212/cjhp.v67i6.1406

Ayanlade, A., & **Drake, N.** (**2016**). Forest loss in different ecological zones of the Niger Delta, Nigeria: Evidence from remote sensing. *GeoJournal*, 81(5), 717–735. https://doi.org/10.1007/s10708-015-9658-y

Babatunde, A. O. (**2020**). Local perspectives on food security in Nigeria's Niger Delta. *The Extractive Industries and Society*, 7(3), 931–939. https://doi.org/10.1016/j.exis.2020.07.011

Babatunde, A. O. (**2023**). Oil exploitation and food insecurity in Nigeria's Niger Delta. *The Journal of Modern African Studies*, 61(2), 165–187. https://doi.org/10.1017/S0022278X23000010

Bala-Gbogbo, E. (**2024**, February 22). Nigeria's economy grows steadily as oil output rises. *Reuters*. Retrieved from https://www.reuters.com/world/africa/nigerian-economy-grows-346-yy-fourth-quarter-2024-02-22/

Balogun, A.-L., **Yekeen, S. T.**, **Pradhan, B.**, & **Althuwaynee, O. F.** (**2020**). Spatio-temporal analysis of oil spill impact and recovery pattern of coastal vegetation and wetland using Landsat 8-OLI imagery and machine learning models. *Remote Sensing*, 12(7), 1225. https://doi.org/10.3390/rs12071225

Bankole, A. O., **Ogunkeyede, A. O.**, **Agboro, H.**, **Ekhorutomwen, P. A.**, **Otuomagie, O. I.**, **Isimekhai, K. A.**, **Fadairo, E. A.**, & **Is mukuru, E. J.** (**2024**). Heavy metal levels and ecological risk in crude oil-contaminated soils from Okpare-Olomu, Niger Delta, Nigeria. *Journal of Environmental Protection*, 15(04), 415–438. https://doi.org/10.4236/jep.2024.154024

Bayelsa commission. (n.d.). An environmental genocide: The human and environmental cost of big oil in Bayelsa, Nigeria. Retrieved October 18, 2023, from https://report.bayelsacommission.org/

Bayramov, E., **Kada, M.**, & **Buchroithner, M.** (**2018**). Monitoring oil spill hotspots, contamination probability modelling and assessment of coastal impacts in the Caspian Sea using multiple satellite sensors. *Journal of Operational Oceanography*, 11(1), 27–43. https://doi.org/10.1080/1755876X.2018.1438343

Bayramov, E., **Knee, K.**, **Kada, M.**, & **Buchroithner, M.** (**2018**). Using multiple satellite observations to quantitatively assess and model oil pollution and predict shoreline risks from oil platforms in the Caspian Sea. *Human and Ecological Risk Assessment*, 24(6), 1501–1514. https://doi.org/10.1080/10807039.2017.1416454

Beaumont, P. (**2021**, October). Failed state? Why Nigeria's fragile democracy is facing an uncertain future. *The Guardian*. Retrieved from https://www.theguardian.com/global-development/2021/oct/25/failed-state-why-nigerias-fragile-democracy-is-facing-an-uncertain-future

Beckstrom, S. (**2014**). Prioritizing pedestrian safety improvement locations: A spatial analytical approach using network kernel density estimation [Unpublished doctoral dissertation]. University of Washington. http://hdl.handle.net/1773/26843

Bello, T. (**2017**). Oil pollution and biodiversity conservation in Nigeria: An assessment of legal framework. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3072168

Benke, K. K., **Sheth, F.**, **Betteridge, K.**, **Pettit, C. J.**, & **Aurambout, J.-P.** (**2015**). Application of geovisual analytics to modelling the movements of ruminants in rural landscapes using satellite tracking data. *International Journal of Digital Earth*, 8(7), 579–593. https://doi.org/10.1080/17538947.2013.872703

Berg, R. C. (**2021**, October 12). The role of the oil sector in Venezuela's environmental degradation and economic rebuilding. Center for Strategic and International Studies. Retrieved from https://www.csis.org/analysis/role-oil-sector-venezuelas-environmental-degradation-and-economic-rebuilding

Bonnington, A., **Amani, M.**, & **Ebrahimy, H.** (**2021**). Oil spill detection using satellite imagery. *Advances in Environmental and Engineering Research*, 2(4), 1. https://doi.org/10.21926/aeer.2104024

Breiman, L. (**2001**). Random forests. *Machine Learning*, 45, 5–32.

Brigden, N., & **Hallett, M.** (**2021**). Fieldwork as social transformation: Place, time, and power in a violent moment. *Geopolitics*, 26(1), 1–17. https://doi.org/10.1080/14650045.2020.1717068

Bruederle, A., & **Hodler, R.** (**2019**). Effect of oil spills on infant mortality in Nigeria. *Proceedings of the National Academy of Sciences*, 116(12), 5467–5471. https://doi.org/10.1073/pnas.1818303116

Bruun, J. M., & **Guasco, A.** (**2023**). Reimagining the 'fields' of fieldwork. *Dialogues in Human Geography*. https://doi.org/10.1177/20438206231178815

Buitrago, D. (**2022**, February 16). Venezuela oil spills caused grave environmental damage over two years—Report. *Reuters*. Retrieved from https://www.reuters.com/world/americas/venezuela-oil-spills-caused-grave-environmental-damage-over-two-years-report-2022-02-16/

Bulgarelli, B., & **Djavidnia, S.** (**2012**). On MODIS retrieval of oil spill spectral properties in the marine environment. *IEEE Geoscience and Remote Sensing Letters*, 9(3), 398–402. https://doi.org/10.1109/LGRS.2011.2169647

Burelli, C. V. (**2021**, April 5). Venezuela's ecological death spiral: Formulating a global response. Center for Strategic and International Studies. Retrieved from https://www.csis.org/analysis/venezuelas-ecological-death-spiral-formulating-global-response

Business & Human Rights Resources Centre. (**2021**). The Hague Court of Appeals rules on Shell in Nigeria. Retrieved from https://www.business-humanrights.org/en/latest-news/commentary-the-hague-court-of-appeals-rules-on-shell-in-nigeria/

Cai, G., **Huang, X.**, **Du, M.**, & **Liu, Y.** (**2010**). Detection of natural oil seeps signature from SST and ATI in South Yellow Sea combining ASTER and MODIS data. *International Journal of Remote Sensing*, 31(17–18), 4869–4885. https://doi.org/10.1080/01431161.2010.488255

Calheiros, D. F., **Seidl, A. F.**, & **Ferreira, C. J. A.** (**2000**). Participatory research methods in environmental science: Local and scientific knowledge of a limnological phenomenon in the Pantanal wetland of Brazil. *Journal of Applied Ecology*, 37(4), 684–696. https://doi.org/10.1046/j.1365-2664.2000.00524.x

Campbell, J. (**2015**, August 4). A primer on Nigeria's oil bunkering. Council on Foreign Relations. Retrieved from https://www.cfr.org/backgrounder/nigerias-oil-bunkering

Cao, Y., **Xu, L.**, & **Clausi, D.** (**2017**). Exploring the potential of active learning for automatic identification of marine oil spills using 10-year (2004–2013) RADARSAT data. *Remote Sensing*, 9(10), 1041. https://doi.org/10.3390/rs9101041

Caretta, M. A., & **Jokinen, J. C.** (**2017**). Conflating privilege and vulnerability: A reflexive analysis of emotions and positionality in postgraduate fieldwork. *The Professional Geographer*, 69(2), 275–283. https://doi.org/10.1080/00330124.2016.1252268

Carroll, S. R., **Garba, I.**, **Figueroa-Rodríguez, O. L.**, … & **Hudson, M.** (**2020**). The CARE Principles for Indigenous Data Governance. *Data Science Journal*, 19. https://doi.org/10.5334/dsj-2020-043

Carroll, S. R., **Rodriguez-Lonebear, D.**, & **Martinez, A.** (**2019**). Indigenous data governance: Strategies from United States Native Nations. *Data Science Journal*, 18(1), 31. https://doi.org/10.5334/dsj-2019-031

Casciello, D., **Lacava, T.**, **Pergola, N.**, & **Tramutoli, V.** (**2011**). Robust satellite techniques for oil spill detection and monitoring using AVHRR thermal infrared bands. *International Journal of Remote Sensing*, 32(14), 4107–4129. https://doi.org/10.1080/01431161.2010.484820

Chang, H., **He, G.**, **Wang, Q.**, **Li, H.**, … & **Zhao, J.** (**2021**). Use of sustainability index and cellular automata–Markov model to determine and predict long-term spatio-temporal variation of drought in China. *Journal of Hydrology*, 598, 126248. https://doi.org/10.1016/j.jhydrol.2021.126248

Chaturvedi, S. K., **Banerjee, S.**, & **Lele, S.** (**2020**). An assessment of oil spill detection using Sentinel-1 SAR-C images. *Journal of Ocean Engineering and Science*, 5(2), 116–135. https://doi.org/10.1016/j.joes.2019.09.004

Che, M., **Nian, Y.**, **Chen, S.**, **Zhang, H.**, & **Pei, T.** (**2023**). Spatio-temporal characteristics of human activities using location big data in Qilian Mountain National Park. *International Journal of Digital Earth*, 16(1), 3794–3809. https://doi.org/10.1080/17538947.2023.2259926

Chemisky, B., **Menna, F.**, **Nocerino, E.**, & **Drap, P.** (**2021**). Underwater survey for oil and gas industry: A review of close range optical methods. *Remote Sensing*, 13(14), 2789. https://doi.org/10.3390/rs13142789

Chen, D., **Huang, J.**, & **Jackson, T. J.** (**2005**). Vegetation water content estimation for corn and soybeans using spectral indices derived from MODIS near- and short-wave infrared bands. *Remote Sensing of Environment*, 98(2–3), 225–236. https://doi.org/10.1016/j.rse.2005.07.008

Chen, J. M., & **Cihlar, J.** (**1996**). Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment*, 55(2), 153–162. https://doi.org/10.1016/0034-4257(95)00195-6

Chen, S., & **Hu, C.** (**2014**). In search of oil seeps in the Cariaco Basin using MODIS and MERIS medium-resolution data. *Remote Sensing Letters*, 5(5), 442–450. https://doi.org/10.1080/2150704X.2014.917218

Chijioke, E. (**2009**). Green crimes, petro-violence and the tragedy of oil: The case of the Niger-Delta in Nigeria. *In-Spire Journal of Law, Politics and Society*, 40–60.

Chilisa, B. (**2012**). Indigenous research methodologies. *Canadian Journal of Program Evaluation*, 29(1), 138–140. https://doi.org/10.3138/cjpe.29.1.138

Chinedu, E., & **Chukwuemeka, C. K.** (**2018**). Oil spillage and heavy metals toxicity risk in the Niger Delta, Nigeria. *Journal of Health and Pollution*, 8(19). https://doi.org/10.5696/2156-9614-8.19.180905

Choubin, B., **Moradi, E.**, **Golshan, M.**, … & **Mosavi, A.** (**2019**). An ensemble prediction of flood susceptibility using multivariate discriminant analysis, classification and regression trees, and support vector machines. *Science of the Total Environment*, 651, 2087–2096. https://doi.org/10.1016/J.SCITOTENV.2018.10.064

Chukwuka, K. S., **Alimba, C. G.**, **Ataguba, G. A.**, & **Jimoh, W. A.** (**2018**). The impacts of petroleum production on terrestrial fauna and flora in the oil-producing region of Nigeria. In *The Political Ecology of Oil and Gas Activities in the Nigerian Aquatic Ecosystem* (pp. 125–142). Elsevier. https://doi.org/10.1016/B978-0-12-809399-3.00009-4

Clinton, A., & **Chinago, A.** (**2019**). Depletion of vegetal resources in Niger Delta: A challenge to environmental sustainable development. *International Journal of Plant, Animal and Environmental Sciences*, 9, 26–32. https://doi.org/10.21276/Ijpaes

Cochrane, L., & **Corbett, J.** (**2018**). Participatory mapping. In *Handbook of Communication for Development and Social Change* (pp. 1–9). Springer Singapore. https://doi.org/10.1007/978-981-10-7035-8_6-1

Cochrane, L., & **Corbett, J.** (**2020**). Participatory mapping. In *Handbook of Communication for Development and Social Change* (pp. 705–713). Springer Singapore. https://doi.org/10.1007/978-981-15-2014-3_6

Cococcioni, M., **Corucci, L.**, **Masini, A.**, & **Nardelli, F.** (**2012**). SVME: An ensemble of support vector machines for detecting oil spills from full-resolution MODIS images. *Ocean Dynamics*, 62(3), 449–467. https://doi.org/10.1007/s10236-011-0510-8

Collison, A., & **Curdoglo, M.** (**2025**). Planet surface reflectance. In *Planet Labs PBC*. Retrieved from https://assets.planet.com/marketing/PDF/Planet_Surface_Reflectance_Technical_White_Paper.pdf

Copes, H., **Tchoula, W.**, **Brookman, F.**, & **Ragland, J.** (**2018**). Photo-elicitation interviews with vulnerable populations: Practical and ethical considerations. *Deviant Behavior*, 39(4), 475–494. https://doi.org/10.1080/01639625.2017.1407109

Corbett, J., **Cochrane, L.**, & **Gill, M.** (**2016**). Powering up: Revisiting participatory GIS and empowerment. *The Cartographic Journal*, 53(4), 335–340. https://doi.org/10.1080/00087041.2016.1209624

Cortes, C., & **Vapnik, V.** (**1995**). Support-vector networks. *Machine Learning*, 20(3), 273–297. https://doi.org/10.1007/BF00994018

Corucci, L., **Nardelli, F.**, & **Cococcioni, M.** (**2010**). Oil spill classification from multi-spectral satellite images: Exploring different machine learning techniques. In C. R. Bostater Jr., S. P. Mertikas, X. Neyt, & M. Velez-Reyes (Eds.), *Remote Sensing of the Ocean, Sea Ice, and Large Water Regions* (p. 782509). SPIE. https://doi.org/10.1117/12.864556

Couldry, N., & **Mejias, U. A.** (**2019**). Data colonialism: Rethinking big data's relation to the contemporary subject. *Television & New Media*, 20(4), 336–349. https://doi.org/10.1177/1527476418796632

Daliman, S., **Anak Michael, M. J.**, **Rendra, P. P. R.**, **Sukiyah, E.**, **Hadian, M. S. D.**, & **Sulaksana, N.** (**2024**). Dual vegetation index analysis and spatial assessment in Kota Bharu, Kelantan using GIS and remote sensing. *BIO Web of Conferences*, 131, 05009. https://doi.org/10.1051/bioconf/202413105009

Davies, T. (**2022**). Slow violence and toxic geographies: 'Out of sight' to whom? *Environment and Planning C: Politics and Space*, 40(2), 409–427. https://doi.org/10.1177/2399654419841063

Davies, T. M., & **Lawson, A. B.** (**2019**). An evaluation of likelihood-based bandwidth selectors for spatial and spatiotemporal kernel estimates. *Journal of Statistical*

Computation and Simulation, 89(7), 1131–1152. https://doi.org/10.1080/00949655.2019.1575066

Davis, L. F., & **Ramírez-Andreotta, M. D.** (**2021**). Participatory research for environmental justice: A critical interpretive synthesis. *Environmental Health Perspectives*, 129(2). https://doi.org/10.1289/EHP6274

Davis, M. (**2016**). Data and the United Nations Declaration on the Rights of Indigenous Peoples. In T. Kukutai & J. Taylor (Eds.), *Indigenous Data Sovereignty* (pp. 25–38). ANU Press.

de Carolis, G., **Adamo, M.**, & **Pasquariello, G.** (**2012**). Thickness estimation of marine oil slicks with near-infrared MERIS and MODIS imagery: The Lebanon oil spill case study. 2012 IEEE IGARSS, 3002–3005. https://doi.org/10.1109/IGARSS.2012.6350794

Diggle, P. (**1985**). A kernel method for smoothing point process data. *Applied Statistics*, 34(2), 138–147. https://doi.org/10.2307/2347366

Dingre, S. K., **Gorantiwar, S. D.**, & **Kadam, S. A.** (**2021**). Correlating the field water balance derived crop coefficient (Kc) and canopy reflectance-based NDVI for irrigated sugarcane. *Precision Agriculture*, 22(4), 1134–1153. https://doi.org/10.1007/s11119-020-09774-8

Dinko, D. H., & **Nyantakyi-Frimpong, H.** (**2023**). The prospects and challenges of using drone-based participatory mapping in human–environment research. *The Professional Geographer*, 75(3), 441–451. https://doi.org/10.1080/00330124.2022.2103723

Douglas, O., & **Okonta, I.** (**2018**, March 10). The Niger Delta: A people and their environment. *Verso Blogs*. Retrieved from https://www.versobooks.com/blogs/3678-the-niger-delta-a-people-and-their-environment

Doust, H. (**1990**). Petroleum geology of the Niger Delta. *Geological Society, London, Special Publications*, 50(1), 365–365. https://doi.org/10.1144/GSL.SP.1990.050.01.21

Duke, N. C. (**2016**). Oil spill impacts on mangroves: Recommendations for operational planning and action based on a global review. *Marine Pollution Bulletin*, 109(2), 700–715. https://doi.org/10.1016/J.MARPOLBUL.2016.06.082

Ite, A., **Harry, A.**, **Obadimu, C. O.**, **Asuaiko, R.**, & **Inim, I. J.** (**2018**). Petroleum hydrocarbons contamination of surface water and groundwater in the Niger Delta region of Nigeria. *Journal of Environment Pollution and Human Health*, 6(2), 51–61. https://doi.org/10.12691/jephh-6-2-2

Earthdata. (n.d.). PlanetScope Full Archive. PlanetScope. Retrieved April 16, 2025, from https://cmr.earthdata.nasa.gov/search/concepts/C1965336933-ESA/15

Eaton, C., & **Volz, D.** (**2021**, May 19). Colonial Pipeline CEO tells why he paid hackers a $4.4 million ransom. *The Wall Street Journal*. Retrieved from https://www.wsj.com/articles/colonial-pipeline-ceo-tells-why-he-paid-hackers-a-4-4-million-ransom-11621435636

Eboh, C. (**2022**, October 6). Nigerian oil export terminal had theft line into sea for 9 years. *Reuters*. Retrieved from https://www.reuters.com/world/africa/nigerian-oil-export-terminal-had-theft-line-into-sea-9-years-2022-10-05/

Eboh, C. (**2023**, October 1). Nigeria pumping 1.67 million barrels of oil and condensates per day. *Reuters*. Retrieved from https://www.reuters.com/world/africa/nigeria-pumping-167-million-bpd-oil-condensates-per-day-nnpc-head-2023-09-01/

Ebrahimi, A., **Zolfaghari, F.**, **Ghodsi, M.**, & **Narmashiri, F.** (**2024**). Assessing the accuracy of spectral indices obtained from Sentinel images using field research to estimate land degradation. *PLOS ONE*, 19(7), e0305758. https://doi.org/10.1371/journal.pone.0305758

Egobueze, F. E., **Rowland, E. D.**, & **Ebizimo, D. S.** (**2022**). Multispectral imagery for detection and monitoring of vegetation affected by oil spills and migration pattern in Niger Delta Region, Nigeria. *World Journal of Advanced Research and Reviews*, 15(1), 447–458. https://doi.org/10.30574/wjarr.2022.15.1.0682

EIA. (**2023**). Country analysis brief: Nigeria. U.S. Energy Information Administration.

EIA, U. S. E. I. A. (**2022**). Libya execute summary. Retrieved from https://www.eia.gov/international/analysis/country/LBY

Ejoh, E. (**2021**, December 28). Pipeline vandalism, sabotage, others culminate in shutdown of 8 oil terminals – Report. *Vanguard*. Retrieved from https://www.vanguardngr.com/2021/12/pipeline-vandalism-sabotage-others-culminate-in-shutdown-of-8-oil-terminals-report/

Eke, S. J. (**2016**). Running to fight another day: Commodification of peace and the resurgence of violence in post-amnesty Niger Delta. *Journal of Peacebuilding & Development*, 9(2), 136–159. https://doi.org/10.2307/48598922

Ekhator, O. C., **Orish, F. C.**, **Nnadi, E. O.**, **Ogaji, D. S.**, **Isuman, S.**, & **Orisakwe, O. E.** (**2023**). Impact of black soot emissions on public health in Niger Delta, Nigeria:

Understanding the severity of the problem. *Inhalation Toxicology*, 1–13. https://doi.org/10.1080/08958378.2023.2297698

Elum, Z. A., **Mopipi, K.**, & **Henri-Ukoha, A.** (**2016**). Oil exploitation and its socioeconomic effects on the Niger Delta region of Nigeria. *Environmental Science and Pollution Research*, 23(13), 12880–12889. https://doi.org/10.1007/s11356-016-6864-1

Elwood, S. A., & **Martin, D. G.** (**2000**). "Placing" interviews: Location and scales of power in qualitative research. *The Professional Geographer*, 52(4), 649–657. https://doi.org/10.1111/0033-0124.00253

Emadi, H. (**2012**). Libya: The road to regime change. *Global Dialogue*, 14(2), 128–142. https://www.proquest.com/docview/1035287146

Emelu, V. O., **Eludoyin, O. S.**, & **Oyegun, C. U.** (**2021**). Preparedness and mitigation measures for oil and gas pipeline vandalization in the Niger Delta Region of Nigeria. *Environmental Management and Sustainable Development*, 10(4), 16–27. https://doi.org/10.5296/emsd.v10i4.18982

Emelu, O. V., **Oyegun, U. C.**, & **Eludoyin, S. O.** (**2021**). Causes of oil and gas pipeline vandalism in the Niger Delta Region of Nigeria. *Journal of Research in Humanities and Social Science*, 9(9). Retrieved from www.questjournals.org

Emery, W., & **Camps, A.** (**2017**). The history of satellite remote sensing. In *Introduction to Satellite Remote Sensing* (pp. 1–42). Elsevier. https://doi.org/10.1016/B978-0-12-809254-5.00001-4

Enns, C. (**2019**). Infrastructure projects and rural politics in northern Kenya: The use of divergent expertise to negotiate land deals for transport infrastructure. *The Journal of Peasant Studies*, 46(2), 358–376. https://doi.org/10.1080/03066150.2017.1377182

Enns, C., & **Sneyd, A.** (**2021**). More-than-human infrastructural violence and infrastructural justice: A case study of the Chad–Cameroon Pipeline Project. *Annals of the American Association of Geographers*, 111(2), 481–497. https://doi.org/10.1080/24694452.2020.1774348

Environmental Pollution Centers. (**2017**). Oil spill pollution. Retrieved from https://www.environmentalpollutioncenters.org/oil-spill/

Epuh, E. E., **Ufot, A. I.**, & **Orji, M. J.** (**2017**). Application of GIS to oil and gas pipeline management: A case study of South-South Nigeria. *Nigerian Journal of*

Environmental Sciences and Technology, 1(2), 337–348. https://doi.org/10.36263/nijest.2017.02.0035

Ering, S. O., **Bassey, G. E.**, & **Odike, E. L.** (**2013**). The Niger Delta crisis in Nigeria: Pre- and post-amnesty situation. *Mediterranean Journal of Social Sciences*, 4(6), 421–427. https://doi.org/10.5901/mjss.2013.v4n6p421

Everest, N. C. (**2021**). Oil pipeline vandalism: Implications on multinational oil corporations and host communities in the Niger-Delta, Nigeria. *Transatlantic Journal of Multidisciplinary Research*, 3, 84–97. https://doi.org/10.5281/zenodo.5039346

Exprodat. (**2015**). Why use GIS in petroleum? Retrieved from https://www.exprodat.com/featured/downloads/why-use-gis-in-petroleum/

Fadl, M. E., **AbdelRahman, M. A. E.**, **El-Desoky, A. I.**, & **Sayed, Y. A.** (**2024**). Assessing soil productivity potential in arid region using remote sensing vegetation indices. *Journal of Arid Environments*, 222, 105166. https://doi.org/10.1016/j.jaridenv.2024.105166

Fertaly, K., & **Fluri, J. L.** (**2019**). Research associates and the production of knowledge in the field. *The Professional Geographer*, 71(1), 75–82. https://doi.org/10.1080/00330124.2018.1455519

Finch-Race, D. A. (**2025**). Symptoms of infrastructural slow violence in Adolfo Tommasi's *Allegory of Work*. *The Professional Geographer*, 1–4. https://doi.org/10.1080/00330124.2025.2468657

Fingas, M., & **Brown, C.** (**2014**). Review of oil spill remote sensing. *Marine Pollution Bulletin*, 83(1), 9–23. https://doi.org/10.1016/j.marpolbul.2014.03.059

Fingas, M., & **Brown, C.** (**2017**). A review of oil spill remote sensing. *Sensors*, 18(1), 91. https://doi.org/10.3390/s18010091

Fingas, M., & **Brown, C.** (**2018**). Oil spill remote sensing. In *Encyclopedia of Sustainability Science and Technology* (pp. 1–37). Springer New York. https://doi.org/10.1007/978-1-4939-2493-6_732-4

Fouché, C. B., & **Chubb, L. A.** (**2017**). Action researchers encountering ethical review: A literature synthesis on challenges and strategies. *Educational Action Research*, 25(1), 23–34. https://doi.org/10.1080/09650792.2015.1128959

Frazier, A. E., & **Hemingway, B. L.** (**2021**). A technical review of Planet Smallsat data: Practical considerations for processing and using PlanetScope imagery. *Remote Sensing*, 13(19), 3930. https://doi.org/10.3390/rs13193930

Gambardella, A., **Giacinto, G.**, **Migliaccio, M.**, & **Montali, A.** (**2010**). One-class classification for oil spill detection. *Pattern Analysis and Applications*, 13(3), 349–366. https://doi.org/10.1007/s10044-009-0164-z

Gandhi, U. (**2021**). Google Earth Engine for water resources management course. Spatial Thoughts. Retrieved from https://courses.spatialthoughts.com/gee-water-resources-management.html

Gbadegesin, A., **Adesina, F.**, **Orimoogunje, O.**, & **Oderinde, F.** (**2023**). Vegetation and human impact. In A. Faniran, L. K. Jeje, O. A. Fashae, & A. O. Olusola (Eds.), *Environmental Protection and Human Health* (pp. 39–52). Springer Nature Switzerland AG. https://doi.org/10.1007/978-3-031-17972-3_3

Gelb, J. (**2021**). spNetwork: A package for network kernel density estimation. *The R Journal*, 13(2), 460. https://doi.org/10.32614/RJ-2021-102

Gelb, J., & **Apparicio, P.** (**2023**). Temporal network kernel density estimation. *Geographical Analysis*. https://doi.org/10.1111/gean.12368

Gholizadeh, A., & **Kopačková, V.** (**2019**). Detecting vegetation stress as a soil contamination proxy: A review of optical proximal and remote sensing techniques. *International Journal of Environmental Science and Technology*, 16(5), 2511–2524. https://doi.org/10.1007/s13762-019-02310-w

Ghorbanian, A., **Kakooei, M.**, **Amani, M.**, **Mahdavi, S.**, **Mohammadzadeh, A.**, & **Hasanlou, M.** (**2020**). Improved land cover map of Iran using Sentinel imagery within Google Earth Engine and a novel workflow for land cover classification using migrated training samples. *ISPRS Journal of Photogrammetry and Remote Sensing*, 167, 276–288. https://doi.org/10.1016/j.isprsjprs.2020.07.013

Gitelson, A. A., **Kaufman, Y. J.**, & **Merzlyak, M. N.** (**1996**). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment*, 58(3), 289–298. https://doi.org/10.1016/S0034-4257(96)00072-7

Gitelson, A. A., **Kaufman, Y. J.**, **Stark, R.**, & **Rundquist, D.** (**2002**). Novel algorithms for remote estimation of vegetation fraction. *Remote Sensing of Environment*, 80(1), 76–87. https://doi.org/10.1016/S0034-4257(01)00289-9

Gokool, S., **Kunz, R.**, **Clulow, A.**, & **Toucher, M.** (**2024**). Leveraging Google Earth Engine and machine learning to estimate evapotranspiration in a commercial forest plantation. *Remote Sensing*, 16(15), 2726. https://doi.org/10.3390/rs16152726

Gómez, C., & **Green, D. R.** (**2017**). Small unmanned airborne systems to support oil and gas pipeline monitoring and mapping. *Arabian Journal of Geosciences*, 10(15), 333. https://doi.org/10.1007/s12517-017-2989-x

Grabowski, Z. J., **Wijsman, K.**, **Tomateo, C.**, & **McPhearson, T.** (**2022**). How deep does justice go? Addressing ecological, indigenous, and infrastructural justice through nature-based solutions in New York City. *Environmental Science & Policy*, 138, 171–181. https://doi.org/10.1016/j.envsci.2022.09.022

Graham, S. (**2004**). Constructing urbicide by bulldozer in the occupied territories. In *Cities, War, and Terrorism* (pp. 192–213). Wiley. https://doi.org/10.1002/9780470753033.ch11

Graham, S. (**2006**). Urban metabolism as target: Contemporary war as forced demodernization. *Urban Studies*, 43(10), 1737–1750. https://doi.org/10.1080/00420980600897942

Grimaldi, C. S. L., **Casciello, D.**, **Coviello, I.**, **Lacava, T.**, **Pergola, N.**, & **Tramutoli, V.** (**2011**). An improved RST approach for timely alert and near real time monitoring of oil spill disasters by using AVHRR data. *Natural Hazards and Earth System Sciences*, 11(5), 1281–1291. https://doi.org/10.5194/nhess-11-1281-2011

Guasco, A. (**2022**). On an ethic of not going there. *The Geographical Journal*, 188(3), 468–475. https://doi.org/10.1111/geoj.12462

Guo, G., **Liu, B.**, & **Liu, C.** (**2020**). Thermal infrared spectral characteristics of bunker fuel oil to determine oil-film thickness and API. *Journal of Marine Science and Engineering*, 8(2), 135. https://doi.org/10.3390/jmse8020135

Guo, Y., & **Zhang, H. Z.** (**2014**). Oil spill detection using synthetic aperture radar images and feature selection in shape space. *International Journal of Applied Earth Observation and Geoinformation*, 30, 146–157. https://doi.org/10.1016/j.jag.2014.01.011

Guoyin Cai, **Jian Wu**, **Yong Xue**, **Wei Wan**, & **Xiaoxia Huang.** (**2007**). Oil spill detection from thermal anomaly using ASTER data in Yinggehai of Hainan, China. 2007 IEEE IGARSS, 898–900. https://doi.org/10.1109/IGARSS.2007.4422942

Guta, A., **Nixon, S. A.**, & **Wilson, M. G.** (**2013**). Resisting the seduction of "ethics creep": Using Foucault to surface complexity and contradiction in research ethics review. *Social Science & Medicine*, 98, 301–310. https://doi.org/10.1016/j.socscimed.2012.09.019

Harahsheh, H. A. (**2016**). Oil spill detection and monitoring of Abu Dhabi coastal zone using Kompsat-5 SAR imagery. *ISPRS Archives*, XLI-B8, 1115–1121. https://doi.org/10.5194/isprsarchives-XLI-B8-1115-2016

Hensen, B., **Mackworth-Young, C. R. S.**, **Simwinga, M.**, … & **Weiss, H. A.** (**2021**). Remote data collection for public health research in a COVID-19 era: Ethical implications, challenges and opportunities. *Health Policy and Planning*, 36(3), 360–368. https://doi.org/10.1093/heapol/czaa158

Hese, S., & **Schmullius, C.** (n.d.). Object oriented oil spill contamination mapping in West Siberia with Quickbird data. In *Object-Based Image Analysis* (pp. 367–382). Springer. https://doi.org/10.1007/978-3-540-77058-9_20

Hoover, F.-A., **Meerow, S.**, **Grabowski, Z. J.**, & **McPhearson, T.** (**2021**). Environmental justice implications of siting criteria in urban green infrastructure planning. *Journal of Environmental Policy & Planning*, 23(5), 665–682. https://doi.org/10.1080/1523908X.2021.194591

Hossen, M. A. (**2016**). Participatory mapping for community empowerment. *Asian Geographer*, 33(2), 97–113. https://doi.org/10.1080/10225706.2016.1237370

Hu, X., **Wu, C.**, **Wang, J.**, & **Qiu, R.** (**2018**). Identification of spatial variation in road network and its driving patterns: Economy and population. *Regional Science and Urban Economics*, 71, 37–45. https://doi.org/10.1016/j.regsciurbeco.2018.04.014

Huang, H., & **Roy, D. P.** (**2021**). Characterization of Planetscope-0 Planetscope-1 surface reflectance and normalized difference vegetation index continuity. *Science of Remote Sensing*, 3, 100014. https://doi.org/10.1016/j.srs.2021.100014

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. *Journal of Forestry Research*, 32(1), 1–6. https://doi.org/10.1007/s11676-020-01155-1

Huete, A., **Didan, K.**, **Miura, T.**, **Rodriguez, E. P.**, **Gao, X.**, & **Ferreira, L. G.** (**2002**). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1–2), 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2

Huete, A. R. (**1988**). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, 25(3), 295–309. https://doi.org/10.1016/0034-4257(88)90106-X

Huete, A. R. (**2004**). Remote sensing for environmental monitoring. In *Environmental Monitoring and Characterization* (pp. 183–206). Elsevier. https://doi.org/10.1016/B978-012064477-3/50013-8

Hughes, M. J., & **Kennedy, R.** (**2019**). High-quality cloud masking of Landsat 8 imagery using convolutional neural networks. *Remote Sensing*, 11(21), 2591. https://doi.org/10.3390/rs11212591

IFAD. (**2009**). Good practices in participatory mapping: A review prepared for the International Fund for Agricultural Development. Retrieved from www.ifad.org

Ikporukpo, C. (**1983**). Petroleum exploitation and the socio-economic environment in Nigeria. *International Journal of Environmental Studies*, 21(2), 193–203. https://doi.org/10.1080/00207238308710076

Ikporukpo, C. (**2020**). The challenge of oil spill monitoring and control in Nigeria. *International Journal of Environmental Monitoring and Analysis*, 8(6), 202–207. https://doi.org/10.11648/j.ijema.20200806.14

Iling, A. (n.d.). Socio-economic implications and environmental effects of oil spillage in some communities in the Niger Delta. *Journal of Integrative Environmental Sciences*, 6(1), 7–23. https://doi.org/10.1080/15693430802650449

Ipingbemi, O. (**2009**). Socio-economic implications and environmental effects of oil spillage in some communities in the Niger Delta. *Journal of Integrative Environmental Sciences*, 6(1), 7–23. https://doi.org/10.1080/15693430802650449

Iyasara, C. A., **Azubuike, O. F.**, & **Solomon, I. O.** (**2013**). Management of oil spills due to pipeline corrosion in the Niger Delta region of Nigeria. *International Journal of Environmental Monitoring and Analysis*, 8(6), 202–207. https://doi.org/10.11648/j.ijema.20200806.14

Jain, S. K., & **Singh, V. P.** (**2003**). Emerging techniques for data acquisition and systems modeling. In *Advances in Water Resources*, 123–205. https://doi.org/10.1016/S0167-5648(03)80057-6

Jiang, Z., **Huete, A. R.**, **Didan, K.**, & **Miura, T.** (**2008**). Development of a two-band enhanced vegetation index without a blue band. *Remote Sensing of Environment*, 112(10), 3833–3845. https://doi.org/10.1016/j.rse.2008.06.006

John, A. O. (**2012**). Environmental degradation and oil industry activities in the Niger-Delta region. *Anuya & Aiyedogbon African Journal of Scientific Research*, 9(1). https://doi.org/10.1017/CBO9780511812705

Johnson, F. I., **Laing, R.**, **Bjeirmi, B.**, & **Leon, M.** (**2022**). Examining the causes and impacts of pipeline disasters in Nigeria. *AIMS Environmental Science*, 9(5), 636–657. https://doi.org/10.3934/environsci.2022037

Jone, M., & **Casserly, J.** (**2022**). Nigeria's illegal oil refineries: Dirty, dangerous, lucrative. *BBC News*. Retrieved from https://www.bbc.co.uk/news/world-africa-61216157

Jordan, C. F. (**1969**). Derivation of leaf-area index from quality of light on the forest floor. *Ecology*, 50(4), 663–666. https://doi.org/10.2307/1936256

Junaid, M., **Sun, J.**, **Iqbal, A.**, **Sohail, M.**, **Zafar, S.**, & **Khan, A.** (**2023**). Mapping LULC dynamics and its potential implication on forest cover in Malam Jabba region with Landsat time series imagery and random forest classification. *Sustainability*, 15(3), 1858. https://doi.org/10.3390/su15031858

Abbas, D. U., & **George, L. E.** (**2022**). The detection of oil spill onshore using the thermal band of Landsat-8. *TELKOMNIKA*, 20(2), 383. https://doi.org/10.12928/telkomnika.v20i2.22462

Kadafa, A. A., **Zakaria, P.**, & **Othman, F.** (**2012**). Oil spillage and pollution in Nigeria: Organizational management and institutional framework. *International Journal of Business and Social Science*, 2(4). Retrieved from www.iiste.org

Kallianos, Y., **Dunlap, A.**, & **Dalakoglou, D.** (**2023**). Introducing infrastructural harm: Rethinking moral entanglements, spatio-temporal dynamics, and resistance(s). *Globalizations*, 20(6), 829–848. https://doi.org/10.1080/14747731.2022.2153493

Kamalu, O. J., & **Wokocha, C. C.** (**2019**). Assessment of land use patterns and land cover change in Igwuruta area of Rivers State, Nigeria. *IIARD International Journal of Geography and Environmental Management*, 5(1), 10–19. Retrieved from www.iiardpub.org

Karatzoglou, A. (**2022**). Applying network kernel density estimation (NKDE) and temporal network kernel estimation (TNKDE) for generating safer routes. *ACM SIGSPATIAL International Workshop on Computational Transportation Science*, 1–10. https://doi.org/10.1145/3557991.35677812

Karra, K., & **Kontgis, C.** (**2021**). Global land use/land cover with Sentinel-2 and deep learning. *IGARSS 2021- IEEE International Geoscience and Remote Sensing*

Symposium. Retrieved from https://www.arcgis.com/home/item.html?id=cfcb7609de5f478eb7666240902d4d3d

Katsouris, C., & **Sayne, A.** (**2013**). Nigeria's criminal crude: International options to combat the export of stolen oil. *Chatham House*. Retrieved from www.chathamhouse.org

Khazov-Cassia, S. (**2021**). The great Russian oil heist: Criminals, lawmen, and the quest for liquid loot. Retrieved from https://www.rferl.org/a/russia-oil-pipeline-theft-transneft/31163179.html

Khilar, P. M., **Chaudhari, V.**, & **Swain, R. R.** (**2019**). Trust-based access control in cloud computing using machine learning. In *Advances in Information and Communication Technology* (pp. 55–79). Springer. https://doi.org/10.1007/978-3-030-03359-0_3

Kim, D.-J. (**2011**). Monitoring of coastal wind and oil spill using KOMPSAT-5. *Journal of Ocean Engineering and Technology*, 25(1), 6–10.

Kim, T.-S., **Park, K.-A.**, **Li, X.**, **Lee, M.**, **Hong, S.**, **Lyu, S. J.**, & **Nam, S.** (**2015**). Detection of the Hebei Spirit oil spill on SAR imagery and its temporal evolution in a coastal region of the Yellow Sea. *Advances in Space Research*, 56(6), 1079–1093. https://doi.org/10.1016/j.asr.2015.05.040

Kim, Y. (**2010**). Spectral compatibility of vegetation indices across sensors: Band decomposition analysis with Hyperion data. *Journal of Applied Remote Sensing*, 4(1), 043520. https://doi.org/10.1117/1.3400635

Kior, A., **Sukhov, V.**, & **Sukhova, E.** (**2021**). Application of reflectance indices for remote sensing of plants and revealing actions of stressors. *Photonics*, 8(12), 582. https://doi.org/10.3390/photonics8120582

Kocur-Bera, K., & **Małek, A.** (**2024**). Assessing the feasibility of using remote sensing data and vegetation indices in the estimation of land subject to consolidation. *Sensors*, 24(23), 7736. https://doi.org/10.3390/s24237736

Kolokoussis, P., & **Karathanassi, V.** (**2018**). Oil spill detection and mapping using Sentinel-2 imagery. *Journal of Marine Science and Engineering*, 6(1), 4. https://doi.org/10.3390/jmse6010004

Kooistra, L., **Leuven, R. S. E. W.**, **Wehrens, R.**, **Nienhuis, P. H.**, & **Buydens, L. M. C.** (**2003**). A comparison of methods to relate grass reflectance to soil metal contamination. *International Journal of Remote Sensing*, 24(24), 4995–5010. https://doi.org/10.1080/0143116031000080769

Koos, C., & **Pierskalla, J.** (**2016**). The effects of oil production and ethnic representation on violent conflict in Nigeria: A mixed-methods approach. *Terrorism and Political Violence*, 28(5), 888–911. https://doi.org/10.1080/09546553.2014.962021

Kovalev, A., & **Tokareva, O.** (**2016**). Using MODIS NDVI products for vegetation state monitoring on the oil production territory in Western Siberia. *MATEC Web of Conferences*, 48, 05003. https://doi.org/10.1051/matecconf/20164805003

Kpae, G. (**2020**). Impact of oil exploration on the Niger Delta: The drivers and dynamics of conflict over environmental degradation. *International Journal of Innovative Studies in Sociology and Humanities*, 5(1).

Kumar, H., **Kumar, R.**, **Dutta, S.**, & **Singh, M.** (**2023**). Google's cloud computing platform-based performance assessment of machine learning algorithms for precise maize crop mapping using integrated satellite data of Sentinel-2A/B and Planetscope. *Journal of the Indian Society of Remote Sensing*, 51(12), 2599–2613. https://doi.org/10.1007/s12524-023-01764-3

Kuta, A. A., **Grebby, S.**, & **Boyd, D. S.** (**2025**). Remote monitoring of the impact of oil spills on vegetation in the Niger Delta, Nigeria. *Applied Sciences*, 15(1), 338. https://doi.org/10.3390/app15010338

Kvande, M. A., **Jacobsen, S. L.**, **Goodwin, M.**, & **Gupta, R.** (**2024**). Using AI to empower Norwegian agriculture: Attention-based multiple-instance learning implementation. *Agronomy*, 14(6), 1089. https://doi.org/10.3390/agronomy14061089

Lacava, T., **Ciancia, E.**, **Coviello, I.**, **di Polito, C.**, **Grimaldi, C.**, **Pergola, N.**, **Satriano, V.**, **Temimi, M.**, **Zhao, J.**, & **Tramutoli, V.** (**2017**). A MODIS-based robust satellite technique (RST) for timely detection of oil spilled areas. *Remote Sensing*, 9(2), 128. https://doi.org/10.3390/rs9020128

Lassalle, G., **Fabre, S.**, **Credoz, A.**, **Dubucq, D.**, & **Elger, A.** (**2020**). Monitoring oil contamination in vegetated areas with optical remote sensing: A comprehensive review. *Journal of Hazardous Materials*, 393, 122427. https://doi.org/10.1016/j.jhazmat.2020.122427

Lau, C. Q., **Cronberg, A.**, **Marks, L.**, & **Amaya, A.** (**2019**). In search of the optimal mode for mobile phone surveys in developing countries: A comparison of IVR, SMS, and CATI in Nigeria. *Journal of Survey Statistics and Methodology*, 7(3), 305–326. https://doi.org/10.1093/jssam/smz010

Laville, S. (**2023**). Nearly 14,000 Nigerians take Shell to court over devastating impact of pollution. *The Guardian*. Retrieved from https://www.theguardian.com/world/2023/feb/02/nearly-14000-nigerians-take-shell-to-court-over-devastating-impact-of-pollution

Lavrova, O. Yu., & **Mityagina, M. I.** (**2013**). Satellite monitoring of oil slicks on the Black Sea surface. *Izvestiya, Atmospheric and Oceanic Physics*, 49(9), 897–912. https://doi.org/10.1134/S0001433813090107

Lazzeri, F. (**2021**). *Machine learning for time series forecasting with Python*. Wiley.

Lee, C. B., **Martin, L.**, **Traganos, D.**, **Antat, S.**, **Baez, S. K.**, **Cupidon, A.**, **Faure, A.**, **Harlay, J.**, **Morgan, M.**, **Mortimer, J. A.**, **Reinartz, P.**, & **Rowlands, G.** (**2023**). Mapping the national seagrass extent in Seychelles using PlanetScope NICFI data. *Remote Sensing*, 15(18), 4500. https://doi.org/10.3390/rs15184500

Lee, M.-S., **Park, K.-A.**, **Lee, H.-R.**, **Park, J.-J.**, **Kang, C.-K.**, & **Lee, M.** (**2016**). Detection and dispersion of thick and film-like oil spills in a coastal bay using satellite optical images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 9(11), 5139–5150. https://doi.org/10.1109/JSTARS.2016.2577597

Lei, S., **Luo, J.**, **Tao, X.**, & **Qiu, Z.** (**2021**). Remote sensing detecting of yellow leaf disease of arecanut based on UAV multisource sensors. *Remote Sensing*, 13(22), 4562. https://doi.org/10.3390/rs13224562

Leifer, I., **Lehr, W. J.**, **Simecek-Beatty, D.**, **Bradley, E.**, **Clark, R.**, **Dennison, P.**, **Hu, Y.**, … & **Wozencraft, J.** (**2012**). State of the art satellite and airborne marine oil spill remote sensing: Application to the BP Deepwater Horizon oil spill. *Remote Sensing of Environment*, 124, 185–209. https://doi.org/10.1016/j.rse.2012.03.024

Lemanski, C. (**2019**). Citizenship and infrastructure. In C. Lemanski (Ed.), *Citizenship and Infrastructure* (1st ed.). Routledge. https://doi.org/10.4324/9781351176156

Li, X., **Zhu, W.**, **Xie, Z.**, **Zhan, P.**, **Huang, X.**, **Sun, L.**, & **Duan, Z.** (**2021**). Assessing the effects of time interpolation of NDVI composites on phenology trend estimation. *Remote Sensing*, 13(24), 5018. https://doi.org/10.3390/rs13245018

Li, Y., **Cui, C.**, **Liu, Z.**, **Liu, B.**, **Xu, J.**, **Zhu, X.**, & **Hou, Y.** (**2017**). Detection and monitoring of oil spills using moderate/high-resolution remote sensing images. *Archives of Environmental Contamination and Toxicology*, 73(1), 154–169. https://doi.org/10.1007/s00244-016-0358-5

Li, Z., **Gurgel, H.**, **Xu, L.**, **Yang, L.**, & **Dong, J.** (**2022**). Improving Dengue forecasts by using geospatial big data analysis in Google Earth Engine and the historical Dengue information-aided LSTM modeling. *Biology*, 11(2), 169. https://doi.org/10.3390/biology11020169

Liamputtong, P. (**2010**). Performing qualitative cross-cultural research. Cambridge University Press. https://doi.org/10.1017/CBO9780511812705

Lillesand, T. M., **Kiefe, R. W.**, & **Chipman, J. W.** (**2015**). Remote sensing and image interpretation (7th ed.). John Wiley & Sons.

Lin, Y., **Yu, J.**, **Zhang, Y.**, **Wang, P.**, & **Ye, Z.** (**2016**). Dynamic analysis of oil spill in Yangtze Estuary with HJ-1 imagery. In *HJ-1 International Symposium* (pp. 345–356). Springer. https://doi.org/10.1007/978-3-662-49155-3_35

Lin, Y.-P., **Chu, H.-J.**, **Wu, C.-F.**, **Chang, T.-K.**, & **Chen, C.-Y.** (**2010**). Hotspot analysis of spatial environmental pollutants using kernel density estimation and geostatistical techniques. *International Journal of Environmental Research and Public Health*, 8(1), 75–88. https://doi.org/10.3390/ijerph8010075

Lindén, O., & **Pålsson, J.** (**2013**). Oil contamination in Ogoniland, Niger Delta. *Ambio*, 42(6), 685–701. https://doi.org/10.1007/s13280-013-0412-8

Little, D. I., **Holtzmann, K.**, **Gundlach, E. R.**, & **Galperin, Y.** (**2018**). Sediment hydrocarbons in former mangrove areas, southern Ogoniland, Eastern Niger Delta, Nigeria. In *Geological Society of America Special Papers* (Vol. 507, pp. 323–342). https://doi.org/10.1130/2018.2507(14)

Liu, P., **Zhao, C.**, **Li, X.**, **He, M.**, & **Pichel, W.** (**2010**). Identification of ocean oil spills in SAR imagery based on fuzzy logic algorithm. *International Journal of Remote Sensing*, 31(17–18), 4819–4833. https://doi.org/10.1080/01431161.2010.4851473

Liu, S., **Chi, M.**, **Zou, Y.**, **Samat, A.**, **Benediktsson, J. A.**, & **Plaza, A.** (**2017**). Oil spill detection via multitemporal optical remote sensing images: A change detection perspective. *IEEE Geoscience and Remote Sensing Letters*, 14(3), 324–328. https://doi.org/10.1109/LGRS.2016.2639540

Loaiza, D. M. (**2023**). Awesome spectral indices for Google Earth Engine. Retrieved from https://awesome-ee-spectral-indices.readthedocs.io/

Loukika, K. N., **Keesara, V. R.**, & **Sridhar, V.** (**2021**). Analysis of land use and land cover using machine learning algorithms on Google Earth Engine for Munneru River Basin, India. *Sustainability*, 13(24), 13758. https://doi.org/10.3390/su132413758

Löw, F., **Stieglitz, K.**, & **Diemar, O.** (**2021**). Terrestrial oil spill mapping using satellite earth observation and machine learning: A case study in South Sudan. *Journal of Environmental Management*, 298, 113424. https://doi.org/10.1016/j.jenvman.2021.113424

Luh Sin, H. (**2015**). "You're not doing work, you're on Facebook!": Ethics of encountering the field through social media. *The Professional Geographer*, 67(4), 676–685. https://doi.org/10.1080/00330124.2015.1062705

Lykhovyd, P. V., **Vozhehova, R. A.**, **Hranovska, L. M.**, & **Bidnyna, I. O.** (**2024**). The link between the normalized difference vegetation index in major crops and meteorological factors. *Agrology*, 7(2), 39–45. https://doi.org/10.32819/202406

Mackenzie, C., **McDowell, C.**, & **Pittaway, E.** (**2007**). Beyond "do no harm": The challenge of constructing ethical relationships in refugee research. *Journal of Refugee Studies*, 20(2), 299–319. https://doi.org/10.1093/jrs/fem008

Mahmoud, I. M. (**2021**). Analysis of oil spill impacts along pipelines and the fate of sensitive environments in Nigeria. *International Oil Spill Conference Proceedings*, 2021(1). https://doi.org/10.7901/2169-3358-2021.1.629863

Maianti, P., **Rusmini, M.**, **Tortini, R.**, **Dalla Via, G.**, **Frassy, F.**, **Marchesi, A.**, **Rota Nodari, F.**, & **Gianinetto, M.** (**2014**). Monitoring large oil slick dynamics with moderate resolution multispectral satellite data. *Natural Hazards*, 73(2), 473–492. https://doi.org/10.1007/s11069-014-1084-9

Mancino, G., **Console, R.**, **Greco, M.**, **Iacovino, C.**, **Trivigno, M. L.**, & **Falciano, A.** (**2022**). Assessing vegetation decline due to pollution from solid waste management by a multitemporal remote sensing approach. *Remote Sensing*, 14(2), 428. https://doi.org/10.3390/rs14020428

Mann, M. (**1984**). The autonomous power of the state: Its origins, mechanisms and results. *European Journal of Sociology*, 25(2), 100–138. https://doi.org/10.1017/S000397560000452

Marghany, M. (**2015**). Automatic detection of oil spills in the Gulf of Mexico from RADARSAT-2 SAR satellite data. *Environmental Earth Sciences*, 74(7), 5935–5947. https://doi.org/10.1007/s12665-015-4617-y

Marshall, C., & **Rossman, G. B.** (**2014**). *Designing qualitative research* (5th ed.). SAGE Publications.

Matemilola, S., **Adedeji, O. H.**, & **Enoguanbhor, E. C.** (**2018**). Land use/land cover change in petroleum-producing regions of Nigeria. In *The Political Ecology of Oil and Gas Activities in the Nigerian Aquatic Ecosystem* (pp. 257–276). Elsevier. https://doi.org/10.1016/B978-0-12-809399-3.00017-3

Maxwell, A. E., **Warner, T. A.**, & **Fang, F.** (**2018**). Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 39(9), 2784–2817. https://doi.org/10.1080/01431161.2018.1433345

Maxwell, A. E., **Warner, T. A.**, & **Guillén, L. A.** (**2021**). Accuracy Assessment in Convolutional Neural Network-Based Deep Learning Remote Sensing Studies—Part 1: Literature Review). *Remote Sensing*, 13(13), 2450. https://doi.org/10.3390/rs13132450

Maxwell, A. E., **Warner, T. A.**, **Strager, M. P.**, **Conley, J. F.**, & **Sharp, A. L.** (**2015**). Assessing machine-learning algorithms and image- and lidar-derived variables for GEOBIA classification of mining and mine reclamation. *International Journal of Remote Sensing*, 36(4), 954–978. https://doi.org/10.1080/01431161.2014.1001086

Mayring, P. (**2000**). Qualitative content analysis. In *Qualitative Method in Various Disciplines*, 1(2), 1–121.

Mba, I. C., **Mba, E. I.**, **Ogbuabor, J. E.**, & **Arazu, W. O.** (**2019**). Causes and terrain of oil spillage in Niger Delta region of Nigeria: The analysis of variance approach. *International Journal of Energy Economics and Policy*, 9(2), 283–287. https://doi.org/10.32479/ijeep.7332

McArdle, G., **Tahir, A.**, & **Bertolotto, M.** (**2015**). Interpreting map usage patterns using geovisual analytics and spatio-temporal clustering. *International Journal of Digital Earth*, 8(8), 599–622. https://doi.org/10.1080/17538947.2014.898704

McFarlane, C., & **Rutherford, J.** (**2008**). Political infrastructures: Governing and experiencing the fabric of the city. *International Journal of Urban and Regional Research*, 32(2), 363–374. https://doi.org/10.1111/j.1468-2427.2008.00792.x

Mena, R., & **Hilhorst, D.** (**2022**). Ethical considerations of disaster research in conflict-affected areas. *Disaster Prevention and Management*, 31(3), 304–318. https://doi.org/10.1108/DPM-03-2021-0075

Mexico News Daily. (**2019**, February 22). Audit slams Pemex for inefficient pipeline monitoring, maintenance and protection. Retrieved from https://mexiconewsdaily.com/news/audit-slams-pemex-for-inefficient-pipeline-monitoring/

Mihoub, Z., & **Hassini, A.** (**2019**). Remote sensing of marine oil spills using sea-viewing wide field-of-view sensor images. *Bollettino di Geofisica Teorica ed Applicata*, 60(1), 123–136. https://doi.org/10.4430/bgta0270

Milić, N., **Đurđević, Z.**, **Mijalković, S.**, & **Erkić, D.** (**2020**). Identifying street hotspots using a network kernel density estimation. *Journal of Criminological Research, Policy and Practice*, 6(4), 272–287. https://doi.org/10.1108/JCIC-06-2020-0021

Mishra, S., & **Mishra, D. R.** (**2012**). Normalized difference chlorophyll index: A novel model for remote estimation of chlorophyll-a concentration in turbid productive waters. *Remote Sensing of Environment*, 117, 394–406. https://doi.org/10.1016/j.rse.2011.10.016

Mitra, D. S., **Majumdar, T. J.**, **Ramakrishnan, R.**, **Dave, H.**, & **Mazumder, S.** (**2013**). Detection and monitoring of offshore oil seeps using ERS/ENVISAT SAR/ASAR data and seep-seismic studies in Krishna–Godavari offshore basin, India. *Geocarto International*, 28(5), 404–419. https://doi.org/10.1080/10106049.2012.715207

Mohajan, H. K. (**2018**). Qualitative research methodology in social sciences and related subjects. *Journal of Economic Development, Environment and People*, 7(1). Retrieved from http://jedep.spiruharet.ro

Mohamadi, B., **Xie, Z.**, & **Liu, F.** (**2015**). GIS-based oil spill risk assessment model for the Niger Delta's vegetation. *Nature Environment and Pollution Technology*, 14(4), 545–552.

Mohammed, K. (**2021**, November 9). A wealth of sorrow: Why Nigeria's abundant oil reserves are really a curse. *The Guardian*. Retrieved from https://www.theguardian.com/global-development/2021/nov/09/a-wealth-of-sorrow-why-nigerias-abundant-oil-reserves-are-really-a-curse

Mohaymany, A. S., **Shahri, M.**, & **Mirbagheri, B.** (**2013**). GIS-based method for detecting high-crash-risk road segments using network kernel density estimation. *Geo-Spatial Information Science*, 16(2), 113–119. https://doi.org/10.1080/10095020.2013.766396

Molony, T., & **Hammett, D.** (**2007**). The friendly financier: Talking money with the silenced assistant. *Human Organization*, 66(3), 292–300. https://doi.org/10.17730/humo.66.3.74n7x53x7r40332h

Monnier-Reyna, M. (**2024**). Researching from home, inside, and the online: Methodological lessons from the pandemic. *The Professional Geographer*, 1–9. https://doi.org/10.1080/00330124.2023.2295343

Mountford, G. L., **Atkinson, P. M.**, **Dash, J.**, **Lankester, T.**, & **Hubbard, S.** (**2017**). Sensitivity of vegetation phenological parameters: From satellite sensors to spatial resolution and temporal compositing period. In *Sensitivity Analysis in Earth Observation Modelling* (pp. 75–90). Elsevier. https://doi.org/10.1016/B978-0-12-803011-0.00004-5

Mountrakis, G., **Im, J.**, & **Ogole, C.** (**2011**). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.001

Msadek, J., **Tlili, A.**, **Chouikhi, F.**, **Ragkos, A.**, & **Tarhouni, M.** (**2025**). Assessing the impacts of climate change scenarios on soil-adjusted vegetation index in North African arid montane rangeland: Case of Toujane region. *Climate*, 13(3), 59. https://doi.org/10.3390/cli13030059

Muhammad, R., **Boothman, C.**, **Song, H.**, **Lloyd, J. R.**, & **van Dongen, B. E.** (**2024**). Assessing the impacts of oil contamination on microbial communities in a Niger Delta soil. *Science of the Total Environment*, 926, 171813. https://doi.org/10.1016/j.scitotenv.2024.171813

Mulla, D. J. (**2013**). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, 114(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

NBS. (n.d.-a). Explore data on multidimensional and monetary poverty in Nigeria. Nigeria Poverty Map. Retrieved February 20, 2024, from https://www.nigeriapovertymap.com/

NBS. (n.d.-b). Nigeria Census. Nigeria Data Portal (National Bureau of Statistics). Retrieved July 11, 2022, from https://nigeria.opendataforafrica.org/xspplpb/nigeria-census

NBS, World Bank, & ILO. (**2023**). Nigeria Labour Force Statistics Report Q2 2023. Nigeria National Bureau of Statistics.

NDDC. (n.d.). The Niger Delta: A brief history. Niger Delta Development Commission. Retrieved July 1, 2022, from http://www.nddconline.org/The_Niger_Delta/

Ndebumog. (n.d.). History of the Niger Delta Region. Niger Delta Budget Monitoring Group. Retrieved July 1, 2022, from https://www.nigerdeltabudget.org/the-niger-delta/

Ndimele, P. E., **Saba, A. O.**, **Ojo, D. O.**, **Ndimele, C. C.**, **Anetekhai, M. A.**, & **Erondu, E. S.** (**2018**). Remediation of crude oil spillage. In *The Political Ecology of Oil and Gas Activities in the Nigerian Aquatic Ecosystem* (pp. 369–384). Elsevier. https://doi.org/10.1016/B978-0-12-809399-3.00024-0

NESG. (**2021**). NESG Q4'2020 Unemployment Alert. Retrieved from https://www.nesgroup.org/download_resource_documents/Unemployment%20Alert%20Q4%272020_1616446680.pdf

Nextier. (**2022**). Nigeria's security situation analysis report: An 18 months report of violent conflicts in Nigeria from the Nextier Violent Conflict Database.

Nezhad, M. M., **Groppi, D.**, **Laneve, G.**, **Marzialetti, P.**, & **Piras, G.** (**2018**, April). Oil spill detection analyzing "Sentinel 2" satellite images: A Persian Gulf case study. https://doi.org/10.11159/awspt18.134

Ngada, T., & **Bowers, K.** (**2018**). Spatial and temporal analysis of crude oil theft in the Niger Delta. *Security Journal*, 31(2), 501–523. https://doi.org/10.1057/s41284-017-0112-3

Nigar, A., **Li, Y.**, **Jat Baloch, M. Y.**, **Alrefaei, A. F.**, & **Almutairi, M. H.** (**2024**). Comparison of machine and deep learning algorithms using Google Earth Engine and Python for land classifications. *Frontiers in Environmental Science*, 12. https://doi.org/10.3389/fenvs.2024.1378449

Nixon, R. (**2011**). *Slow Violence and the Environmentalism of the Poor*. Harvard University Press.

NNPC. (n.d.). History of the Nigerian Petroleum Industry. Nigerian National Petroleum Corporation. Retrieved June 30, 2022, from https://nnpcgroup.com/NNPC-Business/Business-Information/Pages/Industry-History.aspx

Noomen, M. F., **Smith, K. L.**, **Colls, J. J.**, **Steven, M. D.**, **Skidmore, A. K.**, & **Van Der Meer, F. D.** (**2008**). Hyperspectral indices for detecting changes in canopy reflectance as a result of underground natural gas leakage. *International Journal of Remote Sensing*, 29(20), 5987–6008. https://doi.org/10.1080/01431160801961383

NOSDRA. (n.d.). Nigerian Oil Spill Monitor. National Oil Spill Detection and Response Agency. Retrieved October 7, 2023, from https://nosdra.oilspillmonitor.ng/

Nriagu, J., **Udofia, E.**, **Ekong, I.**, & **Ebuk, G.** (**2016**). Health risks associated with oil pollution in the Niger Delta, Nigeria. *International Journal of Environmental Research and Public Health*, 13(3), 346. https://doi.org/10.3390/ijerph13030346

Nuhu, M. M., **Rene, E. R.**, & **Ishaq, A.** (**2021**). Remediation of crude oil spill sites in Nigeria: Problems, technologies, and future prospects. *Environmental Quality Management*, e21793. https://doi.org/10.1002/tqem.21793

Nwajiaku, K. (**2005**). Between discourse and reality. *Cahiers d'études Africaines*, 45(178), 457–496. https://doi.org/10.4000/etudesafricaines.5448

Nwilo, P. C., & **Badejo, O. T.** (**2005**). Oil spill problems and management in the Niger Delta. *International Oil Spill Conference Proceedings*, 2005(1), 567–570. https://doi.org/10.7901/2169-3358-2005-1-567

Obi, O. (**2023**, May 19). Oil among the mangrove trees: A portrait of destruction in the Niger Delta, then and now. *Harvard International Review*. Retrieved from https://hir.harvard.edu/oil-among-the-mangrove-trees-a-portrait-of-destruction-in-the-niger-delta-then-and-now/

Obida, C. B., **Blackburn, G. A.**, **Whyatt, J. D.**, & **Semple, K. T.** (**2018**). Quantifying the exposure of humans and the environment to oil pollution in the Niger Delta using advanced geostatistical techniques. *Environment International*, 111, 32–42. https://doi.org/10.1016/J.ENVINT.2017.11.009

Obida, C. B., **Blackburn, G. A.**, **Whyatt, J. D.**, & **Semple, K. T.** (**2021**). Counting the cost of the Niger Delta's largest oil spills: Satellite remote sensing reveals extensive environmental damage with >1 million people in the impact zone. *Science of the Total Environment*, 775, 145854. https://doi.org/10.1016/j.scitotenv.2021.145854

Ochei, M. (**2024**). Niger Delta bedevilled by environmental, infrastructural challenges – Oborevweri. *Punch*. Retrieved from https://punchng.com/niger-delta-bedevilled-by-environmental-infrastructural-challenges-oborevweri/

Odularu, G. O. (**2008**). Crude oil and the Nigerian economic performance. *OGBUS*. Retrieved from http://www.ogbus.ru/eng/

Ofualagba, G., & **Ejofodomi, T. A.** (**2017**). Exploring the feasibility of robotic pipeline surveillance for detecting crude oil spills in the Niger Delta. *International Journal of Computer Applications*, 5(3), 38–52. https://doi.org/10.14323/ijuseng.2017.7

Ogbuabor, J. E., **Orji, A.**, **Manasseh, C. O.**, & **Nwosu, C. A.** (**2018**). Poor natural resource utilization as the bane of industrialization in Nigeria: Evidence from National Bureau of Statistics petrol price watch. *International Journal of Economics and Financial Issues*, 8(3), 175–181.

Ogeleka, D. F., **Tudararo-Aherobo, L. E.**, & **Okieimen, F. E.** (**2017**). Ecological effects of oil spill on water and sediment from two riverine communities in Warri, Nigeria. *International Journal of Biological and Chemical Sciences*, 11(1), 453–464. https://doi.org/10.4314/ijbcs.v11i1.36

Oghenetega, O. B., **Okunlola, M. A.**, **Ana, G. R. E. E.**, **Morhason-Bello, O.**, & **Ojengbede, O. A.** (**2022**). Exposure to oil pollution and maternal outcomes: The Niger Delta prospective cohort study. *PLOS ONE*, 17(3), e0263495. https://doi.org/10.1371/journal.pone.0263495

Oghenetega, O., **Ojengbede, O.**, & **Ana, G.** (**2020**). Perception determinants of women and healthcare providers on the effects of oil pollution on maternal and new-born outcomes in the Niger Delta, Nigeria. *International Journal of Women's Health*, 12, 197–205. https://doi.org/10.2147/IJWH.S235536

Ohwo, O. (**2018**). Climate change impacts, adaptation and vulnerability in the Niger Delta Region of Nigeria. *African Journal of Environmental Science and Technology*, 8(6), 171–179. Retrieved from www.iiste.org

Ojiako, J. C., & **Duru, U. U.** (**2017**). Use of remote sensing data to detect environmental degradation in the oil rich region of Southern Nigeria between 2003 and 2015. *International Journal of Environment, Agriculture and Biotechnology*, 2(5), 2503–2508. https://doi.org/10.22161/ijeab/2.5.30

Okabe, A., **Satoh, T.**, & **Sugihara, K.** (**2009**). A kernel density estimation method for networks, its computational method and a GIS-based tool. *International Journal of Geographical Information Science*, 23(1), 7–32. https://doi.org/10.1080/13658810802475491

Okabe, A., & **Sugihara, K.** (**2012**). *Spatial Analysis along Networks*. Wiley. https://doi.org/10.1002/9781119967101

Okafor, C. (**2019**). NEITI: Nigeria lost $42bn oil, refined products to thieves. *Thisday Newspaper*. Retrieved from https://www.thisdaylive.com/index.php/2019/11/07/neiti-nigeria-lost-42bn-oil-refined-products-to-thieves/

Okafor, C. (**2020**). NEITI: Oil sector employed 0.03% of Nigeria's workers in 2018. *Thisday Newspaper*. Retrieved from https://www.thisdaylive.com/index.php/2020/04/07/neiti-oil-sector-employed-0-03-of-nigerias-workers-in-2018/

Okogwu, A., & **Ba, A. A.** (**2021**). Oil pipeline vandalization. *Global Journal of Arts, Humanities and Social Sciences*, 9(1), 84–97. https://doi.org/10.5281/zenodo.5039346

Okoli, C. (**2013**). Oil pipeline vandalism and Nigeria's national security. *Global Journals Inc.* (Peer-reviewed journal).

Okoli, C. (**2016**). Petroleum pipeline vandalism and national security in Nigeria. Nigerian Defence Academy.

Okoli, C. (**2019**). Oil pipeline vandalism in the Niger Delta: Need, greed and grievance factors. *Global Journal of Social Sciences*, 18(1), 23–34.

Okonkwo, T., & **Etemire, U.** (**2017**). "Oil injustice" in Nigeria's Niger Delta Region: A call for responsive governance. *Journal of Environmental Protection*, 8(1), 42–60. https://doi.org/10.4236/jep.2017.81005

Okoro, C. (**2004**). Pipeline vandalisation and oil spillage monitoring using remote sensing: Nigeria case. Proceedings of Nigeria SAT Validation Workshop.

Okorobia, A. M., & **Olali, S. T.** (**2018**). The historical trajectory of crude oil exploration and production in Nigeria, 1930–2015. In *The Political Ecology of Oil and Gas Activities in the Nigerian Aquatic Ecosystem* (pp. 17–31). Elsevier. https://doi.org/10.1016/B978-0-12-809399-3.00002-1

Okotie, S., **Ogbarode, N. O.**, & **Ikporo, B.** (**2018**). The oil and gas industry and the Nigerian environment. In *The Political Ecology of Oil and Gas Activities in the Nigerian Aquatic Ecosystem* (pp. 47–69). Elsevier. https://doi.org/10.1016/B978-0-12-809399-3.00004-5

Oladipupo, S. O., **Mudashiru, R. B.**, **Oyeleke, M. O.**, & **Bakare, S. B.** (**2016**). Review of some impacts of oil exploration and production in Niger Delta, Nigeria. *Science, Engineering & Environmental Technology*, 1(13), 90–103.

Olu-Adeyemi, L. (**2020**). The political ecology of oil pipeline vandalism in Nigeria. *International Journal of Research and Innovation in Social Science*, 4(4), 125–133.

Olukaejire, S., **Ifiora, C.**, **Osaro, P.**, **Osuji, L.**, & **Hart, A.** (**2024**). Petroleum exploration in the Niger Delta Region and implications for the environment: A review. *Journal of Energy Research and Reviews*, 16(5), 19–29. https://doi.org/10.9734/jenrr/2024/v16i5350

Oluwaniyi, O. O. (**2018**). The role of multinational oil corporations (MNOCs) in Nigeria: More exploitation equals less development of oil-rich Niger Delta Region. *Review of*

African Political Economy, 45(158), 558–573. https://doi.org/10.1080/03056244.2018.1546687

Oluwatomilola Olunusi, B., & **Emmanuel Adeboye, T.** (**2025**). Situating environmental degradation in Ogoniland, Niger Delta, Nigeria, within an environmental justice framework. *African Journal of Environmental Science and Technology,* 19(2), 54–60. https://doi.org/10.5897/AJEST2024.3276

Omodanisi, E. O., & **Salami, A. T.** (**2014**). An assessment of the spectra characteristics of vegetation in South Western Nigeria. *IERI Procedia*, 9, 26–32. https://doi.org/10.1016/j.ieri.2014.09.036

Omotola, J. S. (**2009**). "Liberation movements" and rising violence in the Niger Delta: The new contentious site of oil and environmental politics. *Studies in Conflict & Terrorism*, 33(1), 36–54. https://doi.org/10.1080/10576100903400597

Onuoha, F. C. (**2007**). Poverty, pipeline vandalisation/explosion and human security: Integrating disaster management into poverty reduction in Nigeria. *African Security Review*, 16(2), 71–86. https://doi.org/10.1080/10246029.2007.9627428

Onuoha, F. C. (**2009**). Why the poor pay with their lives: Oil pipeline vandalisation, fires and human security in Nigeria. *Disasters*, 33(3), 373–389. https://doi.org/10.1111/j.1467-7717.2008.01079.x

Onyango, D. (**2021**, September 2). Pipeline vandalism causes a massive fuel flood in Lagos, Nigeria. *Pipeline Technology Journal*. Retrieved from https://www.pipeline-journal.net/news/pipeline-vandalism-causes-massive-fuel-flood-lagos-nigeria

OPEC. (**2021**). Venezuela facts and figures. Organization of the Petroleum Exporting Countries. Retrieved from https://www.opec.org/opec_web/en/about_us/171.htm

OPEC. (**2024**). Annual Statistical Bulletin 2024. OPEC Digital Publications. Retrieved from https://publications.opec.org/asb/chapter/show/123/2113/2116

Ordinioha, B., & **Brisibe, S.** (**2013**). The human health implications of crude oil spills in the Niger Delta, Nigeria: An interpretation of published studies. *Nigerian Medical Journal*, 54(1), 10–15. https://doi.org/10.4103/0300-1652.108887

Osuagwu, E. S., & **Olaifa, E.** (**2018**). Effects of oil spills on fish production in the Niger Delta. *PLOS ONE*, 13(10), e0205114. https://doi.org/10.1371/journal.pone.0205114

Osuntokun, S. (**2014**, January 31). Nigeria oil theft: The crude cost. BCLP Law Insights. Retrieved from https://www.bclplaw.com/en-GB/Insights/Nigeria-Oil-Theft-the-Crude-Cost.html

Oteh, C. O., & **Eze, C. R.** (**2012**). Vandalization of oil pipelines in the Niger Delta Region of Nigeria and poverty: An overview. *Studies in Sociology of Science*, 3(2), 13–21. https://doi.org/10.3968/j.sss.1923018420120302.2950

Otsuki, K. (**2024**). Infrastructural violence and its temporalities. In *Handbook of Infrastructures and Cities* (pp. 240–254). Edward Elgar Publishing. https://doi.org/10.4337/9781800889156.00026

Owens, E. H., **Taylor, E.**, & **Parker, H. A.** (**2016**). Spill site characterization in environmental forensic investigations. In *Standard Handbook Oil Spill Environmental Forensics* (pp. 1–24). https://doi.org/10.1016/B978-0-12-803832-1.00001-5

Owolabi, T. (**2023**). Blast at illegal Nigerian oil refinery kills 37 people. *Reuters*. Retrieved from https://www.reuters.com/world/africa/blast-illegal-nigerian-oil-refinery-kills-37-people-2023-10-03/

Oyegun, U. C., **Lawal, O.**, & **Ogoro, M.** (**2023**). The Niger Delta region. In *Vegetation and Human Impact* (pp. 107–121). Springer Nature Switzerland AG. https://doi.org/10.1007/978-3-031-17972-3_7

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

Ozkan, C., **Osmanoglu, B.**, **Sunar, F.**, **Staples, G.**, **Kalkan, K.**, & **Balık Sanlı, F.** (**2012**). Testing the generalization efficiency of oil slick classification algorithm using multiple SAR data for Deepwater Horizon oil spill. *ISPRS Archives*, XXXIX-B7, 67–72. https://doi.org/10.5194/isprsarchives-XXXIX-B7-67-2012

Pandey, P., **Kington, J.**, **Kanwar, A.**, **Simmon, R.**, & **Abraham, L.** (**2023**). Planet basemaps for NICFI data program addendum to basemaps product specification. Planet Labs PBC.

Park, S.-H., **Jung, H.-S.**, & **Lee, M.-J.** (**2020**). Oil spill mapping from Kompsat-2 high-resolution image using directional median filtering and artificial neural network. *Remote Sensing*, 12(2), 253. https://doi.org/10.3390/rs12020253

Payne, J. (**2016**, January 15). Nigeria's Delta amnesty programme to continue for at least 1 year. *Reuters*. Retrieved from https://www.reuters.com/article/idUSKCN0UT0CX/

Pengphorm, P., **Thongrom, S.**, **Daengngam, C.**, **Duangpan, S.**, **Hussain, T.**, & **Boonrat, P.** (**2024**). Optimal-band analysis for chlorophyll quantification in rice leaves using a custom hyperspectral imaging system. *Plants*, 13(2), 259. https://doi.org/10.3390/plants13020259

Planet. (**2025a**). NICFI basemaps in GEE. Planet Labs. Retrieved from https://docs.planet.com/platform/integrations/google-earth-engine/nicfi-gee/

Planet. (**2025b**). NICFI basemaps in Google Earth Engine FAQ. Planet Labs. Retrieved from https://developers.planet.com/docs/integrations/gee/nicfi/faq/

Polychronis, K., & **Vassilia, K.** (**2013**). Detection of oil spills and underwater natural oil outflow using multispectral satellite imagery. *International Journal of Remote Sensing Applications*, 3(1), 1–12. Retrieved from www.ijrsa.org

Poudel, U., **Stephen, H.**, & **Ahmad, S.** (**2021**). Evaluating irrigation performance and water productivity using EEFlux ET and NDVI. *Sustainability*, 13(14), 7967. https://doi.org/10.3390/su13147967

Praticò, S., **Solano, F.**, **Di Fazio, S.**, & **Modica, G.** (**2021**). Machine learning classification of Mediterranean forest habitats in Google Earth Engine based on seasonal Sentinel-2 time-series and input image composition optimisation. *Remote Sensing*, 13(4), 586. https://doi.org/10.3390/rs13040586

Prudnikova, E., **Savin, I.**, **Vindeker, G.**, **Grubina, P.**, **Shishkonakova, E.**, & **Sharychev, D.** (**2019**). Deep learning methods used in remote sensing images: A review. *Journal of Environmental & Earth Sciences*, 5(1), 33–64. https://doi.org/10.30564/jees.v5i1.5232

R Core Team. (**2023**). R: A language and environment for statistical computing (Version 4.2.1). R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Radwin, M. (**2021**, October 4). Oil spills plague Venezuelan coast, but cleanup efforts are lacking: Report. *Mongabay*. Retrieved from https://news.mongabay.com/2021/10/oil-spills-plague-venezuelan-coast-but-cleanup-efforts-are-lacking-report/#:~:text=The%20oil%20spills%20are%20doing,estuary%20known%20as%20Lake%20Maracaibo

Raeisi, A., **Akbarizadeh, G.**, & **Mahmoudi, A.** (**2018**). Combined method of an efficient cuckoo search algorithm and nonnegative matrix factorization of different Zernike moment features for discrimination between oil spills and lookalikes in SAR images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 11(11), 4193–4205. https://doi.org/10.1109/JSTARS.2018.2841503

Rainforest Foundation UK. (**2020**). Participatory mapping. Retrieved from https://www.mappingforrights.org/participatory-mapping/

Rajendran, S., **Sadooni, F. N.**, **Al-Kuwari, H. A.-S.**, **Govil, H.**, **Nasir, S.**, & **Vethamony, P.** (**2021**). Monitoring oil spill in Norilsk, Russia using satellite data. *Scientific Reports*, 11(1), 3817. https://doi.org/10.1038/s41598-021-83260-7

Ralby, I. M. (2017). *Downstream oil theft: Global modalities, trends, and remedies.* Atlantic Council of the United States, Global Energy Center.

Ralls, D., & Pottinger, L. (2021). *Participatory mapping methods for change.*

Ramezan, C. A., Warner, T. A., Maxwell, A. E., & Price, B. S. (2021). Effects of training set size on supervised machine-learning land-cover classification of large-area high-resolution remotely sensed data. *Remote Sensing, 13*(3), 368. https://doi.org/10.3390/rs13030368

Rewhel, E. M., Li, J., Hamed, A. A., Keshk, H. M., Mahmoud, A. S., Sayed, S. A., Samir, E., Zeyada, H. H., Mohamed, S. A., Moustafa, M. S., Nasr, A. H., & Helmy, A. K. (2023). Deep learning methods used in remote sensing images: A review. *Journal of Environmental & Earth Sciences, 5*(1), 33–64. https://doi.org/10.30564/jees.v5i1.5232

Rim-Rukeh, A. (2015). Oil spill management in Nigeria: SWOT analysis of the Joint Investigation Visit (JIV) process. *Journal of Environmental Protection, 6*(3), 259–271. https://doi.org/10.4236/jep.2015.63026

Rodgers, D., & O'Neill, B. (2012). Infrastructural violence: Introduction to the special issue. *Ethnography, 13*(4), 401–412. https://doi.org/10.1177/1466138111435738

Rogers, S. R., Singh, K. K., Mathews, A. J., & Cummings, A. R. (2022). Drones and geography: Who is using them and why? *The Professional Geographer, 74*(3), 516–528. https://doi.org/10.1080/00330124.2021.2000446

Romano, B., & Jiang, Z. (2017). Visualizing traffic accident hotspots based on spatial-temporal network kernel density estimation. In *Proceedings of the 25th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems* (pp. 1–4). https://doi.org/10.1145/3139958.3139981

Romsom, E. (2022). WIDER working paper 2022/16—Global oil theft: Impact and policy responses. https://doi.org/10.35188/UNU-WIDER/2022/147-1

Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote Sensing of Environment*, *55*(2), 95–107. https://doi.org/10.1016/0034-4257(95)00186-7

Rouse, J. W., Jr., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. NASA Goddard Space Flight Center 3d ERTS-1 Symposium, Vol. 1, 1.

Roux, J. le, Sundar, C., & Manil, M. (2021). Exploring the use of PlanetScope data for particulate matter air quality research. *Remote Sensing*, *13*(15), 2981. https://doi.org/10.3390/rs13152981

Rowell, A. (1995). Oil, Shell and Nigeria: Ken Saro-Wiwa calls for a boycott. *The Ecologist, 25*(6).

Roy, D., Tripathy, S., Kar, S. K., Sharma, N., Verma, S. K., & Kaushal, V. (2020). Study of knowledge, attitude, anxiety & perceived mental healthcare need in Indian population during COVID-19 pandemic. *Asian Journal of Psychiatry*, *51*, Article 102083. https://doi.org/10.1016/j.ajp.2020.102083

RStudio Team. (2023). *RStudio: Integrated development environment for R* (Version 2023.09.0). RStudio, PBC. http://www.rstudio.com/

Saint, E. (2022, December 22). Timeline: Half a century of oil spills in Nigeria's Ogoniland. *Al Jazeera*. https://www.aljazeera.com/features/2022/12/21/timeline-oil-spills-in-nigerias-ogoniland

Sam, K., & Zabbey, N. (2018). Contaminated land and wetland remediation in Nigeria: Opportunities for sustainable livelihood creation. *Science of the Total Environment, 639*, 1560–1573. https://doi.org/10.1016/j.scitotenv.2018.05.266

Samanlangi, I. (2024). Environmental justice and resource extraction: Analyzing the social dynamics of mining projects. *Global International Journal of Innovative Research, 2*(4), 700–709. https://doi.org/10.59613/global.v2i4.130

Sani, D. A., Shahabi, H., Ahmad, B. A., Mirmokrigh, S., & Ahmad, B. Bin. (2016). Application of Geographic Information System technology in controlling pipeline vandalism of oil and gas industry. *Research Journal of Information Technology*, *8*(1), 39–46. https://doi.org/10.3923/rjit.2016.39.46

Sanusi, A., Onovo, J. C., Isa, & Hauwa'u. (2016). The environmental impact of pipeline vandalism: A challenge to biodiversity in Portharcourt area of Rivers State, Nigeria.

International Journal of Advances in Chemical Engineering and Biological Sciences, 3(1). https://doi.org/10.15242/ijacebs.a0516206

Schlosberg, D. (2013). Theorising environmental justice: The expanding sphere of a discourse. *Environmental Politics, 22*(1), 37–55. https://doi.org/10.1080/09644016.2013.755387

Schreier, M. (2014). *The SAGE handbook of qualitative data analysis*. SAGE Publications. https://doi.org/10.4135/9781446282243

Secor, A. J. (2010). Social surveys, interviews, and focus groups. In B. Gomez & J. P. Jones III (Eds.), *Research methods in geography: A critical introduction*.

Semple, K. (2019, May 5). Mexico declares victory over fuel thieves. But is it lasting? *The New York Times*. https://www.nytimes.com/2019/05/05/world/americas/mexico-fuel-theft.html

Serra-Sogas, N., O'Hara, P. D., Canessa, R., Keller, P., & Pelot, R. (2008). Visualization of spatial patterns and temporal trends for aerial surveillance of illegal oil discharges in western Canadian marine waters. *Marine Pollution Bulletin, 56*(5), 825–833. https://doi.org/10.1016/j.marpolbul.2008.02.005

Shaghaghi, A., Bhopal, R. S., & Sheikh, A. (2011). Approaches to recruiting 'hard-to-reach' populations into research: A review of the literature. *Health Promotion Perspectives, 1*(2), 86–94.

Shaikh, F., Ji, Q., Shaikh, P. H., Mirjat, N. H., & Uqaili, M. A. (2017). Forecasting China's natural gas demand based on optimised nonlinear grey models. *Energy, 140*, 941–951. https://doi.org/10.1016/j.energy.2017.09.037

Shin, J., Mahmud, M. S., Rehman, T. U., Ravichandran, P., Heung, B., & Chang, Y. K. (2022). Trends and prospects of machine vision technology for stresses and diseases detection in precision agriculture. *AgriEngineering, 5*(1), 20–39. https://doi.org/10.3390/agriengineering5010003

Shittu, W. J. (2014). Mapping oil spill human health risk in Rivers State, Niger Delta, Nigeria (Master's thesis). University of Nottingham. http://eprints.nottingham.ac.uk/14115/

Sluka, J. A. (2020). Too dangerous for fieldwork? The challenge of institutional risk-management in primary research on conflict, violence and 'terrorism.' *Contemporary Social Science, 15*(2), 241–257. https://doi.org/10.1080/21582041.2018.1498534

Smith, L. T. (1999). *Decolonizing methodologies: Research and Indigenous peoples*. Zed Books Ltd; University of Otago Press.

Soremi, T. (2020). The implications of oil theft on social and economic development in the Niger Delta. *Global Journal of Social Sciences, 19,* 1–11. https://doi.org/10.4314/gjss.v19i1.1

Southworth, J., Smith, A. C., Safaei, M., Rahaman, M., Alruzuq, A., Tefera, B. B., Muir, C. S., & Herrero, H. V. (2024). Machine learning versus deep learning in land system science: A decision-making framework for effective land classification. *Frontiers in Remote Sensing, 5*. https://doi.org/10.3389/frsen.2024.1374862

Souto, R. D., & Batalhão, A. C. S. (2022). Citizen science as a tool for collaborative site-specific oil spill mapping: The case of Brazil. *Anais da Academia Brasileira de Ciências, 94*(Suppl. 2). https://doi.org/10.1590/0001-3765202220211262

Spitz, A. (2024). Navigating privacy in 2023: Exploring data colonialism, AI advancements, and legal landmarks in Getty Images vs. Stability AI and The New York Times vs. Microsoft and OpenAI. *St Andrews Law Review*. https://www.standrewslawreview.com/post/navigating-privacy-in-2023-exploring-data-colonialism-ai-advancements-and-legal-landmarks-in-gett

Sripada, R. P., Heiniger, R. W., White, J. G., Crozier, C. R., & Meijer, A. D. (2006). Attempt to validate a remote sensing–based late-season corn nitrogen requirement prediction system. *Crop Management, 5*(1), 1–10. https://doi.org/10.1094/CM-2006-0405-01-RS

Sripada, R. P., Heiniger, R. W., White, J. G., & Weisz, R. (2005). Aerial color infrared photography for determining late-season nitrogen requirements in corn. *Agronomy Journal, 97*(5), 1443–1451. https://doi.org/10.2134/agronj2004.0314

Sripada, R. P., Schmidt, J. P., Dellinger, A. E., & Beegle, D. B. (2008). Evaluating multiple indices from a canopy reflectance sensor to estimate corn N requirements. *Agronomy Journal, 100*(6), 1553–1561. https://doi.org/10.2134/agronj2008.0017

Srivastava, H., & Singh, T. P. (2010). Assessment and development of algorithms to detect oil spills using MODIS data. *Journal of the Indian Society of Remote Sensing, 38*(1), 161–167. https://doi.org/10.1007/s12524-010-0007-9

Stevano, S., & Deane, K. (2019). The role of research assistants in qualitative and cross-cultural social science research. In *Handbook of Research Methods in Health Social*

Sciences (pp. 1675–1690). Springer Singapore. https://doi.org/10.1007/978-981-10-5251-4_39

Steyn, P. (2009). Oil exploration in colonial Nigeria, c. 1903–58. *Journal of Imperial and Commonwealth History, 37*(2), 249–274. https://doi.org/10.1080/03086530903010376

Su, W., Su, F., Zhou, C., & Du, Y. (2012). Optical satellite remote sensing capabilities analysis of the marine oil spill. *Geo-Information Science, 14*(4), 523–530. https://doi.org/10.3724/SP.J.1047.2012.00523

Sultana, F. (2007). Reflexivity, positionality and participatory ethics: Negotiating fieldwork dilemmas in international research. *ACME: An International E-Journal for Critical Geographies, 6*(3), 375–384.

Sumangala, N., & Kini, S. (2022). A systematic review of machine learning applications in land use land cover change detection using remote sensing. *International Journal of Applied Engineering and Management Letters*, 327–350. https://doi.org/10.47992/IJAEML.2581.7000.0162

Svejkovsky, J., Hess, M., Muskat, J., Nedwed, T. J., McCall, J., & Garcia, O. (2016). Characterization of surface oil-thickness distribution patterns observed during the Deepwater Horizon (MC-252) oil spill with aerial and satellite remote sensing. *Marine Pollution Bulletin, 110*(1), 162–176. https://doi.org/10.1016/j.marpolbul.2016.06.066

Tahsin, S., Medeiros, S. C., & Singh, A. (2018). Assessing the resilience of coastal wetlands to extreme hydrologic events using vegetation indices: A review. *Remote Sensing, 10*(9), 1390. https://doi.org/10.3390/rs10091390

Talukdar, S., Singha, P., Mahato, S., Shahfahad, Pal, S., Liou, Y.-A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite observations—A review. *Remote Sensing, 12*(7), 1135. https://doi.org/10.3390/rs12071135

Tang, L., Kan, Z., Zhang, X., Sun, F., Yang, X., & Li, Q. (2016). A network kernel density estimation for linear features in space–time analysis of big trace data. *International Journal of Geographical Information Science, 30*(9), 1717–1737. https://doi.org/10.1080/13658816.2015.1119279

Taravat, A., & del Frate, F. (2012). Development of band ratioing algorithms and neural networks to detect oil spills using Landsat ETM+ data. *EURASIP Journal on*

Advances in Signal Processing, 2012(1), 107. https://doi.org/10.1186/1687-6180-2012-107

Taravat, A., & del Frate, F. (2013). Weibull multiplicative model and machine learning models for full-automatic dark-spot detection from SAR images. In *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-1/W3* (pp. 421–424). https://doi.org/10.5194/isprsarchives-XL-1-W3-421-2013

Taylor, A. (2013). Nigeria's illegal oil refineries. *The Atlantic*. https://www.theatlantic.com/photo/2013/01/nigerias-illegal-oil-refineries/100439/

Thatcher, J., O'Sullivan, D., & Mahmoudi, D. (2016). Data colonialism through accumulation by dispossession: New metaphors for daily data. *Environment and Planning D: Society and Space, 34*(6), 990–1006. https://doi.org/10.1177/0263775816633195

The Cable. (2017, March 7). Nigerian troops 'destroy 80 illegal refineries' in Niger Delta creeks. *The Cable*. https://www.thecable.ng/nigerian-troops-destroy-80-illegal-refineries-niger-delta-creeks

The World Bank. (2022, May 28). Nigeria releases new report on poverty and inequality in country. *Living Standards Measurement Study Briefs*. https://www.worldbank.org/en/programs/lsms/brief/nigeria-releases-new-report-on-poverty-and-inequality-in-country

This Day Newspaper. (2022, June 29). Crushing the burgeoning menace of crude oil theft, bunkering and pipeline vandalism in Nigeria. *This Day Newspaper*. https://www.thisdaylive.com/index.php/2022/05/23/crushing-the-burgeoning-menace-of-crude-oil-theft-bunkering-and-pipeline-vandalism-in-nigeria-11/

Thomas, D. (1995, December). Niger Delta oil production, reserves, field sizes assessed. *Oil and Gas Journal*. https://www.ogj.com/general-interest/companies/article/17216431/niger-delta-oil-production-reserves-field-sizes-assessed

Tian, W., Bian, X., Shao, Y., & Zhang, Z. (2015). On the detection of oil spill with China's HJ-1C SAR image. *Aquatic Procedia, 3*, 144–150. https://doi.org/10.1016/j.aqpro.2015.02.204

Tong, S., Liu, X., Chen, Q., Zhang, Z., & Xie, G. (2019). Multi-feature based ocean oil spill detection for polarimetric SAR data using random forest and the self-similarity parameter. *Remote Sensing, 11*(4), 451. https://doi.org/10.3390/rs11040451

Topouzelis, K. (2008). Oil spill detection by SAR images: Dark formation detection, feature extraction and classification algorithms. *Sensors, 8*(10), 6642–6659. https://doi.org/10.3390/s8106642

Transneft. (2021). Transneft lost more than RUB 600 million from illegal tappings in 2020. https://en.transneft.ru/pressReleases/view/id/13131/?re=en

Tuck, E., & Yang, K. W. (2012). Decolonization is not a metaphor. In *Decolonization: Indigeneity, Education & Society, 1*(1).

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment, 8*(2), 127–150. https://doi.org/10.1016/0034-4257(79)90013-0

Tukur, U. A., & Hajj, O. M. S. (2017). Causes and consequences of crude oil pipeline vandalism in the Niger Delta region of Nigeria: A confirmatory factor analysis approach. *Cogent Economics & Finance, 5*(1), 1353199. https://doi.org/10.1080/23322039.2017.1353199

Turlach, B. A. (1993). Bandwidth selection in kernel density estimation: A review (Report No. 9307). Humboldt-Universität Berlin.

Turner, J. (2016). Voicing concerns: (Re)considering modes of presentation. *GeoHumanities, 2*(2), 542–551. https://doi.org/10.1080/2373566x.2016.1211485

Uchechukwu, D., Ayuba, B., & Mohammed, U. (2017). Journal of Resources Development and Management, 38. http://www.iiste.org

Udoh, I. (2020). Oil production, environmental pressures and other sources of violent conflict in Nigeria. *Review of African Political Economy, 47*(164), 1–18. https://doi.org/10.1080/03056244.2018.1549028

Ukhurebor, K. E., Athar, H., Adetunji, C. O., Aigbe, U. O., Onyancha, R. B., & Abifarin, O. (2021). Environmental implications of petroleum spillages in the Niger Delta region of Nigeria. *Journal of Environmental Management, 293*, Article 112872. https://doi.org/10.1016/j.jenvman.2021.112872

Umar, H. A., Abdul Khanan, M. F., Ogbonnaya, C., Shiru, M. S., Ahmad, A., & Baba, A. I. (2021). Environmental and socioeconomic impacts of pipeline transport interdiction in Niger Delta, Nigeria. *Heliyon, 7*(5), Article e06999. https://doi.org/10.1016/j.heliyon.2021.e06999

Umar, H. A., Khanan, M. F. A., Ahmad, A., & Isma'il, M. (2019). Assessing the economic consequences of pipeline sabotage in the Niger Delta Area of Nigeria using

GIS. In *International Graduate Conference of Built Environment and Surveying (GBES2019).*

UNEP. (2011). *Environmental assessment of Ogoniland.* United Nations Environment Programme. https://postconflict.unep.ch/publications/OEA/UNEP_OEA.pdf

UN/ISDR. (2004). *Environmental protection & disaster risk reduction: A community leader's guide.* Umvoto.

United Nations Environment Programme. (2011). *Environmental assessment of Ogoniland.* United Nations Environment Programme.

UNSTAT. (n.d.). Country profile of Nigeria. United Nations Department of Economic and Social Affairs. Retrieved February 20, 2024, from https://unstats.un.org/unsd/dnss/docViewer.aspx?docID=635

UP42. (n.d.). Enhanced vegetation index (EVI). Spectral Indexes. Retrieved April 13, 2025, from Spectral indexes.

Vali, A., Comai, S., & Matteucci, M. (2020). Deep learning for land use and land cover classification based on hyperspectral and multispectral Earth observation data: A review. *Remote Sensing, 12*(15), 2495. https://doi.org/10.3390/rs12152495

Van Horne, Y. O., Alcala, C. S., Peltier, R. E., Quintana, P. J. E., Seto, E., Gonzales, M., Johnston, J. E., Montoya, L. D., Quirós-Alcalá, L., & Beamer, P. I. (2023). An applied environmental justice framework for exposure science. *Journal of Exposure Science & Environmental Epidemiology, 33*(1), 1–11. https://doi.org/10.1038/s41370-022-00422-z

Van Ramshorst, J. P. (2020). Studying migration in the time of Trump: Power, positionality, and formal politics in the field. *The Professional Geographer, 72*(2), 264–271. https://doi.org/10.1080/00330124.2019.1662819

Vélez, S., Martínez-Peña, R., & Castrillo, D. (2023). Beyond vegetation: A review unveiling additional insights into agriculture and forestry through the application of vegetation indices. *J, 6*(3), 421–436. https://doi.org/10.3390/j6030028

Vite, B. N. (2018). Understanding young people's political engagement in Niger Delta, Nigeria. *US-China Education Review B, 8*(5). https://doi.org/10.17265/2161-6248/2018.05.005

Wakefield, S. (2020). Making nature into infrastructure: The construction of oysters as a risk management solution in New York City. *Environment and Planning E: Nature and Space, 3*(3), 761–785. https://doi.org/10.1177/2514848619887461

Wakil, A. U., Yeboah, E., Sarfo, I., Kweku, N. E., Kwang, C., Kofi, A. F., Oduro, C., Darko, G., Ndafira, G. C., Batame, M., & Aboagye Appea, E. (2021). Assessment of oil spillage impact on vegetation in southwestern Niger Delta, Nigeria. *Journal of Geography, Environment and Earth Science International,* 31–45. https://doi.org/10.9734/jgeesi/2021/v25i930307

Wang, F., Huang, J., Tang, Y., & Wang, X. (2007). New vegetation index and its application in estimating leaf area index of rice. *Rice Science, 14*(3), 195–203. https://doi.org/10.1016/S1672-6308(07)60027-4

Wang, J., Ai, T., Wu, H., Xu, H., Xiao, T., & Li, G. (2024). Graph-based spatial co-location pattern mining: Integrate geospatial analysis and logical reasoning. *International Journal of Digital Earth, 17*(1). https://doi.org/10.1080/17538947.2024.2390434

Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Science of the Total Environment, 822*, Article 153559. https://doi.org/10.1016/j.scitotenv.2022.153559

Wang, J., Ulibarri, N., Scott, T. A., & Davis, S. J. (2023). Environmental justice, infrastructure provisioning, and environmental impact assessment: Evidence from the California Environmental Quality Act. *Environmental Science & Policy, 146*, 66–75. https://doi.org/10.1016/j.envsci.2023.05.003

Wekpe, V. O., Whitworth, M., & Baily, B. (2024). Where will the next oil spill incident in the Niger Delta region of Nigeria occur? *Environmental Research Communications, 6*(2), 025018. https://doi.org/10.1088/2515-7620/ad29b5

Whanda, S., Adekola, O., Adamu, B., Yahaya, S., & Pandey, P. C. (2016). Geo-spatial analysis of oil spill distribution and susceptibility in the Niger Delta Region of Nigeria. *Journal of Geographic Information System, 8*(4), 438–457. https://doi.org/10.4236/jgis.2016.84037

Wickramasingha, S. (2023). Constructing (im)perfect geographical knowledge: Negotiating positionality in comparative field sites. *The Professional Geographer, 75*(5), 776–786. https://doi.org/10.1080/00330124.2022.2158887

Williamson, A. E., & Burns, N. (2014). The safety of researchers and participants in primary care qualitative research. *British Journal of General Practice, 64*(621), 198–200. https://doi.org/10.3399/bjgp14X679480

Wong, M. S., Zhu, X., Abbas, S., Kwok, C. Y. T., & Wang, M. (2021). Optical remote sensing. In *Urban Book Series* (pp. 315–344). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-981-15-8983-6_20

Wu, S., Cao, J.-M., & Zhao, X.-Y. (2025). Land cover classification of high-resolution remote sensing images based on improved spectral clustering. *PLOS ONE, 20*(2), e0316830. https://doi.org/10.1371/journal.pone.0316830

Xie, Z., & Yan, J. (2008). Kernel density estimation of traffic accidents in a network space. *Computers, Environment and Urban Systems, 32*(5), 396–406. https://doi.org/10.1016/j.compenvurbsys.2008.05.001

Xie, Z., & Yan, J. (2013). Detecting traffic accident clusters with network kernel density estimation and local spatial statistics: An integrated approach. *Journal of Transport Geography, 31*, 64–71. https://doi.org/10.1016/j.jtrangeo.2013.05.009

Xu, L., Li, J., & Brenning, A. (2014). A comparative study of different classification techniques for marine oil spill identification using RADARSAT-1 imagery. *Remote Sensing of Environment*, *141*, 14–23. https://doi.org/10.1016/j.rse.2013.10.012

Xu, Q., Li, X., Wei, Y., Tang, Z., Cheng, Y., & Pichel, W. G. (2013). Satellite observations and modeling of oil spill trajectories in the Bohai Sea. *Marine Pollution Bulletin, 71*(1–2), 107–116. https://doi.org/10.1016/j.marpolbul.2013.03.028

Yakubu, O. (2017). Particle (soot) pollution in Port Harcourt Rivers State, Nigeria—Double air pollution burden? Understanding and tackling potential environmental public health impacts. *Environments*, *5*(1), 2. https://doi.org/10.3390/environments5010002

Yang, F., & Zeng, Z. (2023). Refined fine-scale mapping of tree cover using time series of Planet-NICFI and Sentinel-1 imagery for Southeast Asia (2016–2021). *Earth System Science Data*, *15*(9), 4011–4021. https://doi.org/10.5194/essd-15-4011-2023

Yang, J., Wan, J., Ma, Y., & Hu, Y. (2019). Research on object-oriented decision fusion for oil spill detection on sea surface. In *IGARSS 2019 – 2019 IEEE International Geoscience and Remote Sensing Symposium* (pp. 9772–9775). https://doi.org/10.1109/IGARSS.2019.8899010

Yang, J.-F., Wan, J.-H., Ma, Y., Zhang, J., Hu, Y.-B., & Jiang, Z.-C. (2019). Oil spill hyperspectral remote sensing detection based on DCNN with multi-scale features. *Journal of Coastal Research*, *90*(sp1), 332. https://doi.org/10.2112/SI90-042.1

Yang, Y., Li, Y., & Zhu, X. (2017). A novel oil spill detection method from synthetic aperture radar imageries via a bidimensional empirical mode decomposition. *Acta Oceanologica Sinica, 36*(7), 86–94. https://doi.org/10.1007/s13131-017-1086-z

Yekeen, S. T., & Balogun, A. L. (2020). Advances in remote sensing technology, machine learning and deep learning for marine oil spill detection, prediction and vulnerability assessment. *Remote Sensing, 12*(20), 1–31. https://doi.org/10.3390/rs12203416

Yengoh, G. T. (2015). *Use of the normalized difference vegetation index (NDVI) to assess land degradation at multiple scales*. Springer International Publishing.

Yucatan Times. (2019, January 12). Where does the term "huachicolero" come from? *The Yucatan Times*. https://www.theyucatantimes.com/2019/01/where-does-the-term-huachicolero-come-from/

Yuh, Y. G., Tracz, W., Matthews, H. D., & Turner, S. E. (2023). Application of machine learning approaches for land cover monitoring in northern Cameroon. *Ecological Informatics*, *74*, Article 101955. https://doi.org/10.1016/j.ecoinf.2022.101955

Zaptia, S. (2018, April 20). $750 million worth of Libyan fuel is stolen. *Libya Herald*. https://www.libyaherald.com/2018/04/750-m-worth-of-libyan-fuel-is-stolen-sanalla/

Zhang, J., Xiao, J., Tong, X., Zhang, J., Meng, P., Li, J., Liu, P., & Yu, P. (2022). NIRv and SIF better estimate phenology than NDVI and EVI: Effects of spring and autumn phenology on ecosystem production of planted forests. *Agricultural and Forest Meteorology, 315*, 108819. https://doi.org/10.1016/j.agrformet.2022.108819

Zhang, X., Lin, X., Fu, D., Wang, Y., Sun, S., Wang, F., Wang, C., Xiao, Z., & Shi, Y. (2023). Comparison of the applicability of J–M distance feature selection methods for coastal wetland classification. *Water, 15*(12), 2212. https://doi.org/10.3390/w15122212

Zhang, X., Shi, Q., Sun, Y., Huang, J., & He, D. (2024). The review of land use/land cover mapping AI methodology and application in the era of remote sensing big data. *Journal of Geodesy and Geoinformation Science, 7*(3), 1–23. https://doi.org/10.11947/j.JGGS.2024.0301

Zhang, Y., Sun, X., Chen, J., & Cheng, C. (2021). Spatial patterns and characteristics of global maritime accidents. *Reliability Engineering & System Safety, 206*. https://doi.org/10.1016/j.ress.2020.107310

Zhang, Z., Dou, G., Zhao, X., Gao, Y., Liu, S., & Qin, A. (2024). Inversion of crop water content using multispectral data and machine learning algorithms in the North China Plain. *Agronomy*, *14*(10), 2361. https://doi.org/10.3390/agronomy14102361

Zhao, D., Cheng, X., Zhang, H., & Zhang, H. (2018). An oil slick detection index based on Landsat 8 remote sensing images. In *2018 International Workshop on Big Geospatial Data and Data Science (BGDDS)* (pp. 1–4). https://doi.org/10.1109/BGDDS.2018.8626850

Zhao, S., Tu, K., Ye, S., Tang, H., Hu, Y., & Xie, C. (2023). Land use and land cover classification meets deep learning: A review. *Sensors*, *23*(21), 8966. https://doi.org/10.3390/s23218966

Zheng, E. (2022, October 4). Bathing our bodies in soot: The crippling health of the Niger Delta. *Harvard International Review*. https://hir.harvard.edu/bathing-our-bodies-in-soot/

Ziaja, S. (2020, September 16). Lessons on race and place-based participation from environmental justice and geography. *Yale Journal on Regulation Symposium*. https://www.yalejreg.com/nc/lessons-on-race-and-place-based-participation-from-environmental-justice-and-geography-by-sonya-ziaja/