# Human and Environmental Exposure to Hydrocarbon Pollution in the Niger Delta: A Geospatial Approach

By

**Christopher Basharu Obida (B.Sc., M.Sc., AFHEA, FRGS, CGeog (GIS))**

This thesis is submitted in partial fulfilment of the requirements for the award of the degree

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**February 2020**

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Lancaster Environment Centre, Faculty of Science and Technology

Lancaster University, United Kingdom

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Supervisors:

Prof. George Alan Blackburn, Prof. James Duncan Whyatt, Prof. Kirk Taylor Semple


## Abstract

This study undertook an integrated geospatial assessment of human and environmental exposure to oil pollution in the Niger Delta using primary and secondary spatial data. This thesis begins by presenting a clear rationale for the study of extensive oil pollution in the Niger Delta, followed by a critical literature review of the potential application of geospatial techniques for monitoring and managing the problem. Three analytical chapters report on the methodological developments and applications of geospatial techniques that contribute to achieving the aim of the study.

Firstly, a quantitative assessment of human and environmental exposure to oil pollution in the Niger Delta was performed using a government spill database. This was carried out using Spatial Analysis along Networks (SANET), a geostatistical tool, since oil spills in the region tend to follow the linear patterns of the pipelines. Spatial data on pipelines, oil spills, population and land cover data were analysed in order to quantify the extent of human and environmental exposure to oil pollution. The major causes of spills and spatial factors potentially reinforcing reported causes were analysed. Results show extensive general exposure and sabotage as the leading cause of oil pollution in the Niger Delta.

Secondly, a method of delineating the river network in the Niger Delta using Sentinel-1 SAR data was developed, as a basis for modelling potential flow of pollutants in the distributary pathways of the network. The cloud penetration capabilities of SAR sensing are particularly valuable for this application since the Niger Delta is notorious for cloud cover. Vector and raster-based river networks derived from Sentinel-1 were compared to alternative river map products including those from the USGS and ESA. This demonstrated the superiority of the Sentinel-1 derived river network, which was subsequently used in a flow routing analysis to demonstrate the potential for understanding oil spill dispersion.

Thirdly, the study applied optical remote sensing for indirect detection and mapping of oil spill impacts on vegetation. Multi-temporal Landsat data was used to delineate the spill impact footprint of a notable 2008 oil spill incident in Ogoniland and population exposure was evaluated. The optical data was effective in impact area delineation, demonstrating extensive and long-lasting population exposure to oil pollution.

Overall, this study has successfully assembled and produced relevant spatial and attribute data sets and applied integrated geostatistical analytical techniques to understand the distribution and impacts of oil spills in the Niger Delta. The study has revealed the extensive level of human and environmental exposure to hydrocarbon pollution in the Niger Delta and introduced new methods that will be valuable for future oil spill monitoring and management.

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## Dedication

To the glory of God

and

Dad and mum for their unwavering guidance, my siblings, my wife Zainab, and my daughters Charis and Chevelle.

"It's a fact of life that there will be oil spills, as long as oil is moved from place to place, but we must have provisions to deal with them, and a capability that is commensurate with the size of the oil shipments."

~ Sylvia Earle

“The environment will continue to deteriorate until pollution practices are abandoned”.

~B. F. Skinner

**Declaration**

This thesis has not been submitted in support of an application for another degree at this or any other university. It is the result of my own work and includes nothing that is the outcome of work done in collaboration except where specifically indicated. Many of the ideas in this thesis were the product of discussion with my supervisors.

Excerpts of this thesis have been published in the following conference manuscripts and academic publications:

Obida, C.B., Blackburn, G.A., Duncan Whyatt, J.D. and 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*, Elsevier, Vol. 111 No. October 2018, pp. 32–42.

Obida, C.B., Blackburn, G.A., Whyatt, J.D. and Semple, K.T. (2019), "River network delineation from Sentinel-1 SAR data", *Int J Appl Earth Obs Geoinformation*, Elsevier, Vol. 83 No. February, p. 101910.

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**Chapter 4: River network delineation from Sentinel-1 SAR data**

Obida, C.B., Blackburn, G.A., Whyatt, J.D. and Semple, K.T. (2019), “River network delineation from Sentinel-1 SAR data”, *Int J Appl Earth Obs Geoinformation*, Elsevier, Vol. 83 No. February, p. 101910.

**Chapter 5: Quantifying the impact of the large-scale release of oil on the environment of the Southern Niger Delta**

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## List of Acronyms

ADK – Aviation Turbine Kerosen

AGO – Automotive Gas Oil

ASCE – American Society of Civil Engineers

AWEI – Automated Water Extraction Index

ASTER - Advanced Spaceborne Thermal Emission and Reflection Radiometer

AVIRIS – Airborne Visible/ Infrared Imaging Spectrometer

CIESIN – Centre for International Earth Science Information Network

CCI – Climate Change Initiative

CSR – Corporate Social Responsibility

DPS – Downstream Pipeline System

DDT - Dichlorodiphenyltrichloroethane

DEM – Digital Elevation Model

DPK – Dual Purpose Kerosene

ESA – European Space Agency

EMS – Electromagnetic Spectrum

ENVISAT – Environmental Satellite

GIS – Geographic Information System

GSFC – Goddard Space Flight Centre

HH – Horizontal Horizontal Polarization

HV – Horizontal Vertical Polarization

HYDROSHEDS - Hydrological data and maps based on Shuttle Elevation Derivatives at multiple Scales

HYPREP – Hydrocarbon Pollution Remediation Project

ICT – Information Communication Technology

JIV – Joint Investigation Visit

KDE – Kernel Density Estimation

LiDAR – Light Detection and Ranging

LaSRC - Land Surface Reflectance Code

LAI – Leaf Area Index

LGA – Local Government Area

LSWI – Land Surface Water Index

LEDAPS - Landsat Ecosystem Disturbance Adaptive Processing System

MEND – Movement for the Emancipation of the Niger Delta

MNDWI – Modified Normalised Difference Water Index

MODIS - Moderate Resolution Imaging Spectroradiometer

MERIS - Medium Resolution Imaging Spectrometer

MPCA – Multi-temporal Principal Component Analysis

NSDI – National Spatial Data Infrastructure

NDDC – Niger Delta Development Commission

NDVI – Normalised Difference Vegetation Index

NHSA – Nigerian Hydrological Services Agency

NNPC – Nigerian National Petroleum Corporation

NASA - National Aeronautics and Space Administration

NDII – Normalised Difference Infrared Index

NOSDRA – National Oil Spill Detection and Response Agency

NKD – Network Kernel Density

NDWI – Normalised Difference Water Index

OECD – Organization for Economic Cooperation and Development

OSM – Open Street Map

OLI – Operational Land Imager

PCA – Principal Component Analysis

PBDEs - Polybrominated Diphenyl Ethers

PAHs – Polycyclic Aromatic Hydrocarbons

POPs – Persistent Organic Hydrocarbons

PMS – Premium Motor Spirit

RADAR – Radio Detection and Ranging

RENA – Removal by Enhanced Natural Attenuation

ROW – Right of Way

SANET – Spatial Analysis along Network

SRTM – Shuttle Radar Topographic Mission

SPDC – Shell Petroleum Development Company

SAR – Synthetic Aperture Radar

SDSS – Spatial Decision Support System

SLAR – Side Looking Synthetic Aperture Radar

SAVI – Soil Adjusted Vegetation Index

SNAP – Sentinel Application Platform

TM/ETM – Thematic Mapper/ Enhanced Thematic Mapper

TAUDEM - Terrain Analysis Using Digital Elevation Models

TPH – Total Petroleum Hydrocarbon

USGS – United States Geological Survey

UNEP – United Nations Environmental Protection

UPS – Upstream Pipeline System

UAVs – Unmanned Aerial Vehicles

VV – Vertical Vertical Polarization

VH – Vertical Horizontal Polarization

## List of Appendices

# Chapter 1 Introduction

## 1.1 Rationale

Nigeria is currently ranked as the largest oil producer in Africa and sixth largest producer in the world (Taft and Haken, 2015), however, it has had its fair share of pipeline oil spill problems. Proceeds from oil exports remain the major source of revenue for the country. The Niger Delta, which is the key oil producing region of Nigeria, is also the largest river delta in Africa (Ndidi et al., 2015). It is a fragile ecosystem consisting of mangrove forest, fresh water swamps and tropical rainforest rich in biodiversity (Anejionu et al., 2015). However, the region has experienced continual problems of environmental pollution and degradation as a consequence of the oil and gas industry (Zabbey et al., 2017).

The delta has suffered severe environmental problems as a result of spills due to poor management and maintenance of oil and gas infrastructure (NDDC, 2006). Pipeline networks carrying petroleum products play a major role in the transportation of crude oil. Although most pipelines are buried underground, natural and human activities often lead to exposure and damage resulting in spills. Deliberate third-party interference with pipelines and related infrastructure are reported to account for 75% of oil spill incidents in the region (SPDC, 2014).

Oil spills in the Niger Delta have caused significant problems for many years. A total of 16,083 pipeline breaks were recorded between 2002 - 2012, with the vast majority (97.5%) of these due to acts of vandalism (Anifowose et al., 2012). Access to data has been a limiting factor in the past. Although the region has gained the attention of many scholars, few have attempted to integrate information on pipeline oil spills with potential impacts. Due to the scale of the problem, there is a need for a regional approach, centred on data integration and spatial analysis.

Given the dearth of spatial data, most studies undertaken in the region have been qualitative and exploratory in nature. For example, the Niger Delta, despite being the fourth largest wetland in the world (Sam and Zabbey, 2018), was not available in detailed digital format at the start of this study. River systems are important because they provide an important source of livelihood and are also easily polluted, serving as pathways for the movement of spilt oil. Inaccessibility of the Niger Delta and security concerns necessitate the development of robust methods for understanding the distribution, dispersal and impacts of oil spills. Combining survey-based oil spill data with spatial data derived from remote sensing imagery offers a plausible solution in this context.

There is therefore a need to integrate spatial data in order to monitor pipeline oil spills and manage their impacts on the environment. Understanding the spatial and temporal dynamics of spills and their impacts can support decision making regarding allocation of security resources in priority areas, and can help to quantify human and environmental exposure to pollution. Recent developments in the availability of free satellite data combined with access to new data on the occurrence of spills can enable a critical examination of exposure to be undertaken.

Hence, this research analyses an extensive newly-available database on oil spills in the Niger Delta to determine human and environmental exposures. It tests the ability of new Sentinel-1 satellite data to delineate the river network in the region since rivers form a major dispersion pathway for oil spills and are critical in present and future oil spill management. Finally, this research examines the spatial extent and exposure risk of the huge Ogoniland oil spill in the Niger Delta, through the use of a combination of Landsat satellite data for impact area delineation and detailed field measurements of pollutants undertaken by UNEP.

The research therefore provides a cost-effective means of investigating the complex spatial problem resulting from oil spills and it impacts across a large geographical region. This research provides regional insights into the magnitude of integrated exposure, patterns and trends of oil spill problems through the application of sourced and generated geospatial data and techniques. In addition, outputs from this study potentially become vital inputs in regional spatial decision support systems.

## 1.2 Aims and Objectives

### 1.2.1 Aim

The aim of this research is to investigate the spatio-temporal extent and potential impacts of oil spills in the Niger Delta. This is achieved through the following objectives:

### 1.2.2 Objectives

a. To examine spatial and temporal trends in oil spills, their causes and the effects on the environment and human exposure through novel network-based hot spot analysis.

b. To derive a detailed geometric river network from Sentinel-1 SAR-C data and compare this to existing river data sets, as a means of accounting for the main pollution distributary pathways.

c. To determine the spatial extent, impact and population exposed to hydrocarbons associated with the major 2008 Ogoniland oil spill.

## 1.3 Overview of the Niger Delta

### 1.3.1 Location and setting

Nigeria is located in West Africa (10°N, 08°E) and occupies 910,768 $km^2$ of land and 13,000 $km^2$ of water (Onuoha, 2008). It is bounded to the North by the Niger Republic, to the West by Benin Republic, to the East by Cameroon and Chad, and to the South by the Atlantic Ocean (Shittu, 2014). Nigeria gained independence from British rule on 1st October 1960 and has since experienced significant political, social and economic change. Currently it is divided into 36 states with a Federal Capital Territory in Abuja. These states are grouped into 6 geopolitical zones namely (1) Northwest (2) Northcentral (3) Northeast (4) Southsouth (5) Southeast and (6) Southwest (Figure 1.1).

The Niger Delta includes all the states in the Southsouth, one from the Southwest and two from the Southeast; these are the oil producing states of Nigeria (Hooper et al., 2002; Imoobe and Iroro, 2009). It extends through Cross River, Akwa Ibom, Abia, Imo, Rivers, Bayelsa, Delta, Edo and Ondo states (Imoobe and Iroro, 2009), covering an estimated 70, 000 $km^2$ of wetland and is among the top ten largest swamps and deltaic ecosystems in the world (Hooper et al., 2002; Phil-Eze and Okoro, 2009).

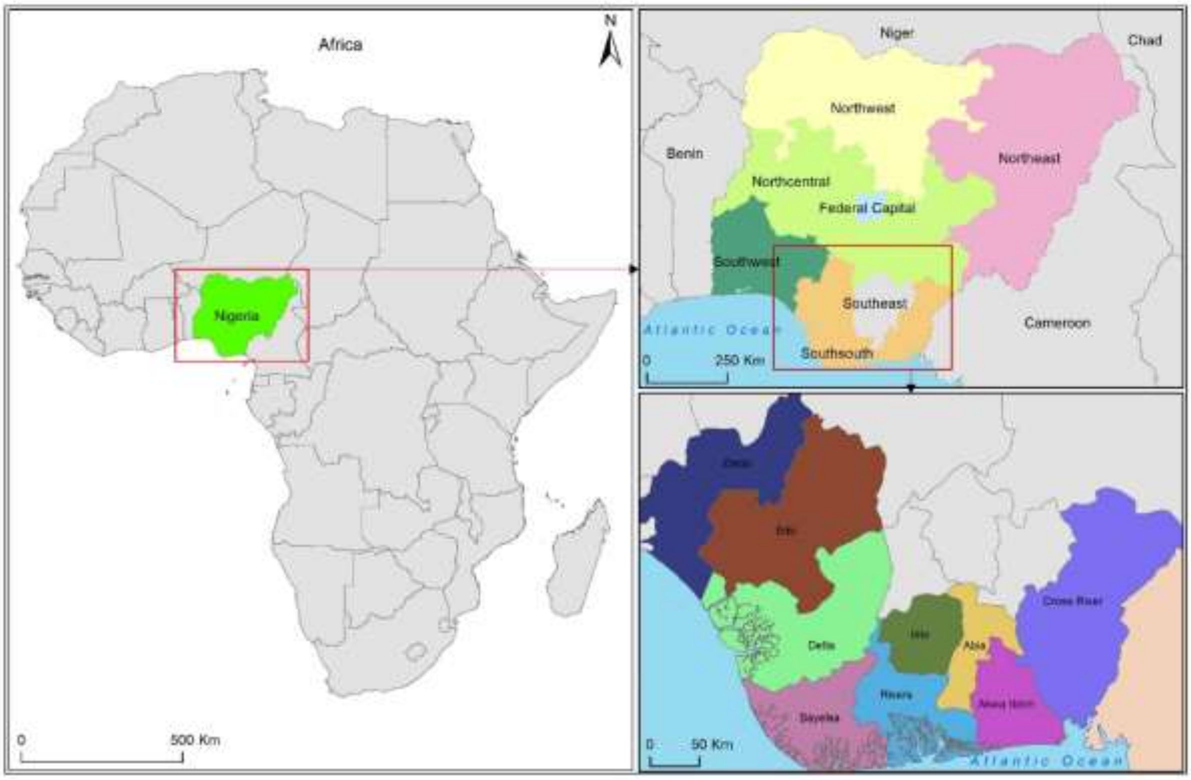


**Figure 1.1**. The position of Nigeria in Africa, with inset maps showing a) the 6 geo-political zones in Nigeria and b) the location of the 9 component states of the Niger Delta.

### 1.3.2 Demography and Cultural Diversity

The Niger Delta region is known for its rich cultural heritage due the presence of over 40 diverse ethnic groups speaking 250 Languages. Ethnic groups include Binis, Bekwarras, Efiks, Anang, Ibibios, Anangs, Yorubas, Ibeno and Oron (NDDC, 2006). The customs of the people are reflected in the way they dress, marriage rights, and traditional and cultural festivals. Traditional economic activities of the communities may be categorised into (1) land- based activities, including hunting, farming, collecting and processing palm fruits, and (2) water-based activities, including fishing and trading.

### 1.3.3 Ecosystems

The Niger Delta encompasses a wide range of ecosystems, with major types including barrier island forest, montane ecosystems, mangrove swamp forest, lowland rain forest, derived savannah and fresh water swamp (Anejionu et al., 2015). The lowland rainforest is made up of a portion of non-riverine areas in addition to the savannah type found in north eastern Niger Delta. The freshwater swamp ecosystem constitutes approximately 17,000 $km^2$ of the Niger Delta (NDDC, 2006). It is home to a wide range of endangered species; ironically, it is also heavily polluted by oil spills leading to the destruction of biodiversity (Kadafa, 2012). The mangrove forest extends an estimated 40 $km^2$ in width, though narrows in the estuaries (Zabbey et al., 2017). Its floor is rich in flora and fauna such as crabs and shrimps (Balogun, 2010). Oil spills pose significant risks to this important biodiversity (Anejionu et al., 2015; Balogun, 2010).

## 1.4 Thesis Structure

This thesis is composed of six chapters: the introduction and literature review, followed by three analytical chapters which address specific objectives described earlier. The sixth chapter provides a synthesis of the main findings and recommendations.

**Chapter 1: Introduction to research rationale, aims and objectives**

This chapter has introduced the central research problem of oil spills in the Niger Delta and the rationale behind development of techniques for understanding their distribution and impacts. It has also defined the overall aim and objectives and provided an introduction to the study area.

## Chapter 2: Literature Review

This chapter reviews the problem of oil spills and the associated challenges of tackling them. The history and potential impacts of oil spills are reviewed and presented. Challenges in managing and monitoring oil spills are then reviewed. The applications of geospatial techniques are then considered as a means of providing cost-effective means of monitoring and management. This includes a review of spatial and temporal models for hotspot detection and methods of river network delineation since rivers form a major pathways for movement of spilt oil. Approaches to environmental and human exposure assessment are then presented. The review concludes with a discussion on the merits of risk assessment approaches and it identifies the key research gaps.

## Chapter 3: Quantifying human and environmental exposure to oil spills in the Niger Delta using advance geospatial techniques

This first analytical chapter sets out to understand the spatial and temporal patterns of oil spills, identifying potential hotspots. The chapter highlights the problem of oil spills in the Niger Delta firstly by adopting and using the SANET tool to identify hotspots along the pipeline network. Human and environmental exposures are then quantified based on distance from the pipeline network for the entire study area. Potential factors explaining the pattern of spills such as proximity to roads, security bases, cities and coast are then examined and presented. This chapter was published in Environment International (2018).

### Chapter 4: High resolution channel delineation and attribution from Sentinel-1 SAR data

The river network forms an important pathway through which oil may move around the environment. In data poor countries such as Nigeria, detailed digital river network is not currently available. This chapter therefore describes how a high-resolution vector river network can be derived from satellite data. The resulting topologically-structured network is then used to demonstrate how spilt oil may be transferred around the delta region. This chapter was published in the International Journal of Applied Earth Observation and Geoinformation (2019).

### Chapter 5: Quantifying the impact of the large-scale release of oil on the environment of the Southern Niger Delta

This chapter determines the spatial extent and potential human exposure of a major oil spill in Ogoniland, Rivers State. A time-series of remotely sensed images are used to determine the spatial extent of impact of the spill, using image differencing of calculated temporal NDVI images. The spill footprint is then integrated with field-based measurements of pollutants taken from UNEP's assessment of Ogoniland to infer the characteristics of the oil deposited in the environment and combined with data on the population distribution to quantify the risks of human exposure.

### Chapter 6: Conclusions

This chapter brings together key themes addressed in the study aims and objectives. The original contributions of the research are highlighted along with limitations and avenues for future research. Finally, based on the key findings of this research, a series of recommendations are made to government, operators and communities concerning the pressing requirements and potential strategies for tackling the problems of oil pollution in the Niger Delta.

# Chapter 2  Literature Review

## 2.1 Pipelines and the oil spill problem

### 2.1.1. Oil spills

Oil spills are a global phenomenon with negative environmental impacts in the places they occur. Spills have been occurring since the discovery of crude oil and have been an integral part of the industrial revolution (Irank, 2016). They can occur both on land and within marine environments, each with varying degrees of impact. In the US for example, an annual 1,300,000 tonnes of oil have been spilled into the marine environment over the last two decades, with tanker vessels contributing 100,000 tonnes, runoff 100,000 tonnes and pipeline leaks 12,000 tonnes (Leifer et al., 2012). As much as tanker spills are reducing in volume, large spills from tankers, such as the merchant vessel Prestige off the coast of Spain in 2002 (63,000 tonnes) are still likely. In contrast, oil spills resulting from pipeline ruptures are on the increase, partly because of ageing infrastructures and partly because of expansion into deeper waters (Jernelöv, 2010).

Oil spills are relatively common occurrences on sea surfaces, and are often occur in major shipping routes, for example, in Southeast Asian waters (Zhang et al., 2008), and in the Yellow and East China seas (Ivanov et al., 2002). Others are associated with offshore installations in the North Sea (Espedal and Johannessen, 2000). Forty-five per cent of oil-related pollution results from operational discharges. When the frequency of occurrence of such spills are taken into account, they constitute greater impacts on the fragile ecosystems than larger spills (Kirkwood, 2014). Nevertheless, spills from oil tankers still occur. In recent times, the grounding of merchant ship tanker Rena off the coast of New Zealand and the subsequent leakage of oil led to excessive environmental damage. Spilled oil is highly toxic, often causing functional and behavioural disorders in plant and animal species. In addition, oil spills affect birds and impact upon fish and shellfish. Oil spills not only affect plants, animals and corals, but humans and their activities, such as fisheries through destruction of fishing boats, floating fishing kits and fishing gear.

The extent of damage is not only related to the volume of spill, but also to the relative vulnerability of the area. For example, a spill of 9,000 tonnes of diesel from the Tampico Maru in 1957 in Baja California badly damaged an estimated 10 km of coastline (Anyanova, 2012a), while a spill of 10,000 tonnes of crude oil by the Argea Prima in 1962 in Puerto Rico caused insignificant damage (Anyanova, 2012a). Similarly, the 476,000 tonnes of crude oil lost by the Ixotic I oil platform blowout in the Gulf of Mexico caused little damage whilst the spill of 50,000 tonnes of fuel oil from the Argo Merchant grounding of the coast Massachusetts in 1976 was significantly damaging. Similarly, the Exxon Valdez oil spill off the vulnerable ecosystems of Prince Williams Sound in Alaska (Cronin et al., 2002), in 1989 led to an ecological disaster and a prolonged and costly clean-up operation. As the use of tankers to transport oil has declined over the years, the use of pipelines has increased significantly and this has resulted in more terrestrial spills (Anyanova, 2012b).

Although oil spills worldwide constitute a general environmental concern for environmentalists, in developing countries they usually receive lesser attention compared to developed nations. Nigeria, for example, which is Africa's largest producer of oil and gas, has witnessed significant oil pollution since oil exploration started in 1952 in the Niger Delta. It has been reported that an estimated 13 million barrels (1.5 million tons) of oil have been discharged into the delicate ecosystem over the last 50 years (Kadafa, 2012); this is up to 50 times the volume of oil spilled by the

Exxon Valdez. There are several causes of spills, ranging from operations largely resulting from the use of old and poorly maintained infrastructure to human error. Other causes are largely unknown although sabotage is commonplace in this region. Sabotage has increased over time resulting in significant economic loss and negative impacts on the environment.

The problem of oil spills is widespread in the Niger Delta. However, to date, patterns of spills over space and time are poorly understood due to their dynamic and complex nature. Many actors have been identified in the process of oil theft, which takes place at different levels of operational sophistication (Boris, 2015). Most of the spills in the Niger Delta occur on pipelines that are key infrastructure elements connecting oil fields to jetties, depots and export terminals. The pipeline network is vulnerable due to lack of enforcement of Rights of Way (ROW) which aims to restrict activities around pipelines. Communities grow, extending into areas containing pipelines as shown in Figure 2.1, further increasing their vulnerability (Anifowose et al. 2012; Shittu 2014). Therefore, the majority of spills in the Niger Delta occur along the pipeline network.

**Figure 2.1.** Pipeline showing violation of Right of Way (ROW) in Port Harcourt Suburbs, showing the author, taken during field survey in 2016.

Since the birth of the petroleum industry in 1956 after a commercial quantity of oil was found in Oloibri (Bayelsa state) in Eastern Nigeria, the country has witnessed numerous challenges. To improve the delivery of petroleum products from the oil producing regions (Niger Delta) to other parts of the country, a network of pipelines was constructed and operated by the government and a number of multi-national corporations (Onuoha, 2008). Nigeria has an estimated 5000 km of pipeline network, comprising of 4315 km of multi-product segments and 666 kilometres of crude oil segments. The pipeline network is divided into the upstream and downstream components. The Upstream Pipeline System (UPS) comprises of flow lines, collecting lines and pipelines used solely for the transportation of petroleum products from wellheads to processing units. The Downstream Pipeline System (DPS) is used to move refined products from refineries to tank farms, depots and sales outlets (Anifowose et al., 2013). The major DPS pipeline systems in Nigeria are shown in Figure 2.2. The research presented in this thesis focuses on the DPS which is regularly subjected to acts of sabotage. These pipelines intersect at various points across the region, forming a network. The network links the 22 storage depots and 4 refineries at Warri, Kaduna, and Port-Harcourt (I & II) including the offshore terminals at Bonny and Escravos. It also links jetties at Alas, Cove, Calabar, Okirika and Warri (Francis et al., 2004).

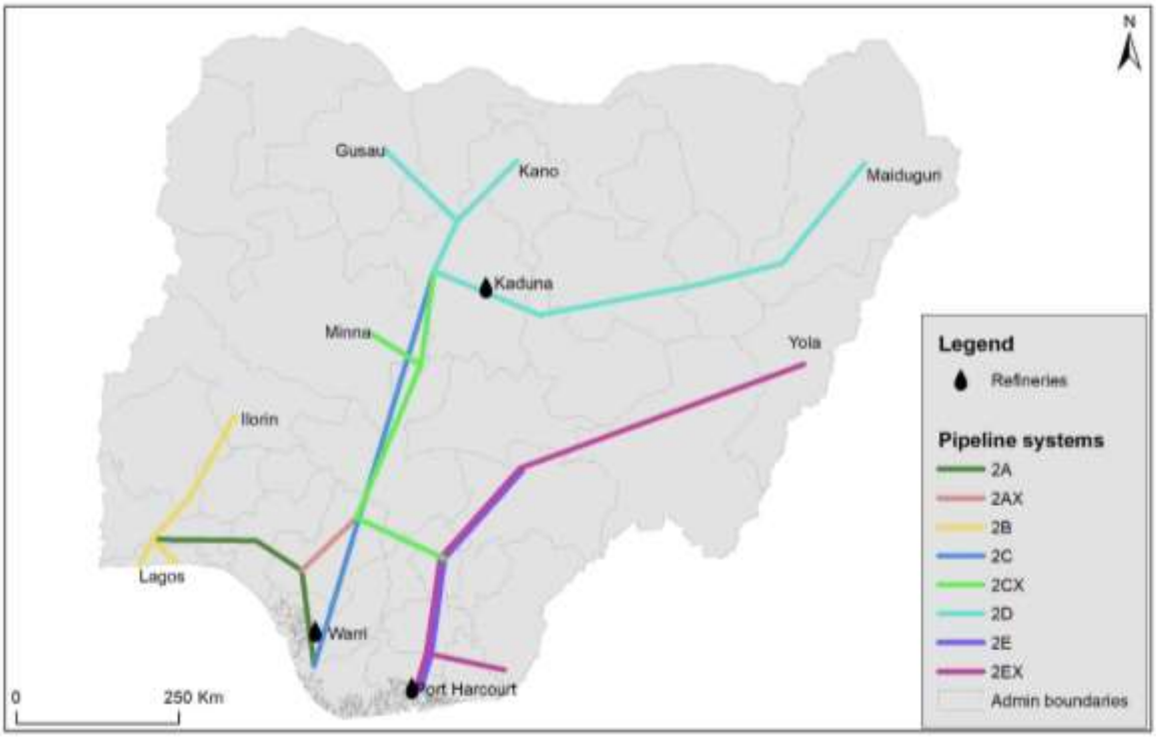


**Figure 2.2.** Major pipeline network connecting pump, flow stations and refineries in Nigeria.

Pipelines of varying diameter connect the storage facilities. They range from 6 to 18 inches and have total installation capacity of 1,266,890 (PMS), 676, 400 (DPK), 1,007,900 (AGO), and 74,000 (ATK) $m^3$ tonnes (Anifowose et al., 2014). The nature and distribution of the pipeline network in Nigeria is shown in Table 2.1 below.

**Table 2.2.1.** Major inter-regional pipeline network in Nigeria.

| Type | Linkages |
|---|---|
| System 2A | Warri – Benin – Ore - Mosimi |
| System 2AX | Auchi - Benin |
| System 2B | (a) Atlas Cove – Mosimi – Ibadan – Ilorin |
| | (b) Mosimi – Statelite (Ejigbo in Lagos) |
| | (c) Mosimi - Ikeja |
| System 2C | Escravos – Warri – Kaduna (Crude lines) |
| System 2D | (a) Kaduna – Zaria – Kano – Zaria – Gusau |
| | (b) Kaduna – Jos – Gombe - Maiduguri |
| System 2E | Port Harcourt – Aba – Enugu - Markurdi |
| System 2EX | Port Harcourt – Aba – Enugu – Markurdi - Yola |
| System 2CX | (a) Enugu – Auchi (Interconnections) |
| | (b) Auchi – Suleja - Kaduna |
| | (c) Suleja - Minna |
| System 2DX | Jos - Gombe |

### 2.1.3. Pipeline sabotage and oil spills in Nigeria

Sabotage is an act involving intentional destruction of public or private possessions (Anifowose et al., 2014). It also connotes wilful damage of infrastructure with political or criminal intent. Therefore, oil pipeline sabotage means intentional breaking into pipelines to cause disruption to oil production or to fraudulently acquire petroleum products (Marle and Vidal, 2011). The pipeline infrastructure in Nigeria has been the subject of sabotage by vandals and opportunists for many years. The frequency of such deliberate attacks has increased in recent times, prompting questions as to whether pipelines were in locations that allow easy sabotage, or are being inadequately policed. Some precautions put in place at the onset of construction included the Government securing a 3.5m Right of Way (ROW) on either side of the pipelines. Some were also buried 1m deep (Francis et al., 2004). Notwithstanding these measures, the wave of sabotage attacks on pipelines in Nigeria has shown that the infrastructure is highly vulnerable with associated negative environmental consequences.

The problems facing the oil industry are diverse, ranging from militancy to pipeline sabotage. The former has reduced in response to the governments Amnesty Programme, however, the latter has escalated (Akhigbemidu and Okoli, 2013). Despite oil pipeline sabotage being categorised as a criminal offence by the Petroleum Act, and the infrastructure being protected by the Criminal Justice Decree of 1975 (Phil-Eze and Okoro, 2009), pipeline vandalism in the Niger Delta continues to increase. Related to the spill events are fire outbreaks that lead to destruction of lives, ecosystems and farmlands.

Most oil pipeline vandalism in Nigeria is committed by well-organized groups who are driven by the desire to steal petroleum products for their own gain. In Nigeria, the entire process is referred to as ‘bunkering’. Table 2.2 shows the statistics of pipeline sabotage in the 2000s. The table show that pipeline sabotage has increased significantly (Akhigbemidu and Okoli, 2013). This trend has been consistent in the past decade. Available statistical data has shown that while 600 breaks were recorded in Port Harcourt in 2003, this increased to 1,650 in 2006. Warri increased from 100 to 600 cases over the same period (Amanze-Nwachukwu and Ogbu, 2007). Although oil pipeline sabotage is more common in the South, there are recorded cases in the northern states of Kaduna and Gombe (Onuoha, 2008).

**Table 2.2.** Sabotage on selected pipeline systems in Nigeria 2002 – 2012 (Ogbeni, 2012).

| Pipeline | Route | No of Sabotage attacks |
|---|---|---|
| System 2E/2EX | Port Harcourt–Aba–Enugu–Markurdi - Yola | 8,105 |
| System 2A | Warri–Benin–Suleja/Ore | 3,295 |
| System 2B | Atlas Cove–Mosimi–Satelite-Ibadan | 2,295 |
| System 2C | Escravos–Warri | 74 |
| Gas System | Trans-Forcados | 55 |

A media report by Ogbeni (2012) highlighted the rate of increase in oil pipeline sabotage in Nigeria. For example, from 2010 to 2012 a total of 2,787 pipeline sabotage events were reported on the Nigerian National Petroleum Corporation (NNPC) pipeline network. This led to the loss of 158 million tonnes of crude oil worth an estimated 12.3 billion Naira (Ogbeni, 2012). Pipeline sabotage also results from political issues. Militants attack pipelines in an attempt to undermine the activities of oil companies and attract national and international attention for their cause (Bassey, 2012). Militancy was sufficiently controlled by an Amnesty Programme introduced by the past government. However, since the present government came into power 2015 there has been an increase in pipeline sabotage. Threats from ex-militants to resume attacks are seen as political. The frequency of pipeline sabotage attacks has a considerable impact on the country’s political economy and environment. This necessitates the need for developing a system of identifying and managing the problem.

In total of 15,685 cases of pipeline sabotage were recorded between 2002 and 2012 as shown in Table 2.2. This further highlights the prevalence of sabotage in Southern Nigeria and the Niger Delta in particular. This partly informs the rationale of choosing this oil-rich region for this research, to develop a framework for mapping and quantifying oil spill impacts on humans and the environment. In addition, most previous studies carried out in this region have been qualitative in nature or have adopted a relatively simple statistical approach. The research presented in this thesis uses advanced geostatistical analytical techniques, coupled with remotely sensed inputs to provide a cost-effective system of managing and monitoring the impact of spills in the Niger Delta.

## 2.2. Application of geospatial techniques in oil spill monitoring and management

Developments in Information Communication Technology (ICT), have led to the generation and availability of large amounts of digital data. This, coupled with parallel developments in software and hardware, has led to the development of computed aided systems known as Decision Support Systems (Wangdi et al., 2016). Such systems have gained prominence in the decision making process, however, problems solved are usually non-spatial, thus location is usually insignificant. Laudien et al., (2006) referred to DSS as logical simulations of data to produce results that aid, or influence decision making towards solving partially structured problems. The primary component in these systems is the availability of data for analysis. Integrated geospatial techniques began to gain prominence in the 1990s (Eissa, 2013). It initiated the use of spatially referenced data in the decision-making flow, linked to complex models of analysis. These systems have helped to solve complex problems that were previously difficult to resolve leading to informed decision making (Natividade-Jesus and Coutinho-Rodrigues, 2007). It provides an interface for the users (analyst) to model and process data and visualized results guided by a set of defined criteria for decision makers.

The problem of pipeline sabotage is a complex one especially in the Niger Delta. Apart from aging pipeline infrastructure, the poverty indices in the region suggest more than half of the population in the Niger Delta are living below one dollar per day. Anifowose et al (2012) noted that there was no correlation between pipeline sabotage and poverty in the region. However, other studies (Oviasuyi & Uwadiae 2010; Francis et al. 2004; Boris 2015; Yeeles & Akporiaye 2016) have indicated the possibility of poverty having an overall impact on rates of sabotage. Other researchers have analysed the specific impacts of pipeline sabotage on health and the environment. For example, Anifowose et al., (2012), looked at the impact of crude oil transportation and sabotage on air quality. They compared trends in the number of sabotage attacks, product loss, fire outbreak, population density, fatality and incidence of poverty (Anifowose et al., 2008). However, their study did not show the temporal and spatial pattern of sabotage or identify the exact pattern in the Niger Delta. The trend shown was based on generic statistical analysis of the six geo-political zones in the entire country. It did not focus on the Niger Delta as the region with highest incidence of pipeline sabotage in Nigeria. This research proposes to address this gap by providing a framework in which to analyse spills and impacts. This is based on the knowledge that using a Spatial Decision Support System (SDSS) approach provides realistic and unbiased means of detecting and potentially managing this particular spatial problem.

In his research on mapping pipeline oil spills and human health risks in the Niger Delta, Shittu (2014) used a multi-criteria decision-making model to delineate hazardous areas and vulnerable communities. His analysis was based on using 443 spill incidents to understand spatial variation (Shittu, 2014). However, given the relatively small number of cases used in his analysis, it is unlikely that this will give a true representation of reality. In this research, a database of approximately 6,000 spill incidences is used in hotspot identification and exposure analysis. It also provides a framework for remotely sensed impact detection to support potential oil spill management systems.

Monitoring and management of pipelines and hazards has mostly evolved from traditional foot patrols, low flying aircrafts and aerial surveys, to more robust, intelligent remote sensing platforms (Eissa, 2013). This is due to the improvements in both spatial and temporal resolutions (Kross et al., 2015). The cost effectiveness and the efficiency of these analytical systems remains the rationale for using an integrated spatial analytical system especially in Nigeria, a developing country with insufficient funds in research investments.

To develop a more cost-effective methodology and reduce guesswork in pipeline management practices, new techniques have evolved over time. This involves timely use of hardware and software in the analysis of pipeline data in a more scientific manner (Roper and Dutta, 2002). In their research, they integrated multi-spectral imagery and Synthetic Aperture Radar (SAR) data in a multi-temporal sequence of an area. They then conducted temporal analysis in order to identify unauthorised encroachment, environmental risk and security threats. Their work demonstrated how satellite systems could be used in environmental impact of human activities. Previous studies have highlighted the use of satellite-based innovations for environmental management. Some satellite data have been applied for slope and ground movement analysis in relation to pipelines in a more cost effective manner (Hartdraft, 1998). A similar method has also been used in pipeline routing by choosing the most cost effective routes using several variables such as least grading, slope terrain, wetlands crossing, existing law and regulations and proximity to population centre (Balogun et al., 2012). Opara (n.d.) generated the most effective route for pipeline in Malaysia; importantly they showed that there was no single general method through which to determine the criteria or derive weights in multi-criteria analysis. Kross et al., (2015) compared the traditional method of pipeline route selection with a geospatial technique approach in Turkey. They found the geospatial technique approach more suitable, with an estimated reduction in cost of 14%.

The integration of remotely sensed and GIS data in this research facilitates advanced analysis. Traditional methods of conducting patrols over Rights of Way periodically for inspection are not only ineffective, but also expose personnel to threats, especially in volatile regions like the Niger Delta. The recent availability of high spatial resolution imagery and development of radar systems and object-based detection procedures has improved pipeline monitoring (Fung et al., 1998). In demonstrating the potency of using satellite based techniques as against the aircraft in pipeline management, Roper & Dutta (2002) used multi-temporal images collected daily, once and twice per week from satellite and airborne platforms. For each category, the use of satellite based system presented 30 to 100 per cent better chances of detecting pipeline security problems (Roper and Dutta, 2002).

The outputs from the Landsat and Sentinel space programmes can potentially be applied to spill management. Nigeria is relatively new in the application of satellite data, therefore timely development of a framework for remote management of pipeline spills is vital. This is especially true in the area of oil spill and impact detection that has damaged the region’s environment for decades. This could save the country millions of dollars in management costs and could help build capacity in environmental management.

## 2.4. Exposure to diffuse and non-diffuse pollutants in the environment

Pollutants in the environment are typically categorised into diffuse sources (non-point) and non-diffuse sources (point) sources (OECD, 2017). Point sources are the ones directly released into the environment from discrete, well known locations such as intensive livestock operation sites, ditches, sewage treatment plants, industrial sites and ruptured crude oil pipes. Diffuse sources, in contrast, are usually indeterminate in nature and originate from less well defined locations, for example agricultural runoff from fields and atmospheric deposition of pollutants (OECD, 2017). Although there are a range of pollutants in the environment, persistent organic pollutants (POPs) from crude oil constitute a significant danger to the environment in which they occur (Sousa et al., 2018). This is due to their bioavailability in biota and harmful effects on human and environment health (Zhang et al., 2013).

Organic pollutants, irrespective of their sources, occur in the air, soil, sediments and water bodies (Cheng et al., 2018; Han and Currell, 2017; Zhang et al., 2013). Therefore, their potential for human and environmental exposure becomes limitless once they are released into the environment (Zhang et al., 2013). Releases of organic pollutants to the atmosphere result from volatilization from water and soil or direct emission. Pollutants released into the atmosphere can impact human health through breathing (Hung et al., 2013). Concentrations of pollutants in the atmosphere are contingent on the chemical and physical properties of the pollutants and their quantity at source (Zhang, Wei, et al., 2013).

The occurrence of organic pollutants, especially from crude oil in soils, has been widely acknowledged (Bruce-Vanderpuije et al., 2019; Gan and Kiat Ng, 2012; Islam et al., 2018; Lu et al., 2016). They persist due to their hydrophophic nature and hold the potential to stick to the soils for prolong periods of time. In aquatic environments, organic pollutants occur in different forms contingent on their physical and chemical properties. In addition, their properties determine the rate of solubility and volatility which determines persistence. They have been reported to persist in freshwater, rivers, bays and estuaries (Sousa et al., 2018). Past studies have found heavy concentrations of DDTs in fishing harbours, which may be due to the use of DDT contained in chemical elements on fishing boats (Li et al., 2007; Zhang, Wei, et al., 2013).

In the Niger Delta, oil is released into water and onto land which are both potential pathways and receptors. Since humans depend upon the environment (air, land and water), the potential for exposure becomes high in the event of release of the pollutants, either from diffuse or non-diffuse sources (Zhang, Wei, et al., 2013). The potential impact on humans is further worsened by bioaccumulation in both plant and animal tissues exposed to pollutants (Ordinioha and Brisibe, 2013). A wide range of studies have shown elevated concentrations of organic pollutants in fish and crops in polluted environments (Collins, 2011; Zhang, Wei, et al., 2013). Most of these studies of exposure are based on sampled measurements of pathways and receptors. Therefore, these studies tend to be highly localised, limited by accessibility issues and sampling bias.

#### 2.4.1. Human exposure and potential health effects

Studies have shown the presence of elements of POPs in human adipose tissues, blood, and human milk (Zhang, Wei, et al., 2013). Concentrations were reported to be consistent with the consumption of contaminated fish from polluted rivers. Since the Niger Delta is a riverine environment and a considerable number of livelihoods depend on fishing, consuming contaminated fish is likely. Therefore, the rivers serve as pathways and receptors. Apart from direct consumption, exposure due to bioaccumulation of pollutants in plants is also possible (Islam et al., 2018). Direct dermal contact, consumption of polluted water and breathing polluted air are other means of direct human exposure to pollutants which constitutes the worst cases (Ordinioha and Sawyer, 2009, 2010). Ingestion and inhalation have been identified as the main pathways of human exposure (Paula et al., 2016).

#### 2.4.2. Environmental exposure

Since the environment serves as both a direct pathway, and in some cases a receptor for pollutants, the ecological impacts of pollutants have been the subject of a number of studies (Kingston, 2002; Lindén and Pålsson, 2013; Mishra et al., 2012; Opukri and Ibaba, 2008; Zhang, Wei, et al., 2013). Different approaches have been adopted when measuring human and environmental exposure to pollutants (Feijtel et al., 1998; Islam et al., 2018; Ordinioha and Brisibe, 2013). These include direct measurement of water, soil, sediments and air, based on standards and guidelines (UNEP, 2011). Since the occurrences of pollutants are contingent on the sources, it is expected that the distance to source potentially determines the level of exposure and damage the pollutants cause in the receiving environment. Differences in environmental sensitivity also account for levels of impact (Ondráček et al., 2014). For example, some environments are more sensitive than others. Furthermore, different land cover types have different resistance capacities. While a forest may resist pollutants for a long time, similar amounts of pollution could smother grassland or other more sensitive ecosystems (Duke, 2016). Developing spatial techniques based on such knowledge is therefore necessary for mapping exposure of large regions such as the Niger Delta.

**2.5 Remote sensing of oil spills and mapping impacts on vegetation**

Traditionally, the role of remote sensing in oil spill response, management and monitoring has been minimal. However, recent advances in sensor technology and availability of data have raised it importance in this field (Leifer et al., 2012). Remote sensing has been applied to oil spill monitoring and management around the world with varying degrees of success. Airborne and satellite remote sensing can assist in oil spill detection and response yet are met with substantial challenges such as temporal and spatial resolution (Tramutoli, 2007). In relation to various sensing approaches, active and passive systems have been adopted in different situations. In the aftermath of an oil spill the public typically demands to be informed about the location and extent of the oil spill. Through the use of contemporary remote sensing instruments, timely information about oil spills can be obtained (Zielinski et al., 2006). However, airborne remote sensing, including using Unmanned Aerial Vehicles (UAVs), and ground-based physical inspection are still commonly employed in oil spill monitoring (Fingas and Brown, 2014). These methods are not only relatively expensive but afford limited spatial coverage.

Satellite remote sensing of oil spills is becoming more common practice, although in some cases analysis is simply restricted to identification of the spill extent (Leifer et al., 2012). There are many documented uses of satellite remote sensing. These include their use for mapping the extent of oil spills, guiding oil spill countermeasures, investigations, detection and inputs in modelling the fates of oil slicks. They are also used in the administration of ship release laws and for providing evidence for legal actions (Fingas and Brown, 2014). A number of review articles have assessed the role of remote sensing in oil spill detection (Fingas and Brown, 2014; Leifer et al., 2012; Science et al., 1997). These reviews recommend that different sensors have different applications and should be directed to suitable objects of interest for potentially good outcomes. For example, radar sensors are more suitable for detection of oil spill on water, while optical sensors can used for spill impact detection on vegetation.

#### ***2.5.1*** **Optical remote sensing of spills**

Optical satellite remote sensing has been used in spill detection. Applications were limited in the early days because of the limited temporal coverage and number of operational satellites, therefore, success was restricted by satellite passage, sky state and event timing (Fingas, 2012). A typical example is the case of the Exxon Valdez spill. The oil stayed on the water surface for over 30 days but was only detected on one, 7 April, 1987 (Fingas and Brown, 2014). Another limitation of older optical systems was the time required to develop algorithms to identify spills on images. In the Exxon Valdez example, it took the analyst over two months to identify spills on the imagery despite knowing their exact location.

On water surfaces, characterising oil sheens heavily depends on patterns in relation to advection and weathering (ASCE, 1996). Current sheer caused by bathymetry, eddies and response efforts such as the application of dispersants can significantly affect how oil spills are identified (Leifer et al., 2012) in optical systems. An important, but not conclusive indication of oil presence in water is a known source point linked to a streak-like configuration. Due to the rapid nature of crude oil emulsification, most spilled oil usually exists as a balance of water and oil-water emulsion that can appear quite distinctive on the imagery. Therefore, its appearance in the visible spectrum is not only dependent on the ratio of oil to water and air content, but also on the relative thickness of the emulsion (Clark et al., 2010). More often than not, weathered oil mixtures look like algae, sargassum and other organic materials accumulating around zones of convergence.

Generally, oil has a greater surface reflectance than water but does not show the same absorption or reflection trends in the visible region of the Electro Magnetic Spectrum (EMS) (400 – 700 nm) (Fingas, 2013). Oil lustres appear silvery and reflect light over a wide spectral range to the blue band. Oil lacks specific properties that separate it from other background information (Fingas and Brown, 1997; Taylor, 1992). This means that methods that differentiate between particular spectral regions do not necessarily increase detection ability.

Optical hyperspectral remote sensing is an area that is continually growing; this involves the collection of hundreds to thousands of images at different wavelengths of the EMS for a particular geographical region (Alonso-González and Valero, 2013). Hyperspectral remote sensing is very complex, processing hyperspectral images requires advanced procedures to meet the requirements of oil spill and chemical contaminant detection. The most commonly used algorithm for processing hyperspectral data is spectral un-mixing, a technique based on pixel by pixel categorization. This is possible because hyperspectral images tend to be very high spectral and spatial resolution (few metres), therefore it is possible to have 'endmembers', a term used in hyperspectral remote sensing to refer to spectrally pure pixels. This procedure, however, is computationally intensive and time consuming. Notwithstanding, hyperspectral multi-temporal remote sensing has been applied in oil spill detection in recent years in relation to large oil spills (Frystacky and Levaux, 2012).

Scientific methods are still being developed to data acquired from visible portion of the

EMS to distinguish water from oil (Nie et al., 2012). However, fully automatic procedures have yet to be developed for characterizing oil spills and this region of the EMS remains a crucial area of research as a practical means of monitoring oil spills (Fingas and Brown, 2014).

Generally, the character of a thin oil sheen in an optical systems depends on the transmission and consequent reflection of light through the sheen. The light includes the incoming solar radiation and upwelling reflected light, including the scattered light from the oil and water beneath. Therefore, there is scope to identify oil by differentiation reflection. This is possible when sub-surface reflected radiance of oil emulsion is greater than sky reflected radiance of the water surface in the range 480-570 nm (Byfield and Boxall, 1999). These reflections and transmission capabilities are heavily depended on wavelengths and angles.

Several optical systems have been applied to oil spill detection. These include the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's TERRA satellite, and the Medium Resolution Spectrometer (MERIS) onboard the European Space Agency's ENVISAT satellite. Their usage is mainly limited by weather, particularly cloud cover. MODIS and MERIS data have been used to assess oil spill discharge in the Mediterranean Sea. Image flattening, oil spill classification and feature extraction techniques were applied. The procedure led to the definition of an optimised reflectance band for the detection of hydrocarbons (Ambientali and Naturali, 2011).

However, these systems only provide data at medium to coarse spatial resolution e.g. 250 – 800m which reduces their capability to detect smaller spills (Begue et al., 2014; Corbera and Schroeder, 2011). This is because the issue of mixed pixel becomes more pronounced at this resolution (Mingwei et al., 2008; Sakamoto et al., 2005). This limitation may be problematic in the study of spills in the Niger Delta and its impact on the environment because some spills occur in low quantities and impact vegetation only within that locality. In addition, MODIS with a wide viewing angle, can be affected by the impacts of Bi-directional Reflectance Distribution Function (BRDF) which can affect especially time series studies (Hansen and Loveland, 2012; Wang et al., 2002).

Older, more established optical systems such as Landsat, with moderate spatial resolution have been applied in oil spill studies both for direct and indirect detection through crop/vegetation change indices. The results showed potential especially when combined with high temporal resolution imagery from MODIS (Laneve and Luciani, 2015). However, such studies are limited by the fact that all the data utilized are medium to very low spatial resolution (Pan et al., 2015). Since the Landsat system has shown capability, developing it for direct and indirect detection of spills will provide a framework for near real time oil spill and impact detection and management.

Satellites such as Quick Bird, Worldview I, II and III, Sentinel-2 and NigerSat-2 offer more regular passes over the earth than older generation optical systems. Recent studies based on these satellite sensors have shown that spill detection using the visible portion of the EMS is dependent upon multiple factors including observation angle and the nature of the spilled oil (Shi et al., 2011; Shidhaye et al., 2008). Cloud cover remains a major drawback for the use of optical systems in oil spill detection. Sun glint can also be problematic in some cases, with some images almost completely masked. Attempts have been made at correcting this problem (Davis and Hu, 2011; Pan et al., 2011). Optical systems were recently used to assess the Gulf of Mexico oil spills, with reasonable success (Leifer et al., 2012).

The need to use higher spatial and temporal resolution imagery cannot be overemphasized. Optical systems such as Landsat TM have also be applied in oil spill detection i.e. Gulf of Mexico oil spill (Khanna, Santos, Ustin, Koltunov, et al., 2013). Their use, however, depends on regular high quality image acquisition (Wang et al., 2010). Unfortunately, the relatively low temporal resolution of products like Landsat TM cannot meet this requirement. In order to overcome such limitations, including those of spatial and temporal resolution, attempts have been made to adopt data fusion techniques to combine high spatial and temporal resolution images from different sensors (Wulder et al., 2011; Yuan et al., 2013; Zhang, Li, et al., 2013).

The near infrared part of the EMS can be used in detection by multi-sensor satellites such as MODIS, MERIS and airborne AVIRIS (Laneve and Luciani, 2015; Leifer et al., 2012). Data from these platforms were successfully used during the Gulf of Mexico's disastrous Deep-water Horizon spill (Bulgarelli and Djavidnia, 2012), detecting oil spills but at a relatively coarse resolution due to their sensor properties.

### ***2.5.2*** **Radar Remote Sensing**

Radar remote sensing is based on the concept of polarization as an active microwave remote sensing system (Zhang et al., 2016). While it has proven applications in the direct detection of spills, it can potentially also be applied in the indirect detection of spills and the extraction of vital oil spill management information such as water bodies. Polarization is the process through which signals are transmitted from radar platforms. It is based on Vertical (V) and Horizontal (H) incident wave energy transmission (Migliaccio and Nunziata, 2009; Velotto et al., 2011). Generally, broadcasts and responses are either in the same or different polarizations. There are four different polarization combinations, known as Quadrupole (Velotto et al., 2011). These include

HH, VV, HV and VH. The vertical VV antenna polarization has shown the greatest potential for both transmission and reception, especially for airborne systems. However, it shows minimal feature extraction if applied at satellite angles (Brekke and Solberg, 2005; Nunziata and Migliaccio, 2012). Some reports suggest that HH polarization shows better results with light winds whereas VV polarization shows better results in stronger winds (Kuzmanić and Vujović, 2010). Nevertheless, HH depends more on incidence angle than the VV polarization.

Sea clutter refers to the signals returned from the wavy and turbulent rough sea surface. Oil spills can easily be detected because oil significantly reduces roughness thus appears dark on the surface or simply as areas lacking sea clutter (Candès et al., 2011). Unfortunately, other features can appear as oil. These include fresh water slicks, whale, fish sperm, wind slicks, biogenic oils, wave shadows behind land or structures, glacial flour and shallow seaweed beds (Sheng et al., 2008). Therefore, in areas with such false inputs such as freshwater and ice inflows, oil spill detection can be particularly difficult. Zhu et al. (2015) revealed that even after advanced processing, 20 percent of an area classified as oil in SAR imagery was actually false. Notwithstanding these limitations, radar systems are very important in oil spill detection because they are practically the only systems that can give global coverage of spill events. In addition, the radar system is the only one that can successfully operate in all-weather i.e. clouds, night and fog.

Synthetic Aperture Radar (SAR) and the Side-Looking Airborne Radar (SLAR) are the main types of radar system used for oil spill detection and environmental remote sensing. SLAR is a comparatively older and cheaper technology, whose spatial resolution is acquired by a long antenna. SAR is based on the principle of forward motion of the aircraft using a long antenna thus acquiring a range of independent spatial resolution. This is however disadvantaged by the requirement of high-tech electronic computation. SAR in contrast has better range and resolution than SLAR. SAR is by far better (Khamayseh and Mastin, 1994) but SLAR is commonly used because of it affordability. Polarimetric SAR has been used to demonstrate the capability of identifying oil slicks and close matches (Brekke and Solberg, 2005; Lavalle et al., 2012). Furthermore, polarimetric phase differences can be used to differentiate oil spills from other close matches (Velotto et al., 2011).

In terms of radar bands, several researchers have demonstrated that the X-band radar produces better results than the L- or C- bands radar (Minchew et al., 2012). The deep-water Horizon oil spill was widely covered by radar; providing many opportunities for study. Generally, radar is very important in oil spill monitoring, especially for large spill episodes and ones which occurred in poor weather conditions. Although the problem of false detection of close matches is common, it can operate effectively in wind speeds of 1.5 – 10 m/s. The all-weather 24 hours capability makes radar the most common method for oil spill detection, however, research is still needed to optimise it immense potential. Furthermore, the success of radar in oil spill detection is based on direct detection over surface waters.

### 2.5.3 Vegetation Response to Oil Spills

Records kept about oil-induced vegetation stress have great implications for restoration, remediation and recovery forecasting. Plants respond to oil by changes in the spectral response of trunks, stems and leaves (Li et al., 2005b). Biochemical changes in the leaves lead to changes in photosynthetic pigments, leading to change from green to pale and yellowish green to yellow in adverse cases. This is the process of chlorosis, which has been attributed to different causes of vegetation stress including oil pollution (Zarco-Tejada et al., 2003). Plant stems become darkened, leaves chlorotic, accelerated defoliation, and seeds become dwarfed. This makes plants more sensitive to other environmental stressors. Other experiments have shown decelerated growth and germination leading to a reduction in overall rates of plant development (Li et al., 2005a). These give an indication of change in water and metabolic processes of plants and seeds, in addition to toxicity caused by the oil. Presence of oil changes the dynamics of competition in plants as more tolerant species use nutrients of dead disadvantaged species.

Previous research has revealed that freshwater organisms such as microphytes (algae) are affected by oil in terms of decreased production (Robertson, 1998). In addition, perennials of different forms submerged, surface floating, and the emergent forms are more tolerant of oil spills in comparison to those in stagnant water such as lakes and ponds. In the terrestrial environment, plant responses to oil vary depending on the prevailing environmental conditions. While some plants may be destroyed by spills, others appear to be more tolerant. It has been suggested that processed crude is relatively more poisonous to vegetation than unrefined crude (Duke, 2016). In a study, crude oil and diesel were applied to various plant groups such as wet marsh, grassland and dwarf shrub heath (Sanches et al., 2013). All the different groups responded to the oil spills within one week of application. All started yellowing, and browning due to the loss of chlorophyll. The authors noted that different plant physiologies had an overall bearing on the response. In addition, wet conditions were more favourable for resistance than dry conditions (Duke, 2016). Generally, vegetation impacts were highest in the dry areas where oil easily penetrated to the roots.

Plant response to oil spills is also determined by their root system. Plants with vertical and shallow root systems have a reduced surface area that comes into contact with the oil, resulting in a lower impacts than for plants with more oblique or horizontal deep root systems. Therefore, plants with sparse root systems are more vulnerable, than those with stocky better formed systems (Michel and Rutherford, 2014). Exposure to oil limited to the surface of plants such as sprays is likely to negatively affect plants but only in the short term due to regrowth in contrast to when the oil has penetrated the soil. Impacts take longer when the oil is underground and within the root system. This is likely to be the case in the Niger Delta, a region that has witnessed widespread oil spills over many years, especially in the delicate forest and mangrove ecosystems.

Tropical forests and mangroves are important habitats and food sources for marine organisms, and spawning areas for shrimps and species of fishes. Their uses for timber, tanning agents and fuel wood have been reported in a number of studies (López-Angarita et al., 2016). Mangroves are common along most coastal shoreline in the tropics as intertidal plant species, thus vulnerable to oil spills. Stress in mangroves in response to oil occurs two weeks after contact leading to visible chlorosis, defoliation and eventual death (Omodanisi et al., 2014). This study also showed there is a correlation between the magnitude of response to the quantity, type of oil and rate of recovery. Due to wave action on oil spills, mangroves are almost always impacted when oil is spilled in marine environments. Furthermore, the inaccessibility of most mangroves makes oil clean up a difficult task. Therefore, most mangroves are characterised by prolonged presence of oil in their root systems thus affecting health for extended periods of time.

These salt tolerant mangrove species have well developed and stabilised root systems, however their roots are always partly submerged, thus, exposing them to oils on the surface, and leading to impairment in their osmoregulation and respiration, which eventually leads to death (Duke, 2016). The change in plants biophysical and chemical properties because of the presence of oil forms the basis for the indirect detection of oil spills through remote measurement of change and eventual death (Arellano et al., 2015).

**2.5.4 Indirect Spill Detection**

Indirect spill detection implies sensing the impact of oil spills on vegetation, rather than the conventional detection of the presence of oil. Multi-temporal investigations over areas of interest can give insights into the magnitude of changes occurring. Satellite imagery is becoming increasingly available and can provide the basis by which up to date information about land cover can be used to develop and maintain inventories (Smith et al., 2014). Ecosystems exposed to oil in close proximity to related infrastructure have been severely damaged (Opukri and Ibaba, 2008). In the case of the Niger Delta, oil is spilled into the environment through equipment failure and acts of sabotage leading to impacts on already fragile ecosystems. Ecosystems around the coast are usually the worst affected because oil exploration activities mainly take place in marine environments (Mendoza-Cant et al. 2011; Ivanov et al. 2002; Ndidi et al. 2015; Khanna et al. 2013). Detection can lead to mapping areas of impact.

Spills can also be detected through the changes they cause to the biochemical and biophysical properties of vegetation (Khanna, Santos, Ustin, Koltunov, et al., 2013; Mishra et al., 2012). As vegetation responds to different types of stress in the environment, this response is a function of the type of stress present (Smorenburg et al., 2002). Oil spills are known to cause stress in vegetation and indication of this stress can signal the presence of oil (Li et al., 2005b; Omodanisi and Salami, 2014).

### 2.5.5 Mapping oil spill impacts

The vegetation of the Niger Delta has witnessed a significant amount of pollution over time from both routine operations and acts of sabotage (Adamu et al., 2014; Kadafa, 2012). This is partly due the inaccessible nature of the terrain. Some areas affected remain unknown to this day; the application of remote sensing to indirectly detect the impact of oil on vegetation thus remains paramount to any remediation planning. To reduce the impact of oil spills in the region UNEP and the federal government of Nigeria have embarked on a flagship clean up and remediation programme in Ogoni land (Konne 2014; Shittu 2014). Therefore, developing techniques for detecting and mapping oil spill impacted areas will assist in prioritising clean up from the knowledge of the extent and degree of impact (Arellano et al., 2015). This can be achieved through the application of quantitative approaches to spill impact detection, which will form the bases for remediation and recovery. This is because application of remediation is based on extent of impact on the environment.

Quantitative impact detection provides insights for remediation and recovery estimates in multi-temporal analysis. However, spill detection in marine environments is much easier than spill detection in terrestrial environments; here it requires further and more thorough investigation of spectral data provided by the sensor (Fingas and Brown, 1997; Goodman, 1994). Presence or absence of oil affects the spectral reflectance. For example, in the visible portion of the EMS oil reduces the reflectance of soil (Cloutis, 1989). These changes in the spectral properties of land cover due to presence or absence of oil form the basis for the identification of stress. A number of studies have been conducted to measure vegetation stress to oil and related pollutants (Emengini et al., 2013; Shruti Khanna et al., 2013), but these have been conducted under laboratory conditions, not the natural environment. Optical sensors measure changes in the biochemical properties of the vegetation, detecting biophysical changes due to change in the canopy structure of trees. Figure 2.5 shows spectral signature of vegetation at various levels of stress.

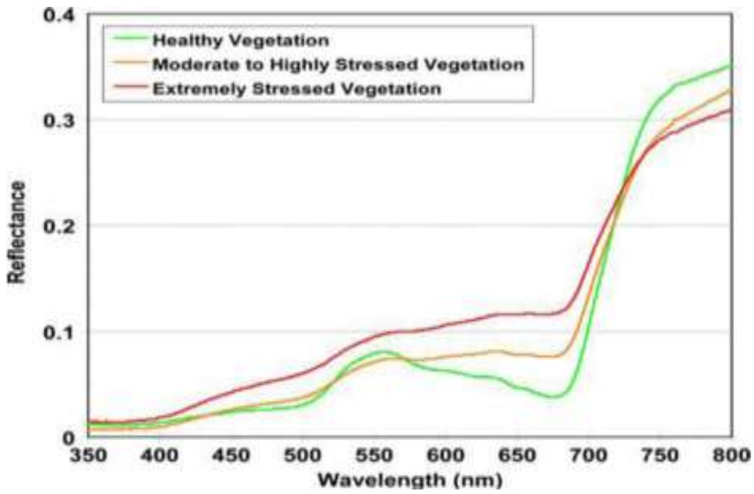


**Figure 2.3**. Spectral reflectance profile of healthy to extremely stressed vegetation.

Plant physiology responds to stressors in the environment and these changes are measured using the changed reflectance properties of the plants. As the intensities of the stressors increase or decrease there is usually a corresponding response in the biophysical properties such as Leaf Area Index (LAI) and biochemical properties such as water and pigments. These properties affect plants spectral response (Houborg et al., 2007; Jurgens, 1997; Ustin et al., 2009) and can be exploited to determine presence or absence of oil, and recovery processes (Khanna, Santos, Ustin, Koltunov, et al., 2013). Stress can be measured using the visible portion of the EMS by assessing particular plant properties (Arellano et al., 2015; Houborg et al., 2007; Ustin et al., 2009) such as plant foliage. Healthy vegetation as shown in Figure 2.5 is characterised by distinct red edge effect, a process that sees a sharp rise in the curve between 680 nm (red) and 780 nm (near infrared). This property can be altered in response to stress for example from oil (Gitelson and Merzlyak, 1994; Li et al., 2005b; Meer et al., 2002; Milton et al., 1991), and provides empirical evidence of the presence of oil. This can be exploited to estimate degree of impact and recovery.

To explore these changes in plant biophysical and chemical properties, several indices have been developed and applied towards detecting and measuring the impact of stressors. When applied over multi-temporal scales these indices can quantify impacts and potential recovery rates. Such indices include the Normalised Difference Vegetation Indices (NDVI), Modified NDVI (mNDVI), Normalised Difference Infrared Index (NDII) and Soil Adjusted Vegetation Index (SAVI) (Arellano et al., 2015; Cheng et al., 2006).

Spatial and temporal resolutions remain crucial requirements contingent on the type of application for example in monitoring oil slicks, river systems and changes in NDVI as in the case of this study. Due to the complexities in ecological processes monitoring vegetation such properties such as phonology or health requires high temporal resolutions and spatial resolutions. Coarse resolution products such as MODIS product with an average spatial resolution of 500m are potentially incapable of detection small scale disturbance (Pan et al., 2015), for example NDVI changes caused by small localised spills. Therefore, in the context of detecting oil spills impact on vegetation, products such as Landsat with medium spatial resolution of 30m and temporal resolution of 15 days is adequate. This is because impacts of oil spills take relatively long periods to be detected using vegetation indices. However, in applications such as monitoring river systems, the dynamic hydrological conditions such as rainfall events, floods and tides require more frequent data of up to 2-3 days temporal resolution. Similarly, in applications such as monitoring oil slicks on surface of water, high spatial and sub daily temporal resolution is required for near real-time monitoring.

### 2.5.6. Vegetation Indices

The most commonly used vegetation index is the NDVI, due in part to its relatively simple application. It is applied mainly in estimating the index of green plant cover and LAI (Kross et al., 2015; Martínez and Gilabert, 2009). NDVI uses the leaf absorption and reflectance properties within the visible and near infrared region of the EMS. This index has been widely used in studies of vegetation including, estimation of crop yields, performance of pastures and oil spill detection (Adamu et al., 2014; Khanna, Santos, Ustin, Koltunov, et al., 2013; Pan et al., 2015; Pérez-Hoyos et al., 2010). It has also been applied to estimate the volume of ground cover, plant photosynthetic health and vigour, quantity and quality of biomass.  NDVI was first applied in 1973 (Rouse and Kershaw, 1973)  at the Remote Sensing Centre in Texas University. Since then, it has been increasingly modified to suit diverse applications. The formula is given as:

$$\frac{NIR_{861} - R_{649}}{NIR_{861} + R_{649}}$$

Since stress in vegetation can affect the spectral character of bands, this index can be used to derive invaluable information about impacts on, and recovery of, stressed vegetation. The formula considers the potential problem whereby two areas with same characteristics could have different values if the data were collected at different times of the day, for example at sunrise and sunset. However, dividing the sum by the reflectance normalises the results. Researchers have applied NDVI at a variety of spatial scales. Khanna et al., (2013) used the indices to explore stress detection in a salt marsh following an oil spill in the Gulf of Mexico. They found that oiled vegetation stress was more pervasive in the tidal zone of the study area; in addition, change detection revealed varying degrees of revegetation in areas affected by the impact. Segah et al., (2010) used NDVI to detect the impact of fire in a tropical peat swamp through integrating SPOT and Landsat TM/ETM data. The approach provided a quantitative identification of the impact and some estimation of recovery. In addition, the potential of data fusion was demonstrated.

### 2.6. Risk assessments and fate of pollutants in the environment

Following the release of pollutants into the environment, they continue to change based on their interaction with other components of the environment (Lu et al., 2016). Their dispersion and fate are largely governed by physical and chemical properties, such as water solubility, volatility, and hydrophobicity (Whitehead et al., 2011). For example, Zhang et al., (2009) reported that a site with bromines had a higher washout ratio of PBDEs than sites without it (Zhang et al., 2009). In addition to these factors, meteorological conditions can also play a crucial role in determining the fate of pollutants in the environment. Temperature conditions, amount of rainfall, humidity and general weather-related conditions all play vital roles. For example, a study in Guangzhou and Hong Kong found phase transition was impacted by atmospheric temperature. This implies transport of pollutants in the atmosphere is affected by variability in the seasonal direction of local winds thus controlling time trends in the pollutants in ambient air (Li et al., 2007). All these interactions are contingent on the pollution medium, such as in the air, land and or water systems.

Regions with extensive river networks, high rainfall and thus high runoff, with varying degree of land use are particularly important for the movement and dispersion of pollutants (Zhang, Wei, et al., 2013). Previous studies have assessed the annual fluxes of component organic hydrocarbons from an inland waterway to the mouth of the ocean for a period of 3 years (Li et al., 2007; Yu-feng Guan et al., 2007). This demonstrates that river networks are important mechanism controlling the fate of organic pollutants.

While there are a range of methods of determining the fate of pollutants in riverine environments, traditionally, field campaigns are conducted to collect samples for subsequent analysis in the laboratory. This is not only time consuming, but requires specialist laboratory testing skills. An increase in monitoring of water quality from regional and national government, has led to the formulation of new regulations and funding (Karydis and Kitsiou, 2013; OECD, 2017). This generally constituted the turning point in water pollution management, coupled with advancement in computer based modelling and general development of ICT.  For example, the European Water Framework directive lists up to 33 chemical pollutants for which Environmental Quality Standards have been formulated (Collins, 2011). This framework and related policy have led to the development of a range of water quality models, focused on water and the fate of pollutants, including concentrations, and loading of sediments.

The use of and adoption of these models have ensured spatial and temporal analysis can be carried out in quick succession, ensuring timely and wide coverage. A range of models have been developed and applied in different regions of the world. These models can be applied for water quality in streams, ground water, and water distributary systems. Some are site and region specific, and require exhaustive data. Whilst models are important, field data remains crucial for the purposes of model calibration and validation (Launay et al., 2015).

While most of the models broadly deal with water quality and stream hydrology, variants that not only determine the fate of pollutants but also determine risk and exposure are particularly important. These models are capable of dynamic processing of pollutants thus form the framework for risk assessment in the general environment. Nevertheless, the fate of pollutants ultimately determines the levels of risk they pose. Risk can be determined by the mere presence or absence of the pollutants or by the concentration levels above a predetermined threshold (Wang et al., 2017).

Risk assessment is driven by the type of hazard causing the risk. Hazards can be physical, biological or chemical agents with the potential to cause serious health impacts (Jacxsens et al., 2016). The level of risk is thus dependent on exposure which is the likelihood of contact with the hazard through the environment or food. Risk assessment to chemical pollution can be deterministic or qualitative in terms of risk ranking (Jacxsens et al., 2016). Deterministic risk assessment is important in decision making such as risk mitigation and prevention, risk acceptance and regulation, ranking measures on different risk sources (Zio, 2018). Risk assessment has been widely studied (Isigonis et al., 2019; Minolfi et al., 2018; Shi et al., 2018; Wenning et al., 2018), but the wide ranging nature of the hazard causing risk makes it difficult to build a universal risk assessment framework. Therefore, the outcome of any risk assessment depends upon assumptions, current knowledge and parameters supplied to a particular adopted model (Zio, 2018).

Oil spills have over the past decades contributed to coastal and maritime pollution. Whether on land on water, the initial challenge of reducing spill impact is to assess its extent (Amir-Heidari and Raie, 2018). While reduction in oil spill frequency should be the immediate step taken, risk assessment of already spilt oil remains crucial in reducing exposure risk. Oil spill risk assessment is difficult because of problems in measurement of spill probabilities, impacts of events and spatial quantification (Jolma et al., 2014). Spatial and attribute data aggregation in models has significantly improved oil spill risk assessment over the years (Nelson et al., 2015). However, most risk assessment models are probabilistic, assembling scenarios of hypothetical spills, simulated to quantify risk. Recent methodologies have been developed for oil spill risk assessment (Guo, 2017; Stefaniak et al., 1983), however, dynamic models capable of integrated risk assessment incorporating potential sources, pathways, receptors, pollutants characteristics and risk levels are crucial to any risk quantification.

## 2.7. Conclusions

Although oil spills have remained a problem globally, they are particularly pervasive in the Niger Delta of Nigeria. The factors causing the spills are multi-dimensional mainly from 3 stakeholders namely, the host communities where oil extractive activities take place, the multi-national oil operators and the government. Extensive studies have been carried out on oil spills in the Niger Delta. These studies largely describe available data from secondary sources and in some cases at smaller scales and in a more qualitative manner. Quantitative studies of oil pollution in the Niger Delta are usually conducted at the local scale. Spatial data enabling larger scale studies and primary quantitative data are generally limited. The integration of spatial data and geospatial techniques is required for a more holistic study in terms of human and environmental exposure, risk assessment and potential fates of pollutants in the Niger Delta.

### 2.7.1. Gaps and future research direction for improved oil spill management and monitoring

Based on the available literature on oil spills and associated problems particularly in the Niger Delta, several gaps have been identified, which this study sets out to partly fill. The analysis of oil spills has been largely qualitative, sometimes based on estimates in the press. This is potentially caused by difficulties in accessing data, or the lack of detailed records of oil spills in the past. Most assertions of potential human and environmental exposure to pollutants have been largely speculative based on the context and scale of pollution. In this study, an effort has been made to quantify human and environmental exposure using integrated data sets from primary and secondary sources. Past studies of the root causes of pollution in the Niger Delta has been largely focused on socioeconomic factors, with little or no attention to geographical factors such as proximity. This study attempts to provide a more holistic approach to causes of oil spills, examining both social, economic and proximity-based dynamics, including proximity to water bodies.

The application of spatial data such as remote sensing and GIS data in the study of oils spills which are largely a spatial problem has been limited in terrestrial and riverine environments. The extent of application of such data in feature extraction purposely for the study of spills is limited. A typical example is rivers which are major pollutant distribution arteries, but spatial data on rivers are crude and incomplete in the Niger Delta. This study attempts to fill that gap by employing the use of new satellite data for river channel delineation to support the analysis of oil spills and related studies. Although some risk assessment to pollution incidents has been carried out in the Niger Delta, the use of primary data is largely lacking. This study has carried out an integrated exposure risk assessment using a combination of methods by mapping spill hazard areas in addition to the analysis of a database of field samples.

# Chapter 3 Quantifying the exposure of humans and the environment to oil pollution in the Niger Delta using advanced geostatistical techniques

Christopher B. Obida, G. Alan Blackburn, J. Duncan Whyatt, Kirk T. Semple

This chapter is a replication of a constituent paper of this research that was published in Environment International.

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## Abstract

The Niger Delta is one of the largest oil producing regions of the world. Large numbers and volumes of oil spills have been reported in this region. What has not been quantified is the putative exposure of humans and/or the environment to this hydrocarbon pollution. In this novel study, advanced geostatistical techniques were applied to an extensive database of oil spill incidents from 2007 to 2015. The aims were to (i) identify and analyse spill hotspots along the oil pipeline network and (ii) estimate the exposure of the hydrocarbon pollution to the human population and the environment within the Niger Delta. Over the study period almost 90 million litres of oil were released. Approximately 29% of the human population living in proximity to the pipeline network has been potentially exposed to oil contamination, of which 565,000 people live within high or very high spill intensity sectors. Over 1000 km$^2$ of land has been contaminated by oil pollution, with broadleaved forest, mangroves and agricultural land the most heavily impacted land cover types. Proximity to the coast,

roads and cities are the strongest spatial factors contributing to spill occurrence, which largely determine the accessibility of sites for pipeline sabotage and oil theft. Overall, the findings demonstrate the high levels of environmental and human exposure to hydrocarbon pollutants in the Niger Delta. These results provide evidence with which to spatially target interventions to reduce future spill incidents and mitigate the impacts of previous spills on human communities and ecosystem health.

### 3.1 Introduction

Nigeria is the largest producer of oil in the entire African continent and has the largest natural gas reserve (Kadafa, 2012). The Niger Delta is the main oil and gas producing region located in Southern Nigeria (Figure 3.1.), providing the main source of revenue for the country. How- ever, the Niger Delta is also one of the ten most important marine and wetland ecosystems in the world (Ambituuni et al., 2014). Since 1958, when oil exploration began, many environmental problems have arisen, such as oil pollution of soil and water, degradation of biodiversity and food production and atmospheric pollution from gas flaring; all of which have impacted upon the health and well-being of communities living in the region (Nwilo and Badejo, 2005; Ordinioha and Brisibe, 2013; UNEP, 2016). For example, in a recent study, it was found that communities with visible pollution had high levels of emotional distress and disease symptoms (Nriagu et al., 2016). Consequently, the Niger Delta is now recognised as one of the five most oil polluted regions in the world (Kadafa, 2012).

Oil spills can result from poor maintenance, insufficient investment and vandalism of pipeline infrastructure (Aroh et al., 2010; Anifowose et al., 2012). In particular, the rise in the level of destruction of oil pipelines by militant groups such as ‘the Niger Delta Avengers’ has led to significant economic hardship through reduction in oil exports and substantial environmental damage. It has been estimated that from 1958 to 2010 approximately 546 million gallons (10.8 million barrels per year) were spilled into the environment (Francis et al., 2004). In addition, from 1986 to 2003 approximately 20,234 ha of mangrove forest have been lost to oil production infrastructure (Francis et al., 2004).

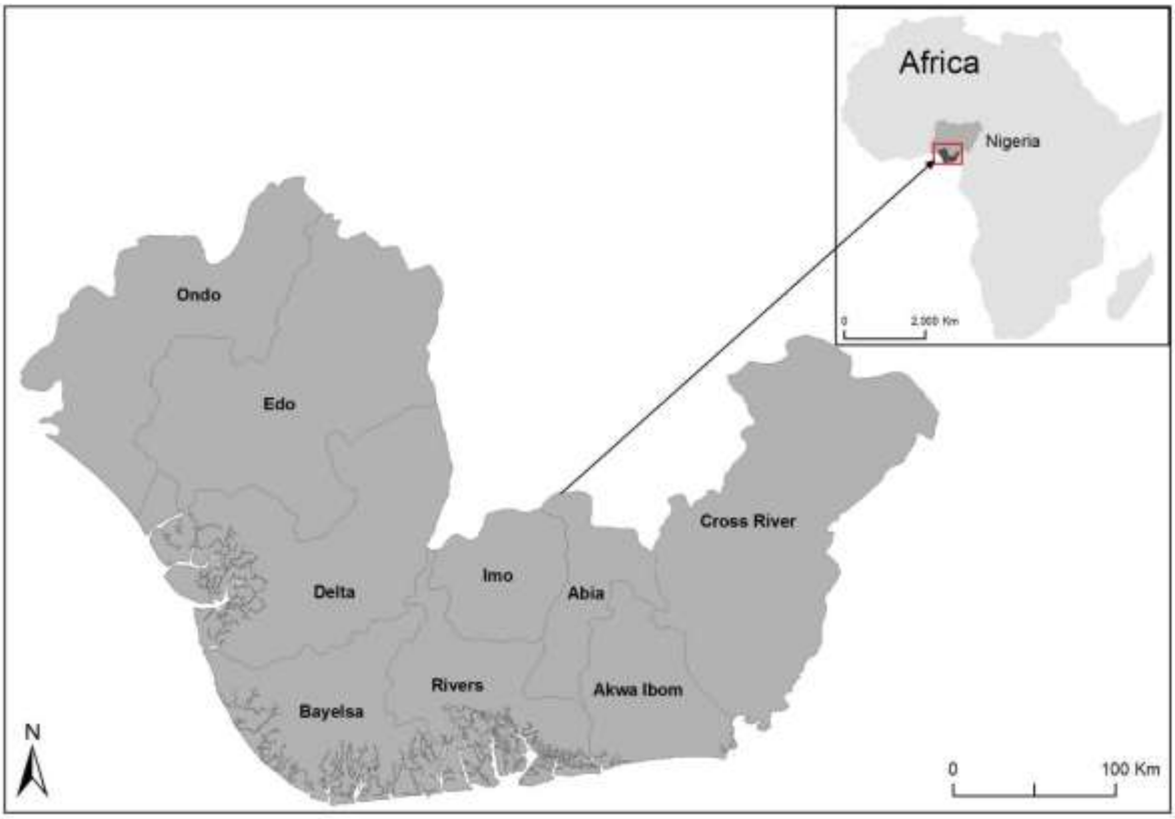


**Figure 3.1.** Niger Delta states with inset map showing Africa and the locations of Nigeria and the Niger Delta.

Oil spills in Nigeria are reasonably well documented but information on potential impacts on the population and environment is limited. Some suggest oil spills are the main source of contamination in rivers upon which the livelihoods of many people are based. This is because most sabotage occurs at river crossings (Anifowose et al., 2014). Major oil spills include the 1979 Forcados Tank 6 spill where 570,000 barrels leaked into the estuary disturbing the aquatic environment and contiguous swamps (Tolulope, 2004; Ukoli, 2005). Similarly, the 1980 Funiwa Field blowout resulted in 421,000 barrels of oil being spilled into the ocean (Tolulope, 2004; Gabriel, 2004; Ukoli, 2005), damaging 338, 836 acres of mangrove forest (Kadafa, 2012). Other spills include the Oyakam oil spill where 30,000 barrels of oil were spilt. The village of Oshika experienced a spill of 500 barrels in 1979 and an additional 5000 barrels in 1983 from the Ebocha Brass pipeline. This led to a significant impact on adjoining swamps, including losses in crabs, fish and shrimp communities (Ukoli, 2005). Oil spills generally occur on land, or in the swamps, but occasionally at sea (Anejionu et al., 2015; Nwilo and Badejo, 2005).

To mitigate against oil pollution in the region, there is a need to adequately understand the geographical and historical patterns of pipeline spills and offer quantitative explanations for the observed patterns. This forensic approach will support the allocation of scarce resources which support environmental and health protection and security in the region. There are several different approaches that may be used to mitigate against the pipeline spills, and spatially targeting interventions towards oil spill hotspot locations can facilitate this process. Oil spills in the Niger Delta typically occur along the pipeline network.

There have been some interesting applications of network analysis over time which have focused on road traffic accident hotspots, which may be applicable to other network-based scenarios such as pipeline sabotage. For example, Xie and Yan (2008) used Kernel Density Estimation (KDE) to identify traffic accidents in Kentucky, Benedek et al. (2016) examined urban traffic hotspots and the social backgrounds of victims whilst Kuo et al. (2013) used network techniques to optimise police patrol routes ensuring better allocation of resources and effective response to issues of public importance. The spatio-temporal analysis techniques used in these studies were adopted in the presented study to identify oil pollution hotspots along the pipeline network, and then quantify the exposure of residents and the environment to oil pollution in the Niger Delta.

The aim of this study, therefore, is to examine the potential for human and environmental exposure to oil pollution by applying hotspot analysis of oil spills along the pipeline network over a 9-year period. Specifically, the objectives were (i) to examine the temporal and spatial patterns of oil spills and their causes; (ii) to identify and characterise oil spill hot spots; (iii) to assess the putative exposure of the human population and the environment to oil spills, and (iv) to characterise the factors responsible for observed patterns. This investigation presents a novel method for using existing data to statistically determine the extent of oil spills in the region and generate new information on trends, patterns, human and environmental exposure. This will inform the prioritisation of decision-making in areas that require rapid response to protect human and environmental health through remedial approaches.

## 3.2. Materials and method

### 3.2.1. Oil spill data

Spill records for the Niger Delta covering 2007–2015 were used in this study. These were provided by the National Oil Spill Detection and Response Agency (NOSDRA) in Nigeria, which is the official government agency responsible for maintaining such records (http://www.nosdra.gov.ng/). The data were compiled through a process of Joint Investigation Visits (JIV) by a team consisting of a host community, NOSDRA staff, and representatives of the pipeline operators. This process of including multiple stake holders can potentially lead to possible interference and conflicts of interest which may potentially introduce some uncertainties._The detailed database contains information such as date, time and location (GPS coordinates) of spills (Figure 3.2.), spill duration, oil type, spill volume and the cause of spill. The database is updated daily contingent on how situations persist. The data used for this study are now publicly available in a live database maintained by NOSDRA, therefore, no request to an official government agency or field visit is required to gain access (https://oilspillmonitor.ng/). However, interrogation of the data suggests some of the oil spills are classified as 'others' or 'mystery spills' denoting that the causes are unknown. This highlights a limitation of the data, but this does not affect the main analysis of this paper which is based on the scale of oil spill occurrence. Correlation analysis was performed between frequency of oil spills occurrence and volume of spills to establish a relationship.

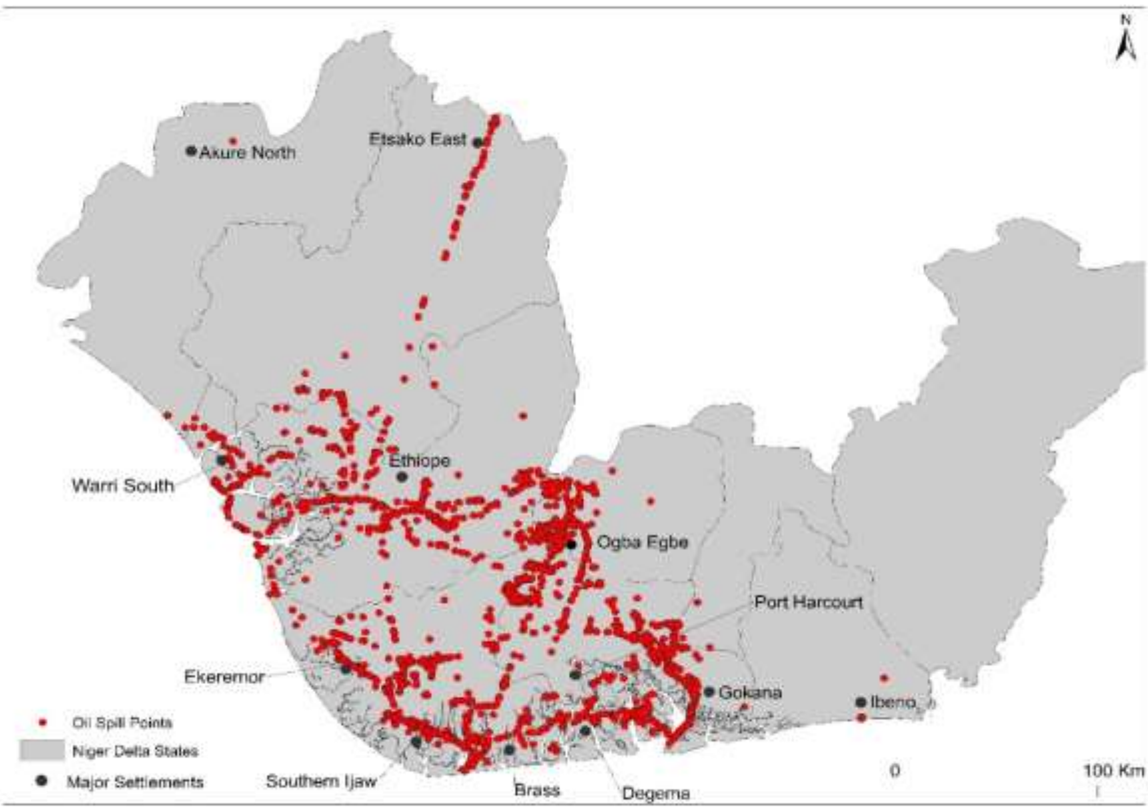


**Figure 3.2.** Spatial distribution of pipeline oil spills in the Niger Delta from 2007-2015.

### 3.2.2. Pipeline, population and land cover data

The Nigerian pipeline network is divided into the upstream and downstream component. The upstream network is usually the subject of sabotage and spills due to ease of accessibility, while the downstream network is less prone to sabotage due to the logistics required. The pipeline data used for this article was sourced from Shell Petroleum Development Company Nigeria. The data contains information on oil and gas infrastructure including pipelines. The pipeline information was digitised using ArcMap 10.4, after the map was georectified and projected to UTM Zone 32 N (Figure 3.3a). Gridded population data at a 1 $km^2$ resolution (Figure 3.3b) was sourced from the Centre for International Earth Science Information Network (CIESIN), Columbia University, New York (http://www.ciesin.org/). The version of the data used in this article is the 2015 estimate which was released in June 2016 after it was adjusted with UN data (CIESIN, 2016). Landcover data was sourced from the European Space Agency's Global Land Cover Climate Change Initiative (http://www.esa-landcover-cci.org/). This was produced from Medium Resolution Imaging Spectrometer data. The original landcover types were regrouped into 7 classes including agricultural land, broadleaved vegetation, shrubs, mangroves, settlement and water bodies to suit the purpose of this study (Figure 3.3c). Pipeline, population and land cover data used in this study are summarized in Figure 3.3.

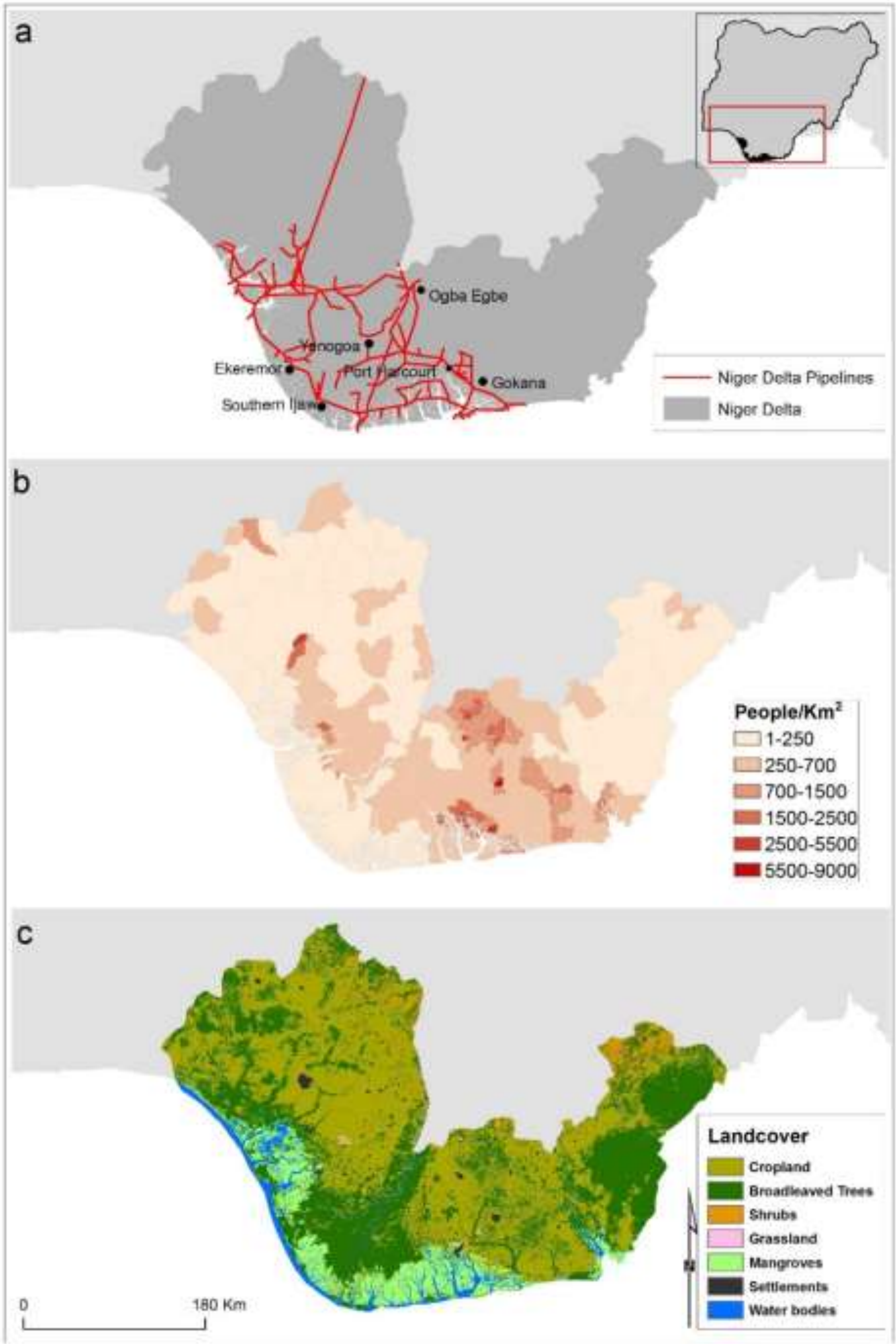


**Figure 3.3.** a: Niger Delta pipeline network showing major towns, b: Niger Delta CIESIN population data and, c: European Space Agency Climate Change Initiative land cover data for the Niger Delta (Source, CIESIN; ESA CCI, 2016).

### 3.2.3. Spatial and statistical analysis

Charts were initially constructed to summarise the major causes of oil spills (sabotage, operations and others) over time. Proportional symbols maps were then used to visualise changing patterns of oil spills in space (across the Niger Delta) and time (for individual years).

#### *3.2.3.1. Getis Ord for oil spills hot spot detection*

Different researchers have used different methods to identify statistically significant hotspots in spatial data (Anderson, 2009; Benedek et al., 2016; Chicas et al., 2016; Lauren, 2012; Mahboubi et al., 2015). Popular methods include Kernel Density Estimation (KDE), which is well suited for point datasets (See Appendix 1). It was developed for epidemiological studies but has been widely applied in transport and other related studies (Kuo et al., 2013; Xie and Yan, 2013). Getis-Ord Gi* statistics (Getis and Ord, 1992; Ord and Getis, 1995) were used in this study as the first method to determine statistically significant spills hotspots.

#### *3.2.3.2. Spatial analysis along pipeline network*

Given the very linear distribution of oil spills points along the pipeline network, an alternative approach to identifying hotspots was adopted. Xie and Yan (2008) have previously applied a network-based KDE to estimate accident hotspots along busy roads. Hotspots are significantly different areas in a given distribution of data based on applied statistics, and are referred to as Local Indicators of Spatial Autocorrelation (McCullagh, 2006). These hotspots are normally based on the frequency of occurrence per unit area. However, here rather than frequency of occurrence, spill volume is used and hotspots are therefore pipeline sections with significantly high volumes in relation to other sections of the network, based on the application of a KDE.

Here we adopt the SANET algorithm (Okabe, 2015) to detect spills hotspots along the pipeline network. This geostatistical technique was designed to identify hotspots of traffic accidents on a road network based on point data of individual accident occurrences. In this study we have modified this technique in order to use the quantity of spills rather than point occurrence as the basis of the analysis, since this gives a much better quantification of the magnitude of spill hotspots, from an environmental and health perspective. The SANET algorithm produces line segments with assigned values which are classified relative to the volume of spills (very high, high, medium, low and none) based on the standard deviation of resulting KDE. Used in combination, Getis Ord and SANET provide powerful insights into the areas most affected by oil pollution. Further details of SANET can be found in the supplementary information.

#### 3.2.4. Potential human and environmental exposure to hydrocarbon contamination

To determine potential human and environmental exposure to spills a buffer of 2.5 km, which is the maximum impact radius a pipeline spill is known to have (Shittu, 2014; United States Department of Transport, 2011), was created around pipelines and individual spill events. The impact radius is consequent upon the pressure, type of pipeline and volume of spills, but the buffer used in this study represented the typical potential area of impact. Human exposure was analysed using the classified SANET outputs with total population living in close proximity to very high, high, medium and low spill intensity sections of the pipeline computed from the 1km$^2$ gridded population data. The percentage of the total population exposed in each Local Government Area (LGA) was also computed. This allowed the ratio of spill volume per head to be computed. In order to measure the extent of environmental contamination, land cover data were combined with spill buffers using an iterative python script to delineate the percentage breakdown of damage per land cover type within each spill zone for the entire period (2007–2015).

### 3.2.5. Factors influencing oil spills

Several factors have been identified as potential causes of oil spills. Some scholars have argued that socioeconomic factors such as poverty are the main drivers (Onuoha, 2008; Oviasuyi and Uwadiae, 2010). Others assert poor operational standards on the part of the companies, or political reasons (Anifowose et al., 2008). Here we examine distance- based factors including proximity to the coast, cities, minor and major roads, and security bases (Trimble, 2016). Euclidean distances from each spill to each influencing factor were computed. Resulting values were exported to SPSS for cluster analysis, to first identify if clusters existed and if so, what the most influential factors were. Initially a non- parametric clustering analysis was applied to the data to identify clusters before applying the K-means clustering analysis for final cluster delineation.

## 3.3. Results

### 3.3.1. Oil spill pollution trend

Figure 3.4 shows how the number of pipeline spills has generally increased over the 9-year study period. In addition to the upward trend, sabotage has been identified as the leading cause of oil spills in the region, accounting for over 40% of spills between 2013 and 2015 as shown in Table 1. The Figure also reveals a significant drop in sabotage and spills in 2015; this can be partly explained by uncertainties associated with the 2015 general elections in Nigeria.

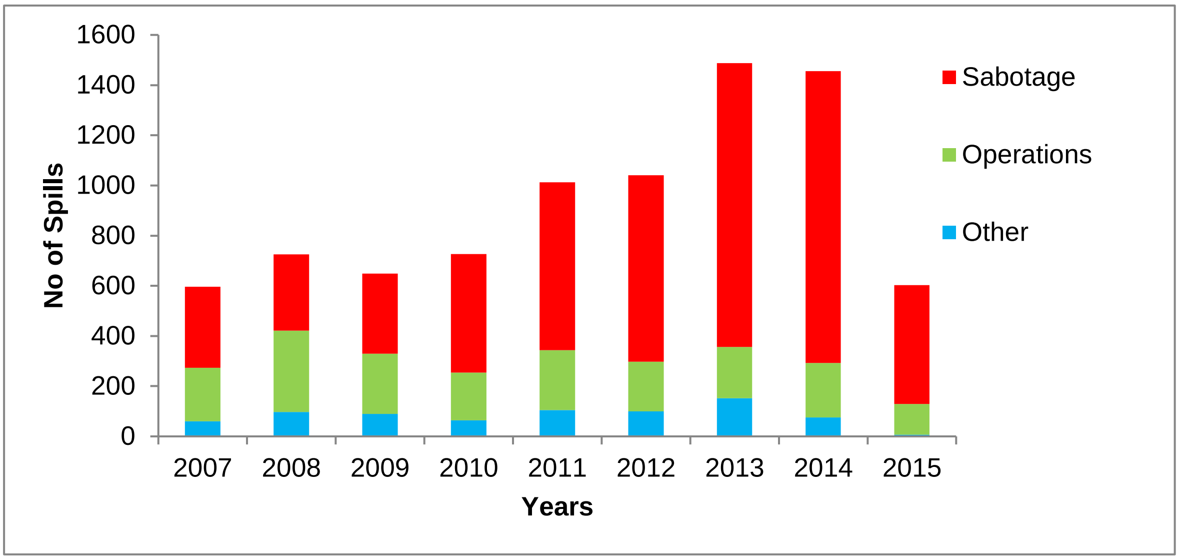


**Figure 3.4**. Oil spills by cause for the Niger Delta (2007 – 2015). Source: NOSDRA.

In terms of the volume of spills, Table 1 shows that sabotage accounted for 66% of all oil spilled over the 9-year period. The 'other' category denotes spills whose immediate causes are not known or have not been recorded due to the remoteness of the location or security threats posed by local communities affected by spills. Table 1 also shows that a total of almost 90 million litres of oil was spilled into the region over the 9-year period. Although volumes vary on an annual basis, 2011 and 2014 were the worst years with more than a quarter of the total spilled volume for the study period occurring in these two years. A correlation analysis between frequency of oil spill incidence and volume of spills indicates a weak to moderate correlation ($R^2$=0.52). Correlation analysis data is presented in the supplementary information. This is because the volume of oil released from each spill incident varies considerably depending on several factors such as pipeline pressure and duration of leakage. Therefore, for example, in 2014 there were 800 spill incidents resulting in over 18 million litres of spilled oil. In contrast, in 2013 there were 1400 spill incidents resulting in 10 million litres of spilled oil.

**Table 3.1.** Volume of oil spilled (litres) attributed to different causes from 2007 - 2015. Source: NOSDRA.

| Year | Sabotage | Operations | Other | Total | % |
|---|---|---|---|---|---|
| 2007 | 8,998,188 | 2,092,804 | 294,216 | 11,385,208 | 13.0 |
| 2008 | 8,634,108 | 1,835,652 | 120,868 | 10,590,628 | 10.0 |
| 2009 | 3,762,652 | 2,348,152 | 379,824 | 6,490,628 | 7.2 |
| 2010 | 4,444,400 | 1,263,292 | 1,046,320 | 6,754,012 | 8.0 |
| 2011 | 4,492,780 | 7,428,052 | 154,652 | 12,075,484 | 14.0 |
| 2012 | 5,783,624 | 544,644 | 115,456 | 6,443,724 | 7.2 |
| 2013 | 8,973,588 | 788,184 | 47,888 | 9,809,660 | 11.0 |
| 2014 | 7,370,160 | 11,141,996 | 41,328 | 18,553,484 | 21.0 |
| 2015 | 7,026,416 | 243,376 | 225,336 | 7,495,128 | 8.6 |
| Total (over entire period) | **59,485,916** | **27,686,152** | **2,425,888** | **89,597,956** | |
| % (over entire period) | 66.4 | 30.9 | 2.7 | | 100 |

### 3.3.2. Temporal and spatial oil spills trends

Figure 3.5 illustrates the spatial and temporal trends of oil spills in the Niger Delta over the study period. The data show that oil spill contamination is more prevalent in the southwest of the region. The spatial distribution of the spills also varies over the 9-year period. Some LGAs, such as Southern Ijaw, Warri South West and Nembe, have experienced oil pollution throughout the time-frame of this investigation. Overall the areas that received the greatest volume of oil spills were the communities in Southern Ijaw, Ogbaegbe and Ibeno. Temporal changes in oil spill volumes are of particular concern in River and Bayelsa states where there has been a consistent increase over time (See Appendix 2).

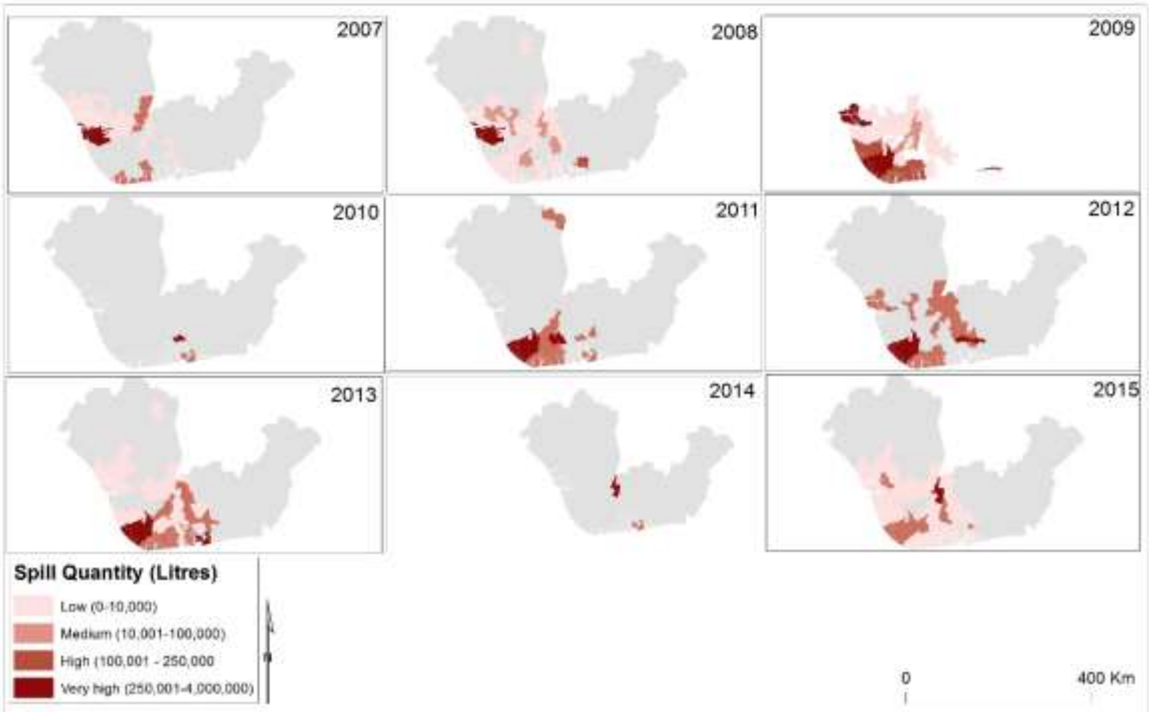


**Figure 3.5.** Temporal and spatial trends of oil spills by volume per Local Government Area (LGA) from 2007-2015

The network-like pattern of the spills (Figure 3.2), is determined by the configuration of the pipeline network. The Figure also shows that apart from the outliers in Akure North in the North, and Ibeno in the South East, the vast majority of spills occur in the Central and Southern part of the Niger Delta. This can partly be explained by the existence of oil and gas infrastructures in the region. The linear pattern of spills northwards towards Etsako East is potentially due to sabotage of the crude oil pipeline transporting crude from the Port Harcourt refinery in the South, to Kaduna refinery in the Northern part of Nigeria.

Figure 3.6 presents pipeline segments that are hotspots of oil spill intensity based on the SANET analysis. Contingent on the kernel density value, the pipeline network has been classified into categories of low, medium and high oil spill intensity. According to this classification, several segments of pipeline have experienced a large volume of oil spills. The Southern Ijaw-Nembe-Brass axis (Figure 3.6C) of the pipeline is by far the most contaminated area in terms of oil spill intensity. Ogbaegbe, located in the Northern Niger Delta region (Figure 3.6A) is also an area of high spill activity; with 29 km of affected pipelines. This can partly be explained by the fact the area is known to have many leased oil fields, thus intensive extractive activities. The Gokana-Bonny-Tai area has also been badly affected by oil spills (Figure 3.6B) with 23 km of pipeline being heavily affected. This indicates pipeline sabotage is a frequent occurrence in the area. Northwest Port Harcourt and Yenagoa are also areas were many spills have occurred. Unsurprisingly, this area is known for agitation and struggle for resource control, and where one of the notorious groups of militants i.e. Movement for the Emancipation of the Niger Delta (MEND) are based. Ekeremor has been highlighted in a similar way to Southern Ijaw in the southern part of the region (Figure 3.6D) because the area is remote and inaccessible, therefor making policing a difficult task.

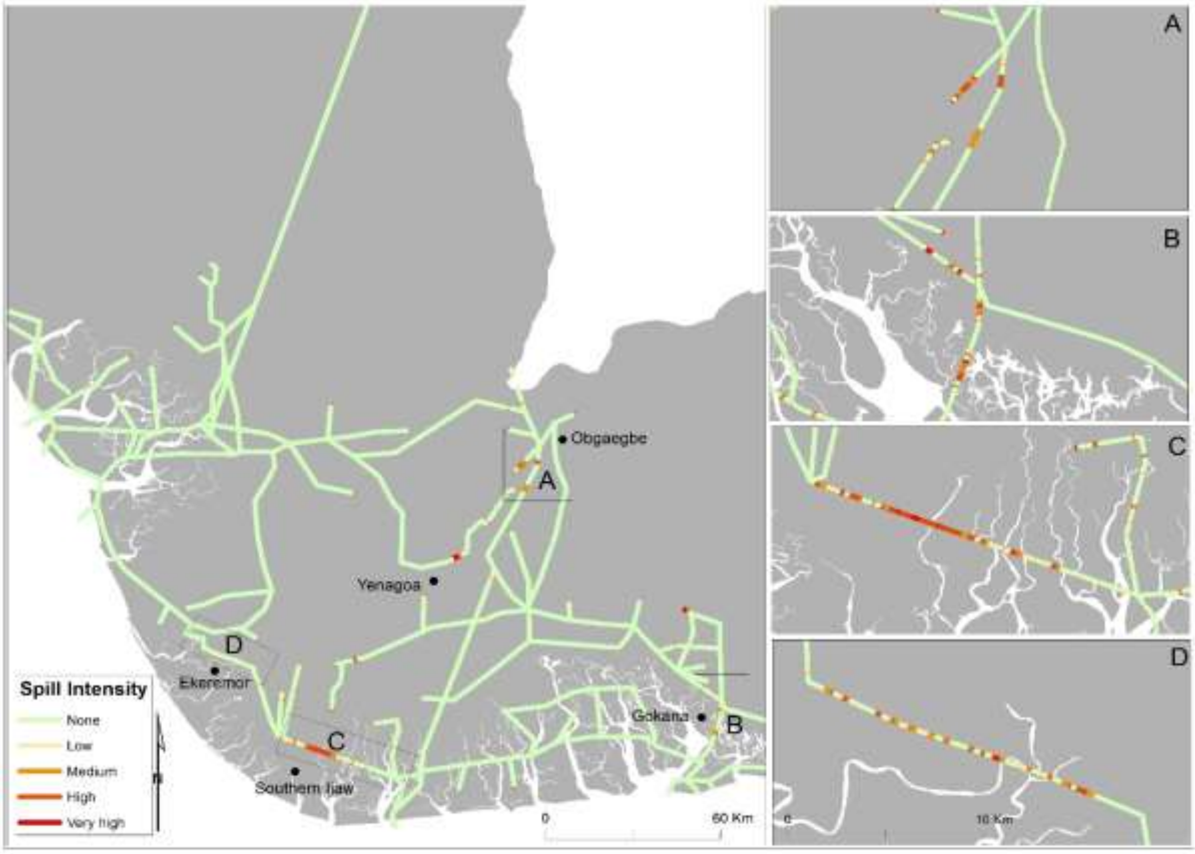


**Figure 3.6.** Oil spills hotspots in the Niger Delta based on the Network Kernel Density estimation (NKD) method applied by the SANET tool.

### 3.3.3. Potential human and environmental exposure to hydrocarbons

Based on the SANET analysis of spill intensities the potential extent of human exposure to hydrocarbons was derived from a 2.5 km buffer around the pipeline network (Table 3.2). This revealed that approximately 29% of the human population living within the buffer is exposed to spills, of which 565,000 people live within high or very high spill intensity sectors. Some LGAs have more than half of their population living within zones impacted by oil pollution (see Supplementary Table S.1). Most notably Uvwie, Tai, Warri South West, and Eleme have in excess of 80% of their population living within contaminated zones.

Figure 3.7 shows the distribution of the percentage of population impacted within each LGA in the Niger Delta, which indicates that the Southern LGAs as the worst affected. However, the volume of oil spilled in these areas varies considerably and this can affect the level of exposure. As shown in Figure 3.8, exposure expressed as litres of spilled oil per person indicates that many people may be exposed to large volumes of oil in Ibeno, Burutu, Ndokwa and Southern Ijaw. In the most extreme case, on average each person in Ibeno has potentially been exposed to 570 l of oil through the study period (see Supplementary Table S.1). The impact of oil spills on different forms of land cover was also evaluated (Table 3.3). The most contaminated land cover types are the broadleaved tropical rainforest followed by mangroves and crop land. Substantial areas of settlements were directly exposed to spills, while the least affected land cover was grassland as it is an uncommon cover type in the region.

**Table 3.2.** Length of pipeline affected and population exposed to oil for each level of spill intensity.

| Spill Intensity | Length (km) | Population | Percentage |
|---|---:|---:|---:|
| None | 1964 | 3,670,810 | 71 |
| Low | 176 | 512,188 | 10 |
| Medium | 151 | 396,059 | 8 |
| High | 140 | 287,314 | 6 |
| Very high | 113 | 278,015 | 5 |
| **Total** | **2,544** | **5,114,386** | **100** |

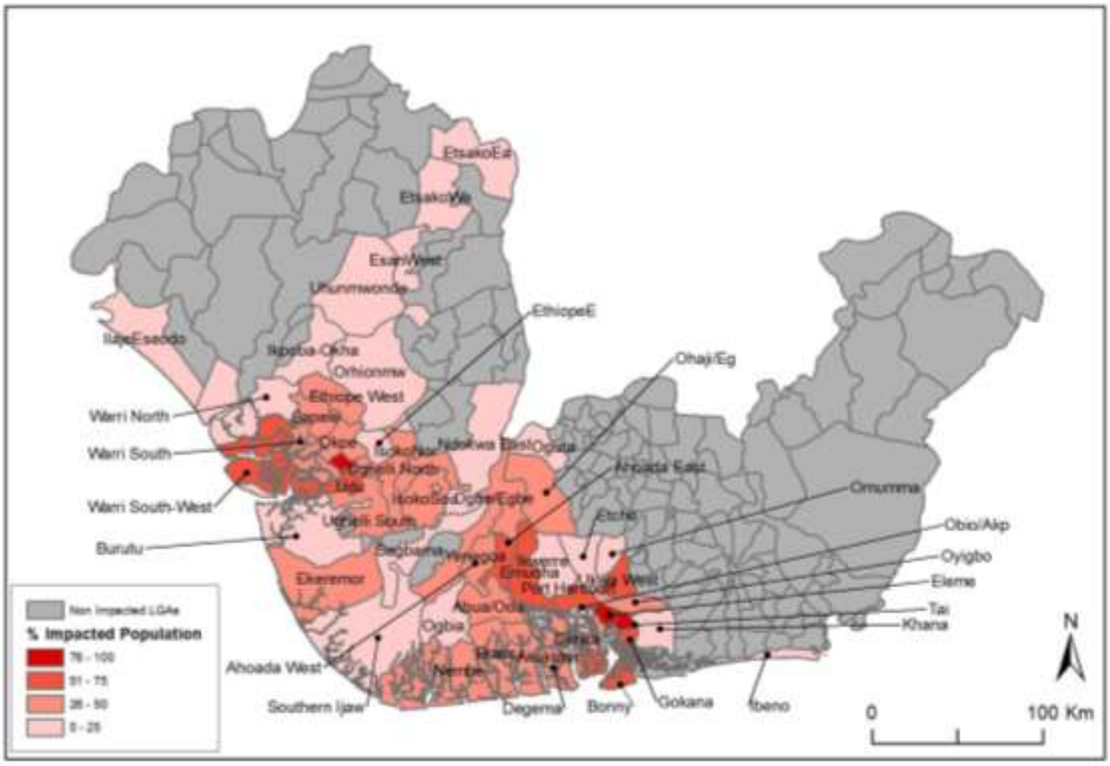


**Figure 3.7.** Oil spill impacted LGAs by percentage of affected population in the Niger Delta.

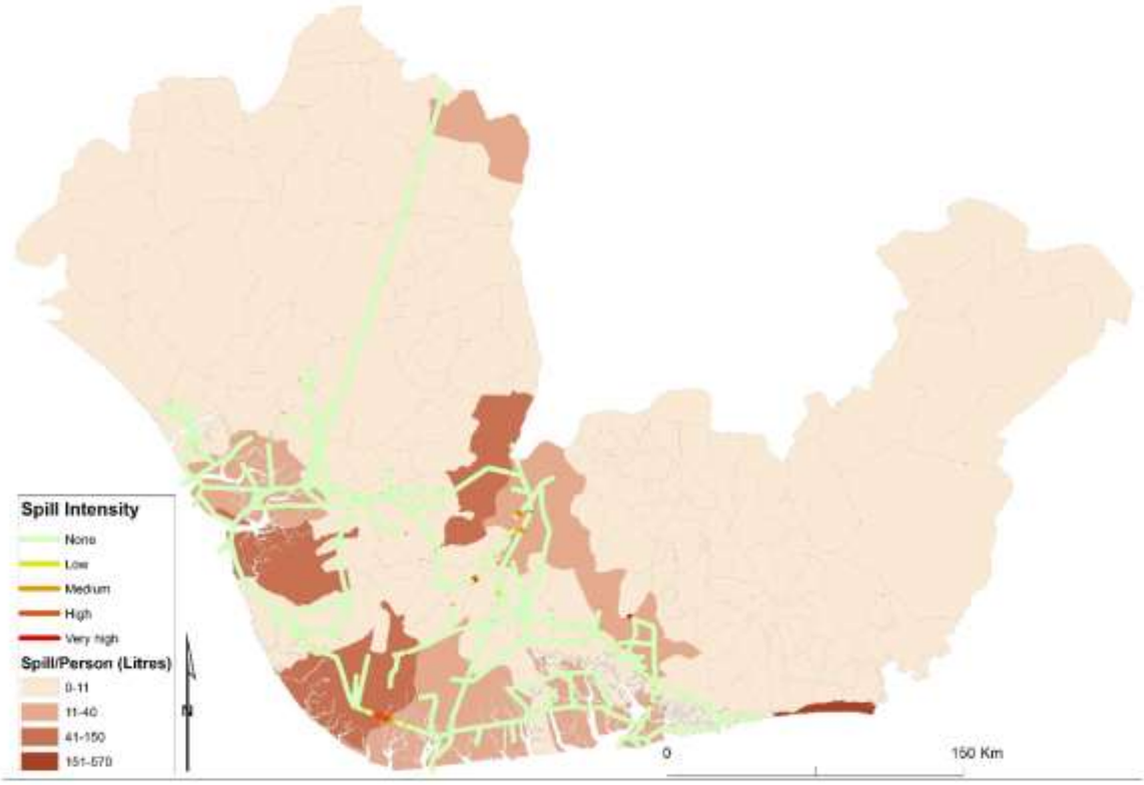


**Figure 3.8.** Pipeline spill intensity overlain on volume of potential oil exposure per person.

**Table 3.3.** Land cover types impacted by spills.

| Land cover | Area(km$^2$) | Percentage |
|---|---:|---:|
| Broadleaved Forest | 483 | 41 |
| Mangroves | 310 | 27 |
| Cropland | 265 | 22 |
| Water | 66 | 6 |
| Shrubs | 21 | 2 |
| Settlements | 16 | 1 |
| Grassland | 3 | <1 |
| **Total** | **1,164** | **100** |

### 3.3.4. Spatial factors contributing to oil spills

Figure 3.9 shows the results of the cluster analysis based on the distances of spills from the coast, cities, security, minor and major roads. A total of 4 clusters were identified and Table 3.4 shows the spatial factors influencing each cluster, and volumes of oil based on cluster configurations. Proximity to the combination of all of the spatial factors tested accounted for the cluster of spills which released the largest volume of oil. The individual spatial factor which accounted for the largest spill volume was proximity to coast. However, the observed pattern of high spill occurrence near the coast can partly be explain by distribution of pipelines near the coast. This is because such pipelines are used for offshore and near shore operations. The results show that proximity to security locations is not a significant factor individually or in most of the clusters except in the first one where all factors were influential.

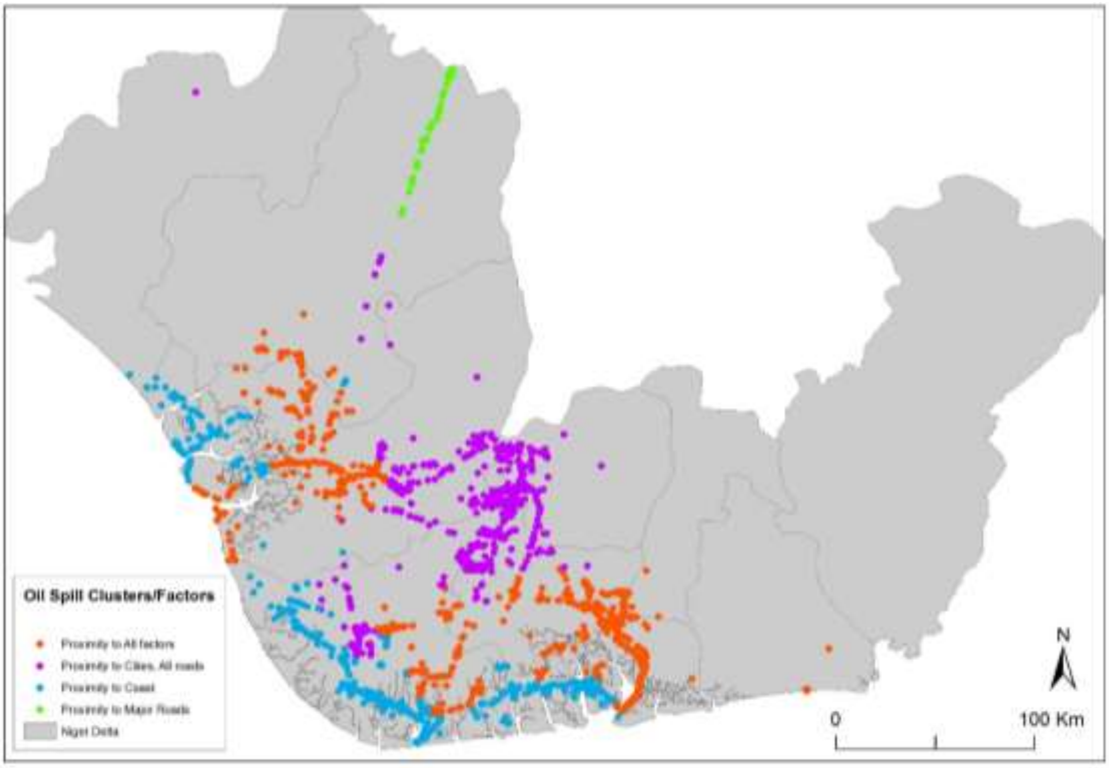


**Figure 3.9**. Spill clusters computed from identified proximity based influencing factors (coast, major roads, minor roads, security and cities).

**Table 3.4.** Spatial factors contributing to oil spills.

| Cluster | Contributory factors | Volume (Litres) | Percentage | No of Spills |
|---|---|---|---|---|
| **1** | Proximity to all factors | 27,822,764 | 54 | 1438 |
| **2** | Proximity to cities and roads | 11,448,020 | 23 | 2079 |
| **3** | Proximity to coast | 11,162,332 | 22 | 2247 |
| **4** | Proximity to major roads | 296,512 | 1 | 45 |
| | **Total** | **50,729,628** | **100** | **5809** |

## 3.4. Discussion

The causes and impacts of oil spills in the Niger Delta have long been a concern for government and industry. Social, economic and political drivers in the region have resulted in different causes of spills, leading to associated environmental and health impacts. Analysis of the oil spill data from 2007 to 2015 reveals that sabotage as the leading cause. This contradicts the notion that oil companies have been largely responsible for pollution incidents (Oviasuyi and Uwadiae, 2010), a claim always denied by the industry. However, operational failures are the next major cause of spills in the region and these are mostly attributed to the practices and production activities of the companies. The companies have been accused of failing to meet acceptable standards of maintenance and sluggish response times to oil spill incidents (Eweje, 2006).

In the present study, operational spills account for 30% of total spills (Table 1), presumably, as argued by Fatoba et al. (2015), the result of ageing pipelines and corrosion. Overall, nearly 90 million litres of oil have been spilled over the 9-year study period, enough to cause significant damage to human health, community well-being and the environment (Nriagu et al., 2016; Ordinioha and Brisibe, 2013). Regrettably, the region has a poor clean up and remediation record, hence the impact of accumulated spills on the environment is highly significant. For example, the 2004 oil spill that occurred in Ogoniland (part of Niger Delta) is only now being considered for clean-up and remediation some 13 years later (UNEP, 2016).

The clean-up action stems from UNEP's 2011 report on the Shell facility incident, demanded by the Nigerian government, which led to substantial environmental damage (UNEP, 2011). In addition, the landmark judicial victory of the community against Shell in a London court is seen as a likely catalyst for future action (The Guardian, 2015). While bioremediation may potentially be a cost-effective alternative to remediation, past studies show it may be effective in reducing soil toxicity and reduces effects on plant growth, aromatic fractions in light oils may be responsible for acute toxicity in soils (Dorn and Salanitro, 2000).

The novel network-based hotspot analysis presented here has revealed the severity of the oil contamination problem in the Niger Delta states of Bayelsa, Rivers, Delta and Akwa Ibom. Most of the areas affected are around the coastline and creeks. This can be partly explained by the remoteness of these coastal fringes, which in turn makes policing more difficult. In addition, coastal locations provide ease of transit for oil that has been illegally extracted from pipelines, so these locations are favoured by criminals. The inland urbanised area of Ogbaegbe has also been highlighted as an oil spill hotspot. It is common to have pipelines in and around cities which make them vulnerable to attacks, and spills from such attacks expose more people to contaminants due to higher population densities. The prevalence of hotspots in the study area demonstrates that the problem of oil spills remains a live issue in the region;

recently, the key perpetrators are the militant group the Niger Delta Avengers (Onuoha, 2016).

The human and environmental exposures were quantitatively assessed based on the outcomes of network-based hotspot analysis. Exposure estimates were based on populations living within low, medium, high and very high spill intensity sectors of the pipeline network. Well over half a million people live in high or very high spill intensity areas. The implication is that this group of people are more likely to be exposed to oil contamination and have a higher likelihood of negative impacts on their health such as irritation, cancer, genetic disorder, and organ failure (Shittu, 2014). There are also considerable health concerns for the nearly 1 million people living within the medium and low spill intensity parts of the pipeline network; this is because it is well known that exposure to even trace levels of oil and its constituents can causes health problems (Nduka and Orisakwe, 2010; Shittu, 2014). The implications for the Niger Delta overall are quite revealing, with 29% of the population living within a spill impact radius; this undoubtedly has the potential to have enormous consequences for the health of the Niger Delta population.

Oil can have both short and long-term effects on the environment and human health. Crude oil, commonly spilled in the Niger Delta, contains chemicals such as polycyclic aromatic hydrocarbons (PAHs) and volatile organic compounds (VOCs – benzene, toluene, ethylbenzene and xylenes) (Mohamadi et al., 2015). Crude oil also contains heavy metals, which potentially have a range of effects on human health (Ndidi et al., 2015; Olobaniyi and Omo-irabor, 2016). Therefore, to properly address and remediate the significant volume of spilled oil, there is the need for the application of detailed hydrocarbon fingerprinting for source identification and characterisation (Wang and

Fingas, 2003). Generally, areas around hotspots are presumed to be more contaminated; therefore, increasing the likelihood of exposure.

Human exposure may occur through direct ingestion and contact with skin or indirectly through bioaccumulation in crop plants (Omodanisi et al., 2014). In this study, it was shown that 22% of the land area contaminated by oil spills is arable land (Table 3.4), offering a significant exposure route to humans. The persistence of oil after a spill in the environment, especially in sediments, suggests that remedial interventions will be required to remove the contaminant. For example, unresolved complex mixtures of petroleum residues were found in West Falmouth sediment extracts 30 years after the spill (Reddy et al., 2002). A study on human health impacts of oil spills in the Niger Delta would be an excellent extension to our work, possibly through focused case studies in hot spot areas that have been identified by our analysis.

Mangroves and broadleaved tropical rainforest are the most polluted land cover types in the region. These classes of land cover serve as significant carbon sinks and play a key role in global climate change mitigation, so disruption form oil spills at the scale observed in this study can have major implications beyond the region. Mangroves and rainforests are known to provide other significant ecosystems services in the context of hydrological and nutrient cycling, but they also provide valuable habitat for the wide range of floral and faunal species, many of which are endemics within the Niger Delta (Mendoza-Cant et al., 2011; Ndidi et al., 2015). The magnitude of the impacts of oil spills on mangroves and rainforests that have been revealed in the present study demonstrate the severe and ongoing threat that is being presented to sustainability of these sensitive ecosystems.

With 66 $km^2$ of water bodies being affected by oil spills in the region their potential for a substantial increase in the mobility of pollution as oil can easily spread across the surface of water and be moved under the action of the incoming and outgoing tides. Most people in the Niger Delta, especially in rural areas, depend on streams for domestic use (e.g. washing and cooking), thereby increasing the potential for exposure to carcinogenic chemicals within oil such as PAHs (Aroh et al., 2010). PAHs have no safe level hence even very low concentrations can cause impacts to human health (Kendal and Strugnell, 2009). For example, certain kinds of cancers such as lung and skin cancers have been reported to be more prevalent in Port Harcourt due to the concentration of PAHs in ambient air compared to Ibadan in Southwest Nigeria (Ana et al., 2010).

Skin contact, consumption, and breathing dangerous constituents can result in acute (short term) and chronic (long term) effects. Acute symptoms include respiratory symptoms such as shortened breath and throat irritation, ocular (eye) symptoms such as soreness and redness. Neurological symptoms include dizziness, irritability, weakness and confusion (Adekola and Fischbacher-Smith, 2016). Longer term effects include respiratory effects like the chronic obstructive lung disease, carcinogenic effects such as leukaemia, skin and lung cancers (Ordinioha and Brisibe, 2013). Furthermore, the people of the Niger Delta who are exposed to oil contamination are more often from rural communities, usually without access to facilities and healthcare. They continue their activities without caution even in the face of health risks from polluted rivers.

The level of oil contamination of water and arable land identified in this study means that no meaningful activities such as farming, and fishing can be undertaken safely in affected areas (Nduka and Orisakwe, 2010). This has wider impacts in the region considering land ownership and availability remains a problem due to continuous destruction of the land as revealed by Wam (2012). This results in people travelling longer distances for their livelihoods due to the reduction in the productive capacity of the land and water bodies (Nriagu et al., 2016; Okoli and Orinya, 2013).

The implication of this level of contamination is severe because people around these areas rely on the environment, therefore the spills end up affecting human health and community well-being many in ways. For example, a study found unusually high concentrations of ascorbic acid in vegetables grown on contaminated land compared with the ones grown on uncontaminated sites (Ordinioha and Brisibe, 2013). In the same study the authors found an unusually high concentration of heavy metals in streams in contaminated areas compared to WHO standards (Ordinioha and Brisibe, 2013). Further, oil pollution has been shown to reduce crop yields due to reduction in soil fertility (Anifowose et al., 2014), as well as destroying crops and vegetation with economic value, such as trees. As most people in the rural areas of the Niger Delta depend on fishing and subsistence farming, the prevalence of food poverty is already problematic and is even more acute in spill contaminated lands (Ordinioha and Sawyer, 2009).

Several factors have been used to explain the causes of oil spills in the Niger Delta (Anifowose et al., 2012; Nwilo and Badejo, 2005). The spatial factors identified in this study include proximity to coast, major and minor roads, cities and security installations. Although all have been influential proximity to coast, cities and roads appear to be the most significant factors. Coastal areas are more prone to spills because of their remoteness and associated low level of security, meaning that acts of oil theft and pipeline sabotage are easier to commit unhindered. In addition, most coastal areas provide an easy means of transit for stolen oil products with little or no interference from security operatives, using vessels that can transport relatively large volumes. This study has demonstrated that > 20% of oil contamination (by volume) resulted from spills close to the coast. Roads connect cities and are also in cities therefore, these two factors are intertwined; they are responsible for over 11 million litres of total oil spill. This brings to light the level of security presence in the Niger Delta (Onuoha, 2016).

More than 50% of security units in the Niger Delta are located over 50 km from identified oil spill hotspots. Such distances cast a doubt on the effectiveness of policing and protection of pipelines. The problem has been made worse by the crisis in the North Eastern part of Nigeria, which has resulted in overstretching already inadequate security. It is quite evident therefore, that current levels of security provision in the Niger Delta are not adequate for protection of oil and gas installations. overall, the findings presented in this study give a starting point for a wider discussion among various stakeholders: Federal and State Governments, companies and local communities on the possibilities of mitigating the problems arising from the release of oil into the Niger Delta.

To fully mitigate the spread and therefore the impact of oil spills, there is a need to understand the potential distributary pathways via river systems. In addition to the findings that over 66km2 of water bodies are affected, many oil spills in the Niger Delta are reportedly occurring at river crossings (Anifowose et al., 2014). The tidal state of the Niger Delta and complex hydrological conditions therefore suggests detailed information on river systems is important to characterise the possible routes of oil movement and potentially assist in modelling and determining the fate of pollutants. However, like many developing countries, detailed information on river systems in the Niger Delta is lacking.

### 3.5. Conclusion

By analysing the extensive oil spill database, sabotage was identified as the leading cause of oil spills in the study area; operational failures were also identified as a key factor contributing to the problem. With a considerable number of spills classified as 'others', it means the level of response and efficiency of government agencies concerned need to be improved, as those spills with lack of proper documentation contribute to the many uncertainties in terms of impact in the sector. The danger from a lack of early detection or even any detection at all becomes apparent. Therefore, there is a need for the development of alternative cost-effective means of oil spill detection, such as employing remote sensing.

Secondly, by using the innovative SANET tool, oil spills hotspots were identified in the study area. This key finding can potentially provide the baseline for implementation of further oil spill monitoring and prevention measures. Thirdly, this study presents new information on the level of putative human and environmental exposure to oil contamination for the entire region, which before now has been largely speculative. Moreover, this novel study provides a spatial framework for any mitigation measures to be employed towards reducing potential human health and environmental implications of oil spills. This paper provides a step-change improvement to rapidly support decision making for security operations, environmental protection and the health for exposed communities in the Niger Delta.

# Chapter 4 River network delineation from Sentinel-1 SAR data

Christopher B. Obida, G. Alan Blackburn, J. Duncan Whyatt, Kirk T. Semple

This chapter is a replication of a constituent paper of this research that was published in the International Journal of Applied Earth Observation and Geoinformation.

Obida, C.B., Blackburn, G.A., Whyatt, J.D. and Semple, K.T. (2019), "Int J Appl Earth Obs Geoinformation River network delineation from Sentinel-1 SAR data", *Int J Appl Earth Obs Geoinformation*, Elsevier, Vol. 83 No. February, p. 101910.

## Abstract

In many regions of the world, especially in developing countries, river network data are outdated or completely absent, yet such information is critical for supporting important functions such as flood mitigation efforts, land use and transportation planning, and the management of water resources. In this study a new method was developed for delineating river networks using Sentinel-1 imagery. Unsupervised classification was applied to multi-temporal Sentinel-1 data to discriminate water bodies from other land cover types then the outputs were combined to generate a single persistent water bodies product. A thinning algorithm was then used to delineate river centre lines which were converted into vector features and built into a topologically structured geometric network. The complex river system of the Niger Delta was used to compare the performance of the Sentinel-based method against alternative freely available waterbody products from USGS, ESA and OpenStreetMap and a river network derived from a SRTM DEM. From both raster-based and vector-based accuracy assessments it was found that the Sentinel-based river network products were superior to the comparator data sets by a substantial margin. The resulting geometric river network was used to perform flow routing analysis which is

important for a variety of environmental management and planning applications. The approach developed in this study holds considerable potential for generating up to date, detailed river network data for the many countries globally where such data are deficient.

## 4.1. Introduction

Rivers are important resources that sustain a substantial proportion of the world's population, through the vital ecosystems services they provide (Zeng et al., 2015). Determining the spatial and temporal dynamics of surface waters remains challenging (Khandelwal et al., 2017). Globally, there has been increased need for monitoring natural water resources in response to changing climate and pollution from anthropogenic sources (Haddeland et al., 2014). Resource managers need efficient ways of monitoring water, determining flow regimes, extent and discharge. Modellers and scientist alike need hydrological information for forecasting extreme events such as floods, and accurate river network data to model the fate of pollutants in rivers globally (Garneau et al., 2017; Zeng et al., 2015). However, detailed maps of river networks do not exist for many developing countries and even where previous surveys have taken place they are often significantly out of date, especially for dynamic systems such as deltas.

Remote sensing offers a low-cost and efficient alternative to ground-based surveys for river network delineation, particularly in light of recent improvements in the temporal and spatial resolution of satellite data, e.g. using frequent acquisitions from MODIS (Khandelwal et al., 2017). Optical remote sensing has been widely used for river network delineation using a range of automatic and semi-automatic techniques (Isikdogan et al., 2017). For example, Landsat data was used to delineate complex braided network of the Brahmaputra river which flows through China, India and Bangladesh and a tidal river network in Berau Bay, New Guinea (Yang et al., 2014). The study revealed that spectral mixture within pixels resulting from the spatial resolution of the imagery resulted in commission and omission errors in river classification. Others have noted that this approach is not suitable for smaller rivers (Domeneghetti et al., 2014; Ogilvie et al., 2015). Allen and Pavelsky (2015) developed NAR-Width (North American River Width) which uses Landsat data in a software suite called RivWidth to delineate and estimate the width of rivers in North America. However, the model is largely restricted to North America, due to the input data and some aspects of the algorithm that prevents it use in other global regions.

Water body extraction from optical imagery has also been achieved using other approaches. These include region growth and edge detection, and water indices such as the Normalised Difference Water Index (NDWI) (Isikdogan et al., 2017; Zeng et al., 2015), Modified Normalised Difference Water index (MNDWI) (Ogilvie et al., 2015; Yang et al., 2014), Automated Water Extraction Index (AWEI) (Feyisa et al., 2014), and Land Surface Water Index (LSWI) (Ogilvie et al., 2015). Isikdogan et al. (2017) introduced the RivaMap mapping engine which is based on Landsat data and was used to delineate rivers at a continental scale (North America). However, the output of RivaMap is an unstructured vector network, which can limit its applicability in studies of hydrological flows. Furthermore, all of the methods that are applied to optical data such as MODIS and Landsat, can be limited by cloud cover, which restricts useable repeat image acquisitions and limits the ability to detect the persistence or dynamics of surface water bodies.

Digital Elevation Models (DEMs) derived from different satellite missions have been widely used for hydraulic studies, hydrologic modelling and river network delineation

(Gülgen, 2017; Kumar et al., 2017). Commonly used DEMs include the Shuttle Radar Topographic Mission (SRTM) 1 arc second, SRTM 3 arc second and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) 30m products (Vimal et al., 2012). Algorithms for river network delineation such as the hydrological tools in ArcGIS version 10, Arc Hydro (Kim et al., 2015), TauDEM (Castronova and Goodall, 2014), HydroSHEDS (Lehner et al., 2008) and GWD-LR (Yamazaki, 2014) all use DEMs as input data (Khan et al., 2014). This approach is popular because important hydrological parameters such as river length, area, slope, flow direction, accumulation, aspect and watershed area can be extracted from DEMs. However, because these methods use the direction of steepest decent for delineation, this can lead to over estimation of river network elements in lowland and delta environments (Gülgen, 2017; Isikdogan et al., 2017; Vimal et al., 2012). Rahman, et al (2010) demonstrated in a study of the delta region of Bangladesh that errors were proportional to degree of flatness. In addition, some researchers have highlighted the inaccuracies of using DEMs for river delineation such as the inability of the algorithms to consider manmade features (Kumar et al., 2017). DEMs can also contain erroneous changes in elevation in some areas, referred to as sinks, which result in computational errors in flow direction and ambiguity in alignment of the delineated river network (Kumar et al., 2017).

Airborne Light Detection and Ranging (LiDAR) has been applied in stream network delineation (Maderal et al., 2016). LiDAR data provides height information that has been used to characterise catchments, generate flow direction and delineate rivers in wide range of landscapes (Li & Wong, 2010). Wavelet-based filtering techniques, curvature analysis, and geodesic operations have all been previously applied to LiDAR data for stream delineation (Cho et al., 2011; Lashermes et al., 2007; Passalacqua et al., 2012). However, airborne LiDAR data capture is expensive, spatially limited in application and requires significant time to process the large point cloud (Hamada et al., 2016). Hence, for the scale of whole fluvial systems, the costs associated with the use of LiDAR can be prohibitive, especially in developing countries.

Citizen science initiatives such as OpenStreetMap (OSM) also constitute a genuine source of digital geographic data (Haklay, 2010). Such web mapping systems offer a step change in the availability of important geographic data such as river networks. As a result, data are now accessible in a searchable and usable format, and the data quality can be as good as that of national mapping agencies (Haklay, 2010). However, the quality of data from such sources is contingent on the level of participation and the experience and knowledge of the contributors (Haklay, 2010), with lower levels of mapping activity in the Global South (Bittner, 2017; Graham et al., 2015), particularly in rural areas, with little emphasis on natural features such as rivers.

Given the above limitations in existing techniques and products, new remote sensing methods are needed for repeatedly mapping river networks in a timely fashion, particularly in developing countries. Sentinel-1 SAR C data acquired by the European Space Agency (ESA) has the potential to overcome the identified limitations. The dual satellites (Sentinels 1A and B) launched in 2014 and 2016 offer global coverage (Haas and Ban, 2017; Miranda et al., 2016), with a combined temporal resolution of 5-6 days and spatial resolution of 20m by 5m and ground sampling distance of 10m (Ardhuin et al., 2017; Malenovský et al., 2012; Veloso et al., 2017). Utilizing these data can potentially enhance scientific studies requiring detailed river network delineation in complex environments.

Therefore, the aim of this study was to develop an effective method of delineating river networks using Sentinel-1 data. The objectives were to: (a) investigate the potential of utilizing a time series of Sentinel-1 images for accurate river network delineation; (b) compare Sentinel-1 outputs with existing river network data sets; (c) build a complete topologically structured geometric river network dataset; (d) demonstrate the potential of the network dataset by tracing the movement of pollution from a point source event through the fluvial system.

## 4.2. Method

### 4.2.1. Study site

The Niger Delta (Figure 4.1) is the largest river delta in Africa and the third largest in the world (Kadafa, 2012; UNEP, 2011). It occupies an estimated 70,000 km$^2$ in area and supports a population of 30 million people. Information on the river network in the region is therefore important because this can enable effective monitoring of changes in the distribution of this highly dynamic fluvial system, and the resultant impacts on resources and threats to the population. Since most of the population depend on fishing and river water for domestic activities, detailed information on the river network is vital within the framework of management and monitoring of key resources. Likewise, flooding is a common occurrence in the Niger Delta which can have devastating effects on the population and infrastructure (Ekeu-Wei and Blackburn, 2018; NHSA, 2014). However, there is a paucity of digital spatial data for the Niger Delta, and there is no national spatial data infrastructure (Anifowose et al., 2012; Nwilo and Badejo, 2005). Accurate and up to date data on the river network are now needed to support the development of flood mitigation schemes and appropriate land use strategies. Furthermore, the Niger Delta is the region in which the majority of Nigeria's oil and gas extraction takes place (Anejionu et al., 2015). There is a long and well-documented history of oil pollution incidents in the region, with rivers among the worst affected environments, therefore, river network data are crucial in employing pollution mitigation measures (Obida et al, 2018). In particular, there is a pressing need for a detailed topologically-structured river network dataset for use in modelling the dispersion and fate of crude oil in the Niger Delta and its impact on the environment and human health.

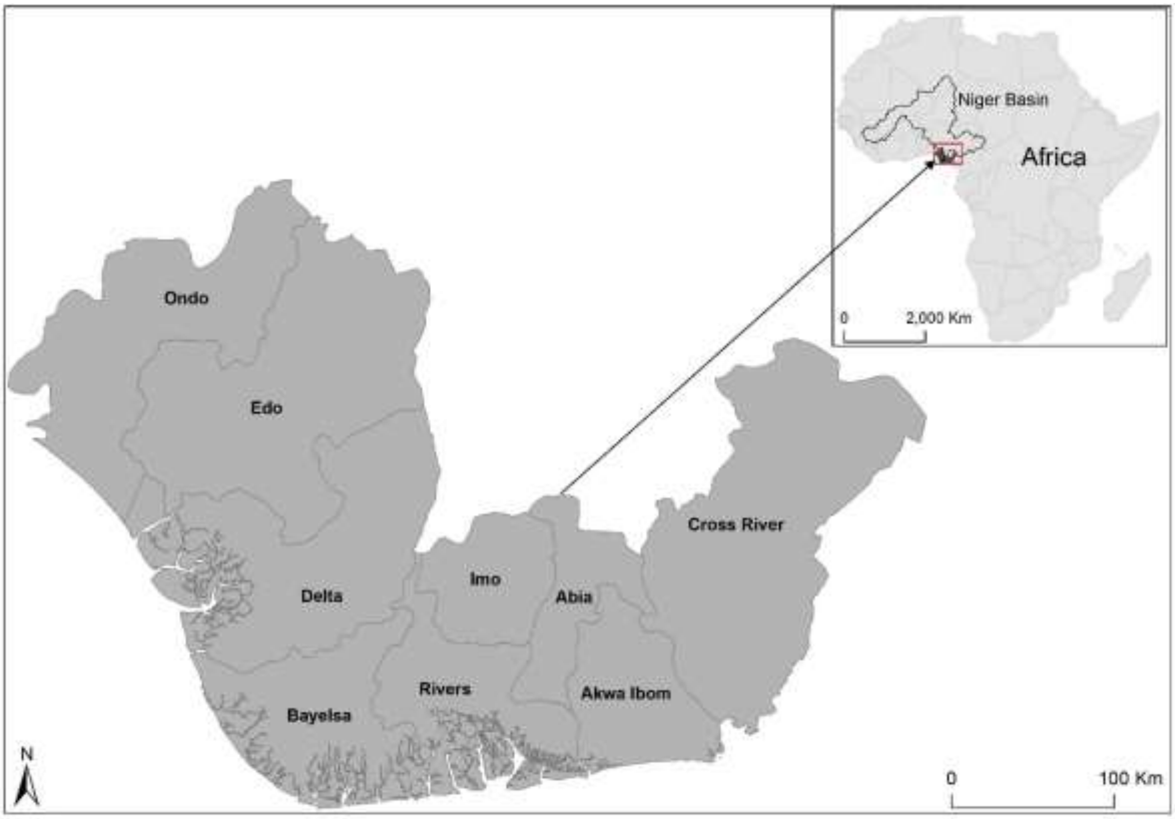


**Figure 4.1**. The study area, the Niger Delta. Inset map shows the location of the Niger Delta in relation the drainage basin that supplies water and sediment to the delta.

#### 4.2.2 Methodological Framework

In this study, multi-temporal Sentinel-1 SAR C were used for both raster-based and vector-based river channel delineation. Raster channels were delineated using classification techniques and thinning algorithms were applied to generate vector data.

Both the raster and vector river delineations from Sentinel-1 were compared to existing river data products by performing accuracy assessments relative to reference river channel data. Network topology and attribution were then added to the Sentinel-derived rivers to allow more complex network analysis. The methodological framework is shown in Figure 4.2.

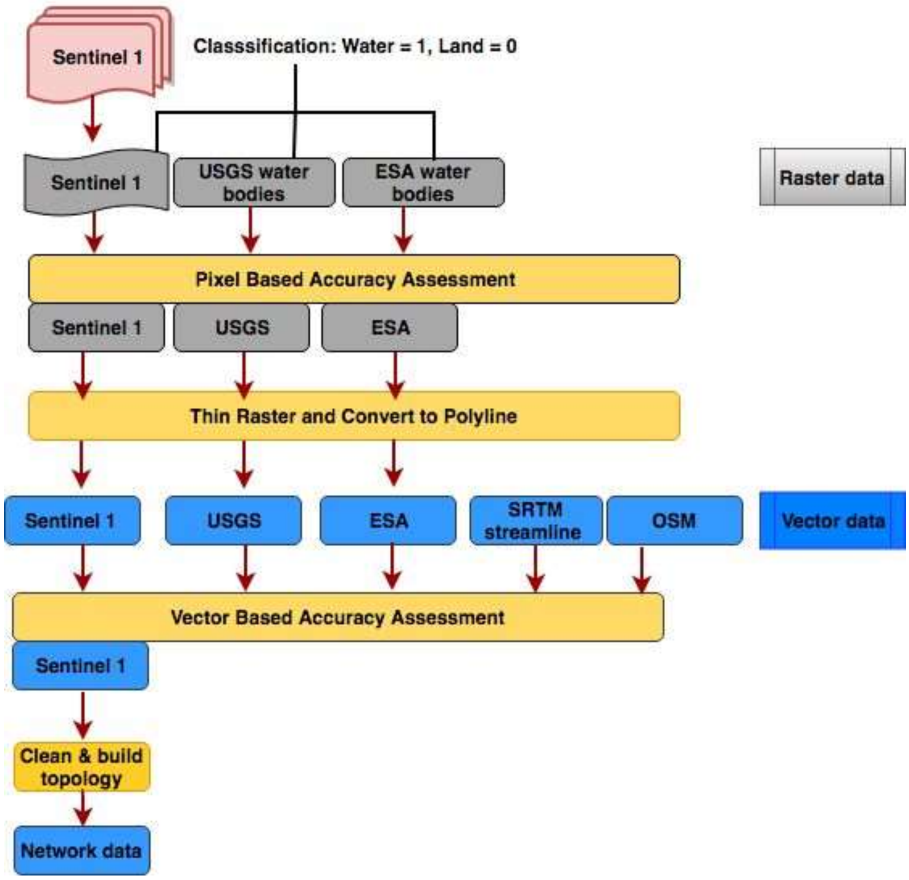


**Figure 4.2.** Methodological framework for accuracy assessment and river network extraction based on the different data sources.

### 4.2.3. Source Data

#### *4.2.3.1 Sentinel-1 data*

The Sentinel-1 data were sourced free of charge from the ESA Copernicus Open Access Hub. Here we used the Interferometric Wide swath mode data, the predefined mode for overland applications. The Level-1 Ground Range Detected product type was used, which has been detected, multi-looked and projected to ground range using an Earth ellipsoid model (Veloso et al., 2017). We used the co-polarised VV data because noise restricts the use of VH data as water has a lower radar-cross section in cross polarization than in co-polarized channels (HH or VV) (Bolanos et al., 2016). Dual polarised HH+HV was not available for the study area. The  Ground Range Detected data used in this study have a spatial resolution of 20 by 22 with a ground sampling distance of 10m (Imperatore et al., 2017).

#### *4.2.3.2 Comparator data*

The Landsat global water bodies product was the result of a collaboration between the United States Geological Survey (USGS) and University of Maryland. This raster dataset represents persistent global surface water bodies over the 2000-2012 time period, and is the highest spatial resolution product available globally. ESA global water cover data derived from Envisat ASAR and MERIS data at 300m resolution over the period 2005-2010 were also used.  OpenStreetMap (OSM) vector data were also used for comparative purposes. Finally, a river network that we derived from 1 arc second SRTM data (method described in 2.5.2 below) was also used. The SRTM data are available globally and were sourced from the USGS Earth Explorer platform.

### 4.2.4 Raster-based analysis

#### *4.2.4.1 Sentinel-1 data processing and analysis*

Image pre-processing routines were performed in the Sentinel Application Platform (SNAP). Geometric correction was carried out by the initial application of orbital files to correct orbit vectors (Zhang et al., 2016).  Range-Doppler Terrain Correction was applied to each image for accurate geocoding, using the 3 arc second SRTM DEM, thus accounting for variations in local elevations (Veloso et al., 2017). Multi-temporal image co-registration was then carried out, since the study involved application of multi-temporal data, consisting of the 14 images available for the study site acquired between May 2015 and January 2017, using the first available image as the master (Sowter et al., 2016). Radiometric correction was applied to the images by calibrating the data to sigma nought, which is the backscatter coefficient (Misra and Balaji, 2017). To reduce speckle in the SAR data, the refined Lee Sigma speckle filter was applied (Fu et al., 2017; Haas and Ban, 2017).

Unsupervised classification was used to distinguish between water and land in the multi-temporal Sentinel-1 data (Ogilvie et al., 2015) as this performed better than supervised classification and thresholding in this context. A K-means unsupervised classification approach was applied to the data in SNAP (Jain, 2010). Since water has a distinctive response in C–band SAR signals, water bodies were partitioned into an output class as a result of the K-means procedure.

Following classification, the outputs were combined into a single image in ArcMap 10.4 with pixel values ranging from 1-14 based on a count of the number of times each pixel was classified as water across the time series of images (Khandelwal et al., 2017). This was to differentiate between persistent and ephemeral water bodies, particularly due to high tides and floods (Rahman & Thakur, 2017). In the combined image, a value of 1 indicates a low probability of the pixel being a persistent water body, while pixels with a value of 14 indicates a high probability of the pixel being a persistent water body. Reference data on the locations of permanent river channels were collected by visual interpretation of ArcGIS World Imagery (Digital Globe GeoEye-1 images from 2013 – 2017 at 0.5m resolution). Using the reference data an optimum threshold was identified for the number of times each pixel was classified as water in order to delineate the river network most effectively. This was determined by incrementally increasing (from 1 to 14) the persistence value required for classifying a pixel as a permanent water body, and for each increment, the output water body map was tested for accuracy against the reference data set. This analysis showed that users' accuracy of the output water body map increased substantially as the required level of persistence increased, up to a value of 12 where it reached a plateau of 89% See Appendix 3. Hence, all pixels with persistence values of 12 and above were used to map permanent water bodies in the study area.

#### *4.2.4.2 Raster-based accuracy assessment*

High-resolution Google Imagery, acquired in 2018, was visually evaluated in order to generate reference data (Feyisa et al., 2014). A total of 700 reference points were captured through 'heads up' digitizing, 350 of which were located in rivers and 350 in other land cover types. The reference data were then compared to the raster-based river networks generated from the Sentinel-1, USGS and ESA data by computing error matrices. Subsequently, user's, producer's, overall accuracies and kappa coefficients were calculated (Felipe De Almeida Furtado et al., 2016; Feyisa et al., 2014).

### 4.2.5 Vector-based analysis

#### *4.2.5.1 River network extraction*

Here we firstly applied a raster-based centre line extraction method using the thin tool in the Spatial Analyst extension of ArcGIS 10.4 on the river raster generated from the Sentinel-1, USGS and ESA data sets. Secondly, we applied the raster to polyline tool in ArcGIS to convert the thinned centre pixels to a series of vector lines. The rationale of reducing variable river widths to centre pixels and subsequently to lines is to develop a network model where connectivity is the most important property.

#### *4.2.5.2 River extraction from the SRTM 1 arc second DEM*

Methods of extracting river channels from DEMs are well established and have been applied at a variety of scales (Khan et al., 2014; Kumar et al., 2017; Vimal et al., 2012). Here we used the hydrological toolset in ArcGIS 10.4 to extract the river network from the SRTM 1 arc second DEM.

#### *4.2.5.3 Vector-based accuracy assessment*

An independent river network dataset, covering a river length of 800km within the study site, was captured through 'heads up' digitizing of high resolution ArcGIS World Imagery. This generated a vector network of river centre lines for use as reference data. These reference data were then used to assess the accuracy of the vector networks derived from Sentinel-1 and the comparator data. Among the comparator data, the OSM and SRTM-derived network data contained river centre lines which could directly be compared to the reference data. In order to facilitate a vector-based accuracy assessment of the ESA and USGS data, these raster based river networks were thinned and converted to polylines.

The vector river networks derived from Sentinel-1 and comparator data were assessed for data completeness (length) and positional accuracy (overlap) against the manually digitised reference network (Li and Wong, 2010; Hamada et al., 2016). The percentage data completeness was calculated based on the stream orders in the network, from small 1$^{st}$ order streams to larger 3$^{rd}$ order streams. In terms of the positional accuracy, 3 different sample sections of the network were assessed by generating 10m, 20m and 30m buffers around the reference network. The percentage of data from the Sentinel-1 and comparator data networks that fell within each of the buffers was used to measure the spatial overlap with the reference data and thereby indicate positional accuracy (Goodchild & and Hunter, 1997).

#### *4.2.5.4 Building river network topology and attributes*

Most river networks derived from remote sensing are devoid of topological properties and connectivity rules such as edges and junctions, meaning that connectivity, flow direction, and flow rate cannot be derived. Building a geometric river network is important to enable its use in a range of applications, including hydrological modelling (Jiang, 2011). Based on the results of the vector-based accuracy assessment the Sentinel-1 river centre line product was selected for building a geometric river network. Initially, the network was cleaned in ArcMap by closing gaps to ensure network connectivity. Gaps <20m were automatically closed by the software, with the few remaining larger gaps being closed manually to ensure complete connectivity. Consequently, the ArcGIS geometric network toolbox was used to build a topologically structured network. In a manually digitised network the flow direction is determined by the direction of digitization as recorded by the software. However, since our network was generated from image data there was no direction of digitization, hence, we used the ‘set flow direction’ tool in ArcGIS’s geometric network toolbox.

#### *4.2.5.5 Application of the river network for tracing the movement of a point source pollution event*

To demonstrate the potential utility of the delineated river network and the attributed topology parameters such as network connectivity and flow direction, an example application was performed. This involves using the geometric network analysis tool to trace the potential pathway of oil released from a spill which enters the river network and moves downstream. We used the example of a known event which occurred on 20$^{th}$ April 2012, where 19,350 litres of crude oil were spilt from a sabotaged 24-inch pipeline in the Nembe LGA of Bayelsa state. The location of this event was recorded in a database maintained by the Nigerian National Oil Spill Detection and Response Agency (https://oilspillmonitor.ng/).

## 4.3. Results

### 4.3.1 Raster-based Analysis

#### *4.3.1.1 Raster river network derived from Sentinel-1*

Figure 4.3 shows the binary land cover classifications of the 14 Sentinel-1 images covering the period May 2015 to January 2017. The images show a high degree of visual similarity, but there are differences, especially in the southern part of the study area, which are attributable to the different prevailing hydrological conditions (e.g. river discharge or tidal state) at the time of image capture. The k-means unsupervised classification appears to effectively distinguish between water and other land cover types.

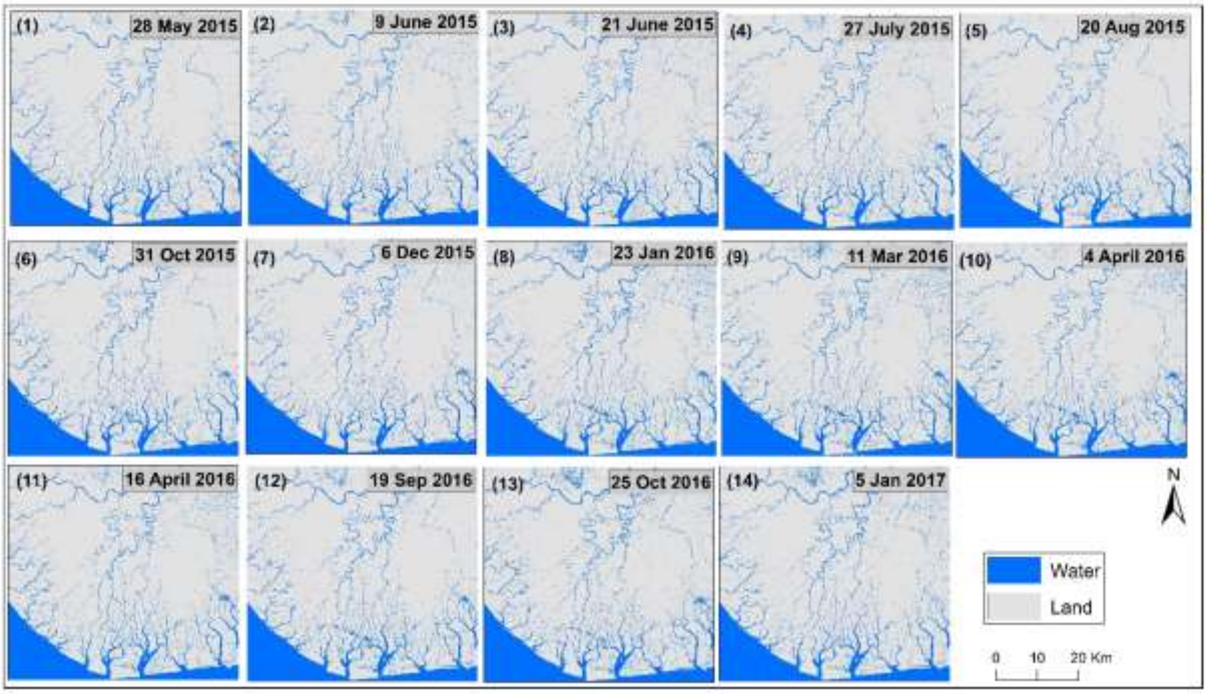


**Figure 4.3**. Binary land cover classifications of the Sentinel-1 image time series.

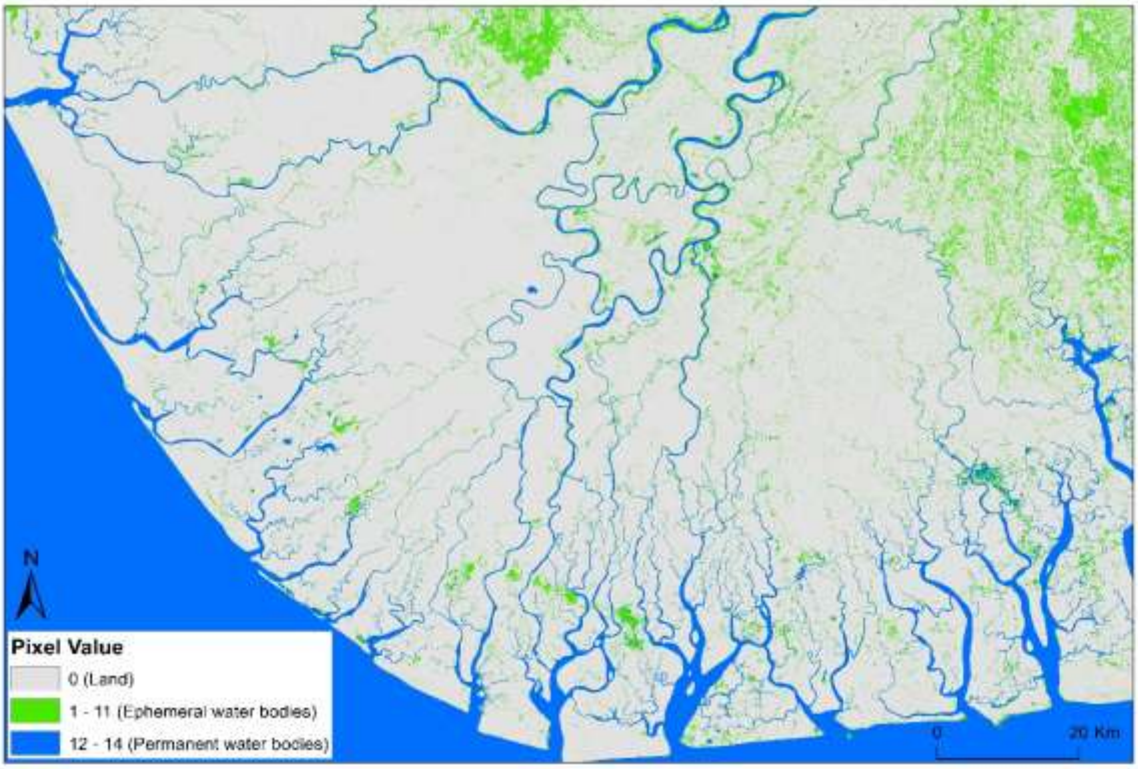


**Figure 4.4.** Combined product from the Sentinel-1 time series with each pixel placed into one of three categories based on a count of the number of times the pixel was

Figure 4.4 shows the outputs of the Sentinel-1 time series combined into a single image with each pixel placed into one of three categories based on a count of the number of times the pixel was classified as water (the persistence). Pixels with lower values (i.e. in the 1-11 category) represent ephemeral water bodies, whilst pixels with higher values (12-14 category) denote permanent river channels. The ephemeral river channels are potentially as a result of several physical processes see Appendix 4.

Figure 4.5 shows a comparison of the ESA and USGS water body products with the Sentinel-derived map for a small sample area. It shows the degree to which raster resolution can impact upon river network delineation and potential to further determine the quality of extracted vector data. Table 4.1 shows the results of the accuracy assessment of the raster-based river networks derived from the Sentinel-1, USGS and ESA data sets. The overall accuracy of the river network derived from Sentinel-1 was much higher than the USGS and ESA products. The user's accuracy for water bodies was consistently higher that than the producer's accuracy which indicated low false positives, across all three data sources. In addition, both the USGS and ESA data had much lower producer's accuracies than the Sentinel-1-derived data which implies an under representation of water in the existing products. USGS and ESA data had low Kappa coefficients while that for the Sentinel-1-derived product was much higher and suggested that classification accuracy was better than random occurrence.

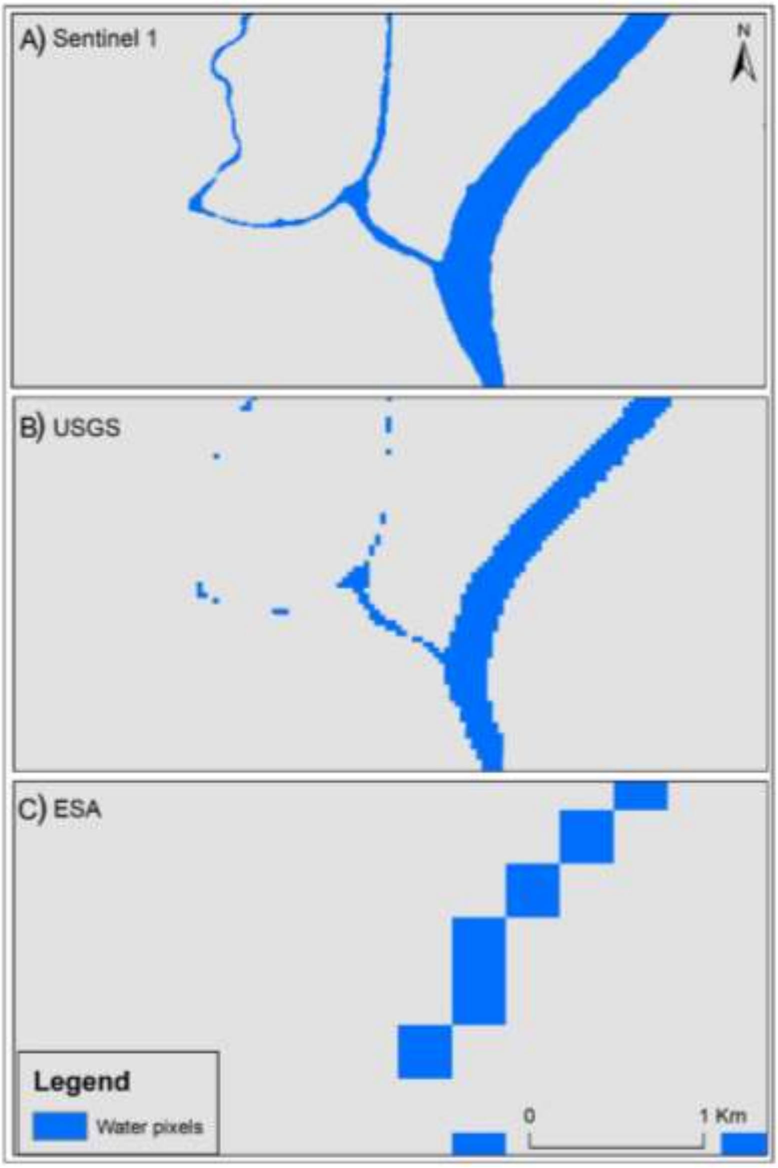


**Figure 4.5**. Comparison of extracted raster data sets from: A) Sentinel-1, and comparator data, B) USGS and C) ESA. Blue pixels indicate water.

**Table 4.1.** Image based classification accuracies for raster-based river networks derived from Sentinel-1, USGS and ESA data.

| Accuracy metric | Sentinel-1 | USGS | ESA |
|---|---|---|---|
| Overall accuracy (%) | 76 | 69 | 60 |
| Producer's accuracy (%) | 61 | 38 | 21 |
| User's accuracy (%) | 89 | 100 | 78 |
| Kappa coefficient | 0.52 | 0.38 | 0.20 |

### 4.3.2 Vector-based analysis

#### *4.3.2.1 River network extraction from the Sentinel-derived river raster.*

Figure 4.6 shows the effectiveness of the thinning algorithm used to generate the river centreline vector data from the raster map. It also shows how isolated water bodies that are separated from the river system are not included in the vector data as the thinning algorithm emphasises the production of a linear network. Figure 4.7 shows the extracted centre line representation of the river network for the entire Niger Delta derived from Sentinel-1 data. The Figure reveals a classic deltaic drainage pattern with multiple outlets into the Atlantic Ocean. This pattern is unlike a typical dendritic hydrological catchment with all tributaries draining into one main channel, then into a larger body of water. Here we have a complex network of distributary channels typical of deltaic systems.

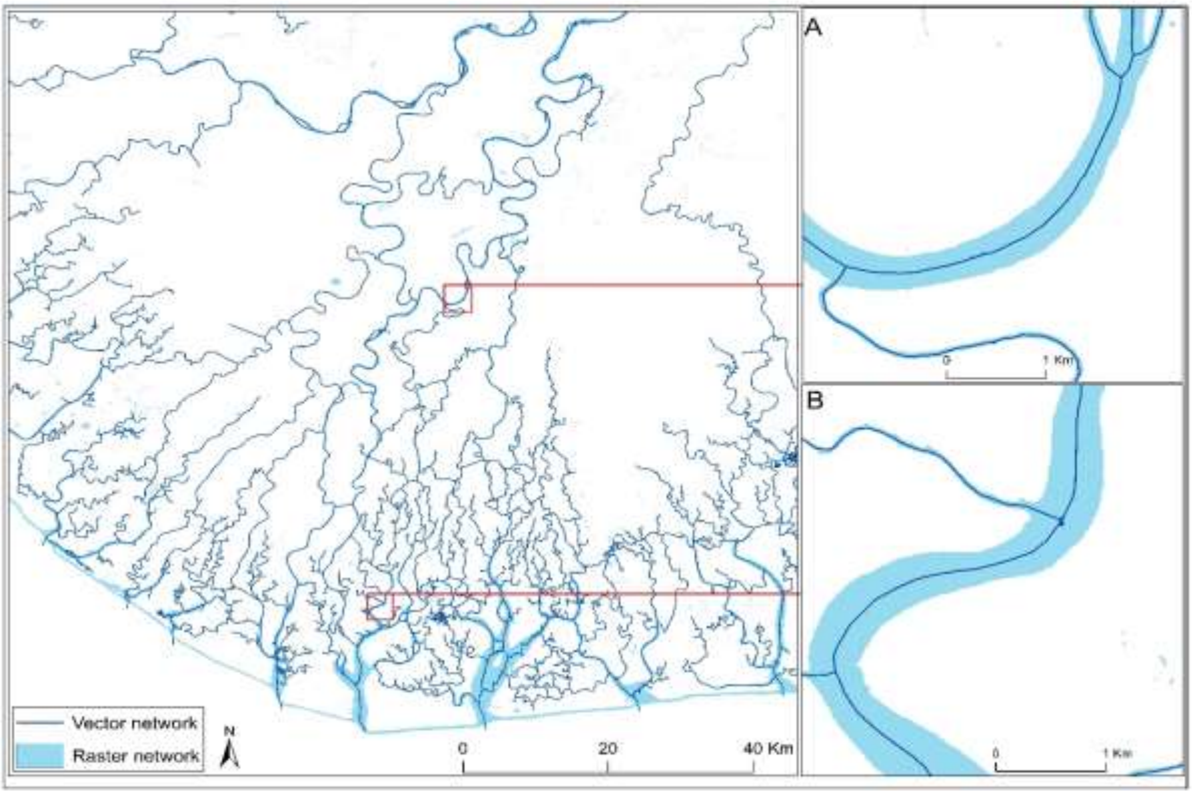


**Figure 4.6**. River centrelines overlaid on the raster river data produced from Sentinel-1 data. Inset maps A and B highlight the detail of the raster thinning and river centreline extraction processes.

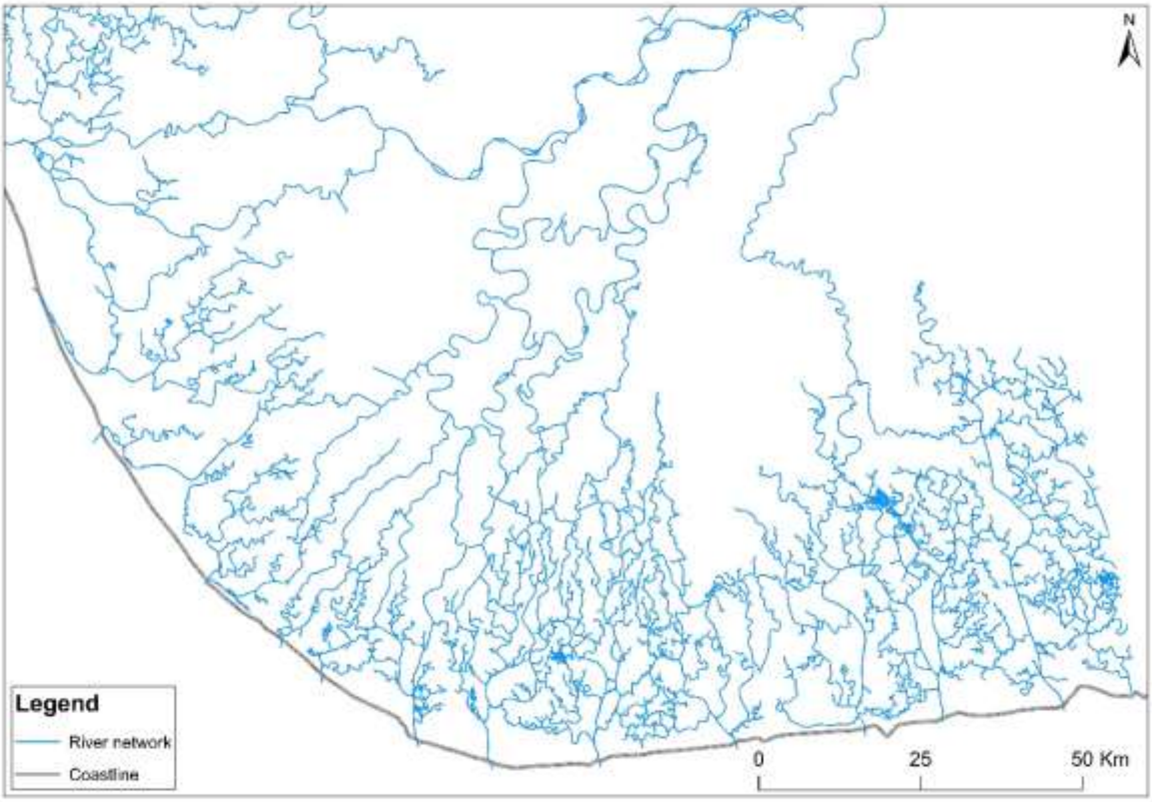


**Figure 4.7.** Extracted vector-based river centreline network for the entire delta.

#### *4.3.2.2 Vector-based accuracy assessment*

Figure 4.8 shows the extent to which the river centre line networks derived from Sentinel-1 and the comparator data sets agree with the reference data. Figures 4.8B - D show that the networks derived from the comparator data have significant limitations in terms of their completeness and positional accuracy relative to the reference data. This confirms that the higher resolution Sentinel-1 data produces a network that has the closest correspondence with the reference data. This is quantified in Table 4.2 which shows the results of the vector-based accuracy assessment and demonstrates the superiority of the Sentinel-derived network in terms of completeness. Importantly, delineation of 1st order streams from Sentinel-1 is more than twice as effective as the next-best performing USGS-derived river network. In terms of positional accuracy, Table 4.3 shows that in all three sections of the network analysed for accuracy, the Sentinel-derived network outperforms all other data sources. It is likely that the superior results for completeness and positional accuracy generated by the Sentinel-derived network result from the higher spatial resolution of the original imagery relative to comparator data sets see Appendix 5.

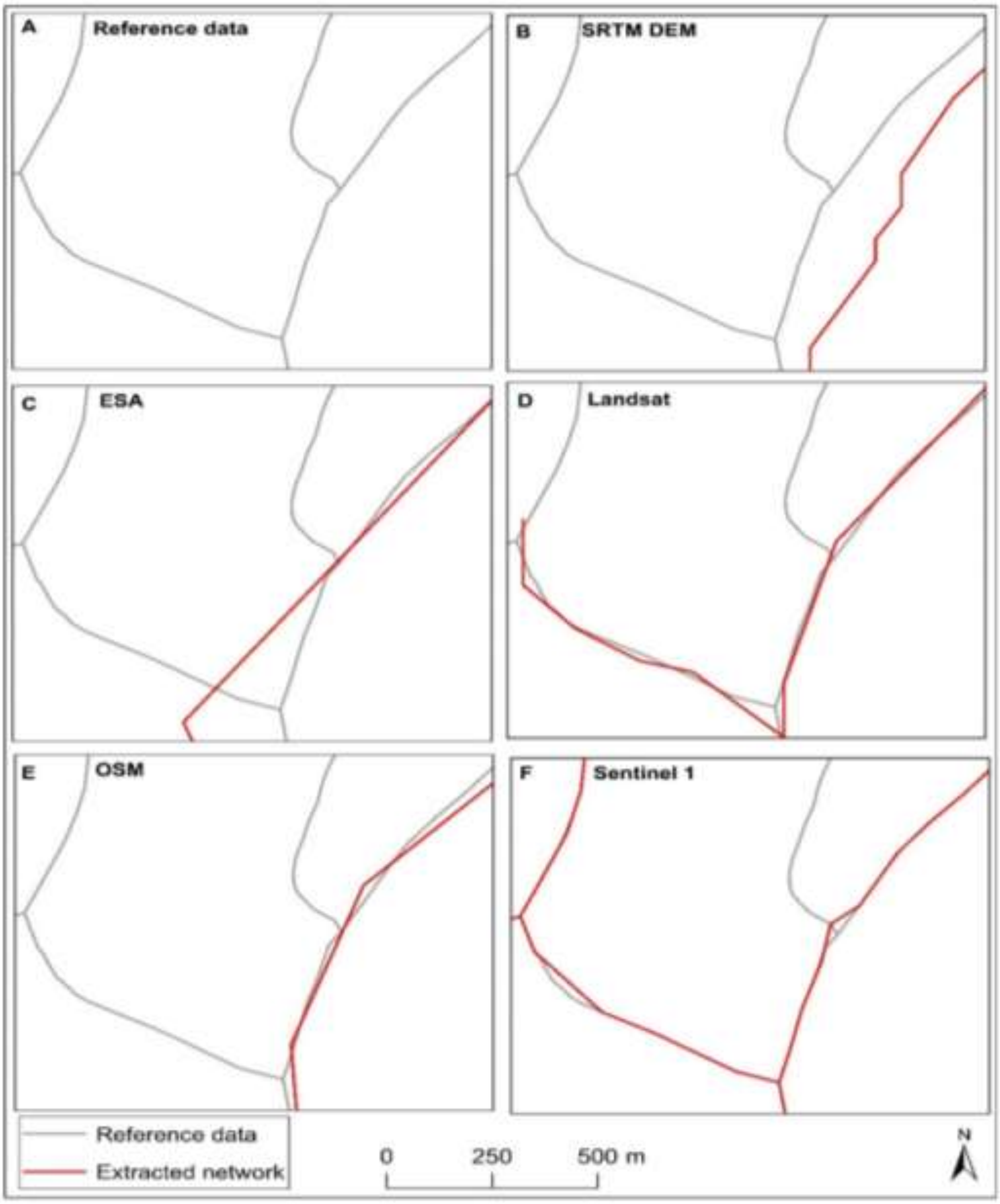


**Figure 4.8.** A sample of the river network used to show the reference network data, networks derived from the comparator data sets (SRTM DEM, ESA, USGS and OSM) and the network derived from Sentinel-1 data. The grey lines shown in all plots are the reference river centrelines which were used for the accuracy assessment.

**Table 4.2.** Results of the network completeness assessment, showing the percentage of the reference network captured by the networks derived from Sentinel-1 and comparator data, for different stream orders and overall.

| Data | 3rd order | 2nd order | 1st order | Overall % |
|---|---|---|---|---|
| Sentinel-1 | 95 | 76 | 45 | 70 |
| USGS | 83 | 46 | 20 | 47 |
| ESA data | 54 | 13 | 2 | 14 |
| DEM | 81 | 40 | 15 | 42 |
| OSM | 10 | - | - | 3 |

**Table 4.3.** Results of the positional accuracy assessment, showing the percentage of the networks derived from Sentinel-1 and comparator data laying within varied sizes of buffers from the reference network, for three sample sections of the network and on average.

| Data | 1st Section | | | 2nd Section | | | 3rd Section | | | Average % | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Buffer size | 30m | 20m | 10m | 30m | 20m | 10m | 30m | 20m | 10m | 30m | 20m | 10m |
| Sentinel-1 | 81 | 72 | 50 | 98 | 95 | 77 | 100 | 93 | 75 | 93 | 87 | 67 |
| USGS | 81 | 60 | 30 | 87 | 70 | 37 | 91 | 78 | 44 | 89 | 69 | 37 |
| ESA data | 14 | 11 | 5 | 17 | 13 | 8 | 26 | 17 | 9 | 19 | 14 | 7 |
| OSM | 60 | 47 | 32 | 49 | 35 | 20 | 27 | 17 | 9 | 45 | 33 | 20 |
| DEM | 4 | 3 | 1 | 8 | 5 | 6 | 13 | 10 | 7 | 16 | 6 | 5 |

#### *4.3.2.3 Case study: application of the geometric river network product to oil pollution dispersal.*

Figure 4.9 shows an example application of the geometric river network in the Niger Delta. This network is topologically structured and comprises edges with attributes such as flow direction and junctions which define connectivity rules between edges. It shows the potential pathway of oil released into the river network from a known point source of crude oil pollution from a broken pipeline and routes pollutants will flow through to the ocean, contingent on network connectivity and flow direction. This example is intended to demonstrate the functionality of the network in permitting a flow routing analysis, rather than a depicting the actual spread of oil from this spill event. While the Figure represents a potential route and maximum spread from the source to the ocean sink, the actual spread will depend on a number of factors such as river discharge and rates of oil emulsification and dispersion. Accounting for these additional factors requires a more sophisticated model, which is being developed in our ongoing work, but the river network product developed here provides a spatial framework for defining the key flow pathways in rivers which enable the long distance dissemination of oil pollution in the Niger Delta.

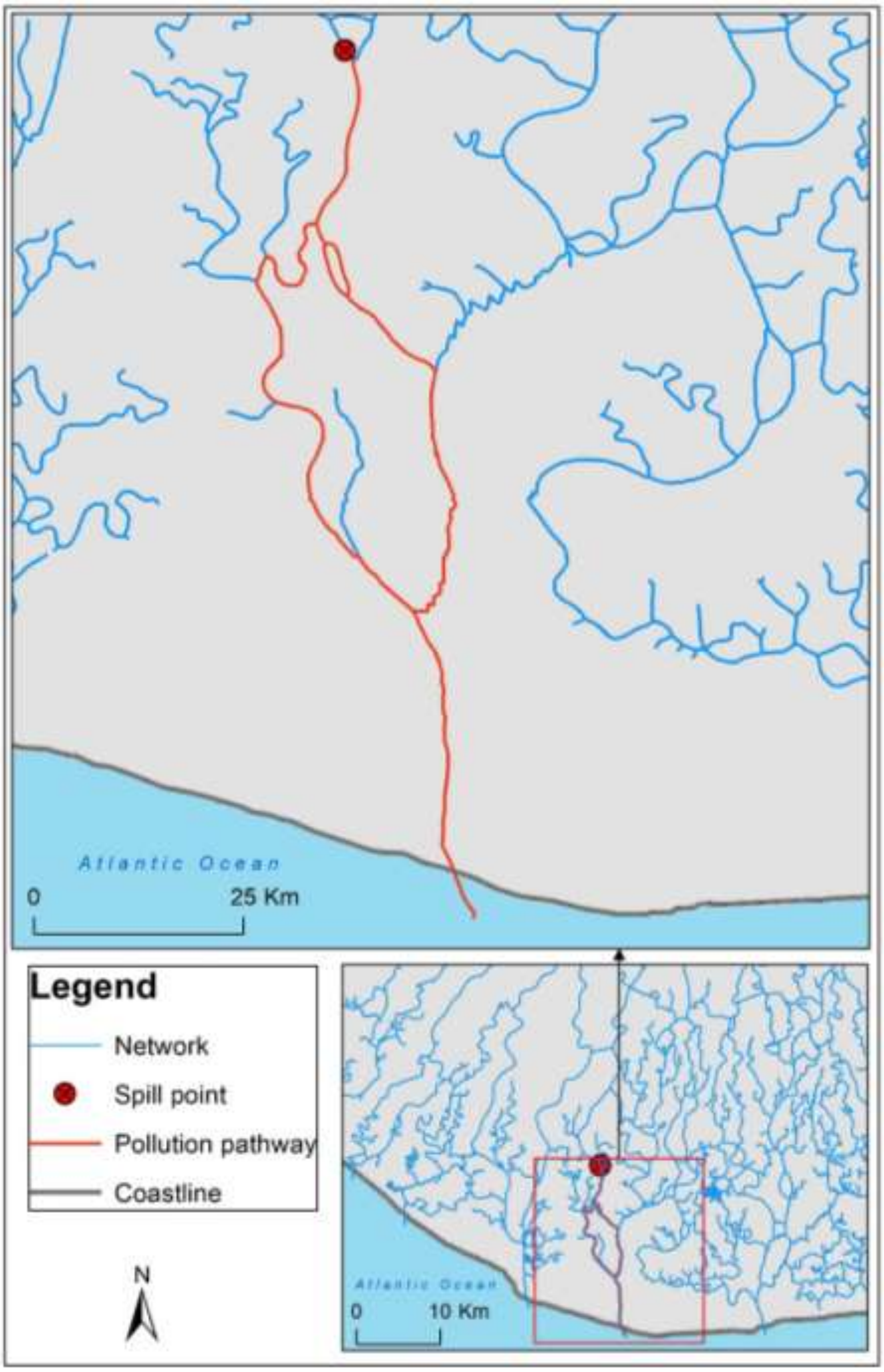


**Figure 4.9.** Tracing the potential pathway of oil released from a spill using the extracted river network based on connectivity and attributed flow direction.

## 4.4. Discussion

### 4.4.1. Unsupervised classification of Sentinel-1 data for water body delineation

As the results demonstrate, the application of unsupervised classification to Sentinel-1 data was effective for mapping water bodies in the study area. This accords with previous work which has found that the application of unsupervised classification to satellite data is an objective, fast and repeatable method of water body delineation (Ogilvie et al., 2015). Unsupervised classification, especially for distinct spectral classes such as water, has been reported to outperform supervised classification or simple thresholding approaches (Zeng et al., 2015). The shortcomings of supervised classification and thresholding in this instance are likely to be associated with the time costs and user subjectivity introduced in selecting training data or appropriate threshold values (Yang et al., 2014; Zeng et al., 2015). The implication is that unsupervised classification is more efficient and accurate.

The k-means unsupervised classification algorithm used in the present study further enhances the robustness of the procedures (Ogilvie et al., 2015; Capó et al, 2017). This is because the algorithm is effective for carrying out segmentation in solving clustering problems (Shah et al., 2011) and because class clustering is performed without prior knowledge of relationships (Tzortzis and Likas, 2014). This is emphasised by the generally high user's accuracy of the Sentinel-1 image classification as shown in Table 1. This suggests that, for anywhere classified as a water body using this algorithm, there is 89% confidence that it is water in the field, meaning that resource managers can be sure of the accuracy of the product (Kennedy et al., 2009).

The time series of Sentinel-1 images used in this study enabled the differentiation of permanent and transient water bodies, in a similar fashion to the use of a MODIS time series by Ogilvie et al. (2015). As shown in Figure 4.3, the Niger Delta contains a complex network of rivers, creeks, lakes and ponds and flooded areas. Identifying what is permanent and ephemeral is therefore important, particularly for determining the hydrological dynamics of the area during extreme events. Analysis of persistence provides an effective means of mapping permanent water bodies (Figure 4.4). This type of output is especially important in applications that require only permanent channels, such as for navigation. These data also provide a more effective input for the process of extracting a vector-based representation of the river system, as a connected geometric network of permanent channels.

#### 4.4.2. River network extraction, topology building and attribution

Vectorization of the classified outputs ensures network data are available in vector formats to accommodate wide-ranging applications (Webster et al., 2016). Figure 4.7 shows the entire extent of the river network that has been delineated in this study. Automation of the river delineation process can ensure high levels of accuracy and consistency relative to traditional cartographic approaches (Maderal et al., 2016; Yang et al., 2014; Zeng et al., 2015) and the awareness that, in this study, the input data for the delineation was accurately classified, gives further confidence in the network data set. However, it is acknowledged that the river network produced in this study has some limitations. This is illustrated in Table 4.3, where although Sentinel-1 presents the best results for network delineation in comparison to existing freely available data sets, it cannot resolve all of the first order streams. This is because some of the individual creeks are less than 10m in width, and in some cases no more than 3m wide (Emmanuel and Onyema, 2007) See Appendix 6. Thus, the 10m spatial resolution of the Sentinel-1 data, combined with tree canopies wholly or partially covering narrow creeks, can limit the ability to delineate the finest features of the river system in the delta. Appendix 7 shows the physical characteristics of river systems and C-band radar interaction with different land cover types.

Although river delineation is an appropriate step, building a geometric network from the output enables more sophisticated forms of analysis. Most applications employing the use of hydrological networks usually require topological information such as flow direction and connectivity rules (Sindhu et al., 2015). As shown in Figure 4.7, this study was able to produce a geometric river network for the entire study area. The example application demonstrated how the network could then be used for flow routing and assessment of the spread of oil pollution, which is important in the context of the Niger Delta. The river network data will enable future detailed source-pathway-receptor modelling to be carried out to determine the fate of oil spilt as a result of sabotage or operator error (Obida et al., 2018) and similar approaches would be more widely applicable for diverse forms of pollution in other countries. Moreover, many communities in the delta are not connected to the road network, with access only by boats using the river system. Hence, the river network data produced in this study holds considerable potential for assisting in planning more effective (river-based) transportation schemes to support the many isolated and vulnerable communities. There is a pressing need for such applications of river network data in many developing countries.

#### 4.4.3. Mapping accuracy assessment and comparison framework

Both raster and vector methods of accuracy assessment indicate that the Sentinel-derived products outperform comparator data sets (Tables 4.2, 4.3). Although the Sentinel-based method delineated a substantial proportion of the network, smaller channels were less well discriminated. The systematic methods used in this study for assessing the accuracy of the extracted river centre line ensures consistency. The superior performance of the Sentinel-based method can likely be explained by the higher spatial resolution of the source imagery compared to the comparator data sets and the better discrimination of water bodies achieved by SAR sensing compared to optical sensing (Sabel et al., 2012). See Appendix 8 for an inter-comparison of the spatial resolution of Sentinel 1 and USGS data. In addition, although there is a time separation between the acquisition of the Sentinel 1 and comparator data sets, in this context the impact on channel delineation is reduced as minimal channel changes are observed even over extended periods (See Appendix 9).

Relatively little data on rivers has been contributed to OSM in the Niger Delta. Lack of OSM content in this region may be explained by the largely rural setting and lack of access to computing hardware and the internet in this region, and a lack of awareness of open-source geospatial technologies like OSM. This accords with studies evaluating the quality of OSM data which revealed substantially greater amounts and detail of digitized data in urban areas compared to remote rural areas (Bittner, 2017; Graham et al., 2015; Neis et al., 2013). To overcome such limitations with user-generated data, the river network data extracted from Sentinel-1 could potentially be fed into OSM to provide better coverage for regions of the world that are less well mapped.

Overall the open access policy for Sentinel-1 data, together with the improved temporal and spatial resolution, constitutes a step change in data supply for resource managers, particularly in developing countries where access to high quality spatial data is limited. The geometric river network that has been generated from Sentinel-1 data in this study opens up opportunities for sophisticated forms of spatial analysis for regions where spatial data is deficient or absent. Therefore, the outputs from this research such as the raster and vector data sets can potentially be made publicly available on sites such as OSM and provided to the Nigeria Hydrological Services Agency, at their request.

The Sentinel 1 raster and vector data in addition to their potential in supporting other complex spatial analysis, can specifically be integrated with satellite data to explain their pollutant distributary roles. This for example is demonstrated in Figure 4.9 showing potential pathways of pollutants from a spill location. Therefore, delineated river network can be integrated with temporal satellite to support understanding of dynamics of pollutant impact on the environment especially mangroves which are inter tidal vegetation occurring at fringes of rivers. Therefore, the complex factors leading to impact of pollutants on vegetation can be better understood, especially when the delineated areas are integrated with raster or vector river networks. This can potentially allow the distributary role of river network in pollutants dispersion and exposure dynamics be better understood.

## 4.5. Conclusion

In this study we demonstrated the capability of using Sentinel-1 data to map a complex river network. This network was assessed for data completeness (length) and positional accuracy (overlap) against a manually digitised reference network. The same accuracy assessment process was conducted for networks derived from the USGS and ESA global water body products, citizen science derived OSM data, and an SRTM DEM. This analysis showed that the network derived from Sentinel-1 is more complete and positionally accurate than those derived from comparator products. Moreover, the topologically-structured geometric river network contains critical information such as flow direction and connectivity rules which permit a range of applications that rely on calculations of flow routes through the system. The open access policy for Sentinel-1 data combined with the straightforward and systematic analytical methods developed in this study open up the opportunity of supplying river network data to the many other regions of the world where such data are out of date, deficient or absent. Consequently, this approach has the potential to generate a step change in the capability of natural resource managers, hydrologist, researchers and government agencies to enhance their workflow and raise their effectiveness in planning and management.

# Chapter 5 Quantifying the impact of the large-scale release of oil on the environment of the Southern Niger Delta

## Abstract

The Niger Delta has a long history of oil and gas exploration and production, but also many oil spills and associated pollution. The Ogoniland oil spill of 2008 was by far the largest in terms of both duration (112 days) and magnitude (380,000 barrels), but little is understood about the extent of impact of this spill. In this study, multi-temporal satellite images were used to delineate an extensive impact area of 393km2 which experienced oil-induced vegetation stress and mortality, which persists to present. Field samples confirmed the high concentrations of hydrocarbon pollutants in the impact area. The extensive tidal river network and mangrove swamps have facilitated the spread of oil, with the delta becoming a sink of oil that is redistributed but not removed. Approximately 392,000 people live within the impact area, with larger numbers in surrounding areas, who have potentially been exposed to pollution through direct and indirect pathways over a prolonged period. The population in the impact area is particularly vulnerable to chronic illness due to its young age structure and pre-existing very low life expectancy. Hence, there is an urgent need to mitigate the impacts of the pollution on environmental and human health, and the outputs from this study are able to guide the future spatial targeting of the limited resources that are available, to achieve positive outcomes.

**Keywords**: Oil Spills, NDVI, Spatial Impact, Risk, Exposure, Assessment.

## 5.1. Introduction

Oil spills significantly increase the risk of human exposure to harmful substances. Many constituents of crude oil are of particular concern due to potential health problems that may result from exposure (Ugochukwu et al., 2018). Such constituents include the polycyclic aromatic hydrocarbons (PAHs), benzene, toluene, ethylbenzene and xylene (Nduka and Orisakwe, 2010; Philibert et al., 2018) and dangerous heavy metals, such as lead, vanadium and cadmium (Chinedu and Chukwuemeka, 2018; Oti, 2016). PAHs, for example, can lead to direct exposure through ingestion and dermal contact (Abha and Singh, 2012). It has been demonstrated that the toxicity of these chemicals and their persistence in the environment can lead to prolonged periods of exposure and chronic illnesses, such as cancers (Afshar-Mohajer et al., 2018). Similar deleterious effects can be induced in other organisms that are exposed to oil pollution and this has serious consequences for wider ecosystem functioning and ecosystem service provision (Mendelssohn et al., 2012). Hence, in order to minimise these effects, it is crucial to delineate the area impacted by an oil spill, identify the key pathways for oil transport, and, importantly, identify which human populations and ecosystems are potentially exposed. This can assist in targeting health services and environmental remedial interventions.

Over the last 50 years, the Niger Delta has suffered from significant oil spillage with an estimated 50 million barrels having been released in the region, leading to the destruction of lives, property and the environment (Kadafa, 2012). Several factors have been identified as the root causes of oil spills in the region including sabotage and operational failures (Obida et al., 2018). Due to the number of oil spills in the region, the Niger Delta has been described as one of the most polluted regions on earth (Chukwubuikem et al., 2014). The oil spills have led to significant environmental degradation, which has greatly reduced ecosystems services (Opukri and Ibaba, 2008), including the fisheries and agriculture which constitute the major sources of livelihood of the region. Human exposure to oil spills occur from consumption of contaminated food resulting from bioaccumulation and air pollution from volatilisation of some components (Afshar-Mohajer et al., 2018; Alharbi et al., 2018; Fu et al., 2019).

In November 2008, one particular spill received national and, in fact, global attention, due the volume of oil released into the low-lying Ogoniland region from a 24-inch Trans Niger Delta pipeline (Fentiman and Zabbey, 2015). An estimated 380,000 barrels were released over a 112-day period before it was finally stopped (UNEP, 2014). This incident led to the widespread environmental destruction in the Ogoniland region and led to a continuous cycle of litigations between the operators Shell Nigeria and the local communities. A relatively recent landmark ruling by a British court in favour of the community led to a compensation payment of 55 million dollars (The Guardian, 2015). However, since the incident, efforts to quantify the magnitude and extent of the impact have been very limited.

UNEP conducted field-based studies in Ogoniland to ascertain the concentration of pollutants at certain locations (UNEP, 2011) and attempts have been made to assess the ecological and human health risk due to the spills in the region (Chikere et al., 2018; Fentiman and Zabbey, 2015; Lindén and Pålsson, 2013). However, these studies were based on sampling regimes, which are limited in spatial extent. The need for clean-up and remediation of contaminated areas in the Niger Delta and Ogoniland, in particular, has been highlighted (Sam et al., 2017; Zabbey et al., 2017). Such remedial activities are necessary for reducing exposure and returning land to agricultural, commercial and residential use. However, it is difficult to develop a detailed remedial plan for this region, partly because of funding constraints but largely due to lack of detailed information on the extent of the spill impact (Ozigis et al., 2019). Likewise, information is needed to target the resource-limited health services in the region towards those communities at greatest risk from pollution (Nriagu et al., 2016). Hence, there is a pressing need to quantify the spatial extent of the environmental impact and the magnitude and distribution of human population exposure resulting from the 2008 Ogoniland oil spill.

Plants can act as effective bioindicators of oil pollution as their physiological functioning is sensitive to exposure to oil (Mishra et al., 2012). The interactions between plants and oil is complex, but can include both physical and chemical effects (Ozigis et al., 2019). The physical impacts typically result from oil coating foliage or root systems, thereby reducing photosynthesis and transpiration, and the uptake and water and nutrients. The chemical impacts occur when toxic substances within oil are absorbed by plants, causing disruption to physiological pathways (Domingues Pavanelli and Loch, 2018; Emengini et al., 2013). These deleterious processes affect the health and vigour of vegetation, ultimately leading to death; therefore, readily observable biophysical indicators including reductions in canopy chlorophyll content, leaf area index and above ground biomass can be used to monitor the impacts of oil pollution (Arellano et al., 2015; Emengini et al., 2013; Mishra et al., 2012). Moreover, these vegetation biophysical indicators can be assessed remotely using well established spectral vegetation indices such as the Normalised Difference Vegetation Index derived from satellite imagery (Díaz and Blackburn, 2003; Kross et al., 2015). Hence, satellite imagery offer the capabilities for detecting oil pollution indirectly via changes to vegetation biophysical characteristics. For example, spectral indices derived from a time series of Landsat images were used to assess the long term impacts of crude oil on mangroves in a coastal region of Brazil (Domingues Pavanelli and Loch, 2018). Similarly, Ozigis et al. (2019) used random forest classification techniques with a range of Landsat-derived vegetation indices to distinguish between oil impacted and non-impacted vegetation in the Niger Delta (Ozigis et al., 2019). Therefore, with their large spatial coverage and repeat sampling capability, satellite imagery offer a valuable means of monitoring the impacts of oil spills on vegetation which is a crucial first step towards identifying areas of risk and ultimately mitigating human exposure.

This study aims to quantify the spatial extent and temporal dynamics of the impact of the 2008 Ogoniland oil spill, then use this to estimate the size and distribution of the impacted human population. This study also examines the relationship between the spill extent and UNEP's detailed field-based pollution measurements at selected locations to potentially provide inference on unmeasured locations. In order to achieve this aim the following objectives were addressed:

a) to determine the spatial extent of the impact caused by the 2008 Ogoniland spill and assess the role of river channels in pollution distribution;

b) to analyse the spatial variation of measured pollutant concentrations in relation to temporal NDVI change in relation to the delineated impact area;

c) to quantify potential human population exposure to pollutants within the delineated impact area.

## 5.2. Materials and Methods

### 5.2.1. Study area

Ogoniland lies in the Southeast of Rivers State and is estimated to cover some 1,000 km$^2$ of the Niger Delta (UNEP, 2014). It is characteristically a mangrove swamp creek system with an estimated population of 1.2 million at 2016, based on the 2006 official census and projected growth rates (https://www.citypopulation.de/php/nigeria-admin.php?adm1id=NGA033). The region is administratively divided into four local government areas (LGAs) namely Tai, Eleme, Khana and Gokana (Lindén and Pålsson, 2013), which lie east of the state capital Port Harcourt. The region has been identified as one of the most polluted regions of the Niger Delta (Obida et al., 2018), with spills impacting upon its delicate biodiversity and affecting the livelihoods of its residents, which are mainly based on fishing and farming. Bodo, located in Gokana, was the epicentre of the 2008 spill incident (Figure 1).

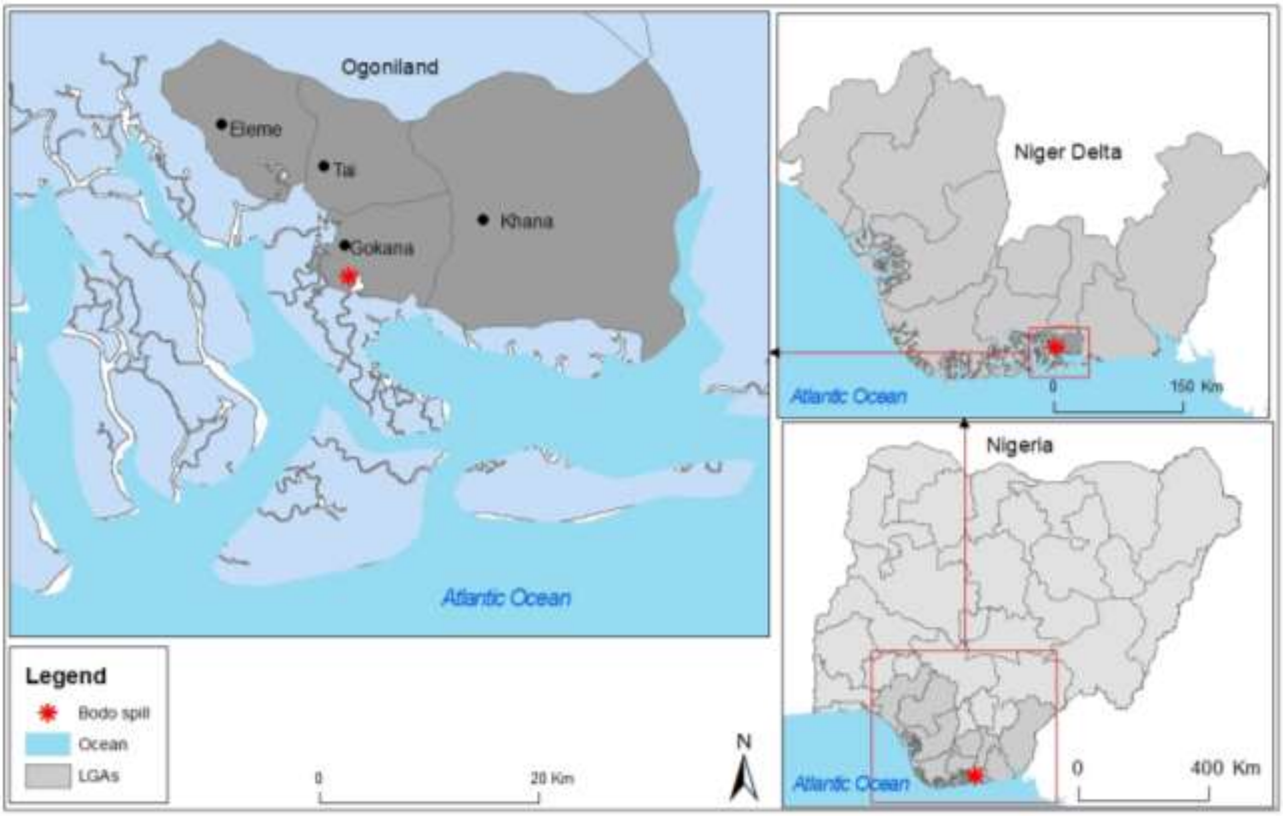


**Figure 5.5.1**. The Niger Delta, with inset maps of Ogoniland showing location of the 2008 spill and Nigeria showing the position of the Niger Delta.

### 5.2.2. Assessing the spatial extent of the oil spill impact

#### *5.2.2.1 Remotely sensed data*

A series of eight Landsat images were acquired for the period 2000 – 2018 inclusive, covering pre-spill and post-spill periods. These include images from the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM) and Operational Land Imager (OLI) sensors, obtained from the USGS (https://earthexplorer.usgs.gov/). The images used represented all of the cloud-free images available for the site over the study period and excluded ETM images affected by the scan line error. All images were geometrically and atmospherically corrected making them suitable for temporal analysis. The TM and ETM data were corrected to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm developed by the National Aeronautics and Space Administration's (NASA) Goddard Space Flight Centre (GSFC) and the University of Maryland (Claverie et al., 2015). The OLI images were corrected to surface reflectance using the Landsat 8 Surface Reflectance Code (LaSRC) algorithm (Vermote et al., 2016).

#### *5.2.2.2. Vegetation indices and image differencing*

The Normalised Difference Vegetation Index (NDVI) (Rouse et al., 1973) was calculated according to Equation 1 for all images in the Landsat time series.

$$NDVI = \frac{\mathrm{NIR-R}}{\mathrm{NIR+R}} \qquad \text{Eq. 1}$$

where NIR is reflectance in the near-infrared waveband and R is the red waveband. It has been demonstrated that NDVI is an effective indicator of physiological stress and biophysical changes caused by the impacts of hydrocarbon pollution on plants (Domingues and Loch, 2018). This is primarily due to an increase in reflectance in the red waveband due to stress-induced leaf chlorosis and a decrease in reflectance in the near-infrared due to wilting and defoliation (Domingues and Loch, 2018; Sanches et al., 2014). In the context of the present study, it is expected that mangrove plants exposed to oil pollution will have lower NDVI values than non-polluted plants pre-polluted plants.

Image differencing was applied to the 2003 (pre-spill) and 2018 (post-spill) NDVI images to ascertain changes in vegetation (Domingues Pavanelli and Loch, 2018) using the Map Algebra tool in ArcGIS 10.4. This was performed by subtracting NDVI value in a pixel in the post spill image from the corresponding pixel in the pre spill image. The output represents the change in NDVI and is normally distributed data with areas of no change around the mean and areas of significant change found on the histogram tails (Chambers and Wynne, 2002). In order to determine the level of change in NDVI that represented a significant impact on vegetation caused by the spill (as opposed to natural variation), the NDVI difference image was classified into 5 change threshold classes (-0.05, -0.1, -0,15, -0.2, -0.25 and -0.3). The accuracy with which each change threshold was able to delineate impacted vegetation was quantified by using reference data of impacted and non-impacted locations collected through manual interpretation of high resolution (0.5m) satellite imagery obtained from ArcGIS Imagery (acquired in 2016). The NDVI change threshold of -0.2 (i.e. all areas with a reduction of NDVI of 0.2 or more) presented the highest overall accuracy (85 %) and was therefore adopted as the threshold for delineating the spill impact area.

***5.2.2.3 Refining the delineation of the impact area***

Since population growth has led to increasing rates of urbanization within the Niger Delta, some areas with a significant NDVI reduction between 2003 and 2018 could potentially be explained by urban construction displacing vegetation. Therefore, an urban land cover data layer derived from the Sentinel-2 African Land Cover Prototype by ESA's CCI (http://2016africalandcover20m.esrin.esa.int/) was used to remove urban areas from the initial delineation of the impact area. To enable further analysis and information extraction the final delineated impact area (as derived from raster image analysis) was converted to polygon features using the raster to polygon tool in ArcGIS 10.4.

#### *5.2.2.4 Assessing the role of rivers in oil dispersion*

The Niger Delta is low lying region, with an extensive river network. Rivers therefore play an important role in the distribution of pollutants within the delta system. Hence, a map of the river network, delineated using Sentinel-1 imagery (see Obida *et al.*, 2019), was used to evaluate the potential routes for oil spill dispersion in the study area by investigating the spatial relationships between the river network, the source of the oil spill and the delineated impact area.

### 5.2.**3. Evidence of pollution from field samples and associated vegetation damage**

Data from a UNEP environmental assessment were used to investigate the key pollutants associated with crude oil spilled in Ogoniland. The environmental assessment was carried out at the request of the Nigerian government (UNEP, 2011) and involved detailed investigations of soil, ground water, surface water and sediments, with over 4,000 samples analysed in total (Lindén and Pålsson, 2013; UNEP, 2014). The samples were collected in 2011, 3 years after the oil spill, using a random spatial sampling strategy, though this was influenced by accessibility issues. The data used in the present study were sourced from the Hydrocarbon Pollution Remediation Project, a Nigerian government agency tasked with leading the clean-up and remediation work in Ogoniland.

For four locations within the delineated impact area at which field samples had been tested for pollutants by UNEP, NDVI values were extracted for all of the 8 images in the Landsat time series. At each location, a window of 4 x 4 pixels (120 $m^2$) centred on the field sampling point were extracted and a mean NDVI value calculated. The same procedure was undertaken for four locations outside of the impact area, where field samples were analysed. The temporal changes in NDVI for the locations within and outside the impact area were compared, alongside the values for Total Petroleum Hydrocarbon (TPH) determined from the field samples.

#### 5.2.4 Quantifying the human population within the impact area

Population data were used to quantify the number of people residing in the area impacted by the 2008 Ogoniland spill. Gridded population data at 100m resolution were sourced from the WorldPop portal (https://www.worldpop.org/). This detailed data product was generated by integrating census data, satellite imagery from a range of sources, settlement and urban area map layers and machine learning algorithms to generate high resolution gridded outputs (Paula et al., 2016; Tatem et al., 2013). Demographic data based on age structure at 5 years intervals were acquired from the same source, as a gridded product, to enable pollution exposure analysis. The gridded population data were integrated with the delineated impact area in ArcGIS 10.4 and the Zonal Statistic as Table tool was used to calculate the sum of raster cell values (persons per pixel) within the impact area. This operation was performed for all age groups by gender.

## 5.3. Results

### 5.3.1 Spatial extent of the oil spill impact

Based on the analysis of the 2003 and 2018 Landsat data, 393km$^2$ of vegetation was impacted by the oil spill (Figure 5.2). The vegetation affected is primarily mangrove swamp, the predominant land cover type in the region, plus some adjoining low-lying estuarine and riparian vegetation. Figure 5.2 indicates that there is a large area of impact around the spill site at Bodo, which is expected since areas closer to a spill site should experience higher concentrations of pollutants, particularly as the hydrophobicity of crude oil compounds results in oil sticking to sediments. However, there is little impact inland of the spill site, to the north east, which is beyond the spatial extent of the river and creek network and mangrove swamp; yet, in almost all other directions from the spill site, impacts have been observed across a very large geographical area. Figure 5.2 shows that all impacted areas are either adjacent/connected to the river network or within/connected to the mangrove swamp. This spill is exceptionally large in relation to average spill volumes of 77 barrels in the region. Therefore, this supports the potential efficacy of the method used in this study. However, the potential implication is that smaller spills may not be detectable using this method or that it may require longer periods of time following a smaller spill for the cumulative effects on vegetation to be manifest to such as level as to be detectable using Landsat data.

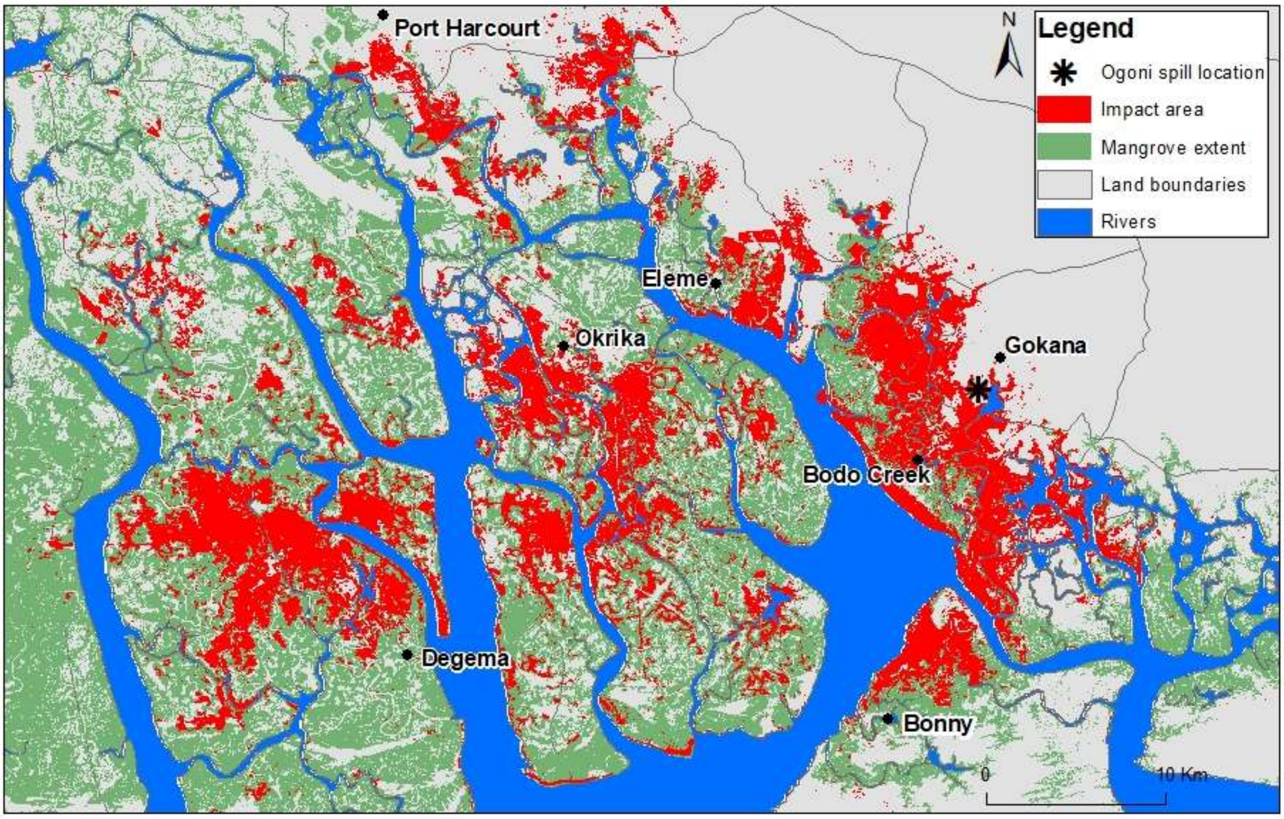


**Figure 5.2.** Area impacted by the 2008 Ogoniland oil spill, based on NDVI image differencing between 2003 and 2018, indicating areas of significant NDVI reduction and location of the spill incident. Delineated river network (from Obida *et al.*, 2019) showing potential role in oil distribution.

#### 5.3.2. Evidence of pollution from field samples and associated vegetation damage within and outside the impact area

Table 1 shows the temporal variations in NDVI values across 8 sites and their corresponding TPH levels as measured from field samples. The 4 sites within the impact area (1-4) all show substantial and persistent reductions in NDVI after the 2008 spill along with very high TPH values. In contrast, the 4 sites outside the impact area (5-8) all have similar NDVI values before and after the spill and much lower TPH values. These observations are an indication that crude oil has killed vegetation within the impact area and, as it persists in the mangrove swamp sedimentary environment for a prolonged period of time, this has prevented any observable recovery of the vegetation even after 10 years post-spill. Figure 3 demonstrates how higher concentrations of pollutants have been observed in field samples obtained within the delineated impact area as compared to those outside the impact area.

**Table 5.1.** Extracted temporal NDVI values at 8 sample locations, with NDVI values within the impact area showing a significant reduction after the 2008 spill and corresponding high TPH values (sediments) in comparison to samples outside the impact area with little or no change in temporal NDVI and low TPH values (sediment).

| | | **Dec 00** | **Jan 03** | **Dec 14** | **Jan 15** | **Dec 15** | **Apr 16** | **Jan 18** | **Dec 18** | **TPH (ug/l)** |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **pre- spill** | | **post-spill** | | | | | | |
| **Inside impact area** | **Site 1** | 0.42 | 0.44 | 0.13 | 0.21 | 0.12 | 0.16 | 0.04 | 0.02 | 12100000 |
| | **Site 2** | 0.30 | 0.33 | 0.09 | 0.15 | 0.1 | 0.12 | 0.05 | 0.01 | 8630000 |
| | **Site 3** | 0.41 | 0.42 | 0.17 | 0.2 | 0.14 | 0.20 | 0.10 | 0.07 | 6470000 |
| | **Site 4** | 0.32 | 0.34 | 0.27 | 0.31 | 0.20 | 0.34 | 0.17 | 0.18 | 4520000 |
| **Outside impact area** | **Site 5** | 0.59 | 0.47 | 0.44 | 0.41 | 0.37 | 0.43 | 0.31 | 0.42 | 92600 |
| | **Site 6** | 0.52 | 0.49 | 0.47 | 0.49 | 0.41 | 0.54 | 0.33 | 0.48 | 72900 |
| | **Site 7** | 0.61 | 0.55 | 0.49 | 0.56 | 0.49 | 0.61 | 0.42 | 0.54 | 1560 |
| | **Site 8** | 0.53 | 0.49 | 0.46 | 0.49 | 0.40 | 0.51 | 0.34 | 0.46 | 24500 |

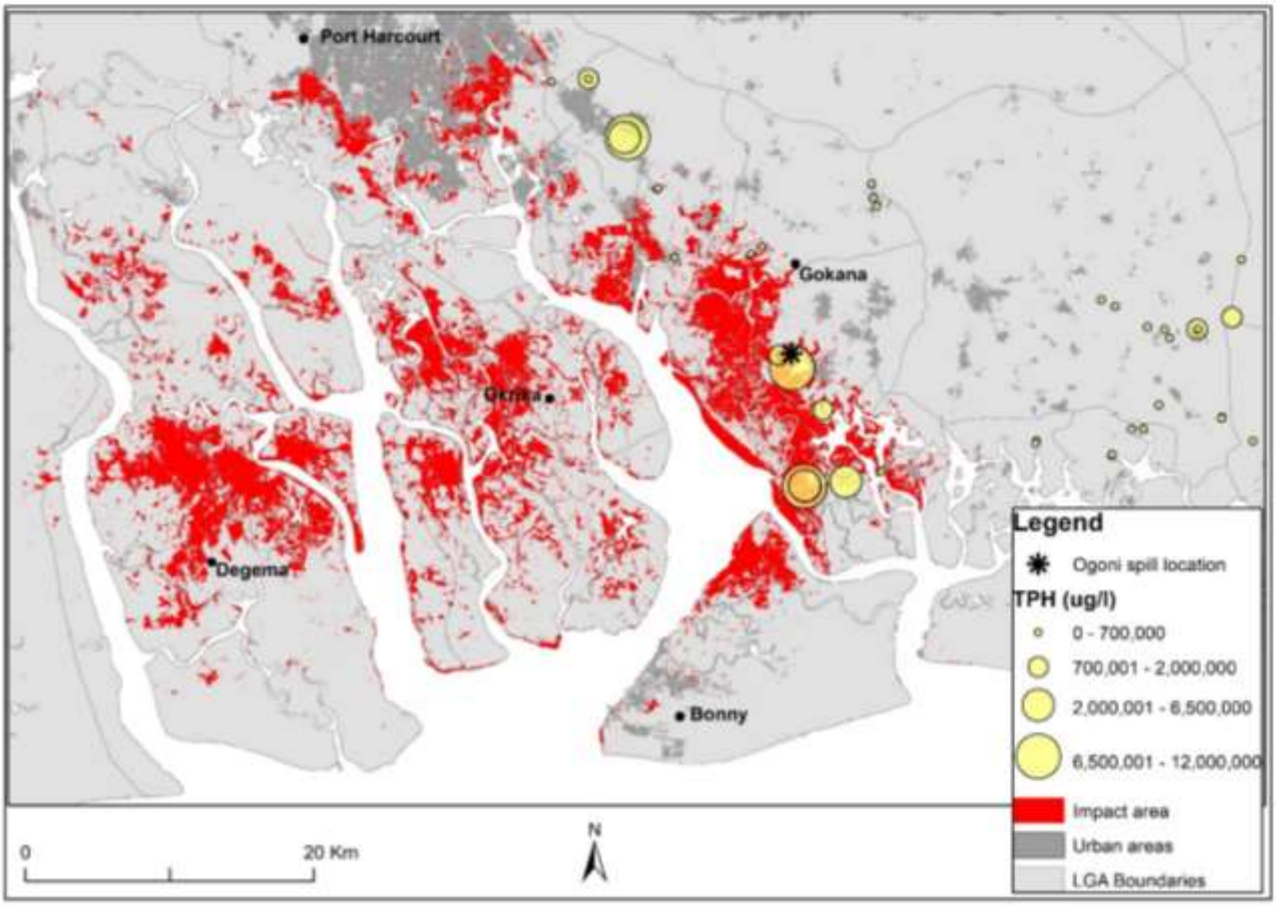


**Figure 5.3.** Distribution of UNEP's sediment samples and results from TPH measurements, showing substantially higher concentrations of pollutants within the delineated impact area.

### 5.3.3. Human population living within the impacted area

An estimated 391,981 people live within the oil spill impact area, of which 70% of the population are below age 30 (Figure 5.4). Indeed, the age structure reveals that the population is dominated by children and teenagers who are potentially most vulnerable to adverse health effects from cumulative exposure to oil. The age group 30 years and over forms a relatively small proportion of the total population exposed and this is likely connected to the very low average life expectancy of the area which is an estimated 50 years. There is little gender disparity across all age groups.

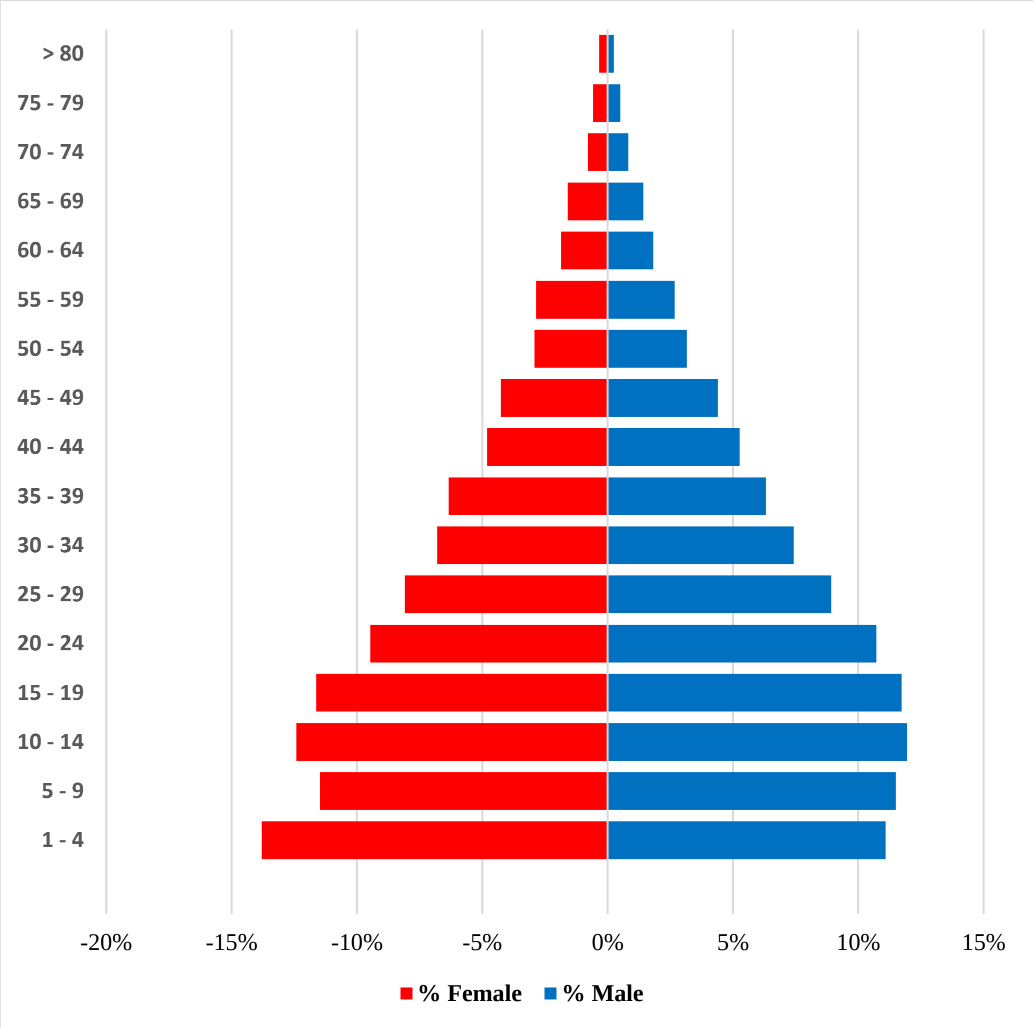


**Figure 5.4.** Age profile as a percentage of total by gender, of people living within the delineated oil spill impact area, as of 2019.

## 5.4. Discussion

This study has mapped the large area impacted by the 2008 Ogoniland spill where an estimated 380,000 barrels of oil were spilled in Bodo land and its adjoining creek system. The estimated size of this impact area (393km$^2$) supports other studies that have reported extensive environmental damage based on the extent of the resulting pollution (Amnesty International, 2011; Chikere et al., 2018). This large area is potentially a direct indication of the presence of toxic components of crude oil capable of destroying mangroves and other low-lying vegetation. Considering the most recent image used for delineating the impact area was 2018, there is no evidence yet of recovery. Persistent organic pollutants (POPs) present in crude oil are highly toxic and their persistence in areas such as the Niger Delta is expected as riparian, estuarine and swamp environments have been reported to act as pollutant sinks (Li et al., 2019). For example, Figure 4 shows evidence of a thick oil slick persisting within a river 5 years after the large Ogoniland spill event, with extensive vegetation damage in areas adjacent to the river network.  Typical POPs such as PAHs are not only detrimental to the environment but also to humans due to their prolonged persistence leading to increased exposure (Alharbi et al., 2018).

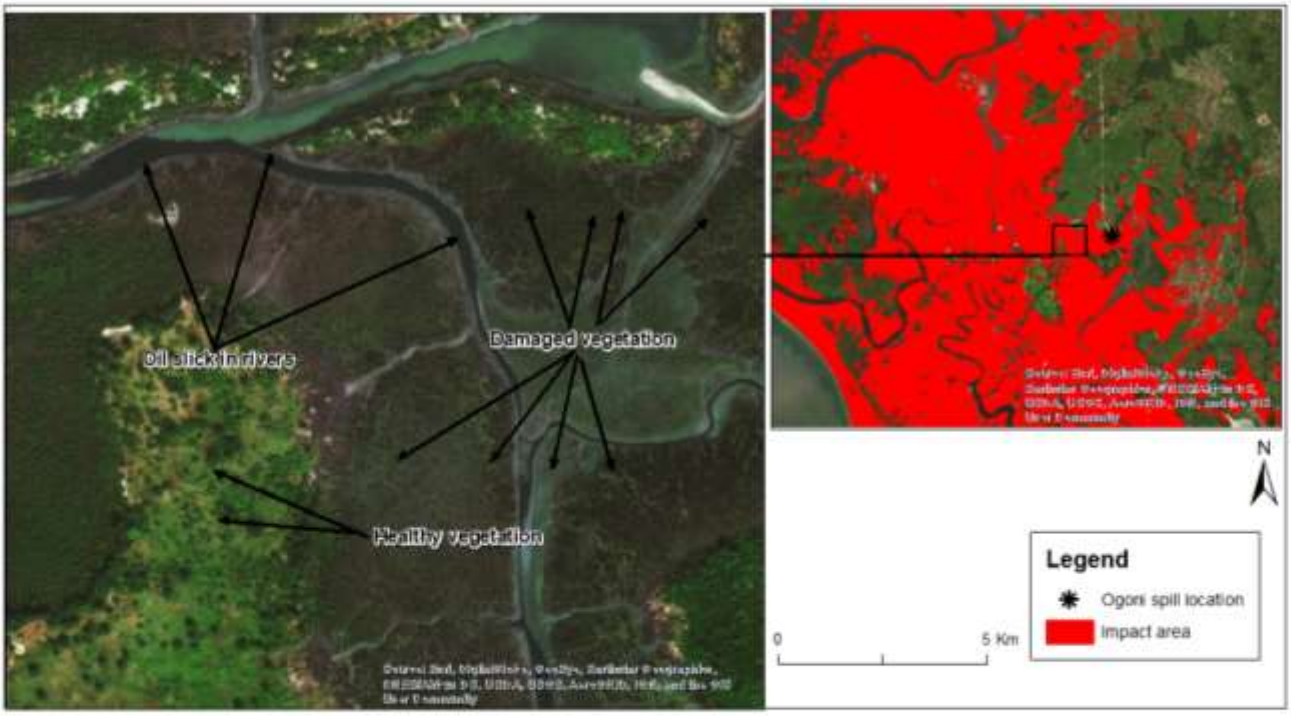


**Figure 5.5.** Visible thick oil slicks in river channels and damaged vegetation close to the Ogoniland oil spill site, captured by a high resolution satellite image acquired 5 years after the incident.

Movement of water within the river network and beneath mangroves has likely been responsible for spreading oil across the site. Although the general direction of fluvial flows from the catchments feeding the Niger Delta is southwards towards the Atlantic, the study area is predominantly tidal. This facilitates the spread of oil in multiple directions (including westwards away from the spill site and northwards away from the Atlantic coast) across a wide area covered by the interconnected tidal river and creek network and within the tidal mangroves. Moreover, the repetitive tidal cycles are likely to increase the possibilities for deposition of oil on sediments associated with the river network and mangrove swamps. Thus, rather than the flushing of contaminants which might occur for spills into a typical fluvial system with unidirectional flow, the tidal action means that this area of the delta is more likely to become a persistent sink of oil that is perhaps reworked and redistributed but not removed. Indeed, the situation is likely to have been exacerbated by the many much smaller spills (average volume 74 barrels) in the area since the large event (Obida et al., 2018).

Destruction of mangroves means important spawning areas for fish, crabs and other aquatic fauna are impacted. Feeding on the polluted and dead fauna potentially leads to a trail of pollution through the aquatic ecosystem and bioaccumulation of POPs in animal tissues along the food chain (Rocha et al., 2018), which can eventually end with human consumption of highly toxic material (Ren et al., 2016). Chronic illness due to prolonged exposure and consumption of potentially polluted food is an important exposure pathway for the local population, with serious health impacts. For example, exposure to POPs has been linked to reproductive problems, diabetes, cancer, endocrine disturbances and cardiovascular problems (Alharbi et al., 2018).

Although mangroves are potentially the most affected vegetation, croplands used for cultivation are also impacted since the people of Ogoniland engage in subsistence farming (Amnesty International, 2013). This is worsened by the large area affected as highlighted in this study. Bioaccumulation in plants is therefore inevitable considering the extent of the pollution. This happens as a result of contact between the plant root and polluted soil, which can lead to uptake and subsequent transport to other vegetative and reproductive organs of the plant (Jia et al., 2018). Consumption of these crops, fruits and vegetables can lead to high exposure risk to pollutants of concern and constitute grave dangers to human health similar to consumption of polluted animals (Commendatore et al., 2018; Islam et al., 2018).

The impacts of oil pollution in this region is further exacerbated by the majority of the population being dependent on the environment for their livelihoods. Since the population around Ogoniland are largely subsistence farmers, commercial farmers and fishermen, direct dependence on the environment is inevitable, thereby leading to exposure to oil pollutants through established pathways such as dermal contact and inhalation. The population living within the delineated impact area are of particular concern because the levels of the toxic chemicals are consequentially higher, however, surrounding areas with different land cover types can potentially be equally of concern. This is because chemicals including POPs can be transported via atmospheric, overland and groundwater flows (Srivastava et al., 2019).

It has been reported that years after the large Ogoniland incident, evidence of substantial pollution, an indication of persistence and lack of remediation, thereby exposing the population to potentially dangerous health outcomes (Amnesty International, 2011). Indeed, the situation is likely to have been exacerbated by the many much smaller spills (average volume 74 barrels) in the area since the large event

(Obida et al., 2018). Studies have reported that based on the levels of pollution, that breathing the air, eating fish, dermal contact with soil and sediments and drinking water in many parts of Ogoniland can be detrimental to human health (UNEP, 2014). Gastroenteritis, hepatoxicity, liver failure and asthma are reported to be now common, in addition to increased miscarriages and sudden or premature death which was not the case prior to the 2008 spill (The Guardian, 2018). Since over 70% of population within the impact area are below 30 years of age, this increases their vulnerability. Prolonged periods of exposure of especially the young population leads to more adverse effects evident in shortened life expectancy which is reported to be an estimated 50 years, 20 years below global average (Effiong et al., 2012). Since oil pollution has been linked to serious health problems, future detrimental effects on life expectancy could be anticipated in an area where it is already extremely low.

UNEP's detailed measurements of pollutants as shown in Table 5.1 indicates significantly high levels of oil-related pollutants in the delineated impact area (UNEP, 2011, 2014). In some locations the concentrations are so high that exposure is almost inevitable based on proximity to such places. Table 1 shows that sampling locations with higher pollutant concentrations correlate with areas of substantial and enduring levels of NDVI reduction within the impact area. This can be explained by the concentration and persistence of heavier hydrocarbon components in the environment leading to a prolonged and sustained pollutant exposure and impact (Alharbi et al., 2018; Kim et al., 2019; Ren et al., 2016).

The delineated impact area is likely to represent the minimum area across which oil has spread because (i) the areas mapped are where vegetation has been killed or significantly stressed (>0.2 reduction in NDVI), whereas oil pollution may have spread into other areas where less severe vegetation stress has been induced and is not detected using the NDVI differencing technique; (ii) when refining the delineation of the impact area, urban areas were removed as the NDVI technique was not appropriate in such locations, but oil may have spread into urban areas via the river network; (iii) the mapping technique identified impacts on vegetation and not aquatic ecosystems which could be more extensive, particularly parts of the river network in between impacted vegetation areas which will have received or conveyed oil. Furthermore, there is some indication that the zone of influence on human health may extend far beyond the area of impact as delineated in this study. There have been indications of impacts of pollution on pregnant women living at some distance from oil-contaminated sites, with babies being at double the risk of dying before turning a month old if mothers lived within 10 km of contaminated sites before conception (The Guardian, 2017). Hence, the population at risk of adverse health effects may be much larger than those living within the delineated impact area.

Clean up and remediation efforts have been planned in Ogonliland following the UNEP report, which estimated that a 30 year period would be required to reverse the damage to the environment and public health (UNEP, 2011). However, the clean-up efforts have been adversely affected by a combination of financial, political and social factors (UNEP, 2014, 2016). This poor remediation record in the region has caused persistent environmental damage and prolonged exposure of people to hydrocarbon pollutants (Oyibo et al., 2017; Singh and Agarwal, 2018; Ugochukwu et al., 2018). In order to promote recovery from this dire situation an integrated strategy is needed which spatially optimises the deployment of the limited human resources, clean up equipment and supplies (Grubesic et al., 2017). The present study potentially provides a spatial framework for supporting such remediation work, as well as the deployment of health services, by highlighting the areas in greatest need in relation to pollution risk.

## 5.5. Conclusion

In this study, the widespread environmental impact of the Niger Delta's largest oil spill has been quantified using satellite imagery, which revealed that an area of 393km$^2$ has been affected. The method used provides a much more spatially comprehensive assessment of the impact than previous studies, which were based on limited point samples. Multi-directional water flows have facilitated the spread of oil across a wide area within the extensive tidal river network and mangrove swamps, with the delta becoming a persistent sink of oil that is redistributed but not removed.

The human population threatened by exposure to hydrocarbon pollutants is high, with approximately 392,000 people living directly within the impacted area and larger numbers in surrounding areas who may have been subjected to various exposure pathways. Considering the high concentrations of pollutants and persistence of impacts highlighted in this study, there is a high risk of a range of chronic illnesses developing as a result of prolonged periods of exposure. An age structure dominated by children and young people increases the vulnerability of the population to pollutants, in an area which already has an extremely short life expectancy. Clearly, there is a pressing need for clean-up, remediation and health interventions in the region, however, progress has been hindered by financial, social and political factors. Moving forwards, the findings of this study hold promise for spatially targeting the limited resources available for mitigating the impacts of the pollution on environmental and human health.

# Chapter 6 Synthesis

Human activities linked to the increasing demand for energy and economic resources come with consequences such as oil pollution. This problem is particularly problematic in developing countries such as Nigeria, where operators employ standards that are far below international best practices. This, in addition to weak enforcement regimes, has led to incessant oil spills in Nigeria for over five decades, with potentially severe impacts on the environment and human health.

This study developed an integrated approach to quantifying the degree of human and environmental exposure to oil pollution by the application of spatial analytics on assimilated data. Primary data collected by key government agencies were combined with remotely sensed data to examine exposure in the region. Since rivers constitute the major pathway to oil spill dispersion and detailed data are lacking for the region, a detailed river network was delineated to aid understanding of pollutant dispersion in the region. Due to the paucity of data on the magnitude and spatial extent of damage caused by the 2008 Ogoniland oil spill, satellite data were used in combination with field data to delineate the impact footprint and assess human exposure.

This study shows that there has been a general increase in oil spills occurrences over the study period. Theft and sabotage have been identified as the leading cause of these spills, accounting for over 40%, with over 90 million litres of oil having been spilled in last decade. Some LGAs Southwest of the region have witnessed the highest volumes of spills over the study period, with Southern Ijaw, Ogba Egbe and Ibeno the worst affected due to their geographical location and density of oil and gas infrastructure.

In terms of human exposure to oil spills, population in the Southern Niger Delta are the worst affected, based on spills volumes and settlement patterns. Over 29% of the population of the Niger Delta is exposed to some degree of oil pollution. Ogoniland which constitutes an integral part of the Niger Delta experienced extensive damage through physical destruction of mangroves and other sources of livelihood for its people, with over 300,000 living near or within oil spill impacted localities. Due to the population dynamics of the region, younger people (<30 years of age) are the worst affected, potentially impacting upon the low life expectancy of the region.

A range of vital ecosystems' and land cover types are directly impacted by crude oil pollutants with broad leaved trees, cropland and mangroves being the worst affected. Mangroves provide important ecosystems services, by not only supporting a range of biodiversity, but also supporting shoreline stabilization and enhancing water quality. Most of the oi spill impacted area delineated in Ogoniland is predominantly mangrove. The level of destruction suggests the potential impacts on biodiversity and ecosystems services are severe.

River channels have been shown to serve as sinks and distributary channels for oil pollution, but lack of detailed river data for the Niger Delta limits the scope to reduce the impacts of oil spills. This study found that Sentinel-1 remotely-sensed SAR data provides a very effective means of delineating the river network. Building a river network with attributes such as flow direction and connectivity is crucial for modelling pollutants dispersion, an essential element in any oil spill management or monitoring programme.

This study has successfully produced vital outputs whose integration provides insights into greater levels of exposure than previously estimated. For example, figure 6.1

shows the integration of derived pipeline spill hotspot data and river networks from Sentinel 1 and USGS data. The figure shows that pipeline river crossings are common and demonstrates the attendant consequences of this, where some crossings are classified as hotspots, likely increasing the risk of river contamination and thus human exposure. In addition, the figure also reveals the comparative advantage of the new Sentinel 1 network with more completeness. For example, there are about 8 locations where pipelines cross the Sentinel 1 river network and the USGS data are absent.

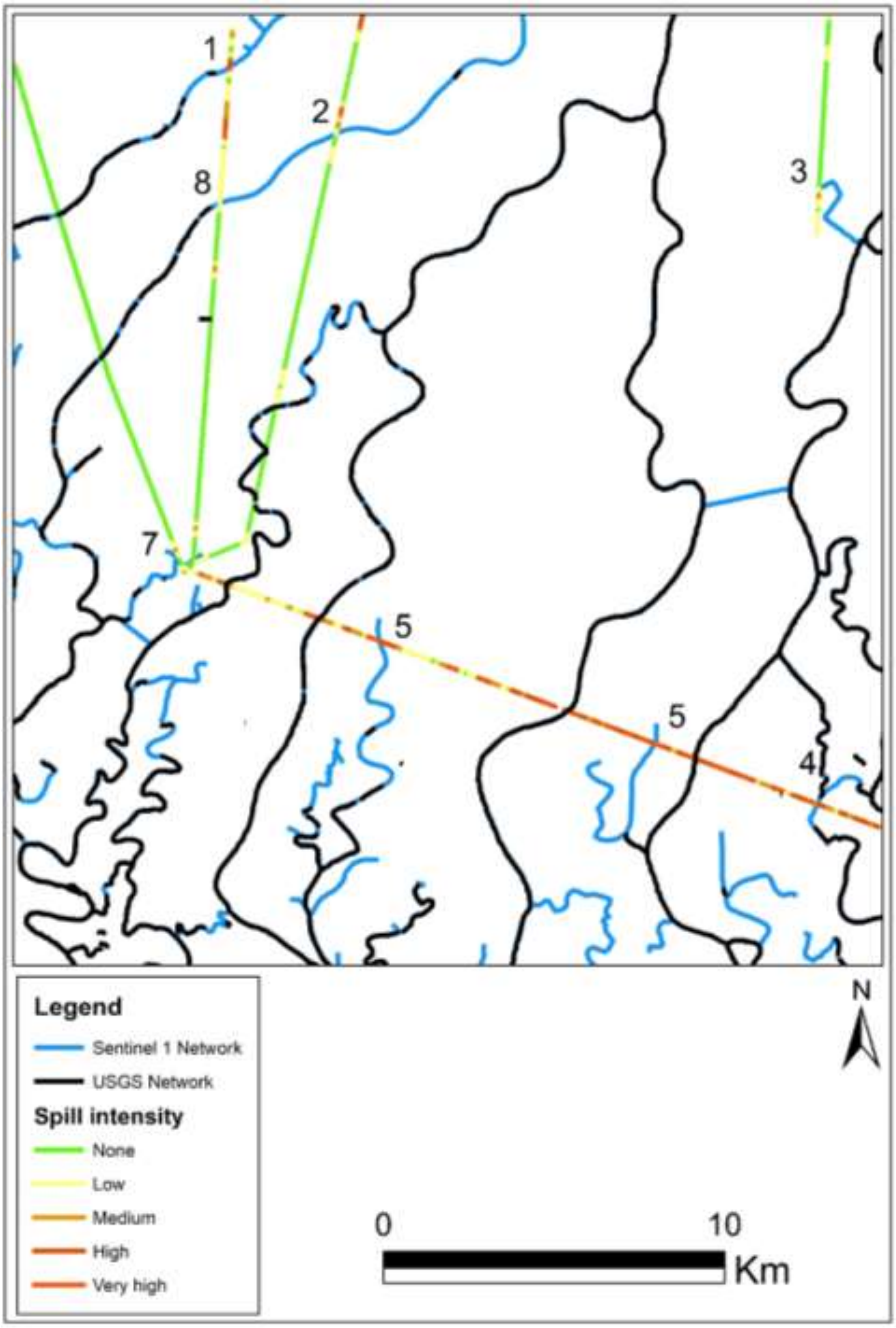


**Figure 6.1**. Pipeline hotspot integrated with USGS river network overlaid on Sentinel 1 data, showing the latter's superiority in terms of completeness. Multiple areas of pipeline intersection with rivers raises concern on potential pollution and exposure.

## 6.1. Contributions

### 6.1.1. Contributions to literature/method

Several attempts have been made to investigate the problems associated with oil spills in many parts of the world and in Nigeria in particular. However, these studies have largely been conducted at small scales, for example in individual local government areas, or at best state level (Aroh et al., 2010; Olobaniyi and Omo-irabor, 2016; Omodanisi et al., 2014). Previous studies have utilized old estimates of oil spills, and have been largely exploratory, lacking statistical rigour (Eweje, 2006; Okoli. Al Chukwuma; Orinya.Sunday, 2013; Opukri and Ibaba, 2008; Oviasuyi and Uwadiae, 2010). Although they offer perspectives into the problem, the localised extent of these studies fails to address the large scale context of the problem and this potentially limits the extent of support they offer for employing appropriate management solutions.

Chapter 2 of this thesis presents a review of oil spills and associated management problems at local, regional and global scales. It reveals the extent of the problem and the need for developing a more holistic approach in its management. This study demonstrated how spatial data integration can provide valuable insights into managing oil pollution at a regional scale. For example, the aggregation of oil spill data, gridded population data, land cover data and pipeline data gives insights into human and environmental exposure to pollution at a regional level. The analysis and results presented in Chapter 3 demonstrates the value of adopting a multi-methods approach to answering research questions, in this case, levels of human and environmental exposure to oil pollution (Obida et al., 2018).

In chapter 3, the study identified water bodies as one of the main polluted land cover types in the Niger Delta. This is corroborated in others studies (Nduka and Orisakwe, 2010; UNEP, 2011). Chapter 4 presented a method of delineating rivers in high-resolution raster and vector format, with associated network attributes such as connectivity and flow direction to aid simple to complex modelling of pollutants in water bodies. The method employed the use of Sentinel-1 data which is freely available for river network delineation. Its quality presents the best available in the region in comparison to other publicly available data sets such as USGS, ESA, SRTM derived network and OSM data. The study also presented a critical comparison of the derived network to existing river products data, thereby demonstrating a method for river delineation that could be widely applied in other regions of the globe, particularly those that experience high cloud cover.

Chapter 5 presents a holistic approach to delineating the area impacted by a large oils spill and estimating population exposure within the footprint. Previous studies have been largely focused on sampling approaches, limited by scale and sampling bias. This study provides a framework and contributes to literature by combining image based analysis and field based sampling of hydrocarbons to provide greater insights into human and environmental exposure.

### 6.1.2. Contribution to remediation efforts in Nigeria

Several studies have been undertaken to determine the best remediation strategies of contaminated spaces in the Niger Delta (Agnello et al., 2016; Zabbey et al., 2017). While it is important to make good decisions on the type of remediation required, the question of where to prioritise remediation remains unanswered. This is particularly important because remediation in the Niger Delta has been largely unsuccessful to date due to the complex nature of the environment and the strategies applied (Sam and Zabbey, 2018). This study presents a holistic view of the problem by presenting hotspots in relation to population exposure which undoubtedly should inform the remediation decision making process. This comes at a time where the Federal Government of Nigeria has shown the political will to commence clean up and remediation of impacted areas based on the recommendations of UNEP (UNEP, 2011), with an estimated 1 billion dollars to be spent in the next 5 years. Prioritising where to remediate is essential in ensuring that scarce resources are deployed to best effect.

This study is timely because of UNEP's recommendation for immediate remediation, since previous remediation strategy was simply Removal by Enhanced Natural Attenuation (RENA) (Sam and Zabbey, 2018). In essence, this is simply a 'do nothing' approach towards remediation, allowing natural processes to breakdown hydrocarbons. This has been reported to take as long as 50 years in some areas (Duke, 2016), thereby further impacting upon the environment and human population. Considering the number and volume of spills in the Niger Delta, this method is largely unsuitable. Nevertheless, the government's willingness to remediate the land is seen as a step in the right direction. This study has identified priority states, LGAs and localities based on hotspots of spill occurrence and levels of human and environmental exposure. Three states have been identified as the worst affected in the Niger Delta, Rivers, Bayelsa and Delta. In addition, the LGAs Ibeno, Burutu, Ndokwa and Southern Ijaw have been identified in the study as areas with highest population exposure by spills volumes, while Uvwie, Tai, Warri South west and Eleme have over half their population within pipeline risk zones. Hence, this study has the potential to guide authorities in prioritising these areas for remedial interventions.

This study identified the land cover types most affected by pollution as broad-leaved tropical trees, mangroves, cropland and water bodies. This can be fed into the decision support mechanisms of the government in their clean-up efforts, for example cropland pollution directly affects sources of livelihoods by their impacts on agricultural production. Similarly, impacts on water bodies affect fishing and recreational activities. The high-resolution river channel delineation presented in this work could potentially be used by remediation managers to determine priority areas for remediation, simple or complex modelling activities. The Hydrocarbon Pollution Remediation Project (HYPREP), an official government body tasked with environmental clean-up, supported this study with data and have indicated interest in the outcome since it is highly relevant to their activities.

#### 6.1.3. Contribution to policy making and environmental practices in Nigeria

Environmental management in Nigeria is domiciled with many government agencies, more often operating within diverse legislative and policy frameworks at federal, state and local levels. Agencies chiefly responsible for petroleum related environmental issues include the Department for Petroleum Resources (DPR), NOSDRA, and HYPREP. However, the operational policies of these various agencies have impacted on their abilities to drive their regulatory roles in managing problems such as oil spills. For example, inter agency rivalry and conflicts arise due to lack of synergy and overlapping roles can further reduce their capacity to address issues such as oil spills. This study has highlighted the unacceptably high impacts of oil spills which it could be argued, are contingent on lack of robust policy implementation.

Since oil exploration began in Nigeria there have been many policy decisions backed by legislation aimed at guiding and regulating the exploration and exploitation activities, including oil pollution. These include the Petroleum Act 1969, Federal Environmental Protection Act, 1988, Harmful Waste Act 1988, Oil Pollution Act 1990 and National Environmental Protection Regulation 1991 (Abatement in industries Generating Wastes). Others include National Environmental Protection Regulation

1991 (Effluent limitation), Environmental Impact Assessment 1992, Constitution of the Federal Government of Nigeria 1999 and the present policy and legislative document is the Environmental Guidelines and Standards from Petroleum Industry in Nigeria (EGASPIN) 2002. Although current legislation is largely seen to be focused on specific aspects of the oil industry, a recent proposal for the all-encompassing Petroleum Industry Bill (PIB) is seen as a testament to the inadequacy of the current legislation.

The Niger Delta has been identified as one of the worst areas in the world for oil spills, which is arguably a symptom of a failing policy framework. This study also identified lapses in clean up processes and inadequacy of RENA, hence, the need for a change in policy approach or implementation mechanisms. For example, this study identified many causes of oil spills in the Niger Delta, with a considerable number classified as 'other' unknown causes, in some cases with large volumes. The study has thus highlighted extant lapses in policy which require complete reconsideration to ensure effective management. This indicates the policy framework on reporting spills through the JIV needs to be more holistic to ensure all spills are captured and standard procedures guided by policy are enforced to reduce the impact of the spills, or at best reduce spill occurrence.

Other policies that this study can potentially contribute to relate to the violation of pipeline right of way, which was identified as a cause of increased levels of human exposure. In terms of environmental exposure, policies associated with locating or laying pipelines need to be reviewed, since this study identified large areas of environmentally sensitive land cover directly impacted by oil spills due to their location. Therefore, it is proposed that an environmental sensitivity index is used to assess future pipeline installations, to minimise the impacts of spills on sensitive environments.

#### *6.1.4. Contribution to spatial data infrastructure*

Spatial data infrastructure supports government and private entities at all levels in social, economic, political and development planning. Many countries have demonstrated the relevance of maintaining spatial databases for the management of natural resources and environmental management. However, in Nigeria, like most developing countries, the National Spatial Data Infrastructure (NSDI) is either non-existent or grossly inadequate to support effective decision making (Agbaje, 2010), even in circumstances where its application is crucial, for example, oil spill detection and management. This study has generated a selection of spatial data that can contribute to Nigeria's spatial data infrastructure. At the least, it should provide an impetus and start point to demonstrate the relevance of spatial data in this context. For example, the pipeline network used in this study was manually digitised from hard copy, which emphasises the dearth of spatial data. The pipeline data are now available for other diverse applications needed in the region, and the data includes processed information on identified pipeline spill hot spot locations. The study also provides processed spatial data of LGAs combined with spills volumes and population data to provide potential levels of exposure in the region.

This study identified water bodies as one of the most polluted land cover types and a medium for the dispersion of pollutants. However, lack of detailed river network data led to the generation of high-resolution raster and vector river data from Sentinel-1 satellite imagery. The delineated river data were empirically compared to existing data sets and this showed they were more consistent and complete. These data have been made available to the Nigerian Hydrological Services Agency (NHSA) and the Niger Delta Development Commission (NDDC). The study also generated a spill impact footprint based on pollution in Ogoniland, which can form the basis for region wide analysis. Outputs from this study can help reinvigorate the development of a national spatial data infrastructure, accessible to all as it has capability for driving development planning.

## 6.2. Limitations

Although the research has fulfilled its aim, there some unavoidable limitations encountered during this study. Investigating oil spills and associated risks, including its driving factors requires both spatial and attribute data that are not only of high quality, but credible. This is because outputs from data analysis are contingent on data quality. Although data used in this research are all from reliable government and reputable private organizations many aspects of the data seemingly can be improved. For example, a considerable number of oil spills with known locations were excluded from the analysis because the quantity of the oil spilled was not recorded. In the same data the causes of oil spills were not documented for all the spills, with some classified as 'other' meaning the causes are unknown. Holistic analysis of spills requires exact and complete knowledge of the causes, where possible.

The age and accessibility of data constituted a form of limitation in this study, for example the ESA, SRTM, USGS and Sentinel-1 data were all collected at different time periods. The ESA, SRTM and USGS data used in this study were the most recent and accessible, however, they were not as up to date as data from Sentinel-1. The topologically-structured river network data generated from Sentinel-1 did contain a small number of geometric loops, which could limit its use for pollution tracing. Promisingly, new techniques such as those implemented within WhiteBox open source GIS (Lindsay et al., 2019) offer solutions to such problems.

Accessing some of the data in this study required the author to undertake long periods of travel and extensive bureaucratic negotiations, which took a considerable amount of time. Notably, the oil spills database and some UNEP environmental measurements of Ogoniland are not publicly available. In several cases, access to potentially relevant data was not granted.

Several factors are potentially responsible for oil spills in the Niger Delta, these can be political, social or economic (Kadafa, 2012; The Guardian, 2010). However, in this study only a subset of factors were analysed on the basis of proximity. These included proximity to coast, cities, roads and security locations. To fully understand what drives spills, other factors need to be considered, such as poverty and socio-economic justice.

## 6.3. Recommendations

This study has confirmed that oil spills leading to pollution of the environment are widespread and that they are severely affecting both human and environmental components of the Niger Delta. Oil spills have continued from pipelines occasioned by breaks, artisanal refining, and operational failures. In order to find solutions to the problem of oil spills and associated damage, the main causes must be identified and dealt with accordingly.

### 6.3.1 Recommendations to Government

| Serial | Recommendation | Reference |
|---|---|---|
| 1 | Emphasis should be placed on curtailing sabotage of pipelines. It is therefore recommended that operators should adhere to best international practice and within the framework of regulatory agencies in terms of compliance | Figure 3.4, Table 3.1. |
| 2 | Identified hotspots states such as Rivers and Bayelsa with increasing incidences of spill volumes should be prioritised over areas with declining incidences. | Figure 3.5 Appendix 2 |
| 3 | it is recommended that the government should enforce immediate measures to ameliorate problems associated with drinking water and health. These measures should result from critical, and consistent monitoring of health and the environment | Tables 3.2. 3.3. |
| 4 | The need for integrated remediation strategy involving multi-method approach, considering the large area potentially impacted by oil spills. | Figure 5.2 |
| 5 | Environmental protective considerations be made especially of pipelines at river crossings to reduce spill and potential human exposure. | Figure 6.1 |

## 6.4. Future research directions

In as much as this research has fulfilled the aims of the study, it has thrown up many questions in need of further investigation. Further work needs to be done to establish and explicitly show the resulting health complications resulting from human exposure to hydrocarbons in the Niger Delta. This is contingent on the fact that some hydrocarbon compounds are carcinogenic and can lead to some maternal health issues, in some cases affecting conception and delivery. In addition, ingested portions can cause gastro-intestinal problems. Future research should focus on the specifics of health issues resulting from exposure. This will undoubtedly necessitate access to detailed historical health records of the exposed population and the unexposed population as a control. It is also recommended that research be carried out specifically to investigate the impacted ecosystems in the Niger Delta, with the aim of analysing the degree of injury and prospects for recovery. This can potentially provide useful information on whether previous remediation strategies have been suitable and which approaches are appropriate in the future.

Early detection of pollutants in the environment ensures quick response and thus ameliorates potential impacts. Future research should focus on the development of remote and early detection techniques by applying current developments in remote sensing technologies with improved temporal and spatial resolution such as the Sentinel series. SAR technologies in particular, are suited to the Niger Delta, because of the long periods of cloud cover. Such satellite based sensing can be carried out and integrated with data from low flying drones for validation purposes.

Future research should leverage integrated environmental data (rainfall, temperature, humidity, slope, soil, and land cover data), spills data, and infrastructure data for the development of a dynamic model purposefully for the Niger Delta that can account for past and present spills, to determine the various region-wide fates of pollutants with respect to various destinations or receptors. The vector and raster river network delineated in this study remains vital in such models.

## 6.5. Concluding remarks

In this study, data sets from primary and secondary sources have been integrated and analysed using a combination of novel and established geospatial techniques in order to understand the magnitude of the problem that is presented by oil pollution in the Niger Delta. Key information on the extent of human and environmental exposure to oil pollution has been generated. Vital spatial data sets for understanding and managing the impacts of oil spills have been generated. The emphasis now lies in efforts to use the important information created in this project to reduce oil spills, alleviate their impacts on the fragile ecosystems of the Niger Delta and to foster environmental justice for its inhabitants.

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# Appendices

## Appendix 1. Hotspot mapping and analysis

Statistical analyses of spatially distributed point data have been a subject of interest in the academic domain for many years. Works by Anselin, (1995), Gatrell et al., (1996) and Getis and Ord, (1992) in particular has led to many studies on the science of spatial clustering. Spatial and temporal clustering methods have been applied in a variety of studies, across both social and ecological domains. Clustering procedures can be applied to point, line and polygon data, however, are most commonly applied to point data, especially crime data (Nakaya and Yano, 2010). These procedures are often referred to as Local Indicators of Spatial Autocorrelation (LISA) (Mccullagh, 2006). Use of hotspot analyses requires caution due to the possibility of "false hotspots", a term used to describe areas which are not statistically significant.

The rationale for hotspot analysis is to identify potential areas of interest using spatial clustering algorithms. The areas of interest usually exhibit statistically significant differences to other areas in context, due to the frequency of occurrence of an event of interest. Analysis is typically based on point data, such as incidents of crime, disease, or poaching or areal data such as administrative boundaries (Mccullagh, 2006). Spatial activities vary over space and time, hence some studies integrate these attributes in order to gain a more holistic view of the trend (Rashidi et al., 2015). This research focuses on point data of pipeline spills in the Niger Delta over a 9-year period from 2007 to 2015. Some commonly used and contemporary hotspot detection algorithms are reviewed.

## Appendix 1.1. Kernel Density Estimation

Kernel Density Estimation (KDE) was developed by Ratcliffe (2010). This algorithm employs the kernel estimation method using the raster grid scan approach (Gatrell et al., 1996). KDE was initially developed to analyse hotspots in epidemiology and remains one of the most commonly used methods for hotspot detection, especially for point datasets. There are two variants, the Planar (2D) Kernel Density Estimation (PKDE) algorithm, and the Network Kernel Density Estimation (NKDE) algorithm (Benedek et al., 2016). PKDE algorithm is better suited to the analysis of nonlinear features, because it uses Euclidean distance in it processing. NKDE is better suited to analysing data along networks, such as road traffic accidents. The formula for PKDE is:

$$\lambda(S) = \sum_{i=1}^{n} \frac{1}{\pi r^2} \mathrm{k} \left(\frac{d_{is}}{r}\right)$$

Given $\lambda(S)$ is density at a location $S$, r is the bandwidth (radius), k weight of points i, at distance $d_{is}$ of location $S$. The NKDE is a modified form of PKDE that operates on a network unlike the PKDE which operates over 2-Dimentional homogenous space. NKDE was chosen for this research because it fits the purpose of the study and nature of data, oil spill points across a network of pipelines in the study area. The formula for NKDE is similar to that used in the PKDE as presented by Xie & Yan, (2008), it is given as:

$$\lambda(S) = \sum_{i=1}^{n} \frac{1}{r} \mathrm{k} \left(\frac{d_{is}}{r}\right)$$

Where *pi* (s) is the density in location *s* and *r* is the search radius (bandwidth) of the KDE. Only features with a given radius are employed in estimating *pi* (s), *k* the kernel function is the assigned weight of point *i*, located at distance of locations. Similar to

PKDE, Many authors have attempted to optimise this function, for example, using negative exponential, Conic, Quartic, Gaussian and Epanechnikov expressions (Hasthorpe and Mount N., 2007). KDE is limited by the fact options of thematic variety is still problematic and most times at the mercy of the producer. In most cases end users are not able to question the statistical significance of the results but are swayed by the visual attractiveness of the output (Remer et al. 2005; Chainey 2015). Other issues include the notion that inadequate data in terms of quantity can lead to inappropriate results. This research employs a relatively new version of NKDE, implemented as GIS toolbox (Spatial Analysis along Network) in 2015.

**Appendix 1.2. Spatial Analysis along Networks**

Due to the relevance of the information derived from hotspots; many methods have been developed over time, each suited to different data types and scenario. However, they all aim to identify priority areas for decision making, management or deployment of resources. Some LISA exists as standard software packages which can be integrated with others. For example, SANET has been integrated into ArcMap specifically for analysis of hotspots along networks (Okabe et al., 2009). The standalone version was developed in 2016. This method was applied by Benedek et al., (2016), to identify statistically significant hotspots of car accidents along roads. SANET uses the simple formula proposed by Xie & Yan (2008), but applies a different method in the calculation of the kernel function (Okabe et al., 2009) given as:

$$k_y(x) = \begin{cases} k(x) & for -h \leq x \leq 2d-h \\ k(x) - \frac{2-n}{n} k(2d-x), & for\ 2d-h \leq x \leq d \\ \frac{2}{n} k(x) & for\ f \leq x \leq h \end{cases}$$

Where k (x) is the basic kernel function, x is a point on the network; n is the node degree, h is the bandwidth in meters and d is the shortest path from y to x in meters.

**Appendix 1.3. Alternative Methods of Hotspot Detection**

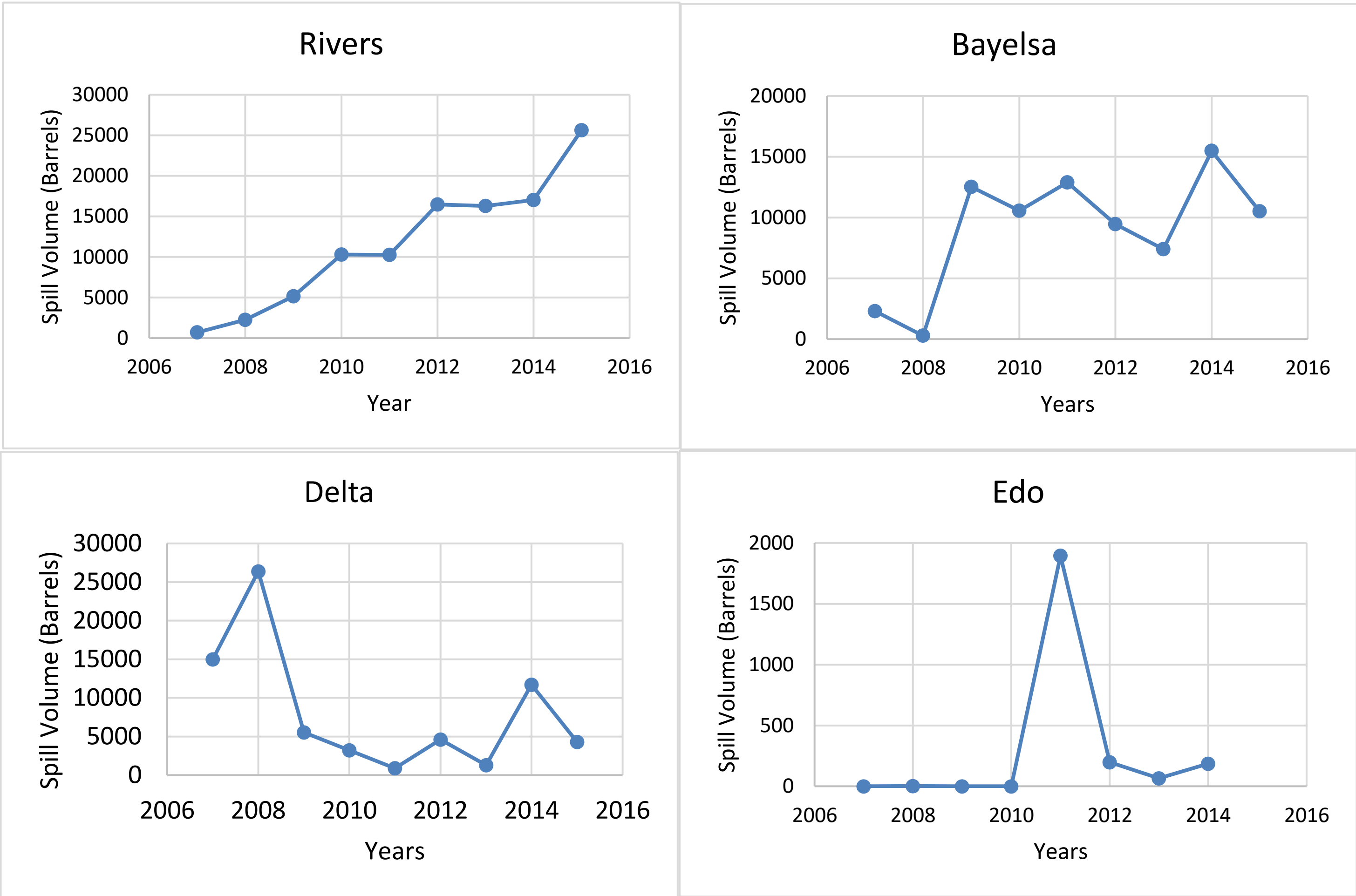
Satscan is a typical example of a tract or grid scanning method applied in the detection and evaluation of outbreaks of disease incidence, providing insights into temporal and spatial patterns (Jung, 2009; Rashidi et al., 2015). This is an important method because it considers the temporal dimension of the data. It uses ellipsoids of various sizes and locations to mark areas in which hotspots are likely to occur in time and space. The method was used in a study involving 80,000 patients for a period of three years in Boston USA. This method uses ellipsoids or circles at the centre of the tracts to process the data but does not reflect the tract shape itself. This is a limitation as rightly observed by Quan et al., (2006), circles do not reflect real-world suitably.

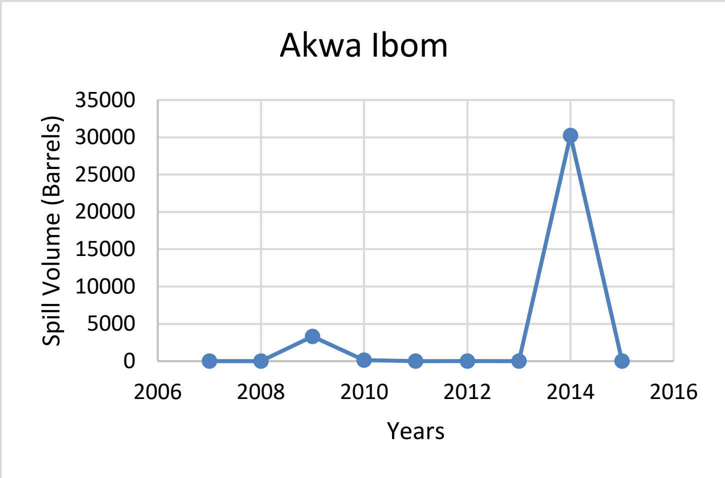
Ellipsoid scanning is a LISA method mainly used in crime hotspot detection. A typical example is the STAC and Crime stat model publicly available and developed by Levine, (2006). This model gives up to seven pathways towards hotspot detection: local Moran statistics, mode, fuzzy mode, spatial and temporal analysis of routine STACK, Nearest Neighbour Hierarchical Clustering (NNHC), K-means clustering and Risk Adjusted Nearest Neighbour Hierarchical Clustering (RNNHC). These different pathways present the user with a wide range of options for analysis at hand. The method has been widely used in crime analysis but has the potential to be applied in epidemiology (Gatrell et al., 1996).

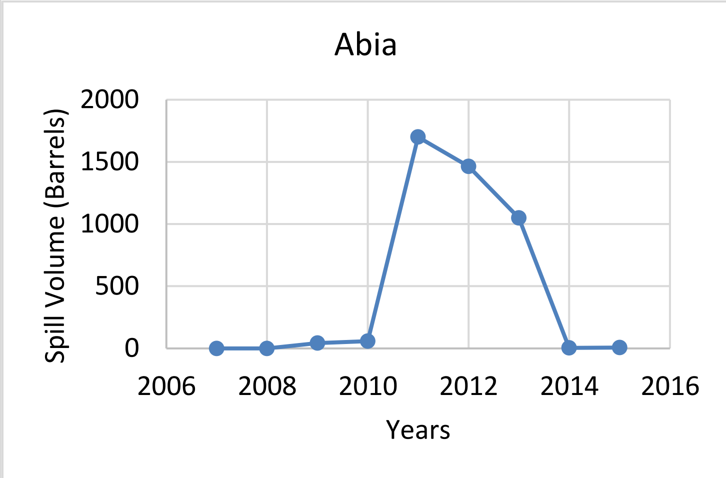
The Geographical Analysis Machine (GAM), was initially developed by (Openshaw et al., 1987), it has been applied in hotspot detection. This method is based on the combination of GIS and computational statistics in the identification of departure from

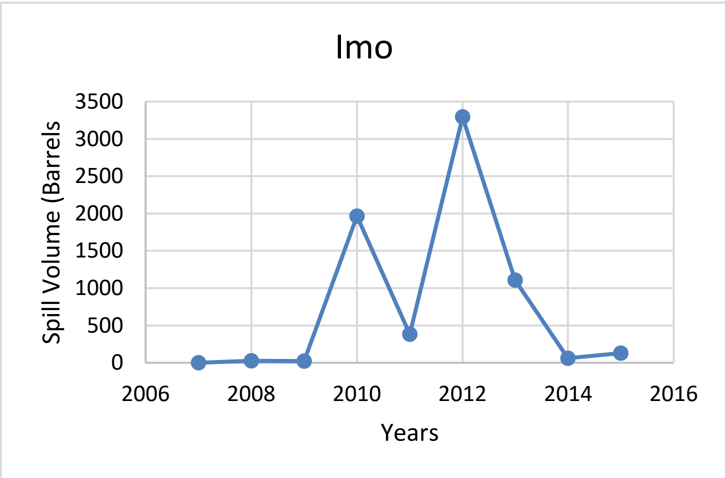
Poisson distribution of rare events. It was applied in the study of leukaemia in children, which came from assumed contamination by nuclear energy stations in the United Kingdom (Openshaw et al., 1988). The method was used in slightly modified form more recently (Openshaw and Turton, 2001). In addition to hotspots detection, this research also seeks to answer the question as to why and explain the existing trend and infer potential exposure risk.

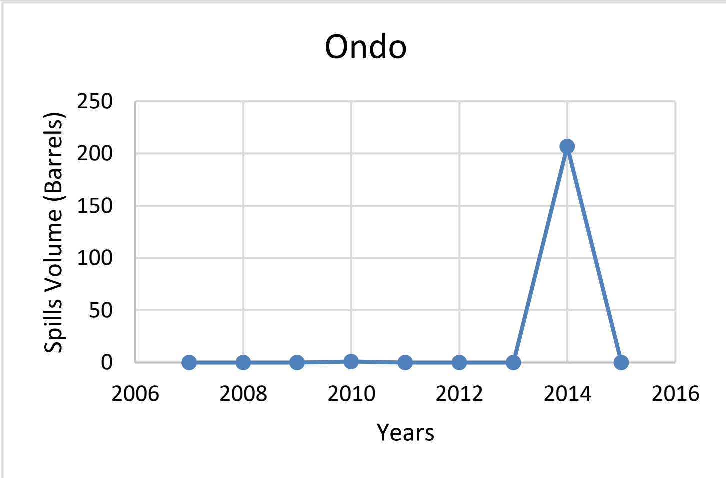
**Appendix 2. Temporal profile of oil spill volumes from 2007 – 2015 according to states of the Niger Delta.**



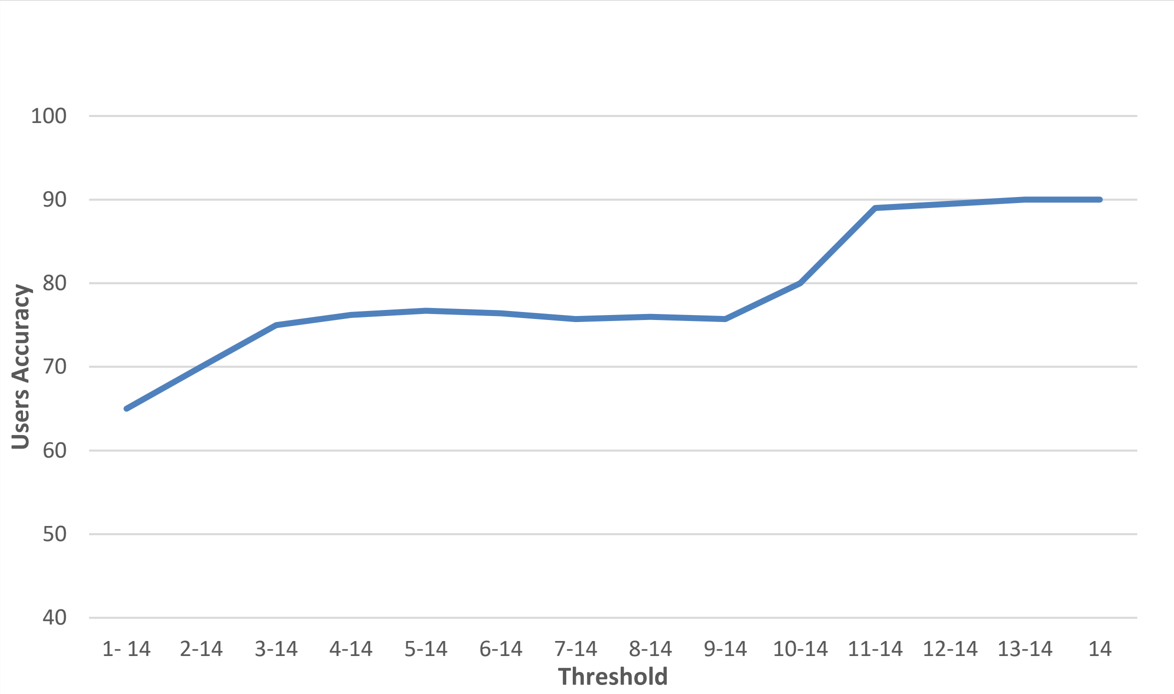

Akwa Ibom
Spill Volume (Barrels)
35000
30000
25000
20000
15000
10000
5000
0
2006
2008
2010
2012
2014
2016
Years


Abia
Spill Volume (Barrels)
2000
1500
1000
500
0
2006
2008
2010
2012
2014
2016
Years


Imo
Spill Volume (Barrels
3500
3000
2500
2000
1500
1000
500
0
2006
2008
2010
2012
2014
2016
Years

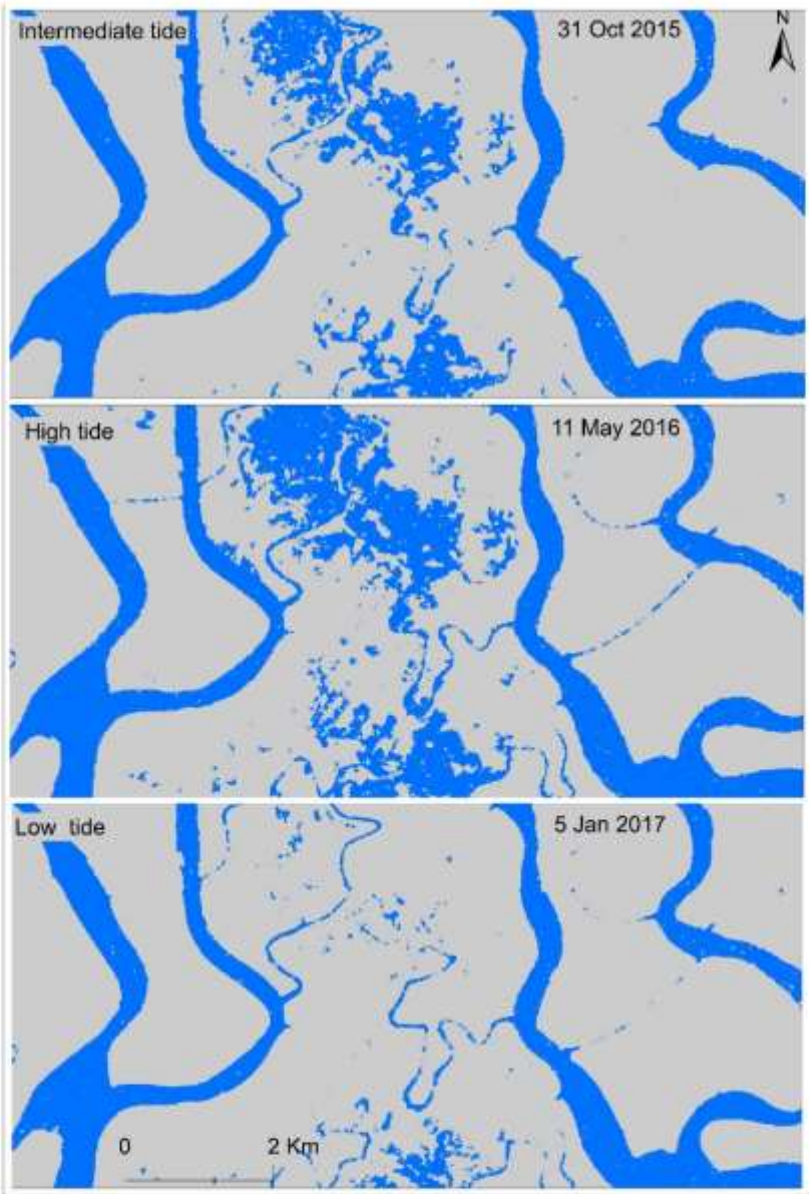

Ondo
Spills Volume (Barrels)
250
200
150
100
50
0
2006
2008
2010
2012
2014
2016
Years

**Appendix 3. Classification accuracy as a function of threshold used for delineation of permanent water bodies.**



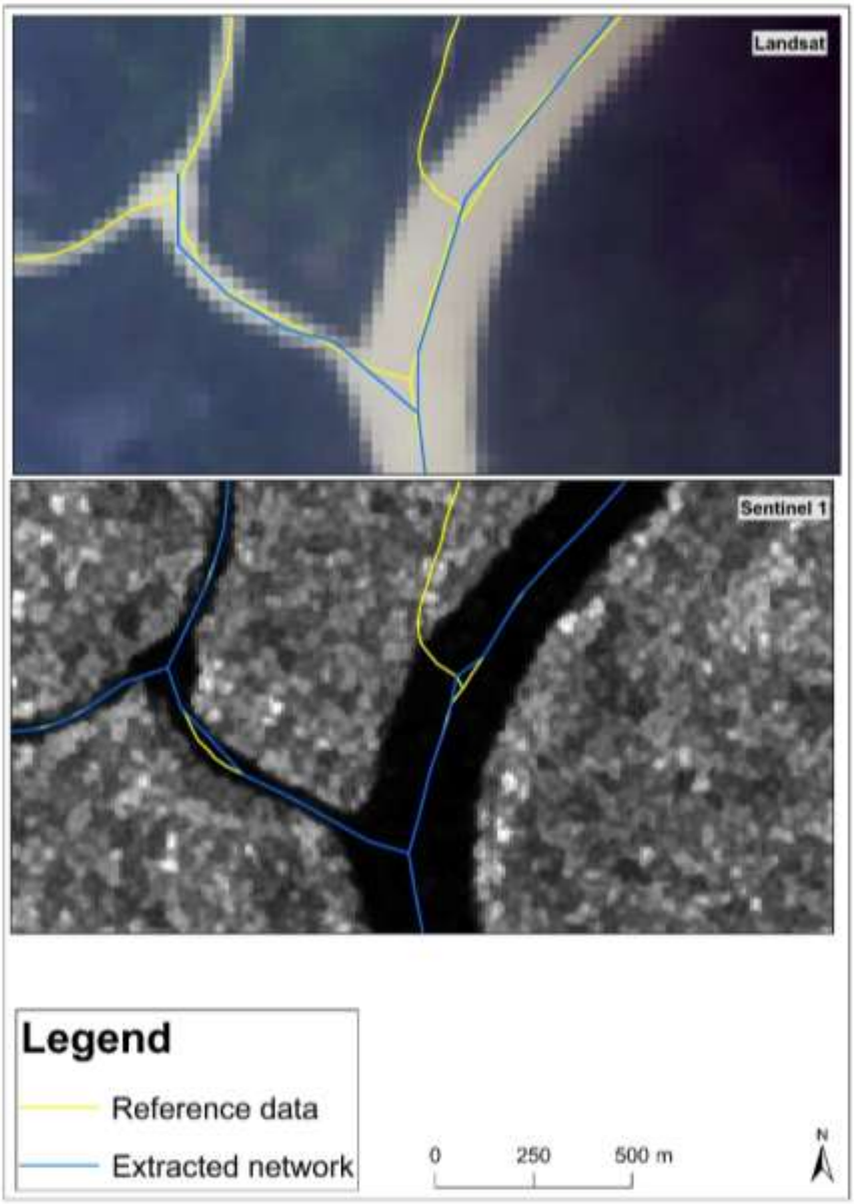

A combination of methods were used in determining the threshold used for delineating persistent water bodies. Initially, standard image classification accuracy assessment technique was used using the range of threshold as a single image (1-14, 2-14, 3-14, 4-14, 5-14, 6-14, 7-14, 8 -14, 9-14, 10-14, 11-14, 12-14, 13-14 and 14). This figure in (Appendix 3) shows the result of the classification accuracy, the reference data was derived from the high-resolution ArcGIS Imagery. As the figure the plateau of the accuracy at 12-14 informed the choice of the threshold as the optimum one. In addition, this was supported by subjective visual interpretation of the various threshold by simple overlay and visual comparison as to which aligns better with reference river systems as shown in Appendix 6.

**Appendix 4. Temporal difference in tidal states of river systems contributing to ephemeral nature of some rivers in the Niger Delta.**



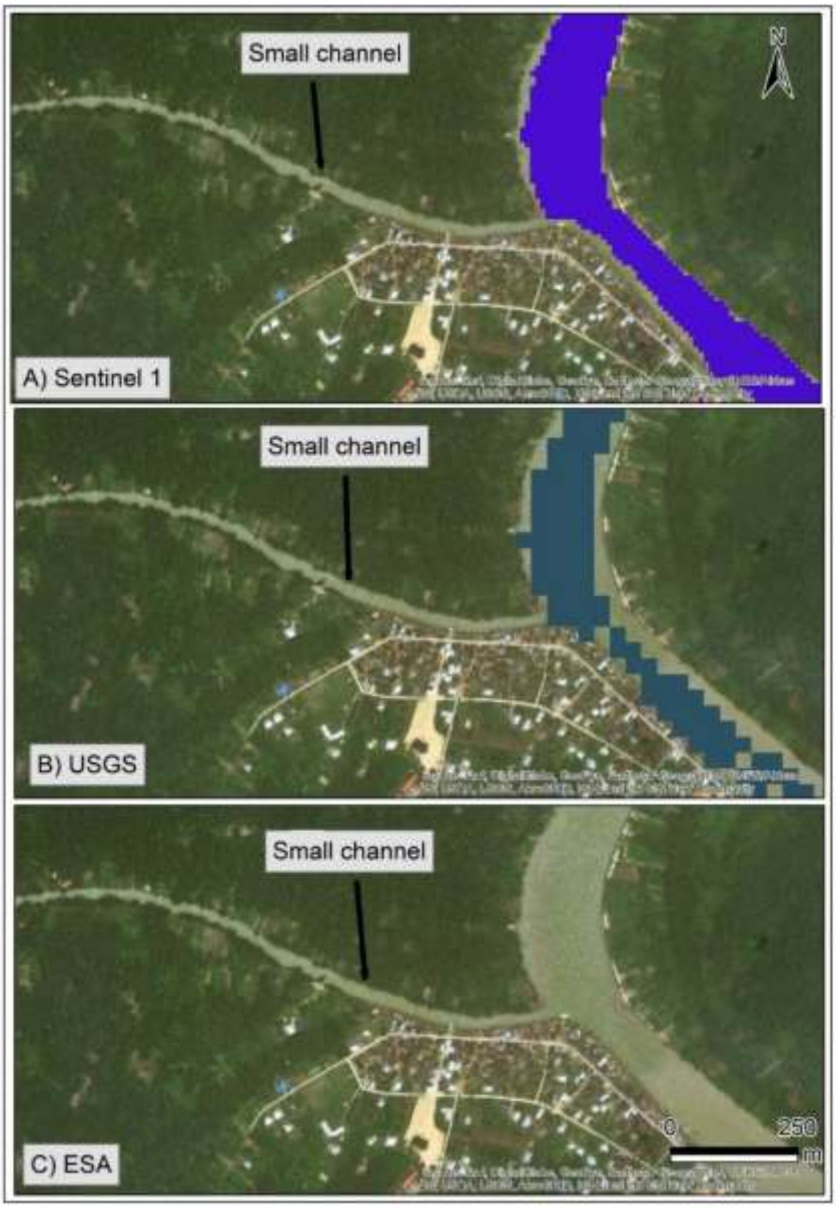

Due to the temporal and spatial variation in many forms of precipitation especially rainfall, this can lead to the occurrence of ephemeral water bodies (Figure 4.4). Since it has been demonstrated that radar is good at detecting water bodies, the occurrence of such ephemeral water entities can be revealed in temporal data. In addition to the temporal and spatial variability of rainfall which contributes to ephemeral streams, hydrological conditions such as tidal states influence the river systems which make some part of such systems transient in time. For example, Appendix 8 shows how tidal state can influence the pattern of river systems contingent on when the image was taken. The image clearly shows variation in what appears to be high, intermediate and low tide conditions, thereby influencing hydrological conditions.

**Appendix 5. Sentinel 1 and USGS delineated networks overlaid on raw Landsat and Sentinel 1 data showing potentials of performance levels.**

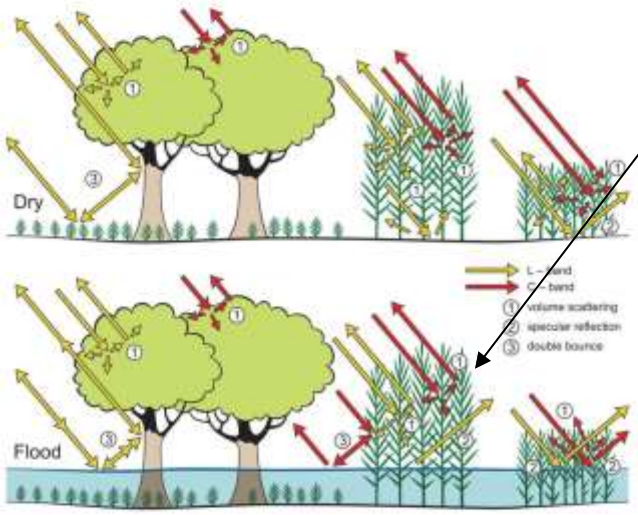



Appendix 5 reveals Landsat optical and Sentinel 1 data drawn at the same scale with the latter visually demonstrating better spatial resolution. This is evident in the visibly pixelated edges of the river network in the optical data compared to Sentinel 1 data. In addition, the relative difference in how optical (reflectance) and radar (backscatter) data detect features contributes to how they resolve difference in land cover features, therefore difference in performance levels.

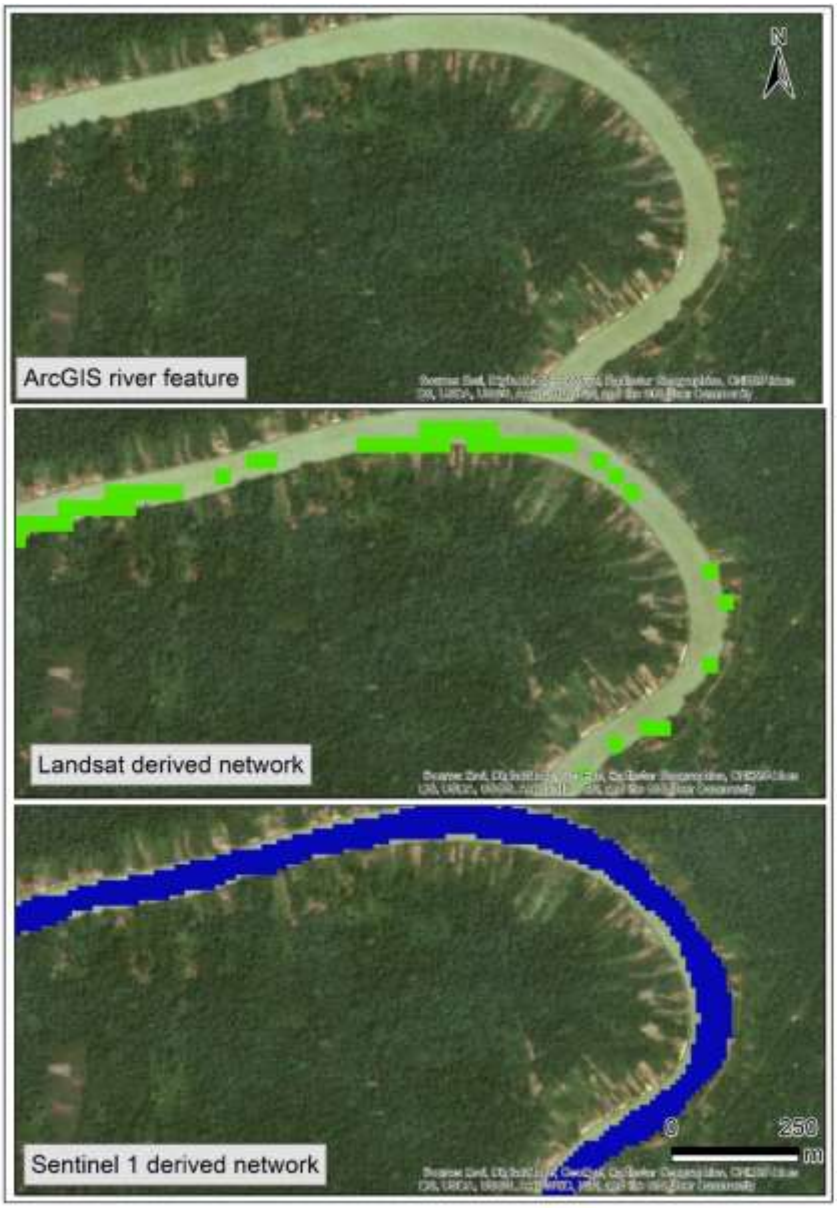
**Appendix 6. Delineated network from Sentinel 1, USGS and ESA data showing the low performance of Sentinel 1 data in resolving small channels. This shows that ESA data did not capture any segment of the small channel.**



**Appendix 7. The physical characteristics of river network in the Niger Delta and C band radar response to land cover types.**



**Appendix 8. Inter-comparison between USGS Landsat derived network and Sentinel 1 data spatial resolution.**



**Appendix 9. Temporal data of Landsat between 2003 and 2018 showing potential stability of river channels.**