Ecological Risk Assessment of Oil Spill Events using a Coupled Geospatial and Weight of Evidence Data-Process Model

Abstract. This research work attempted applying geospatial approach to ecological risk assessment to quantify environmental exposure to oil pollution in the Niger Delta. Spatial data on pipelines, oil spills and land cover data were analysed in order to quantify the extent of ecological resources exposure to oil pollution. Regional scale risk assessment was done using the combination of geospatial and statistical approaches. Spatial analysis was adopted for geospatial approach which will involve Hotspot analysis and Proximity analysis. Weight of Evidence was adopted for statistical computation. Ecological resources were identified from land use map and ranked according to their perceived importance. Hotspots of oil spill incidents were determined using spatial autocorrelation. Ecological resource vulnerability was determined using buffer zoning of 5km and 10km respectively as high and low risk zones, with sample maps made to show extents of resources at risk. Areal extent of ecological resources at risk were calculated and standardized for each of the delineated buffer zones. An aggregate of the weight of each ecological resources and area was computed to categorize the risk as either high, medium or low. 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 procedure was seen as an alternative to existing management processes used for monitoring and management of oil spills.

Keywords: Ecological Risk Assessment, Geoinformatics, Environmental Pollution.

Introduction

Nigeria has consistently been ranked as Africa's top oil producer and the world's sixth largest (Taft et al, 2015). Oil export money is still the country's main source of income. The Niger Delta is Africa's largest river delta and Nigeria's most important oil-producing region (Ndidi et al., 2015). Mangrove forests, freshwater marshes, and biodiversity-rich tropical rainforests make up this endangered habitat (Anejionu et al., 2015). However, the region has been afflicted by environmental degradation and deterioration as a result of the oil and gas industry (Zabbey et al., 2017). The majority of these environmental issues are caused by spills caused by inadequate management, oil and gas infrastructure maintenance, and sabotage (NDDC, 2006).

The transportation of crude oil is primarily reliant on petroleum product pipeline networks. Although most pipes are buried below, natural and human activity regularly exposes them, causing damage and spills. According to reports, 75 percent of oil leak mishaps in the region are caused by third-party tampering with pipelines and related equipment (SPDC, 2014). Crude oil spills have been linked to established and claimed health hazards. TPH chemicals including benzene, toluene, and xylene (found in gasoline) can cause harm to the central nervous system (Bhatnagar et al, 2013). In addition, ingestion of Petroleum Hydrocarbon contaminated food, inhalation, and recurrent contact with the oil-water interface can cause poisoning, increasing flora and wildlife mortality.

According to data from the National Oil Spill Detection Agency, Nigeria recorded 4,919 oil leaks between 2015 and March 2021, losing 4.5 trillion barrels of oil to theft in four years, with the majority of spills attributed to sabotage with a figure of 3,628, against operational maintenance which has a figure of 106. He also stated that Nigeria lost $4.75 trillion on oil activities between 2015 and 2018, equating to 400,000 barrels per day, according to the Nigeria Natural Resources Charter.

The problem of oil leaks is prevalent throughout the Niger Delta. However, due to their dynamic and complex nature, patterns of spills over space and time remain poorly understood. Many players have been identified in the oil theft process, which occurs at various levels of operational sophistication (Boris, 2015). Pipelines, which connect oil fields to jetties, depots, and export terminals, are responsible for the majority of spills in the Niger Delta. The pipeline network is at risk due to a lack of enforcement of rights of way (ROW), which are designed to limit activity near pipes. There were 16,083 pipeline leaks between 2002 and 2012, the vast majority (97.5%) of which were caused by vandalism (Anifowose et al., 2012).

Despite the fact that the region has piqued the interest of many academics, few have attempted to integrate information on pipeline oil spills with potential consequences, particularly attempts to initiate detailed step-by-step ecological risk assessments that would aid regional level ecological risk communication and management processes through predictive modelling, a key step in spatial epidemiology and exposure science. Furthermore, given the magnitude of the problem, a regional approach based on multi-faceted data integration and spatial analysis is required to monitor pipeline oil spills and manage their environmental repercussions through risk assessment, communication, and management.

Oil Spill Pollution and its Impact

Because they are released into the environment from well-known locations such as broken crude oil pipelines, pollution from an oil pipeline is usually categorised as Point Source pollution. 2017 (OECD). With the correct approach, it is possible to identify and quantify the source and extent. Pipeline ruptures are causing more oil spills, partly due to aging infrastructures, expansion into deeper oceans, and sabotage (Jernelöv, 2010).

Crude oil, also known as Petroleum Hydrocarbon, is a natural, sticky, and flammable liquid that is generally released through burst pipes. It has a dark brown color and a chemical makeup that varies widely (Sayed, 2021). Crude oils with low sulphur content are called "mild," whereas those with high sulphur content are called "acid." (Sayed, 2021) . The solubility of petroleum components in organic solvents is divided into four categories. The four primary components in crude oil are saturated aromatics, resins, and asphaltenes, collectively known as SARA (Al-hawash et al, 2018). Although the environment contains a variety of pollutants, persistent organic pollutants (POPs) from crude oil pose a serious threat to the ecosystem in which they occur (Sousa et al., 2018). This is because of their bioavailability in biota as well as their negative effects on human and environmental health (Zhang et al., 2013). Spilled oil is extremely hazardous, and it frequently causes functional and behavioural problems in plants and animals. Furthermore, oil spills harm birds as well as fish and shellfish.

Organic contaminants can be found in the air, soil, sediments, and water bodies, regardless of their source (Cheng et al., 2018). As a result, once released into the environment, their potential for human and environmental exposure becomes endless (Zhang et al., 2013). Organic pollutants are released into the atmosphere through volatilization from water and soil or direct emission. Pollutants emitted into the atmosphere have the potential to harm human health (Hung et al., 2013). The chemical and physical features of pollutants, as well as their quantity at source, determine their concentrations in the atmosphere (Zhang et al., 2013)

Any oil pipeline that ruptures due to sabotage, bad maintenance, or aging equipment will spill its contents into the environment. Depending on the qualities of the chemical or environmental medium, an organism may come into contact with hazardous Petroleum Hydrocarbon through the cutaneous, inhalation, or ingestion pathways (Ferguson et al., 2020). Crude oils are known to cause health problems. TPH chemicals including benzene, toluene, and xylene (found in gasoline) can cause harm to the central nervous system (Bhatnagar et al, 2013).

Oil spills are a global environmental problem for environmentalists, yet they attract less attention in developing countries than they do in industrialized countries. Since oil prospecting in the Niger Delta began in 1952, Nigeria, Africa's largest producer of oil and gas, has experienced considerable oil pollution. Oil spills are a common occurrence in the Niger Delta. However, due to their dynamic and complex nature, patterns of spills through area and time remain poorly understood. Many players have been identified in the oil theft process, which occurs at various levels of operational sophistication (Boris, 2015). The majority of spills in the Niger Delta happen on pipelines, which are important infrastructure elements that connect oil fields to jetties and depots and terminals for export. The pipeline network is at risk due to a lack of enforcement of rights of way (ROW), which are designed to limit activity near pipes. Communities expand, putting them in regions where pipelines threaten them even more (Anifowose et al. 2012; Shittu 2014). As a result, pipeline mishaps account for the vast bulk of spills in the Niger Delta.

Geospatial technique has also been identified as a simple, efficient, and cost-effective method of monitoring, mapping, and assessing environmental risk over a spatial scale. Large volumes of digital data have been generated and made available as a result of advances in information and communication technology (ICT). This, together with parallel software and hardware improvements, has resulted in the creation of computer-assisted decision-making systems known as Decision Support Systems (Wangdi et al., 2016). Such systems have gained traction in the decision-making process, but the problems they answer are typically non-spatial, therefore location is largely unimportant.

Weight of evidence is a process based analytical method that utilizes evident data to assemble, weigh and evaluate information to present a scientific result which can be used for further predictions and aid decision making and is usually a preferred method when there are multiple pieces of evidence to be considered (SETAC,2018).

Identifying the spatial and temporal dynamics of spills and their consequences can aid decision-making on safety resource allocation in priority areas, as well as the extent of ecological resources exposed to pollution and the rate at which they are contaminated. This study aims to close the gap by offering a framework for analyzing spills and their consequences. This is predicated on the understanding that employing a Geographical Decision Support System (SDSS) methodology gives a realistic and unbiased means of detecting and perhaps controlling this specific spatial problem.

Environmental monitoring to ascertain levels of exposure to toxins is critical to ecological sustainability. Over time, different methodologies have been used by various researchers. Direct measurements of water, soil, sediments, and air, based on norms and guidelines, are among them (UNEP, 2011). Because the occurrences of pollutants are dependent on the sources, the distance to the source is believed to influence the level of exposure and damage the pollutants cause in the receiving environment. Levels of influence are also accounted for by differences in environmental sensitivity (Ondráek et al., 2014). Some surroundings, for example, are more sensitive than others. Furthermore, the resistance capacities of various land cover types vary. While a forest may be able to withstand pollutants for a long period, equal levels of pollution could suffocate grassland or other ecosystems that are more vulnerable (Duke, 2016). For mapping the exposure of broad regions like the Niger Delta, spatial methodologies based on this knowledge are required.

Tropical forests and mangroves are significant habitats for marine organisms, as well as spawning grounds for shrimp and other fish species. Several studies (López-Angarita et al., 2016) have documented their use for lumber, tanning agents, and fuel wood. Mangroves are abundant along most coastal shorelines in the tropics as intertidal plant species, making them vulnerable to oil spills, such as in Nigeria's Niger Delta. These salt-tolerant mangrove species have well-developed and maintained root systems, but their roots are usually partially submerged, exposing them to surface oils and resulting in osmoregulation and respiration impairment, which eventually leads to mortality (Duke, 2016).

As a result, the research is a cost-effective way to investigate the complicated spatial problem caused by oil spills and its effects across a vast geographic region. Through the use of sourced and developed geospatial data and tools, this study gives regional insights on the scale of integrated exposure, patterns, and trends of oil spill problems. Furthermore, the findings of this study could be used as critical inputs in regional spatial decision support systems.

Materials and Methods

Study Area

The Niger Delta comprises all of Nigeria's oil-producing states in the south-south, one from the southwest, and two from the southeast (Hooper et al., 2002). It stretches through the states of Cross River, Akwa Ibom, Abia, Imo, Rivers, Bayelsa, Delta, Edo, and Ondo, covering an estimated 70, 000 km2 of wetland and ranking among the top ten largest swamps and deltaic ecosystems in the world (Imoobe et al, 2009). Only a handful of the habitats found in the Niger Delta include barrier island forest, montane ecosystems, mangrove swamp forest, lowland rain forest, derived savannah, and fresh water swamp (Anejionu et al., 2015). The lowland rainforest includes a fraction of non-riverine habitats in addition to the savannah type found in the north eastern Niger Delta. The freshwater wetland ecosystem of the Niger Delta is approximately 17,000 km2 (NDDC, 2006). It is home to a wide range of endangered species, but it is also heavily contaminated by oil spills, resulting in a loss of biodiversity (Kadafa, 2012). The mangrove forest covers around 40 km2, though it narrows as it approaches the estuaries (Zabbey et al., 2017). Crabs and shrimp, among other animals and plants, live on its floor (Balogun, 2010). Oil spills pose a serious threat to this fragile ecology (Anejionu et al., 2015).

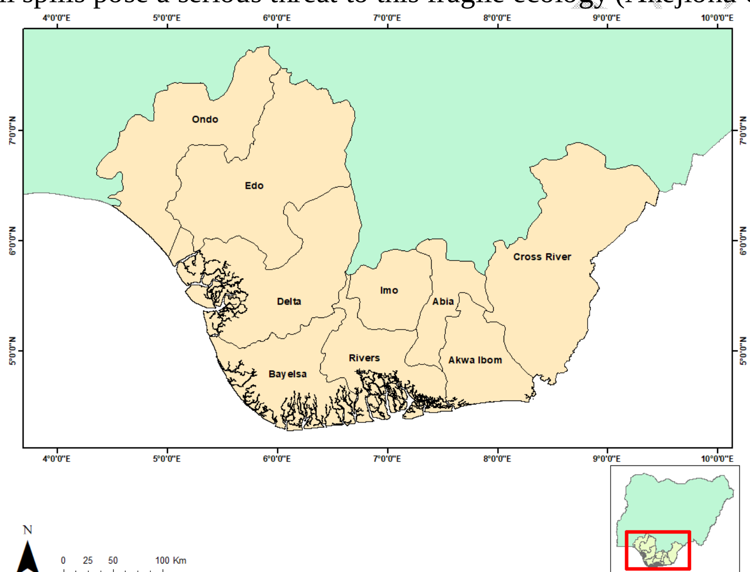

Fig 1. Map of Study Area

Data Collection and Analysis

This research relied on updated database on oil spills in the Niger Delta to determine human and environmental exposures sourced from Shell Oil spill Database.

Oil spill data

This analysis used spill records from the Niger Delta for the years 2018. Shell Nigeria, a multinational corporation that has been active in Nigeria since its inception, provides these. The thorough database includes information on spill dates, times, and locations (GPS coordinates), spill duration, oil type, spill volume, and spill cause. Since 1995, SPDC-JV has published annual oil spill information in the Shell Sustainability Report, and this website adds to the transparency of spills at SPDC-JV facilities in Nigeria (Oil Spill Data, 2022). However, data analysis reveals that some oil spills are categorised as 'others' or' mystery spills,' implying that the causes are unknown. This highlights a limitation of the data, but this does not affect the main analysis of this research which is based on the scale of oil spill occurrence.

Land Cover Data

Landcover data in Niger delta is usually categorized broadly into Built up areas, agricultural land, forested lands and fresh water. However, for this project a second level classification was done to obtain better insight on categorization of ecological resources. The classifications were: Agricultural land, natural water bodies, mangrove forests, salt marsh, forested fresh water, sedge fresh water, minor urban areas, distributed forests, teak plantation, tree crop plantation and undistributed forests.

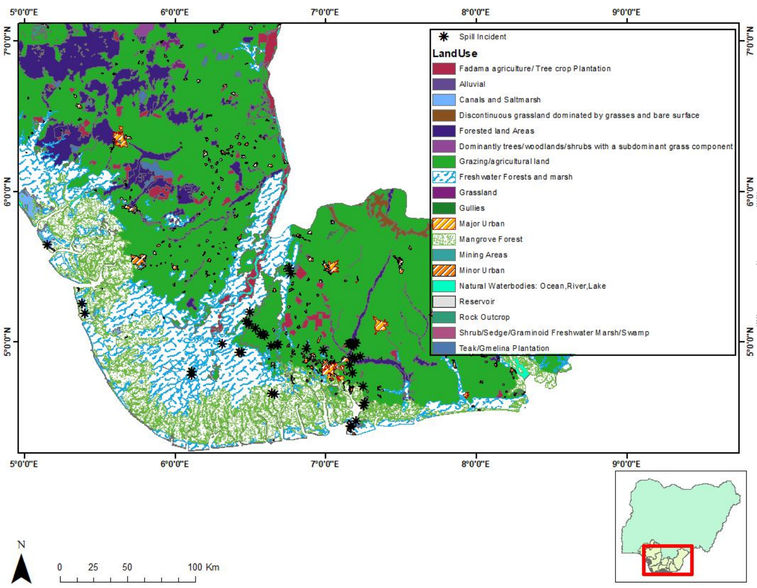

Fig 2. Land Use Map of Study Area

Methods for Data Analysis

Oil spill Hotspot Detection

Due to the relatively linear distribution of oil leak places over the pipeline network, a different method of locating hotspots was used. Previously, Xie and Yan (2008) used a network-based Kernel Density Estimation which is a popular approach for point datasets to estimate accident hotspots on congested roadways. Local Indicators of Spatial Autocorrelation, or hotspots, are significantly distinct places in a particular distribution of data based on applied statistics (McCullagh, 2006). The level of interdependence between the variables, as well as the kind and strength of that interdependence, is measured by spatial autocorrelation. It will depict the dispersal of oil spills across space with varying degrees of severity. Moran's statistic I and Geary's coefficient c are the autocorrelation coefficients for interval and ordinal data, respectively.

Moran's I is based on cross-products to measure value association, and is calculated for N observations on a variable *x* at locations *i, j* as:

$$I = \frac{N}{W}\frac{\Sigma_i \Sigma_j \omega_i j(x_i - \bar{x})(x_j - \bar{x})}{\Sigma_i (x_i - \bar{x})^2} \qquad 1$$

where $\bar{x}$ is the mean of the x variable, *wij* are the elements of the spatial weight's matrix, and W is the sum of the elements of the weight's matrix:

Moran's I varies from -1 to +1, with an expected value approaching zero for a large sample size in the absence of autocorrelation. These hotspots produced by spatial autocorrelation analysis 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.

Proximity Analysis for Ecological Resource Vulnerability.

The number of points under observation that fall within a given radius is calculated using proximity analysis. This is a critical technique in spatial statistics that has been widely used in a variety of domains, including environmental and ecological research. It can, for example, be used to determine how many rivers are at risk of being polluted in the event of an oil spill based on a set radius and spatial distribution. Conducting a proximity analysis can assist oil and gas stakeholders in planning facility management, monitoring, and risk assessments aimed at maintaining environmental resource protection, or in line with the intended goal, as the case may be.

One of the prominent proximity analysis tools available in a GIS software is the buffer Zone analysis where polygons are generated at a distance around features of interest to determine which features fall within defined buffers. Integrating geospatial and spreadsheet data has been successfully used to analyse ecological resources vulnerability which is measured on the basis of ecological sensitivity and is an important aspect of ecological risk assessment (Zhang et al., 2015).

Buffer Zoning type of proximity analysis which is used to show ecological resource vulnerability delaines points under observation that falls within a desired radius. This tool is widely applied in various fields including environmental and ecological studies. Vulnerable areas are further classified based on set criteria for exposure and risk characterization.

Statistical Analysis for Ecological Risk Assessment

Various statistical approaches can be used to calculate the extent to which resources are vulnerable to risk in any hazardous event like an oil spill incident. For this research, we adopted the weight of evidence analysis.

Weight of Evidence Analysis

Ecological resources are seen as critical natural capital and assets that should be protected, hence the need for cost allocation. Weight of evidence approach to ecological risk assessment is seen as a good-fit to be integrated with spatial data to obtain reliable results. The weight-of-evidence framework represents the process of assembling, weighing, and evaluating information from various sources to come to a scientifically defensible conclusion (Burton et al.,2002). Several lines of evidences are considered and each is assigned a weight based on its relevance, strength, and reliability. A line of evidence are similar types of evidences. The weight allocated to each resource would be obtained according to its perceived importance (Lowel et al.,2000).

According to the EFSA Scientific Committee (2017), weight of evidence approach to risk assessment usually follows a precise and organized basic steps which involves; assembling the evidence into lines of evidence of similar type, weighing the evidence, integrating the evidence.

Assembling Lines of Evidence

The lines of evidence for this research work were

1. Landcover/Landuse
2. Oilspills associated by clusters and intensity
3. Areal extent of ecological resources delineated by buffer

Results

Data Presentation

The rank was assigned to land cover based on their importance are shown on the table below:

Table 1 Ranks assigned to Ecological Resources

Land Cover Type	**Rank**
Agricultural Land	5
Natural Water bodies	5
Mangrove Forests	3
Salt Marsh	3
Forested Fresh Water	4

Sedge Fresh Water	4
Minor Urban Areas	5
Distributed Forests	2
Teak Plantation	3
Tree Crop Plantation	4
Undistributed Forests	2

Ecological Vulnerability Coefficient

A. Vulnerability coefficient was assigned to different zones defined by buffers of 5km and 10km from clusters established by hotspot analysis.
B. Areas within 5km had a vulnerability coefficient of 3
C. Areas within 10km had a vulnerability coefficient of 1.5

Data Analysis Process

<u>*Spatial and statistical analysis*</u>

Charts were initially constructed to summarize the major spill incidents (sabotage, operations and others) over time. Proportional symbols maps were then used to visualize changing patterns and extents of oil spills in across in 2018. Graphs and tables detailing weighted lines of evidence were constructed to show variations in magnitude and intensity of spill extent using details from hotspots established.

The processes flow used for hotspot analysis were:

***Creation of Events*:** Point of oil spill across spatial spread was used to create event in order to get an aggregate of clusters at defined distances. This was done using the integrate data tool in arc GIS. This is one of the most important steps involved in hotspot analysis process when using the spatial autocorrelation approach. Events were created at a spatial tolerance of 9km which is the distance that determines the range in which feature vertices are made coincident. This implies that events which are 9km from each other are assumed to be clustered. This spatial tolerance rate was chosen because events were not to be treated as individuals but a subset of an aggregate that would later be treated as a point of pollution.

***Collection of Events*.** After events were created by determination of feature vertices, the events were collected to show weighted counts using the rate of coincident that occurs. These weights are important and would be used to perform the spatial autocorrelation analysis using weights of incidents collected. Oil spill data were aggregated at points of coincident using 9km distances from each other.

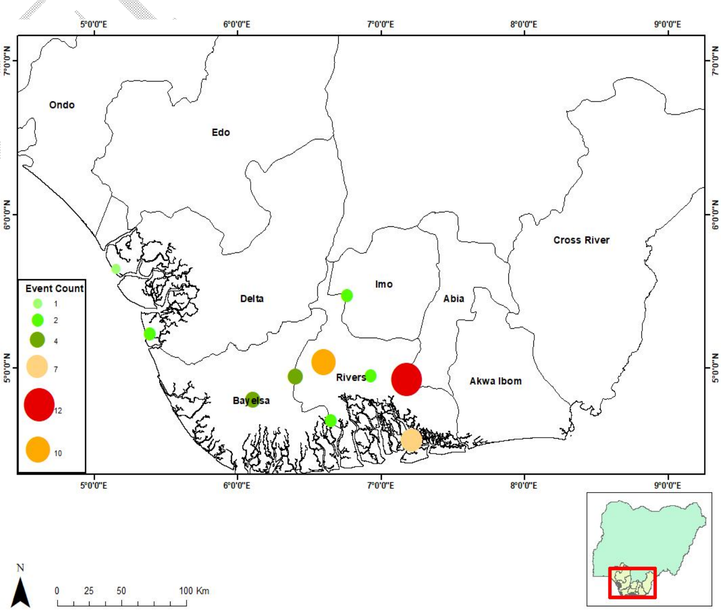

Fig 3 Map showing Spill Events created and collected

The event count table was used to analyse the state with the highest occurrences of oil spill event from result obtained from the spatial autocorrelation process. This gives insight on the state affected the most by oil spill incident.

Table 2 Event Summary Table

Location	**0**	**1**	**2**	**4**	**7**	**10**	**12**	**Total**
Delta		1	2					***3***
Bayelsa				4				***4***
Imo			2					***2***
Abia							12	***12***
Cross-River	0							***0***
Akwa-Ibom	0							***0***
Rivers	1		2	4			12	***19***

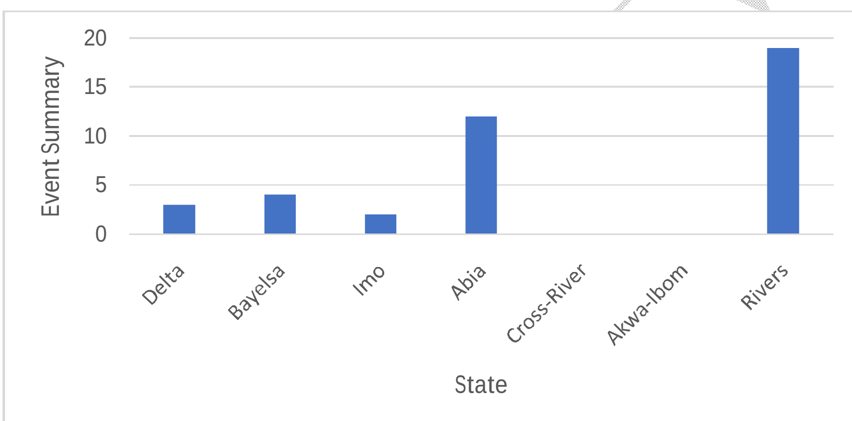

Fig 4 Event Summary Graph

From the graph produced using the event creation matrix, Rivers State had the highest occurrences with 19, followed by Abia state with 12. Bayelsa state had 4 events while Delta State has 3 events and Imo State had 2 events respectively. Cross Rivers and Akwa Ibom had no events recorded for the period under consideration.

Spatial Autocorrelation Analysis**:** This was done according to a model by Moran. Before Moran's can be calculated, the points need to be aggregated by imposing a structure on the data points (grid or geographic unit) that constraints the number of neighbours to be considered. This is done to be able to calculate a weight matrix. This weight matrix can be a measure of contiguity between cells or can be defined as a distance-based weight, which we did in the previous step when we collected and created events. The spatial autocorrelation is computed using the spatial autocorrelation tool in ArcGIS. This will produce a layer of aggregated surface of events with Z and P scores either positive or negative with regards to the correlation of events.

Interpolating Surfaces to show hotspots**:** This is a process of interpolating z-scores obtained from the autocorrelation process to show hotspots as they occur. Simple Inversed distributed weight method was used to interpolate continuous raster surface showing clusters of events with variations in intensity which shows hotspots as thy occur over space in two dimensions.

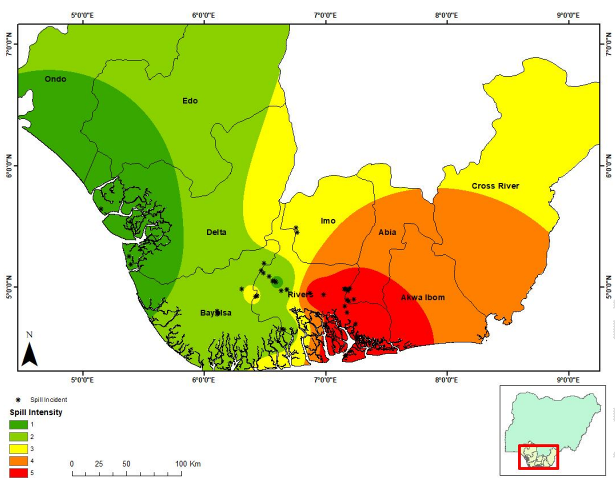

Fig 5 Oil spill Map

<u>Potential human and environmental exposure to hydrocarbon contamination</u>

Proximity Analysis using Buffer Zones

The risk zones were defined using the submission by Shittu that oil spill impact go as far as 2.5km. However, for our research since we are treating clusters and working with hotspots which is a collection of spatially correlated oil spill events, we doubled Shittu's submission and chose 5 km as High-Risk Zones with a risk zone coefficient of 3 and areas that fall within buffer rings 10km away as medium risk zones with risk zone coefficient of 1.5 For the analysis, 5km and 10km buffers were created using the buffer tool in ArcGIS. The buffer rings created were used to clip landcover polygon to extract only ecological resources and the corresponding surfaces that fall within the 5km and 10km risk zones. Areas for each landcover factor that fell within the declined zones were computed and scores standardized.

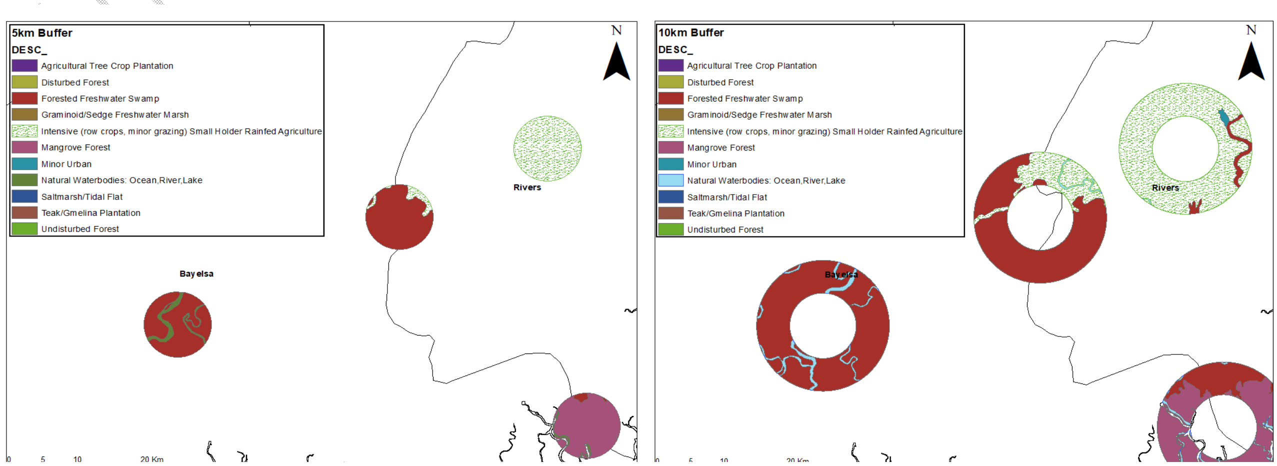

Fig 6 Examples of 5km and 10km buffer from spill points

Standardization of a set of numbers or standard score describes the difference of the raw scores from a sample mean expressed in standard deviation while preserving the absolute variation between the scores (Walrath 2011). It is denoted by

$$z = \frac{x-\mu}{\sigma} \qquad 2$$

Where
z is the standardized score
μ is the mean of the distribution
x is the individual raw score
σ is the standard deviation
Standardized score for area, weight and Rank was summed up and divided by the total possible score to obtain the risk factor which ranges from 0 to 1 according to the Weighted of Evidence approach. This is important to ensure a normalized distribution of scores. For this research, we developed an equation to compute risk factor of ecological resources using results from geostatistical analysis and biostatistics for environmental data analysis. The equation for risk factor computation is:

$$Rf = \frac{\sum Rwz}{TPS} \quad (3)$$

Where,
Rf is the risk factor,
R is the rank of the ecological resource
w is the weight of the ecological resource
z is the standardized area of ecological resource
TPS is the total possible score which is obtained by summing up the row values with the highest lines of evidence.
The computations are shown in the table below:

Table 3 5km Buffer zone with coefficient of 3

Land Cover	**Area (SqKm)**	**Rank(R)**	**Weight(W)**	**Zarea(Z)**	***Rf***	**Category**
Agricultural Land	267.46	5	15	2.15	1	*High*
Natural Water bodies	24.72	5	15	-0.42	0.88	*High*
Mangrove Forests	158.72	3	9	1.00	0.59	*Medium*
Salt Marsh	29.54	3	9	-0.37	0.53	*Medium*
Forested Fresh Water	189.87	4	12	1.33	0.78	*High*
Sedge Fresh Water	0.40	4	12	-0.67	0.69	*Medium*
Minor Urban Areas	9.93	5	15	-0.57	0.88	*High*
Distributed Forests	3.32	2	6	-0.64	0.33	*Low*
Teak Plantation	3.59	3	9	-0.64	0.51	*Medium*
Tree Crop Plantation	2.73	4	12	-0.65	0.69	*Medium*
Undistributed Forests	15.81	2	6	-0.51	0.34	*Low*

Rf* *Risk factor*

Results from analysis performed using a combination of geospatial statistics and weighted evidence analysis clearly shows ecological resources vulnerability at different distances from each cluster where spill had occurred. For ecological resources which falls within the 5km buffer from spill hotspots established by spatial autocorrelation, Agricultural land, Water bodies and urban areas which has risk factors of 1, 0.88 and 0.88 respectively fell under resources at high risk. Sedge fresh water, Tree crop plantations, Mangrove forests, salt marsh and teak plantation with risk factors of 0.69,0.69,0.59,0.53 and 0.51 all fell under the medium risk category. Undistributed and distributed forest resources with risk factor values of 0.33 and 0.34 both fell under the low-risk categories.
These results have been graphically shown below

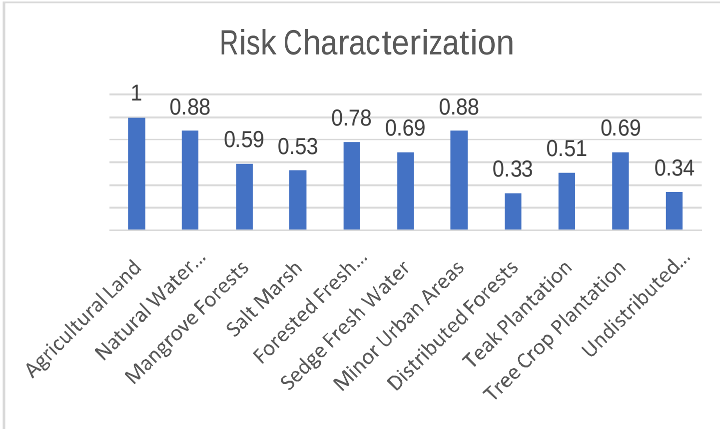

Fig 7 Risk Characterization Distribution within 5km buffer zone

Table 4 10km Buffer zone coefficient of 1.5

Land Cover	**Area (Sqkm)**	**Rank**	**Weight**	**zArea**	***Rf***	**Category**
Agricultural Land	763.95	5	7.50	2.06	1.00	*High*
Natural Water bodies	76.3	5	7.50	-0.40	0.83	*High*
Mangrove Forests	424.67	3	4.50	0.85	0.57	*Medium*
Salt Marsh	14.28	3	4.50	-0.62	0.47	*Low*
Forested Fresh Water	630.25	4	6.00	1.58	0.80	*High*
Sedge Fresh Water	1.84	4	6.00	-0.66	0.64	*Medium*
Minor Urban Areas	52.57	5	7.50	-0.48	0.83	*High*
Distributed Forests	10.98	2	3.00	-0.63	0.30	*Low*
Teak Plantation	4.9	3	4.50	-0.65	0.47	*Low*
Tree Crop Plantation	44.67	4	6.00	-0.51	0.65	*Medium*
Undistributed Forests	40.01	2	3.00	-0.53	0.31	*Low*

For ecological resources which falls within the 10km buffer from spill hotspots established by spatial autocorrelation, Agricultural land, Minor Urban areas, Forested fresh water, Natural water bodies and which has risk factor values of 1, 0.83,0.83 and 0.80 respectively fell under resources at high risk.
Tree crop plantations, sedge fresh water and Mangrove forests, with risk factor values of 0.65,0.64 and 0.57 respectively fell under the medium risk category.
Salt marsh, teak plantation, undistributed forests and distributed forests with risk factor values of 0.47, 0.47, 0.31 and 0.30 fell under the low-risk categories.
These results have been replicated graphically below;

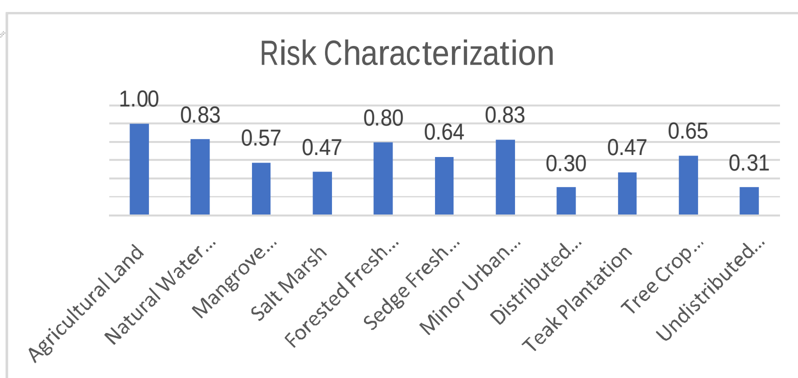

Fig 8 Risk Characterization Distribution within 10km buffer zone

Discussion

A regional scale ecological risk assessment was done. Spatial data on pipelines, oil spills and land cover data were analysed in order to quantify the extent of ecological resources exposure to oil pollution. This was done using the combination of geospatial and statistical approaches. Spatial analysis was adopted for geospatial approach which will involve Hotspot analysis and Proximity analysis. Weight of Evidence was adopted for statistical computation.

A variety of factors are known to contribute to oil spills. Both social and operational factors such as poverty , poor operational standards , use of obsolete equipment and low maintenance culture are key contributors to oil spill events (Anifowose et al., 2008). Using a delineation zone of 5km and 10km, potential human and environmental exposure to an oil spill was assessed in this study. The most significant and sensitive resources inside both buffer zones of vulnerability, according to the tables and graphs in the results, are agricultural lands, fresh water resources, and metropolitan areas. This is hardly surprising considering the fact that Niger Delta has the largest river delta in Africa which plays an important part in ecosystem services in the region and Nigeria at large.

Also, urban areas, although predominantly minor but also important settlements and dwelling where humans live also have medium to high risk factors. This raises serious concern and requires immediate attention to avoid potentials outbreak of hydrocarbon contamination through several pathways. Also, other sources of fresh water, undistributed forests and tree crops are also at risk but at minimal levels.

Ecological resources were identified from land use map and ranked according to their perceived importance. Hotspots of oil spill incidents were determined using spatial autocorrelation. Ecological resource vulnerability was determined using buffer zoning of 5km and 10km respectively as high and low risk zones, with sample maps made to show extents of resources at risk. Areal extent of ecological resources at risk were calculated and standardized for each of the delineated buffer zones. An aggregate of the weight of each ecological resources and area was computed to categorize the risk as either high, medium or low.

Ecological resources within the 5km buffer had Agricultural land, Water bodies and urban areas at high-risk category. Sedge fresh water, Tree crop plantations, Mangrove forests, salt marsh and teak plantation all fell under the medium risk category. Undistributed and distributed forest resources fell under the low-risk categories.

For ecological resources which falls within the 10km buffer Agricultural land, Forested fresh water, Natural water bodies and urban areas fell under resources at high risk. Tree crop plantations, Mangrove forests, sedge fresh water fell under the medium risk category. Salt marsh, teak plantation, undistributed forests and distributed forests fell under the low-risk categories.

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 procedure was seen as an alternative to existing management processes used for monitoring and management of oil spills.

Conclusions and 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. A combination of Geospatial technique (Spatial autocorrelation) and statistical analysis (Weight of Evidence) have proved to be a very good tool for Ecological Risk Assessment, utilizing the Data-Process Coupled Model of analysing environmental data.

For recommendations, Environmental sensitivity should be a perquisite for pipeline construction to forestall oil spill contamination of the environment in future. Also, Government agencies should make sure oil companies adhere to environmental guidelines and standards, activate environmental management systems and strategic environmental assessment of policy document where and when necessary.

Environmental resource managers, remediation experts, project managers, community leaders, and other stakeholders will benefit from this study, which not only identified the threatened resources but also revealed their geographical dimension. It also identified and ranked the most susceptible resources from most vulnerable to least vulnerable. This analysis has also showed huge regions of environmentally sensitive land cover immediately impacted by oil spills due to their location, policies related with placing or installing pipelines need to be evaluated in terms of environmental exposure and sabotage. As a result, it is proposed that an environmental sensitivity index be used to evaluate future pipeline construction in order to reduce spill impacts on sensitive habitats.

This research has also produced a set of spatial data that can be used to improve Nigeria's spatial data infrastructure. The pipeline data is now available for a variety of other regional applications, and it includes processed information on identified pipeline leak hot spots. The study also identified states with the highest risk levels, as well as natural resources with the highest exposure levels, in order to offer data on prospective exposure levels in the region. Water bodies were found as one of the most polluted land cover types and a medium for pollutant dispersion in this investigation. Based on pollutants in the Niger Delta, the study also created a spill effect map. The findings of this study can aid in the construction of a national spatial data infrastructure that is open to anyone.

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