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Geohazard Mapping of Eleme Spill Impacted Areas in Rivers State Using Remote Sensing and GIS

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ABSTRACT

This study provides an in-depth geohazard assessment of the Eleme oil spill's impact in Rivers State, Nigeria. Utilising high-resolution satellite imagery and land cover data, the research investigates the extent of environmental contamination and its implications on local agriculture, biodiversity, and the Eleme community's way of life. The study area encompasses Eleme Local Government Area, spanning approximately 140 square kilometers, and is home to significant agricultural activity, which is the traditional livelihood of the Eleme people. The language and culture of the Eleme, at risk of extinction, are also considered within the scope of the environmental analysis. The aim of the study was to investigate the environmental impact of the spill on the neighbourhood and the materials used covered, ArcGIS 7.1, Google earth engine, MS word 2019 and mixed geospatial methods were brought in to address the issues at hand. The research findings indicate that the 'Spill' class covers a substantial area of 0.700687km², signifying extensive environmental damage. Vegetation (0.007259 km^2) , despite being the most prevalent land cover, showed signs of fragmentation, suggesting habitat loss and potential biodiversity threats. Built-Up areas (0.002186 Km^2) and Roads (0.000658 Km^2), while less affected, highlight the ongoing urban expansion. High-resolution data analysis reveals precise spill mapping, essential for targeted remediation strategies. The study highlighted that resilience of local agricultural practices and cultural traditions amidst industrial impacts. It calls for urgent remediation measures, stricter spill prevention regulations, cultural preservation initiatives, and sustainable agricultural enhancement to ensure the community's well-being and heritage conservation. Recommendations include immediate clean-up actions, regulatory improvements, support for Eleme language and culture, and agricultural resilience building. This research serves as a model for addressing geohazard challenges in similar contexts, emphasising the need for a multifaceted response strategy.

Keywords: Geohazard mapping, Oil Spill, and Environmental Impact

1.0 Introduction

Geohazard mapping serves as a crucial instrument for understanding and managing environmental challenges associated with natural and anthropogenic activities. In the context of Eleme Local Government Area (LGA) of Rivers State, Nigeria, the proliferation of the petroleum industry and the consequent oil spills have created a paradigm necessitating comprehensive geohazard assessments. This paper aims to delineate and analyze the implications of oil spills within the Eleme LGA, employing geospatial technologies and geohazard mapping techniques to render a critical diagnostic of the current situation and future risks.

Eleme LGA, situated in the heart of Nigeria's oil-rich Niger Delta region, has been significantly impacted by oil extraction activities (Nwilo & Badejo, 2005). The frequency of pipeline ruptures and the resulting spills have not only degraded the local environment but also disrupted the socioeconomic fabric of the indigenous communities (Aghalino, 2009). Adopting a multidisciplinary approach that synthesizes inputs from environmental science, geology, and remote sensing, this research highlights the intersection of anthropogenic activities and their deleterious environmental outcomes (Obi & Rust, 2006).

In recent years, remote sensing technologies have advanced to facilitate detailed analyses of oil spills and their environmental repercussions (Ikechukwu et al., 2020). These technologies enable the identification of high-risk zones, assessment of spill extents, and evaluation of the impacts on both the terrestrial and aquatic ecosystems within Eleme LGA (Ologunorisa & Abawua, 2005). By encompassing a temporal dimension, geohazard maps proffer a historical narrative of oil spills, capturing their frequency, severity, and the efficacy of remediation efforts (Odumosu et al., 2013).

The urgency of developing robust geohazard maps is underscored by the increasing environmental regulations and the need for sustainable resource management practices (Ite & Ibok, 2013). These maps serve as strategic tools for policy-makers, environmental agencies, and stakeholders in the petroleum sector, fortifying the decision-making process and aiding in the development of proactive strategies for disaster mitigation and environmental restoration (Osuji & Onojake, 2006).

2.0 Literature Review

2.1 Spill Mapping Approaches

2.1.1 Classification

Classification is an element to categorize pixels of the identical significance or likelihood of land cover classes in an image. The classification could also suggest thematic multispectral information to justify numerical grouping. This process of grouping is based totally on Digital Numbers (DNs) due to spectral reflectance and emittance homes of capabilities found within the geographical space (Thomas & Ralph, 2000; Chudamani et al., 2014). The objective of these operations is to replace the visual evaluation of the picture information with quantitative strategies for automating the identification capabilities in a scene. This usually involves the analysis of multispectral photo facts and alertness of statistically-based decision regulations for figuring out the land cowl identity of each pixel and photograph. When these decision guidelines are primarily based entirely on the spectral radiances located in the facts, these methods fall into the domain of spectral sample recognition.

In both cases, the purpose of the classification method is to categorize all pixels in a digital picture, on to one of the numerous land cover classes. Transient design acknowledgement employments time as help in highlights distinguishing proof. In agrarian edit studies, for illustration, particular ghostly and spatial changes amid developing season can allow segregation on multidate symbolism that would be outlandish given any single date. An elucidation of symbolism from either date alone would be unsuccessful, in any case of the number of ghostly groups (Thomas & Ralph, 2000).

2.1.2 Supervised Classification and Types

A classification procedure is said to be supervised if the user either defines the decision rules for each class directly or provides training data for each class to guide the computer classification (Richards & Jia, 2006). Investigator distinguishes preparing destinations to speak to in classes and each pixel is classified based on factual examination (Jwan et al., 2013). The directed method has a few advantages over the unsupervised one. Within the directed approach, utilize data categories are distinct, to begin with, and after that their unearthly distinguishableness is inspected whereas within the unsupervised approach, the computer decides spectrally divisible course, and after that characterizes their educate esteem (Lillesand & Keifer, 1994). By the by, there are numerous restrictions to major classification strategies (administered and unsupervised) that were realized by (Castellana et al., 2007). Amid autonomous utility, and thus driven them to create an unused classification approach called cross breed classification strategy. This classification outperforms the restrictions said over and allow rise to a computerized classification approach utilized by (Ratanopad & Kainz, 2006), RX classification (Zhang et al., 2007), Information based classification (Chen et al., 2002), Choice Tree classification (Su *et al*., 2011), Bayesian and Crossbreed classifier (Pradhan *et al*., 2010).

2.1.3 Minimum Distance Classifier

Minimum distance classifiers belong to a family of classifiers referred to as sample classifiers. Specifically in minimum distance classification, a sample (i.e. the group of vectors) is classified into the category whose celebrated or calculable distribution most closely resembles the calculable distribution of the sample to be classified. The life of similitude is a distance measure within the house of distribution functions (Wacker & Landgrebe, 2020). This must do with the cruel or normal unearthly esteem in each band for each category. By considering two-channel pixels values as positional facilitates, a pixel of obscure character may be classified by computing the separation between the esteem of the obscure pixel and each of the category implies. The least remove –to- cruel technique is numerically straightforward and computational effective, but it has a certain impediment. Most importantly, it is insensitive to distinctive degrees of fluctuation within the ghastly reaction information (McLachlan, 2004).

The base separation procedure utilizes the mean vectors of each end-member and ascertains the Euclidean good ways from every obscure pixel to the mean vector for each class. All pixels are arranged to the closest class except if a standard deviation or separation limit is indicated, in which case a few pixels might be unclassified if they don't meet the chose criteria (Richards, 1999). The base separation classifier characterizes classes regarding the good ways from a model vector – for the most part, the mean vector for the class. The separate capacity is characterized as far as good ways from the mean.

2.1. 4 Parallelepiped Classifier

Parallelepiped classification uses a simple selection rule to classify SAR images. The choice boundaries shape an n-dimensional parallelepiped classification within the image information space. Within the parallelepiped classification, measurements are characterized based upon a standard deviation edge from the cruel of each chosen lesson. On the off chance that a pixel esteem pictures lies over the moo edge and underneath the tall limit for all groups being classified, it is allocated to that lesson. The range that doesn't drop inside any of the prepared pixels at that point they are assigned as unclassified (Perumal & Bhaskaran, 2010).

Parallelepiped Classifier is delicate to category fluctuation by considering the extent of values in each category preparing set. This run may be characterized by the most noteworthy and most reduced advanced number values in each band and shows up as a rectangular region in our two scramble graphs. This implies that obscure pixel will be classified agreeing to category extend, or choice locale, in which it lies or as ''unknown'' if it lies exterior all districts. The multidimensional analogues of these rectangular regions are called parallelepipeds, and this classification technique is alluded to by that tongue-twisting title. This classification sort is exceptionally quick and productive computationally. Svanitha et al., (2013) also identified its usefulness and applied it to analyse water and ice surface in Coimbatore, India.

2.1.5 Gaussian Maximum Likelihood Classifier

The greatest probability Classifier quantitatively assesses both the fluctuation and covariance of the category ghastly reaction designs when classifying obscure pixels. To do this, and suspicion is made that the dispersion of the cloud focuses shaping the category preparing information is Gaussian. This suspicion of typicality is by and large sensible for common ghastly reaction conveyances. Beneath this presumption, the dispersion of a category reaction design can be depicted by the cruel vector and the covariance network. Putting these parameters in intellect, we will compute the factual likelihood of given pixel esteem being a part of a specific arrive cover course (Pall & Mather, 2005). Greatest Probability (ML) classification on multispectral information by implies of subjective and quantitative approaches.

ML could be a directed classification strategy, which based on the Bayes hypothesis. It makes utilize of a discriminant work to relegate pixel to the lesson with the most noteworthy probability. Course cruel vector and covariance framework are the key inputs to the work and evaluated from the preparing pixels of a specific course (Asmala & Shaun, 2012). The greatest probability strategy has an advantage from the see point of likelihood hypothesis, but care must be taken about the taking after items.

(1) Adequate ground truth information ought to be examined to permit estimation of the cruel vector and the variance-covariance network of population.

(2) The reverse framework of the variance-covariance network gets to be unsteady within the case where there exists an exceptionally lofty relationship between two groups or the ground truth information are exceptionally homogeneous. In such cases, the number of groups ought to be diminished by a foremost component analysis.

(3) When the conveyance of the populace does not take after the typical dissemination, the greatest probability strategy cannot be applied.

2.1.6 Spectral Angle Mapper

Spectral Angle Mapper (SAM) is a physically-based spectral classification that uses a dimensional angle to match pixels to reference spectra. The algorithm determines the spectral similarity between two spectra by shrewd the angle between the spectra and treating them as vectors in an area with spatial property up to the number of bands. The Spectral Angle Mapper is based mostly on a perfect assumption that one element of remote sensing pictures represents one bound ground cowl material, and can be unambiguously appointed to only 1 ground cowl category. The SAM rule has merely supported the mensuration of the spectral similarity between two spectra (Rashmi et al., 2014). This technique, when used on tag reflectivity information, is relatively insensitive to illumination and ratio effects. SAM compares the angle between the end-member spectrum vector and every picture element vector in dimension house. Smaller angles represent closer matches to the reference spectrum. Pixels further away than the nominative most angle threshold in radians are not classified.

SAM classification assumes reflectivity information. However, if you use radiance data, the error is generally not important because the origin remains close to zero (Kruse et al., 1993). The SAM is associate in nursing machine-controlled methodology for directly examination image spectra to noted spectra or associate in nursing end-member. This method treats each spectrum as vectors and calculates the spectral angle between them. This method is insensitive to illumination since the guided-missile algorithmic program uses solely the vector direction and not the vector length. The result of the SAM classification is a picture showing the most effective match at every element. This method is usually used as a primary cut for determinative geology and works well in areas of homogenized regions (Chun & Xiaofang, 2013; Joseph & David, 1996). Hence, Rashmi et al., (2014) used SAM, Hyperspectral images to analysed and extract thematic data such as land cover, water bodies, and clouds.

2.1.7 Mathematical Formulation of Spectral Angle Mapper (SAM)

The mathematical formulation of SAM attempts to obtain the angles formed between the reference spectrum and the image spectrum treating them as vectors in a space with dimensionality equal to the number of bands (Kruse et al., 1993). SAM presents the following formulation:

$$a = \cos - 1 \ \frac{\Sigma xy}{\sqrt{\Sigma(x)^2 \, \Sigma(y)^2}} \qquad (2.1)$$

$$\mathrm{Cos} \ \ \mathrm{a} = \frac{\Sigma xy}{\sqrt{\Sigma(x)^2 \, \Sigma(y)^2}} \qquad (2.2)$$

α = Angle formed between reference spectrum and image spectrum

X = Image spectrum

Y = Reference spectrum

The SAM value is expressed in radians where minor angle α, represents the major similarity among the curves. The angle α, determined by cos-1, presents a variation anywhere between 0° and 90°. The equation above can also be expressed as cos α (Equation 2.1 & 2.2).

In these conditions, the best estimate acquires values close to 1.

$$R = \frac{\sum(X-\bar{X})(Y-\bar{y})}{\sqrt{\sum(X-\bar{X})^2 \sum(Y-\bar{y})^2}} \quad (2.3)$$

The function cos (SAM) is similar to the Pearsons Correlation Coefficient in equation 2.3. The big difference is that the Pearsons Correlation Coefficient standardizes the data, centralizing itself in the mean of x and y. As will be demonstrated, the standardization by average is more beneficial and gathers even better estimates.

2.1.8 Mahalanobis Classifier

The Mahalanobis removal may be a degree of the removal between a point (P) and dissemination (D), introduced by Mahalanobis in 1936. It could be a multi-dimensional generalization of the thought of measuring how numerous standard deviations absent (P) is from the cruel of (D). This remove is zero if P is at the cruel of (D), and develops as (P) moves absent from the cruel along each foremost component hub. In case each of these tomahawks is re-scale to have unit fluctuation, at that point the Mahalanobis remove compares to standard Euclidean remove within the changing space. The Mahalanobis remove is in this way unit-less and scale-invariant and takes under consideration the relationships of the information set and both Euclidean and Mahalanobis are expressed in their linear distance classification (Dan, 1998; De Maesschalck et al., 2000).

Mahalanobis remove protects beneath full-rank direct changes of the space crossed by the information. This implies that in case the information incorporates a nontrivial invalid space, Mahalanobis separation can be computed after anticipating the information (non-degenerately) down onto any space of the fitting measurement for the information. Mahalanobis separate broadly utilize in cluster examination and classification strategies. It is closely relating to Hotelling's T-square conveyance utilized for multivariate statistical testing and Fisher's Straight Discriminant Investigation that is utilized for directed classification. Quadratic and with equal covariance matrices under normally distributed classes obey Bayes classifier (Ricardo, 2020).

In arrange to utilize the Mahalanobis separate, to classify a test point as having a place to one of several classes. One to begin with gauges the covariance framework of each lesson, as a rule-based on tests known to have a place in each course. The smallest Mahalanobis distance classifier is the most favourable condition for normally distributed classes and equal covariance matrices and equal priors. At that point, given a test, one computes the Mahalanobis separate from each lesson and classifies the test point as having a place to that lesson for which the Mahalanobis separate is negligible.

Mahalanobis put off and use is regularly applying to pick out exceptions, particularly inside the improvement of direct relapse models. A point that includes a greater distinguished Mahalanobis put off from the relaxation of the sample populace of focuses is state to have higher use since it encompasses a more noteworthy impact on the incline or coefficients of the relapse condition. Mahalanobis separate is additionally utilized to decide multivariate exceptions. Relapse strategies can be applying to determine in case a specific case interior a check population is an outlier via the aggregate of or more variable scores. For traditional conveyances, a point can be a multivariate exception indeed, in the occasion that it is not a univariate exception for any variable. The Euclidean classifier indicates optimum, for generally distributed training and covariance matrices that are identical to the identity matrix (Ricardo, 2020).

2.1.9 Object- Based Classification

The object-based idea becomes first added to the GIS community within the late Nineteen Eighties (Egenhofer & Frank, 1992), and because then, in particular, after the 1990s, a high-quality deal of studies has been conducted involving the object-oriented approach (Bian, 2007; Antonarakis et al., 2008; Mallinis et al., 2008). In Remote Sensing, photo segmentation, which is generally implemented before picture classification, has a longer record and has its roots in industrial image processing but changed into now not used substantially in the geospatial community inside the Nineteen Eighties and 1990s (Blaschke et al., 2004). Object-oriented image analysis has been in use, increasingly in Remote Sensing packages owing to the appearance of HRSI data (Benz et al., 2004).

Image segmentation merges pixels into objects, and a type then is implementing primarily based on the items as a substitute of individual pixels. In the process of creating items, a scale determines the presence or absence of an item class and the dimensions of object impacts class outcomes. This technique is established to be a higher-class effect than per -pixel -primarily based approaches, specifically for best spatial resolution data (Ehlers, 2007; Faust et al., 1991).

2.1.10 Image Segmentation

Picture division is the way toward dividing a computerized picture into numerous unmistakable locales containing every pixel (sets of pixels, otherwise called superpixels) with comparative properties. Picture division is commonly used to find items and limits (lines, bends, and so forth) in pictures. All the more exactly, Image Segmentation is the way toward allocating a name to each pixel in a picture to such an extent that pixels with a similar name share certain qualities. Picture division is one of the hotspots in picture preparation and computer vision. It is additionally a vital premise for picture acknowledgement. It is based on certain criteria to isolate an input picture into a number of the same nature of the category in arrange to extricate the area which individuals are curious about (Tune & Yan, 2020). Dilpreet and Yadwinder (2014) alluded to picture division as the strategy of partitioning or apportioning a picture into parts, called fragments. It is for the most part valuable for applications like picture compression or protest acknowledgement since for these sorts of applications, it is wasteful to handle the total picture. So, picture division is utilized to portion the parts from the picture to encourage handling.

The picture division approaches can be ordered into two sorts dependent on the properties of the picture. They are brokenness location-based methodology and closeness discovery-based methodology. Intermittence approach in which a picture is portioned into locales dependent on irregularity. The edge location-based division falls right now which edges shaped because of force brokenness are distinguished and connected to frame limits of districts while the similitude identification approach, a picture is portioned into locales dependent on closeness. The strategies that fall under this methodology are thresholding systems, the area developing procedures and district parting and blending. These all partition the picture into districts having the comparative arrangement of pixels. The bunching strategies likewise utilize this approach. These partitions the picture into a set of bunches having comparative highlights dependent on some predefined criteria (Rafael & Richard, 2007; Shraddha et al., 2012). The extension of the classification also embraces structural, stochastic and hybrid segmentation techniques (Khokher et al., 2012; Dey et al., 2010; Inderpal & Dinesh, 2014).

Image segmentation algorithms are the embodiment of region-based segmentation, edge detection segmentation, Sobel operator, segmentation based on clustering, segmentation based on weakly-supervised learning in CNN (Song & Yan, 2020). The provincial technique is a run of the mill sequential district division calculation, and its fundamental thought is to have comparative properties of the pixels together to shape a locale (Wani & Batchelor, 1994). The strategy requires first choosing a seed pixel and afterwards blending the comparable pixels around the seed pixel into the locale where the seed pixel is found. Furthermore, the edge of the article is as irregular neighbourhood highlights of the picture, that is, the most critical piece of the picture changes in nearby brilliance, for example, dim estimation of the transformation, shading transformation, surface changes, etc. The utilization of discontinuities to distinguish the edge, to accomplish the motivation behind picture division.

Edge division is the least difficult strategy for picture division and one of the most widely recognized equal division techniques. It is a typical division calculation that straightforwardly separates the picture dark scale data handling dependent on the dim estimation of various targets. Limit division can be isolated into neighbourhood edge technique and worldwide edge strategy. The worldwide limit technique isolates the picture into two districts of the objective and the foundation by a solitary edge (Saleh et al., 2010).

Division dependent on grouping, there is no broad hypothesis of picture division. Be that as it may, with the presentation of numerous new speculations and strategies for different controls, there have been many picture division techniques joined with some particular hypotheses and techniques. The purported class alludes to the assortment of comparable components. Bunching is as per certain necessities and laws of the characterization of things all the while. The element space grouping strategy is utilized to fragment the pixels in the picture space with the relating highlight space focuses and is called segmentation on clustering (Yambal & Gupta, 2013).

As of late, the profound learning has been in the picture arrangement, recognition, division, high-goals picture age and numerous different territories have made achievement results. In the part of picture division, a calculation is proposed which is progressively powerful right now, is the pitifully and semi supervised learning of a DCNN for semantic picture division (Zhang et al, 2014).

The watershed-based mostly strategies uses the construct of topological interpretation. During this, the intensity represents the basins having a hole in their minima from wherever the water spills. Once the water reaches the border of the basin the adjacent basins are incorporated along. To take care of separation between basins dams are needed and are the borders of the region of segmentation. These dams are created mistreatment dilation. The watershed strategies think about the gradient of an image as geographics surface. The pixels having a lot of gradients are delineated as continuous boundaries (Kang et al., 2009).

The partial differential equation (PDE) primarily based methods are the fast techniques of segmentation. These are appropriate for time-critical applications. There are simple two PDE strategies: non-linear isotropic diffusion filter (used to enhance the rims) and convex non-quadratic variation restoration (used to dispose of noise). The effects of the PDE method is blurred edges and obstacles that may be shifted by the usage of near operators. The fourth-order PDE method is used to lessen the noise from the photo and the second-order PDE method is used to better detect the edges and limitations (Yambal & Gupta, 2013).

The counterfeit neural system based division techniques recreate the learning procedures of the human cerebrum with the end goal of dynamic. Presently days this technique is for the most part utilized for the division of clinical pictures. It is utilized to isolate the necessary picture from the foundation. A neural system is made of an enormous number of associated hubs and every association has a specific weight. This strategy is free of PDE. Right now is changed over to issues that are unravelled utilizing the neural system. This technique has essential two stages, removing highlights and division by the neural system (Senthilkumaran & Rajesh, 2009).

3.0 Material and Method

3.1 Data set

3.2 Study Area

The study is tailored towards Eleme Local Government Area in Rivers State and span from 6°0' 0''E to 8° 0' 0'' E and 4° 0' 0" N to 6° 0' 0'' N. Ten significant towns in Eleme Local Government Area, about 20 kilometres east of Port Harcourt, are home to the Eleme people. Acpajo, Aleto, Alesa, Alode, Agbonchia, Ogale, Ebubu, Ekporo, Eteo, and Onne are a few of them.

The Eleme people occupy an area that spans roughly 140 square kilometers in total. Eleme's borders are Tai to the east, Okrika and Port Harcourt to the west, Obio Akpor and Oyigbo to the north, and Okrika and Ogu Bolo to the south.

3.1 Agriculture

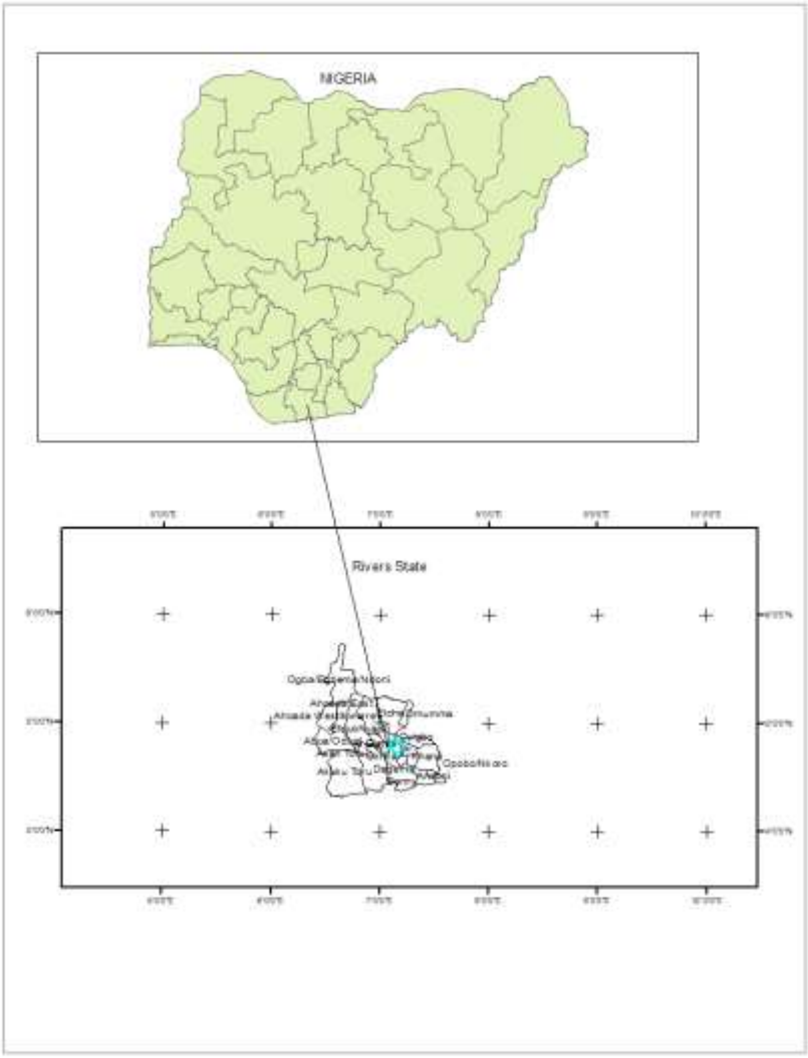
Although white-collar jobs and industrial activities are becoming more prevalent in modern Eleme, the traditional way of life in Eleme is still agriculture, with farmers traveling to farms located around the villages.

Yams, cassava, fluted pumpkin, oil palm fruit, and bitter-leaf are among the crops. The main purpose of the crops grown in traditional Eleme society was subsistence farming, but each family also usually sold their extra produce at one of the town markets. Even if they didn't work in agriculture, family members continued to farm their land to supplement their income. The majority of farmworkers were hired labourers who were women. A pattern that has persisted as typical of Eleme's agricultural labour force. On occasion, the men would assist their wives in the fields.

3.2 Language

Eleme is divided into the Nchia and Odido districts, which speak the same language but different dialects. Both dialects have progressively blended due to mixture and intermarriages. Even so, Odido speakers continue to speak in the proper dialect. The word "eleame" in the eleme language means "who wins."

The language of the Eleme people is Eleme. The language is among those that are most in danger of extinction in Nigeria. This is due to the fact that Pidgin and English are the primary languages spoken by the great majority of people. The publication of books in Eleme and the creation of short comedic videos in Eleme called Ekâ Eleme Ré Pé (Eleme language won't go extinct) are just two of the numerous initiatives to promote Eleme speaking.



3.3 Image Acquisition

The study patterned with Google earth Engine and sub-mapped the area of interest using the four ground control points for visible identification of features on the satellite imagery.

3.4 Materials Used

ArcGIS 7.1, Google earth engine, and MS word 2019 where used as component materials which brought the needed results.

3.5 Image Analysis

A single panchromatic band was analysed using the spectral signature of road, build –up, spill, and vegetation. An unclassified classification was carried out in the study area (Isoclass) where four unique features were identified and spill motion became predominate in the map composition. However, the second view of reality was also done in the classified environment, where spectral angle mapper and maxclass where done to ascertain the level of the results. These analyses proved the presence of spill in the working environment.

4. 0 RESULTS AND DISCUSSION

The Google engine was sub mapped with the top and left bottom information as given in Table 4.1 that showed the ground control points (GCP). The GCPS of right and the bottom of the study area were noted and used for the subset of the imagery in that locale. They were mostly the eastings and the northings values in metres that defined the location of the area of interest.

Table 1: Raster Information

S/N0	Subset	Eastings (m)	Northings (m)
1	Top		536435.60699
2	Left Bottom	286666.026169	
3	Right	301203.929309	
4	Bottom		522307.222248

Table 2 outlined the characteristics of the spatial resolution of pixels in a dataset, commonly used in geospatial analysis or remote sensing.

Pixel Characteristics:

1. Length (m): Each pixel have a length of 25.5948 meters.
2. Width (m): The width of each pixel was the same as its length, 25.5948 meters, which implies that the pixels was a square.
3. Area (M^2): The area of each pixel, found by multiplying the length by the width, and 654.8481 square meters (m^2) was found.

Column & Row:

1. The dataset had 568 columns (width) and 552 rows (height) of these square pixels.
2. The total area covered by the grid of pixels was 313,536 square meters (m^2).

Analysis:

1. This high-resolution data suggests that the pixel grid is detailed, potentially offering precise information for land cover classification or other analyses requiring spatial accuracy.
2. Assuming a one-to-one correspondence between pixels and classified instances (like those in the previous tables), each pixel might represent an individual instance of land cover.
3. The table also provides the overall dimensions of the raster grid: 568 pixels across and 552 pixels high, resulting in 313,536 total pixels. The resolution allows for the mapping and analysis of fine-scale features, which is helpful in assessing land cover changes or detecting small-scale geohazard features.
4. Given that this is high-resolution data, the 313,536 m^2 (approximately 0.314 km^2) represents a relatively small geographic area, useful for localized studies or detailed scrutiny of specific locations.

Table 2 provided the necessary details to understand the granularity of the dataset and the scale at which environmental analyses could be conducted. This granularity was essential for accurate land cover classification and especially pertinent for planning local-level interventions, such as in the case of an oil spill remediation effort.

Table 2: Cell Resolution

Pixel Characteristics	Length (m)	Width (m)	Area (M^2)
1	25.5948	25.5948	654.8481
Colum & Row	568	552	313,536

Table 3 showed the extent of an oil spill's impact. Vegetation was the most prevalent category by count, with 7259 instances, yet have a surprisingly small footprint (0.007259 km²), indicating fragmentation. In stark contrast, the 'Spill' class covered a substantial area of (0.700687 km²), signifying pervasive pollution. 'Built-Up' areas where dense, having 2186 occurrences within just 0.002186 km², and 'Road' instances (508 counts), occupied the smallest land area (0.000658 km²). Widespread contamination from oil spills poses severe environmental and public health risks (Fig 1). The swathes of impacted vegetation hinted at potential habitat fragmentation, endangering ecosystem coherence and biodiversity. The lower coverage of Built-Up and Road categories may suggest minor spill penetration or their reduced vulnerability.

Table 3: Maxclass

S/N	Class	Counts	Area (KM^2)
1	Spill	1070	0.700687
2	Vegetation	7259	0.007259
3	Built-Up	2186	0.002186
4	Road	508	0.000658
TOTAL		11023	0.71079

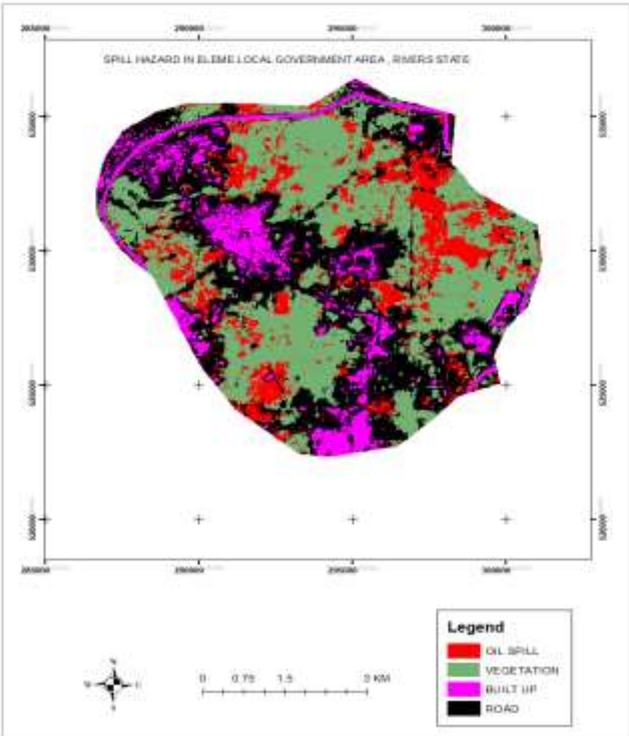


Fig. 1: Spill Hazard in Eleme Local Government Area

Table 4 presented an overview of land cover data designated by 'Isoclass' for a given area, expressed through the types of land cover, their occurrences (count), and the area they cover in square kilometers (km²). There were four distinct land cover classes: Spill, Vegetation, Built-Up, and Road.

The class labelled 'Spill' had 43,617 counts, indicating individual instances or units of area categorized as 'Spill' detected within the surveyed region, amounting to a total affected area of 28.562509 km². This suggests a widespread environmental impact, likely due to an oil spill event or similar contamination within the environmental circle of influence. Fig 2 showed that the vegetation was under the influence of the spill that contributed to high impact of damage.

'Vegetation' was the most extensive both in terms of counts and area, with 97,542 counts and covering an area of 63.875193 km². This showed that, despite possible impacts from events like spills or urban development, vegetation remains the predominant land cover in the area that suffered influence of spill over the region.

The 'Built-Up' category, reflective of urbanization or constructed areas, included 42,763 counts, occupying an area of 28.002965 km². This indicated a significant degree of development and habitation within the region due to the conversion of vegetative cover to build –up.

'Roads' have the lowest presence in the area with 26,964 counts and covering 17.657324 km², which was consistent with roads typically occupying narrower swathes of land compared to other land cover types within or around the study area.

The total values for counts was 210,886 and area 138.097991 (km²) were provided explicitly in the Table 4. This would give an overall picture of the extent and distribution of the different land covers within the study area, which was relevant for environmental assessment, planning, and management purposes.

Table 4: Isoclass

VALUE	CLASS	COUNTS	AREA (KM^2)
1	Spill	43617	28.562509
2	Vegetation	97542	63.875193
3	Built-Up	42763	28.002965
4	Road	26964	17.657324
TOTAL		210,886	138.097991

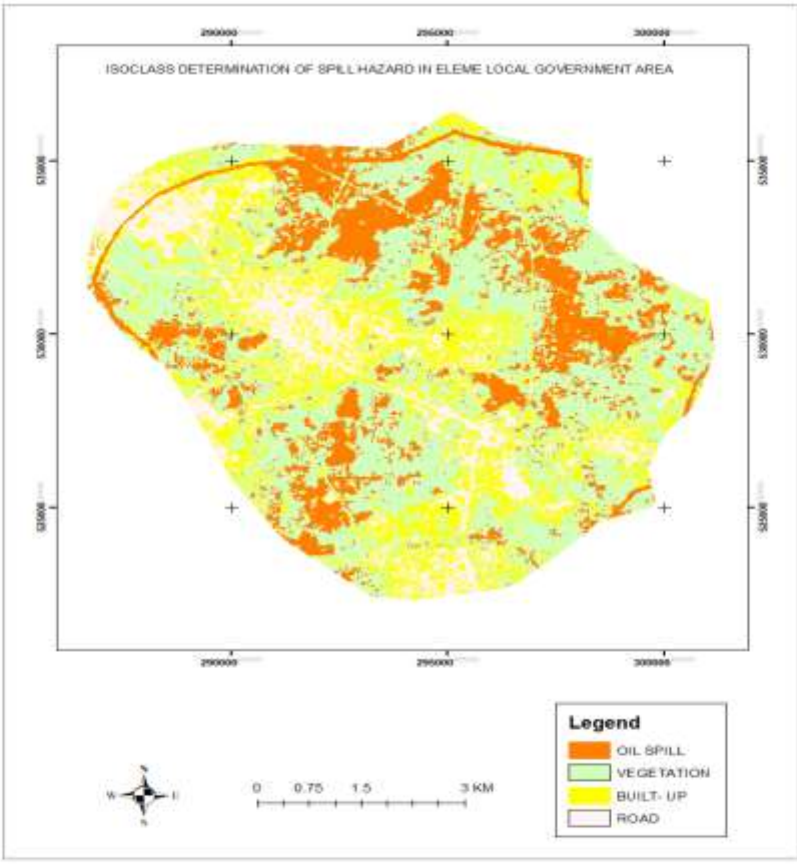


Fig. 2: Isoclass Determination of Spill in Eleme Local Government Area

5.0 Conclusion

In the comprehensive geohazard assessment of the oil spill's impact on the Eleme area in Rivers State, the integrated use of land cover data, local geographical insight, and high-resolution satellite imagery has unveiled poignant environmental dynamics. The expansive spread of contamination, as delineated by the 'Spill' class, which covers 28.562509 km², reveals a pressing environmental emergency, demanding immediate and intensive remediation actions.

Vegetation, the most widely distributed land cover, is nevertheless greatly fragmented—a manifestation of the spill's ecological disruption. This fragmentation potentially accelerates biodiversity loss and threatens the sustainability of traditional agriculture, the livelihood of the Eleme people. The compact 'Built-Up' areas and the scattered 'Road' class further depict a growing urban footprint juxtaposed with persistent survival of rural and subsistence practices.

This study underscores the resilience of local agricultural traditions amidst industrial encroachment and environmental degradation. It resonates with the cultural richness of the Eleme people, whose language, despite the threat of extinction, is sustained through community-driven initiatives, emphasizing the importance of cultural conservation alongside environmental stewardship.

The detailed pixel-level analysis enabled by the cell resolution data (Table 4) has been indispensable in mapping the spill with notable precision, thus informing targeted mitigation strategies. This methodological approach pioneered here could serve as a model for other regions grappling with similar geohazard challenges.

The Eleme oil spill incident calls for a multifaceted response strategy: ecological remediation, safeguarding of local agricultural practices, cultural preservation, and thoughtful urban planning, all of which are critical for the continued well-being and heritage of the Eleme community.

6.0 Recommendations:

The study recommended the following actions to address the findings:

i. Immediate remediation efforts should be initiated to contain and clean up the oil spills to prevent further environmental degradation and health risks.

ii. Implement stricter regulations and monitoring to prevent future spills and ensure compliance with environmental protection standards.

iii. Support and promote the conservation of the Eleme language and culture, given its significance and the threat of extinction.

iv. Enhance agricultural practices to reduce dependency on spill-vulnerable lands and improve the resilience of the local economy.

v. Develop sustainable urban planning strategies that consider the environmental impact and preserve natural habitats.

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