AI-BASED PREDICTIVE MODELLING FOR ASSESSING ECOLOGICAL DEGRADATION IN OIL SPILL AREAS IN THE NIGER DELTA, NIGERIA: A SYSTEMATIC REVIEW

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ABSTRACT

Nigeria is one of Africa's largest oil producers and the oil and gas sector contributes substantially to national revenue and export earnings. However, decades of intensive oil extraction in the Niger Delta have resulted in frequent oil spills and long-term ecological degradation. This study systematically reviews the application of artificial intelligence (AI), particularly predictive modelling techniques, for monitoring and forecasting ecological degradation in oil spill-affected areas of the Niger Delta. Using PRISMA-aligned review methods, peer-reviewed studies, policy reports and remote-sensing, datasets were analysed to assess current AI-based monitoring approaches and their effectiveness. The review indicates that machine-learning analysis of satellite imagery can accurately identify oil-induced environmental damage with repeated spill sites exhibiting significant declines in vegetation indices, such as NDVI that correlate with on-ground ecological degradation. Illustrative modelling using open-source satellite data and convolutional neural networks demonstrated high classification performance in distinguishing degraded from non-degraded areas, enabling spatial mapping of high-risk zones. Despite these advances, major constraints persist, including data quality limitations, sparse ground-truth validation, inadequate technical infrastructure and institutional barriers to adoption. Targeted recommendations are proposed to strengthen environmental data systems, build technical capacity, integrate AI into regulatory enforcement and promote community-inclusive monitoring. AI-driven ecological monitoring offers a pathway towards earlier detection, improved remediation planning and enhanced transparency in environmental governance. With appropriate policy support and sustained investment, AI-based predictive monitoring can contribute significantly to environmental sustainability and resilience in Nigeria's oil-producing regions.

Keywords: artificial intelligence (AI), ecological monitoring, oil spills, Niger Delta, remote sensing, predictive modelling, environmental sustainability.

1 INTRODUCTION

Oil production has played a dominant role in Nigeria's economic development since the discovery of crude oil in the Niger Delta in the mid-20th century. The petroleum sector accounts for approximately 80–90% of Nigeria's export earnings and a substantial share of government revenue [1]. While oil has generated considerable national income, its extraction has imposed severe environmental and social costs on the Niger Delta, where oil spills, gas flaring and inadequate waste management have persisted for decades [2], [3].

Communities in the Niger Delta have experienced widespread contamination of soil and water resources, destruction of mangrove forests, declining fisheries and reduced agricultural productivity [4]. These impacts have undermined livelihoods and contributed to social unrest in a region that remains economically marginalized despite producing most of Nigeria's oil wealth. Traditional approaches to environmental monitoring have largely been reactive, relying on delayed reporting and manual inspections after visible damage has occurred. Regulatory agencies such as the Department of Petroleum Resources and the National Oil



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Spill Detection and Response Agency (NOSDRA) have faced persistent challenges related to limited technical capacity, poor coordination and under-reporting of spill incidents [5].

Recent advances in remote sensing, geographic information systems, and artificial intelligence (AI) have opened new possibilities for environmental monitoring. Predictive modelling using machine-learning algorithms enables the analysis of large volumes of spatial and temporal data to identify early indicators of ecological stress and forecast areas at risk of future degradation [6], [7]. By integrating satellite imagery with environmental datasets, AI-based systems support proactive intervention rather than post-impact response.

This study examines the role of AI-based predictive modelling in monitoring ecological degradation in oil spill-affected areas of the Niger Delta. Through a systematic review of the literature and an illustrative analysis using open-source satellite data, the study synthesizes current evidence, evaluates technical performance, identifies limitations, and proposes policy-relevant recommendations to support more sustainable environmental governance [8], [9].

2 HISTORY OF THE OIL SECTOR IN NIGERIA

The Niger Delta, located in southern Nigeria, is an expansive wetlands region characterized by a network of creeks, mangrove forests, swamps and rivers. Fig. 1 illustrates that it spans about 70,000 km^2 across nine states (Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo and Rivers) and is home to over 30 million people from more than 40 ethnic groups. This makes it one of the most densely populated and ethnically diverse areas of Nigeria. The region's rich biodiversity and fertile lands once supported thriving fishing and farming economies. However, the Niger Delta also contains the bulk of Nigeria's petroleum reserves. Since the first commercial oil find in 1956 at Oloibiri in Bayelsa State, the Delta has been the focal point of intensive oil and gas extraction. Today it contributes an estimated 90% of Nigeria's crude oil output, underscoring its strategic economic importance. The Nigerian National Petroleum Corporation, established in 1977, was tasked with regulating and operating the country's oil and gas sector. Nigeria became a member of OPEC in 1971 but later suspended its membership in 1995 [2], [10].

3 OIL PRODUCTION AND ENVIRONMENTAL DEGRADATION IN THE NIGER DELTA

The Niger Delta is an ecologically sensitive wetland region characterized by extensive mangrove forests, creeks and river systems, spanning approximately 70,000 km^2 across southern Nigeria [11], [12]. Since the first commercial oil discovery in Oloibiri in 1956, the region has become the focal point of Nigeria's petroleum industry. Rapid expansion of oil exploration during the 1970s led to the installation of extensive pipeline networks and production facilities [13], [14].

Environmental management did not keep pace with industrial expansion. Aging infrastructure, operational failures and pipeline sabotage have resulted in frequent oil spills, while routine gas flaring and improper waste disposal have intensified ecological degradation [15]. Long-term contamination of soil and water has caused biodiversity loss, declining fish populations and reduced agricultural productivity, eroding livelihoods dependent on natural resources [16] as shown in Fig. 2.

Although regulatory institutions such as NOSDRA were established to improve spill detection and response, environmental monitoring remains largely reactive and constrained by limited enforcement capacity and fragmented oversight [17]. These persistent challenges underscore the need for data-driven monitoring approaches capable of continuous observation and early warning.

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Figure 1: Map of the Niger Delta showing the geographic distribution of oil-producing states in southern Nigeria.

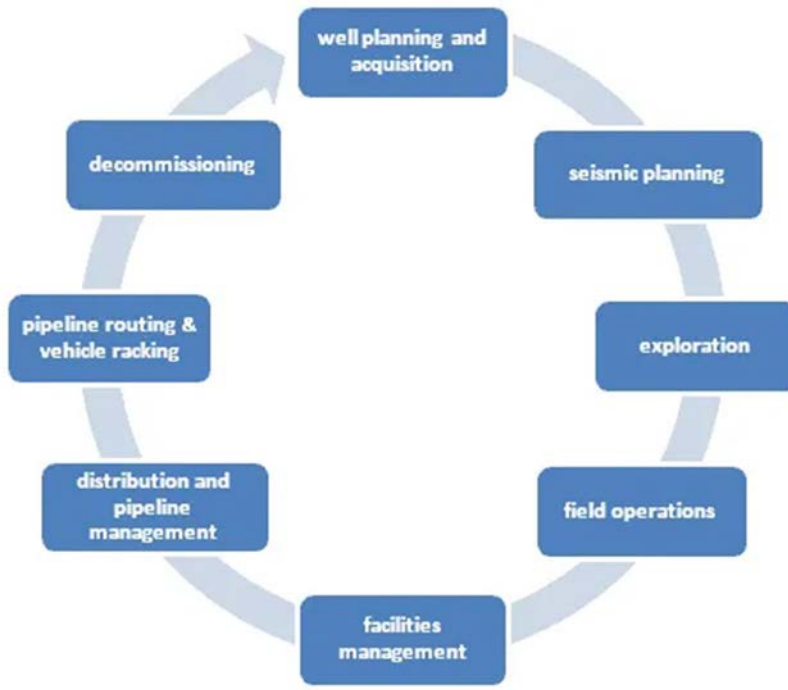


Figure 2: GIS-based monitoring architecture used in oil and gas sector.

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Fig. 2 demonstrates how spatial datasets and remote sensing layers are integrated for environmental monitoring and predictive analysis, while AI-based predictive modelling can forecast areas at risk of degradation, offering real-time data for prompt intervention [18].

4 METHODOLOGY

4.1 Systematic review

This study employed a systematic review methodology guided by PRISMA principles to ensure transparency and reproducibility. Literature searches were conducted across Web of Science, Scopus, Google Scholar and relevant environmental science and engineering journals. Search terms combined oil spills, Niger Delta, ecological degradation, remote sensing, machine learning and AI. Publications from approximately 2010 to 2025 were prioritized, alongside key technical and policy reports [19]. Studies were included if they addressed oil spill impacts, environmental monitoring or AI-based analytical approaches relevant to the Niger Delta or comparable regions. After screening and eligibility assessment, 57 publications were included in the qualitative synthesis.

4.2 Illustrative AI-based analysis

To complement the literature review, an illustrative analysis was conducted using open-source satellite imagery from Landsat-8/9 and Sentinel-2, supplemented by Sentinel-1 radar data to mitigate cloud interference. Two spill-prone locations – Ogoniland (Rivers State) and Gbaramatu Kingdom (Delta State) – were selected based on documented spill histories [8].

A convolutional neural network was trained to classify land areas as degraded or non-degraded using multispectral features, including the Normalized Difference Vegetation Index. Historical spill records informed labelling. Model performance was evaluated using precision and recall metrics. This analysis was intended to demonstrate the feasibility and limitations of AI-driven monitoring under real-world data constraints [20].

4.3 Study area

The Niger Delta hosts over 30 million people across nine states and represents one of Nigeria's most densely populated regions [21]. Fig. 3 shows that the region experiences a tropical monsoon climate, with heavy rainfall during the wet season facilitating the rapid dispersion of oil contaminants through floodwaters and surface runoff [22], [23]. Despite generating the majority of Nigeria's oil revenue, the region remains characterized by high poverty rates and limited infrastructure. Environmental degradation has eroded traditional livelihoods and heightened socio-economic vulnerability [24]. Ogoniland and Gbaramatu were selected as focal areas due to their history of repeated spills and ongoing remediation challenges.

Table 1 describes the conceptual AI-based framework for ecological prediction in oil spill areas (adapted from elements proposed across several studies). The table outlines the main functional components of the system and their roles in environmental monitoring.

Our review finds a broad consensus that applying AI in environmental monitoring can shift efforts from reactive to proactive. The framework involves multiple integrated components:

1. Data ingestion: Collecting multi-source environmental data (satellite imagery, IoT sensor readings, historical spill records, etc.).

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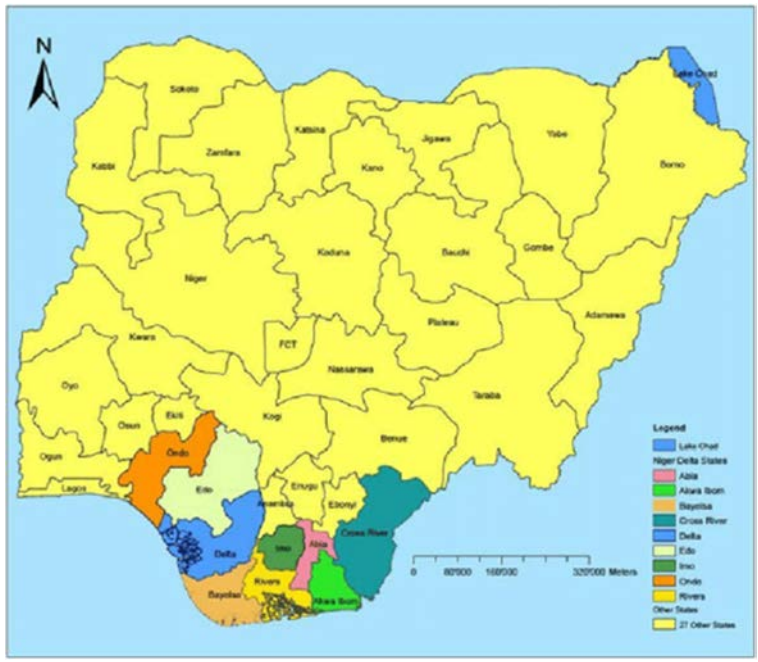


Figure 3: Map of Nigeria highlighting the Niger Delta and selected case study regions. The figure identifies the geographic focus of the ecological assessment.

Table 1: AI-based framework for ecological prediction.

Component	**Function**
Data ingestion	Collects multisource ecological data (satellites, sensors, historical records)
Feature processing	Derives key environmental indicators (e.g., NDVI, TSS, pH levels)
Model training	Learns degradation patterns from historical and spatial data
Prediction engine	Identifies areas at risk of environmental collapse
Visualization layer	User interface for decision-makers and stakeholders

2. Feature processing: Extracting key indicators like NDVI, turbidity (for water), soil pH, etc., from raw data.
3. Model training: using machine learning algorithms to learn patterns linking these features with ecological degradation outcomes.
4. Prediction engine: running the trained models on incoming data to identify or forecast areas at risk of environmental damage.
5. Visualization and decision support: presenting results on GIS maps or dashboards for use by decision-makers and stakeholders. This kind of framework enables continuous monitoring: as new satellite images or sensor data arrive, the AI models update risk maps in near real-time, providing early warnings of potential spills or emerging hotspots.

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One reviewed study by Koroteev and Tekic [25] highlights how such AI frameworks have begun to be tested in oil provinces elsewhere. In the Niger Delta, implementing this requires tackling data integration challenges (combining data from satellites, drones, ground stations) and ensuring computational resources for processing. Cloud computing platforms and large-scale environmental databases can facilitate real-time data integration. A notable development is the use of geospatial dashboards that incorporate AI predictions: for example, a prototype system might show a map of the Delta with colour-coded risk zones updated weekly based on the latest model outputs. During our review, we found references to pilot projects using remote sensing and AI for spill detection in Nigeria; however, many are still at proof-of-concept stage or done by researchers rather than deployed operationally [26], [27].

5 AI AND THE MACHINE LEARNING APPROACH

The reviewed literature demonstrates strong consensus that AI-based methods can enhance environmental monitoring by enabling early detection and predictive risk assessment. Machine-learning algorithms are widely applied to satellite imagery to identify spectral and temporal indicators of oil-related damage [28], [29].

Ensemble models such as Random Forest classifiers are used to identify spill-prone zones based on land use, terrain and proximity to infrastructure. Deep-learning models, particularly convolutional neural networks, have proven effective in detecting vegetation stress and surface anomalies associated with oil contamination [30], [31]. Recurrent neural networks support time-series forecasting of ecological recovery or further degradation. These approaches typically integrate data preprocessing, feature extraction, model training and spatial visualization within GIS environments.

6 RESULTS AND DISCUSSION

The illustrative CNN model successfully identified known oil spill-affected areas with high classification performance. In Ogoniland, locations with documented spill histories exhibited sustained declines in NDVI values, consistent with prolonged vegetation stress [32], [33]. Precision and recall values were comparable to those reported in related studies, confirming the reliability of AI-based detection [34].

Risk maps generated from model outputs highlighted corridors of elevated degradation probability aligned with pipeline routes and historically impacted zones. In some cases, areas not listed in official spill records were flagged, suggesting potential under-reported or chronic pollution. Temporal analysis indicated that without remediation, further vegetation loss is likely in heavily impacted areas.

Limitations included reduced performance due to cloud cover, coarse ground-truth spill location data and occasional confusion between oil-related degradation and other land disturbances such as agricultural clearing [35]. These findings reinforce the need for complementary data sources and field validation.

7 CHALLENGES AND LIMITATIONS

Despite promising results, the implementation of AI-based monitoring systems in the Niger Delta faces significant challenges. Data quality and availability are constrained by persistent cloud cover, limited spatial resolution and sparse in-situ measurements [36]. Technical infrastructure limitations, including unreliable connectivity and insufficient computing resources, further hinder large-scale deployment [14], [37].

Institutional capacity gaps, fragmented data governance and limited regulatory recognition of AI-generated evidence complicate adoption [38]. Ethical concerns related to

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surveillance, data ownership and community trust must also be addressed to ensure legitimacy and acceptance [16].

8 POLICY IMPLICATIONS AND RECOMMENDATIONS

To support effective AI-driven ecological monitoring in the Niger Delta, the following measures are recommended:

- Strengthen environmental data infrastructure through centralized, accessible repositories integrating satellite imagery, sensor data, and spill records [11].
- Building technical capacity via targeted training, institutional partnerships, and local research initiatives [23].
- Enhancing regulatory frameworks to formally incorporate AI-based monitoring into compliance and enforcement mechanisms [39].
- Promoting public–private collaboration to support shared monitoring platforms and data exchange [34].
- Ensuring community inclusion through transparent data sharing and integration of local reporting mechanisms [12].
- Establishing ethical oversight to safeguard data privacy and system security.
- Supporting economic diversification to reduce long-term environmental pressure on the Niger Delta [1].

9 CONCLUSION

This study opens several avenues for further research, although the study demonstrates that AI-based predictive modelling offers substantial potential to enhance ecological monitoring in oil spill-affected areas of the Niger Delta. By enabling early detection, spatial risk mapping and trend forecasting, AI supports more timely and targeted environmental interventions. However, technological capability alone is insufficient. Realizing the benefits of AI requires parallel investments in data infrastructure, institutional capacity, regulatory reform and community engagement.

With sustained commitment and coordinated policy action, AI-driven monitoring can contribute to improved environmental governance and resilience in Nigeria's oil-producing regions, while offering insights applicable to other resource-dependent contexts.

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