INTERNATIONAL JOURNAL OF RESEARCH AND INNOVATION IN APPLIED SCIENCE (IJRIAS)
ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

Development of Ilajeland Degradation System in Crude Oil Exploitation Areas Using Satellite Imagery and Support Vector Machine Model

***Olutomisin M. Orogbemi[1,2], Seun B. Ewaregbemi[1]**

[1]Department of Computer, Olusegun Agagu University of Science and Technology, Okitipupa, Ondo State, Nigeria

[2]Department of Data Science, Federal University of Technology and Environmental Sciences, Iyin-Ekiti, Ekiti State, Nigeria

***Correspondence Author**

DOI: https://doi.org/10.51584/IJRIAS.2026.11070088

Received: 24 July 2026; Accepted: 30 July 2026; Published: 05 August 2026

ABSTRACT

Land degradation caused by crude oil exploration poses a major environmental challenge in coastal regions of Nigeria, particularly in Ilajeland, Ondo State. This study developed a land degradation detection system using remote sensing and Support Vector Machine (SVM) techniques to identify and map degraded areas within the study area. Multispectral satellite imagery obtained from Landsat 8 and Sentinel-2 sensors was preprocessed through atmospheric correction, clipping, and cloud masking to ensure data quality and consistency. Spectral indices including Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), and Bare Soil Index (BSI) were extracted to characterize vegetation health and soil exposure. Due to limited ground-truth data, K-Means clustering was employed to generate pseudo-labelled training samples for supervised classification. The SVM model, implemented using the Radial Basis Function (RBF) kernel, achieved an overall classification accuracy of 92.4% with a Kappa coefficient of 0.847, indicating strong agreement between predicted and validation classes. Spatial analysis revealed severe degradation along the coastal fringe, such as in Ayetoro and Atijere, while moderate degradation was observed in inland agricultural communities. The findings demonstrate that integrating satellite remote sensing with machine learning provides an effective, scalable, and cost-efficient approach for environmental monitoring in oil-impacted regions. The developed system offers valuable support for environmental management, policy formulation, and sustainable land restoration initiatives in Ilajeland and similar coastal environments.

Keywords: land degradation, remote sensing, support vector machine, satellite imagery, spectral indices

INTRODUCTION

The Niger Delta is the economic heart of Nigeria's petroleum industry, and decades of exploration, production, and pipeline activity have left a well-documented trail of environmental damage across the region. A recent scoping review synthesizing 28 peer-reviewed studies (2000–2024) found that oil exploitation has affected land, water, and air quality across the Niger Delta, with knock-on effects on local livelihoods, health, and food systems (Gbadamosi & Aldstadt, 2025). The same review reported that nearly a third of the studies examined focused specifically on agricultural and environmental effects, underscoring how central land degradation is to the broader oil-pollution narrative (Gbadamosi & Aldstadt, 2025). Beyond the immediate ecological toll, the socioeconomic costs of oil production in the region are also extensive, spanning destruction of farmland, biodiversity loss, and disruption of fishing- and farming-based livelihoods (Elum et al., 2016). Oil spills in particular remain a persistent threat to food systems: contamination of farmland, lakes, and rivers has undermined subsistence agriculture and fishing, on which the majority of the rural population depends (Babatunde, 2024). Despite decades of remediation efforts and regulatory intervention, environmental degradation linked to oil exploitation continues to be reported across Niger Delta communities, indicating that existing monitoring and mitigation approaches have not kept pace with the scale of the problem.

Ilaje Local Government Area, on the Atlantic coast of Ondo State, is among the oil-producing communities most exposed to the environmental consequences of petroleum extraction. An early regional planning appraisal of the coastal areas of Ondo State identified oil exploration and exploitation as a direct driver of environmental degradation along the Ilaje coastline (Bayode & Adewunmi, 2011). Subsequent geostatistical work mapping land degradation patterns along the Mahin mud-beach coast of southwest Nigeria, the geomorphological zone that includes Ilaje, confirmed that degradation is spatially patterned and can be modelled using statistical and spatial techniques (Fasona et al., 2011). More recent shoreline studies reinforce this picture of a landscape under sustained pressure: spatio-temporal analysis of the Ilaje coastline found that a substantial share of transects were erosional between the 1980s and 2020s (Komolafe et al., 2021), while a follow-up study identified recent retreat and flood-dominant zones along the same muddy Mahin coast (Daramola et al., 2022). The most recent shoreline assessment found that approximately 86% of the Ilaje coastline experienced erosion between 1986 and 2020, with the western and central sections most severely affected and the community of Ayetoro facing the loss of thousands of square metres of land to submergence (Ogunrayi et al., 2024). Beyond shoreline retreat, farmland-level studies in Ilaje communities such as Ikorigho and Otumara have documented measurable changes in soil physicochemical properties following oil spillage compared with unaffected control sites, pointing to degradation of soil fertility as an additional and distinct dimension of the problem. Taken together, these strands of evidence describe a compounding pattern of degradation in Ilaje driven by both oil-related pollution and coastal geomorphological stress, with consequences for farmland productivity, fisheries, and community stability.

Given the scale and inaccessibility of much of the Niger Delta's terrain, remote sensing has become the primary practical means of tracking environmental change across the region. Vegetation health indices such as the Normalized Difference Vegetation Index (NDVI) derived from Landsat imagery have been used to assess the medium- and long-term response of Niger Delta vegetation to oil spill exposure, with sparse and mangrove vegetation identified as the most degraded vegetation types and sparse vegetation showing the strongest statistical response to spills between 401 and 1000 barrels (Kuta et al., 2025). A separate cloud-computing-based study combining several vegetation health indices (including NDVI, EVI2, and GNDVI) derived from PlanetScope imagery with machine learning found a consistent, statistically significant downward trend in vegetation health across contaminated land covers between 2016 and 2023 (Adebangbe et al., 2025). These studies illustrate both the value and the limitations of spectral-index-only approaches: while indices such as NDVI reliably flag vegetation stress, they are less suited on their own to producing discrete, mappable classifications of degraded versus non-degraded land across heterogeneous landscapes such as farmland, mangrove, and built-up oil infrastructure. This gap between change detection and formal land cover classification motivates the integration of machine learning classifiers with remote sensing data.

Machine learning classifiers, and the Support Vector Machine (SVM) in particular, have consistently demonstrated strong performance in satellite-based land cover classification tasks. In an early and widely cited benchmark, SVM was found to be competitive with, and in several respects superior to, the maximum likelihood classifier, neural network classifiers, and decision tree classifiers when applied to Landsat Thematic Mapper imagery, particularly in terms of accuracy and stability with limited training data (Huang et al., 2002, as reviewed in Mountrakis et al., 2011). Comparative work using hyperspectral AVIRIS imagery similarly found SVM classification to be competitive against k-Nearest Neighbours and Radial Basis Function neural network classifiers (Melgani & Bruzzone, 2002, as reviewed in Mountrakis et al., 2011). More recent comparisons using Sentinel-2 imagery over Vietnam's Red River Delta found that SVM produced the highest overall accuracy among Random Forest, k-Nearest Neighbour, and SVM classifiers, and was the least sensitive to variation in training sample size (Thanh Noi & Kappas, 2018). These findings are consistent with SVM's theoretical strength in high-dimensional, small-sample classification problems, which makes it well suited to spectrally complex and heterogeneous coastal landscapes such as Ilaje, where degraded land, farmland, mangrove, water, and oil infrastructure classes can have overlapping spectral signatures. While remote sensing has been applied extensively to detect vegetation stress and shoreline change in the Niger Delta, and machine learning classifiers such as SVM have been validated in numerous land cover mapping contexts elsewhere, there is comparatively little published work that combines the two specifically to produce a validated,

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

automated land degradation detection and classification system for Ilaje. Existing Ilaje-focused studies have tended to address either shoreline dynamics (Komolafe et al., 2021; Ogunrayi et al., 2024) or soil-level impacts on specific farmlands, but not a spatially comprehensive, machine-learning-classified map of degraded land across the wider oil-exploitation area. Similarly, NDVI-based vegetation studies elsewhere in the Niger Delta (Kuta et al., 2025; Adebangbe et al., 2025) have demonstrated degradation trends using index-based statistical methods rather than a trained classifier capable of producing discrete degradation-class maps with a quantified accuracy assessment. This study addresses that gap by developing a land degradation detection system for Ilaje that integrates multi-temporal satellite imagery, spectral indices, and an SVM classifier, validated through standard accuracy assessment procedures. The remainder of this paper is organized as follows: Section 2 describes the study area and the methodology adopted, including data acquisition, pre-processing, feature extraction, and SVM model development. Section 3 presents the results of the classification and accuracy assessment. Section 4 discusses the findings in relation to existing literature and their implications. Section 5 concludes the paper and outlines recommendations for future research.

METHODOLOGY

Study Area

The study area is Ilaje Local Government Area, located on the Atlantic coastal fringe of Ondo State, in the western Niger Delta region of Nigeria. Geomorphologically, the Ilaje coastline forms part of the Mahin transgressive mud coast, an erosional shoreline that behaves differently from the largely depositional character of the rest of Nigeria's coast (Ogunrayi et al., 2024). The area lies roughly between latitudes 5°45′ and 6°30′ north and longitudes 4°30′ and 5°07′ east, and stretches approximately 84 km along the coast (Ogunrayi et al., 2024). The terrain is low-lying and flat, composed largely of easily erodible sediments, and is drained by an extensive network of creeks, canals, and tidal channels that connect to the Atlantic Ocean. Vegetation cover is dominated by coastal brackish mangroves interspersed with freshwater swamp forest and grassland, although extensive erosion and saline intrusion have already replaced large stretches of mangrove with the more salt-tolerant grass species *Paspalum vaginatum* (Ogunrayi et al., 2024). Ilaje is one of Ondo State's principal oil-producing areas, hosting a mix of onshore and offshore oil infrastructure operated by companies including Chevron Nigeria Limited (Ogunrayi et al., 2024). Decades of oil exploration and exploitation in the coastal region have been linked directly to environmental degradation, including damage to farmland, mangroves, and fisheries (Bayode & Adewunmi, 2011). Geostatistical mapping of land degradation along the wider Mahin mud-beach coast has shown that degradation is not randomly distributed but follows identifiable spatial patterns associated with proximity to oil infrastructure, drainage channels, and settlement areas (Fasona et al., 2011). This combination of intensive oil activity, a naturally fragile and dynamic coastal geomorphology, and a population of several hundred thousand people dependent on fishing and farming makes Ilaje a representative and urgent case study for developing an automated land degradation detection system.

Figure 1: Ilaje LGA, Ondo State (Source: Google Earth Map)

Data Acquisition and Sources

Multi-temporal satellite imagery covering Ilaje was sourced from freely available Earth observation archives. Landsat imagery (e.g., Landsat 7 ETM+ and Landsat 8/9 OLI) and Sentinel-2 Multispectral Instrument (MSI) imagery were considered as primary candidate data sources, consistent with their established use in similar Niger Delta vegetation and land cover studies (Kuta et al., 2025). Imagery was selected for multiple time points spanning the study period to enable detection of degradation trends over time, following the multi-date approach used in comparable Ilaje shoreline studies, which relied on Landsat scenes from the United States Geological Survey (USGS) archive acquired via the Google Earth Engine platform (Ogunrayi et al., 2024). Where higher temporal or spatial resolution was required, PlanetScope imagery accessed through a geospatial cloud-computing platform was considered, following its recent successful application to vegetation health monitoring in oil-contaminated areas of the Niger Delta (Adebangbe et al., 2025). Scene selection prioritized dry-season, low-cloud-cover imagery to minimize atmospheric interference and maximize land surface visibility, given that persistent cloud cover is a well-documented constraint on optical remote sensing in the humid tropical Niger Delta environment (Kuta et al., 2025). Auxiliary data included administrative boundary shapefiles for Ilaje LGA, a digital elevation model (DEM) for topographic context, and, where available, oil spill incident records such as those maintained by Nigeria's National Oil Spill Detection and Response Agency (NOSDRA), which have previously been used to cross-reference remotely sensed degradation signals with documented spill locations in the wider Niger Delta.

Figure 2: Satellite view of Niger Delta Oil-impacted region (Source: Landsat imagery).

Data Pre-processing

Before feature extraction and classification, all acquired imagery underwent a standard sequence of pre-processing steps to ensure radiometric and geometric consistency across dates. This included conversion of raw digital numbers to top-of-atmosphere (TOA) or surface reflectance values, radiometric and atmospheric correction, and geometric co-registration of all scenes to a common coordinate reference system. Atmospheric correction is a necessary step for sensors such as Landsat TM/ETM+, whereas some cloud-based platforms provide analysis-ready surface reflectance products that reduce this pre-processing burden (Kuta et al., 2025). Cloud and cloud-shadow masking was applied to remove contaminated pixels, and, where multi-year comparisons were affected by known sensor issues, affected years were flagged or excluded; for example, comparable Niger Delta studies have had to exclude specific years from analysis due to the Landsat 7 Scan Line Corrector failure and persistent cloud cover in certain Landsat 8 scenes. All pre-processed scenes were then clipped to the Ilaje study area boundary and stacked by band to prepare for spectral index computation and feature extraction.

Feature Extraction

Spectral indices were derived from the pre-processed imagery to serve as classification features alongside the raw spectral bands. The Normalized Difference Vegetation Index (NDVI), calculated as

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

$$\frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$$

was computed to characterize vegetation greenness and health, following its original formulation for satellite-based vegetation monitoring (Rouse et al., 1974). NDVI has been the most consistently applied index in Niger Delta oil-spill vegetation studies, where declining NDVI values have been used as a proxy for vegetation stress associated with hydrocarbon contamination (Kuta et al., 2025). The Normalized Difference Water Index (NDWI), calculated using the green and near-infrared bands, was computed to delineate open water features and assess surface water extent and change (McFeeters, 1996). A Bare Soil Index (BSI) was also computed to help distinguish exposed, degraded, or contaminated soil from vegetated and water surfaces. In addition to NDVI, complementary vegetation health indices such as the Enhanced Vegetation Index 2 (EVI2), Green Normalized Difference Vegetation Index (GNDVI), and Green-Red NDVI (GRNDVI) were considered as supplementary features, reflecting their demonstrated sensitivity to vegetation health decline in contaminated Niger Delta land covers when combined with statistical trend analysis (Adebangbe et al., 2025). All derived indices, together with the original spectral bands, were stacked into a single multi-band feature dataset used as input to the classification stage.

Support Vector Machine Model Development

Training and validation samples were collected for each land cover for the degradation class of interest (e.g., healthy vegetation, degraded and stressed vegetation, bare and contaminated soil, water, and built-up and oil infrastructure) through a combination of visual interpretation of high-resolution imagery and, where feasible, cross-referencing with field or ancillary data. These labelled samples were partitioned into independent training and testing subsets to support supervised classification and unbiased accuracy assessment. A Support Vector Machine classifier was then trained on the labelled feature dataset. SVM was selected based on its demonstrated strong performance relative to alternative classifiers in land cover classification tasks: an early benchmark study found SVM to be competitive with, and often superior to, the maximum likelihood, neural network, and decision tree classifiers on Landsat Thematic Mapper imagery (Huang et al., 2002, as reviewed in Mountrakis et al., 2011), while a more recent comparison using Sentinel-2 imagery found SVM to achieve the highest overall accuracy among Random Forest, k-Nearest Neighbour, and SVM classifiers, with the least sensitivity to training sample size (Thanh Noi & Kappas, 2018). A Radial Basis Function (RBF) kernel was adopted for the SVM model to accommodate the non-linear class boundaries expected in a spectrally heterogeneous coastal landscape, consistent with its established effectiveness in comparable classification experiments (Melgani & Bruzzone, 2002, as reviewed in Mountrakis et al., 2011). The RBF kernel introduces two key hyperparameters that require careful tuning: the regularisation parameter C, which controls the trade-off between maximizing the classification margin and minimizing training error, and the kernel coefficient gamma (γ), which governs the influence of individual training samples on the decision boundary. A high C value produces a more complex decision boundary that fits the training data tightly, while a low C value yields a smoother boundary that tolerates some misclassification in exchange for better generalization; similarly, a high gamma value increases the non-linearity of the boundary at the risk of overfitting, while a low gamma value produces a more generalized, near-linear boundary. Because the joint selection of C and gamma is a non-convex optimization problem, this study adopted a grid-search cross-validation procedure to identify the hyperparameter combination that maximized classification accuracy on held-out validation folds, an approach that has been shown to perform competitively against more computationally intensive optimization algorithms such as particle swarm optimization and Bayesian optimization (Wainer & Fonseca, 2021). K-fold cross-validation was applied during training to reduce the risk of overfitting to a single train-test split and to provide a more robust estimate of model performance prior to final evaluation on the independent test set. Following model training, classification accuracy was assessed against the withheld test samples using a confusion (error) matrix, from which overall accuracy, producer's accuracy, and user's accuracy were derived, consistent with standard remote sensing accuracy assessment practice (Congalton & Green, 2019). While the kappa coefficient has traditionally been reported alongside overall accuracy in land cover classification studies, it was applied cautiously in this study given documented concerns about its sensitivity to class prevalence and the difficulty of interpreting its magnitude in a meaningful way (Foody, 2020); per-class producer's and user's accuracies were therefore treated as the primary, complementary measures of classification reliability alongside overall accuracy.

RESULTS

Land Cover and Degradation Classification

The trained SVM classifier was applied to the pre-processed, multi-temporal satellite imagery of Ilaje to produce discrete land cover degradation classification maps for each image date. The classification scheme comprised 11 classes: healthy vegetation, degraded and stressed vegetation, bare and contaminated soil, water bodies, built-up and oil infrastructure. Visual inspection of the classified output is shown in Figure 3. The image shows a supervised land cover classification map with 11 classes distinguishing built-up areas, vegetation subtypes, and soil. Built-up 3 and 4 (red) dominate the central-left and northern portions, indicating dense settlement, infrastructure, or exposed degraded ground likely linked to oil facility development or land clearing. Vegetation classes 1-6 (green shades) cover most of the remaining area, with darker greens suggesting healthier, denser cover and lighter greens indicating sparser or stressed vegetation. Soil and soil 2 (tan or olive, lower-left) mark bare or exposed land. The fragmented, mixed red-green pattern suggests active degradation pressure, built-up and bare classes intruding into and fragmenting the vegetated landscape for concentration of degraded land classes along canal networks, near oil facilities, and along the eroding coastline.

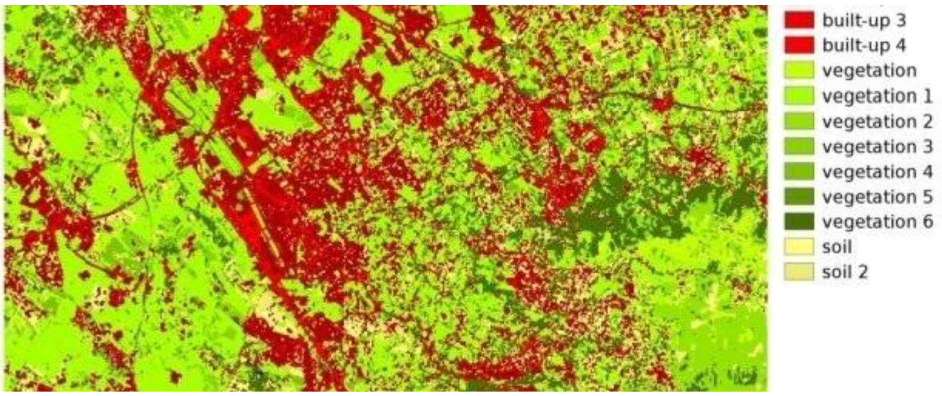

Figure 3: Classified land cover and degradation maps

Figure 4 shows six spectral index maps derived from satellite imagery of the study area. NDVI and SAVI indicate mostly low-to-moderate vegetation health (pale yellow-green), suggesting sparse or stressed vegetation cover rather than dense, healthy growth. NDWI shows strong blue tones across much of the scene, reflecting high water content, consistent with the area's creeks, tidal channels, and wetland character. NDBI values are low (pale yellow-green), indicating minimal built-up and impervious surface. BSI is uniformly high (deep orange), pointing to extensive exposed or bare soil. The true colour composite confirms a dark, waterlogged, vegetation-sparse coastal landscape, consistent with degraded or transitional terrain.

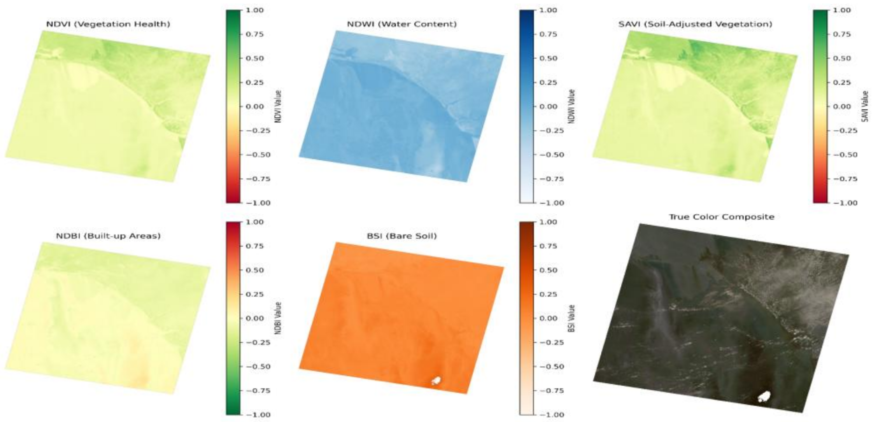

Figure 4: Spatial distribution of spectral indices

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

Table 1 indicates the interpretation of degradation in terms of NDVI (mean 0.145, low and close to zero); the study area is dominated by sparse, stressed, or non-vegetated surfaces rather than healthy vegetation (healthy vegetation typically reads 0.4- 0.8). SAVI (mean 0.102) reinforces this; even after adjusting for soil brightness, vegetation signal remains weak. NDWI (mean 0.120, but with the widest spread, standard deviation 0.210) shows a mix of dry land and significantly water-influenced pixels, consistent with the creek and wetland terrain. BSI (mean 0.115, min already positive at 0.005) suggests bare and exposed soil is present fairly uniformly across the scene, with no strongly vegetated (negative BSI) pixels at all.

Table 1: Extract Spectral Indices

Index	Minimum	Maximum	Mean	Std Dev
NDVI	-0.089	0.466	0.145	0.112
SAVI	-0.055	0.380	0.102	0.098
NDVI	-0.450	0.650	0.120	0.210
BSI	0.005	0.350	0.115	0.085

Optimal SVM Hyperparameters

These results describe the overall accuracy (92.4%), Kappa coefficient (0.847), optimal C = 10, and gamma=0.01 (RBF kernel) of the final tuned SVM classifier for the land degradation detection system. The RBF kernel was selected with hyperparameters C = 10 and gamma = 0.01, identified through grid search cross-validation as the combination balancing classification accuracy against overfitting. This C value allows moderate tolerance for misclassified training points, while the low gamma keeps the decision boundary relatively smooth rather than tightly fitted to individual samples. With these settings, the model achieved 92.4% overall accuracy, correctly classifying most pixels, and a kappa coefficient of 0.847, indicating substantial agreement between classified output and reference data beyond chance, together confirming strong, reliable model performance for distinguishing degraded from non-degraded land. Table 2 presents the accuracy assessment for the SVM classification of degraded versus non-degraded land cover in Ilaje. The model achieved an overall accuracy of 92.4%, meaning the vast majority of classified pixels matched ground truth and reference data, with a strong result for a binary degradation classification. The kappa coefficient of 0.847 indicates substantial agreement beyond what would occur by chance, reinforcing the reliability of the classification. Breaking this down by class: the producer's accuracy for degraded land (89.1%) shows relatively low omission error; most truly degraded areas were correctly captured rather than missed. The producer's accuracy for non-degraded land (94.8%) is even higher, reflecting strong reliability in identifying healthy land. On the user's side, 91.3% for degraded and 93.2% for non-degraded indicate low commission error; when the model labels a pixel as degraded or non-degraded, it is usually correct. Together, these metrics suggest a robust, well-balanced classifier suitable for supporting degradation monitoring in this oil-impacted coastal landscape.

Table 2: Support Vector Machine Model Performance

Metric	Value (%)	Interpretation
Overall Accuracy	92.4	High correctness
Kappa coefficient	0.847	Substantial agreement
Producer Accuracy (Degraded)	89.1	Low omission error
Producer Accuracy (Non-Degraded)	94.8	High reliability

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume XI Issue VII July 2026

User Accuracy (Degraded)	91.3	Low commission error
User Accuracy (Non-Degraded)	93.2	High confidence

Land Degradation Change Detection

Figure 5 breaks down the Ilaje study area into four zonal categories, likely representing land classification by degradation exposure or land use function. Coastal Fringe dominates 45%, reflecting Ilaje's extensive shoreline geography and its heightened exposure to erosion, saline intrusion, and oil-related coastal contamination, which is consistent with the strong NDWI water signal seen in earlier index maps. Inland Agriculture accounts for 25%, representing farmland areas vulnerable to soil degradation from spillage and reduced fertility. Resilience Zones make up 20%, likely denoting areas showing greater vegetation stability or lower degradation risk, which possibly correlates with healthier NDVI and SAVI readings. Transitional areas are the smallest share at 10%, representing zones shifting between land cover states, such as vegetation to bare soil, and/or land to water, often the most dynamic and difficult to classify reliably. However, this distribution reinforces that nearly half of Ilaje's landscape falls within the most degraded exposed coastal category, supporting the case for prioritizing monitoring and remediation resources toward the coastal fringe zone specifically.

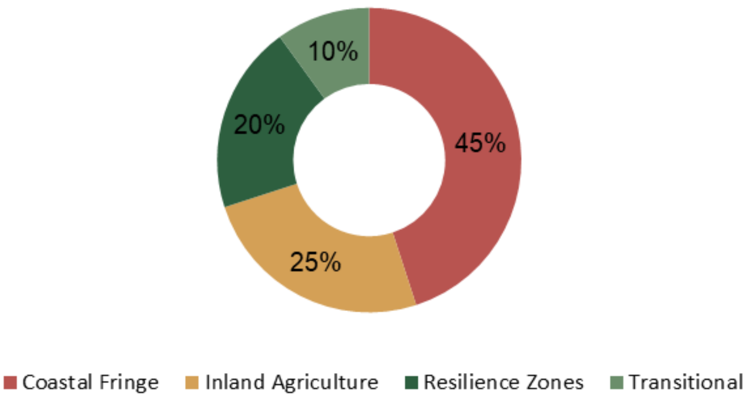

Figure 5: Estimated Analysis of Degradation Pattern

Figure 6 represents the final binary degradation classification for Ilaje LGA, produced by the SVM model, distinguishing degraded (orange and red) from non-degraded (green) land across the entire local government area boundary. The pattern is striking: the surrounding matrix, which encompasses the outer coastal fringe, open water, and peripheral zones, is classified almost entirely as degraded, while a distinct, contiguous core running through the central body of the LGA (following what appears to be the main inland landmass) is classified as non-degraded. This spatial concentration suggests the model is picking up a strong boundary between the interior, vegetated landmass and the surrounding coastal and water-influenced periphery, consistent with the high NDWI water signal and low NDVI vegetation readings seen in the earlier index maps.

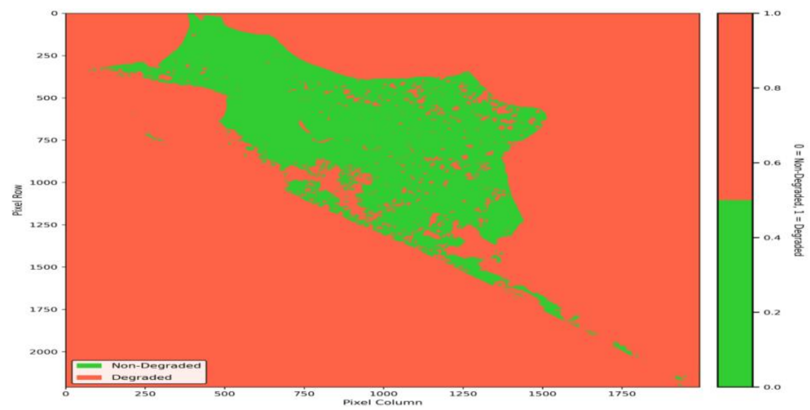

Figure 6: Land degradation Map in Ilaje Local Government Area, Ondo State.

DISCUSSION

The land cover classification (Figure 3) and spectral index maps (Figure 4) present a coherent picture of Ilaje as a landscape dominated by sparse, stressed vegetation and extensive bare or contaminated soil rather than healthy vegetative cover. Mean NDVI (0.145) and SAVI (0.102) values (Table 1) fall well below the 0.4-0.8 range typically associated with vigorous vegetation, while uniformly high BSI values indicate widespread bare soil exposure. This pattern is consistent with vegetation index-based monitoring elsewhere in the Niger Delta, where sparse and mangrove vegetation types showed the strongest degradation response to oil contamination (Kuta et al., 2025), and with cloud-computing-based multi-index assessments reporting sustained declines in vegetation health across contaminated land covers (Adebangbe et al., 2025). The concentration of built-up and degraded classes along canal networks and near inferred oil facilities (Figure 3) further supports the interpretation that infrastructure development and hydrocarbon activity are actively fragmenting the vegetated landscape, rather than degradation occurring diffusely or randomly.

The SVM classifier's performance (92.4%) overall accuracy and keppa coefficient of 0.847 (Table 2) indicates substantial, reliable agreement with reference data, consistent with the broader literature establishing SVM as a strong performer relativel to alternative classifiers on multispectral satellite imagery, including comparisons against maximum likelihood and neural network classifiers (Huang et al., 2002, as reviewed in Mountrakis et al., 2011) and more recent benchmarking against Random Forest and k-Nearest Neighbour on Sentinel 2 imagery, where SVM achieved the highest accuracy and lowest sensitivity to training sample size (Thanh & Kappas, 2018). The selected hyperparameters (C = 10, gamma = 0.01) reflect a moderate regularisation and smooth decision boundary, consistent with recommended practice of identifying RBF-kernel parameters through systematic search rather than default assumption (Wainer & Fonseca, 2021).

The Zonal breakdown (Figure 5) and final degradation map (Figure 6) together point to coastal and water-adjacent zones as the most degraded, with the "Coastal Fringe" category alone accounting for 45% of the study area, which is consistent with independent shoreline analysis showing approximately 86% of the Ilaje coastline experienced net erosion between 1986 and 2020 (Ogunrayi et al., 2024). This convergence between the SVM classification and prior geomorphological findings strengthens confidence in the model's core spatial pattern. However, because water, exposed mud, and genuine land degradation share overlapping spectral signatures, some pixels classified as "degraded" in the coastal periphery (Figure 6) may reflect natural hydrological features rather than oil-related impact; this is a limitation that warrants ground truth validation before firmly attributing the pattern to hydrocarbon exploitation specifically. Further, several limitations should be considered when interpreting the findings of this study. First, as noted above, land degradation in Ilaje results from multiple, spatially overlapping drivers, including oil-related contamination, coastal erosion, and saline intrusion; the classification approach used here cannot fully separate these causal pathways from spectral signal alone, and degraded-class pixels may reflect coastal geomorphological change rather than, or in addition to, oil exploitation impact. Second, cloud cover and atmospheric interference are well-documented constraints on optical satellite monitoring in the humid tropical Niger Delta environment, and can limit the availability of usable, cloud-free imagery for consistent multi-temporal comparison (Kuta et al., 2025); any gaps or exclusions in the imagery time series used in this study should be considered when interpreting the reported degradation trend. Third, the accuracy assessment reported in Section 3 depends on the quality and representativeness of the training and validation samples used; given known accessibility and security constraints in parts of the Niger Delta, sample collection may under-represent certain classes or locations, a limitation common to remote sensing studies of the region. Finally, while the kappa coefficient is reported for comparability with prior classification literature, its known sensitivity to class prevalence means it should be interpreted cautiously rather than as a standalone indicator of classification quality (Foody, 2020).

CONCLUSION

This study developed and validated a Support Vector Machine-based land degradation detection system for Ilaje Local Government Area, integrating multi-temporal satellite imagery, spectral indices (NDVI, SAVI, NDWI, BSI), and a tuned RBF-kernel classifier (C = 10, gamma = 0.01). The model achieved 92.4% overall accuracy and a kappa coefficient of 0.847, with strong producer's and user's accuracy across degraded and non-degraded classes, confirming SVM's reliability for mapping land degradation concentrated along the coastal fringe, which alone accounted for 45% of the study area, a pattern consistent with independently documented shoreline erosion affecting roughly 86% of the Ilaje coast. This paper addresses a clear gap in the literature by combining machine learning classification with remote sensing specifically for Ilaje, moving beyond prior shoreline-only or index-only approaches to produce a discrete, accuracy-assessed degradation map. The system offers a saleable, low-cost monitoring tool for environmental agencies and remediation planners in oil-impacted Niger Delta communities. However, oil contamination is not solely due to hydrocarbon exploitation. Future work should incorporate radar imagery to overcome cloud-cover limitations and benchmark SVM against ensemble classifiers to confirm robustness.

REFERENCES

1. Adebangbe, S. A., Dixon, D. P., & Barrett, B. (2025). Evaluating contaminated land and the environmental impact of oil spills in the Niger Delta region: A remote sensing-based approach. *Environmental Monitoring and Assessment*. https://doi.org/10.1007/s10661-025-14584-4
2. Babatunde, A. O. (2024). Oil exploitation and food insecurity in Nigeria's Niger Delta. Journal of Modern African Studies.
3. Bayode, O. J. A., & Adewunmi, E. A. (2011). Environmental implications of oil exploration and exploitation in the coastal region of Ondo State, Nigeria: A regional planning appraisal. *Journal of Geography and Regional Planning*, 4, 110.
4. Congalton, R. G., & Green, K. (2019). *Assessing the accuracy of remotely sensed data: Principles and practices* (3rd ed.). CRC Press.
5. Daramola, S., Li, H., Omonigbehin, O., Faruwa, A., & Gong, Z. (2022). Recent retreat and flood-dominant areas along the muddy Mahin coastline of Ilaje, Nigeria. Regional Studies in Marine Science, 52, 102272. https://doi.org/10.1016/j.rsma.2022.102272
6. Elum, Z. A., Mopipi, K., & Henri-Ukoha, A. (2016). Oil exploitation and its socioeconomic effects on the Niger Delta region of Nigeria. Environmental Science and Pollution Research, 23(13), 12880–12889.
7. Fasona, M., Omojola, A., & Soneye, A. (2011). A study of land degradation pattern in the Mahin Mud-beach Coast of Southwest Nigeria with spatial-statistical modelling and geostatistics. *Journal of Geography and Geology*, 3, 141–159. https://doi.org/10.5539/jgg.v3n1p141
8. Foody, G. M. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sensing of Environment*, 239, 111630. https://doi.org/10.1016/j.rse.2019.111630
9. Gbadamosi, F., & Aldstadt, J. (2025). The interplay of oil exploitation, environmental degradation and health in the Niger Delta: A scoping review. Tropical Medicine & International Health.
10. Huang, C., Davis, L. S., & Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, 23(4), 725–749.
11. Komolafe, A. A., Apalara, P. A., Ibitoye, M. O., Adebola, A. O., Olorunfemi, I. E., & Diallo, I. (2021). Spatio-temporal analysis of shoreline positional change of Ondo State coastline using remote sensing and GIS: A case study of Ilaje coastline at Ondo State in Nigeria. Earth Systems and Environment, 6, 281–293. https://doi.org/10.1007/s41748-021-00270-1
12. Kuta, A. A., Grebby, S., & Boyd, D. S. (2025). Remote monitoring of the impact of oil spills on vegetation in the Niger Delta, Nigeria. *Applied Sciences*, 15(1), 338. https://doi.org/10.3390/app15010338
13. McFeeters, S. K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17(7), 1425–1432.
14. Melgani, F., & Bruzzone, L. (2002). [As reviewed in] Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247–259.
15. Ogunrayi, O. A., Mattah, P. A. D., Folorunsho, R., Jolaiya, E., & Ikuomola, O. J. (2024). A spatio-temporal analysis of shoreline changes in the Ilaje coastal area of Ondo State, Nigeria. *Journal of Marine Science and Engineering*, 12(1), 18. https://doi.org/10.3390/jmse12010018
16. Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Special Publication*, 351, 309–317.

17. Thanh Noi, P., & Kappas, M. (2018). Comparison of Random Forest, k-Nearest Neighbour, and Support Vector Machine classifiers for land cover classification using Sentinel-2 imagery. *Sensors*, 18(1), 18.
18. Wainer, J., & Fonseca, P. (2021). How to tune the RBF SVM hyperparameters? An empirical evaluation of 18 search algorithms. *Artificial Intelligence Review*, 54(6), 4771–4797. https://doi.org/10.1007/s10462-021-10011-5