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Integrating Geoai and Remote Sensing for Precision Environmental Resource Management in Cross River State, Nigeria.

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Abstract

Environmental Resource Management (ERM) involves the sustainable use and protection of natural resources like land, water, and forests to ensure long-term ecological balance and human welfare. It increasingly demands data-driven precision for these sustainable outcomes. This study explores the integration of Geospatial Artificial Intelligence (GeoAI) and remote sensing in optimising land, water, and forest resource management in Cross River State, Nigeria. The research aims to demonstrate how integrating GeoAI with satellite data can improve environmental resource management by detecting land-use changes, mapping degradation patterns, and supporting evidence-based policy. Using satellite imagery (Sentinel-2 (10 m resolution) and Landsat 8 OLI imagery (2015–2024), which were obtained from the USGS Earth Explorer), machine learning, and GIS-based analytics, the research models spatial patterns of deforestation, soil degradation, and water quality in the Cross River Basin. Deep learning algorithms were applied to detect land-use transitions and predict ecosystem vulnerability under various climate scenarios. Results reveal that between 2015 and 2024, forest cover declined by 14.8%, while agricultural and urban areas expanded by 11.2% and 3.6%, respectively. The RF model identified degradation hotspots mainly in Ikom, Boki, and Obubra LGAs, correlating strongly with agricultural encroachment and logging routes. These demonstrate that

	GeoAI-enabled models achieved over 90% accuracy in classifying vegetation cover and identifying at-risk zones for intervention. The framework also supports participatory decision-making through intelligent mapping dashboards accessible to policymakers. This paper concludes that GeoAI provides a robust, scalable solution for adaptive environmental management, offering early warning systems and dynamic conservation planning tools. It is recommended that governments should invest in national-scale GeoAI infrastructure and training and promote open access to high-resolution environmental data.

1. Introduction

Environmental resources such as forests, water bodies, soils, and biodiversity are fundamental to sustainable development, ecological stability, and human well-being. Across sub-Saharan Africa, including Nigeria, these resources are increasingly threatened by anthropogenic pressures such as deforestation, agricultural expansion, mining, and rapid land-use change, compounded by climate variability and weak environmental monitoring systems. Conventional approaches to environmental monitoring and management, often reliant on field-based surveys and static Geographic Information Systems (GIS), have proven insufficient in addressing the scale, complexity, and temporal dynamics of these challenges (Hansen et al., 2020). Consequently, there is a growing demand for intelligent, data-driven approaches capable of processing large volumes of spatial and temporal data while supporting timely and evidence-based decision-making.

Recent advances in remote sensing technologies, including high-resolution satellite imagery and cloud-based geospatial platforms, have significantly enhanced environmental monitoring capabilities. However, the increasing availability of geospatial big data has also necessitated more advanced analytical frameworks. In this regard, the emergence of Geospatial Artificial Intelligence (GeoAI), the integration of artificial intelligence (AI), machine learning (ML), remote sensing, and GIS has marked a paradigm shift in environmental science and resource management. Foundational work by Reichstein et al. (2019) highlights how AI is transforming Earth system science by enabling the extraction of complex patterns from large-scale environmental datasets, improving predictive modelling, and facilitating real-time environmental monitoring. Similarly, Ma et al. (2019) demonstrated the growing applicability of deep learning techniques in remote sensing, particularly for land-cover classification, object detection, and environmental change analysis, outdoing traditional statistical methods in accuracy and scalability.

The conceptual and methodological foundations of GeoAI have been further articulated by Zhu et al. (2017), who defined GeoAI as a framework for leveraging spatial big data through advanced AI techniques. Subsequent updates (Zhu et al., 2021) emphasised the integration of deep learning, cloud computing, and geospatial data infrastructures, enabling automated feature extraction, spatiotemporal modelling, and scalable environmental analytics. These developments have positioned GeoAI as a critical tool for precision environmental resource management, where high-resolution, timely, and predictive insights are essential.

In the African context, recent studies demonstrate increasing adoption of GeoAI for environmental monitoring, including land-use/land-cover classification, flood risk mapping, and deforestation assessment (Omodasola, 2025). Empirical evidence shows that machine learning models such as Random Forest and Convolutional Neural Networks significantly improve classification accuracy compared to conventional GIS approaches (Li et al., 2021). However, these studies also highlight persistent challenges, including data scarcity, limited computational infrastructure, and capacity gaps, which constrain large-scale implementation. Likewise, while GeoAI applications are expanding across Africa, there remains a relative paucity of localised, context-specific studies focused on integrated environmental resource management frameworks, particularly in Nigeria.

Within Nigeria, the application of remote sensing and GIS for environmental monitoring is well established, with studies focusing on deforestation assessment, land-use change detection, and biodiversity mapping. In Cross River State, one of Nigeria's most ecologically significant regions, characterised by extensive tropical forests, high biodiversity, and complex riverine systems, remote sensing has been applied to estimate above-ground biomass using Sentinel-2 imagery and machine learning algorithms (Afolabi et al., 2023), as well as to model ecological phenomena such as tsetse fly habitats (Daful et al., 2019). While these studies demonstrate the utility of geospatial technologies, they largely rely on conventional or semi-automated analytical approaches and do not fully exploit the predictive, adaptive, and automated capabilities of GeoAI. Emerging evidence from recent Nigerian studies (e.g., Ebri et al., 2025) suggests that although there is significant potential for integrating AI-driven approaches into environmental monitoring, the adoption of GeoAI remains limited and fragmented. Most existing research focuses on isolated applications rather than comprehensive, integrated frameworks that combine remote sensing, machine learning, and decision-support systems for precision environmental management. This gap is particularly evident at sub-national scales, such as Cross River State, where environmental pressures are acute and require more sophisticated monitoring and management tools.

In line with these gaps, the integration of GeoAI and remote sensing presents a timely and critical opportunity to advance precision environmental resource management in Cross River State. By leveraging advanced machine learning and deep learning techniques alongside high-resolution geospatial data, such

an approach can enable automated change detection, predictive modelling of environmental dynamics, and near real-time monitoring. This, in turn, can enhance decision-making processes for policymakers, resource managers, and other stakeholders, while supporting sustainable environmental governance and resilience in the face of ongoing environmental change.

Theoretically, this research is backed by "Systems Theory". Systems theory, originally propounded by Ludwig von Bertalanffy in 1968, provides a holistic framework for understanding complex phenomena as integrated wholes composed of interrelated and interdependent components. It emphasises that systems cannot be fully understood by analysing their individual parts in isolation but rather through the interactions and relationships among those parts. This perspective is particularly relevant to environmental systems, which are inherently complex, dynamic, and characterised by multiple feedback loops and non-linear interactions. A system is typically defined as a set of components (elements) that interact within a defined boundary to achieve a particular function or purpose. Key characteristics of systems include inputs, processes (throughputs), outputs, and feedback mechanisms (Meadows, 2008). Environmental resource systems such as forests, hydrological systems, and ecosystems exhibit these characteristics, as they involve continuous flows of energy, materials, and information across spatial and temporal scales.

Systems Theory posits that all components within a system are interconnected. In environmental resource management, this means that changes in one component (e.g., deforestation) can have cascading effects on others (e.g., soil degradation, biodiversity loss, and hydrological changes). Such interdependencies are particularly evident in tropical ecosystems like those found in Cross River State. The integration of remote sensing and GeoAI aligns closely with Systems Theory by enabling the observation, modelling, and analysis of environmental systems as interconnected wholes. Remote sensing provides continuous spatial and temporal data (inputs), while GeoAI techniques serve as analytical processes that transform raw data into meaningful outputs such as predictive models, classifications, and environmental indicators.

2. Methodology

2.1 Study Area

The study was located in Cross River State (CRS), one of the 36 states of Nigeria (Figure 1). CRS is within the South-South Geopolitical zone and the Niger Delta region. CRS is made of 1024 communities grouped into three senatorial districts, namely: Southern Senatorial District (SSD), Northern Senatorial District (NSD) and Central Senatorial District (CSD). The state's population in 2015 was approximately 3.6 million. The area varies demographically and geographically, encompassing large rural areas such as Akpabuyo and Odukpani in the south with major

conurbations such as Calabar, Ikom and Ogoja (Otu and Uttah, 2022).

The Cross River Basin covers approximately 39,000 km² in southeastern Nigeria, spanning tropical rainforest and mangrove ecosystems. The basin's resources include timber, fertile soils, and freshwater systems critical to local livelihoods (Eneyo *et al,* 2023).

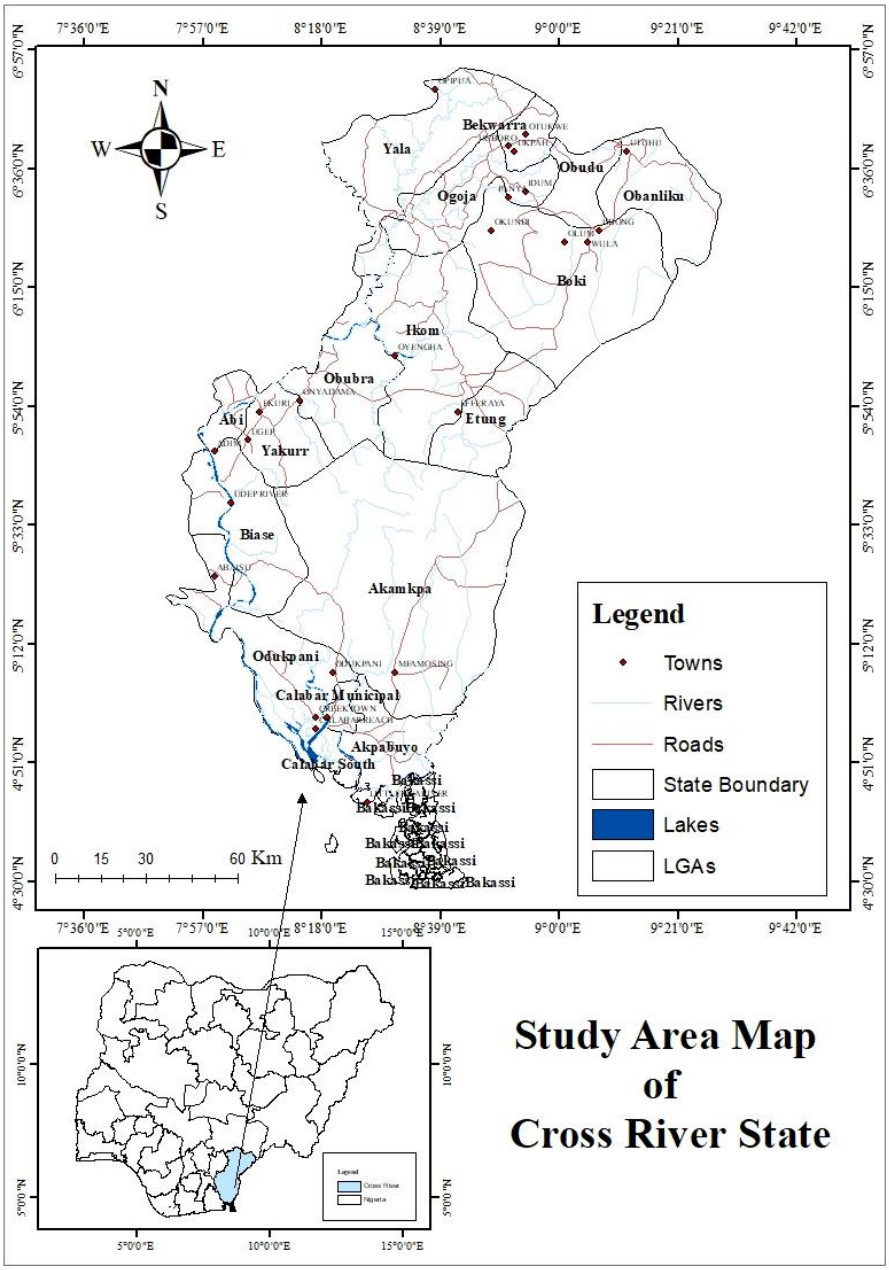

Fig. 1: Map of Study Area: Cross River State

2.2 Data Sources

Data for this study were obtained from the following

i. Satellite Imagery: Sentinel-2 (10 m resolution) and Landsat 8 OLI imagery (2015–2024) were obtained from the USGS Earth Explorer.
ii. Climate Data: Precipitation and temperature data (2010–2024) were sourced from NASA POWER datasets.
iii. Socioeconomic Data: Population and agricultural expansion data from the National Bureau of Statistics (NBS, 2023).
iv. Ground Truthing: 200 GPS-referenced field observations collected between January and March 2024.

2.3 Analytical Framework

The research employed a GeoAI pipeline combining image pre-processing, deep learning classification, and predictive modelling.

i. Pre-processing: Cloud masking, atmospheric correction, and spectral index computation (NDVI, NDBI, NDWI).
ii. Classification: A Convolutional Neural Network (CNN) was trained on labelled satellite samples to classify land cover types (forest, agriculture, water, urban, bare soil).
iii. Prediction: A Random Forest (RF) model predicted areas at risk of degradation based on topography, rainfall, and human pressure indices.
iv. Integration: Results were visualised using ArcGIS Pro and Google Earth Engine (GEE) dashboards for decision support.

2.4 Model Validation

Accuracy assessment was performed using a confusion matrix and Kappa coefficient, comparing classified outputs with field data and high-resolution Google Earth imagery.

2.5 Model Design and Training Procedures

To ensure reproducibility and methodological transparency, this study provides detailed information on the design and training of the machine learning models used.

CNN Architecture and Configuration

A U-Net-based Convolutional Neural Network (CNN) architecture was adopted for land-use and land-cover classification due to its effectiveness in pixel-level image segmentation tasks. The model consists of an encoder-decoder structure with skip connections, enabling the preservation of spatial information across multiple resolution scales. The encoder extracts hierarchical spatial features, while the decoder reconstructs high-resolution classification maps.

Training Parameters

The CNN model was trained using the following parameters:

- **Epochs:** 50
- **Batch Size:** 16
- **Learning Rate:** 0.001 (with adaptive reduction based on validation loss)
- **Optimiser:** Adam optimiser
- **Loss Function:** Categorical Cross-Entropy

Early stopping was implemented to prevent overfitting, based on validation loss convergence.

Dataset Split

The labelled dataset derived from satellite imagery and ground truth points was divided as follows:

- **Training Set:** 70%
- **Validation Set:** 15%
- **Test Set:** 15%

This split ensured that the model was trained effectively while maintaining independent datasets for validation and performance evaluation.

Random Forest Model and Feature Importance

The Random Forest (RF) model was used for predicting environmental degradation risk. Key input variables included:

- Normalised Difference Vegetation Index (NDVI)
- Rainfall patterns
- Elevation and slope
- Distance to roads (proxy for human activity)
- Land-use type

Feature importance analysis revealed that NDVI and distance to roads were the most significant predictors of environmental degradation, indicating strong links between vegetation health, accessibility, and human-induced pressures.

Hyperparameter Tuning

Hyperparameter optimisation for both CNN and RF models was conducted using grid search techniques:

- For CNN: tuning learning rate, batch size, and number of filters
- For RF: tuning number of trees (100–500), maximum depth, and minimum samples per split

The optimal RF configuration consisted of 300 trees with a maximum depth of 20.

Software and Libraries

The analysis was conducted using the following tools:

- **Google Earth Engine (GEE):** for satellite data processing
- **ArcGIS Pro:** for spatial visualisation and mapping
- **Python (version 3.10):** for model development
- **TensorFlow/Keras:** for CNN implementation
- **Scikit-learn:** for Random Forest modelling and evaluation

3. Results

3.1 Land-Use and Land-Cover Change

Between 2015 and 2024, forest cover declined by 14.8%, while agricultural and urban areas expanded by 11.2% and 3.6%, respectively. The CNN achieved a classification accuracy of 92.4% and a Kappa value of 0.88, outperforming traditional maximum likelihood classifiers (82.3%).

Beyond these observed changes, the spatial distribution of forest loss reveals important underlying drivers. The decline in forest cover is strongly associated with the expansion of agricultural activities, particularly smallholder farming and commercial crop production, which have intensified in response to increasing food demand and rural livelihoods. This is especially evident in forest-fringe communities where shifting cultivation practices remain prevalent.

Additionally, the expansion of built-up areas reflects growing population pressure and urbanisation, particularly around key settlements such as Calabar and Ikom. Infrastructure development, including road construction, has further opened up previously inaccessible forest areas, accelerating land conversion.

These patterns indicate that land-use change in the study area is not random but driven by socio-economic pressures, including population growth, food security needs, and economic dependence on natural

resources. The findings underscore the need for integrated land-use planning strategies that balance development with environmental conservation.

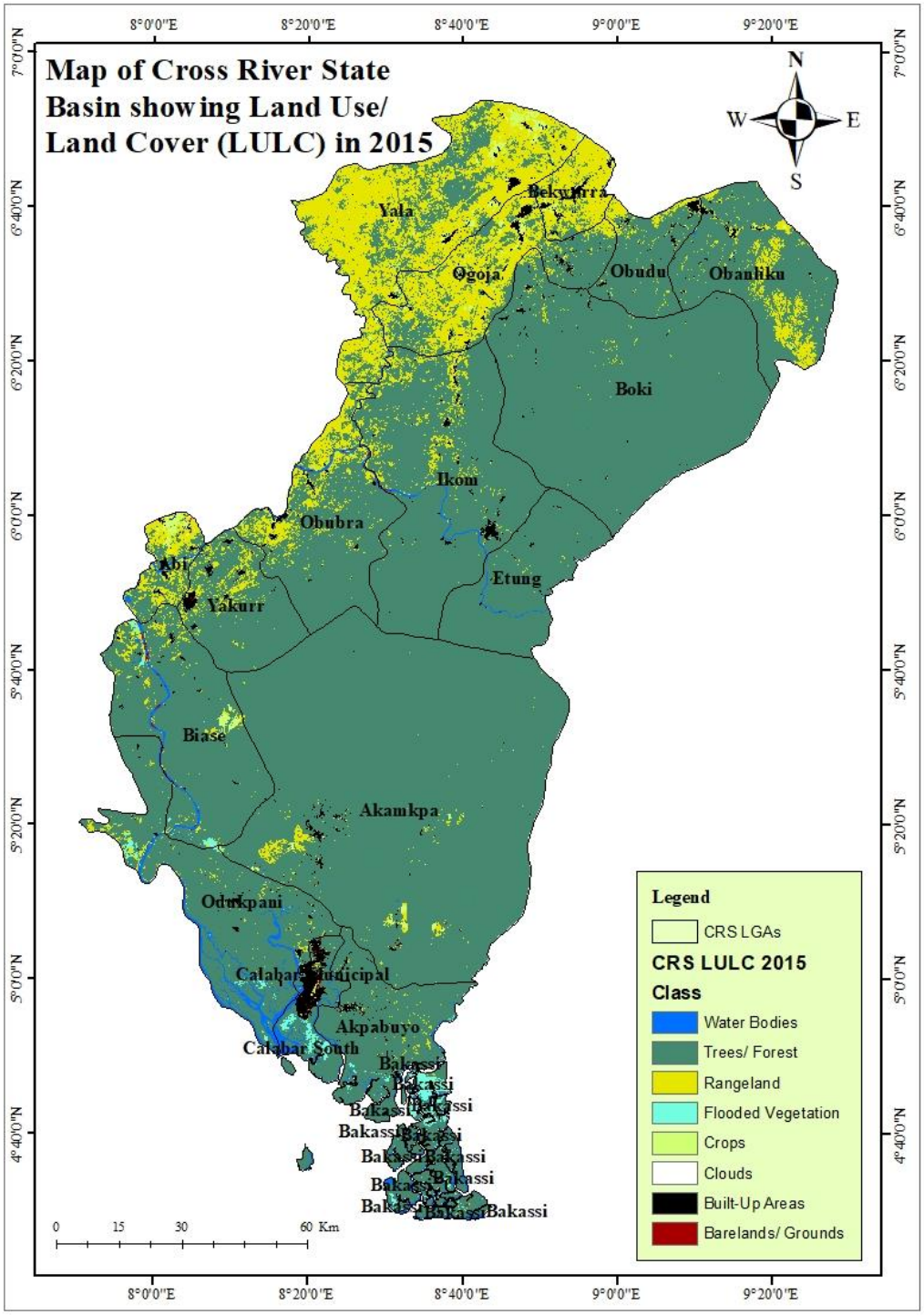

Fig. 2: Map of Cross River State showing Land use/Land Cover in 2015

3.2 Environmental Degradation Hotspots

The RF model identified degradation hotspots mainly in Ikom, Boki, and Obubra LGAs, correlating strongly with agricultural encroachment and logging routes. Predicted vulnerability maps indicate that 19% of the basin will face moderate to high degradation risk by 2030 if current trends continue.

The concentration of degradation in these LGAs can be attributed to a combination of ecological and socio-economic factors. Ikom and Boki, located within the dense tropical rainforest belt, have experienced increased logging activities, both legal and informal, due to the high commercial value of timber resources. Weak enforcement of forest protection policies has further exacerbated this trend.

In addition, agricultural expansion into forested areas has intensified in these regions, driven by population growth and limited availability of arable land in already cultivated zones. Obubra, on the other hand, shows signs of degradation linked to mixed land-use practices, including farming and fuelwood extraction.

The proximity of these hotspots to major transportation routes suggests that accessibility plays a critical role in accelerating environmental degradation. Roads facilitate logging, farming expansion, and settlement growth, thereby increasing pressure on natural ecosystems.

From a policy perspective, these findings highlight priority areas for targeted intervention. Strengthening forest governance, promoting sustainable agricultural practices, and implementing community-based resource management strategies are essential to mitigating further degradation. Without such interventions, the projected increase in vulnerability by 2030 poses significant risks to biodiversity, ecosystem services, and local livelihoods.

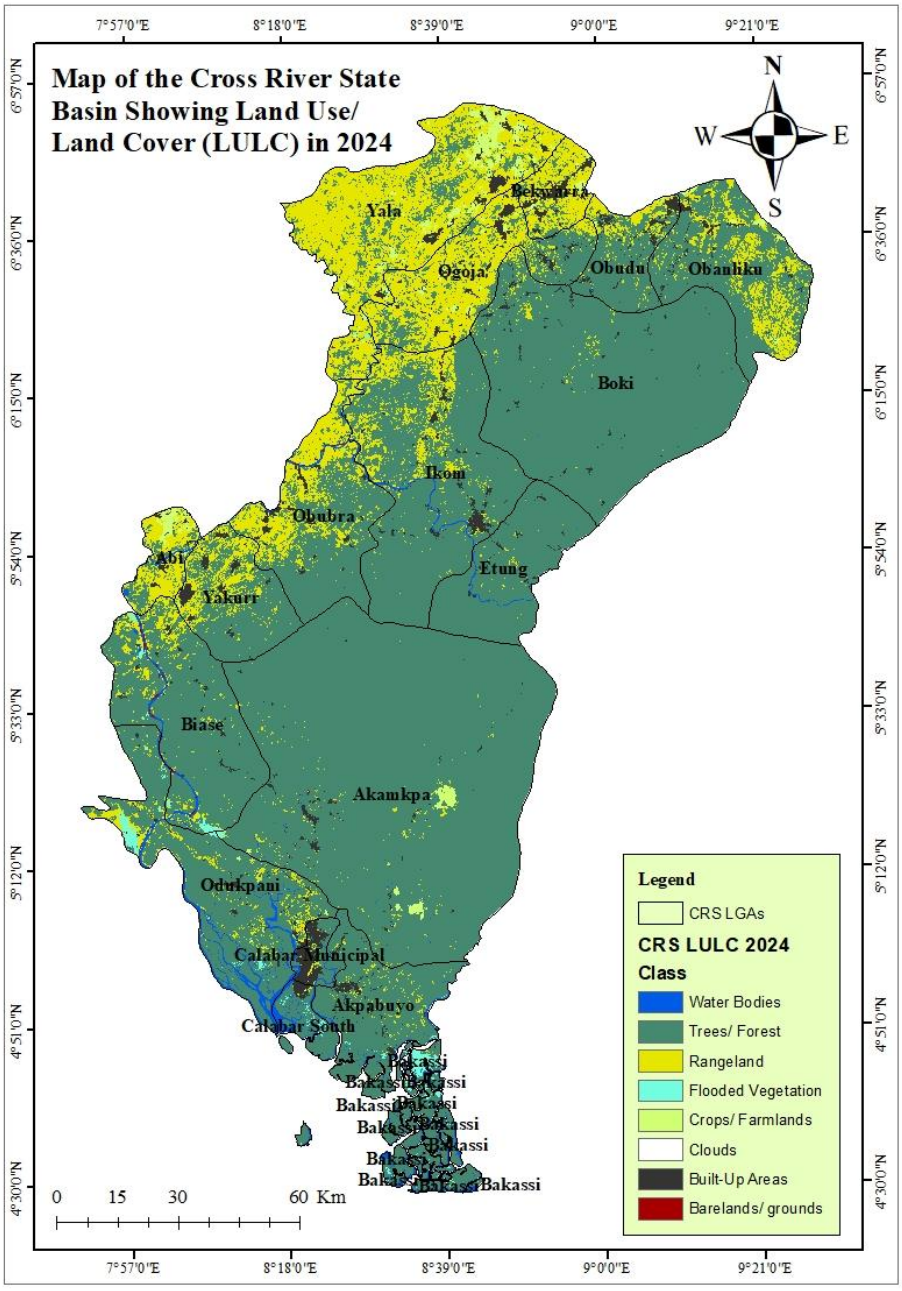

Fig 3: Map of Cross River State Showing Land Use/Land Cover in 2024

Table 1: Amount of Change Detected between 2015 and 2024

S/N	Class	Area in 2015 (Sq.km)	Area in 2024 (Sq.km)	Amount of Change Detected (Sq. km)
1	Water Bodies	331.6813	345.3577	13.6764 increase
2	Trees/ Forest	17613.3015	16616.2459	997.0559 decrease
3	Flooded Vegetation	127.759	108.7324	19.0266 decrease
4	Crops	136.9309	268.8524	131.9215 increase
5	Built-Up Areas	303.9954	577.0224	273.027 increase
6	Barelands/ Grounds	21.0141	12.3997	8.6144 decrease
7	Clouds	2.0712	0.4433	1.6279 decrease
8	Rangelands	2859.4534	3670.8161	811.3627 increase
	Total	**21396.2068**	**21599.8699**	

3.3 GeoAI Dashboard for Decision-Making

An interactive dashboard was developed to visualise environmental indicators such as NDVI trends, deforestation alerts, and water turbidity. Policymakers and conservation agencies can query the system to prioritise intervention areas and monitor reforestation outcomes.

4. Discussion

4.1 GeoAI's Role in Precision Environmental Management

The findings of this study reinforce and extend existing research on the application of geospatial technologies in environmental management. Previous studies have demonstrated the effectiveness of remote sensing and machine learning in monitoring land-use change and environmental degradation (e.g., Reichstein et al., 2019; Li et al., 2021). However, this study advances the field by integrating deep learning (CNN) with ensemble learning (Random Forest) within a unified GeoAI framework tailored to a sub-national context in Nigeria.

Unlike earlier works that rely primarily on conventional classification methods or single-model approaches, the hybrid framework employed here improves both classification accuracy and predictive capability. The

achieved accuracy (92.4%) is consistent with, or exceeds, results reported in similar studies, thereby confirming the robustness of GeoAI approaches in complex tropical environments.

Furthermore, while studies such as Afolabi et al. (2023) focus on disaster prediction, this research broadens the application of GeoAI to continuous environmental resource monitoring and decision support, highlighting its versatility in addressing multiple dimensions of environmental change.

4.2 Scalability of the GeoAI Framework

One of the significant contributions of this study lies in demonstrating the scalability of GeoAI for environmental resource management. The use of cloud-based platforms such as Google Earth Engine enables the processing of large geospatial datasets without the need for extensive local computational infrastructure. This makes the approach adaptable not only across different states in Nigeria but also in other developing regions facing similar environmental challenges.

However, scalability is contingent on data availability and technical capacity. While satellite data such as Sentinel-2 and Landsat are freely available, the implementation of advanced machine learning models requires technical expertise that may be limited in many environmental agencies. Therefore, scaling this framework would require institutional investment in capacity building, training, and digital infrastructure.

4.3 Governance and Institutional Constraints

Despite the technical promise of GeoAI, its practical implementation is constrained by governance and institutional challenges. Environmental management in Nigeria is often characterised by fragmented institutional responsibilities, weak policy enforcement, and limited inter-agency collaboration. These factors can hinder the effective translation of GeoAI-generated insights into actionable policies.

For instance, while the model successfully identifies degradation hotspots, addressing these issues requires coordinated action involving forestry departments, local governments, and community stakeholders. Weak enforcement of logging regulations and land-use policies, as observed in parts of Cross River State, can undermine even the most advanced monitoring systems.

Additionally, issues related to data sharing, policy integration, and political will may limit the adoption of GeoAI tools. Without clear frameworks for incorporating geospatial intelligence into decision-making processes, the full benefits of such technologies may not be realised.

4.4 Implications for Policy and Practice

The integration of GeoAI into environmental management has significant implications for policy and practice. By providing near-real-time insights into land-use changes and environmental risks, GeoAI can

support proactive rather than reactive decision-making. This is particularly important in regions experiencing rapid environmental change.

To maximise impact, there is a need to institutionalise GeoAI within environmental governance frameworks. This includes embedding geospatial analytics into environmental impact assessments, land-use planning, and conservation strategies. Community engagement is also critical, as local populations play a central role in resource use and conservation.

4.5 Future Research Directions

Future studies should explore the integration of GeoAI with emerging technologies such as the Internet of Things (IoT) for real-time environmental monitoring. Additionally, incorporating socio-economic and behavioural data into GeoAI models could provide a more comprehensive understanding of human-environment interactions.

Further research is also needed to assess the long-term effectiveness of GeoAI-driven interventions and to develop frameworks for evaluating their impact on sustainability outcomes.

5. Conclusion and Recommendations

This study demonstrates that integrating GeoAI and remote sensing significantly enhances precision in environmental resource management. The Cross River Basin analysis revealed that deep learning models can effectively monitor land-use changes and predict degradation risks with high accuracy. GeoAI's predictive power and visualisation capacity make it a powerful tool for policymakers and environmental planners. To fully harness its potential, governments should:

- Invest in national-scale GeoAI infrastructure and training.
- Promote open access to high-resolution environmental data.
- Integrate GeoAI analytics into environmental impact assessment (EIA) and land-use planning frameworks.
- Foster collaboration between universities, research institutions, and environmental agencies.
- By doing so, countries can advance toward sustainable environmental management and climate resilience.

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