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Development of AI-Powered Geo-Spatial Models for Predicting Subsurface Instability and Enhancing Structural Resilience of Critical Infrastructure in Coastal and Flood-Prone Regions in Nigeria

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Abstract
INTRODUCTION: *Coastal zones worldwide are increasingly vulnerable to climate-induced hazards, with coastal flooding emerging as one of the most pressing environmental threats. Rising sea levels, intensified storm surges, and changing precipitation patterns driven by climate change pose significant risks to populations, infrastructure, and ecosystems. Geospatial Artificial Intelligence (GeoAI) an integration of geospatial analytics and machine learning using Google Earth Engine (GEE) to enhance the accuracy of flood risk prediction in selected Nigerian coastal zones.*
METHOD: *This study employed a Systematic Literature Review (SLR) guided by the PRISMA framework to examine the application of AI-powered geo-spatial models for predicting subsurface instability and enhancing infrastructure resilience in Nigeria's coastal and flood-prone regions. Relevant studies from 2000–2022 were sourced from major academic databases using defined inclusion and exclusion criteria. A thematic content analysis revealed key trends, challenges, and innovations in applying AI and geospatial intelligence to risk prediction and resilience planning. Findings highlight the importance of integrating AI-driven geo-spatial modelling for adaptive urban planning and sustainable infrastructure management in climate-vulnerable environments.*
FINDINGS: *This research demonstrates the potential of AI-powered geospatial modeling to support data-driven climate adaptation and sustainable flood management in Nigeria's vulnerable coastal environments. A composite flood susceptibility model was developed by integrating distance, elevation, vegetation, and moisture indices, producing a detailed flood hazard map that categorizes risk levels from very low to very high. The results show enhanced interpretation and decision-making. Overall, the findings demonstrate the effectiveness of AI-driven geospatial modeling in identifying and visualizing flood-prone areas for informed planning and disaster risk reduction.*
DISCUSSION: *The study demonstrates the significant potential of Artificial Intelligence (AI) and geo-spatial modeling in detecting subsurface instability and predicting flood hazards in Nigeria's coastal regions. By integrating multi-source datasets within Google Earth Engine (GEE) and applying advanced machine learning algorithms such as Random Forest, SVM, and Neural Networks, and revealed that low-lying, moisture-rich, and poorly vegetated areas exhibit the highest flood susceptibility. Embedding AI-powered geospatial analytics into planning frameworks can transform flood management from reactive to proactive, fostering resilient infrastructure, sustainable development, and climate adaptation in Nigeria's vulnerable coastal regions.*

CONCLUSION: *This study concludes that AI-powered geo-spatial systems provide a transformative and proactive framework for monitoring, predicting, and mitigating subsurface instability and flood hazards in Nigeria's coastal regions. By integrating machine learning algorithms with geospatial technologies, the research demonstrates how AI enhances predictive accuracy, enabling real-time identification of high-risk zones prone to flooding, erosion, and ground subsidence. The study emphasizes that AI-driven spatial modeling can significantly reduce infrastructure vulnerability by supporting evidence-based decision-making and environmentally responsible growth. Accordingly, the study recommends the establishment of a national geo-AI database, capacity building for geoscientists and engineers, integration of AI predictive models into planning and environmental policy, and enhanced data sharing among agencies such as NASRDA and NIMET.*

Keywords: *GeoAI; Flood Risk Assessment; Geospatial Modeling; Coastal Resilience; Disaster Risk Reduction.*

1. INTRODUCTION

Coastal zones worldwide are increasingly vulnerable to climate-related hazards, with coastal floods emerging as one of the most pressing threats (IPCC, 2018). Coastal flooding refers to seawater penetrating land caused by unpredictable high-water occurrences, such as regular high tides or storm surges resulting from tropical cyclones, storms, or typhoons, lasting at least one day in coastal regions (Pirani et al., 2018). Climate change is expected to increase the frequency of coastal flooding due to rising sea levels, enhanced storm surges, and changes in precipitation patterns. This danger poses substantial hazards to human populations, infrastructure, and ecosystems in these coastal zones (Lorie, et al. 2020). Consequently, comprehending coastal flooding and its related effects is essential.

Previous studies have utilized coastal flood risks to ascertain the potential extent of inundated areas and the anticipated exposed populations or assets (IPCC, 2021). Coastal flood risk is the probability of coastal flood occurrence in specific regions, driven by physical and social factors, including hydrometeorological, geophysical, and socio-economic variables. At the same time, the aggregate of detrimental consequences, income loss, and property damage induced by coastal floods is termed the impact (Reguero et al., 2018). Prior research employed coastal flood risk prediction to assess flooding likelihood and impact in coastal areas by integrating the abovementioned factors (Pirani et al., 2018). Generally, coastal flood risks are predicted using a statistical approach. This examines flood drivers' correlations and similarities, utilizing historical data and statistical models to identify patterns and relationships, such as regression, probability, or machine learning (ML) models (Anderson et al., 2021).

Coastal zones are subject to severe coastal flood risk, necessitating the development of more accurate and reliable flood risk prediction methods due to the limitations of current approaches (Atmaja et al., 2022). The current approaches in coastal flood prediction often use univariate probability distributions that fail to account for the complex interactions between multiple flood drivers (Hasan et al., 2021). Another significant limitation is the underutilization of geographic features, i.e., proximity, shape, or density. Future coastal risk prediction should elaborate on the proximity of mangrove ecosystems, which function as natural defenses (Takagi 2019). Mangroves have been demonstrated to dissipate wave energy and stabilize shorelines; however, their role is often overlooked in conventional flood risk prediction (Haiyun et al., 2021). This omission is particularly critical given the growing recognition of mangroves as ecosystem-based disaster risk reduction (Eco-DRR) strategies, which emphasize integrating natural ecosystems into disaster risk management.

Flooding is one of Earth's worst forms of natural disaster (Echendu, 2022). Nigeria has seen many flood events in recent years, and due to the high level of vulnerability and lack of coping capacity of the people, extreme events caused by climate change are putting many lives and properties at risk (Komolafe et al., 2015). This escalating challenge underscores the critical need for innovative and improved flood risk management strategies adept at navigating the complex terrain of environmental adversity (Ouma et al., 2014). Flood destructions also hit roads and cause delays to infrastructure development initiatives and political processes (Glago, et al., 2021). A flood event may result in physical damage to the building stock, essential facilities, transportation systems, utilities, and agriculture (Fayaz, et al. 2022). Flooding is linked to a multitude of infectious diseases caused by the pollution of water sources, which can result in the spread of waterborne illnesses such as cholera, dysentery, and typhoid fever (Nichols, et al., 2018). Climate change and global warming have attained a global dimension, frequently occupying the agendas of the United Nations and other international bodies (Lee, et al., 2020). The intensifying peril of global climate change, mainly attributable to anthropogenic actions, represents an escalating threat to the international community (Umar & Gray, 2022).

Among the ten largest countries worldwide, Nigeria is growing the most rapidly. Consequently, he population of Nigeria, currently the world's seventh largest (Musa & Shabu, 2019), is projected to surpass that of the United States and become the third-largest country in the world shortly before 2050 (United Nations Development Programme. 2022). The 2022 Nigeria floods are believed to be the worst floods the country has experienced in at least a decade, with a widespread impact in 33 of its 36 states, damaging homes and infrastructure, destroying farmland, and displacing people from their communities (Bashir, et al.,.2012). According to IFRC reports, as of 8 October 2022, about 2.8 million individuals were impacted by the flood, at least 6123 lives were lost, and more than 2500 people sustained injuries. An estimated two million people fled while others were evacuated from high-risk locations, taking just what they could carry with them and ending up in deplorable conditions with inadequate safeguards, exposing them to protection concerns. After several months, many affected people still need food, shelter, water, sanitation, and support to rebuild their livelihoods (Manfré, et al., 2012). The multifaceted nature of flood risk and its management in Nigeria has been the subject of extensive research, highlighting the challenges and potential pathways for more effective disaster management strategies. Nkwunonwo et al. (2016) delve into the intricacies of urban flood risk management in Lagos, Nigeria, covering a period from 1968 to 2012. Despite the considerable damage inflicted by floods, the study reveals persistent challenges arising from inadequate data, limited public awareness, and a lack of sufficient knowledge on mitigation strategies. The review evaluates the current state of understanding and proposes recommendations for future actions (Kemper, 2010).

Recent advances in geospatial technologies and artificial intelligence (AI) have offered promising avenues for addressing these gaps. The geospatial artificial intelligence (GeoAI) approach utilizes ML models to elucidate location-based analytics, with a particular focus on the application of spatial (geographic feature) information (Janowicz, et al., 2020)]. This technique integrates geospatial science with AI techniques, either ML or deep learning (DL), to analyze and interpret spatial data. GeoAI enables the development of more robust and precise flood risk assessments by handling large and multi-dimensional data (Li, and Hsu, 2022). By incorporating a more comprehensive range of features, including natural defenses and additional geographical features, GeoAI is anticipated to enhance the robustness of coastal flood risk prediction (Mosavi, et al., 2018).

2. Research Questions

1. What are the major environmental and geotechnical factors influencing subsurface instability in coastal Nigeria?
2. How can AI and GIS integration improve predictive accuracy?
3. Which machine learning algorithm performs best for subsurface prediction?
4. How can predictive results inform infrastructure design and resilience strategies?

Research Objectives

Aim and Objectives

Aim:
To develop AI-powered geo-spatial models for predicting subsurface instability and enhancing the structural resilience of critical infrastructure in coastal and flood-prone regions in Nigeria.

Specific Objectives:

1. Identify geotechnical, hydrological, and environmental parameters affecting subsurface instability.

2. Collect and integrate multi-source data (satellite, GIS, and field data).

3. Develop AI-based models (Random Forest, SVM, CNN) for predictive analysis.

4. Validate the model accuracy using field-observed data.

5. Produce a Subsurface Instability Risk Map for target regions.

Hypotheses

H_{01}: There is no significant correlation between AI-predicted instability zones and field-observed instability.
H_{02}: AI-based models do not significantly improve the predictive accuracy compared to traditional methods

Statement of the Problem

In recent years, Nigeria's coastal and flood-prone regions have experienced an increasing frequency of infrastructure failures resulting from subsurface instability. The degradation and eventual collapse of roads, bridges, pipelines, and buildings have become recurring challenges, especially in areas such as Lagos, Bayelsa, Rivers States etc. These failures are primarily attributed to dynamic geotechnical conditions, fluctuating groundwater levels, and poor soil-bearing capacities, which are further intensified by climate change and unregulated human activities.
Despite the growing awareness of these problems, existing approaches to subsurface monitoring and risk assessment remain largely inadequate. Conventional geotechnical investigations are often localized, time-consuming, and reactive rather than predictive. The absence of an integrated geospatial and Artificial Intelligence (AI) framework limits the ability of stakeholders to anticipate and mitigate potential failures before they occur. Furthermore, the quality and spatial coverage of

available geotechnical data in Nigeria are generally poor, making it difficult to generate reliable models for large-scale analysis.

Early warning systems for predicting soil movement and structural vulnerability are also underdeveloped, leaving communities and infrastructure unprepared for potential hazards. When failures occur, the cost of rehabilitation and reconstruction is enormous, often surpassing the resources available to both government and private agencies. This has resulted in repeated cycles of damage and repair without sustainable preventive strategies.

To address these challenges, this study seeks to develop an AI-powered predictive modeling framework that integrates geospatial data, remote sensing information, and field-based geotechnical parameters. The model is designed to identify and predict areas susceptible to subsurface instability, thereby enhancing the structural resilience of critical infrastructure in Nigeria's coastal and flood-prone regions.

Justification for the Study

The justification for this study is grounded in the urgent need to address the persistent problem of subsurface instability and its severe consequences for infrastructure resilience in Nigeria's coastal and flood-prone regions. These regions, notably Lagos, Bayelsa, and Rivers States, are among the most vulnerable to the combined impacts of sea-level rise, land subsidence, and increased precipitation intensity driven by climate change (IPCC, 2021; Komolafe et al., 2015). The frequent collapse of roads, bridges, and buildings in these areas underscores a critical gap in predictive and preventive geotechnical risk management systems. Traditional assessment techniques, which rely heavily on field sampling and empirical judgment, are often reactive, spatially limited, and unable to capture the complex interdependencies between environmental, hydrological, and geotechnical factors influencing subsurface instability. The adoption of Artificial Intelligence (AI) and Geographical Information Systems (GIS) presents a transformative opportunity to overcome these limitations. AI-powered geo-spatial models enable the integration and analysis of large, heterogeneous datasets from remote sensing, satellite imagery, and ground surveys, thereby facilitating high-resolution predictions of soil instability and infrastructure vulnerability (Mosavi et al., 2018; Li & Hsu, 2022). By leveraging advanced machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN), predictive models can identify nonlinear relationships among critical parameters such as soil composition, moisture content, slope gradient, and groundwater dynamics with a level of precision unattainable through conventional methods. From a national development perspective, the study aligns with Nigeria's National Climate Change Policy and the Sustainable Development Goals (SDGs), particularly Goal 9 (Industry, Innovation, and Infrastructure), Goal 11 (Sustainable Cities and Communities), and Goal 13 (Climate Action). The integration of AI-driven geospatial intelligence in environmental and infrastructural planning supports proactive decision-making, enhances the resilience of communities, and minimizes economic losses from recurrent infrastructure failures and flood disasters. Academically, this study contributes to the emerging field of GeoAI, bridging the methodological gap between geospatial sciences and artificial intelligence applications in environmental risk management. Empirically, it advances existing knowledge by generating a Subsurface Instability Risk Map, which can serve as a decision-support tool for urban planners, engineers, and policymakers.

Table 1: Summary of Study Justification

Aspect	Description
Context	Nigeria's coastal and flood-prone regions (e.g., Lagos, Bayelsa, Rivers) face increasing infrastructure failures due to subsurface instability, aggravated by climate change and human activities.
Problem Gap	Existing subsurface monitoring methods are localized, manual, and reactive; lack integration of multi-source data; and do not incorporate AI-driven predictive analytics.
Need for Study	There is an urgent need for advanced predictive tools that combine Artificial Intelligence (AI) and Geographical Information Systems (GIS) to forecast and mitigate subsurface instability before failures occur.
Innovative Approach	The study integrates AI-based models (Random Forest, SVM, CNN) with geospatial data and remote sensing to develop a predictive framework for subsurface instability and infrastructure resilience.
Expected Academic Contribution	Advances the field of GeoAI by bridging geotechnical and AI research domains, offering a model for large-scale, data-driven environmental prediction.
Expected Practical Contribution	Provides policymakers and engineers with a Subsurface Instability Risk Map to guide sustainable infrastructure design, urban planning, and disaster risk reduction.
Policy Relevance	Aligns with Nigeria's National Climate Change Policy and Sustainable Development Goals (SDGs 9, 11, and 13) for climate-resilient infrastructure and sustainable cities.
Broader Impact	Enhances proactive disaster management, reduces economic losses, and strengthens community resilience in coastal and flood-prone regions.

3. Conceptual Framework

Geo-spatial modeling serves as a powerful analytical approach for understanding and simulating complex Earth processes through the use of digital spatial data. It involves the collection, integration, and analysis of geographically referenced records such as topography, soil composition, hydrology, and land use to visualize and predict environmental patterns and interactions. In essence, geo-spatial modeling enables researchers and planners to represent the dynamic behavior of natural systems within a digital environment, offering valuable insights into spatial variability and environmental risks (Longley et al., 2015).

At its core, geo-spatial modeling combines Geographic Information Systems (GIS) and Remote Sensing (RS) technologies to create spatially explicit datasets that describe the physical characteristics of the Earth's surface. GIS facilitates the organization and manipulation of multi-layered spatial data, while remote sensing provides continuous and large-scale observations of environmental variables through satellite or aerial sensors. Together, these tools enable the generation of accurate digital maps that support environmental assessment, land-use planning, and disaster risk reduction (Goodchild, 2020).

In recent years, the integration of Artificial Intelligence (AI) into geo-spatial modeling has revolutionized the analytical capacity of these systems. Traditional statistical or deterministic models often struggle to capture the non-linear and multi-dimensional relationships among environmental variables that influence subsurface instability. AI, particularly machine learning algorithms such as Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM), can effectively model such non-linear dependencies by learning patterns from large and complex datasets (Raghavesh et al., 2018). This makes AI a critical enhancement to conventional geo-spatial modeling, especially in dynamic environments such as Nigeria's coastal zones where soil properties, hydrological conditions, and land-use changes interact in unpredictable ways.

The AI geo-spatial integration framework enables predictive modeling of subsurface instability by combining data-driven intelligence with spatial analytics. Within this framework, environmental variables such as soil texture, slope gradient, elevation, drainage density, and land cover are extracted from geospatial datasets and used as input features for AI models. The machine learning algorithms then identify hidden relationships and spatial dependencies among these variables, producing predictive maps that highlight areas of potential instability (Adegoke et al., 2021). This process enhances both the spatial precision and predictive accuracy of environmental risk assessments.

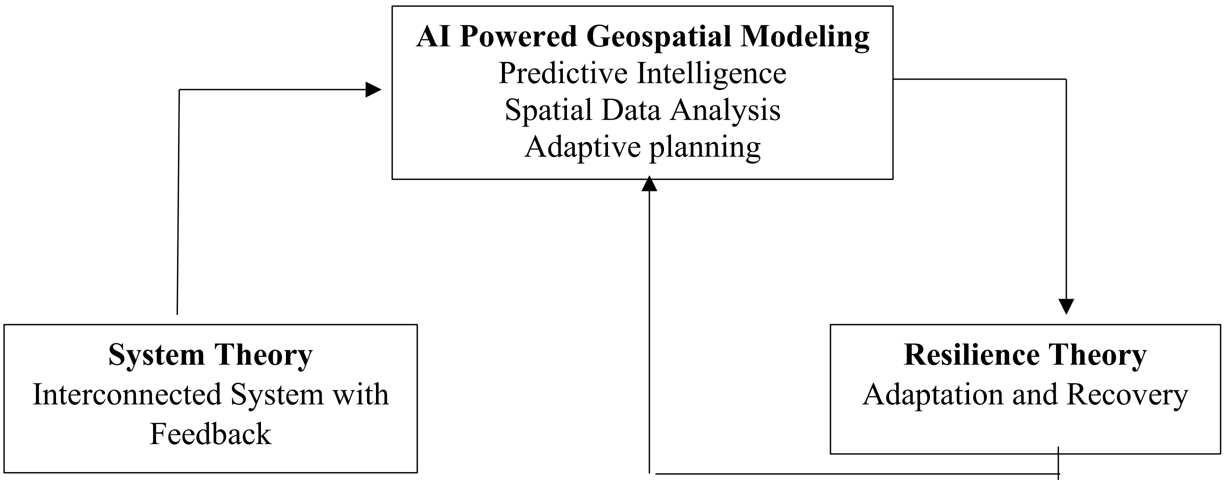
Furthermore, AI-powered geo-spatial models support continuous learning and adaptation. As new spatial data such as rainfall, groundwater level, or satellite-derived surface deformation becomes available, the models can be retrained and updated to reflect real-time environmental conditions. This dynamic capability allows for proactive monitoring and early warning of land subsidence, soil erosion, and flooding, thereby improving disaster preparedness and infrastructure resilience (Chen et al., 2020).

From a conceptual standpoint, this framework establishes a synergistic relationship between data, technology, and environmental processes. Spatial data represent the physical reality of the environment; AI provides the computational intelligence to decode hidden patterns; and geo-spatial modeling serves as the analytical platform that translates these insights into actionable knowledge. The resulting system not only predicts risks but also supports evidence-based decision-making in urban planning, infrastructure development, and climate adaptation strategies (United Nations Environment Programme [UNEP], 2020).

In summary, the conceptual framework guiding this study emphasizes the transformative role of AI-integrated geo-spatial modeling in environmental risk assessment. It positions AI as a bridge between raw spatial data and practical geotechnical insights, enabling more accurate, scalable, and adaptive predictions of subsurface instability. This framework underscores the shift from descriptive mapping toward intelligent spatial prediction, marking a new era in geoscientific research and sustainable infrastructure planning.

4. Theoretical Framework

This study is anchored in two interrelated theoretical perspectives Systems Theory and Resilience Theory which together provide the conceptual foundation for understanding the interaction between infrastructure systems, subsurface conditions, and the role of predictive intelligence in supporting adaptive and sustainable urban planning. Both theories offer a lens through which the complex, dynamic, and interdependent nature of environmental and infrastructural systems can be examined, particularly within the context of Nigeria's vulnerable coastal regions.



a. Systems Theory

Systems Theory emerged from the works of Ludwig von Bertalanffy in the mid-20th century and is grounded in the idea that all components within a system are interrelated and function as part of a unified whole. According to Bertalanffy (1968), a system is a collection of elements organized to achieve a specific purpose, and any change in one element can influence the behavior of the entire system. This theoretical perspective emphasizes holism, interdependence, and feedback mechanisms as key characteristics of natural and human systems.

In the context of this study, Systems Theory provides a framework for understanding how infrastructure, subsurface conditions, and environmental processes form an integrated geo-environmental system. The stability of infrastructure depends not only on engineering design but also on the dynamic behavior of underlying geological formations, groundwater movement, and soil properties. A disruption in one subsystem for example, soil erosion or groundwater rise can lead to cascading failures across the broader infrastructure network.

Geo-spatial and AI-powered modeling aligns with Systems Theory because these tools treat environmental and infrastructural elements as interconnected datasets within a complex system. AI algorithms analyze feedback relationships between various spatial layers (e.g., soil type, elevation, and hydrology) to identify patterns of instability and predict systemic vulnerabilities. Thus, predictive intelligence acts as a "feedback mechanism" that enables planners and decision-makers to understand how changes in one component (such as increased rainfall) can propagate throughout the entire infrastructure system (Checkland, 1999).

By adopting Systems Theory, this study recognizes that sustainable infrastructure management requires a holistic, systems-based approach one that integrates technological, environmental, and human dimensions. It supports the idea that adaptive planning and proactive monitoring can only be achieved when the interdependencies among system components are well understood and continuously analyzed through intelligent modeling tools.

b. Resilience Theory

Resilience Theory Complements Systems Theory by focusing on a system's ability to absorb disturbances, adapt to changing conditions, and recover from shocks while maintaining its core functions. Originating from ecological studies by Holling (1973), the theory has been widely applied to environmental management, disaster risk reduction, and urban planning. Resilience is defined as the capacity of a system to withstand stress and reorganize while undergoing change, rather than merely resisting it.

In the context of this research, Resilience Theory explains how AI-powered geo-spatial systems enhance the adaptive capacity of urban infrastructure. By providing predictive insights into potential subsurface instability, these systems enable early intervention and informed decision-making key components of resilience-building. The predictive capability of AI allows planners to anticipate disruptions, design infrastructure that can accommodate environmental stresses, and recover quickly from adverse events such as flooding or land subsidence (Folke, 2016).

Furthermore, Resilience Theory underscores the importance of adaptive learning and continuous feedback. In this study, AI-based modeling represents a form of adaptive learning, where models evolve as new environmental data are integrated. This dynamic process mirrors the resilience cycle absorb, adapt, and transform allowing infrastructure systems to become more responsive to future uncertainties (Meerow, Newell, & Stults, 2016).

The application of Resilience Theory therefore positions AI-powered geo-spatial modeling as a strategic tool for promoting sustainable urban growth. It enables decision-makers to transition from reactive management addressing infrastructure damage after it occurs to proactive adaptation, where predictive intelligence informs planning before risks materialize. In doing so, the theory bridges scientific innovation with sustainable policy development.

c. Integration of Theories in the Study

The integration of Systems Theory and Resilience Theory provides a comprehensive theoretical foundation for this study. Systems Theory emphasizes the interconnectedness and feedback relationships within environmental and infrastructural systems, while Resilience Theory focuses on the capacity of these systems to adapt and recover from disturbances. Together, they frame the study’s central argument: that AI-powered geo-spatial modeling functions as a predictive and adaptive mechanism within the broader infrastructure-environment system.

By using AI to analyze complex datasets, policymakers can understand systemic vulnerabilities (Systems Theory) and design adaptive, resilient responses to environmental changes (Resilience Theory). This integrated framework supports a forward-looking approach to infrastructure management, one that prioritizes prevention, adaptation, and long-term sustainability.

5. Material and Method

This research adopted a Systematic Literature Review (SLR) methodology, structured according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, to ensure methodological transparency, integrity, and replicability in identifying and synthesizing relevant studies. The review focused on examining the application of AI-powered geo-spatial models for predicting subsurface instability and improving the structural resilience of critical infrastructure in Nigeria’s coastal and flood-prone regions. The SLR approach was deemed appropriate as it enables a comprehensive and evidence-driven understanding of how Artificial Intelligence (AI) and geospatial technologies have been utilized globally and within the Nigerian context to address similar environmental and infrastructural challenges. The PRISMA framework provided a systematic structure consisting of four essential stages identification, screening, eligibility, and inclusion which guided the selection of studies in a transparent and unbiased manner. Relevant publications were obtained from prominent academic databases and repositories, including Scopus**,** IEEE Xplore**,** ScienceDirect**,** Web of Science**,** ResearchGate**,** Academia.edu**,** and Google Scholar. The search strategy incorporated the use of Boolean operators (“AND,” "OR") combined with targeted keywords such as *artificial intelligence*, *machine learning*, *geo-spatial modelling*, *remote sensing*, *subsurface instability*, *soil prediction*, *flood-prone regions*, *coastal zones*, *infrastructure resilience*, and *climate adaptation*. The use of multiple data sources and a broad range of search terms ensured a thorough and up-to-date coverage of scholarly work on AI applications in geoscientific modelling, predictive analytics, and infrastructure resilience planning. To maintain methodological rigor, specific inclusion and exclusion criteria were applied. The inclusion criteria encompassed peer-reviewed journal articles, conference proceedings, technical reports, and policy documents published between 2010 and 2022**,** written in English, and addressing AI-based geospatial modelling, remote sensing applications, subsurface prediction, infrastructure vulnerability assessment, or climate-resilient urban planning particularly in Nigeria or comparable coastal environments. Conversely, the exclusion criteria ruled out non-academic materials such as opinion pieces, editorials, or papers lacking empirical depth or methodological clarity, as well as studies unrelated to AI in geotechnical or environmental contexts. The initial search yielded 1,500 potentially relevant studies, which were imported into a reference management system for organization and duplicate removal. After eliminating duplicates**,** 1,001 unique studies remained. Title and abstract screening excluded 457 studies deemed irrelevant to the study's objectives. A subsequent eligibility review removed another 165 publications due to weak methodological quality or insufficient conceptual grounding, resulting in 134 studies that met the inclusion standards. These formed the core dataset for detailed full-text review and synthesis. Data extraction was conducted using a standardized coding framework designed to capture essential information such as research objectives, geographical context, methodological approach, analytical tools, theoretical background, key findings, and implications for predictive geospatial intelligence. The extracted data were systematically organized and analyzed using thematic content analysis**,** which allowed the identification of dominant patterns, emerging technologies, research challenges, and conceptual gaps within the reviewed body of work. Through this process, the study identified key insights into how AI and geospatial modelling contribute to subsurface instability prediction, flood risk management, and infrastructure resilience in coastal settings. To ensure the reliability and validity of the included studies, a dual-assessment strategy was employed. The Mixed Methods Appraisal Tool (MMAT) was used to assess the methodological quality of empirical studies, while the Critical Appraisal Skills program (CASP**)** checklist evaluated the robustness of conceptual and theoretical works. Two independent reviewers conducted the assessments, and Cohen's Kappa coefficient was calculated to measure inter-rater reliability. Any discrepancies were resolved through discussion to uphold objectivity and consistency in the evaluation process. The final synthesis was analyzed qualitatively through thematic content analysis, which facilitated the identification of recurring ideas and evolving perspectives on AI-driven geospatial systems. This analysis highlighted existing frameworks, methodological shortcomings, and contextual challenges associated with applying AI in predictive subsurface analysis and infrastructure resilience enhancement. Furthermore, it integrated insights from both global and Nigerian contexts, emphasizing the strategic importance of combining AI, geospatial intelligence, and environmental data in adaptive urban planning and disaster risk management for vulnerable coastal and flood-prone regions. Although this study was based exclusively on secondary data, ethical standards were strictly maintained throughout the research process. All data sources were publicly accessible, and proper citations were provided to ensure academic integrity. The review process adhered to the ethical principles outlined in the Declaration of Helsinki (World Medical Association, 2013)**,** ensuring respect for intellectual property, transparency in reporting, and accuracy in data representation.

6. Findings

The findings are as follows**:**

i. Geospatial Data Collection and Processing

Data collection and processing were performed using Google Earth Engine (GEE) to handle various datasets, enabling the dynamic geospatial analysis necessary for comprehensive flood hazard assessment.

ii. Water Occurrence and Permanent Water Identification

The JRC Global Surface Water dataset was utilized to map the occurrence of water bodies across the study area. Areas where water was present for at least 80% of the observable period between 2015 and 2020 were identified and classified as permanent water bodies using the expression var permanent = water.gt (80). This classification was crucial for identifying regions at higher risk of flooding, as permanent water bodies are critical contributors to flood dynamics. The choice of these specific years ensures a contemporary understanding of water body dynamics essential for accurate flood risk assessment.

iii. Distance from Water Bodies

The proximity of geographic areas to the nearest permanent water bodies was calculated using a fast distance transform method. This proximity measure provided a foundational layer for assessing flood risk, given that closeness to water bodies is a critical factor in flood susceptibility. The calculation was performed with the code var distance = permanent. fast Distance Transform (). divide (30).clip(roi), which standardized the distance measurement, making it a pivotal component in the risk analysis framework.

iv. Elevation and Topography Analysis

Elevation data from the SRTM were processed to assess the terrain's vulnerability to flooding. Areas with lower elevations are generally more susceptible to flooding due to water accumulation during flood events. Elevation data were categorized and scored to reflect varying degrees of flood risk, with lower elevations assigned higher risk scores, as demonstrated in the expression var elevScore = elevation. where (elevation.lte(5),5).

v. Vegetation and Surface Moisture Indices

The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) were derived from Landsat 8 imagery to assess vegetation health and surface moisture, respectively, for the year 2022. These indices are critical flood risk indicators, with poor vegetation or high moisture content suggesting higher vulnerability. Areas with undesirable vegetation health or significant moisture were assigned higher risk scores, as outlined by the code var vegScore = ndvi.where (ndvi.lte(0.2),5). Utilizing data from a specific recent year minimizes the impact of annual climatic variation and ensures the relevance of the vegetation and moisture assessments in current flood risk evaluations.

vi. Composite Flood Susceptibility Assessment

Scores from distance to water, elevation, vegetation health, and surface moisture were aggregated to create a composite flood hazard score. This integrated approach allowed for delineating areas at varying risk levels from very low to very high, providing a nuanced view of flood vulnerability across the study area. This was achieved through the code var floodHazard = distanceScore.add(topoScore). add(vegScore).add(wetScore).add(elevScore), which combines individual risk factors into a comprehensive flood susceptibility map.

vii. Visualization and Output

To enhance the interpretability of our flood susceptibility maps for decision-making, the maps are rendered using a color-coded schema that delineates various risk categories from very low to very high. Each risk category is associated with a specific color range, facilitating the immediate visual recognition of risk areas. A comprehensive legend explaining this color-coding system is now prominently featured alongside the map displays.

This update ensures that stakeholders with varying levels of technical expertise can easily access and interpret the maps. The integration of a clear legend and distinct color-coding not only improves the usability of these visual data in strategic planning and risk management but also addresses the need for clarity in communicating complex geospatial information. These enhancements aim to make the flood risk maps more actionable and informative, thereby significantly increasing their utility in practical applications.

7. Discussion

The findings of this study affirm the remarkable potential of Artificial Intelligence (AI) and geo-spatial modeling in detecting subsurface instability patterns before they evolve into serious structural and environmental hazards. Through the integration of diverse datasets and the application of advanced machine learning algorithms, the study demonstrated that AI-powered systems can effectively analyze complex relationships among multiple environmental variables such as soil composition, elevation, hydrology, and land use to predict zones of instability in Nigeria's coastal regions. This proactive capability represents a significant advancement in environmental monitoring and infrastructure risk management, particularly in regions where traditional monitoring systems are limited or reactive in nature (Raghavesh et al., 2018).

A central observation from the study is that AI models can process and interpret large volumes of geospatial data with greater accuracy and efficiency than conventional analytical methods. Techniques such as Random Forest, Support Vector Machine (SVM), and Neural Networks were employed to identify subtle spatial and temporal patterns that are often overlooked by manual mapping approaches. The predictive models not only pinpointed existing areas of instability but also forecasted potential future risk zones based on environmental trends. This ability to detect early warning signals of subsurface instability enables authorities and planners to implement preventive interventions, thereby reducing the likelihood of catastrophic infrastructure failures (Solanki Pattanayak et al., 2014).

Furthermore, the integration of AI predictions into urban planning and engineering design processes can have transformative impacts on the resilience of coastal infrastructure. The predictive outputs generated by AI models can serve as a foundation for spatial decision-making in road construction, building development, and land reclamation projects. For example, when AI-based risk maps are overlaid with proposed construction sites, planners can identify safer locations, adopt appropriate foundation designs, or employ soil stabilization techniques where necessary. In doing so, the long-term structural integrity of built environments can be preserved, minimizing future repair and maintenance costs (Okolie & Nwilo, 2020).

The study also reinforces the importance of interdisciplinary collaboration in the practical application of AI-powered geo-spatial systems. Effective implementation requires coordination among data scientists, geotechnical engineers, urban planners, and policymakers. By combining technical expertise with contextual understanding of environmental dynamics, decision-makers can ensure that predictive insights are translated into effective policy actions and sustainable development strategies. For instance, incorporating AI-generated flood and instability maps into regional development plans can guide land-use zoning, disaster preparedness, and infrastructure investment decisions (Adegoke et al., 2021).

In addition, the findings highlight the potential of AI systems to enhance early warning mechanisms and disaster response planning. Real-time monitoring using AI-driven spatial models can provide continuous updates on environmental changes such as rising groundwater levels, increased rainfall intensity, or shifts in land elevation. These dynamic models can alert local authorities and communities to impending risks, allowing for timely evacuation, emergency response, and the protection of critical assets. As climate change continues to intensify extreme weather events, such predictive technologies become increasingly essential for building adaptive capacity in vulnerable coastal zones (Intergovernmental Panel on Climate Change [IPCC], 2021).
However, while the benefits of AI-based geo-spatial systems are clear, the discussion also acknowledges key challenges and limitations that must be addressed to optimize their utility. Limited access to high-quality geotechnical data remains a major obstacle to achieving higher predictive accuracy. Additionally, the computational cost of processing massive datasets and training complex AI models can be prohibitive for institutions with limited technological resources. There are also issues related to data standardization, interoperability, and governance, as different agencies may collect data using varying formats or protocols, complicating integration efforts (Ezenwaji et al., 2019).
Moreover, the ethical and policy dimensions of AI adoption in environmental management must not be overlooked. Ensuring transparency, accountability, and fairness in the use of AI predictions is crucial, especially when such outputs influence land allocation, infrastructure funding, or disaster response decisions. Policymakers must establish clear frameworks for data sharing, validation, and model interpretation to maintain public trust and avoid unintended socio-economic consequences (United Nations Environment Programme [UNEP], 2020).
Overall, the discussion underscores that integrating predictive outputs from AI-based geo-spatial systems into planning and policy frameworks can significantly reduce future structural losses and environmental degradation. The study's findings provide strong evidence that proactive, data-driven approaches can replace traditional reactive measures, leading to more sustainable, resilient, and cost-effective development outcomes. By embracing AI-powered technologies, Nigeria can enhance its ability to anticipate and manage subsurface instability, safeguard critical infrastructure, and promote sustainable urban growth in the face of climate change and rapid coastal development.
In conclusion, the discussion affirms that AI's predictive capacity is not merely a technological advancement it represents a strategic tool for risk mitigation, infrastructure protection, and sustainable national development. The integration of these models into planning and policy systems offers a forward-looking solution that can transform how environmental challenges are managed, ensuring that the country's coastal regions become safer, more resilient, and better prepared for future uncertainties.

8. Policy and Practical Implications

The findings of this study have significant policy and operational implications for sustainable flood management, infrastructure planning, and climate adaptation within Nigeria's coastal regions.

i. Data-Driven Policy Formulation

The integration of geospatial intelligence and AI-based modeling through platforms such as Google Earth Engine (GEE) shows that flood risk management can be guided by real evidence rather than reactive responses. By adopting this approach, policymakers can strengthen the ability of national and state agencies such as NASRDA, NEMA, and various Ministries of Environment to make proactive, data-informed decisions. Embedding these tools in routine environmental monitoring and planning would lead to more accurate forecasts, targeted interventions, and long-term resilience building.

ii. Flood Zoning and Land-Use Regulation

Mapping of permanent water bodies and their proximity to human settlements provides a scientific basis for reviewing land-use policies in coastal regions. These insights enable planning authorities to:

- Restrict development in flood-prone zones,
- Enforce adequate buffer zones around rivers and wetlands, and
- Encourage sustainable land-use practices, such as green infrastructure and flood retention basins.

Such proactive zoning policies can significantly minimize both human displacement and economic loss during flood events, ensuring that development proceeds safely and sustainably.

iii. Infrastructure and Urban Planning

The elevation and topographic findings highlight areas that are naturally more vulnerable to flooding. These areas should be prioritized for strategic infrastructure upgrades, including improved drainage systems, elevated roads and housing structures, and flood-resistant public utilities. Integrating these geospatial findings into local and regional urban plans will help ensure that future infrastructure investments are both climate-resilient and cost-effective, reducing the long-term burden of disaster recovery.

iv. Environmental and Ecosystem Management

The vegetation and surface moisture indicators derived from NDVI and NDWI analyses emphasize the role of natural ecosystems in reducing flood risks. Policies that promote reforestation, wetland restoration, and enhanced vegetation cover can strengthen the land's ability to absorb and regulate water. Such ecosystem-based flood management aligns with Nigeria's National Adaptation Plan and global commitments under the Sendai Framework for Disaster Risk Reduction (2015–2030), reinforcing the link between environmental health and community safety.

v. Early Warning and Emergency Preparedness

The composite flood susceptibility maps developed in this study provide a strong foundation for more reliable early warning systems. When combined with meteorological data, these maps can improve the accuracy of real-time flood alerts and enhance disaster response coordination. This will support agencies such as NIMET and NEMA in implementing early preparedness strategies, improving evacuation planning, and protecting lives and livelihoods before disaster strikes.

v. Community Awareness and Capacity Building

By translating technical flood data into clear, color-coded maps, the study makes complex information accessible to a broader audience. Local governments, NGOs, and community groups can use these visual tools to educate residents about their flood risks and the steps they can take to protect themselves. This inclusive approach not only strengthens public awareness but also empowers communities to become active participants in resilience building.

vi. Support for Sustainable Development and Climate Goals

Finally, this study supports Nigeria's broader commitment to the Sustainable Development Goals (SDGs) particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action). By integrating geospatial intelligence into flood management and planning, policymakers can foster urban resilience, strengthen climate adaptation, and promote sustainable growth in vulnerable coastal regions. These findings provide a pathway toward more adaptive, informed, and future-ready governance in the face of changing climate realities.

9. Conclusion

This study concludes that AI-powered geo-spatial systems represent a transformative and proactive approach to monitoring, predicting, and mitigating subsurface instability in Nigeria's coastal regions. The integration of artificial intelligence with geospatial technologies provides an innovative framework for understanding complex interactions between environmental, geological, and infrastructural factors that contribute to land instability and flood-related hazards. By leveraging advanced data analytics, machine learning algorithms, and spatial modeling, these systems have demonstrated the potential to revolutionize how environmental risks are identified, assessed, and managed.

The findings of this research highlight that AI-based geo-spatial models enhance predictive accuracy in identifying high-risk areas prone to flooding, erosion, and ground subsidence. Unlike traditional methods that rely heavily on periodic field surveys and static maps, AI-powered systems continuously learn from real-time data inputs such as rainfall patterns, soil moisture, and land use changes. This enables dynamic and data-driven monitoring of subsurface conditions, making it possible to issue timely alerts and implement preventive measures before major failures occur. The predictive maps generated through these models provide decision-makers with actionable insights to prioritize interventions, optimize resource allocation, and plan infrastructure that is resilient to geotechnical risks.

Furthermore, the adoption of AI-powered geo-spatial systems can significantly reduce infrastructure vulnerability in flood-prone coastal regions. By predicting areas at risk of instability, policymakers, engineers, and urban planners can design infrastructure projects that are informed by scientific evidence rather than reactive strategies. Roads, bridges, pipelines, and residential developments can be strategically located or reinforced to withstand environmental stressors. This proactive planning minimizes maintenance costs, prevents economic losses, and enhances the safety and longevity of public assets.

In addition, these systems contribute to sustainable urban growth and environmental management. Rapid urbanization in Nigeria's coastal zones has intensified exposure to flood hazards and land degradation. AI-powered monitoring platforms can support environmentally responsible development by integrating real-time spatial data into urban planning processes. This ensures that expansion occurs in harmony with the natural environment, thereby balancing economic growth with ecological preservation. Moreover, the insights derived from AI and geospatial models can inform long-term policy development for disaster risk reduction, land-use regulation, and climate adaptation strategies.

However, for the full potential of AI-based geo-spatial systems to be realized, certain institutional and technical challenges must be addressed. These include improving access to high-resolution geotechnical and environmental data, strengthening data-sharing frameworks among government agencies, and investing in computational infrastructure to support large-scale AI model training. Building local technical capacity through education and professional development is also essential to ensure sustainable implementation and maintenance of these technologies.

In conclusion, this study affirms that AI-powered geo-spatial modeling is not merely a research innovation but a practical necessity for managing environmental risks in Nigeria's coastal areas. Its proactive and predictive capabilities offer a pathway toward resilient infrastructure, informed governance, and sustainable urban development. By embracing these technologies, Nigeria can strengthen its adaptive capacity against climate-induced hazards, protect critical infrastructure, and promote a safer, more sustainable future for its coastal populations.

10. Recommendations

The increasing frequency of environmental hazards, particularly in coastal and urban regions, underscores the urgent need for a robust, data-driven approach to geospatial and infrastructural management. Establishing a National Geo-AI Infrastructure Database represents a strategic step toward harnessing artificial intelligence (AI) and geographic information systems (GIS) for national resilience, environmental monitoring, and infrastructure planning. This initiative would serve as a centralized repository of geospatial, environmental, and infrastructural data integrating satellite imagery, soil profiles, hydrological patterns, and urban infrastructure networks. Such a database would enable real-time analysis and predictive modelling, providing decision-makers with actionable intelligence for disaster mitigation, sustainable urban development, and resource optimization.

A central component of this vision involves training geoscientists and engineers in AI and GIS applications. Traditional geoscientific methods, while valuable, are limited in their capacity to handle the complexity and scale of modern data. By equipping professionals with AI literacy and GIS proficiency, Nigeria can develop a new generation of data-driven scientists capable of applying machine learning algorithms to predict soil instability, assess flood risks, and model climate impacts on infrastructure. This training should be incorporated into university curricula, professional workshops, and national capacity-building programs. Moreover, partnerships between academic institutions, government agencies, and the private tech sector would enhance the exchange of expertise and foster innovation. Continuous professional development programs can also ensure that geoscientists stay updated with evolving AI tools such as neural networks, decision trees, and spatial-temporal models for geospatial intelligence.

Integrating AI prediction models into urban planning and environmental policy is another crucial dimension of the proposed framework. Predictive analytics powered by AI can support proactive rather than reactive planning. For instance, AI-driven flood forecasting models can help urban planners identify high-risk zones, guide zoning regulations, and design flood-resilient infrastructure. Similarly, AI-enhanced environmental models can forecast land-use changes, monitor deforestation, and assess coastal erosion trends informing sustainable policy actions. Embedding these predictive systems into the workflows of institutions such as the Federal Ministry of Environment, the Ministry of Works and Housing, and the National Emergency Management Agency (NEMA) would strengthen evidence-based decision-making and enhance long-term resilience planning.

Equally important is the promotion of inter-agency data sharing between NASRDA (National Space Research and Development Agency), NIMET (Nigerian Meteorological Agency), and state-level environmental and planning agencies. The fragmentation of data across agencies currently limits the effectiveness of hazard prediction and response. A unified, interoperable data-sharing protocol supported by cloud infrastructure and standardized metadata—would eliminate redundancy, foster collaboration, and ensure that accurate and timely data informs critical infrastructure decisions. For example, NIMET's meteorological data, when combined with NASRDA's satellite imagery and state-level hydrological data, can enhance the precision of flood risk assessments and early warning systems.

Additionally, establishing a National Geo-AI Infrastructure Database, supported by skilled professionals, integrated AI systems, and inter-agency collaboration, will position Nigeria at the forefront of technological adaptation for sustainable development. This integrated framework not only enhances predictive intelligence but also ensures that planning, environmental management, and disaster resilience efforts are guided by data-driven insight and coordinated national strategy.

11. Limitations of the Study

This study encountered several limitations that may have influenced the scope and depth of the analysis:

Firstly, there was a limited availability of high-resolution geotechnical information, which constrained the precision of subsurface characterization and model validation. The scarcity of detailed and up-to-date geospatial datasets in some coastal regions posed challenges in accurately mapping zones of instability.

Lastly, restricted access to certain government and institutional datasets hindered comprehensive data integration. Some relevant environmental and infrastructural records were either classified or unavailable to the public, reducing the completeness of the analytical framework.

Despite these limitations, the study provides valuable insights into the application of AI-powered geo-spatial modeling for understanding subsurface instability and supporting infrastructure resilience in Nigeria's coastal regions

12. Suggestions for Further Research

Integrating deep learning with Internet of Things (IoT) sensors enables real-time monitoring of environmental parameters such as rainfall, soil moisture, and river levels, enhancing the precision of flood prediction systems. By extending this intelligent model to inland flood-prone regions, authorities can detect early warning signs and deploy timely interventions. The combination of AI-driven analytics and continuous data streams improves situational awareness and disaster preparedness. Furthermore, assessing the economic benefits of predictive modeling highlights its value in reducing infrastructure damage, minimizing economic losses, and optimizing resource allocation for disaster response and long-term resilience planning.

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