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Machine Learning and Remote Sensing for Gully Erosion Susceptibility Mapping in Southeast Nigeria: Progress, Challenges, and Research Priorities

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ABSTRACT

Gully erosion remains one of the most destructive forms of land degradation in tropical environments, threatening agricultural productivity, infrastructure, ecosystem services, and human settlements. Southeast Nigeria represents one of the world's most vulnerable gully erosion hotspots owing to its highly erodible geological formations, intense rainfall, rapid land-use change, and increasing anthropogenic disturbances. Recent advances in machine learning (ML), cloud computing, and Earth observation technologies have significantly improved gully erosion susceptibility mapping (GESM); however, the extent to which these innovations have been adopted within Southeast Nigeria remains unclear. This study presents a PRISMA 2020-compliant systematic review of machine learning-based GESM studies published between January 2015 and June 2026. A comprehensive literature search was conducted using structured Boolean search strategies. Random Forest and Extreme Gradient Boosting emerged as the most frequently applied algorithms, and consistently achieving Area Under the Receiver Operating Characteristic Curve (AUC) values ranging from 0.88 to 0.98. Sentinel-2 multispectral imagery and the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model constituted the dominant remote sensing datasets, while slope, vegetation indices, elevation, rainfall, land-use/land-cover, Topographic Wetness Index, and Stream Power Index were the most influential conditioning factors. Despite these global advances, only eighteen studies specifically did research on Southeast Nigeria and three employed ML approach. Furthermore, none integrated Sentinel-1 Synthetic Aperture Radar (SAR) with optical imagery or implemented modern deep learning architectures such as Convolutional Neural Networks or U-Net models. The review reveals major methodological gaps between global developments and current research practices in Southeast Nigeria. Major research gaps include the absence of SAR-optical data fusion, explainable artificial intelligence, deep learning, temporal susceptibility modelling, regional multi-state assessments, and cloud-based Google Earth Engine workflows. A comprehensive methodological framework integrating Sentinel-1 SAR, Sentinel-2 imagery, Google Earth Engine, ensemble machine learning, spatial cross-validation, and SHAP-based model interpretability is proposed to guide future research.

INTRODUCTION

Gully erosion is among the most severe forms of soil degradation worldwide and represents a major environmental challenge in both humid tropical and semi-arid regions (Kuhn et al., 2023. Unlike sheet and rill erosion, gullies develop through complex interactions among surface runoff, subsurface flow, soil characteristics, topography, vegetation cover, and anthropogenic activities, resulting in deep and permanent incisions that fundamentally alter landscape morphology (Irifi et al.,2026). Beyond the direct removal of fertile topsoil, gully erosion accelerates sediment transport, degrades agricultural land, damages transportation networks, threatens critical infrastructure, reduces water quality, and increases downstream flooding and reservoir sedimentation (Bitikoro Phionah J.,2024). Consequently, gully erosion has become an important concern within the broader context of land degradation, environmental sustainability, disaster risk reduction, and climate change adaptation (Iwuchukwu et al.,2023)

Globally, the frequency and intensity of gully erosion have increased over recent decades due to rapid land-use change, deforestation, urban expansion, unsustainable agricultural practices, and increasing rainfall variability associated with climate change (Kumar et al.,2023). The widespread availability of high-resolution satellite imagery, digital elevation models, cloud-computing platforms, and artificial intelligence has transformed the way erosion processes are investigated (Wang et al., 2024). Modern geospatial technologies now enable researchers to predict the spatial distribution of erosion susceptibility with unprecedented accuracy, thereby supporting proactive land management and environmental planning (Christofi et al., 2025).

Among the region's most severely affected by gully erosion worldwide is Southeast Nigeria, comprising the states of Anambra, Enugu, Imo, Abia, and Ebonyi (Iwuchukwu et al., 2023). The region is internationally recognised as one of the largest gully erosion hotspots in sub-Saharan Africa, with more than 2,700 documented active gullies. Several individual gullies exceed several hundred metres in length and attain depths greater than 90 m, causing extensive destruction of roads, residential buildings, farmlands, public utilities, and economic assets (Oyinyechi et al., 2024). The exceptional vulnerability of the region is primarily attributed to the highly erodible Nanka Formation and Ajali Sandstone, characterised by weakly cemented, unconsolidated sandy sediments with high permeability and low shear strength (Unigwe et al.,2022). Combined with annual rainfall exceeding 2,000 mm, steep local relief, rapid vegetation loss, and poorly planned urban development, these geological conditions create an environment highly susceptible to gully initiation and expansion (Kuhn et al., 2023)

Accurate identification of areas vulnerable to future gully development is therefore essential for sustainable watershed management, infrastructure protection, and disaster mitigation (Mokarram et al., 2026). Gully Erosion Susceptibility Mapping (GESM) has consequently become one of the most important spatial decision-support tools in environmental management (Jo et al., 2025). GESM integrates geographic information systems, remote sensing data, environmental conditioning factors, and predictive modelling techniques to estimate the probability of gully occurrence across landscapes (Gelete et al., 2024). These susceptibility maps enable governments, engineers, planners, and conservation agencies to prioritise intervention zones and optimise erosion control investments before catastrophic failures occur (Capobianco et al., 2025).

Traditional GESM studies have largely relied on statistical and knowledge-driven approaches, including Frequency Ratio, Weight of Evidence, Logistic Regression, Analytic Hierarchy Process, and Multi-Criteria Decision Analysis (Wendim et al., 2025). Although these methods have contributed substantially to erosion hazard assessment, they are often constrained by assumptions of linearity, subjective weighting schemes, limited capability for modelling complex interactions among environmental variables, and reduced predictive performance when applied to heterogeneous landscapes (Montien et al., 2026). Such limitations become particularly important in tropical regions, where erosion processes are governed by highly nonlinear interactions among rainfall, lithology, vegetation dynamics, hydrology, and human disturbances (Tania et al., 2026).

Recent advances in machine learning have fundamentally transformed susceptibility modelling (Pugliese et al., 2024). Algorithms such as Random Forest, Extreme Gradient Boosting, Support Vector Machines, LightGBM, Artificial Neural Networks, and deep learning architectures including Convolutional Neural Networks and U-Net have demonstrated superior predictive capability across diverse geomorphological environments (Akingboye et al., 2026). These algorithms effectively capture nonlinear relationships, accommodate high-dimensional datasets, minimise overfitting through ensemble learning, and achieve consistently higher predictive accuracies than conventional statistical techniques (Wilson et al., 2024). Simultaneously, the increasing accessibility of cloud-based geospatial platforms such as Google Earth Engine has enabled efficient processing of large Earth observation datasets, while explainable artificial intelligence methods, particularly SHapley Additive exPlanations (SHAP), have improved transparency by identifying the relative importance of individual environmental conditioning factors (Singh et al., 2025).

Despite these remarkable global advances, the application of machine learning to gully erosion susceptibility mapping remains relatively underdeveloped in Southeast Nigeria (Nwobi et al.,2026). Existing studies continue to rely predominantly on conventional statistical techniques, limited geographical coverage, manually generated gully inventories, and optical satellite imagery without exploiting recent developments in Synthetic Aperture Radar (SAR), deep learning, ensemble modelling, spatial cross-validation, or explainable artificial intelligence (Ayogu et al., 2023). Furthermore, no comprehensive systematic review has critically synthesised global methodological advances while evaluating their

applicability to Southeast Nigeria (Omeka et al.,2023). This lack of synthesis limits both scientific progress and evidence-based decision-making for erosion management within one of Africa's most vulnerable landscapes (Boroko et al., 2026).
The present study addresses this knowledge gap through a systematic review conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. Specifically, the review aims to:

i. synthesise global developments in machine learning-based gully erosion susceptibility mapping between 2015 and 2026;
ii. evaluate the remote sensing datasets, environmental conditioning factors, modelling algorithms, and validation approaches employed in recent studies;
iii. critically assess the current state of GESM research in Southeast Nigeria relative to global best practices; and
iv. identify methodological, geographical, and technological research gaps while proposing a comprehensive framework to guide future investigations. By integrating evidence from diverse geographical settings, this review provides an updated reference for researchers, policymakers, and environmental managers seeking to advance erosion prediction and sustainable land management in Southeast Nigeria and comparable tropical regions.

MATERIALS AND METHODS

Study Design

This study employed a systematic literature review (SLR) to critically synthesise advances in machine learning (ML)-based gully erosion susceptibility mapping (GESM), with particular emphasis on identifying methodological trends, emerging technologies, research gaps, and future opportunities relevant to Southeast Nigeria. The review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, ensuring transparency, reproducibility, and methodological rigor throughout the review process (O'Dea et al., 2021).
Unlike conventional narrative reviews, a systematic review follows a predefined protocol for literature identification, screening, eligibility assessment, quality appraisal, data extraction, and evidence synthesis (Siddaway et al., 2019). This approach minimises selection bias while providing a robust evidence base for evaluating current research and identifying future directions (Shaheen et al.,2023).

Research Questions

The review was guided by the following research questions (RQs):
RQ1: What machine learning algorithms have been employed for gully erosion susceptibility mapping worldwide between 2015 and 2026?
RQ2: Which remote sensing datasets, environmental conditioning factors, validation approaches, and evaluation metrics have been most frequently utilised?
RQ3: What is the current state of ML-based GESM research in Southeast Nigeria compared with global developments?
RQ4: What critical methodological gaps remain, and what future research framework can accelerate scientific and practical progress in Southeast Nigeria?

Literature Search Strategy

A comprehensive literature search was conducted across four major bibliographic databases:

i. Scopus
ii. Web of Science Core Collection
iii. ScienceDirect
iv. Google Scholar

These databases were selected because they collectively index the majority of peer-reviewed literature in geomorphology, environmental science, remote sensing, geoinformatics, and machine learning. The search covered publications from January 2015 to June 2026, corresponding to the period during which ML-based susceptibility mapping experienced rapid development.
A structured Boolean search strategy combined keywords relating to gully erosion, machine learning, remote sensing, susceptibility mapping, and Southeast Nigeria.
The principal search expression was:
("gully erosion" OR "gully susceptibility") AND ("machine learning" OR "artificial intelligence" OR "deep learning" OR "Random Forest" OR "XGBoost" OR "Support Vector Machine") AND ("remote sensing" OR GIS OR "Sentinel-1" OR "Sentinel-2" OR SAR OR DEM OR "Google Earth Engine")
To ensure comprehensive coverage, additional searches incorporated terms including:

i. explainable artificial intelligence
ii. SHAP
iii. CNN
iv. U-Net
v. LightGBM
vi. CatBoost
vii. ensemble learning
viii. erosion modelling
ix. Nigeria
x. Southeast Nigeria
xi. Anambra Basin

Reference lists of eligible studies were manually examined to identify additional relevant publications not retrieved during the database search.

Eligibility Criteria

Studies were selected according to predefined inclusion and exclusion criteria.

Inclusion Criteria

Publications were included if they:

i. were published between January 2015 and June 2026;
ii. were peer-reviewed journal articles;
iii. investigated gully erosion susceptibility mapping;
iv. employed machine learning, statistical learning, deep learning, ensemble learning, or hybrid modelling techniques;
v. utilised GIS and/or remote sensing datasets;
vi. reported quantitative model evaluation metrics such as AUC, Accuracy, F1-score, Recall, Precision, or Kappa coefficient;
vii. were written in English.

Exclusion Criteria

Studies were excluded if they:

i. focused solely on sheet or rill erosion;
ii. investigated landslides without addressing gully erosion;
iii. were conference abstracts, editorials, theses, book reviews, or technical reports;
iv. lacked sufficient methodological detail;
v. did not evaluate predictive model performance;
vi. were duplicate publications.

These criteria ensured that only methodologically robust studies directly relevant to ML-based GESM were included.

Study Selection Process

The study selection process followed the four stages recommended by PRISMA 2020.

Stage 1: Identification

Electronic database searches identified all potentially relevant records.

Stage 2: Screening

Duplicate records were removed.

Titles and abstracts were independently screened for relevance.

Stage 3: Eligibility

Full-text articles were assessed against the predefined inclusion and exclusion criteria.

Stage 4: Inclusion

Studies satisfying all eligibility requirements were retained for qualitative synthesis.

The complete screening procedure is illustrated using the PRISMA flow diagram (Figure 1).

Quality Assessment

To ensure methodological robustness, each included study was evaluated using a structured quality assessment framework adapted from established systematic review protocols in environmental modelling. Each article was assessed across seven quality domains:

i. clarity of research objectives;
ii. adequacy of gully inventory preparation;
iii. description of environmental conditioning factors;
iv. appropriateness of machine learning methodology;
v. validation strategy;
vi. transparency of performance reporting;
vii. reproducibility of methodology.

Each criterion received a score of:

2 = fully satisfied

1 = partially satisfied

0 = not satisfied

Only studies achieving an overall quality score above the predefined threshold were retained.

Data Extraction

A standardised data extraction template was developed to ensure consistency across studies.

The following information was extracted:

i. author(s);
ii. publication year;
iii. country;
iv. study area;
v. machine learning algorithm;
vi. remote sensing datasets;
vii. DEM source;
viii. environmental conditioning factors;
ix. sample size;
x. validation strategy;
xi. performance metrics;
xii. principal findings;
xiii. identified limitations.

The extracted information formed the basis for the comparative analysis presented in the Results section.

Data Synthesis

Given the substantial methodological diversity among the reviewed studies, a quantitative meta-analysis was not considered appropriate.

Instead, evidence was synthesised using qualitative thematic analysis and descriptive statistics.

The synthesis examined:

i. publication trends;
ii. geographical distribution;
iii. popularity of machine learning algorithms;
iv. remote sensing datasets;
v. conditioning factors;
vi. validation approaches;
vii. model performance;
viii. explainable AI adoption;
ix. deep learning applications;

x. emerging research themes.

Comparative analyses were conducted between global studies and those specifically undertaken in Southeast Nigeria to identify methodological disparities and research priorities.

Risk of Bias Assessment

Potential sources of bias were considered throughout the review.

These included:

i. publication bias resulting from preferential publication of high-performing models;
ii. language bias due to inclusion of English-language publications only;
iii. database bias arising from differential indexing across bibliographic sources;
iv. methodological bias caused by inconsistent validation strategies;
v. reporting bias associated with selective presentation of favourable performance metrics.

Recognising these limitations enhances the transparency and reliability of the review findings.

Statistical Analysis

Descriptive statistical analyses were performed to summarise:

i. annual publication trends;
ii. frequency of machine learning algorithms;
iii. frequency of conditioning factors;
iv. popularity of remote sensing datasets;
v. geographical distribution of studies;
vi. reported model performance.

Performance comparisons primarily employed the Area Under the Receiver Operating Characteristic Curve (AUC), which remains the most widely accepted metric for evaluating susceptibility mapping models (Abdelkader et al., 2025). Where available, Accuracy, Precision, Recall, F1-score, Kappa coefficient, and Matthews Correlation Coefficient (MCC) were also synthesised to provide a comprehensive assessment of predictive performance (Imani et al., 2025).

RESULTS AND DISCUSSION

Overview of the Included Studies

The systematic search yielded 1,276 records from the four electronic databases. Following the removal of duplicate entries, 948 unique publications remained for title and abstract screening. A further 782 articles were excluded because they did not address gully erosion susceptibility mapping, did not employ predictive modelling techniques, or failed to satisfy the predefined eligibility criteria. Full-text assessment was subsequently conducted for 166 studies, of which 52 peer-reviewed articles met all inclusion criteria and were retained for qualitative synthesis. The PRISMA screening process demonstrates a marked increase in research interest in machine learning-based gully erosion susceptibility mapping (GESM) over the last decade. The final dataset provides a comprehensive representation of contemporary developments in susceptibility modelling, remote sensing integration, and explainable artificial intelligence across different climatic and geomorphological settings.

Geographically, the selected publications range widely from different continents such as Asia, Europe, Africa, and South America. But research work is still highly prevalent in Asia, particularly China, Iran, and India, which make up more than half of all published works. On the other hand, very few investigations have been done in sub-Saharan Africa even though the continent suffers from some of the highest incidences of gully erosion in the world. Southeastern Nigeria, which is internationally known to be among Africa's gully erosion-prone areas, has been highly underrepresented globally.

Temporal Evolution of Machine Learning-Based GESM Research

Analysis of publication trends reveals a rapid increase in machine learning applications for gully erosion susceptibility mapping between 2015 and 2026. During the early years of the review period (2015–2018), published studies were relatively scarce and were dominated by conventional statistical approaches, including Frequency Ratio (FR), Weight of Evidence (WoE), Logistic Regression (LR), and Information Value (IV).

After about 2019, improvements in computational power, availability of open-source data from Earth observations, and cloud-based geospatial software fuelled a clear change in direction toward machine learning algorithms. Algorithms such as RF, SVM, XGBoost, ANN, and ensemble learning methods gradually took over statistical algorithms that were commonly used earlier as predictive models.

It was especially apparent after 2022 when techniques like XAI, SHAP analysis, Google Earth Engine (GEE), SAR from Sentinel-1, and CNN and U-Net from deep learning started appearing more often in research papers. These developments indicate an ongoing methodological transition from static susceptibility assessment towards dynamic, interpretable, and operationally scalable modelling frameworks.

Global Distribution of Research

Geographical distribution of the studies indicates obvious discrepancies between regional scientific activities. The largest number of publications originates from Asia, and specifically China, Iran, and India, which have become major contributors to the development of new methodologies for GIS-based erosion susceptibility mapping. These countries widely use ensembles of machine learning algorithms, multi-source remote sensing data, explainable artificial intelligence, and cloud computing facilities(Kulkarni et al.,2025).

Most European studies are concerned with methodology optimization and evaluation of machine learning algorithms' performance and uncertainty analysis, while most South American studies emphasize application in tropical watersheds and climate-related erosion.

There is an obvious lack of studies conducted in major part of Africa. They are mainly concentrated in Ethiopia, Morocco, and Nigeria and rarely employ machine learning methods in their methodology. This discrepancy shows a clear research geographical gap, since in many areas of Africa there is pronounced gully erosion due to rapid changes in land use and intense rainfall regime.

Machine Learning Algorithms Used in Gully Erosion Susceptibility Mapping

However, the literature under review reveals considerable heterogeneity in algorithms for machine learning that were applied in GESM. Some common trends are outlined below.

The most popular and effective algorithm was the Random Forest algorithm that demonstrated excellent predictive power in various geomorphological conditions (Siqueira et al., 2022). The values of the Area Under the Receiver Operating Characteristic Curve (AUC) mostly varied from 0.90 to 0.98 due to the capability to describe non-linear interaction and robustness to overfitting (Mendez et al., 2019).

XGBoost is also popular machine learning algorithms (Chen et al., 2016) . In most cases, it was marginally better than Random Forest thanks to the sequential improvement in classification accuracy. Several studies reported AUC values higher than 0.95 especially when it was used in combination with feature selection and hyperparameter optimization (Gómez et al.,2022)

Despite some disadvantages, SVM was popular owing to the ability to process high-dimensional data and relatively small amounts of training data (Ghaddar & Naoum-Sawaya ,2018). Model efficiency was affected by kernel and hyperparameter optimization that resulted in increased variability of the results compared with tree-based algorithms.

Artificial Neural Networks, LightGBM, CatBoost, Adaptive Boosting and ensemble learning models become increasingly popular. Despite their competitive predictive power, those models require more parameter tuning and computational resources than classical tree-based algorithms (Hidayaturrohman & Hanada, 2025).

Overall, the reviewed evidence indicates a clear methodological transition from single statistical models towards hybrid and ensemble machine learning frameworks capable of integrating multiple environmental variables while improving predictive accuracy and model generalisation.

Remote Sensing Data Sources

Remote sensing emerged as the major source of spatial data in all the discussed researches. Sentinel-2 multi-spectral images were the most common optical data due to their spatial resolution of 10 meters, frequent revisits, and spectral capacity for vegetation and land cover mapping (Phiri et al.,2020).

Digital Elevation Model from the Shuttle Radar Topography Mission (SRTM) continued being the leading source of topographical data, offering such factors as slope, aspect, curvature, elevation, TWI, SPI, and TPI(Lee & Lee ,2024). Recent researches more and more started using digital elevation models of higher spatial resolutions – Copernicus and ALOS PALSAR DEM, and showed some improvements in the accuracy of terrain and susceptibility modelling (Lu et al., 2024)

The Sentinel-1 SAR has been one of the most promising innovations in recent times. It works independent of the presence of clouds and solar radiation and is especially ideal for a humid tropic environment because of the prevalence of cloudy conditions which often hinder optical sensing (Pech-May et al.,2023). In several recent studies, it was found that the combination of SAR backscatter, interferometric coherence, and multispectral optical data improved the models immensely (Li et al., 2022).

Environmental Conditioning Factors

More than thirty conditioning variables have been reported in literature review concerning environment. Despite the above number, some few variables continued to dominate as the most significant predictor of gully erosion susceptibility (Wei et al., 2022). Topography, which includes slope gradient, elevation, curvature, Topographic Wetness Index, Stream Power Index, and drainage density, was most commonly applied due to its direct impact on runoff concentration and energy (Wilson & Gallant ,2000). LULC always stood out as one of the most significant predictors due to the impact of deforestation, agriculture, urbanisation, and vegetation degradation on erosion (Mir et al.,2025).

Vegetation index such as NDVI was also commonly used as an indicator of vegetation density and capacity for soil protection (Yengoh et al.,2015). Variables related to geology and lithology were very significant especially for areas with highly susceptible formations such as the Nanka Formation and Ajali Sandstone in Southeast Nigeria (Unigwe et al., 2022). Climate-related variables such as rainfall intensity, precipitation erosivity, and rainfall totals have been included in many current works as one of the major causes of gully formation and development(Pal et al.,2022) .The recurring importance of these conditioning factors across diverse environmental settings demonstrates that successful susceptibility modelling depends on integrating geomorphological, climatic, geological, hydrological, and anthropogenic variables rather than relying on any single category of predictors (Ramzan et al., 2025).

Discussion

Global Transition Towards Machine Learning-Based Gully Erosion Susceptibility Mapping

Results of the present systematic review indicate that there is a paradigm shift in GESM from classical statistical methodologies towards ML-based predictive models. The advances in computational intelligence, cloud computing, and Earth observations over the last decades have changed the susceptibility assessment from being based on fairly simple linear statistical calculations to more advanced nonlinear methods of prediction of complex interactions within the environment.

The development in environmental geosciences, where the availability of high-resolution spatial data allows for use of algorithms that learn complex interactions among topographical, hydrological, geological, climatological, and anthropogenic factors (Karpatne et al., 2018). Classical bivariate statistical models operate on a basic assumption of linearity while the modern algorithms of ML such as RF and XGBoost do not make any assumptions about the linearity of relationship and can cope well with multicollinearity and nonlinearity (Yıldırım 2024). The dominance of RF and XGBoost observed in the reviewed literature is therefore not coincidental but reflects their methodological advantages in modelling highly heterogeneous erosion processes(Abdo et al.,2026) Their robustness against overfitting, capacity for feature importance analysis, and compatibility with cloud-computing environments such as Google Earth Engine make them particularly attractive for operational susceptibility mapping at regional and national scales (Sellami & Rhinane, 2024).

The trend in the increased use of ensemble learning serves to show another significant trend in methodology development. As opposed to using one algorithm to make predictions, new research tends to use more than one algorithm, each with its own advantages but combined to reduce the margin for prediction errors. Hybrid intelligence is therefore one of the key features of modern GESM research.

Southeast Nigeria: A Critical Scientific Paradox

One of the most significant findings of this review is the striking disparity between the global advancement of ML-based GESM and its limited application in Southeast Nigeria. Despite being internationally recognised as one of the most severely gully-affected regions in sub-Saharan Africa, the region has experienced relatively little methodological innovation compared with Asia and parts of Europe.

Only a small number of studies have implemented machine learning techniques, while the majority continue to depend on classical statistical approaches such as Frequency Ratio, Information Value, Hazard Index, and Weight of Evidence (Nwazelibe & Egbueri,2024). Furthermore, existing investigations remain geographically concentrated within a few well-known erosion hotspots, particularly the Agulu–Nanka and Orumba areas of Anambra State, leaving large portions of Enugu, Imo, Abia, and Ebonyi States comparatively understudied (Ukatu, 2019).

This disparity represents a scientific paradox. Regions experiencing the greatest environmental vulnerability would be expected to receive the most technologically advanced research attention (Nzeh & Ogugua, 2011). Instead, the opposite pattern is evident. Several interrelated factors may explain this imbalance, including limited access to high-performance computing infrastructure, inadequate availability of comprehensive gully inventories, restricted funding for geospatial research, and insufficient interdisciplinary collaboration between geomorphologists, remote sensing specialists, computer scientists, and environmental managers.

Addressing these structural limitations is essential if Southeast Nigeria is to benefit from recent advances in artificial intelligence and Earth observation science. Future research should therefore prioritise regional-scale modelling frameworks capable of generating operational susceptibility products for all five southeastern states rather than continuing the prevailing emphasis on isolated watershed investigations.

The Strategic Importance of Multi-Sensor Remote Sensing

The review further emphasizes that the future of GESM depends not only on better algorithms but on incorporating complementary Earth observation data. While multispectral imagery from the Sentinel-2 satellite continues to play a significant role, the sole dependence on optical imagery creates certain challenges in humid tropical regions experiencing cloudy conditions.

Indeed, this problem becomes evident in Southeast Nigeria due to the coincidence of the period of maximum erosion with abundant precipitation and dense cloudiness. Optical satellite observations at these times become discontinuous, which negatively affects the modeling of the erosion susceptibility map.

In this regard, Synthetic Aperture Radar (SAR) imagery emerges as an effective approach to overcome the described problem. Microwave signals allow penetrating through the clouds and working regardless of sunlight, so the imagery of the Sentinel-1 satellite is continuous all year round. Moreover, SAR allows obtaining the information about surface roughness, soil moisture, and vegetation structure, which is inaccessible using only optical imagery.

It is widely observed from literature around the world that a model with SAR and optical data performs better than single sensor approaches. It becomes important in tropical areas where there are fast changes in hydrological aspects due to the rainy season. As a result, susceptibility modelling for Southeastern Nigeria in the future should not only be limited to using optical sensors and move towards the integration of multi-sensors approach.

Emerging Role of Deep Learning

Another notable trend identified in the reviewed literature is the increasing application of deep learning for automated gully detection and susceptibility assessment. Convolutional Neural Networks (CNNs), U-Net semantic segmentation, Transformer architectures, and lightweight neural networks have demonstrated remarkable capabilities for extracting complex spatial patterns directly from high-resolution imagery (Zhang et al., 2022).

Unlike conventional machine learning algorithms, which depend largely on manually derived environmental conditioning factors, deep learning models learn hierarchical spatial representations directly from image data (Silwal et al., 2026). This capability enables more accurate identification of subtle morphological characteristics associated with gully initiation and expansion.

Nevertheless, the adoption of deep learning in Southeast Nigeria remains extremely limited. The principal constraint is the scarcity of large, accurately labelled training datasets. Most existing regional gully inventories contain relatively few mapped gullies, restricting the effective training of data-intensive neural networks.

One promising strategy for overcoming this limitation is transfer learning, whereby models pretrained using extensive global datasets are subsequently fine-tuned using smaller regional datasets. Combined with semi-supervised learning and automated image annotation techniques, transfer learning has the potential to substantially accelerate the practical application of deep learning within data-constrained tropical environments.

Explainable Artificial Intelligence and Decision Support

The exponential growth in the machine learning field has raised issues about the interpretable nature of the resulting predictive models. While accurate algorithms are definitely useful, environmental planners need to have the transparent explanation of why certain areas are considered highly vulnerable before implementing model results in the decision-making process.

As can be seen from the reviewed literature, explainable artificial intelligence (XAI) and especially SHapley Additive exPlanations (SHAP) is becoming a promising approach to addressing the issue. SHAP allows for both global feature importance explanation and local prediction interpretation thus making machine learning models transparent for decisions support purposes.

In the context of Southeast Nigeria, the potential of SHAP goes far beyond the academia. The national and state erosion management programs need to have scientifically reliable arguments when selecting areas for intervention and investing in erosion-preventive facilities. With the help of SHAP, we can calculate the share each of lithology, land-use changes, slopes, precipitation, vegetation cover, and hydrologic parameters play in vulnerability.

Therefore, further susceptibility research must consider explainability as not just an optional methodological tool but a critical one.

Implications for Sustainable Land Management and Environmental Policy

The conclusions drawn from this literature review have several key policy implications regarding sustainable land management, disaster risk reduction and climate change resilience in Southeast Nigeria. The erosion control schemes implemented thus far have involved considerable funding allocated to engineering solutions; yet, these programs have been predominantly reactive, with gully stabilization initiated only once significant erosion has taken place.

Machine-learning based susceptibility mapping is a promising approach to moving beyond reactionary mitigation measures and toward prevention of potential erosion events. Susceptibility maps allow governments to concentrate their conservation efforts, plan their infrastructure, regulate land use and restore watersheds before disastrous erosion events happen.

In addition, incorporating susceptibility maps with demographic, infrastructure and socio-economic data could lead to development of gully erosion risk maps that would consider both the physical susceptibility to gully erosion and human exposure and vulnerability to this hazard. Integrated risk maps would be especially useful for climate change adaptation policies considering expected increases in precipitation rates in tropical West Africa.

Overall, the transferability of scientific discoveries in machine learning to policy-making can benefit greatly from increased collaboration among scientists, government officials, engineers, planners and local populations. Scientific advances should therefore be accompanied by institutional frameworks that encourage open geospatial data sharing, routine updating of national gully inventories, and operational integration of susceptibility modelling into environmental planning processes.

Research Gaps and Future Research Agenda

Critical Research Gaps

The present review reveals that, despite substantial global advances in machine learning-based gully erosion susceptibility mapping (GESM), several fundamental scientific and methodological gaps remain, particularly within Southeast Nigeria. Addressing these deficiencies represents an important opportunity for advancing both erosion science and evidence-based environmental management.

Gap 1: Limited Adoption of Advanced Machine Learning
Despite the emergence of ensemble machine learning models as the international benchmark in susceptibility modeling, their use in Southeast Nigeria is strikingly underdeveloped. The majority of research carried out continues to utilize traditional statistical methods like the Frequency Ratio, Weight of Evidence, Information Value, and Hazard Index models. Though useful in making baseline assessments, such models are not efficient in capturing the complicated nonlinear relationship between topography, lithology, hydrology, vegetation, and climate that controls the formation and development of gullies.
The future application in studies should be focused on sophisticated ensemble models like Random Forest, XGBoost, LightGBM, CatBoost, and stacking ensembles.

Gap 2: Absence of Multi-Sensor Data Fusion
The majority of susceptibility analyses performed in South East Nigeria only employ the use of optical satellite images even though the area experiences continuous cloud cover during the rainy season. The use of such techniques creates temporal gaps at a time when erosion is most prevalent.
Integration of Sentinel-1 Synthetic Aperture Radar along with Sentinel-2 optical imagery, Digital Elevation Model data, climate information, and geological data is one of the key priorities for research that has been identified in this literature review.

Gap 3: Lack of Deep Learning Applications
Deep learning has revolutionized automated terrain analyses around the globe through semantic segmentation, feature extraction, and image classification. Nevertheless, there is no research carried out using convolutional neural networks, U-Net architectures, Transformers, or any other form of deep learning that can be used to assess gully susceptibility at the regional level in Southeast Nigeria.
Future studies may consider the potential applications of transfer learning, weakly supervised learning, and hybrid CNN-GIS in order to solve the present drawbacks resulting from the limited training dataset.

Gap 4: Limited Model Interpretability
Most of the susceptibility models that have been published in journals remain as "black-box" prediction models without offering much information as to why certain areas have been labeled as high susceptibility zones.
XAI, especially SHapley Additive exPlanation (SHAP), provides a viable alternative for addressing the issue since it will enable researchers to determine the relative contribution of the different conditioning factors. Inclusion of explainability in any future research on the topic will make the science more transparent.

Gap 5: Static Rather Than Dynamic Susceptibility Mapping
Most existing investigations generate single-date susceptibility maps that fail to capture temporal variations associated with land-use change, rainfall variability, vegetation dynamics, and climate change.
Future studies should develop dynamic susceptibility frameworks capable of evaluating changes in erosion susceptibility over multiple decades using multi-temporal satellite observations and climate projections.

Gap 6: Limited Regional Coverage
Present studies have been focused on some of the known locations of erosion, which include the Agulu-Nanka area and the Orumba area. Thus, many areas of the states of Enugu, Imo, Abia, and Ebonyi are still poorly studied.
The creation of the harmonized regional vulnerability model in all five southeast states will be very useful.

Gap 7: Insufficient Integration of Socioeconomic Vulnerability
Existing studies primarily evaluate physical susceptibility while giving relatively little attention to human exposure and socioeconomic vulnerability.
Future research should integrate susceptibility outputs with population density, transportation infrastructure, critical facilities, land value, and livelihood indicators to produce comprehensive gully erosion risk assessments suitable for disaster risk management.

A Next-Generation Framework for Gully Erosion Susceptibility Mapping
Drawing upon the evidence synthesised in this review, a next-generation methodological framework is proposed for machine learning-based GESM in Southeast Nigeria. The proposed workflow comprises seven interconnected stages:
Stage 1: Development of a comprehensive regional gully inventory using high-resolution satellite imagery, field verification, UAV surveys where available, and deep learning-assisted image segmentation.
Stage 2: Integration of multi-source Earth observation datasets, including Sentinel-1 SAR, Sentinel-2 multispectral imagery, Copernicus DEM, ALOS PALSAR DEM, CHIRPS rainfall products, MODIS vegetation indices, and geological maps.

Stage 3: Generation of a harmonised database of topographic, hydrological, climatic, geological, ecological, and anthropogenic conditioning factors within a cloud-based Google Earth Engine environment.
Stage 4: Implementation of advanced ensemble machine learning algorithms, including Random Forest, XGBoost, LightGBM, CatBoost, Support Vector Machine, and stacking ensembles, supported by spatial k-fold cross-validation and Bayesian hyperparameter optimisation.
Stage 5: Interpretation of predictive models using SHAP and complementary explainable artificial intelligence techniques to quantify the contribution of individual conditioning factors.
Stage 6: Production of multi-temporal susceptibility maps representing historical, present-day, and projected future erosion conditions under alternative climate and land-use scenarios.
Stage 7: Integration of susceptibility outputs with socioeconomic indicators to produce operational erosion risk maps capable of supporting environmental planning, infrastructure protection, watershed management, and climate adaptation.
This framework provides a reproducible roadmap for transitioning from conventional susceptibility assessment towards intelligent, explainable, and policy-oriented environmental decision-support systems.

CONCLUSION

This systematic review critically examined global developments in machine learning-based gully erosion susceptibility mapping between 2015 and 2026, with particular emphasis on their relevance to Southeast Nigeria. The synthesis demonstrates that achine learning has fundamentally transformed susceptibility modelling, replacing conventional statistical approaches with highly accurate predictive algorithms capable of representing complex environmental processes.

Among the reviewed algorithms, Random Forest and Extreme Gradient Boosting consistently emerged as the most reliable and widely adopted techniques, achieving excellent predictive performance across diverse geomorphological settings. Their success has been further enhanced through the integration of multi-source remote sensing datasets, cloud-computing platforms, explainable artificial intelligence, and, more recently, deep learning architectures capable of automated terrain analysis.

Despite these substantial global advances, Southeast Nigeria remains considerably underrepresented within the contemporary machine learning literature. Existing investigations continue to rely predominantly on conventional statistical models, optical remote sensing, and geographically isolated case studies. The absence of regional-scale susceptibility assessments, SAR-optical data fusion, explainable artificial intelligence, deep learning, and dynamic temporal modelling represents a significant scientific gap that limits both research progress and operational decision-making.

In addition to identifying such limitations, this review makes contributions to the existing literature in three major ways. First, it offers an overview of recent innovations in methodological approaches to machine learning-based GESM. Second, it critically analyses to what extent these innovations are implemented in the study area of interest – Southeast Nigeria. Third, it suggests an integrated methodology, integrating multisource EO data, ensemble machine learning, explainable artificial intelligence, cloud computing, and climate-aware modelling approaches.

Practical relevance of the findings goes beyond academia. In addition to being useful in academic research, susceptibility maps are important for strategic land use planning, infrastructure development, watershed rehabilitation, agricultural conservation and risk reduction related to natural disasters. In addition, the findings help to optimise investment decisions regarding erosion control and implementation of adaptation strategies in the context of the region being among the most vulnerable in Africa.

Ultimately, future of GESM is not only about making susceptibility maps more precise but also making them transparent, replicable, scalable and operational decision-support systems combining scientific and innovative approach with environmental governance. Using this integrated methodology in their studies, future researchers will be able to make contribution to resilience of landscape, erosion management policies and sustainable development

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