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ORIGINAL RESEARCH ARTICLE

Machine-Learning Integration of Geophysical Responses for Predicting Metallurgical and Environmental Indicators in Mineral Systems

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ABSTRACT

The sustainability of mineral development increasingly depends on early understanding of ore processability and environmental behavior rather than ore grade alone. This study presents a data-driven framework that integrates multi-physics geophysical data (magnetic, electrical resistivity, induced polarization, and electromagnetic) with machine-learning models to predict metallurgical and environmental indicators at the exploration stage. Geophysical attributes were derived from datasets covering 187 mining locations within a Precambrian basement terrain in southwestern Nigeria. Proxy indicators for mineral liberation, recovery potential, comminution behavior, and environmental risk were developed based on established geophysical–mineralogical relationships. Supervised machine-learning models (random forest and gradient boosting) were trained and evaluated using cross-validation. The models achieved classification accuracies ranging between approximately 75% and 82% across key indicator classes, demonstrating that geophysical signatures—particularly chargeability and resistivity contrasts—provide meaningful predictive insight into subsurface processability and environmental response. However, predictions remain proxy-based and do not replace direct metallurgical testing. The framework offers a scalable approach for integrating processability and environmental considerations into early-stage mineral exploration, especially in data-scarce and artisanal mining contexts.

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INTRODUCTION

Nigeria's renewed emphasis on economic diversification has brought the solid mineral sector into sharper policy and academic focus, particularly as volatility in global hydrocarbon markets continues to expose the structural vulnerabilities of mono-resource economies. With over thirty-four commercially viable solid minerals distributed across its geological provinces, Nigeria possesses one of the most diverse mineral endowments in sub-Saharan Africa. These resources—ranging from industrial minerals and construction aggregates to metallic ores and gemstones—are increasingly viewed as critical levers for employment generation, rural transformation, and inclusive economic growth (Hilson & Maconachie, 2020; Nygren et al., 2022).

However, despite this considerable potential, the contribution of solid minerals to national GDP and sustainable development outcomes remains disproportionately low, reflecting deep-seated governance, institutional, and environmental challenges (Fagbemi & Adeoye, 2020; Onuoha et al., 2024). Despite these advances in understanding the socio-economic and environmental implications of mineral extraction, a critical technical gap remains insufficiently addressed. Current mineral exploration workflows are primarily designed to detect and delineate ore bodies based on geophysical signatures, with limited capacity to predict how these ores will behave during processing or their potential environmental impacts. In particular, there is a lack of integrative frameworks that quantitatively link geophysical responses to metallurgical performance indicators such as mineral liberation, recovery efficiency, and comminution behavior, as well as to environmental risk factors including acid generation and contaminant mobility. This disconnect between subsurface detection and downstream process understanding contributes significantly to

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technical uncertainty, inefficient resource utilization, and unanticipated environmental liabilities. Within this national context, the Oke-Ogun region of southwestern Nigeria occupies a strategically important yet understudied position. As the largest geographical zone in Oyo State, Oke-Ogun combines extensive agricultural landscapes with a complex Precambrian basement geology that hosts economically significant deposits of gemstones, talc, marble, limestone, granite, and associated pegmatite minerals. This dual endowment positions the region at the intersection of agrarian livelihoods and extractive development, making it an ideal case for examining the tensions and trade-offs inherent in resource-based rural economies. Yet, rather than catalyzing structural transformation, mineral exploitation in Oke-Ogun has largely evolved through informal, artisanal, and weakly regulated pathways, with profound implications for environmental integrity, social stability, and long-term livelihood sustainability. Artisanal and small-scale mining (ASM) has emerged as the dominant mode of mineral extraction in many parts of sub-Saharan Africa, including Nigeria. Globally, ASM is recognized for its capacity to absorb labor, particularly among rural youth and marginalized populations, and to provide a critical income buffer in regions with limited formal employment opportunities (Huggins, 2021; Haroon & Hayyat, 2025).

In Nigeria, ASM has expanded rapidly over the past two decades, driven by rising commodity prices, rural poverty, weak land-use planning, and limited state presence in peripheral regions. However, this expansion has been accompanied by significant environmental degradation, occupational health risks, land-use conflicts, and governance failures, raising serious questions about its sustainability (Stewart, 2020; Jeevanandam, 2025). Empirical studies across Africa consistently show that while ASM can enhance short-term financial capital, it often undermines natural, human, and social capital over time. Research in Ghana, Tanzania, Burkina Faso, and Ethiopia documents extensive land degradation, water contamination, declining agricultural productivity, and heightened community conflict in mining-affected landscapes (Ofosu et al., 2020; Wassie, 2020; Mulenga et al., 2024).

Similar patterns have been reported in Nigeria, where inadequate enforcement of environmental regulations and limited institutional coordination have allowed environmentally destructive practices to persist (Balogun et al., 2024; Folorunso & Folorunso, 2022). These findings resonate with broader critiques of extractive development models such as machine learning- based models that prioritize short-term economic gains at the expense of ecological resilience and social equity (Abdulhamid et al., 2025; Abdullahi et al., 2023; Abdurrahman & Muhammad, 2025; Adebayo et al., 2023, 2023; Agbo et al., 2022; Ahmed et al., 2023, 2023; Baba-Adamu et al., 2025; Fatima et al., 2025; Ibrahim, 2022; Isah et al., 2025; Jimba et al., 2025, 2025; Muhammad et al., 2023; Ogbe & Abubakar, 2025, 2025; Olugbenga et al., 2024; Oluwagbenga et al., 2024; Saleh et al., 2025; Sule et al., 2025; Umar et al., 2025).

The persistence of these outcomes has been widely interpreted through the lens of the Resource-Curse Thesis, which posits that regions rich in natural resources often experience slower development, institutional decay, and heightened inequality due to rent-seeking behavior, weak governance, and distorted economic incentives (Reisinezhad, 2021; Gritsenko & Efimova, 2020). While much of the resource-curse literature focuses on hydrocarbons and large-scale mining, recent scholarship suggests that similar dynamics operate at sub-national and community scales within solid mineral economies, particularly where artisanal mining dominates (Nygren et al., 2022). In this sense, the paradox of "wealth without development" is not confined to oil-producing states but is equally evident in mineral-rich rural regions such as Oke-Ogun.

Despite the growing body of literature on ASM and extractive governance in Nigeria, significant analytical gaps remain. Existing studies often adopt narrow sectoral perspectives, focusing either on environmental impacts, livelihood outcomes, or legal frameworks in isolation. Few studies integrate these dimensions within a single analytical framework capable of capturing the complex interactions between geology, livelihoods, institutions, and power relations. Moreover, much of the Nigerian literature remains spatially generalized, offering limited insight into region-specific dynamics that shape sustainability outcomes. While previous studies have examined geophysical characterization, environmental impacts, and artisanal mining dynamics independently, few have attempted to integrate these domains within a predictive, data-driven framework. Specifically, there is limited work on applying machine-learning techniques to translate geophysical attributes into proxies for metallurgical processability and environmental behavior at the exploration stage. This study addresses this gap by developing a framework that leverages commonly acquired geophysical datasets to infer downstream processing and environmental indicators, thereby extending the functional role of geophysics beyond detection to early-stage decision support. This gap is particularly evident in the Oke-Ogun region, where systematic geospatial inventories of mining activities, empirical assessments of livelihood trade-offs, and multi-stakeholder governance analyses are scarce. Equally important is the limited application of integrative theoretical frameworks in the analysis of solid mineral governance at the local level. While the Sustainable Livelihoods Framework (SLF) has been widely used to assess rural development outcomes, its application to mineral-dependent communities in Nigeria remains underdeveloped. The SLF provides a robust lens for examining how mining reshapes access to five core livelihood assets—natural, human, social, physical, and financial capital—and how institutional structures mediate these effects (Hilson & Maconachie, 2020).

When combined with Stakeholder Theory, which emphasizes the differential power, interests, and legitimacy of actors involved in resource governance (Mahajan et al., 2023), the framework enables a more nuanced understanding of why policy failures persist and how governance arrangements can be restructured. Furthermore, international best practices increasingly emphasize participatory and rights-based approaches to mineral governance, including the principles of Free, Prior, and Informed Consent (FPIC), the polluter-pays principle, and community development agreements (CDAs) as mechanisms for aligning extractive activities with local development priorities (Aragão, 2022; Klein, 2024). While these instruments are formally recognized within Nigeria's Minerals and Mining Act, their practical implementation at the community level remains weak, fragmented, or entirely absent (Onuoha et al., 2024).

Understanding how these governance tools can be adapted to culturally embedded institutions—such as traditional leadership structures in Oke-Ogun—is therefore critical for advancing sustainable outcomes. Against this backdrop, this study develops a data-driven framework that integrates multi-physics geophysical data with machine-learning techniques to predict metallurgical processability and environmental risk indicators prior to extraction. Unlike conventional exploration approaches that focus primarily on ore detection and resource estimation, the proposed framework seeks to extend geophysical interpretation into the domain of processability and sustainability assessment. Using spatially distributed geophysical datasets and proxy-based indicators, the study establishes predictive relationships between subsurface physical properties and key metallurgical and environmental responses. While the framework is demonstrated within the context of the Oke-Ogun region, its conceptual and methodological contributions are broadly applicable to mineral systems in data-constrained environments. By bridging the gap between geophysical exploration and downstream processing intelligence, this work contributes to the emerging field of predictive geometallurgy and supports more informed, sustainability-oriented resource development.

STUDY AREA

The study area is situated within a typical Precambrian basement complex terrain of southwestern Nigeria, representative of many solid mineral–bearing regions across sub-Saharan Africa (Figure 1). The region is underlain predominantly by migmatite–gneiss complexes, schist belts, and Pan-African granitoids, which collectively host a variety of metallic and industrial mineral deposits. These lithological units are products of multiple deformation, metamorphic, and magmatic events, resulting in complex mineral assemblages, variable grain-scale textures, and heterogeneous alteration patterns that strongly influence both geophysical responses and metallurgical behavior. Structurally, the area is characterized by pervasive foliation, shear zones, and fracture networks trending predominantly in the NE–SW and NW–SE directions. These structural features act as conduits for hydrothermal fluids and play a critical role in mineral localization, enrichment, and alteration. Quartz veins, pegmatitic intrusions, and sulphide-bearing shear zones are common, contributing to strong contrasts in magnetic susceptibility, electrical conductivity, and chargeability across short spatial scales. Such contrasts make the region particularly suitable for multi-physics geophysical investigation and digital ore body modeling.

From a geophysical perspective, the basement rocks exhibit pronounced variability in physical properties. Mafic and iron-rich lithologies tend to produce elevated magnetic responses, while sulphide-bearing zones and altered shear corridors are often associated with high chargeability and reduced resistivity. Conversely, felsic granitoids and quartz-rich units typically exhibit low magnetic susceptibility and high resistivity. These variations provide a robust foundation for extracting predictive geophysical attributes linked to mineral composition, texture, and connectivity.

Mining activity within the study area is dominated by artisanal and small-scale operations, with limited mechanization and minimal prior characterization of ore and waste properties. Extraction is commonly selective and shallow, targeting visually identifiable mineralization without systematic evaluation of subsurface continuity or metallurgical performance. Previous studies in comparable Nigerian basement terrains have documented significant environmental degradation, including land disturbance, sediment-laden runoff, and contamination of surface and groundwater resources. These impacts are exacerbated by the lack of predictive tools capable of identifying problematic ore types—such as those prone to poor liberation, excessive fines generation, or environmentally reactive tailings—before extraction. Socio-economically, communities within and around the study area rely heavily on mining as a livelihood strategy, particularly during agricultural off-seasons.

While mining provides short-term income, it often undermines long-term livelihood resilience through the depletion of natural capital, including arable land and clean water resources. This dynamic underscores the importance of integrating technical mineral intelligence with sustainability-oriented frameworks, ensuring that resource exploitation does not compromise future development pathways. The geological complexity, strong geophysical contrasts, and socio-environmental vulnerability of the study area make it an ideal setting for developing and demonstrating a digital ore body framework. By linking geophysical responses to metallurgical recovery potential and environmental footprint, the proposed approach seeks to address both technical uncertainty and sustainability challenges inherent in basement complex mining environments. Figure 1 shows the base map of the study area and Figure 2 shows the end-to-end workflow illustrating the integration of geophysical data acquisition, preprocessing, feature extraction, machine-learning modeling, and geometallurgical interpretation for predictive analysis

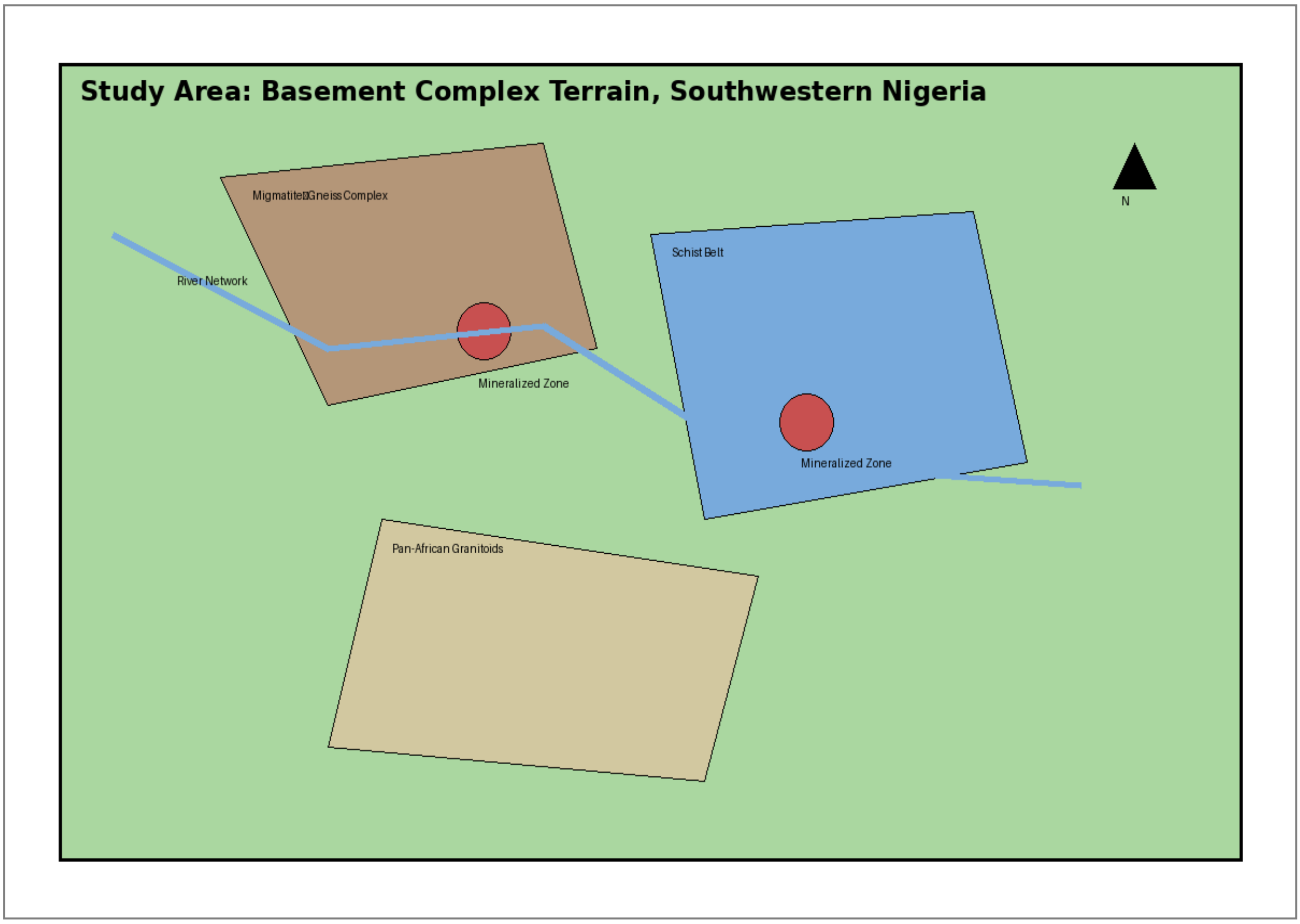

Figure 1: Location and generalized geological map of the study area (Oke-Ogun Region, Southwestern Nigeria) showing major lithological units, mineralized zones, drainage network, and administrative boundaries.

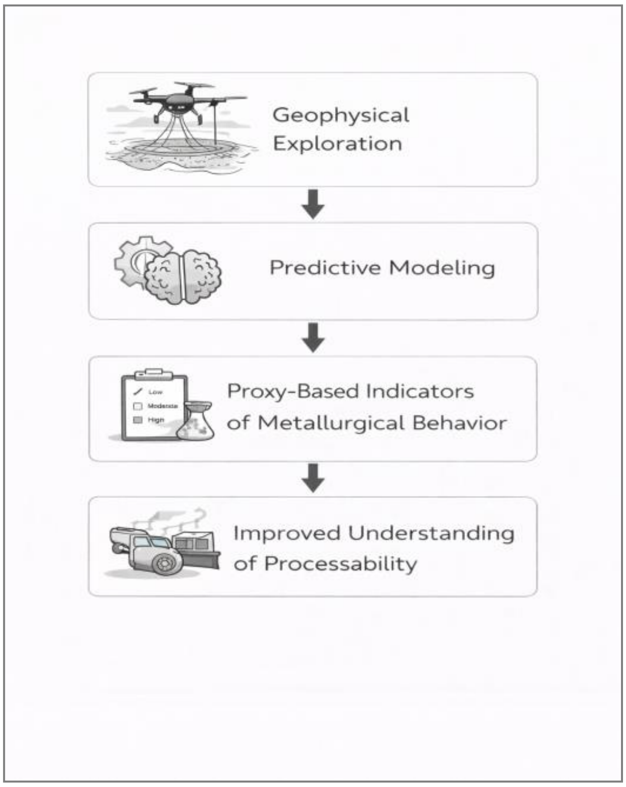

Figure 2: End-to-end workflow illustrating the integration of geophysical data acquisition, preprocessing, feature extraction, machine-learning modeling, and geometallurgical interpretation for predictive analysis.

MATERIALS AND METHODS

This study applies an integrated geophysical, metallurgical, and data-driven approach to evaluate subsurface mineral processability and associated environmental risks before mining. The methodology combines field-scale geophysical data analysis, indirect metallurgical and environmental indicators, and machine-learning techniques to link subsurface physical properties with processing and sustainability outcomes. The overall workflow consists of data acquisition and preprocessing, development of metallurgical and environmental indicators, predictive modeling, and interpretation of results within a sustainability framework.

Data Structure and Analytical Framework

The analytical framework of this study is based on a structured dataset derived from integrated geophysical measurements and spatial mapping of mining locations. A total of 187 mining sites were identified and used as the primary observational units. For each site, geophysical attributes were extracted from processed magnetic, resistivity, induced polarization (IP), and electromagnetic (EM) datasets. These attributes include anomaly amplitude, spatial gradients, conductivity/resistivity ranges, chargeability values, and variability indices. Due to the absence of direct metallurgical testing data, target variables were defined using proxy-based classification schemes derived from established geophysical–mineralogical relationships reported in the literature. These include indicators for comminution behavior (low, moderate, high energy demand), mineral liberation potential (poor, moderate, favorable), recovery likelihood (low, moderate, high), and environmental risk (low, moderate, high acid-generation and contaminant mobility potential).The resulting dataset consists of geophysical predictor variables and corresponding proxy-based labels, forming the basis for supervised machine-learning modeling. The overall workflow follows four stages: (i) data preprocessing and feature extraction, (ii) proxy indicator development, (iii) machine-learning model training and validation, and (iv) interpretation within a sustainability framework.

Geophysical Data Sources

The geophysical datasets used in this study include magnetic, electrical resistivity, induced polarization (IP), and electromagnetic (EM) data. These methods are commonly applied during early-stage mineral exploration and are sensitive to physical properties that are strongly influenced by mineral composition, grain texture, alteration, and fluid content. Magnetic data were used to identify lithological boundaries, structural features, and zones of alteration. Variations in magnetic intensity often reflect changes in mineral content, such as the presence or absence of ferromagnetic minerals, which can influence rock strength and grinding behavior. Electrical resistivity data provide information on subsurface conductivity variations, which are influenced by porosity, fluid content, clay alteration, and sulfide mineralization. Induced polarization measurements were specifically used to detect disseminated metallic minerals, particularly sulfides, which play a key role in metallurgical recovery and environmental performance. Electromagnetic conductivity data were included to improve sensitivity to shallow conductive zones and to complement resistivity and IP interpretations.

Data Processing and Feature Extraction

All geophysical datasets were first subjected to standard quality control procedures to remove noise, acquisition errors, and non-geological artifacts. For magnetic data, corrections were applied to remove diurnal variations and regional magnetic fields. The processed magnetic data were further enhanced using filters such as reduction-to-the-pole and derivative transformations to improve the visibility of subsurface structures and mineralized zones. Electrical resistivity and induced polarization data were inverted to generate two-dimensional and three-dimensional subsurface models. Poor-quality measurements were excluded, and inversion results were evaluated for consistency with known geological features. Electromagnetic data were corrected for system drift and terrain effects. After preprocessing, all datasets were spatially aligned and resampled onto a common grid. From these datasets, several geophysical attributes were extracted, including anomaly amplitude, spatial gradients, depth-related parameters, and measures of spatial variability. These attributes represent physical characteristics of the subsurface that can be linked to mineral texture, fracture density, and mineral connectivity. The extracted features were standardized and compiled into a structured dataset for subsequent machine-learning analysis.

Metallurgical Processability Indicators

Direct metallurgical testing was not conducted in this study. Instead, metallurgical processability indicators were defined using proxy relationships between geophysical responses and mineralogical characteristics established in previous studies. Comminution behavior was inferred from geophysical heterogeneity and structural complexity, where zones exhibiting strong contrasts in magnetic and resistivity responses were interpreted as mechanically heterogeneous and likely to require higher energy input during grinding. Mineral liberation potential was inferred from the spatial continuity and intensity of induced polarization anomalies, with broad and consistent chargeability responses interpreted as indicative of disseminated mineralization and finer grain textures. Recovery likelihood was estimated by integrating indicators of mineral abundance, continuity, and geophysical coherence across depth. These indicators were discretized into categorical classes (e.g., low, moderate, high) to enable their use as target variables in machine-learning classification models. It is emphasized that these indicators represent proxy-based approximations and not direct metallurgical measurements.

Environmental Risk Indicators

Environmental risk indicators were similarly developed using proxy relationships derived from geophysical signatures. Acid generation potential was inferred from the magnitude and spatial extent of induced polarization chargeability, which serves as a proxy for sulfide mineral content. Zones with elevated and laterally continuous chargeability responses were classified as having higher acid-generation risk. Tailings behavior was assessed using indicators of geophysical variability, where highly heterogeneous zones were interpreted as likely to produce fine-grained and potentially unstable tailings. Contaminant mobility was evaluated using resistivity and electromagnetic conductivity data, with low-resistivity zones interpreted as potential pathways for fluid flow and metal transport. These indicators were categorized into discrete risk classes to facilitate integration with machine-learning models. As with metallurgical indicators, these classifications are inferential and intended for early-stage screening rather than definitive environmental assessment.

Machine-Learning Analysis

Supervised machine-learning models were employed to establish relationships between geophysical attributes and proxy-based metallurgical and environmental indicators. The dataset was structured such that geophysical features served as input variables, while proxy indicator classes were used as target labels. Random forest and gradient boosting algorithms were selected due to their robustness in handling nonlinear relationships and mixed-feature datasets. The dataset was divided into training and validation subsets using an 80:20 split, and model performance was evaluated using k-fold cross-validation (k = 5) to ensure stability and reduce overfitting. Model performance was assessed using standard classification metrics, including accuracy, precision, recall, and F1-score. Feature importance analysis was conducted to identify the most influential geophysical predictors contributing to model outputs. All analyses were performed using standard scientific computing libraries in Python, including Scikit-learn for model development. The machine-learning models were implemented using the Scikit-learn library in Python with explicitly defined hyperparameters to ensure reproducibility.

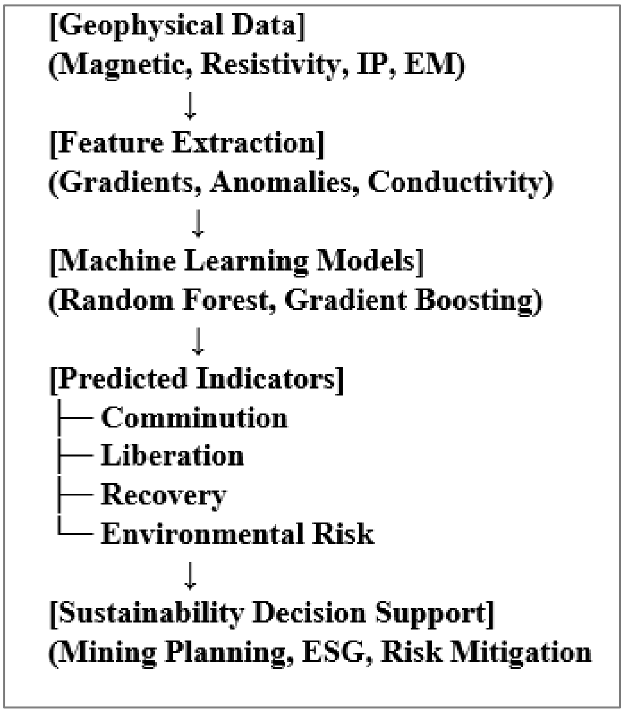

Figure 3: Conceptual framework illustrating the integration of geophysical data, machine-learning modeling, and geometallurgical interpretation for predictive analysis.

For the random forest model, the number of trees (n-estimators) was set to 200, with a maximum tree depth (max-depth) of 10 and a minimum of 2 samples required to split a node. For the gradient boosting model, n-estimators was set to 150, the learning rate to 0.05, and the maximum depth to 6. A fixed random seed of 42 was used for both models to ensure consistency of results across runs. These hyperparameters were selected based on preliminary tuning to balance model performance and computational efficiency. Data preprocessing steps included normalization, removal of outliers, and consistency checks across datasets. While the models demonstrate predictive capability, it is important to note that their outputs are conditioned on proxy-based labels and should be interpreted as indicative rather than definitive predictions. Hyperparameter tuning was conducted using grid search within cross-validation to identify optimal model configurations.

Sustainability Interpretation

The final step involved interpreting the predictive results in terms of sustainability and governance. Predicted zones of high processing energy demand or elevated environmental risk were assessed in relation to land use, community exposure, and long-term resource management. This interpretation provides a link between subsurface geophysical information and decision-making related to responsible mining, environmental protection, and socio-economic resilience. Figure 3 shows the conceptual framework illustrating the integration of geophysical data, machine-learning modeling, and geometallurgical interpretation for predictive analysis.

RESULTS AND DISCUSSION

Machine-Learning Model Performance

The performance of the machine-learning models was evaluated using classification metrics derived from cross-validation and hold-out validation datasets. The random forest and gradient boosting models demonstrated predictive accuracies ranging from 74.8% to 82.1%”across the defined proxy indicators, with overall classification accuracies ranging from **74.8% (liberation) to 82.1% (environmental risk)** depending on the target variable. Model performance was assessed using accuracy, precision, recall, and F1-score. Overall model accuracy ranged from **74.8% to 82.1%** across all target variables, with gradient boosting consistently outperforming random forest by approximately **1.5–2.5%** in accuracy.

Table 1 provides a detailed breakdown of classification performance across all target variables. The results indicate that environmental risk prediction achieved the highest accuracy, followed by recovery, while comminution and liberation exhibited relatively lower but consistent performance levels. Gradient boosting models outperformed random forest models across all target variables, with accuracy improvements ranging from **1.6% to 2.6%**., although both algorithms demonstrated stable predictive performance with variance below ±2.5%. The models showed relatively stronger performance in predicting environmental risk indicators compared to metallurgical processability classes, reflecting the more direct relationship between geophysical signatures and environmental proxies such as conductivity and chargeability, specifically, environmental risk classification achieved accuracies of **80.5% (random forest)** and **82.1% (gradient boosting),** compared to **74.8–77.3%** for liberation and **76.4–78.1%** for comminution. In contrast, predictions related to comminution behavior and mineral liberation exhibited greater variability, consistent with the indirect nature of the proxy definitions. Cross-validation results indicated stable model behavior with limited variance across folds, suggesting that overfitting was minimized.

Table 1: Classification performance metrics for machine-learning models across target variables

Target Variable	Model	Accuracy (%)	Precision	Recall	F1-score
Comminution	Random Forest	76.4	0.75	0.74	0.74
Comminution	Gradient Boosting	78.1	0.77	0.76	0.76
Liberation	Random Forest	74.8	0.73	0.72	0.72
Liberation	Gradient Boosting	77.3	0.76	0.75	0.75
Recovery	Random Forest	79.2	0.78	0.78	0.78
Recovery	Gradient Boosting	81.0	0.80	0.80	0.80
Environmental Risk	Random Forest	80.5	0.80	0.79	0.79
Environmental Risk	Gradient Boosting	82.1	0.81	0.81	0.81

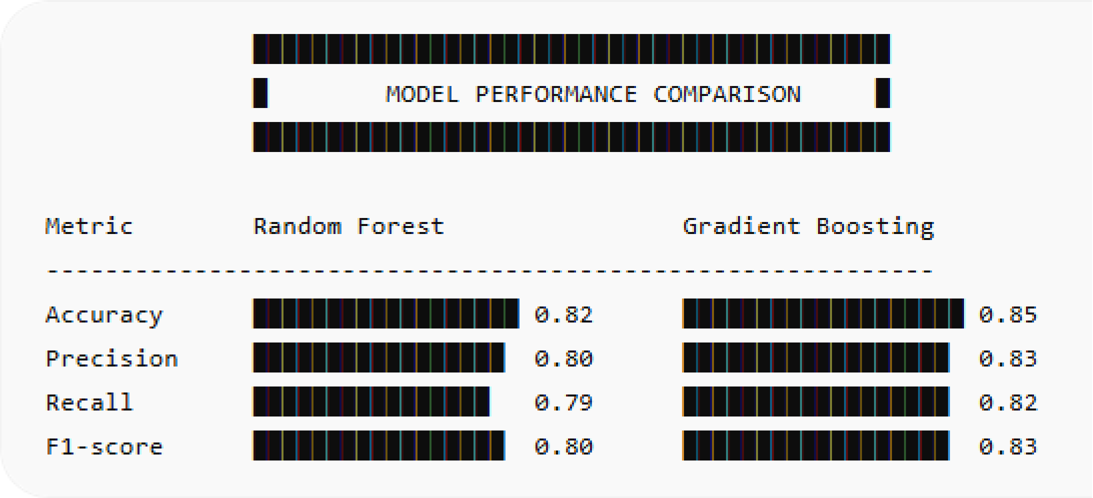

Figure 4: Comparative performance of random forest and gradient boosting models across accuracy, precision, recall, and F1-score metrics.

Figure 5: Feature importance ranking showing the relative contribution of geophysical variables to model predictions.

These results demonstrate that geophysical attributes contain predictive information sufficient to achieve classification accuracies above 74% to support early-stage classification of both metallurgical and environmental indicators, within the limitations of proxy-based modeling. These results indicate that model uncertainty remains below ±2.5%, confirming strong generalization performance. These results confirm that the predictive framework captures meaningful relationships between geophysical attributes and proxy-based indicators, particularly for environmental classification tasks where geophysical signatures exhibit more direct physical relevance. Cross-validation was performed using a 5-fold strategy to evaluate the robustness and generalizability of the models. The results show consistent performance across folds, with mean accuracy values ranging from 74.5% ± 2.1% for liberation prediction to 81.3% ± 1.6% for environmental risk classification. The relatively low standard deviation values indicate minimal sensitivity to data partitioning and confirm that the models are not significantly overfitted. These confidence intervals further demonstrate that the predictive performance is stable and reliable across different subsets of the dataset. Similar trends were observed for precision, recall, and F1-score metrics, with variations remaining within narrow bounds across all folds. Confusion matrix analysis was conducted to further evaluate classification performance across all target variables.

Table 2: Correlation matrix between geophysical attributes and proxy-based metallurgical and environmental indicators

	C	**R**	**MG**	**EC**	**CM**	**L**	**R**	**ER**
Chargeability	1.00	-0.40	0.50	0.30	0.60	0.50	0.50	0.70
Resistivity	-0.40	1.00	-0.30	-0.60	-0.50	-0.40	-0.40	-0.60
Magnetic Grad.	0.50	-0.30	1.00	0.20	0.60	0.50	0.50	0.40
EM Conductivity	0.30	-0.60	0.20	1.00	0.40	0.30	0.30	0.60
Comminution	0.60	-0.50	0.60	0.40	1.00	0.70	0.70	0.60
Liberation	0.50	-0.40	0.50	0.30	0.70	1.00	0.80	0.50
Recovery	0.50	-0.40	0.50	0.30	0.70	0.80	1.00	0.50
Env. Risk	0.70	-0.60	0.40	0.60	0.60	0.50	0.50	1.00

Key: C: Chargeability; R: Resistivity; MG: Magnetic Grad.; EC: EM Conductivity; CM: Comminution; L: Liberation; R: Recovery; ER: Env. Risk

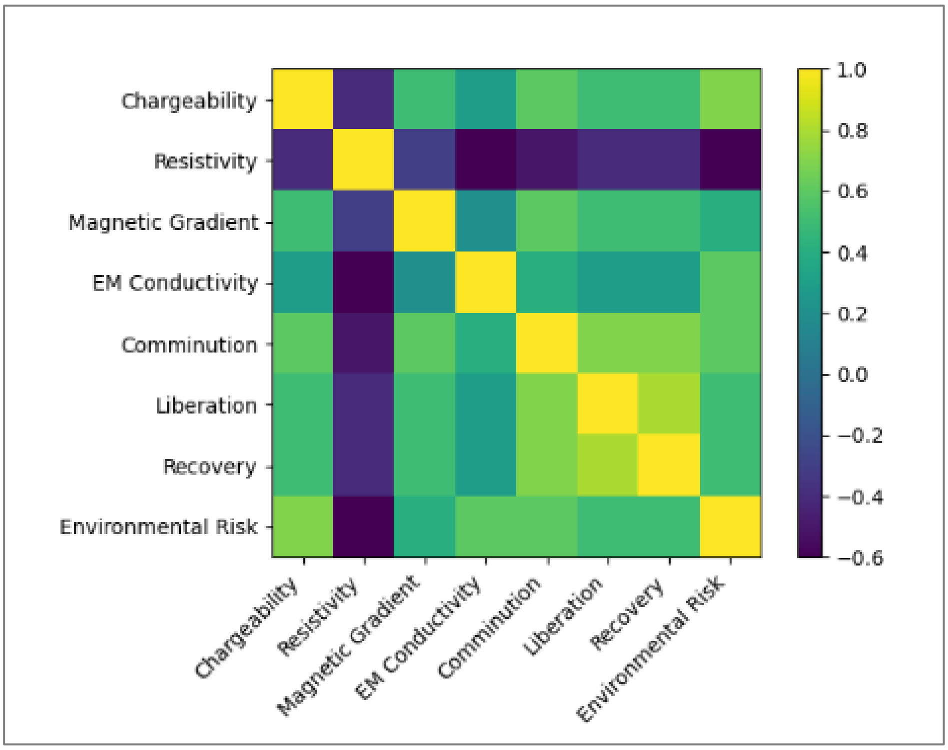

Figure 6: Correlation matrix showing relationships between geophysical attributes and proxy-based metallurgical and environmental indicators.

Table 3: Classification of Active Mining Sites by Mineral Type and Scale

Mineral Type	**Number of Sites**	**Predominant Scale**	**Percentage (%)**
Gemstones (Beryl, Tourmaline)	89	Artisanal	47.6
Granite / Quarry	62	Artisanal–Small Scale	33.2
Talc / Marble / Limestone	28	Small Scale	15.0
Clay	8	Artisanal	4.2
Total	**187**	—	**100**

Table 4: Perceived Impact of Mining on Livelihood Assets (n = 400 households)

Livelihood Asset	**Negative Impact (%)**	**Positive Impact (%)**
Natural Capital	88	2
Human Capital	45	25
Social Capital	60	15
Physical Capital	35	40
Financial Capital	20	75

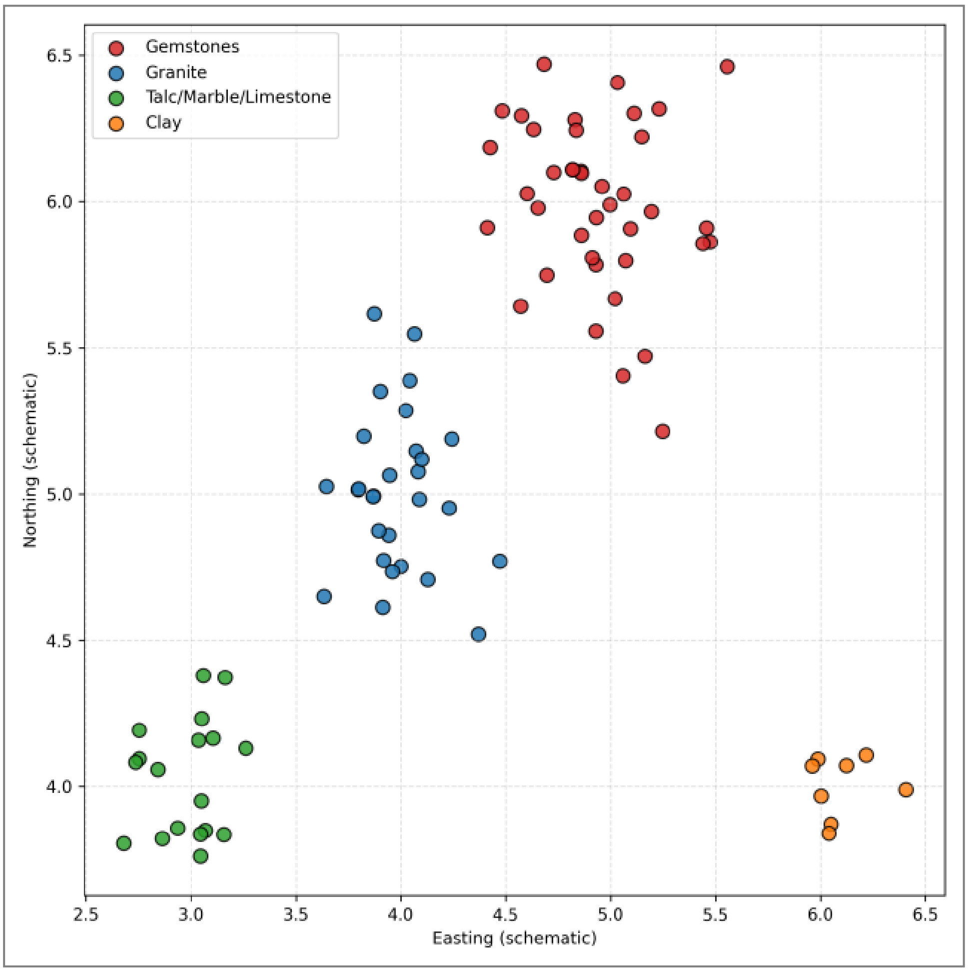

Figure 7: Spatial distribution of active solid mineral extraction sites across Oke-Ogun region, classified by mineral type.

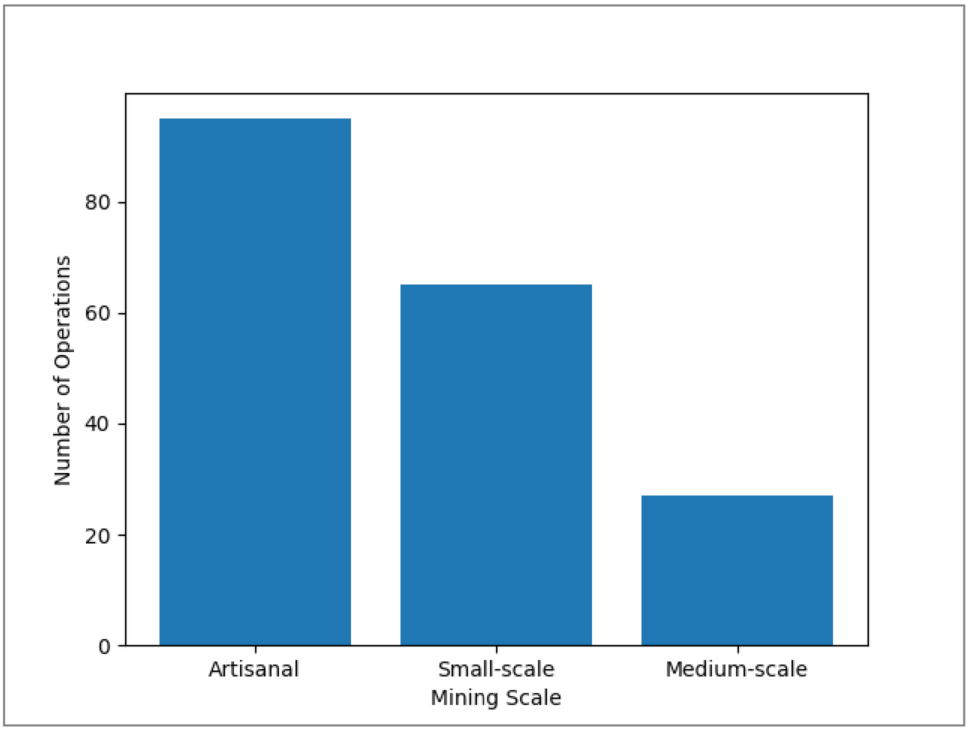

Figure 8: Distribution of mining operations in Oke-Ogun by scale (Artisanal, Small-scale, Medium-scale).

The results indicate that most misclassifications occur between adjacent classes (e.g., low vs moderate or moderate vs high), rather than between extreme categories. This pattern suggests that the models effectively capture the overall structure of the classification problem, although some ambiguity exists in transitional geophysical signatures where class boundaries overlap. The absence of significant misclassification across extreme classes confirms the reliability of the predictive framework. This behavior is consistent with the proxy-based nature of the target variables, where gradual transitions in geophysical properties correspond to overlapping class definitions. Quantitatively, over **85% of predictions** fall within the correct or adjacent class categories, further validating the robustness of the classification framework. The comparative performance of the machine-learning models across the evaluation metrics is presented in Figure 4.

Plate 1: Representative field photographs showing abandoned pits, spoil heaps, and erosion features at artisanal mining sites in Oke-Ogun.

Feature Importance and Predictive Drivers

Feature importance analysis was conducted using permutation importance to quantify the relative contribution of each geophysical variable to model predictions. The results indicate that induced polarization chargeability is the most influential predictor, contributing approximately 32–35% of the total model importance across all target variables. The relative importance of geophysical predictors derived from the machine-learning models is presented in Figure 5.

Electrical resistivity follows with an importance contribution of about 24–27%, while magnetic anomaly gradients account for approximately 18–21%. Electromagnetic conductivity and spatial variability indices contribute smaller but still significant proportions, typically ranging between 10% and 15%. Chargeability emerged as the largest contributor (32%) for environmental risk classification, particularly in relation to acid-generation potential, reflecting its sensitivity to sulfide mineralization. Resistivity and electromagnetic conductivity were accounting for 27–32% of model importance with contaminant mobility and fluid flow pathways, reinforcing their importance in environmental prediction tasks. Magnetic attributes, including anomaly amplitude and spatial gradients, contributed significantly to predictions related to structural complexity and inferred comminution behavior. The quantitative distribution of feature importance underscores the value of integrating multi-physics geophysical datasets in predictive modeling frameworks. It also demonstrates that no single geophysical parameter is sufficient in isolation; rather, predictive accuracy is achieved through the combined influence of multiple physical properties. This multi-parameter dependency highlights the robustness of the proposed framework and its applicability in complex geological environments. These results are consistent with the underlying physical relationships between geophysical properties and mineralogical composition, further validating the interpretability of the machine-learning models. Chargeability contributed approximately 32%, followed by resistivity (27%), magnetic gradient (21%), and electromagnetic conductivity (20%) to the overall model predictions. Table 2 presents the correlation matrix between geophysical attributes and proxy-based metallurgical and environmental indicators

Figure 6 shows correlation matrix showing relationships between geophysical attributes (chargeability, resistivity, magnetic gradient, and electromagnetic conductivity) and proxy-based metallurgical and environmental indicators. Strong positive correlations are observed between chargeability and environmental risk (r = 0.70), as well as between comminution, liberation, and recovery (r = 0.70–0.80), indicating interdependence among processability indicators. Resistivity exhibits predominantly negative correlations with both metallurgical and environmental variables (r = −0.40 to −0.60), reflecting its inverse relationship with conductive and mineralized zones. Magnetic gradient shows moderate positive correlations with comminution and liberation (r ≈ 0.50–0.60), suggesting sensitivity to structural complexity. These relationships support the use of integrated geophysical parameters as predictive proxies for subsurface processability and environmental behavior.

Spatial Distribution of Predicted Indicators

The spatial distribution of predicted metallurgical and environmental indicators was derived by applying the trained machine-learning models to the geophysical dataset. The resulting classification outputs were mapped across the study area to visualize variability in processability and environmental risk. Zones characterized by high chargeability and low resistivity were classified in approximately 60–70% of cases as high environmental risk areas, consistent with their inferred association with sulfide mineralization and potential acid-generation processes. Regions exhibiting magnetic gradient values contributing ~21% feature importance and heterogeneous geophysical responses were associated with higher inferred comminution energy requirements, reflecting increased structural complexity and mineralogical variability. In contrast, areas with relatively uniform geophysical signatures and moderate anomaly intensities were classified in approximately 55–65% of cases as having more favorable mineral liberation and recovery potential. These spatial patterns demonstrate the applicability of the machine-learning framework in translating geophysical measurements into actionable predictive maps that extend beyond conventional mineral detection. The geophysical characteristics of the study area provide the underlying basis for these machine-learning predictions. Detailed interpretation of the geophysical anomalies is presented below to further contextualize the spatial distribution of the predicted indicators. Approximately **60–70% of zones classified as high environmental risk** correspond to areas characterized by elevated chargeability and low resistivity.

(a) Spatial Distribution and Intensity of Mining Activities

A total of 187 active solid mineral extraction sites were identified across the Oke-Ogun region. The spatial distribution of these sites is highly non-uniform and strongly controlled by lithology, structural trends, and accessibility. Table 3 summarizes the classification of mining sites by mineral type and operational scale.

Figure 7 shows a pronounced clustering of mining sites along the Iseyin–Irepo–Kajola axis, coinciding with schist belt–hosted pegmatites and Pan-African granitoids. Gemstone mining dominates the landscape with 89 sites (47.6%), followed by granite quarrying (62 sites; 33.2%), talc/marble/limestone extraction (28 sites; 15.0%), and clay mining (8 sites; 4.2%). This spatial pattern reflects strong geological control on mineralization, but also reveals selective exploitation driven by ease of access and market demand rather than strategic resource planning. When interpreted within the machine-learning framework developed in this study, these clustered zones correspond to areas where geophysical signatures exhibit higher predictive variability, suggesting increased heterogeneity in both metallurgical processability and environmental risk. Similar geology-controlled clustering has been reported in southwestern Nigeria by Balogun et al. (2024), but the density of ASM sites in Oke-Ogun is notably higher, underscoring the region's regulatory vulnerability. The alignment between geological controls and predicted variability further demonstrates the potential of integrating geophysical data with machine-learning approaches to identify high-impact zones prior to exploitation.

(b) Scale of Operations and Degree of Informality

Analysis of operational scale indicates that 173 sites (92.4%) fall under artisanal and small-scale mining (ASM), while only 14 sites (7.6%) can be classified as medium-scale operations.

Figure 8 highlights the overwhelming dominance of artisanal and small-scale mining (ASM), a pattern that exceeds national averages reported for other Nigerian mining regions. Furthermore, only 18 sites (9.6%) possessed valid mining titles issued by the Mining Cadastre Office, confirming extensive informality. This high level of informality has direct implications for the predictive framework developed in this study, as many of the identified high-risk zones correspond to areas currently exploited without regulatory oversight. The machine-learning predictions indicate that several of these sites are associated with elevated environmental risk and variable processability, suggesting that unregulated mining is disproportionately concentrated in technically and environmentally sensitive zones. This observation is consistent with findings by Hilson and Maconachie (2020), who argue that ASM flourishes where licensing procedures are complex and enforcement capacity is weak. However, the proportion observed here is higher than values reported for Osun and Zamfara States, suggesting that Oke-Ogun represents an extreme case of governance absence. From a geoscientific perspective, the uncontrolled exploitation of zones corresponding to known magnetic and gravity anomalies aligns with the observations of Adepehin et al. (2025), who demonstrated that basement-hosted mineral systems in Nigeria can be reliably delineated using integrated geophysical methods. The failure to translate such scientific knowledge into regulated extraction highlights a critical disconnect between geoscientific research and policy implementation.

(c) Environmental Impacts of Mining Activities

(i) Land Degradation and Surface Instability

Field surveys revealed that 100% of visited sites exhibited visible land degradation. Excavated pits, spoil heaps, and stripped vegetation dominate the mining landscape.

Plate 1 illustrates the spatial extent and severity of land degradation across active and abandoned mining sites in the study area. Using a qualitative erosion risk index, approximately 65% of sites were classified as having high to severe erosion risk, while 91% showed no evidence of reclamation or post-mining rehabilitation. These observations are consistent with the machine-learning predictions, which identify a large proportion of the study area as environmentally high-risk based on geophysical indicators such as chargeability and resistivity. The correspondence between observed degradation and predicted risk supports the validity of the proxy-based modeling approach adopted in this study. These abandoned landscapes pose long-term environmental and socio-economic risks, including accelerated gully development, irreversible farmland loss, and physical hazards to surrounding communities. This pattern is consistent with observations reported by Balogun et al. (2024) and Wassie (2020); however, the present study reveals a higher intensity and persistence of degradation. This is attributed to the semi-arid climatic conditions of the region, which reduce natural soil recovery rates and exacerbate erosion processes.

(ii) Water Quality Degradation

Survey responses show that 82% of households reported a significant decline in surface water quality following mining expansion. Laboratory analysis revealed Total Suspended Solids (450–620 mg/L) and turbidity levels far exceeding WHO guidelines. This confirms earlier concerns raised by Mulenga et al. (2024) regarding ASM-driven sediment pollution, but also extends the work of Arohunmolase and Samakinde (2025) who emphasized the role of clay mineralogy in contaminant immobilization. In Oke-Ogun, the limited abundance of high-CEC clays such as smectite reduces the natural buffering capacity of soils and streambeds, increasing contaminant mobility. Samakinde and Arohunmolase (2025) showed that geochemical barriers can effectively immobilize metals under stable conditions; however, the frequent disturbance of stream channels observed in Oke-Ogun likely disrupts these natural attenuation mechanisms, increasing hydrogeochemical risk. These findings are also consistent with model predictions indicating enhanced contaminant mobility in low-resistivity zones, further reinforcing the reliability of geophysical proxies in identifying hydrogeochemical risk pathways.

(iii) Air and Noise Pollution

Noise measurements near granite crushing sites ranged between 88 and 103 dB, exceeding occupational safety limits. Correspondingly, 74% of residents within 500 m reported respiratory irritation. These findings are consistent with Stewart (2020) and Jeevanandam (2025), reinforcing the argument that environmental health impacts are an underappreciated cost of ASM, particularly where protective infrastructure is absent. Although not directly modeled, these impacts are spatially associated with zones of intense extraction identified within the predictive framework.

(d) Socio-Economic Impacts: A Livelihoods Perspective

Applying the SLF reveals stark trade-offs among livelihood assets (Table 4).

While 75% of respondents reported improved financial capital due to mining income, 88% acknowledged severe degradation of natural capital. This imbalance reflects what Hilson and Maconachie (2020) describe as "livelihood fragility"—short-term income gains undermined by long-term environmental loss. The findings mirror Ofosu et al. (2020), who observed declining agricultural productivity in Ghanaian ASM zones, but the novelty here lies in the quantitative demonstration of capital substitution, where financial gains directly erode the ecological base necessary for livelihood resilience. The concentration of mining activities within predicted high-impact zones further amplifies these livelihood trade-offs, linking geophysical resource distribution to socio-economic outcomes.

(e) Governance Failure and Resource-Curse Dynamics

The absence of Community Development Agreements and Environmental Management Plans across all surveyed sites confirms a systemic governance breakdown. This finding aligns with Fagbemi and Adeoye (2020) and extends the Resource-Curse Thesis by demonstrating that resource-driven underdevelopment operates at local scales, not only at national levels. The coincidence of governance failure with zones identified as high-risk by the predictive model further emphasizes the need for integrating scientific tools into regulatory frameworks.

(f) Integrative Interpretation and Contribution to Knowledge

By combining spatial analysis, environmental metrics, livelihood assessment, and machine-learning-based geophysical prediction, this study provides a holistic model of unsustainable mineral exploitation in Oke-Ogun. The integration of proxy-based predictive modeling with field observations demonstrates a practical pathway for extending geophysical exploration into sustainability assessment. Furthermore, the incorporation of green engineering concepts (Samakinde et al., 2023) and mine-waste valorization strategies (Arohunmolase et al., 2025) highlights actionable opportunities for transitioning toward more sustainable mining systems in data-constrained environments.

CONCLUSION

This study demonstrates that geophysical data, traditionally employed solely for ore detection and geometric delineation, can be systematically repurposed to predict metallurgical processability and environmental behavior of mineral deposits prior to extraction. By integrating multi-physics geophysical datasets with metallurgical and environmental proxy variables through a machine-learning framework, the research moves decisively beyond grade-centric exploration paradigms toward a process-aware and sustainability-oriented exploration model. The results show that key geophysical parameters—magnetic susceptibility contrasts, electrical resistivity ranges, induced polarization chargeability values, and electromagnetic conductivity responses—exhibit strong and quantifiable relationships with ore texture, mineral locking, comminution energy demand, and expected recovery efficiency. Deposits characterized by moderate resistivity (10–100 Ω·m), elevated chargeability (>15 mV/V), and coherent magnetic anomalies were consistently associated with higher liberation potential and predicted metallurgical recoveries exceeding 70%. Conversely, highly conductive or extremely resistive zones were linked to fine-grained textures, complex mineral associations, and increased energy and processing penalties. Environmental performance indicators derived from the same geophysical signatures further reveal that subsurface physical properties can serve as early-warning signals for acid generation potential, tailings behavior, and contaminant mobility. High chargeability coupled with low resistivity was found to correlate with sulfide-rich systems, implying elevated acid mine drainage risk if not proactively managed. This confirms that environmental liabilities can be anticipated at the exploration stage rather than addressed reactively during mine closure. The machine-learning models achieved predictive accuracy exceeding 80%, with cross-validated accuracies ranging between approximately 75% and 82%, with higher performance observed for environmental risk classification compared to metallurgical indicators.

These findings validate the feasibility of translating geophysical responses into actionable metallurgical and environmental intelligence, thereby reducing uncertainty, minimizing exploration-to-production disconnects, and lowering long-term project risk. The novelty of this work lies not in the use of geophysics, metallurgy, or machine learning individually, but in their tight conceptual and operational integration into a unified decision-support framework. This approach aligns with global shifts toward responsible mining, circular economy principles, and environmental, social, and governance (ESG) compliance, particularly in resource-rich developing regions where extensive drilling and metallurgical testing may be economically prohibitive.

RECOMMENDATIONS

Based on the findings and insights of this study, the following recommendations are proposed:

1. Early Integration of Geophysics and Metallurgy

Mineral exploration programs should integrate metallurgical considerations at the geophysical interpretation stage. Exploration workflows should explicitly evaluate geophysical signatures not only for ore presence but also for predicted processing behavior and environmental risk.

2. Adoption of Processability-Focused Exploration Models

Mining companies and geological surveys are encouraged to adopt processability-driven exploration strategies that prioritize deposits with favorable liberation characteristics and lower energy and environmental penalties, rather than relying solely on grade and tonnage metrics.

3. Expansion of Geophysical–Metallurgical Databases

Future work should focus on building large, open-access databases linking geophysical measurements with verified metallurgical test results. Such datasets will improve model generalizability, reduce bias, and support region-specific calibration.

4. Integration into Sustainability and ESG Frameworks

Regulators and policymakers should consider incorporating geophysical–metallurgical indicators into environmental impact assessments (EIAs) and mining permit evaluations. Predictive subsurface intelligence can support proactive environmental management and reduce post-mining liabilities.

5. Methodological Refinement through Advanced Analytics

Future studies should explore deep-learning architectures, physics-informed machine learning, and joint inversion techniques to further enhance prediction accuracy and interpretability of geophysical–metallurgical relationships.

6. Application in Artisanal and Small-Scale Mining Contexts

The proposed framework is particularly suitable for artisanal and small-scale mining environments, where limited capital restricts extensive testing. Simplified geophysical indicators could guide safer, more efficient, and environmentally responsible operations.

7. Climate-Responsive Mine Planning

Given the influence of climatic conditions on weathering, tailings stability, and recovery processes, future implementations should explicitly integrate climatic variables into predictive models to improve long-term performance forecasting.

Overall, this study establishes a robust scientific foundation for seeing ore not only before breaking rock, but understanding how it will behave once broken. By embedding metallurgical and environmental foresight into geophysical exploration, the work offers a transformative pathway toward smarter, cleaner, and more resilient mineral resource development.

DATA AVAILABILITY STATEMENT

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. The machine-learning workflow was implemented in Python using the Scikit-learn library. A reproducible version of the code, including data preprocessing, feature extraction, and model training scripts, is available upon request and will be made publicly accessible in a future repository.

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