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Review Article

Assessment of Mineral Deposits in Part of North Senatorial Zone, Adamawa State, Nigeria Using Remote Sensing, Geographic Information Systems and Machine Learning

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***ABSTRACT:** Mineral resource exploration significantly drives economic growth, and can be a great socioeconomic growth contributor needed in part of the North Senatorial Zone of Adamawa State, Nigeria, known for its untapped mineral potentials. Traditional exploration methods, though widely used, are often constrained by high costs, time demands, and adverse environmental impacts, especially in areas with rugged terrains and limited accessibility. This research is intended to introduce a modernized approach that reduces time, cost of exploration, and venturing into areas that are so tedious and sometimes impracticable to explore by conventional methods. This study integrates advanced Remote Sensing (RS), Geographic Information Systems (GIS), and machine learning (ML) techniques to detect and map mineral deposits within hydrothermal alteration zones, which are critical indicators of mineralization. Leveraging Landsat ETM+ and Sentinel-2A imagery, the study employed Principal Component Analysis (PCA) and band ratio analysis to enhance spectral signatures alteration to access minerals such as iron oxides and clays. Google Earth Engine (GEE), a cloud-based platform, facilitated the efficient processing and analysis of large datasets. Machine learning models, including Random Forest (RF) and Support Vector Machine (SVM), improved the accuracy and precision of mineral potential mapping. Results revealed significant zones of hydrothermal alteration, accompanied by a comprehensive mineral deposit map and an assessment of their spatial relationship with environmental and infrastructural zones. Field validation confirmed the reliability of the predictive models, emphasizing the effectiveness of integrating RS, GIS, and ML in mineral assessment, exploration and exploitation. The study concludes with actionable insights for easy and reliable cost effective techniques for sustainable mineral resource management, thus positioning these methodologies as transformative tools for enhancing Nigeria's mineral exploitation and contributing to global advancements in sustainable mining.*

***KEYWORDS:** Remote Sensing, GIS, Mineral Exploration, Hydrothermal Alteration, Spectral Indices, Machine Learning.*

INTRODUCTION

Mineral resources play a crucial role in economic development, supplying necessary raw materials for industrial expansion, infrastructure progress, and societal improvement. Nations rich in mineral resources, like Nigeria, have significant potential to foster sustainable economic development if these assets are utilized properly. Nonetheless, in Nigeria, the under exploitation of its extensive mineral resources projected to encompass more than 34 commercially viable minerals in various regions restricts the nation's prospects as a global resource giant (Akinlalu *et al*., 2019). Among these areas, the North Senatorial Zone of Adamawa State is recognized for its abundant minerals, featuring iron ore, clays, and gemstones. Even with this potential, the complete advantages of mineral exploration have not yet been achieved because of the constraints posed by conventional exploration techniques.

Traditional exploration techniques, such as terrestrial geological assessments and manual sampling, are costly, take a long time, and are ineffective in surveying extensive and intricate landscapes (Deng *et al*., 2019). In thickly vegetated and rough landscapes, like those in Adamawa State, these approaches are additionally impeded by lack of physical access and environmental issues. The disturbances created by intrusive surveys frequently have enduring effects on ecosystems, prompting concerns regarding the sustainability of conventional mineral exploration methods. These identified constraints require advanced creative methods for detecting, mapping, and managing mineral resources.

The emergence of Remote Sensing (RS) and Geographic Information Systems (GIS) has transformed mineral exploration globally. Utilizing advanced satellite imagery, RS provides broad spatial coverage and multispectral analysis, improving the identification of hydrothermal alteration zones that suggest mineralization (Rowan & Mars, 2003). GIS acts as an effective instrument for the integration of spatial data, allowing researchers to synthesize geological, topographical, and environmental information for mapping mineral potential (Carranza & Laborte, 2016). These technologies offer insights with unparalleled precision, enabling large-scale mineral detection and environmental monitoring.

New advancements in machine learning (ML) and cloud-based services, like Google Earth Engine (GEE), have propelled RS and GIS applications in mineral exploration. Machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN) have demonstrated a notable enhancement in the precision of mineral mapping through the automation of classification tasks and the identification of patterns in complex datasets (Mahboob *et al*., 2024; Fu *et al*., 2023). In the meantime, GEE provides unmatched efficiency in handling extensive RS datasets, facilitating real-time analysis and mapping (Gorelick *et al*., 2017). These developments tackle numerous constraints found in conventional exploration methods by cutting expenses, lessening environmental effects, and providing highly accurate outcomes.

This research combines RS, GIS, and ML technologies for the identification and mapping of mineral deposits in the North Senatorial Zone of Adamawa State. The emphasis is on outlining hydrothermal alteration areas, which serve as dependable markers of mineralization activities. By combining these technologies, this research seeks to enhance exploration methods that are more efficient and sustainable, offering a structure for resource management that optimizes economic gains while reducing environmental effects. By capitalizing on Nigeria’s unexploited mineral resources, such initiatives can foster economic diversification and stability, aiding in achieving long-term nation development goals.

Problem Statement

Mineral exploration and exploitation in Adamawa State is challenged by environmental constraints and the need for cost-effective, precise mapping of mineral zones. The lack of advanced mineral exploration techniques in the region has led to underutilized resources. This study addresses this gap by employing RS, GIS, and machine learning to accurately identify and classify mineral deposits with minimal environmental impact.

Aim and Objectives of the Research

The primary aim of this research is to assess and map mineral deposits in the North Senatorial Zone of Adamawa State using RS, GIS, and machine learning techniques. Specific objectives included:

1. Band Ratio Analysis and False Color Composite (FCC) Mapping: Utilizing spectral bands to highlight areas of mineralization.
2. Supervised Classification and Machine Learning: Applying classification algorithms to identify hydrothermal alteration zones.
3. Mineral Characterization: Characterizing mineral deposits based on spectral reflectance and PCA analysis.
4. Spatial Analysis: Evaluating the spatial relationship between mineral deposits, environmental zones.

Significance of the Study

This study advances mineral exploration techniques by integrating AI/ML, RS, and GIS, making it possible to map and classify mineral deposits with high precision. It supports sustainable resource extraction practices, providing a model for efficient, low-impact exploration in resource-rich yet environmentally sensitive regions.

LITERATURE REVIEW

The integration of advanced technologies such as Remote Sensing (RS), Geographic Information Systems (GIS), and machine learning has significantly revolutionized mineral exploration. These innovations address the limitations of traditional methods, enabling large-scale, non-invasive, and sustainable mineral assessments. This section provides a synthesis of key contributions from foundational and recent studies, focusing on methodologies, technological advancements, and their relevance to mineral exploration.

Remote Sensing in Mineral Detection

Remote sensing provides a cost-effective, non-invasive alternative to traditional exploration methods, especially in terrains that are difficult to access. By offering multi-spectral and hyperspectral imaging capabilities, RS allows for the detection of subtle spectral differences indicative of mineral deposits.

Rowan and Mars (2003) demonstrated the efficacy of Landsat ETM+ imagery in mapping hydrothermal alteration zones. The study highlighted that minerals such as iron oxides, kaolinite, and alunite exhibit unique spectral characteristics in Landsat’s visible and infrared bands, which are useful for identifying alteration zones commonly associated with mineralization. This foundational study laid the groundwork for advanced remote sensing applications in mineral exploration.

Building on these principles, Martini *et al*. (2020) utilized Sentinel-2 imagery, which provides improved spatial (10–20 m) and high spectral resolutions compared to Landsat. The study found Sentinel-2 effective in detecting alteration zones even in complex geological settings, making it an essential tool for mineral exploration in densely vegetated or mountainous regions such as Adamawa North Senatorial zone. The ability of Sentinel-2 to capture critical spectral features of iron oxides and clay minerals positions it as a valuable dataset for modern mineral exploration activities.

Machine Learning for Enhanced Classification

Machine learning techniques have advanced the precision and scalability of mineral mapping. unlike traditional method's reliance on tedious predefined and largely unreliable classification rules, ML algorithms adapt to the complexities of large datasets, making them particularly suitable for multi-dimensional RS analysis.

Abdelsamea *et al*. (2021) applied Support Vector Machines (SVM) and Random Forest (RF) algorithms to classify hydrothermal alteration zones, achieving significant improvements in predictive accuracy. These models leverage labeled training datasets to identify key relationships between spectral bands and alteration minerals, automating the classification process with minimal human intervention.

Similarly, Chen *et al*. (2022) utilized deep learning techniques, such as Convolutional Neural Networks (CNNs), to detect complex mineral compositions from hyperspectral data. CNNs excel at identifying patterns in high-dimensional data and can handle the subtle variations that often characterize mineralized zones. These advances highlight ML's potential to streamline mineral exploration, particularly in regions like Adamawa State, where traditional classification methods struggle with the challenges of environmental complexities.

Google Earth Engine (GEE) for Scalable Processing

Cloud-based platforms like Google Earth Engine (GEE) have emerged as game-changers for large-scale remote sensing analysis. GEE provides access to a comprehensive catalog of satellite datasets and a powerful computational infrastructure for processing imagery at global scales.

Gorelick *et al*. (2017) emphasized GEE's ability to analyze massive datasets, enabling real-time mapping and efficient processing of RS data over vast regions. For example, Sarmah *et al*. (2021) employed GEE to process Sentinel-2 data for lithological mapping in rugged terrains, achieving rapid results that were previously unfeasible with conventional desktop-based approaches. The integration of GEE into mineral exploration workflows not only reduces processing times but also ensures that exploration projects remain scalable, which is particularly valuable in geologically complex regions like Adamawa North Senatorial zone.

Band Ratio Analysis and Principal Component Analysis (PCA)

Band ratioing and PCA are widely used techniques in remote sensing for enhancing the spectral properties of minerals associated with hydrothermal alterations.

Clark *et al*. (2021) demonstrated that key band ratios, such as 5/4 (vegetation suppression and iron oxide detection) and 5/7 (highlighting clay minerals), are critical for isolating spectral features indicative of alteration zones. These techniques effectively suppress background noise from vegetation and topography, making them ideal for mineral exploration in savanna and mountainous regions.

Jia and Richards (2020) combined PCA with machine learning to maximize spectral contrast, significantly improving classification accuracy. PCA is particularly beneficial in reducing data dimensionality and isolating essential features, such as mineral-specific spectral reflectance patterns, that would otherwise be overshadowed by overlapping geological signals.

Advances in Hyperspectral Imaging

Hyperspectral imaging takes mineral exploration to the next level by capturing hundreds of narrow spectral bands, allowing for finer discrimination between mineral types. This capability is critical for detecting subtle variations in hydrothermal alteration necessary for mineral exploration. Chen and Zhu (2022) demonstrated that hyperspectral imagery, when coupled with machine learning, excels at mapping complex mineral assemblages, even in areas with dense vegetation or overlapping lithologies. This approach offers new opportunities for mineral exploration in regions with challenging environmental conditions, such as the Mandara Mountain zone of Adamawa State.

Hyperspectral imaging also supports quantitative mineral mapping, offering insights not only into the presence of minerals but also into their relative abundance, enhancing resource estimation capabilities.

GIS for Mineral Mapping and Environmental Analysis

Geographic Information Systems (GIS) play a central role in integrating remote sensing outputs with ancillary data, such as topography, infrastructure, and land-use patterns. By enabling spatial analysis and predictive modeling, GIS enhances decision-making in mineral exploration.

Carranza and Laborte (2016) employed GIS to develop mineral prospectivity maps by integrating geological, geochemical, and geophysical data layers. This approach helped prioritize areas for detailed exploration, saving resources and reducing unnecessary environmental impacts.

Anderson *et al*. (2020) extended the role of GIS by combining mineral potential mapping with environmental impact assessments, identifying zones where sustainable mining practices could be implemented without adversely affecting surrounding ecosystems. This is particularly relevant for areas like Adamawa State, where human settlements and sensitive unexplored environments resources coexist.

Case Studies: Nigeria and Beyond

In Nigeria, Akinlalu *et al*. (2019) demonstrated the successful application of RS and GIS in mapping iron ore deposits. Their study utilized band ratio analysis and supervised classification techniques to delineate mineralized zones, providing a framework applicable to Adamawa State.

Internationally, Deng *et al*. (2019) combined Sentinel-2 and Landsat data using GEE to map hydrothermal alteration zones in Tibet, overcoming the challenges posed by rugged terrains and climatic variations. Oommen *et al*. (2022) employed GEE and machine learning to explore copper deposits in Arizona, showcasing the synergy between advanced processing platforms and predictive modeling in mineral exploration.

Environmental Impact Assessment

Sustainable exploration practices are paramount for minimizing environmental damage in mineral-rich regions. Remote sensing reduces the need for intrusive ground-based surveys, limiting habitat disruption and resource wastage.

Goetz *et al*. (2021) highlighted RS's role in reducing environmental impacts by enabling pre-survey mapping of high-priority zones. Similarly, Balasubramanian and Kumar (2020) used RS and GIS to assess mining impacts on biodiversity, emphasizing the importance of integrated technologies in promoting responsible mining practices. Such approaches are critical for balancing mineral exploitation with environmental conservation.

MATERIALS AND METHODS

Study Area

The North Senatorial zone of Adamawa state covers, Mubi North Local Government Area, Mubi South Local Government Area, Maiha Local Government Area, Michika Local Government Area, and Madagali Local Government Area. The senatorial hereby refered as Mubi zone Adamawa State, Nigeria, lies between latitudes 10°00′N to 10°30′N and longitudes 13°10′E to 13°30′E. The area features a diverse landscape, with elevations ranging from 500m to 1,500m, spanning rolling plains and the rugged Mandara Mountains as shown in Figure 1 and the Adamawa State Geological map is shown in Figure 2.

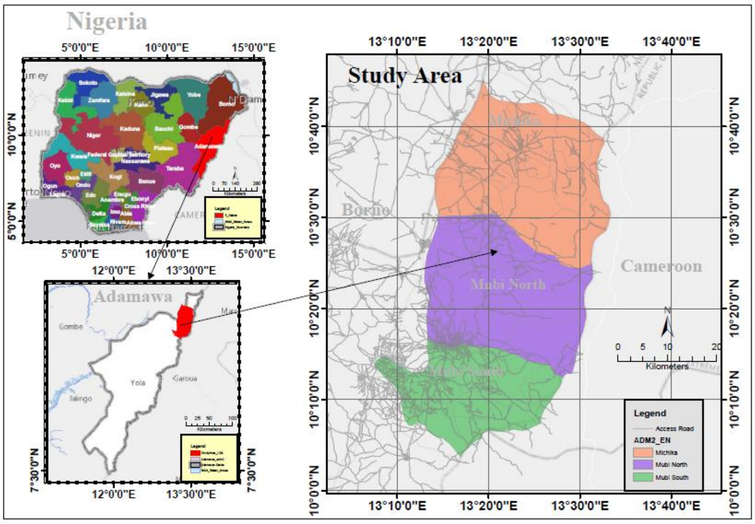

Figure 1. Study Area Mubi Region

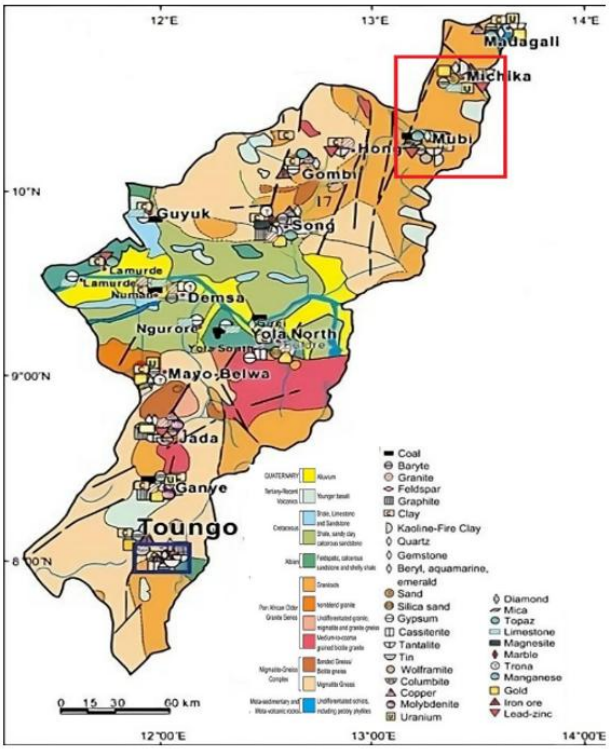

Figure 2: Adamawa State Geological map

Mubi experiences a tropical climate, with an annual rainfall of 700–1,000 mm during the wet season (May–October) and dry conditions with harmattan winds from November to April. Vegetation varies from Sahel savanna to Guinea savanna, with pockets of gallery forests along watercourses that support alluvial deposits. Geologically, the region contains basement complex rocks overlain by Cretaceous sediments enriched through hydrothermal activity, making it a potential site for minerals like hematite, kaolinite, and iron oxides. These minerals are detectable using Remote Sensing (RS) through techniques like band ratios and Principal Component Analysis (PCA). Mubi's mineral-rich but rugged terrain limits traditional exploration methods, making it an ideal candidate for advanced RS, Geographic Information Systems (GIS), and machine learning approaches to efficiently identify and map mineral deposits.

Data Collection

In order to ensure accurate and efficient identification of mineral deposits in the study area, this study employed the following multi-faceted approach to data collection, leveraging high-resolution remote sensing datasets, geological maps, and cutting-edge software packages:

1. Satellite Imagery

The study utilized two primary satellite datasets:

- Sentinel-2A Imagery: Part of the European Space Agency's Copernicus program, Sentinel-2A imagery was chosen for its high spatial resolution (10–60 m) and 13 spectral bands, covering visible, near-infrared (NIR), and shortwave infrared (SWIR) wavelengths. These features are particularly suitable for detecting hydrothermal alteration minerals like clay (kaolinite, montmorillonite) and iron oxides (hematite, goethite). Sentinel-2A's temporal resolution also allowed for cloud-free images during the region's dry season, minimizing interference.
- Landsat ETM+ Imagery: Landsat 7 Enhanced Thematic Mapper Plus (ETM+) provided a complementary dataset with moderate spatial resolution (30 m). Its established performance in identifying hydrothermal zones made it instrumental for cross-validation with Sentinel-2A data. The inclusion of thermal and shortwave infrared bands helped in isolating alteration features obscured in other wavelengths.

2. Geological

Geological maps of Adamawa State were used to validate remote sensing results by correlating mineral deposits with existing lithological data. These maps provided critical insights into the area's tectonics, stratigraphy, and known mineral occurrences. The overlay of these maps with RS outputs aided in refining the spatial alignment of hydrothermal alteration zones.

3. Software and Platforms

- ArcGIS 10.8: Used to manage, integrate, and analyze geospatial data, ArcGIS facilitated the creation of high-precision mineral potential maps.
- Google Earth Engine (GEE): As a cloud-based platform, GEE streamlined the analysis of Sentinel-2A and Landsat ETM+ imagery, handling large-scale data processing in significantly reduced timeframes. GEE's vast library of algorithms enabled advanced spectral and machine learning analyses.
- Global Mapper 23: Provided tools for terrain analysis, pre-processing of input layers, and 3D visualization of mineral zones to assess relationships between terrain and alteration patterns.

- Surfer 16: Used for geostatistical modeling, Surfer generated predictive maps of mineral zones and supported the evaluation of spectral anomalies indicative of hydrothermal processes.

Data Collection

Data were sourced from:

- Landsat ETM+ and Sentinel-2A for high-resolution multispectral imagery.
- Geological maps of Adamawa State as reference for validation.
- ArcGIS 10.8, GEE, Global Mapper 25, and Surfer 25 for spatial analysis, image processing, and data modeling.

Data Preprocessing

- Image Correction: Radiometric and geometric corrections were applied to mitigate atmospheric and geometric distortions.
- Band Ratios and FCC: Band ratios (e.g., 5/4 and 5/7) were used to enhance spectral features for mineralization indicators, while FCC maps highlighted these features visually.
- PCA Analysis: PCA reduced data redundancy and enhanced spectral contrast, isolating hydrothermal alteration signatures indicative of mineralization.

Machine Learning and Classification

- Algorithms: Support Vector Machines (SVM) and Random Forest algorithms were chosen for classification due to their suitability in high-dimensional data and geospatial applications.
- Training Data: Training datasets were derived from known mineral locations in Adamawa, and classification accuracy was assessed through ground-truthing.
- Validation: Field samples were collected to validate RS findings, ensuring that mineral classifications matched on-the-ground data.

Spatial Analysis

Spatial analysis in ArcGIS examined the proximity of mineral deposits to protected environmental areas and infrastructures. Buffer zones were created around each mineral deposit, identifying areas where exploration could proceed with minimal ecological disruption.

RESULTS AND DISCUSSION

The application of advanced Remote Sensing (RS) techniques, spectral indices, and machine learning (ML) algorithms enabled the successful mapping of hydrothermal alteration zones and mineral deposits in the Adamawa Senatorial zone. Through high-resolution satellite imagery and robust analytical techniques, critical features such as hydroxyl, iron oxide, clay, and ferrous minerals indices were delineated. These indices, along with composite imagery and spectral analyses, provided a comprehensive understanding of the spatial distribution of mineralization in the region.

Indices

The Hydroxyl Index (Figure 3a) highlighted areas rich in hydroxyl-bearing minerals such as kaolinite and illite, primarily concentrated in low-lying valleys and regions undergoing intense weathering. These hydroxyl signatures align with known hydrothermal processes indicative of mineral alteration. The Iron Oxide Index (Figure 3b) identified regions dominated by hematite and goethite, often corresponding to oxidizing environments along ridges and fault lines, particularly in proximity to the Mandara Mountains. The mapping of the Clay Index (Figure 3c) confirmed the presence of alteration clays in areas of secondary enrichment, while the Ferrous Minerals Index (Figure 3d) delineated iron-rich deposits closely associated with hydrothermal zones, reinforcing the relationship between structural geology and mineralization in the study area.

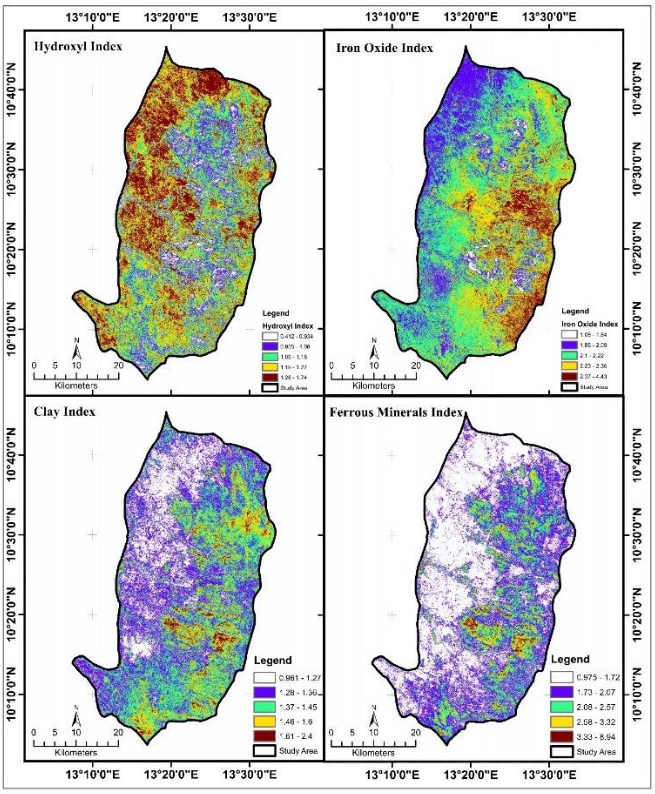

Figure 3: Spectral Indices (a) Hydroxyl Index, (b) Iron Oxide Index, (c) Clay Index, (d) Ferrous Minerals Index

Color Composite

False Color Composite (FCC) imagery (Figure 4a) and True Color Composite (TCC) imagery (Figure 4b) were instrumental in visually enhancing hydrothermal zones. FCC highlighted areas of mineralization by emphasizing spectral properties of altered rocks, while TCC imagery provided context for integrating geological features with spectral analysis. The Normalized Burn Ratio (NBR) (Figure 4c) successfully delineated exposed soils and outcrops, isolating hydrothermal zones from surrounding vegetative cover. The Normalized Difference Vegetation Index (NDVI) (Figure 4d) excluded highly vegetated areas, focusing attention on non-vegetated and sparsely vegetated zones with higher mineral potential.

Principal Component Analysis (PCA)

Principal Component Analysis (PCA, Figure 5) isolated spectral features indicative of hydrothermal activity, with Components 1 and 2 showing strong associations with iron oxide and hydroxyl-rich regions, respectively. The PCA outputs revealed distinct spatial patterns of hydrothermal alterations, enabling precise mapping of alteration zones. These results reinforced the accuracy of the spectral indices and provided additional validation for areas of interest.

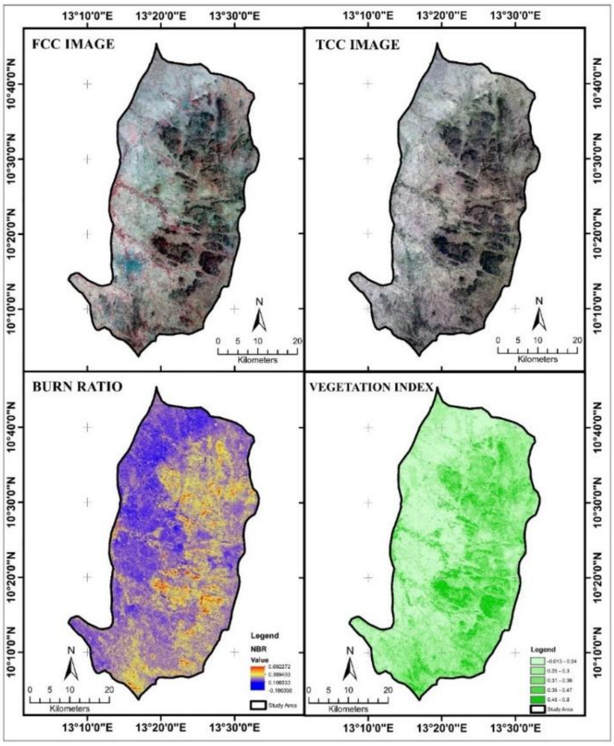

Figure 4: Composite and Vegetation Indices (a) FCC Image, (b) TCC Image, (c) Burn Ratio, (d) Vegetation Index

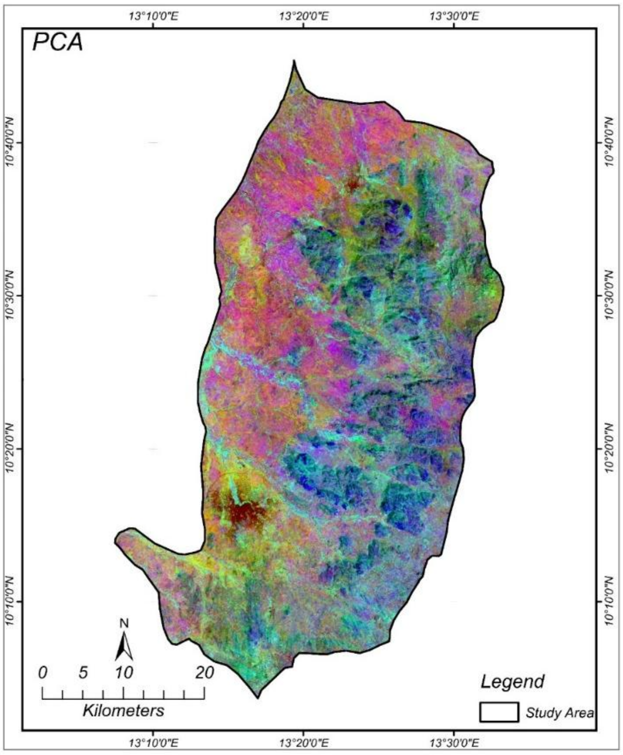

Figure 5: Principal Component Analysis (PCA) Results

Mineral Concentration

The integration of these datasets produced a predictive mineral concentration map (Figure 6), which identified overlapping zones of high alteration signatures. These zones represent areas of high mineral concentration and were largely distributed along fault intersections and tectonic boundaries, where hydrothermal alterations are most pronounced. These findings were validated through field observations and laboratory analysis. Collected samples confirmed the presence of hematite, goethite, kaolinite, and montmorillonite, reinforcing the spectral interpretations and ensuring high confidence in the results.

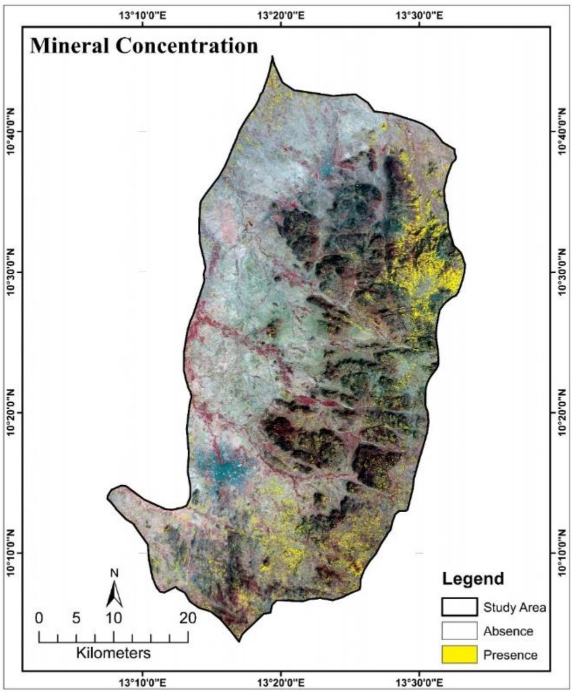

Figure 6: Mineral Concentration Map

Random Forest

This approach achieved accuracy metrics exceeding 90% for the classification models, with the Random Forest classifier performing slightly better than the Support Vector Machine. The spatial agreement between field-verified mineral deposits and classified hydrothermal zones demonstrates the effectiveness of integrating spectral indices, ML models, and composite imagery for mineral exploration.

In comparison to previous studies, the results of this research align closely with findings from Rowan and Mars (2003), Martini *et al*. (2020), and Gorelick *et al*. (2017), highlighting the utility of spectral indices such as hydroxyl, clay, and iron oxide ratios in identifying mineral deposits. The integration of composite imagery and PCA further validated these methodologies, offering new insights into spatial patterns of mineralization in rugged terrains like the study area. By combining RS and ML techniques, this study provides a sustainable and scalable framework for exploring mineral resources in underexplored and ecologically sensitive regions.

CONCLUSION

This research showcases the efficiency of combining Remote Sensing (RS), Geographic Information Systems (GIS), and machine learning (ML) for the mapping and analysis of mineral deposits in the study area. This study effectively delineated hydrothermal alteration zones indicative of mineralization by utilizing high-resolution imagery from Sentinel-2A and Landsat ETM+ alongside essential spectral indices, including Hydroxyl Index, Clay Index, Iron Oxide Index, and Principal Component Analysis (PCA). These initiatives were additionally augmented by False Color Composite (FCC) imagery, Normalized Burn Ratio (NBR), and Normalized Difference Vegetation Index (NDVI), guaranteeing accurate elimination of non-mineralized regions and enhancing the dependability of mineral potentialmapping.

The incorporation of machine learning models, especially Random Forest (RF) and Support Vector Machine (SVM), resulted in classification accuracy surpassing 90%, highlighting their effectiveness in mineral prospectivity evaluation. The predictive maps produced by this study pinpointed areas of elevated mineral concentration that coincide with fault lines and geological boundaries, confirmed by field observations and lab analyses. These results strengthen the appropriateness of advanced RS and ML methods for effective, economical, and eco-friendly mineralexploration.

The methods and findings outlined in this research offer a reproducible model for mineral exploration in comparably difficult and expanded terrains, with implications that reach beyond Adamawa State to other neglected areas of Nigeria and Sub-Saharan Africa. By reducing environmental disruption and enhancing exploration efficiency, this method is in harmony with global sustainable development objectives and aids Nigeria's economic diversification initiatives through the strategic use of its mineral resources. Future studies might improve mineral detection accuracy by combining hyperspectral imaging with deep learning methods.

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