Communication in Physical Sciences, 2026, 13(8):1292-1318

Prediction of Economic Potential of Lithium-bearing Rocks using Machine Learning Tools in Areas around Keffi and Akwanga, North Central Nigeria

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Received: 22 April 2026/Accepted: 20 July 2026/Published: 28 July 2026
https://doi.org/10.4314/cps.v13i8.5

Abstract{Resource estimation is essential for sustainable mining, mineral processing, and economic development. This study integrated remote sensing, geological mapping, and artificial neural networks (ANN) to identify, estimate, and predict the economic potential of lithium-bearing rocks in Keffi Sheet 118NE and Akwanga Sheet 119, North Central Nigeria. Landsat 8 multispectral imageries were processed, corrected, enhanced and Regolith Pattern Mapping delineated pegmatite mineralization trends, guiding geological exploration conducted in accordance with JORC standards. A total of 42 samples (35 rock and 7 soil) were analyzed using a field portable spectroradiometer and X-ray fluorescence (XRF), identifying major lithium-associated minerals including spodumene, lepidolite, quartz, albite, muscovite, and hematite. The measured Li_2O resource before ANN prediction was 2,260 g/t, with statistical analysis showing positive correlations of Li_2O with K_2O, Na_2O, and MnO, and a threshold value of 20. An ANN model (10→64→32→16→1) developed in MATLAB predicted Li_2O with an average accuracy of 76.35% and 100% confidence. Model validation produced $R^2 = 0.99$, VAF = 0.63, and RMSE = 99.7, confirming excellent agreement between predicted and measured values. The predicted lithium resource increased to 3,236.64 tons, valued at ₦1,024,937,946.50, with Angwan Doka (locations 026R and 027R) contributing 72.3% of the total economic potential. Zone A (82.4%) contained the highest lithium concentration, followed by Zones B (8.3%) and C (1.2%), demonstrating the model's effectiveness for resource estimation, mine planning, and sustainable economic development.

Keywords: *Lithium-bearing pegmatites; Machine learning; Artificial neural network; Mineral prospectivity; Remote sensing.*

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1.0 Introduction

The growing global transition toward low-carbon energy systems has substantially increased the demand for critical minerals required for advanced energy-storage and electronic technologies. Among these minerals, lithium has emerged as a strategically important commodity because of its extensive application in rechargeable lithium-ion batteries used in electric vehicles, portable electronic devices, grid-scale energy-storage systems, and other renewable-energy technologies. Consequently, the identification and evaluation of new lithium resources have become important components of mineral exploration and sustainable economic development. For mineral-rich developing countries such as Nigeria, the systematic evaluation of lithium-bearing geological formations presents an opportunity to diversify the mineral sector, stimulate industrial development, generate employment, and strengthen the country's position in the emerging global critical-minerals economy.

Nigeria is endowed with a complex and diverse geological framework consisting principally of the Precambrian Basement Complex, Younger Granites, and sedimentary formations. This geological diversity has facilitated the occurrence of numerous metallic and industrial mineral deposits, including tin, tantalum, niobium, gold, barite, gemstones, and lithium-bearing minerals. Nasarawa State, located within the central Nigerian Basement Complex, is particularly significant because of its extensive occurrence of pegmatites and associated rare-metal mineralization. The Keffi–Akwanga region forms part of this mineralized geological environment and contains pegmatitic bodies associated with lithium-, tantalum-, niobium-, tin-, and other rare-element mineralization. Previous investigations have established that several Nigerian pegmatite fields belong to highly evolved rare-metal systems and may contain economically important lithium minerals such as spodumene and lepidolite (Jacobson & Webb, 1946; Matheis & Caen-Vachette, 1983; Okunlola & Ocan, 2009).

Lithium mineralization in hard-rock environments is commonly associated with highly evolved granitic pegmatites. The mineralogical and geochemical characteristics of these pegmatites are strongly controlled by processes such as fractional crystallization, crustal anatexis, fluid–rock interaction, and the progressive enrichment of incompatible elements during magmatic evolution. Consequently, the spatial distribution and economic significance of lithium-bearing pegmatites may vary considerably over relatively short distances. The complex lithological, structural, mineralogical, and geochemical characteristics of such terrains make conventional mineral exploration challenging, particularly where mineralized bodies are discontinuous, structurally controlled, or concealed beneath weathered materials and soil cover.

Conventional geological, geochemical, and geophysical exploration techniques remain fundamental to mineral exploration; however, they are often expensive, time-consuming, and dependent on extensive field investigations. The increasing availability of satellite remote-sensing data, geographic information systems (GIS), geochemical datasets, and computational intelligence has created new opportunities for improving mineral prospectivity assessment. Remote sensing provides spatially continuous information that can be used to identify lithological variations, alteration patterns, structural features, and spectral signatures associated with mineralization. When integrated with geological and geochemical information, these datasets can provide valuable predictors for delineating prospective mineralized zones.

The emergence of machine learning (ML) has further expanded the capability of mineral exploration by enabling complex and nonlinear relationships among geological, mineralogical, geochemical, geophysical, and remote-sensing variables to be identified. Machine-learning models can learn patterns from existing observations and subsequently use those relationships to predict the occurrence or concentration of mineralized zones in areas where direct observations are limited. Artificial neural networks (ANNs), in particular, are capable of approximating complex nonlinear relationships between multiple input variables and target mineralogical or geochemical parameters. This capability makes ANN-based approaches potentially useful for predicting lithium concentration and evaluating the economic potential of lithium-bearing rocks in geologically heterogeneous environments (Simpson, 1990; Li et al., 2021).

Recent developments in predictive mineral exploration have demonstrated the effectiveness of machine-learning techniques for mineral prospectivity mapping. Cracknell and Reading (2014), Rodriguez-Galiano et al. (2015), and Sun et al. (2020) demonstrated that machine-learning algorithms can integrate multiple geological and geospatial datasets and identify complex patterns associated with mineralization. Similarly, recent Nigerian studies have applied machine-learning and predictive modelling approaches to mineral exploration and geological interpretation. Usman et al. (2024, 2025) and Abraham et al. (2022, 2024a) demonstrated the increasing application of predictive modelling to geological and mineral exploration problems, while Faruwa et al. (2025) applied machine-learning predictive models to mineral prospectivity mapping for gold mineralization in part of the Ilesha Schist Belt, southwestern Nigeria. Ema et al. (2025) also demonstrated the application of machine learning to the classification of geological structures from magnetic-anomaly data in the Northern Nigerian Basement Complex. These studies demonstrate the growing relevance of data-driven methods to mineral exploration in Nigeria.

Despite these advances, significant gaps remain in the application of machine learning specifically to the prediction of the economic potential of lithium-bearing rocks in the Keffi–Akwanga region. Previous studies in the area have largely concentrated on pegmatite classification, mineralogy, geochemical evolution, rare-metal enrichment, and the geological processes responsible for mineralization. Although these investigations have provided valuable information on the occurrence and characteristics of lithium-associated pegmatites, relatively limited attention has been given to integrating remote-sensing information, field observations, mineralogical characteristics, geochemical data, and ANN-based predictive modelling into a unified framework for estimating lithium concentration and evaluating its economic potential. Furthermore, there remains a need to establish quantitative relationships between Li_2O and associated major-element variables that can be used to support predictive assessment of lithium-bearing rocks.

Therefore, the present study seeks to integrate remote sensing, geological investigation, mineralogical characterization, geochemical analysis, and artificial neural-network modelling to identify and predict the economic potential of lithium-bearing rocks in areas around Keffi and Akwanga, North Central Nigeria. The study specifically evaluates the distribution of lithium-bearing mineralization, establishes relationships between Li_2O and associated geochemical variables, develops an ANN model for predicting lithium concentration, and uses the predicted results to assess the spatial distribution and economic potential of lithium mineralization.

The significance of this study lies in its potential to provide a more efficient and quantitative approach to lithium exploration in the Nigerian Basement Complex. By integrating conventional geological information with remote sensing and machine learning, the study provides an approach that can reduce uncertainty associated with mineral targeting, improve prioritization of exploration areas, support preliminary resource evaluation, and provide useful information for future detailed exploration and mine planning. The resulting predictive framework may also serve as a basis for applying data-driven mineral exploration techniques to other lithium-bearing pegmatite provinces in Nigeria and comparable geological environments elsewhere.

1.1 Literature Review

1.1.1 Lithium, Critical Minerals and Mineral Exploration

Lithium is increasingly recognized as a strategically important critical mineral because of its essential role in rechargeable energy-storage technologies. The rapid expansion of electric vehicles, portable electronics, renewable-energy systems, and grid-scale battery storage has resulted in increasing interest in the discovery and development of new lithium resources. In hard-rock environments, lithium commonly occurs in minerals such as spodumene, lepidolite, amblygonite, and other lithium-bearing silicates and phosphates. In Nigeria, lithium-bearing pegmatites form part of the extensive rare-metal pegmatite province extending across several parts of the Nigerian Basement Complex. Olade (2019) reported the occurrence of lithium-rich minerals, including spodumene, lepidolite, and amblygonite, within the Nigerian pegmatite province.

The economic significance of lithium-bearing pegmatites is closely related to their degree of magmatic evolution and enrichment in incompatible elements. Highly fractionated pegmatites may become enriched in lithium and other rare elements such as rubidium, cesium, beryllium, tantalum, niobium, tin, and boron. Consequently, mineralogical and geochemical characteristics can provide important indicators of the degree of pegmatite evolution and its potential economic significance.

The exploration of lithium-bearing deposits is, however, complicated by geological heterogeneity, structural controls, variable weathering conditions, discontinuous mineralization, and the spatial complexity of pegmatite bodies. Conventional exploration techniques based exclusively on geological mapping, geochemistry, trenching, and drilling can therefore require considerable financial and logistical resources. These limitations have encouraged the development of integrated exploration approaches involving remote sensing, GIS, geophysical and geochemical datasets, and machine-learning algorithms.

1.1.2 Geological Setting and Lithium-Bearing Pegmatites of Central Nigeria

The Nigerian Basement Complex contains extensive Pan-African granitoids and associated pegmatites that constitute important hosts for rare-metal mineralization. Central Nigeria, particularly parts of Nasarawa State, has historically been recognized for its tin, tantalum, niobium, gemstone, and rare-metal mineralization. The Keffi, Wamba, Nasarawa, and Akwanga areas are associated with numerous pegmatite bodies and historical mining activities.

One of the earliest systematic investigations of the region was undertaken by Jacobson and Webb (1946), who documented the mineralogy, field relationships, structural characteristics, and zoning patterns of pegmatites in several major mining districts, including Jemaa, Wamba, Nasarawa, and Keffi. Their work provided an important geological foundation for understanding the distribution and mineralogical evolution of Central Nigerian pegmatites.

Matheis and Caen-Vachette (1983) subsequently investigated the rare-metal pegmatites of Wamba and related areas using geochemical and isotopic approaches. Their study demonstrated the progressive enrichment of incompatible elements during pegmatite evolution and identified elevated concentrations of rubidium, cesium, tin, niobium, and tantalum in highly evolved pegmatitic systems. These findings established the importance of trace-element geochemistry and mineral chemistry in distinguishing economically significant pegmatites from relatively barren bodies.

Okunlola and Ocan (2009) classified the Keffi pegmatite field within the Lithium-Cesium-Tantalum (LCT) pegmatite family and identified it as a highly evolved rare-metal system. Their investigation showed significant enrichment of incompatible elements associated with advanced fractional crystallization. The study further indicated that lepidolite is particularly important within the Keffi pegmatite system, although spodumene and other lithium-bearing minerals occur in other Nigerian pegmatite fields.

Dada et al. (2016) further contributed to the understanding of rare-metal mineralization and structural controls within the Nasarawa–Keffi pegmatite province. Their work emphasized the importance of structural deformation and geological controls in determining the distribution of mineralized pegmatites. Goki et al. (2018) also highlighted the historical and geological significance of abandoned pegmatite and tin-mining sites and proposed opportunities for preserving selected mining landscapes for geotourism and educational purposes.

1.1.3 Pegmatite Genesis and Classification

The genetic evolution of pegmatites provides an important basis for understanding the distribution and enrichment of lithium and other rare elements. Early models of pegmatite formation emphasized the evolution of residual granitic melts through fractional crystallization. Jahns and Tuttle (1963) and Jahns and Burnham (1969) proposed that pegmatites could develop from residual granitic melts involving interaction between silicate melt and a hydrous fluid phase. According to this model, progressive crystallization of the parent granitic melt results in the concentration of incompatible components, while increasing water content eventually promotes fluid saturation and pegmatitic crystallization.

Jahns and Burnham (1969) therefore emphasized the role of water-rich fluids in the generation of pegmatitic textures and the transition from granitic to pegmatitic systems. However, subsequent experimental investigations have challenged the necessity of a separate aqueous vapour phase for the formation of all pegmatitic textures. London (1992, 2005) demonstrated that pegmatitic textures can develop under conditions where a discrete hydrous vapour phase is not necessarily present. Nevertheless, the classical models remain important for understanding the processes of magmatic differentiation, volatile enrichment, and concentration of rare elements in pegmatitic systems.

Pegmatites can also be classified according to their geological environment, pressure-temperature conditions, and degree of mineralogical evolution. Cerný (1991) proposed a classification scheme consisting of five principal pegmatite classes: abyssal, muscovite, muscovite–rare-element transitional, rare-element, and miarolitic pegmatites. The rare-element class is particularly important in lithium exploration because it includes highly evolved pegmatites enriched in incompatible elements such as Li, Cs, Ta, Nb, Sn, and Be.

Table 1 summarizes the principal pegmatite classes and their characteristic geological conditions based on the classification of Cerný (1991). The classification is relevant to the present study because the economic significance of lithium-bearing pegmatites is closely related to their degree of magmatic evolution and rare-element enrichment.

Table 1. Five Principal Pegmatite Classes Based on Cerný (1991)

Pegmatite class	General geological characteristics
Abyssal (AB)	High-grade metamorphic conditions associated with relatively high pressure and temperature
Muscovite (MSC)	Relatively high-pressure conditions and lower temperatures than abyssal pegmatites
Muscovite–Rare Element Transitional (REL-MSREL)	Transitional characteristics between muscovite and rare-element pegmatites
Rare Element (REL)	Relatively low-temperature and low-pressure conditions; commonly enriched in Li,

	Cs, Ta, Nb, Sn and other incompatible elements
Miarolitic (MI)	Generally formed at shallow crustal levels and commonly characterized by miarolitic cavities

1.1.4 Geochemical and Mineralogical Characteristics of Nigerian Pegmatites

Several studies have investigated the mineralogical and geochemical characteristics of Nigerian pegmatites and their implications for mineralization. Adekeye and Akintola (2007) reported that mineralized pegmatites in the Nasarawa area possess geochemical characteristics comparable to those of peraluminous late-Pan-African granites. They further noted that magmatic fractionation is reflected in the compositions of primary mica and potassium feldspar, with enrichment in aluminium, phosphorus, and other incompatible elements.

Razak and Akinade (2020) investigated beryl-bearing pegmatites in the Olode area of southwestern Nigeria and demonstrated that mineralized and barren pegmatites can occur within the same broader geological environment while exhibiting differences in mineralogical and chemical composition. Their findings indicated that fractional crystallization and partial melting can contribute to the development of different pegmatitic evolutionary trends.

Similarly, Okonkwo and Idakwo (2020) used geochemical discrimination criteria to evaluate pegmatite mineralization and reported that some pegmatites and associated host rocks were relatively barren based on their positions below established mineralization boundaries. Tanko and Chime (2021) also evaluated rare-element indicators including Nb, Ta, Ga, Rb, and Sn and demonstrated their usefulness in distinguishing mineralized from barren pegmatites.

Anthony and Obiora (2021) reported that rare-metal pegmatites are generally more fractionated than associated host rocks and biotite–microcline pegmatites. They identified enrichment in elements such as Rb, Li, Cs, B, Be, Nb, and Ta and suggested that some Nigerian rare-metal pegmatites may have developed through crustal anatexis of sedimentary protoliths during post-collisional tectonic events. Anthony (2022) similarly reported that complex pegmatites contain quartz, albite, muscovite, tourmaline, and rare-metal minerals and are more strongly enriched in Li, Rb, B, Cs, Sn, Nb, Be, and Ta than simple pegmatites.

The Angwan Doka area is of particular interest because its pegmatite dykes host gem-quality elbaite and exhibit geochemical characteristics typical of highly evolved pegmatitic systems. Akoh and Ogunleye (2014) reported systematic replacement of biotite by muscovite in fractionated granodiorites and increasing concentrations of boron, lithium, and fluorine in muscovite toward the lepidolite-bearing units. These characteristics demonstrate the potential value of mineral chemistry as an indicator of pegmatite evolution and mineralization.

Collectively, these studies demonstrate that lithium-bearing pegmatites in Central Nigeria are characterized by complex mineralogical, geochemical, and structural relationships. However, most previous investigations have focused on conventional geological and geochemical characterization rather than developing predictive models capable of integrating multiple variables to estimate lithium concentration and economic potential spatially.

1.1.5 Remote Sensing and Machine Learning in Mineral Exploration

Remote sensing has become an increasingly important component of modern mineral exploration because satellite imagery provides spatially continuous information on surface mineralogy, lithology, alteration, geomorphology, and structural features. Multispectral datasets such as Landsat imagery can be processed using band combinations, spectral transformations, enhancement techniques, and thematic mapping procedures to identify areas that may correspond to hydrothermal alteration and mineralized geological units. When integrated with geological mapping and geochemical observations, remote sensing can improve the identification and prioritization of mineral exploration targets.

The development of machine-learning techniques has further improved the interpretation of large and heterogeneous exploration datasets. Machine-learning algorithms can identify nonlinear relationships between predictor variables and mineralization responses that may be difficult to recognize using conventional statistical approaches. Breiman (2001) demonstrated the effectiveness of Random Forest (RF) methods for handling complex datasets by constructing multiple decision trees from bootstrapped samples and aggregating their predictions to reduce variance and overfitting.

A number of studies have demonstrated the applicability of machine learning to geological mapping and mineral prospectivity assessment. Cracknell and Reading (2014) demonstrated that machine-learning methods could be used to integrate geological datasets for mineral prospectivity mapping. Rodriguez-Galiano et al. (2015) highlighted the robustness of Random Forest methods when dealing with noisy, nonlinear, and redundant geospatial datasets. Sun et al. (2020) similarly demonstrated the effectiveness of machine-learning approaches for mineral prospectivity mapping and reported strong predictive performance from Random Forest models.

Machine learning has also increasingly been applied to mineral exploration problems in Nigeria. Abraham et al. (2022, 2024a) and Usman et al. (2024, 2025) demonstrated the potential of predictive modelling approaches for geological and mineral exploration applications. Faruwa et al. (2025) used machine-learning predictive models and thematic predictor maps to delineate high-potential gold mineralization zones within the Ilesha Schist Belt of southwestern Nigeria. Ema et al. (2025) applied machine-learning-based classification to geological structures derived from magnetic-anomaly data in the Northern Nigerian Basement Complex. Arogundade et al. (2026) also integrated geophysical data with fuzzy-logic modelling to delineate high-potential mineralization zones within the Maru Schist Belt.

These studies collectively establish that machine learning can improve mineral prospectivity assessment by integrating multiple geological and geospatial variables. However, the majority of existing applications have focused on gold and other mineral commodities, with comparatively limited attention given to quantitative prediction of lithium concentration and economic potential in Nigerian lithium-bearing pegmatites.

1.1.6 Artificial Neural Networks for Prediction of Lithium Potential

Artificial Neural Networks (ANNs) constitute an important class of machine-learning models capable of representing complex nonlinear relationships between input and output variables. An ANN generally consists of interconnected processing units organized into input, hidden, and output layers. The network learns relationships within training data through an iterative adjustment of connection weights according to a defined learning algorithm. Simpson (1990) described neural networks as computational models capable of approximating complex functions whose explicit mathematical relationships may be difficult to establish.

The suitability of ANN for mineral exploration arises from its ability to simultaneously process multiple geological, mineralogical, geochemical, and spatial variables. In lithium exploration, variables such as Li_2O, K_2O, Na_2O, MnO, Al_2O_3, Fe_2O_3, SiO_2, and other geochemical indicators may exhibit nonlinear and interdependent relationships. An ANN can therefore be trained to recognize these relationships and predict lithium concentration or prospectivity in locations where direct measurements are unavailable.

The application of artificial intelligence and machine learning to geological and mineral-resource assessment is increasingly attracting attention because of the ability of these methods to improve predictive accuracy and support exploration decision-making (Li et al., 2021). Nevertheless, predictive performance depends strongly on the quality, representativeness, and spatial distribution of training data. Consequently, ANN-based prediction should be supported by geological interpretation, field observations, laboratory measurements, and appropriate model validation rather than being considered a replacement for conventional exploration.

1.1.7 Knowledge Gap and Rationale for the Present Study

The reviewed literature demonstrates that considerable progress has been made in understanding the geology, mineralogy, geochemistry, and genesis of Nigerian pegmatites. Previous investigations have established the presence of highly evolved rare-metal pegmatites in the Keffi–Wamba–Nasarawa region and have identified lithium and other incompatible elements as important indicators of pegmatite evolution and mineralization. Studies have also demonstrated the applicability of remote sensing and machine-learning approaches to mineral prospectivity mapping in Nigeria and elsewhere.

However, three important gaps remain. First, most previous investigations of the Keffi–Akwanga region have emphasized geological, mineralogical, and geochemical characterization without quantitatively predicting the economic potential of lithium-bearing rocks using artificial intelligence. Second, relatively few studies have integrated remotely sensed information, geological observations, mineralogical data, and multivariate geochemical relationships into a single predictive framework for lithium exploration. Third, there is limited published work demonstrating the application of ANN models to the quantitative prediction of Li_2O concentration and subsequent estimation of the spatial distribution and economic potential of lithium-bearing rocks in the study area.

The present study addresses these gaps by integrating remote sensing, geological mapping, mineralogical characterization, geochemical analysis, and ANN-based prediction. The approach is intended to establish relationships between lithium concentration and associated geochemical variables and to use these relationships to predict lithium potential beyond the locations directly investigated in the field.

Accordingly, the aim of this study is to predict the economic potential of lithium-bearing rocks in areas around Keffi and Akwanga, North Central Nigeria, using integrated remote sensing, geological, geochemical, mineralogical, and artificial neural-network techniques.

The specific objectives are to:

1. identify and delineate prospective lithium-bearing geological zones around Keffi and Akwanga using remote sensing and geological mapping;
2. characterize the mineralogical and geochemical composition of selected rock and soil samples from the identified prospective zones;
3. determine the relationships between Li_2O and associated major and minor elemental oxides;
4. develop and validate an artificial neural-network model for predicting Li_2O concentration;

5. estimate the spatial distribution and potential quantity of lithium-bearing material using the validated predictive model; and
6. evaluate the economic potential of the identified lithium-bearing zones to support future exploration, resource evaluation, and sustainable mineral development.

The study is significant because it provides an integrated, data-driven framework for improving lithium exploration in a region with considerable rare-metal potential. The combination of remote sensing and ANN modelling can facilitate the rapid identification of prospective zones, reduce dependence on extensive preliminary field investigations, improve exploration targeting, and support more efficient allocation of exploration resources. In addition, the study provides a quantitative basis for prioritizing areas for subsequent detailed geological investigation, drilling, resource evaluation, and mine-planning activities. More broadly, the methodology may be adapted for lithium and other critical-mineral exploration in comparable geological terrains within Nigeria and other developing mineral economies

2.0 Materials and Methods

This section outlines the procedures employed for sample collection, preparation, and chemical composition analysis.

2.1 Research Design

The sampling design was based on a systematic approach to ensure the selection of representative samples from various pegmatite formations within the study areas as revealed from the remote sensing pegmatite signatures. Major consideration was the security and accessibility of the sample locations. The workflow chart for the study is as displayed in Fig. 1.

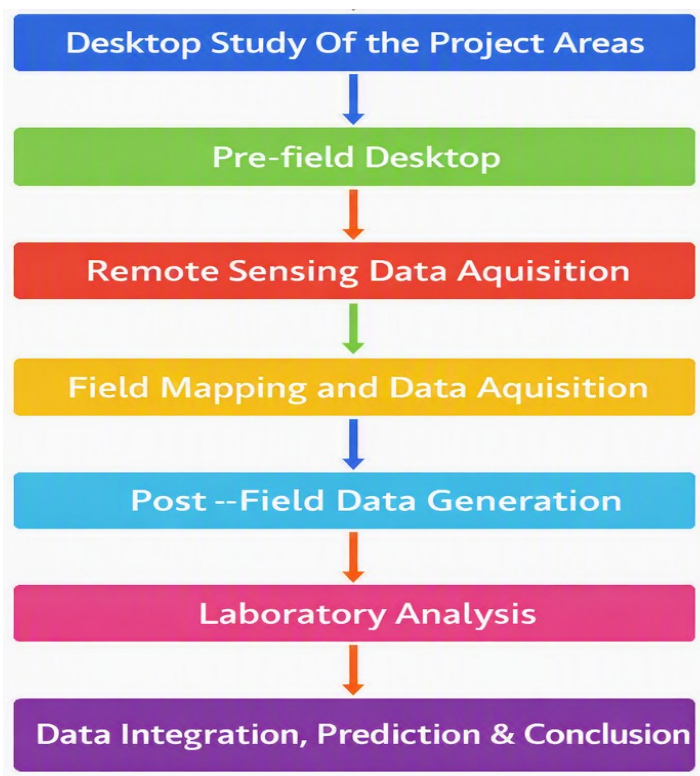


Fig. 1: Workflow Chart for the Project.

3.2 Description of the Study Areas

The study area for the research on prediction of economic potential of lithium bearing rocks using machine learning is in Keffi and Akwanga metropolis, Nasarawa State, North Central Nigeria. Keffi and Akwanga sheets are situated within the Benue Trough, which is a major geological feature in Nigeria known for its mineral potential. The study area is about 2,289Km^2 with coordinates 8° 53′ 24″ N, 7° 50′ 24″ E and 8° 36′ 36″ N, 8° 24′ 00″ E. The region is characterized by its complex geology, which includes a variety of rock formations and mineral deposits. It spans a sharp structural transition zone between the ancient, crystalline Precambrian Basement Complex to the North and West, and the younger, hydrocarbon-and-saline-bearing Middle Benue Trough sedimentary basin to the south and east. This dual geological setting hosts an exceptional variety of metallic ores, industrial minerals, high-grade energy resources, and gemstones

The selection criteria for choosing the study area includes the presence of pegmatite formations and the known mineral potential of the region. Pegmatite in the Keffi Sheet 208NE and Akwanga sheets 209 are believed to have formed during the Pan-African Orogeny, a period of intense tectonic activity around 600 million years ago. The region's geology is also characterized by faulting and fracturing, which provided pathways for magma intrusion and the formation of pegmatite bodies.

Mineral potential in the Keffi Sheet 208NE and Akwanga sheet 209 are significant, with the presence of valuable minerals such as Tantalum, Niobium, Tin, and Rare Earth Elements (REE) within the pegmatite. These minerals are highly sought after for use in various industries, highlighting the economic importance of the region's mineral resources.

Keffi and Akwanga metropolises are easily accessible, making it feasible for geological and mineral exploration activities to be conducted. The presence of infrastructure and support services in the region further contributes to the suitability of the study area for investigating pegmatite deposits and their mineral potential.

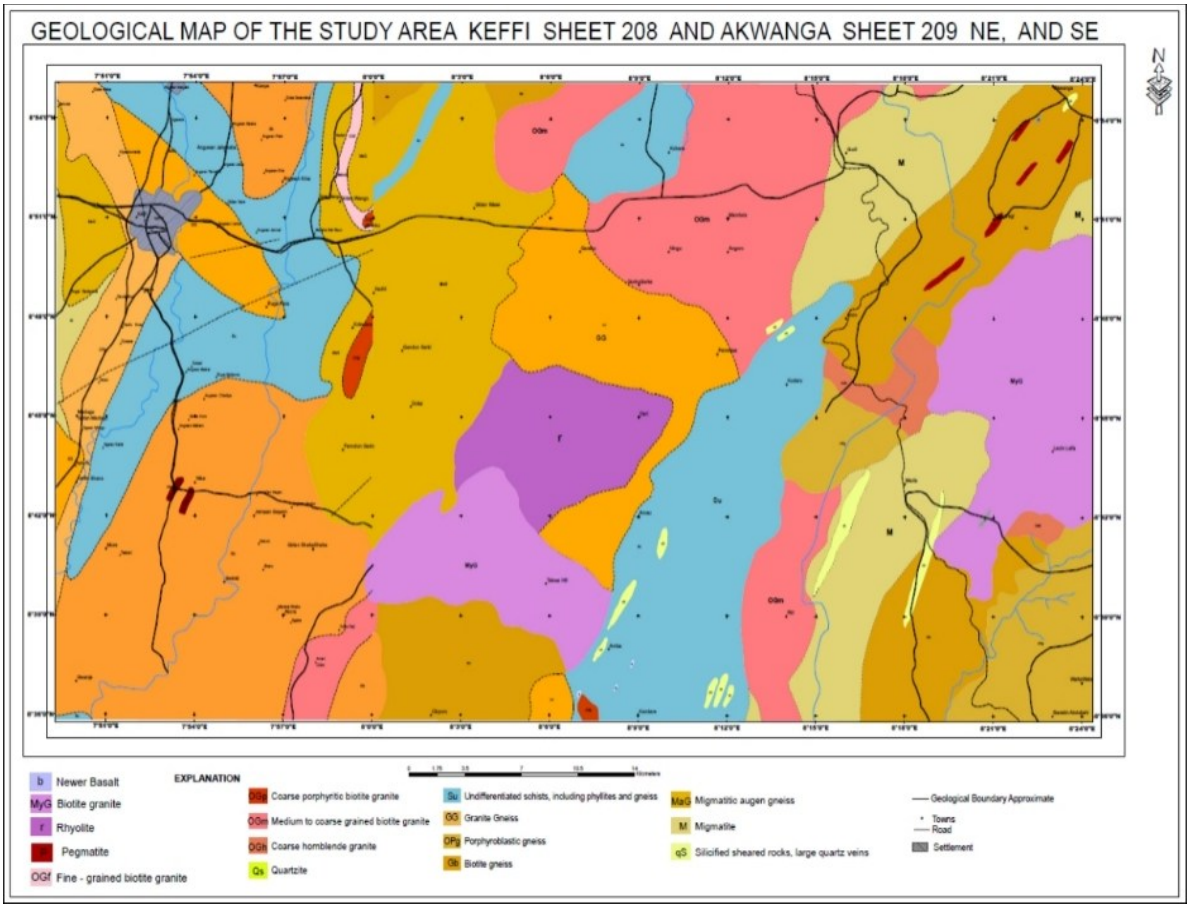
2.3 Geology of the Study Area

The study area is within Keffi Sheet 208NE and Akwanga sheet 209. The geological map of the area shows underlain majorly by younger granite series, basement complex and meta-sedimentary/ meta-volcanic rocks (Fig. 2). The geological details extracted were updated using remote sensing and Geographic Information System (GIS) technologies, such as satellite imagery and aerial photography, alongside traditional fieldwork. This process involves understanding the detailed maps of the area interested, noting features such as rock types, structures, and alterations related activities within the study area. This information provides valuable clues about the geology of the area and the potential location of mineral deposits.

2.4 Remote Sensing

In mineral exploration, remote sensing aims to detect anomalies or patterns that may indicate the presence of mineral deposits. This is achieved through the analysis of spectral signatures – the patterns of reflection or absorption of different wavelengths of light by materials (Cardoso-Fernandes *et al.*, 2018). Modern geological mapping combines traditional fieldwork with advanced technologies. Remote sensing data, aerial photography, and satellite imagery provide a broad-scale view of the geological setting, while field observations and sample analysis give more detailed information at the ground level. This combination allows for a comprehensive understanding of the site's geology (Sabins, 1999).

The intrigue of exploration lies in the quest to find and identify potentially profitable mineral deposits, a task that combines scientific understanding, technological capability, and a touch of traditional methods. Image map was produced to reveal the composite view of the geological details, terrain and relief showing the evidence of orientated and occasional concordant quartz or veins confirmed from literature review on Basement complex of Nasarawa state. The details identified were seen to be aligned with the geological structures that were delineated and approximate measured size of the distinct details was estimated from the image map.



Fig/ 2: Geological map of the study area (Keffi Sheet 208NE and Akwanga Sheet 209) Scale 1:100,000 (Source: Modified to Nigerian Geological Survey Agency, 2023)

3.5 Image Display and Visual Analysis

In this project, Landsat thematic mapper (TM) satellite images were used to reveal the lithology, structures and hydrothermal alteration of the location as related to mineralization. Digitally processed TM ratio images have the advantage in identifying hydrothermal alteration mineral zones, iron minerals, and clay minerals better and faster. Mapping the lithology and fracture patterns at regional and local scales for mineral exploration has long recognized the importance of regional and local fracture patterns as controls on ore deposits. LANDSAT ETM 8 was downloaded and used primarily for mineral and rock discrimination, whereas bands 4 and 5 were primarily used for vegetation monitoring (http://LANDSAT.gsfc.nasa.gov). Spectral analysis exploits spectral properties of rocks to interpret lithological variations or rock alterations that are expressed as variations in color intensity values within color composite images.

The first three LANDSAT bands (1, 2, and 3) correspond to the blue, green, and red portions of the visible spectrum, which are captured as gray-scale images, together with ETM+ bands 4, 5, 6, and 7.

3.6 Hydrothermal Alteration

By integrating Landsat image data with various analytical methods, the user can effectively delineate hydrothermal alteration zones and mineralization occurrences, supporting exploration efficiency and accuracy. While Landsat imagery provides valuable insights into mineral exploration, it is essential to complement these findings with field investigations and laboratory analyses to confirm the presence and geometry of mineral deposits. This multi-faceted approach ensures a more reliable assessment of mineral resources. In addition to the benefits of applying remote sensing images to explore mineral deposits. It can facilitate mapping of geological features and lineaments as identified in the distributed rocks by spectral signature. These techniques in mineral exploration help to acquire valid processed information and interpret all recorded signals of the interaction between rocks and electromagnetic energy through sensor. Remote sensing images process can be used for mineral exploration by understanding the geology, faults and the fractures that localize the ore deposits and identifies areas of hydrothermally altered rocks through specially selected spectral signatures.

The regolith is the weathered and transported blanket of material covering fresh rock. It may be defined as the entire unconsolidated and secondarily re-cemented cover that overlies more coherent bedrock, which has been formed by weathering, erosion, transport and/or deposition of older material.

It includes fractured and weathered basement rocks, saprolites, soils, organic accumulations, glacial deposits, colluvium, alluvium, evaporitic sediments and aeolian deposits. Regolith materials may represent economically significant material deposits (Fe, Al, or supergene enrichment) Regolith is a product of weather as a loose, unconsolidated rock, mineral and glass fragments in the soil. Regolith helps to support exploration process to show area that may host mineral deposits, such as mineral sands, uranium, and lateritic mineral deposits. Understanding regolith properties, especially geochemical composition, is critical to geochemical and geophysical exploration for mineral deposits beneath it. The image showed the surface geology by revealing the area to be mapped. It indicated highly fractured zone along areas identified as sheared zones in relations to the trends NE – SW directions revealing in blue colors and interpreting the sub-surface geological pattern. The techniques help to understand the structural and lithological patterns including the hydrothermal alteration areas, and the complex relationships existing between regolith development, landform evolution and geochemical signatures occurring within the landscape. The result helps reduce risk of exploration targets during sample collections. The spectral signature depicted areas of both circular and lenticular anomalies mostly trending NE – SW directions; the folded areas in rocks exposures appears in shades of greenish and the blue colors in rock exposures are attributed to the alteration minerals within the lithological units. Hydrothermal alteration processed area was used to understand the proximal to many base and precious metal deposits that provide insights into the characteristics of hydrothermal systems.

Alteration type on mineralizing style reveals more information about the deposit and exploration target of the main economic deposit. It is distinctly clear that alteration image analyzed shows an insight into the patterns and distribution of hydrothermal systems recorded in richly deep-green and dark footprint color that may be attributed to the alteration of minerals within the lithological units' due mineralogical changes. Using this approach, hydrothermal alteration was processed from an exploration perspective and discovering areas tends to have high metals concentration in the most intensely altered rocks in the study area.

Mineral Composite Analysis (MCA) explicitly identified areas with rocky outcrops that could be interpreted as: quartz, porphyry, basalts or quartzite in shades of purple and blue. The image further reveals the structural features and some variations of regolith appearing as a patch work of yellow brown and green. Likewise, the dark green could equally be described as meta-sediment and rose to red color identified as granitoids. Identified pegmatite areas from remote sensing leads to ground truthing for rock and soil samples collection and laboratory analysis as displayed in Fig. 3.

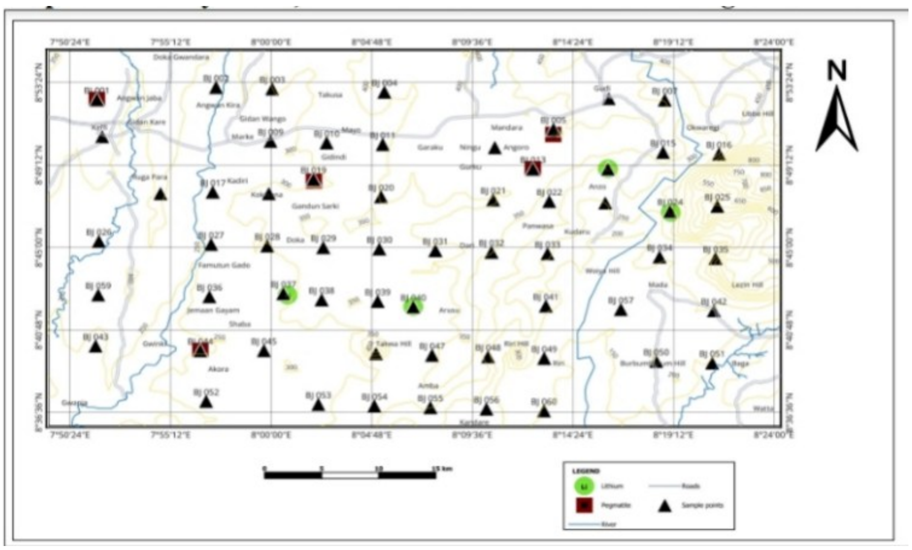


Fig. 3: Map of the study areas showing the sampled locations

3.7 Prediction of Economic Potential of Lithium Bearing Rock Deposit Model Using ANN

Power regression analysis model was used in this project because it considers all response variables (associated minerals) no matter how small in quantity with its correlation with predictor variable lithium oxide (Li_2O). Equation 1 was used for the model. Because the number of dependent variables were not much as to use correlation matrix which would display strong relationships between individual pairs of dependent variables with Li_2O, hence, dependent variables with equal length as independent variable (Li_2O) from the laboratory analysis were used for the prediction. Figure 4 shows the Flowchart diagram illustrating the machine learning pipeline as modified after Abraham *et al* 2024).

$$Y = AX^{B} \quad (1)$$

where Y = the dependent variables (Associated Minerals), X = the independent variable (Li_2O), A and B are the regression coefficients which describe the relationship between the response variable (X) and Predictor Variable (Y).

Li_2O (%) = f (SiO_2, CaO, MgO, K_2O, Na_2O, SO_3, P_2O_5, MnO, Al_2O_3, Fe_2O_3) (2)

where f is a trained neural network function

3.8 Validation Method for Prediction

The accuracy of the economic potential of Li_2O in the study areas were computed using correlation coefficient (R^2), root means square (RSME), and Variance accounted for (VAF) as shown in equations 3-5

$$R^2 = \frac{\sum_{i=1}^{r}(\alpha-\beta)^2 - \sum_{i=1}^{r}(\alpha-\omega)^2}{\sum_{i=1}^{r}(\alpha-\beta)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\alpha-\beta)^2} \tag{4}$$

$$VAF = \left(1-\frac{var(\alpha-\omega)}{var(\alpha)}\right) * 100 \tag{5}$$

where α is the measured associate mineral quantity in g, ω is the ANN predicted associate mineral quantity in g.

4.0 Results and Discussions

4.1 Interpretation of Remote sensing data in the Project Areas

Integrating Landsat image data with various analytical methods produced the mineralization occurrences as shown in Processed image for Regolith pattern map figure 5. and the image effectively delineated hydrothermal alteration zones as displayed in Fig. 6.

The regolith is the weathered and transported blanket of material covering fresh rock. It is the entire unconsolidated and secondarily re-cemented cover that overlies more coherent bedrock, which has been formed by weathering, erosion, transport and/or deposition of older material.

It includes fractured and weathered basement rocks, saprolites, soils, organic accumulations, glacial deposits, colluvium, alluvium, evaporitic sediments and aeolian deposits.

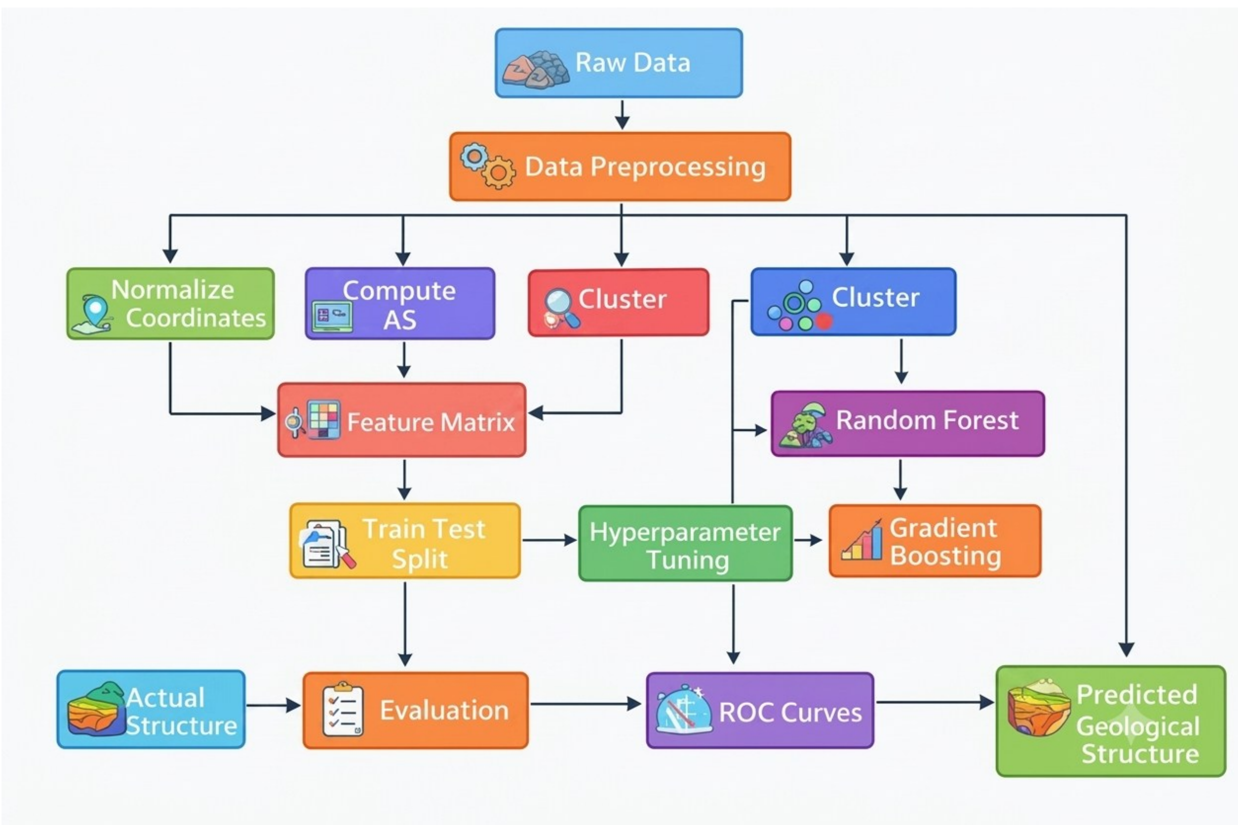


Fig. 4: Flowchart diagram illustrating the machine learning pipeline (modified after Abraham *et al* 2024).

Regolith materials may represent economically significant material deposits (Fe, Al, or supergene enrichment) Regolith is a product of weather as a loose, unconsolidated rock, mineral and glass fragments in the soil. Regolith helps to support exploration process to show area that may host mineral deposits, such as mineral sands, uranium, and lateritic mineral deposits. Understanding regolith properties, especially geochemical composition, is critical to geochemical and geophysical exploration for mineral deposits beneath it.

Mineral Composite Analysis (MCA) identified areas with rocky outcrops that could be interpreted as: quartz, porphyry, basalts or quartzite in shades of purple and blue. The image further reveals the structural features and some variations of regolith appearing as a patch work of yellow brown and green. Likewise, the dark green could equally be described as meta-sediment and rose to red color identified as granitoids. Identified pegmatite areas from remote sensing leads to ground truthing for rock and soil samples collection and laboratory analysis.

The integration of satellite imagery, band ratio analysis, and change detection enabled the detection of subtle geological features and vegetation anomalies, leading to targeted field exploration and successful discovery of lithium mineralization within the rock bearing minerals in the study areas was followed with ground truthing. Fig. 9 shows the direct zonation and identification of mineralization-validation bearing zone which depicts the NE-SW and NNE - SSW directions.

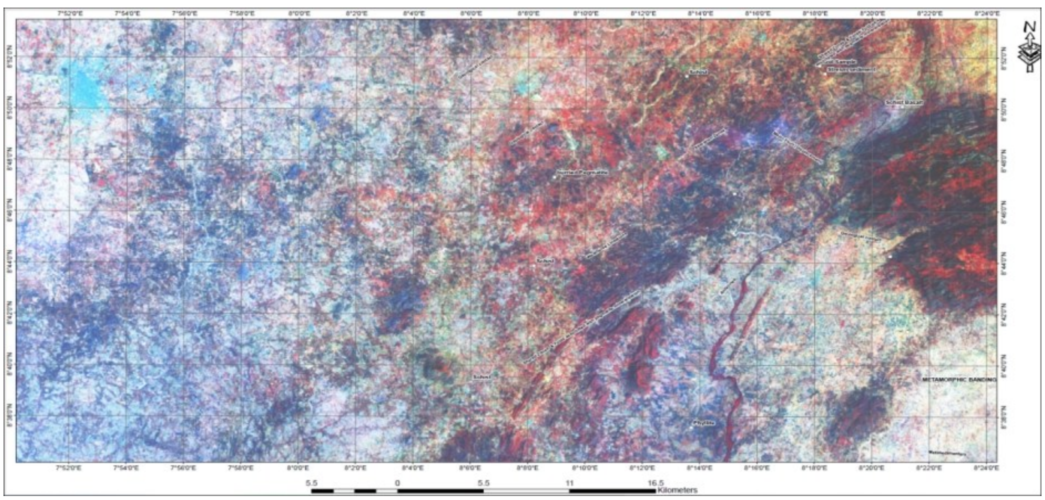


Fig. 5: Lithology Image Validation Map

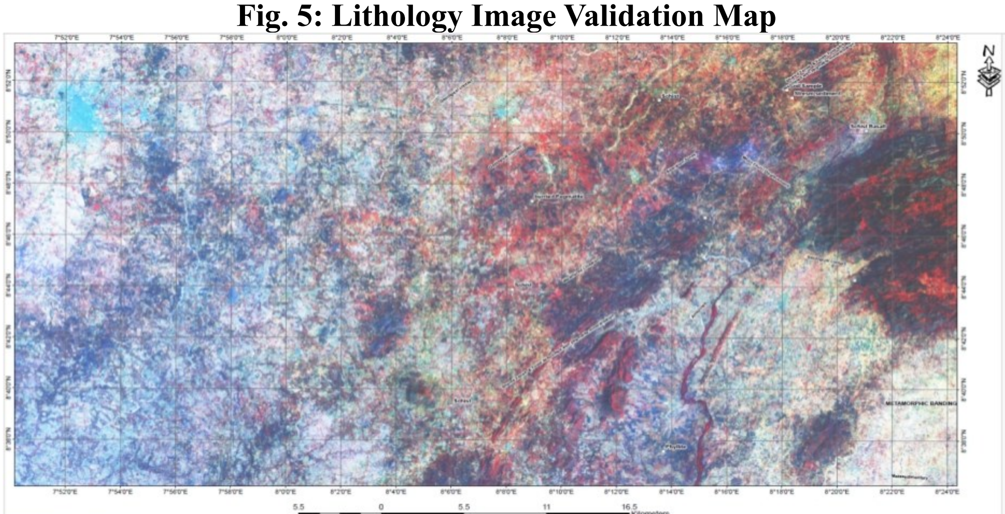


Fig. 6: Regolith Image Validation Map

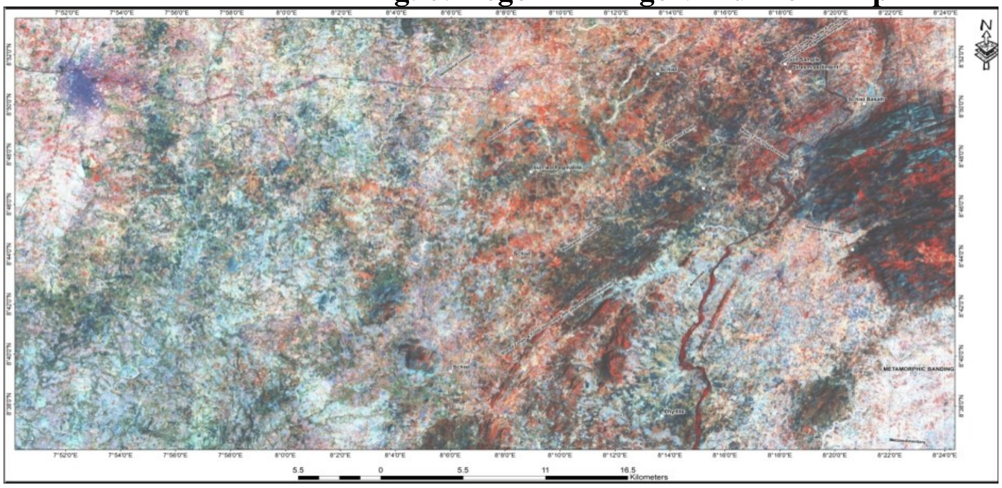


Fig. 7: Hydrothermal Image Validation Map

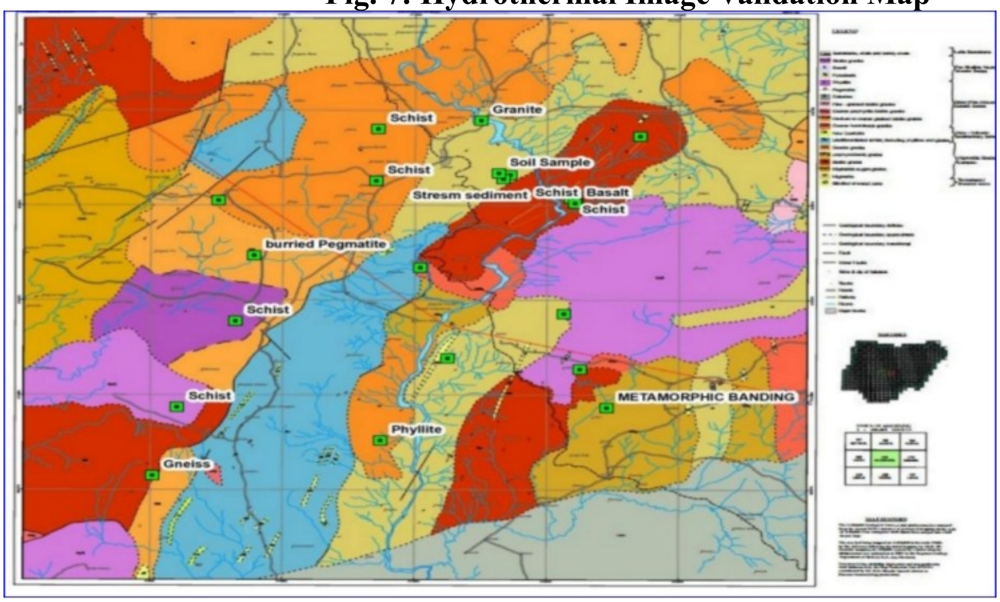


Fig. 8: Potential pegmatite sample points from remote sensing

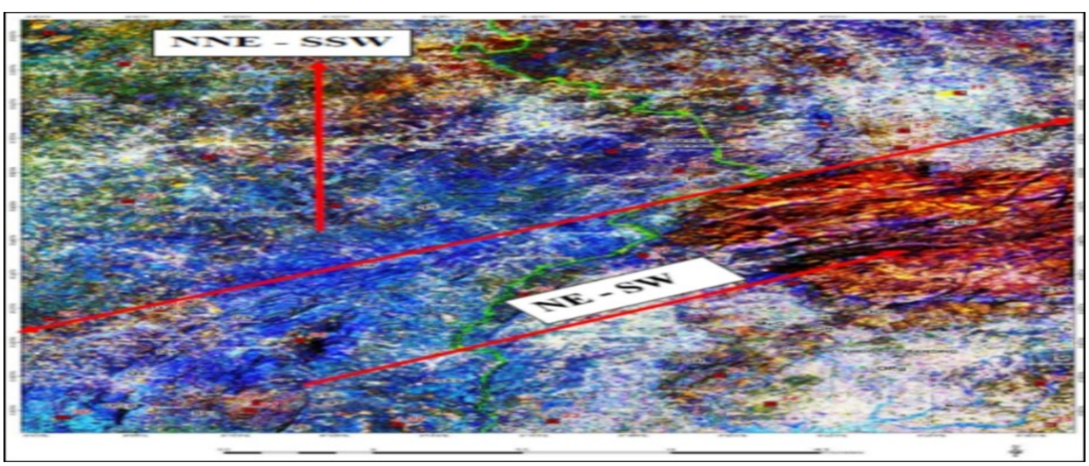


Fig. 9: Direct Zonation and Identification of Mineralization-Validation Bearing Zone

4.2 Analysis of Geochemical and Mineralogical Composition of XRF Laboratory

Results of the laboratory analysis for lithium oxides (Li_2O) and other oxide minerals in g/t are as presented in Table 1 and the total value of Lithium oxide in the project areas amounts to 2,260g/t before ANN prediction. While descriptive statistics of associated oxides with Li_2O is presented in Table 2.

Table 1: Lithium oxides (Li_2O) and other oxide minerals in g/t

S/N	SAMPLE ID	Li_2O(g/t)	SiO_2(g/t)	K_2O (g/t)	Na_2O(g/t)	Al_2O_3(g/t)	Fe_2O_3 (g/t)	L.O. I
1	003R	13	72130	3500	1500	19680	1890	1
2	004R	27	79340	2100	800	13210	3190	1
3	005R	5	79220	1900	900	15380	1470	0.8
4	006R	2.3	79450	1400	700	15770	1260	1
5	006RD1	15	53860	2400	1200	11140	27220	1.2
6	006RD2	2.6	55730	3200	1600	31860	3520	3.8
7	007RD	7	80340	3200	1400	12110	1750	0.8
8	009R	2.4	78790	1200	600	15600	2440	0.7
9	0010R	7	96360	800	200	200	1600	0.6
10	011R	8	62930	2800	1400	16900	13050	1.1
11	012R	10	79480	1300	500	16780	880	0.8
12	013SS	15	63940	1200	600	10790	15820	5.3
13	E	4	46410	300	200	6620	35230	6.7
14	015R	36	67370	1800	900	21440	3160	4.3
15	016R	7	77840	400	200	14280	3390	1.5
16	017R	263	81310	500	250	11100	3970	0.9
17	018R	1	81750	200	400	12180	2430	0.5
18	019R	9	76050	100	300	15880	2170	0.4
19	020SS1	10	77460	350	200	9790	3770	2.2
20	020SS2	8	63730	1600	800	13330	11510	5.3
21	021R	36	74370	400	300	12940	9180	2.3
22	022R	10	96390	2100	960	250	1200	0.3
23	022RD	590	56840	900	600	16610	21310	2.6
24	023R	12	76150	1600	800	16180	3380	1.4
25	024R	15	38650	0001	0001	12240	40480	6.8
26	025 SS	14	47500	0001	0001	14350	29710	9.2
27	026R	170	23590	1700	600	7850	50740	10.6
28	027R	2260	72010	3000	1470	16300	1840	2.3
29	028R	11	15980	1600	800	6110	64150	10.6
30	029R	75	74350	400	600	19080	3040	2
31	030R	1	15980	100	200	200	880	0.3
	Total(g/t)	2260	96390	3500	1600	31860	64150	10.6

Table 2: Descriptive Statistics

	Li_2O	SiO_2	K_2O	Na_2O	MnO	Al_2O_3	Fe_2O_3
N	33	36	32	32	34	35	36
Mean	111.161	69153.89	1589.06	765	347.65	13649.43	10847.22
Median	10	74360	1500	650	200	13330	3285
Std. Deviation	401.4487	17825.329	1051.093	439.861	548.624	5731.099	15508.306
Minimum	1	15980	100	200	30	200	880
Maximum	2260	96390	3500	1600	2680	31860	64150

Table 3: Correlation Matrix

	Li2O	SiO2	K2O	Na2O	MnO	Al2O3	
Li2O	**1.0**						
SiO2	-0.009	**1.0**					
K2O	0.198	-0.039	**1.0**				
Na2O	0.243	-0.072	0.959	**1.0**			
MnO	0.145	-0.423	-0.138	-0.166	**1.0**		
Al2O3	0.098	-0.011	0.346	0.461	-0.174	**1.0**	
Fe2O3	-0.061	-0.923	-0.073	-0.082	0.441	-0.332	**1.0**

4.4 Predictive Economic Potential of Lithium Oxide (Li_2O) in the study areas using machine learning

Equations 1 and 2 were used for 31 normalized sample results in Table 3 for ANN prediction. With model architecture layer of (10 → 64 → 32 → 16 → 1). The average prediction value was 76.35% with 100% confidence score. The predicted Li_2O is presented in Table 4 with total value of 3,236.64g/t of Li_2O.

The percentage of Significance of all Independent Input Variables (IIV) and Distribution Pie Chart of Independent Variables to Dependent Variable (Li_2O) are presented in Figure 10. SiO_2 has the highest value of 25%, Al_2O_3 (20%), Fe_2O_3 (18%), CaO (15%), MgO (12%) and MnO with no value (insignificant).

4.5 Model Validation Results

Validation results of the models were carried out using coefficient of correlation (R^2), Root means square error (RSME), and Variance account for (VAF). R^2 and VAF show high correlation with low variance between the predicted and the dependent input Variables. RSME values show low results which indicate that the predicted values of lithium oxide are closer to the measured values.

Figure 12 presents the validation results for the prediction of lithium oxide using coefficient of correlation (R^2), Root means square error (RSME), and Variance account for (VAF). In terms of R^2 and VAF, the model shows high correlation with low variance between the predicted and the measured quantity of Li_2O. According to the root mean square error values, the low results revealed that the predicted values of Li_2O are closer to the measured values. As a result, the developed model prediction performance is appropriate for the estimation of lithium oxide f economic benefits.

Table 6: Median Absolute Deviation and Background Values

SAMPLE ID	Li_2O (g/t)	Median Absolute Deviation	SiO_2 (g/t)	Median Absolute Deviation	K_2O (g/t)	Median Absolute Deviation	Na_2O (g/t)	Median Absolute Deviation	MnO (g/t)	Median Absolute Deviation
001R	0	10	73040	475	3100	1900	1200	600	50	150
003R	13	3	72130	1385	3500	2300	1500	900	90	110
004R	27	17	79340	5825	2100	900	800	200	120	80
005R	5	5	79220	5705	1900	700	900	300	130	70
006R	2.3	7.7	79450	5935	1400	200	700	100	220	20
006RD	0	10	79970	6455	1100	100	500	100	50	150
006RD1	15	5	53860	19655	2400	1200	1200	600	490	290
006RD2	2.6	7.4	55730	17785	3200	2000	1600	1000	90	110
007R	10	0	72680	835	0	1200	0	600	260	60
007RD	7	3	80340	6825	3200	2000	1400	800	190	10
008SS	5	5	60720	12795	0	1200	0	600	200	0
009R	2.4	7.6	78790	5275	1200	0	600	0	60	140
0010R	7	3	96360	22845	800	400	200	400	30	170
011R	8	2	62930	10585	2800	1600	1400	800	240	40
012R	10	0	79480	5965	1300	100	500	100	50	150
013R	8	2	92120	18605	3500	2300	1500	900	50	150
013SS	15	5	63940	9575	1200	0	600	0	240	40
014SS	4	6	46410	27105	300	900	200	400	200	0
015R	36	26	67370	6145	1800	600	900	300	80	120
016R	7	3	77840	4325	400	800	200	400	80	120
017R	263	253	81310	7795	500	700	250	350	300	100
018R	1	9	81750	8235	200	1000	400	200	300	100
019R	9	1	76050	2535	100	1100	300	300	0	200
020SS1	10	0	77460	3945	350	850	200	400	100	100
020SS2	8	2	63730	9785	1600	400	800	200	200	0
021R	36	26	74370	855	400	800	300	300	2030	1830
022R	10	0	96390	22875	2100	900	960	360	40	160
022RD	590	580	56840	16675	900	300	600	0	0	200
023R	12	2	76150	2635	1600	400	800	200	280	80
024R	15	5	38650	34865	0	1200	0	600	200	0
025 SS	14	4	47500	26015	0	1200	0	600	720	520
026R	170	160	23590	49925	1700	500	600	0	2680	2480

Table 4: ANN prediction

SAMPLE ID	Predicted Li_2O(g/t)	Li_2O(g/t)	SiO_2(g/t)	K2O (g/t)	Na_2O(g/t)	Al_2O_3(g/t)	Fe_2O_3(g/t)	L.O.I
003R	13.03	13	72130	3500	1500	19680	1890	1
004R	27.01	27	79340	2100	800	13210	3190	1
005R	5.00	5	79220	1900	900	15380	1470	0.8
006R	2.32	2.3	79450	1400	700	15770	1260	1
006RD1	14.98	15	53860	2400	1200	11140	27220	1.2
006RD2	5.71	2.6	55730	3200	1600	31860	3520	3.8
007RD	7.03	7	80340	3200	1400	12110	1750	0.8
009R	2.38	2.4	78790	1200	600	15600	2440	0.7
0010R	7.00	7	96360	800	200	200	1600	0.6
011R	8.04	8	62930	2800	1400	16900	13050	1.1
012R	10.00	10	79480	1300	500	16780	880	0.8
013SS	14.95	15	63940	1200	600	10790	15820	5.3
014SS	4.00	4	46410	300	200	6620	35230	6.7
015R	54.76	36	67370	1800	900	21440	3160	4.3
016R	6.49	7	77840	400	200	14280	3390	1.5
017R	262.98	263	81310	500	250	11100	3970	0.9
018R	1.02	1	81750	200	400	12180	2430	0.5
019R	9.81	9	76050	100	300	15880	2170	0.4
020SS1	8.40	10	77460	350	200	9790	3770	2.2
020SS2	36.04	8	63730	1600	800	13330	11510	5.3
021R	9.99	36	74370	400	300	12940	9180	2.3
022R	12.00	10	96390	2100	960	250	1200	0.3
022RD	136.41	590	56840	900	600	16610	21310	2.6
023R	76.68	12	76150	1600	800	16180	3380	1.4
024R	105.48	15	38650	0001	0001	12240	40480	6.8
025 SS	143.70	14	47500	0001	0001	14350	29710	9.2
026R	82.32	170	23590	1700	600	7850	50740	10.6
027R	2259.99	2260	72010	3000	1470	16300	1840	2.3
028R	11.02	11	15980	1600	800	6110	64150	10.6
029R	61.73	75	74350	400	600	19080	3040	2
030R	1.02	1	15980	100	200	200	880	0.3
Total(g/t)	**3236.64**	**2260**	96390	3502	1602	31860	64150	10.6

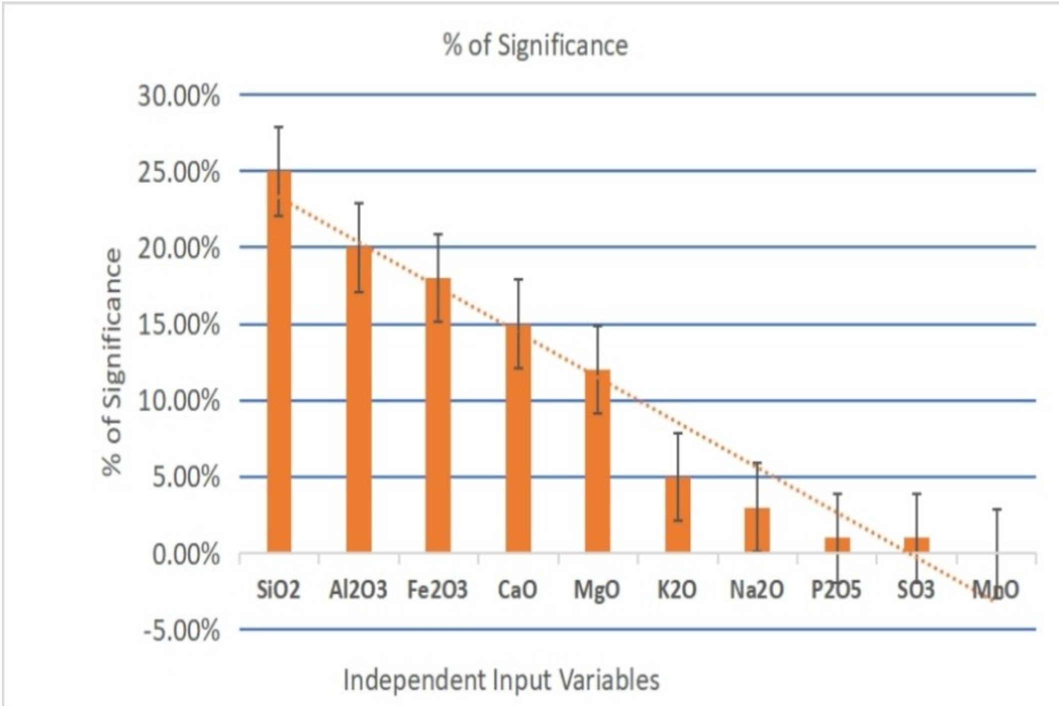


Fig. 10: Percentage of Significance of all Independent Input Variables

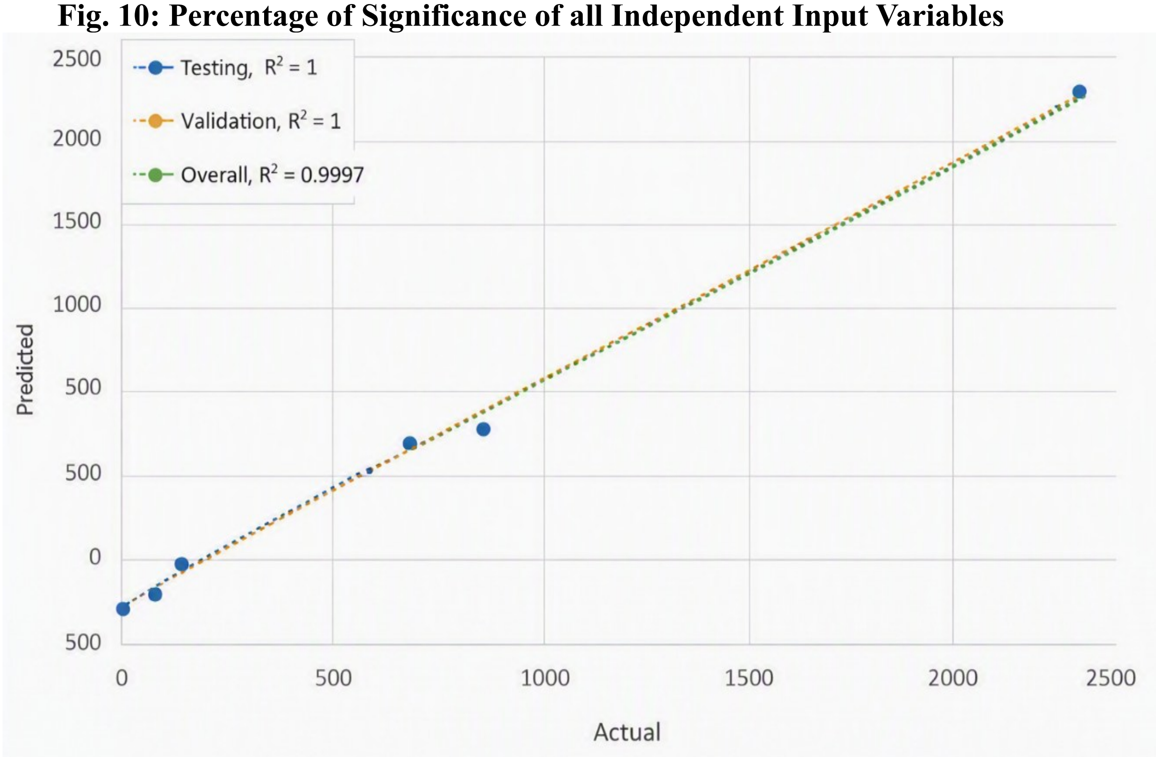


Fig. 11: Regression Analysis – Testing, Actual vs Predicted and Validation

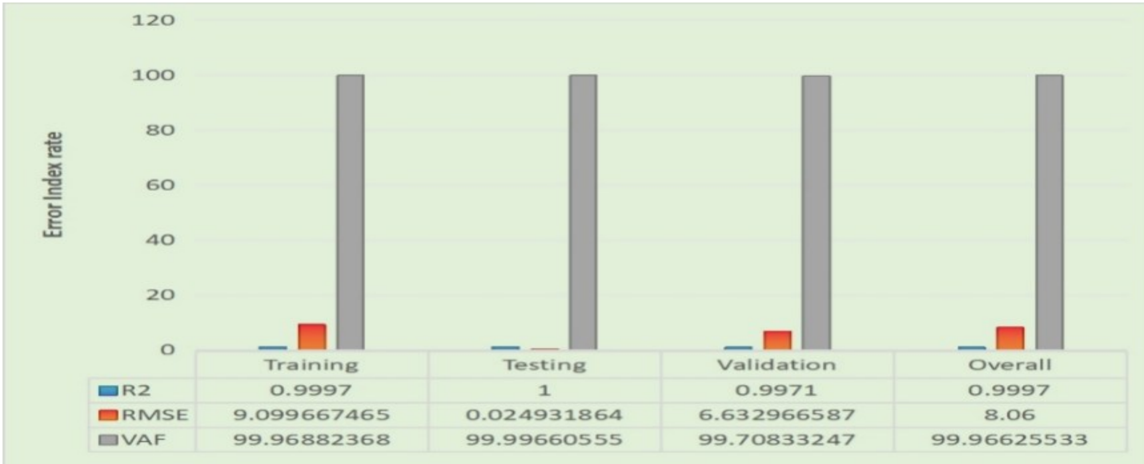


Fig. 12: ANN predicted Value Validation

4.6 Economic Potential of Lithium Bearing Rocks in the study Areas

The potential of lithium bearing rocks is very enormous, particularly for green energy and this era of climatic change. The value of Li_2O at each sampled location as predicted by ANN is as presented in the mineral economic for Lithium Oxide Table 8 and Predictive Mineral Economic Potential Map for lithium Oxide in Keffi sheet 208NE and Akwanga Sheet 209 is presented in Fig. 13. From the map, sampled locations with ID 026R and 027R which are located within Angwan Doka, are the most highly economic potential for lithium ore with a total value of 2,259.99tons which represent 72.3% of the total value of economic potential of lithium ore in the study areas. Fig. 14 shows the Map of Lithium Mineral Ore Potential and Zonal Percentage Distribution Map of Lithium Mineral Ore Potential in the Study Areas. Zone A has the highest mineral potential with total value of 2,667.7tons equivalent to 82.4% 0f the total mineral potential in the study areas. According to official price commodities market price in Nigeria, NGSA Newsletter Volume 1, N0 2 20205, Lithium ore is put at N316,667/ton. Locations with ID 017R and 027R show exceptional high potentials with economic value of N83,278,508.31 and N715,664,955.32 respectively. The total value of Li_2O potential in the entire project area is estimated to be N1,024,937,946.50

Table 8: Mineral Economic for Lithium Oxide Ore

Sample ID	Predicted	Economic Value (N)
003R	13.025	4,124,607.17
004R	27.009	8,552,871.86
005R	5.001	1,583,778.67
006R	2.321	735,035.12
006RD1	14.984	4,745,015.95
006RD2	5.714	1,809,546.79
007RD	7.032	2,226,857.74
009R	2.379	753,348.78
0010R	6.999	2,216,433.01
011R	8.035	2,544,497.27
012R	10.003	3,167,513.12
013SS	14.952	4,734,702.58
014SS	3.997	1,265,679.32

015R	54.758	17,340,039.88
016R	6.487	2,054,170.17
017R	262.984	83,278,508.31
018R	1.016	321,837.72
019R	9.807	3,105,491.86
020SS1	8.396	2,658,614.98
020SS2	36.045	11,414,252.17
021R	9.988	3,162,893.94
022R	11.998	3,799,241.48
022RD	136.408	43,195,796.36
023R	76.680	24,282,025.56
024R	105.480	33,402,035.16
025 SS	143.700	45,505,047.90
026R	82.320	26,068,027.44
027R	2,259.992	715,664,955.32
028R	11.022	3,490,188.05
029R	61.734	19,549,150.00
030R	1.016	321,837.72
Total(g/t)	**3,236.643**	**1,024,937,946.50**

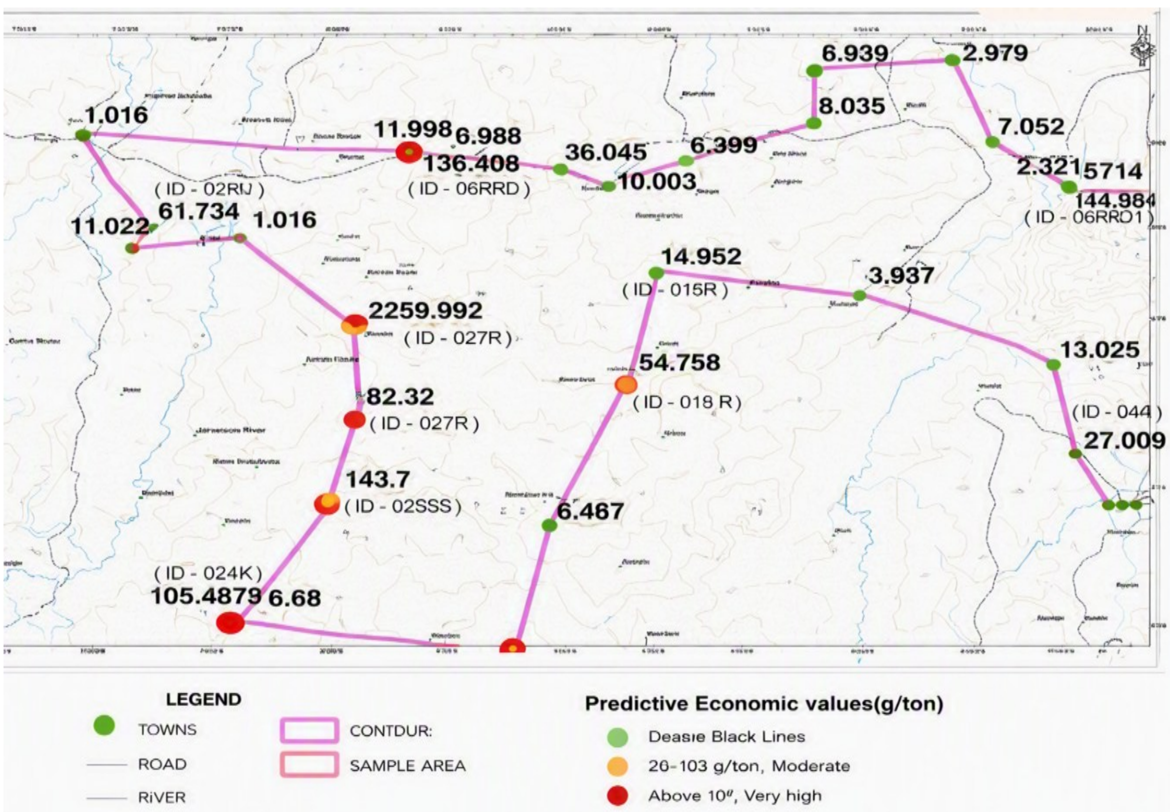


Fig. 13: Map of Lithium Mineral Ore Potential Zones in Keffi sheet 208NE and Akwanga Sheet 209

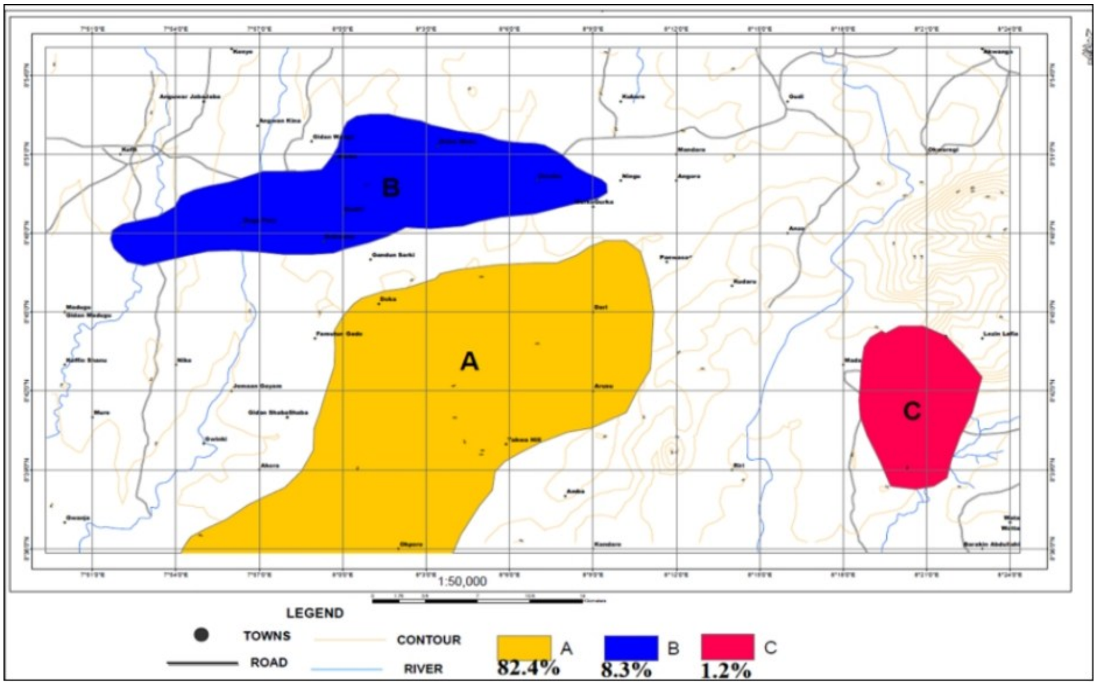


Fig. 14: Distribution Map of Lithium Mineral Ore Potential in the Study Areas.

5. 0 Conclusion

The analysis of geochemical and mineralogical composition from the XRF laboratory indicates that the material containing Li_2O is composed of oxides such as SiO_2 with the highest value at 25%, followed by Al_2O_3 at 20%, Fe_2O_3 at 18%, CaO at 15%, MgO at 12%, and MnO with no significant value. Machine learning was utilized to predict the economic potential of lithium in the study areas, where the quantitative values of lithium-bearing rock predicted by the artificial neural network were found to be enormous. The total estimated value of Li_2O potential across all project areas stands at $\text{N}1,024,937,946.50$, with locations labeled ID 017R and 027R demonstrating exceptionally high potential valued at $\text{N}83,278,508.31$ and $\text{N}715,664,955.32$ respectively. These predicted quantitative values were validated using the coefficient of determination (R^2), root mean square error (RMSE), and variance accounted for (VAF). High correlations and low variance between the predicted and dependent input variables were reflected in the R^2 and VAF results, while low RMSE values confirmed that the predicted lithium oxide values align closely with the measured data.

Based on the findings of this study, artisanal miners and investors are advised to employ remote sensing methods prior to undertaking geophysical, geological, and geochemical explorations to minimize overall costs. Machine learning has established itself as an essential tool in mining activities for effectively delineating and maximizing the exploitation of mineralized zones, which subsequently lowers mine development costs and enhances profit margins. Because lithium mining projects require substantial investment and carry inherent risks, predicting the economic potential of lithium-bearing rock deposits significantly mitigates the financial exposure of investing in unreliable ventures. Furthermore, machine learning algorithms enhance resource estimation accuracy by revealing critical relationships among geological variables such as lithology, structure, and geochemistry. Implementing these machine learning tools to forecast economic potential reduces exploration costs by directing efforts toward the most promising sites. Ultimately, this research contributes to the creation of advanced predictive modeling methodologies and tools within the mining industry, driving progress in the field and supporting future mining operations.

6,0`References

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Declarations

Consent for Publication

Not applicable.

Availability of Data

The data used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Competing Interests
The authors declare that they have no competing interests and no conflict of interest regarding the publication of this manuscript.

Ethical Consideration
Not applicable.

Funding
The authors declared no source of external funding.

Authors' Contributions
Musiliu Adebanji Gbolagade conceived the study, conducted field investigations, collected and analyzed samples, processed remote-sensing data, developed and validated the ANN model, interpreted the results, and drafted the manuscript. Nathaniel Goter Goki contributed to study design, geological interpretation, methodology, data analysis, manuscript review, and critical revision. Both authors discussed the results, approved the final manuscript, and accepted responsibility for its scientific content and integrity.