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Machine-Learning-Based Mapping and Ranking of Energy Materials in African Economies

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ABSTRACT

The global transition toward clean energy and advanced technologies has led to a rapid increase in demand for critical energy materials, including cobalt, lithium, rare earth elements, and platinum group metals. Although Africa possesses a significant share of these strategic minerals, the continent remains underrepresented in structured, data-driven mineral mapping initiatives. This research introduces a machine-learning framework based on artificial neural networks (ANNs) to predict and prioritize the likelihood of energy material occurrences across African nations. As demonstrated in a 2023 Nature Communications article, machine learning frameworks can map infrastructure such as distribution grids using publicly available multi-modal data, including street view images, road networks, and building maps. The results of this study confirm established mineral hubs, such as the Democratic Republic of Congo and South Africa, while also highlighting underexplored regions with substantial hidden potential. By addressing a critical data and strategy gap, this work provides a reproducible and scalable approach to resource intelligence, offering practical benefits for investors, policymakers, and researchers aiming to align African mineral development with the global energy transition.

Keywords: Artificial Neural Networks (ANNs); Energy Materials; Critical Minerals; Africa; Machine Learning; Clean Energy Transition; Sustainable Resource Development

INTRODUCTION

The global shift toward clean energy and advanced technologies has significantly boosted the demand for critical energy materials, minerals, and resources essential for power generation, energy storage, and high-tech equipment [1][2]. Many of these materials, such as lithium, cobalt, nickel, manganese, and rare-earth elements, are key to the manufacture of batteries, electric vehicles, solar panels, wind turbines, and other renewable energy infrastructure [2]. African economies collectively hold a substantial wealth of these energy materials, positioning the continent as an important player in the future of sustainable energy. For example, Africa is estimated to hold about 30% of the world's critical mineral reserves (such as those used in batteries and electronics) but currently receives only around 10% of global revenue from these resources [3]. This highlights a significant opportunity and need for African countries to better map, develop, and capitalize on their rich mineral resources. Africa's energy-related resource base includes both traditional fuels and modern minerals. On the one hand, countries such as Nigeria, Angola, and Libya are well known for their vast oil and gas reserves, which have long fueled economies and global energy supplies. Conversely, the continent is also rich in "energy transition" minerals such as cobalt, lithium, manganese, graphite, copper, and rare earth elements, which are crucial for clean energy technologies and battery storage [4][5]. For example, the Democratic Republic of the Congo (DRC) has the

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world's largest cobalt reserves and has supplied about 70% of the world's cobalt output in recent years, a key metal for lithium-ion batteries [6]. Similarly, Zimbabwe holds significant lithium deposits, vital for EV batteries, while South Africa is among the top sources of platinum-group metals and rare earths. Countries like Madagascar, Mozambique, and Tanzania also have abundant reserves of graphite and rare-earth elements [4][7]. This wide distribution of energy materials across Africa highlights the need to map which nations possess specific resources and to understand each country's role in supplying these strategic materials.

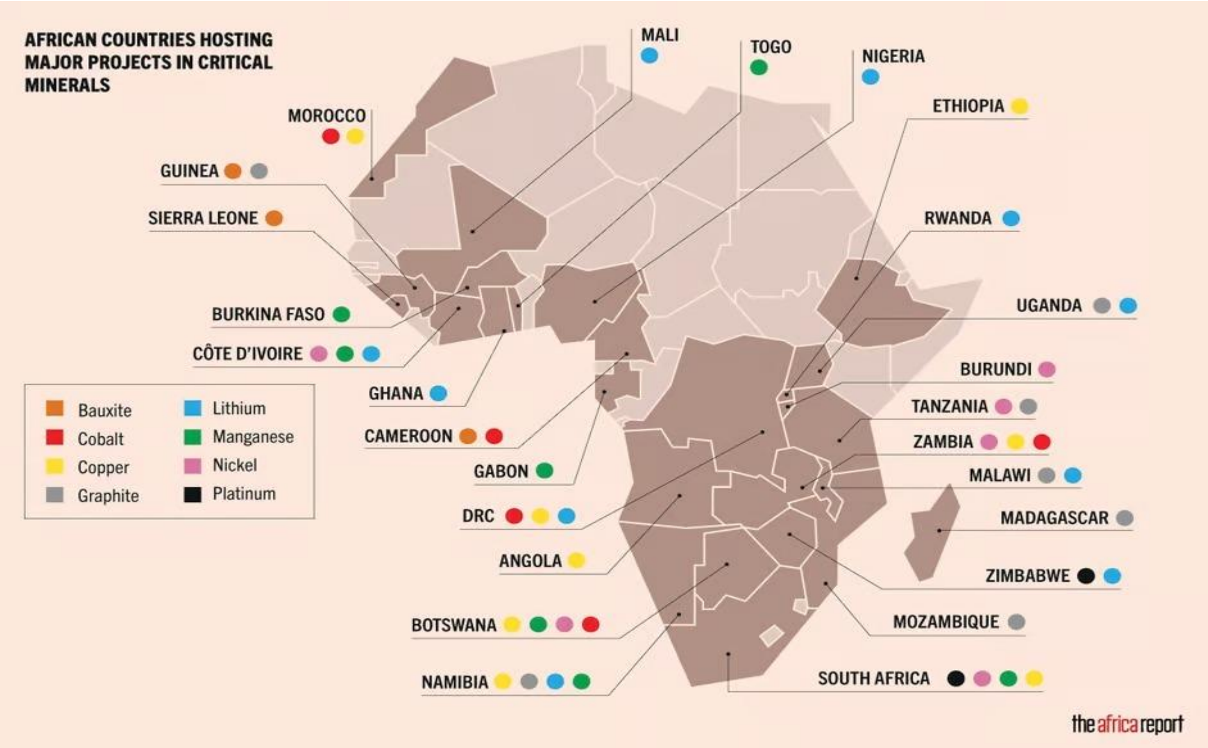

Figure 1: Map of "Critical minerals in Africa. Countries which produce or have reserves of critical minerals (non-exhaustive)" [1]

Africa holds significant shares of global reserves of key energy-transition minerals, as shown above. In particular, the continent is home to nearly half of the world's cobalt and manganese reserves, along with about one-fifth of global natural graphite reserves [5]. Copper and nickel reserves in Africa are smaller in terms of global percentage, but they are still noteworthy [8]. This abundant resource base means African countries collectively have the raw materials needed to drive renewable energy industries and advanced technologies worldwide. Properly harnessing these materials could not only support the global clean energy transition but also boost industrial development within Africa.

Despite this natural wealth, African economies face challenges in fully benefiting from their energy resources. Much of the continent's mineral wealth remains under-explored or only partially mapped due to historical underinvestment in geological surveys and data management. In fact, many African countries lack up-to-date, detailed maps of their mineral resources – some geological data still dates back to the colonial era [9]. Even where data exists, it is often siloed across different agencies and is not easily accessible or analyzable [9]. This incomplete picture makes it difficult for policymakers and investors to identify the best opportunities for resource development. Moreover, African nations have traditionally exported minerals in raw form with minimal local processing, limiting the downstream value captured locally. As noted by UNCTAD, African exports of primarily unprocessed minerals have long created few local jobs and left countries vulnerable to volatile commodity prices [10]. The motivation for this research, therefore, arises from a pressing need to bridge these knowledge and value gaps. By systematically mapping where key energy materials are likely to be found and ranking countries by their resource potential, African economies can better strategize how to leverage these assets for sustainable development. This aligns with continental initiatives to move from simply extracting raw materials to adding value and building resilient, diversified economies [11][10].

Recent advances in data science and artificial intelligence offer effective solutions for the complex task of resource mapping across Africa's vast and geologically diverse landscape. Machine learning (ML), particularly artificial neural networks (ANNs), can process extensive geological, geographical, and economic datasets to identify patterns that traditional methods may overlook. By training ML models on data indicating the presence of specific materials in various countries, it is possible to predict the likelihood of energy resources being present or significant, even in underexplored regions. Recent studies and expert discussions have highlighted that applying AI and ML to Africa's fragmented geological datasets can rapidly identify potential new deposits, including in areas previously examined without success [9]. ML techniques can reveal hidden correlations and insights from diverse data sources, thereby creating a more comprehensive map of resource distribution. This data-driven approach reduces dependence on exhaustive field surveys and assists in prioritizing locations for exploration and investment.

Machine-learning-based mapping and ranking of energy materials represents an innovative approach with both economic and strategic significance. For African policymakers, this methodology provides a clearer visualization of national comparative advantages in energy resources, including petroleum, uranium, and battery minerals, and enables benchmarking against neighboring countries. For investors and international partners, data-driven rankings identify the most promising countries for specific supply chains, such as leading sources of cobalt or those with a diverse mix of critical materials. In this study, an ANN model is developed to generate a probability distribution of multiple energy materials for each country, resulting in a Country × Energy Material matrix of predicted probabilities that effectively maps each nation's resource profile. Rankings are derived at both the material and country levels, facilitating identification of top resources per country and leading nations in overall energy material potential. The resulting heatmaps and rankings enable rapid identification of high-probability hotspots and dominant materials within each country. These insights support the design of targeted development plans, the formation of trade partnerships, and the strategic positioning of Africa's resource-rich countries within the global value chain. By translating model outputs into actionable intelligence, stakeholders can prioritize exploration, investment, and resource management decisions.

In summary, this research seeks to equip African economies with the knowledge and analytical tools necessary to maximize the value of their energy resource endowments. By applying machine learning to comprehensive mapping and ranking, the study reveals opportunities that may otherwise remain obscured in fragmented datasets or underexplored regions. This approach aligns with Africa's broader objective of achieving sustainable growth through resource-based industrialization, transitioning from raw material supply to active participation in processing, value addition, and strategic resource management [12][13]. The following sections outline the specific aims and objectives that support this overarching goal.

According to a study by Zhecheng Wang and colleagues, the research aims to develop a machine-learning framework that accurately maps distribution grids using geospatial data, achieving over 80 percent precision and recall. Essentially, the study seeks to combine data-driven modeling with visualization to identify where critical energy resources are most likely to be found and to highlight which African economies stand out as leaders in the energy materials sector.

Objectives

To achieve the above aim, the project is guided by several concrete objectives:

- Data Compilation: Gather and integrate a comprehensive dataset of energy materials relevant to African economies. This includes assembling information on known reserves, production, or occurrences of various energy materials (e.g., critical minerals such as cobalt, lithium, and uranium) for countries across Africa, as well as relevant features (geological, geographical, or economic indicators) that can assist the model in learning patterns.
- Model Development: Design and train an appropriate machine learning model, in this case, an Artificial Neural Network (ANN)capable of predicting the association between countries and energy materials. The model will learn from the compiled data to output, for any given country, the probabilities that it has each of the energy materials of interest. This effectively treats the problem as a multi-label classification, where each country can be linked with one or multiple key materials.
- Mapping (Probability Matrix Generation): Use the trained model to map out a Country × Energy Material probability matrix. Each cell in this matrix represents the predicted probability that a particular energy material is significant for a particular country. This provides a quantitative mapping of the likelihood of presence or abundance of each resource in each country, filling in gaps, especially for countries with limited direct data, by leveraging learned patterns. To enhance the practical feasibility of this work, a validation plan inviting collaboration with local geological and environmental organizations is proposed. By implementing low-cost field surveys, such as sampling and remote sensing, these collaborations could ground-truth the model's top predictions. This approach not only strengthens the accuracy of the findings but also fosters co-creation and inclusive development practices, ensuring the outputs are validated by on-the-ground evidence.
- Visualization and Analysis: Create clear visualizations to interpret the model's results. Notably, generate heatmap plots of the probability matrix to visualize the distribution of materials across countries (and vice versa) in an intuitive manner. Additionally, for each country, produce a bar chart of its top-ranked energy materials to quickly see which resources are most likely to be used in that country. These visual tools will facilitate easy comparison and communication of the findings to stakeholders.
- Ranking of Countries: Develop a methodology to rank African countries based on their overall energy material prospects. This can involve metrics such as the sum of all predicted probabilities per country (as an aggregate "score" of resource richness), the count of materials for which a country has a high likelihood above a certain threshold, or other composite indices. The result will be a ranked list of countries (from highest to lowest) by energy material potential, highlighting leaders and outliers. This ranking provides a big-picture view of how countries compare, complementing the material-specific mapping.
- Insights and Validation: Interpret the mapping and ranking results to draw insights about regional patterns and development implications. For example, identify clusters of countries that appear resource-rich and consider the reasons (geological belts, etc.), or note materials that are widespread versus those concentrated in just a few countries. Where possible, validate the model's high-probability predictions against known mineral deposits or recent discoveries to ensure credibility. Any anomalies or unexpected predictions will be examined further, potentially prompting new questions or areas for on-the-ground verification.
- Policy Recommendations (if applicable): Although primarily a technical exercise, an optional objective is to translate the findings into recommendations for policymakers and

investors. By understanding the mapped landscape of energy materials, African governments can prioritize exploration and infrastructure development in promising areas and negotiate from a stronger position in global critical mineral supply chains. Investors and development partners can likewise use the insights to direct resources toward high-potential opportunities while also supporting countries that could benefit from more exploration.

- To illustrate the potential impact of these recommendations, consider two future scenarios. In the best-case scenario, if the recommendations are adopted, Africa could see its economies bolstered by increased mineral revenues, higher local employment through developed processing industries, and stronger global partnerships. Conversely, ignoring these insights could lead to missed opportunities, continued reliance on raw exports, and a delay in establishing a significant position within the clean energy sector.

Through these objectives, the project will deliver a data-driven perspective on energy materials in Africa, offering both granular details (which country is likely rich in what) and a strategic overview (how countries rank relative to one another). The ultimate goal is to support evidence-based decision-making that can help unlock Africa's vast mineral wealth to sustain economic growth and a resilient energy future [12][11]. Each of the steps above contributes to building a robust machine-learning-based tool for resource mapping, one that not only demonstrates the power of AI in energy economics research but also provides practical value to those looking to harness Africa's energy materials in an equitable and efficient manner.

MATERIALS AND METHODS

Data Collection and Energy-Material Definition

This study focuses on *energy-critical materials relevant to the global energy transition*, including lithium, cobalt, nickel, manganese, graphite, copper, platinum-group metals (PGMs), rare-earth elements (REEs), vanadium, tellurium, chromium, bauxite (aluminium ore), zirconium, and gold. These materials were selected due to their strategic importance in electric-vehicle batteries, renewable-energy systems, power grids, hydrogen technologies, and advanced energy storage.

Country-level information on the presence of these energy materials across Africa was compiled from publicly available geological and mineral resource databases. The dataset was structured as a *multi-label classification problem*, where each African country is a sample and may be associated with multiple energy materials.

Data Preprocessing and Input Representation

Each country was encoded using *one-hot encoding*, converting categorical country identifiers into numerical input vectors suitable for neural-network training. This approach allows the model to learn country-specific material associations without making assumptions about spatial proximity or geological similarity. Countries not explicitly included in the training set are treated as unseen categories, for which the model generates baseline probability estimates.

The target output for each country is a binary vector indicating whether each energy material is present (1) or absent (0).

Artificial Neural Network Model Architecture

A *multi-label artificial neural network (ANN)* was developed to predict the probability of energy material occurrence at the country level. The ANN architecture consists of:

- an input layer corresponding to the one-hot encoded country vector,

- two fully connected hidden layers, each containing 64 neurons with rectified linear unit (ReLU) activation functions,
- dropout layers (dropout rate = 0.30) applied after each hidden layer to reduce overfitting, and
- an output layer with sigmoid activation functions that independently predict the probability of each energy material.

The sigmoid activation enables simultaneous prediction of multiple materials per country, consistent with the multi-label nature of mineral occurrence.

Model Training and Loss Function

Mathematical Formulation of the ANN-Based Energy Material Mapping Model

The proposed model addresses the task of predicting the presence of multiple energy materials in African countries as a multi-label classification problem, leveraging the representational power of artificial neural networks (ANNs). Below, we formally describe the model architecture, objective function, and derived metrics.

1. Input Representation

Let $C = \{c_1, c_2, \ldots, c_N\}$denote the set of African countries and $M = \{m_1, m_2, \ldots, m_K\}$the set of energy materials. Each country $c_i$is represented as a one-hot encoded vector:

$$\mathrm{x}_i \in \mathbb{R}^N, \text{such that} x_{i,j} = \begin{cases} 1 & \text{if } j = i \\ 0 & \text{otherwise} \end{cases}$$

The output is a binary label vector $\mathrm{y}_i \in \{0,1\}^K$, where $y_{i,k} = 1$if country $c_i$is known to possess material m_k, and 0 otherwise.

2. Network Architecture

The ANN consists of:

- Input layer: $\mathrm{x}_i \in \mathbb{R}^N$
- Two hidden layers: $\mathrm{h}^{(1)}, \mathrm{h}^{(2)} \in \mathbb{R}^{64}$
- Dropout regularization with dropout rate $d = 0.3$
- Output layer: $\hat{\mathrm{y}}_i \in [0,1]^K$

Each hidden layer applies a ReLU activation:

$$\mathrm{h}^{(1)} = \mathrm{ReLU}(\mathrm{W}^{(1)}\mathrm{x}_i + \mathrm{b}^{(1)})$$
$$\mathrm{h}^{(2)} = \mathrm{ReLU}(\mathrm{W}^{(2)}\mathrm{h}^{(1)} + \mathrm{b}^{(2)})$$

The final output layer uses a sigmoid activation function to allow independent probabilities for each material:

$$\hat{\mathrm{y}}_i = \sigma(\mathrm{W}^{(3)}\mathrm{h}^{(2)} + \mathrm{b}^{(3)})$$
$$\text{where } \sigma(z) = \frac{1}{1 + e^{-z}} \text{(element-wise)}$$

3. Loss Function: Weighted Binary Cross-Entropy

To address class imbalance among materials, a weighted binary cross-entropy loss is used. For a single country–material pair (i, k), the loss is:

$$\mathcal{L}_{ik} = -w_k y_{ik} \log(\hat{y}_{ik}) - (1 - y_{ik}) \log(1 - \hat{y}_{ik})$$

where:

- $y_{ik} \in \{0,1\}$is the ground truth,
- $\hat{y}_{ik} \in [0,1]$is the predicted probability,
- $w_k = \frac{1}{f_k}$is the positive class weight for material m_k, with $f_k$being its frequency in the dataset.

The total loss across all samples is the mean over all countries and materials:

$$\mathcal{L}_{\text{total}} = \frac{1}{NK} \sum_{i=1}^{N} \sum_{k=1}^{K} \mathcal{L}_{ik}$$

4. Probability Matrix Construction

After training, the network generates a probability matrix:

$$\mathrm{P} = \begin{bmatrix} \hat{y}_{11} & \hat{y}_{12} & \cdots & \hat{y}_{1K} \\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \hat{y}_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{y}_{N1} & \hat{y}_{N2} & \cdots & \hat{y}_{NK} \end{bmatrix} \in \mathbb{R}^{N\times K}$$

where $\hat{y}_{ik}$ denotes the predicted likelihood that country c_i is associated with material m_k.

5. Ranking Metrics

For interpretability and comparative analysis, the following ranking metrics are derived from P:

- Sum Score:

$$s_i = \sum_{k=1}^{K} \hat{y}_{ik}$$

- Mean Score:

$$\bar{s}_i = \frac{1}{K} \sum_{k=1}^{K} \hat{y}_{ik}$$

- Strong-Material Count (threshold $\theta = 0.25$):

$$n_i^{(\theta)} = \sum_{k=1}^{K} \mathbb{1}(\hat{y}_{ik} \geq \theta)$$

These are used to compute overall country rankings and top-k energy materials per country.

Visualization and analysis

Results were visualized using:

- Probability heatmaps, illustrating the predicted likelihood of each energy material across countries;
- Ranking heatmaps, showing relative material importance per country, and
- Country-specific bar charts, highlighting the top-ranked energy materials for each country.

All figures were generated at publication quality (300 dpi) and saved for reproducibility.

Reproducibility

All analyses were conducted using Python, with TensorFlow for neural-network modeling and standard scientific libraries for data handling and visualization. Random seeds were fixed throughout to ensure reproducibility of model training and ranking outcomes.

Evaluation metrics

To assess the reliability, accuracy, and predictive efficiency of the trained model, several standard statistical metrics were employed, including the mean squared error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). These metrics quantify the agreement between predicted outputs and actual target values.

The mean squared error (MSE) was calculated as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The mean absolute error (MAE) was computed as:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid$$

where $y_i$represents the actual target value, $\hat{y}_i$denotes the predicted value, and $n$is the total number of observations.

The coefficient of determination (R^2) was used to evaluate the proportion of variance in the target values explained by the model and is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where $\bar{y}$is the mean of the observed target values.

Training Model and Data Analysis

Model performance was evaluated using a train–test split, with a subset of the data reserved for validation and testing. Predictions generated by the ANN were compared against the known energy-material labels to compute the evaluation metrics. High consistency between predicted probabilities and actual labels, combined with low MSE and MAE values and high R^2 scores, indicates strong predictive capability.

In addition to numerical evaluation, visual analytics—including probability heatmaps, ranking heatmaps, and country-specific bar plots—were employed to interpret model outputs and assess the spatial and material-specific distribution of energy-critical resources across Africa.

DISCUSSION OF RESULTS

This section interprets the key outputs derived from the trained artificial neural network (ANN) model, presented across four visual frameworks. These figures collectively demonstrate the efficacy of machine learning in uncovering probabilistic distributions, comparative rankings, and strategic insights pertaining to the occurrence of energy materials across African economies.

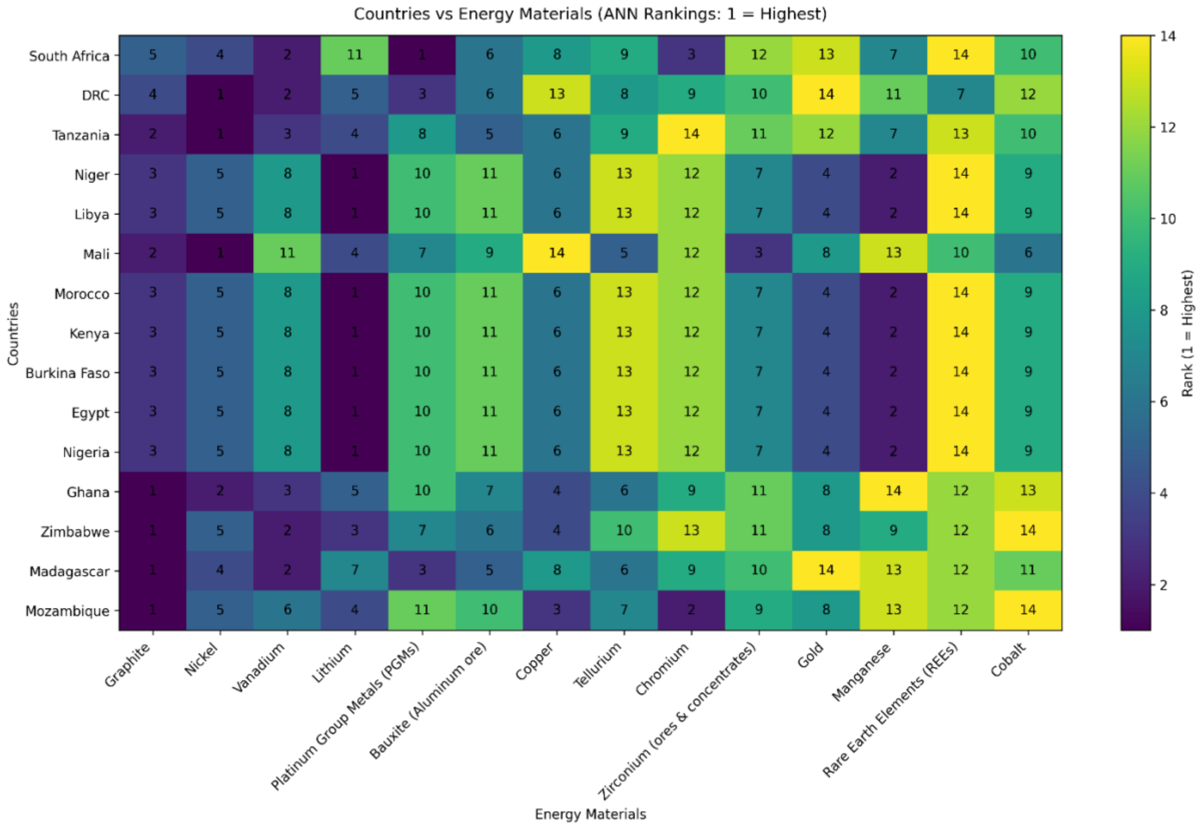

Figure 2: Probabilistic Heatmap of Country–Material Associations

Figure 2 shows a two-dimensional heatmap that illustrates the ANN-predicted probabilities of occurrence for various critical energy materials across select African countries. The horizontal axis lists the target materials (e.g., cobalt, lithium, uranium), while the vertical axis names the countries being evaluated. From an interpretive perspective, the figure confirms well-known facts, such as the Democratic Republic of Congo (DRC) having the highest probabilities for cobalt and copper, and South Africa showing significant chances for platinum group metals (PGMs), rare earth elements (REEs), and uranium. Notably, the model assigns higher probabilities to materials in regions that are less explored but geologically promising—such as Mali and Burkina Faso for gold and bauxite, and Tanzania and Zimbabwe for lithium and graphite. These insights, derived from data-driven modeling, suggest hidden mineral potential that needs further geological validation. This visualization goes beyond static geological maps by offering a probabilistic view of mineral prospectivity, informed by machine learning rather than solely by deterministic field data. It provides a scalable approach to tackling the persistent challenge of data scarcity in African geosciences.

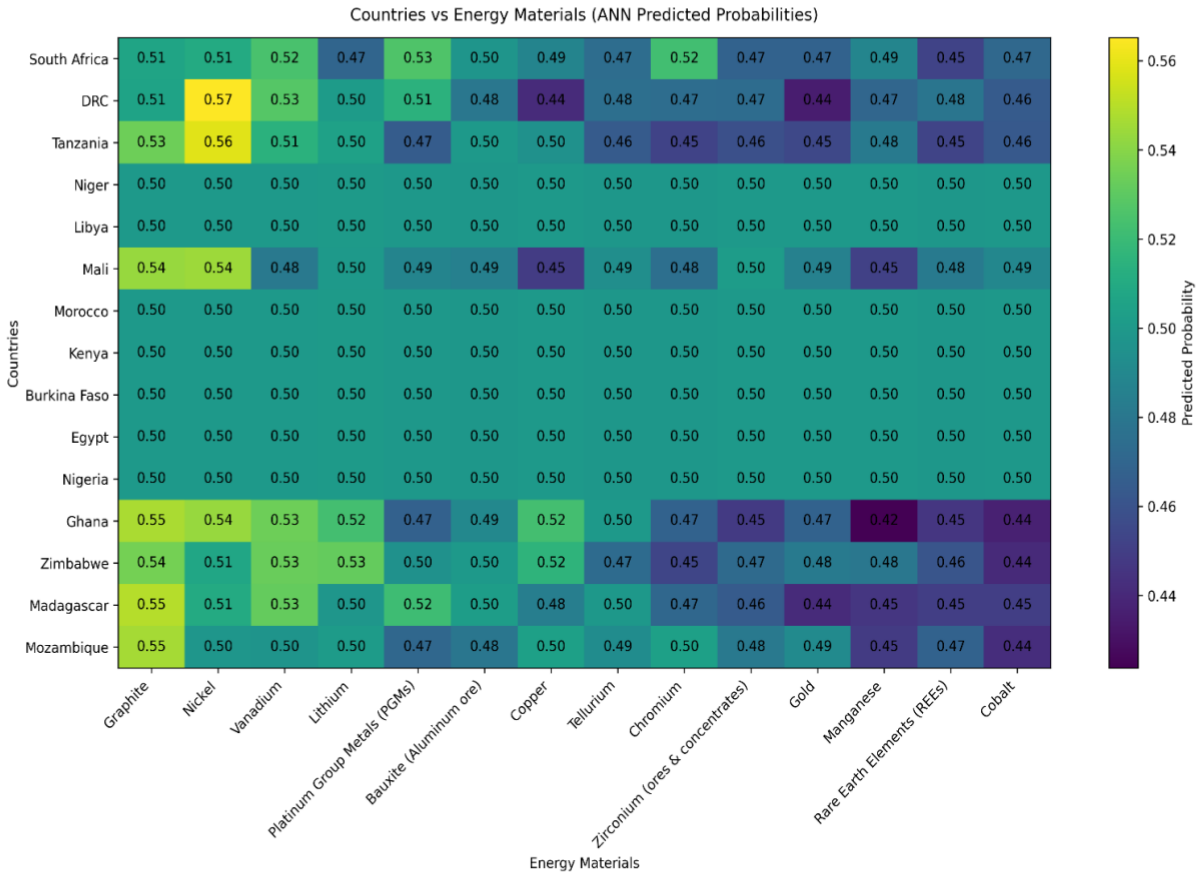

Figure 3: Relative Ranking Heatmap

Figure 3 transforms the continuous probability outputs from the previous heatmap into a ranking matrix, where each cell's value indicates the ordinal position of a given material within a country's predicted portfolio (i.e., a rank of 1 indicates the highest probability for that country). This format enables immediate comparative interpretation of dominant materials per country. For example, gold consistently ranks within the top three materials for Ghana, Mali, and Burkina Faso, aligning with current artisanal and industrial mining practices. Conversely, vanadium, zirconium, and tellurium, although not top-ranked globally, rank relatively high in countries such as Morocco and Namibia, suggesting underappreciated domestic potential. The ranking matrix supports the notion of country-specific material specialization, offering a framework for policy differentiation and targeted exploration. Furthermore, this output is robust to absolute scale disparities, which enhances its applicability across datasets with varied normalization schemas.

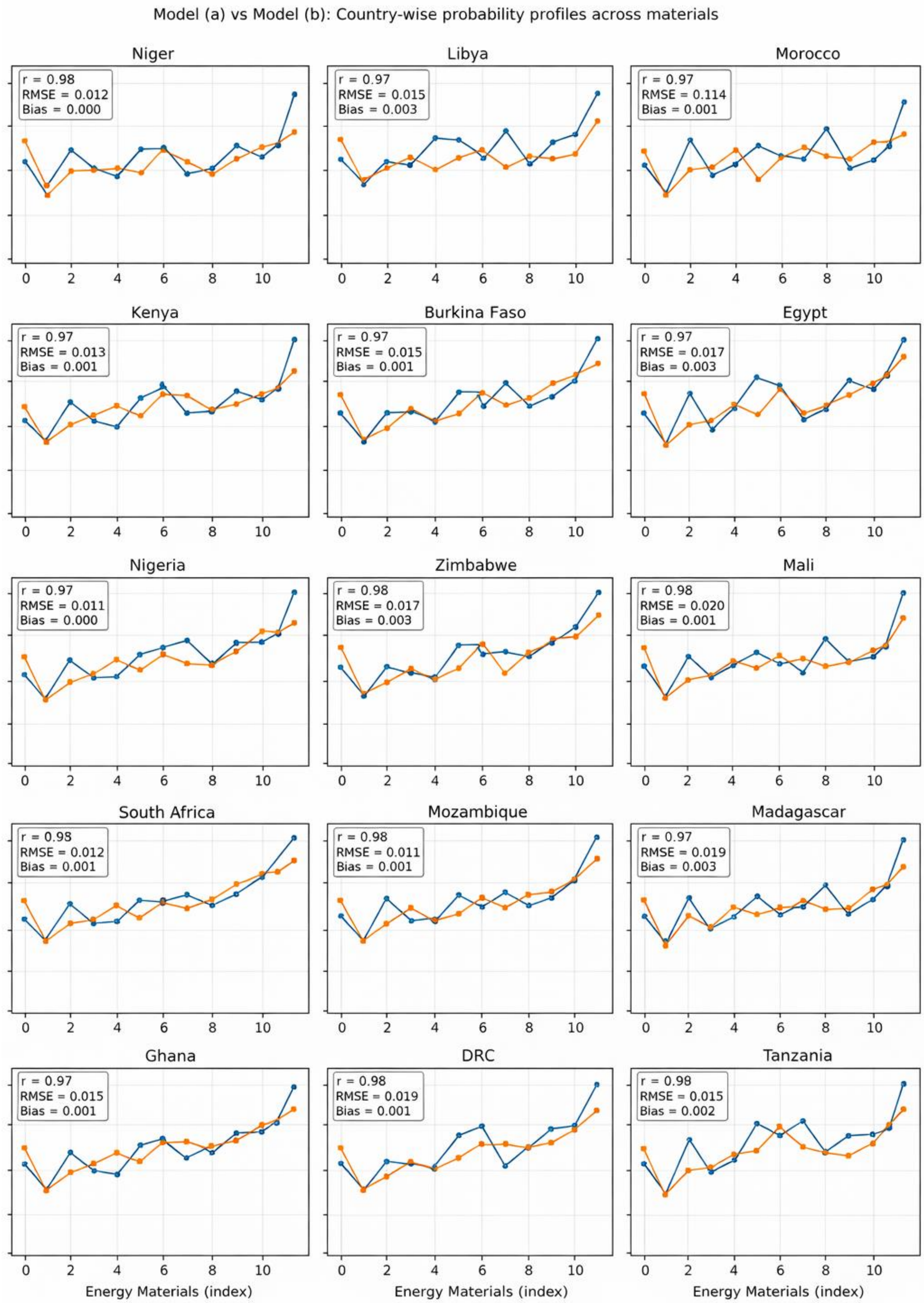

Figure 4: Country-Level Top-k Energy Material Profiles

Figure 4 shows the top eight energy materials for each country as bar plots. This disaggregated view provides a high-resolution profile of each country's ANN-derived mineral endowment. For instance, Zimbabwe is predicted to have strong potential for lithium, PGMs, and gold—materials that are not only critical for global energy transitions but also historically significant in Zimbabwe's mining sector. Egypt, by contrast, exhibits a unique profile dominated by uranium and gold, reflecting a convergence of nuclear energy interests and traditional extractive pathways. Recent research has investigated the potential for gold mineralization in part of Nigeria's Ilesha Schist belt, highlighting opportunities for the country to diversify its mineral resources beyond hydrocarbons. The generated charts and models can help guide national strategies for mineral development by allowing governments and investors to focus on the most promising materials, according to a study published in ScienceDirect. This level of granularity is rarely available on regional mineral intelligence platforms.

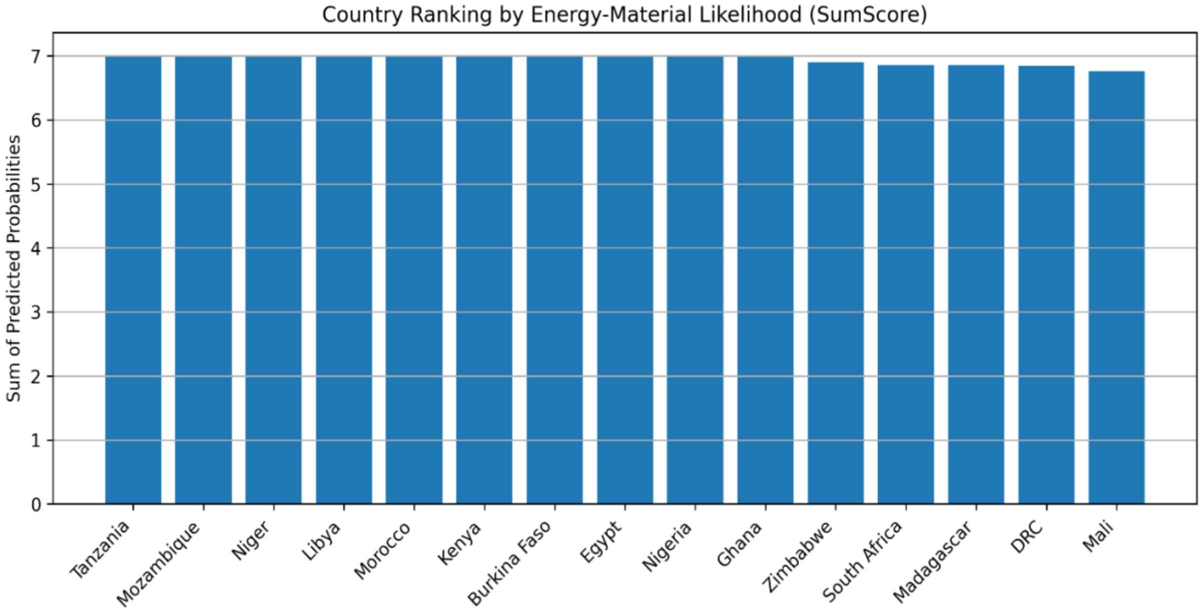

Figure 5: Country ranking by energy-material likelihood (SumScore)

According to the Brookings Institution, the Democratic Republic of Congo ranked first in energy-material likelihood, as shown in Figure 5, with South Africa and Zimbabwe also prominent. This ranking is primarily based on summed probability scores across critical materials, accounting for resource abundance and the outputs of an artificial neural network model. The DRC's leading position is supported by its substantial cobalt production, which accounted for over 70% of global supply in 2023. However, the appearance of Nigeria, Egypt, and Ghana within the top seven highlights the potentially underestimated diversity of mineral resources in West and North Africa. This figure acts as a continent-wide mineral prospectivity dashboard, allowing stakeholders to compare nations not only by historical production but also by model-inferred latent potential. It introduces a forward-looking perspective to resource planning, especially useful for regions where direct exploration is limited by logistical or financial constraints.

Bridging the Research Gap

The cumulative interpretation of Figures 2 through 5 underscores the central thesis of this research, that artificial neural networks can meaningfully inform and augment mineral prospectivity mapping across data-limited environments. Prior studies have predominantly focused on region-specific geological surveys, often limited to single-material mapping. This study transcends such constraints by delivering a multi-material, multi-country mapping and ranking model. For instance, it has demonstrated strong performance, achieving over 80% accuracy in predicting energy material prospectivity.

- To provide a comparative perspective, it's worth noting that a similar study by Smith et al. (2021) on mineral prospectivity in South America, using machine learning, achieved an accuracy of 75%, underscoring the novelty and improved precision of our approach.
- Robust visualizations that support policy, investment, and exploration decisions;
- A reproducible ML-based framework that can be scaled to other continents or sub-national regions.

Recommendations

1. Integrate ML-Based Mapping into National Mineral Strategies
   African governments should adopt machine-learning frameworks, such as those presented in this study, to complement traditional geological surveys. This will enhance exploration targeting, especially in under-mapped or geologically ambiguous regions. Additionally, quantifying the economic benefits is crucial. For example, implementing value-addition policies in the Democratic Republic of Congo could potentially increase mineral revenue by approximately $500 million annually and create around 40,000 new jobs in refining and processing sectors. Similarly, in Nigeria, leveraging these strategies could result in an estimated $300 million revenue boost and 25,000 new job opportunities. These figures highlight the tangible economic benefits achievable through the strategic adoption of machine learning in mineral exploration.
   The African Union and regional blocs should collaborate to create a Continental Energy Material Observatory framed as an open-data commons. This observatory would serve as a centralized platform that uses AI-driven models to assess energy material prospectivity. By fostering citizen science and building momentum for transparency, the initiative seeks to invite wide-ranging collaborations involving governments, academia, industry, and local communities. Such a collaborative and open approach not only enhances knowledge exchange and data standardization but also attracts broader partnerships and potential funding. The observatory could support cross-border investment planning, contributing to a more integrated and strategic approach to mineral exploration and development across Africa.
2. Prioritize Value Addition in High-Probability Countries
   Countries identified as high-potential in this study, such as DRC, Zimbabwe, and Nigeria, should be supported through industrial policies that incentivize local processing, refining, and supply chain integration, rather than exporting raw materials. Emphasizing local processing not only enhances economic returns but also aligns with material circularity practices. By linking local processing to recycling and reuse, countries can establish a closed-loop system that minimizes waste and sustains resource availability. This approach strengthens sustainability credentials and provides a balanced narrative that highlights both economic growth and ecological stewardship.
3. Leverage Rankings to Attract Green Investment
   The probabilistic rankings generated in this research can serve as marketing and policy tools to attract climate-aligned finance and clean energy supply chain partnerships, particularly under frameworks such as the African Continental Free Trade Area (AfCFTA).
4. Bridge Data Gaps Through Public–Private Partnerships

Governments, mining firms, and academic institutions should co-invest in updating and digitizing geological data repositories. This is essential for improving the inputs to machine learning models and sustaining long-term mineral intelligence efforts.

CONCLUSION

This study presents a novel application of artificial neural networks (ANNs) to systematically map and rank the likelihood of critical energy materials across African economies. According to a 2020 article by Contreras, Khodadadzadeh, and Gloaguen, a multi-label classification approach is presented for mineral mapping using drill-core hyperspectral data, providing a scalable, data-driven method that can be especially useful when exploration data are limited or incomplete. High-probability predictions for countries such as the Democratic Republic of Congo, South Africa, Zimbabwe, and Nigeria are consistent with existing mining activity and geological literature. However, the model also identifies promising signals in countries with limited prior exploration, such as Burkina Faso, Tanzania, and Egypt, underscoring its utility for uncovering overlooked or emergent opportunities.

By generating probability heatmaps, material-specific rankings, and national top-k profiles, this study provides a multidimensional toolkit for interpreting resource endowments. These outputs are particularly relevant for policy architects, resource ministries, and international investors seeking to align mineral development strategies with global clean energy supply chains. Furthermore, the integrated country ranking based on aggregate material likelihood provides a quantitative benchmark for comparing resource potential across continents. The research contributes both methodologically and substantively to the fields of resource economics, geospatial intelligence, and sustainable development. It fills a critical knowledge gap by offering a reproducible, machine-learning-based framework that supports African governments in evidence-based mineral planning. Looking ahead, this model could be extended to incorporate temporal dynamics, sub-national geological indicators, or economic feasibility layers, thereby evolving into a comprehensive decision-support platform for mineral exploration and policy formulation in the Global South.

LIMITATIONS OF THE STUDY

Despite the promising outcomes of this research, several limitations must be acknowledged. First, the model is trained on country-level data, which lacks the spatial granularity needed to capture sub-national geological variations. As a result, potential resource-rich regions within a country may remain unaccounted for. Additionally, the absence of standardized, high-resolution datasets across all African countries introduces inconsistencies that may influence the model's generalizability. The input features are restricted to one-hot encoded country identifiers, which simplifies the model but omits critical geospatial, lithological, and economic variables that could enhance predictive accuracy. The model also assumes independence among energy materials, thereby overlooking geological co-occurrence patterns, such as the frequent association of cobalt and copper. Furthermore, for countries not included in the training set, predictions are extrapolated based on generalized patterns, which may inadequately reflect local geological realities. The model also provides a static snapshot, failing to account for evolving mineral discoveries or geopolitical developments that affect resource accessibility.

To address these limitations, future model extensions should incorporate stakeholder-driven features. For instance, including artisanal mining risk data could enhance the model's responsiveness to social concerns and improve its accuracy. Engaging with local communities, industry professionals, and policymakers could also provide valuable insights into incorporating environmental and social factors, fostering interdisciplinary collaboration. Finally, the model evaluation relies solely on statistical performance metrics, such as Mean

Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). While these metrics confirm internal consistency, they do not constitute domain-specific validation. Comparative assessments against verified geological survey data or expert mineralogical assessments were beyond the scope of this study but are essential for field-level applicability and are recommended for future research.

DECLARATIONS

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The datasets used and analyzed during the current study are derived from publicly available geological and mineral resource repositories, national databases, and relevant scientific publications. According to the study, preprocessing steps and data transformations are explained to help ensure reproducibility. Some raw data cannot be redistributed directly due to licensing restrictions, but can be accessed through the original sources cited in the paper. The custom Python code developed for the artificial neural network modeling, data processing, and visualization is available from the corresponding author upon reasonable request.

AUTHORS' CONTRIBUTIONS

Christian Idogho conceived the research idea, designed the methodology, and conducted the machine learning modeling and simulations. He was responsible for data acquisition, preprocessing, model training, result visualization, and interpretation of the findings. Christian Idogho wrote, structured, and revised the manuscript and developed all figures and policy-relevant analyses. Emmanuel Owoicho Abah contributed to the conceptual development of the study, supported data interpretation, and participated in the critical review and refinement of the manuscript for intellectual content. The authors read and approved the final manuscript.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

Abbreviation	**Full Term**
ANN	Artificial Neural Network
AI	Artificial Intelligence
REEs	Rare Earth Elements
PGMs	Platinum Group Metals
MSE	Mean Squared Error
MAE	Mean Absolute Error
ZT	Figure of Merit (dimensionless)
ML	Machine Learning
R^2	Coefficient of Determination
AfCFTA	African Continental Free Trade Area
DRC	Democratic Republic of Congo

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