Employing Geospatial Technology for Mineral Exploration in South Africa

Priyanka Devdath (South Africa), Dr Moreblessings Shoko (South Africa), Associate Prof. Alastair Sloan (South Africa)

Key words: Machine learning, Remote sensing, Mineral exploration, Google Earth Engine.

SUMMARY

The global transition to clean energy is driving a surge in demand for lithium, a critical mineral for batteries and electrification. South Africa hosts significant potential in lithium-bearing pegmatite deposits, such as those in the Orange River Pegmatite Belt (ORPB). However, the application of modern, data-driven exploration techniques using geospatial technology and machine learning (ML) remains underdeveloped, creating a critical knowledge gap. This study, therefore, tests the effectiveness of satellite remote sensing and ML as efficient, complementary tools for identifying lithium-rich mineral targets.

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1. INTRODUCTION

The global shift toward clean energy has significantly increased demand for lithium, a critical mineral for modern technology. South Africa's economy has long relied on its mineral-rich mining sector, which now faces the challenge of resource depletion alongside the need to explore new deposits like lithium-bearing pegmatites. However, conventional exploration methods are often time-consuming, costly, and inefficient, particularly in complex geological terrains such as the Orange River Pegmatite Belt (ORPB). While geospatial technology and machine learning offer advanced, data-driven solutions for mineral detection, their application in South Africa remains underdeveloped. This study, therefore, aims to address this gap by evaluating the effectiveness of satellite imagery and machine learning algorithms, specifically Random Forest and Gradient Boosting, to provide a more efficient and targeted method for lithium exploration in South Africa.

2. DATA COLLECTION

The data collection for this study employed a two-phase methodology utilizing both primary remote sensing data and secondary geological studies.

The first phase involved the acquisition and preprocessing of freely available multi-temporal satellite imagery, specifically Sentinel-2 and Landsat 8, accessed and processed via the Google Earth Engine (GEE) cloud platform. A spectral library was created from known deposit locations to identify critical spectral indicators, confirming the Aluminium-Hydroxyl (Al-OH) absorption feature in specific shortwave infrared bands as the most effective for distinguishing lithium-bearing pegmatites.

The second phase focused on compiling and preparing ground-truthing data. Known locations of Lithium-Caesium-Tantalum (LCT) and Niobium-Yttrium-Fluorine (NYF) pegmatites within the Orange River Pegmatite Belt were digitized from existing literature into GIS shapefiles. These points were used to generate balanced training and validation datasets, which were then integrated with the processed satellite imagery stacks, including derived band ratios and vegetation indices, to train and evaluate the machine learning classifiers.

3. STUDY AREA

The study focuses on the Orange River Pegmatite Belt (ORPB), located within the Northern Cape province of South Africa. This belt forms part of the Namaqua-Natal Metamorphic

Province, a significant geological region rich in mineral deposits, and stretches along the Orange River bordering Namibia. The area is characterized by an arid to semi-arid climate with sparse vegetation, which reduces spectral interference and makes it particularly suitable for satellite-based remote sensing. Historically, the Northern Cape has been a vital contributor to South Africa's mining sector. The ORPB itself is prospectively important for its lithium potential, primarily hosting Lithium-Caesium-Tantalum (LCT) pegmatites in its western sector, which are a key target for exploration due to the global demand for lithium in clean energy technologies.

4. METHODOLOGY

The study methodology is structured around four integrated parts utilizing geospatial and machine learning tools within a cloud and desktop GIS environment.

Data Acquisition and Preprocessing: Primary satellite imagery (Sentinel-2 and Landsat 8) was acquired and processed via the Google Earth Engine (GEE) cloud platform. This involved creating multi-year composites, applying cloud and temporal filters, and performing radiometric calibration. Key spectral indices, including the Aluminium-Hydroxyl (Al-OH) ratio and the Normalized Difference Vegetation Index (NDVI), were calculated and stacked to create a multi-feature input image.

Training and Validation Data Preparation: Known locations of Lithium-Caesium-Tantalum (LCT) and non-lithium-bearing (NYF) pegmatites within the study area were digitized from the geological literature into point shapefiles using ArcGIS Pro. These points were imported into GEE, balanced to prevent algorithmic bias, and randomly split into training (80%) and validation (20%) datasets.

Machine Learning Classification: Two supervised classifiers, Random Forest (RF) and Gradient Boosting (GB), were trained in GEE on the prepared datasets to distinguish LCT pegmatite signatures. The algorithms were applied at two scales: a focused analysis of the Orange River Pegmatite Belt and a national-scale assessment across South Africa.

Analysis and Visualization: The classification results were statistically analyzed to estimate area and mass. Accuracy was formally assessed using confusion matrices, Overall Accuracy, and the Kappa coefficient. Final classification maps and density heatmaps were produced and visualized using ArcGIS Pro to spatially present the identified prospective zones and algorithm performance.

5. CONCLUSION

The effective exploration of critical minerals, such as lithium, is fundamental to supporting the global clean energy transition and national economic development. This process is significantly hindered by the limitations of conventional geological methods, which are often slow, costly, and inefficient over large areas. The integration of modern geospatial technology and machine learning offers a transformative approach, yet its application requires a robust, tailored data system to be truly effective. This study establishes that such a data-driven system, utilizing satellite imagery and algorithms like Random Forest, serves not as a replacement but as a vital complementary tool to traditional geology. It enables the efficient prioritization of exploration targets, thereby optimizing resource allocation.

However, the system's success is highly context dependent; a single national algorithm is insufficient for a geologically diverse country like South Africa. The implementation of region-specific models, underpinned by improved field validated data and guided by geological principles, is essential to minimize misclassification and maximize accuracy. Furthermore, the unexpected identification of inland salt pans as areas of interest by the system reveals its potential to generate novel, testable hypotheses for new deposit types, such as lithium brines. Therefore, building and refining this integrated geospatial and geological information system is critical. It provides an essential, strategic foundation for planners, exploration geologists, and policymakers, enabling more informed, efficient, and sustainable mineral resource development for the future.

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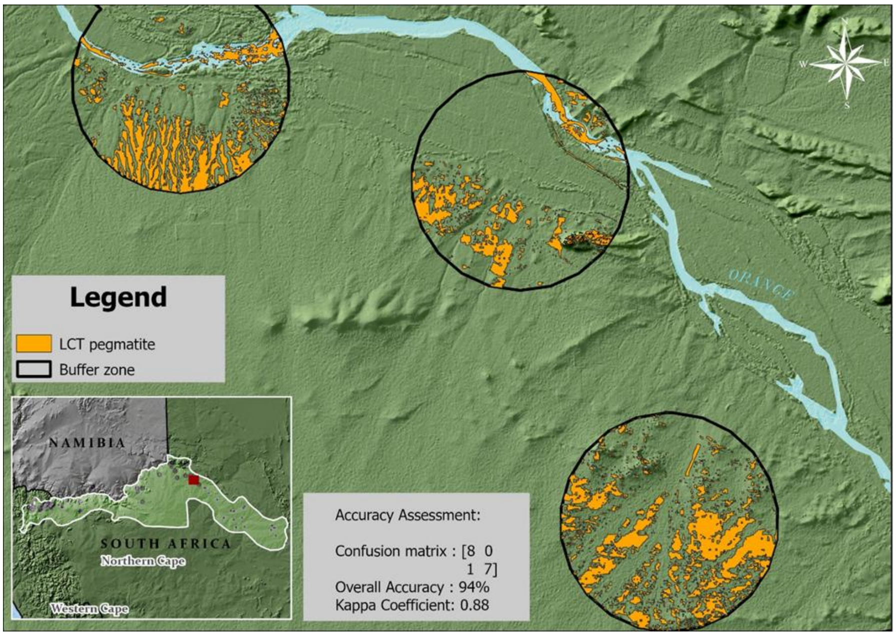
BIOGRAPHICAL NOTES

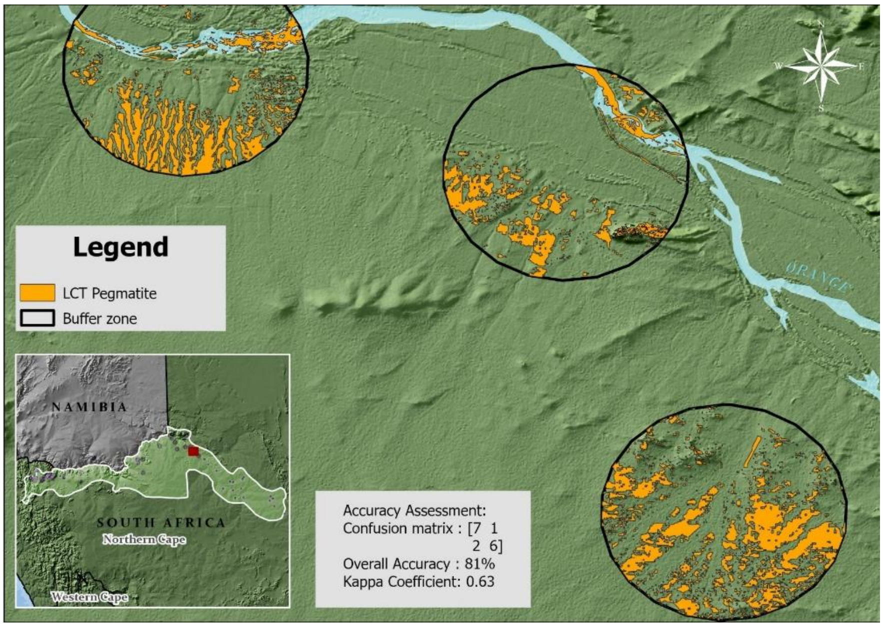
This study was done in partial fulfillment of my Bachelor of Science in Geomatics: Geoinformatics stream at the School of Architecture, Planning & Geomatics (APG) at the University of Cape Town, South Africa. I am a member of the FIG Young Surveyors Network: South Africa chapter.

CONTACTS

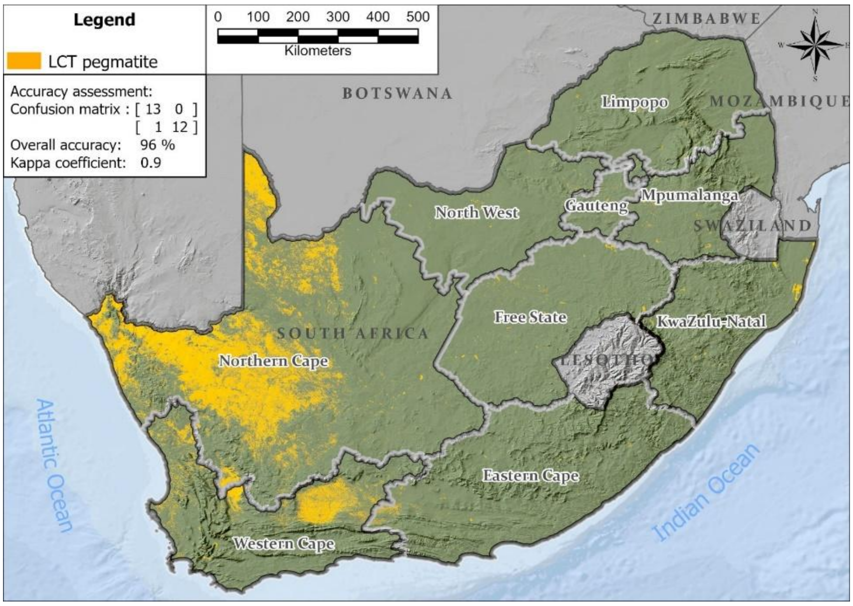
Priyanka Devdath
Cape Town
South Africa
Email: priyankadevdath@gmail.com



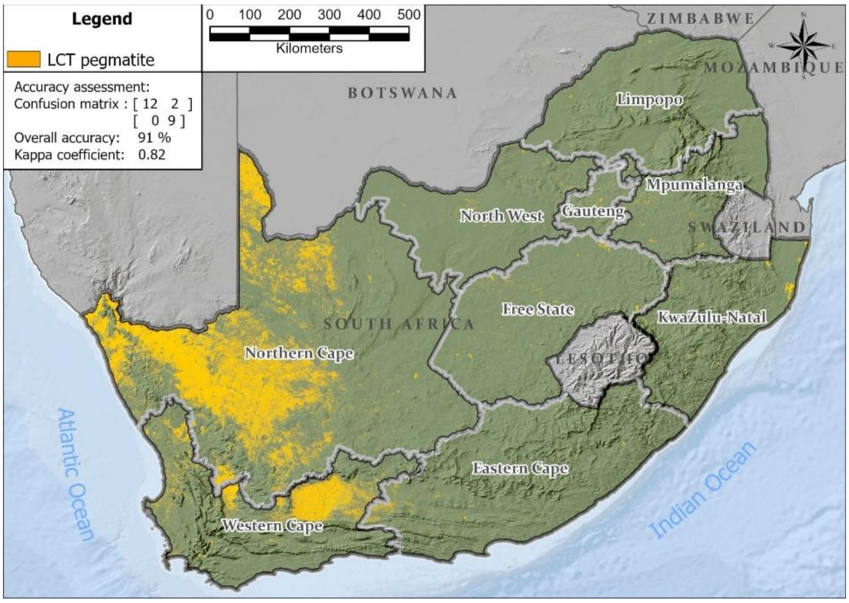
Appendix 1: Map showing Random Forest classification over the study area. (Source: Own compilation).



Appendix 2: Map showing Gradient Boosting classification over the study area. (Source: Own compilation).



Appendix 3: Map showing RF classification of LCT pegmatite over SA. (Source: Own compilation).



Appendix 4*:* Map showing GB classification of LCT pegmatites over SA. (Source: Own compilation).