

MACHINE LEARNING AND GEOSTATISTICAL APPROACHES TO RARE EARTH ELEMENT PROSPECTIVITY IN RADIOTHERMIC CARBONATITES

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Background/Introduction

- Rare Earth Elements (REEs) are critical to the advancement of modern technologies, including renewable energy systems, electric vehicles, and defense applications.
- Radiothermic carbonatites are promising hosts for REEs, yet remain underexplored due to their complex geological settings.
- Traditional exploration methods are often insufficient in predicting mineralization zones accurately.
- By leveraging Machine Learning (ML) and geostatistical techniques, particularly kriging, this study aims to enhance the precision and efficiency of REE prospectivity modeling.

Objectives

Main Objective

- To develop a scalable, repeatable prospectivity model for REEs in radiothermic carbonatites using machine learning and geostatistical methods implemented in Python.

Specific Objectives

- Compile and preprocess geochemical and spatial data.
- Apply kriging for spatial interpolation.
- Train ML models (e.g., random forest, decision trees).
- Validate models using known REE occurrences.
- Assess model scalability and adaptability.

Possible Results

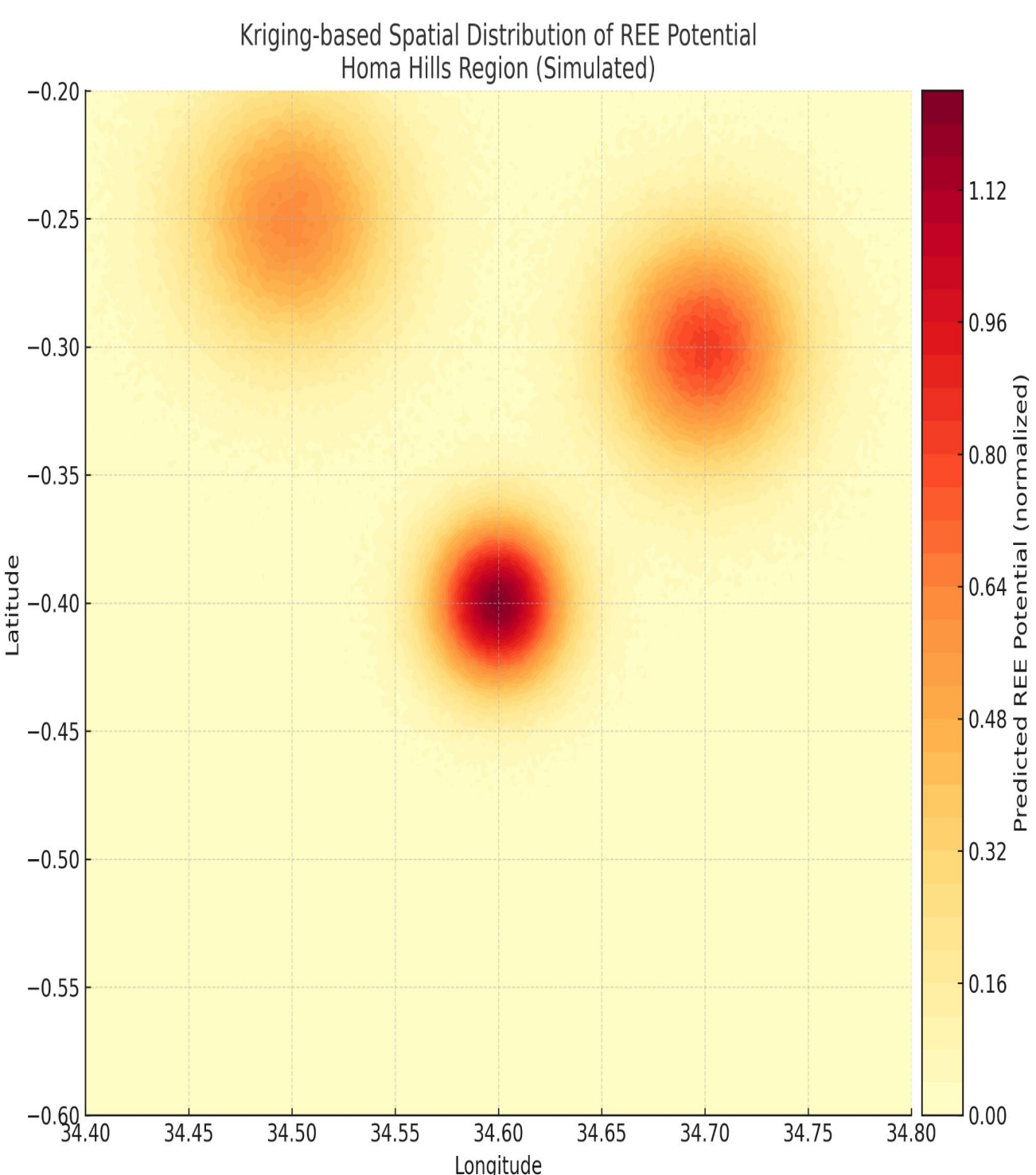


Figure 2: Kriging-based spatial distribution maps of REE potential

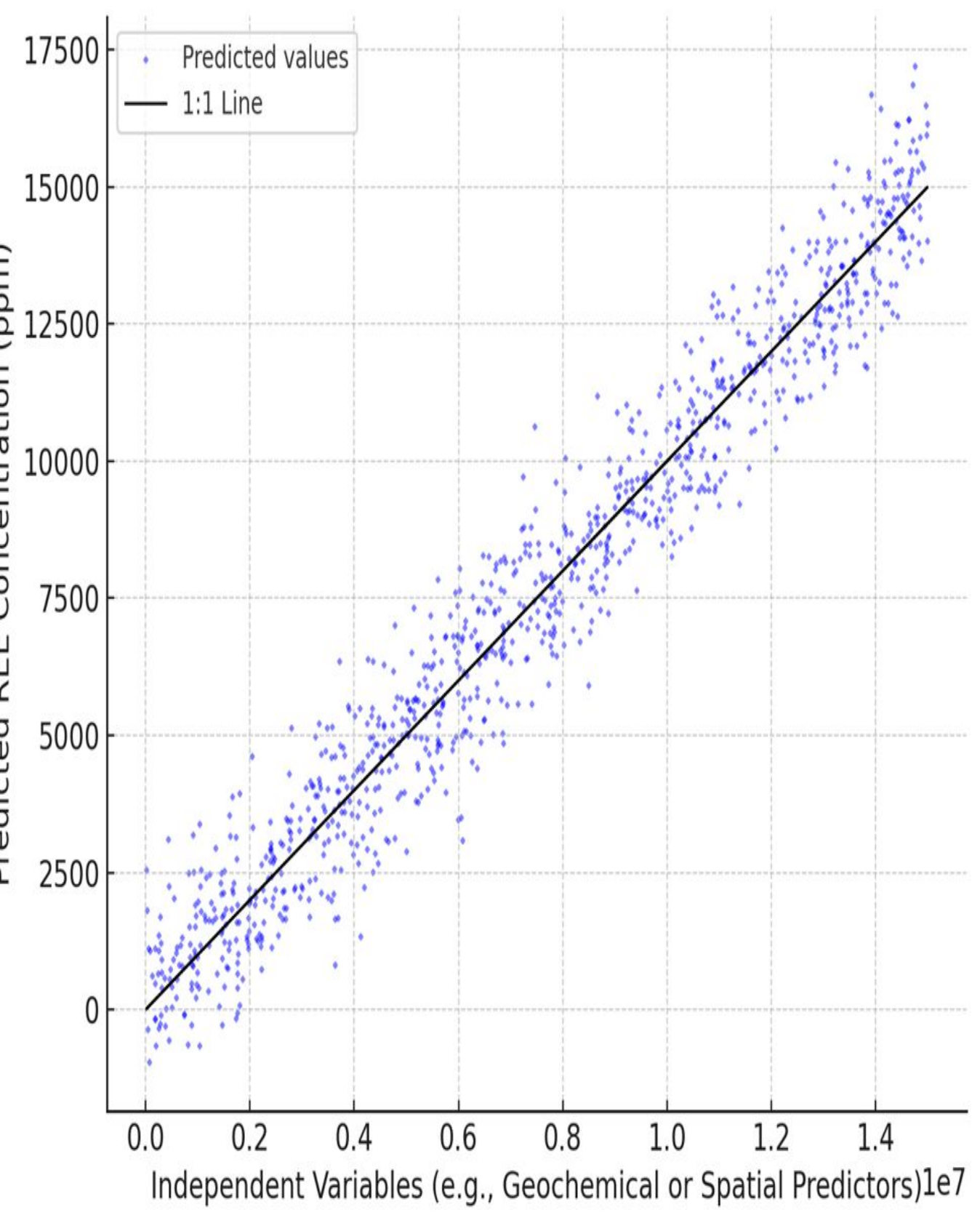


Figure 3: Linear Regression of Predicted REE Occurrences Values

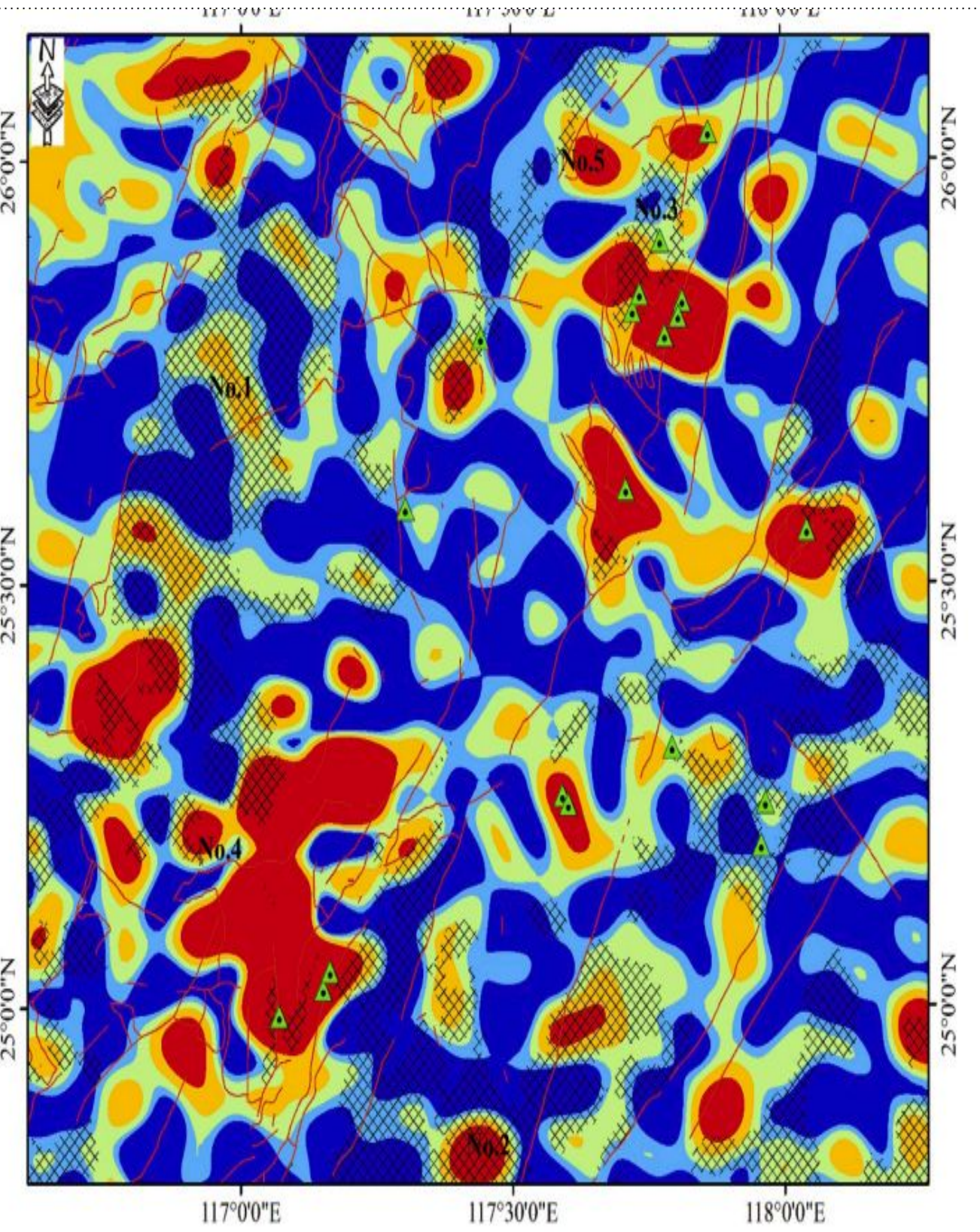


Figure 4: High-accuracy predictions validated with known REE zones

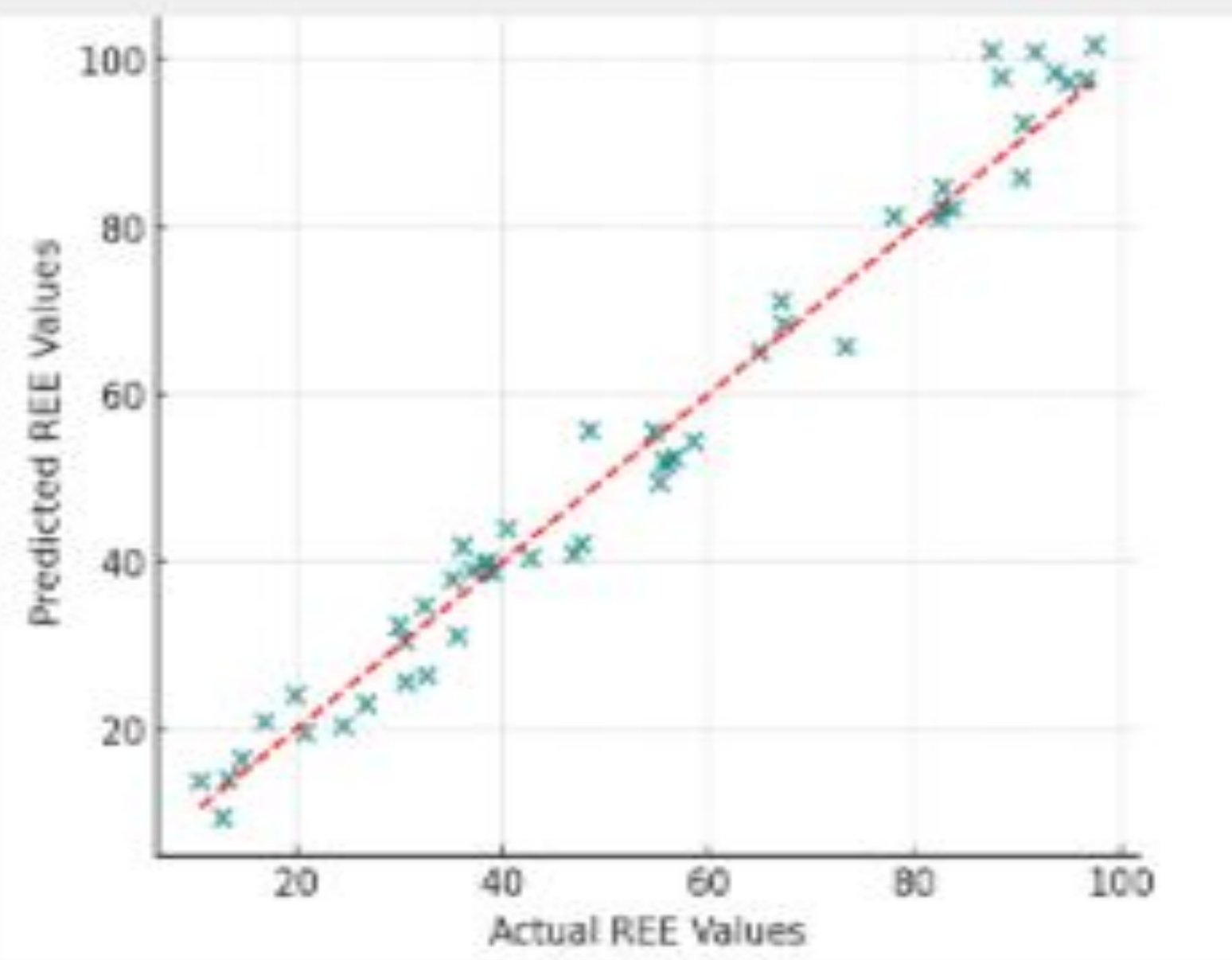


Figure 5: Cross Validation Known vs Predicted REE Occurrences

Conclusion and Expectations

- Bridges classical geostatistics with modern AI/ML techniques.
- Develops a flexible and adaptable exploration framework.
- Enhances prediction accuracy in mineral prospectivity modeling.
- Reduces exploration costs through data-driven targeting.
- Minimizes environmental impact by promoting efficient prospecting.
- Produces a Python-based workflow for broad applicability across mineral exploration settings.

References

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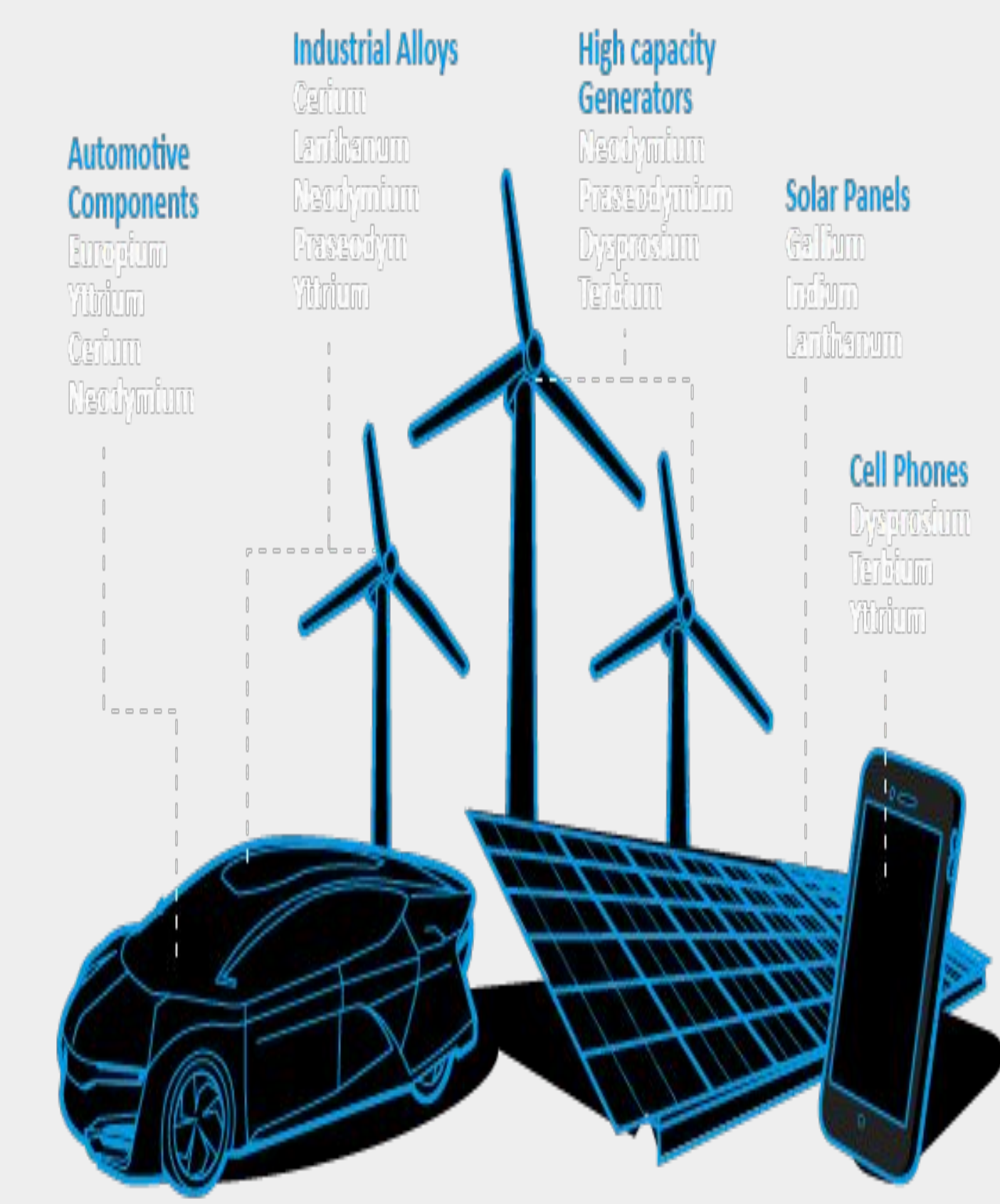


Figure 1: Green Energy Technologies

Problem Statement

- Conventional exploration is costly and ineffective in complex geology like carbonatites.
- There is a lack of scalable, repeatable, and data-driven prospectivity models.
- Integration of spatial interpolation (kriging) with ML remains limited for REEs.
- A modern, predictive framework is needed to enhance exploration outcomes.

Methodology

Tools and Software

- **Python Libraries:** pandas, scikit-learn, pykrige, geopandas, matplotlib, xgboost
- **GIS Tools:** QGIS / ArcGIS for map creation and spatial data analysis

Workflow

Data Collection and Preprocessing

- Compile REE assay data and geological features
- Normalize and clean data

Geostatistical Analysis

- Apply kriging to interpolate REE concentrations

Machine Learning Modeling

- Train supervised models (e.g., decision trees, random forest)
- Analyze model performance and feature importance

Validation and Scalability Testing

- Compare predictions with known data
- Apply methodology to alternate datasets