Predicting Rare Earth Element Concentrations Using Multiphysical Sensor Data

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Introduction

Rare Earth Elements (REE) are crucial for advanced technologies such as renewable energy, electronics, and defense systems. However, traditional methods for quantifying REE concentrations rely heavily on costly and time-consuming chemical analyses.

The objective of this research is to assess whether multiphysical sensor data can serve as an efficient, reliable alternative to direct chemical measurements for predicting REE concentrations in coal mine tailings.

Data Analysis & Processing

REE Data

Mine tailing samples from two coal mining sites;

Site 1 (coal refuse)

Site 2 (coal ash)

78 total samples (in two batches: 28 initial samples and 50 samples in the second run) were analyzed by Conti Lab for concentration of eight REE elements – Sc, Y, La, Ce, Pr, Nd, Tb, and Dy.

Sensor Data

Four different sensor measurements over area:

- Hyperspectral Imaging: Reflectance spectrum ranging from 200nm to 1000nm (at spacing of 0.33nm)
- Radiation Sensors: Raw and averaged gross decay event count
- Magnetometers: Recorded magnetic flux density.
- Electromagnetic Interference (EMI) Sensors: Soil conductivity at various depths (0.25-4.5 meters, plus infinite depth).

For a total of >2000 features, the vast majority of which are hyperspectral

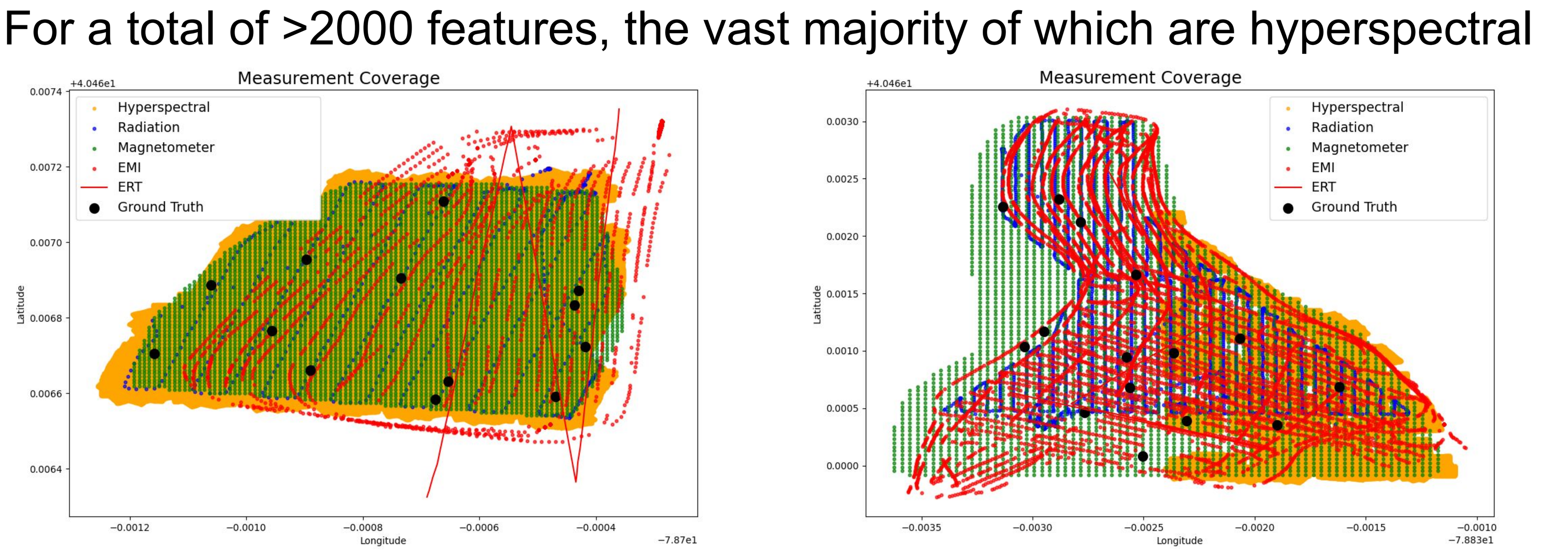

Figure 1: **Sensor measurement points and ground sample locations across Site 1 (left) and 2 (right).** Gaps in hyperspectral data (e.g., west side of Site 2) and limited spatial coverage for EMI and radiation sensors are visible.

Data Challenges

Deviations between sites: The two sites show very different ranges of REE concentration values – Difference in petrological composition? Or some other factor (e.g. the state difference in tailings)?

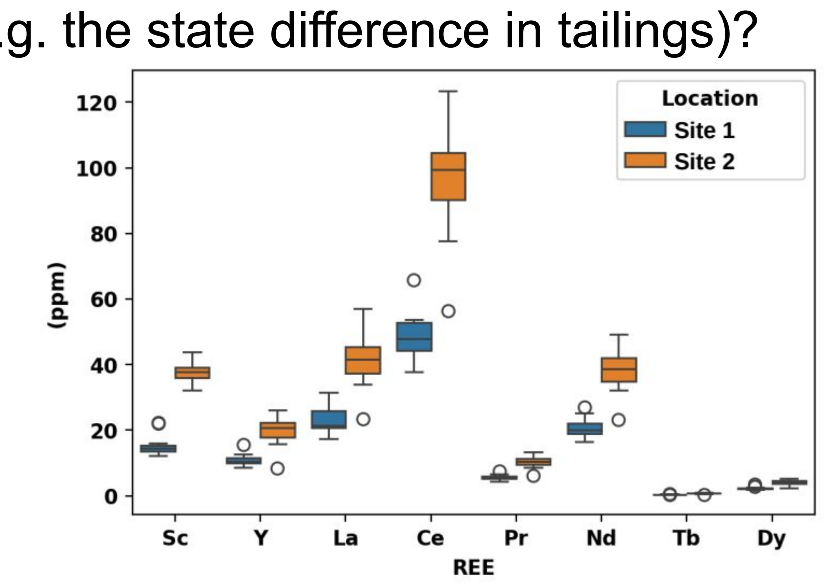

Figure 2: **Distribution of REE concentrations between the two sites.** The ranges are clearly distinct, with little overlap.

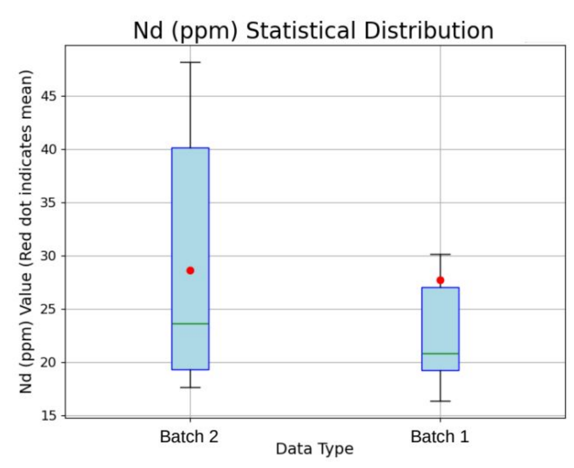

Figure 3: **Distribution of Nd concentration for Site 2 measured between two batches w.r.t. Lab 1.** While the mean is similar, the standard deviation has changed significantly.

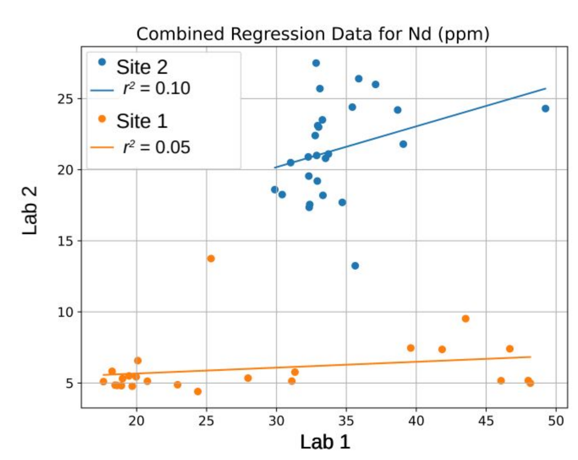

Figure 4: **Distribution of Nd concentration values between different labs.** In addition to the difference in value ranges, the relationship between them is very weak.

Deviations in measurement: different labs, and even different batches w.r.t. the same lab seem to have differences in range even within the same site.

Modeling Approach & Results

Models & Techniques

Due to the low number of samples, simpler machine learning models were selected to ensure effective convergence and robust predictions - we apply the following three models, which are all relatively simple models that can converge with small amounts of data:

- Multilayer Perceptron (MLP)
- Gradient Boosting (XGBoost)
- Random Forest

MSE loss with LOO cross-validation was applied.

Feature Engineering

Principal Component Analysis (PCA) was utilized to reduce dimensionality

- Reduced co-linearity significantly improved XGBoost model, although effect on other models was limited.
- PCA also showed that EMI seems to have the largest effect on components, followed by hyperspectral.

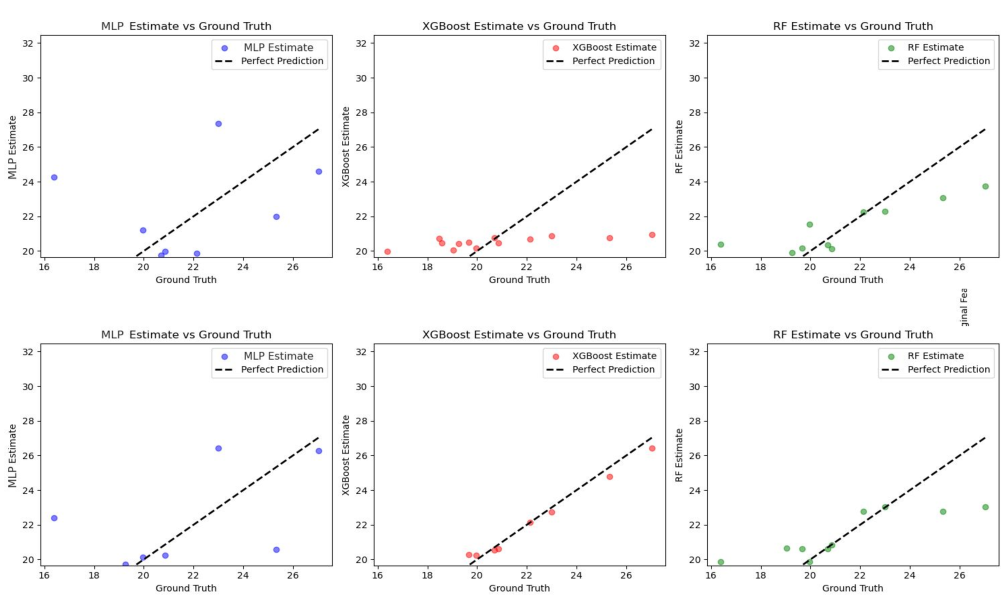

Figure 5: **LOO results w.r.t first batch for Site 1 and Nd before (above) and after (below) PCA.** A substantial improvement is seen for XGBoost.

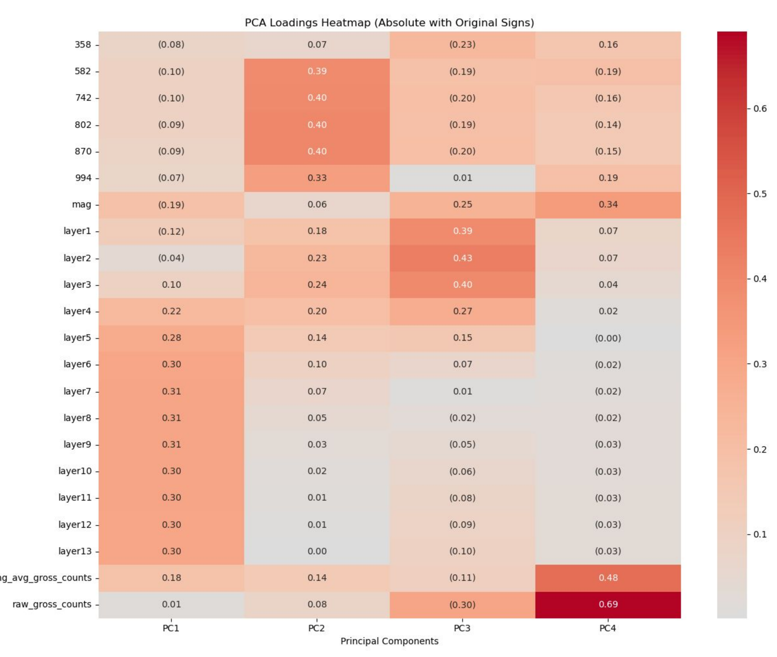

Figure 6: **PCA loadings.** First component (~50% of total variance) is dictated by EMI, and the second (~20%) by hyperspectral.

Batch Differences

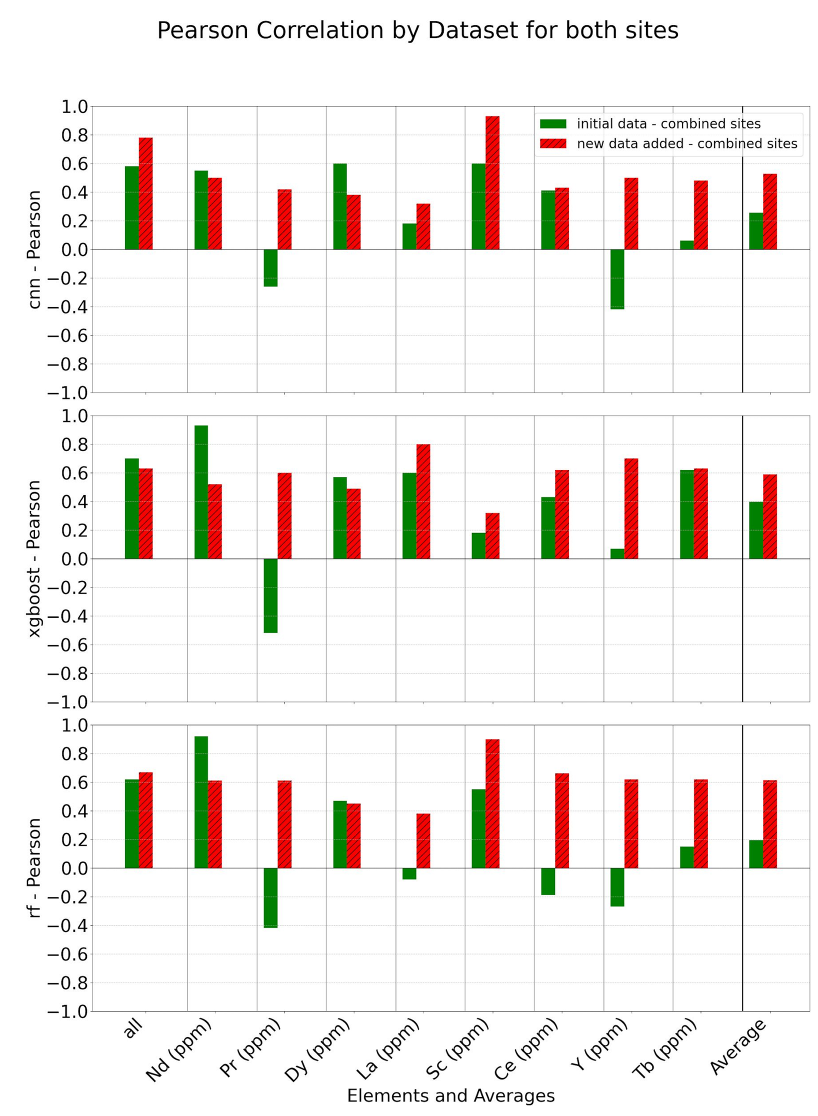

Figure 7: **Pearson correlation for second-batch test data using models trained on first-batch only vs. combined data.** Accuracy improves slightly with second-batch data included in training, but overall remains low.

Models trained on the first batch of samples performed reasonably well when tested on data from the same batch. However, their predictive accuracy dropped significantly when applied to the second batch.

Adding samples from the second batch into the training set led to some improvement, but overall performance remained limited.

This drop in transferability may reflect differences in measurement procedures, sample handling, or other batch-specific factors. However, further testing is needed to clearly identify the source of variability and assess whether it is due to measurement inconsistencies or underlying differences in the samples themselves.

Future Work

The limited sample size and number of sites leave several open questions:

- Can models trained on one site or tailing type be transferred to others?
- Is it valid to combine data from different sites or tailing states? If not, can those differences be reliably accounted for?
- How reliable are lab measurements across different batches or facilities? What level of variability is introduced by the measurement process, and how should this uncertainty be factored into modeling?

To address these challenges and better assess model generalizability, obtaining (and measuring) samples from diverse sites will be essential.