A Two-Stage Machine Learning Framework for FeO Prediction in Lunar Hyperspectral Data

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Why FeO?

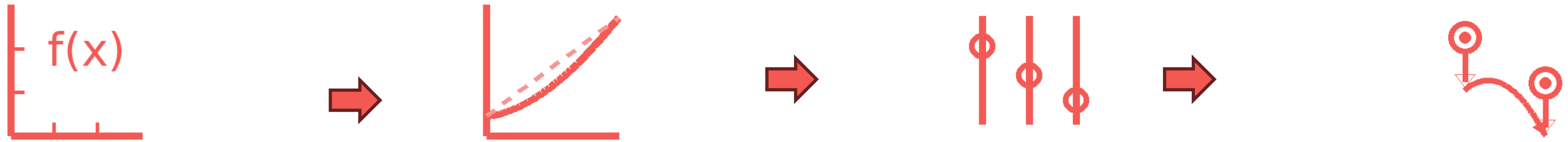
Provides important information about:

- Moon’s geological evolution
- Mantle composition

highly relevant for in-situ resource utilization

- Iron-rich materials can be used for extracting oxygen and metals.

CLASSIC METHODS FOR ESTIMATING FeO
Limitations



Based on empirical relationships between reflectance and composition.

Do not capture the nonlinear complexity of the reflectance-composition relationship

Sensitivity to non-compositional variations

Limited generalization

MOTIVATION TO USE HYPERSPECTRAL DATA

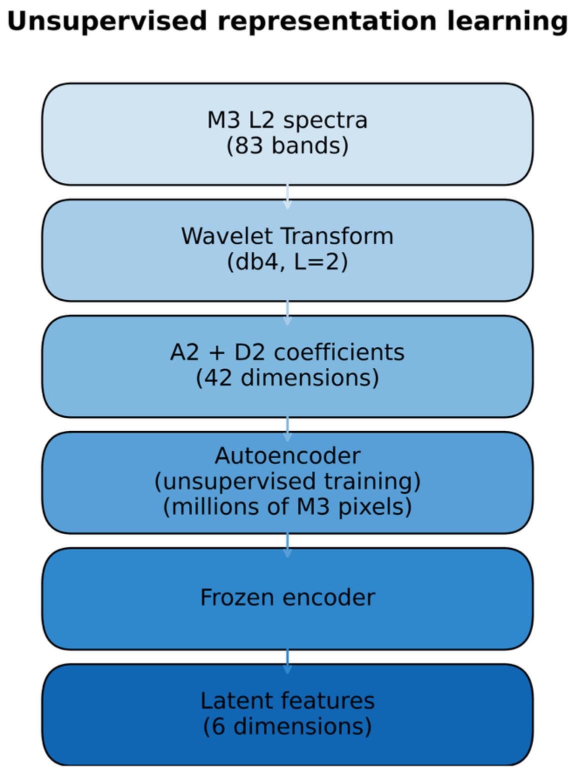
Multispectral data Limitations

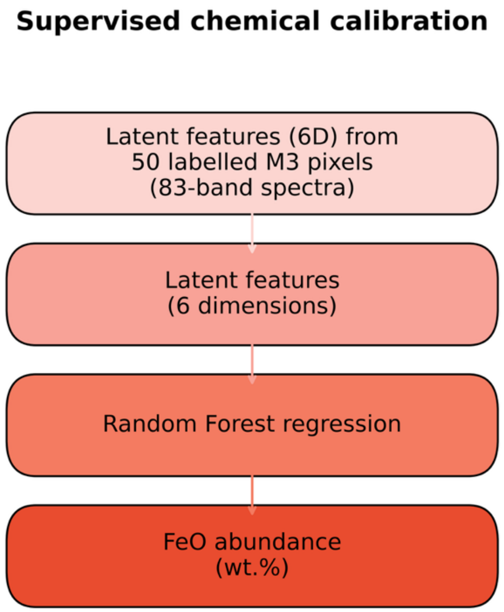
Hyperspectral Advantage (M3)

- 83 bands
- 475–3000 nm

Key Issue

- High dimensionality





DISCRETE WAVELET TRANSFORM

Using DWT

- Multiscale separation
- Preservation of relevant spectral morphology

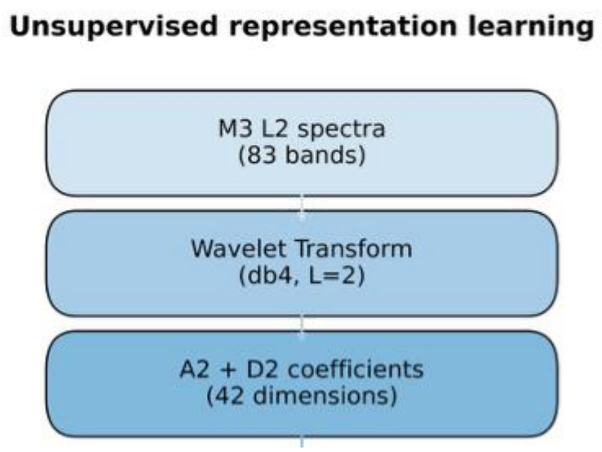
Order 4 Daubechies Wavelet (DB4)

- Compromise between softness and compact support
- Suitable for mineral absorptions

Coefficients A2, D2 and D1

DB4 CHOICE AND REDUCTION TO {A2, D2}

COEFFICIENTS	PRESERVED SPECTRAL ENERGY	RMSE Reflectance Reconstruction
83 → 42	96%	$< 5 \times 10^{-3}$

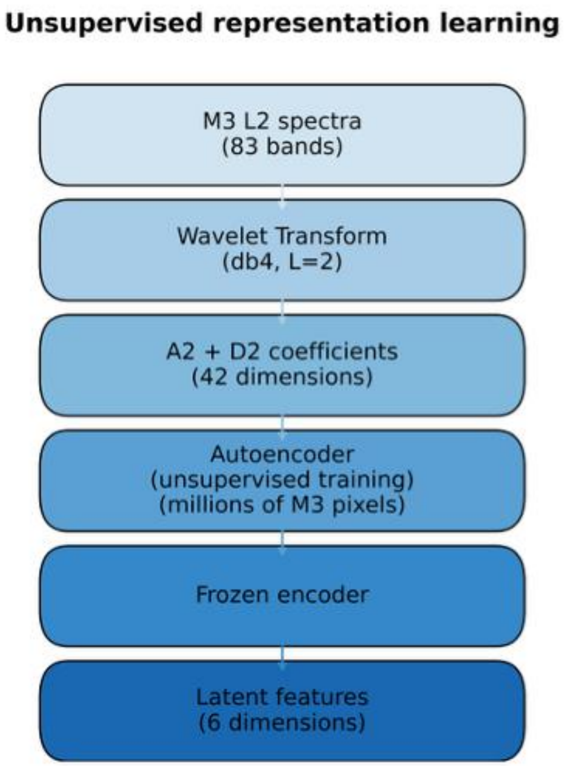


AUTOENCODER: ARCHITECTURE

Symmetrical architecture

42 → 32 → 16 → 6 → 16 → 32 → 42

LeakyReLU activations+ batch normalization → Ensure stable training
Linear latent layer→ Prepreserves the structure of the spectral space



REDUCTION TO 6 DIMENSIONS

Comparison

PCA / ICA / AE

Criteria

- Rebuild RMSE
- Geometric stability

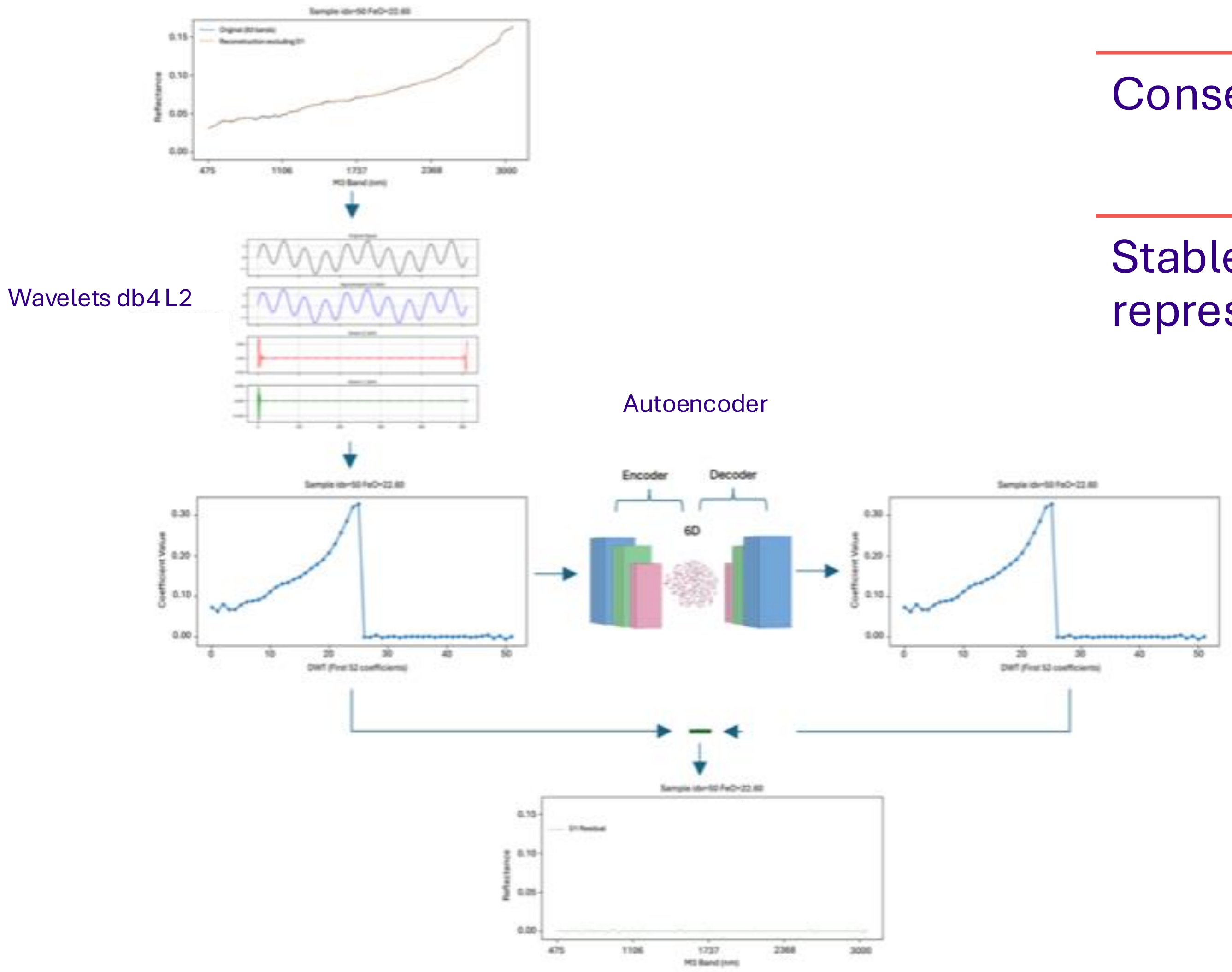
AE superior

Non-linearity

Less geometric distortion

Better compression and performance for d=6

DWT REDUCTION AND SPECTRAL REPRESENTATION + AUTOENCODER

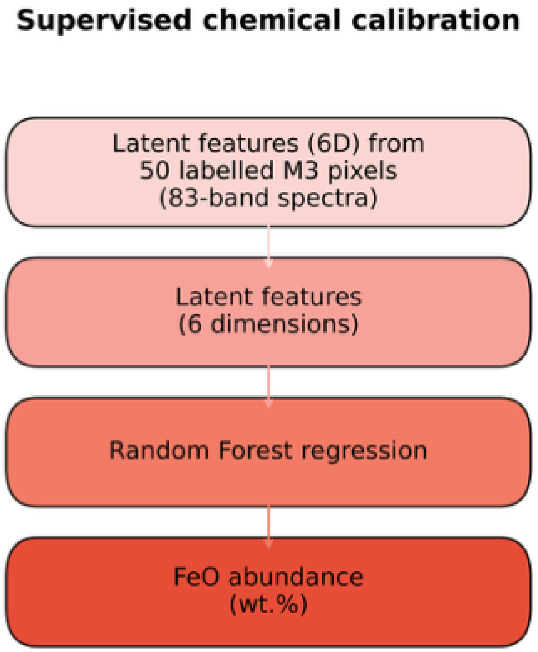


Conservation of the spectral structure

Stable and scalable spectral representation

SUPERVISED REGRESSION: GEOCHEMICAL CALIBRATION

Dataset	50 FeO Samples (49 Apollo/Moon + 1 Chang'E-6)
Entrance	6D latent vector (after DWT+AE)
Models	Lasso, SVR lineal, SVR RBF, Random Forest
Validation	10-fold CV (90%) + test 10%



SELECTION OF THE FINAL MODEL

RF Better Error–Ruggedness Balance

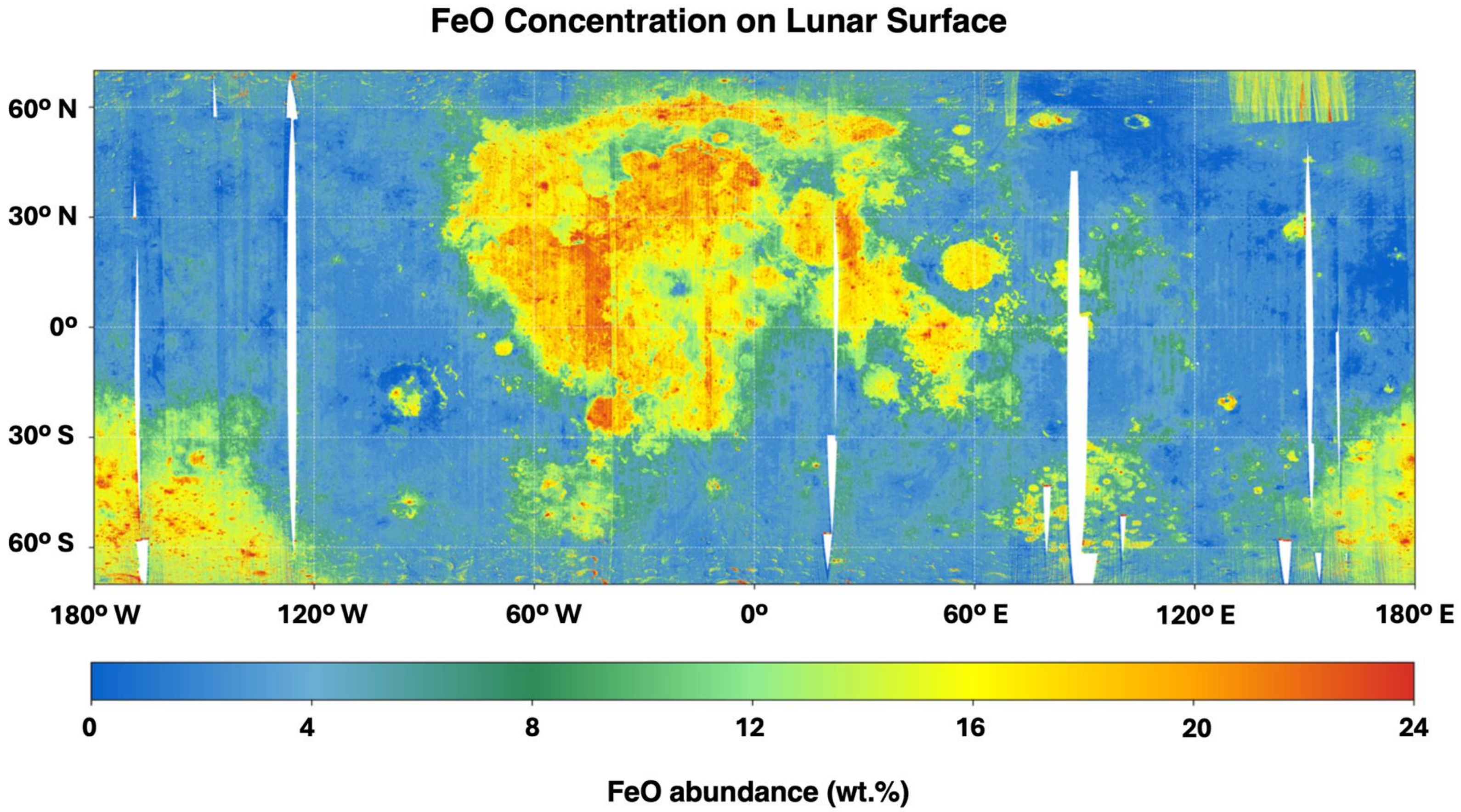
- MAE ≈ 1.20 wt.%,
- $R^2 \approx 0.82$.

Model	MAE (wt. %)	RMSE (wt. %)	R^2
Lasso	1.87	2.41	0.62
SVR (lineal)	1.54	1.98	0.71
SVR (RBF)	1.32	1.67	0.78
Random Forest	**1.20**	**1.48**	**0.82**

Global Application

Application to 806 M3 orbits

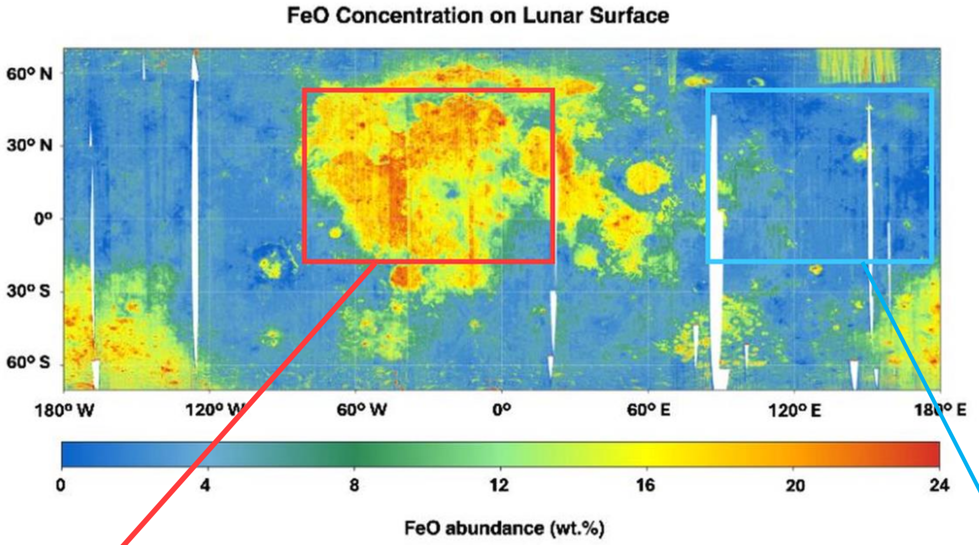
Spatial resolution of 150 m/pixel

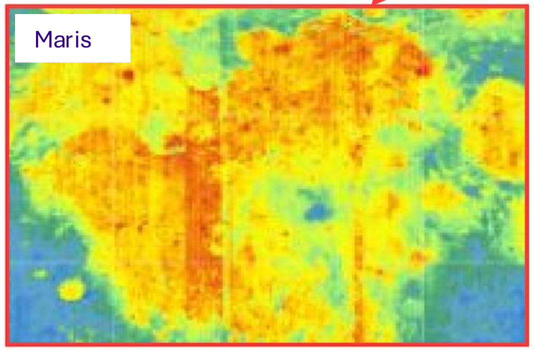


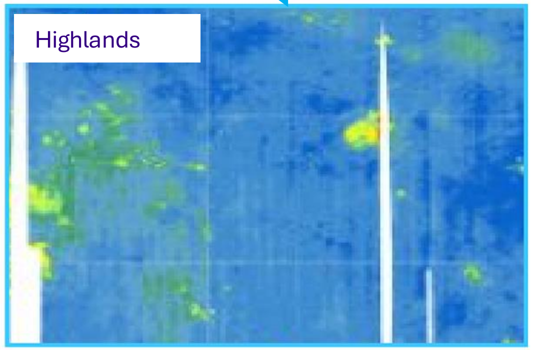
Geological Assessment

Maris: high FeO

Highlands: Low FeO





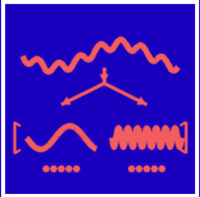


LIMITATIONS

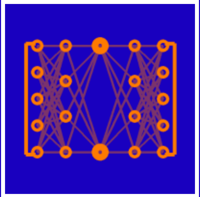
Reduced number of geochemical samples

Geolocation dependency

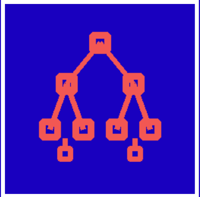
No explicit mineralogy



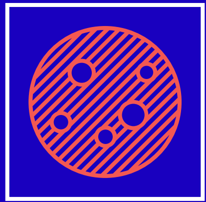
Effective wavelet compression



Latent nonlinear representation



Robust supervised calibration



Validated and stable global product

PUBLICATION

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Global Lunar FeO Mapping via Wavelet–Autoencoder Feature Learning from M3 Hyperspectral Data

by Julia Fernández–Díaz [1,2,*], Fernando Sánchez Lasheras [1], Javier Gracia Rodríguez [1], Santiago Iglesias Álvarez [1], Antonio Luis Marqués Sierra [1] and Francisco Javier de Cos Juez [1,2]

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