GEOMIX

Geometric methods for non-linear spectral unmixing

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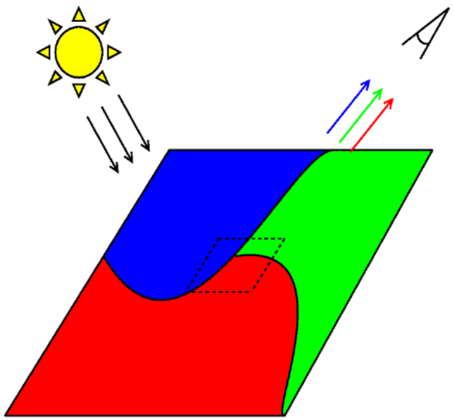
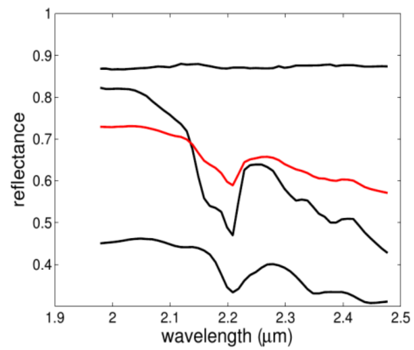
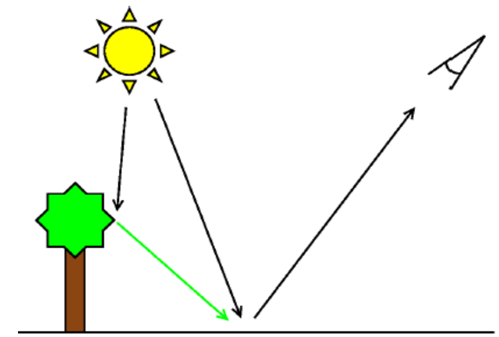
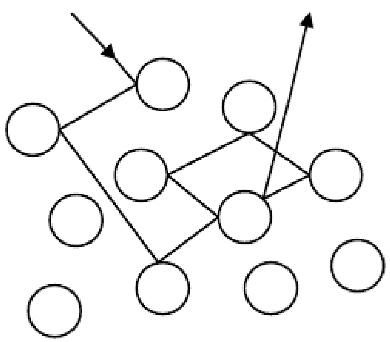
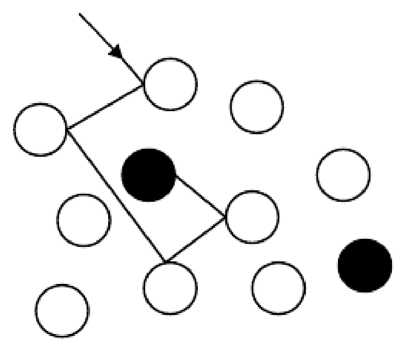
General context: Nonlinear Spectral mixing





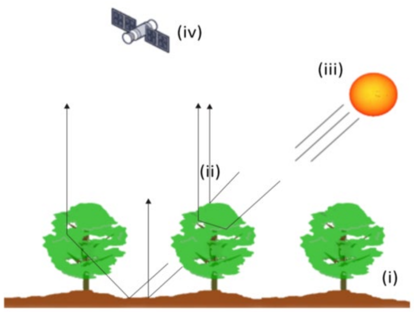


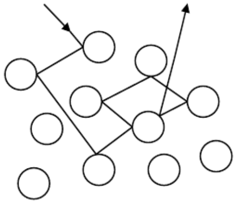


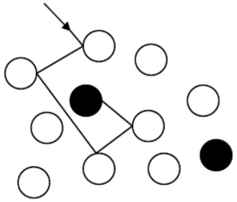


Specific goals

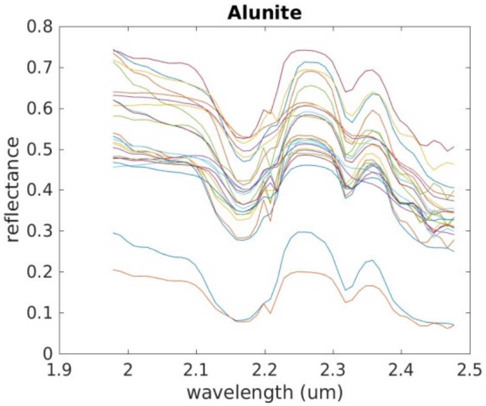
Nonlinear effects







Spectral variability



Validation

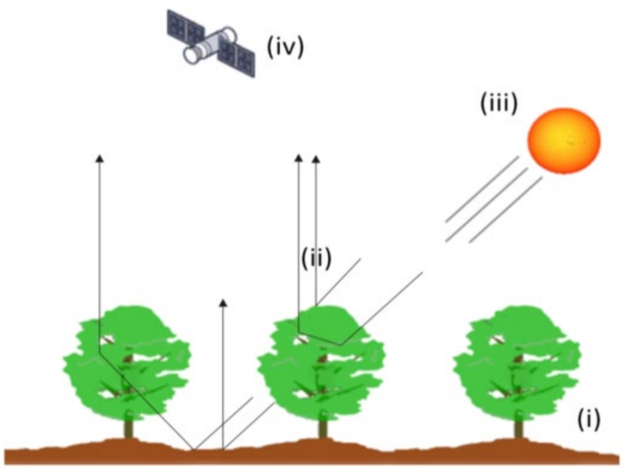
Approaches

1. A physics-based nonlinear model
    - Easy to use:
        - Model easy to invert and fit to data
        - Parameters have clear physical meaning
    - Allows to include shadows, skylight, neighbor effect

2. A data driven method nonlinear unmixing framework
    - Flexible, independent of specific model
    - Supervised approach (ground truth training and validation data)
    - Accounts for spectral variability

1. Multilinear mixing model

Parameter P for multiple reflections

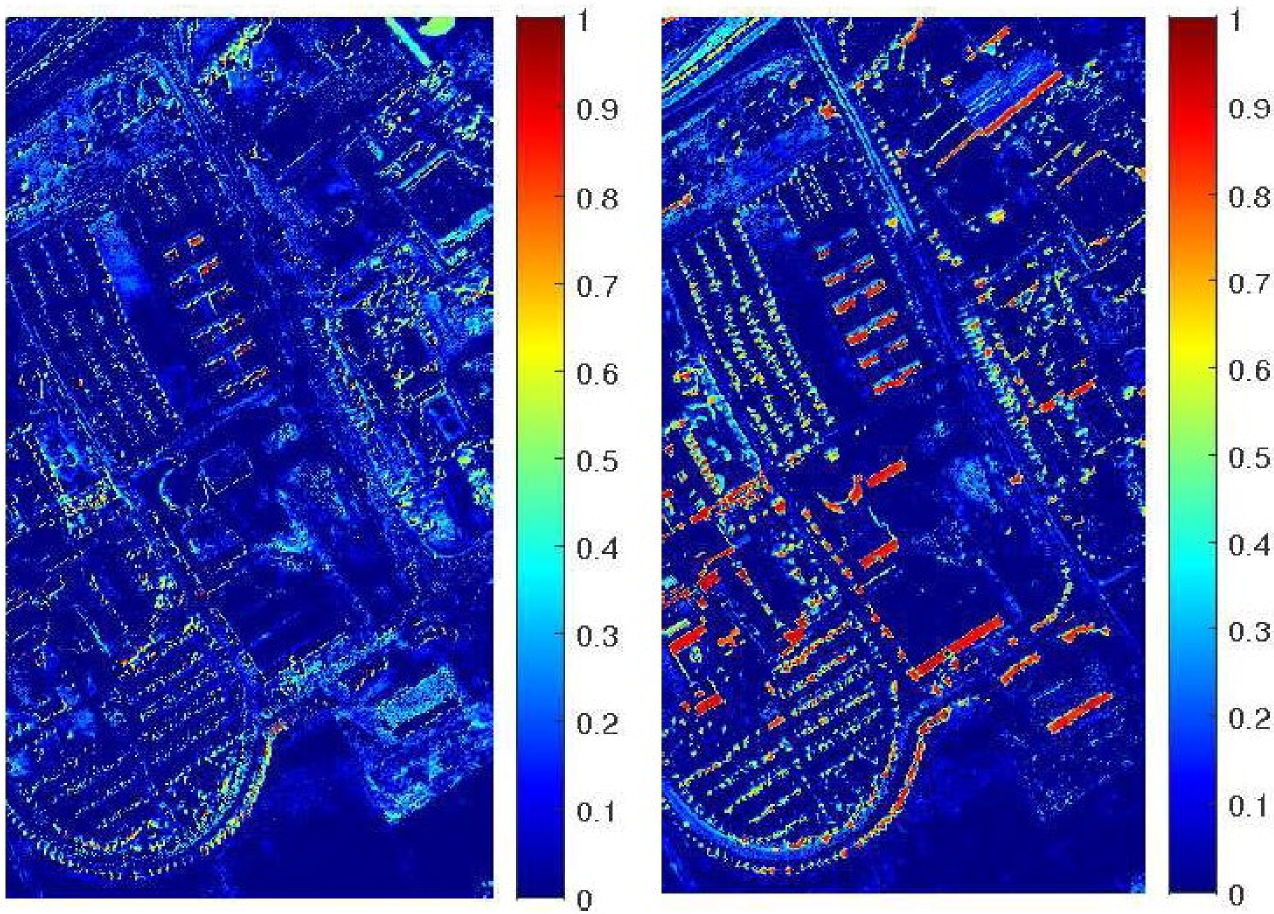


Parameter Q for shadow

$$
\begin{aligned}
&= (1-P)\sum_{i=1}^{p} a_i \boldsymbol{e}_i + (1-P)P\sum_{i=1}^{p}\sum_{j=1}^{p} a_i a_j \boldsymbol{e}_i \odot \boldsymbol{e}_j \\
&\quad +(1-P)P^2\sum_{i=1}^{p}\sum_{j=1}^{p}\sum_{k=1}^{p} a_i a_j a_k \boldsymbol{e}_i \odot \boldsymbol{e}_j \odot \boldsymbol{e}_k \ldots \\
&= \frac{(1-P)\sum_{i=1}^{p} a_i \boldsymbol{e}_i}{1-P\sum_{i=1}^{p} a_i \boldsymbol{e}_i}
\end{aligned}
$$

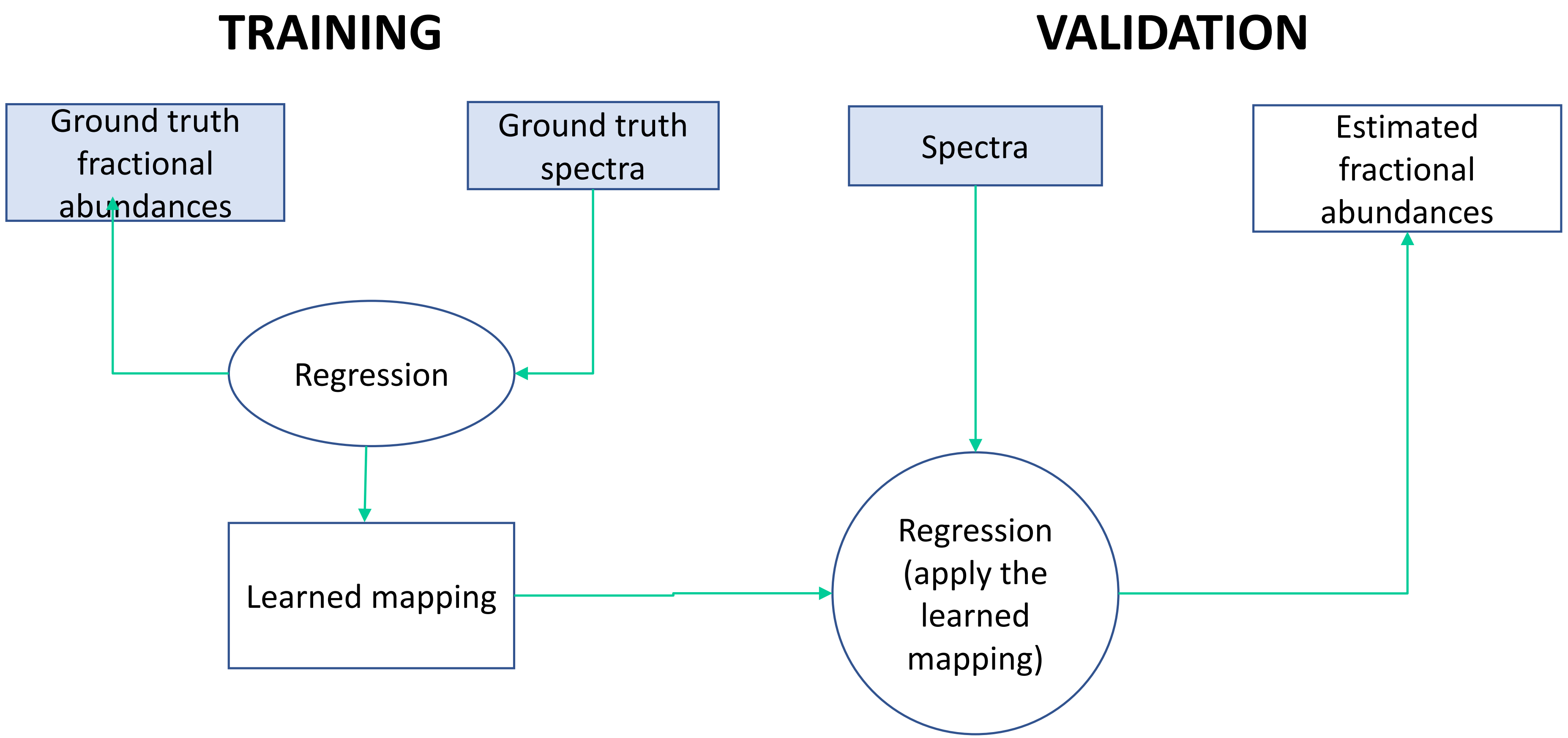
$$
-\,Q(1-P)\sum_{i=1}^{p} a_i \boldsymbol{e}_i
$$

1. Multilinear mixing model



R. Heylen, V. Andrejchenko, Z. Zahiri, M. Parente, P. Scheunders. Nonlinear hyperspectral unmixing with graphical models. *IEEE Transactions on Geoscience and Remote Sensing*, 57 (7), 4844-4856, 2019.

2. Supervised nonlinear unmixing framework



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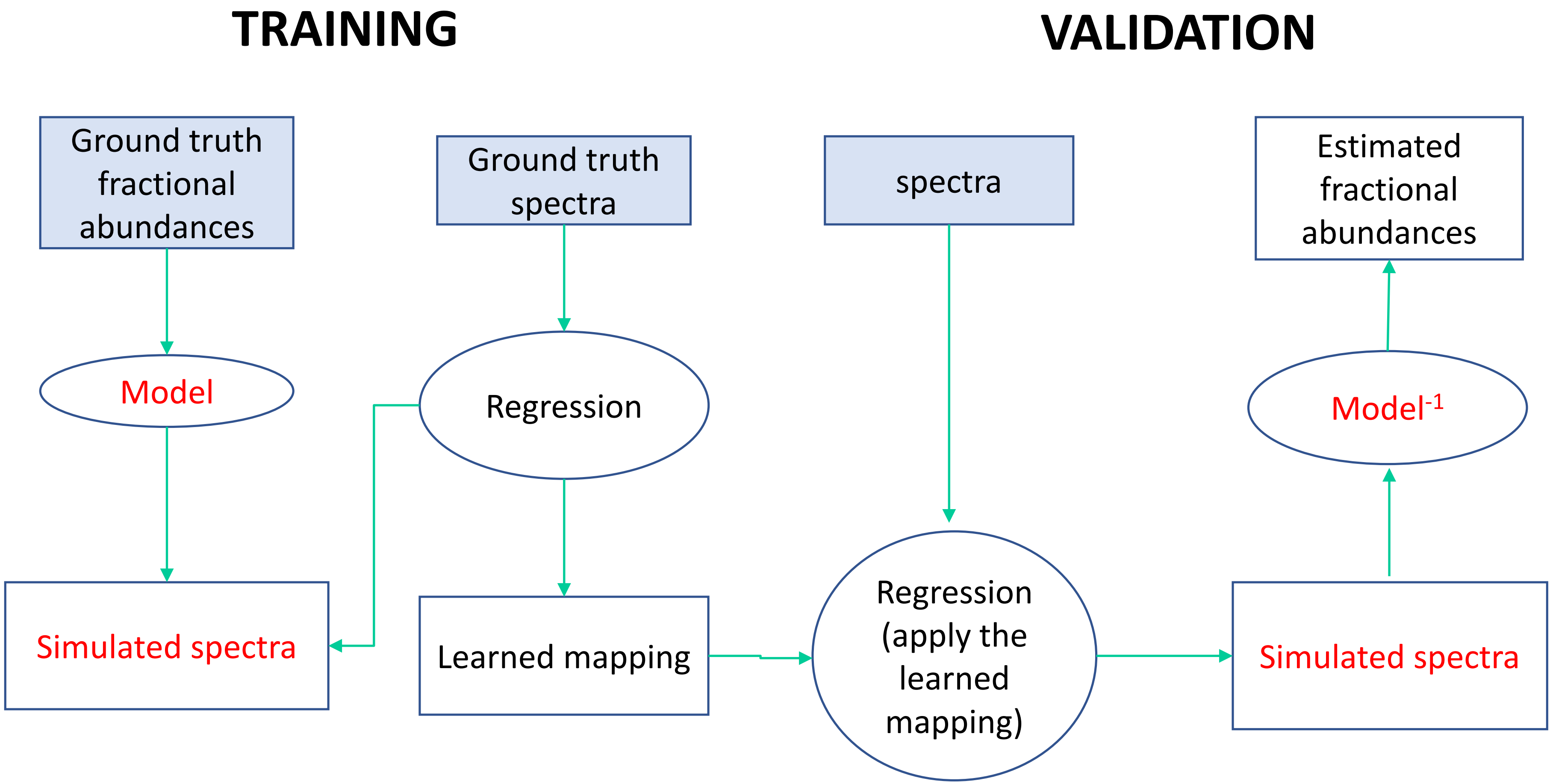
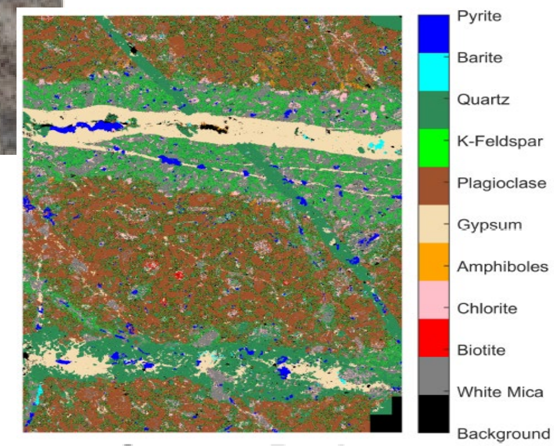
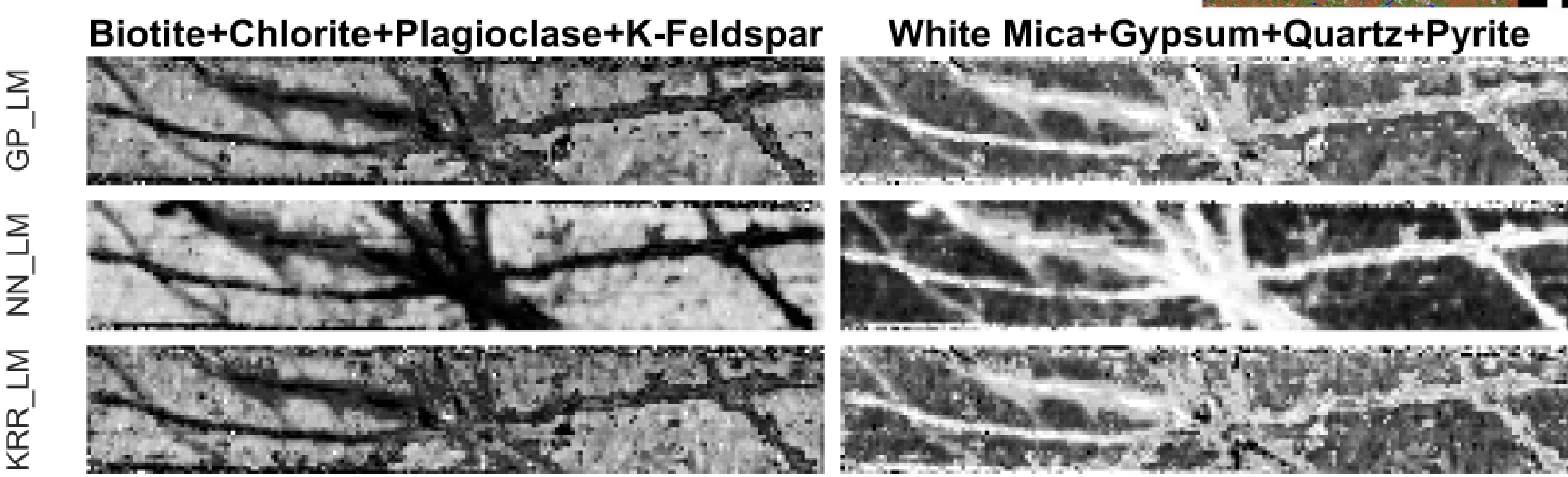


2. Supervised nonlinear unmixing framework

Drill core hyperspectral dataset

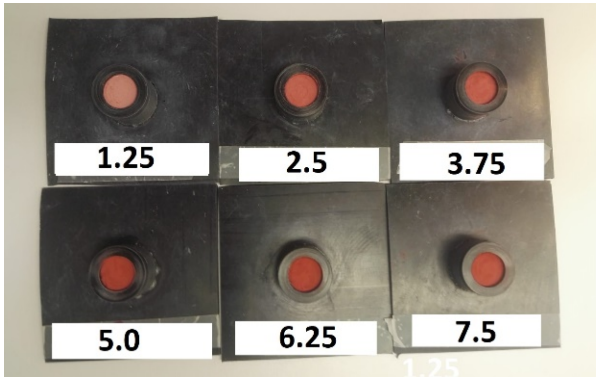


Collaboration with Helmholtz-Zentrum Dresden-Rossendorf (HZDR), Helmholtz Institute Freiberg for Resource Technology (HIF), Germany



B. Koirala, M. Khodadadzadeh, C. Contreras, Z. Zahiri, R. Gloaguen, P. Scheunders, A supervised method for nonlinear hyperspectral unmixing, *Remote Sensing*, 11, 2458, 2019.

2. Supervised nonlinear unmixing framework



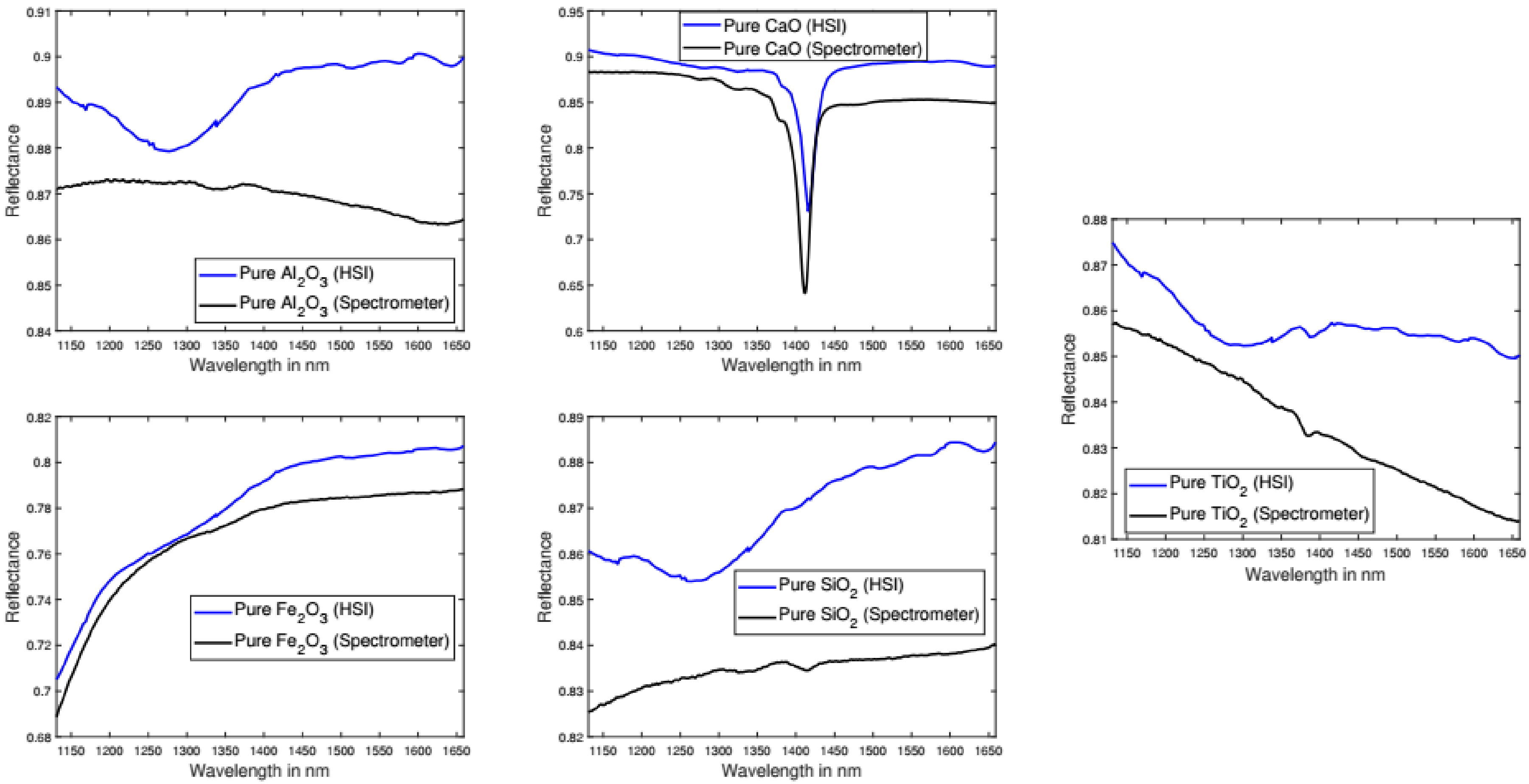
Pure Mineral	Density (g/cm3)	Grain size (µm)
Fe_2o_3	5.25	0.8
Al_2o_3	3.98	3.5
Sio_2	2.64	23
Tio_2	3.89	0.5
Cao	3.34	2.7

Mineral powder mixtures

Different binary mixtures	
Endmember 1	Endmember 2
Al_2o_3	Sio_2
Cao	Sio_2
Cao	Tio_2
Fe_2o_3	Al_2o_3
Fe_2o_3	Cao
Fe_2o_3	Sio_2
Sio_2	Tio_2

B. Koirala, Z. Zahiri, P. Scheunders. A machine learning framework for estimating leaf biochemical parameters from ts spectral reflectance and transmission measurements.*IEEE Transactions on Geoscience and Remote Sensing,* 58 (10), 7393-7405, 2020.

2. Supervised nonlinear unmixing framework



Mineral powder mixtures

2. Supervised nonlinear unmixing framework

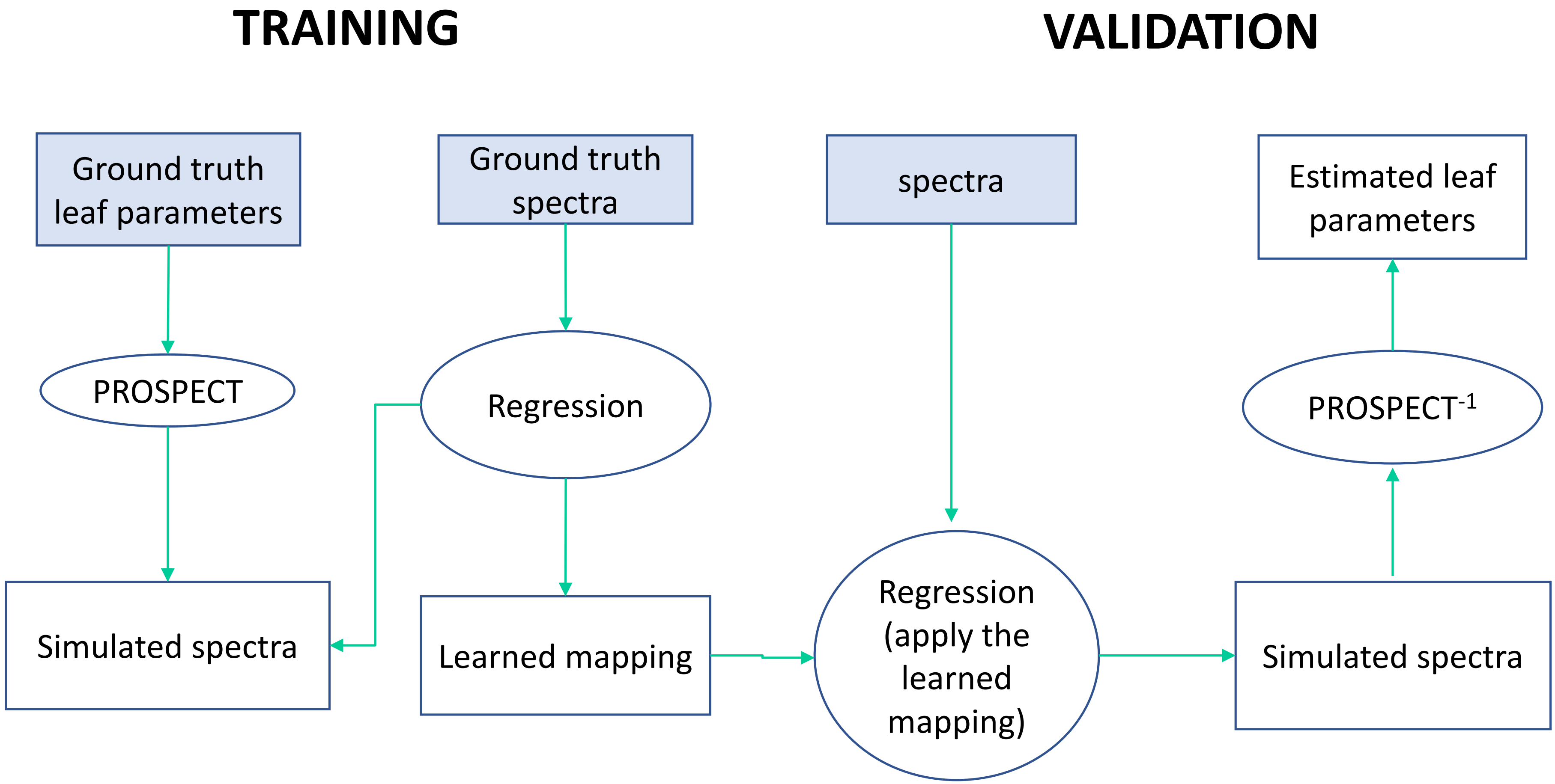
Conclusions

- Mixing models completely fail (even Hapke model): not robust to spectral variability.

- Data-driven approaches fail, physical relation between the spectra and the fractional abundances is lost.

- The proposed hybrid approach: error rates of only a few percent.

2. Supervised nonlinear unmixing framework



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Future activities 2020-2021

Fundamental research a real quantitative approach

- Understand spectral variability
- Reduce dependence on training data

Damage detection for Industrial application

- Mixtures of active minerals and water
- Corrosion
- Concrete damages
- Coating problems
- …

Remote sensing applications

- crop leaf parameter estimation from remote sensing time series