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Convention & Exhibition Center

BUILDING A HYPERSPECTRAL LIBRARY AND ITS INCORPORATION INTO SPARSE UNMIXING FOR MINERAL IDENTIFICATION

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Thanh M. BUI

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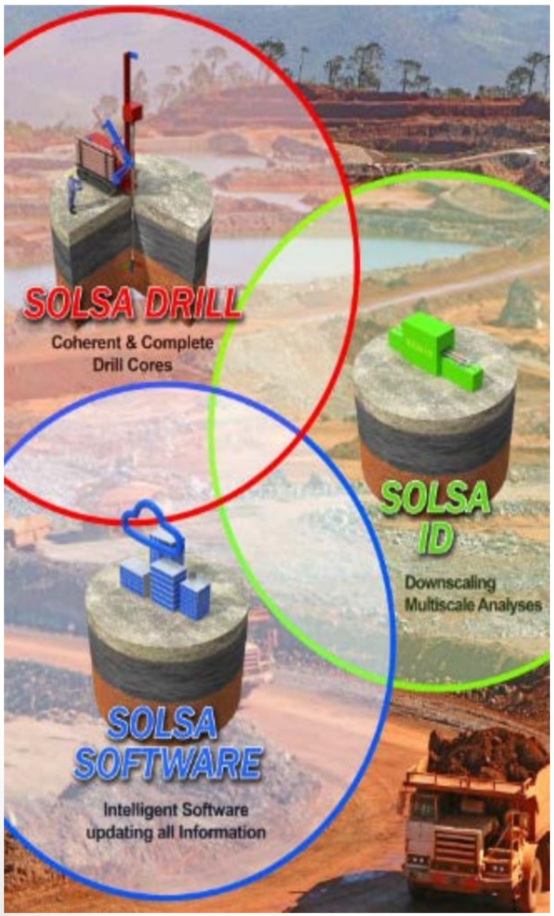
SOLSA project

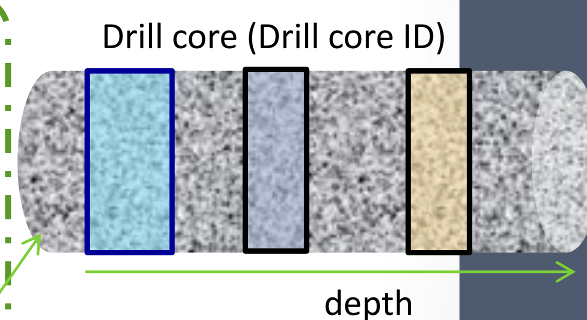
H2020 SOLSA (Sonic Online and Sample Analysis) project aims at constructing an analytical expert system for on-line-on-mine-real-time mineralogical and geochemical analyses on sonic drill cores.



SOLSA ID
Analyse & Identification in
field and industrial applications

↓

SOLSA ID A, measurement	Profilometer, RGB camera, VNIR/SWIR cameras, XRF
SOLSA ID A, processing	Localisation of ROIs on drill cores
SOLSA ID B, measurement	XRD – XRF – Raman on ROIs
SOLSA ID B, processing	Data processing



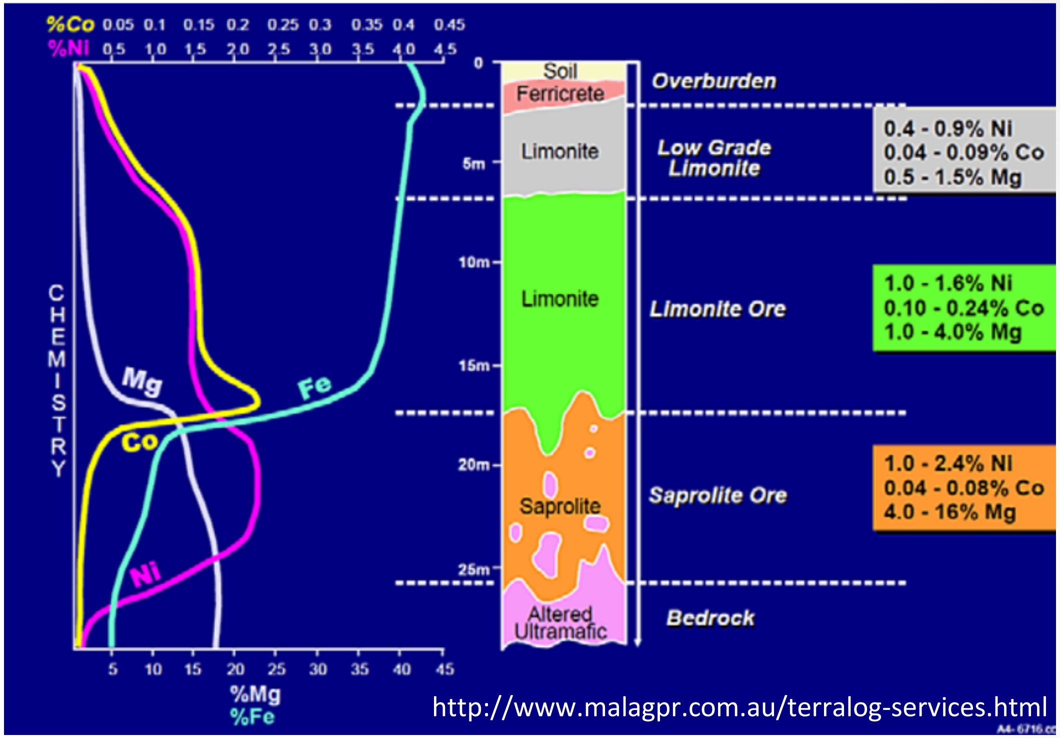
Nickel laterites

- Ni resources:
  - Sulfide ores
  - Ni laterites

- Ni laterites
  - Consitute 60 – 70% of the world's Ni resources
  - Reach 60% of total Ni production in 2014
  - Contribute 20 – 30% of the total Co supply.

Butt *et al.*, 2013

Average chemical variations on the laterite profile:

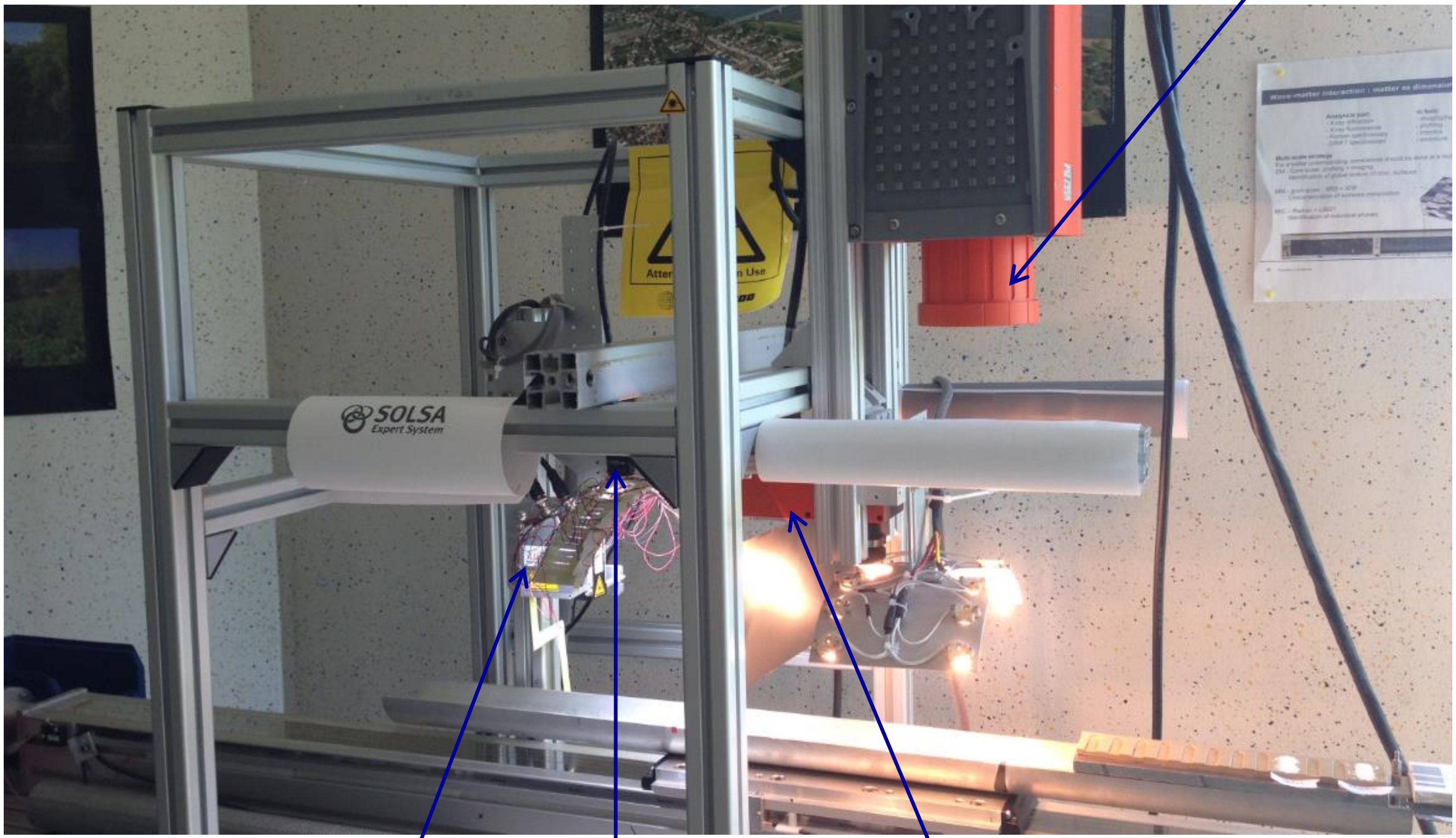


- Three nickel laterite ore types, based on the dominant minerals hosting Ni:

Ores	Mean grades of Ni	Principle ore minerals	% of total Ni laterite resources	Position in lateritic profiles
Oxide	1.0 – 1.6 wt%	Goethite, absolane, lithiophorite	60%	Mid to upper saprolite and upwards to the plasmic zone
Hydrous Mg silicate	1.44 wt%	Serpentine, talc, chlorite, sepiolite	32%	Mid to lower saprolite
Clay silicate	1.0 – 1.5 wt%	Smectite, saponite	8%	Mid to upper saprolite

SOLSA ID A system

SWIR (1000 – 2500 nm) camera

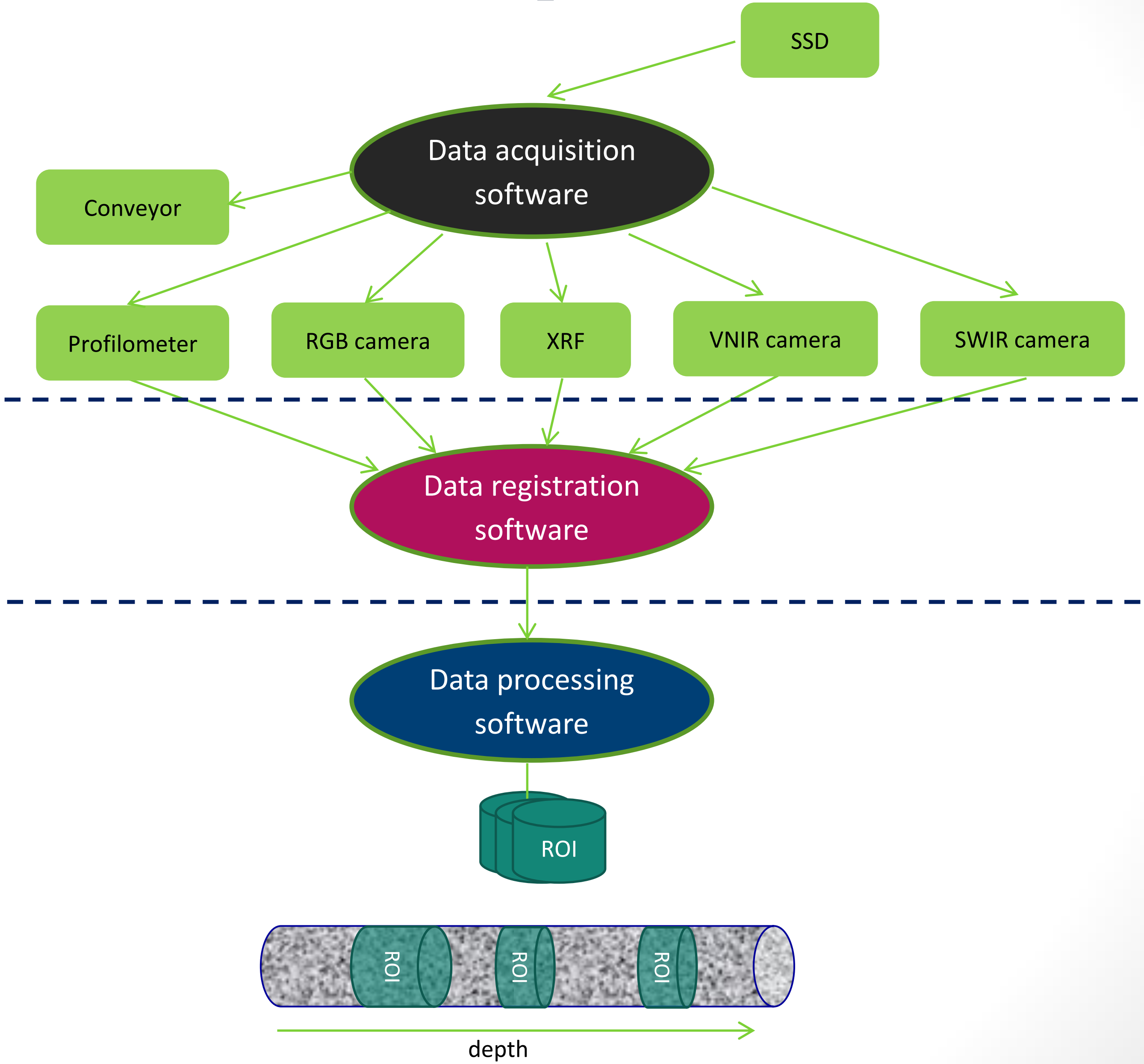


Profilometer

RGB camera

VNIR (400 – 1000 nm) camera

Software development scheme



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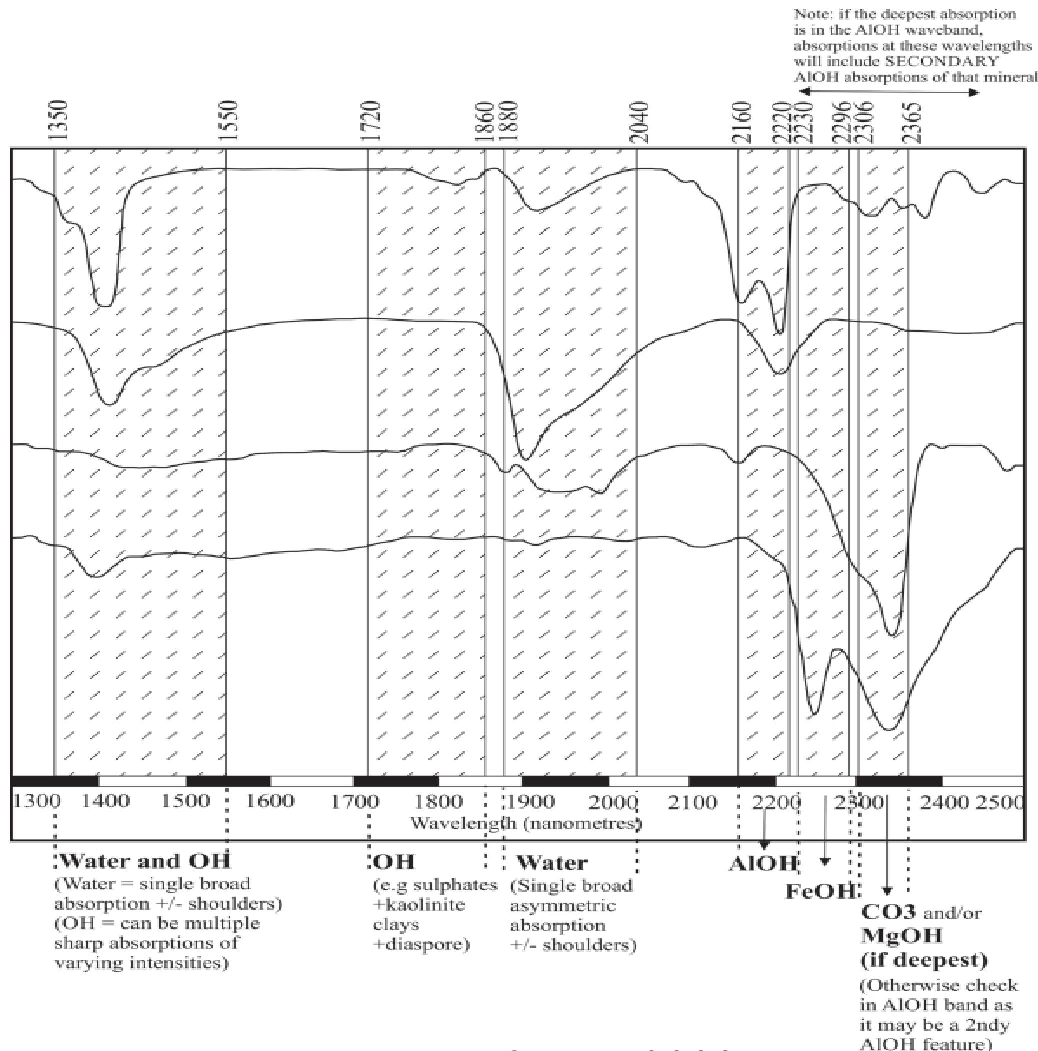
Hyperspectral imaging for mineralogy identification

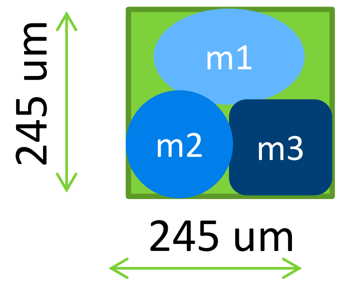
Molecules	Dominant absorption features
OH	1400nm (1550nm and 1750-1850nm in some minerals)
Water	1400nm and 1900nm
AlOH	2160-2228nm
FeOH	2230-2295nm
MgOH	2300-2370nm
CO_3	2300-2370nm (and also at 1870nm, 1990nm and 2155nm)

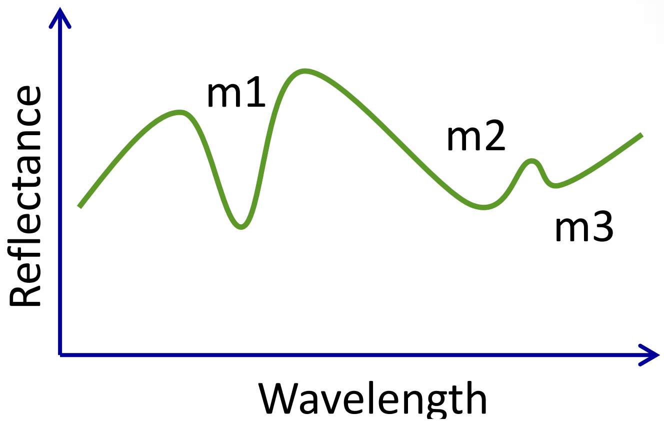


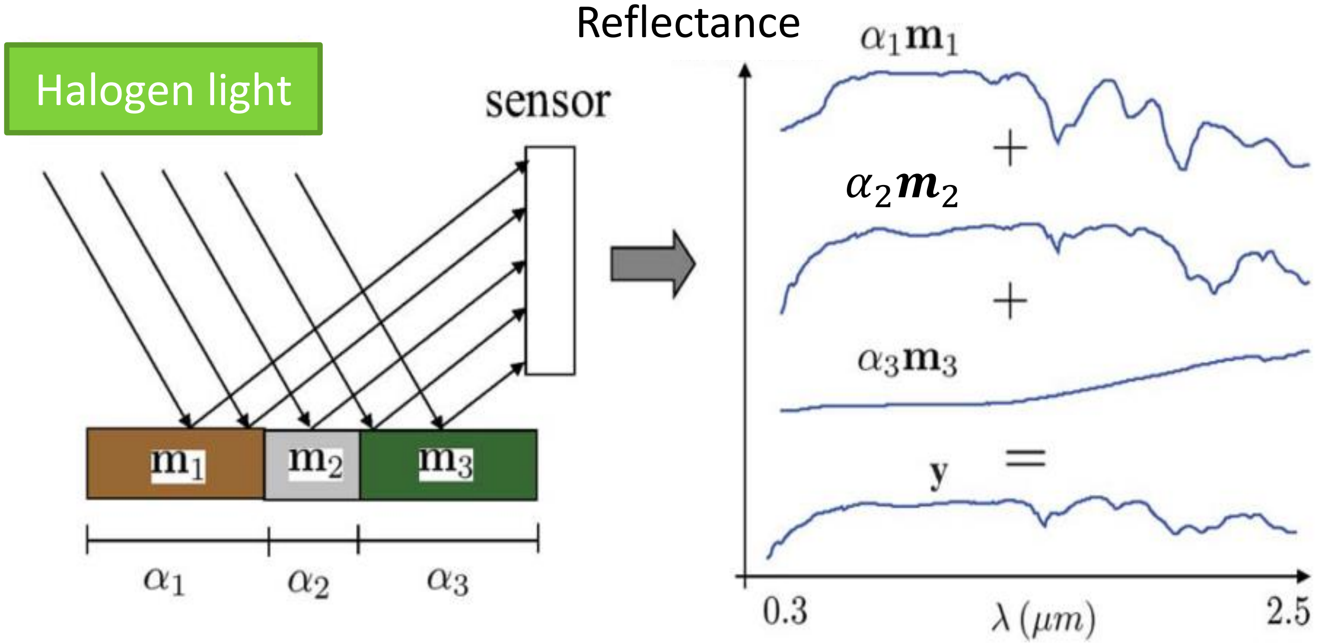
Crystallinity variations -> shape variations
Compositional variations -> wavelength shifts

GMEX, 2008,
Pontual et al. 1997

Hyperspectral unmixing





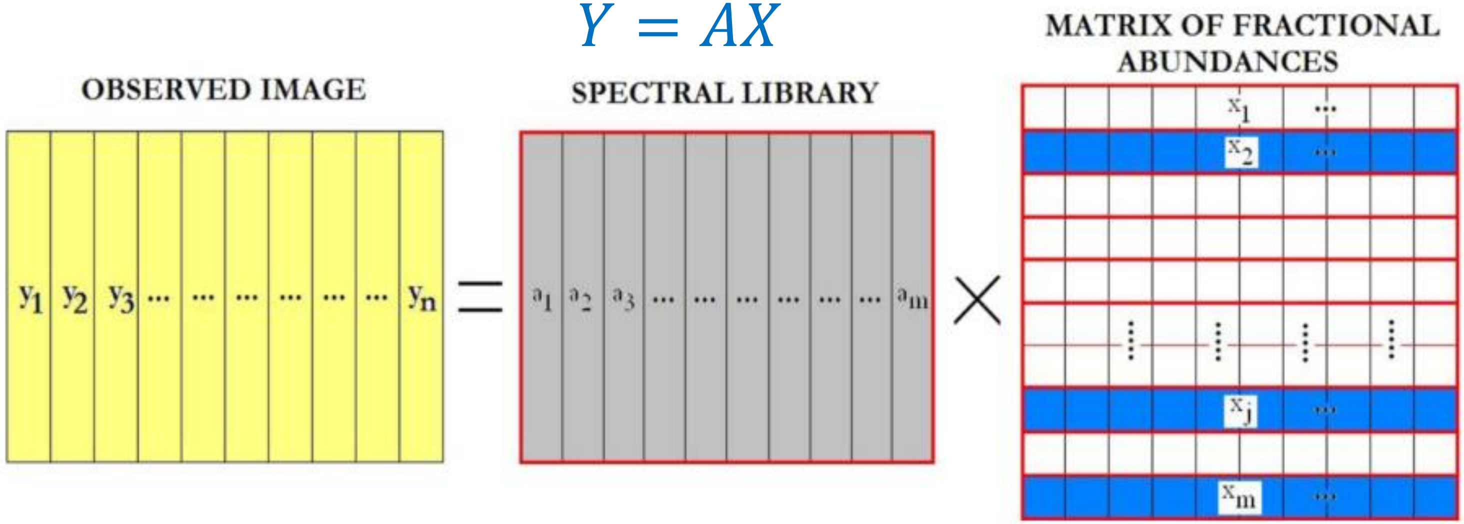


Hyperspectral unmixing

- Statistical approaches (Debigion et al. 2008 ; Altmann et al., 2015)
  - The likelihood: data generation models
  - Priors: constraints on the endmembers
- Geometrical approaches (Nascimento et al., 2005; Bioucas-Dias et al. 2009)
  - The observed hyperspectral vectors: simplex set whose vertices correspond to the endmembers.
- Sparse regression

Sparse unmixing

$$Y = AX$$



Iordache *et al.*, IEEE Trans, 2014

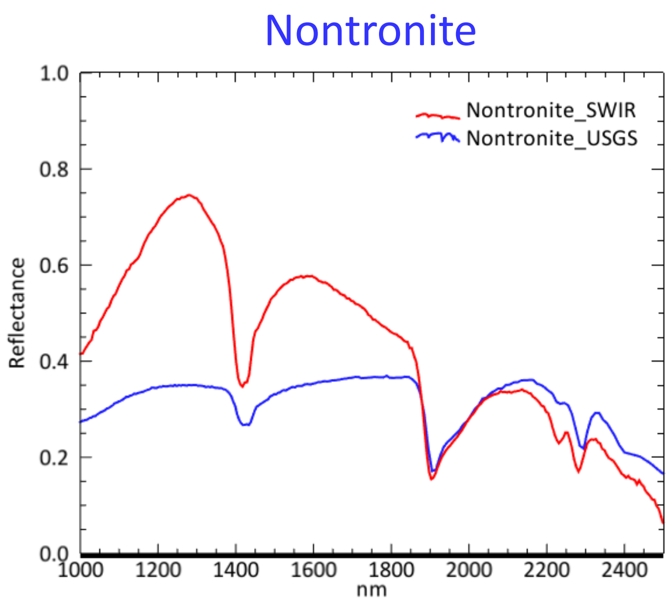
Y L x n | **A** L x m | **X** m x n

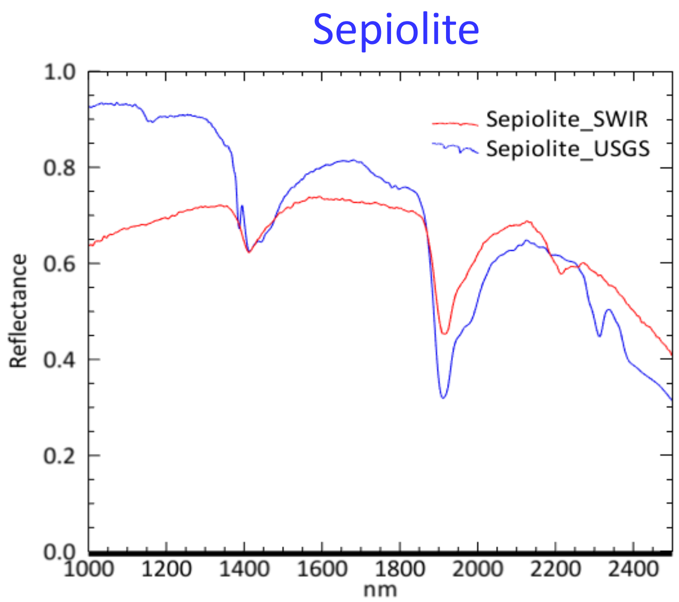
$$\min_X \|AX - Y\|_F^{\,2} + \lambda \|X\|_{2,1}$$ *subject to:* $X \geq 0$, $\mathbf{1}^T X = 1$

- The observed image signatures can be expressed in the form of linear combinations of a number of pure spectral signatures known in advance (spectral library).
- Unmixing amounts to finding the optimal subset of signatures in a spectral library that can best model each mixed pixel in the scene.
- The sparse unmixing exploits the usual very low number of endmembers (maximum of 4, Berman *et al.*, CSIRO, 2017) present in real images, out of a spectral library.

Hyperspectral library

- Other libraries (e.g., USGS) may not contain spectra of pure minerals.
- We wish to include spectra that are collected with our instruments used in our operational exploration.
- Minerals found in Ni laterites in New Caledonia may not be present in other libraries.





Reference spectral libraries:
USGS: https://speclab.cr.usgs.gov/
NASA ASTER: https://speclib.jpl.nasa.gov/

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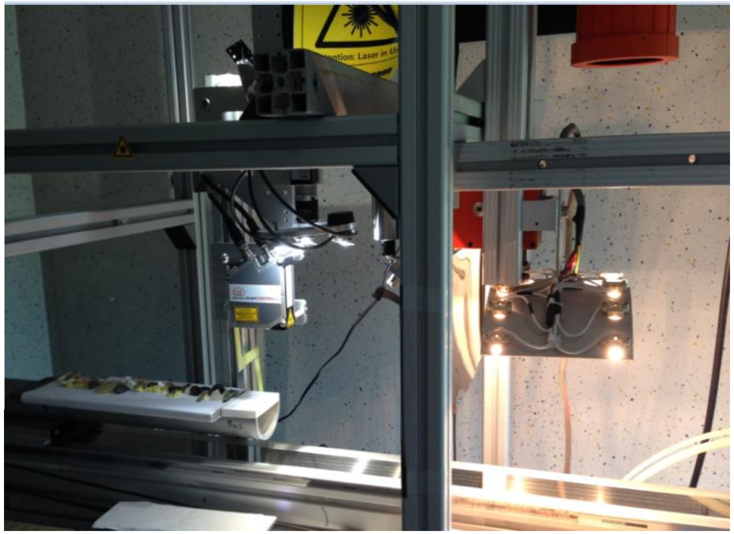
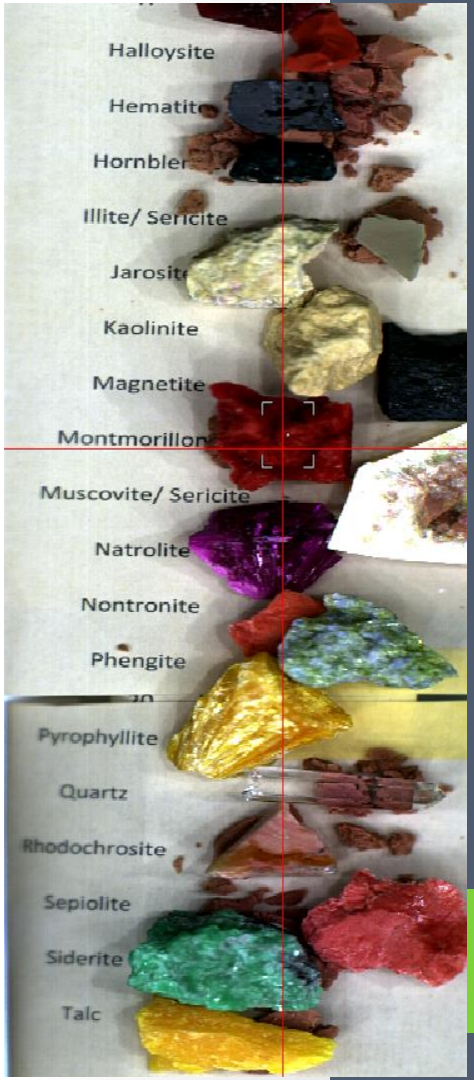
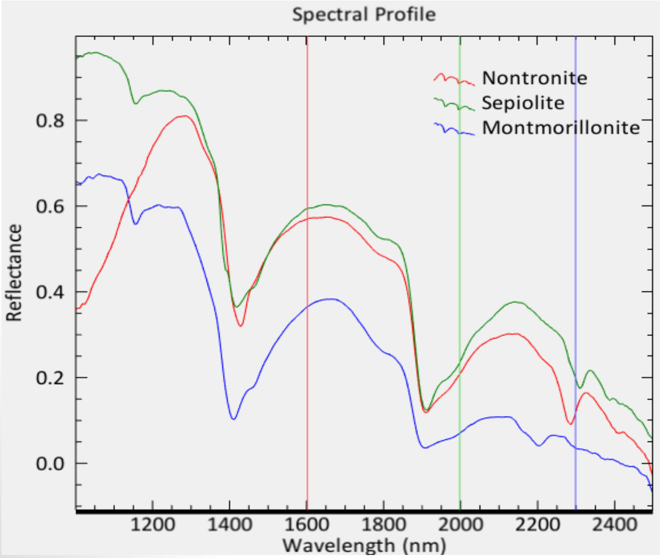
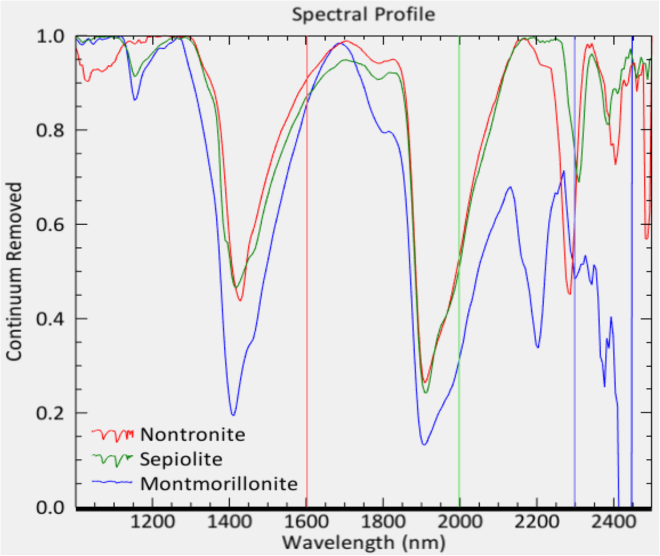
Hyperspectral library

- Rock and mineral samples provided by BRGM, ERAMET and the National Museum of Natural History, France
- Spectra extraction: ENVI 5.4 and G-MEX by taking into account the wavelength positions and the relative intensities of the absorption features.









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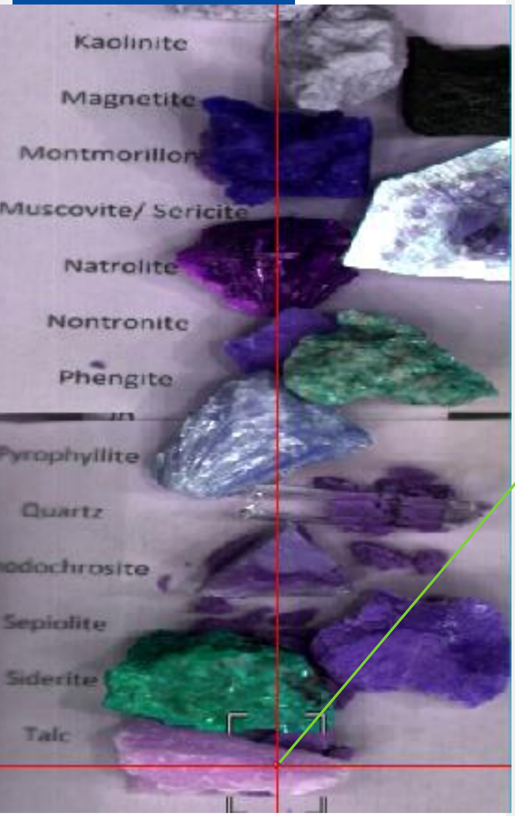
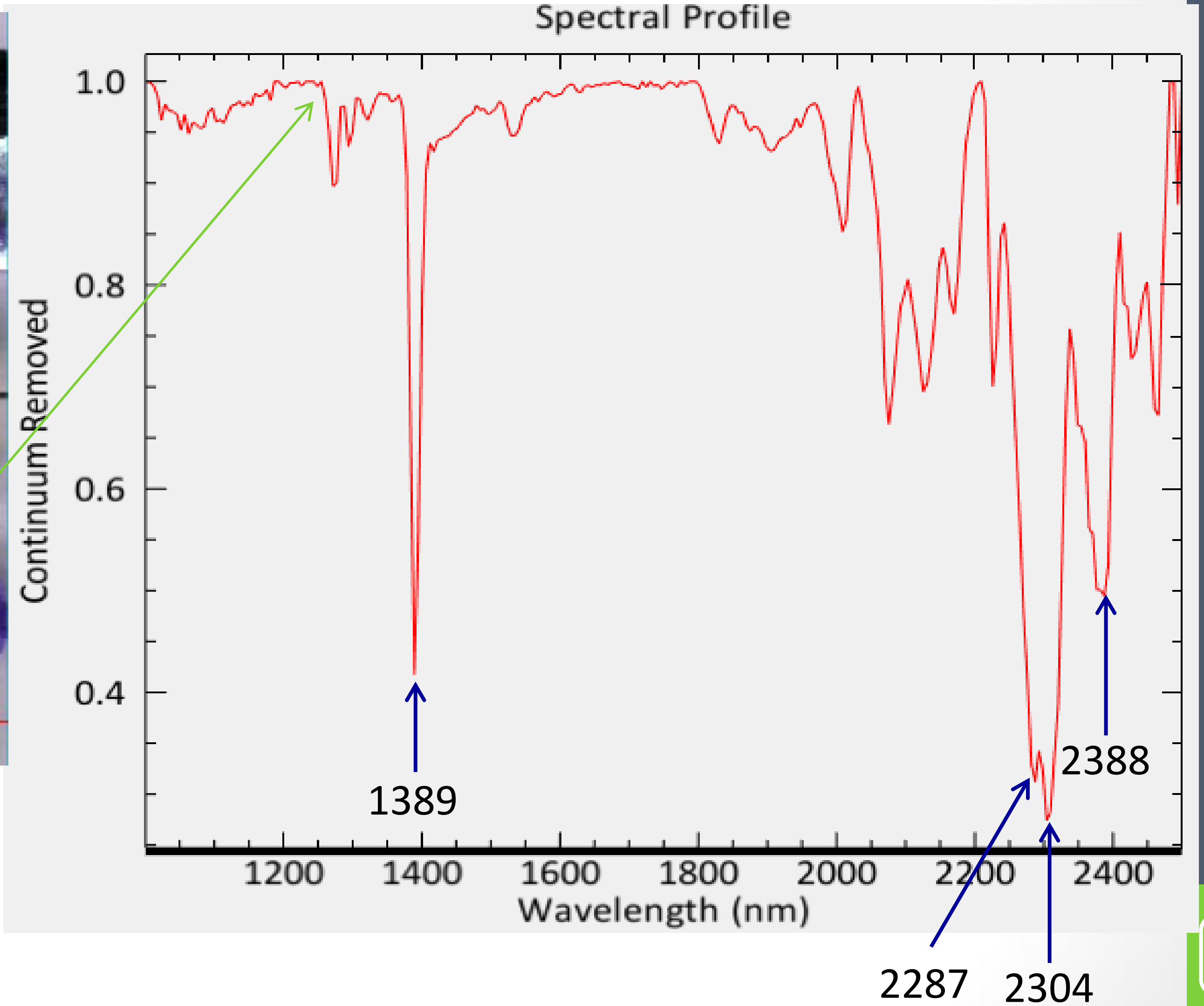
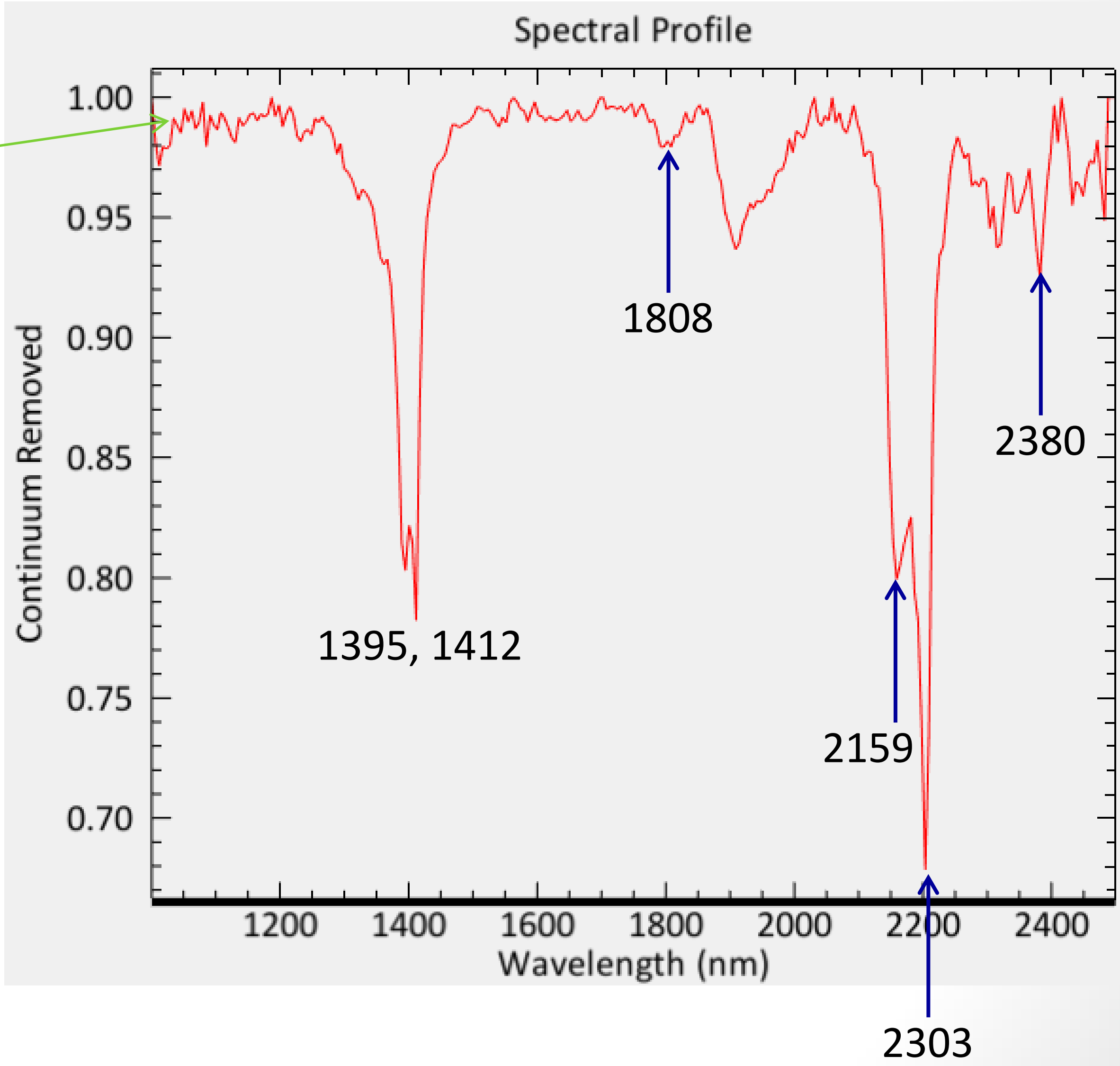
Talc: $Mg_3Si_4O_{10}(OH)_2$





Kaolinite: $Al_2Si_2O_5(OH)_4$



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Sparse unmixing techniques

CLSUnSAL
(Collaborative sparse unmixing by variable splitting and augmented Lagrangian):

$$\min_X \|AX - Y\|_F^{\ 2} + \lambda \|X\|_{2,1}$$

subject to: X ≥ 0, $\mathbf{1}^T$X = 1

SUnSAL
(Sparse unmixing by variable splitting and augmented Lagrangian):

$$\min_X \|AX - Y\|_F^{\ 2} + \lambda \|X\|_{1,1}$$

subject to: X ≥ 0, $\mathbf{1}^T$ X = 1

FCLS
(Fully contrained least squares):

$$\min_X \|AX - Y\|_F^{\ 2}$$

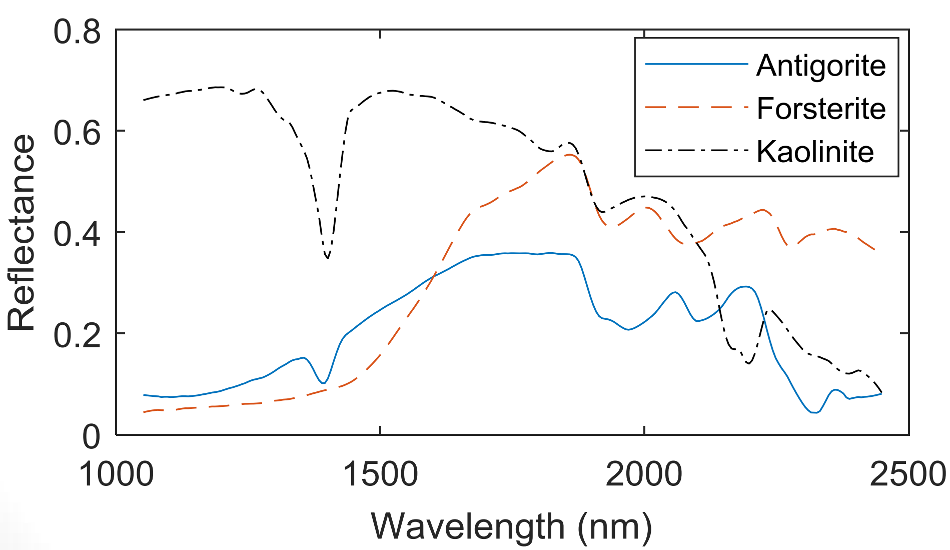
subject to: X ≥ 0, $\mathbf{1}^T$ X = 1

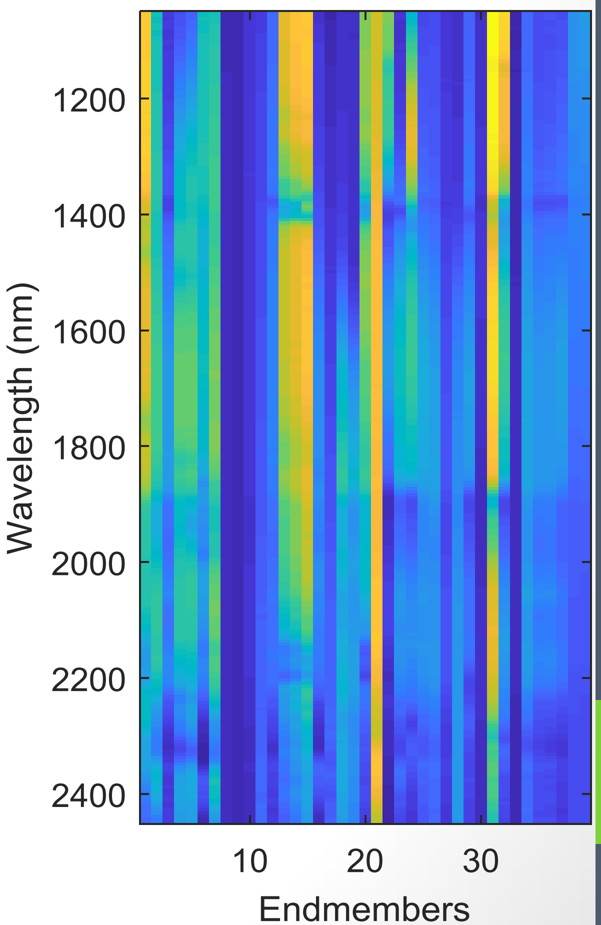
The optimization is based on the alternating direction method of multipliers (ADMM)

Bioucas-Dias *et al.*, 2010
Iordache *et al.*, IEEE Trans, 2014
Afonso *et al.*, IEEE Trans, 2011

Hyperspectral library

37 spectra representing 21 minerals have been collected:
- ankerite, calcite, dolomite, magnesite
- lizardite, nepouite, antigorite, chrysotite,
- saponite, montmorillonite, nontronite, kaolinite, pimelite, talc, sepiolite,
- alunite, asbolane, chromite, diaspore, enstatite, forsterite





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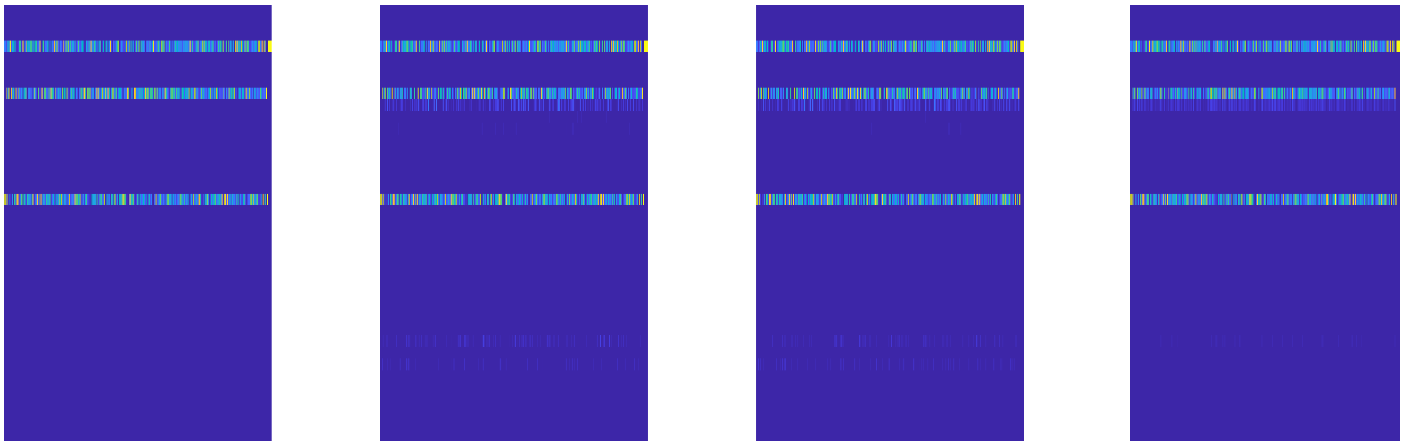
Hyperspectral unmixing

Simulated data: SNR = 40 dB

Original X **FCLS** **SUnSAL** **CLSUnSAL**



Signal to reconstruction error (SRE) ratio:

$$SRE = 10 \log \frac{E\|\boldsymbol{x}\|^2}{E\|\boldsymbol{x} - \widehat{\boldsymbol{x}}\|^2}$$

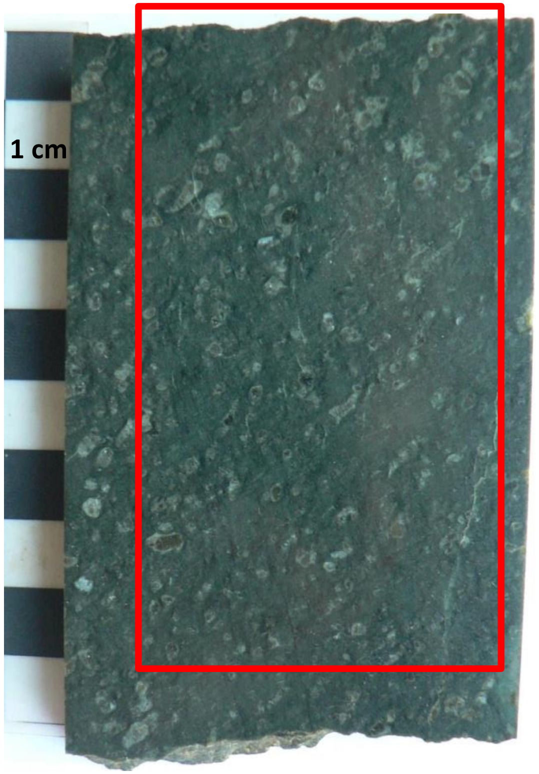
K	FCLS		SUnSAL		CLSUnSAL	
	SRE	Time	SRE	time	SRE	time
2	14.24	0.022	14.94	0.254	16.74	0.228
3	6.41	0.019	7.45	0.259	11.95	0.230
4	5.25	0.022	7.07	0.499	7.16	0.453

FCLS: Fully constrained least squares
SUnSAL: Sparse unmixing by variable splitting and augmented Lagrangian
CLSUnSAL: Collaborative sparse unmixing by variable splitting and augmented Lagrangian

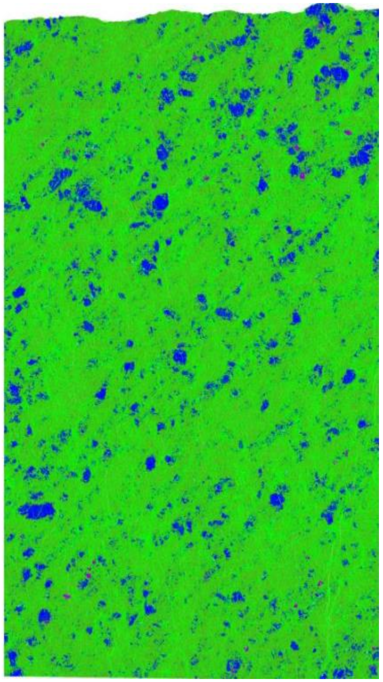
Hyperspectral unmixing

Data acquired from a serpentinized harzburgite sample

RGB image

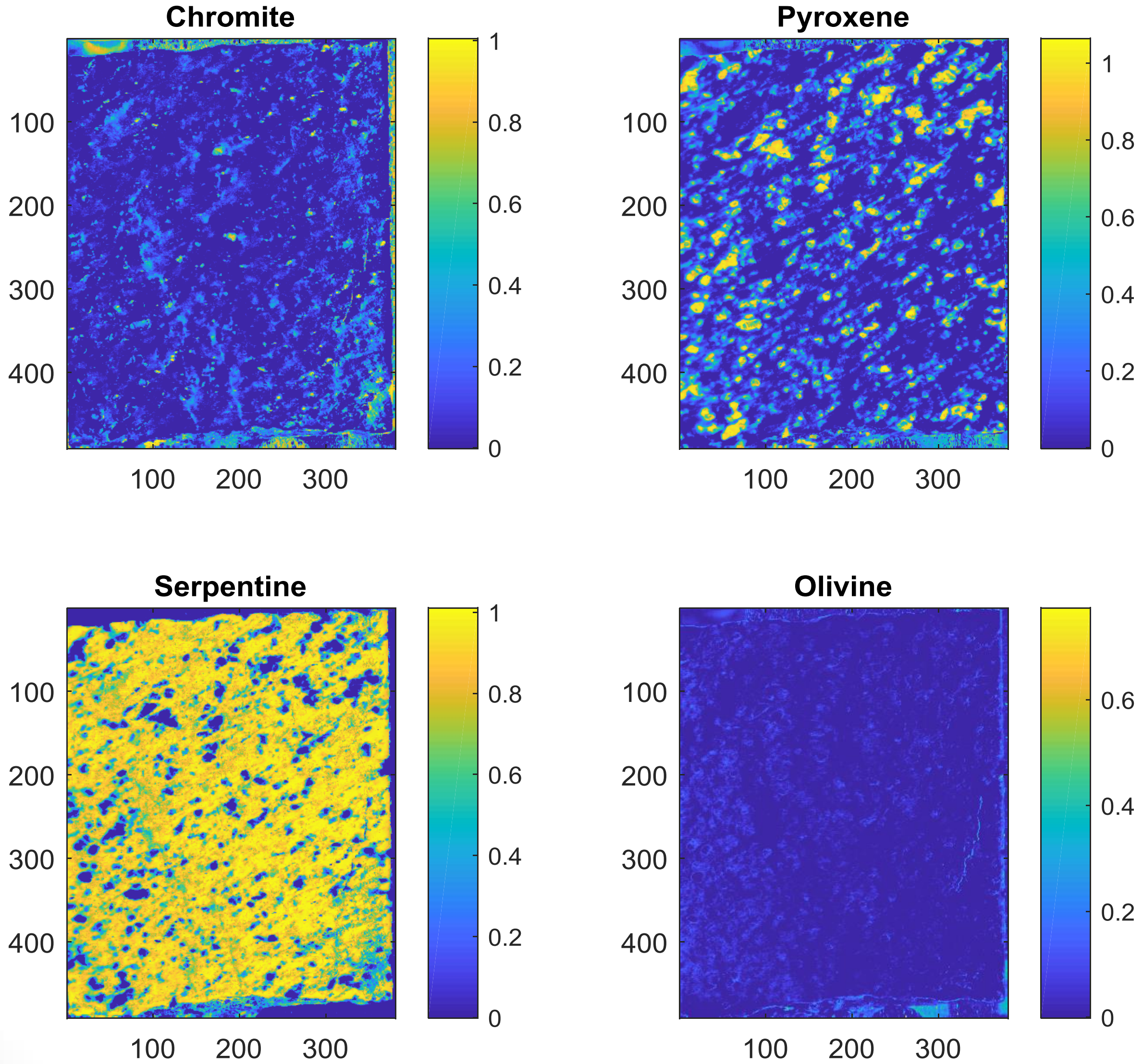


QEMSCAN results



Hyperspectral unmixing

Proportion (abundance) of each mineral:

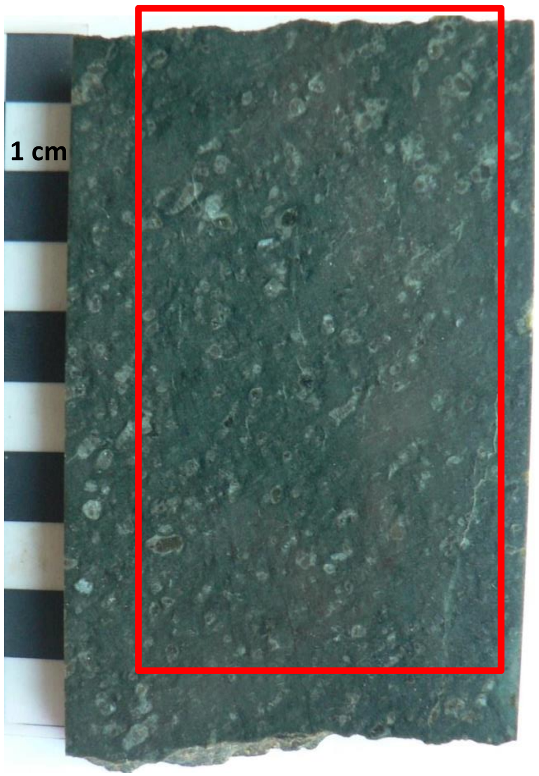


Computation time: 4 mins

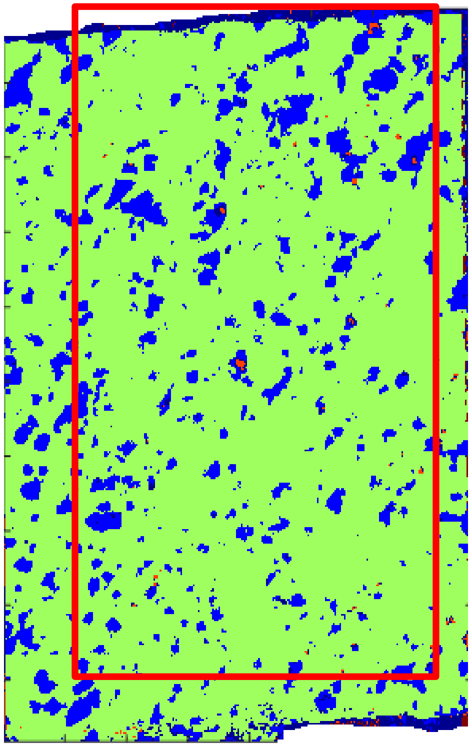
Hyperspectral unmixing

Data acquired from a serpentinized harzburgite sample

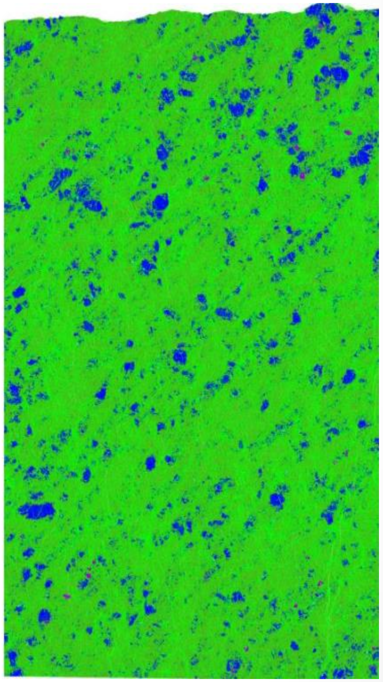
RGB image



Unmixing results



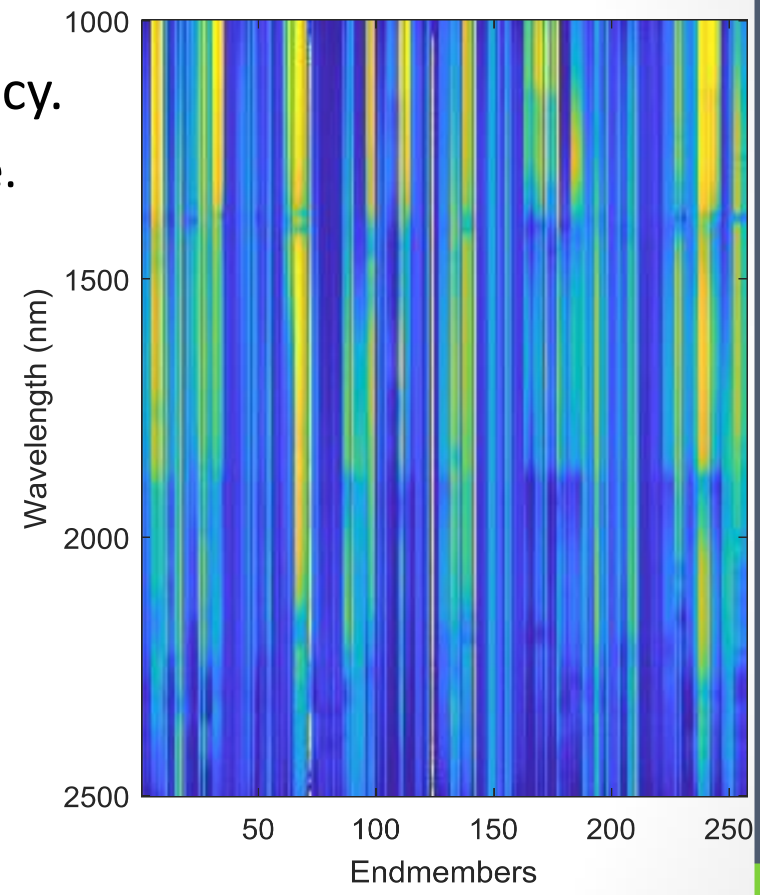
QEMSCAN results



Computation time: 4 mins

Conclusions and perspectives

- Using our hyperspectral library, the CLSUnSAL provided the highest accuracy.
  - Need to improve the computation time.
  - Incorporate the spatial context to the unmixing problem
- The library is constantly extended
  - 257 spectra have been extracted for 49 minerals
- A graphic user interface is under development
- Machine learning classification approaches have been implemented.



Thank you for your attention!

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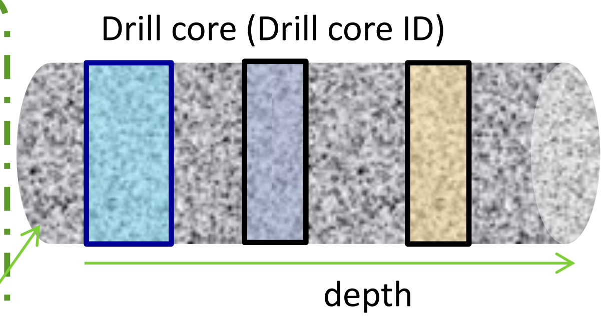
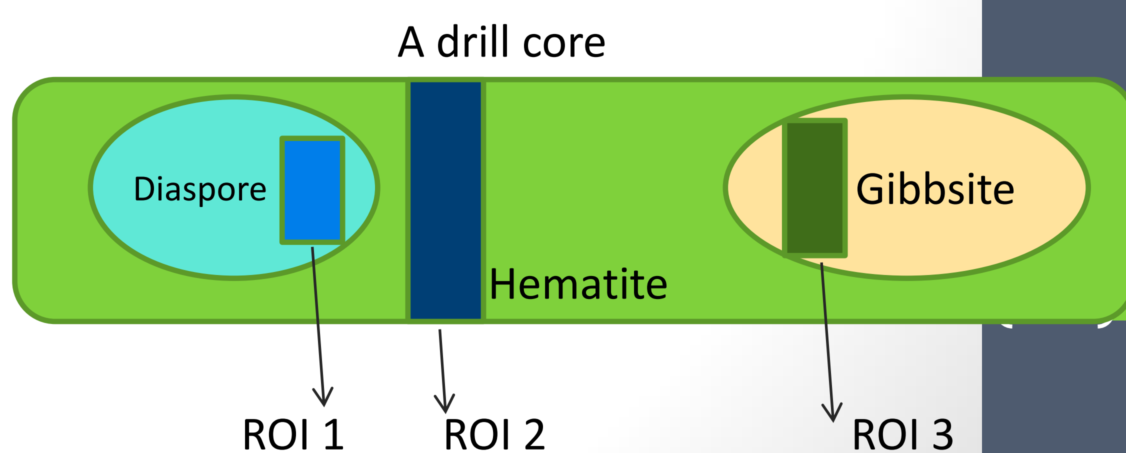
SOLSA ID B, processing	Data processing





SOLSA software

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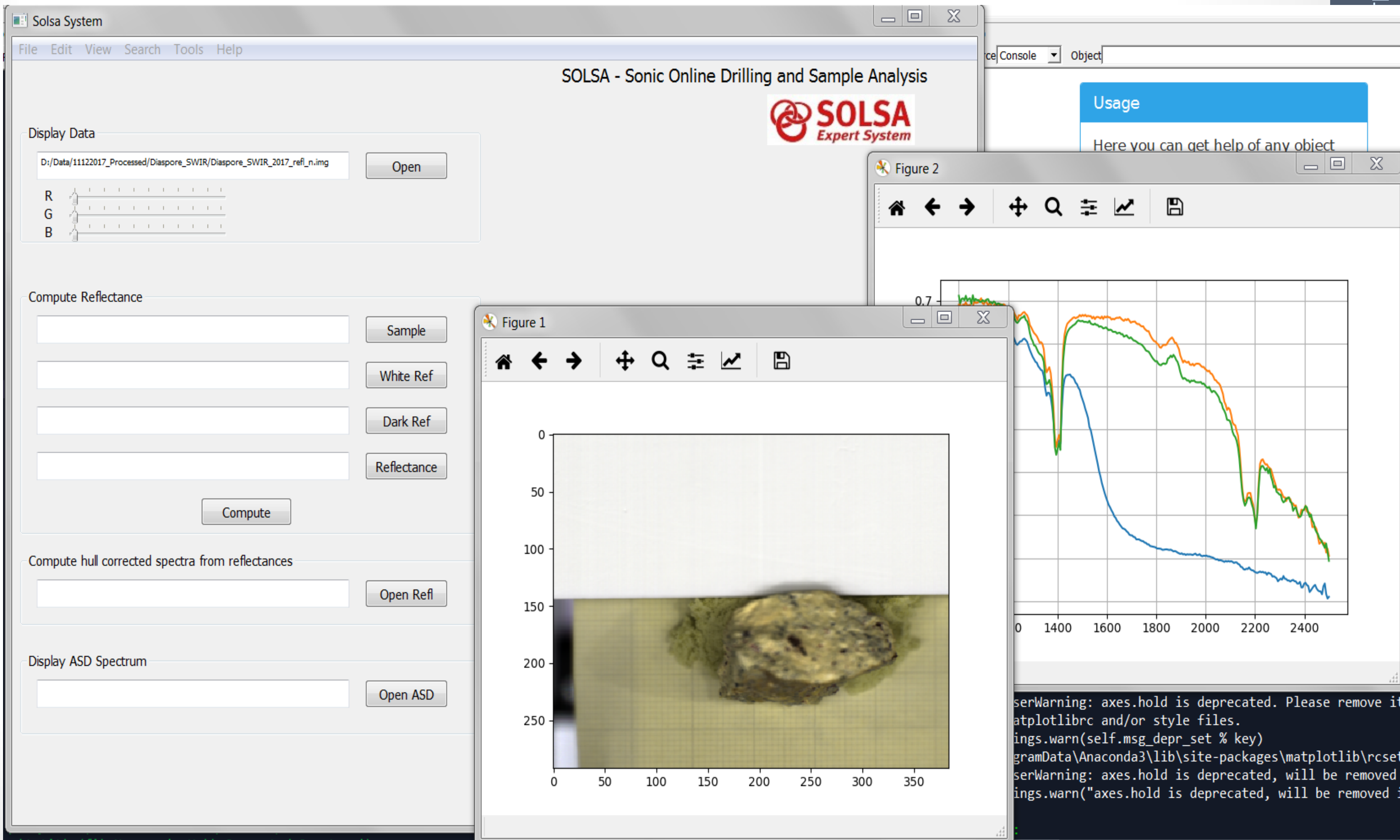


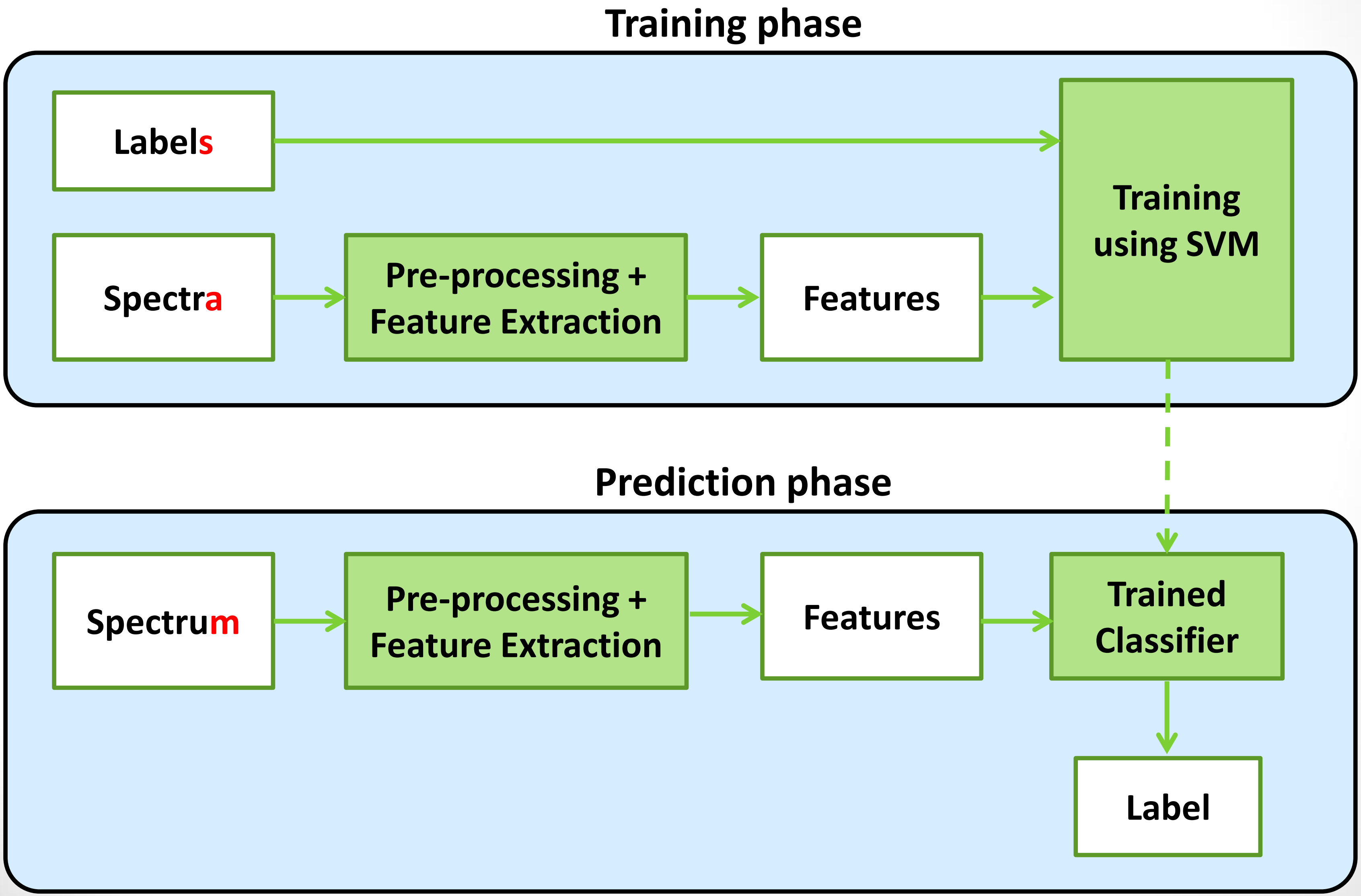
Hyperspectral classification and unmixing techniques are being integrated

SOLSA

VNIR/SWIR camera parameters

Parameters	FX10 VNIR	SWIR OLES30
Spectral range (nm)	400 - 1000	1000 - 2500
Spectral bands	224	288
Spectral FWHM (nm)	5.5	12
Spatial sampling	1024	384
FOV (degree)	38	17
Maximum frame rate (fps)	330	450
Exposure time range (ms)	0.1 – 20	0.1 – 20
Aperture	1.7	2
Focal length (mm)	15	30
Measurement distance (m)	0.118	0.316
Field of View (mm)	81.26	94.45
Spatial resolution (um)	79.36	245.97
Depth of Field (mm)	1.91	9.64

Spectral classification using machine learning techniques



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Spectral classification - results

540 samples (randomly selecting 360 for training, 180 for testing);

C-SVC, C = 100; RBF, γ = 0.999

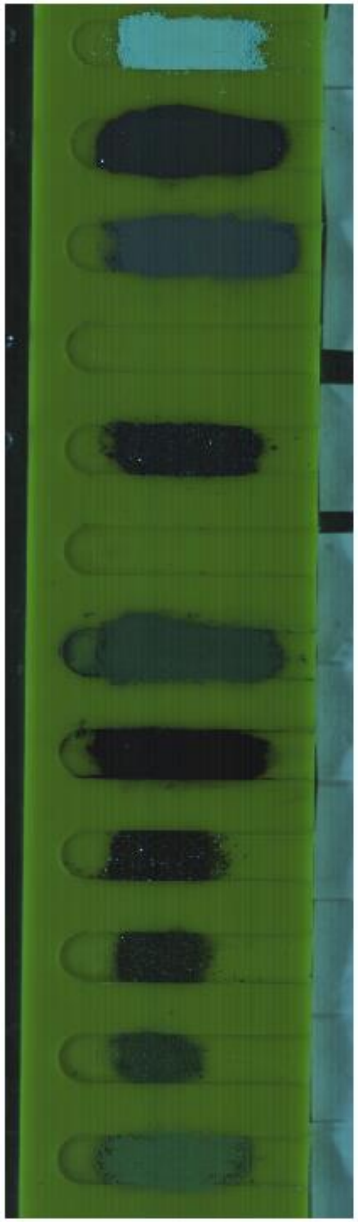
Iteratively evaluated in 50 times

Features	Training (%)	Testing (%)
SAM	99.97 ± 0.07	99.56 ± 0.60
Filtered spectra	100	99.64 ± 0.55
Continuum removal	100	98.62 ± 0.84
Filtered spectra + PCA	**99.97 ± 0.07**	**99.29 ± 0.78**
Continuum removal + PCA	99.70 ± 0.28	98.02 ± 1.08

SOLSA

Spectral classification - results

66 mm



Goethite

Hematite 2

Hematite 1

Magnetite 2

Chromite

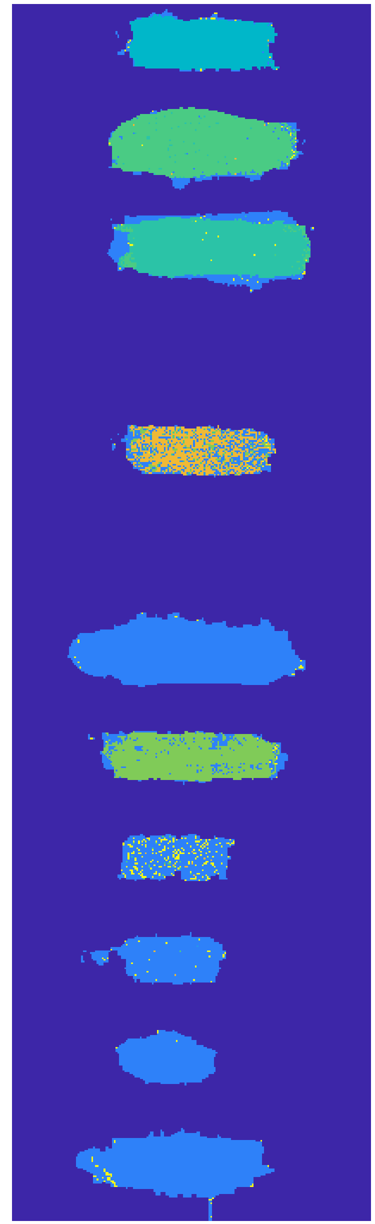
Magnetite 1

Chromite

Chromite

Chromite

Chromite



Goethite

Hematite 2

Hematite 1

Olivine,
Chromite

Chromite

Magnetite 1

Chromite

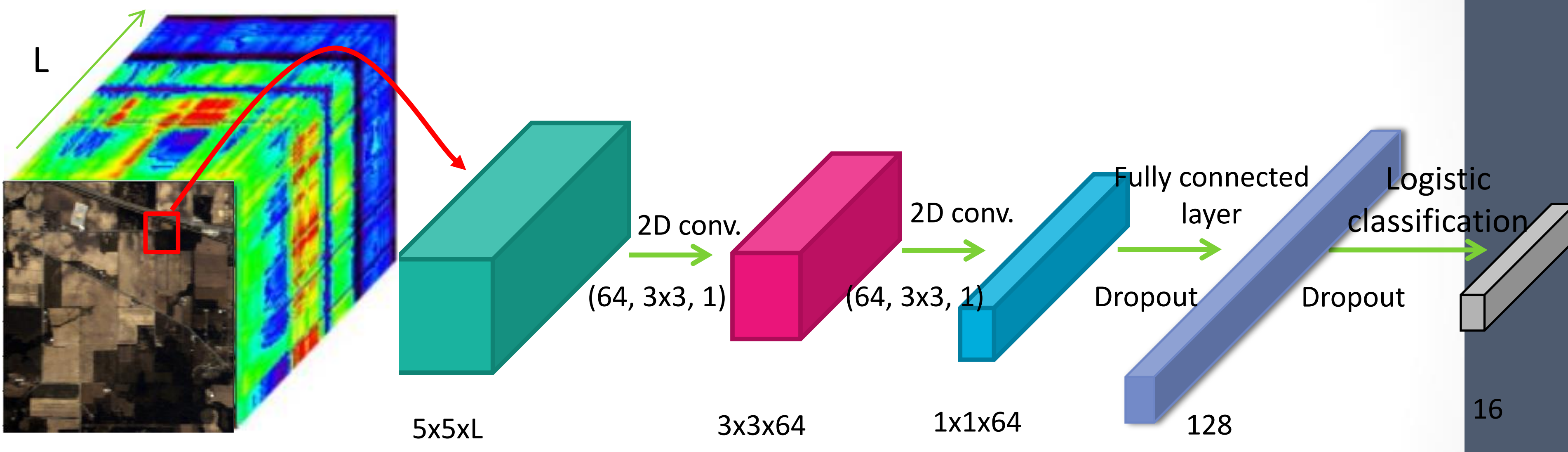
Chromite

Chromite

Chromite

Hyperspectral classification

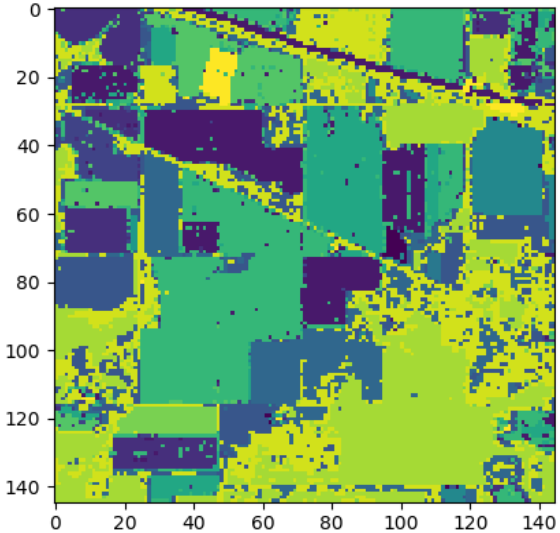
2D CNN

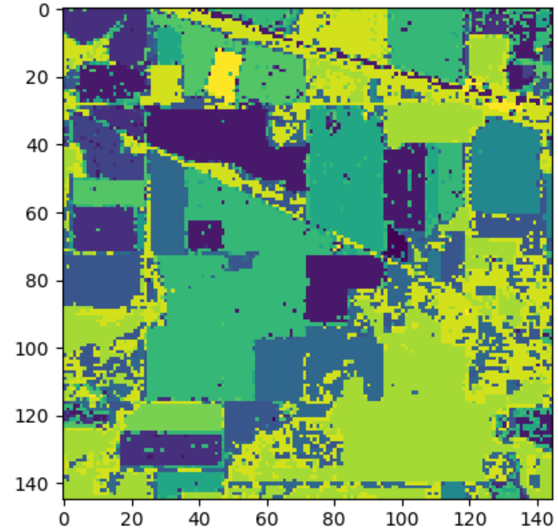


Hyperspectral classification

Random Forest:
n_estimators=500,
max_features=15,
bootstrap=False

Accuracy: 0.888

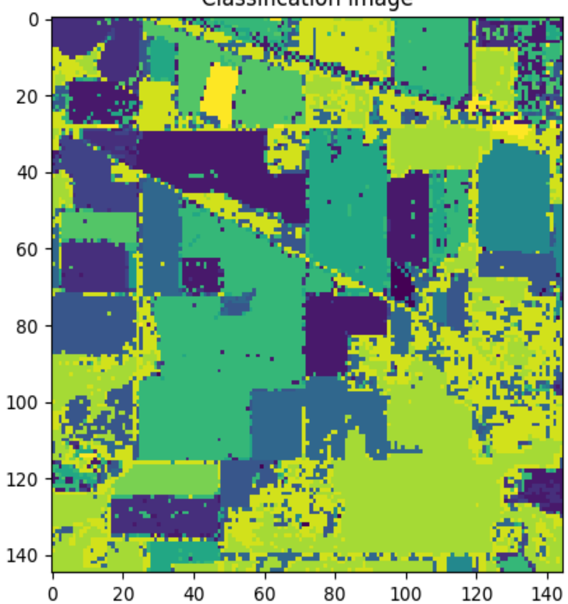




Gradient boosting machines:
n_estimators=500,
max_features=15

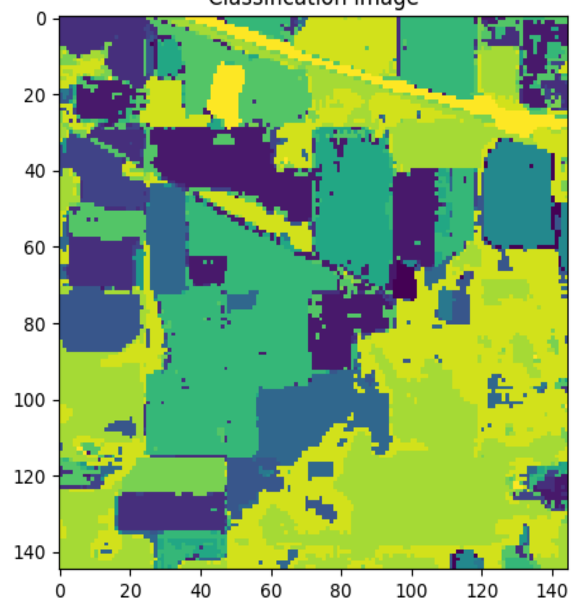
Accuracy: 0.892

Classification image



1D CNN,
Accuracy: 0.926

Classification image



2D CNN,
Accuracy: 0.953

Indian Pines scene, 224 bands from 0.4 – 2.5 um