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# Earth Observation Data for Resource Exploration and Prospecting

Birhan A. Kebede – EIT RawMaterials

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# Presentation outline

- Why Earth observation in resource exploration?
- Earth observation (EO) sensors
- EO & raw material exploration
  - Multispectral sensors
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- Hyperspectral mapping & exploration workflow
- Radiometric foundations: preprocessing
- Spectral processing techniques
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- Integration with other geoscience data
- Limitations of EO in exploration
- Takeaways

# Why Earth observation in resource exploration?

- Large area observation
- Open-source data
- Repeatable - cost effective
- Accessibility - remote and hazardous terrains

- Regional scale mineral & lithology mapping
- Structural analysis and targeting
- Quantitative abundance estimation

Complement to field, geological, geochemical and geophysical data

Used in mining, petroleum, geothermal, groundwater and environmental studies

https://www.esa.int/Enabling_Support/Operations/Sentinel-2_operations#

# Earth Observation for resources

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# Earth Observation (EO) sensors

## Widely using sensors:

**Optical/ Multispectral**
Visible & Near-Infrared

Spaceborne
Land cover, vegetation, geological mapping

**Hyperspectral**
Visible & SW-Infrared

Spaceborne + airborne
Detailed mineral identification

**Radar/ SAR**
Microwave signals

Spaceborne; Surface structures & motion

**Thermal Infrared**
Surface temperature & emissivity

Spaceborne + airborne
Surface temperature & emissivity

**LiDAR**
Laser pulses

Airborne + Drone based
High-precision elevation models

# EO & raw material exploration

Most common sensors:

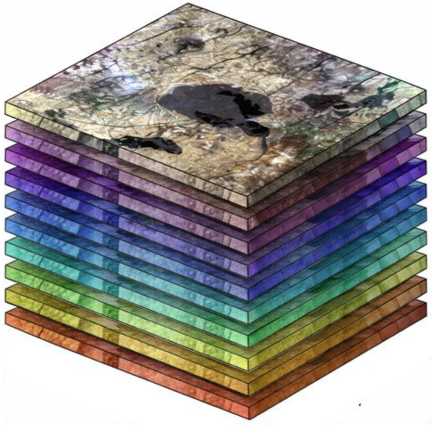
## Multispectral sensors

A few (3-14) discrete broad bands.

Lower spectral detail. (Landsat, Sentinel-2, …).

Suitable for regional reconnaissance.

Detects mineral groups/ alteration zones, lithology.



*Representation of multispectral bands.*

## Hyperspectral sensors

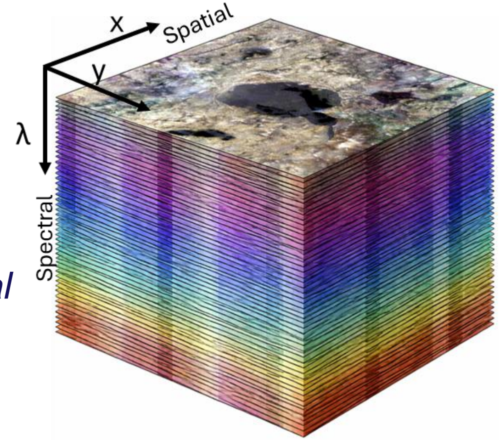
100-300+ contiguous narrow bands.

Very high spectral detail. (PRISMA, EnMAP, …).

Represented as a data cube (x, y, λ ; spatial + spectral).

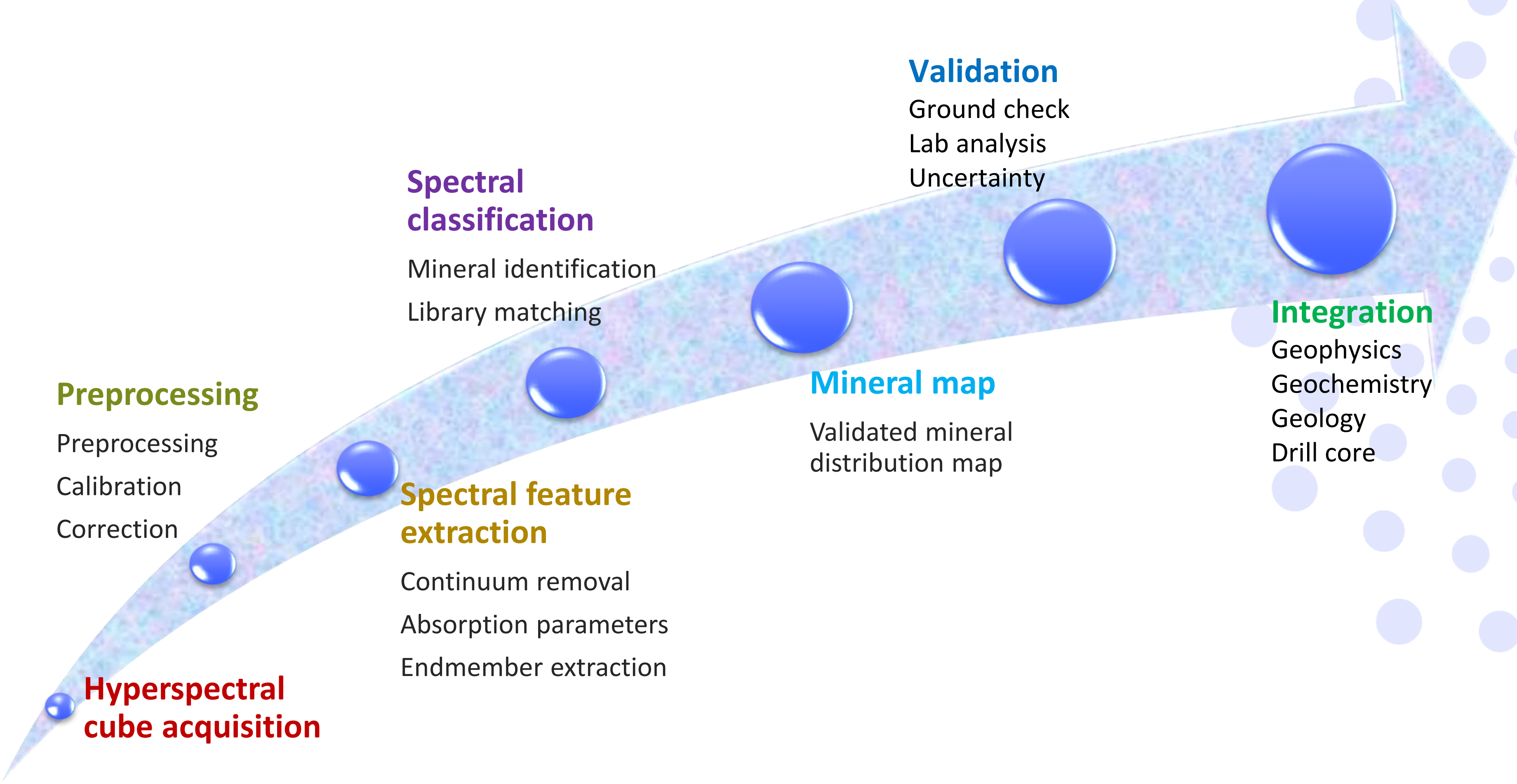
Precise characterization of absorption.

Identifies specific minerals (more powerful).




*Representation of hyperspectral data cube.*

# Hyperspectral mapping & exploration workflow



# Radiometric foundations

# Preprocessing

Earth observation relies on solar reflected and emitted (TIR) radiation.

Radiation is absorbed, scattered, emitted, and transmitted between surface, atmosphere, and sensor.

*Radiance received at the sensor* is given as:

$$L = T[E(\lambda)\cos\theta_s + E_D]\frac{R}{\pi} + L_P$$

*$L$ = radiance received at the sensor (W m⁻² sr⁻¹ μm⁻¹)*
*$E(\lambda)$ = available solar irradiance at wavelength $\lambda$*
*$\theta_s$ = solar zenith angle*
*$E_D$ = diffuse sky irradiance*
*$R$ = surface reflectance factor*
*$T$ = atmospheric transmittance*
*$L_p$ = path radiance*

*(Richards, 2013)*

Digital Number should convert to Radiance (Raw data to Physical measurement).

Digital Number (DN)⇒ Radiance

$$L = {}_kDN + Lmin \qquad k = \frac{\Delta L}{DN_{max}}$$

*$DN_{max}$ = the highest possible digital count for the sensor*
*$L_{min}$ = offset (radiance at DN = 0)*
*k= gain (radiance per DN unit)*

# Continued

Sensor radiance converted to Surface reflectance (atmospheric correction) before using the data.

*Radiance ⇒ Surface reflectance*

$$R(\lambda) = \frac{\pi\left[L(\lambda) - L_p(\lambda)\right]}{T(\lambda)\,\mathrm{E}(\lambda)\cos\theta_s}$$

*(Richards, 2013)*

Sensors measures surface reflected radiance versus wavelength to detect rock/ mineral related absorption features.

Preprocessing: Radiometric Calibration, Geometric correction, atmospheric Correction

# Spectral processing techniques

- Data products and techniques selection depends on the target material & area.

Most common techniques:

- **Band Ratios**

Enhance mineral spectral contrasts.

$$\text{Band Ratio (Br)} = \frac{\text{Reflectance of Band}_a}{\text{Reflectance of Band}_b}$$

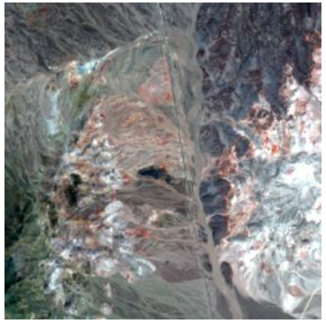
Mainly applied in mineral mapping.

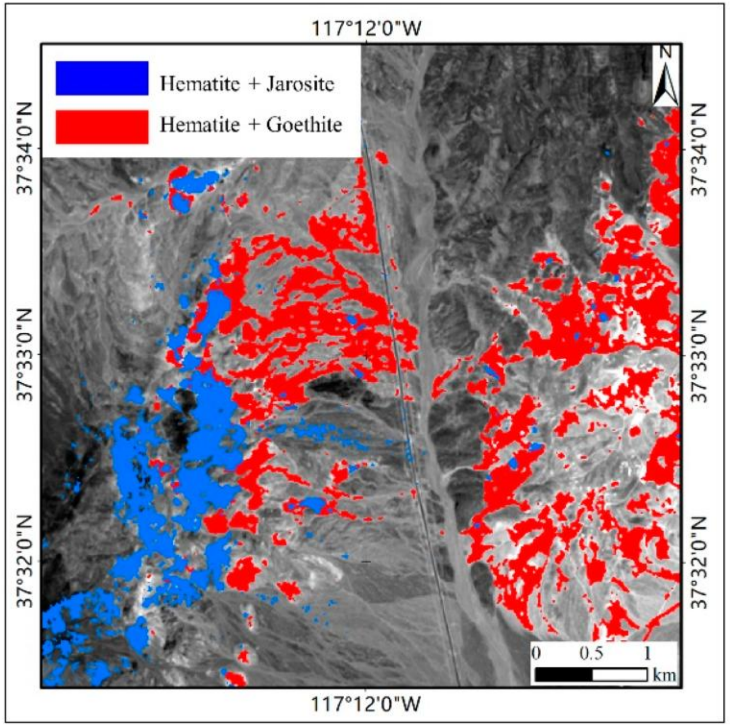
- ✓ Hydrothermal alteration,
- ✓ Iron Oxides detection,
- ✓ Lithological discrimination.

E.g., ASTER: Br= (7 + 9)/8 → Carbonate/chlorite/epidote (e.g., Van der Meer et al., 2012).

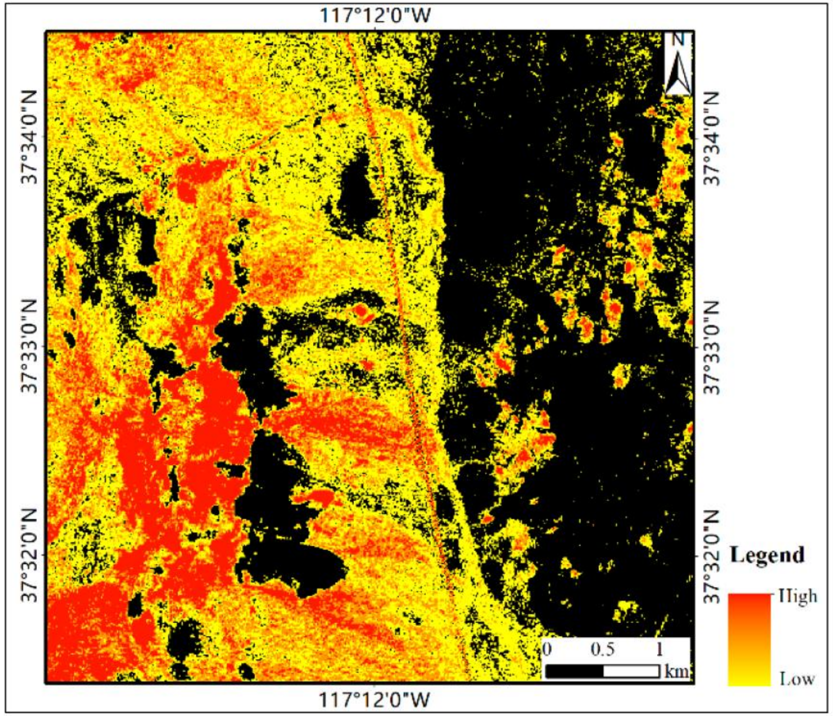
Sentinel-2: Br= band 6/band 8A → Fe- bearing minerals

# Case study











*Spatial distribution of iron minerals in the Cuprite area derived from Sentinel-2 data. (a) Band ratio computed using the original native resolution bands. (b) Band ratio derived from fused Sentinel-2 data with all bands resampled to 10 m resolution, resulting in improved spatial consistency and mineral discrimination (Ge et al., 2020).*

# Continued

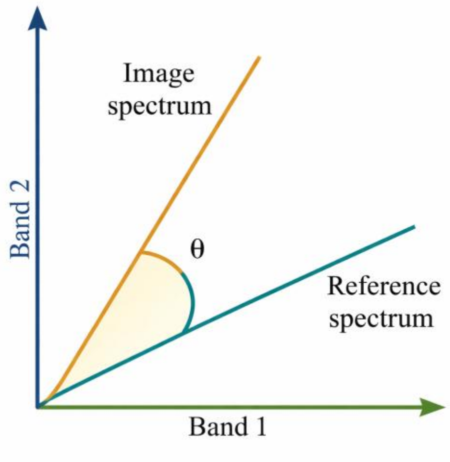
- <u>**Spectral angle mapper**</u>

Is spectral similarity classification.

Uses the angle between spectral vectors in n-dimensional space.

$$\theta = \cos^{-1}\left(\frac{\sum_{i=1}^{n} t_i r_i}{\sqrt{\sum_{i=1}^{n} t_i^2}\sqrt{\sum_{i=1}^{n} r_i^2}}\right)$$

*t = image pixel spectrum at band i*
*r = reference spectrum at band i*
*n = number of spectral bands*
*θ = spectral angle*




*Kruse et al. (1993)*

Small angle → high spectral similarity
Large angle → low spectral similarity

# Continued

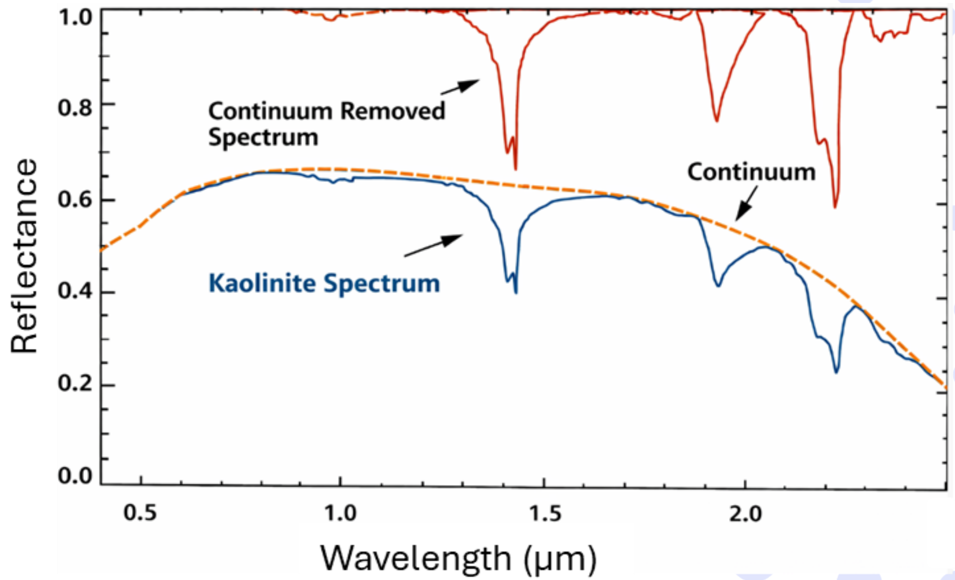
- <u>**Continuum removal**</u>

Enhances diagnostic absorption features.

Removes the overall spectral background (continuum).

The continuum (convex hull) is fitted over spectral maxima.

Allows direct comparison of absorption band position, depth, and shape between different materials or pixels.




*Reflectance spectrum with the continuum and the continuum removed spectrum modified from Kruse & Lefkoff (1999).*

**Other important techniques:** Principal Component Analysis, Advanced spectral analysis, Derivative spectroscopy, Spectral indices, and Minimum Noise Fraction.

# Machine learning for EO exploration

Common Algorithms:

- **Random Forest (RF)**

A supervised Machine Learning.

Ensemble of decision trees used to classify spectral features & predict material types.

Classifying land cover or mineral types from spectral data.

- **Support Vector Machine (SVM)**

Supervised Machine Learning .

Finds optimal boundaries between classes in feature space.

Detect mineral types or anomalies in spectral data.

- **Convolutional Neural Networks (CNN)**

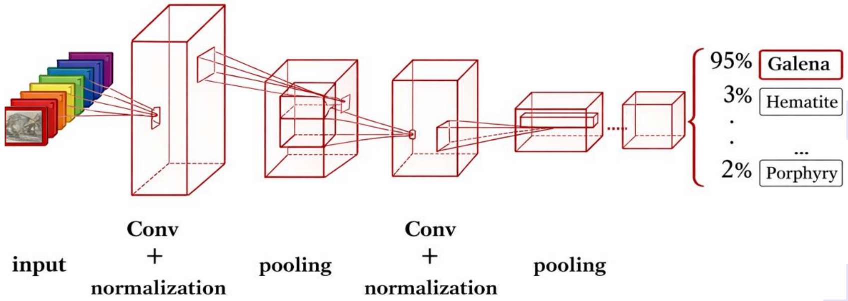
Deep Learning.

Deep models learn and extract spatial patterns from satellite images.

Uses convolutional filters to detect patterns

Detect and classify high resolution satellite images .

Detect ore deposits or lithologies & geologic structures.




*Structure of the CNN for hyperspectral data (Okada et al., 2020).*

# Spectral basis of mineral & rock detection

# Absorption feature mechanisms

Different surfaces have unique spectral reflectance curves.

Rocks and minerals show diagnostic absorption in VNIR–SWIR (0.4–2.5 μm).

Diagnostic absorption feature is controlled by mineral chemistry and structure.

**Electronic Processes**

- VNIR Region (0.4 – 1 μm)
- Transition metal ions
  E.g., ($Fe^{2+}$, $Fe^{3+}$, $Mn^{2+}$); $Fe^{2+} \rightarrow Fe^{3+}$
- Absorption features: Iron-bearing minerals (e.g., oxides, mafic silicates)

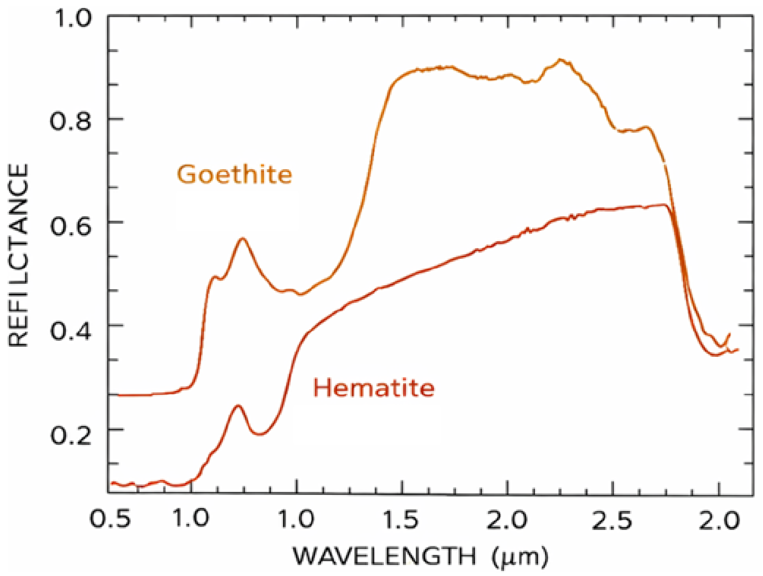
**Electronic Processes**

- SWIR Region (1 – 2.5 μm)
- Molecular bonds and anions
  E.g., $H_2O$, $OH^-$, $CO_3^{2-}$, $SO_4^{2-}$
- Absorption features: clays, carbonates, hydroxyl minerals (e.g., Van der Meer et al., 2012).

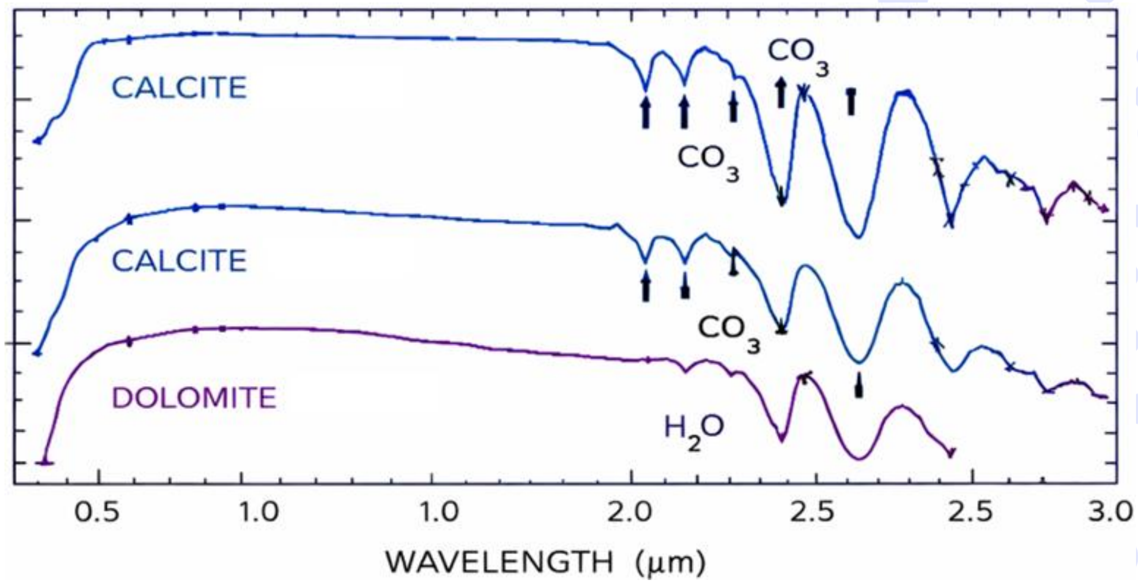
Absorption feature parameters (center, depth, width, asymmetry) → composition ⇔ abundance ⇔ grain size ⇔ mixing.

# Continued

## Case study




*Reflectance spectra of the Fe-oxide due to electronic process*




*Reflectance spectra of minerals showing vibrational bands due to OH, CO3 and H2O.*

*Modified from Clark et al. (1990)*

# Interpretation

## Diagnostic Absorption Features:

Appear as dips in reflectance spectra

Wavelength position ⇒ mineral type

Depth/shape ⇒ abundance or composition variation

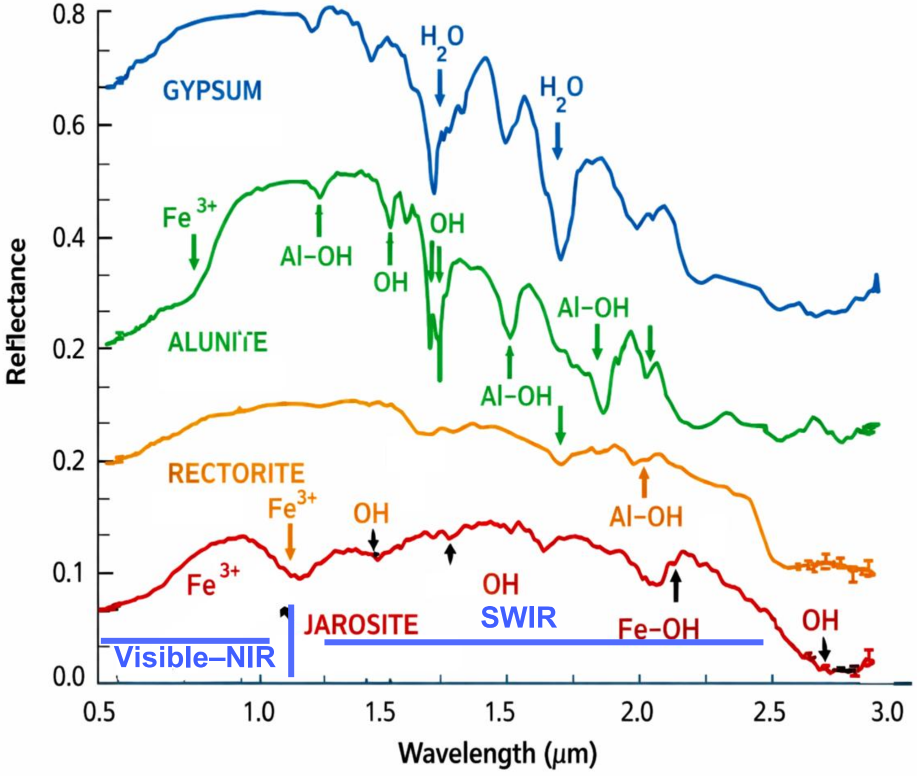
## Main Spectral Regions:

Visible–NIR (0.4–1 μm): Fe-minerals (hematite, goethite).

SWIR (1–2.5 μm): Clays, carbonates, hydroxyl minerals (kaolinite, illite, smectite, chlorite, calcite).

Clay alteration detection (SWIR OH absorption).

(argillic, phyllic, propylitic alteration zones).



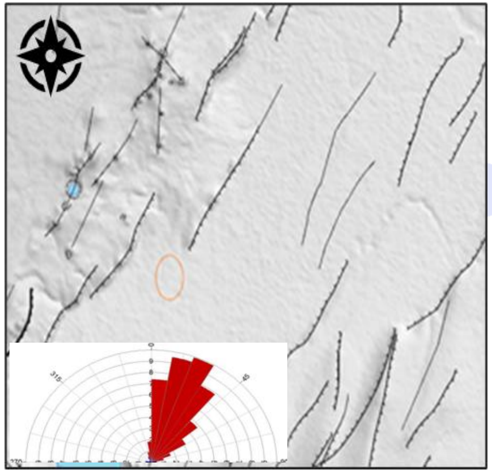

*A case study illustrating the reflectance spectra of selected minerals in the VNIR–SWIR region, showing diagnostic absorption features associated with water ($H_2O$), hydroxyl (OH), Al–OH, Fe–OH, and $Fe^{3+}$. Modified from Clark et al. (1990).*

# Structural mapping from EO

- ✓ Structural detection supports targeting.
- ✓ Faults, fractures, and shear zones facilitate fluid flow and mineralization.

## Main data sources:

- Optical imagery
- SAR (hidden fractures & weather effects)
- Digital Elevation Models (DEMs)
- LiDAR



*A map showing faults digitized on the DEM*

*Minerals infilling the fractures (vein)*

*Field photograph of a fault*

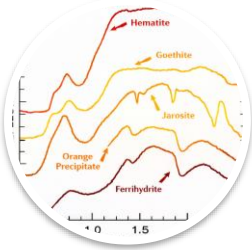
## Mapping techniques (selection):

- Manual digitization
- Hillshade DEM analysis, slope, roughness
- Hough Transform
- Edge detection

✓ Integrated structural + mineral/ alteration mapping = improves exploration success.

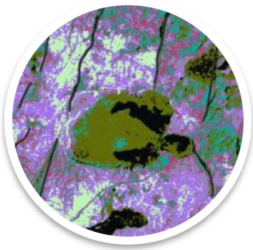
# Validation of EO mapping

**Field check**




**Standard spectral libraries**
(USGS, JPL)

**Lab analysis**
Petrography, XRD



**Existing maps & data**

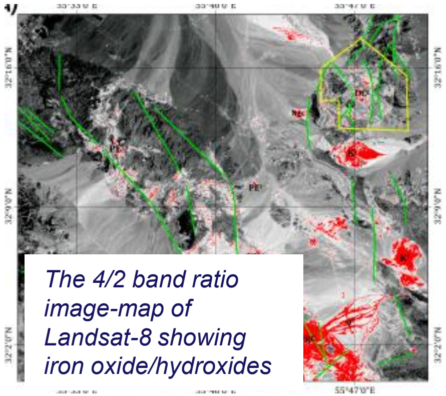
**Uncertainty evaluation**

# Case study

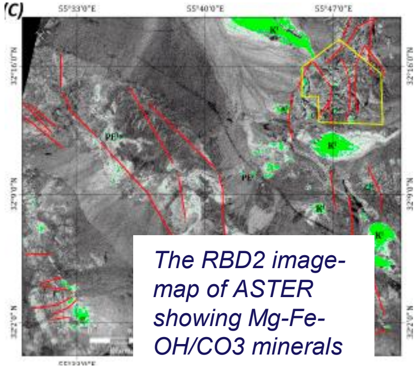
Multisource satellite data, including Landsat-8, Sentinel-2, ASTER and WorldView-3 satellite data used to map hydrothermal alteration and lithology for carbonate hosted Pb–Zn prospectivity in Iran.

It applies specialized band ratios and principal component analysis (PCA) to extract mineral spectral features and fuses thematic layers via fuzzy logic.

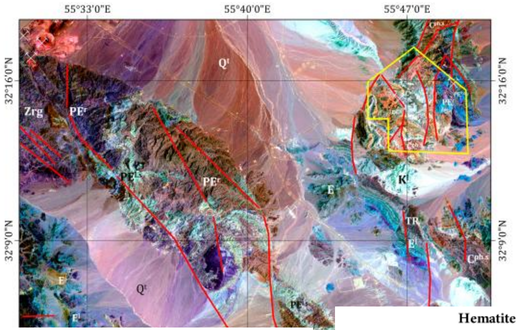
Prospectivity maps were validated with fieldwork, laboratory analysis and a confusion matrix, showing effective remote sensing mineral targeting (Sabeti et al., 2020).



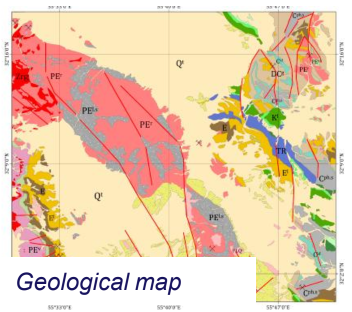
The 4/2 band ratio image-map of Landsat-8 showing iron oxide/hydroxides



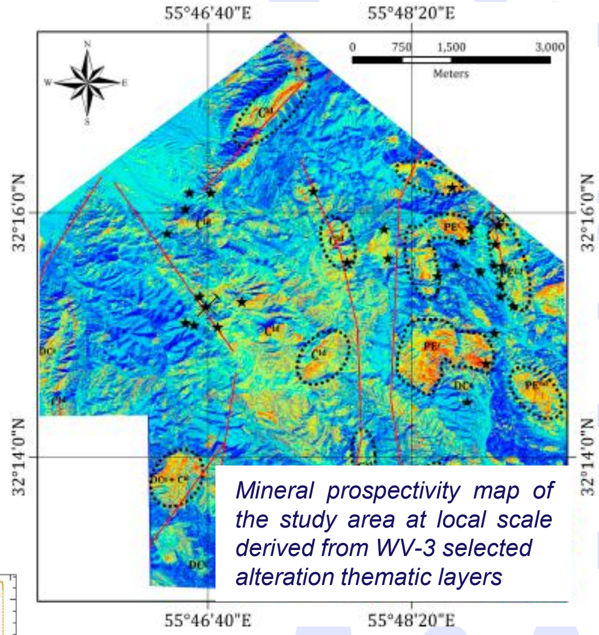

The RBD2 image-map of ASTER showing Mg-Fe-OH/CO3 minerals



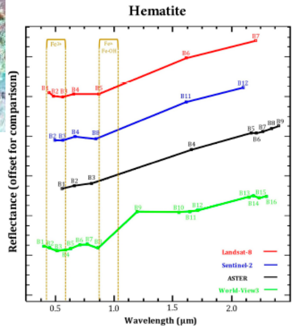

RGB false color composite of bands 2, 8 and 12 for Sentinel-2 show lithological units and alteration zones

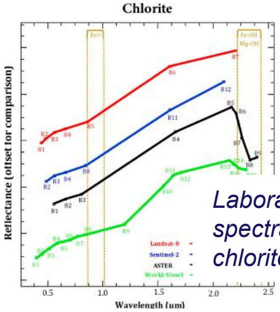


Geological map




Mineral prospectivity map of the study area at local scale derived from WV-3 selected alteration thematic layers



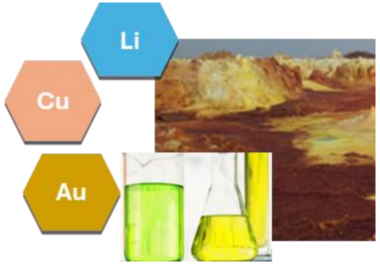

Laboratory reflectance spectra of hematite and chlorite

# Integration with other geoscience data

- **Results of EO must be integrated with:**

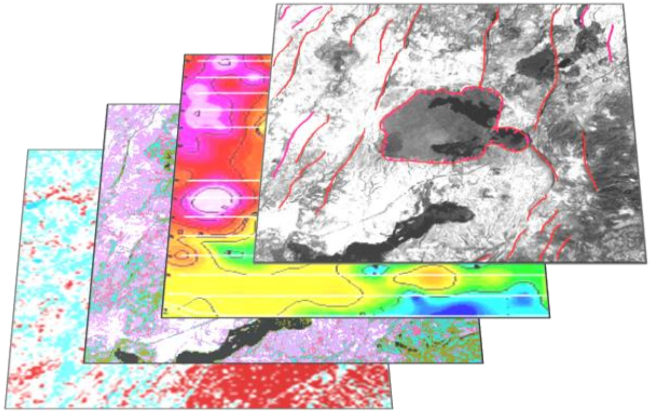
Geophysics (e.g., magnetic, resistivity, gravity)

- Detects alteration zones
- Anomalous mineralization
- Subsurface structures




Geochemistry (stream, soil, rocks, groundwater)

- Alteration minerals
- Minerals anomalous background
- REE concentration



**EO analysis**
**Geophysics anomalies**
**Geochemistry anomalies**
⇓
**prospectivity model**
⇓
**Ranked targets**

Geology (sampling; pitting, trenching)

- Tectonic framework
- Lithology
- 3D geological and prospectivity models
- Depth estimation

# Limitations of EO in exploration

Dense vegetation cover

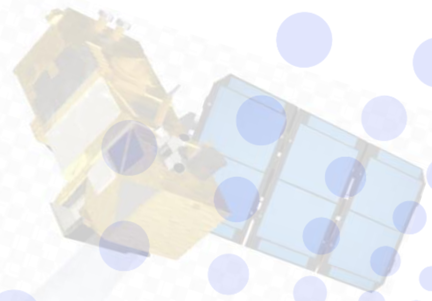
Weathering and soil masking: thick soil cover targets

Atmospheric effects: cloud cover and seasonal effects

Mixed pixels: materials spectral similarity

Need for ground validation: geophysics, geochemical sampling geological mapping, drilling

# Takeaways



EO provides surface indirect observations of the ground

EO is a first pass exploration tool

Ideal for first to intermediate level of raw material exploration

Multispectral and hyperspectral data are the most powerful techniques in exploration

EO adds the greatest value at regional screening and target ranking stages

Spectral similarity does not imply unique mineralogical solutions

Strong complement to ground surveys

Success depends on integration, validation, and uncertainty evaluation

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# Questions & Answers

## Contact Details

Birhan A. Kebede

birhank00@gmail.com

Michele Rubino

Michele.rubino@eitrawmaterials.eu

Fierce space project website

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