



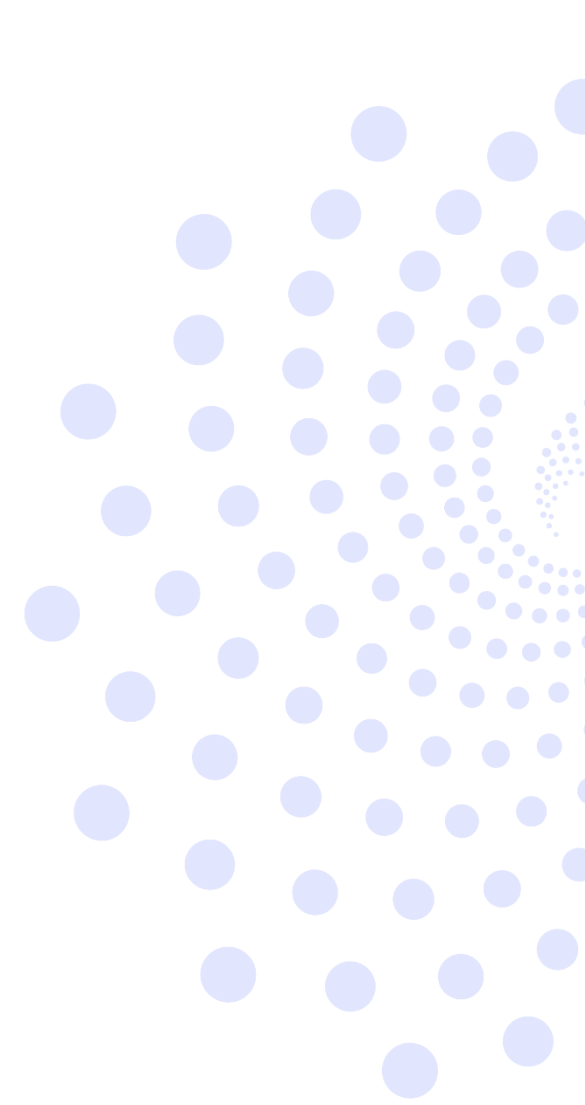
# Advanced remote sensing techniques and data integration for raw materials

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# Presentation outline

- Remote sensing techniques
  - Multispectral
  - Hyperspectral
  - Thermal Infrared (TIR)
  - SAR (Synthetic Aperture Radar)
  - LiDAR
- Data integration
  - Data integration techniques
    - Pixel level fusion
    - Feature level fusion
    - Decision level fusion
  - Classification
- Takeaways



# Advanced Remote Sensing for raw materials

## Why it works

- Diagnostic mineral signatures
- Repeatable coverage
- Cost effective regional mapping
- Multi sensor data integration (optical, SAR)
- Supports sustainability goals

## Advanced Remote Sensing

Multidimension raw material intelligence

spectral • structural • temporal

## Value delivered

- Structural controls detection
- Spectral contrast of minerals
- Spatial continuity
- Reduced uncertainty & risk
- Better targeting & decision making
- Complements geoscience data

## Constraints

- Geological complexity
- Surface masking (cover)
- Limited surface exposure
- Data uncertainty

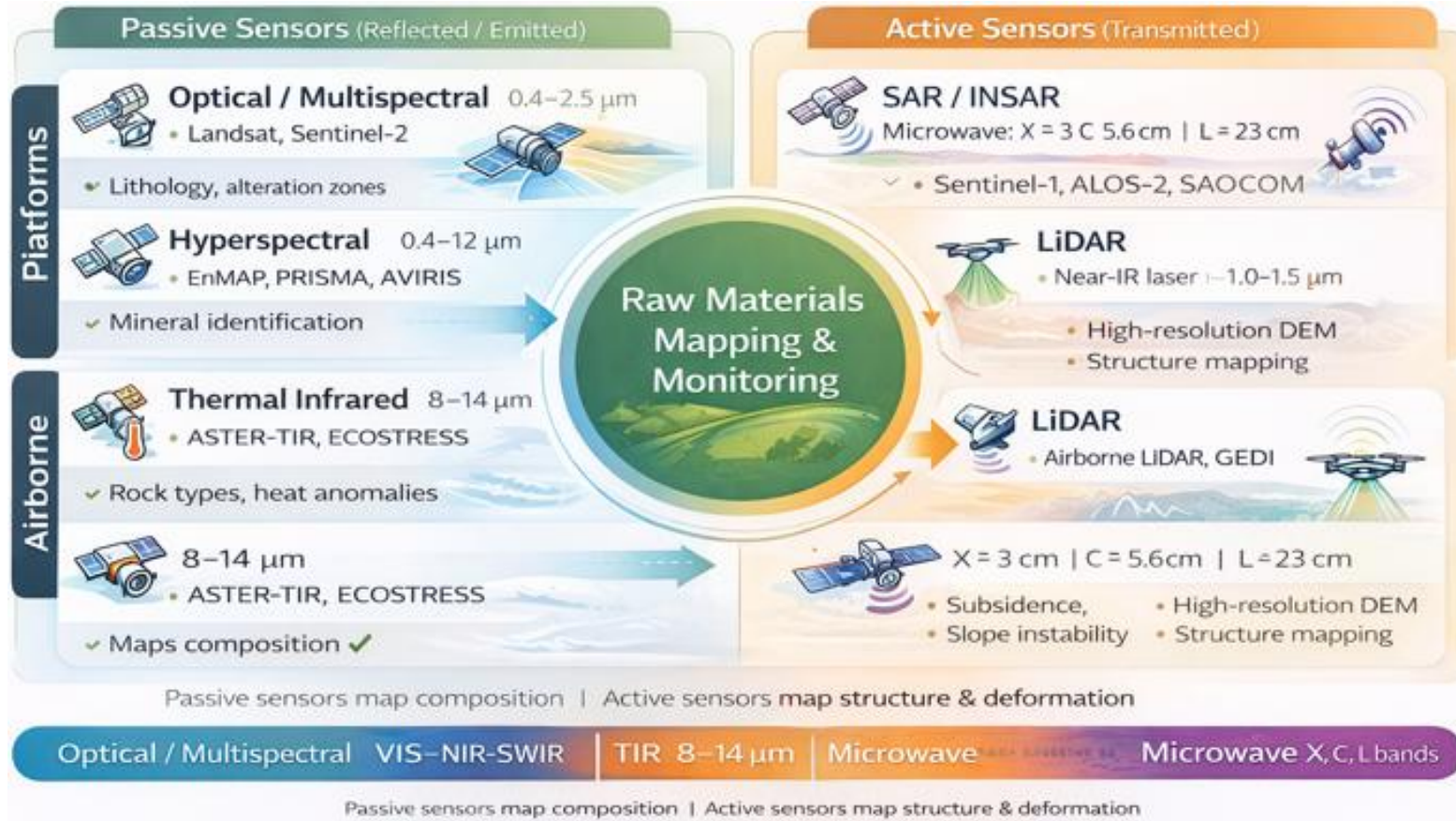
Regional screening → Targeting → Monitoring

Remote sensing transforms raw material exploration by enabling integrated and low risk decision making



# Remote sensing techniques

Advanced remote sensing technique  $\Rightarrow$  the use of modern technologies to collect detailed information about the Earth remotely.  
 Information  $\Rightarrow$  physical, structural, and temporal



Summary of common Earth observing sensors applied in raw materials.

# Multispectral

Uses wavelength: 0.4–2.5  $\mu\text{m}$  (VNIR/SWIR).

3–13 spectral bands.

Widely used sensors in various fields.

Measures reflected solar radiation from the Earth's surface.

The energy interaction at surface is given by:

$$E_i = EA + ER + ET$$

Where:

$E_i$  = energy incident

$E_A$  = component of incident energy absorbed

$E_R$  = component of incident energy reflected

$E_T$  = component of incident energy transmitted

At Sensor Radiance, the total spectral radiance measured by the sensor (multispectral and hyperspectral)

$$\longrightarrow L = \frac{\rho ET}{\pi} + L_p$$

Applied for:

- ✓ For lithology mapping
- ✓ Hydrothermal alteration zoning mapping

Example:

Sentinel-2 (10–20 m spatial resolution)

Landsat-7/8/9 (30 m spatial resolution)

ASTER (15–30 m spatial resolution)

Where:

$L$  = total spectral radiance measured by the sensor

$\rho$  = surface reflectance

$E$  = irradiance on object

$T$  = atmospheric transmission

$L_p$  = path radiance (scattered by atmosphere)

(Lillesand et al., 2004)

# Hyperspectral

Measures reflected solar radiation.

Uses 0.4–2.5  $\mu\text{m}$  (VNIR–SWIR)

100–300+ spectral bands.

Narrow bands provide detail analysis of minerals.

- ✓ Detailed mineral identification Compositional analysis (minerals & rocks)
- ✓ Alteration mapping
- ✓ Monitoring (mining)

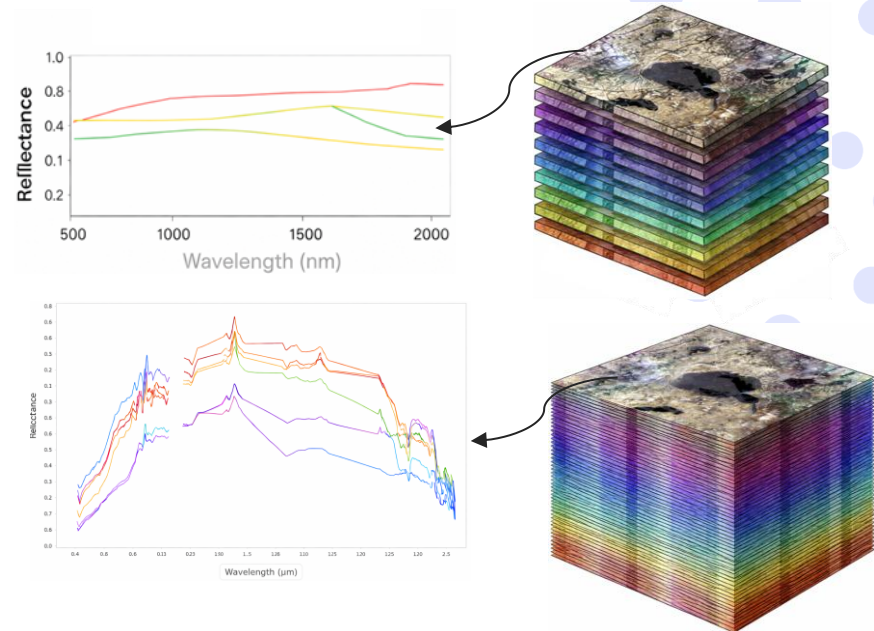
Example:

PRISMA (30 m spatial resolution), ~240 bands

EnMAP (30 m spatial resolution), 244 bands

More sensors: EMIT, AVIRIS, HyMap (air born).

- ✓ SWIR is critical for minerals identification
- ✓ Spectral libraries (e.g., USGS) check



*Representations of multispectral (Sentinel-2) and hyperspectral (PRISMA) reflectance processed on ERDAS Imagine and SNAP GIS software.*

# Thermal Infrared (TIR)

Measures emitted radiation from the Earth due to temperature.

Using TIR bands (8–12 μm); 1–5 spectral bands .

The spectral radiance of a black body at temperature T (K) and wavelength (λ) is given as:

$$B_{\lambda}(T) = \frac{C_1}{\lambda^5 \left[ \exp\left(\frac{C_2}{\lambda T}\right) - 1 \right]}$$

Where:

$B_{\lambda}(T)$ : Spectral radiance of a blackbody at λ and T

T: Absolute temperature (Kelvin)

λ: Wavelength

$C_1 = 2hc^2$ : First radiation constant

$C_2 = hc/k$ : Second radiation constant

h: Planck's constant

c: Speed of light in vacuum

k: Boltzmann constant

Applied for:

- ✓ For surface temperature,
- ✓ Lithology (Mafic/ultramafic) mapping
- ✓ Mineral mapping (sensitive to silicates)
- ✓ Atmospheric gas monitoring

The infrared radiance received by a sensor at the top of the atmosphere (TOA) can be written as:

$$L_i(\theta, \varphi) = R_i(\theta, \varphi)T_i(\theta, \varphi) + R_{\text{at}\uparrow}(\theta, \varphi) + R_{\text{sl}\uparrow}(\theta, \varphi)$$

Where:

$L_i(\theta, \varphi)$ : Radiance measured by the sensor at the top of the atmosphere in spectral channel

$R_i(\theta, \varphi)$ : Surface leaving radiance in spectral channel

$T_i(\theta, \varphi)$ : Atmospheric transmittance along the sensor line of sight

$R_{\text{a},i}(\theta, \varphi)$ : Atmospheric thermal emission radiance

$R_{\text{s},i}(\theta, \varphi)$ : Atmospheric path scattered radiance

θ: Sensor zenith angle

φ: Sensor azimuth angle

i: Spectral channel (band index) (Li *et al.*, 2013).

Example:

Landsat 7/8 TIR (60–100 m spatial resolution).

ASTER TIR (90 m spatial resolution).

Sentinel-5P

# SAR (Synthetic Aperture Radar)

Measures backscattered microwave energy transmitted by the sensor. Expressed as:

Uses microwave; X, C, L bands (3 cm, 5.6 cm, 23 cm).

Penetrates through vegetation & clouds (X-band = lower penetration; L-band = higher).

The physical measurement process can be stated as:

$$P_r = \frac{P_t + G_t G_r \lambda^2 \sigma}{(4\pi)^3 R^4}$$

$$\sigma = \sigma^0 \cdot A$$

Show the image  
representation of SAR data

Where:

$P_r$  = received power

$P_t$  = transmitted power

$G_t/G_r$  = transmit/receive antenna gains

$\lambda$  = wavelength

$R$  = range (distance to target)

$\sigma$  = radar cross section (backscatter strength)

$\sigma^0$  = normalized radar backscatter

$A$  = ground area

(Curlander & McDonough, 1991)

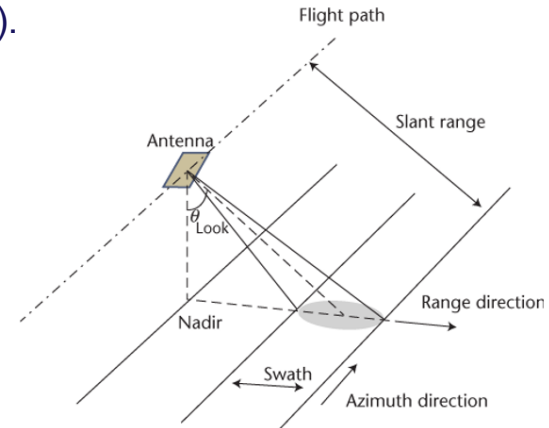


Illustration of Radar geometry (NASA).

- ✓ Applied for:
- ✓ Structural mapping (fracture network).
- ✓ Deformation monitoring (subsidence, slope instability).

Example sensors:

Sentinel-1 (C-band, 10 m spatial resolution)

COSMO-SkyMed (X-band, 3 cm)

TerraSAR-X (X-band, 1–3 m)

# LiDAR

LiDAR (Light Detection And Ranging) is an active laser scanning instrument.

Near-infrared (905–1550 nm).

Measures range via time of flight.

Generates high density 3D point clouds.

Applied for:

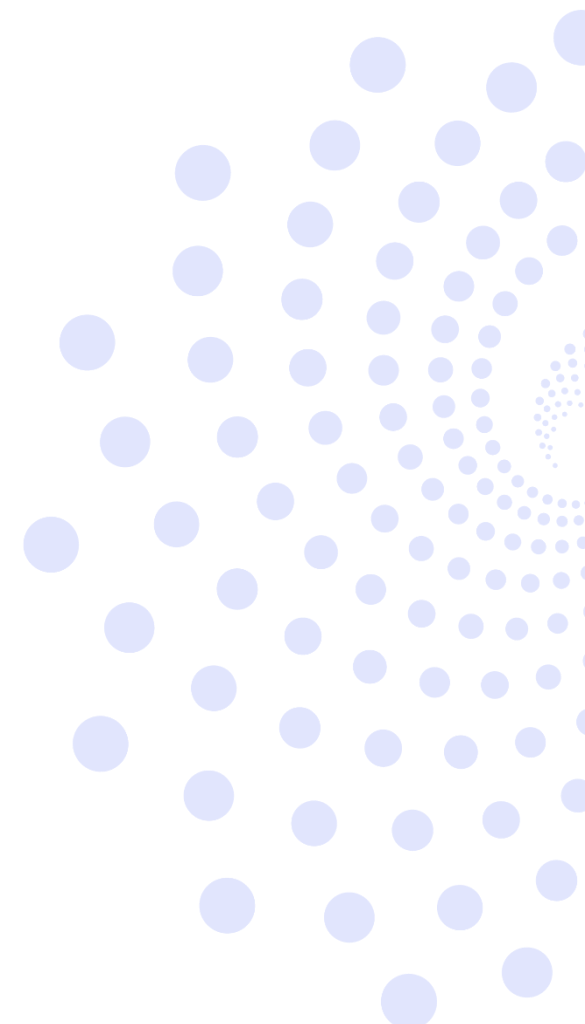
- ✓ Structure extraction/ lineaments.
- ✓ Lithological boundaries.
- ✓ Drainage extraction
- ✓ Slope stability (monitoring).

Characteristics of UAV & Drone based LiDAR:

- ✓ High spatial resolution (cm level)
- ✓ Site specific exploration
- ✓ Suitable for rapid mine site monitoring



LiDAR drone. Source: <https://www.gpsworld.com/>



# Remote sensing along the raw materials value chain





# Data integration

# Why data integration?

Data integration is an important step in remote sensing due to limitations on:

➤ Sensor

Absence of signals

Noise

Geometric distortions...

➤ Data

Spectrally ambiguous materials

Overlapping spectral signatures

➤ Target complexity

Faults, fractures

Lithological complexity

Slope effect

➤ Environment and seasonal changes

Clouded, vegetation cover

atmospheric issues

These limitations can be mitigated through data fusion / integrations



# Data integration techniques

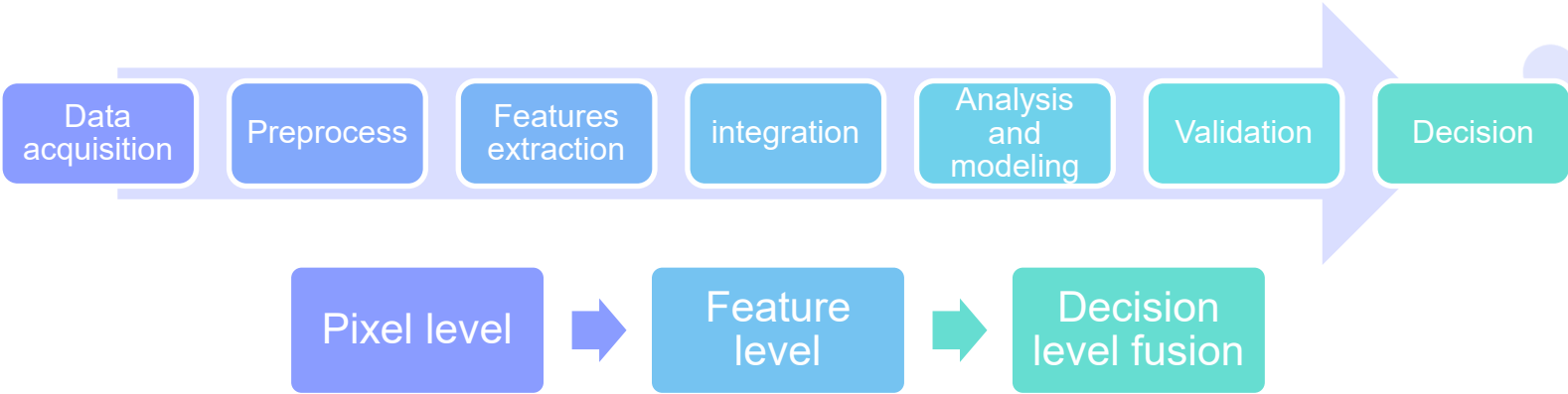
Data integration/ fusion  $\Rightarrow$  a process of combining multi source data using advanced techniques.  
Used to enhance information quality and support robust decision making.

Data fusion = image 1 + Image 2 + Image n....



Processing levels of data fusion:

**Pixel level, Feature-level, and Decision-level fusion** (e.g., Pohl & Van Genderen, 1998).



# Pixel level fusion

Fusion between the raw raster data of different sensors into a single new. (Beginning level data processing)

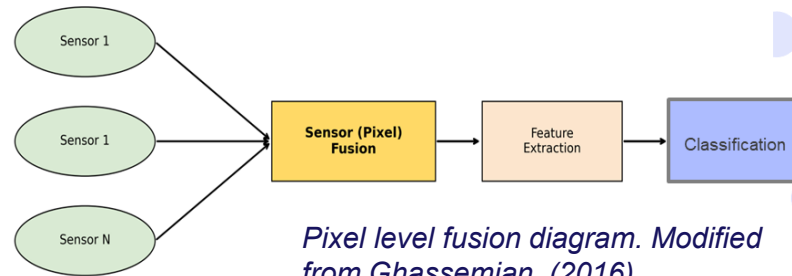
Works with: **Radiance / reflectance values** ➔ **Enhanced, sharpened and geometrically improved data**  
**Backscatter values and**  
**Elevation grids**  
(Improved spatial & spectral quality).

Uses signal processing algorithms.

## Common techniques

❖ Principal component analysis: a statistical technique transforms correlated image bands into uncorrelated components.

❖ High pass filter: Inject high frequency spatial details from a high resolution image into multispectral data.



❖ Brovey transform: high resolution panchromatic lower resolution multispectral ratio based image fusion technique to enhances spatial resolution.

# Case study

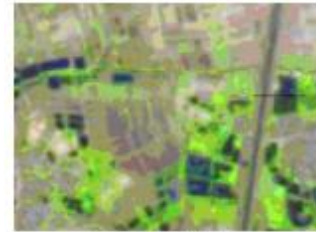
Pixel level fusion:

The purpose of monitoring evolution of mining-induced subsidence using fused high resolution imagery.

- High resolution PAN image
- Multispectral image
- Low-resolution SPOT & TM images
- Fusion using multi-band wavelet + RGB feature technique.

Resulted

- ✓ improved spatial resolution
- ✓ Enhanced image clarity
- ✓ Preserved spectral information
- ✓ Better visual detection of subsidence areas
- ✓ Effective monitoring of mining induced ground deformation. (Liang jun et al2024)



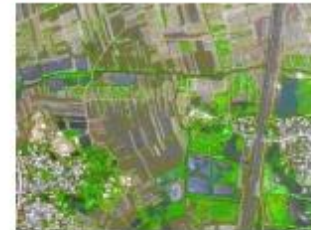
(a) Original TM images



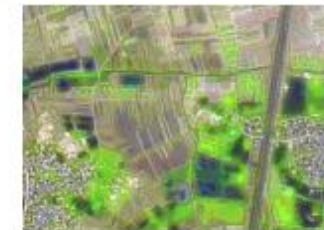
(b) Original SPOT-PAN images



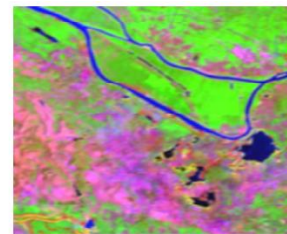
(c) Result images by HIS method



(d) Result images by binary wavelet transform in combination with RGB method



(e) Result images by multi-ary wavelet transform in combination with RGB method



(a) Original TM 2,3, and 4 images in 1987 in Kongji coal mine-Bagongshan-Caijiagang area



(b) SPOT-PAN image in 2004 in Kongji coal mine- Bagongshan-Caijiagang area



(c) Image fused with the multi-ary wavelet method

# Feature level fusion

At intermediate level data processing technique before classification.

Fuses extracted specific features from sensors  
(e.g., edges, lineaments, texture, spectral indices)



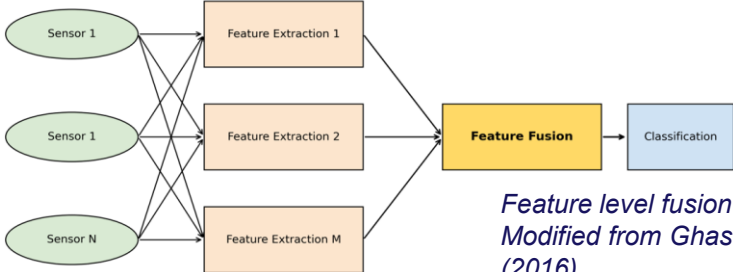
Reduces data size and noise  
Detailed view of observed features

Feature Combination (represents stacking or concatenating features from multiple sensors)

Feature Extraction can be represented as:

- $\mathbf{F}_1 = (f_{11}, f_{12}, \dots, f_{1n})$  ⇒ Each sensor image is first transformed into a feature space using a feature extraction function.
- $\mathbf{F}_2 = (f_{21}, f_{22}, \dots, f_{2n})$  Each sensor produces its own feature vector.
- $\mathbf{F}_{fusion} = [\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_n]$  ⇒ Feature vectors integrated from different sensors.

Where  $F_1$  = extracted feature from sensor 1  
 $F_2$  = extracted feature from sensor 2  
 $n$  = number of sources



Feature level fusion diagram.  
Modified from Ghassemin,  
(2016)

# Continued

## Common techniques

Various ways to feature level fusion: statistical, feature transformation, feature concatenation, ... .

Classification at this level can be performed using ML algorithms (e.g., RF, SVM, Neural Networks).

- ❖ Spectral feature extraction: create indices. e.g.,
  - Spectral Indices: Mathematical ratios like Iron/ Clay Mineral Index.  
Normalized Difference Vegetation Index: plant health (NDVI) = Red/Near-Infrared (environmental monitoring).

- ❖ Feature concatenation/stacking: the feature vectors from multiple sources are joined together. E.g., DEM slop + VNIR Fe-oxide.

- ❖ Feature transformation: transform multi source features into a new lower dimensional space. e.g., Fe index + feature (texture).
  - Wavelet Coefficients: taking information at different scales simultaneously.

- ❑ Multi-Modal Feature Fusion: extract different features from various sensors. E.g., spectral indices from (Sentinel), texture (SAR), elevation (LiDAR).

# Case study

Feature-Level Fusion

Multi-Source Features: Geochemical Features  $\Rightarrow$  Geochemical anomaly maps, element zonality.

Remote Sensing Features  $\Rightarrow$  alteration indices, mineralogical spectral features, lithological layers.

Fusion Strategy:

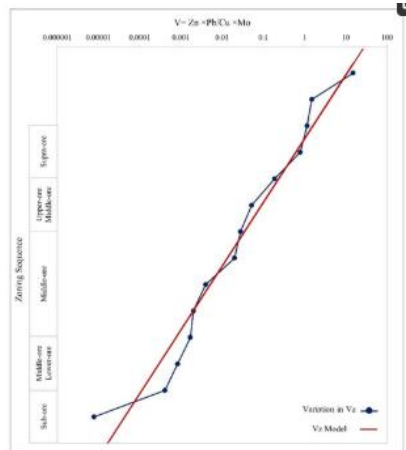
Extract evidential variables from each dataset

Stack features into a unified feature space

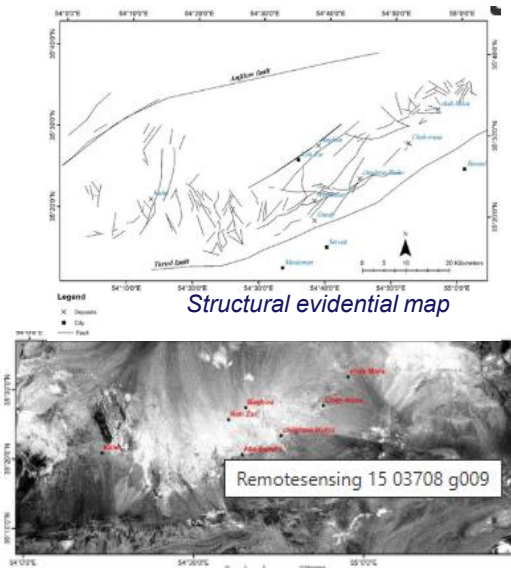
Input into Random Forest classifier

Sarcheshmeh copper district, Iran.

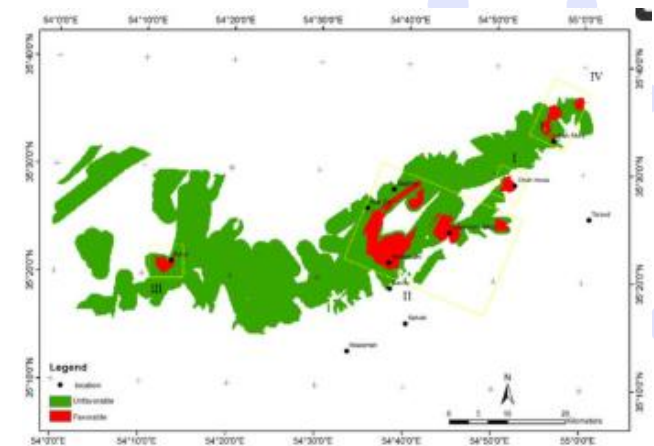
- ✓ Generated provincial scale copper prospectivity map.
- ✓ Enhance mineral prospectivity mapping performance.



Vertical geochemical zonality model for porphyry copper deposits.



Alteration map (argillic and phyllic alteration zones)



porphyry copper prospectivity map

(Abedini et al., 2023)

# Decision level fusion

After classification (highest) stage.

Integration occurs after each sensor/ model has produced its own decision.

May combine outputs of ML classifiers (e.g., ensemble RF, NN voting, Bayesian combination).

Integrates interpretations/ final decisions (results of classifiers, maps, or analytical models).



Enhance robustness and reliability.  
Improve interpretation .

Decision fusion can be expressed as:

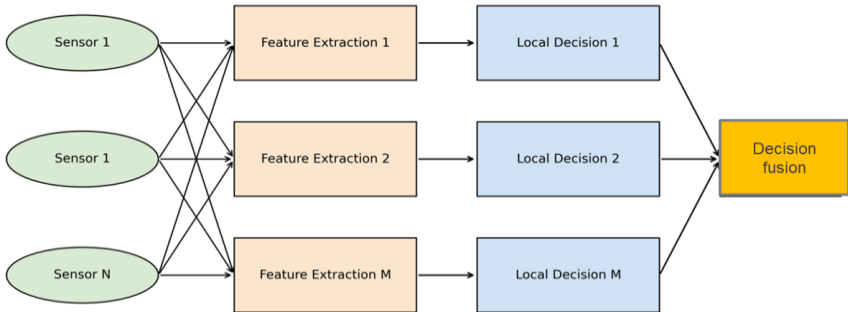
$$D_{fusion} = r(D_1, D_2, \dots, D_n)$$

Where:

D1= independent decisions

D = is the final fused decision

r = fusion rule



Decision level fusion diagram. Modified from Ghassemian, (2016)

# Continued

## Common techniques

- ❖ Majority voting: a simple, robust baseline, used for a diverse model.

Each classifier casts a vote for a class so the final decision = the class with the most votes.

- ❖ Weighted Voting: advanced version of majority voting.

Each sensor's vote is multiplied by a weight based on its historical accuracy or spectral resolution.

- ❖ Bayesian fusion: combines probabilistic outputs from each model to compute a posterior probability.

It calculates the probability the likelihood that a mineral exists based on prior knowledge.

- ✓ Decision level fusion integrates: Structures, geophysical anomalies, geochemical data, ... .

**Raw data (Pixel level)** → **Features** → **Classification** → **Decision**

# Case study

## Decision level fusion

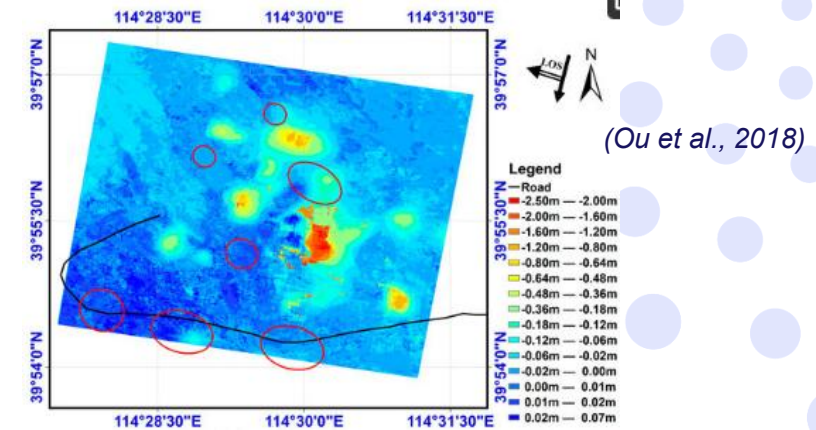
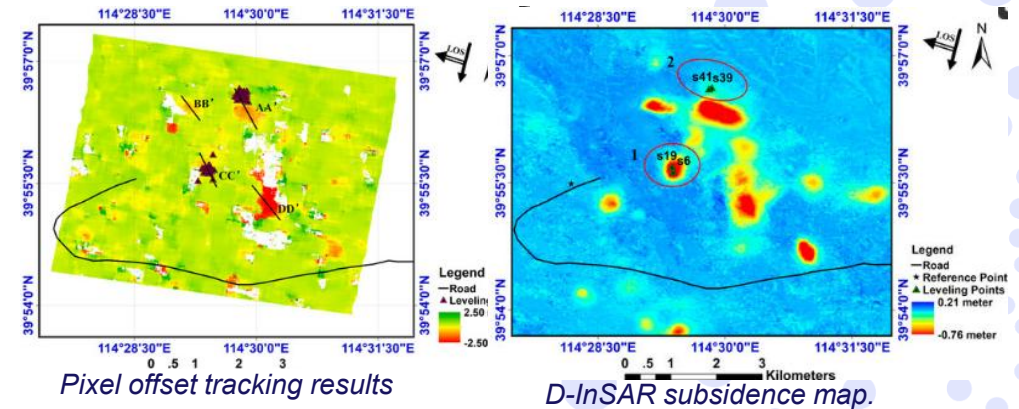
To improve monitoring accuracy of coal mining induced subsidence at Cuijiazhai Mine, Hebei Province, China .

Using TerraSAR-X SpotLight images; fusing :

- D-InSAR and
- Pixel Offset Tracking

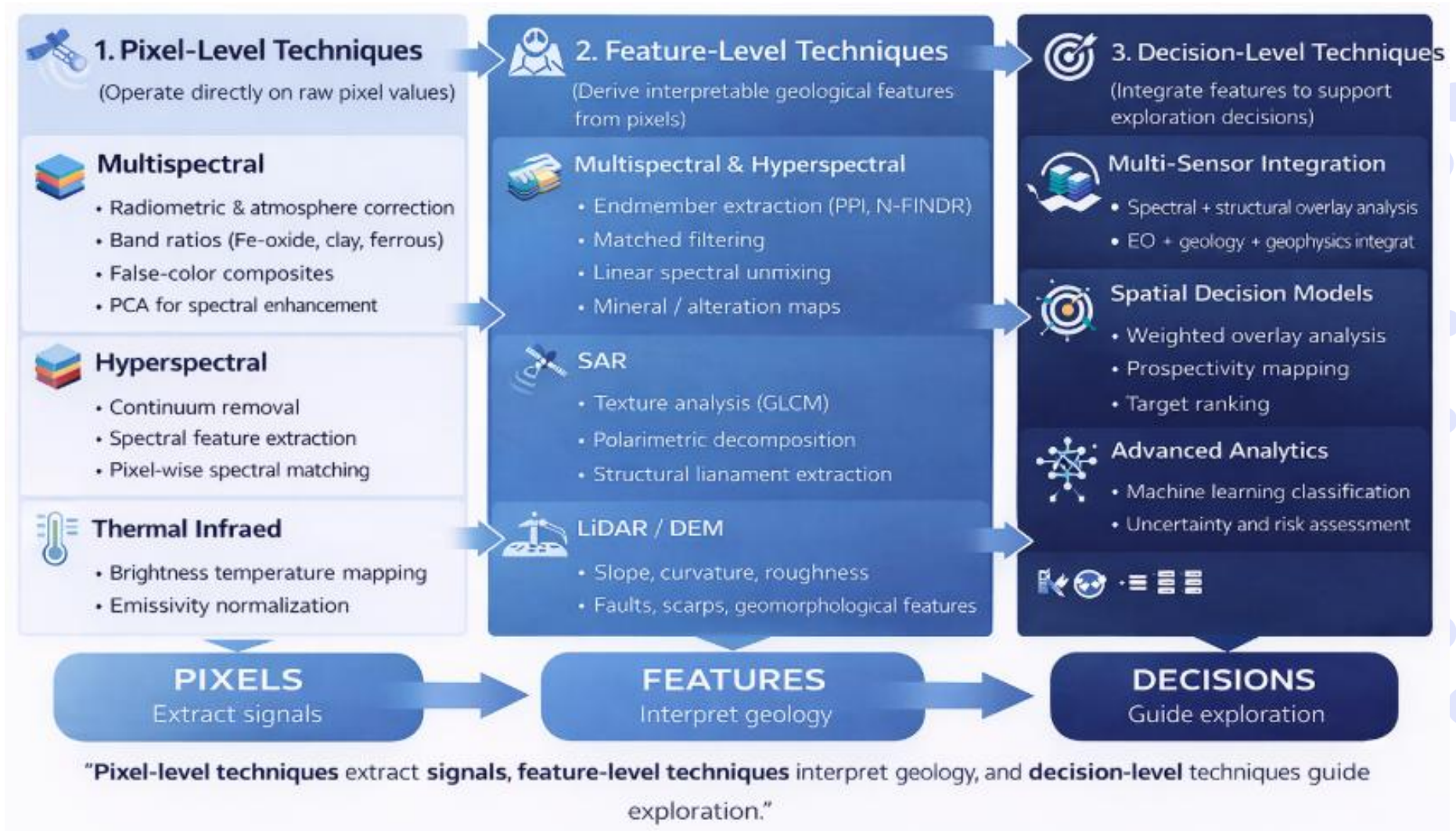
(for low gradient deformation + for high gradient deformation)

- ✓ Each method produces independent deformation results.
- ✓ Final output selected/weighted based on decision criteria.
- ✓ The fusion method provides more accurate subsidence measurements than using D-InSAR or offset tracking alone.



The fusion result of D-InSAR and offset tracking

(Ou et al., 2018)



Summary of data fusion techniques vs sensors

# Classification

Is the bridge between feature-level and decision level in material exploration workflows.

Converts **fused features into mineral maps** ⇒ **Input** to decision level fusion (**lithology, alteration, prospectivity maps**)

Can be classified as Supervised and Unsupervised.

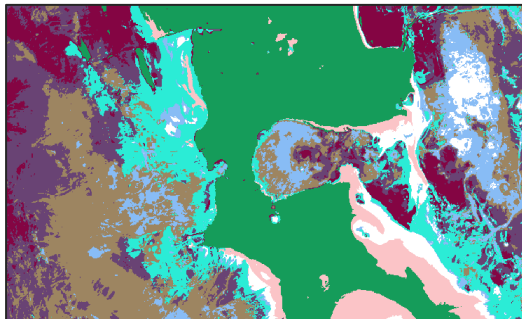
Predict mineral occurrence probability.

Supervised classification: User guided, labelled training samples (pixels) based on prior knowledge (lithology/ alteration).

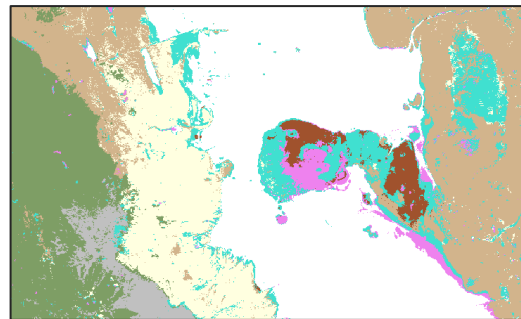
Methods applies: e.g., Random Forest, Neural Networks

Unsupervised classification: groups pixels based on spectral similarity without prior labels.

Methods applies: e.g., K-means clustering, ISODATA



Lithological mapping performed using unsupervised classification.



Lithological mapping performed using supervised classification of the same area.

# Beyond the theory ... .

Let's practice a fusion strategy designing for hydrothermal alteration mapping.

Try accessing these sensors:

- **Sentinel-2 multispectral imagery** (<https://apps.sentinel-hub.com/eo-browser/>)
- **ASTER (SWIR) bands** (<https://asterweb.jpl.nasa.gov/>)
- **SAR (Sentinel-1)** (<https://dataspace.copernicus.eu/data-collections/copernicus-sentinel-missions/sentinel-1>)
- **DEM** ([https://dataspace.copernicus.eu/ecosystem/services?field\\_data\\_managed=Digital+Elevation+Model](https://dataspace.copernicus.eu/ecosystem/services?field_data_managed=Digital+Elevation+Model))

**1\_What can each dataset detect?**

**2\_Which fusion level would you choose? Why ?**

(\*The fusion level mainly depends on the geological objective).

**3\_ Show a Simple Workflow (Data acquisition.....Map)**

# Takeaways

Advanced Earth Observation for raw materials is no longer sensor centric; it is integration driven.

Multispectral, hyperspectral, SAR, and DEM datasets provide complementary physical measurements.

Data fusion at pixel, feature, and decision levels enhances information content and reduces uncertainty.

Decision level fusion increases robustness in deformation monitoring and mineral prospectivity mapping.

Machine learning frameworks enable scalable multi source geoscience data.

Future: Real time monitoring

Cloud based platforms

Digital twins of mines

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# Questions & Answers



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Fierce space project website

<https://project-fierce.eu/>





*Thank you!*



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