# Machine Learning for SAR Image analysis

*From zero to hero*

**Dr. Francescopaolo Sica**
Deputy Head - Earth Observation Lab
Faculty of Aerospace Engineering
University of the Bundeswehr Munich

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# Outline

- Intro: *From zero to hero*
- SAR basics, missions and the Sentinel-1
- Machine Learning for SAR image analysis
    - Choice of the data and procurement
    - SAR processing
    - Pre-processing for ML
- Takeaways

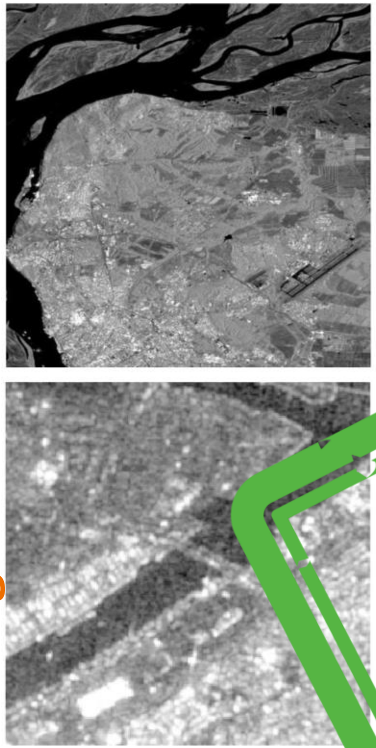
# Tools

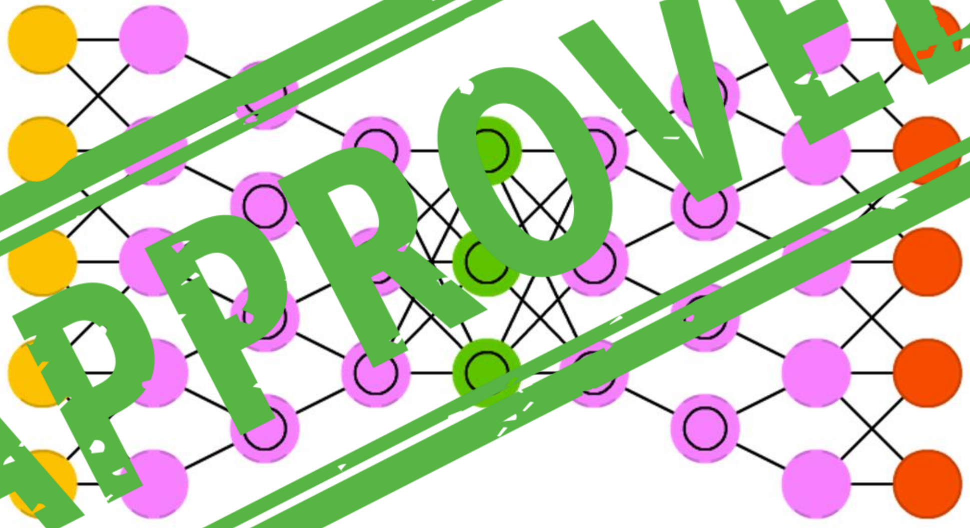
- Interactive lecture – Hands on approach
- Materials:
  - Slides
  - Online data access
  - Free and open software (SNAP)
  - Google Earth
  - Jupyter notebook
- Questions: anytime during the lecture

# "ML4SAR" with *FancyNet*

Mid-Res

High-Res



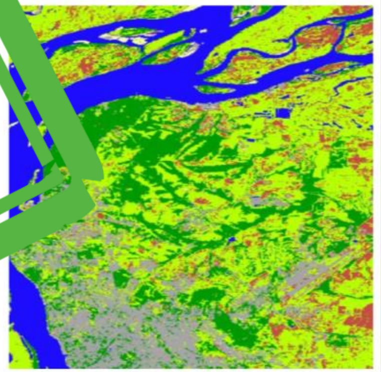


APPROVED

*https://www.asimovinstitute.org/neural-network-zoo/*

**„City“**

**„City, river, vegetation“**



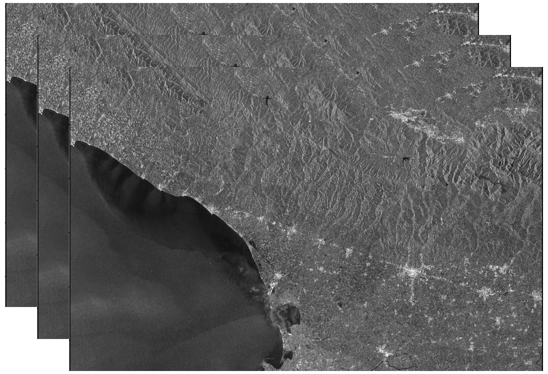
***Accuracy: 99.8%***

**NO LABEL**

# So you want to apply ML to SAR data - brainstorming

- Who among you has experience with SAR?
- Where should we start?
- What can go wrong?
- What went wrong for you in the past?
- What are your main "open points"?

# In one slide

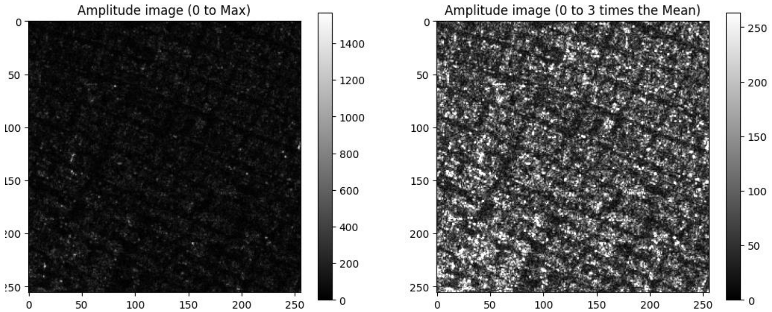


**Data download**

*Data type*

*Sensor*

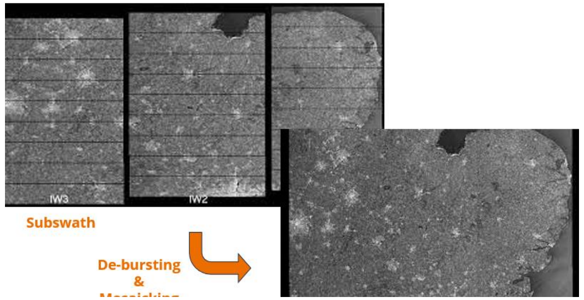
*Download*




**Preprocessing for ML**

*Dataset generation*

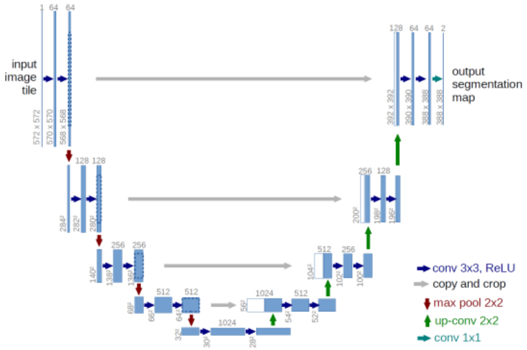
*Data normalization*




**SAR processing**

*Reading the data*

*Input variables*




**ML Training**

*Dealing with biases*

*Dealing with data independence*

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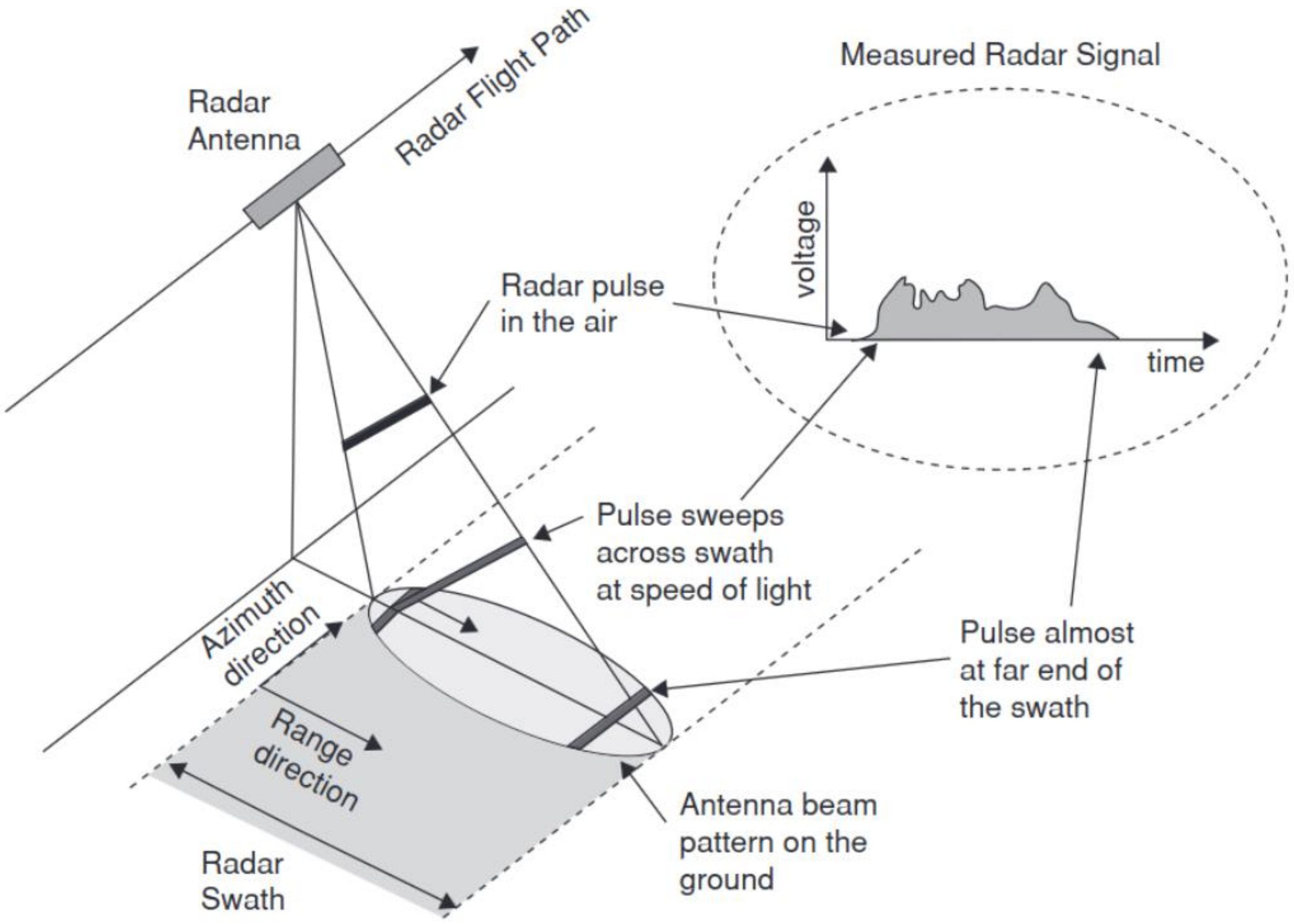
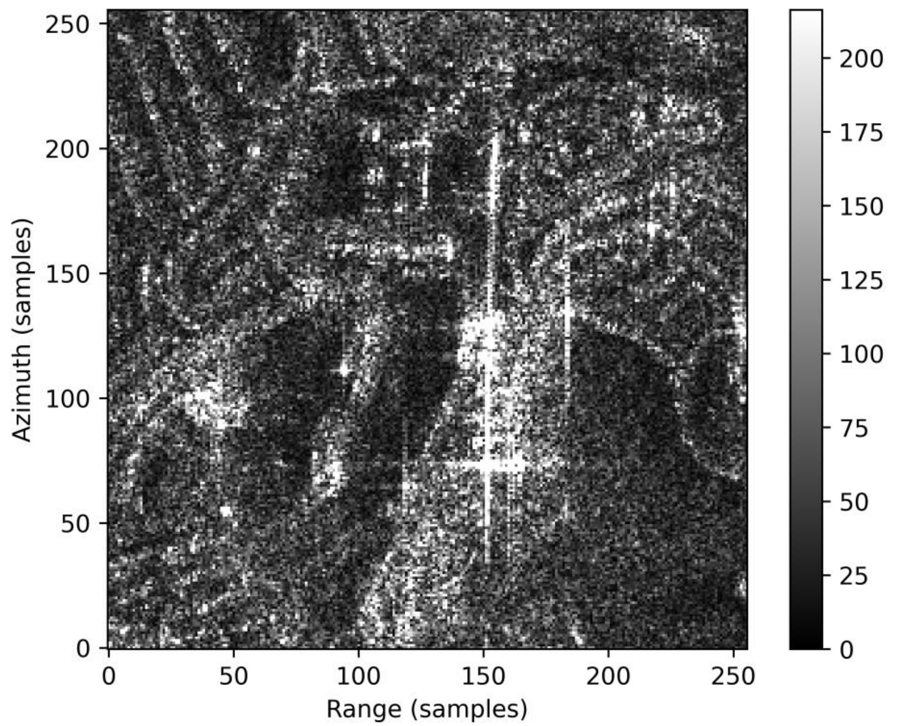
# SAR basics




**Complex valued image**




Van Zyl & Kim (2011) Synthetic Aperture Radar Polarimetry. John Wiley & Sons, Inc

# SAR missions

**Existing**

**TanDEM-X**

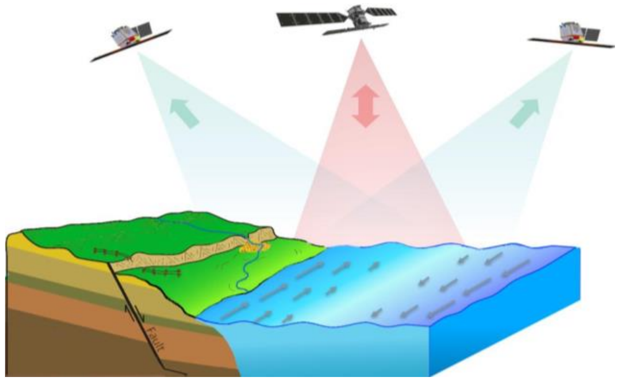
**COSMO-SkyMed**

**ALOS-2**

**Sentinel-1**

**Upcoming**

**Harmony**



**ROSE-L**

**NISAR**

**BIOMASS**

*Artist's concept - Credits: DLR, ESA, NASA-JPL, JAXA*

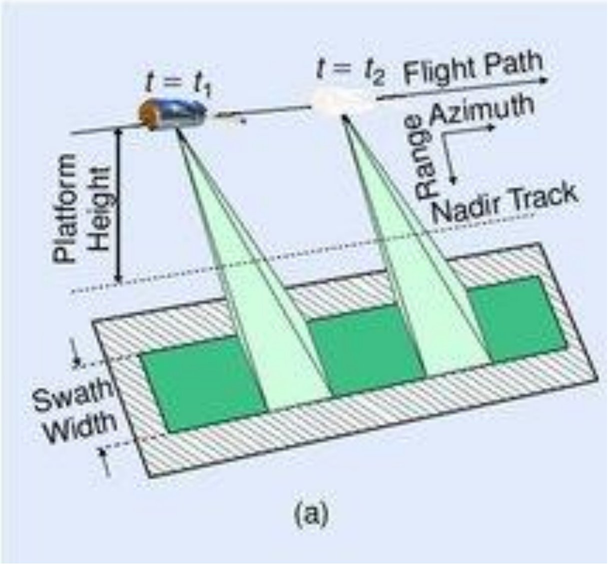
# Sentinel-1

**Some info:**

- C-Band SAR Instrument
- Different acquisition modes
- Interferometry
- VV, VH polarizations
- Constellation of 2 satellites
- Continuity assured through multiple satellites: S1-A, -B, -C, -D
- Revisit time (IW mode): 12 days (6 days)

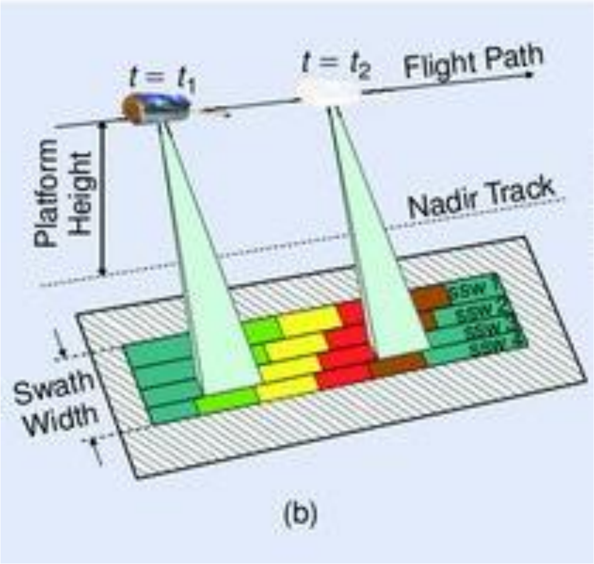
# Acquisition modes

**Stripmap**



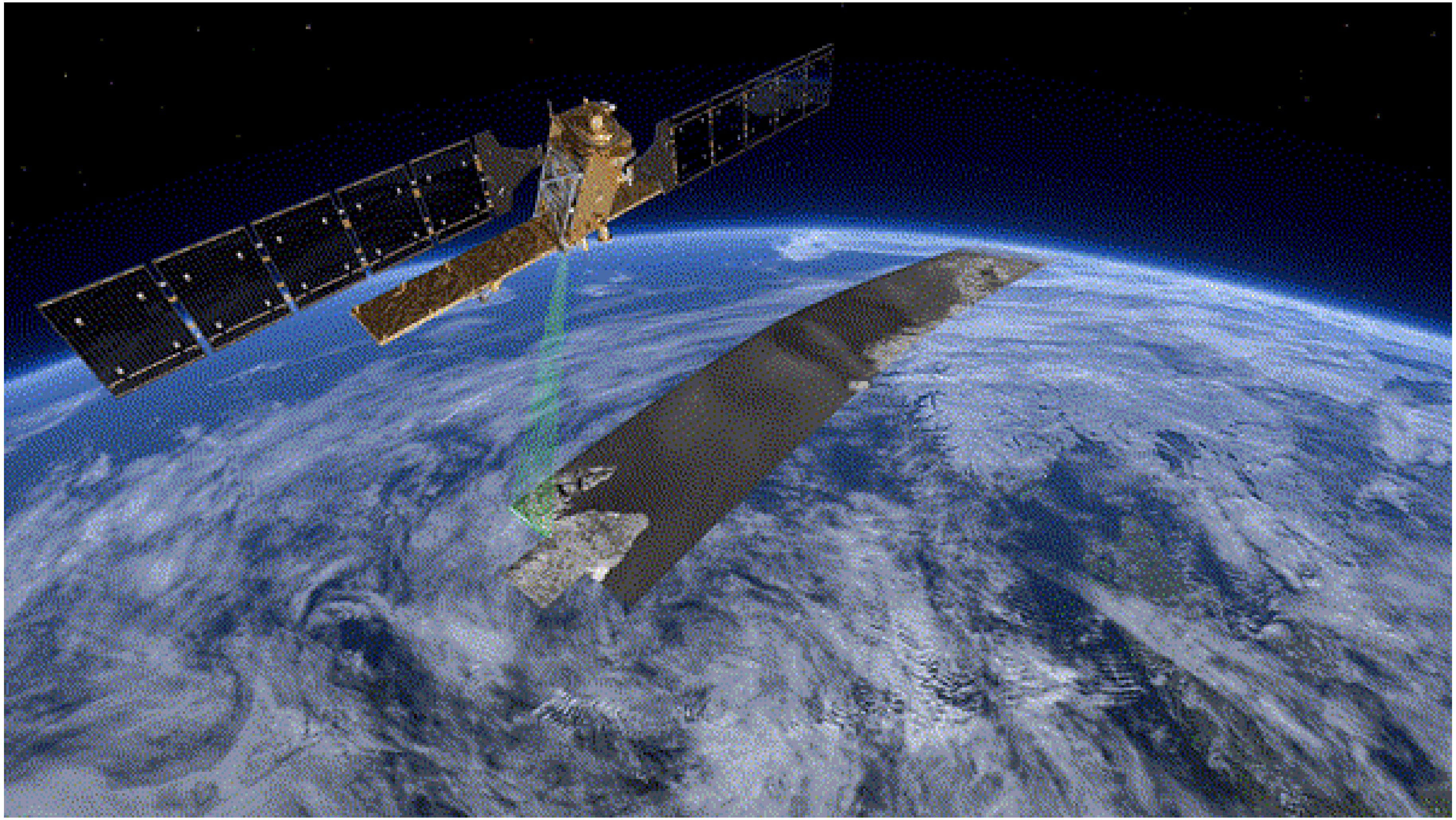

- Mid to high resolution
- Low coverage
- Today: X-band systems
- Science + Surveillance
- TerraSAR-X, ICEYE, Capella
- Commercial + free options for research

**SCANSAR, TOPSAR**




- Low to mid resolution
- High coverage
- Today: C- and L-band systems
- Science
- Sentinel-1, ROSE-L, BIOMASS
- Open data

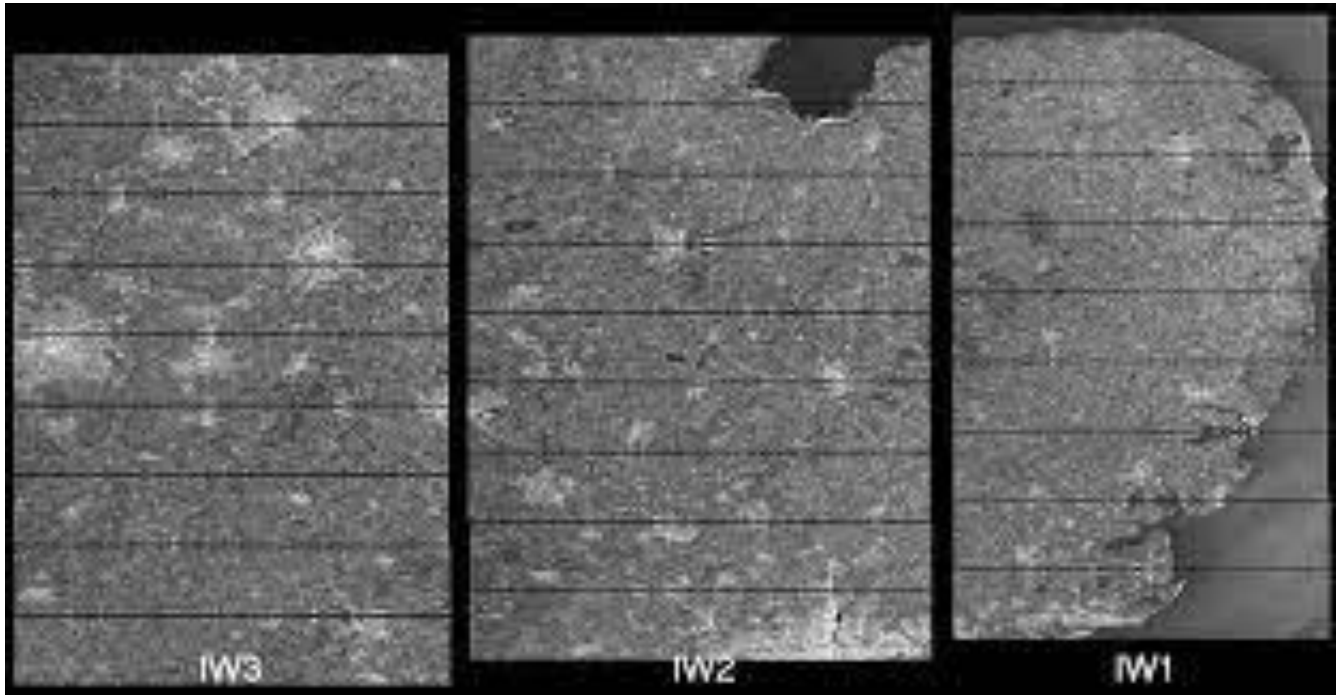
# Sentinel-1



*Artist's concept - Credits: ESA*

# Sentinel-1 – TOPS data

**Burst**

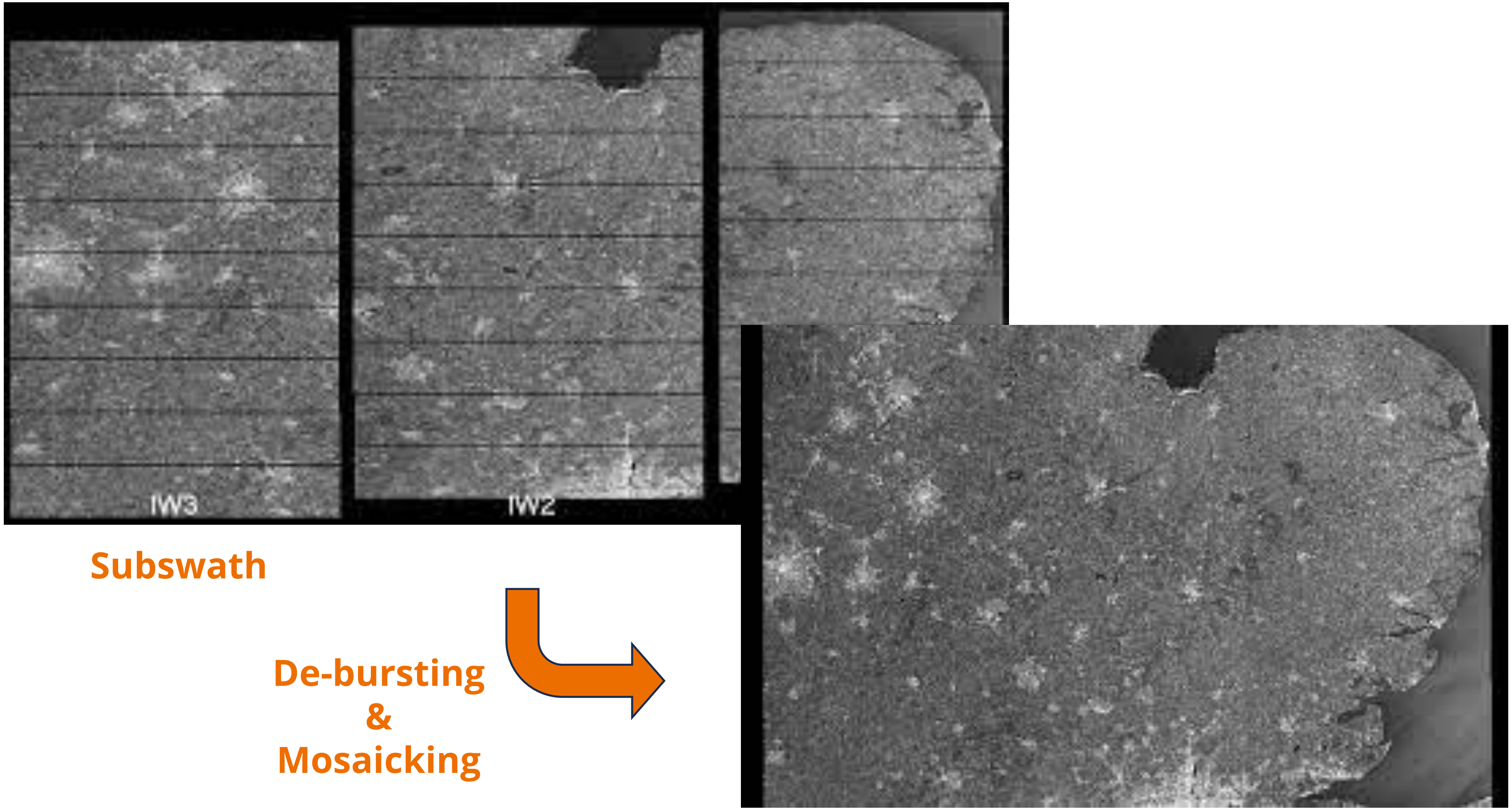



**Subswath**

**Flight direction**

# Sentinel-1 – TOPS data

**Burst**



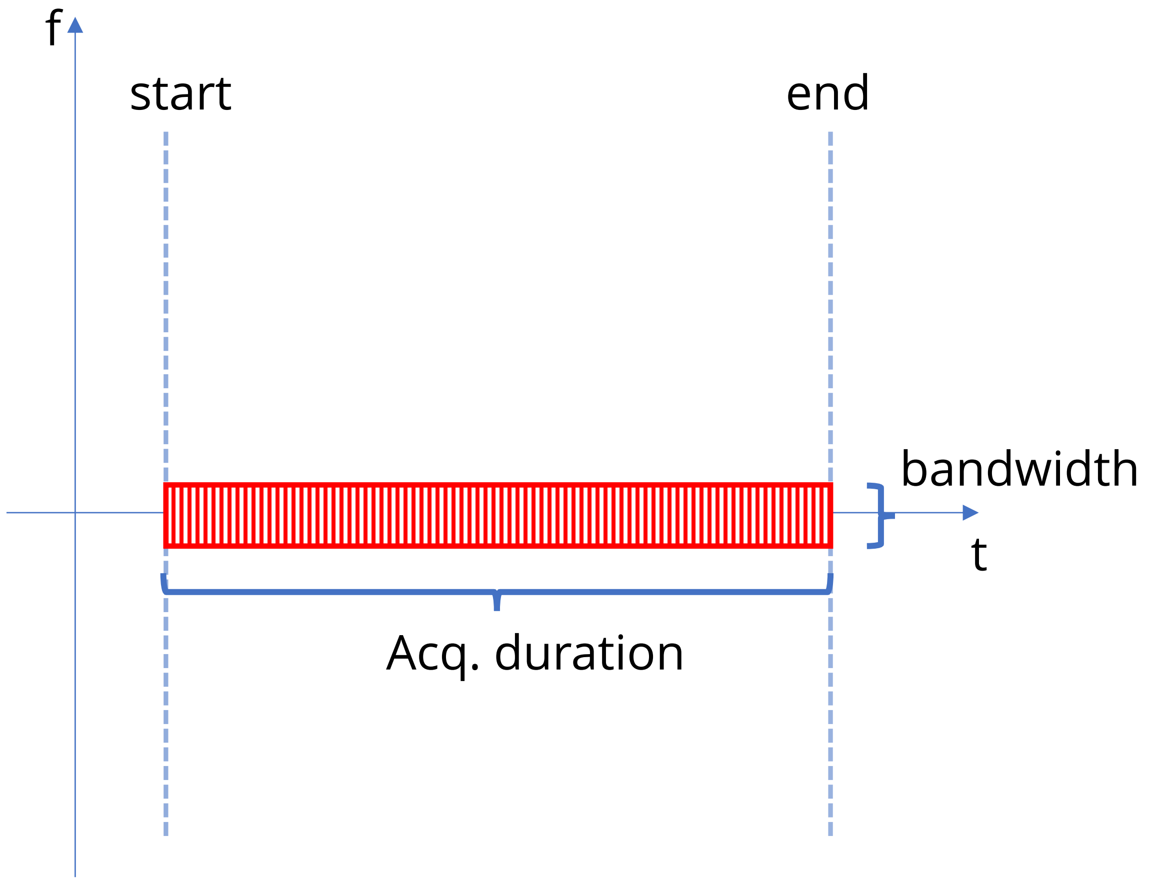

**Subswath**

**De-bursting**
**&**
**Mosaicking**

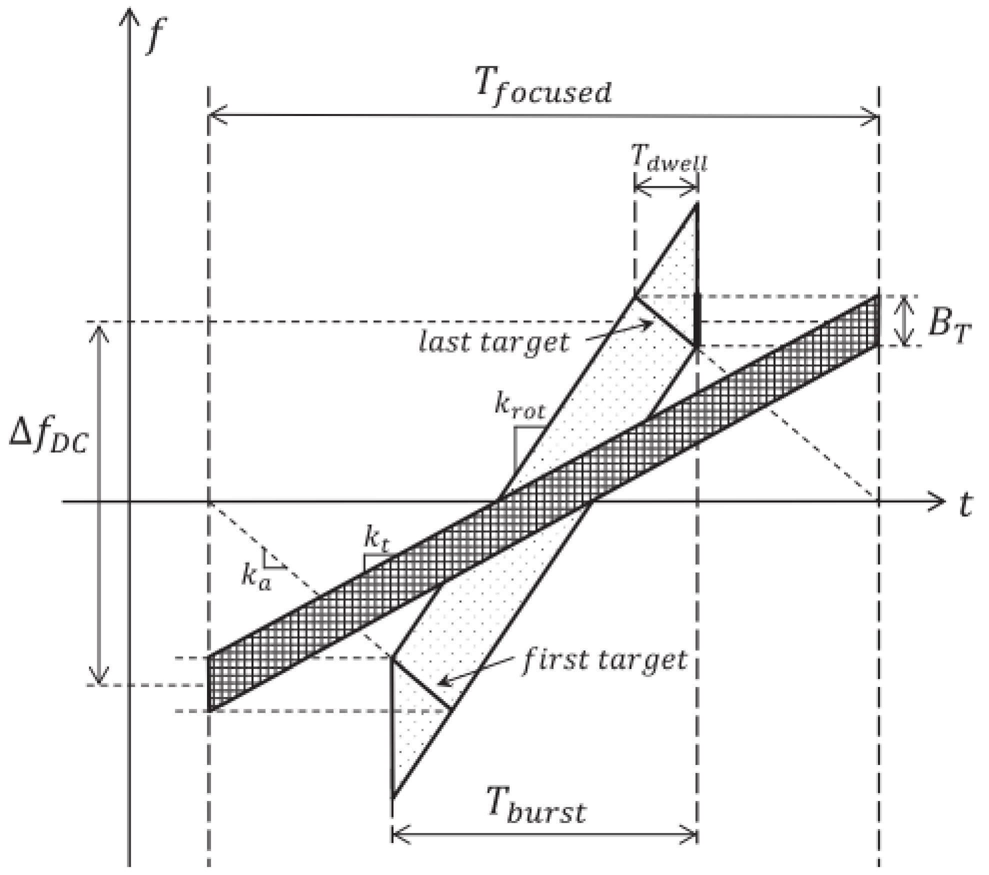
**Flight direction**

# Sentinel-1 – frequency modulation in TOPS data

**Stripmap mode**

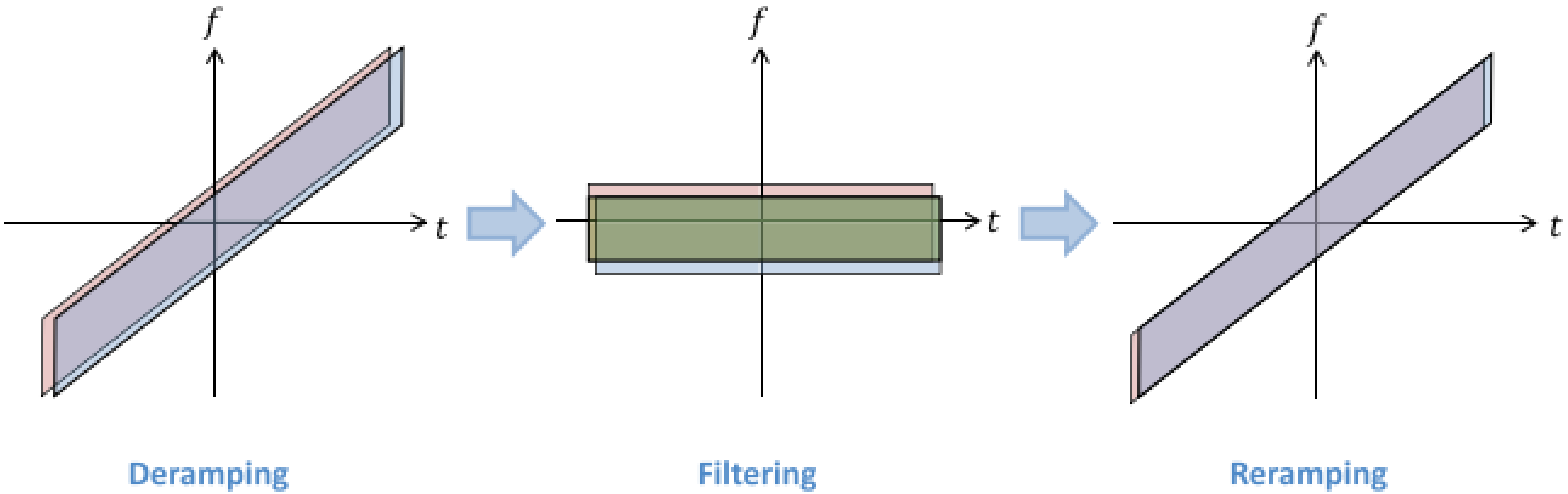



**TOPS mode**




Interferometric Processing of Sentinel-1 TOPS Data. Nestor Yague-Martinez et al.

# Sentinel-1 – frequency modulation in TOPS data



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# Data procurement

Different **missions** provide only some data free of charge

- **National missions** often have policies to share selected data
- **Private companies** are increasingly sharing part of their data

  Good for prototyping, but less suitable for science and technology applications requiring systematic acquisitions or a specific region of interest

**New free and open data policies led by ESA**

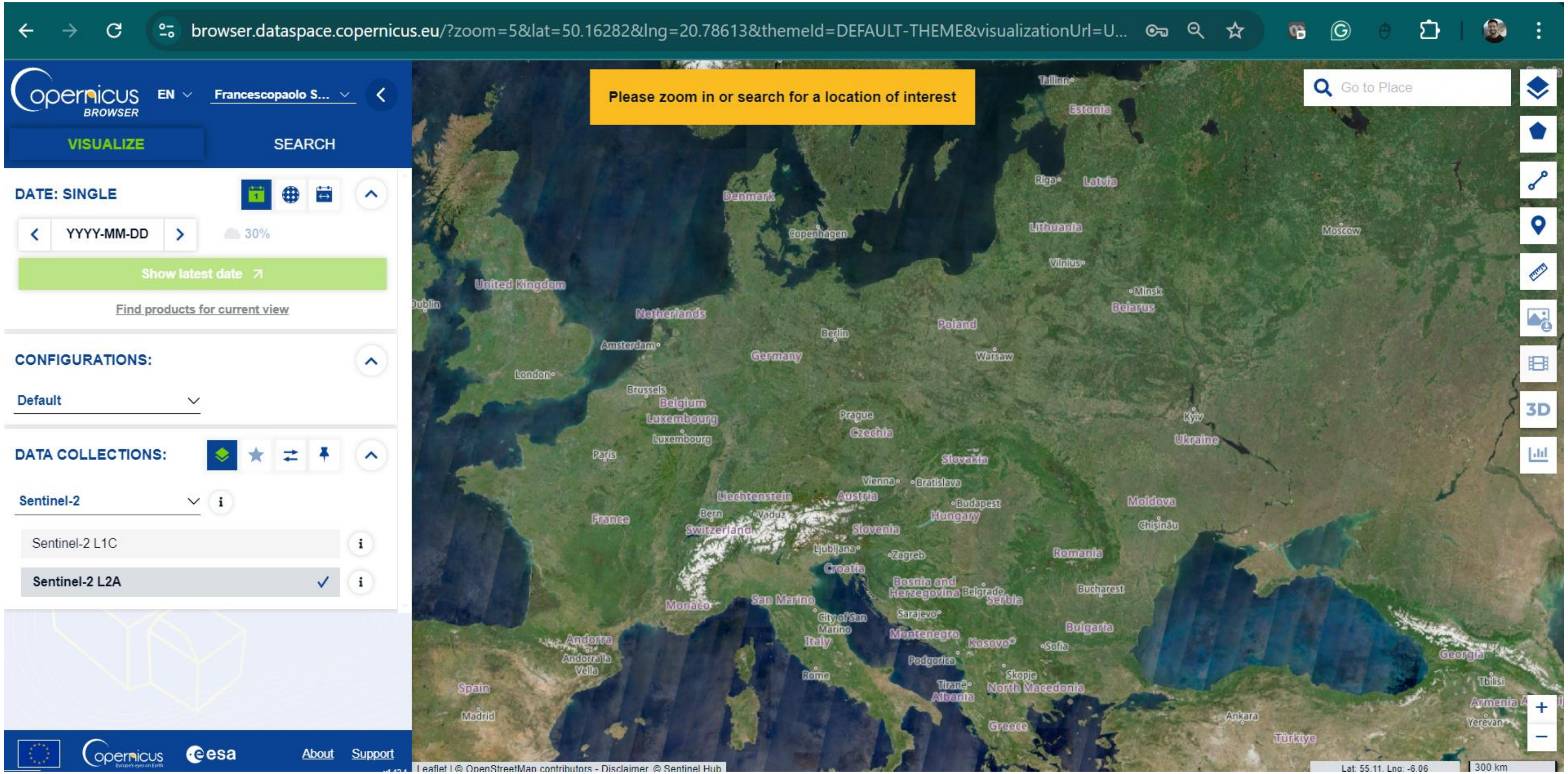
- Example: Copernicus and Sentinel-1, specifically for SAR applications.
- ESA also serves as a hub for third-party mission data, including:
  - DLR's TerraSAR-X and TanDEM-X, JAXA's ALOS, ICEYE

**Google Earth Engine** also provides Sentinel-1 data (GRD format)

# Data download

Create an account on:
https://browser.dataspace.copernicus.eu/

- Provided by ESA
- Only recent data are available – offline archive data
- Possible use of python interfaces



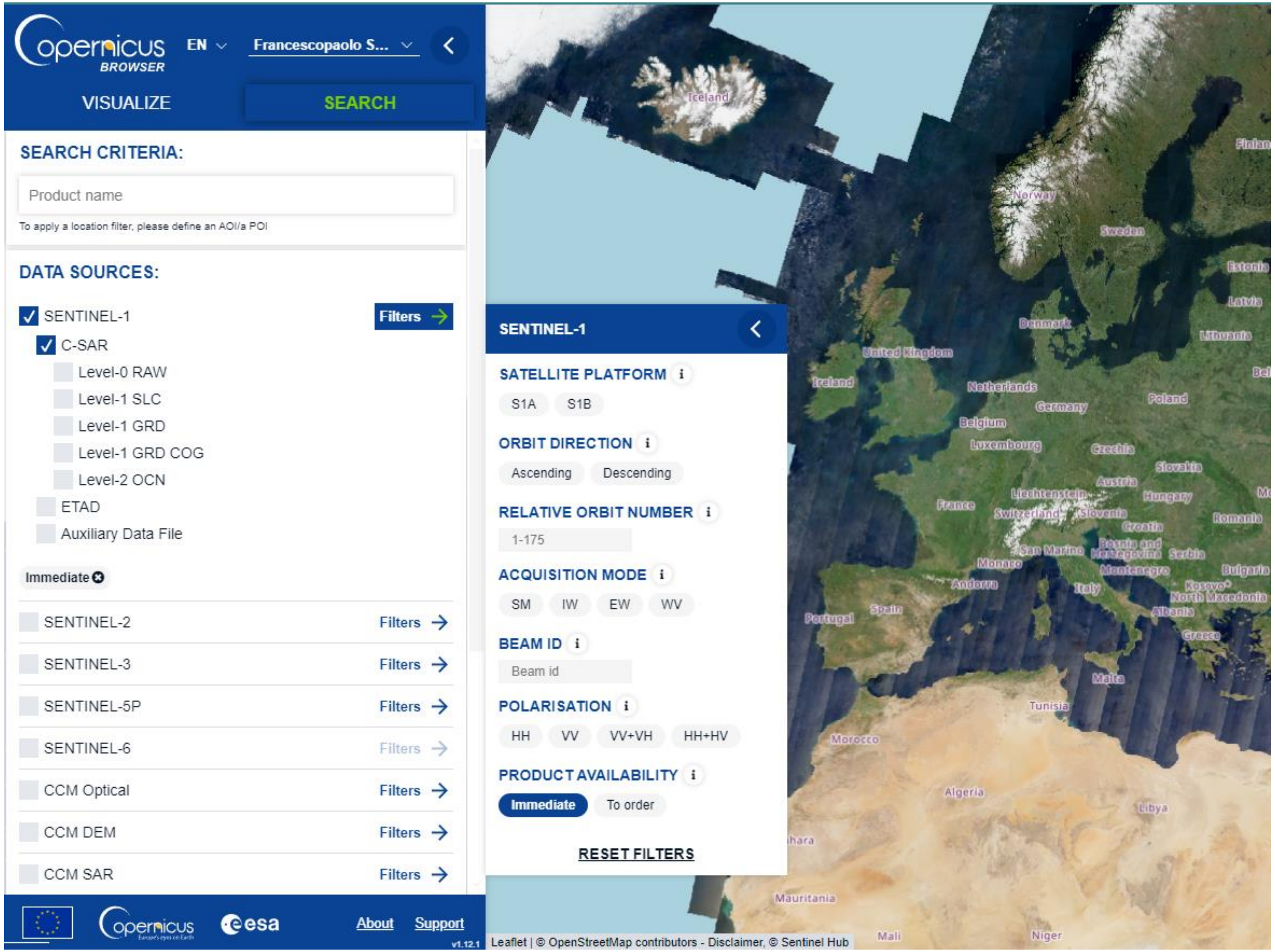
# Data download

**Graphic interface**

- Select the area
- Select the data

**Data parameters**

- Sensor
- Acquisition mode
- Dates
- Acquisition geometry
- Orbit
- etc.

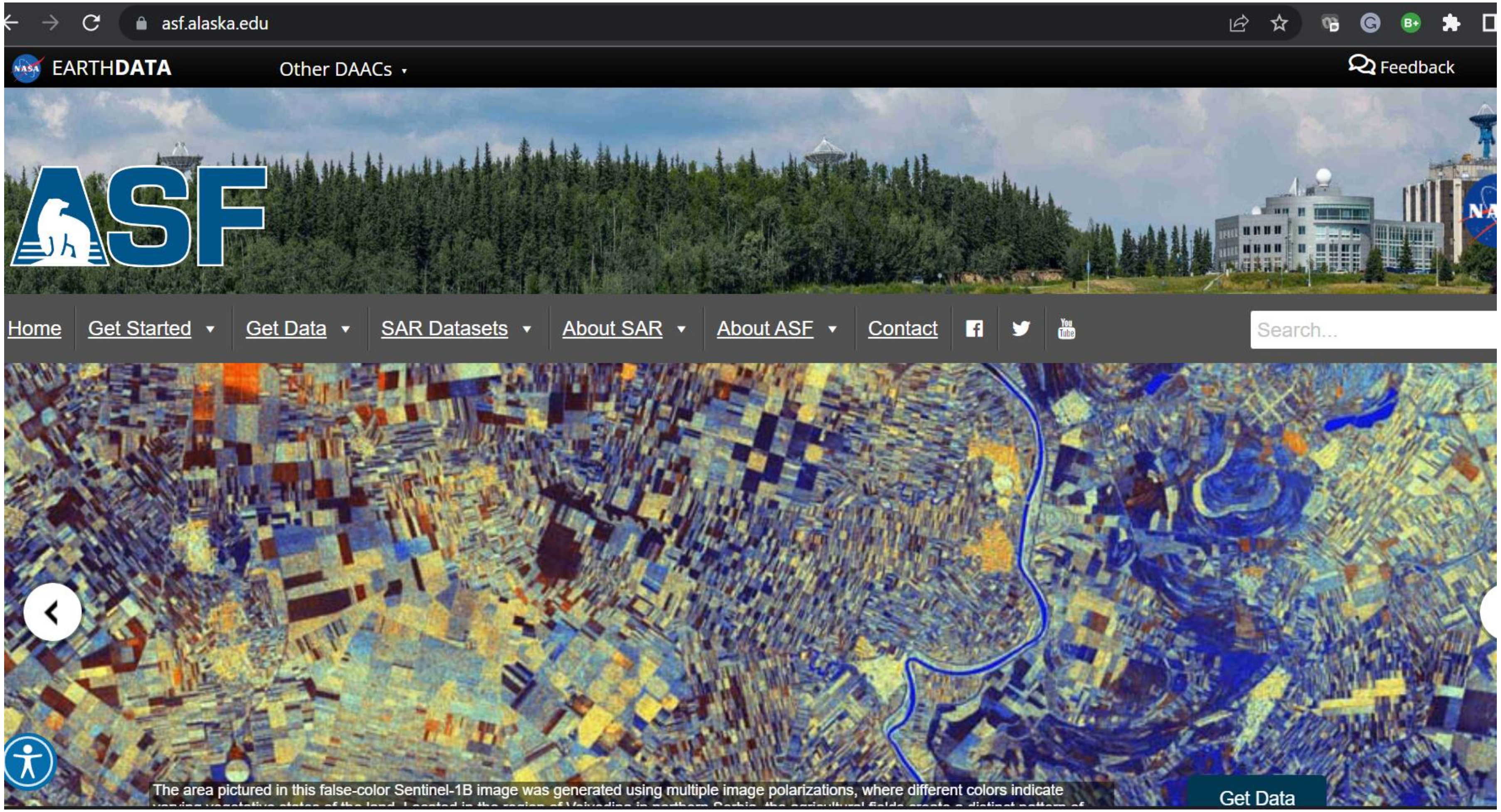


# Data download

Alaska Satellite Facility
https://asf.alaska.edu/

Create an account
https://urs.earthdata.nasa.gov/

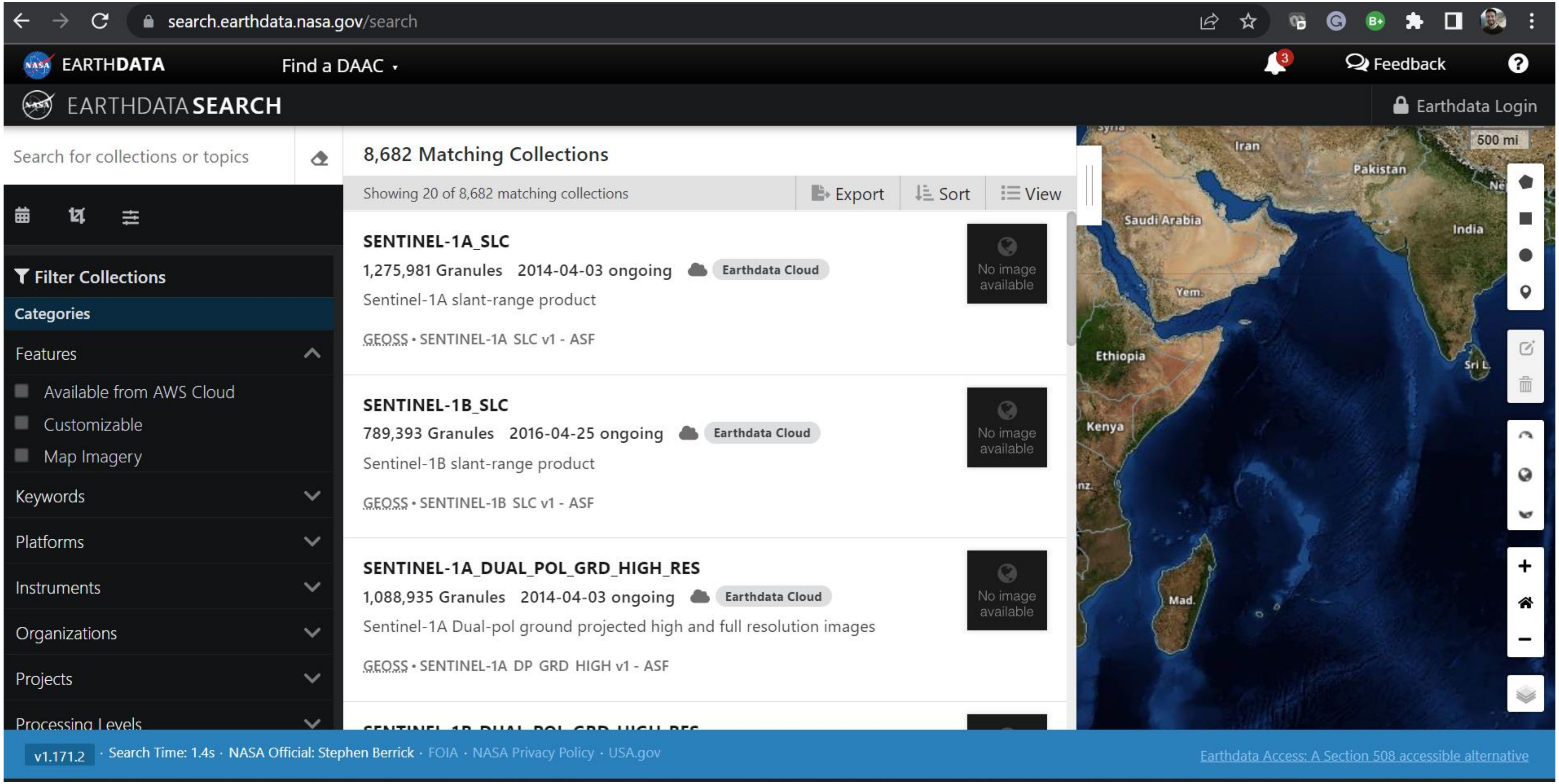
Education platform SAR training



# Data download

https://www.earthdata.nasa.gov/

# Data download https://search.earthdata.nasa.gov/search



# Online demo: Sentinel-1 data download

(acquisition mode, type of data, orbits, etc.)

- Intro: *From zero to hero*
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    - **SAR processing**
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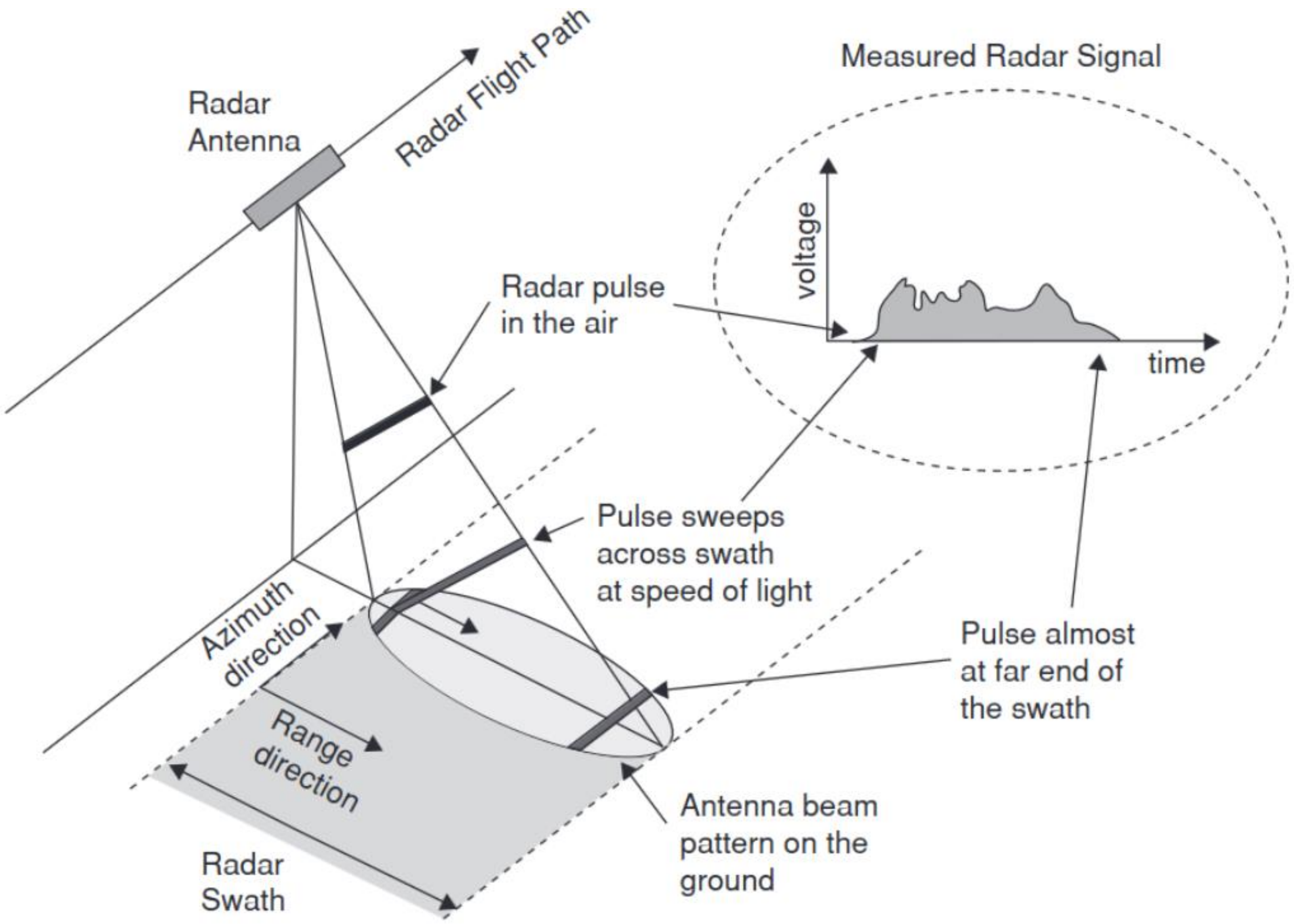
# SAR image characteristics



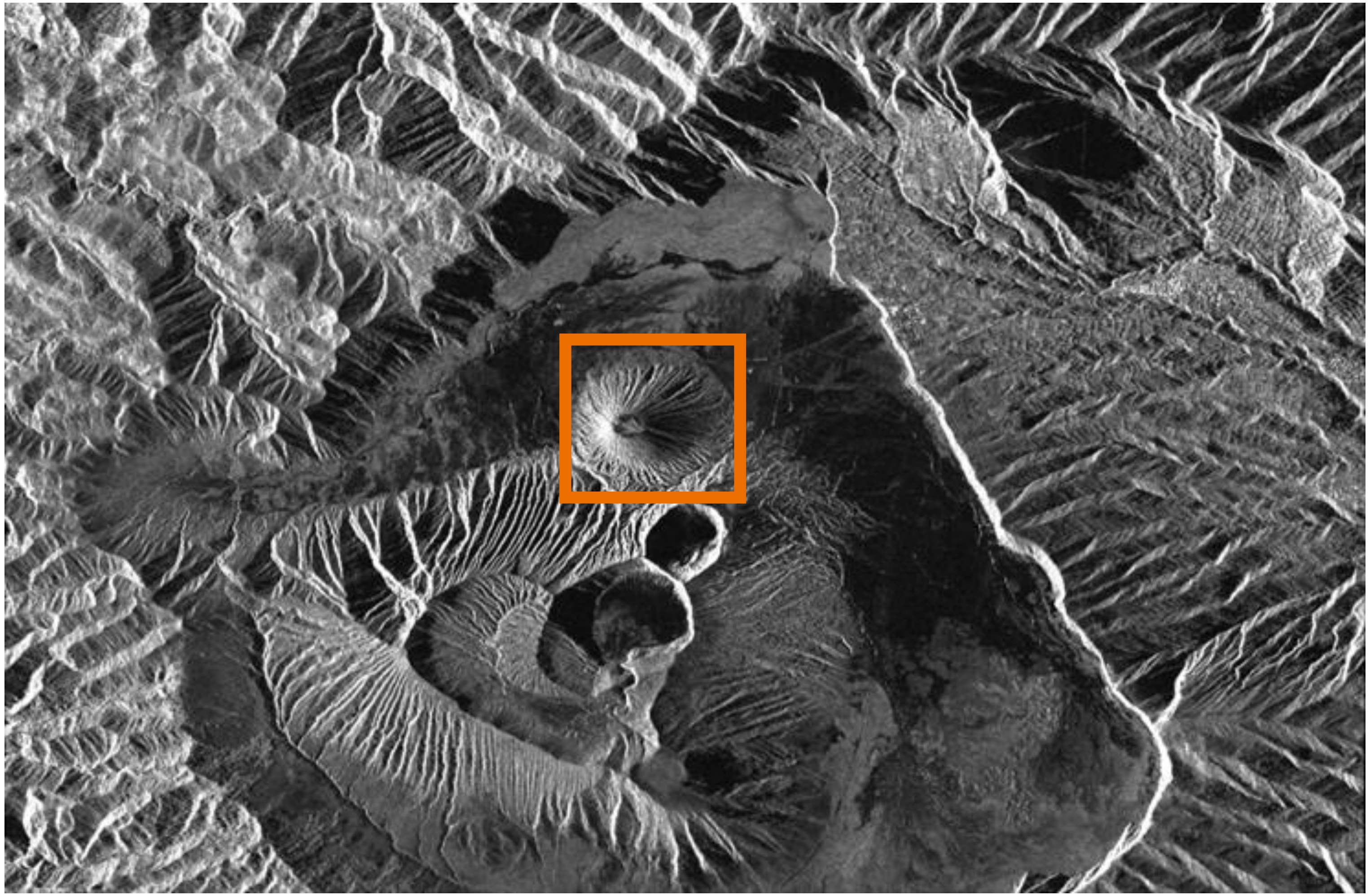

- **Spatial properties:** geometrical deformations
- **Radiometric properties**: brightness of a pixel
- **Statistical properties:** speckle

Van Zyl & Kim (2011) Synthetic Aperture Radar Polarimetry. John Wiley & Sons, Inc

# SAR image characteristics

Mount Bromo (Indonesia) – **optical image** – Google Earth (Maxar)

# SAR image characteristics

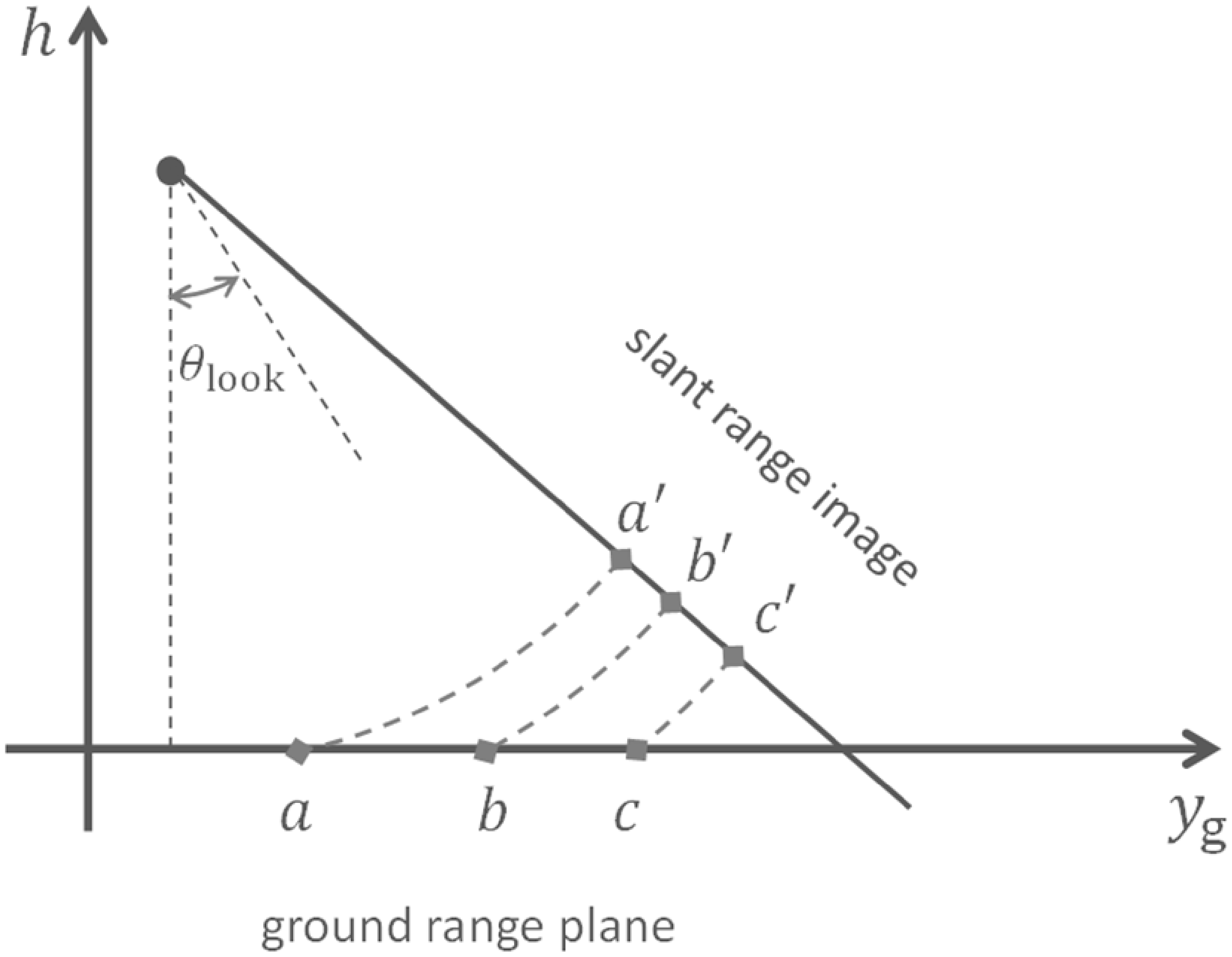


Mount Bromo (Indonesia) – **SAR image** – TerraSAR-X Spotlight image

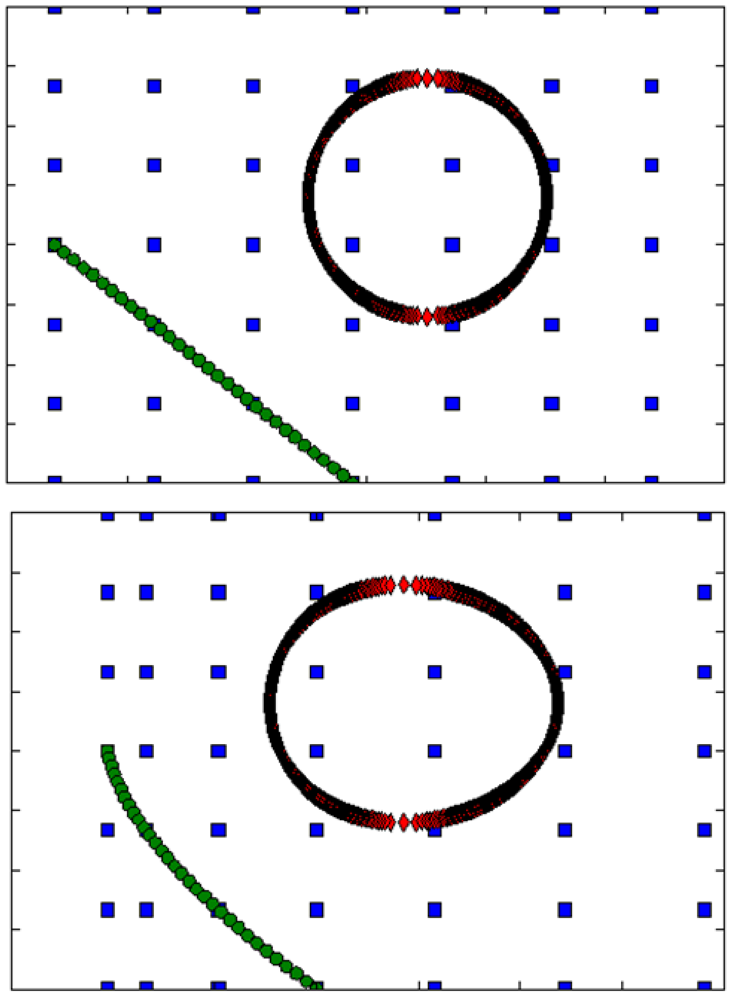
# SAR image characteristics

# SAR image characteristics

# Spatial characteristics: geometric distortions

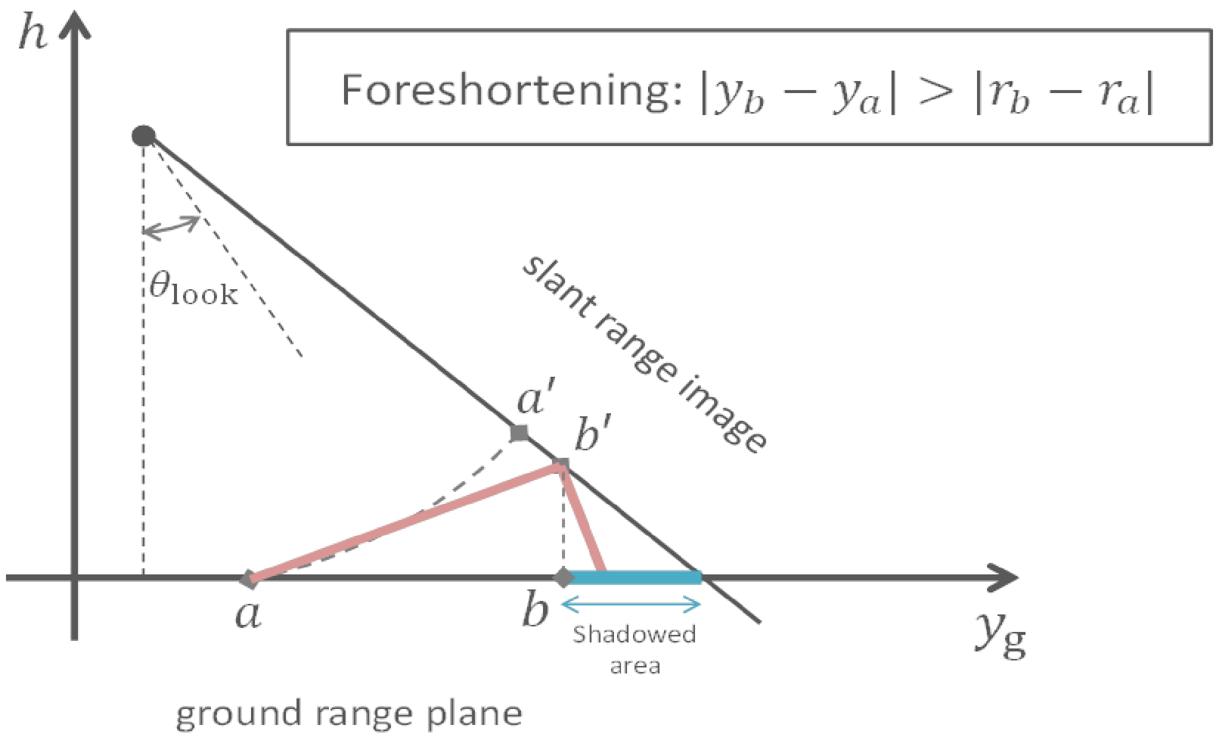


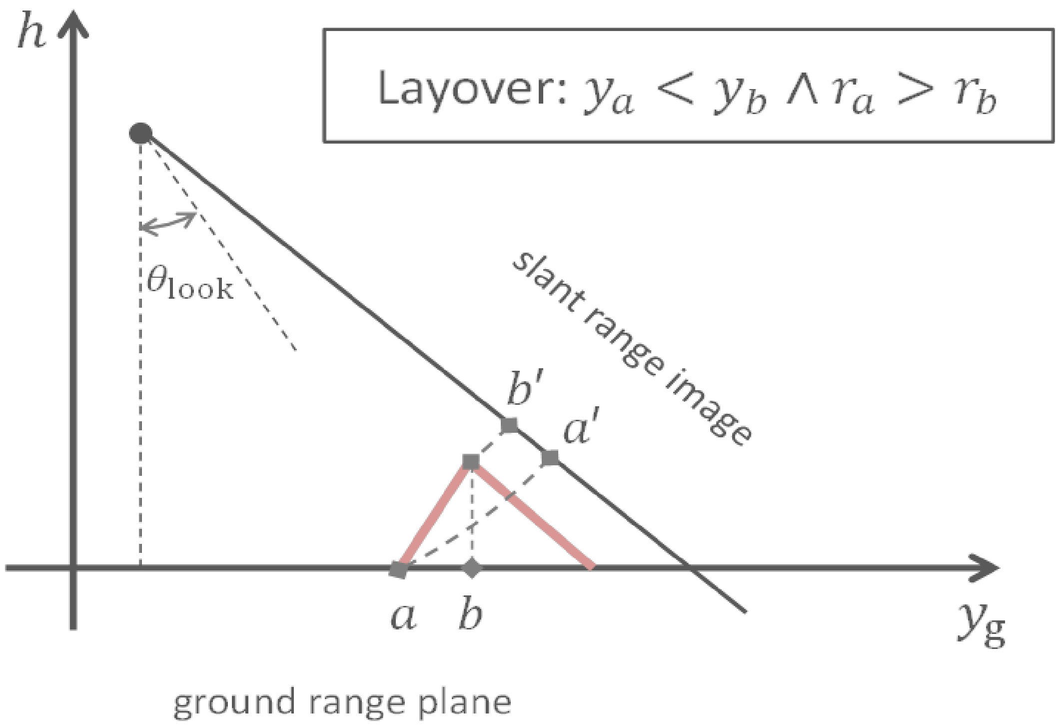

**Actual geometry**



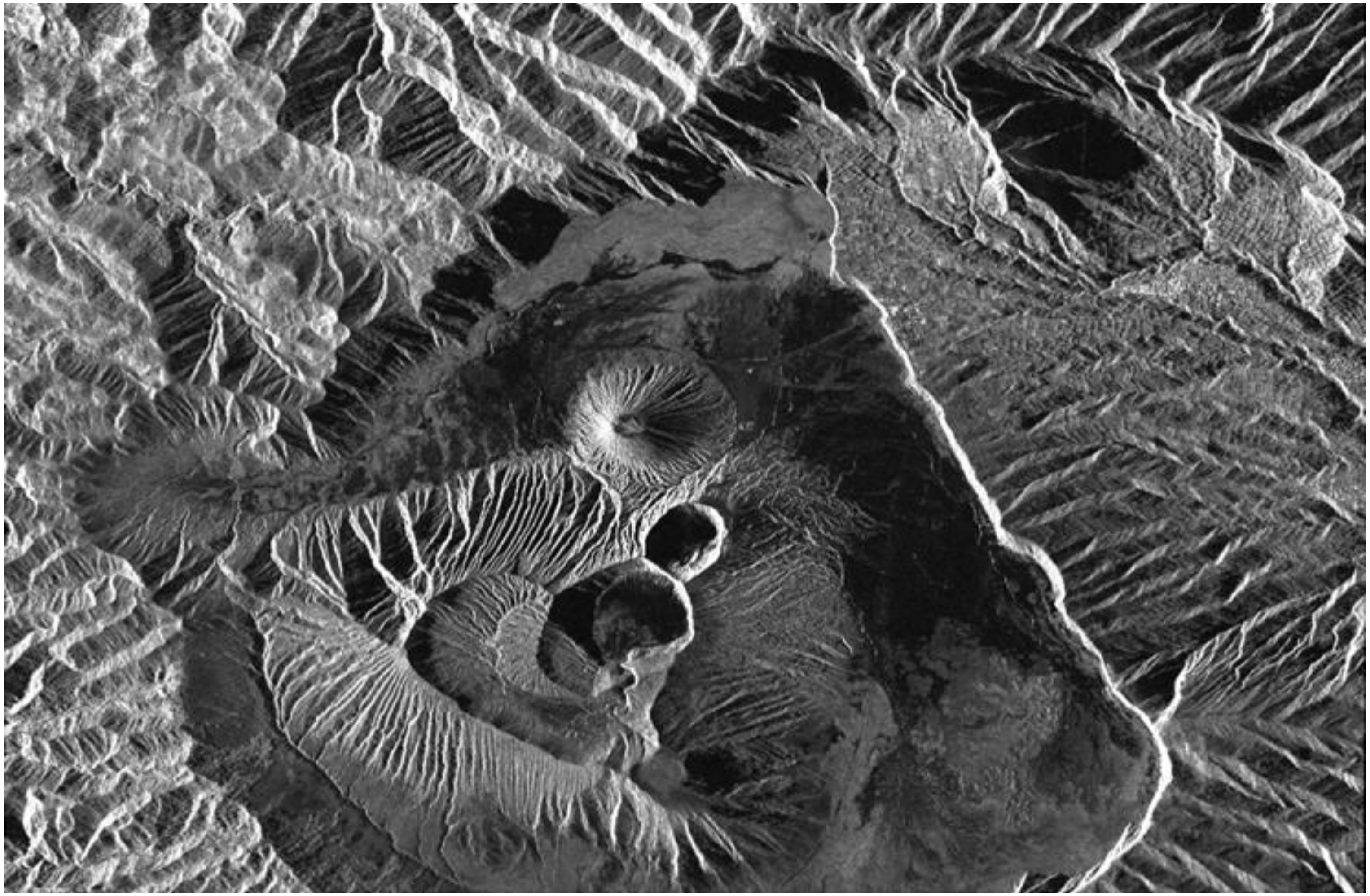
**SAR geometry**

# Spatial characteristics: geometric distortions



# Spatial characteristics: geometric distortions

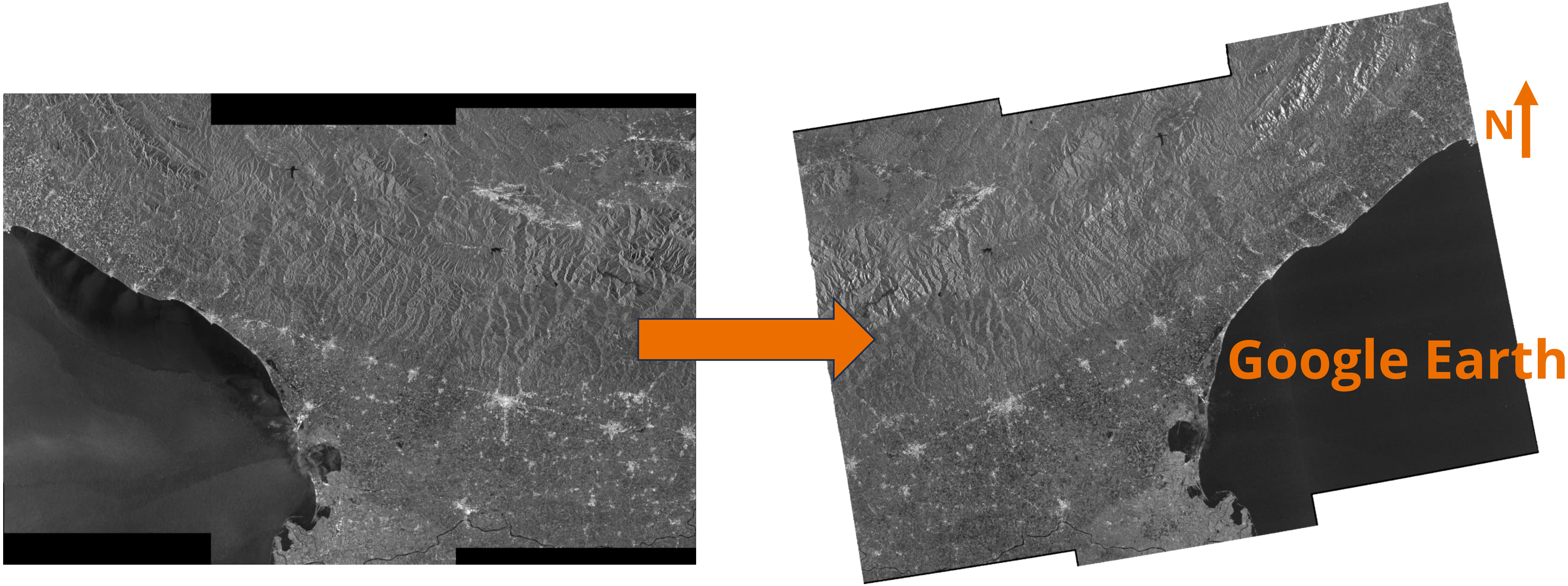


# Spatial characteristics: geometric distortions

# Distortion correction: Geocoding (a.k.a. Terrain Correction)

**Slant-range / Azimuth grid**

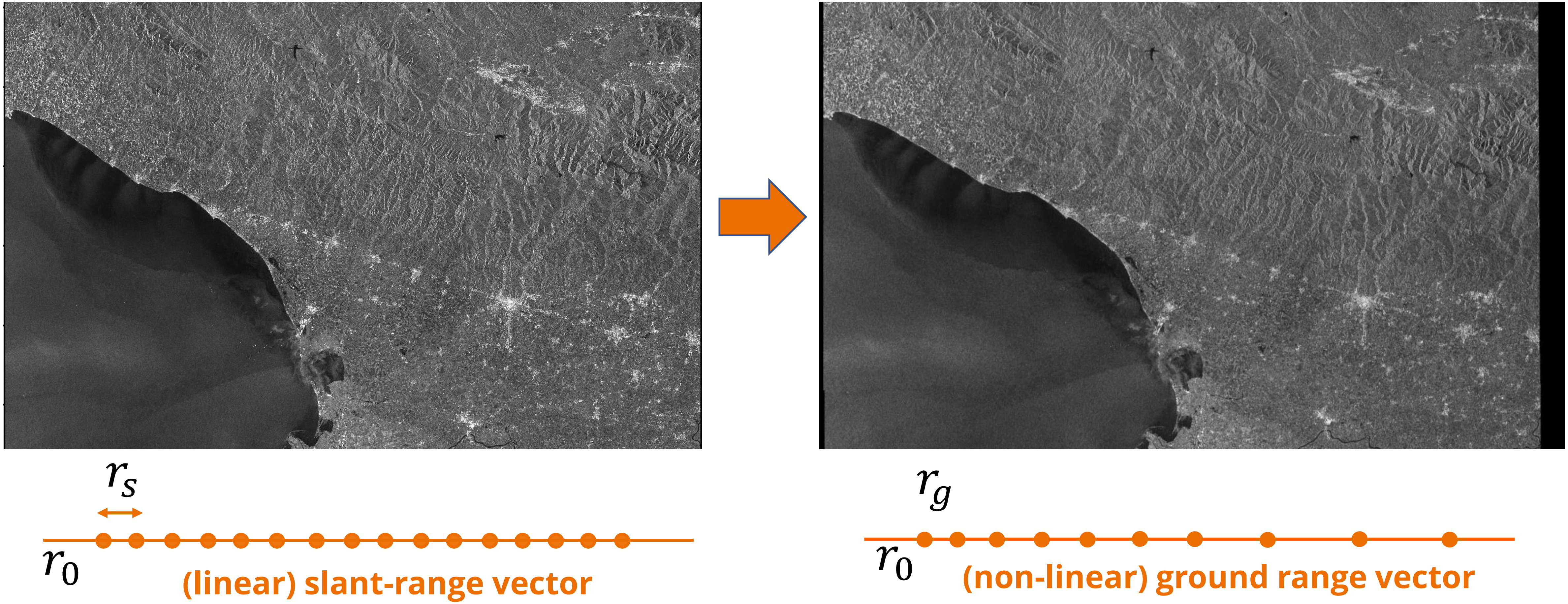
# Distortion correction: Geocoding (a.k.a. Terrain Correction)



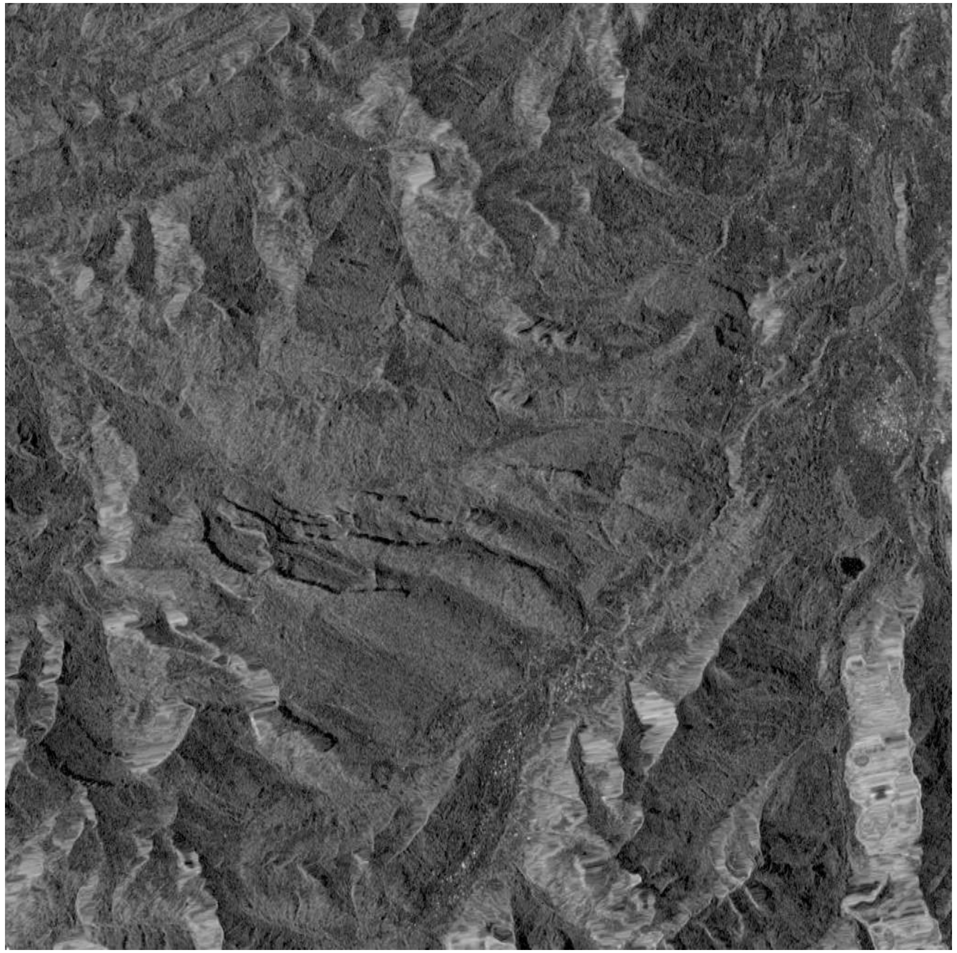

**Slant-range / Azimuth grid** **Geocoding** **Latitude / Longitude grid**

# What about GRD data?

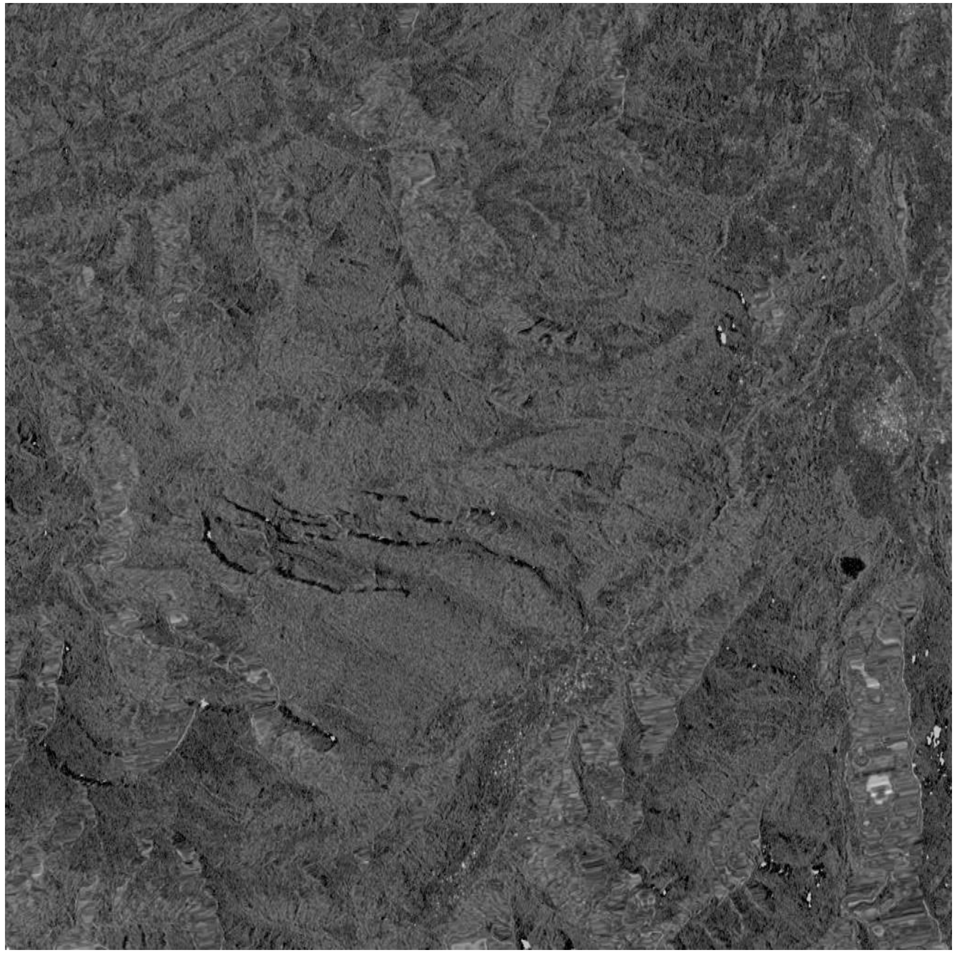
GRD: *Ground Range Detected*
Only amplitude data – no geocoded grid!



# Radiometric characteristics



**$\sigma^0_{VV}$, with Terrain Correction (TC)**



**$\sigma^0_{VV}$, with Radiometric Terrain Correction a.k.a. TC + Terrain Flattening (TF)**

# Radiometric characteristics

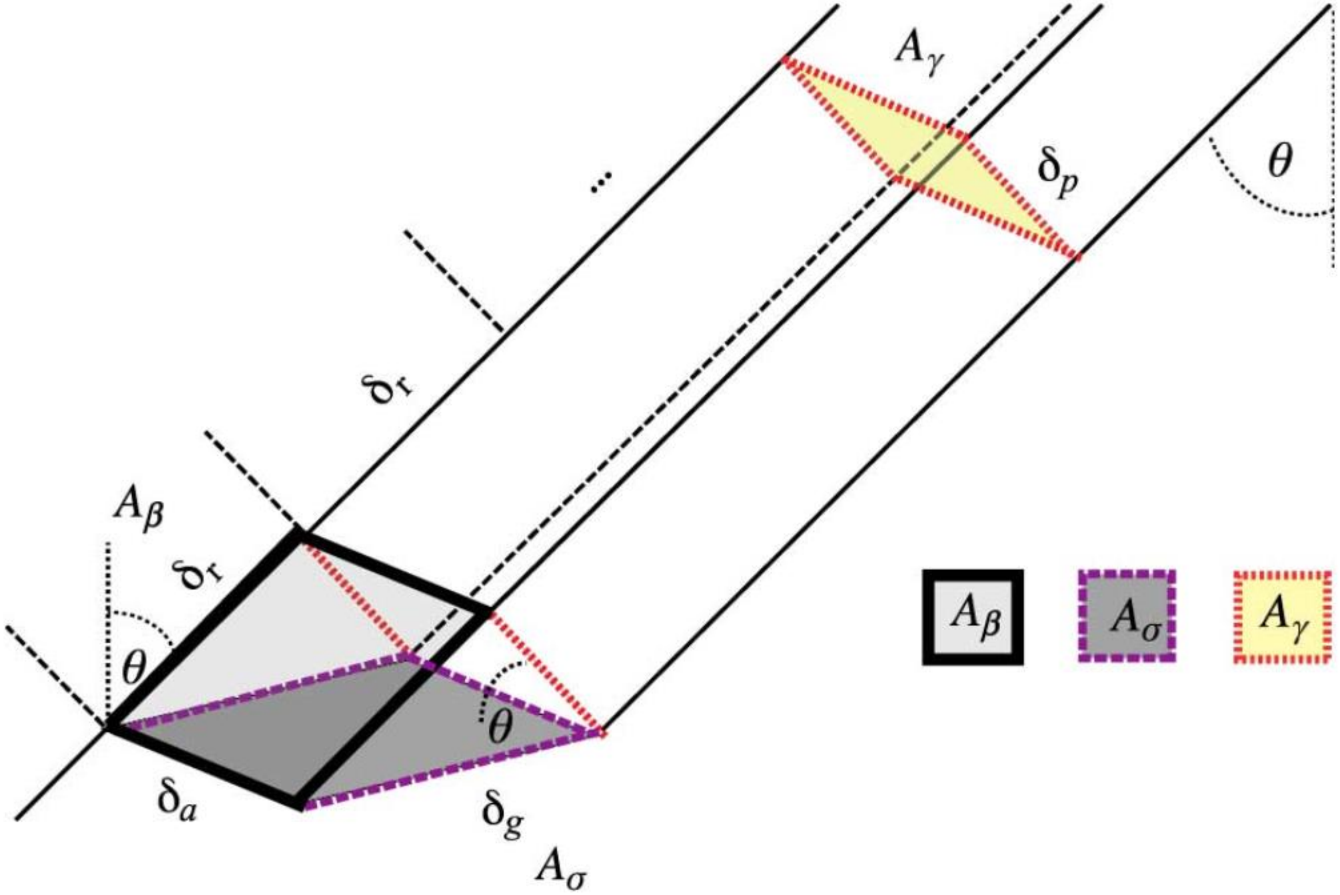
Radar measures **physical properties** of the imaged target. Specifically, we can describe the target through its capability to reflect an electromagnetic wave, given by the **Radar Cross Section** (RCS)

$$\sigma = \frac{P_r}{P_i} 4\pi r^2 \qquad \sigma^0 = \frac{\sigma}{A}$$

Derived by the radar equation, RCS tells us how well a target reflects the signal in a given direction with respect to a uniform sphere.

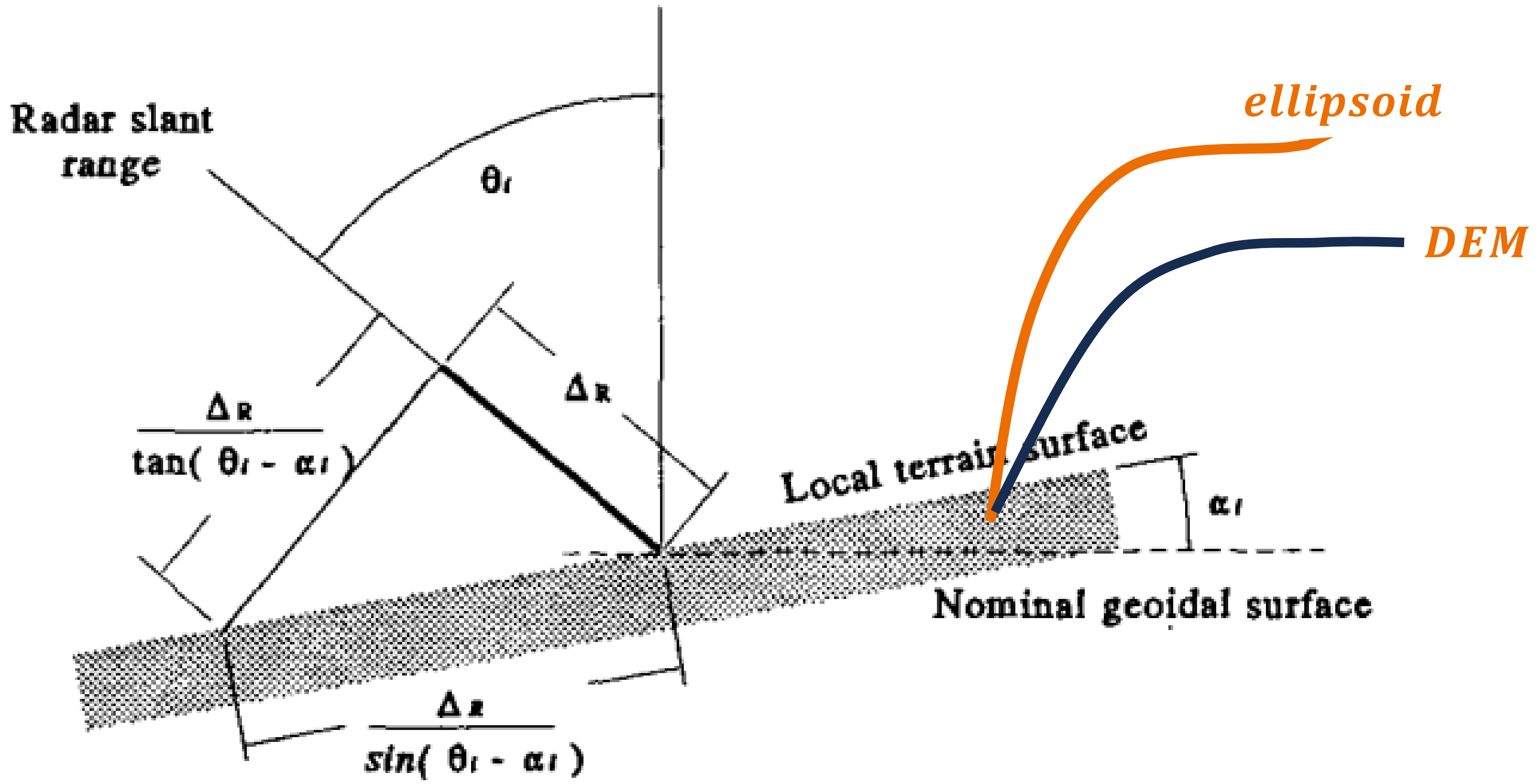
Emery, W., & Camps, A. (2017). *Introduction to satellite remote sensing: atmosphere, ocean, land and cryosphere applications*. Ch.5. Elsevier.

# Radiometric characteristics: geometry




*D. K. Atwood, D. Small and R. Gens, "Improving PolSAR Land Cover Classification With Radiometric Correction of the Coherency Matrix," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 5, no. 3, pp. 848–856, June 2012, doi: 10.1109/JSTARS.2012.2186791.*

# Radiometric characteristics: geometry




Raney, R. K., Freeman, T., Hawkins, R. W., & Bamler, R. (1994, August). A plea for radar brightness. In *Proceedings of IGARSS'94-1994 IEEE International Geoscience and Remote Sensing Symposium* (Vol. 2, pp. 1090-1092). IEEE.

# Radiometric characteristics: what about Sentinel-1 data?

What do we get once we download Sentinel-1 data? The **Digital Number (DN)**

$$\beta^0 = \frac{|DN|^2}{A_\beta}$$

$$\sigma^0 = \frac{|DN|^2}{A_\sigma}$$

$$\gamma^0 = \frac{|DN|^2}{A_\gamma}$$

- DN is the digital number read from the Sentinel-1 data.
- $A_\beta, A_\sigma, A_\gamma$ are the incremental areas (relative to Small's paper*, given as the square root) found on the official Sentinel-1 (calibration) datum.

In addition

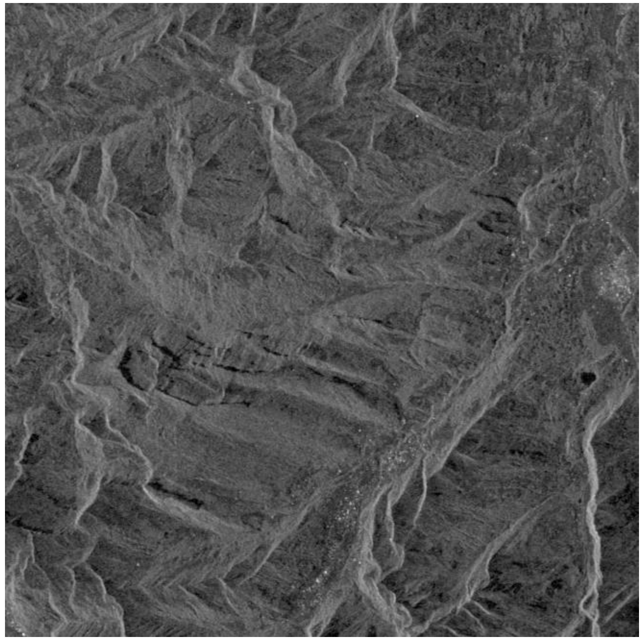
- these areas are undersampled and need a cubic interpolation to resample them to the SLC
- $A_\beta$ is constant and therefore DN and Beta0 differ by a scaling factor.
- $A_\sigma, A_\gamma$ approximation of what one could do by using the local incidence angle.

**Note that: no DEM is taken into account. Areas (i.e. local incidence angle) are related to the ellipsoid**

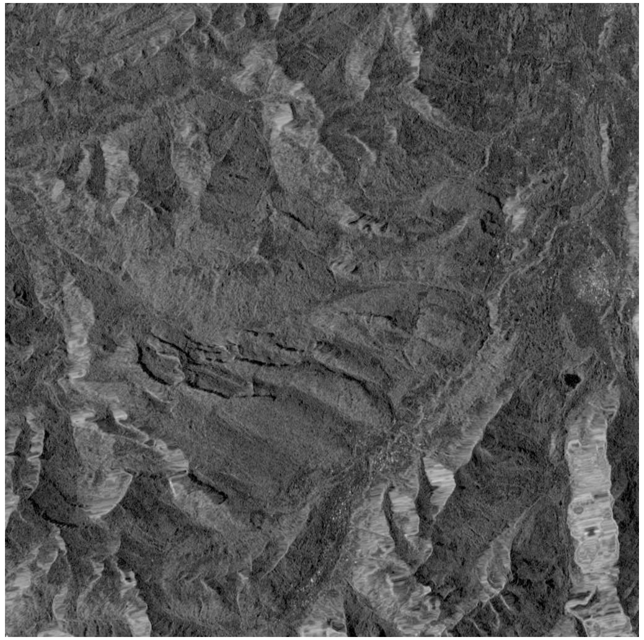
https://sentinels.copernicus.eu/web/sentinel/radiometric-calibration-of-level-1-products

*Small, D. (2011). Flattening gamma: Radiometric terrain correction for SAR imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *49*(8), 3081-3093.

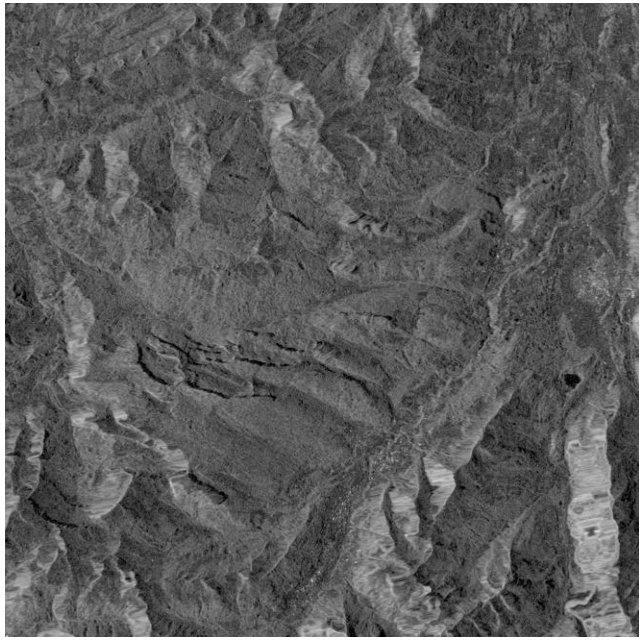
$\sigma^0_{VV}$, no TF, no TC



$\sigma^0_{VV}$, no TF, with TC

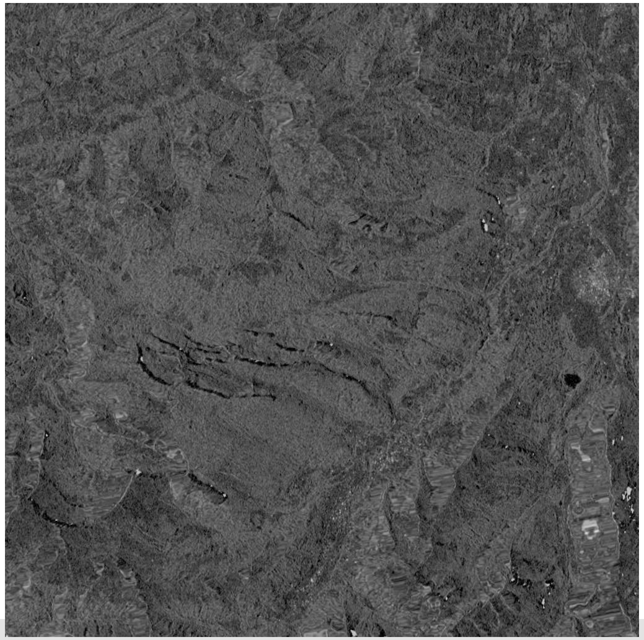


$\gamma^0_{VV}$, no TF, with TC

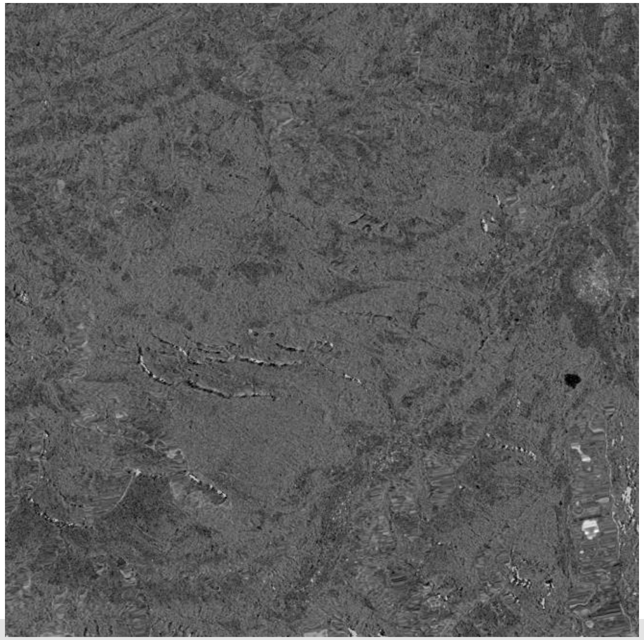


# Comparison between different projections and radiometric corrections

**TC – Terrain Corrected**
**TF – Terrain Flattened**



$\sigma^0_{VV}$, with TF, with TC



$\gamma^0_{VV}$, with TF, with TC

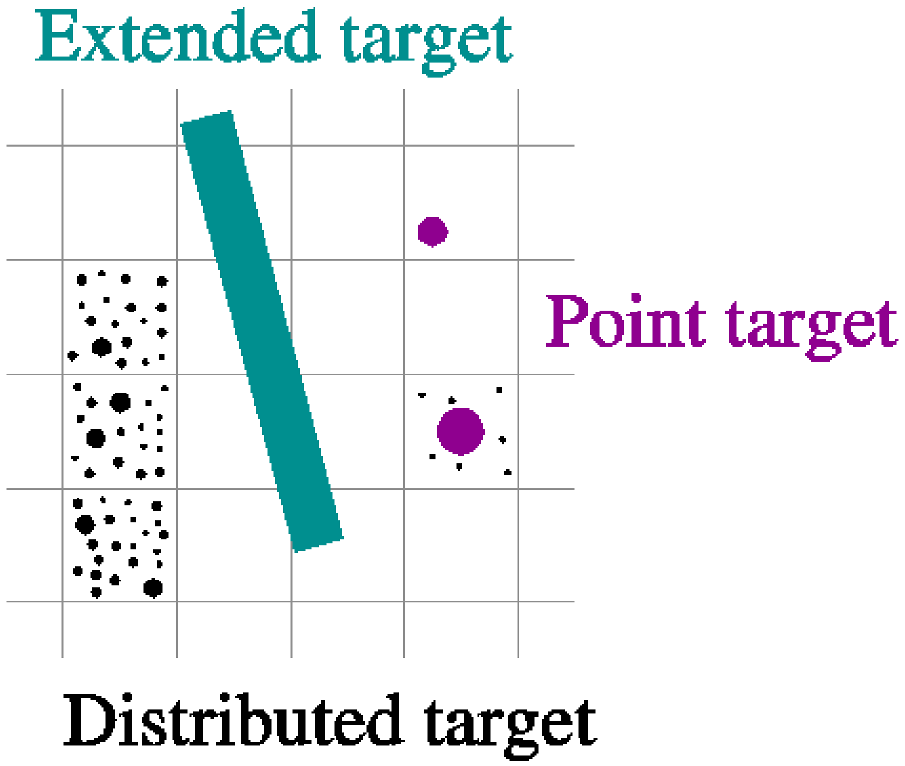
Credits: data processed by Thomas Roßberg (UniBw)

# Radiometric characteristics: what to use?

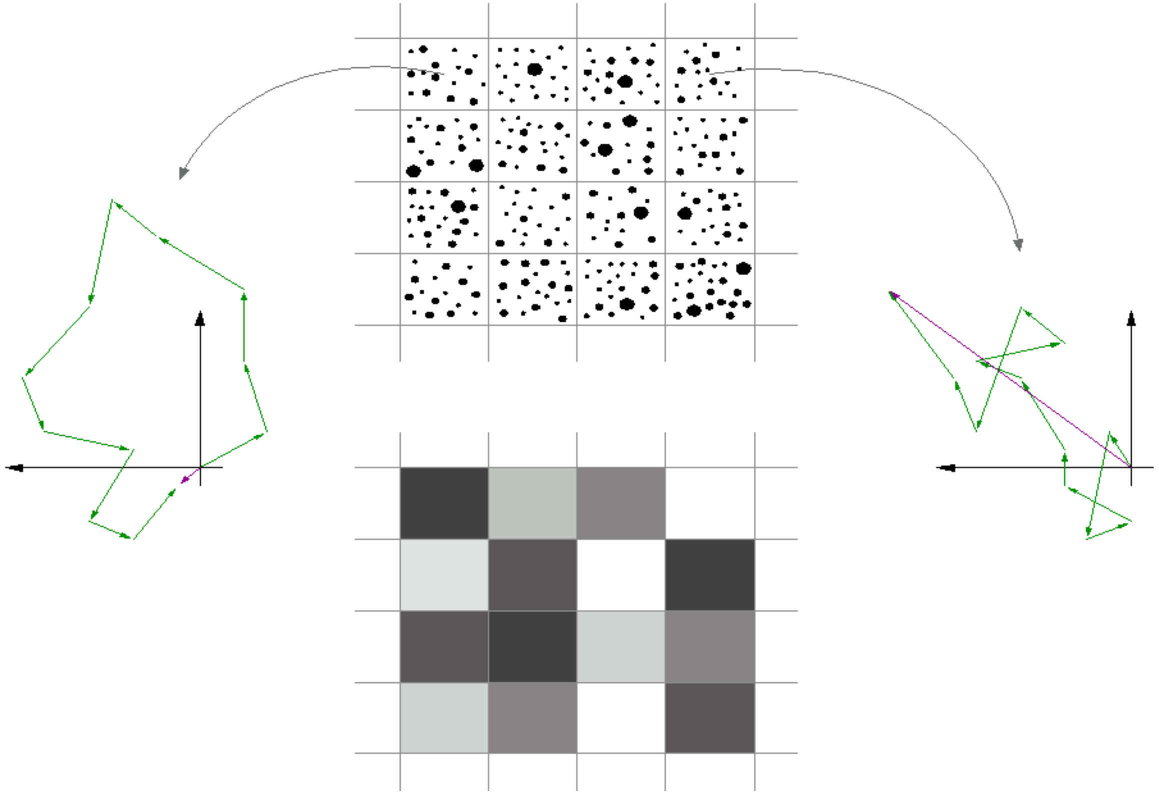
| | Pro | Contra | Use it when… |
|---|---|---|---|
| $\beta^0$ | • Most general term<br>• No variation with the incidence angle<br>• No need of an external DEM | • May suffer from strong variations due to geometry | • No knowledge of the scene's topography<br>• The local incidence angle is something you want to retrieve (i.e. geology)<br>• The satellite system has few look angle option (difference between TSX and S1) |
| $\sigma^0$ | • Physical meaning<br>• Scattering properties of the target for a specific incidence angle. | • Need precise DEM<br>• Despite normalization, still varies due to local incidence angle | • Applications where you want to invert scene parameters (Land cover classification, soil moisture, etc.)<br>• Geometry dependent characterization (i.e., need to additionally use the local incidence angle) |
| $\gamma^0$ | • Values are independent on range and local incidence angle | • Need precise DEM | • Achieving complete independence on local incidence angle (sensors like TSX may use different look angles)<br>• Achieve sensor independence target characterization (e.g. change detection) |

# SAR signal properties

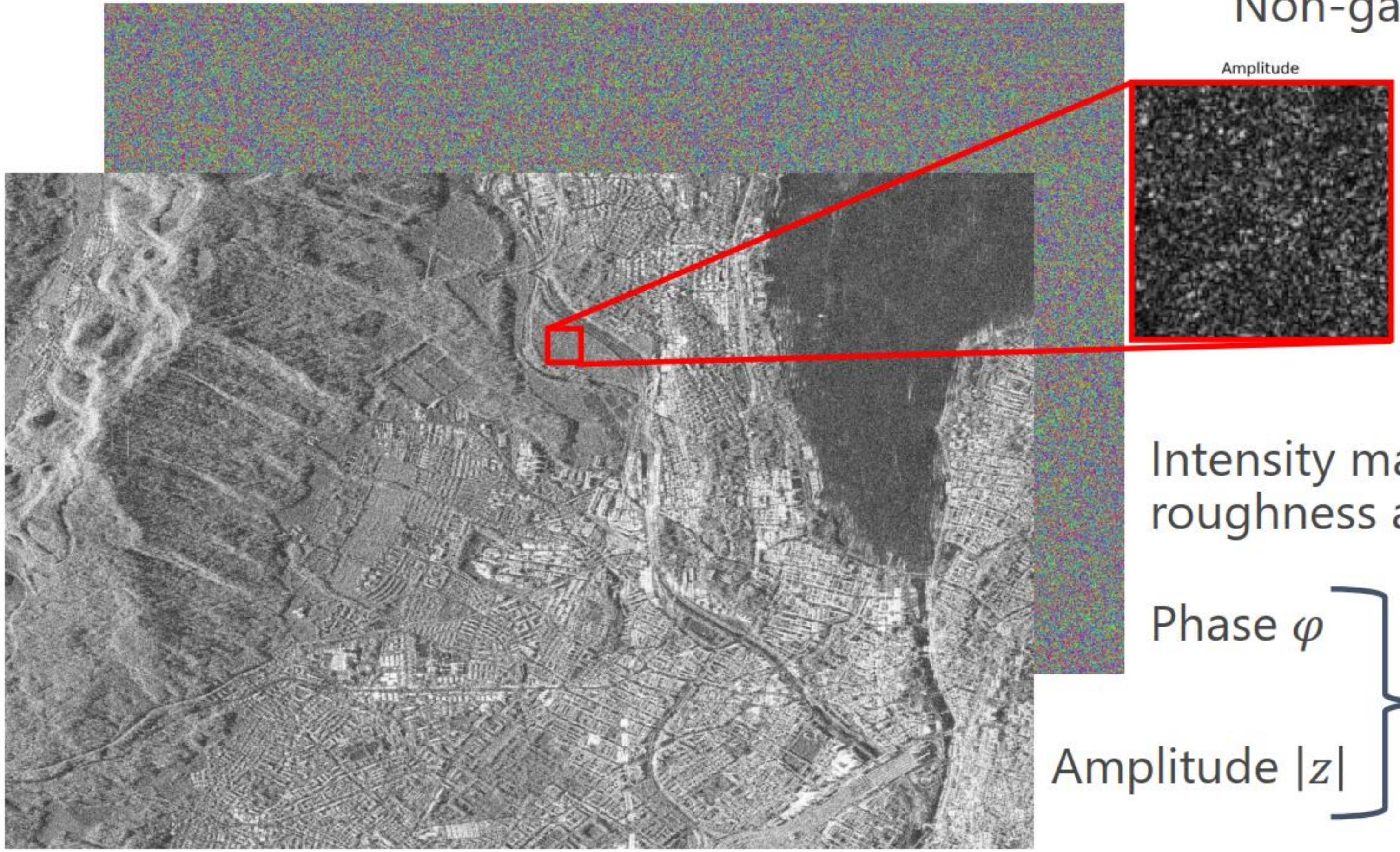
**Type of scatterers**



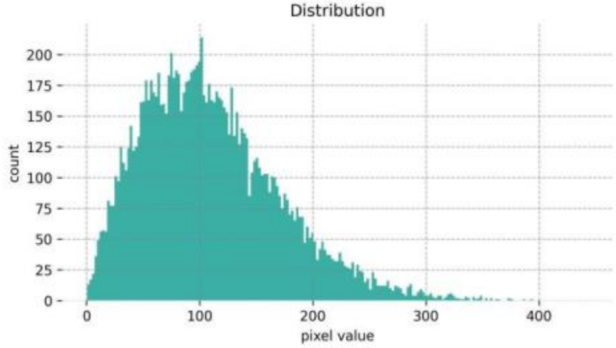

**Speckle effect**



# Statistical properties




## Non-gaussian speckle statistics




Intensity mainly dependent on roughness and geometry

Phase $\varphi$

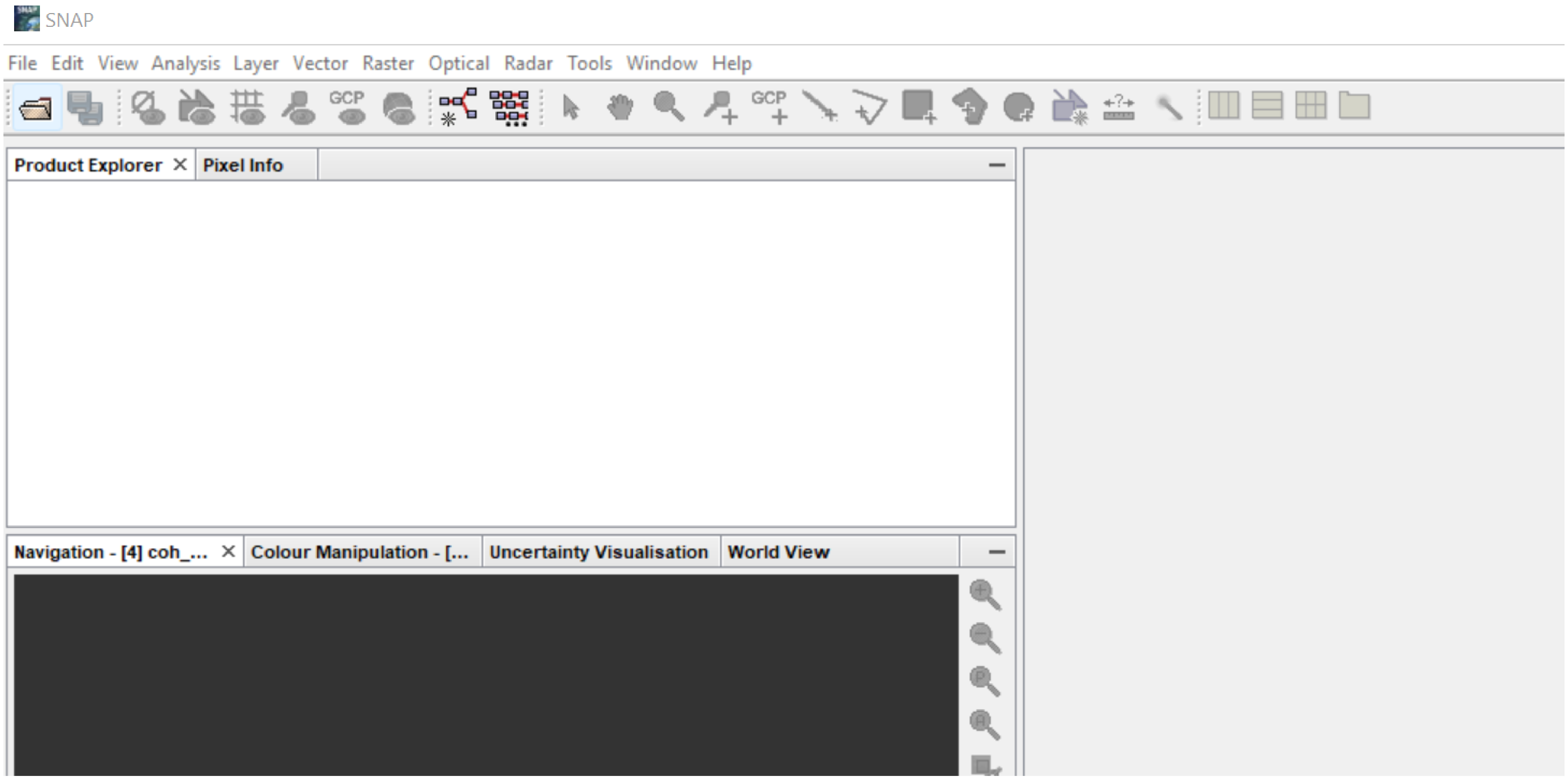
Amplitude $|z|$

Complex signal $z = |z|e^{j\varphi}$

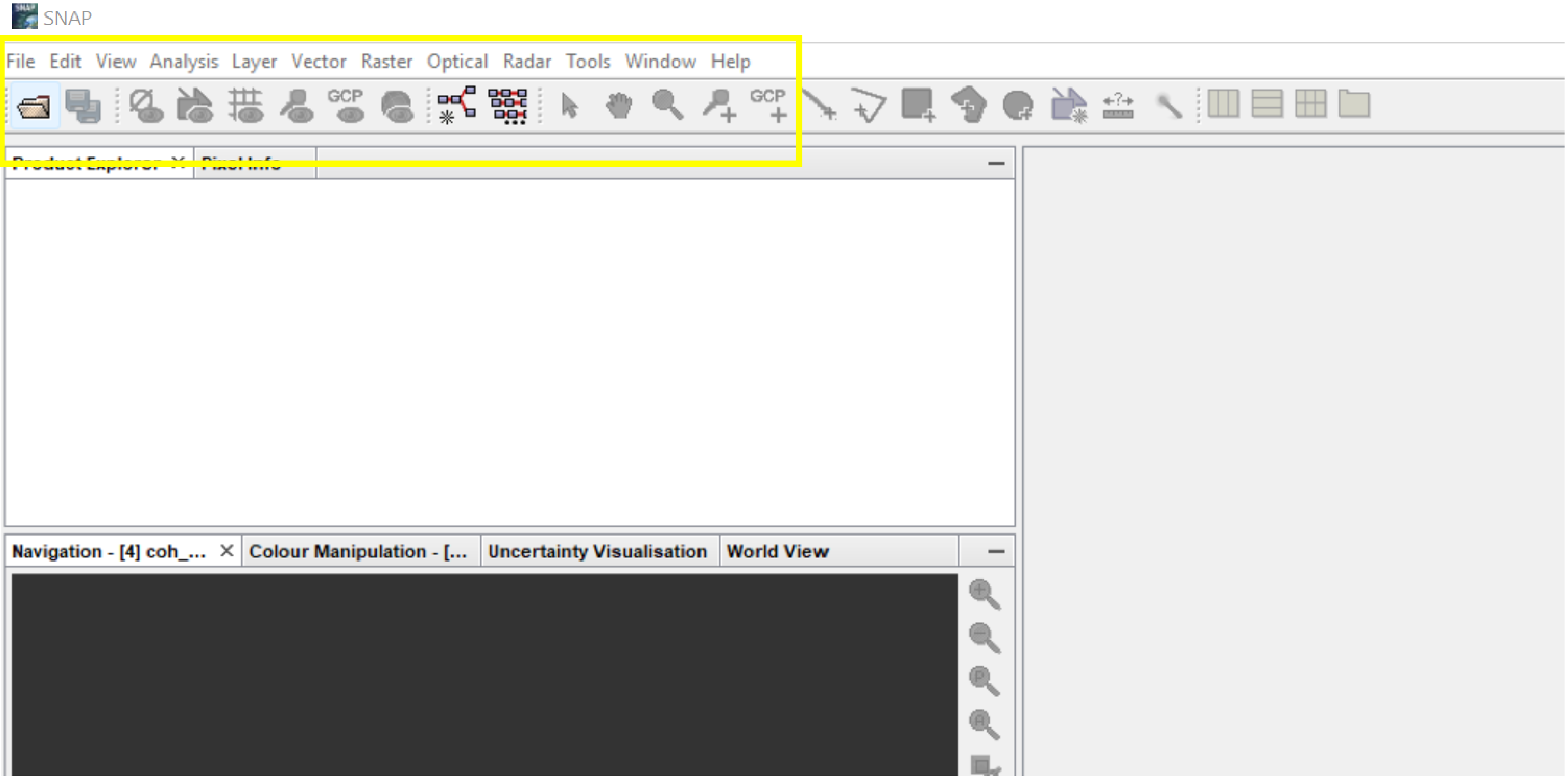
# Data preparation


- ESA
- Data from Sentinel missions
- Free software and open source
- Sentinel-1, -2, -3
- Good system specifications required
- Download from: https://step.esa.int/main/download/snap-download/

# SNAP interface

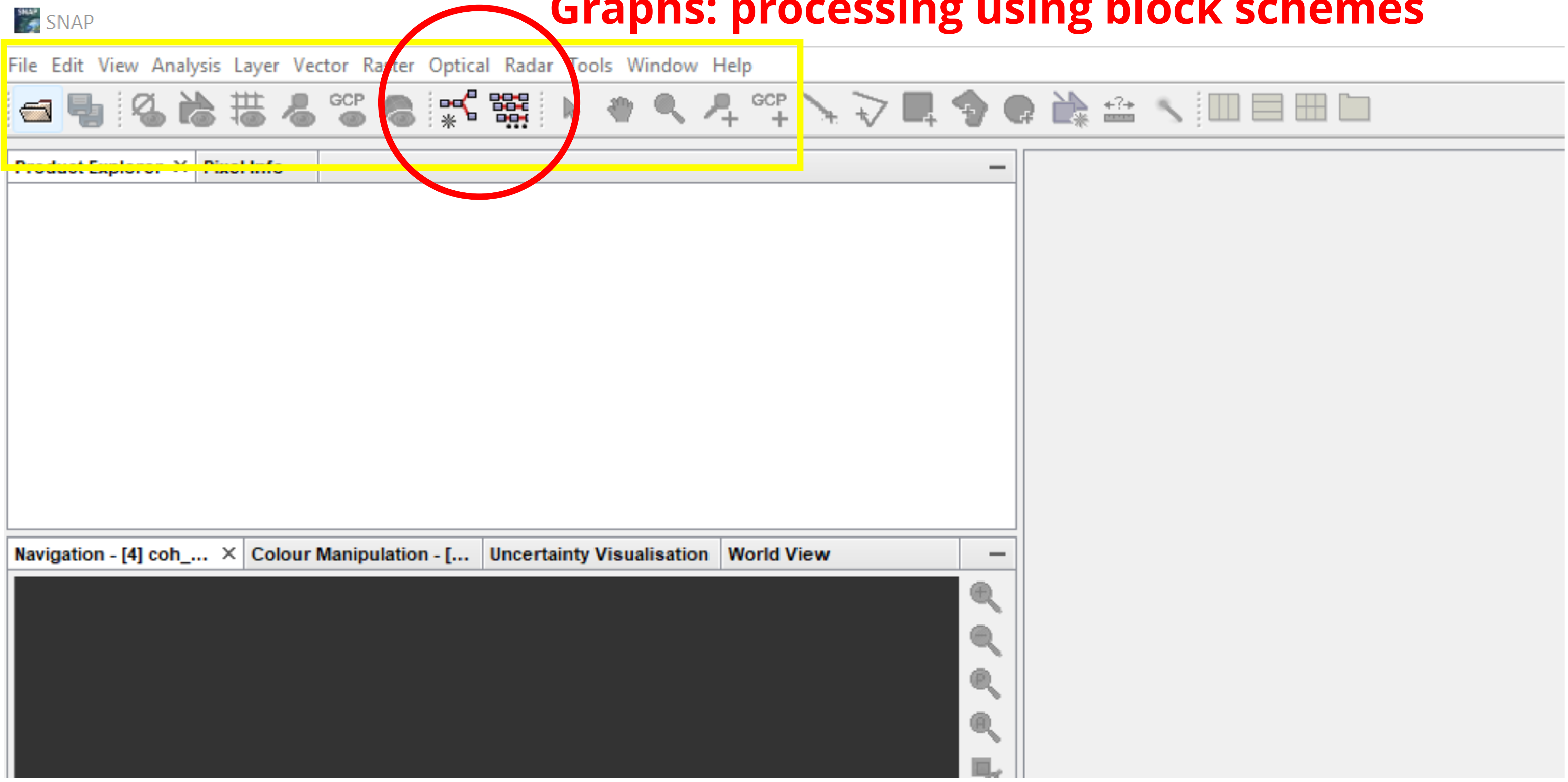


# SNAP interface

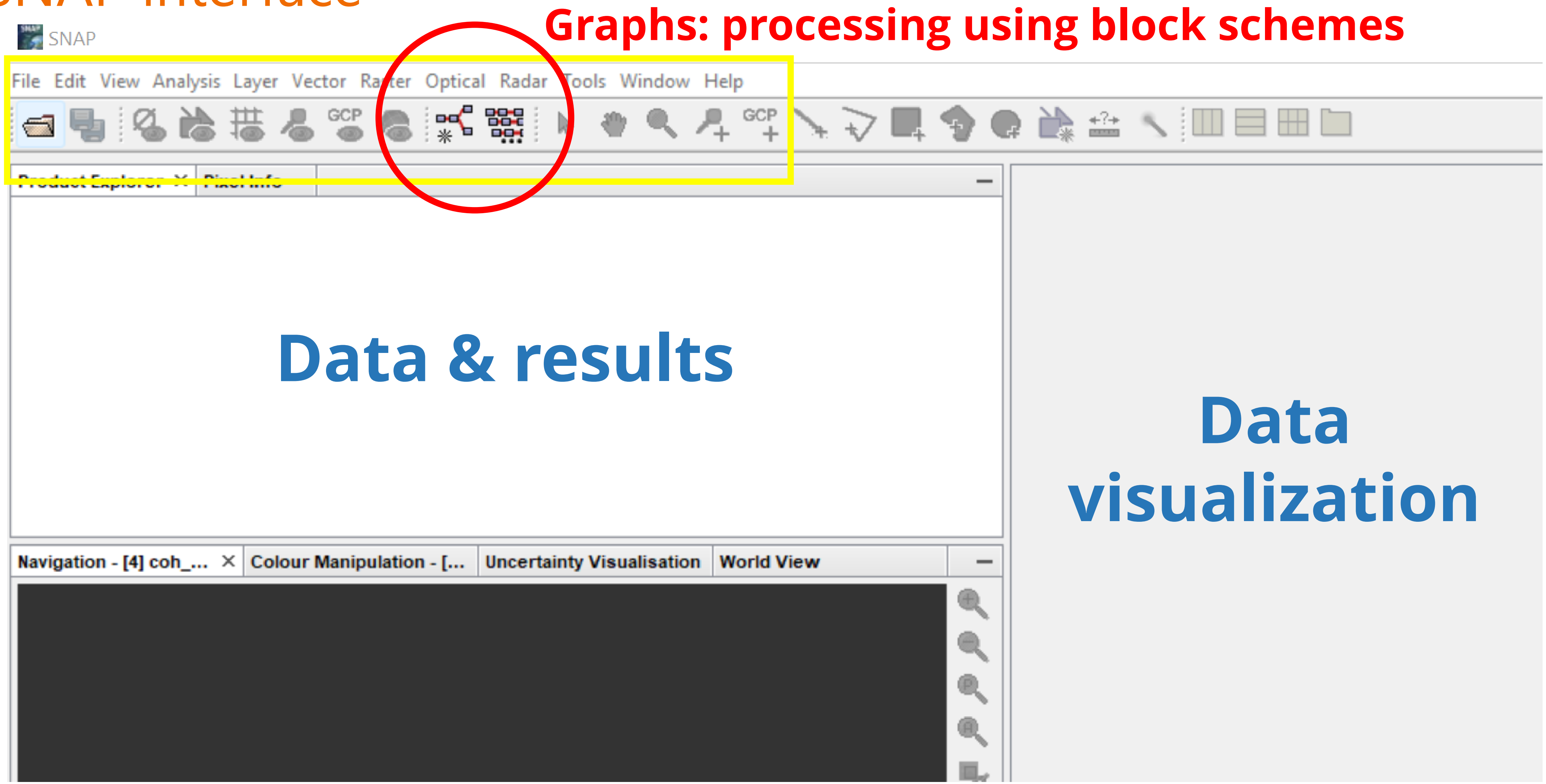


# SNAP interface

Graphs: processing using block schemes



# SNAP interface



# Demo: SNAP (short) tutorial

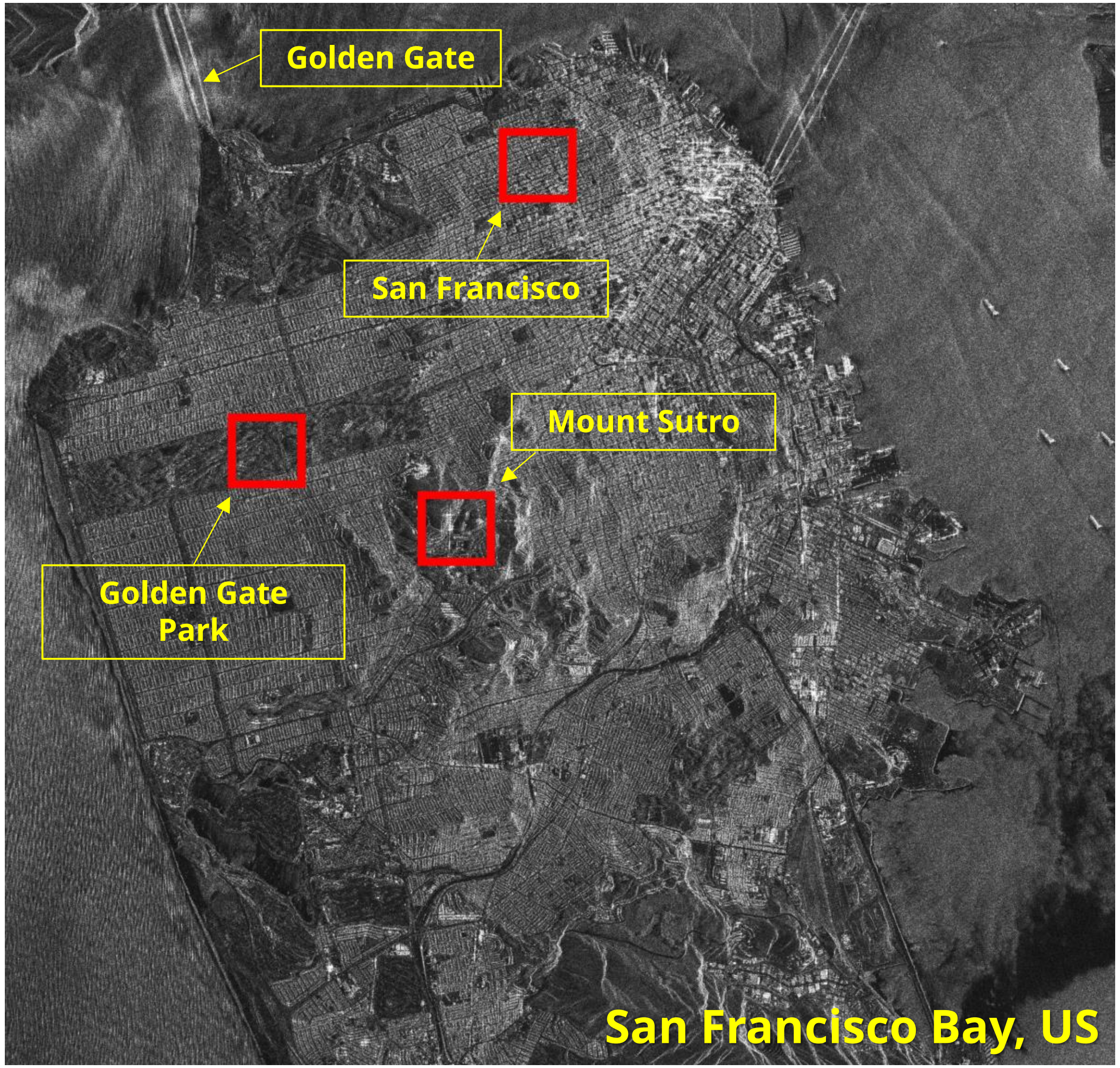
- Intro: *From zero to hero*
- SAR basics, missions and the Sentinel-1
- Machine Learning for SAR image analysis
    - Choice of the data and procurement
    - SAR processing
    - **Pre-processing for ML**
- Takeaways

# Pre-processing of SAR data

Once we have created the correct quantities that we want to use, we are ready to create the actual input to our network. At this purpose we will see:

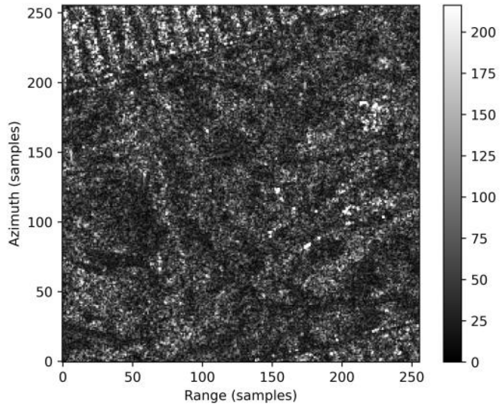
- Distribution of amplitude, intensity, and phase
- Distribution of real and imaginary parts of the SLCs
- ML-ready SAR data: how to pre-process
- Log-transformation: why and what implication it has

# Sample SAR data

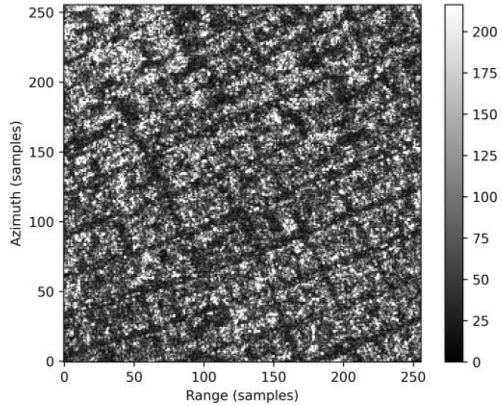



**Type of scatterers:**

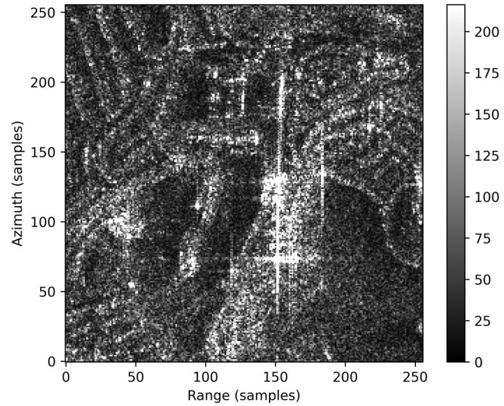
**(1) Distributed**




**(2) Extended**



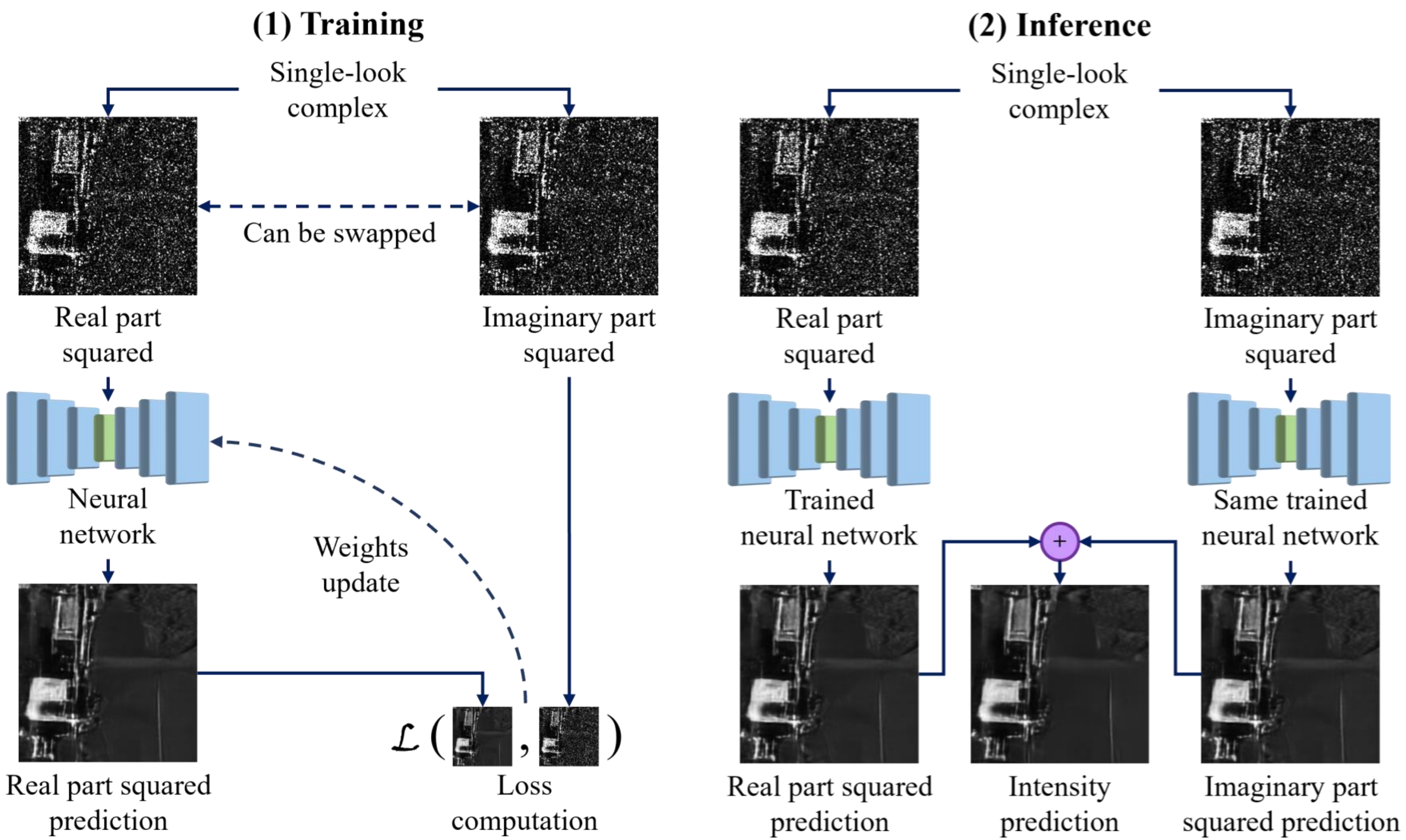

**(3) Point**



# Demo: Jupyter notebook

# Training examples: Self-supervised despeckling

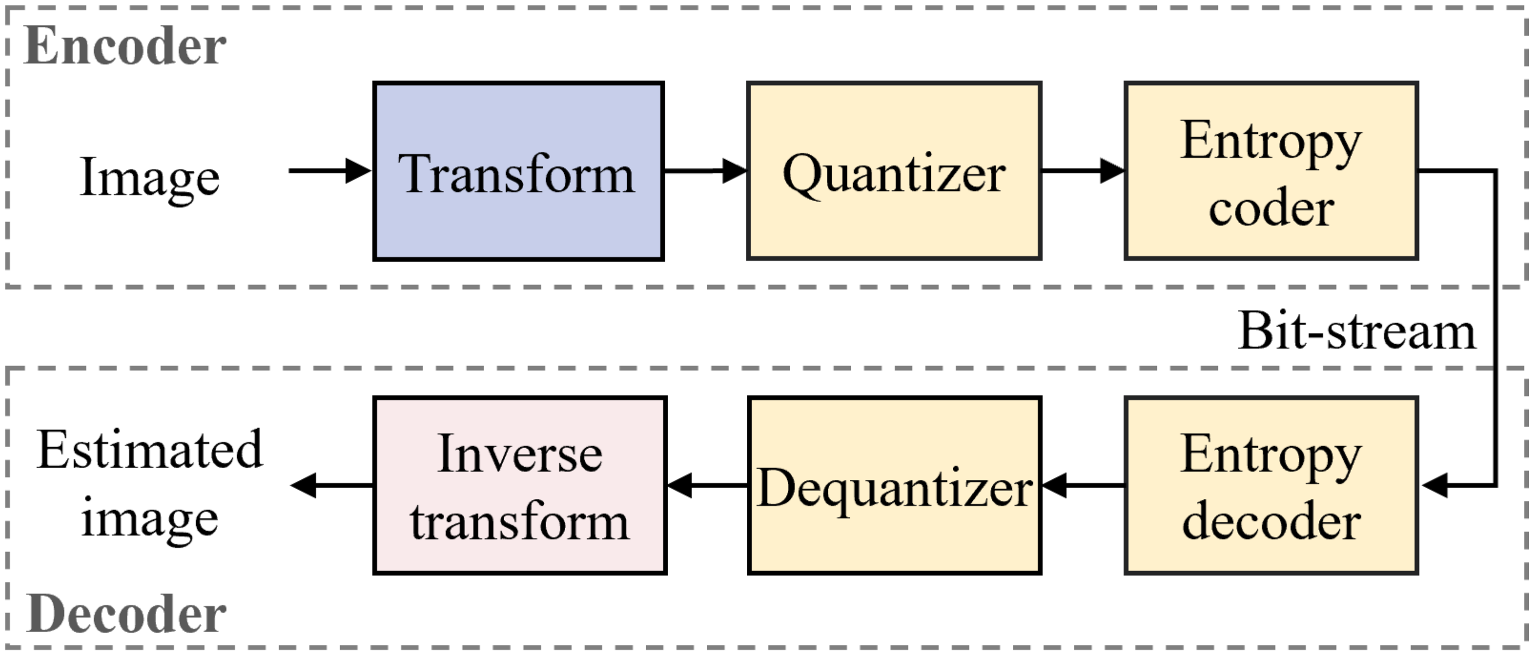
- Single Look Complex : $z = a + \boldsymbol{i}b$
- Gaussian, independent and identically distributed
- Intensity image : $\boldsymbol{I} = a^2 + b^2 =$ $= \boldsymbol{Re}^2 + \boldsymbol{Im}^2$



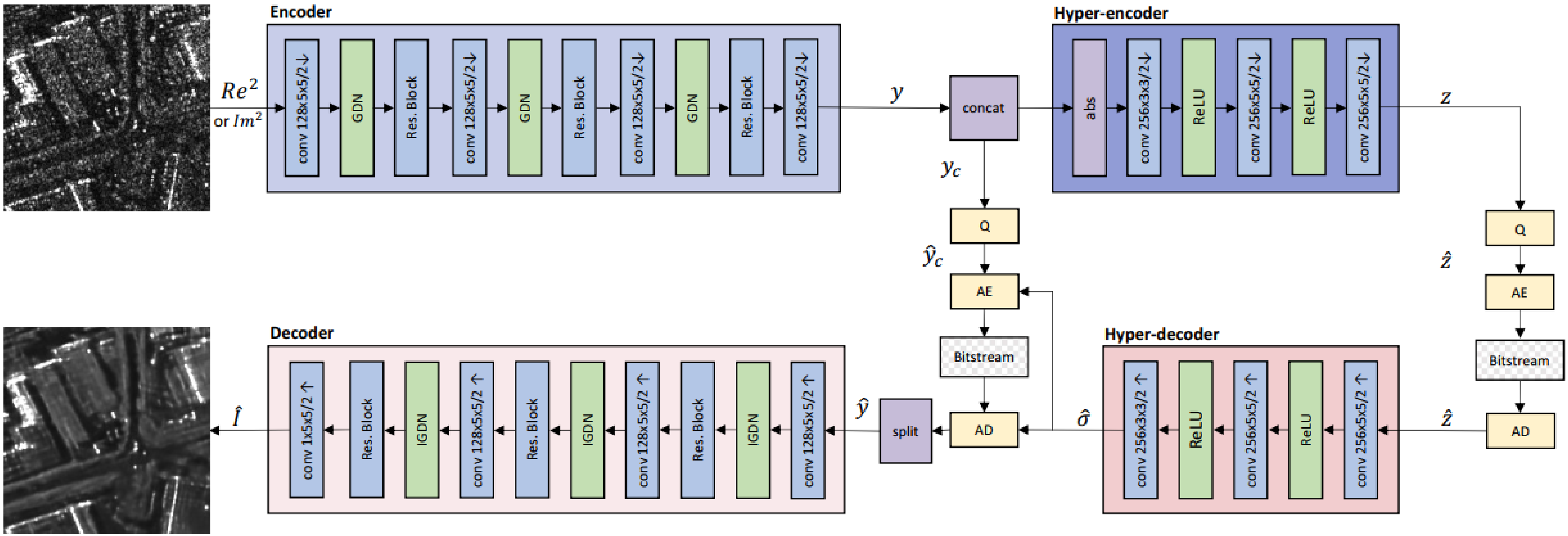

E. Dalsasso, L. Denis, and F. Tupin, "As If by Magic: Self-Supervised Training of Deep Despeckling Networks With MERLIN", *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–13, 2022.

# Joint SAR despeckling and compression

Objective: To obtain an algorithm capable of generating a compressed version of the SAR detected image as small (data size) as possible and reconstructing a despeckled version with the least possible distortion.

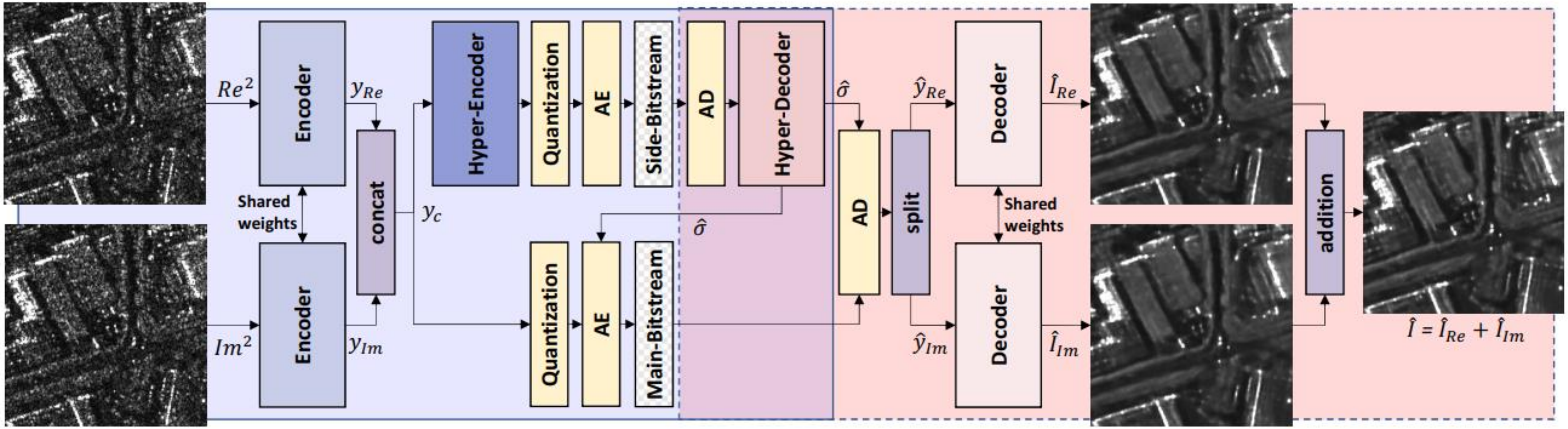


# Joint SAR despeckling and compression: training




Sica, F., Foix-Colonier, N., & Amao-Oliva, J. (2024, July). Self-Supervised Joint SAR Image Compression and Despeckling. In *IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium* (pp. 2188-2190). IEEE.

# Joint SAR despeckling and compression: estimation




Sica, F., Foix-Colonier, N., & Amao-Oliva, J. (2024, July). Self-Supervised Joint SAR Image Compression and Despeckling. In *IGARSS 2024-2024 IEEE International Geoscience and Remote Sensing Symposium* (pp. 2188-2190). IEEE.

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# Takeaways

**Most of the effort is required in data preparation**

- Data processing is highly **application-dependent**
- A **deep understanding of the problem** you aim to solve is crucial

**Preprocessing challenges**

- Standard preprocessing techniques may not be applicable or are more complex for SAR data
- **Preprocessing choices** can complicate post-processing or even **compromise** results

**In-depth SAR domain knowledge** is essential for specific applications

- Understanding key concepts such as **Beta nought**, **Sigma nought**, and **Gamma nought**
- Familiarity with **polarizations**, **acquisition geometries**, and **acquisition modes**
- Awareness of **data availability** for your region or application

**Training** models must be adapted to the **unique statistical properties** of SAR signals.

# Thank you for the attention

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