

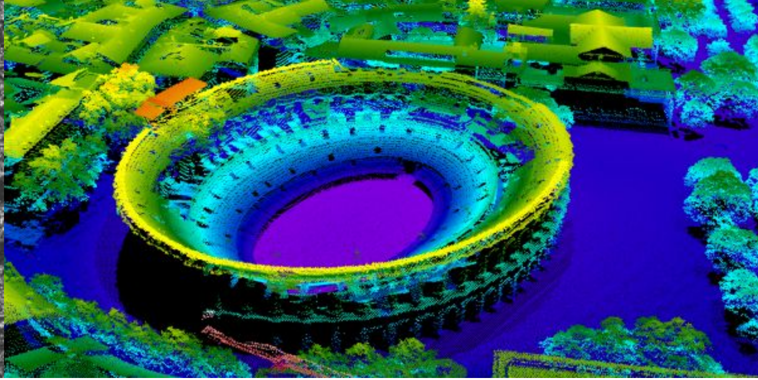

Earth Observation and Remote Sensing Image Mining

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ONERA
THE FRENCH AEROSPACE LAB

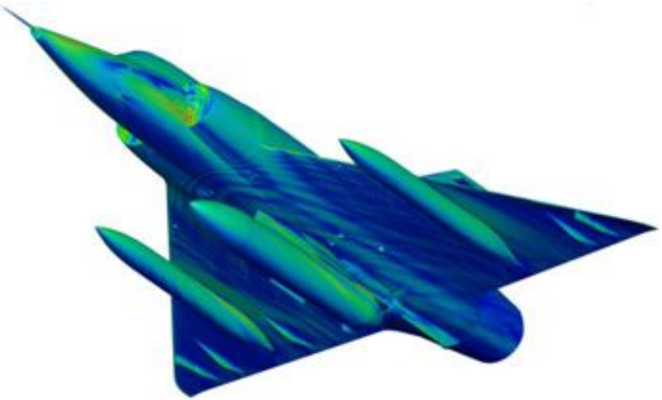
ONERA in a nutshell

Research center in

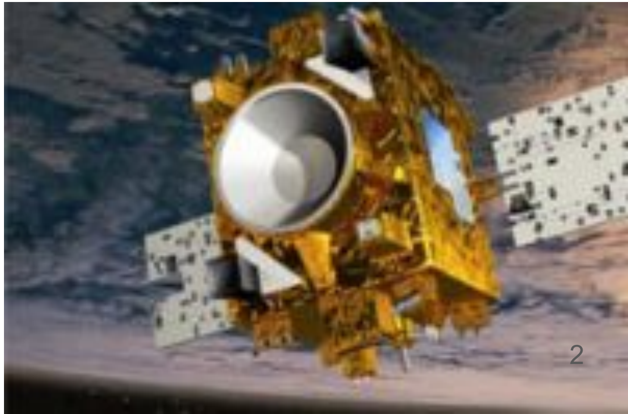
- Aeronautics
- Defence
- Space

Wind tunnel

Electromagnetic signature



Microscope satelllite



Remote sensing

What is remote sensing

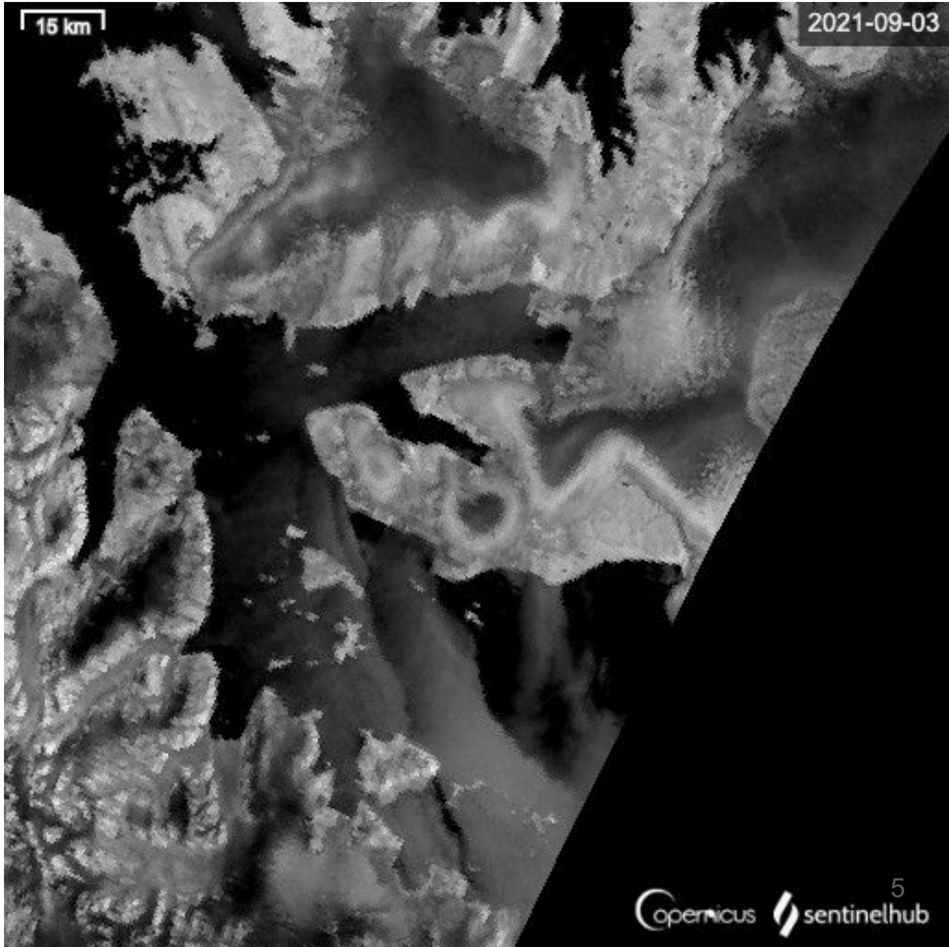
Timelapse of Sierra Nevada
Spain

Sentinel-2 Optical sensor RGB images

What is remote sensing

Time Lapse of Hinlopenstretet
Svalbard Norway

Sentinel-1 SAR sensor VV images

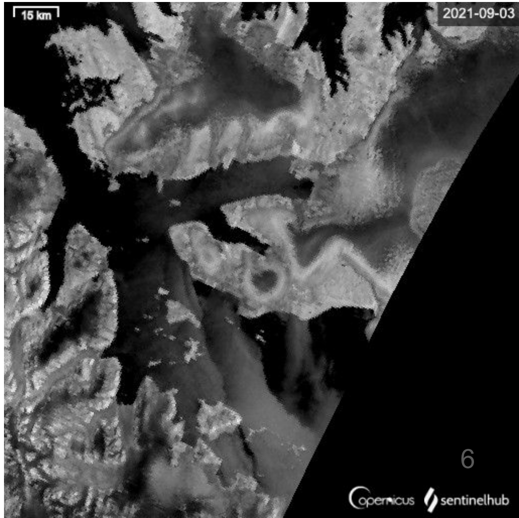


What is remote sensing

Observing the Earth (but it can be another planet) from afar, but not too far (generally with a satellite or airborne sensor)

Multiple questions :

- How much are the water reserve in snow ?
- Is the water free for sailing or is the sea ice too thick ?
- What are the damage after an earthquake ?
- Did another country build a nuclear power plant ?
- How do crops grow this year ?
- What was planted ?
- Did someone build a house without permission ?
- …



Outlines

Objectives

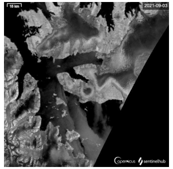
1. Knowing what remote sensing is, and what are the different sensors
2. Assimilating image processing techniques for remote sensing
3. Getting some specificities of machine-learning/AI for remote sensing
4. Your case study

Outines

- Sensors presentation
- Optical remote sensing with applications
- LiDAR remote sensing
- SAR remote sensing with applications
- Radar altimeter
- Radiometer
- The need for co-registration

A. Sensors

Sensors

	Optical wavelength: **400 to 2200 nm**	**Electromagnetic** wavelength: **1cm to 1m**
Passive: measure energy that is naturally available	● Optical imaging sensors 	● Radiometers
Active: provide their own energy source for illumination	● LIDAR	● SAR imaging sensors  ● Radar altimeters

Satellite VS Airborne sensors

Airborne sensors **Sensor on plane or drones**	**Observation satellite**	**Weather satellite**
Cover a “small” area	Cover large areas	Cover VERY large areas
Close to the earth (10km)	Far from the earth (700km)	VERY far from the earth (36000km)
Choice of the track	Fixed orbit	Fixed position
Flexible repeat time Temporal stack on a mission timescale (few month or few month per year)	Fixed repeat time (~10 days) Temporal stack on multiple year	Fixed repeat time (~15 min)
Sub meter resolution	meter to 10 meters resolution	3km resolution

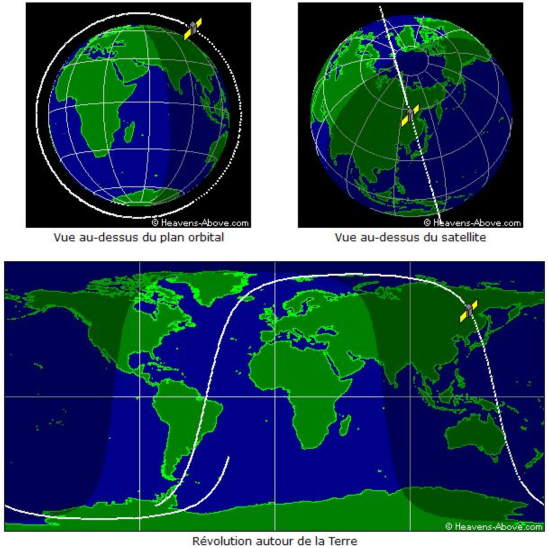
Sun synchronous orbits

Optical satellites:

Half of the orbit is in the sun and half is in the night

Take images around noon local time

Sentinel-2 orbit (Heavens above)

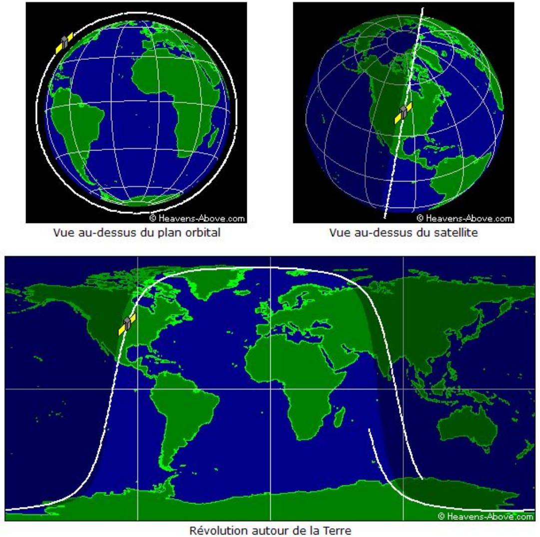


Radar satellites:

Stay at the sun/night limit

The solar panel are always directed to the sun

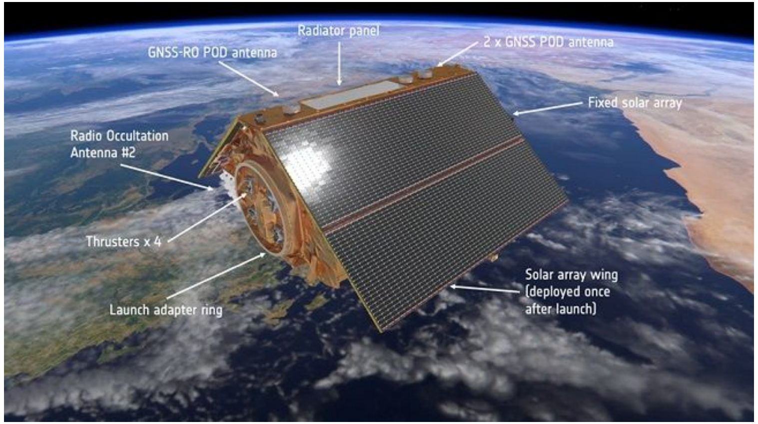
TerraSAR-X orbit (Heavens above)

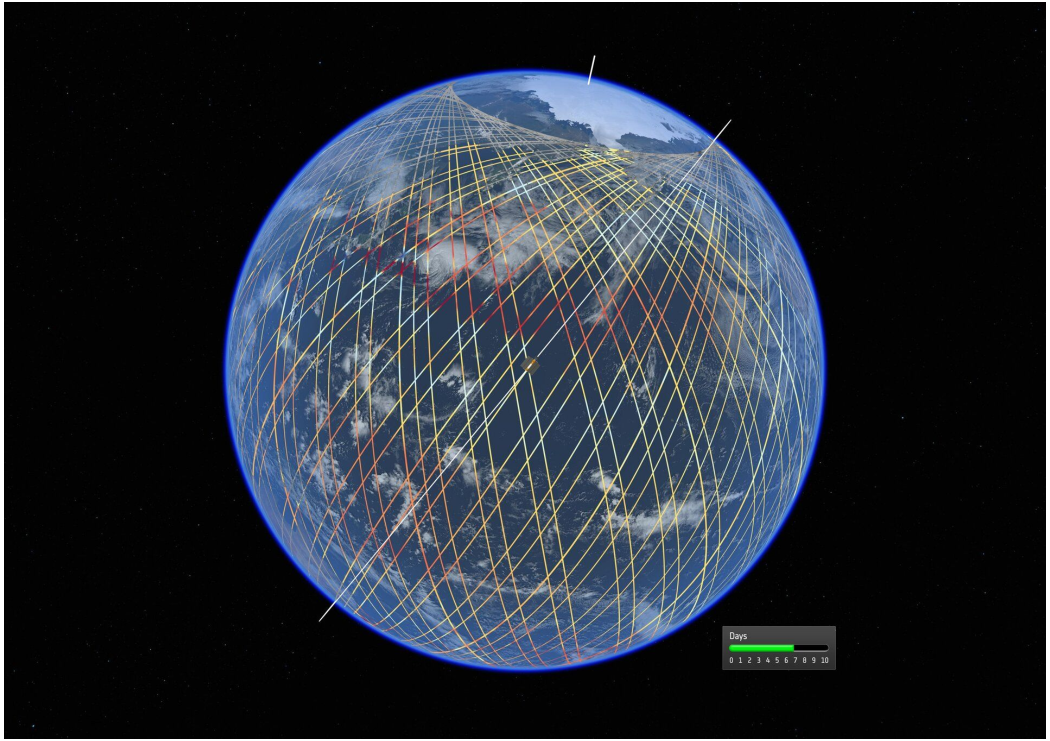


Sentinel-6 non sun synchronious orbit

Altimetry satellite missions:
Near-real-time measurements of sea-surface heights

- Cover most of the oceans
- TOPEX/Poseidon and Jason measures continuity

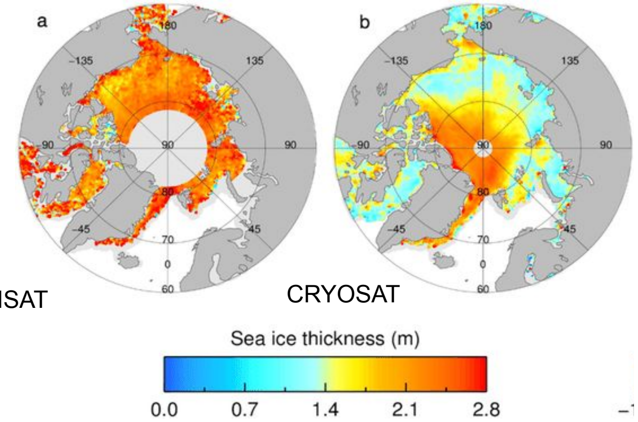




CryoSat-2 non sun synchronious orbit

Go to higher latitudes than sun synchronious sensors

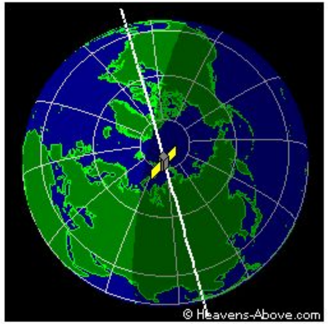
Journal of Geophysical Research: Oceans. 124.
10.1029/2019JC015232/ R&R Tilling, A. Shepherd (2019)



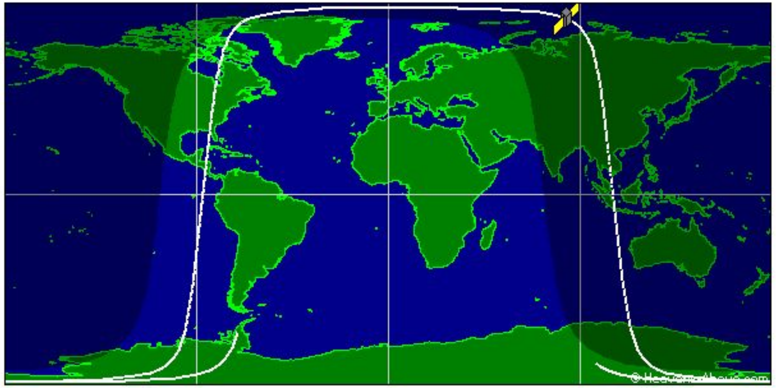
ENVISAT

CRYOSAT

Vue au-dessus du plan orbital



Vue au-dessus du satellite

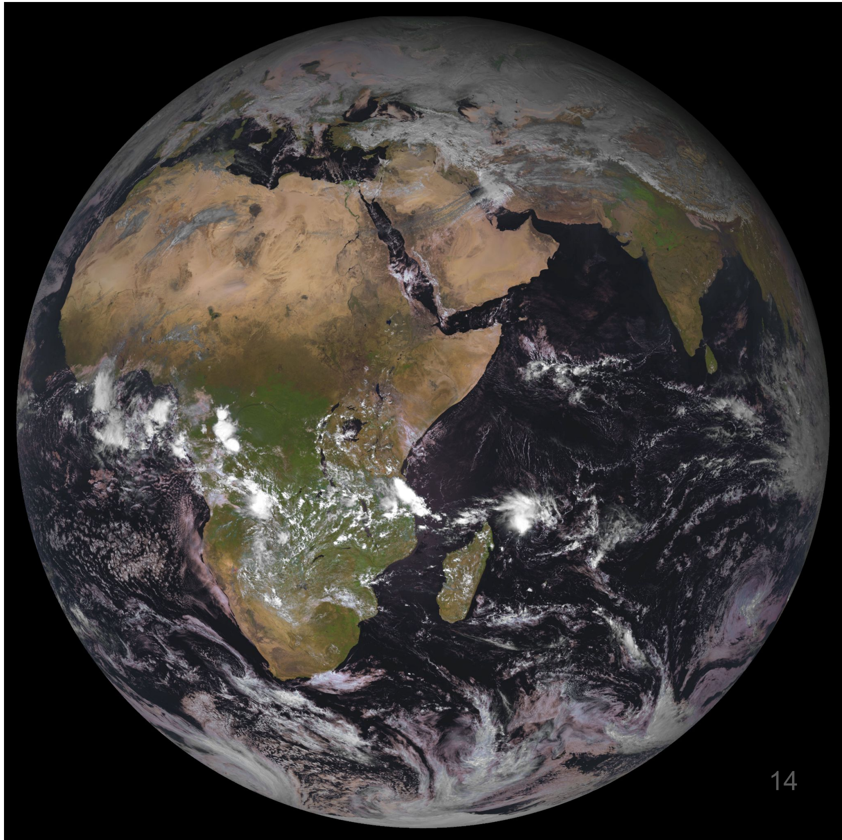


Révolution autour de la Terre

Geostationary orbits for weather forecast

The orbit is at 36 700km

Fixed point above the earth



B. Optical remote sensing

Optical sensors

Some current sensors :

- ESA : Sentinel-2 *opendata*
- NASA : Landsat (Landsat-9, Landsat-8,...) *opendata*
- MAXAR (ex-Digital global) : Worldview-3, Worldview-2
- AIRBUS/CNES : Pléiades Neo, Pléiades, Spot-7

	Sentinel-2	Landsat-9	Worldview-3	Pleiade Neo
Spatial resolution RGB	10m	30m	1.24m	0.3m
Radimetric resolution/quantization	12 bits	14 bits	11 bits	12 bits
Number of bands	10	11	29	6
Swath	290km	185 km	13 km	14 km
Revisit time	5 days	8 days	14 days / on demand	26 days / on demand

Wavelength and bandwidth

- Each band has a special target :
  - RGB bands
  - Infrared for vegetation or snow
  - Bande 10 for cloud detection
- Trade off between spatial resolution and spectral resolution

Pleaides	Spectral resolution	Spatial resolution
Panchromatique (PA)	470 – 830 nm	50cm
Blue (B0)	430 – 550 nm	2m
Green (B1)	500 – 620 nm	2m
Red (B2)	590 – 710 nm	2m
NIR (B3)	740 –940 nm	2m

Sentinel-2 spectral bands

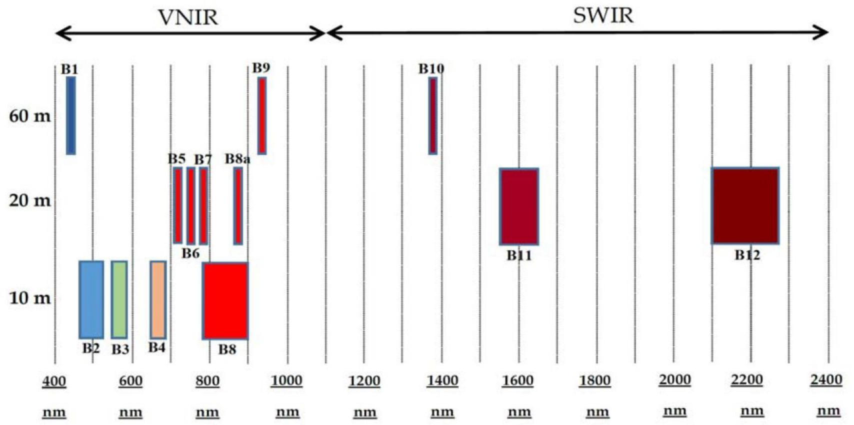


Figure 1. MSI spectral bands vs. spatial resolution with corresponding FullWidth at Half Maximum (FWHM). Source: [9]

Band combinations for vegetation or snow detection

NDVI: Normalized difference vegetation index

NDVI = (NIR - R) / (NIR + R)

NIR: near infrared, R: Red

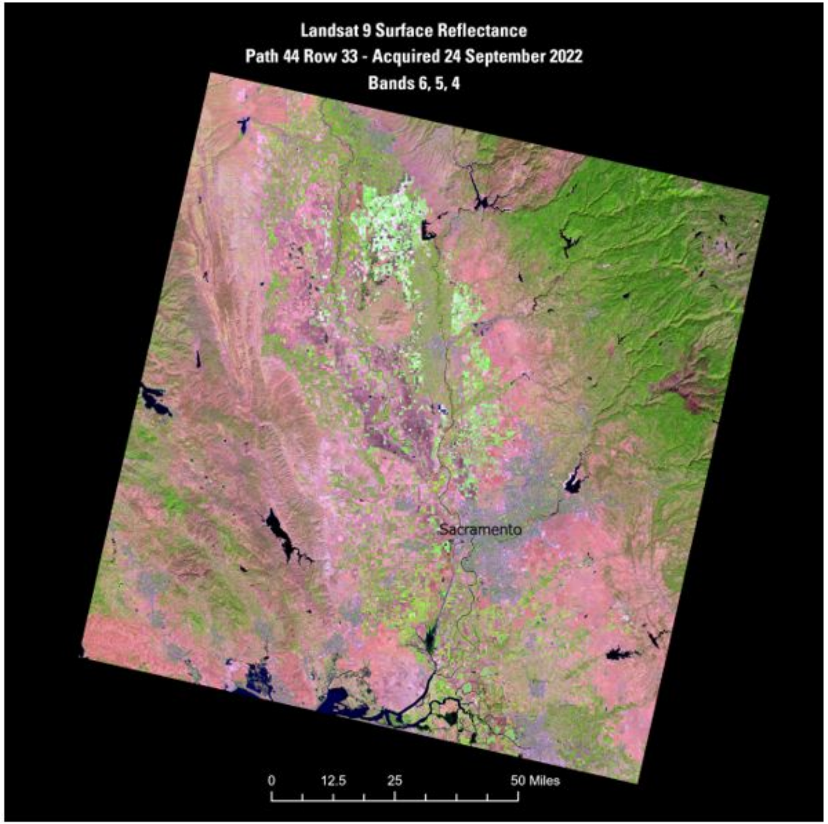
NDSI: Normalized Difference Snow Index

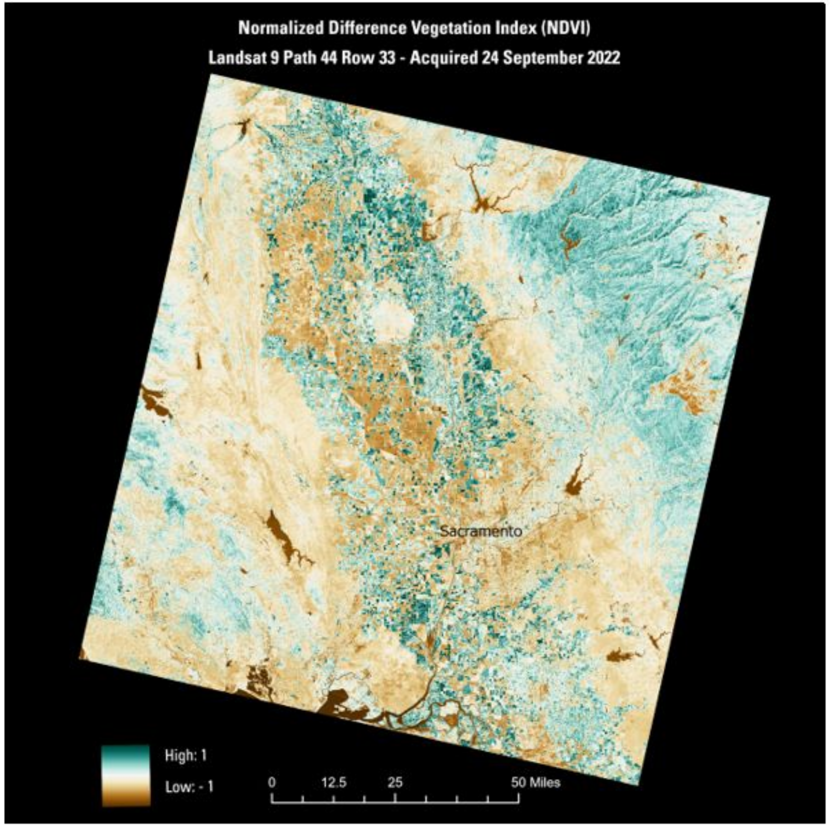
NDSI = (NIR - G) / (NIR + G)

NIR: near infrared, G: Green

NDVI example

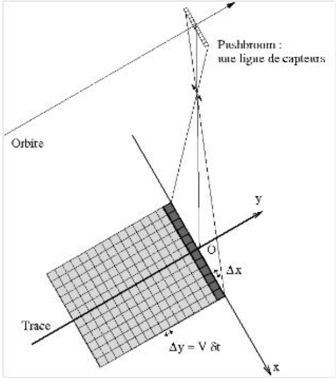
https://www.usgs.gov/media/images/landsat-surface-reflectance-and-normalized-difference-vegetation-index





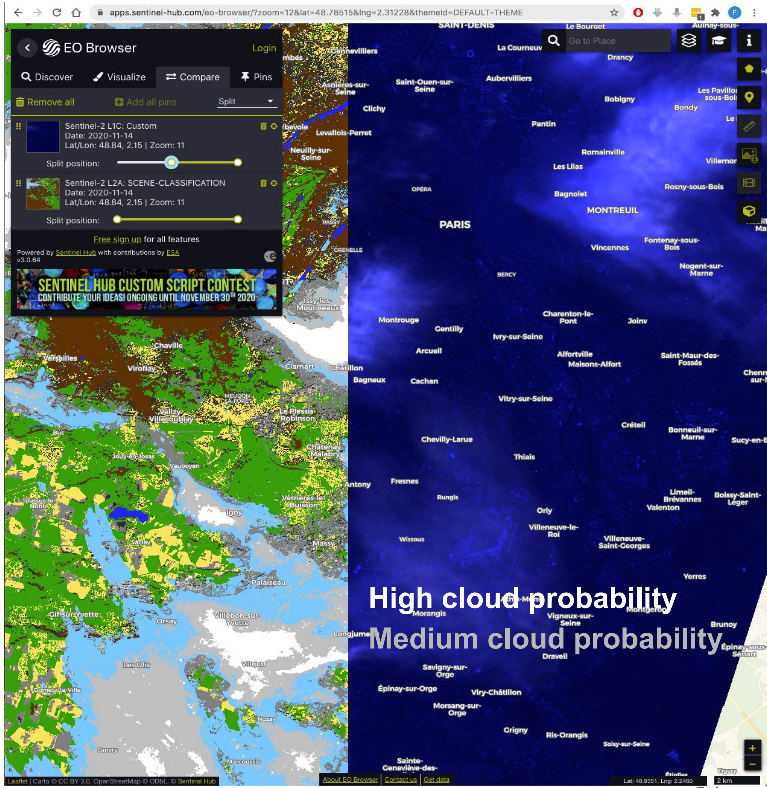
Pushbroom acquisition

- Line are acquired one at a time
- Use the sensor displacement to create an image
- The line need to be merged LOD0 “as acquired by a CCD matrix”
- There may be vibrations



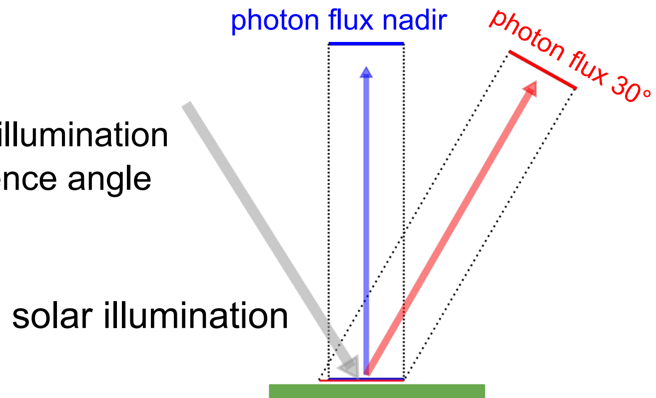
Level of processing and impact of the atmosphere

L0	Original data
L1C	Orthorectified images, Top of Atmosphere (with clouds mask)
L2A	Orthorectified images, Ground surface reflectance (with clouds removed)



Cloud detection :
- Bande 2 : Detect dense clouds (spatial resolution 10m)
- Bande 10 : Detect thin cloud (spatial resolution 60m)

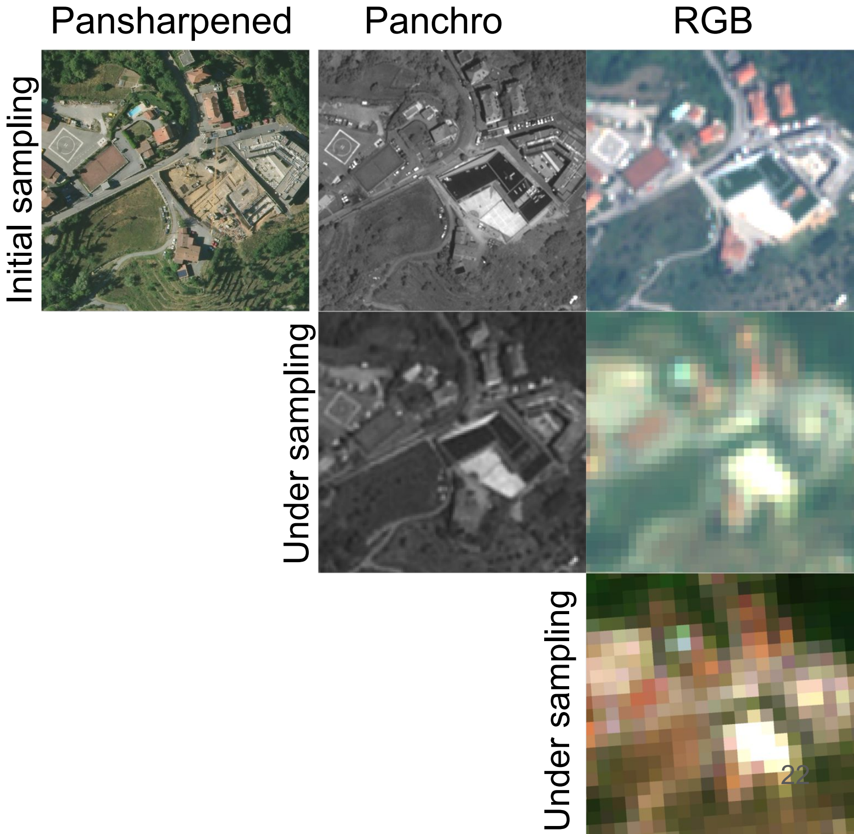
Reflectance :
- Compensate from the solar illumination
- Compensate from the incidence angle



Resolution, pixel spacing and pan-sharpenning

- Resolution: capacity to separate two similar target
  Depends on the acquisition system
- Pixel spacing: size of a pixel in the image domain

For real images, when sampled at Shannon, the pixel spacing is half the resolution



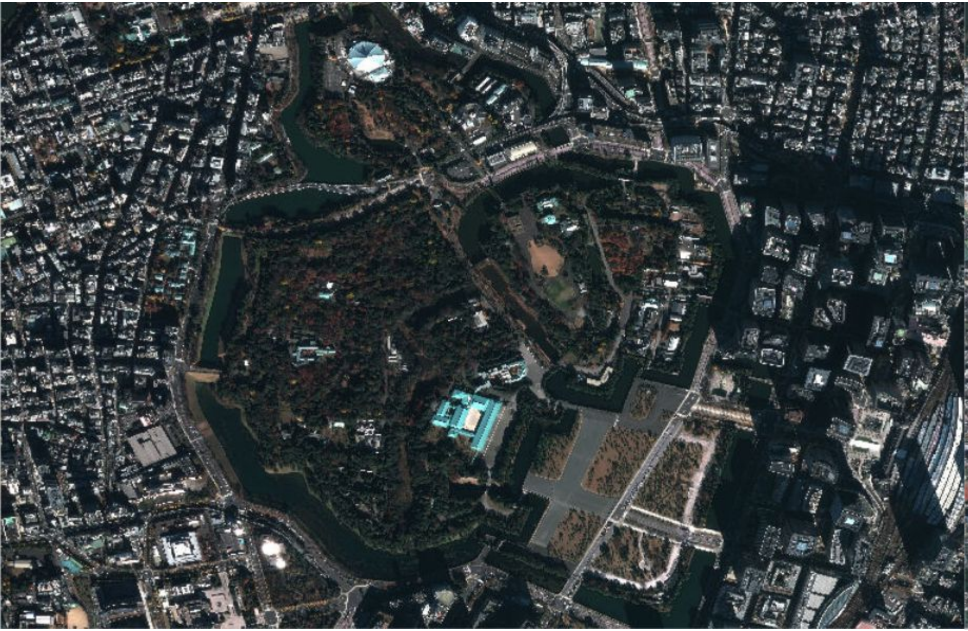
Pansharpening

Panchromatic band **finer resolution** than RBG bands.

Pansharpening : Pachro + RGB to have a fine resolution RGB image

Illumination and seasonal change

17-12-2020

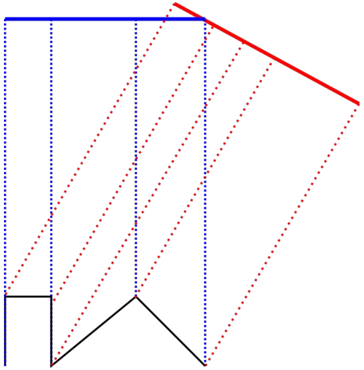


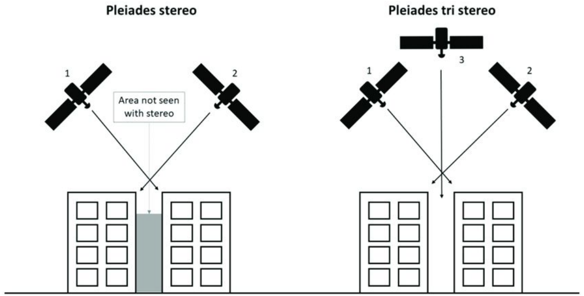
01-06-2014

Differences in season mean differences in shadows, vegetation state.
Colorimetric data augmentation can help

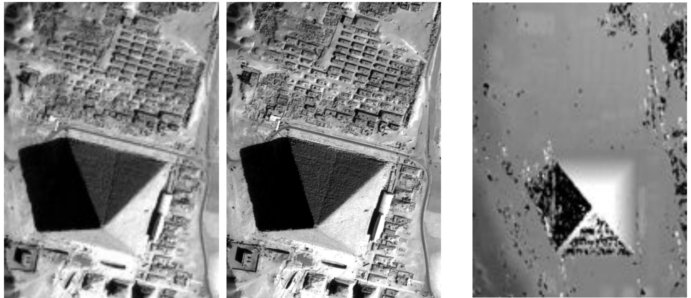
Incidence angle and 3D from stereo acquisition

- **Nadir (0°)**
  - No visible façades
  - Mountains are flattened
- Off Nadir (here 30°)
  - Façades are visible
  - Reduce repeat-time
  - 3D is possible using stereo acquisition





Panagiotakis, E.; Chrysoulakis, N.; Charalampopoulou, V.; Poursanidis, D. Validation of Pleiades Tri-Stereo DSM in Urban Areas. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 118. https://doi.org/10.3390/ijgi7030118



https://www.orfeo-toolbox.org/CookBook/recipes/stereo.html

B1. Mapping cities

Manually defined procedures

Pattern recognition

- Edge detection
  - 1. Edge detection (Canny filter) [Wei2004]
  - 2. Edge selection and grouping
  - 3. Edge linking: line or polygon fitting [Tupin2003]
- Texture feature
  - Co-occurrence matrices (Harralick) [Moya2019]
- Image segmentation (regions having similar attributes)
  - Mathematical morphology
- Shadow detection

Use of stereo images

Deep-learning

Multiple dataset with different tasks :

- Building semantic segmentation
- Building instance segmentation
- Building monitoring through time
- Land Cover semantic segmentation
- Road extraction and graph construction

Databases : Inria

Task: Semantic segmentation - Roof detection

Images : 30 cm resolution

Different cities : San Francisco, Lienz (Austria), Kitsap County, WA Transfert/Generalization

Chicago

Vienna

Databases : AIRS

Task: Building detection

City: Christchurch

Images: Very High Optical data

Databases : Semcity

Task: instance building segmentation
City: Toulouse
Image: very high resolution multi-spectral images

HAL Id : **hal-02948177, version 1** DOI : 10.5194/isprs-annals-V-5-2020-109-2020

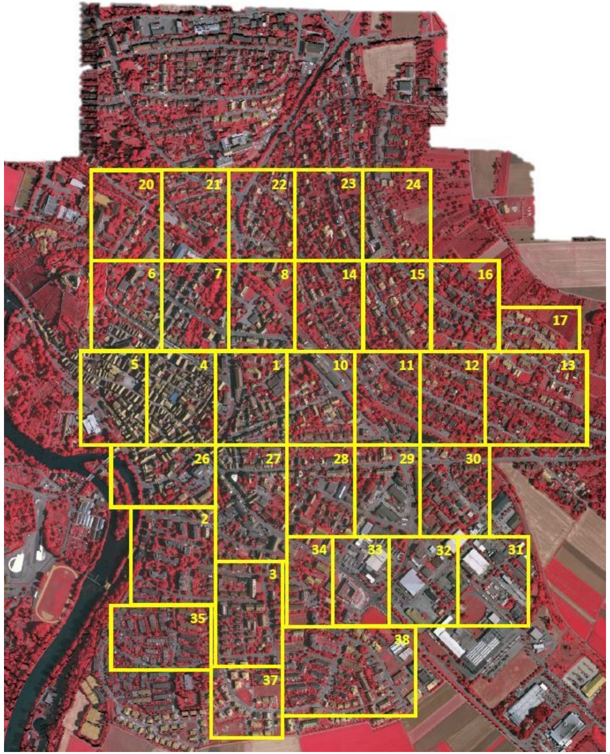
Datasets : Spacenet 7

Task: building detection and tracking through time
Cities: ~100 unique geographies
Images: Very high optical images

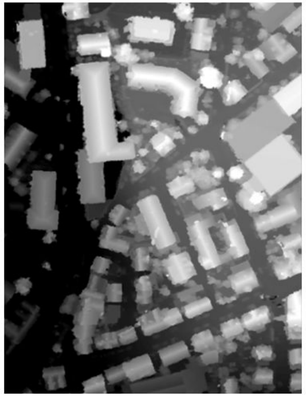
Datasets : ISPRS Vaihingen and Potsdam

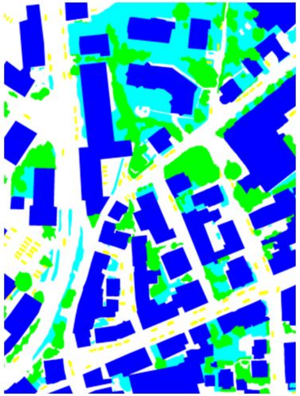
Very nice dataset to start:

- All the patches come from the same image
- three RGB bands : infrared, red and green + DSM
- 5 labels : building, impervious surfaces, tree, low vegetation/grass, car.




(a)


(b)


(c)

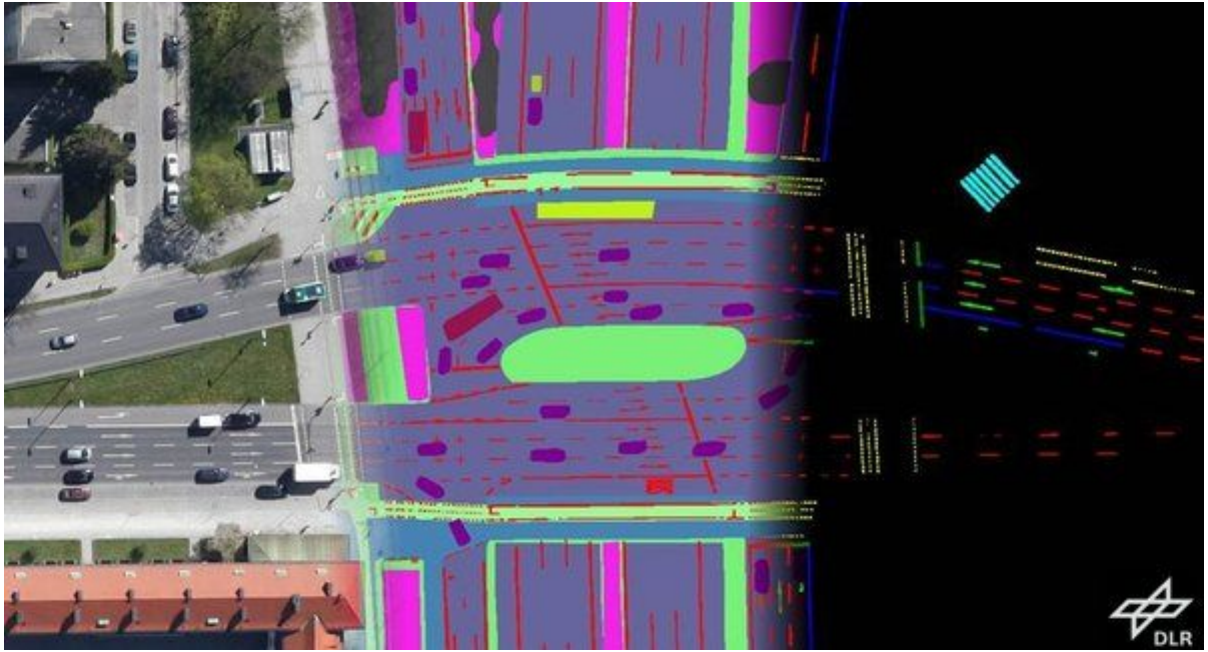
Datasets : Spacenet 5

Task: Road network extraction
Cities: Moscow, Mumbai, San Juan
Image: very high resolution optical images

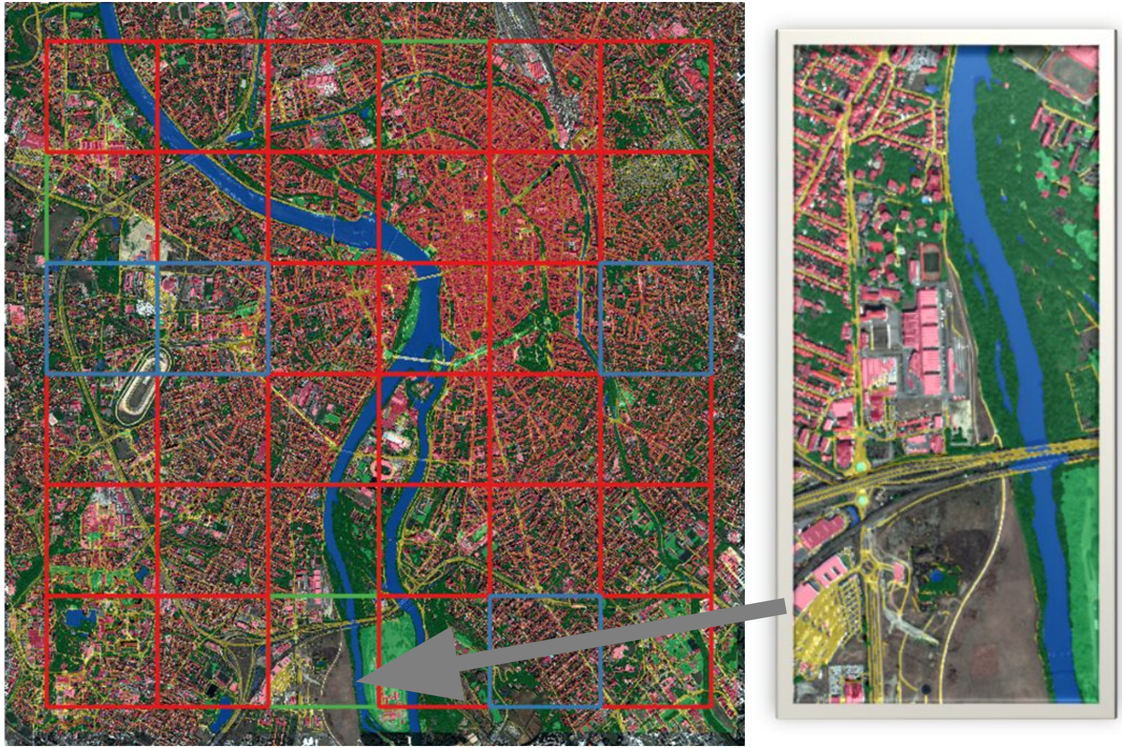
Datasets : DLR-SkyScapes: Aerial Semantic Segmentation Dataset for HD-mapping

- 31 classes
- Road marking
- Airborne optical acquisition

S. Azimi, C. Henry, L. Sommer, A. Schaumann, and E. Vig, " Skyscapes -- Fine-Grained Semantic Understanding of Aerial Scenes," in International Conference on Computer Vision (ICCV), October 2019.



Images are large! What to annotate, how to evaluate ?



Toulouse Pleiades image, annotated using open street map (AI4GEO)

Manual annotation are expensive:

- What to label
- Where to label

Automatic annotation from external database

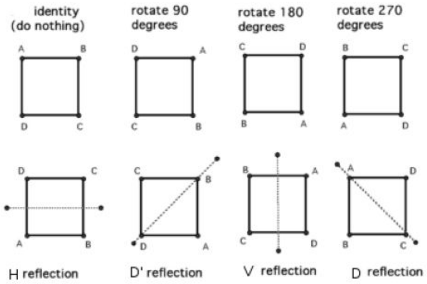
- Coregistration in space
- Time matchig

Images are heterogeneous : how to create Train/Val/Test ensembles that make sense ?

- Avoid overfitting
- Test for generalization
- Test for domain change

Geometrical data augmentation

D4 group: 7 data augmentation



Original image + label

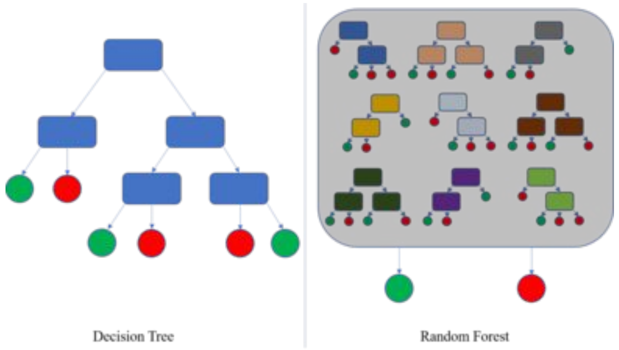
Rotate 90° image + label

Question in remote sensing:

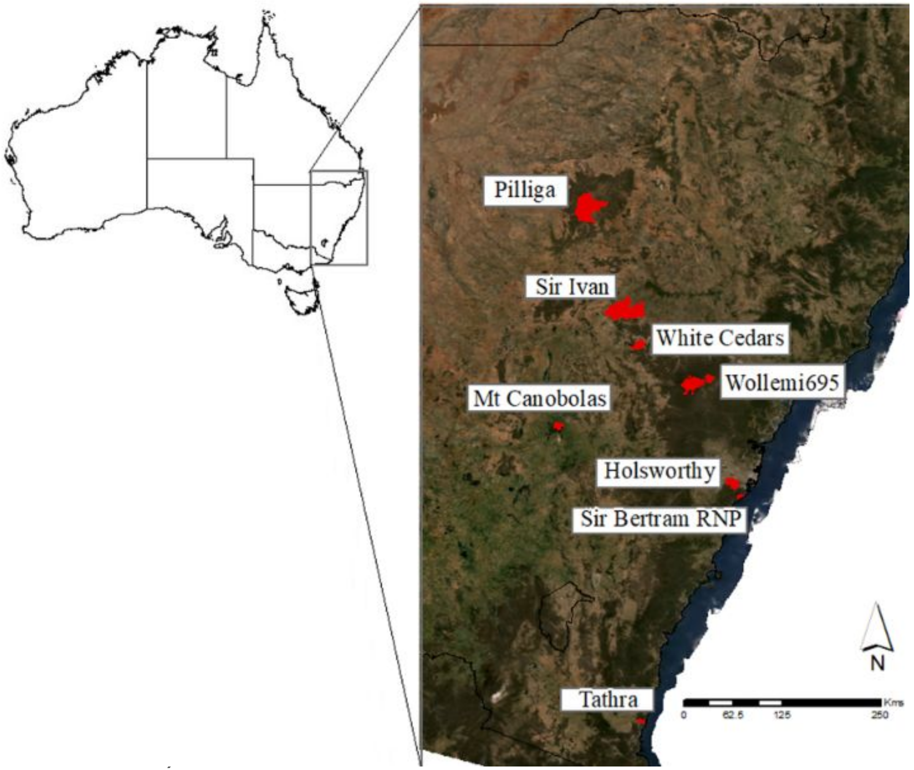
Help generalisation for another city but not always generalisation within the same image

B2. Mapping at large scale

Mapping fire severity with random forest [Gibson2020]



https://fr.wikipedia.org/wiki/For%C3%AAt_d%27arbres_d%C3%A9cisionnels



Pixel classifier developed based on :

- A set of classified images
- A set of a priori criteria
  - NDVI (NIR, Red)
  - NDVR : differenced normalised burn ratio (N
  - …

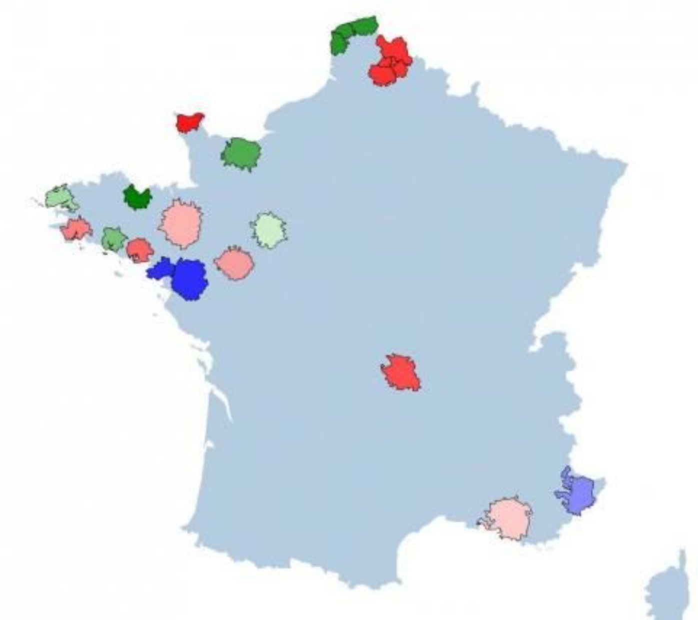
Datasets: Mini France

Task: Semantic segmentation

Cities:
Labeled training data: Nice, Nantes/Saint Nazaire.
Unlabeled training data: Le Mans, Brest, Lorient, Caen, Calais/Dunkerque and Saint-Brieuc.
Test data: Marseille/Martigues, Rennes, Angers, Quimper, Vannes, Clermont-Ferrand, Cherbourg, Lille

Images: RGB IGN aerial images

Labels: 15 classes
0: No information - 1: Urban fabric - 2: Industrial, commercial, public, military, private and transport units - 3: Mine, dump and contruction sites - 4: Artificial non-agricultural vegetated areas - 5: Arable land (annual crops) - 6: Permanent crops - 7: Pastures - 8: Complex and mixed cultivation patterns - 9: Orchards at the fringe of urban classes - 10: Forests - 11: Herbaceous vegetation associations - 12: Open spaces with little or no vegetation - 13: Wetlands - 14: Water - 15: Clouds and shadows



Datasets: Resisc45

Task: image classification
Number of classes:

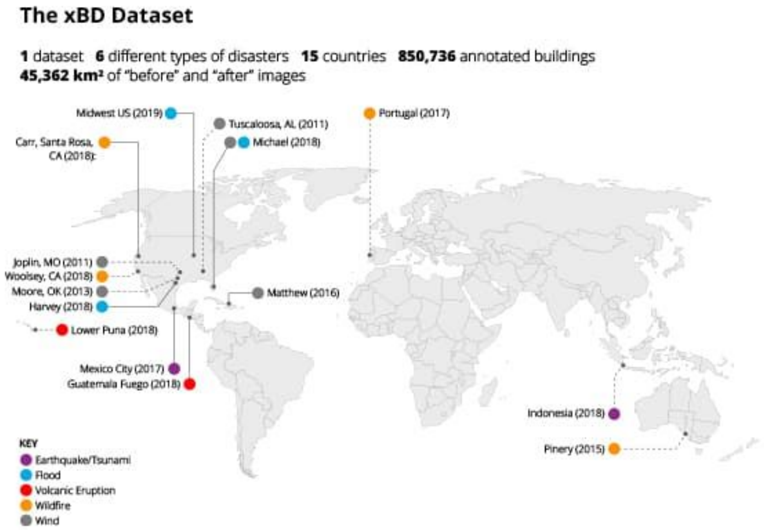
B3. Change detection

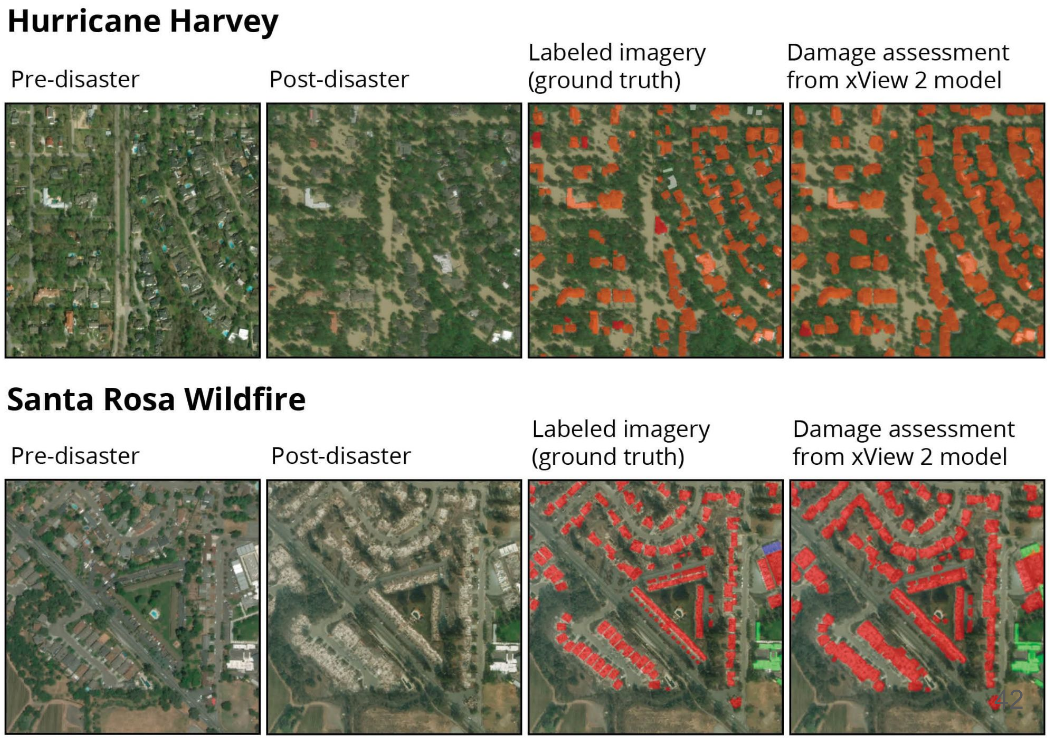
Datasets : Xview 2

Task: Assessing building damage after a disaster is a critical first step in disaster response.

Images: Before/After optical images

Location:



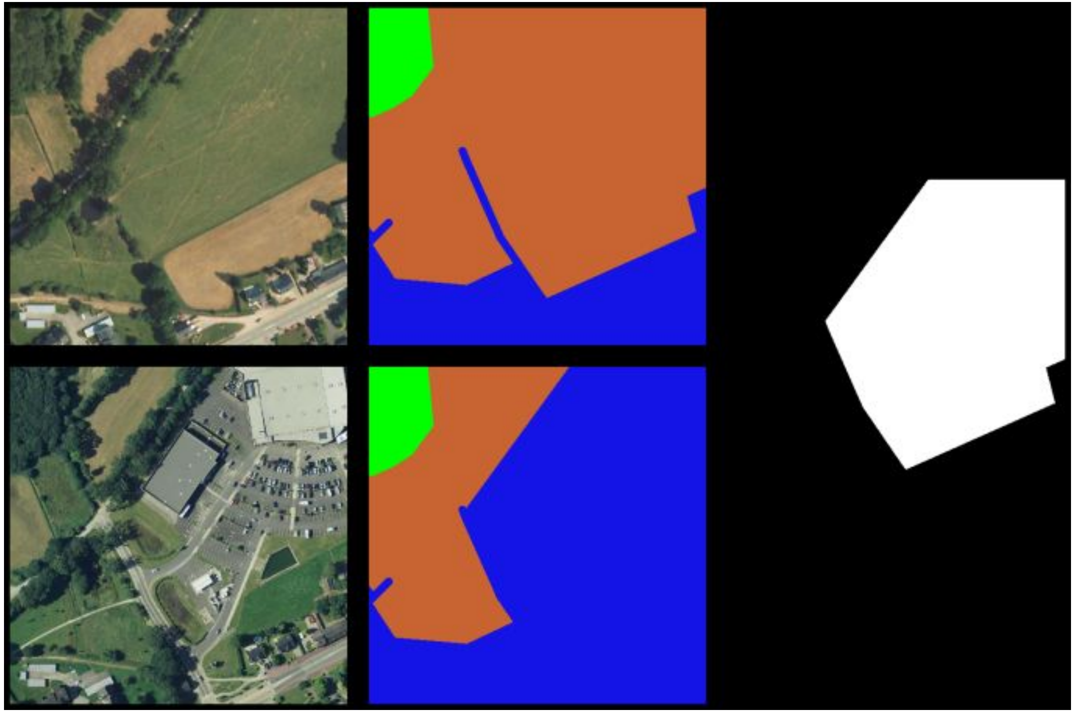


Dataset : HRSCD

Task: semantic change detection

Images: RGB aerial images from IGN BD ORTHO database

Labels: 5 labels from Urban Atlas



Class imbalance HRSCD example

The most represented class is often the best predicted

Small classes may never be predicted

Options:

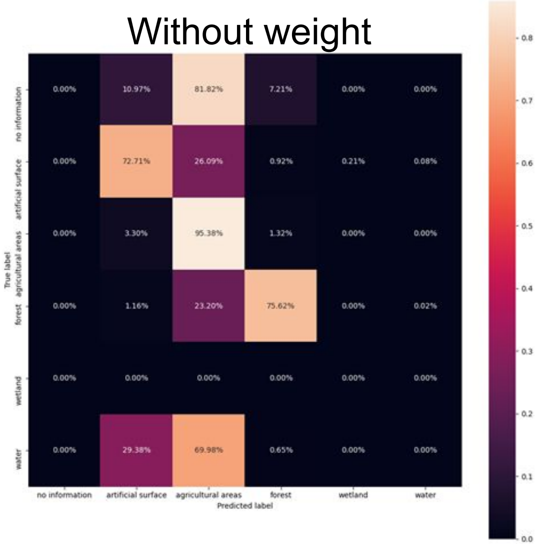
- Non uniform sampling
- Loss weighting
  w = 1/class_frequency

Cannot compensate very big imbalance

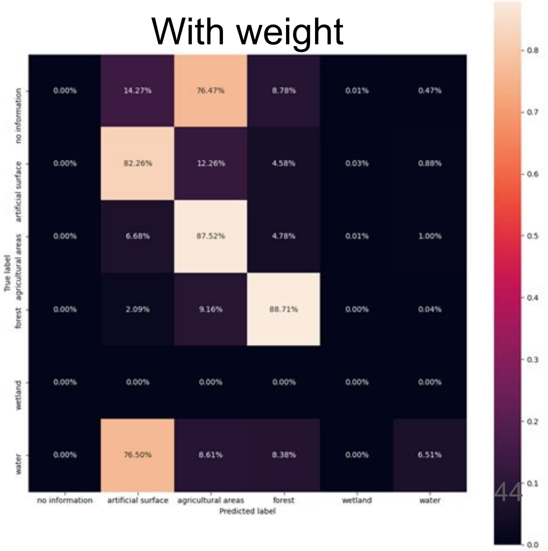
Imbalance even larger for changes
No change: 99.232%

Label	Proportion
0 Background	0.176959
1 Artificial surfaces	0.11508
2 Field	0.618345
3 Forest	0.0836437
4 Wetland	**0.000195238**
5 Water	0.00577677

Without weight

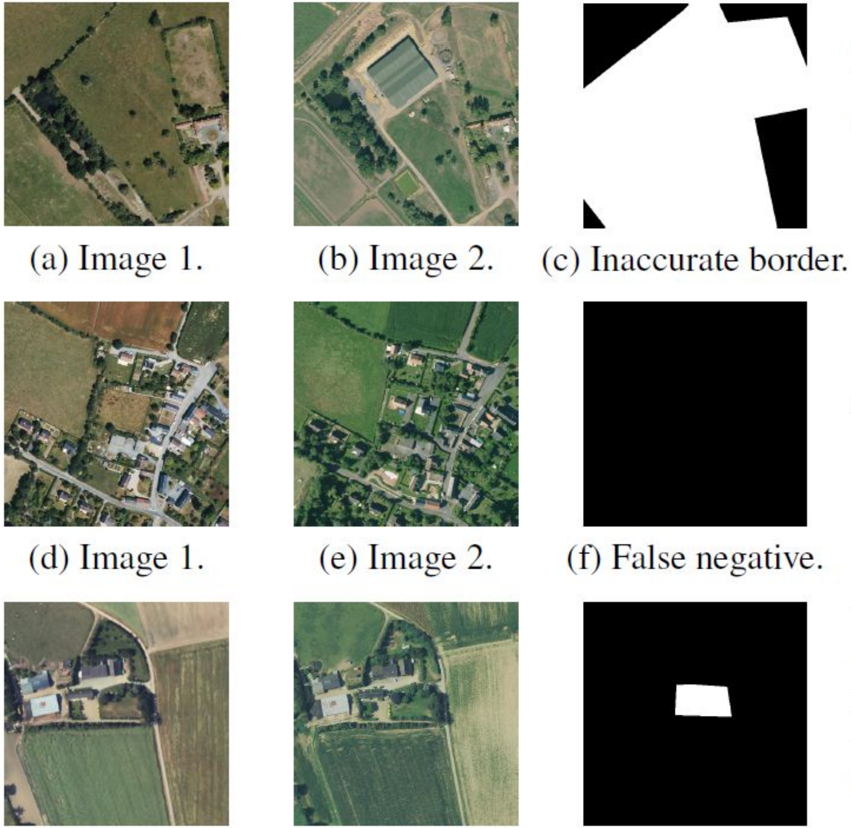


With weight



Ground truth precision

- They maybe error in the ground truth
- They are variation between annotators
- It is difficult to have very precise borders
  BUT **border account for a large proportion of the pixel** in a dataset

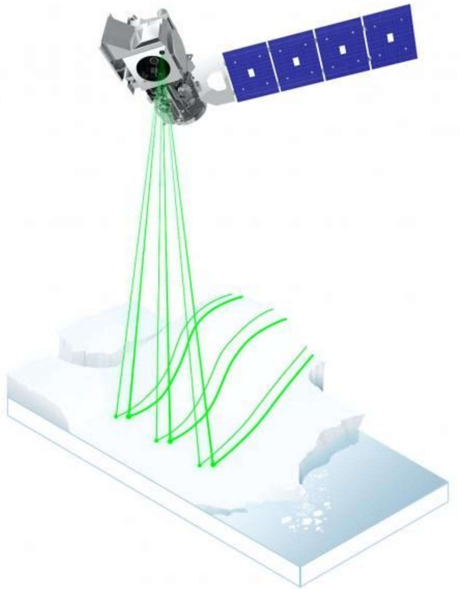


(a) Image 1. (b) Image 2. (c) Inaccurate border.
(d) Image 1. (e) Image 2. (f) False negative.
(g) Image 1. (h) Image 2. (i) False positive.

Daudt, R.C., Le Saux, B., Boulch, A. and Gousseau, Y., 2019. *Multitask learning for large-scale semantic change detection*. Computer Vision and Image Understanding, 187, p.102783.

C. LiDAR remote sensing

LIDAR acquisitions



Some current sensors :

- NASA: IceSAT-2 et GEDI (https://gedi.umd.edu/mission/mission-overview/)

Some current products :

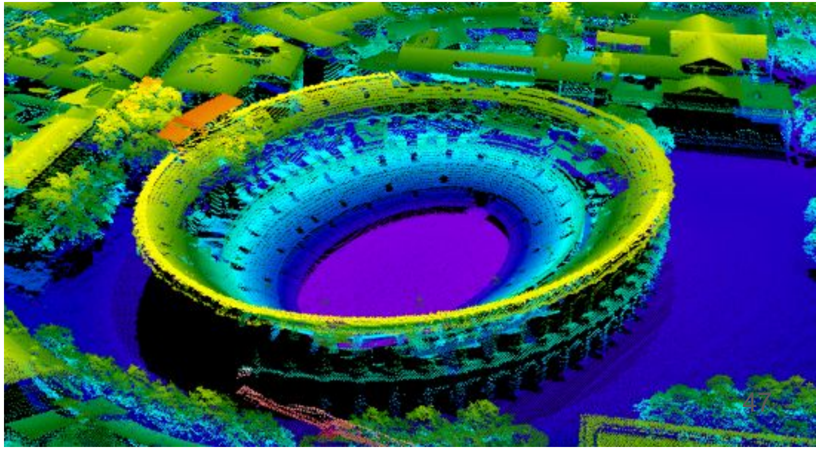
- IGN : https://geoservices.ign.fr/lidarhd

Waveform :

The energy scattered back from the earth through time

Point cloud :

Sampled waveform

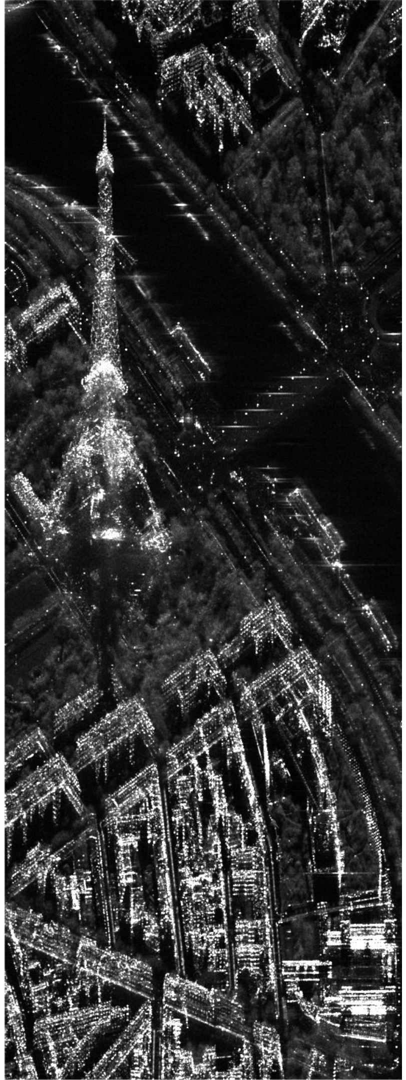


D. SAR remote sensing

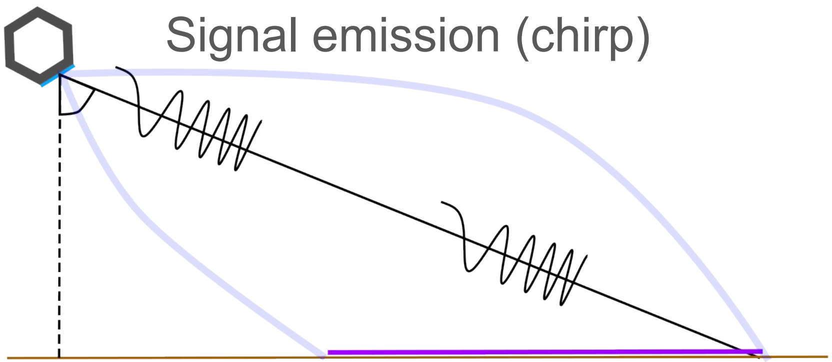
SAR imaging sensor

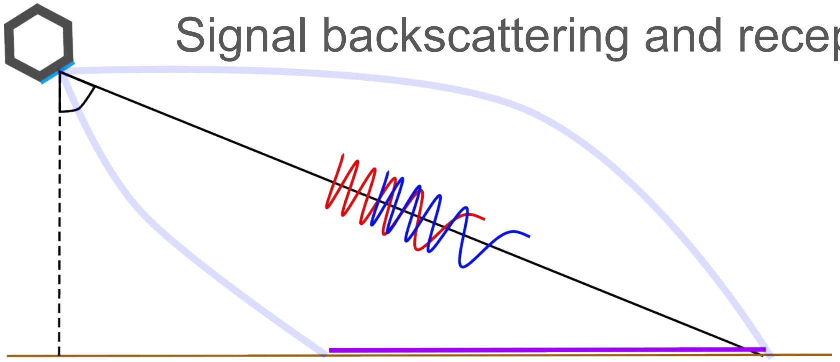
Pleiades   TerraSAR-X

What do we see on this image ?



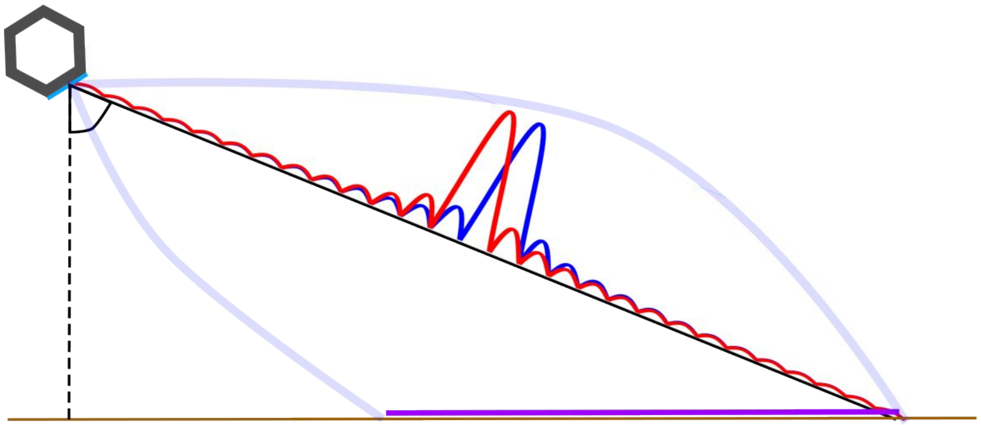
What does SAR measure? Range: the distance to the sensor





Measure the distance between the sensor and the object thanks to the **autocorrelation** of the chirp.

The Point Spread Function is a cardinal sine



Current sensor

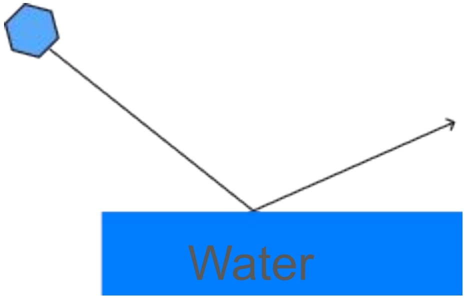
Sensor	Space agency	Band (λ)	Revisit	Mode	Resolution	Swath
Biomass	ESA	P (70cm)	25-45 days	To be launched in 2025		
Alos/Palsar	JAXA	L (23.62cm)	14 days	Fine	10 m	70 km
				ScanSAR	100 m	350 km
Sentinel-1	ESA	C (5.5cm)	12 days	Interferometric Wide Swath	20 m x 5 m	240 km
				Extra Wide Swath	40m	400 km
Radarsat-2	CSA	C (5.5cm)	24 days	Fine	5.2 x 7.7 m	50km
				Wide	13.5 x 7.7 m	150km
TerraSAR-X TanDEM-X	DLR	X (3.1cm)	11 days	Starring Spotlight	25cm	4 x 3.7 km
				ScanSAR	40m	270×200 km

What does SAR measure? Amplitude: Backscattered energy

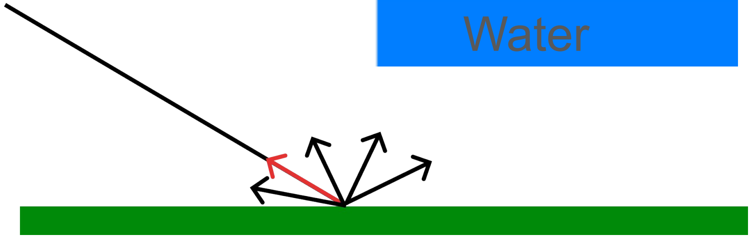
Low energy: Mirrors

The energy is backscattered at the opposite of the satellite

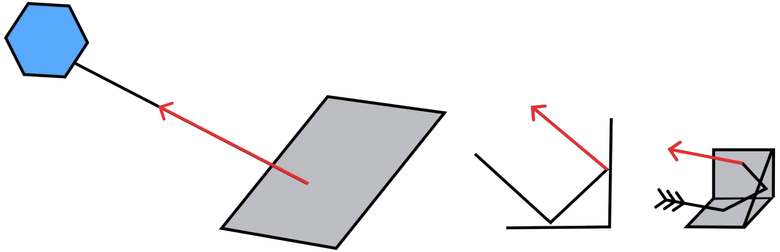
Example: water



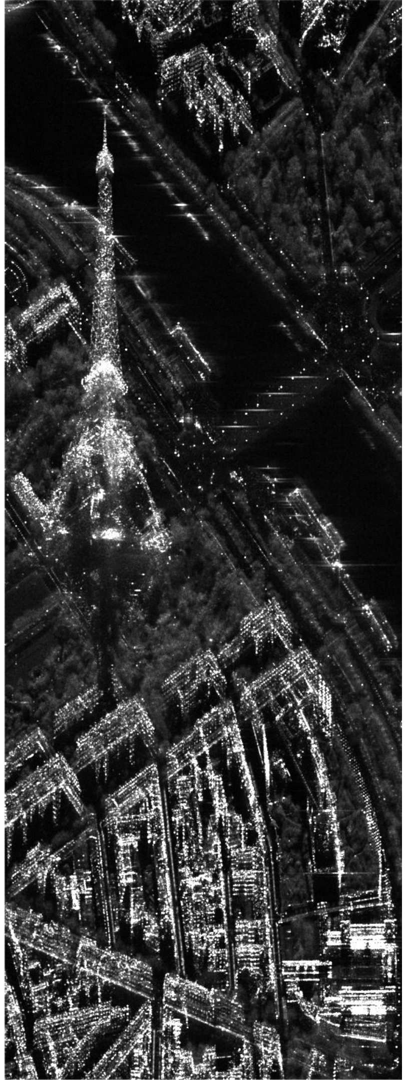
Medium energy: Very scattering surfaces



High energy: (Metallic) structure well oriented

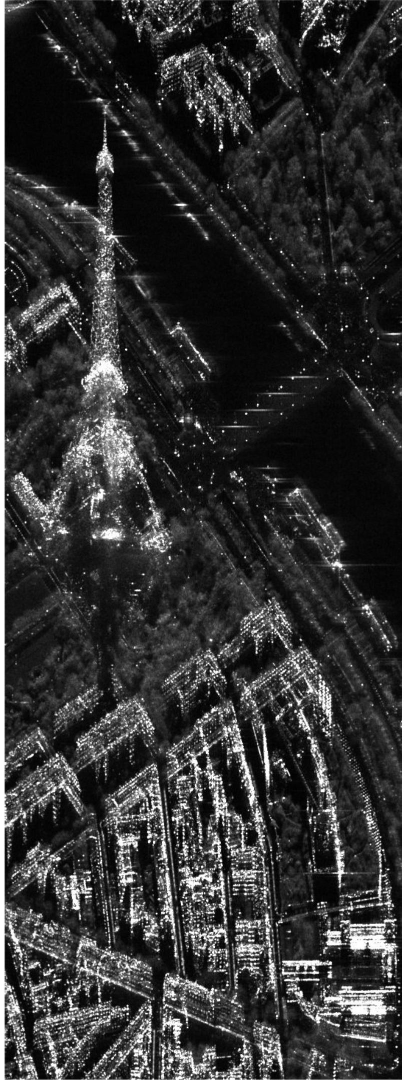


What do we see on this image ?



What do we see on this image ?

- Low energy pixels:
  - The Seine river
  - Roads
  - The Eiffel Tower shadow
- Medium energy pixels:
  - Trees/Bushes/Lawn
- High energy pixels:
  - The Eiffel Tower
  - Buildings
  - Boats
  - Street lamps



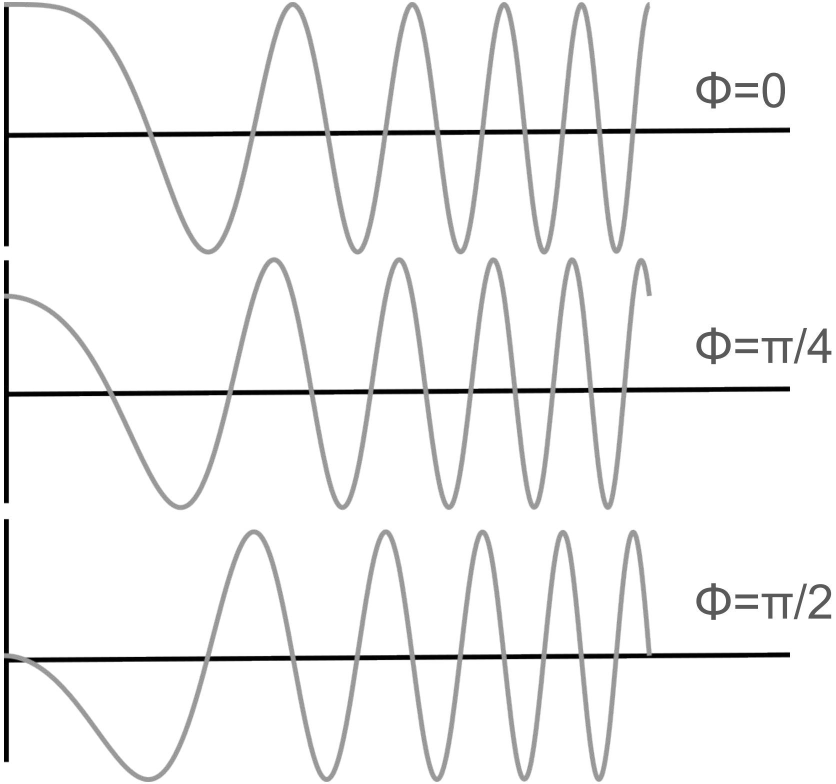
Stealth ships

https://en.wikipedia.org/wiki/USS_Zumwalt

- No 90° corners
- Surfaces oriented to directed the energy not in the emitted direction

Backscatter the same energy as a fishing ship despite being much larger

What does SAR measure? Phase: the residual distance



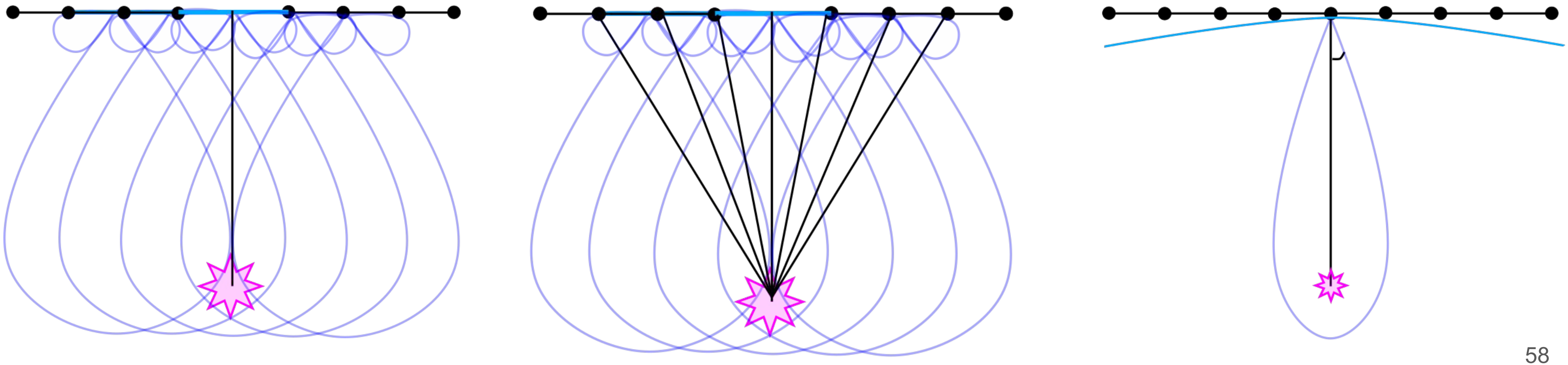
The phase of the chirp change with the distance

$\Phi=2\pi D/\lambda$, D the distance and λ the wavelength

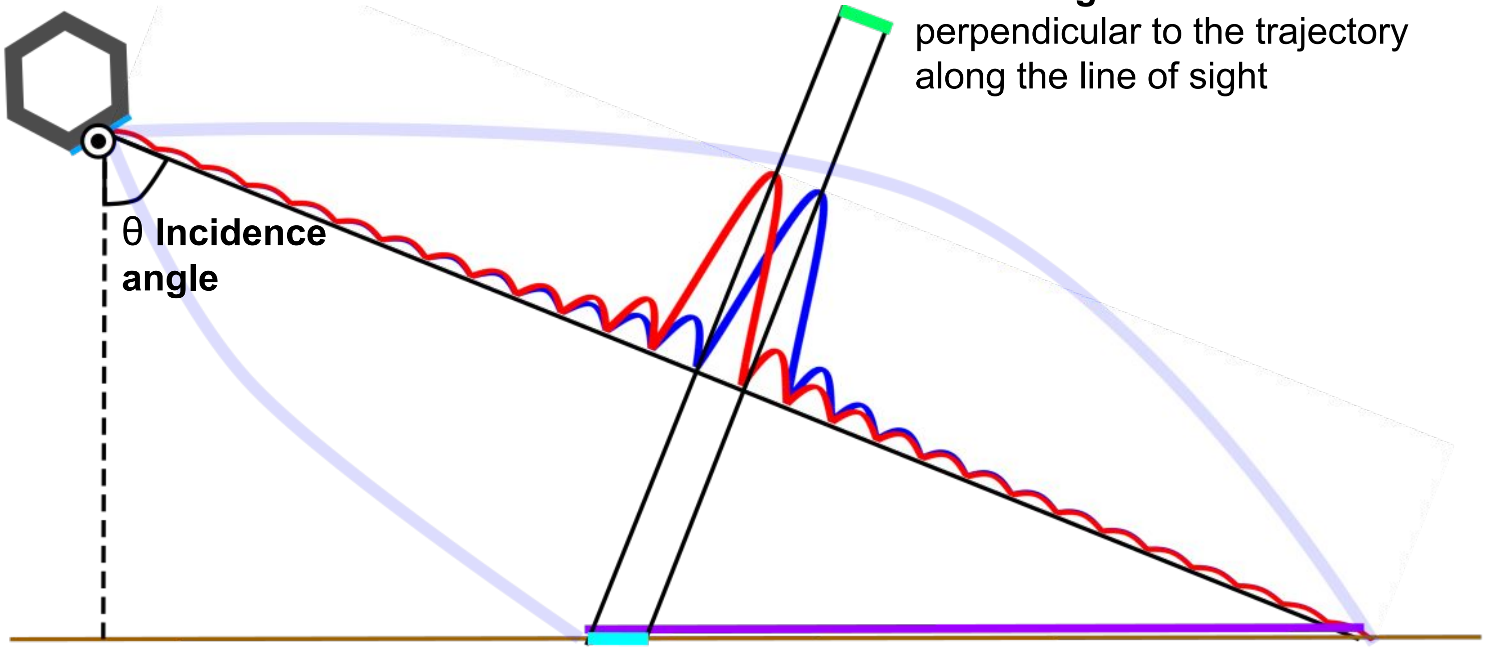
Synthetic aperture

1. Multiple pulses are emitted along the trajectory
2. The backscattered signal is measured and focus in range
3. The backscattered echoes are **focused in azimut** in a larger converging antenna
   Point Spread Function : cardinal sine

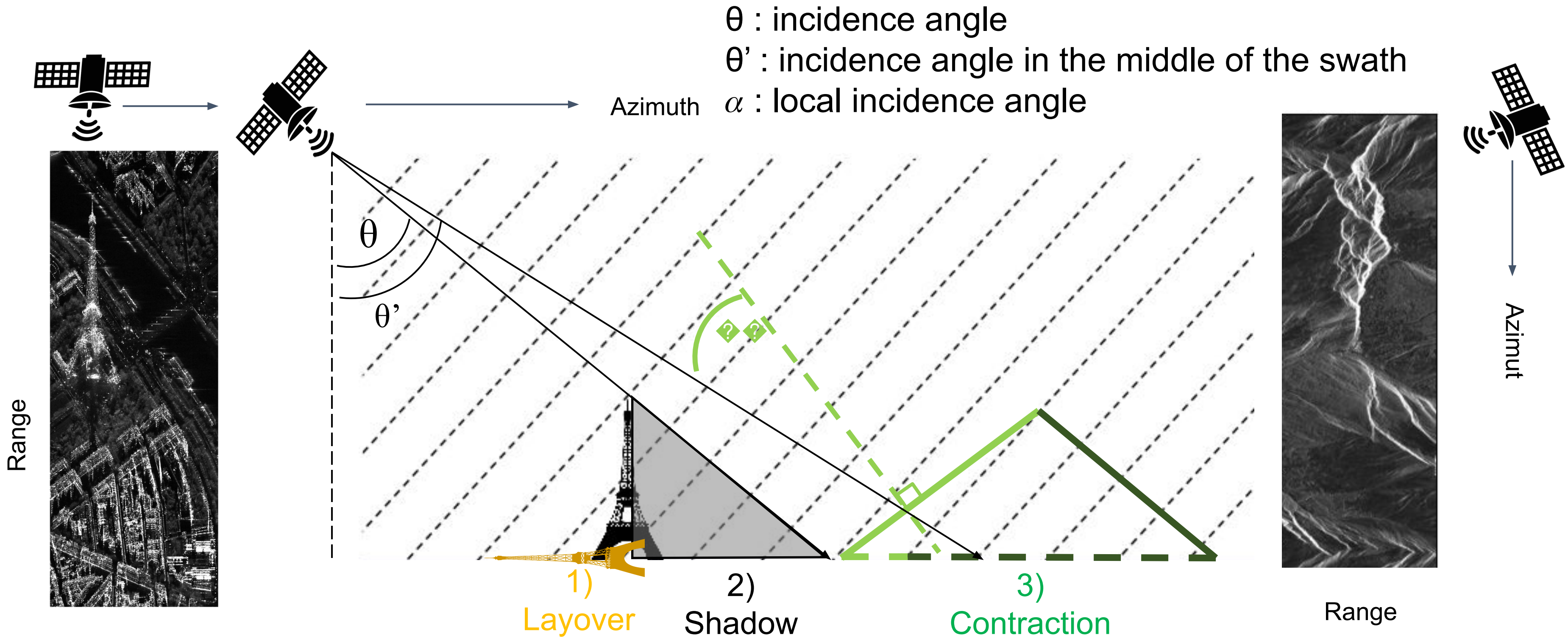
The resolution of the signal is refined and an image is formed



Geometry of SAR sensors



Geometric effects in SAR images



Courtesy of Mathias Montginoux, PhD Student ONERA/LS2N

Speckle noise

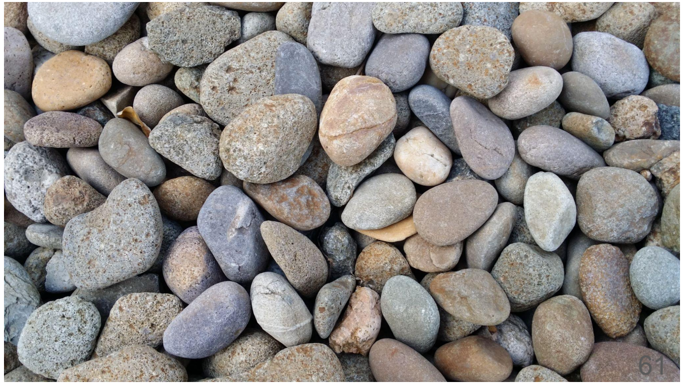
Fully developped speckle (Goodman, 1976) : sum of scatterers:

1. Independent and identically distributed
2. Modulus and phase are independant
3. Phase uniformly distributed on a 2π intervalle

For N channel, the backscattering pixel p follows a complexe circular normal distribution :

$$p \sim \mathcal{N}_c(0, \mu) = \frac{1}{\pi\mu} e^{-p^\dagger \mu^{-1} p}$$

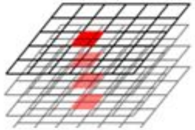
Real part follows a normal distribution of variance μ/2
Imaginary par follows a normal distribution of variance μ/2
Phase is uniformly distributed on a 2π intervalle
The modulus follows a Rayleigh distribution of parameter μ



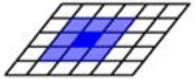
Filtering

Maximum likelihood estimator

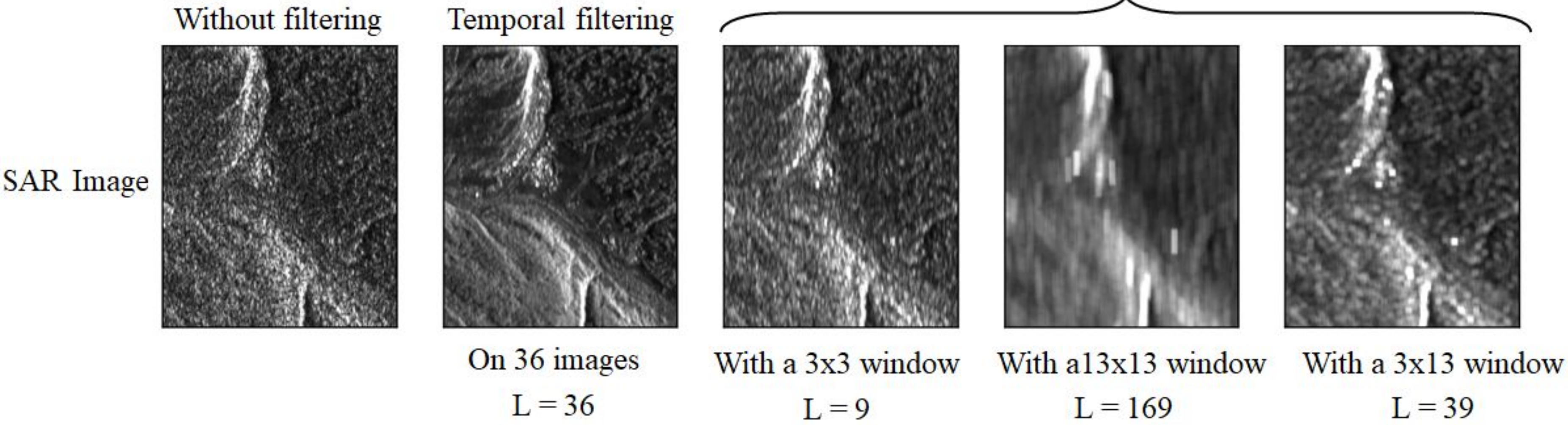
$$\hat{\mu}_{MV} = \sqrt{\frac{1}{L}\sum_{l=1}^{L} x_l^2}$$



L = number of image

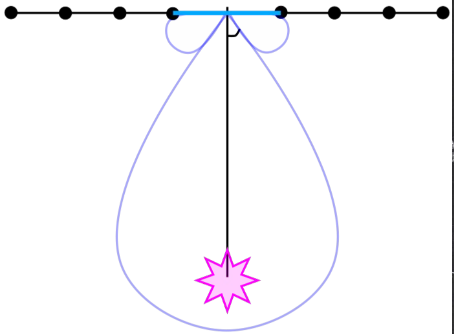


L = number of neighbouring pixels



Courtesy of Mathias Montginoux, PhD Student ONERA/LS2N

Side lobes

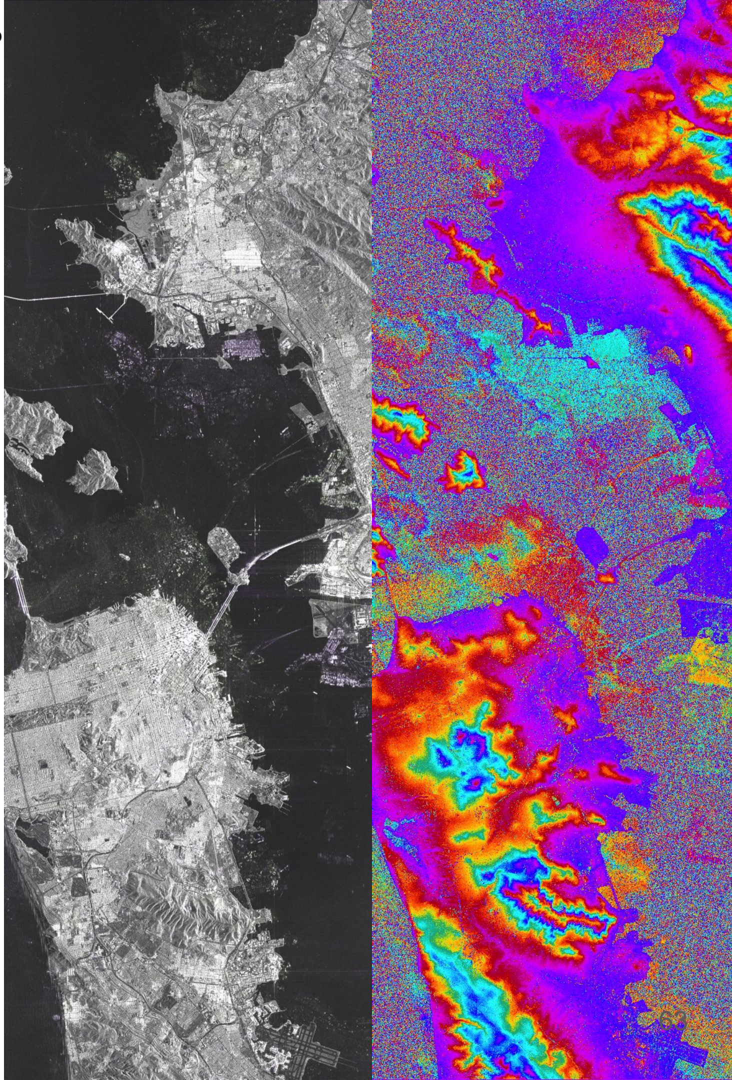


Antennas side lobes->

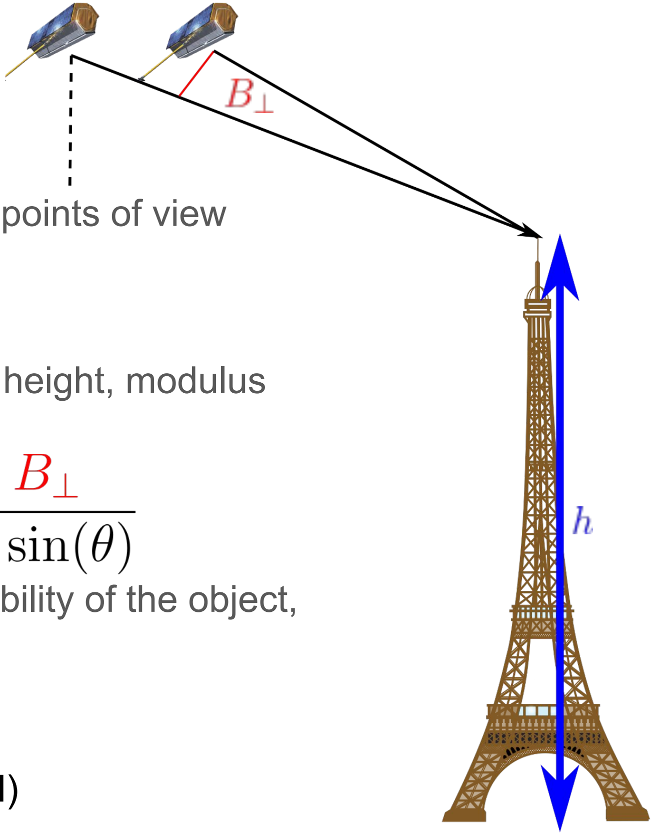
Create replicas visible in the sea
San Francisco, TanDEM image

<-Target side lobes

Cardinal Sine Point Spread Function
Salon de Provence SETHI/ONERA image



Interferometry



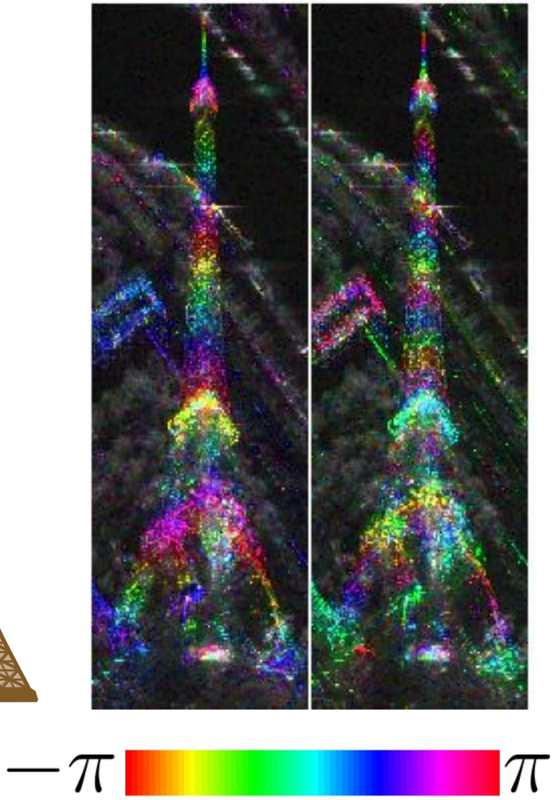
Two acquisitions from two slightly different points of view

$$\phi \equiv 2\frac{2\pi}{\lambda}(R_1 - R_2) \quad [2\pi]$$

The phase difference is proportional to the height, modulus the ambiguity height

$$h \equiv \frac{1}{k_z}\phi \quad [h_{\mathrm{amb}}] \qquad k_z = 2\frac{2\pi}{\lambda}\frac{B_\perp}{R\sin(\theta)}$$

The noise in the phase depends on the stability of the object, measured by the coherence $\gamma \in [0, 1]$



Applications :

- Create Digital Elevation Model (DEM)
- Measure deformation
  - Earthquake
  - Landslide
  - Sea terminating glacier grounding line

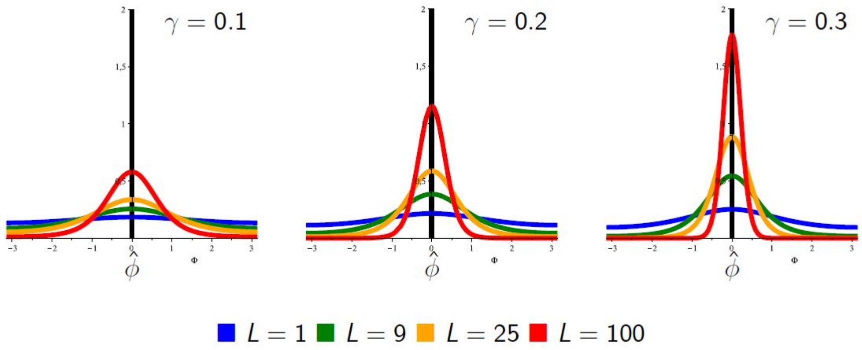
Estimating covariance matrices

- If p_k is a pixel with multiple channels: $p_k = [r_1 e^{i\varphi}, r_2 e^{i(\varphi+\Phi)}]$
- The covariance matrix C =

$$\begin{vmatrix} r_1^2 & r_1 r_2 \gamma e^{i\Phi} \\ r_1 r_2 \gamma e^{-i\Phi} & r_2^2 \end{vmatrix}$$

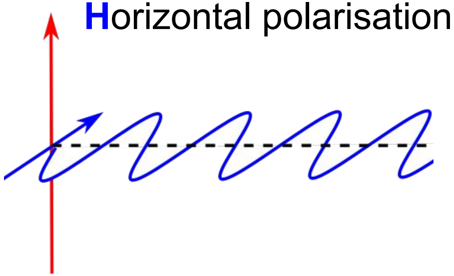
  - Φ is the phase difference
  - γ is the degree of coherence

- It is estimated using the maximum likelihood estimator using L pixels: $\hat{\mathbf{C}} = \frac{1}{L}\sum_{k=1}^{L} \mathbf{p}_k \mathbf{p}_k^{\dagger}$
- The distribution of the estimated phase

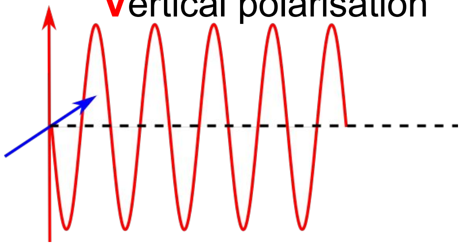


Polarimetry

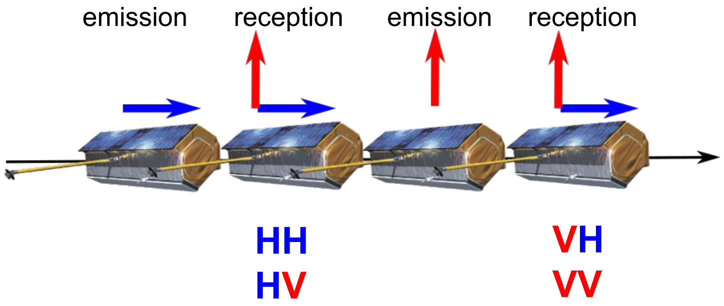
Horizontal polarisation

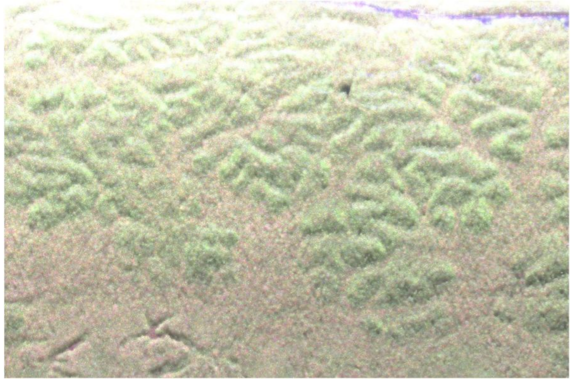


Vertical polarisation

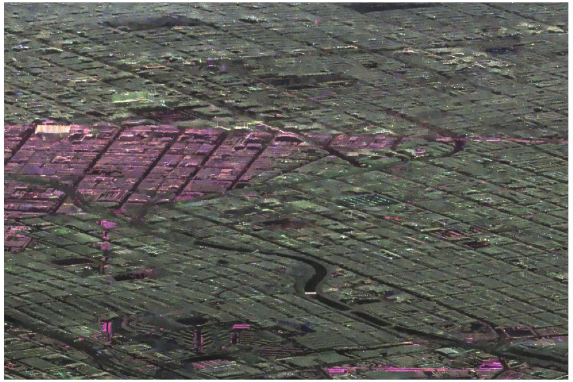


4 polarimetric channels





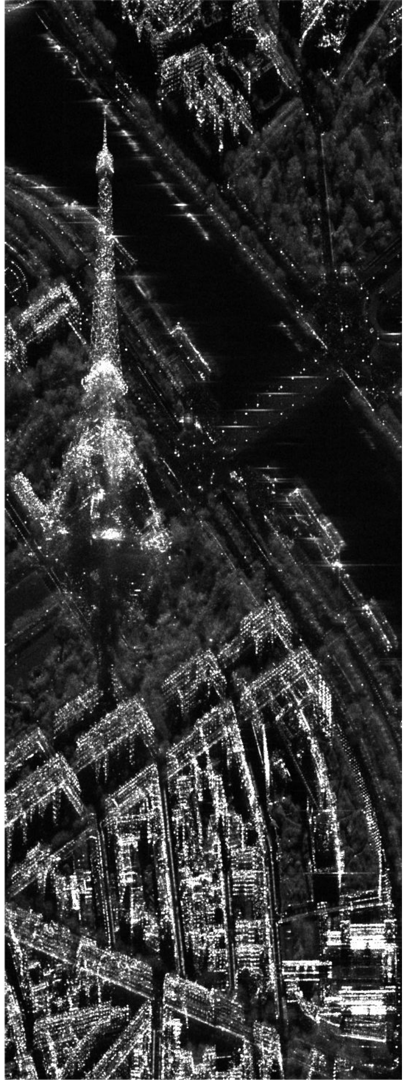
Tropical forest, French Guyana,
SETHI images (NLSAR denoised)

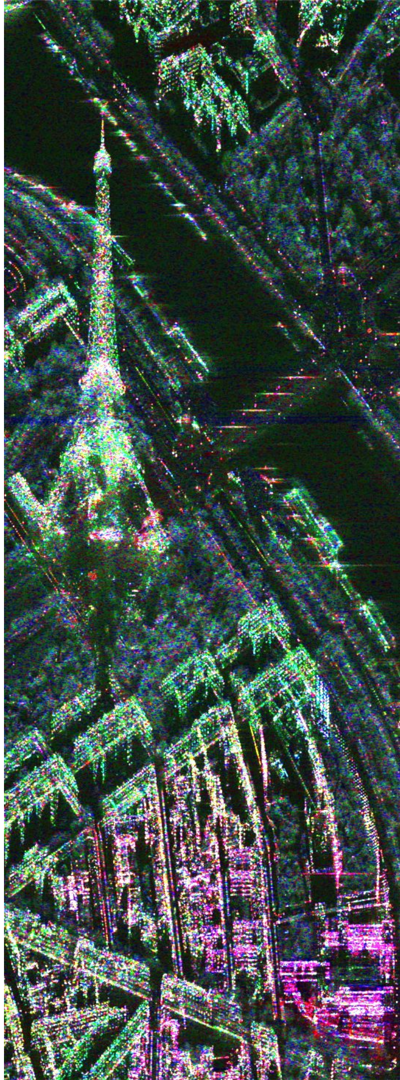


SOMA district, San Francisco,
UAVSAR images (NLSAR denoised)

Color composiion
R: HH
G: HV
V: VV

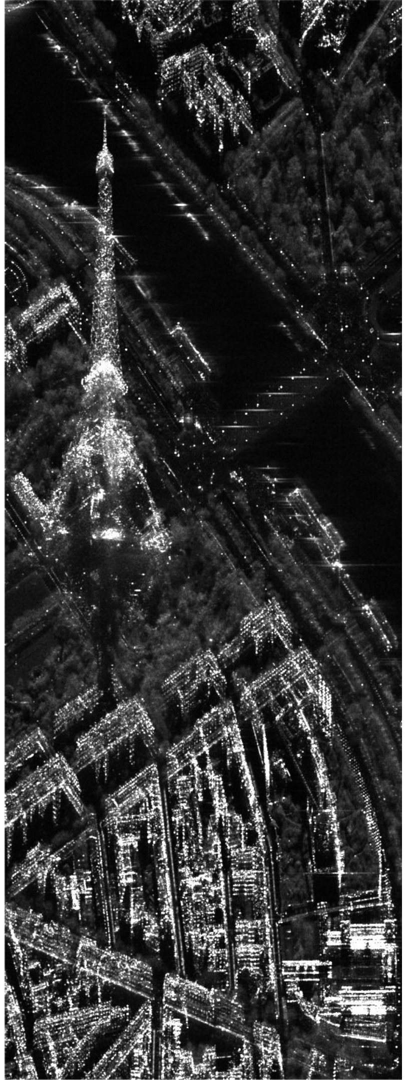
What do we see differently thanks to polarimetry on this image ?

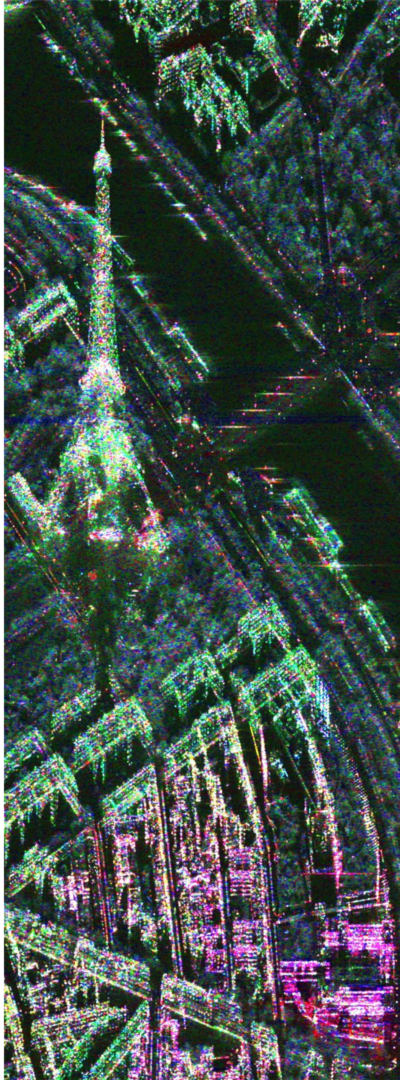




What do we see differently thanks to polarimetry on this image ?

- Low energy pixels don’t change
- Medium energy piels:
  - Tree are more green
  - Lawn are more blue
- The orientation of the buildings:
  - Red/blue: parallel to the trajectory
  - Green: 45° to the trajectory

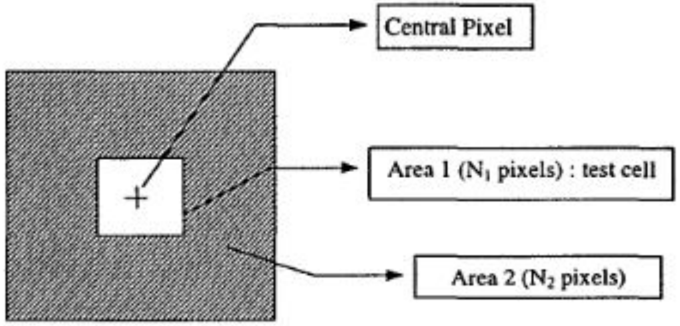


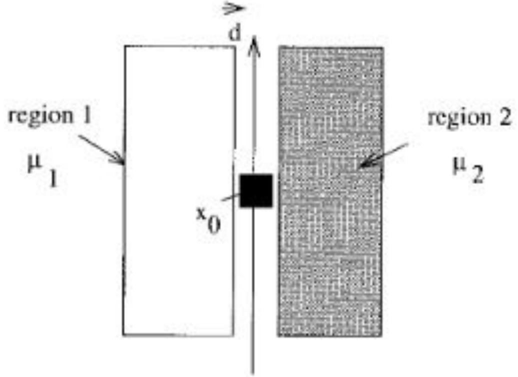


D1. Detecting ships

Bright target detection [Lopez1998]

- Compare the intensity I_1 in the central area to the intensity of the neighbouring pixels I_2
- Use of speckle pdf :
  - Gamma distribution for intensity
  - Rayleigh distribution for modulus
- False alarm rate depends on :
  - $r = I_1 / I_2$
  - N_1: the number of pixels of the central area
  - N_2: the number of pixels in the neighbouring area
- Same idea can be apply with 2 or 3 regions to detect edges or roads [Tupin1998]



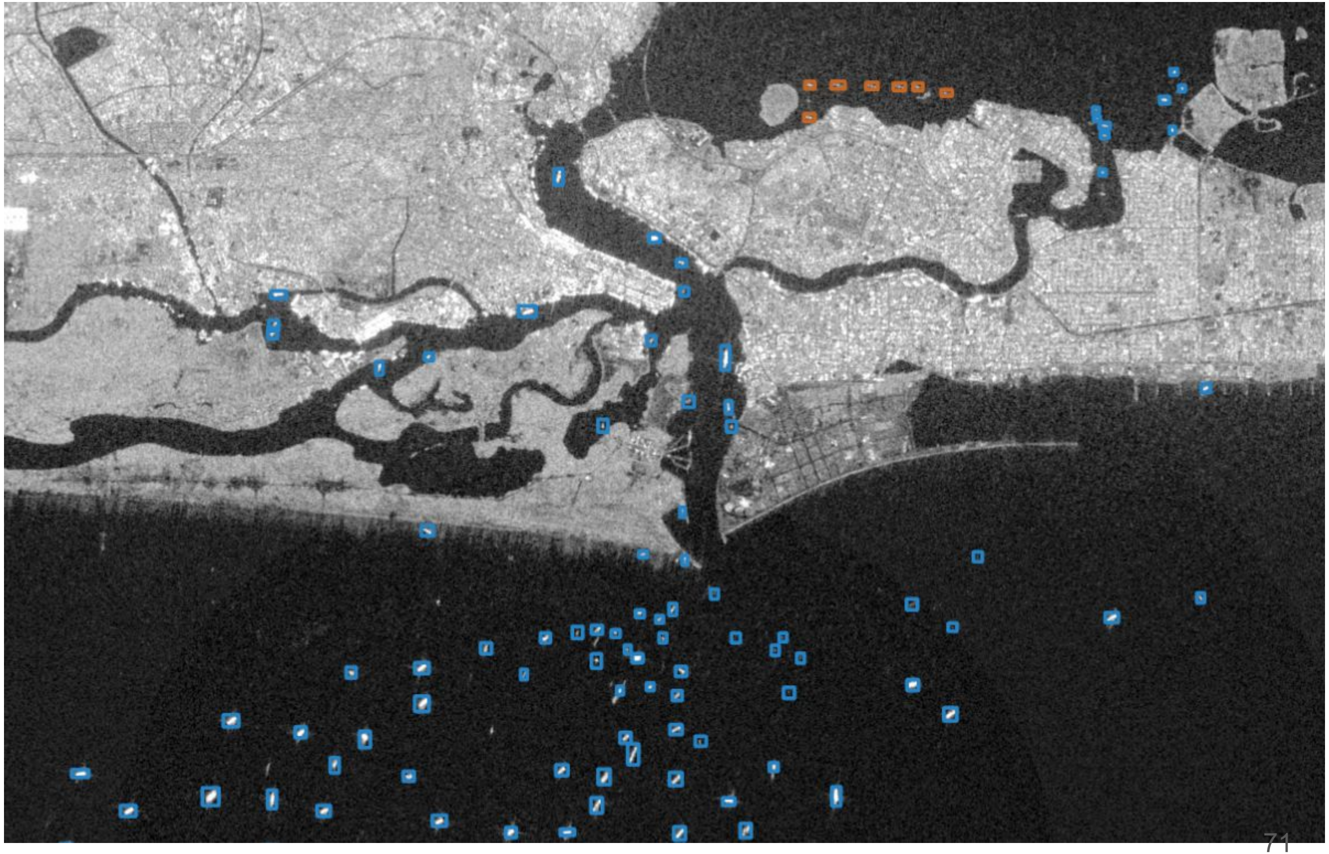


Datasets : Xview 3

Task: Detect “dark” vessels (the one without AIS)

Detect vessel and classify them “fishing” vs. “not fishing”

Images: SAR Sentinel-1 images

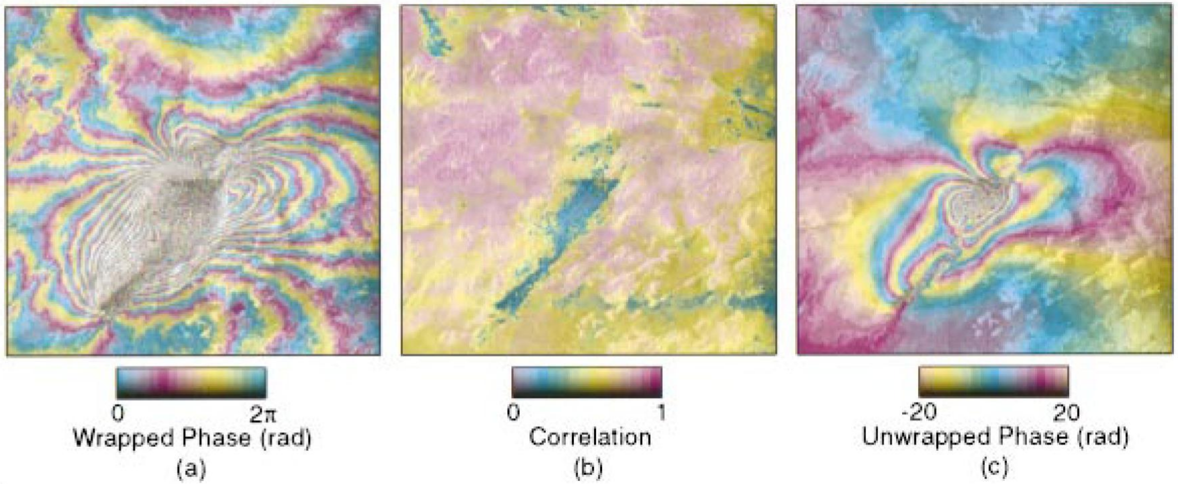


D2. interferometric phase estimation

Snaphu [Chen2001] - Phase unwrapping based on network optimisation

- a maximum a posteriori probability (MAP) estimation problem
- Cost function where :
  - unwrapped gradients ΔΦ
  - wrapped gradients ΔΨ
  - f(ΔΦ|ΔΨ) conditional probability density function

$$\text{minimize}\left\{-\sum_{k} \log\left[f(\Delta\phi_k \mid \Delta\psi_k)\right]\right\}.$$



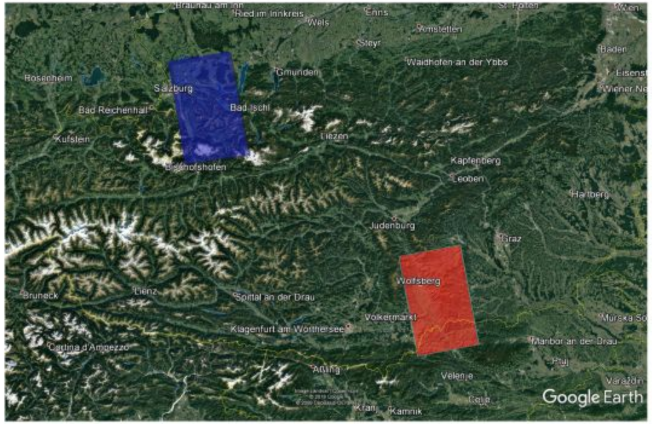
Estimating the phase in mountainous areas

- Discontinuous patterns
- A lot of different scenarios:
  - Small slopes
  - Large slopes
  - Cities
- Speckle “noise”
- No ground truth

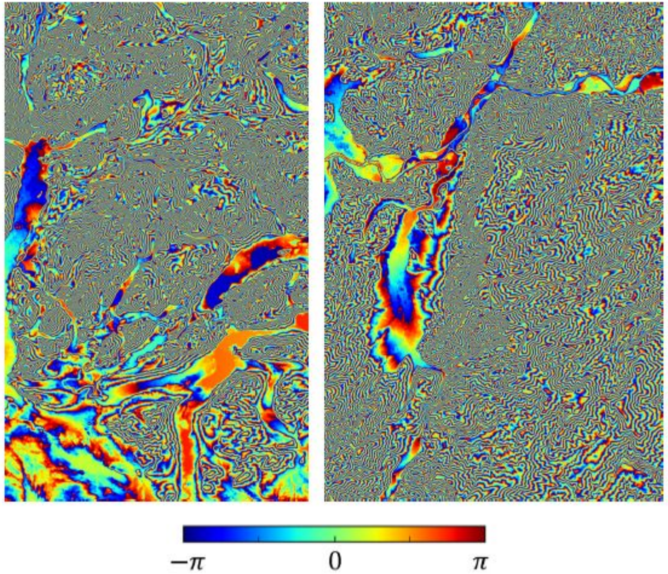
IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING 1

Φ-Net: Deep Residual Learning for InSAR Parameters Estimation

Francescopaolo Sica, *Member, IEEE*, Giorgia Gobbi, Paola Rizzoli, and Lorenzo Bruzzone, *Fellow, IEEE*

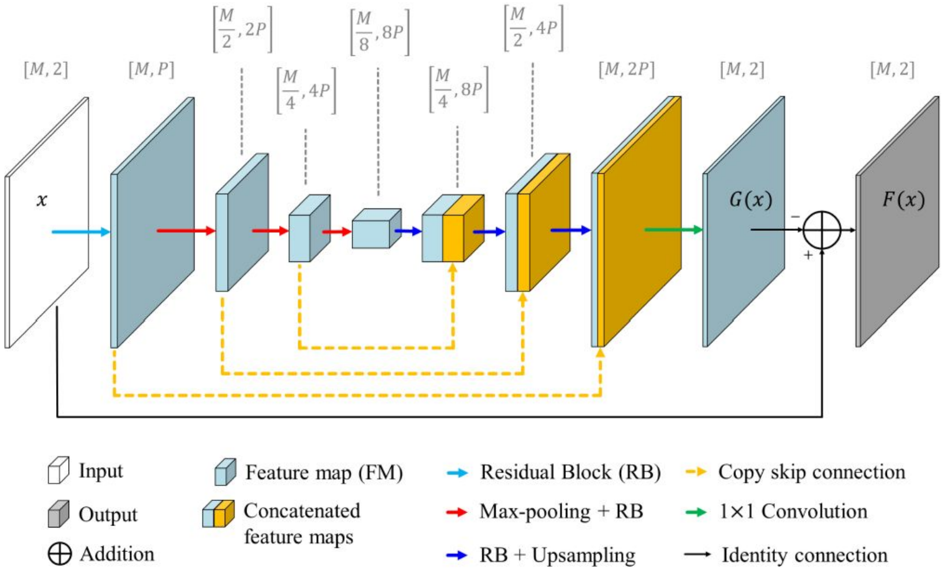


(a)

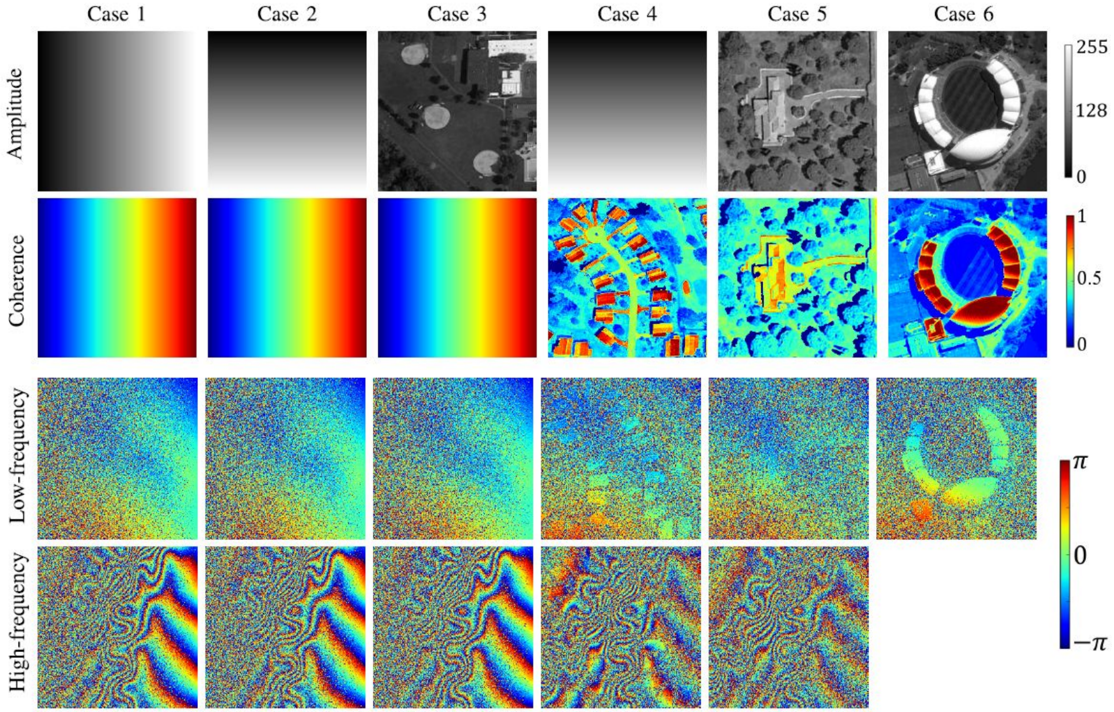


Goal, architecture and inputs

- Goal: Estimate the noise instead of the clean signal
- Network close to the U-Net architecture
- Inputs:
    - Not the phase, that is discontinuous
    - But the corresponding real and Imaginary part, that are continuous



Training procedure

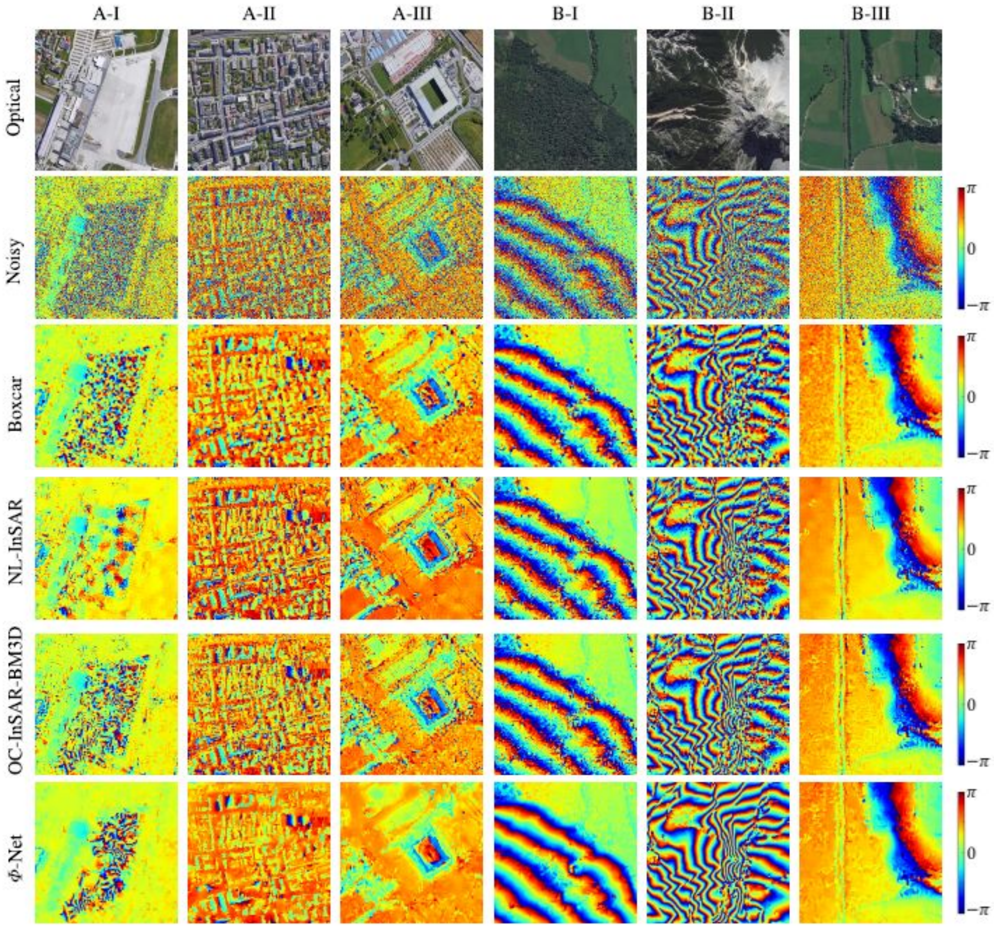


Simulation to create not realistic but diverse training example

Results

Very smooth on flat surfaces

Preserve fine details

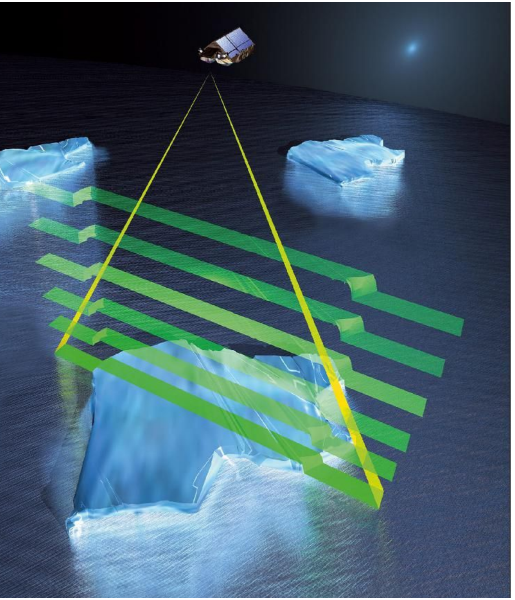


E. Radar altimeter

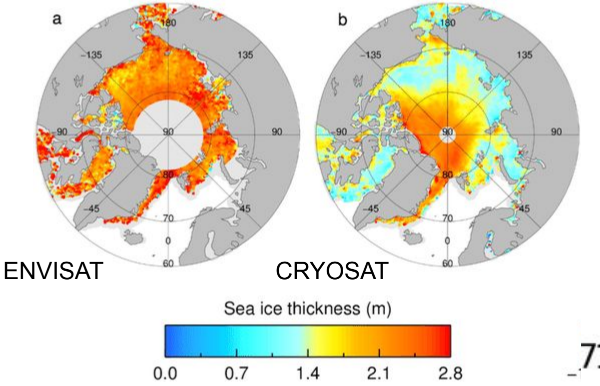
Radar altimeter

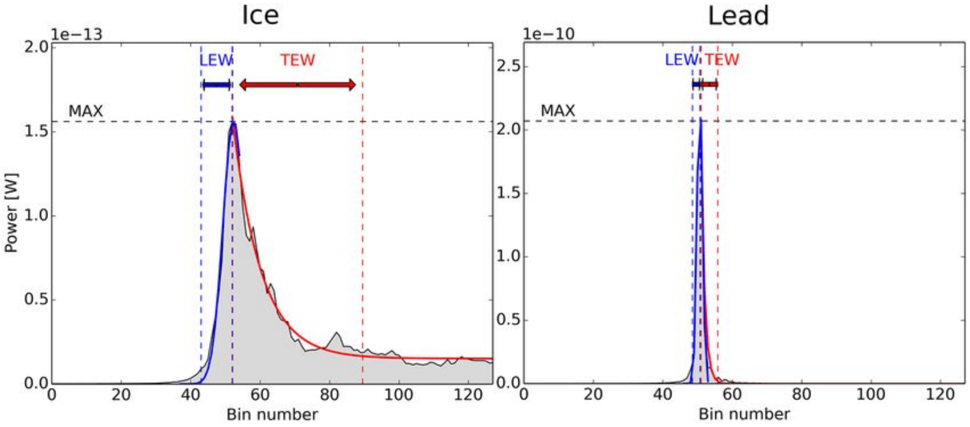
Some current sensors :

- CryoSat-2
- SIRAL/AltiKa

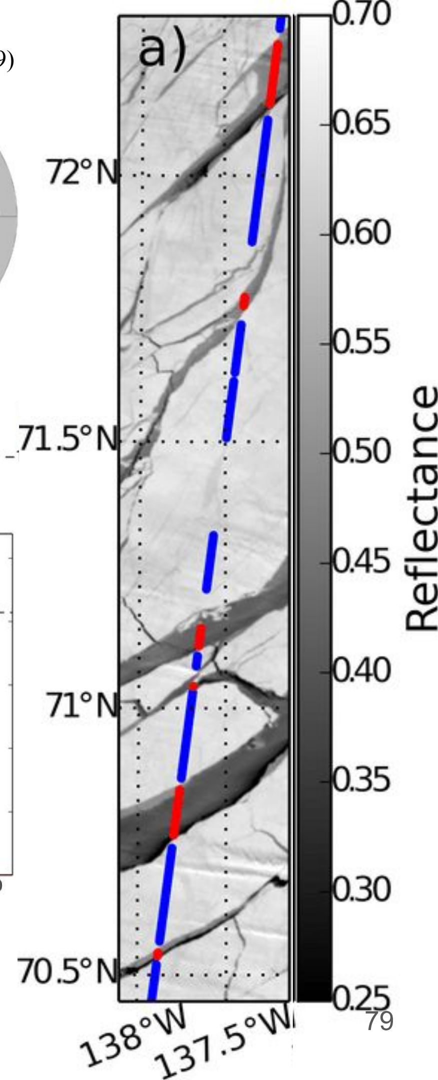


Journal of Geophysical Research: Oceans. 124. 10.1029/2019JC015232/ R&R Tilling, A. Shepherd (2019)





Wernecke, A. and Kaleschke, L.: Lead detection in Arctic sea ice from CryoSat-2: quality assessment, lead area fraction and width distribution, The Cryosphere, 9, 1955–1968, https://doi.org/10.5194/tc-9-1955-2015, 2015.$



F. Radiometer

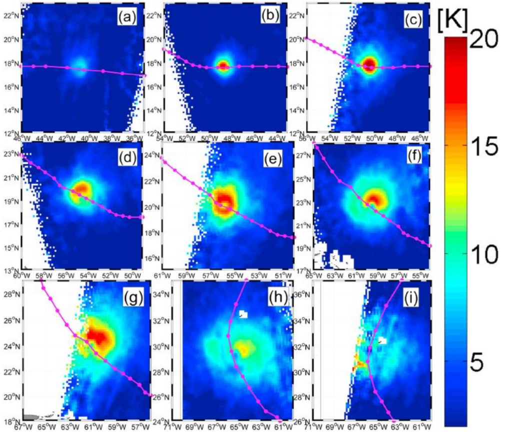
Radiometer

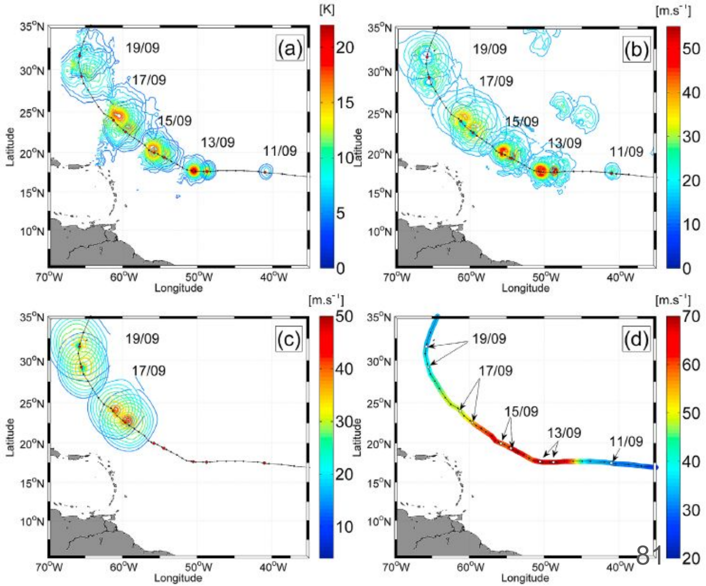
Current instrument :
- SMOS

Passif radar instrument
Measure the faint microwave emissions from Earth's surface

Application : levels of soil moisture, sea surface salinity, sea ice thickness, wind speed over the ocean

Ex : Hurricane surface wind field measurement
Reul Nicolas, Tenerelli Joseph, Chapron Bertrand, Vandemark Doug, Quilfen Yves, Kerr Yann (2012). **SMOS satellite L-band radiometer: A new capability for ocean surface remote sensing in hurricanes**. *Journal Of Geophysical Research-oceans*, 117, -. Publisher's official version : https://doi.org/10.1029/2011JC007474 , Open Access version : https://archimer.ifremer.fr/doc/00067/17805/





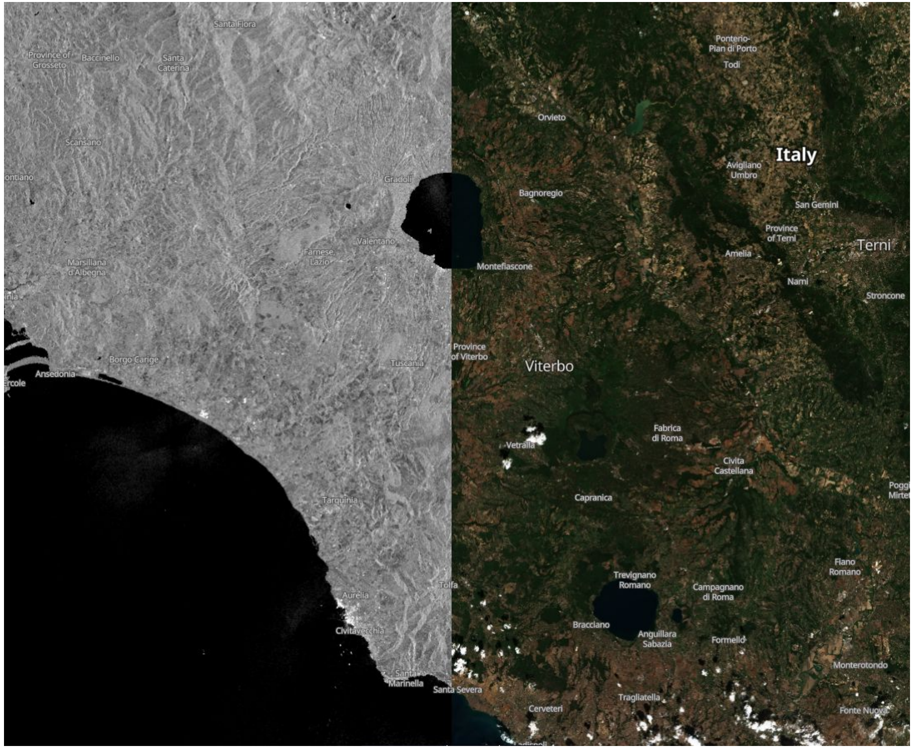
G. Corregistration

Coregistration

Having multiple images/signals on the same grid

Two main options:

1. Having all the images on a geographical grid
   EO browser / google earth engine idea
   - Correcting all the acquisitions specificities
2. Choosing the geometry of one image and transforming the other images
   - Using image properties (Gefolki)
   - Using geographical information

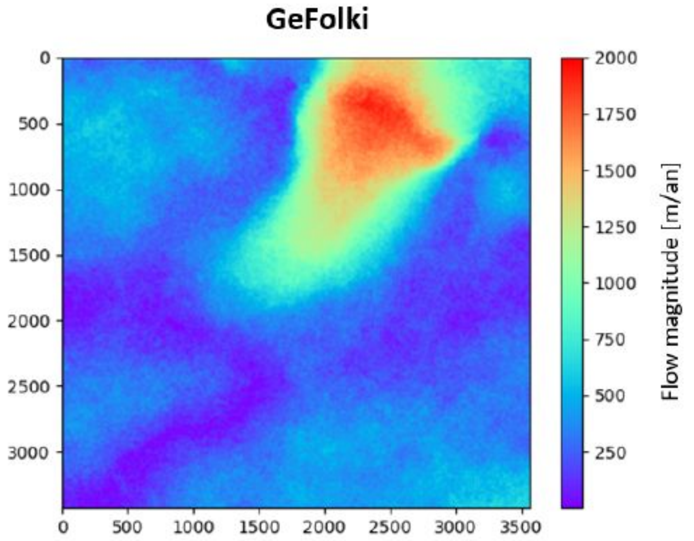


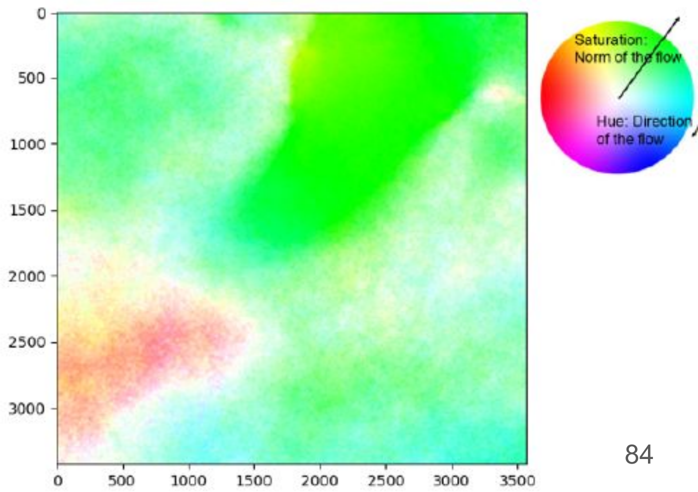
EO Browser S1/S2 over Italy

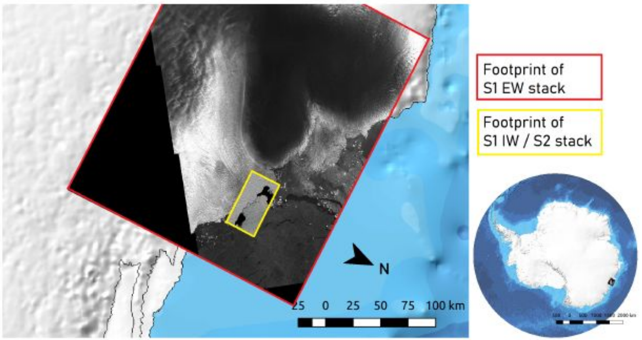
GeFolki https://github.com/aplyer/gefolki

Optical flow method used in:

- Computer vision
- Particle image velocity
- Mono and multi modal remote sensing
  - Coregistration
  - Flow estimation

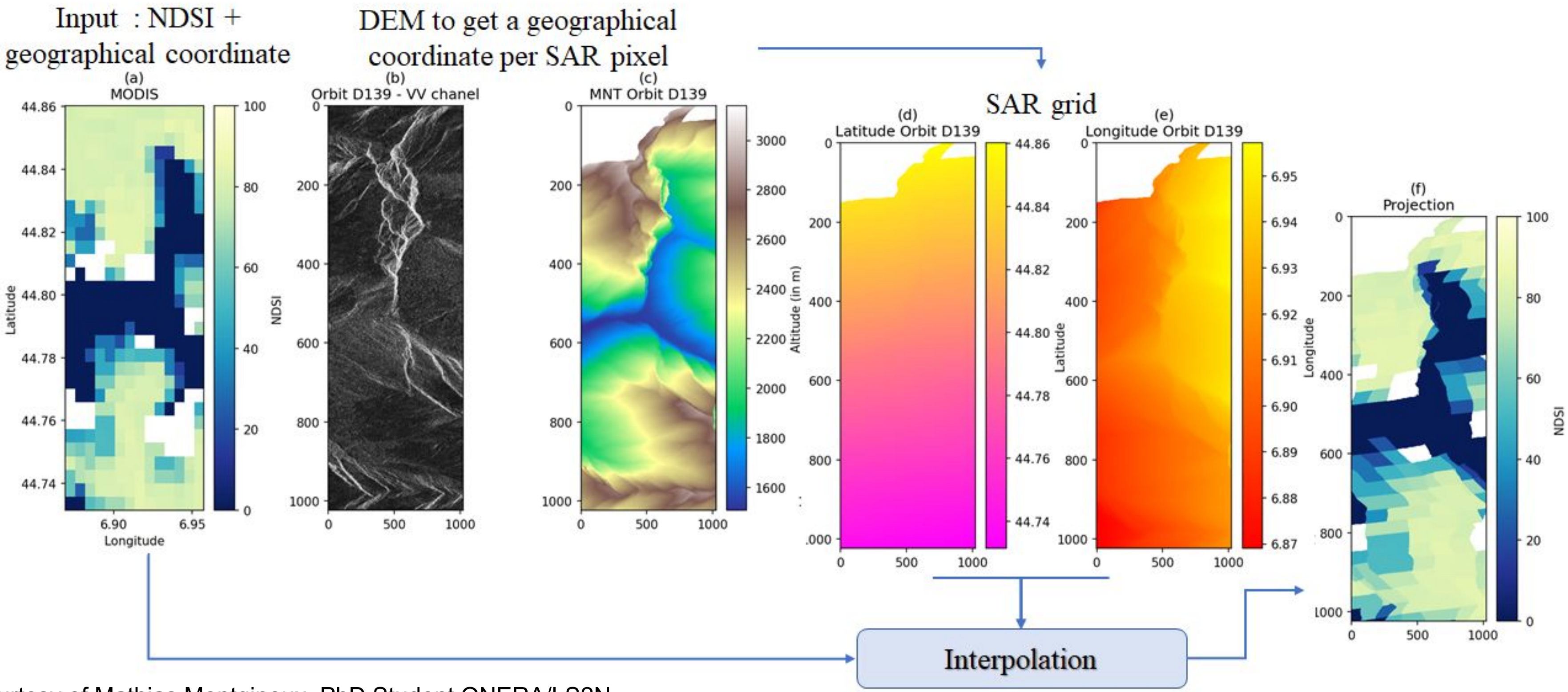






L. Charrier, P. Godet, C. Rambour, F. Weissgerber, S. Erdmann and E. C. Koeniguer, "Analysis of dense coregistration methods applied to optical and SAR time-series for ice flow estimations," *2020 IEEE Radar Conference (RadarConf20)*, 2020, pp. 1-6, doi: 10.1109/RadarConf2043947.2020.9266643.

Geographical link



Courtesy of Mathias Montginoux, PhD Student ONERA/LS2N

Conclusion

Conclusion

Earth Observation is fun!

There are lots of challenges in AI:

- Optimize the processing for the acquisition constraints (orbit, resolution)
- Take into account the physic of acquisition
- Take into account the specificity of the monitored
    - Urban areas are very discontinuous
    - Sea ice can change and move very fast
    - Snow characteristics are very dependant of the terrain geometry
    - To understand agricultural changes, we need to go back through time

H. Your case study

Questions

1. For this application, what would be the advantages and the drawbacks of :
    a. optical sensors
    b. SAR sensors
    c. Lidar
    d. Sar altimeter
2. Will you select one sensor or try a multi-modal approach ?
3. Will you ask for new VHR commercial satellite (TerraSAR-X/Pleiades) images or will you download open HR images (Sentinel-1/Sentinel-2) ?
4. What type of non-learning approach could you use **(mandatory)** ? Test it on one well selected example that you have yourself downloaded
5. Is there a already existing DL dataset **(optional)** ?
    a. https://github.com/chrieke/awesome-satellite-imagery-datasets
    b. If so, test a vanilla methodology on the dataset and report your results. How does it compare to the non-learning approach ?
    c. If not, could you use an existing source of annotations?

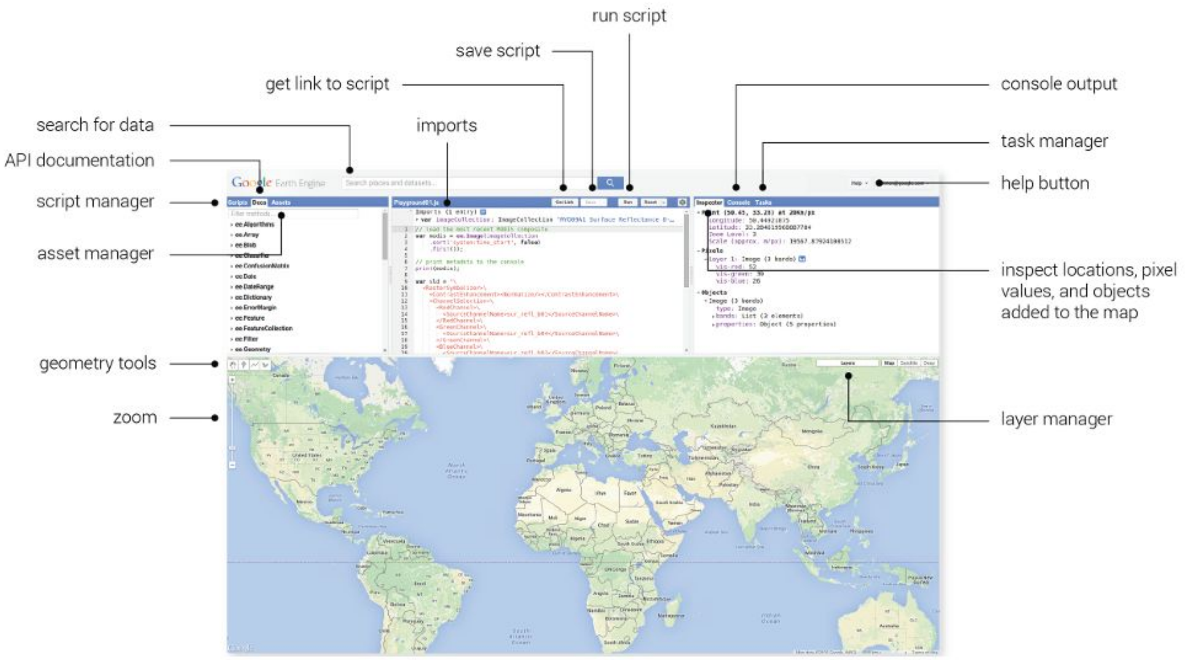
Data platforms and GIS tools

Data platform: Copernicus browser

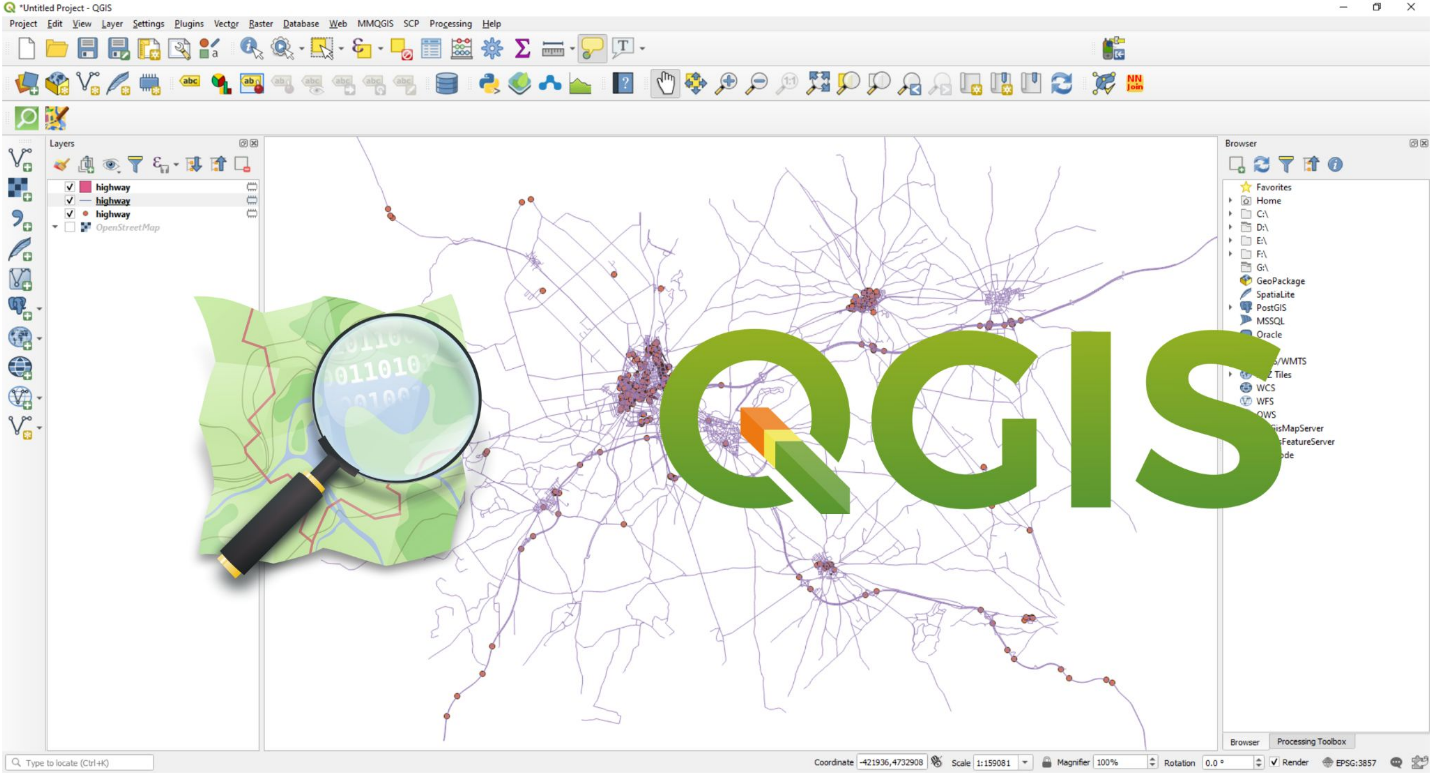
https://browser.dataspace.copernicus.eu/

Data platform: Google Earth Engine

code.earthengine.google.com



QGIS


*Untitled Project - QGIS
Project Edit View Layer Settings Plugins Vector Raster Database Web MMQGIS SCP Processing Help
Layers
highway
highway
highway
OpenStreetMap
Browser
Favorites
Home
C:\
D:\
E:\
F:\
G:\
GeoPackage
SpatiaLite
PostGIS
MSSQL
Oracle
WCS
WFS
QGIS
Browser
Processing Toolbox
Type to locate (Ctrl+K)
Coordinate -421936,4732908
Scale 1:159081
Magnifier 100%
Rotation 0.0 °
Render
EPSG:3857

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