

# A Bird's Eye View On Multispectral Satellite Imagery

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topnetwork

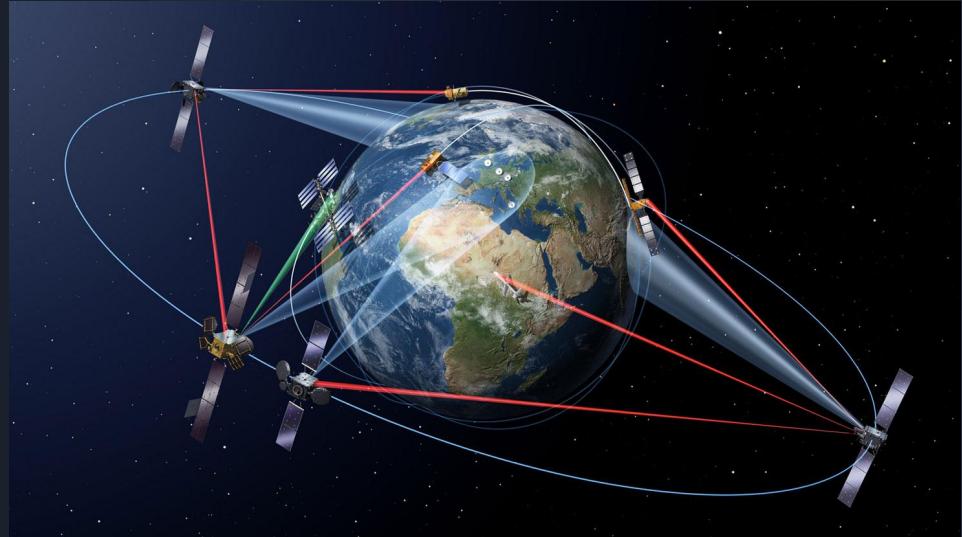
# SUMMARY

## Data

Synthetic Aperture Radar (SAR)

Multi Spectral Images (MSI)

Data sources



## ML & AI

Data preparation

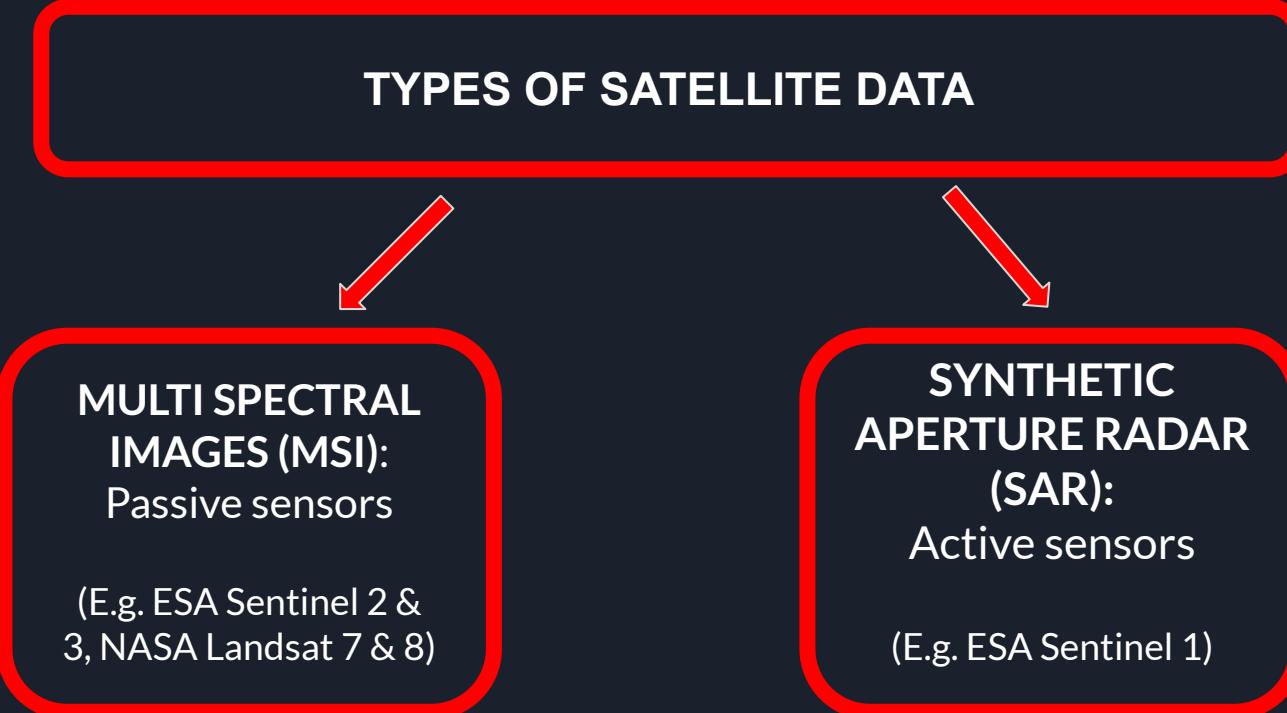
Training

Real world applications



# REMOTE SENSING THROUGH SATELLITES

## TYPES OF SATELLITE DATA



**MULTI SPECTRAL IMAGES (MSI):**  
Passive sensors

(E.g. ESA Sentinel 2 & 3, NASA Landsat 7 & 8)

**SYNTHETIC APERTURE RADAR (SAR):**  
Active sensors

(E.g. ESA Sentinel 1)



# SAR DATA

## Pro:

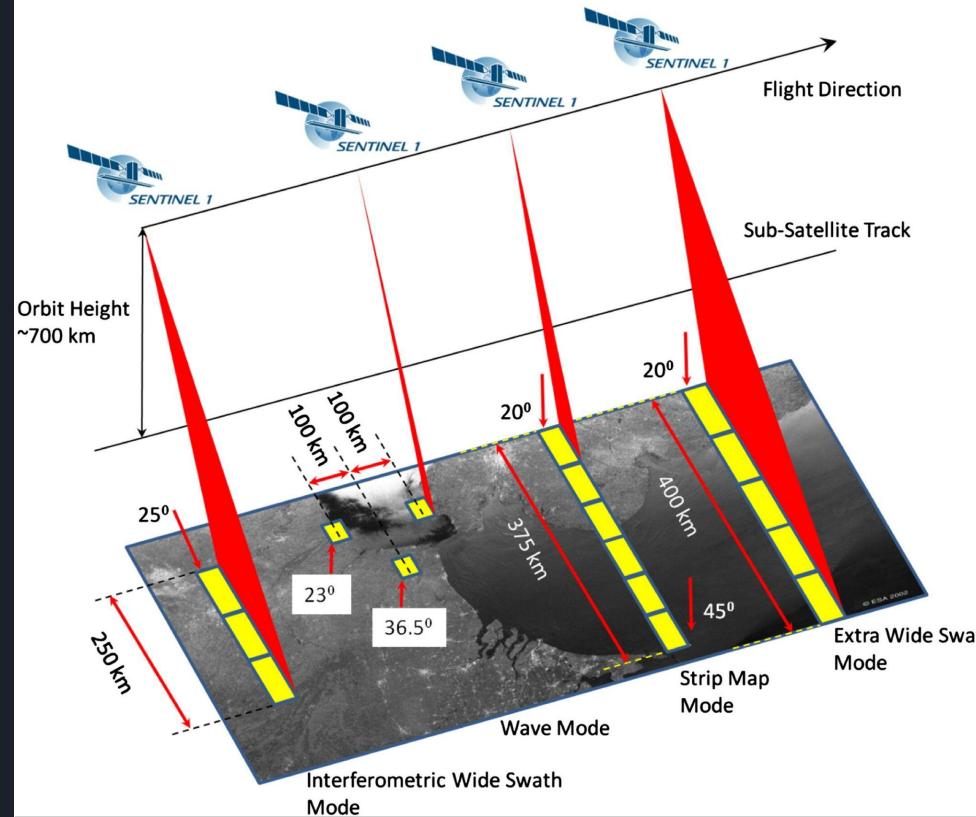
Weather-free measurements

Signal processing through time  
allows to detect cm-scale  
variations

## Contra:

No true color information (false  
color with polarization)

Post processing is complex





*SAR image of the Bosphorus Strait*



# MSI DATA

Pro:

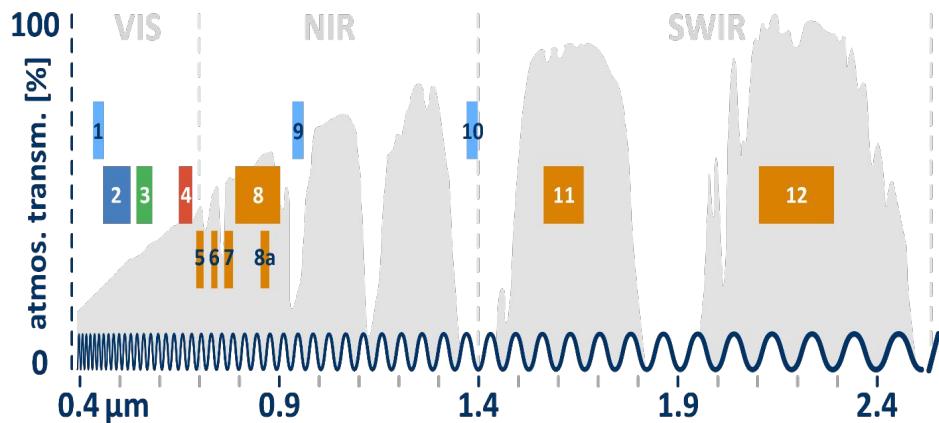
Directly understandable (**RGB**)

Many different wavelengths  
(Visible, Near Infra Red, Short Wave  
Infra Red)

Contra:

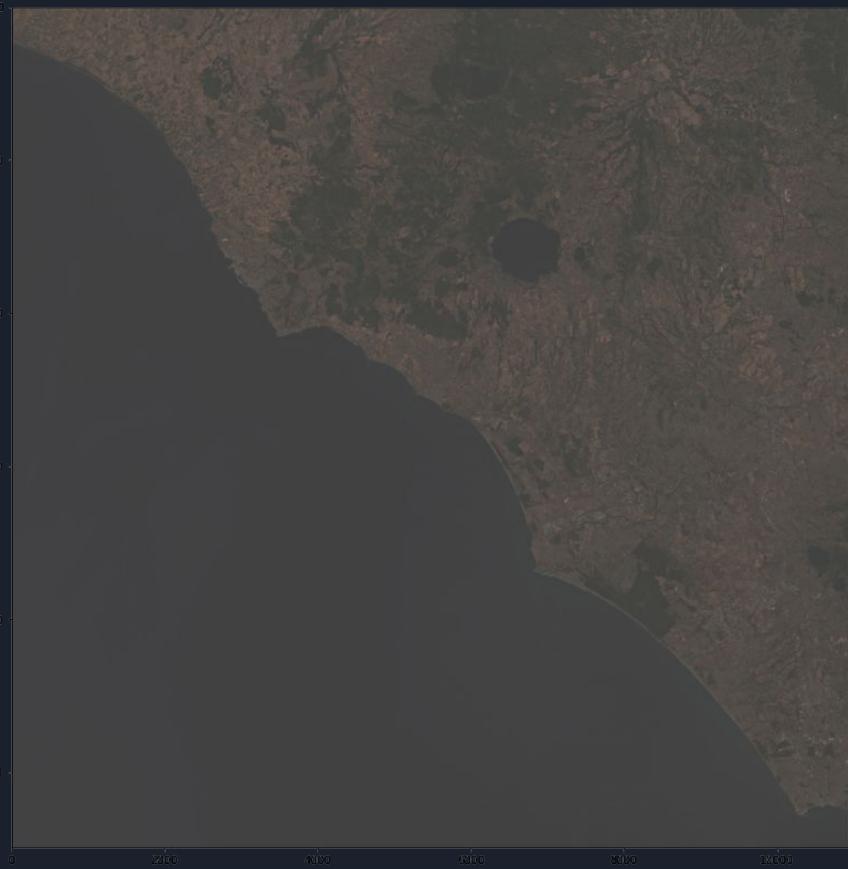
Atmospheric corrections

Clouds



BAND	SPECTRAL	WAVELEN. [μm]	GEOM. [m]	SENSOR
1	aerosols	0.429 – 0.457	60	MSI
2	blue	0.451 – 0.539	10	MSI
3	green	0.538 – 0.585	10	MSI
4	red	0.641 – 0.689	10	MSI
5	red edge	0.695 – 0.715	20	MSI
6	red edge	0.731 – 0.749	20	MSI
7	red edge	0.769 – 0.797	20	MSI
8	NIR	0.784 – 0.900	10	MSI
8a	narrow NIR	0.855 – 0.875	20	MSI
9	water vapour	0.935 – 0.955	60	MSI
10	SWIR cirrus	1.365 – 1.385	60	MSI
11	SWIR	1.565 – 1.655	20	MSI
12	SWIR	2.100 – 2.280	20	MSI

# MSI IMAGES: RGB & NIR OF ROME AREA



# ESA SATELLITE MISSIONS

## **Sentinel-1**

SAR data

Two satellites (S1A & S1B), orbit period of 12 days

5m of spatial resolution

## **Sentinel-2**

MSI data (12 bands, from UltraViolet to Short Wave Infra Red)

Two satellites (S2A, S2B), orbit period of 10 days

Spatial resolution 10m (R, G, B, NIR) to 20m and 60m

## **Sentinel-3**

MSI mission for environmental monitoring

4 instruments on board, from 250m to 1km spatial resolution

Orbital period: 27 days

# HOW TO ACCESS THE DATA

## Copernicus Open Access Hub

<https://scihub.copernicus.eu/> (Sentinel 1, 2, 3)

Free access with API registration

## Google Earth Engine

<gs://gcp-public-data-sentinel-2> (Sentinel 2)

Free access with API registration

## Sentinel Hub

<https://www.sentinel-hub.com/> (Sentinel, Landsat, Airbus ...)

Free trial access

# DIRECT APPLICATION: SPECTRAL INDICES

Using a direct algebraic combination of the bands we can highlight some properties of the terrain:

## **NDVI: Normalized Difference Vegetation Index**

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{RED} + \text{NIR})$$

## **NDWI: Normalized Difference Water Index**

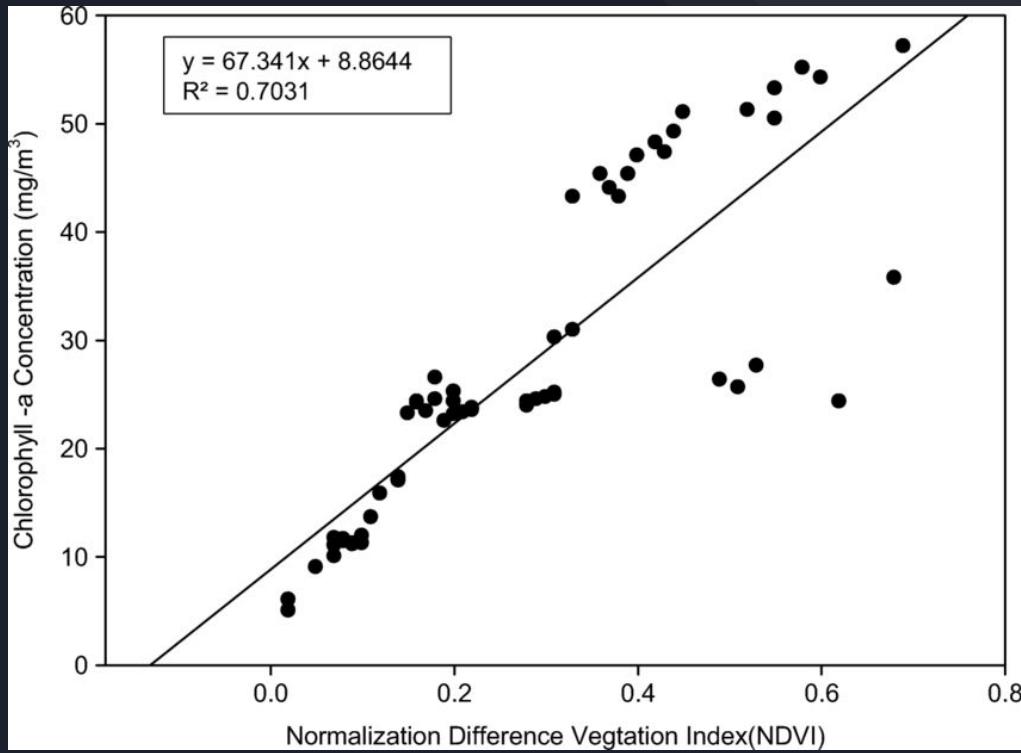
$$\text{NDWI} = (\text{GREEN} - \text{NIR}) / (\text{GREEN} + \text{NIR})$$

## **NBR: Normalized Burned Ratio**

$$\text{NBR} = (\text{NIR} - \text{SWIR}) / (\text{SWIR} + \text{NIR})$$

More custom indices: <https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel/>

# NDVI IS A GOOD PROXY FOR CHLOROPHYLL



**NDVI**

**NDWI**

# ML & AI APPLICATIONS

Urban Trend (app within the DataFactor project, funded by Italian MISE):

- Use open data
- Identify in land use (buildings, trees etc.)
- Seasonality, trends forecasts
- Works with very different kinds of terrains, time, light



## AI / ML TOOLS:

Classic ML, pixel-based algorithms:

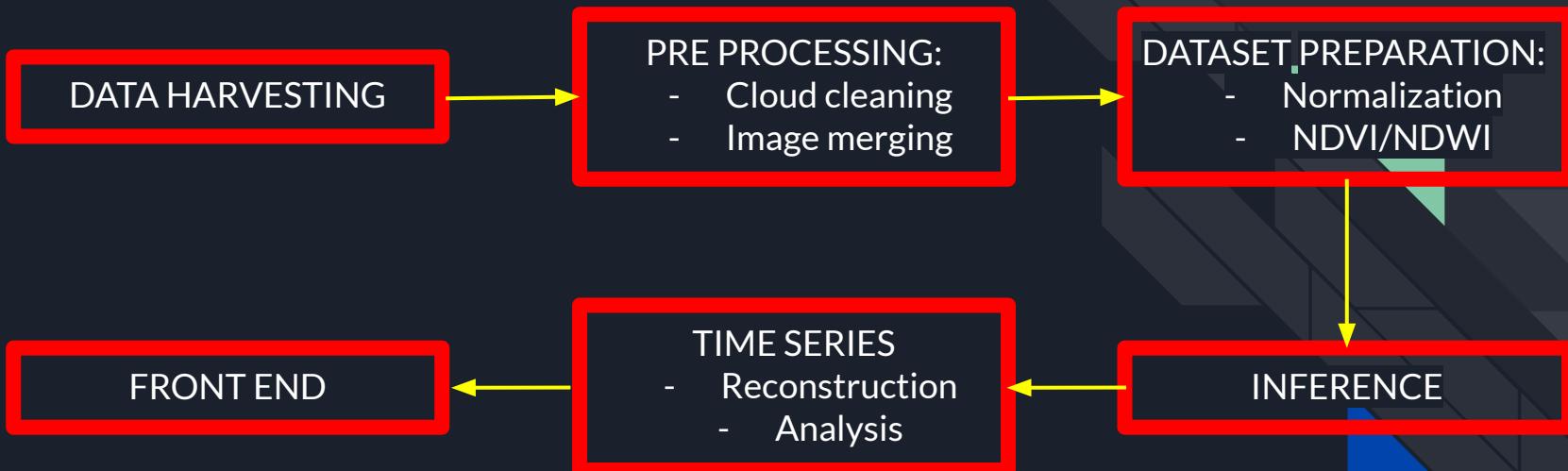
- Random Forest
- SVM
- Gradient boosting

Deep learning: CNN and U-Net for semantic segmentation



# SYSTEM PIPELINE AND ARCHITECTURE

(deployed on prem with Valohai MLOps orchestrator)

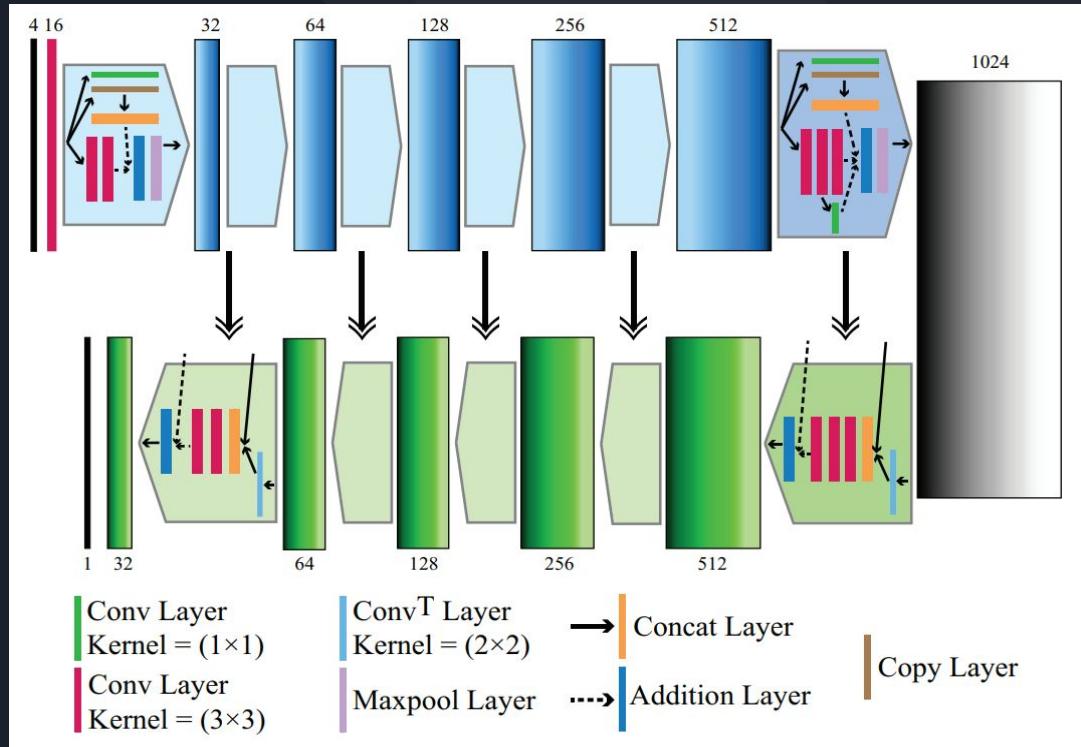


# CLOUD SEGMENTATION

**Cloud-Net:**  
U-Net [1], trained on Landsat 8, 4-band  
images (RGB + NIR)

**Transfer learning:**  
Using S2 cloud dataset [2]

**Stacking and merging:**  
Collect cleaned images over 30  
days windows

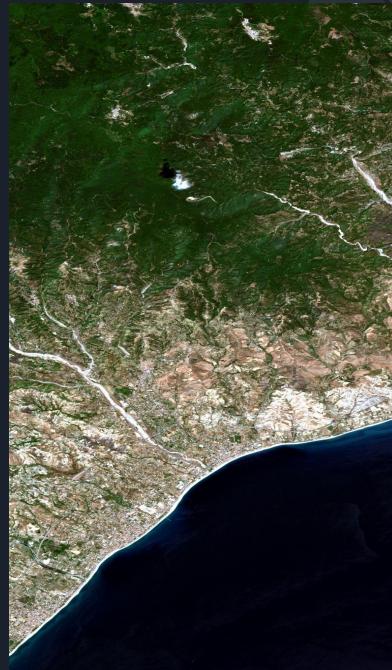
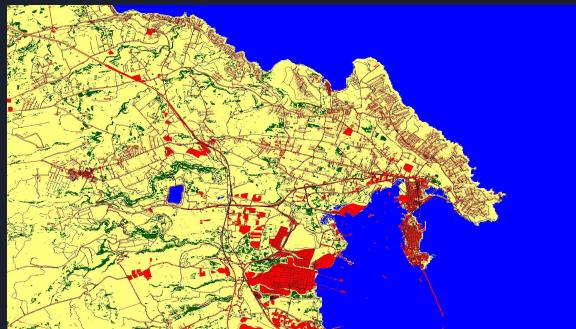


[1] Mohajerani, Saeedi (2019) <https://arxiv.org/abs/1901.10077v1>

[2] Sentinel 2 Cloud Segmentation Dataset (2020) <https://mlhub.earth/10.34911/rdnt.hfq6m7>

# IMAGE SEGMENTATION TRAINING SET

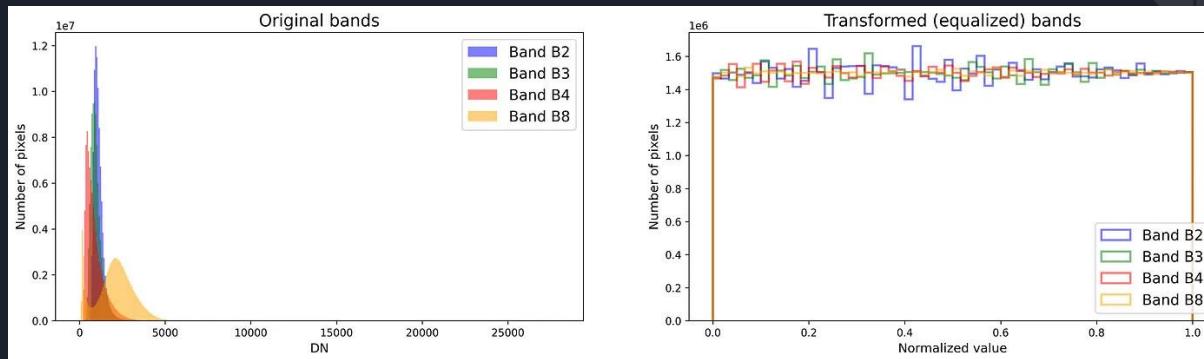
150 cloud free (mostly) images, 4 bands, varying size 1024x512 to 3984x2048



# DATA PREPARATION PIPELINE

Custom labeling on 4 classes: water, trees, terrain, building

Image normalization: Histogram Normalization [1] & K-Means for the ground truth values:



Patchification and augmentation: extract NxN patches, rotate and zoom in

[1] Kadunc et al. (2022) <https://medium.com/sentinel-hub/how-to-normalize-satellite-images-for-deep-learning>

# TERRAIN SEGMENTATION: U-NET ARCHITECTURE

Cannot use pre-trained models (e.g. Imagenet) due to Nchannels

Base Architecture: UNet/CloudNet with bridge 1024/2048

**Multiclass:** Water, Terrain, Trees, Buildings (ESRI classification, works better under different geo & weather conditions)

**Input channels:** R, G, B, NIR, NDVI, NDWI

**Tensor shape =** (Nchannels, Xpatch, Ypatch)

**Nchannels =** 4, 5, 6

**X/Ypatch =** 64, 96, 128, 256, 384

# U-NET TRAINING STRATEGY

Loss Function: Weighted cross entropy

$$\ell(x, y) = L = \{l_1, \dots, l_N\}^\top, \quad l_n = -w_{y_n} \log \frac{\exp(x_{n,y_n})}{\sum_{c=1}^C \exp(x_{n,c})}$$

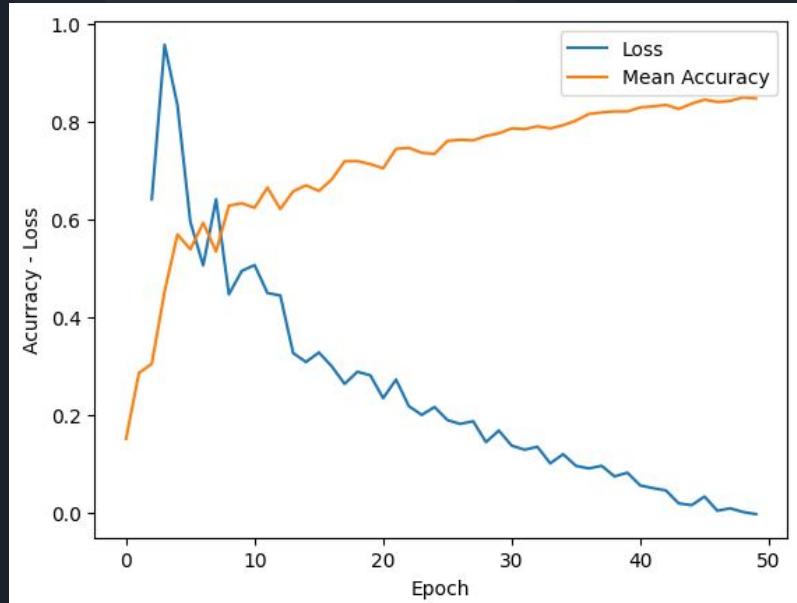
Relevant metrics:

Mean accuracy (per-class)

Hardware:

NVIDIA A6000 (48 GB),

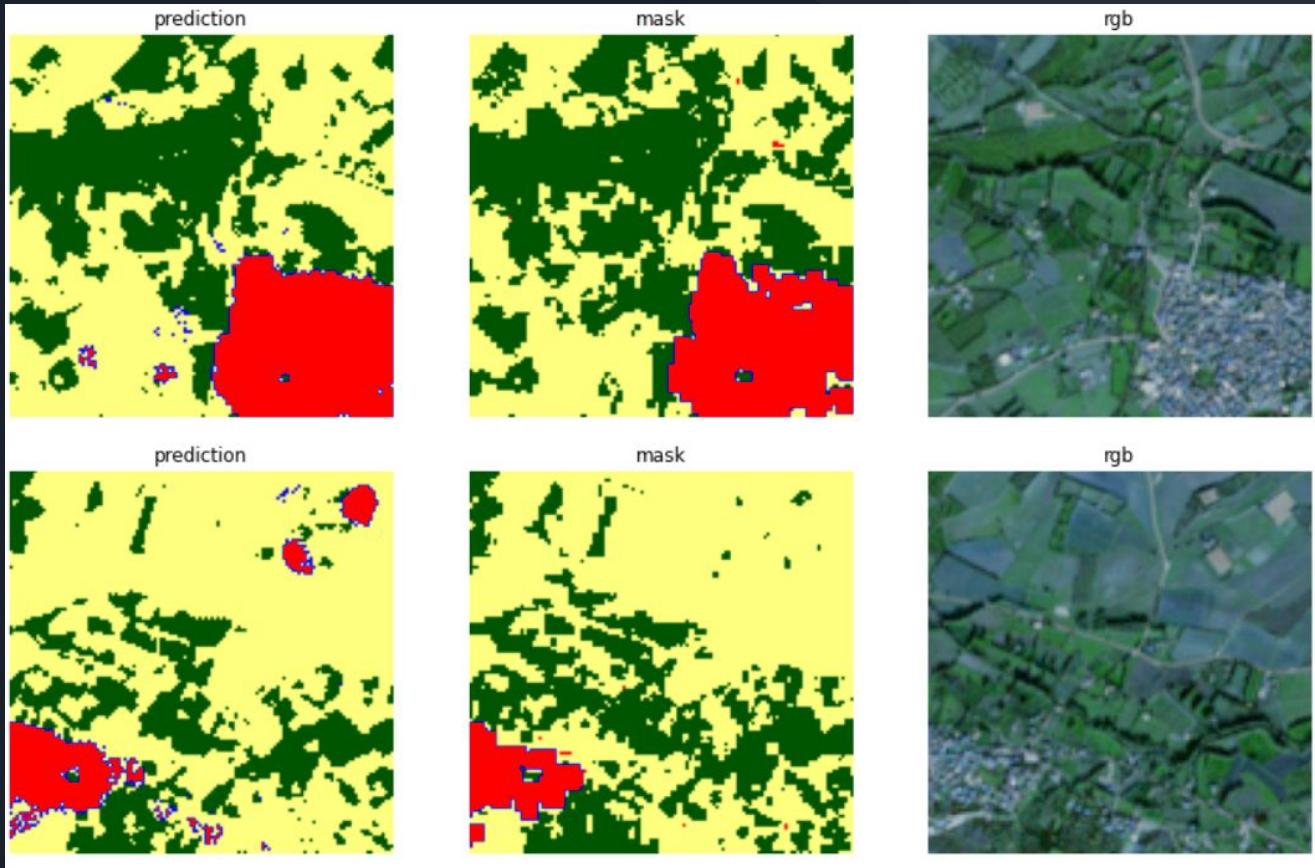
NVIDIA Quadro RTX 6000 (24GB)



- 0) Correct pixels: 405260/449951, 0.9006758513704826
- 1) Correct pixels: 2046548/3099872, 0.6602040342310909
- 2) Correct pixels: 13863621/15315429, 0.9052061812959999
- 3) Correct pixels: 8016909/9073564, 0.883545759968189

Mean : 0.8374079567164403

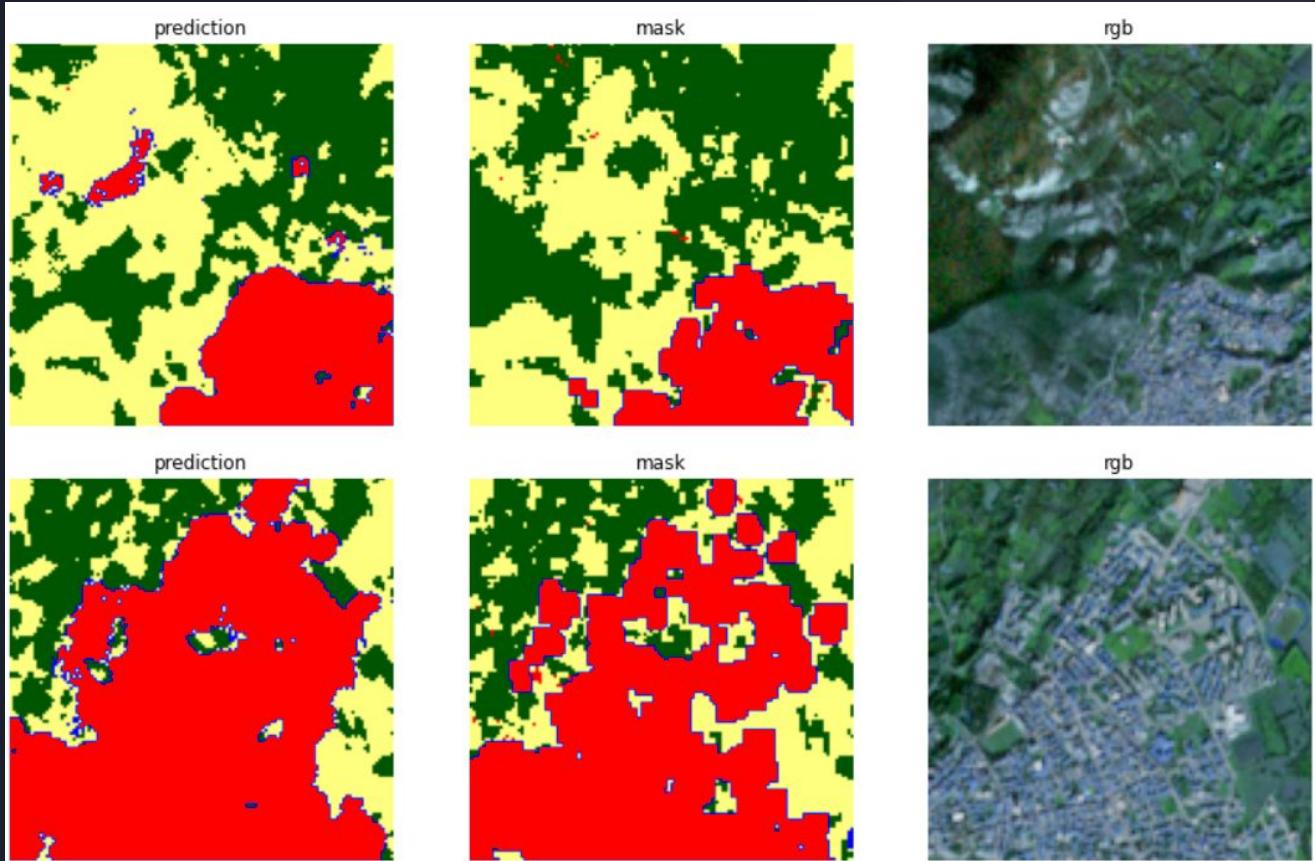
# U-NET APPLICATION



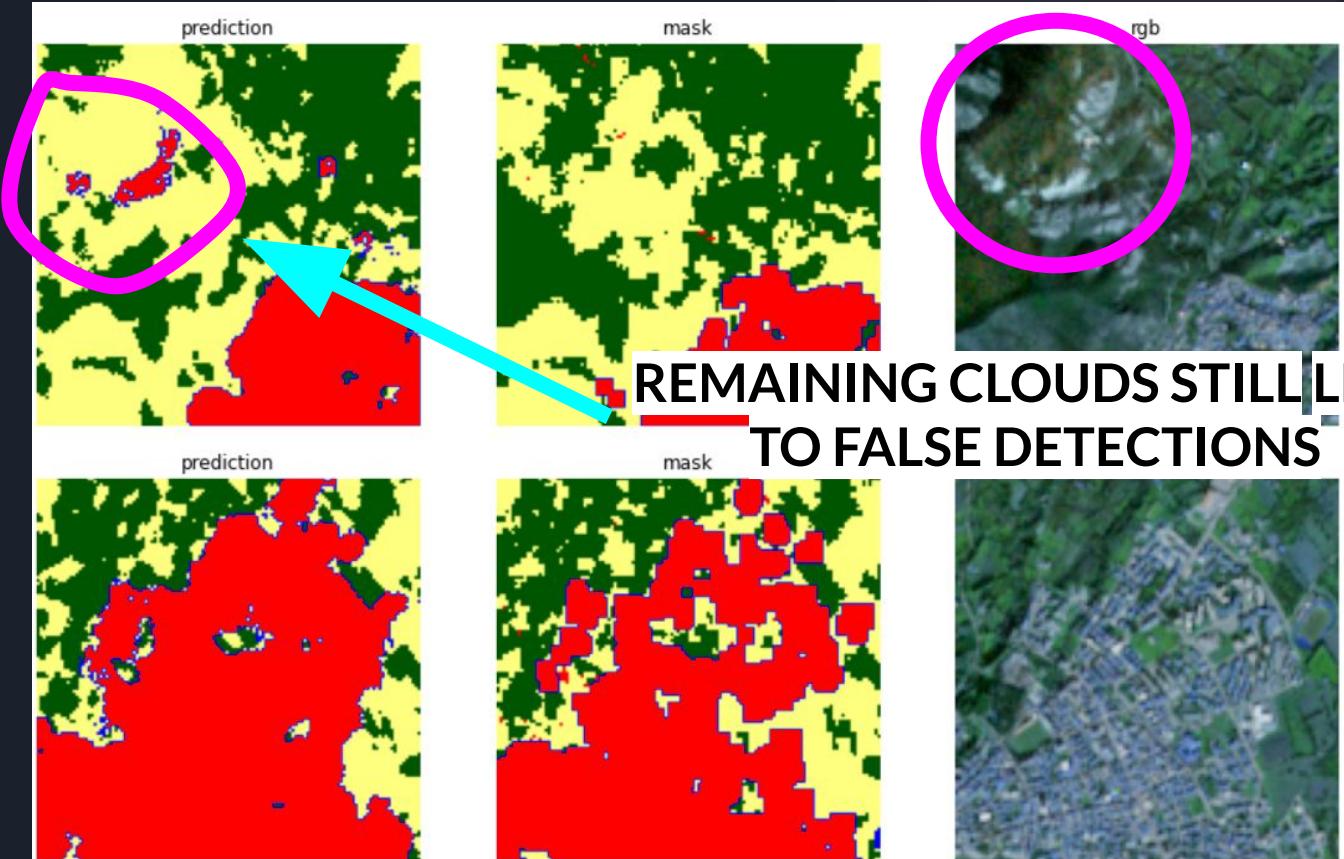
# U-NET APPLICATION



# U-NET APPLICATION



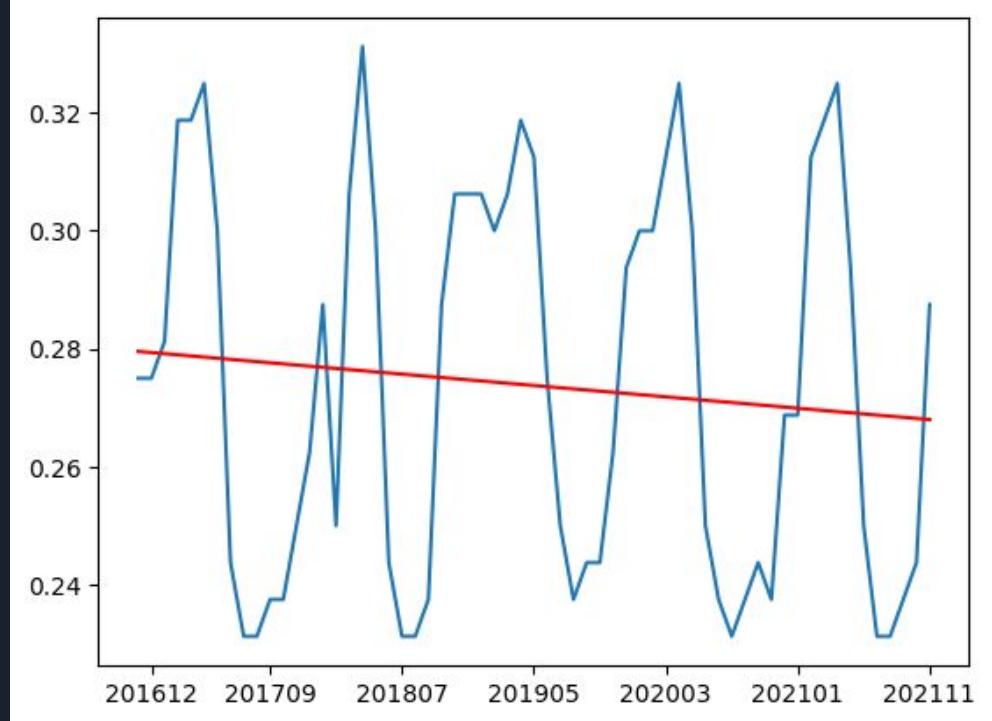
# U-NET APPLICATION



# FOREST AREA TIME SERIES APPLICATION



Municipality of Comitini (Agrigento), Sicily



# CONCLUSION

SATELLITE IMAGERY IS ABUNDANT, FREE AND  
POWERFUL

HAVE FUN WITH IT!