OIL SPILL DETECTION ON LANDSAT-8/9 IMAGES BASED ON DEEP LEARNING METHODS

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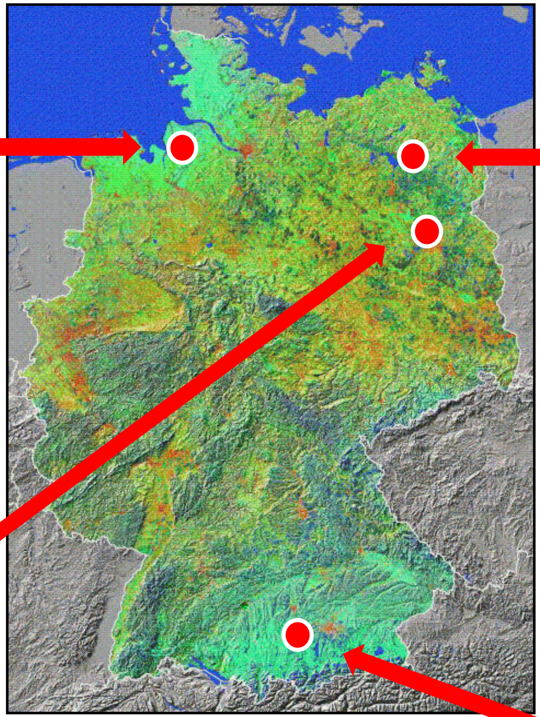


Neustrelitz
National Ground Segment
Maritime Safety and Security Lab

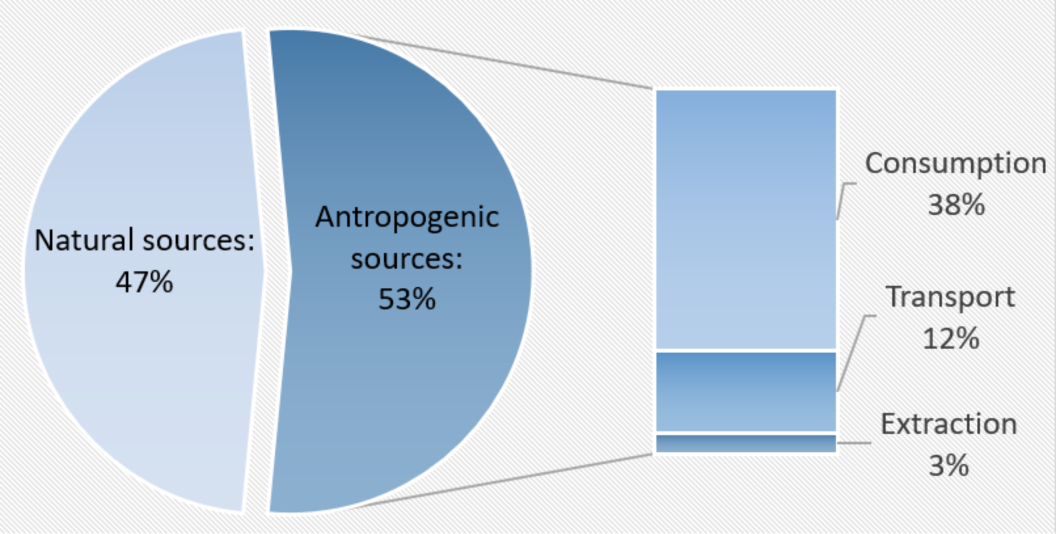
Berlin

- Appr. 350 employees at 4 sites
- Chairs at 2 universities

Oberpfaffenhofen

Motivation

- Oil pollution has a major impact on the marine and coastal environment
- The main sources of oil pollution:



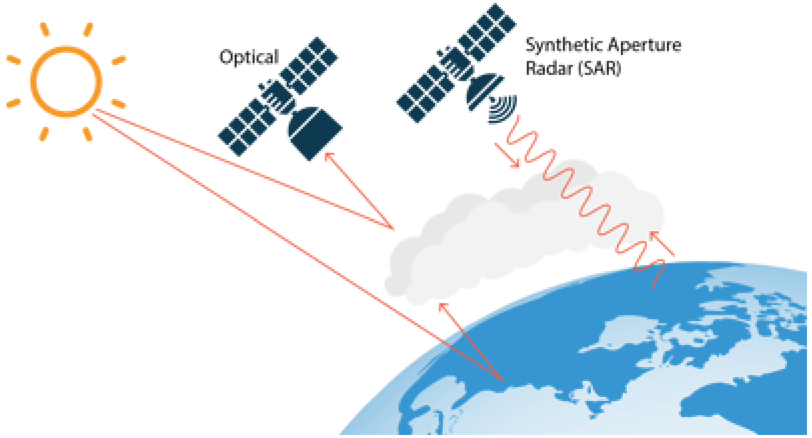
- Natural sources (seeps): ecosystems can adapt
- Antropogenic sources: ecosystems are damaged

Oil Spill Detection using Remote Sensing

- Identification and monitoring of oil pollution
- Support of clean-up operations following accidents or illegal spills

Synthetic Aperture Sensors (SAR), active sensors:

- Day and night capability; independent of clouds, dust or smoke
- Look-alikes: areas with very low wind and strong wind



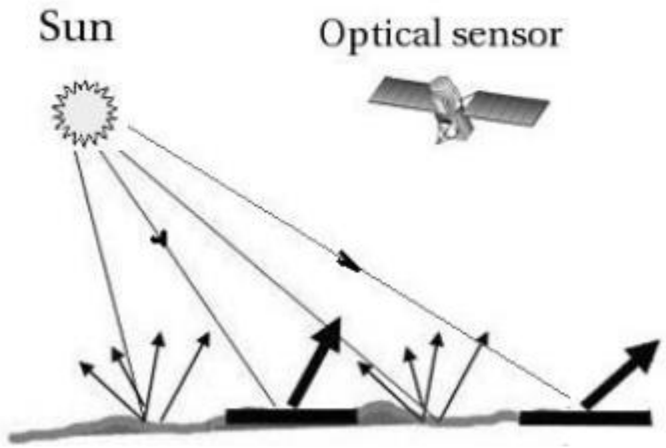
https://blog.descarteslabs.com/hs-fs/hubfs/GDS%20Blog%20series/SAR_clouds.png?width=400&name=SAR_clouds.png

Optical sensors, passive sensors:

- Spectral bands provide features of oil spills; oil thickness, oil type
- Look-alikes: thin clouds, cloud shadows, dust, suspended sediments, shallow water areas

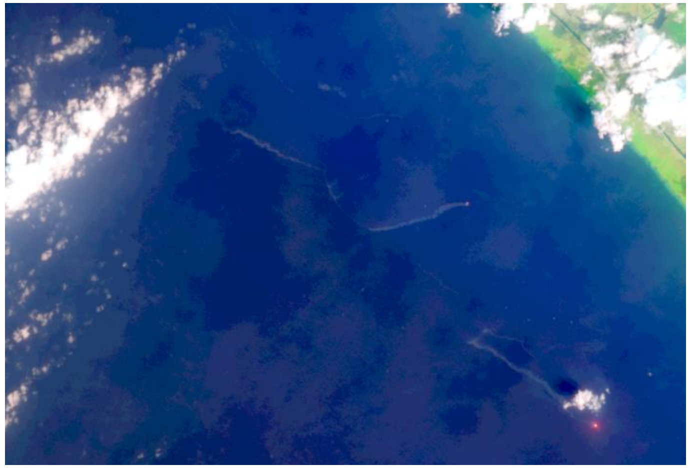
Oil Spills on Optical Satellite Images

- Oil changes the spectral characteristics of water
- Oil spills can appear darker (negative contrast) or brighter (positive contrast) than the surrounding water
- Contrast variation is depending on position of sun and optical sensor
- Contrast intensity is influenced by:
  - optical properties of oil (oil type, oil thickness)
  - scattering of the sea water
  - sea state (wind patterns)
  - depth of the sea
  - bathymetry



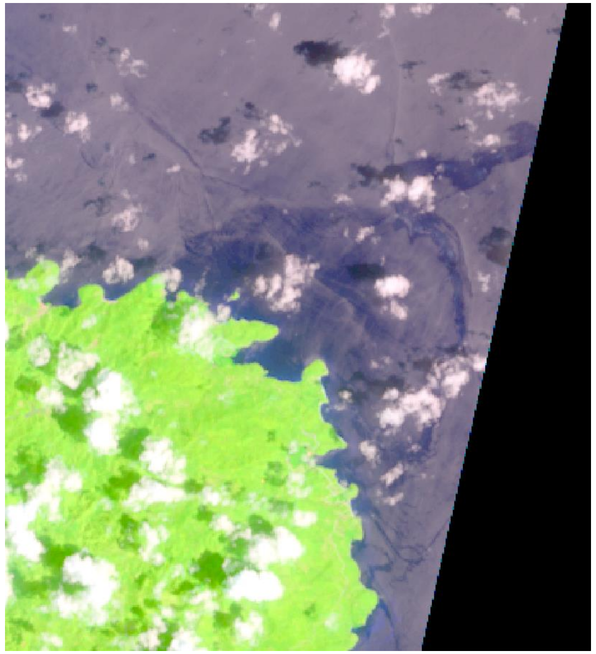
Alawadi, Fahad A. M., 2011

Oil Spills on Landsat-8/9 Images



LC09_L1TP_190056_20220211_20220211_02_T1, Nigeria

LC09_L1TP_190056_20220227_20220228_02_T1, Nigeria



LC09_L1TP_116051_20230312_20230313_02_T1, Philippines

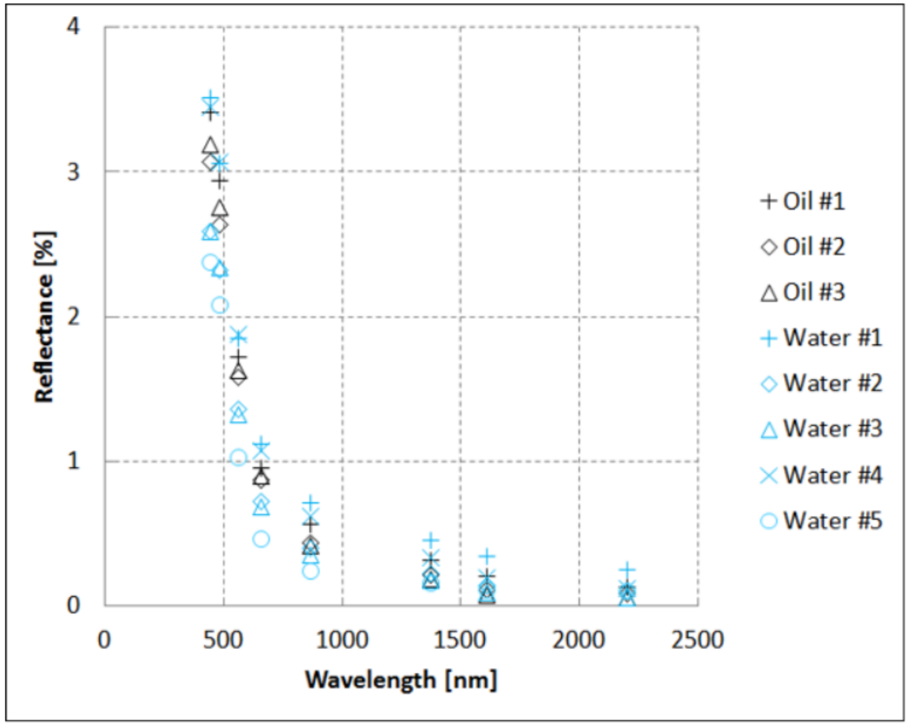
LC08_L1TP_191021_20210903_20210910_02_T1, Baltic Sea

- False color images (SWIR2, NIR and blue) with applied logarithmic stretch

Oil Spills on Landsat-8/9 Images

But:

- Spectral characteristics of oil and water are similar in all wavelength
- Nevertheless, oil spills are visible after image manipulation



→ *Task of study:*

- Oil spill detection on Landsat-8/9 optical images using Deep Neural Network (DNN) and U-Net (Convolutional Neural Network, CNN)

Training Data
Oil Mask Preparation for Deep Learning

- Segmentation method based on the Normalized Difference Oil Index (NDOI), the Green-Shortwave Infrared Index (G-SWIR) and Coastal Aerosol (Band 1)

$$\mathrm{NDOI} = \frac{\rho_\lambda(\mathrm{green}) - \rho_\lambda(\mathrm{NIR})}{\rho_\lambda(\mathrm{green}) + \rho_\lambda(\mathrm{NIR})}$$

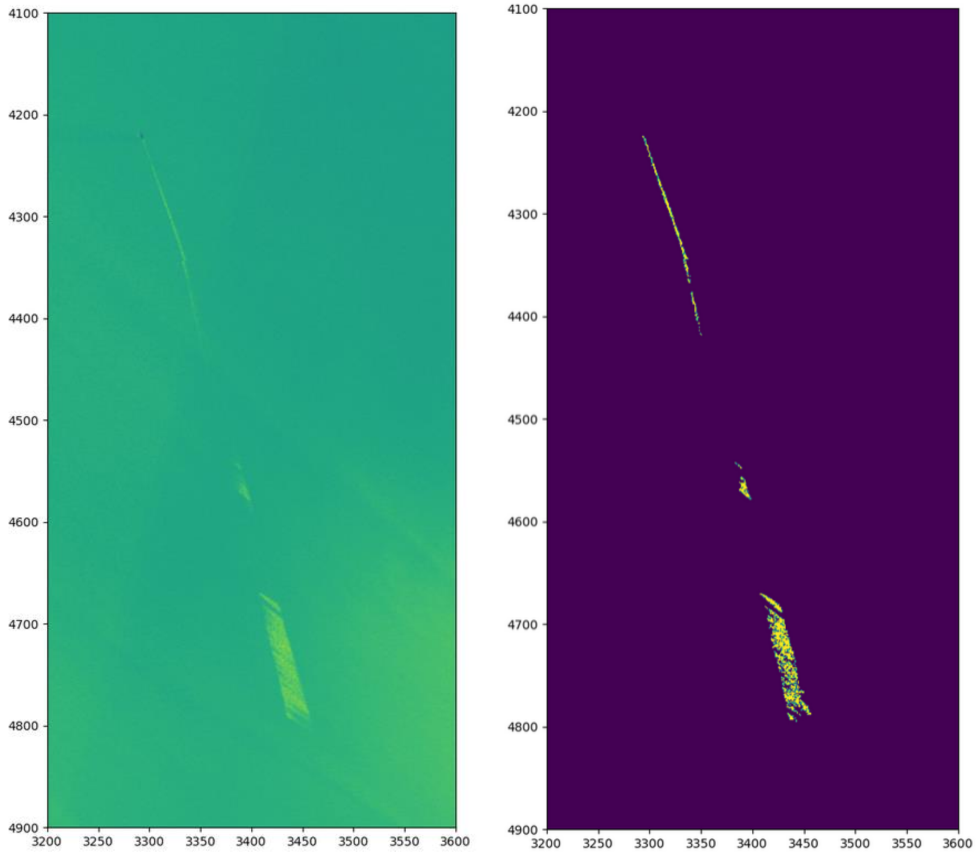
$$\mathrm{G-SWIR} = \frac{\rho_\lambda(\mathrm{green}) \; - \rho_\lambda(\mathrm{SWIR2})}{\rho_\lambda(\mathrm{green}) + \rho_\lambda(\mathrm{SWIR2})}$$

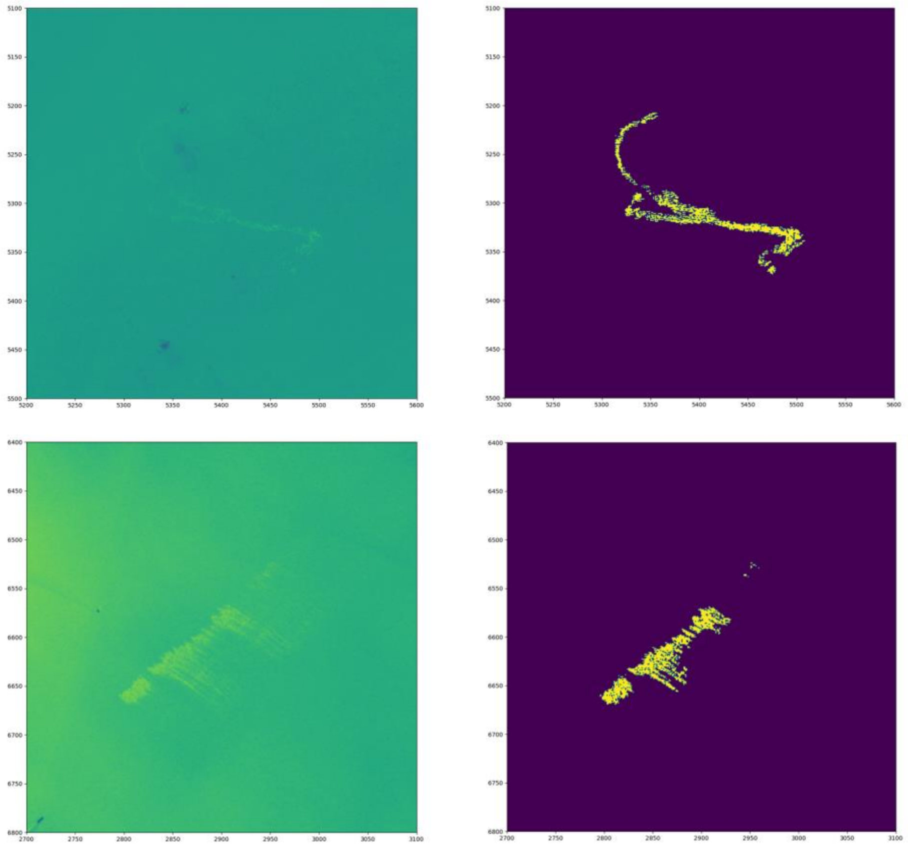
Bands	Wavelength (nm)
Band 1 - Coastal Aerosol	430–450
Band 3 - Green	530–590
Band 5 - Near Infrared (NIR)	850–880
Band 7 - Shortwave Infrared (SWIR) 2	2110-2290

→ Enhancement of the visual differentiation between oil slicks and the surrounding waters

→ Enhancement of the contrast

Training Data
Oil Mask Preparation for Deep Learning

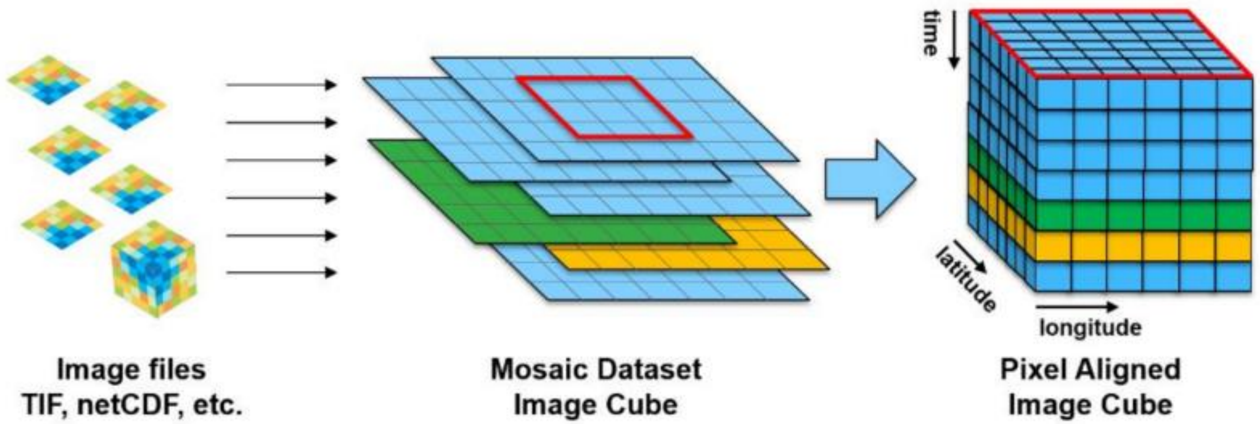




- LC08_L1GT_199022_20170527_20200903_02_T2, North Sea (left + bottom right)
- LC08_L1GT_200021_20170705_20200903_02_T2, North Sea (top right)

Training Data Handling

- Open Data Cube:
  - Open Source Geospatial Data Management and Analysis Software project
  - Data sets are stored as multidimensional arrays
  - Simplifying the access, management and analysis of large satellite data sets



https://eox.at/images/eodcaas-mosaic-data-cube-kopp.png

Methods
Training Data

$$\mathrm{NDOI} = \frac{\rho_\lambda(\mathrm{green}) - \rho_\lambda(\mathrm{NIR})}{\rho_\lambda(\mathrm{green}) + \rho_\lambda(\mathrm{NIR})}$$

$$\mathrm{G-SWIR} = \frac{\rho_\lambda(\mathrm{green}) - \rho_\lambda(\mathrm{SWIR2})}{\rho_\lambda(\mathrm{green}) + \rho_\lambda(\mathrm{SWIR2})}$$

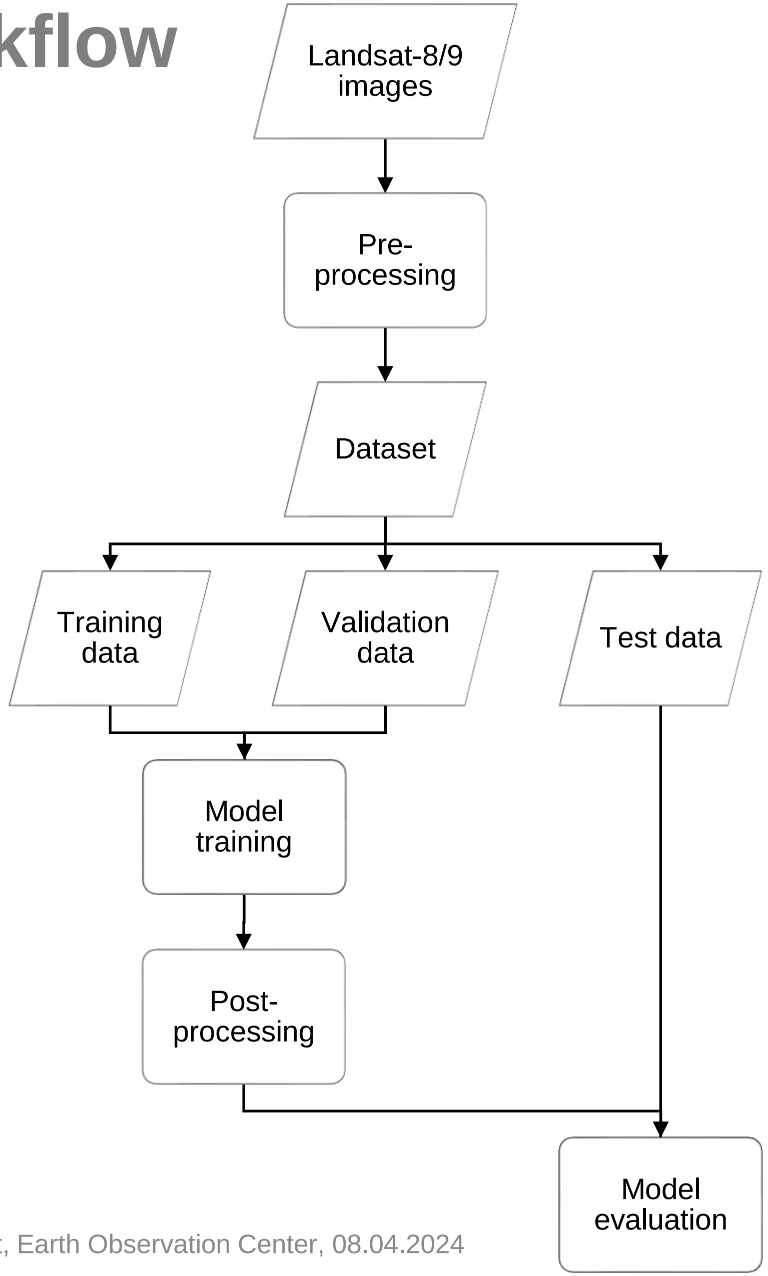
$$\mathrm{CaBGS} = \frac{\rho_\lambda(\mathrm{coastal\_aerosol}) + \rho_\lambda(\mathrm{blue})}{\rho_\lambda(\mathrm{green}) + \rho_\lambda(\mathrm{SWIR2})}$$

Bands	Wavelength (nm)
Band 1 - Coastal aerosol	430–450
Band 2 - Blue	450–510
Band 3 - Green	530–590
Band 5 - Near Infrared (NIR)	850–880
Band 7 - Shortwave Infrared (SWIR) 2	2110-2290

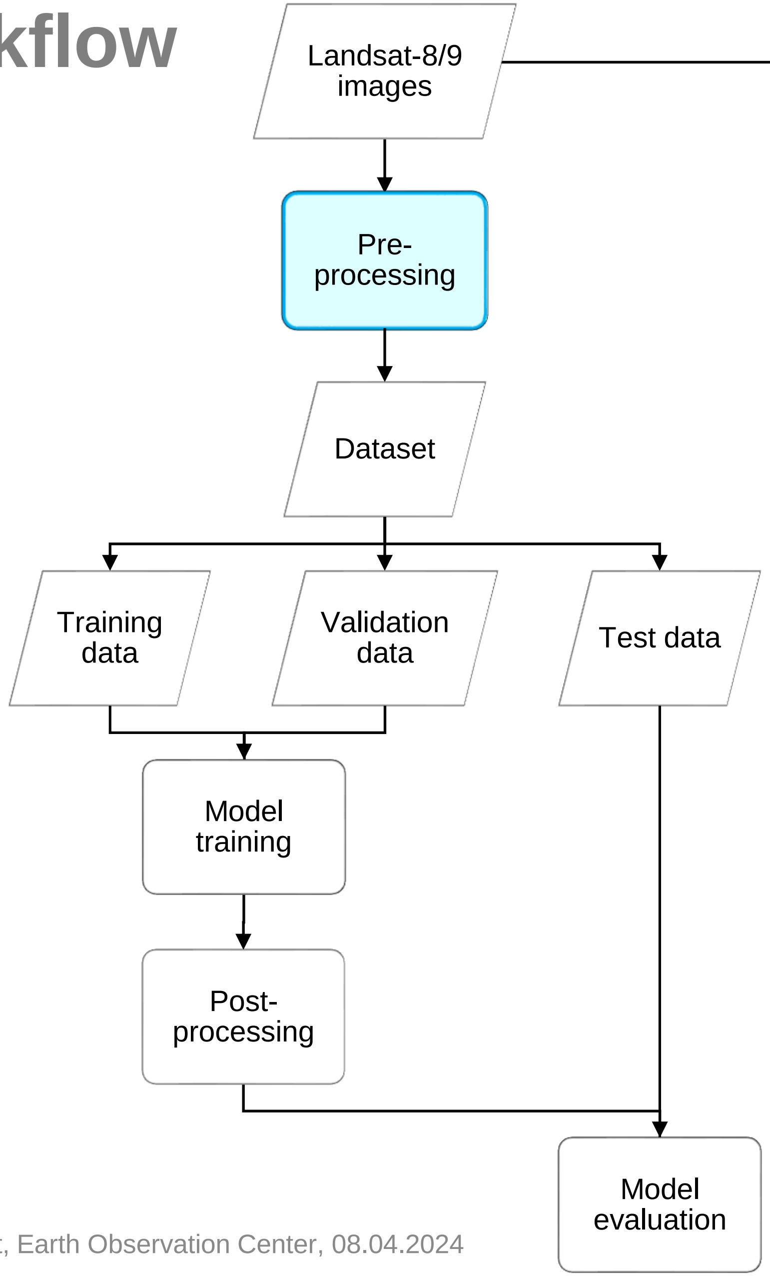
Pixel	Number of pixels, DNN	Number of pixels, CNN (128x128)
Oil	130,411	91,962
Non-Oil	130,411	521,677
	→ balanced	→ imbalanced

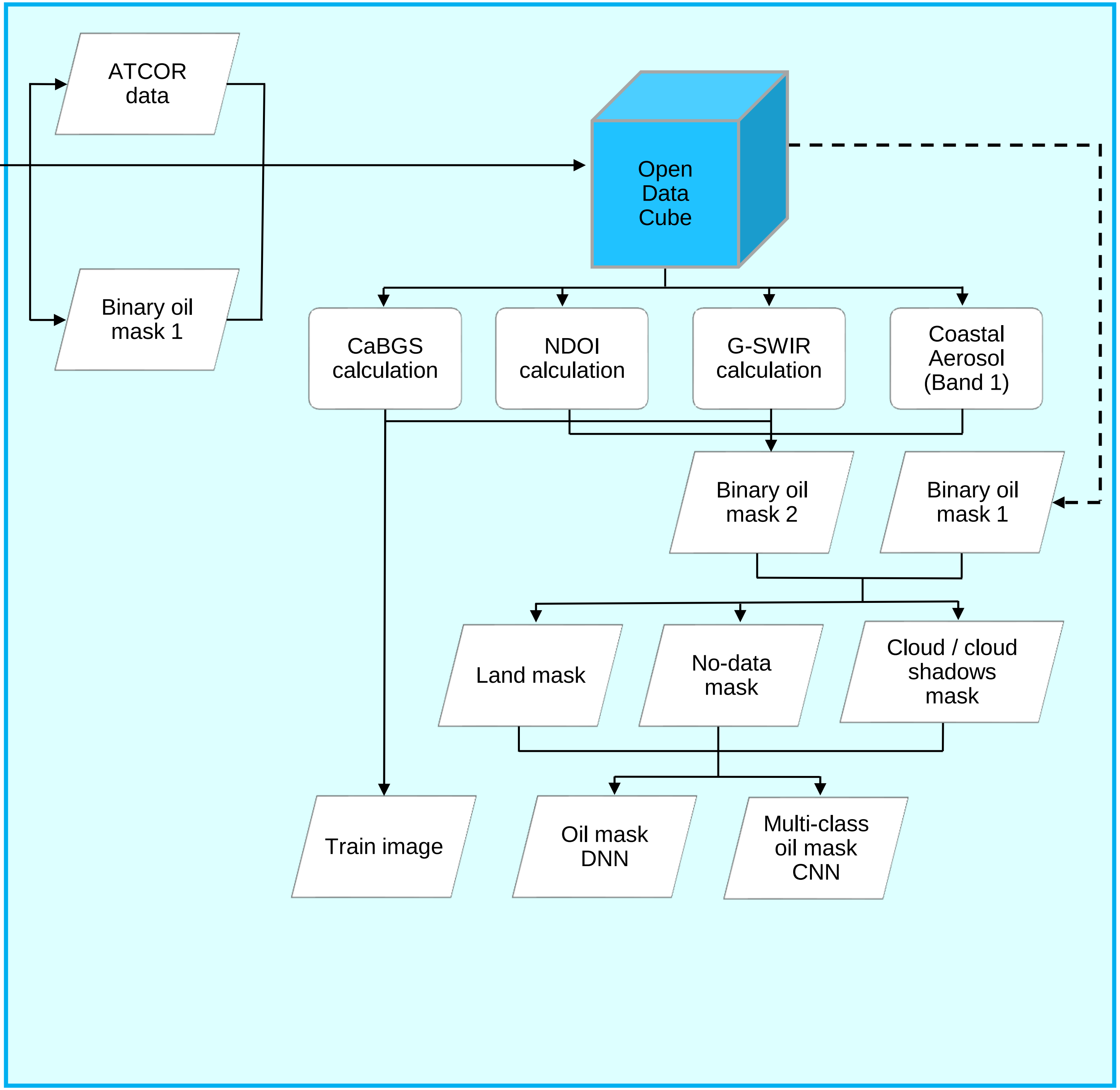
→ 26 Landsat-8/9 Images
North Sea, Baltic Sea, Mediterranean Sea, Red Sea, South China Sea and Gulf of Guinea

Methods
Workflow

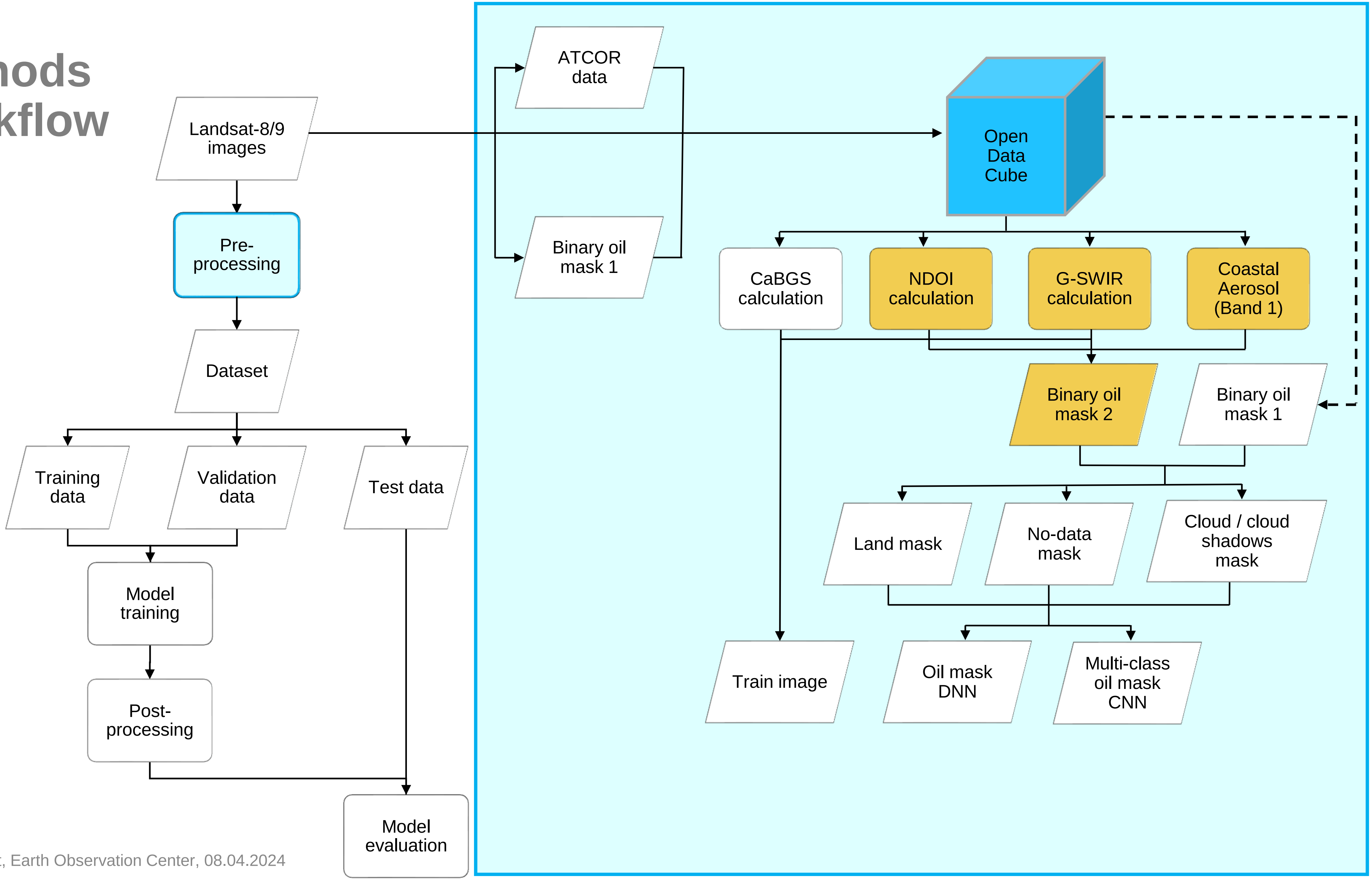


Methods Workflow

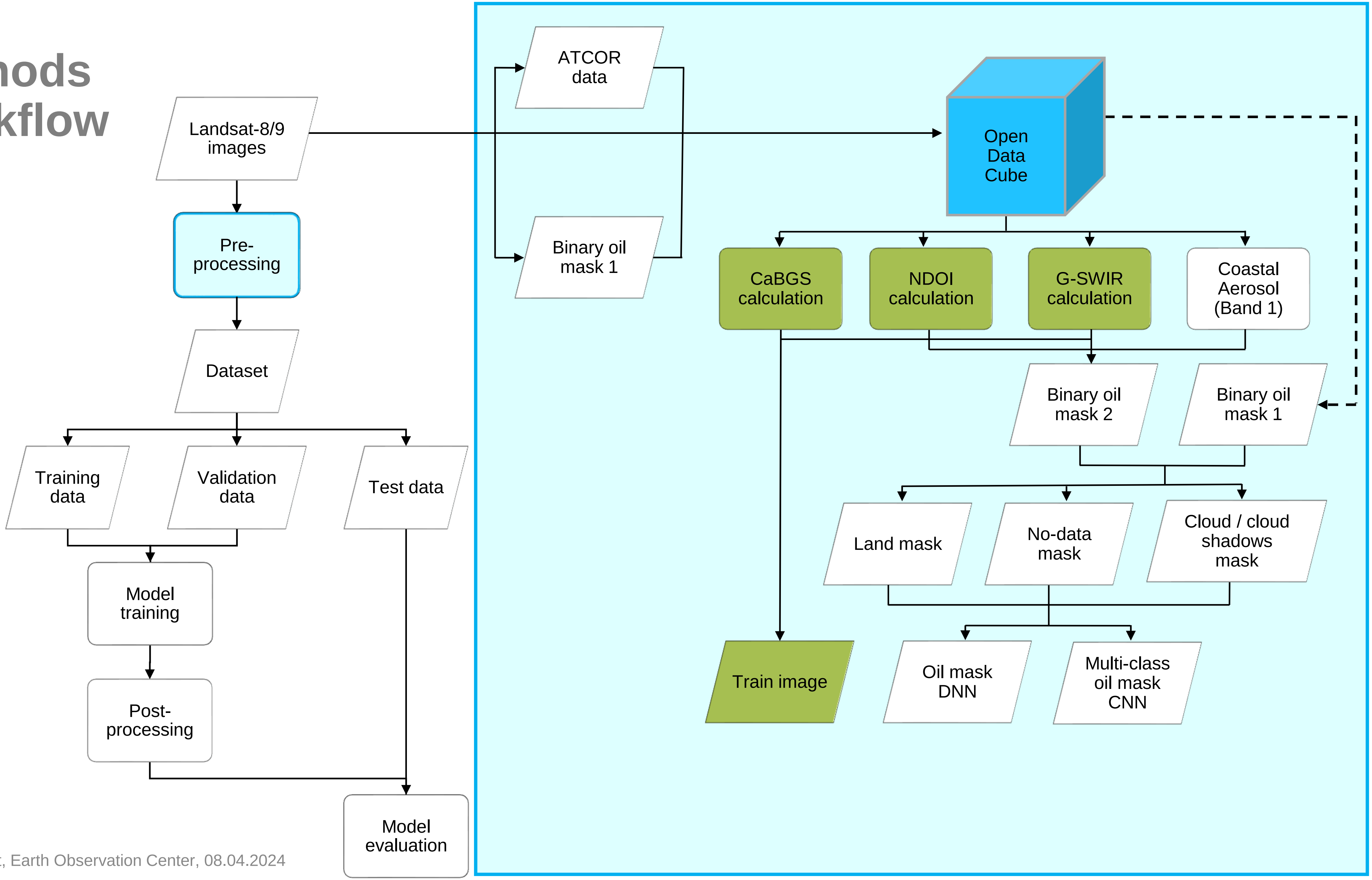




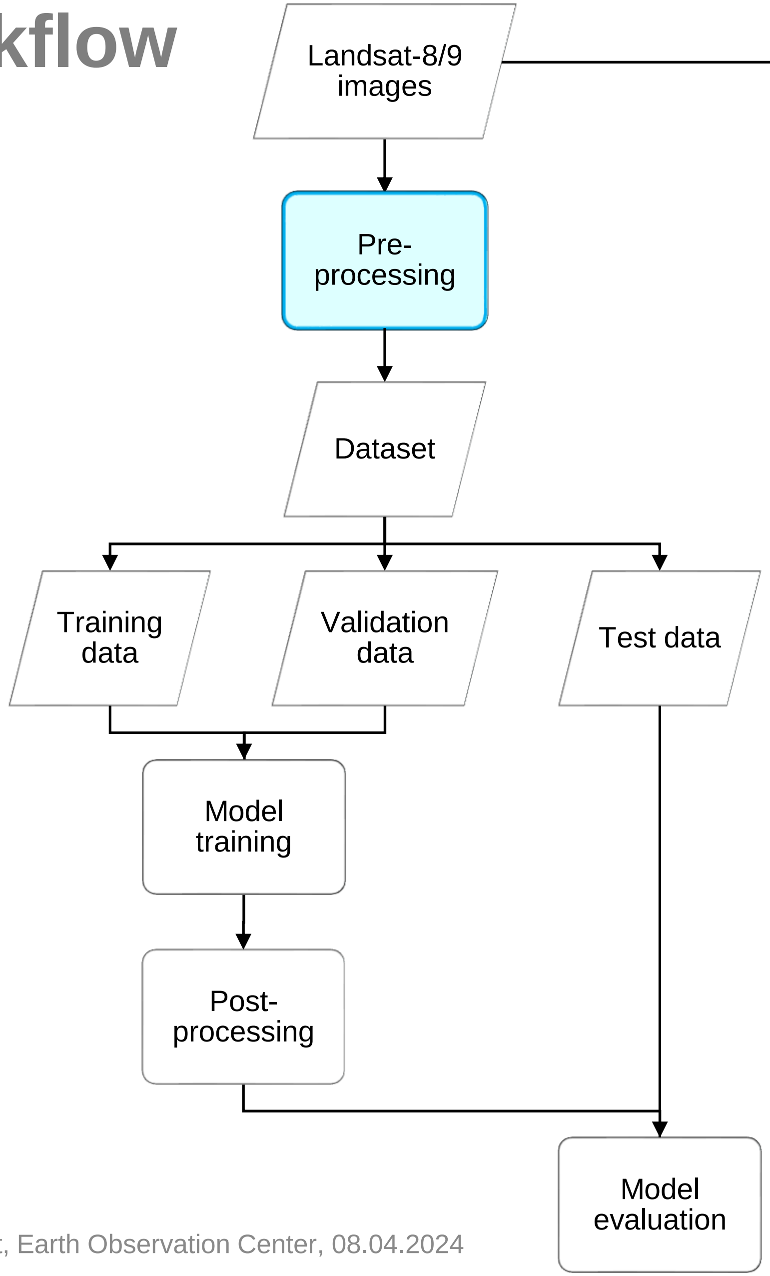
Methods Workflow

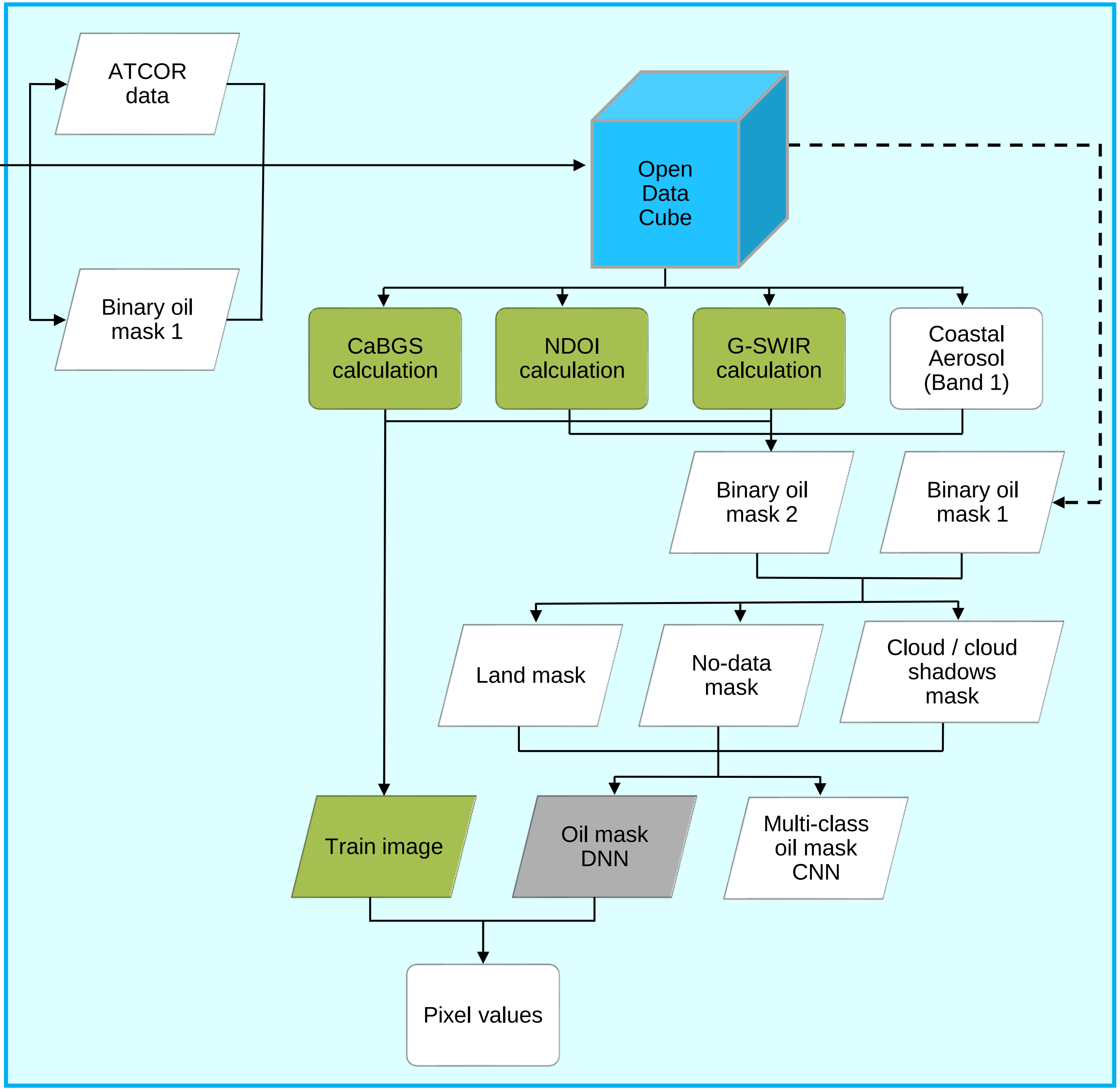


Methods Workflow

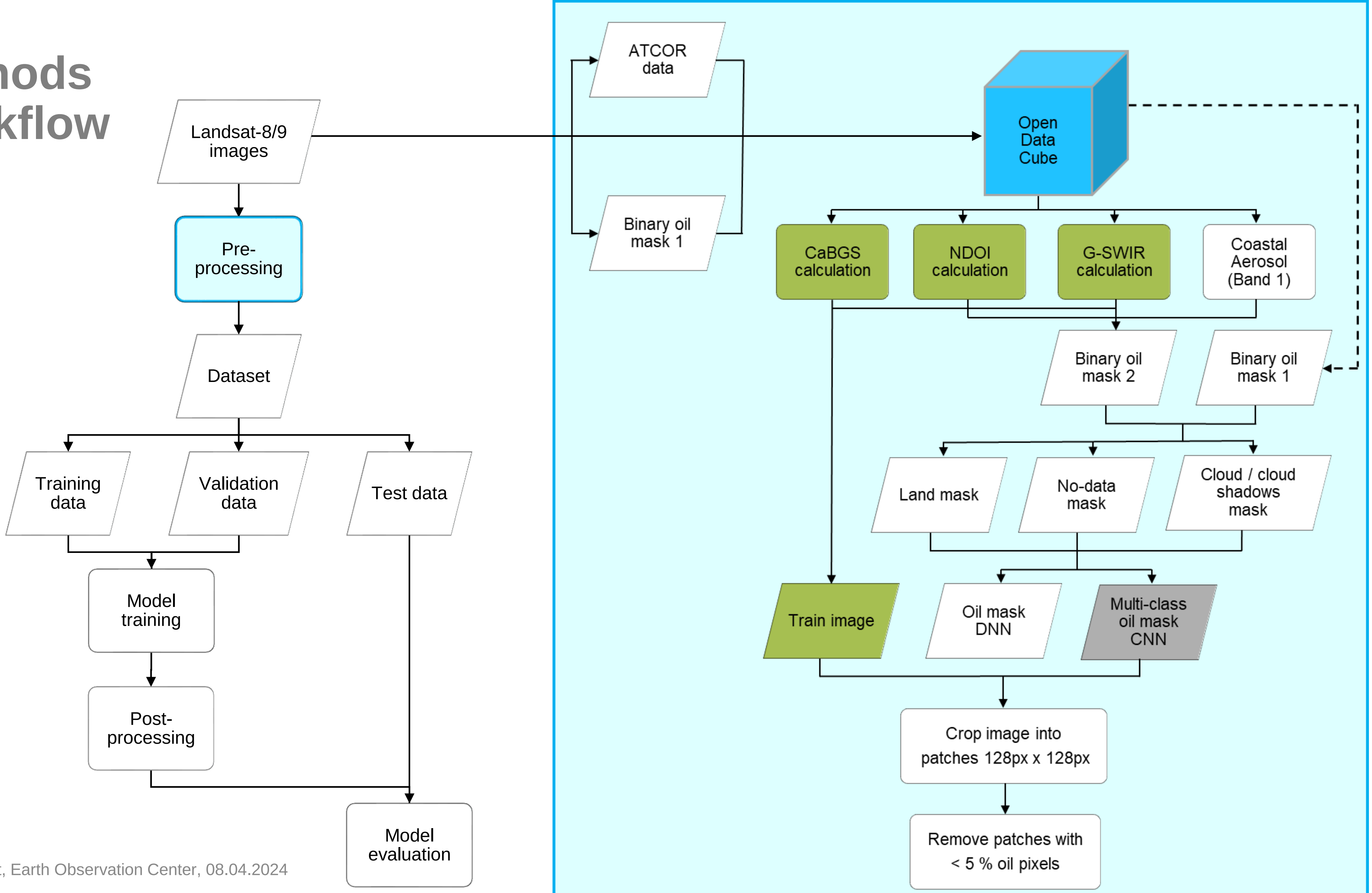


Methods Workflow



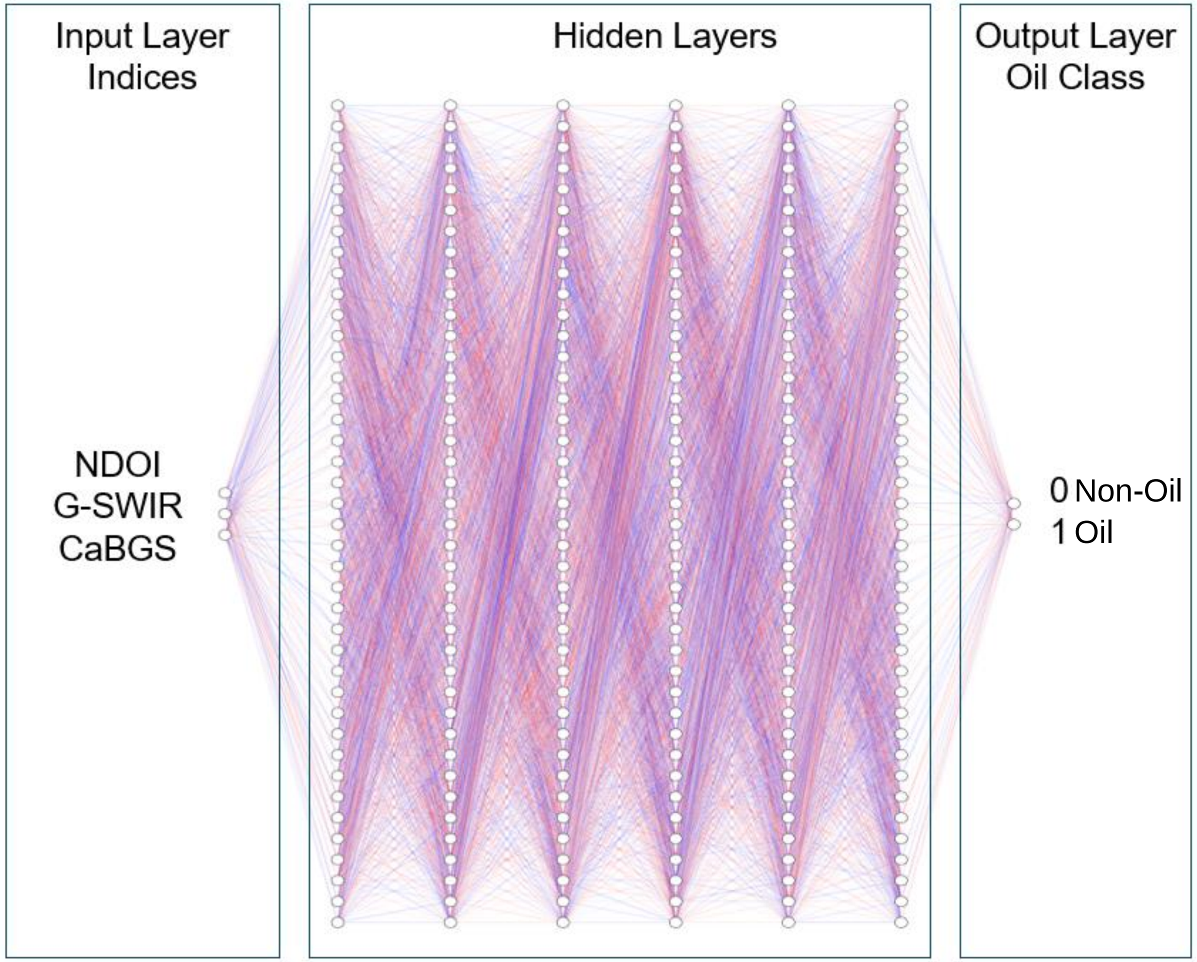


Methods Workflow



Methods
Deep Neural Network DNN

- Hidden layers are the key component
- The data is processed by linear (weights, biases) and non-linear functions (activation function)
- Weights are updated iteratively according to a backpropagation using the gradient descent optimization method which minimizes the loss using a loss function

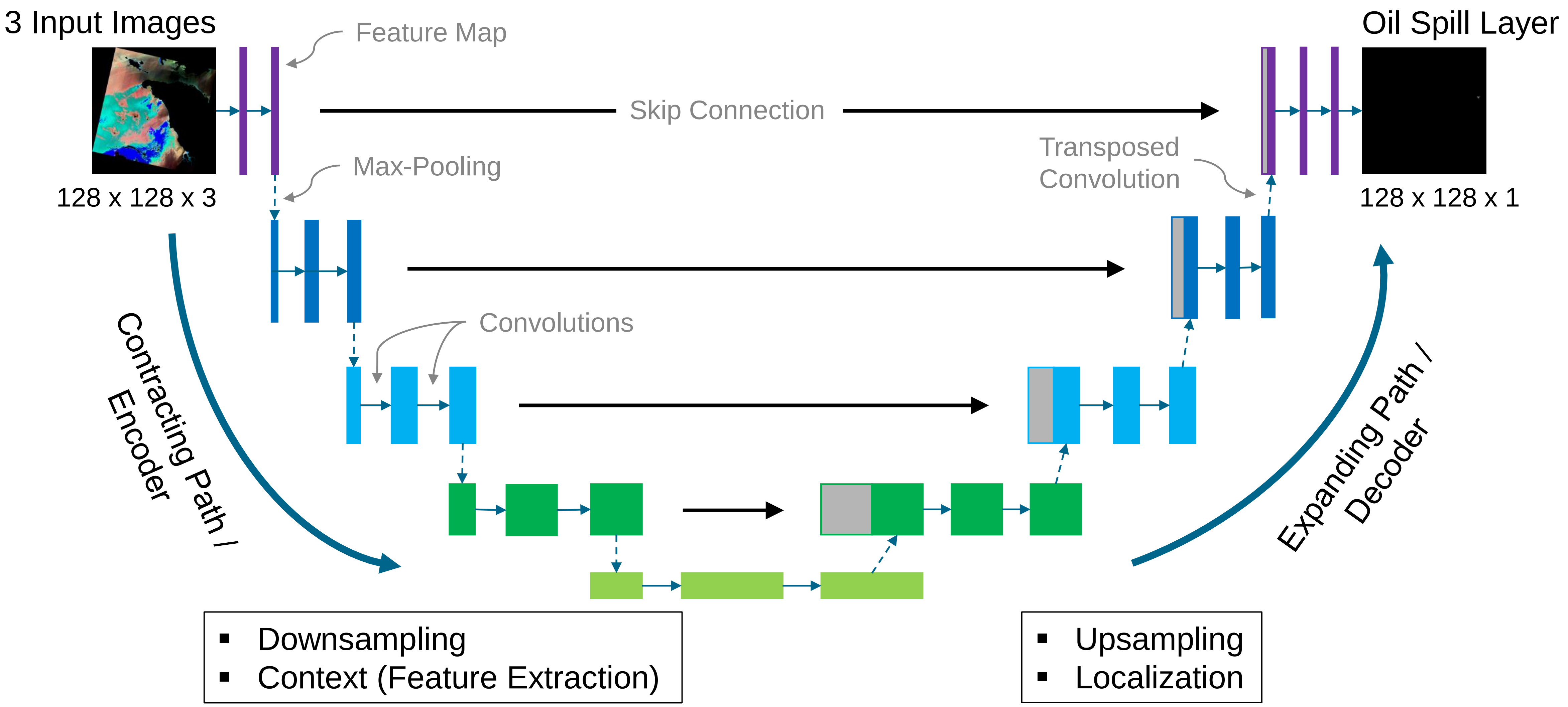


→ *Aim of study:*

- find the optimal combination of weights and biases in the hidden layers to estimate the output with the lowest loss

Input	DNN
Loss function	Binary cross-entropy
Optimizer	Adam
Activation function	ReLU
Classification rule	Sigmoid

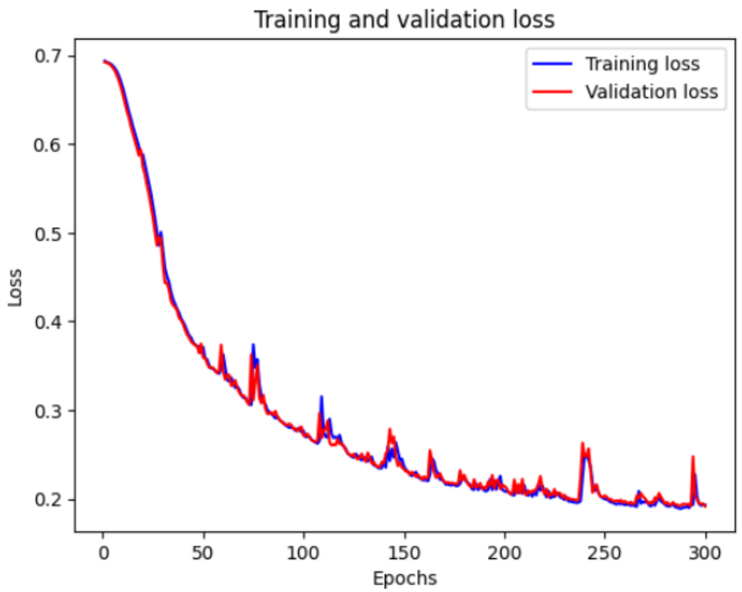
Methods
U-Net (Convolution Neural Network, CNN)

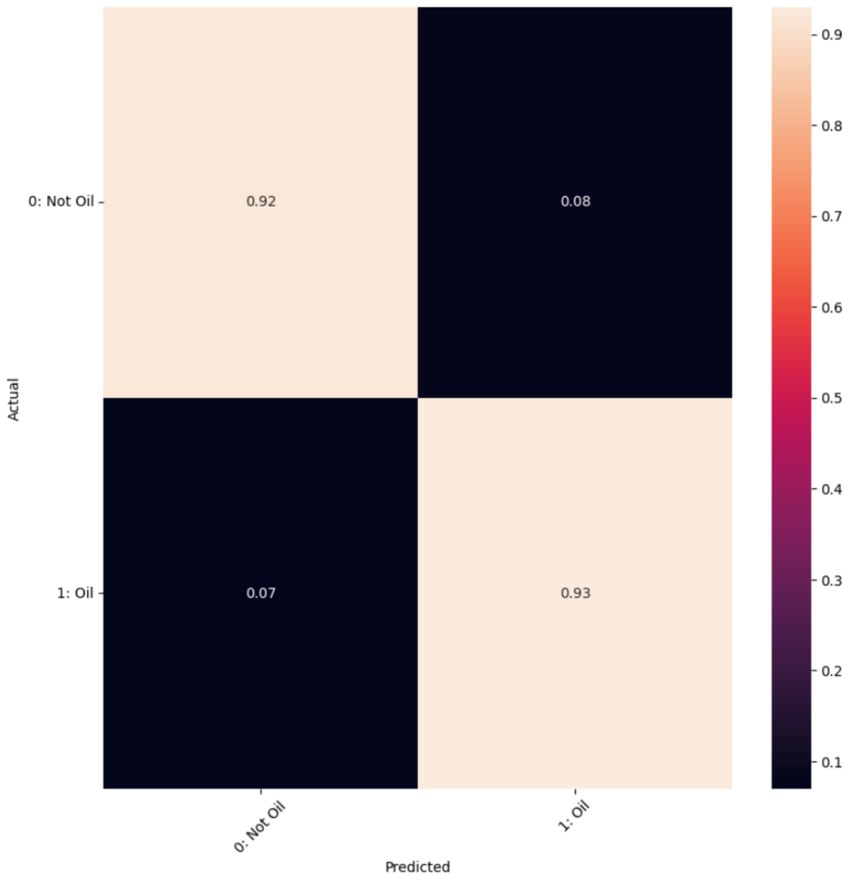


Methods
U-Net (Convolution Neural Network, CNN)

Input	DNN	U-Net (CNN)
Loss function	Binary Crossentropy	Sparse Categorical Crossentropy
Optimizer	Adam	Adam
Activation function	ReLU	ReLU
Classification rule	Sigmoid	Softmax

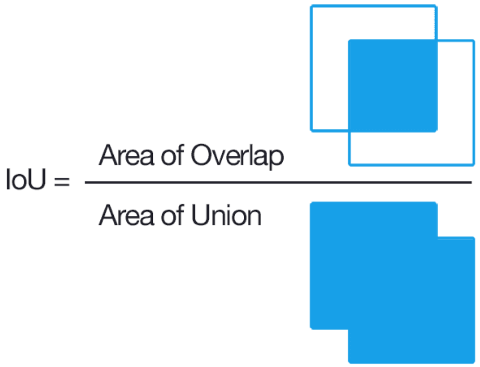
Results
Deep Neural Network



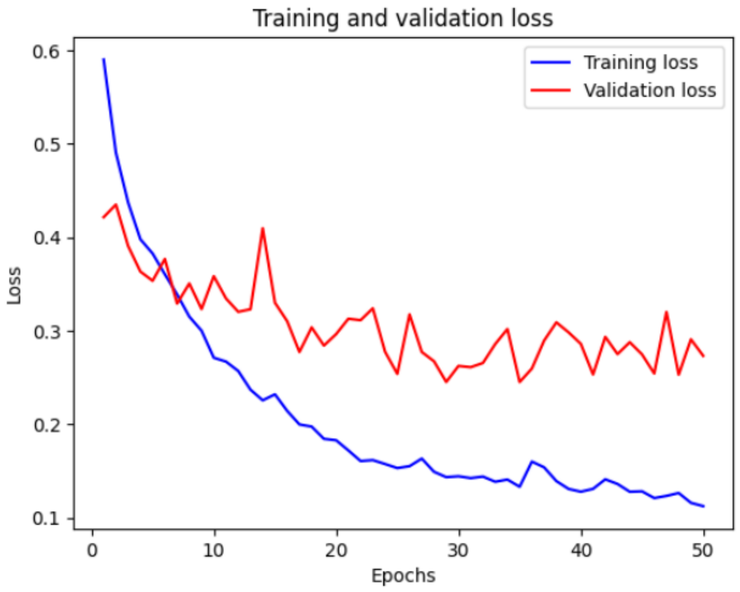


→ Intersection over Union: 0.86

	precision	recall	f1-score	support
0	0.93	0.92	0.93	12971
1	0.92	0.93	0.93	13112

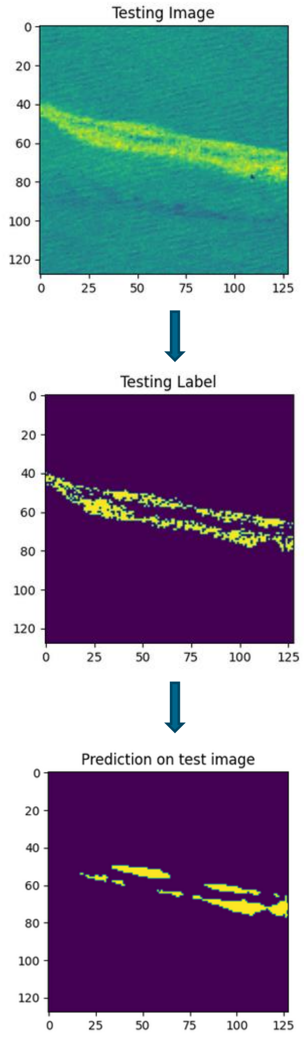


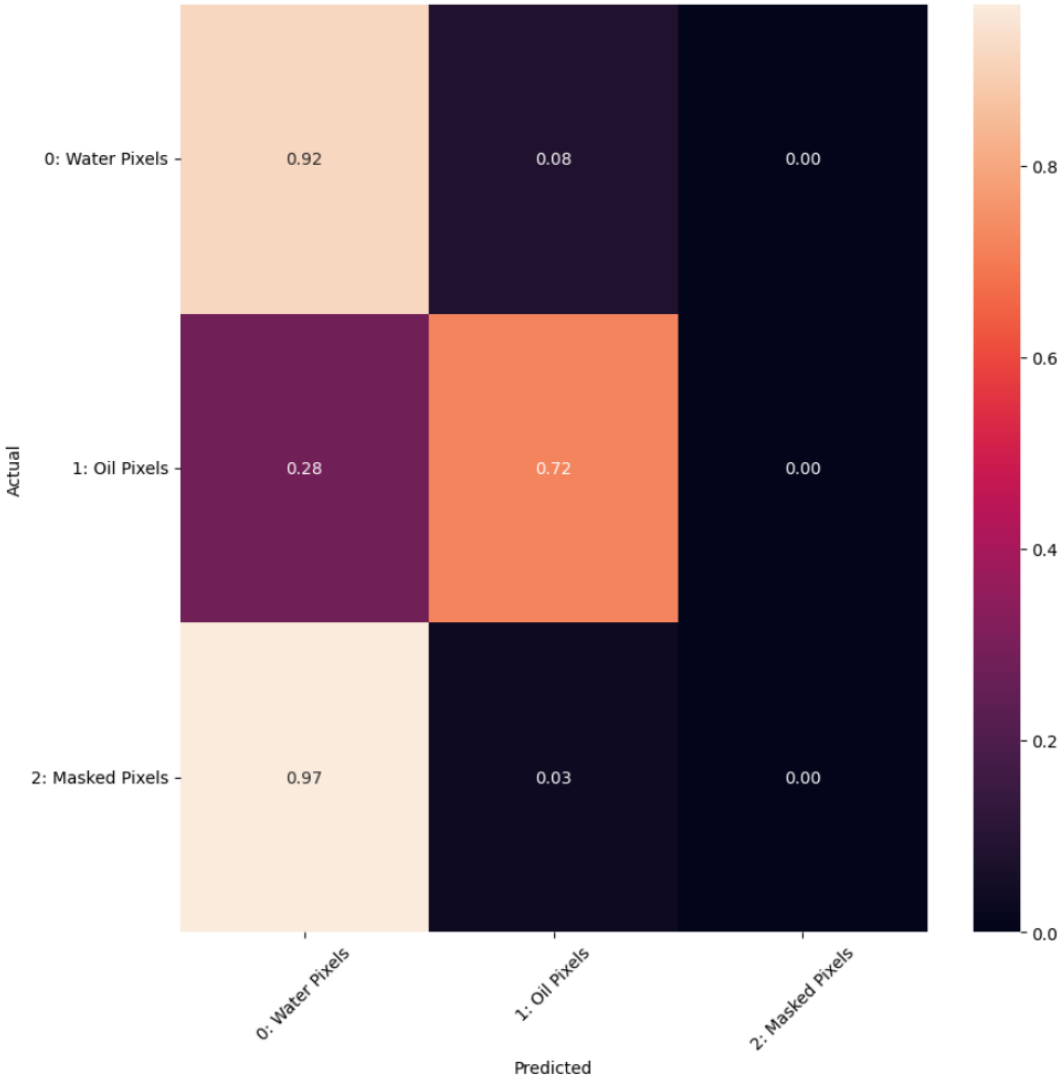
Results
U-Net (Convolutional Neural Network)



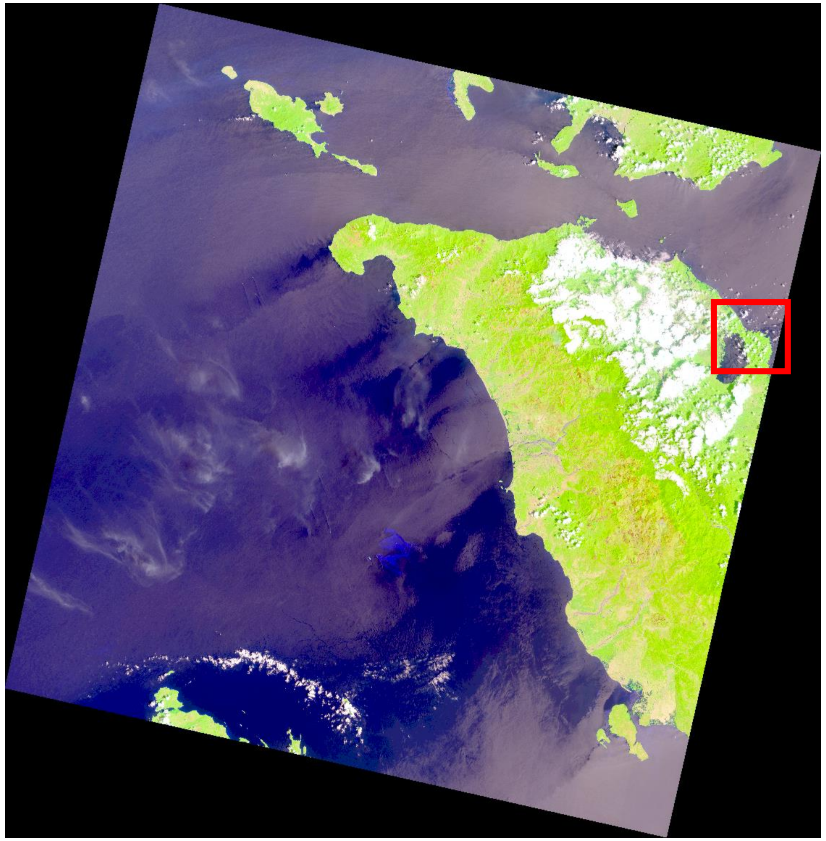
→ Intersection over Union: 0.52

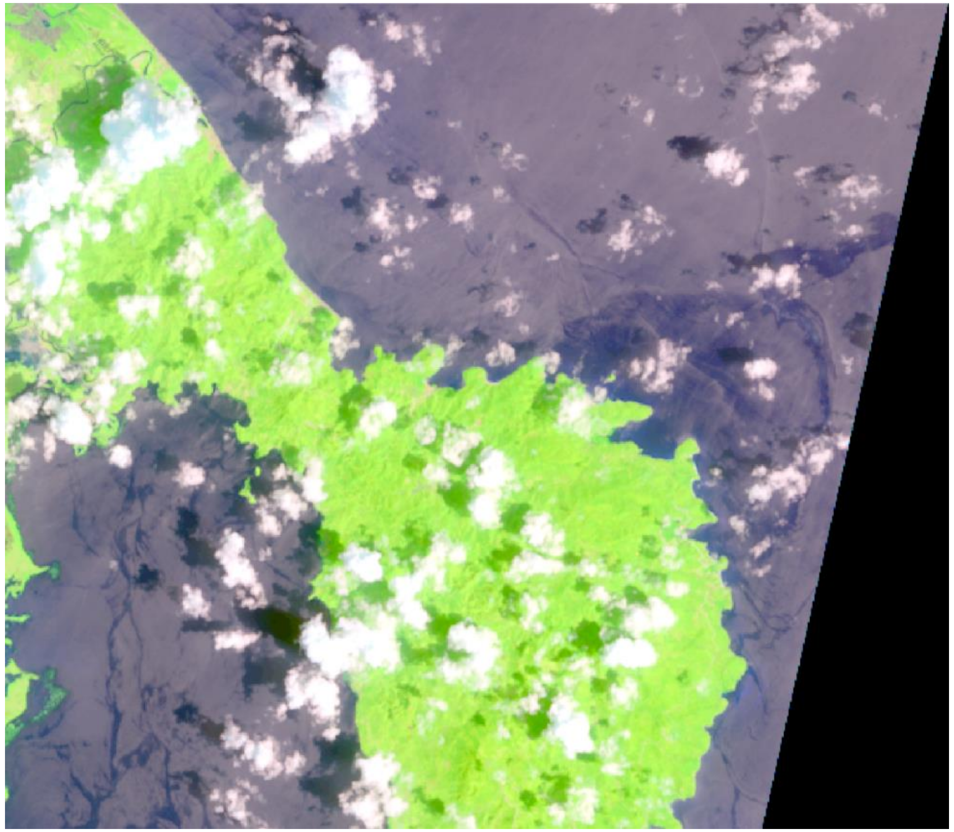
	precision	recall	f1-score	support
0.0	0.63	0.92	0.75	39065
1.0	0.55	0.72	0.62	6413
2.0	0.00	0.00	0.00	20058





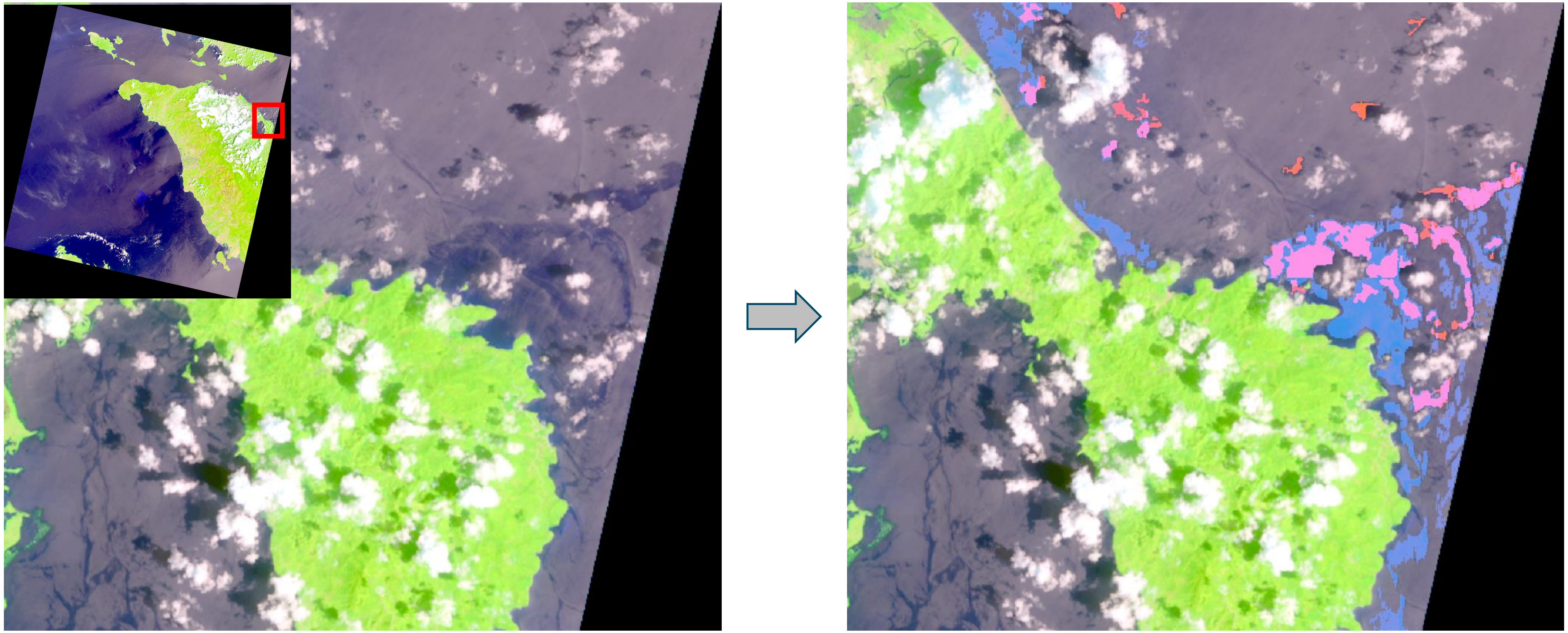
Results
Comparison DNN - CNN





- LC09_L1TP_116051_20230312_20230313_02_T1
- Incident: sinking of the oil tanker MT Princess Empress carrying 800,000 liters of industrial fuel, Mindoro, Philippines, South China Sea

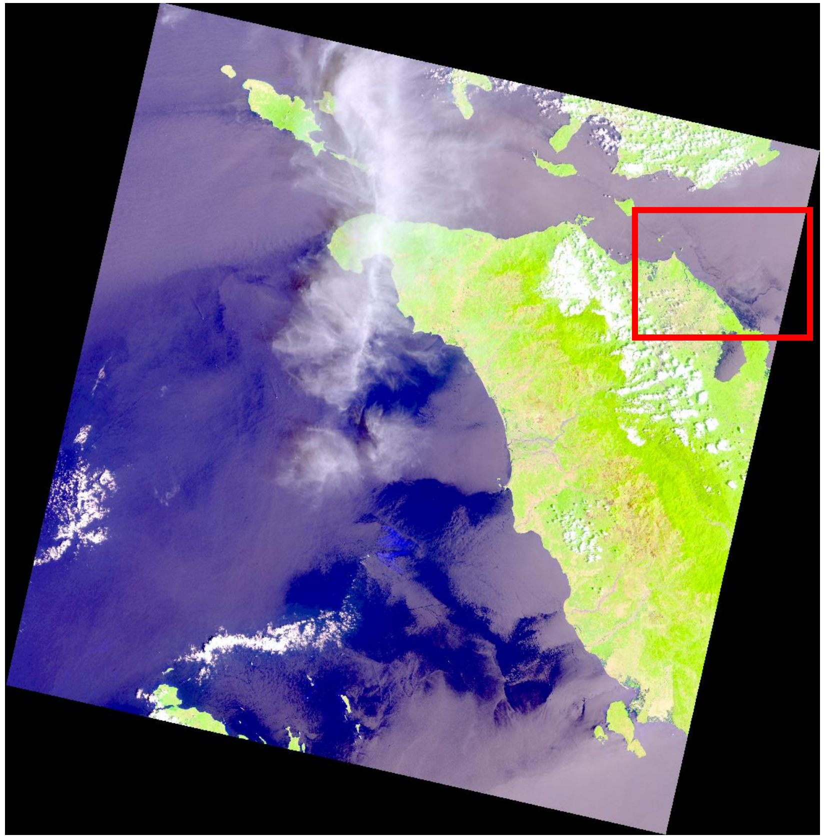
Results
Comparison DNN - CNN



- LC09_L1TP_116051_20230312_20230313_02_T1
- Incident: sinking of the oil tanker MT Princess Empress carrying 800,000 liters of industrial fuel, Mindoro, Philippines, South China Sea

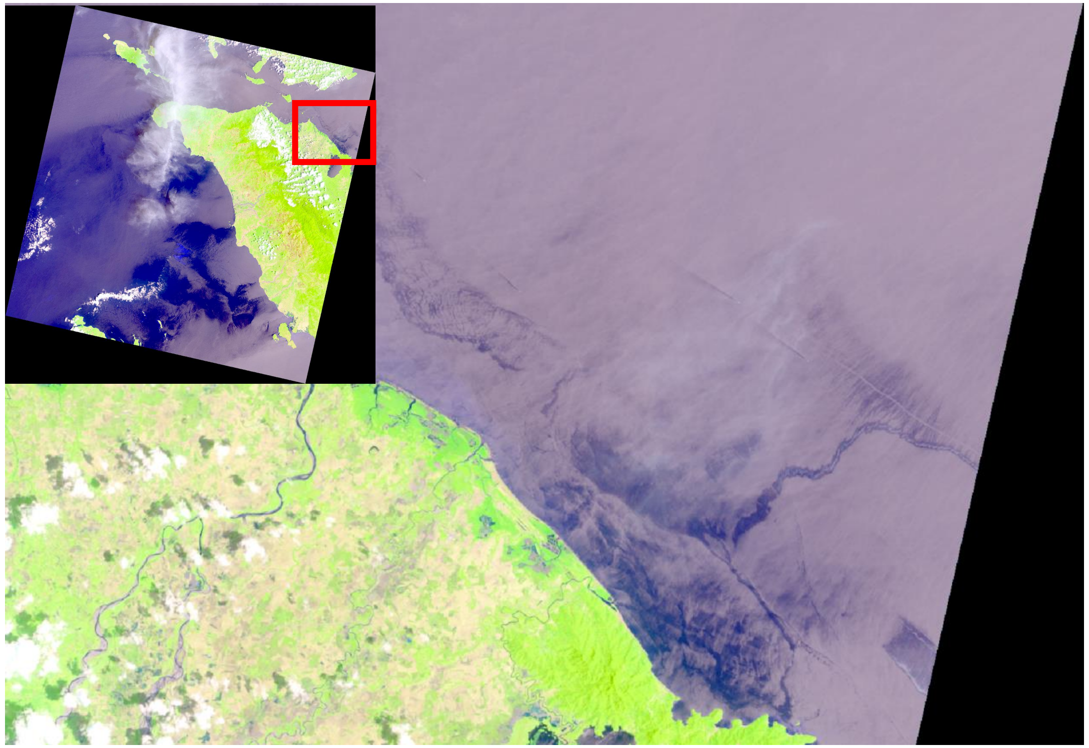
DNN
U-Net (CNN)
Overlap of DNN and CNN

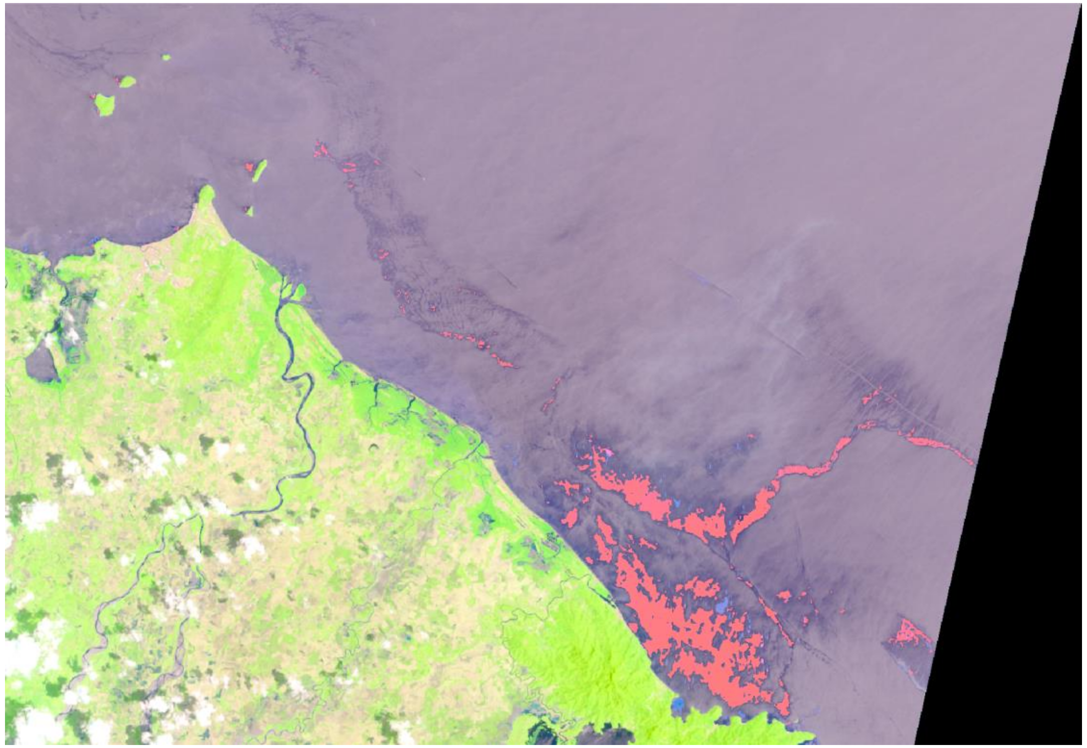
Results
Comparison DNN - CNN



- LC08_L1TP_116051_20230320_20230320_02_RT
- Incident: sinking of the oil tanker MT Princess Empress carrying 800,000 liters of industrial fuel, Mindoro, Philippines, South China Sea

Results
Comparison DNN - CNN

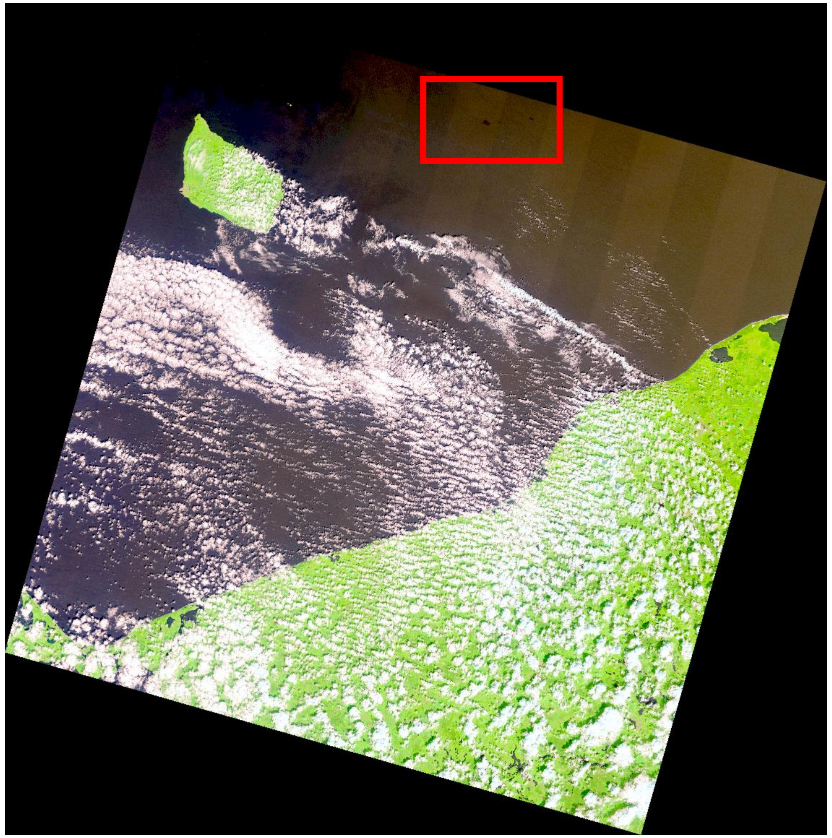


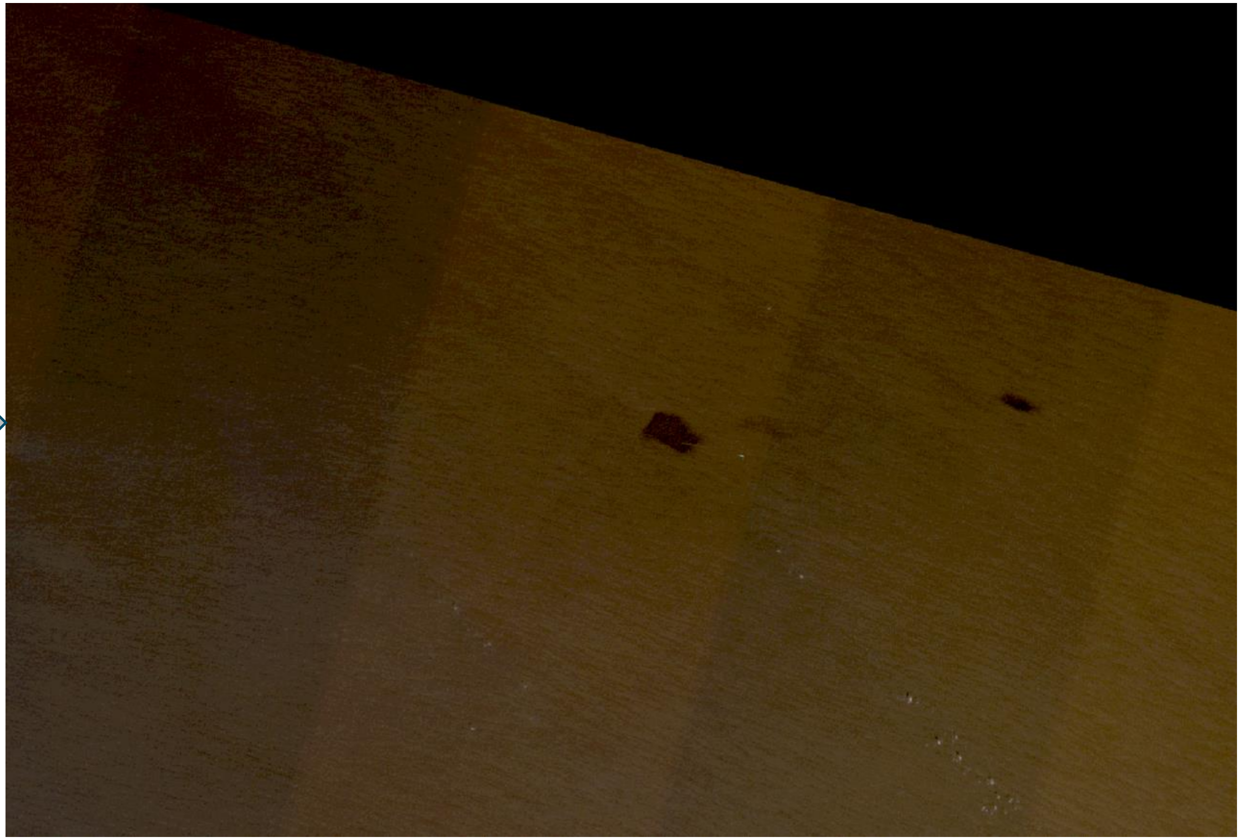


- LC08_L1TP_116051_20230320_20230320_02_RT
- Incident: sinking of the oil tanker MT Princess Empress carrying 800,000 liters of industrial fuel, Mindoro, Philippines, South China Sea

DNN
U-Net (CNN)
Overlap of DNN and CNN

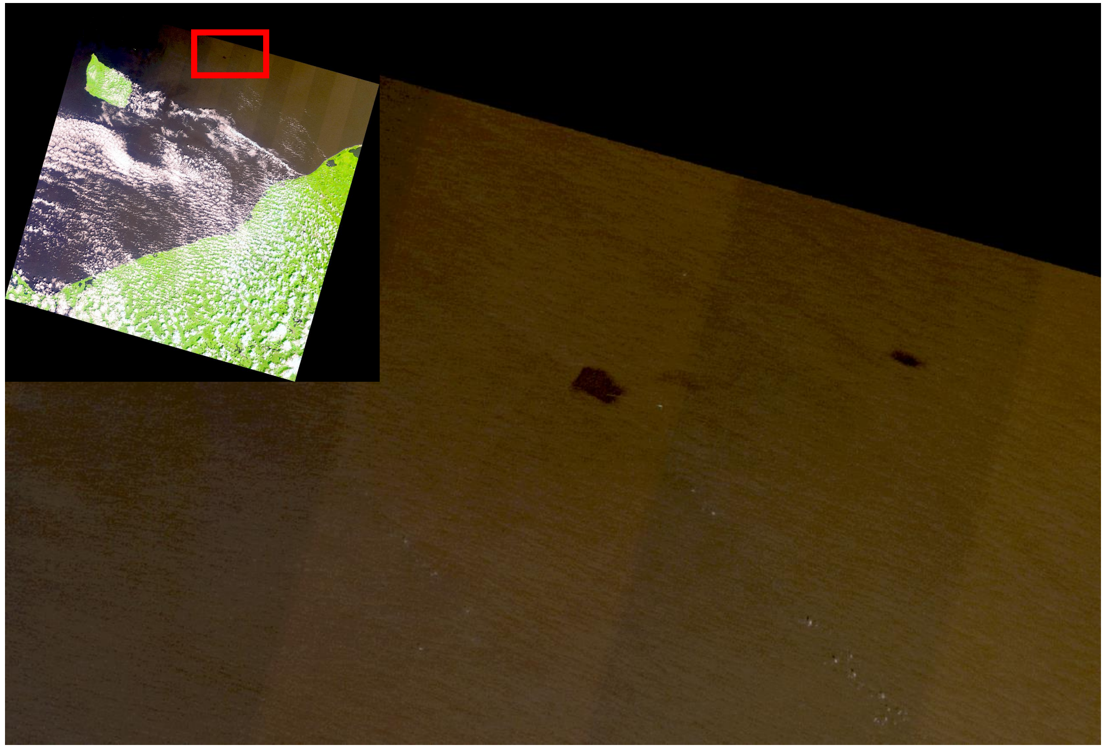
Results
Comparison DNN - CNN

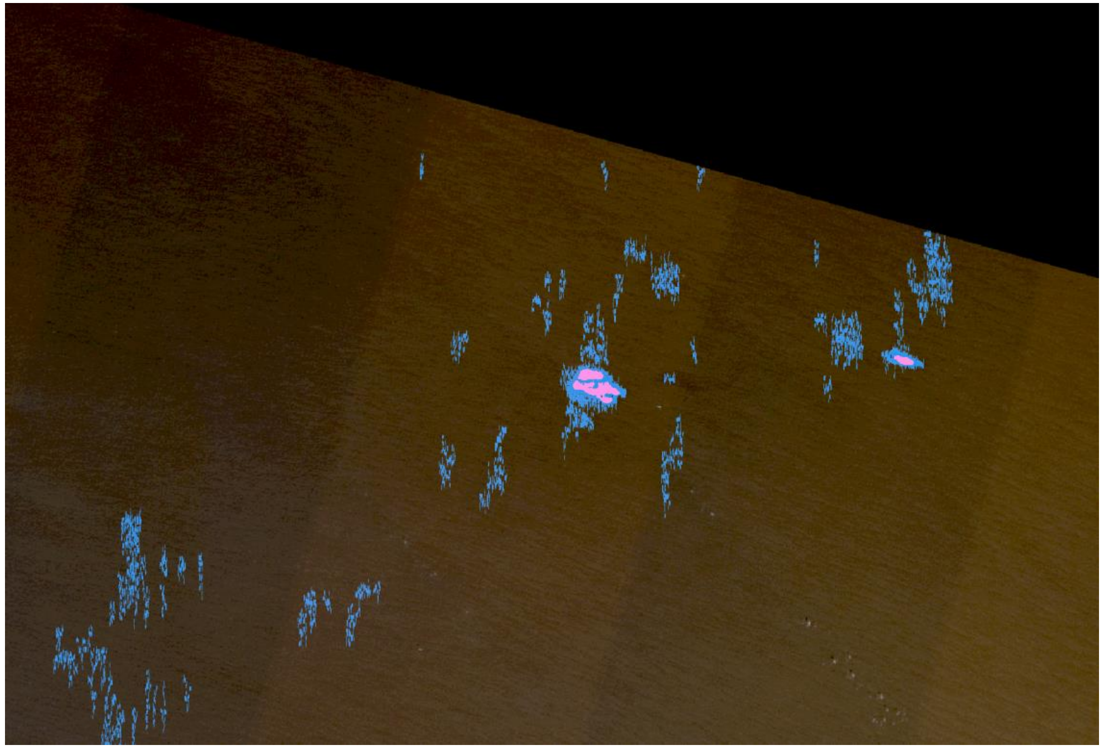




- LC08_L1TP_192022_20170713_20200903_02_T1
- Baltic Sea

Results
Comparison DNN - CNN





- LC08_L1TP_192022_20170713_20200903_02_T1
- Baltic Sea

DNN
U-Net (CNN)
Overlap of DNN and CNN

Conclusion

- approach for oil spill detection on Landsat-8/9 images using DNN and U-Net (CNN)
- DNN model with IoU = 0.86 & U-Net model with IoU = 0.52

- DNN tends to overestimate oil spills or oil detection is missing
- U-Net (CNN) tends to underestimate oil spills, better performance of oil spills with a wide shape
- Both methods show too many false positive detections, especially due to image illumination (dark image areas), cloud shadows and suspended sediments

→ Expand the number of Landsat images in the model training

→ Apply an additional, more accurate cloud shadow mask

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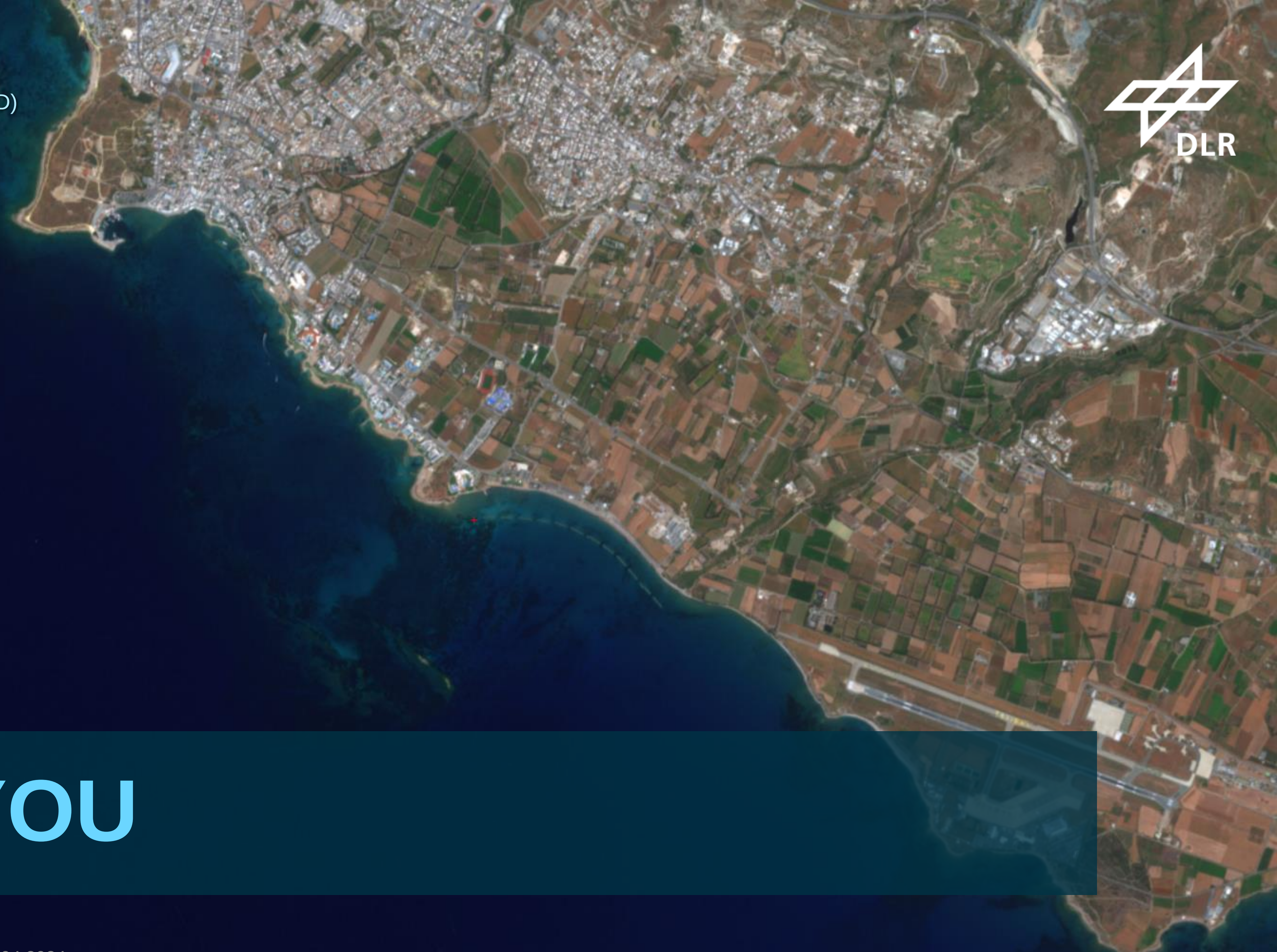
THANK YOU



Paphos, Copernicus Sentinel-Data [2024] für Sentinel-2