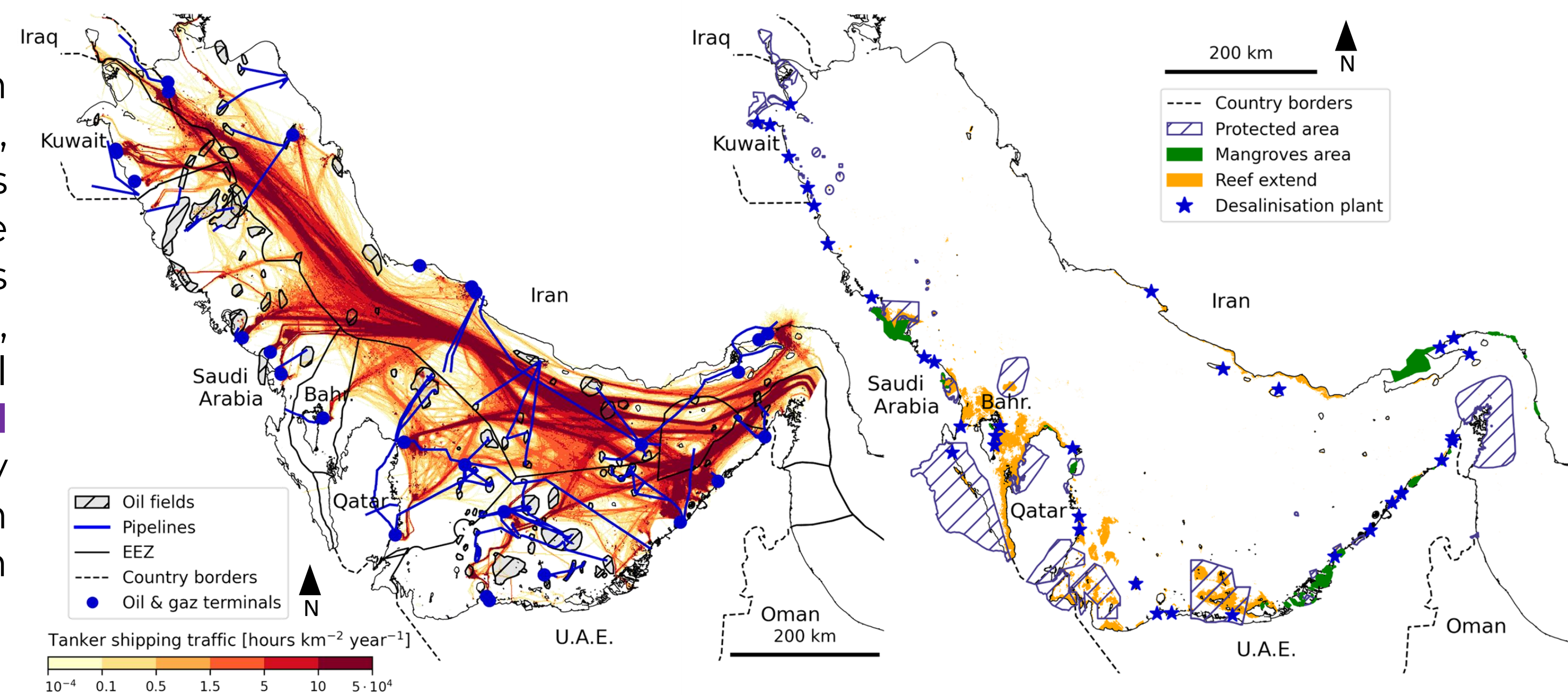


Alexis Culot¹, Qiang Wang^{1,2} and Emmanuel Hanert^{1,3}

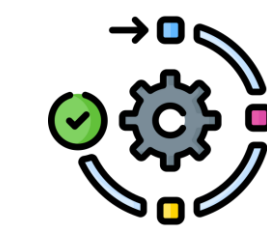
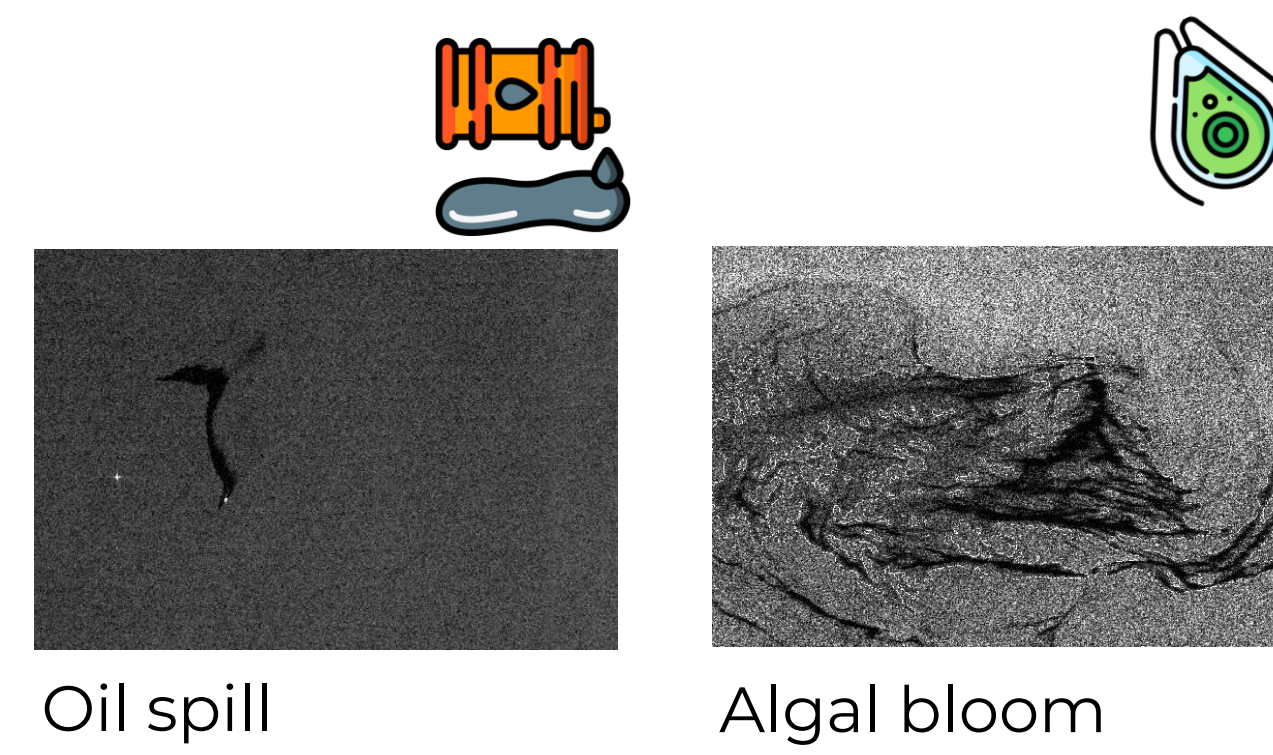
¹UCLouvain, Earth and Life Institute, Louvain-la-Neuve, Belgium, ²Royal Belgian Institute of Natural Sciences (RBINS), Brussels, Belgium, ³Institute of Mechanics, Materials and Civil Engineering, UCLouvain, Louvain-la-Neuve, Belgium

Oil extraction and shipping activities are a major source of oil spills, which continue to pollute marine environments despite the decline in major incidents, fueled by growing global energy demand. To mitigate the consequences of this pollution, **early detection of oil spills is essential**. The Persian Gulf, home to 3 of the world's largest oil exporters is particularly vulnerable to hydrocarbon pollution. In this region, oil-related infrastructures—including **pipelines**, oil and gas **terminals**, offshore oil fields and major **tanker routes**—coexists with highly sensitive coastal ecosystems and facilities such as **mangroves**, **seagrass beds**, **coral reefs**, **protected areas** and **desalination plants**. Despite this, the region remains largely uncovered by dedicated oil spill early warning systems. Here we develop a robust oil spill detection approach based on **Sentinel-1 SAR imagery**, with particular emphasis on **distinguishing** oil spills from **look-alikes** that frequently mislead detection systems.



Two step approach

Oil spill detection is performed using **two complementary** approaches—**object** and **pixel-based**—both aiming to **distinguish** oil spills from **look-alikes**. After preprocessing, the images are analyzed by both methods to produce a **unified detection output**.



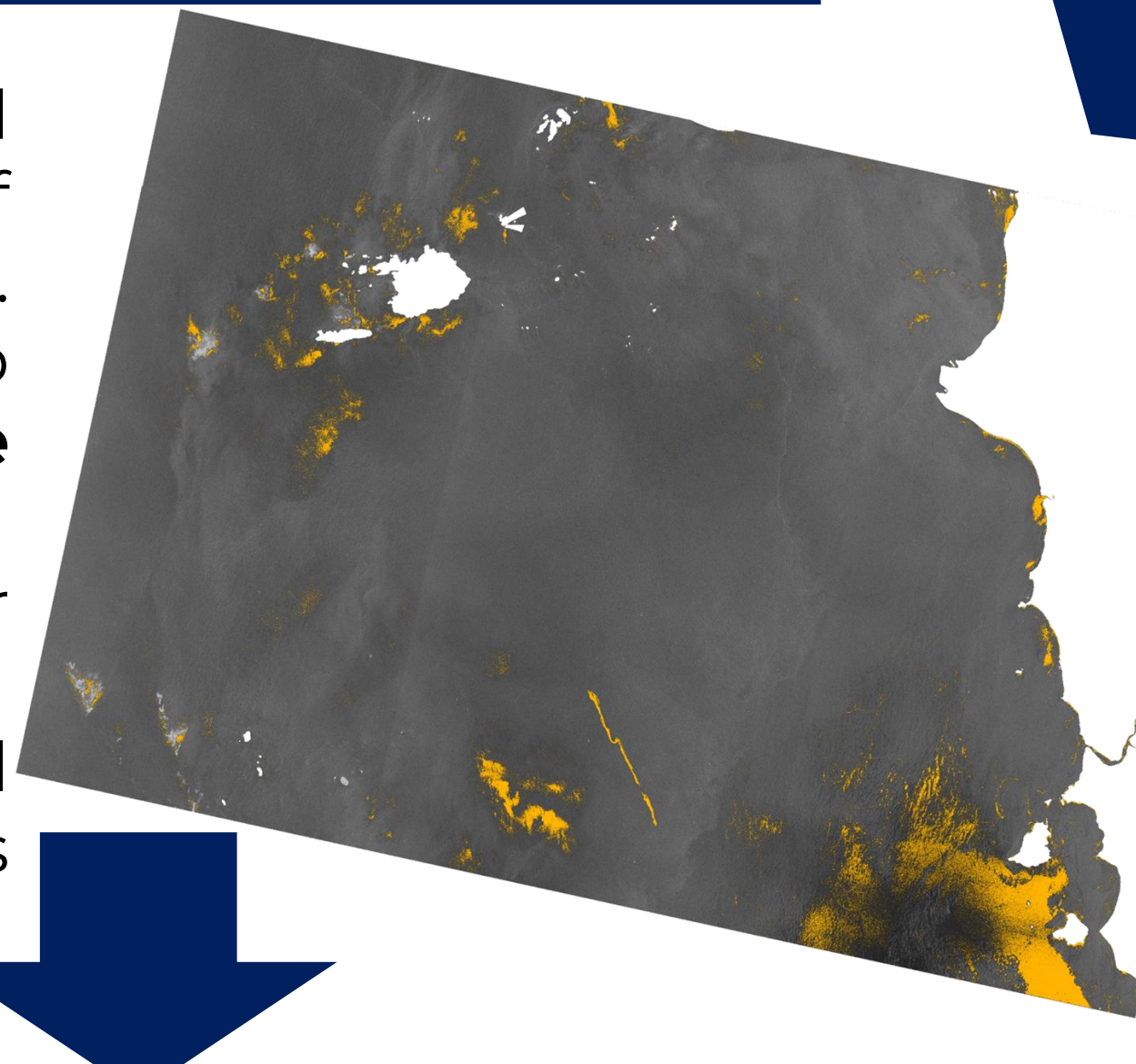
Sentinel Application Platform (SNAP) : Dual Preprocessing Workflow

Sentinel-1 GRD products are pre-processed with SNAP using **two workflows** tailored to each detection method : the **empirical** approach applies calibration, speckle filtering, land masking, decibel conversion, and ellipsoid correction; the **ML** approach includes orbit file correction, noise removal, calibration, speckle filtering, terrain correction, and decibel conversion.

Object-based approach

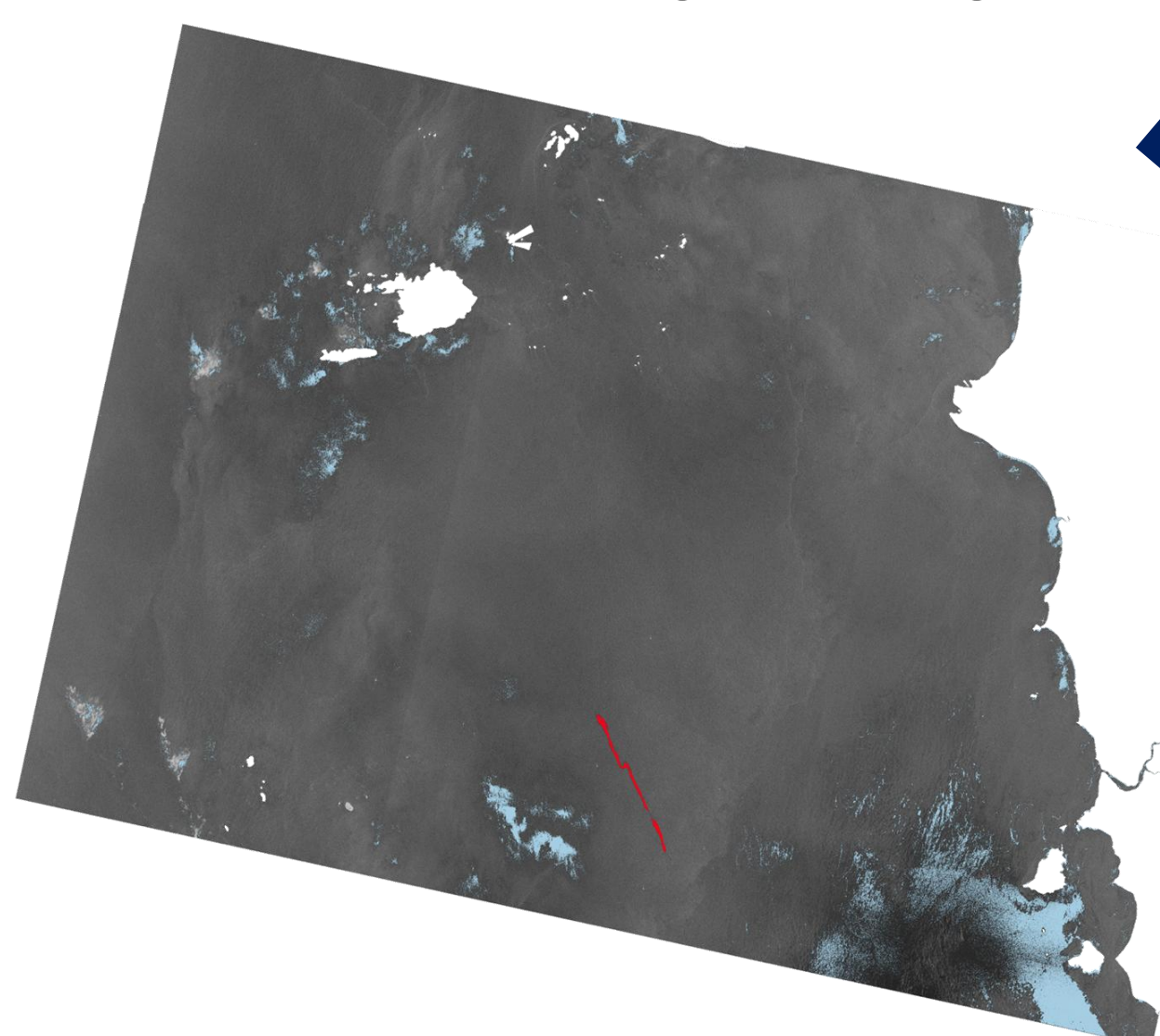
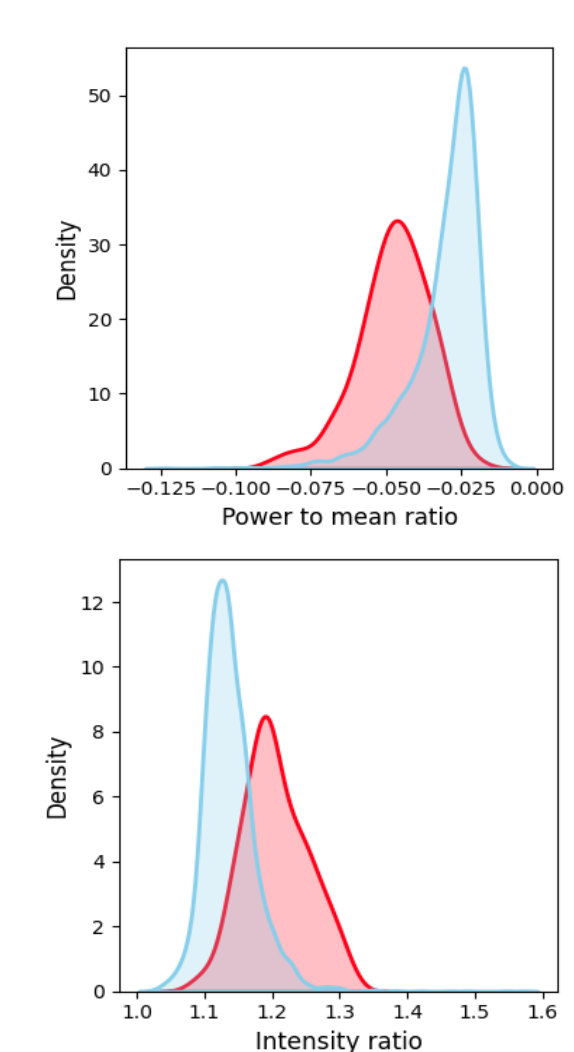
Adaptive Thresholding for Oil Spill Segmentation

The object-based method consists of two main steps. The first step applies an **adaptive thresholding** algorithm for segmentation, which highlights all dark regions as **potential oil spills**.

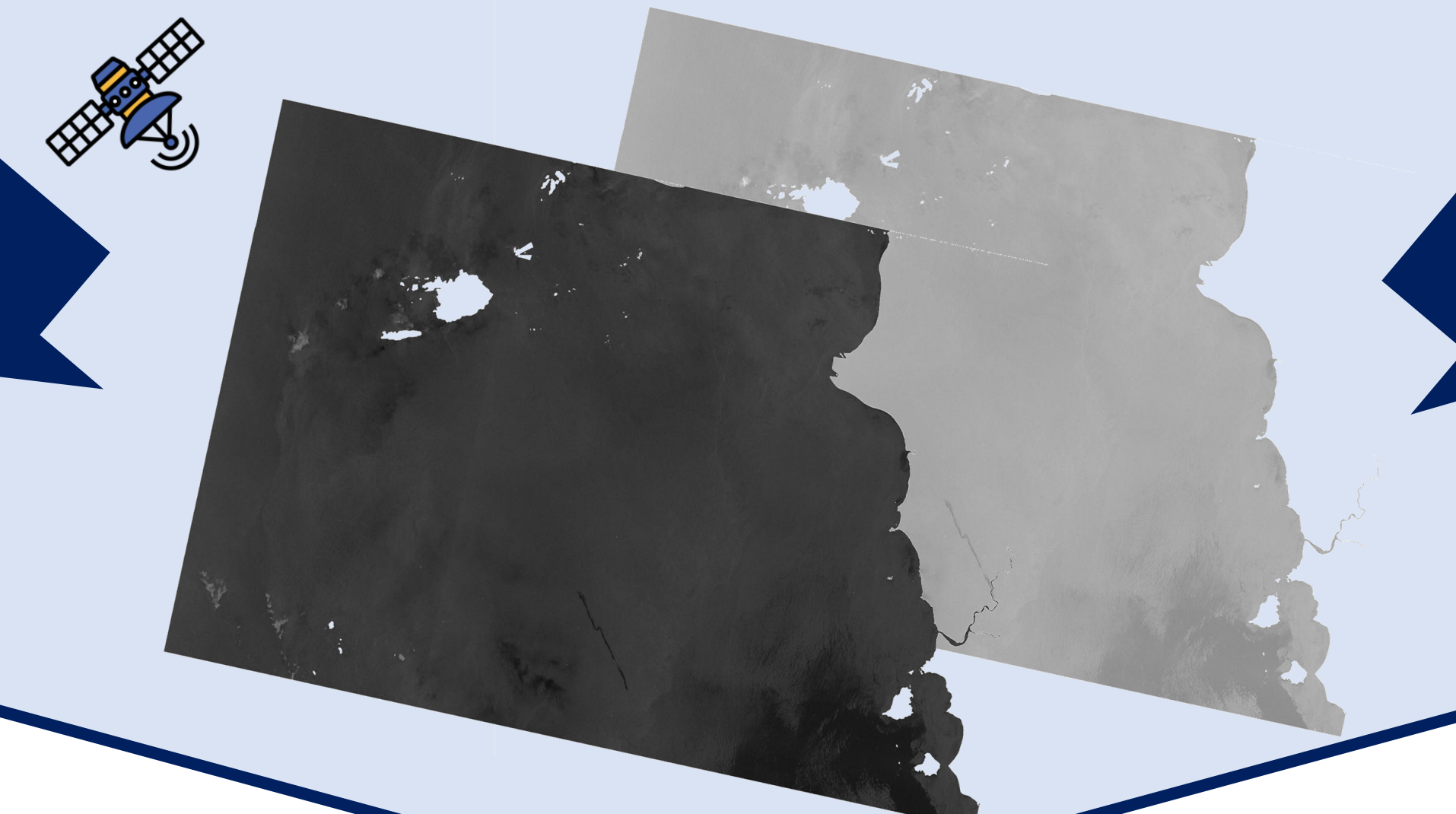


XGBoost-Based Classification of Candidate Oil Spills

The second step uses the **XGBoost** algorithm to **classify** oil spill **candidates**. The model is trained on both oil spill and look-alike samples. To differentiate **real oil spills** from **look-alikes**, features are extracted from each candidate and used during training.



Sentinel-1 Level-1 GRD VV+VH Polarization



Evaluation Object-based approach

Ground Truth	Prediction	
	Sea	Oil
Sea	95%	5%
Oil	9%	91%

Accuracy : 93%
F1-Score : 93 %

Evaluation Pixel-based approach

Ground Truth	Prediction	
	Sea	Oil
Sea	98%	2%
Oil	16%	84%

Accuracy : 94%
F1-Score : 90 %

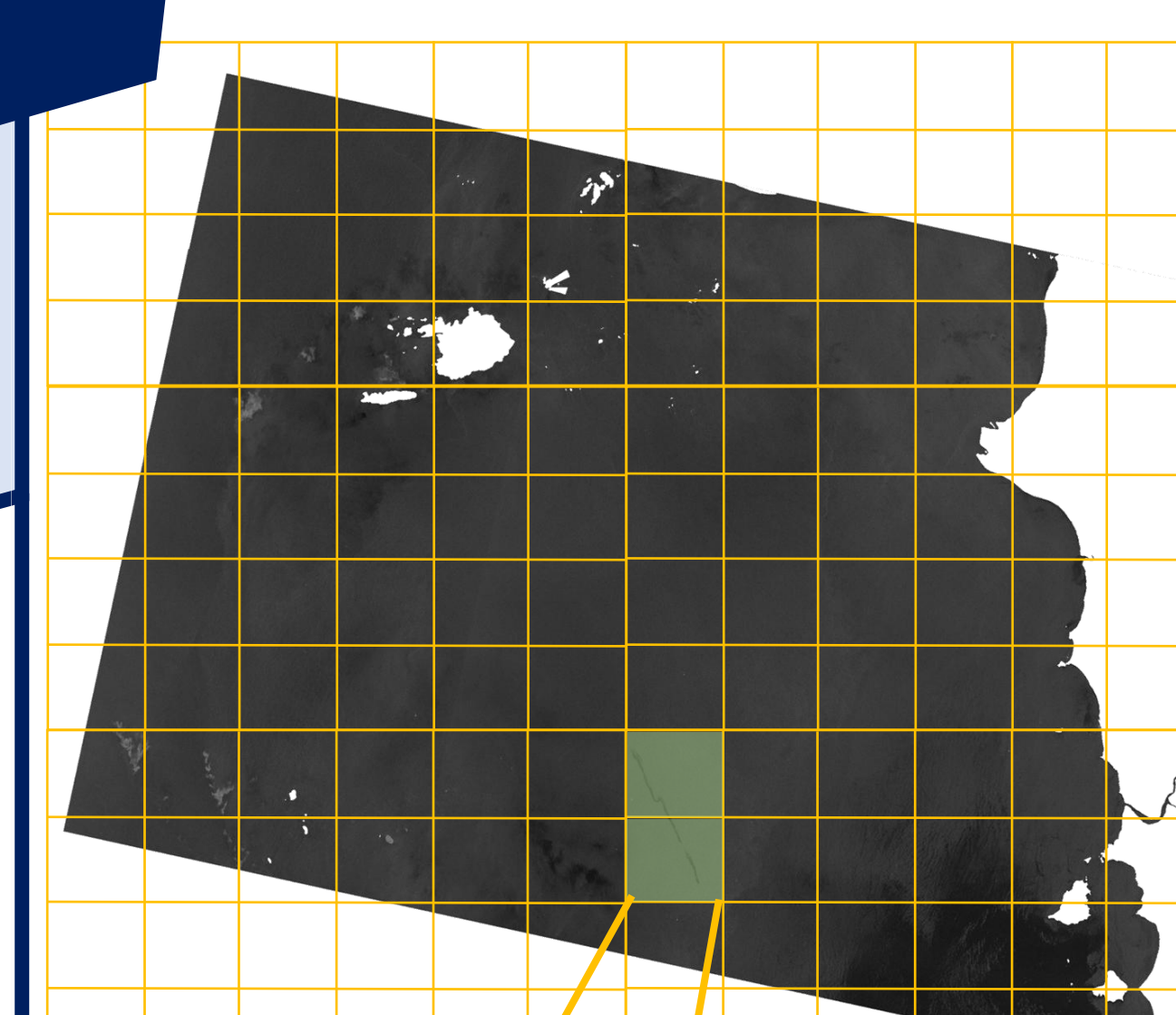
Combination of object and pixel-based methodology

The final step combines the results of both approaches to reduce false positives. Each method offers complementary strengths: The object-based approach is better at detecting larger oil spills, while the pixel-based approach is more effective for smaller ones.



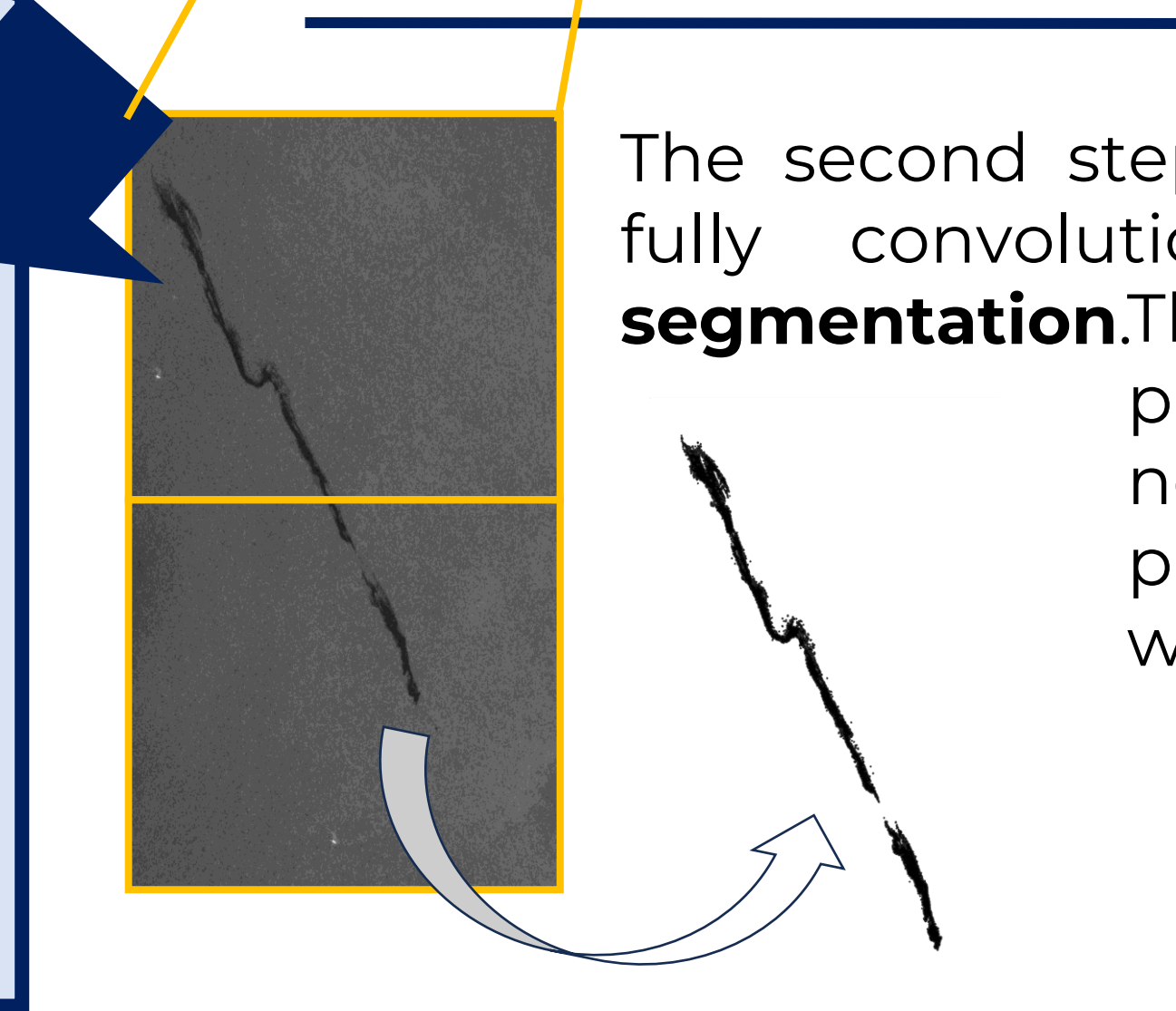
Pixel-based approach

CNN-Based Tile Classification for Oil Spill Detection



The pixel-based approach relies on a two-step ML workflow. First, the images are divided into **sub-images**, which are then fed into a convolutional neural network to identify **those containing oil spill pixels**.

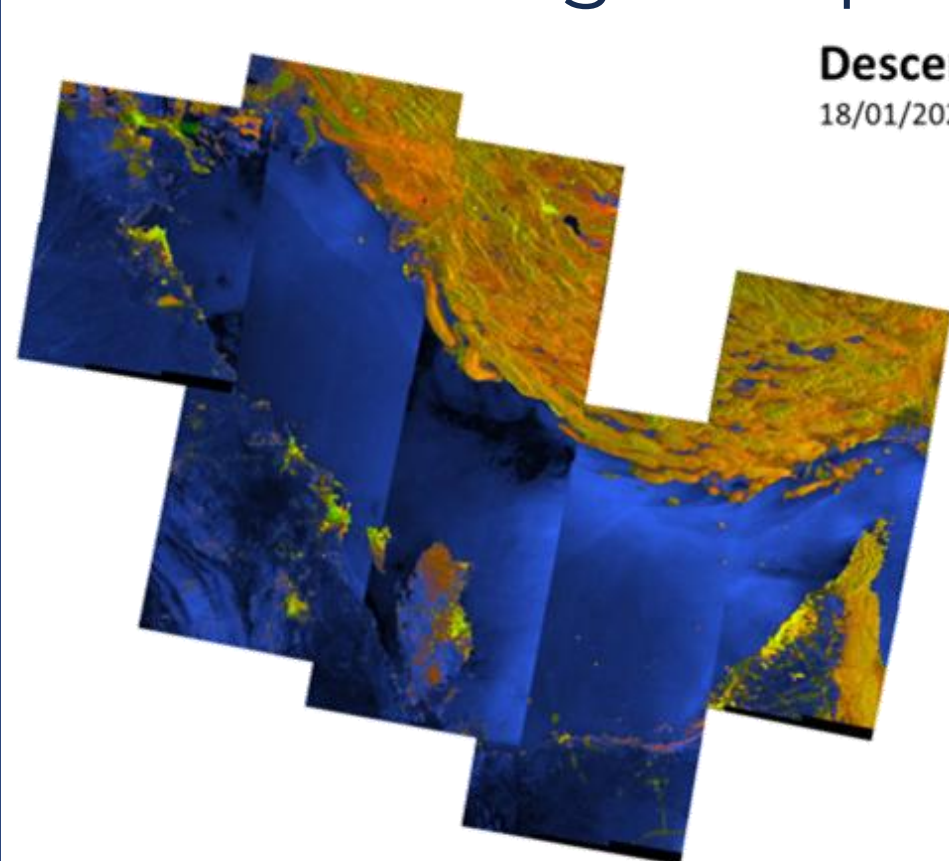
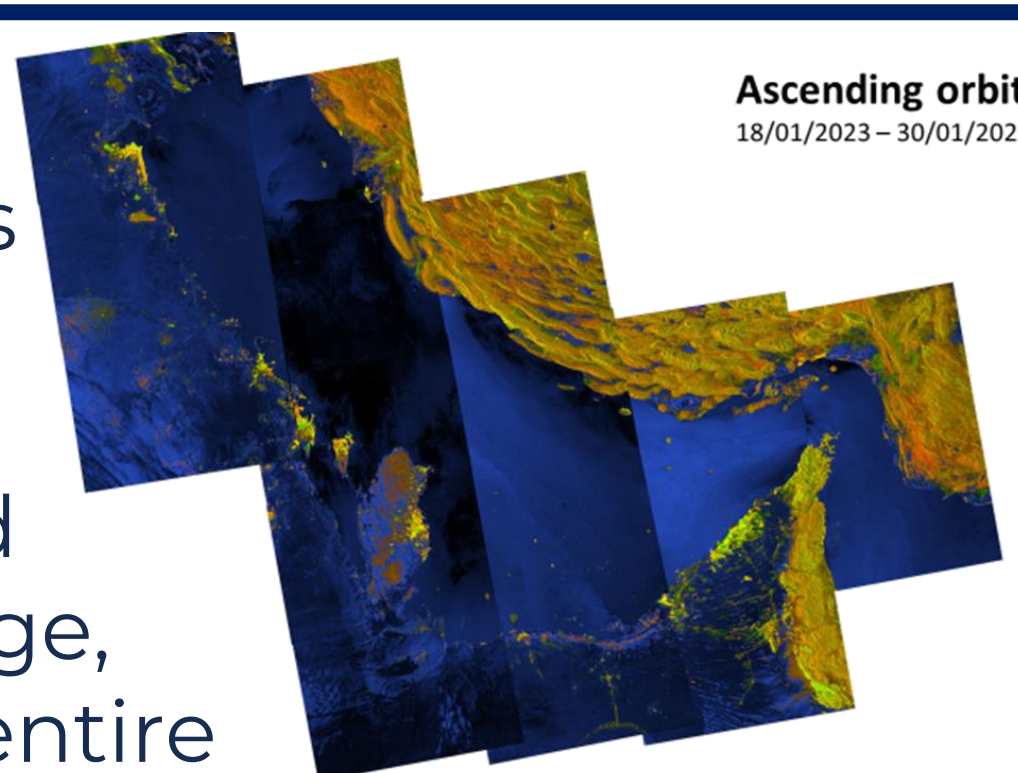
U-Net Architecture for Oil Spill Segmentation



The second step employs a **U-Net** fully convolutional network for **segmentation**. The selected tiles are passed through the network to highlight pixels associated with oil spills.

The Gulf is fully covered by Sentinel-1 data.

A complete image of the region requires 17 scenes from the ascending orbit and 16 from the descending orbit, resulting in approximately 1,200 images per year. Our algorithms take around 30 minutes to download and process a single image, which translates to roughly 7 days to analyze the entire dataset using four parallel processes.



This will enable the application of the detection method over several years of SAR data to assess annual oil pollution levels in the region. The results may also help identify pollution hotspots and at-risk ecosystems or infrastructure. The next objective is to develop a complementary detection system using Sentinel-2 data to improve temporal coverage and support more comprehensive monitoring.

How far have we progressed?

- SAR Oil Spill Data Collection & Sentinel-1 Preprocessing method with SNAP.
- Object and pixel-based approach training and validation.
- Comparing the Advantages of Both Methods for Integration into a Unified Detection Model
- Application of the Detection Method to multiple years of SAR Images in the Gulf

<https://www.slim-ocean.be/>
alexis.culot@uclouvain.be
linkedin.com/in/alexis-culot-63b944237