AI Applications in Geoscience and Remote Sensing

Case study: Oil spill detection in Pakistan's Exclusive Economic Zone (EEZ), using deep learning on sentinel-1 images

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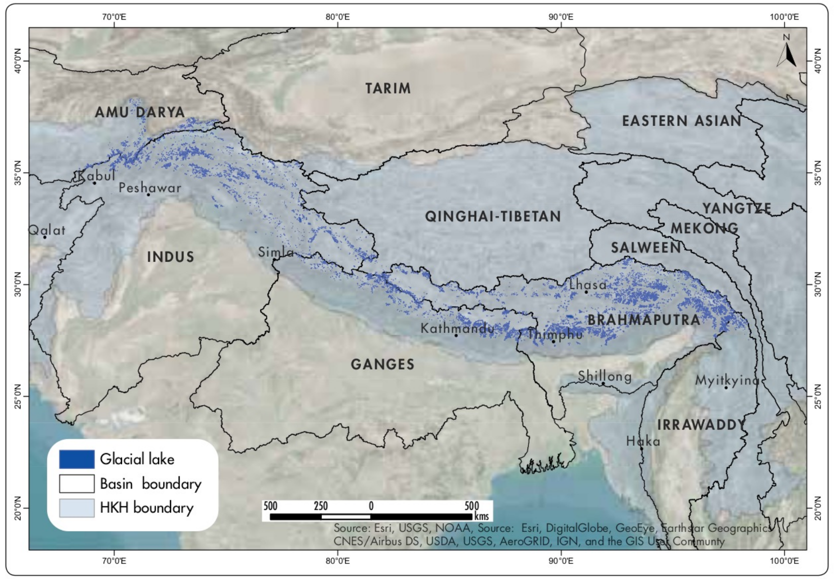
INTRODUCTION

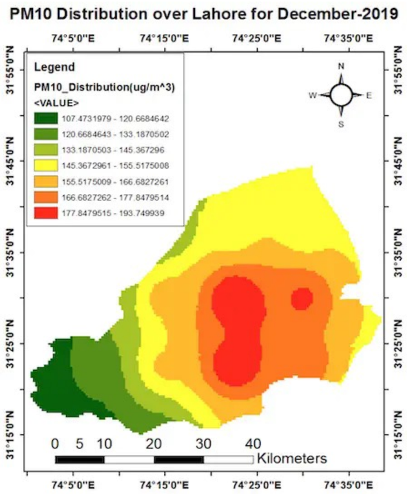
Focus » Environment

... a few examples:

- Cryosphere:
  - The Artic, Hindu Kush Himalayas (HKH), the European Alps, the Andes
    - glacial lake outburst floods, avalanches, iceberg calving, permafrost thawing, etc.
- Atmosphere:
  - Droughts, wild fires, crop burning, heatwaves, urban heat islands, air pollution
    - Massive smog blankets in the Pakistan/India Punjab » PM10/2.5, NOx, SOx, etc.
- Hydrosphere
  - Coastal flooding and erosion, marine pollution
    - Oil spill and bilge dump detection in the Arabian Sea

Source: ICIMOD





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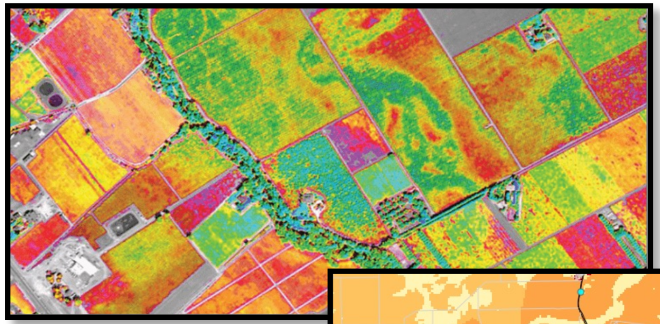
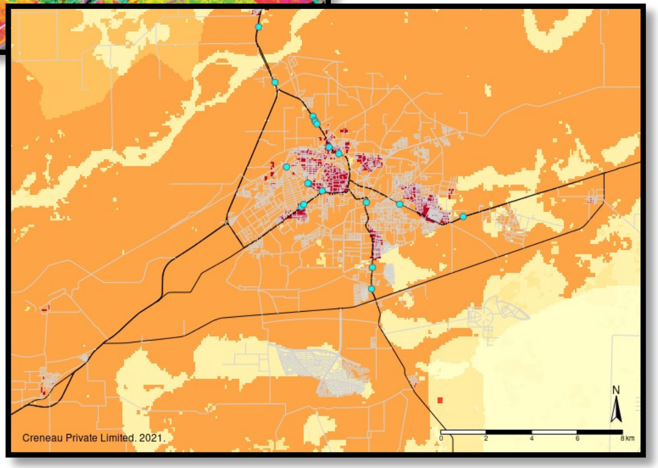
Focus » Technology

- Remote Sensing
  - Methods employed to acquire data and process information, without physical contact or close proximity
  - Imaging (radar & optical) + instrumentation
  - change detection, interferometry, tomography and polarimetry, spectral indices, data fusion, etc.





- Machine Learning
  - Information is contained in the imagery and requires carefully processing
  - How to extract it?
  - Pattern recognition, image/signal processing, machine learning, artificial intelligence…

- Spatial Analytics
  - hotspot analysis, spatial correlations, variograms, etc.

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MARINE POLLUTION

OIL SPILLS

14 LIFE BELOW WATER

SUSTAINABLE DEVELOPMENT GOALS

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Oil Spills

- An oil spill occurs when crude oil or petroleum products are deliberately or accidentally released into the marine environment during transport.
- Oil spills threaten marine ecosystems and are increasing annually in some parts of the world [6].
- Effective monitoring and detection of oil spills are crucial for mitigating the damage.
- Traditional oil spill monitoring techniques, such as airborne or field investigation are not cost effective for large-scale monitoring.
- Satellite imagery provides a scalable and efficient alternative.

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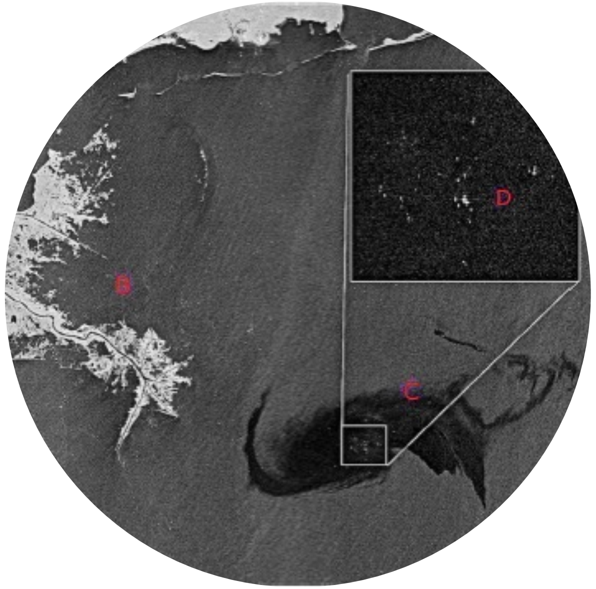
Example incidents



- Deepwater horizon oil spill (Gulf of Mexico)
- April 2010
- 3.19 million barrels of oil spilled

- Greece oil spill
- September 2017
- 45 years old vessel with 2500 tons of crude oil

- Mauritius oil spill
- July 2020
- 1000 tons of oil spilled

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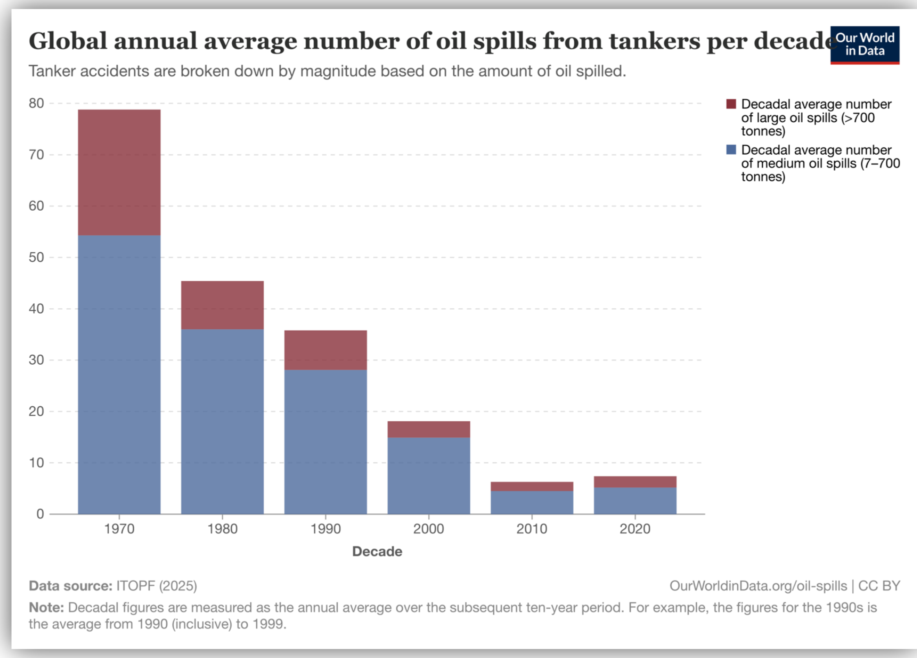
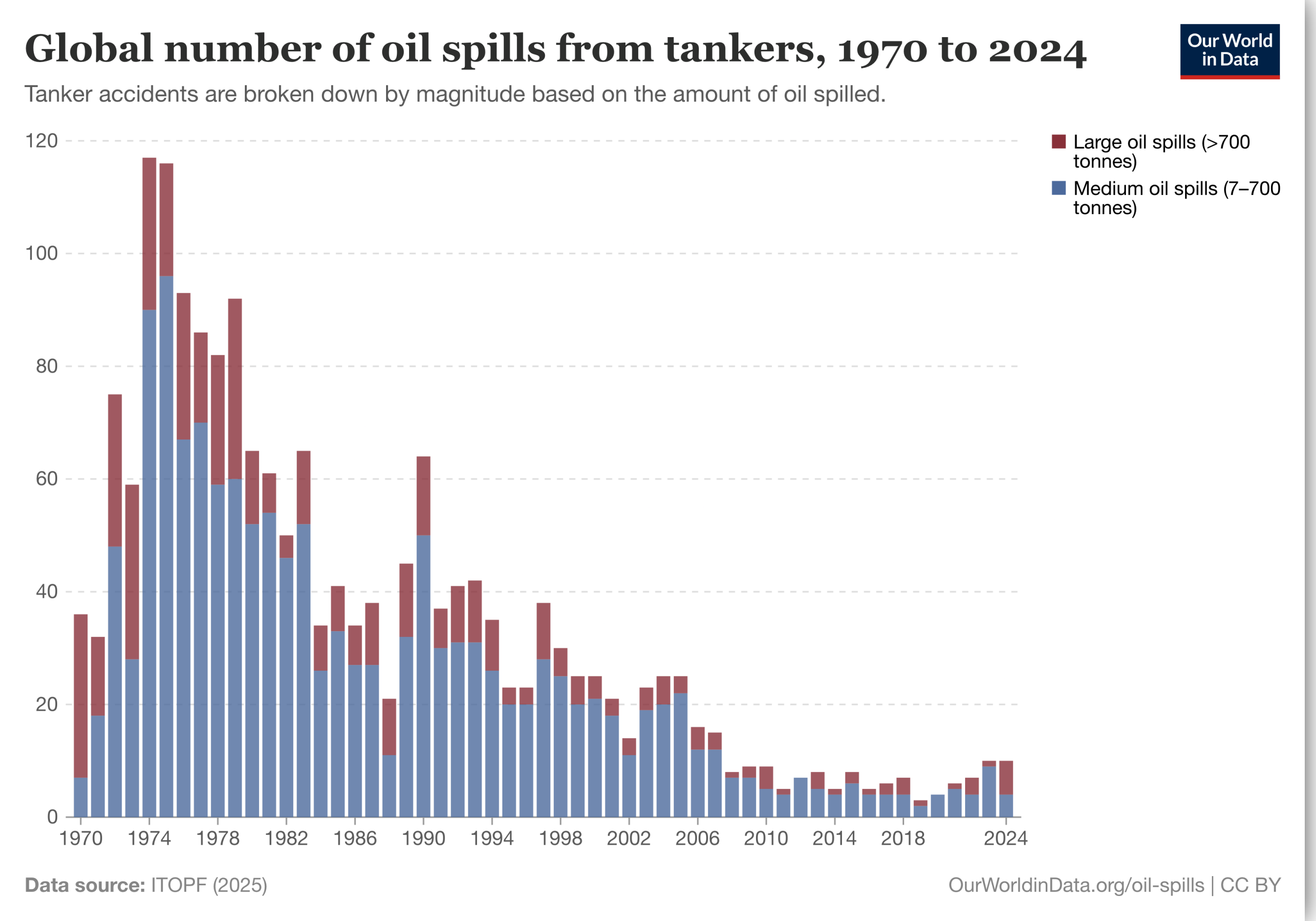
Global Statistics





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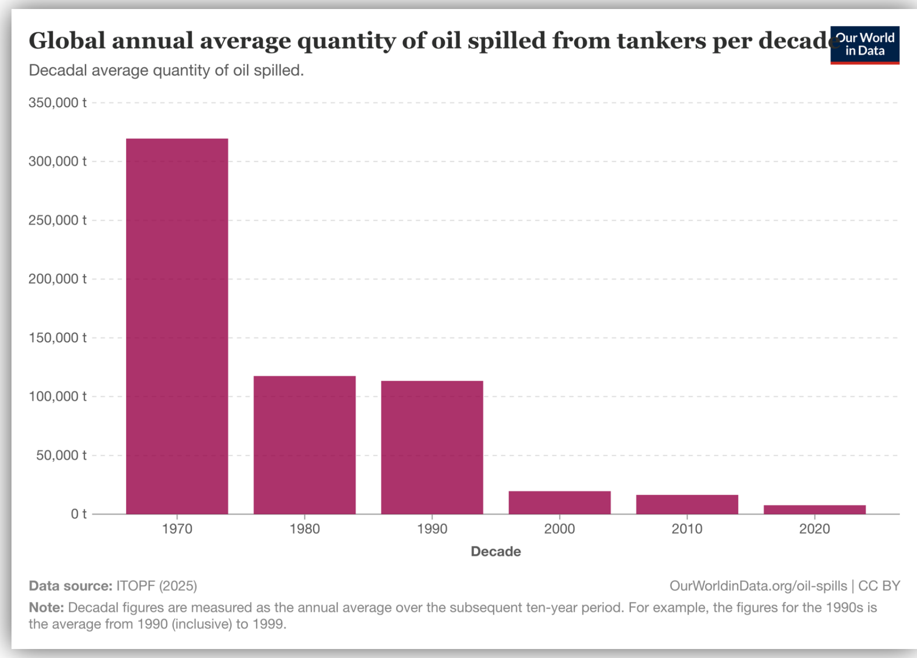
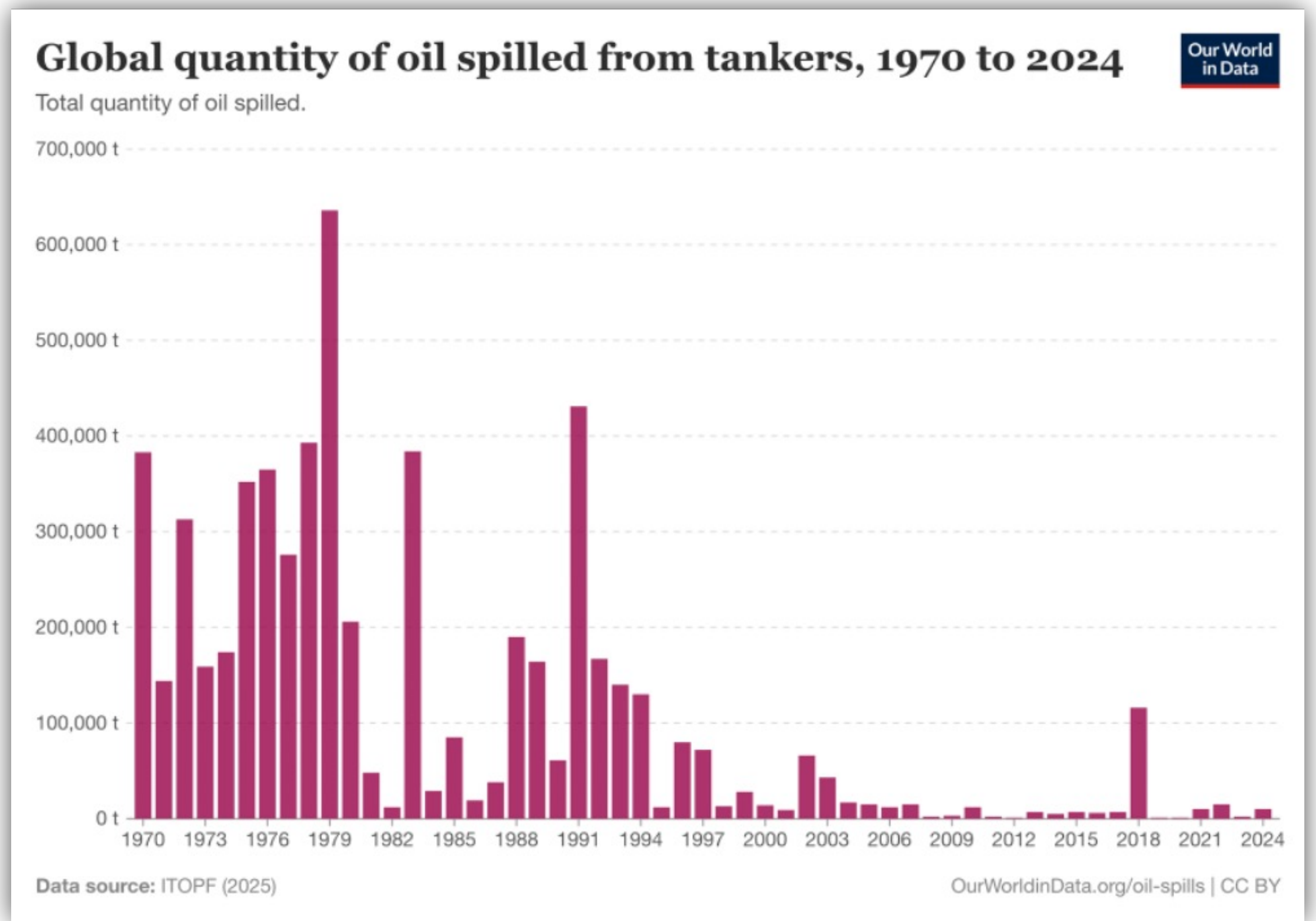
Global Statistics





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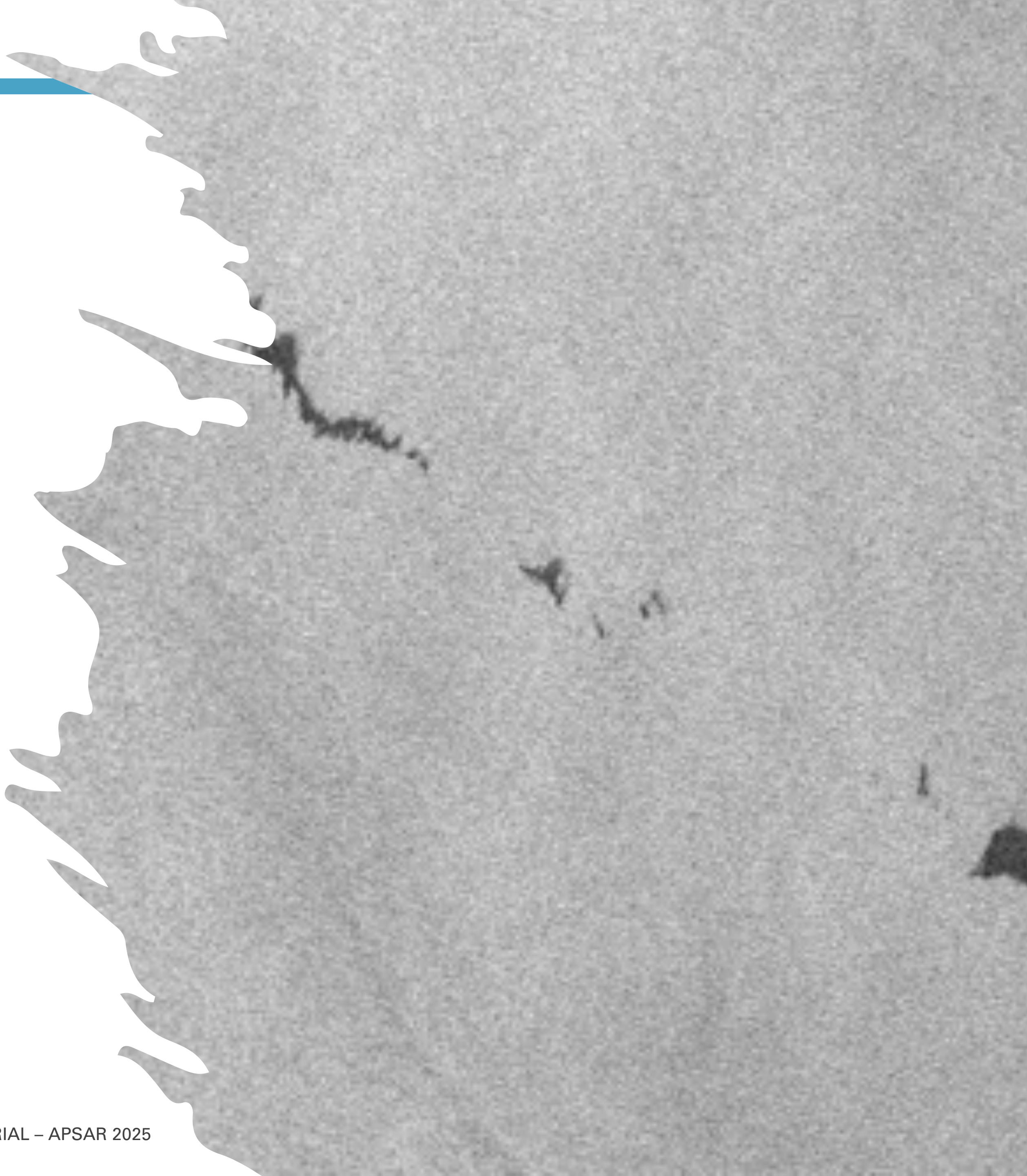
OIL SPILL DETECTION

Why Synhetic Aperture Radar (SAR)?



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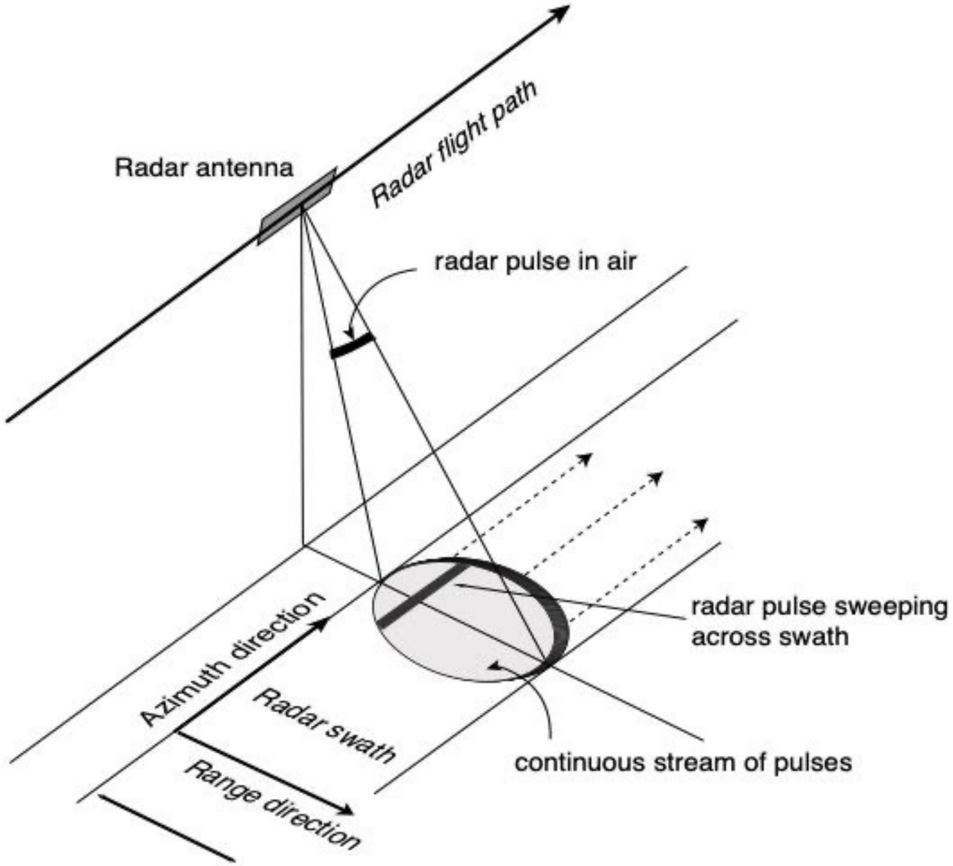
Synthetic Aperture Radar (SAR)

- Both optical and radar sensors have been used for spaceborne oil spill detection [2][3].
  - Oil spills can occur day or night!
  - While optical imagery may provide high spatial and visual clarity, its effectiveness is limited by cloud cover and daylight dependence.

- SAR is preferred over optical sensors in this scenario, as microwaves penetrate through clouds, hence SAR can operate day or night, under all weather conditions.



Credit: NASA

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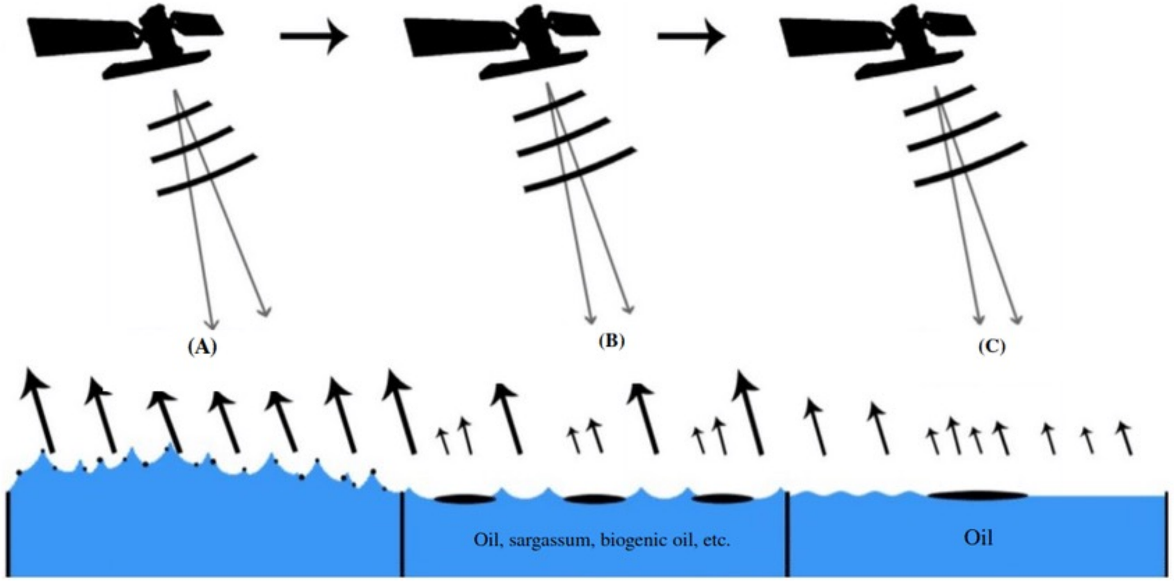
Oil spill response in SAR imagery

- SAR collects backscattered energy [modelled typically with Bragg surface scattering]
- **Marine oil spills are visible as areas of low backscatter power in synthetic aperture radar(SAR) images. [1]**

Levels of Radar backscatter	*Typical scenario*
• *Very high backscatter (above -5 dB)*	*Man-Made objects (urban)* *Terrain Slopes towards radar* *very rough surface* *radar looking very steep*
• *High backscatter (-10 dB to 0 dB)*	*rough surface* *dense vegetation (forest)*
• *Moderate backscatter (-20 to -10 dB)*	*medium level of vegetation* *agricultural crops* *moderately rough surfaces*
• *Low backscatter (below -20 dB)*	*smooth surface* *calm water, road* *very dry terrain (sand)*

Reference: Prof. A. Moreira, SAR lecture notes, KIT/DLR, Germany



Emna Amri et. al, Offshore Oil Slick Detection: From Photo-Interpreter to Explainable Multi-Modal Deep Learning Models Using SAR Images and Contextual Data, MDPI Remote Sensing

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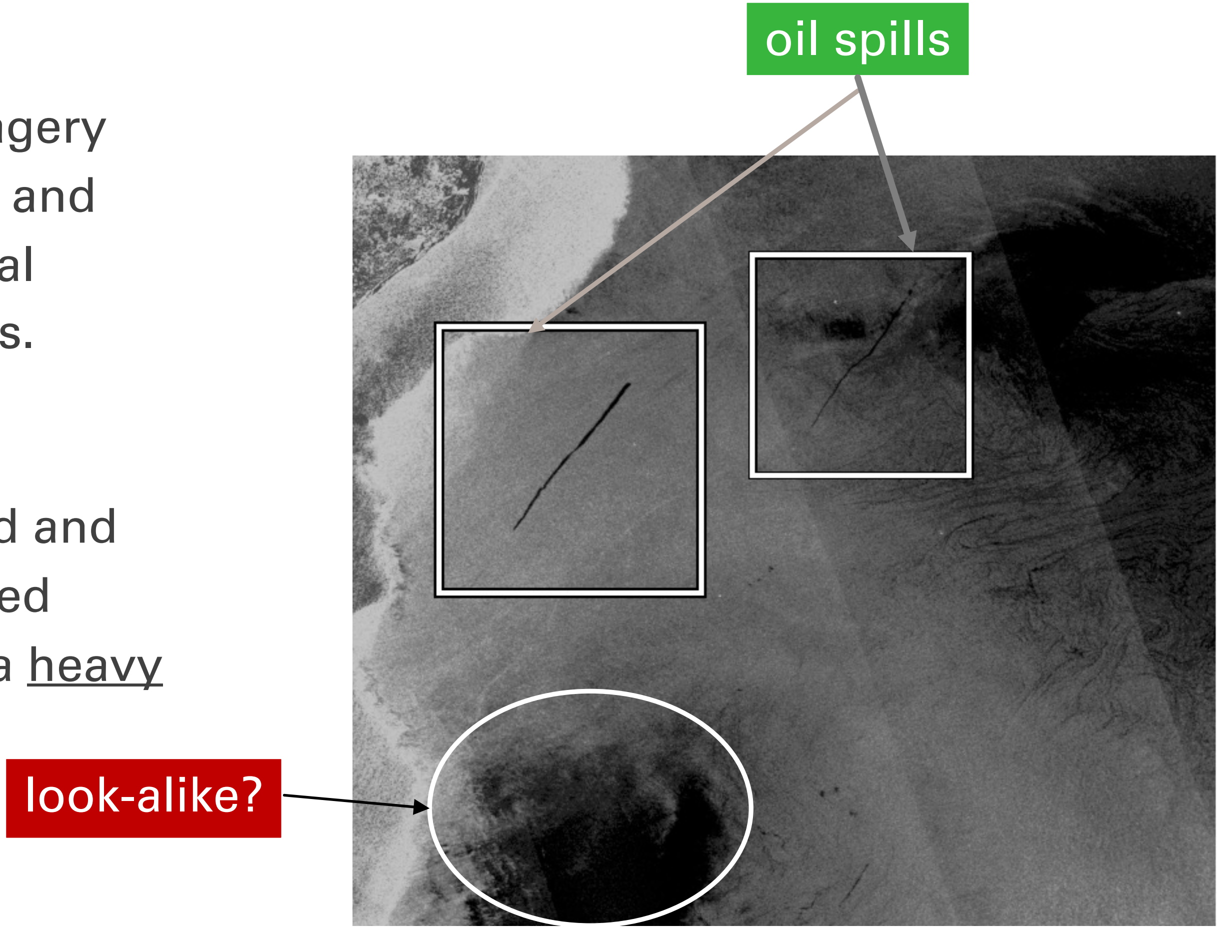
Detection

- Historically, oil-spill identification in SAR imagery evolved from heuristic "dark-spot detection" and texture-based discriminators toward statistical classifiers that relied on hand-crafted features.

- While these approaches were straightforward and computationally cheap, it suffered from limited robustness to environmental variability and a heavy dependence on expert tuning.



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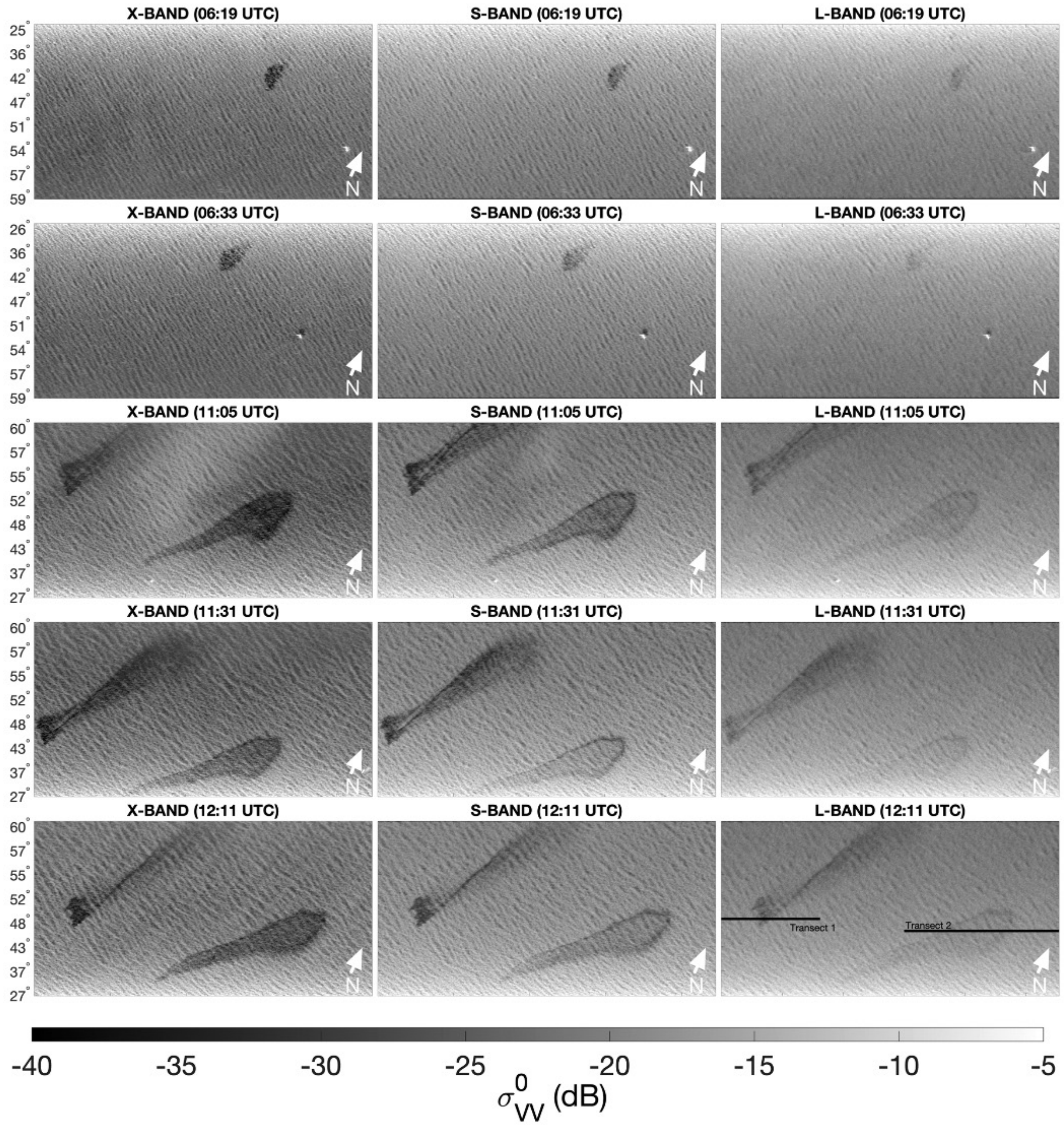
C. Brekke et. el. (2020)

- controlled release of two biodegradable oil slicks in the North Sea in June 2019
- F-SAR images in multiple bands [X, S, and L]
- X-band offers more contrast!

Brekke, C., Espeseth, M. M., Dagestad,K.-F., Röhrs, J., Hole, L. R., & Reigber,A. (2021). Integrated analysis ofmultisensor datasets and oil driftsimulations—a free-floating oilexperiment in the open ocean. Journalof Geophysical Research: Oceans,126, e2020JC016499



Courtesy: ESA

Before-and-after satellite images from Sentinel-1 show the extent of the oil spill off the coast of Trinidad and Tobago in February 2024. The incident occurred when the vessel The Gulfstream ran aground and capsized off the southern shores of Tobago Island, releasing oil into the surrounding waters.

Courtesy: ESA

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Deep Learning (DL)

- With the rise of data-driven approaches, deep learning (DL) has shown significant promise in oil spill detection.
  - Convolutional Neural Networks (CNNs) to automatically extract features
  - capture complex spatial and contextual patterns in SAR imagery
  - learn hierarchical feature representations, removing the need for manual feature engineering [5]
- **Require training data!**

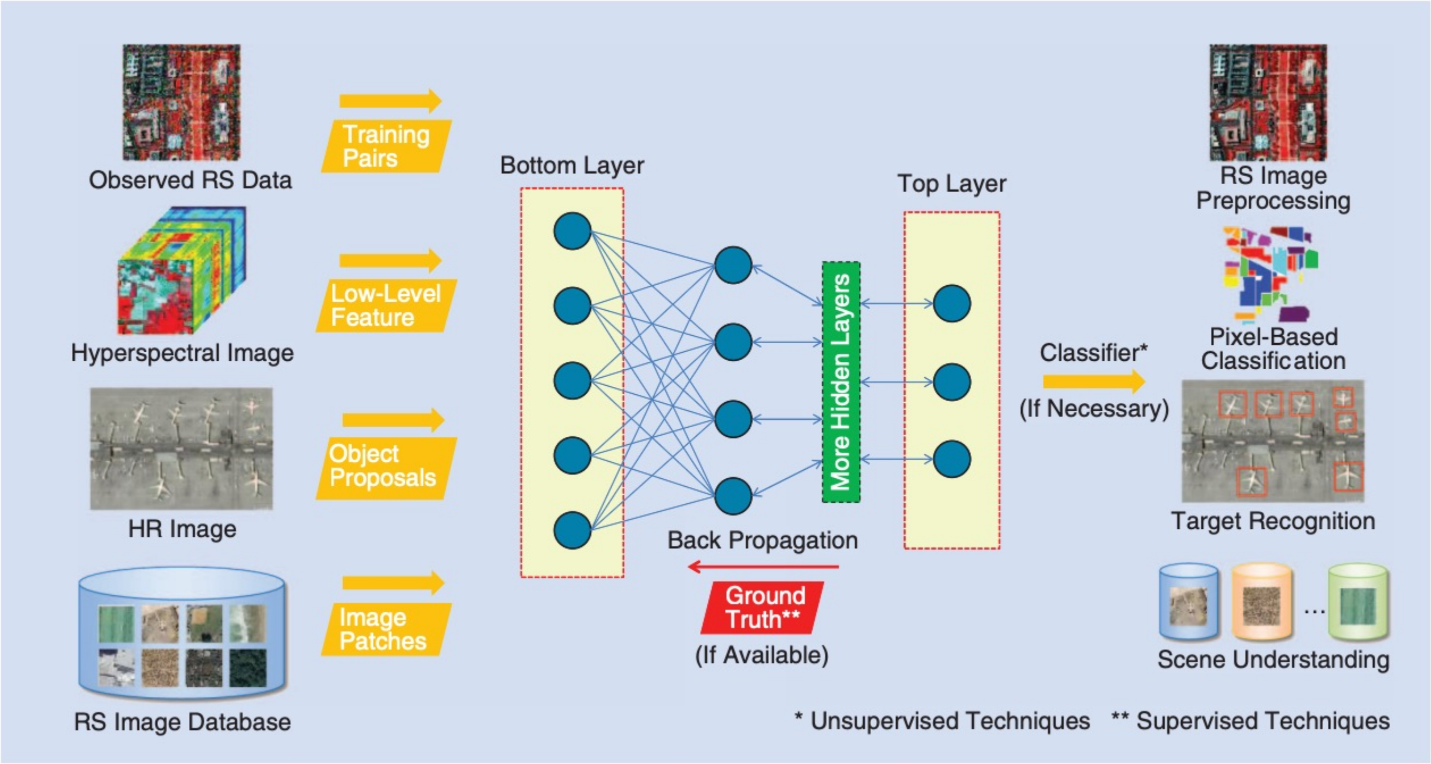

FIGURE 1. A general framework of DL for RS data analysis.

L. Zhang, L. Zhang and B. Du, "Deep Learning for Remote Sensing Data: A Technical Tutorial on the State of the Art," in IEEE Geoscience and Remote Sensing Magazine, vol. 4, no. 2, pp. 22-40, June 2016, doi: 10.1109/MGRS.2016.2540798.

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Training Dataset – Deep SAR Oil Spill (SOS)

ALOS-2 PALSAR

Characteristics

We can only do binary classification here!

- **Band**: L-Band
- **Study Area**: Gulf of Mexico
- **Acquisition Period**: May 2010 - Aug 2010
- **Image Size**: 256 x 256 [pixels]
- **Data Augmentation**: Cropping, rotation, and noise addition.
- **Train Images**: 3101 (80%)
- **Test Images**: 776 (20%)

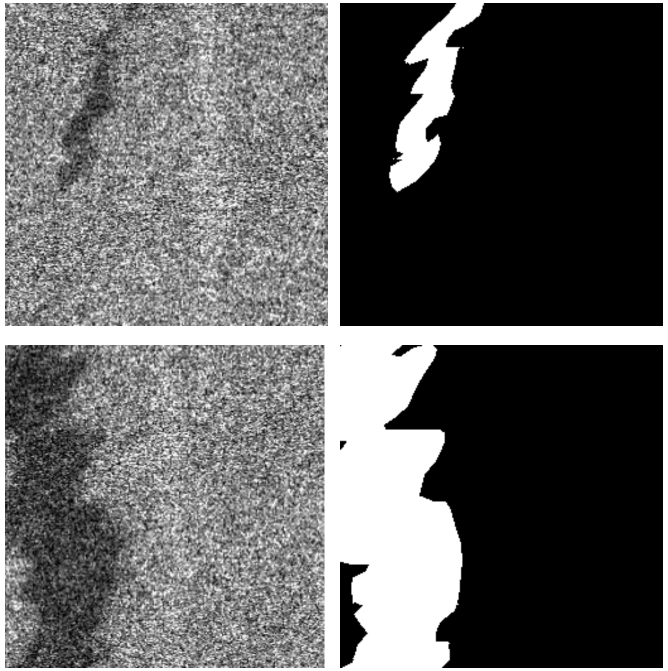

Fig. Samples of ALOS PALSAR images along with ground truth masks (right column). White color represents oil spill while black color represents background.

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Q. Zhu et al., "Oil Spill Contextual and Boundary-Supervised Detection Network Based on Marine SAR Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-10, 2022

Training Dataset – Deep SAR Oil Spill (SOS)

Sentinel 1

Characteristics

We can only do binary classification here!

- **Band**: C-Band
- **Study Area**: Persian Gulf
- **Acquisition Period**: Aug 5 - Aug 14, 2017
- **Image Size**: 256 x 256 [pixels]
- **Data Augmentation:** Cropping, rotation, and noise addition.
- **Train Images**: 3354 (80%)
- **Test Images**: 839 (20%)

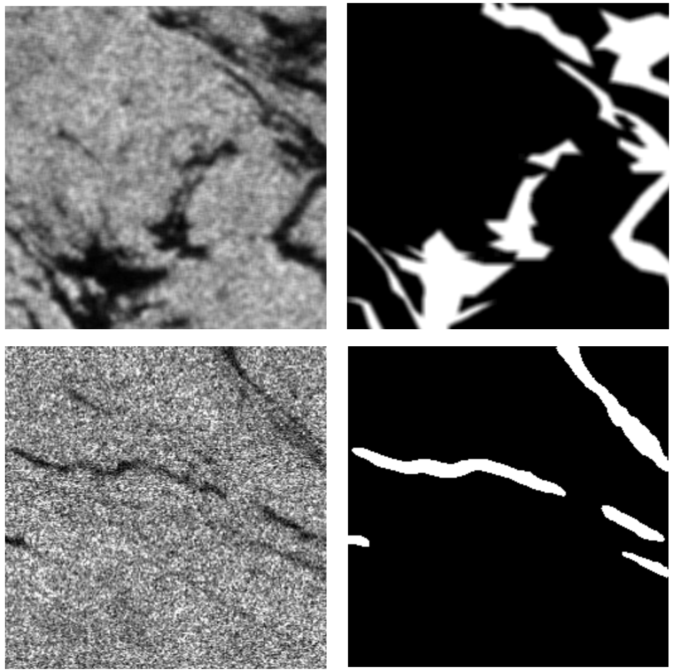

Fig. Samples of Sentinel-1A images along with ground truth masks (right column). White color represents oil spill while black color represents background.

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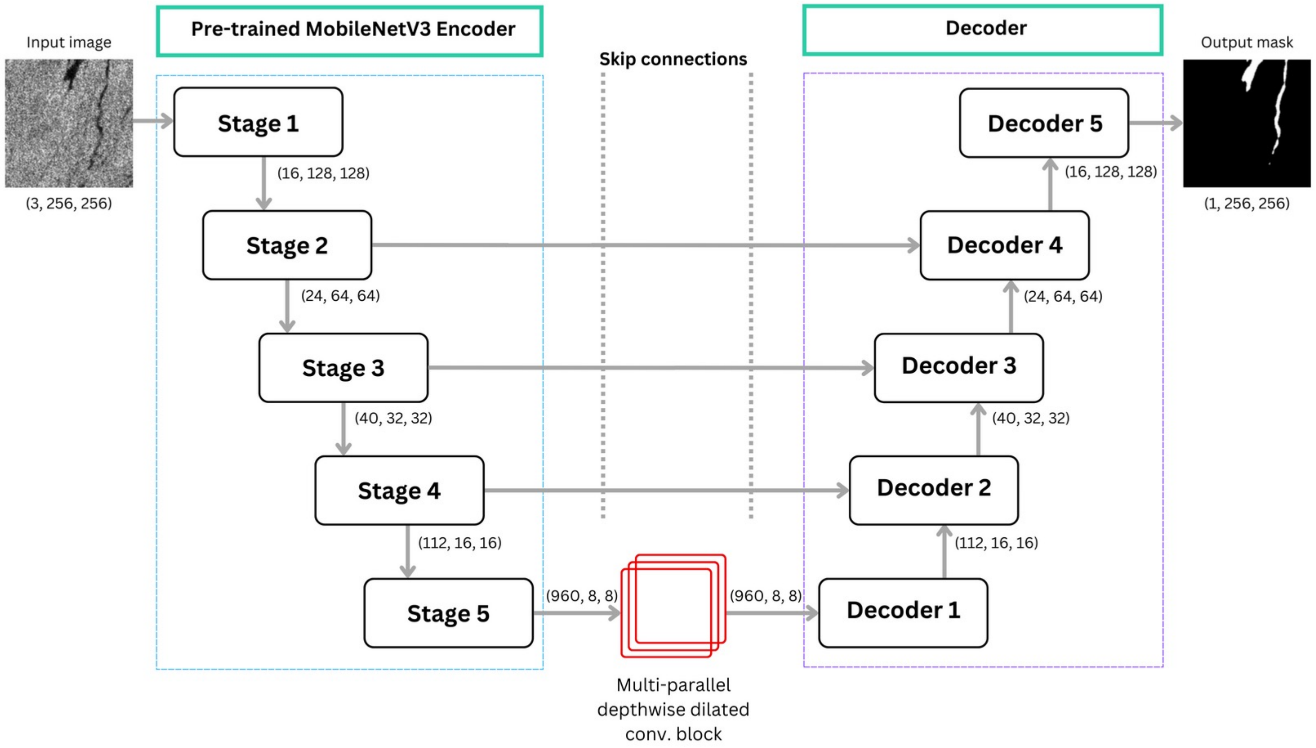
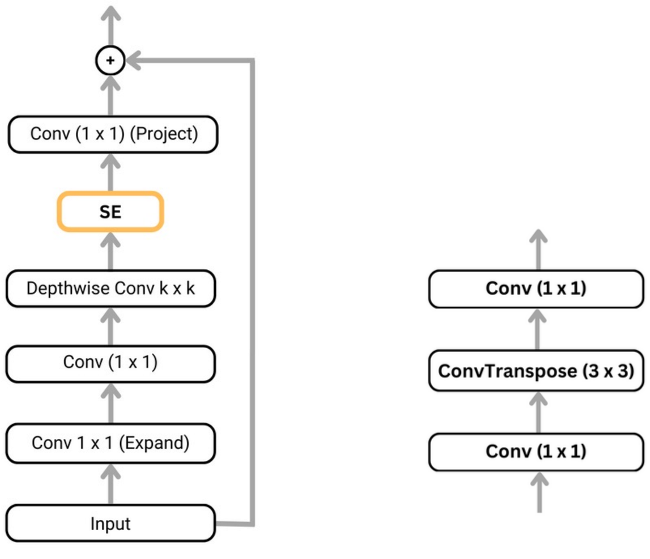
Q. Zhu et al., "Oil Spill Contextual and Boundary-Supervised Detection Network Based on Marine SAR Images," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-10, 2022

Training

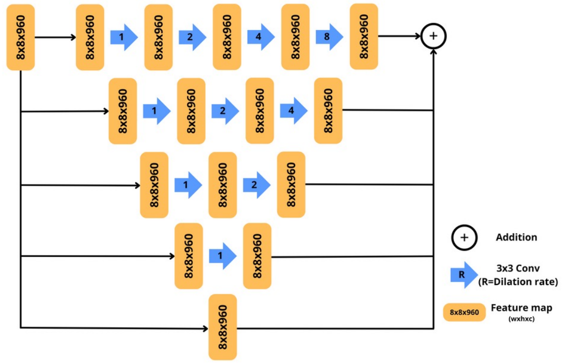
Architecture Overview





MobileNetv3 bottleneck block

Decoder block



Multi-parallel depthwise dilated convolutional block

Training & Results

Experimental Setup

- Epochs: 600
- Batch Size: 12
- Learning Rate: 2 x 10^{-4}
- Loss Function: Binary Cross Entropy
- Optimizer: Adam
- Input Image Size: 256 x 256

Evaluation Metrics

- Mean Intersection Over Union (mIoU)

$$IoU_k = \frac{TP_k}{TP_k + FP_k + FN_k}$$

$$mIoU = \frac{1}{C}\sum_{k=1}^{C} IoU_k$$

Table: Comparison with other studies that used SOS dataset.

Model/Method	Parameters (M)	mIoU (%)	
		ALOS PALSAR	Sentinel-1
CBDNet [8]	31.45	83.31	83.42
DAENet [9]	31.53	85.0	86.1
Ours	**7.49**	**86.04**	**88.20**

Published in IGARSS 2025, Brisbane

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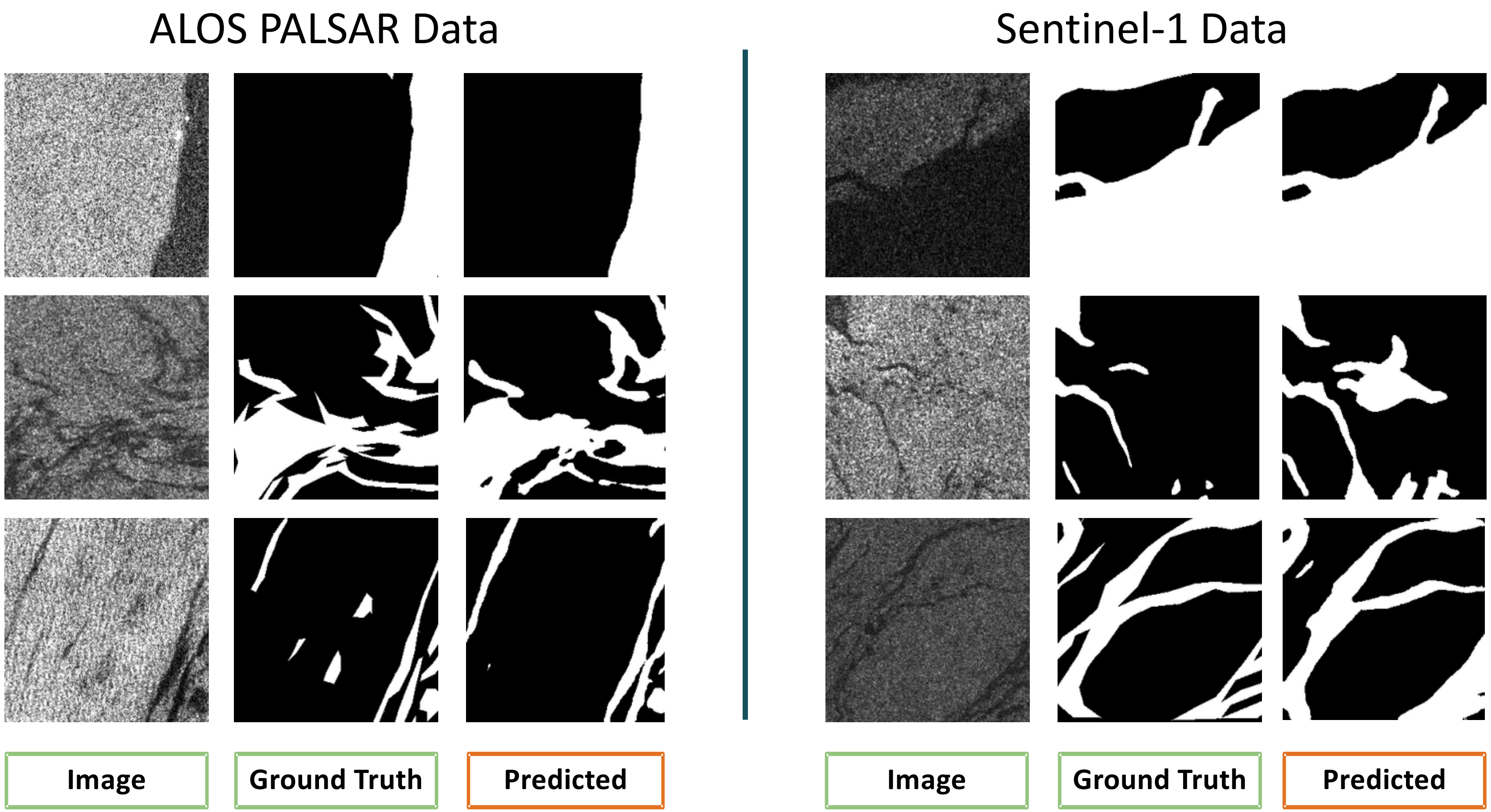
Qualitative Results



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PAKISTANI WATERS

Case study on Pakistan’s Exclusive Economic Zone (EEZ) in the Arabian Sea

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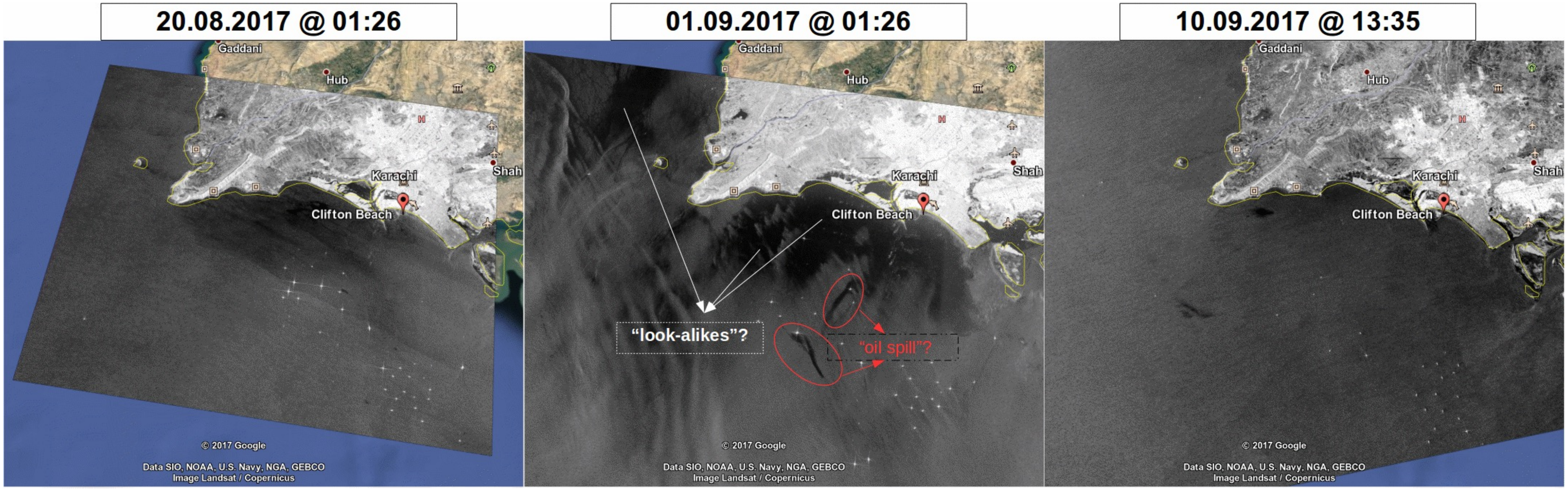
Oil spill in Pakistani waters …?

On the third day of *Eid-ul-Azha*, September 4, 2017, beachgoers in Karachi reported oil or oil-like substance washing ashore on the Clifton Beach. [Geo News]



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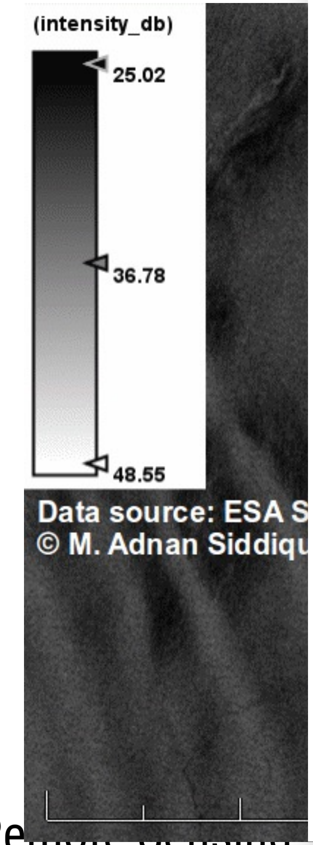
Oil spill in Pakistani waters …?



Dear Adnan. really it's good to see your scholary work.

It is not like that the institutions at Pakistan are sleeping but they have an open eye on these types of disaster and are well aware how to respond. The first patch of this slick hit the coastal areas near to Sandspit on 28th May 2017. we (KPT oil spill response team) collect the samples from field and Pakistan Maritime securoty agency through their aeroplane got the actual data from air. The 4th September slick was also monitored by KPT and PMSA jointly. we are of the view that the slick pf 4th Sept is actually the part of the same slick which hitted during last days of May.

you did an excellent work. with your permission i will share it with others in upcoming meeting of stakeholders on oil spill preparedness in the month of November. Your analysis supported our idea that this slick comes from unknown resource from the sea.

According to our field analysis it was crude oil slick and the slick was months old and had gone through the weathering processes.

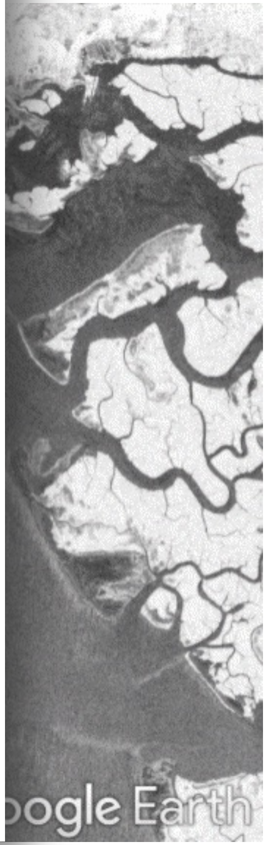
Best regards

Fayyaz Rasool

Manager

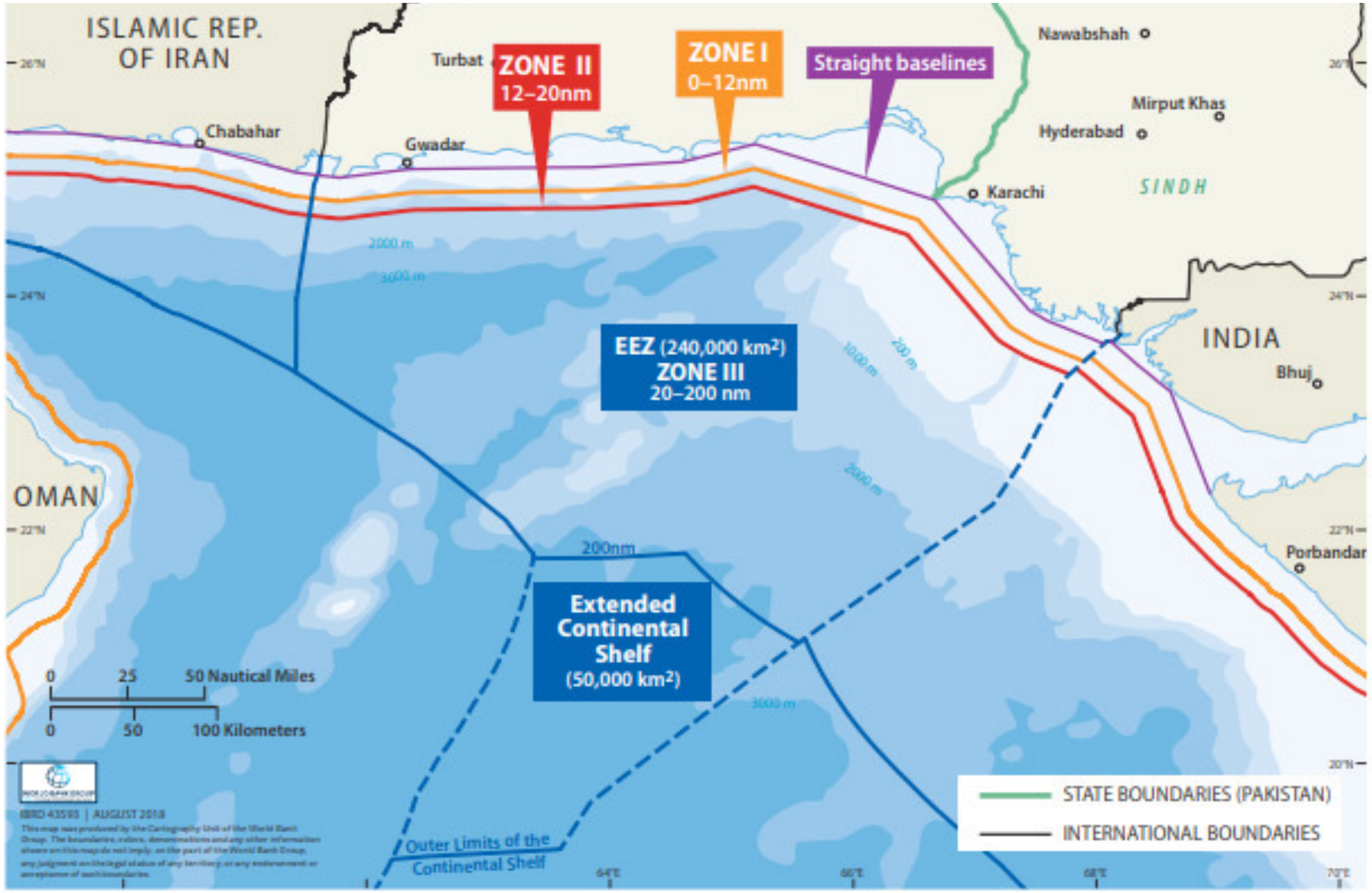
Marine Pollution Control Department

Karachi Port Trust



Oil Spills in Arabian Sea

- Pakistan's Exclusive Economic Zone (EEZ)
- Sentinel-1/2 are European Space Agency (ESA) satellites that acquire imagery over the Arabian Sea.
- Under the ESA Copernicus program, it acquires regularly around the world, and covers oceans.



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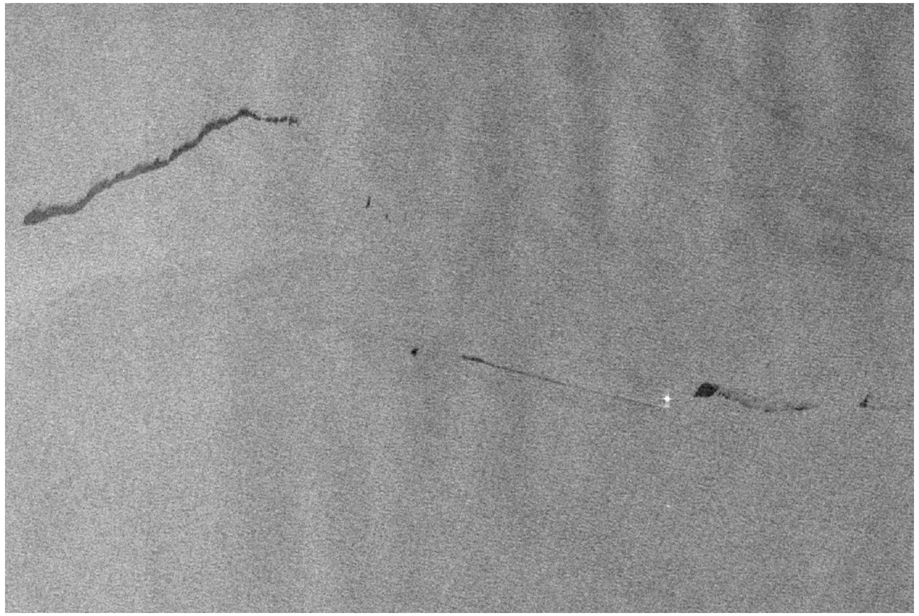
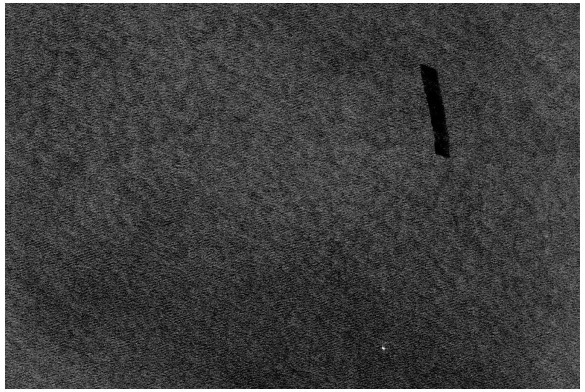
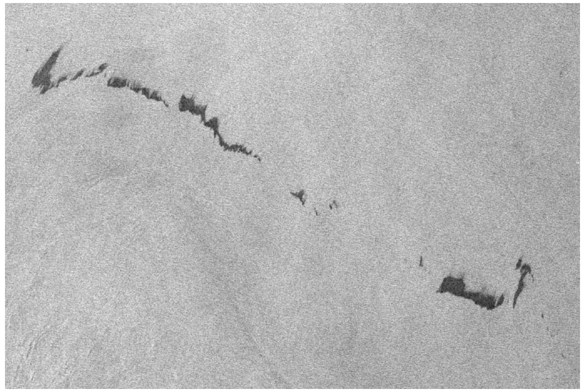
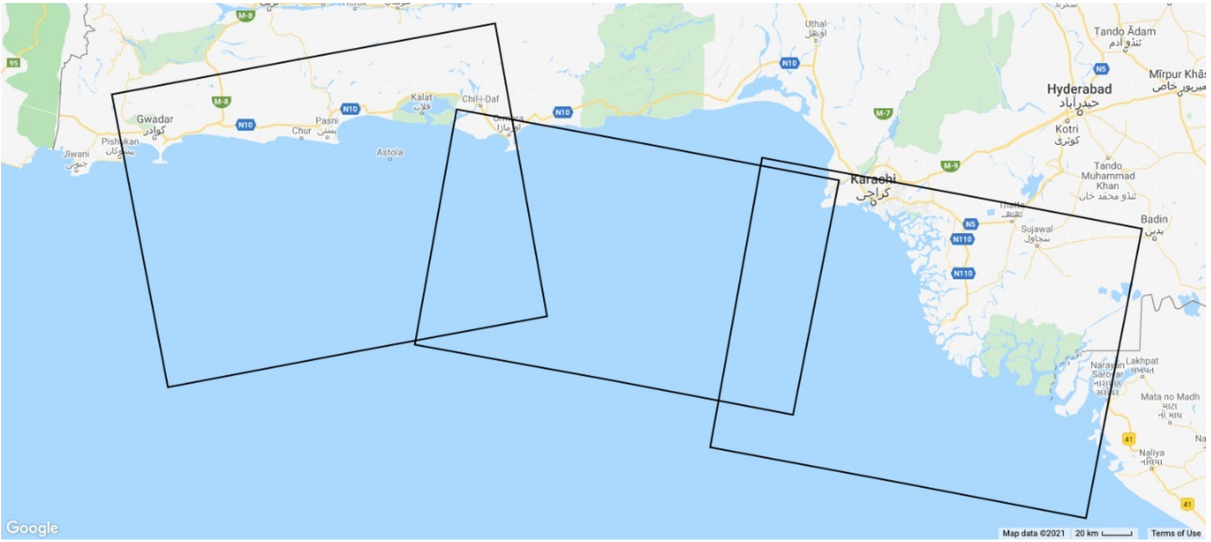
Example imagery

- Duration: Jan – Dec 2020
- Relative orbits: 78, 151, 13 (Setinel-1)









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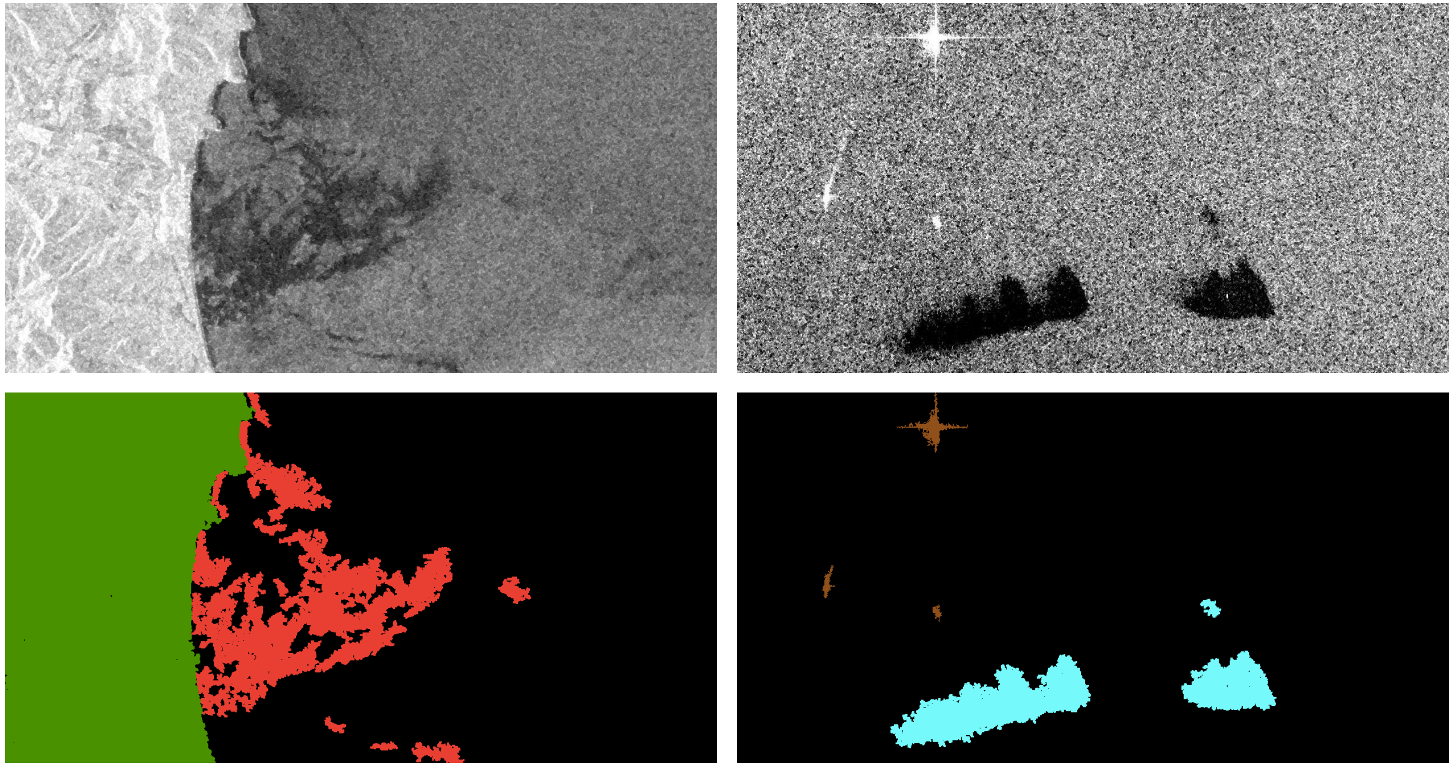
Dataset » for training

- Multimedia Knowledge and Social Media analytics laboratory (MKLab), Greece developed a publicly available dataset for oil spill detection
- Dataset
  - Total images: 1112
  - Train images: 1002
  - Test images: 110
  - Ground truth mask for each SAR image in the dataset
- Information regarding the geographic coordinates and timestamps of the pollution event were provided by the European Maritime Safety Agency (EMSA) through the CleanSeaNet service.



M. Krestenitis, G. Orfanidis, K. Ioannidis, K. Avgerinakis, S. Vrochidis, I. Kompatsiaris, “Oil spill identification from satellite images using deep neural networks.” Remote Sens. 2019, 11, 1762.

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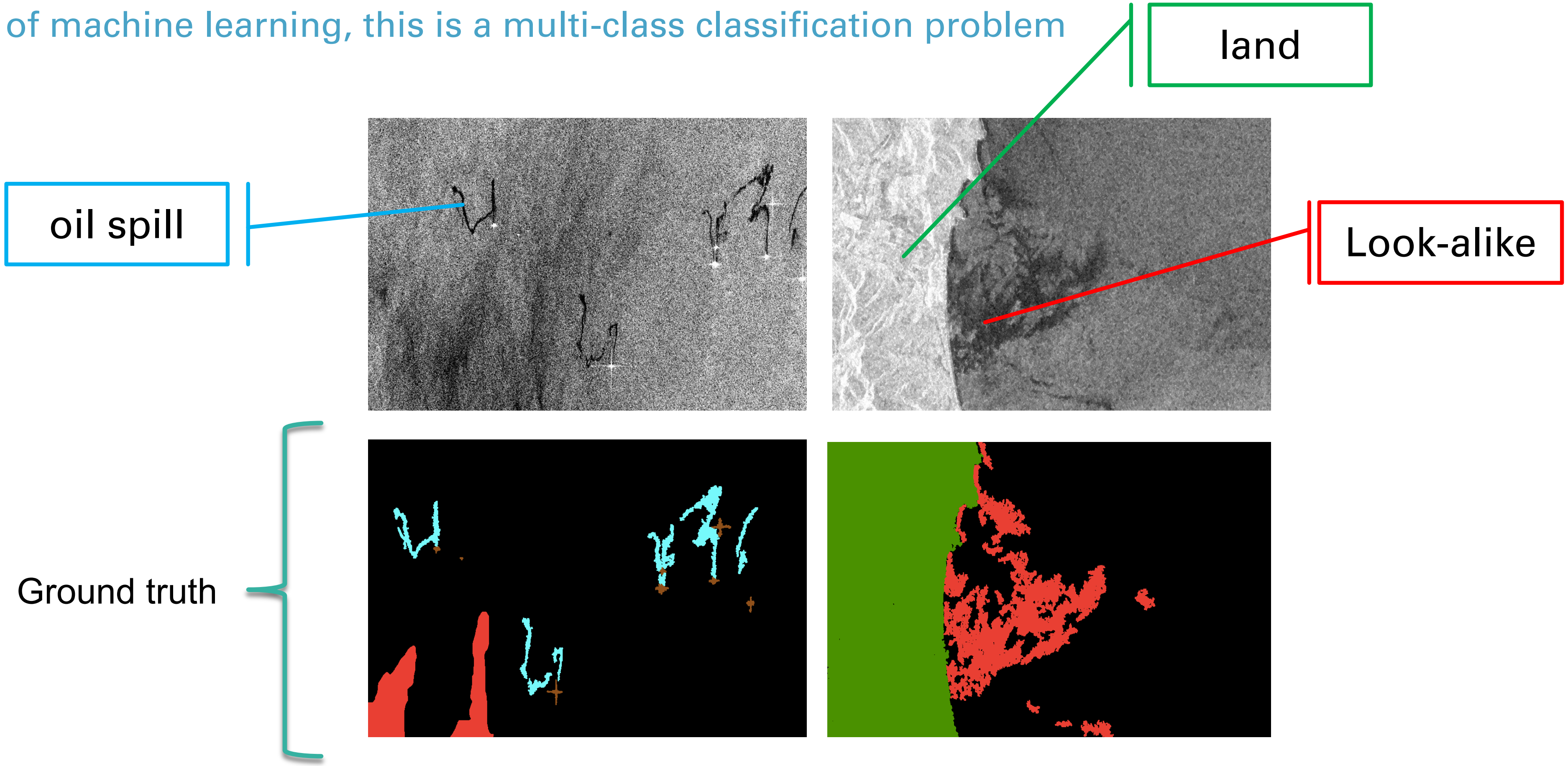
Relevant classes

In the context of machine learning, this is a multi-class classification problem



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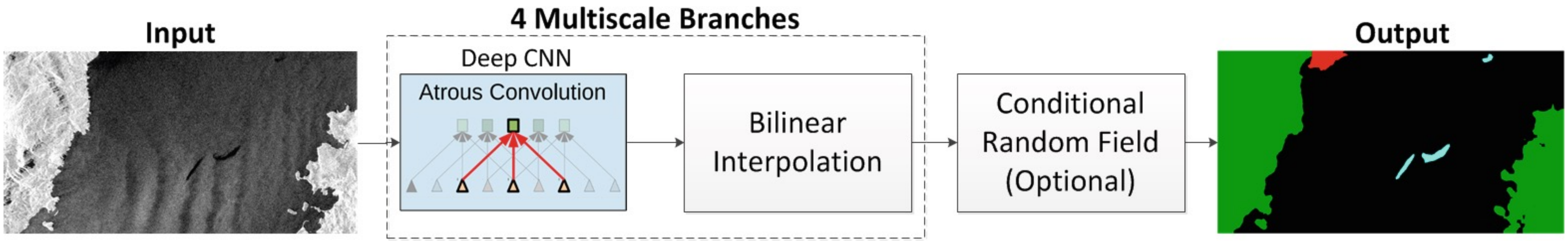
Courtesy: Multimedia knowledge and social media analytics laboratory (MKLab) & European Maritime Agency

Deep learning for multiclass classification of oil spills and look-alikes

- A multi-scale deep convolutional neural network (Multi-scale DCNN) is designed based on DeepLab.
- Evaluation metric: Intersection over union (IoU).



M. Krestenitis, G. Orfanidis, K. Ioannidis, K. Avgerinakis, S. Vrochidis, I. Kompatsiaris, "Early identification of oil spills in satellite images using deep CNNs." MDPI Remote Sensing

Steps	Test images	Sea surface	Oil spill	Look-alike	Ship	Land	**Mean IoU**
10k	110	95.6%	49.7%	54.9%	15.7%	86.9%	**60.06%**

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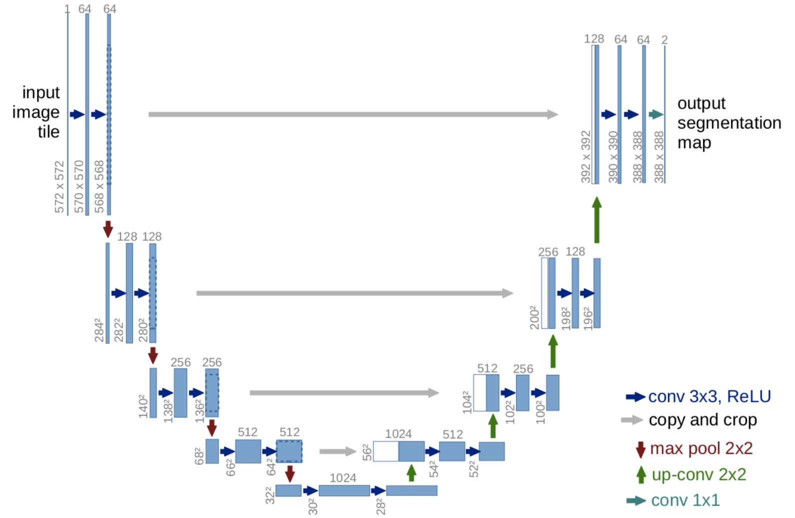
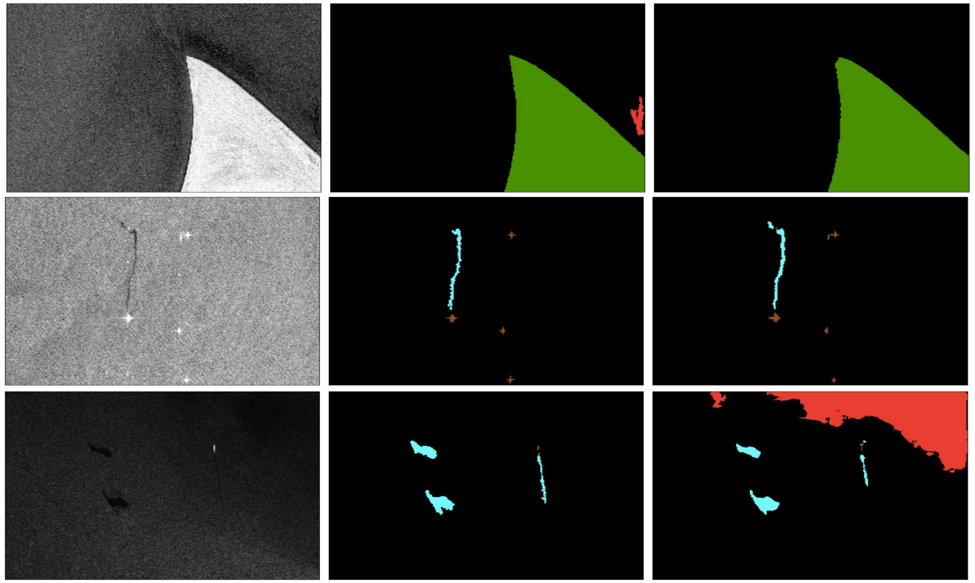
Deep learning

- Backbone: Efficientnetb0.
- Pre trained weights: ImageNet.
- Trainable parameters : 10 million (less as compared to the Resnet backbones).
- Loss function: cross entropy
- Performance: 10% improvement over state of the art with mean intersection over union (mIoU) value of 75.70%.



Model	Backbone	Sea surface	Oil spill	Look-alikes	Ships	Land	mIoU
UNet	Resnet101	93.90%	53.79%	39.55%	44.93%	92.68%	64.97%
DeepLabv3+	Mobilenetv2	96.43%	53.38%	55.40%	27.63%	92.44%	65.06%
UNet	**Efficientnetb0**	95.69%	**60.85%**	54.90%	**70.27%**	**96.79%**	**75.70%**



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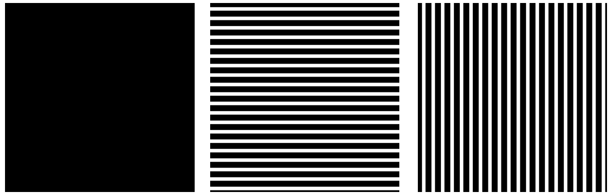
A. Basit, M. A. Siddique and M. S. Sarfraz, "Deep Learning Based Oil Spill Classification Using UNet Convolutional Neural Network," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, 2021, pp. 3491-3494.

Deep learning with spatial profile loss

Gradient profile loss



Source A Target B Target C

<u>Pixel-based</u>

L(A,B) = 0.3750
L(A,C) = 0.3750

<u>Gradient profile</u>

L(A,B) = 10.9545
L(A,C) = 6.7082

Formally, the similarity over each image channel is measured as follows:

$$S(y, y') = \sum_c \left(\frac{1}{H}\left(tr\left(y_c \,.\, y'^{T}_{c}\right) + \frac{1}{W}\left(tr\left(y_c^T \,.\, y'_c\right)\right)\right)\right),$$

where y represents ground truth mask of size H X W, y' represents predicted mask, tr (.) represents trace of a matrix and subscript c represents each image channel.

$$L_{GP}(y, y') = argmin \ - S(\nabla y, \nabla y').$$

Model	Backbone	Loss Functions	Sea Surface	Oil Spill	Look-Alike	Ship	Land	Mean intersection over union (mIoU)
UNet	Resnet-101	Cross Entropy	93.90%	53.79%	39.55%	44.93%	92.68%	64.97%
UNet	Resnet-101	Gradinet Profile + Focal + Jaccard	96.00%	63.95%	60.87%	74.61%	96.81%	**78.45%**
DeepLabv3+	Mobilenetv2	Cross Entropy	96.43%	53.38%	55.40%	27.63%	92.44%	65.06%
DeepLabv3+	Mobilenetv2	Gradinet Profile + Focal + Jaccard	96.00%	53.84%	59.34%	70.73%	97.29%	75.44%

Comparison of classification results with the state of the art assessed over the test SAR images in terms of the intersection over union (IoU) score.

A. Basit, M. A. Siddique, M. K. Bhatti, and M. S. Sarfraz, “Comparison of CNNs and Vision Transformers-Based Hybrid Models Using Gradient Profile Loss for Classification of Oil Spills in SAR Images,” Remote Sensing, vol. 14, no. 9, p. 2085, Apr. 2022.

ABLATION STUDIES » RESNET backbones

Ablation on different ResNet backbones and different loss functions, evaluated over the test SAR images in terms of the IoU and $F1$ scores.

Row	UNet Backbone	Loss Functions	Trainable Parameters	Sea Surface	Oil Spill	Look-Alike	Ship	Land	mIoU	F_1 Score
1	Resnet50	Jaccard + focal	32.5 M	95.28%	59.51%	**61.18%**	71.88%	95.17%	76.60%	80.83%
2	Resnet50	GP + Jaccard + focal	32.5 M	95.71%	62.76%	59.50%	72.08%	97.50%	77.51%	81.50%
3	Resnet101	Jaccard + focal	51.5 M	95.19%	58.85%	60.93%	73.07%	94.54%	76.52%	80.42%
4	Resnet101	GP + Jaccard + focal	51.5 M	**96%**	**63.95%**	60.87%	**74.61%**	96.81%	**78.45%**	**82.47%**
5	Resnet152	Jaccard + focal	67.1 M	95.04%	58.35%	54.64%	71.96%	**98.02%**	75.60%	79.49%
6	Resnet152	GP + Jaccard + focal	67.1 M	95.98%	62.10%	62.05%	72.87%	97.66%	78.13%	82.03%

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A. Basit, M. A. Siddique, M. K. Bhatti, and M. S. Sarfraz, “Comparison of CNNs and Vision Transformers-Based Hybrid Models Using Gradient Profile Loss for Classification of Oil Spills in SAR Images,” Remote Sensing, vol. 14, no. 9, p. 2085, Apr. 2022.

Ablation studies » efficientnetv2 backbones

Row	Model	Loss Functions	Trainable Parameters	Sea Surface	Oil Spill	Look-Alike	Ship	Land	mIoU	F_1 Score
1	Small	Jaccard + focal	30.0 M	**95.39%**	51.81%	59.86%	69.09%	95.95%	74.42%	78.02%
2	Small	GP + Jaccard + focal	30.0 M	94.91%	55.10%	61.17%	**73.81%**	**97.01%**	76.40%	80.36%
3	B0	Jaccard + focal	15.7 M	94.45%	50.63%	**63.32%**	23.82%	90.96%	64.64%	68.61%
4	B0	GP + Jaccard + focal	15.7 M	95.09%	54.03%	! 60.40%	70.47%	96.38%	75.27%	79.26%
5	B1	Jaccard + focal	16.7 M	94.97%	51.98%	62.00%	69.09%	95.33%	74.67%	78.39%
6	B1	GP + Jaccard + focal	16.7 M	95.19%	**56.42%**	62.23%	72.80%	96.59%	**76.65%**	**80.85%**
7	B2	Jaccard + focal	19.2 M	94.91%	52.16%	61.88%	69.09%	95.64%	74.74%	78.59%
8	B2	GP + Jaccard + focal	19.2 M	95.32%	55.40%	! 61.75%	70.95%	96.85%	76.05%	80.08%
9	B3	Jaccard + focal	24.1 M	94.79%	51.67%	59.53%	71.18%	95.78%	74.59%	78.73%
10	B3	GP + Jaccard + focal	24.1 M	94.69%	53.91%	62.12%	69.09%	96.62%	75.29%	79.06%

A. Basit, M. A. Siddique, M. K. Bhatti, and M. S. Sarfraz, “Comparison of CNNs and Vision Transformers-Based Hybrid Models Using Gradient Profile Loss for Classification of Oil Spills in SAR Images,” Remote Sensing, vol. 14, no. 9, p. 2085, Apr. 2022.

Ablation studies » CNNs+ViTs hybrid models

Row	Model	Loss Functions	Trainable Parameters	Sea Surface	Oil Spill	Look-Alike	Ship	Land	mIoU	F_1 Score
1	CMTTiny	Jaccard + focal	18.0 M	94.98%	43.57%	**59.95%**	46.01%	91.30%	67.16%	70.82%
2	CMTTiny	GP + Jaccard + focal	18.0 M	94.71%	50.06%	57.54%	69.09%	90.77%	72.43%	76.10%
3	CMTXS	Jaccard + focal	23.8 M	93.11%	26.66%	54.47%	13.23%	89.49%	55.39%	58.39%
4	CMTXS	GP + Jaccard + focal	23.8 M	**95.50%**	**51.40%**	58.95%	64.49%	93.27%	72.72%	76.78%
5	CMTSmall	Jaccard + focal	34.6 M	90.15%	12.86%	40.16%	16.73%	45.07%	41.00%	43.43%
6	CMTSmall	GP + Jaccard + focal	34.6 M	95.02%	33.14%	56.98%	69.09%	68.26%	64.50%	67.29%
7	CoAtNet-0	Jaccard + focal	29.4 M	92.53%	41.03%	55.02%	54.22%	92.20%	67.00%	70.77%
8	CoAtNet-0	GP + Jaccard + focal	29.4 M	95.40%	50.22%	58.85%	**69.09%**	**94.49%**	**73.61%**	**77.00%**

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A. Basit, M. A. Siddique, M. K. Bhatti, and M. S. Sarfraz, "Comparison of CNNs and Vision Transformers-Based Hybrid Models Using Gradient Profile Loss for Classification of Oil Spills in SAR Images," Remote Sensing, vol. 14, no. 9, p. 2085, Apr. 2022.

Comparison

Table: Comparison of the proposed classification framework with state-of-the-art classification methods based on SAR images in terms of the SAR datasets, number of classes, mIoU, and F1 scores.

Row	Related Work	mIoU Score	F_1 Score	Oil Spill Dataset	Number of Classes
1	Shaban et al. [31]	-	80.00%	MKLab ITI-CERTH, Greece.	2: Oil spills and lookalikes.
2	Fan et al. [32]	61.90%	-	MKLab ITI-CERTH, Greece.	5: Sea surface, oil spills, lookalikes, ship and land.
3	Krestenitis et al. [28]	65.06%	-	MKLab ITI-CERTH, Greece.	5: Sea surface, oil spills, lookalikes, ship and land.
4	Hidalgo et al. [34]	-	71.00%	Spanish Maritime Safety and Rescue Agency (SASEMAR).	3: Oil spills, ship and land.
5	Zeng et al. [35]	-	**84.59%**	ORSI, Ocean University of China.	2: Oil spills and lookalikes.
6	**Proposed methodology**	**78.45%**	82.47%	MKLab ITI-CERTH, Greece.	5: Sea surface, oil spills, lookalikes, ship and land.

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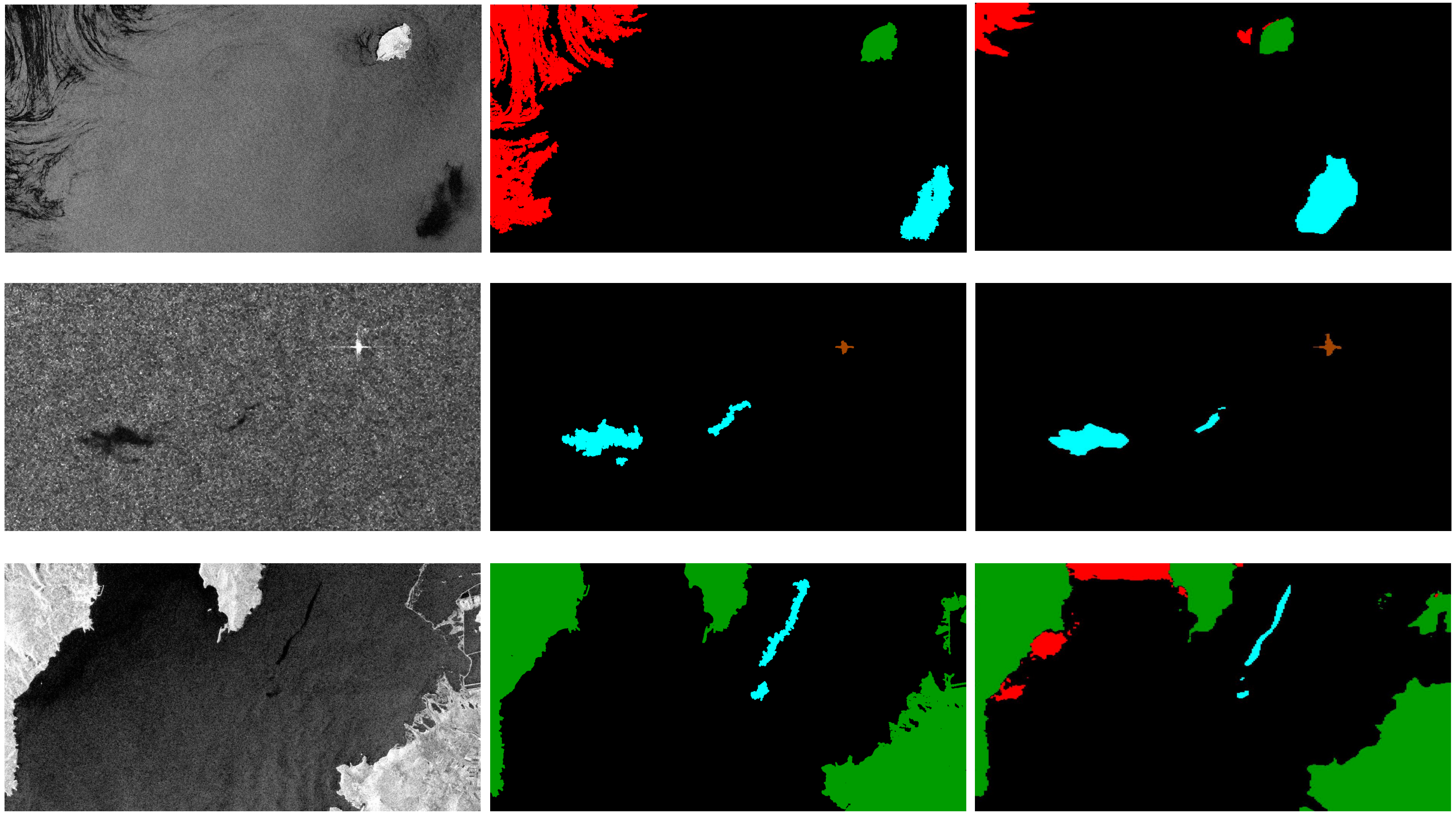
A. Basit, M. A. Siddique, M. K. Bhatti, and M. S. Sarfraz, “Comparison of CNNs and Vision Transformers-Based Hybrid Models Using Gradient Profile Loss for Classification of Oil Spills in SAR Images,” Remote Sensing, vol. 14, no. 9, p. 2085, Apr. 2022.

Qualitative comparison

A set of 3 SAR images along with their ground truth masks and predicted class labels:

- Row#1: The model accurately classified oil spill and land area. Some look-alikes are wrongly classified as sea surface.
- Row#2: The model accurately classified two oil spill patches and a nearby ship.
- Row#3: The model accurately classified oil spill and land area. Some look-alikes are detected that are not labeled in the ground truth. It corresponds to a labelling error that will be removed in our future work.



SAR images   Ground truth mask   Predicted mask

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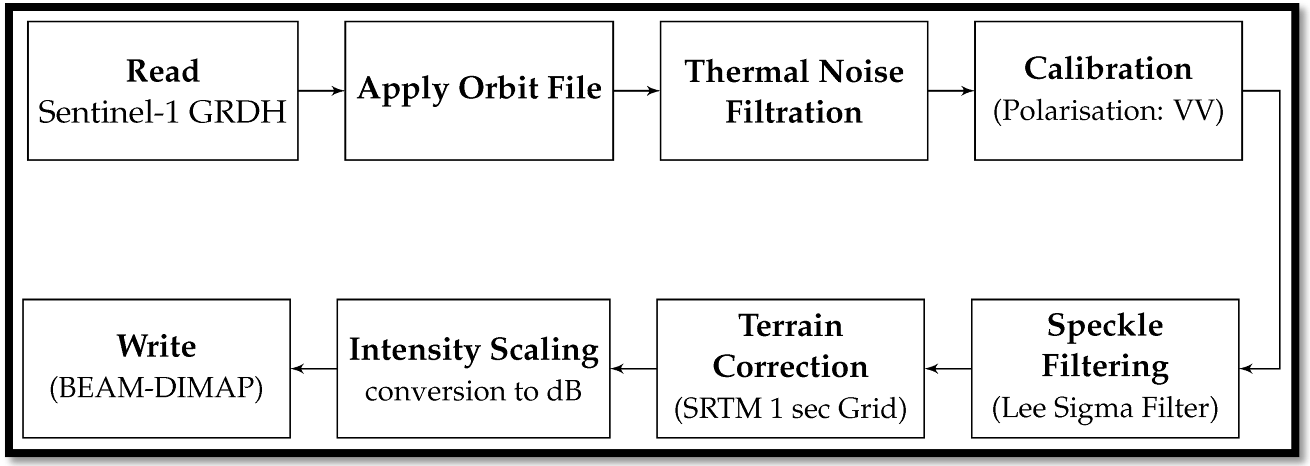
Testing in Arabian Sea?

- This is end goal, and as such, it’s not trivial!

- Having trained the deep learning model on a dataset of verified spills—and exceeding the performance benchmark by nearly 13%—we are assured that the model could be reliably used to detect oil spills in unseen data from the same sensor, processed similarly to the benchmark training data.

Data Preparation

- Sentinel-1 Ground Range Detected High-resolution (GRDH) imagery over Pakistan's EEZ, available from the Copernicus Open Access Hub, for the duration January 2017–December 2023.
  - IW mode, with a grid spacing of 10 m, resolution of [**20 x 22 m**]
  - The data were dual-polarized, i.e., VV and VH, but we retained only VV polarization (as for the training dataset).
- The images were radiometrically calibrated and a 7 × 7 median filter was applied, to reduce speckle.
- A patch size of 320 × 320 was used for testing.



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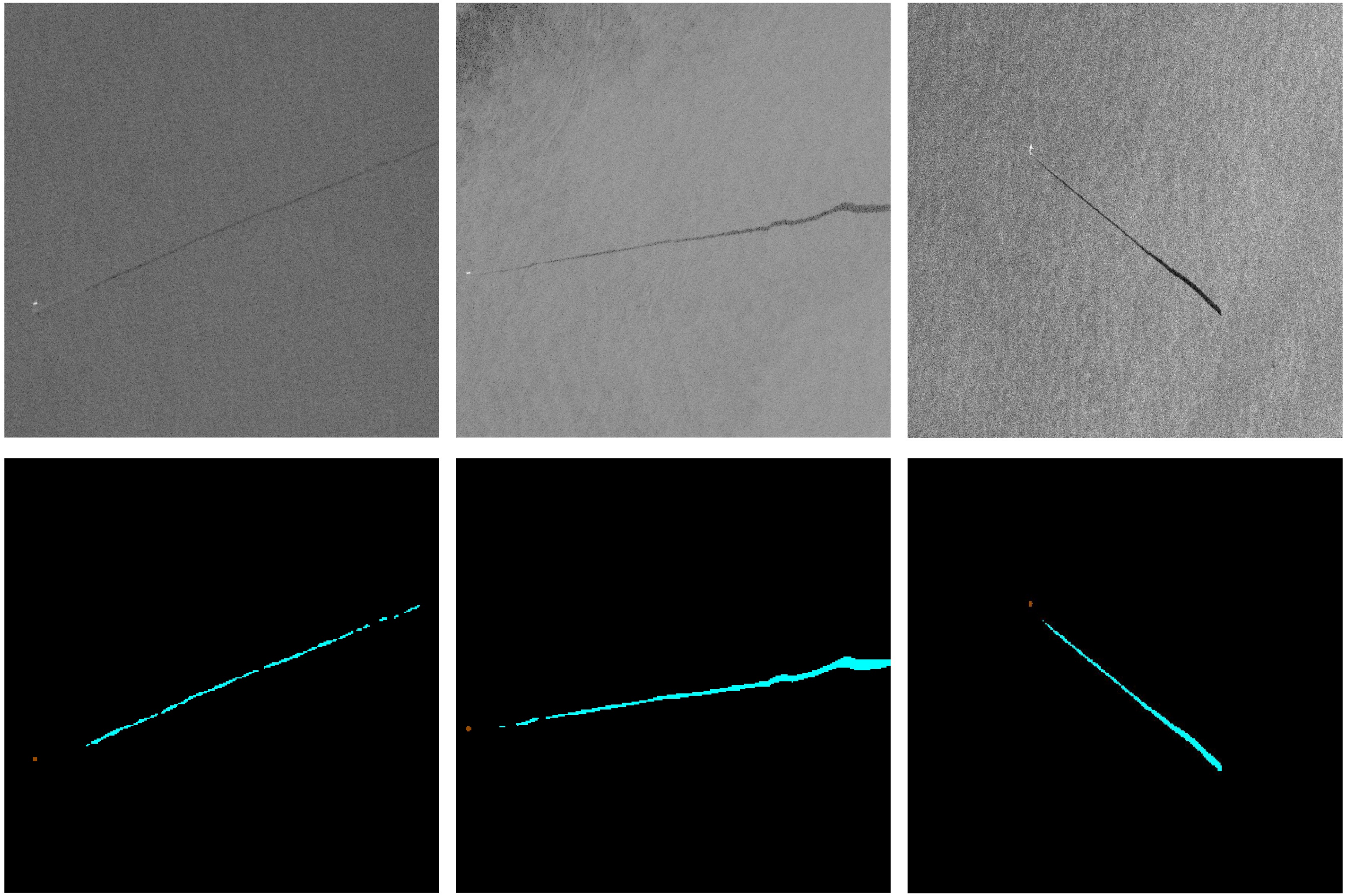
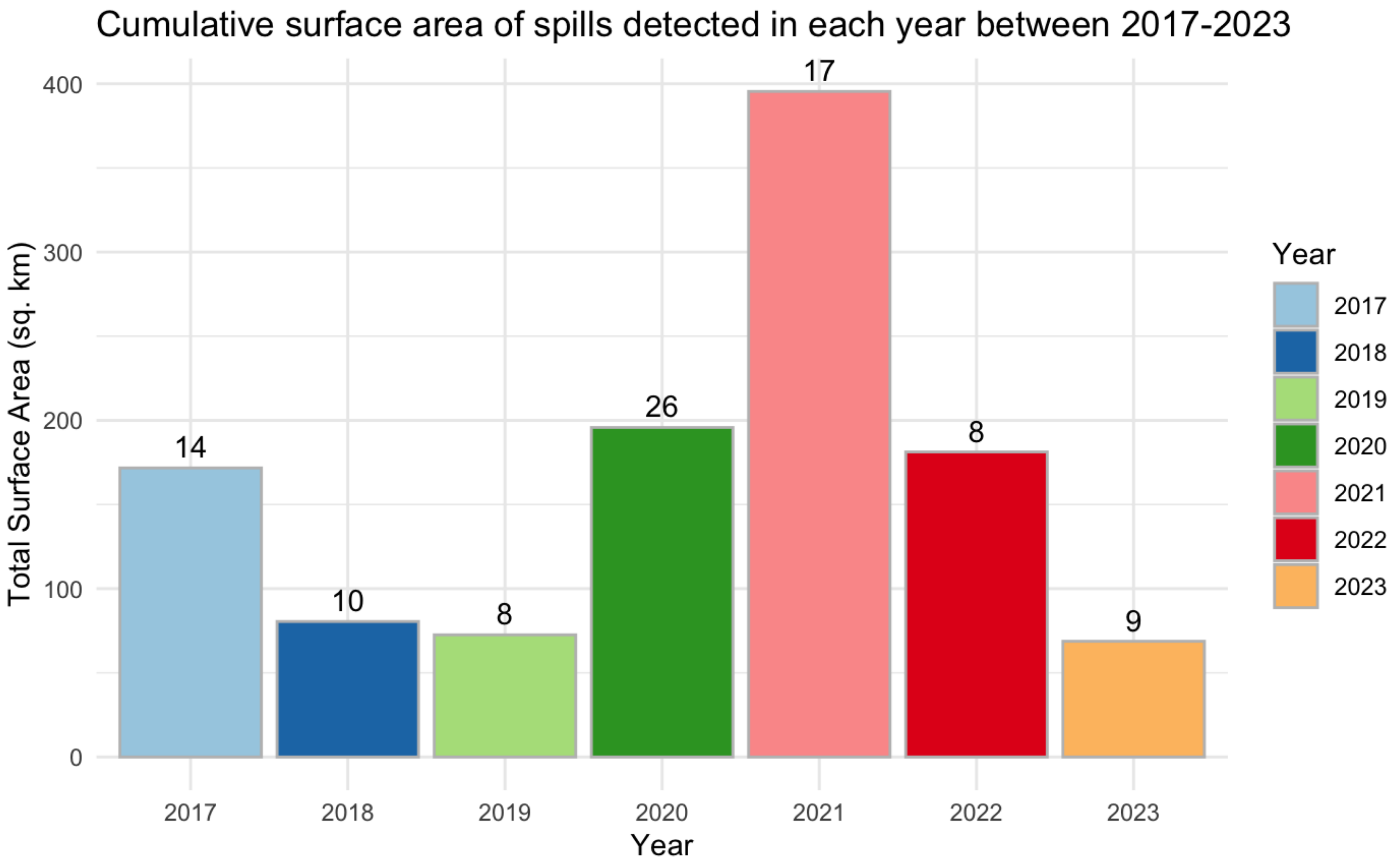
TESTING

Three SAR images (top row) from the test set prepared by acquiring imagery over the Arabian sea along with predicted class labels (bottom row) containing potential oil spills in Pakistan territorial waters. Black color shows sea surface, cyan color shows oil spill and brown color shows ships.



Results

- 92 oil spills detected
- 1162 sq. km area affected in total!



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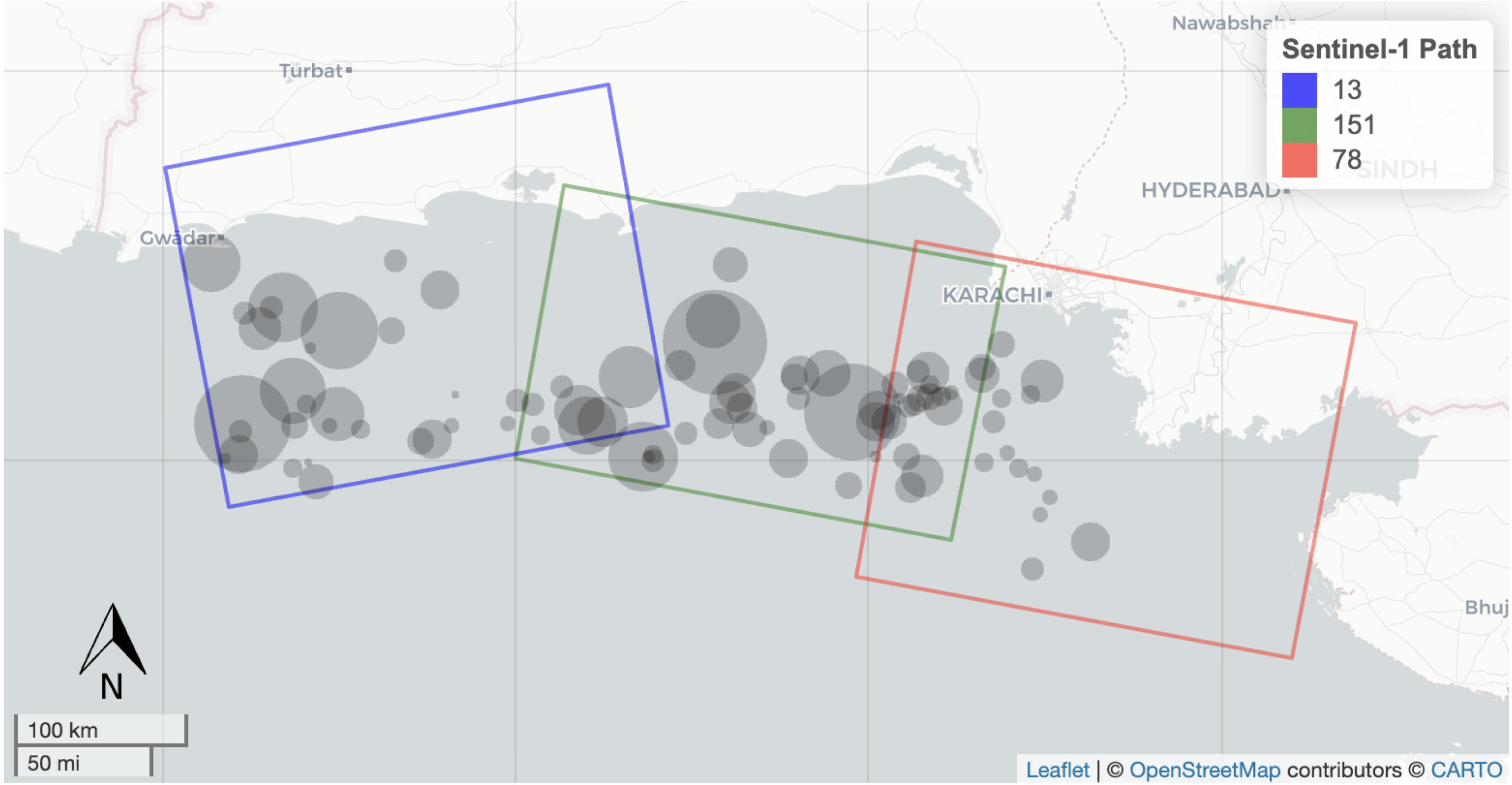
Results



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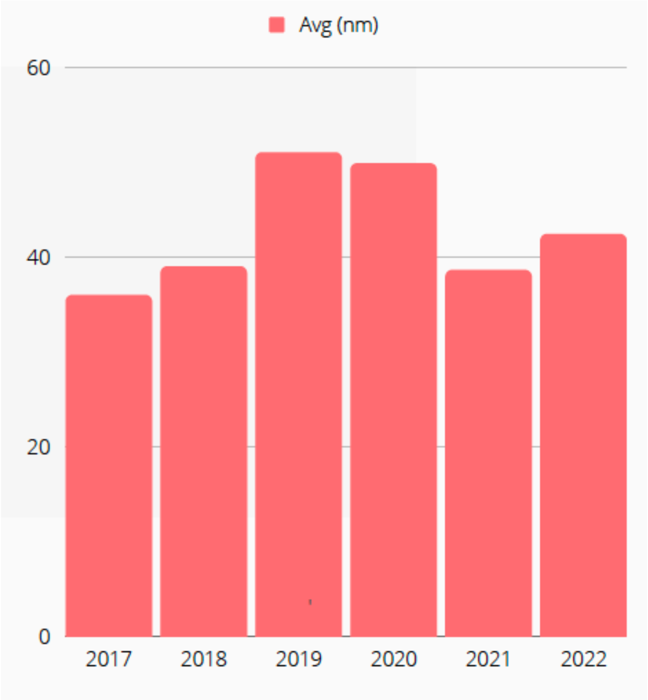
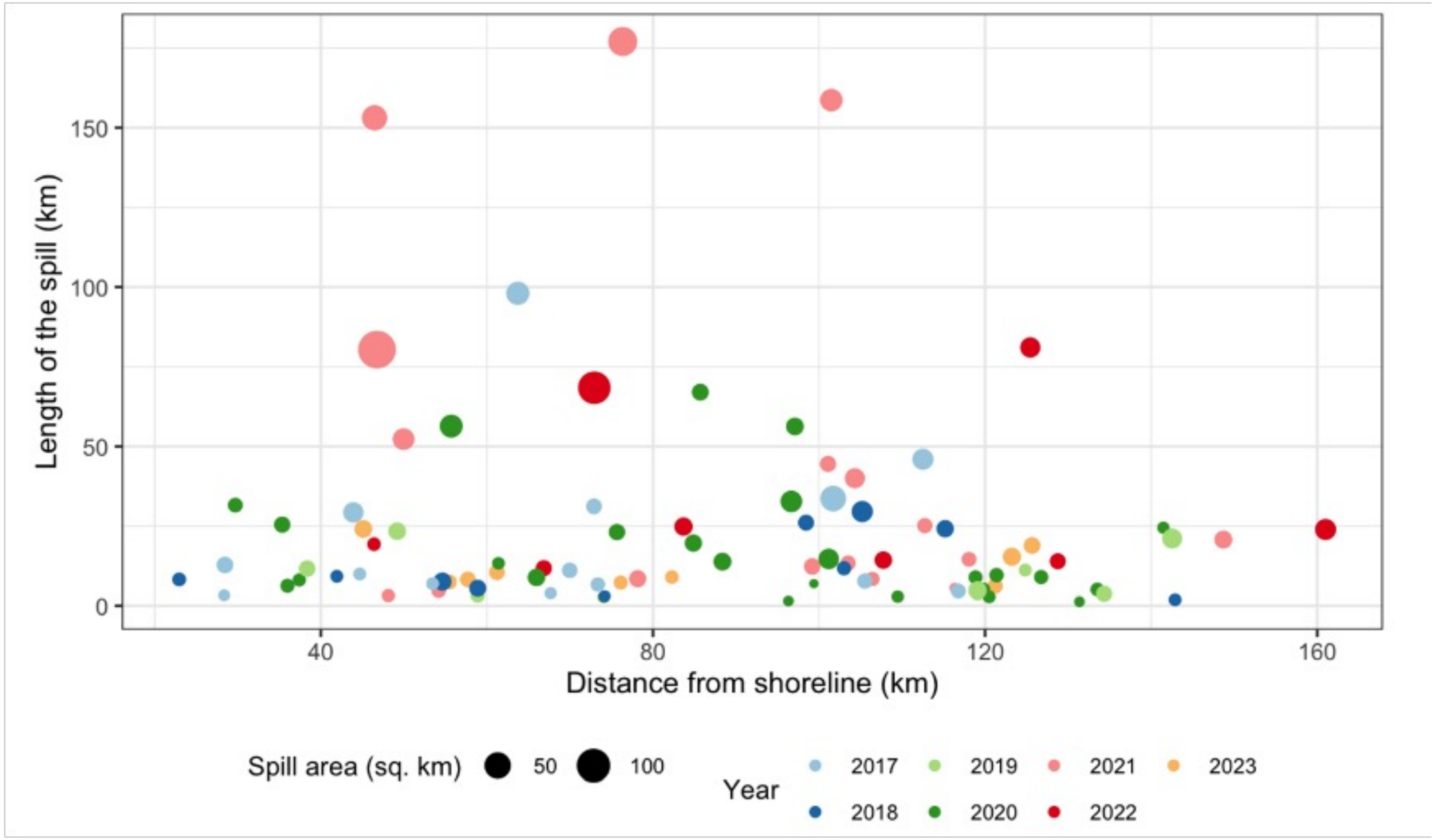
Results

Average Distance From Coast





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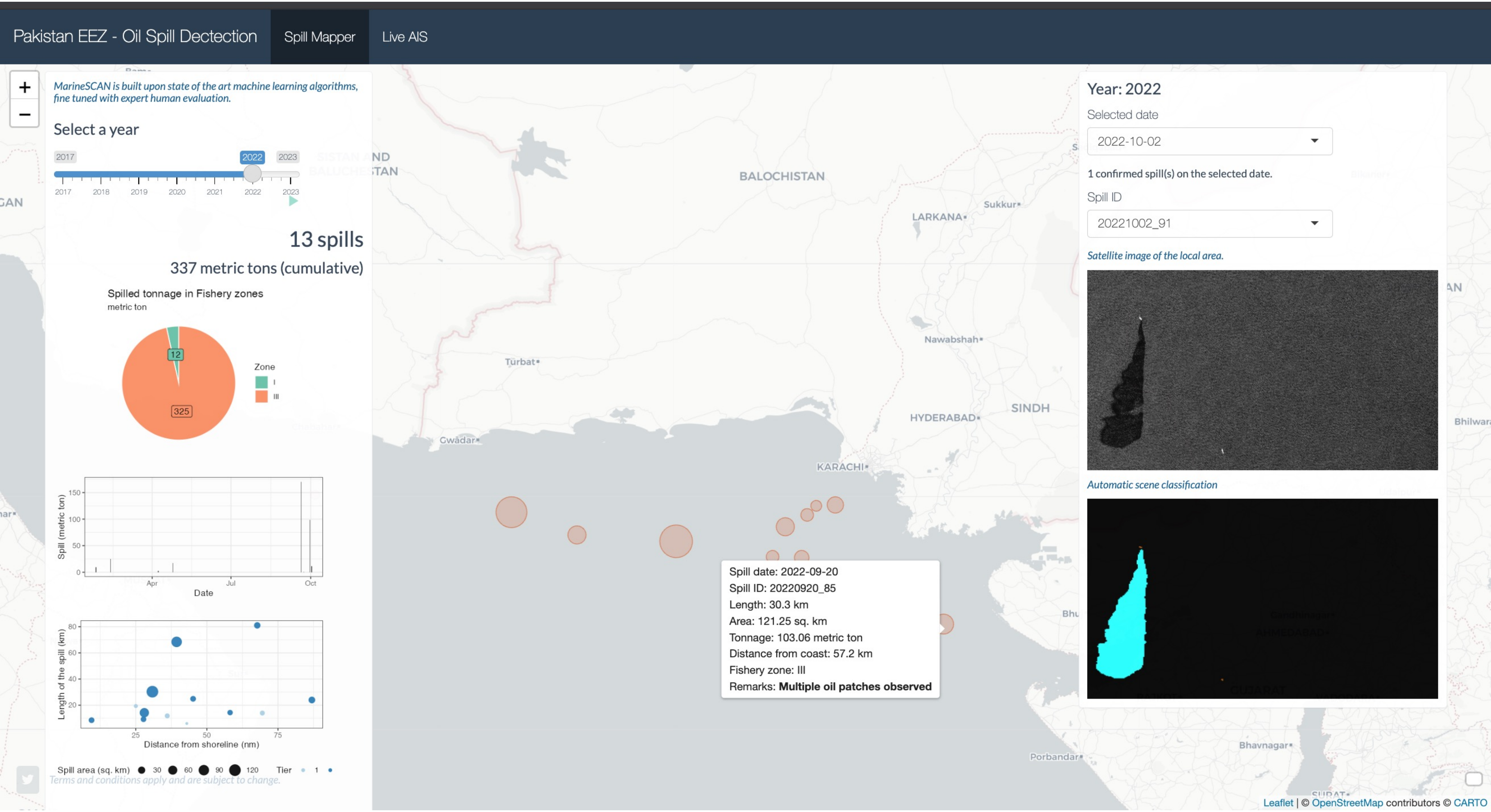
Pakistan EEZ - Oil Spill Dectection
Spill Mapper
Live AIS
MarineSCAN is built upon state of the art machine learning algorithms, fine tuned with expert human evaluation.
Select a year
2017
2022
2023
2017 2018 2019 2020 2021 2022 2023
13 spills
337 metric tons (cumulative)
Spilled tonnage in Fishery zones
metric ton
12
325
Zone
I
III
Spill (metric ton)
Date
Apr
Jul
Oct
Length of the spill (km)
Distance from shoreline (nm)
Spill area (sq. km)
30
60
90
120
Tier
1
Terms and conditions apply and are subject to change.
BALOCHISTAN
LARKANA
Sukkur
Nawabshah
Turbat
Gwadar
HYDERABAD
SINDH
KARACHI
Porbandar
Bhavnagar
Spill date: 2022-09-20
Spill ID: 20220920_85
Length: 30.3 km
Area: 121.25 sq. km
Tonnage: 103.06 metric ton
Distance from coast: 57.2 km
Fishery zone: III
Remarks: Multiple oil patches observed
Year: 2022
Selected date
2022-10-02
1 confirmed spill(s) on the selected date.
Spill ID
20221002_91
Satellite image of the local area.
Automatic scene classification
Leaflet | © OpenStreetMap contributors © CARTO

DATASETS

RSA Lab – Datasets are shared publicly

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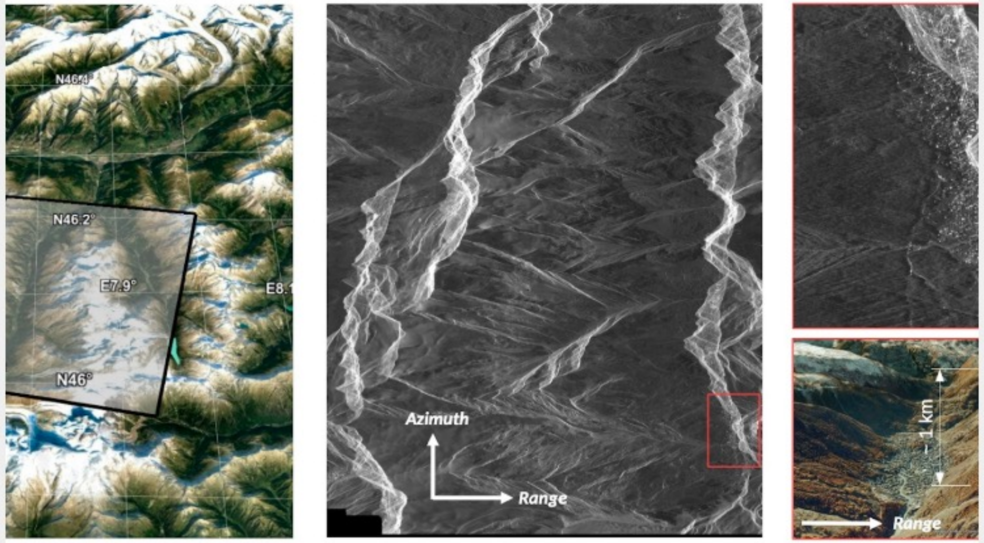


HKH-PK-2020

Glacial Lake Inventory of the Hindu Kush-Himalaya (Pakistan)

PlanetScope Imagery

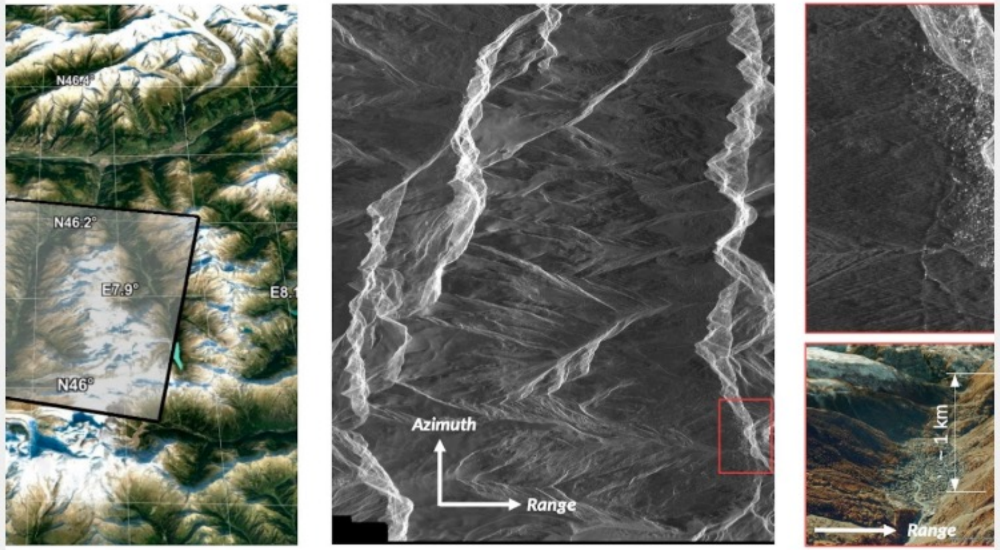
About the dataset

This dataset contains 8,808 glacial lake boundaries (total area: ~136 km²) mapped from PlanetScope satellite imagery (September 2020) across the Hindu Kush-Himalaya (HKH) region of Pakistan. The lakes were delineated manually with careful inspection, as part of a broader effort to monitor cryospheric hazards (e.g., GLOF risks) in the HKH. This work is supported by the National Geographic Society and Microsoft through its "AI for Earth Innovation" program. The imagery used in this work is a Planet Labs product - 2023 PBC., and has been accessed freely under their education and research support program. The inventory is provided as ESRI shapefiles (inside a zipped folder). The CRS is EPSG:4326. The column "Shape_Area" in the attributes table provides lake areas in square meters.

Funded by: National Geographic Society

Download Data

To download the dataset, please visit https://zenodo.org/records/15476013



Glacial Lakes

Glacial Lakes Detection Dataset

Sentinel-2 True Color Imagery

About the dataset

Glacial lake outburst floods (GLOFs) are a major threat to the local communities and important infrastructures in the high mountain regions. Early detection of glacial lakes can prevent these disastrous events. Towards this end, we collected Sentinel 2 true color scenes of High-Mountain Asia (HMA) region using glacial lakes inventory of this region. It covers an area of 2080.12 km^2 with nearly 30,121 glacial lakes. After data collection, we retained 1200 cloud free true color images and manually generated their ground truth masks. The train and test sets contain 1000 and 200 images, respectively. The dataset covers lakes with different shapes, sizes and radiometric signatures.

Funded by: National Geographic Society and Microsoft

Download Data

To download the dataset, please visit https://ieee-dataport.org/documents/glacial-lakes-detection-dataset

IEEE Geoscience & Remote Sensing Society (GRSS)

REACT + Lahore Chapter

Remote Sensing & Spatial Analytics

REACT

- Remote sensing: Environment, Analysis & Climate Technologies
  - A technical committee of the IEEE Geoscience & Remote Sensing Society (GRSS)

- It aims at advancing science, defining requirements for science driven mission concepts and data products in the domain of
  - Cryosphere, Biosphere, Hydrosphere, Atmosphere and Geosphere.

- REACT contributes to mutliple UN Sustainable Development Goals (SDGs)

Remote Sensing & Spatial Analytics

GRSS - REACT

- Remote sensing Environment, Analysis and Climate Technologies (REACT)

MISSION

The **R**emote sensing **E**nvironment, **A**nalysis and **C**limate **T**echnologies **T**echnical **C**ommittee (REACT TC) is a venue for all scientists and engineers in the domain of environment and the impact on the environment due to climate change forcing in order to exchange ideas and share knowledge. It aims at advancing science, defining requirements for science driven mission concepts and data products in the domain of Cryosphere, Biosphere, Hydrosphere, Atmosphere and Geosphere.

JOIN REACT

- Local Focus Area:
  - Cryosphere and related hazards in HKH

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GRSS Lahore Chapter

- Opportunities for everyone!
  - … from professors to students, to industry professionals, etc.

- Become a member!
  - IEEE student membership for Pakistan: $7.00 / $13.50 (graduate students)

Essential Package	Preferred Package
Price:*	**Price:***
IEEE member: US$15.00	IEEE member: US$45.00
IEEE student: US$1.00	IEEE student: US$15.00
Non-IEEE member: US$103.00	Non-IEEE member: US$133.00

THANK YOU

Q&A

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