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Credit: Guilhem Banc-Prandi

Remote sensing enables monitoring life above and under water

Devis Tuia

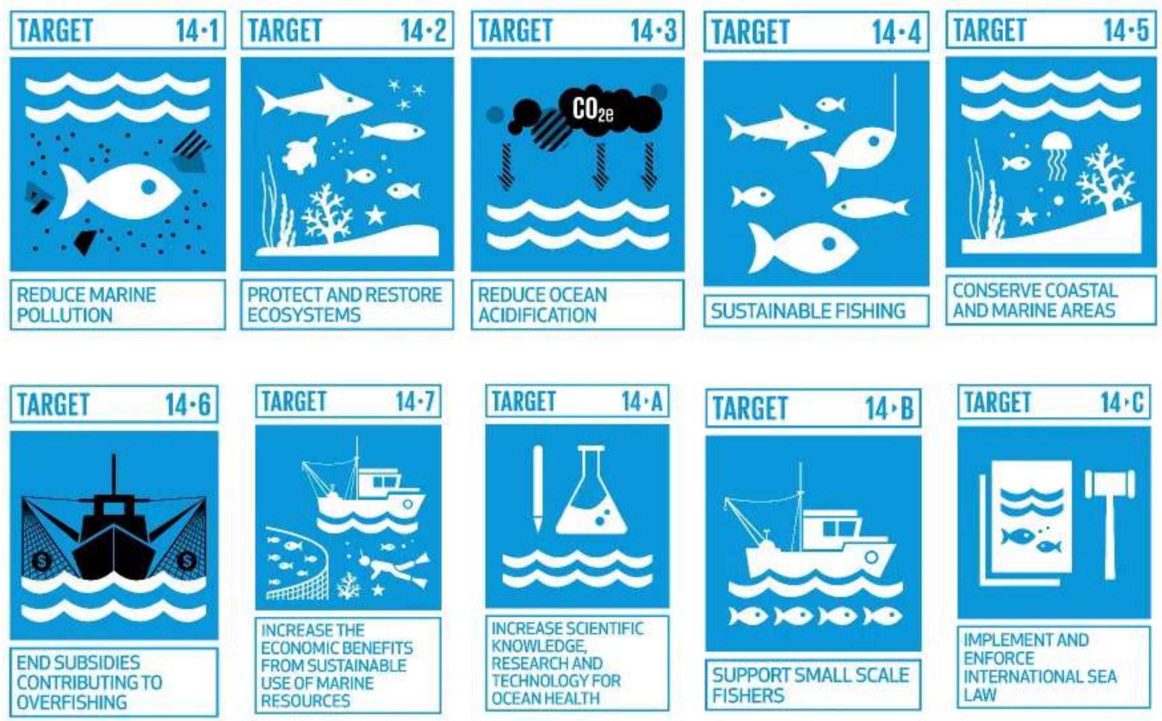
ECEO laboratory

EPFL

ITU AI for Good, May 2023

École polytechnique fédérale de Lausanne

Today we talk about life above and under water.



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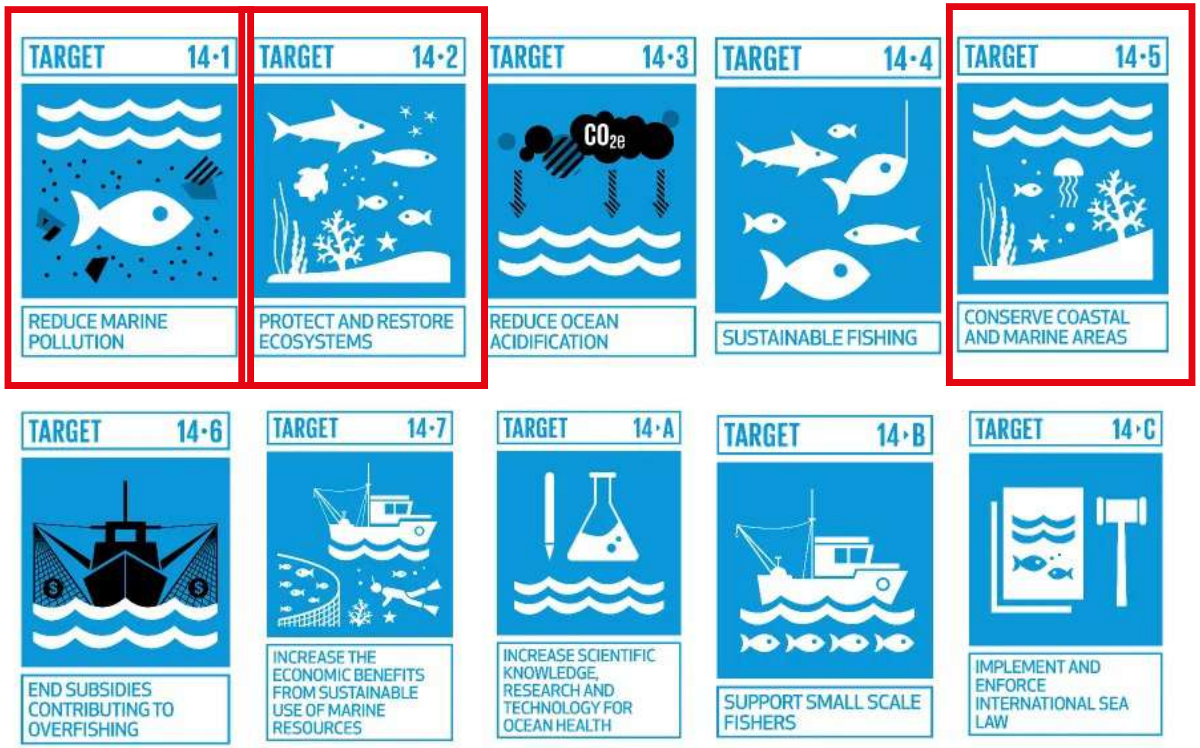
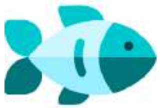


Why is that important?

The health of oceans is tied to the health of our planet (and ours).



- Food: 3 billion people rely on fresh seafood as main source of proteins, sustainable fishing is key.

- Health: The fish we eat should not be contamined with microplastics!

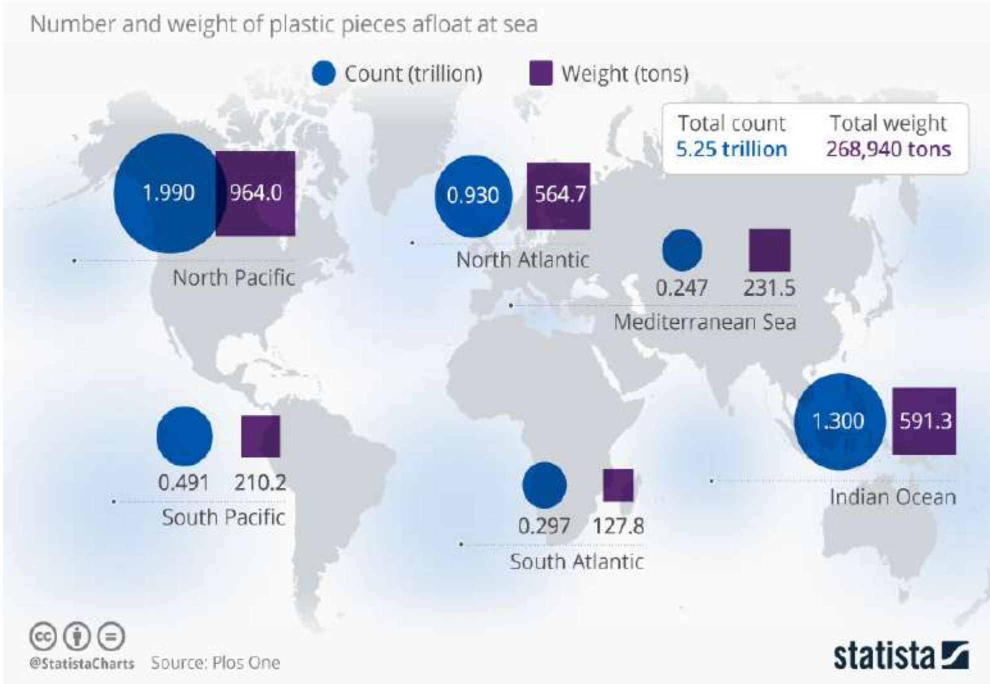
- Biodiversity: Coral reefs cover only 0.1% of oceans, but host 25% of all marine life. If too many coral die, entire marine ecosystems will disappear.

- Protection: Coral reefs protect coastlines from erosion and storms, and support tourism and its revenue to local population.

Source: wwf

Despite of this...

- In 50 years, we have lost half our corals.
- Oceans are infested with plastic waste.



Credit: Guilhem Banc-Prandi

A talk in two parts

Part I
Above waters

Part II
Below waters

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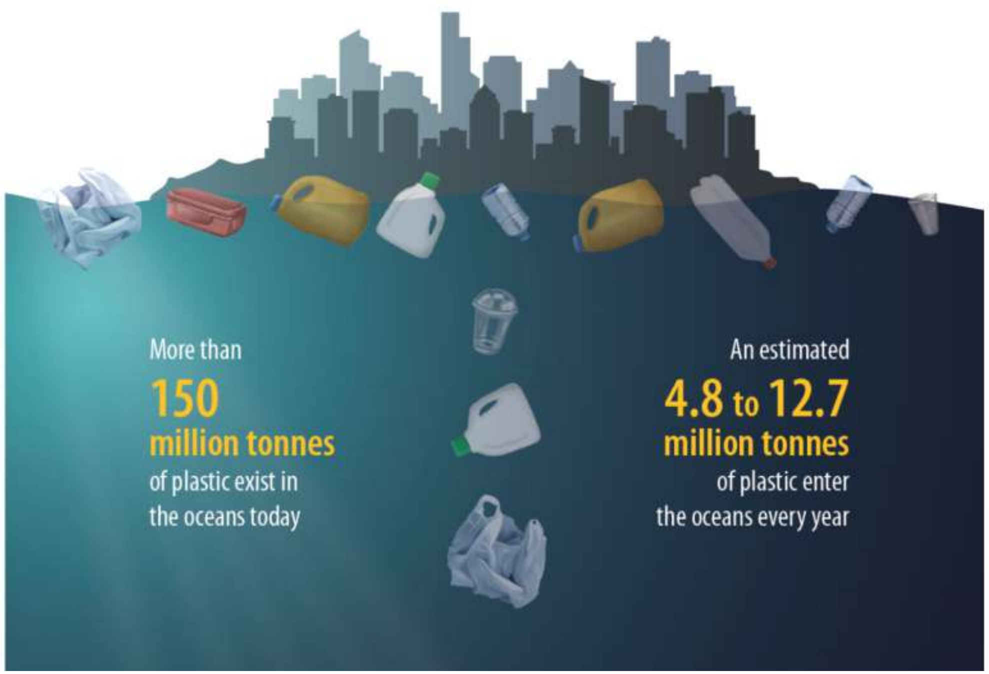
Source: the New Yorker

Part I

Above waters

Detecting marine litter from space

Marine litter is a BIG problem



Macro-plastics decompose in microplastics that are

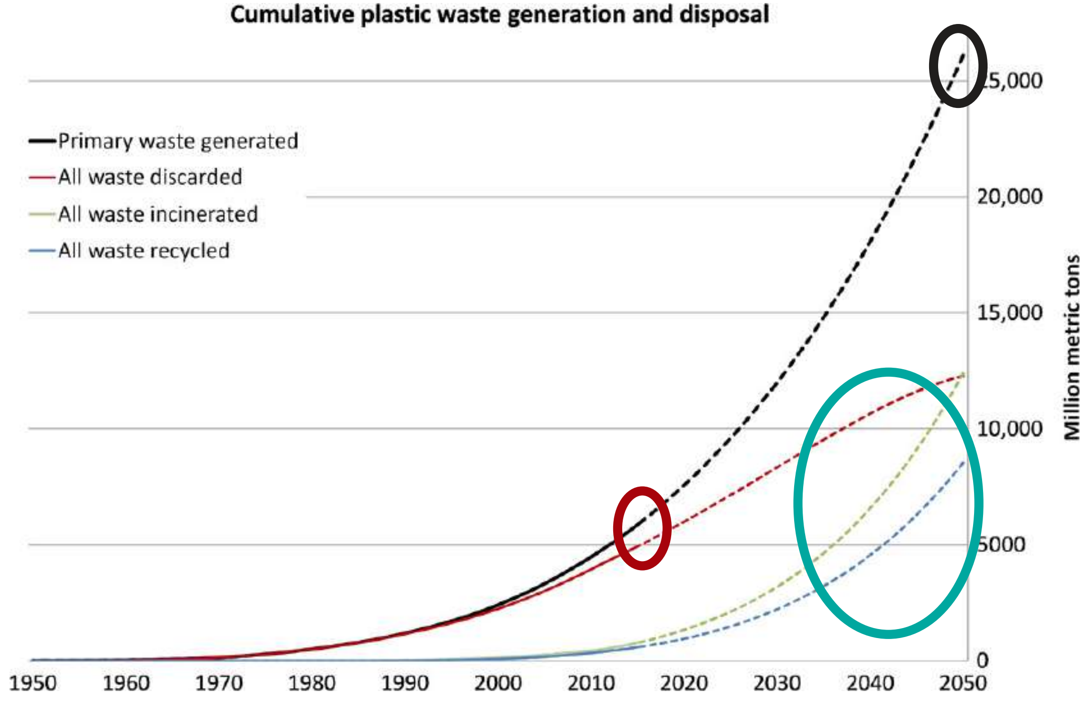
- a direct danger to animals

- have been found in
    - Antarctic Penguins
    - deep-sea sediments
    - human stool
    - …

with unclear and potentially harmful impact on human health

Recycling is going better, but...

- Usage of plastics is expected to increase
- Today a majority is discarded
- Incineration and recycling expected to increase



Geyer, R., Jambeck, J. R., & Law, K. L. (2017). Production, use, and fate of all plastics ever made. *Science advances*, *3*(7), e1700782.

Detecting Marine litter

1) Marine litter permanently pollutes our environment and is a health risk (e.g. E.Coli)

Cuttings Beach, Durban (South Africa)
Image: Lisa Guastella

2) Single campaigns collect marine litter at small scale, e.g. [Ruiz et al., 2020]

Bay of Biscay, France
Image: Oihane Basurko

Ruiz, I., Basurko, O. C., Rubio, A., Delpey, M., Granado, I., Cózar, A. (2020). Litter windrows in the south-east coast of the Bay of Biscay: an ocean process enabling effective active fishing for litter. Frontiers in Marine Science, 7, 308.

Detection of Visible Marine Debris as Marine Litter proxy

Photo twitter @oihanecb

Oceanic processes aggregate debris on the water surface: **windrows**

2018:
16.2 tons in 68 working days collected plastic litter in the Bay of Biscay [Ruiz et al., 2020]

Windrows are **marine debris** that **may contain marine litter**

Ruiz, I., Basurko, O. C., Rubio, A., Delpey, M., Granado, I., Cózar, A. (2020). Litter windrows in the south-east coast of the Bay of Biscay: an ocean process enabling effective active fishing for litter. Frontiers in Marine Science, 7, 308.

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Detecting Marine litter at scale

1) Marine litter permanently pollutes our environment

Cuttings Beach, Durban (South Africa)
Image: Lisa Guastella

2) Single campaigns collect marine litter at small scale, e.g. [Ruiz et al., 2020]

Bay of Biscay, France
Image: Oihane Basurko

3) Lack of large-scale satellite-based detection methods limits collection efforts

even though

an abundance of satellite data is freely available:

Sentinel-2, PlanetScope

Mifdal, J., Longépé, N., and **Rußwurm, M.**: Towards detecting floating objects on a global scale with learned spatial features using Sentinel-2, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., V-3-2021, 285–293, https://doi.org/10.5194/isprs-annals-V-3-2021-285-2021, 2021.

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Detecting Marine litter at scale

D. Tuia, 2023

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marine litter at small scale, e.g. [Ruiz et al., 2020]

Bay of Biscay, France
Image: Oihane Basurko

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PlanetScope

How well can we

detect, map and monitor

marine litter from satellite data?

Mifdal, J., Longépé, N., and **Rußwurm, M.**: Towards detecting floating objects on a global scale with learned spatial features using Sentinel-2, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., V-3-2021, 285–293, https://doi.org/10.5194/isprs-annals-V-3-2021-285-2021, 2021.

Available Satellite Data

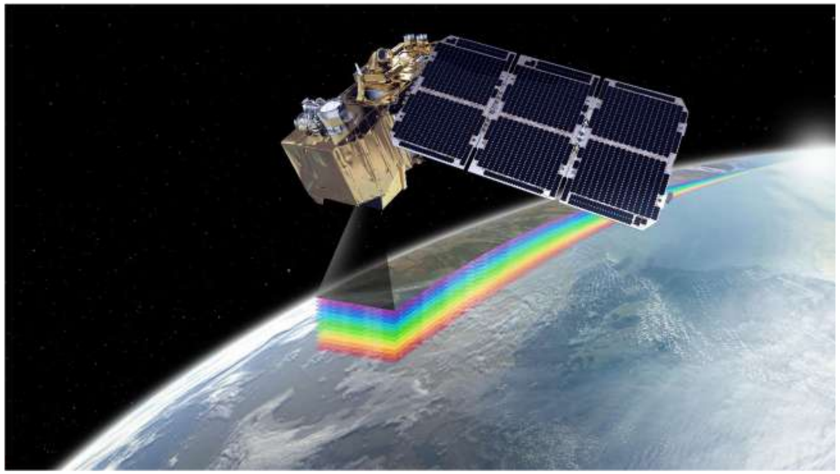
D. Tuia, 2023

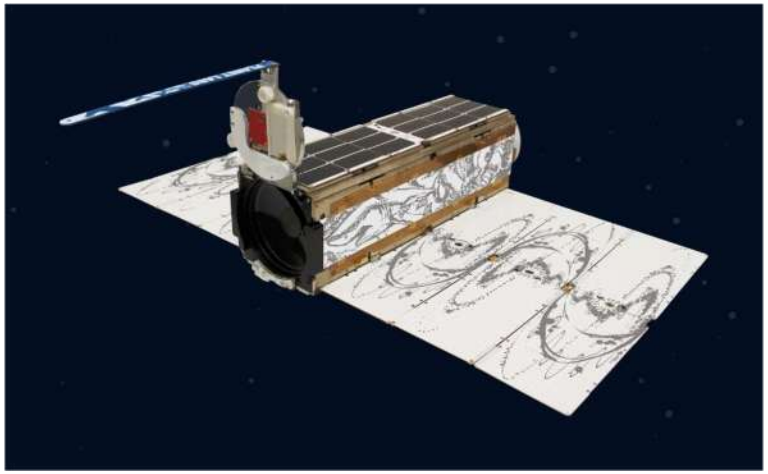
Sentinel-2

- 2 satellite constellation
- free of charge
- 12 spectral bands
- 10m pixel size
- every 2-5 days

PlanetScope Doves

- >160 satellites
- commercial (= $!)
- 4 spectral bands (RGB-IR)
- 3m pixel size
- every day





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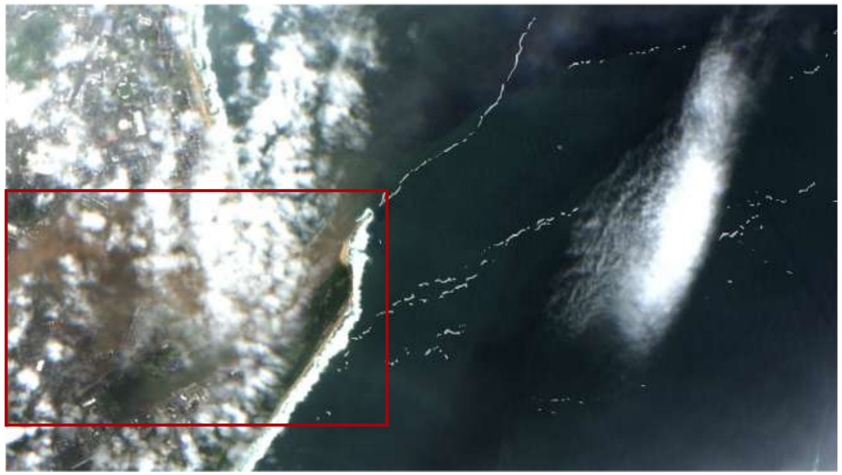

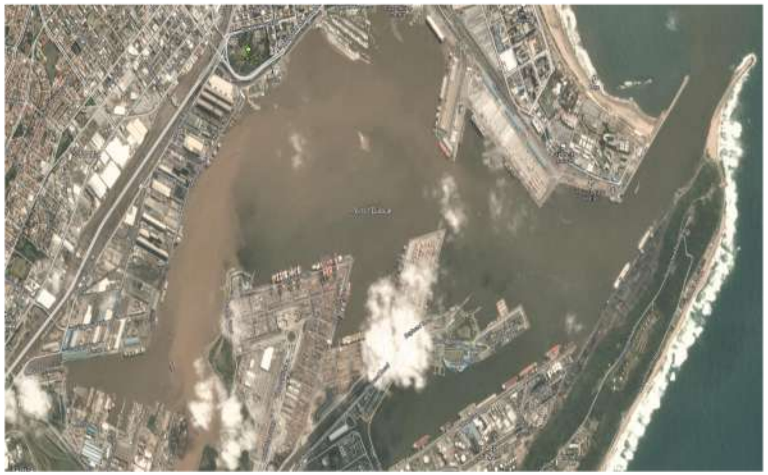

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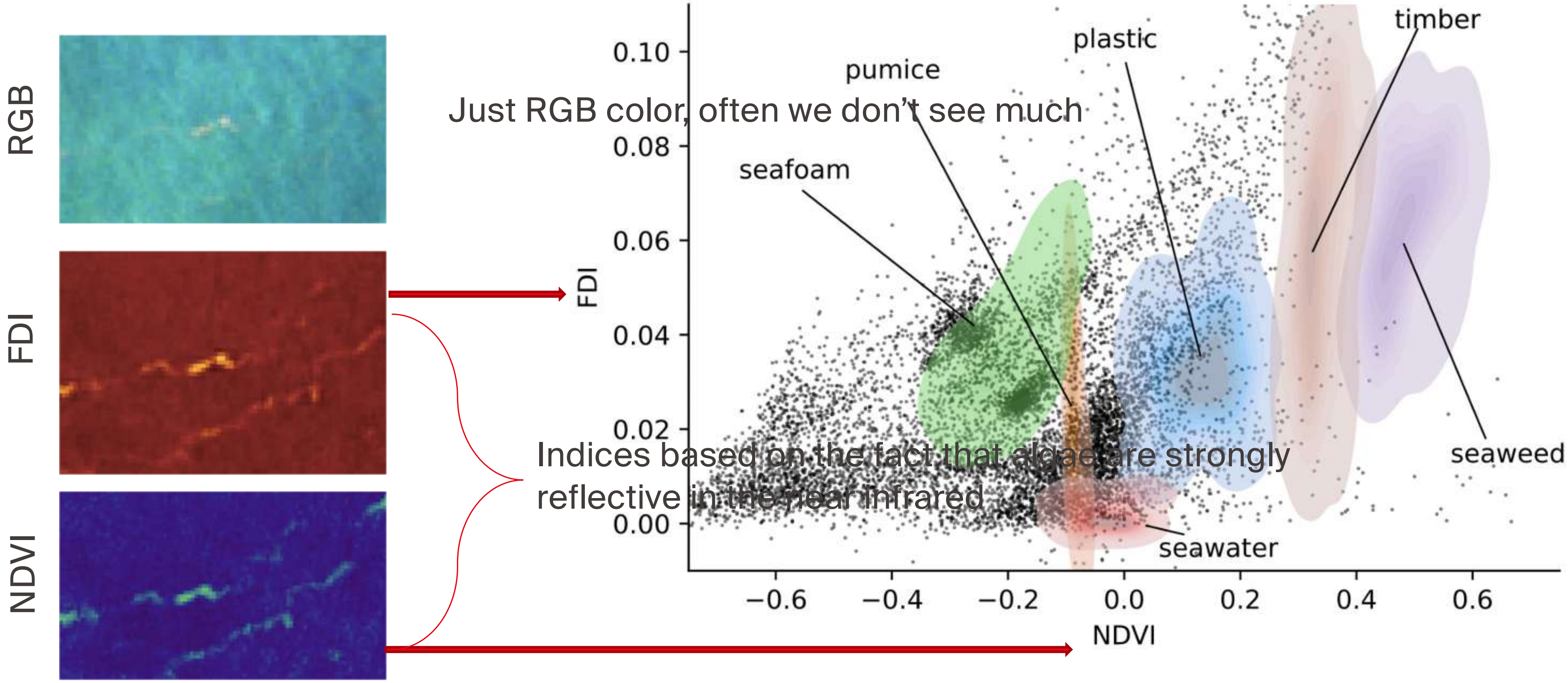
Spectral indices do not guarantee linear separability.



Just RGB color, often we don't see much

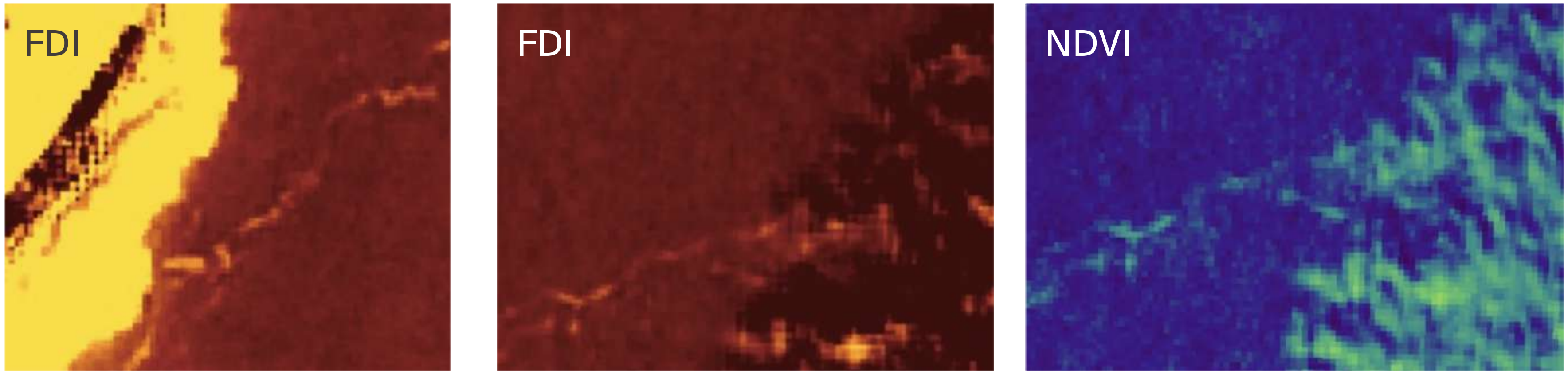
Indices based on the fact that algae are strongly reflective in the near infrared

Mifdal, J., Longépé, N., and **Rußwurm, M.**: Towards detecting floating objects on a global scale with learned spatial features using Sentinel-2, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., V-3-2021, 285–293, https://doi.org/10.5194/isprs-annals-V-3-2021-285-2021, 2021.

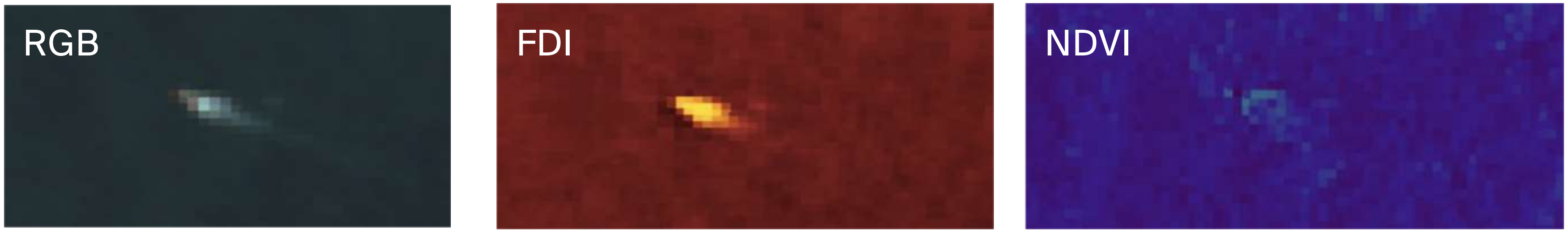
Indices sensitive also to

D. Tuia, 2023

coastline and sea spray clouds clouds

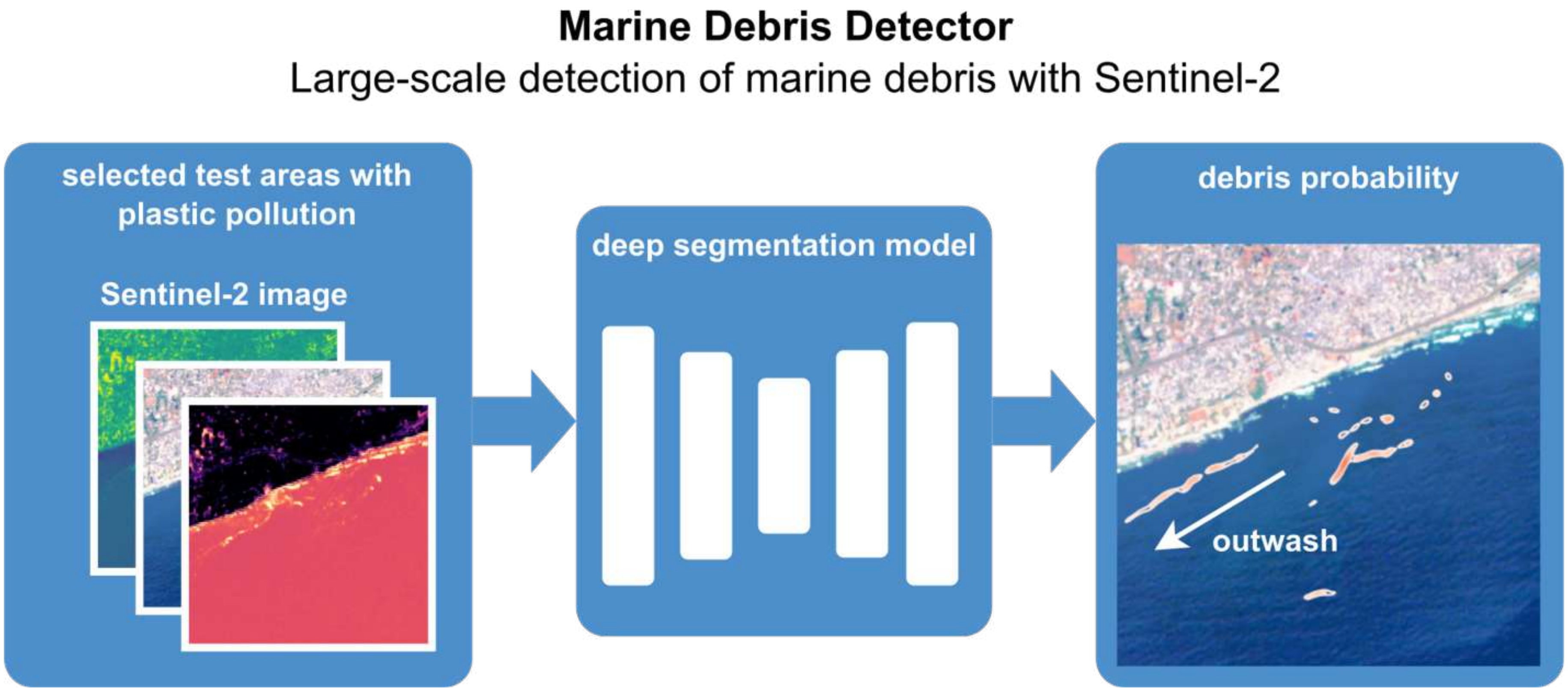


ships



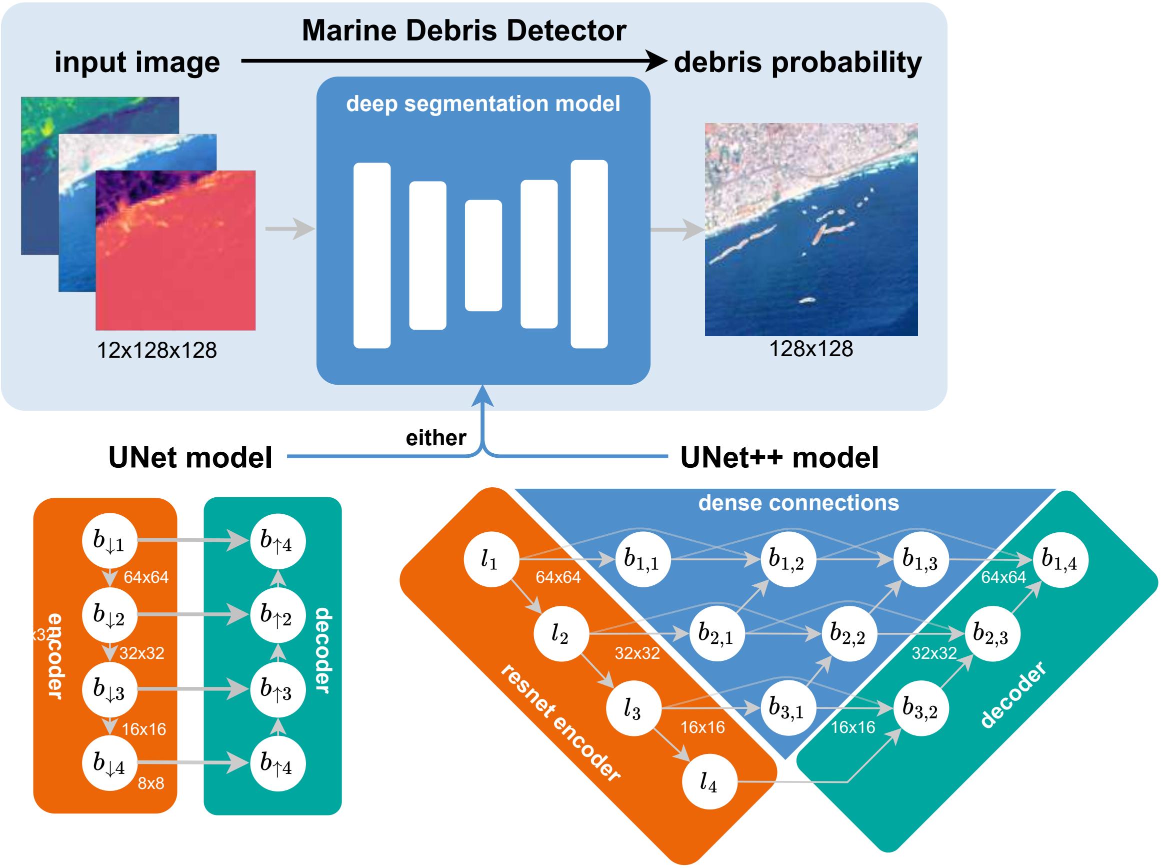
Indices are good for visualization, but pixel-wise classifiers on spectral indices are too simple

Learning to map debris with CNNs



M. Rußwurm, S. J. Venkatesa, and **D.Tuia**. Large-scale Detection of Marine Debris in Coastal Areas with Sentinel-2. *Under review*

Learning Spatial Context with CNNs



M. Rußwurm, S. J. Venkatesa, and D.Tuia. Large-scale Detection of Marine Debris in Coastal Areas with Sentinel-2. *Under review*

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Datasets

FloatingObjects Dataset

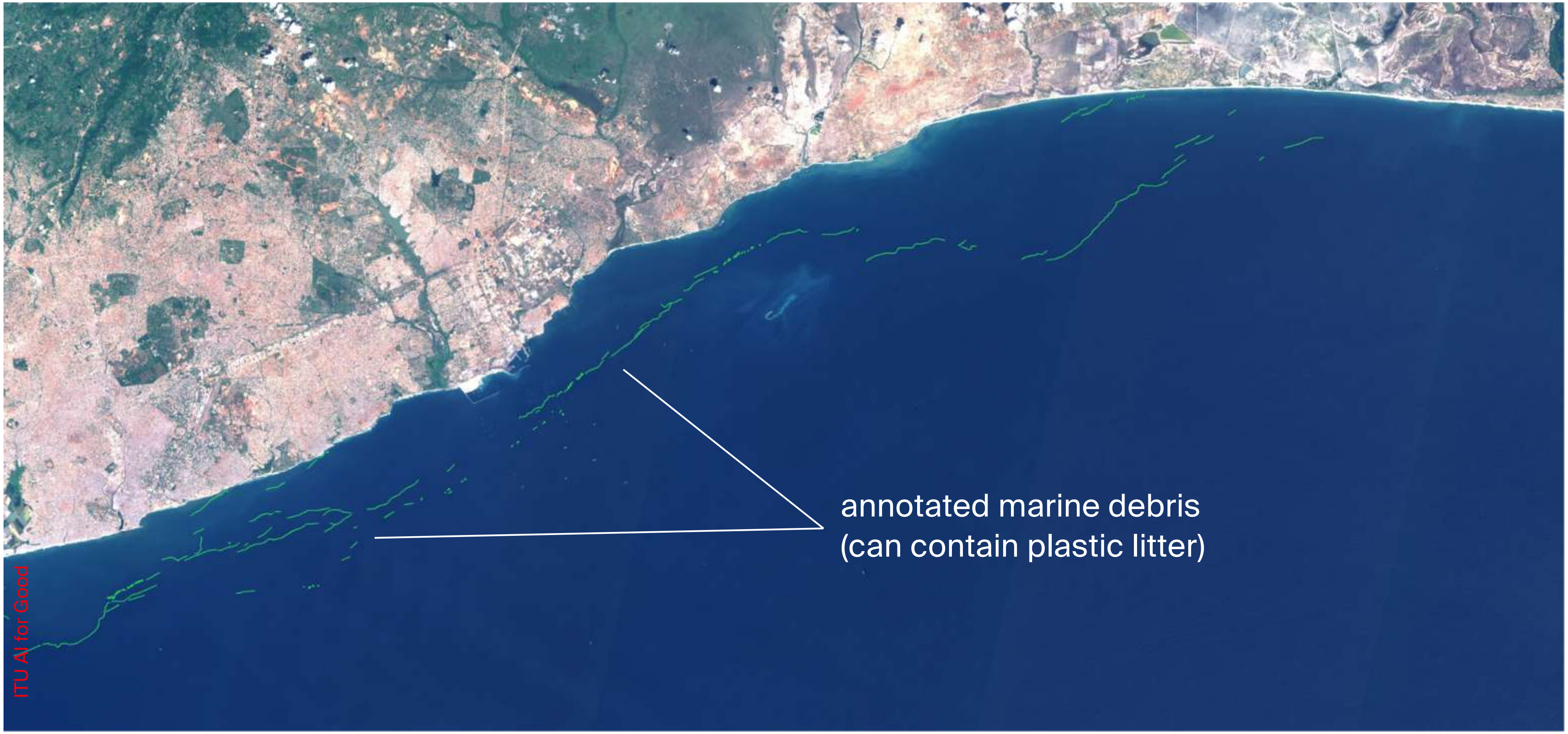
Mifdal et al., 2020,Carmo et al., 2021

Marine Debris Archive (MARIDA)

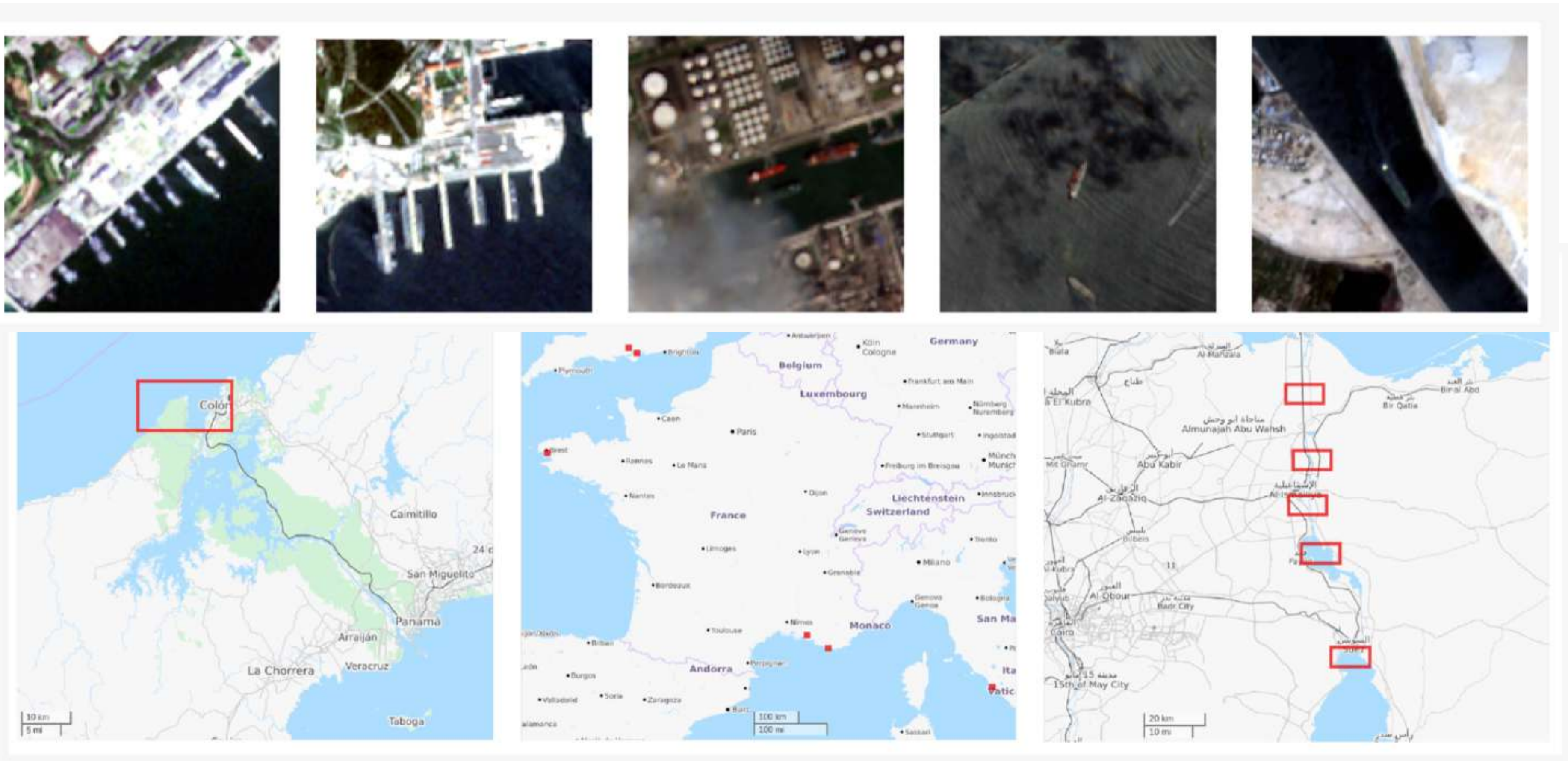
Kikaki et al., 20021

Hand-labelled debris visible on satellite images **to the best of their knowledge**

Accra (Sentinel-2 scene 2018-10-31)



Focus on the negatives: S2ships



Ciocarlan, Alina, and Andrei Stoian. 2021. "Ship Detection in Sentinel 2 Multi-Spectral Images with Self-Supervised Learning" *Remote Sensing* 13, no. 2

Results

Takehome

- DL models outperform traditional RF

Accra trained on	original data RF	original data UNET	our train set RF	our train set UNET	our train set UNET++
ACCURACY	0.653	0.882	0.680	**0.924** $\pm$ 0.016	**0.930** $\pm$ 0.016
F-SCORE	0.464	0.871	0.545	**0.920** $\pm$ 0.018	**0.926** $\pm$ 0.018
AUROC	0.246	0.965	0.899	**0.978** $\pm$ 0.008	**0.981** $\pm$ 0.006
JACCARD	0.302	0.772	0.374	**0.852** $\pm$ 0.030	**0.862** $\pm$ 0.031
KAPPA	0.301	0.764	0.357	**0.848** $\pm$ 0.031	**0.859** $\pm$ 0.031

Durban trained on	original data RF	original data UNET	our train set RF	our train set UNET	our train set UNET++
ACCURACY	0.781	0.587	0.811	0.908 $\pm$ 0.010	**0.934** $\pm$ 0.018
F-SCORE	0.105	0.497	0.708	0.756 $\pm$ 0.032	**0.837** $\pm$ 0.053
AUROC	0.376	0.765	0.862	0.850 $\pm$ 0.030	**0.914** $\pm$ 0.018
JACCARD	0.055	0.330	0.548	0.609 $\pm$ 0.042	**0.722** $\pm$ 0.048
KAPPA	0.082	0.245	0.569	0.704 $\pm$ 0.037	**0.797** $\pm$ 0.063

Marida-test set trained on	original data RF	original data UNET	our train set RF	our train set UNET	our train set UNET++
ACCURACY	0.697	0.838	0.811	**0.865** $\pm$ 0.006	**0.867** $\pm$ 0.005
F-SCORE	0.288	0.701	0.708	**0.741** $\pm$ 0.012	**0.749** $\pm$ 0.009
AUROC	0.488	0.764	0.862	**0.738** $\pm$ 0.012	**0.746** $\pm$ 0.021
JACCARD	0.168	0.539	0.548	**0.589** $\pm$ 0.015	**0.598** $\pm$ 0.012
KAPPA	0.197	0.593	0.569	**0.654** $\pm$ 0.016	**0.661** $\pm$ 0.012

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Results

Takehome

- DL models outperform traditional RF
- Data more important than models!

FlObs+MARIDA+S2Ships

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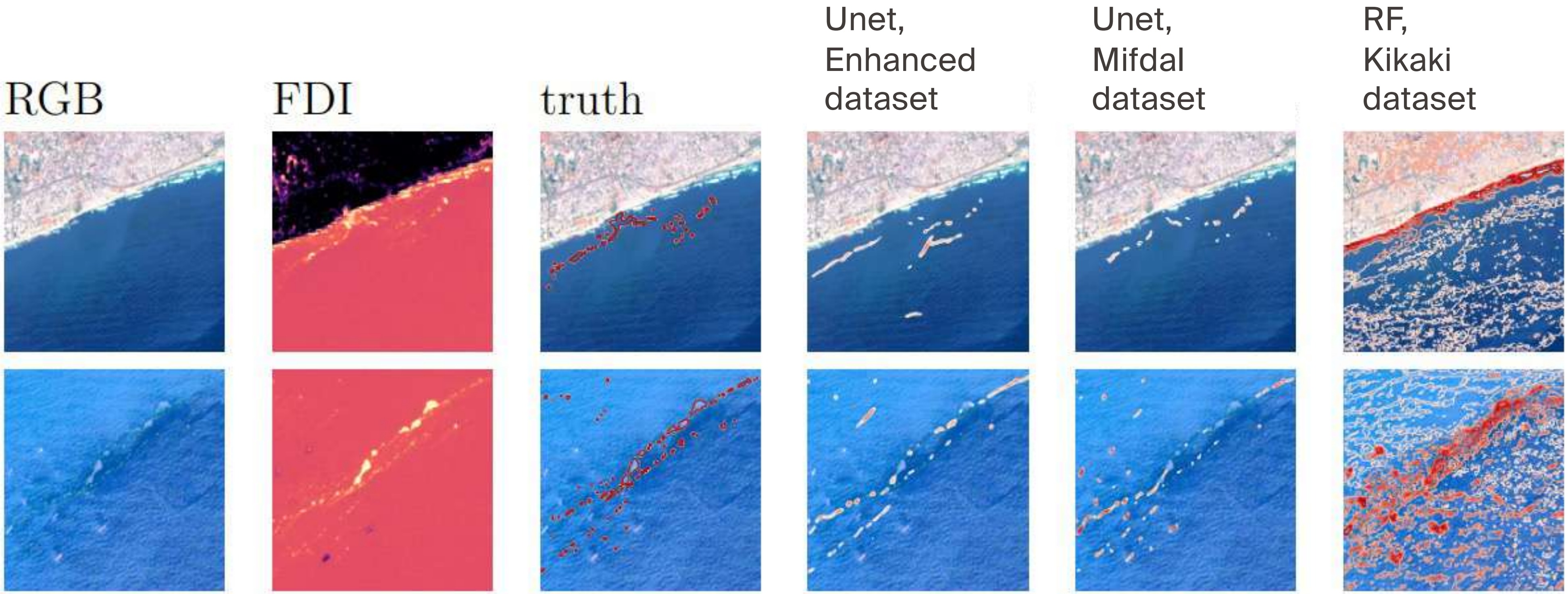
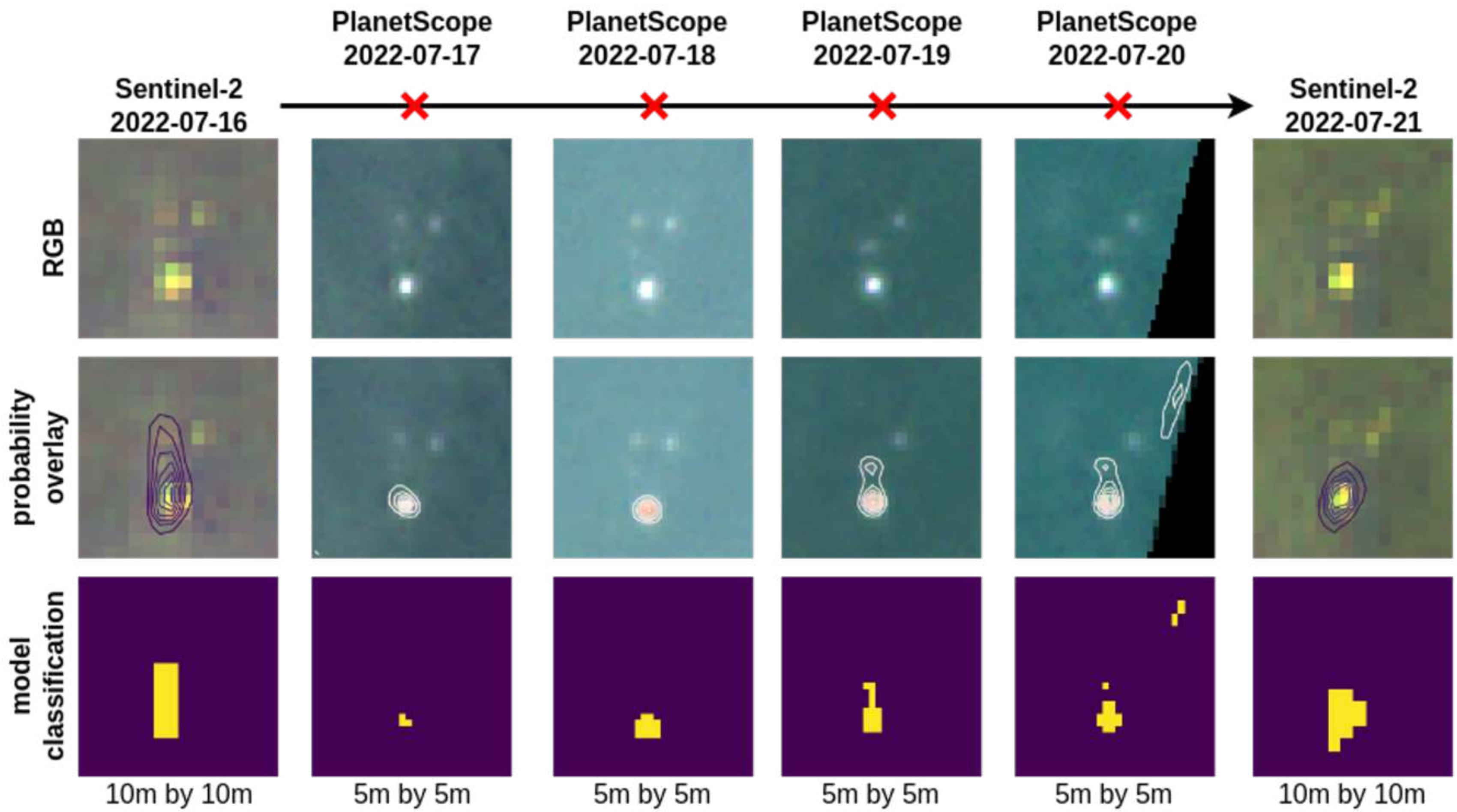
Prediction examples



Qualitative examples: https://marcrusswurm.users.earthengine.app/view/marinedebrisexplorer

Detections on the Plastic Litter project 2022



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Part II

Underwater

Characterizing coral reefs at scale

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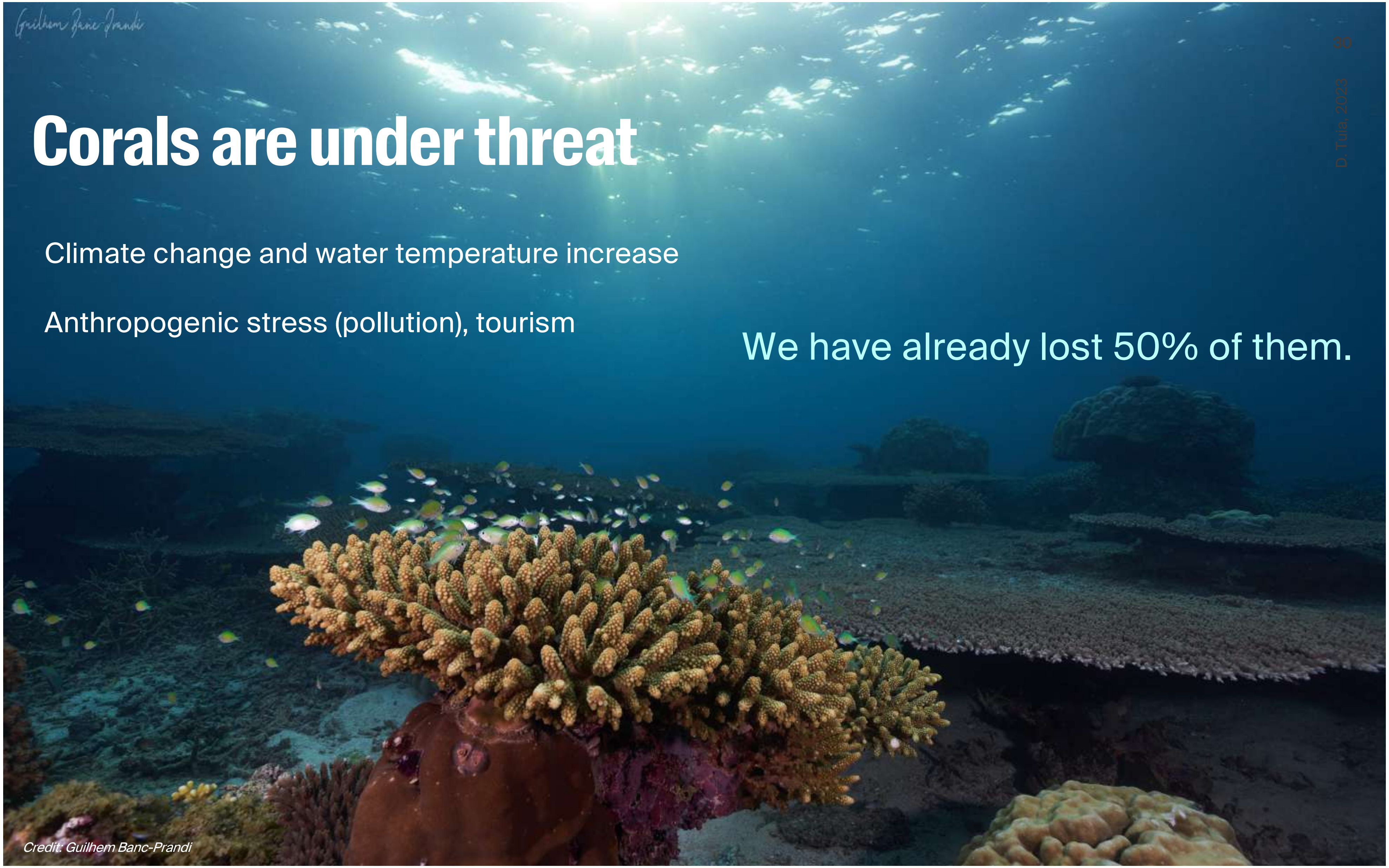
Corals are under threat

Climate change and water temperature increase

Anthropogenic stress (pollution), tourism

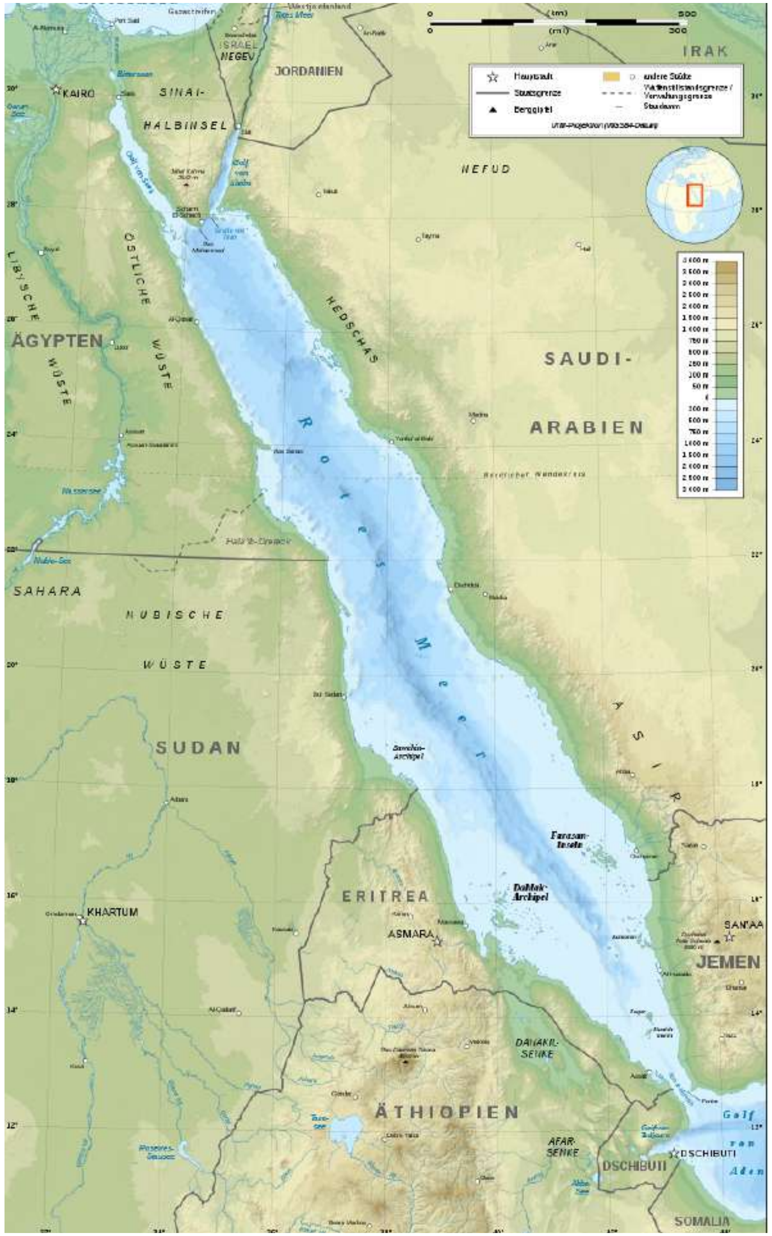
We have already lost 50% of them.



Credit: Guilhem Banc-Prandi

Still, in some places corals resist.

- Red sea corals are much more resistant to heat
- We need to understand ***why***
- We need to map and monitor, to better follow the evolution of reefs’ health and protect them

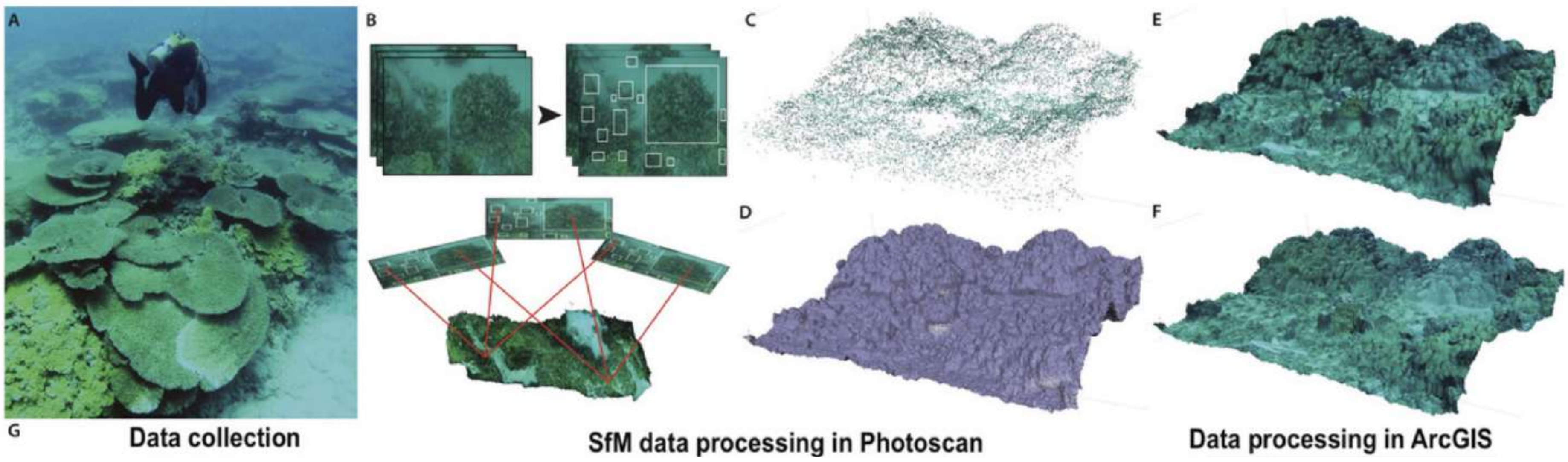


When the technology does not scale well, monitoring is difficult.

28 x 6 m plot

1h with proprietary software

20h manual work
to extract information



[Burns et al., 2015, https://peerj.com/articles/1077/]

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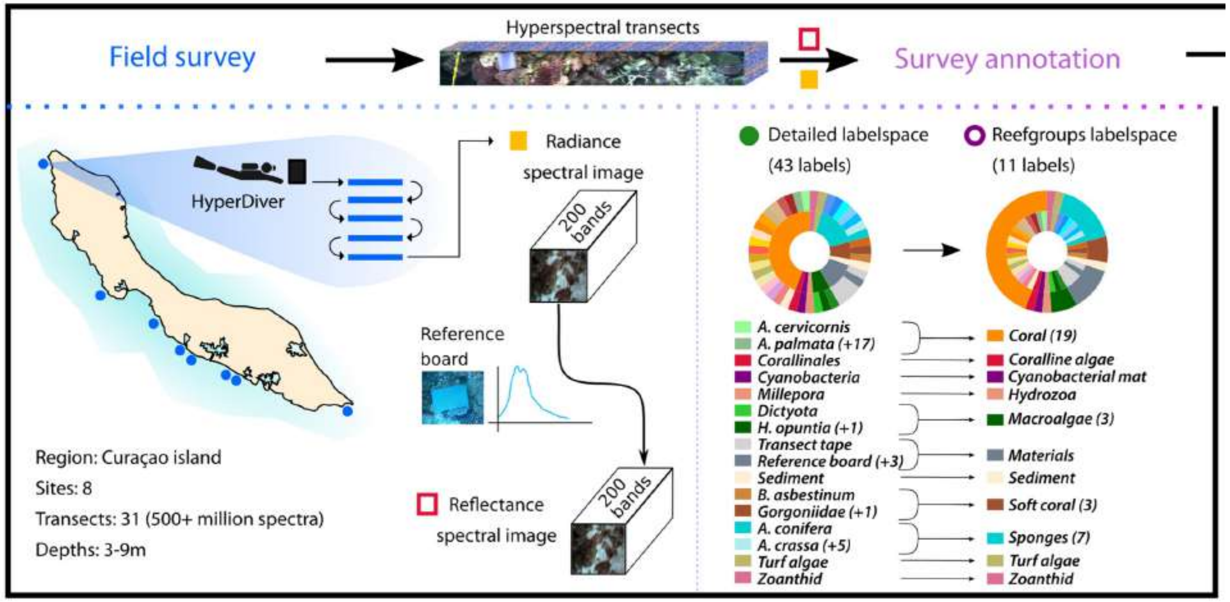
When the setup is unique: great results, but difficult to apply elsewhere

- Published models often rely on complex setups, very expensive
- E.g. hyperspectral sensors



Schürholz and Chennu, Methods in Ecology and Evolution, 2022

Our bet: affordable setups

- Scalable to other reefs
- Easy to acquire / replace
- Can train local communities

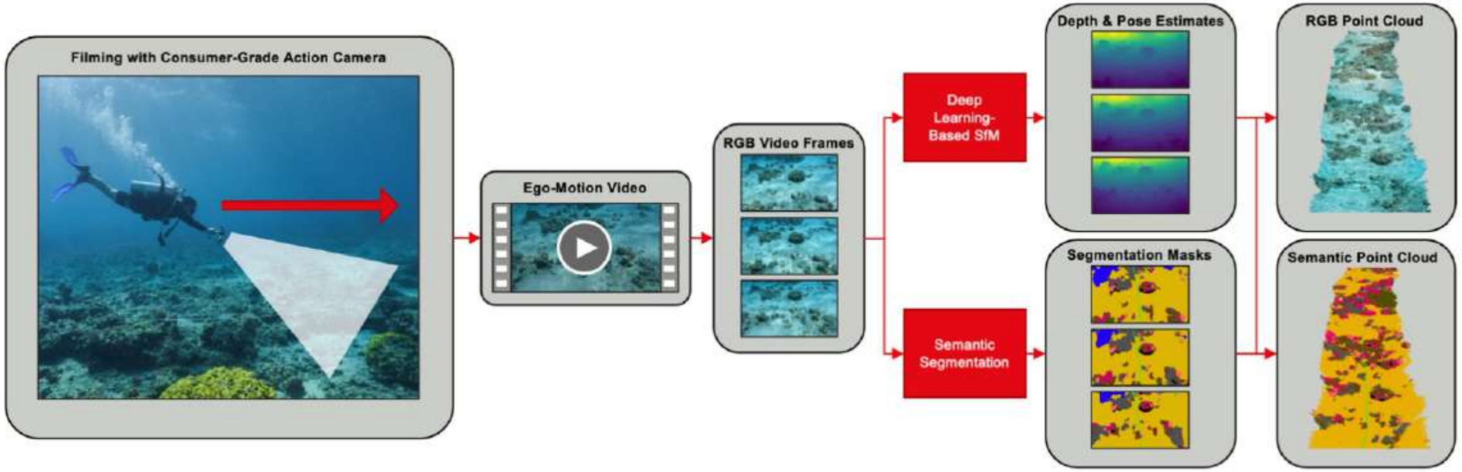
Mark I: March 2022 – Isreal / Jordan

Mark II: August 2022 – Djibouti

Photo credits: Guilhem Banc-Prandi, 2022

Enabling scalable reef monitoring: Open source, fast, large scale.

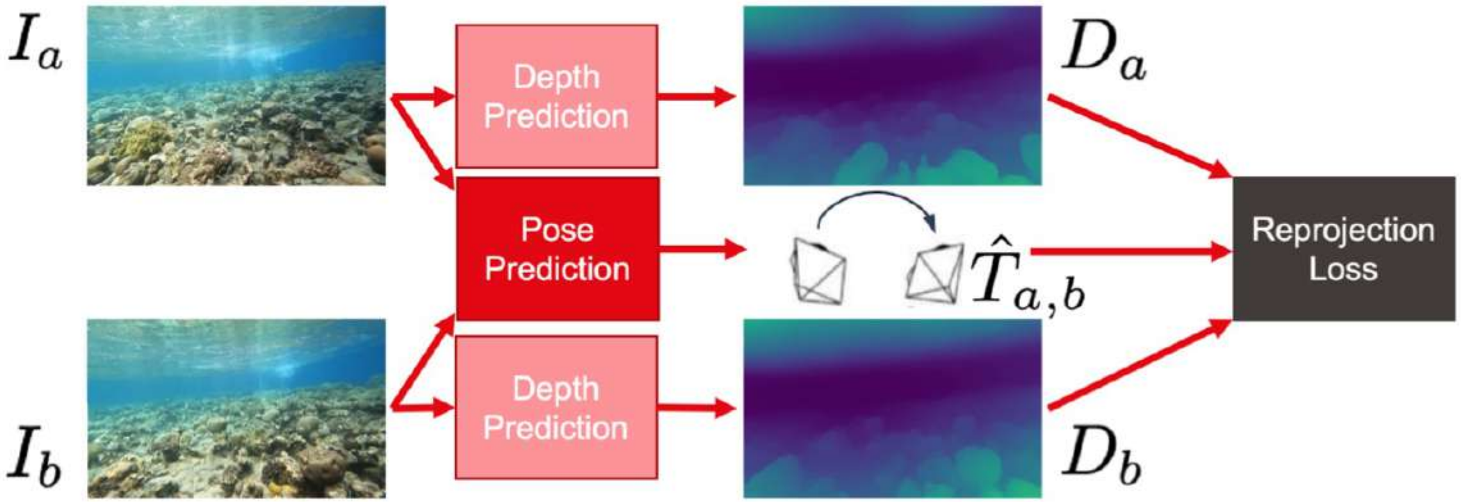
- A model that works on videos, leveraging 2 tasks
- Once trained, 3D reconstructs a 100m transect in playing video time
- Tested in Israel, Jordan and Djibouti in 2022



J. Sauder, G. Banc-Prandi, A. Meibom, and **D. Tuia**. Scalable semantic 3d mapping of coral reefs with deep learning. *Under review*.

Pose and depth estimation

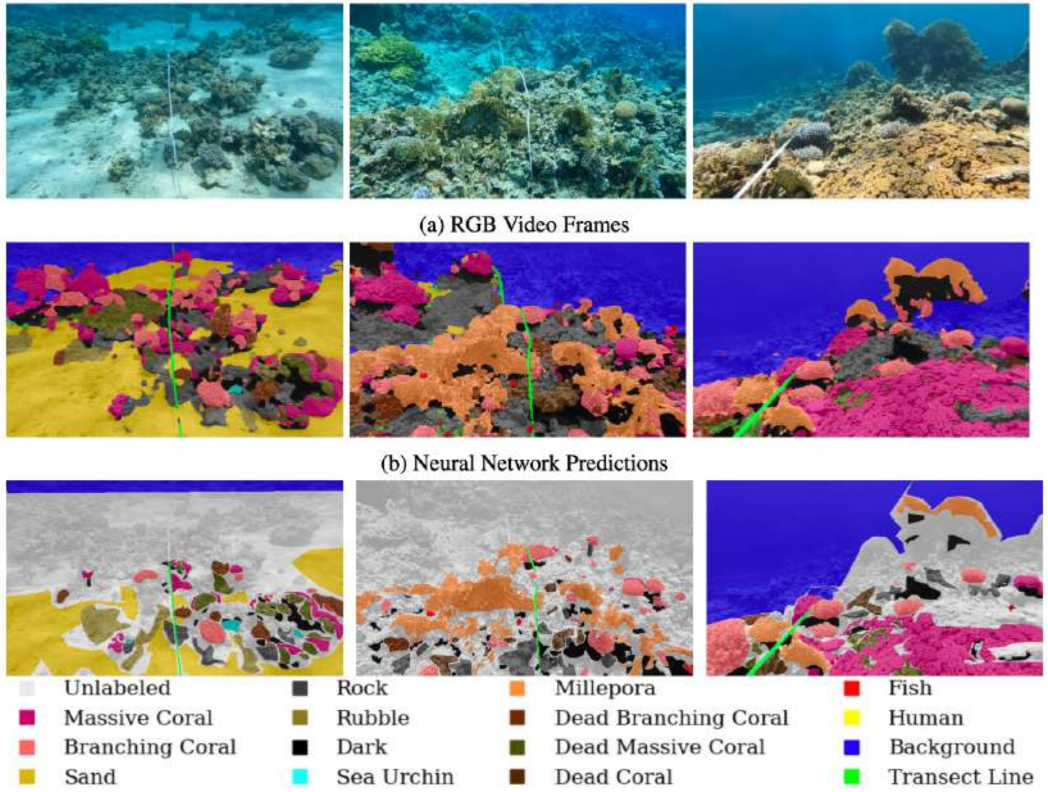
- Encoders based on ResNet-34
- Can create the 3D map at 18 frames per second



J. Sauder, G. Banc-Prandi, A. Meibom, and **D. Tuia**. Scalable semantic 3d mapping of coral reefs with deep learning. *Under review*.

Semantic segmentation

- Unet with ResNeXt backbone
- ~85% accurate in Jordanian and Israeli reefs
- Used to remove unwanted classes prior to 3D reconstruction
  - Diver body
  - Fishes



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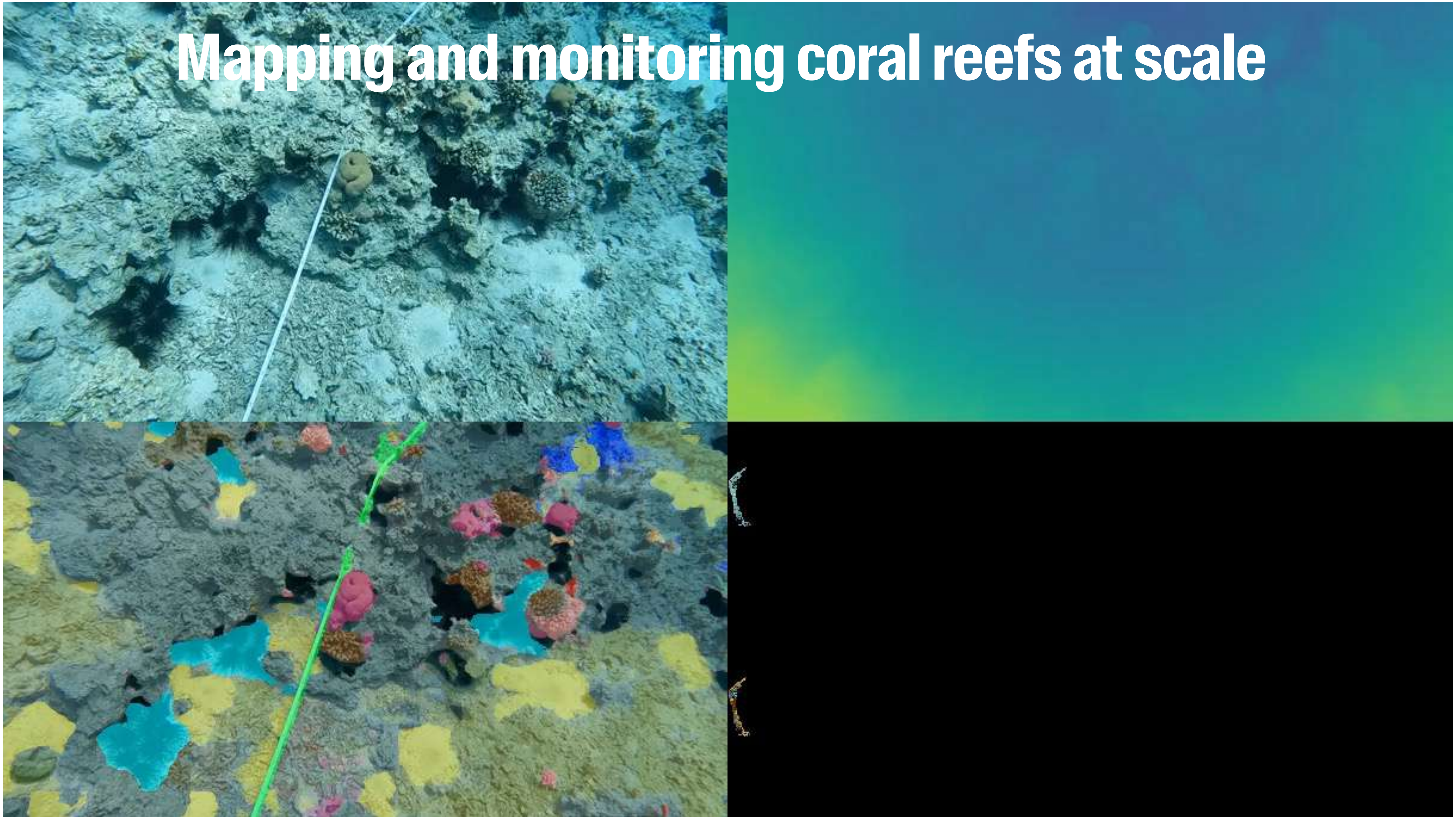
Mapping and monitoring coral reefs at scale



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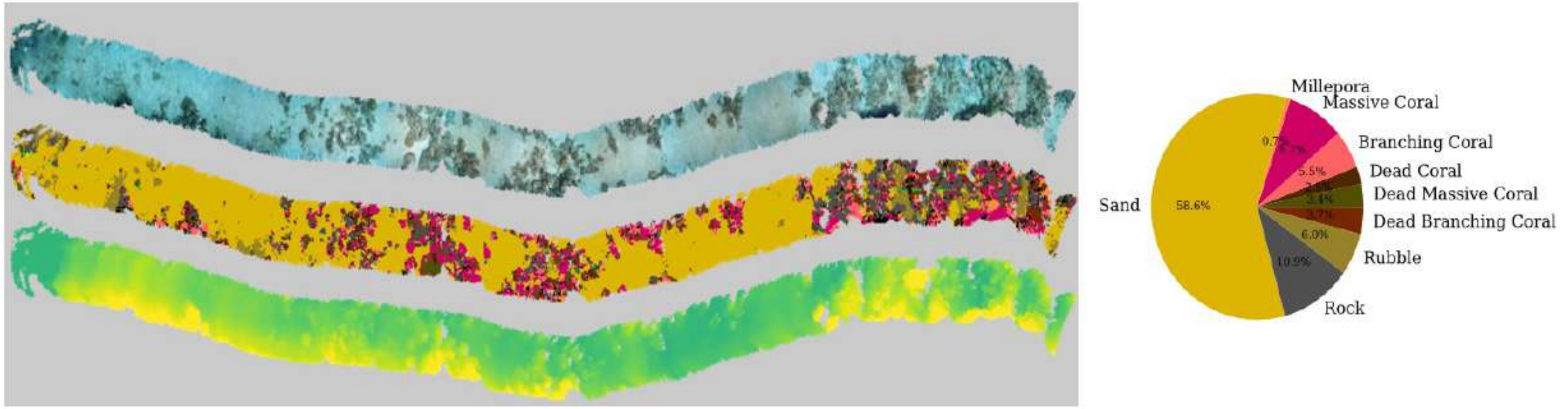
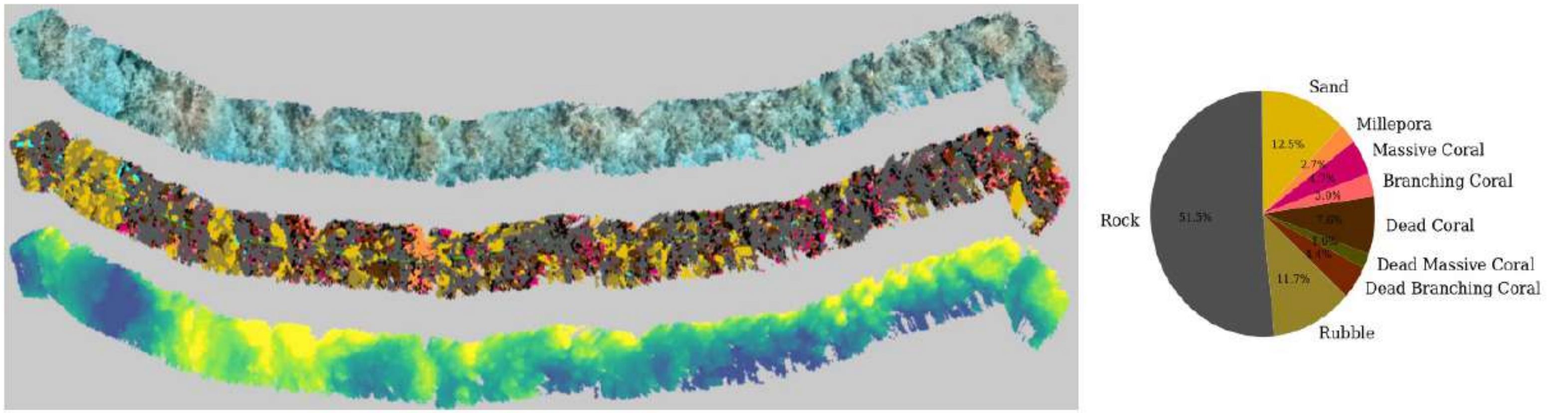
Mapping entire dive sites
(here: 100m long)



(a) King Abdullah Reef (Sandy)



(b) King Abdullah Reef (Rocky)

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Remote sensing + AI enable monitoring acquatic ecosystems

- Threats on oceans are real and impact us all (in)directly.
- Oceans without fishes and corals leave coasts unprotected and increase food insecurity.
- Monitoring life above and underwater is possible with new AI tools.
- It requires interdisciplinary teams!

@devistuia

Researches in collaboration with: Transnational Red Sea Center, THE OCEAN CLEANUP, SDSC