EPFL

Remote sensing and machine learning for the environment

Devis Tuia

ECEO laboratory

EPFL

EPFL, Intro to Env. Sci. Eng.

École
polytechnique
fédérale
de Lausanne

EPFL

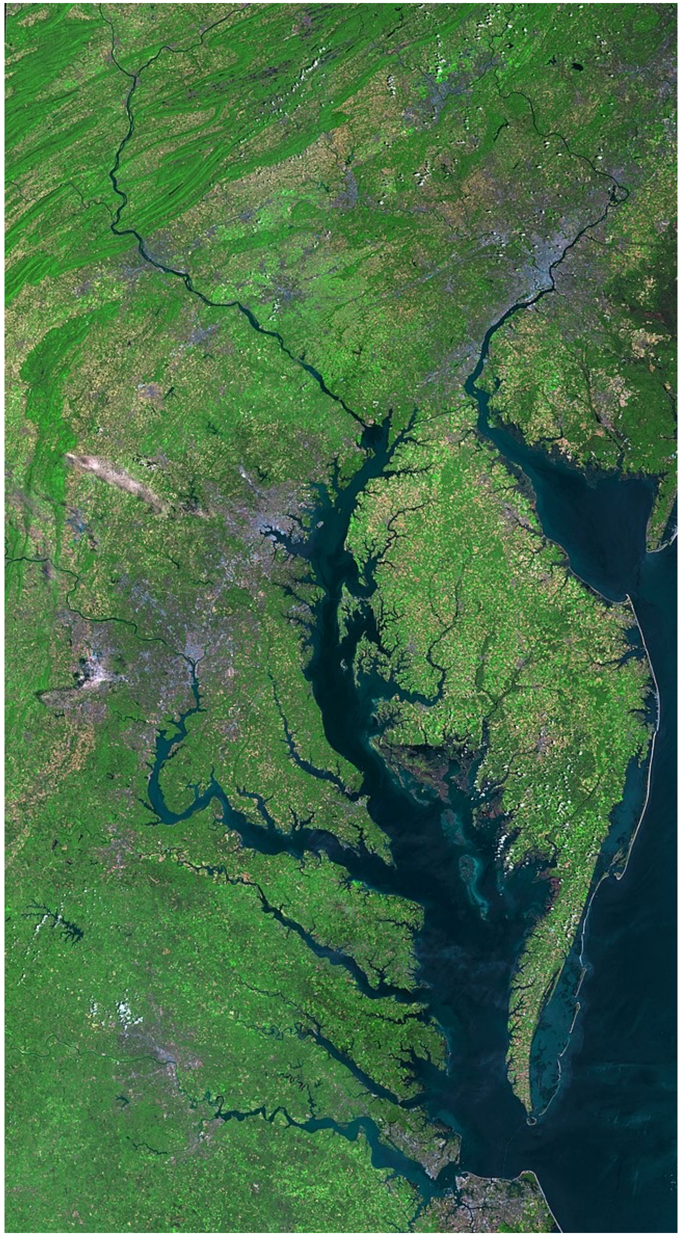
Environmental Computational Science and Earth Observation

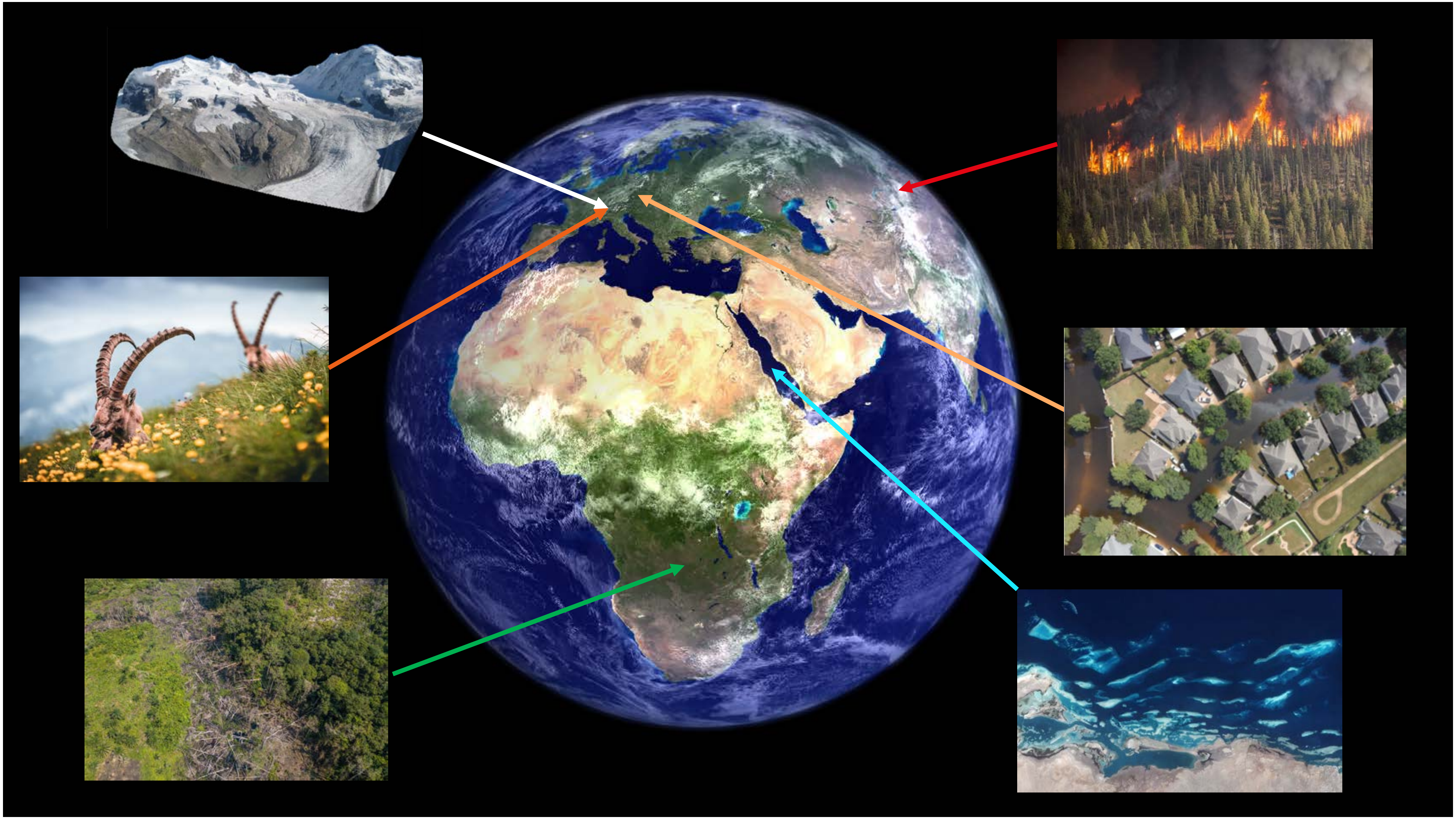
Started September 1st, 2020

Our mission

- **Monitor** our planet with Earth observation technology, from the drone to the satellite
- **Develop** fair, transparent machine learning technology
- **Serve applications** with high impact on society

Web: eceo.epfl.ch





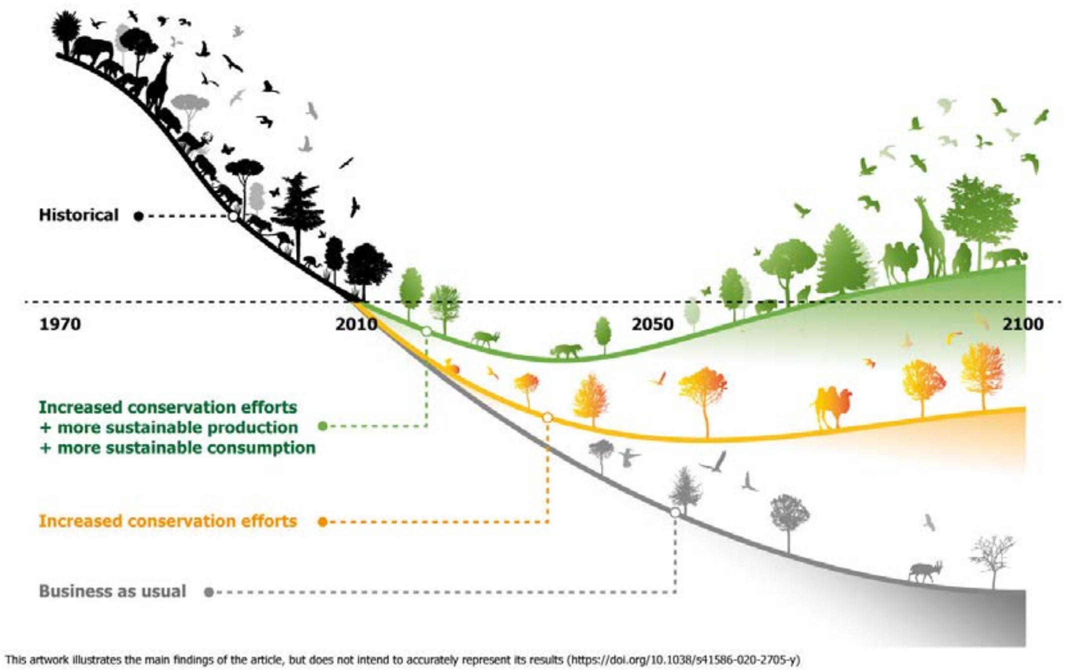
The biodiversity crisis is yet to hit us...

- 15-37% of species risk extinction to 2050

  [Thomas et al., Nature (2004)]

- Thousands of populations have been lost in a century. It is accelerating

  [Ceballos et al., PNAS (2020)]



Ihttps://earthjustice.org/features/biodiversity-crisis

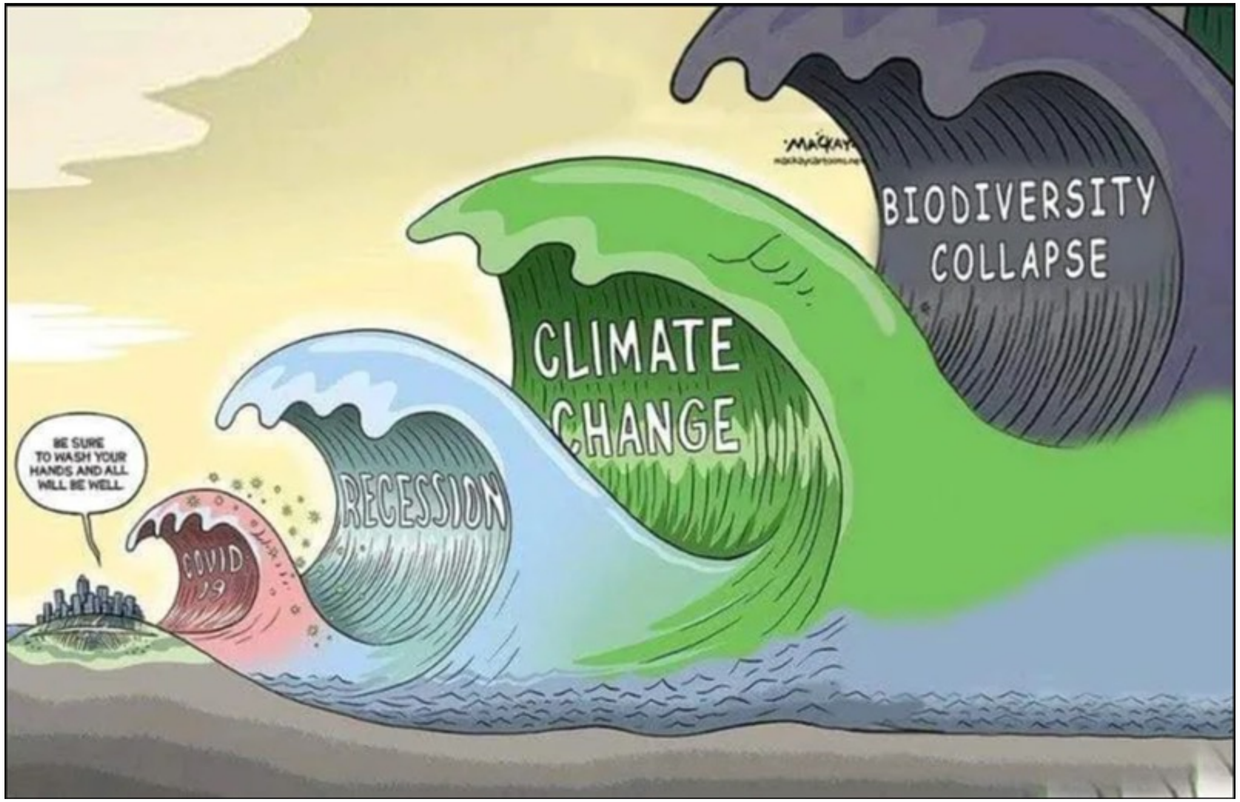
Source: www.unep-wcmc.org

Biodiversity needs to be protected

Consequences on

- Health,
  pest and diseases,
  medicines

- Food security
  soil formation
  purification of air/water
  detoxification of waste
  food availability
  crop variety



Source: The Hamilton Spectator, 2020

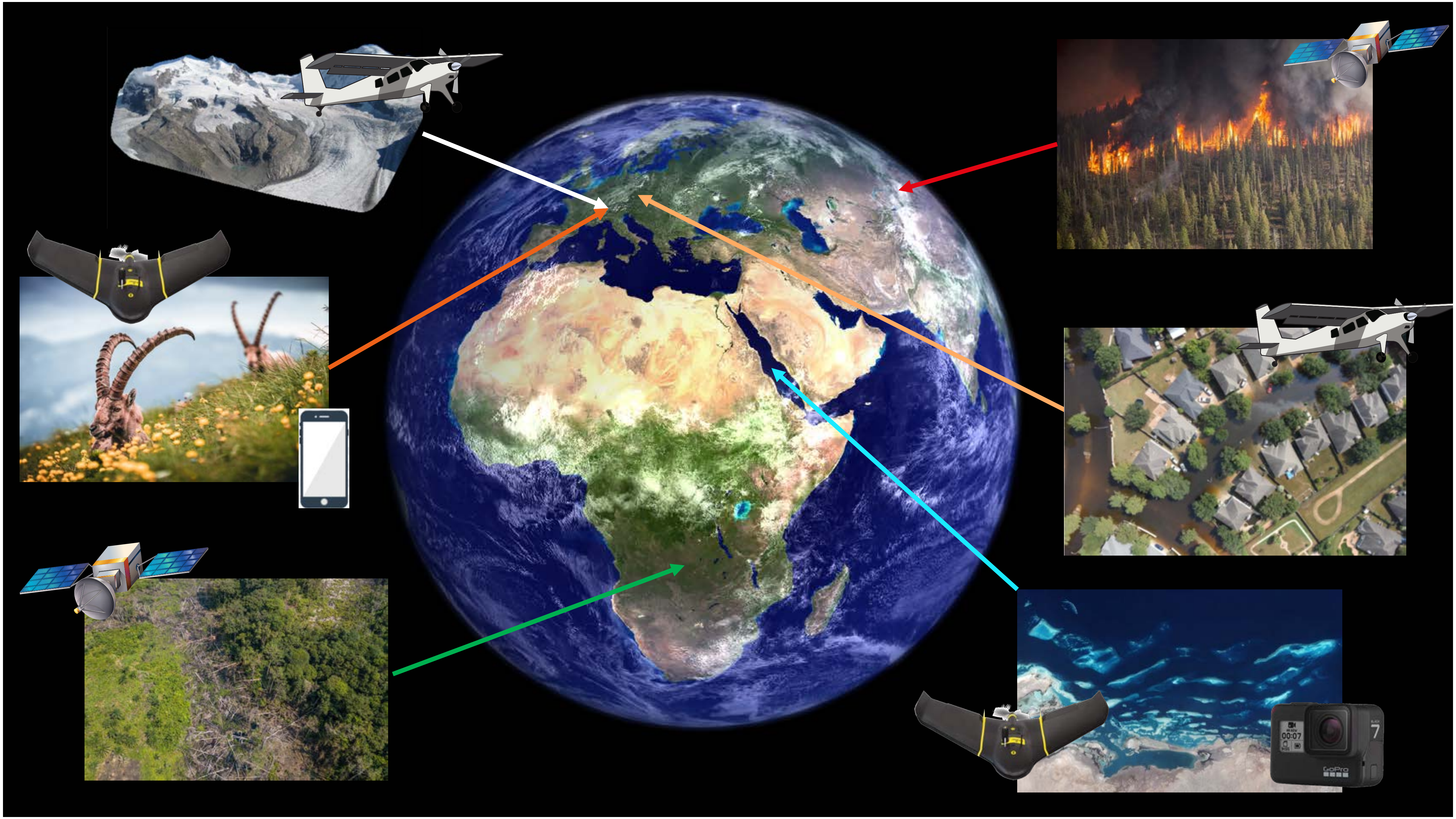
Why should I care?

- Conservation actors work hard to protect populations
- They record and control populations, establish laws, fight poaching
- They do **everything by hand**
  - Data samples are very small
  - When they have data, they are years behind processing

Ol pejeta reserve, Kenya

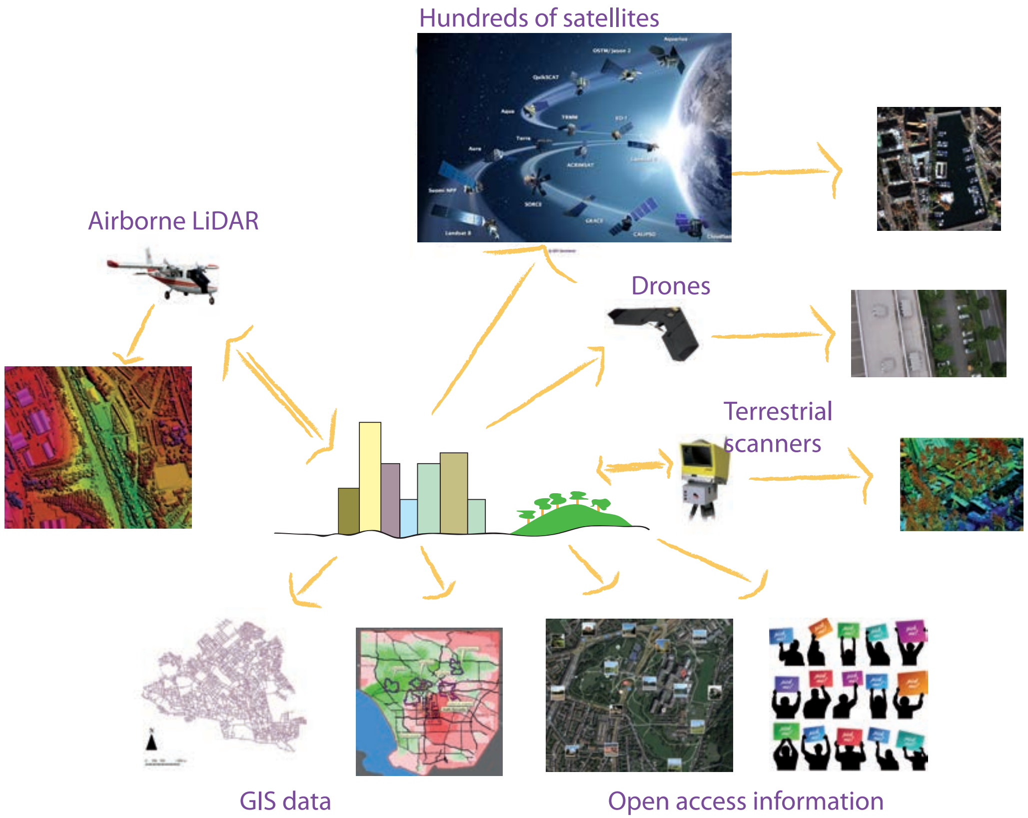
Kuzikus reserve, Namibia

What can we do to help?



There are many sensor data to monitor Earth in 2015

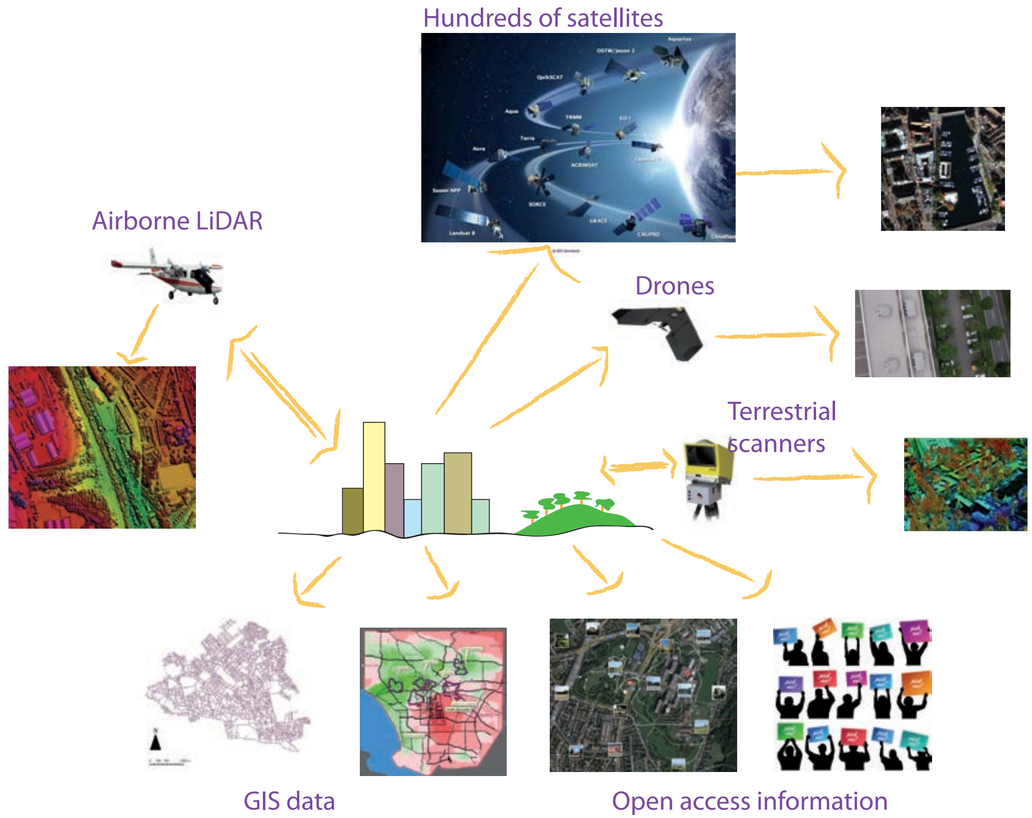
- 333 Earth Observation satellites in orbit in 2015 [ucsusa.org].
- 10'000 recreational drones registered in the U.S. by 2020 [FAA].
- 20 Pb of oblique photos in Google Street View in 2015 [Google Maps].



Sources of figures: usgs, astrium, aerialsurvey, sensefly, vimeo, GEOSS, Purdue, Google, thelogofactory

There are many sensor data to monitor Earth in ~~2015~~ 2024

- ~~333~~ 1'005 Earth Observation satellites in orbit in 2023 [ucsusa.org].
- ~~10'000~~ 1'100'000 recreational drones registered in the U.S in 2023. [FAA].
- 170 billions of oblique photos in Google Street View in 2020 [Google Maps].



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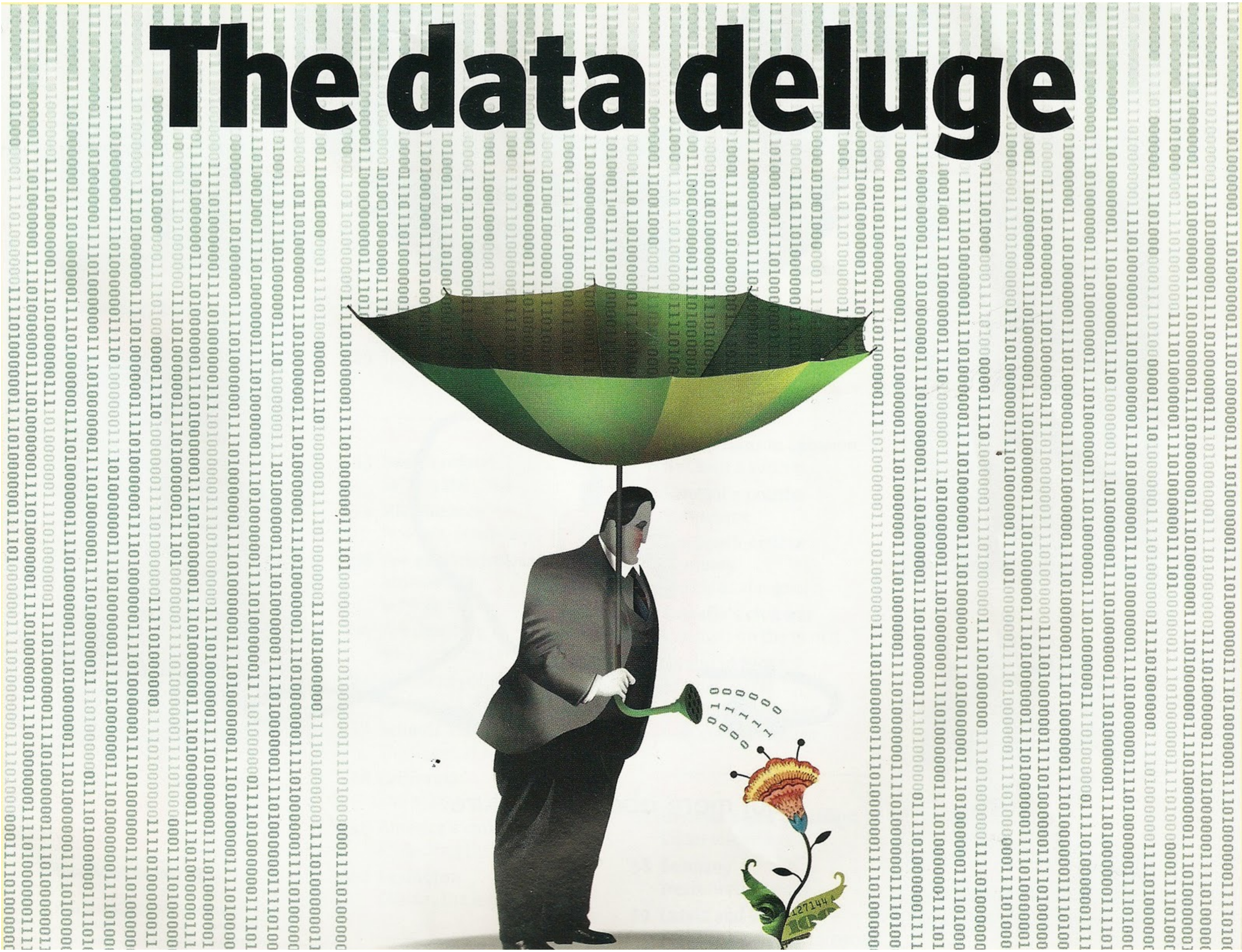
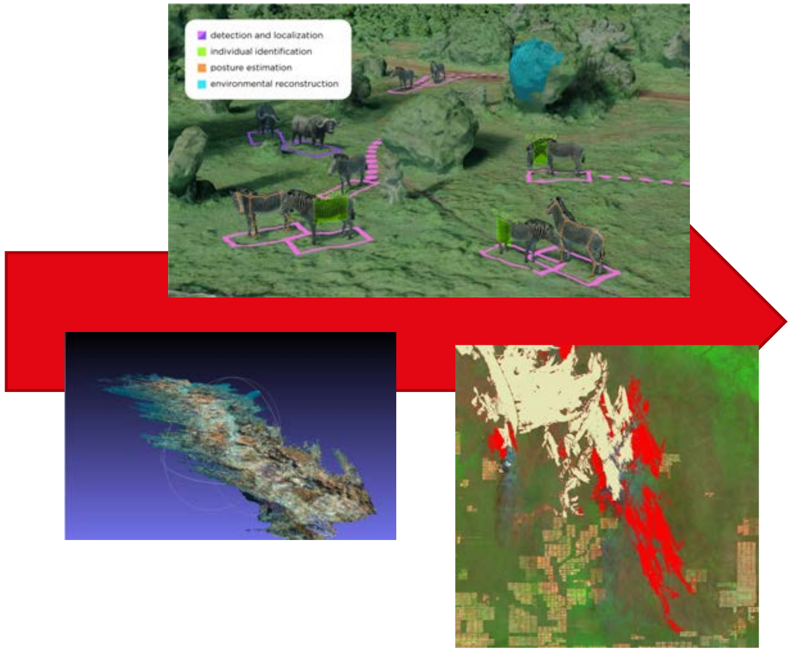
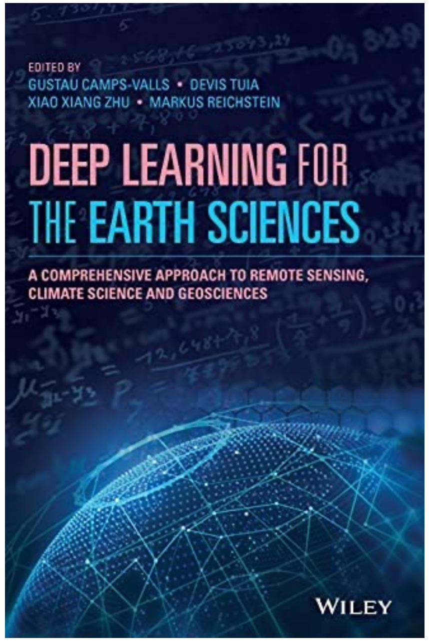

The data deluge

Why now : statistical and computational models are good enough

- Machine learning has reached a certain maturity… and percolated in many fields of science.

2022





2015

In today's talk

- We will discuss some avenues where machine learning can make the difference for environmental sciences.
- I will show you some examples of success stories from my lab.
- Hopefully it will inspire you to use ML for good,
- Maybe engage in actions such as

Climate Change AI

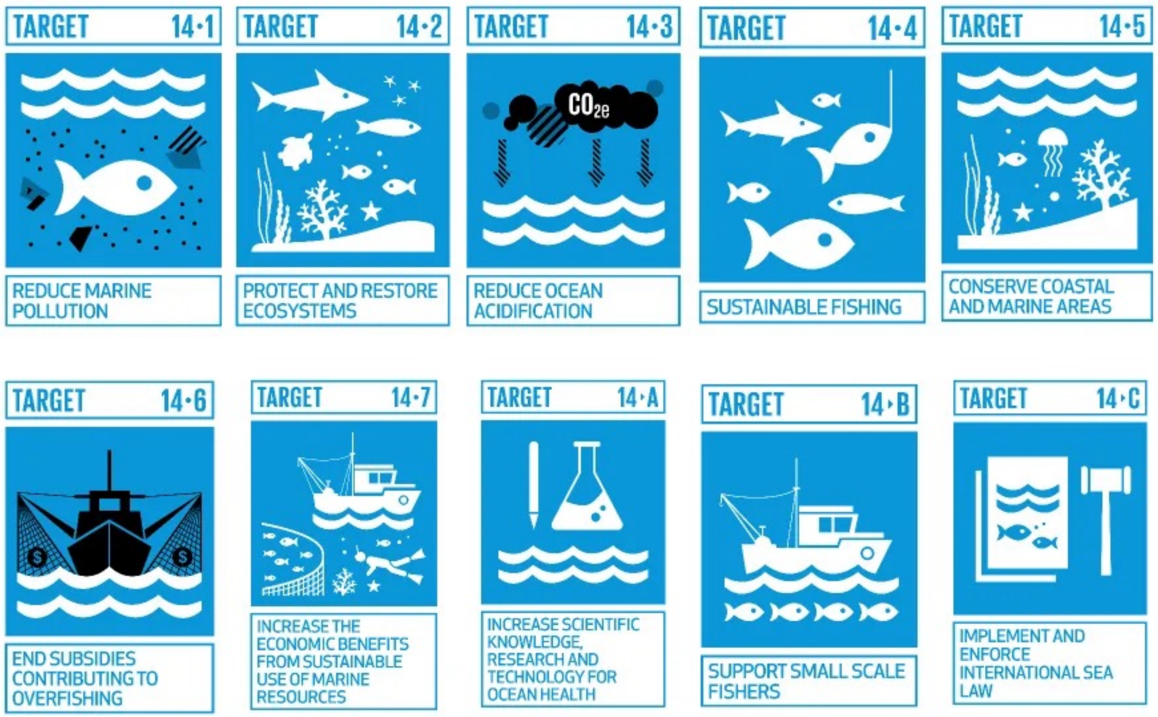
Remote sensing above and underwater.

An adventure to understand and protect our oceans.

The sustainable development goals

Source: undp.org

Today we talk about life above and under water.



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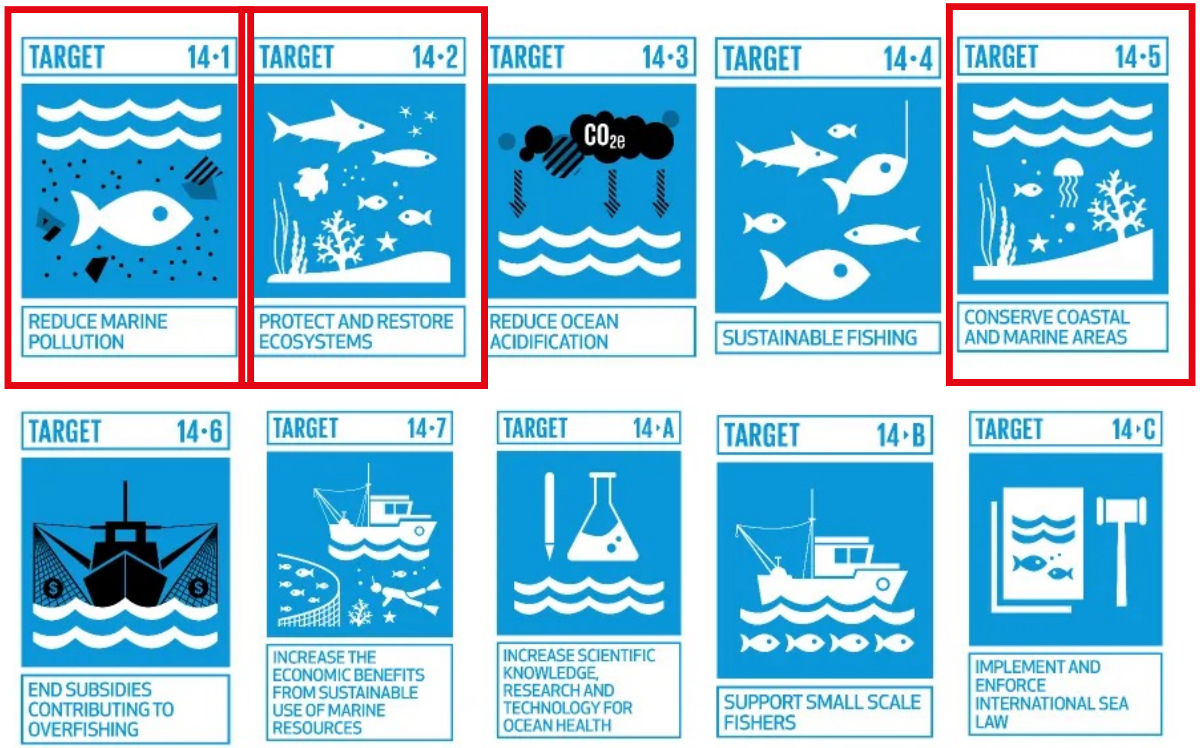


Why is that important?

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.

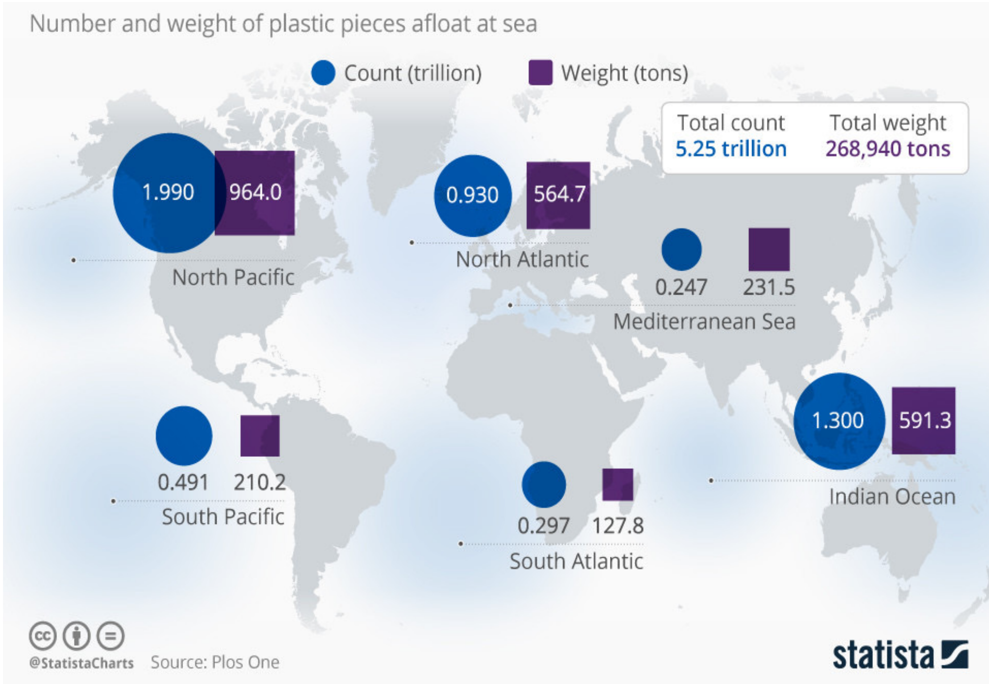
- Protection: Coral reefs protect coastlines from erosion and storms, and support tourism and its revenue to local population.

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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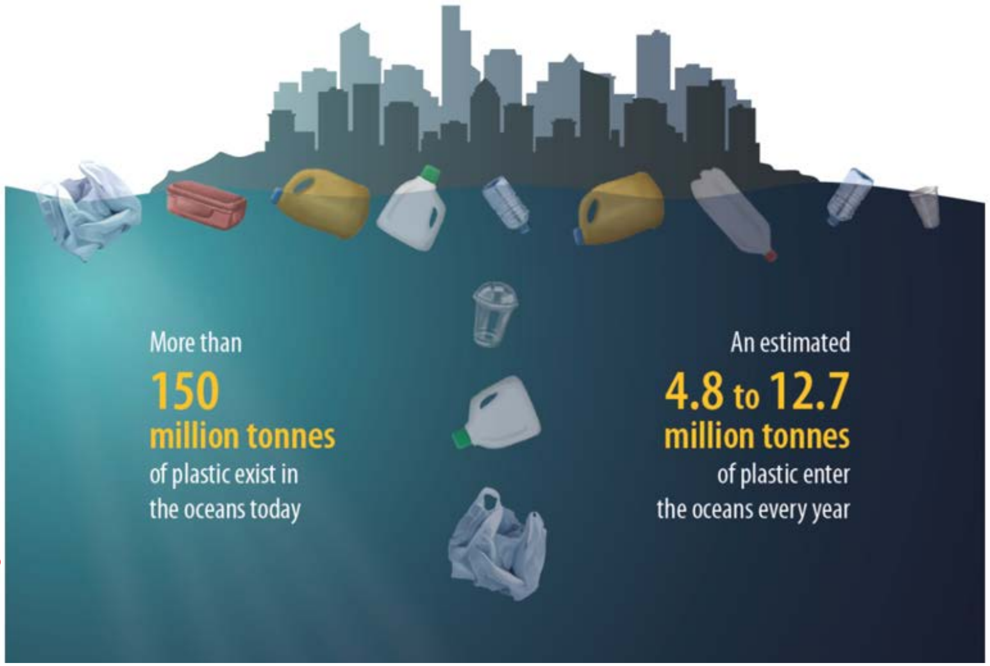
Source: the New Yorker

Part I

Above waters

Detecting marine litter from space

Marine litter is a BIG problem



Macro-plastics decompose in microplastics that are

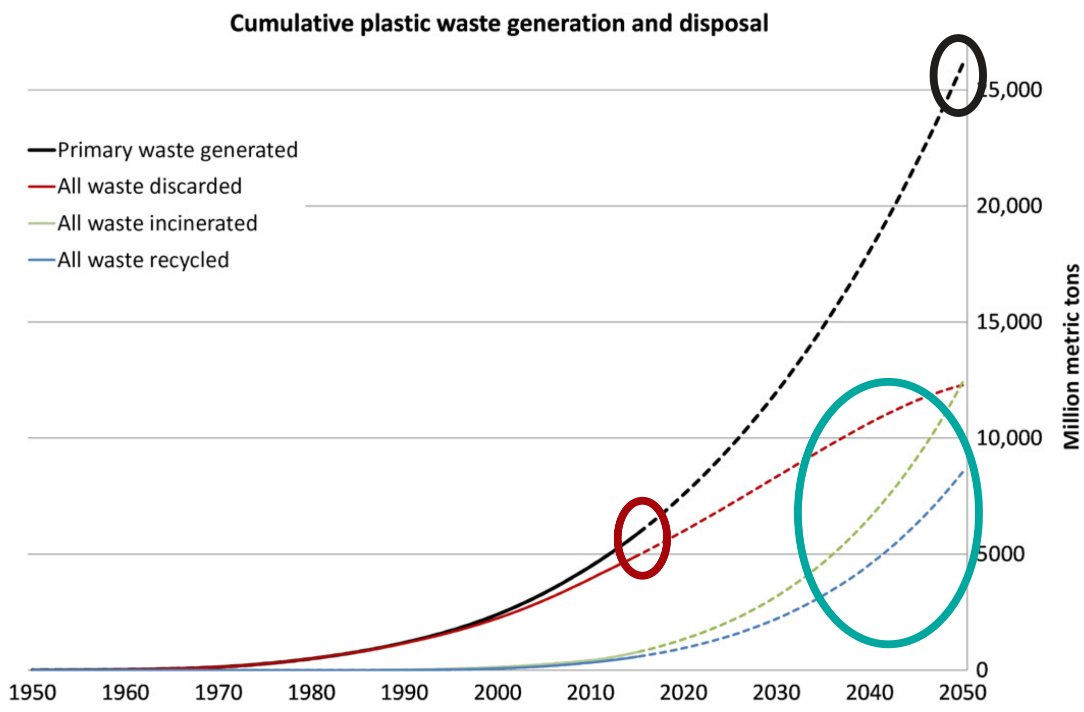
- a direct danger to animals

- 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.

Detecting Marine litter at scale

1) Marine litter permanently pollutes our environment

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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.

Detecting Marine litter at scale

How well can we **detect, map and monitor** marine litter from satellite data?

1) Marine litter permanently pollutes our environment

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

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

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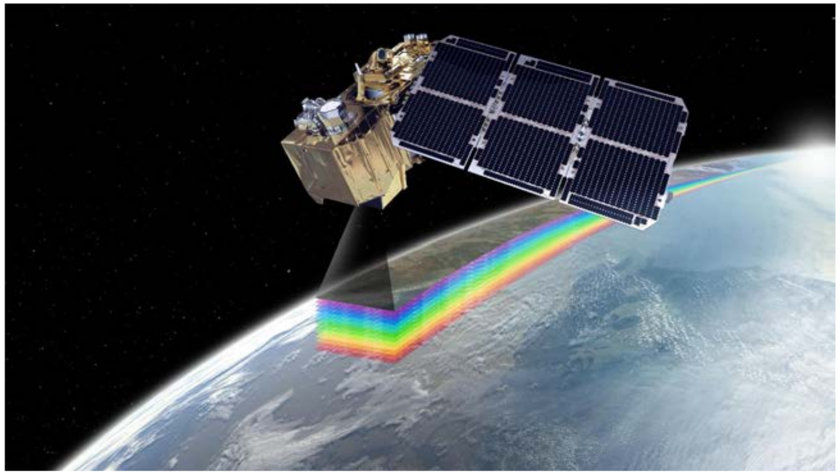
Available Satellite Data

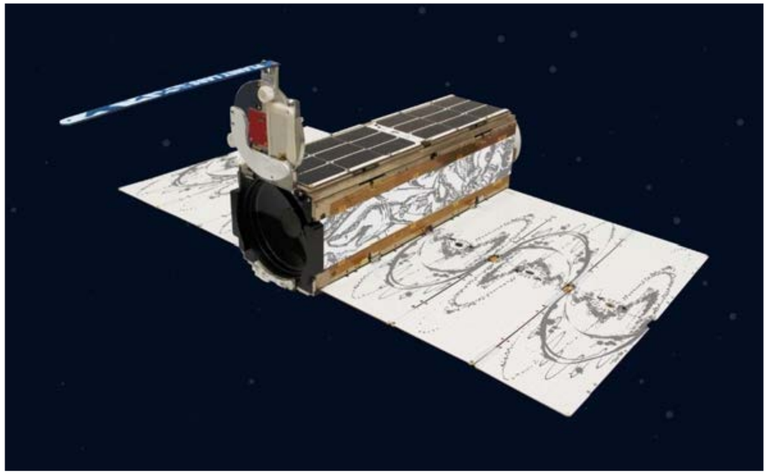
Sentinel-2

- 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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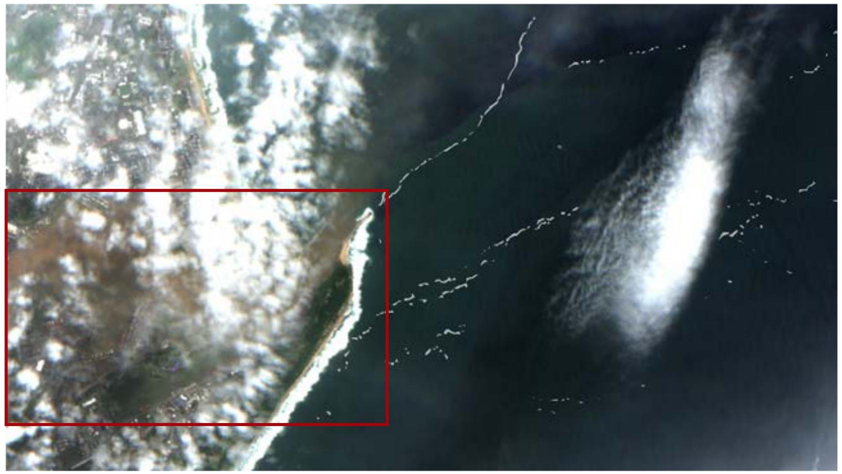
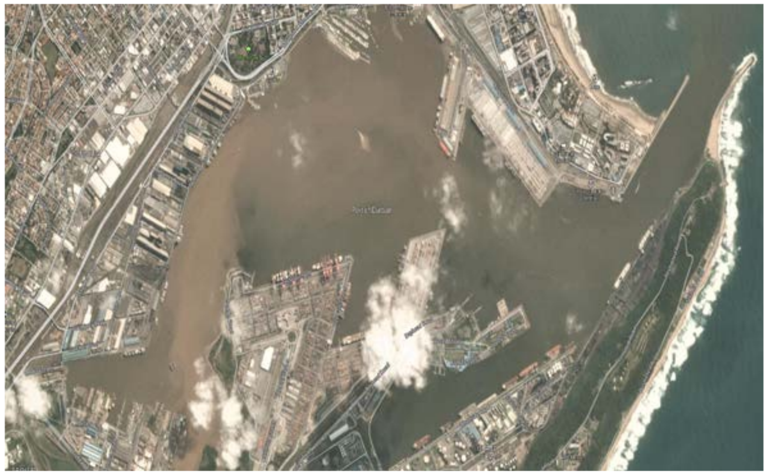
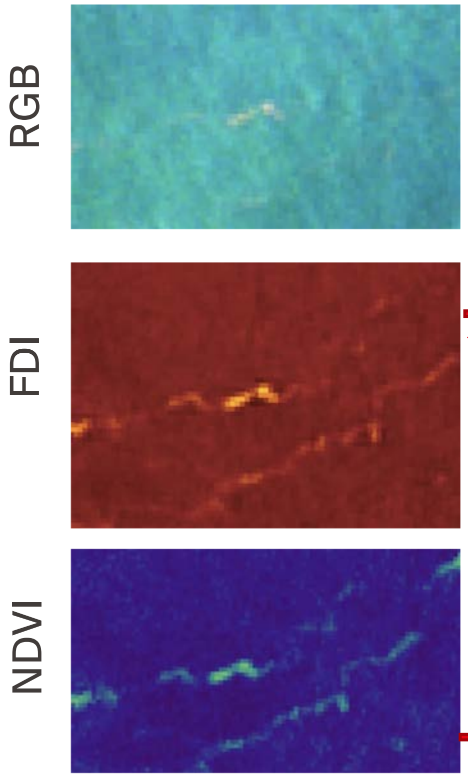
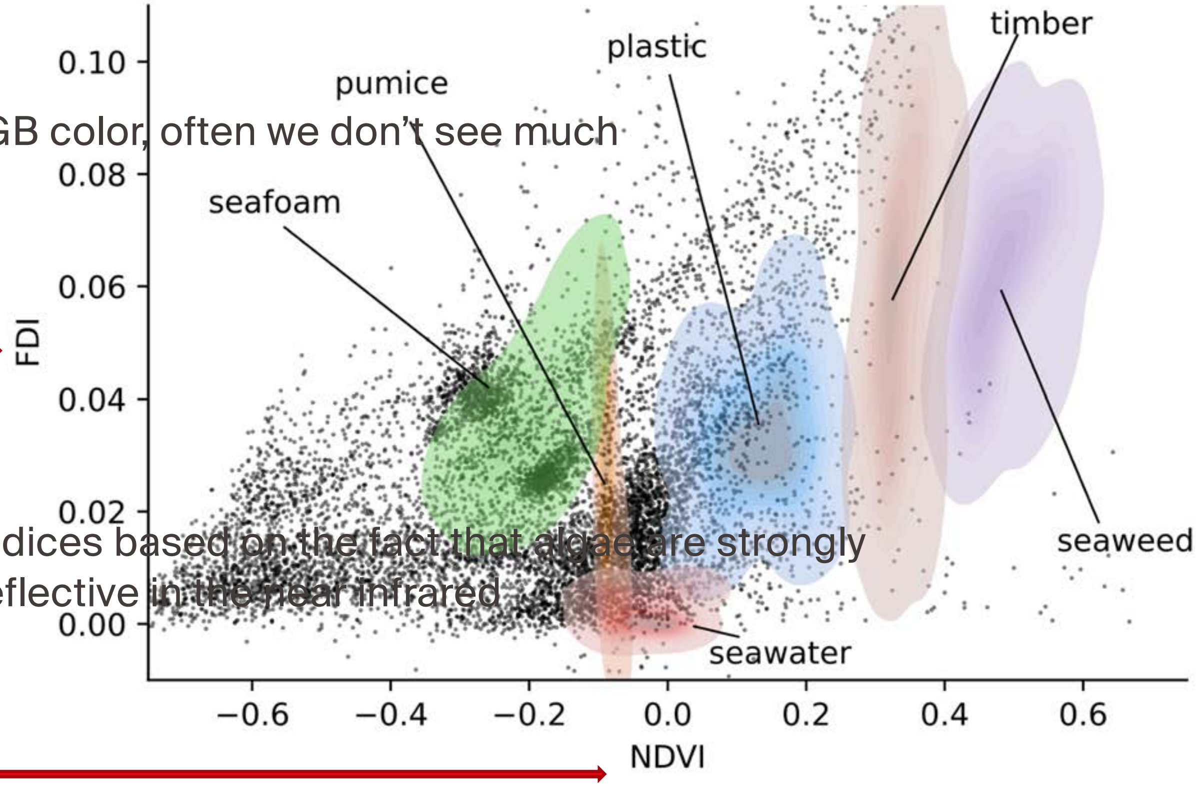




Spectral indices do not guarantee linear separability.



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.

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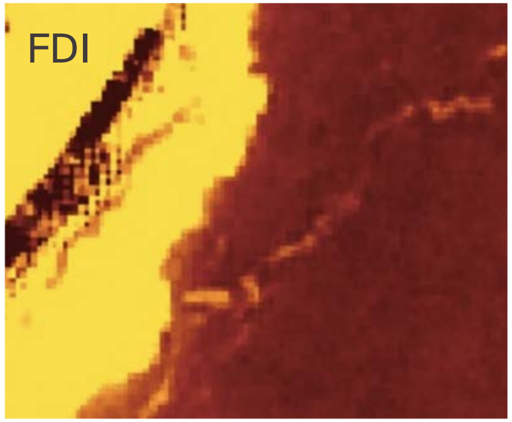
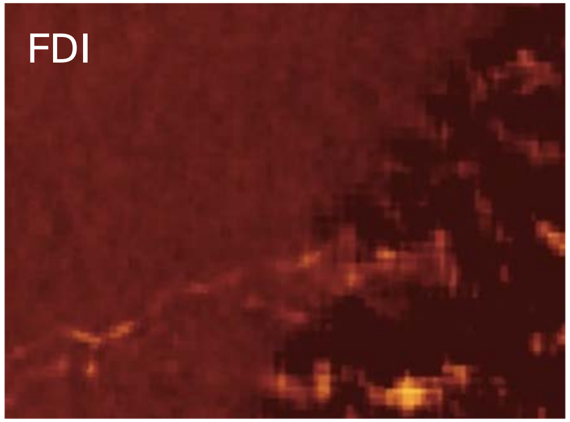
Indices sensitive also to

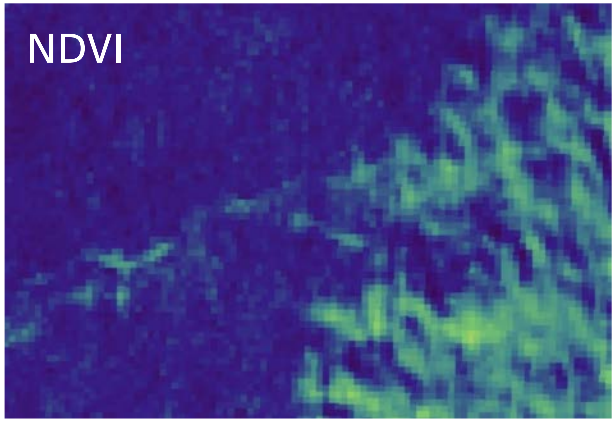
D. Tuia, 2024

coastline and sea spray

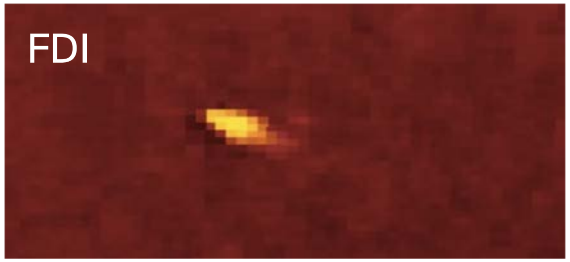
clouds

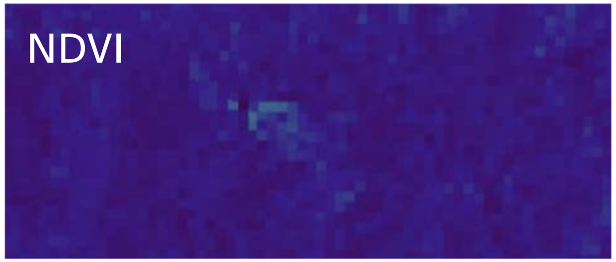






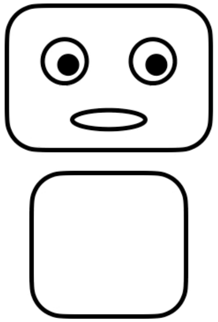
ships



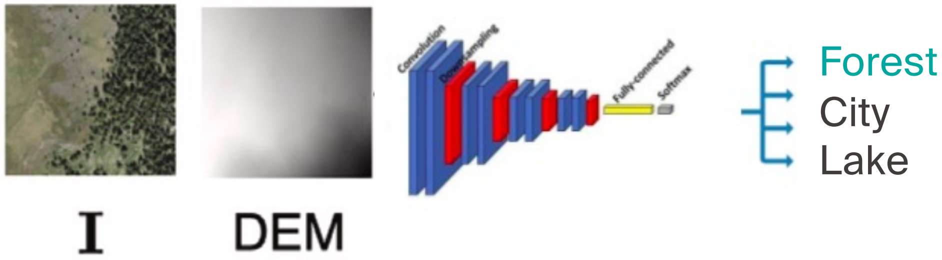


Indices are good for visualization, but pixel-wise classifiers on spectral indices are too simple

Ok we have data, but how to convert it into information?



But how to do segmentation?

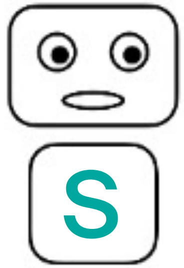


https://divamgupta.com/image-segmentation/2019/06/06/deep-learning-semantic-segmentation-keras.html

We need a mirrow structure!

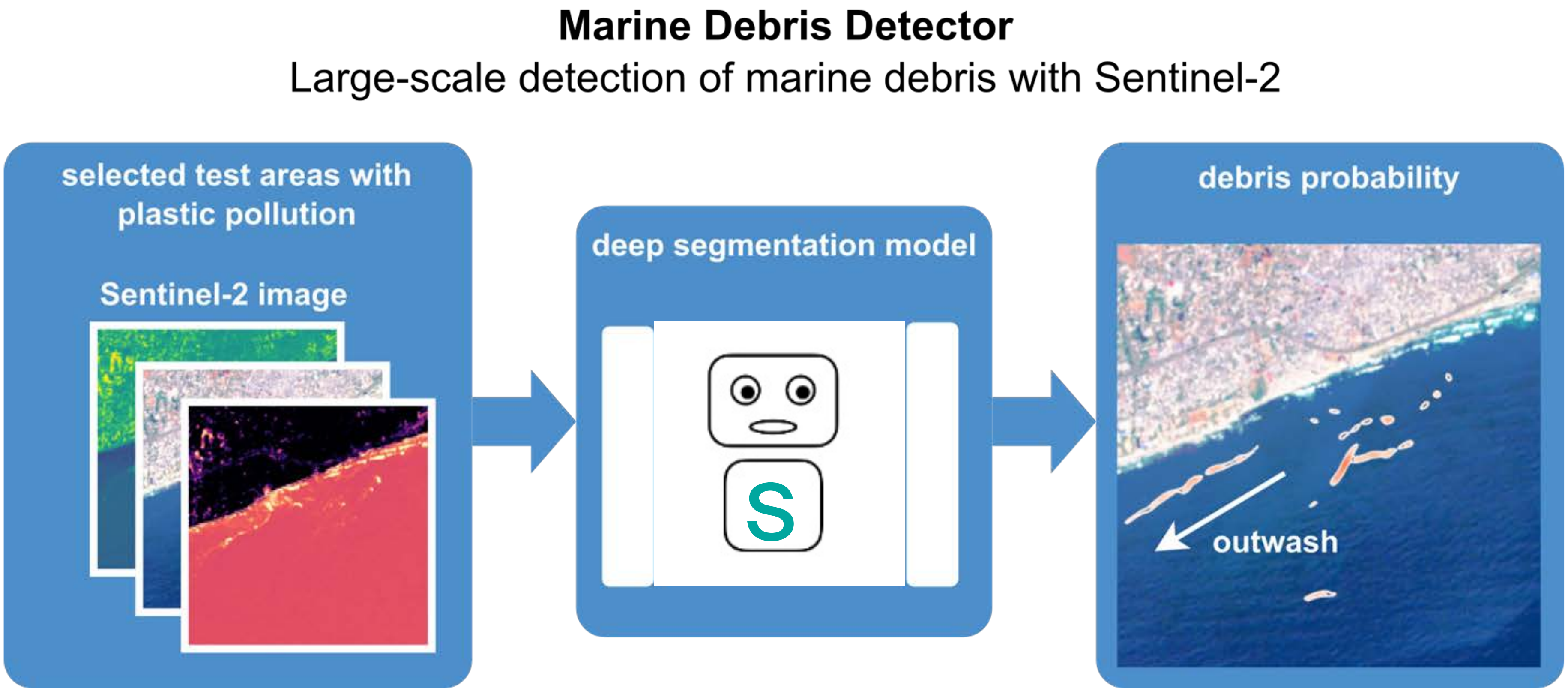
A hourglass structure for segmentation!

AI that maps in space



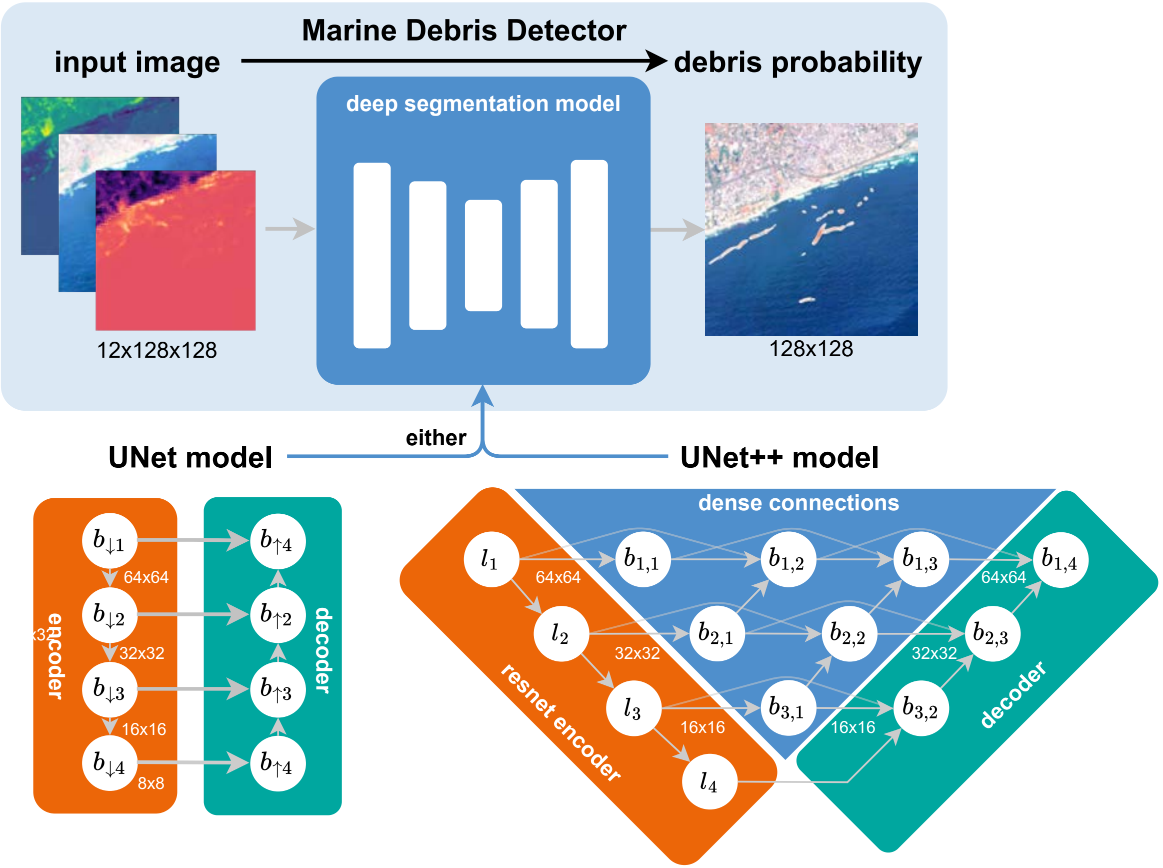
https://divamgupta.com/image-segmentation/2019/06/06/deep-learning-semantic-segmentation-keras.html

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. *iScience, 108402,* 2023. Available: https://www.sciencedirect.com/science/article/pii/S2589004223024793

Learning Spatial Context with CNNs



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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**

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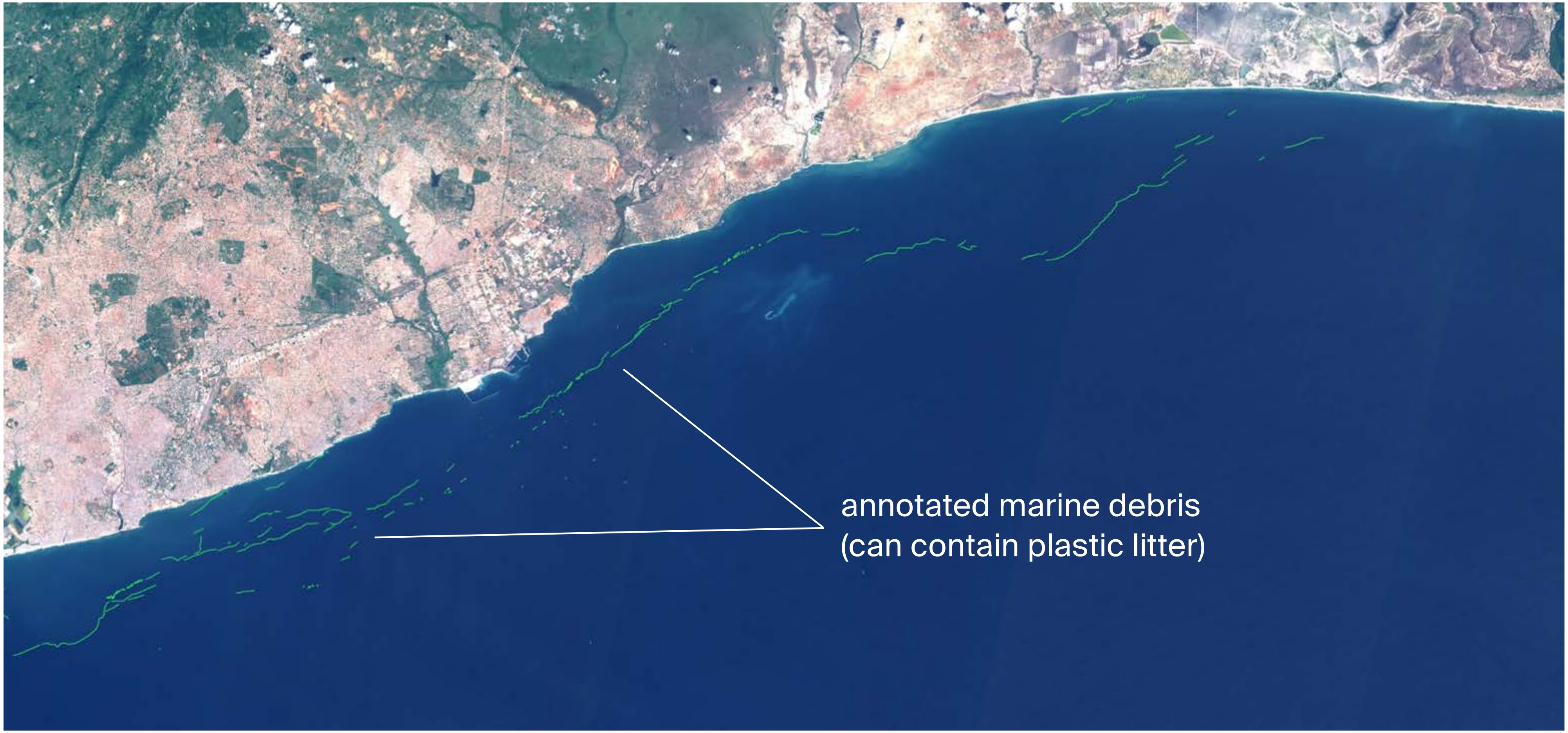
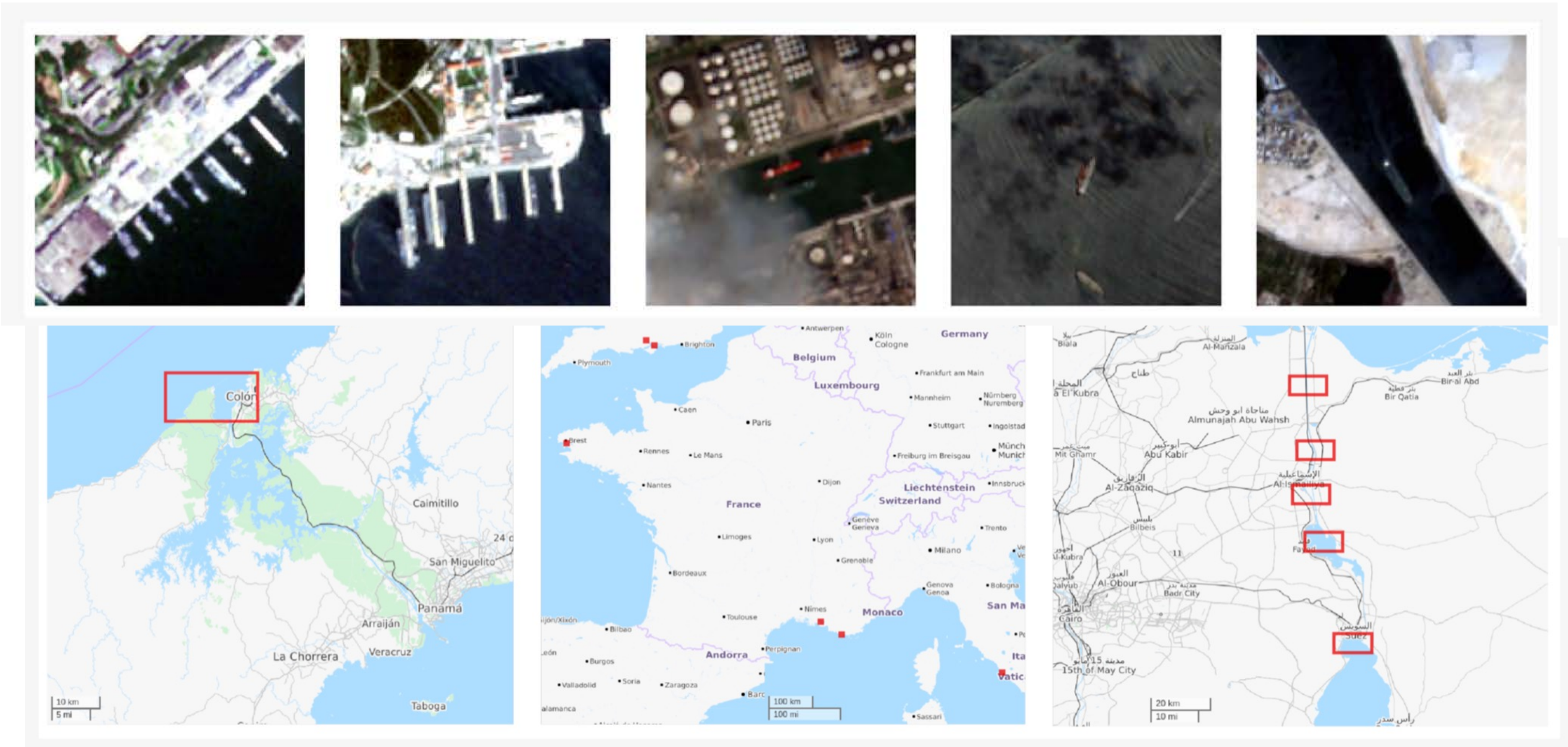
Accra (Sentinel-2 scene 2018-10-31)

D. Tuia, 2024



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

- Complex models (Deep learning) tend to outperform simple ones

Accra trained on	original data		our train set		
	RF	UNET	RF	UNET	UNET++
ACCURACY	0.653	0.882	0.680	**0.924** ± 0.016	**0.930** ± 0.016
F-SCORE	0.464	0.871	0.545	**0.920** ± 0.018	**0.926** ± 0.018
AUROC	0.246	0.965	0.899	**0.978** ± 0.008	**0.981** ± 0.006
JACCARD	0.302	0.772	0.374	**0.852** ± 0.030	**0.862** ± 0.031
KAPPA	0.301	0.764	0.357	**0.848** ± 0.031	**0.859** ± 0.031
Durban trained on	**original data**		**our train set**		
	RF	UNET	RF	UNET	UNET++
ACCURACY	0.781	0.587	0.811	0.908 ± 0.010	**0.934** ± 0.018
F-SCORE	0.105	0.497	0.708	0.756 ± 0.032	**0.837** ± 0.053
AUROC	0.376	0.765	0.862	0.850 ± 0.030	**0.914** ± 0.018
JACCARD	0.055	0.330	0.548	0.609 ± 0.042	**0.722** ± 0.048
KAPPA	0.082	0.245	0.569	0.704 ± 0.037	**0.797** ± 0.063
Marida-test set trained on	**original data**		**our train set**		
	RF	UNET	RF	UNET	UNET++
ACCURACY	0.697	0.838	0.811	**0.865** ± 0.006	**0.867** ± 0.005
F-SCORE	0.288	0.701	0.708	**0.741** ± 0.012	**0.749** ± 0.009
AUROC	0.488	0.764	0.862	**0.738** ± 0.012	**0.746** ± 0.021
JACCARD	0.168	0.539	0.548	**0.589** ± 0.015	**0.598** ± 0.012
KAPPA	0.197	0.593	0.569	**0.654** ± 0.016	**0.661** ± 0.012

M. Rußwurm, S. J. Venkatesa, and **D.Tuia**. Large-scale Detection of Marine Debris in Coastal Areas with Sentinel-2. *In press*
https://arxiv.org/abs/2307.02465

Results

Takehome

- Complex models (Deep learning) tend to outperform simple ones
- Data more important than models!

FlObs+MARIDA+S2Ships

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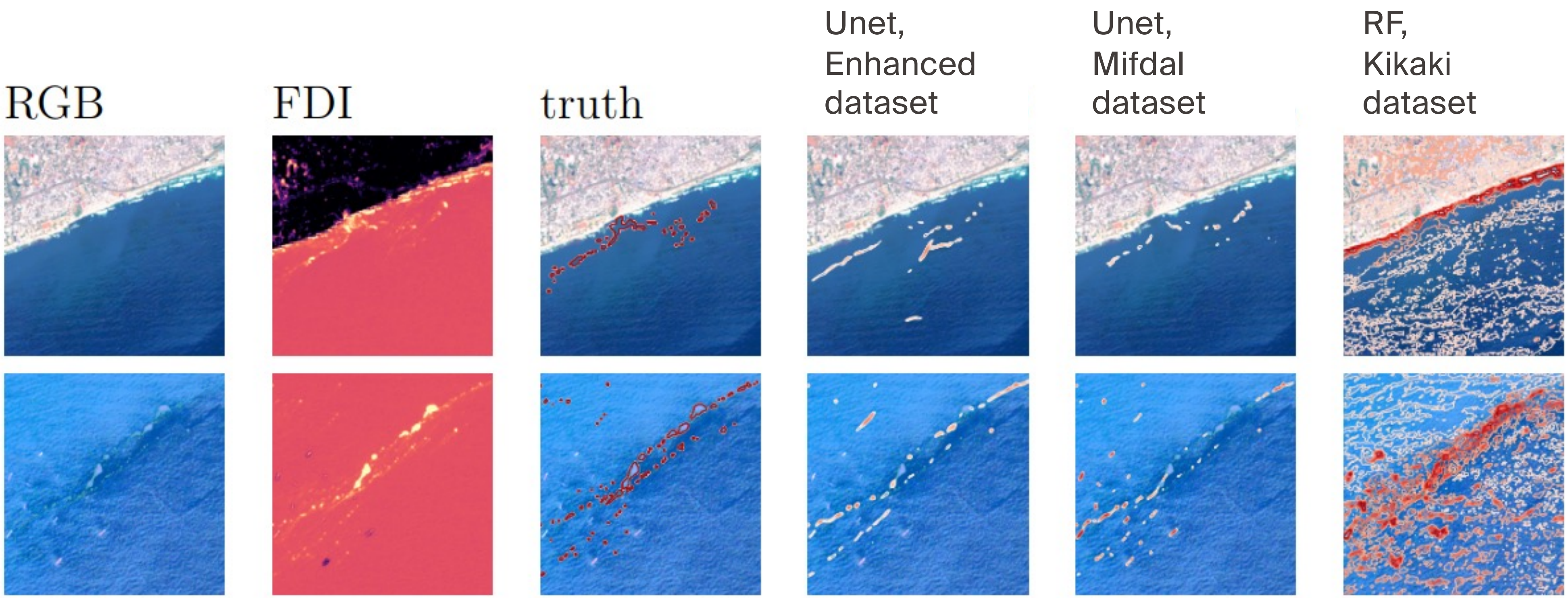
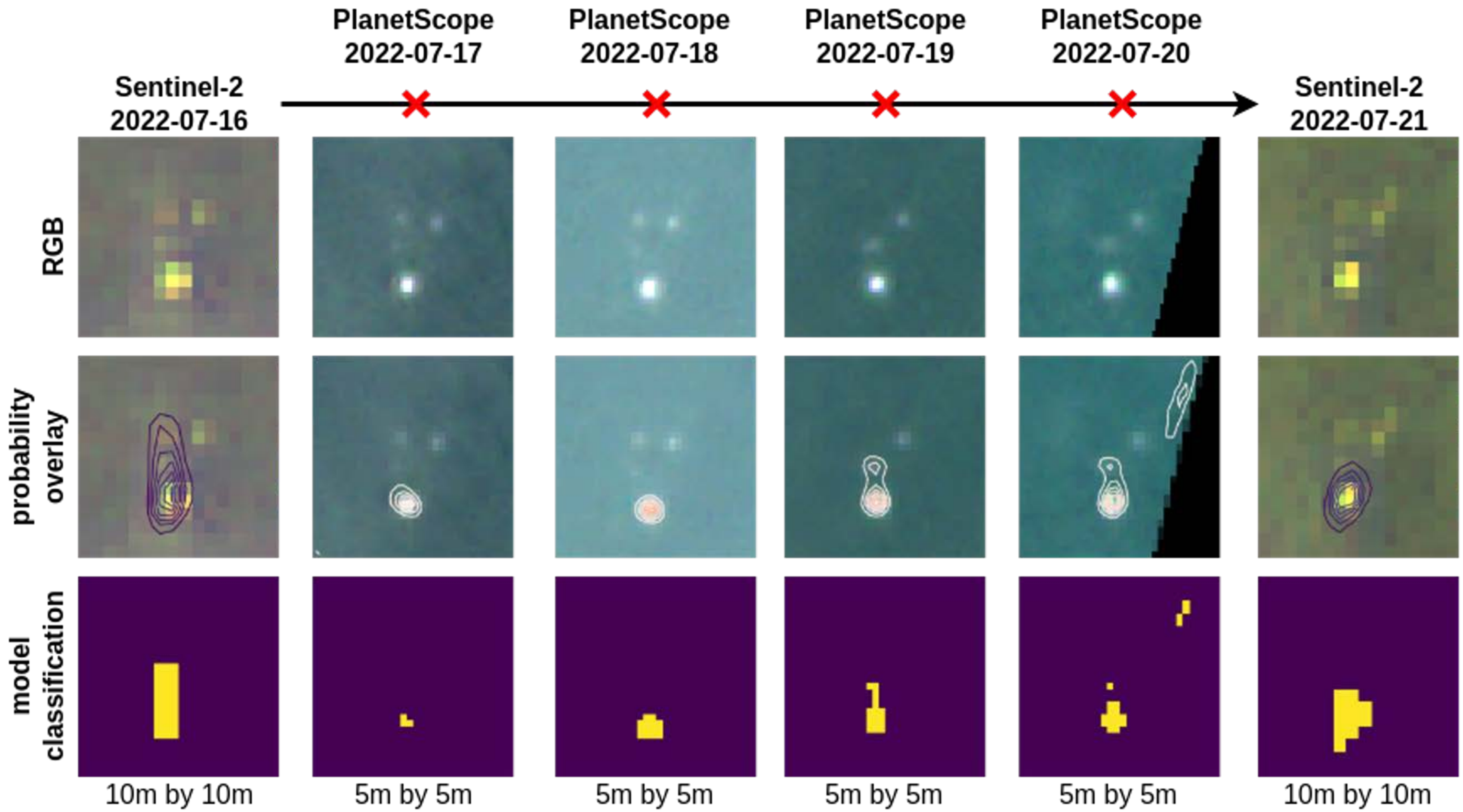
Prediction examples



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

Detections on the Plastic Litter project 2022



M. Rußwurm, S. J. Venkatesa, and **D.Tuia**. Large-scale Detection of Marine Debris in Coastal Areas with Sentinel-2. *iScience, 108402,* 2023.
Available: https://www.sciencedirect.com/science/article/pii/S2589004223024793

Part II

Underwater

Characterizing coral reefs at scale

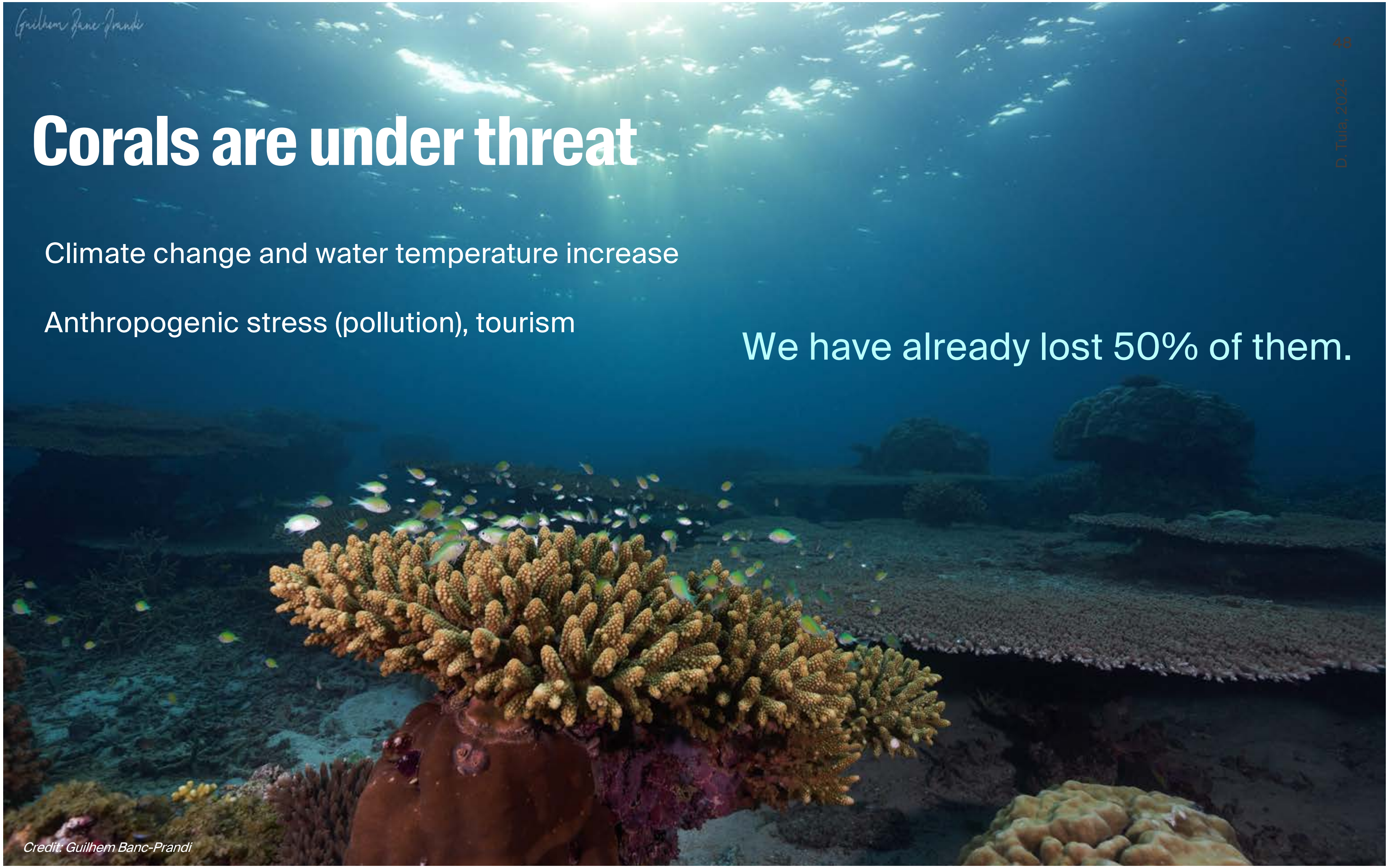
EPFL

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

D. Tuia, 2024

EPFL

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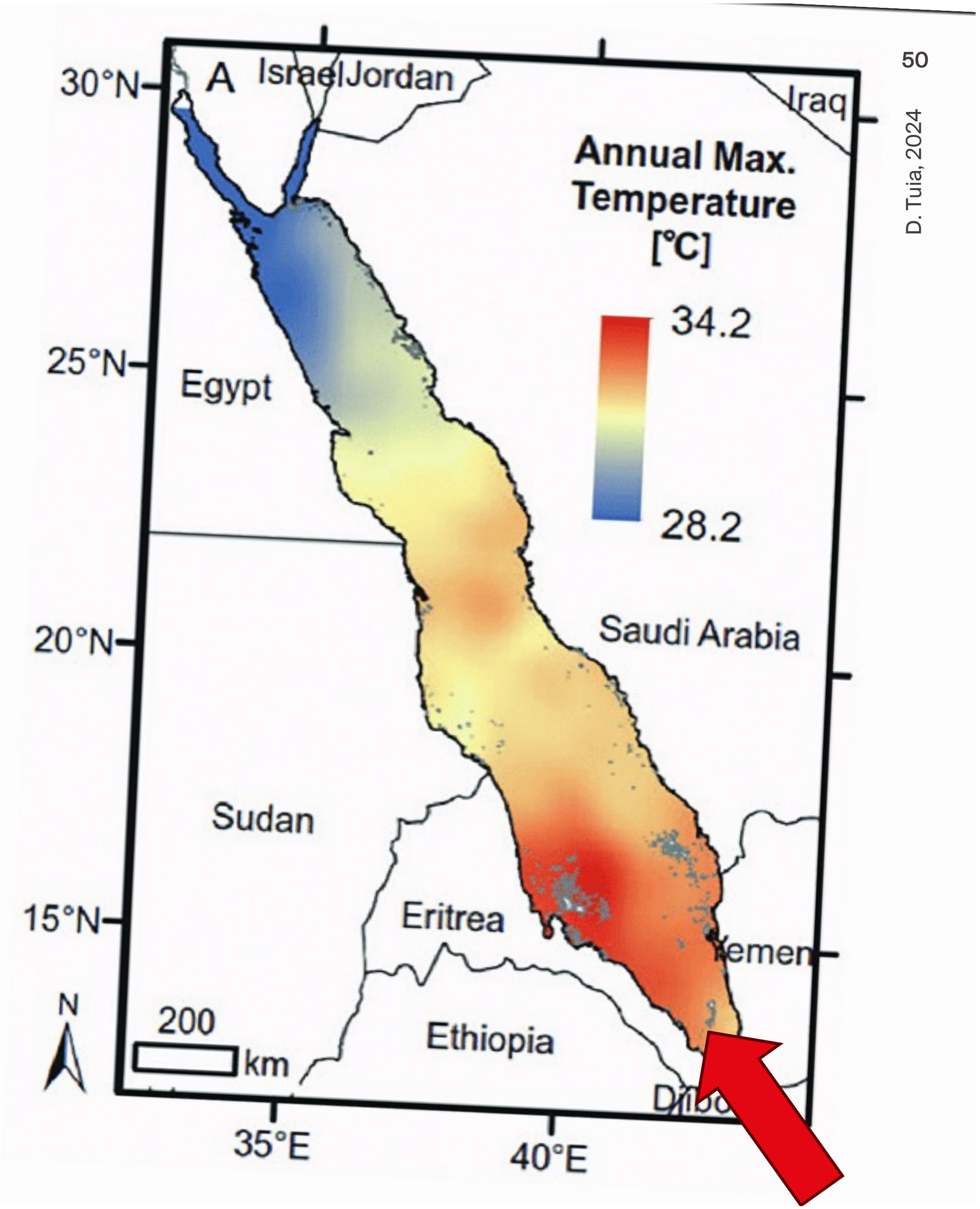


D. Tuia, 2024

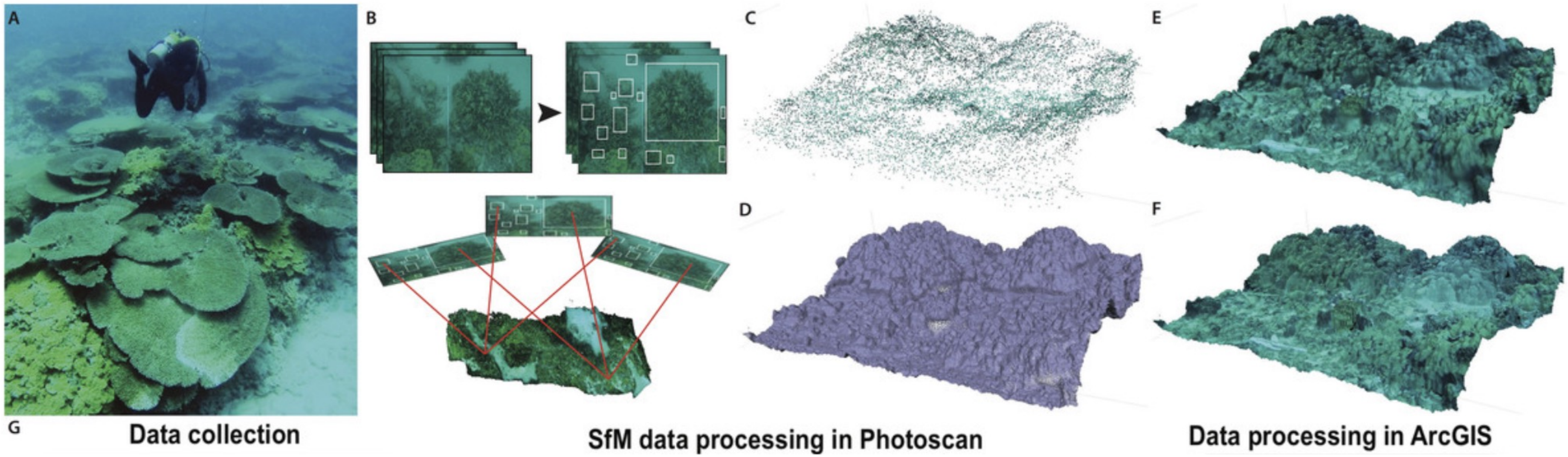
EPFL

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

28 x 6 m plot

1h with proprietary software

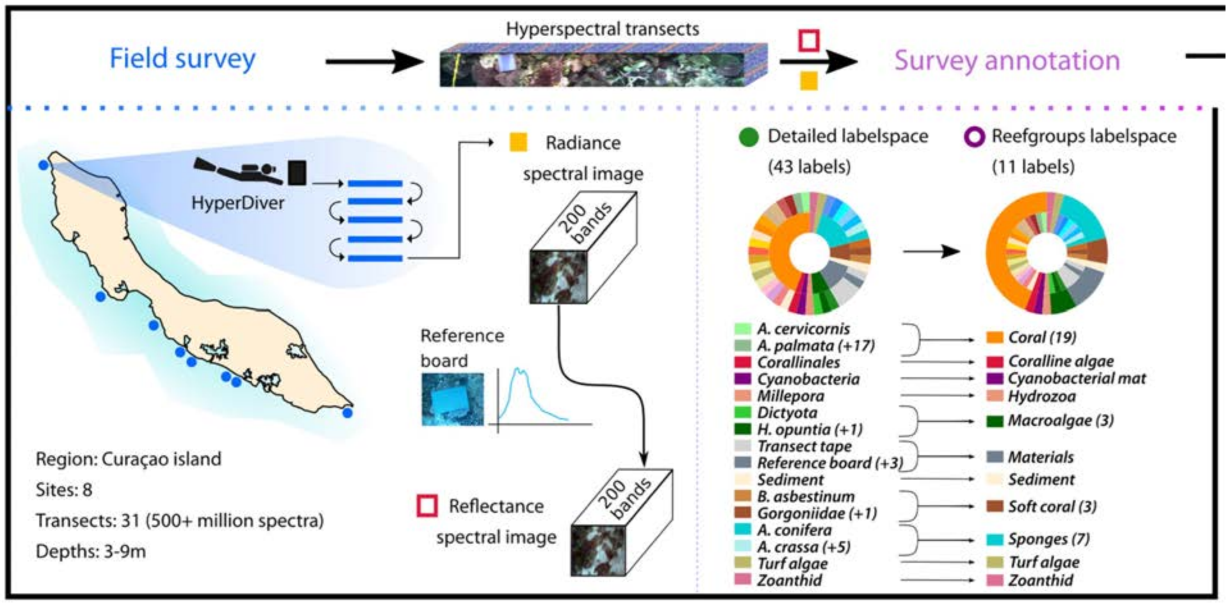
20h manual work
to extract information



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

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

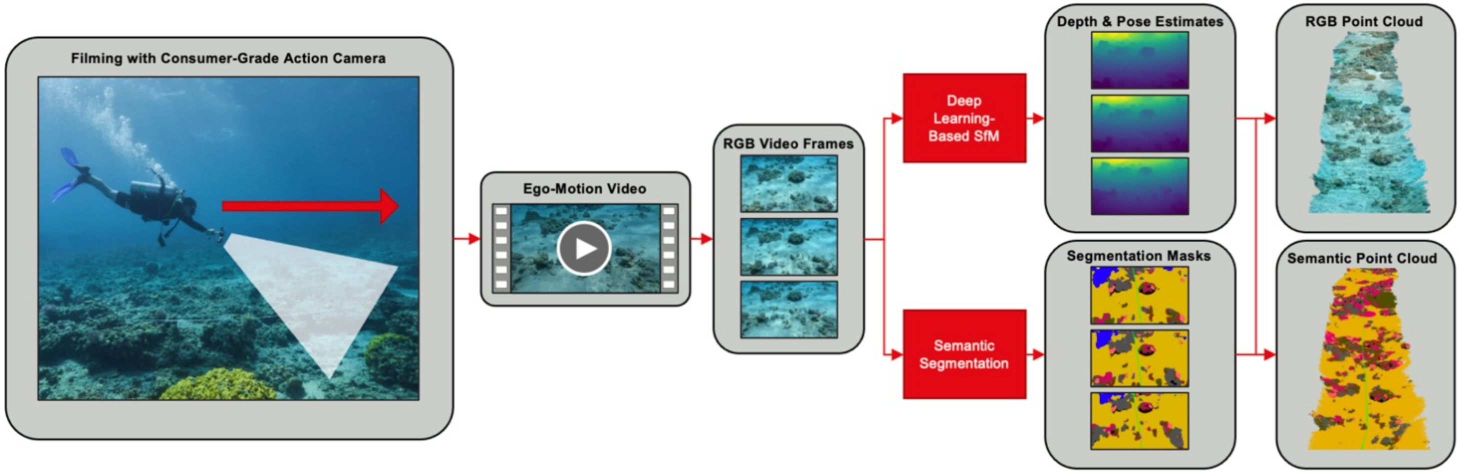
Mark II: August 2022 – Djibouti

Photo credits: Guilhem Banc-Prandi, 2022

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

- A model that works on videos, leveraging 2 tasks

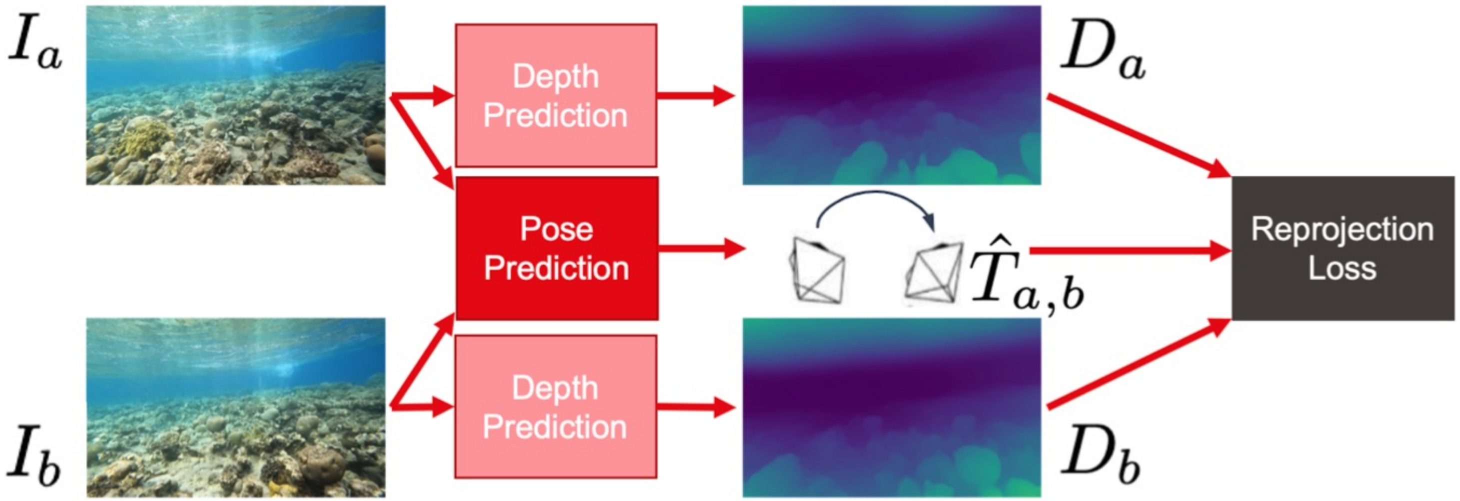
- Once trained, 3D reconstructs a 100m transect in playing video time
- Tested in Israel, Jordan and Djibouti in 2022/2023



J. Sauder, G. Banc-Prandi, A. Meibom, and **D. Tuia**. Scalable semantic 3d mapping of coral reefs with deep learning. *Methods in Ecology and Evolution,* 2024. https://arxiv.org/abs/2309.12804

Pose and depth estimation

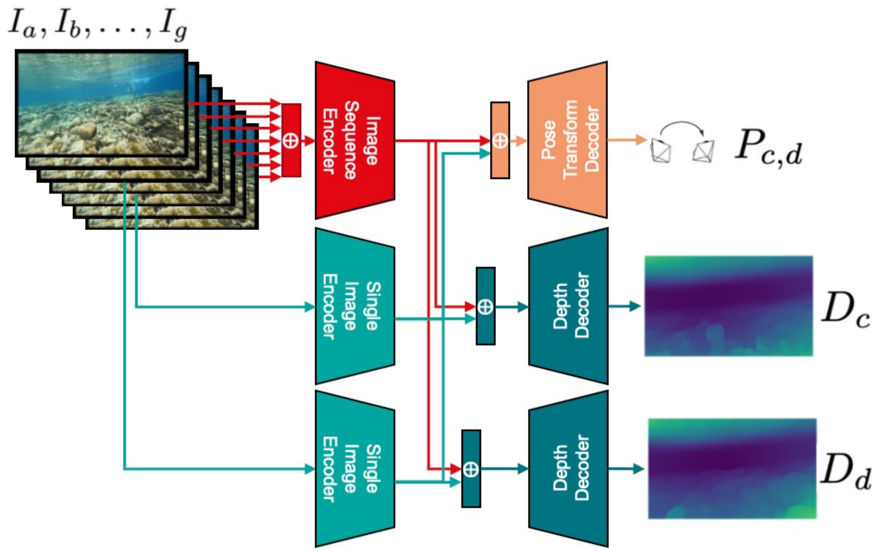
- Encoders based on ResNet-34
- Can create the 3D map at 18 frames per second



J. Sauder, G. Banc-Prandi, A. Meibom, and **D. Tuia**. Scalable semantic 3d mapping of coral reefs with deep learning. *Methods in Ecology and Evolution*, 2024. https://arxiv.org/abs/2309.12804

Pose and depth estimation

- We enforce temporal consistency by encoding 7 frames at a time
- 3 before and 3 after
- Each decoder uses the frame + the sequence features



J. Sauder, G. Banc-Prandi, A. Meibom, and **D. Tuia**. Scalable semantic 3d mapping of coral reefs with deep learning. *Methods in Ecology and Evolution,* 2024. https://arxiv.org/abs/2309.12804

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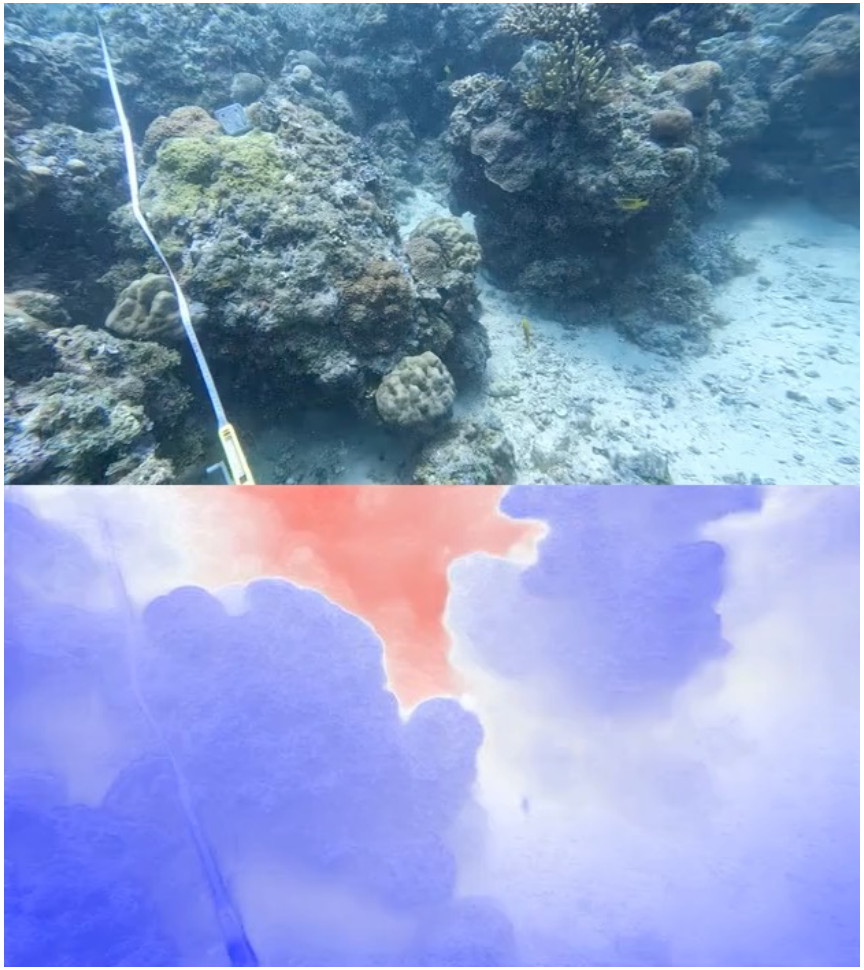
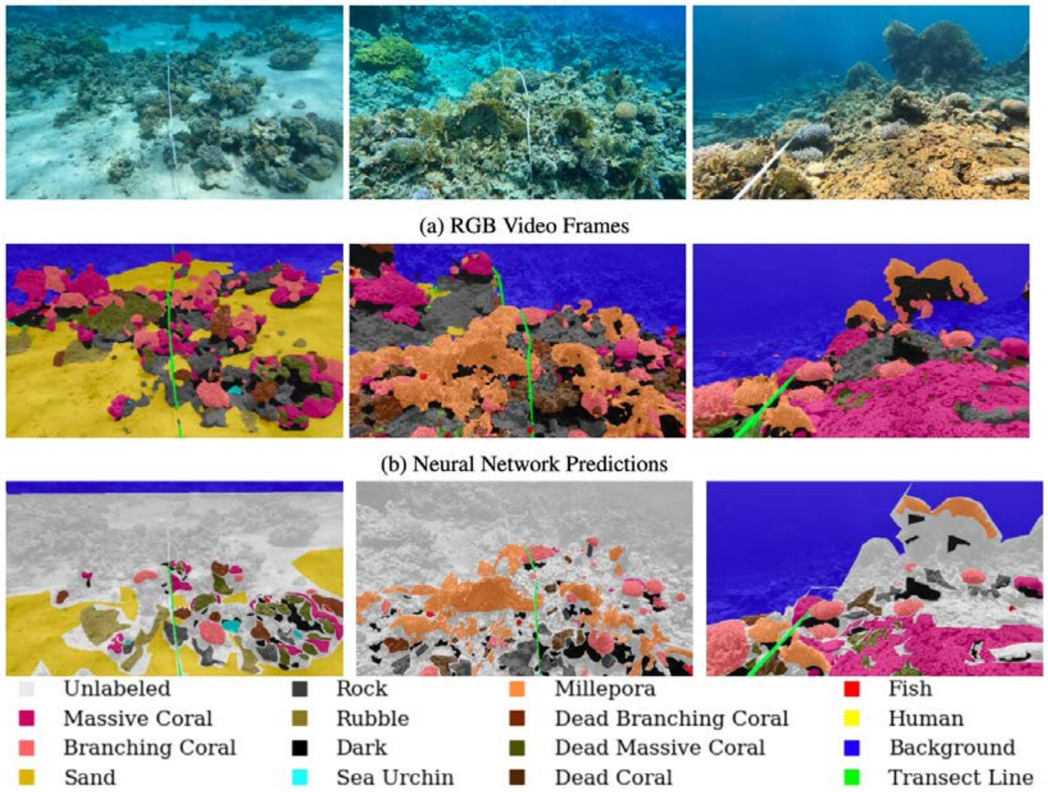


Semantic segmentation

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

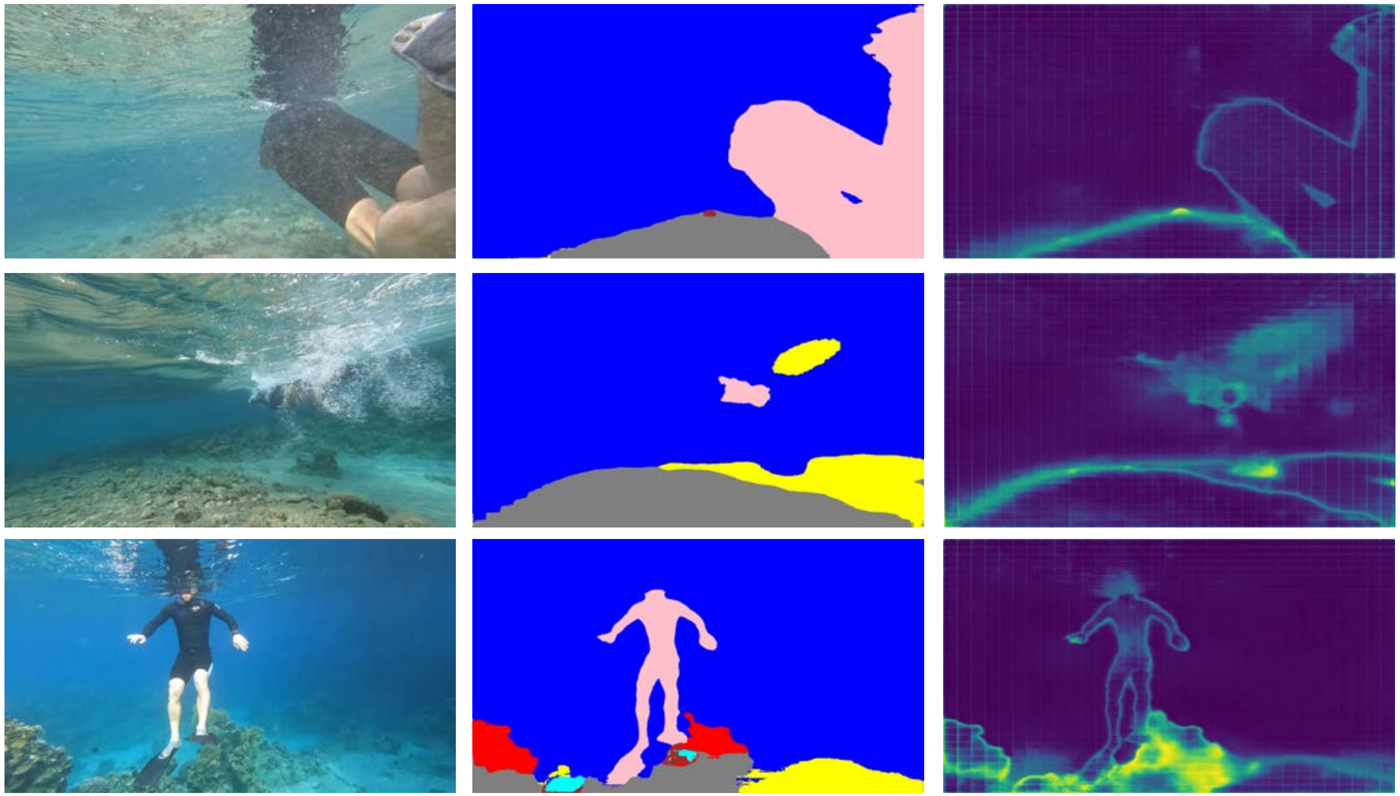


J. Sauder, G. Banc-Prandi, A. Meibom, and **D. Tuia**. Scalable semantic 3d mapping of coral reefs with deep learning. *Methods in Ecology and Evolution,* 2024. https://arxiv.org/abs/2309.12804

Learning to detect unwanted classes

Used to remove unwanted classes prior to 3D reconstruction

- Diver body
- Fishes
- Far away pixels

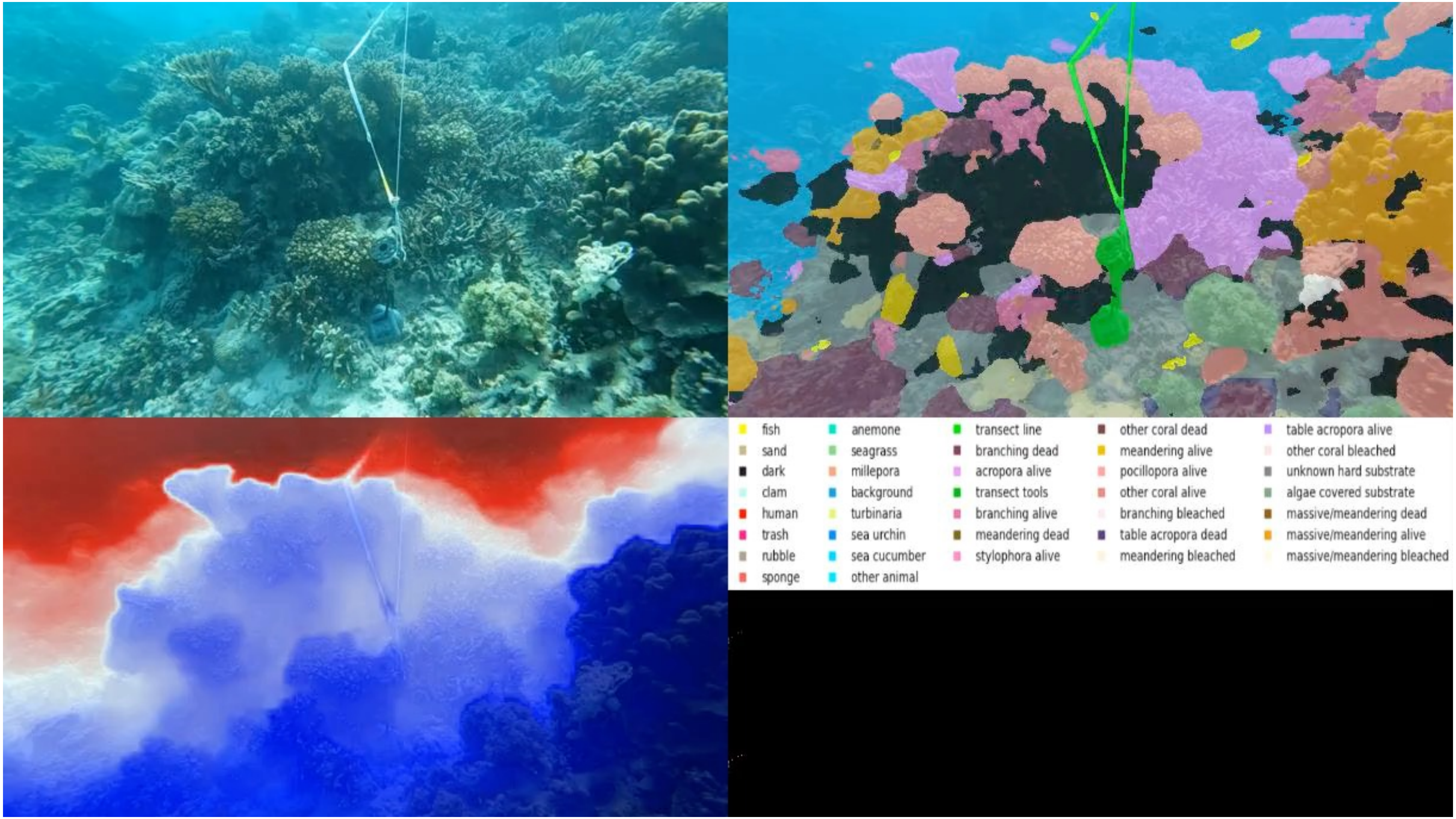


Video frame | Segmentation | Uncertainty

Learning to detect unwanted classes

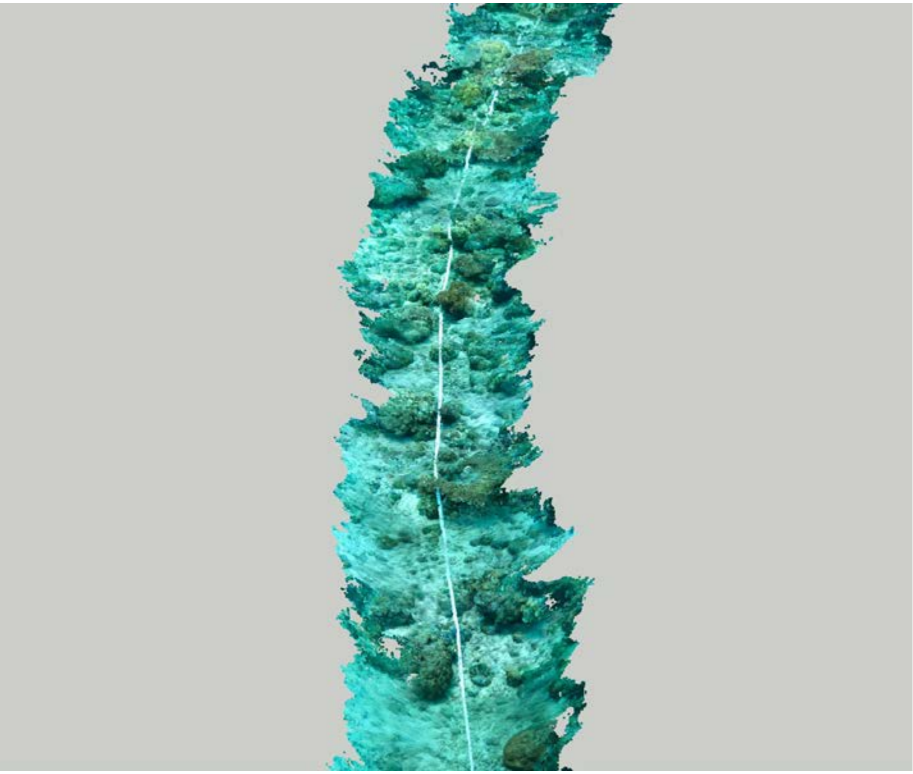
Used to remove unwanted classes prior to 3D reconstruction

- Diver body
- Fishes
- Far away pixels

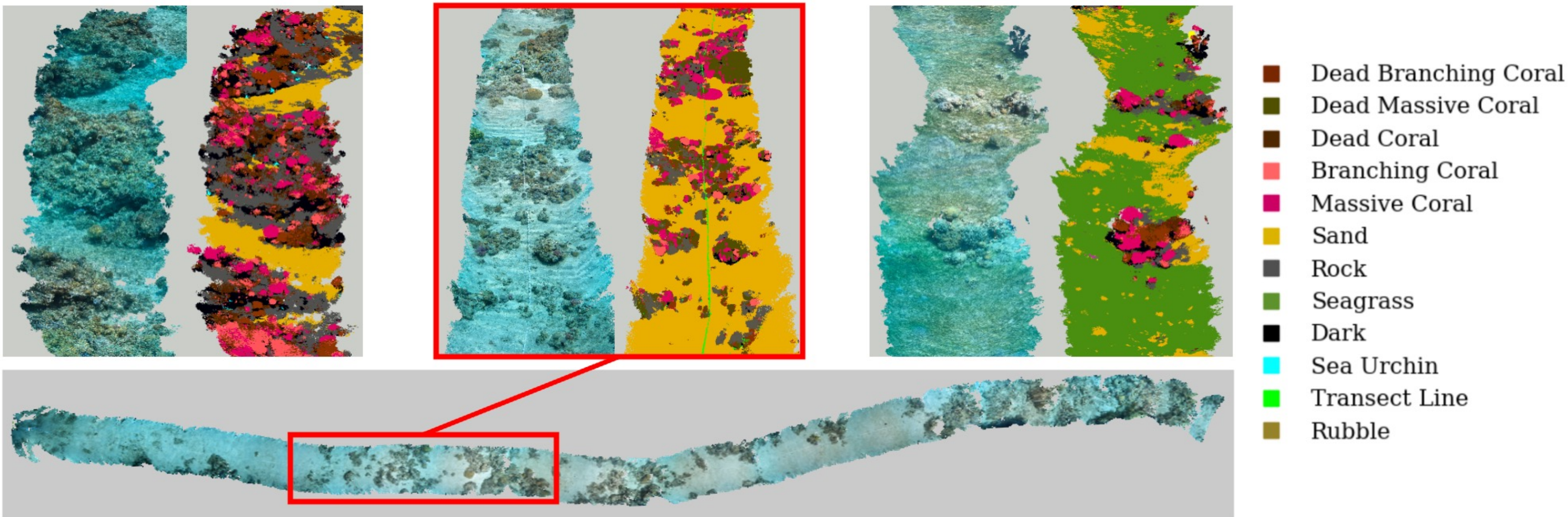

fish
sand
dark
clam
human
trash
rubble
sponge
anemone
seagrass
millepora
background
turbinaria
sea urchin
sea cucumber
other animal
transect line
branching dead
acropora alive
transect tools
branching alive
meandering dead
stylophora alive
other coral dead
meandering alive
pocillopora alive
other coral alive
branching bleached
table acropora dead
meandering bleached
table acropora alive
other coral bleached
unknown hard substrate
algae covered substrate
massive/meandering dead
massive/meandering alive
massive/meandering bleached

The multitask model allow us to create reliable 3D reconstructions of the reef

D. Tuia, 2024



Mapping entire dive sites
(here: 100m long)



Mapping entire dive sites
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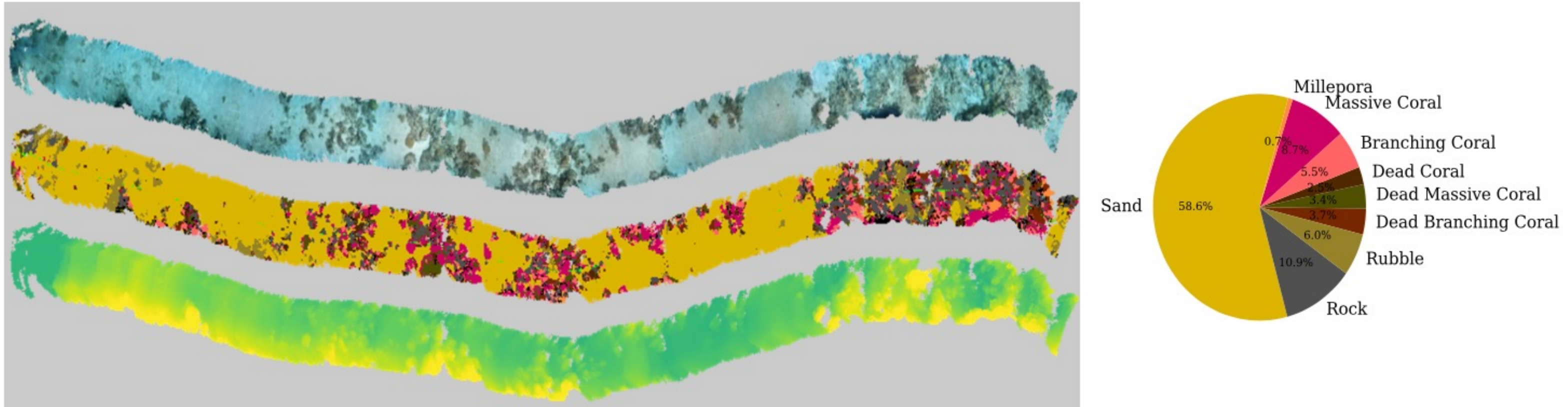
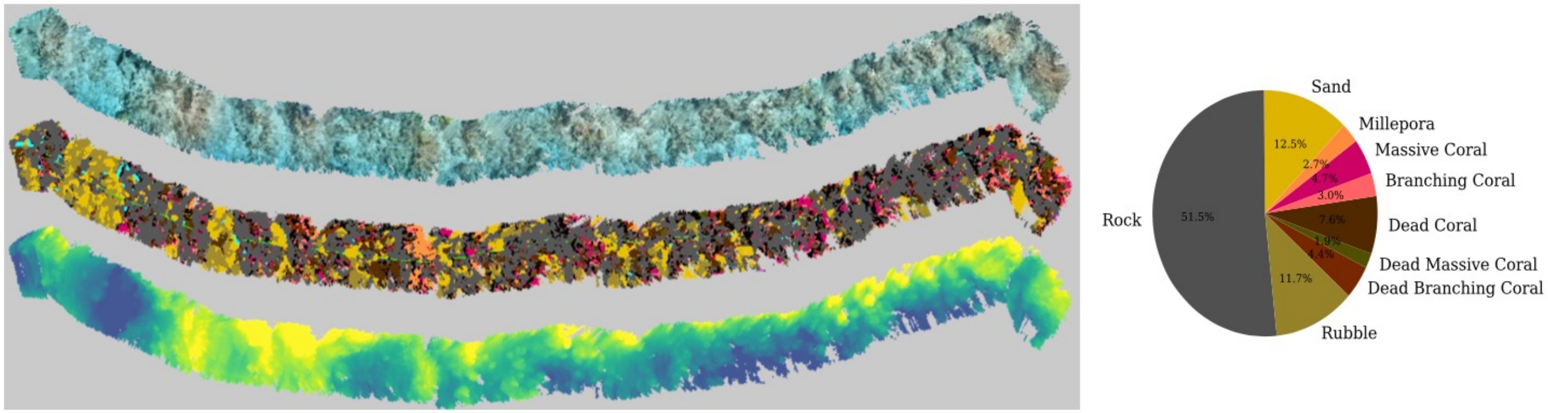


(a) King Abdullah Reef (Sandy)



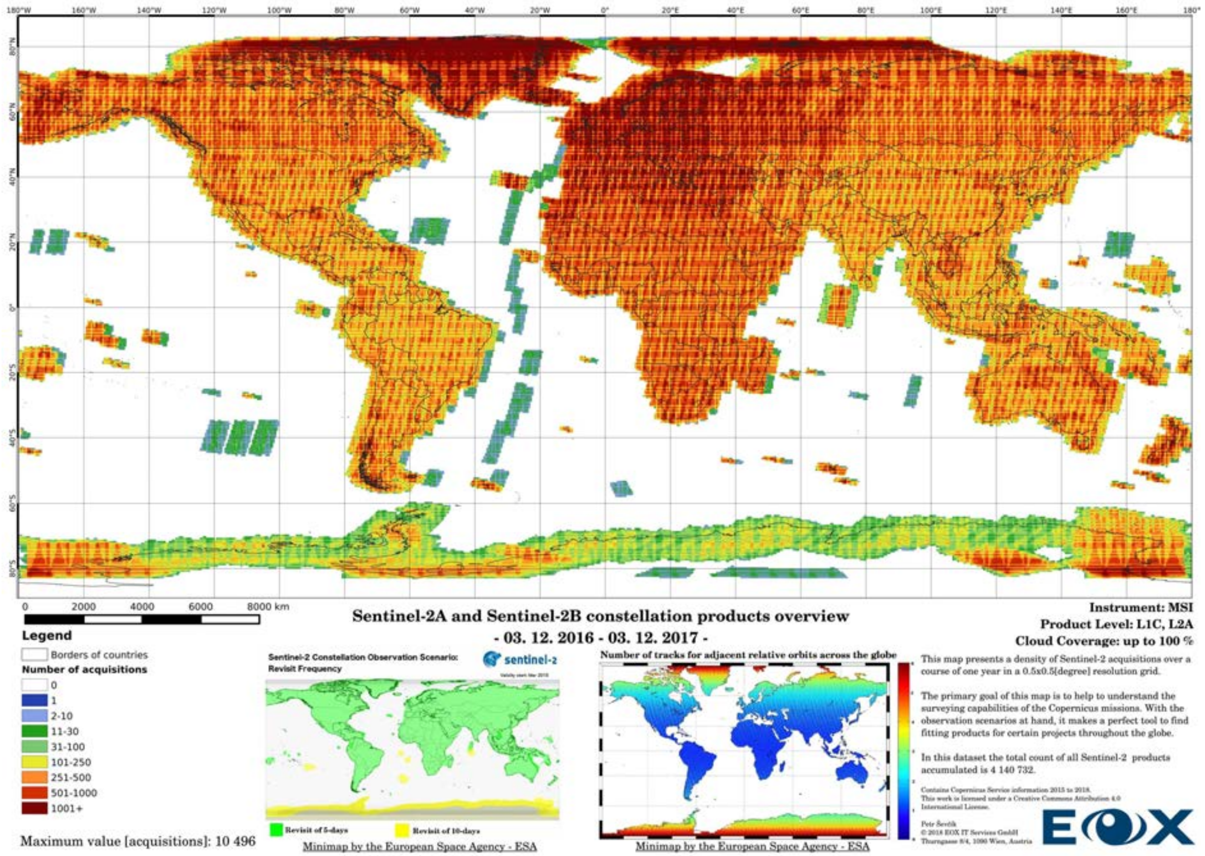
(b) King Abdullah Reef (Rocky)

Part III bonus

What about lands?

Remote sensing observes everywhere!

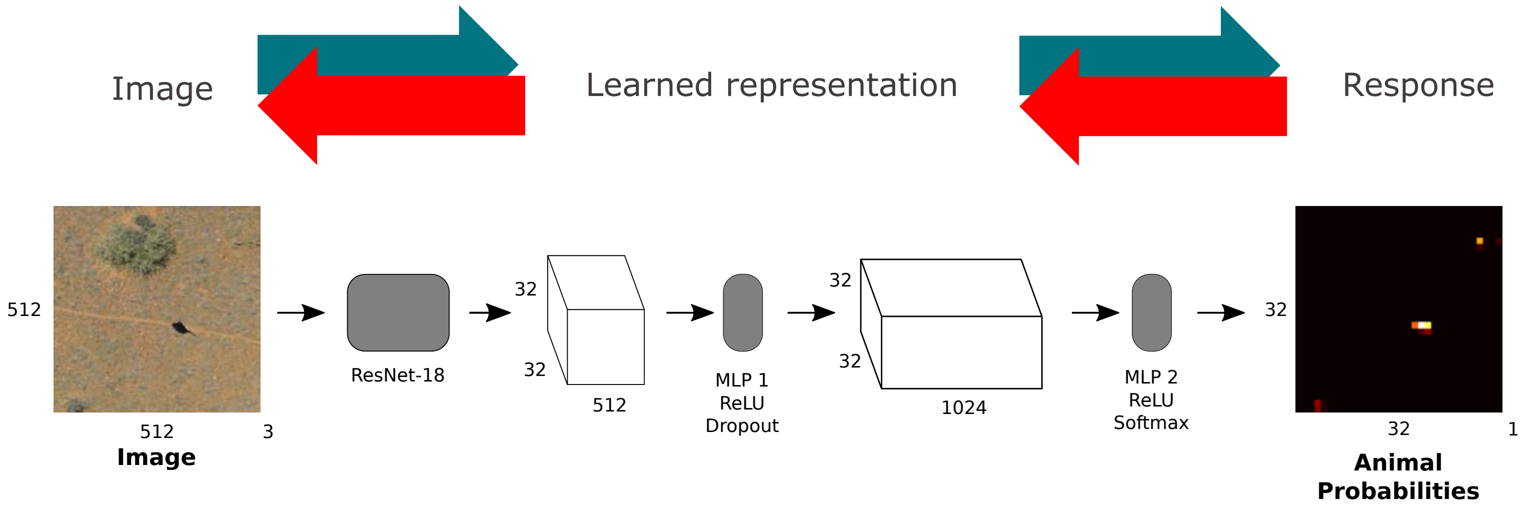
- Remote sensing has the advantage of being .. remote.
- We can observe Earth basically everywhere.



But the images alone won’t give you much.

- This is why we focus on technology to convert data into information and collaborate with domain specialists.
- Interdisciplinarity is the way!
- Let’s see a couple of examples

Ecology: accelerating animal censuses

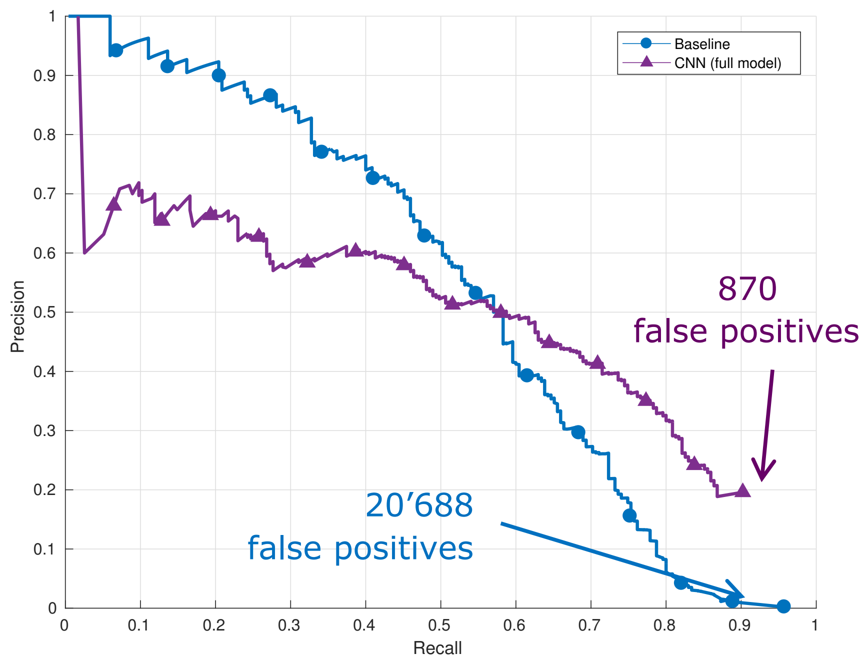


- Together with park rangers, we develop systems to help them detect and count wildlife
- Census can be accellerated by a factor 100! (Desplanque et al., 2024)

EPFL

An example in Kuzikus park, Namibia

- Compared to EESVMs [Rey et al., 2017 RSE]
-
- The CNN outperforms it for high recall rates

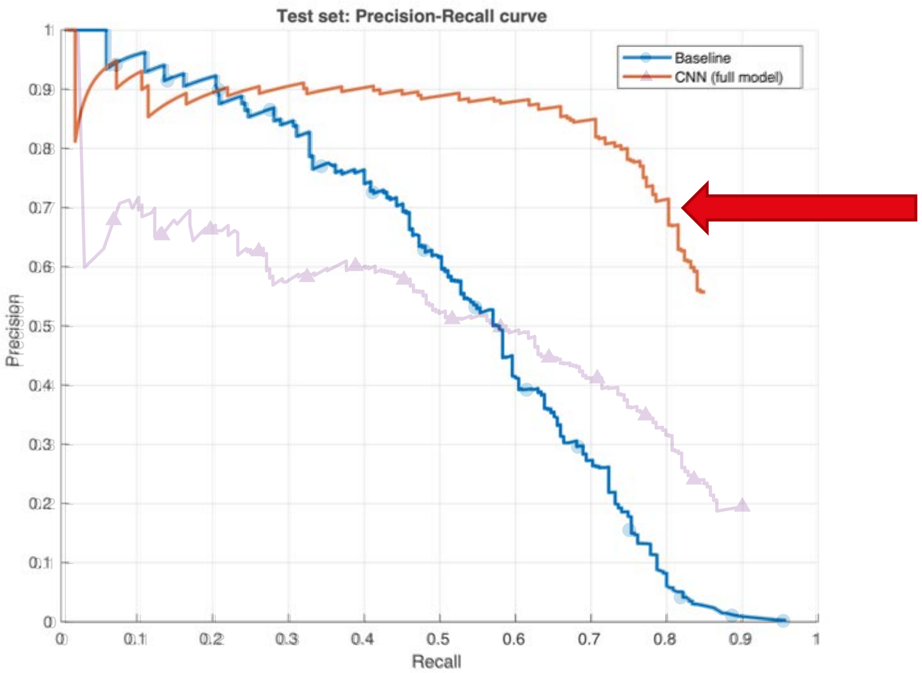


Paper. Kellenberger, Marcos, Tuia: Detecting Mammals in UAV Images: Best Practices to address a substantially Imbalanced Dataset with Deep Learning. Remote Sensing of Environment, 216:139-153, 2018. https://arxiv.org/abs/1806.11368

An example in Kuzikus park, Namibia

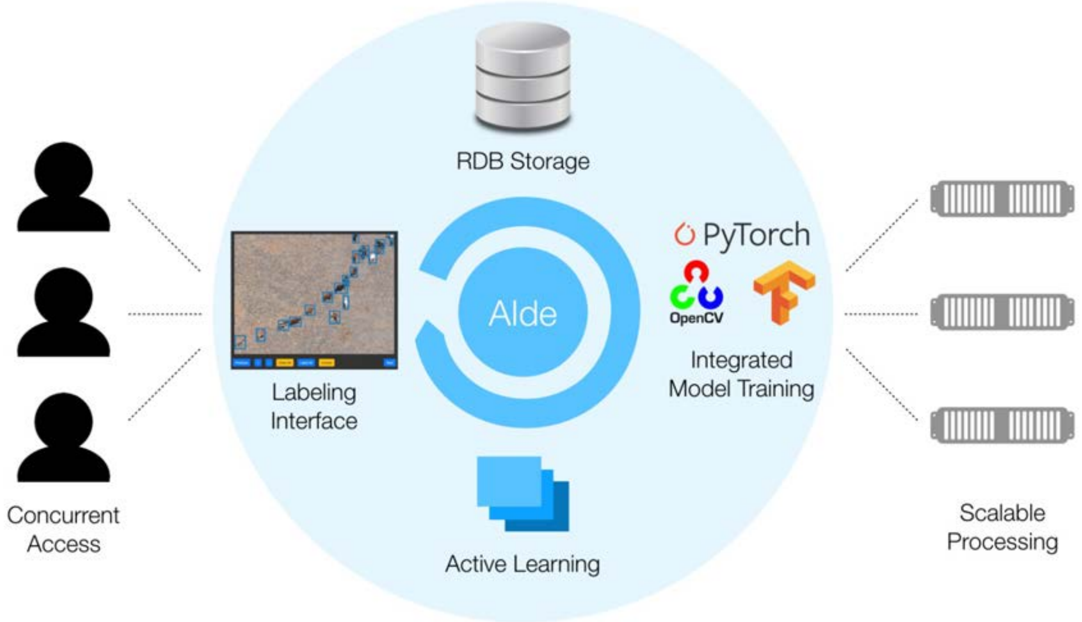
- And we keep working on it and improving it.
- This is the 2024 situation.

- At 80% recall i.e. when finding 80% of the animals
- Has a 65% precision (116 false positives)




[May et al., ECCVw, 2024]

We also build open source software



https://github.com/microsoft/aerial_wildlife_detection

Kellenberger, Tuia, Morris. AIDE: accelerating image-based ecological surveys with interactive machine learning
Methods in Ecology and Evolution, 11(12):1716-1727, 2021. https://besjournals.onlinelibrary.wiley.com/doi/full/10.1111/2041-210X.13489

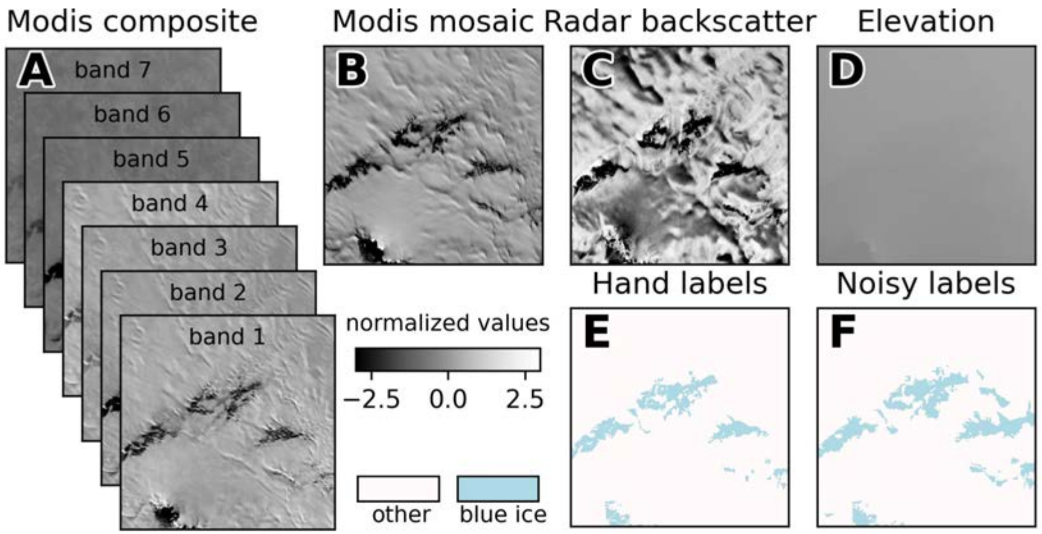
Cryosphere: treasure hunting for blue ice

- Blue ice areas are resurgences of very old ice
- They also hold most meteorites found of Earth
- They are easy to spot
- But Anctartica is BIG!

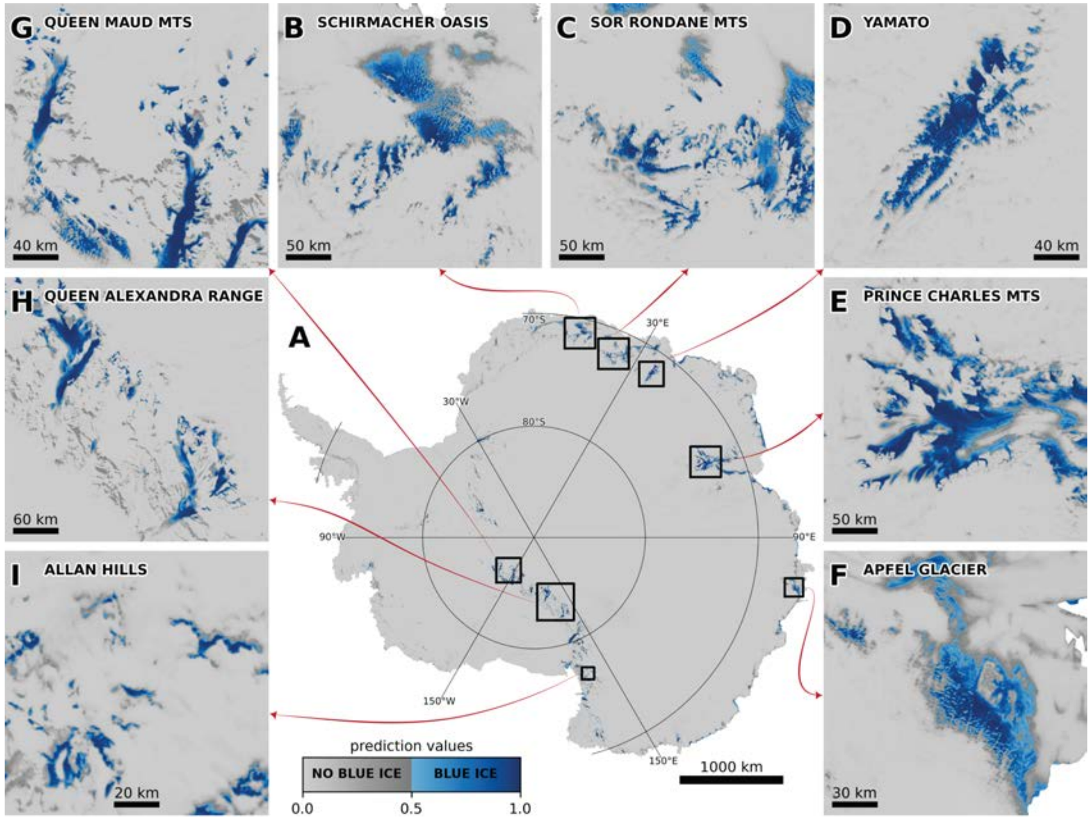
e.g., Yan et al., Nature (2019)

Cryosphere: treasure hunting for blue ice

- We collected continental-scale remote sensing data
  - Optical (MODIS)
  - Rarar (RADARSAT)
  - Elevation
- And learned a neural network to predict blue ice locations



Cryosphere: treasure hunting for blue ice

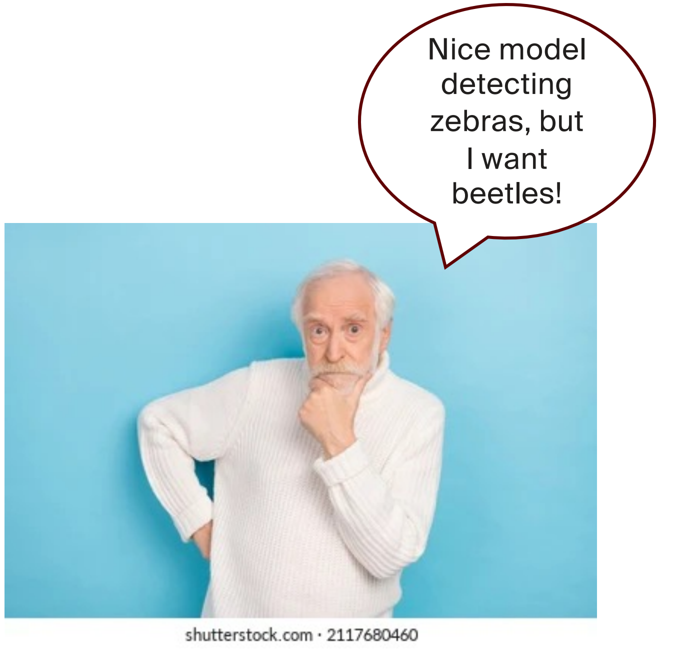


Tollenaar et al., Where the white continent is blue: deep learning locates bare ice in Antarctica. *Geophysical Research Letters*, 51(3):e2023GL106285, 2024. https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2023GL106285

Beyond images: integrating language in interactions

- We can create AI models to extract information from images
- With proper training sets, we can reproduce observations and scaleup!
- But the level of interaction remains low

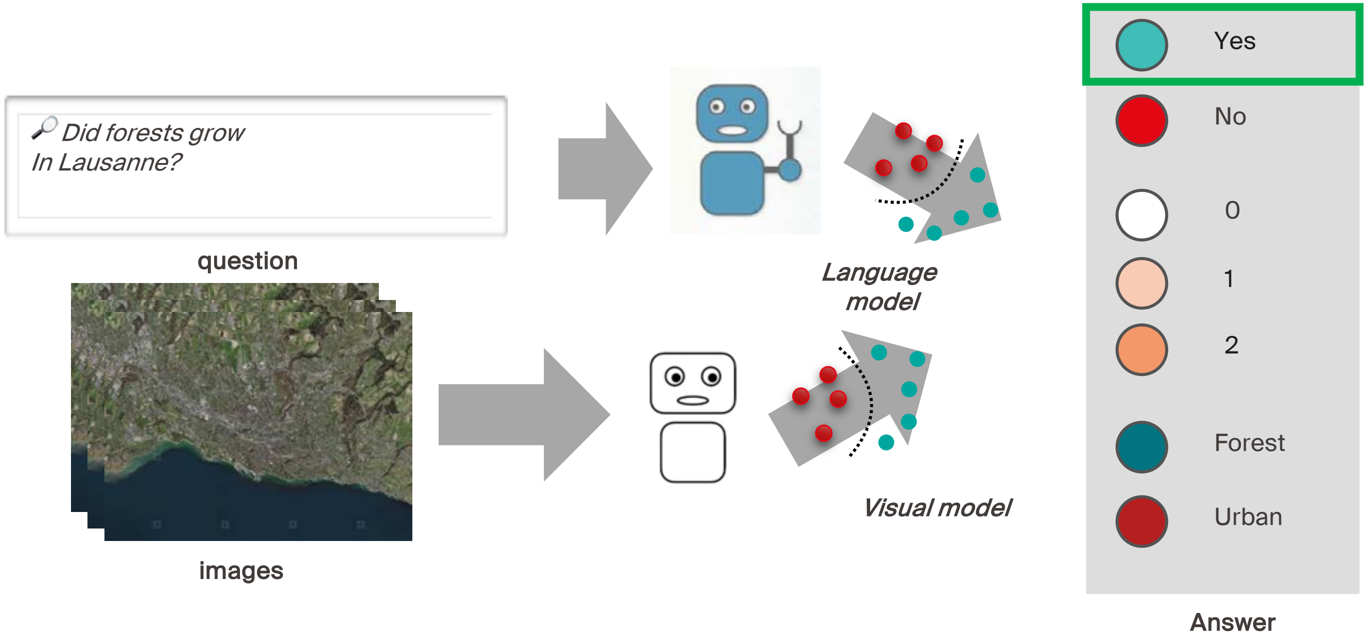
- Should we create new models for each application?



Vision language models in remote sensing

S. Lobry, D. Marcos, J. Murray, and D. Tuia. RSVQA: visual question answering for remote sensing data. *IEEE Trans. Geosci. Remote Sens.*, 58(12):8555–8566, 2020.

- By using language, we can
  - Improve the access to Earth observation for non-specialists

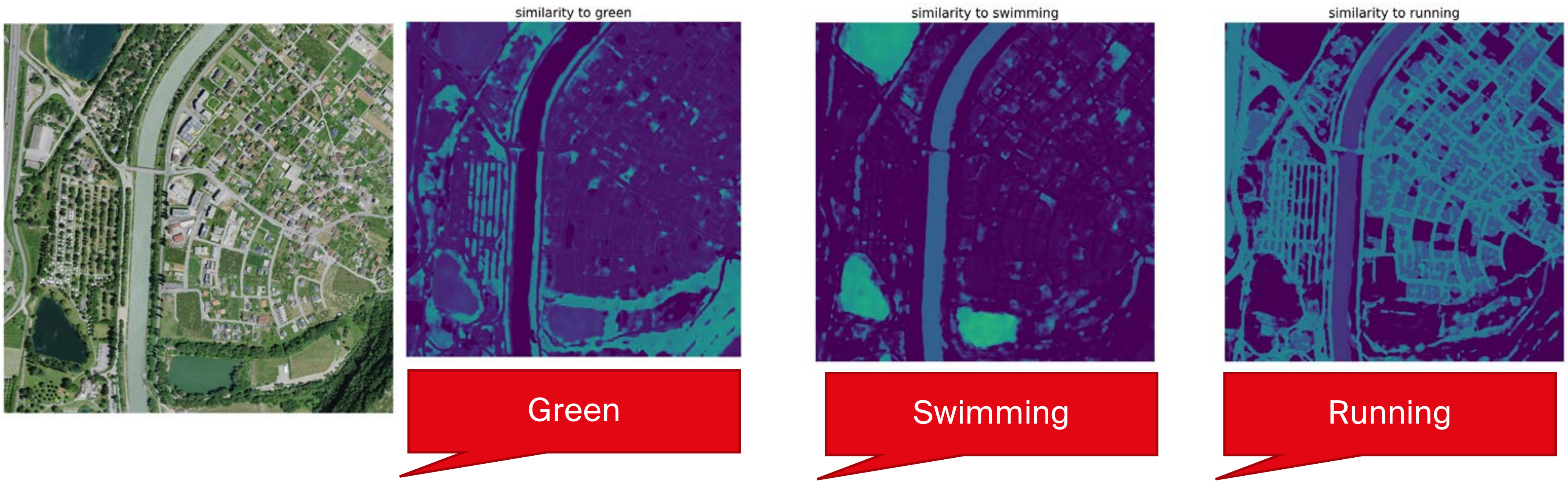


Aerial image credits: swisstopo

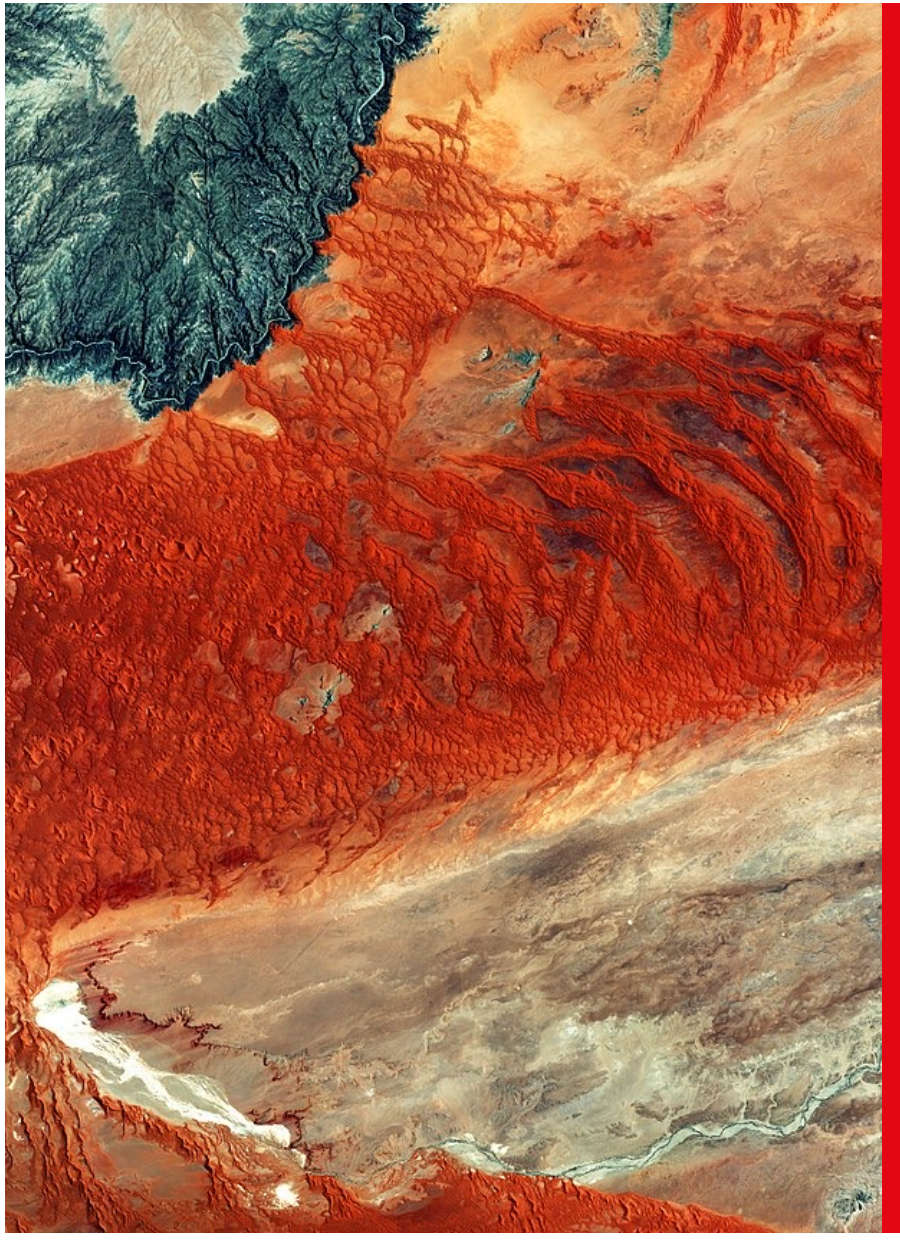
Vision language models in remote sensing

V. Zermatten, J. Castillo Navarro, L. Hughes, and D. Tuia. Text as a richer source of super- vision in semantic segmentation tasks. In *IEEE International Geoscience and Remote Sensing Symposium, IGARSS*, Pasadena, CA, 2023.

- By using language, we can
  - Improve the access to Earth observation for non-specialists
  - Allow dynamic class definitions and exploration



Concluding remarks



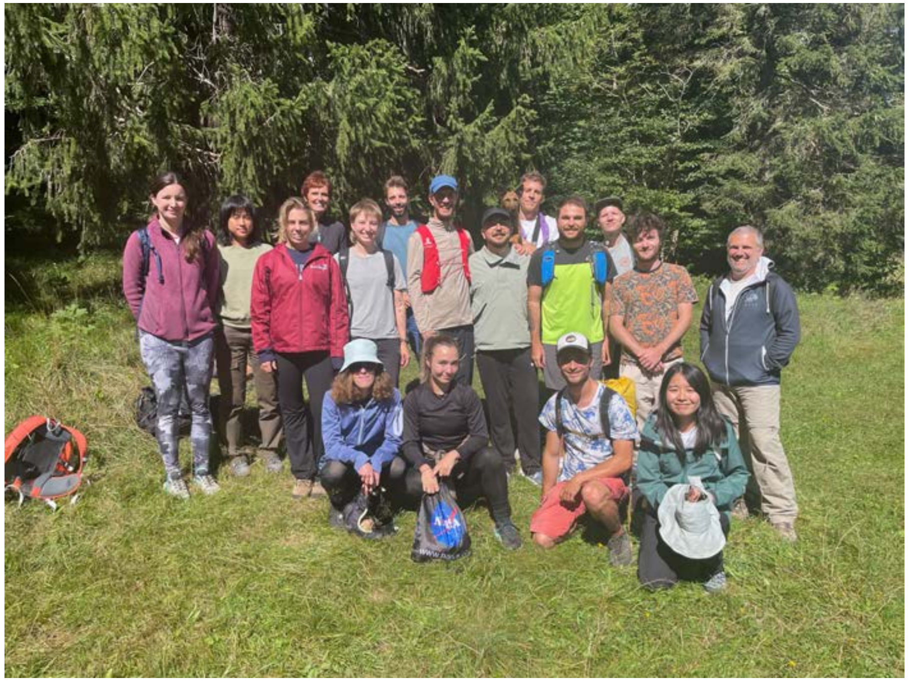
My view on Remote sensing and AI

Advance remote sensing science to monitor and protect Earth

Interface disciplines and approaches

Bring new, open tools making EO science accessible to anyone

@devistuia



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