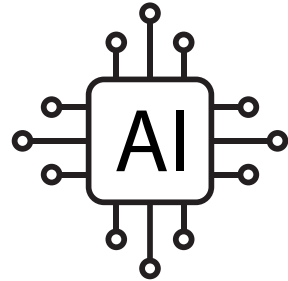
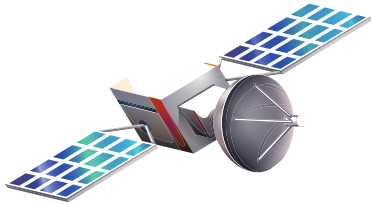
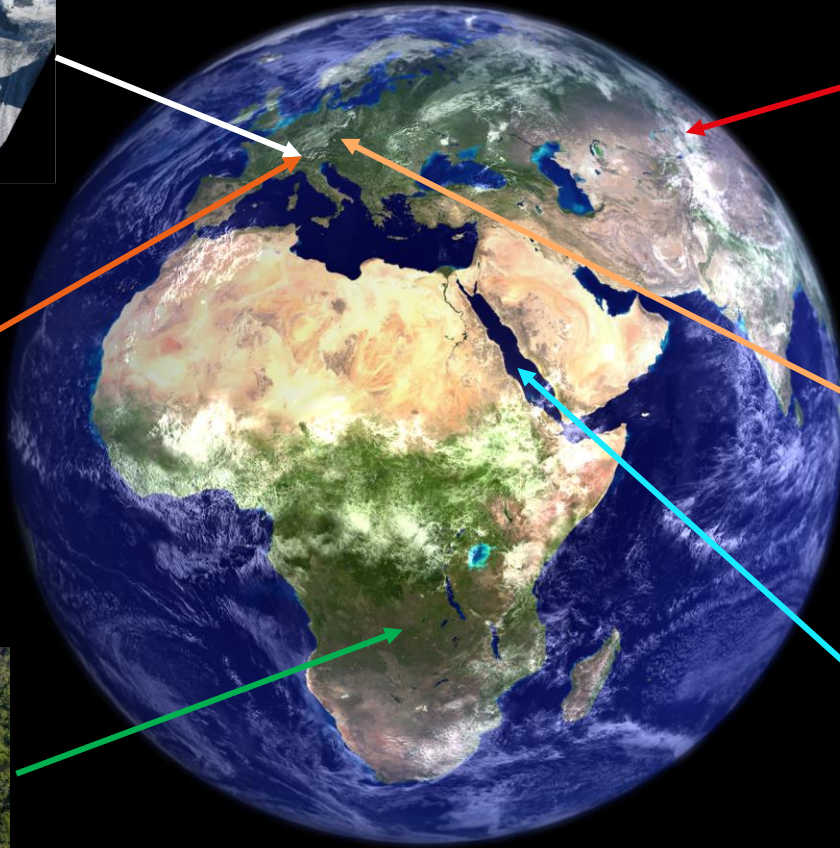
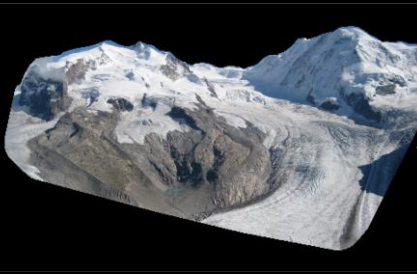


Machine learning for the environment: monitoring the pulse of our Planet with remotely sensed data

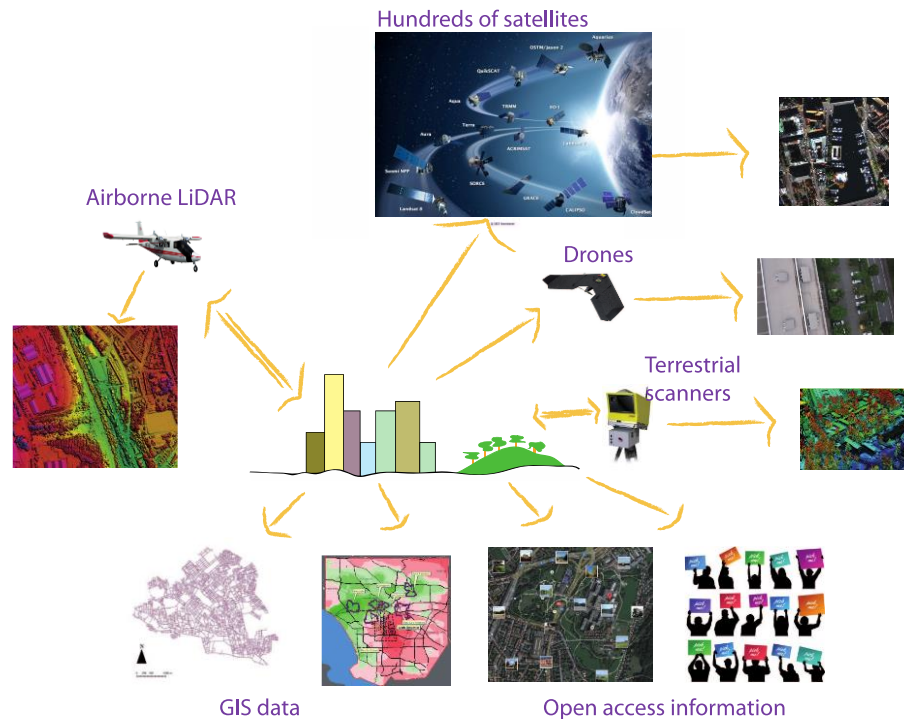
Prof. Devis Tuia, EPFL





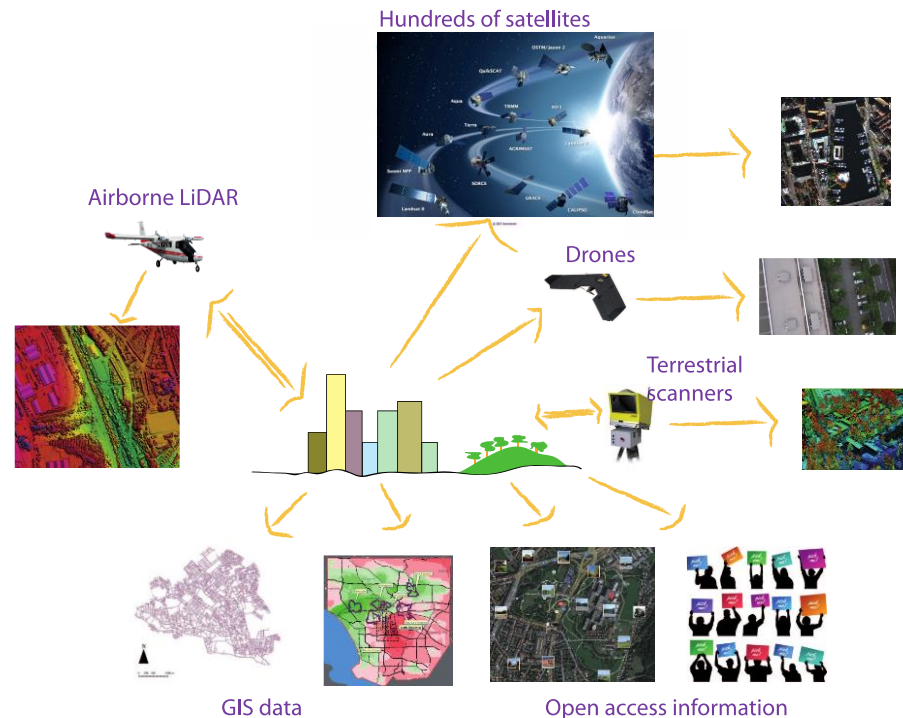
There were many sensor data to monitor Earth in 2015

- 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].



There are many sensor data to monitor Earth in ~~2015~~ 2023

- **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].



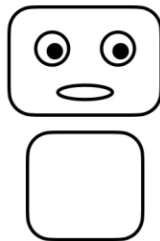
The data deluge



A 3D rendering of a globe with a dark, textured surface of question marks and a bright yellow question mark in the center. The globe is shown from a perspective that highlights the Americas. The background is a dark, textured surface of question marks, with a bright yellow question mark in the center. The globe is shown from a perspective that highlights the Americas. The background is a dark, textured surface of question marks, with a bright yellow question mark in the center.

MACHINE LEARNING

Machine learning in two minutes



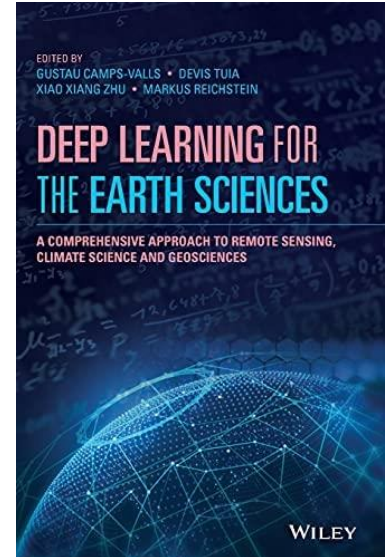
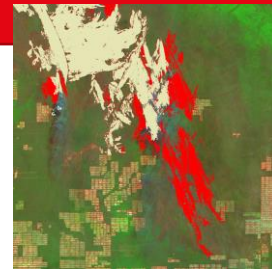
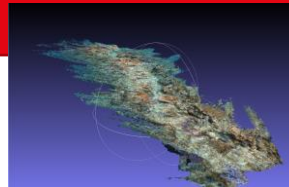
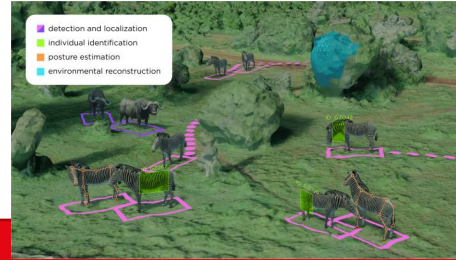
Why now : statistical and computational models are good enough...

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

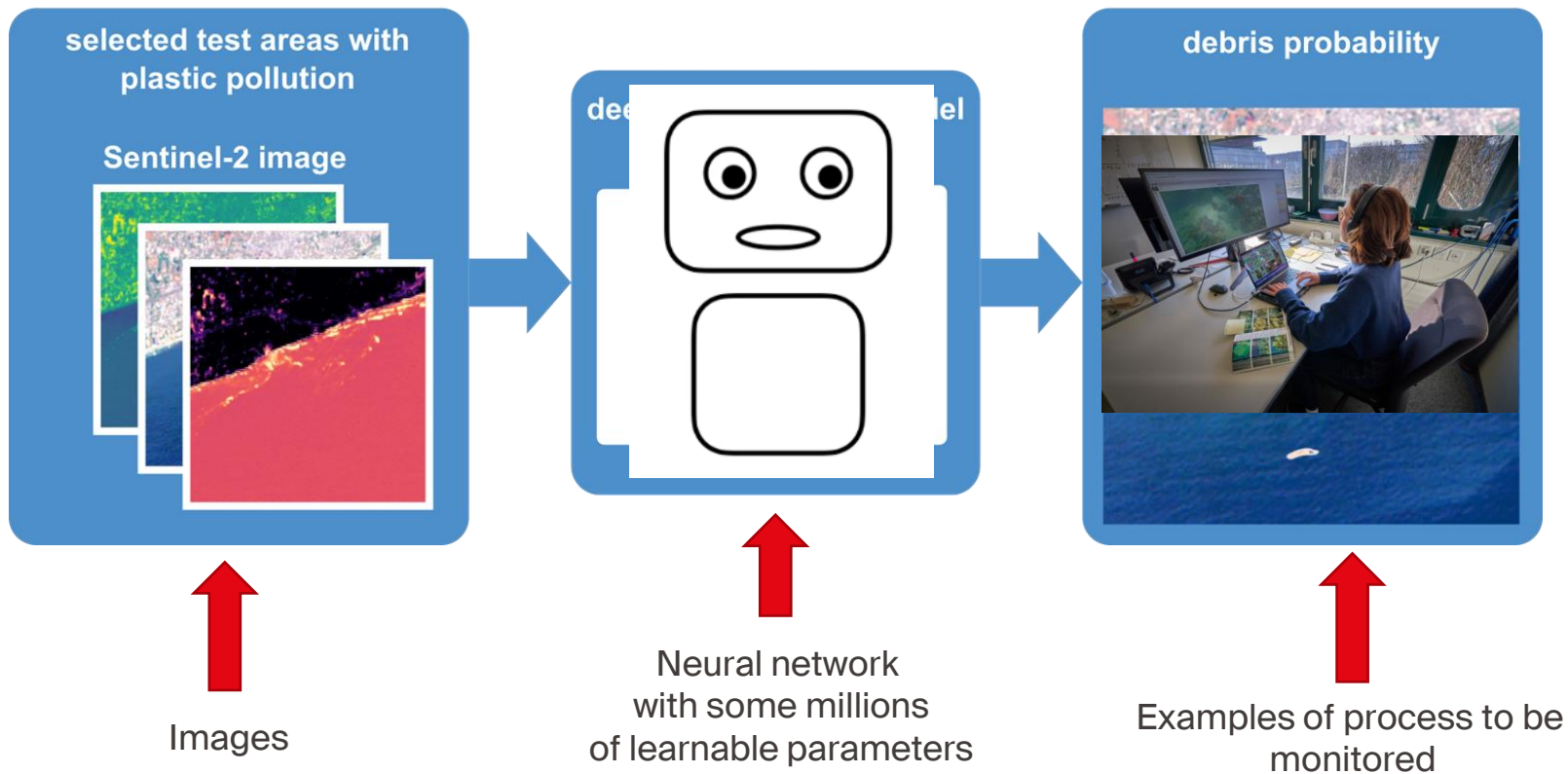
2022



2015



Building environmental deep learning models



Building environmental deep learning models

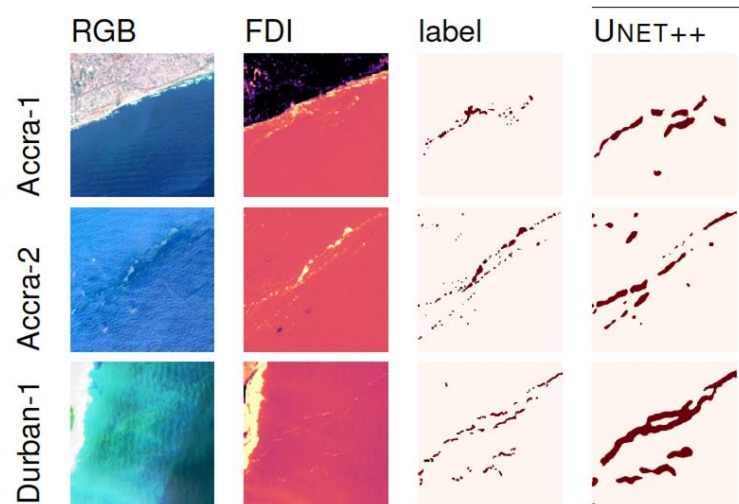
- We used debris events found in news and social media, then hand labeled on images by experts.



[Mifdal et al., 2020]

Building environmental deep learning models that are accurate

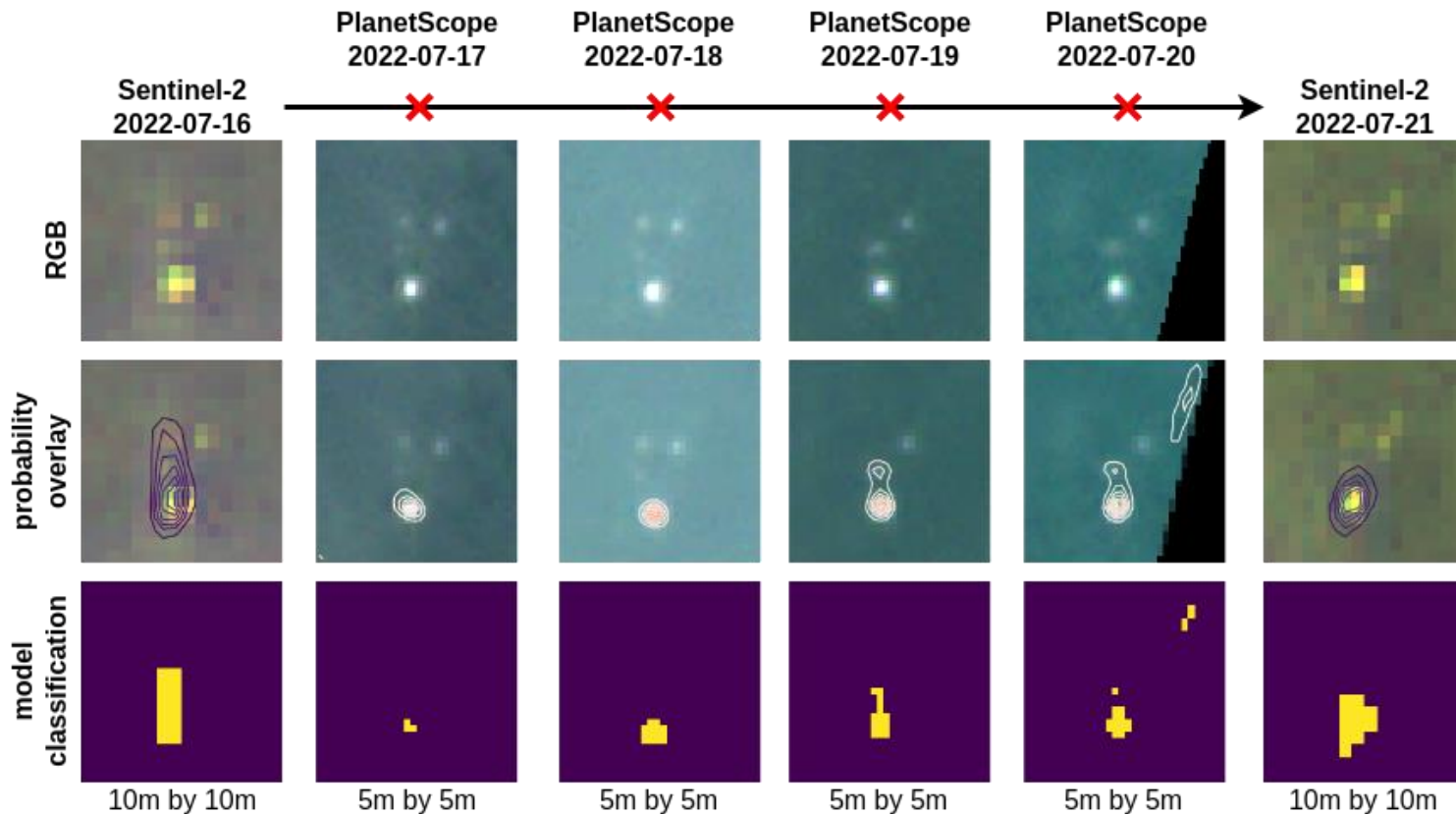
- We used debris events found in news and social media, then hand labeled on images by experts.
- Our learning models detect plastics at sea from space with $\sim 85\%$ accuracy



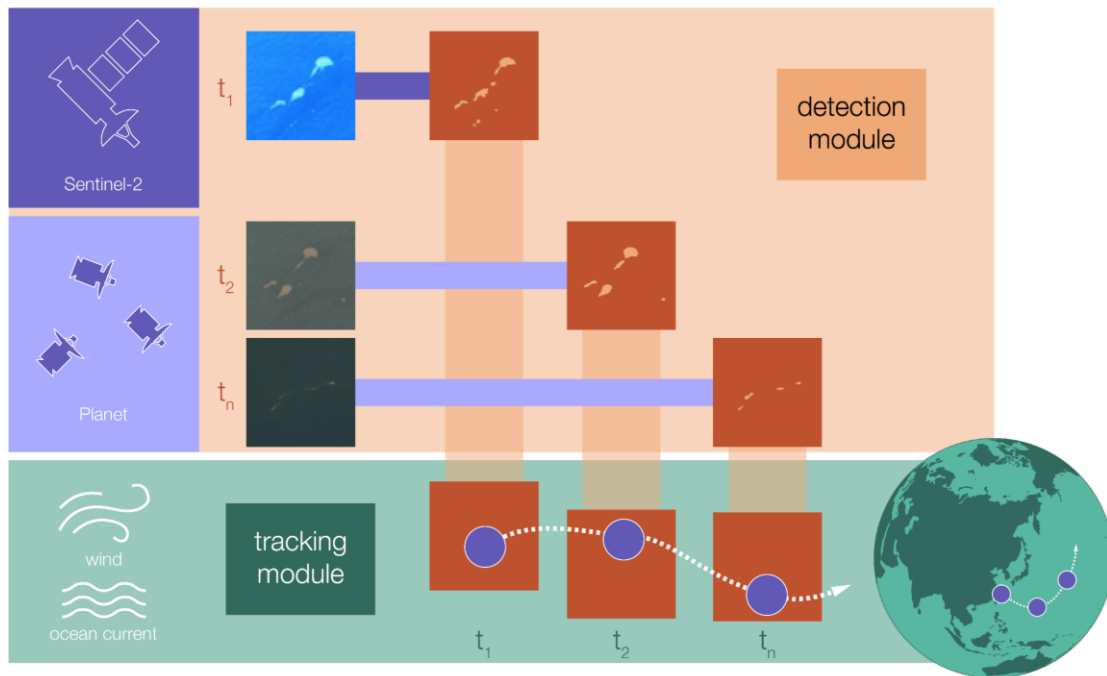
■ **M. Russwurm**, Venkatesam S. J., and **D. Tuia**. Large-scale detection of marine debris in coastal areas with Sentinel-2. *Under review*.



Detections on the Plastic Litter project 2022

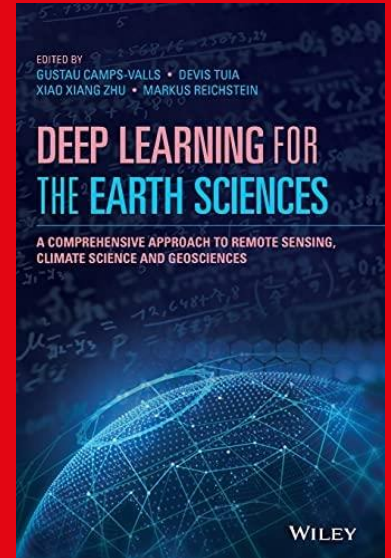


Building environmental deep learning models that are accurate and useful



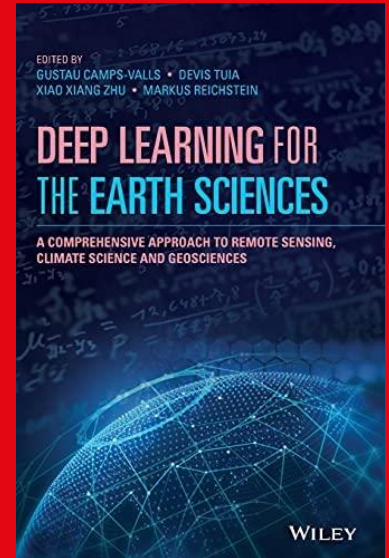
With Earth observation and AI, we can

develop computational approaches
to the environmental sciences
that are **accurate**



With Earth observation and AI, we can

develop computational approaches
to the environmental sciences
that are **accurate**, but also
scalable,
knowledge-driven and
accessible to everyone.





Towards environmental deep learning that is

Accurate

Scalable

Knowledge-driven

Accessible to anyone

- No model should work only on
 - one image
 - one region of the world
 - one task



- No model should work only on

- one image
- one region of the world
- one task

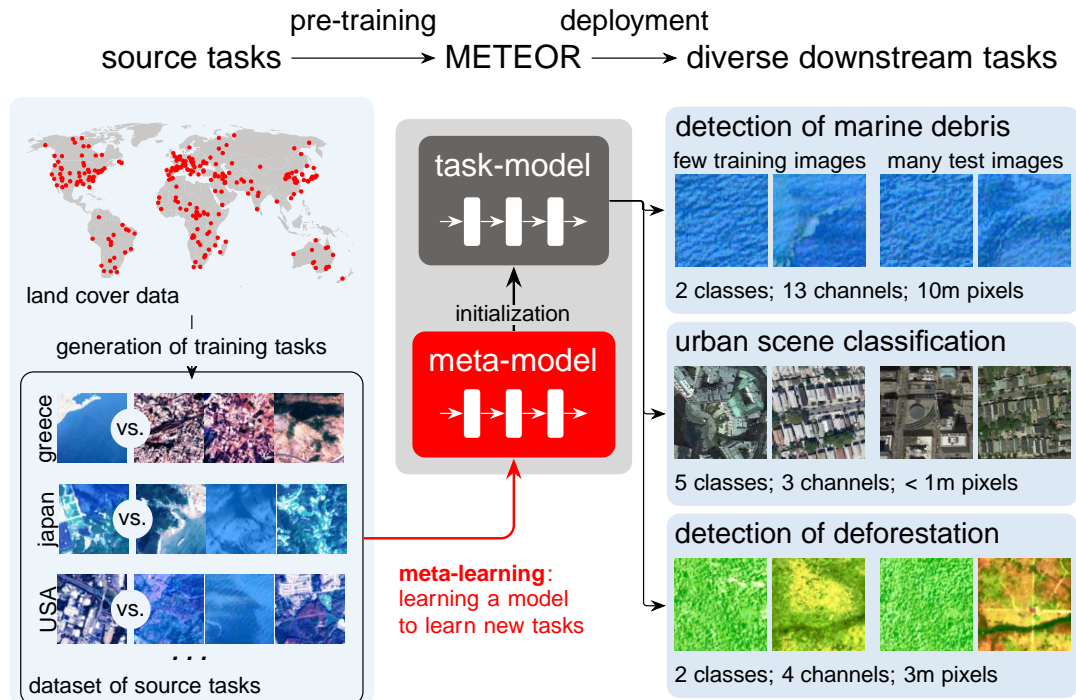


[Mifdal et al., 2020]



D. Tuia, B. Kellenberger, S. Beery, B. Costelloe, S. Zuffi, B. Risse, A. Mathis, M. W. Mathis, F. van Langevelde, T. Burghardt, R. Kays, H. Klinck, M. Wikelski, I. D. Couzin, G. van Horn, M. C. Crofoot, C. V. Stewart, and T. Berger-Wolf. Perspectives in machine learning for wildlife conservation. *Nature Comm.*, 13(792), 2022.

Going even further: scaling across locations and tasks



M. Russwurm, S. Wang, B. Kellenberger, R. Roscher, and D. Tuia. Meta-learning to address diverse earth observation problems across resolutions. *Under review.*



Going even further: scaling across locations and tasks

Small, but distributed learning problems!

5-shot problem

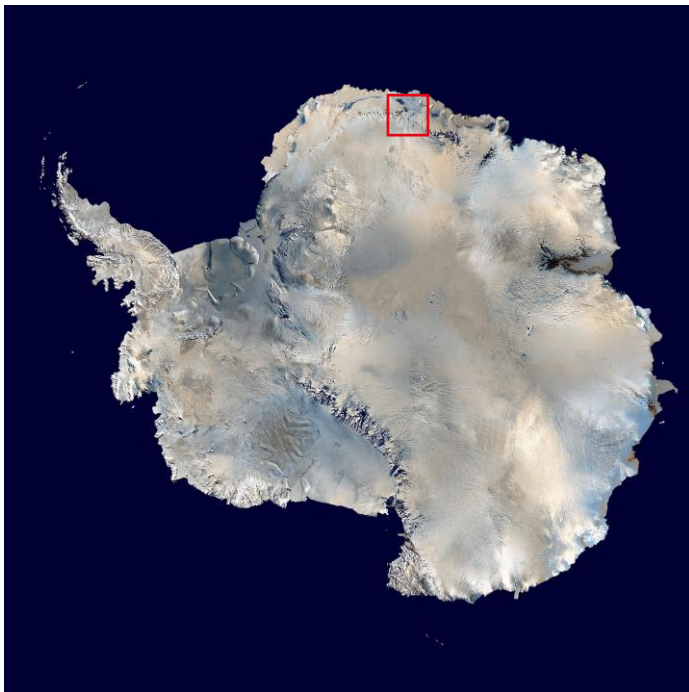
| | human influence | crop type mapping | land cover classification | | marine debris | urban scenes |
|-----------------|-----------------|-------------------|---------------------------|--------------|---------------|--------------|
| dataset | AnthPr. [40] | DENETHOR [20] | DFC2020 [37] | EuroSAT [14] | fl. obj. [26] | NWPU [8] |
| spatial res. | 10m | 3m | 10m | 10m | 10m | < 1m |
| spectral res. | 10 bands | 4 bands | 13 bands | 13 bands | 12 bands | 3 bands |
| # classes | 2 | 3 | 5 | 10 | 2 | 5 |
| # training imgs | 10 | 15 | 25 | 50 | 10 | 25 |

Meta-L
Self-sup.
Traditional

| model | rank (↓) | accuracy (↑) | | | | | |
|-----------------|--------------|--------------|-------------|-------------|-------------|-------------|-------------|
| METEOR | 3.6 | 83.7 | 75.6 | 87.7 | 60.9 | 90.8 | 57.4 |
| SwAV [5] | 4.2 | 96.7 | 69.8 | 54.2 | 67.7 | 65.4 | 70.4 |
| MOSAIKS [31] | 4.3 | 86.4 | 76.4 | 82.3 | 57.9 | 88.8 | 54.0 |
| DINO [6] | 5.0 | 91.2 | 66.2 | 56.6 | 61.3 | 65.1 | 70.6 |
| SECO [24] | 4.7 | 91.4 | 61.7 | 67.6 | 62.7 | 65.9 | 67.4 |
| SSLTRANSRS [34] | 5.3 | 90.7 | 65.5 | 76.3 | 59.7 | 78.9 | 52.1 |
| SSL4EO [52] | 5.5 | 96.2 | 58.0 | 80.2 | 59.1 | 82.4 | 49.9 |
| BASELINE | 6.8* | 89.0 | 60.8 | 87.4 | 39.8 | 69.8 | 36.7 |
| PROTO [39] | 8.3** | 59.7 | 56.2 | 76.9 | 46.1 | 67.3 | 39.1 |
| IMAGENET | 8.8* | 83.7 | 59.7 | 50.8 | 42.7 | 64.1 | 60.5 |
| SCRATCH | 9.5** | 64.8 | 61.1 | 66.5 | 25.7 | 64.4 | 32.3 |



<https://earthobservatory.nasa.gov/images/149554/finding-meteorite-hotspots-in-antarctica>



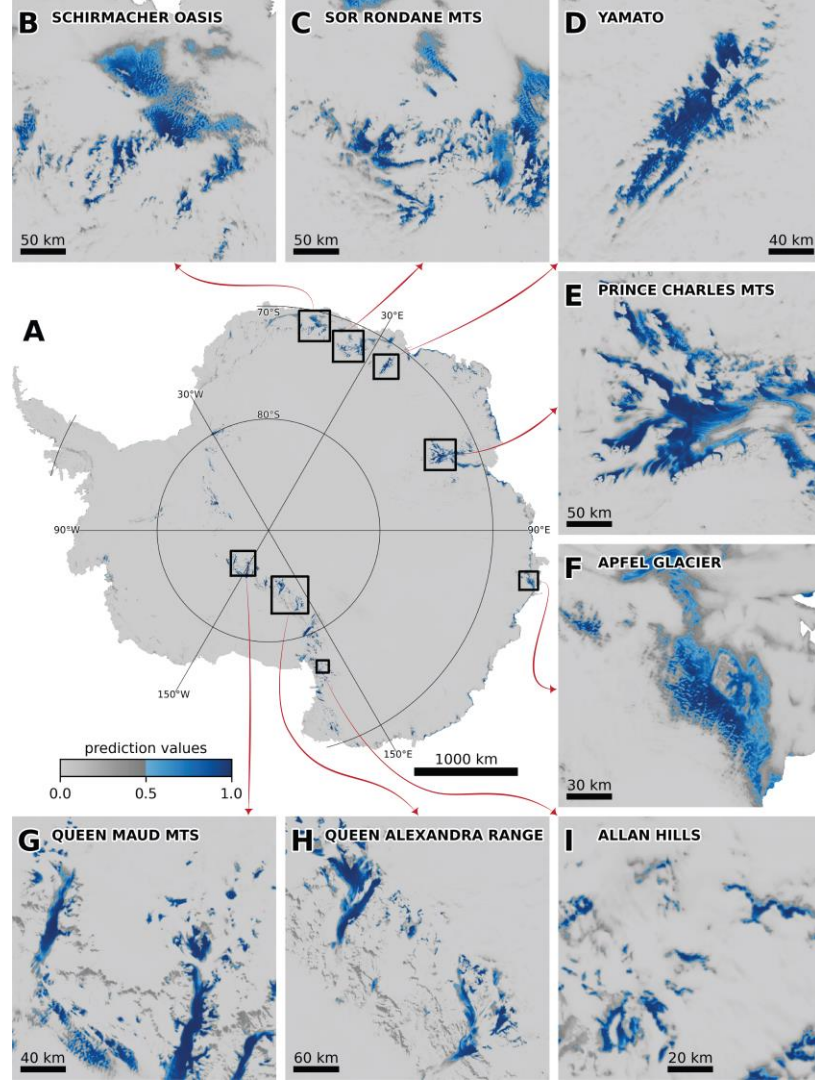
V. Tollenaar, H. Zekollari, M. Russwurm, B. Kellenberger, S. Lhermitte, and F. Pattyn, D. Tuia. A new blue ice area map of Antarctica. In *European Geoscience Union (EGU) Meeting*, 2023.



And here comes the BIA map!

- Based on
 - 3 years of MODIS data (Jan-March 2008-2010)
 - RadarSat data 2008
 - Surface elevation data

- Developed a deep learning algorithm to predict presence of blue ice





Towards environmental deep learning that is

Accurate

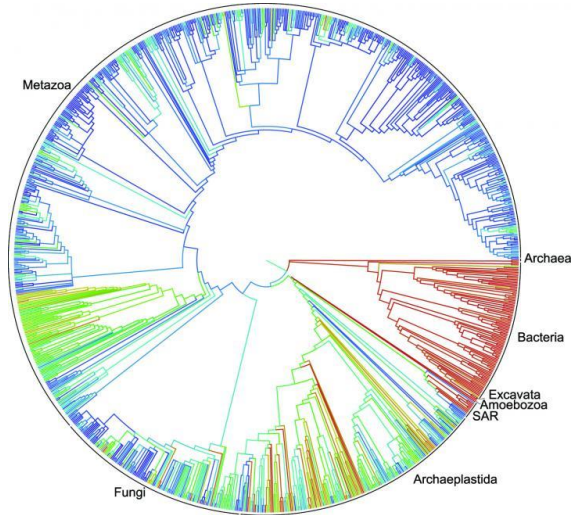
Scalable

Knowledge-driven

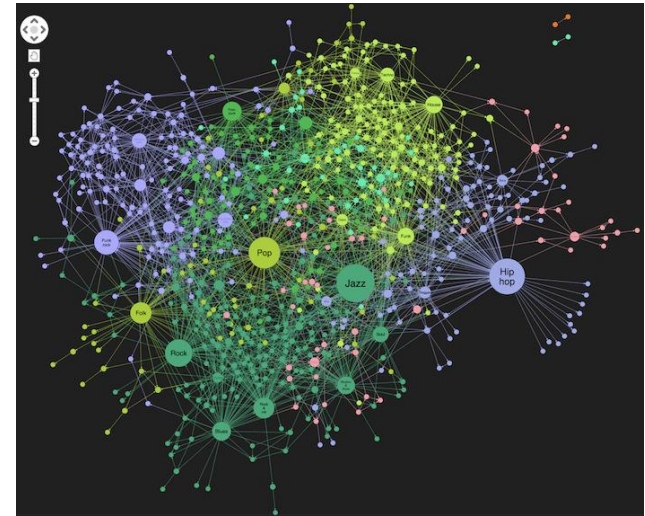
Accessible to anyone

Do we need to extract all information from data?

- Many things about the world, we know them from knowledge



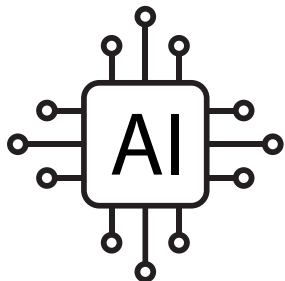
Scientific knowledge



Common sense knowledge

Do we need to extract all information from data?

- Many things about the world, we know them from knowledge.
- Machine learning models tend to learn everything from data, as if we knew nothing about the world.

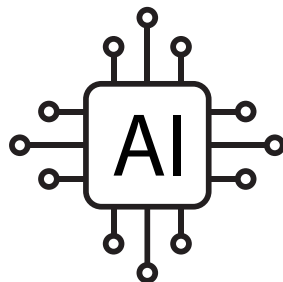


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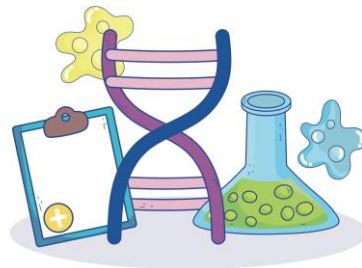


Do we need to extract all information from data?

- Many things about the world, we know them from knowledge.
- Machine learning models tend to learn everything from data, as if we knew nothing about the world.
- **Integrating domain knowledge** is crucial for models that are meaningful



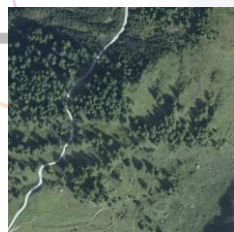
+



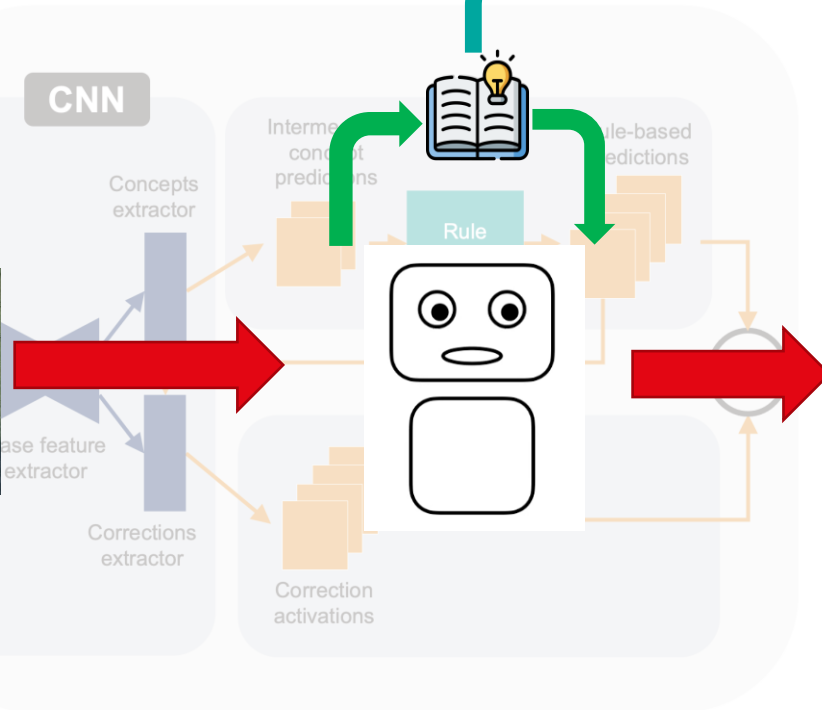
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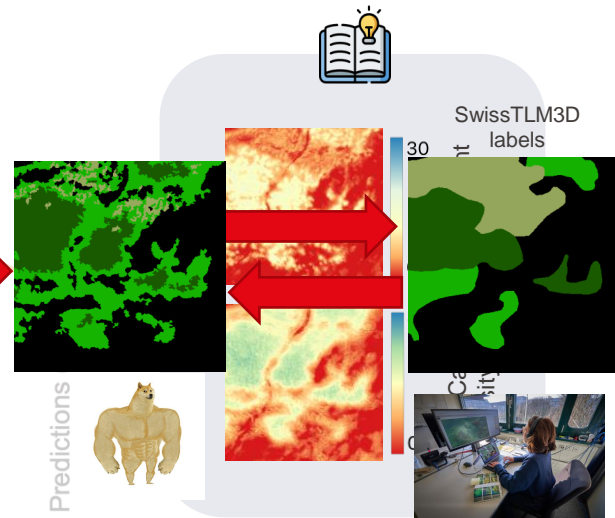
Integrating forest definitions in segmentation models



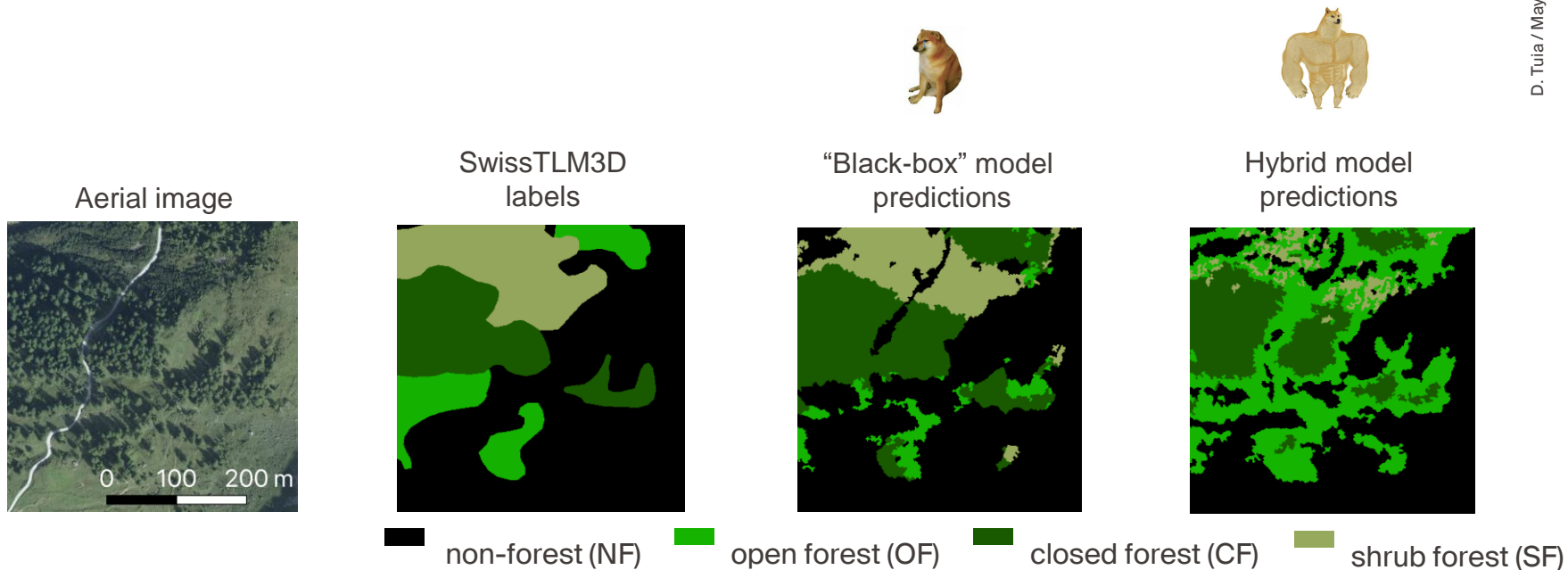
Aerial image (0)

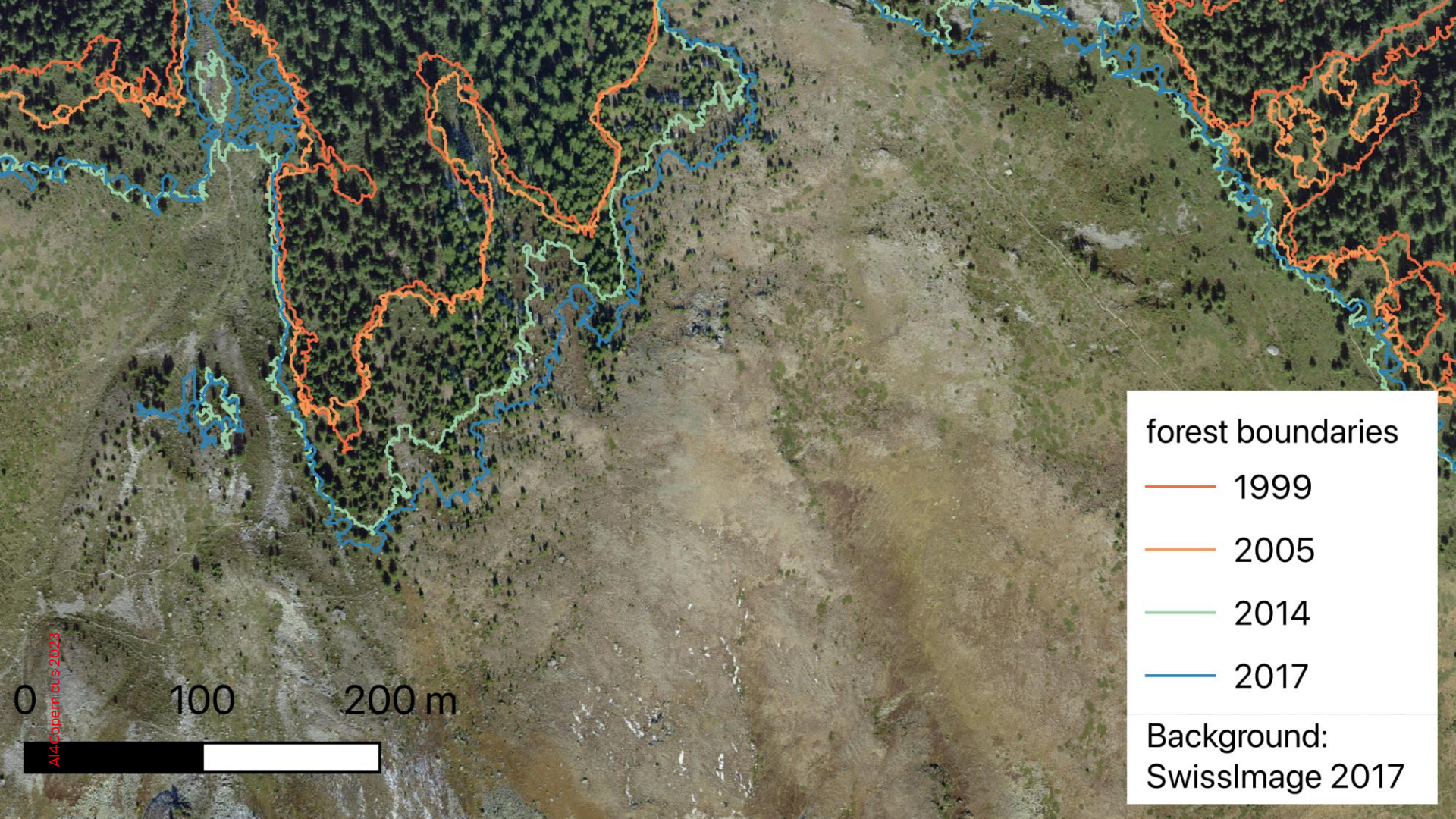


| Tree height (m) | Tree canopy density (%) | [0, 20) | [20, 60) | ≥ 60 |
|-----------------|-------------------------|---------|----------|-----------|
| [0, 1) | | NF | NF | NF |
| [1, 3) | | NF | NF | NF/SF |
| ≥ 3 | | NF | OF | CF/SF |

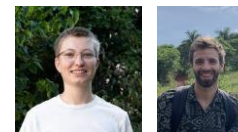
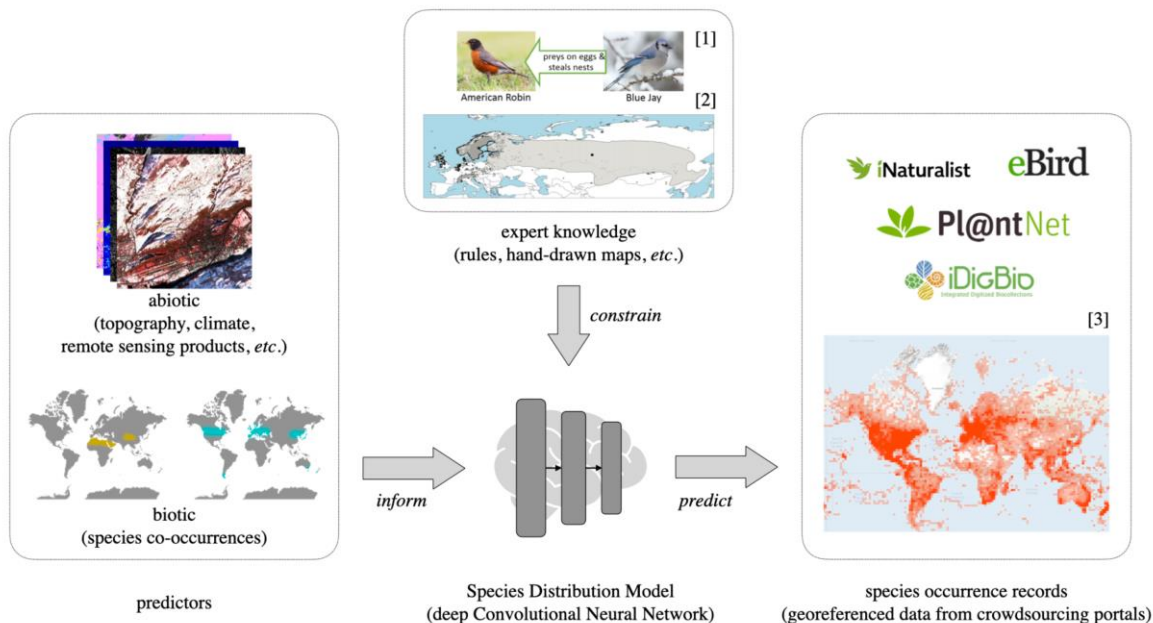


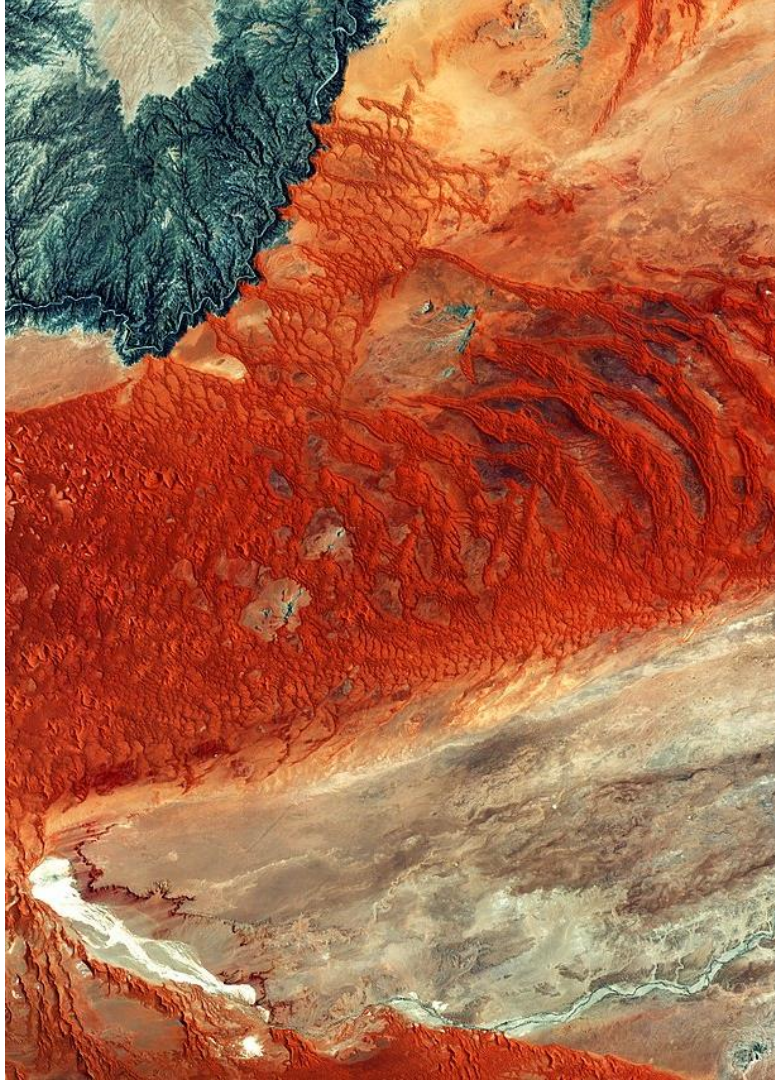
Results better align to forest definitions





Injecting domain knowledge in species distribution models





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



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