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Machine learning for animal conservation : from sensors to knowledge

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Photo: © F. Reinhardt, Kuzikus reserve

CCAI, 2024

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fédérale
de Lausanne

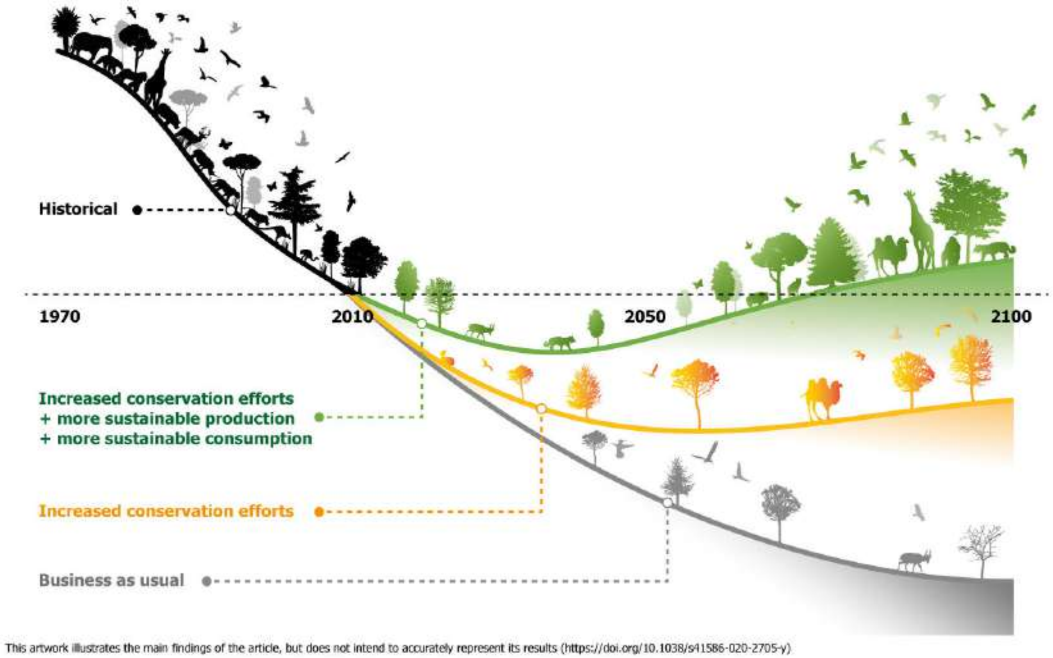
The biodiversity crisis is yet to hit us...

- 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)]



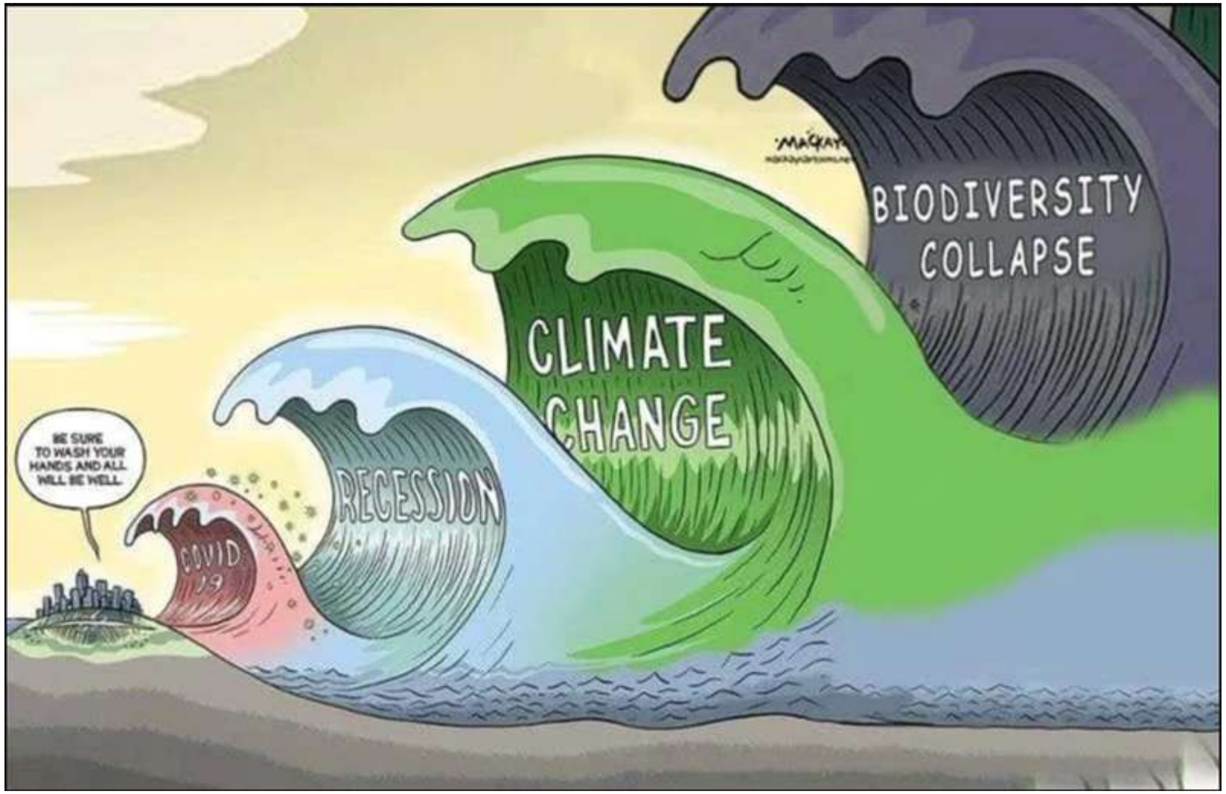
Ihttps://earthjustice.org/features/biodiversity-crisis

Source: www.unep-wcmc.org

Biodiversity needs to be protected

Consequences on

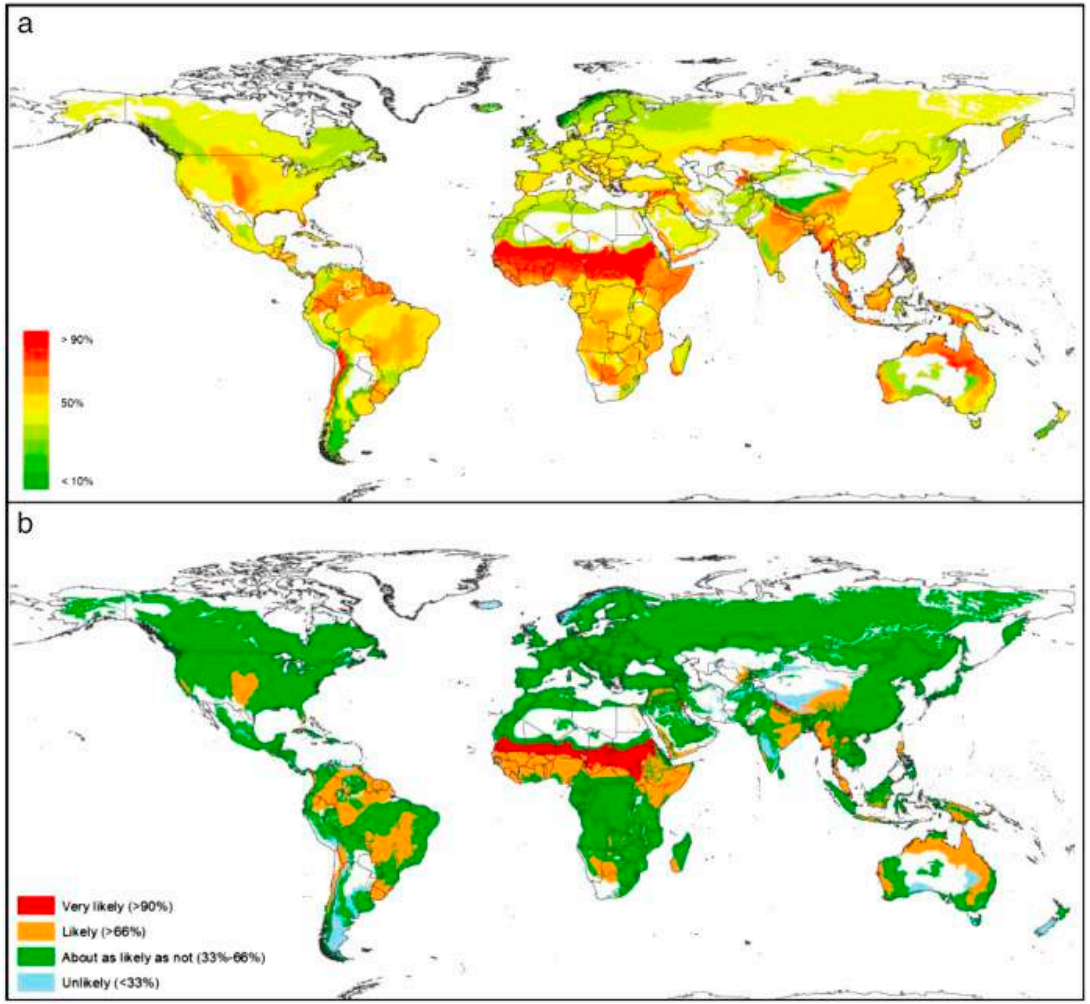
- Health,
  - pest and diseases,
  - medicines
- Food security
  - soil formation
  - purification of air/water
  - detoxification of waste
  - food availability
  - crop variety



Source: The Hamilton Spectator, 2020

It's a global phenomenon

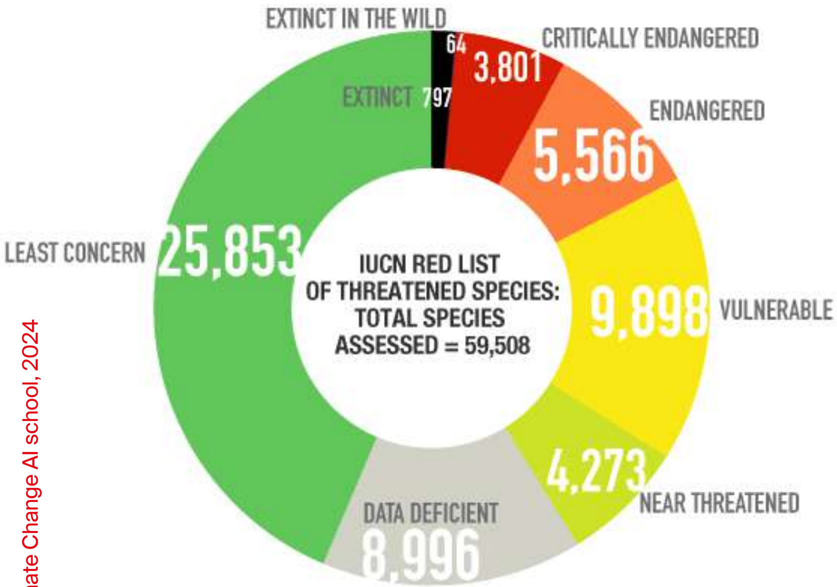
- Habitat loss is expected to happen everywhere
- Areas of highest loss are the most likely

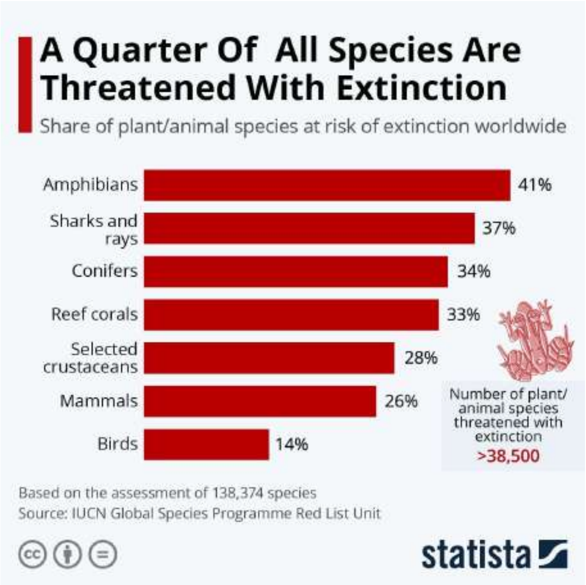


From: Segan et al. 2016

Consequences on species survival

- 28% of assessed species are threatened: “vulnerable” to “extinct”.
- 10% more are “data deficient”.





Which future do we want?

Credit: Guilhem Banc-Prandi

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There is political willingness to action

- In 2021, UNEP disclosed a new Global Biodiversity Framework (GBF), among which
  - At least 30% of land and sea areas global must be conserved as protected areas,
  - 50% reduction in the introduction of invasive alien species,
  - 50% reduction in nutrients loss,
  - 60% reduction in pesticides,
  - $500 billions per year reduction in financing actions actions harmful to biodiversity

- In december 2022, the COP15 conference gathered governments of 188 countries and agreed to the GBF.

How can I help as a data scientist?

- Conservation actors work hard to protect populations
- They record and control populations, establish laws, fight poaching
- Much work is done **by hand**
  - Data samples are very small
  - When data is there, sometimes years behind processing

Ol pejeta reserve, Kenya

Kuzikus reserve, Namibia

A tale in two parts about AI for conservation

- **Part I**

  data and sensors

- **Part II**

  machine learning
  approaches to conservation

Photo: Tanya Berger-Wolf

Sensors and data

New ways of “seeing” biodiversity

The diversity of sensors for biodiversity

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. https://www.nature.com/articles/s41467-022-27980-y

On animal sensors

Biologging allows to measure single individuals

- Movement, trajectories, speed
- Physiological variables (heart rate, body temperature, etc.)
- Behavioral data

- Limited to few individuals
- Bound to GPS inaccuracies
- Limited bandwidth, battery, etc.

Source: MEE blog

Stationary sensors: camera traps

- Probably the most used sensor to monitor biodiversity
  - Inexpensive, easy to install
  - High resolution, both in image and video
- Community efforts to make them available: https://lila.science/datasets
- Amount of data collected quickly surpasses what can be annotated manually

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Sources: Dan Morris, snapshot serengeti, Laurent Geslin, thelocal.ch

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- Community efforts to make them available: https://lila.science/datasets
- Amount of data collected quickly surpasses what can be annotated manually
- Data quality varies
  - Motion blur
  - Day/night
- Presence of camera modifies behavior
  - Animal/camera interactions
  - Flash
- Gives a partial view of the territory (limited to field of view)

Stationary sensors: passive acoustic monitoring

- Microphones / hydrophones
- Study vocal animals and their habitats
- Omnidirectional, all weather

- Data size acquisitions are very large
- Need for noise-robust solutions
- Relative recent field, not so many datasets around (compared to camera traps)

Listen to whales with hydrophones!
https://www.mbari.org/project/soundscape-listening-room/

Bird, grasshoppers and bats dialects!
https://xeno-canto.org

Ear to wild foundation

Synature.ch

Remote sensing: drones

- Allow to cover more ground
- Can be deployed rapidly and navigation software is quite mature
- Limit risks on the field

- But also need permits to be flown
- Often cannot fly beyond line of sight (technology exists but legislation is restrictive)
- Many drones around: fixed wings vs multirotors
- Noise of rotors can disturb/stress wildlife and modify behavior

https://github.com/agentmorris/agentmorrispublic/blob/main/drone-datasets.md

Source DJI

SAVMAP kalahari mapping project

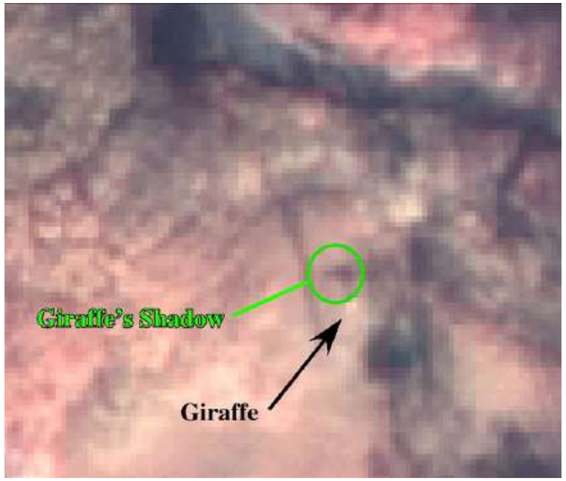
Kuzikus

Source: F. Reinhardt, 2014

Remote sensing: satellites

- Satellites are the ultimate scaleup
- They can cover entire reserves in a single image
- But resolution is often limited
  - Free data: 10m (Sentinel2) - 30m (Landsat)
  - Commercial: 0.5-3m, but $$$
- So studies focus mostly on very large species

- Often we use indirect observations
  - Penguin droppings or black mass of individuals to locate colonies



Quickbird: 2.4m (source: NASA)

WorldView-4: 30cm, after super-resolution (source: maxar)

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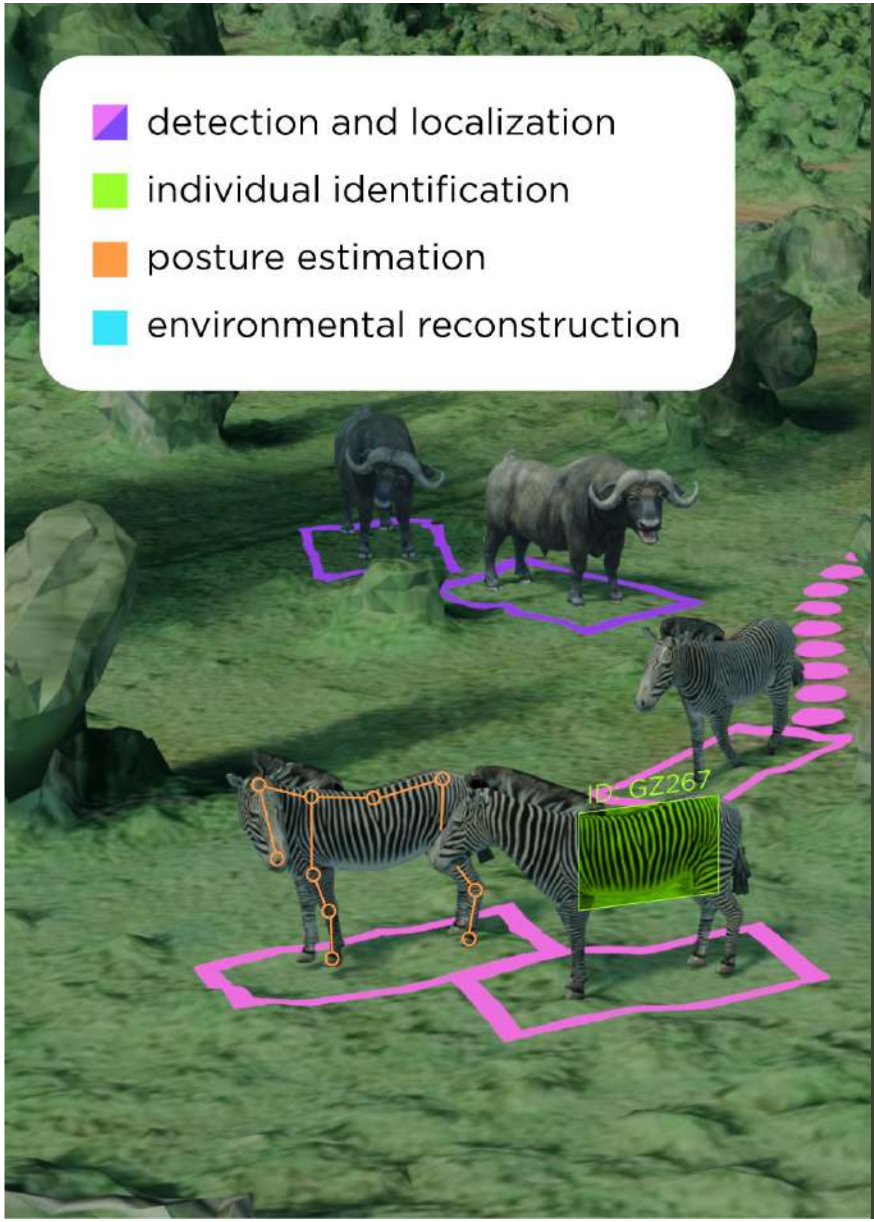
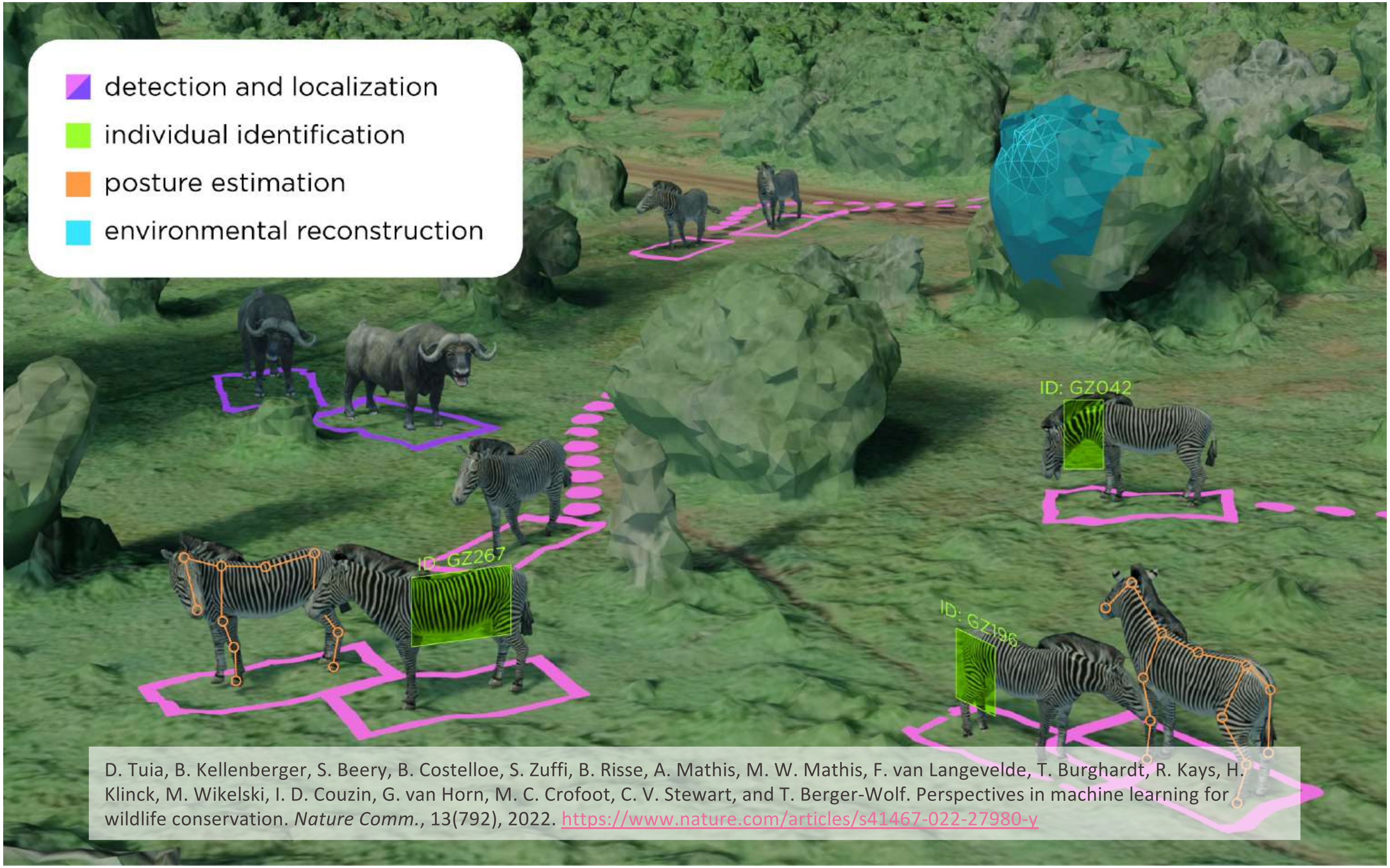


Machine learning approaches for conservation

We have the data, let's extract information now.



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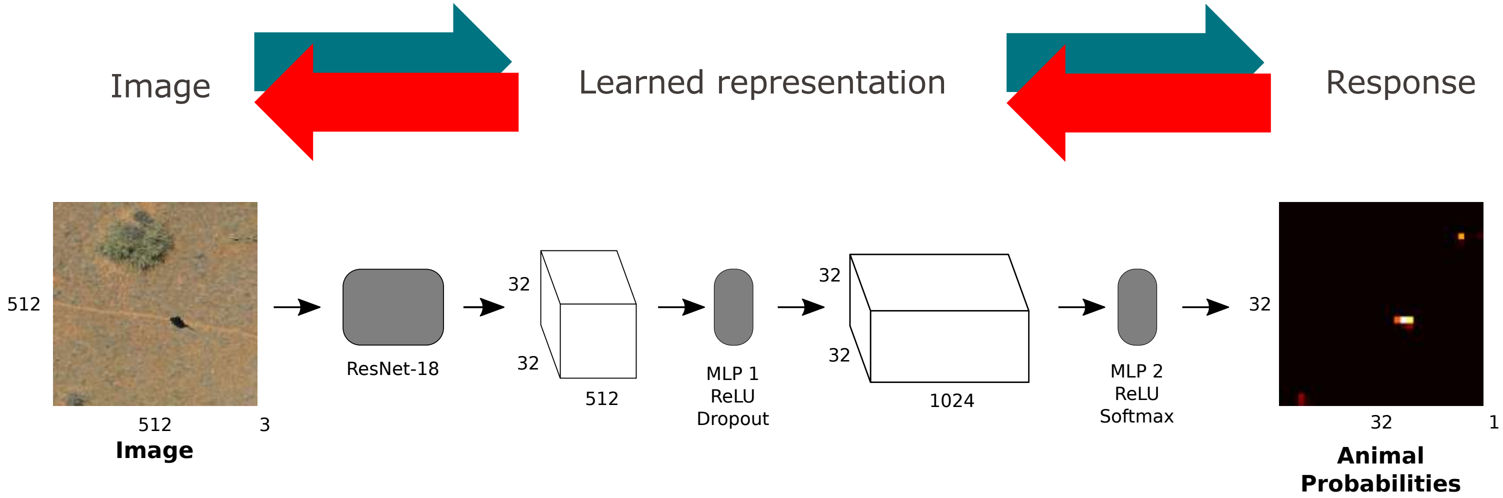
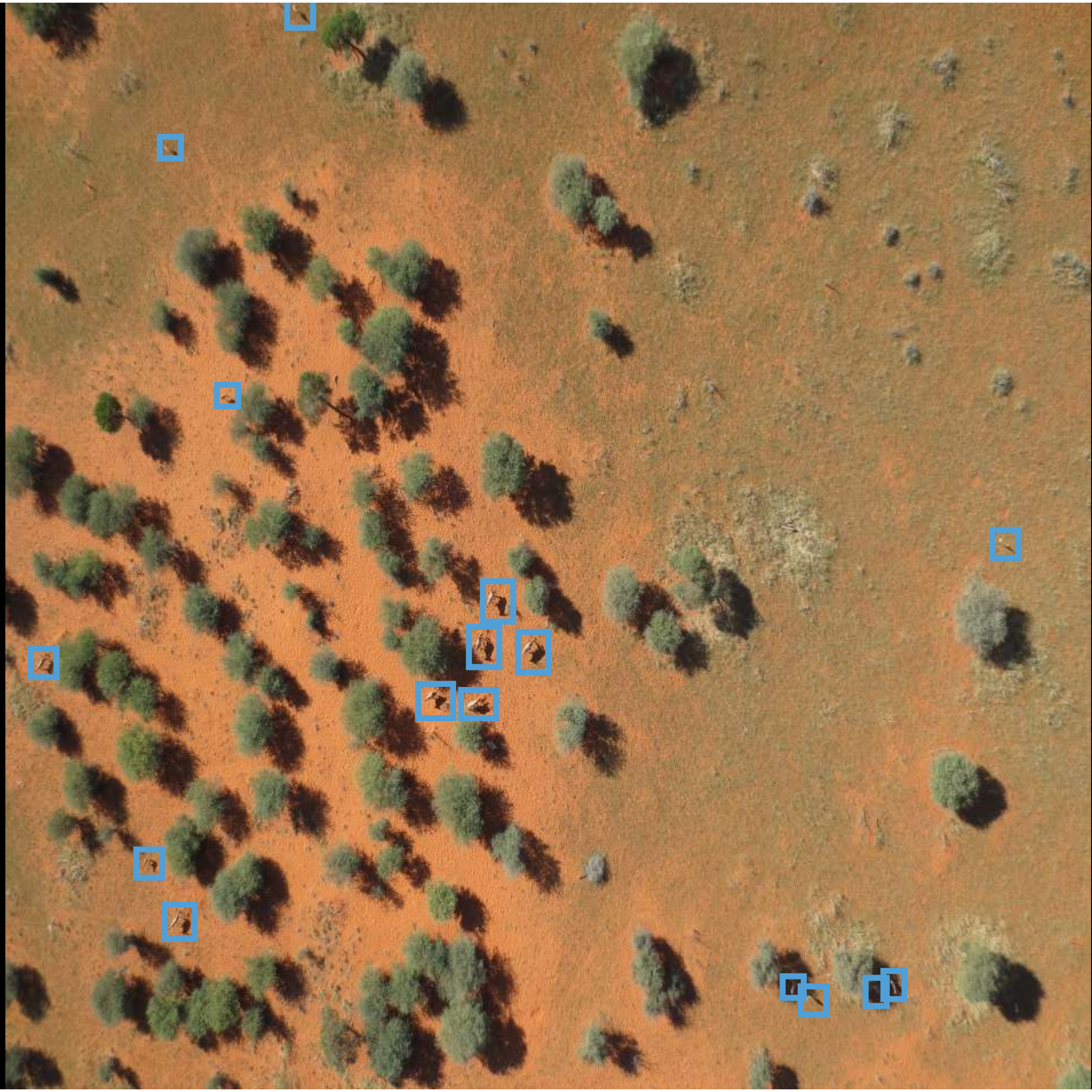
Animal detection and localisation



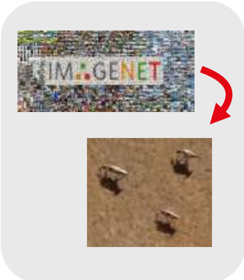








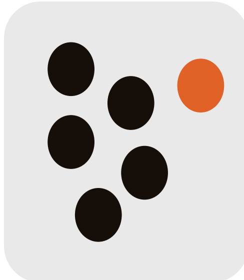

How to train a CNN



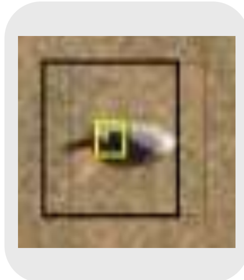
pre-training

class-weighting

curriculum learning



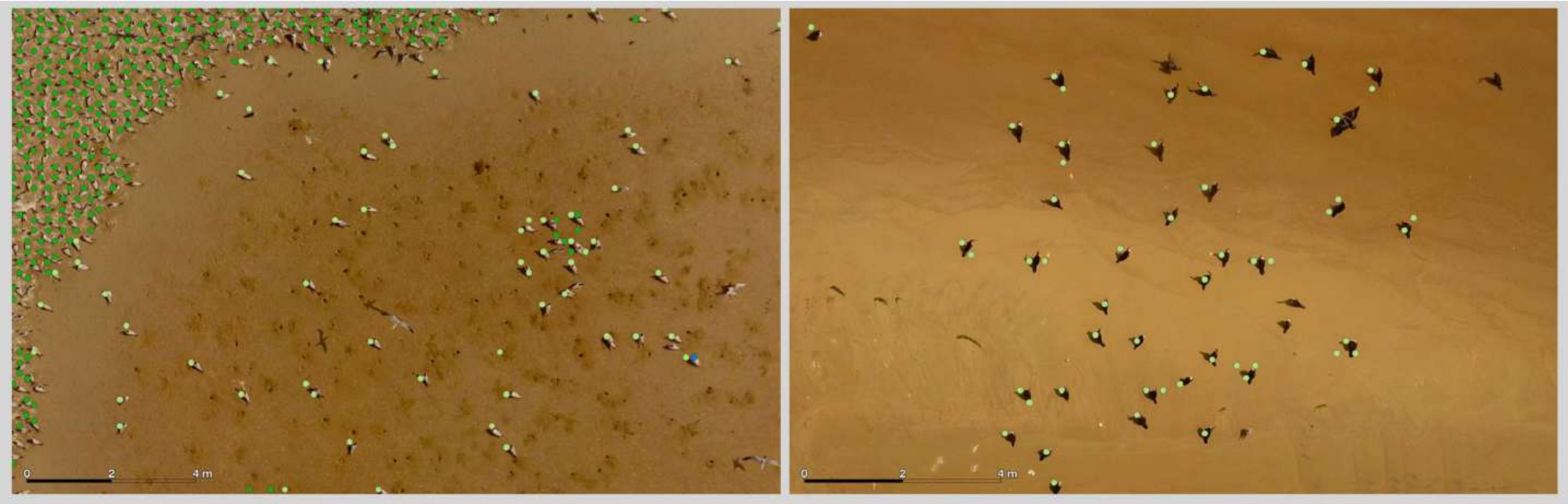
hard negative mining



border class

B. Kellenberger, D. Marcos, and D. Tuia. Detecting mammals in UAV images: Best practices to address a substantially imbalanced dataset with deep learning. *Remote Sens. Environ.*, 216:139–153, 2018. https://arxiv.org/abs/1806.11368

Counting migratory birds



- Migratory birds in Western Africa
- 21.000 birds detected in 4.5 hours (including training)

B. Kellenberger, T. Veen., E. Folmer, and D. Tuia. 21,000 birds in 4.5 hours: Efficient large- scale seabird detection with machine learning. *Remote Sens. Ecology and Conservation*, 2021. https://zslpublications.onlinelibrary.wiley.com/doi/full/10.1002/rse2.200

Improving interactively: AIDE

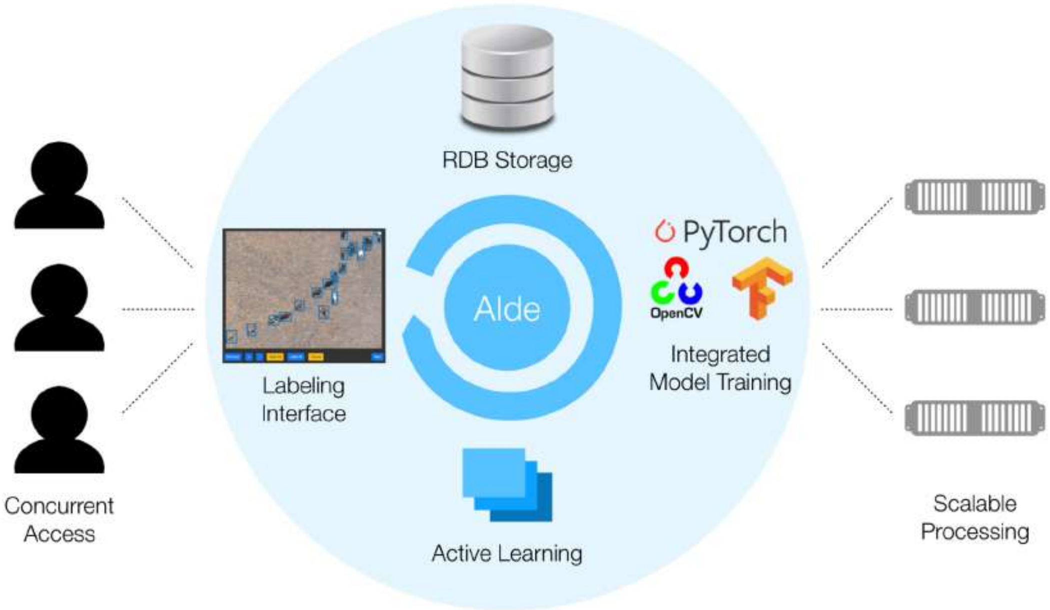



Image-level


Point-based

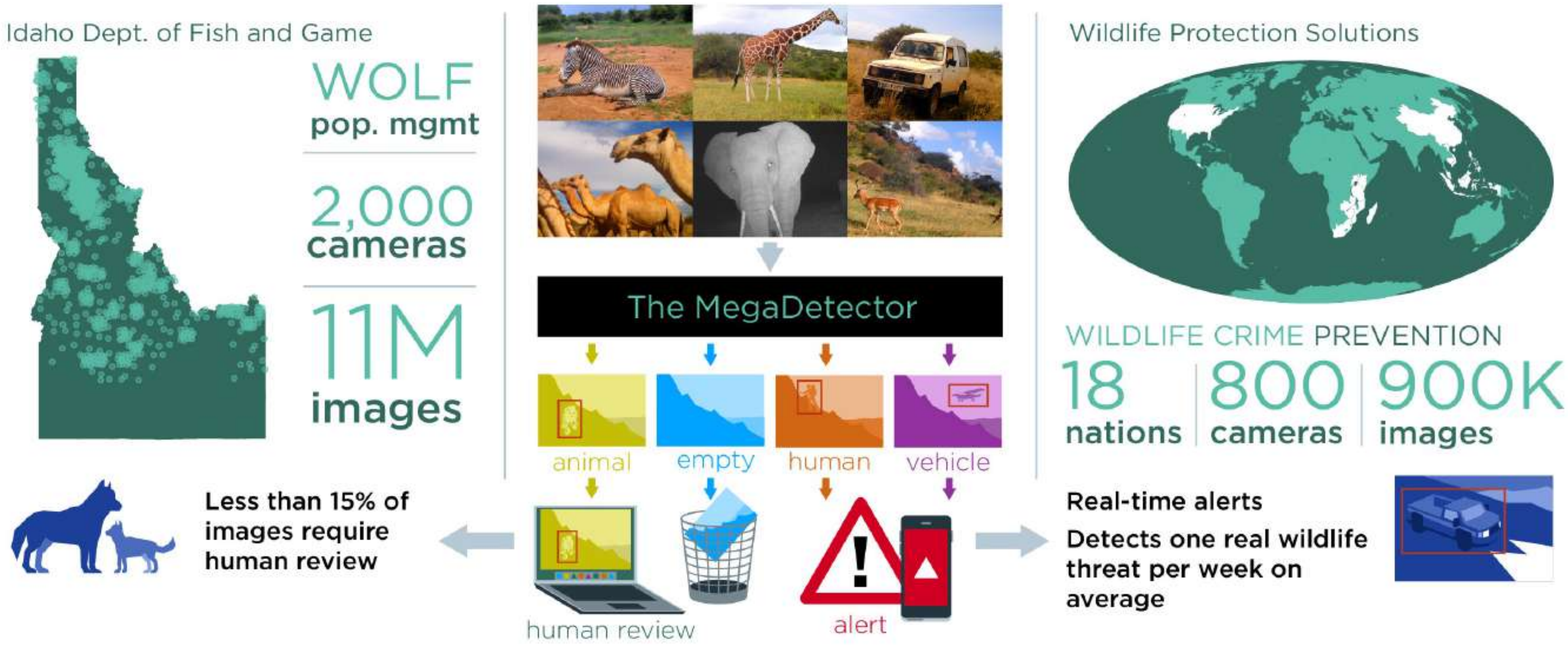

Bounding boxes


Pixel level

Paper. Kellenberger et al., AIDE: accelerating image-based ecological surveys with interactive machine learning. *Methods in Ecology and Evolution*, 2021

https://github.com/microsoft/aerial_wildlife_detection

Scaling things up with the megadetector

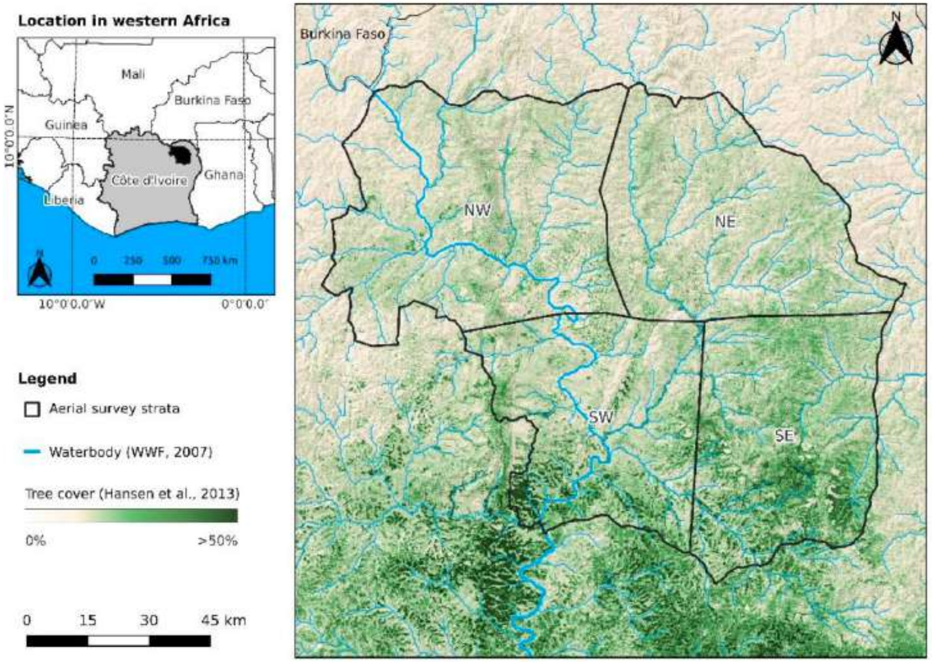


Source: Tuia et al., *Nature Comm.* (2022), https://www.nature.com/articles/s41467-022-27980-y

The megadetector: https://github.com/microsoft/CameraTraps/blob/main/megadetector.md

Do AI approaches really speed up vs manual work?

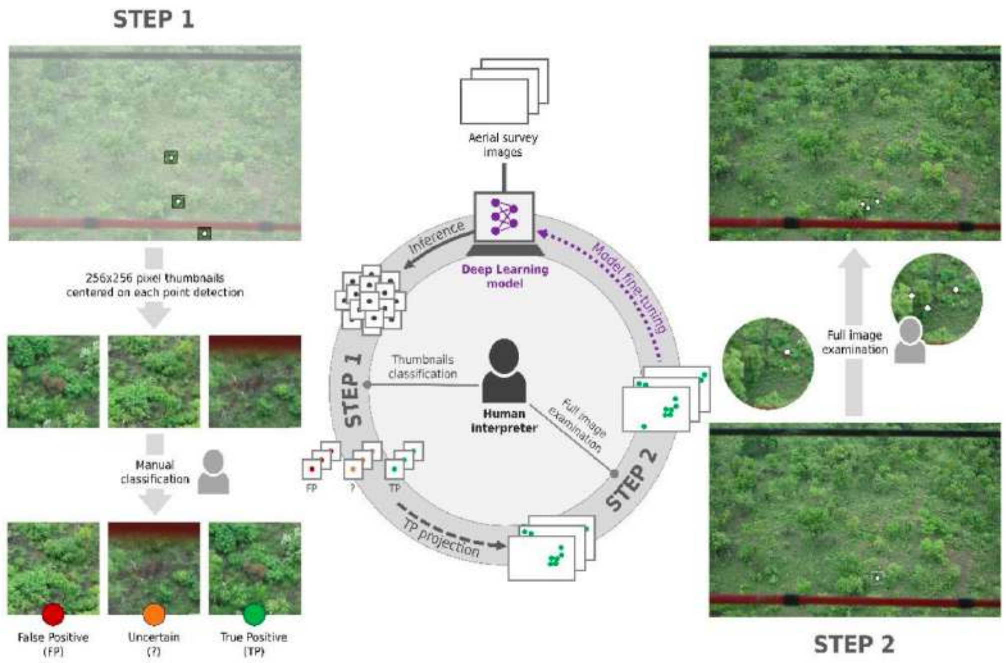
- Recent study in Ivory Coast [A]
- Compared manual labeling of images from visual oblique survey (airplane) against a DL counting approach
- DL = HerdNet [B]



[A] A. Delplanque, J. Linchant, X. Vincke, R. Lamprey, J. Théau, C. Vermeulen, S. Foucher, A. Ouattara, R. Kouadio, P. Lejeune , *Ecological Informatics , 82, 2024.*
[B] A. Delplanque, S. Foucher, J. Théau, E. Bussière, C. Vermeulen & P. Lejeune, *ISPRS Journal of Photogrammetry and Remote Sensing*, 197, 167-180. DOI: 10.1016/j.isprsjprs.2023.01.025

DL is used interactively with rangers

- In step 1, Herdnet [A] is applied
- In step 2, experts look into hard negative detections at full image resolution to improve
- Model is retrained with new confirmed detections



[A] A. Delplanque, S. Foucher, J. Théau, E. Bussière, C. Vermeulen & P. Lejeune, *ISPRS Journal of Photogrammetry and Remote Sensing*, 197, 167-180. DOI: 10.1016/j.isprsjprs.2023.01.025

The scaleup is significant!

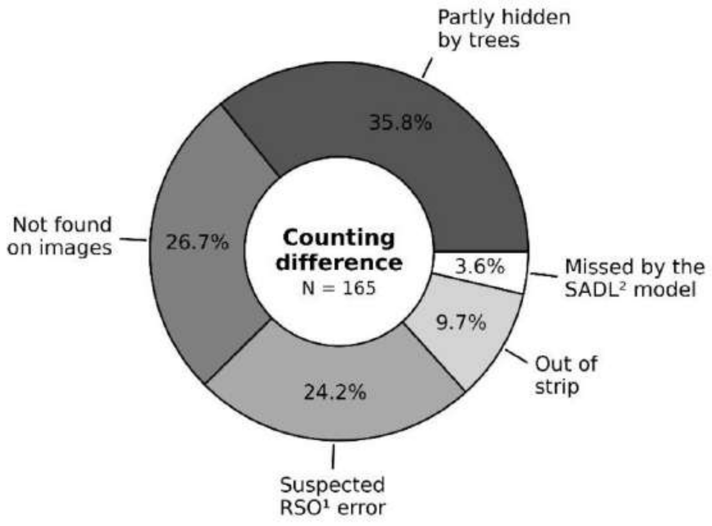
- Human : 5-6000h
- AI: 111 hours

	Number of items		Allocated time	
Human task	**First pass**	**Final pass**	**Total (relative share)**	**8h-workday equivalent**
Thumbnails classification	85,779 thumbnails	93,472 thumbnails	24.0 hours (33%)	4.7 days
Full 24MP image examination	3,188 images	529 images	64.3 hours (58%)	8.0 days
Duplicate removal	1,739 images	163 images	9.5 hours (10%)	1.1 days

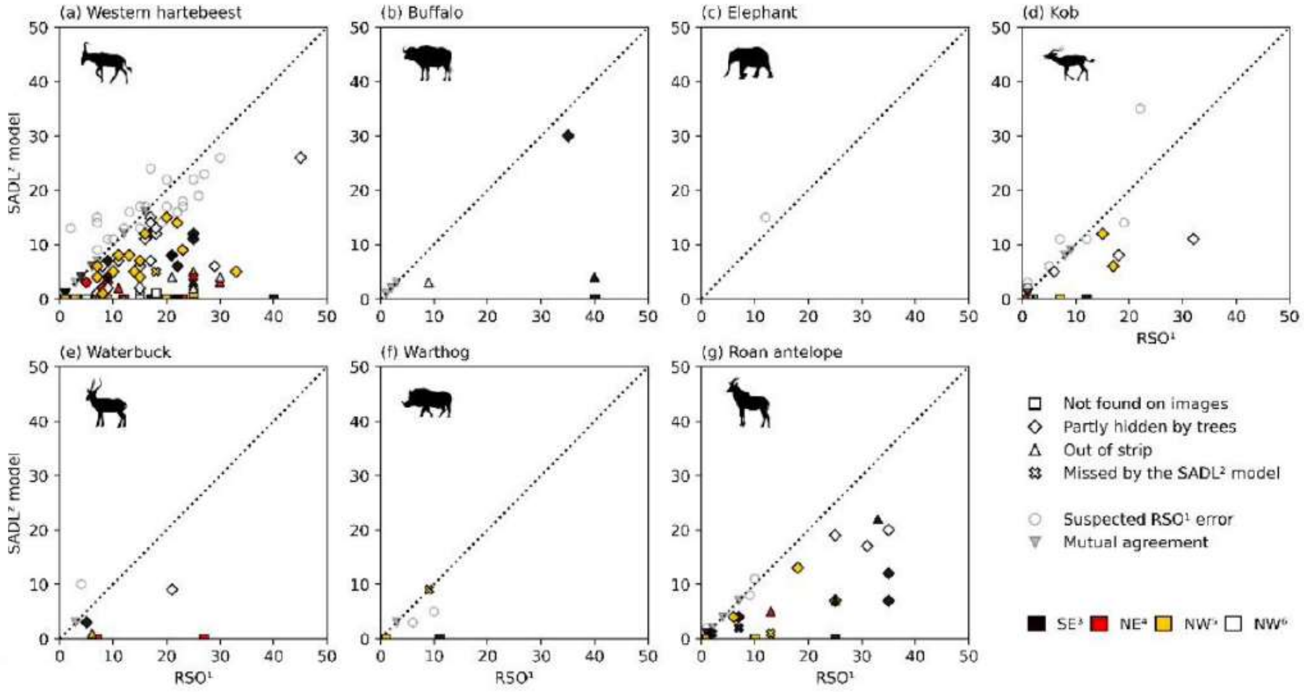
A. Delplanque, J. Linchant, X. Vincke, R. Lamprey, J. Théau, C. Vermeulen, S- Foucher, A. Ouattara, R. Kouadio, P. Lejeune , *Ecological Informatics , 82, 2024.*

DL underestimates counts, but why?

[Here a sample of manually validated 200 images]



¹RSO, rear-seat observer; ²SADL, semi-automated deep learning.



¹RSO, rear-seat observer; ²SADL, semi-automated deep learning; ³SE, south-east; ⁴NE, north-east; ⁵NW, north-west; ⁶SW, south-west.

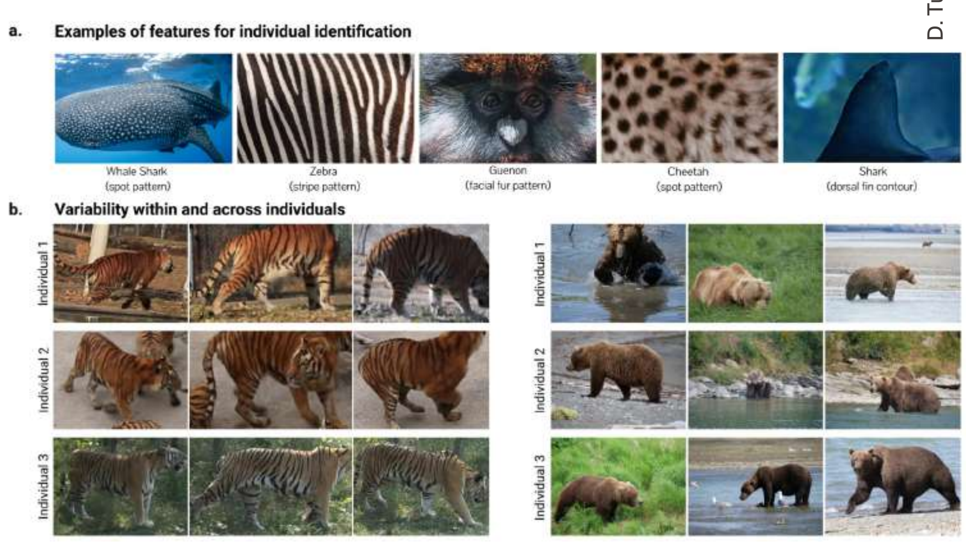
A. Delplanque, J. Linchant, X. Vincke, R. Lamprey, J. Théau, C. Vermeulen, S- Foucher, A. Ouattara, R. Kouadio, P. Lejeune , *Ecological Informatics , 82, 2024.*

Beyond detection: individual identification

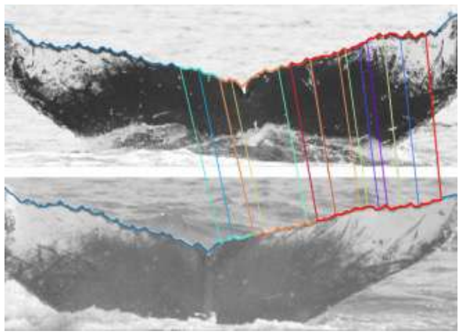
- Identification is usually done via DNA profiling
- Using images can scale up significantly!

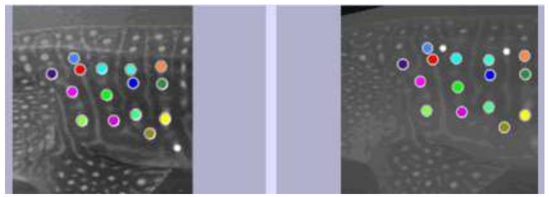
- First approaches were based on traditional vision
  - Matching fluke features
  - Matching fur or body patterns

- Wildme.org is a great resource
  - Gamified approach for identification
  - Bots scan social media (e.g. Youtube videos)



Source Vidal et al., 2021





Source: whalebook and sharkbook

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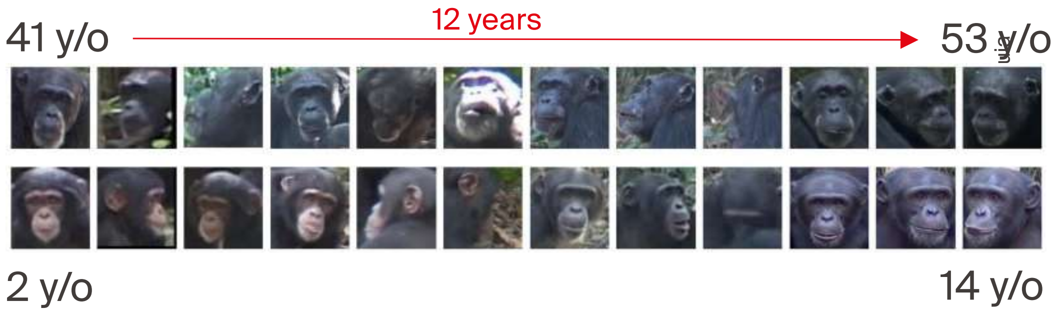
Beyond detection: individual identification



Challenges

- Animals evolve in time in their visual appearence
  - From cub to adult
  - Stags lose their antlers every year
- Single individuals are rare sights
- New individuals enter the system in time (few shot learning)
- Images are subject to occlusion, motion blur, etc.

Source: Schofield et al., 2019

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Beyond detection: individual identification

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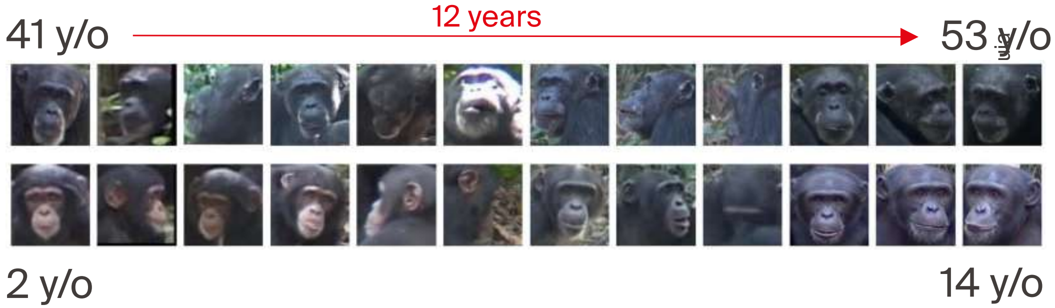
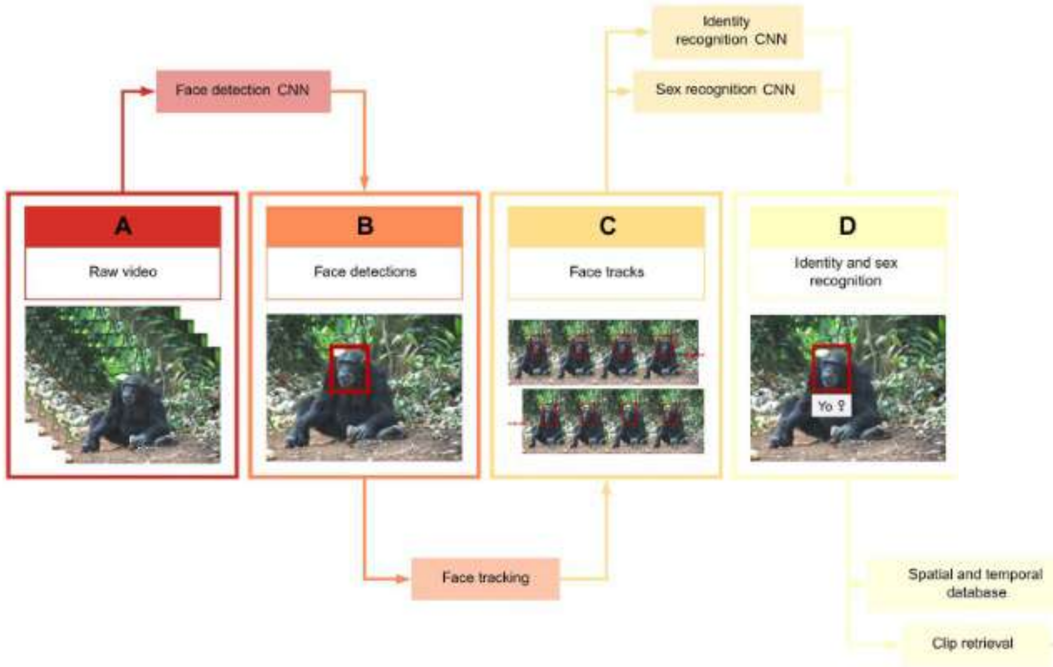
- Images are subject to occlusion, motion blur, etc.

- Still DL approaches perform well, sometimes outperforming humans significantly
  - Chimpanzees identification was 90% (AI) vs 42% (humans) and much faster

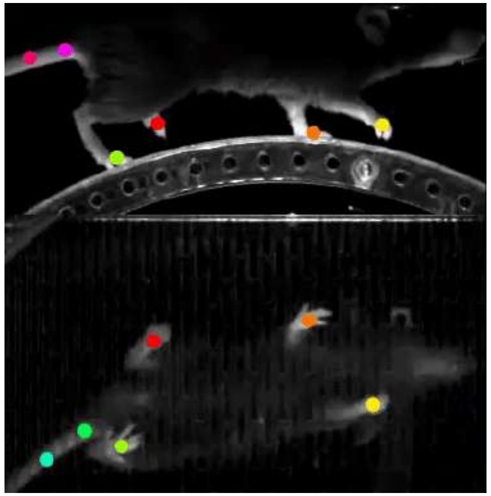




Source: Schofield et al., 2019

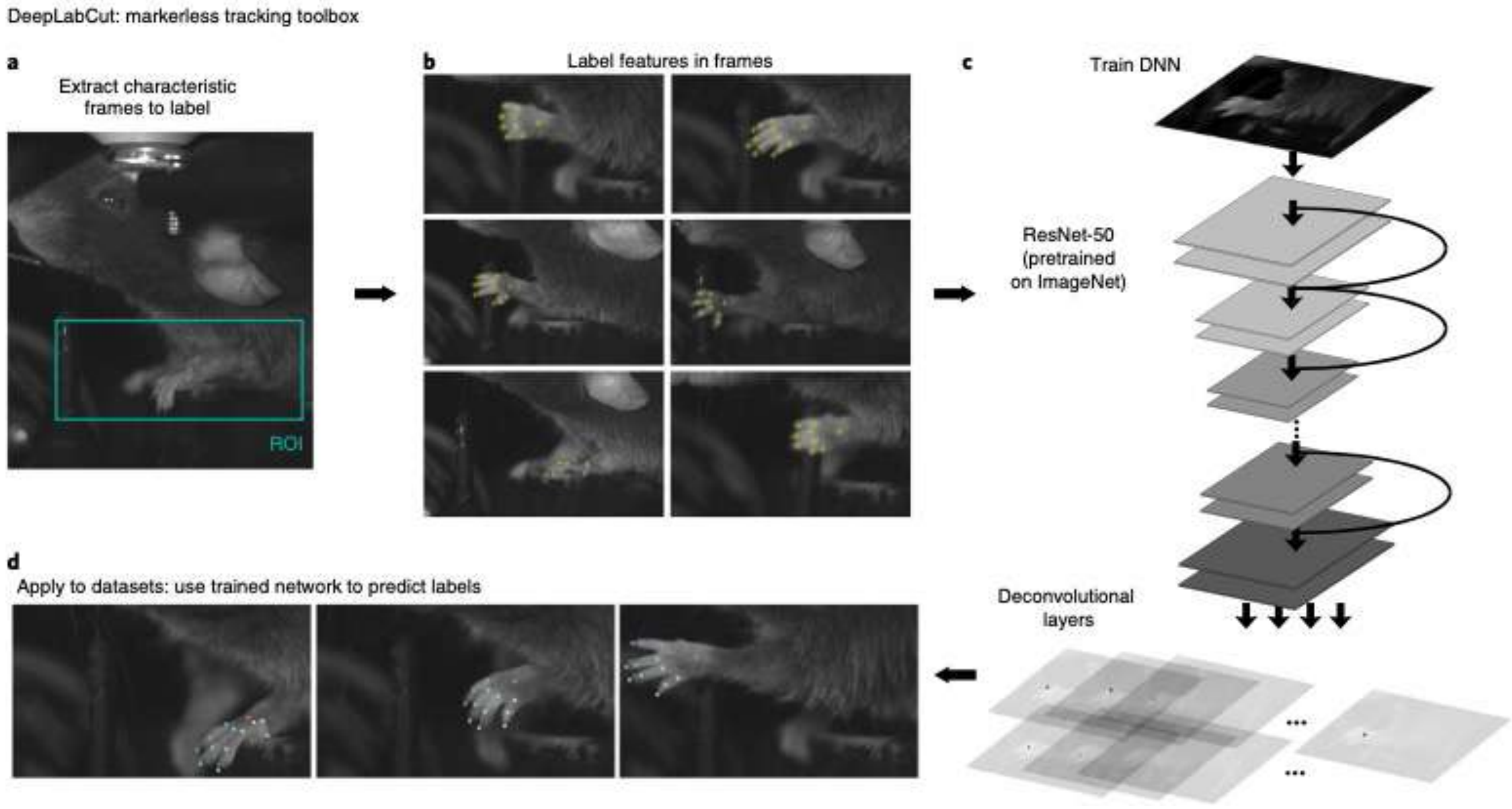
Pose estimation

- With pose estimation, we detect and identify animals body parts
- Here examples from DeepLabCut
- Each color is a different body part, tracked along the frames of the video



Source: http://www.mackenziemathislab.org/deeplabcut-home

Pose estimation

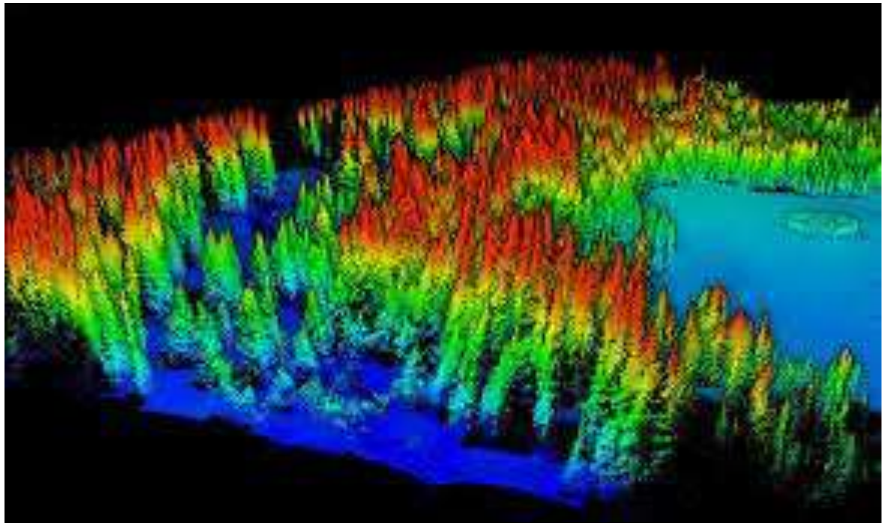


Source: Mathis et al., 2018

Pose estimation

- Pose estimation has really taken off and model zoos are available
- http://www.mackenziemathislab.org/dlc-modelzoo
- Ye et al.: https://arxiv.org/abs/2203.07436

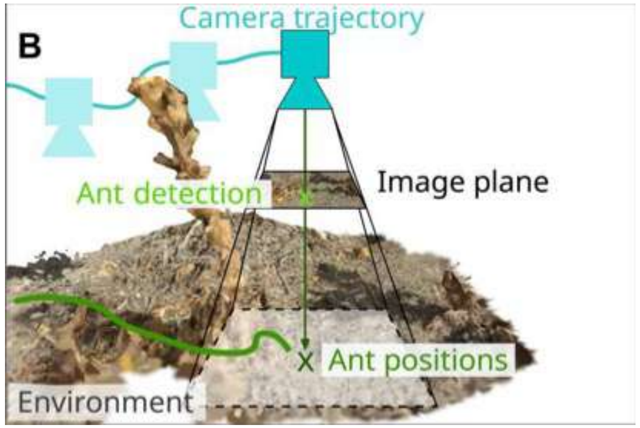
Reconstructing the environment



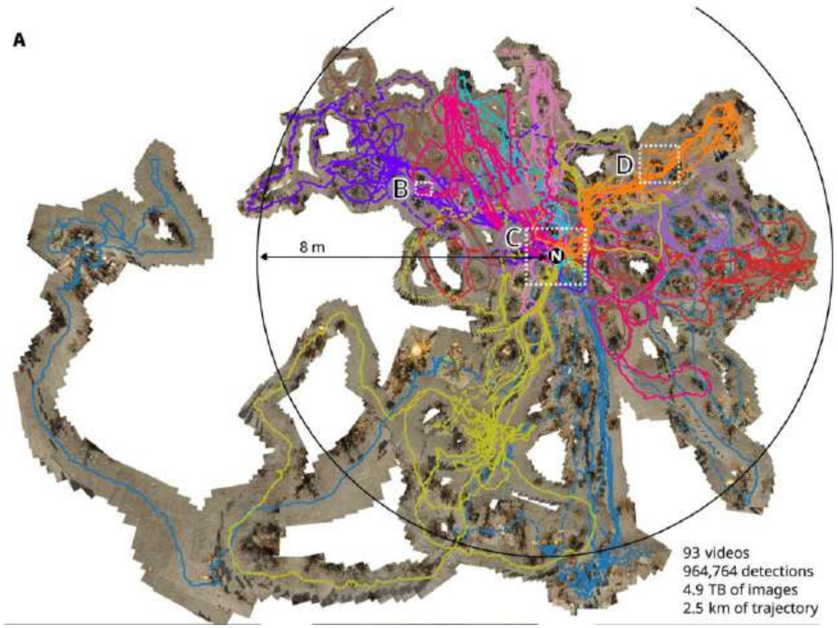
- Environmental context influences
  - Visibility
  - Chances for hiding
  - Temperature
- Finally, it influences behavior!

- 3D reconstruction can be obtained from
  - LiDAR (laser scanning systems)
  - Computed from overlapping images (photogrammetry, structure from motion SfM or SLAM)

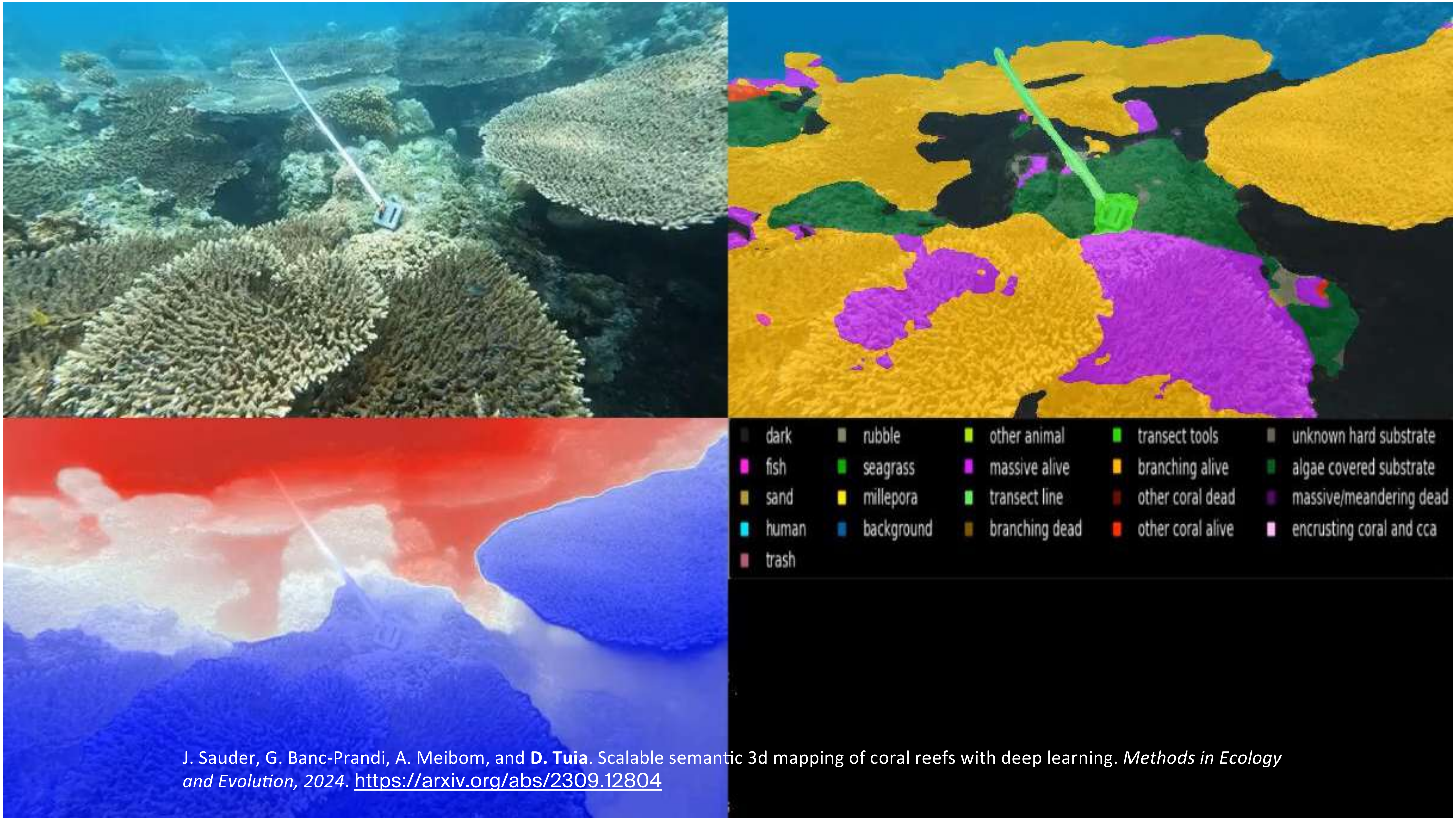
Reconstructing the environment



- 3D reconstruction can be obtained from
  LiDAR (laser scanning systems)
  Computed from overlapping images (photogrammetry, structure from motion SfM or SLAM). Here example from Haalck et al. 2023:
  https://www.science.org/doi/pdf/10.1126/sciadv.adg2094



- Challenges
  - High res videos generate a lot of data, need efficient 3D reconstruction pipelines (learned SfM, see next slide)
  - Errors accumulate over time
  - Compensate for inappropriate camera motions (e.g. from a drone)



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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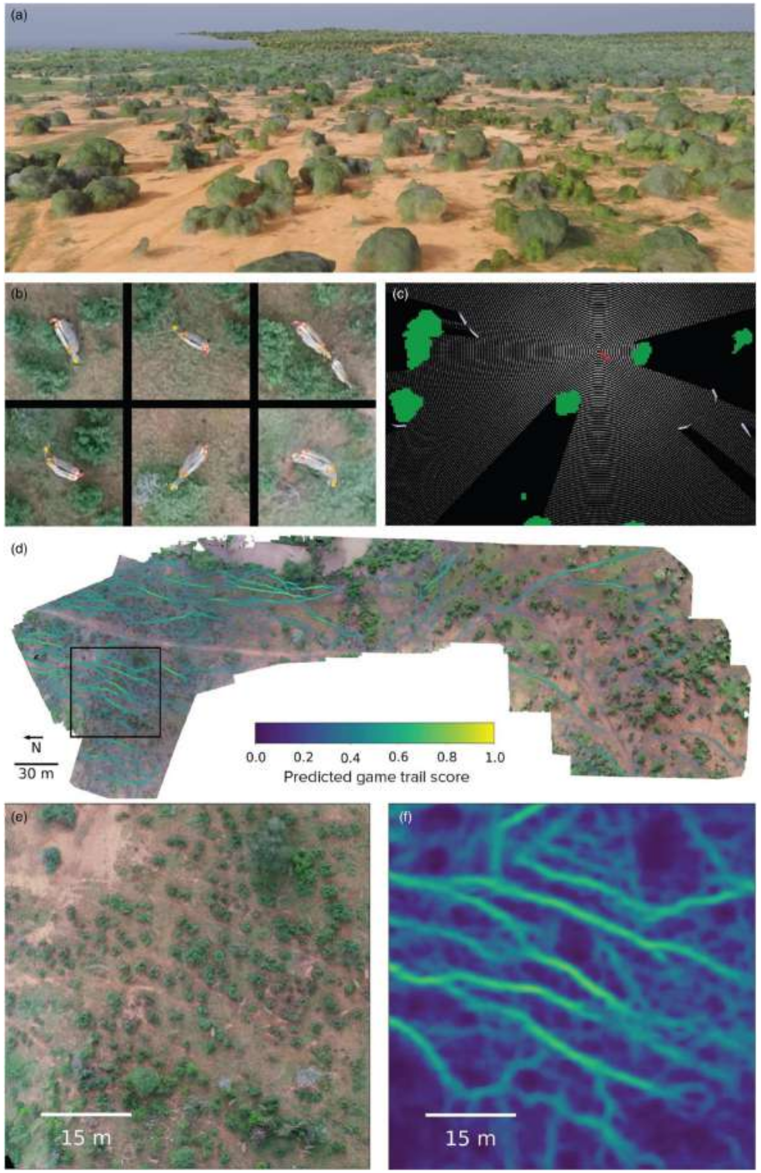
Putting everything together!

- Once we have all the ingredients, we can move into very exciting behavior science!
- From Koger et al., 2023 https://besjournals.onlinelibrary.wiley.com/doi/full/10.1111/1365-2656.13904



3D model

View analysis

Tracks Prediction + orthophoto

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Species distribution modeling

- Detecting / identifying, etc. gives us a snapshot of the population
- But it remains incomplete
- Species distribution models (SDMs) can fill the gap

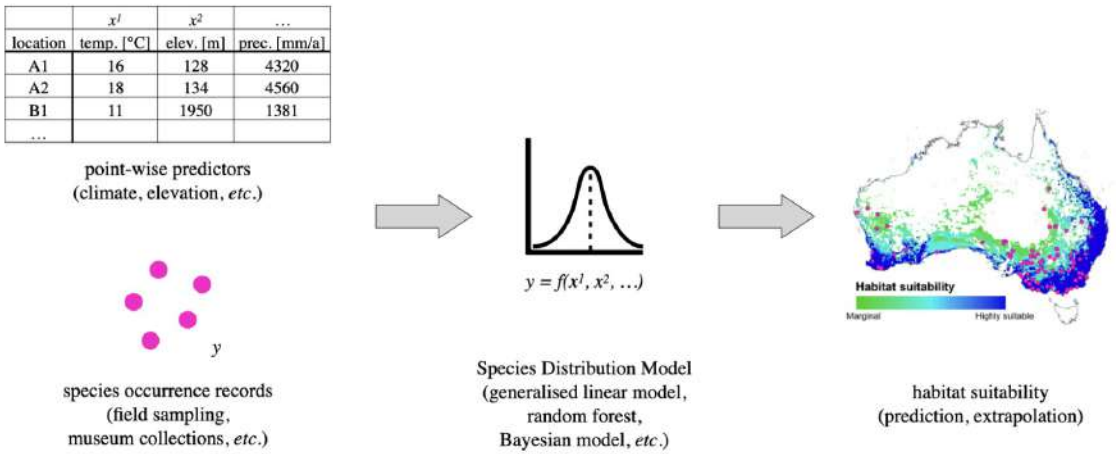

Fig. 1: Conventional habitat suitability studies employ point-wise environmental predictors (top left), limited numbers of species occurrence records (bottom left) and prediction models of comparably low complexity (middle). Habitat suitability map from Madani et al. (2016).

Machine learning and SDMs

- First DL models for species distribution models are appearing https://arxiv.org/pdf/2107.10400.pdf
- Performance are getting better!
  - https://ceur-ws.org/Vol-3180/paper-167.pdf
  - https://hal.science/hal-01834227

- The real plus is to work at scale and cover continental, global distributions!
- The availability of remote sensing data and community-based observation archives (e.g. iNaturalist) make it possible!

N. van Tiel, L. Lyu, F. Fopp, P. Brun, J. van der Hoogen, D. N. Karger, C. M. Casadei, **D Tuia.**, N. E. Zimmermann, T. Crowther, and L. Pellissier. Regional uniqueness of tree species composition and response to forest loss and climate change. *Nature Comm.*, 15(4375), 2024.

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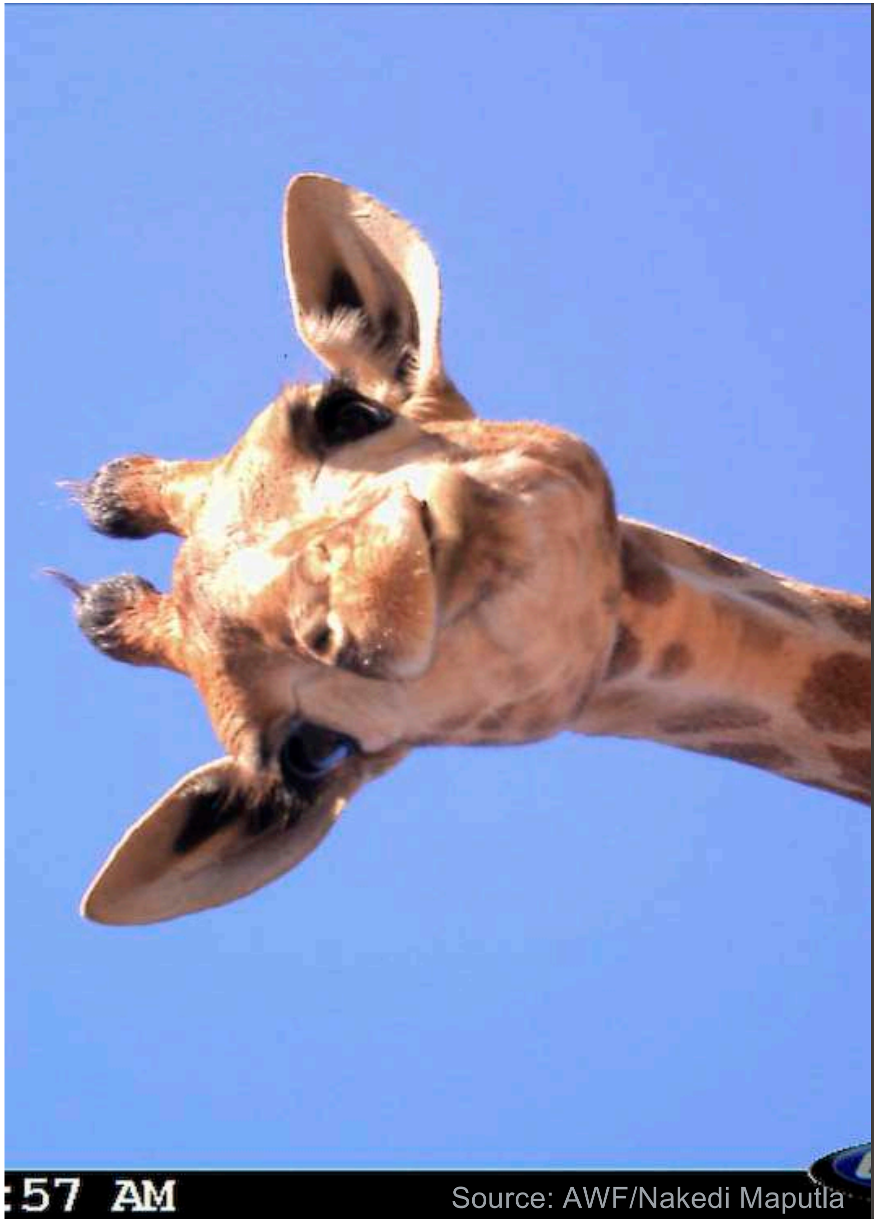
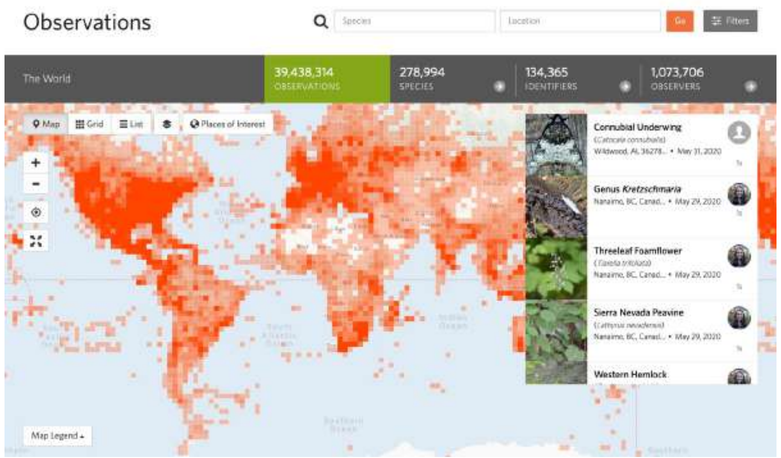


Concluding remarks

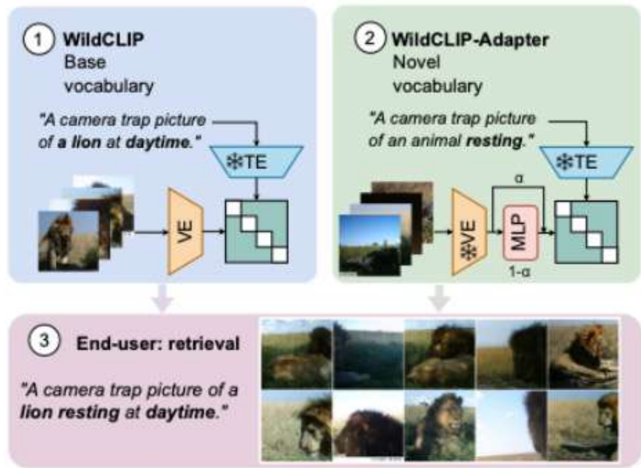
What can we do better?

Source: iNaturalist



Better care to biases

- Some regions of the world more represented in datasets
- Biases are at all levels! and are related to population, accessibility, but also socio-economic history, etc.
- Use of large language models inherits their biases



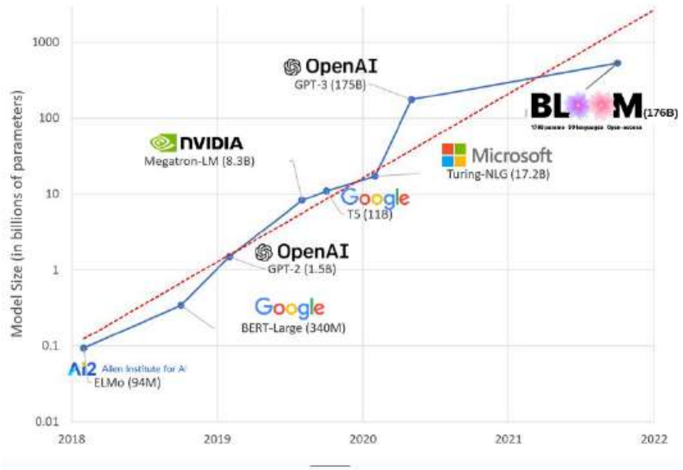
Source: Gabeff et al., IJCV 2024
https://link.springer.com/article/10.1007/s11263-024-02026-6

Open data? Yes, but with care

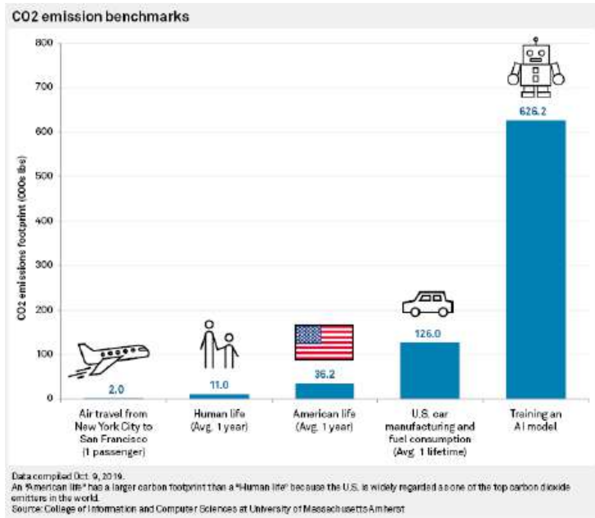
- Animals are endangered, what are the ethical risks?

What can we do better?

Standards are required
- Prediction must come with uncertainties
- We need quality control, limits of AI models need to be clearly reported



AI has a cost
- Running models costs $ and energy, mostly fossil
- Access to model should be global
- Models should not be oversized



New and exciting times!

Never have we seen such an acceleration and engagement

- We need to keep the pace
- Inderdisciplinary work is key!
- Education is key!

We need to take down walls between discipines

- Hybrid models
- Expert knowledge encoded in models
- Ethics of AI and conservation

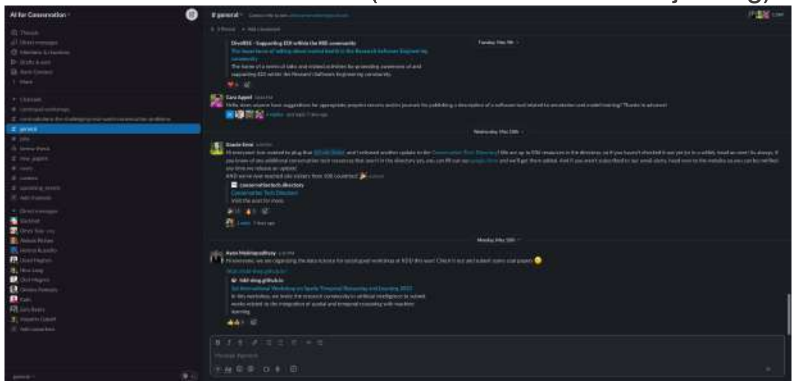
https://wilddrone.eu

MARIE CURIE ACTIONS

BioAcousticAi

https://bioacousticai.eu

AI for conservation slack (send me an email for joining)



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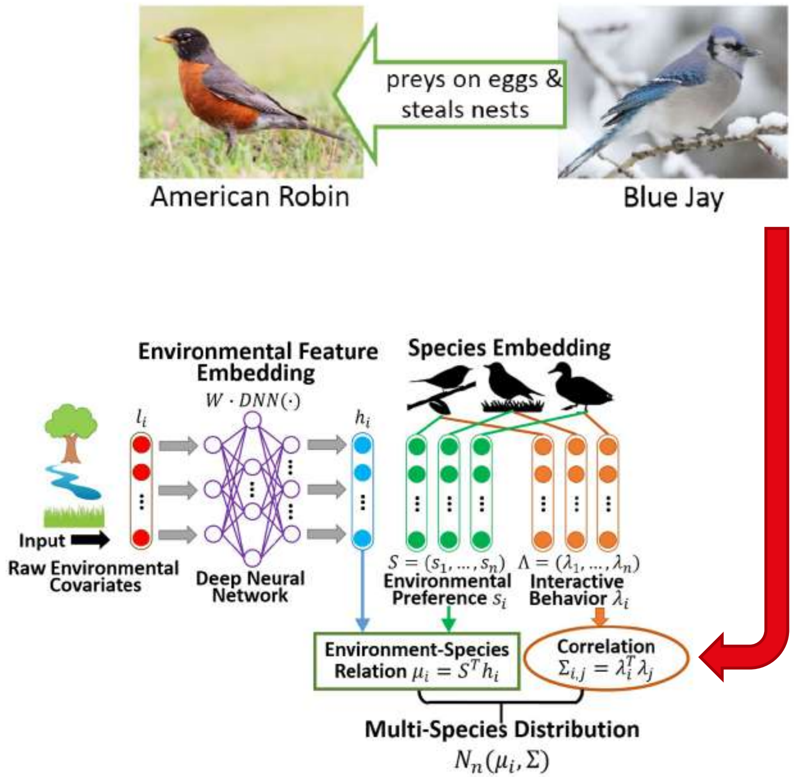

[Source: Chen et al., IJCAI 2016]

New data + AI enable effective wildlife conservation

- Threats on biodiversity are real and impact us all (in)directly.
- New sensors give us unprecedented insights on species distribution and behavior
- Monitoring life above and underwater is possible with new AI tools.
- It requires interdisciplinary teams!

Get in touch!

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