From neural networks to nature

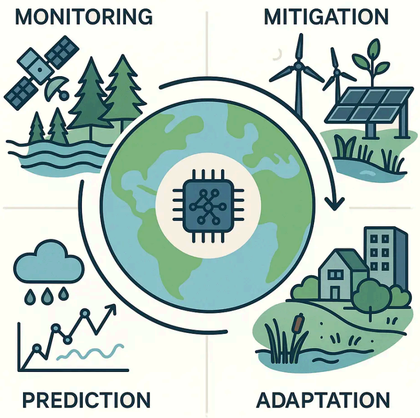
Robust AI for climate action and biodiversity monitoring

Olof Mogren, RISE Research Institutes of Sweden

Climate change

A multifaceted challenge benefiting from AI at many levels

- **Monitoring**
  - remote sensing, sensor networks, bioacoustics
- **Mitigation**
  - Emission reduction and carbon sequestration
- Adaptation
  - Resilience planning
- Prediction
  - Weather systems and extreme events



Key Milestones in AI for Climate

1972: Launch of Landsat 1 (The birth of modern remote sensing data)

2012: AlexNet (Deep Learning revolution makes computer vision viable for ecology)

2017: Transformer models (Paving the way for today's foundation models)

2019: Seminal Paper: "Tackling Climate Change with Machine Learning" (Rolnick et al.) – Defined the field

2023: Rise of "Foundation Models" for Earth (NASA/IBM Prithvi, etc.)

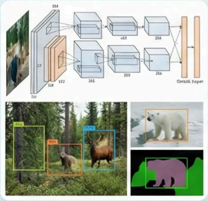
1972

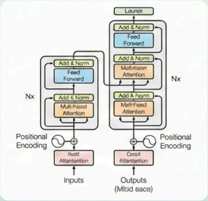
2012

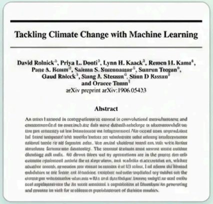
2017

2019

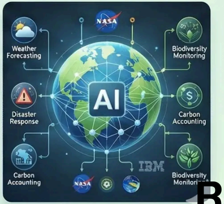
2023



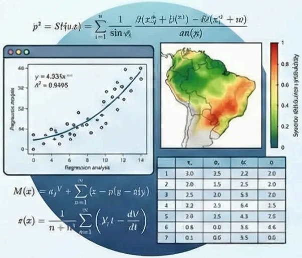


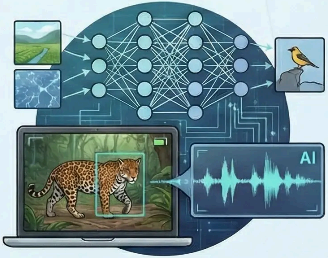

Tackling Climate Change with Machine Learning

Abstract



The evolution of ecological monitoring





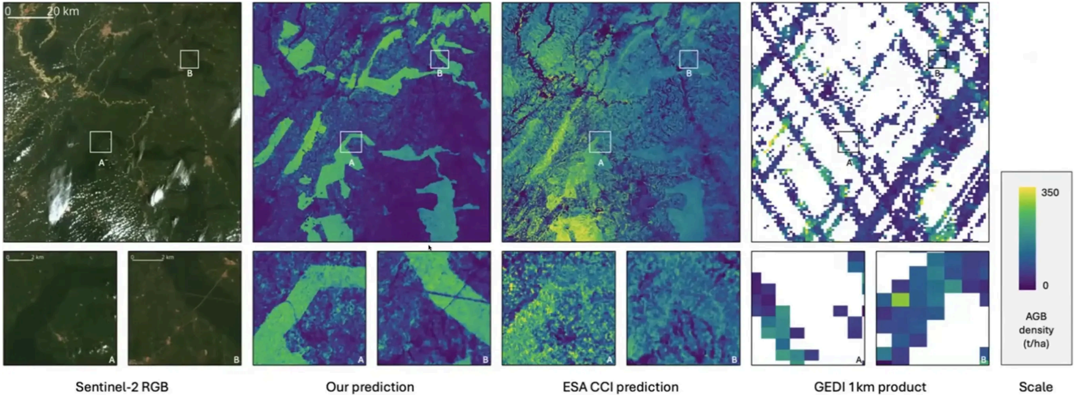
Past: A field notebook
(Manual counts)

Recent Past: Statistical models
(MaxEnt/Regression)

Present: Deep Learning
(Automated perception at scale)

Remote sensing
(land use classification)

Above ground biomass estimation
with sparse annotations



Remote sensing for deprived urban areas

Malaria mapping

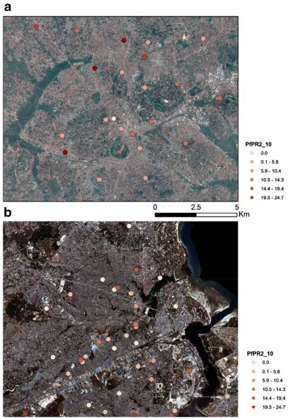
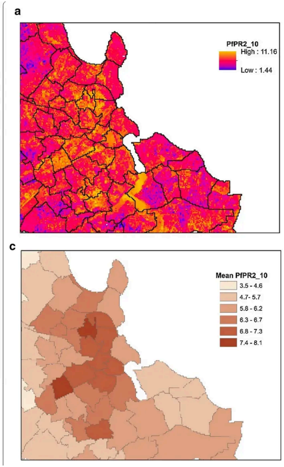
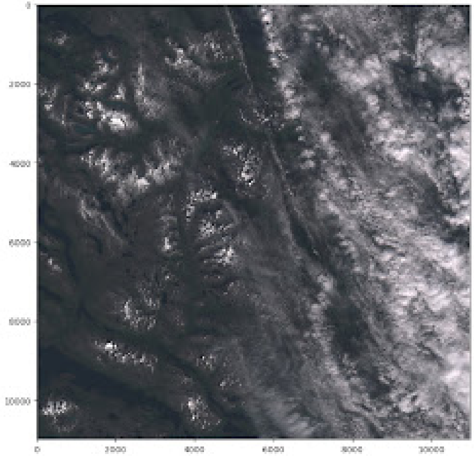


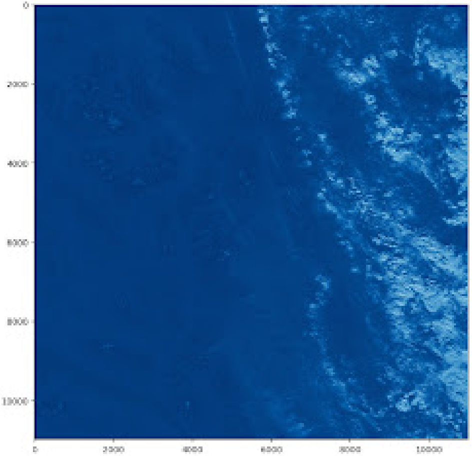
Fig. 3 Overview of geolocated malaria surveys over a subset of the urban extent of **a** Kampala and **b** Dar es Salaam



Morlighem et.al., 2023

Cloud thickness estimation



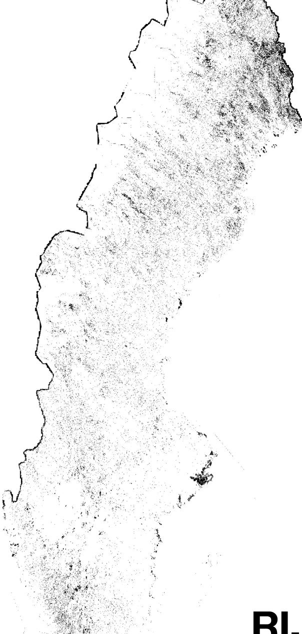


 Pirinen et al., 2023

Wetland mapping

- Input: remote sensing data
- U-net (fully convolutional)
- Annotations from field work
- Generated map, crucial for
    - Wetland restoration
    - Biodiversity
    - Climate adaptation

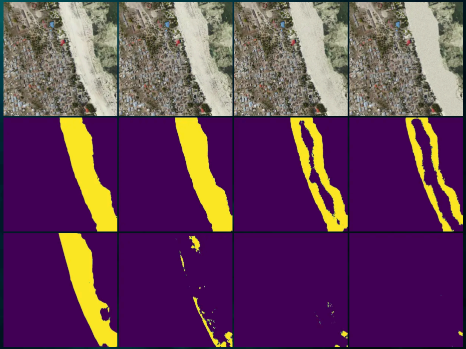
Annotations

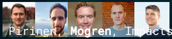


Predictions

Trust

- Important to quantify
  - model uncertainty
  - feature importance
- Right: robustness in state-of-the-art land use classification
  - Relies on texture, context
  - Less on color





 Willbo, Listo Zec, Martinsson, Pirinen, Mogren, Impacts of color and texture distortions on earth observation data in deep learning, ML4RS at ICLR (2024)

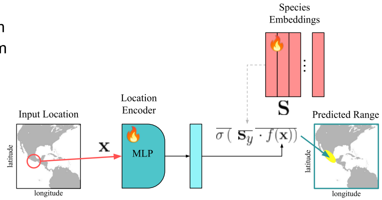
Species distribution modeling

- ~8.7M species, only ~100k have mapped ranges
- Traditional SDMs (e.g. MaxEnt, HMSC)
    - need environmental covariates
    - struggle at global scale
- Citizen science*: >10 000 000 presence-only observations
- Predicting ranges with only (lat,lon)
- Modelling using satellite data

Spatial Implicit Neural Representations (SINR)

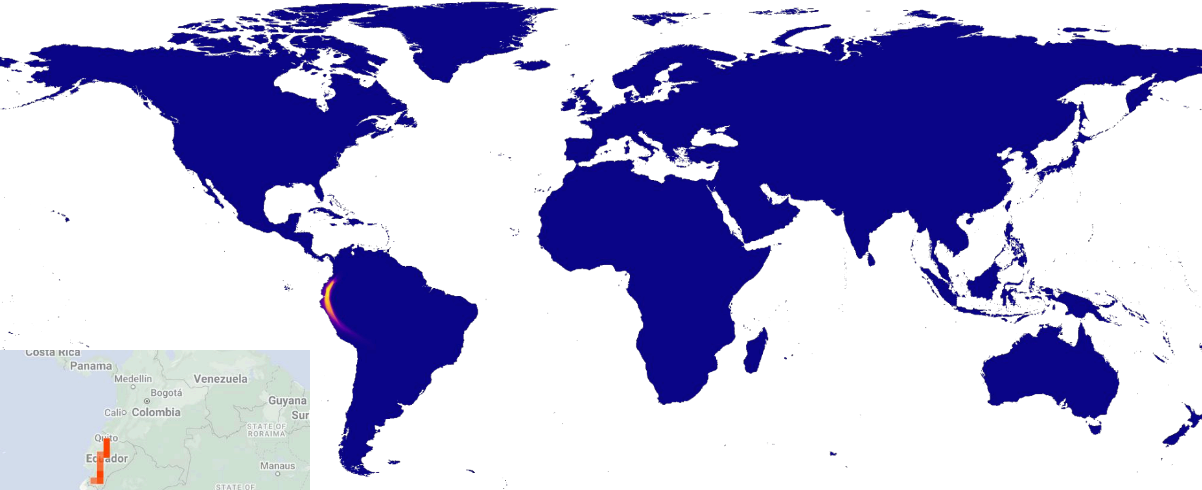
Train this model on citizen science observations from iNaturalist

~50k species
~35M observations
Model <100 MB

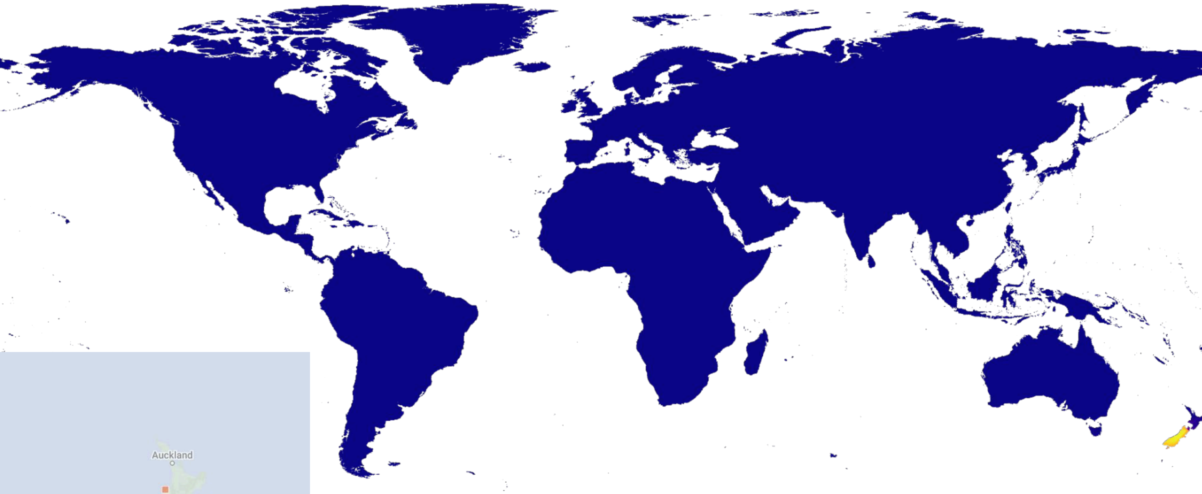


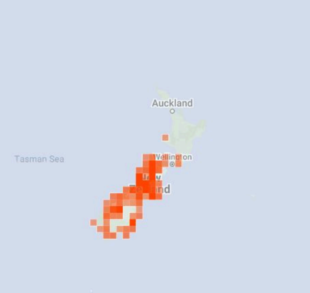
Cole et al. Spatial Implicit Neural Representations for Global-Scale Species Mapping, ICML 2023

1 Oisin Mac Aodha et al., Mélisande Teng et al., 2023, *iNaturalist, eBird, PlantNet



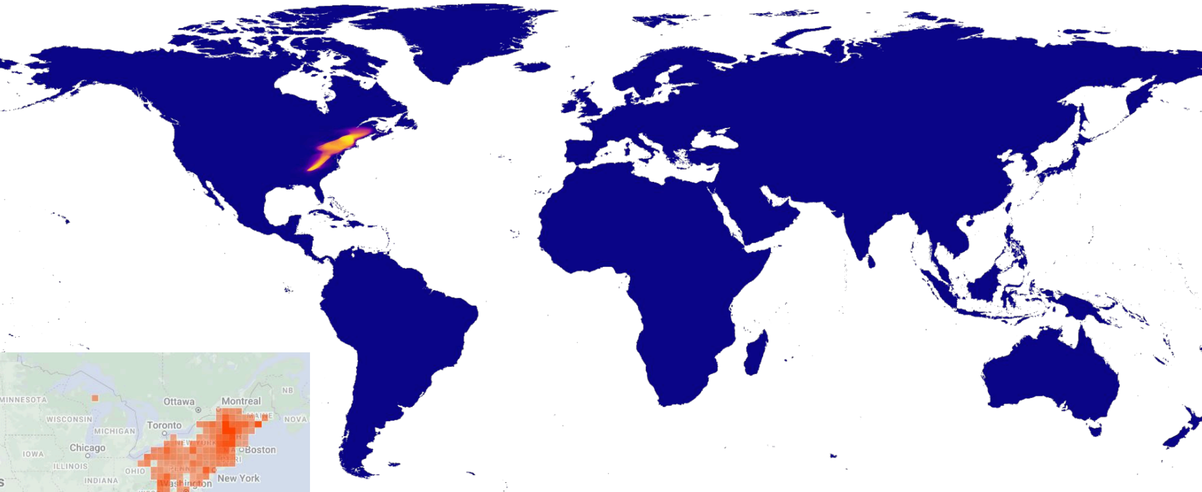
(Oxyallagma dissidens)

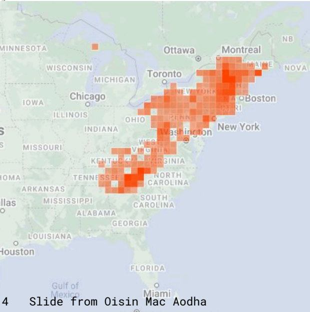




Mangrove-leaved Daisy-Bush
(Olearia avicenniifolia)

 Slide from Oisin Mac Aodha



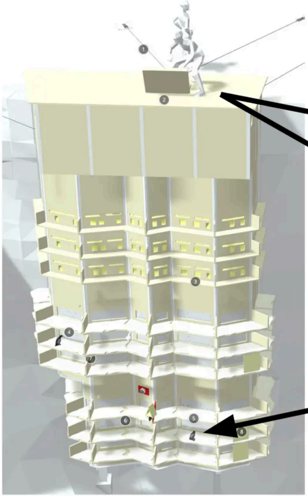


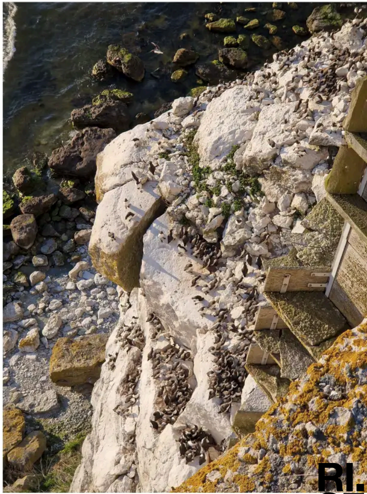
Round-leaved Violet
(Viola rotundifolia)

Sensing, less remote

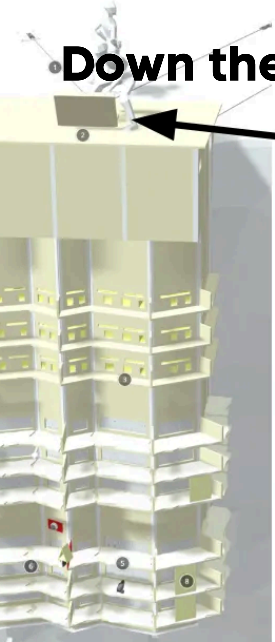
Auklab

Unique field site at Stora Karlsö





Down the hatch



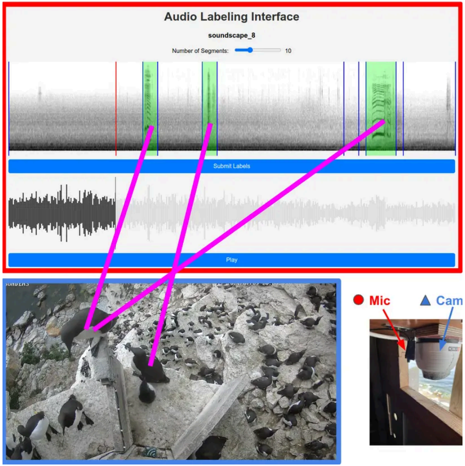
Extensive video monitoring for many years.

Other sensors such as thermal camera, weight scales, weather data.

Unique long-term and seasonal multimodal dataset.

Auklab
recordings and video

- Guillemots indicative of overall ecosystem health
- Can dive more than 150 meters deep
- Linking audio and video events
- Deeper understanding, more granular data

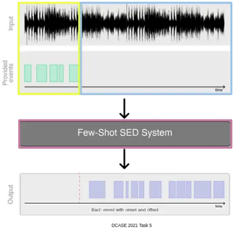


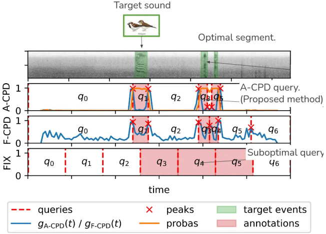
Letting data modalities inform each other
(Work in progress)

- Use **vision models** trained on synced video → provide event labels
- Transfer this knowledge to **audio-only recordings**
- Detect **events and behaviours** from soundscapes alone
- Reduce annotation workload by leveraging **cross-modal supervision**
- Unlock long-term monitoring where only **audio data** is available

Efficient Soundscape Analysis
Overcoming data scarcity

- Massive data - limited human annotation time.
- **Few-shot learning:** Generalizing from minimal examples.
- **Active learning:** Model queries humans only for the most "confusing" samples.
- **Result:** High accuracy with a fraction of the labels.

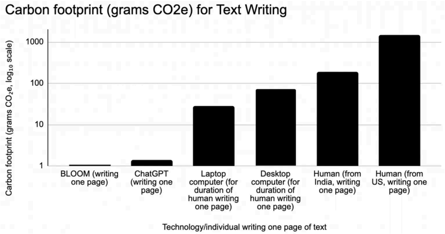


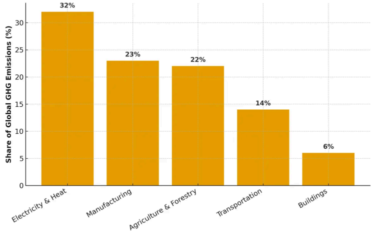


 [Martinsson et al. (DCASE 2022; openreview.net)], [Martinsson et al. (EUSIPCO 2024; arxiv:2403.08525)], [Martinsson et al. (TMLR 2025; arxiv:2502.09363)]

Footprint

- Generating a page of text with AI emits less than human writing (Tomlinson, et al, 2024)
- One prompt to Chat GPT: two to five grams of CO_2 equivalents
- Current AI emissions: ~1% (but may be growing)
- Big potential for savings





 Tomlinson, et al. Nature Sci Rep (2024). Kucukelbir, et al., 2024

Climate AI Nordics

Connecting researchers, technologists, and policymakers across the Nordic region to foster collaboration on AI-driven solutions for climate change and ecological resilience

Founded in Oct 2024 | 200+ members

Core team: 10 people (🇸🇪 | 🇩🇰 | 🇫🇮 | 🇳🇴)

Events: Recurring webinars & workshops

Monthly newsletter highlighting activities, job opening, events, etc

Slack community and social media presence

Partners: climes Swedish centre for impacts of climate extremes, AfriClimate AI, ellis, Global Wetland Center, Klimatkollen, NORDIC AI

Climate AI Nordics
climateainordics.com

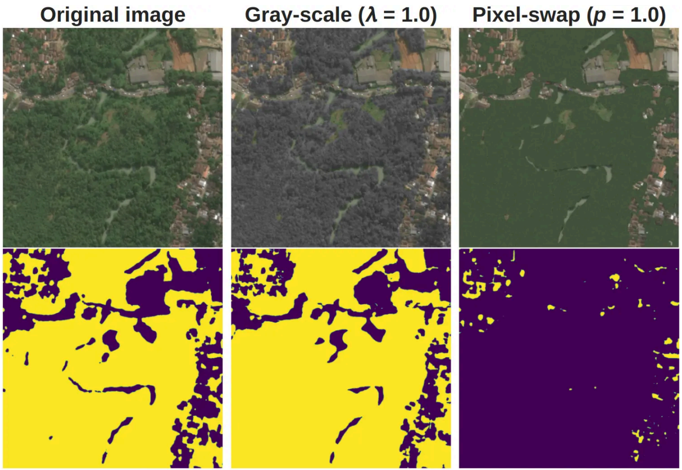
In conclusion

- AI can help with monitoring, mitigation, adaptation, and prediction
- AI has its own climate impact, but the benefits overweigh
    - If we use it right
- AI makes us more efficient
    - A problem in manufacturing or e-commerce
    - Desperately needed in climate mitigation and adaptaion, and in biodiversity monitoring

Thank you

Appendix

Robustness
of state-of-the-art earth observation models



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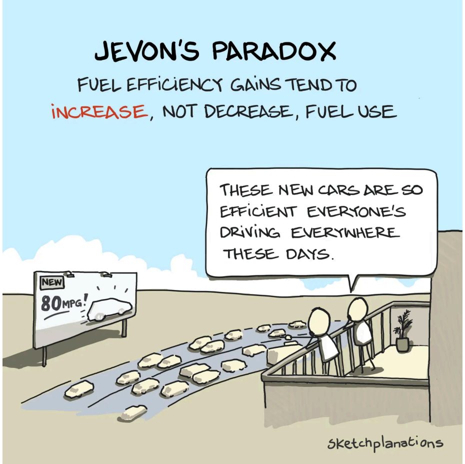
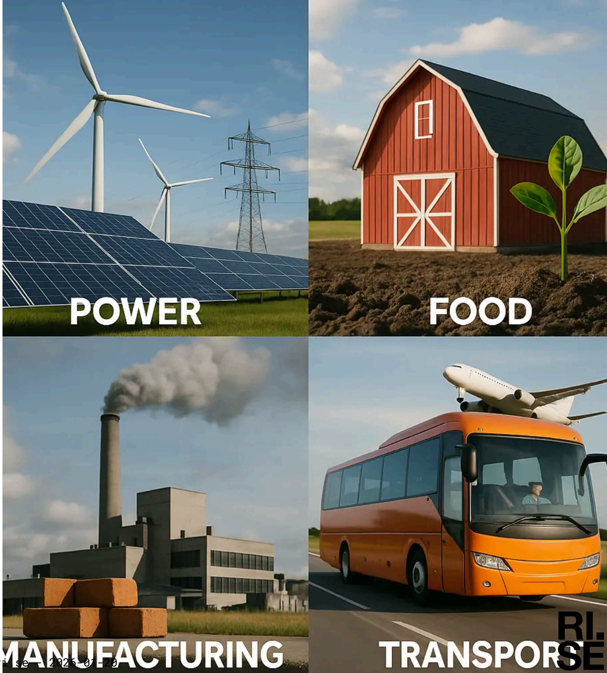
Indirect environmental effects of AI

- AI can make us more efficient
- Fast-fashion is already a burden to the environment
- Jevon's paradox/rebound effects

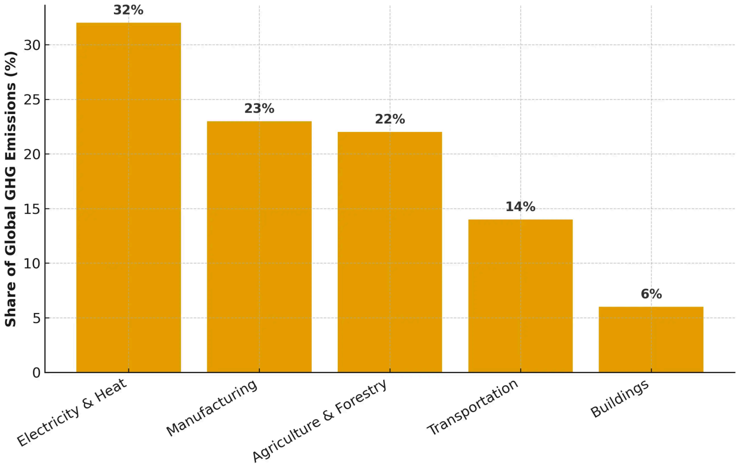


The potential of AI

- Incremental gains
  - Enhancing solar energy output
  - Improving building efficiency
- Transformational gains
  - Discovering new clean energy sources, materials, etc.



GHG emissions by sector



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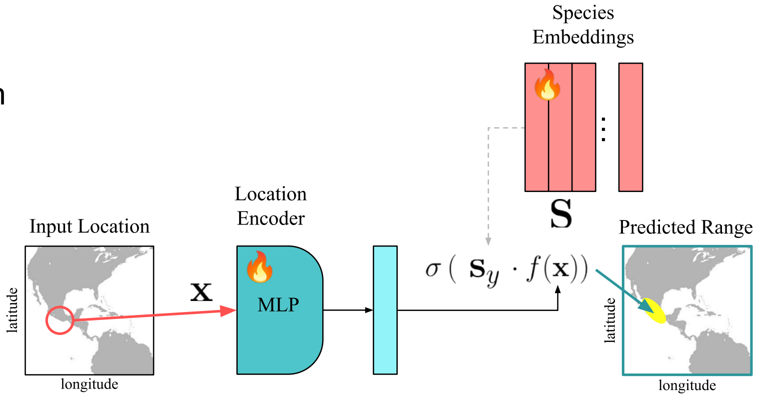
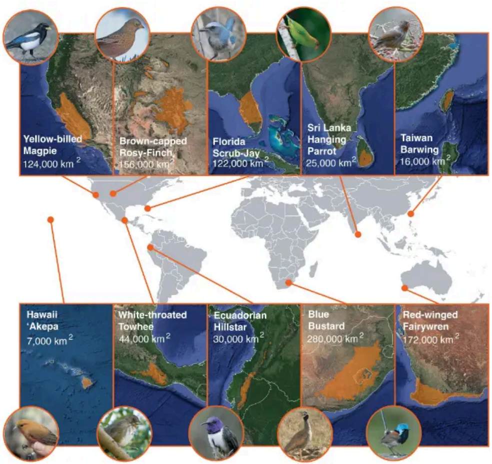


Cole et al. Spatial Implicit Neural Representations for Global-Scale Species Mapping, ICML 2023

Learned location embeddings

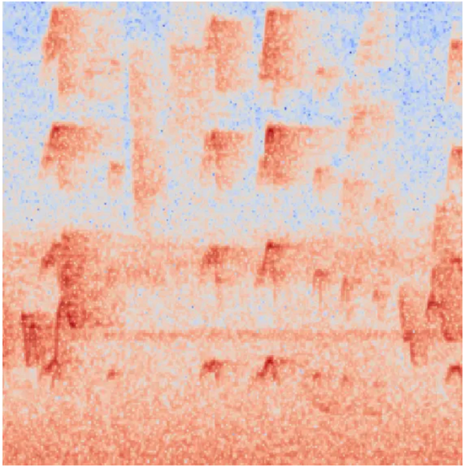
 Slide from Oisin Mac Aodha

Remote sensing for species distribution



Bird species identification

- Modelling sound using spectrograms and convolutional neural networks
- Altitude and location information improves results



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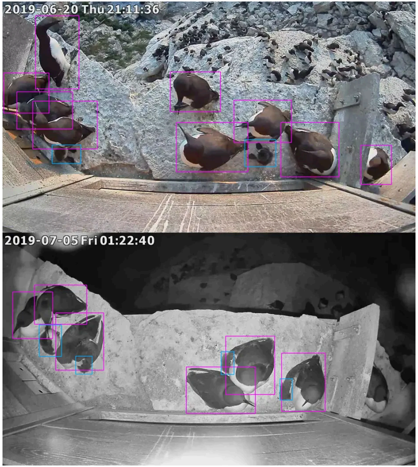
Cameras for seabirds

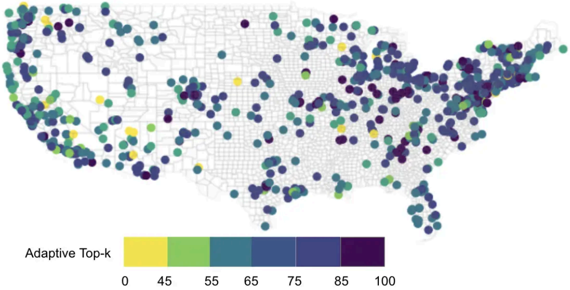


Jonas Hentati Sundberg
SLU

 Jonas Hentati-Sundberg, et al. (2023). Common guillemot.

Remote sensing for species distribution

Satellite data + environmental variables better than either only sat or only env



Object detection for
coffee berry disease

- Help detect infected plants
- Highly dependent on climate change and factors such as rainfall, humidity, and temperature
- Limited data
    - Few raw images **and** few annotations