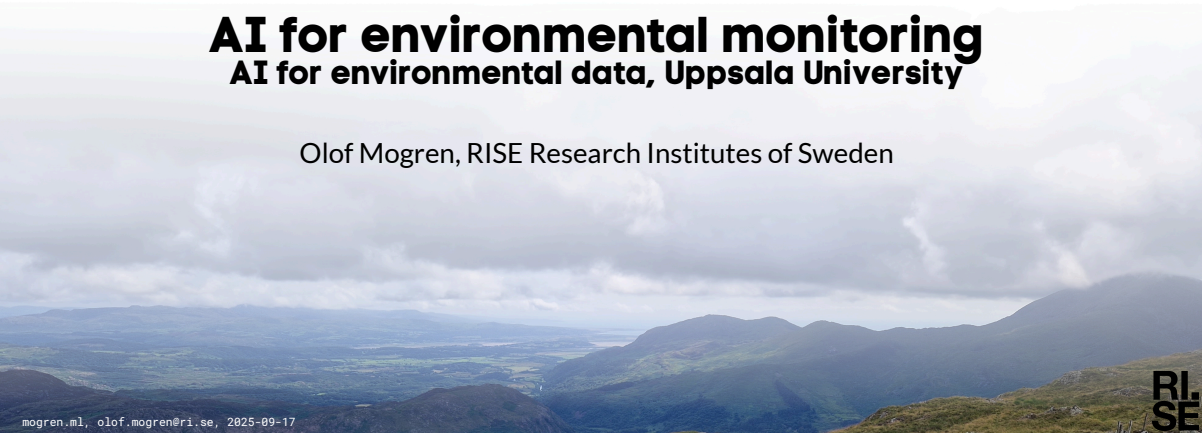
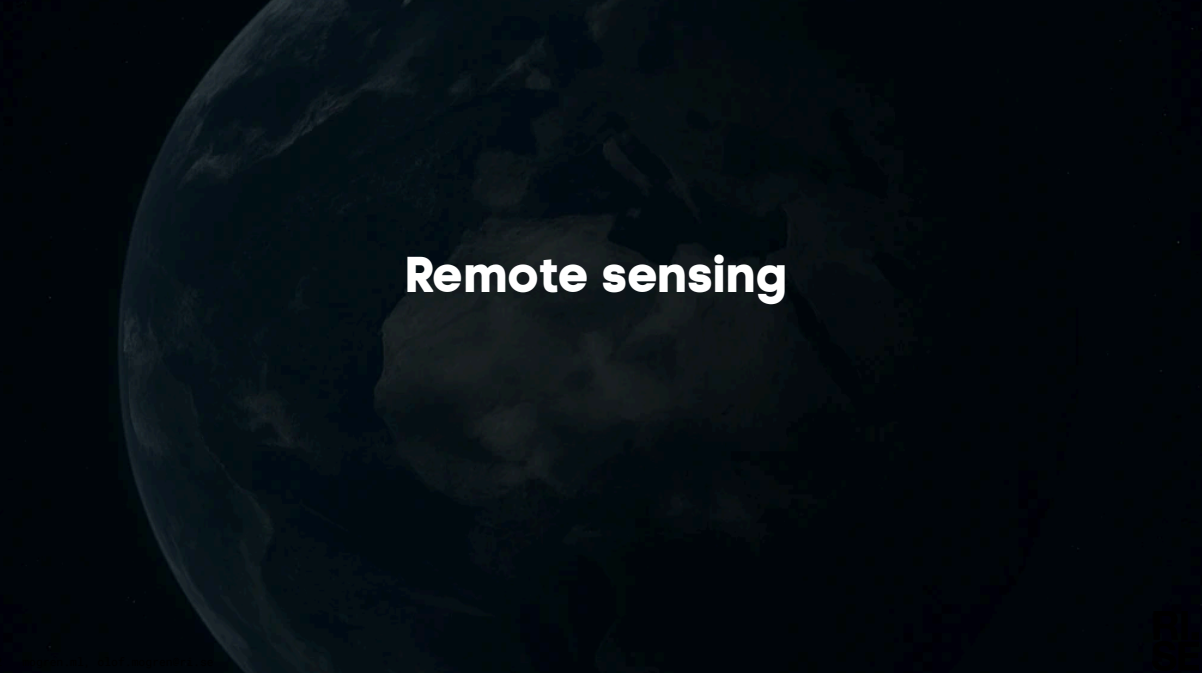
AI for environmental monitoring
AI for environmental data, Uppsala University

Olof Mogren, RISE Research Institutes of Sweden




Remote sensing


mogren.ml, blof.mogrensri.se --- OpenEarthMap
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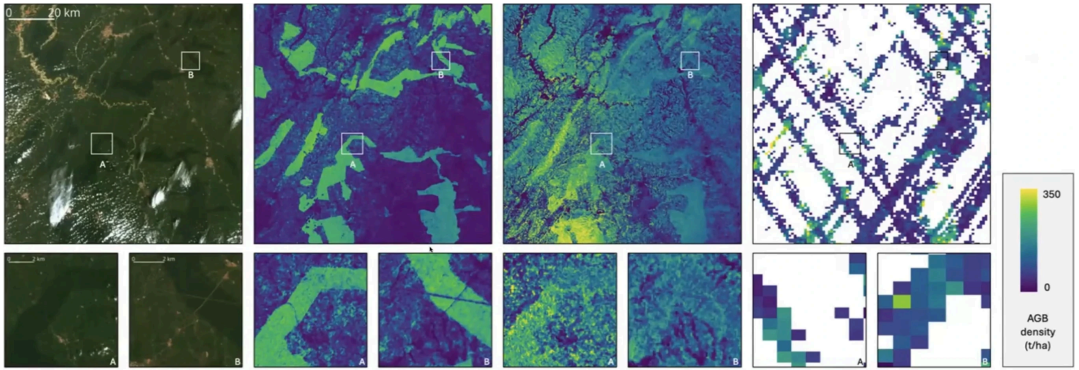
Above ground biomass estimation



Remote sensing for deprived urban areas

Malaria mapping

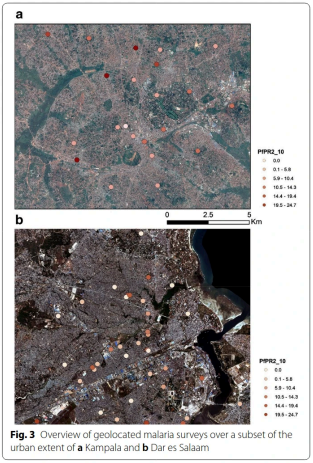
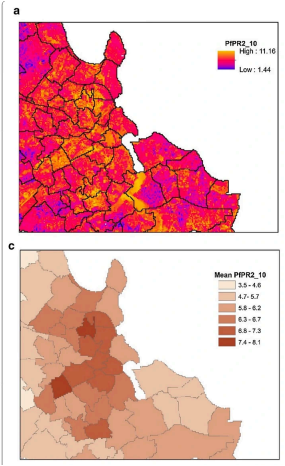
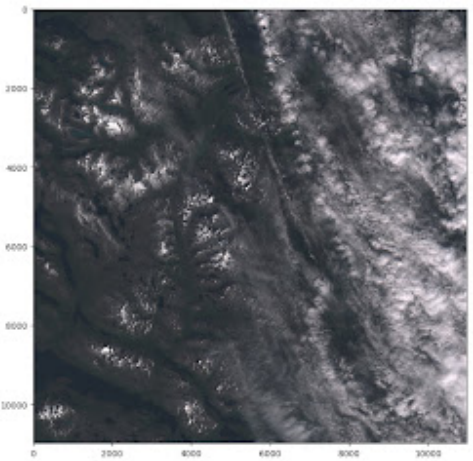


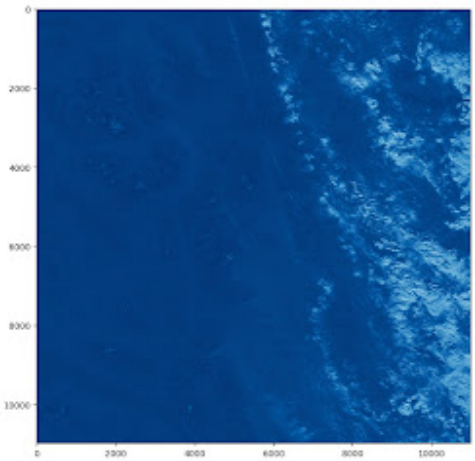
Fig. 3 Overview of geolocated malaria surveys over a subset of the urban extent of **a** Kampala and **b** Dar es Salaam



Morlighem et.al., 2023

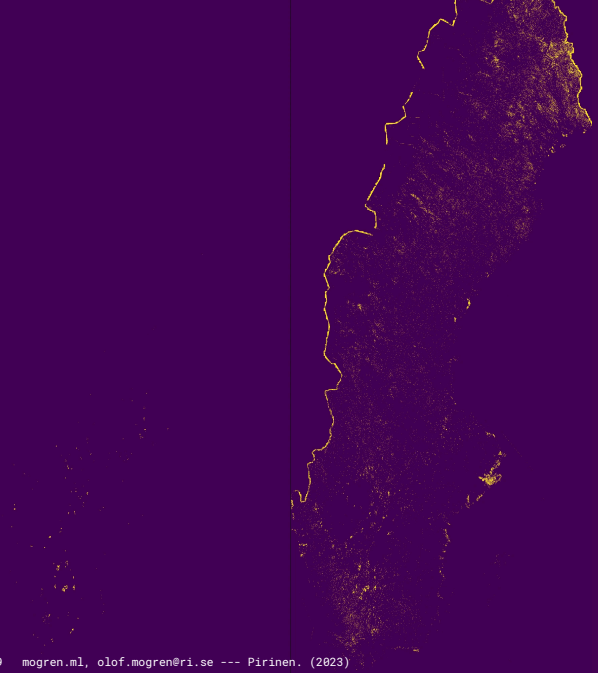
Cloud thickness estimation





7 Pirinen et al., 2023


Powerful carbon sink



Earth observation
for wetland estimation

- Generated map, crucial for
  - Wetland restoration
  - Biodiversity
  - Climate adaptation

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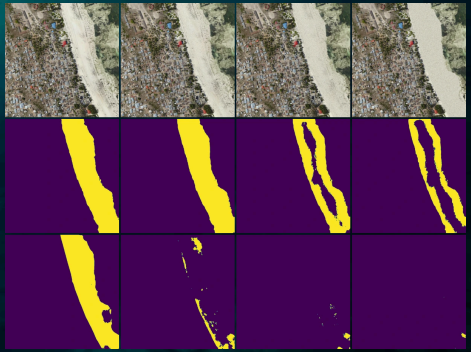
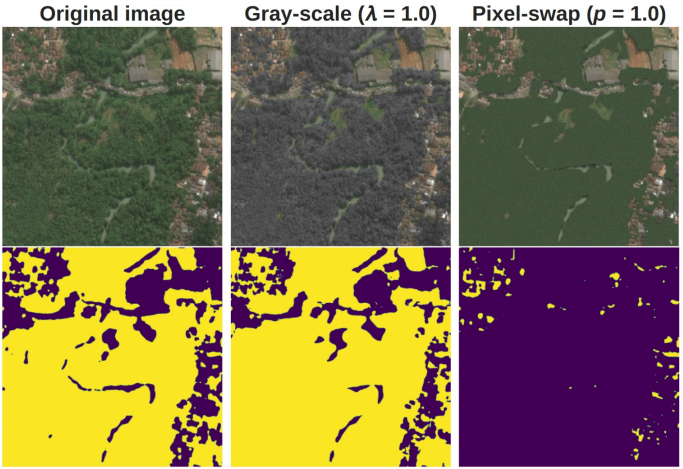
Robustness in ML for remote sensing

- Existing state-of-the art models sensitive to pixel perturbations
- Relies on texture, context
- Not strong reliance on color
- Work published at ML4RS Workshop at ICLR 2024



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

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



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

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Species distribution modeling
Habitat suitability

- ~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
- Can we predict species ranges with only locations (lat,lon)?

Mac Aodha et al., *iNaturalist, eBird, PlantNet

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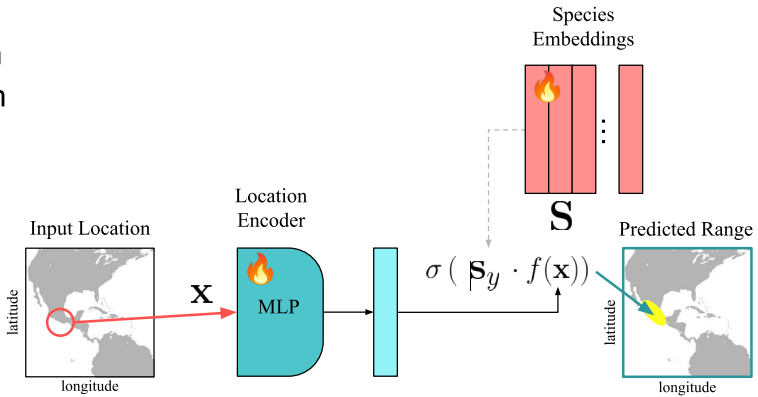
Spatial Implicit Neural Representations (SINR)

Train this model on citizen science observations from iNaturalist

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

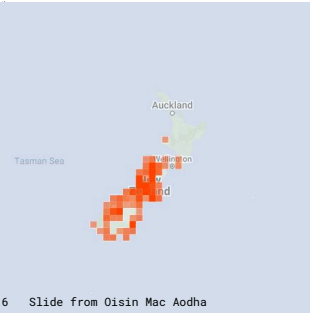


Cole et al. Spatial Implicit Neural Representations for Global-Scale Species Mapping, ICML 2023

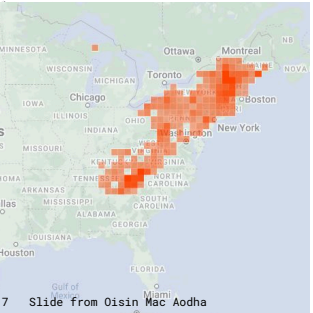
Learned location embeddings

 Slide from Oisin Mac Aodha

(Oxyallagma dissidens)



Mangrove-leaved Daisy-Bush
(Olearia avicenniifolia)



7 Slide from Oisin Mac Aodha

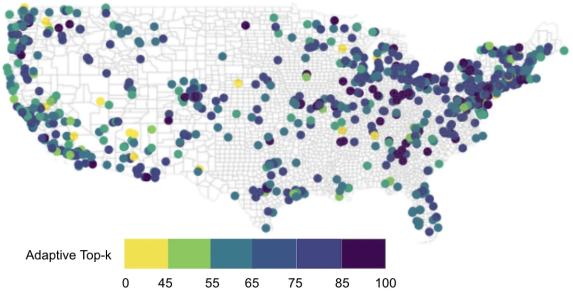
Round-leaved Violet
(Viola rotundifolia)

Remote sensing for species distribution

 Oisin Mac Aodha, 2023

Remote sensing for species distribution

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




Sensing, less remote

Image: wildlabs.net

2 Image: wildlabs.net

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3 Image: wildlabs.net

24 Image: wildlabs.net

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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

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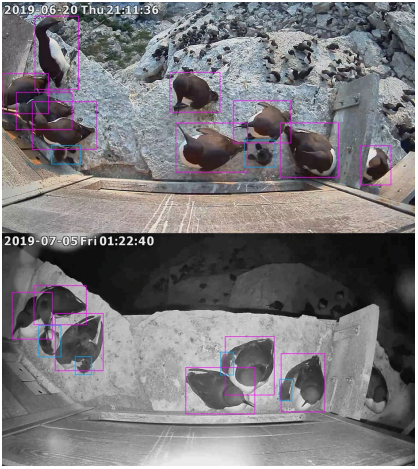
Cameras for seabirds

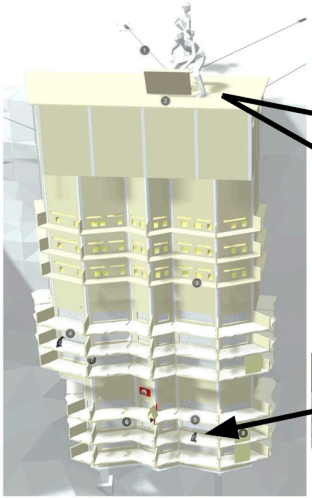


Jonas Hentati Sundberg
SLU

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

Auklab

Unique field site at Stora Karlsö



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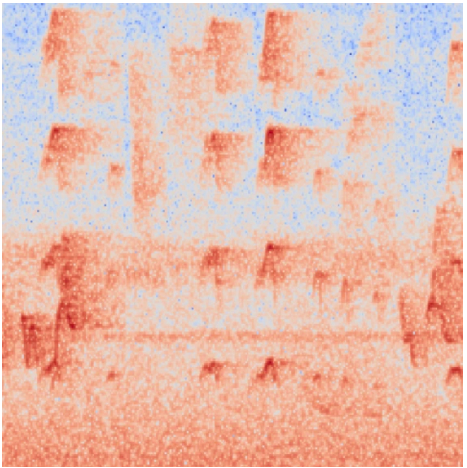
Soundscape analysis

Bird species identification

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



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Sound event detection

- Large amounts of data
- Labour intensive annotation
- Few-shot learning

DCASE 2021 Task 5

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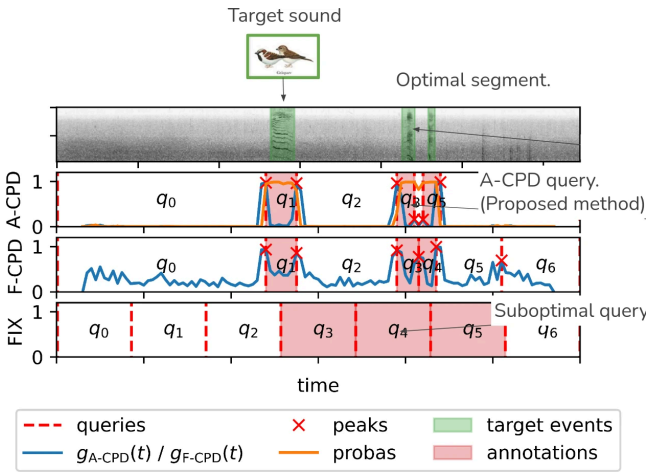
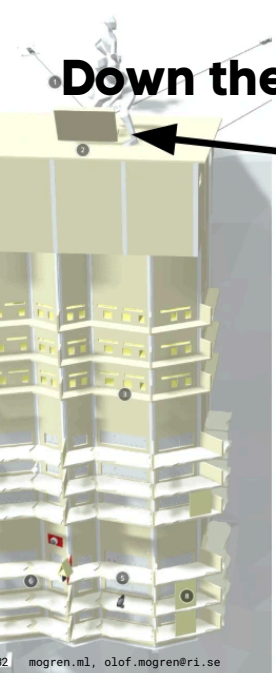
Active learning and active annotation



 Martinsson, **Mogren**, Sandsten, Virtanen. EUSIPCO (2024)

Down the hatch



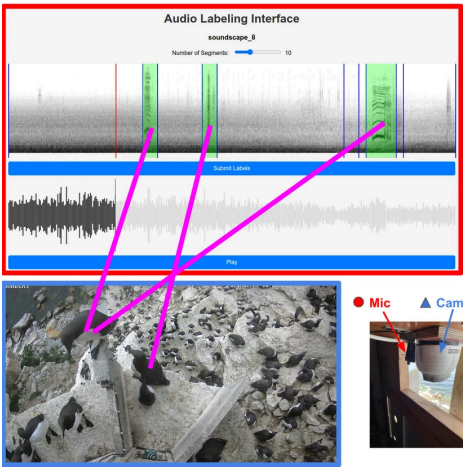
Extensive video monitoring for many years.

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

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Schedule

Yesterday:

- 10: Introduction to AI and Machine Learning
  - Olof Mogren
- 11: Introduction and Brief History of Natural Language Processing (NLP)
  - Murathan Kurfalı
- 13: AI for Climate Adaptation and Mitigation
  - Olof Mogren
- 14: Exercises

Today:

- 10: AI for Environmental Monitoring
  - Olof Mogren
- **11: AI for Prediction and Earth System Modelling**
  - Olof Mogren
- 13: Using NLP and Large Language Models: General Concepts and Climate Applications
  - Murathan Kurfalı
- 14: Exercises