Remote Sensing in Transition: What talent do we actually need?

Kirsten de Beurs

Laboratory of Geo-information Science and Remote Sensing, Wageningen University

WAGENINGEN UNIVERSITY & RESEARCH

Geo-information Science and Remote Sensing Laboratory

Sytze de Bruin
GIS chair

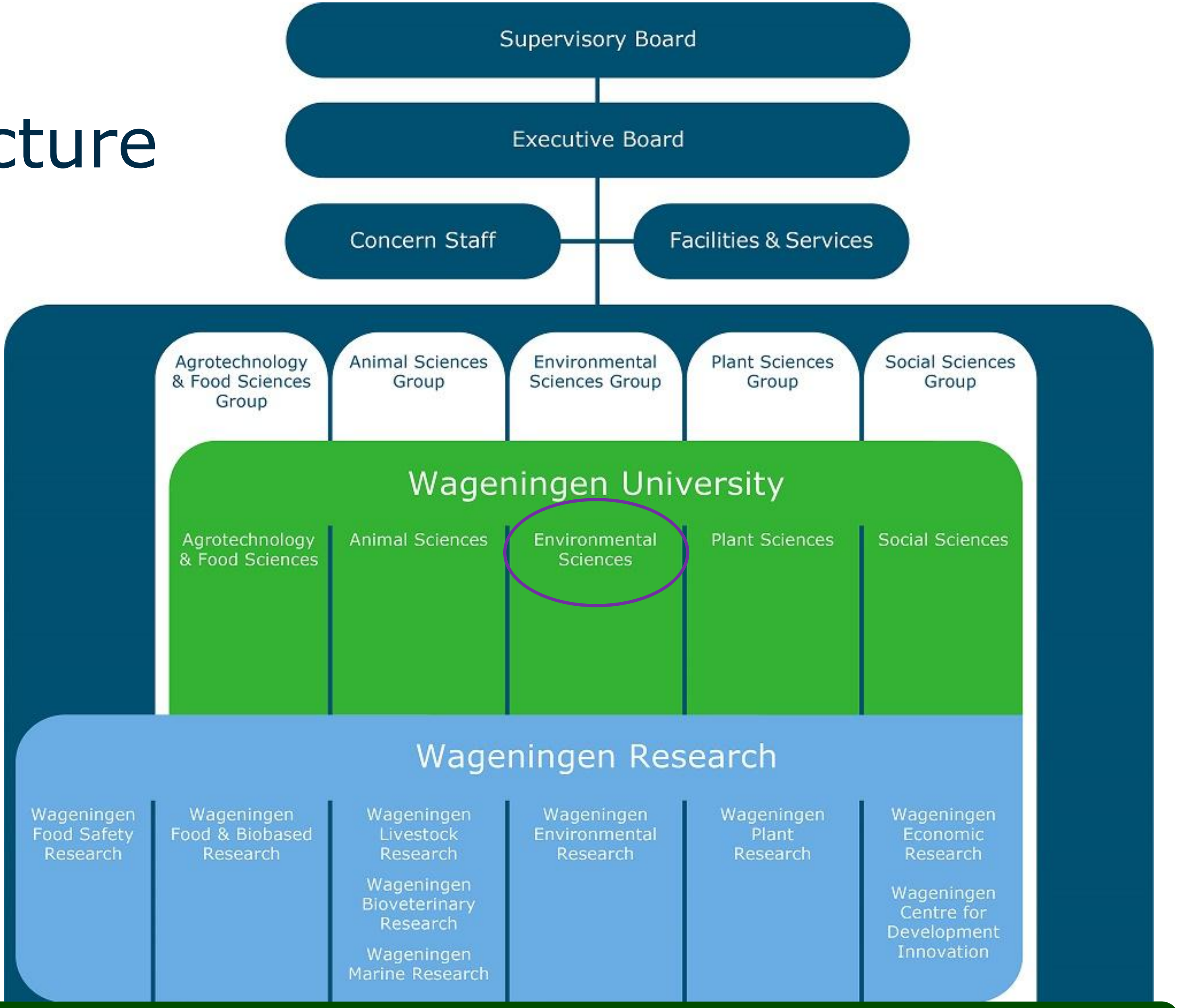
Kirsten de Beurs
RS chair

Kirsten.deBeurs@wur.n

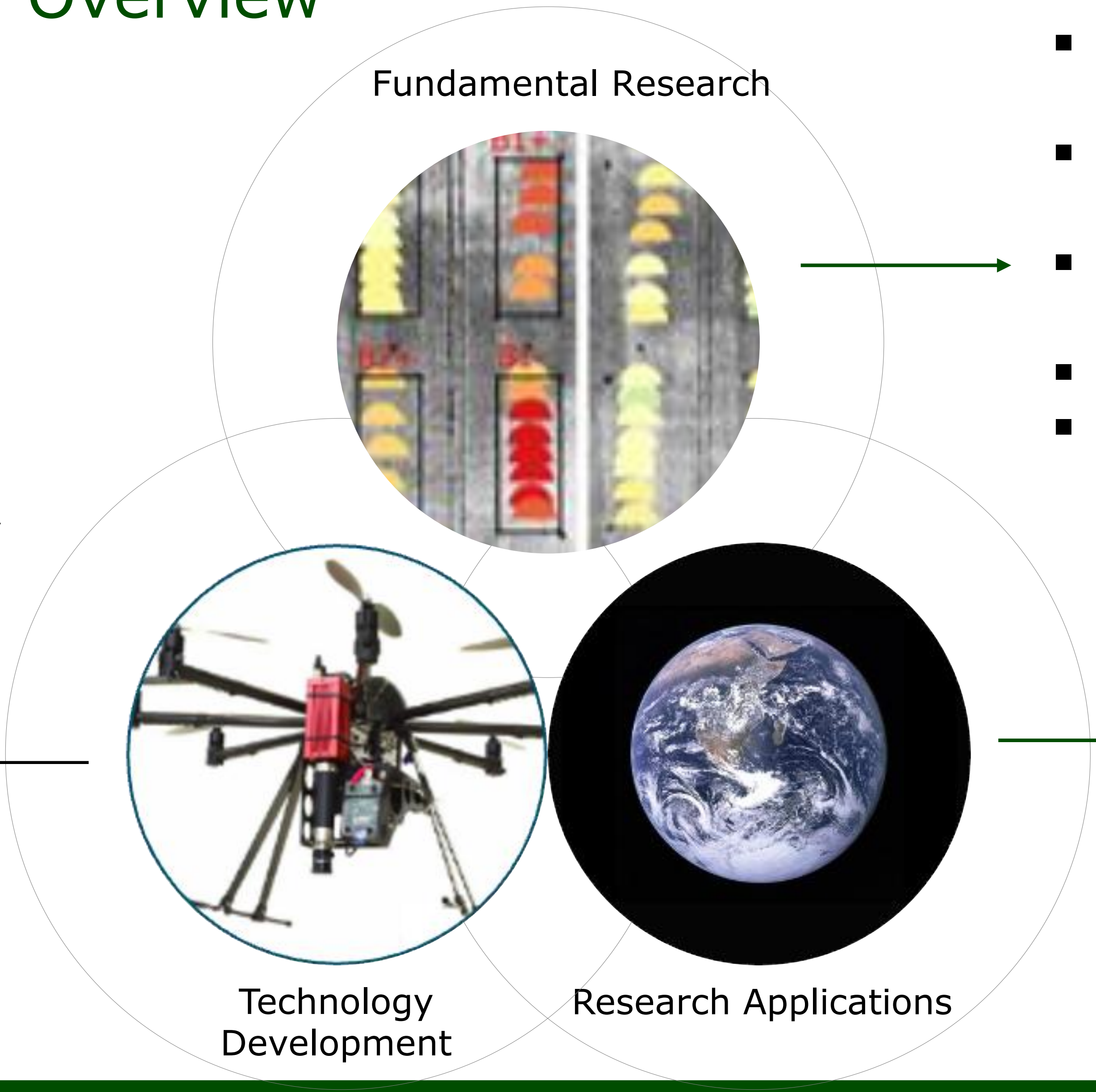
- 15 assistant/associate prof. + 9 lecturers
- ~6 postdocs & ~30 PhDs
- Msc "Geoinformation Science and Remote Sensing"
  – 50 students/year (50% international)

Wageningen UR: organizational structure

Where is GRS?



GRS Research Overview



- Laser Technology
- Thermal Sensing
- Fluorescence / Hyperspectral Cameras
- Augmented Reality
- Digital Twins

- Map Accuracy / Uncertainty
- State of the art data processing and analysis approaches
- Interpretability of different sensor data
- Machine learning methodology development
- Serious games
- Spatiotemporal modelling

- Land Use Change Impact Assessment:
    - Tropical Forests
    - Grasslands
    - Urban areas
- Climate Impacts
- Health Impacts
- Crop stress and disease monitoring

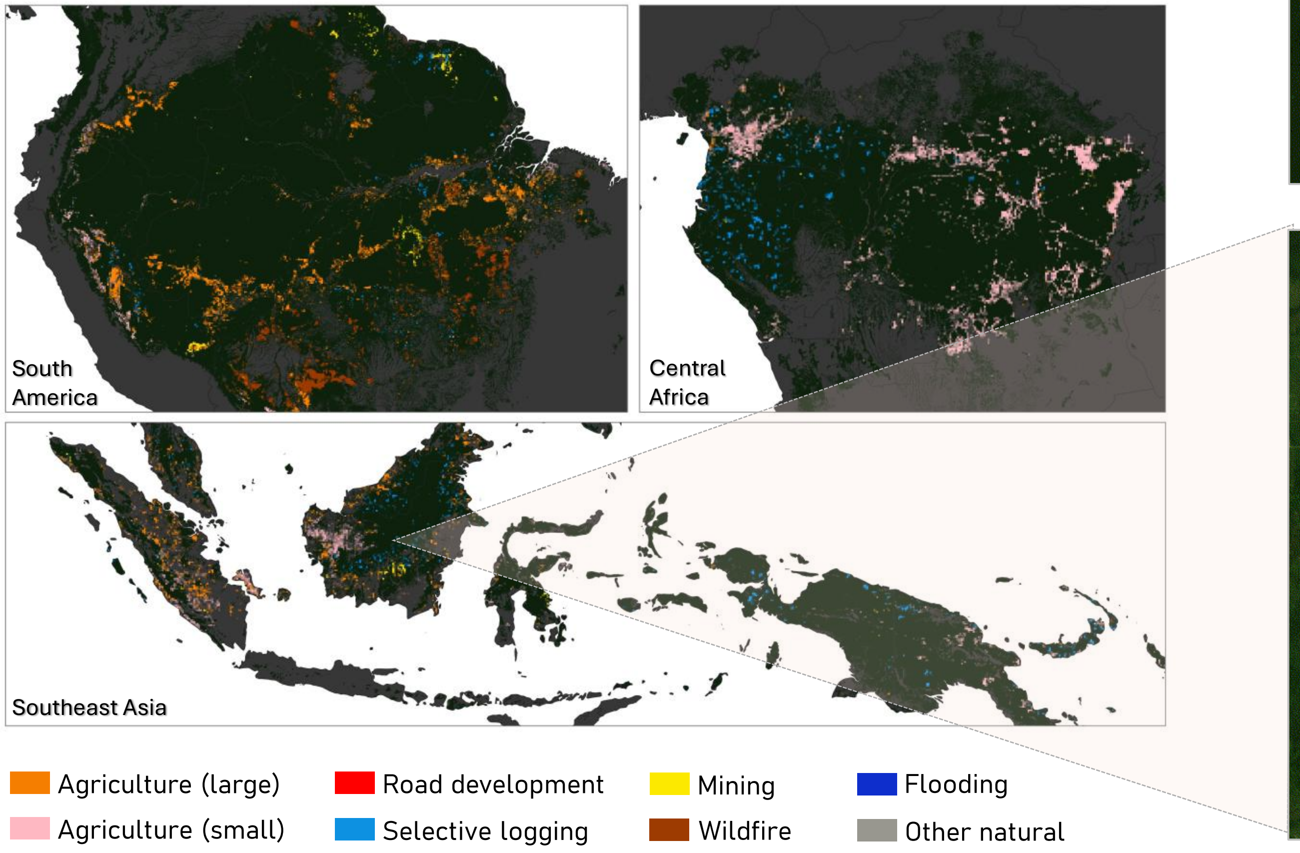
Forest Monitoring and AI

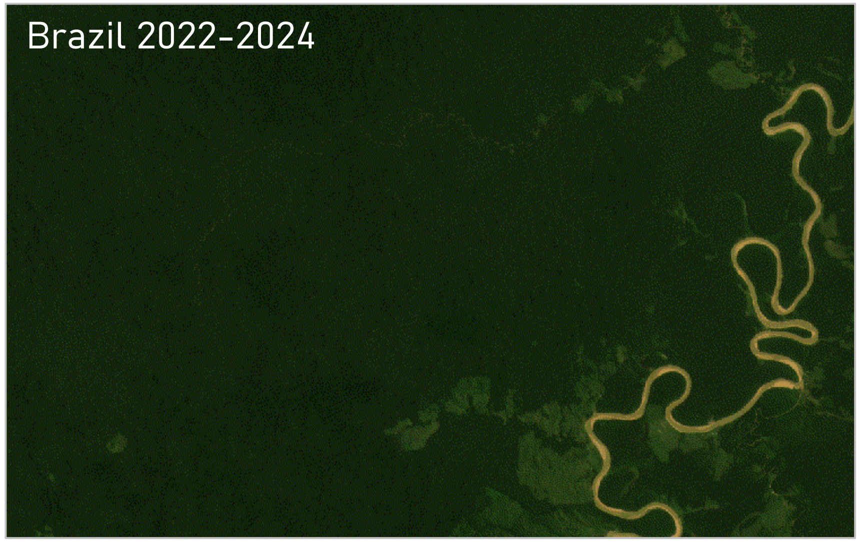
Photo by Kristaps Ungurs on Unsplash

Bart Slagter

DRIVERS OF FOREST LOSS

- Near real-time monitoring of forest loss and its drivers
- Based on a deep learning model applied to Sentinel-1 and -2 satellite data



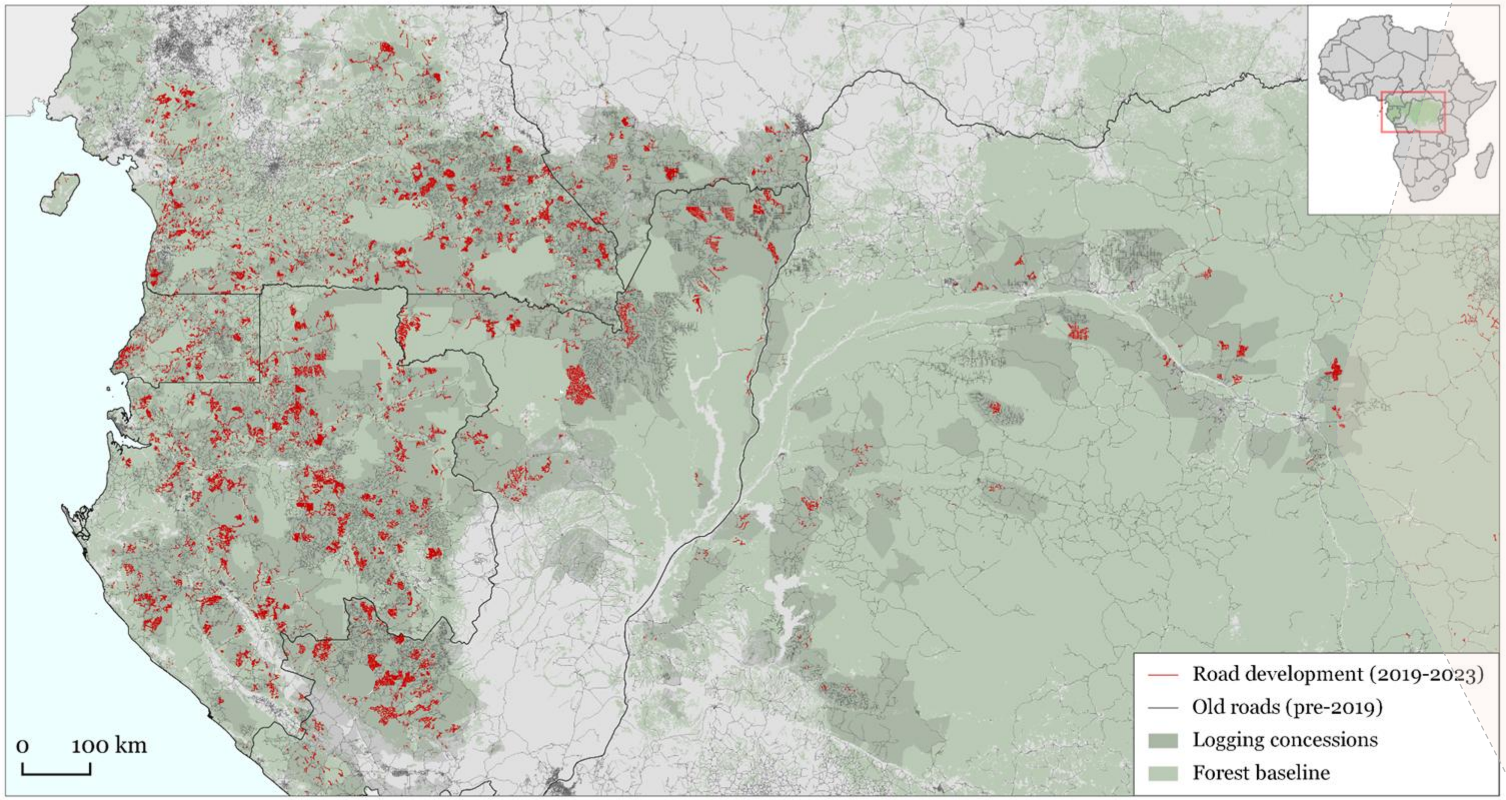


convolutional neural network
ResUNet

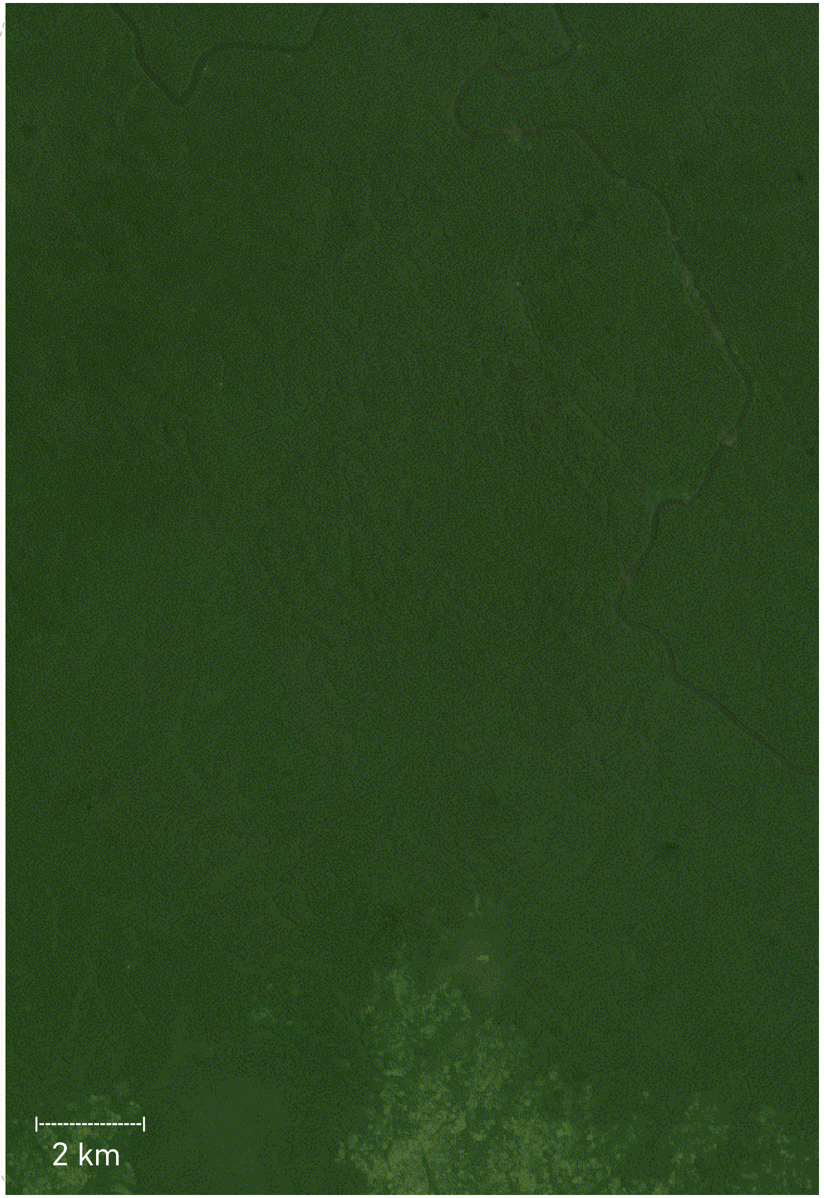
Slagter et al. (2023) Monitoring direct drivers of small-scale tropical forest disturbance in near real-time with Sentinel-1 and -2 data. Remote Sensing of Environment.
Slagter et al. (in revision). Rapid satellite monitoring reveals complexity of tropical tree cover loss drivers at fine scale. Nature Communications.

ROAD NETWORKS IN THE CONGO BASIN

- Monthly monitoring of new road development in high spatial detail
- Based on a deep learning model applied to Sentinel-1 and -2 satellite data



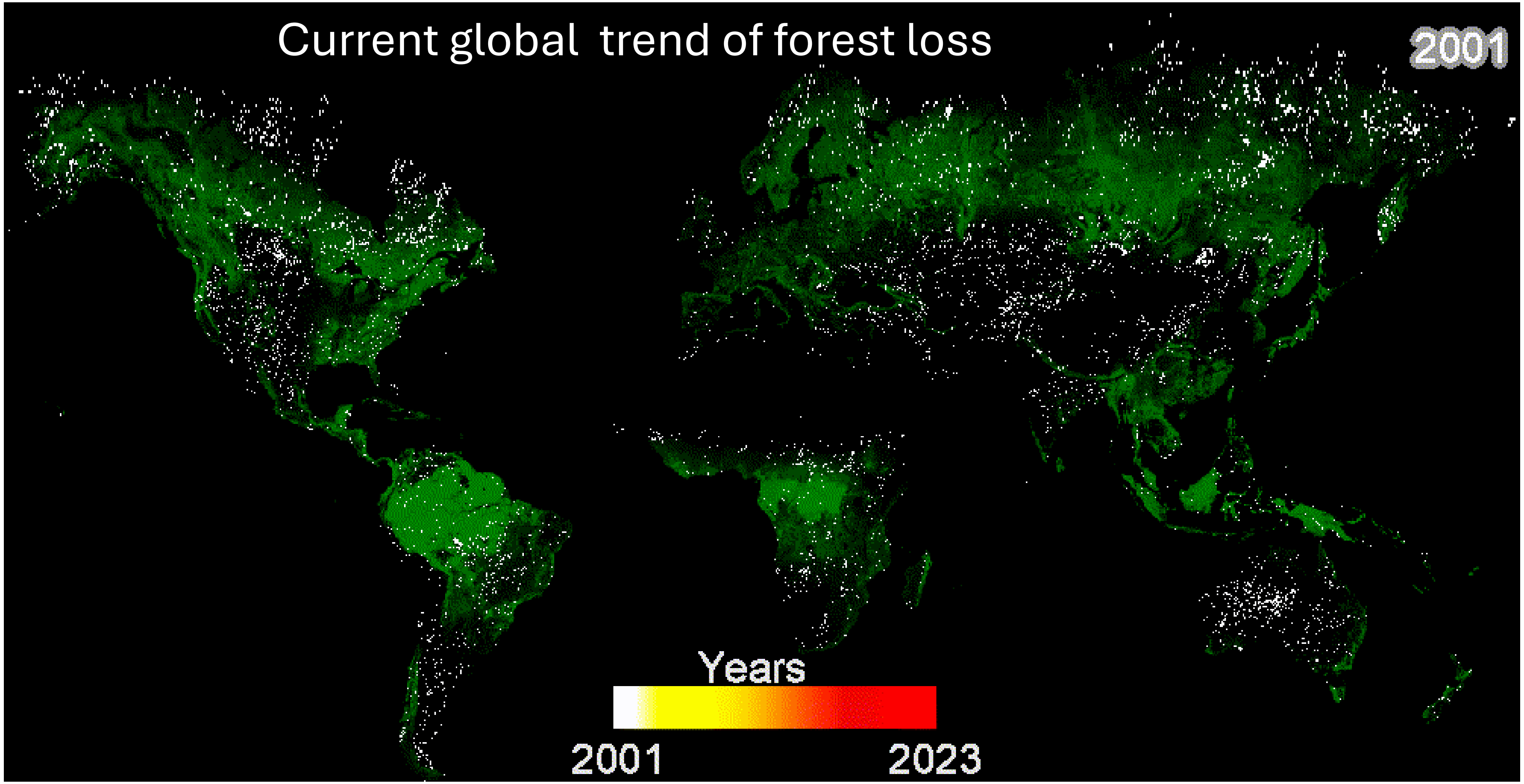
Monthly road development



Slagter et al. (2024) Monitoring road development in Congo Basin forests with multi-sensor satellite imagery and deep learning. Remote Sensing of Environment.

Robert Masolele

What happens after forest is lost?



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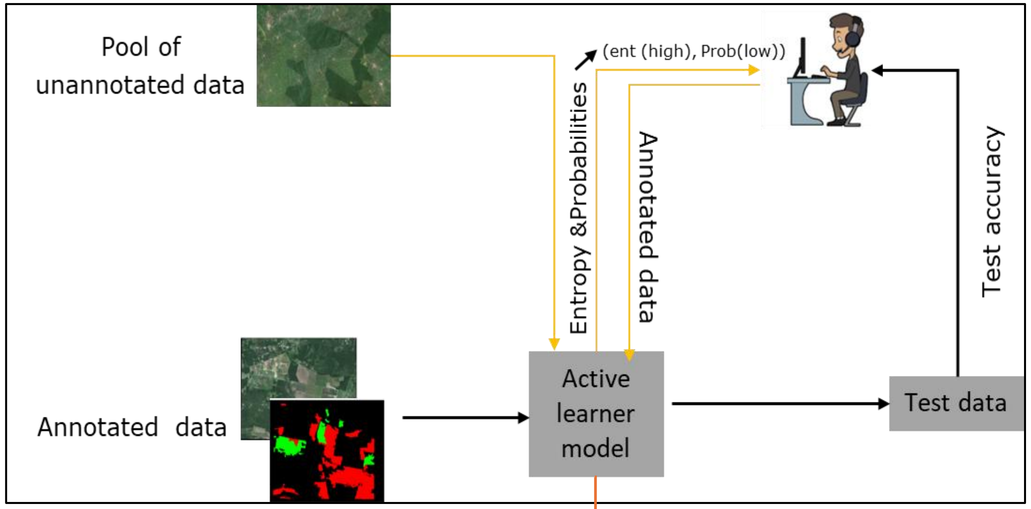
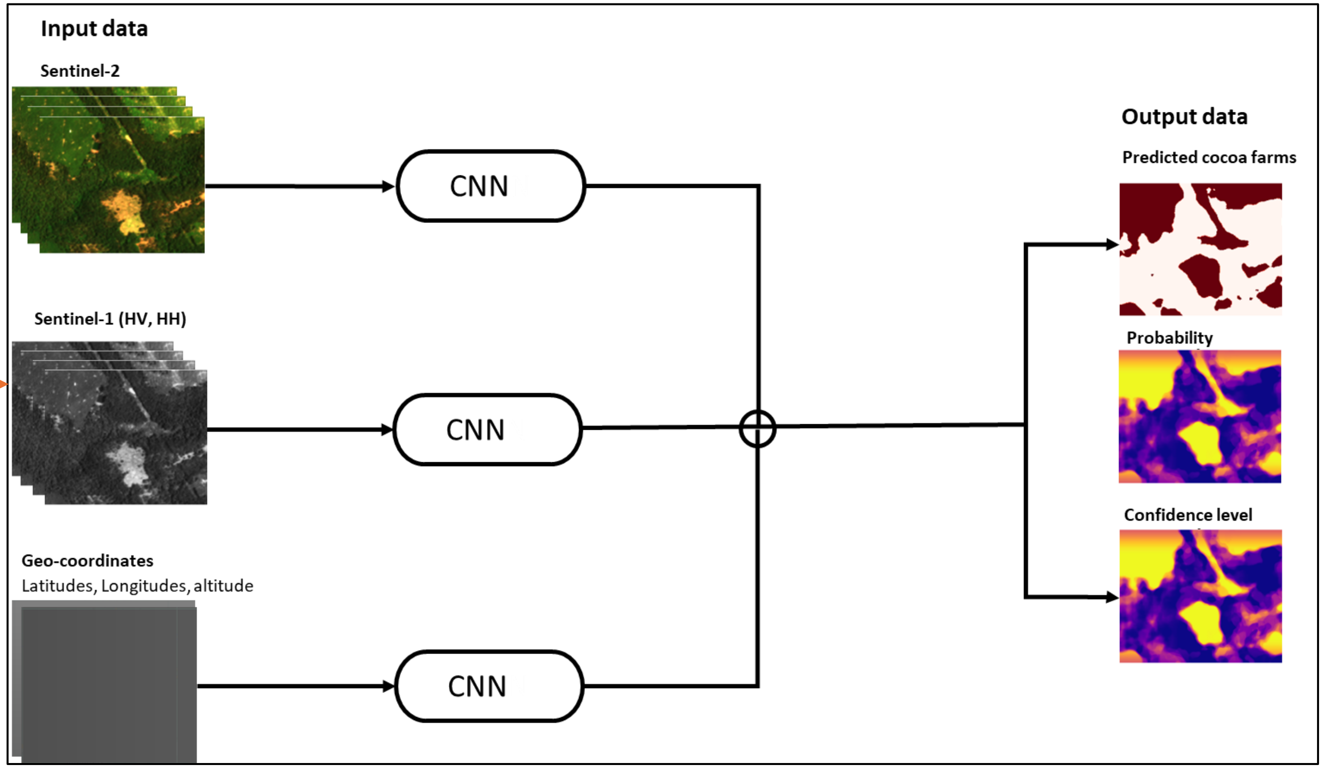
Using machine learning for mapping land use followig forest loss

We use an active learning framework



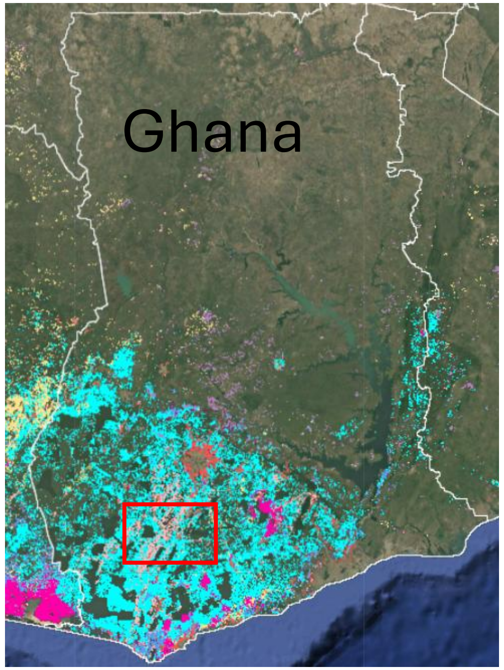


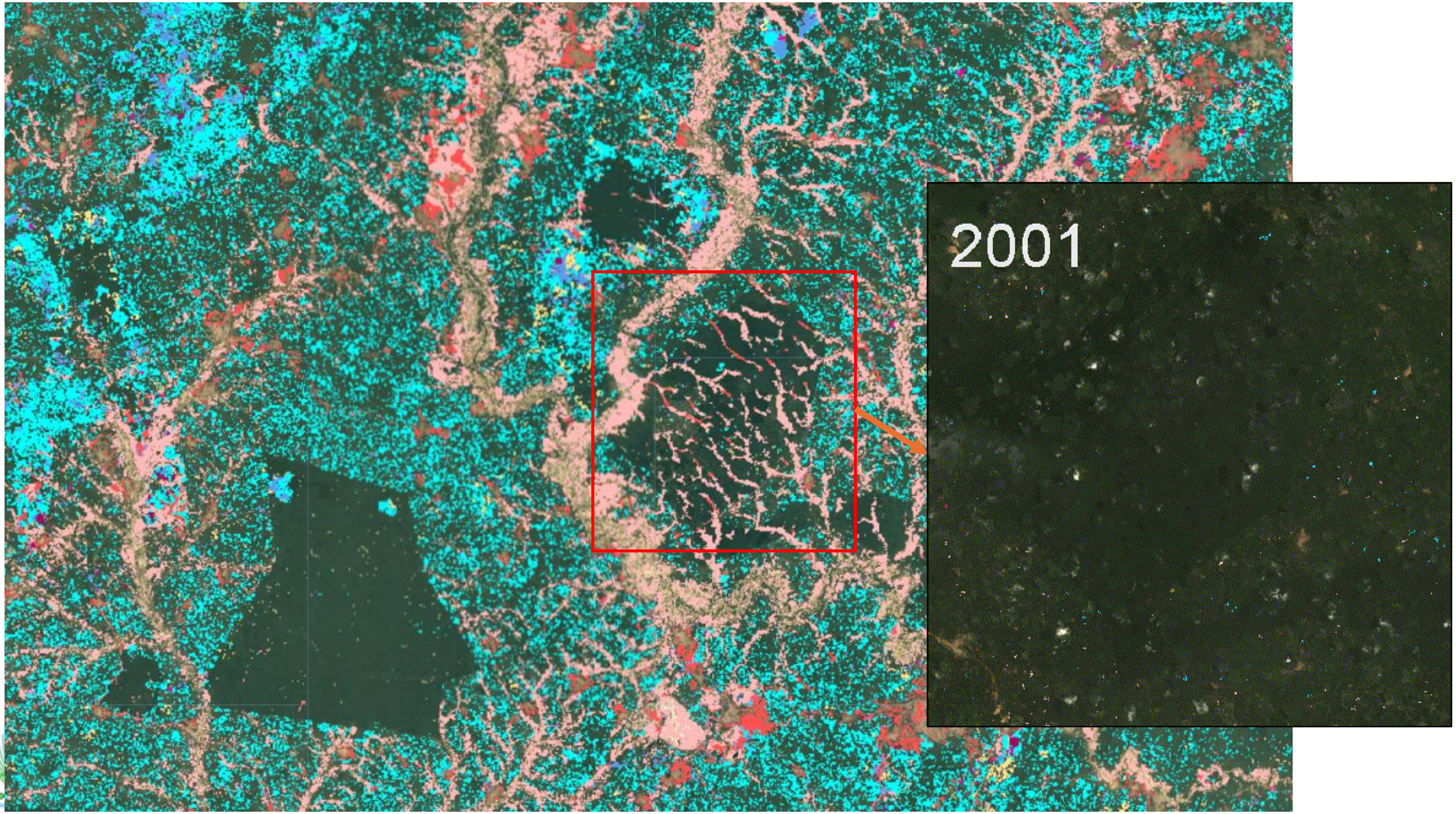
Training modules

- Three – parallel DL model
- One sees colors (optical)
- One senses textures, structure, moisture (radar)
- One understands geography
- Active learning

Example land use following forest loss detected in Ghana

Here we see just within three years a forest reserve degraded by mining expansion in Ghana





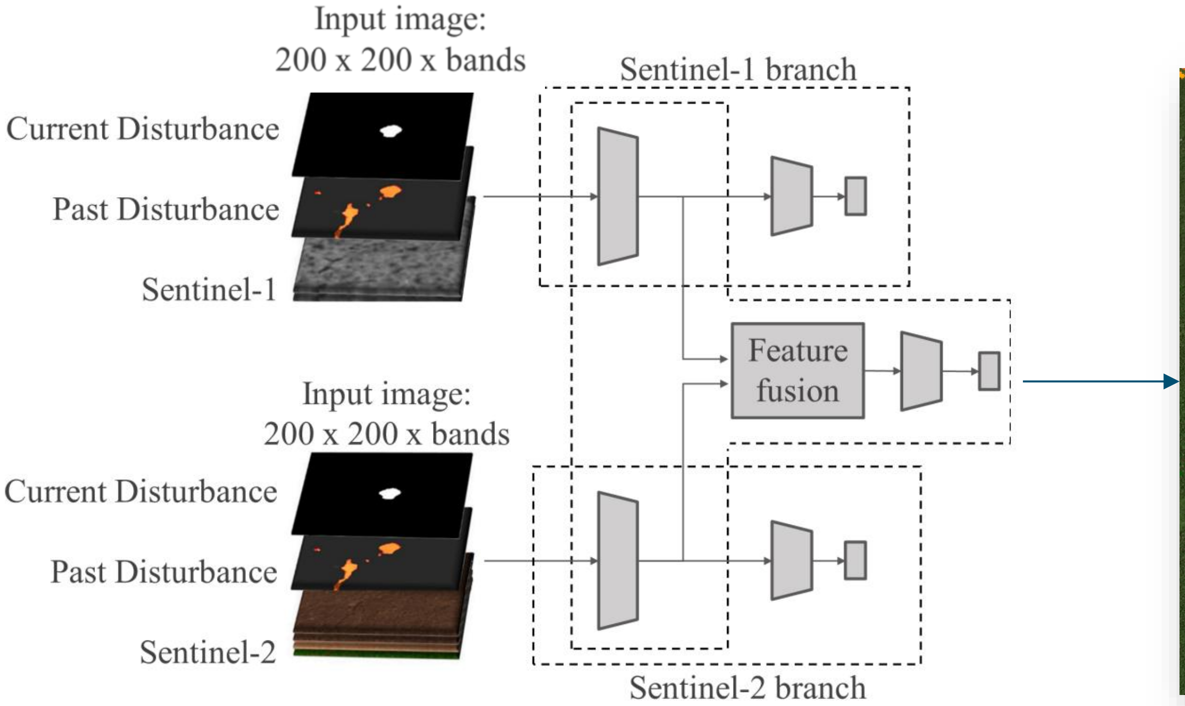
Legend

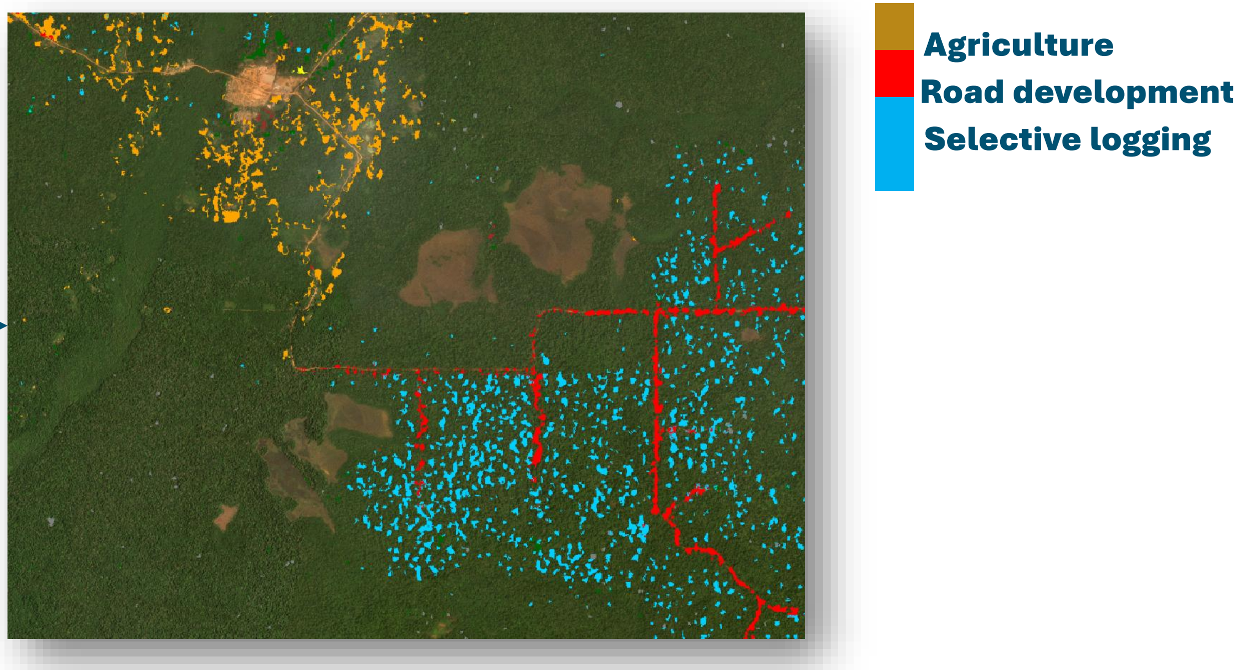
- Mining
- Cocoa

eXplainable AI (XAI) for forest disturbance driver classification from Sentinel-1 and -2 data.

Laura Cue la Rosa

Feature-level fusion CNN





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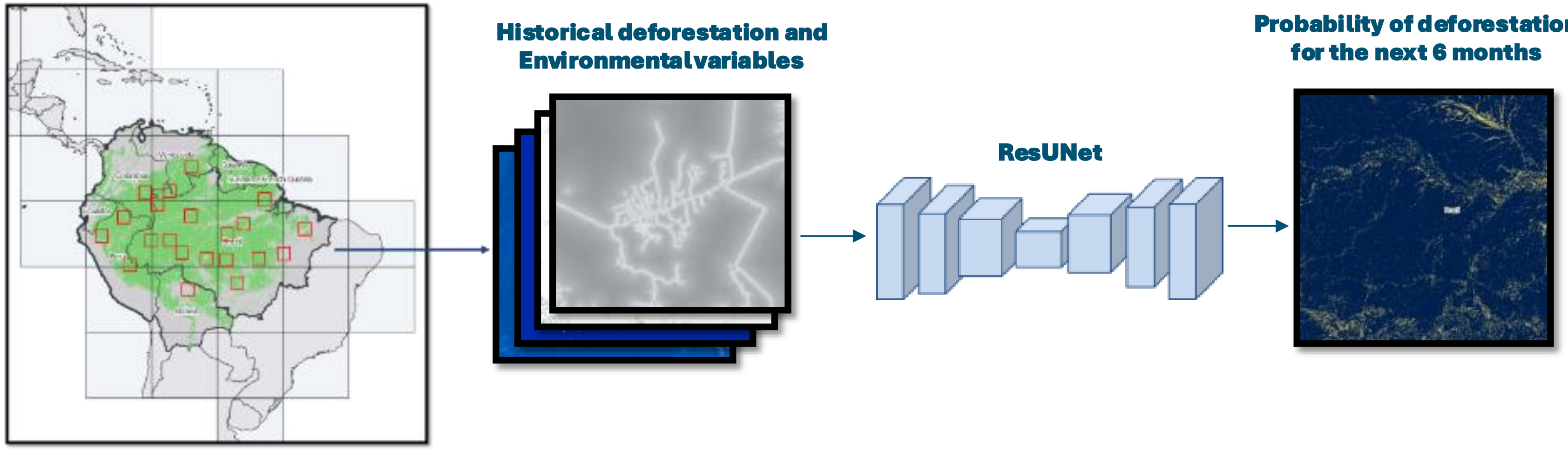
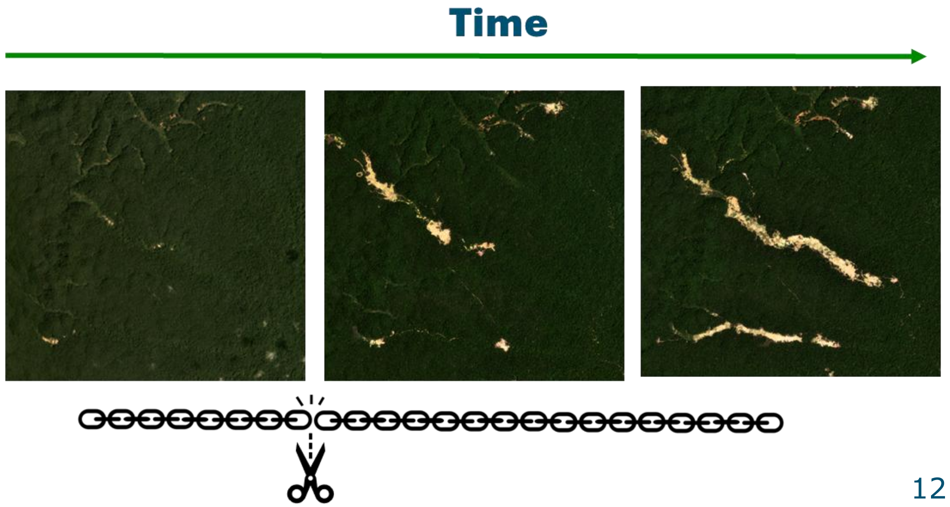
Predicting near-future deforestation with ML

ML-based prediction system



Objective: Predict high-risk areas up to six months in advance by combining deforestation alerts, with a variety of open-access geospatial datasets, using a machine learning framework.

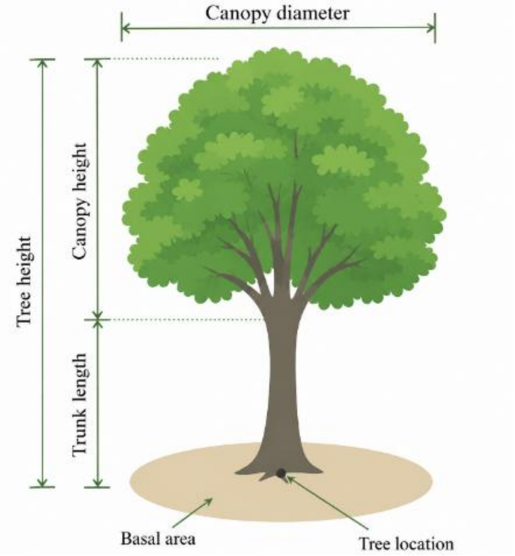
Enable early intervention

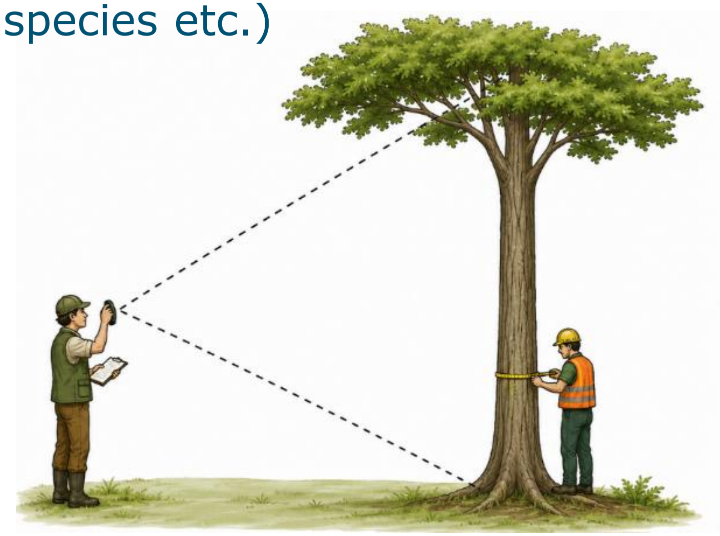


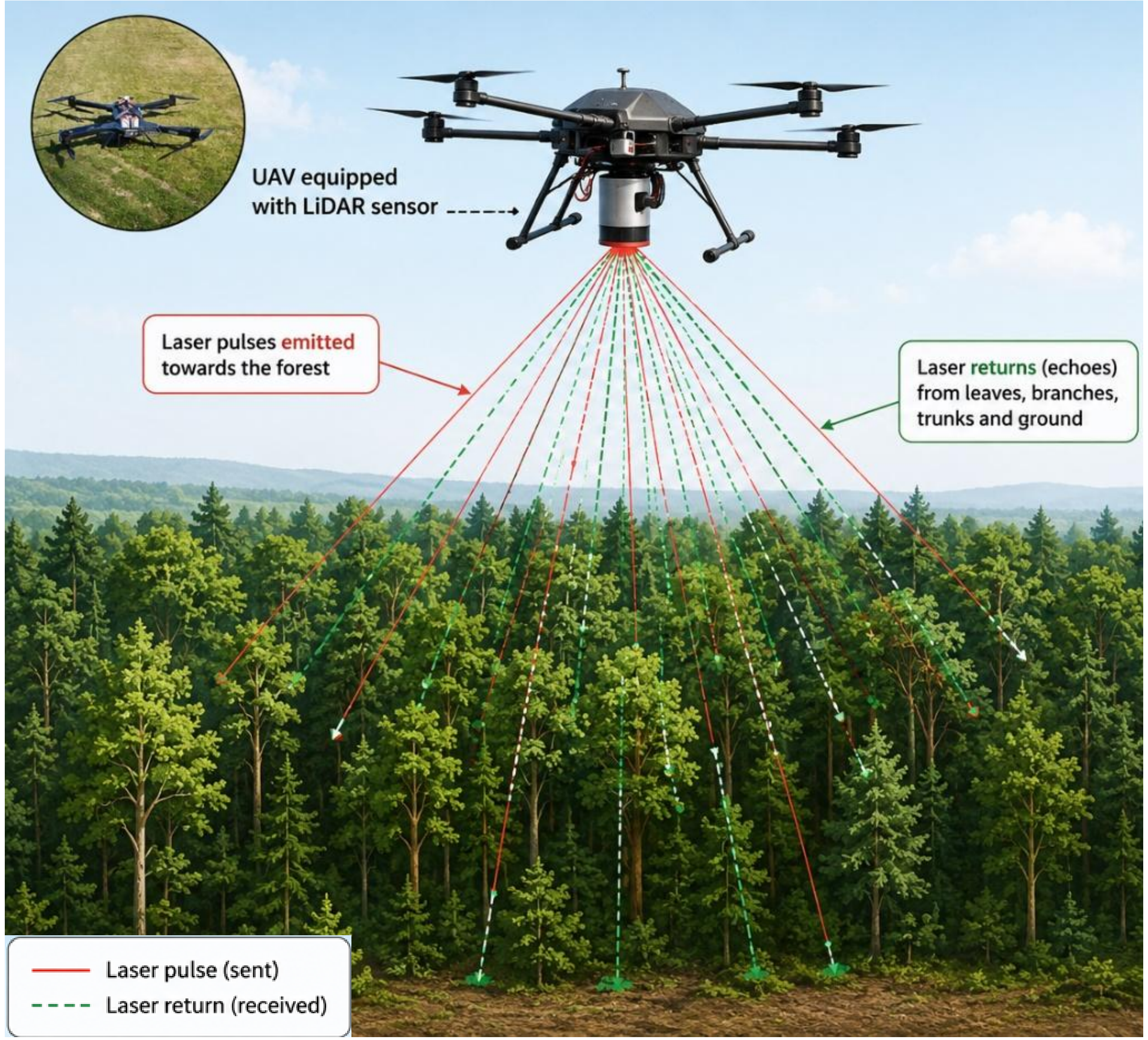
UAV-LiDAR based Individual Tree Species Identification in Mixed Temperate Forest

Mudassar Umar

Accurate individual tree features are fundamental for understanding forest ecosystems, e.g. (tree height, crown size, canopy height, species etc.)







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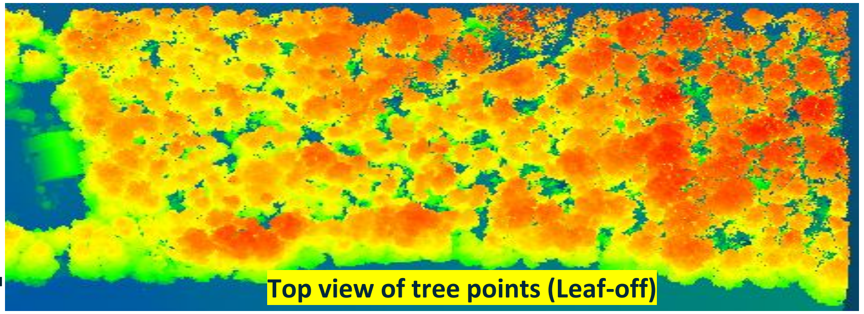
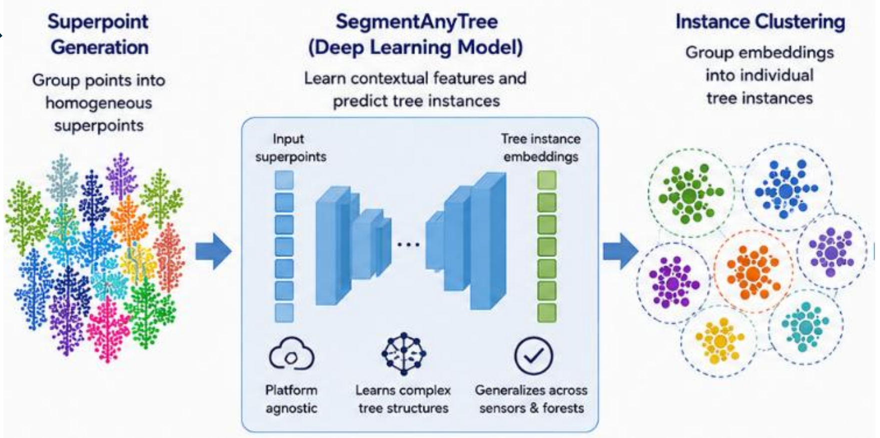
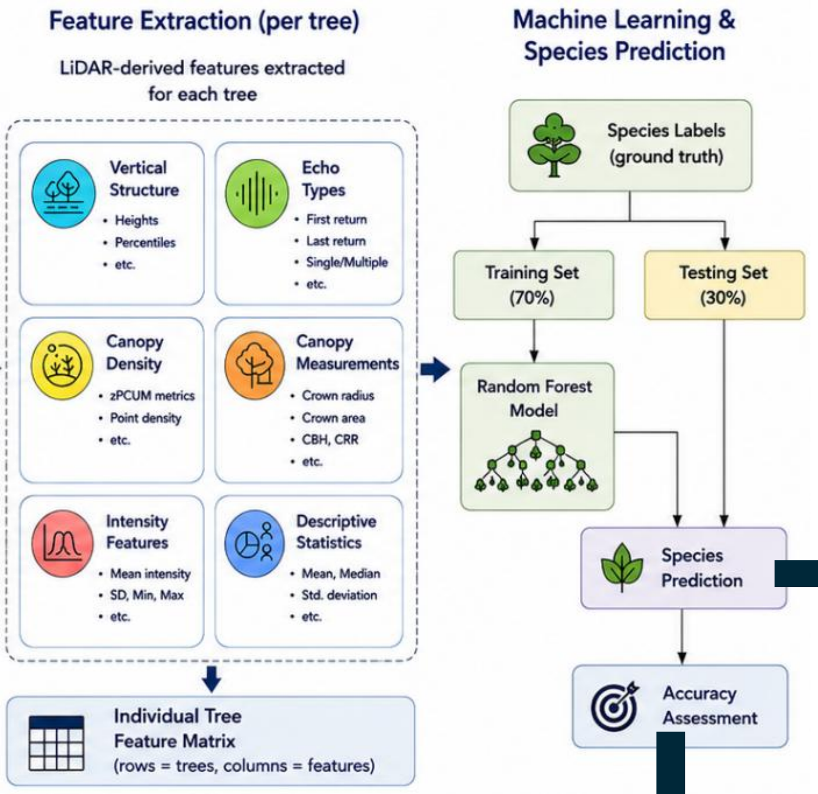
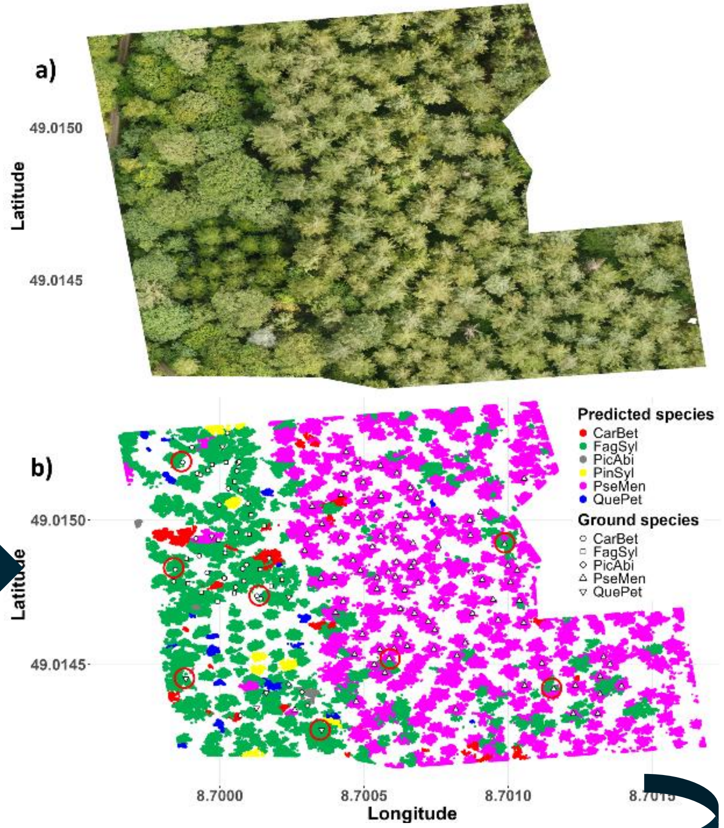
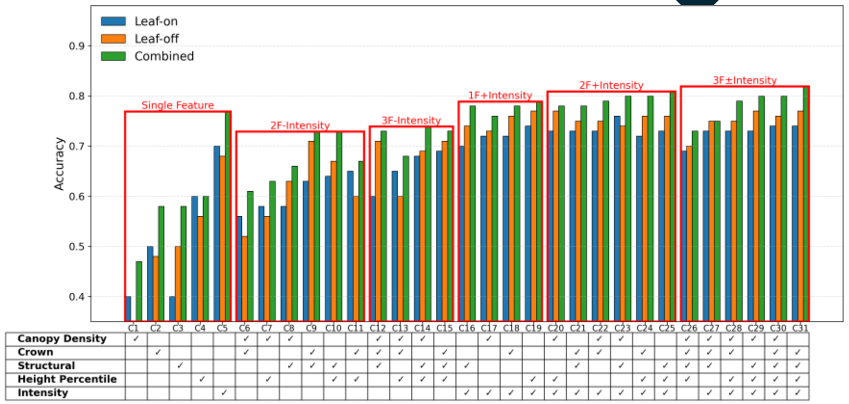
UAV-LiDAR based Individual Tree Species Identification in Mixed Temperate Forest

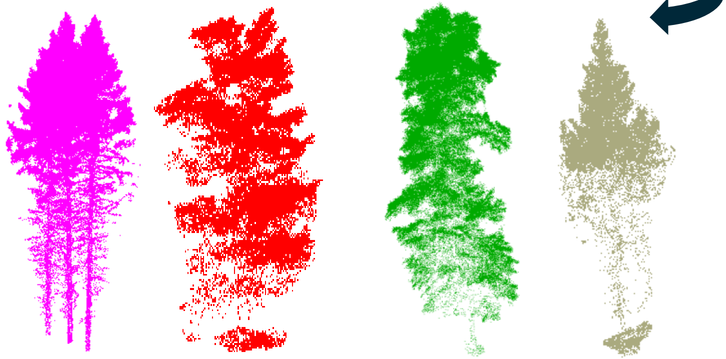












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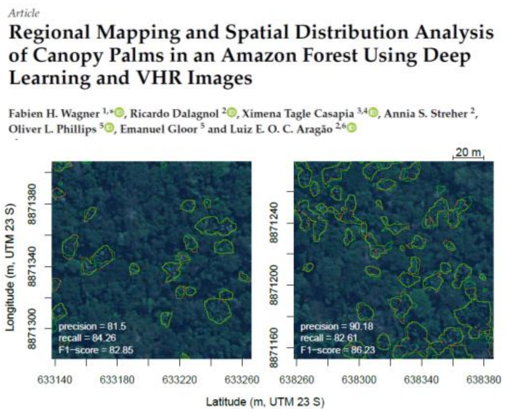
Multi-Scale Palm Mapping for Tropical Forest Management

Ximena Tagle

Regional

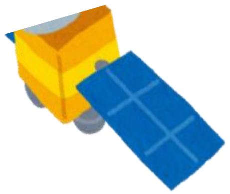
Mauritia flexuosa density mapping integrating AlphaEarth foundations and UAV imagery

Tagle et al., in prep


Article

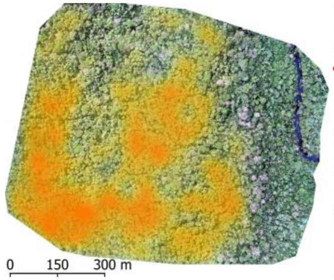
Regional Mapping and Spatial Distribution Analysis of Canopy Palms in an Amazon Forest Using Deep Learning and VHR Images

Fabien H. Wagner [1,*], Ricardo Dalagnol [2], Ximena Tagle Casapia [3,4], Annia S. Streher [2], Oliver L. Phillips [5], Emanuel Gloor [5] and Luiz E. O. C. Aragão [2,6]



Strategic & tactical

Landscape

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Effective integration of drone technology for mapping and managing palm species in the Peruvian Amazon

Ximena Tagle Casapia, Rodolfo Cardenas-Vigo, Diego Marcos, Ernesto Fernández Gamarra, Harm Bartholomeus, Eurídice N. Honorio Coronado, Silvana Di Liberto Porles, Lourdes Falen, Susan Palacios, Nandin-Erdene Tsenbazar, Gordon Mitchell, Ander Dávila Díaz, Freddie C. Draper, Gerardo Flores Llampazo, Pedro Pérez-Peña, Giovanna Chipana, Dennis Del Castillo Torres, Martin Herold & Timothy R.

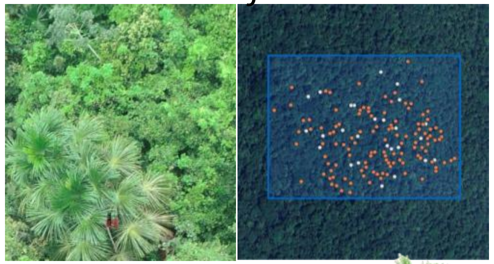
Tagle et al., 2025

QGIS

PalmsCNN - Palm Tree Detection RPAs
by Susan Palacios, Rodolfo Card...

Palacios et al., 2025

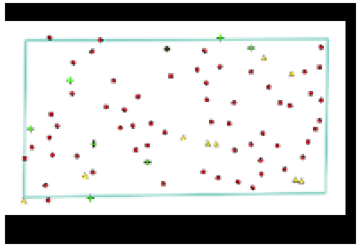
Automatic detection and location of *M. flexuosa* fruits

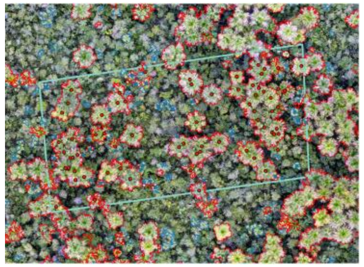


Cardenas et al., in prep

Operational

Local



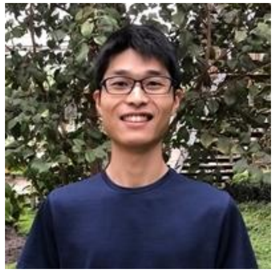


Tagle et al. 2020

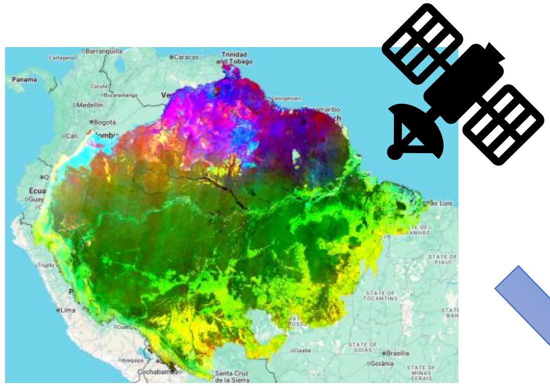
Reference

WAGENINGEN UNIVERSITY & RESEARCH · UNIVERSITY OF LEEDS · UNIVERSITÀ DEGLI STUDI DI BRESCIA · iiap Instituto de Investigaciones de la Amazonía Peruana · CSIC Consejo Superior de Investigaciones Científicas · USFQ TIPUTINI Biodiversity Station · SERNANP Perú Servicio Nacional de Áreas Naturales Protegidas por el Estado · OSINFOR · CITEforestal Amazónicos por la Amazonía · WWF · Russell E. Train Education for Nature · Newton Fund · CONCYTEC · giz · USAID From the American People

Satellite embeddings for functional biodiversity

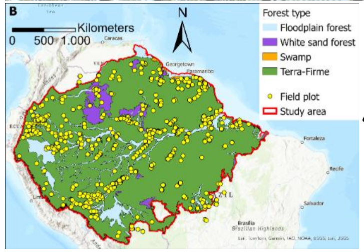


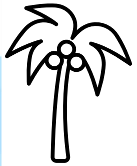
Shoyo Nakamura



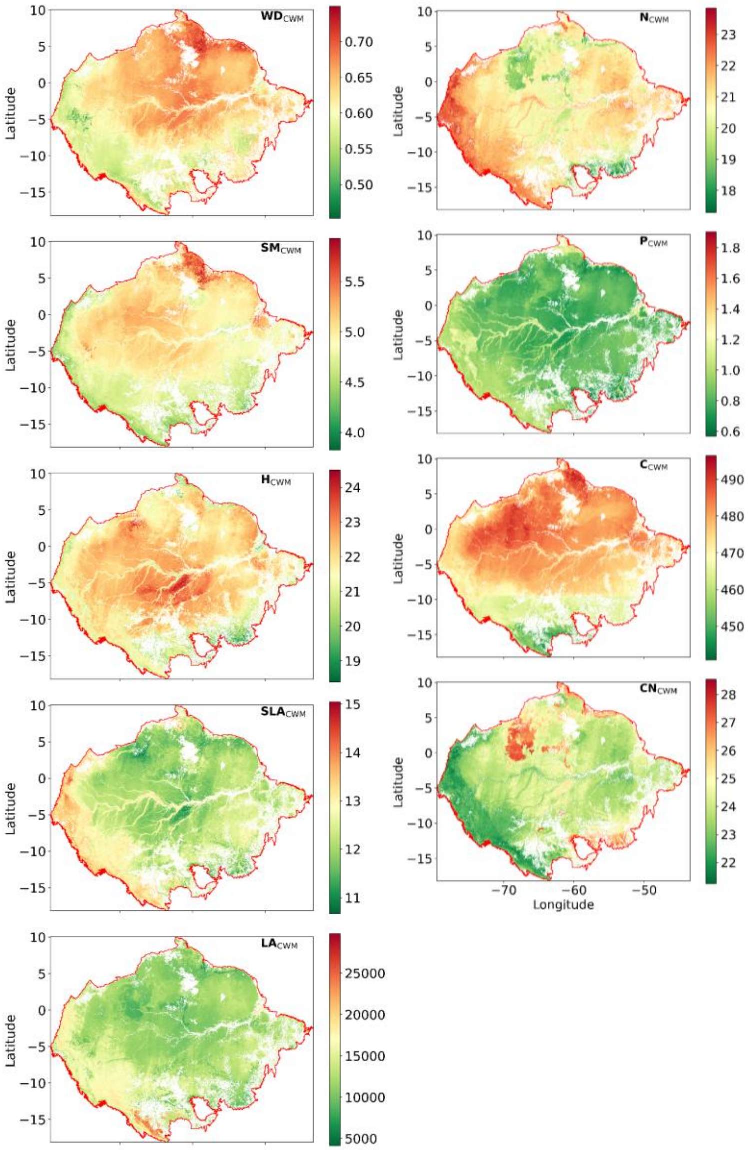
Embeddings

Machine learning

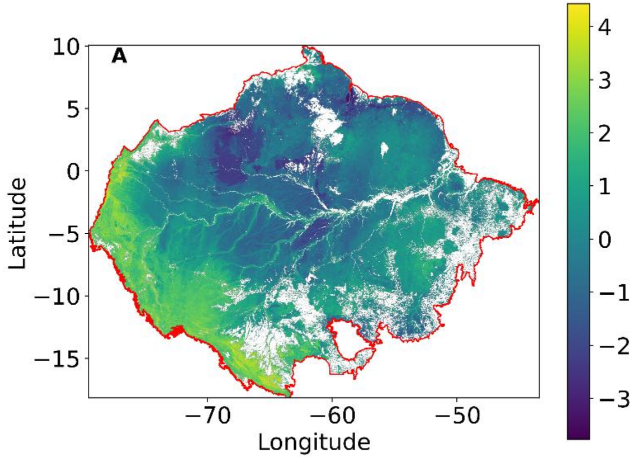




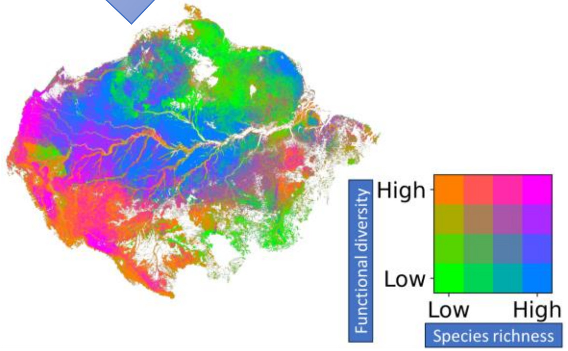
Field data



Plant functional trait maps



Functional diversity



Resilience, vulnerability, and conservation values

Agricultural Monitoring and AI

Photo by no one cares on Unsplash

Deep Learning on field photos to derive soil cover fractions

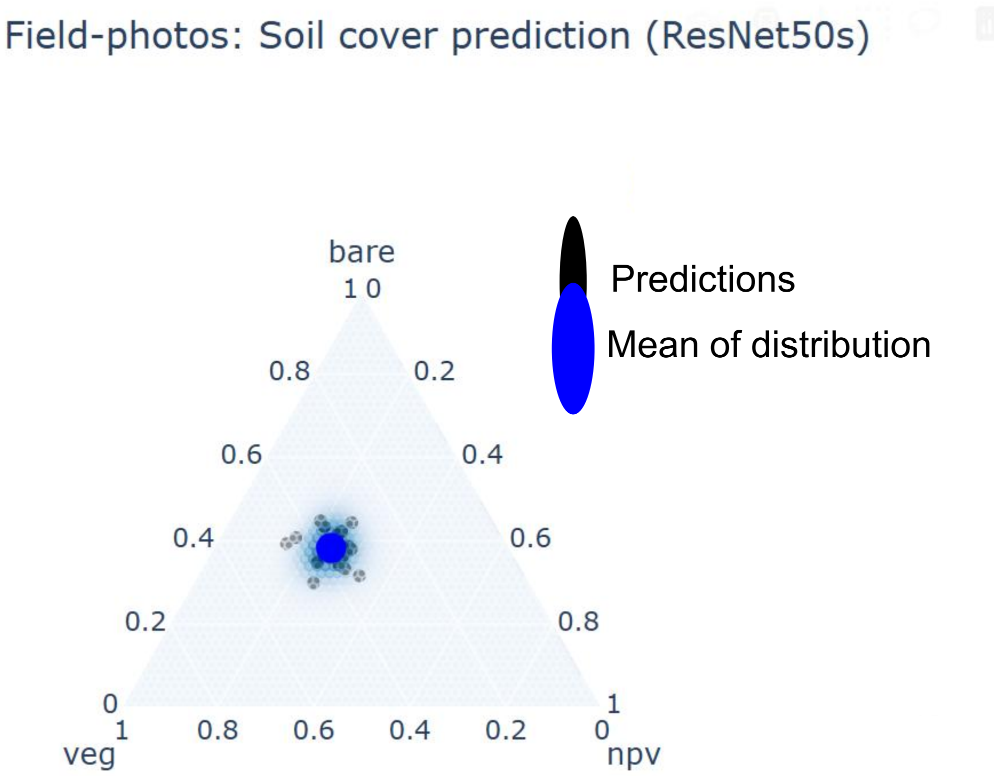
Fine-tuning CNN models to output a % per class on the LUCAS agricultural field photos

Paolo Dal Lago

bare: 0.36±0.05

npv: 0.26±0.02

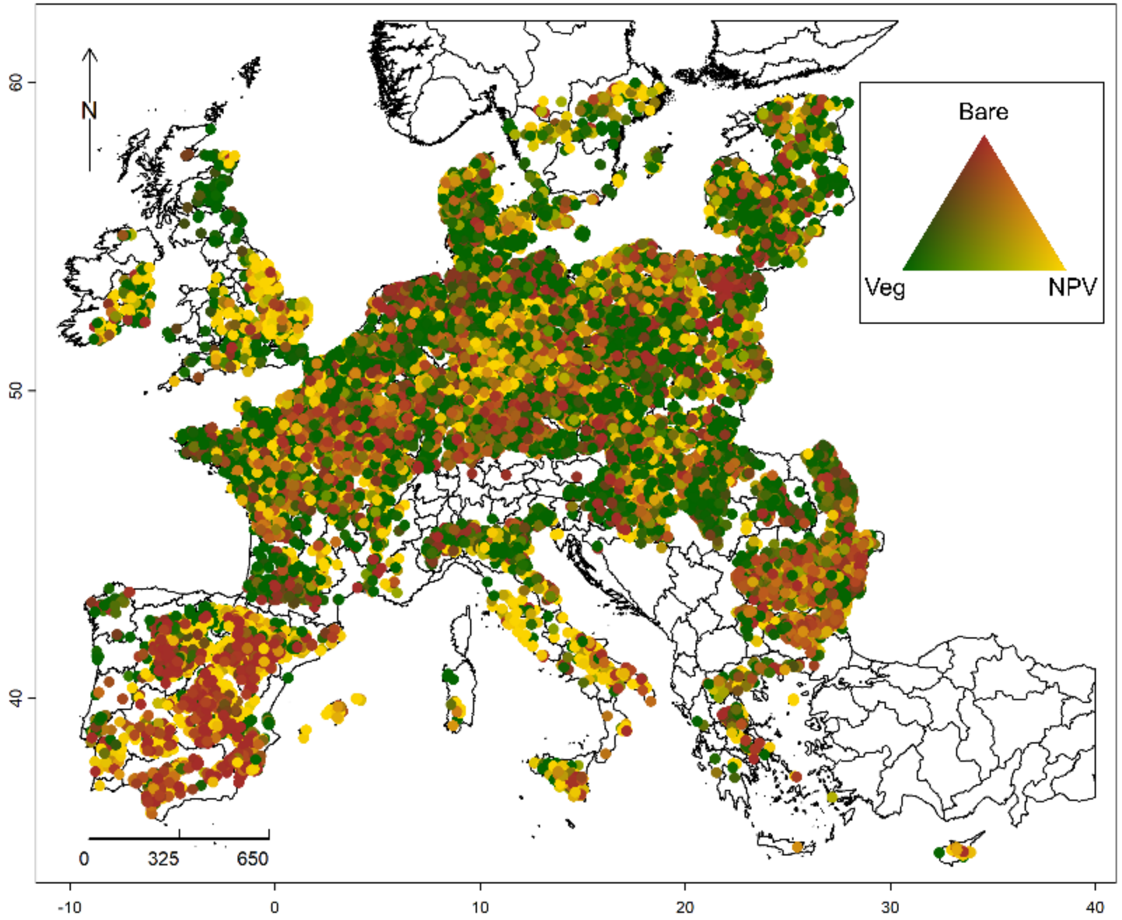
veg: 0.38±0.05



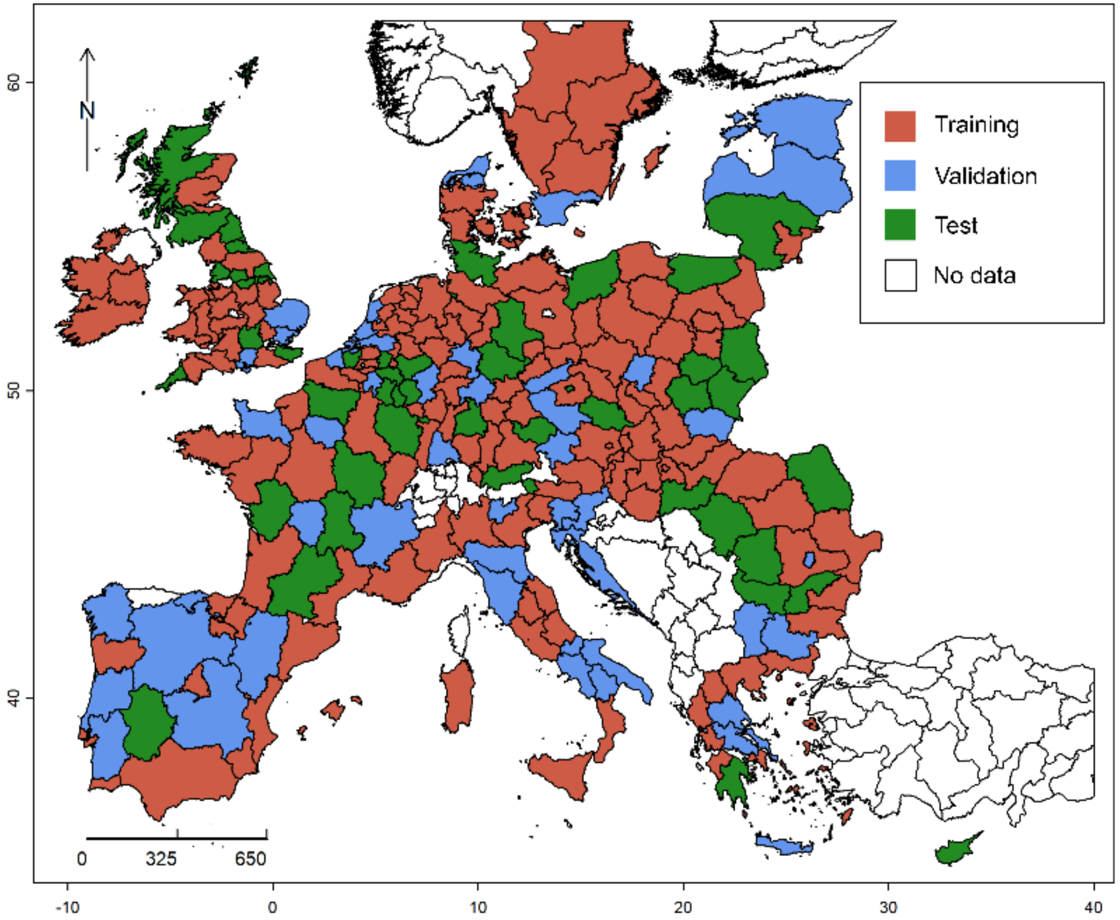
Reference dataset generated across EU arable fields

The CNN model is applied to geotagged, time-stamped photos acquired in 26’000 locations

Predicted soil cover on the date of field photo acquisition



Dataset is split regionally to train satellite-based model



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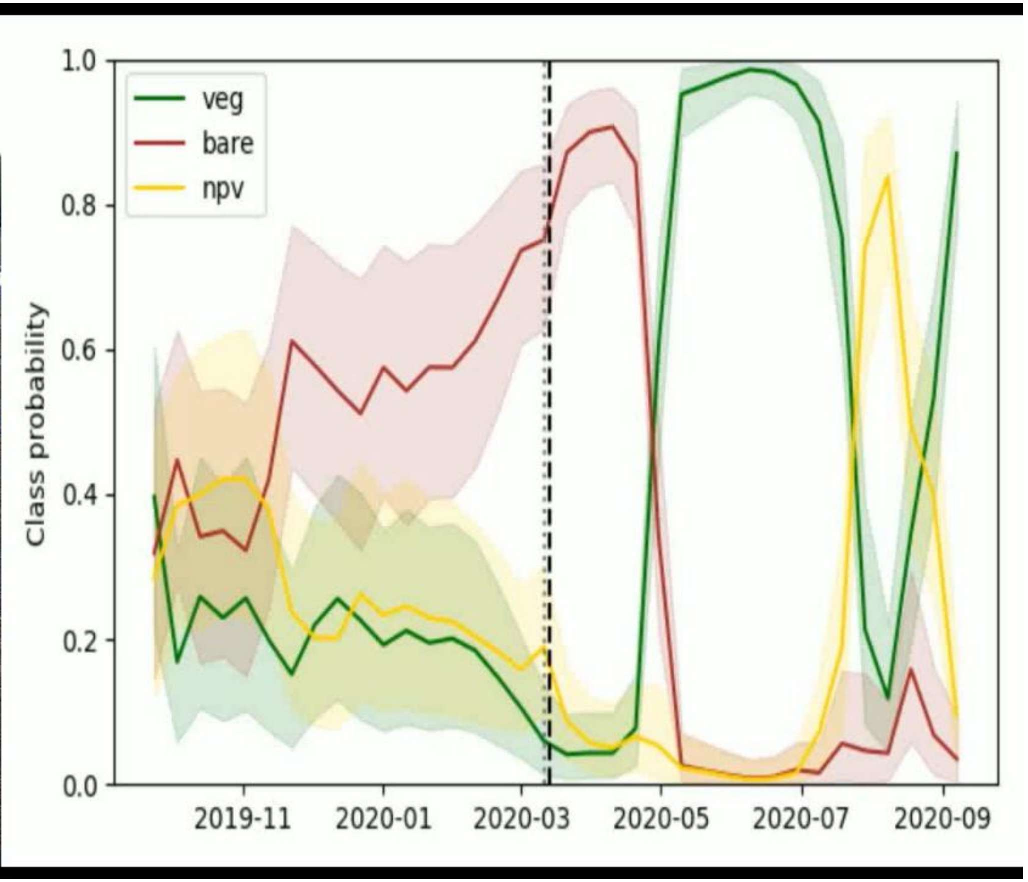
Temporal application of the satellite-based model

Example field in Denmark, where a fixed camera acquires daily photos

PhenoCam daily acquisitions

MLP Sentinel-based 10-day predictions

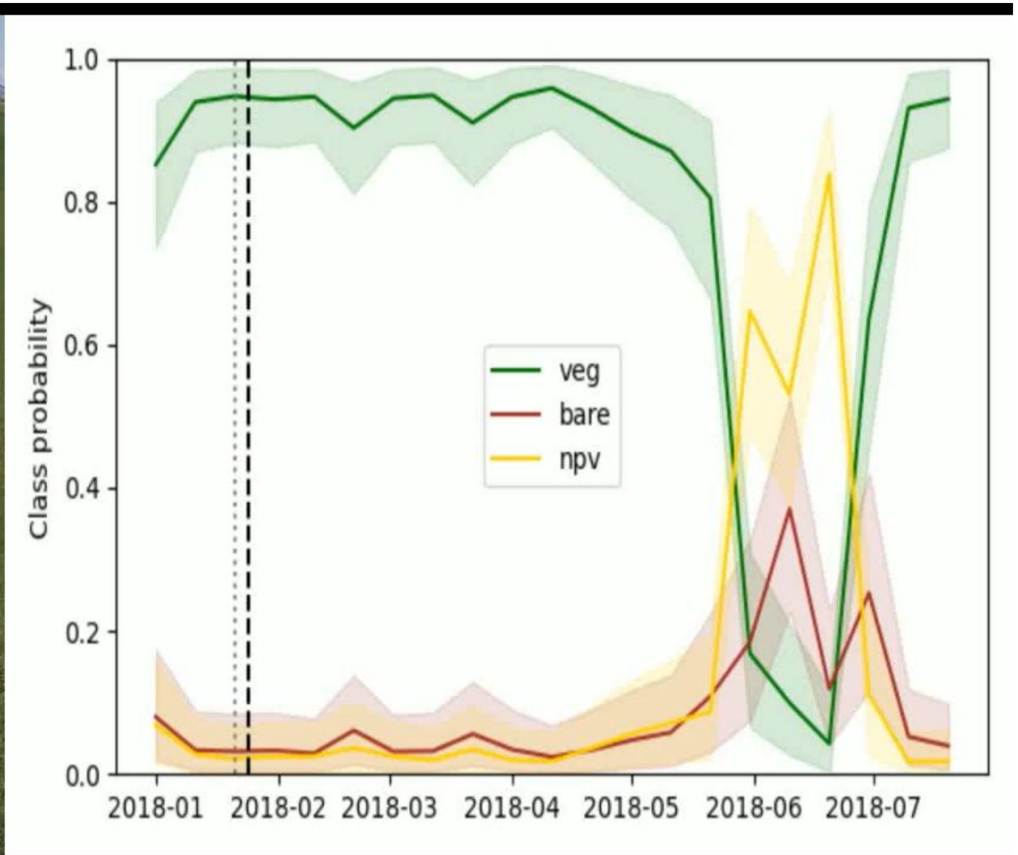


Temporal application of the satellite-based model

Example field in Italy, where a fixed camera acquires daily photos

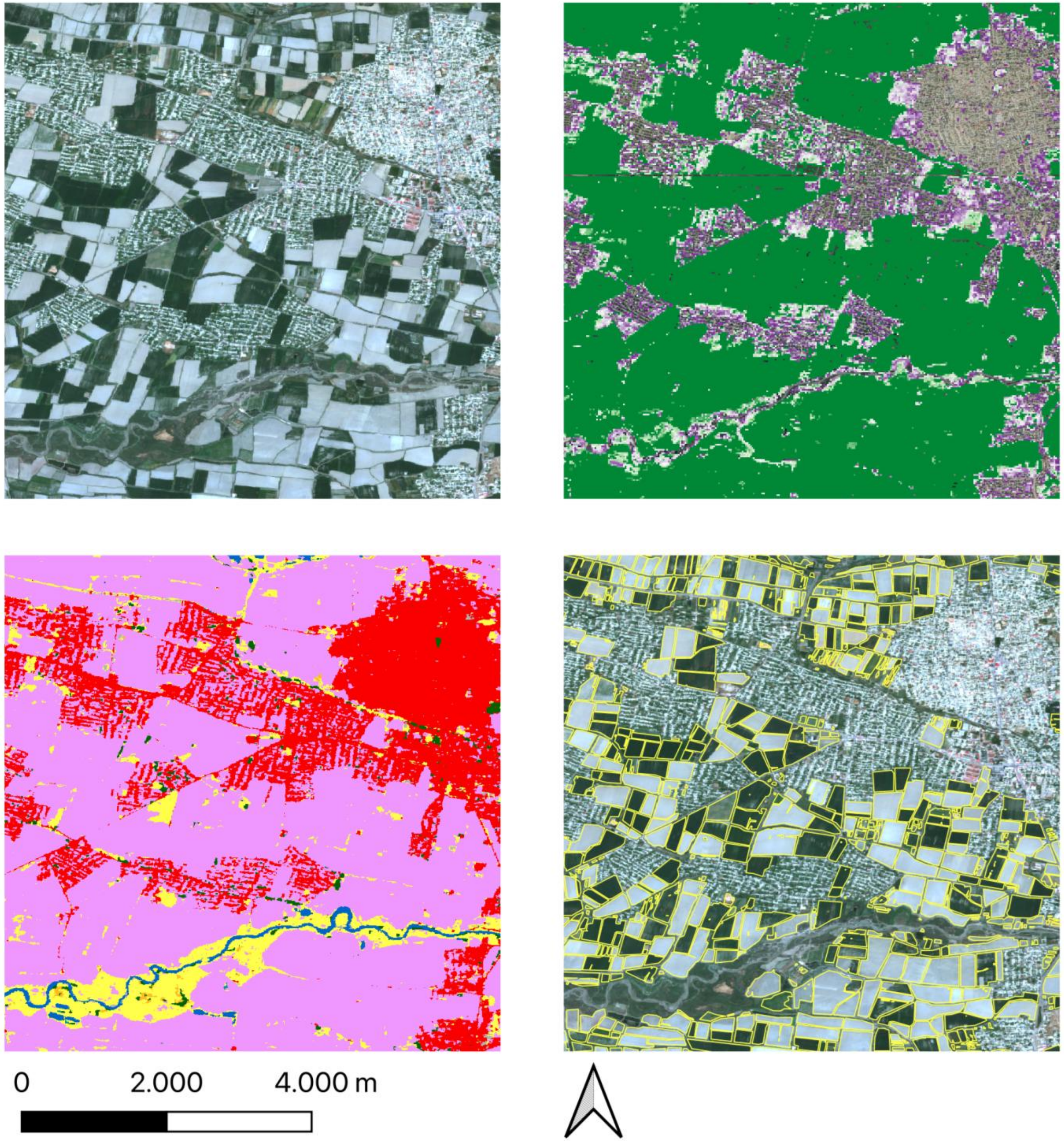
PhenoCam daily acquisitions

MLP based on Sentinel1-2: 10-day predictions



Agricultural Decisions

- Made per field:
  - Crop type
  - Improvements
  - Drip irrigation installation
  - Fertilizer
  - Pest / diseases
  - Farming practices
  - Yield
- Field boundary availability creates a limitation.

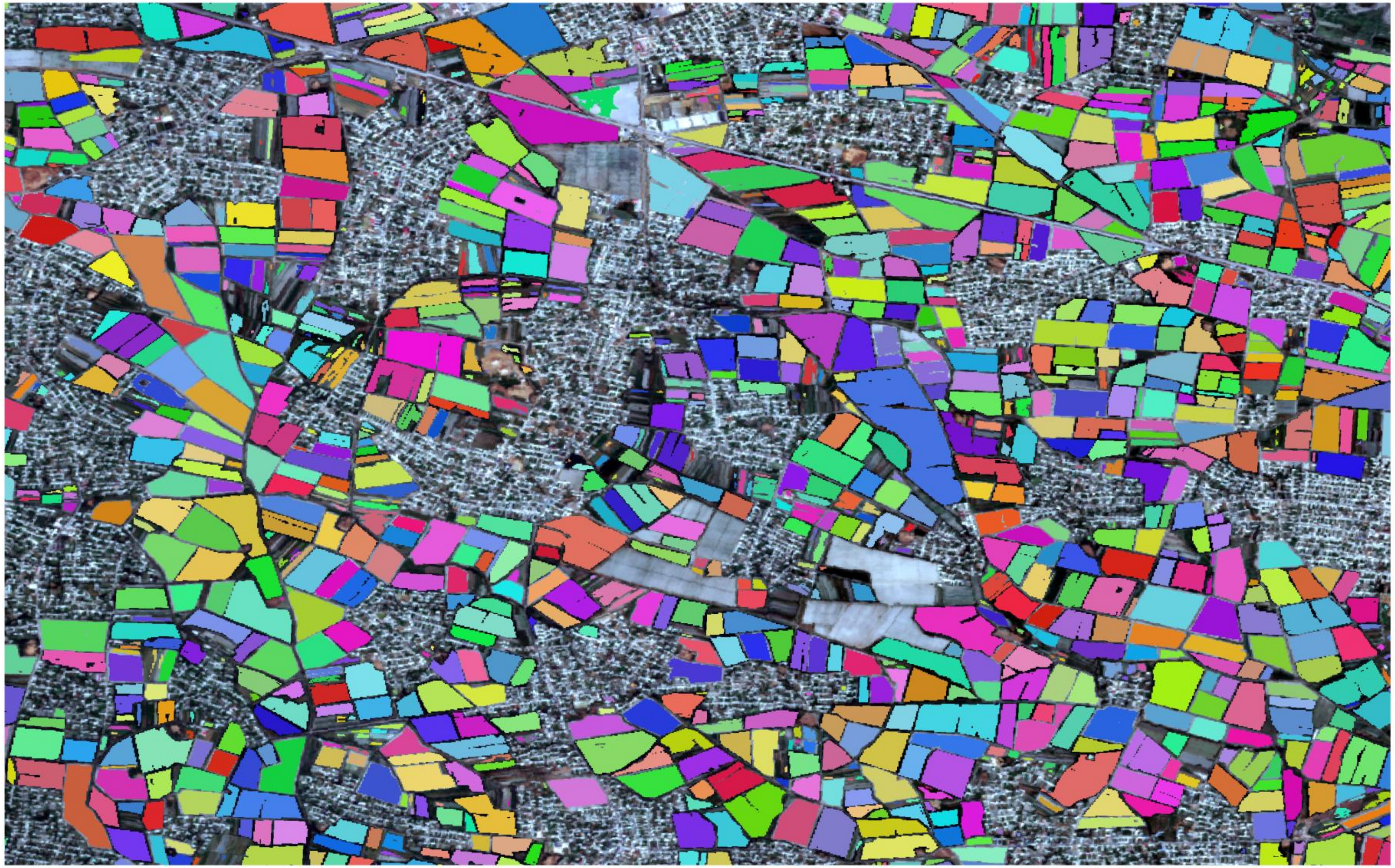


Fields of The World

- Crop fields differ dramatically across the world
- Machine learning: U-net with EfficientNet-b3 backbone
- ML benchmark dataset for agricultural field segmentation for 24 countries from four continents.
- Input: Sentinel-2 images with RGB-NIR for two dates
- Semantic (pixel-level) and instance (object-level) segmentation metrics.

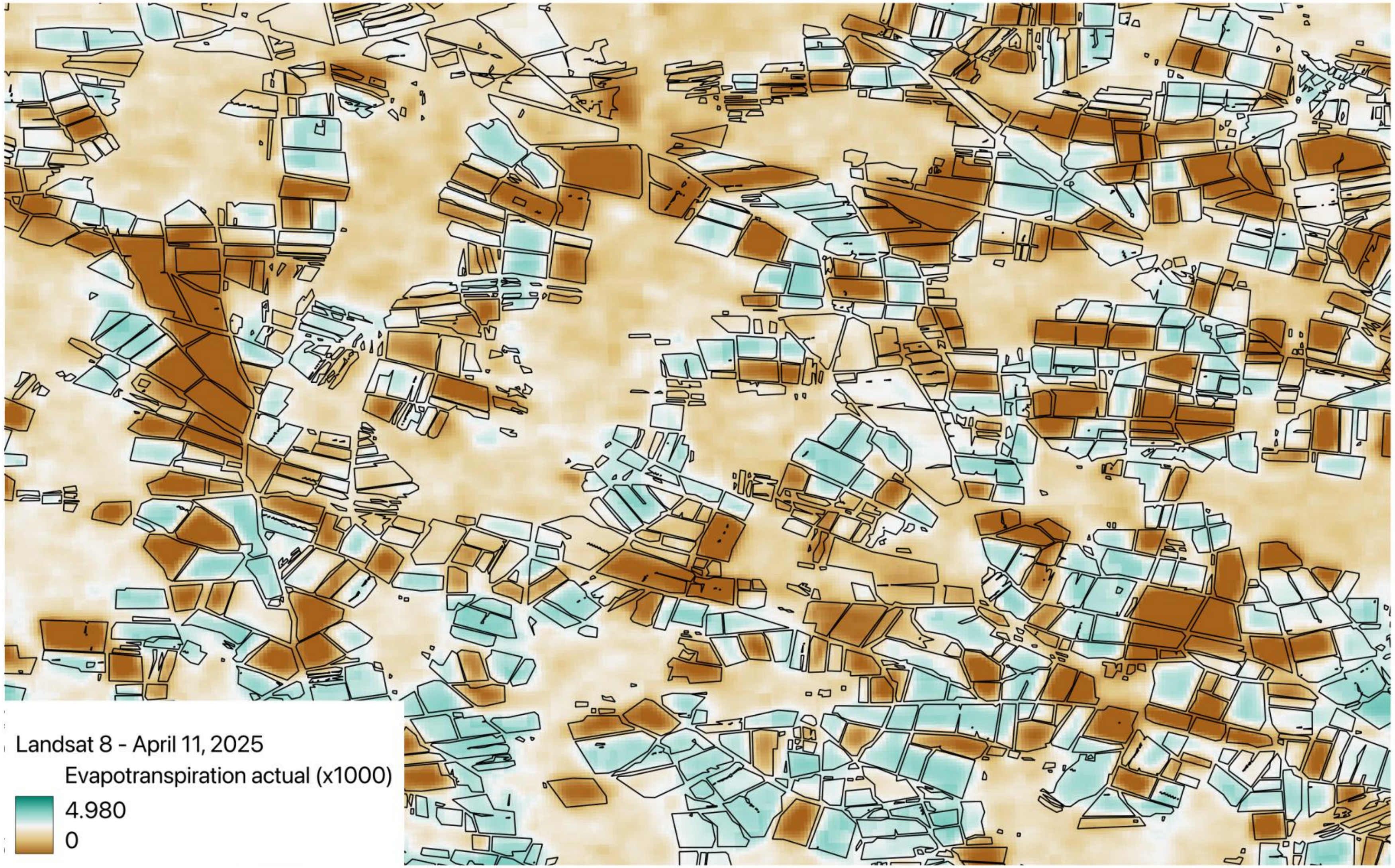
Kerner, H., Chaudhari, S., Ghosh, A., Robinson, C., Ahmad, A., Choi, E., Jacobs, N., Holmes, C., Mohr, M., Dodhia, R., Lavista Ferres, J. M., & Marcus, J. (2025). Fields of The World: A Machine Learning Benchmark Dataset for Global Agricultural Field Boundary Segmentation. *Proceedings of the AAAI Conference on Artificial Intelligence*, *39*(27), 28151-28159. https://doi.org/10.1609/aaai.v39i27.35034

Crop fields in Samarkand



Agricultural fields in Samarkand. Data source: Sentienl-2 based field segmentation with Fields of The World. Spatial resolution: 10m. Minimum field size: 0.05ha.

Kirsten de Beurs
kirsten.debeurs@wur.nl
Wageningen University



Agricultural fields in Samarkand. Data source: Sentienl-2 based field segmentation with Fields of The World. Spatial resolution: 10m. Minimum field size: 0.05ha.

Landsat 8 –

Evapotranspiration (ETa) in mm

April 11, 2025

Kirsten de Beurs
kirsten.debeurs@wur.nl
Wageningen University

Sampling and reference data collection

Photo by Joshua Sortino on Unsplash

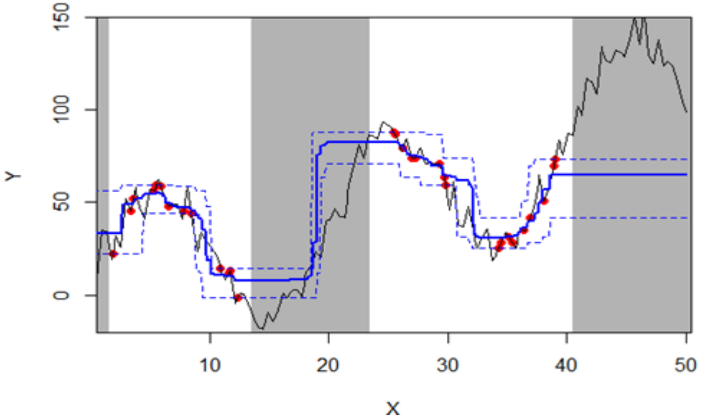
Spatial sampling: (feature) space coverage

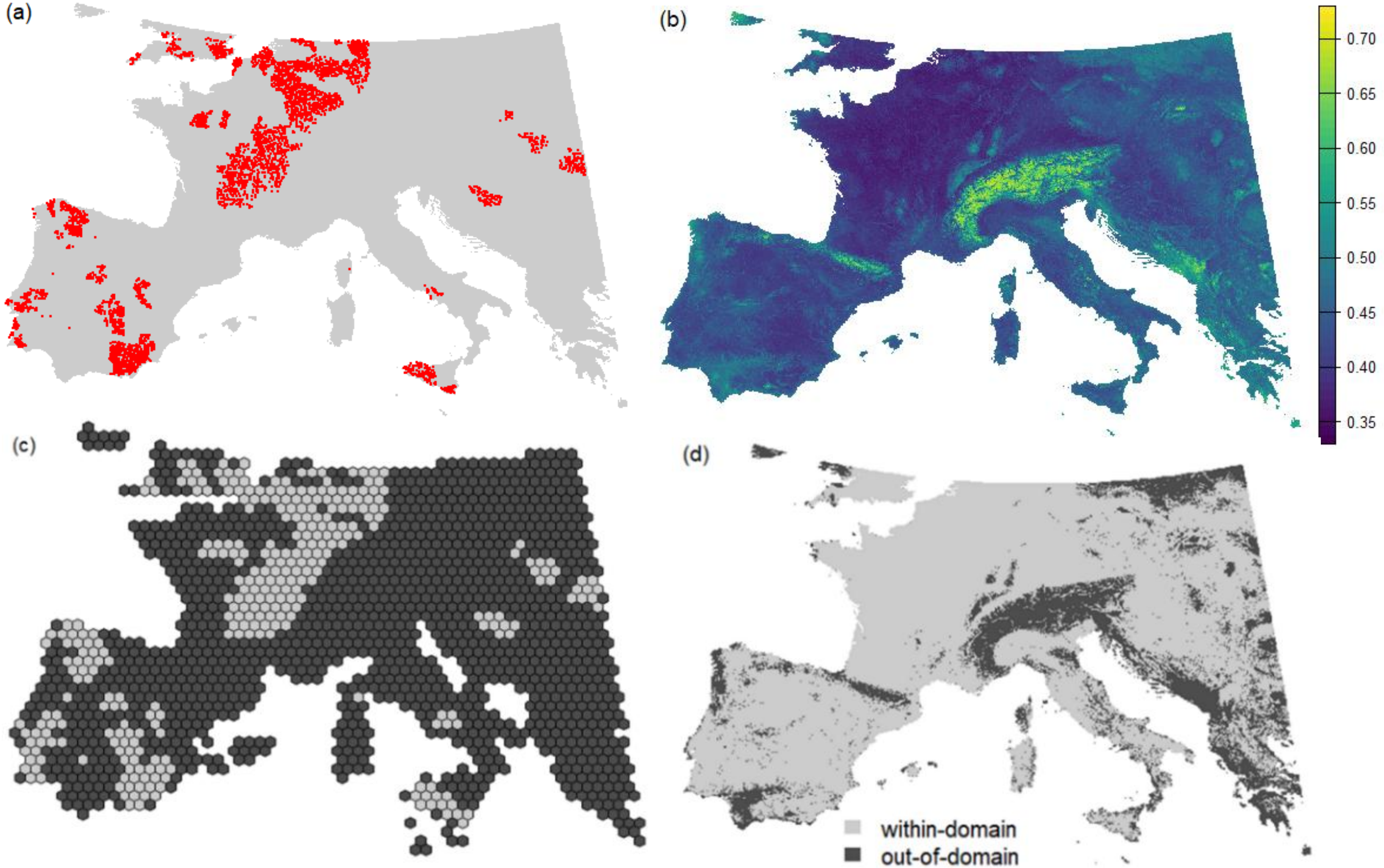
Sytze de Bruin

Spatial cross-validation is not the right way to evaluate map accuracy.
Ecological Modelling

Dealing with clustered samples for assessing map accuracy by cross-validation.
Ecological Informatics

Where can we rely on model predictions?





Reference labels are evidence, not just answers.

Weixiao Gao

Turning expert Sentinel-2 interpretation into traceable reference evidence for trustworthy AI.

01 Scientific problem

Labels depend on evidence, uncertainty, and human judgement.

Annotation includes

- label
- evidence
- uncertainty
- rationale

Variation arises from

- ambiguous signals
- expertise
- interface friction

02 Project objective

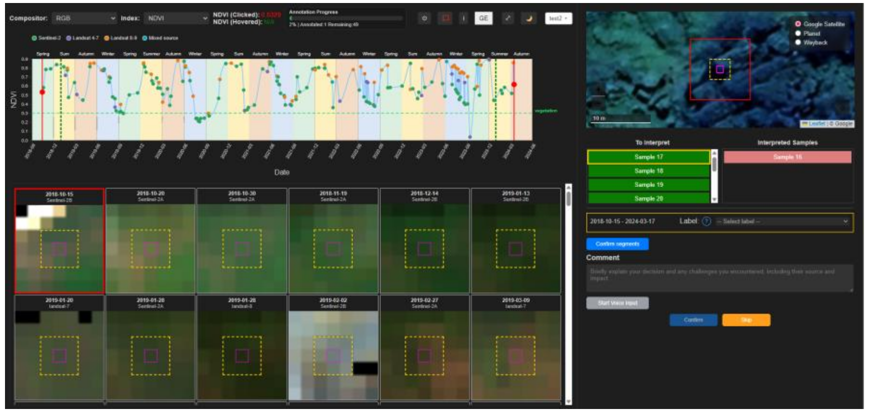
Diagnose why annotators disagree or make errors by linking labels with eye-tracking and interaction evidence.

Focus

- error sources
- interpreter variability
- visual attention

03 Method pipeline

1. **Define task** — sample unit, label protocol
2. **Inspect evidence** — Sentinel-2 chips, indices
3. **Record response** — label, difficulty, reason
4. **Capture behavior** — gaze/AOI, clicks, timing
5. **Diagnose** — errors + attention



Verytree annotation workspace: temporal signal, image chips, map context, and response form

04 Expected outcomes

Outputs for linking annotation quality, attention patterns, and workflow design.

- **Error taxonomy** — perceptual / cognitive
- **Attention evidence** — gaze + AOI + logs
- **Design guidance** — workflow improvements

AI vs simple methods

Research frontier

Earth Observation Foundation models

Physics-informed Neural Networks

Multimodal sensor fusion: optical + SAR, 3D & Hyperspectral

Real-time planetary scale environmental intelligence?

Operational reality

Random forest

Gradient boosting

Linear models

Spectral indices

Physical models

AI is transforming workflows

- Fundamentals remain essential
- Applications prioritize robustness → societal relevant applications
- The field is structurally changing

The hiring dilemma

What are we hiring for?

Teaching tension

Fundamentals are not obsolete: interface between data and reality

Students need:

Physical intuition	Statistical reasoning	AI literacy

Not just one of these

What are we hiring for?

- Three expectations:
  - AI fluency:
    - Deep learning
    - Foundation models
  - Physical grounding:
    - Remote Sensing science
  - Academic profile
    - Grants, papers, teaching

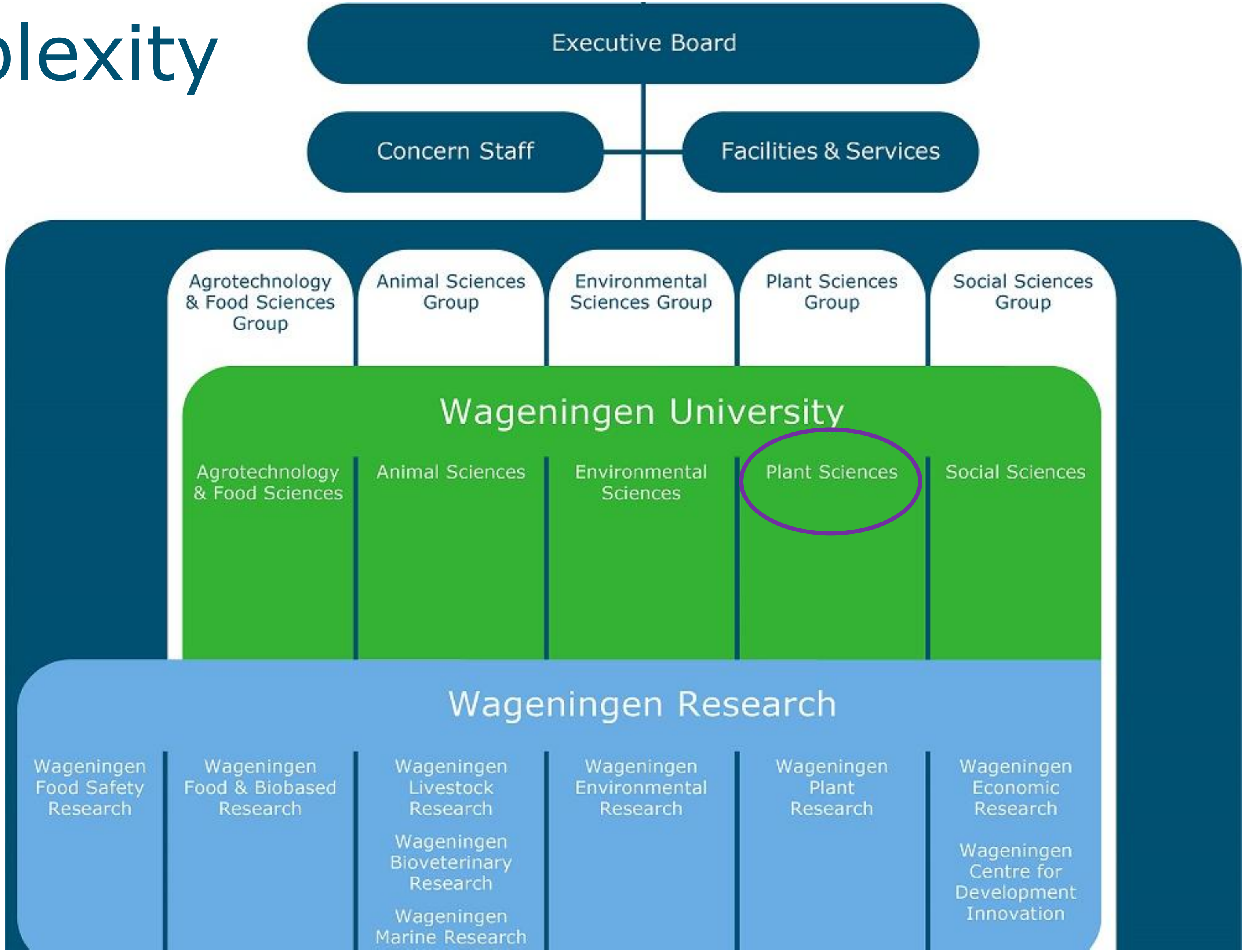
Can one person realistically optimize all three?

Additional complexity

Wageningen UR:

Organizational structure

Where is AIN?



Open Questions

What does excellence look like now?

The future of remote sensing is not AI vs fundaments → how do we make them reinforce each other?

Questions?

prof.dr. KM (Kirsten) de Beurs

Professor/Chair

Prof. de Beurs was born in Netherlands but lived and worked in the United States of America since 2002. During her Master of Science in Agricultural System Science at Wageningen University, Prof. de Beurs became interested in studying land cover and land use change using satellite images. After graduating she moved to the United States to further her interest in Remote Sensing, and to pursue a PhD in Natural Resource Sciences at the University of Nebraska. Before joining WUR, Kirsten climbed the academic ranks to full Professor in the department of Geography and Environmental Sustainability at the University of Oklahoma and from 2015 to 2020 she chaired the Department. Prof. de Beurs' research is centred around the analysis of earth observation data related to terrestrial and freshwater ecosystems. She works at the intersection of remote sensing and environmental sustainability, finding answers to large-scale problems such as climate change, biodiversity loss, and emerging infectious diseases. She has experience working with large-scale datasets which are increasingly important within environmental research, especially to scale from field measurements to global ecosystems.