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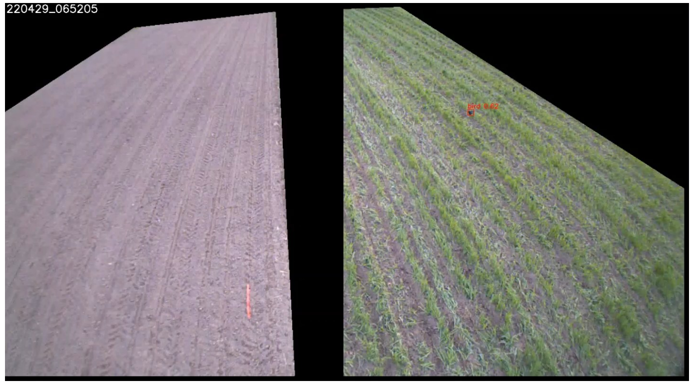
Federal Department of Economic Affairs,
Education and Research EAER
Agroscope

How can AI-powered precision agriculture become a driver of sustainability?

Hassan-Roland Nasser, PhD
Research Scientist, AI in Agriculture
Agroscope, Digital production group

04 November 2025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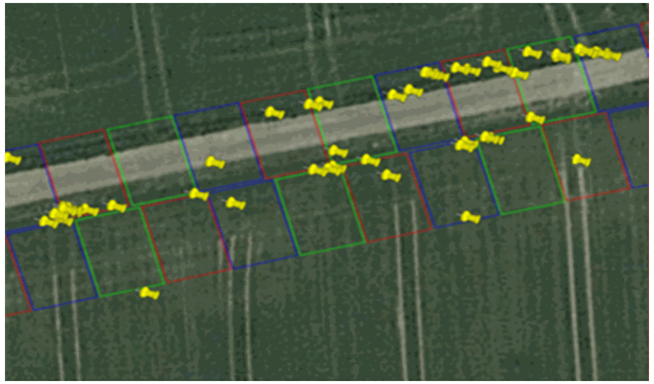


DIGITAL FARMING
Gelbfangschale jetzt digital: Die MagicTrap


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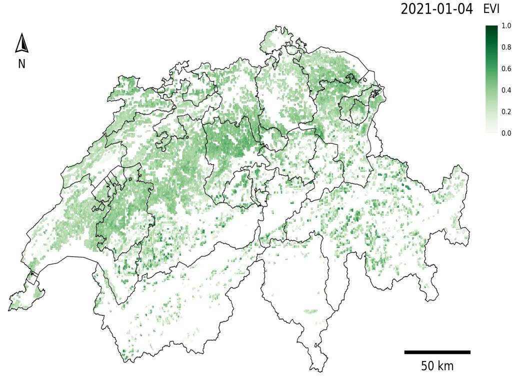

2021-01-04
EVI
N
50 km

About Agroscope

Plan

- 10 min: What’s happening outside?
- 20-30 min: What’s happening in Agroscope:
  - Examples from solved problems
  - Examples from work in progress
- 30-40 min:
  - Collaborative problem solving.
  - Synthesis and project speed dating.

Group work

Segment	Duration	Purpose
1. Individual idea generation	5 min	Personal reflection
2. Pitches	12 min	Share ideas concisely
3. Voting	5 min	Prioritize key ideas
4. Group work	15 min	Develop solutions
5. Presentations & synthesis	8 min	Share insights & align themes

Topics

Computer Vision

Earth Observation

Smart Irrigation

Spot-sprayers: Single plant recognition is real!

The Swiss company Ecorobotix is selling a sprayer that automatically recognises and treats individual weeds!

Machine learning solved an old problem!
→ research ongoing since 40 years after started in the UK.

Thomas Anken
Agroscope, Tänikon, CH 8356 Ettenhausen

Japanese beetle - Digital monitoring of pests

- New pests are increasingly migrating due to climate change (cherry vinegar fly, corn stalk borer, Japanese beetle...)
- **Intelligent camera** traps automatically detect pests and send the information to the cloud
- Citicen Science: Images can be uploaded to www.japankaefer.ch

→In collaboration with partners Agroscope developed an app for citizens

Bayer “Magic Trap” Take an image per day and sends it to the cloud where images are analysed.

→ Laborious handling of traps is much easier

→ Experts and advertisers have the pest situation in a region under control

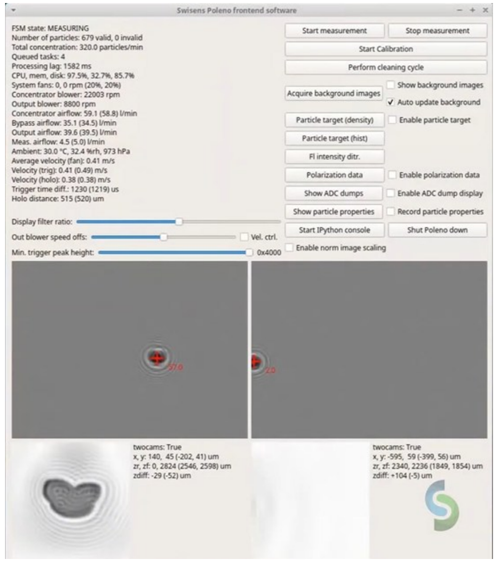
→ Much better control of pests is possible!

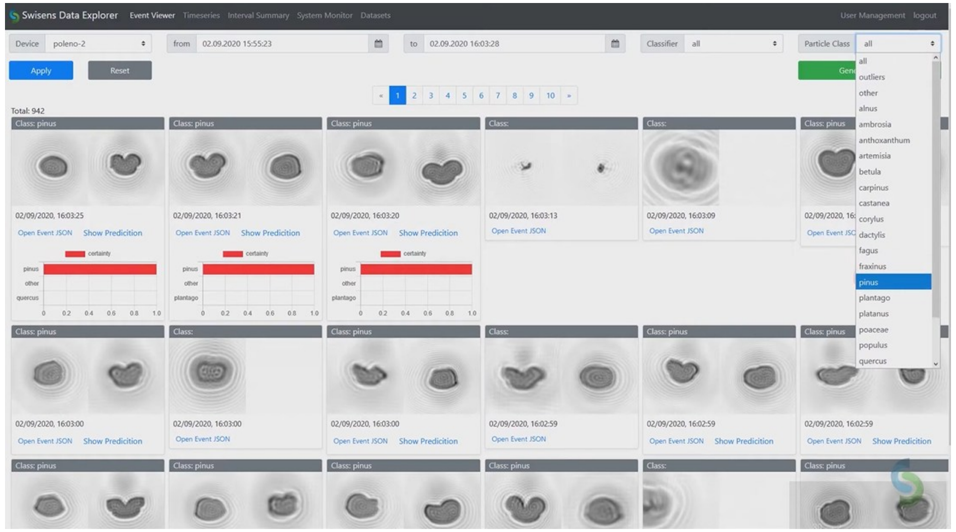
8

Next step in disease forecast: Spore detection

SwisensPoleno Jupiter is already detects pollen

→Pollen situation in App «Meteo Schweiz»





Thomas Anken
Agroscope, Tänikon, CH 8356 Ettenhausen

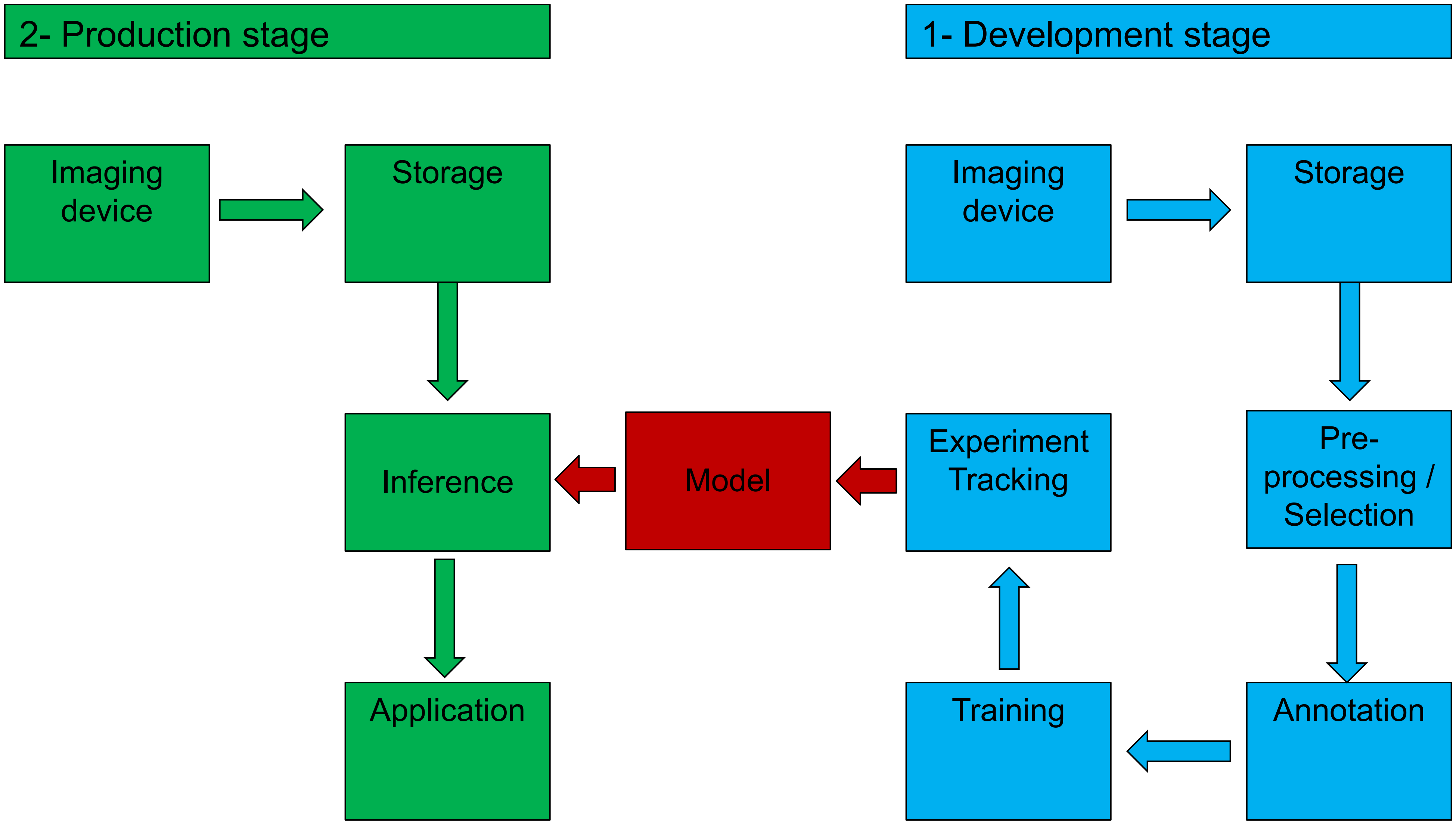
Dairy farms: Over 3000 milking robot in CH

→ AI is used to locate the tits

→ Robots are use in combination with other sensors, today automated determination of the right time for insemination is possible (only possible with AI)

→ better health, productivity and longevity of cows

How computer vision is done (+ slides at the end)



Rumex detection from drones

- Rumex are invasive plants with deep roots.
- Difficult to extract.
- Reduce the meadow quality.
- Highly reproductive.

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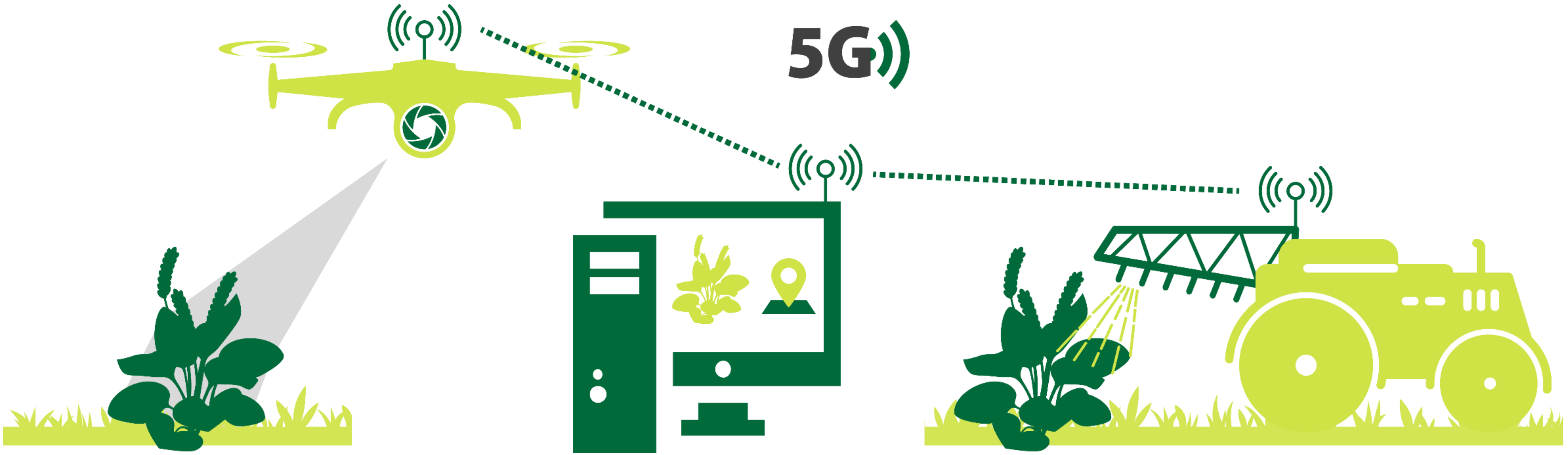
All-Field Spraying

Manual Digging

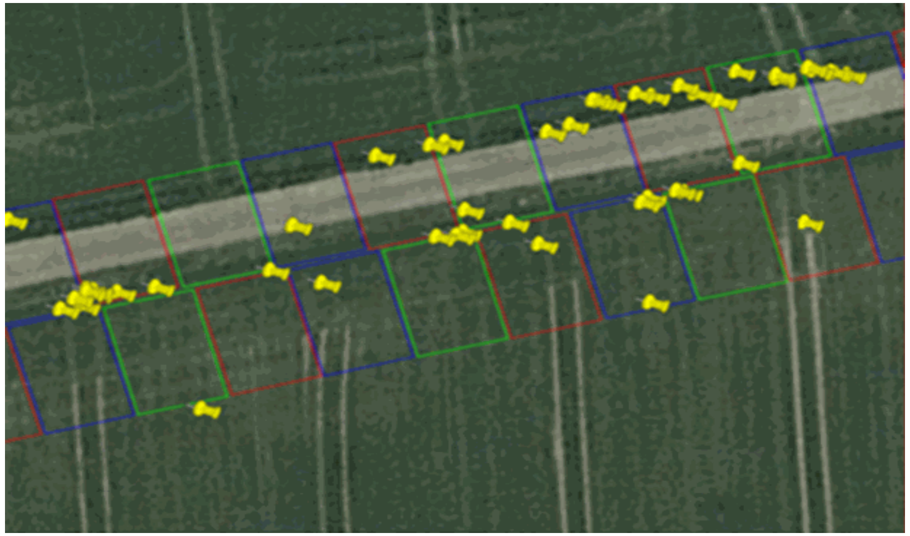


Precision spraying

Ecorobotix

How about detecting the rumex with drones?

- Detect ➔ Map
- Map ➔ Tractor / hot water treatement



+

Drones + Models as a generic platform for multiple tasks

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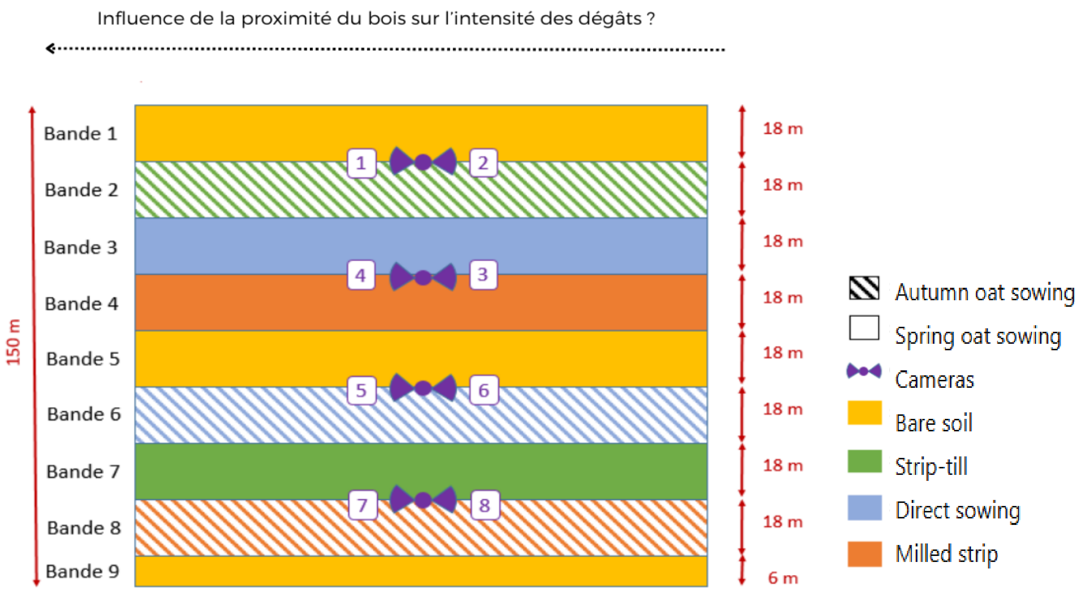
The solution is now deployed at Fenaco and being tested for commercialization

Helping researchers counting 5.5 years of data

Study the effect of different sowing and undersowing techniques



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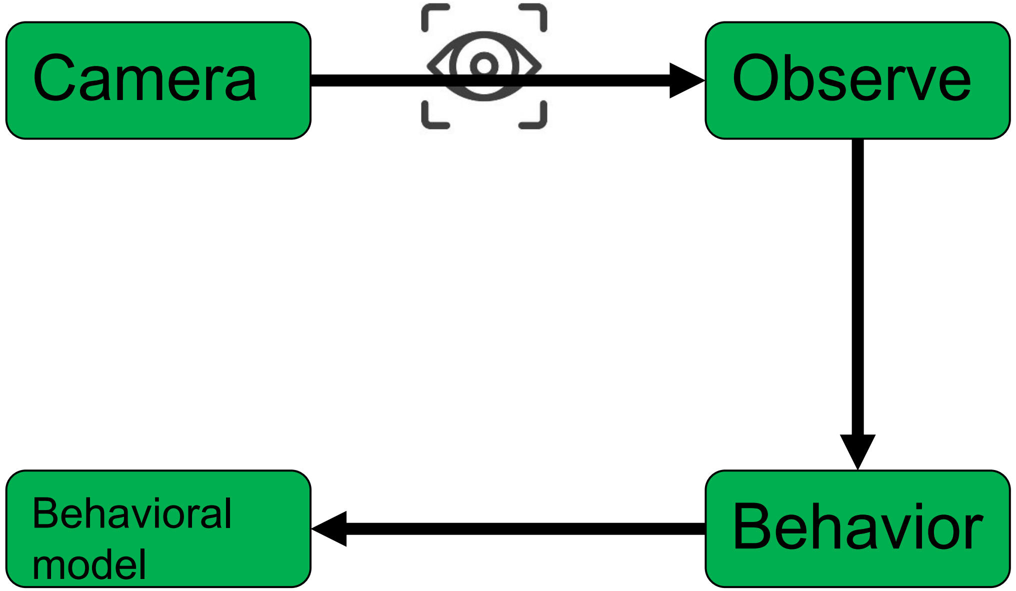
Data

- 8 cameras:
  - 2 months of recording
  - 4 years of experiments.

➔64 months of recordings ➔ ~5.5 years.

➔Not very practical to count them manually

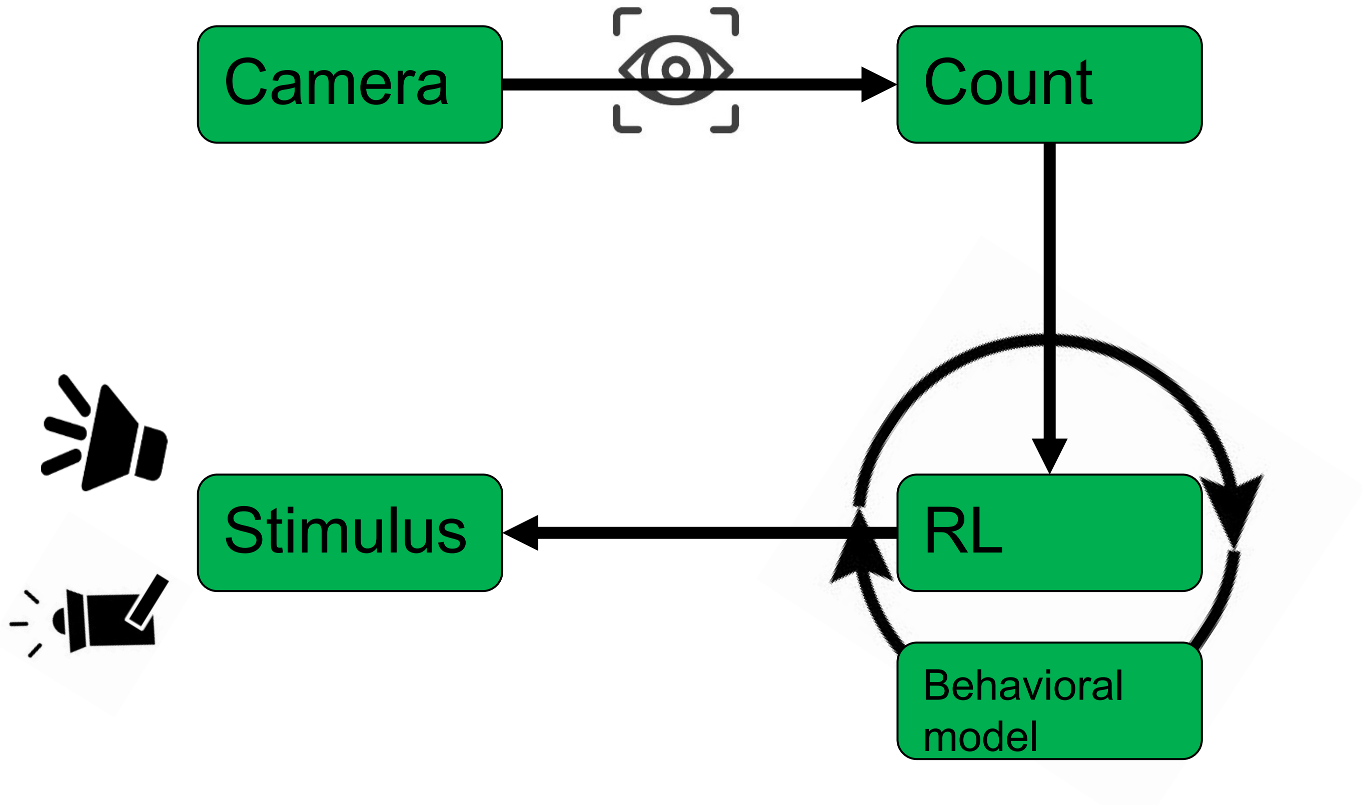
Future projet 'ETHIC'
Supported by OFAG (2026-2030)



Step 1: Learn how the crows think (Inverse Reinforcement Learning).

Future projet ‘ETHIC’

Reinforcement learning



Step 2: Train our deterrent system to “outsmart” that model (Reinforcement Learning)

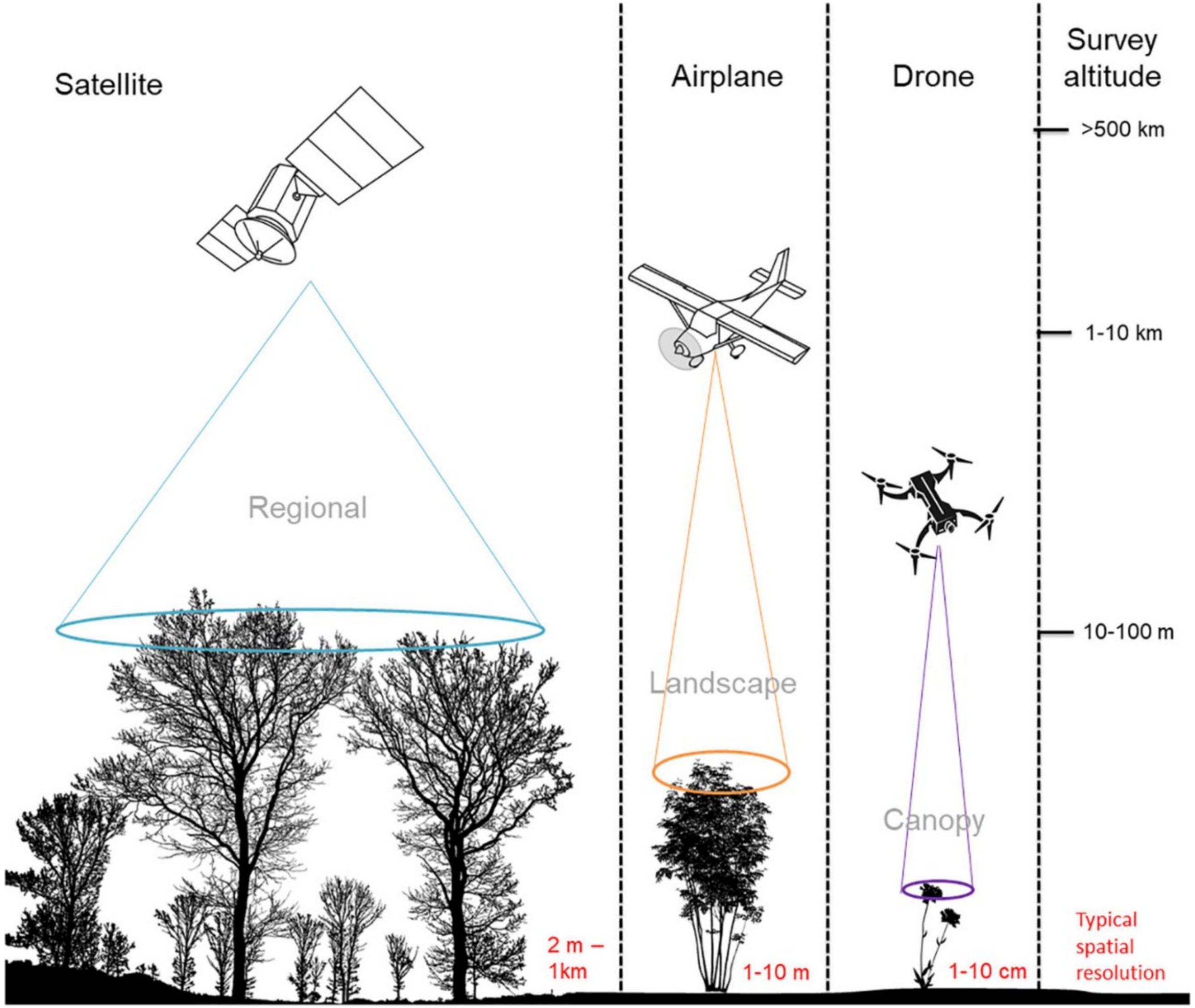
Using AI to assess biodiversity

Biodiversity: In brief

Switzerland's biodiversity is under pressure. Although incentive measures are having an effect locally, biodiversity remains in a poor state and continues to decline. A third of all species and half of all types of habitat in Switzerland are threatened. Occasional gains are not enough to make up for the losses caused mainly by a lack of land area, soil sealing, fragmentation, intensive use, and nitrogen and pesticide inputs. Subsidies that harm biodiversity exacerbate this negative trend. There is an urgent need for resolute action to preserve the services that biodiversity provides. Rich and resilient biodiversity also helps to mitigate climate change and its consequences.

Source: Federal Office for the Environment

- Expensive assessement
- Subjective
- Logistics



Satellite
Airplane
Drone
Survey altitude
>500 km
1-10 km
10-100 m
Regional
Landscape
Canopy
2 m – 1km
1-10 m
1-10 cm
Typical spatial resolution

Measuring biodiversity with drone is not scalable → same (or even worse) logistic problem

Measuring them with Airborne is not possible because there is no ground truth data

Satellite are impossible in this case because of the resolution

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Measuring biodiversity with drone is not scalable ➔ same (or even worse) logistic problem

➔ Used to get ground truth for the airbone model

Measuring them with Airborne is not possible because there is no ground truth data

➔ Used for scalability

Satellite are impossible in this case because of the resolution

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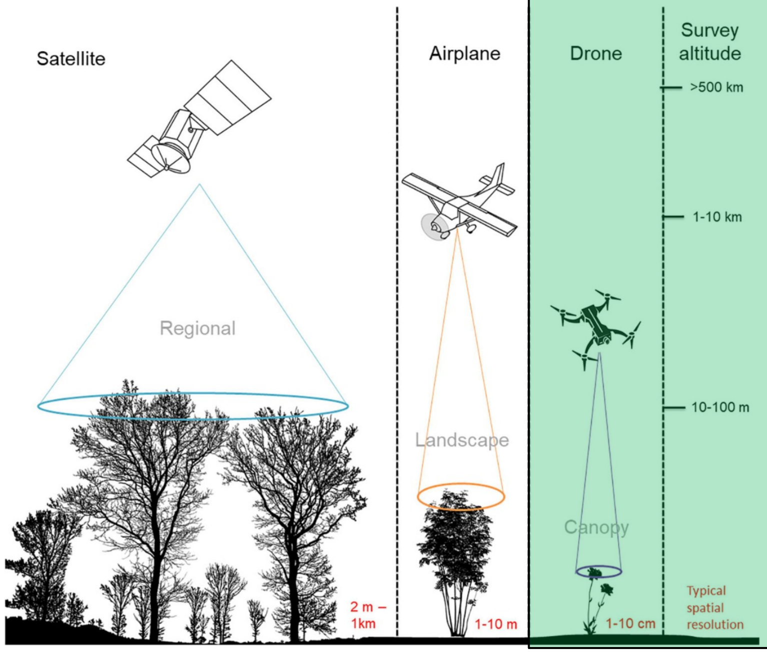
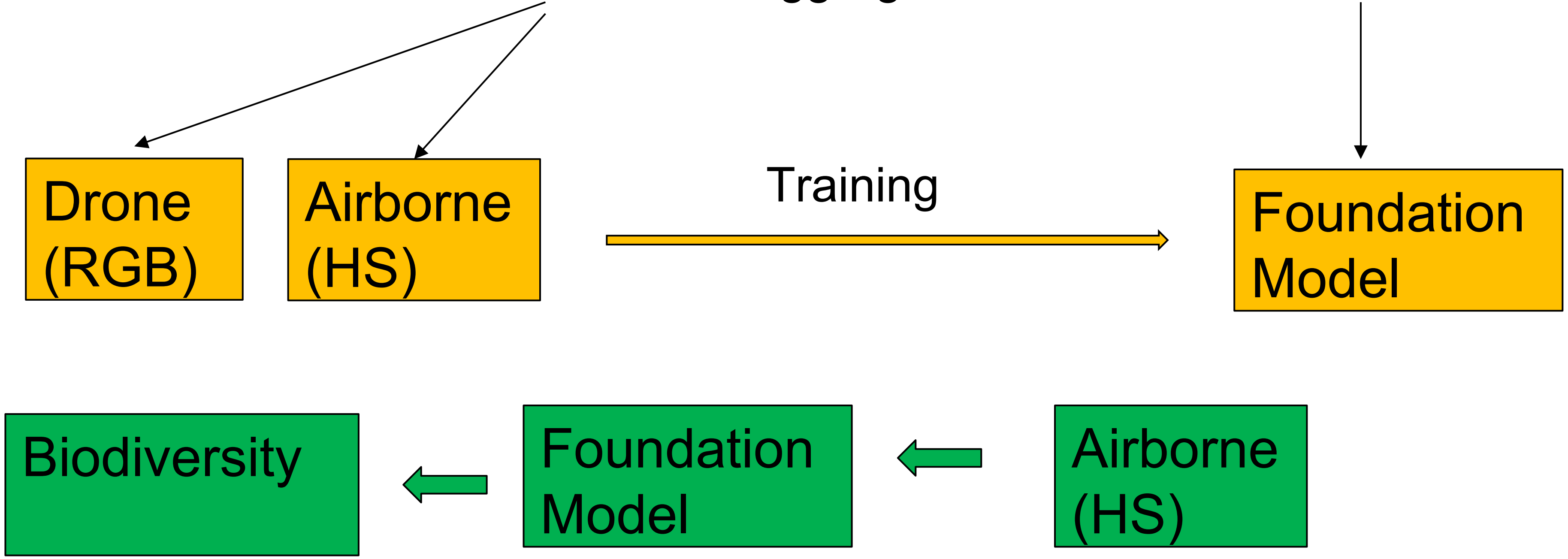
Develop unsupervised or weakly supervised models to get ground truth data using drones.

Sure ground truth data



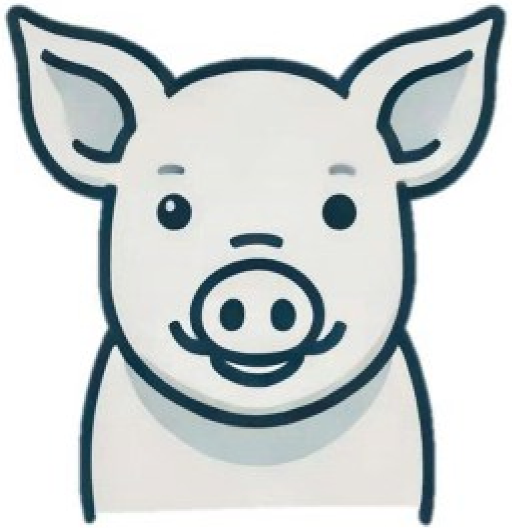
Foundation models

Data from different scale and modalities are aggregated into the same model



Inference

Breeding pigs with higher stress resilience



- In addition to improved management!
- Coping with stress has genetic basis
  Kadarmideen & Janss 2007; Kasper et al., 2020
- Tail biting is heritable
  Breuer et al., 2005
- Goal: Identify pigs with higher stress resilience to become parents of the next generation.
- In collaboration with Claudia Kasper (Animal PhenoGenomics group).

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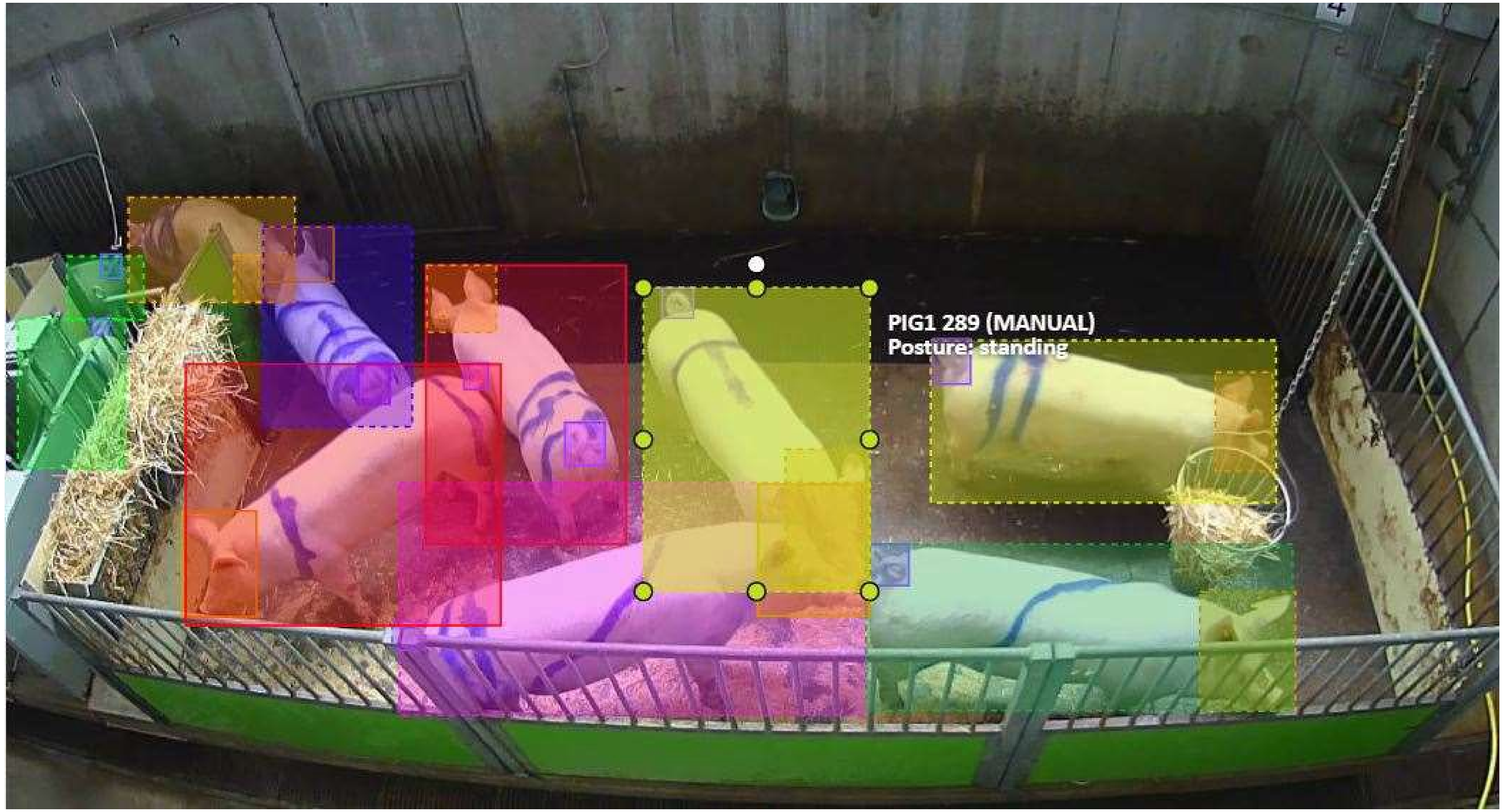
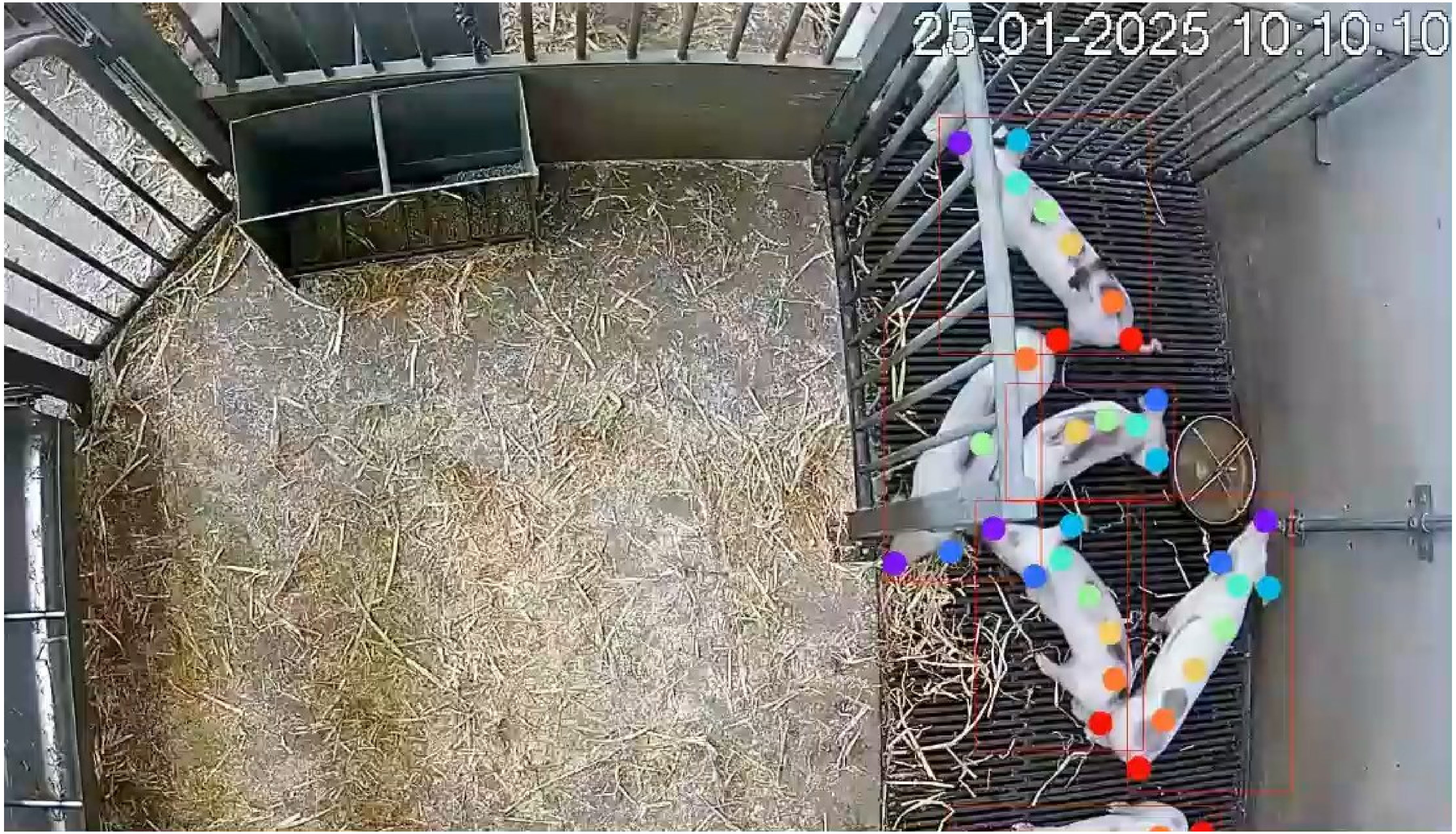

PIG1 289 (MANUAL)
Posture: standing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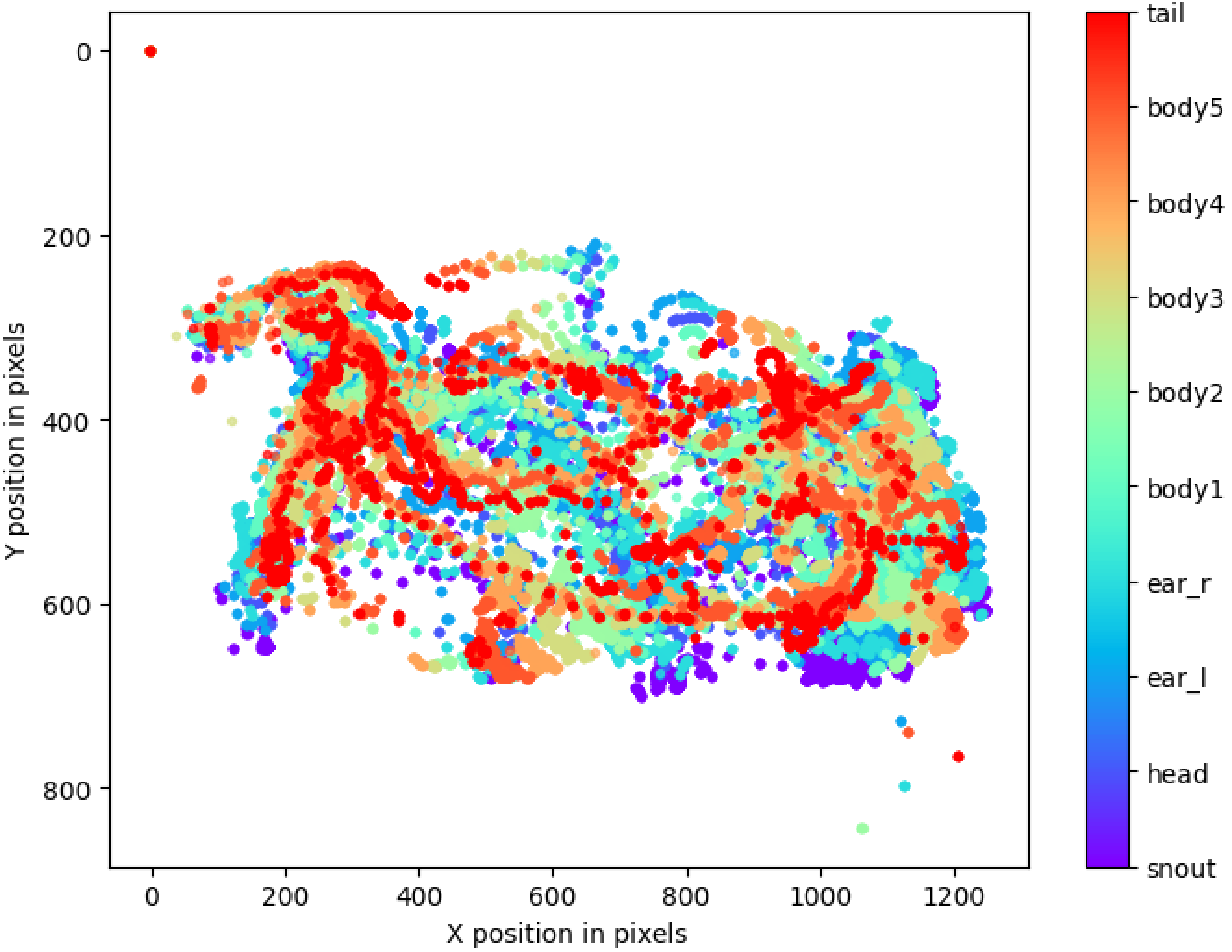
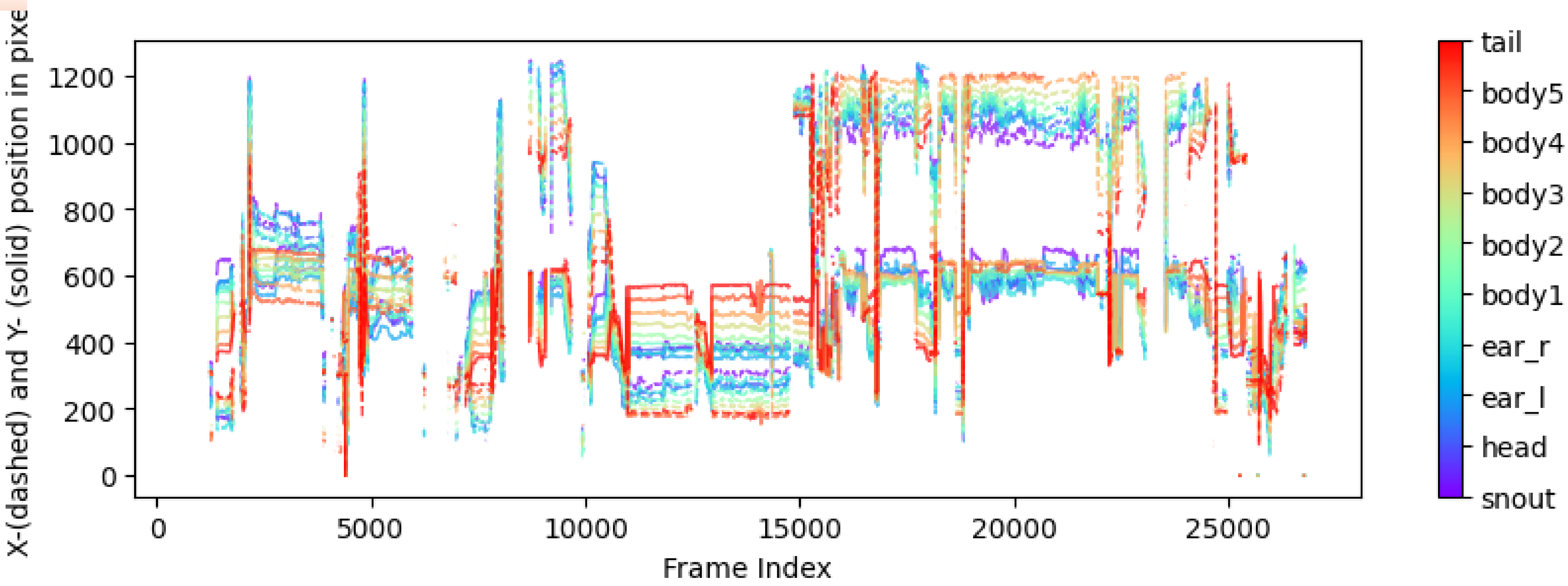

Y position in pixels
X position in pixels
0
200
400
600
800
1000
1200
tail
body5
body4
body3
body2
body1
ear_r
ear_l
head
snout


X-(dashed) and Y- (solid) position in pixe
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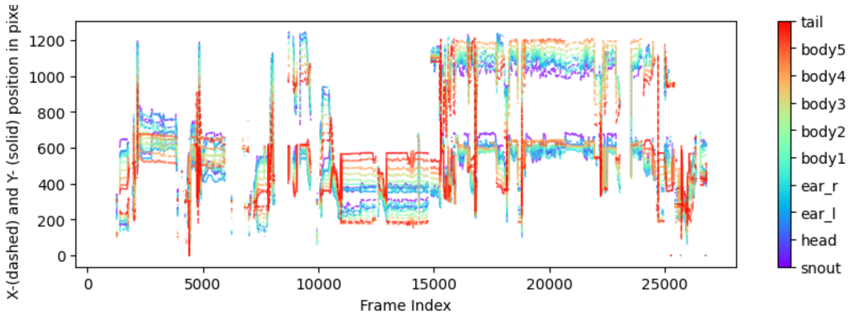
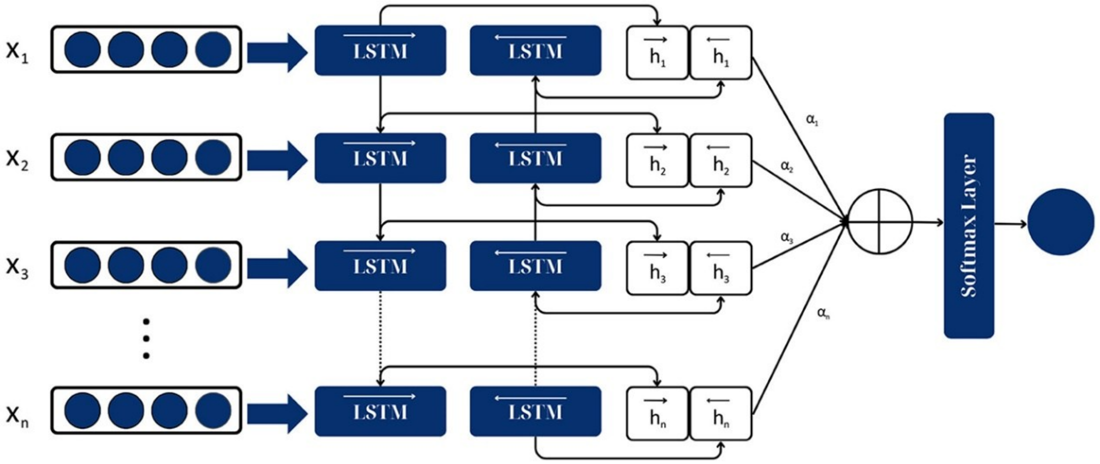
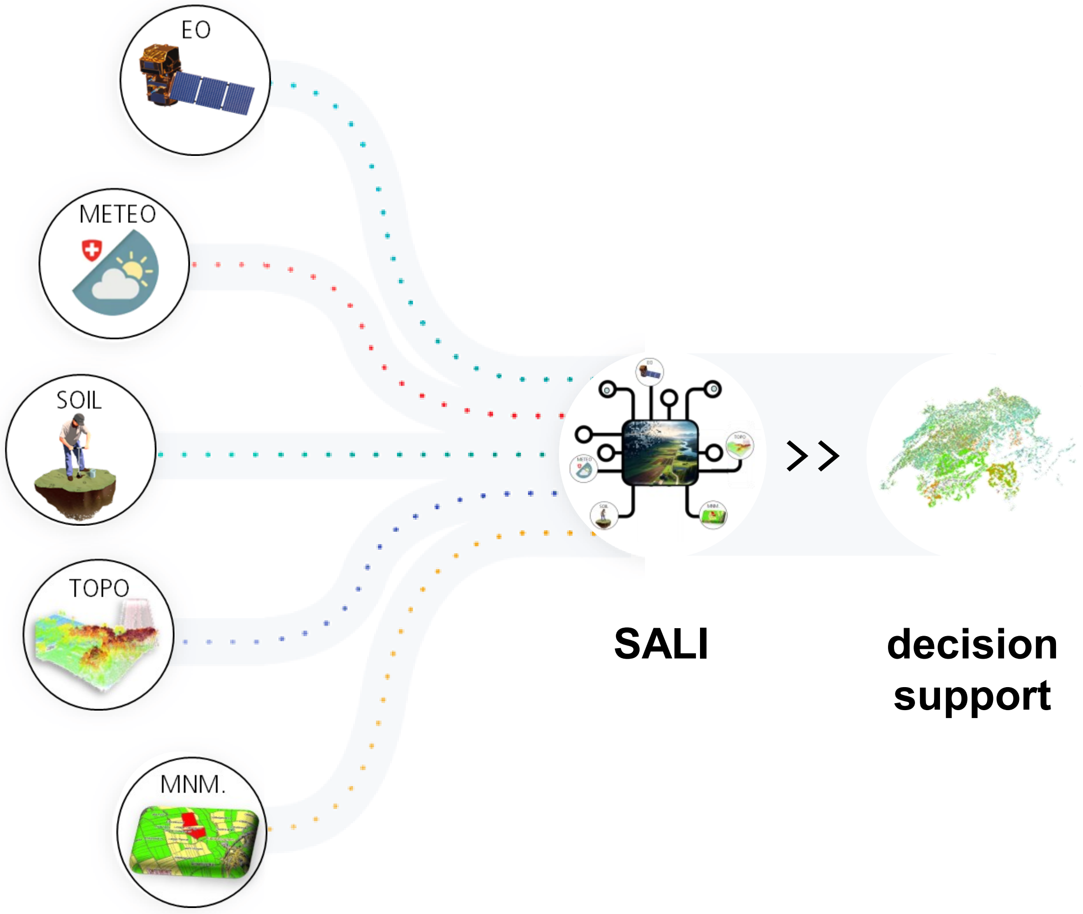




Behavioral class

Padalko H. 2024

Swiss Agricultural Landscape Intelligence (SALI) platform

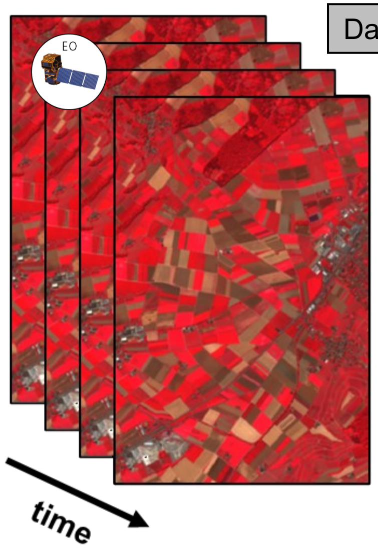


- Digital representation of Switzerland's agricultural ecosystems
  - enables monitoring, analysis and simulation
  - continuously updated with harmonized EO data streams
  - machine learning ready

- ➢ near real-time analysis
- ➢ annual reporting
- ➢ long-term trend estimations

Satellite data processing

Satellite data



Data preprocessing

Inference

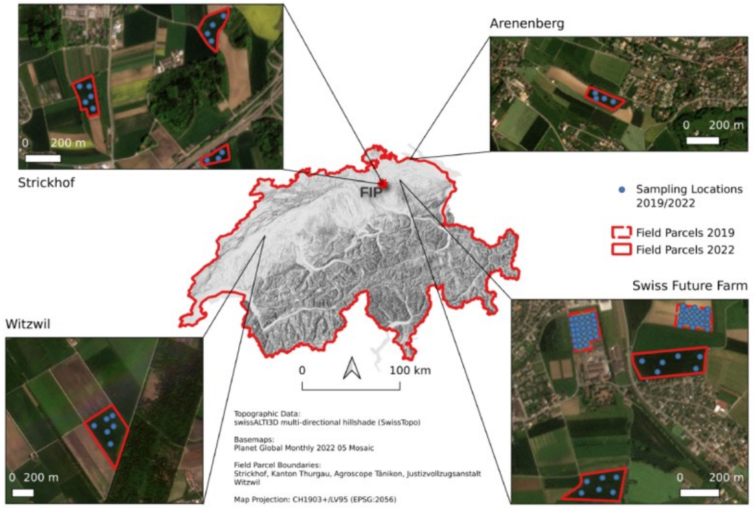
Training

Productivity proxy

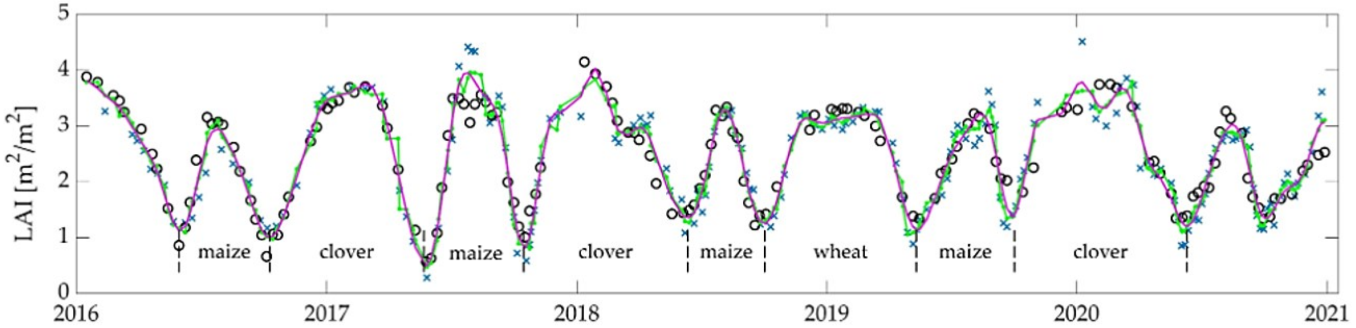
Uncertainty estimate

validation

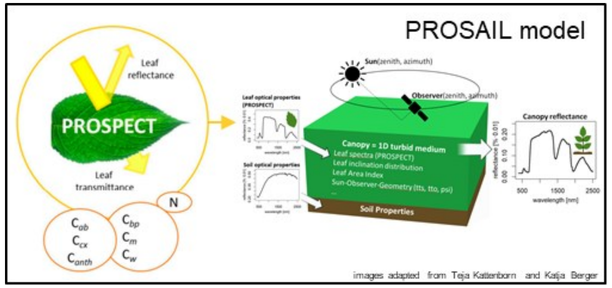
Training and validation sites*



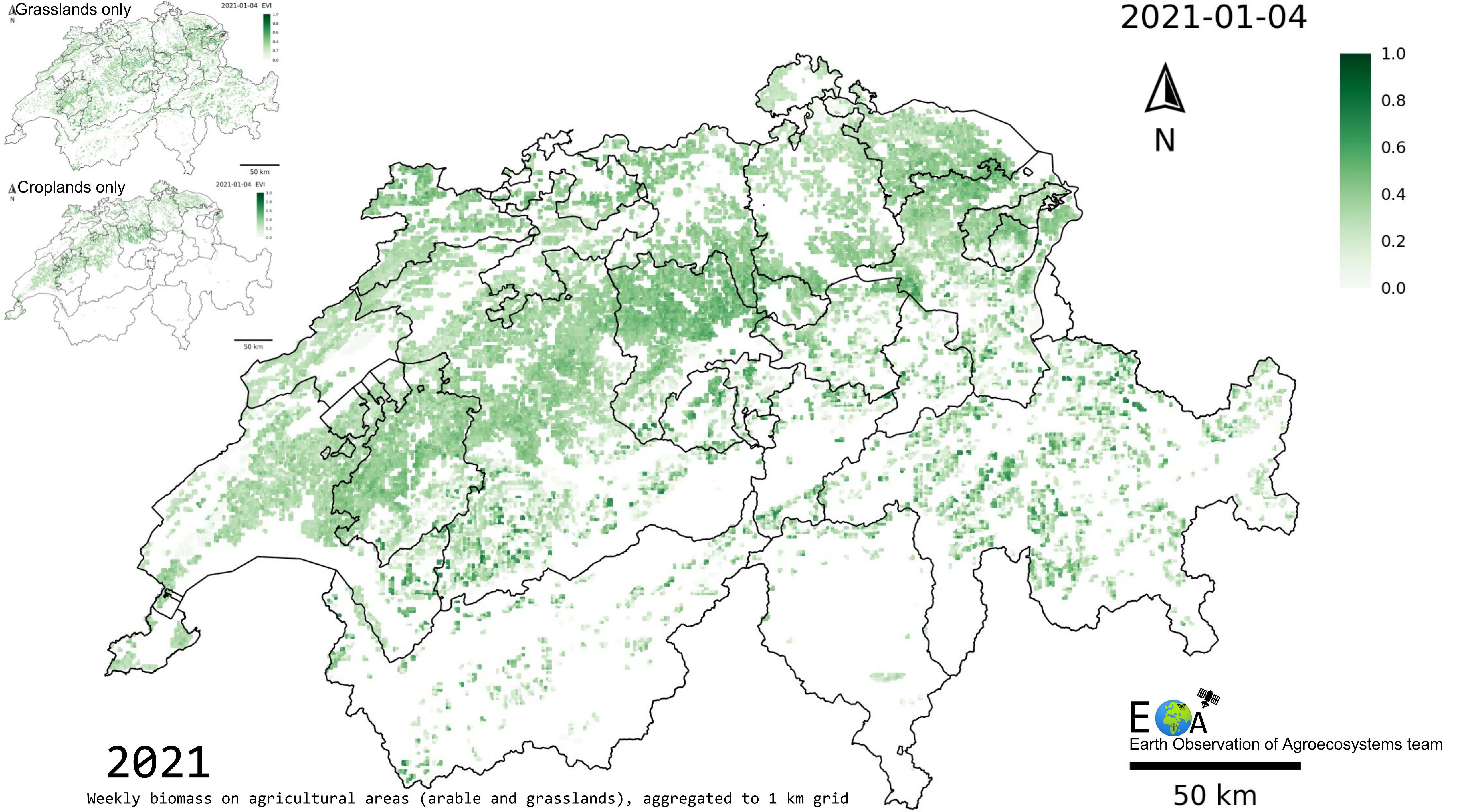
Time series



Physically based model



*** thanks a lot to our colleagues and partners!**
(NABO, MAUS, SwissFutureFarm, VS Luzern, ETH CS, HAFL, Strickhof, Arenenberg, Grangeneuve)



Weekly biomass on agricultural areas (arable and grasslands), aggregated to 1 km grid

Optimizing management in mountain grasslands

Objective: Investigating the impact of climate variability to optimize the management on mountain grasslands

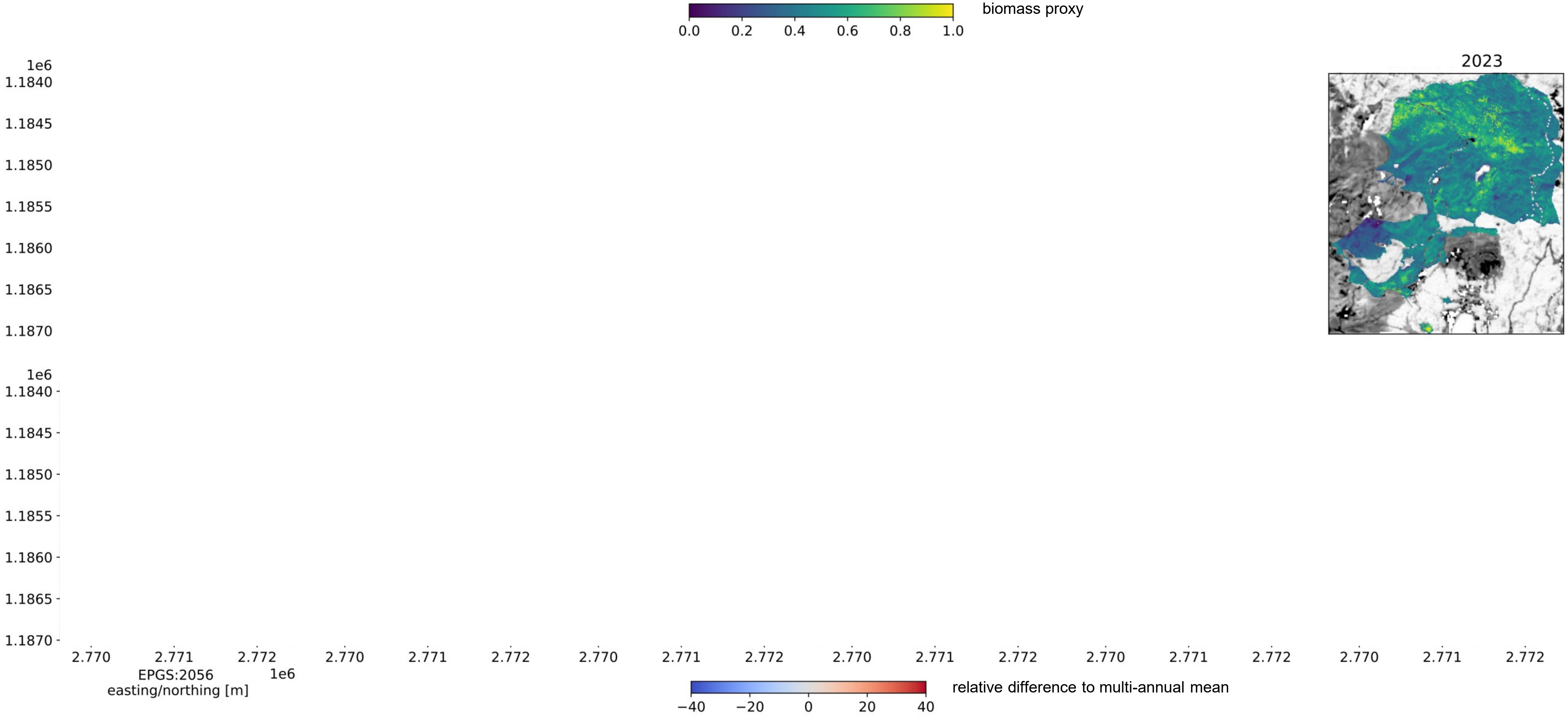
Agroscope Swiss centre of excellence for agricultural research

Main researcher: Fabio Oriani, Project: Mountain GrassSense
Collaborators: Manuel Schneider (mountain grassland team)

helge.aasen@agroscope.admin.ch

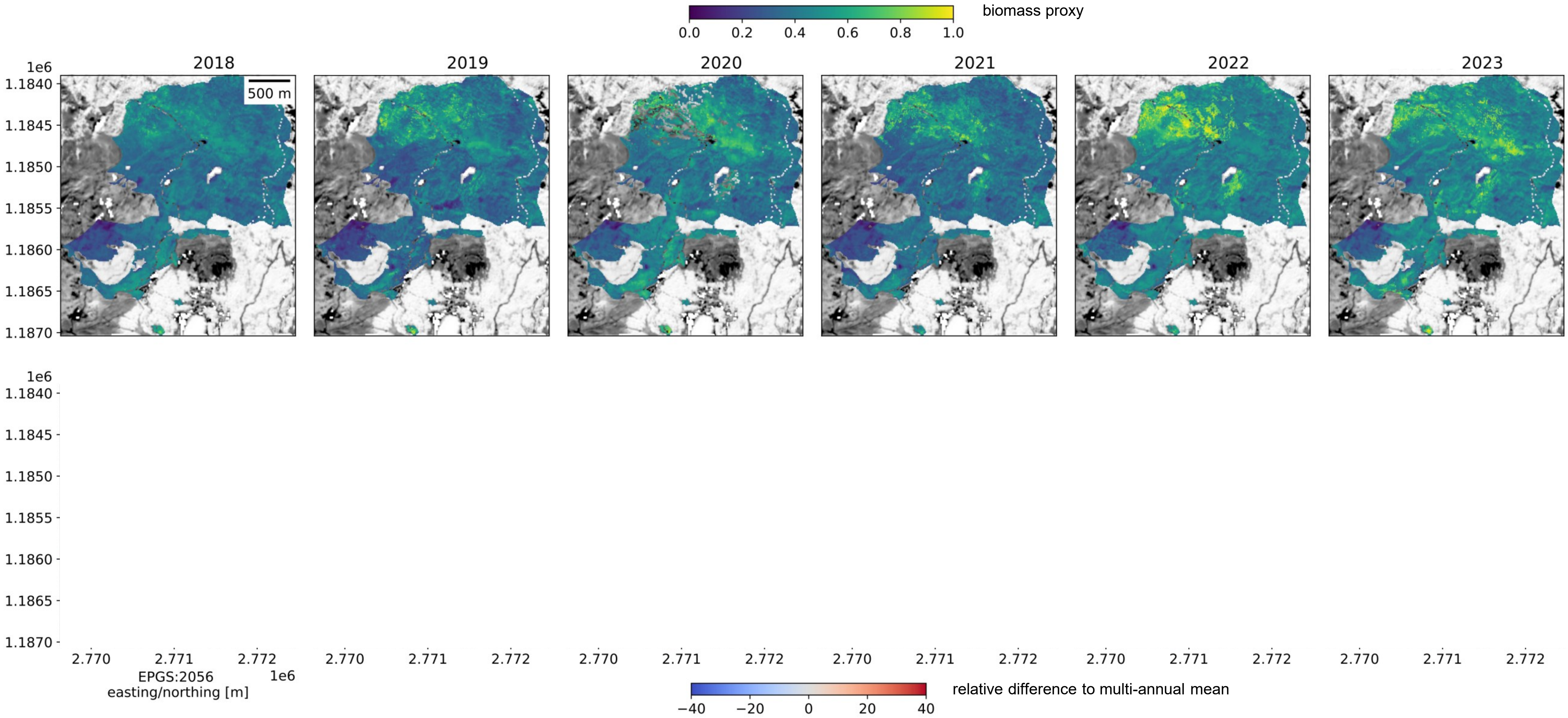
Optimizing management in mountain grasslands

Objective: Investigating the impact of climate variability to optimize the management on mountain grasslands

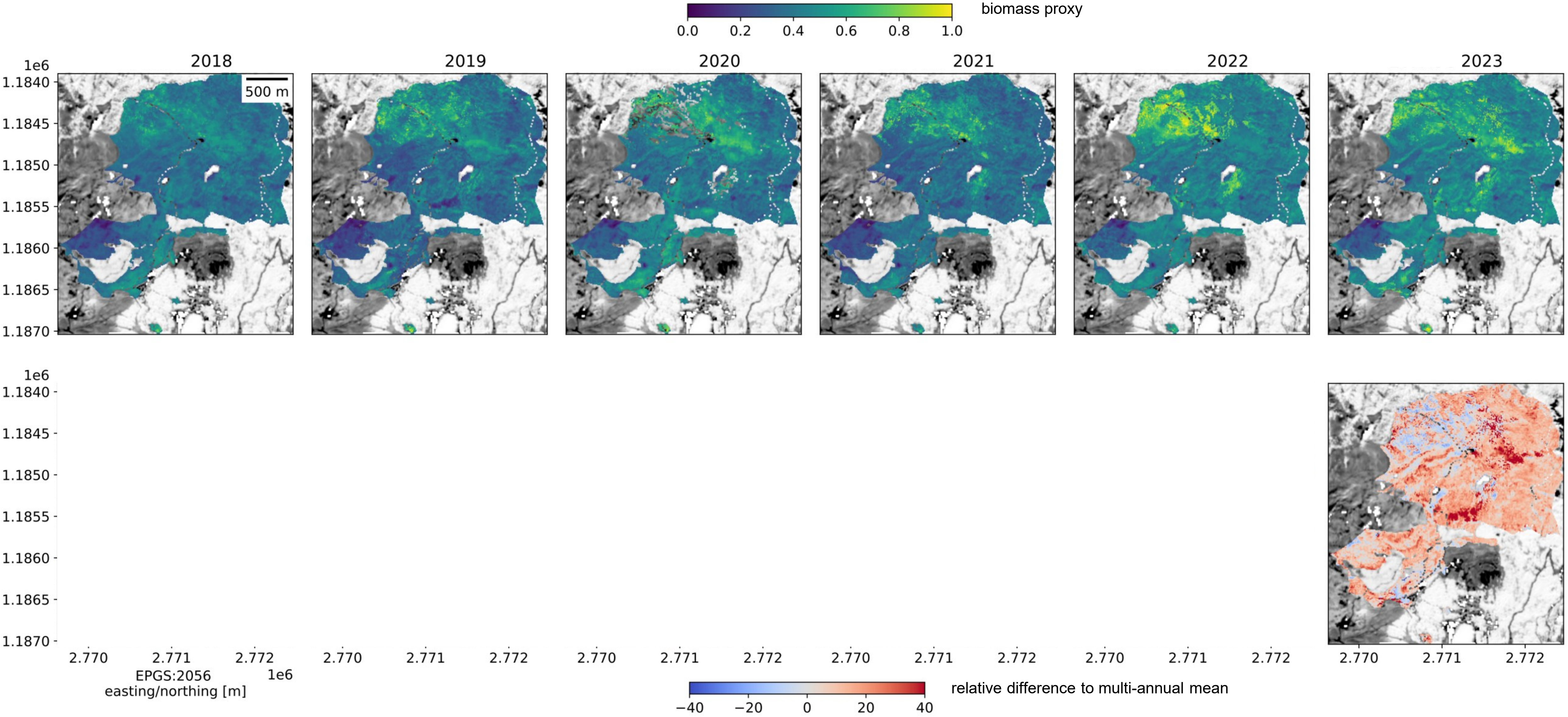


Agroscope Swiss centre of excellence for agricultural research

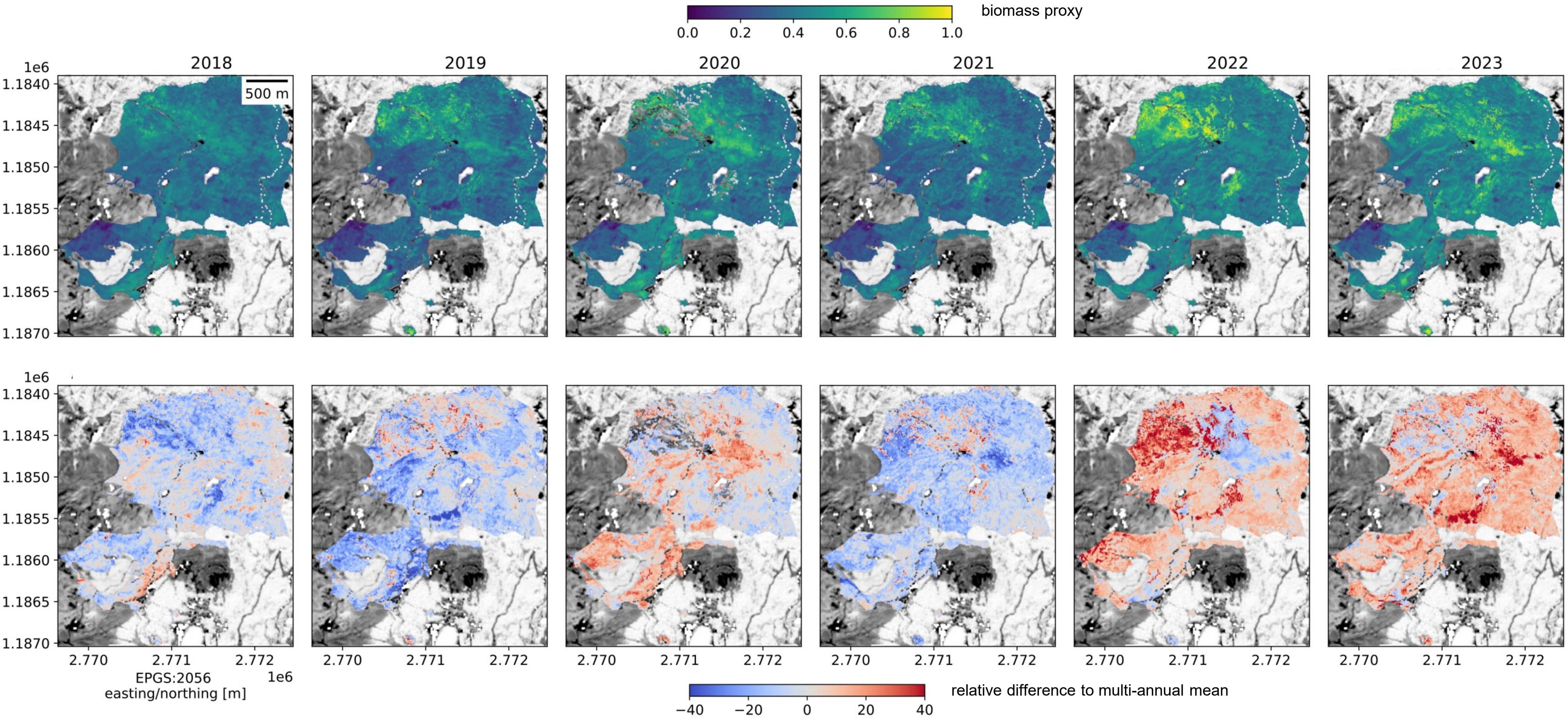
Optimizing management in mountain grasslands



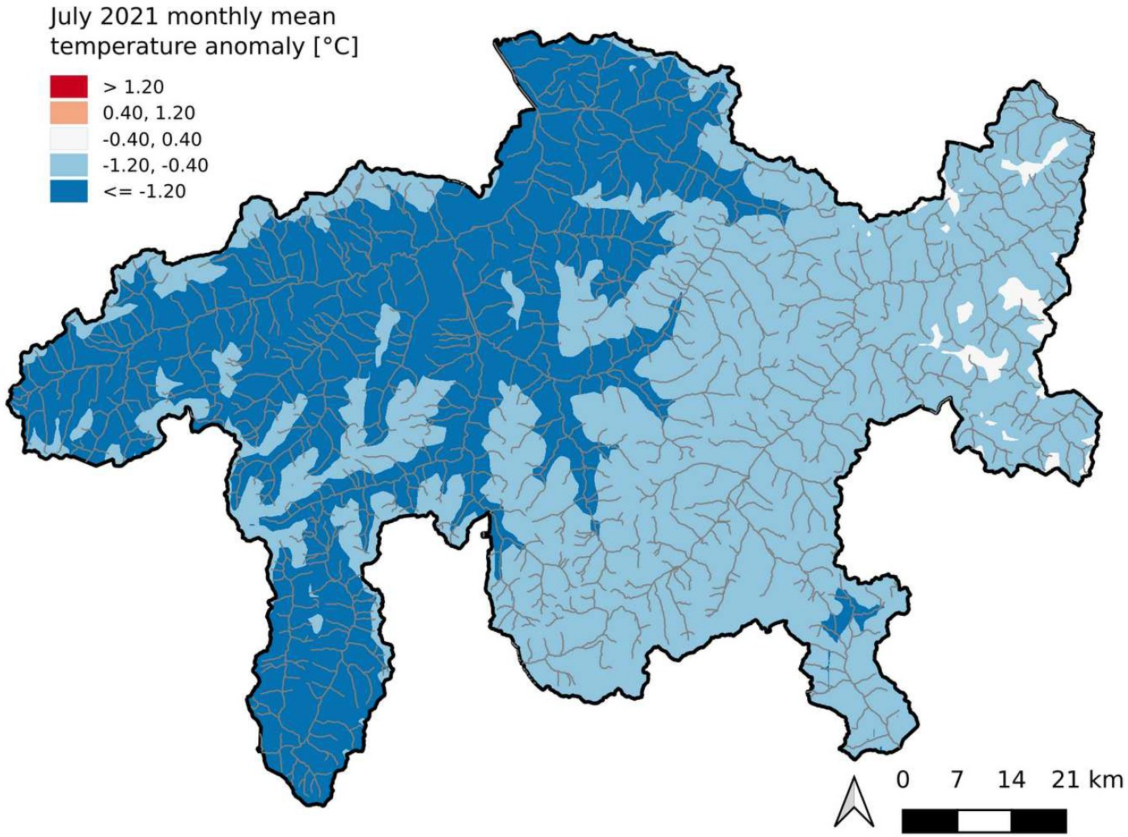
Optimizing management in mountain grasslands

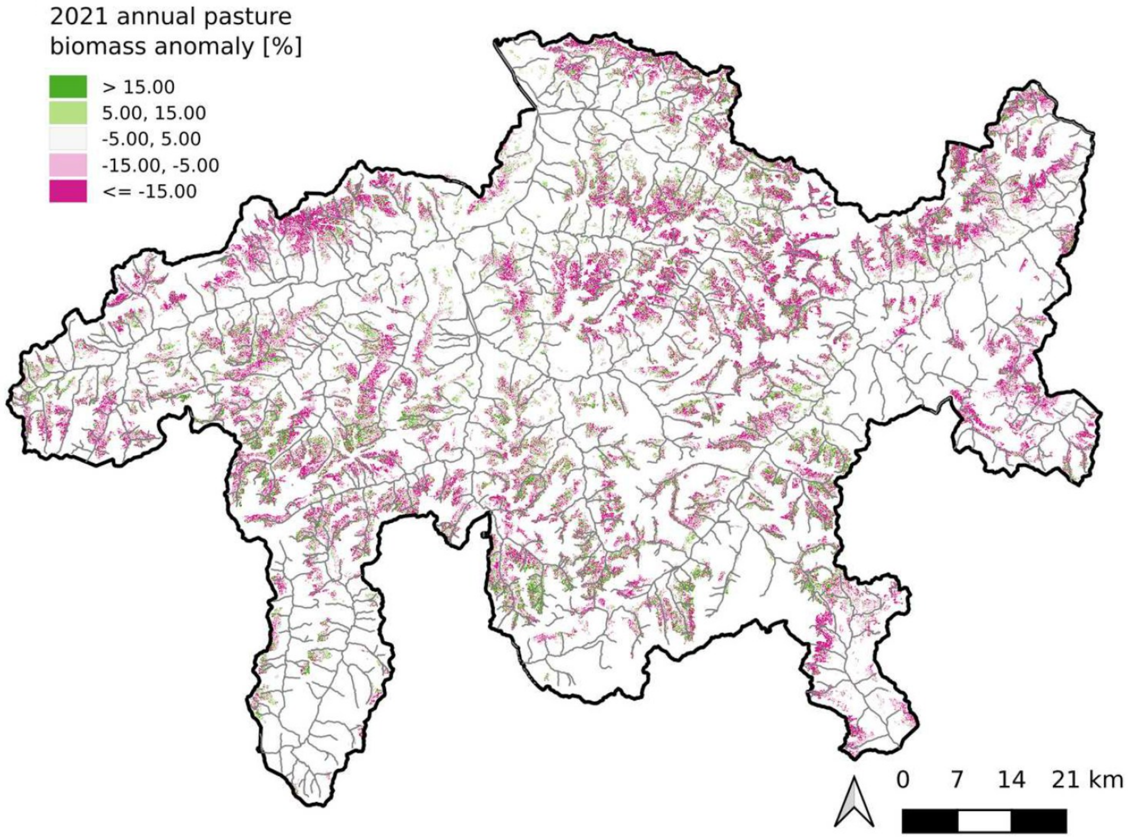


Optimizing management in mountain grasslands



Optimizing management in mountain grasslands

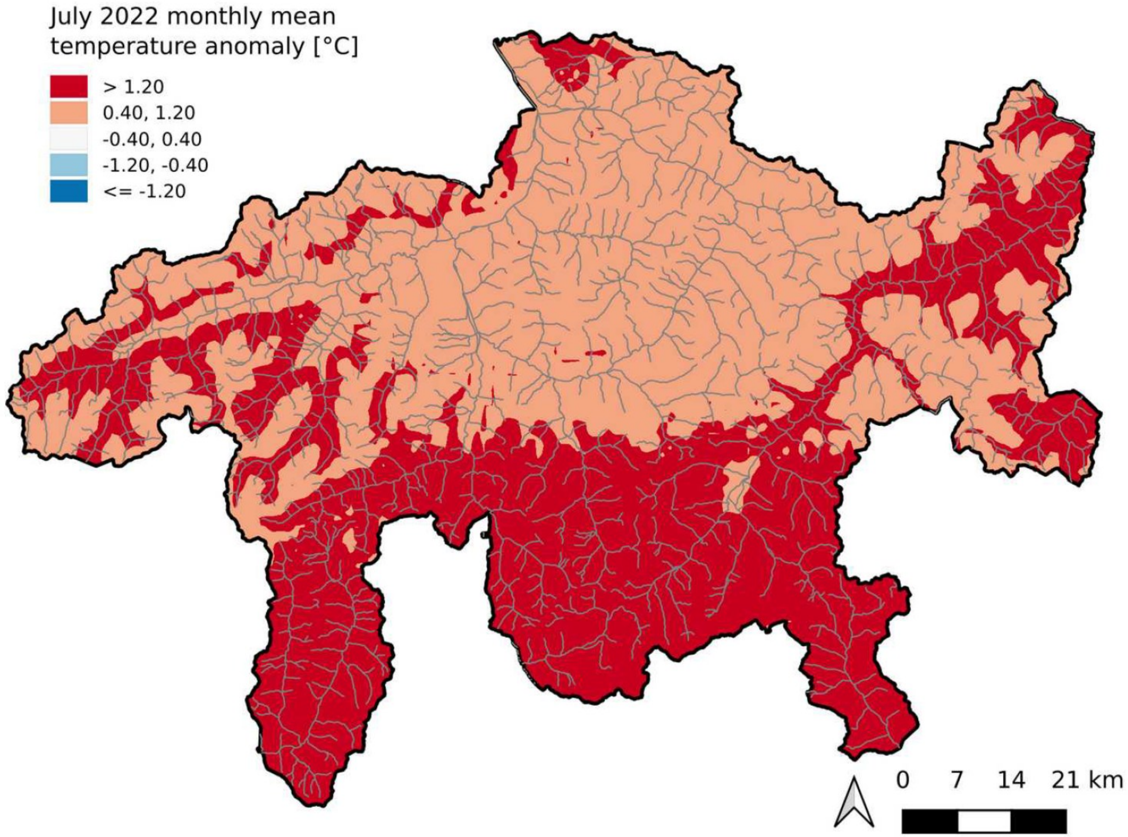


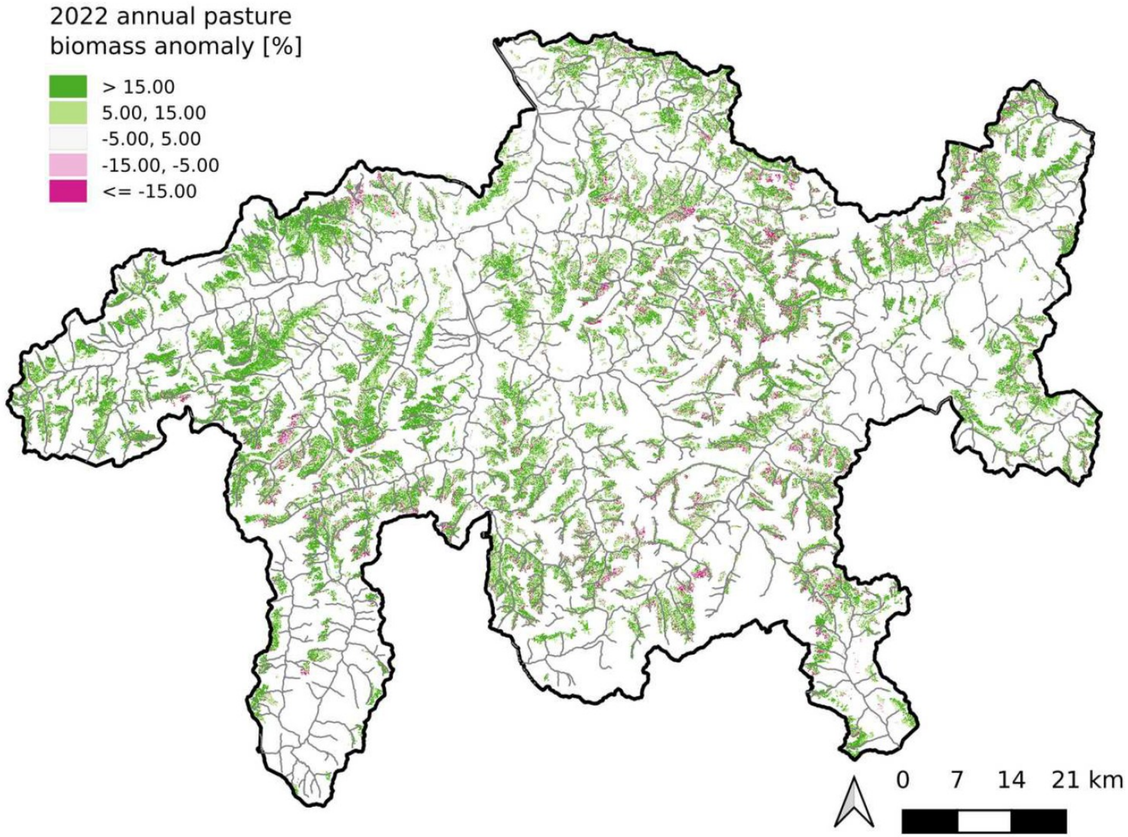


Canton of Grisons

Helge Aasen | 01.12.2025 | 48
helge.aasen@agroscope.admin.ch

Optimizing management in mountain grasslands

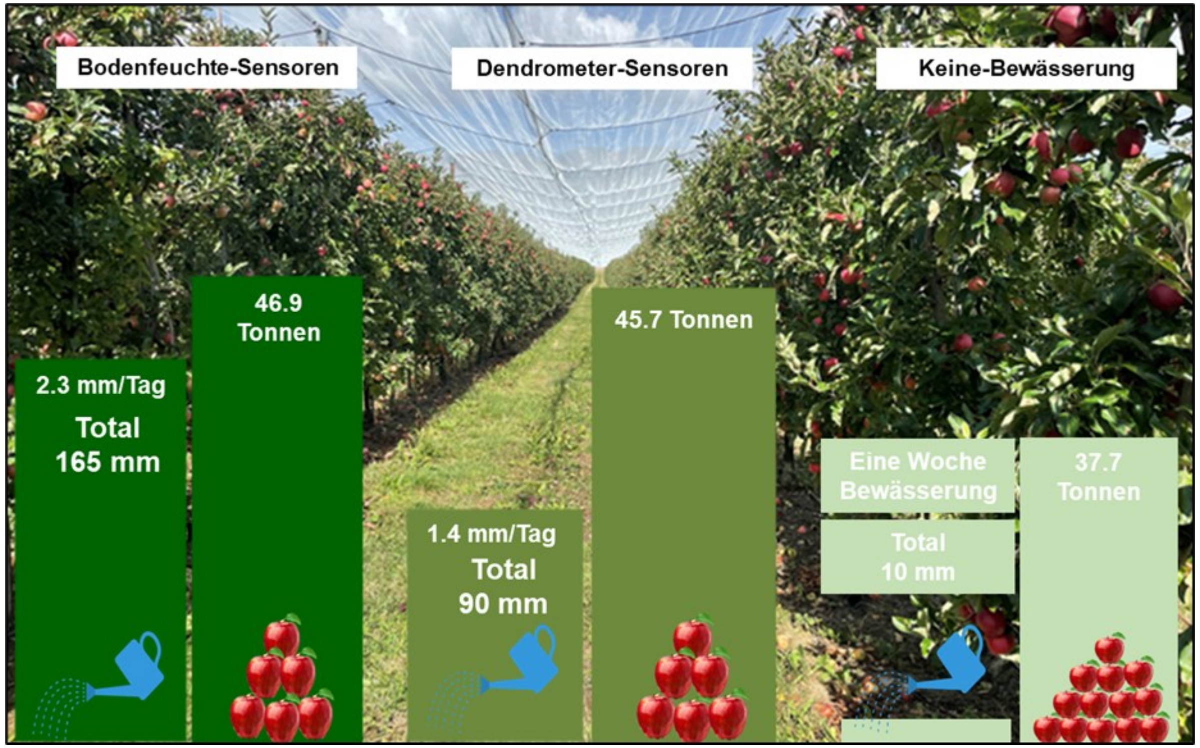




Canton of Grisons

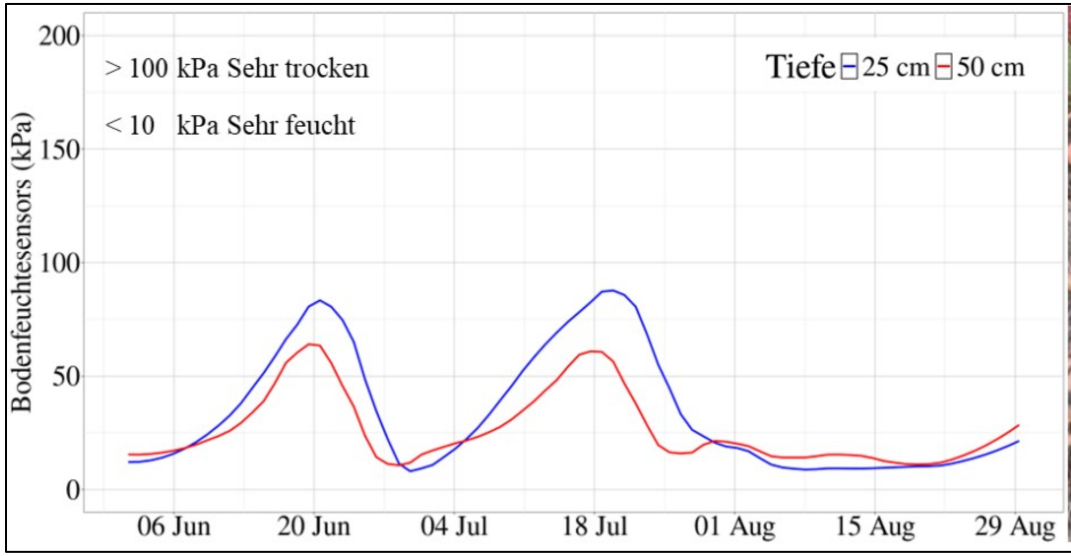
Efficient smart irrigation

- Dry years: 2003, 2018, 2022
- Western Switzerland: >50% of apple growers use irrigation
- Less sensor technology, more experience and platforms



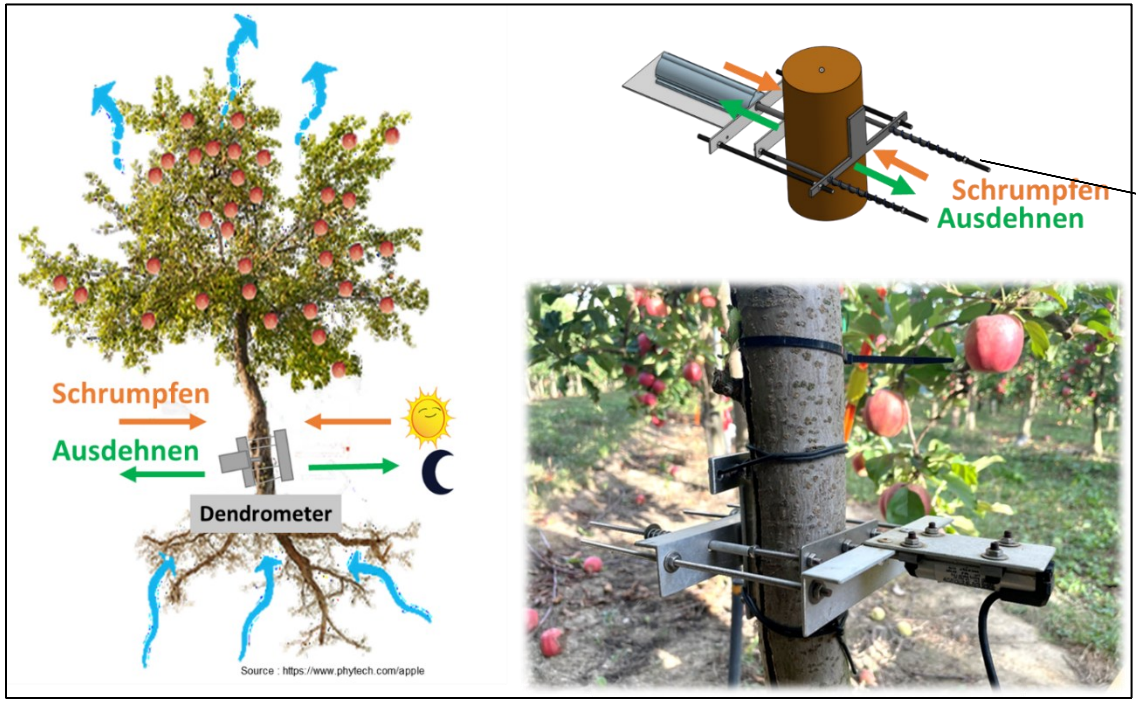
Soil moisture sensors

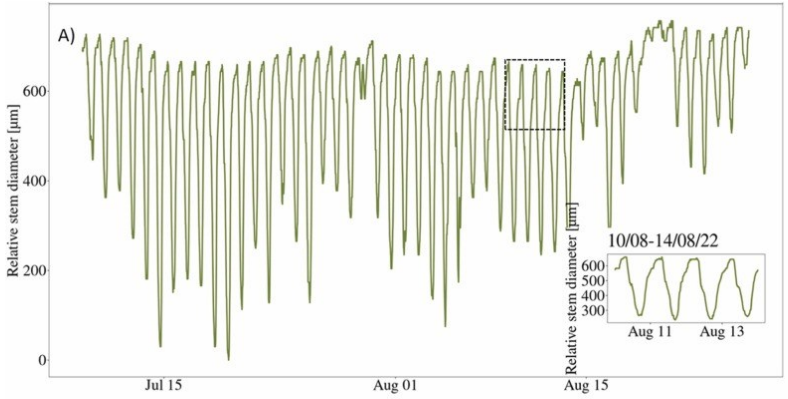
- Measurement at a depth of 20–60 cm
- Automatic irrigation control
- Cost-effective models such as Watermark
- Problem: deeper layers cannot be measured



Dendrometer – measurement directly on the plant

- Trunk diameter = water status
- Daily fluctuations
- Cost-effective, but installation is challenging





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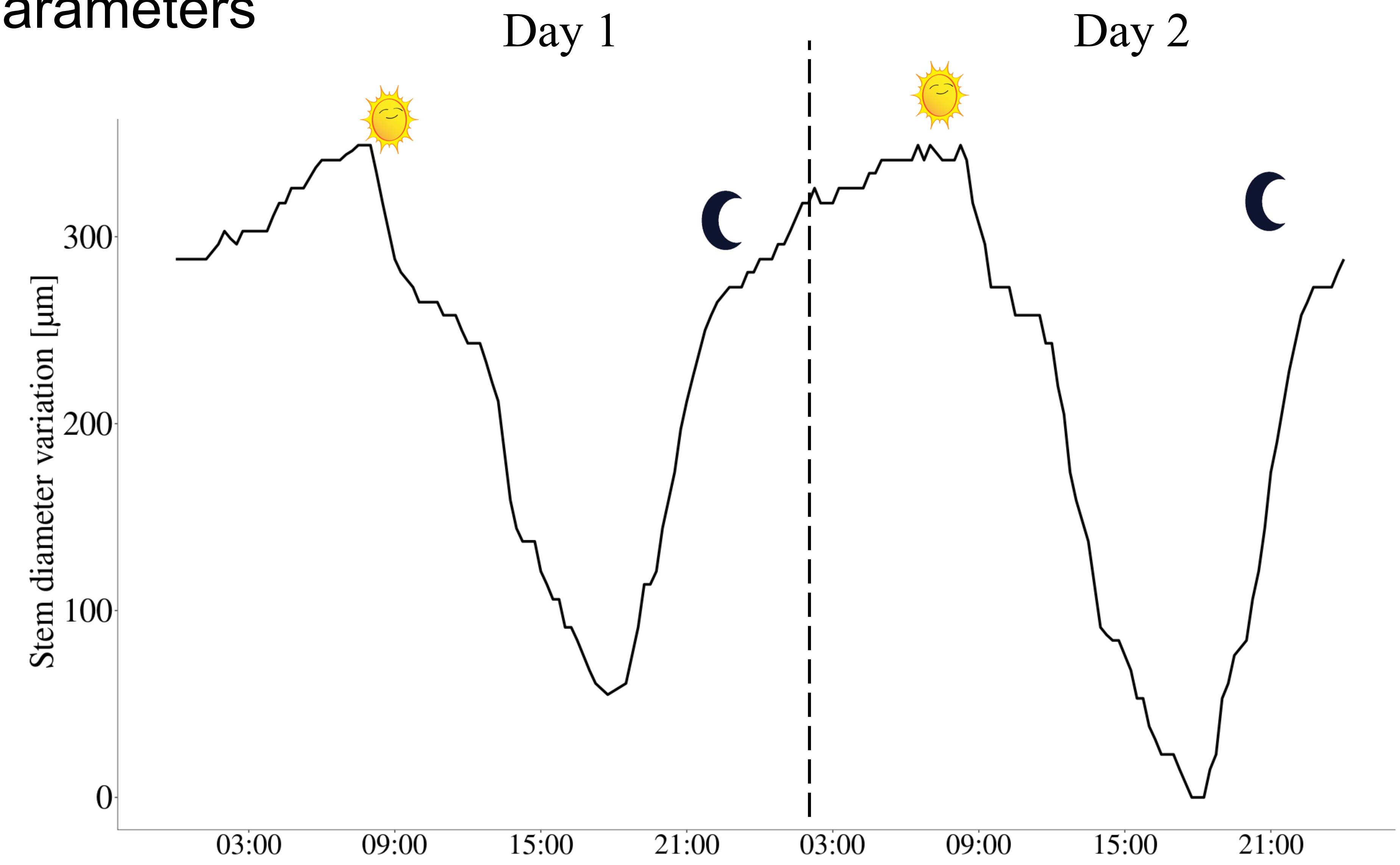
Dendrometer parameters

Apple tree
(11/07/22- 12/07/22)

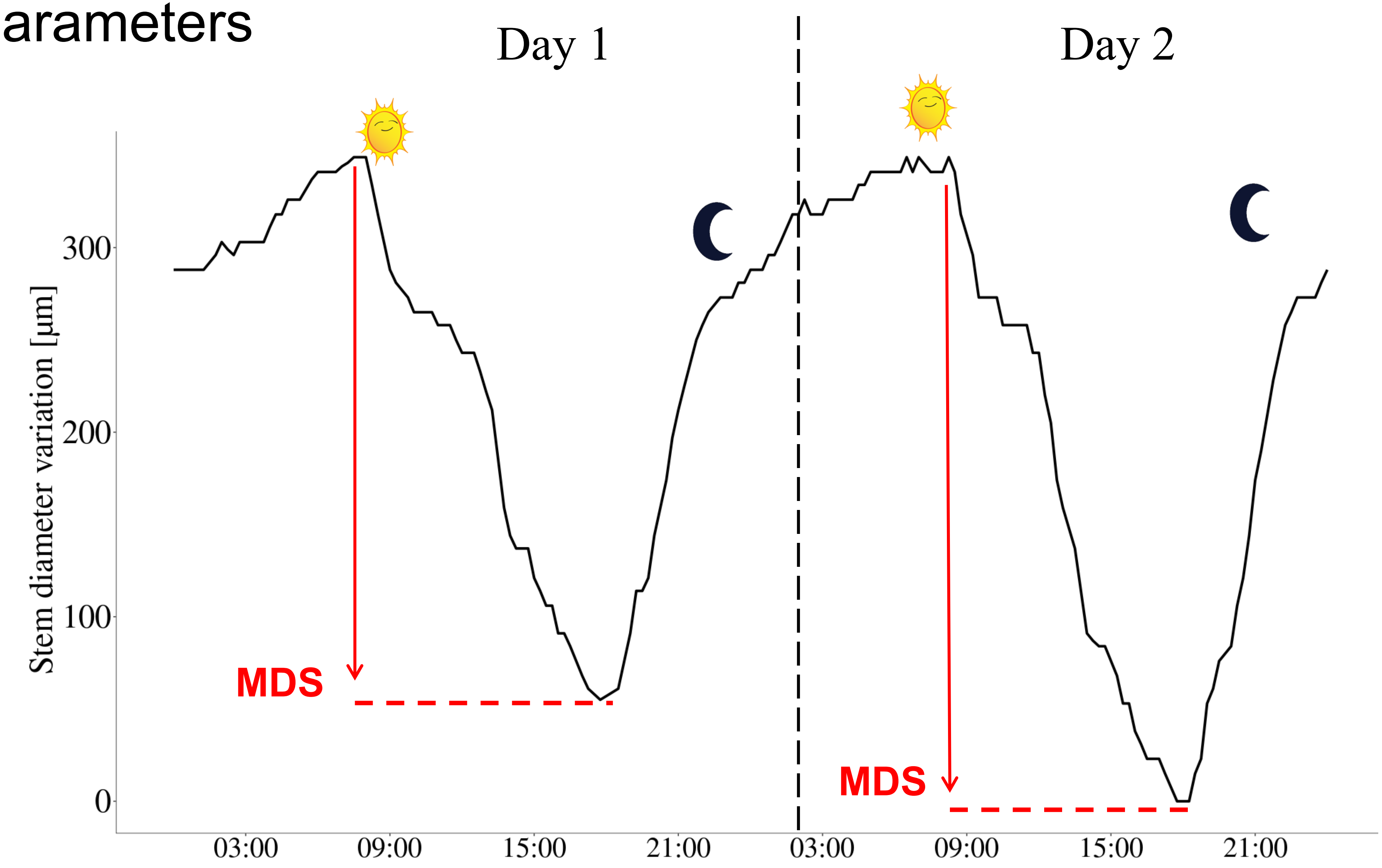
± 05:40 – 06:05 am

± 20:45 - 21:10 pm



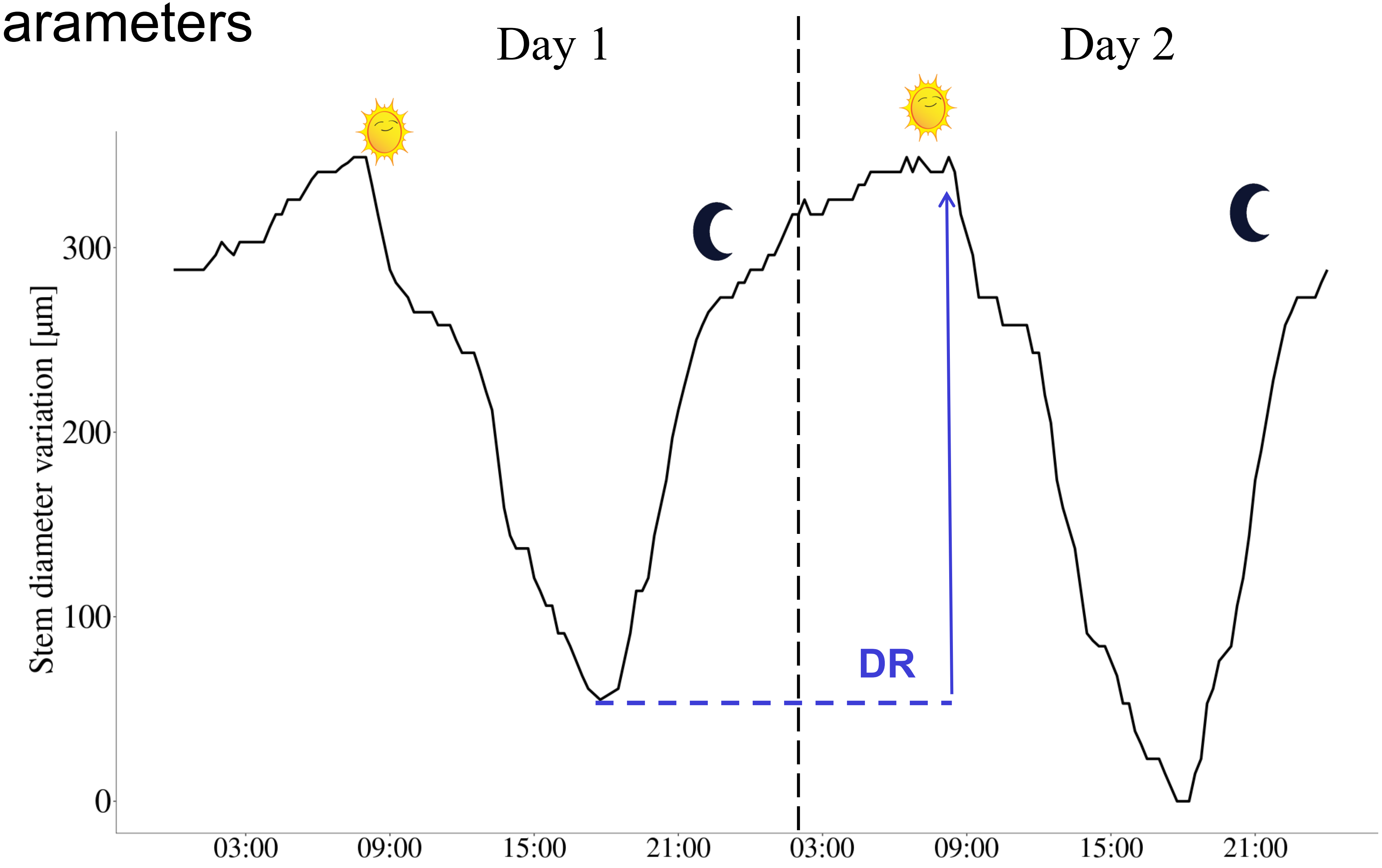
Dendrometer parameters

MDS
Maximum daily shrinkage

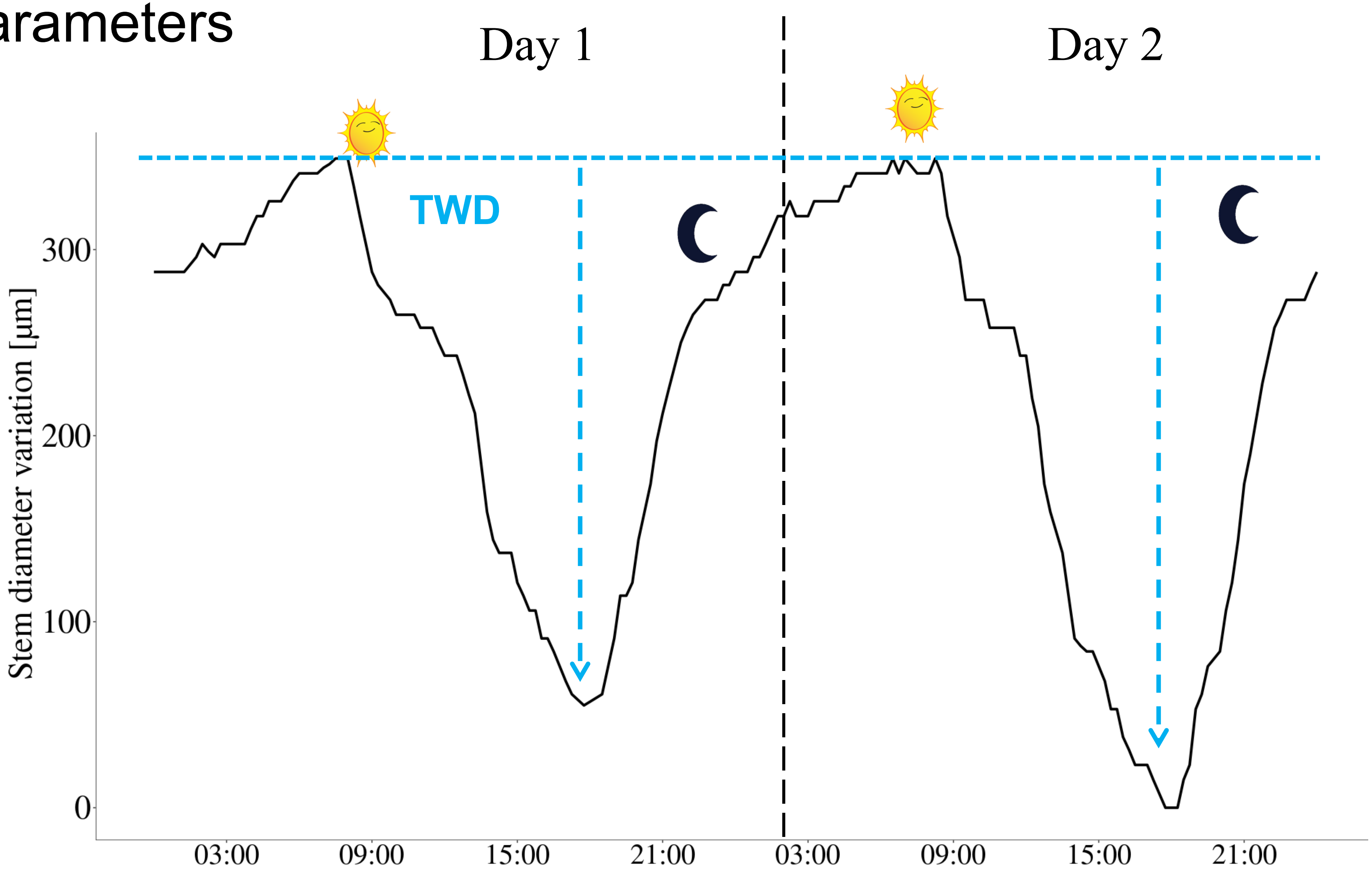


Dendrometer parameters

DR
Daily recovery



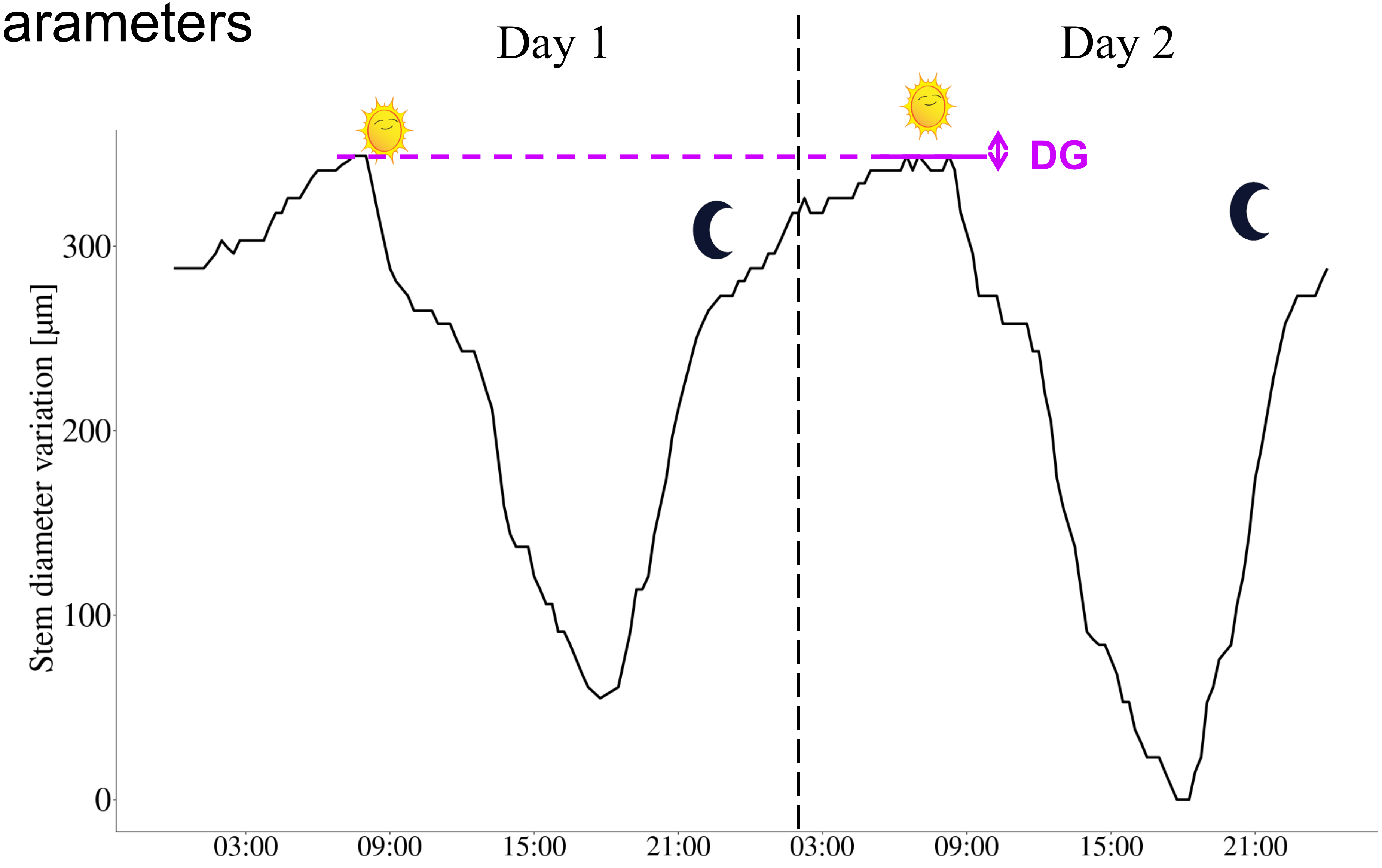
Dendrometer parameters



TWD

Tree water deficit

Dendrometer parameters



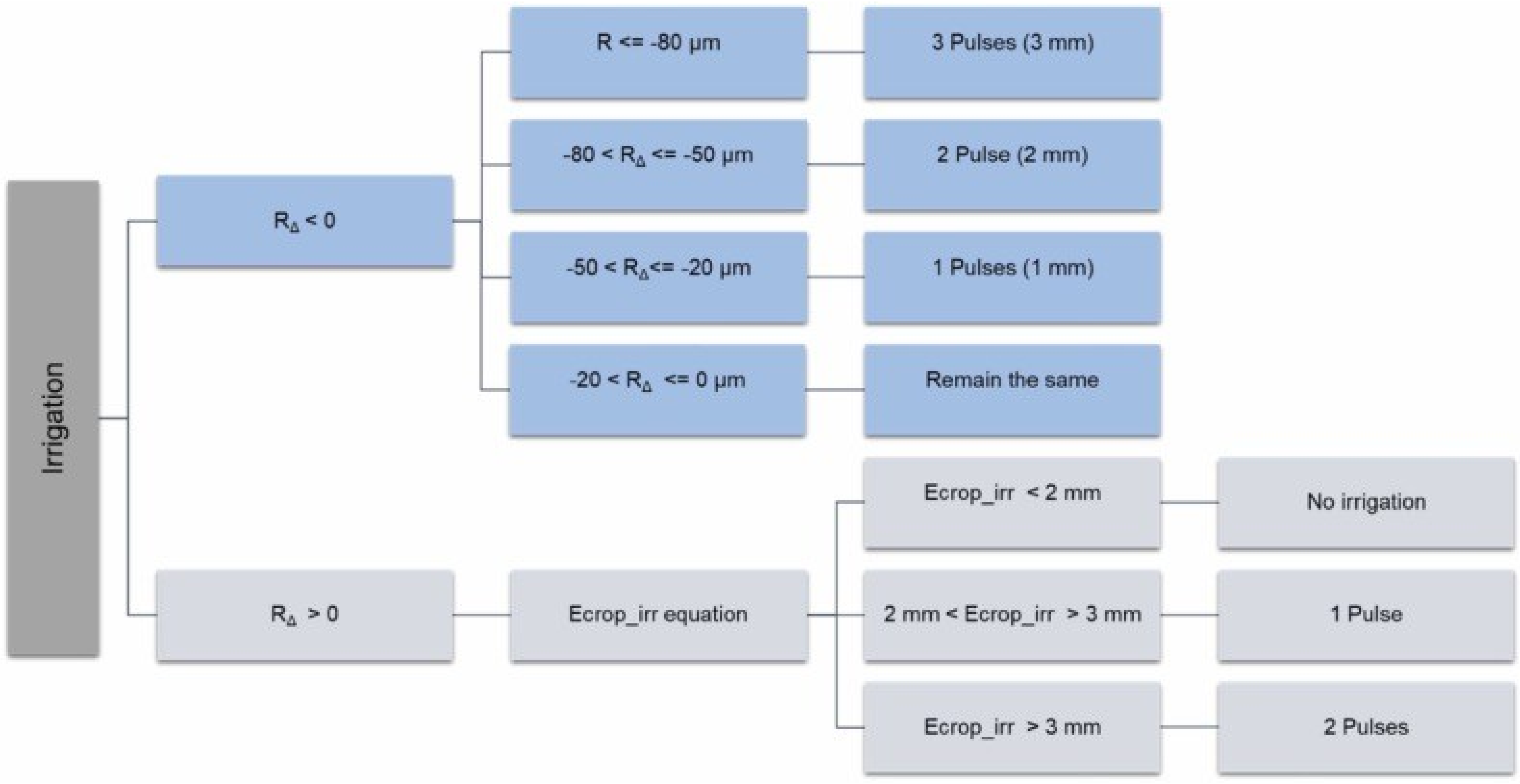
DG

Daily net growth

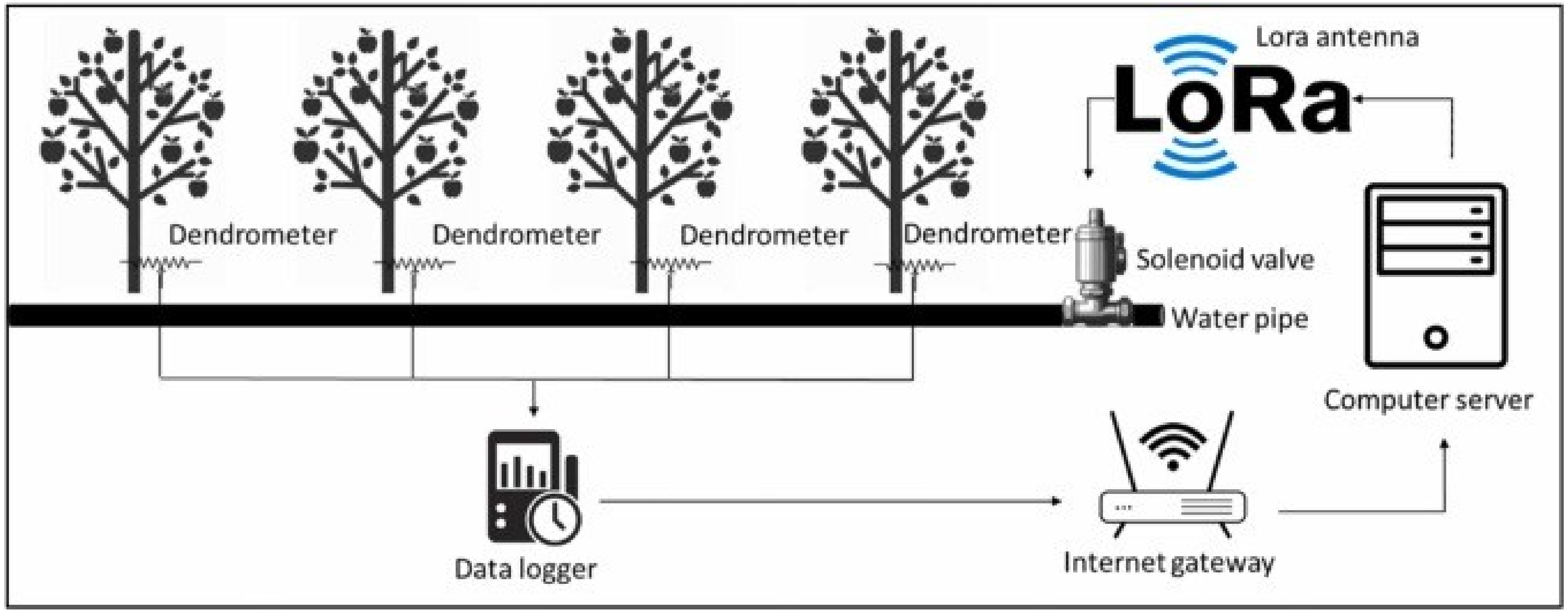
Irrigation decision tree:

DeltaR = DR (current) – DR (Previous)

$$Ecrop\_irr = 1.51 + 0.004 * MDS_{(avg.\quad 7\ days)}$$



IoT System



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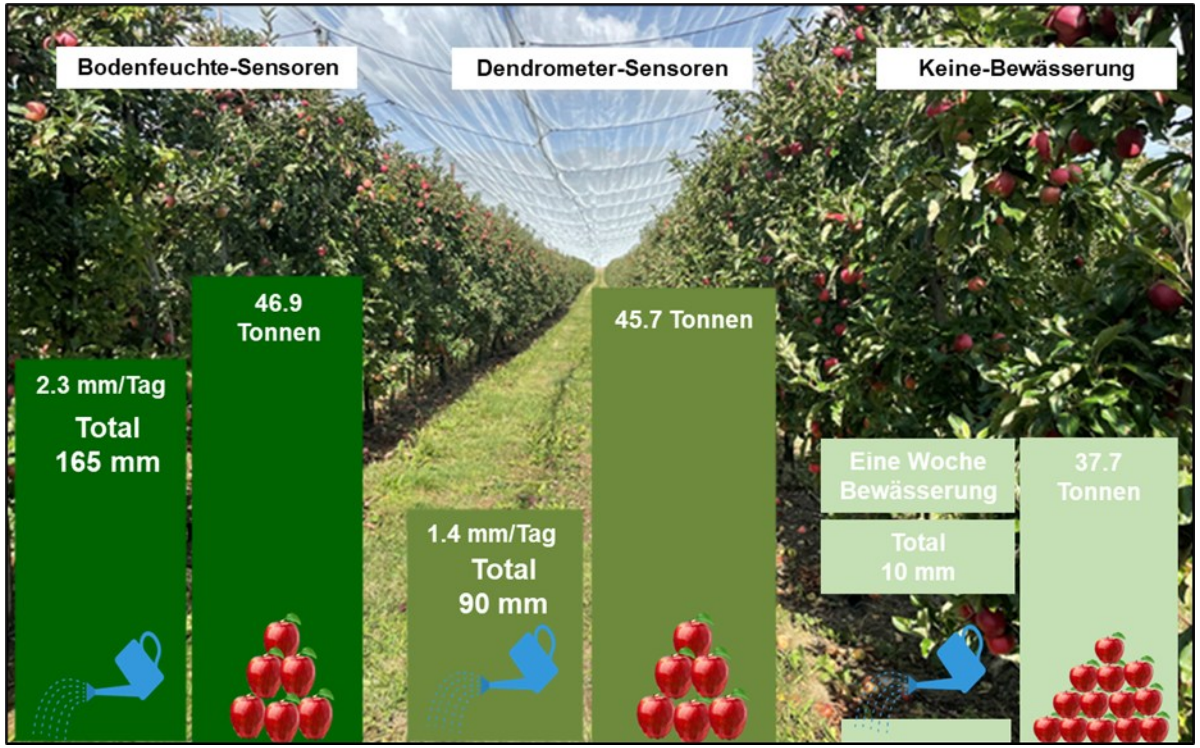
Results from the pilot plant



- Dendrometer: 45% less water consumption
- No difference in fruit size and yield
- Without irrigation: small fruit, low yield, fewer first-class fruits

When will have a self-operating farm?

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Département fédéral de l'économie,
de la formation et de la recherche DEFR
Agroscope

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Eidgenössisches Departement für
Wirtschaft, Bildung und Forschung WBF
Bundesamt für Landwirtschaft BLW

Schweizerische Eidgenossenschaft
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Swiss Confederation

Federal Department of Economic Affairs,
Education and Research EAER
State Secretariat for Education,
Research and Innovation SERI

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Confederazione Svizzera
Confederaziun svizra

Bundesamt für Umwelt BAFU
Office fédéral de l'environnement OFEV
Ufficio federale dell'ambiente UFAM
Uffizi federal d'ambient UFAM

Swiss National Science Foundation

LIBERTÉ ET PATRIE

EPFL

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ETH zürich CROP SCIENCE

Berner Fachhochschule

OST

arenenberg

AG GIS & FERNERKUNDUNG

HUAWEI

fenaco

Sunrise upc

NOSTRADAMUS

SWISS FUTURE FARM

strickhof

World Food System Center

Agroscope Swiss centre of excellence for agricultural research

Thank you for your attention

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Agroscope good food, healthy environment
www.agroscope.admin.ch

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1. Individual Reflection (5 min)

Goal: Problems discovery

Each participant writes down one sustainability related problem they would like to solve with AI-powered precision agriculture.

✅ Tip:

“Which sustainability pain point most affects your organization?“
"Where could data or automation make the biggest impact?"
“How could AI help verify or quantify the environmental impact of agricultural practices?”
“Where does current AI fail to scale or adapt in real agricultural conditions?”
“How could we use drones, sensors, or satellite imagery to track soil or crop health sustainably?”
“Which sustainability problems depend most on better prediction or classification?”
“Where is data missing or underused for making farming more regenerative?”
“Where are the biggest gaps in agricultural data sharing between public and private actors?”

2. Idea Pitches (10–12 min)

- **Goal:** Share ideas.
- Each participant gets 45 seconds to pitch.

✅ Tip:

“What problem do you want to solve → Why it matters → what is the data/AI angle”

Agroscope

3. Dot Voting (5 min or less)

- **Goal:** Identify shared priorities and team formation.
- Each participant gets 2 votes to place on their favorite ideas.
- A vote = empty sticker on the idea line.

✅ Tip:

“Vote for ideas that matter for your institution”

4. Group Work (20 min total)

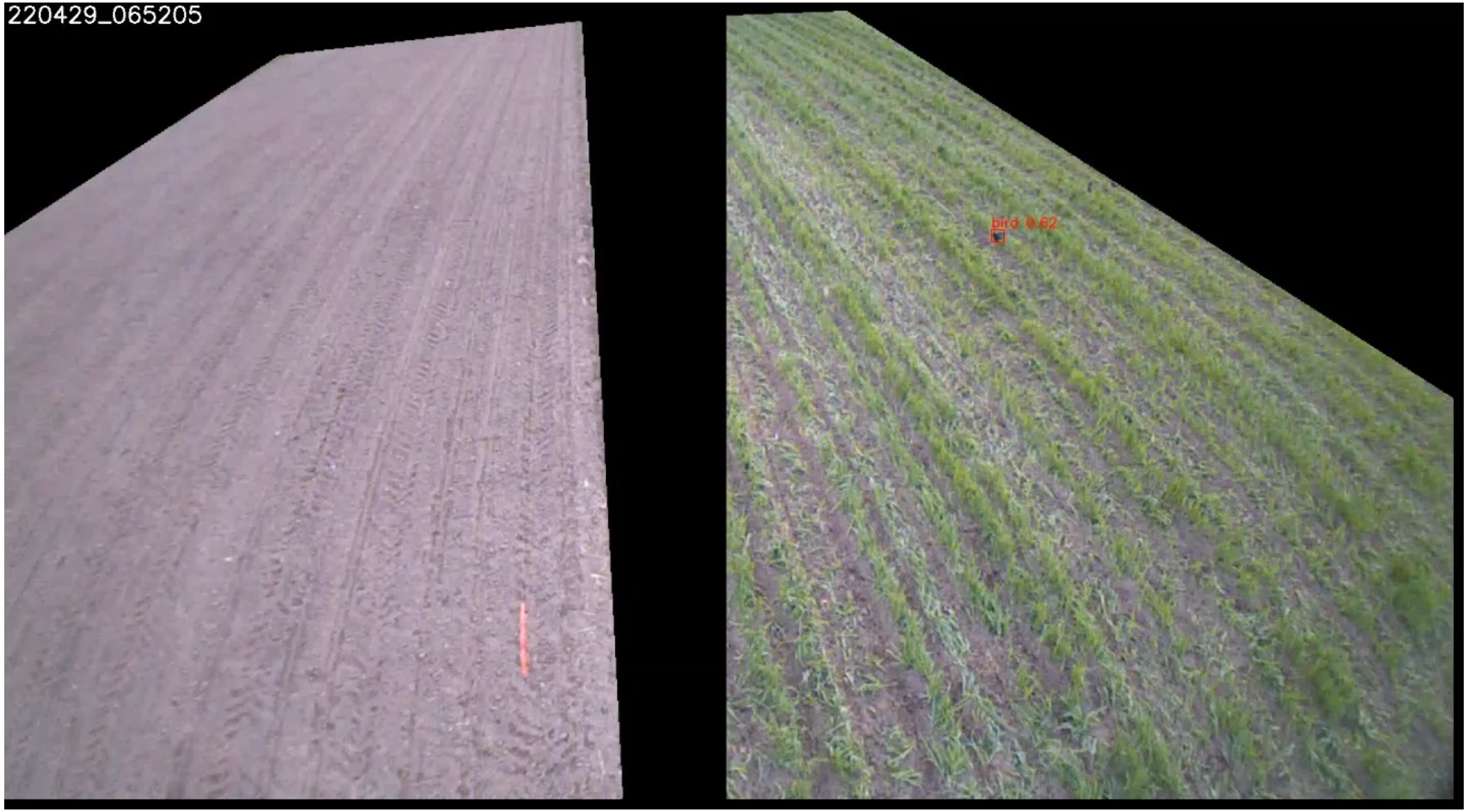
- **Goal:** Co-develop solution sketches around top ideas.

✅ Tip:

- What is the sustainability goal?
- How could AI or data help?
- What barriers exist (data, cost, adoption, policy)?
- What would success look like?
- Who can be involved?

5. Presentations (10–12 min)

- Each group gives a short 2-min pitch of their idea/solution.
- Synthesis of ideas:
  - You can post-work collaboratively on your idea ➔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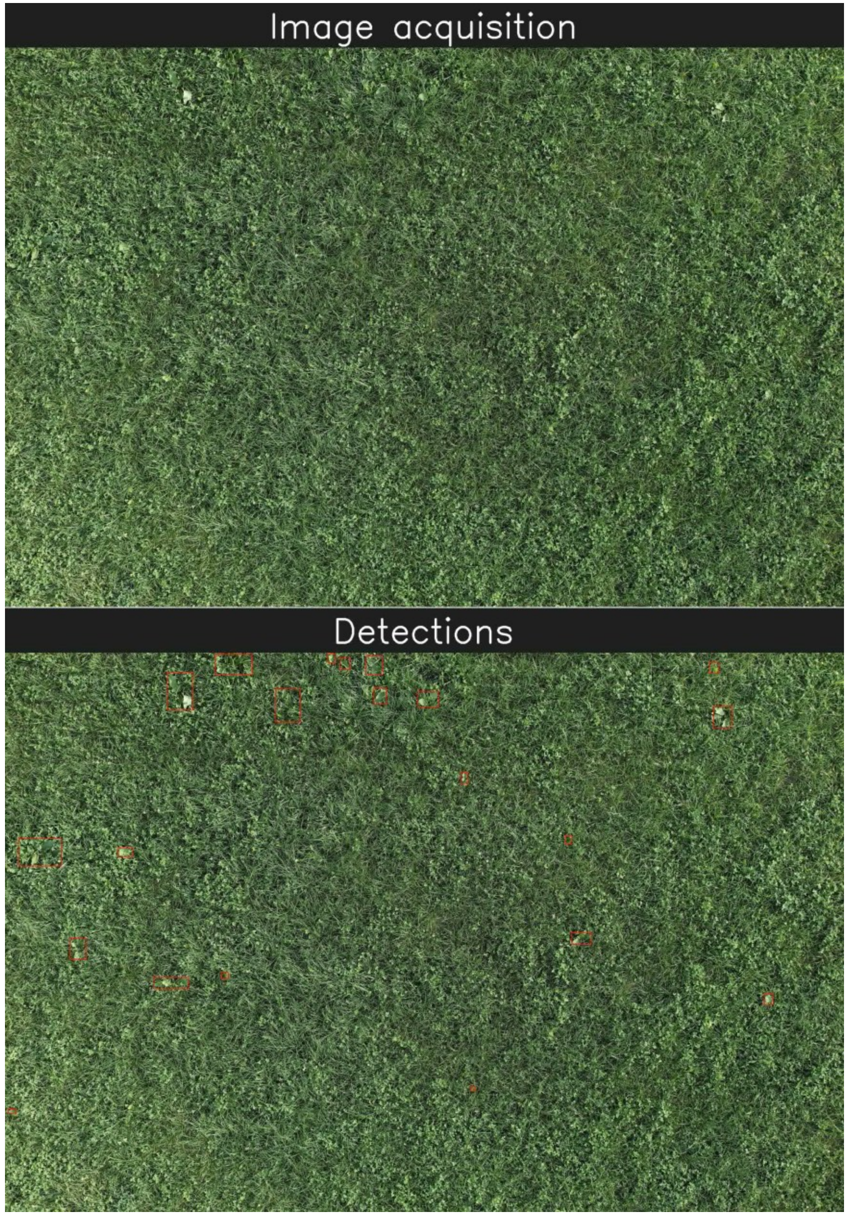
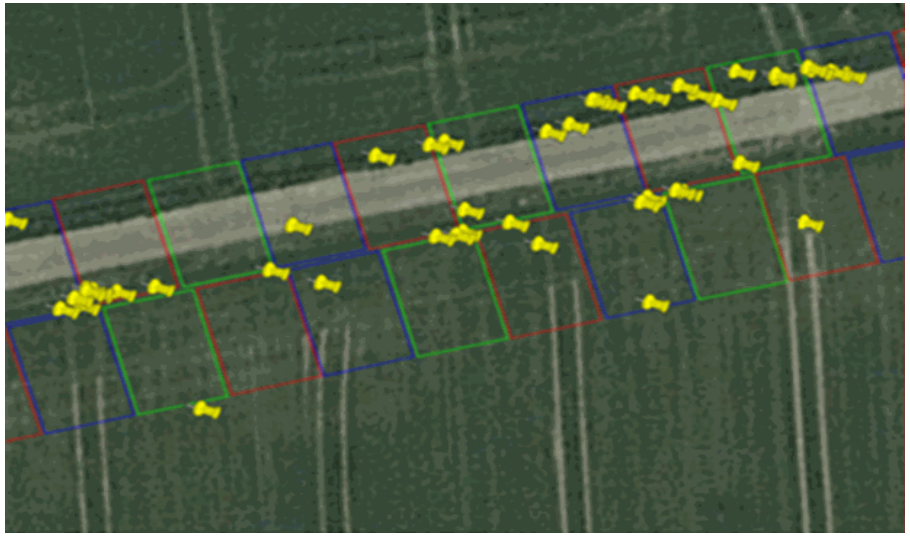
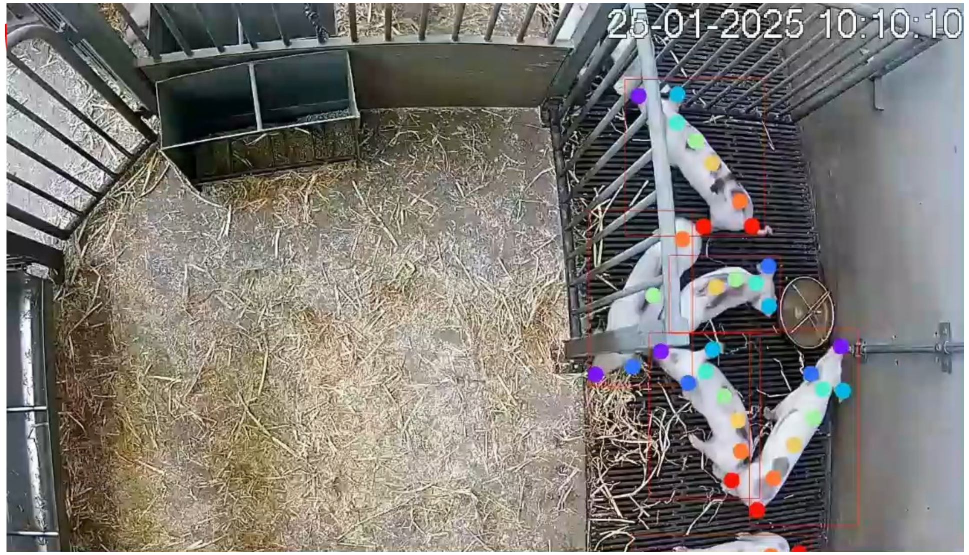
bird 0.62

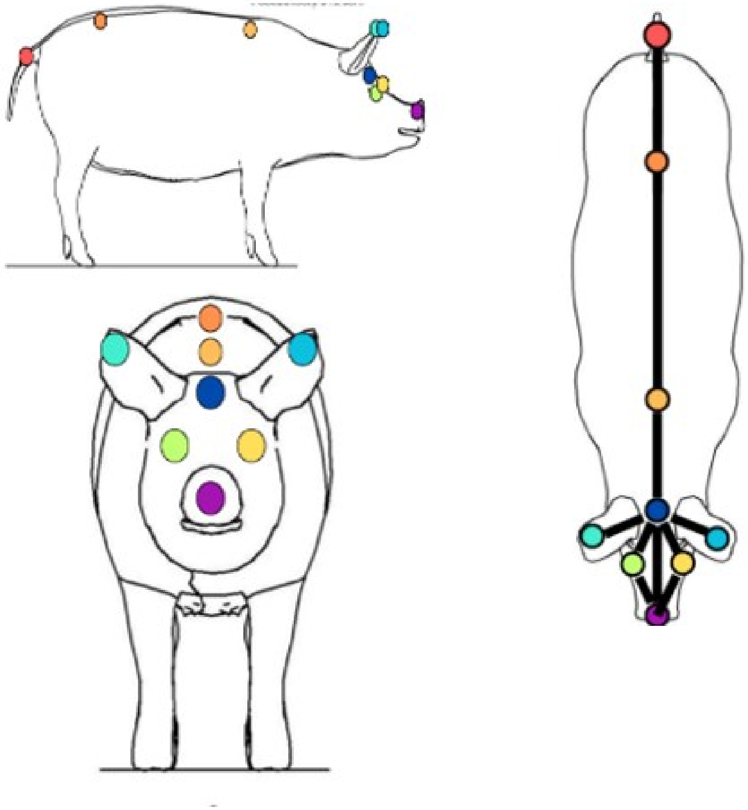


Innosuisse Project with Fenaco and OST



Challenges and future directions





Can we breed better pigs with AI?

First projects and future steps.

Computer Vision with Deep Learning

- Using artificial neural networks to automatically analyze and understand images or videos, e.g., **classification**, object detection, segmentation or key points detection.

Pig 1

Pig 2

Pig 3

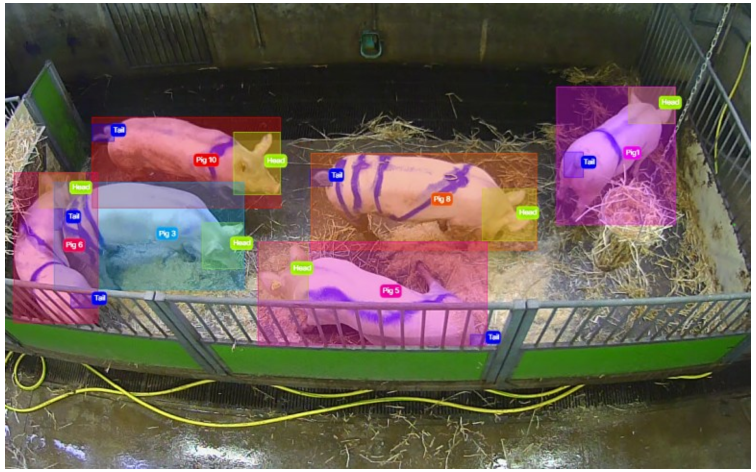
Pig 4

Classification ➔

Determine the class of the image. In this case, the pig ID.

Computer Vision with Deep Learning

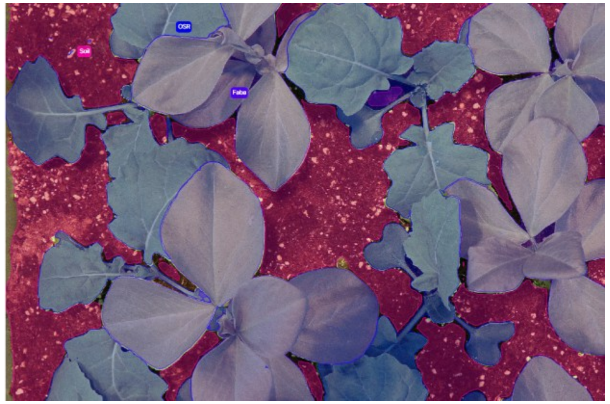
- Using artificial neural networks to automatically analyze and understand images or videos, e.g., classification, **object detection**, segmentation or key points detection.



Object Detection ➔
determine the class and positions of objects in an image. Pig IDs, birds, weeds, …

Computer Vision with Deep Learning

- Using artificial neural networks to automatically analyze and understand images or videos, e.g., classification, object detection, segmentation or key points detection.



Segmentation➔

determine the class of each pixels / masks for objects. Soil, plants, …

Computer Vision with Deep Learning

- Using artificial neural networks to automatically analyze and understand images or videos, e.g., classification, object detection, segmentation or key **points detection**.

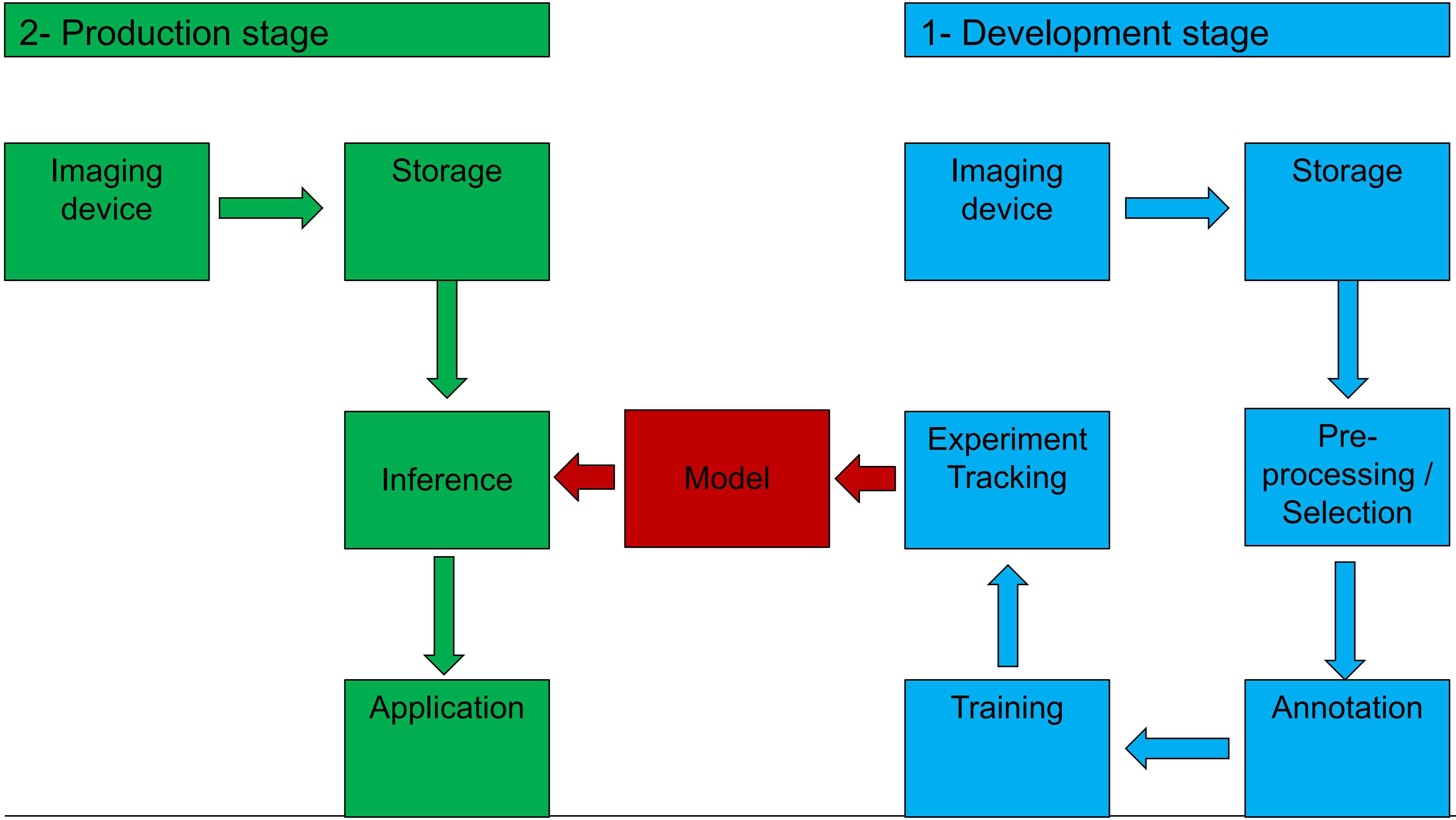
Key points detection➔

Determine point-positions for specific landmarks.
Pig nose, pigs ears, pig tail, joints, …

What can we do with all these models?

- Pigs: studies on behavior (Aggression, social, …) …
- Birds: Detecting presence to design deterrence systems …
- Rumex: map with Rumex positions for farmers (or weeding robots) …
- Automation, Scalability, Standardization, …

How do we do it?



1- Development stage

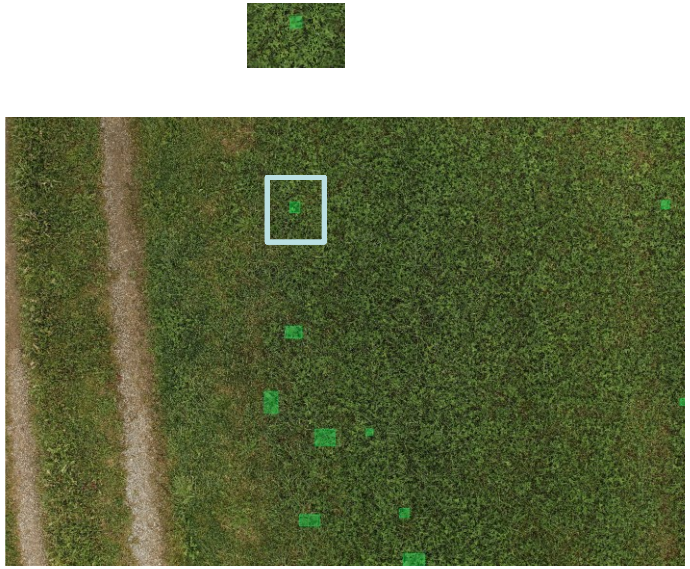
Preprocessing:

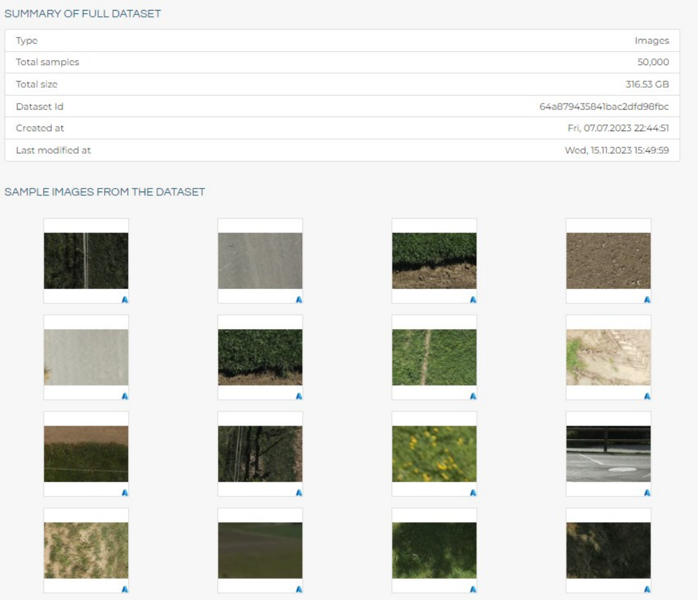
- Splitting a video into frames.
- Cropping images to the region of interest.
- Tiling drone images.

Imaging device

Storage

Pre-processing / Selection

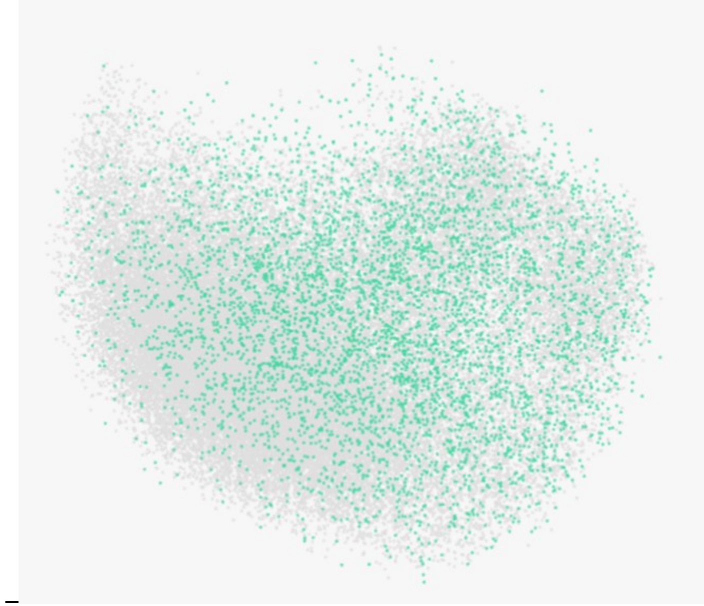




SUMMARY OF FULL DATASET

Type	Images
Total samples	50,000
Total size	316.53 GB
Dataset Id	64a879435841bac2dfd98fbc
Created at	Fri, 07.07.2023 22:44:51
Last modified at	Wed, 15.11.2023 15:49:59

SAMPLE IMAGES FROM THE DATASET



1- Development stage

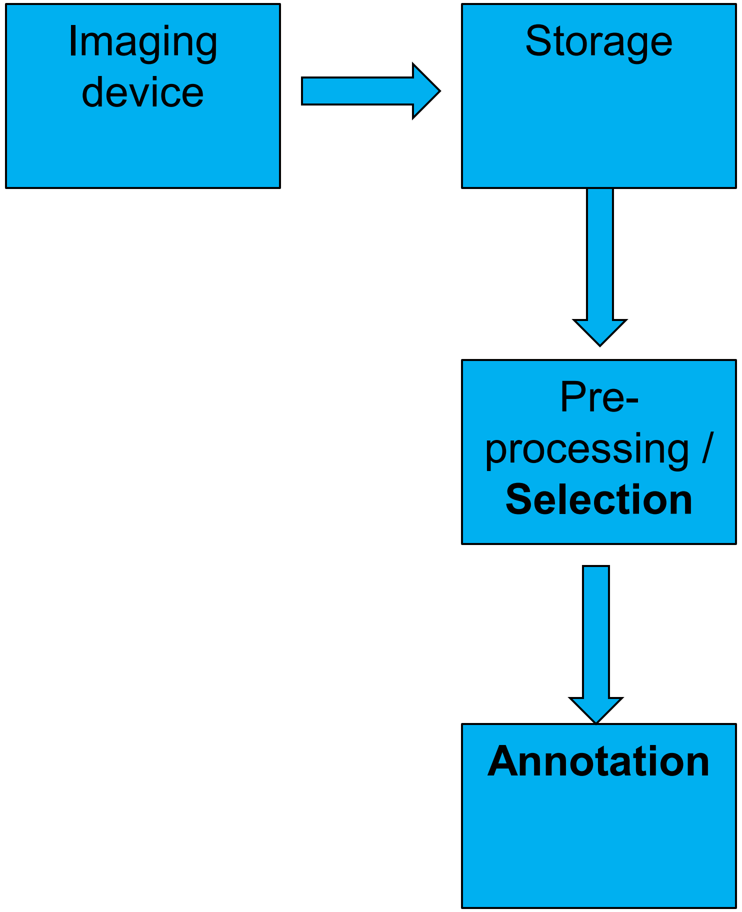
Imaging device → Storage → Pre-processing / **Selection** → Annotation

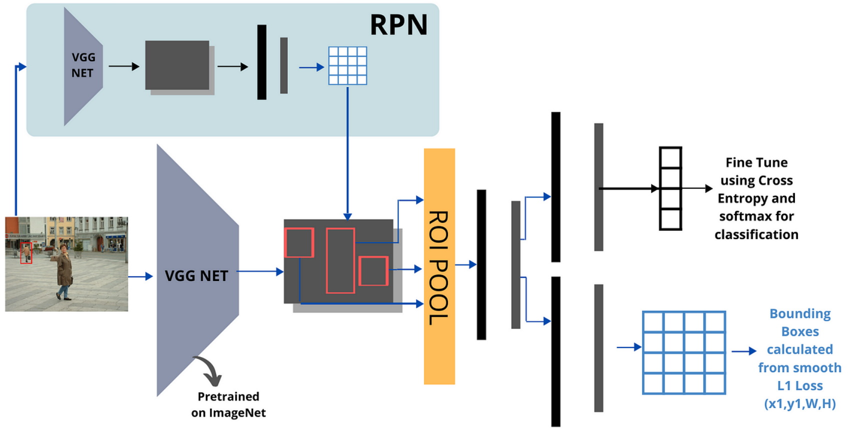
1- Development stage

Masks

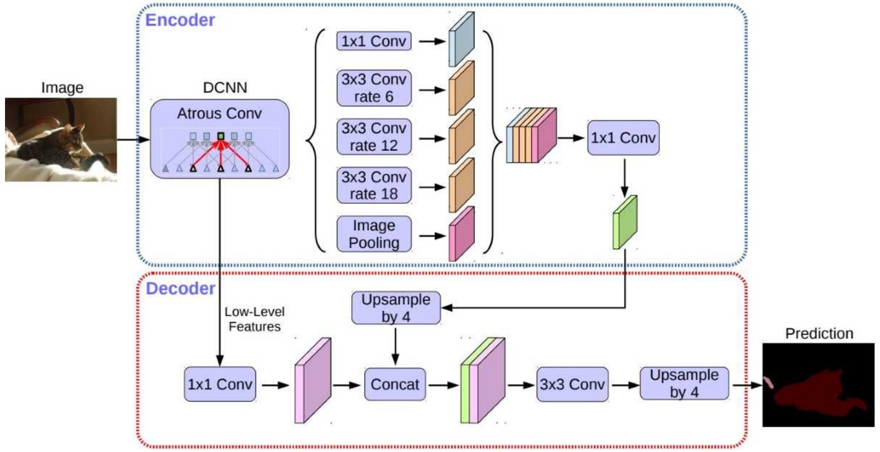
Bounding boxes

Key points





FasteRCNN, Object detection

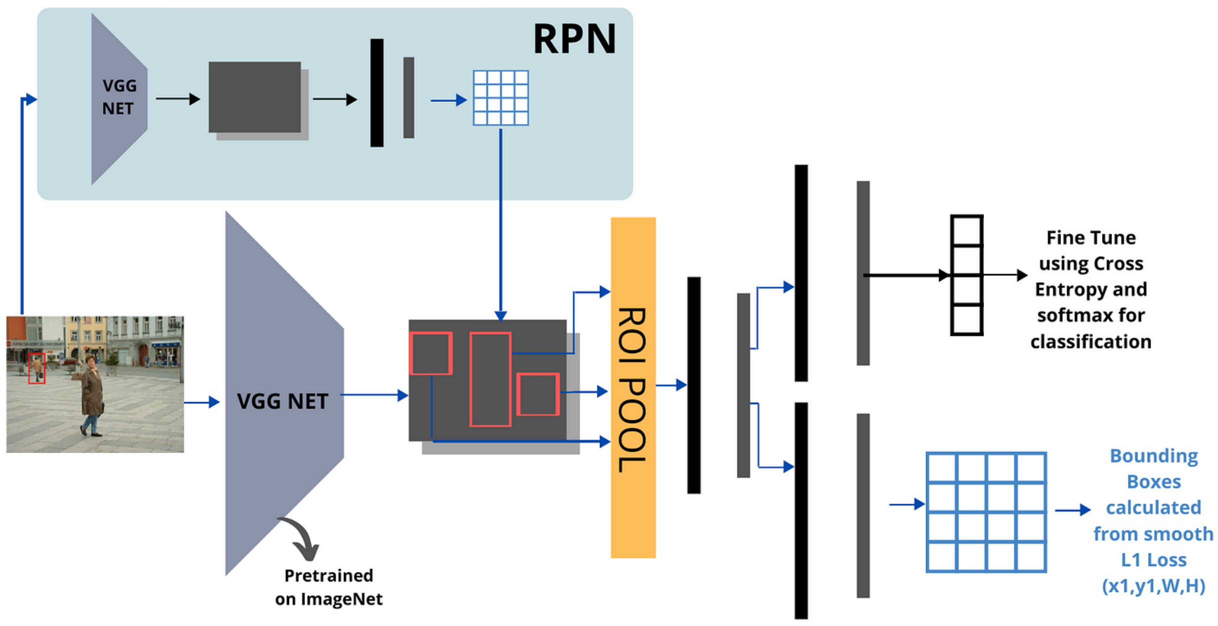


DeepLabV3, Mask segmentation

1- Development stage

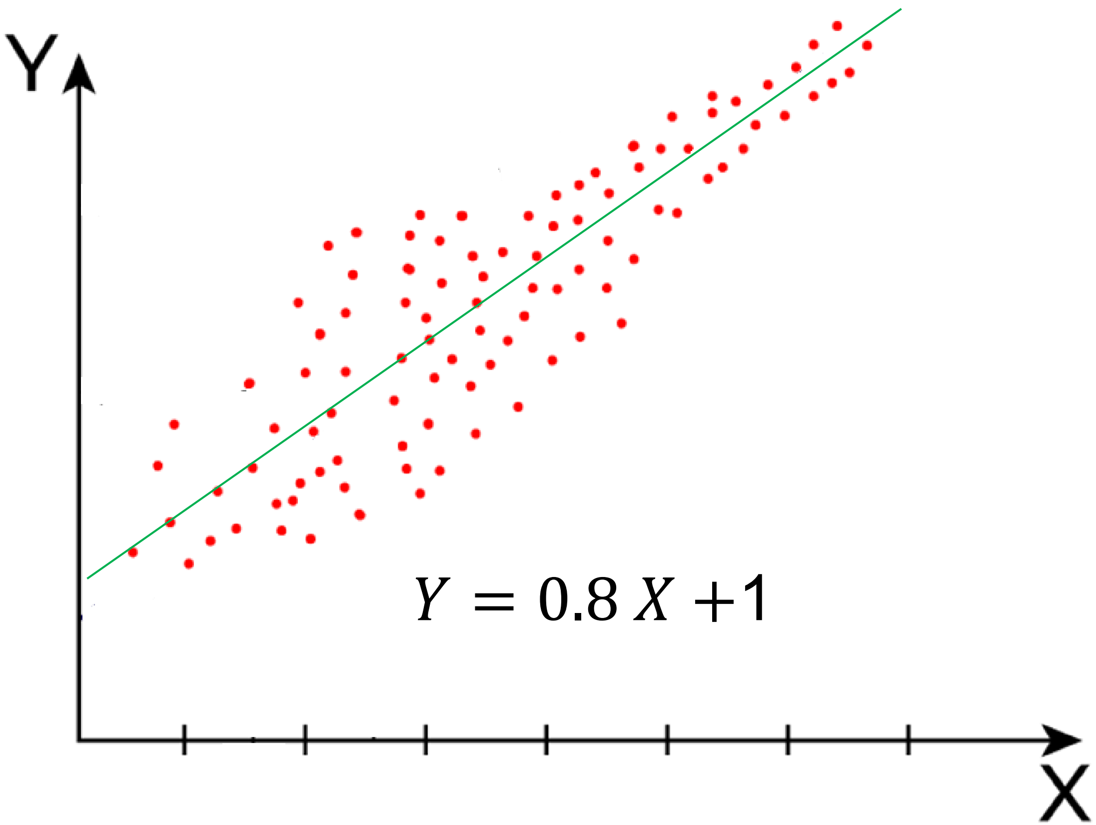
Imaging device → Storage → Pre-processing / Selection → Annotation → **Training**

Object Detection Model



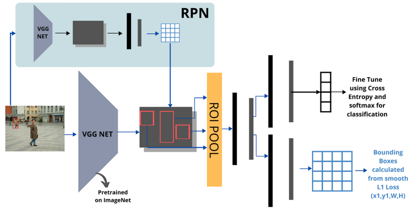
How many parameters do you think such model can have?

Linear model

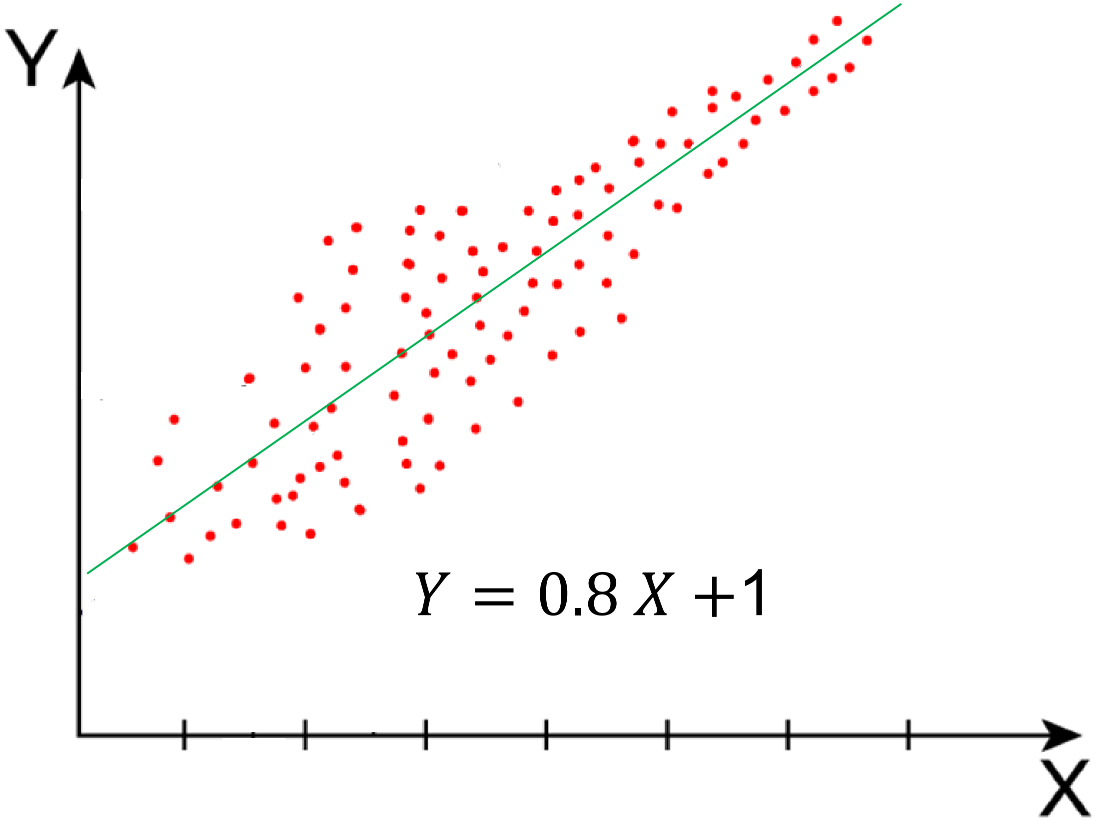


Object Detection Model

Model Variant	Parameters (M)
YOLOv8n (nano)	~3.2 M
YOLOv8s (small)	~11.2 M
YOLOv8m (medium)	~25.9 M
YOLOv8l (large)	~43.7 M
YOLOv8x (xlarge)	~68.2 M
Faster R-CNN (R50-FPN)	~41 M
Faster R-CNN (R101-FPN)	~60–63 M
Faster R-CNN (ResNeXt / Swin)	80M+

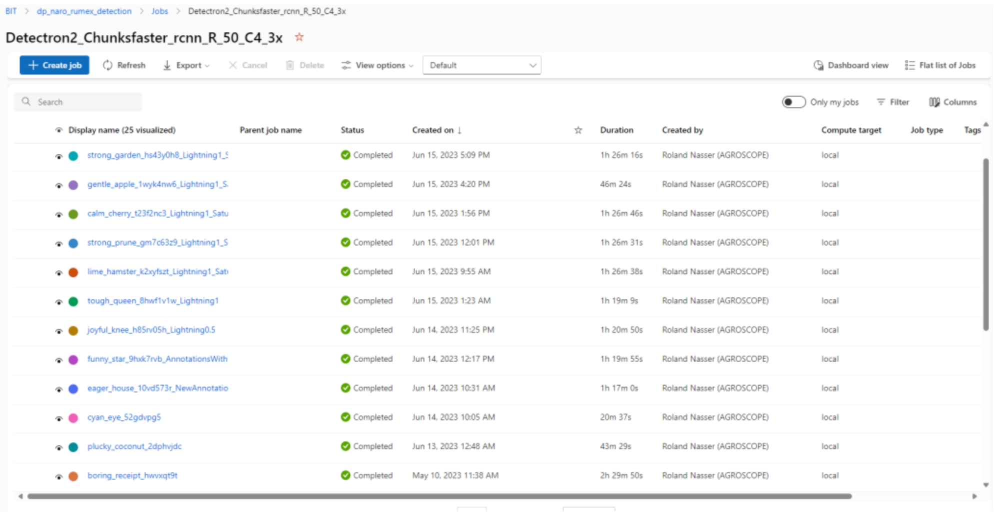


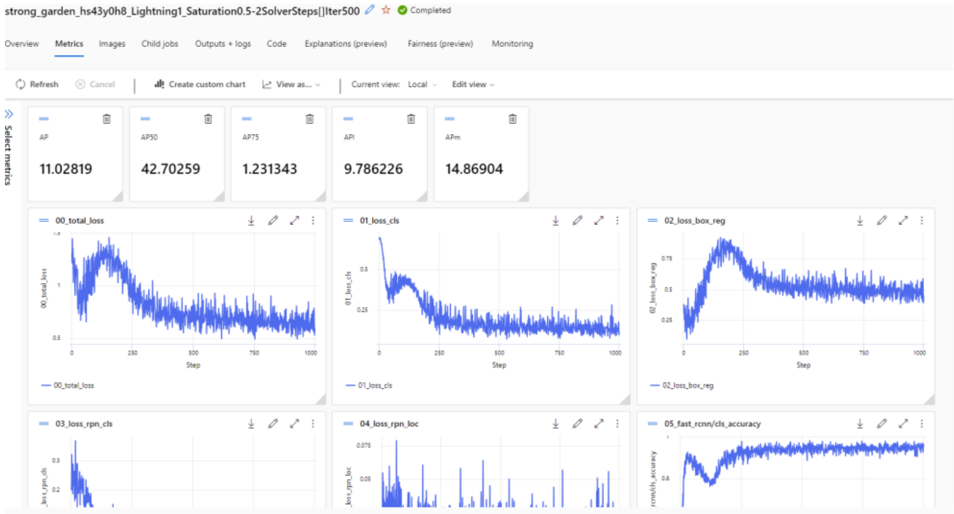
Linear model



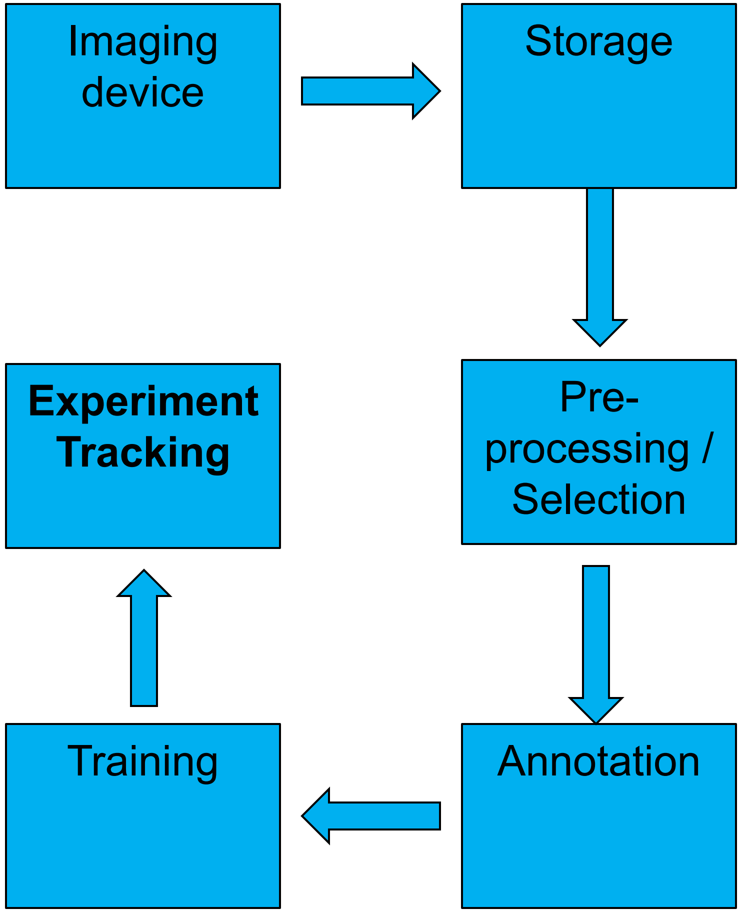
$$Y = 0.8\,X + 1$$

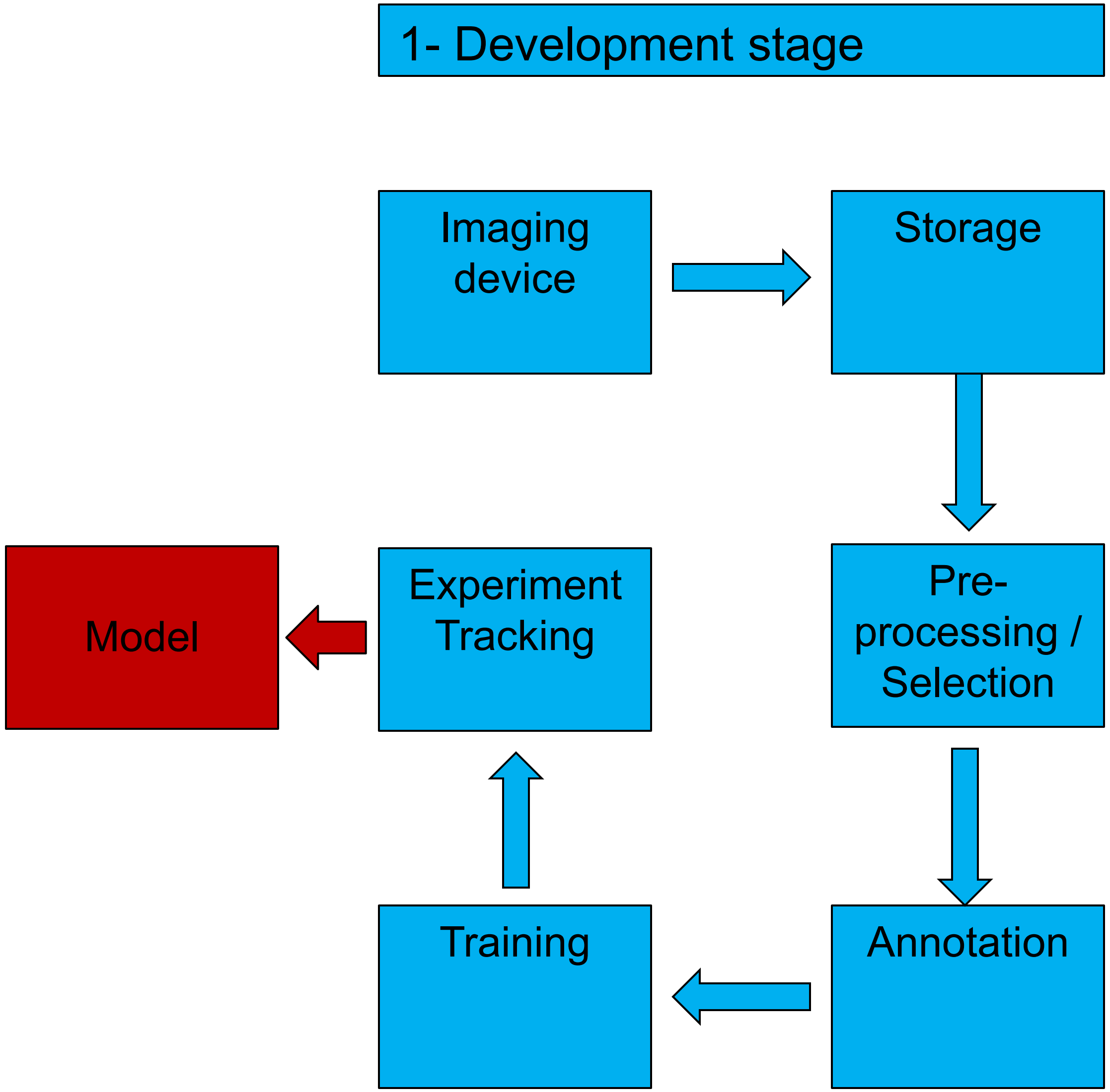
Agroscope



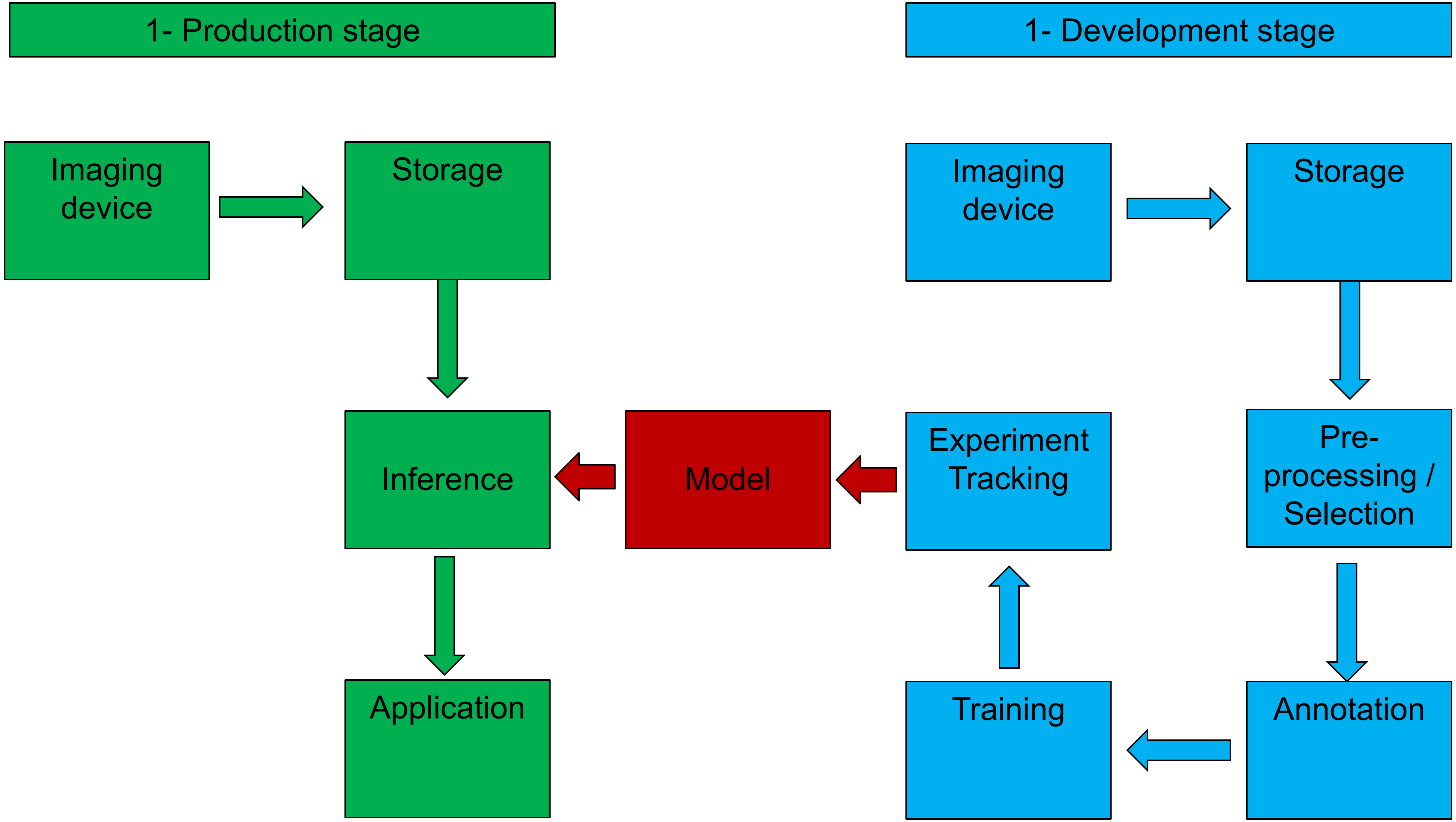


1- Development stage

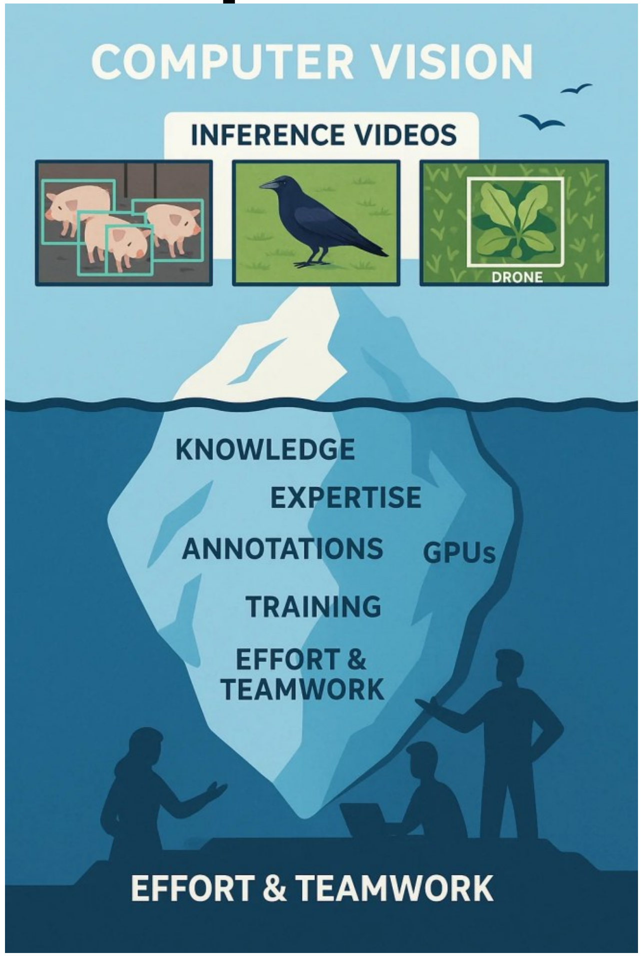



1- Development stage
Imaging device
Storage
Pre-processing / Selection
Annotation
Training
Experiment Tracking
Model

Agroscope


1- Production stage
1- Development stage
Imaging device
Storage
Imaging device
Storage
Inference
Model
Experiment Tracking
Pre-processing / Selection
Application
Training
Annotation

Ressources needed for a computer vision powered product

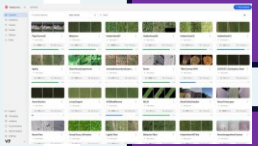


Skills and HR

- Computer vision
- Programming

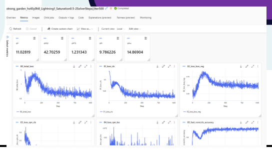
IT Infrastructure

- Compute GPUs
- Storage



Specific Tools

- Annotation tools
- Experiment Tracking



Agroscope

Questions