rom Data to Decisions: Algorithms, Machine Learning and I in Modern Agriculture

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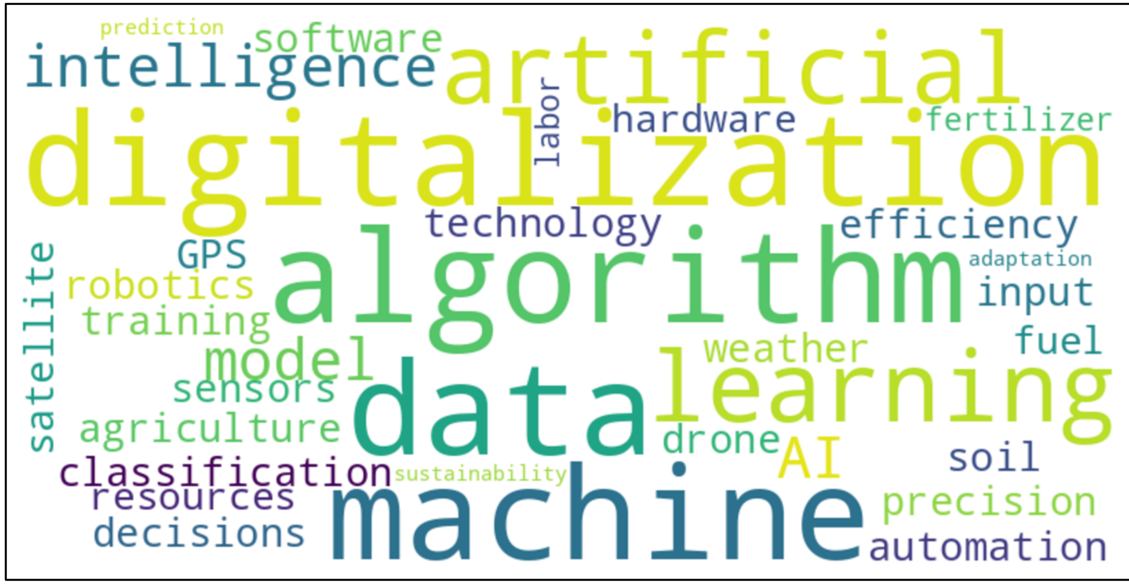
rom data to decisions – AI in modern agriculture

oal: Understand how algorithms, machine learning, and AI turn raw data into
eful decisions

- What are algorithms, ML and AI?
- Applications in agriculture
- Why is data quality so important?
- Benefits, risks, and future outlook
- Discussion



hat does “Digitalisation” in agriculture mean?

Mechanization (1900)

- Introduction of the tractor
- Increase in work efficiency
- Labour-intensive systems
- Relatively low productivity

Green Revolution (1950)

- New agronomic practices
- Use of inputs (mineral fertilizers and PPPs)
- Improved sowing quality
- Yield increase

Precision Farming (1990)

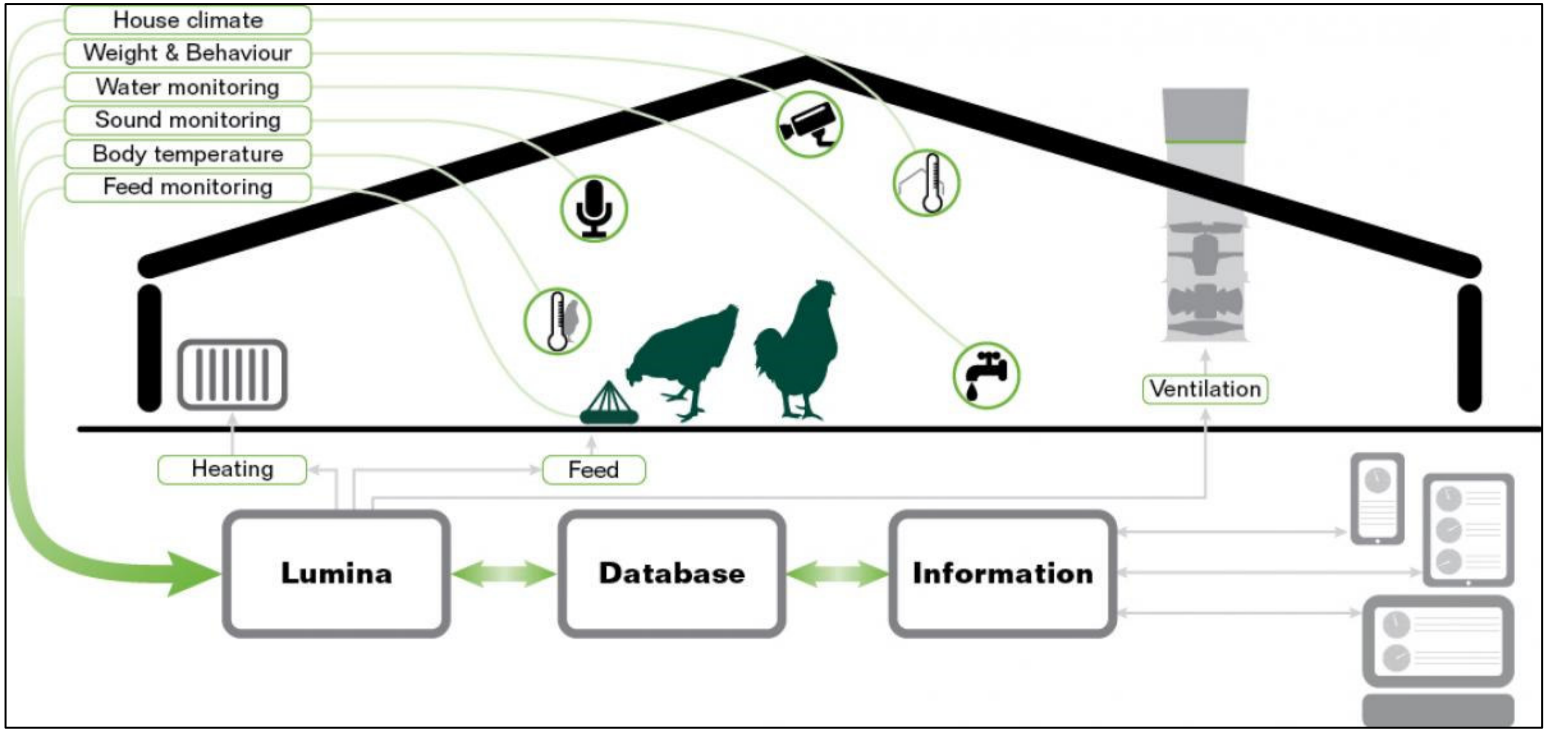
- GNSS (Global Navigation Satellite System)
- Steering systems
- Yield mapping
- Variable Rate Application (already in English)
- Telemetry
- Data management

Smart Farming (2010)

- IoT/Sensors
- Robotics/Automation
- Drones
- Artificial Intelligence
- Data processing

/hat does “Digitalisation” in agriculture mean?

se of digital technologies to collect, process and use data



https://www.fancom.com/blog/precision-livestock-farming

Goal: More precise decisions

Reduced use of resources such as fertilizers, fuel, and labor …

/hat is an Algorithm?

Definition: A step-by-step set of rules to solve a problem

Not always “intelligent” – just fixed logic

vo main types:

Mechanistic (rule-based): based on known equations (e.g. biology, physics)
Example: ModVege – simulates plant growth using temperature, light, etc.

Data-driven: learns patterns from data→ Leads to Machine Learning (more on that next)

/hat is an Algorithm?

Mechanistic example (Jouven et al. (2006))

$$GRO = PGRO \cdot ENV \cdot SEA$$

$$PGRO = PAR_i \cdot RUE_{max} \cdot (1 - e^{-0.6 \cdot LAI}) \cdot 10$$

AR_i: Incident photosynthetically active radiation $[MJ\ m^{-2}]$
JE_{max}: Maximum radiation use efficiency $[3\ \mathrm{g\ DM}\ MJ^{-1}]$ (Schapendonk et al., 1998)
I: Leaf area index

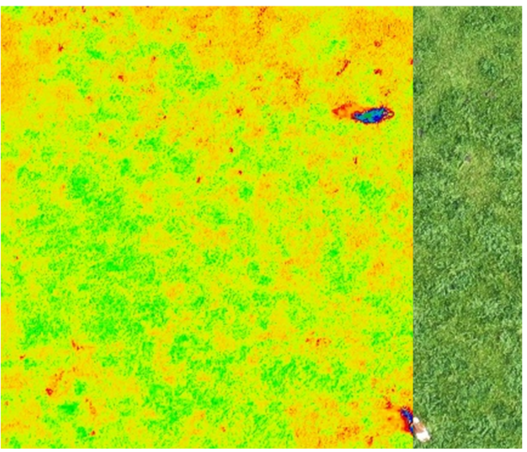
hat is an Algorithm?

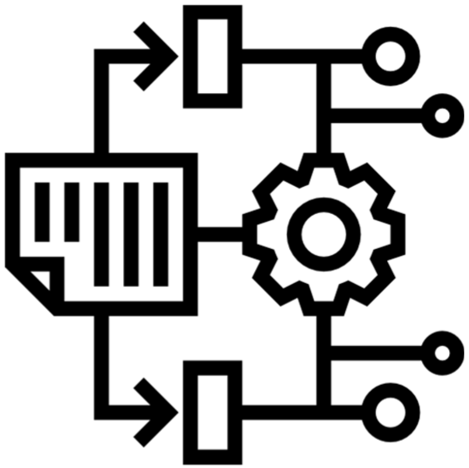
hat is Machine Learning?

- **Data driven example** (estiGrass3D+, Aebischer et al. (2024))

don't follow pre-written equations, but instead learns from data

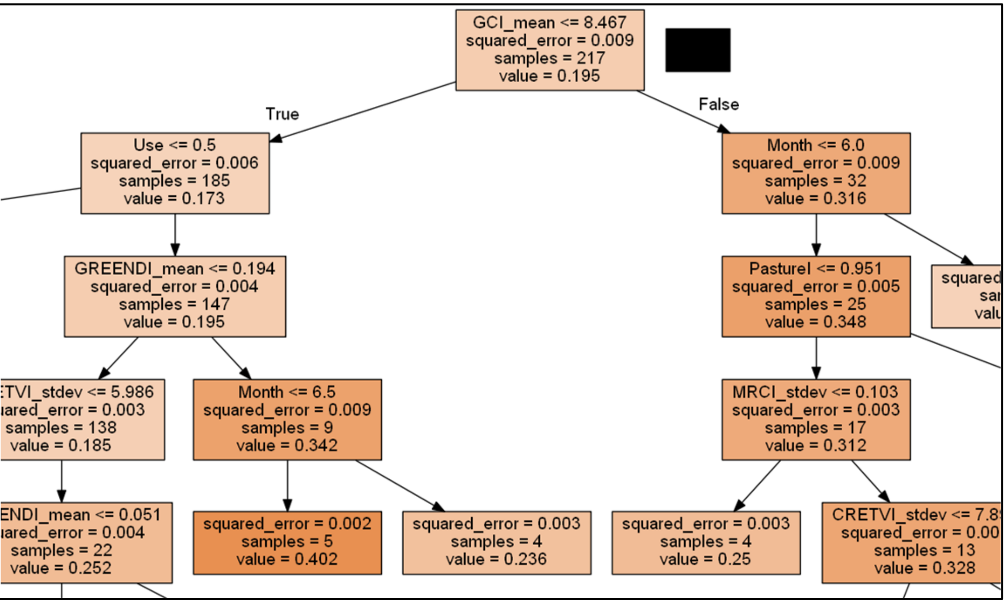
egetation indices





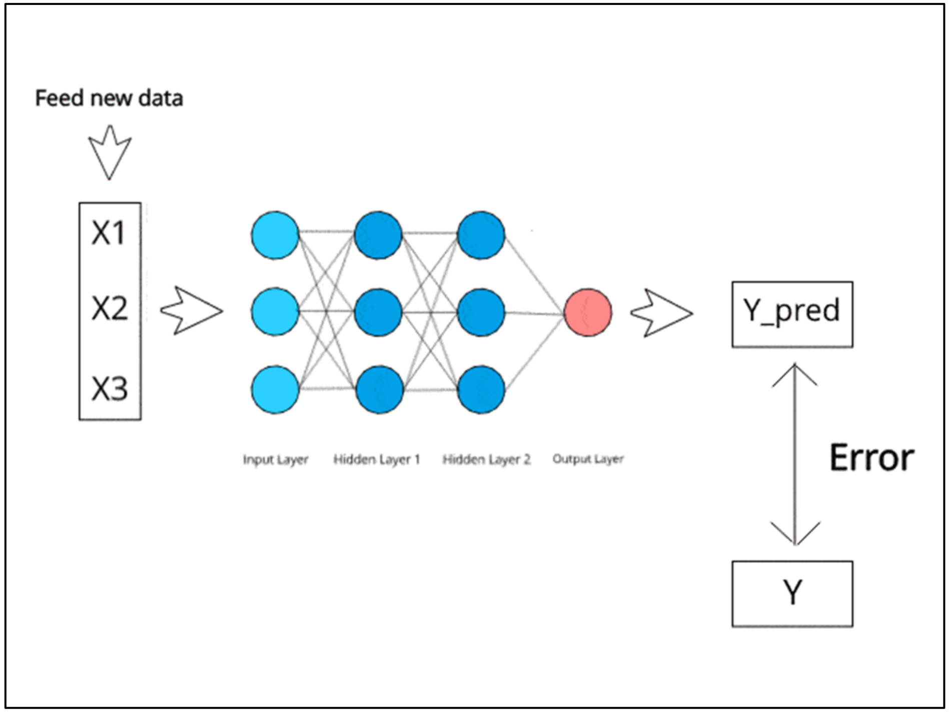
Regression	**Classifca**
200 kg DM/ha	healthy
3200 kg DM/ha	unhealthy

/hat is Machine Learning?



Random Forest

Neural Network



https://medium.com/deep-learning-demystified/introduction-to-neural-networks-part-2-c261a99f4

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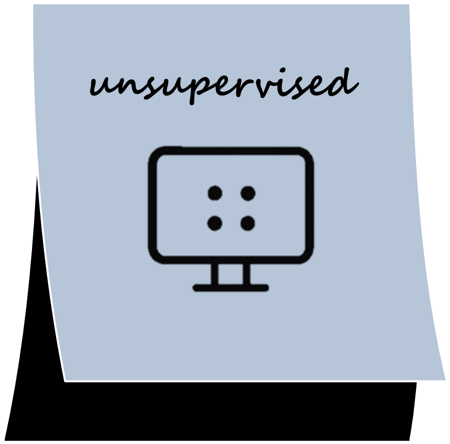
wo types of Machine Learning (ML)

ervised Learning
rn with teacher (estiGrass3d+)

Unsupervised Learning
Find hidden patterns

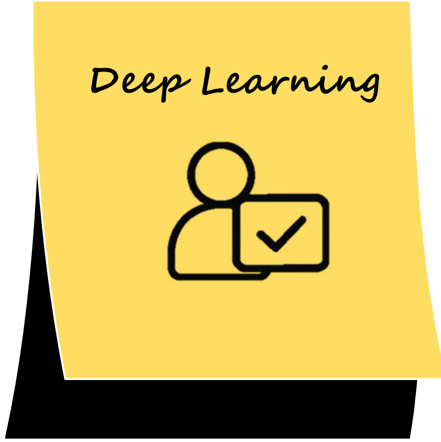


upervised ML

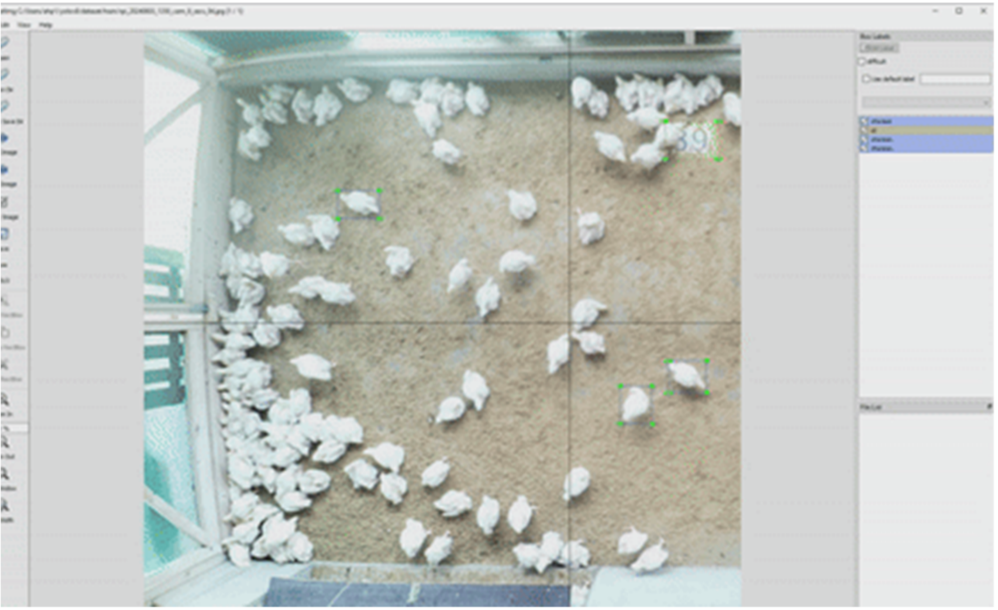
ubsets:

eural networks (**Deep Learning**),
andom forest, …

xample: Object detection

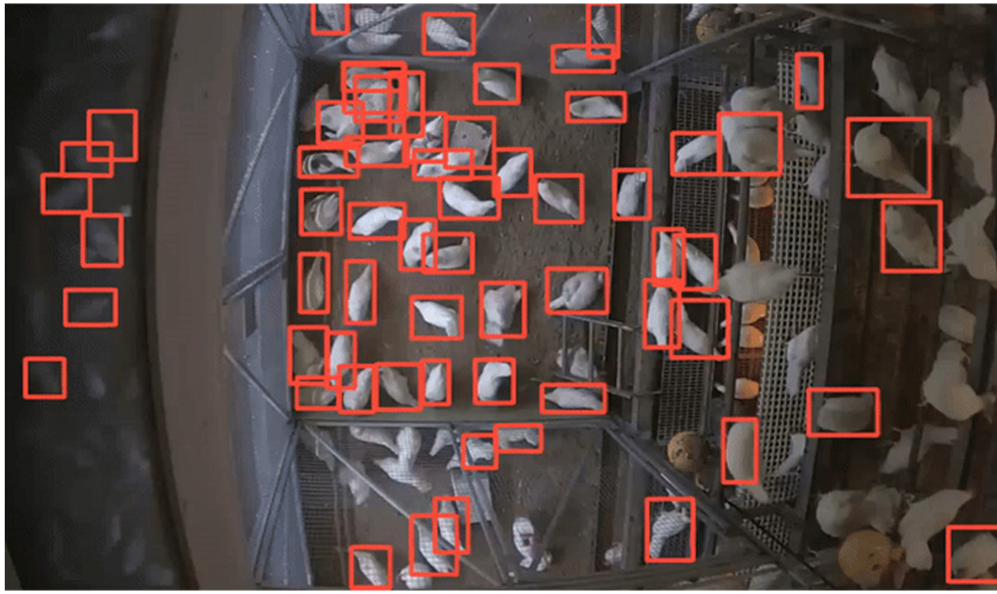


Annotate



Train

Detect



xample: estiGrass3D+

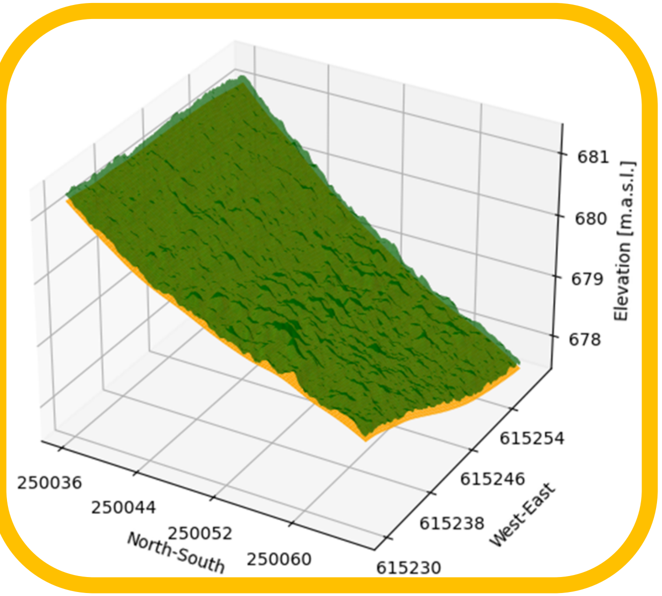
Orthomosaic & digital surface model (DSM)

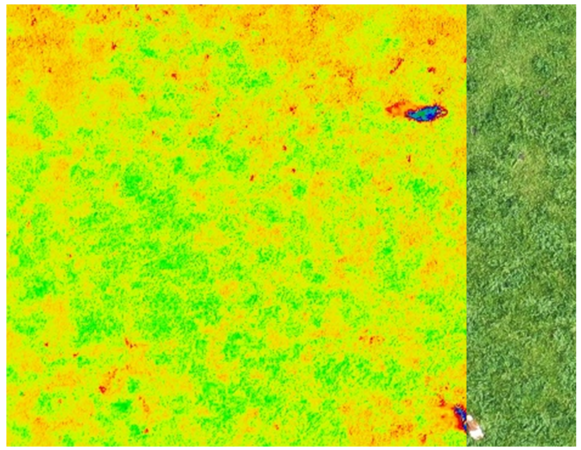
Surface model

Orthomosaic

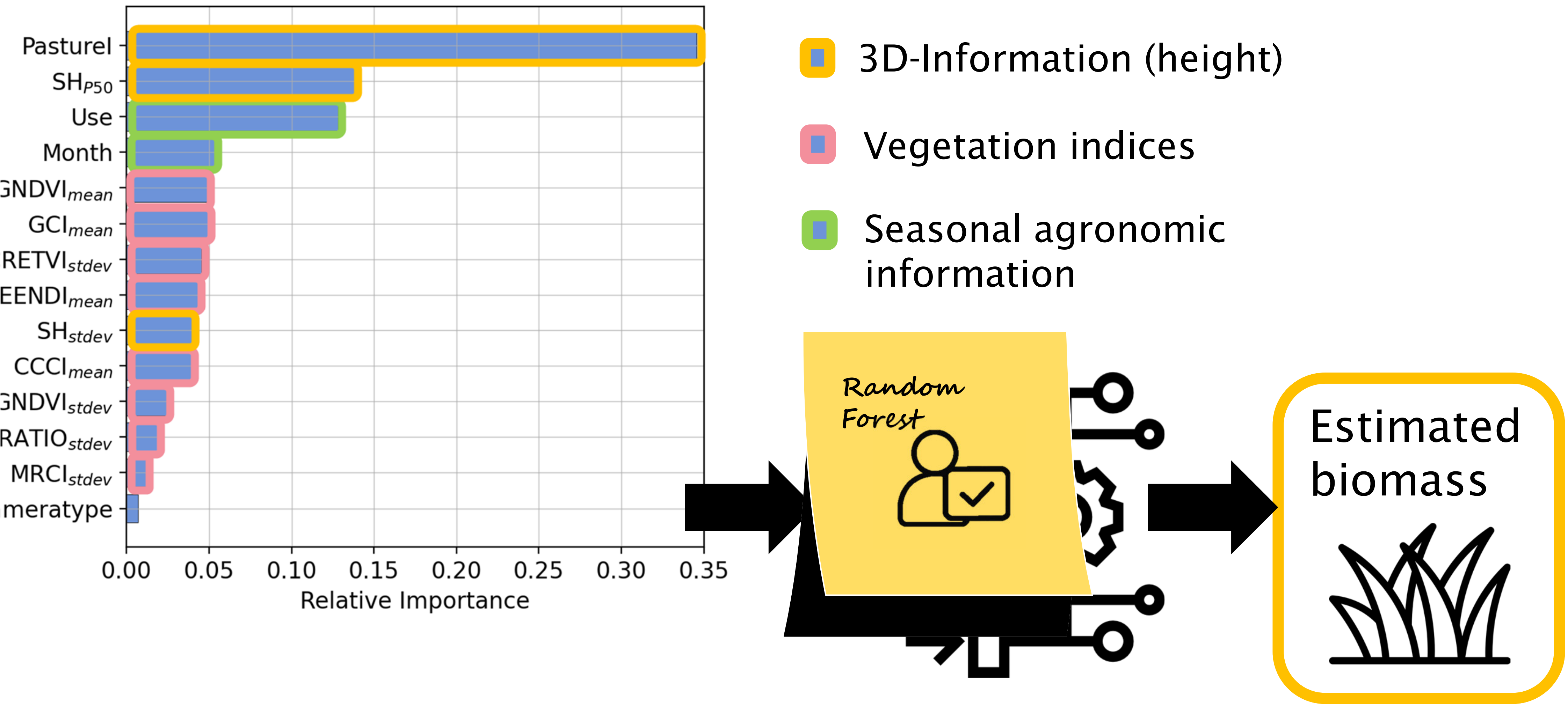
Crop height model

Vegetation indices

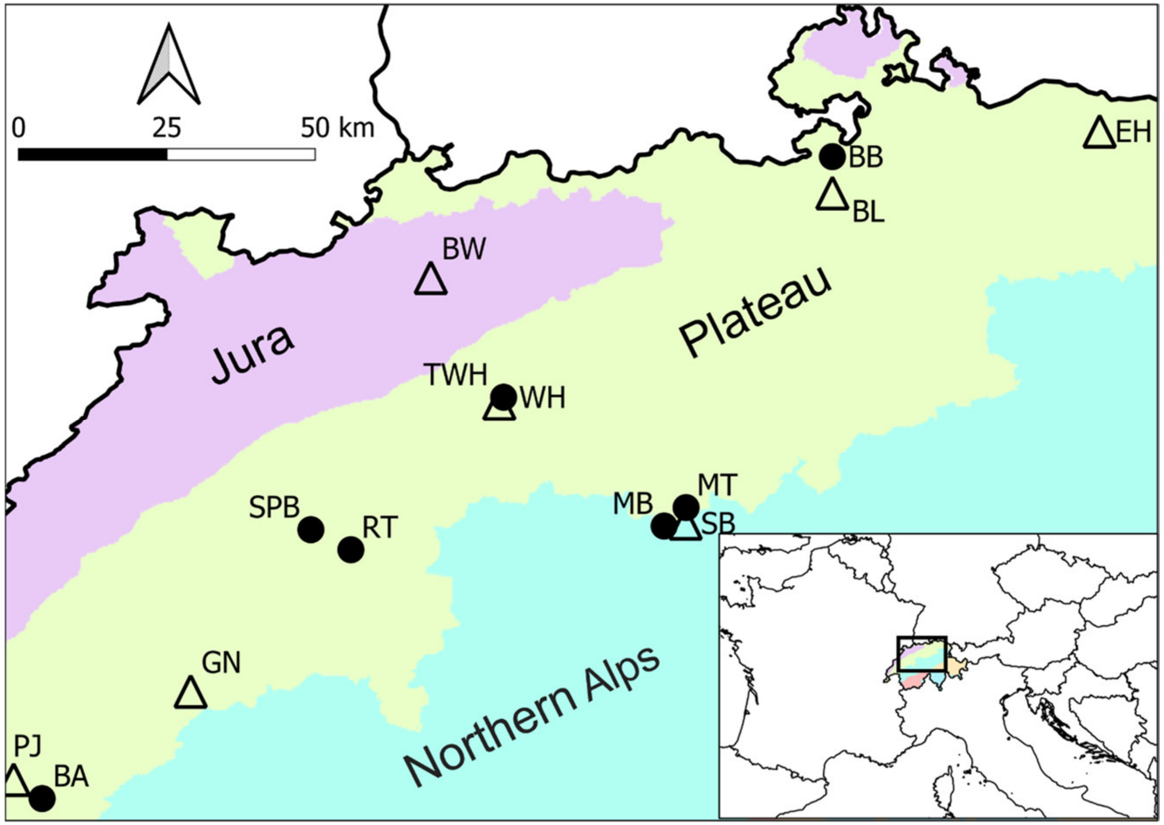




Results: Herbage biomass predictions



esults: Herbage biomass predictions

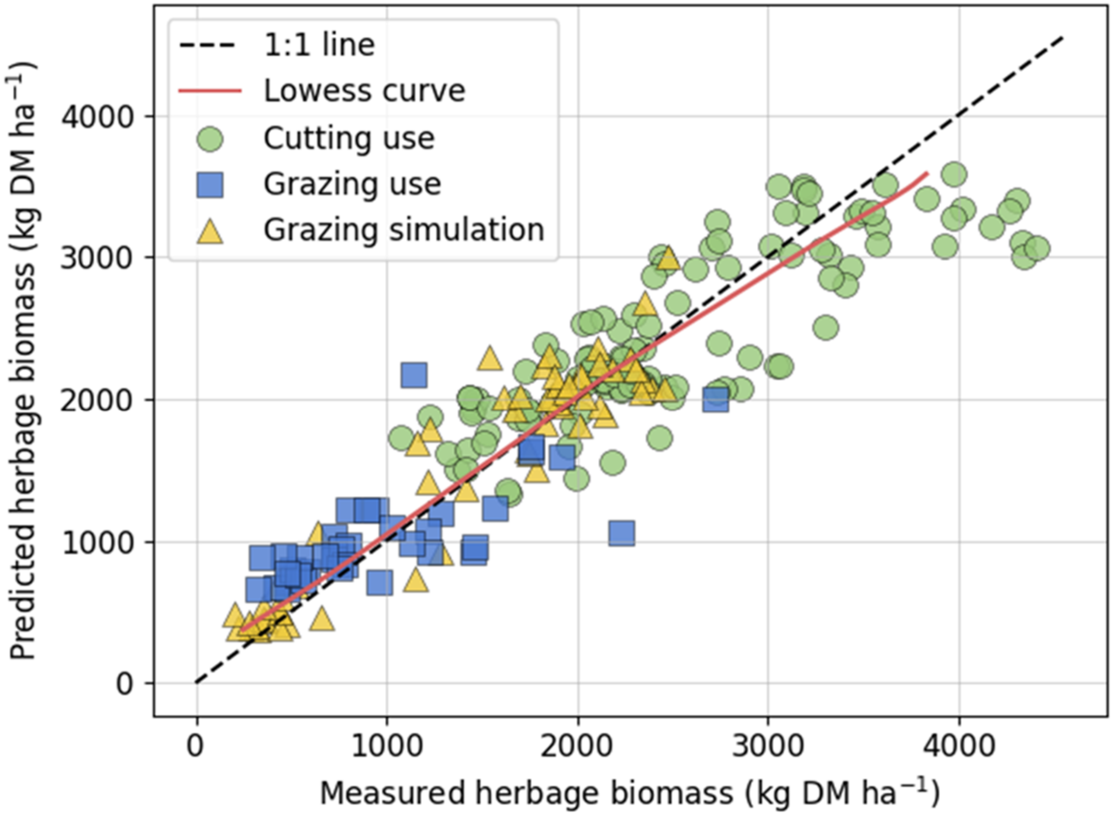


14 locations

● 430 training samples

△ 220 test samples

esults: Herbage biomass predictions



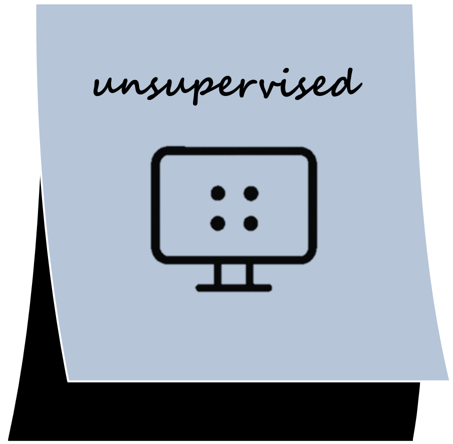
$R^2 = 0.82$

$NRMSE = 20.3\ \%$

Unsupervised ML

ubsets:

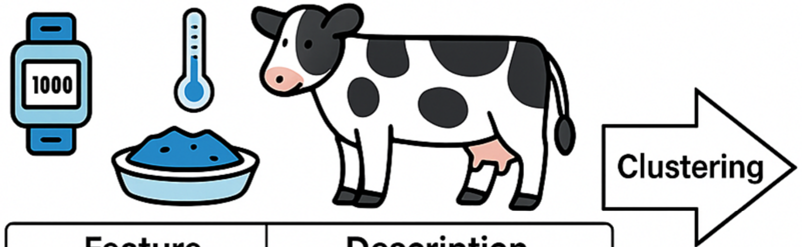
-**Means**, DBScan, …



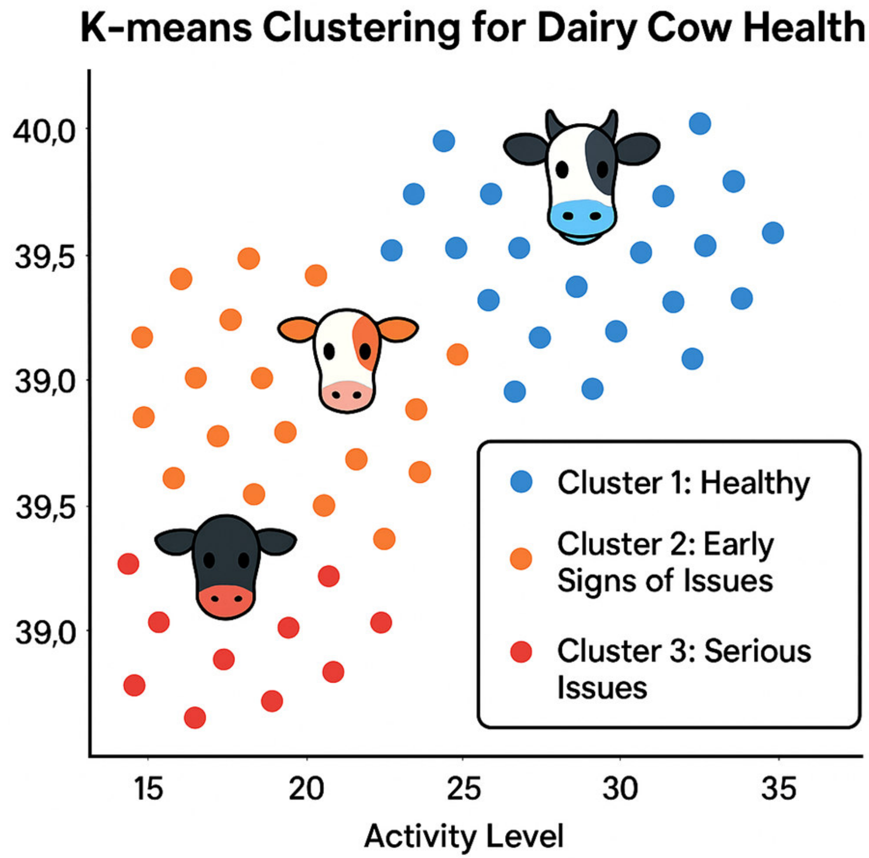
xample: Clustering

Input Data for K-Means Clustering

Collected from smart sensors on dairy cows
(e.g. pedometers, thermometers, feed monitor)



Feature	Description
Steps per Day	Measures daily activity
Body Temperature	Indicates possible fever or health shifts
Feeding Duration	Time spent eating per day
Milk Yield	Liters per day
Ruminating Time	Chewing activity (digestive health)



'hen do we call it Artificial Intelligence (AI)?

refers to systems that perform tasks which usually require human intelligence
e understanding, deciding, adapting.

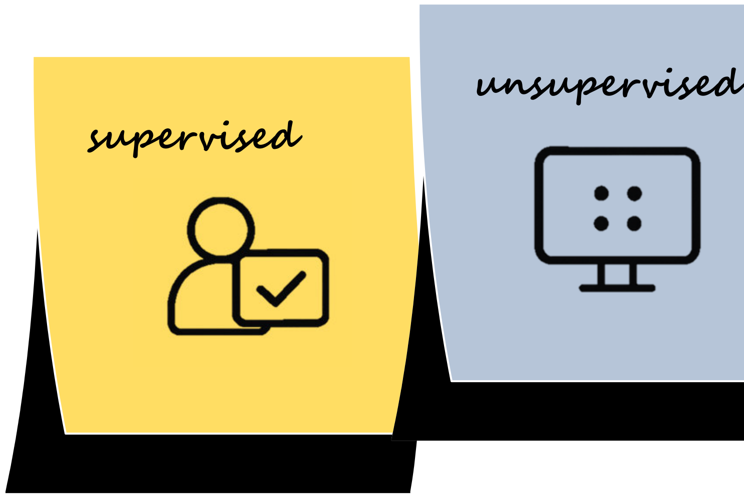
r example:

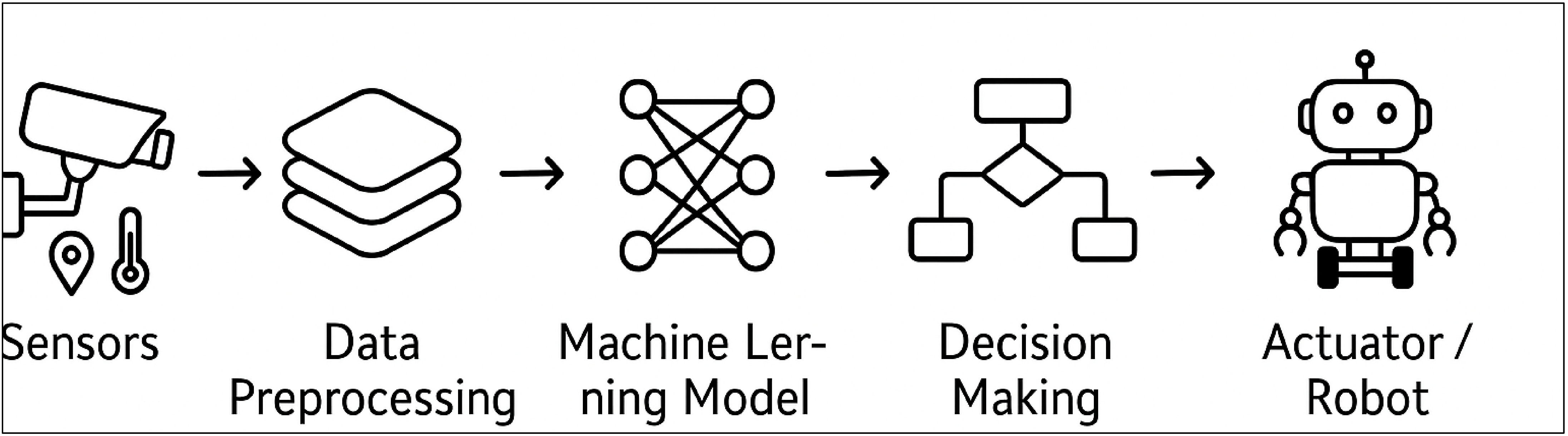
A model like **estiGrass3D+** that predicts yield is
helpful – but it's still **just a tool.**

Robot in the field: it recognizes where crops and
weeds are, decides how to act, and adapts when
conditions change – **that's AI.**

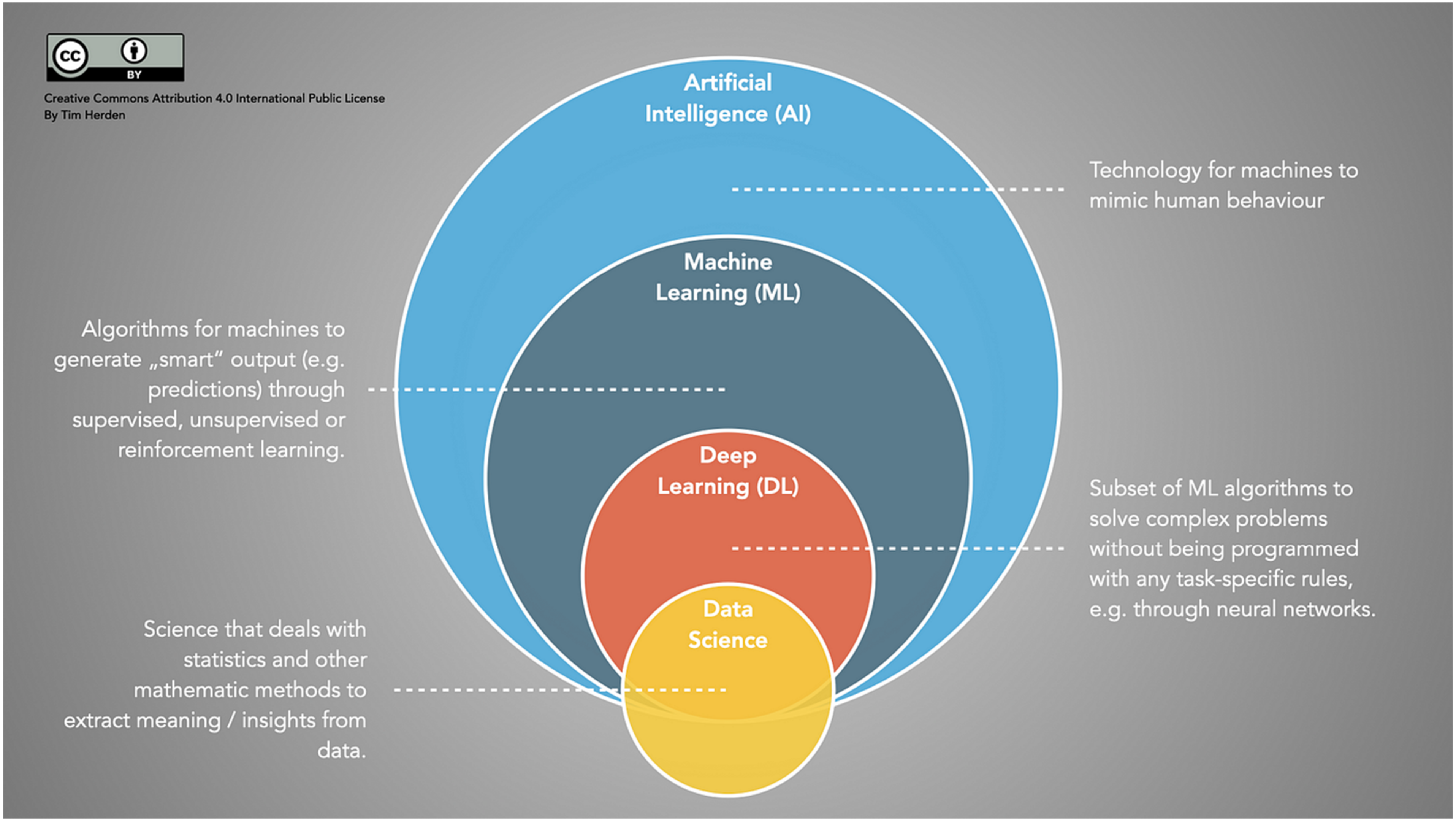
hat’s inside an AI System

pical components:





n summary



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By Tim Herden
Artificial Intelligence (AI)
Technology for machines to mimic human behaviour
Machine Learning (ML)
Algorithms for machines to generate „smart" output (e.g. predictions) through supervised, unsupervised or reinforcement learning.
Deep Learning (DL)
Subset of ML algorithms to solve complex problems without being programmed with any task-specific rules, e.g. through neural networks.
Data Science
Science that deals with statistics and other mathematic methods to extract meaning / insights from data.

he value of data – Why input quality matters

arbage in – Garbage out

Machine learning depends heavily on data quality
Input errors reduce prediction accuracy!

Example:
Wrong mower used or incorrect cutting height
Incorrect drying, …

Bad data = bad model

heap **or** precise?

- Estimated data is cheaper – but often less accurate
- Sensor data is more precise – but costs more (maintenance)
- … and again → **Wrong assumptions** → **wrong predictions**

- Weather station 10 km away ≠ real microclimate

heap **and** precise?

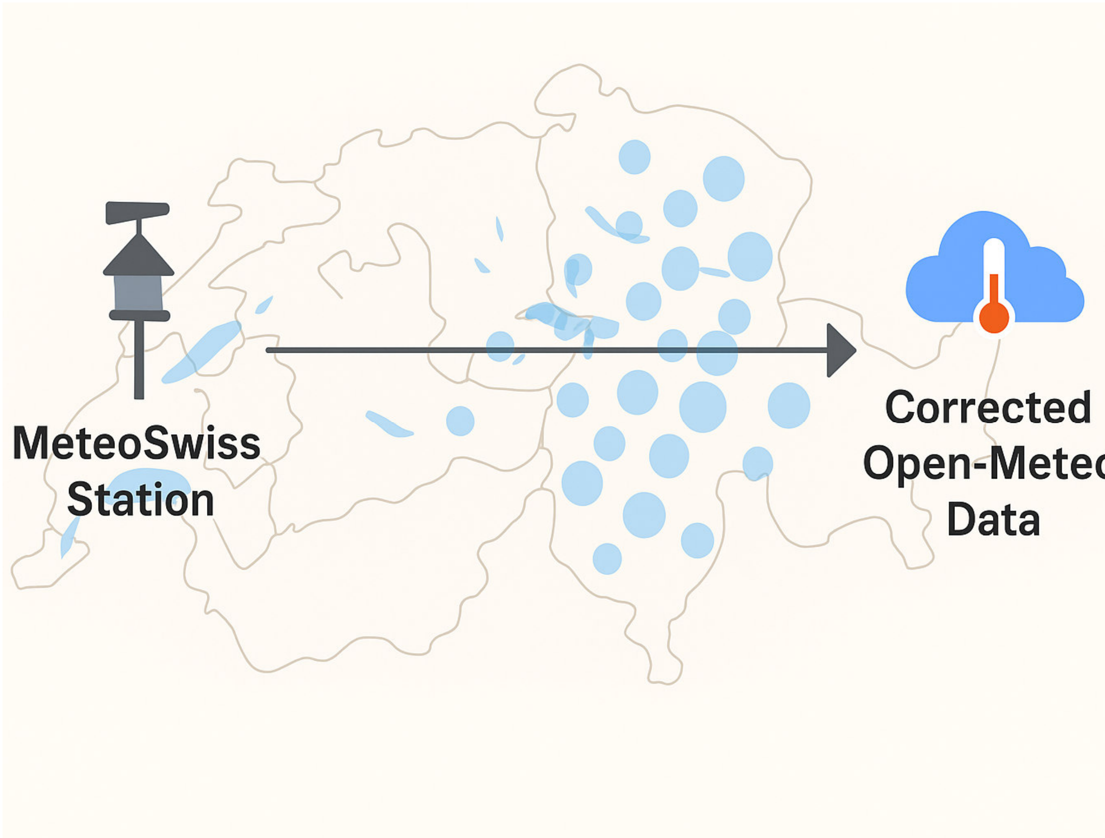
We measure weather data at one precise SwissMeteo station

- high-quality ground truth

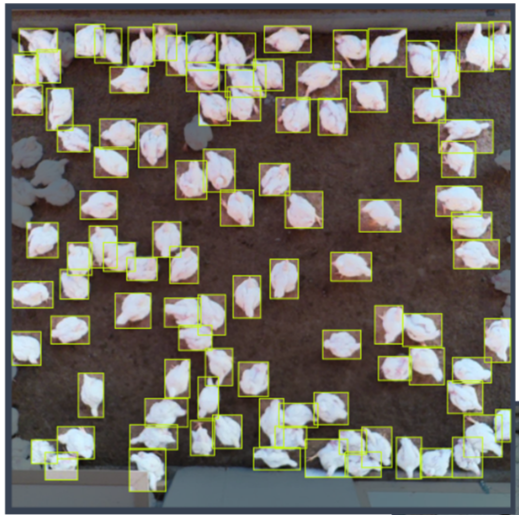
OpenMeteo (or similar APIs) provide broad, interpolated data

- fast, cheap, but less accurate

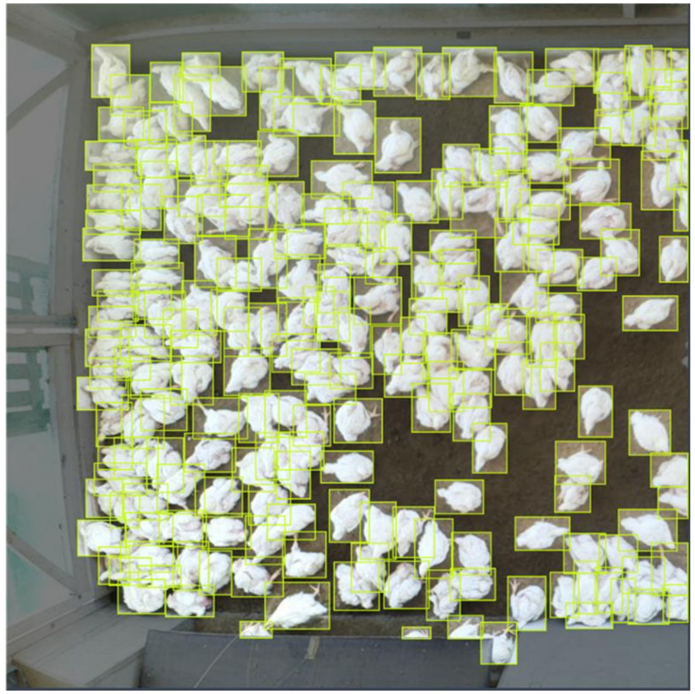
We combine both: use station data to correct, calibrate, or validate surrounding OpenMeteo estimates.



Not only sensors can be inaccurate – humans too!

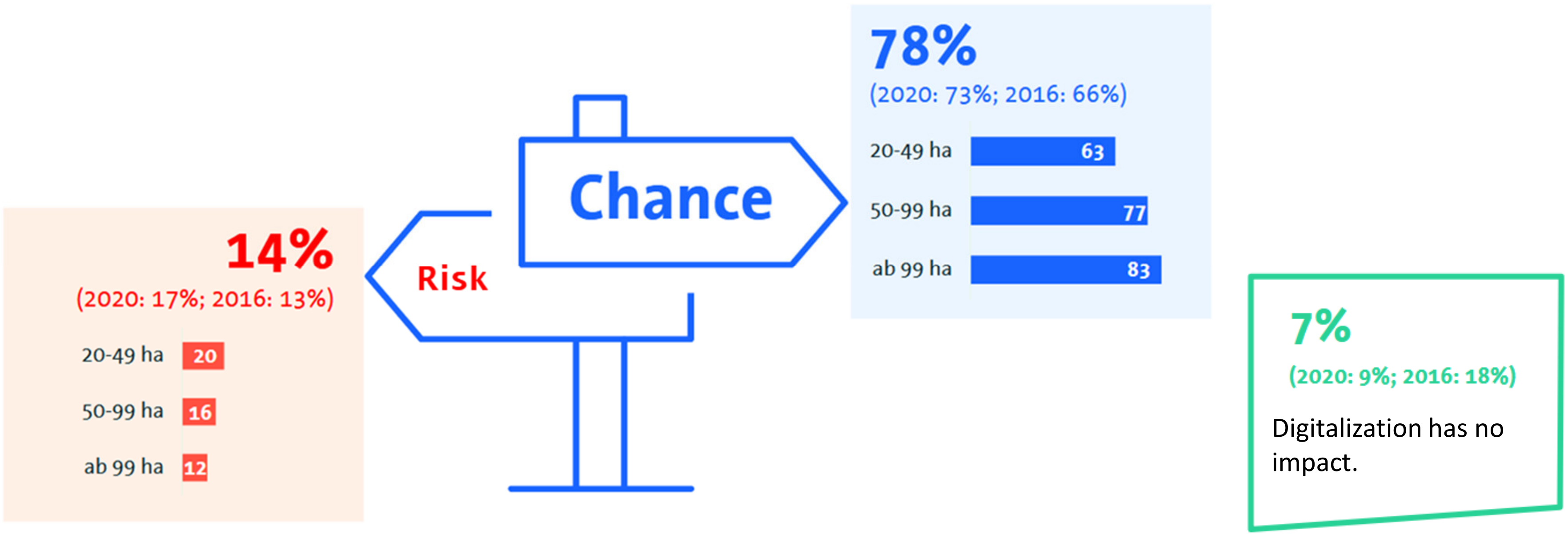


Students



Commercial labeling service

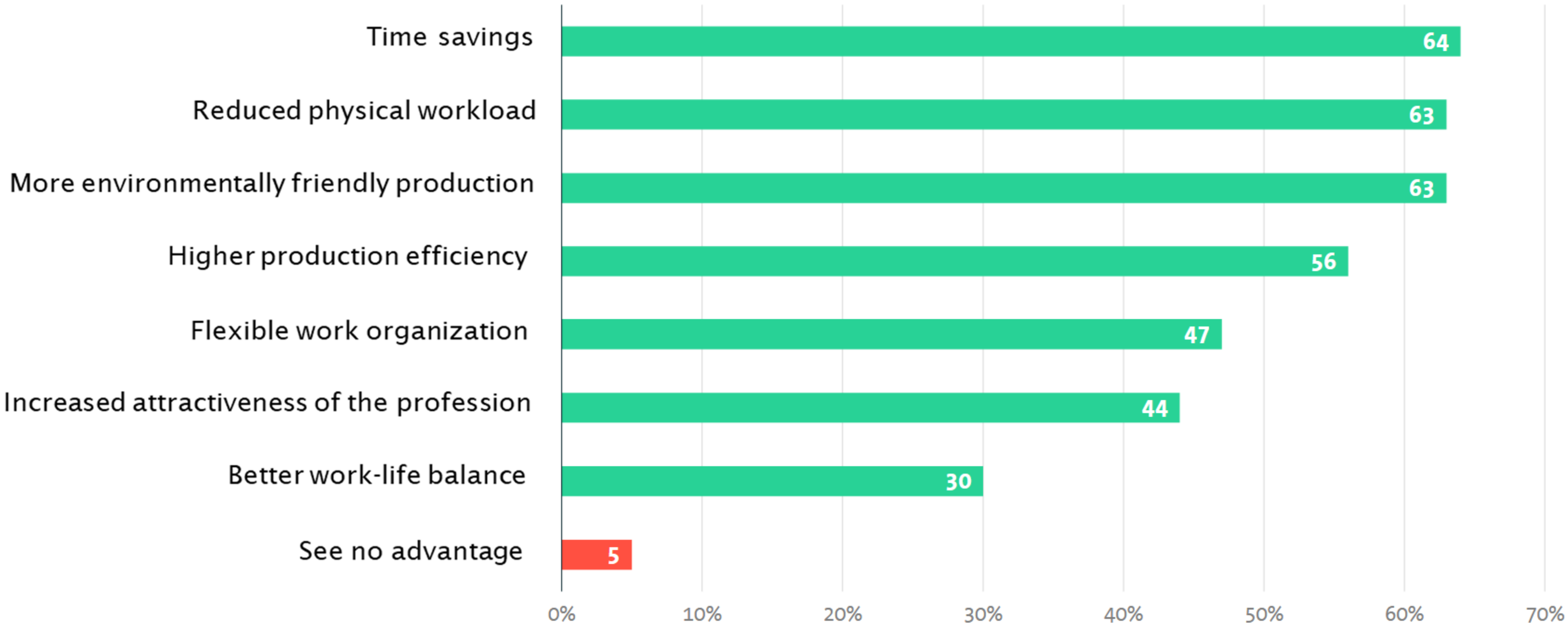
o you see digitalization more as an opportunity or a risk or your farm/business?



Surveyed farmers (n=500) | Multiple answers possible | Source: Bitkom Research 2022

igitalization in Agriculture – Pros

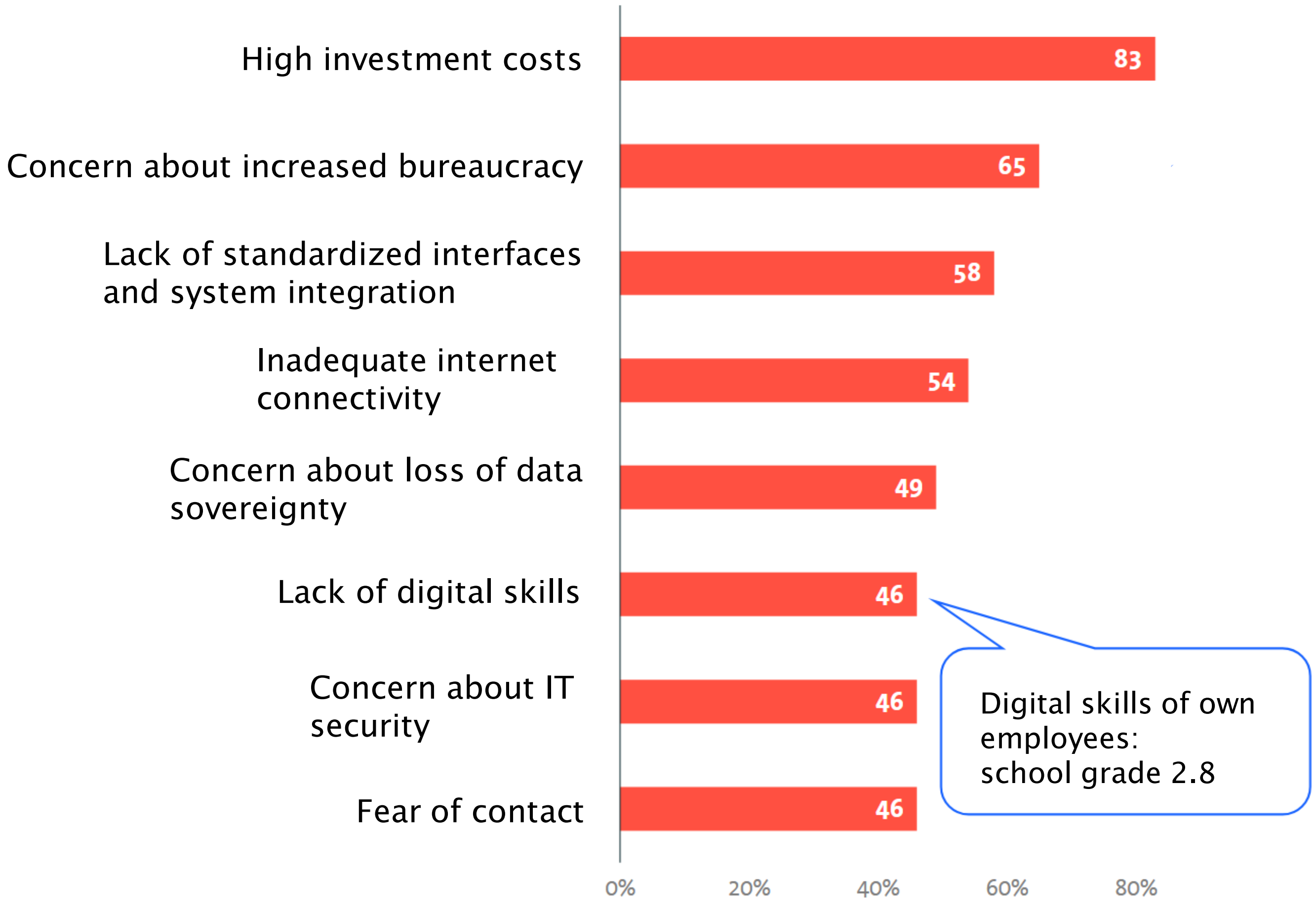
hat are the greatest advantages of digital applications on the farm?



Surveyed farmers (n=500) | Multiple answers possible | Source: Bitkom Research 2022

igitalization in Agriculture – Cons

 your opinion, what are the biggest obstacles slowing down the digitalization of agricult



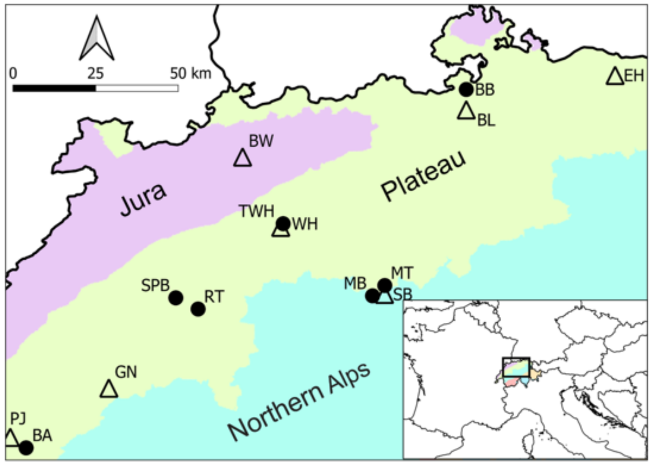
Surveyed farmers (n=500) | Multiple answers possible | Source: Bitkom Research 2022

eld vs. Lab – Bridging the Gap

Great models often fail outside ideal conditions

Field implementation = the real challenge

Example: sensor failures, user acceptance, local context



14 locations

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he human factor – AI needs expertise

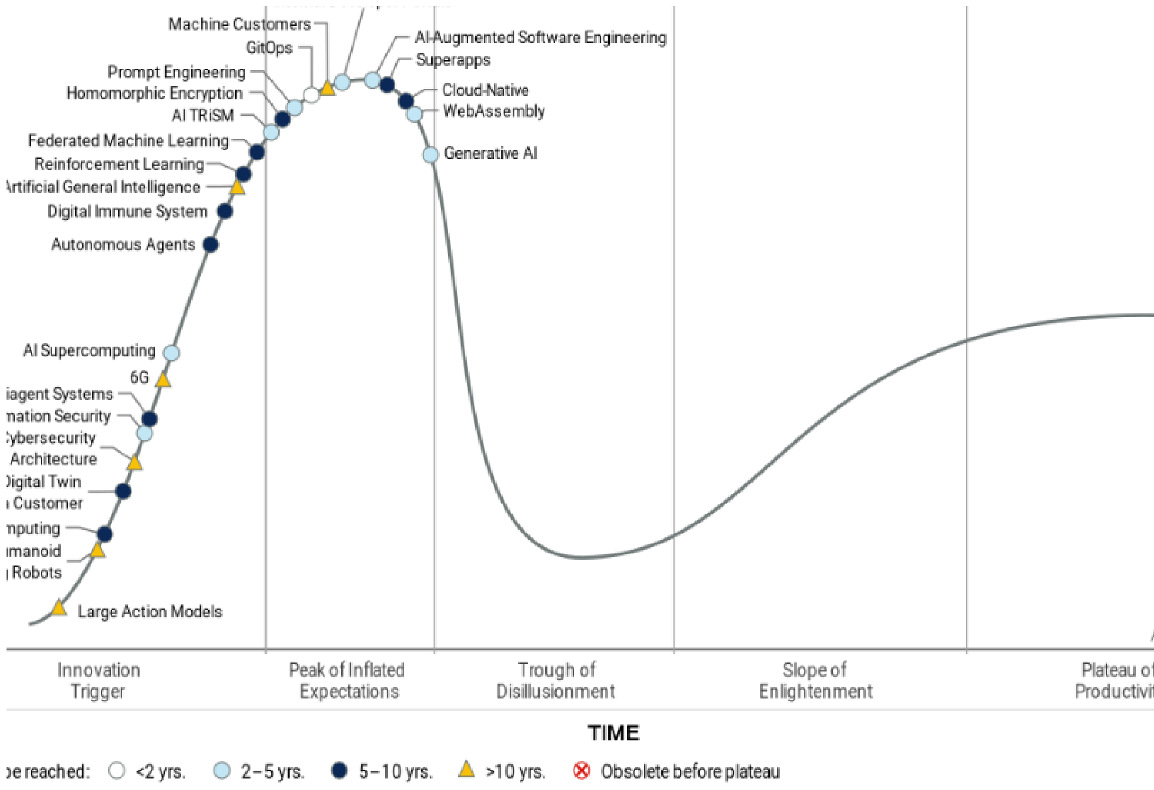
- AI learns from human-created data
- Local knowledge still essential
- Farmers and advisors must stay involved

https://aifarming.ca/blogs/ai-in-agriculture-the-future-of-farming-in-canada/

here Are We Going?

- AI is already part of modern agriculture
- You can’t fix bad data with more technology.
- Best future:

humans + AI = smarter decisions



hank You!

Herbage biomass predictions from UAV data ing a derived digital terrain model d machine learning

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ORIGINAL ARTICLE

Herbage biomass predictions from UAV data using a derived digital terrain model and machine learning

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Abstract
More than 70% of Switzerland's agricultural area is covered by grasslands that often exhibit highly diverse species compositions and heterogeneous growth patterns. An essential requirement for efficient and effective pasture management is the regular estimation of herbage biomass. While various methods exist for estimating herbage biomass, they are often time-consuming and may not accurately capture the variability within pastures. This highlights the need for more efficient, accurate estimation techniques. To help improve herbage biomass estimation, we present *estiGrass3D+*, a Random Forest model. This model predicts pasture biomass using a digital terrain model (DTM) derived from a digital surface model (DSM) for sward height modelling, along with vegetation indices and agronomic variables from UAV images only. The model was successfully evaluated with independent test data from different sites on the Swiss central plateau, including both grazed and mown areas. Model performance on an independent validation dataset achieved a NRMSE of 20.3%, while the training dataset had an NRMSE of 21.5%. These consistent results confirm that *estiGrass3D+* is both transferable and applicable to unseen data while maintaining accuracy and reliability across different datasets. The wide applicability of our method demonstrates its practicality for predicting herbage biomass under different pasture management scenarios. Additionally, our method of deriving a DTM directly from a DSM simplifies the measurement of grass sward height by UAVs, eliminating the need for prior ground control point (GCP) marking and subsequent aligning, enhancing the efficiency of herbage biomass estimation.

KEYWORDS
aerial imagery, grazing, multispectral sensor, pasture aboveground biomass, Random Forest algorithm, surface modelling

1 | INTRODUCTION

More than 70% of Switzerland's agricultural area is composed of grasslands and 85% of Swiss dairy cows consume at least some of their daily ration directly on pasture (Lüscher et al., 2019). Various studies have emphasized the importance attributed to grazing by dairy consumers (Jackson et al., 2020; Weinrich et al., 2014), making grassland-based production systems significant pillars of cattle feeding