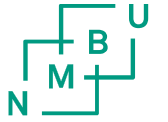


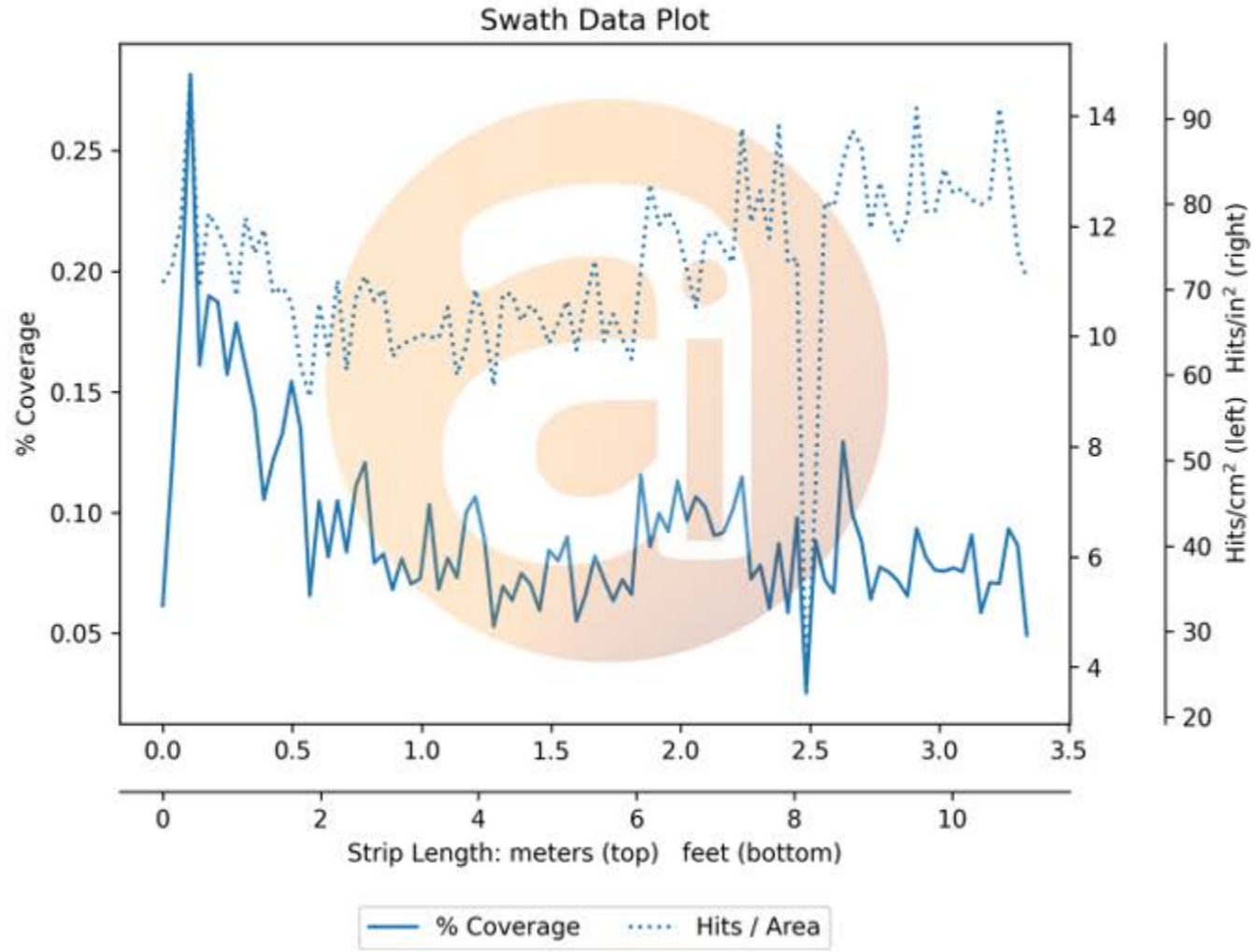
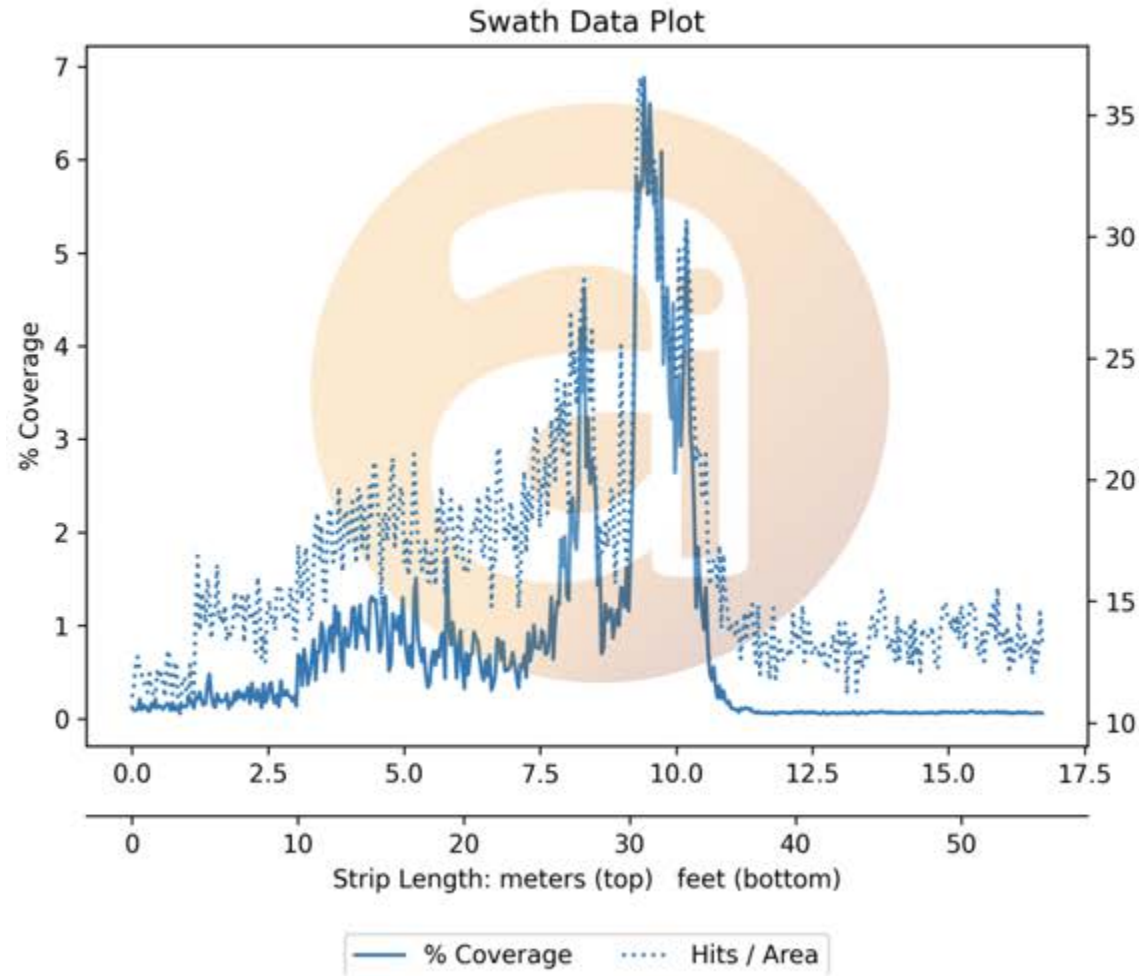
Drone with 16 nozzles of 110 01

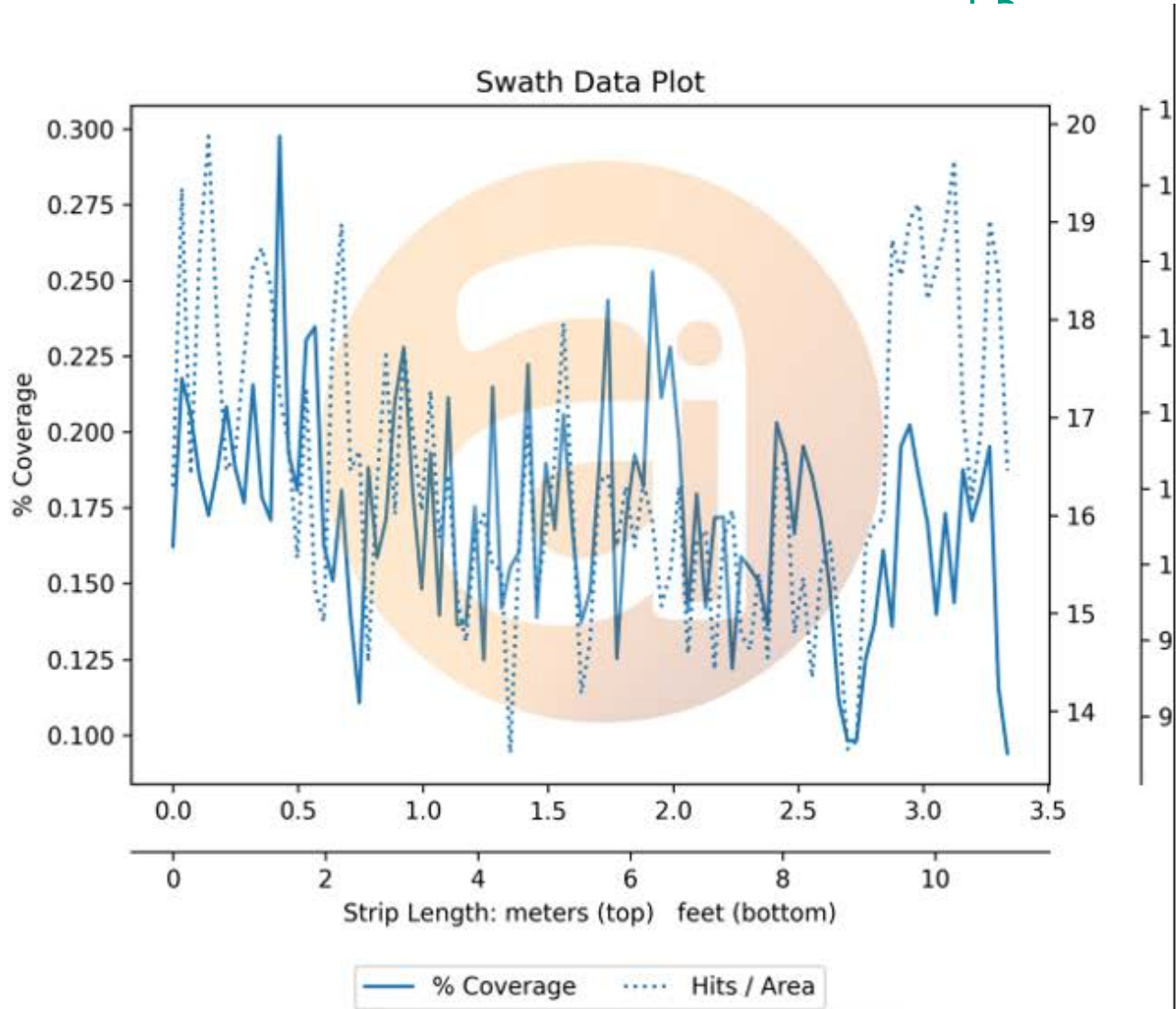
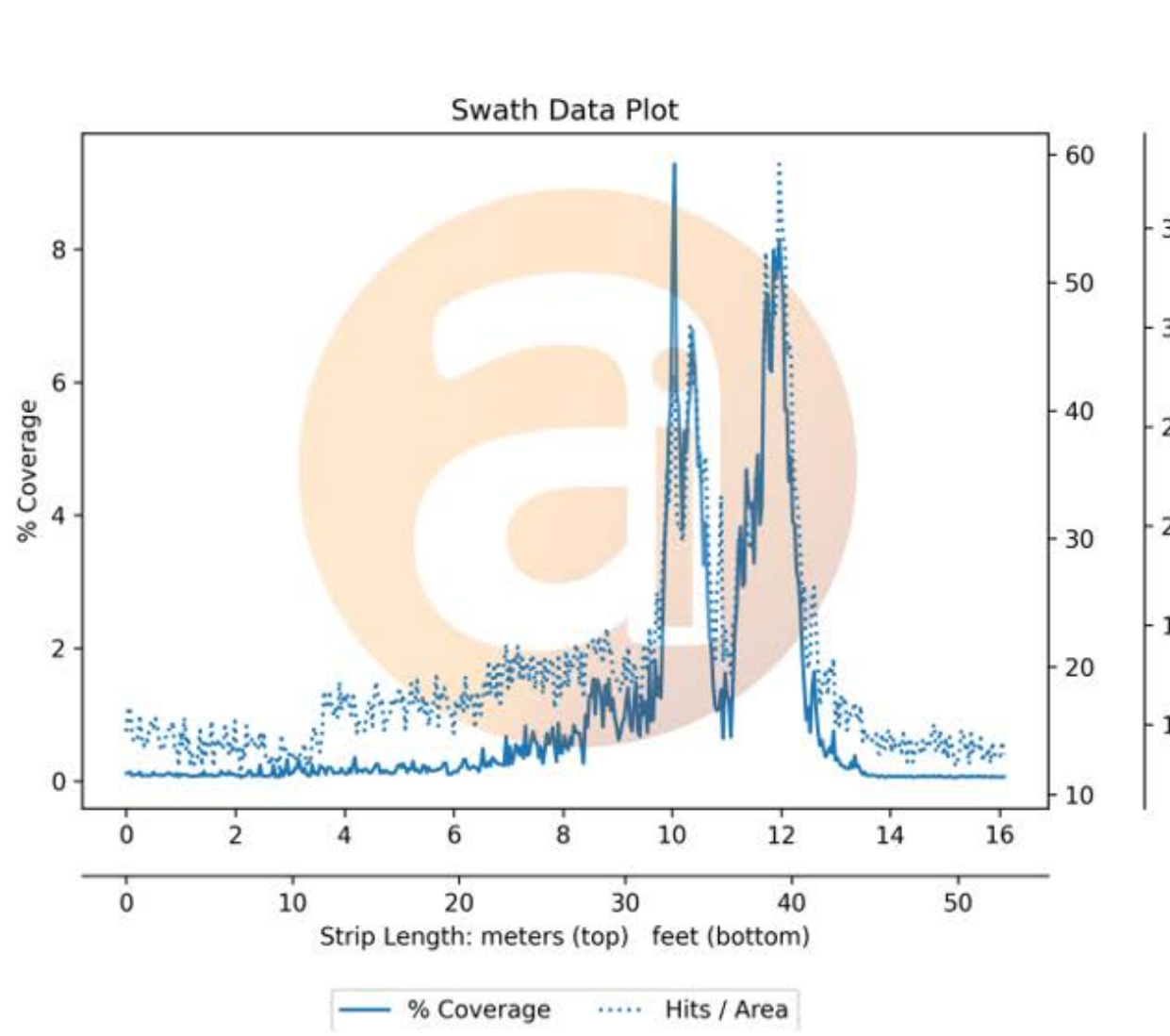


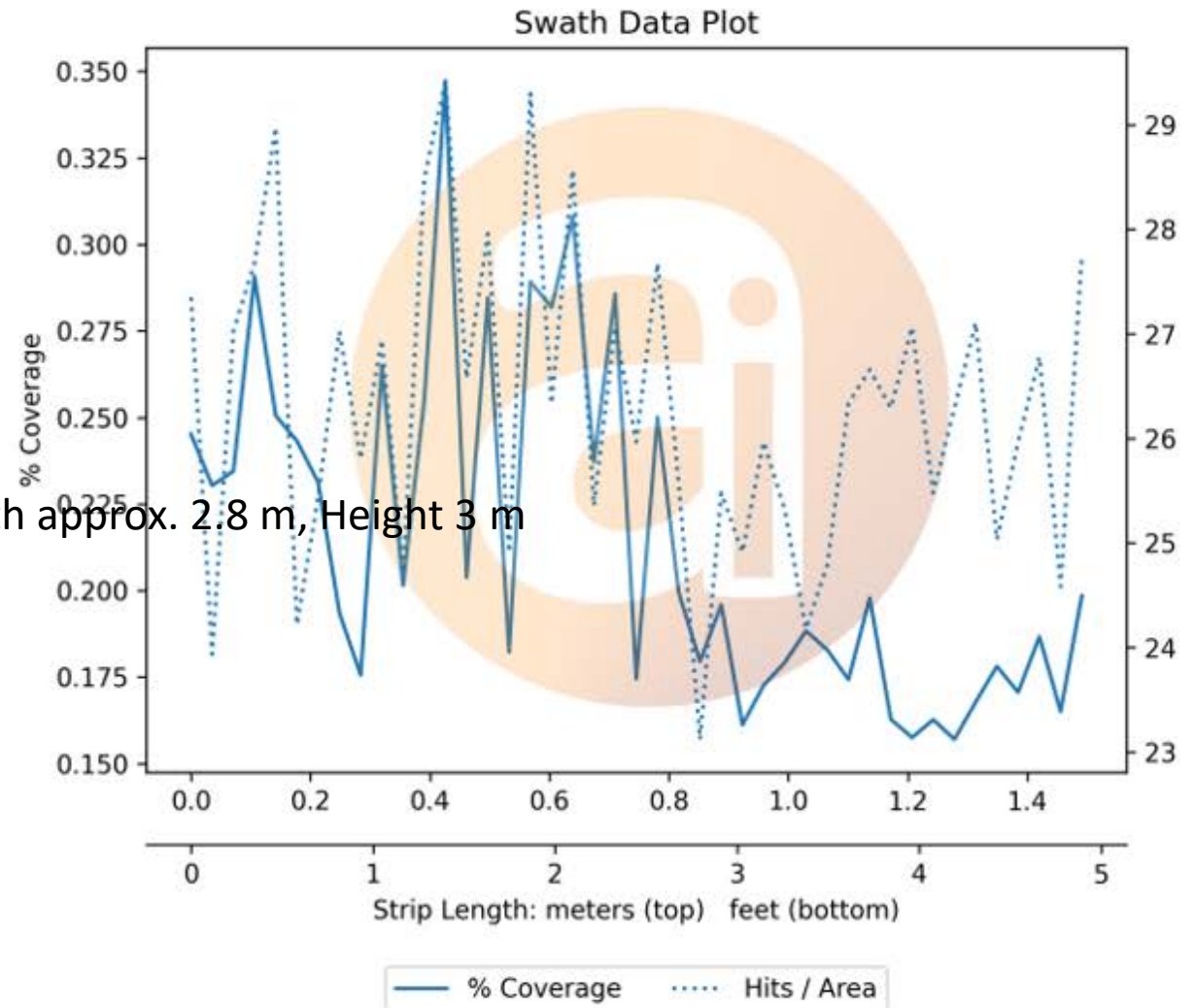
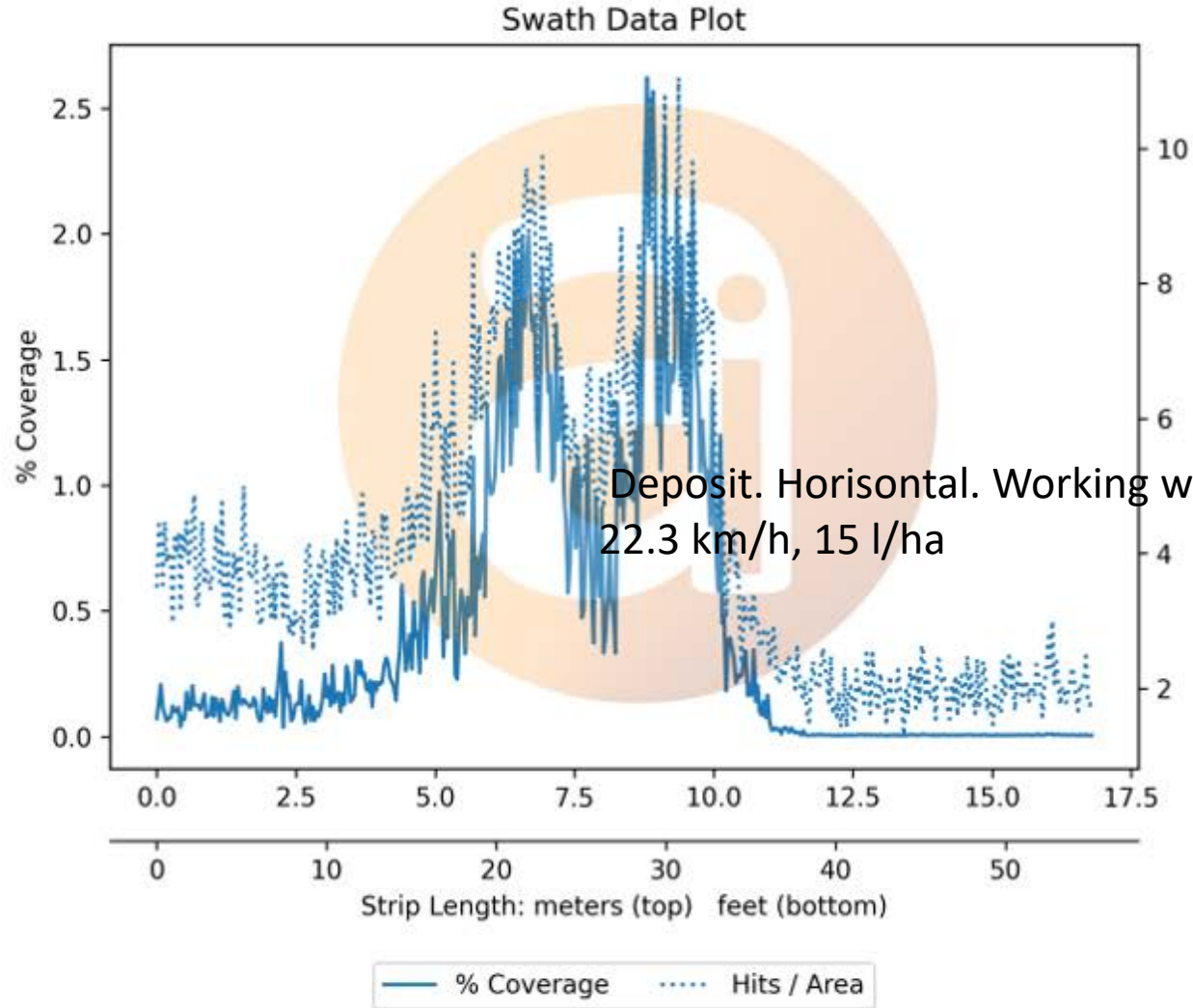


Agras T30 with 16 x 110 01 nozzles

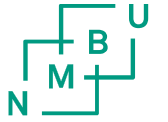
Trial	Wind m/s	Temp.	RH	Height m	Working Width m	Speed km/h	L/ha
3	3.7	18.6	44.8	3.0	2.8	22.3	15
4	3.9	19.5	44.0	1.5	2.8	22.3	15
5	3.4	19.5	43.2	3.0	2.8	14.8	22
6	3.9	19.6	47.7	1.5	2.8	14.8	22
7	3.1	18.1	55.2	3.0	2.8	22.3	15







Spray drone with rotating discs



Agras T30 with rotating discs

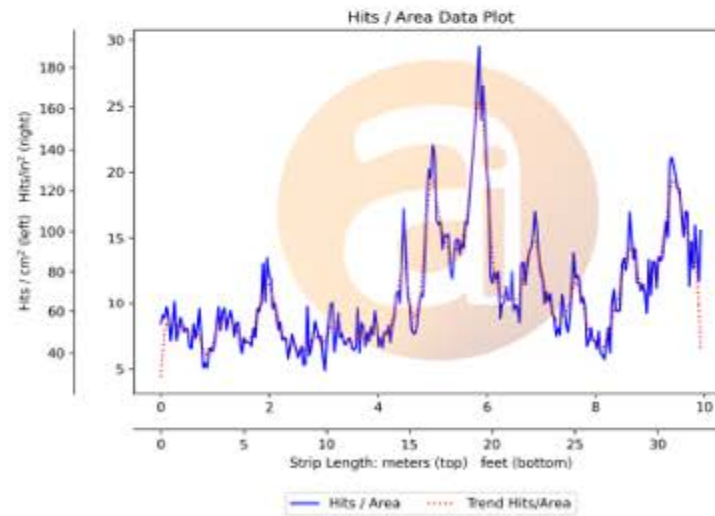
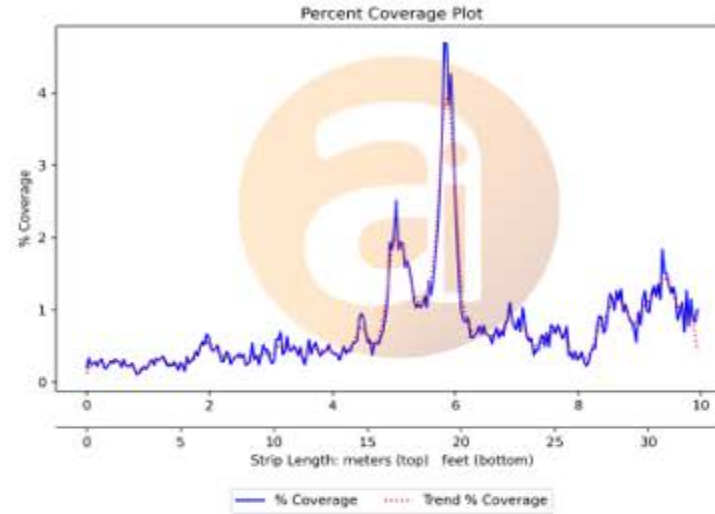


Trial	Wind m/s	Temp.	RH	Height m	Work. Width m	VMD μm	Speed	With betw. vert. m	L/min	L/ha
1.1	0	26.5	44.8	3.0	3	320	18	10	2.64	30
1.2	0	24.8	52.3	2.5	3	320	18	10	2.64	30
1.4	1.6	26.6	38	2.5	3	100	18	10	2.64	30
2.1	2.8	21.2	61.5	2.5	3	100	18	12.7	2.64	30
2.2	1.8	20.1	65.3	2.5	3	320	18	12.7	2.64	30
2.3				2	3	500	18	12.7	2.64	30

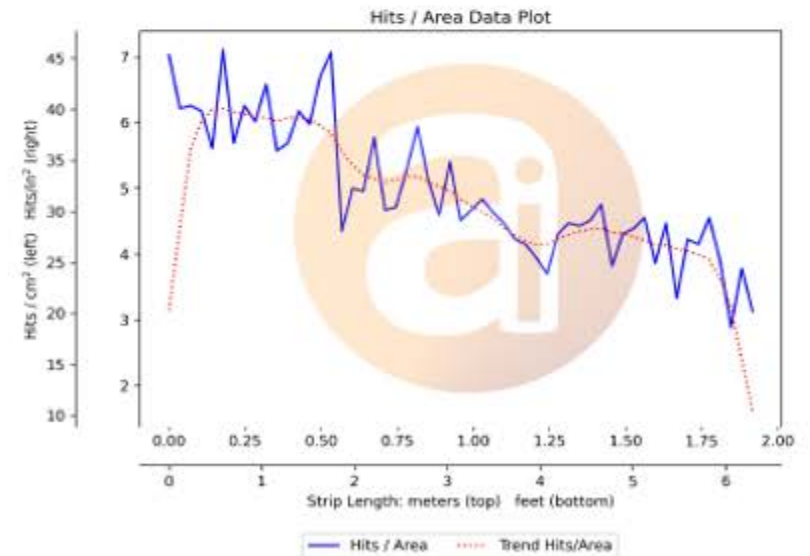
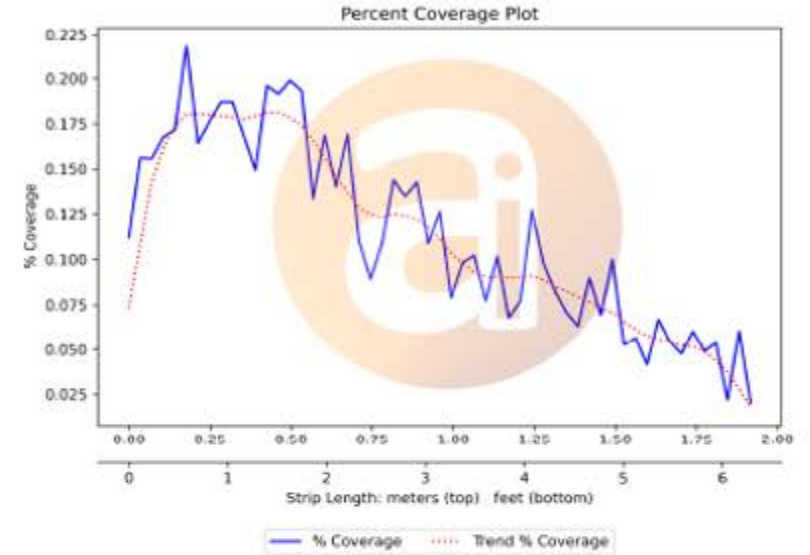
Swath Gobbler Report: SG-106-2024-08-11T0852



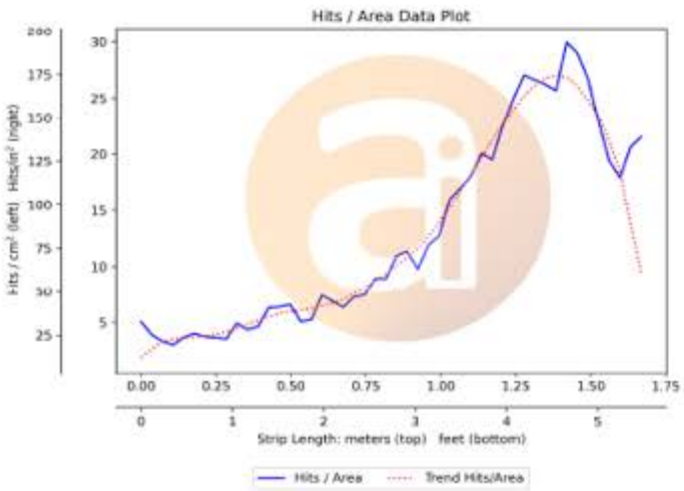
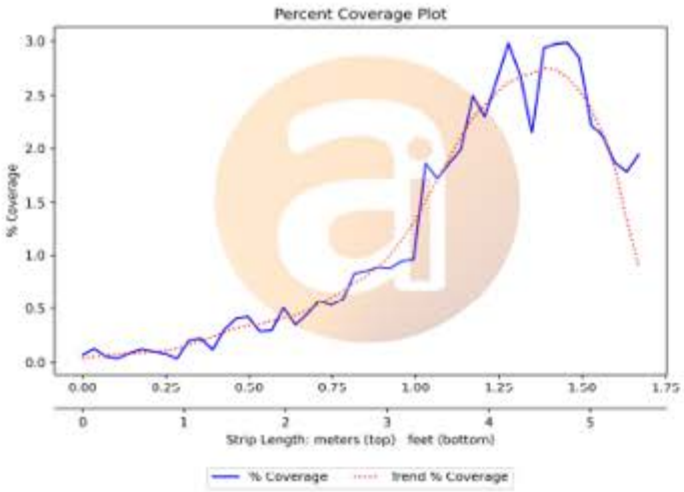
Swath Gobbler Report: SG-106-2024-08-11T0852



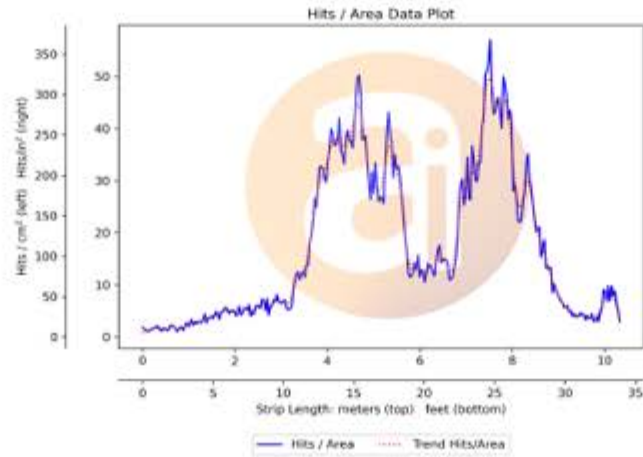
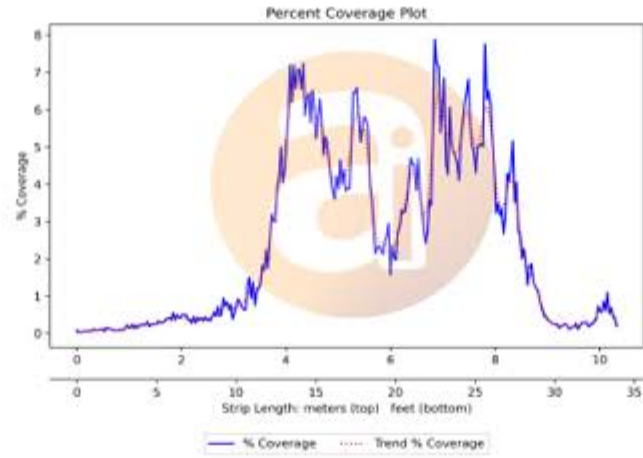
Swath Gobbler Report: SG-106-2024-08-11T0852



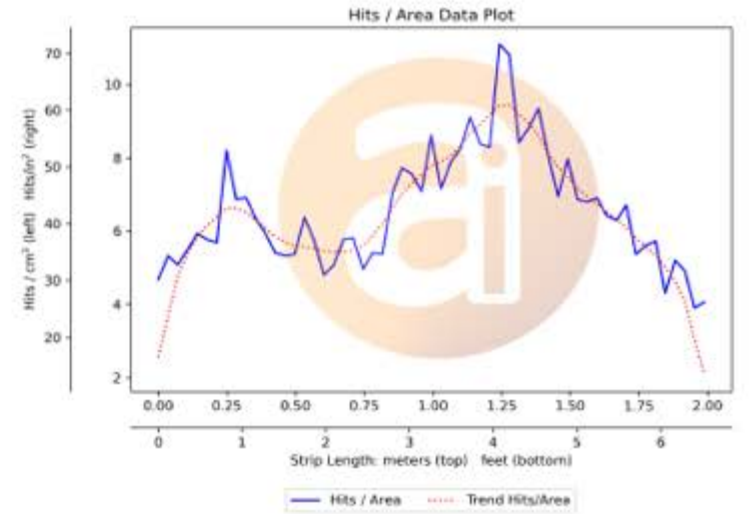
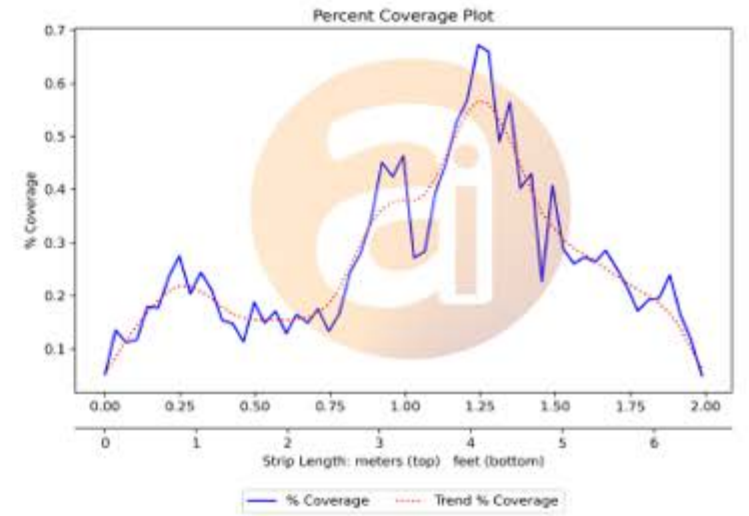
Swath Gobbler Report: SG-11B-2024-08-11T1310



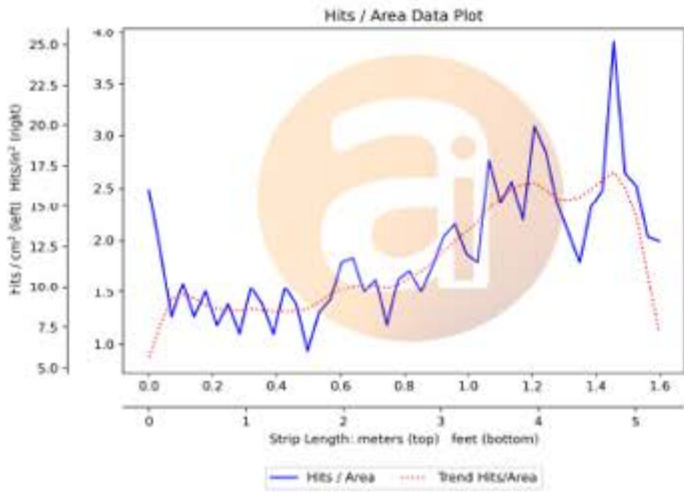
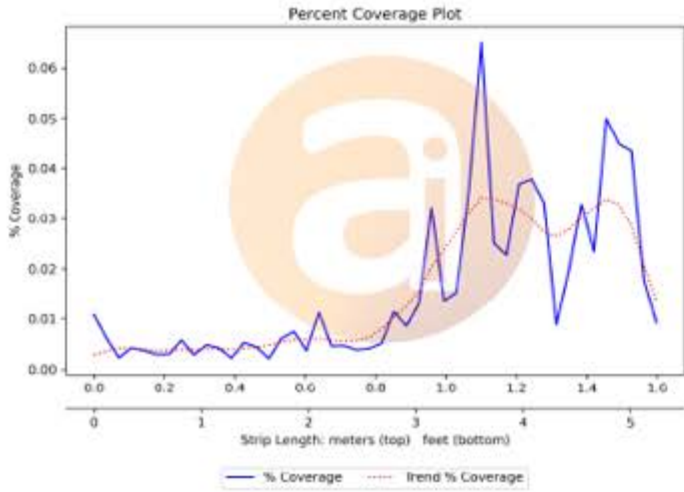
Swath Gobbler Report: SG-106-2024-08-11T0852



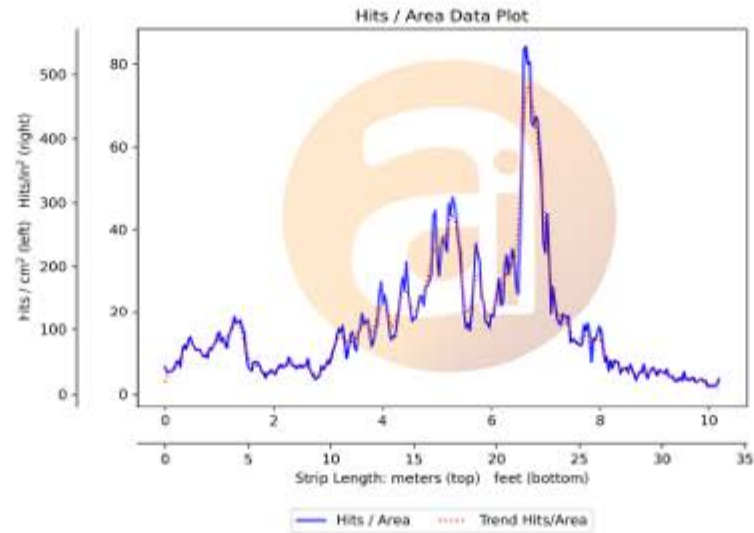
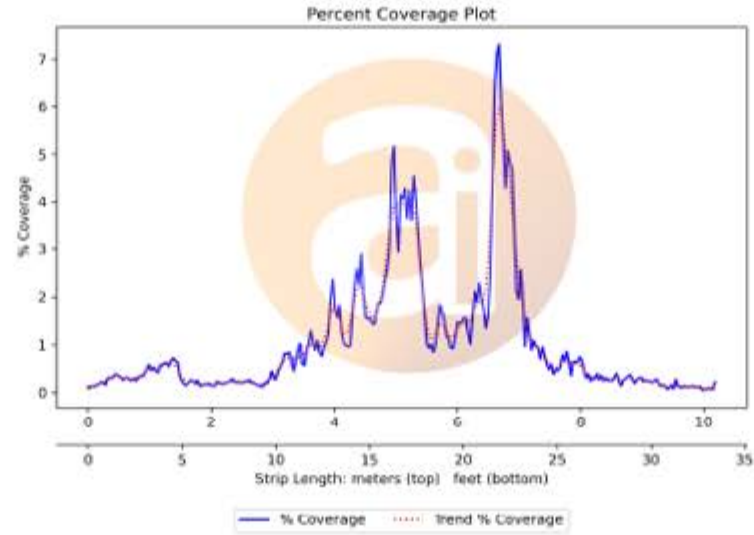
Swath Gobbler Report: SG-106-2024-08-11T0852



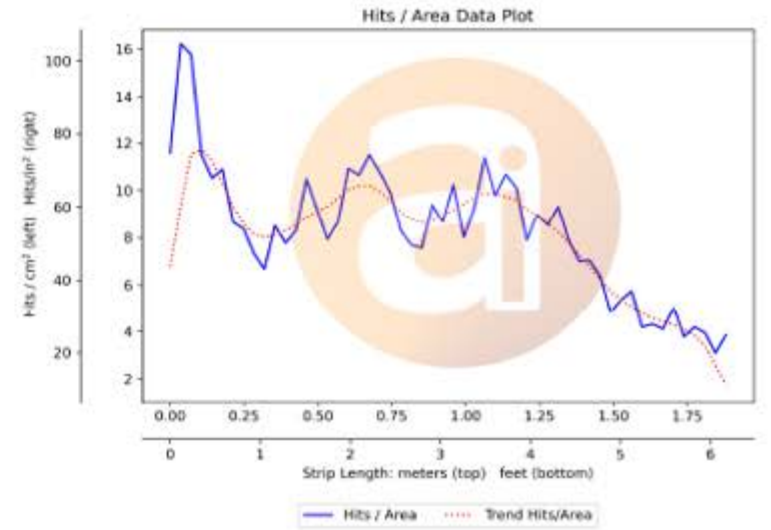
Swath Gobbler Report: SG-106-2024-08-11T0852



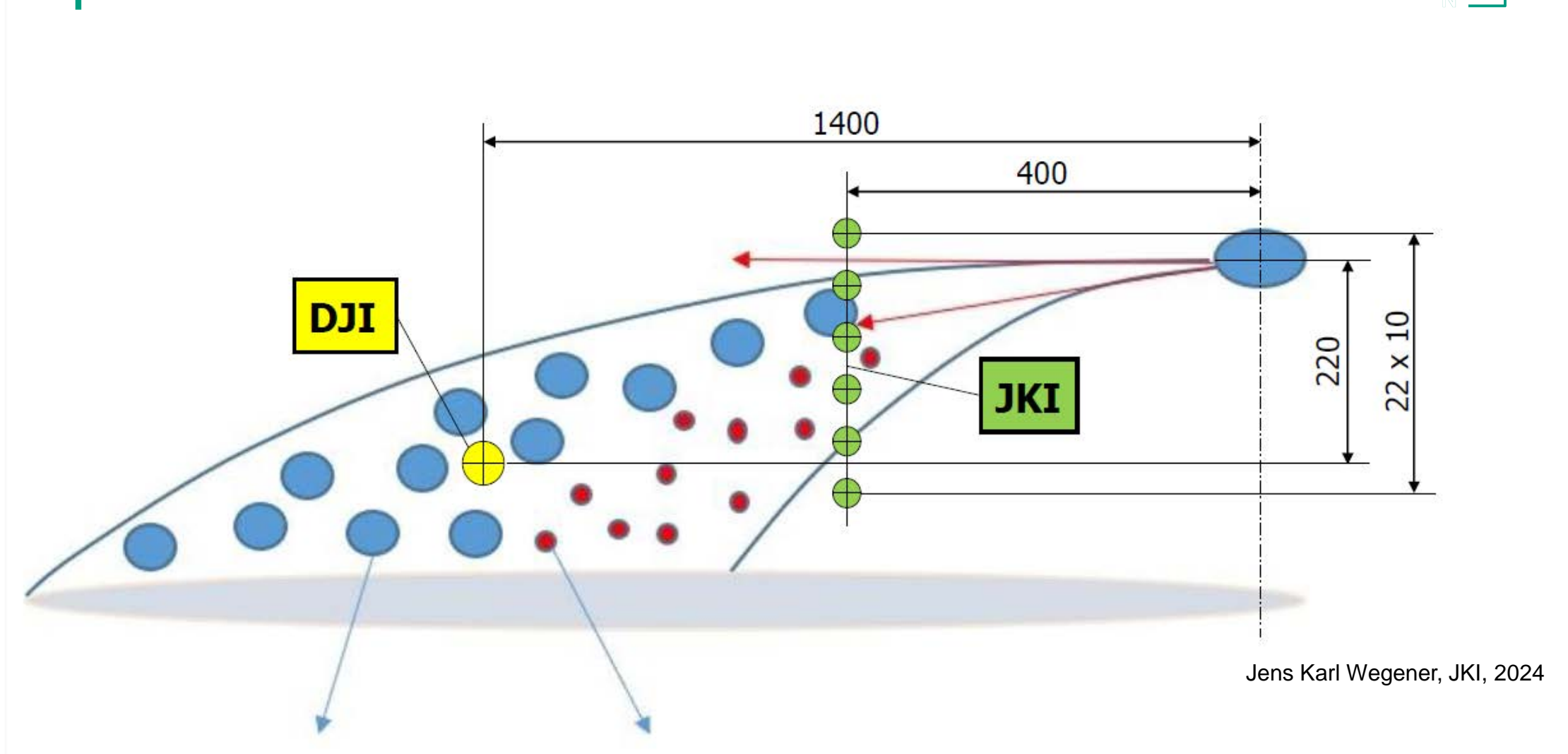
Swath Gobbler Report: SG-106-2024-08-11T0852



Swath Gobbler Report: SG-106-2024-08-11T0852



Drop size measurements



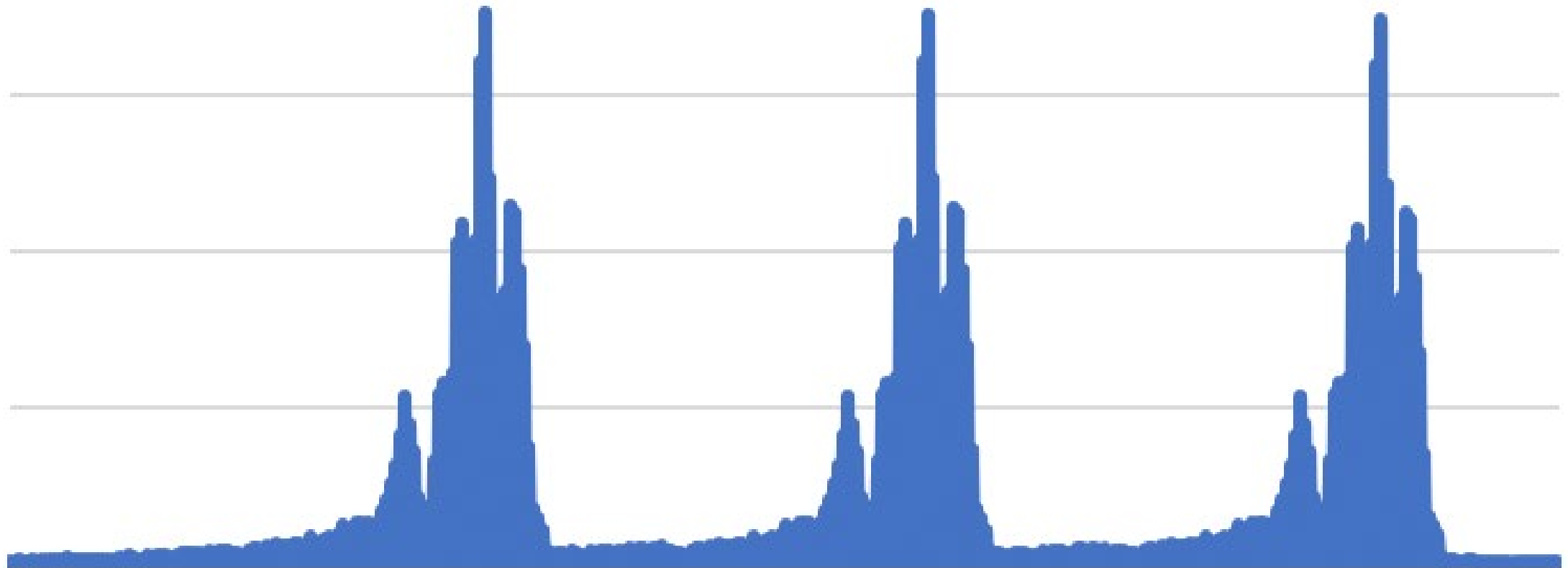
Drone vs field crop sprayer



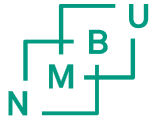
Distribution of multiply swaths



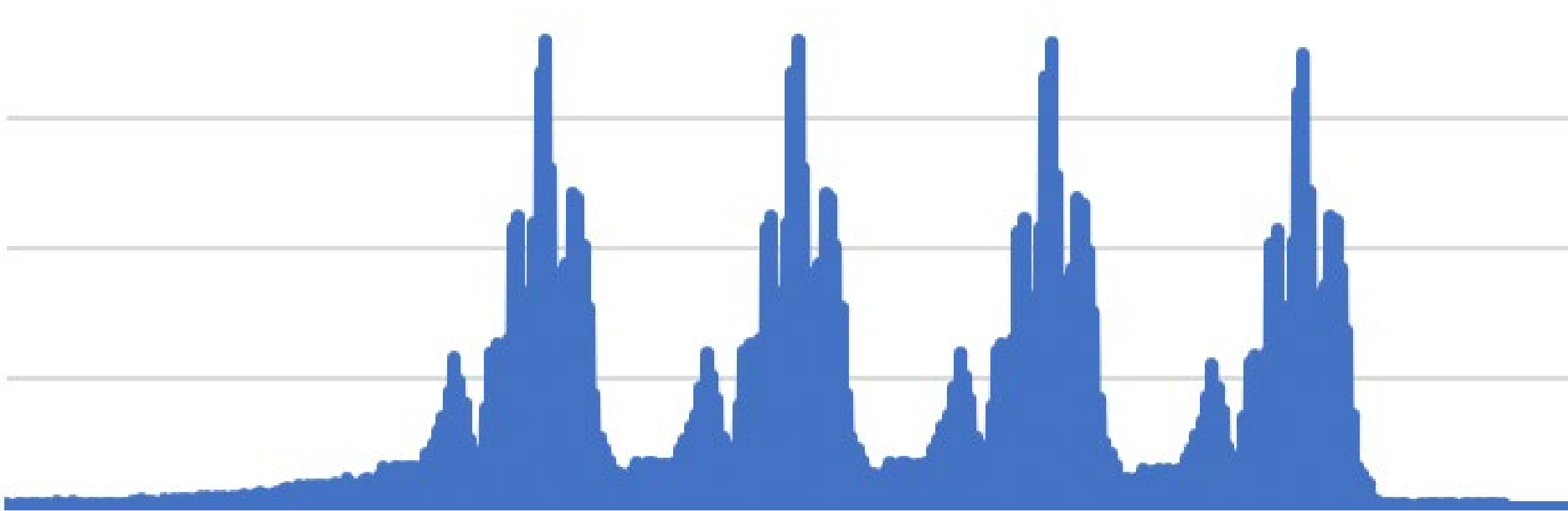
Working width 10 m, CV 150%



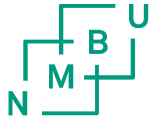
Distribution of multiply swaths



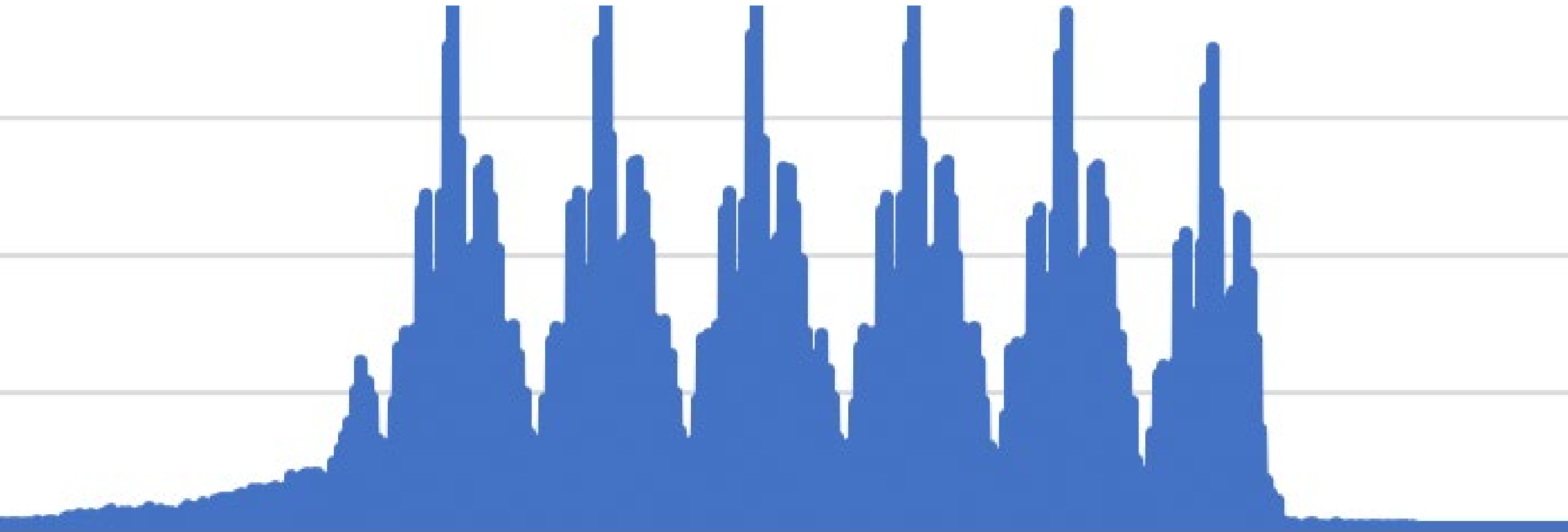
Working width 5 m, CV 130%



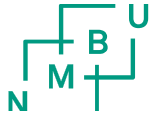
Distribution of multiply swaths



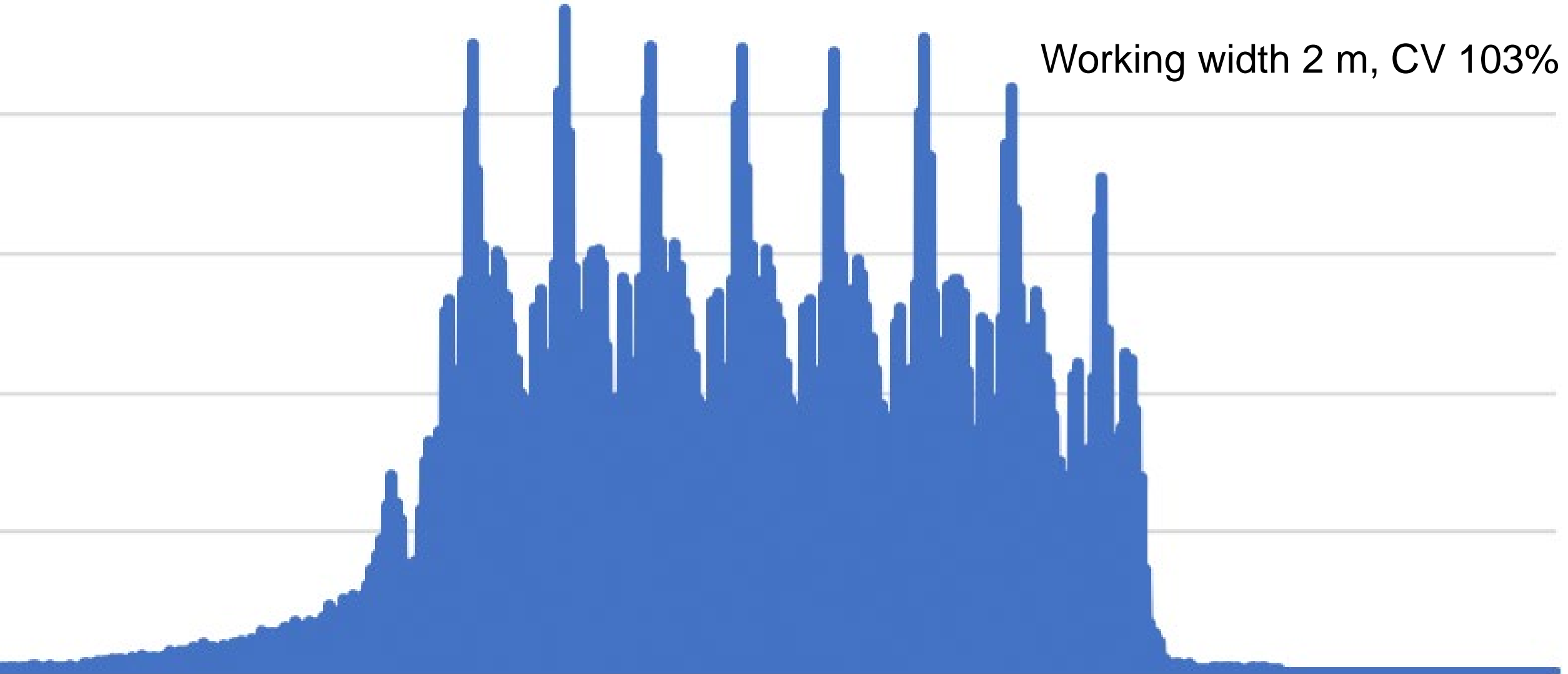
Working width 3 m, CV 107%



Distribution of multiply swaths

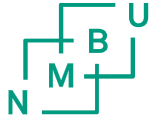


Working width 2 m, CV 103%



Spray drone

vs Field crop sprayer



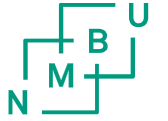
CONS

- Lower volume rate
- Poorer coverage
- Poorer distribution
- Higher nozzle height
- Higher speed
- More prone to drift
- Costs & licence & availability

PROS

- No soil compaction
- Independent of topography or soil conditions
- Easier spot spraying
- Easier to treat small, irregular fields
- Easier in hilly areas & safety
- Low operator exposure
- For spot spraying
 - Less use of PPP
 - Less drift
- CO2 friendly

Conclusions



- Spray drone cannot obtain so even distribution as field crop sprayers
- Areas where spray drones may have benefits in Norway;
 - In fields; potential for spot spraying e.g. against weeds
 - In hilly terrain due to operator safety and application
 - In orchards at early stage without leaves in steep fields
 - Areas where only knap sack sprayers are possible e.g. difficult grazing areas
 - Special situations, e.g. due to soil compaction and none existing access to field with ground based equipment

New Project **SUSDOCK**

Sustainable control of docks (Rumex spp.)

Synergies of detection, mapping, and innovative weed control





NMBU Sustainable Arena

Smart Farming and Green Innovation




Bærekraftsarena
Smart Farming



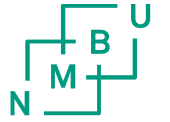
Smart Farming | Grønn Innovasjon
Green Innovation Student LAB



Norges miljø- og
biovitenskapelige
universitet
NMBU.no



Funding– «Smart farming and green innovation»



Year	2021	2022	2023	2021-2024
NOK	700.000	700.000	700.000	2.800.000
EUR	60.000	60.000	60.000	240.000



Research groups within, robotics, drones, precision agriculture, GIS and GNSS, sensors, image analysis, computer science, phenotyping, plant sciences, fertilizer sciences and soil sciences are included in the group, which can also be expanded as needed.

DEVELOPMENT OF AGRICULTURE

TECHNOLOGICAL REVOLUTIONS



1.0

WORK-INTENSIVE

- Work intensive
- Low productivity
- 1/3rd of population involved-required



2.0

GREEN REVOLUTION

- Artificial fertilizers
- pesticides
- More efficient equipment
- Productivity dramatically increased



3.0

PRECISION AGRICULTURE

- Precision operations within crops
- Individual treatment of animals vs total flock
- Automatic steering with 10mm precision
- Sensors and controls



4.0

SMART FARMING

- Internal and external network integration of agricultural operations
- Cloud service usage, large data sets processed
- Cheap and advanced sensors
- Big data analytics
- New algorithms that transform raw data into insight



5.0

ROBOT FARMING

- Operations without human presence
- Artificial intelligence, self-learning systems
- Production systems adapted to plant/animal needs
- Food production, consumer needs fulfilled
- Controls of ingredients/internal components

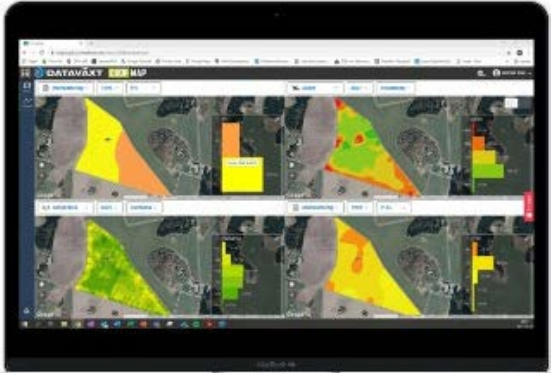
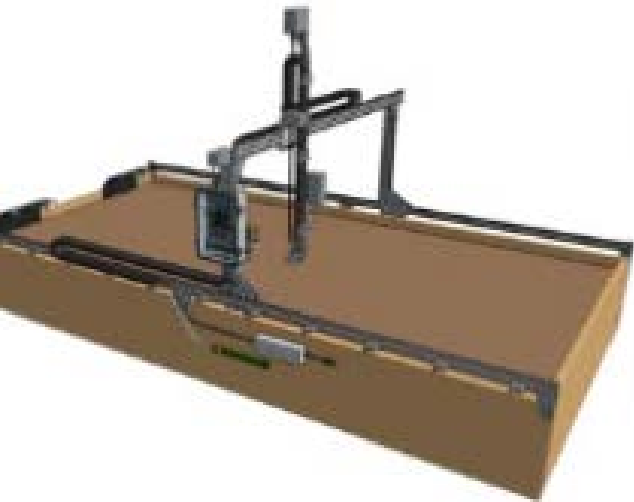
Research groups and topics at NMBU



SKP – Centre for Plant Research in Controlled Climate (senter for klimaregulert planteforskning)

SHF – The livestock Production Research Centre (senter for husdyrforsøk)

Smart Farming & infrastructure



PheNo - Norwegian Plant Phenotyping Infrastructure

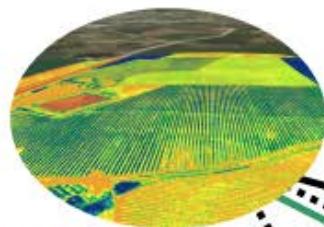
Coordinator



Consortium partners



Computing and
data analysis
services



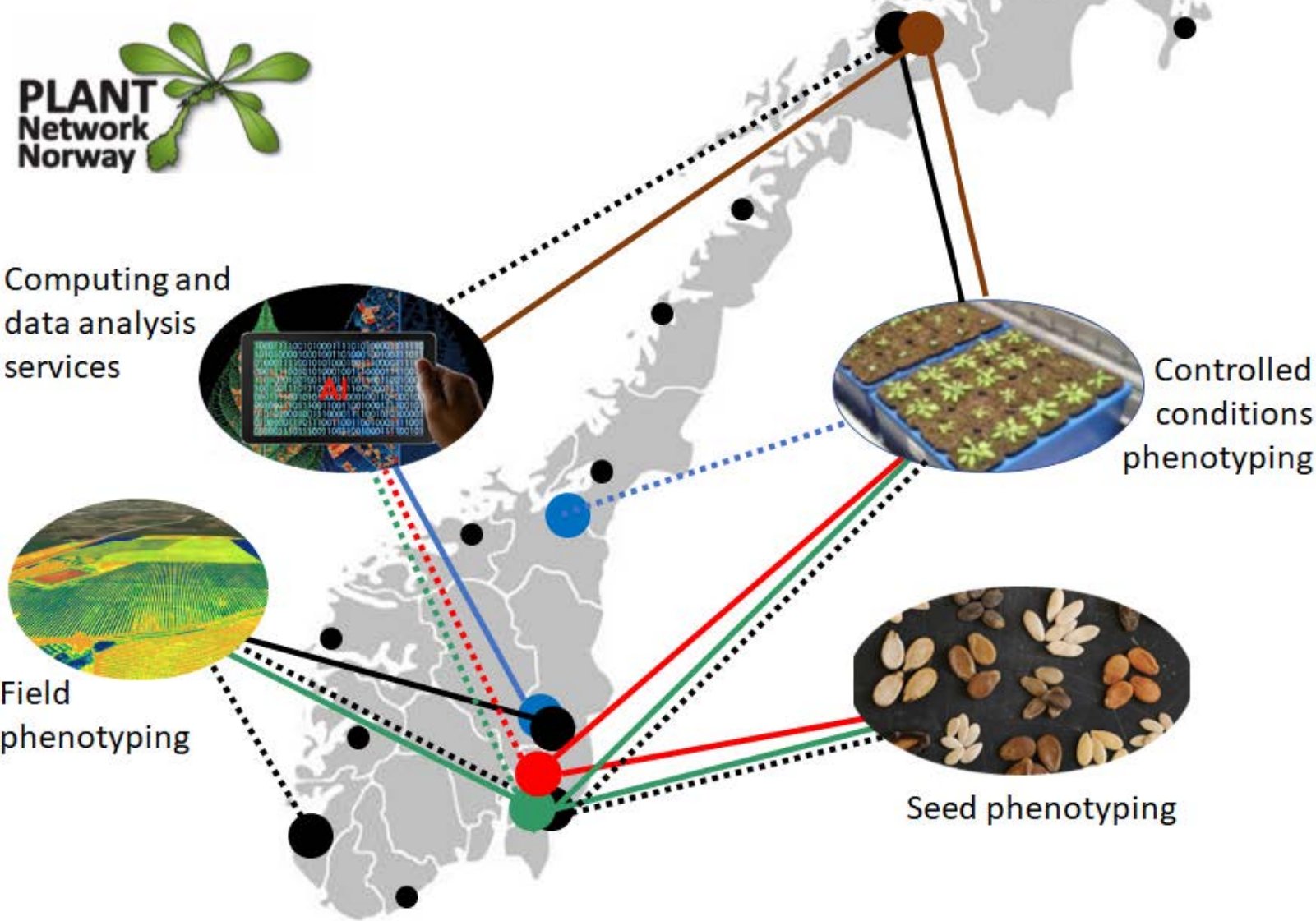
Field
phenotyping



Controlled
conditions
phenotyping

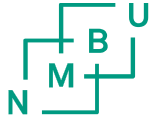


Seed phenotyping





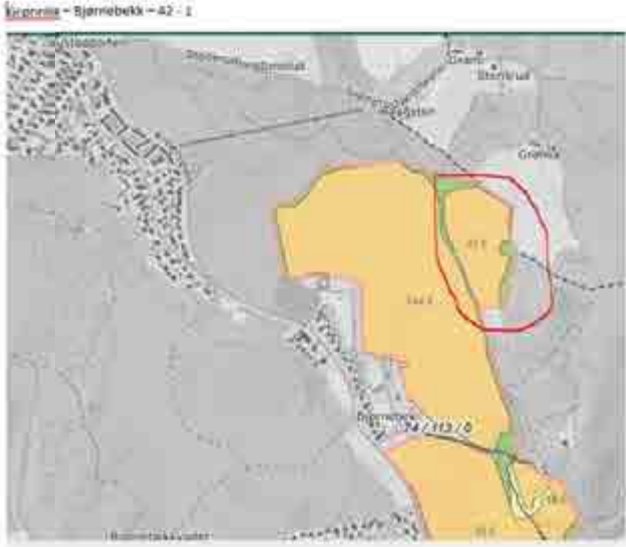
Pilot areas for education and research at NMBU



20 daa Kjærringjordet



14 daa Vollebekk



Grønne - 42 daa
Høybråten - 20 daa





autoagri.no



NMBU

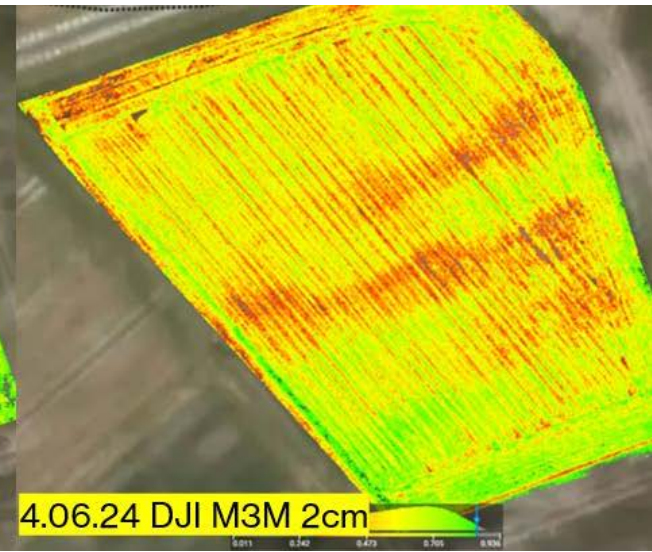
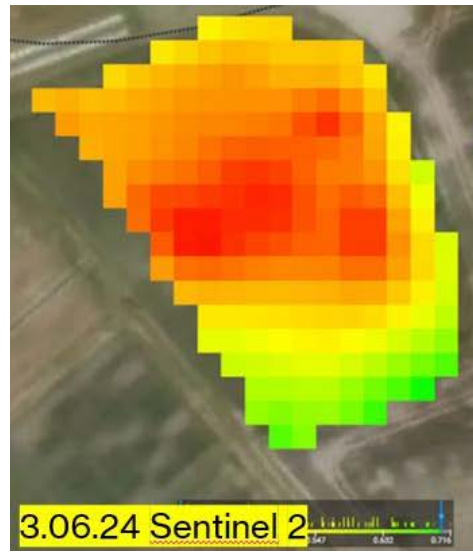
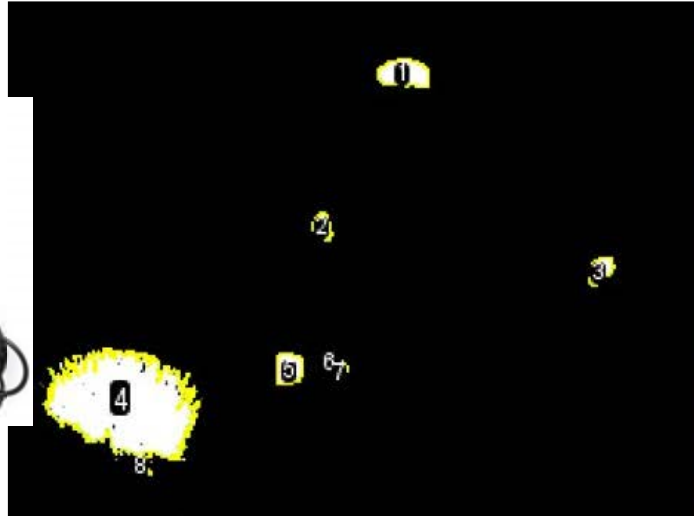


NMBU



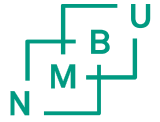
Kilter

BootCamp 2024 - student innovation



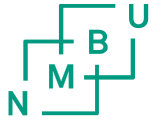


Autonomous grass harvesting





Projects -Smart Farming



ProteinBar

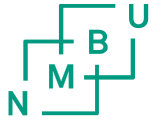


Projects -Smart Farming



Drone svever over forsøksfelt for å samle informasjon om hveteplantens vekst og helse.Foto: Tomasz Mroz

Projects -Smart Farming



AgriSol

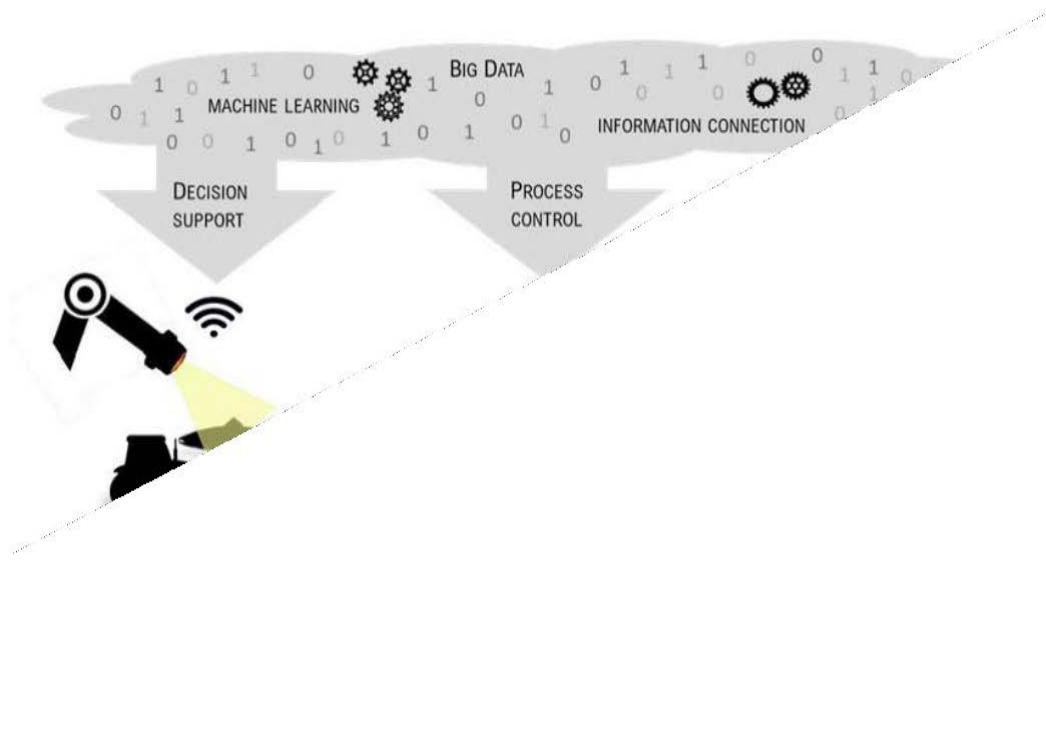
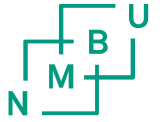


Some projects within Smart Farming

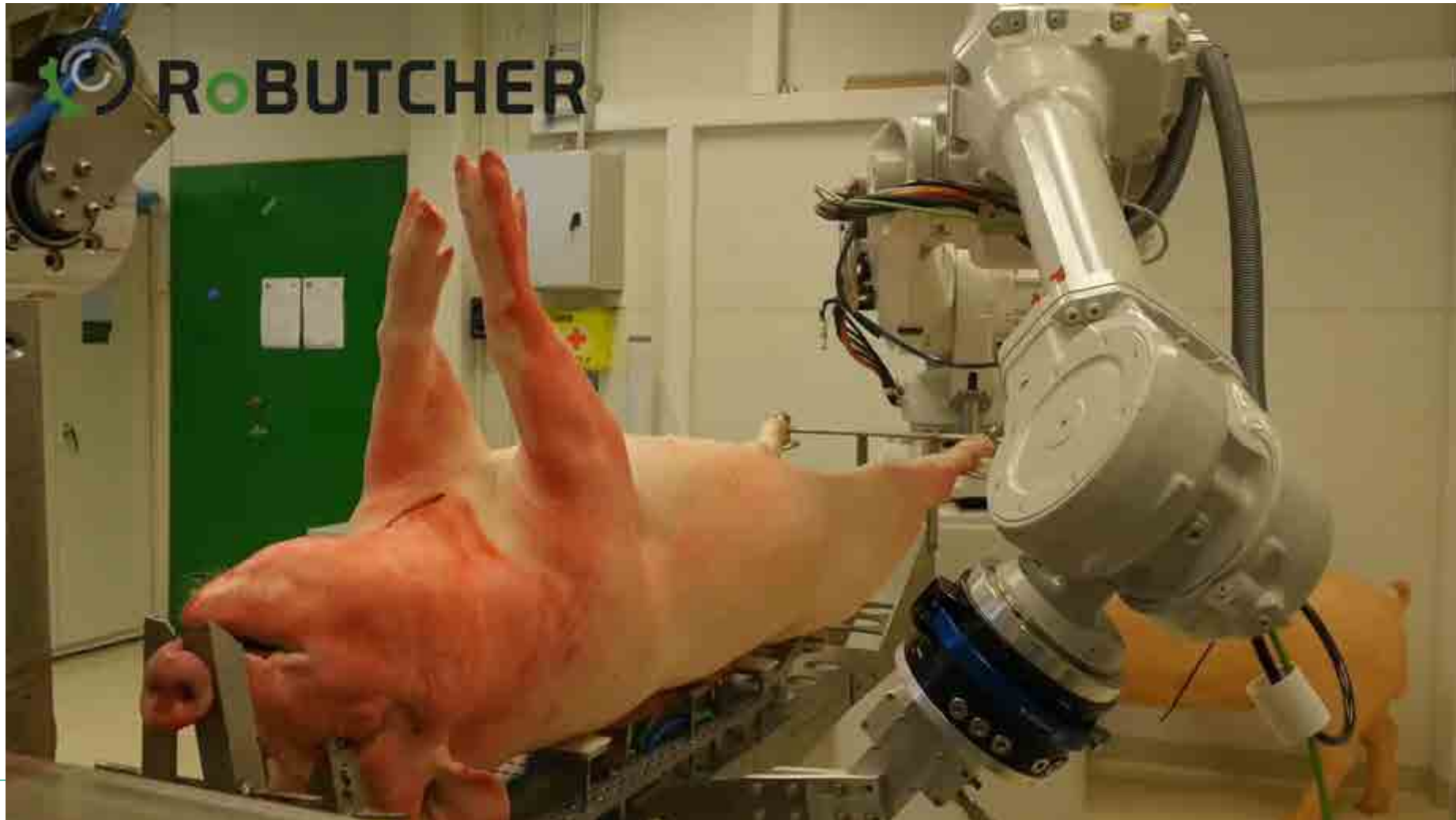
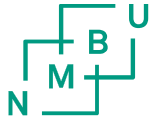


- RoboFarmer - Safe and reliable sensing, learning and control of an autonomous multi-arm agri-robot platform
- DLT farming Data-Led Transformation Solution for Sustainable Forage Grass Farming using Robotics, Energy-Efficient Sensors and Genomics
- ProteinBar and soil sensors
- Spray drones and drift measurements (2024-)
- SUSDOCK: Sustainable control of dock (*Rumex* spp.) (2025-)
- AgriSol (2025-)
- Smart farming – green production – long time learning digital modules
- SmartWeat (2025-2028) Harnessing AI models for climate-resilient wheat varieties in sustainable agriculture

RoboSense

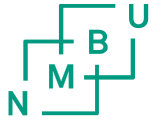


RoBUTCHER





Center application AgriFoodTech



Consortium:



Thank you for your attention!



Bærekraftsarena
Smart Farming



Smart Farming | Grønn Innovasjon
Green Innovation Student LAB



Norges miljø- og
biovitenskapelige
universitet

NMBU.no

Robotic and AI solutions for field Phenotyping

Sahameh Shafiee
Department of plant science
Norwegian University of Life Sciences (NMBU)

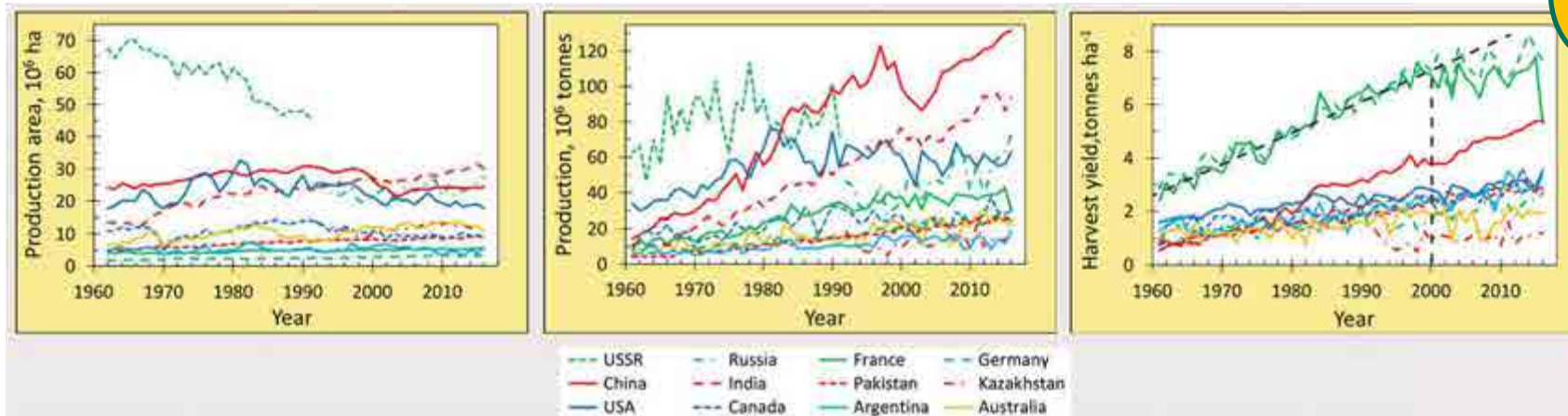


Current Challenges in Crop Breeding



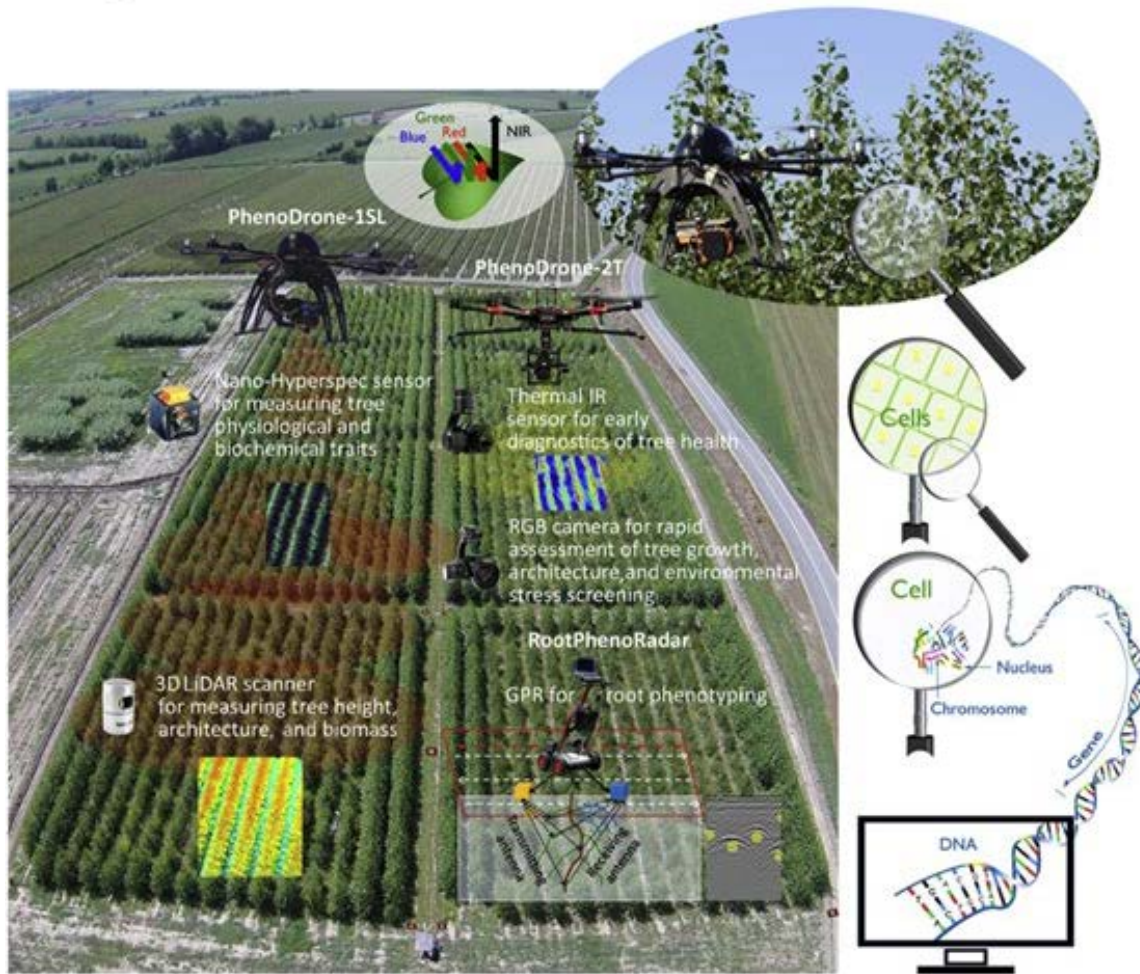
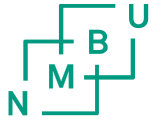
- The yearly increase of yield in major crops is flattening from 2000
- Climate Change:
 1. More extreme weather
 2. Heat and drought stress (reduced yield)
 3. Disease and pest pressure

Emphasizing the need for breeding for multiple stress resilience.

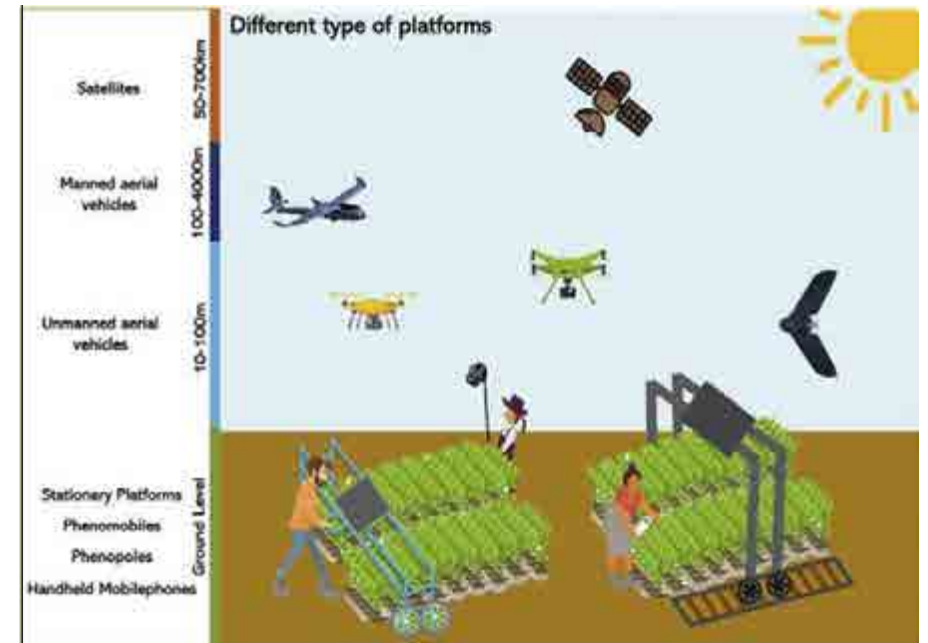


<http://www.fao.org/faosata/en/#data/QC>
Top 12 wheat producers by area

What we are really looking for?



PhenoBotix Lab: field high-throughput phenotyping is ready for a close-up

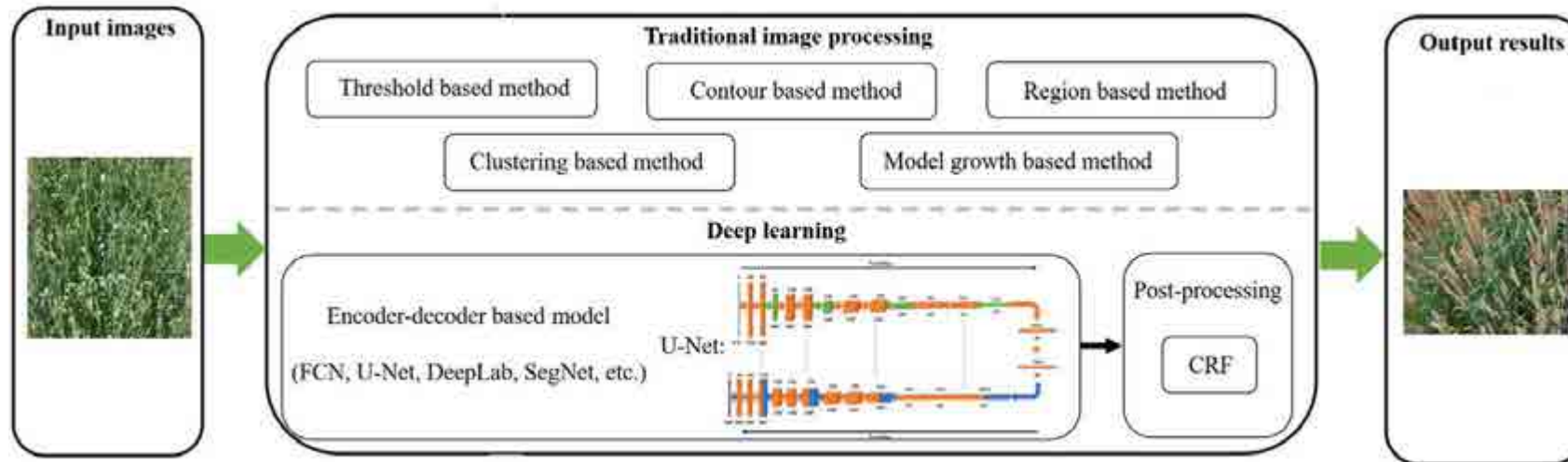
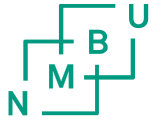


[Field Based High Throughput Phenotyping Rapidly Identifies Genomic - gn.racesociety.com](https://www.gn.racesociety.com)

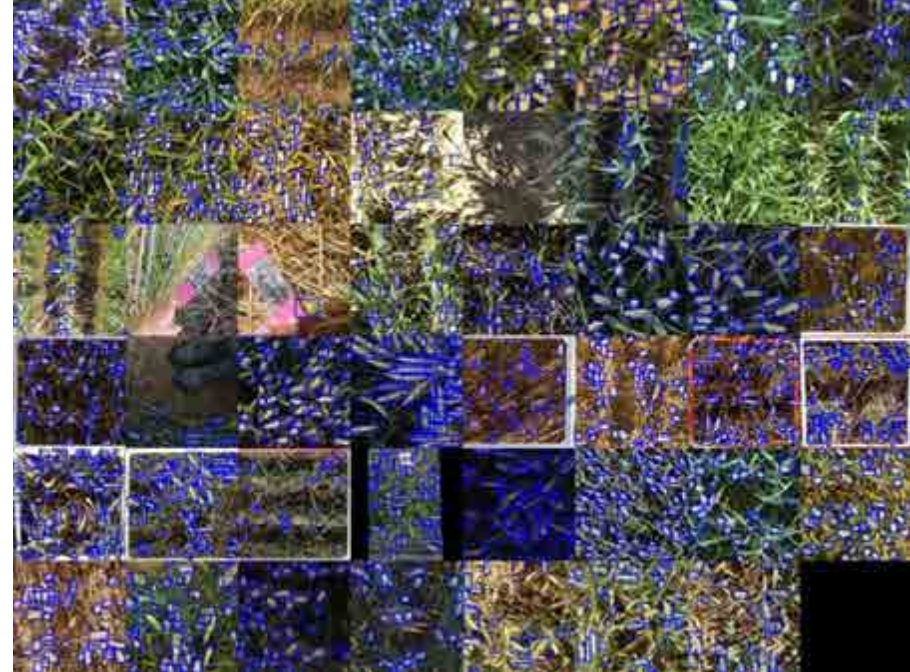
Case studies in Norwegian Wheat Breeding



Can we simplify some tasks using AI?

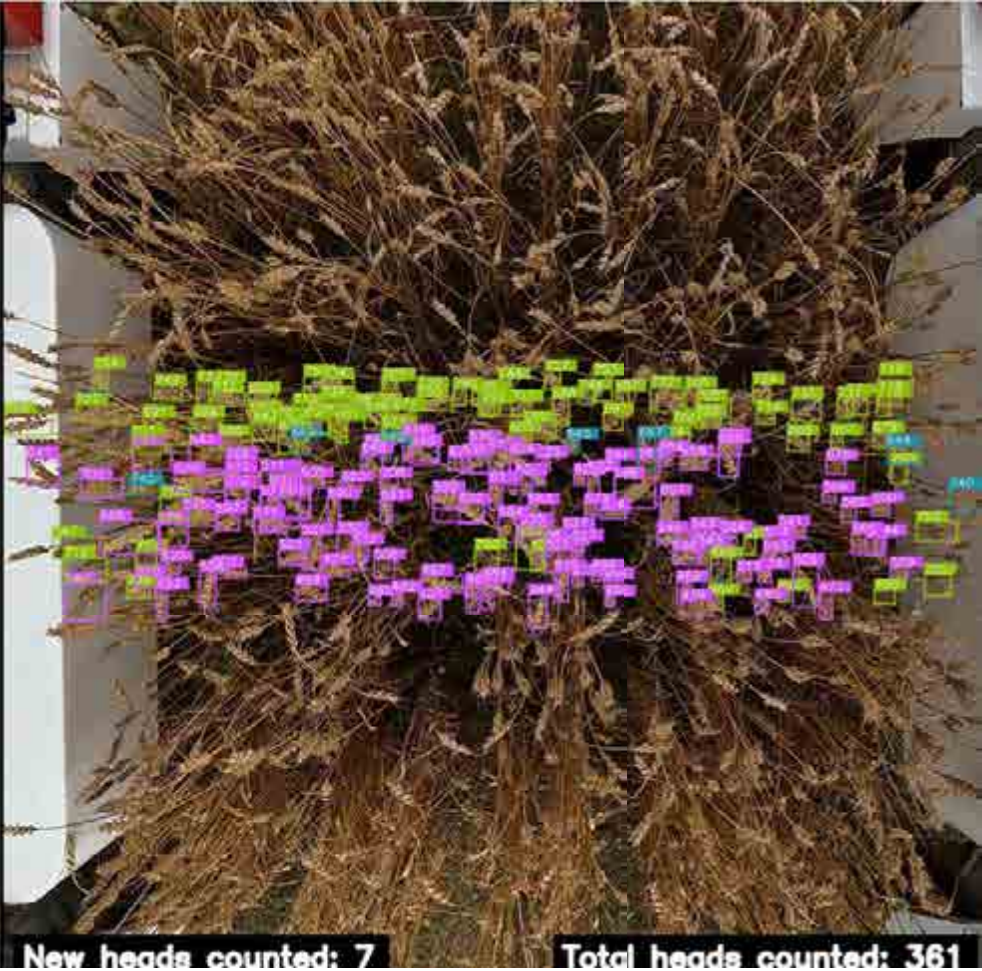
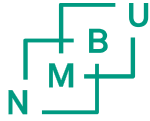


Global Wheat Head Dataset (GWHD)

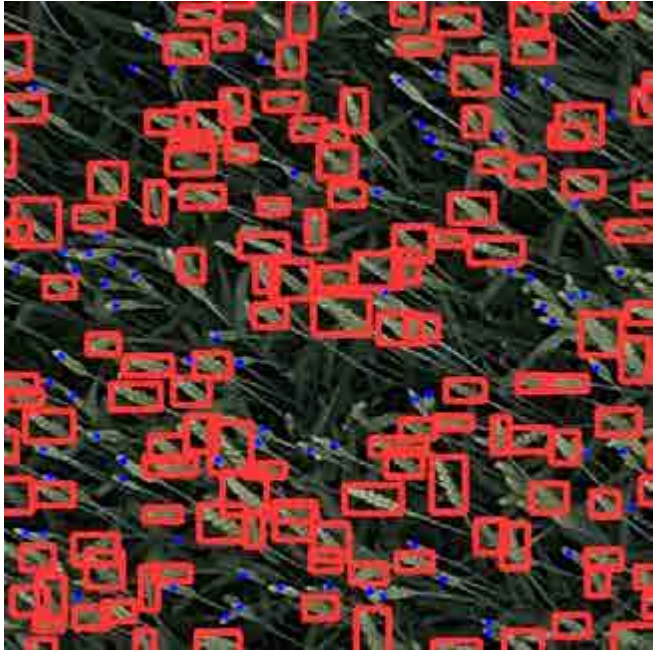


CNN and YOLO5

Can we make it on-the-og?

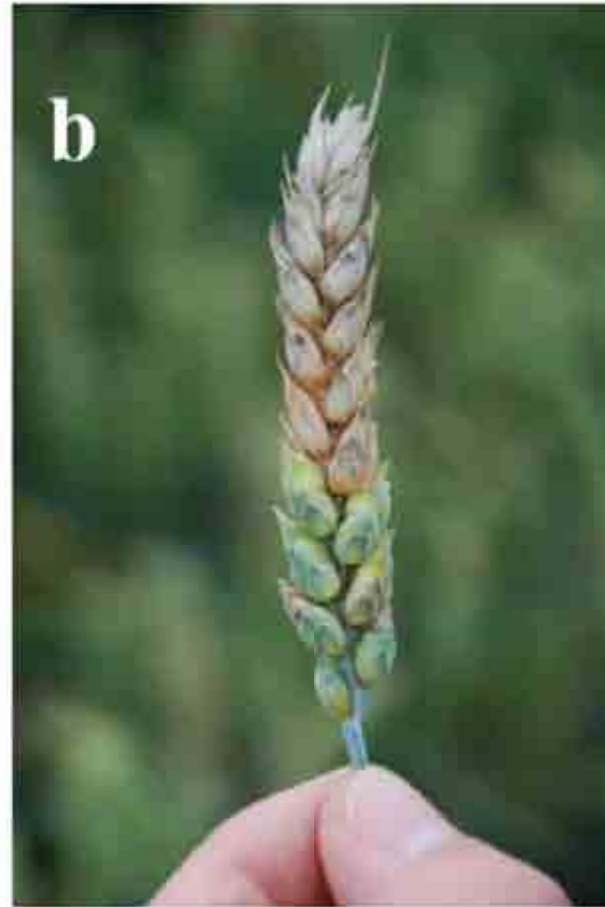
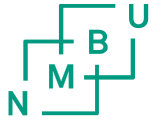


Applying YOLO5 model on drone images



Best Accuracy: 62%

Can we add another layer? FHB detection?



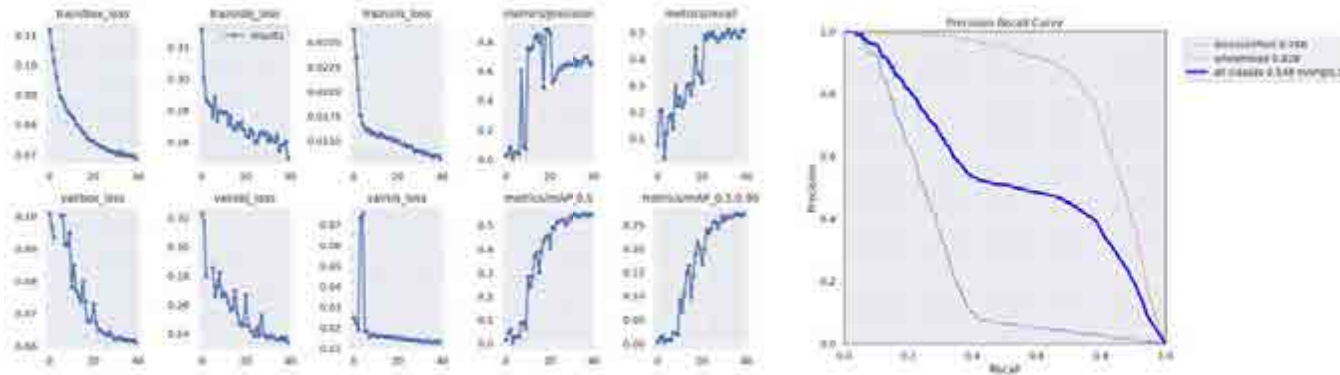
Data Collection & annotation



- Coco annotator to annotate the images
- Total of 700 images in the dataset
(25706 instance of wheat heads,
10866 instance of diseased parts)
- Splitting the dataset to train, validate and test (70%, 20%, 10%)

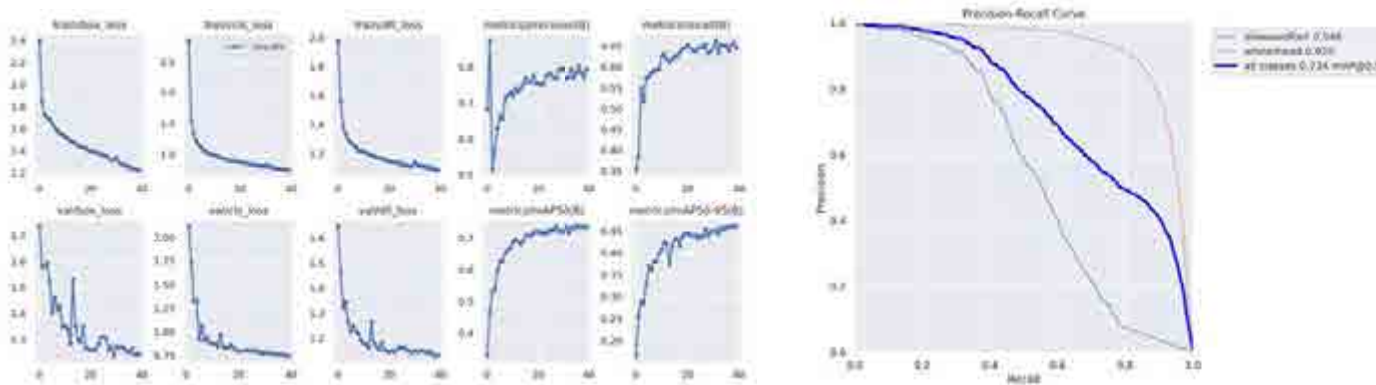


YOLOV5 and YOLOV8



YOLOV 5

- 82% for wheat heads detection
- 26% for FHB detection

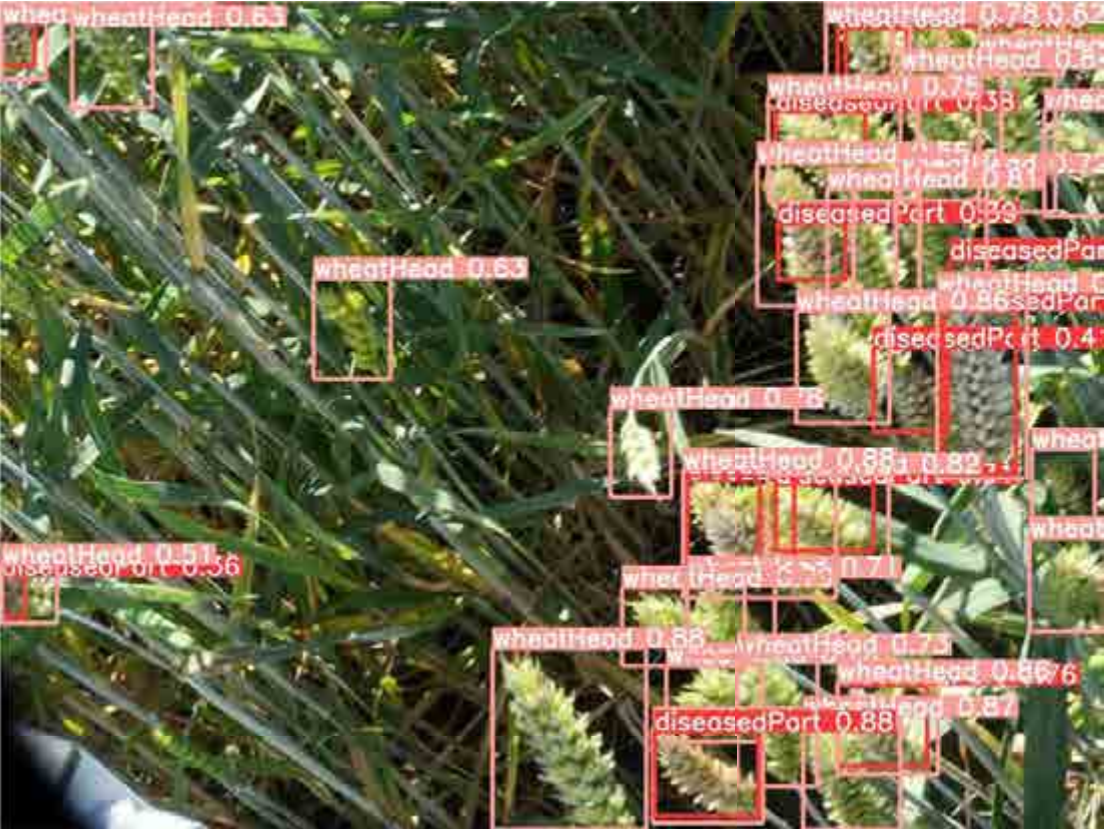
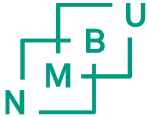


YOLOV 8

- 92% for wheat heads detection
- 54% for FHB detection



Testing both models' performance on the same image

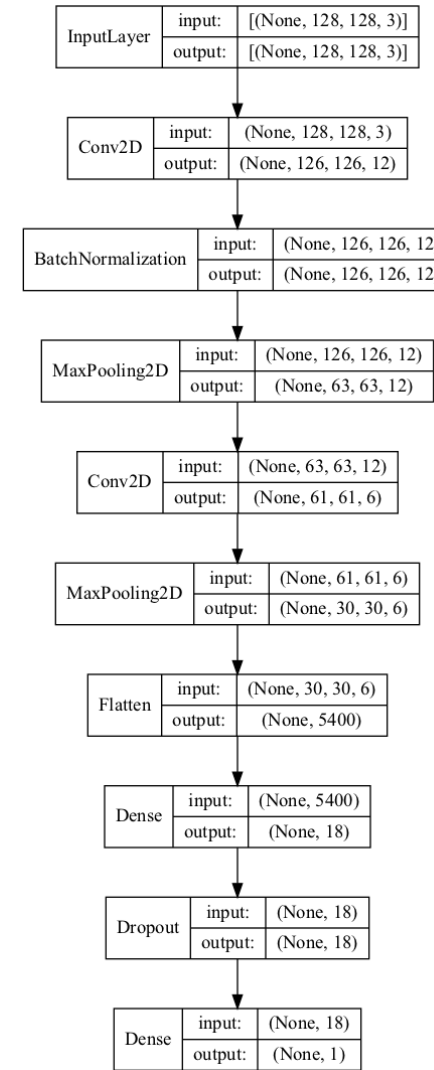
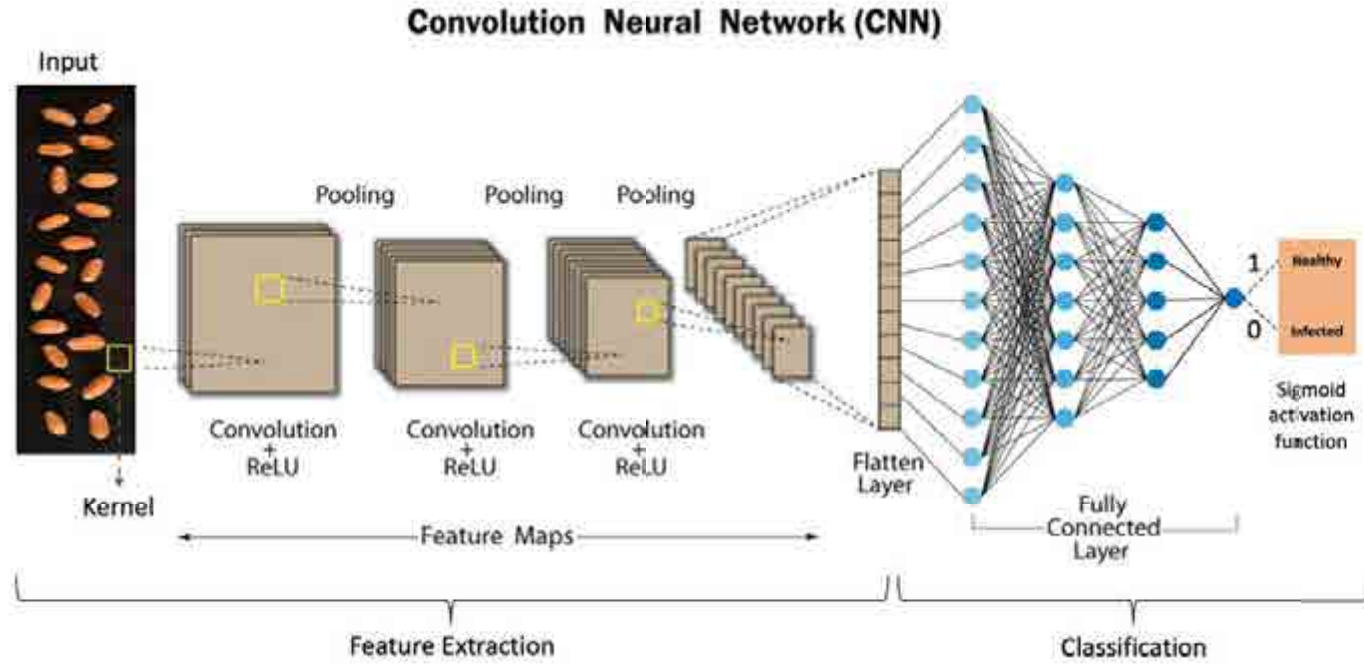


Yolov8



Yolov5

What about detection in seed level?



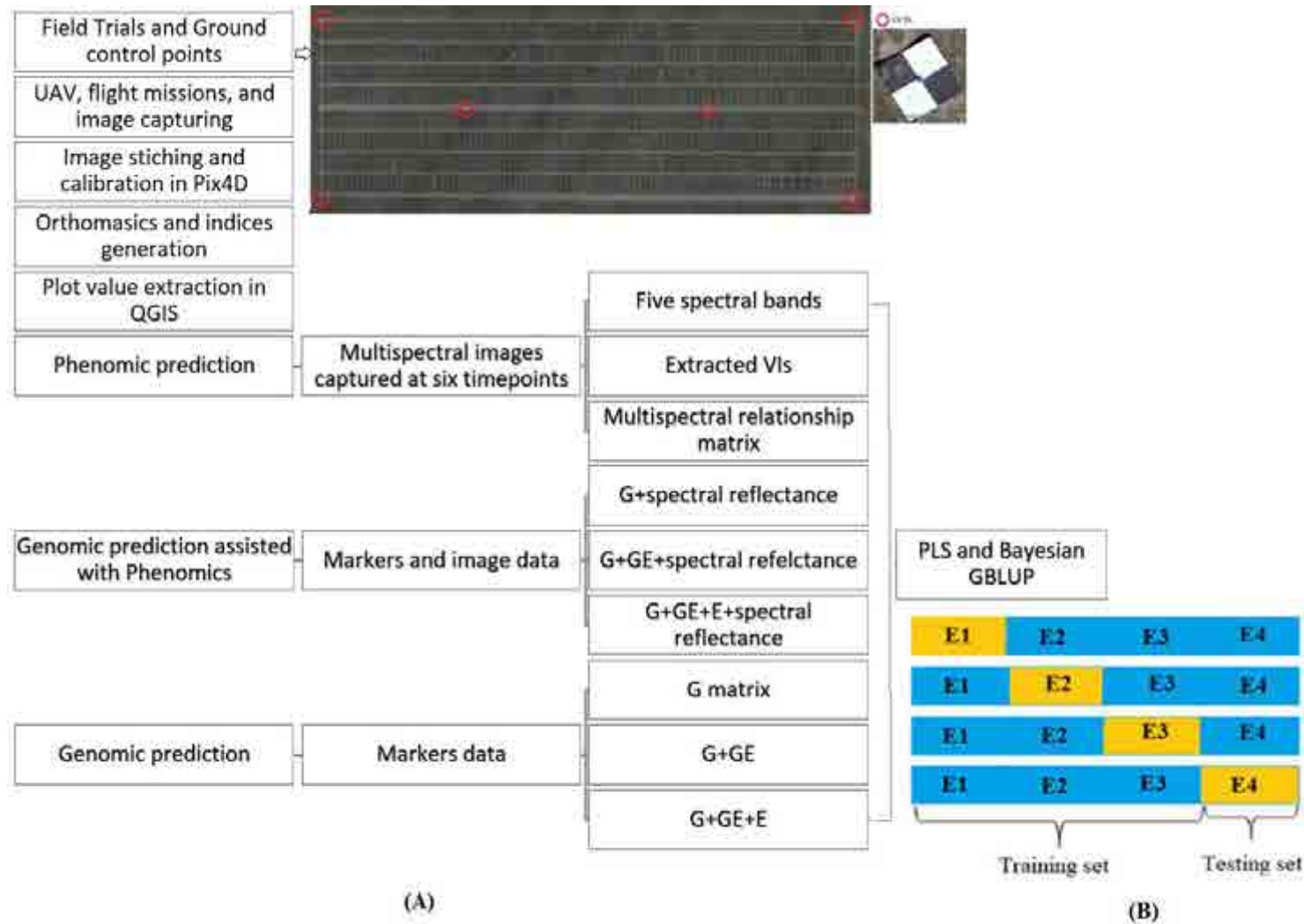
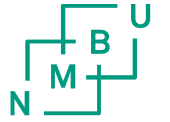
Confusion Matrix

	Healthy	Infected
Healthy	79	2
Infected	1	78
	Healthy	Infected

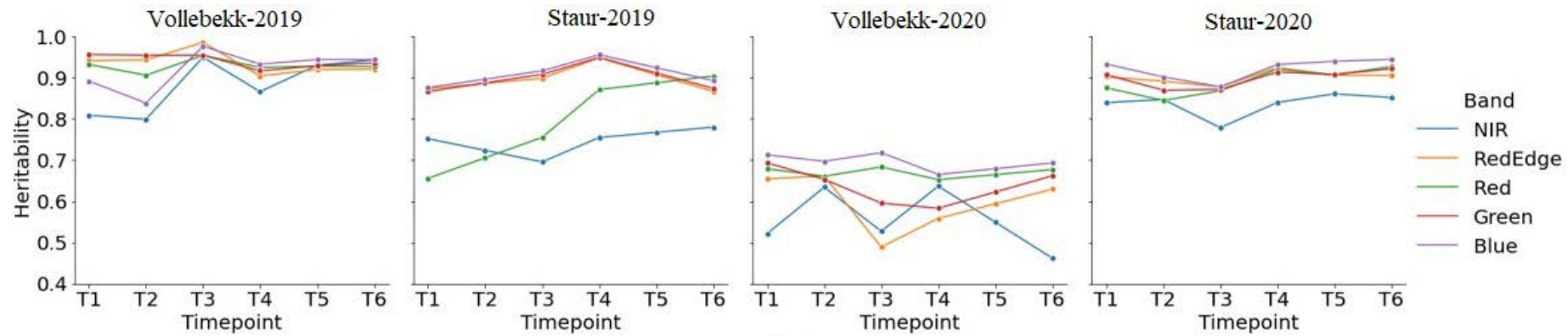
True Labels (rows) vs Predicted Labels (columns)

Condition	Precision	Recall	F1-score
Healthy	0.975	0.988	0.981
Infected	0.987	0.975	0.981

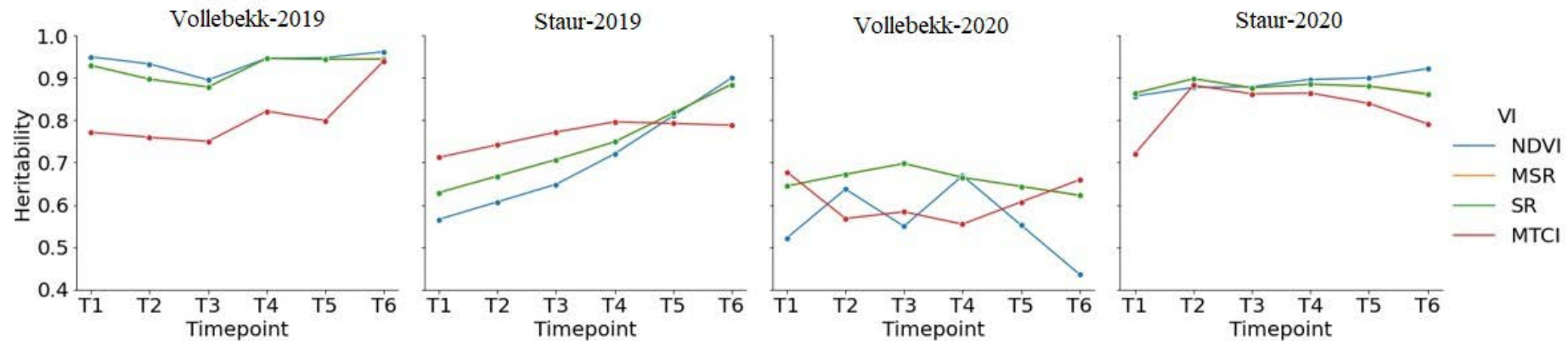
G2P? Genomic and Phenomic prediction



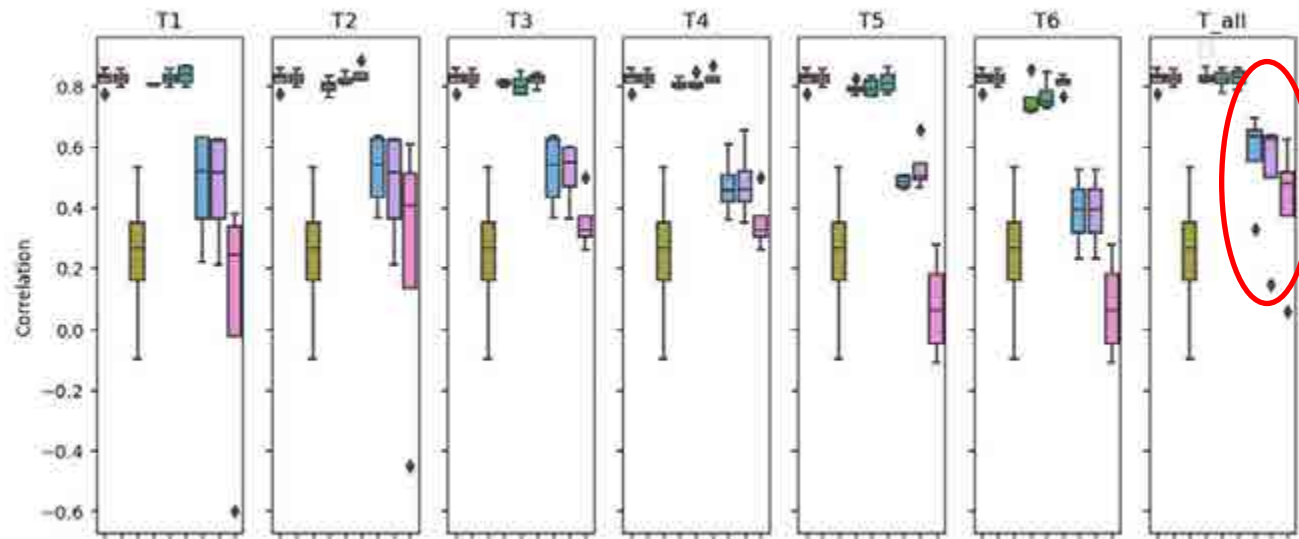
Looking into Heritability!



(a)

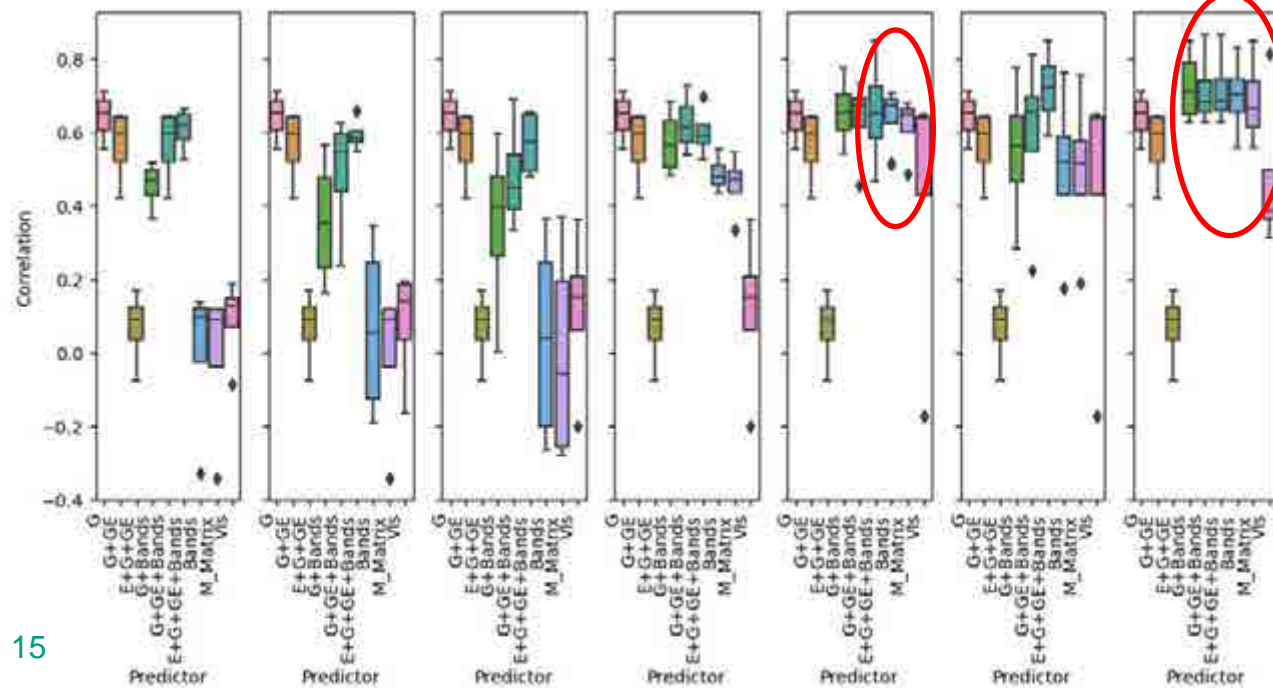


(b)



(a)

The genomic prediction (GP) results for grain yield (GY) (a) and days to maturity (DM) (b)



(b)

Future work

- How can we make the models robust?
- Explainable AI
- Hybrid models
- Feature engineering
- SmartWheat: Harnessing AI Models for Climate-Resilient Wheat Varieties in Sustainable Agriculture



Norges miljø- og
biovitenskapelige
universitet



Thank you for your attention
Questions?
Sahameh.shafiee@nmbu.no



- Håkon Bråten & Mathias Johan Dyrén
- Norwegian University of Life Sciences
- 26. november 2024

On the Go Wheat Head Counting Using Robotics and AI

*A robot autonomously navigates fields,
counting wheat heads to predict yield and quality*

Agenda

- Introduction
- Methods
- Equipment
- Navigation
- Wheat Head Counting
- Results
- Future work



Research questions

Can a robot autonomously navigate a row of wheats without making crop damaging mistakes using only an RGB camera?

Is it possible to use YOLOv5 and a counting algorithm to recreate the results of a human count without deviating significantly?

Equipment



GoPro Hero 11



RealSense D435



Thorvald

Navigation

Navigation

Data Collection

- Drove Thorvald in field
- Capturing diverse scenarios
- Total of 550 images



Navigation

Preprocessing

What should the model do?

- Segmentation mask
- Reference line

Train/Test/Validation 70/15/15

Data augmentation



PATH

VEGETATION

GROUND

Navigation

Deep Learning Model

Convolutional Neural Network (CNN) model

- DeepLabV3+ with ResNet50 backbone
- Atrous Convolutional Layer

Loss

- Sparse Categorical Crossentropy
- Mean Absolute Error (MAE)

Optimizer

- Adam (learning rate of 0.0001)



Goal of the model:

Predict reference line and segmentation mask to guide the robot's navigation

Navigation

Robot Controller

- Constant speed while adjusting turning angle
- X_0 and X_1 are the distances from the reference line to the predicted line at the top and bottom

Goal of the controller:

Adjust the robot's angular velocity to minimize these offsets, ensuring the robot stays on the detected path



— Reference line
— Predicted line

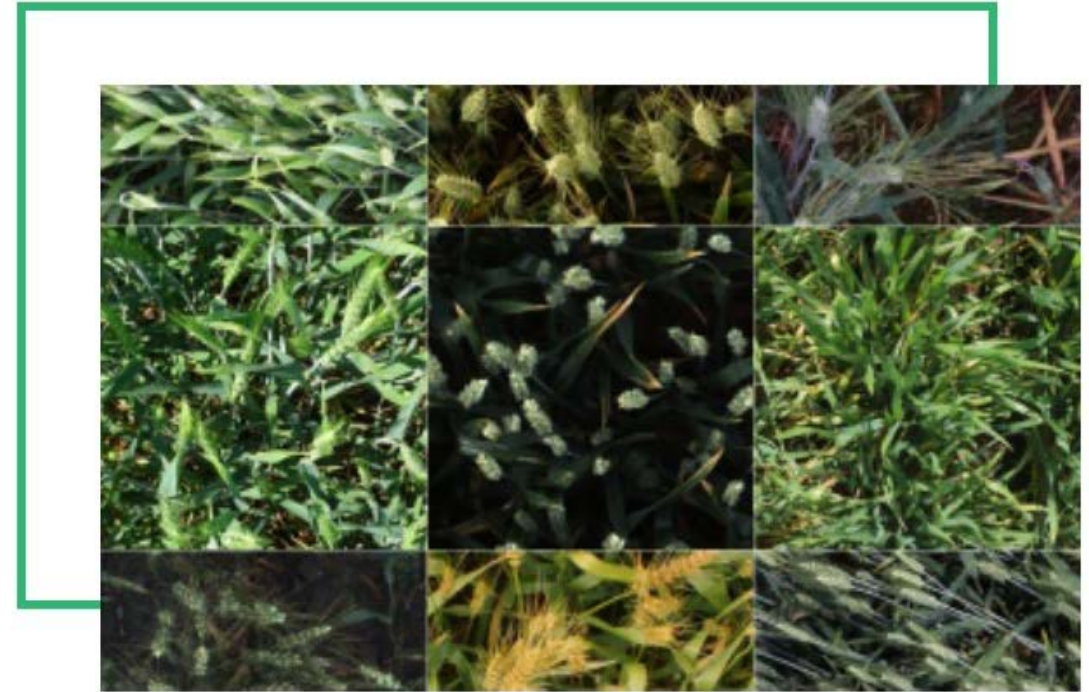
An aerial photograph of a wheat field, showing rows of wheat plants stretching across the landscape. The image is overlaid with a color gradient that transitions from a dark green on the left to a deep red on the right. The text 'Wheat Head Counting' is centered in the middle of the image in a white, bold, sans-serif font.

Wheat Head Counting

Wheat head counting

Detection

- **Global WHEAT Head Dataset 2021**
 - 6k+ images
 - 300k unique heads
 - Training and test
- **Global WHEAT CHALLENGE 2021**
 - By University of Saskatchewan
 - Winning team: randomTeamName



GWHD 2021

Figure 1: Global Wheat Dataset, 2024,
<https://www.global-wheat.com/gwhd.html>)



Global WHEAT CHALLENGE 2021

Figure 2: Global WHEAT CHALLENGE 2021, 2024,
<https://www.aicrowd.com/challenges/global-wheat-challenge-2021>)

Location: Vollebekk, Ås, Norway

- 96 plots (1.5 m × 6.5 m)
- 8 columns , 12 rows
- 24 spring wheat cultivars
- Different nitrogen fertilization levels



Wheat head counting Algorithm

App: GoPro Quick

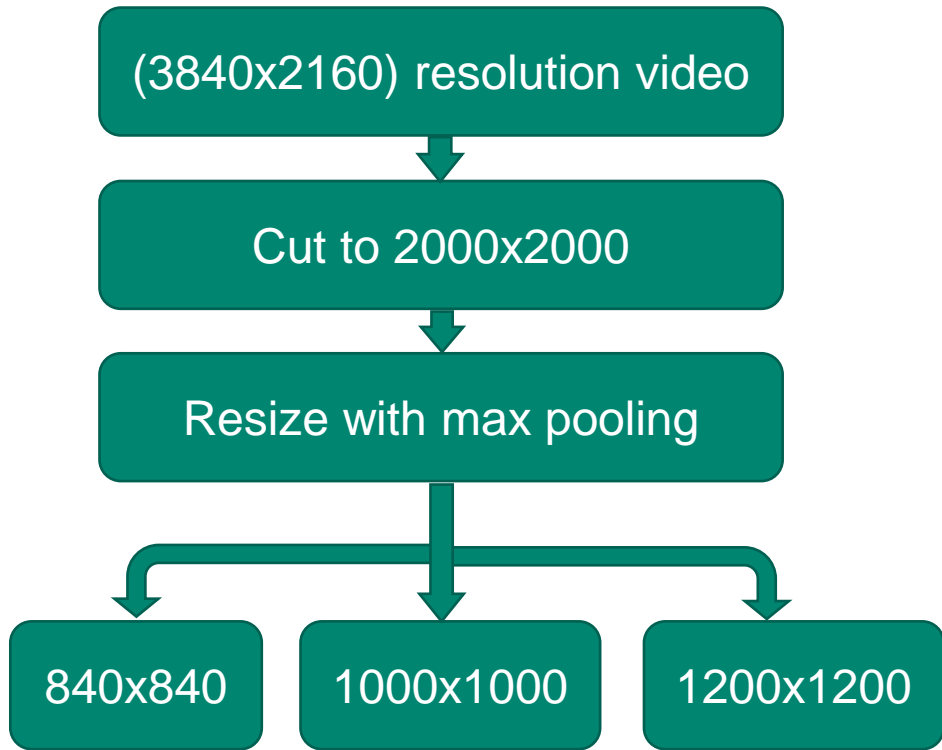
Start video when approaching plot

End once droven past

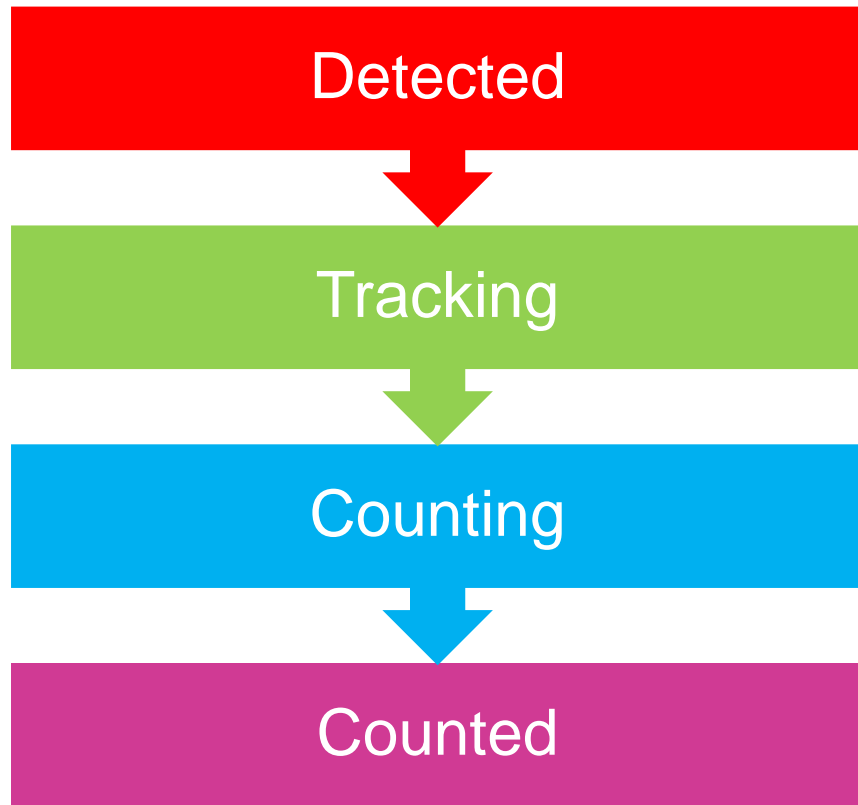
Video stored in camera and
extracted afterwards



Wheat head counting Algorithm



Wheat head counting Algorithm



New heads counted: 38

Total heads counted: 1540

Wheat head counting

Algorithm

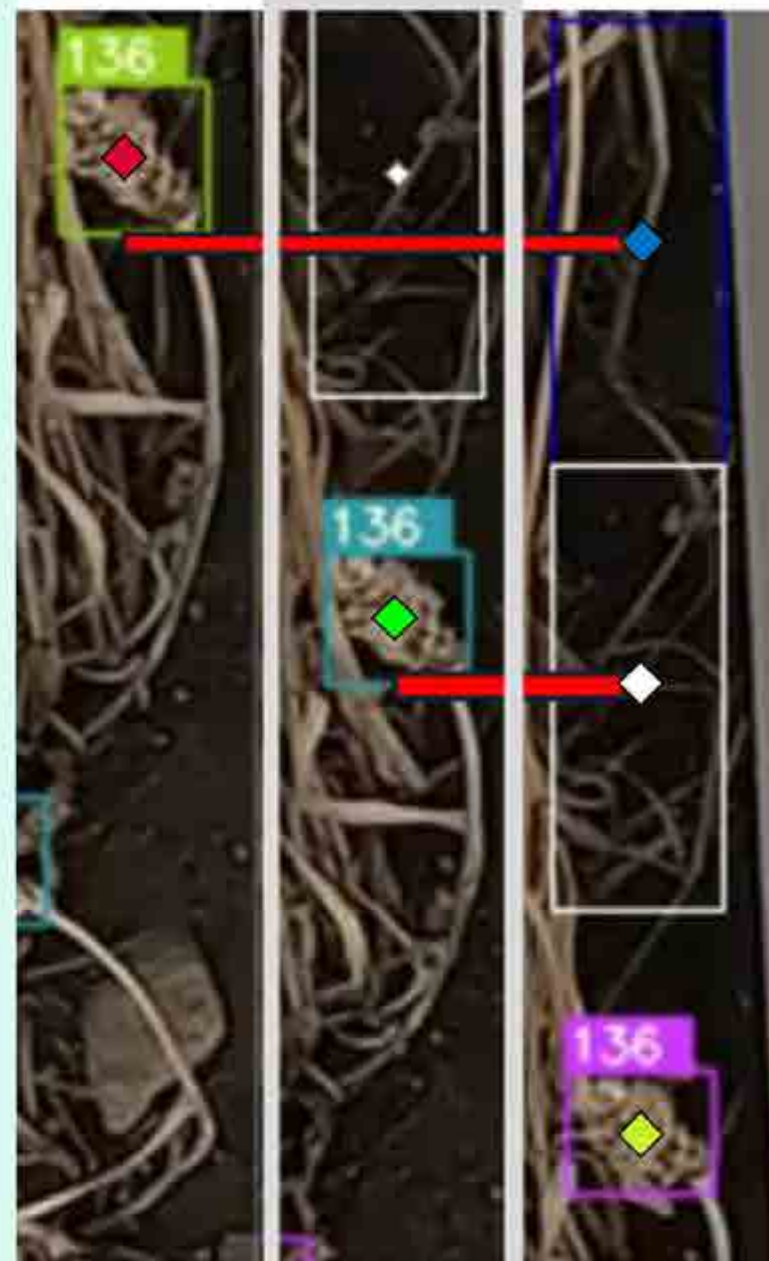
A new wheat is detected
Frame 0

In frame $y - 1$
 $DIST_Y1 = |\blacklozenge - \blacklozenge|$
Goal:
Find wheat in frame Y-1
Within \square compare
With lowest DIFF

In frame $y - 2$
 $DIST_Y2 = |\blacklozenge - \blacklozenge|$
Goal:
Find wheat in frame Y-2
Within \square compare
With lowest DIFF

Enherit ID
of wheat with lowest
 $DIST_Y1 + DIST_Y2$

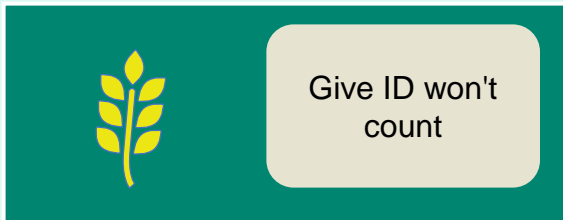
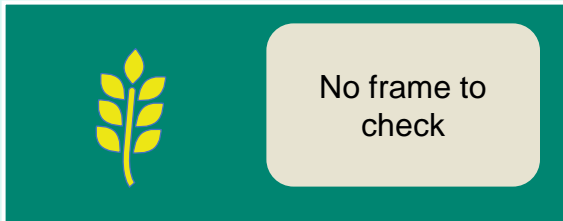
Frame y-2 Frame y-1 Frame y



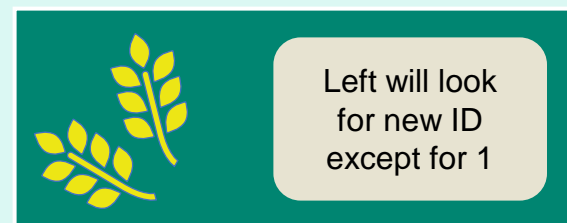
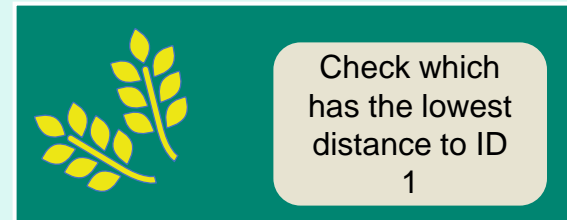
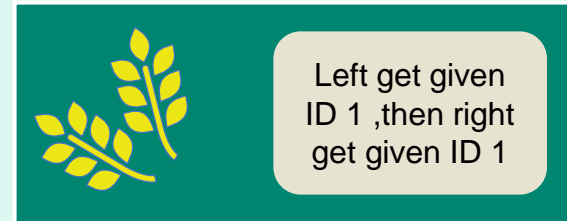
Wheat head counting

Algorithm – Special situations

No previous frame



Same ID given



No wheat found in previous frame

