TRACKING OF SUGAR BEETS VISUALLY



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TRACKING OF SUGAR BEETS VISUALLY

Raw vs Tracked - Key Findings

- ➢ Initial Sugar Beet detection: 40.31% → 44.69% (4.38% accuracy increase) with tracking
- 8.75% of detections are improved with tracking in early-stage detections
- Sugarbeets often confused with Dicot Weeds
- ➤ Tracking improves stability of classification
- Monocot and dicot weed detection remains highly accurate (>95%)
- Tracking helps maintain consistent classification across frames



EURAGENG JOINT SEMINAR 2024

RASMUS NYHOLM JØRGENSEN



TRACKING WITH YOLOV11 WAS NOT STRAIGHTFORWARD!



Enhanced YOLOv11 Tracking in Our Study

- Constrained Motion Tracking:
 - Leverages FarmDroid FD20's consistent forward motion.
 - Predicts frame-to-frame displacement (RMSE: 4.92 pixels).
- Custom Weighted Cost Function:
 - Factors for track association:
 - Position displacement (35%).
 - Object size (20%).
 - Aspect ratio (20%).
 - Class confidence consistency (25%).

Row Awareness Component:

- Clusters sugar beet detections to track crop rows.
- Validates positions against expected row geometry.
- > Improved Multi-Frame Tracking:
 - Maintains object identity across 4+ frames.
 - Filters uncertain detections for better
 - accuracy.



5TH NJF- AGROMEK - EURAGENG JOINT SEMINAR 2024 MICHAEL SØNDERGAARD NØRBO MADSEN*, SØREN KELSTRUP SKOVSEN, BO MELANDER, RASMUS NYHOLM JØRGENSEN



KEY TAKEAWAYS

Early-stage crop detection

- Early-seeded beets (larger): 75.84% detection accuracy
- Late-seeded beets (smaller): 44.69% detection accuracy
- \blacktriangleright Biggerplants = Betterdetection

Tracking Benefits

- Improves detection of smaller plants (8.75% of cases)
- ▷ Increases stability $(81.56\% \rightarrow 85.31\%)$
- → Reduces classification volatility $(0.44 \rightarrow 0.26 \text{ changes})$
- Better performance in challenging conditions

Practical Implications

➢ Foundation for 2025 organic spraying trials







ACKNOWLEDGMENTS

We extend our gratitude to the following collaborators and supporters:

FarmDroid:

For providing the test field and enabling the FarmDroid FD20 to carry the OREICam during trials. **RoboWeedMaps Service:**

For access to their crop and weed instance detection model, significantly simplifying the annotation process.

Funding Support:

The Organic Research and Extension Initiative (OREI) grant: "Building Resilient Organic Weed Management Systems with Precision Smart Technologies and Autonomous Robots" (Tracking Number: GRANT13005541).

Team and Colleagues:

For their invaluable contributions to research and development.



AARHUS UNIVERSITY

For more information, please visit:

https://www.youtube.com/watch?v=1xF7YKUcBSE



INTERPRETING AND ADAPTING REGULATORY STANDARÐS FOR COMPLIANCE OF DISRUPTIVE AGRICULTURAL TECHNOLOGIES: A CASE STUDY ON HIGH-PRECISION HERBICIDE SPRAYING ROBOT

Inhouse development and production



Located at Langhus in Norway (30 min from Oslo) 29 full-time employees

Current herbicides practice are damaging and inefficient



Current herbicide spraying practices do not yield sufficient results and require **manual weed control at later stages**, which is costly and labor-intensive.



Available herbicides for vegetables have **phytotoxic effect on crops** because they are not tailored to vegetable use.



Farmers are dependent on easy access to labor in order to perform weed control, which is **becoming increasingly challenging**



Pests **reduce global potential crop yield by up to 40%**; That could be twice as large if no agrochemicals were used

There is a **political push** towards reducing use of chemical herbicides by 50% in weed control, limiting farmers' ability to perform effective weed control.





Kilter

Kilter manufactures the AX-1, an herbicide spraying robot that enables farmers to perform more efficient weed control by:

- Targeting weed, not the crop, nor the soil.
- Ejecting 1µL droplets with a 6x6 mm resolution, at up to 100
 Hz per nozzle outlet, having 210 nozzle outlets per robot.
 - Being completely autonomous.
 - Reducing herbicide usage, reducing manual labor, and increasing crop yield.

Underlying magic

Artificial Intelligence Patented, single droplet tech.







Take picture



Distinguish weed, crop, and soil



Spraying decision



SDT Single Drop Technology

Generate individual droplets on demand

Proven technology



Already in use at farms; 20 units sold in Norway, Sweden and Germany, as well as 3 on their way to Australia



Deep learning neural network (in-house developed AI technology)



Patented (Norway, USA, China, Europe, India, Eurasia) droplet generator with revolutionizing spraying precision



AX-1 can be used in all open fields

Kilter's **tested**, **proven** and **patented deep-tech** droplet technology drops a precise amount of herbicide onto weeds, also **allows the use of alternative**, **less polluting**, **herbicides** such as pelargonic acid, vinegar, or citrus oil without touching and killing the crop



Kilter Systems in balance



Celeriac



Sweede



Spinach



Shallots

Parsley root

Beetroot

Basil



Carrot



Ruccola

Corn salad



Available classifiers

Infrastructure in place to develop new classifiers quickly.

Proven technology

The image below is **drone footage of a customer's field** (July 2023) where the robot has treated weeds in parsley (midseason). Based on **automated tests performed** by the machine, some areas are left untreated by the robot to demonstrate the effectiveness of the treatment. The large plants in the squares labeled **"F" are all weeds**, whereas the small plants in the rest of the image are all crops, indicating the high precision and effectiveness of the treatment. The consistent outcomes have been **verified through third-party testing** conducted by SGS and NIBIO.

"F+R" indicates where the farmer is aerating the soil + robot application. "F" is where aeration has been applied with no robot application.



F+R: Farmers + Robot spraying practice F: Farmers spraying practice

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3rd party field trial Farmer – NIBIO -NLR

Kilter AX-1 with Finalsan in parsley root

Kilter AX-1 v.s

Farmers practice



NIBIO NORWEGIAN INSTITUTE OF BIOECONOMY RESEARCH

Kilter Systems in balance



The mean sellable crop yield in weeding strategy 'Robot' (**12.03 tons**/ha) was significantly higher (paired t-test, p=0,042) than the mean yield of Farmer strategy (**8.11 tons**/ha). The number of sellable roots of strategy Robot (120 486 roots/ha) was significantly higher (p=0.025) than the strategy Farmer (86 806 roots per ha)



Farmer's practice

Traditional blanket spraying Fenix and Sencor



AX-1 with Glyphosate

Standards URL:https://xkcd.com/927/ Accessed 26.11.2024



Regulation, Standards and tests

- ISO 5681. Equipment for crop protection Vocabulary. 2020
- ISO 16119-1. Agricultural and forestry machinery Environmental requirements for sprayers Part 1 General. 2013
- ISO 16119-2. Agricultural and forestry machinery Environmental requirements for sprayers Part 2: Horizontal boom sprayers. 2013
- ISO 5682-1. Equipment for crop protection Spraying equipment Part 1: Test methods for sprayer nozzles. 2017
- ISO 5682-2. Equipment for crop protection Spraying equipment Part 2: Test methods to assess the horizontal transverse distribution for hydraulic sprayers. 2017
- ISO 5682-3. Equipment for crop protection Spraying equipment Part 3: Test method to assess the performance of volume/area adjustment systems. 2017
- ISO 10625. Equipment for crop protection Sprayer nozzles Colour coding for identification. 2018
- ISO 16122-1. Agricultural and forestry machinery Inspection of sprayers in use — Part 1: General. 2015
- ISO 16122-2. Agricultural and forestry machinery Inspection of sprayers in use Part 2: Horizontal boom sprayers. 2015
- ISO 4254-1. Agricultural machinery Safety Part 1: General requirements. 2013
- ISO 4254-6. Agricultural machinery Safety Part 6: Sprayers and liquid fertilizer distributors. 2020
- ISO 12100. Safety of machinery General principles for design Risk assessment and risk reduction. 2010
- ISO 4102. Equipment for crop protection Sprayers Connection threading. 1984
- ISO 22369-2. Crop protection equipment Drift classification of spraying equipment — Part 2: Classification of field crop sprayers by field measurements. 2010
- ISO 22856. Equipment for crop protection Methods for the laboratory measurement of spray drift Wind tunnels. 2008
- ISO 22866. Equipment for crop protection Methods for field measurement of spray drift. 2005

CE - Standards

Standards relevant for AX-1

- ISO 5681. Equipment for crop protection Vocabulary. 2020
- ISO 16119-1. Agricultural and forestry machinery Environmental requirements for sprayers Part 1 General. 2013
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- ISO 22856. Equipment for crop protection Methods for the laboratory measurement of spray drift Wind tunnels. 2008
- ISO 22866. Equipment for crop protection Methods for field measurement of spray drift. 2005

CE - Standards

Standards relevant for AX-1

• Inspection of sprayers in use





(b) Måling av væskefordeling



(c) Mäling av dräpestørrelsen

Kilter AX-1

Periodic inspection of sprayers

- From a legal standpoint, it is considered a field sprayer
- Guidelines have been developed to align with the current periodic inspection regime
- Some of the main differences include
 - Velocity calibration
 - Testing of nozzle performance
 - Additional tests due to differences in the working principles

Spray-module vs a standard nozzle

Kilter's spray module

- Discrete droplets with defined droplet volume
- Precise positioning of every shot
- Areal dosage controlled by droplet size, and spacing between droplets

Standard nozzles

- A continuous flow of droplets (size characterized by a distribution)
- Continuous application of spray over a width
- Areal dosage controlled by flowrate, distribution, and velocity of the nozzle



Areal dosage =
$$\frac{1.0\mu L}{(6mm)^2}$$
 = 278L/ha

Kilter AX-1

Software variable droplet size.

- Areal dosage controlled by:
 - Droplet volume
 - Droplet spacing



Inspection of Pesticide Application Equipment Traditional equipment

• ISO 16119-2 • ISO 16122-2 • ISO 5682-2





Containers with scale mounted on Kilter AX-1 spray unit. In this test, each container have accumulated the volume from 1000 droplets, proving even distribution (photo: Kilter)



Figure 4 Automatic read-out of an uneven distribution. The green dots are levels that the vision-based system reads out and converts to numerical values (photo: Kilter)

Example solution for SDT systems

Measuring droplet volume and distribution

- Measure the accumulated droplet volume from each droplet generator
- Array with containers with scale
- Test program on the robot
- Vision-based system for automatic reading and documenting the results.



Obtaining allowed standard deviation for 6mm patternator from sample mean and standard error





Systems in balance

	100mm patternator	6mm patternator
COV for new equipment	7%	28.6%
COV for used equipment	10%	40.8%
		Kilter

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Interval approach

If none of the 42 (or 210) observed values exceed the limit of $(\mu \pm x)$, there is at least a 99.9% certainty that the COV is below 41% on a 6mm patternator.





Key differences from a pure COV approach:

- More conservative
- More sensitive to outliers
- Criterion applied to every single droplet generator

Interval approach: visual tool

- 2 in 1 tool:
- Assess COV with lower part
- Measure average droplet volume in the upper part



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Interval approach, simplified version



Velocity calibration



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Positioning of droplets

- Standards were not developed for precision sprayers
- There are more tests which should be governed by the standards
- Due to missing guidelines, we develop our own test procedures
- This test should be done by the machine by itself







Automated self-testing Key to suksess?

- Barrier and cost for conducting the inspection can be lowered
- Test frequency can be increased
- Dys-functional systems will be detected as soon as possible
AX-1 marks a paradigm shift



Selectivity moved from chemistry to software (AI)

Precision allows early treatment

Patented droplet generator with revolutionizing spraying precision

Kilter's **tested**, **proven and patented** droplet technology drops a precise amount of herbicide onto weeds, **which allows for the use of bioherbicides** such as pelargonic acid without touching and killing the crop.







UAV-BASED VEGETATION BIOMASS ANALYSIS WITH RGB, THERMAL AND MULTISPECTRAL IMAGERY

Mikael Änäkkälä, Asko Simojoki, Pirjo Mäkelä, Laura Alakukku, Antti Lajunen



- UAVs are versatile tools for data collection, offering the ability to carry a range of sensors
- UAVs have been utilized in agricultural research, including studies on crop water balance, yield and biomass estimation, as well as weed identification (Crusiol et al. 2020, de Camargo et al. 2018, Li et al. 2022, Viljanen et al. 2018)

 The aim of this research was to investigate how different cameras installed on UAV can be used to estimate the amount of crop dry matter biomass. The key advantage of this study is the wide variety of crops and the use of multiple types of cameras to capture images from the crops during the growing season.



- Located in Haltiala, Helsinki, Finland
- Two different field trials
- 72 plots in total
 - Plot size 1.5 m x 15 m (22.5 m²)
- The crops:
 - wheat (*Triticum aestivum* L.)
 - Winter wheat (n=8)
 - Spring wheat (n=8)
 - oats (*Avena sativa* L.) (n=32)
 - rapeseed (*Brassica napus* L.) (n=16)
 - pea (Lathyrus oleraceus Lam.) (n=4)
 - faba bean (*Vicia faba* L.) (n=4)





DJI Phantom 4 Advance



Tarot T960





EQUIPMENT - CAMERAS

- RGB camera:
 - DJI Phantom 4 Advance
 - Thermal camera:
 - Flir Duo Pro R
 - Multispectral cameras:
 - Micasense Rededge 3 (Red, Green, Blue, NIR and Rededge)
 - Mapir Survey3W RGN (Red, Green and NIR)

DJI Phantom 4 Advance



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Mapir Survey3W RGN



Flir Duo Pro R



Micasense Rededge 3



5



FLIGHT MISSIONS

- Softwares: Mission planner (Tarot), Pix4Dcapture (DJI)
- Flight altitude
 - 50 m: multispectral (Micasense) and Thermal (Flir)
 - 20 m: RGB (DJI) and multispectral (Mapir)
- Double grid for RGB image collection
- Simple grid for multispectral and thermal imaging
- Overlap ~80%
- 5 ground control points for georeferencing



DJI Phantom: RGB and Mapir



Tarot T960: Micasense and Flir



- All the images were processed with Pix4Dmapper to create orthomosaic images and pointclouds/3D models
- Multispectral images were calibrated with their own reflectance panels
- Matlab was used to extract pixel values and height values from the tiff files



7



DATA COLLECTION

Date			Cameras		Field measurements							
	D1I	Flir	Micasense	Mapir	Pea	Faba bean	Oats	Spring wheat	Winter wheat	Rapeseed		
1.6.2021	х	x	x									
9.6.2021	х	x	x		х	x	х	x	x			
20.6.2021	х				х	x	х	x	x			
5.7.2021	х	x	x	Х	х	x	х	x	x	x		
19.7.2021	х	х	x	Х	х	x	Х	x	х	х		
6.8.2021	х	x	x	Х						x		
16.8.2021	х	x	x	Х	х	x	Х					
30.8.2021	х	x	x	Х						x		

UAV data was collected 1-2 days before/after the field measurements



- The plots were divided into two sections for analysis
- One of the sides (Blue rectangle) where used to collect biomass samples
 - Crop samples (Red square) were collected from a area of 0.25 m² from each plot
- The other side (Yellow rectangle) was left untouched and was analyzed from the UAV images



CHALLENGES WITH MEASUREMENT

- GPS drift problems with Mapir camera
- A very dry summer caused uneven growth in the experimental plots

DJI 6.8.2021

Mapir 6.8.2021





RESULTS - THERMAL

Many of the Pearson correlations (R) were negative
 → plots with higher biomass had lower temperature



HELSINGIN YLIOPISTO HELSINGFORS UNIVERSITET UNIVERSITY OF HELSINKI Flir

0.03

0.37

0.35

0.08

0.24

0.9

0.8

0.7

0.6

0.5

0.4

0.3

0.2

0.1

Oats (9.6.2021)

Oats (5.7.2021)

Oats (19.7.2021)

Oats (16.8.2021)

Spring wheat (9.6.2021)

Spring wheat (5.7.2021)



RESULTS – 3D MODEL

- Negative height values are possibly caused by inaccuracies in georeferencing or in the creation of 3D model/pointcloud
 - Height model performed weaker at the beginning of crop growth. Bareth et al (2018) had similar results with their ČHM model for grass swards



	D		
Oats (9.6.2021)	0.02	0.02	
Oats (20.6.2021)	0.05	0.15	0.9
Oats (5.7,2021)	0.26	0.13	
Oats (19.7.2021)	0.44	0.43	0.8
Oats (16.8.2021)	0,18	0.04	
ipring wheat (9.6.2021)	0.07	0.26	0.7
pring wheat (20.6.2021)	0.02	0.32	0.6
pring wheat (5.7.2021)	0.81	0.55	12534
oring wheat (19.7,2021)	0.6	0.6	0.5
Rapeseed (5.7.2021)	0.72	0.29	
Rapeseed (19.7.2021)	0.05	0.08	- 0,4
Rapeseed (6.8.2021)	0.03	0.01	-03
Rapeseed (30.8.2021)	0,18	0.33	
Vinter wheat (9.6.2021)	0.01	0	- 0.2
inter wheat (20.6.2021)	0.23	0.24	
Vinter wheat (5.7.2021)	0.51	0.26	- 0.1
inter wheat (19.7.2021)	0.18	0.04	
	Height	Volume	0

Coefficient of determination (R²) values



RESULTS – MULTISPECTRAL CAMERAS

 Small differences between the correlations of two multispectral cameras

					Mi	caser	150				
Oats (9.6.2021)	0.04	0.04	0.02	0.07	0.05	0.06	0.01	0.05	0.04	0	0.19
Oats (6.7.2021)	0.4	0.37	0.48	0.24	0.26	0.37	0.14	0.32	0.42	0.53	0.54
Oats (19.7.2021)	0.03	0.02	0.31	0,18	0.06	0/	0.18	0.02	0.05	0.33	0.68
Oats (16.8.2021)	0.05	0.05	0.15	0.09	0.11	0.09	0.13	0.1	0.02	0.15	0.27
oring wheat (9.6.2021)	0.02	0	0	0.23	0	0.01	0.01	0	0.04	0	0.57
pring wheat (5 7 2021)	0.72	9.74	0.74	0.69	0.72	0,73	0.63	A.72	0.73	0.74	0.96
ring wheat (19.7.2021)	0.54	0.27	0.48	0.35	0.05	0.01	0.11	0.02	0.03	0.22	0.86
Rapeseed (5.7.2021)	0.16	0.32	0.11	0.42	0.39	0.36	0.35	0.37	0.34	0.02	0.59
Rapeseed (19,7.2021)	0	0.02	0.02	0	0.01	0.01	0	0.01	0.01	0.02	0.28
Rapeseed (6.8.2021)	0,14	0.12	0	0.34	0.3	0.22	0.3	0.28	0,13	Ū(1)	0.41
Rapeseed (30.8.2021)	0.03	0	0.08	0.04	0.02	0	0.04	0.02	0.01	0.04	0.38
Winter wheat (9.6.2021)	0.04	0.03	0.15	0.01	0.01	0	0.01	0	0.01	0.05	0.83
Winier wheat (5.7.2021)	0.04	0.57	0.02	0.23	0.44	6.49	0.4	0,48	0.36	0.1	0.85
inter wheat (19.7.2021)	0.04	80.0	0.01	0.06	0.01	0	0.01	0.01	0	0	0.13

-				. 1	Марія				
Oats (9.6.2021)									-
Oats (5.7.2021)	0.43	0.51	0.4	0.33	0.41	0.16	6.37	0.41	0.53
Oats (19.7.2021)	0.15	0	0.31	0.05	0.01	0.16	0.03	0.27	0.5
Oals (16.8.2021)	0	0.14	0.2	0:09	0.09	0.09	0.09	0.07	0.22
inng wheat (9.6.2021)									
ring wheat (5.7,2021)	0.81	0.76	0.89	0.72	0.74	0.67	0.73	0.59	0.92
ing wheat (19.7.2021)	0.76	0.28	0.74	0.01	0	0.01	0.01	0	0.78
Rapeseed (5.7.2021)	0.33	0	0	0.4	0.38	0.34	0.4	0	0.41
apeseed (19.7.2021)	0.07	0.2	0.27	0.07	0	0.18	0.04	0.38	0,46
Rapeseed (6.8.2021)	0.09	0	0	0.17	0.22	0.05	0.2	0.01	0.36
apeseed (30.8.2021)	0.01	0	0.02	0.01	0.01	0.02	0.01	0.02	0.09
nter wheat (9.6.2021)				-					-
inter wheat (5.7.2021)	0.19	0.07	0.04	0.42	0.54	0.3	0.47	0.09	0.54
ter wheat (19.7.2021)	0.04	0.02	0.05	0.01	0	0	0.01	0	0.04

Coefficient of determination (R²) values

MLR5 = Multiple linear regression using the five spectral bands (Blue, Green, NIR, Red and Rededge) MLR3 = Multiple linear regression using the three spectral bands (Green, Red and NIR)



NDVI MAPS (MICASENSE AND MAPIR)

Mapir showed smaller NDVI values than Micasense

Micasense (5.7.2021)









PEA AND FABA BEAN

• The correlations are calculated from 5.7, 19.7 and 16.8 measurements



Coefficient of determination (R²) values.

MLR5 = Multiple linear regression using the five spectral bands (Blue, Green, NIR, Red and Rededge)

MLR3 = Multiple linear regression using the three spectral bands (Green, Red and NIR)



- Height model performed better on later growth stages of the crops and thermal in the beginning/middle growth stages
- Quite small differences between the two multispectral cameras
- Multiple linear regression achieved highest correlations with the five spectral bands
- The UAV data needs closer inspection for potential issues, and further preprocessing could improve its quality



The project was funded by Maatalouskoneiden tutkimussäätiö (Agricultural Machinery Research Foundation).

The field trials were part of Leg4Life STN-project. Plant samples were collected by Jaakko Haarala, Saana Hakkola, Jenni Orjala ja Noora Vihanto.



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THANK YOU

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DEVELOPMENT OF A LOW-COST TELEMATICS SYSTEM FOR SMART FARMING OPERATIONS

Antti Lajunen, Henrik Hovio, Niila-Sakari Keijälä Department of Agricultural Sciences, University of Helsinki, Finland

Advances and Innovations in Agricultural Engineering The 5th NJF - EurAgEng -Agromek Joint Seminar, November 26-27, 2024, Herning, Denmark

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 Faculty of Agriculture and Forestry



BACKGROUND



Soil scanning



Soil sampling



Crop sensor



- COLORADO

Field operations



Field conditions



Automatic penetrometer



Aerial imaging





Crop yields



- Evaluate the technical requirements for a telematics system that can be used to monitor farming operations from tractors in real time.
- Automatically saving measurement data on a server and using the database for continuous analysis.
- Efficient and secure methods for transferring measured CAN bus data and other sensor data from the tractor to the server for storage.
- Using open-source software and low-cost system components.



- The measurement system consisted of three main elements
 - CAN bus served as the source of information.
 - Raspberry Pi decoded and sent the messages with location data using the MQTT protocol.
 - Data was stored in a server computer and could be monitored in real time.
- The data was transferred using Tosibox
 - Tosibox devices created closed and protected network connection from the tractor to the server (<u>https://www.tosibox.com/</u>).





- Raspberry Pi 3B+
- CAN shield: PiCAN 2 CAN-Bus Board for Raspberry Pi 2/3 with SMPS
- GNSS card: SparkFun GPS-RTK2 ZED-F9P
- GNSS antenna: u-blox, ANN-MB-00-00
- 7-inch touch screen
- Power supply from a power bank (or tractor's 12V outlet)
- Tosibox 175 remote connection device with 4G sim card
- A Linux computer acting as the database server
- Tosibox 650 remote connection device for the server















Kvaser Database Editor

 Generating DBC file for python program

GPSD

- Receiving positioning data from GNSS card
- Positioning data processing for Node-RED

Node-RED

- Data acquisition, processing and transfer to database in
- Raspberry Pi
- Graphical interface (dashboard) and sending data in a database in the server computer

Eclipse Mosquitto

 Message broker for MQTT

MySQL

 Database for measured data

phpMyAdmin

 Graphical interface for database



- Raspberry Pi
 - Data: location (GNSS), CAN bus
 - Processing: python code for CAN message interpretation and GPSD for location data processing. Local Node-RED code for saving data locally and sending it to the database as JSON-object format.
- Tosibox 175 and 650
 - Sending data securely from tractor to the server computer
- Server computer

HELSINGIN YLIOPISTO

HELSINGFORS UNIVERSITET UNIVERSITY OF HELSINKI

- Running Node-RED for real-time dashboard
- MySQL database







DATA MONITORING

■ Case





- Operational data was measured from two different tractors during silage production:
 - 2014 Case Puma 160 CVX
 - 2008 Valtra N141
- Tractors were used for mowing, baling and pulling a forage wagon.
- The measurements were performed at the University of Helsinki's Viikki research farm during the 2023 growing season.
- Measurements were done in five different fields.



MEASUREMENT RESULTS – TRAJECTORY

Mower

Forage wagon

Baler



Longitude



MEASUREMENT RESULTS – DATA

Mower

Forage wagon

Baler











MOWER DATA SUMMARY

	Field A	Field B	Field C		
Duration (h)	2.8	1.8	0.5		
Average speed (km/h)	8.9	8.8	10.8		
Distance (km)	23.6	15.5	5.7		
Average engine power (kW)	41.5	43.0	55.1		
Fuel consumption (I/h)	14.7	15.9	18.3		
Area (ha)	5.5	3.8	1.3		



- The developed measurement system fulfilled the research objectives
- Data processing and transfer required most of the work
- Except for Tosibox devices, low-cost system components were used
 - Tosibox devices was considered very robust solution for secure data transfer
- Open-source software were rather easy to use and well available
- Only basic level of programming experience was required
- Database needs to be further developed e.g. using PostgreSQL
- Recorded data was high quality and can be used multiple purposes



THANK YOU



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Innovating Smart Agriculture: How Finnish Future Farm is shaping the future of farming

Finnish Future Farm

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Co-funded by the European Union

Our motto: sustainability though digitalization





 \rightarrow Speeding up the uptake of the needed technologies



5th NJF-Agromek-EurAgEng joint seminar 2024 I Hannu Haapala


The Finnish Future Farm



 Smart Bioeconomy Testbed* with physical and virtual farm environments.
Biosystems Engineering Education: Comprehensive training in biosystems engineering.
BioBoosters : Incubation, mentorship, funding, and global market opportunities tailored for AgriTech startups.

Making data-based decisions Speeding up uptake of the needed technologies Own data!



5th NJF-Agromek-EurAgEng joint seminar 2024 I Hannu Haapala



Finnish Future Farm 2023-2026

(JTF, 3.5 M€) (keski-suomen liitto

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The <u>co-development environment</u> promotes the adoption of new Smart Farming technologies and methods.

This involves <u>both physical and virtual co-development</u> <u>environments.</u>





https://www.jamk.fi/fi/projekti/finnish-future-farm



Finnish Future Farm (FFF)

- develops a unique co-creation platform for RDI, education, and startup acceleration in precision farming and smart farming technologies.
- both an existing physical smart farm and a digital twin are utilized.

