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Estonian University of Life Sciences

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Institute of Agricultural and Environmental Sciences

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Euroopa Maaelu Arengu
Põllumajandusfond:
Euroopa investeeringud
maapiirkondadesse

The prospect of UAVs and smart farming applications in Estonia

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Estonian University of Life Sciences.

2022



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Contents

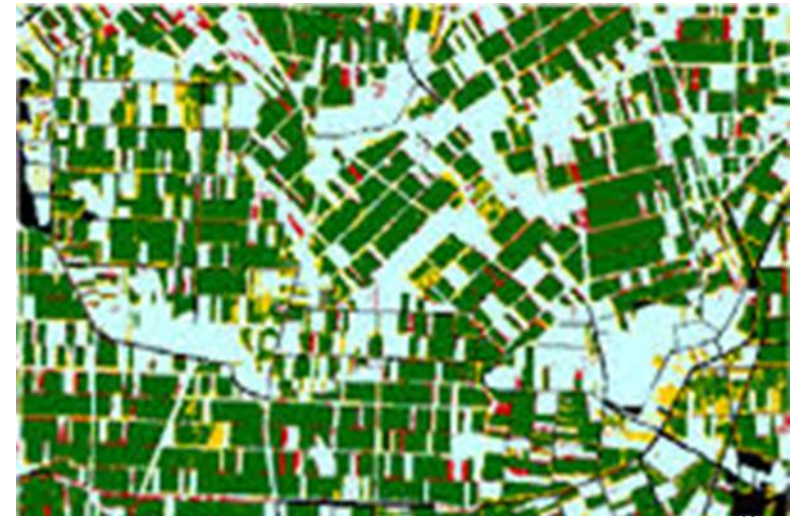
- The concept of UAS used in sustainable agriculture
- UAV in Precision Agriculture
- UAV in Crop Phenotyping
- Our Current Studies in Estonia

About me

I worked in Ministry of Agriculture in Taiwan.

My study is focus on Precision agriculture management.

The first focus of work is agricultural farming and fallow subsidies.



About me

The second focus is on agricultural natural disasters.



Illegal mountain development monitoring



FORMOSAT-2 Pass twice daily over Taiwan

The concept of UAS used in sustainable agriculture

Hypotheses and expected goals

Organic cultivation, anti-pesticides and herbicides, reduce ploughing and soil erosion



Decision-making

Data processing and cloud management in real time, and formulate sustainable agriculture strategies accordingly.



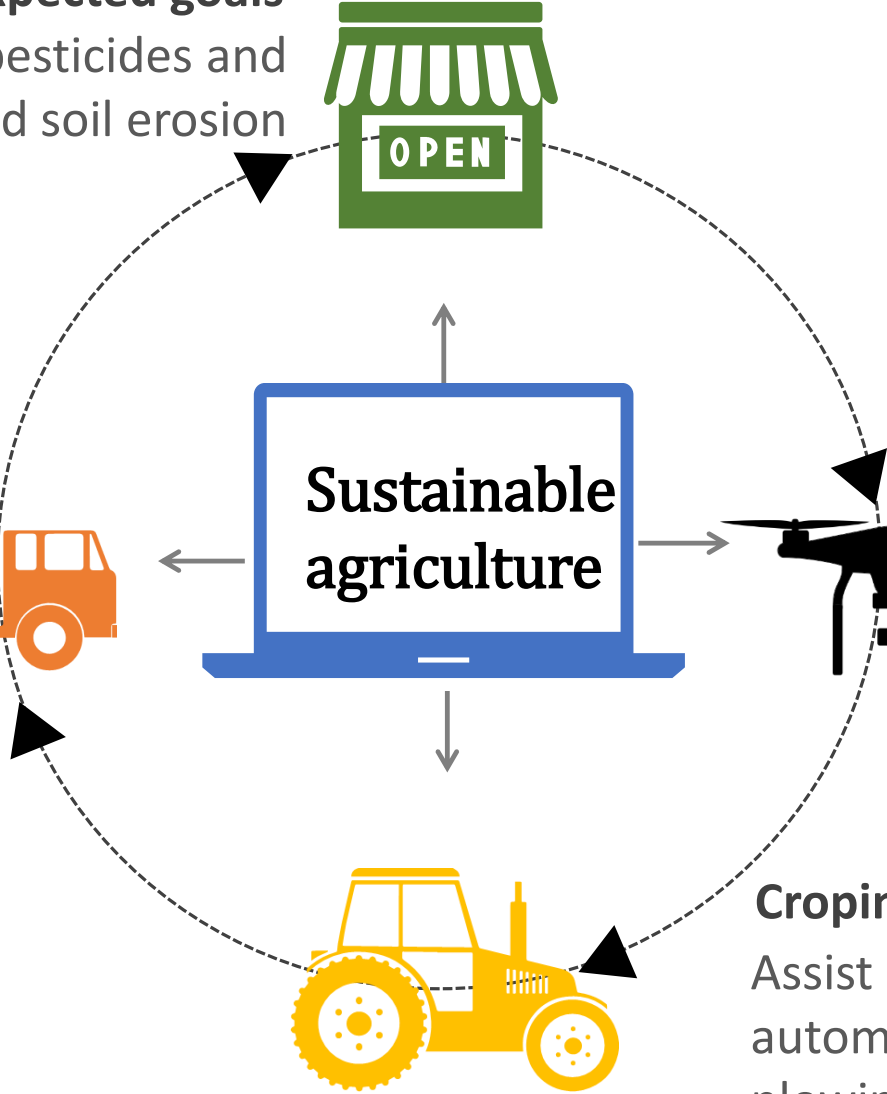
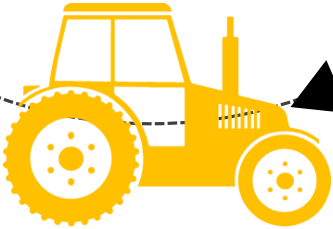
UAS data collection

non-destructive crop, soil and agri-management practice analysis, crop monitoring and health assessment implementation.



Cropping management

Assist in environmentally friendly automated breeding selection, planting, plowing methods and irrigation operations.





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The application of UAV in Precision Agriculture



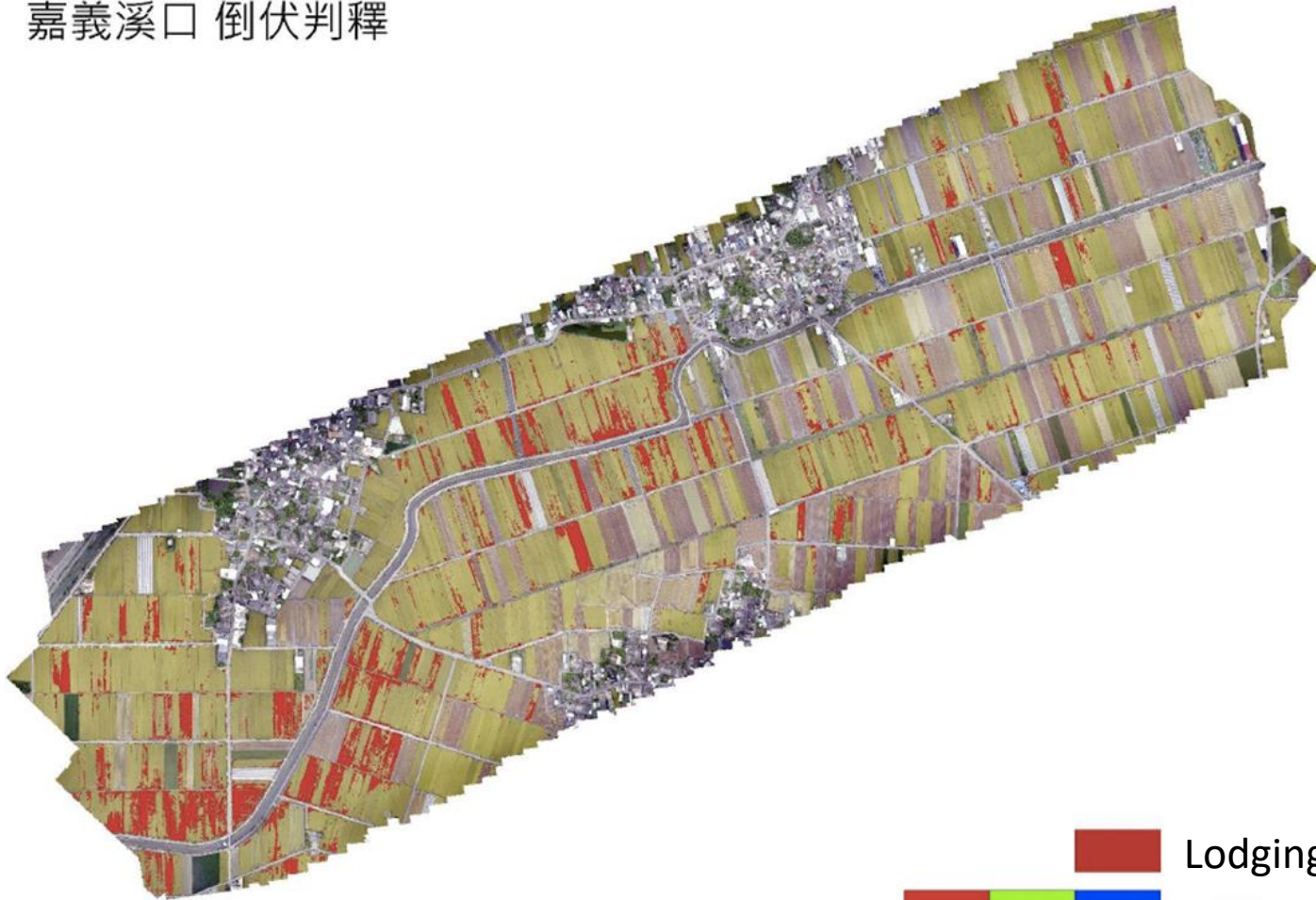
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Banana Lodging Detection - Disaster Subsidy

嘉義溪口 倒伏判釋

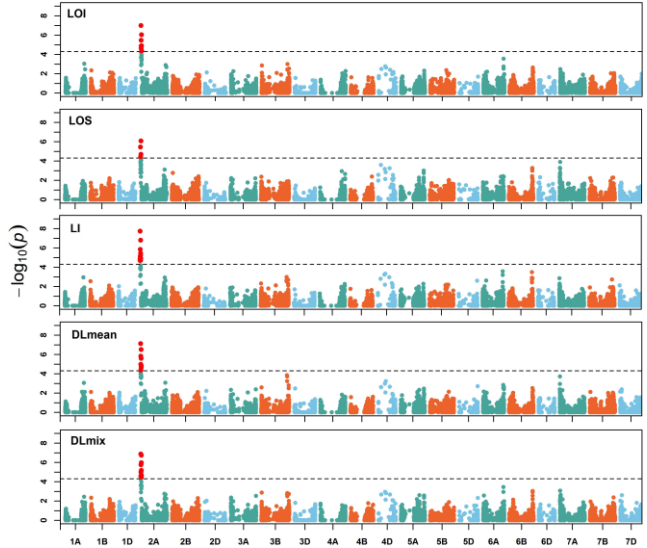
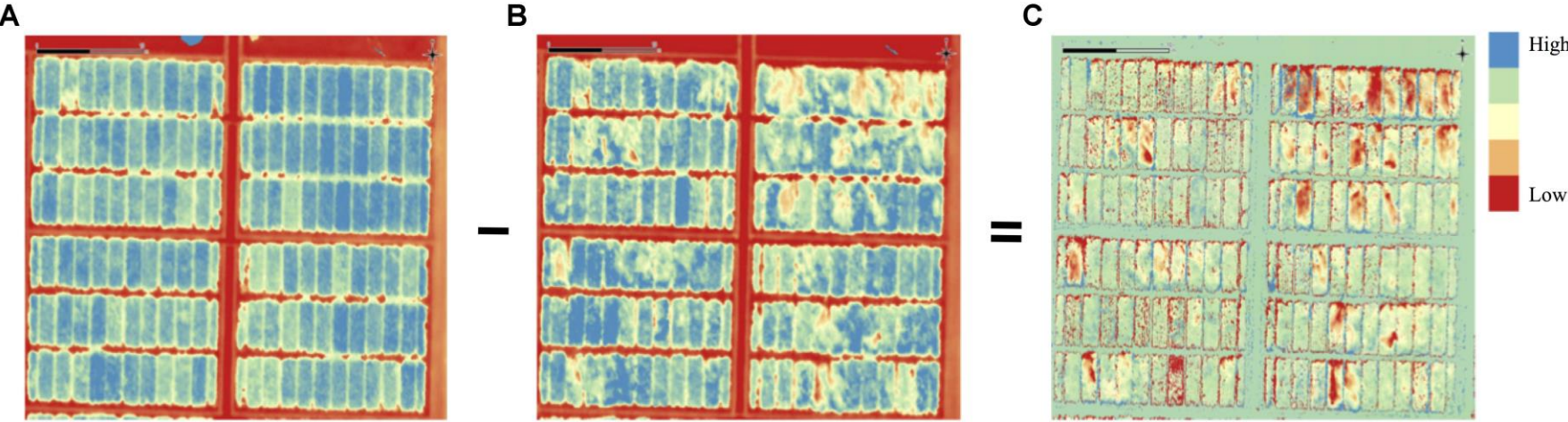


Damage Assessment



Agricultural disaster assessment and subsidies

High-Throughput Phenotyping Enabled Genetic Dissection of Crop Lodging in Wheat



Processing of pre- and post-lodging digital elevation models (DEM) to obtain differential DEM of lodging. Post-lodging DEM is subtracted from pre-lodging DEM to generate a differential DEM of lodging. Panels are (A) pre-lodging, (B) post-lodging, and (C) differential DEM.

Manhattan plot of genome-wide associations.

(Singh, Daljit, et al. 2019)

Crop Spraying

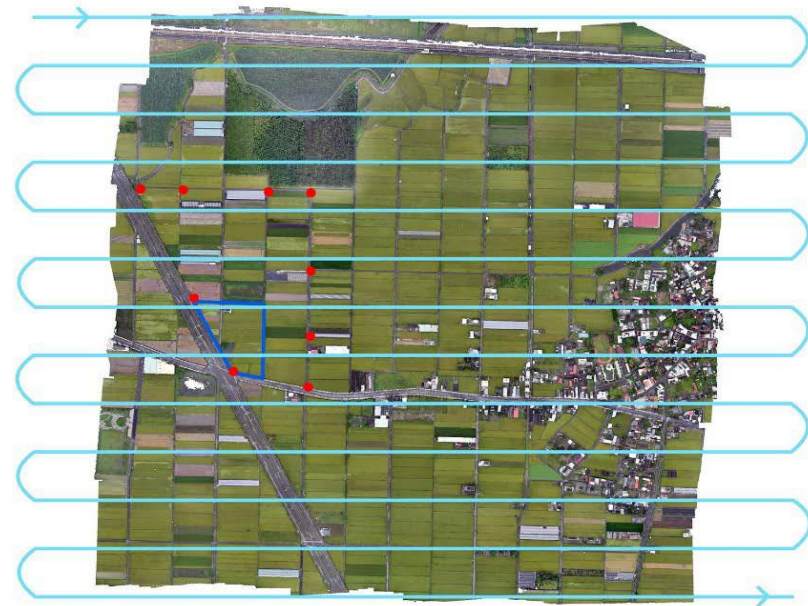


Thanks to the affordability of distance-measuring technology, drones can be fitted with ultrasonic echoing and lasers. This allows them to adjust their location and altitude across any terrain and prevent accidents while spraying a crop. Crops are evenly sprayed despite location without being overly saturated or missed entirely. The reliability of the drones also results in quick ground overage, completing a crop spraying up to five times faster than traditional means.

Spraying management in Taiwan



- Pesticide application license
- UAV flight license
- Upload flight path everytime after spraying



Flight restricted area in Estonia



Military operations area



Nature reserve-Lahemaa



Tallinn Airport



Urban area- Tartu

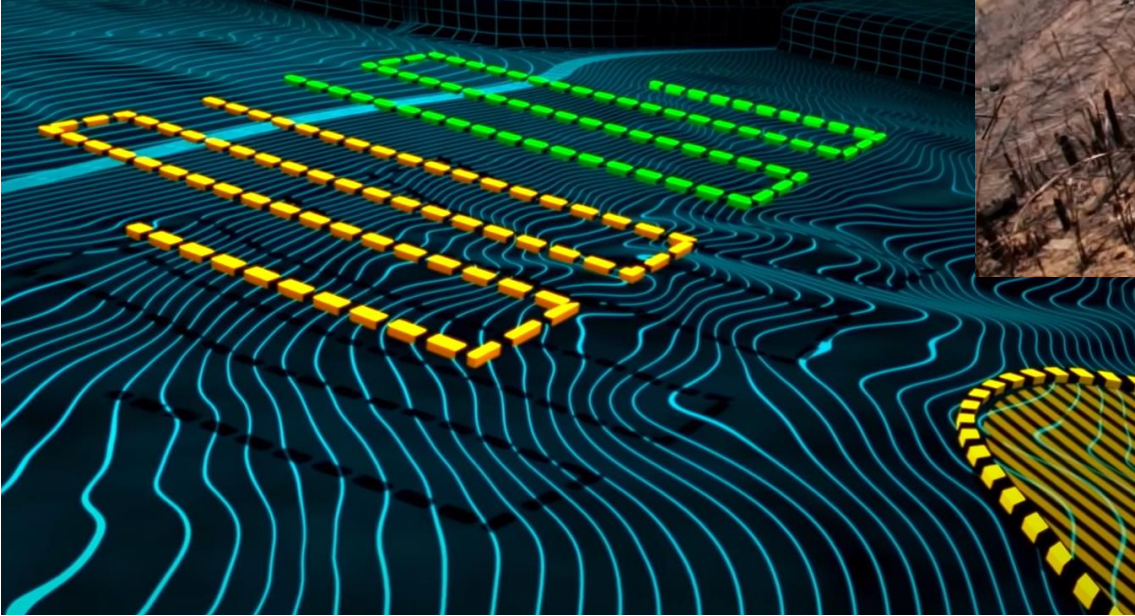
Drone Irrigation



Autonomous soil moisture mapping system and microwave sensing technology on drones

Engineers from Australian Monash University in Melbourne are using autonomous drone technology to improve irrigation practices. Eventually the drone technology will be used to reduce the use of water and optimise yield.

Planting Trees



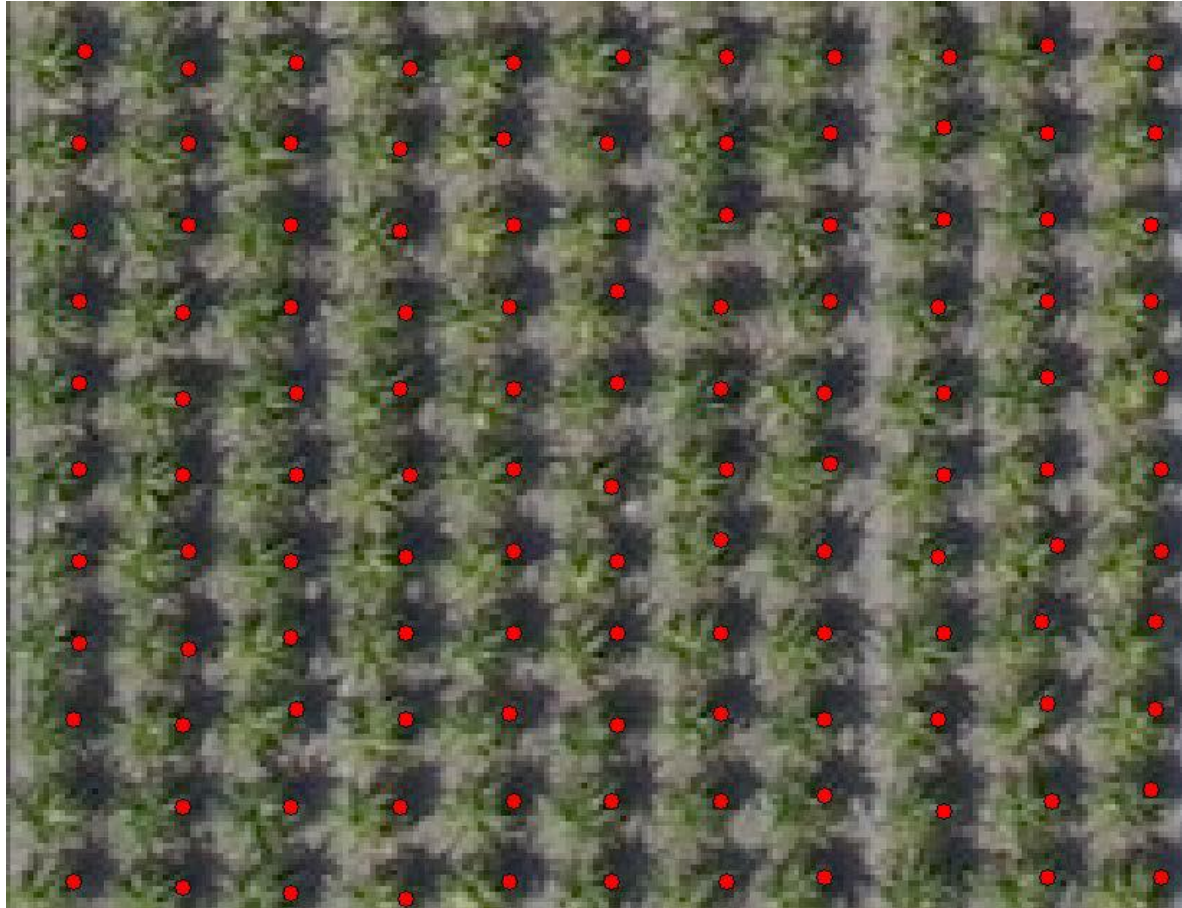


Orthographic mosaic image
DSM(Digital Surface Model)
Point cloud
Near-infrared image
Multi-spectral image
Hyperspectral image
Thermal image
AI identification Model



Leaf age
Rice height
Dry weight
Fresh weight
Number of deliveries
Leaf color
Chlorophyll index
Rice health
Rice production

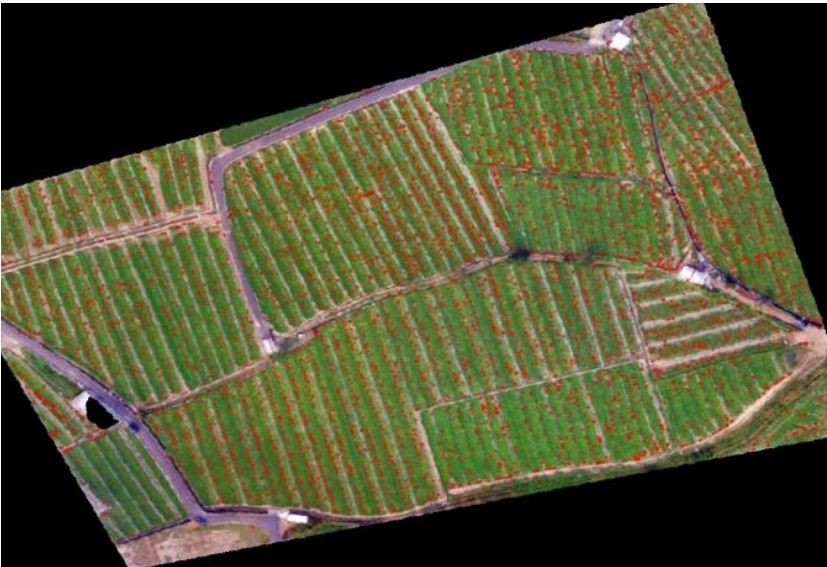
Counting: Dragon fruit - Production estimate



Accuracy : 96.3% (642/648)

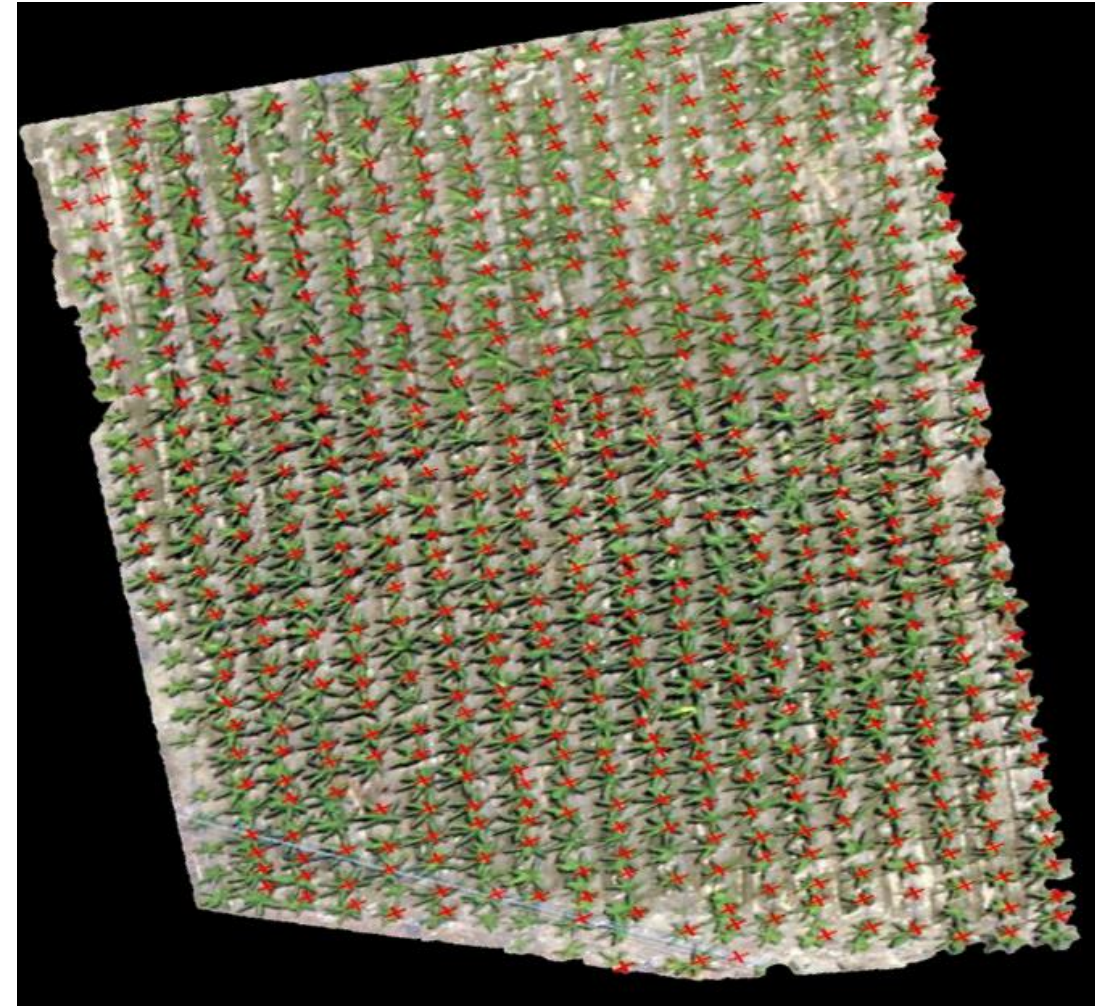
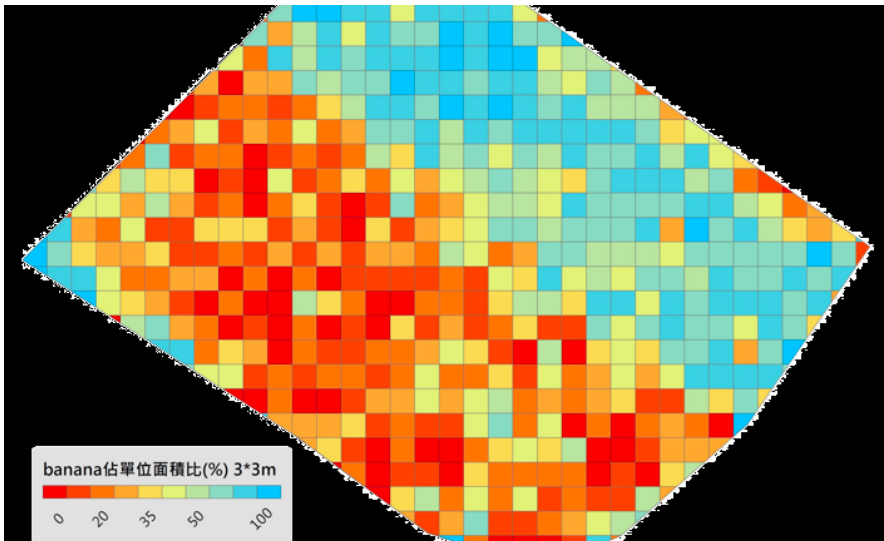
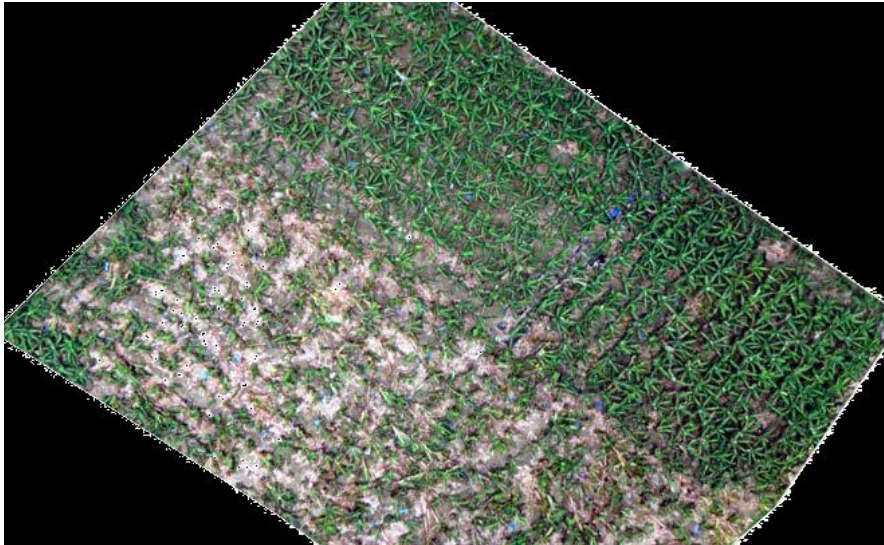


Counting: Watermelon- Production estimate



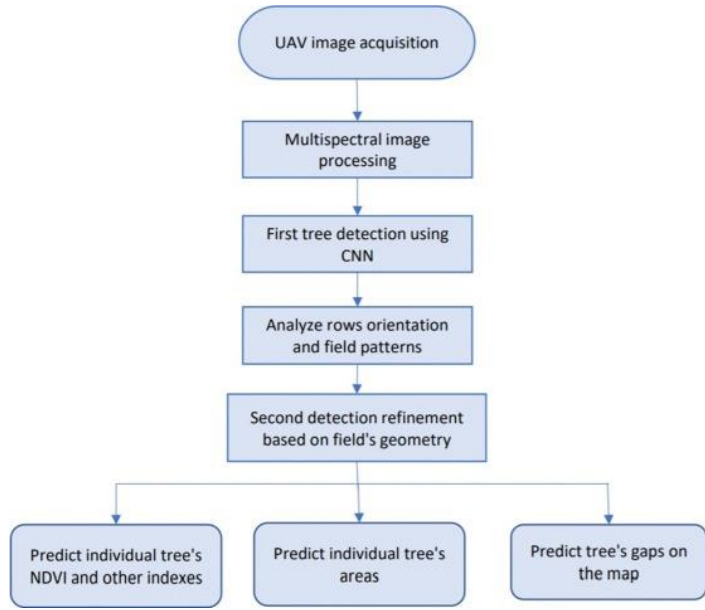
Accuracy : 88.57%

Counting: Banana- Production estimate



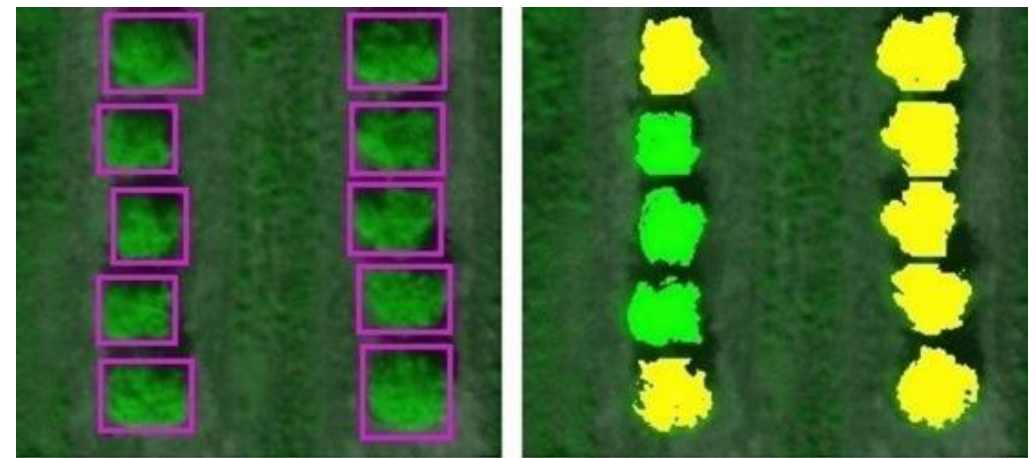
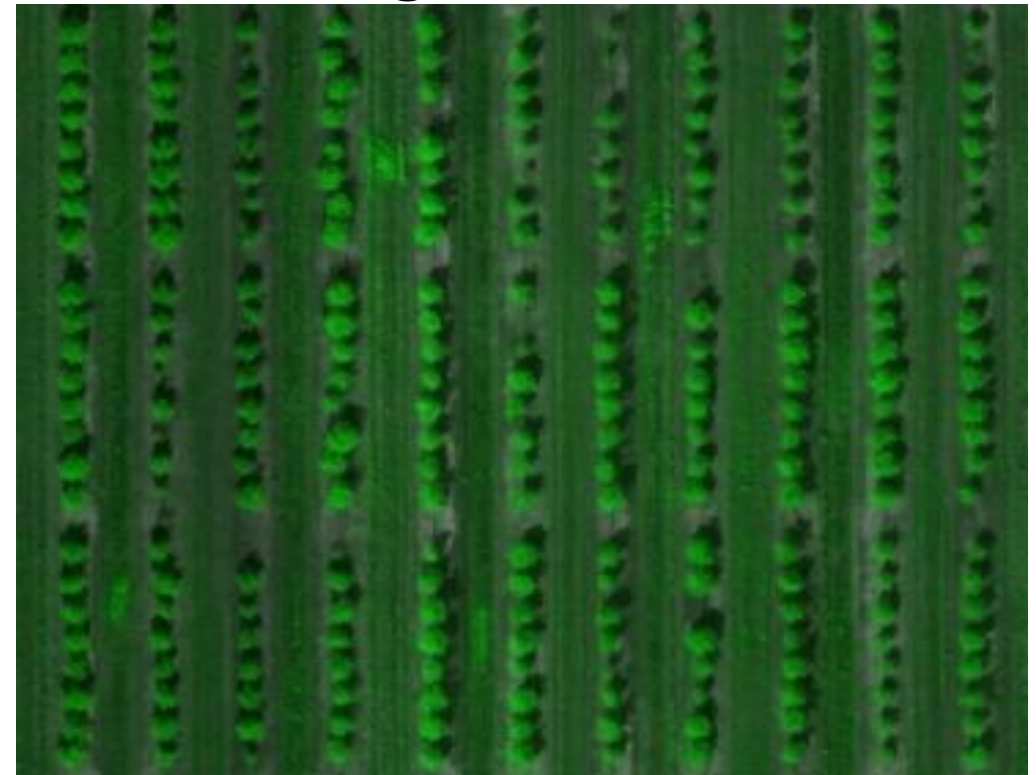
Accuracy : 94.68% (534/564)

Citrus tree count utilizing UAV and artificial intelligence



Deep convolutional neural network (CNN)

Detect and count citrus trees with high precision (99.9%) in an orchard of 4931 trees and estimate tree canopy size with a high correlation ($R = 0.84$)



(a)

(b)

(Ampatzidis, Yiannis, et al. 2019)

QR code- Traceability System in Taiwan



檢視履歷資訊

追溯號碼:00000000

農民經營業者:000

產品名稱:池上米(3.5KG/包)

產地名稱:00縣00市00路

碾製日期:0000年00月00日

UAV影像:



病蟲:瘤野螟、二化螟蟲

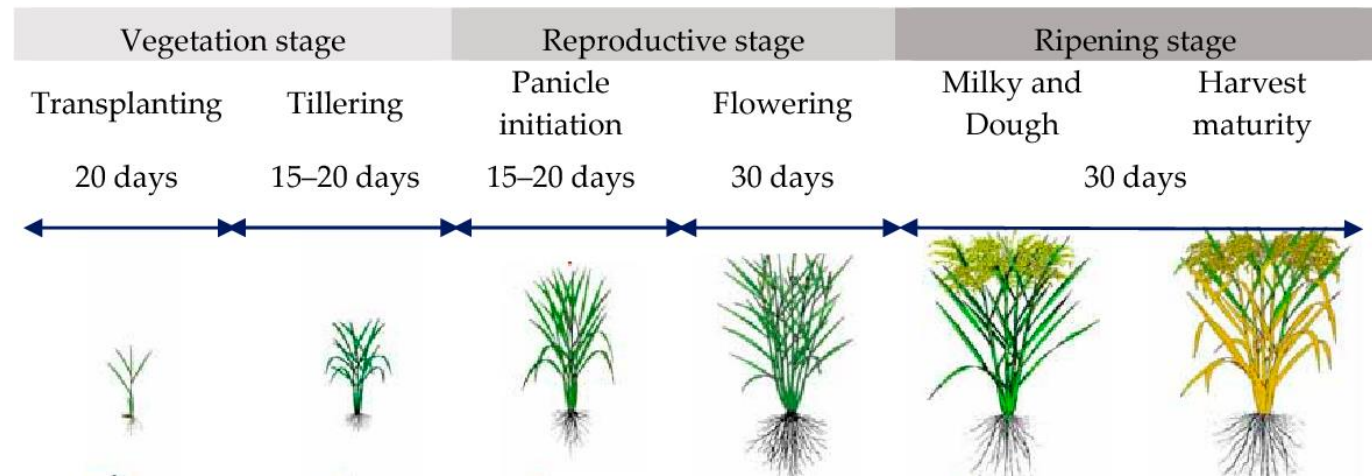
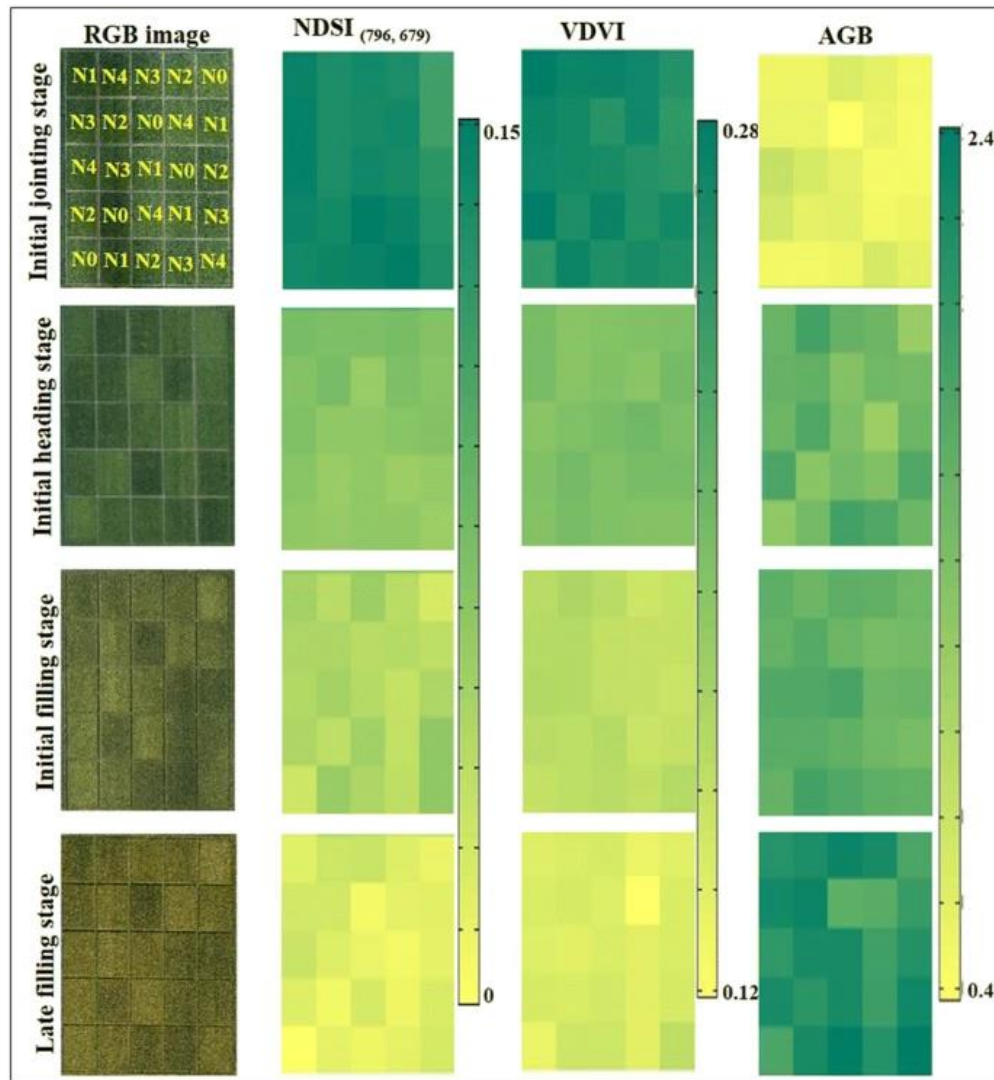
病害:稻熱病、紋枯病

災損:有, 20%

施用農藥:聯速利、加因素

At food stage, a complete life cycle of crops can be retrieved from the traceability system such as agricultural practices, UAV images, and associated analyses.

Dynamic monitoring



(Prathumchai, Kulapramote, et al. 2019)

Spatial and temporal variations in RGB, NDSI, VDVI and AGB of rice. NDSI, VDVI, AGB in different rice stage (Cen, Haiyan, et al., 2019)



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The application of UAV in Crop Phenotyping

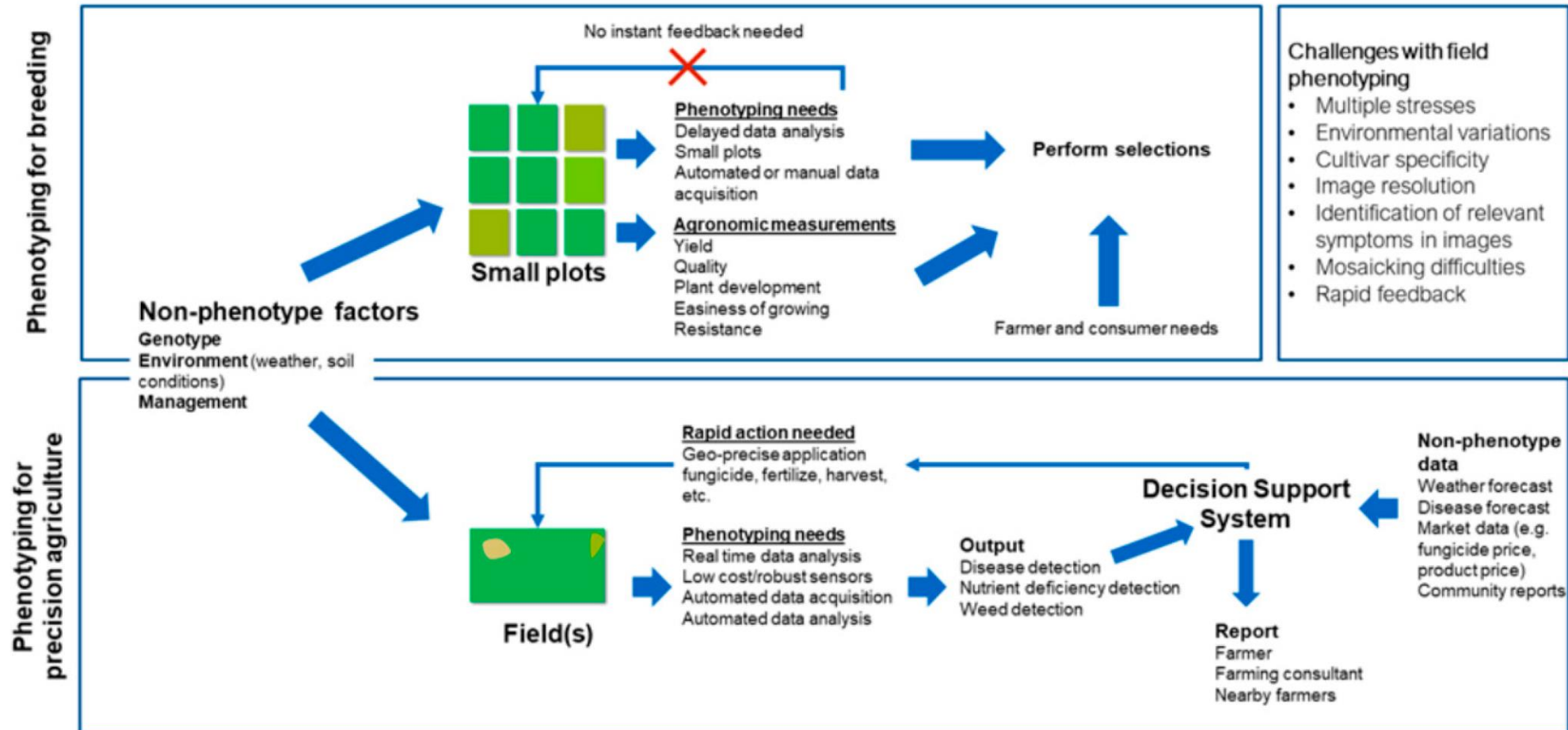


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The UAV application in Precision Agriculture and plant phenotyping



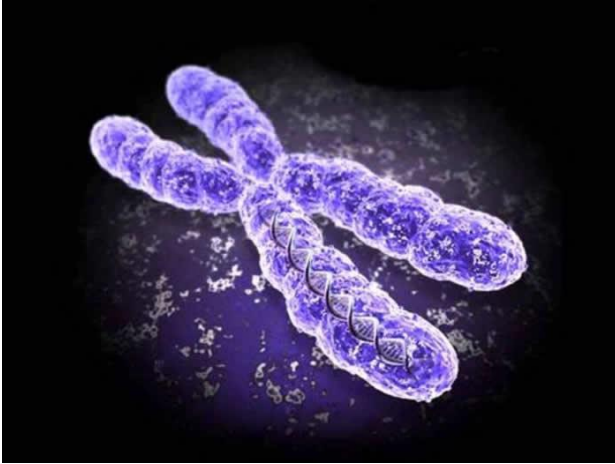
An overview of differences in the phenotyping needs and subsequent actions needed for plant breeding and precision agriculture.

(Chawade, Aakash, et al. 2019)

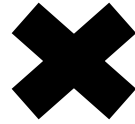
What is plant Phenotyping?

From laboratory greenhouse to real environment

Plant Genotype (G)



Environment (E)



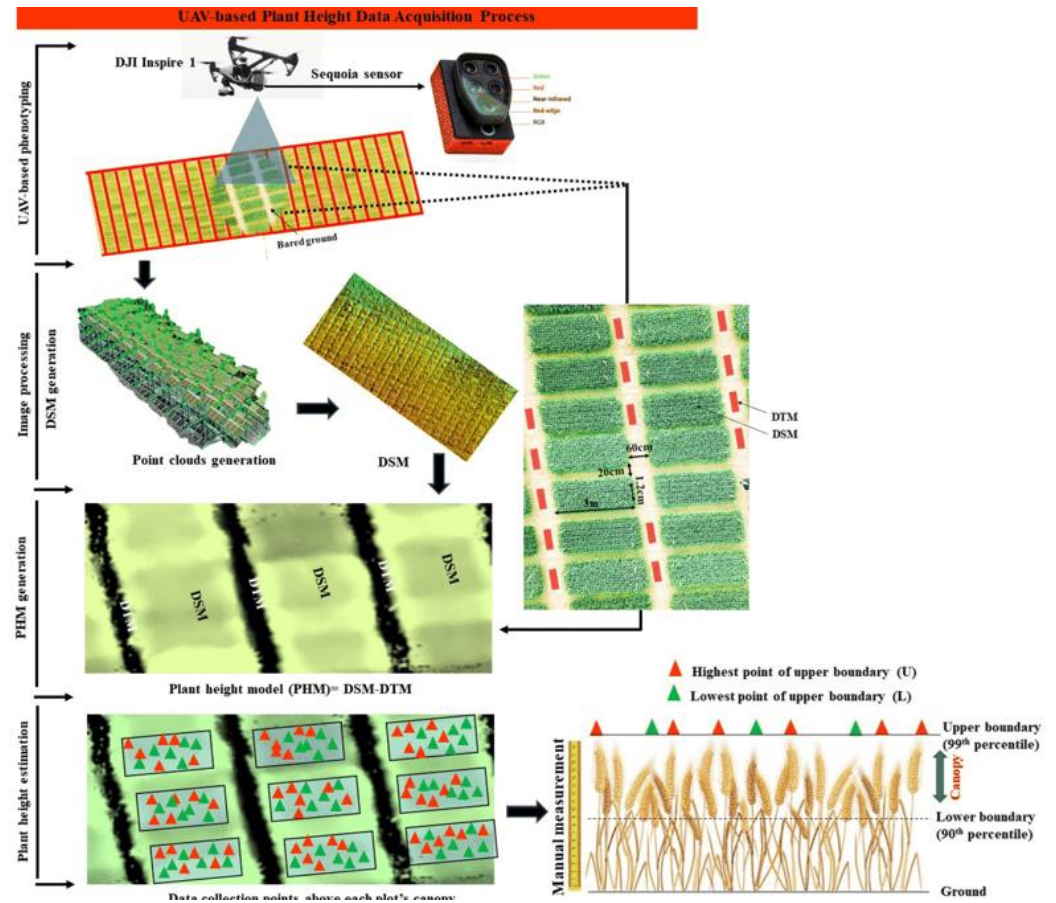
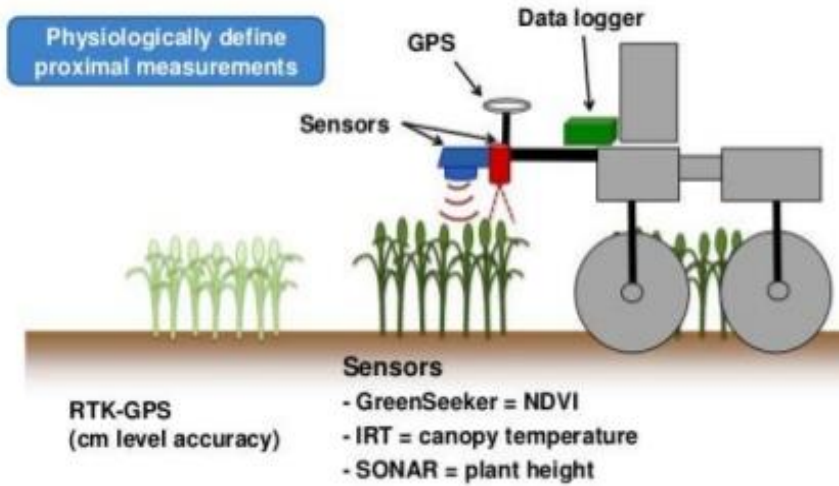
Phenotyping

Analyze gene-environment (G × E) interactions and model phenotypic responses.

Ground-based Small-scale phenotyping system

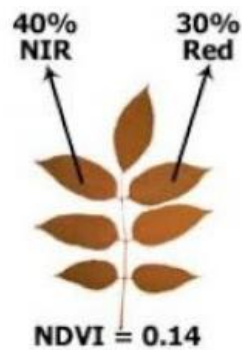
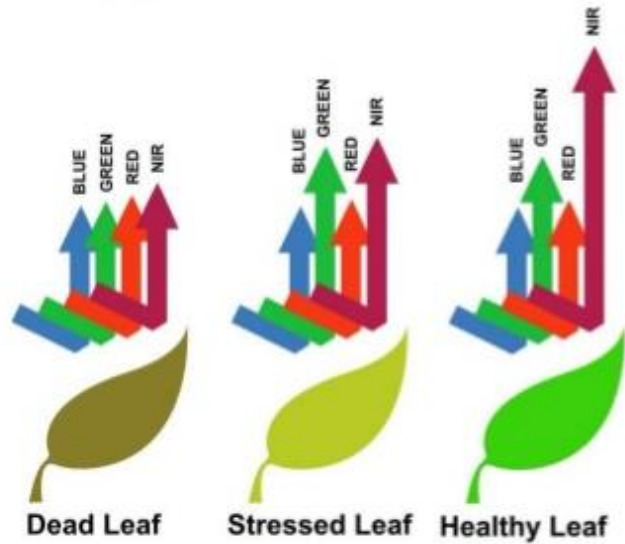
UAV-based phenotyping system

HTP: "Geo-referenced proximal sensing"

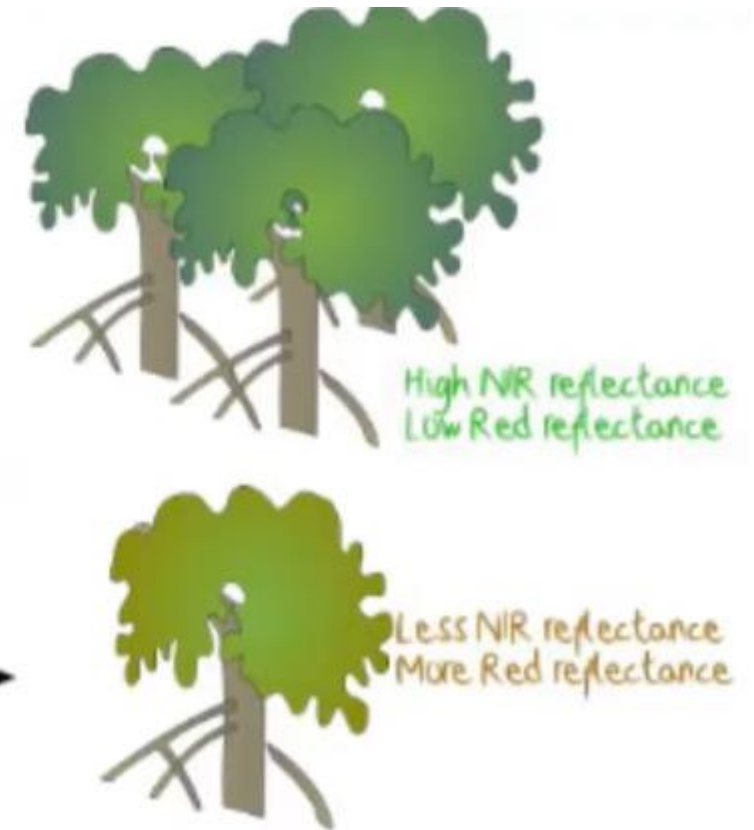
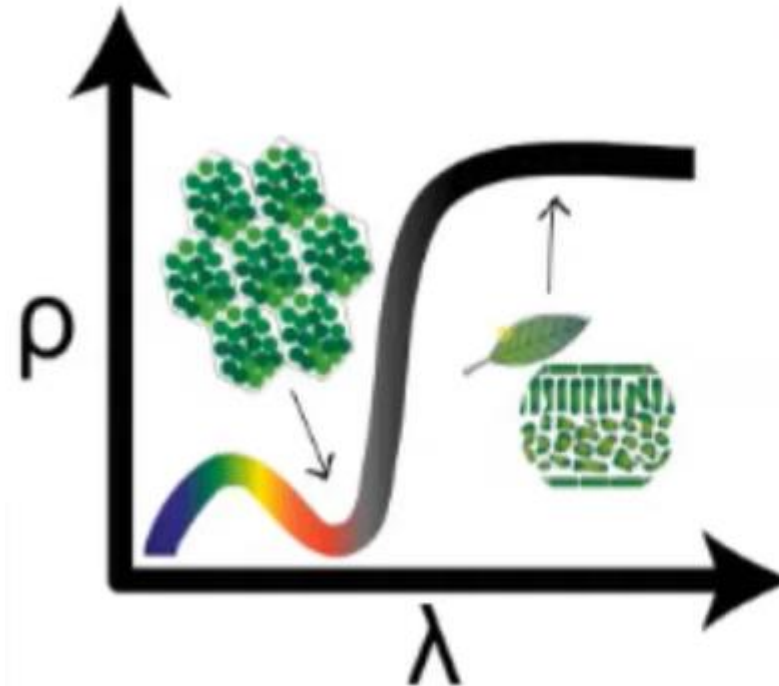


Cost-efficient and non-destructive. Utilized across a wide range of areas such as crop breeding, agricultural decision-making, and crop yield prediction, etc.

Vegetation index



$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$$



UAV application in Estimating Nitrogen Status of Turfgrasses

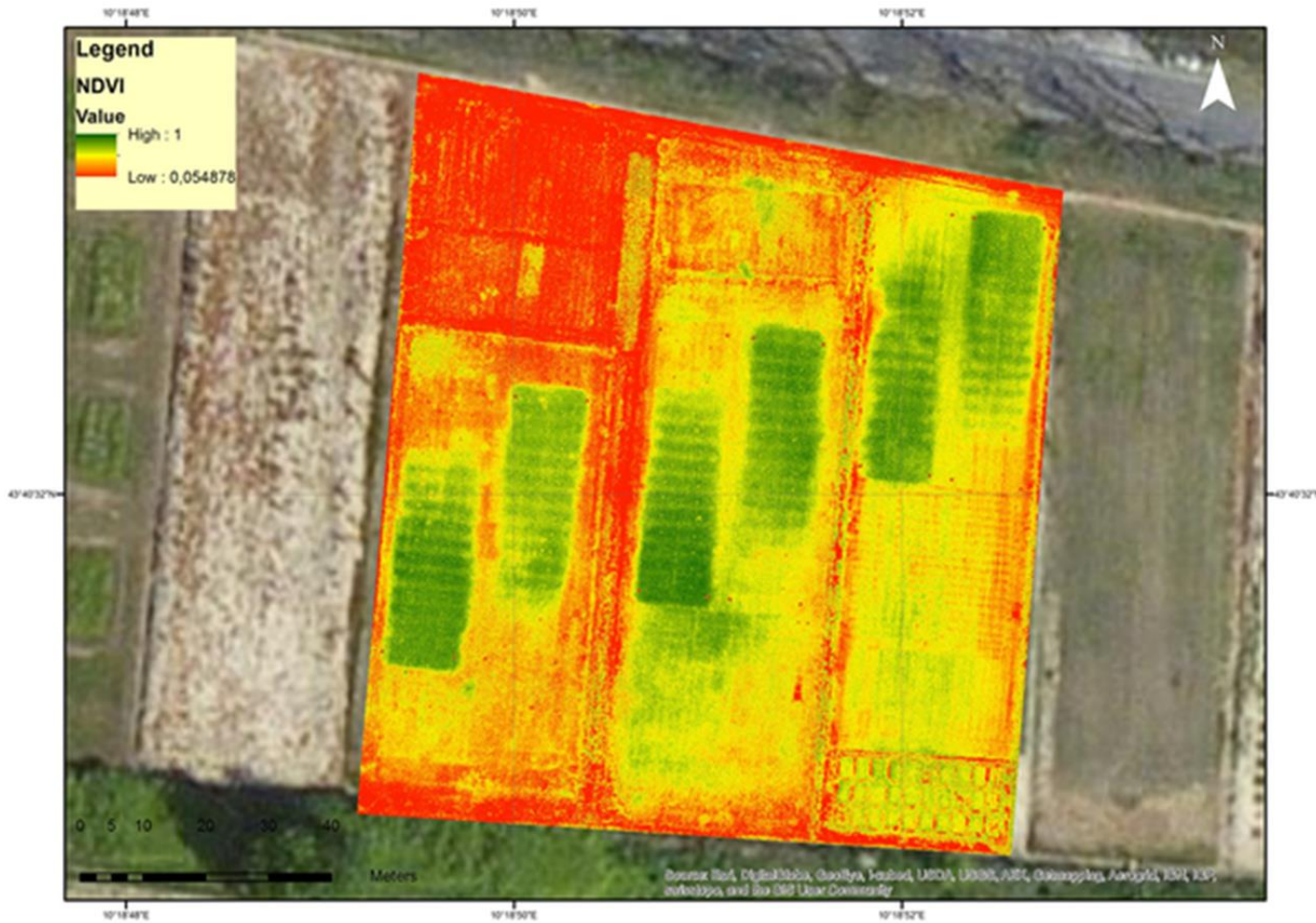
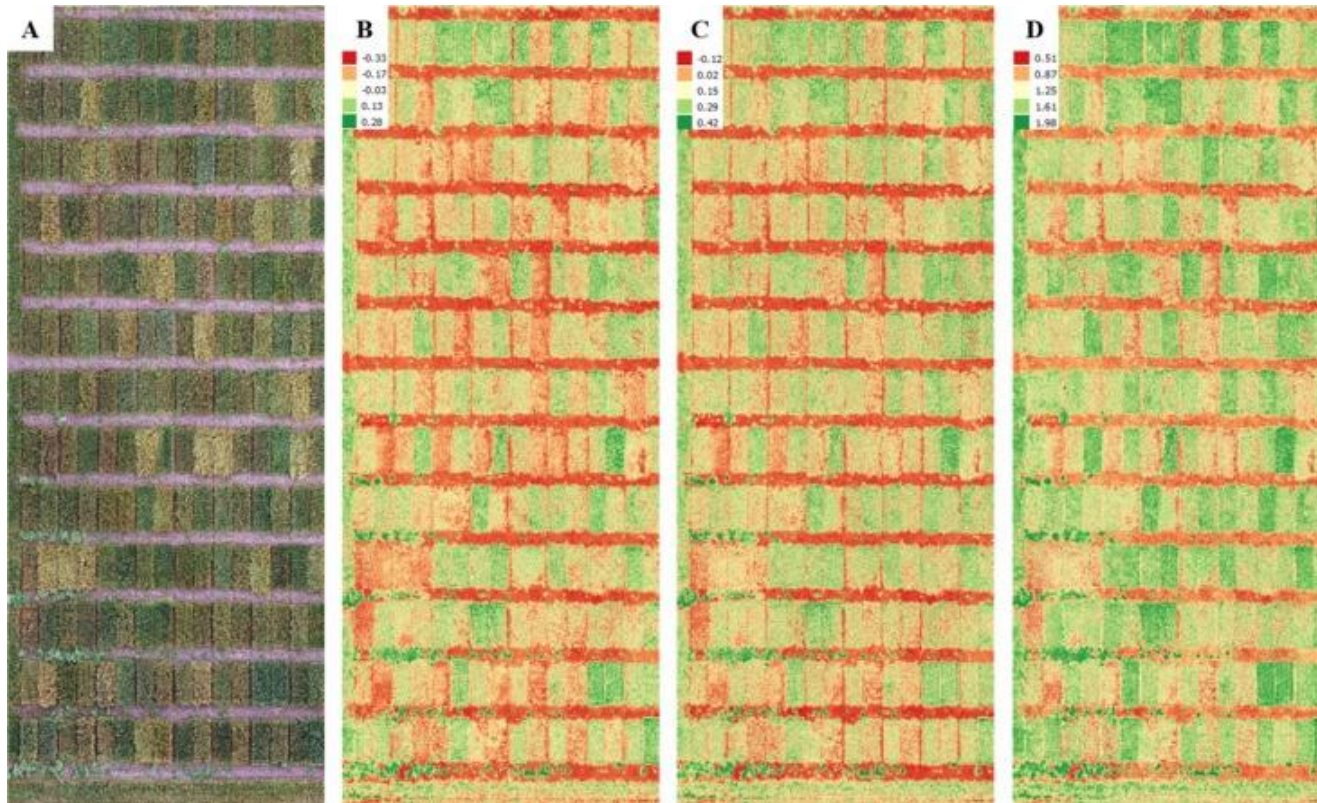


Figure 1. The NDVI image of the turfgrass fields



Valuable tool to monitor plant nutrition, reduce nitrogen (N) application to real needs, thus producing both economic and environmental benefits.

UAV application in winter wheat leaf rust disease detection



UAV obtained orthomosaic and vegetation indices maps. (A) RGB orthomosaic obtained on April 14, 2017, (B) Normalized Difference Index (NDI), (C) Green Leaf Index (GLI), and (D) Green Index (GI).

Deep learning

Most background pixels (99.8%) are correctly classified from the confusion matrix.

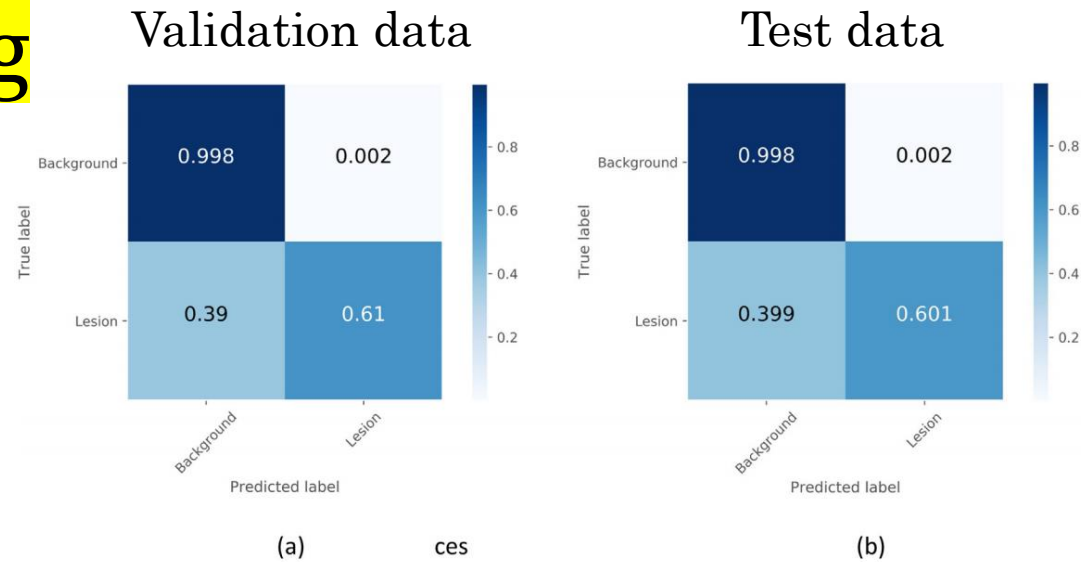


Fig. 7. Confusion matrix in the validation dataset (a) and in the test dataset (b).

Raw sub-images

Ground truth

Predicted images



Most lesions, marked as the **red areas** in the images, can be correctly segmented.

Fig. 8. Examples of sub-image predictions (512×512) in the test dataset (row #1: raw sub-images, row #2: ground truth, row #3: predicted images). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Junfeng Gao ^{a,*}, Jesper Cairo Westergaard ^b, Ea Høegh Riis Sundmark ^c, Merethe Bagge ^c, Erland Liljeroth ^d, Erik Alexandersson ^{d,*}

False positives in a test image



Fig. 10. False positives in a test image (5472 × 3648).

UAV application of Weed Seedling Detection in sunflower cropping

-site-specific weed management operations

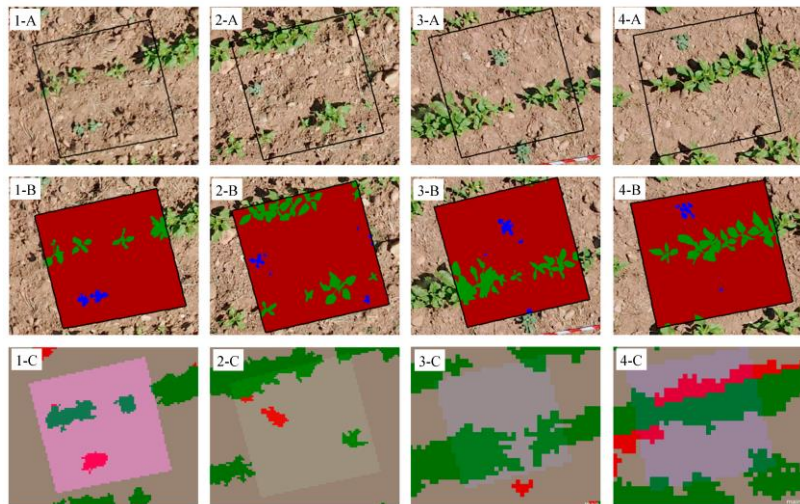


Figure 1. Image classification performed by the OBIA algorithm.

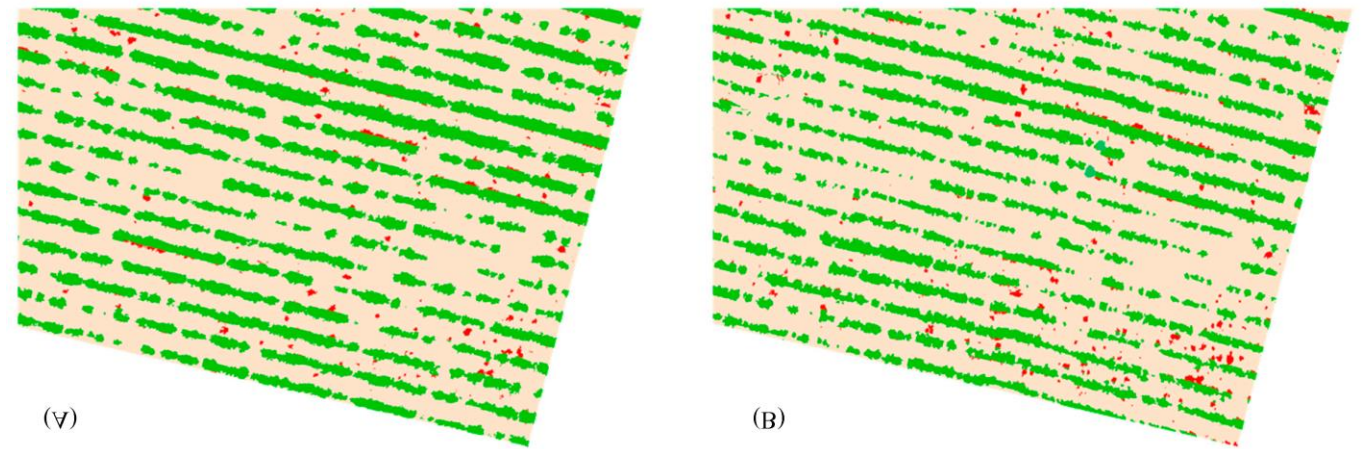
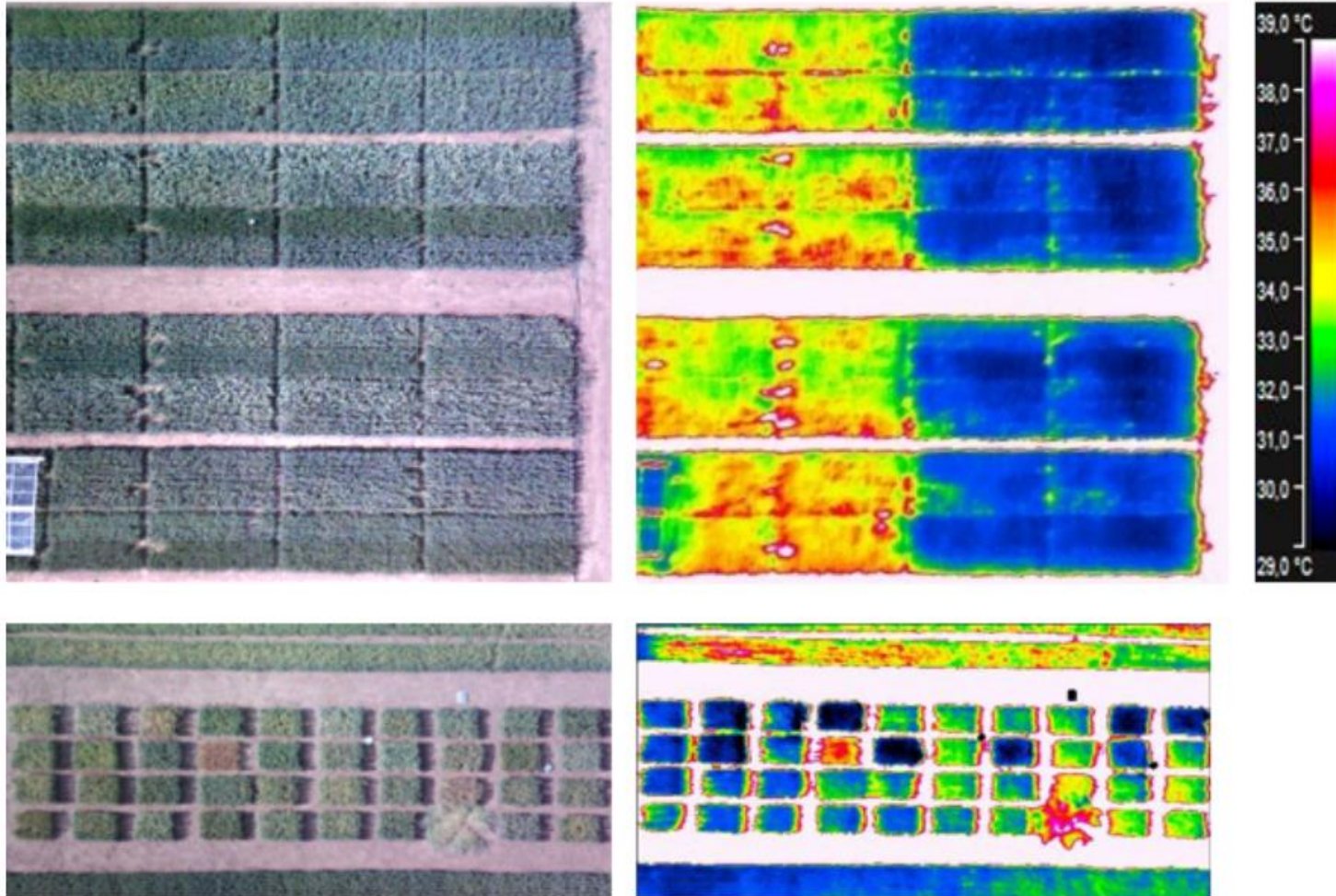


Figure 2. Image classified in weeds (red), sunflower crop rows (green) and bare soil (brown) using an UAV flying at 40 m altitude with: (A) visible-light camera (ExG index); and (B) multispectral camera (NDVI index).

Application in Detection of Water Stress in Cereals



Crop water management

Drought indicator

During droughts, plants close their stomata, and the vital transpiration process that cools vegetation slows.



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Crop research center in Estonia, study area

Estonian Crop Research Institute (ECRI)

Breeding and crop phenotyping center. Seed Bank



Crop Variety performance test center

Goals- For environmental tests that have become crop



One type of drone we use SenseFly eBee plus and X Fixed Wing Drone



SEQUOIA- Multispectral Camera



S.O.D.A- RGB Camera

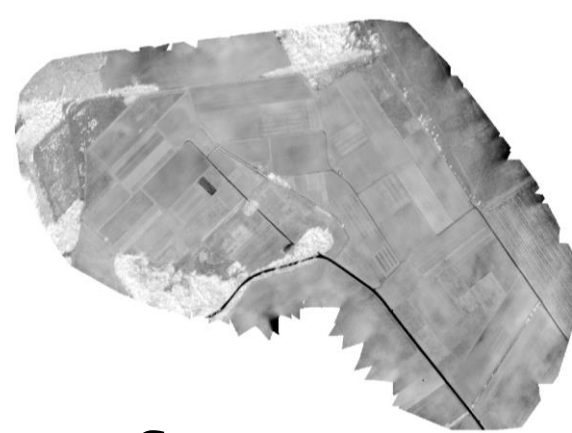


Thermal Mapping Camera

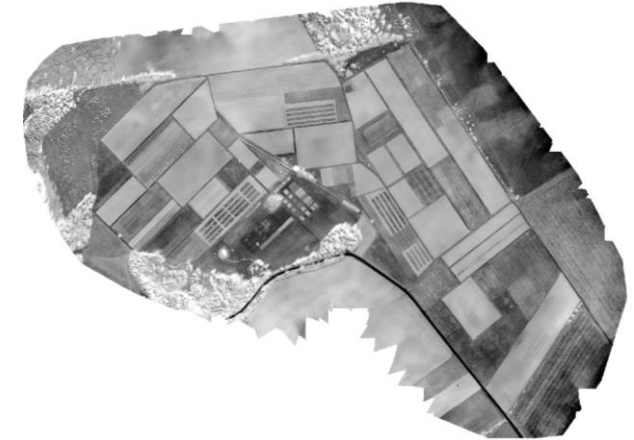
Multispectral camera



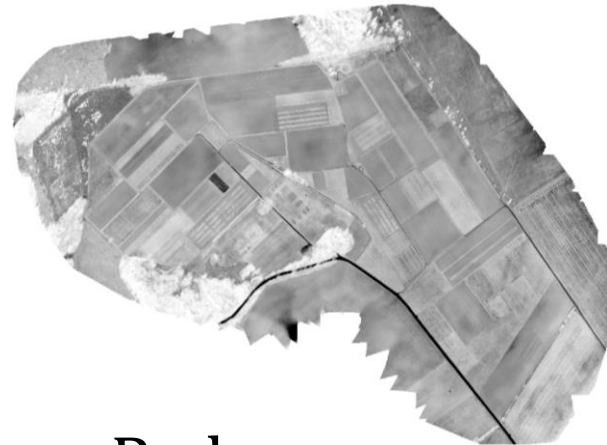
SEQUOIA- Multispectral Sensor



Green



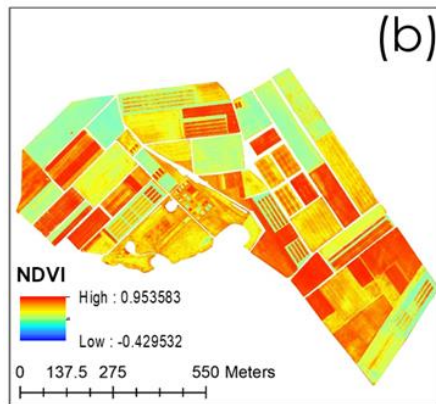
NIR



Red



Red-edge



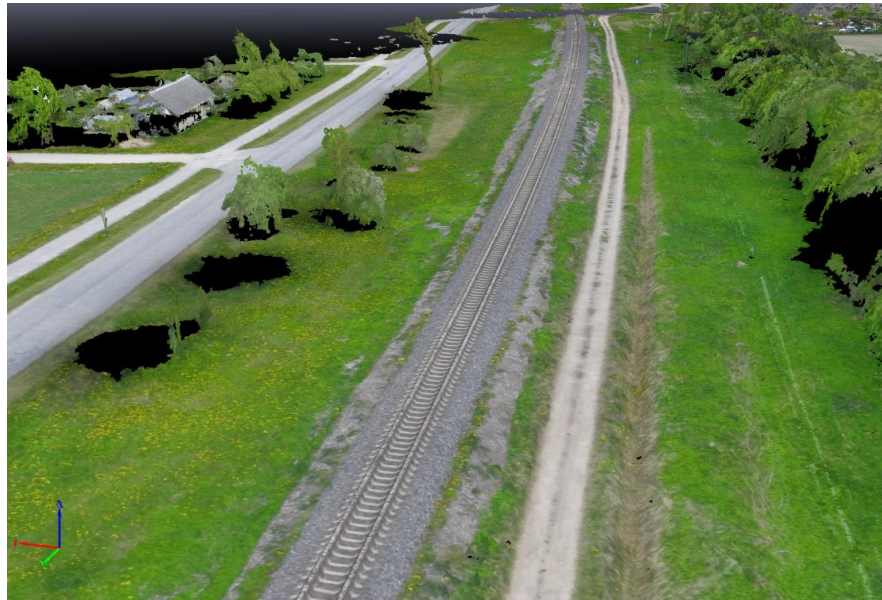
Normalized Difference Vegetation Index (NDVI) in Kuusiku

Grayscale reflection images of Green, Red, NIR, Red-edge in Kuusiku

S.O.D.A. RGB camera



Forest RGB imagery from Lahemaa National Park, Estonia



Point cloud and 3D modelling, Jõgeva, Estonia

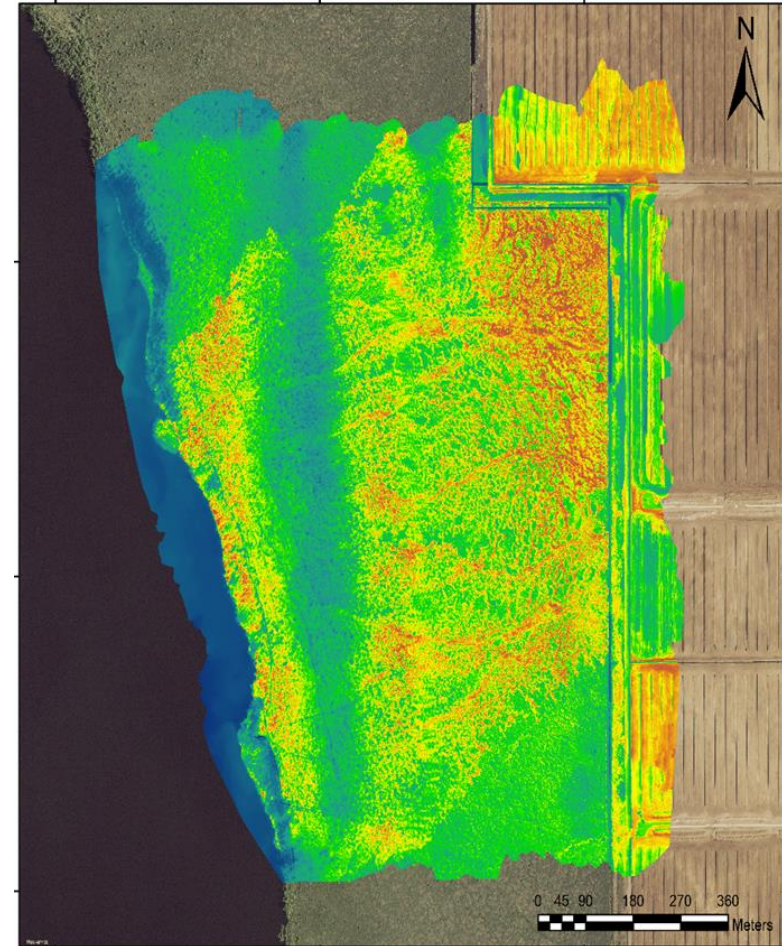


Farmland RGB imagery from Kuusiku, Estonia

Thermal camera



Surface Temperature



Some of our UAV research in agriculture

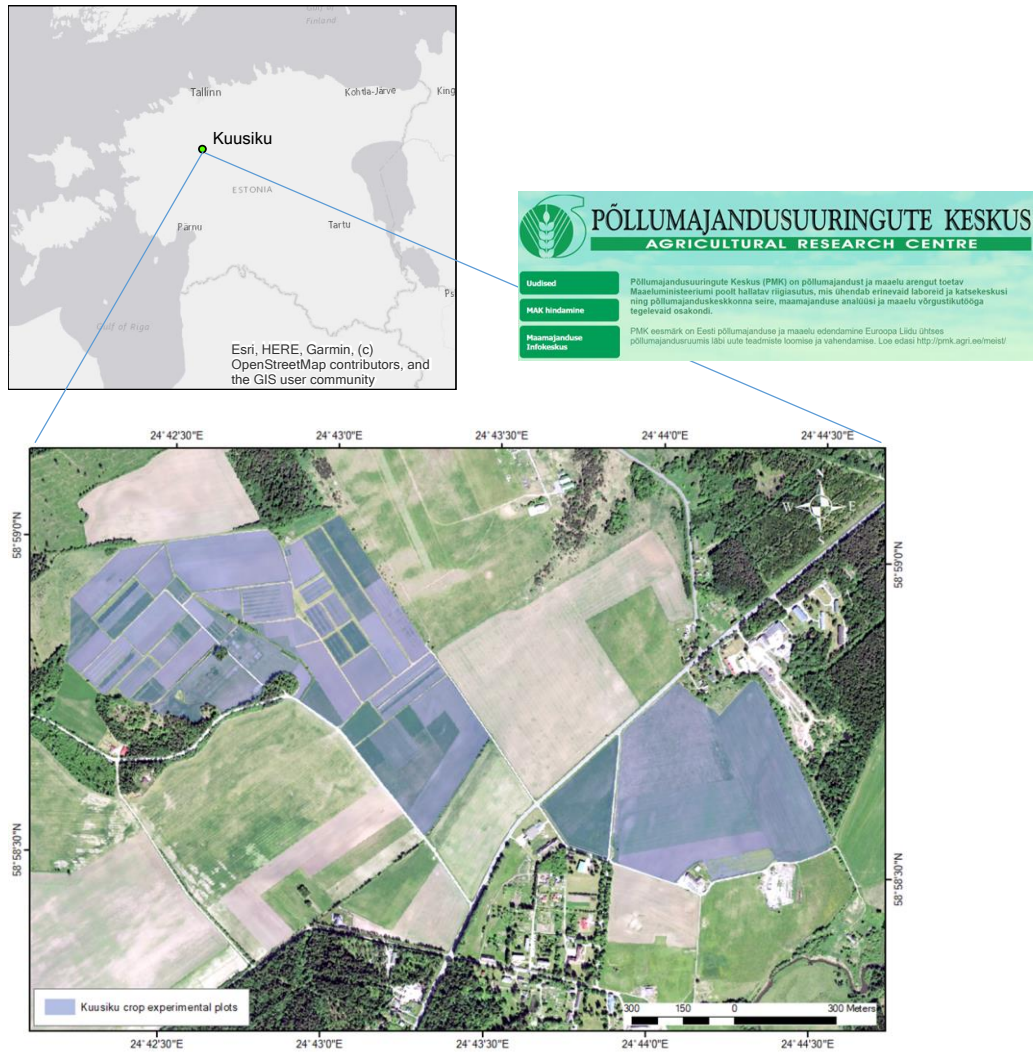


Fig 1. The total research area covers 103.7 ha with 45 different crop types.



Fig 2. Orthomosaic photo of the study area (by Pix4D)



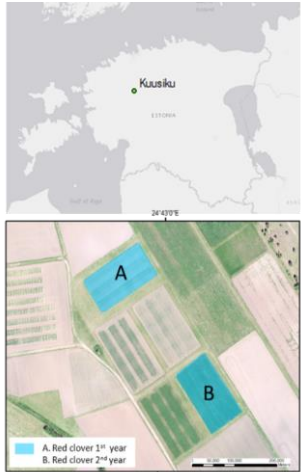
Fig 3. Wheat experimental field



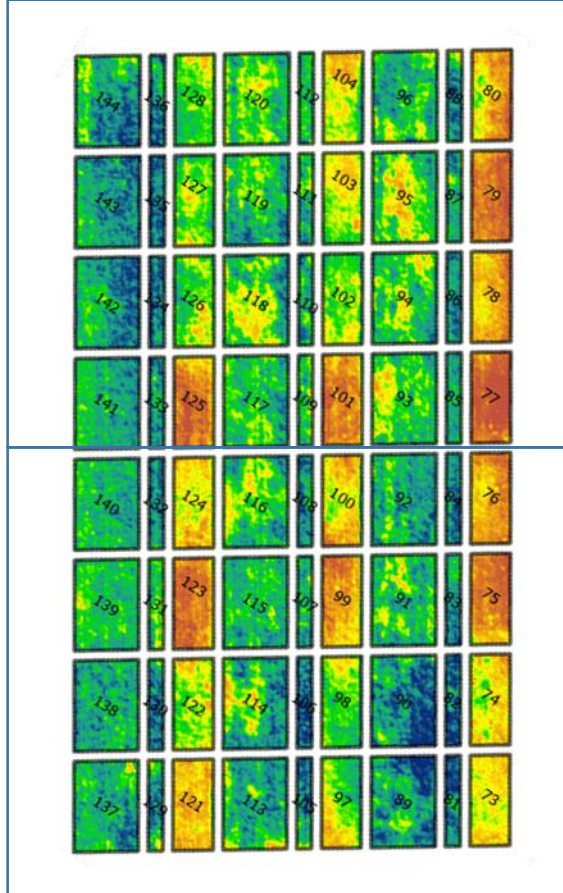
Fig 4. The eBee takes off

Red Clover-grass Mixture Yield Estimation from UAV and Machine Learning Techniques

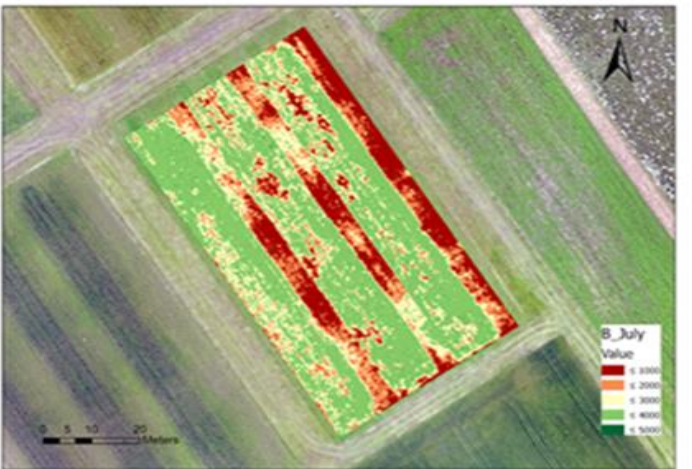
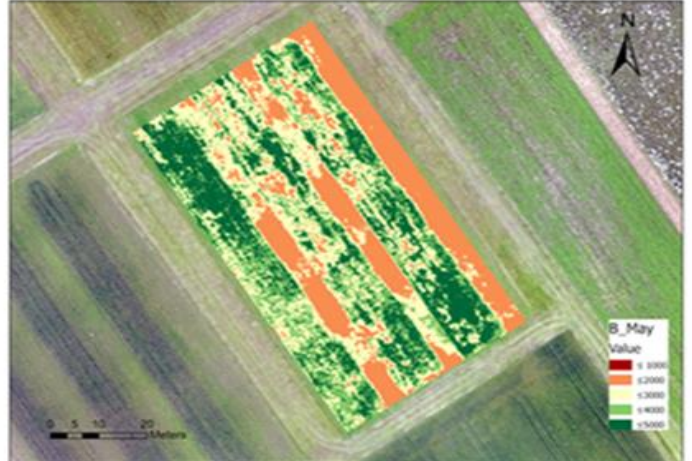
- In Kuusiku agricultural center



Training site



Predicting site



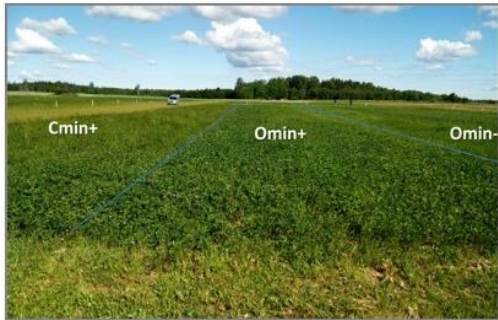
The Random Forest dry matter prediction models from Vegetation indices in raster level

My first experiment- Traditional Machine Learning Techniques for Red Clover-grass Mixture Yield Estimation Under Variety Performance Trials.

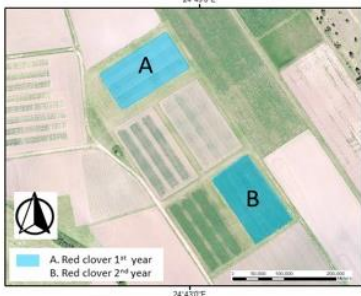
UAS data capturing



Treatments of red clover-grass fields



Clover-grass mixture DM yield sampling

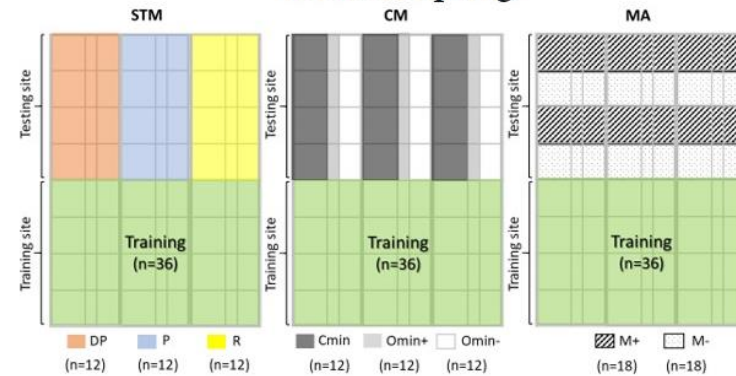


Muti-UAS data collection

VI's calculation



Plots sampling



Machine Learning Regression

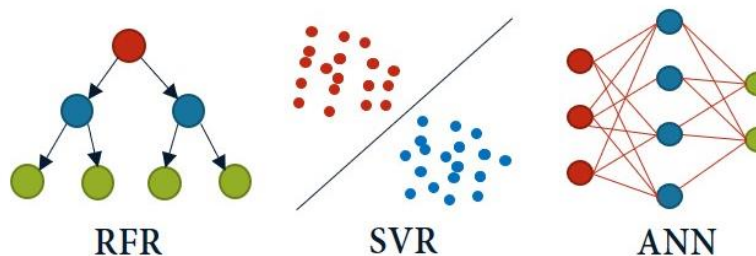
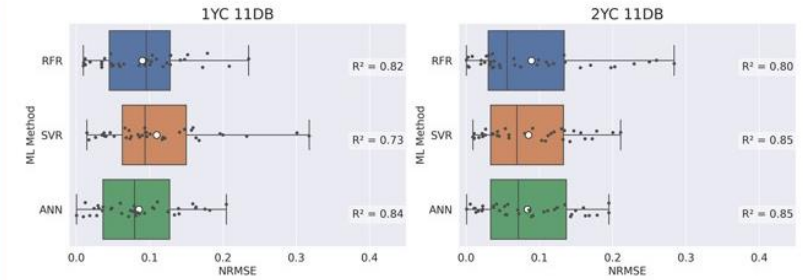
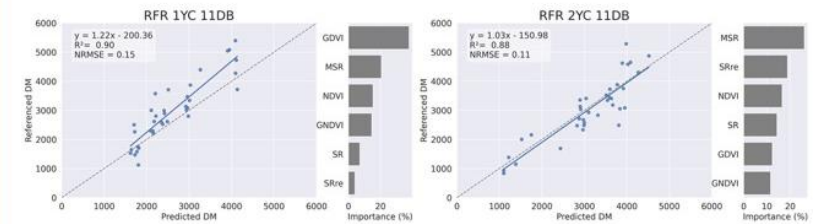


Image processing and model selection

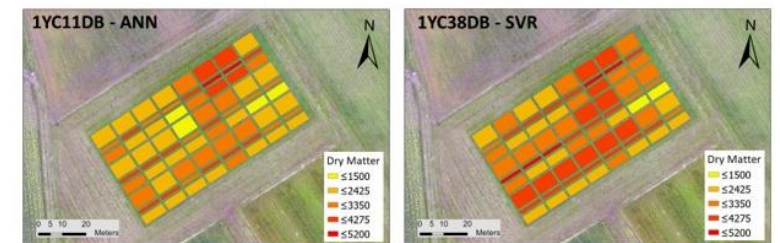
LOO cross-validation



Model prediction

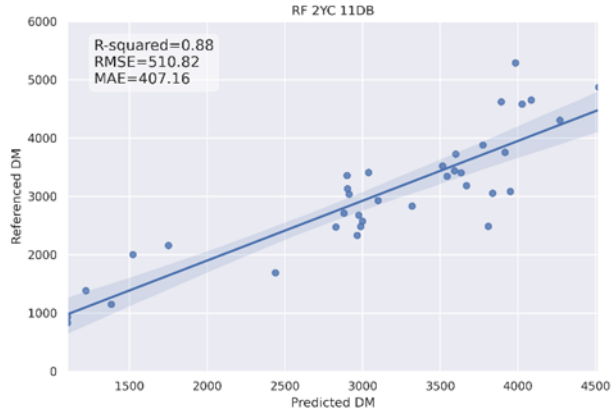


DM yield spatial mapping

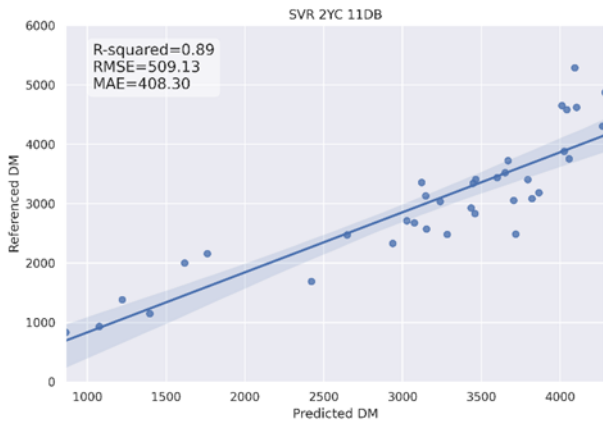


Model building and evaluation

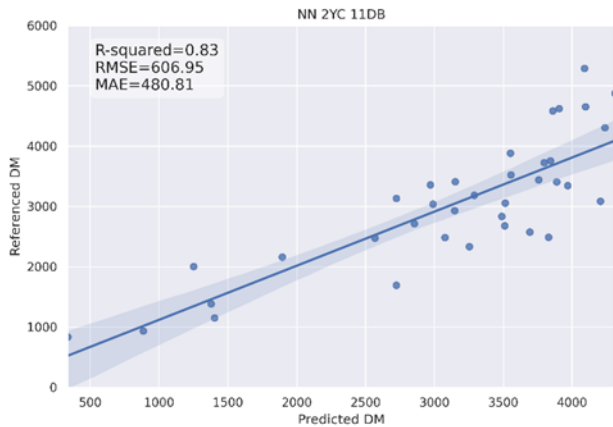
Random forest (RF)



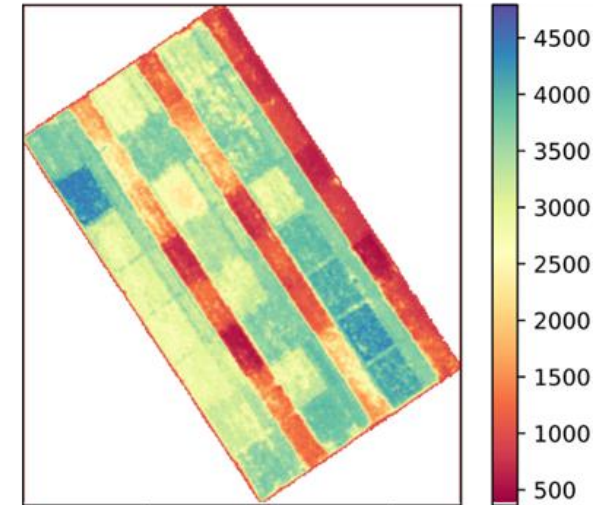
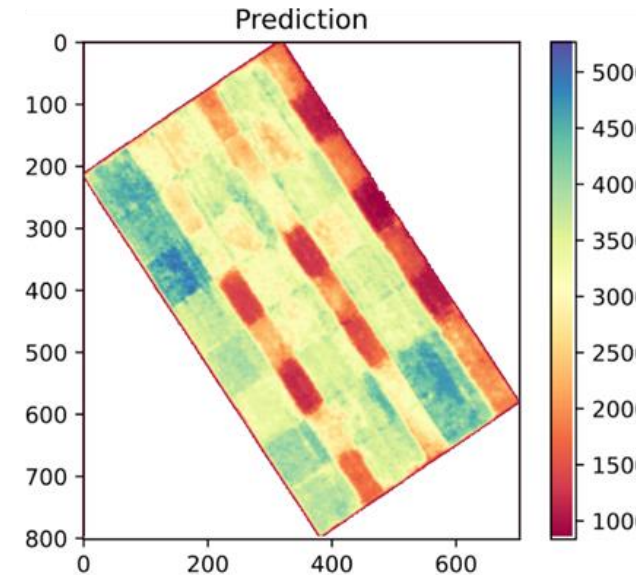
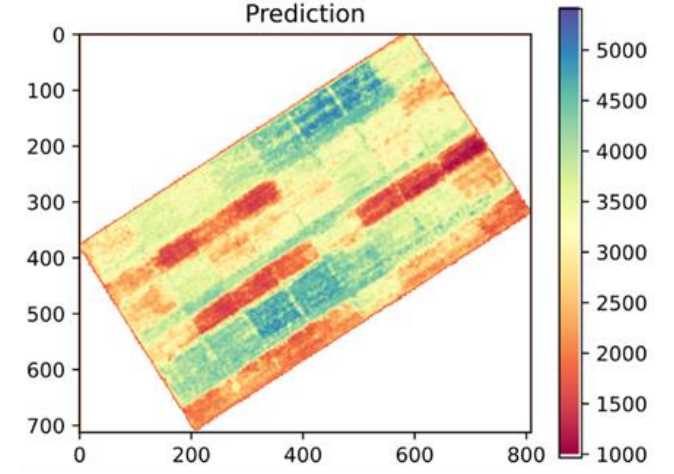
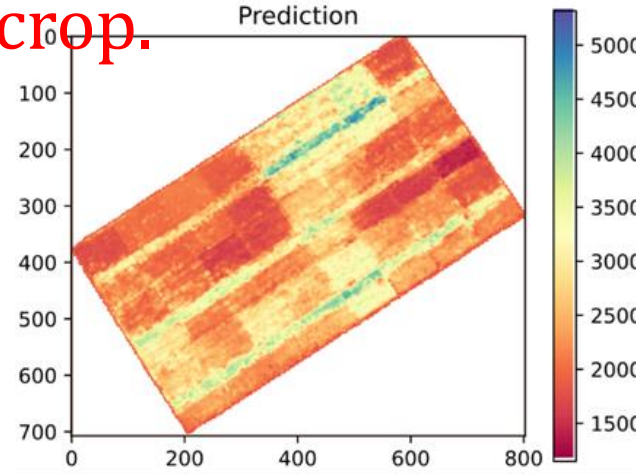
Support vector regression (SVR)



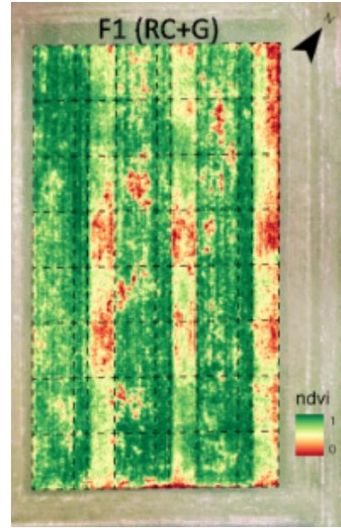
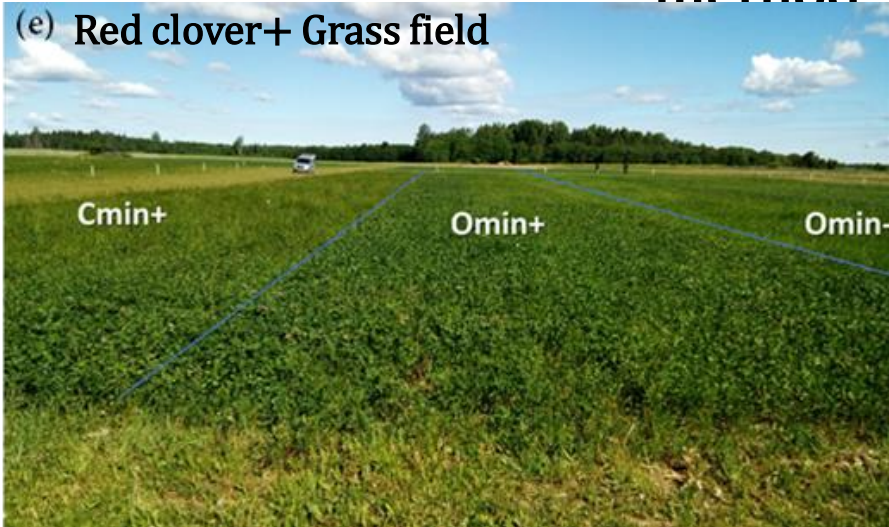
Neural Network (NN)



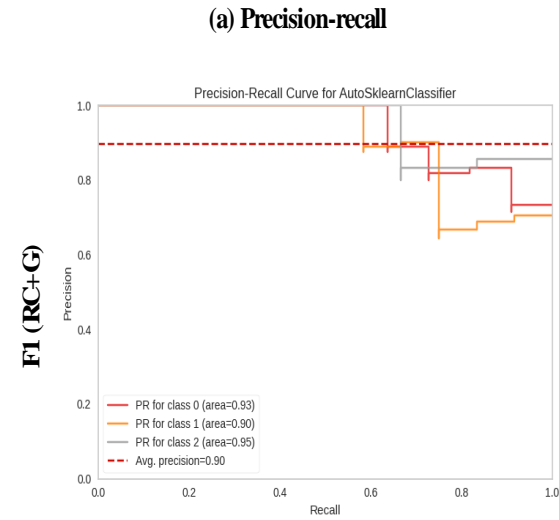
It was promising, we can predict the high-precision yield at the early stage of forage crop.



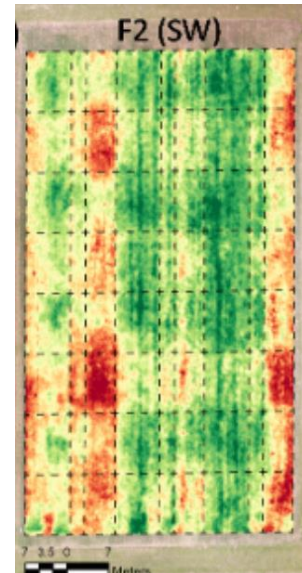
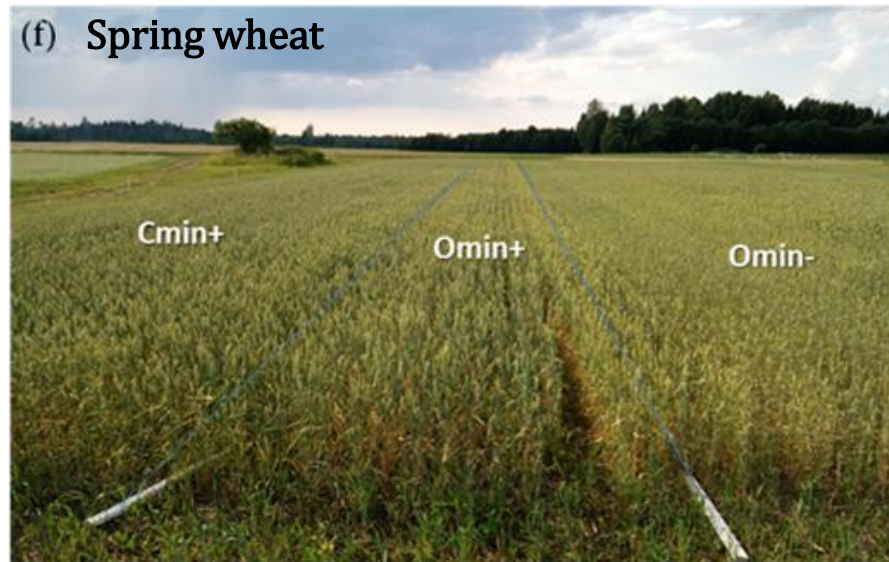
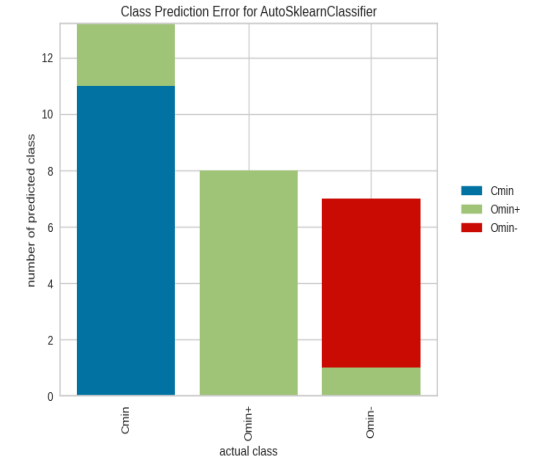
AutoML Identifying the cultivation method



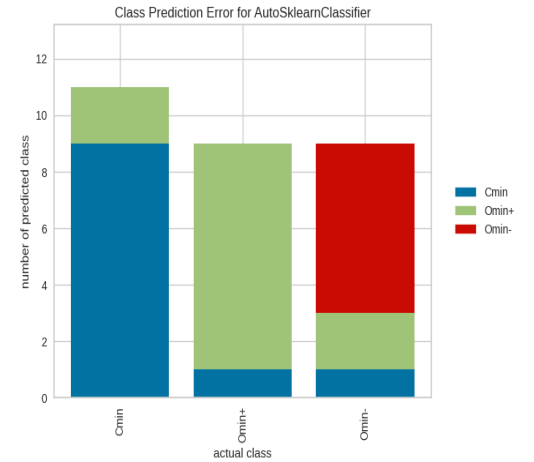
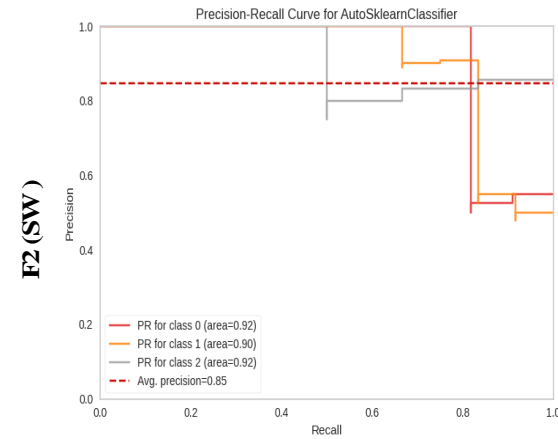
Average precision: 0.90



(b) Prediction Error



Average precision: 0.85



Cmin : conventional farming

Omin+ : organic farming with mineral fertilizer

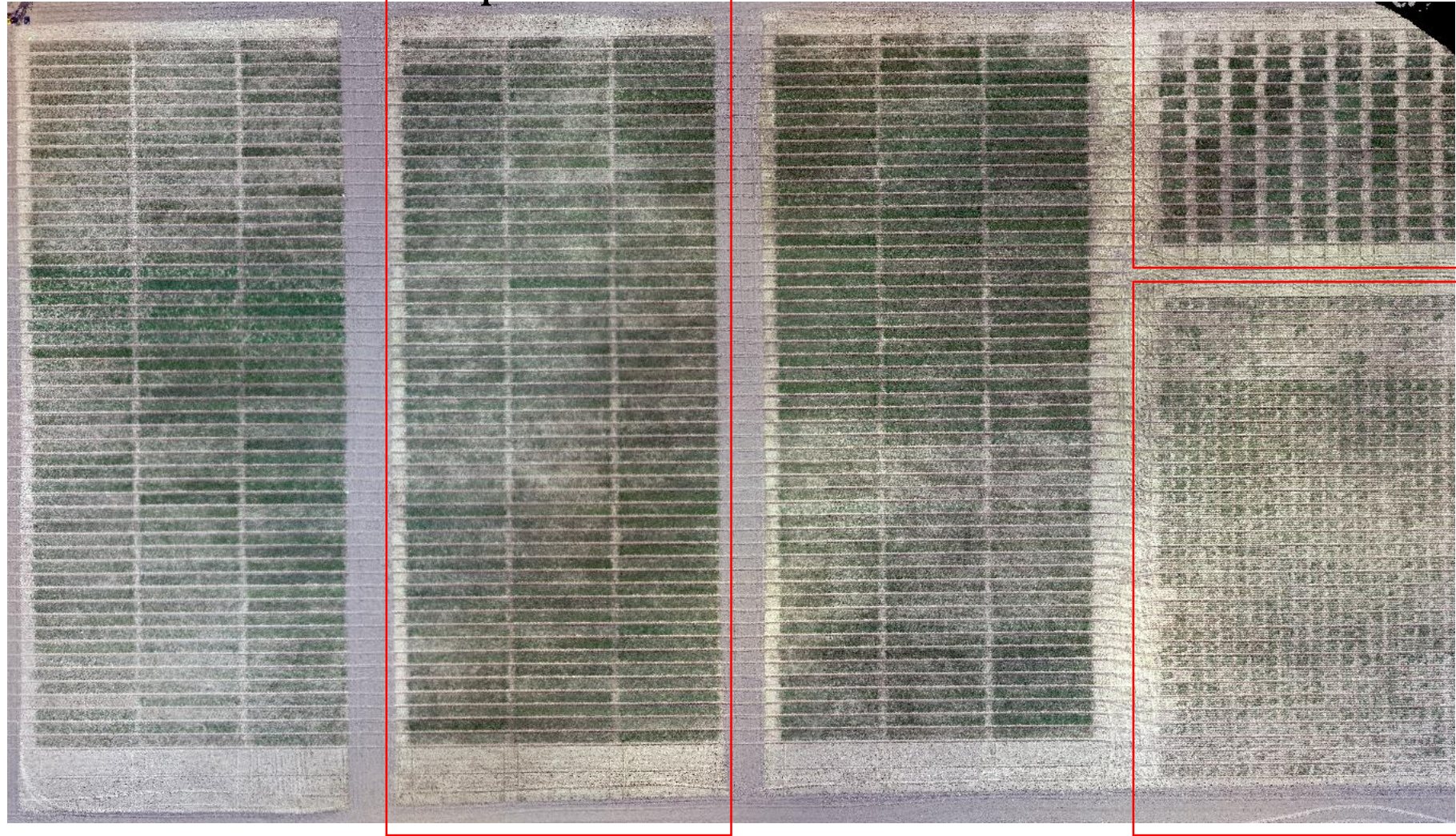
Omin- : and organic farming without mineral fertilizer

Jõgeva breeding centre of the Estonian Crop Research Institute

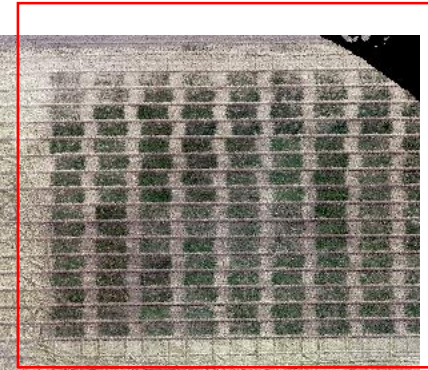


1*9 m² plot for advanced breeding material yield

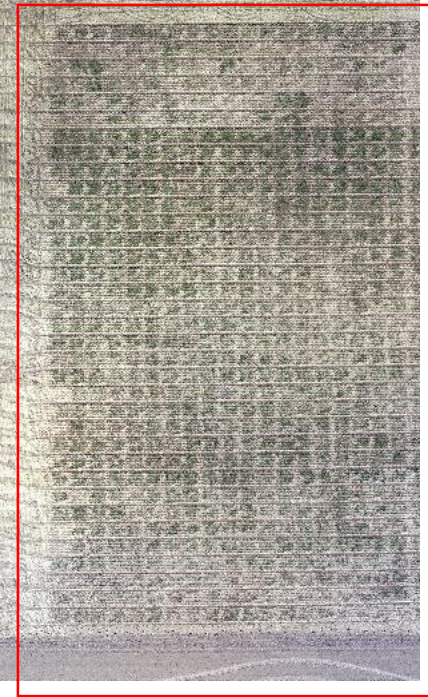
comparison



1*3m² plot for
F5 generation
breeding material



1*1m² plot
F1-F4, first 4 years
breeding material

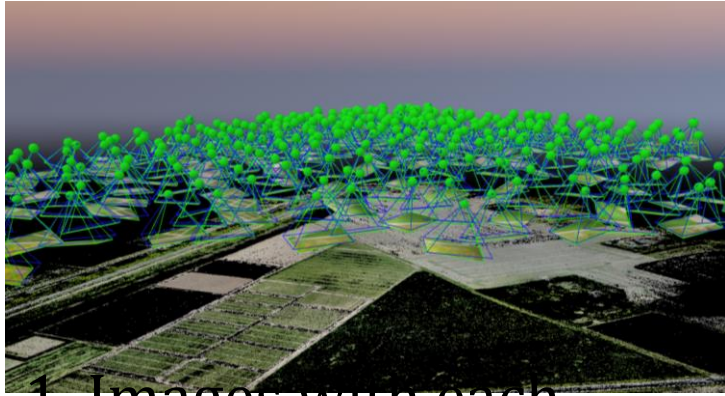


04/20/2021 Jogeva Breed Centre with P4 DJI-RGB

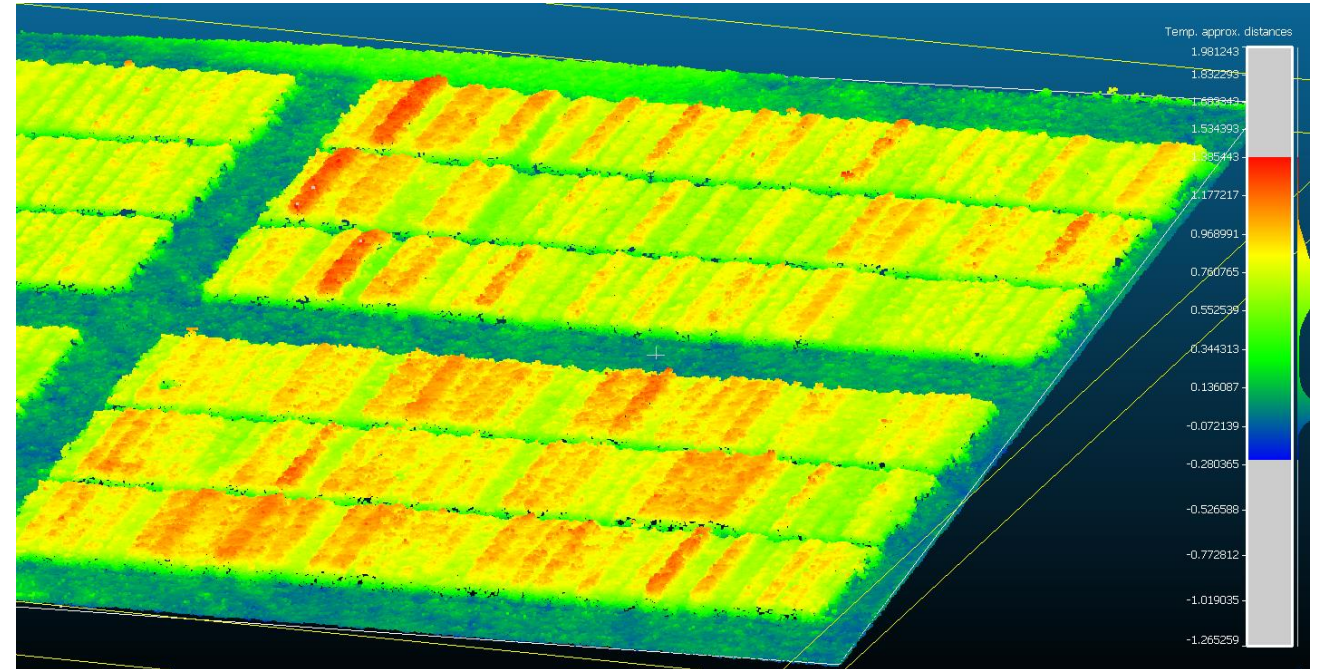
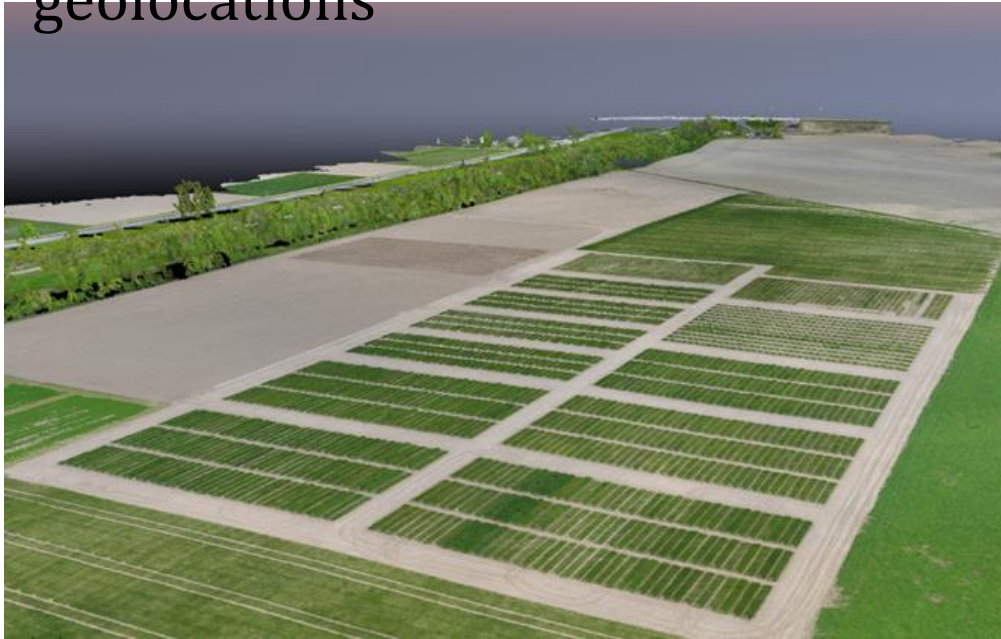
UAS application in wheat phenotyping-SfM

- Jõgeva Plant Breeding Institute breeding selection

3D models and real-time monitoring for wheat selection

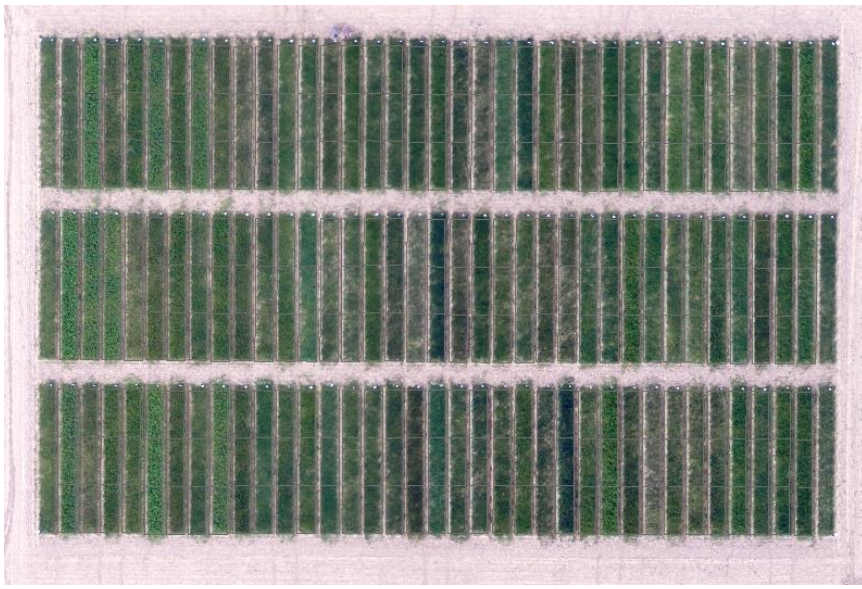


1. Images with each geolocations

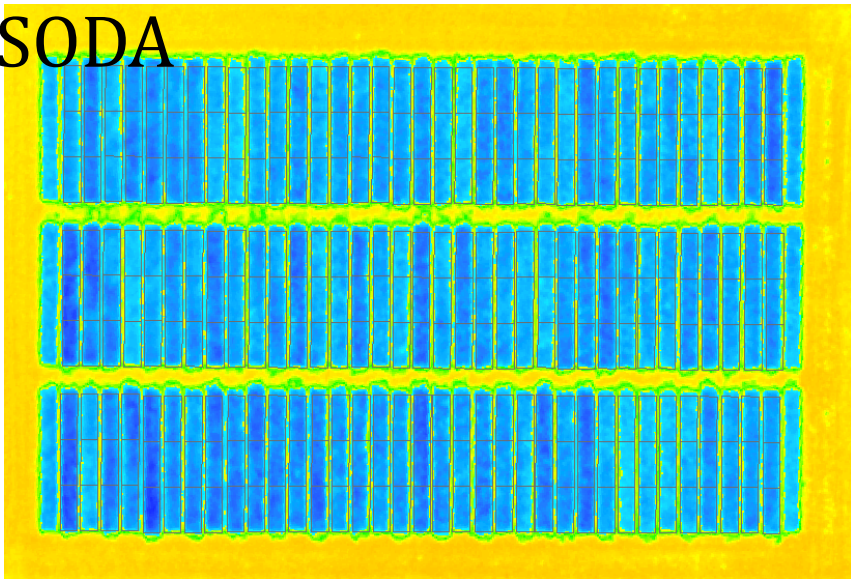


2. Create point cloud 3D mapping

3. Canopy Height Model (CHM)

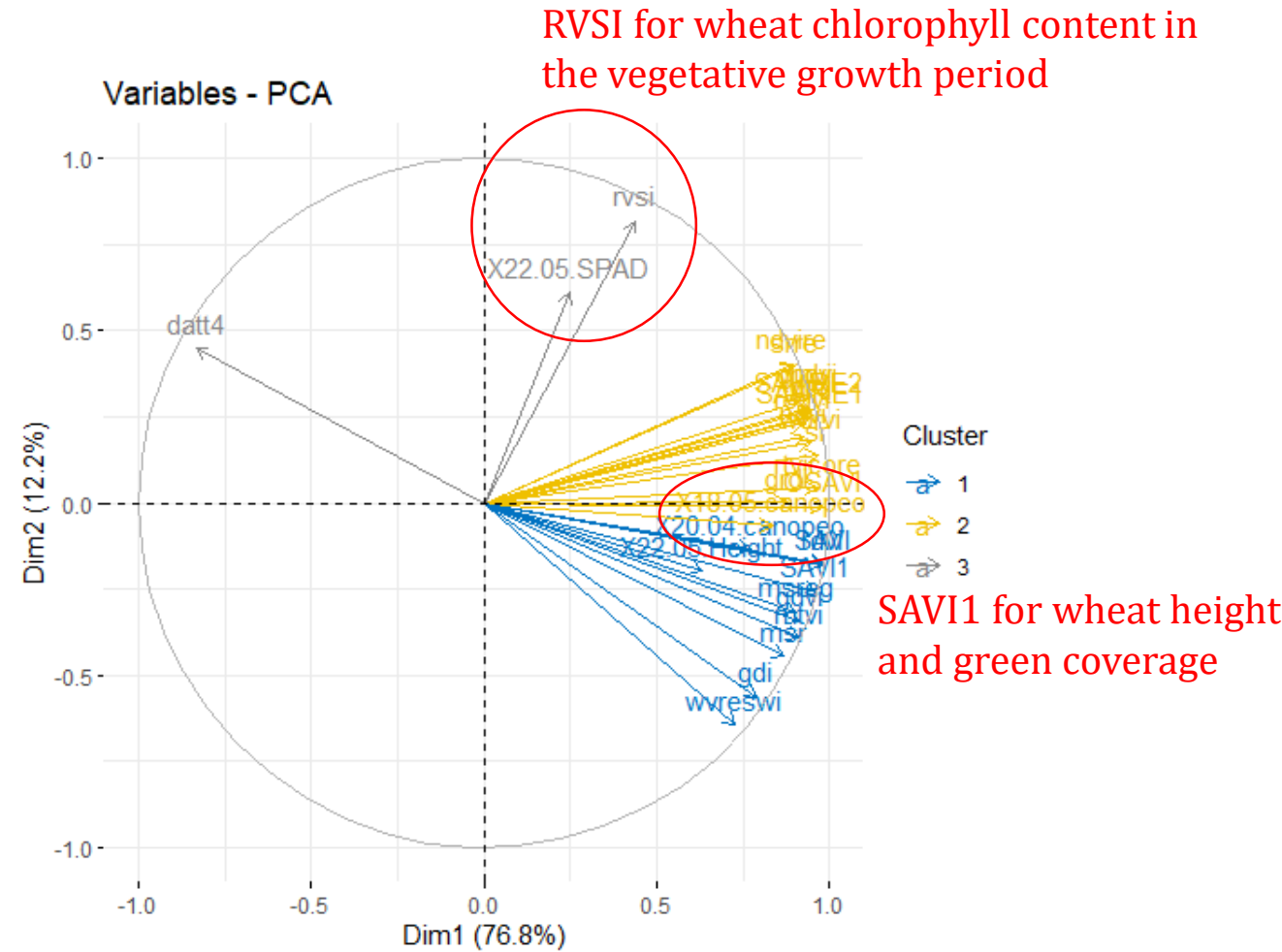


Wheat RGB image from SODA



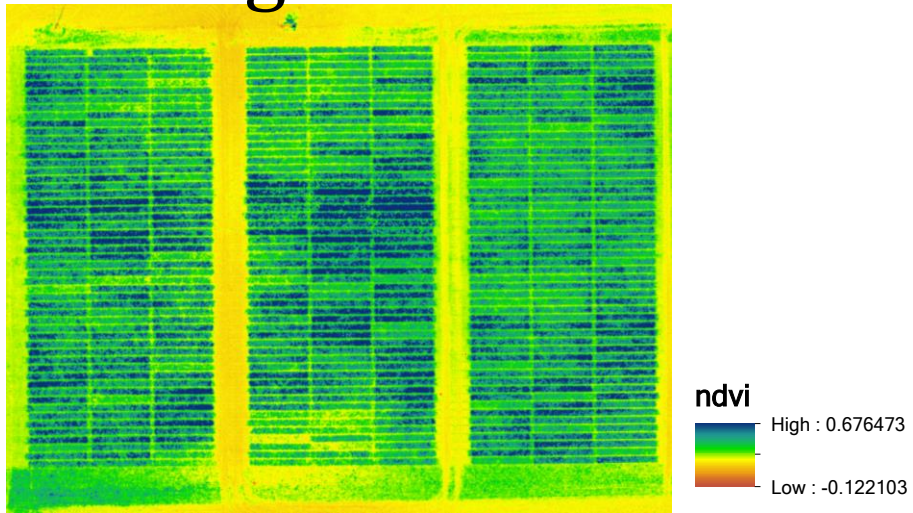
Wheat SAVI1 (Vegetation index)

PCA and kmeans clustering for wheat phynotyping

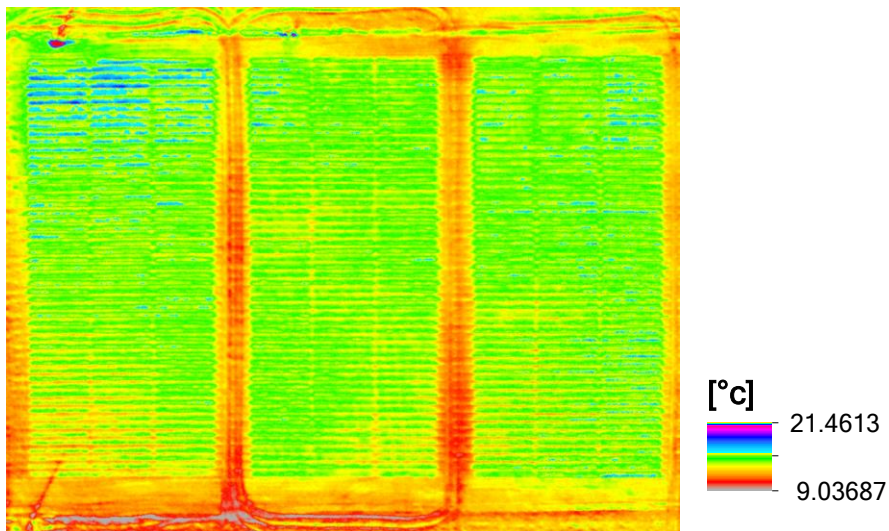


UAS application in Wheat Freeze Restriction and Recovery

Estimating



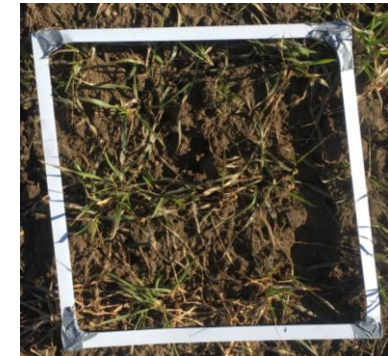
The normalized difference vegetation index (NDVI)



Thermal image

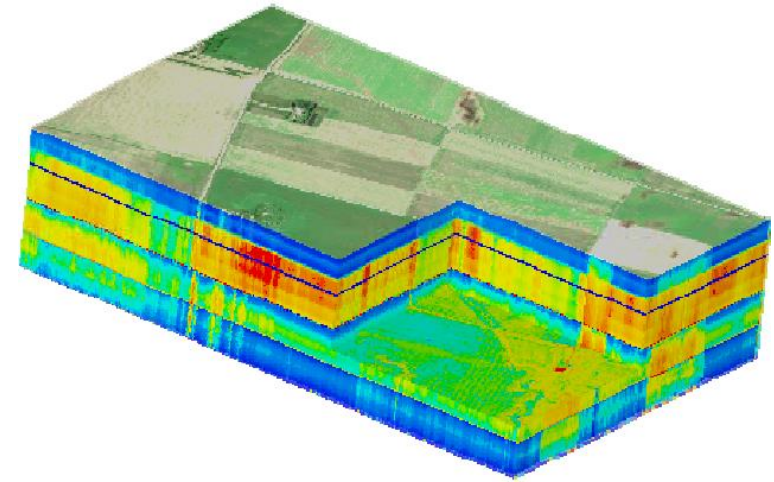
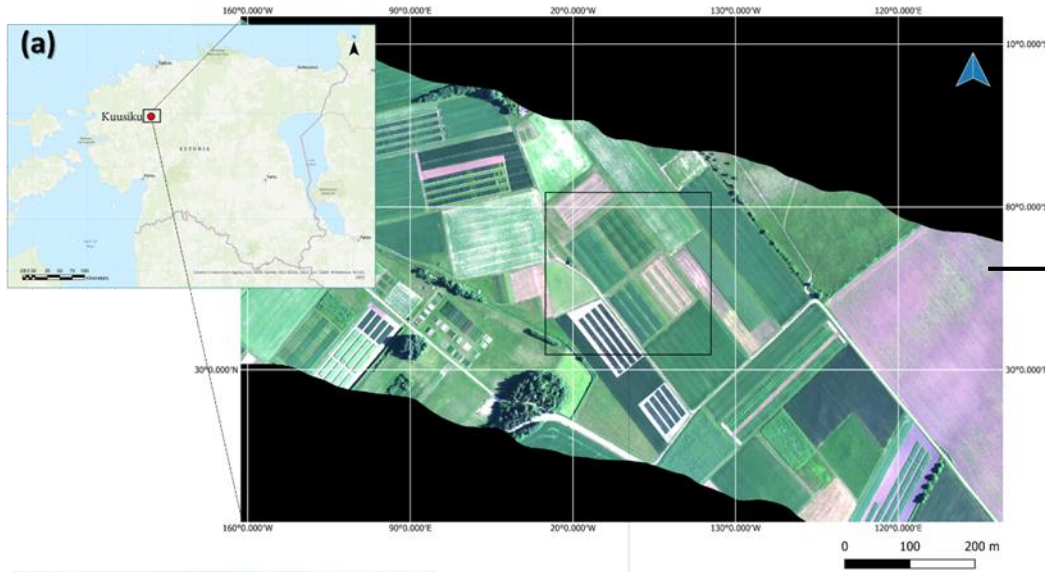


Freeze damage on winter wheat

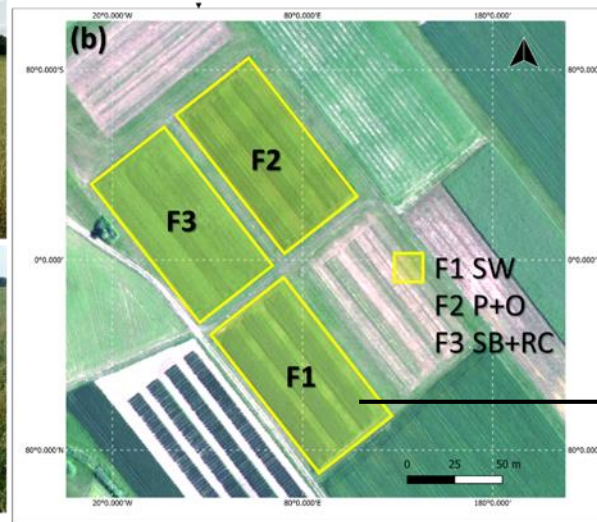
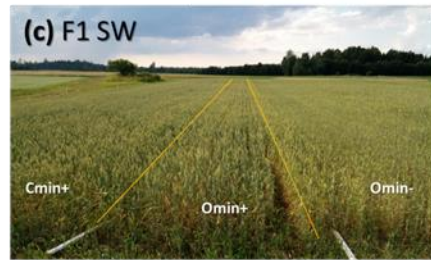


quadrat was used to study the degree of recovery and green canopy cover

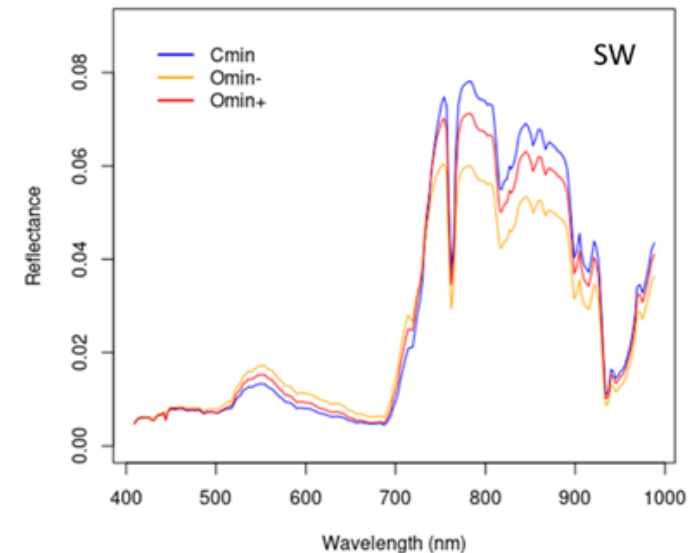
AutoML applied to hyperspectral analysis



hyperspectral image data cube

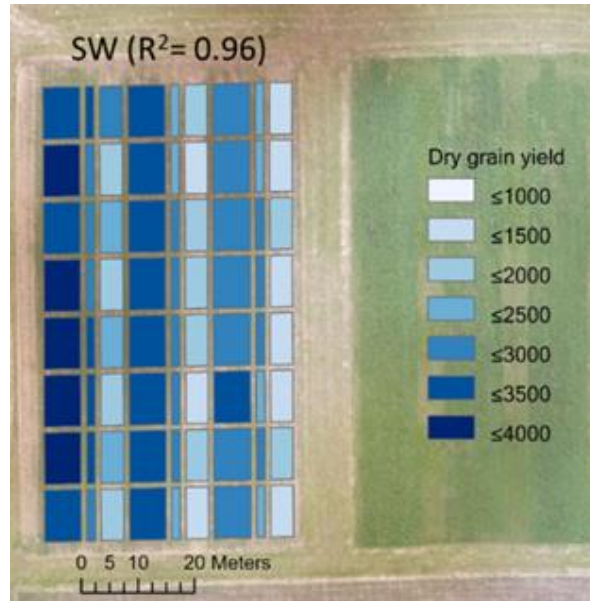
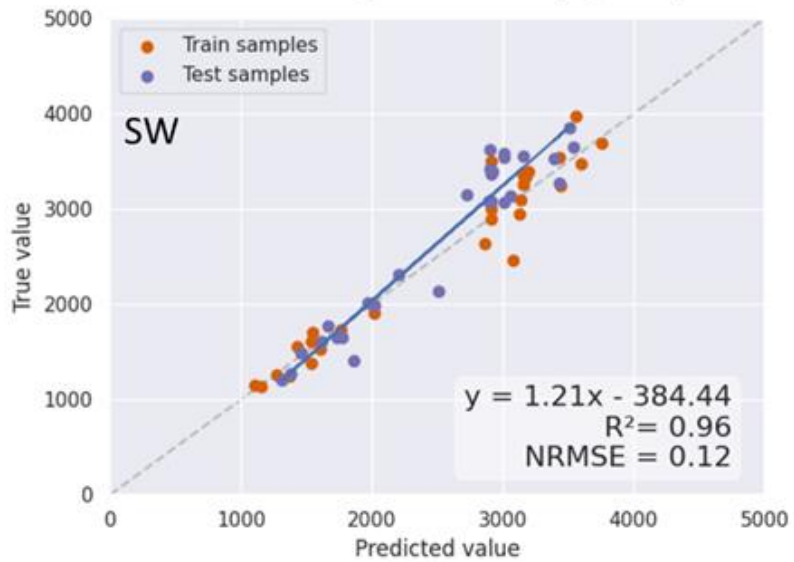


B. Mean of Reflectance - CM



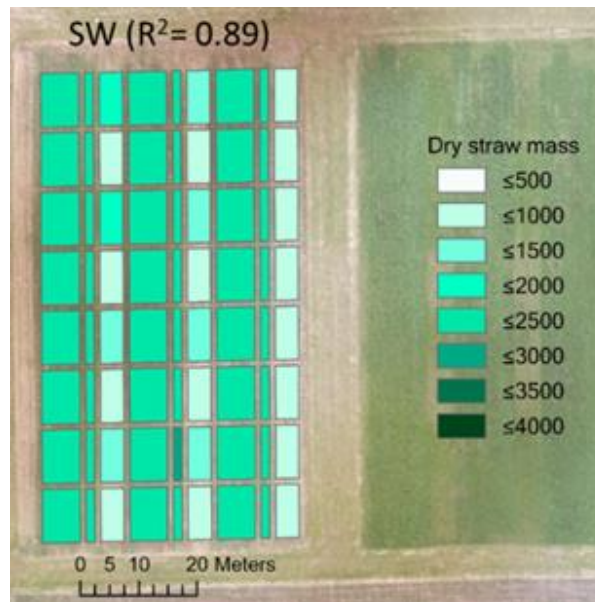
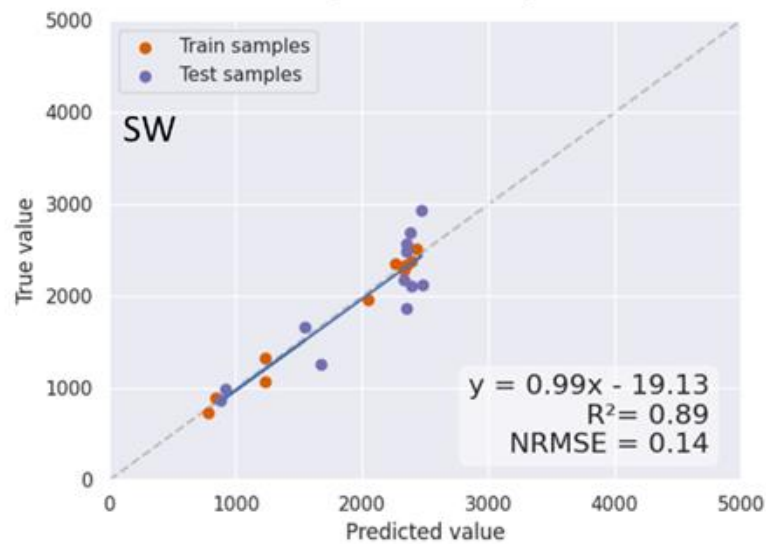
Airborne push-broom hyperspectral image

A. AutoML regression- Dry grain yield



Grain yield (kg ha^{-1})

B. AutoML regression- Dry straw mass



straw mass (kg ha^{-1})



Estonian University of Life Sciences in winter



Estonian University of Life Sciences in early autumn

email me: kai-yun.li@student.emu.