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Tree species detection using UAV imagery and YOLOv12 model: A comparison between consumer grade and MicaSense sensors

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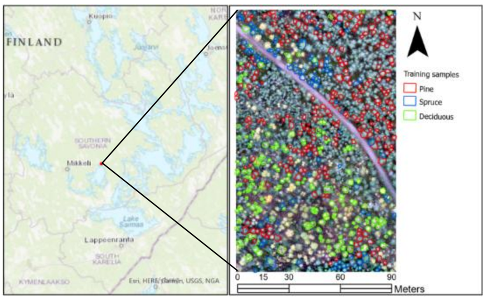
The young forest serves as a biomass reserve for bioenergy in Finland. Continuous monitoring is essential for its sustainable growth. Detecting tree species at the individual tree level is critical for assessing carbon sequestration in young trees. Therefore, the objective of this research is to detect Scots pine, Norway spruce, and deciduous tree species using UAV imagery and the yolov12 neural network model. The specific objective is to compare the yolov12 tree species detection accuracy between imageries from consumer grade RGB camera and advance MicaSense camera design for specific UAV ortho image analysis.

The study area (27.87°E 61.73˚N) is located in Juva, Finland. UAV drone scanning was carried out during the fall of 2024 over approximately 30 hectares of forest. The multispectral (RGB+NIR+red edge) imagery was captured using MicaSense and processed in Pix4D Mapper. Moreover, high resolution RGB image were also taken using consumer grade sony camera. 1.5-hectare Pine, spruce, and silver birch dominated young forest was chosen for this work. Training samples for the yolo model were created manually using ArcGIS Pro 3.5. In total, 537 polygons (Pine: 250, Spruce: 107 and Deciduous:180) were created for crown delineation and training sample preparations (figure, right). Although we had access to additional red-edge and near-infrared (NIR) bands, we used only the RGB channels from the MicaSense sensor to ensure a balanced comparison. The table below shows the comparison between consumer grade and MicaSense camera used in this study. The biggest tradeoff between the sensors is the output image resolution (12cm and 1.4 cm).

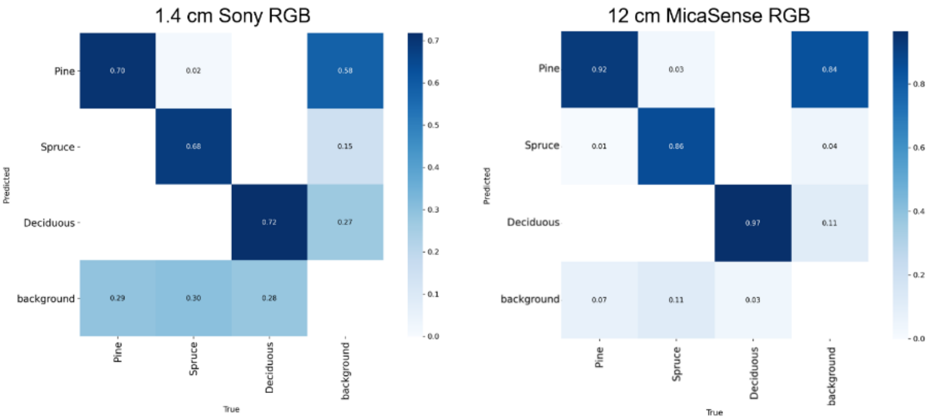


Characteristics	MicaSense	Sony
Model	Altum	DSC-RX1RM2
F-stop	f/1.8	f/4
Exposure (sec)	1/830	1/1600
Focal length (mm)	8	35
Bit depth	16	24
Spatial resolution of the image (cm)	12	1.4

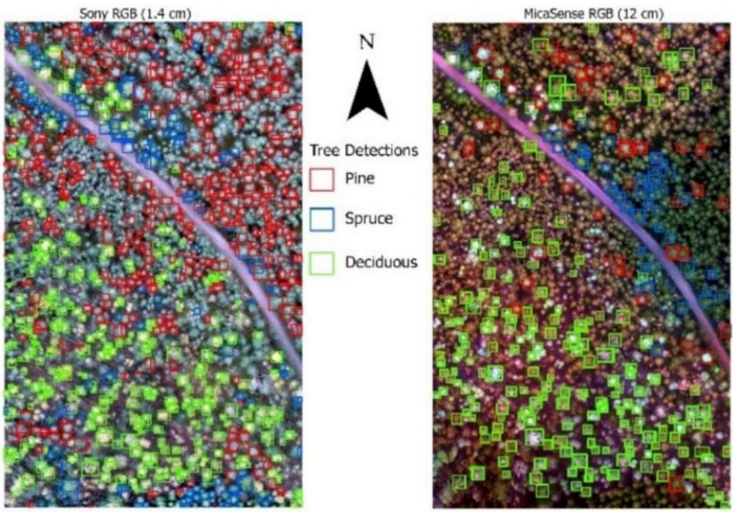
Hence, it is mainly a study of the comparison of species detection between high resolution (1.4 cm) consumer grade product RGB and low resolution (12 cm) advance MicaSense product RGB imagery utilizing yolov12 neural network model. The yolov12 is the latest version of the yolo series. The model was trained in python using Google Colab. The model was trained with a batch size of 10, image size of 640 and with 100 epochs. We used Ultralytics 8.3.182 Python-3.12.11 torch-2.8.0+cu126 CUDA:0 (Tesla T4, 15095MiB) and model: yolo12s.pt.

The performance of our object detection model was highly dependent on spatial resolution (Table below). The model trained on 12 cm MicaSense imagery demonstrated excellent proficiency, with an overall mAP50 of 0.94 and a strict mAP50-95 of 0.76, indicating robust detection and precise localization for all species. In contrast, the model trained at 1.4 cm Sony imagery performed significantly worse (mAP50: 0.76, mAP50-95: 0.56). Notable drop in mAP50-95 reveals a key weakness: while the high-resolution model can find objects, it fails to localize them with high accuracy.

Camera	Class	Precision	Recall	mAP50	mAP50-90
Sony (1.4 cm)	All	0.88	0.67	0.76	0.56
	Pine	0.84	0.65	0.74	0.56
	Spruce	0.93	0.68	0.76	0.56
	Deciduous	0.87	0.69	0.79	0.58
MicaSense (12 cm)	All	0.94	0.91	0.94	0.76
	Pine	0.89	0.90	0.95	0.75
	Spruce	0.96	0.89	0.89	0.74
	Deciduous	0.96	0.94	0.99	0.77



The confusion matrices (figure, right) for the 1.4 cm resolution model reveals significant misclassification, with substantial off-diagonal values indicating frequent confusion between all species, whereas the matrix for the 12 cm model demonstrates near-perfect classification, evidenced by the intense concentration of predictions along its main diagonal. This implies that for tree detection tasks, there is a point beyond which increased resolution introduces detrimental fine-grained variance, and a coarser resolution can yield more generalizable and effective features for accurate object detection. However, when applied to the entire study area, the model trained on higher-resolution imagery (1.4 cm/pixel) detected a greater quantity of instances than the model trained on lower-resolution imagery (12 cm/pixel), despite the latter's superior overall accuracy (see figure above).



In conclusion, while the model trained on 12 cm imagery demonstrated superior classification accuracy and precision in bounding box placement on the validation dataset, the model trained on 1.4 cm imagery exhibited a higher sensitivity for tree detection, resulting in a greater total count of identified trees across the extensive study area. This paradox highlights a critical trade-off between localization precision and detection sensitivity inherent in object detection models. Therefore, further research is recommended to investigate the optimal balance between spatial resolution and sensor specifications for UAV-based tree detection utilizing yolo neural network models, particularly for large-area.

Closed and Open Operational Models in EASA Certified UAV Operations: Competency and Organisational Implications

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Abstract

From 1 May 2025, the European Union Aviation Safety Agency (EASA) certified category for unmanned aircraft systems (UAS) enters into force, harmonising requirements for airworthiness, operational authorisations, and organisational approvals. The framework builds on Regulations (EU) 2019/945 (products) and 2019/947 (operations), consolidated in EASA's Easy Access Rules (EAR), and is extended by the 2024 certified-UAS package (2024/1108, 2024/1107, 2024/1109, 2024/1110). Information security obligations under Regulation (EU) 2023/203 will apply from 22 February 2026.

This regulatory milestone enables integration of large UAS into civil airspace but leaves open questions on organisational models and competencies. Two paradigms are emerging:

- **Closed systems** – vertically integrated, manufacturer-led architectures in which design, production, maintenance, training, and operations are contained within a single organisational boundary. These systems emphasise regulatory clarity, procedural uniformity, and operational predictability.
- **Open systems** – distributed, multi-platform architectures where multiple manufacturers, training providers, and maintenance organisations collaborate. These systems emphasise adaptability, innovation, and socio-technical resilience, but require more complex coordination and oversight.

This study analyses the implications of Closed versus Open models through the lens of the Knowledge, Skills, and Attributes/Other (KSA) framework as defined in ICAO Doc 9868 and EASA's Area 100 KSA provisions. The research combines three elements:

1. **Regulatory review** – systematic analysis of the certified-UAS package, including AMC/GM material, to map organisational and competency requirements.
2. **Literature synthesis** – drawing on research from manned aviation, air traffic control, remotely piloted aircraft systems, and socio-technical innovation theory (tight coupling, open innovation, resilience engineering, knowledge-creation models).
3. **Practitioner insight** – lessons learned from planning an EASA-certified Continuing Airworthiness Organisation (CAO.UAS),

maintenance and MRO systems, and training capability for certified UAS.

Findings. The analysis shows that Closed systems provide regulatory simplicity and reduce variability, aligning with tightly coupled environments where compliance demonstration is paramount. By contrast, Open systems broaden the competency profile of personnel, strengthen adaptability, and diffuse innovation across platforms, but at the cost of higher organisational complexity. The operational model choice cascades into CAO scope, maintenance arrangements, training curricula, operations-centre design, data governance, and ground-handling practices. Hybrid approaches appear promising, where a Closed “core” ensures compliance efficiency and oversight, while Open interfaces enable adaptability and innovation.

Implications. The study highlights the strategic trade-offs inherent in model choice. Closed systems risk long-term rigidity and vendor dependency, whereas Open systems demand more from oversight and competence management but support resilience and technology uptake. Competency-based training and assessment (CBTA/EBT), informed by both explicit knowledge (procedures, regulatory requirements, technical manuals) and tacit knowledge (experience, situational awareness, adaptability), emerges as a critical enabler in both models. Regulatory authorities, operators, and training organisations must therefore collaborate to ensure training infrastructures can accommodate diverse competence demands.

Application relevance. For FinDrones 2025 domains—logistics, security, environmental monitoring, and infrastructure—operational model choice shapes readiness, safety, scalability, and cost. Logistics may prioritise Closed integration, while environmental monitoring may benefit from Open adaptability.

Conclusion. The introduction of the EASA certified category marks the beginning of a new regulatory era for UAS operations. By framing operational design choices through the KSA lens, this study provides a structured way to align organisational models, competency frameworks, and regulatory compliance. The results support operators, regulators, and training providers in anticipating the cascading effects of model choice, and they encourage further exploration of hybrid solutions that combine regulatory assurance with adaptive capacity.

Keywords: Certified UAS; Closed and Open models; KSA; CAO.UAS; MRO.

Mapping Large European Aspens (Populus tremula L.) Using National Aerial Imagery and a U-Net Convolutional Neural Network

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Abstract

Biodiversity supports boreal forest stability, with European aspen (*Populus tremula* L.) enhancing it by providing crucial habitats and resources for dependent species. Despite existing aspen remote sensing methods, there is no efficient method for mapping it over large areas to support forest management and conservation. In this study, we developed a deep learning-based semantic segmentation model to detect aspen from openly available national aerial imagery, evaluated its accuracy using field data, and compared the detection performance between leaf-on and leaf-off conditions. The study was conducted in three areas in southern Finland: Helsinki, Lohja, and Evo. We employed a U-Net encoder-decoder architecture using four-band aerial imagery (RGB and NIR) with a spatial resolution of 0.5 meters, captured during both seasonal conditions. Training data consisted of visually identified aspen locations from imagery between 2010 and 2023, covering 290 sites across Finland. We found notable differences in detection accuracy between leaf-on and leaf-off conditions and aspen size. The F1-score was higher in leaf-off (0.577) than leaf-on (0.463), with intersection over union (IoU) values of 0.280 and 0.256 for leaf-off and leaf-on, respectively. The diameter at breast height (DBH) of the detected aspens was similar for both conditions. Moreover, detection accuracy improved for larger aspens, with F1-scores reaching 0.663 (leaf-off) and 0.551 (leaf-on) for aspens >20 cm DBH, and 0.710 (leaf-off) and 0.594 (leaf-on) for those >30 cm. The developed model reasonably locates aspen distribution and abundance, assisting forest managers make informed management decisions.

Keywords: Biodiversity, keystone species, deep learning, semantic segmentation, U-net

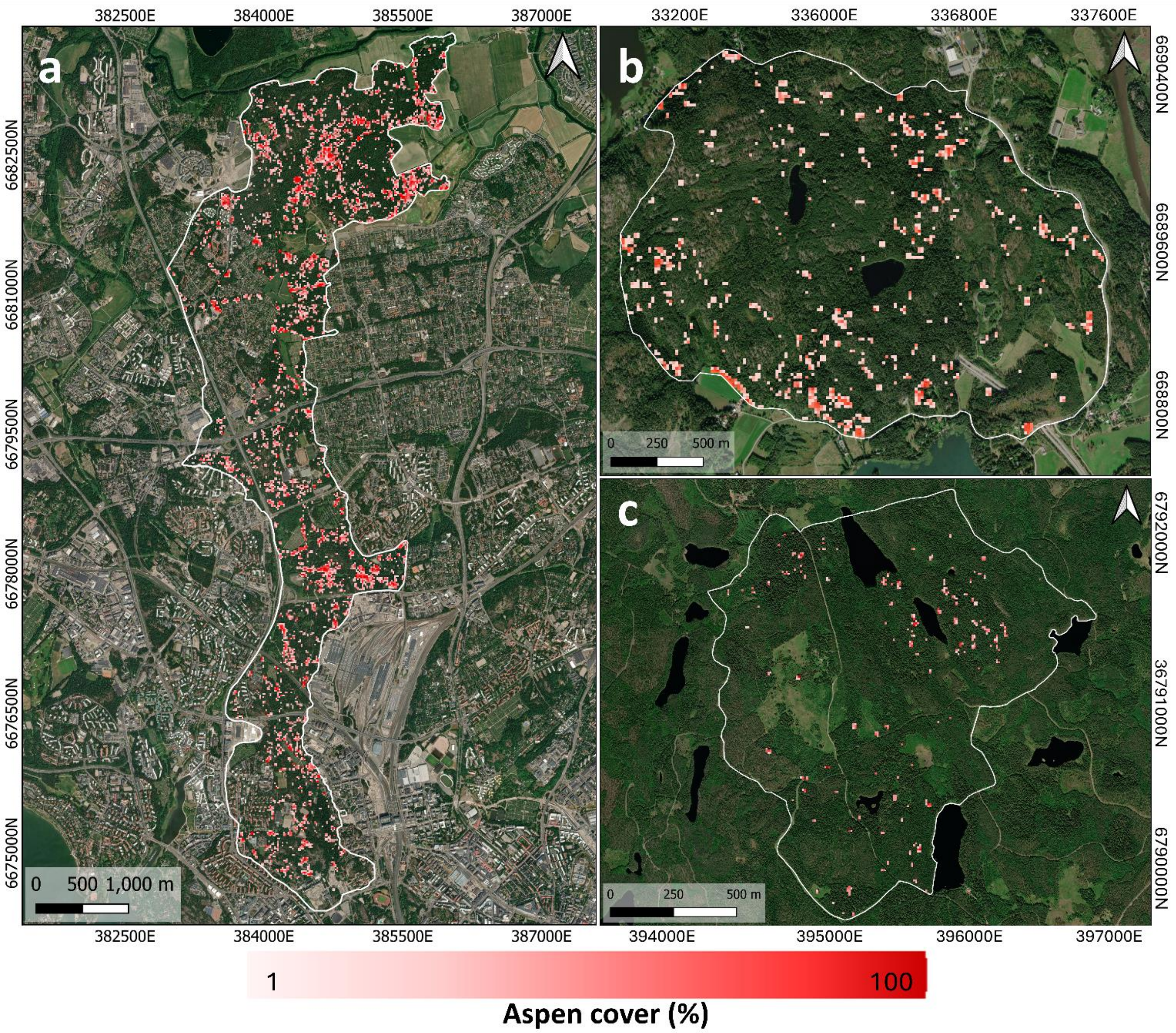

Figure 1: Aspen cover estimation using the best model (leaf-off) for the study areas: a) Helsinki, b) Lohja, c) Evo (16×16 m², ETRS89-TM35FIN)

DRONEAI: Disaster Recovery Optimization with European DroneAI - Advancing European-Made Drone Components, Software, and AI

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The European disaster recovery optimization with European DroneAI (DRONEAI) paper aims to revolutionize disaster recovery by developing cutting-edge drone and AI solutions produced in Europe, to enhance resilience in areas affected by natural disasters and human-made disasters.

The DRONEAI paper targets the development of an advanced drone system capable of optimizing recovery from both human and natural disasters. This includes scenarios such as the reconstruction of war-torn areas, as well as responses to storms, forest fires, pest infestation, soil desertification, floods, microplastic waste, and oil and fuel spills in the seas.

The paper exposes state-of-the-art European drone component manufacturers, sensor technology developers, and artificial intelligence (AI) algorithm companies. The goal is to elucidate a comprehensive European drone solution that integrates cutting-edge microtechnology with sophisticated AI algorithms to optimize disaster recovery.

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Drone imaging at the Bioeconomy Campus

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Agriculture is evolving through predictive modeling, data-based decision-making, and the creation of environments for experimentation, demonstration, and co-development. By combining drone imaging, sensor technologies, and digital tools, cultivation practices are being refined to support more informed and timely decisions in farming.

Since 2021, an applied research team in smart agriculture has been operating at the Bioeconomy Institute of JAMK University of Applied Sciences, located on the Bioeconomy Campus in Saarijärvi. The team focuses on smart field cultivation and data utilization, automation, farmer data storage and data licensing, as well as the Digital Twin of the Farm. Collaboration with the POKE Vocational College enables a broad testing environment. Poke has 100 hectares of fields, 700 hectares of forest, and a robot dairy barn. Some of the field plots are equipped with soil sensors and weather stations, and continuous monitoring is conducted throughout the growing season using, for example, drone imaging.

Research activities began on the Huipuri field plot, where drone imaging has been used to observe crop growth over four growing seasons. At Huipuri, drone imaging has supported selective harvesting planning, identification of problem areas, monitoring of crop development, and moisture assessment in combination with soil sensor data. Extensive data collection using various sensors combined with drone imaging enables a comprehensive examination of the field. For two growing seasons, drone imaging has also been applied to grass fields. During the past growing season, imaging of both cereals and grasses was expanded to farmers' fields in the Saarijärvi and Jyväskylä areas to support cultivation decision-making. Imaging was conducted frequently throughout the season and targeted at specific decision-making phases, such as assessing the overwintering of winter cereals in the spring.

Imaging has utilized both the fixed-wing EbeeX drone and the Phantom 4 quadcopter. Both drones support RGB and multispectral imaging. The EbeeX drone also features a Duet T combination camera, which enables the detection of temperature differences in vegetation.

At the Bioeconomy Institute, drone imaging is part of a broader development in smart agriculture. In the Finnish Future Farm and the pioneers of Datapelto – the reform of grain trade with community data projects, drone imaging is integrated into a larger smart agriculture framework. This development strongly involves, for example, automation, IoT, artificial intelligence, and the digital twin of the farm.

Through the Finnish Future Farm project, smart agriculture development has been further expanded to include modeling and data-driven decision-making. A key goal of the project is to create an environment for experimentation, demonstration, and co-development in smart agriculture. Drone imaging and other measurements conducted at Huipuri field plot play a central role, particularly in the digital twin environment.

In the Optimizing the Harvest Time of Silage project, drone imaging and NIR analyzers are used to determine the optimal harvest time and assess the yield quantity and quality. The goal is to create a tool or model that improves the timing of grass silage harvesting.

In the pioneers of Datapelto – the reform of grain trade with community data project, the aim is to collect data to support decision-making within the farming community and to base decisions on data in accordance with fair data economy principles. In this project, drone imaging has been used to investigate potential winter damage in winter rye. Based on the imaging results, a decision was made to renew the crop due to extensive winter damage.

Frequent observations allow farmers and researchers to monitor crop development, detect stress and identify issues early. Multispectral imaging helps monitor plant health and nutrient deficiencies which are not visible to the naked eye. The goal of drone imaging at the Bioeconomy institute is to develop and enhance decision-making in cultivation practices. A bird’s-eye view provides a broader understanding of field conditions, and various sensors enable the detection of phenomena beyond human capabilities.

Human-Drone Swarm Interaction System for Persistent Monitoring of Large Disperse Area

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Abstract:

Persistent monitoring is a continuous observation of a target area over time. Although applications such as wildfire detection and agricultural maintenance still depend on a single drone, its limited flight time and vulnerability to failure make a swarm-based approach preferable. Swarms provide greater efficiency, resilience, and uninterrupted coverage. As a result, drone swarms are increasingly being used for environmental monitoring and wildfire detection.

We present a human–drone swarm interaction system for adaptive and prioritized persistent monitoring using an ergodic coverage control algorithm (Fig. 1). A human operator can flexibly designate or modify areas of interest in real time, with target points automatically clustered to enable simultaneous monitoring of multiple regions. An ergodic controller ensures proportional coverage of a user-defined probability density function. Unlike prior ergodic control work, our method integrates the controller into a quadratic programming (QP) framework with control barrier functions (CBFs) to guarantee inter-drone collision avoidance, enforce velocity limits, and confine drones within the designated monitoring area.

To enhance robustness, a fault-tolerance mechanism detects and removes failed drones from the potential threat in the field and allows uninterrupted coverage. Real-time visualization via RViz enables operators to observe trajectories, assess coverage performance, and make informed adjustments during operation.

The system is validated through real-world experiments using Crazyflie 2.1 nano-quadrotors from Bitcraze. Results demonstrate that the proposed approach optimizes the ergodic coverage metric while ensuring safety and maintaining operational integrity even under drone failures. These findings highlight the potential of combining human–swarm interaction, safety-critical control, and fault-tolerant coordination for real-world persistent monitoring missions.

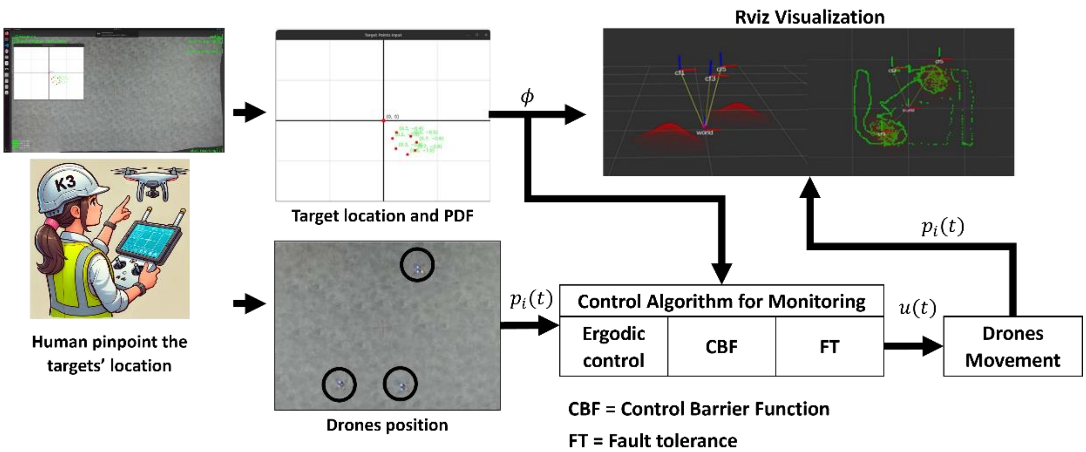

Figure 1. Our proposed framework for human-drone swarms persistent monitoring. The persistent monitoring scenario begins with human operators pinpointing the target location, which is then converted into a PDF. The PDF and the drone trajectories are visualized in Rviz. Video of the experiment can be viewed in https://youtu.be/iXuJmhCI0rQ

Self-supervised learning for close-range multispectral remote sensing images

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1. Introduction

In recent years, deep learning has received significant attention in the field of remote sensing and has become increasingly integrated into precision agriculture research. While fully supervised and transfer learning are the predominant techniques for training deep learning models, recent progress in computer vision has led to development of numerous foundation models tailored to remote sensing applications. These models are typically trained in a self-supervised manner on sensor-specific data.

The contribution of this research lies in the self-supervised training of a MicaSense-based model, and thereby advancing self-supervised learning for UAV imagery, with a focus on precision agriculture. The pretrained weights will be made publicly available and furthermore, the trained model will be integrated into SpecDeepMap, an open-source application within the EnMAP-Box QGIS plugin (v.3.16 experimental release) that allows users to train or fine-tune models via a graphical user interface (Jakimow et al., 2023).

3. Methodologies

3.1 Data collection

A custom-built hexacopter from the Agrotechnology research group of University of Helsinki equipped with a MicaSense Rededge 3 camera is used for the data collection. The images were captured during summer months over a five-year period from 2020 to 2024 on agricultural fields owned by the Research Farm of University in Helsinki, located in Helsinki. For the acquisition two different flight altitudes were used 50 meters and 10 meters. The crop types included in the data collection among others were barley, faba bean, oat, rapeseed, and couch grass.

3.2 Data preprocessing

3.2.1 Self-supervised training

The data was calibrated and mosaiced and spectral indices were created using the PIX4D software. The data was split into 256x256 image chips for self-supervised training, with each chip containing 7 channels: Blue, Green, Red, Red Edge, NIR, Normalized difference vegetation index (NDVI), and NDVI_RedEdge. This process resulted in 22,383 image chips from the flight at 50 meters, and 4,883 image chips from the flight at 10 meters. All image chips were combined into a single dataset for use in the self-supervised training (Fig. 1).

Figure 1. Image chips of Dataset visualized as RGB.

3.3 Experimental set up

3.3.1 Self-supervised Training

For self-supervised learning, Momentum Contrast (MoCo-v3) is utilized. MoCo-v3 incorporates extensive data augmentation techniques, such as color jittering and blurring, during the self-supervised learning process for the image reconstruction task (Chen et al., 2021). For the trainable encoder, the Swin-Transformer architecture is selected (Liu et al., 2021). The Swin-Transformer encoder was trained using MoCo-v3 with a batch size of 84, a learning rate of 0.0075, a learning rate scheduler, and 50 epochs of training.

4. Preliminary Results

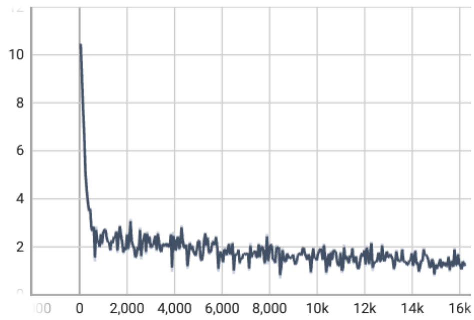

Figure 2: Loss of MoCo-v3 during training of 50 epochs.

As indicated by the loss graph (Fig. 2), the MoCo-v3 training of the Swin-Transformer performs well, and the loss is steadily decreasing with more training epochs indicating that the encoder continues to learn meaningful features.

5. Discussion & Conclusion

The self-supervised training has shown first promising results, but the trained encoder will be further evaluated on suitable downstream tasks using multiple MicaSense image datasets. However, the detailed comparison against the randomly initialized encoder has yet to be concluded. Furthermore, different pretraining settings of the MoCo-v3 training will be evaluated.

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Dronet osana robotiikkajärjestelmää

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Drone-teknologiat ovat jatkaneet nopeaa kehitystään viime vuosina, ja niiden rajapinnat tarjoavat yhä monipuolisempia mahdollisuuksia kolmansien osapuolien sovelluksille. Yksi droneteknologioiden tulevaisuuden sovellutussuunta on niiden käyttäminen osana laajempaa heterogeenista robotiikka- tai automaatiojärjestelmää. Esimerkiksi maataloudessa kartoitusdrone voi tuottaa työtehtäviä reaaliajassa työkoneautomaatiolle, ruiskudrone voi jakaa työtehtäväänsä peltorobotin kanssa olosuhteiden mukaan, tai erillinen sensoriverkosto voi hälyttää valvontadronen tietylle peltolohkolle. Vastaava koordinointi ja yhteisvaikutus ovat keskeinen osa tulevaisuuden dronetoimintaa myös lukuisilla muilla sovellutusalueilla. Tällainen muuhun automaatiojärjestelmään liittäminen vaatii käyttökelpoista rajapintaa drone-järjetelmään, mikäli kyseistä järjestelmää ei haluta rakentaa ja kehittää alusta alkaen vaan halutaan käyttää olemassa olevaa drone-kokonaisuutta. Tässä tutkimuksessa selvitimme eri dronevalmistajien mahdollistamia rajapintoja.

Useiden valmistajien tarjoamat rajapinnat ja SDK:t (Software Development Kit) mahdollistavat laajan sovelluskehityksen drone-teknologian ympärille. Rajapintamahdollisuuksista DJI:n Cloud API on noussut keskeiseksi työkaluksi, joka mahdollistaa DJI:n uusimpien laitteiden integroinnin pilvipohjaisiin järjestelmiin. Cloud API:n avulla voidaan hallita droneja etänä, suunnitella reittejä, suorittaa tehtäviä ja siirtää dataa kuten kuvia ja telemetriatietoja reaaliaikaisesti pilvipalveluihin. Rajapinta perustuu MQTT-protokollaan (Message Queuing Telemetry Transport), joka tukee sekä manuaalista ohjausta (Pilot-to-Cloud) että automaattista operointia (Dock-to-Cloud) esimerkiksi DJI Dock -järjestelmien eli maa-asemien kautta. Skydio SDK Cloud tarjoaa Skydion dronejärjestelmille RESTful API:n muiden järjestelmien integrointiin mutta lähinnä analytiikkapuolelle, Remote Ops mahdollistaa Skydion etä-operoinnin jopa selaimella. Parrotin OpenFlight-rajapinta mahdollistaa yhteyden kolmannen osapuolen analytiikkatyökaluihin ja pilvipalveluihin. Näiden rajapintojen avulla voidaan rakentaa räätälöityjä sovelluksia, jotka yhdistävät dronejen keräämän datan muihin järjestelmiin, kuten paikkatieto-ohjelmistoihin tai tuotannonohjausjärjestelmiin. Parrot tarjoaa myös avoimen FreeFlight 7 core SDK:n, jonka avulla dronejärjestelmää voi ohjata esimerkiksi Githubista löytyvien esimerkkien avulla. Autel Robotics tarjoaa avoimia rajapintoja erityisesti EVO II -sarjan droneille. Autelin SDK tukee reitinsuunnittelua, sensorien hallintaa ja datan siirtoa pilvipalveluihin. Intel Aero SDK keskittyy datan prosessointiin ja analytiikkaan. Intelin rajapinnat tukevat myös monimutkaisia laskentatehtäviä, kuten reaaliaikaista kuvantunnistusta ja ympäristön mallinnusta. DroneKit on avoimen lähdekoodin SDK, joka tukee MAVLink-protokollaa ja toimii useilla alustoilla, kuten Android, Linux ja web. DroneKit mahdollistaa autonomisen lentämisen, reitinsuunnittelun ja telemetrian hallinnan. Se on erityisen suosittu tutkimusprojekteissa ja prototyyppien kehityksessä, koska se on ilmainen ja laajasti dokumentoitu.
Nämä erilaiset SDK:t tarjoavat mahdollisuuden ohjelmoida dronen toimintaa reaaliajassa ulkopuolisella järjestelmällä. Maataloudessa on luotu CAN-väylään perustuva ISOBUS-standardi työkoneen, traktorin ja ohjainlaitteiden väliselle kommunikoinnille, sekä EFDI

(Extended Farm Management Information Systems Data Interface) ISOBUS-yhdistelmien sekä maatilan tiedonhallintajärjestelmän välille. VDA5050 (Verband der Automobilindustrie) on saksalaisen autoteollisuuden kehittämä standardi logistiikka- ja varastointipuolelle, joka mahdollistaa eri valmistajien autonomisten mobiilirobottien (AMR) yhteistoiminnan MQTT-pohjaisen ohjausjärjestelmän kautta REST-rajapinnalla. Droneteknologioiden ympärillä kehitystä tapahtuu jatkuvasti. Menetelmät, kuten MAVLink sekä ROS2 (Robot Operating System 2) käsittelevät dronejärjestelmän sisäistä toimintaa, mutta mahdollistavat myös kolmannen osapuolen integraation esimerkiksi MAVSDK API sekä RTPS (DDS) Real-Time Publish-Subscribe protokolla. Flexigrobots-hankkeessa testasimme dronejärjestelmiä yhdessä peltorobottien kanssa (kuva 1), hankkeessa rakennettiin erillinen Mission Control Centre (MCC), jonka käytössä olivat mm. MQTT, ROS, MAVLink.

Kuva 1. Drone osana robotiikkaa pellon kunnostustyössä (Flexigrobots hankkeen pilotti).

Mahdollisuuksia erilaisiin kolmannen osapuolen integraatioihin on siis runsaasti. Dronetoiminnassa erilaiset haavoittuvuudet ovat helposti kriittisiä, ja esimerkiksi DJI on lopettanut tuen Cloud Apin Github-esimerkeille juuri haavoittuvuuksien takia. Lähtökohtaisesti kolmannen osapuolen droneoperointi ja sen kehitys on haastavaa. Kehitystyötä ei voi tehdä yrityksen ja erehdyksen kautta. Tarvittaisiin selkeämpää määritystä siihen, mikä kuuluu dronevalmistajalle ja millä geneerisellä tasolla dronen toimintaan pystyisi reaaliajassa vaikuttamaan ilman, että ilmailutoiminta vaarantuu.

Estimation of Red Clover Flowering using Drone Imaging

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Increasing the use of nitrogen fixing species, such as red clover, in grassland leys is among the most effective ways to improve nitrogen self-sufficiency on cattle farms in Finland (Leino et al. 2023). However, limited seed production and lack of well adapted seed strains for northern conditions have partly hindered wider adoption. Our aim was to develop novel drone-based methods for red clover seed producers to assess factors influencing seed yield, including pollination and the relationship between flowering intensity and duration to seed yield.

Data, including reference and drone data, was collected from five fields in North Savo region used for red clover seed production. Reference data used for drone data interpretation included pollinator counts (transect method), seed yields measured at transect endpoints and at the field level, and manual flower counts at transect endpoints.

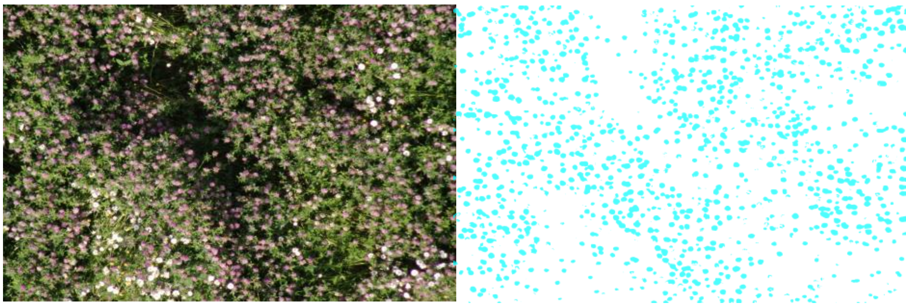
Drone data were collected for two primary purposes: 1) locating potential habitats in the surrounding environment that affect pollinator abundance near the fields, and 2) estimating flowering intensity and dynamics. Imaging for flowering intensity was conducted four times during the 2024 growing season on all fields, aiming to cover majority of the flowering period. Images for flowering intensity estimation were collected using DJI Matrice 350 RTK drone equipped with H20t camera collecting simultaneously accurate zoomed-in images for flower counting and images with wider lense for photogrammetric mapping of the field. Flights were carried out using a height of 60 meters. In addition, drone imaging was carried out on all fields to estimate spring density of swards on 23rd-24th May.

Flowering intensity was estimated as the coverage of red clover flowers in the images. Images were segmented using RootPainter (Smith et al. 2022). Semantic segmentation models were trained using a subset of 100 images, achieving a Dice score over 0.98.

Drone data were generally of sufficient quality for flower coverage estimation in the images (Figure 1).

Drone and reference data collection will continue in 2025 and 2026. When these data become available, the flowering intensity estimation technique developed and evaluated here can be used to further examine factors influencing pollination success and the relationship between seed yield to flowering.

a)



b)

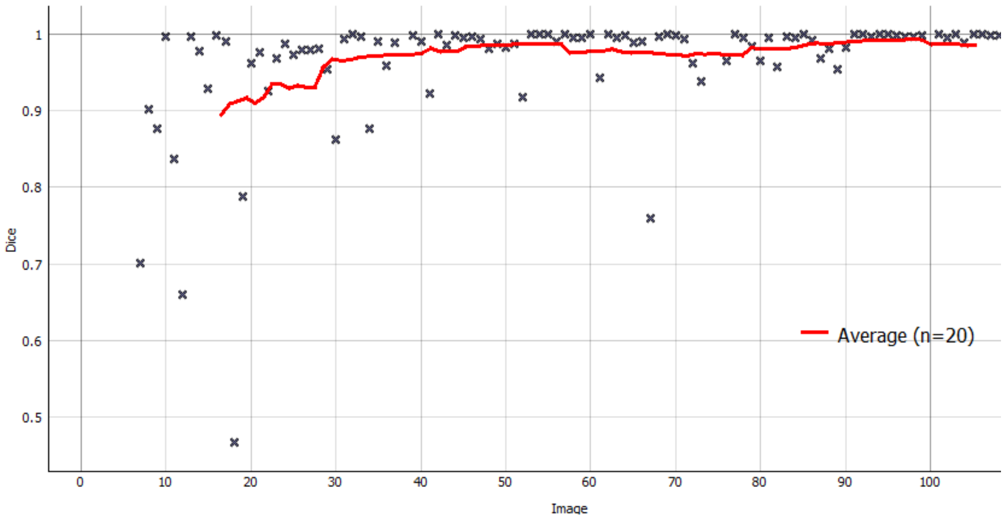


Figure 1. Image segmentation was done using RootPainter where a) flowers were recognized from images (resolution 5184x3888 pixels) collected using DJI H20t camera's zoom lense and flying height of 60 meters, and b) segmentation model was trained using 100 annotated images, achieving a Dice score over 0.98.

The developed method for assessing red clover flowering from drone images proved sufficiently accurate to facilitate further analysis of the data against factors influencing pollination.

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