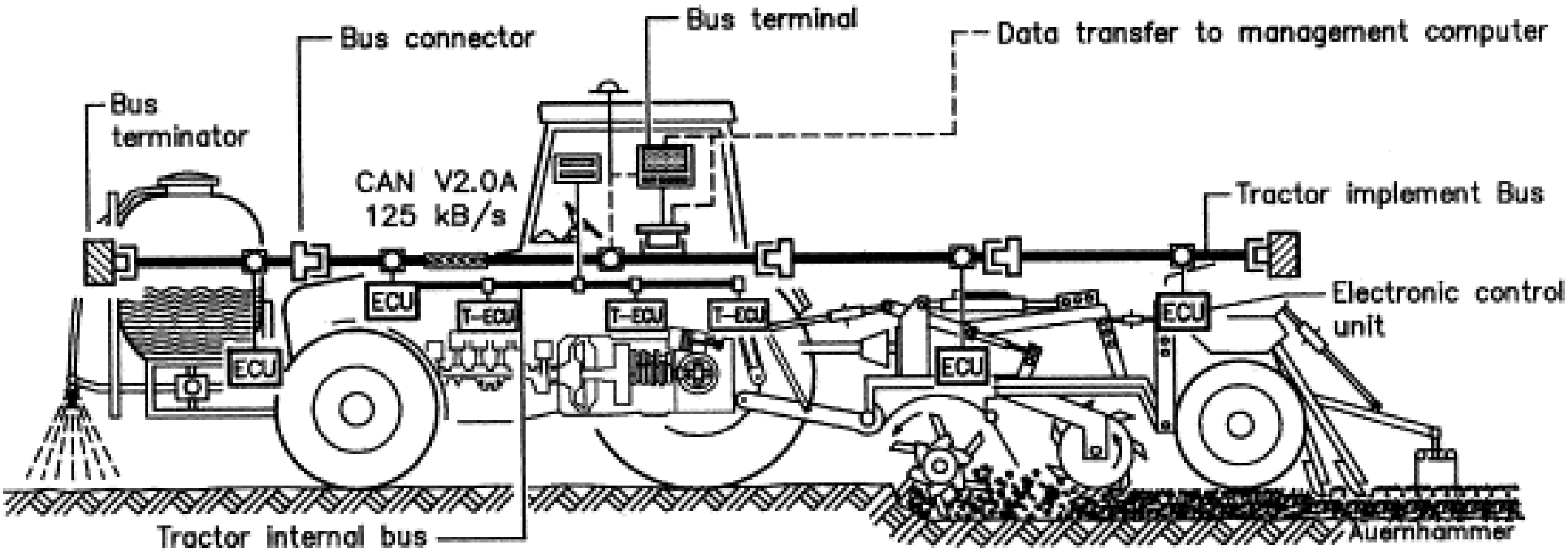
Artificial Intelligence in agriculture: discover new correlations and trends in big data collected by machines

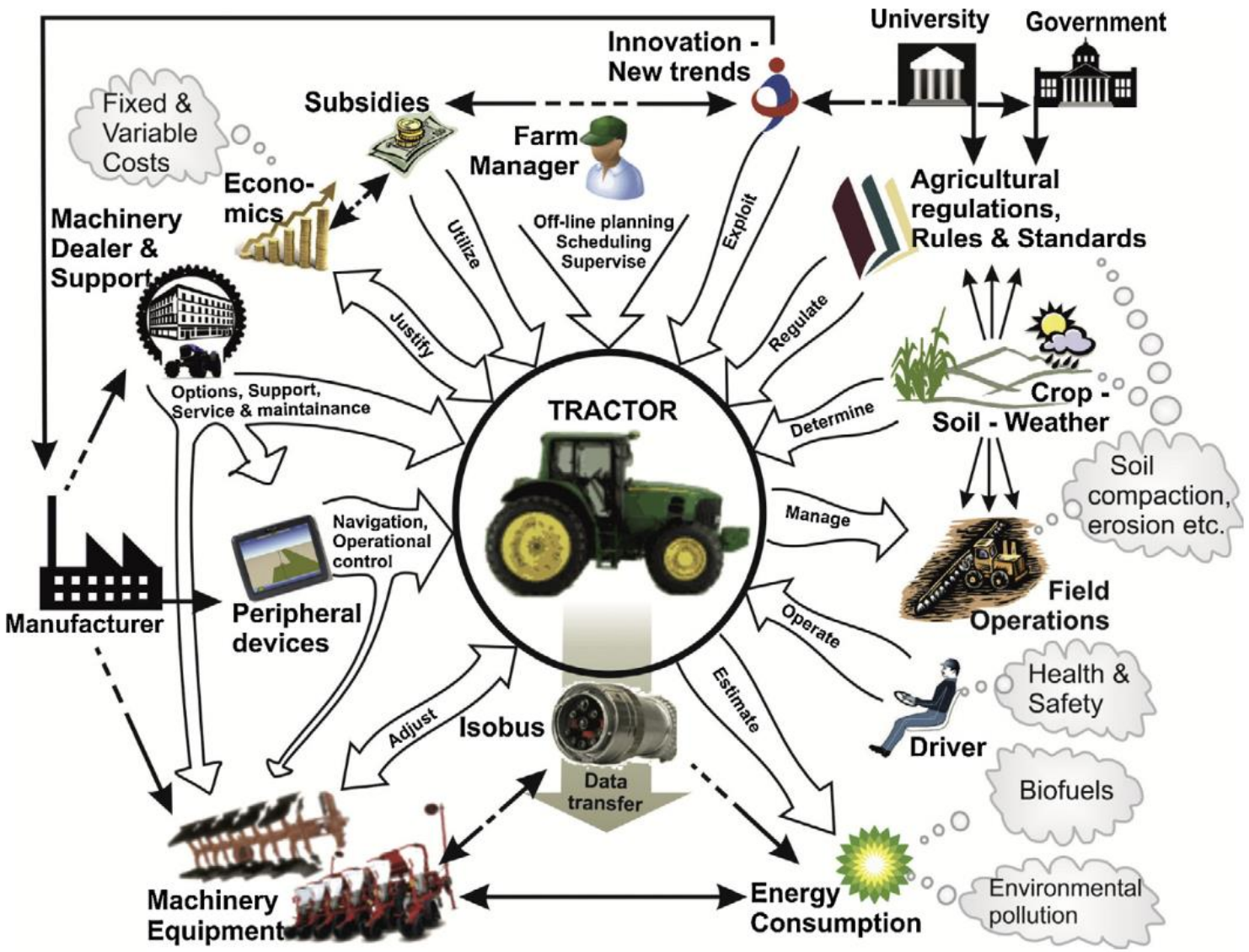
Prof. Spyros Fountas
Agricultural University of Athens

Problem: Farm machinery is related to big data



Prof. Hermann Auernhammer, Club of Bologna 2002

Problem: Farms are a very complex system



Fountas, S., Sorensen, C., et al. (2015). Computers and Electronics in Agriculture 110 (2015) 131–138

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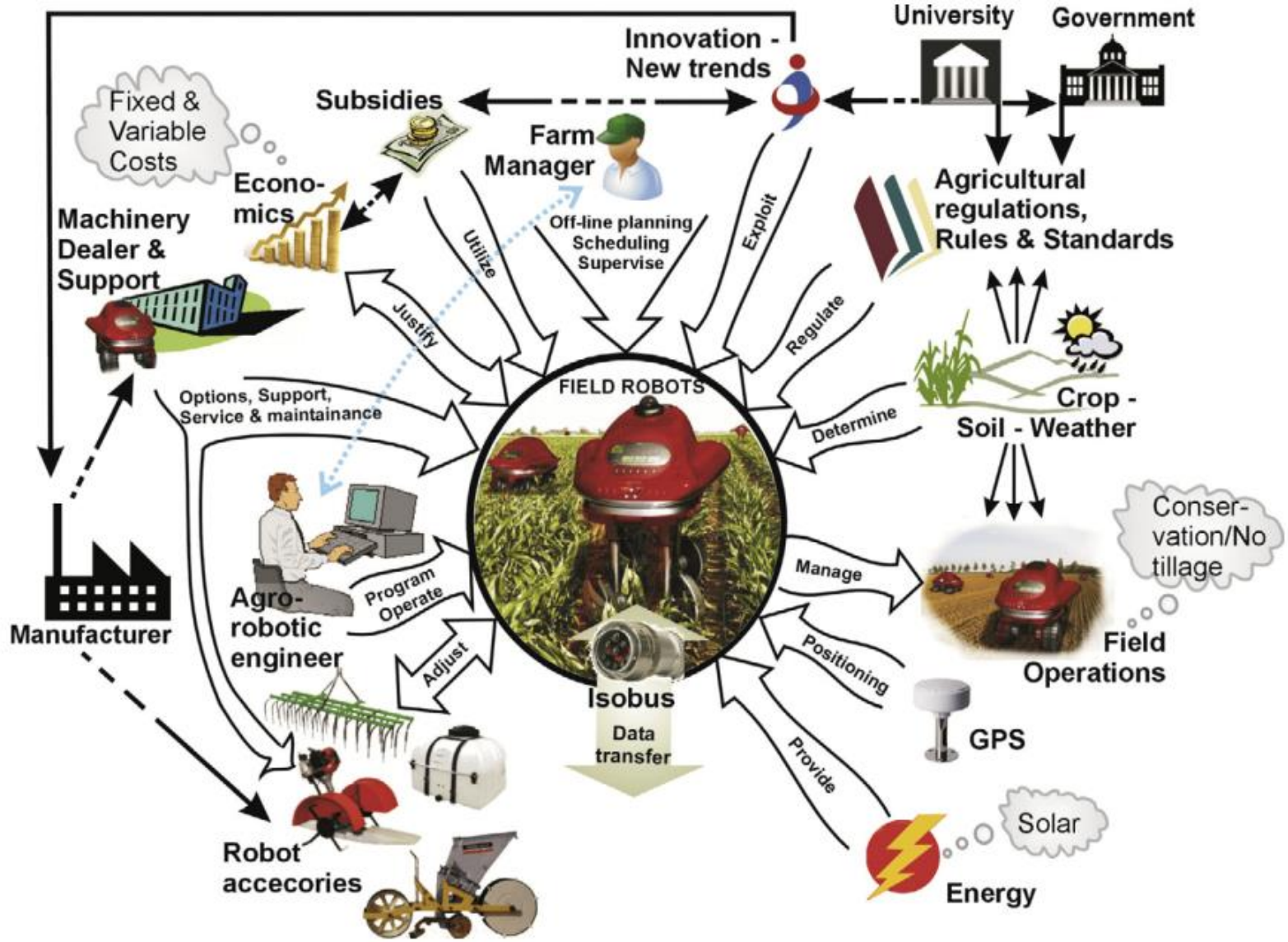
Opportunity: Robotics and AI



Fountas, S., Sorensen, C., et al. (2015). Computers and Electronics in Agriculture 110 (2015) 131–138

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European Parliament
EUROPEAN PARLIAMENTARY RESEARCH SERVICE

"I think that in the future AI will help improve our crop production and our crop protection. We could better understand the biology and the ongoing processes at the smaller scale to better manage the whole process of growth and production, and eventually bring it to the market".

Robotics and AI in Agriculture

AI-based systems use **computer vision** & present **quick**, **non-invasive**, and **non-destructive** way: **weed identification**, **disease detection**, **phenotyping**, **harvesting**, **spraying**, **navigation**

Early 2010s

Computer vision uses simple methods (such as SVM) and hand-crafted features such as colour, shape and texture. The performances are low and **the features do not generalize**.

2016

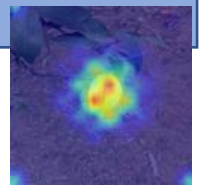
Deep learning and CNNs, as promising solutions for computer vision PlantVillage dataset appears; but lab based and the methods implemented can't generalize.

2019

Larger datasets under real-world conditions. **Transfer learning** for reusing knowledge from one previous problem to the other report promising performances.

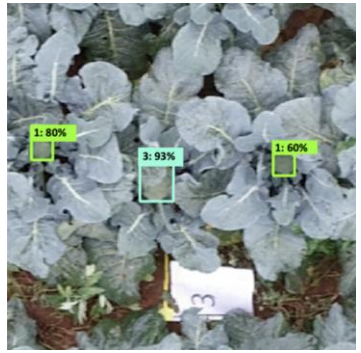
Present

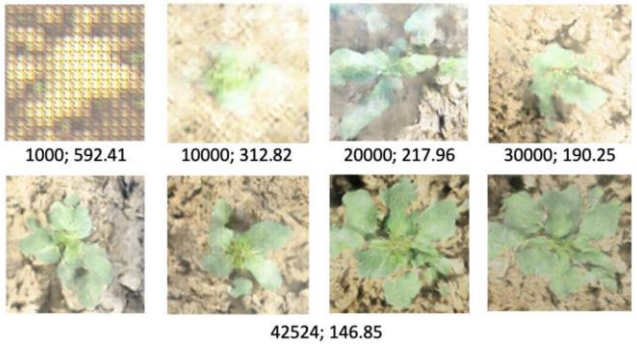
New powerful techniques such as **Transformers, GANs** to create realistic synthetic images and good performances.

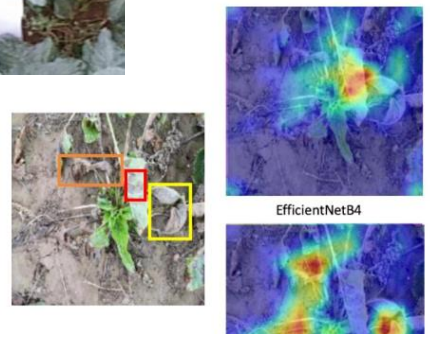


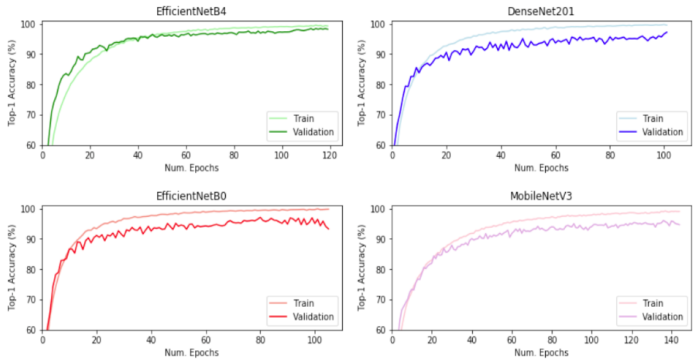
Case studies for the use of A.I.

1. Plant Species Classification
   - Early Weed identification
2. Nutrient Deficiency detection
3. Plant Phenology Recognition
4. Quality Attributes Prediction









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Early Weed Identification

Transfer learning

- **Domain Problem**:
  - EU has set a target to **reduce pesticide use by 50% in the next 10 years** since they can cause ground environmental pollution, chemical residues on the crops, and future drug resistance
- **Technical Problem**: How can we **reuse the knowledge** from one problem to another? (Transfer learning)
  - Deep Learning networks require “good” weights (previous knowledge) in the initialization.
    - Faster training
    - Better final performance
  - Transfering knowledge from general problems (ImageNet) could not improve performance in agriculture

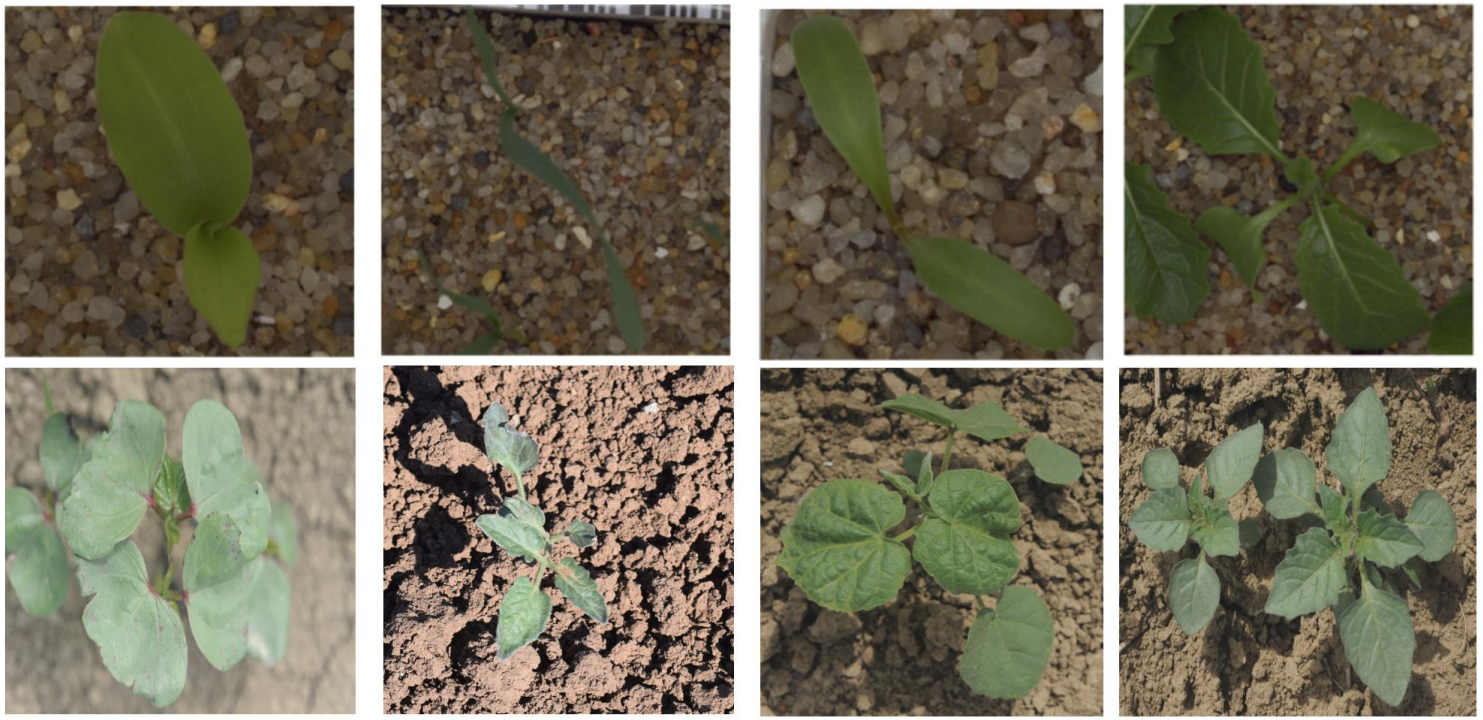
Early Weed Identification

Transfer learning

- **Datasets**:
  - Two datasets were used: (i) Plant Seedling Dataset (960 images) AU-Denrmak – pre-training ; (ii) In-house Early Crop Weed Dataset (504 images) – final problem
  - Precision reached **up to 90% on weed identification** on target domain

(i)

(ii)



- Espejo-García, B., Fountas, S., etal (2020). Improving weeds identification with a repository of agricultural pre-trained deep neural networks. Comput. Electron. Agric., 175.
- Espejo-García, B., Fountas, S., etal (2020). Towards weeds identification assistance through transfer learning. Comput. Electron. Agric., 171.

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Early Weed Identification

Data augmentation with GANs

- **Domain Problem**: **Lack of images** for training the Deep learning models. Thousands of images are necessary. Traditional data augmentation (rotation, translation, brightness modification, etc.) lacks the ability to create real novel simples - overfitting is not avoided
- **<u>Method to solve th problem:</u>**
  - Use **Generative Adversarial Networks (GANs)** for creating synthetic images
  - Use those synthetic images to **improve the performance** over traditional data augmentation methods
- **Datasets**:
  - Two datasets were used: (i) In-house Early Crop Weed Dataset (tomato and cotton); (ii) PlantVillage (different leaves)
  - The first dataset has real-world conditions and theoretically, it should be more challenging

Early Weed Identification

Data augmentation with GANs

- **Results and Conclusions**:
  - The **GANs created realistic synthetic images** from random noise
    - 42,000 images under real-world conditions / 10,000 mages under laboratory conditions
  - Better images were obtained with images **under laboratory conditions**
  - Synthetic images resolution was **128x128**
  - Using these images as input for data augmentation **improved the final weed identification performance**

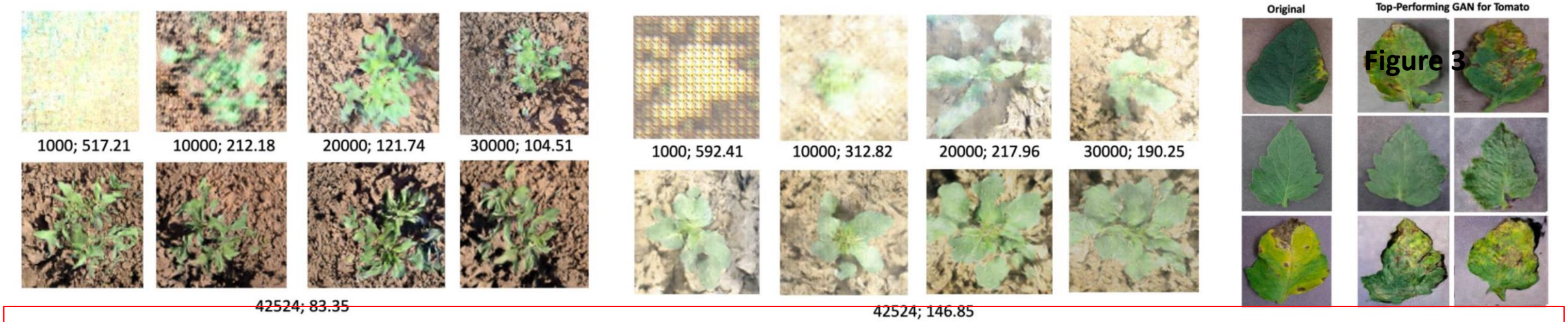


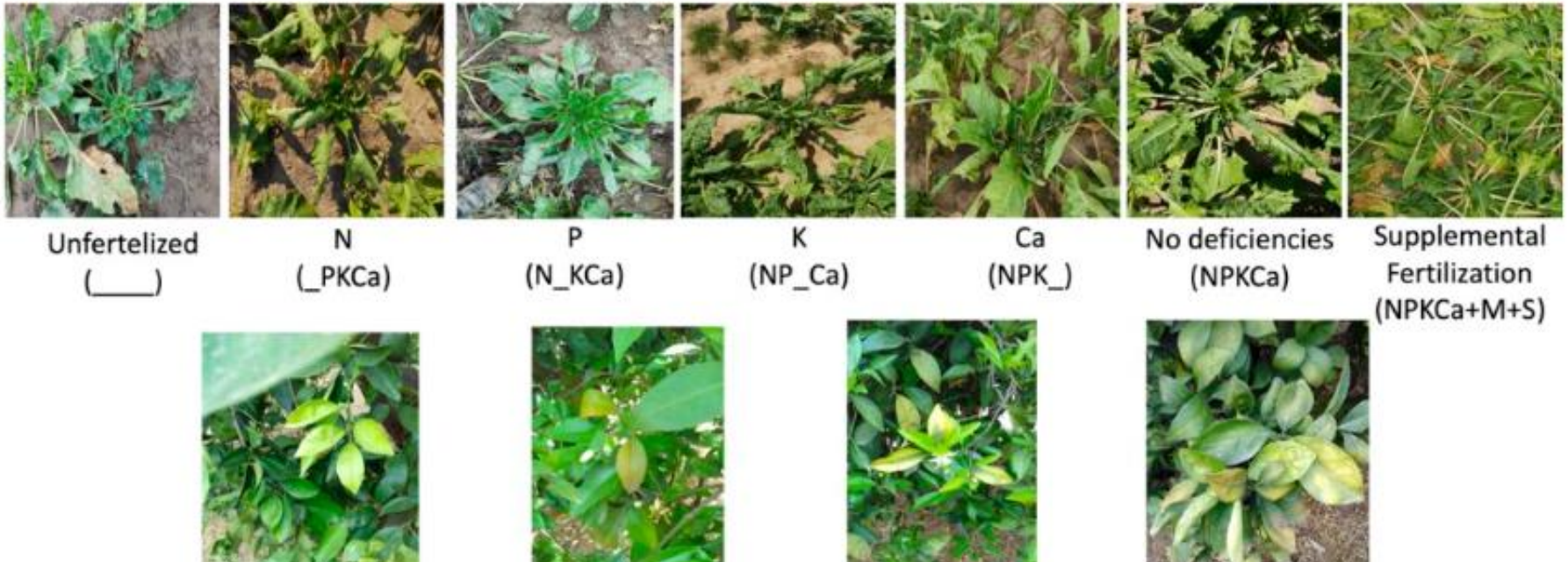
Figure 3

- Espejo-García, B., Fountas, S., etal (2021). Combining generative adversarial networks and agricultural transfer learning for weeds identification. Biosystems Engineering, 204, 79-89.

Nutrient Deficiency Detection

Transfer Learning + Explainability

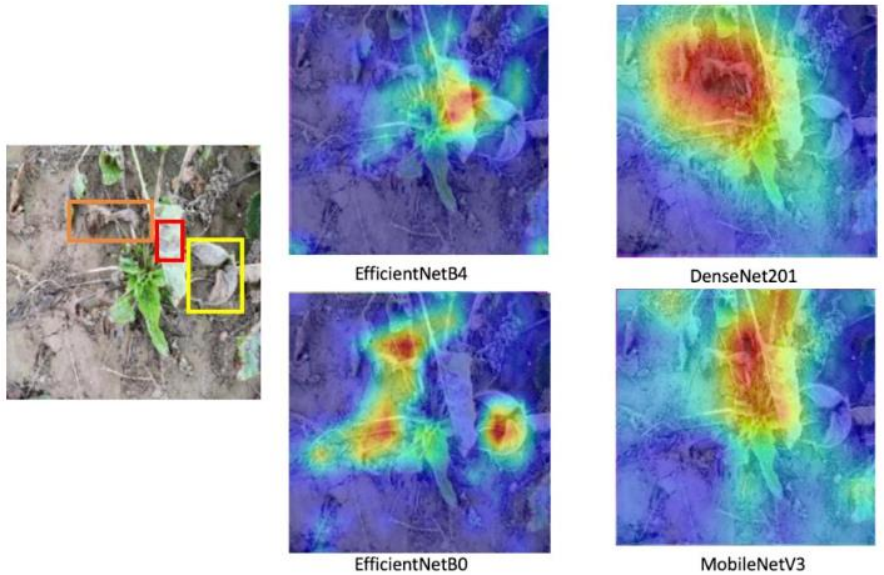
- **Domain Problem**: **Early diagnosis of nutrient deficiencies** can play a major role in avoiding significant agricultural losses
- **Technical Problem:** Is it possible to **understand** which are the benefits of transfer learning?
- **Datasets used**: Two datasets were used: (i) Deep Nutrient Deficiency for **Sugar Beet (5,648 images)**; (ii) **Oranges Nutrient Deficiency (170 images)**. Sugar Beet dataset used for pre-training; Oranges for fine-tuning and problem-solving

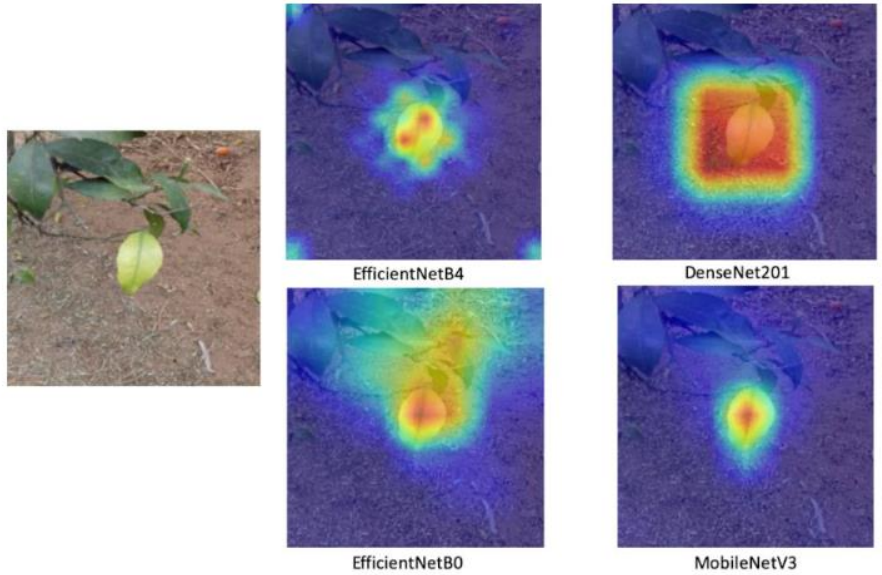


Nutrient Deficiency Detection

Transfer Learning + Explainability

- **Results (Transfer Learning)**:
  - Architectures that obtained the **best performances were the larger ones (**EfficientNet-B4 and DenseNet201)
  - **EfficientNet-B4 reached 98.4% high performance** on the Sugar Beet dataset
  - **Training on the large dataset (Sugar Beet) was smoother** than the smaller one (Orange Tree)





- Espejo-García, B., Malounas, I., Mylonas, N., Kasimati, A., & Fountas, S. (2022). Using EfficientNet and transfer learning for image-based diagnosis of nutrient deficiencies. Comput. Electron. Agric., 196.

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Maturity level classification

Object detection from UAV images

- **Domain Problem**:
  - There is a very **strict time window of "optimal maturity"** when the high-end quality broccoli heads should be harvested
  - Even slight **delays** from this time window **can result in major losses** in the final production
  - **Manual harvesting is a very laborious task** and the scouting takes time
- **Technical Problem:**
  - In every image, several broccoli heads appear, and therefore, it is necessary to detect each of them and classify them according to their maturity level -> **Object detection**
  - **Four different data augmentation strategies** (No augmentation, Colour augmentation, geometrical augmentation, and both colour-geometrical augmentation)

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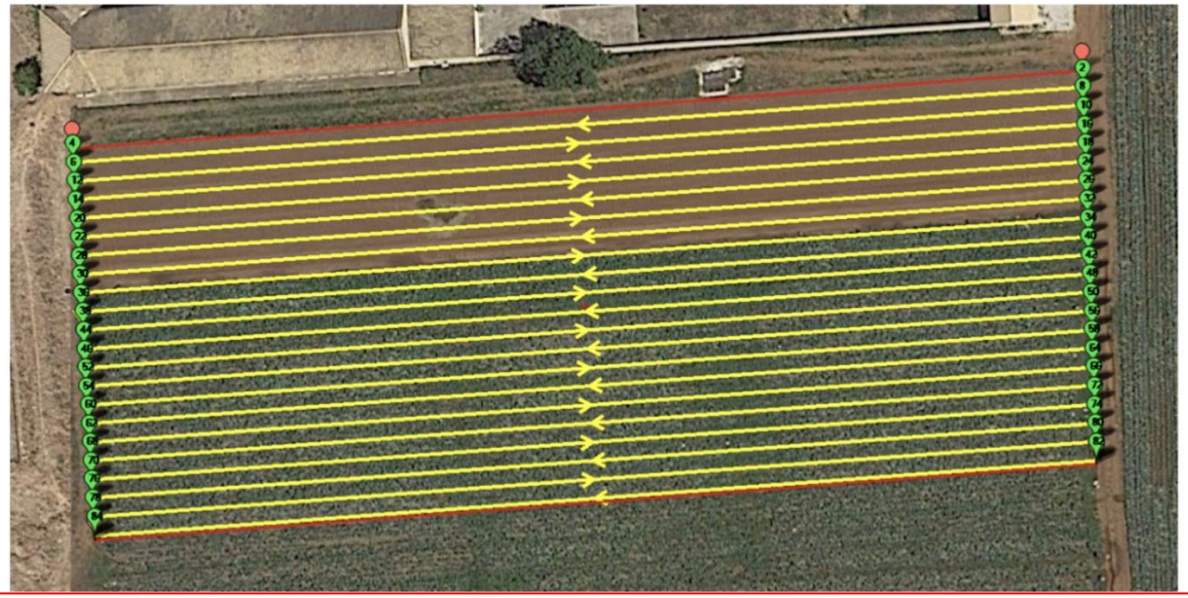
Maturity level classification

Object detection from UAV images

- **Dataset**:
  - Use of a quadcopter **drone** equipped with a **20-megapixel camera in <u>MARATHON</u>**
  - **Three classes identified: (a)** immature crops that would not be harvested in 15 days; **(b)** heads to be harvested in a week; **(c,d)**: "ready to harvest" heads (Figures 2c and 2d)
  - **<u>Correlations reached: 91% accuracy</u>**



Psiroukis, V., Espejo-García, B., Chitos, A., & Fountas, S. (2022). Assessment of Different Object Detectors for the Maturity Level Classification of Broccoli Crops Using UAV Imagery. Remote. Sensing, 14, 731.

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Vineyards Grape Sugar Content Prediction

- **Domain Problem**:
  - Wine grapes need frequent monitoring to achieve high yields and quality. **Analysis of laboratory** samples is the most popular method for determining the quality characteristics of grapes, although it **is time-consuming and expensive**
  - **Non-destructive methods, such as proximal and remote sensing**, are commonly used to estimate crop yield and quality characteristics, and spectral vegetation indices are often used
- **Technical Problem:**
  - Currently, there are tons of machine learning algorithms to implement a regression model. It is **impossible to know which of them will be the best one** for the specific task
  - **Grid-search** of hyper-parameters for every machine learning algorithm **is a non-efficient solution**

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Grape Sugar Content Prediction

- **Results and Conclusions**:
- **When combining multiple sensors and growth stages** per year, best coorection **reached 66%**
- **Véraison and Flowering** proved to give the highest correlations

- Kasimati, A., Espejo-García, B., Vali, E., Malounas, I., & Fountas, S. (2021). Investigating a Selection of Methods for the Prediction of Total Soluble Solids Among Wine Grape Quality Characteristics Using Normalized Difference Vegetation Index Data From Proximal and Remote Sensing. Frontiers in Plant Science, 12.
- Kasimati, A., Espejo-García, B., Darra, N., & Fountas, S. (2022). Predicting Grape Sugar Content under Quality Attributes Using Normalized Difference Vegetation Index Data and Automated Machine Learning. Sensors (Basel, Switzerland), 22

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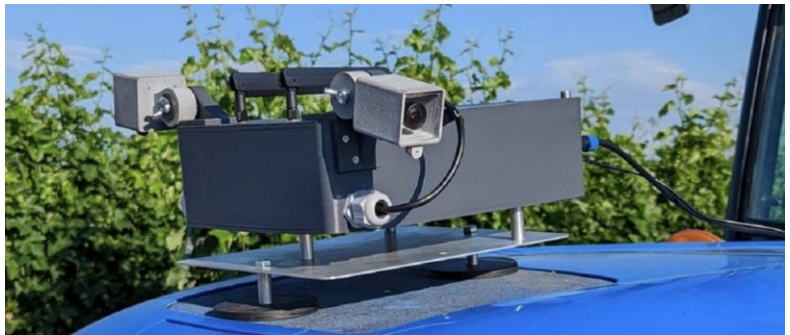
Robotics and AI in Agriculture

Future and current benefits

- Artificial intelligence is currently providing **functionalities never seen before**:
  - **Better than human performances** in disease detection, weed identification, yield prediction, etc.
  - Ability to **create new realistic samples** of crops, plants, diseases, fruits, etc.
- Different **farm machinery can integrate** with these AI techniques:
  - Disease scouting and detection
  - Fruit counting and forecasting
  - Real-time spraying
  - Navigation without GPS
- Example of the integration: **The Eden Library Viewer** powered by EdenCore.



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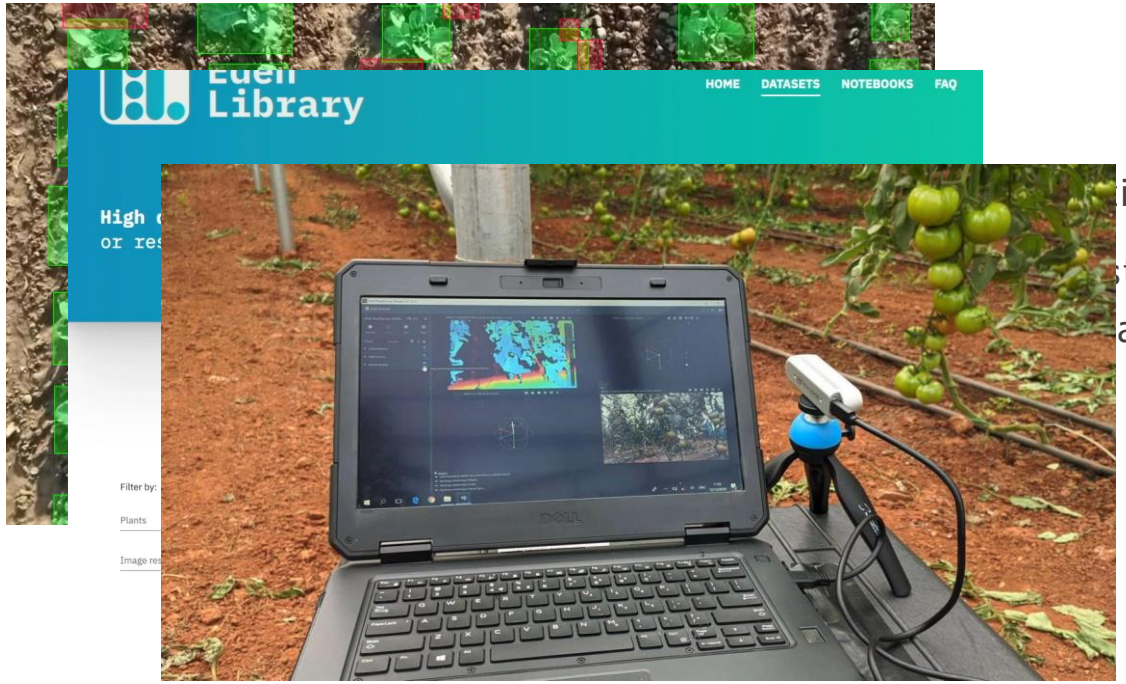
The Eden Library Viewer

powered by EdenCore

Eden Library offers



ion services for agri-tech industry

sted annotation & active learning

asets for AI training

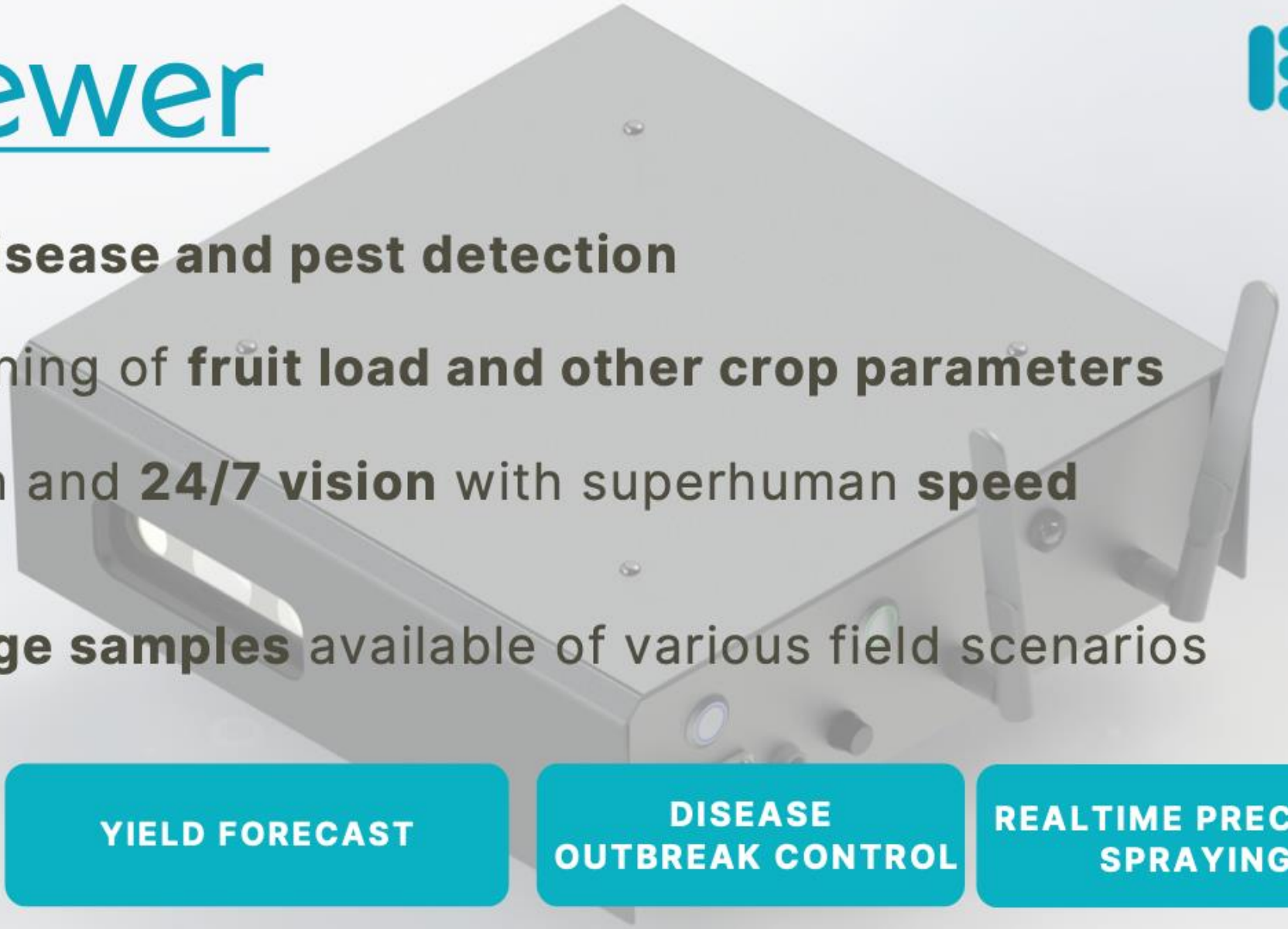
-AIaaS

-Project lifecycle support

- Over **30k. agro-images** & **150k. annotations**
- **35 crops** with **60 pest/disease/weeds/nutrient deficiencies**

N Mylonas, I Malounas, S Mouseti, E Vali, B Espejo-Garcia, S Fountas. "Eden Library: A long-term database for storing agricultural multi-sensor datasets from UAV and proximal platforms" **Smart Agricultural Technology** (2021), 10028.

The Viewer



- Real time **disease and pest detection**
- Vision scanning of **fruit load and other crop parameters**
- Superhuman and **24/7 vision** with superhuman **speed @10fps**
- **>150k. image samples** available of various field scenarios

AVOID TEDIOUS INSPECTIONS

YIELD FORECAST

DISEASE OUTBREAK CONTROL

REALTIME PRECISION SPRAYING

- **FLEXIBLE DESIGN**

Multiple mounting options based on crop characteristics

- **POWER SUPPLY**

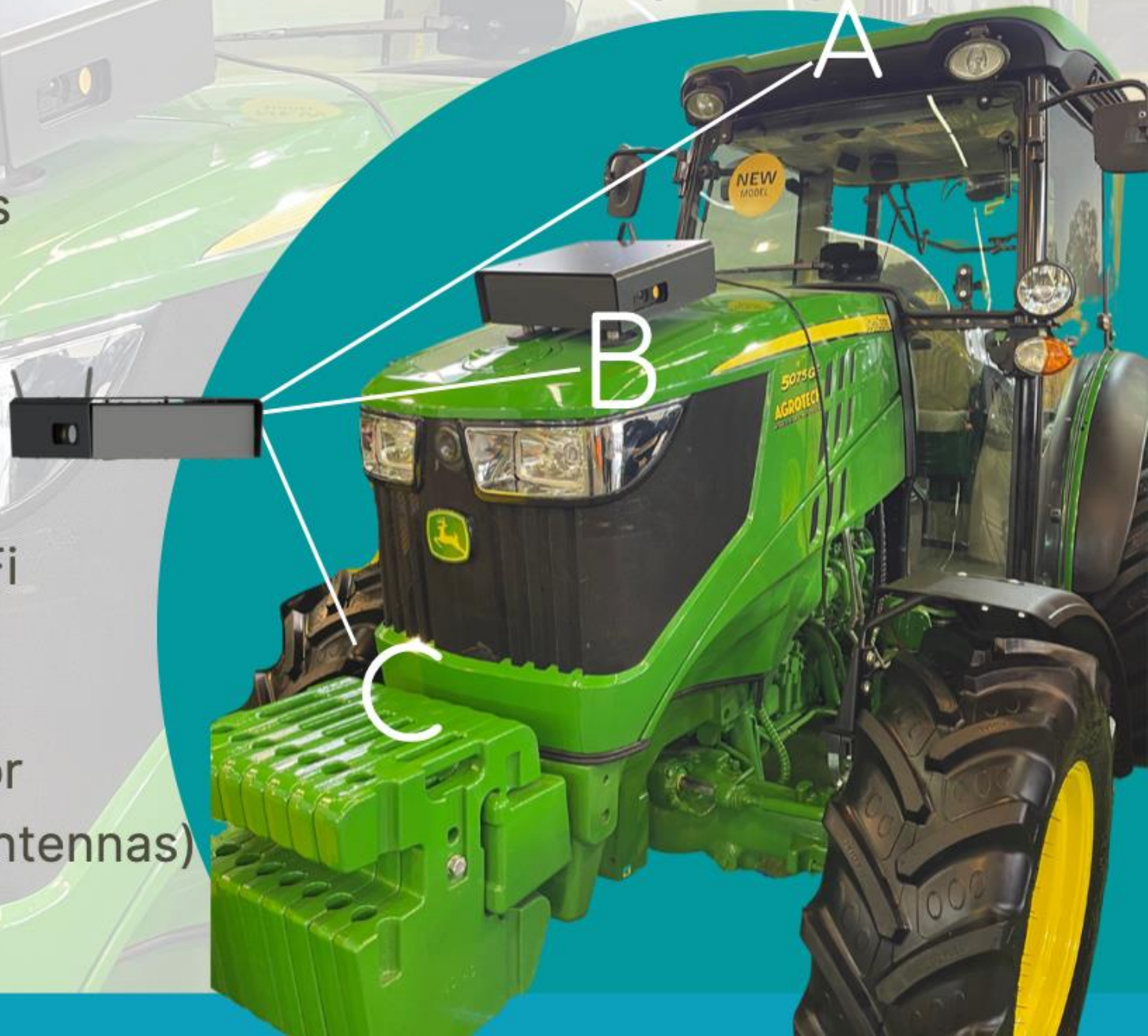
12V directly from the tractor

- **INTERNET**

4G connectivity and local WiFi network

- **GPS**

Embedded antenna <2m error (options for more accurate antennas)



Features 2 high-resolution cameras and built-in LEDs for superior vision scanning on both sides under any lighting conditions

Compatible with tractors and sprayers - ISOBUS 11783 and generic J1939 protocol communication.

Viewer Dashboard

- Monitor the data generated after every operation
- Get powerful insights about health status and disease presence
- Plan accurately your next plant protection action

Many functionalities - On demand selection

1.Disease scouting & detection

2.Fruit counting & forecasting

(upon request):

3.Real-time spraying with Viewer-sprayer communication

Detection of pests and anomalies

- **Disease identification** and **alerts**
- Spot **disease outbreak areas**
- Health and disease **(prescription) maps**

Growth & yield forecasts

- **Blossom & fruit counting**
- Yield forecast **2-3 months before harvest**

Precision spraying

- **Up to 40% reduction** in plant protection costs
- Application for **chemical thinning and growth regulator** products
- Reduction of **pest resistance** to chemicals

GRAPE

Downy & powdery mildew, botrytis, eriophyes vitis, N deficiency, empoasca spp

APPLE

apple scab, disaphis, eriosoma lanigerum,

PEACH

Bacterial necrosis, taphrina deformans, plum pox virus, wilsonomyces carpophilus, hail, monilinia spp, myzus persicae, grapholita molesta, tetranychus urticae, peach cracking, Fe deficiency

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ΓΕΩΠΟΝΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

CAFFINI SPRAYERS EQUIPMENT

OPTIMA

Redefining Pest Management - a Holistic Approach

UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

CERTH CENTRE FOR RESEARCH & TECHNOLOGY HELLAS

iBO

OPTimised Integrated Pest MAnagement

for precise detection and control of plant diseases in perennial crops and open-field vegetables

DISAFA
Università degli studi di Torino

Fede
Conectados a la agricultura

Advanced prediction and early detection of plant diseases

Development of a smart sprayer

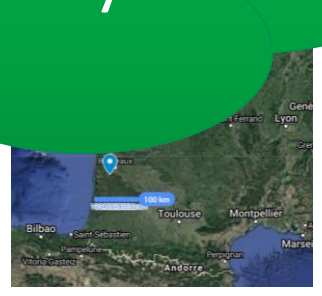
Spray & drift reduction performances

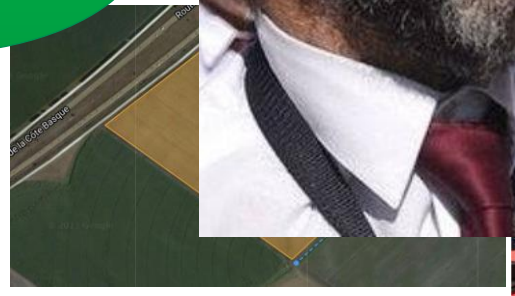
Features	Bed spraying, variable nozzle spacing, drift reducing + off-center nozzles, VRA, air support, electric fan	Optimized air flow set flat fan + drift reducing + off center nozzles, ultrasonic canopy detection, VRA, electric fan, variable air flow rate	Optimized air flow settings, flat fan + drift reducing nozzles, ultrasonic canopy detection, zone spraying technology	**Assessment indicators**
Benefits	+ 50 to 80% (early) + 10 to 50% (late)	+ 110%	+ 30 to 40%	- 30%
	- 15%	- 20%	+ 75%	- 30%
	- 50 to - 75%	- 5 to - 25%		- 30%
	- 25 to - 70% (air)	- 60 to - 95% (air)	- 15 to - 55% (air)	- 30% (air)

Pilot testing of developed technologies

DSS, Smart Sprayers & Vision System managed to reduce the use of PPPs in apples by 82%!

-
-
-
- Global eva





Sprayer 1

- Reference 0

Sprayer 2

- Reference 1
- Reference 3

Sprayer 3

- Reference 2
- Reference 4
- Reference 5

Smart Spraying

http://optima-h2020.eu

Assembled Smart Sprayer in the field

Plant Disease Detection

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Intelligent Spraying Control

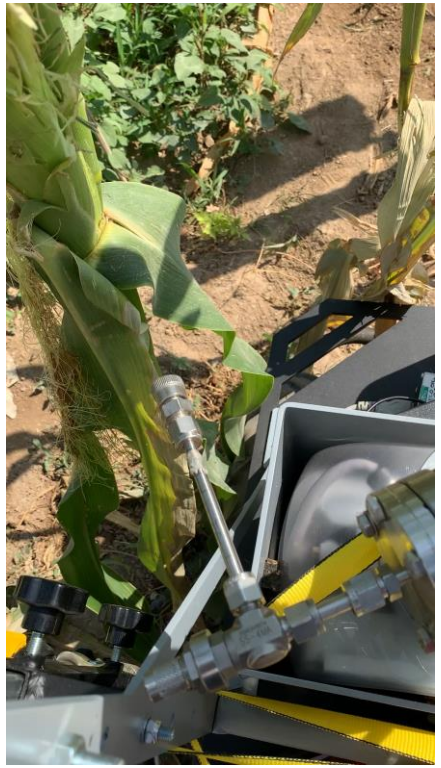
- Smart Density Estimation
- Intelligent VRA across the sprayer:
  - PWM implementation for precision spraying
  - Nozzle-level accuracy
- RTK-GPS implementation
- Electrically actuated Air assistance

Robotic Spraying

https://agrobofood.eu/project

Autonomous Navigation

- Robotic Olfaction system
- Spot Spraying Problematic Areas
- Autonomous Driving
- Sensor Fusion system



Disease Scouting

Field Application

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SMART FARMING TECHNOLOGY GROUP

www.icaerus.eu

ICAERUS

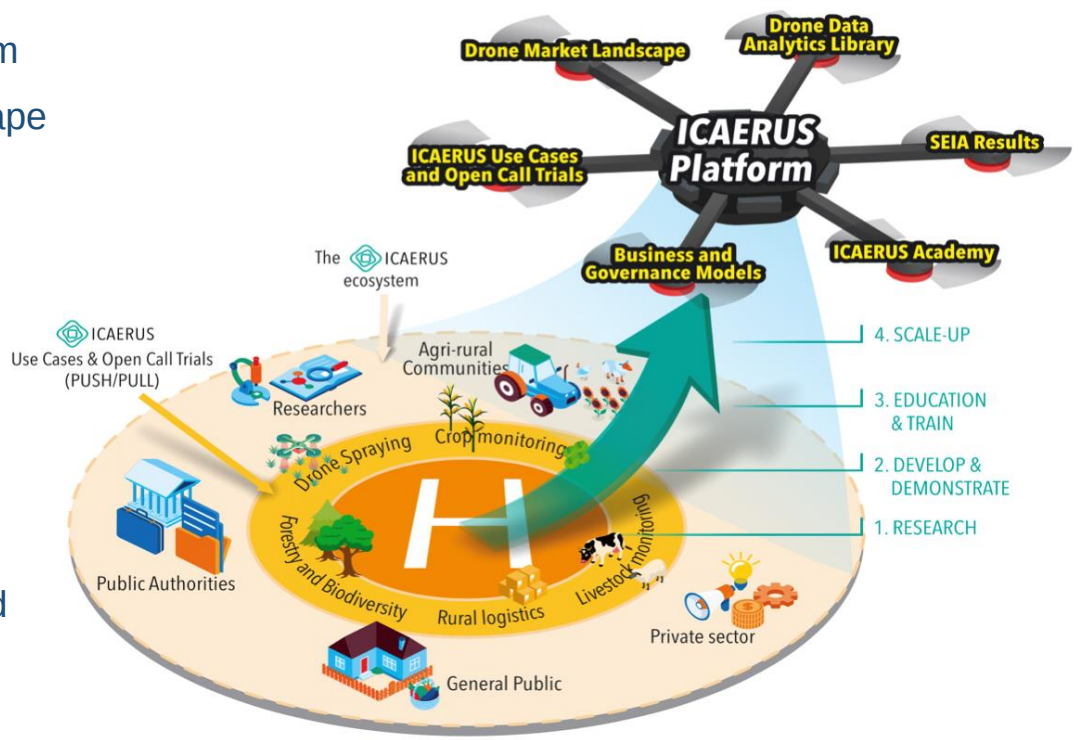
Innovations and Capacity building in Agricultural Environmental and Rural UAV Services

ICAERUS Project

Funded by
the European Union
Grant agreement N° 101060643

What are we going to develop?

- The ICAERUS Platform
- Drone Market Landscape
- Drone Data Analytics Library
- ICAERUS Use Cases and Open Call Trials
- Socio-economic and Environmental Impact Assessment (SEIA) Results
- Inclusive Business and Governance Models
- ICAERUS Academy



ICAERUS Use Cases & Open Call Trials

THANK YOU…

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https://www.linkedin.com/company/sftgaua/