Sustainable Farming Beyond Earth: Growing Plants Anywhere, Anytime

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Supervisors: Nicolas Drougard & Thibault Gateau, name.surname@isae.fr, ISAE SUPAERO

isae Institut Supérieur de l'Aéronautique et de l'Espace SUPAERO

Master's Student in Aerospace Engineering

Major in Space Systems

isae SUPAERO

Jet Propulsion Laboratory
California Institute of Technology

SupaeroMoon Co-Founder

Research Project
in Life Support

ALICE
AI for Life In spaCE

Chopper: the next generation Mars Helicopter

Aerodynamic modeling of the interaction between rotors, experiment & CFD simulation

Aerodynamics engineer at ONAerospace

MELiSSA Conference 2025

7th Oct - 9th Oct

My trip sponsored by:

esa academy

Space Studies Program 2023

"Luck is what happens when effort meets opportunity"

Systems Engineer

The Spring Institute for Forests on the Moon

WBA Analog Astronaut

LunAres Habitat, 10th Oct - 28th Oct

Background

- **ALiCE** (AI for Life in spaCE) contributes to the research domain of Precision Agriculture in Life Support Systems with the general goal of using Artificial Intelligence for maximizing production and minimizing resource consumption

- **There are many plant habitats with inspiring goals:**
  - **Advance Plant Habitat** (NASA) successfully produced fruit on the ISS. It offers environmental control (CO2, lights, moisture, temperature, etc.)
  - **Veggie** (NASA)
  - **EDEN ISS** (DLR)
  - **EDEN LUNA** (DLR)

- But few of them use **Artificial Intelligence** (e.g. Interstellar Lab)

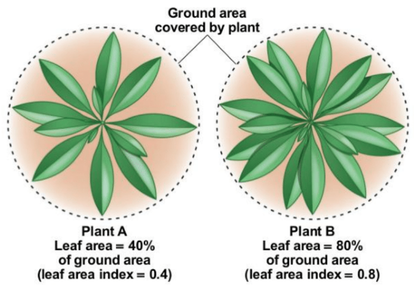
Objectives

Monitor and predict the plant growth in extreme environments

Credit image: Abdellatif, Mostafa & Valdenebro, Esaiy. (2016). Storm-water Management: Evapo-transpiration & Cooling with Water. 10.13140/RG.2.2.24862.23360.

ISAE SUPAERO

Objectives



Compute Leaf Area through Computer Vision and regression models in a non-destructive way*

Monitor and predict the plant growth in extreme environments

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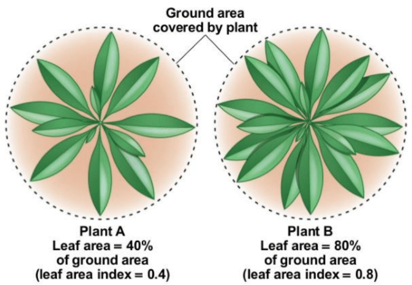

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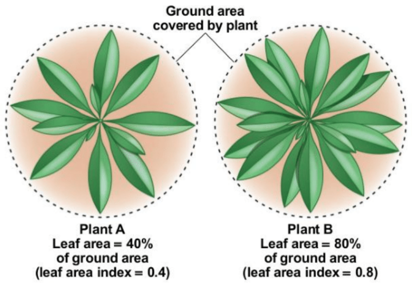

Compute Leaf Area through Computer Vision and regression models in a non-destructive way*

Monitor and predict the plant growth in extreme environments

Model the growth dynamics as a function of the environment conditions

Credit image: Abdellatif, Mostafa & Valdenebro, Esaiy. (2016). Storm-water Management: Evapo-transpiration & Cooling with Water. 10.13140/RG.2.2.24862.23360.

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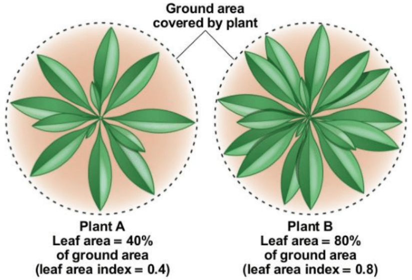

Compute Leaf Area through Computer Vision and regression models in a non-destructive way*

Analyze different light conditions effect on plant monitoring

Monitor and predict the plant growth in extreme environments

Model the growth dynamics as a function of the environment conditions

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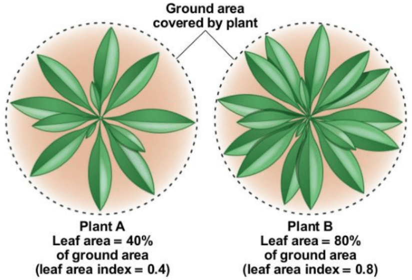

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Planning of Dry Matter Production for resources limitation purposes

Credit image: Abdellatif, Mostafa & Valdenebro, Esaiy. (2016). Storm-water Management: Evapo-transpiration & Cooling with Water. 10.13140/RG.2.2.24862.23360.

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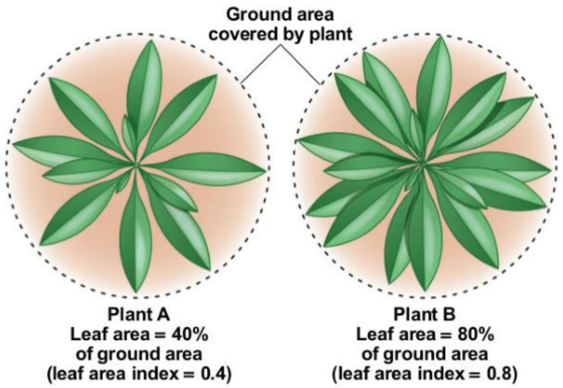

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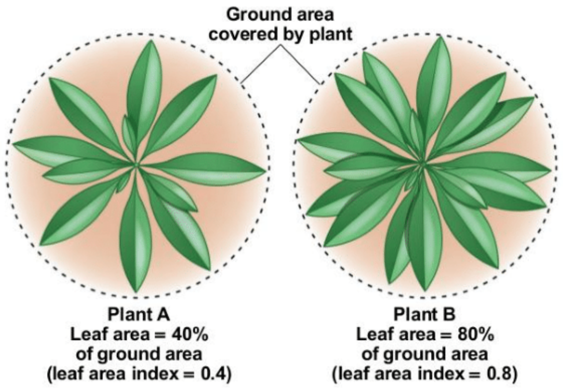

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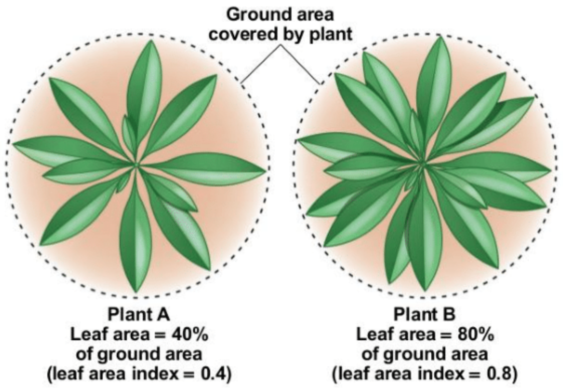
Create a dataset of images of plants grown using hydroponics

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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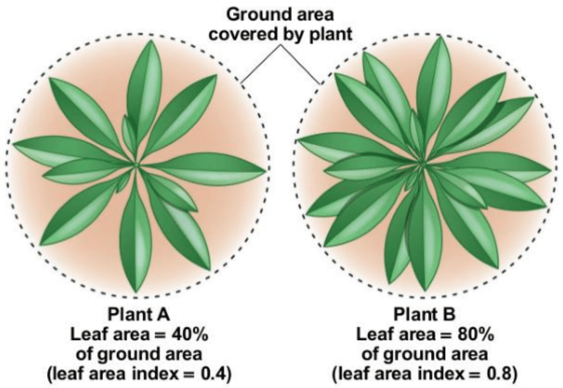
Create a dataset of images of plants grown using hydroponics

Take images of each pot from the top

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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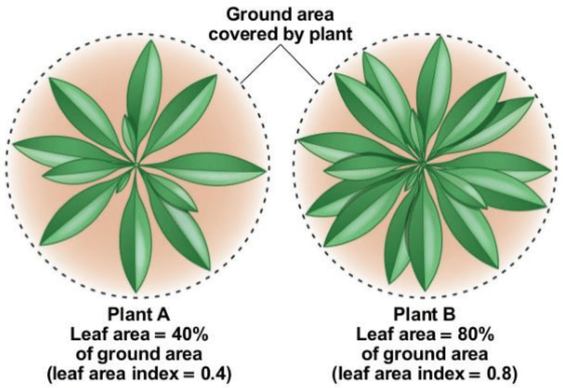
Create a dataset of images of plants grown using hydroponics

Take images of each pot from the top

Record environmental data (humidity, temperature and light)

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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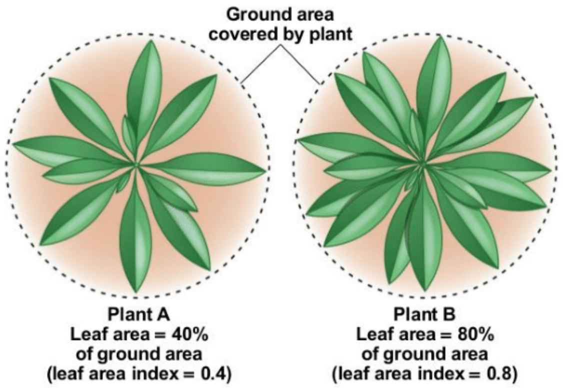

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Create a dataset of images of plants grown using hydroponics

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Record environmental data (humidity, temperature and light)

Measure the leaf area physically

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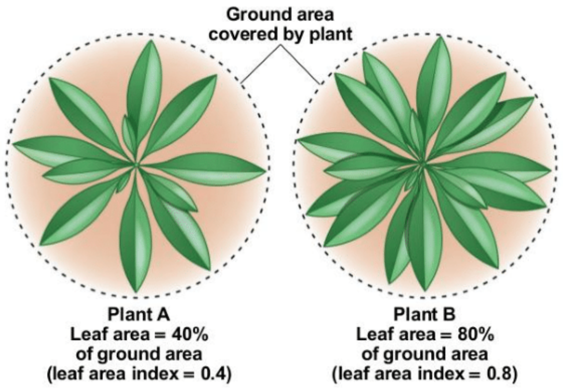
Creation of the **Space Farming Dataset**

(No ground-truth segmentation mask provided)

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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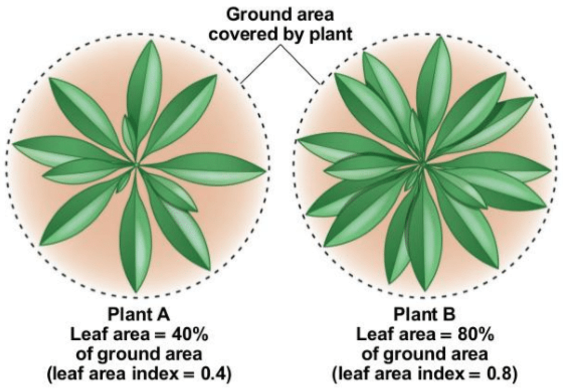
Create a dataset of images of plants grown using hydroponics

Train available plant segmentation models to the expected image input

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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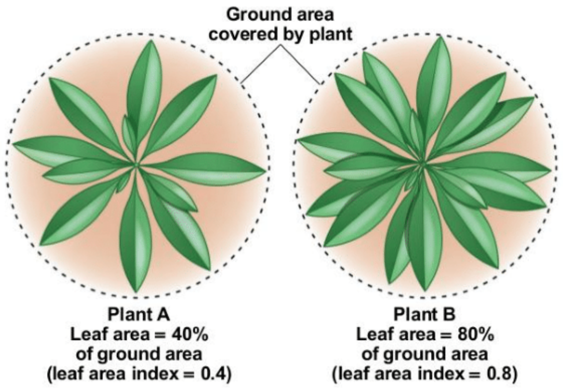
Train available plant segmentation models to the expected image input

Find currently labeled datasets similar to our target

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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Create a dataset of images of plants grown using hydroponics

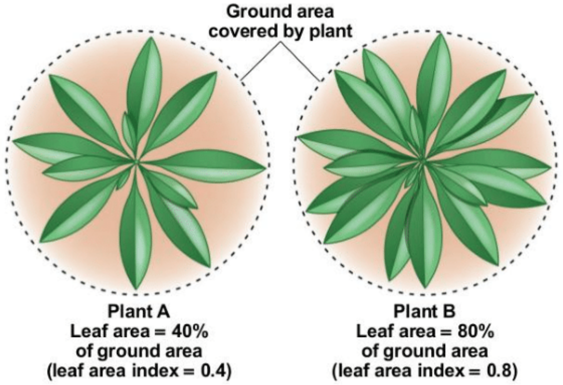
Train available plant segmentation models to the expected image input

Find currently labeled datasets similar to our target

Train object segmentation models with the best fit

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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Create a dataset of images of plants grown using hydroponics

Train available plant segmentation models to the expected image input

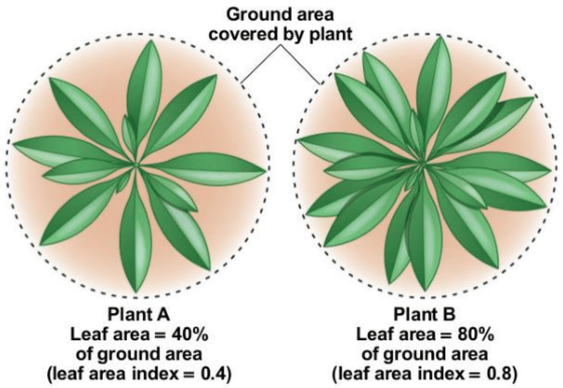
Find currently labeled datasets similar to our target

Train object segmentation models with the best fit

Implement the model on our Space Farming Dataset

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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Create a dataset of images of plants grown using hydroponics

Train available plant segmentation models to the expected image input

Test the model on the image data generated to extract Leaf Area

Objectives

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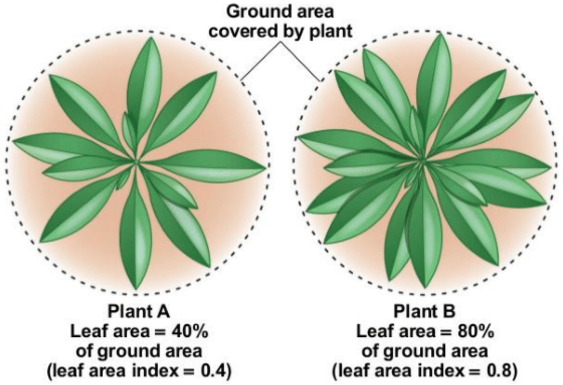

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Create a dataset of images of plants grown using hydroponics

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Count the prediction mask pixels from plant segmentation

Objectives

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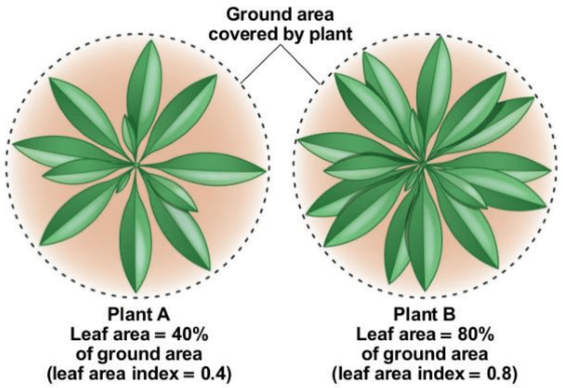

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Create a dataset of images of plants grown using hydroponics

Train available plant segmentation models to the expected image input

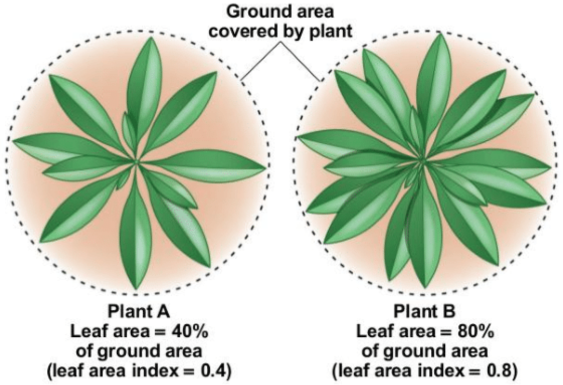
Test the model on the image data generated to extract Leaf Area

Count the prediction mask pixels from plant segmentation

Use linear regression to define a model that matches # of pixels with real area

Objectives

Compute Leaf Area through Computer Vision and regression models in a non-destructive way



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Create a dataset of images of plants grown using hydroponics

Train available plant segmentation models to the expected image input

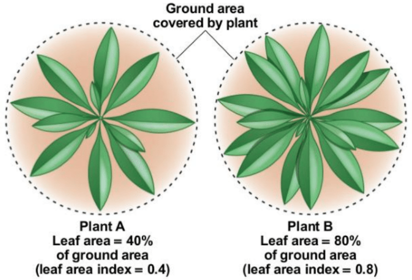
Test the model on the image data generated to extract Leaf Area

Count the prediction mask pixels from plant segmentation

Use linear regression to define a model that matches # of pixels with real area

Test the results with a new sample and compare to the real area (obtain the segmentation + regression trained model)

Objectives



Compute Leaf Area through Computer Vision and regression models in a non-destructive way

Analyze different light conditions effect on plant monitoring

Monitor and predict the plant growth in extreme environments

Model the growth dynamics as a function of the environment conditions

Planning of Dry Matter Production for resources limitation purposes

**Credit image: Abdellatif, Mostafa & Valdenebro, Esaiy. (2016). Storm-water Management: Evapo-transpiration & Cooling with Water. 10.13140/RG.2.2.24862.23360.*

Objectives

Model the growth dynamics as a function of the environment conditions

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Adapt a dynamic growth model to Arugula’s growth dynamics

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Model the growth dynamics as a function of the environment conditions

Adapt a dynamic growth model to Arugula's growth dynamics

Measure physically the Leaf Area of a real Arugula evolution

Objectives

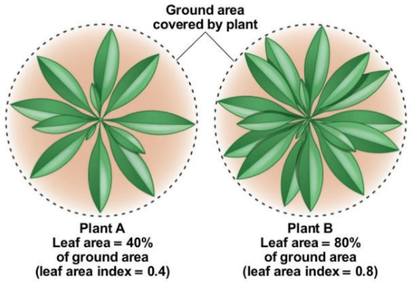
Model the growth dynamics as a function of the environment conditions

Adapt a dynamic growth model to Arugula's growth dynamics

Measure physically the Leaf Area of a real Arugula evolution

Compare the results obtained by the dynamic model and the real measures

Objectives



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Objectives

Analyze different light conditions effect on plant monitoring

Objectives

Analyze different light conditions effect on plant monitoring

Challenge the segmentation + regression model with different lightning set ups

Objectives

Analyze different light conditions effect on plant monitoring

Challenge the segmentation + regression model with different lightning set ups

Compute the predicted growth of Leaf Area with the dynamic model

Objectives

Analyze different light conditions effect on plant monitoring

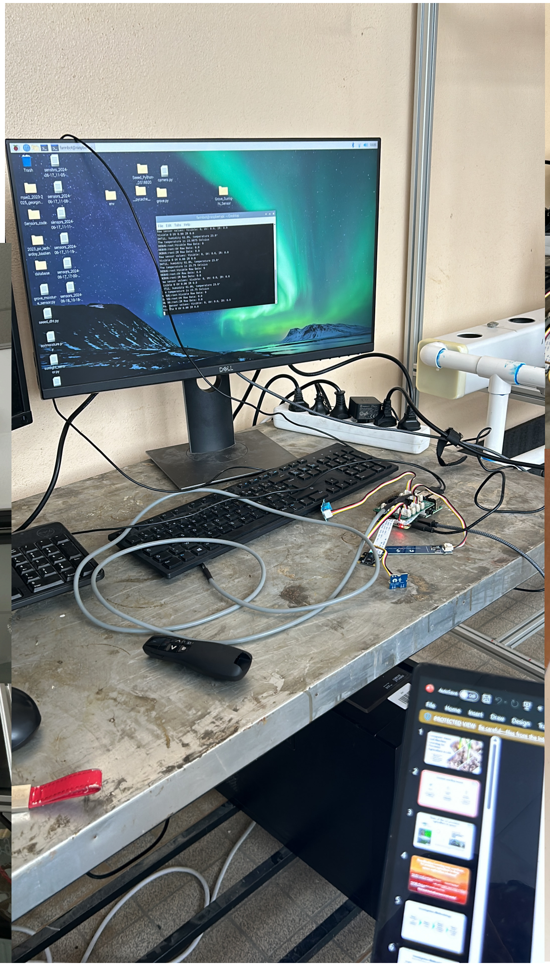
Challenge the segmentation + regression model with different lightning set ups

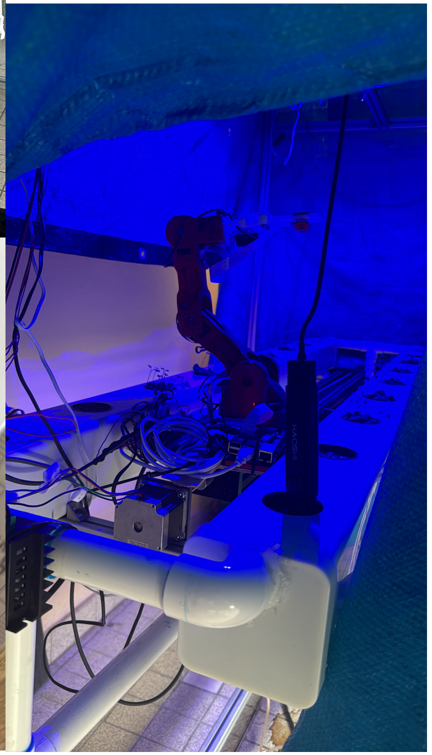
Compute the predicted growth of Leaf Area with the dynamic model

Compare the results with the physical measurements

Pictures of the experiment

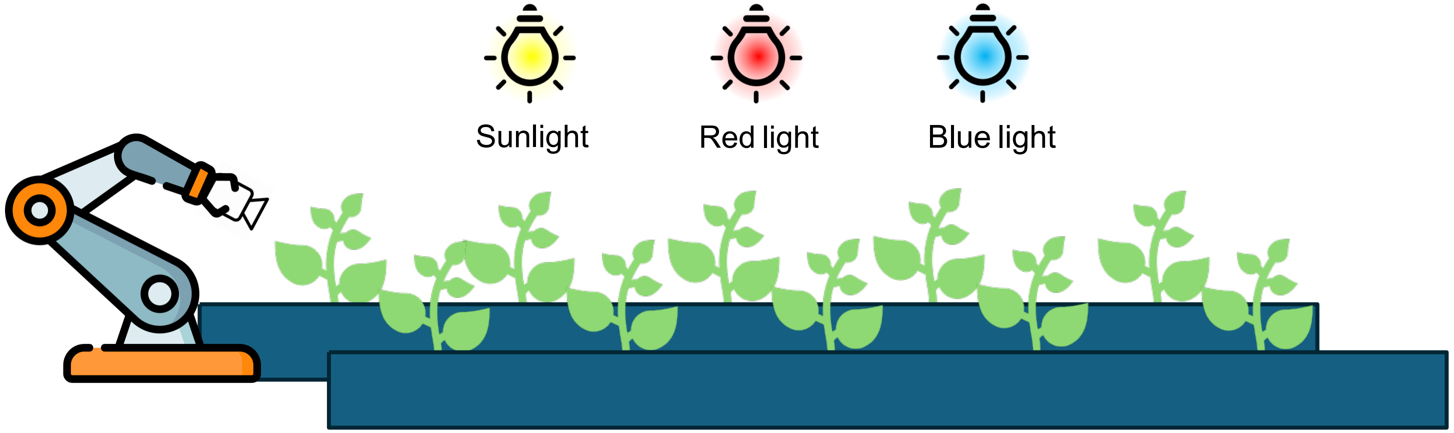




Space Farming Dataset

Experiment (2 weeks each)



Measurements:

Arugula's seeds

- Nutritional
- Medicinal
- Vitamin K (bone health and bone formation)
- Antioxidants
- Source of carotenoids (macular degradation slowed down)

Hydroponics systems are the most optimal choice in terms of **complexity, mass, volume and power** consumption [1].

[1] Marina Mileni Munari, Nicolas Drougard, and Thibault Gateau. Modeling and optimization of the design of a robotic hydroponic system. The VIIth Space Resources Conference (KGK2024), 2024

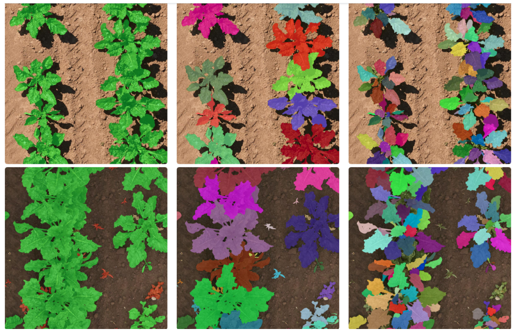
Plant Segmentation Model Training

Training: Phenobench datset + Phenotyping dataset

Model: RESN50

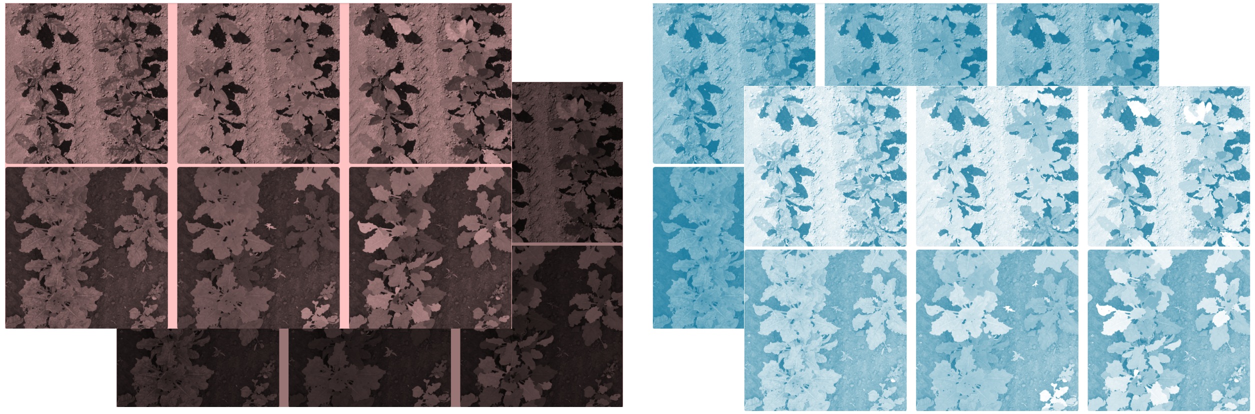
Data augmentation - filter by color + change intensity

Phenobench [2]



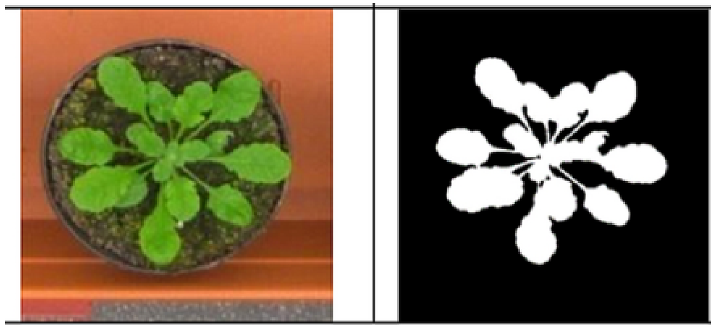
+

Phenotyping[3]



[2] *Jan Weyler, Federico Magistri, Elias Marks, Yue Linn Chong, Matteo Sodano, Gianmarco Roggiolani, Nived Chebrolu, Cyrill Stachniss, and Jens Behley. PhenoBench — A Large Dataset and Benchmarks for Semantic Image Interpretation in the Agricultural Domain. arXiv preprint, 2023.*
[3] *M. Minervini, A. Fischbach, H.Scharr, and S.A. Tsaftaris. Finely-grained annotated datasets for image-based plant phenotyping. Pattern Recognition Letters, pages 1-10, 2015, doi:10.1016/j.patrec.2015.10.013*

From estimated mask to LA (sunlight)



Linear Regression

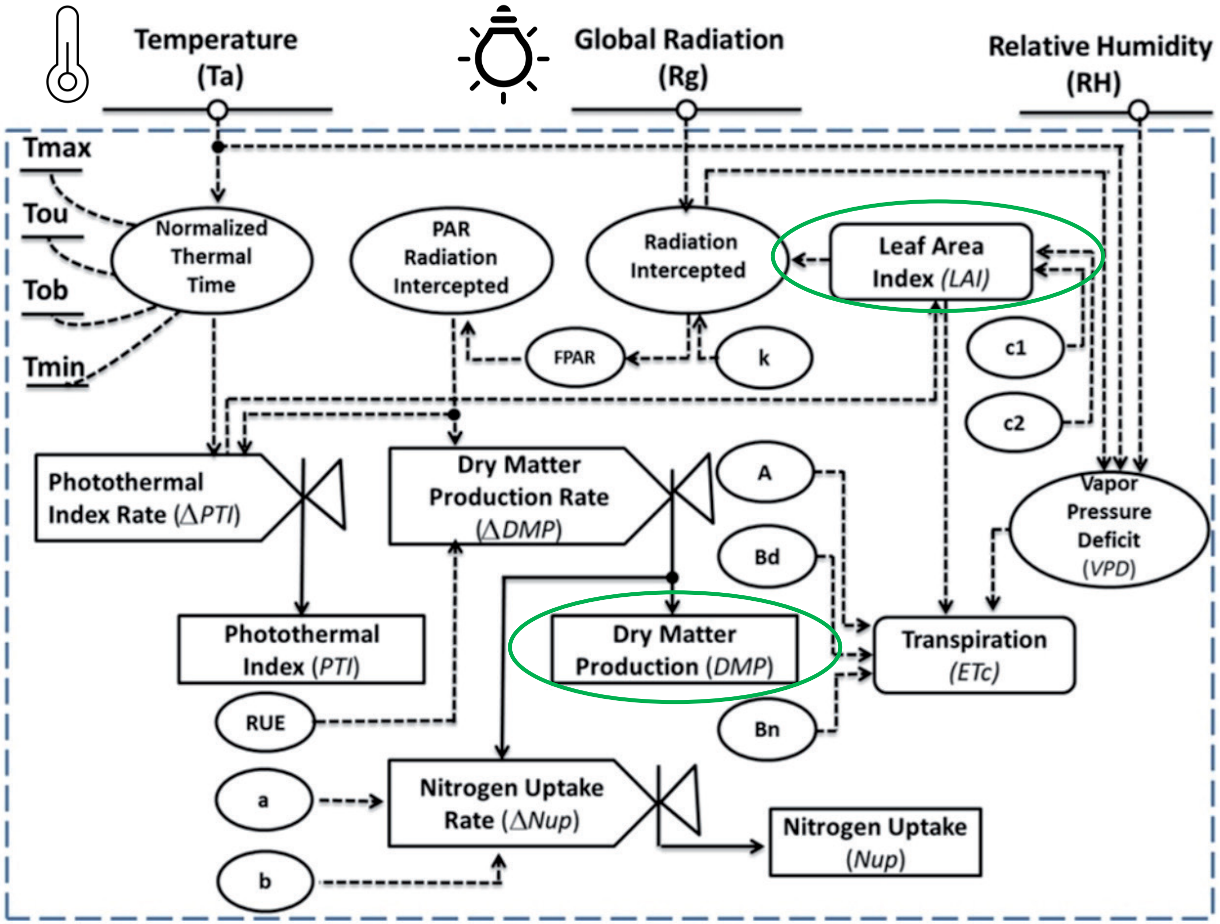
$$LA = a * x + b$$

x: #pixels

LOOCV
(Leave-One-Out Cross Validation)

Step 1: Pick one measurement. Hide it.
Step 2: Fit the regression using the other N–1 points.
Step 3: Predict the hidden leaf area from its pixel count.
Step 4: Compute the error based on the true value.
Step 5: Repeat for each measurement → every point is left out once.
Step 6: Compute the average error.

Arugula's Dynamic Model



Simple model!

[4] *Antonio Martínez-Ruiz, Irineo Lopez-Cruz, Agustin Ruiz Garcia, Joel Pineda, and Jorge Prado Hernández. Hortsyst: A dynamic model to predict growth, nitrogen uptake, and transpiration of greenhouse tomatoes. Chilean journal of agricultural research, 79:89–102, 02 2019.*

Arugula's Dynamic Model

Output	Parameter	Symbol	Units	Nominal value	Source
DMP	Maximum temperature	T_{max}	$°C$	15	Measured
	Minimum temperature	T_{min}	$°C$	30	Measured
	Lower optimal temperature	T_{ol}	$°C$	13	
	Upper optimal temperature	T_{ou}	$°C$	24	
	Radiation use efficiency	RUE	gMJ^{-1}	1.45	[27]
PTI	Extinction coefficient	k	-	0.7	[1]
	PTI Initial condition	PTI_0	MJd^{-1}	0.025	[1]
Nup	N*	a	gm^{-2}	TBD	Data acquisition
	Slope of the relationship	b	-	TBD	Data acquisition
LAI	Slope of the curve	c1	-	TBD	Data acquisition
	Intersection coefficient	c2	-	TBD	Data acquisiton
ETc	Radiative coefficient	A	-	0.49	[28]
	Daytime aerodynamic coefficient	B_d	Wm^{-2}, kPa^{-1}	11.2	[28]
	Nighttime aerodynamic coefficient	B_n	Wm^{-2}, kPa^{-1}	8.28	[28]

TBD To be determined

* Nitrogen concentration in dry biomass at the end of the exponential growth period.

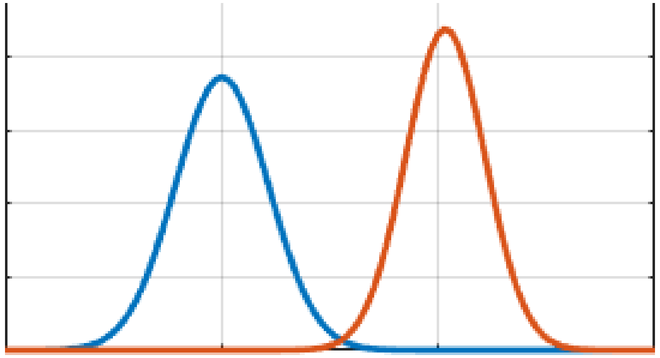
[4] *Antonio Martínez-Ruiz, Irineo Lopez-Cruz, Agustin Ruiz Garcia, Joel Pineda, and Jorge Prado Hernández. Hortsyst: A dynamic model to predict growth, nitrogen uptake, and transpiration of greenhouse tomatoes. Chilean journal of agricultural research, 79:89–102, 02 2019.*

Experiment statistics

Statistical method: One Way ANOVA

Software: Python

	One Way ANOVA
Independent variables	Light
Dependent variables	LAI

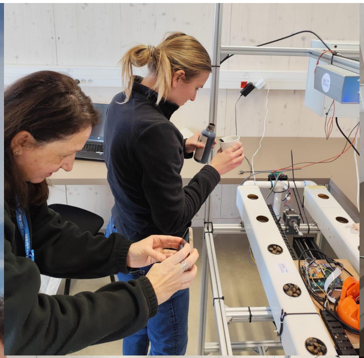
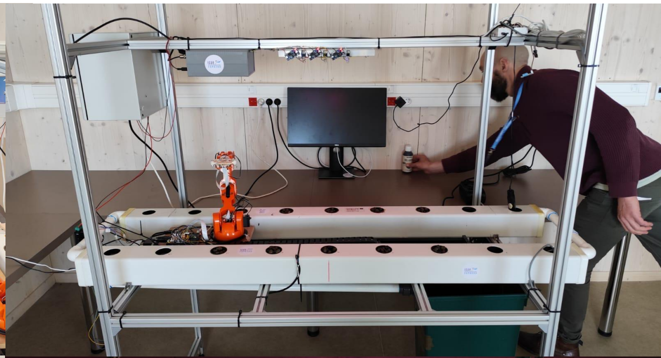
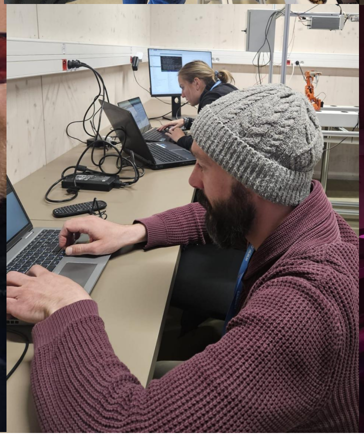


Level of Significance: 0.05

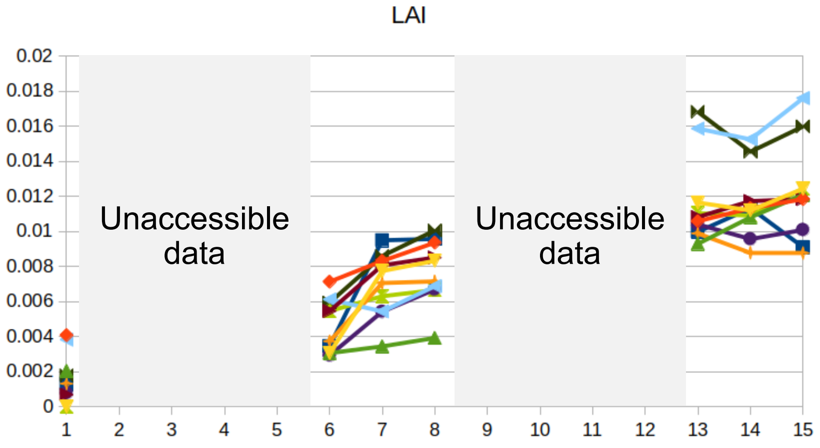
If p-value < than Level of Significance: Post-hoc analysis

Pic du Midi Experiment

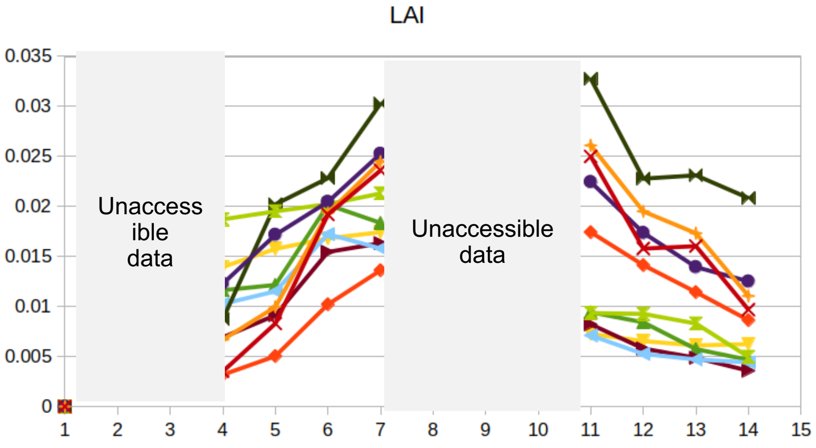


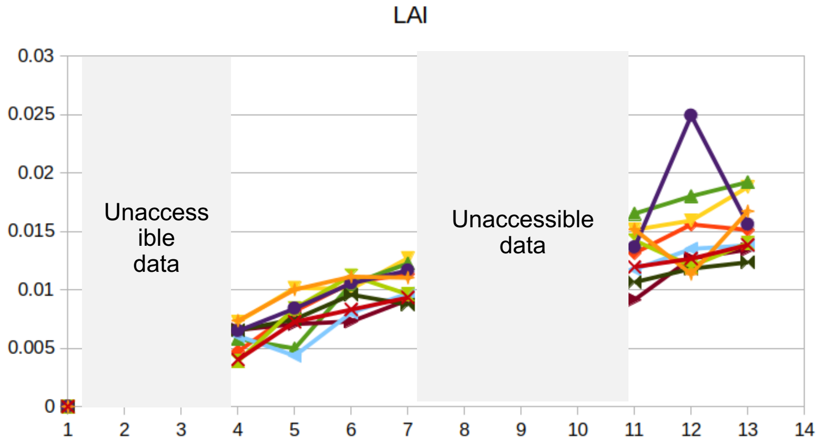

Experimental data



Sunlight case



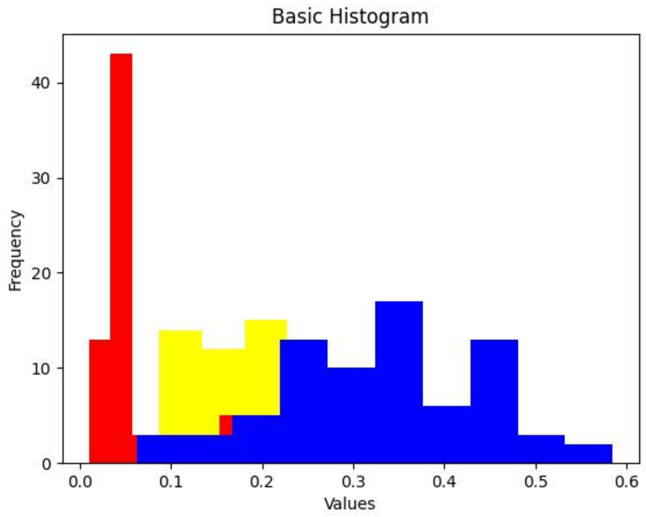
Redlight case

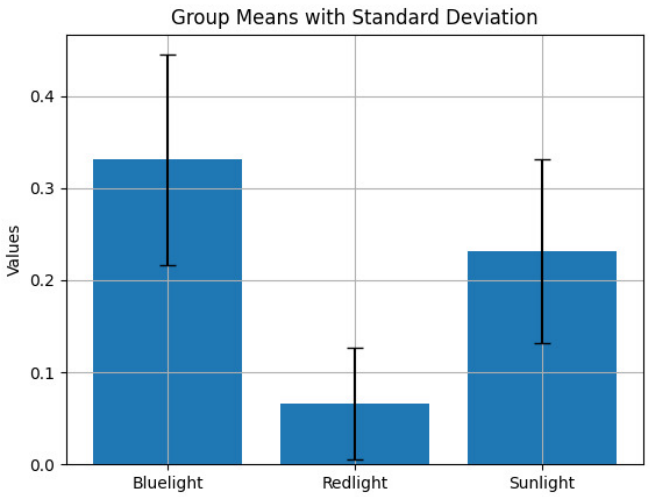


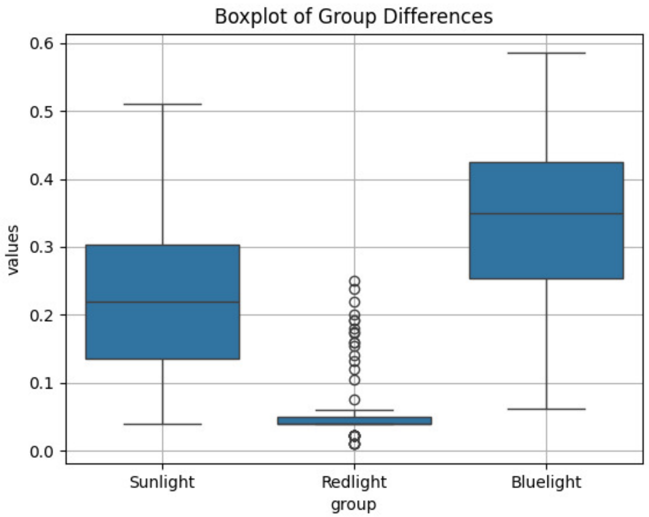
Bluelight case

One-way Anova Statistics

Conditions:
- One day (day 13 experiment),
- 75 crops per case



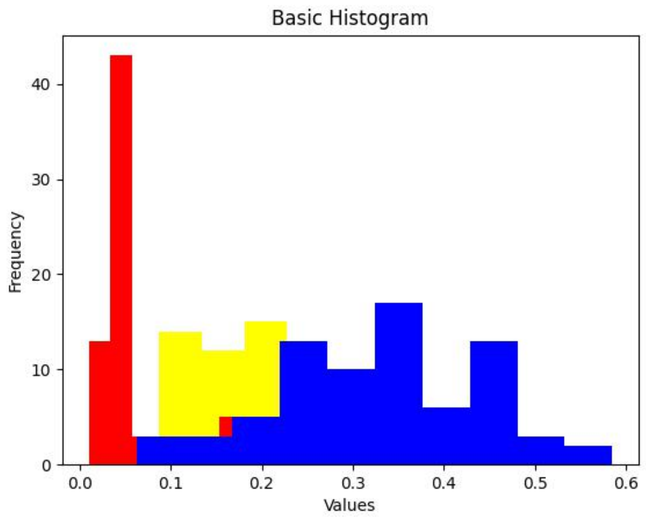


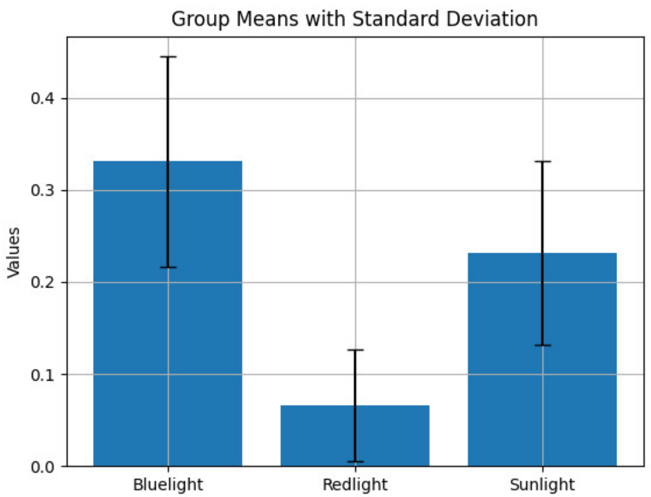


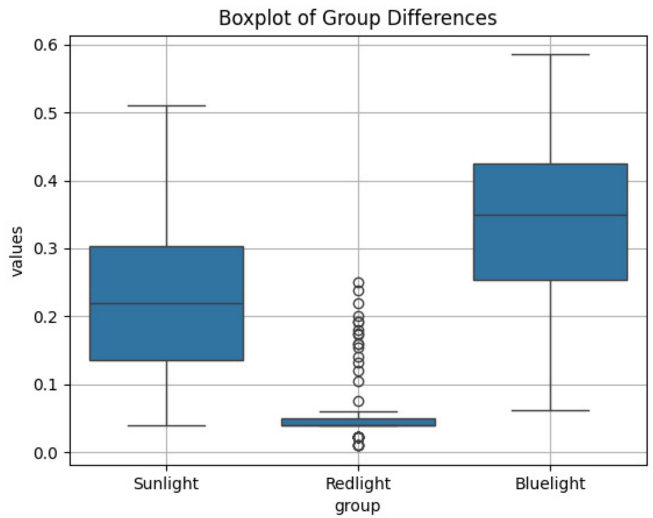
$p < 0.05$

Post-hoc results

Conditions:
- One day (day 13 experiment),
- 75 crops per case





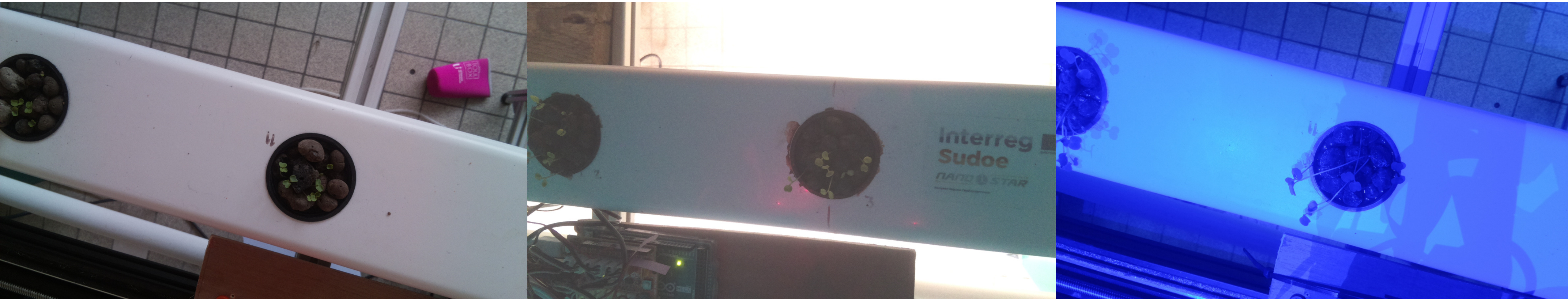


$p < 0.05$

Multiple Comparison of Means - Tukey HSD, FWER=0.05

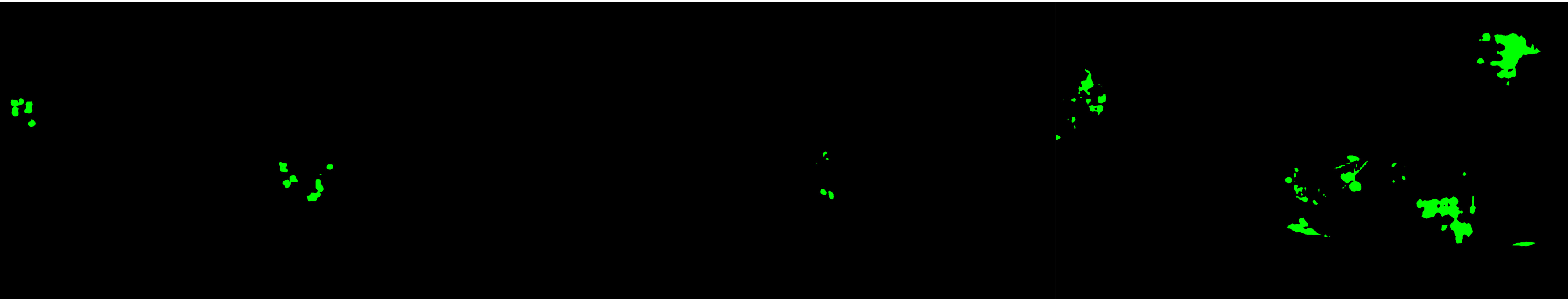
group1	group2	meandiff	p-adj	lower	upper	reject
Bluelight	Redlight	-0.2647	0.0	-0.3011	-0.2284	True
Bluelight	Sunlight	-0.0991	0.0	-0.1354	-0.0627	True
Redlight	Sunlight	0.1657	0.0	0.1293	0.202	True

Plant segmentation



Qualitative assessment

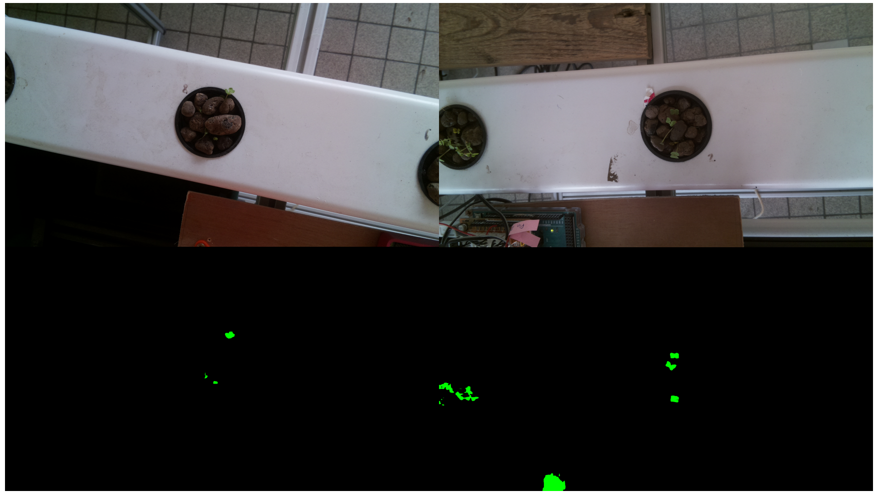
Plant segmentation



Qualitative assessment

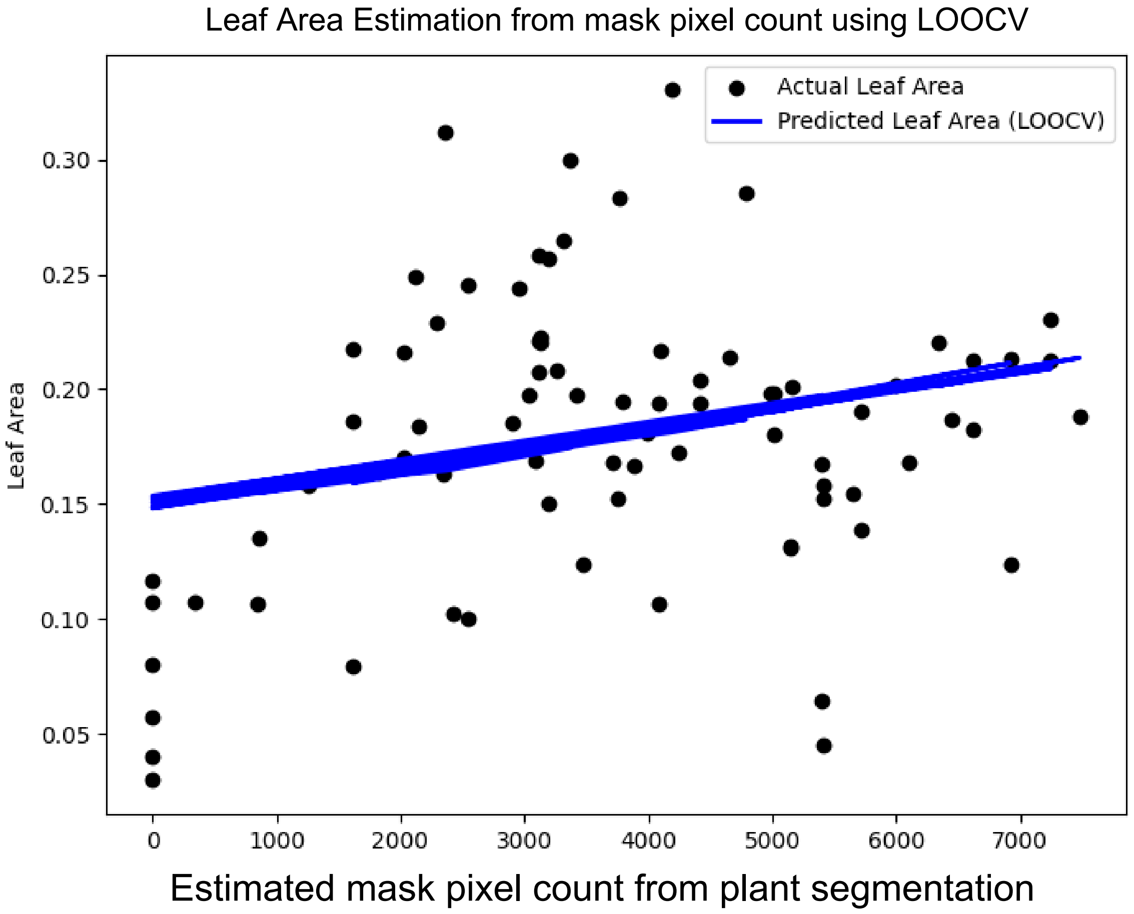
Dataset created!

redlight-case		110 items	21 mar 2025	☆
sunlight-case		102 items	20 mar 2025	☆
bluelight-case		100 items	20 mar 2025	☆
final_database_images.ods	“„	63,7 kB	21 mar 2025	☆



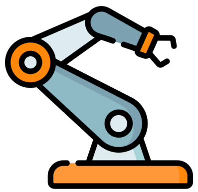
Days	case	pot	Normalized_LA_cm	date	Temp	RH	Temp Water	Light	PH Water	Image
1	bluelight	1	0	07/25/24	26	59	25.4375	173.91	6.66	image_2024-
2	bluelight	1	0	07/26/24	25	59	25.25	215.81	6.93	
3	bluelight	1	0.0235266864513187	07/27/24	26	61	25.625	215.81	6.91	
4	bluelight	1	0.0702586206896552	07/28/24	26	65	26.25	187.98	6.92	
5	bluelight	1	0.149479310344828	07/29/24	27	54	26.1875	139.47	6.96	image_2024-
6	bluelight	1	0.194310344827586	07/30/24	27	57	26.9375	147.68	7.06	image_2024-
7	bluelight	1	0.222789655172414	07/31/24	27	58	27.0625	142.47	6.86	image_2024-
8	bluelight	1	0.25008137731964	08/01/24	27	61	27.5625	134.65	6.43	image_2024-
9	bluelight	1	0.271155869402724	08/02/24	27	62	27	168.69	6.74	image_2024-
10	bluelight	1	0.284151546122281	08/03/24	25	55	25.8125	167.42	6.72	image_2024-
11	bluelight	1	0.258120689655172	08/04/24	26	54	25.75	125.66	6.72	image_2024-

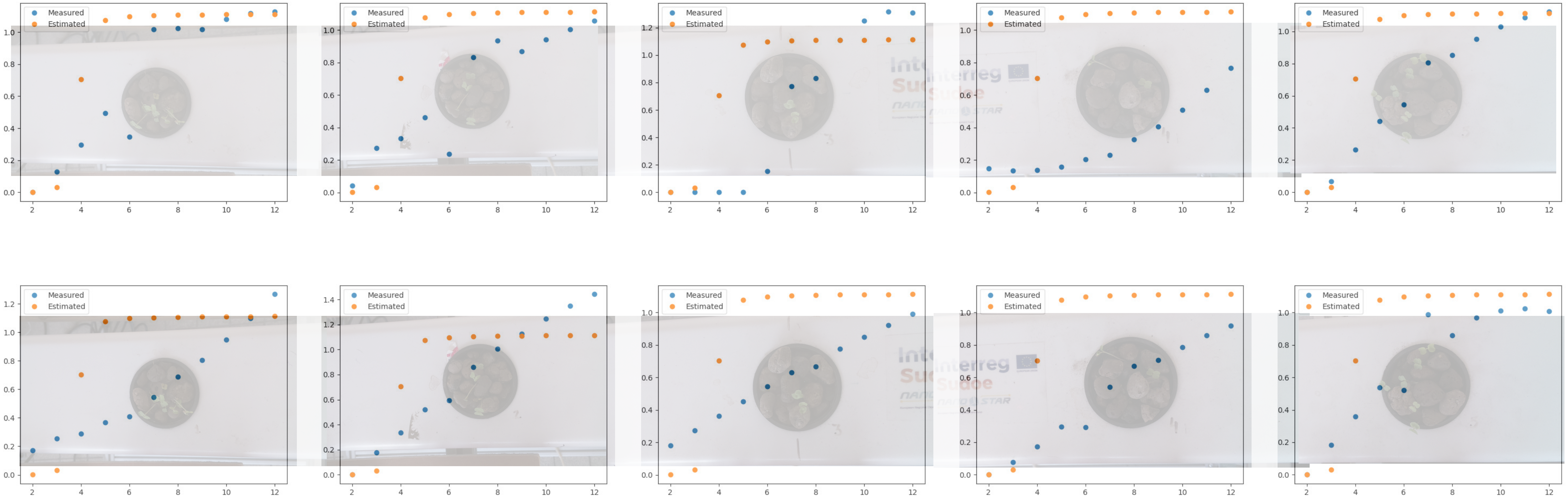
LA regression from segmentation mask



- Coefficient: [8.781e-06]
- Coefficient of determination (R^2): 0.03

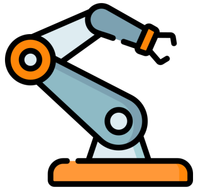
Arugula’s Dynamic Model: Sunlight Case

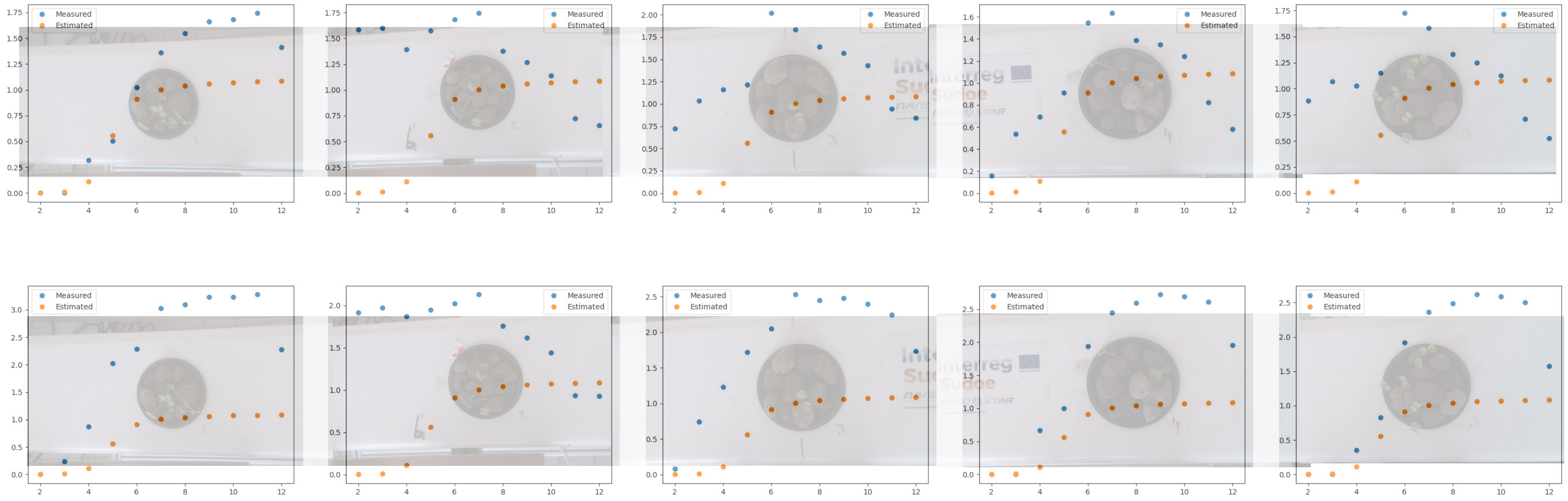




Measured   Estimated

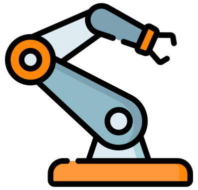
Arugula's Dynamic Model: Redlight Case

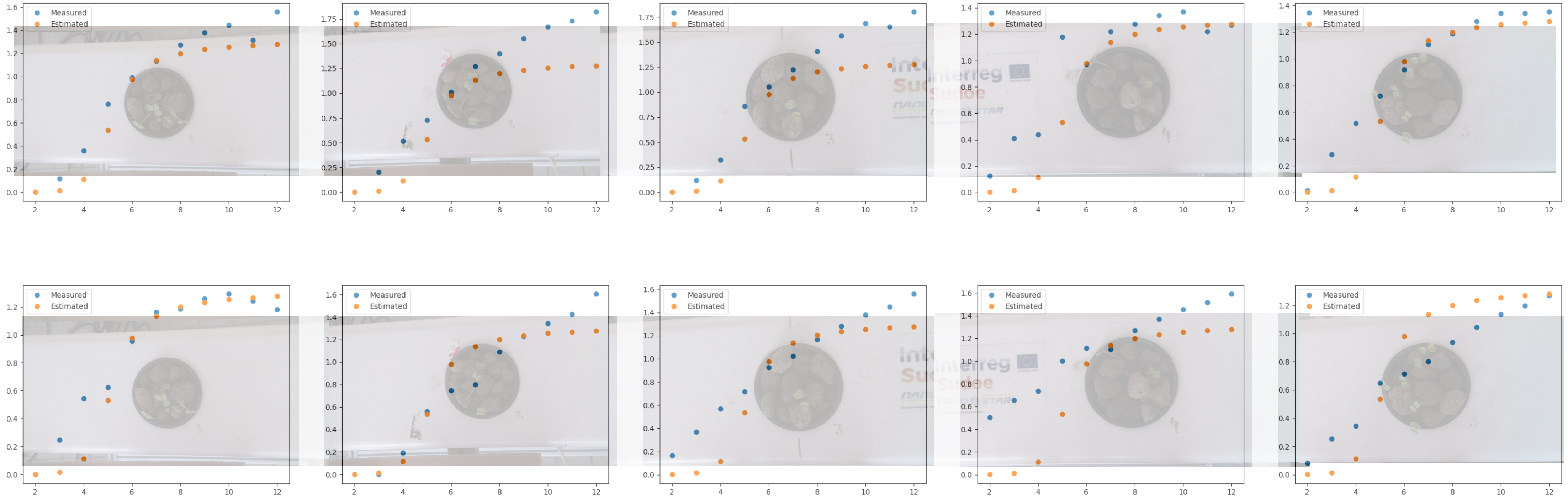




● Measured ● Estimated

Arugula’s Dynamic Model: Bluelight Case





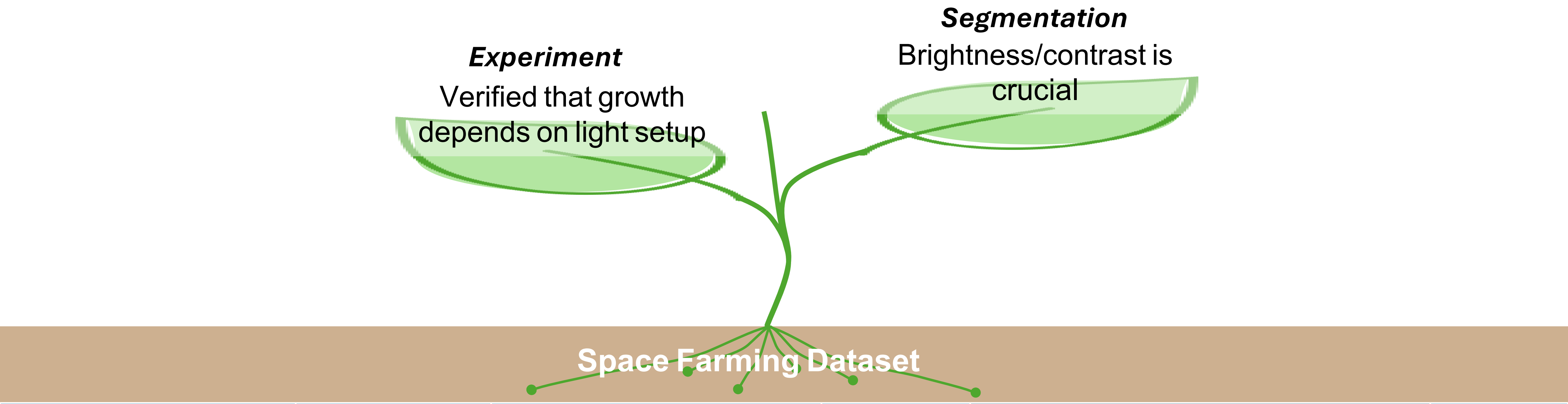
● Measured ● Estimated

Conclusions

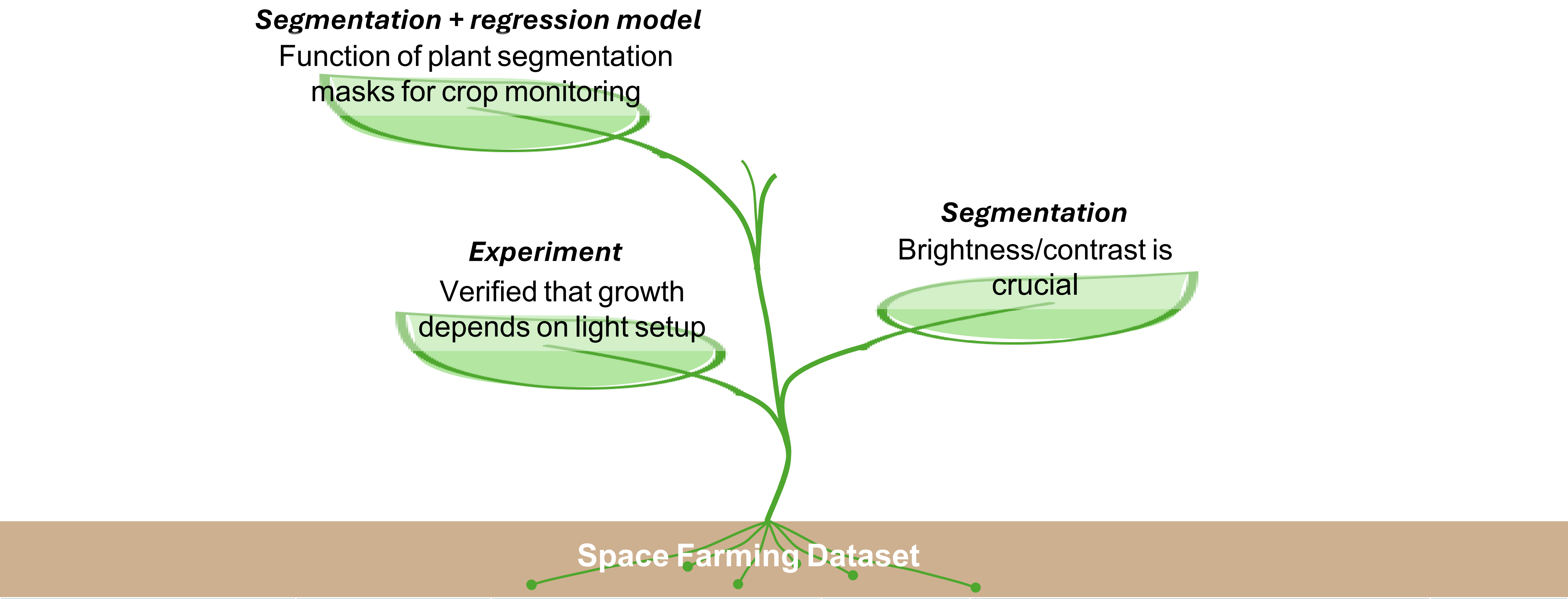
Space Farming Dataset

Conclusions

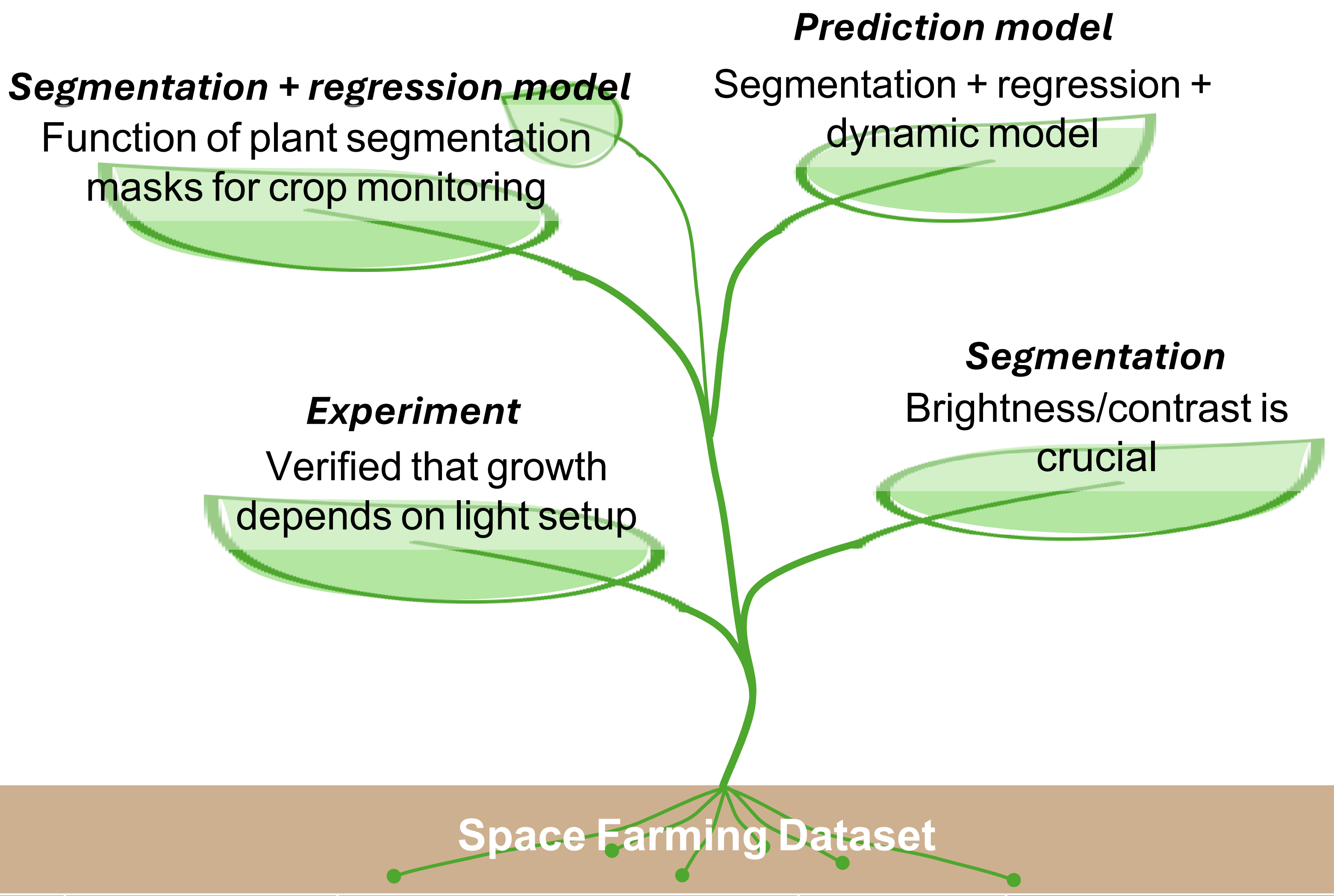
Conclusions



Conclusions



Conclusions



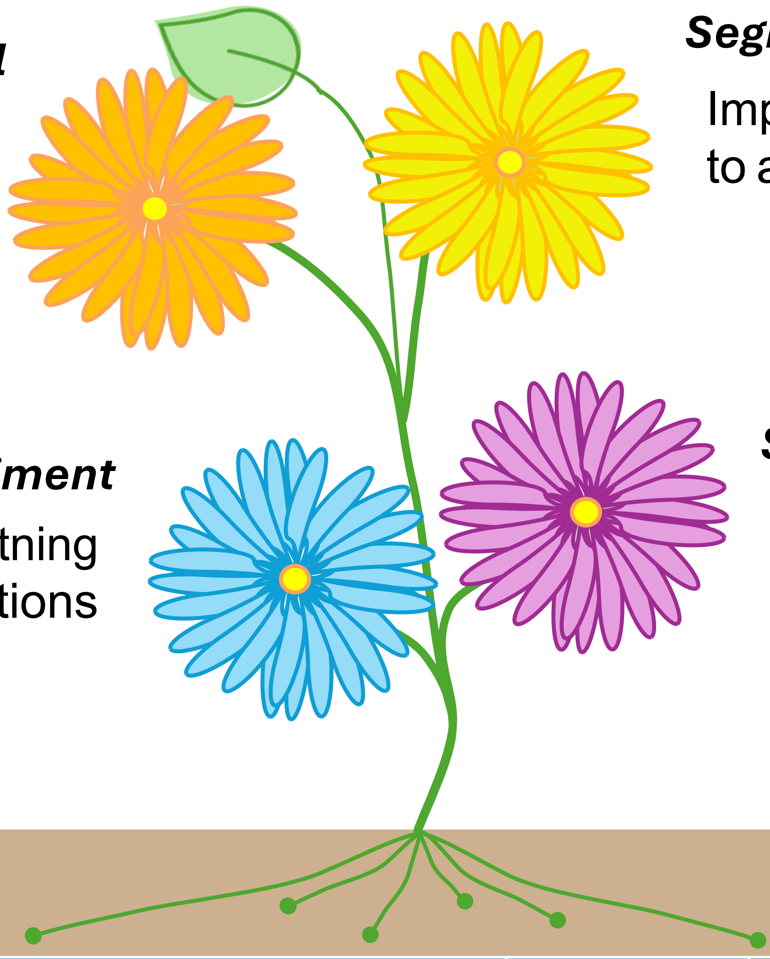
Future Work

Prediction model

Add as an input the PH of the Water and the wavelength

Segmentation + Regression

Improve and extend the model to all lightning conditions



Experiment

Test other lightning conditions

Segmentation

Train the model with more datasets

Acknowledgement

Thank you ESA Academy for the amazing opportunity to present my work at MELiSSA Conference