



Digital Agriculture: Managing Data from Images and Sensors in Irrigated and Rainfed Crops

Lorena Parra

Postdoctoral Researcher at:

Universitat Politècnica de València, Spain

RESUME OF THE PRESENTER

Background:

- Bachelor's degree in Environmental Sciences in 2012.
- Master's Degree in Environmental Assessment and Monitoring of Marine and Coastal Ecosystems in 2013 and his Master in Aquaculture in 2014.
- PhD in Science and Technology of Animal Production 2018.

Experience:

- Author/coauthor of 54 publications and in 60 participations in congresses.
- Editor of proceedings, panelist, and chair in various congresses.
- Guest editor of several Special Issues of indexed journals.

Main research topics:

- Low-cost sensors for aquaculture.
- Sensors and remote sensing for precision agriculture.



RESUME OF THE UPV

Education:

The UPV in the 3 campuses (Valencia, Gandia, and Alcoy) offers 44 degrees and double degrees, 80 master's degrees, and 30 PhD programs.

The UPV is the only technological university in Spain that appears in all the international rankings.

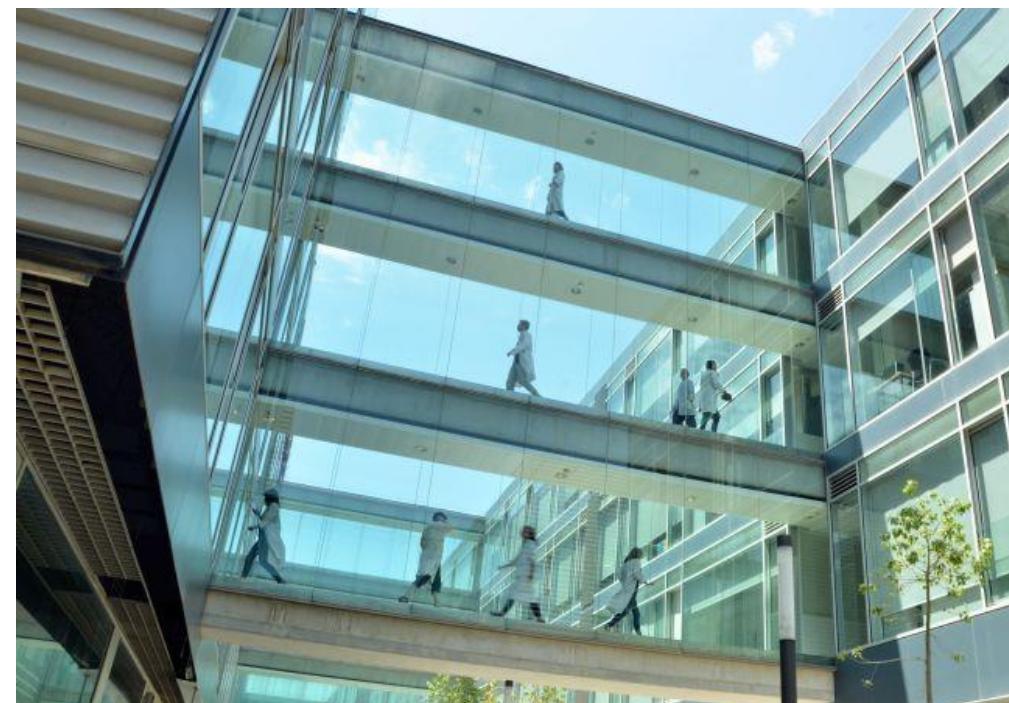
It is the fourth university in Europe in received Erasmus students, out of a total of 4,500 institutions participating in the program, and the sixth in sent students.

Research:

The UPV is the national leader in the number of patents (391 between patents and software).

24 Research centers with more than 2500 researchers.

In its 50-year history, the UPV has produced more than 115,000 scientific publications.



RESUME OF THE IGIC



IGIC was created in July 2007 with the aim of assembling and strengthening the research capabilities at the Gandia Campus.

Its general objective is to promote and develop scientific research of excellence on different aspects of integrated coastal management.

Nowadays the IGIC includes 62 researchers, clustered in 11 research groups, working in three research areas:

- i) Environmental and biological resources studies and conservation,
- ii) Knowledge, planning, and management of coastal areas and
- iii) Marine and coastal technological monitoring and analysis tools.
 - i) Communications and networks



<http://igic.webs.upv.es/>





- ❑ Introduction
- ❑ Data in Digital Agriculture
 - ❑ Data and its relevance
- ❑ Examples of proposed solutions in real cases
 - ❑ Applications based on satellite
 - ❑ Applications based on drones
- ❑ Future perspective



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INTRODUCTION - WHY IS IT SO IMPORTANT TO USE IMAGES IN DIGITAL AGRICULTURE?

Images are, in several cases, the **unique available approach** to measure or estimate several parameters from the crops.

Such as the presence of pests and diseases or to estimate the yield.

In other cases, the huge spatial variability of a parameter requires a **high number of sensors** for its accurate monitoring which can **be replaced by an image** covering the whole area.

Such as soil moisture

Finally, in other cases, **the result of a sensor** or a group of sensors is used to generate an image.

Such as the GreenSeeker, which measures the Normalized Difference Vegetation Index (NDVI), a measure of plant vigor, or the Laser Imaging Detection and Ranging (LiDAR).



INTRODUCTION - WHAT IMAGE SOURCES WE CAN IDENTIFY?

During the last decades, remote sensing was based on satellite imagery with a relatively high temporal resolution, low spatial resolution, and high spectral resolution.

The inclusion of aerial images has also been used but with very low temporal resolution and spatial resolution.

In the last years, drones have become an important source of images due to their flexibility in spatial and temporal resolution and including multispectral cameras.

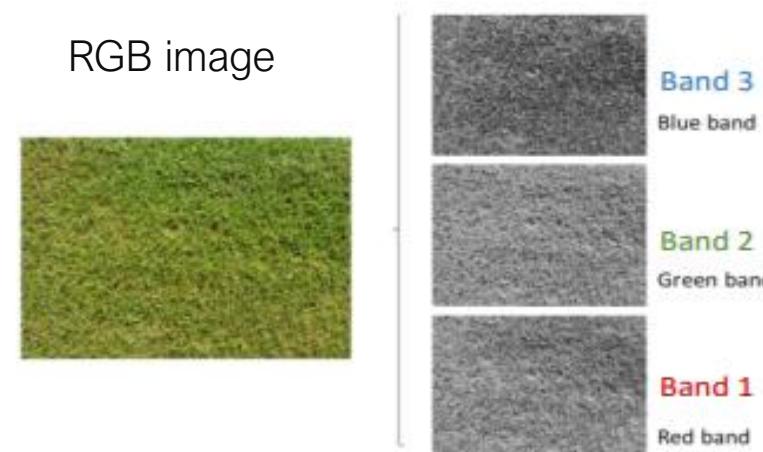
The use of RGB cameras and hyperspectral cameras as proximal sensing should not be underestimated.

Finally, other devices such as certain NDVI meters or LiDAR stations can generate images with information as a result.

INTRODUCTION - WHAT IMAGE SOURCES WE CAN IDENTIFY?

In most cases, the images provide information about the reflection of light at a certain wavelength of the surfaces.

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In other cases, we use multispectral images composed of more than three bands.



True color image



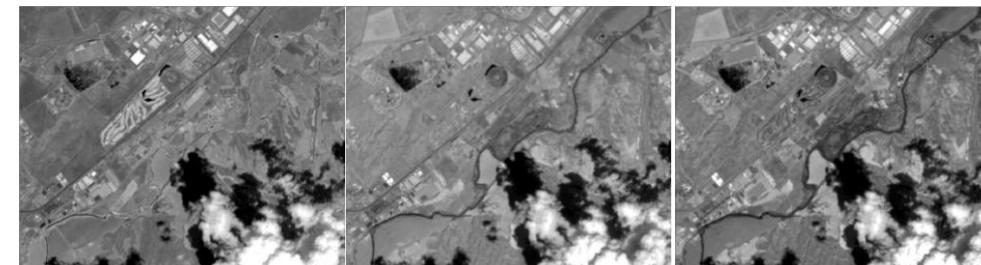
B2

B3

B4

B5

B6



B7

B11

B12

and more...

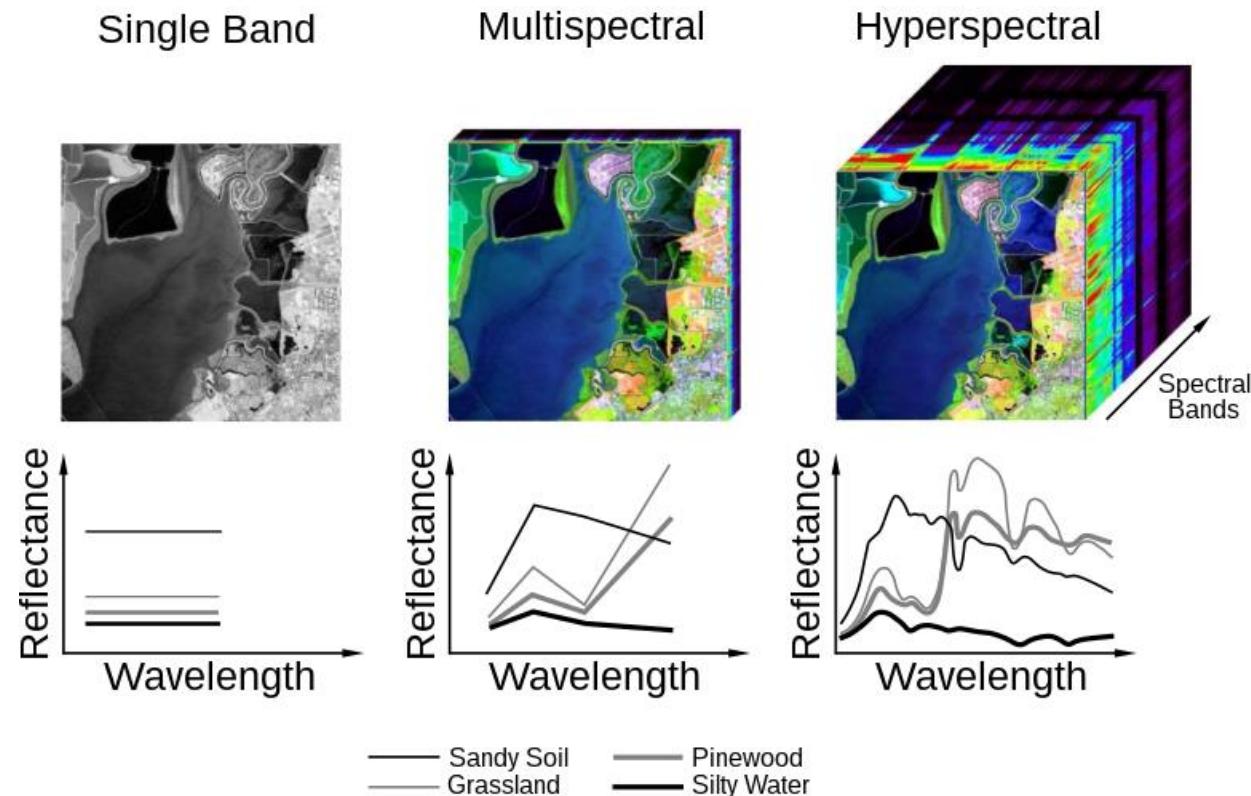
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Finally, we can find hyperspectral images composed of thousands of bands.





INTRODUCTION - WHAT IMAGE SOURCES WE CAN IDENTIFY?

In most cases, the images provide information about the reflection of light at a certain wavelength of the surfaces.

On the other hand, some images do not provide information about the reflection at a certain wavelength. We can find two cases:

Processed products based on the mathematical operation of images with information about the reflection at a certain wavelength.

For example, the NDVI, is based on the combination of red and infrared images.

The application of filters to a single image or the reclassification of the pixel values.

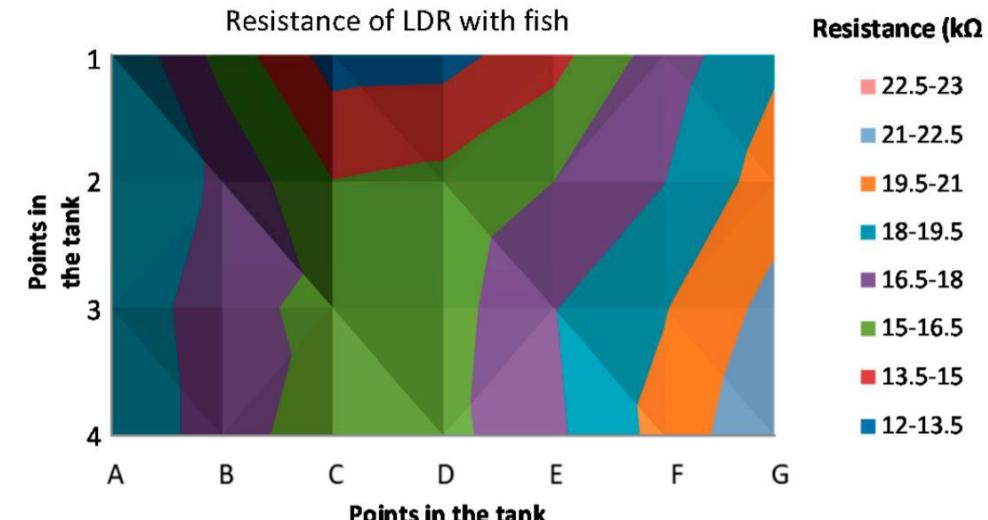
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Generated images based on the spatial variation of data of a sensed variable and the interpolation of the sensed values.



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On the other hand, some images do not provide information about the reflection at a certain wavelength, we can find two cases:

In all the cases, the images are composed of pixels that have the sensed parameter value. Images can be considered as huge matrixes of data.





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Considering the cost of data storage in terms of energy and the economic cost of renting the virtual space, we must evaluate the profit of data storage.

There are several aspects to consider:

- Data periodicity (Data gathered every X minutes)
- Data resolution (Nº bits per data)
- Number of measurement devices (Nº nodes per point)
- Data sending (Message every X data gathered)

These values should be defined according to the future use of data.

Let us see a practical case for data resolution:

Monitoring Tº of the soil in a field of cereal every 5 min to determine the risk of fungi diseases we can use:

16 bit sensor (resolution ± 0.25 °C)

8 bit sensor (resolution ± 1 °C)

= 2240 or 4480 bits each day...
= 16,128 or 32,256 bits each week...
= 67,200 or 134,400 bits each month...



For images, it is even worse

Considering the variability of image sources, not all of them can be processed equally.

If we expect to have an autonomous system operating in the fields, capable of activating or deactivating actuators locally and in real-time or near-real-time, based on images the system becomes complex.

Drones or cameras mounted on machinery are the sole options, and simple image processing is preferred.

If we expect to create an online platform to assess the farmers, more flexibility is allowed since more powerful computing resources and higher bandwidth is allocated.

In this case, no restrictions should be applied.



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If we expect to have an autonomous system operating in the fields, capable of activating or deactivating actuators locally and in real-time or near-real-time, based on images the system becomes complex.

- The images should be processed as matrix data using mathematical operators, combining bands, aggregation techniques, etc. The application of preestablished rules as thresholds to reclassify the image is also possible. Edge detection based on filters and aggregation techniques is feasible too.
- Finally, the solutions must be tailored for each crop or group of crops since the problems and the characteristics of each one is different.
 - The size and distribution of crops are important.
 - The problems of each crop might be different.

Rainfed vs. irrigated crops.

Annual vs. pluriannual crops.

Monocrop vs. intercropping managements.

We will see examples it in this keynote



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APPLICATIONS BASED ON SATELITE

Motivation: Identify different management options.

Task: Identify the plot with spontaneous vegetation maintenance in vineyards with satellite imagery.

Objectives:

1. Evaluate if time series analysis can be applied to obtain information that cannot be obtained with the actual pixel dimensions.



Basterrechea, D.A., Parra, L., Lloret, J., Mauri, P.V.. (2020, October). Identifying the Existence of Grass Coverage in Vineyards Applying Time Series Analysis in Sentinel-2 Bands. The Twelfth International Conference on Advanced Geographic Information Systems, Applications, and Services (GEOProcessing 2020), Valencia, Spain, 21-25 November, 2020.

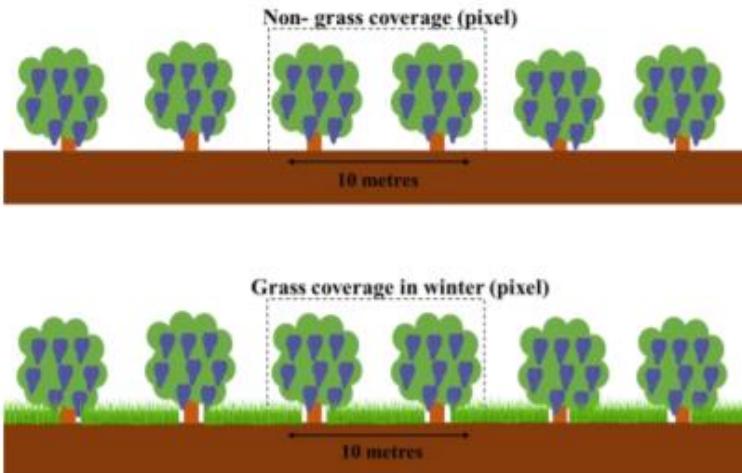
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Bands	Reflectance GC=1	Reflectance GC=0	Differences in reflectance GC=1	Differences in reflectance GC=0
B2	Low	Low	Low	Low
B3	Higher	High	High	Low
B4	Low	High	High	Low
B8	High	High	Low	Low
B9	Higher	High	High	Low
Pixels of:	GC=1 Winter	GC=1 Summer	GC=0 Winter	GC=1 Summer
Vid	High percentage	High percentage	High percentage	High percentage
Soil	Almost null	Low percentage	Low percentage	Almost null
Green grass coverage	Low percentage	Almost null	Almost null	Almost null

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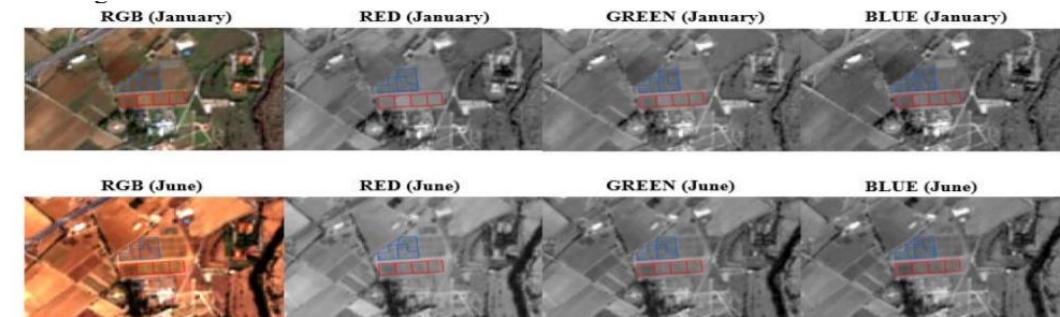


Figure 3. Visible spectrum bands.

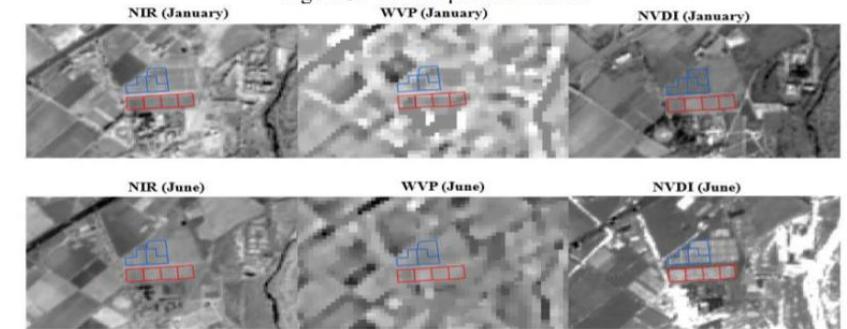


Figure 4. Near-infrared band, water vapour band, and vegetation index band.

Results

Combined images of January and June as:
$$\text{Pixel value in January} - \text{Pixel value in June}$$

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Best information is from the NIR band.

With grass coverage: pixel values from -1000 to -1200.

Without grass coverage: pixels with values from -1200 to -1500.

Is it possible to use time series to evaluate different management options

Results

Combined images of January and June as:

Pixel value in January- Pixel value un June

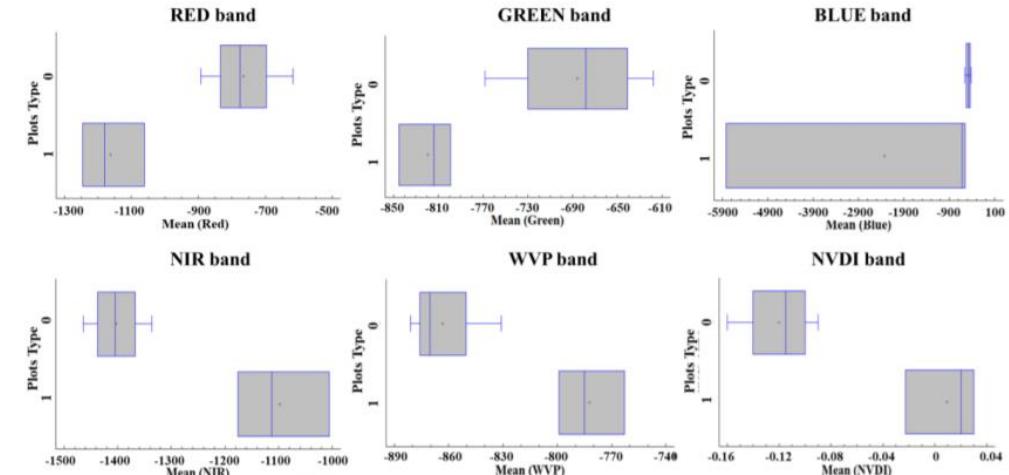


Figure 6. Box and Whiskers diagram of band values.

Type 1=With spontaneous vegetation

Type 0=Without spontaneous vegetation

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Task: Correlate soil moisture data from sensors in soil and data from remote sensing sources.

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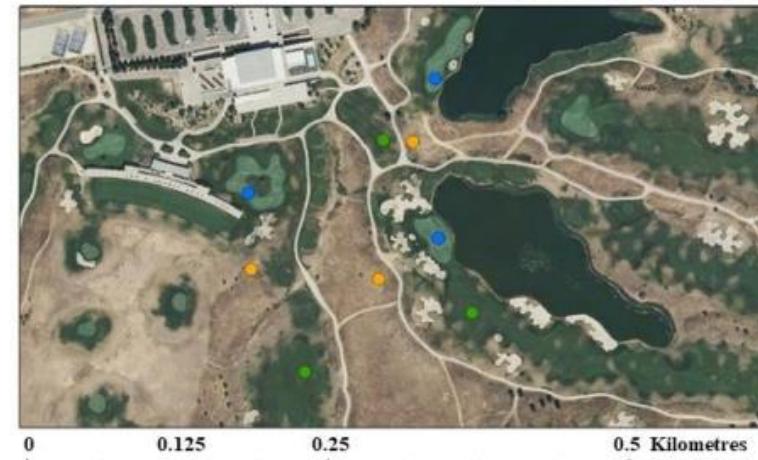
1. Find the best band or band combination to estimate soil moisture in irrigated crops (turfgrass).

Different soil characteristics.
Different irrigation regimes.

Encín Golf Course

Legend

- Sandy-clay soil
- Sandy soil
- Clay soil



Community of Madrid



Spain



Mauri, P. V., Parra, L., Mostaza-Colado, D., Garcia, L., Lloret, J., & Marin, J. F. (2021). The Combined Use of Remote Sensing and Wireless Sensor Network to Estimate Soil Moisture in Golf Course. *Applied Sciences*, 11(24), 11769.

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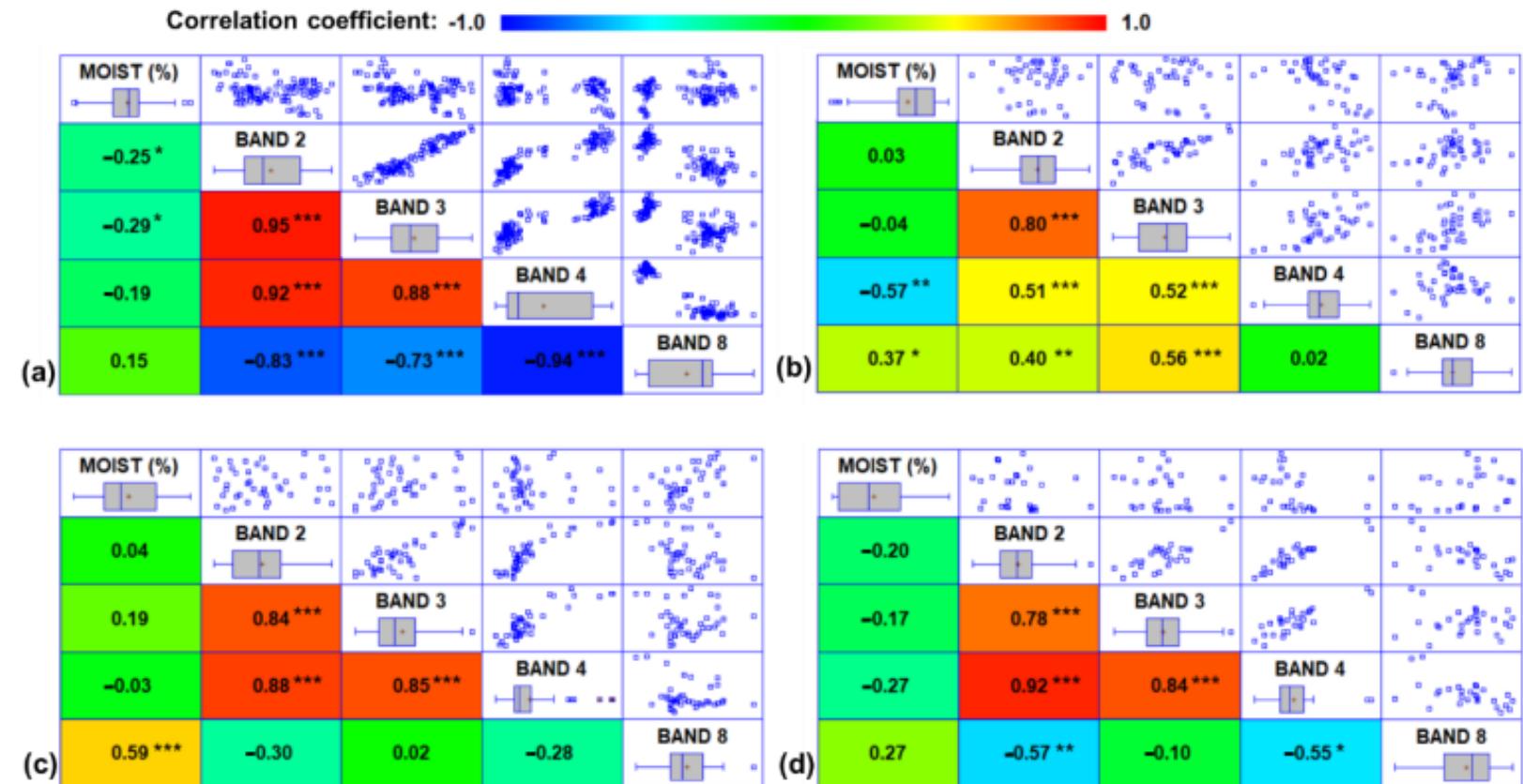
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Summary of multivariate analyses. (a) all soil types, (b) clay soil, (c) sandy soil, (d) sandy-clay soil. Significance levels (Sig): *** $p < 0.001$; ** $p < 0.010$; * $p < 0.010$

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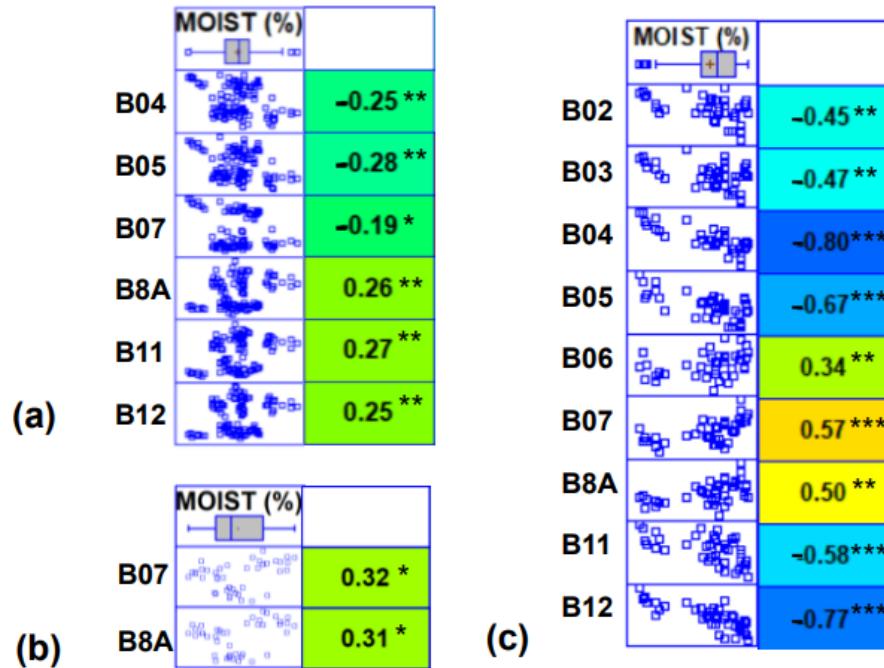
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Correlation coefficient: -1.0  1.0



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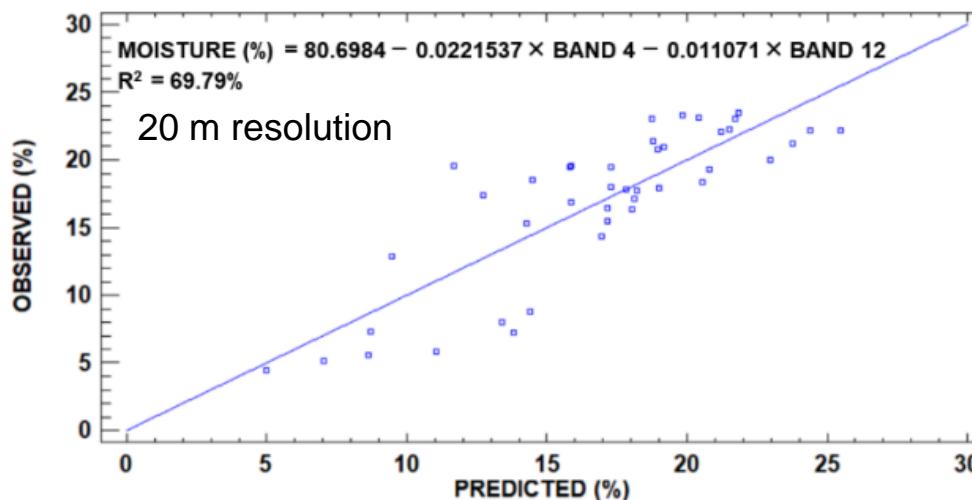
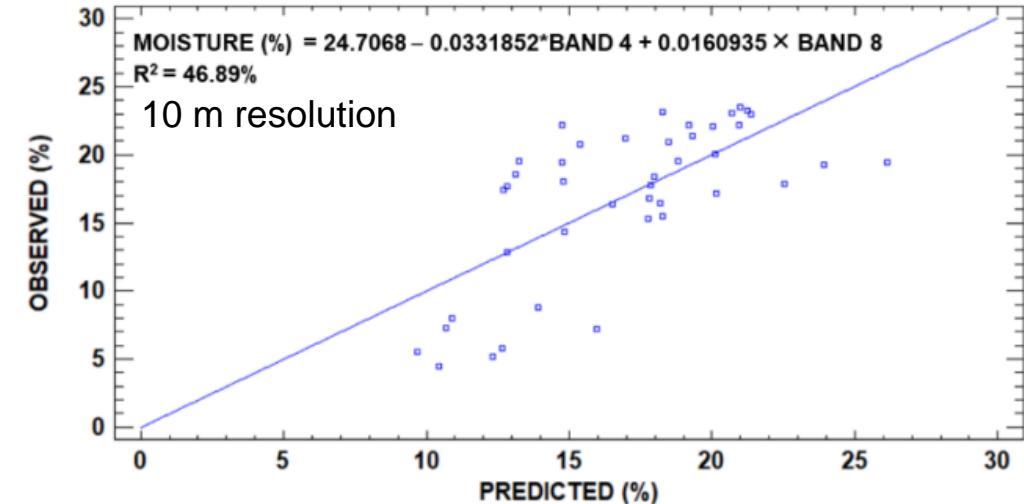
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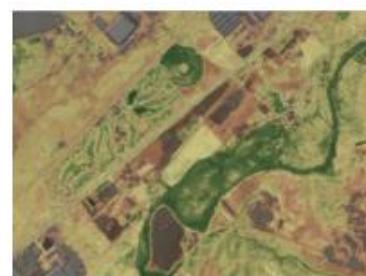
VERIFICATION

20/09/2021

10 m eq.



20 m eq.

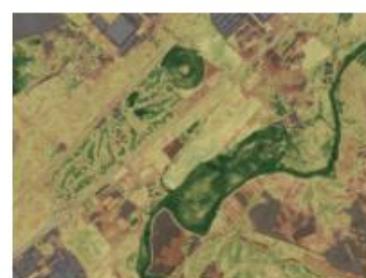


10 m eq.



12/06/2021

20 m eq.



APPLICATIONS BASED ON SATELITE

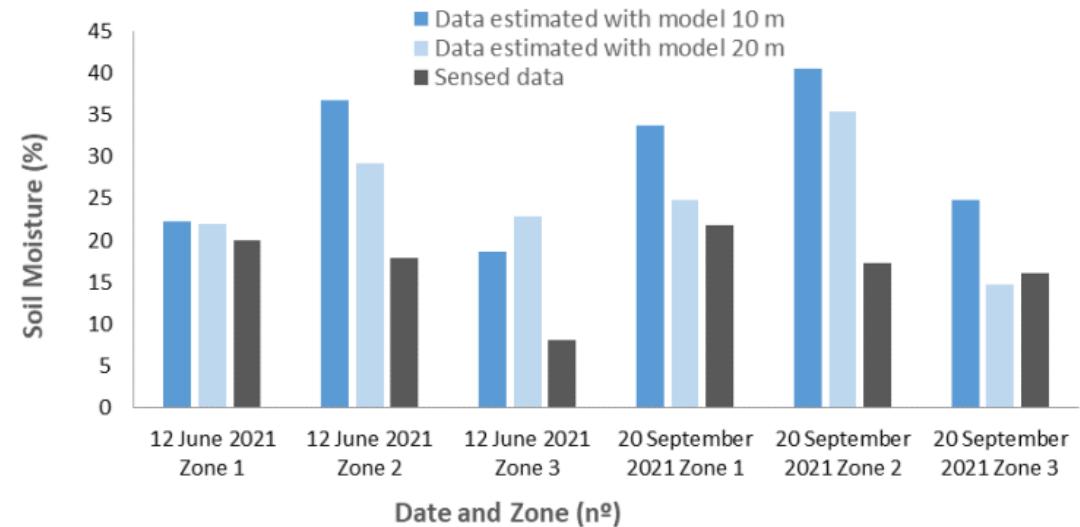
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The mean absolute error (MAE) is 12.5% and 8.4% for the models calculated with bands with resolutions of 10 m and 20 m respectively.

APPLICATIONS BASED ON SATELITE

Motivation: Identify the best variety according to its production.

Task: Correlate harvested seeds with remote sensing information.

Objectives:

1. Find the best band or band combination to estimate the production of *Camelia sativa*.



Parra, M., Parra, L., Mostaza-Colado, D., Mauri, P., & Lloret, J. (2020). Using satellite imagery and vegetation indices to monitor and quantify the performance of different varieties of Camelina Sativa. In GEOProcessing 2020 The Twelfth International Conference on Advanced Geographic Information Systems, Applications, and Services. IARIA, Valencia, Spain (pp. 42-47).

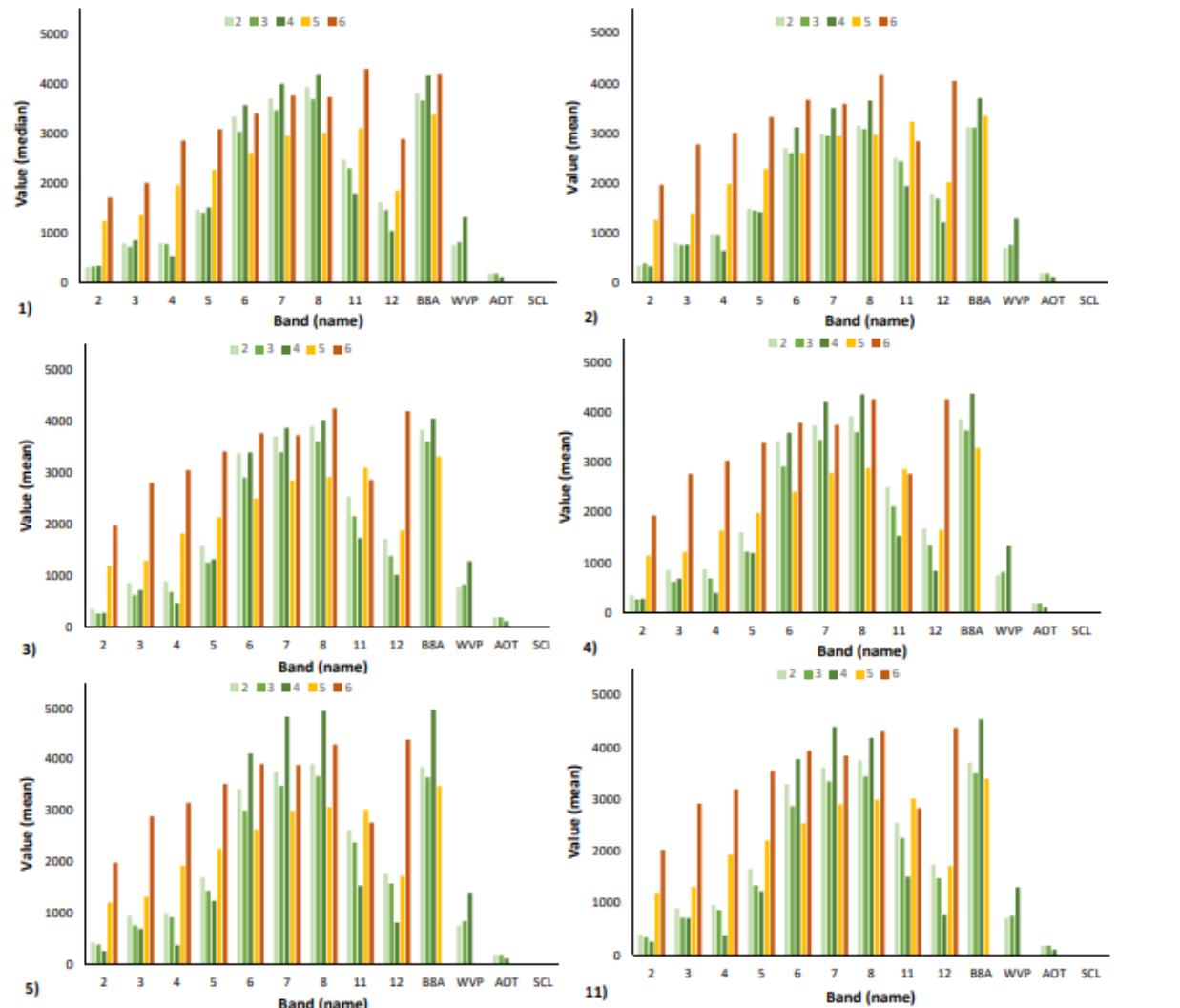
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Spectral signatures for different varieties and periods (February to June)

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We can affirm that there is no correlation between different tested indices and harvested seeds

TABLE I. VALUES OF NDWI FOR DIFFERENT VARIETIES

Month	NDWI per Varieties					
	5)	2)	1)	4)	11)	3)
2	-0.61	-0.66	-0.66	-0.65	-0.61	-0.64
3	-0.66	-0.65	-0.67	-0.71	-0.65	-0.71
4	-0.76	-0.68	-0.66	-0.73	-0.72	-0.70
5	-0.40	-0.36	-0.37	-0.41	-0.39	-0.39
6	-0.33	-0.31	-0.30	-0.32	-0.31	-0.31

TABLE II. VALUES OF NDMI FOR DIFFERENT VARIETIES

Month	NDMI per Varieties					
	5)	2)	1)	4)	11)	3)
2	0.20	0.12	0.23	0.22	0.19	0.21
3	0.21	0.12	0.23	0.26	0.21	0.25
4	0.53	0.31	0.40	0.48	0.49	0.40
5	0.01	-0.04	-0.02	0.00	0.00	-0.03
6	-0.05	-0.07	-0.07	-0.06	-0.06	-0.07

TABLE III. VALUES OF EVI FOR DIFFERENT VARIETIES

Month	EVI per Varieties					
	5)	2)	1)	4)	11)	3)
2	1.08	0.84	1.23	1.18	1.06	1.14
3	1.09	0.88	1.24	1.27	1.06	1.28
4	2.18	1.49	1.86	2.13	2.12	1.87
5	0.51	0.46	0.48	0.75	0.47	0.56
6	0.29	0.27	0.27	0.31	0.27	0.30

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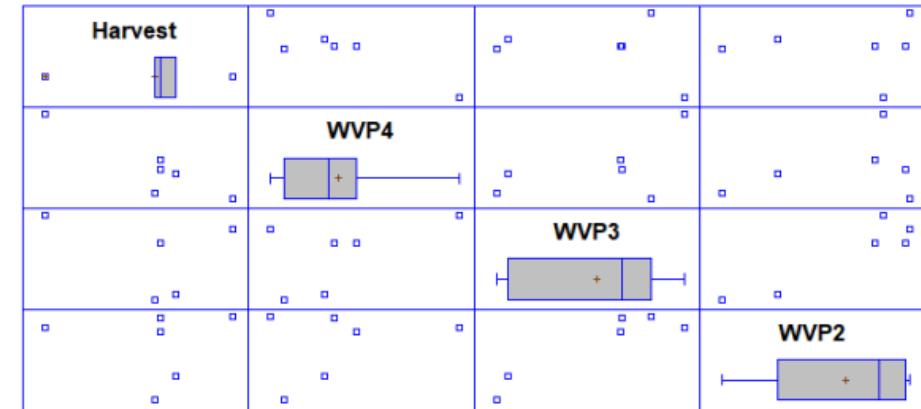
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All this data confirms that the model is accurate and it can be used to predict in the future the harvest of *Camelina sativa* crops based on data of WVP.



$$\text{Harvest} = 1 / (-0.00229478 + 1.95954 \times 10^{-9} \times \text{WVP4}^2)$$

correlation coefficient is 0.926

R² 85.81

standard error is 0.0001

mean absolute error is 0.00007

p-value of the model is 0.0079.

APPLICATIONS BASED ON DRONE

Motivation: Identify weed plants.

Task: Determine the maximum flying height which can be used to detect weed plants on a golf course.

Objectives:

1. Define a methodology to detect weed plants in greens.
2. Identify the maximum height at which methodology can be applied.

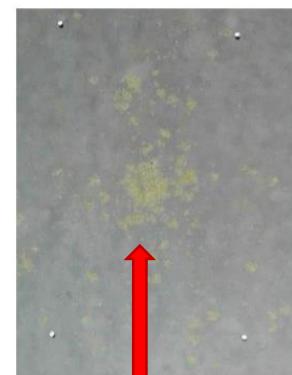


3 testing areas with variable weed presence

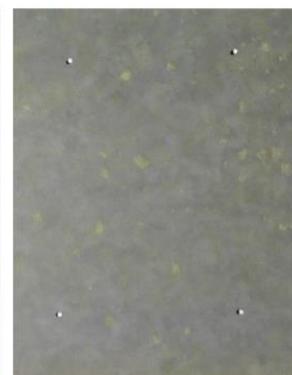
High

Medium

Low



Weed plant



Tested flying heights:
4, 8, 10, 12, and 16m

Vegetation Index= $B1+B2-B3$

Marin, J.F., Mostaza-Colado, D., Parra, L., Yousfi, S., Mauri, P.V., Lloret, J., (2021). Comparison of Performance in Weed Detection with Aerial RGB and Thermal Images Gathered at Different Height. The Seventeenth International Conference on Networking and Services (ICNS 2021), Valencia, Spain, 30 may – 3 June, 2021.

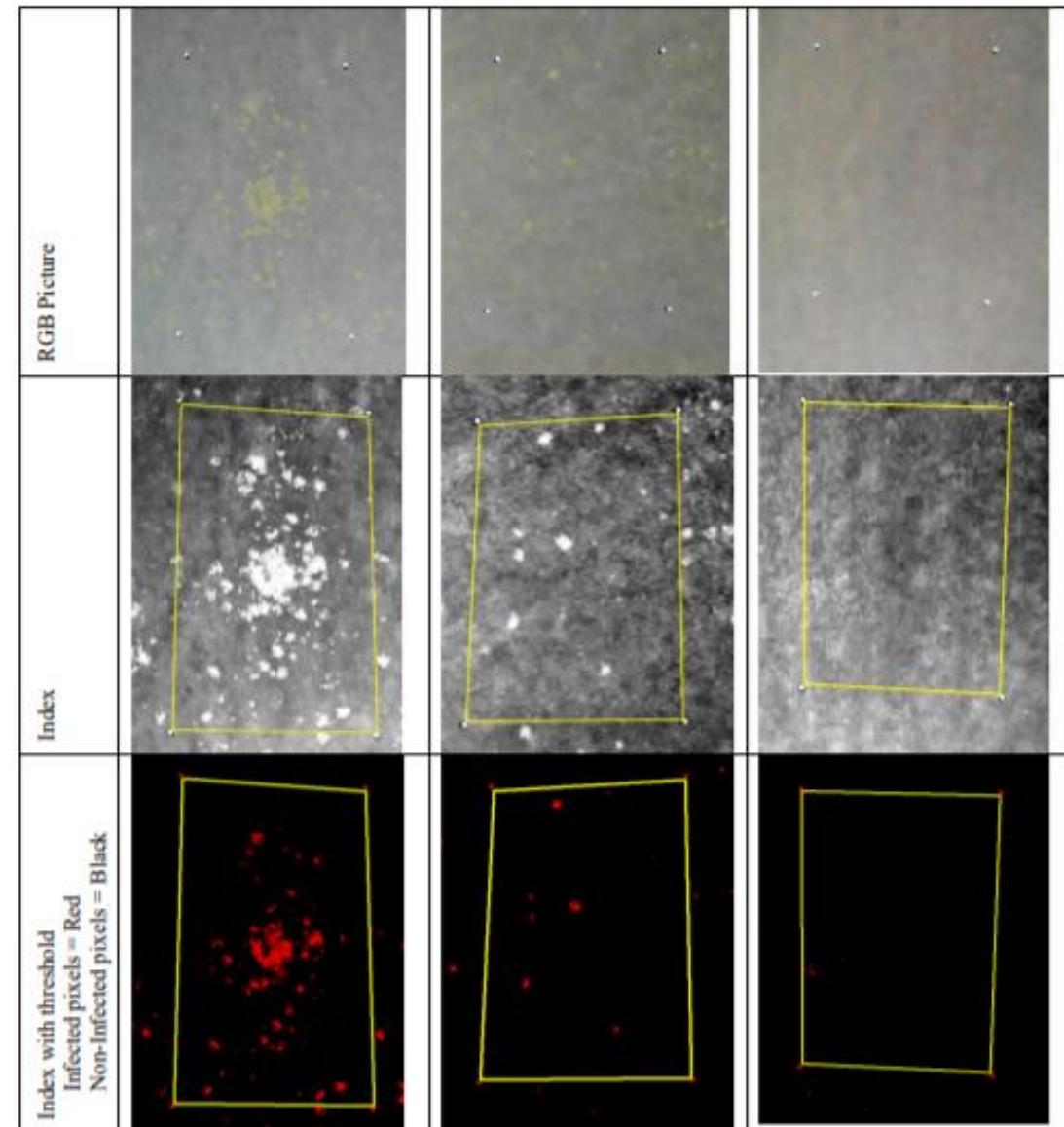
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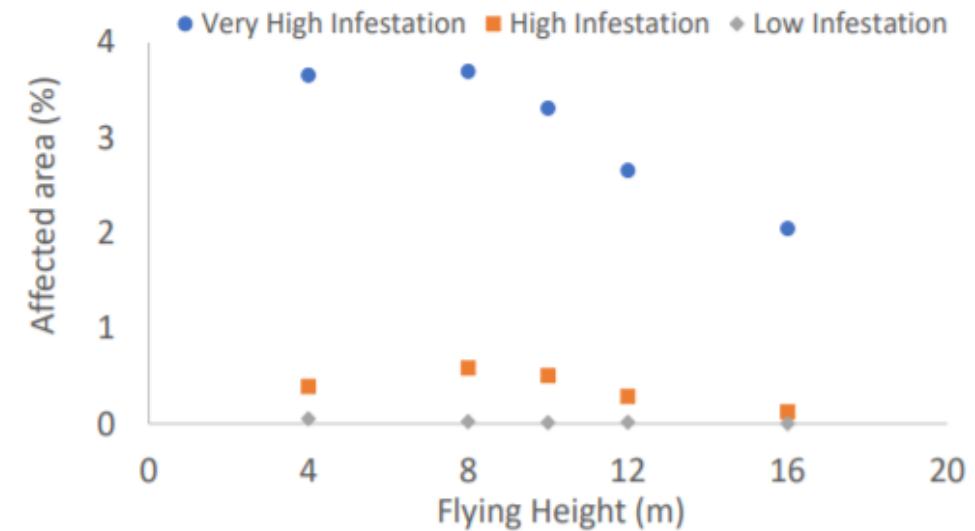
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Maximum height of 10 m for this methodology

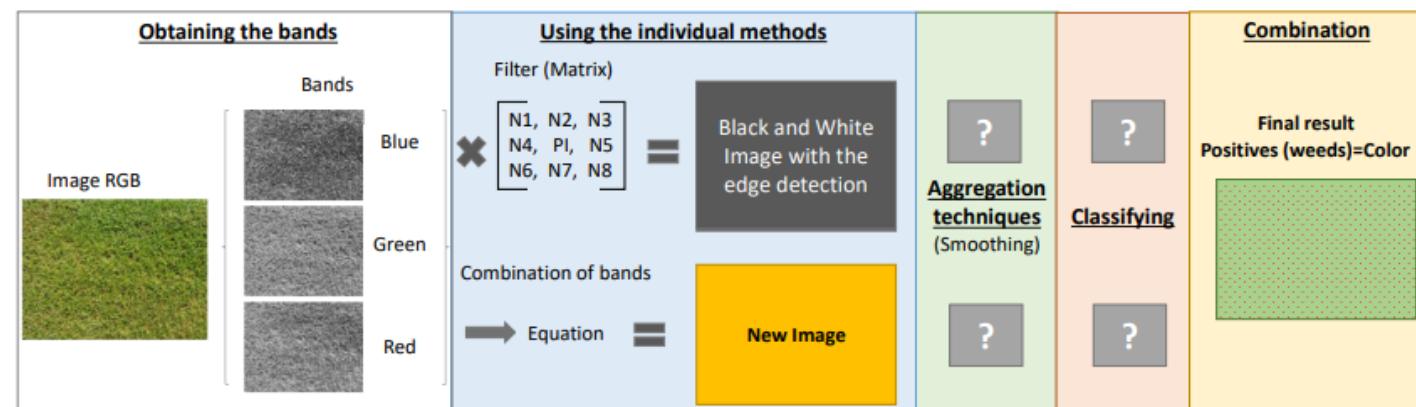
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APPLICATIONS BASED ON DRONE

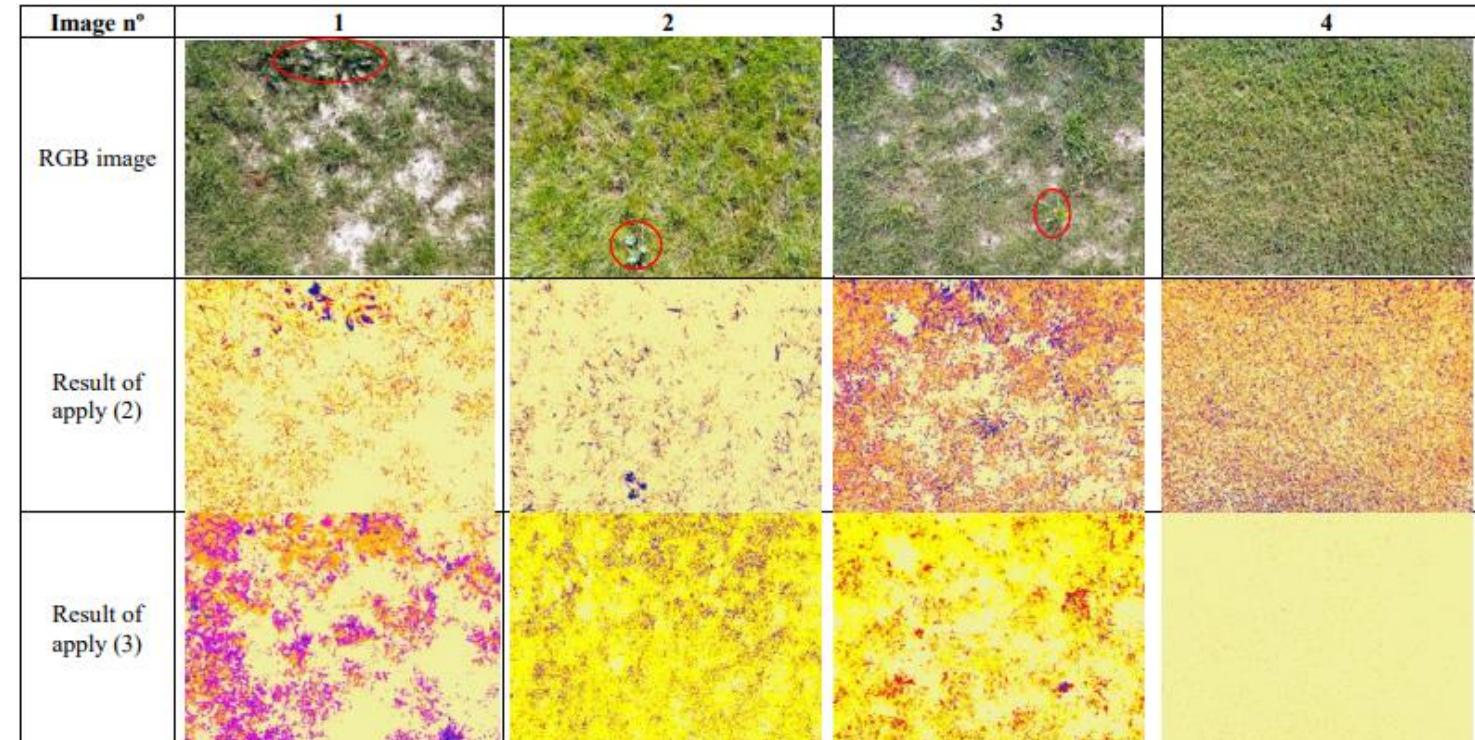
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Results of analysis with band combination



APPLICATIONS BASED ON DRONE

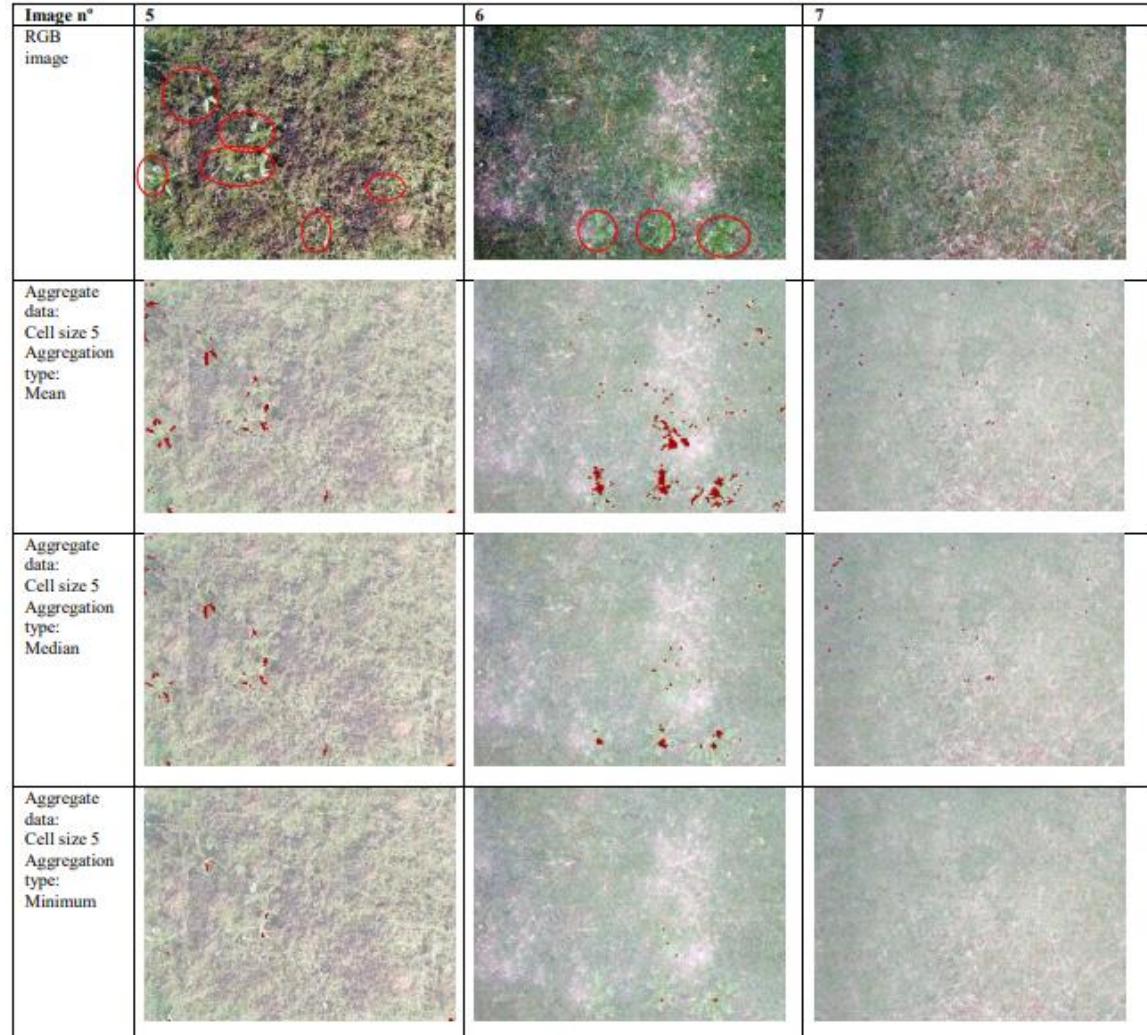
Motivation: Identify weed plants.

Task: Determine the best methodology to detect the weed plant.

Objectives:

1. Define a methodology to detect weed plants in greens.

Results of analysis with band combination



APPLICATIONS BASED ON DRONE

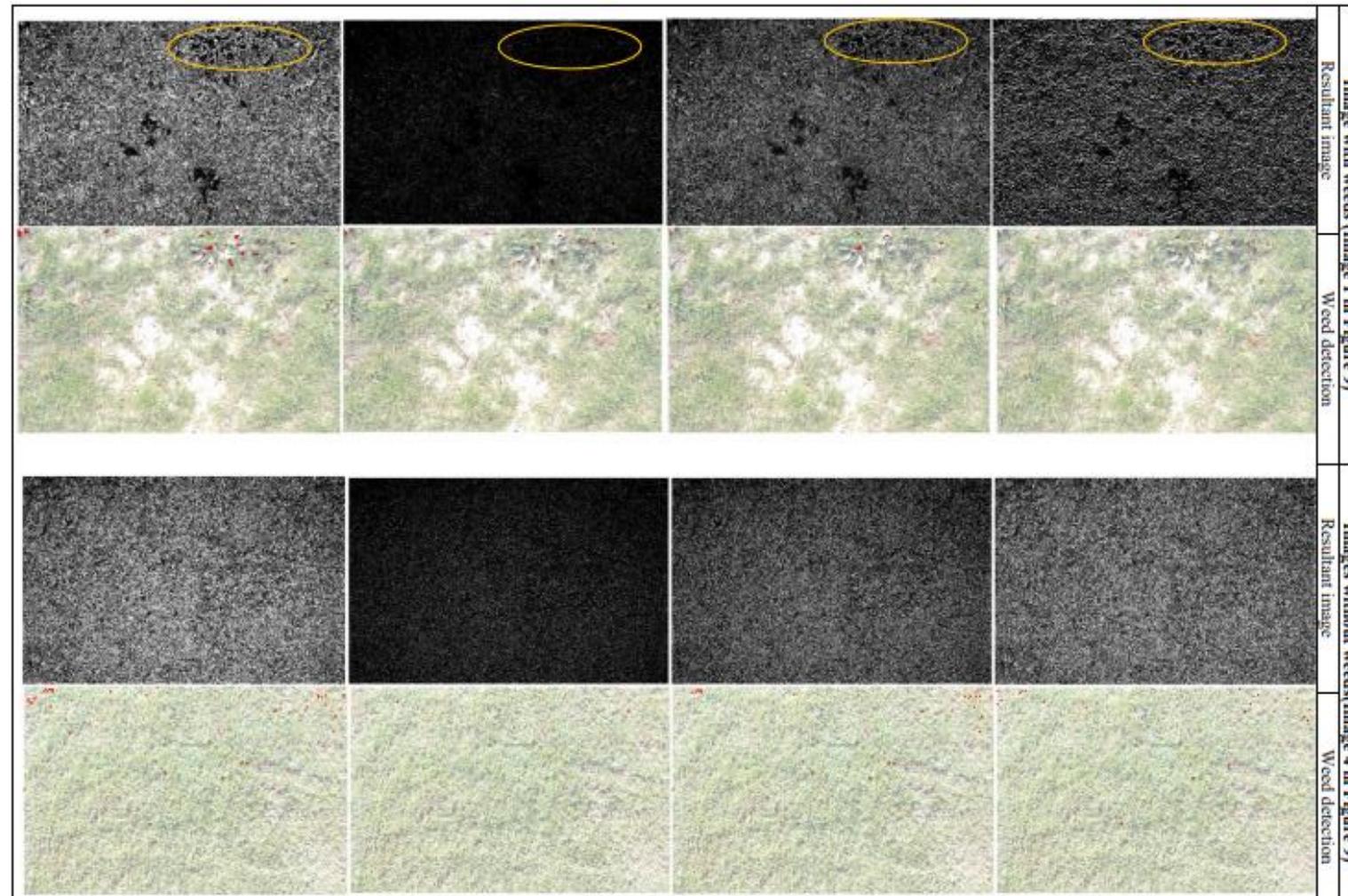
Results of analysis with different edge filters

Motivation: Identify weed plants.

Task: Determine the best methodology to detect the weed plant.

Objectives:

1. Define a methodology to detect weed plants in greens.



APPLICATIONS BASED ON DRONE

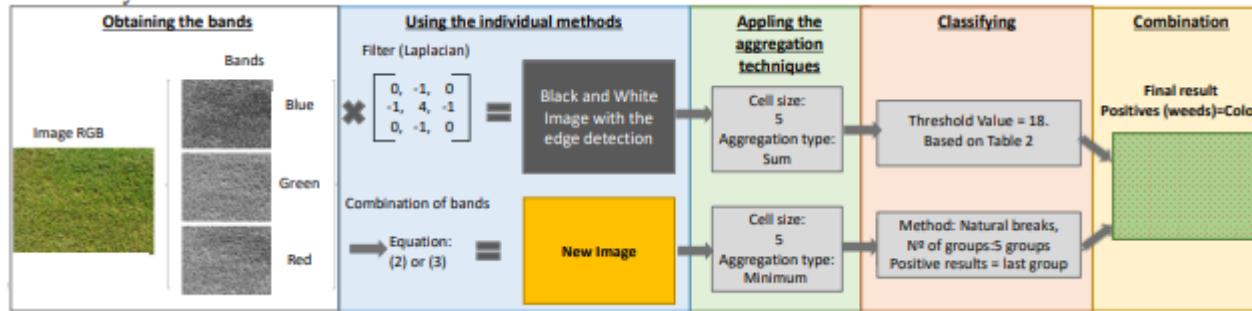
Results of analysis combining both methodologies

Motivation: Identify weed plants.

Task: Determine the best methodology to detect the weed plant.

Objectives:

1. Define a methodology to detect weed plants in greens.



The proposed methodology offers an accurate detection

Image	1)	2)
RGB image		
Image of RGB Band Operations using (3)		
Image of Edge detection		
Resultant image of combinations:	<ul style="list-style-type: none">• Blue pixels (positive results of RGB)• Pink pixels (positive results of edge detection)• Black pixels (positive results of combination)	

APPLICATIONS BASED ON DRONE

Motivation: Identify resistance to hydric stress in different turfgrass species.

Task: Determine the best parameters to differentiate between turfgrass species.

Objectives:

1. Compare remote (drone) and proximal (camera) sensing to evaluate the response of different species to hydric stress.
2. Compare the correlations between remote and proximal sensing with other parameters.



APPLICATIONS BASED ON DRONE

Motivation: Identify resistance to hydric stress in different turfgrass species.

Task: Determine the best parameters to differentiate between turfgrass species.

Objectives:

1. Compare remote (drone) and proximal (camera) sensing to evaluate the response of different species to hydric stress.
2. Compare the correlations between remote and proximal sensing with other parameters.

Significance is equal for both proximal and remote sensing.

	Limited irrigation	High irrigation	Level of significance
NDVI	0.65	0.80	0.000***
GA_{ground} RGB	0.49	0.78	0.000***
GA_{aerial} RGB	0.50	0.79	0.000***
CT	20.00	13.70	0.000***
SM	24.05	45.02	0.000***

	Limited irrigation			High irrigation		
	Mixtures		Significance	Mixtures		Significance
	Festuca-C ₄	Poa-C ₄		Festuca-C ₄	Poa-C ₄	
NDVI	0.69	0.58	0.000***	0.77	0.80	0.000***
GA_{ground} RGB	0.59	0.40	0.000***	0.75	0.81	0.000***
GA_{aerial} RGB	0.57	0.44	0.000***	0.76	0.83	0.001***
CT	18.33	20.51	0.000***	13.33	14.20	0.065 ^{ns}
SM	23.50	24.5	0.179 ^{ns}	44.78	45.27	0.095 ^{ns}

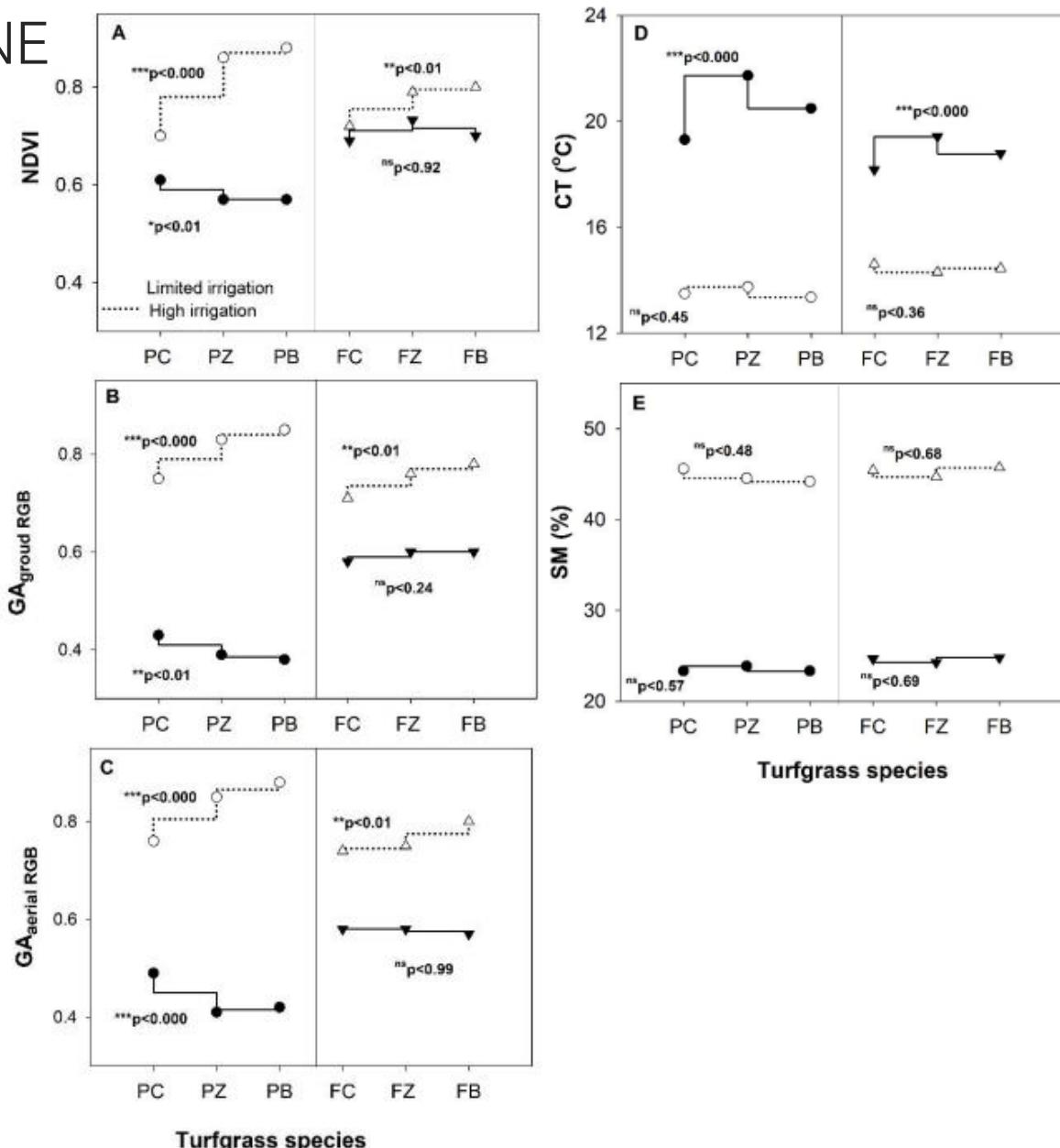
APPLICATIONS BASED ON DRONE

Motivation: Identify resistance to hydric stress in different turfgrass species.

Task: Determine the best parameters to differentiate between turfgrass species.

Objectives:

1. Compare remote (drone) and proximal (camera) sensing to evaluate the response of different species to hydric stress.
2. Compare the correlations between remote and proximal sensing with other parameters.



Yousfi, S., Marín, J., Parra, L., Lloret, J., & Mauri, P. V. (2022). Remote sensing devices as key methods in the advanced turfgrass phenotyping under different water regimes. Agricultural Water Management, 266, 107581.

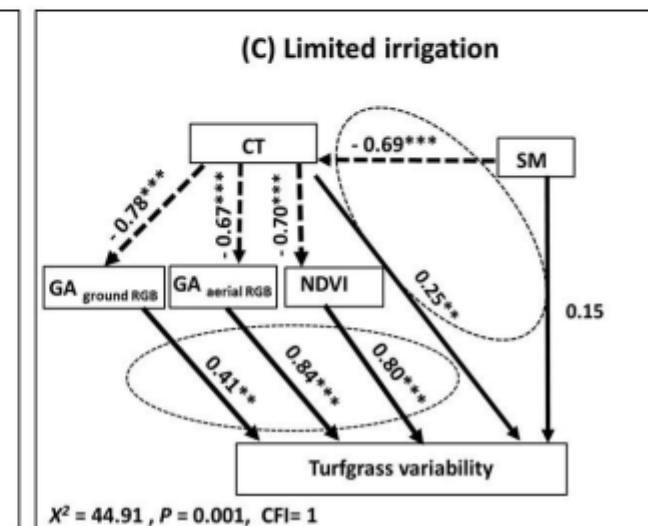
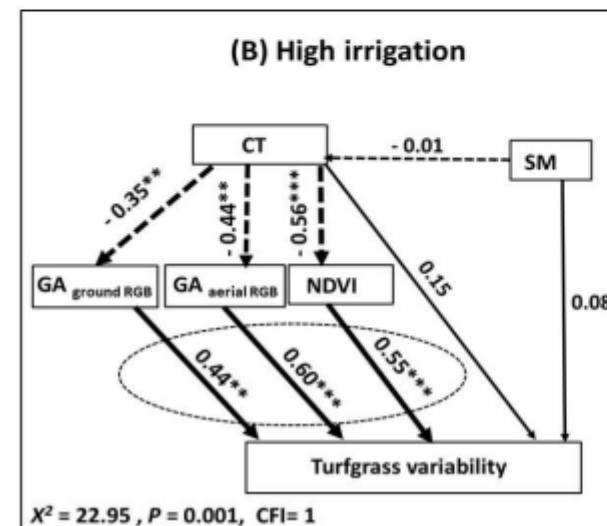
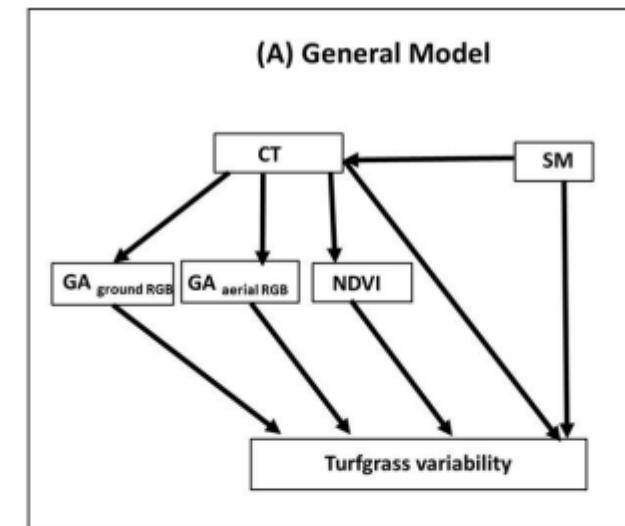
APPLICATIONS BASED ON DRONE

Motivation: Identify resistance to hydric stress in different turfgrass species.

Task: Determine the best parameters to differentiate between turfgrass species.

Objectives:

1. Compare remote (drone) and proximal (camera) sensing to evaluate the response of different species to hydric stress.
2. Compare the correlations between remote and proximal sensing with other parameters.



APPLICATIONS BASED ON DRONI

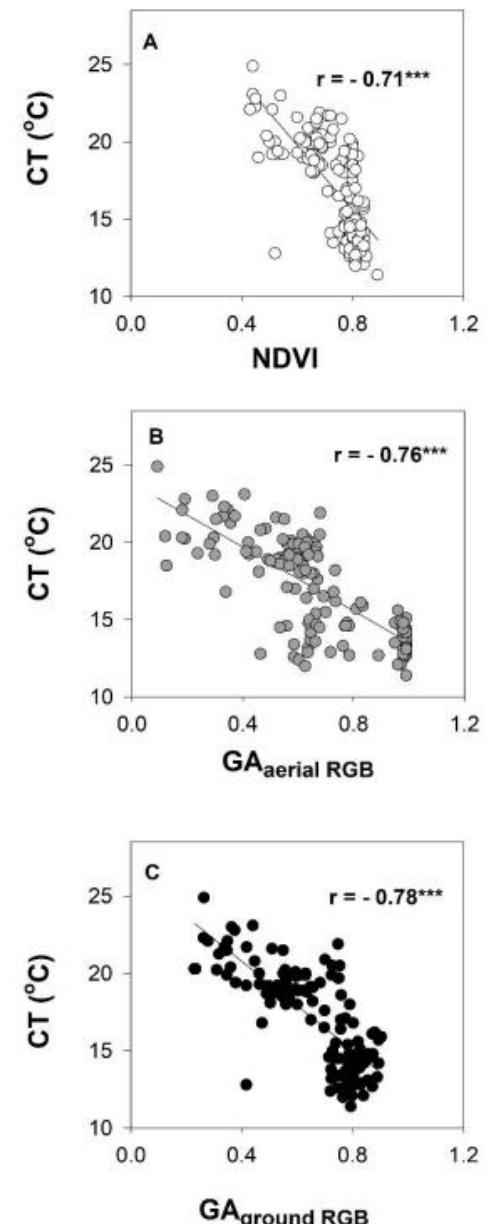
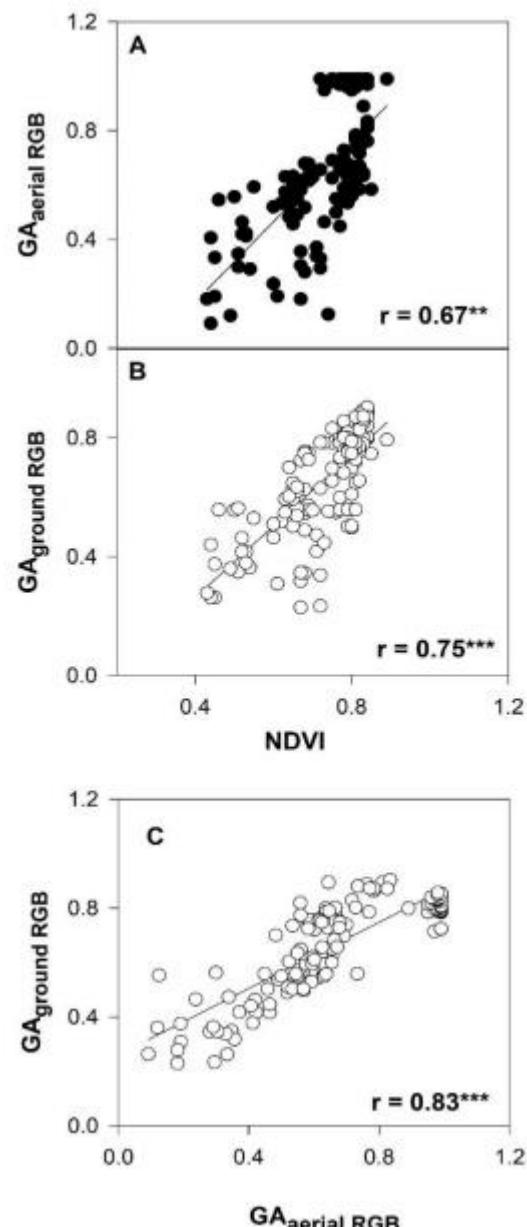
Motivation: Identify resistance to hydric stress in different turfgrass species.

Task: Determine the best parameters to differentiate between turfgrass species.

Objectives:

1. Compare remote (drone) and proximal (camera) sensing to evaluate the response of different species to hydric stress.
2. Compare the correlations between remote and proximal sensing with other parameters.

Proximal sensing offer more accurate correlations than remote sensing



APPLICATIONS BASED ON DRONE

Motivation: Identify establishment success.

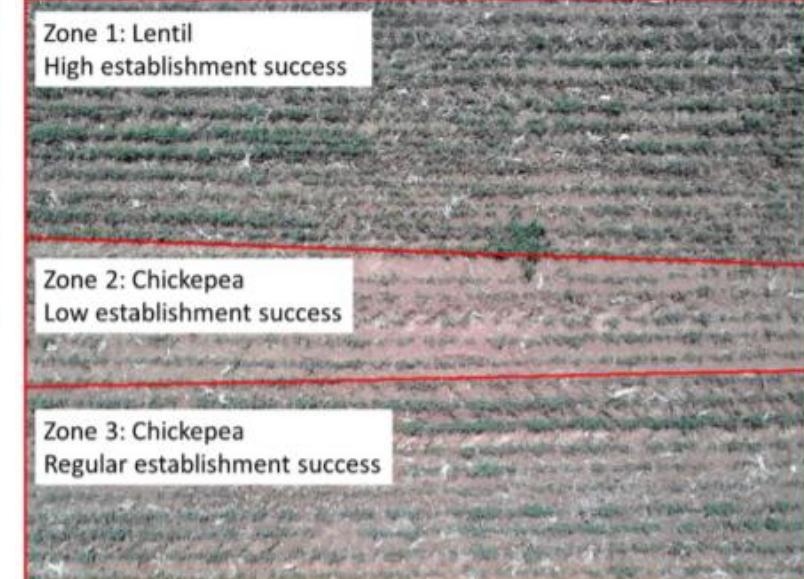
Task: Compare the establishment success of a given area with lentil and chickpea.

Objectives:

1. Evaluate the use of band combinations to estimate the establishment success of legumes.
2. Evaluate the use of different aggregation techniques and flying height that maintain the accuracy while reducing the required storage capacity.



Selected drone:
Parrot BeBop 2 Pro Thermal



APPLICATIONS BASED ON DRONE

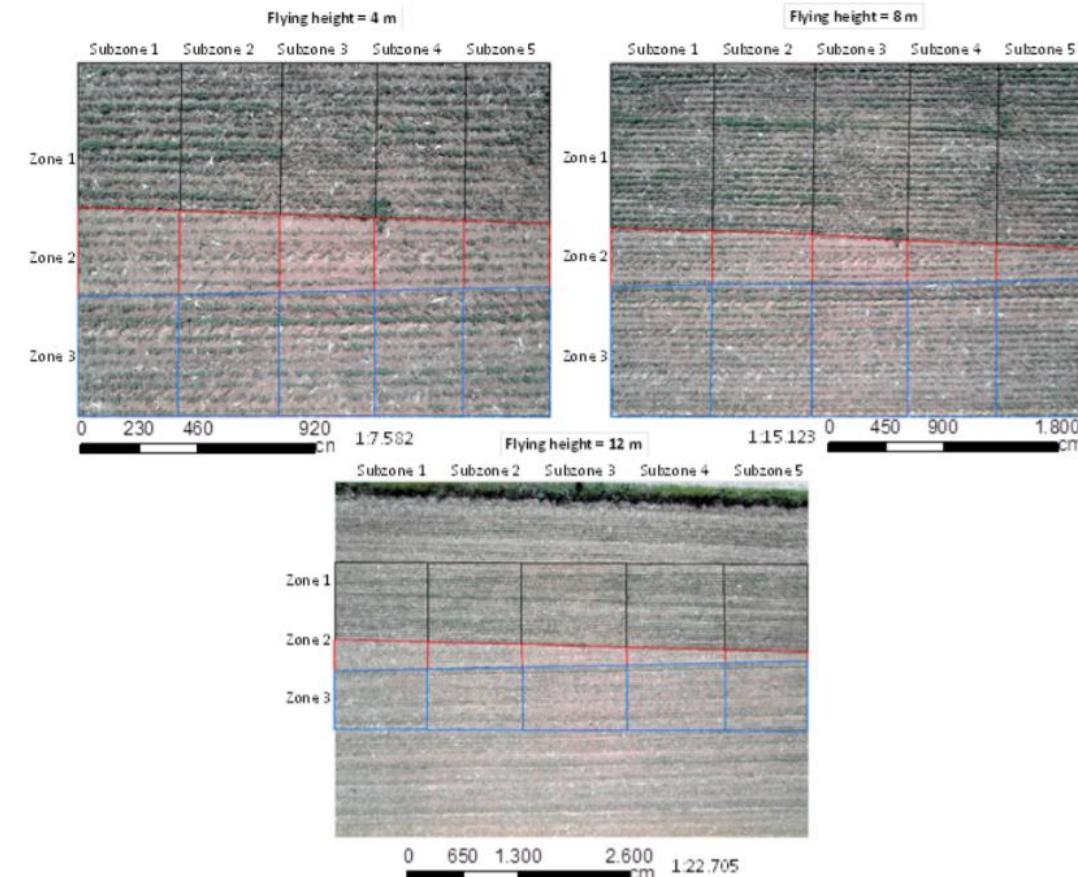
Motivation: Identify establishment success.

Task: Compare the establishment success of a given area with lentil and chickpea.

Objectives:

1. Evaluate the use of band combinations to estimate the establishment success of legumes.
2. Evaluate the use of different aggregation techniques and flying height that maintain the accuracy while reducing the required storage capacity.

Images are gathered at 3 different height, and divided into 5 subzones for each zone



APPLICATIONS BASED ON DRONE

Motivation: Identify establishment success.

Task: Compare the establishment success of a given area with lentil and chickpea.

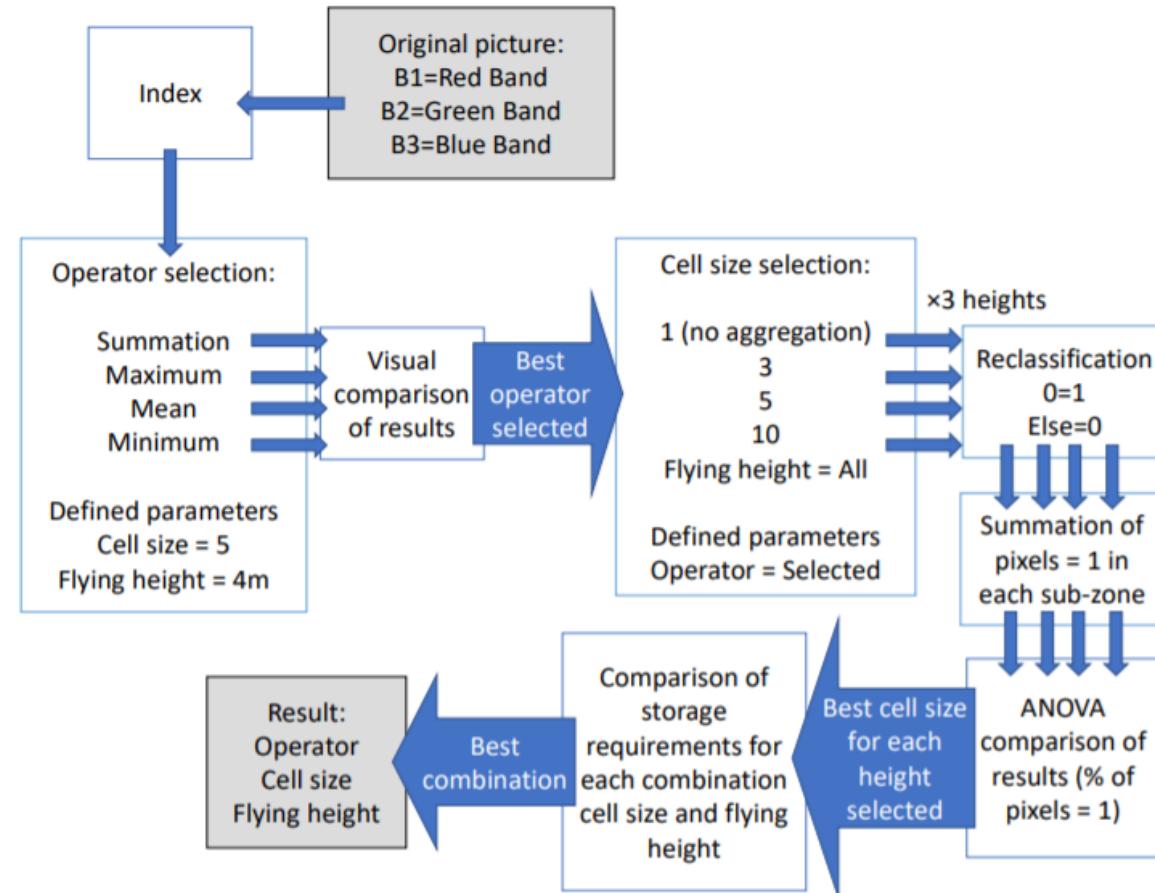
Objectives:

1. Evaluate the use of band combinations to estimate the establishment success of legumes.
 2. Evaluate the use of different aggregation techniques and flying height that maintain the accuracy while reducing the required storage capacity.

Followed approach:

Differentiate the green leaves from the soil with an index and apply the following process:

Index: B1/B2



APPLICATIONS BASED ON DRONE

Motivation: Identify establishment success.

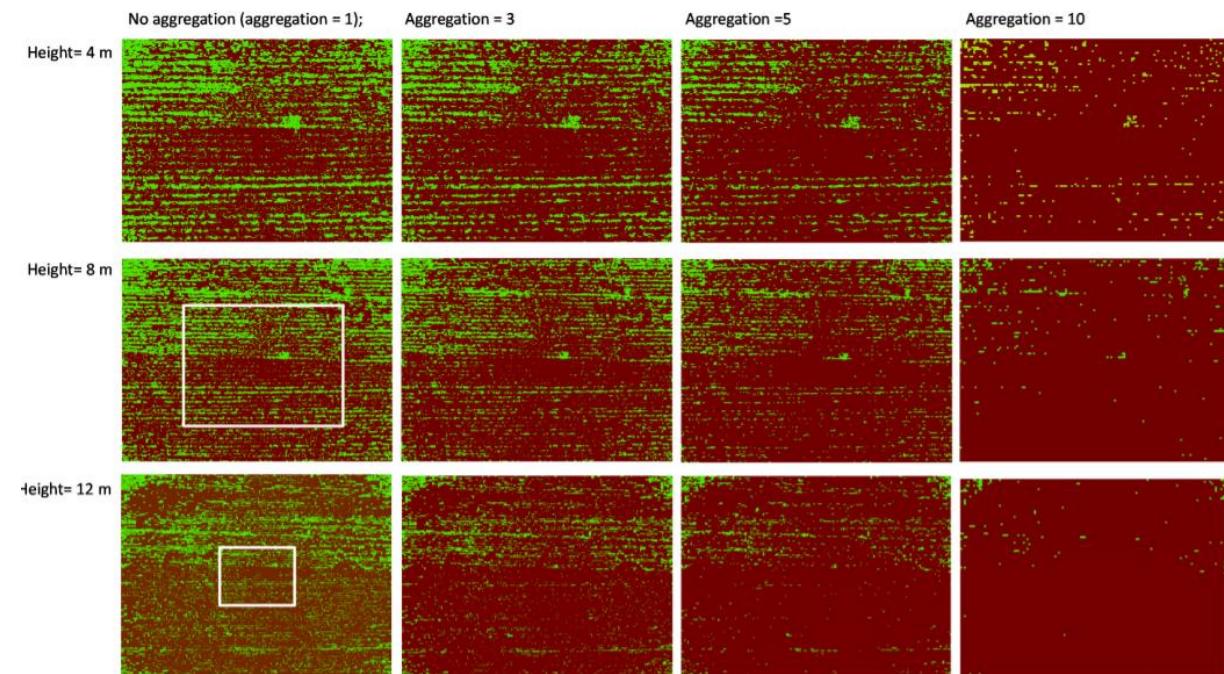
Task: Compare the establishment success of a given area with lentil and chickpea.

Objectives:

1. Evaluate the use of band combinations to estimate the establishment success of legumes.
2. Evaluate the use of different aggregation techniques and flying height that maintain the accuracy while reducing the required storage capacity.

Initial results:

Differentiate the green leaves from the soil with an index
and apply the following process:
Index: B1/B2



APPLICATIONS BASED ON DRONE

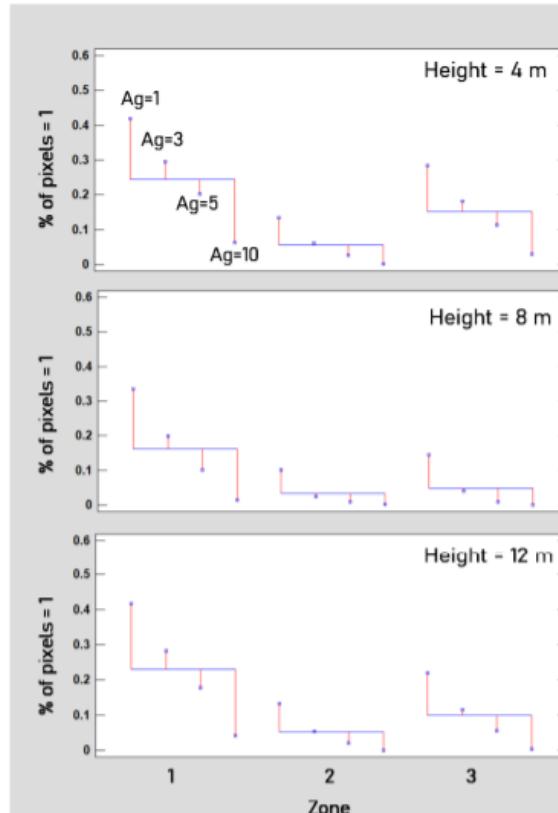
Classification of results for different flying height and aggregation techniques

Motivation: Identify establishment success.

Task: Compare the establishment success of a given area with lentil and chickpea.

Objectives:

1. Evaluate the use of band combinations to estimate the establishment success of legumes.
2. Evaluate the use of different aggregation techniques and flying height that maintain the accuracy while reducing the required storage capacity.



Combination flying height and cell size	4 m 1 pixel	4 m 3 pixel	4 m 5 pixel	4 m 10 pixel
p-value	0.0001	0.0003	0.0010	0.0097
Nº of groups	3	3	3	2
Zone 1	C	C	C	B
Zone 2	A	A	A	A
Zone 3	B	B	B	AB

Combination flying height and cell size	8 m 1 pixel	8 m 3 pixel	8 m 5 pixel	8 m 10 pixel
p-value	0.0000	0.0000	0.0002	0.0012
Nº of groups	3	3	2	2
Zone 1	C	C	B	B
Zone 2	A	A	A	A
Zone 3	B	B	A	A

Combination flying height and cell size	12 m 1 pixel	12 m 3 pixel	12 m 5 pixel	12 m 10 pixel
p-value	0.0000	0.0000	0.0000	0.0061
Nº of groups	3	2	2	2
Zone 1	C	B	B	B
Zone 2	A	A	A	A
Zone 3	B	A	A	A

Band combination is useful to estimate establishment success

APPLICATIONS BASED ON DRONE

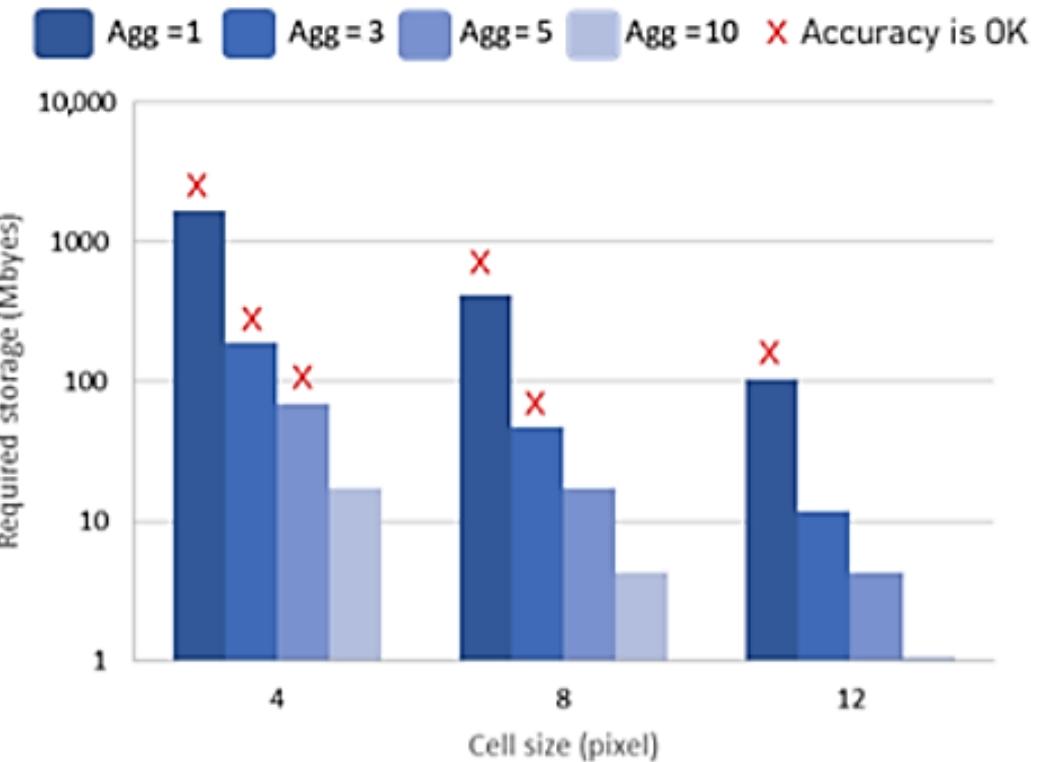
Motivation: Identify establishment success.

Task: Compare the establishment success of a given area with lentil and chickpea.

Objectives:

1. Evaluate the use of band combinations to estimate the establishment success of legumes.
2. Evaluate the use of different aggregation techniques and flying height that maintain the accuracy while reducing the required storage capacity.

Required storage capacity for each option



The combination of a flying height of 8 m and an aggregation technique with cell size = 3 is the one that minimizes the required storage capacity.

APPLICATIONS BASED ON DRONE

Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.



APPLICATIONS BASED ON DRONE

Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
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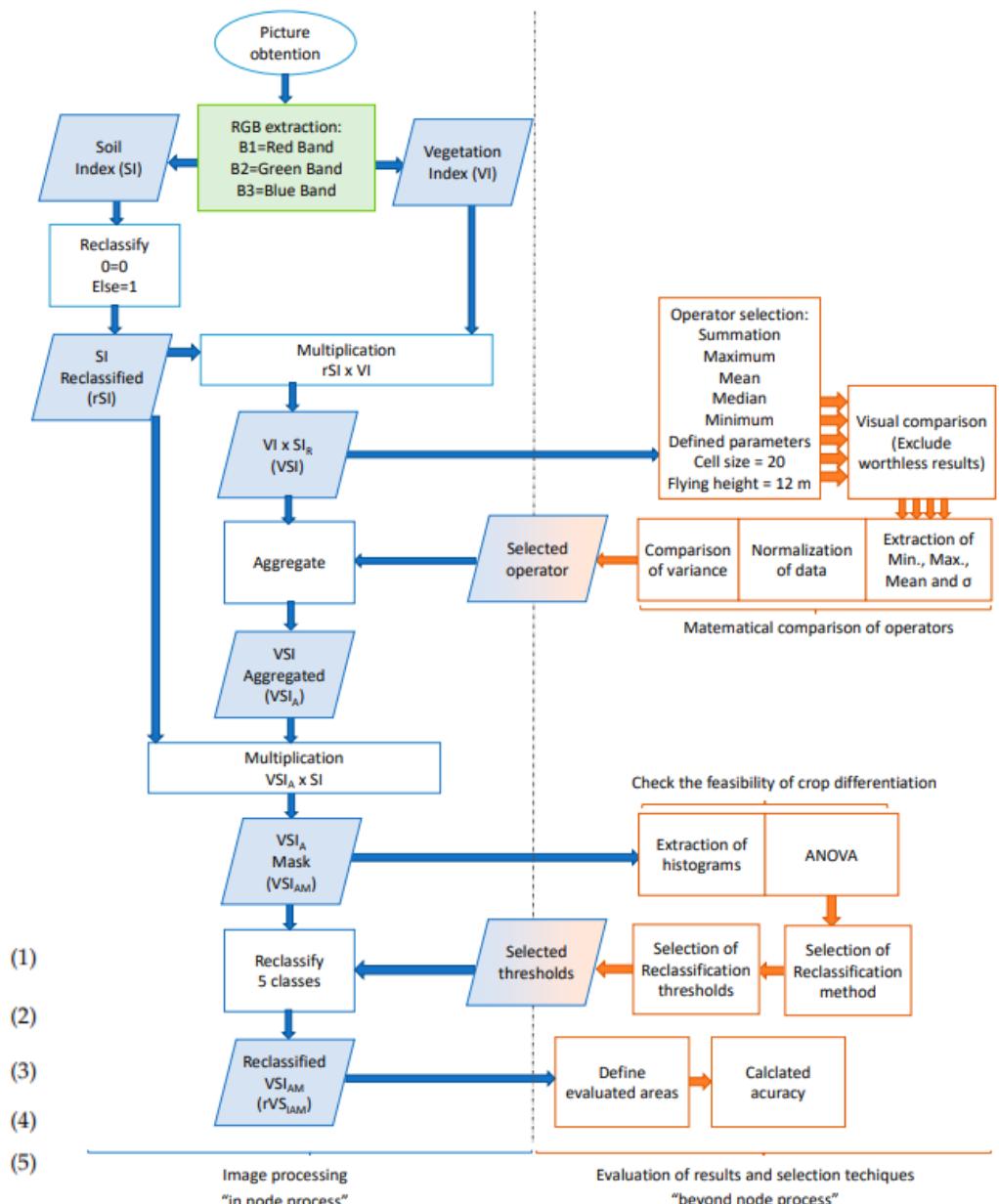
$$SI = \frac{B_2}{B_1}$$

if ($SI = 0$) $rSI = 0$ [else $rSI = 1$]

$$VI = \frac{B_3 \times 10}{B_2}$$

$$VSI = rSI \times VI$$

$$VSI_{AM} = VSI_a \times VrSI$$



APPLICATIONS BASED ON DRONE

Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.

$$SI = \frac{B_2}{B_1} \quad (1)$$

if ($SI = 0$) $rSI = 0$ [else $rSI = 1$] (2)

$$VI = \frac{B_3 \times 10}{B_2} \quad (3)$$

$$VSI = rSI \times VI \quad (4)$$

$$VSI_{AM} = VISA \times VrSI \quad (5)$$

Algorithm 1: The Code for Aggregate Operation

```
# Code for Aggregate Operation
import arcpy
from arcpy import env
from arcpy.sa import *
env.workspace = "C:/sapyexamples/data"
outAggreg = Aggregate("VSI", 20, "SUMMATION", "TRUNCATE", "DATA")
outAggreg.save("C:/sapyexamples/output/VSIa")
```

Algorithm 2: The Code for Reclassify Operation

```
# Code for Reclassify Operation
import arcpy
from arcpy import env
from arcpy.sa import *
env.workspace = "C:/sapyexamples/data"
outReclass1 = Reclassify("VSlam", "Value",
RemapRange ([[0,1], [0,a,2], [a,b,2], [b,c,3], [c,d,4], [d,e,5]]))
outReclass1.save("C:/sapyexamples/output/rVSlam")
```

APPLICATIONS BASED ON DRONE

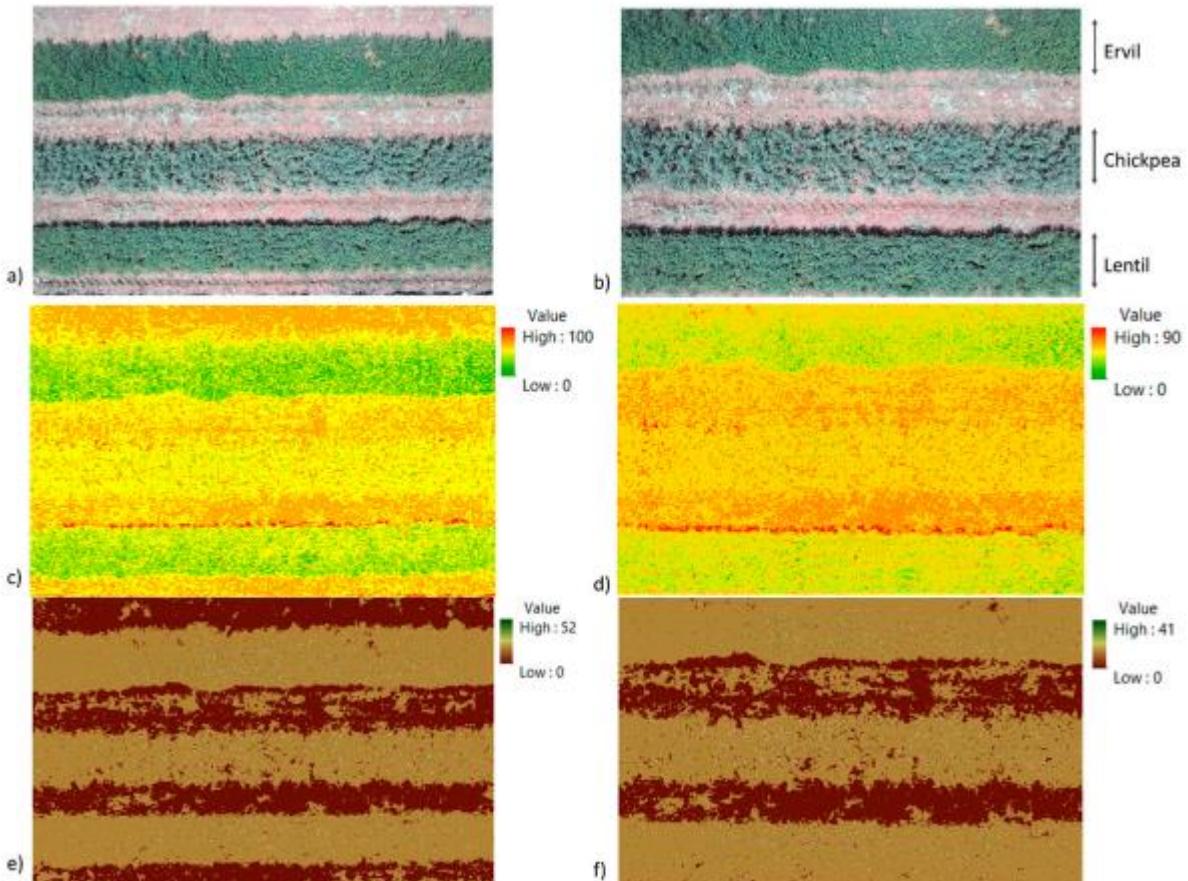
Results of vegetation and soil index

Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.



APPLICATIONS BASED ON DRONE

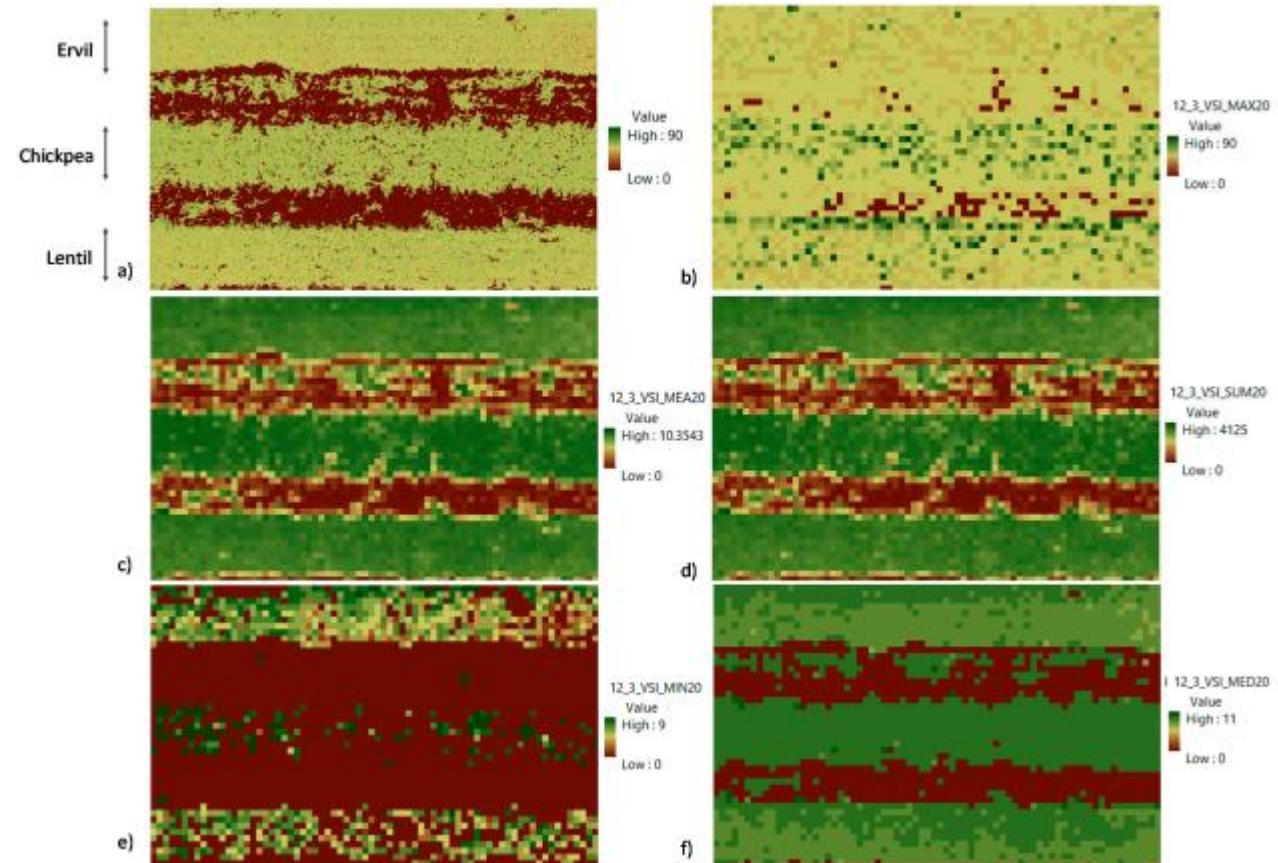
Results of aggregation (different operators)

Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.



APPLICATIONS BASED ON DRONE

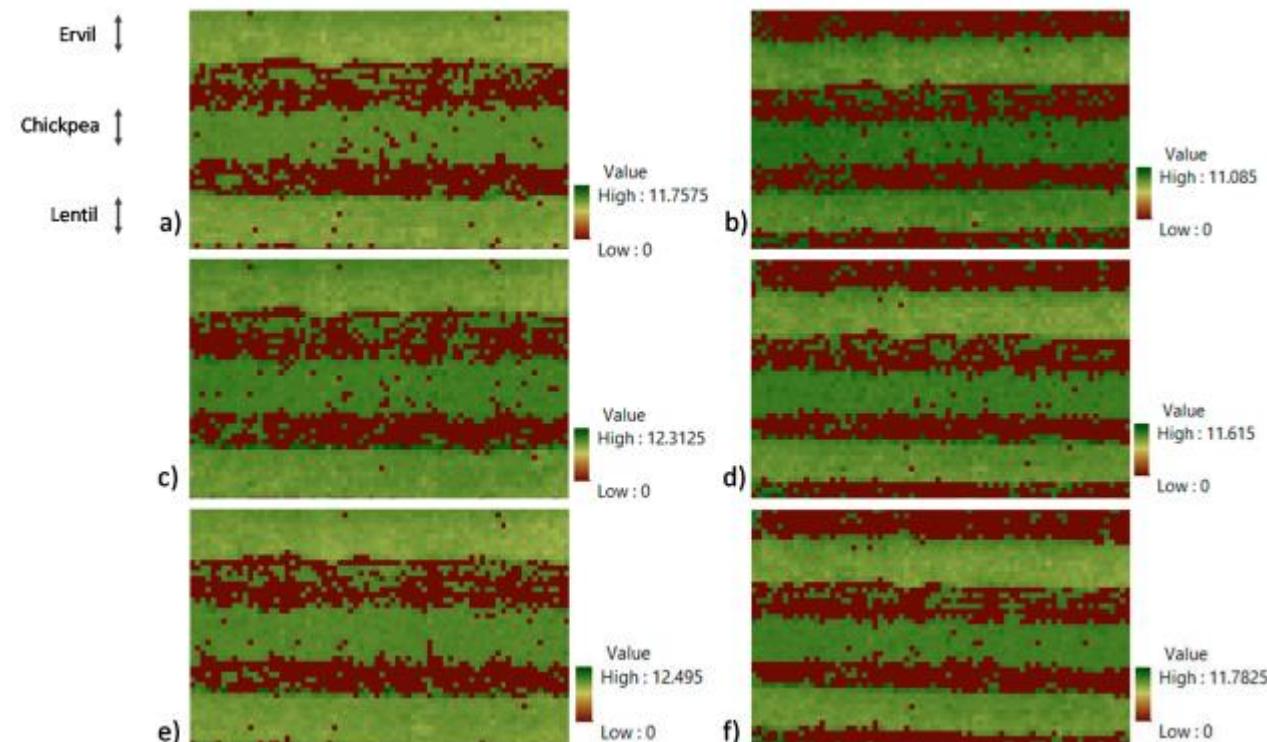
Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.

Results of aggregation for different pictures



APPLICATIONS BASED ON DRONE

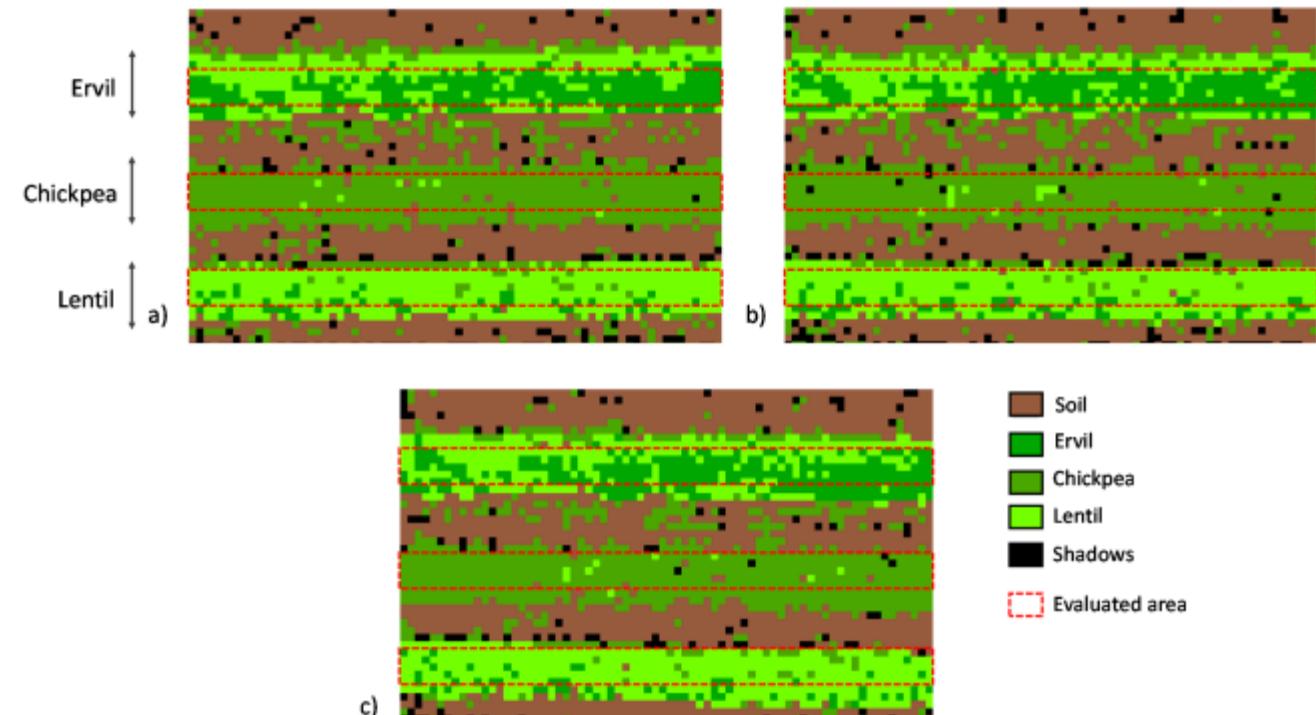
Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.

Classification results for 16 m picture



APPLICATIONS BASED ON DRONE

Motivation: Differentiate species in intercropping.

Task: Differentiate three legumes (chickpea, lentil, and ervil).

Objectives:

1. Evaluate if a low-cost drone with an RGB camera can serve as an information source to differentiate crops.
2. Generate a procedure based on an index to differentiate crops.
3. Evaluate if results vary with the flying height.

Comparison of confusion matrix

Table 6. Confusion matrix of the three studied zones for the three rVSI_{AM} using the threshold values as a classification option.

Crop Type	Ervil	Assigned Crop Type		
		Chickpea	Lentil	Other
Ervil	60% (649)	0% (0)	40% (436)	0% (1)
Chickpea	1% (9)	95% (1021)	1% (14)	3% (36)
Lentil	8% (82)	5% (54)	86% (932)	1% (7)

Table 7. Confusion matrix of the three studied zones for the three rVSI_{AM} using the threshold values and RT as classification options.

Crop Type	Ervil	Assigned Crop Type		
		Chickpea	Lentil	Other
Ervil	67% (483)	1% (6)	32% (232)	0% (0)
Chickpea	0% (1)	95% (687)	4% (26)	0% (0)
Lentil	18% (130)	4% (27)	77% (556)	0% (0)



- ❑ Introduction
- ❑ Data in Digital Agriculture
 - ❑ Data and its relevance
- ❑ Examples of proposed solutions in real cases
 - ❑ Applications based on satellite
 - ❑ Applications based on drones
- ❑ Future perspective



Regarding data from sensors and images

- More powerful nodes will come with the strongest capacity for data processing and analysis, in which we can implement statistical tools to have better decisions.
- Adaptable event-triggered algorithms: Variable measuring periodicity or variable data resolution after the event.
- Inclusion of similar algorithms in other network elements (not only in the nodes).
- Sending the variation vs. sending the data.



Regarding sensors for agriculture

- New sensors will allow monitoring of more variables with better accuracies.
- New cameras will incorporate better spatial and spectral resolutions.
- The barriers (mostly high cost of sensors and lack of reliability on technology from farmers) that are stopping its application in real cases will be overcome, and their use will spread.
- Collaborative platforms joining data of several networks will be offered to farmers to manage their activity better, predict yields and diseases, and increase resource efficiency.



Regarding images for agriculture

- Drones will have an even more relevant role in the digitalization of agriculture, and satellites will enhance the spatial resolutions.
- The use of images will be common and will be integrated with sensors, creating a diverse network.
- Including multispectral or hyperspectral cameras will allow for better agriculture management. The generated data will be used for new applications such as phenotyping or selecting individuals in breeding lines



Future problems

- The use of images will be integrated with sensors, creating heterogeneous networks in areas with limited resources (energy, bandwidth, etc).
- The storage capacity will be a real constraint, which should be addressed soon.
- The multispectral cameras will require more powerful nodes to be able to process the generated information. At the same time, this will exacerbate the problems related to storage requirements.
- Nevertheless, the new multispectral cameras and the enhanced spatial resolution will incorporate new processing requirements.



LIST OF PAPERS INCLUDED IN THE KEYNOTE

Basterrechea, D.A., Parra, L., Lloret, J., Mauri, P.V.. (2020, October). Identifying the Existence of Grass Coverage in Vineyards Applying Time Series Analysis in Sentinel-2 Bands. The The Twelfth International Conference on Advanced Geographic Information Systems, Applications, and Services (GEOProcessing 2020), Valencia, Spain, 21-25 November, 2020.

Mauri, P. V., Parra, L., Mostaza-Colado, D., Garcia, L., Lloret, J., & Marin, J. F. (2021). The Combined Use of Remote Sensing and Wireless Sensor Network to Estimate Soil Moisture in Golf Course. *Applied Sciences*, 11(24), 11769.

Parra, M., Parra, L., Mostaza-Colado, D., Mauri, P., & Lloret, J. (2020). Using satellite imagery and vegetation indices to monitor and quantify the performance of different varieties of Camelina Sativa. In GEOProcessing 2020 The Twelfth International Conference on Advanced Geographic Information Systems, Applications, and Services. IARIA, Valencia, Spain (pp. 42-47).

Marin, J.F., Mostaza-Colado, D., Parra, L., Yousfi, S., Mauri, P.V., Lloret, J., (2021). Comparison of Performance in Weed Detection with Aerial RGB and Thermal Images Gathered at Different Height. The Seventeenth International Conference on Networking and Services (ICNS 2021), Valencia, Spain, 30 may – 3 June, 2021.

Parra-Boronat, L., Parra-Boronat, M., Torices, V., Marín, J., Mauri, P. V., & Lloret, J. (2019). Comparison of single image processing techniques and their combination for detection of weed in Lawns. *International Journal On Advances in Intelligent Systems*, 12(3-4), 177-190.

Yousfi, S., Marín, J., Parra, L., Lloret, J., & Mauri, P. V. (2022). Remote sensing devices as key methods in the advanced turfgrass phenotyping under different water regimes. *Agricultural Water Management*, 266, 107581.

Parra, L., Mostaza-Colado, D., Yousfi, S., Marin, J. F., Mauri, P. V., & Lloret, J. (2021). Drone RGB images as a reliable information source to determine legumes establishment success. *Drones*, 5(3), 79.

Parra, L., Mostaza-Colado, D., Marin, J. F., Mauri, P. V., & Lloret, J. (2022). Methodology to Differentiate Legume Species in Intercropping Agroecosystems Based on UAV with RGB Camera. *Electronics*, 11(4), 609.



ACKNOWLEDGMENT

The research presented in this keynote was funded by:

“Proyectos de innovación de interés general por grupos operativos de la Asociación Europea para la Innovación en materia de productividad y sostenibilidad agrícolas (AEI-Agri)” in the framework “Programa Nacional de Desarrollo Rural 2014-2020”, GO TECNOGAR,

Proyecto financiado por Programa Nacional de Desarrollo Rural (2014 - 2020): FEADER y MAPA



Unión Europea
Fondo Europeo Agrícola
de Desarrollo Rural
Europa invierte en las zonas rurales



PNDR
Programa Nacional
de Desarrollo Rural
2014-2020





ACKNOWLEDGMENT

The research presented in this keynote was funded by:

Conselleria de Educación, Cultura y Deporte with the Subvenciones para la contratación de personal investigador en fase postdoctoral, grant number APOSTD/2019/04.







THANK YOU FOR YOUR ATTENTION

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