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# **The Use of Images in Digital Agriculture:** *Current Limitations and Examples*

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### Introduction

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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 disease or to estimate the yield.

In other cases, the huge spatial variability of a parameter requires a **high number of sensors** for its acurate 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 in used to generate an image.

• Such as the GreenSeeker, which measures the Normalized Difference Vegetation Index (NDVI), a measure of plant vigour, 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 relative 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 as certain NDVI meters or LiDAR stations can generate images with information as a result.

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

The most common images are the Red-Green-Blue (RGB) pictures.



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



True color image





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

The most common images are the Red-Green-Blue (RGB) pictures.

In other cases, we use multispectral images, compose of more than 3 bands.

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

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, which is on based the combination of red and infrared images.

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

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

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

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



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:

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.



# **Current limitations**

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

Satellite images have a huge size, formed of up to 15 bands (example of Sentinel 2), including information of 100 x 100 km. The whole document downloaded from their database is greater than 1 GB. A single band contains up to 120,560,400 pixels

Images from drones or cameras mounted on machinery have fewer bands, generally 3 to 5. Usually, they to contain only the information of the target area. The bands are composed of fewer pixels.

Example of reflex camera Canon EOS 77D: 24,000,000 pixels

Example of images form Parrot BeBop-Pro Thermal: 1,555,200 pixels

Example of images from CMOS OV7670 Camera Module: 307,200 pixels

# **Current limitations**

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

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

Several issues must be considered before having this sort of systems in the fields:

The system itself must gather the images. It cannot rely on satellite images due to the huge bandwidth required to download the images and their low temporal resolution. Therefore, drones or cameras mounted on machinery are the sole options.

The use of object recognition should be avoided if a fast response is needed. The large size of images precludes cloud computing. **Therefore, simple image processing is preferred.** 

# **Current limitations**

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

If we expect to have and autonomous system operating in the fields, capable of activating or disactivating 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 are allocated.

In this case, no restrictions should be applied.

# **Current limitations – Simple image processing**

In the case that we expect to have a node in the field collecting images and connected into a network with actuators, we should ensure that the node can process the data.

The images should be processed as data matrices 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 are feasible too.

# **Current limitations – Simple image processing**

Finally, the solutions must be tailored for each crop or group of crops since the problems and characteristics are different.

The size and distribution of the crop are important.

To identify the harvest moment, the spatial resolution needed for oranges (diameters of fruit 6-10 cm) is not the same as that for chickpeas (diameter of pod <2 cm).

To identify weed plants, the technique for cereals (sowed in lines) is not valid for urban lawns (sower to cover the whole surface).

# **Current limitations – Simple image processing**

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 crop is important. The problems of each crop might be different. Rainfed vs. irrigated crops. Annual vs. pluriannual crops. Monocrop vs. intercropping managements.

### **Motivation: Identify weed plants**

When weeds are detected from an image gathered with a drone with the aim of applying the appropriate phytosanitary product, the system needs to process data in real-time or near-real-time. Thus, simple image processing methods should be applied.

On the other hand, given the size of weed plants, drones or cameras mounted on machinery must be used.

Motivation: Identify weed plants

Task: Determine if band combination can be used to detect weed plants in chickpea

### Objectives:

- 1. Define a methodology based on band combination to identify weed plants in chickpea.
- 2. Compare the proposed index with existing ones.



Chickpea Prickly burweed Crop Weed plant

Parra, L., Yousfi, S., Mostaza, D., Marín J.F., Mauri P.V. (2021). Propuesta y comparación de índices para la detección de malas hierbas en cultivos de garbanzo. XI Congreso Ibérico de Agroingeniería 2021, Valladolid, Spain, 11 November 2021.

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- 2. Compare the proposed index with existing ones.

# Proposed indexes improve the performance of existing ones

Parra, L., Yousfi, S., Mostaza, D., Marín J.F., Mauri P.V. (2021). Propuesta y comparación de índices para la detección de malas hierbas en cultivos de garbanzo. XI Congreso Ibérico de Agroingeniería 2021, Valladolid, Spain, 11 November 2021.



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Image is subdivided into six fragments, and Fasle Negatives (FN) with proposed indexes are analyzed



In blue n<sup>o</sup> of weed plants in orange, grey and yellow, the n<sup>o</sup> of FN for proposed indexes

# 10xAGRI and 5xAGRI show similar performance in weed detection

Parra, L., Yousfi, S., Mostaza, D., Marín J.F., Mauri P.V. (2021). Propuesta y comparación de índices para la detección de malas hierbas en cultivos de garbanzo. XI Congreso Ibérico de Agroingeniería 2021, Valladolid, Spain, 11 November 2021.

### **Motivation: Identify weed plants**

Task: Determine if edge detection can be used to detect weed plants in golf course

### Objectives:

1. Define a methodology based on edge detection to identify weed plants in turfgrass





1.

#### **Motivation: Identify weed plants** Zoom to part of the picture with weed Task: Determine if edge detection can be used to Results of application of detect weed plants in golf course individual filters Horizontal Line Vertical Line Left Diagonal Line **Right Diagonal Line Objectives**: North Gradient West Gradient East Gradient South Gradien Define a methodology based on edge detection to identify weed plants in turfgrass Sharpening (I) [3x3] Sharpening (II) [3x3] Sharpening [5x5] Laplacian [3x3]

**RGB** composition

RGB composition without soil

Red band without soil

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Parra, L., Marin, J., Yousfi, S., Rincón, G., Mauri, P. V., & Lloret, J. (2020). Edge detection for weed recognition in lawns. Computers and Electronics in Agriculture, 176, 105684.

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Value of Precision (Pre), Recall (Rec) and F1 Score (F1) for the different thresholds.

	Threshold = 78		Threshold = 85			Threshold = 92			
	Pre	Rec	Fl	Pre	Rec	F1	Pre	Rec	F1
Picture D)	80%	86%	83%	83%	68%	75%	84%	57%	68%
Picture E)	67%	86%	75%	71%	71%	71%	75%	43%	55%

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Proposed methodology has good performance



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### **Motivation: Identify weed plants**

Task: Determine the maximum flying height which can be used to detect weed plants in a golf course with a low-cost drone.



Objectives:

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

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Three testing areas with variable weed presence



Weed plant

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

Vegetation Index= B1+B2-B3

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# Proposed index is good for weed detection



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## Maximum height of 10 m for this methodology



Figure 2. Comparison of estimated affected areas at each height

### **Motivation: Identify different crops in intercropping**

In some scenarios, the presence of two species is not related to the crop+weed case. Intercropping is the simultaneous cropping of two or more species. In this case, it is essential to identify the species initially before applying other operations correctly. Different crops might have different plant vigour without implying a stress condition of a disease.

Since posterior indexes might be applied in real-time to take the appropriate decisions, this task has the same restrictions as the subsequent ones.

Depending on the size of the crops and the lines of the crops, satellite images can be used or not.

# **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.

Drone used: Parrot BeBop2 Pro Thermal

2. Generate a procedure based on an index to differentiate crops.





Parra, L., Yousfi, S., Mostaza-Colado, D., Marin, J.F., Lloret, J., Mauri, P.V. (2021, October). Evaluación del uso de imágenes para diferenciar garbanzos, lentejas y yeros en cultivos mixtos. XVI CONGRESO NACIONAL DE CIENCIAS HORTÍCOLAS, Cordoba, Spain, 17-22 October 2021.

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### It was possible to differentiate the crops in intercropping with low-cost drone

Parra, L., Yousfi, S., Mostaza-Colado, D., Marin, J.F., Lloret, J., Mauri, P.V. (2021, October). Evaluación del uso de imágenes para diferenciar garbanzos, lentejas y yeros en cultivos mixtos. XVI CONGRESO NACIONAL DE CIENCIAS HORTÍCOLAS, Cordoba, Spain, 17-22 October 2021.

#### Index





### **Motivation: Differentiate species in intercropping**

Task: Use pictures gathered at 1.5m to differentiate grass species with Green Area (GA) and Greener Area (GAA) index.

**Objectives:** 

- 1. Evaluate if GA and GAA can differentiate plant species.
- 2. Compare its performance with other variables measured from sensors

Mauri, P.V, Parra, L. Lloret, J., Yousfi, S., Marín J.F. (2020, October). Testing and Validation of Monitoring Technologies to Assess the Performance and Genotyping of Poa pratensis (C3) Mixed with Other Grass Species (C4). The Twelfth International Conference on Advances in System Testing and Validation Lifecycle (VALID 2020) (pp. 1-6)



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#### GA is the best indicator of grass species

IU .	c plain species	•				
		SM	СТ	NDVI	GA	GGA
_	Control	35.2583 <sup>a</sup>	14.6125 <sup>a</sup>	0.76 <sup>a</sup>	0.67875 <sup>b</sup>	0.35 <sup>a</sup>
	PC	35.5 <sup>a</sup>	14.8417 <sup>a</sup>	0.745 <sup>a</sup>	0.61805 <sup>a</sup>	0.295 <sup>a</sup>
	PB	34.3944 <sup>a</sup>	14.6056 <sup>a</sup>	0.79 <sup>b</sup>	0.77944 °	0.48 <sup>b</sup>
_	PZ	36.3722 <sup>a</sup>	14.4694 <sup>a</sup>	0.77 <sup>b</sup>	0.76472 <sup>c</sup>	0.425 <sup>b</sup>
-	Level of significance	0.8727 <sup>ns</sup>	0.9579 ns	0.0005***	0.0000***	0.0000***

Mauri, P.V, Parra, L. Lloret, J., Yousfi, S., Marín J.F. (2020, October). Testing and Validation of Monitoring Technologies to Assess the Performance and Genotyping of Poa pratensis (C3) Mixed with Other Grass Species (C4). The Twelfth International Conference on Advances in System Testing and Validation Lifecycle (VALID 2020) (pp. 1-6)

### **Motivation: Identify different management options**

In certain cases, weed plants might not be a problem itself and are considered as a potential benefit since they stabilize and even improve some soil parameters. The evaluation of the most common management options in a given area can be done without the constrictions of real-time.

Nonetheless, the future application of these processes in large areas to evaluate the management option of a river basing, for example, precludes the use of drones. Thus, it is necessary to focus on satellite imagery.

The main problem is that open sources satellite imagery has lower spatial resolution than the required one. Therefore, it will be impossible to identify the spontaneous vegetation and the crop.

### **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 The Twelfth International Conference on Advanced Geographic Information Systems, Applications, and Services (GEOProcessing 2020), Valencia, Spain, 21-25 November, 2020.

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Figure 1. Scheme of pixel information content.

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

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.

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#### Original information from satellite





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

Results Combined images of January and June as: *Pixel value in January- Pixel value un June* 

### **Motivation: Identify different management options**

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

### Objectives:

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

#### Results Combined images of January and June as: *Pixel value in January- Pixel value un June*



Type 1=With spontaneous vegetation Type 0=Without spontaneous vegetation

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

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.

### **Motivation: Identify establishment success**

In agriculture, the establishment success, correct germination, and crop emergence is a vital moment. While some crops have elevated establishment success rates, other crops such as chickpea have relatively low establishment success.

In this case, no real-time is needed, but the small size of the plants requires drone imagery. Although artificial intelligence and object recognition might be planned, the local processing of images as the drones fly, allows the farmer to have a prompt evaluation of the lands.

A secondary issue arises at this moment. The continuous collection of images is starting to suppose a problem for the drone operator, the required space to store the generated information is growing exponentially.

### **Motivation: Identify establishment success**

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

### Objectives:

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



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.

### **Motivation: Identify establishment success**

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#### Selected drone: Parrot BeBop 2 Pro Thermal



#### The area is divided into three zones



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



Figure 3. The division into zones and subzones of the used images with scale and text bar.

Followed approach:

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

Index: B1/B2

### **Motivation: Identify establishment success**

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### **Motivation: Identify establishment success**

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### Objectives:

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

#### Initial results:

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



Classification of results for different flying height and aggregation techniques

### **Motivation: Identify establishment success**

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### Objectives:

- 1. Evaluate the use of band combination to estimate the establishment success of legumes.
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# Band combination is useful to estimate establishment success

### **Motivation: Identify establishment success**

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

## Objectives:

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

Required storage capacity for each option



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

In the near future, drones will have an even more relevant role in the digitalization of agriculture.

The use of images will be common and will be integrated with sensors, creating a diverse network.

The storage capacity will be a real constrain, which should be addressed soon.

The inclusion of multispectral or hyperspectral cameras will allow a better management of agriculture. The generated data will be used for new applications such as phenotyping or selecting individuals in breeding lines.

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.

The advances in telecommunication of devices and its nodes will allow the management of a greater amount of data, allowing the inclusion of object detection techniques and cloud computing in the fields.

Nevertheless, the new multispectral cameras and the enhanced spatial resolution will incorporate new processing requirements.

The continuous improvement of the different included technologies (cameras, nodes, and telecommunication infrastructure) will solve and incorporate different bottlenecks to this process.

Therefore, there will always be constraints in each technology that will need to be overcome.

The optimal solution in many cases will be to find the balance between the available technology and the required accuracy to the specific problems offering a tailored solution.

#### List of papers included in this tutorial:

Parra, L., Yousfi, S., Mostaza, D., Marín J.F., Mauri P.V. (2021). Propuesta y comparación de índices para la detección de malas hierbas en cultivos de garbanzo. XI Congreso Ibérico de Agroingeniería 2021, Valladolid, Spain, 11 November 2021.

Parra, L., Marin, J., Yousfi, S., Rincón, G., Mauri, P. V., & Lloret, J. (2020). Edge detection for weed recognition in lawns. Computers and Electronics in Agriculture, 176, 105684.

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, L., Yousfi, S., Mostaza-Colado, D., Marin, J.F., Lloret, J., Mauri, P.V. (2021, October). Evaluación del uso de imágenes para diferenciar garbanzos, lentejas y yeros en cultivos mixtos. XVI CONGRESO NACIONAL DE CIENCIAS HORTÍCOLAS, Cordoba, Spain, 17-22 October 2021.

Mauri, P.V, Parra, L. Lloret, J., Yousfi, S., Marín J.F. (2020, October). Testing and Validation of Monitoring Technologies to Assess the Performance and Genotyping of Poa pratensis (C3) Mixed with Other Grass Species (C4). The Twelfth International Conference on Advances in System Testing and Validation Lifecycle (VALID 2020) (pp. 1-6)

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.

#### **Other similar published papers:**

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).

Garcia, L., Parra, L., Basterrechea, D. A., Jimenez, J. M., Rocher, J., Parra, M., ... & Andrés, J. (2019). Quantifying the production of fruit-bearing trees using image processing techniques. *Proceedings of the INNOV*.

Parra, L., Torices, V., Marín, J., Mauri, P. V., & Lloret, J. (2019, March). The use of image processing techniques for detection of weed in lawns. In *Proceedings of the Fourteenth International Conference on Systems (ICONS 2019), Valencia, Spain* (pp. 24-28).

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.

Marín, J. F., Parra, L., Lloret, J., Yousfi, S., & Mauri, P. V. (2020, December). Correlation of NDVI with RGB Data to Evaluate the Effects of Solar Exposure on Different Combinations of Ornamental Grass Used in Lawns. In *International Conference on Industrial IoT Technologies and Applications* (pp. 207-220). Springer, Cham.

Marín, J., Yousfi, S., Mauri, P. V., Parra, L., Lloret, J., & Masaguer, A. (2020). RGB vegetation indices, NDVI, and biomass as indicators to evaluate C3 and C4 turfgrass under different water conditions. *Sustainability*, *12*(6), 2160.

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# **The Use of Images in Digital Agriculture:** *Current Limitations and Examples*

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