Analysis and Application of Multispectral Image Processing Techniques Applied to Soybean Crops from Drones Vision System

Evelio González[1], Cristhian Núñez[1], José Salinas[2], Jorge Rodas[3], Mariela Rodas[4], Enrique Paiva[3], Yassine Kali[5], Maarouf Saad[5], Fernando Lesme[1], Jose Lesme[1], Luis Gonzalez[1], Belen Maldonado[1] and José Rodríguez-Piñeiro[6]

[1]*Unidad Pedagógica de Caacupé, Universidad Católica Nuestra Señora de la Asunción, Caacupé, Paraguay*
[2]*TECHA, Caacupé, Paraguay*
[3]*Laboratory of Power and Control Systems, Facultad de Ingeniería, Universidad Nacional de Asunción, Luque, Paraguay*
[4]*Instituto Paraguayo de Tecnología Agraria, Caacupé, Paraguay*
[5]*GRÉPCI Laboratory, École de Technologie Supérieure, Montreal, Canada*
[6]*College of Electronics and Information Engineering, Tongji University, Shanghái, China*

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Abstract: Drones are important in precision agriculture applications since they represent a new tool that can increase crop production. In this context, the digital processing of the images obtained from multispectral cameras integrated into the drones makes it possible to analyze the stress state of the crops, their vigor, a burned area, among others. The latter are usually obtained through proprietary applications with very high subscription costs. For this reason, this article presents the step-by-step implementation process of the different methods or algorithms to be applied to multispectral images using the open-source Python programming language. We use a soybean crop as an example of the application, and the results obtained from applying the digital image processing algorithms are presented.

1 INTRODUCTION

Agriculture provides food and raw materials and employment opportunities to a significant amount of the population. The agricultural potential of any country contributes to the process of economic development through different channels of influence such as the growth of the farming sector as sustenance for other sectors of the economy, contributions of productive factors from the rural sector to other industries, the assistance of the agricultural industry to the reduction of poverty, the rural sector as a source of the domestic market and the agro-export sector as a source of foreign exchange (Cervantes-Godoy and Dewbre, 2010).

Agriculture is of paramount importance for the economic development of several countries and guarantees the food security of its inhabitants. However, there is still low penetration of new technologies in agriculture in most developing countries, which has repercussions in the lack of efficiency, productivity, sustainability, optimization of costs and resources (Puri et al., 2017). In this context, the use of drones (also known as unmanned aerial vehicles) as an ally of farmers has recently appeared and consolidated. The use of drone technology contributes to multiple processes in agriculture because it will be possible to capture important information and evaluate the conditions of the monitored land and thus detect existing problems, applying high definition camera technologies and georeferenced information. for your exact location (Stehr, 2015). The importance lies in the possibility of detecting prematurely and efficiently diseases, pests, and the possible effects that may occur in the future about climate damage such as frost and droughts (Patel, 2016).

Digital image processing using a drone's camera focuses on the possibility of having a versatile photogrammetric solution, rapidly deployed in remote locations and delivering detailed information. It is possible to obtain an up-to-date photographic coverage of the growing area of interest using a high-resolution multispectral digital. The global positioning systems can georeference the obtained photographs (or video) and reconstruct a 2D or 3D model using computational tools (Jurado et al., 2020). To perform the analysis of crops such as

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the Vegetation Index (VI), water stress (drought), measure flowering, make an inventory by zones or plants, identify zones without production, etc. (Shah et al., 2021).

On the market, there is commercial software capable of processing multispectral images obtained by drones. Among the best known and most famous cases is Pix4Dfields and DJI Terra. The first one offers the Green Normalized Difference Vegetation Index (GNDVI), Leaf Chlorophyll Index (LCI), Modified Chlorophyll Absorption in Reflectance Index (MCARI), Normalized Difference Red-Edge (NDRE), Normalized Difference Vegetation Index (NDVI), and LSIPI2 indices. This software also allows us to configure any other index as long as it only requires the red (R), green (G), near-infrared (NIR), and red-edge (RE) bands of the spectrum. Another similar software is the DJI Terra, which offers the NDVI, GNDVI, NDRE, LCI, and OSAVI indexes. However, both the Pix4Dfields and the DJI Terra are paid applications under the subscription model; For the first case, the annual cost at the date of publication of this article is USD 2,000.00, while for the second case, the yearly cost of the basic plan is USD 1,199.00.

We first identify the most popular methods and algorithms applied to multispectral images obtained by drones and applied to crops. The main contribution of this paper is applying step-by-step of the most relevant algorithms in state of the art (e.g., NDVI or GNDVI) using an open-source Python programming language. The rest of the document is divided as follows. Section 2 introduces the main essential issues about drones. Section 3 presents the results obtained by applying the different techniques using multispectral images obtained from a soybean crop. The Python codes applied to implement the various methods are also presented in the same section. The main conclusions and future work are shown in the last section.

2 DRONES IN AGRICULTURE

2.1 Drones: Definition, Classification, and Applications

Drones are reusable aircraft that can maintain autonomous flight or pilot through the use of radio control. When referring to the types of drones, there are several sets of nomenclatures. They are based on various parameters such as weight, designed application, level of autonomy, type of operation, whether civil or military or structural configuration.

The latter encompasses several properties and topologies that modify these aircraft (Nguyen et al., 2020; Paiva et al., 2021). Multirotor drones have several engines that generate thrust using the propellers and can thus sustain in air. They are aircraft that provide:

- Better maneuverability.
- Ease of use.
- Increased load capacity.
- Greater comfort for transport due to the compactness.

On the other hand, the flight ranges are lower and present difficulties in recovering from engine failure (Paiva et al., 2018).

The fixed-wing drones use motors for propulsion and stay thanks to the lift of the winds aloft. These drones have a wide flight range (especially in linear flights) and recovery controls in case of failures. However, for landing and take-off, large areas are not needed, there are difficulties in maneuvering, and they are less compact. Finally, hybrid drones are a combination of fixed-wing and multirotor configurations, thus inheriting the advantages of both technologies (Segales et al., 2016). Still, the control of these drones is quite complex (Kali. et al., 2019; Paiva et al., 2019a; Gomez et al., 2020; Paiva et al., 2019b; Kali. et al., 2018; Kali et al., 2018).

According to the classifications expressed above, these aircraft are ideal for use in different areas of agriculture. Some examples are the assistance to crop pollination, automatic precision fumigation. The use of multispectral imaging by cameras to measure the analyzed crop is the main focus of this paper.

2.2 Multispectral Images Obtained by Drones

Most of the drones available in the market typically have mounted an RGB camera. These types of cameras mount a sensor that measures the capacity of light within the visible spectrum. That is, the spectrum that the human eye is capable of seeing. With an RGB camera, we will only capture and interpret colors as we see them. Therefore, we can only detect problems that are already visible to the naked eye from an aerial view, such as areas with little vegetation. There are other ranges of radiation in the electromagnetic spectrum that go beyond RGB and are of great importance for precision agriculture. To see this type of radiation (the human eye is unable to see them), we need a multispectral sensor (Mogili and

Deepak, 2018). Multispectral cameras have this type of sensor capable of capturing various spectra of light. They are small and can take values of up to 6 spectral bands.

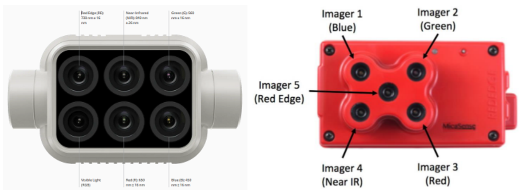

Figure 1: Examples of multispectral cameras.

From the multispectral images captured by this type of sensor, different VIs can be calculated that indicate the health and well-being of the vegetation. These values represent some of the characteristics of the plants that we analyze in detail in the next section.

3 IMAGING PROCESSING TECHNIQUES

For this paper, we use a multispectral image of a soybean crop in Rostock, Germany. Differents VIs is analyzed for the beforementioned crops by applying differents digital image processing techniques.

VIs are quantitative measurements based on reflectance values that tend to measure biomass or plant vigor. VI is a combination of different arithmetic operations applied to other spectral bands, used in a way designed to produce a simple value that indicates the amount of vigor of vegetation within a pixel. This makes it possible to estimate and evaluate the health status of the foliage, based on the measurement of radiation that plants absorb or reflect.

For instance, chlorophyll, which is the green pigment in leaves, strongly absorbs visible light for the photosynthesis process. On the other hand, the cellular structure of the leaves strongly reflects the light of the *NIR* band; the more leaves a plant has, the more wavelengths of light are affected.

3.1 NDVI

NDVI represents an index that allows you to generate an image showing greenness (the relative biomass). This index takes advantage of the contrast between the characteristics of two electromagnetic bands, the absorption of chlorophyll pigment in the *R* band, and the high reflectivity of plant leaves in the *NIR* band (Drisya et al., 2018).

$$NDVI = \frac{NIR - R}{NIR + R}. \quad (1)$$

This index is the most widely used because its basic principle relies on that the spongy layers of leaves reflect a lot of light in the *NIR*, in stark contrast to most non-plant objects. When the plant becomes dehydrated or stressed, the spongy layer collapses, and the leaves reflect less infrared light but the same amount in the visible range. The mathematical combination of these two signals can help differentiate non-plant plants and healthy plants from diseased plants. (Esser A,). The code with the Python language to obtain NDVI is:

```
#  We start with the import of the modules
# necessary
import rasterio
from rasterio import plot
import matplotlib.pyplot as plt
import numpy as np
import os

# {We read the R band}
imgPath = 'C:/Img/'
red = rasterio.open(imgPath+'IMG_0142_RED.TIF')
# {We read the NIR band} %leemos la banda NIR
nir = rasterio.open(imgPath+'IMG_0142_NIR.TIF')

# {We visualize the image}
plot.show(nir)

#{We convert to float}
red = red.read(1).astype('float64')
nir = nir.read(1).astype('float64')

# {Error handling in the division}
np.seterr(divide='ignore', invalid='ignore')

# {We calculate NDVI using numpy arrays}
#  {Empty cells or cells}
# {no data is reported as zero.}
ndvi = np.where((nir + red) == 0., 0,
                (nir - red) / (nir + red))

# {We plot the results with the colors}
#{Red, Yellow and Green}
plt.imshow(ndvi, cmap='RdYlGn')
# {We add color palette}
plt.colorbar()
```

3.2 GNDVI

GNDVI is an index used to estimate photosynthetic activity estimates and is commonly used to determine the water and nitrogen consumption of the vegetation

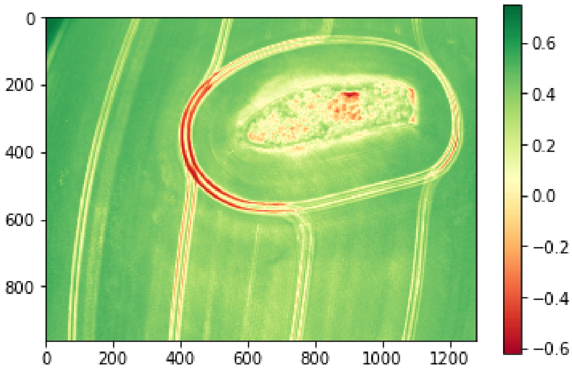

Figure 2: Results obtained when applying the NDVI technique.

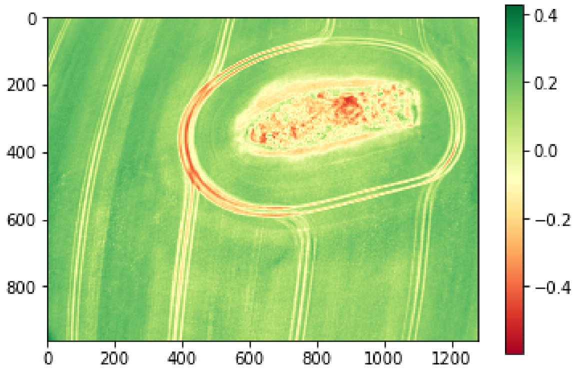

Figure 3: Results obtained when applying the GNDVI technique.

cover (Kross et al., 2015).

$$GNDVI = \frac{NIR - G}{NIR + G}. \quad (2)$$

It is associated with the green color of the vegetation (chlorophyll levels). It is one of the most used to establish water and nitrogen absorption levels in the foliage of the different crops. Nitrogen is a primary structural component present in leaves and is an indicator of plant health, which is why a deficiency of this nutrient can cause low productivity. GNDVI is resistant to atmospheric effects since it has a more excellent range of wavelengths (from 560 nm to 840 nm) than the NDVI (from 650 nm to 840 nm). Moreover, GNDVI is five times more sensitive to the concentration of chlorophyll-a. This VI avoids the problem of NDVI saturation at relatively low chlorophyll concentrations (it saturates, depending on the species, with amounts as low as 2 μg/cm of chlorophyll-a).

```
# Read band G
green = rasterio.open(imgPath+'IMG_0142_GRE.TIF')

# We compute GNDVI using numpy arrays
gndvi = np.where((nir + green) == 0., 0,
                 (nir - green) / (nir + green))
```

3.3 SAVI

Soil Adjusted Vegetation Index (SAVI) is an index that attempts to minimize the influences of soil brightness by using a brightness correction factor. SAVI is regularly using in arid regions where vegetation cover is low.

$$SAVI = \frac{NIR - R}{NIR + R + L} + (1 + L). \quad (3)$$

Equation (3) also contains the parameter L (when $L = 0$, SAVI = NDVI). L can take different values depending on the amount of vegetation in the area of interest and vary between -1 and 1. A low value is used in fields with a high vegetation density; a high value should be used for fields with little vegetation.

```
# We coompute SAVI using numpy arrays
savi = ((nir - red) / (nir + red + 0.5)) * (1 + 0.5)
```

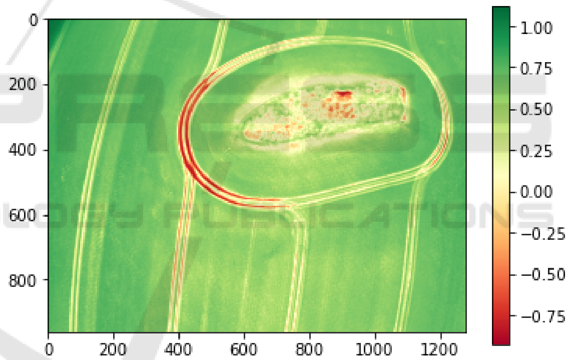

Figure 4: Results obtained when applying the SAVI technique.

3.4 BAI

Burn Area Index (BAI) uses the reflectance values of the R and NIR bands of the spectrum to identify the areas of the ground affected by a fire.

$$BAI = \frac{1}{(0.1 - R)^2 + (0.06 - NIR)^2}. \quad (4)$$

BAI constitutes a helpful parameter to discriminate the area affected by the fire over other covers. SAVI uses the spectral ranges of charred materials and ashes produced after a fire, recognizable by relating the reflectance values of the R and NIR bands. Then, SAVI is quite helpful for mapping burned areas, allowing clear discrimination between burned and unburned, compared to other spectral indices such as NDVI, SAVI, and GEMI. SAVI can be helpful in countries with a dry season or after the fires that affect agricultural and forestry crops.

```
# We compute BAI using numpy arrays
bai = 1 / (np.power((0.1 - red), 2)
       + np.power((0.06 - nir), 2))
```

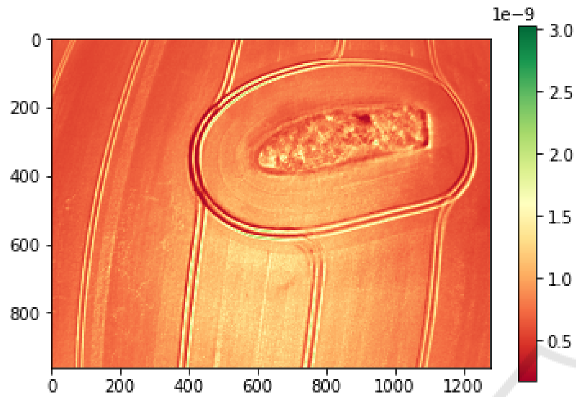

Figure 5: Results obtained when applying the BAI technique.

3.5 CIg

Chlorophyll Index - Green (CIg) is an index that allows obtaining an estimate of the chlorophyll content of the leaves from the reflectivity rate in the *NIR* and *G* bands (Broge and Mortensen, 2002).

$$CIg = \frac{NIR}{G} - 1. \tag{5}$$

```
# We compute CIg using numpy arrays
CIg = (nir / green) - 1
```

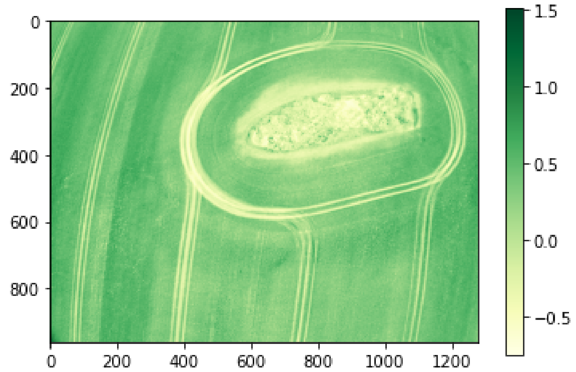

Figure 6: Índice de Clorofila: CIg.

3.6 CIre

Chlorophyll Index - Red-Edge (CIre) is a vegetation index that makes it possible to estimate the leaves' chlorophyll content from the reflectivity rate in the *NIR* and *RE* bands.

$$CIre = \frac{NIR}{RE} - 1. \tag{6}$$

```
# We read RE band
re = rasterio.open(imgPath+'IMG_0142_RE.TIF')
# We compute CIre using numpy arrays
CIre = ((nir / re) - 1)
```

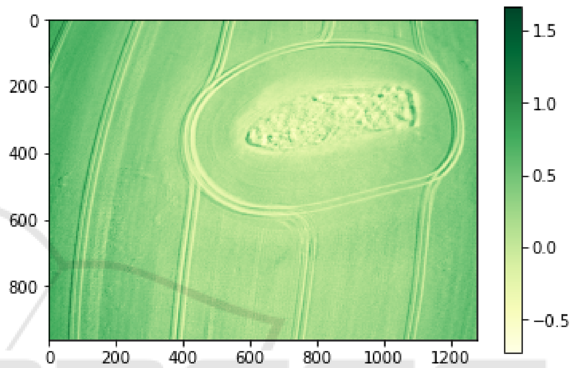

Figure 7: Results obtained when applying the CIre technique.

3.7 GEMI

The Global Environmental Monitoring Index (GEMI) is a non-linear index for global environmental monitoring from satellite images. It is similar to NDVI but is less sensitive to atmospheric effects. It is affected by the uncultivated land. Therefore, GEMI is helpful for areas of sparse or moderate vegetation.

$$GEMI = eta\,(1 - 0.25\,eta) - \frac{R - 0.125}{1 - R}, \tag{7}$$

being *eta*:

$$eta = \frac{2\,(NIR^2 – R^2) + 1.5\,NIR + 0.5\,R}{NIR + R + 0.5}. \tag{8}$$

```
nir2 = np.power(nir, 2)
red2 = np.power(red, 2)
# We compute theta
theta = (2 * (nir2 - red2) + 1.5 * nir + 0.5 * red)
        / (nir + red + 0.5)

# We compute GEMI using numpy arrays
gemi = theta * (1 - 0.25 * theta) - ((red - 0.125)
        / (1 - red))
```

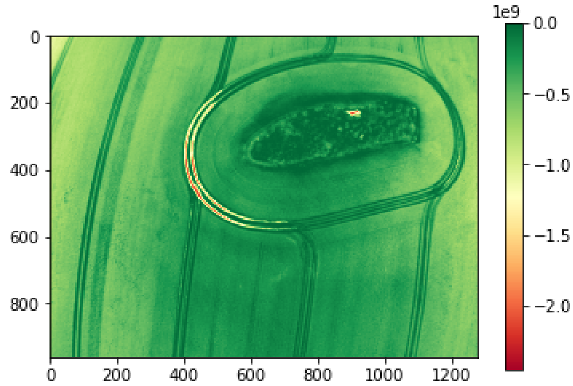

Figure 8: Results obtained when applying the GEMI technique.

3.8 MSAVI2

Modified Adjusted Soil Vegetation Index 2 (MSAVI2) is a recursion of the MSAVI index and attempts to minimize the effect of bare ground on the SAVI.

$$MSAVI2 = \frac{1}{2}[2\,(NIR+1) - \sqrt{\theta}], \tag{9}$$

being θ defined as follows:

$$\theta = (2\,NIR+1)^2 - 8\,(NIR-R). \tag{10}$$

```
# We compute MSAVI2 using numpy arrays
msavi2 = 0.5 * (2 * (nir + 1)
        - np.sqrt(np.power((2 * nir + 1), 2)
        - 8 * (nir - red)))
```

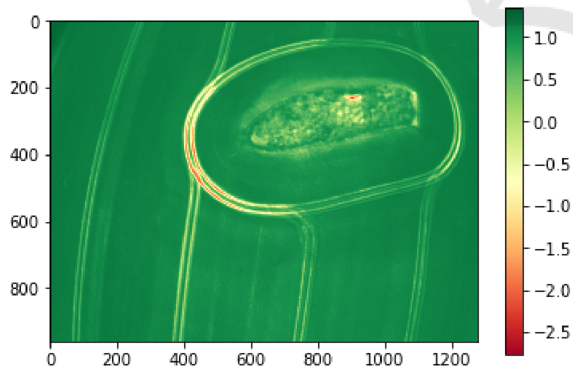

Figure 9: Results obtained when applying the MSAVI2 technique.

3.9 MTVI2

Modified Triangular Vegetation Index 2 (MTVI2) is an index that allows detection of the leaves' chlorophyll content at the tree canopy scale. However, it is relatively insensitive to the index of the area with foliage. It uses reflectance in the G, R, and NIR bands.

$$MTVI2 = 1.5[1.2\,(NIR-G) - 2.5\,(R-G)]\sqrt{\theta}, \tag{11}$$

where θ is:

$$\theta = (2NIR+1)^2 - (6\,NIR - 5\sqrt{R}) - 0.5. \tag{12}$$

```
# We compute MTVI2 using numpy arrays
mtvi2 = (1.5 * (1.2 * (nir - green) - 2.5
        * (red - green))
        * np.sqrt(np.power((2 * nir + 1), 2)
        - (6 * nir - 5 * np.sqrt(red)) - 0.5))
```

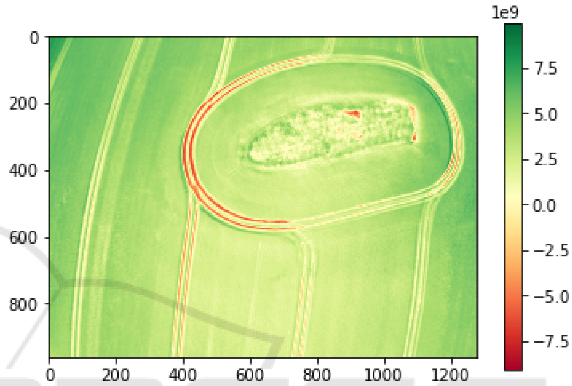

Figure 10: Results obtained when applying the MTVI2 technique.

3.10 NDRE

NDRE is an index used to estimate vegetation health using the RE band. When evaluating the health of crops in the middle and late stages of growth, it is advantageous where the chlorophyll concentration is relatively higher. Additionally, NDRE can be used to map nitrogen variability in field leaves to understand the fertilizer needs of crops better.

$$NDRE = \frac{NIR-RE}{NIR+RE}. \tag{13}$$

```
# We compute NDVIre using numpy arrays
ndre = np.where((nir + re) == 0, 0,
               (nir - re) / (nir + re))
```

3.11 NDWI

The Normalized Difference Water Index (NDWI) is an index that serves to define and monitor changes in surface water content. It is calculated with the NIR and G bands. The Normalized Difference Water Index (NDWI) is an index that defines and monitors changes in surface water content. Crops suffer from

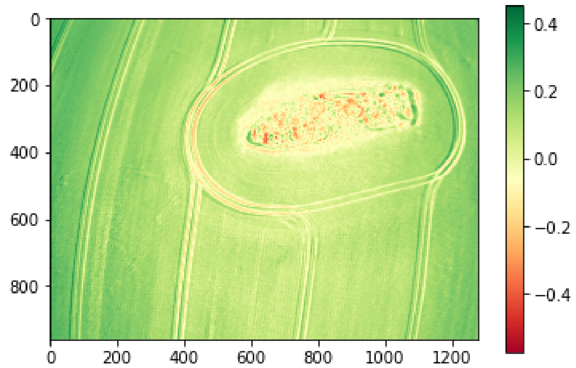

Figure 11: Índice de Vegetación: NDRE.

severe water stress during times of drought or lack of irrigation, so this index detects in time the areas affected by lack of water and prevent negative impacts on crops. It is also helpful for evaluating the risk of fire, determining moisture in the vegetation cover. Higher NDWI values indicate sufficient humidity, while a low value suggests water stress.

$$NDWI = \frac{G - NIR}{G + NIR}. \tag{14}$$

```
# We compute NDWI using numpy arrays
ndwi = np.where((green + nir) == 0, 0,
        (green - nir) / (green + nir))
```

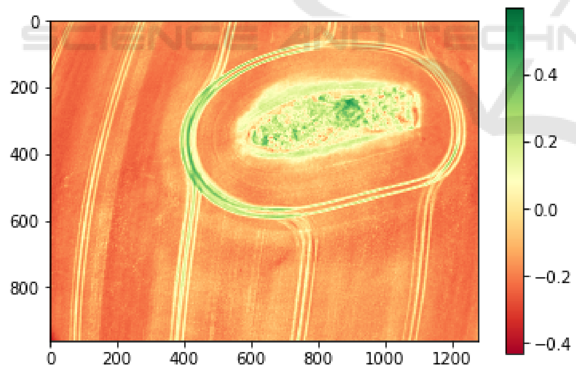

Figure 12: Results obtained when applying the NDWI technique.

3.12 RTVICore

The Red-Edge Triangulated Vegetation Index - Core Only (RTVICore) is used to estimate the area index with foliage and biomass. RTVICore uses NIR, RE, and G spectral bands.

$$RTVICore = [100\,(NIR - RE) - 10\,(NIR - G)]. \tag{15}$$

```
# We compute RTVICore using numpy arrays
rtvicore = (100 * (nir - re) - 10 * (nir - green))
```

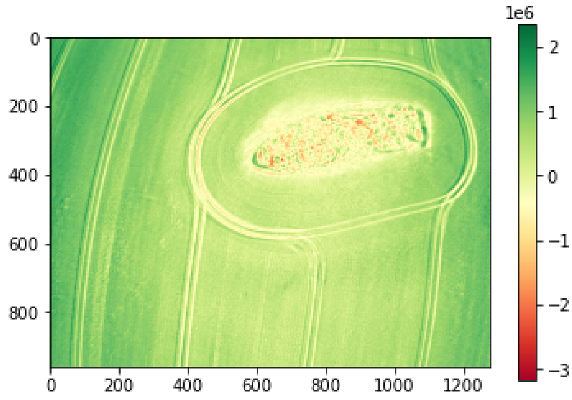

Figure 13: Results obtained when applying the RTVICore technique.

3.13 SRre

Red-Edge Simple Ratio Index (SRre) is a vegetation index used to estimate healthy and distressed vegetation. The ratio of light is scattered in the *NIR* and *RE* bands. Then, it reduces the effects of the atmosphere and topography.

$$SRre = \frac{NIR}{RE}. \tag{16}$$

```
# We compute SRre using numpy arrays
srre = nir / re
```

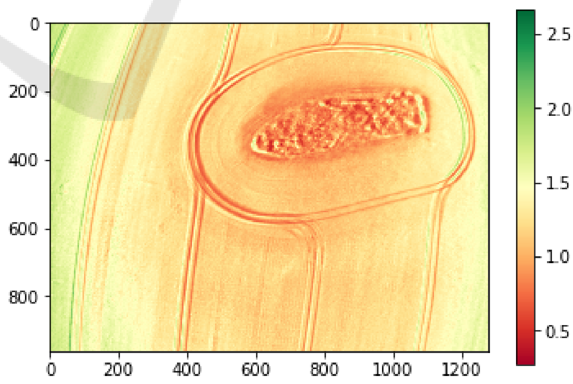

Figure 14: Results obtained when applying the SRre technique.

To summarize, Table 1 presents the output of each technique according to the Calcination Index (Cal-I), Geological Index (GI), and Chlorophyll Index (Chl- I). On the other hand, Table 2 shows the spectral bands used by each index. All the indexes presented in this paper are the most used in practical applications. However, the proper VI selection for a specific crop is beyond the scope of this paper.

Table 1: Result of the algorithms.

Method	VI	Cal-I	GI	WI	Chl-I
NDVI	✓	x	x	x	x
GNDVI	✓	x	x	✓	x
SAVI	✓	x	x	x	x
BAI	x	✓	x	x	x
CIg	✓	x	x	x	✓
CIre	✓	x	x	x	✓
GEMI	✓	x	x	x	x
MSAVI2	✓	x	x	x	x
MTVI2	✓	x	x	x	✓
NDRE	✓	x	x	x	x
NDWI	x	x	x	✓	x
RTVICore	✓	x	x	x	x
SRre	✓	x	x	x	x

Table 2: Spectral bands used by each index.

Method	*R*	*G*	*B*	*RE*	*NIR*
NDVI	✓	x	x	x	✓
GNDVI	x	✓	x	x	✓
SAVI	✓	x	x	x	✓
BAI	✓	x	x	x	✓
CIg	x	✓	x	x	✓
CIre	x	x	x	✓	✓
GEMI	✓	x	x	x	✓
MSAVI2	✓	x	x	x	✓
MTVI2	✓	✓	x	x	✓
NDRE	x	x	x	✓	✓
NDWI	x	✓	x	x	✓
RTVICore	x	✓	x	✓	✓
SRre	x	x	x	✓	✓

4 CONCLUSIONS

This paper has addressed the use of drones in agriculture. Different algorithms used by commercial applications have been analyzed, also incorporating others. Then we have studied a soybean crop and applied the different algorithms using an open programming language. The programming process for each algorithm has been presented to be applied directly to readers and the results obtained have shown their correct operation.

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