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Data acquisition and analysis methods in UAV-based applications for Precision Agriculture

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***Abstract*—Emerging technologies such as Internet of Things (IoT) can provide significant potential in Precision Agriculture enabling the acquisition of real-time environmental data. IoT devices like Unmanned Aerial Vehicles (UAVs) equipped with cameras, sensors, and GPS receivers can deliver a variety of IoT services and applications related to fields management, by capturing images from great heights. However, there are many issues to be resolved before the effective use of UAVs in the agriculture domain, including the data collection and processing methods. There is still no standardized workflow and processes for most UAV-based applications for Precision Agriculture. In this paper we summarize the data acquisition methods and technologies to acquire images in UAV-based Precision Agriculture and appoint the benefits and drawbacks of each one. We also review popular data analysis methods of remotely sensed imagery and discuss the outcomes of each method and its potential application in the farming operations.**

***Keywords*-Remote Sensing, IoT, UAV, UAS, Unmanned Aerial Vehicle, Unmanned Aerial System, Image processing, Precision Agriculture, Smart Farming, Review**

I. Introduction

Agricultural productivity growth is considered imperative (a recent study estimates that an increase of 70% is needed until the year 2050 [1]) to meet the increased needs arising from the estimated increase in the population of the Earth and the decrease in the area under cultivation. In recent years, agricultural productivity has significantly increased, due to the use of improved farming practices like Precision Agriculture. In general, Precision Agriculture involves better management of farm inputs (like fertilizers and herbicides) by applying the right management practice at the right place and at the right time. This is very important considering the fact that under conventional farming, large farm fields usually receive uniform applications of fertilizers, herbicides, irrigation etc, while they may not need to. With the use of Precision Agriculture, a field can be divided into management zones that each one receives a customized management.

In our days the IoT (Internet of Things) paradigm offers a new perspective for precision agriculture enabling the site-specific, fine-grid management of corps. In this context real-time environmental information can be remotely acquired from the agricultural fields, timely processed and used to support critical decisions. In IoT based farming, a system is built for monitoring the crops consisting of autonomous or embedded remote sensors targeting in the automation of various farming operations (monitoring, irrigation process, application of fertilizers etc.).

Remote Sensing is commonly used to monitor crop fields, providing effective solutions for Precision Agriculture the last 35 years [2]. Remote Sensing is generally the acquisition of information about something without making physical contact with it. In this context, satellite imaging technologies have become an extremely useful tool for imagery data acquisition in Precision Agriculture [3]. UAV-based remote sensing have taken one step further remote sensing systems offering great possibilities to acquire field data for precision agriculture applications in a fast, easy and cost- effective way compared to satellite systems.

UAV-based IoT technology is considered as the future of Remote Sensing in Precision Agriculture. UAVs can fly at a low altitude resulting in ultra-high spatial (up to a few centimeters) resolution imagery, which may significantly improve the performance of the system. In addition, UAV systems have the ability to collect the data with high temporal resolution which can enhance the flexibility of the data acquisition process. Furthermore, UAVs are a lot cheaper and simpler compared to manned aircrafts and more efficient than the ground systems because they can cover a large area in a shorter amount of time in a non-destructive way.

Unmanned Aerial Systems (UAS) are now very commonly used for monitoring crop fields. Carrying several different sensors, UAS can be used by farmers to identify which zones of the crops need improvements or some kind of input and react properly on time. UAS can be used in a plethora of applications of Precision Agriculture. The most common applications of UAS are:

- Weed detection and management [4], [5]
- Monitor the growth of the vegetation and estimation of yield [6]–[8]
- Monitor vegetation health and detection of diseases [9], [10]
- Irrigation management [11], [12]
- Mammal detection [13]
- Assessment of soil electrical conductivity [14]
- Corps spraying [15], [16].

As the use of UAVs is considered the future of remote sensing in Precision Agriculture, several studies exist review-

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ing their application in agriculture. Most of the reviews focus on the different applications UAVs can have in agricultural crops [17]–[22] or environmental monitoring in general [23]. Maes et al. [24] focus on the suitability of sensors or techniques for each application, providing with important perspectives for the use of UAVs, without reviewing in detail the techniques used for exploiting UAV acquired data. In [25] the authors reviews the hyperspectral imagery and the techniques used in these cases. Also, a survey for the use of Deep Learning in agricultural data has been conducted [26].

We believe that a review of the most used techniques exploiting UAV imagery is currently missing from literature, despite its necessity. This is mainly supported by the fact that one of the limitations affecting the wide use of UAVs in commercial applications is the absence of a standardized data workflow regarding the most popular applications of precision agriculture. This fact results in the adoption of a variety of heterogeneous procedures and techniques to achieve a certain goal, without always achieving the expected outcome. In addition, as the research in the use of UAVs in agriculture is advancing really fast, we think that a study reviewing the most recent practices is necessary. Thus, we focused on the most used techniques applied on UAV imagery in recent works to monitor crop fields in Precision Agriculture.

The rest of the paper is structured as follows. In Section II we recall the basics of aerial imaging acquisition and the sensors used. Next, Section III focuses on the image processing methods, including the photogrammetric techniques, the calculation of vegetation indices and the use of machine learning. Finally, Section IV makes some concluding remarks.

II. UAV Data Acquisition

Equipped with specialized sensors, UAVs are becoming powerful sensing systems that complement the IoT-based techniques. The role of sensors, embedded in a UAV, is to acquire high-spatial and temporal images that can help towards studying crop and soil variations in a field. A variety of sensors can be used in an agricultural UAV depending on the different vegetation parameters that should be acquired [19]. Though, the need of low payload capacity and the utilization of usually small platforms pose several limitations to sensor selection. Among the criteria that the sensors must meet are the low weight, the low energy consumption and the small size combined with the ability to acquire high resolution imagery. Modern commercial on-board sensors complying with the above restrictions mainly belong to the following four types:

- Visible light sensors (RGB)
- Multispectral sensors
- Hyperspectral sensors
- Thermal sensors

Figure 1 presents examples of the main types of sensors used. Each type can monitor specific parameters of agricultural crops such as the color and texture of vegetation and the geometric outline of the crops. Additionally some types of sensors can measure the radiation in certain wavelength ranges, information that can be further used to monitor plant biomass, vegetation health and other important crop characteristics at different growth stages.

Fig. 1. Sensors used on UAVs for Precision Agriculture. a) Thermal sensor [27] b) RGB sensor [28] c) Multispectral sensor [29] d) Hyperspectral sensor [30]

In more details:

- **Visible light sensors (RGB)** are the most commonly used type of sensor for crop monitoring. These sensors are relatively low cost compared to the others, provide high resolution imagery, are lightweight and easy to use and operate. Also, RGB sensors provide data that require simple processing in low power environments. Data-images can be captured in different conditions, both on sunny and cloudy days, but a specific time frame is required based on weather conditions to avoid inadequate or excessive exposure of the image. Among the negative aspects of RGB sensors is the fact that they are inadequate for accurately analyzing various crop characteristics that require other spectral information. In addition, there is a significant effect of the internal orientation and camera distortion on the image quality. Thus, images often need to be corrected.
- **Multispectral or hyperspectral sensors** embedded in UAVs can obtain information related to the spectral absorption and reflection of the crops in several bands. This information can then be used to calculate vegetation indices and monitor the crops based on them. These types of sensors use the reflection on specific bands to extract information for some parameters of the vegetation. Spectral information can help significantly in assessing a lot of biological and physical characteristics of agricultural crops. For example, visible radiation in the red channel is absorbed by chlorophyll, while near infrared (NIR) radiation is strongly reflected. In this way, healthy vegetation can be identified in an image. Multispectral and hyperspectral imaging sensors are highly used by UAV systems, despite the higher costs they present. Though,

a disadvantage of these sensors arises from the need to apply complex pre-processing methods so as to extract useful information from the images. The pre-processing procedure of spectral images usually contains the radiometric calibration, geometric correction, image fusion and image enhancement. The main difference between multispectral and hypercpectral sensors is the number of bands (or channels)that they can capture and their width. Multispectral sensors captures from 5 to 12 bands while hyperspectral sensors usually consists of hundreds or thousands bands, but in a narrower bandwidth. Although in recent research multispectral sensors are used more frequently due to their lower cost, hyperspectral technology is considered as the future trend for crop phenotyping research [19].

- **Thermal infrared sensors** generate an image that displays objects based on their temperature and not their visible properties. Thermal cameras use infrared sensors and an optical lens to receive infrared energy. All objects warmer than absolute zero (-273 C / -459 F) emit infrared radiation at specific wavelengths (MWIR and LWIR) in an amount proportional to the temperature of the object. Thus, thermal imaging focuses and detects this radiation and then usually translates it into a grayscale image, using brighter and darker shades of heat representation. Many thermal imaging devices can also apply colors to these images, showing warmer objects as yellow and cooler objects as blue. Thermal sensors are used in very specific applications such as irrigation management or water stress detection. Hence, their use is not so frequent in UAV applications that focus on monitoring other elements of the vegetation.

UAV data acquisition often uses overlapping images, which in most cases includes both front and side overlap. The overlapping of the images is desirable as it contributes to the construction of various three-dimensional models and orthomosaics of the agricultural crops. The overlap rate varies depending on the application, with the front overlap ranging between 60%-95%, the side overlap between 40% -95% to produce three-dimensional models and between 25% -40% for other applications.

Another important observation is that it is quite often to use RGB Sensors and modify them to capture also the radiation in other bands, especially the Near Infrared band. This is done by modifying the filters and replacing one of the original optical filters by another that enables the perception of near-infrared channel, resulting often in an hybrid (Near Infrared RGB) sensor. The channel that is not captured by this sensor is often captured by another RGB sensor mounted on the UAV. This is done due to the higher costs of the multispectral cameras.

III. UAS Data Processing

In this Section we review the processing methods adopted to analyze the images provided by the UAVs. In particular we focus on the various types of data that can be acquired from the images coming from the UAV flights and the ways these data can be exploited to study different crop features. Some of the crop features that can be studied with a remote sensing UAV-based system are presented in Table I:

TABLE I
Crop features acquired from UAS

	Crop features
Vegetation	spatial position of an object height of vegetation vegetation color spectral behavior of chlorophyll biomass nitrogen status moisture content temperature size and shape of different elements and plants vegetation indices
Soil	biomass moisture content temperature electrical conductivity

With the use of different sensors, we can extract information for various features describing the crop field, though there is still no standardized workflow or well established techniques for analyzing and visualizing the information acquired. According to recent research, the techniques used mostly to analyze UAV agricultural images are:

- **Photogrammetric techniques** for extracting three-dimensional digital surface or terrain models [31]–[33] and / or orthophotos [34], [35]. UAV flights at low altitude enable the creation of 3D Models with a much higher spatial resolution compared to other remote sensing technologies. This fact requires the collection of many photographs in order to capture the entire field under study. Thus, in most cases, it is necessary to collect many overlapping images to make orthophotos (also referred as orthomosaics) or construct Digital Elevation Models of the agricultural field, containing all the information necessary to monitor the growth of vegetation. These models depict three-dimensional information of the vegetation based on the structure of the agricultural crops (e.g. the vegetation height, the canopy, the density etc.).
- **Machine Learning and Data Mining techniques.** In addition to the direct use of the three-dimensional or spectral characteristics collected by UAVs, Machine Learning techniques can also be applied to exploit the information from the large amount of data collected. Machine Learning can be used to estimate some parameters of the crop growth rate, the health of corps or even to identify objects in the images. The use of Machine Learning techniques has increased a lot with the advancements taking place especially in the research field of Deep Learning.
- **Calculation of various vegetation indices**. In the majority of cases, various vegetation indices are calculated and used to draw conclusions, either on each photograph individually or after the production of orthophotos depicting the whole crop. Calculating vegetation indices may serve

in the identification of useful crop characteristics, such as biological and physical parameters of the vegetation.

All the aforementioned techniques process the data in real time, providing the relevant visualization models to the producer that can help him into taking informed, timely decisions regarding the crops management. Since the processing of data may be time consuming several software tools and techniques have been developed to enable faster data processing. The software solutions that can be adopted to support and accelerate the data analysis procedure are summarized in Table II.

In the following sub-sections we provide the details of the three data processing techniques that are mostly used to analyse data acquired from UAV flights in the agricultural domain.

A. Photogrammetric techniques

Photogrammetric techniques involve the construction of orthophotos or Digital Elevation Models (DEMs) in order to depict three-dimensional information regarding the vegetation. This is achieved by capturing as many overlapping images of the crops as the aerial systems allow. Recent advancements in photogrammetry and computer vision have lead into a number of algorithms that are capable of matching hundreds of overlapping images and detecting common objects in them. The construction of the 3D Digital Elevation Models (Surface and/or Terrain Models) can provide to the producer information about the altitude of the earth surface, the natural and artificial objects/structures on the surface, the density of the vegetation and their growth among others. There are two types of DEMs:

- The Digital Terrain Model (DTM), which represents the altitude of the surface without taking into account other objects that may exist in the site, either natural or artificial (e,g. trees, vegetation, buildings). It is simply the elevation of the bare earth. Figure 2 presents a Digital Terrain Model from [36].
- The Digital Surface Model (DSM) representing the altitude of the surface first encountered by the remote sensing system (i.e. when the aerial image captures the top of a building, tree, the vegetation etc.). Thus, the final elevation model that is constructed in this case includes the elevation of bare ground along with natural and artificial objects that exist on it.

The DEMS can be used either to extract information directly from them or to generate orthophotos of the fields. An orthophoto, orthomosaic or orthoimage is an aerial photograph geometrically corrected (referred as orthorectified) such that the scale of the final image is uniform. Thus, the final image has the same lack of distortion as a map. In contrast with an uncorrected, simple, aerial image of crops or in general of a field, an orthophoto can be used to measure true distances and can be used to calculate other 3D parameters, because it is an accurate representation of the Earths surface, having been adjusted.

For the construction of orthophotos the accurate estimation of the internal and external camera parameters is required. Accordingly the photogrammetric techniques create point cloud representations of the 3D surface and combine all objects into a single DEM or use the DEMs to construct an orthomosaic. One of the most used set of algorithms for this purpose is Structure from Motion (SfM) [37]. The main advantage of SfM is that it does not require any information regarding the camera parameters or the environmental settings.

These photogrammetric imaging techniques are also used to construct 3D structures from two-dimensional sequences of overlapping images. For this purpose, large ranges of RGB images are processed by applying aerial triangulation and adjusting camera orientation. Computer vision is then applied to match the images and their characteristics. To achieve object tracking in overlapping images as well as to calculate the scale and orientation of the photo, in many cases, some Ground Control Points (GCPs) are used, distributed within the field being monitored. These GCPs are then identified within sequential images so as to a) link the images and b) identify the coordinates of each image and its slope.

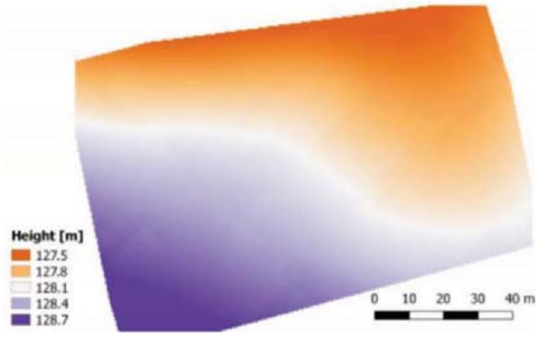

Fig. 2. A Digital Terrain Model [36]

The representation of the three-dimensional characteristics of the vegetation by producing the corresponding models was found to be preferable usually in cases where it was not possible to collect multispectral or hyperspectral data. Only in a few cases three-dimensional data were used together with the spectral data derived from the vegetation indices [38]. While in the literature the most common is the construction of DEMs using images in the visible spectrum to represent various characteristics of agricultural crops (such as height, density, etc.), in some cases there was also production of models from multispectral data to identify other characteristics [39], [40].

B. Using Machine Learning

Complementary to the three- dimensional models and the calculation of vegetation indices, Machine Learning (ML) techniques are also widely used in Precision Agriculture to extract useful information from the images captured by UAV systems. Machine Learning can be applied in various domains such as medicals systems [41], marketing and sales [42], biology [43] etc. It is estimated that considering the high amounts of data collected from agricultural fields Machine Learning can boost the performance of UAV systems by extracting

TABLE II
DATA AND IMAGE PROCESSING TOOLS

Software tool	Description
Adobe Photoshop	Applied to correct distortion and use of other image processing techniques
Agisoft Photoscan	Used for the construction of three-dimensional models and orthophotos. In addition, it allows the calculation of vegetation indices
QGIS	Used to calculate the vegetation indices from multispectral data
MATLAB	Applied mainly for the calculation of vegetation indices, but also for the application of other image processing techniques
Pix4Dmapper	Exploited for the calculation of vegetation indices and the construction of three-dimensional models

knowledge regarding several parameters of the crop fields. ML techniques are used in several cases and for different purposes. Both supervised and unsupervised learning is exploited by using clustering, classification and regression methods.

ML has been used to estimate spectral vegetation indices by *analyzing data acquired from RGB images* [44], presenting generally good results. Another application of ML techniques is to identify objects through Object Based Image Analysis (OBIA) within agricultural images from UAVs [31], [45] and/or classify them by recognizing and detecting weeds or discriminating species. Except from the above, ML techniques are also applied for direct *extraction of conclusions* on the growth and/or health of vegetation by classification techniques such as neural networks [46]–[49] and the Random Forest algorithm [50]–[52]. These algorithms are directly used in the data of the image acquired, by using the RGB colors, the intensity or other characteristics and in some cases data concerning the neighborhood of each pixel. In addition to the above features, ML was combined with the use of vegetation indices in some papers by using them as features in the model, presenting high accuracy.

The use of *Deep Learning (DL)* in Precision Agriculture applications is a recent, modern and promising technique, having growing popularity. Deep learning techniques extend typical ML by adding more complexity into the derived models. DL techniques transform the data using various functions that allow data representation in a hierarchical way, through several levels of abstraction. Advancements and applications of Deep Learning into other domains indicate the large potential it has. As indicated by [26], [53], the use of Machine Learning and more particular Deep Learning will be even more widespread the next years.

C. Vegetation indices

Vegetation Indices (VIs) are considered very effective and appropriate metrics for monitoring the growth and health of crops in qualitative and quantitative vegetation analysis [39], [54], [55]. They are widely used for the exploitation of information derived from UAVs for Precision Agriculture and Smart Farming. Vegetation Indices are based on the absorption of electromagnetic radiation by the vegetation. Vegetation indices are mathematical quantitative combinations of the absorption and scattering of plant in different bands of the electromagnetic spectrum. The reflectance in several bands is affected by parameters like vegetation biochemical properties, physical properties, environmental effects, soil background properties, moisture content etc. Therefore, the understanding of the spectral behavior of plants is considered to be fundamental to remote sensing applications in monitoring various vegetation features (e.g. biomass [38], nitrogen status [38], [56], vegetation health [9], etc.)

It has been proved that certain VIs are significantly associated with several characteristics of the crops. VIs can combine the reflections of different channels to eliminate ”noise” from external factors (e.g. sensors calibration, atmosphere, lighting, etc.) that affect the radiation in some channels that are being detected. For example, as mentioned in the previous Section, visible radiation to the red is absorbed by the chlorophyll while the near infrared (NIR) radiation is strongly reflected. In this way, vegetation can be discriminated by the soil in the image and also detect unhealthy plants. Vegetation Indices calculated based on the two above-mentioned radiation, such as the RVI or the NDVI index, enhance the contrast between soil and vegetation, because they are less affected by the effect of normalizing lighting conditions. The relationship between the reflections of the two zones allows for the elimination of disturbances by factors that affect the radiation of each zone in the same way.

The effort to model the biophysical parameters of vegetation has led to the creation of several different vegetation indices [57]–[59]. The vegetation indices can be divided into two main categories:

1) Vegetation Indices based on multispectral or hyperspectral data. Most of the developed Vegetation Indices use multispectral and/or hyperspectral information that can combine several bands.
2) Vegetation Indices based on information from the visible spectrum. Several VIs in the visible spectrum have been developed and are widely used due to the high cost of multispectral and hyperspectral sensors.

Concerning the multispectral vegetation indices, one of the first well-known indices was Ratio Vegetation Index (RVI). This index enhances the contrast among vegetation and soil. Though, it is sensitive to the optical properties of ground. The best known and most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI), which is the evolution of RVI and is calculated by the visible and near infrared light reflected from the vegetation. Unhealthy or sparse vegetation reflects more visible light and less near infrared light, making it easy to monitor the growth and health of many agricultural crops. It is based on absorption in Red due to chlorophyll and reflectance in NIR. RVI and NDVI are calculated as follows:

$$RVI = \frac{NIR}{R} \tag{1}$$

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

where R is the reflectance in the Red band and NIR is the reflectance in the Near Infrared band. Several other VIs have been developed based on the idea of NDVI. NDRE used the method of NDVI to normalize the ratio of NIR radiation with Red Edge (RE) radiation. The same applies for GNDVI with NIR and Green (G) bands.

$$NDRE = \frac{NIR - RE}{NIR + RE} \tag{3}$$

$$GNDVI = \frac{NIR - G}{NIR + G} \tag{4}$$

Figure 3 shows examples of crop maps constructed from information of spectral VIs (NDVI and NDRE) in different growth stages. We can see that the difference in the maps while the vegetation grows is quite clear.

Focusing on the VIs extracted from RGB images, Excess Greenness Index (ExG) and Normalized Difference Index (NDI) are the most used indices. ExG is based on the assumption that plants display a clear high degree of greenness, and soil is the only background element. Thus, it is calculated by doubling the radiation in the Green channel minus the radiation in Red and Blue channel, as (5) shows.

$$ExG = 2 * G - R - B \tag{5}$$

NDI was proposed to separate plants from soil and residue background images, using only green and red channels as (6) presents.

$$NDI = \frac{G - R}{G + R} \tag{6}$$

Although the VIs that use information in the visible light can be useful for crop monitoring, they cannot provide information for several parameters of the vegetation and also they are sensitive to the working environment properties like the atmosphere, the lighting etc. Hyperspectral remote sensing is expected to be the future trend in crop monitoring and this is mainly because it allows the development of new bands combination of vegetation indices. In many cases, it has been proved that hyperspectral vegetation indices are less sensitive to saturation, change in viewing/lighting geometry, and atmospheric contamination. The combination of new bands can eliminate noise from the working environment and in the same time exploit the information of certain bands and extract information for more biophysical features of the vegetation.

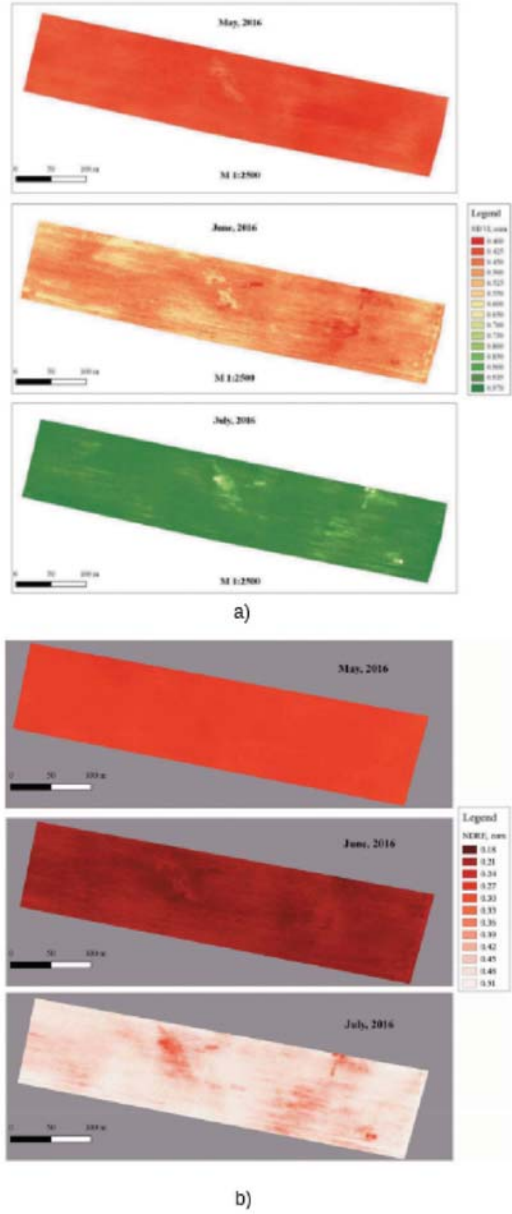

Fig. 3. Vegetation indices maps of crops in different growth stages [39] a) NDVI maps b) NDRE maps

IV. Discussion & Conclusions

In this study we briefly reviewed the techniques used to exploit UAV imagery for Precision Agriculture. In the literature, three main methods have stand out and are used either stand-alone or combined:

1) Photogrammetry techniques for constructing Orthomosaics or Digital Elevation Models: used to monitor the crops through their 3D characteristics. Mainly when only RGB Sensors are available.
2) Machine Learning: can be used for monitoring several

characteristics of the vegetation. Used for exploiting both RGB and/or multispectral/hyperspectral data.
3) Vegetation Indices: Used in the most studies. They have been proved to be very effective in monitoring various parameters of the crops. Most effective when multispectral or hyperspectral imagery is used.

We observed that in most of the cases the researchers use different techniques to exploit UAV data for the same application. For example, considering **weed management**, some studies use machine learning techniques to detect weeds while others use the 3D characteristics of the crops though DEMs. Weed detection with UAVs based on object-based image analysis is in an advanced stage and can be used for site-specific weed management.

On the other hand, **disease detection** with UAVs is relatively premature and mainly is applied through temporal analysis of the vegetation's growth. Though, hyperspectral data shows great potential for monitoring the health of the crops. A UAV-based approach adopting hyperspectral sensing technologies could reliably deliver Vegetation Indices, revealing both healthy and unhealthy portions of a cultivated field. With the help of this information, possibly coupled with spectral calibration data, a producer could locate the weak corps field areas and take timely decisions to save the part of the crop production that is in danger.

Yield prediction with UAVs is really promising through a lot of different methods but it seems that the integration of them or the use of a standardized workflow can improve its applicability. Yield prediction is usually performed with the use of RGB and multispectral images for estimating the density of production and biomass. The findings of this review appoint that combining information coming from Vegetation Indices with data coming from RGB images can improve the accuracy of yield estimation methods.

On the contrary, the use of UAVs for **irrigation management** has a standard workflow that involves the use of thermal imagery to monitor the crops and the needs of water. UAVs equipped with thermal cameras are able to detect possible pooling or leaks in irrigation. All this information can be processed into a single high-resolution, geo-located map of the field that highlights stressed areas. This map can also be used in the context of Variable Rate Irrigation (VRI) applications. VRI applications have as a target to optimize the irrigation of fields, automating the process based on data collected by sensors, maps, and gps.

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