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Crop Monitoring using Unmanned Aerial Vehicles: A Review

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ABSTRACT

Unmanned aerial vehicles (UAVs) or drones have been developed significantly over the past two decades, for a wide variety of applications such as surveillance, geographic studies, fire monitoring, security, military applications, search and rescue, agriculture, *etc*. In agriculture, for example, remote sensing by means of unmanned aerial vehicles has proven to be the most efficient way to monitor crops from images. Unlike remote sensing from satellite images or taken from manned aircraft, UAVs allow capturing images of high spatial and temporal resolution, thanks to their maneuverability and capability of flying at low altitude. This article presents an extensive review of the literature on crop monitoring by UAV, identifying specific applications, types of vehicles, sensors, image processing techniques, among others. A total of 50 articles related to crop monitoring applications of UAV in agriculture were reviewed. Only journal articles indexed in the Scopus database with more than 50 citations were considered. It was found that cereals are the most common crops where remote sensing has been applied so far. In addition, the most common crop remote sensing applications are related to precision agriculture, which includes the management of weeds, pests, diseases, nutrients and others. Crop phenotyping is also a common application of remote sensing, which consists of the evaluation of a crop's physical characteristics under environmental changes, to select the plants or seeds with favorable genotype and phenotype. Besides, multirotor is the most common type of UAV used for remote sensing and RGB and multispectral cameras are mostly used as sensors for this application. Finally, there is a great opportunity for research in remote sensing related to a wide variety of crops, crop monitoring applications, vegetation indexes and photogrammetry.

Key words: Crop monitoring, Phenotyping, Precision agriculture, Remote sensing, UAV, Vegetation indices.

It is calculated that the world population in 2050 will be over 9 billion people, so food demand could double this figure. In the face of this, the need arises to increase farming production; nonetheless, conventional agriculture is carried out applying agrochemical products in a uniform manner over a whole crop without considering its specific variability as regards climate, topography, soil properties, humidity, weeds, pests, diseases. This managing leads to the inefficient use of natural resources and agricultural input, which at the same time generates low profitability and environmental degradation (Leiva, 2008).

This therefore demands the need to optimize agricultural production, which can be achieved by adapting new techniques and practices regarding crop management which, based in spatial and temporary variations in a piece of land, will permit to diagnose and apply the adequate agrochemical doses in its different sectors. This manner of agricultural production, known as precision agriculture, has been developed in different countries since the 80s, with remarkable advances in the last years (Gebbers *et al*., 2010).

Precision agriculture requires geographical information systems (GIS), remote sensors, digitalized maps, databases, global positioning systems (GPS), robotics, among others. Regarding the latter are ground and aerial robots capable of carrying out operations such as planting, crop management (pests, weeds, disease control), phytosanitary product spraying, harvest, remote sensing and others (Tom *et al*., 2018).

In the literature there are different developments of unmanned air vehicles for application in precision agriculture. One of these applications is crop monitoring through high-resolution multispectral images. In this way it is possible to extract different vegetation indexes that permit to locate weeds, pests, diseases, nutrients, water stress, among others (Bendig *et al*., 2014; López-Granados, 2011; Shi *et al*., 2016; Vega *et al*., 2015, Kumar *et al*., 2020). With this information it is possible to take located control actions applying, for example, agrochemicals in a specific site and in the adequate amount (Gonzalez *et al*., 2016; Huang *et al*., 2009), which leads to savings in agricultural inputs, reducing the environmental effect and improving profitability. These intelligent spray systems may be accompanied by computer vision systems and artificial intelligence techniques that guarantee the effective recognition of crop weeds or diseases (Gao *et al*., 2019).

Unlike manual on-site monitoring, remote sensing allows non-invasive, fast and efficient crop monitoring. This is possible thanks to significant advances in unmanned

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aerial vehicles, different types of sensors, georeferencing systems and image processing algorithms (Gogoi *et al*., 2018). Remote sensing using unmanned aerial vehicles, unlike satellite sensing, allows images of higher spatial and temporal resolution to be taken at a low cost, with less interference from atmospheric conditions.

A bibliographic review on the application of unmanned aerial vehicles in agriculture is presented below, placing emphasis on remote sensing for crop monitoring as it ends up being their main application. It starts by describing the methodology applied to compile and filter the articles. It continues by going in depth into the most common remote sensing application such as pests and disease detection and phenotyping. The main image processing techniques and the corresponding sensors are described as well. A summary of the crops with which the said monitoring has been carried out using UAVs and the type of aerial vehicles used is also included.

To carry out an analysis that will permit to provide a vision of the development in precision agriculture and that will allow to contribute to this food safety field, a data search is carried out in a high-impact database in the academic field, using a search equation with relevant key words. After using the search equation in the data bases, an analysis of the articles, authors and years is done to filter those with a greater impact and identify the authors who have written the most on precision agriculture. When selecting relevant articles and authors, this database is analyzed in a bibliometric analysis program thus permitting to interpret the search results and make decisions to reduce and eliminate non-relevant data in the research.

An initial search was carried out at the Scopus database with the following equation: (quadrotor OR multirotor OR drone OR uav OR *copter) AND (agriculture OR farming OR crop), the result of the authors' expertise and mastery of the issue. In this way 2076 articles were found in the said database. To have a pertinent filtering, key words were analyzed, leaving out those that are not a topic of interest for the research, to have in the end 1519 articles. Some keywords considered were "remote sensing", "monitoring" and "mapping".

Because the number of articles, only journal articles were selected, rejecting those from conferences, book chapters, general reviews, among others. This way, from 1519 articles 692 were chosen, reducing the resulting documents by 55%. The next criterion to reduce articles to review was the number of paper citations of each one of them. Those with fewer than 50 citations were rejected, thus permitting to review the ones that generate a greater impact in the academic field. In this way, 51 articles were obtained out of which this review was made.

Crop monitoring

Crop monitoring by means of remote sensing has different objectives. One of them is in precision agriculture, to determine and handle weeds, pests, diseases, nutrients, hydric stress, among others. Another objective is crop phenotyping, where seeds with the best phenotypic characteristics are selected, such as height and biomass production. In the literature is found that crops that have been monitored the most through remote sensing are cereals such a wheat, corn and barley, as shown in Fig 1. The corresponding references are shown in Table 1.

Crop monitoring for precision agriculture

Precision agriculture is a set of techniques through which, by monitoring of temporal and spatial variation in a crop, it is possible to set up a prompt treatment at a specific site. Precision agriculture comprises the following stages: data collection, variability mapping, decision making and application of the management practices. Variable remote sensing is important in the first three stages and it is complemented with other technologies such as geographic information systems (GIS) and machinery for the adequate treatment (Vega *et al*., 2015). As applications of this type there is the management of weeds, pests, diseases, nutrients, hydration, among others.

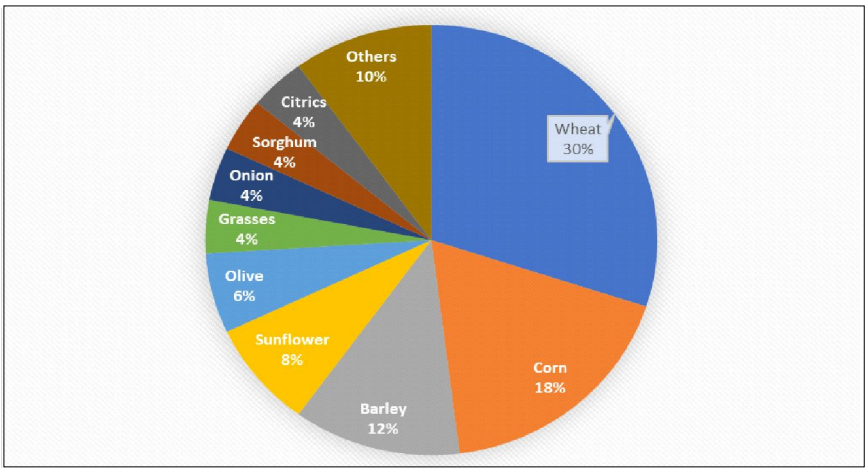


Fig 1: Crops monitored using remote sensing.

Weed management

Weed management by means a precision agriculture approach initially requires detecting weed localized areas to then take a control action through spraying or mechanical removal. This can be done in real time, by means of capturing geo-referenced images, a weed recognition system and one for their management (López-Granados, 2011). These practices to handle weeds increase profitability and reduce environmental impact (López-Granados, 2011), since, different from conventional treatments whereby herbicides are uniformity distributed (Gómez-Candón *et al*., 2014), with precision agriculture, agrochemical spraying is done at a specific site thus optimizing the amount of the agrochemical required.

Weed management is a priority in early-phase crops. To recognize weeds at this phase, high spatial resolution is required (less than 5 cm per pixel, since crop reflectance and weeds are quite similar at this phase (Gómez-Candón *et al*., 2014). To do so it is necessary to have a high altitude topographic survey (less than 100 m) that permits to discriminate each one of the plants by means of high resolution (Torres-Sánchez *et al*., 2013) (Gómez-Candón *et al*., 2014) (Pérez-Ortiz *et al*., 2016). This implies a challenge since the lesser the altitude, the higher number of images is required, as well as the greater UAV autonomy (Gómez-Candón *et al*., 2014). Computer vision techniques and machine learning may be used for this task (Pérez-Ortiz *et al*., 2016).

In some cases when differentiating soil weeds is simply required, it is sufficient to determine the green excess index (ExG), which is obtained from RGB images (Pérez-Ortiz *et al*., 2016). In other cases it may be necessary to determine the different plant species (weeds and crop) and identify, for example, dominant plants and their size (Shi *et al*., 2016). To do so, a multispectral sensor may be useful or even a hyperspectral one that permits to evidence quite small reflectance variations (López-Granados, 2011; Torres-Sánchez *et al*., 2013).

Management of pests, diseases and crop condition

The localized and timely detection of crop pests and diseases permits to take corrective and preventive decisions and their application in an effective manner. Thus, for example, a commonly monitored parameter is the biomass contents as it is strongly related to a crop production. This way, early problem detection in the crop, such as nutrient deficiency, permits to take timely measures without having to wait until the harvest to detect low production zones (Vega *et al*., 2015). On the other hand, in case of detecting zones with sufficient nutrient contents (Nitrogen, for example) it permits to avoid a crop over fertilization, saving agricultural input (Bendig *et al*., 2014). Disease detection may be carried out through vegetation indexes since some diseases produce changes in reflectance (Garcia-Ruiz *et al*., 2013).

Pest, disease and nutrient deficit detection can be fought through agrochemical spraying, including pesticides, fungicides, fertilizers, *etc*. Using UAV for spraying is ideal for small lots or difficult access areas (Huang *et al*., 2009). In (Faiçal *et al*., 2014) for example, a UAV fumigation technique is used as well as a ground-based sensor network. As a control strategy, they generate route adaptation for an agrochemical spraying vehicle depending on speed and wind intensity. To do so, they have wireless sensors located on the ground which feedback data on the amount of agrochemicals they are receiving.

The crop condition is evaluated not only by means of pest and disease detection but also by estimating other parameters such as plant density (Jin *et al*., 2017), biomass contents (Vega *et al*., 2015), crop height (Geipel *et al*., 2014), canopy area, nitrogen contents (Bendig *et al*., 2014), solid clay contents (Shi *et al*., 2016), crop hydric stress contents (Berni *et al*., 2009), among others.

Table 1: Sample references for different crops monitored using remote sensing.

Crop	Sample references
Wheat	(Chapman *et al*., 2014; Gómez *et al*., 2014; Haghighattalab *et al*., 2016; Holman *et al*., 2016; Hunt et al., 2010; Jin *et al*., 2017; Lelong *et al*., 2008; Rasmussen *et al*., 2016; Schmale III *et al*., 2008; Shi *et al*., 2016; Suomalainen *et al*., 2014; Tattaris *et al*., 2016; Torres-Sánchez *et al*., 2015; Torres-Sánchez *et al*., 2014; Verger *et al*., 2014).
Corn	(Geipel *et al*., 2014; Li *et al*., 2016; Liebisch *et al*., 2015; Peña-Barragán *et al*., 2013; Pérez-Ortiz *et al*., 2016; Schmale III *et al*., 2008; Shi *et al*., 2016; Tattaris *et al*., 2016a; Torres-Sánchez *et al*., 2015).
Barley	(Aasen *et al*., 2015; Bendig *et al*., 2014, 2015; Lucieer *et al*., 2014; Rasmussen *et al*., 2016; Schmale III *et al*., 2008).
Sunflower	(Pérez-Ortiz *et al*., 2016; Torres-Sánchez *et al*., 2015; Torres-Sánchez *et al*., 2013; Vega *et al*., 2015).
Olive	(Berni *et al*., 2009; Díaz-Varela *et al*., 2015; Torres-Sánchez *et al*., 2015).
Grasses	(Lucieer *et al*., 2014; Von *et al*., 2015).
Onion	(Córcoles *et al*., 2013; Suomalainen *et al*., 2014).
Sorghum	(Shi *et al*., 2016) (Chapman *et al*., 2014).
Cítrics	(Garcia-Ruiz *et al*., 2013) (Stagakis *et al*., 2012).
Cotton	(Shi *et al*., 2016).
Rapeseed	(Verger *et al*., 2014).
Sugarcane	(Chapman *et al*., 2014).
Grape	(Zarco-Tejada *et al*., 2013).
Rice	(Swain *et al*., 2010).

Crop monitoring for phenotyping

Remote sensing has proved to be a great potential in crop phenotyping processes, where a specie's response to different environmental conditions is evaluated. Crop phenotyping requires measuring and evaluating observable physical characteristics (Holman *et al*., 2016), for a species' different phenotypes, different generations and at different growth stages (Tattaris *et al*., 2016a). Traditional phenotyping with direct field observations demands much time and costs (Haghighattalab *et al*., 2016). In the face of this, non-invasive phenotyping by means of unmanned aerial vehicles is more common now-a-days due to the possibility to take temporal and spatial high-resolution images that permit to collect different patterns conforming crop phenotype (Shi *et al*., 2016).

Thanks to phenotyping it is possible to collect plant or seed species that better adapt, those of higher production and, overall, those with a favorable genotype and phenotype. Thus, for example, how a crop responds to different fertilizers can be evaluated (Holman *et al*., 2016), or how they perform against pests and diseases (Chapman *et al*., 2014).

The most common phenotypic traits considered are:

-Canopy height (m), biomass amount (kg/m2) and crop's crown volume (m3). These are indicators for good growth, crop vitality, efficient use of light, production during harvest, carbon reserves and nutrient availability (Bendig *et al*., 2014; Holman *et al*., 2016; Li *et al*., 2016; Shi *et al*., 2016; Torres-Sánchez *et al*., 2015).

-Foliar area index and canopy cover are good indicators of how much vegetation there is per surface unit (Liebisch *et al*., 2015; Shi *et al*., 2016). This is related to the plant photosynthetic capacity, respiration and evaporation-transpiration and efficiency in the use of light (Córcoles *et al*., 2013; Verger *et al*., 2014). The foliar area index reflects the crop's growth potential and it permits to estimate biomass production (Córcoles *et al*., 2013; Hunt *et al*., 2010; Lelong *et al*., 2008; Liebisch *et al*., 2015; Shi *et al*., 2016; Verger *et al*., 2014).

A crop phenotype from remote sensing can be carried out in two complementary manners: from vegetation indexes and from photogrammetry. Each approach allows to determine different phenotypic traits, as it is described in the following sections.

Vegetation indexes

Vegetation indexes are quantitative indicators calculated as of crop images. These indexes allow to monitor a crop or soil condition, providing information on growth, biomass contents, crop health, crop condition, weed presence, *etc*.

Some indexes which are gotten from red or infrared bands are related to the biomass contents (Aasen *et al*., 2015), the canopy structure and the foliar area index (LAI) (Aasen *et al*., 2015; Lelong *et al*., 2008; Tattaris *et al*., 2016). Other indexes only depend on visible bands and are related to pigment concentration in the leaves and nitrogen contents (Lelong *et al*., 2008). On the other hand, some indexes such as canopy temperature (Berni *et al*., 2009), which is calculated as of infrared radiation, permit to evaluate a plant's transpiration rate in an indirect manner. It is a performance indicator of a plant with low hydric stress (Tattaris *et al*., 2016b).

(Henrich *et al*., 2009) have compiled ample data on different sensors, vegetation indexes and remote sensing applications, available presently only in a free-access web site. Fig 2 shows the most common vegetation indexes used in remote sensing. Table 2 summarizes some vegetation indexes with some applications found in the literature and the corresponding formula to estimate them based on different spectral bands.

Taking images to extract vegetation indexes is a great challenge, as it demands stable lighting conditions during capture. Since these indexes depend of reflectance, the time of the day when images are captured may have an influence on the same (Vega *et al*., 2015), as well as the angle used to take the images (Rasmussen *et al*., 2016). On the other hand, it must be taken into account that plant reflectance varies depending on their growth stage (López-Granados, 2011).

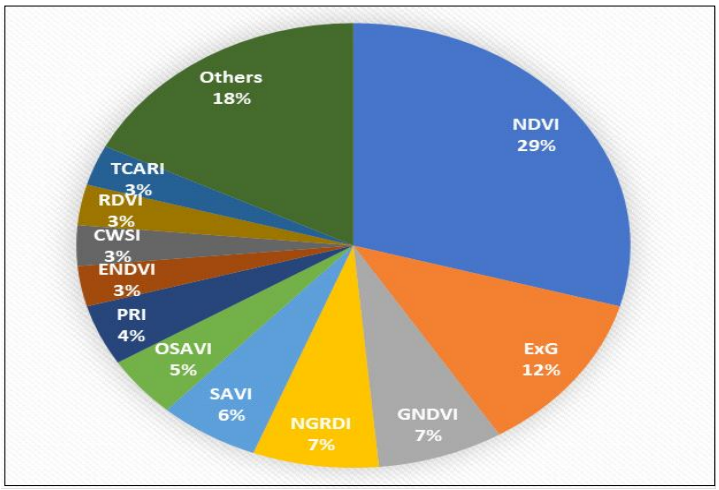


Fig 2: Vegetation indexes used in remote sensing.

Table 2: Vegetation indexes with some applications.

Index	Sample references	Some applications	Index formula*
GNDVI (green normalized difference vegetation index)	(Garcia-Ruiz *et al.*, 2013; Haghighattalab *et al.*, 2016; Hunt *et al.*, 2010; Lelong *et al.*, 2008; Shi *et al.*, 2016)	Related to nitrogen contents.	$GNDVI = \frac{NIR-Green}{NDVI-Green}$
NDVI (normalized different vegetation index)	(Bendig *et al.*, 2015; Berni, Zarco-Tejada, Suarez, *et al.*, 2009; Díaz-Varela *et al.*, 2015; Garcia-Ruiz, *et al.*, 2013; Haghighattalab *et al.*, 2016; Hunt *et al.*, 2010; Lelong *et al.*, 2008; Liebisch *et al.*, 2015; Lucieer *et al.*, 2014; Matese *et al.*, 2015; Rasmussen *et al.*, 2016; Shi *et al.*, 2016; Stagakis *et al.*, 2012; Swain *et al.*, 2010; Tattaris *et al.*, 2016; Torres-Sánchez *et al.*, 2015; Torres-Sánchez *et al.*, 2013, 2015; Vega *et al.*, 2015; Zarco-Tejada *et al.,* 2013)	Related to foliar area index, foliar biomass. It permits to calculate hydric stress. It permits to detect soil vegetation.	$NDVI = \frac{NIR-VIS}{NIR+VIS}$ or $NDVI = \frac{NIR-Red}{NIR+Red}$
NGRDI (Normalized green -red difference index)	(Geipel *et al.,* 2014; Li *et al.*, 2016; Rasmussen *et al.*, 2016; Torres-Sánchez *et al.*, 2014; Torres -Sánchez *et al.*, 2013)	Used to discriminate vegetal layer from soil.	$NGRDI = \frac{Green-Red}{Green+Red}$
SAVI (soil-adjusted vegetation index)	(Bendig *et al.*, 2015; Garcia-Ruiz *et al.*, 2013; Lelong *et al.,* 2008; Shi *et al.*, 2016)	Its uses are similar to NDVI's but with adjustments to soil reflection. It is ideal for places where the vegetal area is less than 40%.	$SAVI = \frac{NIR-Red}{NIR+Red+L} * (1+L)$ Where L is the plant density factor ranging from 0 to 1.
MSAVI (modified SAVI)	(Bendig *et al.*, 2015)	It is an improved version of SAVI.	$MSAVI = \frac{(2*NIR+1-\sqrt{[(2*NIR+1)^2-8*(NIR-Red)]}}{2}$
OSAVI (Optimized soil-adjusted vegetation index)	(Bendig *et al.*, 2015; Lucieer *et al.*, 2014; Zarco-Tejada *et al.,* 2013)	These indexes are related to the leaves' physiological conditions and the canopy structure. Its application is similar to NDVI's	$OSAVI = (1+0.16)_* \frac{R800_{nm}-R670_{nm}}{R800_{nm}+R670_{nm}+0.16}$
NRI (normalized ratio index) or GnyLi Index	(Bendig *et al.*, 2015)	Related to dry biomass	$GnyLi = \frac{R900_{nm}*R1050_{nm}-R955_{nm}*R1220_{nm}}{R900_{nm}*R1050_{nm}+R955_{nm}*R1220_{nm}}$
GRVI (green red vegetation index)	(Bendig *et al.,* 2015)	It permits to estimate biomass amount.	$GRVI = \frac{Green-Red}{Green+Red}$
GRVI (Modified green red vegetation index)	(Bendig *et al.*, 2015)	It permits to estimate biomass amount.	$MGRVI = \frac{Green^2-Red^2}{Green^2+Red^2}$

Table 2: Continue...

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RGBVI (Red green blue vegetation index)	(Bendig *et al*., 2015)	It permits to estimate biomass amount.	$RGBVI=\frac{Green^2-(Blue*Red)}{Green^2+(Blue*Red)}$
ExG (Excess green index)	(Geipel *et al*., 2014; Li *et al*., 2016; Pérez-Ortiz *et al*., 2016; Rasmussen *et al*., 2016; Torres-Sánchez *et al*., 2015, 2014; Torres-Sánchez *et al*., 2013, 2015)	Useful to differentiate soil from vegetation.	ExG=2*Green-Red-Blue
RENDVI (Red-edge normalized difference vegetation index)	(Haghighattalab *et al*., 2016)	Uses similar to NDVI's but calculated with a red edge band instead of red.	$RENDVI=\frac{NIR-Red_edge}{NIR+Red_edge}$
ENDVI (enhanced normalized difference vegetation index)	(Haghighattalab *et al*., 2016; Rasmussen *et al*., 2016)	Uses similar to NDVI's but calculated with other bands.	$ENDVI=\frac{NIR+Green-2*Blue}{NIR+Green+2*Blue}$
GIPVI (Infrared percentage vegetation index)	(Haghighattalab *et al*., 2016)	Uses similar to NDVI's but its calculation is simpler.	$GIPVI=\frac{NIR}{NIR+Green}$
PRI (Photochemical reflectance index)	(Berni *et al*., 2009; Stagakis *et al*., 2012; Zarco-Tejada *et al*., 2013)	Hydric stress indicator.	$PRI=\frac{R570_{nm}-R531_{nm}}{R570_{nm}+R531_{nm}}$
CWSI (Crop water stress index)	(Berni *et al*., 2009; Berni *et al*., 2009)	Hydric stress thermal indicator	$CWSI=\frac{(Tc-Ta)-(Tc-Ta)_{LL}}{(Tc-Ta)_{UL}-(Tc-Ta)_{LL}}$ (Tc-Ta): Temperature difference between leaf and air. $(Tc-Ta)_{LL}$: Prospective lower limit of the temperature difference between leaf and air for a canopy that transpires. $(Tc-Ta)_{UL}$: Prospective upper limit of the temperature difference between leaf and air for a canopy that does not transpire.
RDVI (Renormalized difference vegetation index)	(Stagakis *et al*., 2012; Zarco-Tejada *et al*., 2013)	Similar applications to those of the NDVI. This index is related to the leaves' physiological conditions and canopy structure. Applications similar to NDVI's.	$RDVI=\frac{R800_{nm}-R670_{nm}}{\sqrt{R800_{nm}+R670_{nm}}}$
TCARI (Transformed chlorophyll absorption in reflectance index)	(Lucieer *et al*., 2014; Zarco-Tejada *et al*., 2013)	Chlorophyll contents indicator.	$TCARI=3*[(R700_{nm}-R670_{nm})-0,2*(R700_{nm}-R550_{nm})*(R700_{nm}/R670_{nm})]$
Red edge index	(Zarco-Tejada *et al*., 2013)	Sensible to chlorophyll contents.	$Red_edge=R700nm \diagup R670nm$

Table 2: Continue...

Table 2: Continue...

MTVI2 (Modified triangular vegetation index 2)	(Lucieer *et al.*, 2014)	It permits to estimate green biomass density by means of foliar area index.	$MTVI2=\frac{1,5[1,2(R800_{nm}-R550_{nm})-2,5(R670_{nm}-R550_{nm})]}{\sqrt{(2R800_{nm}+1)^2-(6R800_{nm}-(5,\sqrt{R670_{nm}})-0,5)}}$
MTVI (Modified triangular vegetation index)	(Stagakis *et al.*, 2012)	It permits to calculate foliar area index.	$MTVI=0,5[120(R800_{nm}-R570_{nm})-200(R670_{nm}-R570_{nm})]$
CIVE (Color index of Vegetation)	(Torres-Sánchez *et al.*, 2014)	It permits to discriminate objects from vegetation since its grey scale values are different from other objects.	$CIVE=0,441Red-0,881Green+0,385Blue+18,78745$
ExGR (Excess green minus excess red index)	(Torres-Sánchez *et al.*, 2014)	It permits to face the problem of natural lighting variability; it facilitates green color pixel identification.	$ExGR=ExG-1,4Red-Green$
Woebbecke Index	(Torres-Sánchez *et al.*, 2014)	Woebbecke found a green excess index that is used for automated analysis based on vegetal phenology.	$WI=\frac{(Green-Blue)}{(Red-Green)}$

*NIR: Near infrared; R# is the reflectance at a certain wavelength; VIS: Visible wavelength.

Finally, to guarantee a good spatial resolution, images must be taken at a height of 30 to 100 m (Rasmussen *et al.*, 2016).

Photogrammetry

Photogrammetry is a technique for the tridimensional reconstruction of an object from multiple images taken on it. Photogrammetry permits to generate digital models of a 3D surface as of which it is possible to measure distances, areas, volumes, with high accuracy. UAV have a great potential for this since they permit to take high-resolution aerial images at a low altitude.

The photogrammetry process is carried out under the following phases: flight planning, location and measuring of control points, flight execution to capture images and processing of the georeferenced images (Córcoles *et al.*, 2013). For geo-referenciation different ground control points (GCPs) are commonly used in order to ensure accuracy in the mosaicking process (Gómez-Candón *et al.*, 2014).

By means of the tridimensional reconstruction of lands and crops (CSM crop surface models) it is possible to determine the crop height, the canopy volume, the crop area (Bendig *et al.*, 2014; Díaz-Varela *et al.*, 2015; Li *et al.*, 2016; Torres-Sánchez *et al.*, 2015), parameters that cannot be obtained from vegetation indexes (Geipel *et al.*, 2014). It is also possible to determine a crop growth rate if the process takes place under different growth phases (Bendig *et al.*, 2014; Holman *et al.*, 2016).

For the tridimensional reconstruction a computer vision technique is normally used known as Structure from motion, which offers high topographical resolution from the different sequences of images (Bendig *et al.*, 2014; Geipel *et al.*, 2014; Holman *et al.*, 2016; Lucieer *et al.*, 2014; Zahawi *et al.*, 2015). Generating 3D hyperspectral maps permits to get hyperspectral data by pixel in an image from a camera that has been previously characterized and calibrated using radiometric methods (Aasen *et al.*, 2015). Some software tools used in the literature to carry out this process are Agisoft Photo Scan Proffessional (Bendig *et al.*, 2014; Geipel *et al.*, 2014; Haghighattalab *et al.*, 2016), Smart3DCapture (Li *et al.*, 2016) and Leica Photogrammetry Suit (Gómez-Candón *et al.*, 2014).

For image georeferencing, UAVs use GPS. Nonetheless, since the GPS receptor provides the UAV position with an ample error margin (of several meters) normally land control points (GPC) are used in order to obtain a minor error less than 10 cm (Li *et al.*, 2016; Lucieer *et al.*, 2014; Vega *et al.*, 2015).

Sensors for remote sensing

According to the reviewed articles, crop monitoring can be done through remote sensing, based mainly on RGB, multispectral and hyperspectral sensors, as shown in Fig 3. The corresponding references are shown in Table 3.

RGB sensors provide 3 bands (red, green and blue) of the visible spectrum, as shown in Fig 4, with a wavelength ranging from 380 nm up to 750 nm. These bands allow the

calculation of some of the vegetation indexes shown in Table 2, which are mainly intended to discriminate vegetation from the soil and estimate biomass amount.

Multispectral sensors are the most utilized in remote sensing with UAVs as they are more accessible and offer a good number of bands aside from RGB (Verger *et al*., 2014). These sensors capture between 3 and 12 bands from around 100nm width each (Adão *et al*., 2017; López-Granados, 2011). These bands allow the calculation of different vegetation indexes as shown in Table 2. One of the most common vegetation indexes is NDVI, which requires the near-infrared band and a visible band, allowing the detection of vegetation in a more effective way than the ExG index, which is based on the RGB bands.

On the other hand, hyperspectral sensors detect up to hundreds of narrow bands for a width less than 10 nm (López-Granados, 2011; Lucieer *et al*., 2014). Thanks to this they allow to analyze variables manifesting in a very small band such as, for example, chlorophyll contents in a 670-780nm band and obtain high resolution thermic images

Table 3: Sample references for different image sensors used in remote sensing.

Sensor type	Sample references
Multispectral	(Berni *et al*., 2009; Díaz-Varela *et al*., 2015; Garcia-Ruiz *et al*., 2013; Haghighattalab *et al*., 2016; Hunt *et al*., 2010; Lelong *et al*., 2008; Matese *et al*., 2015; Minoz-Marí *et al*., 2010; Peña-Barragán *et al*., 2013; Rasmussen *et al*., 2016; Shi *et al*., 2016; Stagakis *et al*., 2012; Swain *et al*., 2010; Tattaris *et al*., 2016; Torres-Sánchez *et al*., 2015, 2014; Torres-Sánchez *et al*., 2013, 2015; Vega *et al*., 2015; Verger *et al*., 2014; Von *et al*., 2015; Xiang *et al*., 2011; Zarco-Tejada *et al*., 2013).
RGB or real color, visible band	(Bendig *et al*., 2014, 2015; Córcoles *et al*., 2013; Geipel *et al*., 2014; Holman *et al*., 2016; Jin *et al*., 2017; Li *et al*., 2016; Liebisch *et al*., 2015; Rasmussen *et al*., 2016; Shi *et al*., 2016; Sugiura *et al*., 2005; Torres-Sánchez *et al*., 2015; Torres-Sánchez *et al*., 2013, 2015; Vega *et al*., 2015; Von Bueren *et al*., 2015).
Hyperspectral	(Aasen *et al*., 2015; Bendig *et al*., 2015; Berni *et al*., 2009; Lucieer *et al*., 2014; Minoz-Marí *et al*., 2010; Suomalainen *et al*., 2014).
Thermic	(Berni *et al*., 2009; Chapman *et al*., 2014; Liebisch *et al*., 2015; Tattaris *et al*., 2016; Zarco-Tejada *et al*., 2013)
Near-infrared (NIR)	(Chapman *et al*., 2014; Swain *et al*., 2010; Von *et al*., 2015).
Land laser scanner (TLS)	(Holman *et al*., 2016).
High spectral resolution spectrometer	(Von *et al*., 2015).

Table 4: Sample references for types of UAV used in remote sensing.

UAV type	Sample references
Fixed wing	(Díaz-Varela *et al*., 2015; Hunt *et al*., 2010; Lelong *et al*., 2008; Rasmussen *et al*., 2016; Schmale III *et al*., 2008; Shi *et al*., 2016; Verger *et al*., 2014; Zarco-Tejada *et al*., 2013).
Multirotor	(Aasen *et al*., 2015; Bendig *et al*., 2014, 2015; Córcoles *et al*., 2013; Garcia-Ruiz *et al*., 2013; Geipel *et al*., 2014; Gómez-Candón *et al*., 2014; Haghighattalab *et al*., 2016; Jin *et al*., 2017; Li *et al*., 2016; Lucieer *et al*., 2014; Peña-Barragán *et al*., 2013; Pérez-Ortiz *et al*., 2016; Rasmussen *et al*., 2016; Shi *et al*., 2016; Tattaris *et al*., 2016; Torres-Sánchez *et al*., 2015; Torres-Sánchez *et al*., 2013, 2015; Vega *et al*., 2015).
Helicopter	(Berni *et al*., 2009; Chapman *et al*., 2014; Sugiura *et al*., 2005; Swain *et al*., 2010; Xiang and Tian, 2011; Huang *et al*., 2009)
Dirigible	(Liebisch *et al*., 2015).
Not specified UAV	(Barrientos *et al*., 2011; Berni *et al*., 2009; Matese *et al*., 2015; Suomalainen *et al*., 2014; Tattaris *et al*., 2016b; Tokekar *et al*., 2013; Torres-Sánchez *et al*., 2014; Von Bueren *et al*., 2015).

Table 5: UAVs for remote sensing and their characteristics. Adapted from (García, 2017).

Characteristic	Multirotors	Fixed wing	Helicopters	Dirigible
Hover capability	3	0	3	4
Velocity	2	4	3	1
Maneuverability	4	1	3	1
Flight autonomy	2	3	2	4
Wind resistence	2	4	2	1
Stability	2	3	1	4
Vertical flight capacity	4	1	4	2
Payload capacity	2	4	3	1
Maximum altitude	1	4	2	3

0=null; 1=bad; 2=Fair; 3=Good; 4=Excellent.

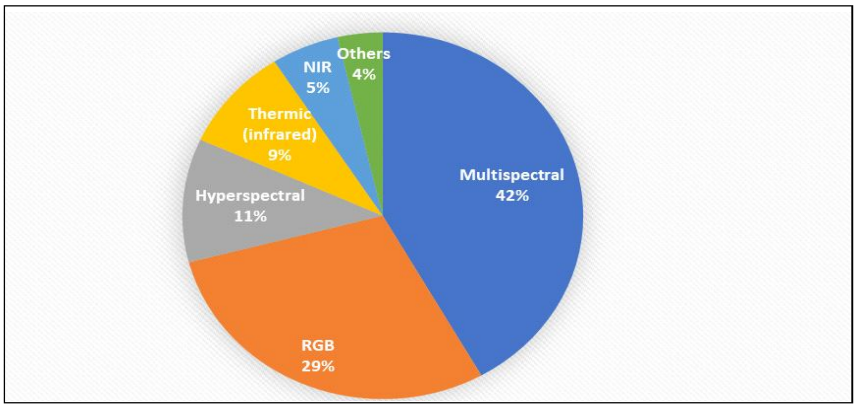


Fig 3: Image sensors used for remote sensing.

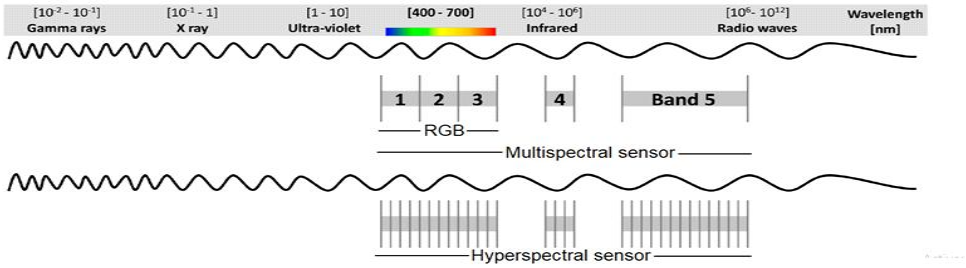


Fig 4: Spectrum representation showing examples of RGB, multispectral and hyperspectral sensors. Adapted from (Adão *et al.*, 2017).

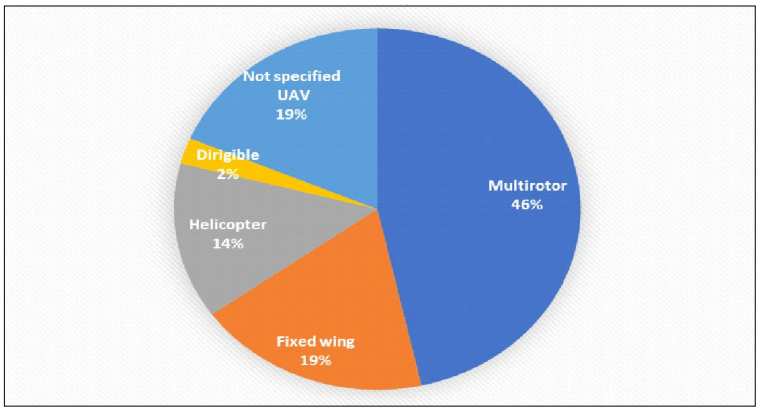


Fig 5: Types of UAV used in remote sensing.

(Berni, Zarco-Tejada, Sepulcre-Cantó, *et al.*, 2009). Overall, hyperspectral sensors allow us to discriminate components that may be grouped by multispectral bands. A wide review of hyperspectral sensors is done in (Adão *et al.*, 2017).

Both multispectral and hyperspectral sensor may be useful for the detection of weeds, diseases and pests, as they lead to small spectral variations that require high spectral resolution.

Aerial vehicles for remote sensing

For remote sensing traditional satellite images or those taken from manned aerial vehicles have been used. They present limitations as to temporal and spatial resolution and depend on climate conditions, such as cloudiness (Torres-Sánchez *et al.*, 2013). In the last years UAV have shown a great potential to carry out this task at a lower cost and with better performance. Unmanned aerial vehicles permit to take high spatial resolution images due to their maneuverability to fly at a low altitude. Fig 5 summarizes the types of UAV used in different studies on remote sensing. The corresponding references are shown in Table 4.

Multirotor is the most common type of UAV used for remote sensing, since they allow us to take multispectral images at low altitude and high spatial resolution, they have low operating costs and high maneuverability. However, multirotors face challenges including lower flight autonomy, slower velocity and lower payload capacity compared to fixed wings UAVs. These last ones are intended for large areas

and flat terrains, whereas multirotors are more suitable for small areas regardless of the terrain topography. Table 5 summarizes the overall characteristics of different types of UAVs, that may be considered for remote sensing applications.

CONCLUSION

This review has evidenced the great variety of crops monitored by remote sensing. However, cereals like corn, wheat and barley accounts for about 60% of the total articles reviewed, which indicates the need for further research in other crops. Likewise, RGB and multispectral sensors are mostly used, accounting for about 70% of the studied cases. While RGB cameras permit to calculate some simple vegetation indexes that are good detectors of the vegetal area in a crop, multispectral cameras have the capacity to capture images within specific wavelength ranges that provide details on plant diseases and plant types.

Among the most common crop remote sensing applications by means of UAVs are found: precision agriculture, which includes management of weeds, pests, diseases, nutrients and others; crop phenotyping, which consists of the evaluation of a crop's physical characteristics in the face of environmental changes. In any case, high spatial and temporal resolution images end up being essential since, as of them, it is possible to determine vegetation indexes and/or tridimensional surface models that provide data on different variables both of the crop and the soil. Some of the most common vegetation indexes in the literature are: NDVI, EXG, GNDVI, NGRDI and SAVI, accounting for more than 60% of the total studied cases. Among the most common study variables or parameters are found the foliar area index, foliar biomass, hydric stress, contents of vegetation in the soil and nitrogen contents.

Finally, almost 50% of the unmanned aerial vehicles used in remote sensing are multirotors thanks to the easiness for their construction and control. Their maneuverability permits to take images at a low altitude, guaranteeing a good spatial resolution. Different from fixed wing vehicles, they allow flying over places of difficult access or mountainous terrains. However, almost 20% of the reviewed articles were based on fixed wing UAVs, since this type of aerial vehicle allows the monitoring of large areas at a higher speed.

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