REVIEWARTICLE

UAV based remote sensing in crop monitoring: Current status and future perspectives

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ABSTRACT

Precision agriculture (PA) remote sensing entails applications of a set of technologies that improve the farming inputs to enhance the agricultural yields and decrease the input losses. The practices of remote sensing (RS) technologies in PA developments have rapidly increased in the past few decades. The technologies such as the Internet of Things (IoT) can provide significant potential in precision agriculture and smart farming practices, allowing the real-time acquisition of environmental data. In IoT tools, the Unmanned Aerial Vehicles (UAVs) remote sensing sensors have now become very intelligent and miniaturized with a large application potential in ecological, geological, forestry, and agriculture growth monitoring and evaluations. UAVs-based sensors have significant potential in spatial data acquisition with many advantages such as short revisiting time, low cost, flexibility, and high accuracy and have played a great role in crop management providing high spatial-spectral and temporal resolution data. Nowadays, UAVs are very popular in agriculture research. The recent advances in remote sensing due to availability of spatial, spectral and temporal high-resolution satellite data have many applications in PA including crop health monitoring, nutrient management, irrigation managements, pest-disease management, and applications of yield forecasting. This paper reviews UAV remote sensing platforms and different sensors in crop monitoring for PA. The remote sensing-based PA tools such as site-specific nutrient management application technology in the green cover seeker and cropping patterns have already been integrated into commercial cultivation agriculture. In the last few decades, the increased demand for UAVs because of their flexibility and cost-efficiency in acquiring the high spatial resolution images (in cm-scale) for desired PA applications. At the same time, availabilities satellite data has encouraged the researcher to search for advanced methods in data storing and processing such as cloud computing and machine-learning.

INTRODUCTION

Climate change is a big challenge which has a major impact on various sectors comprising agriculture. Agricultural growth yields are considered imperative, according to the Food and Agriculture-Organization of the United-Nations

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(FAO) and the International-Telecommunication-Union (ITU), the world populations have to find new solutions to increase 70% of the food production by 2050. The solution to this critical challenge needs the implementation and utilization of Information and Communication Technologies (ICT) services, having abilities to increase the production rate of the agrochemical products such as fertilizers and pesticides with minimizing their cost efficiently. The introduction of Internet of Things (IoT) technologies especially the rapid growth and development of Unmanned Aerial Vehicle systems (UAVs) and Wireless Sensor Networks (WSNs) have played a major role in crop monitoring, innovative spraying tasks, and at real time economic for the applications of Precision Agriculture (PA).

Nowadays, UAVs are very popular and frequently used for crop monitoring. Farmers can use UAVs with different various sensors for identifying the crop-specific and damaged areas that need improvements or other inputs to respond timely. The most common UAV applications in PAs are; crop growth monitoring and yield estimation, soil characteristics assessment, weed detection and managements, irrigation management, fertilizers & pesticides spraying (Delavarpour *et al.,* 2021; Wang *et al.,* 2019; Lu *et al.,* 2020; Srivastava, *et al.,* 2020). As per the study and increasing demand of UAVs technologies are considered as the future of remote sensing for PA. Various studies are available and reviewing their application in agricultural practices. Major reviews are focused on the different application of UAVs in agriculture crop monitoring and their growing environment, i.e. soil and atmosphere (Khanal *et al.,* 2017). Maes & Steppe (2019) focused on the sensors suitability or techniques for each major application, provided the significant perspective usages of UAVs technologies without reviewing the detail methods for UAV data acquisition. The hyperspectral data and methods (Adão *et al.,* 2017) are reviewed for these cases and also, a survey was conducted for the use of AI-Deep Learning for agricultural data (Kamilaris & Prenafeta-Boldú, 2018).

Agriculture is a backbone of Indian economics, about 70% rural population depends upon the agricultural yields. Beyond this India is far away to adapting latest technologies in farming to get better yield. The developed countries have already adapted UAV systems in precision farming, photogrammetry and RS (Velusamy *et al.,* 2021). It is cost effective and it could reduce the work load and farming inputs to the farmers. In PA, UAVs equipped camera and sensors are generally used for crop monitoring/forecasting and pesticide/insecticide spraying.

Agriculture is facing several economic challenges, such as production and cost-effectiveness insufficient technologies, as well increasing labor costs because of the depopulation from rural areas. PA is used for crop forecasting concerned with the foods, feeds, and fibers production. The main aim of the PA is to the holistic management method of farming practices. The three most relevant methods '3-R' is using in PA are, the right-input, at a right-time and at a right-location. Remote Sensing high spatial resolution data and IoT tools are able to identify the similarity and differences in agriculture in the same cropping system (Boursianis *et al.,* 2022). Many farmers facing challenges of the high loss due to natural calamity, false monsoon prediction and also poor irrigation facilities. Few of the major issues were identified by the farmers that, the difficulties in on-time monitoring agricultural field at larger scale (Villa-Henriksen *et al*., 2020). Therefore, the UAV can allow the farmers to frequently real time monitor the crop growth & health condition and relate with field data for the validation assessment in real way. Remote Sensing is usually considered one of the most significant technologies for smart agriculture, frequently used for crop fields monitoring and providing current solutions for PA in the last 37 years (Triantafyllou *et al.,* 2019). RS monitor the several crop and vegetation parameters using images at different wavelengths. Earlier RS was frequently based on satellite data or data acquired through manned aircraft in order to monitor crop status at different vegetative phases. Although, satellite data acquired is often not suitable because of their low spatial resolution and the limits of the temporal resolution, as per the satellites are not presented always to acquire on real time necessary images. Moreover, it needs to wait for a period of time between the acquisition and reception of imageries. In addition, weather conditions, like cloud covers is major problems for optical imageries in consistent use. Following this, the manned aircraft use results the high costs, and sometimes it is impossible to carry out multiple flights to cover the targeted area.

The recent growth and development of UAV-remote sensing systems have made advance the remote sensing and precision farming. Crop monitoring using UAVs provide better opportunities to acquire fields imageries timely, easy and cost-efficient than previous systems. UAVs bases IoT systems are upcoming remote sensing technologies in PA.

UNMANNED ARIAL VEHICLE (UAV)

Precision-Agriculture or Smart-Farming can be defined as 'a management plan that uses the IOTs tools to record data from various sources to take a decision related to crop productions'. UAVs or manned airborne platform offers the opportunity to view the world from sky and make possibilities for the study of vegetation from an uncommon point of view, detecting some peculiarities of land coverages which is hardly detectable from ground. Usually, the satellite and manned aircrafts are the primary platforms was used to acquire remote sensing imageries of earth's surfaces, but the adequate temporal and spatial resolution and a frequent revisit from these instrument is not possible.

UAVs are autonomous aircraft which can fly without any pilot. It is operated through remote using aerodynamics forces carrying numerous types of payloads. UAVs are RS platforms growing as an essential, reasonable, module of PA and crop growth. It permits the spectator and sensors to be above on the target or phenomenon of area interest. Generally, the UAV flight mission is predefine or the pilot control its speed and path from ground station from remote tele-operation.

UAVs are not a new system. Earlier in 1916 it was first used to develop a powered UAV (Taylor & Munson, 1977). UAVs were first exploited and begin for military purposes; but now the use of UAVs have extended their rapid growth in commercial, scientific, forestry, agriculture, etc. and other applications also. The broader use of UAVs were led by the systems advancement and miniaturization of the related hardware throughout in 1980s and 1990s. But the recent growth and development in UAVs technologies are generally used in RS applications for PA. UAVs equipped with different types of sensors can be measured and identify the affected zones of crop and provide timely management of inputs. The surplus use of UAVs in various application for PA as in crop growth and health monitoring, disease detection, weed detection and managements, and yield estimation etc. For PA applications, the use of UAVs are very frequent in last few years and also considered as future of Remote-Sensing and has emerged in this area and paid a lot of attentions. There are several reviews available of UAVs-based remote sensing systems in Smart Farming and Precision Agriculture applications. Many reviewers are primarily focused on various types of UAVs applications for crops as well as environmental monitoring (Ren *et al.,* 2019). And (Adão *et al.,* 2017) reviewed that hyperspectral imageries and sensors used in these areas. Maes & Steppe (2019) focused on available different sensors suitability, that providing the key perspective of UAVs used for different PA applications. On the other hand, this work does not review the methods used for exploiting the acquired data information. Significantly, a survey has been conducted that talks about the use of Deep-Learning in agricultural data (Kamilaris & Prenafeta-Boldú, 2018).

In the past, the drawback of its high cost, big sensor, less durable, and primitive piloting mode caused slow in the development of civilian UAV use, and some bad-quality materials seen in scientific research earlier in the 21st century. With the rise of different technologies have served UAVs attain a good transformation from military to civilian purpose. Now several UAVs are available for scientific and other field work, and many of these with the different aerodynamic configurations of aerial platforms such as fixed-wings, multi-rotary wings, and hybrid systems are used in present scientific surveys.

Fixed-wings UAVs

With the fixed-wings UAVs look like a passenger aeroplane which require runway to take-off from the earth or a propel. These UAVs are long durable and have the high flight speeds with large coverage areas of monitoring. The first fixed-wing UAV has a pre-defined airfoil of statics and fixed-wings that allow lift UAV in forward airspeed. UAVs are accomplished with rudder, elevators and ailerons attached from the wings to control the UAV. Actually these manufacture appearances allow UAV to turn around Roll, Pitch and Yaw direction respectively (Delavarpour *et al.,* 2021). Although, the fixed-wing UAV cannot take-off and land vertically, it needs a definite space which is difficult to fly in small-area missions. Moreover, the fixed-wing UAV possesses a small payload and prone to the wind speed at the time of landing and take-off. These UAVs are able to larger flight time about 45 minutes and above consecutively than multi-rotatory UAVs. The fixed-wings UAVs are illustrated in (Fig.-1).

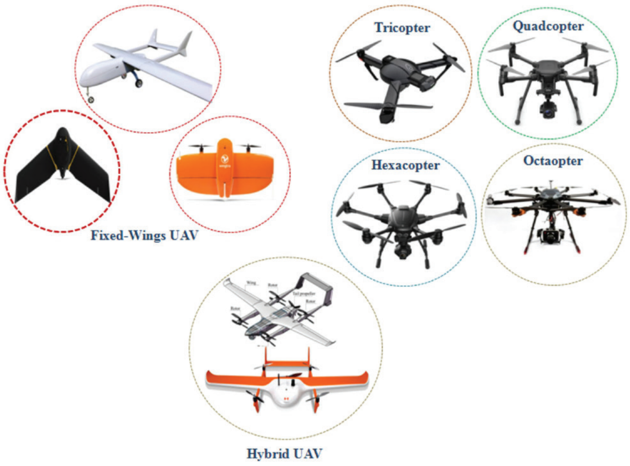

Figure 1: UAV types used in agriculture

Multi-rotatory wings UAVs

Multi-rotatory wings are like helicopters also named rotorcraft or vertical take-off and landing (VToL), relying on the revolution of the wings to provide lift. Airflow in these UAVs are composed of numerous rotors that produce the proper energy require for lifting. In this type of airflow UAV does not requires forward airspeed in lifting. Flexible flight speed and smooth operations make them extensively used in small regions required low altitude flights only. It can capture images from different angles to take multiple views of the target. But, it should be pointed-out that with the multi-rotatory wings, UAVs are have limited endurance and less suitable for long-term flight missions. In comparison of fixed-wings, multi-rotatory wing UAVs offer significantly advantages in enclosed or controlled environments. The DJI-series and AscTec, Falcon8 are mainly used in crop monitoring and precision agriculture (González-Jorge *et al.,* 2017). Based on the numbers of rotors, the rotatory wings UAV are classified into different categories represented in (Fig. 1) (1). Tricopter (2). Quadcopter (3). Hexacopter (4). Octacopters.

Hybrid UAVs

This types of UAVs are the combinations of fixed-wing and rotatory wing. In this rotators are used to take-off and landing and including the fixed-wings utilization in covering the large areas (Fig. 1).

SENSORS PAYLOADS BY UAVS

UAVs are basically a remote sensing platform; but the images acquisition and monitoring missions are succeeded from camera/sensors are mounted with this platform. With the growth and development of UAVs performances, various types of sensor also have been developed rapidly. UAVs equipped with precise sensors make it more efficient in imaging systems that the advantages in IoT technologies. UAVs provide flight platforms to sensors that can capture high spatial and temporal resolutions images, which advantages in monitoring different parameters of vegetation. Now, there are different kinds of sensors available that are used in UAVs in crop monitoring depending upon the different parameters studies. However, according to payload capability and the use of small UAVs pose many constraints in sensors collections. The main criteria of sensors selection are the low weight, small size, and low energy consumption having the ability to acquire high resolutions imagery. According to several research studies, remote sensing sensors such as RGB, multispectral, and hyperspectral were mainly used in crop monitoring.

RGB sensor

RGB (blue, green and red) or real color sensor of visible spectrum cover the wavelength ranging in-between 380 to 750 nm. RGB sensors are the most often used on UAVs platform in precision farming systems (Fig.-2). These are comparatively low cost sensors than the other which can capture

Figure 2: RGB sensors (A) DJI Zenmuse X7, (B) MAPIR Survey3, (C) senseFly S.O.D.A, (D) Phase One iXU-RS 1000, (E) Sony-ILCE-QX1

Table: Vegetation indices and their usage in agriculture

Vegetation Indexes (VI_s)	Wavebands equation	Applications in Crop	References
Normalized Difference Vegetation Index (NDVI)	$R_{NIR}-R_{Red}$ / $R_{NIR}+R_{Red}$	Uses in biomass, yield, soil moisture, hydric-stress, breeding, phenotyping, disease, N-management, leaf area index.	Ballester *et al.*, 2018
Green-NDVI (GNDVI)	$R_{NIR}-R_{Green}$ / $R_{NIR}+R_{Green}$	Uses in evaluation of nitrogen contents, biomass, yield, hydric-stress, disease.	Khan *et al.*, 2020
GIPVI (Green-Infrared percentage vegetation index)	$R_{NIR}/R_{NIR}+R_{Green}$	Similar to NDVI's but, its calculation is simple.	Strong *et al.*, 2017
Normalized Difference Red-Edge (NDRE)	$R_{NIR}-R_{Red-Edge}/R_{NIR}+R_{Red\text{-}Edge}$	Uses in evaluation of biomass yield, disease, N-management, irrigation management	Kanke *et al.*, 2016
Red-Edge Index	R_{700}/R_{670}	It is sensitive to chlorophyll contents.	Zarco-Tejada *et al.*, 2013
Red-Edge Inflection Point (REIP)	$700+40\ \{[(R_{667}+R_{782})/2]-R_{702}/R_{738}-R702\}$	Uses in LAI, Yield and biomass	Kanke *et al.*, 2016
NGRDI (Normalized Green-Red Difference Index)	$R_{Green}-R_{Red}/R_{Green}+R_{Red}$	Uses in discrimination of vegetation layer from soil.	Rasmussen *et al.*, 2016
Enhanced Vegetation Index (EVI)	$2.5(R_{NIR}-R_{Red})/(R_{NIR}+6R_{Red}-7.5R_{Blue}+1)$	Uses in high LAI areas where, NDVI may saturate, biomass, disease	Zhou *et al.*, 2016
Enhanced Normalized Difference Vegetation index (ENDVI)	$R_{NIR}+R_{Green}-2{*}R_{Blue}/R_{NIR}+R_{Green}+2{*}R_{Blue}$	Uses to calculate Chlorophyll value and in plant health indicators	Rasmussen *et al.*, 2016
Soil-Adjusted Vegetation Index (SAVI)	$(R_{NIR}-R_{Red})\ {*}(1+L)/R_{NIR}+R_{Red}+L$ L-soil conditioning index	Similar to NDVI, uses in evaluation of biomass, yields, diseases, hydric stress, N-concentration and uptake	Zhou *et al.*, 2016
Modified Soil-Adjusted Vegetation Index (MSAVI)	$2R_{NIR}+1-\sqrt{}(2R_{NIR}+1)^2-8(R_{NIR}-R_{Red})/2$	Uses in Crop yields, biomass, chlorophyll contents, N-uptakes	Ranjan *et al.*, 2019
Optimized Soil-Adjusted Vegetation Index (OSAVI)	$1.16(R_{NIR}-R_{Red})/R_{NIR}+R_{Red}+0.16$	Similar to NDVI uses in evaluation of Chlorophyll content vegetation density and vegetation amounts, disease, soil-moisture	Cui *et al.*, 2019
Transformed Soil-Adjusted Vegetative Index (TSAVI)	$\alpha(R_{NIR}-\alpha R_{Red}-b)/R_{Red}+\alpha R_{NIR}-\alpha b$	Uses in sparse vegetation regions, crop yield, hydric-stress	Marino and Alvino, 2015
Renormalized Difference Vegetation Index (RDVI)	$R_{NIR}-R_{Red}/\sqrt{}R_{NIR}+R_{Red}$	Uses in biomass, crop yields, soil moisture, N-uptake	Zhou *et al.*, 2016
Ratio Vegetation Index (RVI)	R_{NIR}/R_{Red}	Evaluation in crop biomass yields and disease	Ranjan *et al.*, 2019
Difference Vegetation Index (DVI)	$R_{NIR}-R_{Red}$	Evaluation of LAI, disease, yield	Ranjan *et al.*, 2019
Red-Edge-DVI (REDVI)	$R_{NIR}-R_{Red\text{-}Edge}$	Estimation of crop yield biomass, crop biomass, N-concentration and uptake	Kanke *et al.*, 2016
Red Green Blue Vegetation Index (RGBVI)	$R_{Green}{}^2-(R_{Blue}{*}R_{Red})/R_{Green}{}^2+(R_{Blue}{*}R_{Red})$	Uses in biomass monitoring, biomass amount.	Bendig *et al.*, 2015
Wide Dynamic-Range Vegetation Index (WDRVI)	$\alpha R_{NIR}-R_{Red}/\alpha R_{NIR}+R_{Red}$	Crop growth estimation, LAI, Crop Yield, N-management, disease	Bajwa *et al.*, 2017
Atmospherically Resistant Vegetation Index (ARVI)	$R_{NIR}-R_{RedBlue}/R_{NIR}+R_{RedBlue}$	Uses in disease detection and weed managements	Mudereri *et al.*, 2019
Atmospherically Effect Resistant Vegetation Index (IAVI)	$R_{NIR}-(R_{Red}-\lambda(R_{Blue}-R_{Red}))\ /\ R_{NIR}+(R_{Red}-\lambda(R_{Blue}-R_{Red}))$	Elimination of atmospheric interferences and yield estimation	Khosravirad *et al.*, 2019

NRI (Normalized Ratio Index) or GnyLi Index	$R_{Green}-R_{Red}/R_{Green}+R_{Red}$	Evaluation of crop growth, dry biomass and biomass amount	Jenal *et al.*, 2020
Plant senescence reflectance index (PSRI)	$R_{680}-R_{550}/R_{750}$	Uses in crop biomass, yield, disease	Das *et al.*, 2015
PRI (Photochemical reflectance index)	$R_{570}-R_{531}/R_{570}+R_{531}$	Sensitive to changes in Carotenoid pigments, water-stress indicator.	Stagakis *et al.*, 2012
Normalized Pigment Chlorophyll Ratio Index (NPCI)	$R_{680}-R_{430}/R_{680}+R_{430}$	Plant pigment contents, nitrogen and water-stress analysis	Klem *et al.*, 2018
Chlorophyll Absorption Ratio Index (CARI)	$(R_{700}/R_{670})*\alpha R_{670}+b$ $R_{670}/\sqrt{\alpha^2+1}$	Estimation of leaf Chlorophyll content	Cui *et al.*, 2019
Modified chlorophyll and reflectance index (MCARI)	$R_{Red\text{-}Edge}/R_{Red}*\{(R_{Red\text{-}Edge}-R_{Red}-0.2(R_{Red\text{-}Edge}-R_{Green})\}$	Estimation of Crop growth and chlorophyll content	Cui *et al.*, 2019
TCARI (Transformed Chlorophyll Absorption in Reflectance Index)	$3*[(R_{700}-R_{670})-0{,}2*(R_{700}-R_{550})*(R_{700}/R_{670})]$	indicator of Chlorophyll contents.	Cui *et al.*, 2019
Chlorophyll Vegetation Index (CVI)	$R_{NIR}/R_{Green}*R_{Red}/R_{Green}$	Estimation of Crop growth and Chlorophyll content, crop yield	Cui *et al.*, 2019
Chlorophyll Index (CI)	$R_{NIR}/R_{Red\text{-}Edge}-1$	Uses in Chlorophyll and N-content	Cui *et al.*, 2019
Normalized Water Index (NWI)	$R_{970}-R_{900}/R_{970}+R_{900}$	Uses in plant water contents-water stress, soil-moisture and crop yield	Ceccato *et al.*, 2001
Water Balance Index (WABI)	$R_{1500}-R_{531}/R_{1500}+R_{531}$	Plant water status, Irrigation-scheduling	Rapaport *et al.*, 2017
Normalized Difference Water Content (NDWI)	$R_{NIR}-R_{SWIR}/R_{NIR+}R_{SWIR}$	Uses in Vegetation water contents, drought assessment	Gao *et al.*, 2015
Crop Water-Stress Index (CWSI)	$T_C-T_{WET}/T_{DRY}-T_{WET}$ T_C = actual canopy temperature	Measures the canopy-temperature of a plant, Hydric-stress thermal indicator	Çolak *et al.*, 2015
Shortwave-Infrared Water-Stress Index (SIWSI)	$R_{858.5}-R_{1640}/R_{858.5}+R_{1640}$	Evaluation in leaf water contents, moisture status	Olsen *et al.*, 2013
Degrees Above Non-stressed Canopy (DANS)	$\min(0,T_C-T_{CNonStressed})$	Use in Evapotranspiration, Water stress and Schedule irrigation	Zhang *et al.*, 2019
Degrees-Above Canopy Threshold (DACT)	$\max(0, T_C-T_{Critical})$	Uses in a plant canopy-temperature and water-stress, evapotranspiration	DeJonge *et al.*, 2015
Triangular-Vegetation Index (TVI)	$0.5[120(R_{NIR}-R_{Green})-200(R_{Red}-R_{Green})]$	Estimating green LAI, sensitive to the Chlorophyll, disease	Broge *et al.*, 2000
Modified Triangular-Vegetation Index (MTVI)	$0.5[120(R_{800}-R_{570})-200(R_{670}-R_{570})]$	LAI estimations	Stagakis *et al.*, 2012
Modified Triangular-Vegetation Index1 (MTVI1)	$1.2[1.2(R_{800}-R_{550})-2.5(R_{670}-R_{550})]$	It allows to calculate LAI	Stagakis *et al.*, 2012
Modified Triangular-Vegetation Index2) (MTVI2)	$1.5[1.2(R_{800}-R_{550})-2.5(R_{670}-R_{550})]/\sqrt{(2R_{800}+1)2-(6R_{800}-(5*\sqrt{R_{670}})-0.5)}$	It allows to estimate green biomass density by means of LAI.	Lucieer *et al.*, 2014
Color-Index of Vegetation (CIVE)	$0.441*R_{Red}-0.881*R_{Green}+0.38*R_{Blue}+18.78745$	Greenness identification, discrimination of objects from vegetation	Yang *et al.*, 2015
Woebbecke-Index	$R_{Green}-R_{Blue}/R_{Red}-R_{Green}$	Woebbecke determine a Green Excess Index that is uses for automatic analysis based on vegetation phenology	Beniaich *et al.*, 2019

high-resolution imageries. It has been widely used to gather the information on crop lodging and plant height (Guan *et al.*, 2019). Moreover, these are light-weighted, simple to operate and the informations are captured in easy processing. It can acquire images in both sunny and cloudy conditions, but an accurate time is required of weather conditions to avoid the atmospheric hindrance exposure from the images. These bands are permit to calculate some of the vegetation indices given in the (Table. 1), which mostly intended to distinguish vegetation from soil and estimation of biomass yield. Considering the disadvantages of the sensors, it cannot cover the spectral data in the non-visible regions that the several vegetation parameters are required for analysis. They are normally used in tandem by the other kinds of sensors. With the rise of IoTs, new systems for analysing terrain images, such as SFM (Structure from Motion), can use several images to improve camera signals and image features automatically, building UAVs mounted with RGB cameras are highly applicable in terrain surveying and 3D modelling (Esposito *et al.*, 2017).

Multispectral or optical sensors

Multispectral or Optical sensors provide multiple numbers of bands apart from RGB, are the most practiced sensor in Remote Sensing with UAVs (Fig. 3). These sensors can take the data between 3 to 12 no. of bands about 100 nm bandwidth each (Adão *et al.*, 2017). The multispectral bands are permit to calculate different types of vegetation indices representing in (Table 1). Normalized Difference Vegetation Index (NDVI) is one of the most common vegetation indexes calculated from the ratio of visible and near-infrared bands, which allows vegetation detection in a more efficient way than the other indices calculated from RGB bands.

Hyperspectral sensors

The hyperspectral sensors can sense up to hundreds of narrow spectral bands for a bandwidth less than 10nm. Hyperspectral remote sensing is a system with a high perspective for observing and assessing the plant physiological parts. This technique allows calculating the physiological abnormalities of the crops even prior to the appearance of visual symptoms. The narrow bands are able to assess the accurate typical absorption peaks of plant pigments and thereby give better information about plant health. In general, the hyperspectral sensors permit to distinguish the components which may be clustered by the multispectral bands. An extensive review is done on hyperspectral sensor in (Adão *et al.*, 2017). Both sensors multispectral and hyperspectral may be suitable in detection of weeds, pests and diseases, as per they lead a small-spectral changes that need high-spectral resolutions. Some of them are used in UAV represented in (Fig. 4).

Figure 3: Multispectral sensors (A) Buzzard Camera six, (B) Sentera Quad, (C) Tetracam ACD Micro, (D) Tetracam MiniMCA6, (E) Parrot-Sequoia+, (F) MicaSense Altum.

Figure 4: Hyperspectral sensors (A) SPECIM FX – hyperspectral cameras AVICON, (B) Headwall® VNIR Hyperspectral E-Series, (C) Nano-Hyperspectral Headwall, (D) VIS-NIR Hyperspectral Camera OPTOSKY, (E) OCI™-OEM Ultra-compact Hyperspectral Camera BaySpec, (F) OCI™-F Hyperspectral Imager (VIS-NIR, SWIR) BaySpec.

CROP MONITORING

Crop monitoring is one of the most important application of Remote Sensing for Precision Agriculture to detect the weeds, diseases, pests, nutrients and water stresses. In addition, crop phenotyping in which the seeds have the best phenotypic physiognomies are selected, such as plant height and biomass yield. PA is a set of systems that, monitor the temporal and spatial variations in a crop. It is capable to set-up prompt treatments at the specific sites. PA consists the different phases such as data collections; variability mapping; regular monitoring; decisions making and the application for the management practices. Variable Remote Sensing is a crucial thing in these phases and it added with Geographical Information System (GIS) and other machineries for the adequate treatments (Andreo, 2013). There are various PA applications of this in management of the weeds, nutrients, diseases & pests, irrigations, among others.

Weed management

Weeds are considering as undesirable plants, which commonly grow in agricultural fields and create several problems. These are competing with resources available in soil such as water, nutrients or even spaces, affecting the crops growth as well as their yields. Additionally, weeds cause problems in crop growth and also in harvesting time. The use of weedicides is the main choice of farmers to their control.

Precision Agriculture practices require the early detecting weeds patches and formerly take an action to removal of weeds via spraying or machinery processes. This is done by the capturing the real-time geo-referenced imageries, applied weed recognition systems and their management. These processes are to check the weed growth rates and minimize the environmental impacts then, different from the traditional methods whereby the weedicides are consistently sprayed (Rana & Rana, 2016), with the precision farming, agrochemicals are sprayed at a definite area thus precise the amount of agrochemicals as per required.

In precision farming practices Site-Specific-Weed-Management (SSWM) is applied. This consign to the spatial variability application of weedicide rather-than uniformly distributed in the entire field. Usually weeds are spread in few patches or spots in the field, so for this the entire field is divided into different management regions that every region can receive precise management. To reach this aim, it is compulsory to create an exact weed covers map for customize spraying of weedicide. UAV systems can capture images and obtain data from the entire field which can be applied to create a weed cover map describing the patches where the herbicides are required: (a) the least; (b) the most; or (c) they should not be applied at all.

Weed management and detection is the main-concern in early-stage crops. The weed detection at this stage, required high spatial-resolution, < 5cm per-pixels, as crop and weeds reflectance are almost similar at that stage. For this, it is important to capture high resolution images (< 100 m altitude) that allow to discriminate each-one of the plants (Gómez-Candón *et al.,* 2014). In some cases, when discriminating soil and weeds are needed then it is enough to determine the Green Excess Index (ExG), which is generated from the RGB images. On the other hand, it may be essential to determine the diverse plant species (Crop and weeds) and identify, e.g. dominant species and their size (Shi *et al.,* 2016). So for this, an optical sensor may be helpful or the hyperspectral sensors which allow to evidences quite small-reflectance differences.

Irrigation management

Crop irrigation managements is a very crucial thing of UAV systems for Precision Agriculture. About 70% of the water consumed through crop irrigation worldwide (Siebert *et al.,* 2010), the facts that highlights the requirement for precision irrigation practices. The precision irrigation practices can increase the water use efficiency, so that the resources are applied well: (i) in the right time; (ii) at the right place and (iii) in the right amount. The detection of regions which needed the major irrigation can help the farmers for saving time and water resources. And at this time, such precision agricultural practices can lead to enhanced the crop yields and qualities. In this context of precision faming the farms are divided into different irrigation regions, to accurately manage the water resources. Use of Unmanned Aerial Vehicle platform mounted with specialized sensor types have potential to identify the crop zones that require more irrigation. At the same time, above practices allow to creation of specified maps that demonstrate the soil morphology, thus each crop supporting separately for more efficient irrigation plans.

Nutrients Management

Timely and accurate fertilization application is important to enhance crop growth and yields whereas, minimizing environmental effects from nutrient wastes to surface and groundwater. Generally, a recommended dose of fertilizers are applied uniformly at the planting time and later on plant growth stages. Whereas, the fertilizers requirement by crop differs temporally and spatially with seasons due to dissimilarity in soil, topography, managements, weather and hydrology. Such types variability mapping in crop nutrients status or requirements for Precision Agriculture application could be challenging with the traditionally used equipments like chlorophyll meters (Marino & Alvino, 2015).

Various Vegetation Indices such as NDVI; GNDVI; SAVI etc. calculated from Remote Sensing imageries, have been represented to be significantly correlated with leaf chlorophyll contents, photosynthetic activities and plants productivity (Maleki *et al.,* 2020). Studying of these vegetation indices can help in understanding the spatial variability of crop nutrients status, which play significant role for PA. In recent, various tractor equipped with remote-sensing sensors, such as Green-Seeker; Yara N-sensor; Crop Circle are available that can assess. Although the commercialization of variable-rate of N-management practices using proximal-remote-sensing, farmer's adoptions remain low in several agriculture sectors (Higgins *et al.,* 2019). Due to not availability of a clear proof on significant economical benefits such as crop yields and profits mainly in large farms settings, is a limiting cause for the adoption of these things in large-scale. To further improve using of these remote sensing technologies and increase of benefits, the study is being performed with UAV systems and other remote sensing-sensors in various types of crop in diverse climatic zones. Maresma *et al.,* (2016) studied UAV data to find the suitability of various vegetation indices and plant heights in determining in-seasons fertilizers application rates in Corn farm at Spain. (Cao *et al.,* 2017) represented that Crop-Circle and Green-Seeker sensors resulted in minimizing the use of N-fertilizer and enhanced the N-productivity for the winter wheat crop yields in China. In general, remote sensing based crop nutrients status mapping for PA can help to increase crop nutrients use efficiency while increasing or maintaining the crop productions and reduction of off-site nutrients losses that are affecting the environment.

Crop health monitoring, pest & disease managements

Crop health is a very crucial parameter that requires to be monitored regularly. Since disease causes significant economic losses in crop due to reduction of yield and their quality. So it is important to monitor crop regularly to detect the disease on timely and should avoid the spraying problems. Conventionally, the expert farmers performed this task directly in the farms. However, this is costly and time-taking, since it can take a month to observe a crop preventing potentials of "regular" monitoring. In precision agriculture the site-specific pest-disease control methods takes place. Pest-disease and nutrients deficiency detection can be fought throughout the agrochemical spreading, including fungicides, pesticides, fertilizers, etc. From UAV spraying technique is an ideal in small patches or complex access regions (Delavarpour *et al.,* 2021). An UAV fumigations system is used with the ground based sensor network. As the control plan, they make a route-adaptation for the agrochemicals spreading depends on the vehicle speed and wind velocity. For this, using wireless-sensors, located on the ground surface which helps data receiving of the amount of agrochemicals. The crop status are evaluated not only for the pest-diseases detection but also for the estimation of other parameters like plant density (Koh *et al.,* 2017), biomass yields, plant height, canopy cover, nitrogen contents (Bending *et al.,* 2015), soil clay contents (Shi *et al.,* 2016), crop water stress condition (Barnes *et al.,* 2000) etc.

Crop phenotype monitoring

Remote Sensing has proven to be a large potential in crop phenotype monitoring, where a species responds to diverse environmental conditions are estimated. Crop phenotyping needs measuring and assessing the visible physical appearances of a species with different phenotypes, generations, and at different growth phases. Conventional phenotype monitoring includes direct observations from the field which takes much time and is costly (Yang *et al.,* 2017). In this context, now-a-days the non-invasive crop phenotyping using UAV is more common due to the probability to capture the spatio-temporal high resolution imageries that allow in collection of different information compatible with crop phenotypes (Shi *et al.,* 2016).

This is possible from phenotyping to collect seed or plant species which can better adapt for higher productions and overall for the good genotype and phenotype. Hence, e.g. how a crop response to the fertilizers that can be estimated (Holman *et al.,* 2016), and how it performs against pest-diseases (Yang *et al.,* 2017). Generally, the phenotyping traits taken are the plant height (m), canopy cover volume (m^3) biomass yields (kg/m^2). These indicate the crop growth, crop vigor, efficient light use, yield at time of harvest, nutrient availability and carbon reserves. Foliar-area-index and canopy cover are the good indicator of how much vegetation's present per-unit earth surface. This shows the plant photosynthetic capability, respiration, evapotranspiration and efficiency in light use. The foliar-area-index shows the potential of a crop's growth and it allow to estimate the biomass yields (Shi *et al.,* 2016). Crop phenotyping using Remote Sensing can be carried-out in two ways i.e. from Vegetation Indices and Photogrammetry approaches. Each-one permits to find out different phenotypic traits.

VEGETATION INDICES

EMR from sun strike on plant and reflected back depends upon morphological and chemical characteristics of the plants. Plant types, water contents canopy cover affects light reflectance in all spectral bands differently. Reflected lights measured in Ultraviolet; Visible (blue, green, red), Near-infrared, Mid-infrared and Short wave-infrared region of spectrum has been used mainly in calculation of Vegetation Indices that gives valuable information of plant structures and status. VIs are spectral transformation measured of two or many spectral band that enhance the contributions of vegetation characteristics and permit reliable spatio-temporal inter-comparisons of terrestrial photosynthetic activities and canopy cover variations. Mapping with these VIs can help in understanding of spatial and temporal variability's in crop condition, which is important for PA practices. These VIs permit the monitoring of crop and soil conditions, giving information on crop growth, health, biomass yields, weed existence, etc.

Usually used VIs such as Normalized Difference Vegetation Index (NDVI); Green NDVI (GNDVI) and Soil Adjusted Vegetation Index (SAVI) (Table 1) utilize the information within the NIR and visible range spectrum, the plant absorbs light spectrum in blue and red regions and the reflection shows in green and NIR regions. Some indices that are generated from red or NIR bands are related to the crop biomass, canopy cover and leaf area index (LAI). Another indices which generated from visible regions are providing the information of plant pigments concentrations and nitrogen content. On the other-hand, some indices provide canopy temperature information (Barnes *et al.,* 2000), generated from infrared bands, allow to calculate a plant's evapotranspiration rate in an indirect approach. This perform as a plant indicator with low water-stress. There are some VIs with some applications and the related wavebands equations to evaluate them from different spectral regions represented in (Table 1).

The image capturing to extract the VIs is a big challenge, as it requires a stable light intensity during acquisition. Because these indices depend on reflectance properties during the daytime when the images are acquired may have on the same influence and the angles used to acquire the images. While, it must be taken into account that plants reflectance differs with their growth stages. After all, to find out a good spatial-resolution the images must be acquired from a height of 30m to 100m (Rasmussen *et al.,* 2016).

PHOTOGRAMMETRY

Photogrammetry considers the true reconstruction of an image or a features from many overlapping images. Photogrammetry methods can process two-dimensional data and makes a geometric relationship in-between the different features and images to obtain the three-dimensional models. It allows to create a 3D digital surface model, from that can measure the distances, areas, volumes with the high accuracy. UAVs have a big potential to this as they allow to acquire high-resolution aerial imageries at a low-altitude. The processing is carried out in different stages: flight planning; location and ground-control-points (GCPs) measuring; flight execution to acquire images and georeferenced image processing. For the geo-referencing different ground-control-points are mainly used to assure the accuracy while mosaicking processes (Gómez-Candón *et al.,* 2014).

From the three-dimensional reconstruction of lands and crops i.e. Crop Surface Model (CSM) permits to calculate the crop height, canopy cover/volume, crop areas (Tilly *et al.,* 2014). These parameters cannot be calculated from VIs. CSM can also obtain a crop growth rate, if the process takes-place under various growth stages (Holman *et al.,* 2016). Generating the three-dimensional hyperspectral maps allow to obtain hyperspectral data of pixels of an image by a camera which has been earlier characterized and calibrated radio-metrically. UAV usages GPS for image geo-referencing. However, as the GPS receiver offer the UAV positions with an ample error margins (of some meters) so usually ground control points (GCPs) are used to minimize these errors less than 10 cm (Lucieer *et al.,* 2014). Photogrammetry methods are basically used in all types of remote sensing applications since this is also used in reconstruction of VIs maps. These techniques are majorly used in recent studies (~93%) to develop and extract information of three-dimensional characteristics of the crops. Nonetheless, photogrammetric methods are in several cases used to compliment other kinds of data processing techniques.

CONCLUSION

With the rising technologies, UAV systems are readily used in Agricultural, ecological, land resources monitoring and survey along with the scientific research works. This review introduces the PA based applications using the more advanced UAV remote sensing platforms and different sensors in crop monitoring. Now-a-days UAV applications in crop monitoring is in the rapid development phase. The selection of UAV and sensor according to the targets needed is the main concern in crop monitoring research. Likewise, the multispectral and RGB sensors are mainly used in mreost of the about 70% research studies. As the RGB cameras allow to generate some vegetation indices that are good recognition of vegetation areas in a crop, the multispectral cameras have potential to take images in particular wavelength ranges that gives the details of vegetation health and vegetation types.

For the most common crops UAV remote sensing applications for precision agriculture are in managements of weeds, irrigation, pest-diseases, nutrients etc. And crop phenology means the estimation of physical properties of a crop with different environmental conditions. In some cases, spatio-temporal high-resolution imageries end up being necessary while, as of them, it is feasible to generate vegetation indices and three-dimensional surface models which offer data on different parameters for soil and crop. There are some of the most-common vegetation indices in various studies are NDVI, GNDVI, NDRE, SAVI, EXG, NGRDI, etc. In this the most-common studies parameters found that Leaf Area Index, biomass yields, water stress, plant contents in soil and nitrogen contents. After all, mostly multirotors unmanned aerial vehicles are used in remote sensing due to the easiness of their manufacturing and control systems. The manoeuvrability of them allow to acquire images at very low altitude and assuring a reliable spatial-resolutions. They permit to fly over difficult places or hilly terrains where the fixed-wings UAV faces problems. Although, many studies found on fixed-wings UAV, because these vehicles permit to monitoring large regions at a higher speed.

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