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A Survey of Unmanned Aerial Sensing Solutions in Precision Agriculture

Anandarup Mukherjee[1], Sudip Misra

Department of Computer Science and Engineering, Indian Institute of Technology Kharagpur

Narendra Singh Raghuwanshi

Department of Agriculture & Food Engineering, Indian Institute of Technology Kharagpur

Abstract

The gain in popularity of unmanned aerial vehicles (UAV), platforms and systems (UAS) can be attributed to its ease of operation, versatility and risk-free piloting. The primary UAV application domain has expanded, from recreational and military flights, to include scientific surveys and agriculture. The popularity of UAVs in scientific data gathering and applications, especially the use of small, multi-rotor UAVs is quite widespread. These multi-rotor UAVs are small, portable, low-cost, highly manoeuvrable, and easy to handle. These features make such UAVs attractive to scientists and researchers worldwide. There has been a sudden spurt of UAV use in niche domains, such as agriculture. Agriculturalists are choosing UAV-based field operations and remote sensing over the time-tested satellite-based ones, especially for local-scale and high spatiotemporal resolution imagery. In this survey, we explore various UAV application areas, types, sensors, research domains, deployment architectures. Comparisons between various UAV types, sensing technologies (UAV, WSN, satellites), UAV architectures and their utility in precision agriculture has been provided. Additionally, crop stress, its types, and detection using various remotely-sensed vegetation indices have been explored for their use in UAV-based remote sensing.

Keywords: Unmanned Aerial Vehicles, UAV sensors, UAV classification, UAV architectures, precision agriculture, crop-stress, vegetation index

1. Introduction

The advent of aerial machinery and devices has proved to be beneficial for the overall development of the human race – both technologically and strategically (Valavanis & Vachtsevanos (2014)). In the present times, countries with advanced aerial systems have a clear upper-hand in technological, scientific, as well as military matters, as compared to countries lacking this technology (UAV (-)). In the present times, the major use of these aerial pieces of machinery is for commercial and military applications. However, scientific and technological advancements (Fletcher et al. (2016), Maja et al. (2016)) have allowed for the use of these aerial systems in much smaller and customized applications such as surveys (Sonaa et al. (2016)), tracking (Razinkova & Cho (2016)), public safety networks (Sikeridis et al. (2018)), and others (Valavanis & Vachtsevanos (2014)). Furthermore, some of these

Email address: anandarupmukherjee@gmail.com (Anandarup Mukherjee)

aerial systems are being used, sans onboard pilots. A remote pilot on the ground can operate these systems just as well as an onboard pilot. These pilot free systems are now popularly being called unmanned aerial systems (UAS), or unmanned aerial vehicles (UAV). Besides remote pilots on the ground, controlling these unmanned systems, technological advancements in sensors have allowed for the use of autonomous algorithms and techniques, which does away with the need for human pilots altogether (Martín et al. (2016), Saleem et al. (2015)). The use of unmanned aerial systems in scientific studies has gained momentum due to the following reasons:

- Speed of deployment (Zhou et al. (2016))
- Consistency of sensing (Lootens et al. (2016))
- Obstacle free navigation (Cetin & Yilmaz (2016))
- Ability to aquire and condense information over much larger areas (Meyer et al. (2015))

The rapid gain in popularity of unmanned aerial platforms can also be attributed to its low acquisition cost, low maintenance, low set-up time and live-data transmission ability. These features of the UAVs make them the preferred choice for regular users for all kinds of situations, be it farming, surveying, planning or military applications. Additionally, these UAVs can be used safely in high-risk zones without any threat to its human operator(s). As UAVs do not generally need long runways to get airborne or land, they can be deployed in, virtually, any situation or terrain. UAVs with vertical take-off and landing (VTOL) Austin (2011) capabilities for low-range applications are popular as they generally, do not require flight permissions, are not affected by bad weather, are easy to maneuver and provide fast, reliable and repetitive data-capture with live data-transmission capabilities.

Besides common usage for disaster management and mitigation operations (Tuna et al. (2014)), the use of these aerial platforms is dominating all spheres of scientific data gathering and monitoring tasks. Domains such as remote sensing, mapping, architecture, and agriculture are increasingly making use of aerial platforms, specifically unmanned (UAV) ones, due to their ease of relocation, low-cost and easy maintenance (Austin (2011)). These platforms can be easily integrated with an array of radios and sensors to suit specific needs and that too in a short span of time. This gain in popularity of UAVs can be attributed to the miniaturization of electronics and easy availability of portable and low-power sensor solutions, which makes it suitable for use in domains like communication relaying (Sharma et al. (2017)), remote-sensing and agriculture (Fletcher et al. (2016)).

1.1. Motivation

The established trend of using satellite-based remote-sensing and imagery for detection of various earth-based parameters in riverine, forest, desert, agricultural, glacial and volcanic ecosystems is effective to a certain range of resolution. The temporal sensitivity of this method is very low due to the large return-time of the satellite above the same zone. Additional factors such as the presence of volcanic ash and plumes during eruptions, smoke, bad-weather, and others hinder the proper visualization of the ground conditions. Moreover, satellite-based systems are highly periodic, with a long waiting time for a repeat fly-by over the monitored zone, resulting in hindered operations, which need real-time monitoring. Specialty applications such as disaster monitoring and management, precision agriculture and tracking cannot be fully integrated with the satellite-based systems. In agriculture, there is a need for quick and immediate monitoring and sensing systems, which can remotely monitor and sense large swathes of land on a daily basis. The satellite-based remote-sensing applications are being actively challenged by UAV-based remote-sensing. As there is no comprehensive survey on the use of UAV-based remote sensing in precision agriculture, we try to summarize the UAV types and their capabilities for real-time monitoring problems in precision agriculture.

1.2. Contributions

In this manuscript, we highlight the important features and requirements for unmanned aerial sensing in precision agriculture. The various contributions of this survey can be summarized as follows.

1. A comparison between various UAV types concerning agricultural applications is tabulated.
2. An overview of UAVs is provided with insights into various UAV types and the sensors used. The sensors are further categorized for their degree of usefulness to the UAV's flight operations.
3. The broad research domains of UAVs which are being extensively worked upon, and the use of UAVs in agriculture is discussed.
4. A comparison between the feasibility of agricultural usage among UAV-based remote sensing, WSN-based sensing, and satellite-based remote sensing is provided.
5. A brief overview of plant stress is given which is followed by a tabulation of various spectral indices for remotely detecting these plant stresses.
6. Various UAV deployment techniques for precision agriculture and their corresponding architectures is summarized. A comparison between these architectures is also provided.

2. A Sketch of Unmanned Aerial Vehicles

The importance of UAVs in various domains is highlighted by dividing this section into three broad categories – *Types*, *Sensors* and *Research Domains*. Section 2.1 on *UAV types* categorize UAVs based on their structure and functionality. Section 2.2 on *UAV Sensors* highlights the various sensors needed for the operation of UAVs and for the use of these UAVs in agriculture. Depending on the criticality of usage, the UAV sensors are further divided into – *primary sensors* and *secondary sensors*. Section 2.3 outlines the various challenges and their solutions in applications of UAVs for various tasks.

2.1. UAV Types

Fig. 1 shows the broad division of unmanned aerial platforms being used in the present times for a plethora of applications, in various domains and fields such as recreation, scientific surveys, and military applications. Table 1 compares the various UAV types and their usefulness in agricultural applications.

UAVs can be broadly classified into three parts, based on their structure – winged, wing-less and ones based on bio-mimicry. Fixed wing UAVs can be further classified as ones requiring a runway or clearing for take-off and landing, or ones which can be launched as projectiles by humans or mechanical contraptions designed for the same. The wingless UAVs can be classified as shown in Fig. 1. The balloon types are the ones dependent on gas-filled balloons for lift-off and altitude control (e.g., Blimps). Bi-rotor UAVs have two rotors, one controlling the thrust and lift-off, and the other controlling the direction of the vehicle. Multi-rotor UAVs are named based on the number of motors present. Generally, this class of UAVs is the more widely used due to their low cost, versatility, and maneuverability. Parachute-based UAVs are either dropped from a high altitude (generally from an airplane), or they require a motorized ground vehicle tethered to the parachute. The horizontal motion of the vehicle causes the parachute to lift-off, which, in turn, lifts-off the vehicle from the ground. Additional fans fitted on the vehicle helps in direction and altitude control. Bio-mimicry based UAVs are typically equipped with a bio-inspired air-frame, functionality, or capabilities. UAVs

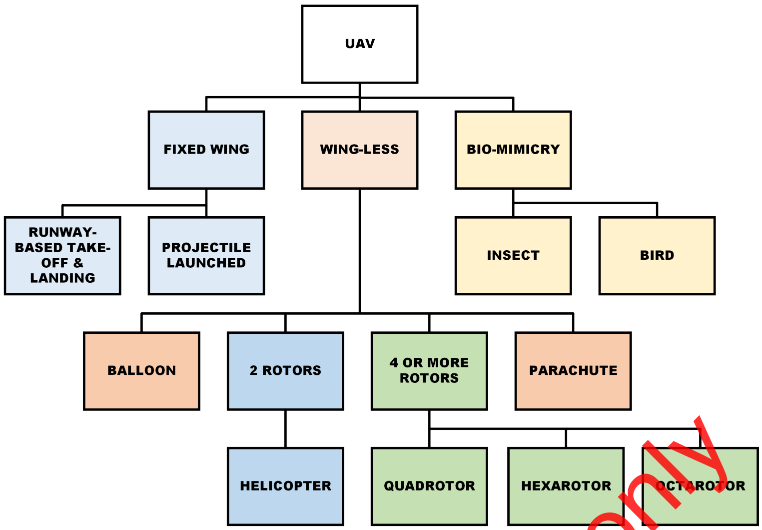


Figure 1: Categorization of UAVs, based on their structure and functionality.

Table 1: Comparison between UAV types, based on their regular application in agriculture.

Type	Payload	Cost	Ease of Control	Manoeuvrability	Agricultural Significance
Fixed Wing	High	High	Low	Medium	Medium
Bio-mimiked	Low	High	Medium	Low	Low
Balloon	Low	Low	Low	Low	Low
Parachute	Low	Low	Low	Low	Low
Helicopter	Medium	Medium	Medium	Low	High
Quadcopter	Medium	Medium	High	High	High
Hexacopter	Medium	Medium	High	High	High
Octacopter	Medium	Medium	High	High	High

with flapping wings for better maneuverability and a bird-like structure for lower wind resistance and stability are among some of the bio-inspired UAVs. This class of UAVs is still under development and are yet to gain popular market acceptance. Some manufacturers and models of these UAV types are given in Table 2.

Table 2: Selected manufacturers and models of various classes of UAV.

Type	Manufacturer	Model
Fixed Wing	558 ARP	GRIF-1
	AAI Corp.	Aerosonde MK4.7
	AAI Corp.	RQ-2 Pioneer
	Adcom Systems	YABHON United 40
	Aerial Monioring Solutions	Eagle-Owl
	DRDO	Nishant, Kapothaka, Lakshya
Bio-mimiked	DARPA	Goshawk
	Blue Bear	iMorph
Helicopter	Aerodreams	Chi-7
	CybAero	APID-60
Quadrotor	3D Robotics	IRIS+, 3DR Solo
	Parrot	Bebop
	Aerialtronics	Altura Zenith ATX-4
	DJI	Phantom
	Aeryonlabs	SkyRanger
Hexarotor	Aibotix	Aibot-XU, Aibot-X6
Octarotor	Draganfly	Draganflyer-X8

2.2. UAV Sensors

The main functions and unmanned capabilities of the UAVs are accredited to various sensors responsible for the perception of UAV's location to the Earth's frame of reference, and sensors responsible for keeping the UAVs airborne. The various sensors generally integrated with UAVs can be divided into two broad groups based on the criticality and role of the sensor in the functioning of these aerial platforms (Fig. 2). These sensor groups are divided as:

1. *Primary* – Necessary for operating and controlling the UAV.
2. *Secondary* – Externally mounted on the UAV, which may or may not be directly associated with its functioning.

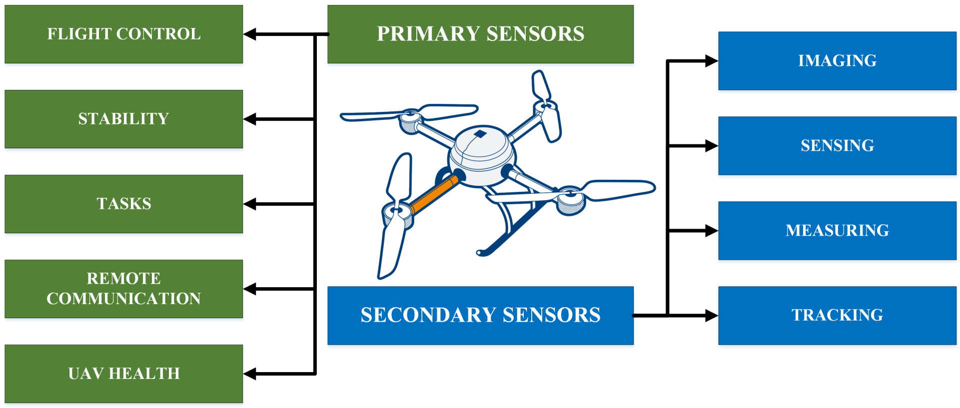


Figure 2: A broad outline of UAV sensor types, based on its functional importance to a UAV.

2.2.1. Primary Sensors

The primary sensors of a UAV include the inertial, navigational and the positioning sensors. These sensors are directly integrated to the UAV and affect the functioning and flight of the UAV. These sensors – voltage sensors, accelerometers, gyroscopes, magnetometers, Global Positioning System (GPS), rotary encoders, temperature sensors, proximity sensors, barometer, and radios – prove critical to the flight of a UAV. Fig. 3 shows some of the primary sensors used in UAVs.

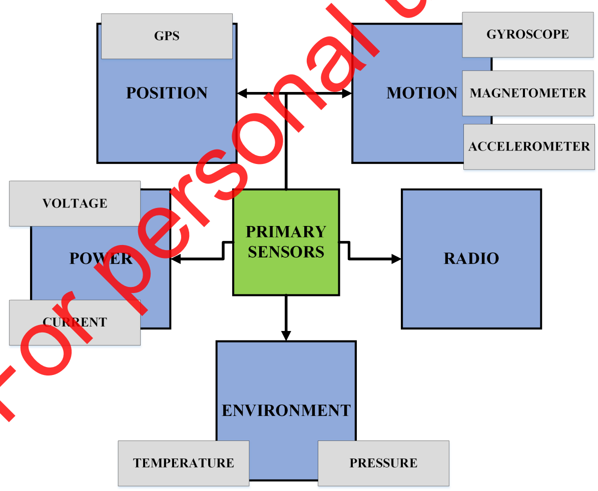


Figure 3: Categorization of a UAV's primary sensors, based on its functionality.

A typical UAV's primary sensors can be broadly categorized into five groups as shown in Fig. 3.

1. *Position*: The onboard position sensors in a UAV primarily deals with the task of localization, concerning a remote control station and the Earth's frame of reference. Sensors such as GPS, Gyroscopes, and Magnetometers fall into this category.

2. *Motion*: The motion sensors on a UAV are tasked with measuring the velocity and acceleration of the UAV as a whole, as well as, keeping a check on the individual motor rotations. Sensors, such as accelerometers deal with the motion of the UAV as a whole, while rotary encoders deal with individual motor's rotations.
3. *Environment*: Environmental parameter monitoring using sensors such as barometers and temperature sensors, ensure the proper working of UAVs at all times. In cases of over-heating or during extremely windy situations, these sensors alert the controller without fail.
4. *Radio*: This category of sensors is responsible for maintaining two-way communication between a UAV and its controller. The controller may be a human controller or automated algorithms on a remote processing machine. Nonetheless, various UAV parameters (yaw, pitch, roll, thrust) and onboard status of the sensors are continuously communicated to the controller. Commands from the controller are communicated back to the UAV using this category of sensors.
5. *Power*: This category of sensors is responsible for monitoring and maintaining the proper power levels of a UAV, and generating alerts upon detection of power anomalies. The sensors in this category include current and voltage sensors.

Some of the individual sensors such as the voltage sensors primarily keep track of the UAV's onboard power requirements and power consumption. Commonly, in the commercially available UAVs, the voltage sensors decide the flight status of the UAV. In case a UAV's power requirements are not sufficient to complete a pre-assigned mission, the UAV may auto-land to avoid a crash. Accelerometers, gyroscopes, and magnetometers are termed as the IMU sensor. IMU stands for inertial measurement unit and calculates the orientation, bearing, and velocity of the UAV to the Earth's inertial frame of reference. The IMUs are also responsible for stability and control of the UAV in the air. Barometric sensors provide altitude and air-speed information to the UAV. GPS is responsible for positioning and localization of the UAV to the constellation of the GPS satellites rotating around the Earth. GPS is mainly used for automatic path planning and waypoint-based navigation in the UAV. Proximity sensors are of two types – infra-red and ultrasonic. The ultrasonic proximity sensors are highly directional, whereas the infra-red ones are omnidirectional. These proximity sensors are used for avoiding obstacles and ground detection when the UAV is air-borne. Rotary encoders are mainly used for keeping track of the rotations a motor is undergoing. These encoders are used for very high precision applications, where exact accuracy is required for controlling the UAV. The radios themselves are sometimes used as passive sensors for estimating the distance of the UAV from the controller or the surrounding environment. The sensed signal strength from the radios is also used for decision making – a UAV may be programmed to return to its starting point in the event of a feeble radio signal from the remote handler or complete loss of signal.

2.2.2. Secondary Sensors

The secondary sensors are not linked directly to the functioning and controlling of the UAV and can be changed, based on the UAV's application. These sensors include – gas sensors, temperature sensors, radiation sensor, humidity sensor, color sensor, RGB camera, hyper-spectral camera, multi-spectral camera, spectrometer, Light Detection and Ranging (LiDAR) sensor, flux sensor, thermal imaging camera, Sound Navigation, and Ranging (SoNAR) sensor and gimbals-based stabilization sensors. Fig. 4 shows some of the secondary sensors used in UAVs.

Scalar sensors such as gas, temperature, humidity, flux, and radiation, when attached to UAVs, quantify the environmental parameters in the vicinity of the UAV. The UAV needs to be manipulated in order physically re-position it so that it can gather readings from various 3D spatial coordinates in its mission path. Non-scalar sensors such as cameras, LIDARS and SONARS can be positioned or rotated towards any spatial co-ordinate in the 3D-space, it has to observe, without physically changing or re-positioning the UAV. These can quantify the various environmental variables near as well as far from the UAV. A UAV's secondary sensors can be broadly categorized into five groups as shown in Fig. 4.

1. *Visual*: The visual sensors comprise of sensors or devices which capture data in the form of light within the visible spectrum of light. These sensors include cameras, color sensors, and LiDARs.
2. *Spectral*: The spectral sensors capture data beyond the visible spectrum of light. It includes hyper-spectral imaging, multi-spectral imaging, and thermal imaging. Most of the information contained in these spectra are not visible to the human eye and need to be processed and converted to a form which is recognizable by humans.
3. *Stabilization*: The sensors for stabilization are mainly responsible for the balance and counter-balance of sensors and external loads carried by a UAV. For example, a gimbal-based stabilization unit is used with visual imaging devices in UAVs. This unit counter-balances the tilt and turns of a UAV, allowing for a seamless, jitter-free and smooth video recording during flight.
4. *Environment*: Sensing the environment around a UAV increases its functionality by allowing for a much more full range of parameters and factors to be sensed. These environmental sensors include sound sensors, temperature sensors, barometers, flux detectors, and radiation sensors, among others.
5. *Proximity*: The primary task of proximity sensors, if armed on a UAV, is to detect obstacles around the UAV and continually measure its distance from the ground. This helps in its safe and hinderance-free navigation.

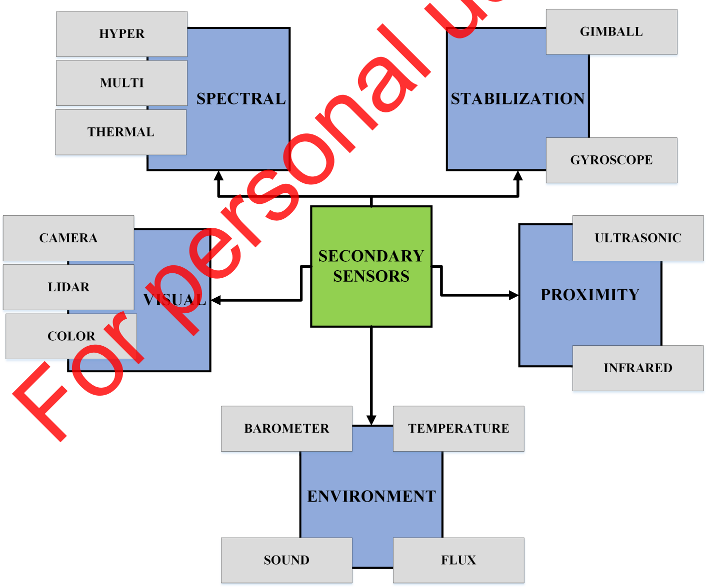


Figure 4: Categorization of a UAV's secondary sensors, based on its functionality.

2.3. UAV Research Domains

The various UAV research domains are categorized into eight broad groups – *Imaging*, *Networks*, *Swarms*, *Localization*, *Path Planning*, *Mapping*, *Stabilization and Controls* and *Applications*.

Path-planning is one of the primary requirements for non-Line-of-Sight (NLOS) operation of UAVs. de la Cruz et al. (2008) demonstrates an evolutionary algorithm based path planning approach. Their method selects the optimal path of several simultaneous UAVs based on external threat perception and extrinsic factors Mahjri et al. (2018). Yang et al. (2014) describe the state-of-the-art and various approaches for 3D UAV path planning. They divide the 3D path planning algorithms into five approaches – *sampling-based*, *node-based*, *mathematical model-based*, *bio-inspired* and *multi-fusion-based*. Samad et al. (2013) discuss the potential of UAVs in civilian use and mapping applications. They base their study on the current needs of the industry. Chao et al. (2013) survey the use of optical-flow techniques for UAV navigation and collision avoidance in urban areas and indoor environments. Additionally, the traditional path planning approaches include GPS-based waypoint selection, vision-based navigation, and fixed waypoint based navigation.

The use of multiple-UAVs for achieving a common goal in the fraction of the time it would have taken a single UAV is termed as UAV-swarm. Danoy et al. (2015) implement a heterogeneous network of UAVs consisting of – an upper layer (high altitude, fixed-wing UAV), controlling multiple lower layer (low altitude UAVs) – to form a swarm with improved network stability in wide range operations. Howden & Hendtlass (2008) discuss a collective intelligence algorithm focusing more on localized control rather than on centralized control. Vincent & Rubin (2004) analyze the performance of cooperative strategies for UAV-based search in hazardous environments. An analysis is also provided on the trade-off between UAVs in use and search time. Pan et al. (2009) describes a particle swarm optimization (PSO) inspired, multi-objective-based non-stationary UAV assignment strategy. White et al. (2008) discuss the use of UAV swarms in contaminant cloud-boundary detection and modeling.

The knowledge of the UAV location and orientation in remotely operated and unmanned missions is important, especially in NLOS scenarios, which makes localization another important and yet, challenging domain in UAV research. Zhang et al. (2010) give an approach for estimating the position and orientation of a UAV during vision-based guidance and navigation. Zhou (2010) describes a geo-referencing approach for UAV-acquired video data. Roberts & Tayebi (2011) gives position tracking of VTOL UAVs adaptively. Another method of UAV localization, which exploits data-muling from acoustic sensor networks is proposed by Klein et al. (2013). They present an architecture for an on-the-fly inference for UAVs while the UAVs collect data from sparse sensor networks. Bayesian inferences are drawn by the UAV-system from the gathered data to generate its consecutive actions. Nemra & Aouf (2010) give an Inertial navigation sensor (INS)-GPS sensor fusion scheme for UAV localization using state-dependent *Riccati* equations.

Post-path-selection, formation control and localization of UAVs, aerial imaging is one of the most application-oriented domains. Johnson et al. (2003) demonstrate the use of a small UAV for collecting hyper-spectral images of vineyards. The images are transmitted to a remote station in near real-time and are used for determining crop vigor from canopy reflectance measurements. Similarly, Herwitz et al. (2004) demonstrate the prolonged use of UAVs by remotely monitoring coffee plantations in Hawaii, from the mainland United States. The UAV is controlled wirelessly, and the images from this UAVs are received via a WLAN infrastructure in real-time. Grenzdörffer et al. (2008) discuss the use of UAV's photogrammetric potential in forestry and agriculture from an image and GIS-based data-acquisition point-of-view. Zhang & Kovacs (2012) discuss the use of small UAVs in precision agriculture. Mauriello & Froehlich (2014) demonstrate the use of UAV-based imaging in automated thermal profiling of buildings to map leakages, improper insulation, and heat loss. Tahar (2015) demonstrate the use of UAVs in slope mapping and then generating a digital ortho-photo and the associated digital elevation model of their study area.

The network and communication aspects of UAV have been addressed in various literature, such as those by Schleich et al. (2013), Jawhar et al. (2017), and Chen et al. (2014). Schleich et al. (2013)

propose algorithms for UAV mobility control, which follow a decentralized and localized approach. The algorithms have been designed for real-time constrained networks in surveillance tasks. Chen et al. (2014) give a comprehensive survey on the area-coverage problem in cooperative UAV networks. Additionally, Gupta et al. (2015) provide a survey of various architectures for UAV networks. They also discuss the option of SDN as a means of flexible, low-cost deployment method in UAV packet routing.

One of the primary work areas of UAVs is their control. Works, such as those by Chen et al. (2009), Lee et al. (2016), and Feng et al. (2016) explore the various options in autonomous control of UAVs. Azinheira & Moutinho (2008) discuss the back-stepping design and its asymptomatic stability for the hover control of a UAV. Bateman et al. (2011) describe a method for fault diagnosis and fault-proof control strategy for UAVs. The use of neural networks in output feedback control of UAVs is demonstrated by Dierks & Jagannathan (2010).

Applications and customization of UAVs for various applications is a domain requiring high levels of skills, accuracy, and precision. Ruangwiset & Higashino (2012) describe the use of video cameras mounted on UAVs in water resource survey. Chahl & Mizutani (2012) propose the use of bio-mimetics for UAV compass design. Their proposed approach uses the spectral and polarized distribution of light in the environment to generate accuracies that are comparable to those generated by solid-state sensors. Cho et al. (2011) propose wind and air-speed estimation technique using a single GPS antenna and a *Pitot* tube. Lin et al. (2011b) study the possibility of using mini-LiDAR systems and luminosity (Lux) sensors on UAVs for fine-scale mapping of tree heights, pole detection, road extraction, and digital terrain model refinement. Bryson & Sukkarieh (2008) proposed an approach for path-planning using a SLAM unit attached to a UAV. Lin et al. (2011a) propose combining satellite-based remote sensing with UAV-based aerial imaging for a non-invasive survey of archaeological sites. An approach for 3D motion error analysis for motion compensation in UAV synthetic aperture radar (SAR) is described by Xing et al. (2009). Their method is primarily developed for low and medium altitude UAV-SAR systems. Another exciting and challenging application of UAVs with high stakes is disaster management. Ferworn et al. (2013) use a game-engine simulation-based approach for disaster scene reconstruction of urban building collapse and rubble. This simulation is used for formulating UAV-based urban search and rescue operations. A brief categorization of various research areas in UAVs is shown in Fig. 5.

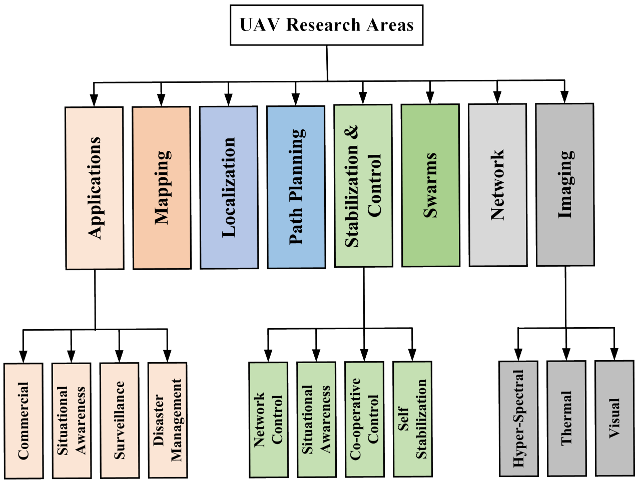


Figure 5: Categorization of UAV research domains.

2.4. UAV Application Areas

The present-day applications of UAVs are wide and span various domains. This prominence of UAVs as a technology enabler in various domains is mainly attributed to its ability to cover large areas in very short periods of time Zorbas et al. (2016). The use of UAV in architectural studies is demonstrated by Grün et al. (2001) and Fernández-Lozano & Gutiérrez-Alonso (2016). The present applications and future use of UAVs in Glaciology is described by Bhardwaj et al. (2016). Chianucci et al. (2016) explore the use of fixed-wing UAVs in forest canopy-cover estimation using UAV-acquired RGB images. Yahyanejad & Rinner (2015) discuss the system of multiple low-scale UAVs for visual and thermal image registration from low-altitude images. A case study of the *Wairakei Tauhara geothermal fields* in New Zealand using UAV-based thermal IR imaging techniques is discussed by Nishar et al. (2016). Shaad et al. (2016) explore high-resolution and cost-effective terrain mapping of river corridors using UAVs. Similarly, use of UAVs for hyperspectral remote sensing in coastal wetlands is explored by Ma et al. (2016). UAVs are also being used for checking plant infestations, as demonstrated by Douglass et al. (2016) for detecting *Tamarix sp.* infestations. The use of UAVs in crop water-stress detection has been demonstrated and discussed by Zarco-Tejada et al. (2012), Gago et al. (2015), Irmak et al. (2000) and many others. The use of UAVs in other agricultural domains such as precision agriculture (Das et al. (2015)), thermal imaging of crops (Bellvert et al. (2016)), crop biomass estimation (Jannoura et al. (2015)) and others are being extensively explored.

3. Possibilities for UAVs in Agriculture

It is due to the vast application domains and advantages of unmanned aerial systems that they are actively considered for use in various domains which have big dependencies on traditional methods and techniques passed on from generation to generation. One such domain is agriculture which, until now in major parts of the world, still relies on traditional techniques and methods. The need for constant scientific intervention in age-old agricultural practices to meet the ever-increasing load of the population has given rise to optimization of existing techniques and resources in agriculture.

Table 3: Comparison between UAVs and traditional sensing technologies in agriculture.

Parameters	**Sensing Technologies in Agriculture**		
	UAV	**WSN**	**Satellite**
Implementation Cost	Low	Low	High
Spatial Resolution	Customizable	High	Low
Temporal Resolution	Customizable	High	Low
Ease of Relocation	High	Low	Low
Grid Size	Customizable	Point	Medium
Ease of Control	Medium	High	Low
Resistance to Environmental Effects	High	Low	High
Resilience to Failure	High	High	Low
Data Cost	Low	Low	high
Computation Cost	Medium	Low	High
Network Cost	Low	Low	High
Need for Control Infrastructure	Maybe	No	Yes
Multiple Devices/units Required	Maybe	Yes	No
Master-Slave Architecture	Maybe	Maybe	No

Keeping track of vegetation using remotely sensed satellite data, precision irrigation, and fertilization, using ground-based sensor and actuator networks, and local weather-stations for micro-climate prediction are among the few technologies being aggressively applied in agriculture. Studies have been being done to detect various plant-stress conditions for plant phenotyping remotely. Studies, such as those by Buitrago et al. (2016) describe the changes in thermal infra-red (IR) spectrum of plants due to the effect of heat and, water-stress. Similarly, Dutta et al. (2016) report the accumulative moisture-stress of potatoes by analyzing their spectral response. A technique of underground plant biomass accumulation by studying the leaf-area from digital images is described by Joalland et al. (2016), whereas a method for water-stress detection in lemon trees by studying their chlorophyll fluorescence is demonstrated by McFarlane et al. (1980).

In addition to remote sensing and spectroscopic characterization, various technologies are being used in direct or allied domains of agriculture. Arnó et al. (2013) and Tao et al. (2015) explore the agricultural application of Light Detection and Ranging (LIDAR). Arnó et al. (2013) describe their approach of using a ground-based LIDAR for leaf-area estimation in vineyards. Tao et al. (2015) propose a method of using LIDAR data to segment tree crowns and detect tree trunks. Similar approaches include autonomously guided four-wheel-drive rovers for precision field operations, as described by Cariou et al. (2009). Additional domains such as automation in agriculture are also being explored. Buitrago et al. (2016) demonstrate a family of re-configurable vehicles that perform tasks such as pruning, thinning, harvesting, mowing and spraying, which allows them to increase agricultural work efficiency by 58%. Singh et al. (2010) discuss automation for specialty crops and discuss the lessons learned from it. They developed sensor systems to monitor insects, crop-load scouting and caliber measurement, which resulted in increased yield and reduced labor costs.

In much recent times, even satellite-based remotely sensed data is inadequate for precision applications, which need almost instantaneous field parameter readings. The infrequent data update intervals for a particular land area, the low resolution of sensed data and other factors have led to the increased use of UAVs in agriculture. In this paper, we use the term unmanned aerial vehicles, unmanned aerial systems and unmanned aerial platforms interchangeably, as they point to the same objective – human-less, airborne sensing and actuation platforms. Although there are works which address the issues of satellite-based remotely sensed data and their optimization (Li et al. (2015), Anghel et al. (2016) and Zhang et al. (2016)), the UAV-based remote sensing of plots and fields are expected to be more accurate (O'Brien (2016)), provide higher imagery resolutions (Hunt et al. (2016), O'Brien (2016)), and are more stable (Wójtowicz et al. (2016)). Moreover, the data from these aerial platforms can be regularly generated and even, generated on-demand, to create a local knowledge-base, which is not possible using satellite data.

4. Architecting UAVs for Precision Agriculture

Modern-day agricultural practices are becoming increasingly dependent on advanced scientific methods and techniques. The rise in popularity of precision agriculture – the use of minimum resources to maximize crop output – demands highly accurate, timely and frequent information updates about the soil, plant, and weather conditions for maintaining an optimum environmental, nutritional and stress balance for plants and crops. One of the commonly used ways of providing these information updates is through the use of wireless sensor networks (WSN). However, this approach is quite costly, as a huge number of sensors and sensor nodes are required for monitoring large tracts of land for precision agriculture. A new and upcoming approach of measuring the field parameters is using remote sensing using UAVs, which provide on-demand, highly accurate, and high-resolution spatiotemporal measurements, which are necessary for precision agriculture. Much research is being pursued in this domain, and continuous innovations in UAV technology for agricultural purposes highlight the use of UAVs in agriculture. Mcfadyen et al. (2014) assess the deployment of UAVs in plant biosecurity. Rokhmana (2015) describe their practical experiences in using an unmanned aerial system for remote sensing in precision agriculture mapping tasks such as land preparation information, cadaster boundary detection, vegetation monitoring, plant health monitoring, and stock evaluation. Zhao et al. (2015) performed a detailed field study of correlations between UAV-acquired Normalized Difference Vegetation Index (NDVI) measures and ground-truth values of crop stress. Rasmussen et al. (2016) discuss and evaluate the possibility of using UAV mounted consumer-grade cameras for deriving vegetation indices and accessing land parameters.

Various uses of UAVs in plant water stress detection have been described by Zarco-Tejada et al. (2012), Gago et al. (2015), and Irmak et al. (2000), whereas works by Jannoura et al. (2015) and Irmak et al. (2000) demonstrate the use of UAVs for biomass estimation. Zarco-Tejada et al. (2012) use a micro hyper-spectral camera, along with a thermal camera mounted on a UAV platform, for detecting the fluorescence, temperature and narrow-band indices of vegetation. These parameters are then used for estimating crop water-stress in citrus orchards. The results of the study show high sensitivity of the indices – Renormalized Difference Vegetation Index (RDVI), Modified Triangular Vegetation Index (MTVI1) and Triangular Vegetation Index (TVI) – to stomatal conductance and water potential. Gago et al. (2015) report a positive correlation of water-stress indicators to the following reflectance indices – NDVI, Optimized Soil Adjusted Vegetation Index (OSAVI) and Normalized Photochemical Reflectance Index (PRI norm). The performance of these indices is reported to be dependent on the crop-type being investigated. They also evaluate the performance of different remote sensing UAVs with ground-truth plant-stress data. Irmak et al. (2000) conduct experiments for quantifying and monitoring water-stress of summer corn in Mediterranean, semi-arid regions. The results of the study converge into an actionable generation of irrigation-scheduling plans and even provides yield estimation from the crops. Jannoura et al. (2015) use true-color aerial images acquired using a remotely operated UAV to monitor crop biomass. The true color images and the derived Normalized Green–Red Difference Index (NGRDI) have been reported to be useful indicators for biomass estimation and estimation of yield in site-specific agricultural decision making.

Senthilnath et al. (2016) demonstrates a spectro-spatial classification method for the detection of tomatoes. They exploit UAV-acquired RGB images for the detection of tomatoes. Techniques such as k-means clustering, expectation maximization, and SOM are used for spectral clustering. Berni et al. (2009) use UAV-based thermal and narrow-band multi-spectral imaging for remote sensing and vegetation monitoring. Bio-physical parameters such as – NDVI, soil-adjusted vegetation index (SAVI), PRI – are estimated for the detection of water stress and canopy temperature sensing. Vega et al. (2015) applied UAV-based multi-temporal imaging for sunflower crop monitoring during its growing season. The effect of time of day on NDVI generation is also analyzed. Hunt et al. (2010) test the acquisition of near infra-red (NIR) green-blue crop monitoring digital photographs from UAV. They apply their approach on variably fertilized fields of winter wheat. They report a good correlation between leaf area index and NDVI in their experiments. Costa et al. (2013) review the use of thermography in exploring plant-environment interactions. Gonzalez-Dugo et al. (2013) discusses the heterogeneity in water-stress of five different fruit tree species using UAV-based thermal imagery. They use this approach for precision agriculture management.

Similarly, an agricultural water-conservation approach by seasonal evaluation of crop water status in peach and nectarine orchards is described by Bellvert et al. (2016). UAV-based thermal imagery is used to estimate crop water stress index (CWSI). Additionally, the authors relate the CWSI to leaf-water potential.

Table 4: Some of the popular commercially available UAV solutions for precision agriculture.

S. No.	Product	Single Flight Range	Flight Control	Type	Sensors	Applications	Specifications
1	senseFly eBee SQ	500 acres	Semi	Fixed wing	Sequoia multi-spectral sensor	Vegetation indices, Plant count, Soil water levels, Soil temperature, Topography mapping	1.1 Kg, 55mins flight, USD 12000+
2	Precision Hawk Lancaster 5	300 acres	Semi	Fixed wing	Multispectral sensor, humidity, temperature, air pressure along with incident light,	Plant height, Plant count, Enhanced NDVI, Field Uniformity, Volume measurement, Optimized Soil Adjusted Vegetation Index (OSAVI), Water pooling	3.4 Kgs, 45 mins flight, USD 25000+
3	Honey Comb AgDrone	600 acres	Semi	Fixed wing	NDVI, visual, stereoscopic and NIR (thermal imaging)	NDVI, High-definition visible maps, Topography mapping	55 mins flight, USD 10000+
4	Sentera Phoenix 2	700 acres	Semi	Fixed wing	RGB visual, NIR, NDVI and Live NDVI (streaming)	NDVI, High-definition visible maps, Topography mapping	1.8 Kgs, 59 mins flight, USD 18000
5	Precision Hawk	Max. 50 acres	Semi	Multi rotor	RGBvisual, NIR, NDVI, LiDAR	Plant count, Plant height, Yield prediction, Plant health, Plant canopy mapping, Biomass estimation,	Varies with the multirotor options available. Approx. USD 1800.
6	DJI M100	Max. 50 acres	Semi	Multi rotor	Visual sensor, Multispectral sensor	Plant counting, 3D drainage mapping, Plant health monitoring, NDVI, Enhanced NDVI	35 mins flight, USD 8300
7	AGCO Solo	Max. 30 acres	Semi	Multi rotor	Visual sensor, NIR sensor	High-resolution orthomosaics, NDVI maps, Field Health and Management Zone maps.	20 mins flight, USD 7850
8	Sentera Omni Ag	Max. 30 acres	Semi	Multi rotor	Double 4K multispectral sensor, RGB visual, NIR, NDVI and NDVI Live (streaming)	Plant health, Plant stress	25 mins flight, USD 13000
9	Lockheed Martin InDago AG	Max 75 acres	Semi	Multi rotor	Configurable with various imaging sensors	Depends on the sensors used.	45 mins flight, USD 30000
10	ATI AgBot	Max. 30 acres	Semi	Multi rotor	IR, Multispectral and HD video sensors	Plant health, Plant stress	4.7 Kgs, 26 mins flight, USD 8000

UAVs in precision agriculture is proving to be immensely popular with agriculturalists. Das et al. (2015) discuss a system design and methods for automated monitoring of crops in precision agriculture. Their particular multi-spectral 3D imaging system consists of a suite of sensors, specifically, thermal imagers, multi-spectral cameras, and navigational sensors, which extract plant morphology, canopy volume, leaf area index, and fruit counts. Besides the UAV-mounted system, they additionally deploy a manually carried harness to gather ground-based images. Zecha et al. (2013) review the available sensor platforms used for research in precision farming. Zhang & Kovacs (2012) review the application of small UAVs for precision agriculture. The comparison of these UAVs with satellite-based data-acquisition establishes the potentiality of low-altitude UAVs in environmental monitoring – low cost, high temporal resolution, and flexibility in data acquisition. Tokekar et al. (2013) propose a sensor planning approach for UAV-unmanned ground vehicle (UGV) coordination in precision agriculture. The ground and aerial measurements obtained by them are used for generating Nitrogen deficiency map of the fields. Chance et al. (2016) use spectroscopic images from UAVs in detecting certain unwanted species of weed amongst useful vegetation. The abundance of UAV-based agricultural research and applications, which are regularly reported, highlight its importance in modern-day agriculture. Table 3 highlights the advantages of UAV-based sensing in agriculture, as compared to other sensing technologies.

4.1. Image Processing and Correction

The imagery acquired from UAV flights, be it visual RGB, NIR, or multispectral, needs to be corrected to eliminate noise and jitters and processed to obtain useful information for further analysis. Typical problems encountered during aerial image capture include:

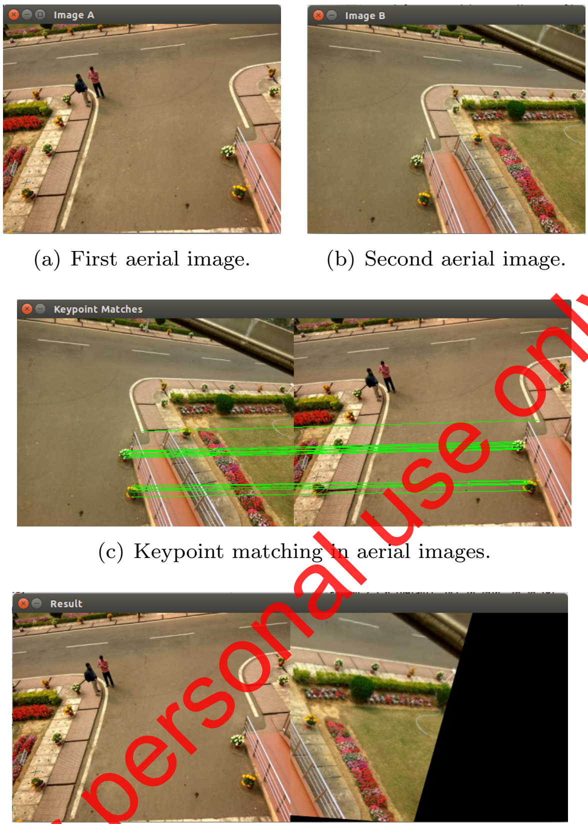
1. Jitters in images due to motion or vibration of the UAV.
2. Overlapping images of the same area.
3. Non-overlapping image patches of an area under survey
4. Determining the correct orientation of the image (locating North in the image)
5. Variations in images due to angle and altitude of flight.

(a) Noisy aerial image with jitter. (b) Stabilized aerial image.

Figure 6: Aerial images of experimental agricultural plots captured using an assembled quadrotor UAV, with and without image stabilization.

The vibration in the UAVs, especially multi rotors cause jitters in the captured images unless the imaging mechanism is sufficiently padded. Fig. 6(a) shows an image captured from a UAV, where the camera is directly attached to the UAV frame without any vibration-proofing or stabilization. This results in distorted images resulting in loss of information in the captured images. In contrast to this, Fig. 6(b) shows a gimbal stabilized camera attached to a UAV resulting in much clearer and precise capture of images.

The second problem of image overlap is handled by a mechanism known as image stitching. Primarily, image stitching looks for matching key points in images. Based on the key points, the images are stitched to generate a single continuous image with the inclusion of the overlapping region. Figs. 7(a) and 7(b) show two aerial images of a region of interest with significant overlaps. The detected key points in these images are shown in Fig. 7(c), resulting in a stitched image with the overlapping region included as shown in Fig. 7(d).



(a) First aerial image. (b) Second aerial image.

(c) Keypoint matching in aerial images.

(d) Final stitched image.

Figure 7: The process of image stitching demonstrated using two aerial images captured using a quadrotor UAV.

Modern imagery software for GIS such as the Sentinel Toolbox, QGIS Semi-automatic Classification Plugin (SCP), SAGA GIS: System for Automated Geoscientific Analyses, GRASS: Geographic Resources Analysis Support System and others generally handle the issues enumerated previously, especially overlaps, direction and orientation of images, and radiometric corrections.

4.2. Remote Indices

The bulk detection and analysis of plants for crop-stress is an important aspect of UAV-based precision agriculture, and it may be considered as one of the crucial stages of precision agriculture. Instead of inspecting each plant individually, certain indices have been designed, which exploit the difference of reflectances of various spectral bands – vegetation indices – allowing for bulk detection of vegetation and changes therein. The vegetation indices are designed to highlight certain vegetation

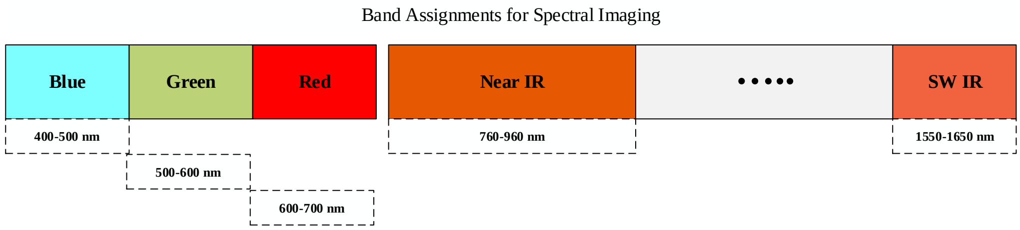


Figure 8: Some of the spectral bands used in remote sensing of vegetation indices.

properties. They are derived from two or more surface reflectance wavelengths, signifying reflectance properties of the vegetation under observation (HarrisGS). Since the dawn of space-age, satellite-sensed reflectance from large swathes of land are being used for inferring these indices. Currently, with the advent of cheap, reliable, and light-weight UAV remote sensing platforms, it is possible to calculate these indices locally, more accurately, and much more speedily. We broadly categorize some of these indices into three groups – *Broadband Greenness*, *Narrowband Greenness* and *Others*. The various vegetation indices derived and inferred from remote sensing are listed in Tables 6, 7, and 5.

The Broadband Greenness indices are primarily simple indicators of green vegetation quantity and quality. The constituent reflectance measurements are sensitive to foliage cover, chlorophyll concentration, canopy area, and architecture. They compare reflectance peaks of vegetation in NIR and red range of the spectrum (see Fig. 8). These indices indicate the presence of photosynthetically active components in the vegetation and are mainly applied in land-use studies, climatic impact assessment and vegetative productivity (HarrisGS). Some of these indices are listed in Table 6.

The Narrowband Greenness indices are similar to Broadband indices, but are much more sensitive, as they use the red edge of the spectrum (see Fig. 8) for their measurements. The Broadband indices tend to saturate in dense foliage, which is overcome by the Narrowband indices. These are mainly designed for use with imaging spectrometers. These indices are immensely useful in precision agriculture for identifying, analyzing, and managing site-specific spatiotemporal variations of the soil (HarrisGS). Some Narrowband Greenness indices are listed in Table 7.

The other indices include Nitrogen and Carbon-based indices. The Nitrogen concentration in foliage is sensed by reflectance measurements in the short-wave IR region (see Fig. 8). Carbon, which is present in the dry states of lignin and cellulose, is also measured in the short-wave IR region. The increase in carbon index of vegetation indicates that the vegetation is undergoing senescence/ aging (HarrisGS). Some of these indices are listed in Table 5.

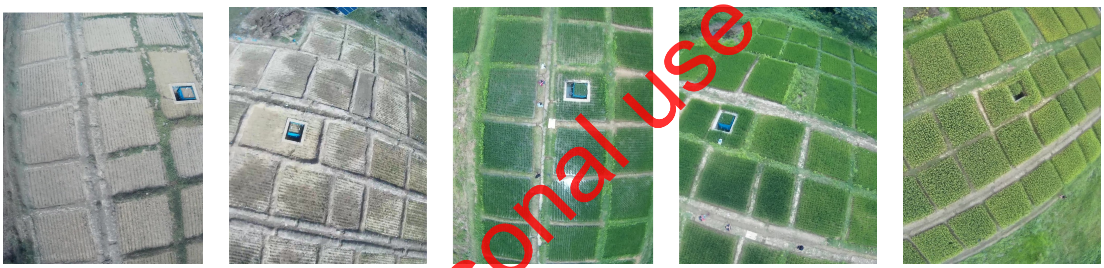
Table 5: Other Indices.

Acronym	Index	Highlight	Reference
NDNI	Normalized Difference Nitrogen Index	Experimental in nature and shows strong sensitivity to changing nitrogen content during green canopy	Fourty et al. (1996), Serrano et al. (2002)
NDLI	Normalized Difference Lignin Index	Experimental in nature and Lignin-sensitive. Lignin is contained in vegetation canopies	Serrano et al. (2002), Fourty et al. (1996), Melillo et al. (1982)

CAI	Cellulose Absorption Index	Indicates exposed surfaces containing dried plant material	Daughtry (2001), Daughtry et al. (2004)
PSRI	Plant Senescence Reflectance Index	Maximizes the sensitivity of the ratio of bulk caretenoids to chrolophyll	Merzlyak et al. (1999)

4.3. Agro Analytics

Post acquisition and processing of images, the eventual applicability of UAVs in precision agriculture is the generation of usable information from the gathered data in the form of agro analytics. As an example, we monitored the growth of maize in our experimental agricultural plots for a full cropping cycle using a UAV-mounted RGB camera, the various stages of which are shown in Fig. 9. The quadrotor UAV images for this exercise were not corrected for direction or orientation. However, they do adhere to the restrictions of GPS-based plot positions. Fig. 9(a) shows the prepared field for the sowing of seeds. Fig. 9(b) shows the field after sowing and an initial watering regimen. Figs. 9(c), 9(d), and 9(e) show the progress of crop growth after 30, 42, and 72 days of field preparation. The main objective of this example is to highlight the usefulness of aerial image based information gathering for agro analytics. The quantum of information provided by RGB images (as shown in Fig. 9) can be vastly improved by using more advanced sensors such as multispectral and thermal imagers.



(a) Day 0 (b) Day 10 (c) Day 30 (d) Day 42 (e) Day 72

Figure 9: Monitoring the progress of Maize in a controlled agricultural experimental facility using UAV-based RGB imaging. The RGB camera is stabilized. However, no further processing such as direction correction or orientation correction has been applied to these images.

Agro analytics, in the present day, encompass the following three major application domains – 1) Plant stress, 2) Yield prediction and 3) Insurance payouts.

4.3.1. Plant Stress

Abiotic plant-stress is mainly due to water, temperature or nutrient deficiency, or a combination of few or, all of them. Additionally, another class of plant-stress is due to disease attacks on the plants, which somehow damage their chemical and biological cycles, causing Biotic-stress in plants. Cantore et al. (2016) discuss their study on the assessment of induced abiotic-stress in the form of water-stress and reduction of biotic-stress in the form of application of fungicide for physiological and yield response of tomatoes. Elazab et al. (2016) report their approach on detecting abiotic-stress – nitrogen fertilization and heat stress – on maize productivity. They use a multi-spectral camera for calculating the Normalized Difference Vegetation Index (NDVI) and Normalized Green Red Difference Index (NGRDI) in estimating the Aerial Biomass (AB) and Grain Yield (GY) from the plants. King & Shellie (2016) describe their method of applying neural networks on leaf-temperature

Table 6: Broadband Greenness Indices.

Acronym	Index	Highlight	Reference
ARVI	Atmospherically Resistant Vegetation Index	Resistant to atmospheric factors	Kaufman & Tanre (1992)
DVI	Difference Vegetation Index	Distinguishes between soil and vegetation	Tucker (1979)
EVI	Enhanced Vegetation Index	Corrects soil background signals and reduces effects of aerosol scattering	Huete et al. (2002)
GARI	Green Atmospherically Resistant Index	High chlorophyll sensitivity, low atmospheric sensitivity	Gitelson et al. (1996)
GEMI	Global Environmental Monitoring Index	Global environment monitoring from satellite imagery, affected by bare soil	Pinty & Verstraete (1992)
GDVI	Green Difference Vegetation Index	Predicting nitrogen requirements of corn	Sripada et al. (2006)
GRVI	Green Ratio Vegetation Index	Sensitive to photosynthetic rates in forest canopies	Sripada et al. (2006)
GNDVI	Green Normalized Difference Vegetation Index	More sensitive to chlorophyll content than NDVI	Gitelson & Merzlyak (1998)
GVI	Green Vegetation Index	Emphasizes green vegetation by minimizing the effects of background soil	Kauth & Thomas (1976)
IPVI	Infrared Percentage Vegetation Index	Same as NDVI, but computationally faster	Crippen (1990)
LAI	Leaf Area Index	Estimates foliage cover and forecasts crop growth and yield	Boegh et al. (2002)
MNLI	Modified Non-Linear Index	Enhancement of non-linear index and uses SAVI to compensate background soil	Yang et al. (2008)
MSR	Modified Simple Ratio	Increased sensitivity to vegetation biophysical parameters	Chen (1996)
NLI	Non-Linear Index	Linearizes non-linear surface parameters	Goel & Qin (1994)
NDVI	Normalized Difference Vegetation Index	Measure of healthy and green vegetation	Rouse Jr et al. (1974)
OSAVI	Optimized Soil Adjusted Vegetation Index	Provides greater soil variation than SAVI	Rondeaux et al. (1996)
RDVI	Renormalized Difference Vegetation Index	Highlights healthy vegetation	Roujean & Breon (1995)
SAVI	Soil Adjusted Vegetation Index	Suppresses effects of soil pixels	Huete (1988)
TDVI	Transformed Difference Vegetation Index	Monitoring vegetation cover in urban areas	Bannari et al. (2002)

Table 7: Narrowband Greenness Indices.

Acronym	Index	Highlight	Reference
MCARI	Modified Chlorophyll Absorption Ratio Index	Relative abundance of chlorophyll with minimized effects of soil and non-photosynthetic surfaces	Daughtry et al. (2000)
MCARI2	Modified Chlorophyll Absorption Ratio Index - Improved	Better than MCARI and incorporates soil adjustment factor and resistance to chlorophyll influence	Haboudane et al. (2004)
MRENDVI	Modified Red Edge Normalized Difference Vegetation Index	Detects small changes in canopy foliage, gap fraction and senescence by harnessing the sensitivity of vegetation red-edge	Datt (1999), Sims & Gamon (2002)
MRESR	Modified Red Edge Simple Ratio	Modification of Simple Ratio (SR) which makes use of bands in the red-edge and incorporates leaf spectacular reflection correction	Sims & Gamon (2002), Datt (1999)
TVI	Triangular Vegetation Index	Good for estimating LAI but highly sensitive to chlorophyll and canopy density	Broge & Leblanc (2001)
MTVI	Modified Triangular Vegetation Index	Makes TVI suitable for LAI estimations using 800 nm wavelength and counteracting the effects of changes in leaf and canopy structures	Haboudane et al. (2004)
MTVI2	Modified Triangular Vegetation Index - Improved	Defines background soil signature while preserving LAI sensitivity and chlorophyll-resistance	Haboudane et al. (2004)
RENDVI	Red Edge Normalized Difference Vegetation Index	Exploits red-edge vegetation sensitivity to minute changes in canopy foliage, gap fraction and senescence	Gitelson & Merzlyak (1994), Sims & Gamon (2002)
REPI	Red Edge Position Index	Sensitive to changes in chlorophyll concentration	Curran et al. (1995)
TCARI	Transformed Chlorophyll Absorption Reflectance Index	Indicates relative abundance of chlorophyll and is affected by underlying soil reflectance	Haboudane et al. (2004)
VREI	Vogelmann Red Edge Index	Sensitive to effects of combination of changes in foliage chlorophyll, canopy leaf area and water content	Vogelmann et al. (1993)

measurements to calculate crop water stress index in wine-grapes. Lawley et al. (2016) present their perspectives on vegetation monitoring remote sensing methods and indicators, which are primarily site-specific. Lima et al. (2016) check for variations in physiological indicators in papaya trees by incorporating different watering regimes. They link these physiological variations to thermal imaging. Additional works by Magney et al. (2016), Liu et al. (2016), Mateos & Araus (2016), Wang et al. (2016), Silva et al. (2016), Tari (2016), and Yousfi et al. (2016), deal with crop abiotic-stress detection, reduction, and management techniques.

Hou et al. (2016) describe their approach of detecting biotic-stress in grapevines, based on spectral imagery and use ant-colony based clustering for detecting this stress from acquired images. Ivanov & Bernards (2016) use chlorophyll fluorescence imaging for monitoring biotic-stress caused by root pathogens in perennial plants. Mahlein (2016) use imaging sensors for plant biotic-stress detection and phenotyping in precision agriculture.

4.3.2. Yield Prediction

The aerial images acquired using UAVs can be processed to derive information enabling the prediction of yields based on the progress of the crop growth and stress. Maresma et al. (2018) employ UAV-based imagery to study nitrogen application response of *Zea Mays*. The response of plants is eventually translated in the form of yield forecast for the crop at the end of the cropping cycle. Similar approaches have been used for estimating the yields of heterogeneous crops in small landholdings Schut et al. (2018), forage yield in grassland Lussem et al. (2018), wheat crop yields using a combination of UAVs and ground sensor networks Zecha et al. (2018), yield prediction of Chinese cabbage using broadband indices acquired using UAV imagery Kang et al. (2018), and others Sanches et al. (2018).

4.3.3. Insurance

One of the most effective schemes in modern-day agriculture using UAVs is the estimation of crop insurance Navalgund (2018). Countries such as India are negotiating policies with private players such as banks and insurance companies in order to implement a UAV-based crop damage assessment in the event of natural calamities, or other such factors. Various Government schemes in India such as Pradhan Mantri Fasal Bima Yojna (which translates to Prime Minister's Crop Insurance Scheme) is one of the key policies, which considers making use of technologies such as UAVs for accessing crop damage for insurance payouts Gulati et al. (2018).

5. UAV Deployment Architectures for Precision Agriculture

The various architectures for deploying UAVs in agricultural applications can be categorized into five broad groups – *Manual UAV control*, *Autonomous UAV control*, *UAV-WSN symbiosis*, *UAV Swarms*, and *UAV-UGV symbiosis* – which are described in Sections 5.1 to 5.5. Various features of these architectures are summarized in Table 8.

5.1. Manual UAV Control

This architecture involves human operator-based, manual UAV control. Senthilnath et al. (2016) demonstrate the use of this architecture in their work. As this architecture is easy to set up, it can be used for a wide range of agricultural applications with simple changes or modifications to the UAV's secondary sensors. However, as this architecture relies on manual, line-of-sight (LOS) operation, the stability, control and recovery time of the UAV is heavily dependent on its human controller, often rendering it less reliable, as compared to autonomous methods of UAV control. In Fig. 10, a user controls the UAV's flight and directs it to various locations over the fields for gathering data which may in the form of visual recordings of a camera or spectroscopic readings or others, depending on the application scenario.

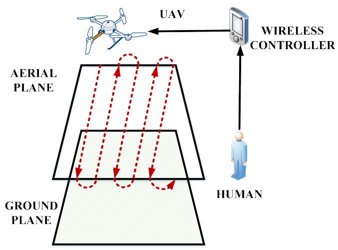


Figure 10: Manual UAV deployment architecture.

5.2. Autonomous UAV Control

The autonomous control of UAVs may be divided into two parts – (a) Fully autonomous, as shown in Fig. 11) and, (b) Partially autonomous, as shown in Fig. 12. Choi et al. (2016) and Xiang & Tian (2011) demonstrate the use of autonomous architectures for their work on and with UAVs. UAVs following this deployment architecture have their task pre-defined and need elaborate changes for redefining their behavior or flight path. The controller may be implemented on a remote server, or a computer with proper radio-interfacing to guide the UAV to and from its target, autonomously. The autonomous behavior of these UAVs is achieved through various algorithms which optimize and alter the behavior of the UAVs even in the presence of external disturbances, enabling them to complete their objective successfully. This is not possible using the manual architecture discussed previously. Fig. 11 shows a fully autonomous architecture, where a remote controller is controlling multiple

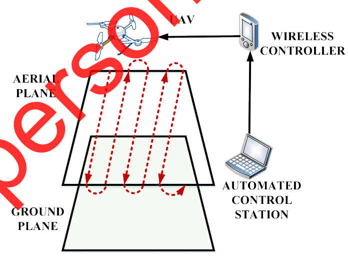


Figure 11: Fully Autonomous UAV deployment architecture.

UAVs without any human intervention. The tasks and objectives of the UAVs are pre-defined. Changes in the tasks and the UAV's mission objectives need considerable changes in the controlling algorithms in the remote controller. Fig. 12 shows a partially autonomous architecture for UAV deployment. The autonomous controller depends on passive inputs from a user for controlling these UAVs. A user has the freedom of defining the UAVs area of operation, tasks to achieve, flight-path, and other such parameters, during every flight. Autonomous algorithms control the UAVs' stability and optimize the overall mission-objective, taking into account, the environmental factors and other UAV parameters such as battery life and sensors. Here, the autonomous algorithms are bounded by the human-input parameters.

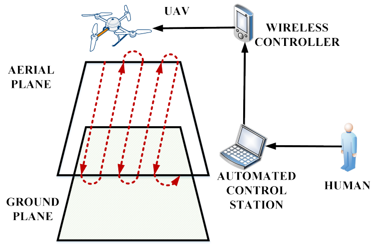


Figure 12: Partially autonomous UAV deployment architecture.

5.3. *UAV-WSN Symbiosis*

This UAV deployment architecture is dependent on the use of ground-based WSN for completion of the UAV's objectives. However, the ground-based WSN may not directly control the UAV's flight. Dong et al. (2014), Valente et al. (2011), Jawhar et al. (2017), and Costa et al. (2012) demonstrate the use of this architecture in their work. The WSNs continually record ground parameters which are not possible using UAVs. The recorded parameters are transferred to the UAV whenever it is in range of the WSN node, using a short-range wireless communication protocol, as shown in Fig. 13. The UAV's path, stability, and mission parameters are, however, controlled by a remotely located controller. The UAV facilitates the transfer of data from the ground as well as air to the remote station.

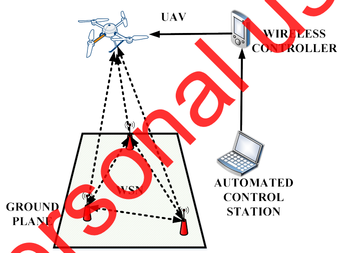


Figure 13: UAV deployment architecture with UAV-WSN symbiosis.

5.4. *UAV Swarm*

Brust & Strimbu (2015) demonstrate the use of a UAV swarm in their work. A remote controller directly controls a single UAV – *swarm leader* – which in turn, controls other UAVs – *followers* – within the *leader's* swarm. This architecture makes it possible to control multiple UAVs using a single high-power, long-range transmitter, which connects to a single UAV, as shown in Fig. 14. The *swarm leader* connects to other UAVs in its swarm using low-power radios and is responsible for controlling the behavior of its *followers*. Having multiple UAVs performing parts of the same task can reduce the time taken to complete an objective. However, this is achieved at the cost of increased computations in the UAV and the remote controller (Couceiro et al. (2014)). In continuation, decentralized approaches such as the one proposed by De Benedetti et al. (2017) do not require a centralized controller for command and control of the swarm. The swarm itself is self-sufficient till the completion of its assigned task/mission. However, the use of swarms for accomplishing a task requires the aid of special algorithms, which help in optimally deciding the positions of the UAVs for better and cost-efficient coverage (Zorbas et al. (2016), Ari et al. (2016)).

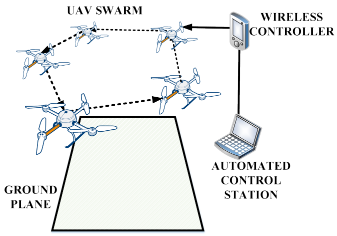


Figure 14: UAV deployment architecture with UAV swarm based sensing.

5.5. UAV-UGV Symbiosis

The unmanned aerial vehicle (UAV)- unmanned ground vehicle (UGV) symbiosis architecture relies on a mobile ground-rover to extend the range of communication between UAVs and the remote station as shown in Fig. 15. The mobile-rover doubles as a local ground-station, albeit with lesser processing and control functions as compared to the remote control station. The UGV can additionally be used to gather ground-based parameters (geophysical and terrain data) along with its primary assignment as the UAV's relay station with the remote control station. Tokekar et al. (2013) use UAV-UGV symbiosis in their work.

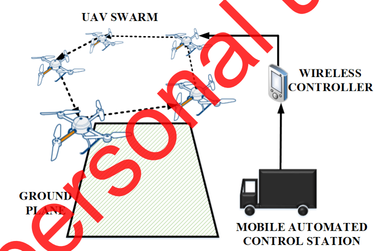


Figure 15: UAV deployment architecture with UAV swarm and UGV collaboration.

6. Leveraging Networked Automation in UAVs for Precision Agriculture

The UAV deployment architectures highlighted in Section 5 highlight the robustness, flexibility, and efficacy of using UAVs for tasks such as precision agriculture. However, certain prominent concerns exist in the usage of UAVs for tasks such as precision agriculture. These concerning factors are enumerated as:

1. *Effects of wind*: The effects of strong winds are generally detrimental to the flight time of UAVs. Typically winds tend to alter the regular flight path of fixed-wing UAVs, which are low on maneuverability. In contrast, multirotor UAVs tend to use up much energy to stabilize themselves and maintain their designated paths during winds, which further puts constraints on their already low energy budget.

Table 8: Comparison between UAV architectures.

Parameters	Architectures				
	Manual	**Autonomous**	**UAV-WSN**	**Swarm**	**UAV-UGV**
Range of Control	Low	Medium	Medium	High	High
Non-LOS Operation	No	Yes	Yes	Yes	Yes
UAV Stability	Low	High	High	High	High
UAV Manoeuvrability	Low	High	Medium	Medium	Medium
Recovery Time	Medium	Low	Low	High	Medium
Network Cost	Very Low	Medium	Low	High	High
Computational Cost	Low	Medium	Medium	High	Medium
Implementation Cost	Low	Medium	Medium	High	High
Heterogenity of Applications	Yes	No	No	Yes	Yes
Architecture Setup Time	Low	Medium	High	Medium	Medium
Coverage Area	Small	Medium	Medium	Large	Large
Ground-based Sensor Dependencies	No	Maybe	Yes	No	Maybe
Remote Response Time	Low	Medium	Medium	High	High

2. *Coverage*: The coverage of UAVs are restricted by their energy budgets, which are typically low for commercially available, non-military grade UAVs. Additionally, manual control or manual supervision of UAVs generally require a line-of-sight operation. In continuation, the dependence of UAVs on ground units for control are restricted by the transmission power of radio control links, which is typically in the range of $2-3$ kilometers for commercially available solutions.
3. *Ground equipment*: The range of radio control units restricts the dependence of conventional UAV-based architectures on ground equipment for controls and decisions. Moreover, the requirement of ground control units restricts the mobility, speed of deployment, and robustness of the UAV-based solutions.
4. *Flight-control expertise*: The use of UAV-based solutions in the present day agricultural applications are either manual or semi-autonomous (humans monitor flight). This requires proper training of the person controlling or monitoring the UAVs, generally at the cost of more money and time. Despite proper training, human errors of judgment are a likely possibility during human control and supervision.
5. *Task completion time*: The use of UAVs in standalone mode require significant time to accomplish tasks assigned, which is a major concern especially due to the restricted flight times of these UAVs. Additionally, the typical tasks assigned to UAVs in precision agriculture require covering large swathes of land, which could result in a significant consumption of time and energy resources.
6. *Manpower required*: Traditional control strategies of UAVs require the presence of a person per UAV. Sometimes, a person may be tasked with more than one UAV, which significantly raises the chances of errors of judgment leading to disastrous consequences.

All of these concerns can be readily addressed by a new paradigm in the domain of UAVs – autonomous UAV networks/ UAV swarms. These networked UAV swarms have the capability of collective decision making and performing actions in tandem. This capability of swarms can be extended to address the challenges posed due to limited coverage areas, task completion times, that too with a minimal number of human interventions required. The swarms act as force multipliers in domains such as agriculture by enabling very few human controllers to have complete control over a much larger number of UAVs, each performing separate tasks. These solutions are outlined in Section 6.1.

6.1. Agricultural Force Multiplier Networked UAV Topologies

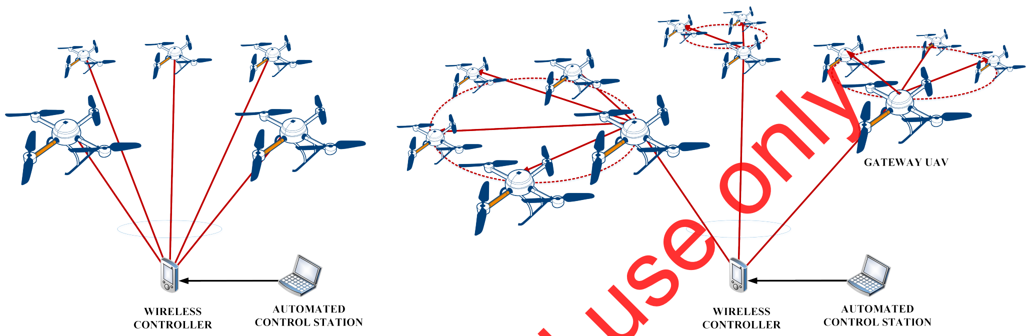
The use of UAVs as force multipliers in agriculture, especially precision agriculture would require the usage and handling of multiple UAVs, preferably UAV swarms over a network. This networked setup would enable a person or very few persons to monitor or control a large number of UAVs, each of which may or may not be assigned similar tasks. The networked control of such system can be divided into two broad topologies – 1) Star topology, and 2) Mesh topology. Table 9 summarizes the features of star and mesh UAV network topologies.

6.1.1. Star Topology

The star topology of networked UAV control encompasses a single ground control unit/server connected to multiple aerial UAVs via multiple radio interfaces, one for each UAV. The coordination among the UAVs is maintained by the central ground control server as shown in Fig. 16(a). However, as the UAVs need to communicate with the central ground unit, any failure at this point would prove detrimental for the whole star network as a whole resulting in high possibilities of singular point of

Table 9: Comparison between main features of star and mesh networked UAV topologies.

Parameter	Star	Mesh
Intercommunication between members	Via a central hub UAV or a ground server	Directly with the members
Network latency	High	Low
Single point of failure	High	Low
Reliability of system as a whole	High	High
Network bandwidth required	Low	High
Extension of communication range	Not possible	Possible
Network cost	Low	High
Distributed decision making	Not feasible	Extremely feasible



(a) Simple star topology (b) Multi-star topology

Figure 16: Star topology for agricultural force multiplier using networked UAVs.

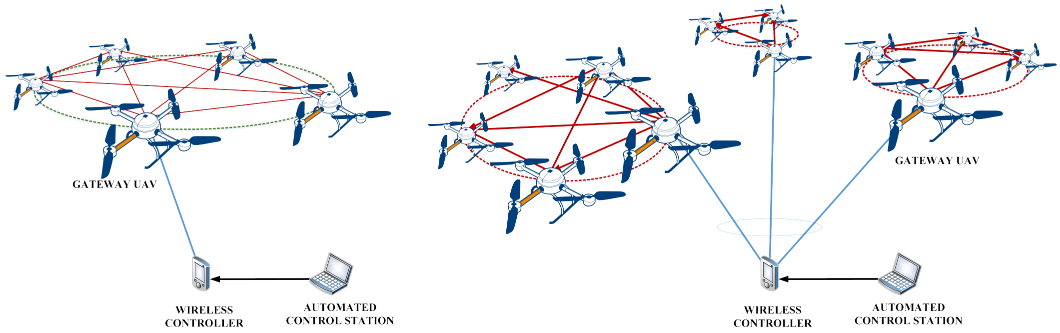
failures and high network latencies. Additionally, the possibilities of distributed decision making in the air, in the advent of a ground unit failure are not possible in this topology.

The star topology can be further divided into – 1) Simple star and 2) Multi star Gupta et al. (2015) as shown in Fig. 16. A simple star topology has multiple UAVs connected to a central hub, which may be a UAV or a ground-based control station as shown in Fig. 16(a). The ground controller acts as the gateway for communication between the human handler as well as between the UAVs in the star network.

In continuation, a multi-star topology has multiple communication gateways, either in the form of one ground control station and multiple aerial gateways or the form of all aerial gateways communicating with the member UAVs. A multi-star topology is shown in Fig. 16(b).

6.1.2. Mesh Topology

The mesh topology, in contrast to the star topology, encompasses multiple networked UAVs connected with each other in such a manner that each of the UAVs can directly communicate with other member UAVs without the need for a central hub or gateway. The ground link-up with the UAV mesh, as shown in Fig. 17, is optional and allows a human handler to communicate with the aerial network from time to time to allow for updated tasks and commands. As all the UAVs can communicate with all other UAVs in the network, single point of failures are avoided such that even if a ground device or UAV fails, the integrity of the network is intact. This topology allows for distributed processing within the mesh, which may be useful in case of loss of link with ground control stations or in case the communication range between the ground station and the UAVs is to be increased.



(a) Simple mesh topology (b) Hierarchical mesh topology

Figure 17: Mesh topology for agricultural force multiplier using networked UAVs.

The UAV mesh topology can be further sub-divided into two groups – 1) Simple mesh topology, and 2) Hierarchical mesh topology Gupta et al. (2015) as shown in Fig. 17. A simple mesh topology has UAVs, which can communicate with each other without the need for a communication gateway. A communication gateway may be established using one of the UAVs, enabling the aerial network to communicate with a ground control station to update controls and relay information to its human handlers. Fig. 17(a) shows a simple UAV mesh topology. However, the cost of establishing the network is significantly high as the number of connections rapidly goes up as the number of UAVs in the network increases.

In continuation, in a hierarchical mesh topology, multiple UAV meshes are connected to a single ground control station employing a single UAV per mesh acting as the communication gateway of that mesh to the ground control station and the other meshes. This topology is quite complex and expensive and is rarely implemented for practical uses.

7. Future Scope

Although much work is being done by exploiting the advantages of UAVs in agriculture, still scopes are remaining to be further exploited. There are some application areas and architectures, which have not been comfortably explored by the researchers till now. This section tries to list these gaps and suggests alternative application domains for UAVs in agriculture.

7.1. Scope of Improvement

Some of the scopes of improvement, based on the reviewed literature, are summarized below. These improvements are more specifically domain-specific and may not apply to UAV usages outside agriculture.

- *Ease of Handling*: The present-day UAVs require minimal training on the part of the human handler for its operation. Every person requires varying amounts of time to build up the skill and dexterity to handle UAVs in real-time. Various self-stabilization algorithms can be integrated with the UAV controls so that a person with very little training can also handle these UAVs.

- *Power Efficiency*: Power consumption and usage efficiency need to be drastically improved for the commercially available UAVs. Addressing this issue would enable the UAVs to operate for longer hours and increase their reach.

- *On-board processing*: Increase in onboard processing capabilities of commercially available UAVs may lead to low-network bandwidth requirements for controlling them. The recent developments in commercially available, low-cost, miniaturized computing boards having the processing power of a regular PC can be explored for these applications. Their power requirements are also minuscule, as compared to other computing platforms of the same caliber.

- *Weather-proofing*: It is yet another important aspect which has been looked-over for long. The use of these UAVs in agriculture would require them to be resistant to variations in weather and environmental conditions while maintaining the ability to perform in those conditions.

- *Collision Avoidance and Assessment*: The automation of UAVs require significant processing and control resources for ensuring safety of flights, safety of the platform, and safety of infrastructure around it. Faster and precise assessment of collision risks and calculation of the best possible collision avoidance measure are instrumental in the success of a reliable aerial monitoring or sensing platform.

7.2. Application Scope

Some futuristic applications, which may be challenging, yet, may prove to be beneficial in precision farming and farmland management, are listed below.

- *Control*: More emphasis is needed on the autonomous control of UAVs, so that multiple UAVs can accomplish a set of tasks at the same time, even while being supervised by a single human controller. Multiple UAVs being controlled by a single user will act as a force multiplier and result in increased operational efficiency of the handler. Mechanisms such as gesture-based control, and video-based tracking and control, are expected to make the handling of these UAVs easier.

- *Control Range*: Better and cost-effective radios need to be developed for long-range operations of these UAVs. As the field sizes may be huge, it is not always feasible for a human controller to follow the UAV everywhere. For a futuristic scenario, a single high-altitude UAV may be used for controlling and relaying commands to several low-altitude UAVs, forming a heterogeneous network of UAVs.

- *Cloud-based storage and Analysis*: A cloud-based UAV system would bring down the cost of implementation of this solution in the long run. Buying UAV-cloud services on a pay-per-use basis will result in an increased number of people trying and using this service, who otherwise would have been intimidated by the initial set-up cost of UAV-based monitoring systems.

- *Modular Functionality*: Putting-in explicit goals in the controller, instead of manually controlling and guiding, will result in efficient utilization of time by the human handler. Moreover, as these systems are considered for agricultural use, it is not always possible to have trained UAV operators or provide training to the end users in UAV handling and maneuvering techniques.

7.3. Upcoming Application Areas

In the context of the applications of UAVs in precision agriculture, we list some of the significantly challenging, yet impactful usages of UAVs in precision agriculture under the following heads:

- *Task synchronization*: Autonomous UAVs can be used to accomplish tasks in a spatiotemporally synchronized manner Skobelev et al. (2018), Carbone et al. (2018). As the energy budget of the present day UAVs is severely restricted, this approach can significantly reduce the task completion time if multiple UAVs divide the task amongst themselves and cover the smaller tasks within their energy budget. Alternatively, the UAVs can work one after the other as the energy of the previous UAV gets depleted.

- *Plot demarcation*: The demarcation of agricultural plots, especially small landholdings is not possible digitally using satellite-based imagery. The use of UAVs in such cases proves useful, which also enables the electronic autonomous demarcation of small landholdings and detection of cadastral boundaries Ramadhani et al. (2018).

- *Spraying*: The traditional tasks of fertilizer and pesticide spraying are experimentally tried using UAVs. Although successes have been reported DroneSeed (2018), Tang et al. (2018), the task is extremely challenging as the fluidic nature of the UAV payload tends to tamper with the stability of the UAV during its flight. Additional challenges of aerial spraying include the effects of winds on the area of coverage of the spray.

- *Seeding*: Seeding is one of the most simple yet innovative uses of UAVs in agriculture. The aerial deployment of seeds on prepared lands can be explored for some crop types DroneSeed (2018).

- *Damage assessment*: UAV-based crop damage assessment is being actively taken up by various government agencies as well as private players across the globe Gulati et al. (2018). The ability of the UAVs to visually monitor and access the damage to crops in the event of crop failures, human, as well as natural disasters is a quick, cost-effective, and promising approach.

8. Conclusion

In this manuscript, we have explored the utility and application of UAVs in various agricultural domains, but with a special emphasis on precision agriculture. Firstly, we have categorized the UAVs based on their structures and mechanisms, sensors used, in and with the UAVs, and the associated research areas in UAVs. Secondly, we have explored the utility of UAVs in agriculture, followed by the exploration of the works on plant stress detection. We have also listed the remote vegetation indices used in estimating plant health which is useful in developing a UAV-based system for agricultural use. Finally, a categorization of agricultural UAV deployment architectures, based on popular usage, has been provided. We found that there is a paradigm shift taking place concerning remote monitoring in precision agriculture. The UAVs are being opted-for as the more feasible and preferred mode for remote spatiotemporal imaging of crops at a local scale, as compared to satellites. However, some of the technological aspects of this approach need improvement, and newer approaches could also be integrated with the UAVs for gaining increased efficiency in precision agriculture.

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