6 Advances in Unmanned Aerial Systems and Payload Technologies for Precision Agriculture

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6.1 INTRODUCTION

Today's farmers have to deal with an increasingly complex industry and international competition to market their products. Issues such as water use, climate change, regulations, soil quality, commodity prices, and input prices are common concerns, to name a few. As a result, growers are turning to precision agriculture (PA) to address some of these challenges. PA can be defined as the use of spatial and temporal information of crops in order to perform site-specific management. Its main aim is to increase crop yield and farm profitability through a more efficient use of resources. It is highly beneficial for the economy to have a competitive agricultural industry with high quality standards. Nonetheless, the benefits of PA to society also include the creation of high-tech jobs, for instance, for remote sensing systems and machinery guidance, as well as the mitigation of negative environmental impacts arising from an excessive application of chemical inputs (Mulla, 2013).

Conventional farm management techniques are often based on applying uniform quantities of crop inputs, such as seeds, water, fertilizers, pesticides, and herbicides. On the contrary, PA consists of delivering customized inputs based on georeferenced crop information and the partition of fields into zones with particular treatment requirements. With the advent of miniaturized sensor technologies and the ever-increasing number of PA applications, a variety of agricultural equipment of increasing complexity is progressively being developed. Since the 1990s, variable-rate technology (VRT), which describes any technology that enables the variable application of inputs, is one of the most popular PA techniques (Zhang and Kovacs 2012). Some of the most common inputs are fertilizer, pesticides (herbicide, insecticide, and fungicides), manure, seeding, tillage, and irrigation. By optimizing their usage, farm managers can increase productivity while minimizing the environmental and health risks of chemical inputs.

6.1.1 Remote Sensing in Precision Agriculture

Precision agriculture relies on actionable information obtained from sensors and data analysis software in order to achieve efficiency in farm practices. Actionable information is the result of integrating different sources of approximate real-time sensor information into a decision support system. Some of the most common platforms from which the sensors acquire the data include satellites, manned aircraft, unmanned aircraft, tractors, and handheld devices. Remote sensing (RS) is the science of obtaining information and measuring properties of objects on the Earth's surface from a distance, typically from aircraft or satellites; as opposed to proximal sensing, which refers to sensor data acquisition from ground vehicles and handheld devices (Mulla, 2013).

Objects on the Earth's surface reflect, absorb, transmit, and emit electromagnetic energy from the sun. Digital sensors have been developed to measure all types of electromagnetic energy as they interact with objects. Figure 6.1 shows the visible and infrared portions of the electromagnetic spectrum, which are used predominantly for remote sensing in PA.

Traditional RS technologies based on satellite and aircraft platforms are continuously improving in terms of spatial and temporal resolution, thus enhancing their suitability for PA applications. As the distance between the sensor and the crop increases from an aircraft to a satellite, the surveyed area will increase from a farm scale to a regional scale. Each combination of sensor and platform has pros and cons for a given application, which involve technological, operational, and economic considerations. Satellite surveys typically survey larger areas and the user can access the imagery in the following days or weeks after, however, satellite data providers typically require a large minimum surface in square kilometers, which may not be cost-effective for the farmer to purchase on a regular basis for PA applications. Additionally, satellite imagery may suffer from cloud cover, atmospheric distortion, and lack of flexibility to capture imagery following the phenology phases. On the other hand, surveys carried out by general aviation aircraft can be scheduled more flexibly than satellite imagery, but they often require complex and costly campaign organization efforts (Berni et al. 2009).

The operational success of VRT relies heavily on timely sensor data collection and the accurate computation of prescription maps describing crop vigor, deficiencies, disease, weeds, and pests, as well as soil variables, such as moisture and nutrient content. The data can be obtained in a variety of ways, such as the traditional remote sensing platforms described previously; more recently other platforms, such as unmanned aerial vehicles (UAVs), or sensors are mounted on vehicles can provide higher sensor proximity to the crops as well as near real-time information. Only in the last 10 years have UAVs and miniaturized sensor technologies become widely available at cost-effective prices and are demonstrating a significant suitability for PA applications. In fact, UAVs are not only facilitating remote sensing data acquisition, but also present an interesting business case for deployment as VRT platforms, where only a small quantity of input is required.

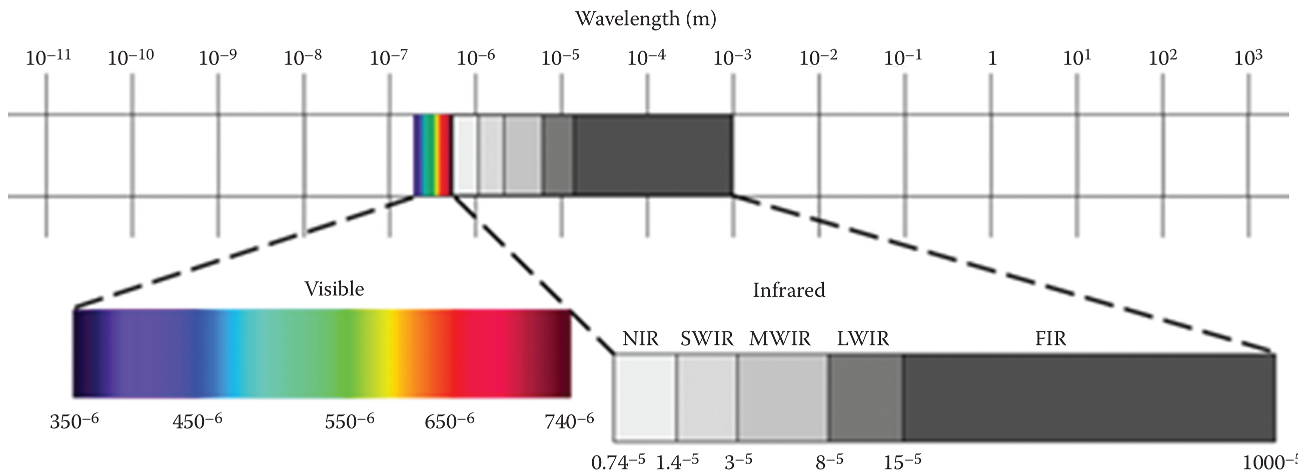

FIGURE 6.1 Visible and infrared portions of the electromagnetic spectrum. The infrared is populated by near-infrared (NIR), short-wave infrared (SWIR), mid-wave infrared (MWIR), long-wave infrared (LWIR), and far-infrared (FIR).

6.1.2 UAVs in Precision Agriculture

There are a variety of terms and acronyms used in the context of unmanned aircraft in addition to the UAV, which generally refers only to the vehicle as a platform including all systems necessary to fly. The term “unmanned aerial system” (UAS) is also very common in the aviation industry to refer not only to the UAV hardware but the sensor payload, data processing units, and ground station equipment. From a regulatory perspective, the International Civil Aviation Organization (ICAO) uses the terms “remotely piloted aircraft” (RPA) and “remotely piloted aircraft systems” (RPAS) roughly with the same meanings as UAV and UAS, respectively. National aviation regulators are expected to converge and adopt the terms established by ICAO in official documents. Nonetheless, the most widely-used term for unmanned aircraft by the general public is “drone,” particularly for consumer-level UAVs.

UASs often contain a more cost-effective and flexible sensor platform than satellite or general aviation aircraft, particularly for farm-scale areas up to hundreds of hectares. A relevant factor on the use of UASs by farm managers, agricultural consultants, and researchers is their relatively lower cost, either when purchased directly from the market or alternatively as an on-demand service provided by a specialized company. For that reason, UASs can be deployed as frequently as required based on the phenology phase and weather conditions, often in a more cost-effective way than manned aircraft or satellites. The use of UASs allows the end-user to plan in advance the type of sensor that will be used to survey the farm, as well as the spatial and temporal resolutions requirements for a given application. In fact, commercial UASs involved in agricultural operations are typically required to fly below the ceiling of 400 ft above ground level. For any given imaging sensor, the closer the UAV flies from the crop, the higher the spatial resolution is. Similarly, the more surveys conducted along the crop season, the more temporal resolution the dataset will contain. Multi-temporal studies require datasets along one or multiple seasons of a crop field. In order to obtain comparable data from multiple dates, it is helpful to carry out the survey in similar light conditions. For that purpose, the optimal time is usually around peak sunlight and clear skies to avoid cloud shades. In terms of the type of sensor, each PA application may benefit the most from one or a combination of sensor technologies, such as such as high-resolution RGB (visible spectrum), thermal, multispectral, or hyperspectral cameras. In general, UAVs and most of the sensor technologies require a modest capital investment when compared to most farm equipment. However, cost-recovery relies not only on the data capture, but also on the ease of use and the data processing costs to generate accurate actionable information. Operating UASs is relatively simple and becoming easier with the increased autonomy in every new generation of unmanned aircraft.

One of the main advantages of deploying UASs in farm environments is their capability to perform autonomous flights without being actively controlled by a ground-based operator. As a result, UASs can be deployed to survey an area of interest by accurately following predefined flight parameters. Some of the most critical flight parameters are the flight altitude, which determines the spatial resolution of an imaging sensor; the forward velocity; and frontal and lateral overlaps between images, which may be required to facilitate data processing. For a farm containing a few hundred hectares of land, UAV operations can be performed within visual line-of-sight (VLOS). In optimal light conditions with clear skies and maximum visibility, VLOS may be up to 1 km from the human operator.

The lifecycle representation of a PA application that relies on UAS for data acquisition to generate prescription maps is presented in Figure 6.2. Initially, a UAS service starts with the definition of the area of interest, the sensor technology required for that particular application, as well as relevant data acquisition parameters such as the spatial and spectral resolutions. If the application requires monitoring the crop along a period of time, the frequency in which the surveys are carried out is described as temporal resolution. Once the flight parameters are inserted into the ground station software, the flight can be performed autonomously, following a set of predefined waypoints to maximize the accuracy of the data collection campaign. An increasing number of countries have

FIGURE 6.2 Life cycle of a sample PA application with UAS as a support tool.

developed or are in the process of developing regulations to operate UAV platforms for commercial operations. Therefore, all flights performed on the farm will be subject to the applicable rules, and often will require a preflight safety assessment. Once the data acquisition is completed, the post-processing and analysis can be performed with specialized software onboard the UAV's computer or by using a separate ground-based computer or cloud service. The resulting actionable information will feed into the VRT system as a prescription map that delivers customized inputs to the crop. The VRT system is typically a ground vehicle that can carry significant volumes of input. However, in certain applications, such as pest hotspots or weeds, only modest quantities of pesticide may be required. In those cases, UAS may be more cost-effective and accurate in delivering custom amounts of inputs.

In regards to the data post-processing and analysis, some UAV and sensor manufacturers include a fully or partially automated data processing service as part of their product package. In the instances which the farm manager lacks the expertise to collect and manage the data, it is likely that the same UAV company that performs the aerial data collection also has the capability to deliver the actionable information in a short timeframe.

6.1.3 Adoption and Economic Impact of UAV Technology

The first UAV designs can be traced back decades ago with applications mostly in the defense domain. However, only in the last 10 years did UAVs take off as a widely available technology and with an ever-expanding international market. The rapid growth can be attributed primarily to the miniaturization and progressive cost reductions of electronic devices, such as GPS receivers and inertial sensors, which lower the market's entry barriers for companies with new ideas. Moreover, open source communities, such as ardupilot.org or diydrones.com, are also having a major impact in facilitating the understanding and manageability of complex flight systems to the general public.

The UAV industry encompasses not only the hardware that allows the platform to perform flight operations and the sensor technologies that collect aerial data, but also the software, data

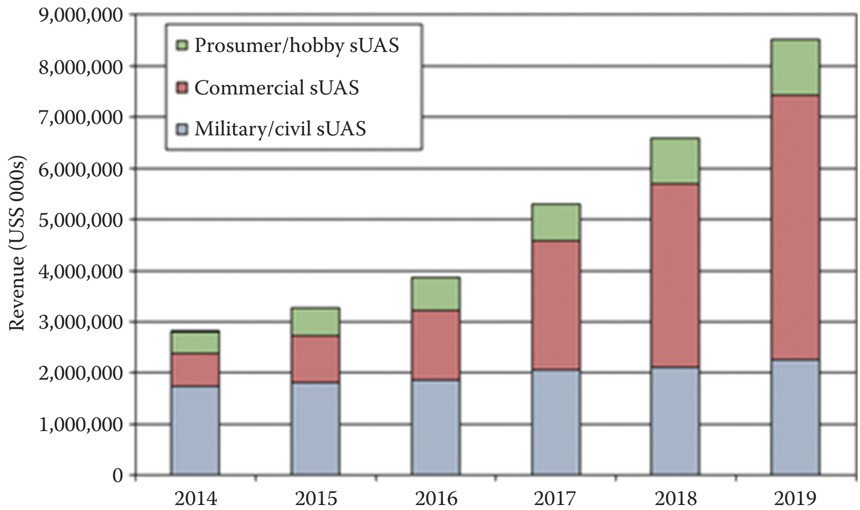

FIGURE 6.3 World sUAS revenue by segment between 2014 and 2019.

processing services, licensing, and legal services that comprise the commercial use of UAVs. Figure 6.3 presents a forecast released in 2015 of the UAV industry, with revenue in the global market for small platforms that weigh less than 25 kg, also known as small UASs (sUASs). The forecast reflects an exponential increase of revenue from less than 1$US billion in 2014 to 5$US billion in 2019.

Unlike other UAV applications (such as real estate photography or mail delivery) that can take place in urban areas, agricultural applications mostly take place in low population density areas, with few structural obstacles and few privacy concerns. Consequently, the use of UASs in agriculture is a primary candidate for minimal regulation and easier adoption by industry end-users. As a result, UASs operated in crop fields and livestock rangelands represent a minimal safety threat to people on the ground or other aircraft, provided that the UASs are operated following the applicable aviation rules and guidelines.

Considering the technical, economic, and safety aspects discusses in previous sections, it is reasonable to argue that the use of UASs in agricultural environments will keep increasing in the upcoming years. A recent research report published by the Association for Unmanned Vehicle Systems International (AUVSI), concluded that by 2025 agriculture will make up about 80% of the commercial UAS industry (AUVSI, 2015). In more specific terms, the American Farm Bureau has forecast that farmers using drone services to monitor their crops could see a return on investment of $12 per acre for corn, $2.60 per acre for soybeans, and $2.30 per acre for wheat. Also in the near future, farmer managers and companies will start adopting UASs for targeted application of herbicides and pesticides (AFBF, 2015).

6.2 UAV PLATFORMS AND REGULATIONS

6.2.1 Overview

UASs represent a technological opportunity for PA applications by improving safety, reducing liability, increasing accuracy, and saving time and money when used in a systematic and effective way. An important aspect when compared to manned aircraft is that the risk to an aircraft pilot and crew during an incident or accident is eliminated. Many types of UAVs are available today for precision agriculture and related fields, such as environmental monitoring. Types of UAVs can be classified into three categories: fixed-wing, multi-rotors, and helicopters. Similarly, UAVs are often classified in terms of weight for regulation reasons. Some countries, like Australia and Canada, have been international pioneers in defining a specific regulation for the use of UASs in their airspace. Both countries have followed a similar approach in dividing weight types into: very small (<2 kg), small (2.1 kg to 25 kg) as well as medium and large with different weight limits. In both cases an exemption is available for commercial operators to not apply for special flight operation certificates. Considering the work, investment, and training required to obtain certification, the sub–two kilograms exemption is likely to increase the adoption of UAS technology by farm managers and contractors, but also for agricultural and environmental research in universities.

6.2.2 UAV Platforms

The UAV designs mostly used for commercial applications are fixed-wing and rotary-wing aircraft. Among rotary-wing designs, helicopter and multirotor configurations are the most common. Multirotors are the most popular and easiest UAV type to manually control using radio transmitters. There are a number of multirotor configurations generally named after the quantity of rotors that form the propulsion system, such as quadcopters (four-rotor), hexacopters (six-rotor), and octacopters (eight-rotor). Taking into consideration recent statistics on the UAV platforms used in the United States for commercial operations (AUVSI, 2016), Table 6.1 shows the approximate percentage of each type of platform. Across all applications, multirotors represent nearly 90% of the entire market, demonstrating UAV operators have a clear preference for multirotor over fixed-wing. For agriculture in particular, nearly one-third of UAV platforms are fixed and two-thirds are multirotor.

Among the UASs typically used in agriculture, helicopters and multirotors tend to have less payload bay limitations, allowing for an increased variety of on-board sensors to be integrated. While fixed-wing aircraft can also be large enough to accommodate heavy payloads, large fixed-wing aircraft also present the need for a relatively flat runway to land and take off. Therefore, lightweight (less than 15 kg) fixed-wing UASs that can be hand launched are the most common type of fixed-wing aircraft used in agricultural applications.

In terms of power requirements, multirotors rely mostly on LiPo batteries, which allow for a typical flight endurance of 10 to 25 minutes. Hand launched fixed-wing aircraft are usually made of foam

TABLE 6.1
Percentage of Each Type of UAV Platform in the US Commercial Industry

Design Type	% of Platforms
Across commercial applications	
Rotary-wing	90%
4-Rotor (Quadcopter)	67.23%
8-Rotor (Octocopter)	17.01%
6-Rotor (Hexacopter)	4.96%
Helicopter	0.54%
12-Rotor and other	0.27%
Fixed-wing	10%
Hand launch	8.30%
Launcher	1.70%
Agricultural applications	
Rotary-wing	72.70%
Fixed-wing	28.30%

or other light materials and are also powered by LiPo batteries, usually enduring for 30 to 60 minutes. On the other hand, larger fixed-wing aircraft that require runways for takeoff and landing, usually require more robust airframes and fuel engines. The endurance in the latter case is typically above one hour and up to several days if the aircraft is designed for military applications. However, these UAVs are rarely used for agriculture due to high costs and operational complexities. Depending on the sensors used, multiple data sets may be collected with a high spatial and temporal resolution. However, with more complexity and capability comes higher operational requirements, and additional specialist skills may be required. Usually larger platforms are costly and a significant financial investment is required. Additionally, and perhaps more importantly, are the safety implications of using such platforms in commercial applications. They have the potential to cause considerable damage (to humans and property) and, as such, fall under stricter operating guidelines than smaller UAVs (see Section 6.2.3).

In the latter discussion, no discrimination between aircraft type was made. It is important to recognize the differences in capability between aircraft type in the context of plant biosecurity. Fixed-wing aircraft typically can cover more areas over a given time interval and provide flexibility in sensor mounting points. As they are unable to hover and have minimum operating height requirements, high spatial diversity can be achieved at the cost of decreased spatial resolution.

Unmanned aircraft systems can be used in standalone operations involving a single platform or more advanced systems utilizing multiple aircraft. In each case a ground station is usually required for remote piloting and mission command. Multiple UAVs can be flown in a swarm or coordinated to fly separate with complementary trajectories for a given application. This requires advanced centralized or decentralized control and guidance algorithms, but has the potential to increase quality and quantity of data collected at reduced operator workload. Currently, the use of multiple UAVs has been demonstrated for a range of related applications, but also in agriculture (Techy, Schmale III, and Woolsey 2010).

The market is rapidly evolving and new innovations are presented every year. According to AUVSI (AUVSI, 2016), more than two-thirds of all UAV platforms used by companies operating in the USA are manufactured by DJI Innovations (Shenzhen, China). The DJI Phantom, the most common UAV, is followed only by other models of the same company. In the agricultural domain, 76 operated fixed-wing platforms while 192 operated rotary-wing platforms (AUVSI, 2016). The USA market is a good representative of world trends, a prudent interpretation of the study is that is that UAS users tend to favor low-cost (smaller platforms) and multirotor aircraft (easier use). However, when endurance is a limitation, fixed-wing platforms such as the popular Sensefly eBee series (Cheseaux-sur-Lausanne, Switzerland) or the PrecisionHawk models (Raleigh, North Carolina) are also regularly being used.

6.2.3 Regulation

In many countries, the operation of UAVs for both commercial and research requires certification and needs to be carried out under regulated conditions. That is a consequence of UAVs operating in the same airspace as manned aircraft. Aviation regulatory bodies define the rules and restrictions that govern who can access the national airspace and under what conditions. They can be thought of as road rules for aircraft aimed at protecting the general public and other airspace users by ensuring that safety standards are met. Some rules may only apply to a particular type of aircraft, while some may apply to all aircraft operating under certain weather conditions or flight types. For example, consider commercial road vehicles. They may have relaxed parking restrictions, but, depending on their size, they may be restricted from operating in particular areas at certain times of the day. On the contrary, small personal vehicles are relatively free to access public road networks, regardless of the time of operation, and require a different driver's license class.

From an international perspective, ICAO published the first edition of the remotely piloted aircraft systems manual (2015). The manual shows how the existing regulatory framework that was developed for manned aviation applies to unmanned aircraft. Moreover, it serves as an educational tool for states, industries, service providers, and other stakeholders on most of the topics that comprise the regulatory framework. Rulemaking on a new technology is a difficult task, especially when the implications of UAS rules impact critical aspects of a country such as national airspace, public safety, and privacy. In Sections 6.2.3.1 and 6.2.3.2, we'll be presenting an outline of the current regulation in the United States and Australia. The United States is a good representative of the countries that are developing the regulations at a slow pace, while Australia has been one of the most proactive countries since the early 2000s.

6.2.3.1 United States

In February 2012, President Obama signed the FAA Modernization and Reform Act of 2012 (FMRA; P.L.112-95). The legislation mandated that the Federal Aviation Administration (FAA) develop a comprehensive plan to integrate unmanned aircraft systems (UASs) into the national airspace and begin implementing the plan starting in October 2015.

Under a special rule established by the FMRA, model aircraft and hobby UAVs operated strictly for noncommercial, recreational purposes are permitted to fly below 400 feet, so long as they remain within sight of the operator, outside of restricted airspace, and away from airports, unless appropriate prior notification has been given to airport operators and air traffic control towers. Under this rule, operations of hobby UAVs have proliferated, creating significant enforcement challenges for the FAA (Elias, 2016).

Meanwhile, the FAA has proceeded slowly and cautiously in complying with the FMRA mandate related to government and commercial operations. It has allowed government agencies and operators of small commercial drones to obtain permits on a case-by-case basis under section 333 of the FMRA. As of September 2015, the FAA approved 1407 applications out of 2650 petitions, and the agency approves about 50 new operations a week, a process expedited by the FAA rolling out a summary grant process, whereby similar petitions are batched and analyzed together, rather than individually (AUVSI, 2016). In February 2015, the FAA released its "Notice of Proposed Rulemaking for Small UAS[s]," a set of rules that, once finalized, are expected to govern the commercial drone industry for platforms up to 55 pounds. Until this set of rules is reviewed and completed, the Section 333 exemption process remains the most effective way for commercial entities to gain access to the airspace for UAS operations (AUVSI, 2016).

Civil operators are authorized via Section 333 that grants of exemption are automatically issued a "blanket COA" to conduct civil UAS operations nationwide. The blanket COA authorizes flights at or below 400 feet to any UAS operator with a Section 333 exemption for aircraft that weigh less than 55 pounds, operate during daytime Visual Flight Rules (VFR), operate within visual line of sight (VLOS) of the pilots, and stay away from airports or heliports at the following distances:

- 5 nautical miles (NM) from an airport having an operational control tower
- 3 NM from an airport with a published instrument flight procedure, but not an operational tower
- 2 NM from an airport without a published instrument flight procedure or an operational tower
- 2 NM from a heliport with a published instrument flight procedure

6.2.3.2 Australia

In 2002, Australia was the first country in the world to regulate UAS with Civil Aviation Safety Regulation (CASR) Part 101. In April 2016, CASA is reviewing CASR Part 101 in two phases, and will eventually modernize it into CASR Part 102. Up until 2016, with CASR Part 101, commercial and research operations with UAVs required the companies to have an operator certificate and their pilots a remote pilot license. Despite these requirements, there are 550 companies currently registered in Australia as of May 2016. Taking effect on September 2016, the amendment to CASR Part 101

TABLE 6.2
Classes of RPA as Defined by CASA to Take Effect in Late 2016

Subclass	Very Small	Small	Medium	Large
Max Weight (kg)	<2 kg	2–25 kg	25–150 kg	>150 kg

will open new opportunities for farmers and companies to use UAS without the need of certification. Firstly, five new weight classes of remotely piloted aircraft (RPA) have been created (Table 6.2).

Secondly, commercial operators flying very small RPAs, i.e., weighing less than two kilograms, will not require an operator certificate or a remote pilot license. Operators will only have to provide one notification to CASA at least five days before their first commercial flight and operate by the standard operating conditions. Moreover, private land owners will be allowed to carry commercial-like operations on their own land with a small RPA without needing an operator certificate or a remote pilot license, provided that they follow the standard operating conditions and none of the parties involved receive remuneration:

- You must only fly during the day and keep your RPA within visual line-of sight.
- You must not fly your RPA higher than 120 meters (400 ft) AGL.
- You must keep your RPA at least 30 meters away from other people.
- You must keep your RPA at least 5.5 km away from controlled aerodromes.
- You must not fly your RPA over any populous areas. These include beaches, parks, and sporting ovals.
- You must not fly your RPA over or near an area affecting public safety or where emergency operations are underway (without prior approval).
- This could include situations such as a car crash, police operations, fire and associated firefighting efforts, and search and rescue.
- You can only fly one RPA at a time.

Autonomous flight is prohibited under the current amendments. CASA is still developing suitable regulations for autonomous flight. However, there is scope for CASA to approve autonomous flight on a case-by-case basis.

6.3 PAYLOAD TECHNOLOGIES

6.3.1 Overview

Some inexpensive consumer UASs can be used out of the box to take a video or still photo from above a field, which may be useful to some extent for those applications that only require high-resolution RGB imagery. However, to obtain valuable data for PA applications it is often necessary to use specialized payloads, as well as an autopilot system to survey a field following a predefined flight path. There are a wide variety of payload technologies currently used for PA applications with different levels of consolidation and adoption in commercial environments. In this chapter, we briefly describe the essentials of both imaging and non-imaging payload technologies.

6.3.2 Imaging Sensors

The ability of sensors to measure the reflected energy coming from land and water allows us to use remote sensing to quantify features and changes on the Earth’s surface. The amount of energy reflected from these surfaces is usually expressed as a percentage of the amount of energy striking the objects. Reflectance is 100% if all of the light striking an object bounces off and is detected by the sensor. If none of the light returns from the surface, reflectance is said to be 0%. In most cases, the reflectance value of each object for each area of the electromagnetic spectrum is somewhere between these two extremes. Across any range of wavelengths, the percent of reflectance values for landscape features such as water, sand, roads, forests, etc. can be plotted and compared. Such plots are called "spectral response curves" or "spectral signatures." Differences among spectral signatures are used to help classify remotely sensed data into different classes. Figure 6.4 shows a typical spectral signature for healthy vegetation across visible and infrared bands. The photosynthetically active region of the wavelength is between 400 nm and 700 nm, with the rest of the wavelengths being related to cell structure and water content. The valleys in the signature are the primary absorption areas which are related to the chlorophyll and water content in plants. For each plant species, significant reflectance variations from the healthy signature will reflect the presence of a deficiency. The type of deficiency can be inferred from the individual wavelengths where the difference is most significant. The rapid change region between the wavelengths at 680 nm and 730 nm is known as "red edge" and represents a critical portion of the spectrum to measure plant qualities such as chlorophyll and nitrogen content.

Imaging sensors measure the radiation emitted or reflected from the object of interest, which in PA are mostly crops, weeds, and soil. The objective of imaging surveys is to estimate crop attributes at the leaf or canopy level with the reflectance values at various wavelengths. A spectral variation index (VI) is typically defined as an arithmetic operation of various reflectance values applied to each pixel of an area of interest. From a biological perspective, VIs are used to explain the biological phenomena that the crop is experimenting. From a PA perspective, VIs are also used to segment and classify the surveyed area into various partitions that share similar characteristics. The spatial information generated can be used by the farmer to assess the crop status or the progress of a crop treatment. When maps are converted to a suitable format for the VR equipment, the farmer can deliver site-specific treatments to the crop with GPS assistance.

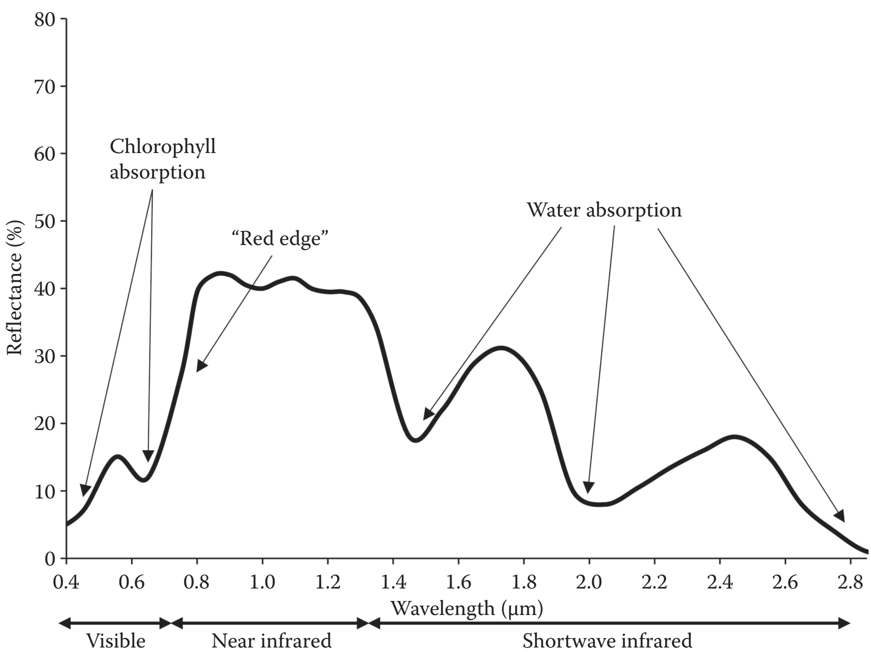

FIGURE 6.4 Typical spectral signature of healthy vegetation across the visible, near-infrared, and short-wave infrared portions of the spectrum. Highlighted are the areas of the signature affected by chlorophyll and water absorption, as well as the steep climb known as "red edge."

VIs are often classified as broadband indices when the bands used have a bandwidth higher than 10 nm, while narrowband VIs are often defined as requiring bands of bandwidths below 10 nm. Some of the most widely used broadband VIs in aerial and satellite remote sensing are presented in Table 6.3.

Relatively small RGB (visible spectrum), multispectral and hyperspectral cameras are currently available for UAVs. Depending on the type of camera, multiple wavelengths may be measured simultaneously to varying degrees of spectral resolution. A lower ground resolution, also known as ground sampling distance (GSD), in centimeters per pixel will deliver more detail of the target crop that is being surveyed. However, achieving higher ground detail (lower GSDs) implies flying lower, which, in turn, leads to surveying less area for a given forward overlap between consecutive images. Therefore, the flight planning for optimal data collection will require a balance between the area to cover and the GSD obtained. Figure 6.5 shows an instance of a graph relating the flight height (in meters) and ground resolution (in centimeters per pixel) as well as the ground speed (in meters per second) necessary to achieve an 80% overlap between forward images.

An important part of the data analysis is producing an orthoimage (also known as an orthophoto) in order to visualize the entire crop field in a single image. The orthoimage can be described as the result of geometrically correcting each individual image and then stitching them together into a larger mosaic. This is a fairly complex algorithm that requires significant computational resources and specialized software. In the context of drone surveys, orthoimages are often created by using specialized, structure-from-motion (SfM) software, such as Pix4D or Agisoft Photoscan. To effectively create the orthoimage, it is recommendable to plan for a flight path that maintains around 80% forward and a 60% lateral overlap between images. Thus, it is generally imperative to fly the UAV in autonomous mode using the autopilot ground station software, rather than flying manually with a radio transmitter, which wouldn't be as accurate.

It is generally accepted that a finer spectral resolution can provide more information. By quantifying light reflectance in narrower bands of the spectrum, it is possible to measure subtler changes and confirm the presence, absence, or severity of a particular deficiency, pest, or disease. Often the most relevant bands to evaluate crop health are the NIR and red edge, which are not perceived by the human eye. Sections 6.3.2.1 through 6.3.2.3 describe RGB (visible spectrum), multispectral, and hyperspectral cameras in further details.

TABLE 6.3
List of VIs, Their Formula, and Reference

Index	Formula	Reference
NDVI	(NIR − Red)/(NIR + RED)	Rouse *et al.* (1973)
NDRE	(REDedge – RED)/(REDedge + RED)	Barnes *et al.* (2000)
GNDVI	(NIR − GREEN)/(NIR + GREEN)	Gitelson *et al.* (1998)
DVI	NIR − RED	Tucker *et al.* (1979)
EVI2	2.5*(NIR-RED)/(NIR + 2.5*RED + 1)	Jiang *et al.* (2008)
GRVI	NIR/GREEN	Sripada *et al.* (2006)
IPVI	NIR(NIR + RED)	Crippen *et al.* (1990)
MSR	[(NIR/RED) − 1]/[(NIR/RED)^(1/2) + 1]	Chen *et al.* (1994)
SAVI	1.5*(NIR − RED)/(NIR + RED + 0.5)	Huete *et al.* (1988)
ExR	1.4*REDedge − GREEN	Meyer *et al.* (1998)
GVI	(GREEN – REDedge)/(GREEN + REDedge)	Gitelson *et al.* (2002)

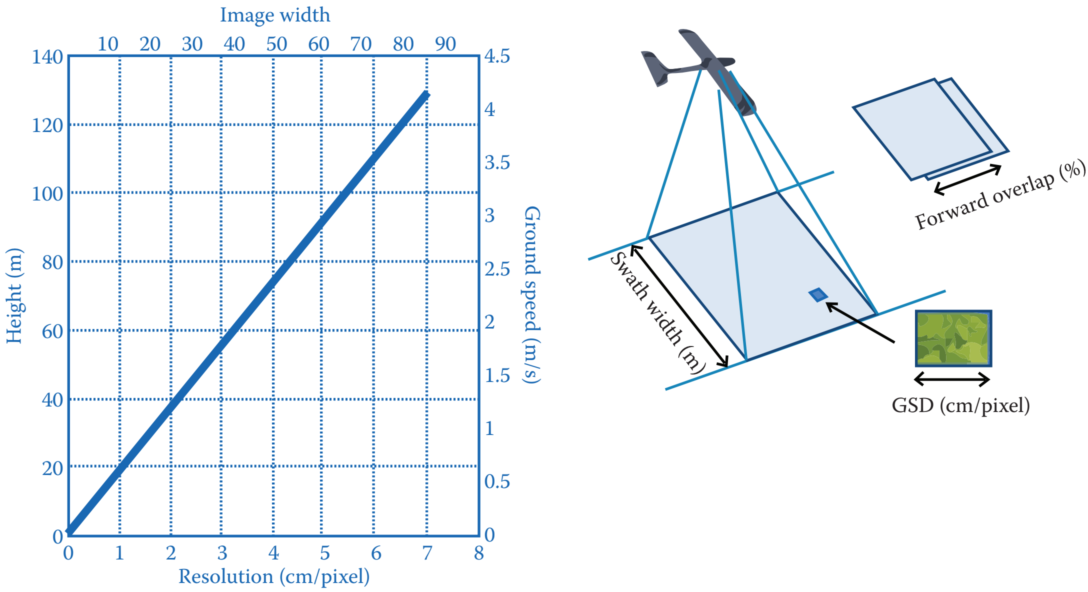

FIGURE 6.5 Sensor performance for the Micasense MCA multispectral camera with Ground sampling distance, ground speed and ground swath in relation to flight height.

6.3.2.1 Visible Spectrum Cameras

Visual imaging devices, such as consumer-level digital cameras, can be a much cheaper alternative to multispectral and hyperspectral sensors. Although they offer high resolutions between 10 and 50 megapixels, the spectral resolution is limited to three bands of the visible spectrum, namely red, green, and blue (RGB). In order to assess crop health, the most relevant bands are NIR and red edge, which are outside the visible spectrum. However, consumer-level digital cameras may be suitable to detect crop diseases that appear in green or yellowish tones. Thanks to the high spatial resolution, the imagery provided by these cameras may also be useful to visually identify weeds or other unwanted elements in the field, or to assess crop damage.

In Laliberte *et al.* (2010) two visual imaging (RGB) cameras were used on-board UAVs to monitor and classify the vegetative composition of rangelands and arid landscapes. Spatial resolutions less than 2 m/pixel were observed, highlighting the potential for crop or district level monitoring depending on available flight time and supported data storage and transmission capability. A further increase in spatial resolution was reported in a recent publication on pest damage assessment (Puig, 2015). The spatial resolution achieved in this study was below 2 cm/pixel with a Sony NEX-5. The results presented demonstrate how various levels of crop damage and the areas they occupy can be automatically mapped from RGB imagery.

6.3.2.2 Multispectral Imaging

Typically, multispectral images provide intensity information from up to 10 wavelengths of approximately 10 nm bandwidths, usually discontinuous and not overlapping. This is achieved by a set of board level cameras each with a particular band filter or a modified RGB camera that presents sufficient sensitivity on the NIR bands by changing the manufacturer's original filter. In the latter approach, various filters are used to isolate spectral regions of interest (such as NIR reflectance for vegetation monitoring) (MaxMax). This provides a lower cost solution for obtaining specific spectral data without using a specialized multispectral camera (Micasense or Tetracam). Such camera arrangements may also have faster shutter times, simplifying image rectification. These cameras are often called modified NIR cameras and have become quite common due to lower costs. However, depending on the specific setup, novel image correction methods (due to ambient conditions) may be required to utilize various vegetation indices. In terms of actual multispectral cameras, in some cases, it is possible to replace filters in the field or in the lab, allowing these systems to be repurposed to detect different wavelengths at different times for different applications. Also, some cameras can be used off the shelf and others have been designed explicitly for a particular application (Yang, 2012).

Airborne, satellite, or ground-based imagery has been used for disease detection in cereal crops (Franke and Menz, 2007). A project in Colorado, for example, conducted field experiments to measure the effects of aphid infestations on cereal crops using an airborne multispectral camera (Pearson, Golus, and Hammon, 2012). In Oklahoma, multispectral imaging was able to accurately discriminate between plant stress caused by Russian aphids and other factors using airborne imagery (from manned aircraft) (Backoulou *et al.*, 2013). This is an important result, highlighting the benefit of aerial imagery for disease discrimination. Using a UAV at lower altitude is expected to increase the spatial resolution, and therefore improve detail and thus accuracy of such results.

Using fixed-wing UAVs, fruit crop health was monitored in Suarez *et al.* (2010) whilst various vegetation monitoring tasks were studied in Berni *et al.* (2009). Similarly, water stress detection in cereal crops has also been detected from UAVs using the thermal band. Leaf area index (LAI) was measured for winter wheat under varied fertilization schemes using a single, modified EO camera onboard a small UAV (Hunt *et al.*, 2012). NIR-green-blue imagery was obtained and was able to provide comparable results to NIR-red-green color infra-red cameras with considerably less post processing required. Flights above and below 400 ft were conducted demonstrating that this type of system would be useful for plant and crop level monitoring onboard small UAVs.

In Lucieer *et al.* (2012); Turner, Lucieer, and Watson; and Nebiker, Annen, and Scherrer (2008) multispectral imaging was used onboard rotary wing UAVs to detect moss and grape vine health with relatively high spatial resolution. In Merz and Chapman (2011), only the near infrared band was used onboard an autonomous, custom-built helicopter to measure LAI on wheat plots for phonemics and plant level monitoring, with a resolution of 1–2 cm that was recorded over multiple flights covering up to 1 ha. In Inoue, Morinaga, and Tomita (2000) four CCD cameras and associated filters were used on a blimp to monitor rice and soy leaf area index from low altitude between 30 and 400 m. Later, a blimp was used for wheat field monitoring with respect to nutrient levels using two CCD cameras for visual and NIR imagery of a 2 ha plot (Jensen *et al.*, 2007). Parasails and multispectral cameras have also been used for ecological monitoring (Clark, Woods, and Oechsle, 2010) and agriculture (Antic, Culibrk, Crnojevic, and Minic, 2010).

6.3.2.3 Hyperspectral Imaging

Hyperspectral images typically provide low spatial resolution compared to consumer level cameras, but very high spectral resolution is typically more than 100 bands. For instance, the Nano-Hyperspec (Headwall) delivers 272 spectral bands in the visible and NIR spectrum from 400 nm to 100 nm, while the spatial resolution is limited to 640 spatial bands. They are often continuous, overlapping bands or spread over a wide bandwidth spanning the visible to near-infrared (NIR) and long-wavelength infra-red (LWIR) regions. This means subtler changes may be detected in the context of plant stress and disease lifecycles. A single camera is required but can be prohibitively large. Recently, smaller hyperspectral cameras amendable to UAV implementation have become available at a relatively low cost. Many such hyper-spectral cameras have GPS/IMU included (Eaglet, Headwall) providing synchronized data for effective image rectification and improving data post-processing.

As with other imaging, hyperspectral imaging (Figure 6.6) can be used in a passive or active manner. In the former, the plant reflectance due to sunlight is measured. In the latter, a light source temporarily illuminates the observed structure and the reflectance is measured. This is also referred to as fluorescence. Additionally, it may be difficult to adapt fluorescence-based imaging approaches to

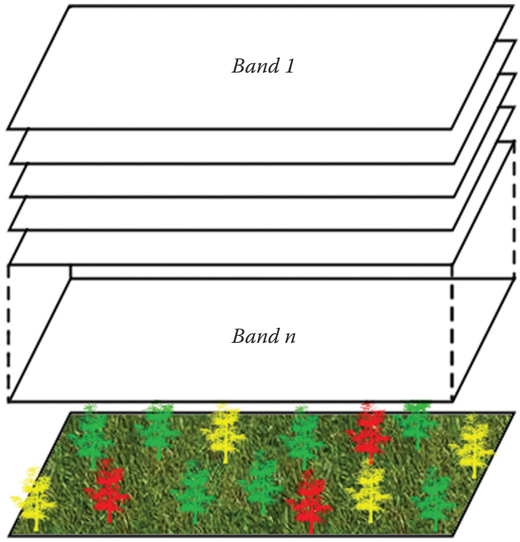

FIGURE 6.6 Basic principle for hyperspectral imaging, fine spectral partitions.

UAV. Payload restrictions may limit the activating sources that can be used and stability of the camera platform may be inadequate to achieve comparable results.

Although some recent results are based on ground or lab-based experiments, they suggest sampling in a subregion of the EM spectrum specific to the particular disease is only required, relaxing the need for a hyperspectral camera. This implies that cheaper multispectral imaging may suffice; pending reliable indices have been developed. The focus then is on collecting good quality images and ensuring the indices have been comprehensively tested against a range of in-field conditions. UAV can provide a means to gather large amounts of the required test data for such an analysis.

6.3.3 Non-Imaging Sensors

Volatile organic compounds (VOCs) are emitted throughout the lifecycle or plants. Different compounds are emitted from leaves and stems depending on plant species, growth stages, and relative health condition. By measuring VOCs emitted from healthy plants and those under stress, it may be possible to distinguish between various diseases and provide early stress detection. It can be considered a maturing technology that provides a relatively reliable and non-invasive approach to detection and monitoring. Although suggested as a research opportunity in recent literature reviews (Sankaran *et al.*, n.d.), it has not been applied to UAVs. The difficulty arises due to the way in which samples must be taken, and the weight of the compounds to be sampled. Close proximity to the plant or leaf is required and the volatile compounds are typically very light. This implies a rotorcraft type UAV would be required, however, the downwash from the rotors may disperse the compounds away from the sensor. As such, this type of sensor may be better suited to ground robots that could perhaps work in coordination with UAVs. A UAV could sample the broader area using optical sensors and relay information regarding site-specific points of interest. The data from both platforms can then be fused to provide greater depth of information. Alternatively, the sensor could be suspended and a slow, hover-like flight would be required to move through the field and obtain reliable measurements.

In physical sampling methods, a tissue or spore sample is collected, and by microscope observation and/or DNA identification, a pest may be detected. They are useful for detecting invertebrate pests such as fruit flies, or fruit and spores from disease-causing fungal pathogens such as *Fusarium*. More importantly, collecting a spore as opposed to infected tissue or an insect directly has the advantage of early detection and, as such, improves the chances of effective preventive measures.

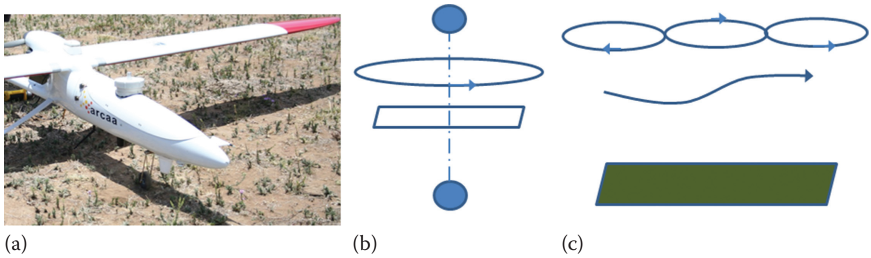

FIGURE 6.7 Example aerial spore trap and sampling trajectories (gray and red). In (a) an aerial spore trap is shown. In (b) example sampling trajectories about the focus of an infestation is shown. In (c) sampling along an arbitrary trajectory (red) and along a predicted plume line (gray) is shown.

Many physical sampling methods for invertebrates, such as vacuum aspirators, water sumps, nets, and small aperture funnels are not amendable to UAV implementation due to size, weight, and aerodynamic restrictions.

Smaller mobile spore traps using adhesive surfaces or substances (agar type jellies) can be used (Savage *et al.*, 2012). Originally used on remotely piloted vehicles (Gottwald and Tedders, 1985), they have since been demonstrated onboard UAVs in a number of applications locally (Gonzalez *et al.*, 2011) and overseas (Schmale III, Dingus, and Reinholtz, 2008; Aylor *et al.*, 2011; Schmale III *et al.*, 2012). Given the dispersal of the spores is relatively unknown and difficult to determine, it is unclear what flight path should be flown for data collection, so a number of solutions have been proposed (Schmale III, Dingus, and Reinholtz, 2008; Lin *et al.*, 2013; Techy, Woolsey, and Schmale III, 2008; Wang *et al.*, 2007). A zero sample is not enough to confirm the absence of a pathogen and large presence is not enough to assume broad scale exposure or infection. Recent simulation work provides insight as to more efficient flight path with respect to spore sampling (Savage *et al.*, 2012). Depending on the UAV type, specific flight paths may be favored, but will result in different data, and thus make comparative analysis difficult. Multiple UAVs may help to alleviate these problems. Two UAVs have been used simultaneously with advanced flight control to improve the sample size on a given sortie and, along with previous results, has allowed researchers to consider modeling dispersal and arrival paths of particular fungal pathogens (Figure 6.7) (Tallapragada, Ross, and Schmale III, 2011).

6.4 UAS APPLICATIONS IN PA

Most of the current agricultural applications of UAS involve either the acquisition of aerial data from a variety of sensors or the mechanical release of different inputs for site-specific crop treatment. In terms of the operation. Digital cameras are the most commonly used data collection sensors aboard UASs. Additionally, UASs may be equipped with infrared sensors that provide information on crop and soil temperature, more specialized imaging sensors such light detection and ranging (LIDAR) systems that use laser scans to capture high-resolution contour maps and images, or hyperspectral and multispectral imaging systems that capture a broad spectral range of light reflectance both within and beyond the limits of human vision. With the development of new sensor technologies, there is an ever-increasing number of UAS applications for PA. Some of the most common applications are:

- Crop health assessments, such as nitrogen content and plant vigor
- Crop disease detection and severity assessments
- Soil moisture content and irrigation efficiency assessments
- Field drainage assessments with digital elevation models

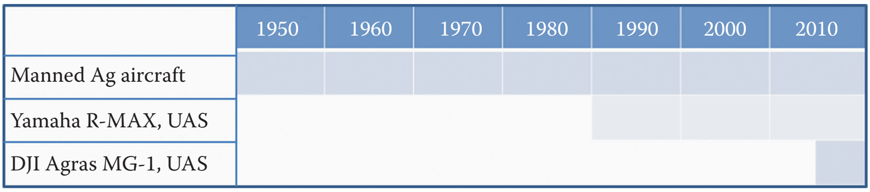

FIGURE 6.8 Timeline of crop spraying technologies from manned agricultural aircraft to remotely controlled aircraft by a pilot on the ground, such as the Yamaha R-MAX, and, more recently, waypoint flight capable UASs, such as the DJI Agras MG-1.

- Yield estimate assessments
- Aerial surveys for weed detection
- Aerial application of crop inputs such as fertilizers and pesticides
- Aerial surveys to detect the presence and damage from insect pests
- Direct release of benign insects for weed control or insect pest mitigation
- Collection of pathogen samples with spore traps
- Farm surveillance to monitor livestock

6.4.1 Case Study: UAS as a VR Tool

A successful transition from a manned aircraft agricultural practice to a modern unmanned approach is progressively taking place in the practice of crop dusting (Figure 6.8). The first manned aircraft designed specifically for aerial application were introduced in the early 1950s. Beginning in Japan and South Korea in the late 1990s, UAVs, such as the Yamaha R-MAX, became common in mountainous terrain and were used by relatively small, family-owned farms, where lower-cost and higher precision spraying was required. More recently the R-MAX has been used in other countries such as the United States and Australia as the regulation for UAS has been developed. Despite featuring more than 20 kg of payload capacity and an endurance of up to one hour, the R-MAX appears to be a good alternative to agricultural aircraft. However, there are some limitations such as the required pilot on the ground flying the aircraft with a radio transmitter as well as the limitation of 150 m distance between the pilot and the aircraft. The ability for low-cost UAS to fly autonomously has only become available in the last decade.

A good representative of the new generation of crop spraying UAS aimed at commercial use is the DJI Agras MG-1 (Figure 6.8). Although 10 kg payload capacity is nearly half the capacity of the R-MAX, the price of the R-MAX costs $100,000, while the price of the Agras MG-1 is $10,000. Most importantly, unlike the Yamaha R-MAX, the Agras MG-1 is capable to fly autonomously a waypoint flight and deliver custom volumes of liquid in predefined GPS locations. This technology is better aligned with the principles of PA, and it represents a further step towards facilitating the adoption of cost-effective UAS technologies to farm managers, agricultural consultants, and researchers.

6.5 DISCUSSION AND CONCLUSIONS

As PA practices are increasingly becoming a more cost-effective approach to grow crops, farm managers are called to adopt new technologies and become more competitive. PA practices involve using only the necessary volumes of inputs such as water, fertilizers, herbicides, and pesticides, which helps reduce costs but also minimizes the ecological impact of chemicals on the soil, aquifers, and rivers. The product cycle of a PA application generally consists of data collection, the development of prescription maps, and delivering custom input applications.

UAVs have become a widely accessible technology for the past 10 years, while aviation regulators are converging towards facilitating commercial operations. Farm managers and agricultural consultants are slowly adopting UAV technologies lead by a sharp increase in research publications by universities worldwide. UAVs provide an aerial platform for specialized sensors to collect aerial data, and often represent a cost-effective alternative to manned aircraft and satellite imagery. Additionally, UAVs have can also be deployed with spraying mechanisms to deliver custom volumes of input in predefined locations over the crop.

The use of UAVs for remote sensing, has reached a relatively high level of maturity. By acquiring aerial imagery with multispectral and hyperspectral sensors, the farmer can obtain quantitative information of the crop. As these sensors can collect spectral information in multiple bands, it is possible to generate maps of crop vigor, nitrogen content, chlorophyll content, and many other crop properties. Also, the use of thermal sensors provides valuable information on the moisture content in the crops and soil, which can be used to optimize the use of irrigation.

The UAS market is growing internationally and many companies are focusing on developing integrated UASs for agriculture. Currently, it is fairly common for UAV service providers and knowledgeable farm managers to acquire a low-cost UAV from a company, purchase a sensor from another company, and have the data processed yet by another company. This trend is likely to continue and remain a strong option for clients that require minimum investment. However, in the near future we can expect integrated products that will meet the need to simplify the adoption of this technology. Also, as single-board computers become small, lighter, and more powerful, it will become possible to process the data onboard the UAV, practically delivering real-time, actionable information for immediate farm management actions.

From a technological perspective, the introduction of PA represented an important step towards managing a farm, based not only on experience but also on actual quantitative information. Subsequently the introduction of GPS-guided VRT tractors and more recently the expansion on the use of UASs, reflect the fact that farming practices are gearing towards a fully-automated industry. The farm of the future is likely to present ground and air vehicles that will monitor the crop and communicate with each other to efficiently perform the necessary tasks. In order to remain competitive, humans may no longer be required to execute manual labor but progressively will become supervisors and controllers of technology systems.

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