CHAPTER ONE

Drones in agriculture

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Abstract

The use of drones has become widespread in agriculture, and it is associated with unique opportunities and challenges. The most common role of drones in agriculture is as a remote sensing platform to assess and monitor crops, but emerging agricultural applications include precision distribution of agricultural chemicals and biological

Advances in Agronomy, Volume 162
ISSN 0065-2113
https://doi.org/10.1016/bs.agron.2020.03.001

control agents, livestock health monitoring, and remote sampling. Several different drone designs and sensor types are used, each with its associated advantages and limitations. The use of sensors with wide angles of view at relatively low altitudes above ground level presents challenges that require unique data capture and data processing procedures to overcome. This chapter provides an overview of the development of agricultural drone use, approaches and methods used to ensure that data quality is adequate for agricultural applications, and a selection of traditional and emerging agricultural drone applications.

1. Introduction

1.1 Remote sensing in agriculture

Modern remote sensing began with the invention of the camera in the mid 1800s. Militaries of the world used the acquisition of photography early on from a hot air balloon and airplane as a method of reconnaissance. Much of the advancement of remote sensing acquisition and processing (photogrammetry) at these times were made because of military applications. Color infrared photography was used during World War II for detection of military equipment and facilities hidden behind camouflaging materials because vegetation produces a strong reflectance in near infrared light wavelengths compared to visible light wavelengths. This characteristic of vegetation is extensively used today in the assessment of agricultural crops because the degree of difference in reflectance between visible and near infrared light is related to vegetation health and growth potential (Slonecker et al., 2001).

The modern era of digital remote sensing began with the launch of the Landsat series of satellites in the early 1970s, and this mission continues at present. Earth observation satellite spatial resolutions used for earth surface studies are mostly in the 1.0–30 m (moderate resolution) range. The temporal or return frequencies of the moderate resolution sensors that are often used in agriculture varies from a few days to nearly monthly. One of the greatest challenges in using satellite imagery for agricultural applications is that in many regions of the world, especially the equatorial regions, cloud cover often obscures viewing of the earth from space. It is common to not acquire a cloud free image over an area of interest at a critical time in the production cycle of a crop (Tucker and Sellers, 1986). A second challenge is spatial resolutions that are too coarse to resolve important features of interest (Wulder et al., 2004). This is particularly important when the causes of variation in vegetation performance can only be identified using spatial patterns or textures that become visible at relatively fine spatial resolutions. Satellites, therefore, do not provide a complete remote sensing solution to agricultural needs. Other remote sensing platforms, including manned and unmanned aircraft systems, are needed to fill the gaps, and in recent years drones have become a practical and widely applied remote sensing tool in agriculture.

This chapter will provide an overview of the use of drones in agriculture, including discussions of some of the important advantages and disadvantages of drone use in this role, and brief discussions of specific agricultural drone applications.

1.2 Definition of a drone

The word "drone" first appeared in the early 16th century to indicate a male honeybee. The honeybee drone has a single purpose, to fertilize a queen bee during a mating flight, followed by the death of the drone. After World War Two this concept was applied to coin a word for pilotless aircraft used for target practice—a mission with a single purpose involving the destruction of the aircraft. By the 1990s military unmanned aircraft had morphed into weapons systems used to remotely deploy munitions in conflict zones around the world, but they were still referred to as drones. Within the last decade the word underwent yet another expansion in meaning, and is now used to describe both military and civilian unmanned aircraft, from toy remote-controlled quad-copters to sophisticated unmanned aircraft used in a wide range of commercial applications including aerial photography, surveying, infrastructure inspection, emergency response, package delivery, and agriculture. Prominent alternative terms commonly used in various parts of the world and different contexts include Remotely Piloted Aircraft (RPA) and Unmanned Aircraft Systems (UAS). Within the context of this chapter, a drone is defined as a remotely piloted aircraft controlled directly by a human operator via a radio link, or with various levels of autonomy achieved by using autopilot technology.

1.3 Drone types

Drone designs include many different forms, features, and functions (Vergouw et al., 2016). The four primary types of drones are fixed-wing, single-rotor, multi-rotor, and hybrid. Ducted fan drones are another type, but they are not covered in this chapter due to their limited use. Each drone type comes with unique advantages and disadvantages which are highlighted in Table 1.

Table 1 Typical characteristics of different drone types.

Type	VTOL	Flight time	Payload capacity
Fixed-wing	No	High	Medium-High
Single-rotor	Yes	Medium-High	Medium-High
Multi-rotor	Yes	Low	Low
Hybrid	Yes	Medium-High	Medium

The cost, power source, material composition, and complexity to operate each type varies greatly between makes and models. However, in the categories of vertical takeoff and landing (VTOL), endurance, and payload capacity, the above table applies generally.

The ability of a drone to take off and land vertically (VTOL) requires only a small operational footprint, whereas many fixed-wing drones need a long and flat landing space that is clear of obstructions in the landing area and in the approaches to landing and take-off. Depending on the location, these space requirements can be an important hindrance to fixed-wing drone operations. However, with the latest autopilot programming, some fixed-wing drones can take off and descend at steep angles to minimize the needed space for takeoff and landing.

Next, the drone type significantly impacts the flight time or endurance. Overall, fixed-wing drones are the most efficient, as the lift generated by the wings of the aircraft reduces the amount of energy needed to keep the drone airborne. The next most efficient drone types are hybrid systems, hybrid systems use either a single-rotor, multi-rotor, or ducted fan configuration to allow a VTOL capability and then transition to fixed-wing flight to enable greater endurance. Single-rotors and multi-rotors are the least efficient drone types because energy is continuously demanded to drive the motors and propellers keeping the drone airborne and controlled. Single-rotor systems are typically more efficient than multi-rotors because single rotors have less energy losses related to parasitic drag at rotor-tips.

2. Electromagnetic energy interaction with plants and soils

During daytime, exposed surfaces on earth are constantly awash with electromagnetic radiation originating from the sun and spanning a wide range of wavelengths. For most agricultural remote sensing applications from drones a relatively small spectrum of wavelengths in the visible to near infrared range are used. The relevant wavelengths are detectable by the silicon-based optical imaging sensors used in modern digital cameras, and although only part of this spectrum, from c. 400 to 700 nm, are visible to the human eye, in this chapter the spectrum detectable by silicon-based optical sensors (c. 380–1150 nm) will be referred to as "light."

Drone-mounted sensors for agricultural applications are typically pointed in a downward direction and detect light that is reflected from surfaces in the direction of the sensor. The intensity of the light reaching the sensor depends on the fraction of light from the sun that penetrates through the earth's atmosphere to ground level, and the efficiency of reflection of this light from surfaces in the direction of the sensor. The information that can be gleaned from images regarding surface characteristics are mostly due to alterations in the characteristics of light after it interacted with surfaces, together with the spatial patterns of reflections. Although most light reaching sensors are due to reflection, a portion can be derived from other processes, particularly fluorescence derived from ultraviolet light in the case of plants (Buschmann et al., 2000). The plant fluorescence-contribution to total light reaching airborne sensors is, however, relatively minor and negligible in most practical remote sensing scenarios.

2.1 Reflection, absorption and transmission

Light that interacts with soil or plant surfaces can be reflected, absorbed or transmitted. The absorption efficiencies of various wavelengths are determined by the quantum nature of light interactions with matter. Specific wavelengths cause specific energy-transitions in atoms and molecules that lead to conversion of light energy to other forms, such as heat. In the case of plants, the absorbed energy can also be utilized to drive photosynthesis (Kiang et al., 2007). If light does not encounter atomic or molecular structures that can absorb its energy, it will be reflected or transmitted.

A degree of light transmission is typical for most green vegetation, and transmitted light passing through the surface layer of plant tissue will interact with lower tissue layers. The secondary interactions include a degree of reflection back toward the surface layer, where it can interact with the surface layer again. This process results in a degree of added apparent reflectance from the surface layer, and therefore the total reflected light that reaches an airborne sensor (Yamada and Fujimura, 1991).

Primary reflection of light from surfaces is, however, the major source of information reaching airborne sensors in most practical scenarios. The information derived from analysis of relative reflection efficiency at various wavelengths therefore relates mostly to the material composition of the uppermost exposed surfaces of soil and plants.

2.2 Light scatter patterns

The amount of reflected light that is directed toward a sensor in the sky is influenced by the light scatter patterns from surfaces. The scatter pattern depends on the location, size, shape and texture of reflecting objects. Specular (mirror-like) reflection occurs to some extent from most natural surfaces, including plants, and the amount is related to plant structure and growth stage. The majority of reflected light from natural surfaces, however, scatter in a variably diffuse patterns depending on the specific surface characteristics (Vanderbilt and Grant, 1985). This leads to changes in reflected light intensity reaching a sensor depending on the changing location of the sensor (Nilson and Kuusk, 1989). Therefore, as a drone moves through the air, the reflectance value from an object will change as the view angle changes. The resulting data patterns are typically referred to as bidirectional reflectance, and it is a commonly encountered artifact of remotely sensed data that often requires correction (Roujean et al., 1992). Bidirectional reflectance artifacts are particularly significant in drone-derived data due to the relatively wide-angle lenses used on drone-mounted sensors and the low flight altitudes typical of agricultural drone applications. These artifacts (Fig. 1) must be considered in the processing and analysis of aerial images.

2.3 Practical considerations in agricultural applications

Sensors are most useful when they can differentiate between wavelengths that are differentially absorbed depending on management-relevant plant and soil characteristics. This must be achieved in a way that is sensitive enough for relevant changes in vegetation to be measurable. It must also avoid the masking of differences, or introduction of apparent vegetation differences that are not related to actual plant characteristics, by data artifacts. Data must be translated into useful information about reflecting surfaces. This may include a wide spectrum of analytical complexity and sophistication, from simple classification surfaces into soil or leaves, to advanced analysis related to the morphology and physiological status of plants.

Fig. 1 A color-infrared aerial image of a relatively homogeneous alfalfa field. Pixel values in different parts of the image vary depending on the view angle from the perspective of the sensor.

Comparison of light reflectance in near infrared and visible wavelengths is particularly important because it is related to vegetative biomass and/or growth vigor in crops (Hansen and Schjoerring, 2003). It therefore allows differences between vegetation at different locations in a field to be quantified—greatly enhancing the ability to use aerial imaging-based computational methods for vegetation analysis. Additional information can be derived by targeting the transition between visible to near infrared reflectance (the so-called "red edge") (Horler et al., 1983), or by using specific, relatively narrow wavelength ranges that respond uniquely to specific changes in vegetation (Hansen and Schjoerring, 2003).

The low altitudes typically used when deploying drone-based sensors translate into relatively fine spatial resolutions compared to other aerial sensor platforms. This allows information to be related to relatively small objects, in many cases to the level of individual plants or small sections of fields, and it reveals spatial patterns that are often useful in the identification of the causes of anomalies (Fig. 2). However, there is an increased risk of data quality degradation due to use of non-standardized sensors and wide-angle lenses at low altitudes (Rasmussen et al., 2016).

In summary, the intensity of reflected light reaching a sensor depends primarily on the absorption/reflectance characteristics of the surface, the light scatter characteristics of the surface, and the position of the reflecting surface in relation to the light source. Sensor data can be interpreted in terms

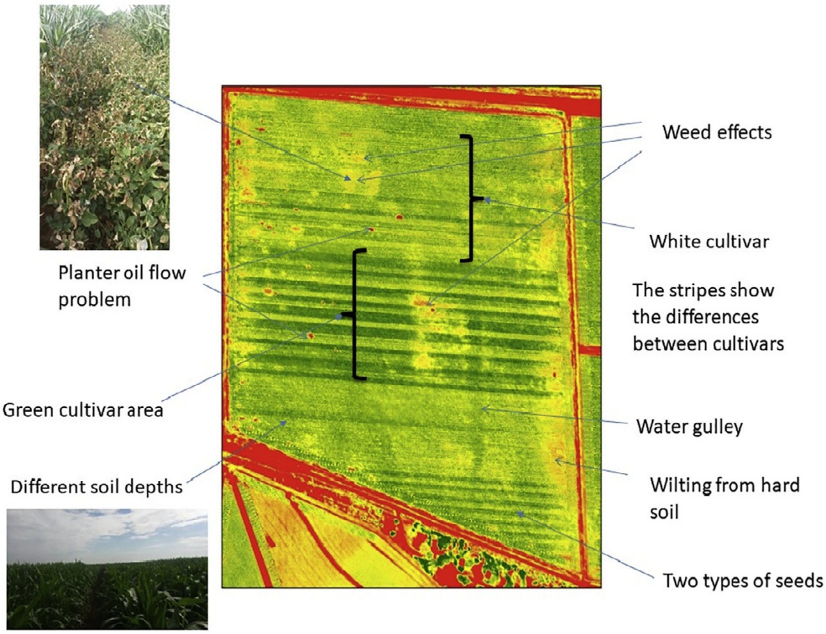

Fig. 2 A normalized difference vegetation index map of a corn field, derived from high spatial resolution aerial images, demonstrating the power of fine spatial resolution to assist in the identification of the causes of variability within a crop field. Data and images provided by Petrus Roux, Viljoenskroon, South Africa.

of sunlight characteristics, surface chemical composition, surface morphology, and object location. Complex interactions between these factors lead to significant challenges in the interpretation of sensor data.

3. Aerial imagery collection

3.1 General considerations

A drone is merely a means to carry a sensor airborne and thereby enable an aerial perspective of the scene below. Sensors detect energy in specific wavelengths of the electromagnetic spectrum, as discussed previously. Sensors can be classified into two categories: passive and active. Passive sensors are the most common type used in agriculture and measure the emitted or reflected energy from a scene. Active sensors also emit energy and detect the reflection of that emitted energy. There are a variety of advantages and disadvantages to passive and active sensors. Passive sensors are typically lightweight and low cost, but they are highly influenced by ambient conditions. Active sensors generally are heavier and more costly than passive sensors, but they can produce repeatable data despite changing ambient conditions (Erdle et al., 2011).

Remote sensing from drones is a powerful tool, but the accurate interpretation of aerial imagery still requires subject matter expertise and ground truthing. The specific spectral readings of an aerial map can indicate different things to people of varying experience. A sample measured directly on the ground by an expert will often be the most accurate method of identifying the causes of variations in aerial data. Aerial maps are therefore not an end-all solution, but it is a tool that can greatly enhance the efficiency of subject matter expertise and ground truthing, resulting in improved management decisions.

3.2 Drone-mounted sensors in agriculture

3.2.1 Visible light

Red, green, blue (RGB) sensors are the least expensive and most common passive sensor type used on drones. These sensors capture visible light (400–700 nm wavelengths) in overlapping red, green, and blue channels, similar to human vision. The ratios of signal strengths in the three channels are used to calculate the color of each pixel in an image. They are most useful in applications where variations in features of interest produce variable reflectance in the visible light spectrum. Data from visible light sensors are often relatively easy to interpret qualitatively, even by relatively inexperienced people, because the type of information is familiar. However, some vegetation indices, such as the green leaf index, can be calculated to extend the use of visible light sensors to more quantitative applications (Broge and Leblanc, 2001).

3.2.2 Broad band color-infrared

Broad band color-infrared sensors are modified variants of RGB sensors. Notch and band pass filters are used to isolate near infrared (NIR) light in a single channel (red or blue, depending on the design), while visible light is captured in the two remaining channels. This method leverages the relatively high degree of investment and development associated with consumer camera development, resulting in high quality sensors with good spatial resolution at relatively low cost. Measuring NIR light in comparison with visible light, even if it is done using relatively broad wavelength bands, is an excellent indicator of the photosynthetic activity of plants (Viña et al., 2011). Modifying RGB sensors is the most cost-effective method of obtaining this type of data in relatively high-quality imagery, particularly when there is a need for fine spatial resolution, and it has become a widely used in agriculture (Rasmussen et al., 2016). Unfortunately, however, the quality of camera conversions from RGB to color-infrared varies widely in the industry, and lack of standardization can hinder comparative data analysis.

3.2.3 Multispectral and hyperspectral

There is no explicit definition or differentiation between a multispectral and hyperspectral sensor, but multispectral sensors typically capture 4–10 discrete bands of light, while hyperspectral sensors capture more than 10 bands. Hyperspectral sensors may capture hundreds of discrete bands at narrow wavelength ranges. This fine spectral resolution comes at the cost of increased equipment cost, complexity, data processing times and storage requirements (Mulla, 2013). Hyperspectral sensors are still mostly used in research applications due to high cost and complexity. Multispectral sensors, on the other hand, are improving due to relatively high levels of investment in research and development. Data quality is improving, combined with decreasing cost and operational complexity, resulting in their rapidly expanding use in agriculture.

3.2.4 Thermal

Objects emit light in the infrared range based on their temperature. Thermal cameras used in agriculture are passive, uncooled microbolometer image sensors that capture infrared light in the relevant wavelength range: 7.5–13 μm. These sensors usually have low spatial resolution compared to visible or near infrared sensors. Radiometric resolutions are good, however, typically up to 14-bit. The resulting thermal precision is adequate for most agricultural applications where temperatures are analyzed comparatively (Berni et al., 2009). Targets of known temperature in the area of interest can be used to calibrate thermal images for applications requiring absolute temperature accuracy. Thermal cameras and lenses should be carefully selected to ensure that the spatial resolution of the images are appropriate for the size of the objects or areas of interest to be assessed, camera parameters must be correctly implemented, and flight missions must be appropriately designed to capture accurate data at the necessary levels of image overlap and spatial resolution. Discrete distinction if the surface temperature of an object or area of interest is only possible if an adequate number of pixels fall within the object surface or area of interest (four minimum for an object or area with a homogeneous surface, and more when the temperature is variable and an accurate average temperature must be obtained) (Fig. 3A). If not conducted correctly, data may not accurately represent true canopy temperature due to edge-effects and insufficient data points to calculate robust average or median values (Fig. 3B). Overall, canopy temperatures extracted from thermal orthomosaics, captured with modern, uncooled thermal cameras of high quality, have an expected error range of ±1 °C of the actual plant temperature (Sangha et al., 2018).

3.2.5 LiDAR

LiDAR is an active sensor type that can be defined as a portmanteau of light and radar, as it uses a laser to emit light and then measures the time for that light to reflect off an object and return to the sensor. This time delay measurement creates three-dimensional points indicating distance from the sensor, typically thousands of times per second. The resulting data can be used to describe a surface, usually in the form of a point cloud. If available, it can

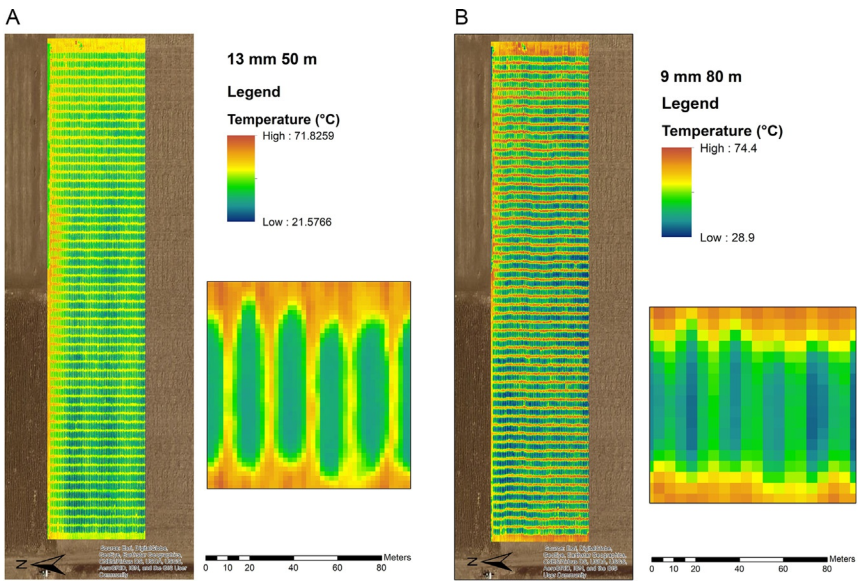

Fig. 3 Thermal orthomosaic map generated for 13 and 9 mm focal length thermal sensors at flying altitudes of 50 and 80 m, respectively, over a partially closed soybean canopy. Edge-effects prevent derivation of accurate canopy temperatures when the spatial resolution is too low (B).

be combined with other information, such as intensity and color of reflected visible light. LiDAR data excels at providing topography data without the image overlap requirement associated with regular aerial imagery, thereby increasing topographical mapping efficiency. It can also differentiate between plant canopy height and ground height, allowing plant canopy volumes to be calculated (Rosell et al., 2009).

3.3 Reflectance measurement

Analysis of vegetation based on reflectance characteristics is the most widely used, and arguably the most important, application of drone technology in agriculture. The quality of reflectance measurement is critical to the success or failure of this application. Poor quality of reflectance measurements has been an Achilles heel of the industry. It can have many causes, including inadequate sensors, inappropriate image collection methods, and inappropriate image processing.

Some problems are unique to remote sensing at the relatively low altitudes where agricultural drones operate, typically 400 ft above ground level or lower, because the sensors must have a relatively wide angle of view to of practical use. Objects on the ground are therefore not observed from a NADIR perspective, except for a small area directly below the drone, and the view angle changes through the image, becoming progressively more slanted toward the edges of an image. As discussed previously, the view angle influences the value of reflected light detected at an airborne sensor, and the variable view angel therefore results in variations in reflectance values independent of vegetation condition. Specific strategies during image collection and approaches to data processing are needed to overcome artifacts caused by view angle variation.

Another common cause of reduced reflectance data quality is variability in ambient conditions. Constant light conditions during image capture flights are ideal, but not always achievable under practical conditions. When images are intended for comparative analysis over time, consistent light conditions between image capture sessions is also desirable, but this is even less likely to be achieved in real-world conditions. The brightness values of various plant structures will be different under different ambient light conditions, even if the overall image exposure level is the same. An example of the effects of differences in ambient conditions is shown in Fig. 4.

Various approaches to image capture and processing are used to reduce the impact of inconsistent light conditions. In general, completely sunny or

Fig. 4 Aerial color infrared images of the same area taken on different days and using the same exposure level as indicated by the average brightness of the image. Notice the differences in the shadow patterns within the canopy and the brightness of plant structures in the sunny image versus cloudy image.

completely overcast conditions are preferred over partly cloudy conditions because partly cloudy conditions introduce variability in both light intensity and spectral quality. Even when ambient conditions appear to be relatively consistent while collecting imagery, inconsistencies in lighting from one image to the next, or from one time to another, are still commonly seen due to differences in atmospheric conditions that may not be apparent to the human eye.

Normalization of images to reduce the effects of inconsistent ambient light is a commonly used processing approach to reduce variability. Conversion of pixel values to reflectance is often used as a method of normalization. It is done by dividing the measured intensity of light reflecting from a surface by the measured intensity of incoming light, also referred to as insolation. While this approach is simple in principle, practical insolation measurements, at the location of each pixel of an image, is not. Different methods have been developed. Each method is associated advantages and limitations, and its application may be variably successful depending on the specific scenario and conditions.

First, there are two types of upward-looking cosine receptor insolation sensors, drone-borne and ground-based. These sensors measure insolation in a 180-degree hemisphere to account for direct and indirect light. Insolation must be measured in the same wavelengths as those collected by the downward-facing sensor. The sensor should view only open sky because objects on the horizon will alter insolation readings. The orientation of the insolation sensor is therefore critical, as changing its view angle will result in the view disk dipping below the horizon. The sensor should also not view the sun directly. Diffusion filters are therefore used and need to be accounted for in the interpretation of measured values. An inherent limitation of upward-looking insolation sensors is that they measure light only at the location of the sensor, and not over the whole footprint of aerial images. Light quality variation due to variable atmospheric conditions, particularly clouds, can have a spatial resolution that is finer than the image footprint. Light conditions can therefore vary depending on the location within an image, while an upward-looking sensor only senses light in one location within an image, and in the case of ground-based insolation sensors, the insolation value may be taken at a location away from the image footprint. Spatially consistent ambient light conditions are therefore critical to the successful use of insolation sensors for reflectance calculation and are assumed when this approach is used.

Another approach is to use invariant reflectance targets. Such targets are calibrated in a laboratory under known lighting conditions to determine the reflectance of the target in relevant wavelengths. This known reflectance information is then assumed to remain constant under field conditions. Targets are used to calibrate imagery by taking images of targets around the same time as areal images, and/or by placing targets in the flight area. Due to the high cost of appropriate targets and practical limitations of target deployment, calibration targets typically only appear in a few images from a flight, and it is standard practice to capture an image of the target before and after each flight to calibrate all the images for the flight. This practice highlights a disadvantage of this approach in that it assumes consistent ambient light conditions throughout the flight, including images taken without a target in the image footprint. The assumption of spatially consistent lighting conditions applicable to upward-looking sensors are also relevant to invariant targets. In addition, it is extremely difficult to produce true Lambertian targets, where the degree of reflectance from the target is independent of the view angle. Even when near-Lambertian reflectance from targets can be achieved, it cannot be assumed for natural surfaces in the image. Differences in light scatter patterns between targets and vegetation therefore lead to normalization errors associated with variation in the view angle.

Advantages and disadvantages of the different approaches to reflectance estimation are summarized in Table 2. It should be noted, however, that normalization based on reflectance is not a complete solution to the normalization requirements of drone-based aerial imaging. The use of normalized indices offers an additional approach to reducing normalization errors, and forms an important component of image processing in many agricultural applications.

Table 2 Summary of major advantages and disadvantages of reflectance measurement approaches.

Solution	Advantages	Disadvantages
Drone-borne cosine receptor	• Captures conditions at the location of the mapping sensor	• Potential variability of insolation values if un-gimbaled • Assumes spatial consistency of lighting conditions
Ground-based cosine receptor	• Fixed sensor, thereby eliminating measurements of objects in the horizon	• Must be mounted on a tall structure with clear 180-degree view of the sky • Assumes consistent lighting conditions between the receptor and mapping imager • Assumes spatial consistency of lighting conditions
Reflectance target	• Laboratory-calibrated reflectance information	• Assumes uniform conditions throughout the mapping mission • Assumes spatial consistency of lighting conditions • Assumes Lambertian reflectance from targets

4. IMAGE processing

4.1 Orthomosaicking

Unprocessed digital aerial images are files that contain data in the form of numerical values associated with pixel locations. It is not possible to interpret these data, or to derive useful information for decision-making, without the generation of an information product in an accessible format. Image processing is an essential step in the extraction of information from aerial images, and ultimately in the extraction of knowledge that can form the basis of decision-making.

Aerial image processing consists of several possible workflows aimed at preparing data for analysis in image processing software or a geographic information system (GIS). One of the most commonly used processing workflows used in agricultural applications of aerial imaging is known as orthomosaicking. Individual images collected by an aerial camera are subject to geometric distortion, meaning that distances and areas cannot be accurately measured from an uncorrected aerial image. Orthomosaicking composites aerial images into a single, seamless, geometrically corrected image. Following georegistration, it can be used for measurements of attributes typically derived from maps, including distances between objects, the geographic locations of objects, and measurement of areas. It can also be used in a GIS environment in conjunction with other data sources.

Orthomosaicking is typically performed using one of several desktop software packages designed for this purpose. A variety of cloud-based orthomosaic processing software options are also available. These software packages utilize a machine vision technique known as structure-from-motion photogrammetry to align aerial images, stitch them together into a larger, seamless image, and produce a point cloud, or three-dimensional model of the imaged area. Using this model, the imagery is *orthorectified* such that artifacts such as lens distortion, tilt, and elevation effects are removed from the output dataset. If the imagery was collected without geotags (metadata tags containing the geographic coordinates where each image was recorded during flight), the orthomosaics must also be georegistered, or correctly aligned with its real-world coordinates before it can be used in a GIS.

The success of structure-from-motion photogrammetry for production of aerial orthomosaics depends on the characteristics of the aerial imagery used, and the environmental conditions during image capture. Factors, and common practical examples, that may reduce the success of structure-from-motion photogrammetry include:

- Surface movement (for example movement of tall vegetation due to wind)
- Inconsistent and excessive variation in camera angle and altitude above ground level (for example due to an inconsistent flight patterns due to excessive and variable wind, autopilot malfunction, or camera gimbal malfunction)
- Highly reflective surfaces (for example open water)
- Consistent, repetitive patterns (for example homogeneous fields with precisely planted row crop, or smooth surfaces)
- Images with very low pixel density or low effective spatial resolution (for example low-end thermal images, or images that are out of focus)
- Excessive variation in ambient light intensity during image collection (for example partial cloud conditions)

4.2 Pixel value allocation

The allocation of values to each pixel in an orthomosaic is another critical processing step. It may include procedures such as adjustments to brightness, contrast, or colors, aimed at producing an image that enhances the ability of a human observer to recognize patterns and textures of interest. This approach can often be useful in agriculture because it extends the efficiency of the innate human ability to make use of visual information, and it is technically relatively simple to achieve. However, the goal in many agricultural applications of remote sensing is not to obtain an optically useful image, but rather to derive quantitative information for comparative and statistical analysis of the attributes of imaged objects or areas of interest. To achieve this goal, the values of pixels in the orthomosaic must be quantitatively, and reliably, related to relevant characteristics of the location of each pixel in the real world.

Conversion of pixel values to reflectance as a normalization process, as discussed previously, can help to reduce data artifacts. But, as indicated before, this does not offer a complete solution. Another commonly used normalization method is to make use of normalized differences between wavelength bands. One of the most used algorithms for generating this type of normalization is known as the Normalized Difference Vegetation Index (NDVI). The NDVI has been used extensively, and with remarkable success, for vegetation assessment over a wide range of spatial scales and remote sensing platforms (Carlson and Ripley, 1997; Defries and Townshend, 1994; Mogili and Deepak, 2018). It is derived using the following equation:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{VIS})/(\mathrm{NIR} + \mathrm{VIS})$$

where NIR is near infrared light (typically used wavelengths between 700 and 900 nm), and VIS is visible light (typically in the red wavelengths between 600 and 700 nm).

A higher NDVI value generally indicates a higher vegetative biomass and/or growth vigor. It allows differences between vegetation at different locations to be quantified—greatly enhancing the ability to use aerial imaging-based computational methods for vegetation analysis. However, the NDVI approach is also not a complete solution because the NDVI value is influenced by the view angle. The view angle affects the surface area of a plant facing the sensor, and the sunlit versus shadow ratio of the plant surfaces facing the sensor. Shadowed vegetation surfaces are exposed to a different light intensity and quality compared to sunlit vegetation surfaces, which affect the degree of difference between bands used to calculate the NDVI. This data artifact is of particularly high significance in data derived from sensors with wide angle fields of view, deployed at relatively low altitude (Fig. 5).

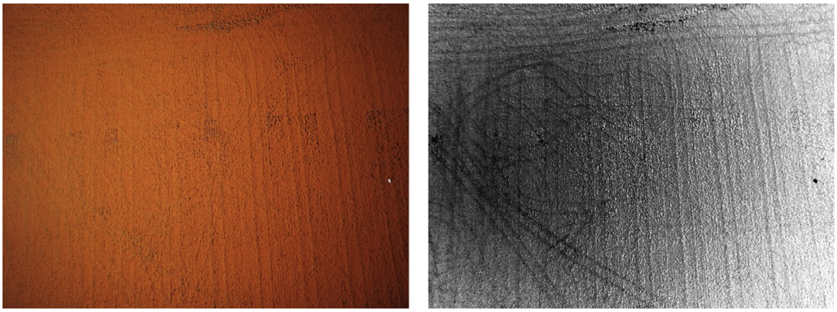

Fig. 5 A color-infrared aerial image, and an NDVI derived from the image, of a relatively homogeneous alfalfa field. The NDVI image is in a gray scale where brighter pixels indicate higher NDVI values. NDVI values tend to be higher where the view angle from the perspective of the sensor is more acute, and relatively more of the viewed surface area of plants are in shadow.

Several additional normalized indices that relate to plant characteristics have been developed, for example targeting the transition between visible to near infrared (the so-called "red edge") or targeting specific visible wavelengths that change in reflectance depending on the growth stage (such as reproductive stage), or physiological status (such as drought-stress), of plants. The most appropriate index is highly dependent on the sensor used to capture aerial data, and the specific application. An extensive review of vegetation indices is beyond the scope of this chapter, but several reviews and empirical evaluations are available in the scientific literature (Bannari et al., 1995; Kim et al., 2010; Thenkabail et al., 2004). A degree of bidirectional artifacts is typical of most vegetation indices derived from drone-mounted sensors and must be effectively reduced to achieve optimal index efficiency in detecting vegetation differences and avoiding data interpretation errors due to bidirectional data artifacts.

Two pixel-value allocation methods are commonly used to overcome bidirectional data artifacts: image location-based value allocation and statistical value determination. In the first method, the pixel-value of a location is derived from the image that was taken closest to that location. When applied to aerial imagery, this approach tends to use the value from the image in a set that has the view angle closest to NADIR for each pixel in the orthomosaic. This reduces the overall degree of bidirectional artifacts because the difference between the actual view angle compared to NADIR generally determines the size of the bidirectional data artifact.

The second method is to use a statistical approach to pixel-value allocation by making use of multiple overlapping images that contain the location of interest in the image footprint. One of the commonly used statistical approaches is to use the average value, from all the images that contain the location of interest. This approach is effective in achieving robust pixel values with little or no bidirectional data artifacts, but requires the values derived from the utilized images to be high enough in number to produce a calculated average with an acceptable level of statistical confidence. The second requirement is to have a normal distribution of values to ensure that the average is not influenced by a skewed data distribution. In practical terms, this requires a flight plan that results in a relatively high degree of image overlap, and an image overlap pattern that is consistent in all directions from the perspective of the pixel location of interest. Typical image distribution patterns resulting in successful application of this approach has image overlap of 75% or more, with the same image overlap front-to-back and side-to-side.

The weight given to a particular image may be weighted depending on the image location, resulting in a hybrid pixel-value strategy between purely statistical and purely location-based methods. The algorithms used to achieve this differ between software packages used to generate orthomosaics and are often considered proprietary and kept hidden by software developers. In applications requiring certainty regarding pixel-value allocation methods, such as scientific research projects, this may be a consideration in the selection of software.

5. Examples of agricultural drone applications

5.1 Seedling emergence assessment

Seedling emergence measurement and mapping is a common agricultural application of imagery collected using sUAS. If crop germination is delayed or unsuccessful in portions of the field due to environmental factors, there is often a short window after plant emergence during which the producer could attempt replanting. At the early stages of crop development, the field can be mapped at very high resolution in order to view the seedlings and identify zones in which germination was unsuccessful (Sankaran et al., 2015). The required resolution depends upon the size of the plants' leaves just after emergence. Some crops have thin, wispy leaves at emergence that are more difficult to see from above (e.g., wheat), requiring greater spatial resolution, while other crops produce larger leaves that do not require the same fine resolution in order to be successfully mapped. Aerial mapping of the field should be conducted prior to canopy coalescence so individual plants can be clearly seen in the imagery. While emergence mapping is possible using RGB imagery, multispectral imagery offers greater flexibility in calculating various vegetation indices that rely upon a near-infrared spectral band. Vegetation indices often yield better results when spectrally separating small leaves from the surrounding soil background.

Once the field has been imaged and an orthomosaic produced, the plant cover visible in the orthomosaic must be classified in order to correlate seedling density classes in the orthomosaic with ground-truthed seedling counts. This can be done in one of two ways. The first method entails using a pixel-based classifier, such as ISODATA (unsupervised) (Venkateswarlu and Raju, 1992) to classify plant pixels. This can be combined with object-based image analysis (OBIA) methods (Yu et al., 2006) to improve the accuracy of the classification. The second method involves creating a density slice of a vegetation index produced from the original orthomosaic image. The density slicing process (Knight et al., 2009) requires the analyst to find spectral thresholds, identifying ranges of digital numbers in the vegetation index image that represents plant cover and not soil background. The second method tends to be faster but less accurate, while the first method can produce a more accurate emergence map at the cost of the analyst's time to train the classification algorithm and interpret the results. When the classification is complete, GIS tools enable the analyst to group adjacent pixels classified as emerging plants and convert them to vector features representing individual plants. The analyst would later divide the field into zones where seedling density is inadequate and where re-planting should be attempted by the producer.

5.2 Weed detection and mapping

Weed mapping is a commonly used application of remote sensing in agriculture (Thorp and Tian, 2004), and drones offer advantages in this application due to the high degree of flexibility in spatial resolution (Rasmussen et al., 2013). Weed mapping is a similar problem to seedling emergence mapping in terms of how the aerial mapping phase is conducted and how the imagery is analyzed. Multispectral imagery is typically most appropriate for mapping weeds within the crop field. Successful mapping of weeds requires the agronomist to work closely with the image analyst to ensure understanding of the form and phenology of the weed and how they are different from the crop species. Some weeds are visually and spectrally similar to the crop species and are difficult or impossible to separate, while other weed species may be very different from the crop species, and weed identification and classification are therefore possible using aerial imagery.

Following aerial data acquisition, the analyst must preprocess the imagery and classify crop cover, weed cover, and soil cover using the density slicing or image classification techniques described previously. Within-field zones where weed density is greater can be identified using vectorized weed and crop cover maps.

5.3 Crop damage assessment

Within production agriculture, crops can experience a wide variety of damage that causes a structural or spectral change. Causes of structural change can include weather damage, such as wind and hail. Drone mapping can aid in the location and quantification of crop damage after weather events, and a wide variety of other causes including insects and diseases (Puri et al., 2017). These changes can be as minor as a slight shift in a vegetation index, to as extreme as a complete change in color as when sooty mold covers sorghum leaves. This type of inspection occurs at the discretion of the user. Research is ongoing to determine proper inspection intervals using drones which compliments existing mapping assets like satellites and manned aircraft. The refinement of this sensor ecosystem will lead to earlier identification of insect infestations and disease outbreaks, and mitigation of their impacts due to better informed management decisions.

5.4 Water management

Limited availability of water is one of the most significant challenges facing agriculture today, and pressures on water resources are expected to increase into the future. Protecting crops from drought-related losses requires water management systems that respond to changing water needs in near real time, and therefore requires accurate data that reflect developing water deficits before those deficits lead to loss of production.

Soil moisture sensors are typically deployed at few selected locations within the field to quantify soil moisture depletion in the soil profile. Irrigation system managers used information from soil moisture sensors including prior knowledge of crop type, soil characteristics, and environmental conditions such as temperature, precipitation and humidity to judge water needs. However, the limitations of these sources of information become apparent when the system becomes stressed because it is often not possible to see damaging stress before it becomes relatively severe and results in losses. Current soil moisture sensing systems often do not provide an opportunity to examine water stress at the desired spatial and temporal scale, which is particularly relevant due to the inherent variability of soil moisture depletion within the field. Modern variable rate water distribution systems allow irrigation managers to alter water distribution to sections of a field according to its specific needs. Such systems are available today, but sensing systems to rapidly collect crop growth, analytics to drive decisions, and models to use decision for irrigation scheduling, need to be matched with the spatial and temporal data requirements to make optimal use of these systems. Data need to be generated at the time of need, and at spatial scales that allow in-field adjustments to be optimized. Drones can play an important role in the evolution of irrigation systems by increasing the efficiency of data-generation (Gago et al., 2015). Aerial sensing systems can provide robust spatial and temporal assessment of crop water stress (Fig. 6) under diverse environmental conditions, and with unmatched levels of data generation efficiency. The use/installation of newer variable rate irrigation technologies can be expected to rise as user confidence in spatial crop water assessment technologies is increasing and older systems are replaced or upgraded. This evolution of irrigation systems, from blunt instruments that often over- or under-supply water to different parts of fields, to systems that can optimize water supply in all areas of a field, greatly enhances the sustainability of available water resources while optimizing crop yields.

5.5 Livestock applications

5.5.1 Livestock observation using visible light cameras

The use of drones in livestock production systems has become much more common with the increased availability of low-cost consumer drones that are easy to use and can deliver high quality video and still images. With some notable exceptions, such as the use of thermography discussed below, the use of drones in animal mustering, and the use of drones to track animals tagged with radio transmitters, the vast majority of livestock applications revolve around the simple observation of livestock and livestock production systems from the elevated perspective of a drone, using visible light cameras to stream video directly to the operator or to generate aerial images. Video streaming is used for tasks including observation of behavior and movement, finding individual animals or herds in large pastures, and observing the status of infrastructure that is relevant to livestock management such as fences, gates and water supply. Still images are usually more detailed and may be

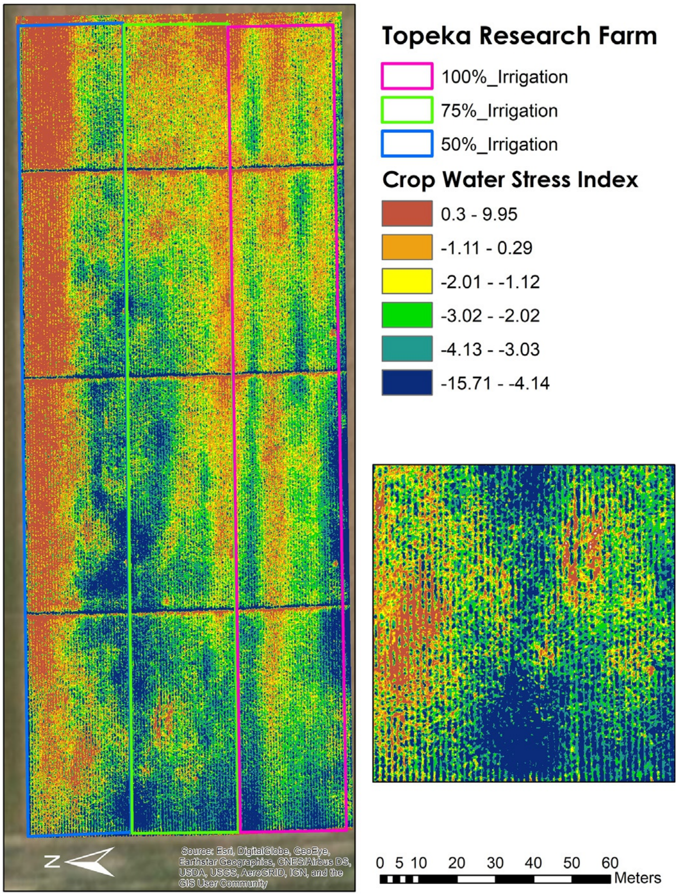

Fig. 6 A crop water stress map generated from a thermal infrared imagery of corn crop using environmental parameters. The three irrigation regimens are shown in boundaries marked with pink, green and blue solid lines (Sharda et al., 2018).

captured for tasks that require more detailed observation, and where a delay in the image analysis until the images can be transferred to a ground-based system for detailed viewing is feasible. Tasks include the documentation of numbers and locations of animals, documentation of pasture status and signs of degradation due to factors such as woody plant encroachment and erosion, monitoring feed trough fill status in feedlot systems, and the monitoring of supply status of bulk feeding materials, such as silage and hay bales. Although most of these tasks can be performed from ground level, drones have the potential to greatly enhance the efficiency of routine observations needed in the management of livestock production systems.

5.5.2 Body temperature screening

Elevated body temperature is often associated with infectious diseases in livestock, and measurement of body temperature is therefore an important tool in the screening of livestock for the possible presence of infections (Gloster et al., 2011). Skin surface temperature can also be used to detect heat stress in livestock, and changes in local blood flow patterns associated with inflammation can be used to locate inflammatory lesions (McManus et al., 2016). Most traditional methods of temperature measurement require restraint and close physical contact with animals. This has several serious disadvantages, including poor efficiency in terms of speed and labor, increased stress in livestock that results in decreased performance and animal well-being, and an increased potential for the spread of infections through close contact between animals and close contact between workers and successive groups of animals. High resolution thermography, based on uncooled, light weight thermal cameras mounted on drones, offers an alternative screening method that is highly efficient, and does not require livestock to be restrained or physically handled. Thermography sensors detect the infrared radiation emitted by objects at biologically relevant temperatures, in the wavelength range of approximately 8–12 μm (Mccafferty, 2007; McCafferty et al., 2011). It should be noted, however, that body temperature screening is not by itself enough to identify and diagnose infections but is best used as an adjunct to ground-level inspections that can make those inspections more efficient. The potential benefits are particularly high in areas of livestock concentration, such as feedlot systems, where groups of animals can be screened based on pen locations, followed by detailed ground-based inspections of pens where animals with elevated body temperature were identified.

Important factors need to be considered include: the relationship between skin surface temperature and core body temperature, the effects of environmental conditions on body surface temperature, the body parts where temperature estimates have adequate consistency, and the needed thermal resolution and spatial resolution of the thermographic data. The skin surface temperature is influenced by the temperature of blood circulating through the skin, which in turn is related to the core body temperature, even though the core body temperature and skin surface temperatures differ from each other due to skin heat loss or gain from the environment. When other factors that may influence skin surface temperature are controlled, animals that have a fever-reaction due to infections can be differentiated from

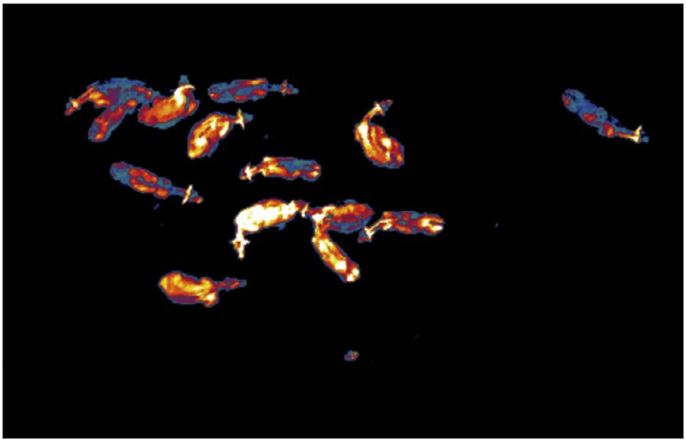

Fig. 7 A colorized thermal image demonstrating observable differences in skin surface temperatures associated with fever reactions in cattle (yellow to white coloration), compared to normal animals (red to blue coloration).

animals that do not have a fever by comparing body surface temperatures. The degree of surface temperature change during fever reactions typically exceeds 1 °C, which is well within the radiometric resolution capacity of currently available sensors (Fig. 7).

However, skin surface temperatures are also influenced by the direct absorption of heat from the environment, and by absorption of light energy from sunlight. Weather conditions such as air temperature, wind, precipitation, and sunlight intensity are therefore important factors affecting the consistency and reliability of skin surface temperature as an indicator of core body temperature. The skin color of the animal is another important factor under sunlit conditions (Fig. 8).

In practical use, aerial thermography is therefore most reliable when groups of animals are screened in comparison with each other, thereby controlling for most environmental effects. Currently available thermal sensors are capable of differentiating temperatures comparatively within single images. Controlling for sunlight-artifacts is not practically feasible under outdoor conditions, and the screening of animals is therefore most effective during the twilight period before sunrise, when sunlight does not affect skin surface temperatures, or during periods of heavy cloud cover. The large surfaces of the dorsal thorax and rump are ideal for temperature comparisons from drone-mounted sensors because reliable temperature estimates depend on the availability of adequate numbers of thermograph pixels on surfaces of

Fig. 8 A thermal image (top) and its equivalent visible light image (bottom). Dark skin colors are associated with a higher degree of heating in sunlight compared to lighter skin colors.

interest to ensure that other surfaces or objects do not influence the readings. Sensor manufacturers typically suggest a minimum of 10 pixels in a linear transect across the surface of interest. The screening efficiency is influenced by the resolution of the sensor because it determines the size of the image footprint that can be used. The flight altitude must be selected based on the size of the screened animals, the pixel density of the sensor, and the focal length of the lens used on the sensor. Effective altitudes typically range between 20 and 100 m depending on the sensor characteristics.

5.6 Non-remote sensing drone applications in agriculture

Previous sections of this chapter are dedicated to the remote sensing applications of drones in agriculture. However useful, remote sensing is not the only beneficial domain for drones in agriculture. Some of the most innovative uses for drones in agriculture are those that execute tasks outside the realm of remote sensing.

5.6.1 Aerial application of fluids, solids, and biological control agents

Precision aerial application of chemical products such as herbicides is a growing use-case of drones, particularly in intensively managed small farm scenarios (Yang et al., 2018). Commonly applied chemical products include pesticides and nutrients and can be divided into fluids and solids. Distributing biological control agents is another growing area of drone application. The distribution of Trichogramma wasps for insect control is an example (Li et al., 2013). Fluid application with drones has over 20 years of history through the application of chemicals to small scale agriculture such as rice paddies. This small-scale application could eventually lead to large scale application with the automation of currently manned aerial application aircraft. The application of solids finds a specific use-case in the planting of trees at scale, where drones shoot biodegradable seed capsules into the soil (Elliott, 2016).

5.6.2 Remote sampling (collecting specimens with a drone)

Another non-remote sensing application of drones for agriculture is remote sampling. This technique pertains to using a suitably equipped drone to retrieve physical samples from the field, which aids the ground truthing efforts by reducing the time needed to walk through fields. This area of drone application is still in early stages of development, but aerial drone-based water sampling (Ore et al., 2015) provides an indication of the potential of this application.

6. Agricultural drone development: Challenges and future opportunities

There are countless future agricultural uses of drones, and expectations are that it will have broad impacts (Daponte et al., 2019; Milics, 2019). It is associated with many novel and emerging opportunities, along with unique challenges.

Autonomous monitoring and sampling are expected to become increasingly reliable and sophisticated and could play important roles in the future development of precision agriculture and food security. Lack of universal public acceptance and unsuitable regulatory frameworks are some of the challenges that limit the pace of application development and expansion of drone use. If these challenges can be surmounted, future drones could be hosted at strategic locations, and will execute a variety of local crop monitoring tasks that are controlled through autonomous features under the direction of centralized operations centers where large amounts of data can be utilized to extract reliable, near-real time information for use in management decision-making. Next, drones could assist in the small- and large-scale application of agricultural chemicals, at an unprecedented level of precision, resulting in optimal production while minimizing environmental pollution. The adoption of larger unmanned aircraft, though a daunting thought due to current safety concerns, will likely increase refinement and safety of dangerous jobs that are currently performed by manned aircraft pilots. Lastly, regional monitoring for agriculture applications, based on relatively large autonomous aircraft with long flight endurance, could take over those tasks now performed by manned aircraft. Notably, the development of high-altitude pseudo satellites are expected to impact this use-case (Gonzalo et al., 2018).

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