Chapter 4

# The use of unmanned aerial systems (UASs) in precision agriculture

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## 1 Introduction

Agricultural production is particularly sensitive to both environmental conditions and management practices. Furthermore, farmers are often confronted with large variations in soil moisture, plant nutrition, crop growth and crop yields due to terrain, weather, tillage, drainage and other factors. Fast crop canopy changes make continuous monitoring of crop canopy necessary (Schirrmann et al., 2016). It is thus critical that farmers know, in a timely fashion, where these variations exist in their fields in order to adjust their practices accordingly.

Remotely collected images have been applied to identify soil and crop conditions (Zhang and Kovacs, 2012) and numerous types of satellite imagery (e.g. IKONOS, QuickBird, GeoEye-1 and WorldView- 2 and -3) have been used successfully in crop yield prediction (e.g. Shanahan et al., 2001; Chang et al., 2003; Seelan et al., 2003; Yang et al., 2006a,b, 2013; Inman et al., 2008). However, the shortcomings of satellite images which include availability and coarse spatial and temporal resolutions make their application in precision agriculture quite limited. With finer spatial resolution and real-time monitoring capability,

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airborne multispectral (e.g. Yang et al., 2000, 2004, 2013) and hyperspectral (e.g. De Tar et al., 2008) sensors have been applied to monitor vineyard and crop condition and yield. Aerial imagery has been shown to be as effective as high-resolution satellite imagery in monitoring spatial variation of crop condition and crop yield.

The recent technical developments in small unmanned aerial systems (UASs) (<25 kg), also known as unmanned aerial vehicles (UAVs), unmanned aircraft systems, drones and remotely piloted vehicles (Nex and Remondino, 2014; Whitehead and Hugenholtz, 2014), make their application for precision agriculture more practical than ever. Decreasing costs, ultra-high spatial imagery resolution (in cm) and flexibility of imagery acquisition make the UAS an important alternative and perhaps the ideal tool for monitoring and mapping crop conditions and for field scouting. Although there remains concern (e.g. privacy, security) regarding the increased use of UAS for civilian purposes, the public has already accepted that UASs could greatly benefit society, particularly in their potential role for precision agriculture (Freeman and Freeland, 2016).

Agriculture is the largest commercial market for UAS with a recent telephone survey indicating that there would be an increasing market share (80–90%) for UAS applications in agriculture (Association for Unmanned Vehicle Systems International, 2013). Presently, UASs have been applied primarily to monitor crop physiological parameters, leaf area index (LAI), yield, diseases and crop water stress with more applications to be discussed later. UASs have been shown to be particularly effective in monitoring crop growth during the growing season (e.g. Bendig et al., 2013; Geipel et al., 2014; Tilly et al., 2014; Kyratzis et al., 2015; Vega et al., 2015). Additionally UASs have also been used for air broadcasting seeds (Li et al., 2016), removing rainwater (Zhou et al., 2016), and spraying pesticide, herbicide and fungicide (Faiçal et al., 2014; Pan et al., 2016; Xue et al., 2016). UASs have been designed to also be able to measure and map environmental variables (temperature, humidity, luminosity and $CO_2$ concentration) within a greenhouse environment (Roldán et al., 2015) and to monitor the evolution of landslides in an olive grove (Fernández et al., 2016).

# 2 Platforms and sensors

The main components of a UAS are the UAV(s) and the sensor(s). Essentially, the UAV acts as the platform for the sensor(s) as well as other equipment such as an altimeter and a global navigation and satellite system (GNSS). Generally, UASs can be categorized as either fixed wing or rotary wing (Sankaran et al., 2015). Fixed-wing UASs generally tend to have a longer range and a faster speed than rotary-wing UASs. However, it is often a challenge to find an ideal take-off and landing spot for fixed-wing UAS. In contrast, rotary-wing UASs normally have a shorter flight duration and a limited range but better manoeuvrability. Most UASs have a GNSS and an inertial measurement unit (IMU). While the GNSS provides the positional information for the platform, the IMU provides the attitude data of the platform (yaw, pitch and roll). Information of the position, altitude and attitude of the UAV is often integrated with the autopilot system, which adjusts the course of the UAS according to the flight planning as well as controlling the acquisition of images at preset locations. However, if necessary, the operator can, at any time, override the autopilot to take back control of the UAS via the ground control station.

Current UAS regulations can considerably restrict the operation of UASs. In Canada, for example, it is generally required that UASs do not fly higher than 90 m and that the UASs remain at all times in unaided (i.e. no binoculars) visual range. Low flight height results in an image of ultra-high spatial resolution but of small footprint. Consequently, it is typically a challenge to map large crop fields, particularly since the average Canadian crop farm was 315 ha in 2010 (Statistics Canada, 2016). Therefore several flights may be necessary to collect a large enough array of images with adequate overlap to create an image mosaic for any given farm area. This can also pose some challenges for photogrammetric processing including changing light conditions (i.e. clouds) during lengthy flight times.

There are a variety of sensors/cameras available for UAS. Optical (either metric or commercial scale) or infrared (metric or commercial with modified filter to record near-infrared radiation) sensors are the most commonly used ones for crop monitoring (Table 1). Thermal infrared sensors have been shown to be useful for monitoring soil moisture and crop water stress (Table 1). Most recently, hyperspectral sensors on board a UAV have also been applied to examine leaf physiological parameters (Table 1). Chlorophyll fluorescence could also potentially be a useful tool for monitoring plant photosynthesis and water use efficiency under water stress (Table 1). However, such elaborate sensors are very expensive in comparison to optical sensors and hence will likely remain limited to scientific investigations on crop phenotyping.

When comparing the performance of a commercial scale camera to a multispectral metric camera for measuring ground spectral responses, overall good performance has been recorded for both types of camera (Haghighattalab et al., 2016). Although there are some concerns about the data quality from commercial scale cameras (e.g. poor calibration limiting conversion from digital numbers to radiance and reflectance) (Whitehead and Hugenholtz, 2014), the low cost of data acquisition still makes it an appealing choice for many agricultural applications. Specifically, results from various studies indicate that simple RGB cameras are not only cost-effective but also powerful tools for monitoring plant condition and plant phenology (e.g. Geipel et al., 2014; Gómez-Candón et al., 2014; Jannoura et al., 2015; Schirrmann et al., 2016). Moreover, qualities of point cloud and digital terrain model (DTM) from low-cost commercial scale cameras were found to be comparable to those derived

**Table 1** Sensor types and crop monitoring variables

| Sensor | Variable monitored | Example references |
|---|---|---|
| Optical (RGB and infrared) | Crop conditions | Hunt et al. (2005), Bendig et al. (2014), Diaz-Varela et al. (2014), Torres-Sánchez et al. (2014), Verger et al. (2014), Pérez-Ortiz et al. (2015) and Rasmussen et al. (2016) |
| Thermal | Soil moisture and crop stress | Sujiura et al. (2007), Berni et al. (2009), Baluja et al. (2012), Gonzalez-Dugo et al. (2013), Bellvert et al. (2014), Hoffmann et al. (2016), Sepúlveda-Reyes et al. (2016) and Martínez et al. (2017) |
| Hyperspectral | Leaf physiological parameters | Zarco-Tejada et al. (2012, 2013), Uto et al. (2013), Lucieer et al. (2014), Duan et al. (2014), Aasen et al. (2015), Torres-Sánchez et al. (2015b) and Willkomm et al. (2016) |
| Chlorophyll fluorescence | Plant photosynthesis and water use efficiency | Zarco-Tejada et al. (2012) and Gago et al. (2015) |

from DSLRs (Micheletti et al., 2015; Smith et al., 2016). However, consumer-grade cameras are sensitive to changes in illumination, and thus they should be used either in stable light conditions or when incoming light is measured concurrently in order to make adjustments in accordance with the variable illumination (Rasmussen et al., 2016).

# 3 Flight planning and imagery acquisition

The majority of UASs that adopted autopilot flight planning methods for acquiring images/photos are based on predetermined flight plans. Although it is possible to fly the UAS through manual control, it may cause issues for image post-processing. For example, an image gap for the field may be caused by limited overlap between images.

For autopilot, flight planning software is generally utilized to create a predetermined flight plan. A flight plan includes, for example, the flying area, the flight height, the forward lap, the side lap, the flight course, the flight speed and the camera settings. Normally high-resolution imagery or a large-scale map is shown as the background for the flight planning. High-resolution images for the study area may be downloaded/cached for use in the field prior to the field trip especially when Internet access is not feasible, which is likely the case for many applications. Flight planning software is either provided with the UAS or is acquired as a third-party application. In recent years, a few free downloadable apps have become available for field mapping for both Android and Apple cell phones (e.g. DroneDeploy and Pix4DCapture). In addition to the imagery, GNSS and IMU data are also typically recorded throughout the flight. These data can be used to assist in the image stitching stage for determining image centre position and camera orientation estimations (Whitehead and Hugenholtz, 2014; Smith et al., 2016). For most UASs, the acquired images and log data are stored in a peripheral storage device located on the UAV and, consequently, need to be downloaded to a computer for further processing.

The flight altitude of the UAS helps in determining the spatial resolution of the imagery; images collected with lower flight altitudes providing higher spatial resolution. It is not uncommon to set the UAS flight altitude somewhere between 100 and 120 m. A much lower flight altitude, such as 30 m, would result in much higher spatial resolution that may be required for particular tasks such as weed mapping. However, for many applications, aviation regulations determine the maximum flight altitude (e.g. 90 m in Canada and 120 m in Spain). Although the flight altitude generally does not impact the calculation of vegetation indices (VIs), it can greatly influence image segmentation with more mixed pixels present in those images collected at higher altitudes (Rasmussen et al., 2016). It is necessary to have a minimum of four pixels to identify one ground object.

Another crucial factor to consider in the flight planning stage is the image overlap setting. Normally it is suggested that the forward lap and side lap be set at a minimum of 80% and 60%, respectively (e.g. Colomina and Molina, 2014). This is partly because the low flight height and low accuracy of on-board navigational sensors can cause mismatching between the estimated image footprint and the actual ground coverage of the image (Haala et al., 2011; Whitehead and Hugenholtz, 2014). Additionally the greater overlap assists the photogrammetric software in identifying common points between image pairs. Finally, high overlap between images also helps to minimize bidirectional reflectance impacts by allowing the image processing software to extract only the central portion of each image for the image mosaic (Hunt et al., 2010).

Prior to the UAS image data acquisition, many researchers position artificial targets in the field. These targets can be used as ground control points (GCPs) or for spectral calibration. The GCP quality is critical for overall final product quality (position and elevation) (Smith et al., 2016). The position of these GCPs should be measured using a total station or a differential GNSS (d'Oleire-Oltmanns et al., 2012). This would guarantee the positional accuracy of subsequent image mosaics since the positional accuracies of the GPS on board the UAS could be as coarse as several metres. Normally it is suggested that a minimum of three GCPs be used in the photogrammetric adjustment. Moreover, it is recommended that these GCPs cover the entire study area and be well distributed (Smith et al., 2016). If used for spectral calibration, the surface of the targets could be painted in a different albedo whose reflectance would be measured using a ground spectroradiometer. An empirical line calibration could then be later applied to the image mosaic to convert the digital numbers to reflectance (e.g. Shi et al., 2016). The targets may also be applied to adjust digital numbers from image mosaics of different dates.

# 4 Image processing: stitching and ortho-rectification

Applying photogrammetry algorithms to rectify and mosaic images is a common task in the use of UAS. After downloading the images and log files, photogrammetric software is often used to generate ortho-rectified mosaics. Generally a semi-automated workflow needs to be followed in order to finish block bundle adjustment and ortho-rectification. The log file, previously mentioned, is used to provide initial estimates for the position and orientation of each image. There is a variety of software available for the photogrammetric processing including, for example, Trimble Inpho (e.g. Haala et al., 2011; Whitehead et al., 2013), LPS (Laliberte and Rango, 2011; d'Oleire-Oltmanns et al., 2012; Gómez-Candón et al., 2016), ENVI (Gómez-Candón et al., 2011), GeoLink (Selsam et al., 2017) and MicMac (Ballesteros et al., 2014a; Candiago et al., 2015).

In recent years, Structure from Motion (SfM) photogrammetry has also been applied in many UAS applications. SfM uses bundle adjustment algorithms to establish the structure of a scene, the internal orientation and the external orientation (Aasen et al., 2015; Smith et al., 2016). The main advantage of the SfM method is the ability to calculate the camera position, the orientation and the scene geometry purely from the overlapping images provided; this offers a simple processing workflow as compared to the alternative photogrammetry techniques. Specifically, SfM does not require camera calibration parameters as these parameters are estimated from the image tags and the large array of images available (Smith et al., 2016). This approach may be most convenient since many of these parameters are not readily available for many commercial scale cameras placed on UAVs. Furthermore, SfM photogrammetry can extract height information from two-dimensional images and there have been many examples of applications of SfM photogrammetry for geomorphology and physical geography in the production of high-resolution DTM (Smith et al., 2016). Such models are now being used to monitor crop growth during the growing season (e.g. Bendig et al., 2013, 2014). The most commonly used commercially available SfM software include Pix4dmapper (e.g. Zhang et al., 2014; Mesas-Carrascosa et al., 2015; Rasmussen et al., 2016; Shi et al., 2016), Agisoft PhotoScan Pro (e.g. Mathews and Jensen, 2013; Bendig et al., 2014; Geipel et al., 2014; Candiago et al., 2015; Fernandez et al., 2016; López-Granados et al., 2016) and Automatic Photogrammetric Processing Station (Caturegli et al., 2016).

There are also freely available SfM Web services including Autodesk 123D Catch (e.g. Micheletti et al., 2015) and Microsoft Photosynth. However, post-processing in other software for cleaning and editing is first needed (Smith et al., 2016). Unfortunately, both services were discontinued in late 2016 or early 2017. Open-source SfM packages are currently available. Some examples include Bundler and Patch-based Multi-View Stereo (PMVS2), VisualSFM and Ecosynth (Smith et al., 2016). Although there have been some criticisms regarding the computational time, the complicated applications and the reliability of these freeware, their performance has sometimes been found to be comparable with that of commercial ones (Smith et al., 2016). Moreover, Microsoft ICE has also been reported to be useful for panoramic image stitching (Wulfsohn and Lagos, 2014; Rasmussen et al., 2016).

# 5 UAS imagery applications

Within the past few years researchers have been able to extract a plethora of agricultural data from UAS imagery including: plant height, crop biophysical parameters, plant stress, and thematic information extraction for many crop species (Table 2) such as barley, cassava, chickpea, corn, cotton, onion, opium poppy, potato, rice, rye, sorghum, soybean, sugar beets, sugarcane, sunflower, tomato and wheat. In particular, there has been considerable work with UAS in vineyard monitoring most likely due to the high cash value of these crops.

## 5.1 Plant height

Plant height is a key indicator of crop biomass and yield potential prediction, plant cultivars separation, growth stages monitoring, treatments and stress monitoring (Bendig et al., 2013). It can also provide information about underlying ecological, hydrological and biophysical processes (Zarco-Tejada et al., 2014). Extracted crop height data have been used for the construction of crop surface models for biomass/yield monitoring (Geipel et al., 2014) and, as a time series, crop surface models can be used to accurately monitor crop growth (e.g. Bendig et al., 2013, 2014; Holman et al., 2016; Willkomm et al., 2016). In combination with VIs, plant height data have also been used to improve the accuracy of biomass estimation for barley crops (Bendig et al., 2014). Currently, plant height can be derived either from LiDAR data or from SfM-based photogrammetry. Terrestrial laser scanning has been applied to accurately measure plant height for crop surface modelling and growth monitoring (e.g. Tilly et al., 2014; Hoffmeister et al., 2016; Shi et al., 2016). Although there are numerous examples of UAS-based LiDAR applications to map forests and geomorphological properties (e.g. Hugenholtz et al., 2013; Wallace et al., 2014), no similar applications can be found for crop mapping.

While the direct DEM product of SfM algorithms is a digital surface model (with canopy information), it is possible to filter out vegetation canopy points from the point cloud and thus obtain the ground surface elevation (DTM). The separation of ground and non-ground points facilitates the estimation of biomass and other relevant measurements (Geipel et al., 2014; Aasen et al., 2015; Zahawi et al., 2015; Holman et al., 2016; Smith et al., 2016). However, efforts to filter out vegetation information may only be partially successful (Rokhmana, 2015; Fernández et al., 2016). Alternatively, a DTM could be extracted from UAS images taken before or after the growing season (e.g. Bendig et al.,

**Table 2** Crop species being monitored using UAS images

| Crop species | Example references |
|---|---|
| Barley | Bendig et al. (2014), Hoffmann et al. (2016) and Rasmussen et al. (2016) |
| Cassava | Selsam et al. (2017) |
| Chickpea | Sankaran et al. (2015) |
| Corn | Hunt et al. (2005), Link et al. (2013), Ballesteros et al. (2014b), Maresma et al. (2016) and Shi et al. (2016) |
| Cotton | Shi et al. (2016) |
| Onion | Córcoles et al. (2013) and Ballesteros et al. (2014b) |
| Opium poppy | Calderón et al. (2014) |
| Potato | Sankaran et al. (2015), Zhou et al. (2016), Hunt and Rondon (2017) and Hunt et al. (2017) |
| Rice | Inoue et al. (2000), Swain et al. (2010) and Uto et al. (2013) |
| Rye | Hunt et al. (2014) |
| Sorghum | Shi et al. (2016) |
| Soybean | Inoue et al. (2000) and Zhang et al. (2014) |
| Sugar beets | Martínez et al. (2017) |
| Sugarcane | Luna and Lobo (2016) and Duan et al. (2017) |
| Sunflower | Torres-Sánchez et al. (2013), Pérez-Ortiz et al. (2015), Vega et al. (2015), López-Granados et al. (2016) and Pérez-Ortiz et al. (2016) |
| Tomato | Candiago et al. (2015) |
| Wheat | Hunt et al. (2010), Honkavaara (2013), Geipel et al. (2014), Gómez-Candón et al. (2014), Lucieer et al. (2014), Torres-Sánchez et al. (2014) and Shi et al. (2016) |
| Vineyard | Baluja et al. (2012), Primicerio et al. (2012), Guillen-Climent et al. (2012), Garcia-Ruiz et al. (2013), Gonzalez-Dugo et al. (2013), Mathews and Jensen (2013), Zarco-Tejada et al. (2013), Bellvert et al. (2014), Zarco-Tejada et al. (2014), Burgos et al. (2015), Candiago et al. (2015), Comba et al. (2015), Matese et al. (2015) and Gómez-Candón et al. (2016) |

2013, 2014). When compared with height information based on TLS, SfM-based height measurements have been found to provide high levels of accuracies (Holman et al., 2016). It has also been found that a lower flight (40 m) altitude creates more accurate crop height measurements (Holman et al., 2016).

## 5.2 Crop biological parameters

Variations in leaf pigment contents, leaf size, leaf angles and other canopy properties can also be detected using UAS-based imagery (Table 3). For example, UAS images have been applied to estimate crop emergence, crop lodging, planting gap, crop vigour, biomass, LAI, yield, pigment contents, protein and nitrogen and vegetation fraction. Moreover, UAS images have been applied to identify soil parameters and soil carbon emissions, as well as to identify the location of tile drains.

Yet another important UAS application is for crop phenotyping. Information extracted from UAS images has been used for evaluating plant growth, estimating biomass and determining physiological changes caused by biotic/abiotic stresses where high-yielding, stress-tolerant varieties could be selected (Li et al., 2014; Sankaran et al., 2015; Holman et al., 2016). Expensive LiDAR, hyperspectral and thermal sensors could be applied in this aspect of research (Tables 3 and 4).

## 5.3 Plant stress

Crop biological parameters should show abnormal measurements if the crop is stressed due to environmental/abiotic (e.g. drought and heat waves) or biotic (e.g. pests, fungus, weeds) factors. Not surprisingly, there are now numerous examples of UAS imagery for monitoring plant stress including crop water stress, crop diseases, crop pests and pest management, weed detection and weed management.

Irrigated cropland (16% of world cropland area) yields 36% of global harvest (Food and Agriculture Organization, 1996). Furthermore, nearly 20% of irrigated land in the world has higher than normal salt concentration (Metternicht and Zinck, 2003). Crop water, salinity and heat stress can cause stomatal closure, decreased stomatal conductance, increased leaf temperature and decreased photosynthesis (Zarco-Tejada et al., 2012; Sankaran et al., 2015). Periodical thermal and visible to near-infrared UAS imaging throughout the growing

**Table 3** Crop biological parameters being monitored using UAS images

| Crop biological parameters | Example references |
|---|---|
| Biomass | Hunt et al. (2005, 2010), Honkavaara et al. (2012, 2013), Bendig et al. (2014) and Jannoura et al. (2015) |
| Crop emergence | Sankaran et al. (2015) |
| Crop lodging | Liu et al. (2014) and Zhang et al. (2014) |
| Crop vigour | Primicerio et al. (2012), Zhang et al. (2014) and Sankaran et al. (2015) |
| Leaf area index | Hunt et al. (2010), Córcoles et al. (2013), Mathews and Jensen (2013), Jannoura et al. (2015) and Ballesteros et al. (2014b) |
| Yield | Hunt et al. (2010), Swain et al. (2010), Geipel et al. (2014), Wulfsohn and Lagos (2014), Kyratzis et al. (2015), Maresma et al. (2016) and Khot et al. (2016) |
| Pigment contents | Hunt et al. (2005), Zarco-Tejada et al. (2013) and Hunt et al. (2014) |
| Planting gap | Luna and Lobo (2016) |
| Protein and nitrogen | Jensen et al. (2007), Caturegli et al. (2016) and Hunt et al. (2017) |
| Vegetation fraction | Torres-Sánchez et al. (2014) and Ballesteros et al. (2014b) |
| Soil parameters | d'Oleire-Oltmanns et al. (2012), Hassan-Esfahani et al. (2014) and Quiquerez et al. (2014) |
| Soil carbon emissions | Wehrhan et al. (2016) |
| Drainage pipes identification | Zhang et al. (2014) |

**Table 4** Plant stress being monitored using UAS images

| Plant stress | Example references |
|---|---|
| Crop water stress | Sullivan et al. (2007), Berni et al. (2009), Suarez et al. (2010), Zarco-Tejada et al. (2012) and Gago et al. (2015) |
| Crop diseases | Garcia-Ruiz et al. (2013), Sankaran et al. (2010) and Calderón et al. (2014) |
| Crop pests and pest management | Huang et al. (2009), Yue et al. (2012), Severtson et al. (2016) and Hunt et al. (2017) |
| Weed detection | Herwitz et a. (2004), Peña et al. (2013), Rasmussen et al. (2013), Torres-Sánchez et al. (2013), Pérez-Ortiz et al. (2015, 2016), Shi et al. (2016) and Castaldi et al. (2017) |
| Weed management | López-Granados et al. (2016) and Castaldi et al. (2017) |

season can provide qualitative and quantitative data for crop stress monitoring (Sankaran et al., 2015).

Leaf temperature can be an indicator of stomatal conductance and response of plants to water stress. Temperature measurements from thermal imagery taken from UAS (Berni et al., 2009; Zarco-Tejada et al., 2012; Gago et al., 2015) have been used to calculate the Crop Water Stress Index or Water Deficit Index for leaf/canopy anomalies (Gonzalez-Dugo et al., 2013; Bellvert et al., 2014; Hoffmann et al., 2016; Sepúlveda-Reyes et al., 2016). Other crop biophysical parameters that may be monitored by thermal remote sensing include soil moisture, soil texture, evapotranspiration, crop residue cover, tillage, field drainage tiles and yield (Khanal et al., 2017). Although water stress is primarily monitored using thermal remote sensing techniques, optical remote sensing can also be applied to identify plant/canopy condition (e.g. chlorophyll content and biomass) (Sankaran et al., 2015).

Plant nutrient deficiencies can result in visual symptoms such as lower chlorophyll content, lower growth speed, tissue necrosis and higher disease susceptibility (Sankaran et al., 2015). Most importantly, nutrient deficiencies can make crops more susceptible to herbivorous pests (Severtson et al., 2016) and optical UAS images have been applied to identify such symptoms (Cilia et al., 2014; Li et al., 2015; Severtson et al., 2016).

Weeds compete with crops for solar radiation, water and nutrition and consequently impact the production potential. The mapping of weeds could provide data for site-specific weed management, which would ideally lower the cost of production and minimize environmental impacts. UAS images have been shown to provide ultra-high resolution images, which are necessary to identify weed species, weed density and weed patches (e.g. Peña et al., 2013; Borra-Serrano et al., 2015; Pérez-Ortiz et al., 2015; López-Granados et al., 2016). Such applications are available for early-season weed detection and late-season weed detection (e.g. Torres-Sánchez et al., 2013; López-Granados et al., 2016). In particular, hyperspectral sensors are believed to be more advantageous than multispectral sensors in detecting weeds due to the spectral similarity of weeds and crops (López-Granados, 2011). The analytical results could be further integrated into a herbicide spraying plan for the current or upcoming year. It has been shown that patch spraying can be a considerably cheaper alternative to blanket applications (e.g. López-Granados et al., 2016; Castaldi et al., 2017).

UASs have been reported to be used in assessing pest/disease development and symptoms and in assessing and monitoring pathogen in the atmosphere (e.g. Schmale et al., 2008; Aylor et al., 2011) and for precision spraying. There are a few reports of

UAS-based sensing for disease monitoring in fruit tree production (e.g. Garcia-Ruiz et al., 2013; Calderón et al., 2014). However, the application of UAS-based sensing for evaluating disease severity and susceptibility of different varieties to diseases is still relatively undeveloped (Sankaran et al., 2015).

# 6 Image analysis

## 6.1 Qualitative (thematic information extraction) analysis of UAS images

In many situations, it is necessary to extract categorical information (e.g. crop type, stressed crop, lodged crop) from UAS images prior to further analysis. Although visual interpretation proves to be straightforward for many image analysts (e.g. Selsam et al., 2017), more researchers adopt a variety of classification methods for assigning class labels. The most commonly adopted method is object-based image segmentation, which is quite useful given the ultra-high spatial resolution of UAS images (e.g. Gonzalez-Dugo et al., 2013; Peña et al., 2013; Diaz-Varela et al., 2014; Torres-Sánchez et al., 2015a,b; Borra-Serrano et al., 2015; Comba et al., 2015; López-Granados et al., 2016; Pérez-Ortiz et al., 2016; Selsam et al., 2017). Other methods, for example, include supervised classification – support vector machine (Garcia-Ruiz et al., 2013; Castaldi et al., 2017; Pérez-Ortiz et al., 2015), K-nearest neighbour (Pérez-Ortiz et al., 2015), linear discriminant analysis (Luna and Lobo, 2016), maximum likelihood (Vega et al., 2015; Haghighattalab et al., 2016) and random forest (Yu et al., 2016). However, it is not uncommon for researchers to use unsupervised classification approaches, such as K-means (Pérez-Ortiz et al., 2015; Shi et al., 2016) and Iterative Self-Organizing Data Analysis Technique (Quiquerez et al., 2014) to determine pixel classes. Other machine learning algorithms have also been developed to segment vegetation and bare soil (e.g. Duan et al., 2017).

## 6.2 Quantitative analysis of UAS images

VIs are commonly computed to identify the relationships between spectral data and field biological data (e.g. Hunt et al., 2005, 2010; Torres-Sánchez et al., 2014; Candiago et al., 2015). Digital numbers, reflectance and VIs can all be linked to crop biological and environmental variables through a variety of methods. The most commonly used methods include Pearson's correlation, linear regression (Hunt et al., 2005, 2010; Swain et al., 2010), partial least squares regression (Jensen et al., 2007) and k-nearest neighbour estimator (Honkavaara et al., 2013). In several cases, biomass/yield has been modelled by further incorporating plant height (Bendig et al., 2014; Huang et al., 2016; Maresma et al., 2016) or fractional vegetation cover (Geipel et al., 2014; Duan et al., 2017).

The most commonly used VI is the Normalized Difference Vegetation Index (NDVI), which has been applied to measure biomass, chlorophyll content, nitrogen content and many other biological variables. Another useful VI is the Soil Adjusted Vegetation Index which is often employed to enhance spectral differences between vegetation and soil (Shi et al., 2016) as well as sensitivity to crop damage (Zhou et al., 2016). VIs based on RGB cameras [e.g. Excess Green Index (ExG), Green NDVI and Green Ratio Vegetation Index] have also been found to be good indicators of pigment contents, leaf area and canopy structure and, indirectly, of biomass (Erdle et al., 2011; Rasmussen et al., 2016). Various VIs (e.g. NDVI, TCARI/OSAVI) have also been used to identify vineyard water stress (e.g. Baluja et al., 2012). Most importantly, studies (Primicerio et al., 2012; Matese et al., 2015) have even shown that UAS-derived VIs were found to be comparable to those calculated from satellite, manned-aircraft images and from ground measurements and that they also provided more spatial details.

# 7 Case study

## 7.1 Study area

The case study took place in a small farming community of Verner, Ontario, Canada (46° 24′ N, 80° 07′ W). The region has an annual mean temperature of 4.7°C and the annual mean length of the growing season is 180 days with roughly 110 frost-free days. The annual precipitation is 1008 mm of which 273 mm is in the form of snow. The short growing season makes timely monitoring of the field crop conditions of critical importance. Moreover, the large area and scattered distribution of the fields, typical of this region, make personal visits and ground scouting a difficult task.

During the 2013 growing season, the authors were contacted by a local producer (Ferme Roberge) to monitor fertilizer field trials (spring wheat, *Triticum* spp.). Permission to fly the UAS over this region of Ontario was provided to Nipissing University, Canada, by Transport Canada (Special Flight Operations Certificate, SFOC, # 5812-15-33-2012-1).

## 7.2 Data collection and methods

A quadrocopter UAV, Aeryon Scout (Aeryon Labs Inc., Waterloo, Canada), was utilized to acquire images for the study area. The Aeryon Scout is equipped with an infrared camera, ADC lite camera (Tetracam, Chatsworth, USA). It is electrically powered by rechargeable lithium polymer batteries and has a maximum flight time of 25 minutes per battery. The control station allows the user to create flight plans that can be reused at a later date. The Aeryon Scout collects GPS/INS data for each photograph. The area of study was photographed on 21 July and on 30 July 2013.

The ADC lite has three bands: near infrared, red and green. The images captured with the ADC lite are stored directly on a flash card located on the camera. The flight altitude was set at 120 m as per the approved SFOC. Consequently, the spatial resolution for the NIR images was set at 5 cm. The front overlap and side overlap were set at 85% and 65%, respectively.

GCP were set up to help in the ortho-rectification of the final mosaic images. Each GCP consisted of a 30 cm × 30 cm colour foam pad placed on the top of a wood stake at a height of 1.5 m. Six GCPs were dispersed throughout the field prior to each UAS flight. Locations of the GCPs were recorded using a Trimble GeoXH GPS (Trimble, Sunnyvale, United States). Positional accuracy of this unit is sub-decimetre after real-time differential correction.

A variable nitrogen application experiment was conducted on the field to examine the impacts of N application on wheat grain yield. Specifically, fertilizer was applied at rates of 0, 50, 100 and 150 kg/ha to various sections of the field (Fig. 1). The treatments were arranged in a randomized complete block design with three blocks of replicate treatments. Regularly spaced field sampling sites were predetermined prior to the field season using ArcGIS (ESRI, Redlands, USA). Coordinates of these points were input into a Garmin GPSMAP 62s (Garmin, Olathe, United States) receiver so that these points could be easily located during the field season. The study area was visited once a week during the growing season (early May to mid-August). For each visit, the LAI was acquired using an AccuPAR LP-80 Ceptometer (Decagon Devices, Pullman, USA). Five LAI measurements were collected in a circle around the central point and then averaged to provide one LAI value per sample point. Plant phenology was measured using a BBCH scale (Zadoks et al., 1974). A one-metre long strip of the crop was harvested and the wet and dry biomass weighed. A CCM-200 Chlorophyll Content Meter (Opti-Sciences, Hudson, USA) was also used to measure chlorophyll content from still intact wheat leaves. At every sample location, five readings were acquired around the centre of each sample point. Images captured were exported and vignetting effect correction conducted using the PixelWrench2 software (Tetracam, Chatsworth, USA). Images were then mosaicked and ortho-rectified using Pix4dmapper (Pix4D, Lausanne, Switzerland). A log file with geotagged information and GCP locations were integrated during the image processing stage. An NDVI band [(near infrared-red)/(near infrared+red)] was then created using the Pix4D software.

A polygon shapefile layer with doughnut-shaped polygons (circles of 1 and 2 m radius, which corresponded to the field plot size and shape) was created using ArcGIS, which was used to extract digital numbers for each sampling point. No pixels within the central part of the donut were extracted as these corresponding areas were trampled by the field staff during the *in situ* measurements. Statistical data (mean, min, max, range and standard deviation) for each plot were then calculated using the extracting pixel values. Analysis of variance was then conducted using IBM SPSS (IBM, North Castle, USA) to identify whether significant differences between different treatments existed. Finally, correlation and regression analyses were used to identify any relationships between the spectral responses and the field data using IBM SPSS.

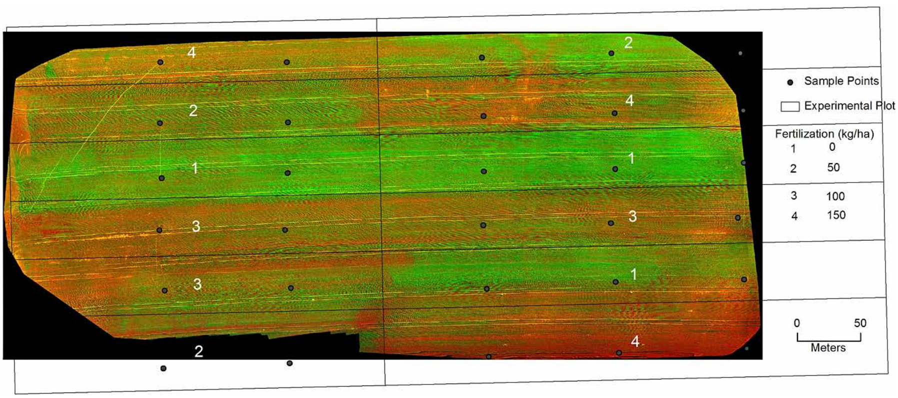


**Figure 1** Nitrogen experiment design and spatial distribution of sampling points. Background is the false colour-composite (RGB: near infrared, red and NDVI) image mosaic for 21 July 2013 flights.

## 7.3 Results and discussion

An adequate amount of nitrogen is critical for crop growth and thus to support a profitable crop yield. However, nitrogen use efficiency is generally low (Ma and Biswas, 2016) and unused nitrogen can cause water pollution and eutrophication. Consequently, it is critical that nitrogen application rates match crop demand. As expected, in this investigation there was a contrasting pattern between plots of various fertilization levels in the image (red band, $P = 0.048$; near-infrared band, $P = 0.011$) (Fig. 1). The largest differences were found between fertilization 1 (0 kg/ha) and 4 (150 kg/ha) (red, $P = 0.046$; near infrared, $P = 0.002$). However, there were not many significant differences in the spectral responses between treatments 1, 2 and 3.

The crop was flowering and in the early ripening stages when both UAS flights were taken. The average height of the wheat crop on 24 July and 30 July 2013 was 93 cm and 92 cm, respectively. The corresponding BBCH stages for these two sampling dates were 65–69 and 83, respectively. Various relationships between the spectral indicators and the crop biological parameters were recorded. Although the correlation between crop biological parameters and spectral indicators could be moderate (Fig. 2a and b), there were strong correlations between red reflectance, biomass and chlorophyll content (Fig. 2c and d). The results are consistent with those reported in previous studies. Normally correlations between VIs and ground measurements are strong to very strong (e.g. Jannoura et al., 2015; Shi et al., 2016; Zhou et al., 2016). However, it is not uncommon to record correlations that are weak or medium in strength (e.g. Jannoura et al., 2015; Shi et al., 2016). Zarco-Tejada et al. (2013) even noted that coefficients of determination ($r^2$) between some crop biological variables and structural indices (e.g. NDVI) can be generally low. As a matter of fact, the strength of the correlation may be impacted by phenology, canopy coverage (i.e. the fraction of soil and shadows), illumination condition variations and bidirectional reflectance.

# 8 Future trends and conclusion

From this review, it is clear that in the past few years, there has been a quick adoption of UAS for agricultural sciences with many research papers with promising results having been published in various academic journals. It is thus safe to say that UAS imagery can and will continue to be applied for monitoring a variety of crop biological and environmental variables. However, for many scientists and farmers without considerable expertise of UAS and remote sensing, it may appear that this field of work is somewhat overwhelming to consider. It is suggested that the main barriers to UAS adoption in precision agriculture are:

1 UASs are still relatively expensive and require trained technicians to use them effectively. This could certainly be overcome in the near future with advances in UAS technology and with decreasing costs.
2 There is no agreed autonomous procedure/tool to finish all steps in UAS remote sensing. Specifically, the image processing, interpretation and analysis are not straightforward and require highly qualified technicians (Ballesteros et al., 2014a). The analysis and interpretation of UAV images lie behind the interpretation of satellite and ground-remote sensing and thus need to be fairly straightforward in order to be adopted by the entire agricultural sector (Rasmussen et al., 2013, 2016). An automated procedure/tool would allow for a much broader adoption (Shi et al., 2016).

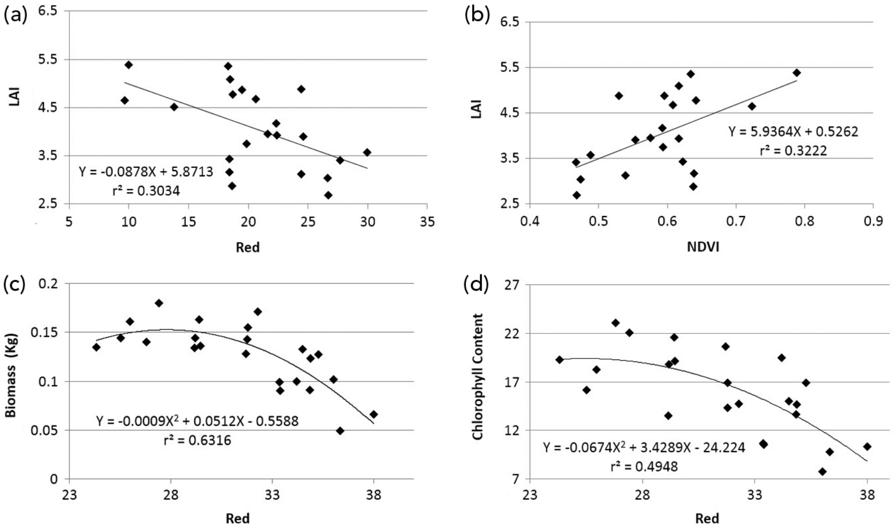


**Figure 2** Statistical relationships between crop biological parameters and spectral indicators. Images for (a) and (b) were acquired on 12 July 2013, and images for (c) and (d) were acquired on 30 July 2013. Ground measurements were collected on 16 July 2013 and 25 July 2013. Digital numbers for red band were applied for the regression analyses.

3 The area covered by most UASs may not be large enough which can result in many technical difficulties as mentioned in Section 3. A loosening of the aviation regulation and further development of UAS technology (allowing longer flight time) may help in this direction.

It is anticipated that there will be a continued interest in the application of UAS remote sensing, testing of new sensors and expansion of study topics in the agricultural sciences. However, it is suggested that the next step is to inform the local producers on what UAS technology is available for them and to convince them as to what versions/options would be most cost-effective for them. Certainly, the cost of acquiring relevant equipment is expected to continue to decrease and it will be much easier to use the equipment in the near future. However, it is unlikely that farmers will understand the whole process of UAS remote sensing. Because of the involvement of a variety of equipment and the need for research expertise from different academic disciplines, it is recommended that a group of researchers work together in attaining these tasks (Zhang et al., 2014; Shi et al., 2016). Further, it is also quite feasible that farmers simply contact a UAS consulting company either individually or as a group in order to receive proper service (Huang et al., 2013; Zhang et al., 2014).

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# 10 Where to look for further information

This chapter provides a comprehensive review of the application of UASs in precision agriculture. Readers can find more detailed information on the topics covered in this chapter by reading papers listed in the References. For a general review of UAS remote sensing and SfM photogrammetry, we suggest reading Colomina and Molina (2014), Whitehead and Hugenholtz (2014) and Smith et al. (2016).

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