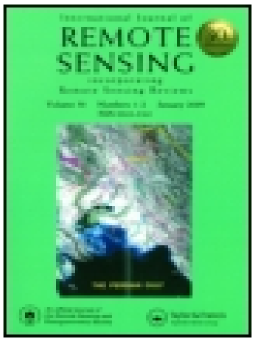

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What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture?

E. Raymond Hunt Jr. and Craig S. T. Daughtry

USDA ARS Beltsville Agricultural Research Center, Hydrology and Remote Sensing Laboratory, Beltsville, MD, USA

ABSTRACT
Remote sensing from unmanned aircraft systems (UAS) was expected to be an important new technology to assist farmers with precision agriculture, especially crop nutrient management. There are three advantages using UAS platforms compared to manned aircraft platforms with the same sensor for precision agriculture: (1) smaller ground sample distances, (2) incident light sensors for image calibration, and (3) canopy height models created from structure-from-motion point clouds. These developments hold promise for future data products. In order to better match vendor capabilities with farmer requirements, we classify applications into three general niches: (1) scouting for problems, (2) monitoring to prevent yield losses, and (3) planning crop management operations. The three different niches have different requirements for sensor calibration and have different costs of operation. Planning crop management operations may have the most environmental and economic benefits. However, a USDA Economic Research Report showed that only about 20% of farmers in the USA have adopted variable rate applicators; so, most farmers in the USA may not have the technology to benefit from management plans. In the near-term, monitoring to prevent yield losses from weeds, insects, and diseases may provide the most economic and environmental benefits, but the costs for data acquisition need to be reduced.

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1. Introduction

Agricultural sustainability describes farmer practices and governmental policies that prevent degradation of the environment, maintain farmer and rural livelihoods, and increase agricultural production for the growing global human population (NRC 2010). During the 1980s, precision agriculture evolved from advances in soil sampling, statistics, and computing power, which highlighted the connection between soil variability and crop yield (Robert 2002; Oliver 2013; Franzen and Mulla 2016; Mulla and Khosla 2016). Precision agriculture is defined as a set of farmer practices to achieve agricultural

CONTACT E. Raymond Hunt, Jr. raymond.Hunt@ars.usda.gov USDA ARS Beltsville Agricultural Research Center, Hydrology and Remote Sensing Laboratory, 10300 Baltimore Ave, Bldg 007, Room 104, BARC-West, Beltsville, MD 20705, USA

USDA is an equal opportunity provider and employer sustainability based on the four Rs: right application, right amount, right time, and right place (Fixen 2007; Roberts 2007). Remote sensing was viewed as an important technology for precision agriculture right from the beginning (Robert 1982; according to Mulla and Khosla 2016; Moran, Inoue, and Barnes 1997; Brisco et al. 1998).

Remote sensing from manned aircraft and satellite platforms for agricultural management has been the subject of research for over 60 years (Colwell 1956; Jackson 1984; Pinter et al. 2003). Whereas remotely sensed data from satellites are very important for monitoring agricultural production by governmental agencies (Allen 1990; Doraiswamy et al. 2003; Atzberger 2013), farm-scale applications have not been adopted as widely as expected because of coarse pixel resolutions, infrequent coverage, clouds, and slow delivery of information to users (Jackson 1984; Pinter et al. 2003; Mulla 2013). Unmanned aircraft systems (UAS), also called remotely piloted aircraft, unmanned aerial vehicles, or drones, provide a remote-sensing platform with the characteristics for data acquisition that farm managers have long demanded: small pixel sizes, coverage on demand, and quick delivery of information (Zhang and Kovacs 2012; Mulla 2013; Zhang, Walters, and Kovacs 2014).

There are numerous optimistic reports and speculative white papers on the role of UAS in precision agriculture, which will eventually lead to discouragement in farmers and even slower adoption of promising UAS applications (Freeman and Freeland 2015). Our objective is to generalize the applications for UAS remote sensing into a few niches for precision agriculture in order to highlight differences in costs and benefits for each niche. Many advances in UAS remote sensing were made in rangeland ecosystems (Laliberte and Rango 2009; Laliberte et al. 2010, 2011), which will not be covered here. Little emphasis will be placed on recent advances of aircraft, because the state of the art is rapidly advancing (Pajares 2015; González-Jorge, Martínez-Sánchez, and Bueno 2017). Furthermore, we will not discuss uses of UAS for aerial application of agro-chemicals, which is an important subject in its own right (Lan et al. 2010; Huang et al. 2013; Colomina and Molina 2014). Finally, we describe some recent advances in UAS remote sensing that may lead to better applications in precision agriculture.

1.1. *Precision agriculture overview*

Locally and globally, actual crop yields are significantly less than potential yields, and closing this yield gap will contribute to food security for the world's increasing human population (Anderson 2010; Mueller et al. 2012; van Ittersum et al. 2013; Hatfield and Walthall 2015). Much of the yield gap occurring in wealthier countries is from interactions among the crop genotype (cultivar or variety), environment (including soils and weather), and management (including tillage and fertilization), designated as $G \times E \times M$ (Hatfield and Walthall 2015). For example, crop responses to fertilizer applications are well known, but in the field, differences in soils will affect fertilizer uptake, so yields will vary spatially. Furthermore, poor weather reduces growth and potential yield and thus reduces the amount of fertilizer required for that year (Shanahan et al. 2008). Multiple years of data at multiple locations are required to show the effectiveness and economic returns of a management change on yields and farmer income (Yost et al. 2017).

Uniform crop management based on the field average would apply too much fertilizer on areas in a field where crop yield potential was low and would apply too little fertilizer where crop yield potential is high. In practice, farmers apply fertilizer at rates in excess of requirements for areas in the field with the highest yield potential (Williamson 2011; Oliver 2013). Excess fertilizer enters the ground and surface waters degrading water quality (Banger et al. 2017). Furthermore, excess nitrogen in wet soils is converted by bacteria to nitrous oxide, a greenhouse gas more potent than carbon dioxide (Banger et al. 2017). Today, precision agriculture embraces all agricultural inputs and management options based on site-specific information.

There are three general methods to assess spatial variability within a field: measuring plant growth, measuring soil properties, and measuring yields. Most of this review will focus on using UAS to remotely sense plant growth to determine whether changes in management could increase crop yields to be closer to the yield potential. However, remote sensing does not have a monopoly on providing information required for precision agriculture.

Environmental factors affecting soil formation over long periods of time are used as the basis for soil classification (Buol et al. 2011; Soil Survey Staff 2014; IUSS Working Group WRB 2015); so, digital-elevation and digital-soil data are the starting points for assessing soil variation. For a single field, soil properties such as texture, soil organic matter, and nutrient contents may be assessed by sampling at points selected using geostatistical methods (Oliver 2013; Stoorvogel, Kooistra, and Bouma 2016). Point sampling is laborious, so proximal soil sensing is often used to measure soil properties by technologies such as ground penetrating radar or electrical induction (Corwin 2013; Viscarra Rossel and Adamchuk 2013). Remote sensing with both imaging and non-imaging spectrometers is an important method for assessment of soil variation, particularly variation in soil organic matter content (Barnes et al. 2003; Brown 2007; Ben-Dor et al. 2009). Usually, changes of soil properties are continuous over a landscape with few abrupt transitions. To simplify management, variation of soil properties is often used to divide a field into management zones, with different zones receiving inputs tailored for those zones (Corwin 2013).

Historically, plant height was used to measure crop growth, but measurements of plant dry biomass proved to be better (Hunt 1981). Plant biomass is correlated with remotely sensed spectral vegetation indices, because in general, plants with more leaves have more biomass and cover more of the soil surface. Canopy scattering of near-infrared (NIR) radiation is a function of the leaf area index (LAI) and leaf distribution. Canopy absorption of visible radiation is a function of leaf chlorophyll concentration. Spectral vegetation indices, such as the normalized difference vegetation index (NDVI), use the reflected NIR and red radiation to estimate LAI and biomass (Tucker 1979). Plant height provides additional information that complements biomass or spectral vegetation indices for predicting growth and yields (Yin et al. 2011; Freeman et al. 2007; Boomsma et al. 2010). Remote-sensing methods for plant height will increase in importance for precision agriculture, using either lidar or structure-from-motion (SfM) photogrammetry. Therefore, plant height needs to be incorporated into the suite of field measurements made to assess yields.

1.2. *Adoption of precision agriculture technologies*

As discussed in many reviews, the two fundamental technologies for precision agriculture are global navigation satellite systems (GNSS) and yield monitors (Pierce and Nowak 1999; Koch and Khosla 2003; Mulla and Khosla 2016). Maps of crop yields by yield monitors and GNSS are used to estimate yield potential and delineate management zones; so, remote sensing is not essential for implementing precision agriculture. Along with yield monitors, optical sensors in the combine are used to estimate grain protein content while the grain is being harvested (Long, Engel, and Carpenter 2005).

The rate of adoption of precision agriculture technology has been slower than expected (Daberkow and McBride 2003; Adrian, Norwood, and Mask 2005; Isgin et al. 2008; Tey and Brindal 2012; Pierpaoli et al. 2013; Schimmelpfennig 2016). These studies indicate that there are several characteristics which predict implementation of precision farming: farm size (>500 ha), producer age and education (especially familiarity with computers), ownership of the land (owners more likely), perceived costs and benefits, and prior use of farming consultants. The total area of maize and soybean fields managed by any one technology is substantially larger than the number of farms that use the technology (Table 1), providing evidence that large farms are more likely to use some form of precision agriculture. Figure 1Figure 2

There are different adoption rates among the major technologies of precision agriculture (Table 1). About half of farmers have yield monitors, although only about half of those use their yield monitor data to derive yield maps used for management with other technologies. The number of farmers using yield or soil maps is approximately equal to the number that employs variable rate technologies (Table 1). It is the farmers using variable rate technologies that will be able implement recommendations made from UAS remote sensing and other data. Technology adoption rates for other crops are lower than those for maize and soybean, but they are increasing (Schimmelpfennig 2016).

There is an important caveat to Schimmelpfennig's (2016) report; the data were acquired just after a major economic recession, during which it would have been logical for farmers to defer purchasing new machinery. Surveys of agricultural-service dealers by Erickson and Widmar (2015) and Erickson and Lowenberg-DeBoer (2017) reported recent exponential growth for all precision agriculture technologies, including the use of UAS remote sensing. However, the caveat for these recent surveys is that only a small percentage of the surveys sent out were returned (about 10%). It may have been that agricultural-service dealers with better success selling precision agriculture technologies were much more likely to respond to the survey compared to the non-responders.

Table 1. Overall adoption of precision agriculture technologies from Schimmelpfennig (2016).

	Maize (2010)		Soybean (2012)	
Technology	Proportion of farms (%)	Proportion of area (%)	Proportion of farms (%)	Proportion of area (%)
Yield monitor	48	70	51	69
Yield map	25	44	21	40
Soil map	19	31	16	28
Guidance system	29	54	34	53
Variable rate technology	19	28	26	34

The different data sources from all the precision-agriculture technologies are integrated into geographic information systems (GIS), particularly for interpolating point data by geostatistical methods (van der Meer 2012). One of the current trends is to merge GIS with decision support systems, which would show how optimal crop and environmental management could be achieved spatially (Khot et al. 2016; Lindblom et al. 2017; Banger et al. 2017).

Many UAS vendors advertise high returns on investment for precision nitrogen management, but critical information was not provided to evaluate their claims. Specifically, were the high returns on investments from 'best practices of precision agriculture with UAS' *versus* 'best practices of precision agriculture without UAS'? Or rather, were the high returns from 'precision agriculture with UAS' *versus* 'no precision agriculture'? We found two instances where it was the latter. Also, were multiple years of data, multiple locations, multiple management systems, and multiple genotypes compared to account for $G \times E \times M$ interactions? Initially, research with UAS for precision agriculture was simple, is it possible? Now that this question was answered affirmatively, the difficult question is will the technology result in economic and environmental benefits to increase agricultural sustainability.

1.3. *Remote sensing from satellites and manned aircraft*

The important advantage of remotely sensed imagery, from any source, is knowledge about the state of growing crop at the time the data were acquired. However, remote sensing doesn't show what needs to be done; without interpretation or analysis, the images are fascinating pictures. Aerial true-colour and colour-infrared photography are well established for locating nitrogen stress (Blackmer and Schepers 1996; Blackmer et al. 1996) and other agricultural problems. Comparison of aerial photographs with respect to photographs of well-fertilized fields allow calculation of the economic optimum nitrogen rate of fertilization (Scharf and Lory 2002; Scharf, Wiebold, and Lory 2002; Sripada et al. 2006; Sripada et al. 2007; Kyveryga, Blackmer, and Pearson 2012). Furthermore, aerial photography may be used to guide efficient field sampling for fertilization recommendations (Kyveryga et al. 2011; Kyveryga, Blackmer, and Pearson 2012).

Aerial photographs have high spatial resolution but poor spectral resolution with only three bands. Imaging spectrometers (also called hyperspectral sensors) have a hundred or more contiguous bands for deriving a pixel's reflectance spectrum, which may be used to identify plant biochemical composition (Asner and Martin 2016a, 2016b). The new generation of high-spatial-resolution satellites include a red-edge band specifically for agriculture. Basso et al. (2016) used rapid-eye data to determine in-season nitrogen rates for wheat already stratified into management zones (Basso et al. 2013).

Adrian, Norwood, and Mask (2005) reported that only 9% of producers in their survey used remote sensing and that 73% do not plan to use remote sensing. Isgin et al. (2008) reports a similar number, only 5% of the producers used remote-sensing data for their operations. These two studies were published just as the high-spatial-resolution satellites were being launched. However, airborne remote-sensing data were available, and the low rates of adoption may indicate farmer dissatisfaction with either the data products they received (e.g. NDVI maps) or the cost for data acquisition. If farmers were dissatisfied with the data, then farmers may not be willing to adopt UAS data until there is a significant body of evidence showing good returns on investment.

1.4. *Proximal and ground-based remote sensing*

One of the main advances in precision nutrient management was the development of active proximal sensors, also called 'on-the-go sensors' (Raun et al. 2002; Adamchuk et al. 2004; Miao et al. 2007; Shanahan et al. 2008; Barker and Sawyer 2010; Barker and Sawyer 2012). The basic procedure starts with light emitting diodes at different wavelengths to illuminate the canopy, and sensors measure the reflected light (Holland, Lamb, and Schepers 2012). Spectral indices from the sensors are calibrated with a well-fertilized crop reference strips. Active proximal sensors mounted on the front of variable rate applicators are used to control the amount of fertilizer applied (Solari et al. 2010; Franzen et al. 2016). Evaluations of active proximal sensors show that in most cases, there are both economic and environmental benefits (Li et al. 2009; Kitchen et al. 2010; Roberts et al. 2010; Scharf et al. 2011; van Evert et al. 2012; Diacono, Rubino, and Montemurro 2013).

Besides active proximal sensors, there are two more alternatives for on-the-go sensing: measuring reflected solar radiation with passive sensors and measuring chlorophyll fluorescence (Samborski, Tremblay, and Fallon 2009; Tremblay et al. 2009; Tremblay, Fallon, and Ziadi 2011; Tremblay, Wang, and Cerovic 2012). Both alternatives could be mounted either on variable rate applicators or on a UAS (Zarco-Tejeda et al. 2012).

With the small fraction of farmers adopting variable rate technology (Table 1), the important question is how many of these adopters currently use yield maps, soil maps, or active proximal sensors to determine spatially varying nutrient rates? Based on the percentages (Table 1), adopters of variable rate technologies currently have some method (or methods) for determining nutrient recommendations. Therefore, there may be little demand by farmers for nutrient recommendations from UAS, unless the recommendations are more accurate and have lower costs over multiple years.

1.5. *Future technologies for precision agriculture*

Because precision agriculture is technology driven, it is possible that newer technologies will be adopted in lieu of UAS remote sensing, particularly for water and nutrient management. The first promising technology is autonomous ground-based robots (Zermas et al. 2015; Han, Steward, and Tang 2016; Bechar and Vigneault 2016; Bechar and Vigneault 2017; Bonadies, Lefcourt, and Gadsden 2016). These robots travel along the rows based on GNSS position, acquire imagery of leaves from below, and use computer vision with well-established symptoms of nutrient deficiencies to identify the specific nutrient limiting growth (Zermas et al. 2015). Currently, the main limitation to these robots is low detection accuracy (Bechar and Vigneault 2016; Bechar and Vigneault 2017). The second promising technology is installation of wireless sensor networks (Dong, Vuran, and Irmak 2013; Aqeel-ur-Rehman et al. 2014; Anisi, Abdul-Salaam, and Abdullah 2015; Ndzi et al. 2014; Ojha, Misra, and Raghuwanshi 2015). Capacitance sensors may be buried in the soil to sense soil water content directly for irrigation scheduling. The primary limitation to wireless networks is supplying power to the network of sensors.

2. UAS remote sensing in precision agriculture

In the early 1980s, a number of groups published their research on photography from remotely piloted vehicles in remote-sensing journals (e.g. Wester- Ebbinghaus 1980; Tomlins and Lee 1983). Analysis of data from Landsats 1, 2, and 3 had already demonstrated various problems of using satellite data for crop management; so, Jackson and Youngblood (1983) and Youngblood and Jackson (1983) put forward a serious proposal to build a dedicated unmanned high-altitude powered platform (HAPP) for agricultural remote sensing. The NASA Pathfinder UAS used by Herwitz et al. (2004) and Johnson et al. (2004) was based on the HAPP design proposed two decades earlier. Other studies examined a wide variety of unmanned platforms: helium-filled blimps (Inoue, Morinaga, and Tomita 2000), a fixed-wing model aircraft (Quilter and Anderson 2000), small radio-controlled helicopters (Hongoh, Kajiwara, and Honda 2001), and powered parachutes (Moran et al. 2001). In summary, scientists have long recognized the potential contributions UAS could make to agricultural remote sensing.

The current emphasis on UAS and precision agriculture came from corporations that worked with military UAS and were looking to expand with civilian applications. The Association of Unmanned Vehicle Systems International released a very influential report on the economic impact of civilian UAS in the USA (Jenkins and Vasigh 2013). They concluded that precision agriculture would be the economic sector that would drive explosive growth of the domestic UAS market. To their credit, Jenkins and Vasigh (2013) were very transparent on how their numbers were calculated; so, it was easy to conclude that their growth estimates of agricultural UAS were very optimistic. The slew of economic reports that followed were considerably less transparent, and therefore harder to assess objectively.

The sensors used for agricultural remote sensing with UAS are based on sensors available for manned aircraft but are smaller in size. Data analyses follow the same procedures long used in remote sensing, notably calculation of NDVI or other spectral indices. However, there are three important exceptions that take advantage of low altitudes above ground level during flight. The first is the acquisition of images with very small ground sample distances. The second is having up-looking sensors for instantaneous calibration to reflectances. The third is construction of SfM point clouds, which provide high-resolution canopy height models.

2.1. *Available sensors for remote sensing*

2.1.1. *Digital cameras*

The difference between multispectral sensors and digital cameras is primarily how the spectral bands are created. Digital cameras have a colour filter array (such as a Bayer pattern) covering a single silicon chip, each pixel is boxed in by the two other colours of the filter array. For image formation, the raw picture file has to be demosaiced to get the three spectral bands. The camera usually applies various corrections for light sensitivity, white balance, dark pixel noise, and gamma to create an image that is pleasing to human trichromat vision.

It is a simple matter of optics that low-altitude flights with the same camera will have smaller ground sample distances compared to high-altitude flights. Digital cameras used for UAS remote sensing vary substantially in price, lens quality, and features from consumer-oriented point-and-shoot cameras to professional cameras that have a high degree of control over the results (Lelong et al. 2008; Nguy-Robertson et al. 2016; O'Connor, Smith, and James 2017; Crusiol et al. 2017). Lens quality affects the ability to resolve differences between 2 pixels; so, the total number of pixels in a camera is not a good indication that an image will have a small ground sample distance (Candiago et al. 2015).

Camera sensitivity or gain (termed ISO for the International Organization for Standardization) sets the maximum light level corresponding to the camera's maximum digital number (based on its RAW format: 255 for 8 bits per spectral band, 1023 for 10 bits, 4095 for 12 bits, etc.). For cameras with an automatic ISO setting, the ISO is usually set by the shutter speed. A camera's aperture and shutter speed are selected to achieve the exposure value calculated from the measured luminance off of the target. However, luminance sensors are only accurate to ±1/2 or ±1/3 of an exposure value, so accuracy of luminance metres decreases with increasing light level. Furthermore, estimation of surface reflectance requires the illuminance onto the target. Therefore, it is unlikely that a digital camera's luminance sensor may be used for image calibration, especially when exposure and ISO are set automatically.

2.1.2. *Hyperspectral and multispectral sensors*

Multispectral sensors typically have bands that cover large wavelength ranges (50–100 nm wide), where hyperspectral bands have contiguous bands that cover narrow wavelength intervals (10–20 nm wide). More and more, multispectral sensors have bands with narrow wavelength ranges for more accurate estimates of vegetation amount (Elvidge and Chen 1995). There is no disadvantage to using narrowband multispectral sensors in UAS compared to hyperspectral sensors if it is known in advance that specific spectral bands are required (i.e. the red edge). However, having too many spectral bands (literal definition of hyperspectral) is better than not enough when the band wavelengths are not known *a priori*.

Hyperspectral and many narrowband multispectral sensors have bands at the red-edge of the chlorophyll-*a* absorption spectra (from 710 to 740 nm) for detection of chlorophyll content. Before atmospheric correction to surface reflectance became routine in remote sensing, the wavelength position of the red-edge was one of the better estimates of chlorophyll content (Horler, Dockray, and Barber 1983). Surface reflectances at the red edge are combined with red and NIR reflectances to form indices that are strongly correlated to chlorophyll content (Daughtry et al. 2000; Gitelson et al. 2005; Haboudane et al. 2008; Fitzgerald, Rodriguez, and O'Leary 2010; Li et al. 2014).

Spectral vegetation indices have been important since the launch of Landsat 1 (Tucker 1979), and NDVI has been among the better indices time and time again. Indices are affected by amount of vegetation, positions of the Sun and sensor in relation to the target (i.e. bidirectional reflectance distribution function), spectral transmittance of the atmosphere, contents of chlorophyll and other leaf pigments, reflectance of the soil or ground cover, and other factors. As a result, most spectral vegetation indices are correlated (Gnyp et al. 2014; Liu, Zhu, and Wang 2017), but the sensitivities of the indices to the above factors are different, which led to the development of combined spectral indices (Daughtry et al. 2000; Haboudane et al. 2008). With powerful simulation tools, such as the PROSAIL canopy radiative transfer model (Jacquemoud et al. 2009), new indices may be created as hypotheses, which are then evaluated with experimental data (Eitel et al. 2008, 2009).

Instead of relying on general vegetation indices, hyperspectral sensors are used more and more to measure physiological processes such as photosynthesis. The photochemical reflectance index (PRI) uses narrowbands at two green wavelengths (531 and 570 nm) to track changes in leaf xanthophyll pigments in direct response to changes in photosynthetic rate (Sims and Gamon 2002; Inoue and Peñuelas 2006; Garbulsky et al. 2011; Zarco-Tejada, González-Dugo, and Berni 2012; Magney et al. 2016; Zhang et al. 2016). Other leaf parameters may be retrieved by inverting the PROSAIL model, which estimates unknown model inputs from measured model outputs (Zarco-Tejada et al. 2013; Duan et al. 2014).

2.1.3. *Thermal and multiple sensors*

Thermal sensors are either accurate and expensive or inaccurate and inexpensive; so, there are considerably fewer papers in the literature on thermal remote sensing in agriculture, compared to the fraction of agricultural land that is irrigated. There are two related goals for thermal remote sensing: (a) detect spatial variability of insipient water stress, and (b) manage irrigation more effectively. When crops have sufficient water, the rate of transpiration is high, and the foliar temperature is low to balance the energy fluxes in and out of a plant canopy. With water stress, the rate of transpiration decreases, and the foliar temperature becomes higher to maintain energy balance. The objective is to map the spatial variability of transpiration and water stress, which may be related to topography and the spatial variability of soils. Micrometeorological data are required to calculate the actual amount of water for irrigation.

Thermal sensor readings include a mixture of canopy, shadow, and bare soil. By comparing the canopy temperature to that of well-watered crops, the amount of water stress may be calculated (Jackson et al. 1981; Jackson, Kustas, and Choudhury 1988). To correct for differences in the amount of vegetation cover, a relationship between spectral vegetation indices and canopy temperatures is established empirically (Moran et al. 1994). These methods continue to be highly effective for determining the amount of water stress (Cohen et al. 2017).

Changes in canopy temperature with respect to water stress are large in environments where there is high solar irradiance and low atmospheric humidity (Gonzalez-Dugo et al. 2013; Gonzalez-Dugo et al. 2015) and may be small in subtropical environments with high humidity (Sullivan et al. 2007; Thomson et al. 2012). A promising trend for detection of water stress is to use several sensors, combining canopy temperature, fluorescence, and PRI (Berni et al. 2009a; 2009b; Zarco-Tejeda et al. 2012; Gago et al. 2015).

2.2. *Small ground sample distances*

One of the characteristics of satellite and airborne imagery is the large ground sample distance between two pixels; so, each pixel will contain several components (soil, leaves, residue, shadow), i.e. a mixed pixel with several spectral end-members. Over a given area, the relative frequencies of end-members in pixels tend towards an average, and thus, the spectral reflectance of these pixels becomes representative for a land-cover class. With smaller ground sample distances, pixel-to-pixel variation (texture) increases, providing another source of information for image classification (Blaschke 2010) – object-based image analysis (OBIA). The goal of OBIA is to segment an image into clusters of similar pixels (i.e. objects) based on reflectances and texture (Liu and Xia 2010; Kim et al. 2011; Peña-Barragán et al. 2011; Laliberte et al. 2012). Currently, the drawback of OBIA is that the classifications are scale dependent and require extensive user interventions (Liu and Xia 2010; Kim et al. 2011; Gao, Xu, and Li 2015).

One of the biggest advantages of small ground sample distances for precision agriculture is that the soil and shadow between the rows of a crop may be identified using OBIA (Mathews 2014). During a nitrogen-application experiment in potato (Hunt et al. 2017), the initial response to nitrogen deficiency was a slower growth rate, leaving more bare soil and shadow between rows (Figure 1). NDVI within the rows was not significantly different among treatments, whereas NDVI of the whole plot was lower because there was a less vegetation cover.

With smaller ground sample distances, 0.5–2.5 cm, fractions of vegetation cover are calculated by counting pixels (Hunt et al. 2014; Torres-Sánchez et al. 2014; Fang et al. 2016; Yun et al. 2016). Pixel counting is effective for determining plant germination rates for different cultivars and varieties (Gnädinger and Schmidhalter 2017; Jin et al. 2017). Pure leaf pixels may be selected for calculation of chlorophyll indices to enhance

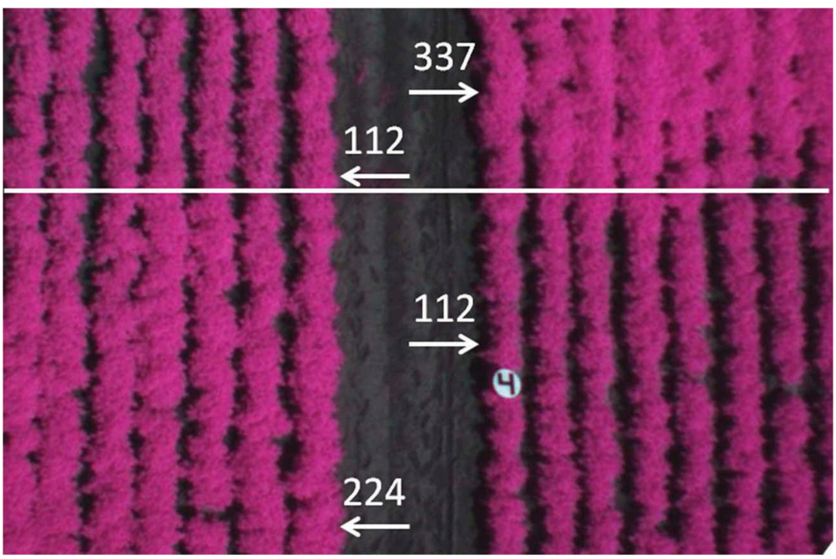

Figure 1. Colour-infrared photograph of a N-fertilization experiment in potato on 22 June 2013 at the Hermiston Agricultural Research and Extension Center, Oregon State University (45.8141° N, 119.2863° W). The ground dimensions of the image are 10 m by 16 m; the top of the photograph points north. The numbers show the amount of N fertilizer (kg ha^{-1}) applied (Hunt et al. 2017). Within the rows, there were no differences in NDVI. The differences were the amount of shadow and bare soil between rows.

sensitivity to leaf chlorophyll concentration and reduce sensitivity to LAI and vegetation cover (Hunt et al. 2014).

Another term for small ground sample distances is very-large-scale resolution, from the map scale of the image (1:100 is a larger map scale than 1:25,000). Remote sensing from light sport aircraft developed faster than UAS, in part because they have pilots and can carry heavier payloads (Booth and Cox 2008, 2011). One of Booth and Cox (2008, 2011) innovations was employing two or three cameras with lenses of different focal lengths, for nested sampling with the very-large-scale photograph situated within a large-scale photograph, which was situated within a small-scale photograph. Photographs acquired from flight transects over large areas were used to document the sparse cover of invasive species (Blumenthal et al. 2007; Booth, Cox, and Teel 2010) with much higher accuracies than advanced hyperspectral sensors such as the Advanced Visible Infrared Imaging Spectrometer (Hunt et al. 2007).

2.3. *Sensor and atmospheric correction*

Physical and biochemical properties of plants and soils may be estimated from spectral reflectances by inverting radiative transfer models (Jacquemoud et al. 2009; Duan et al. 2014; Verger et al. 2014). Calibrating sensor output to reflectance is a necessary step for inversion. The problem is second-to-second variations in atmospheric transmittance occur because of invisible clouds occurring in what appears to be a clear sky. Changes in the atmospheric transmittance will affect the measured radiances from the ground; so, changes in digital values are not representative of changes in spectral reflectance. Flights could be made only on extremely clear days, which would negate a major advantage for UAS.

The most common method for camera and multispectral sensor calibration uses targets of known reflectance to generate an empirical linear relationship between sensor values and spectral reflectances (Hunt et al. 2005, 2010; Hruska et al. 2012; Wang and Myint 2015; Yun et al. 2016; Crusiol et al. 2017). When ground-sample distances are small, the total area covered in a single image is also small (or very distorted from wide-angle lenses); therefore, numerous targets with known reflectances must be distributed throughout the field in order to calibrate each image with its own empirical line.

When there are few calibration targets available, spectral vegetation indices based on ratios or normalized differences become essential, because much of the second-to-second variation in atmospheric transmittance affects all spectral bands proportionally. Therefore, an empirical calibration line between measured and sensor index values is effective (Hunt et al. 2005, 2010; Hunt and Rondon 2017), with two important caveats: the spectral distribution of solar radiation is constant; and there are no changes in sensor settings.

One of the recent innovations in UAS sensor technology was the addition of up-looking or incident-light sensors for atmospheric correction. The important advantage of up-looking light sensors is that the second-by-second variation in incident light levels will be measured directly. When flying at low altitudes, radiances measured by down- and up-looking sensors will be close to those measured on the ground. For example, at 150 m (≈500 ft) above mean sea level, only 2% of the atmosphere is below the down-looking sensor. At higher altitudes, say 1500 m (≈5000 ft) above mean sea level, about 17% of the atmosphere is below the down-looking sensor and 83% of the atmosphere is above the up-looking sensor. Higher UAS flight altitudes above ground level will have shorter path lengths through the atmosphere to the incident light sensor, and longer path lengths to the nadir-looking sensor, changing the measured reflectance. Changes in the cosine of the incidence angle with respect to the Sun caused by tilting the aircraft will affect irradiance measured by the up-looking sensor. Furthermore, the path length through the atmosphere from the ground to the down-looking sensor will also change. The measured reflectance will then differ due to aircraft tilt. Therefore, up-looking, incident-light sensors are most useful for direct calibration of camera and multispectral sensors for level flight at low altitudes above ground level. For higher altitudes and aircraft tilt, variation in incident light will need to be estimated from the images themselves using atmospheric models such as MODTRAN (Berk et al. 1998) or 6S (Vermote et al. 1997).

2.4. *Plant height and SfM photogrammetry*

Digital orthomosaic images are a standard data product derived from aerial photography. Ground control points (GCPs) were identified where imagery overlapped and the images were rotated and warped to get the best agreement between predicted and measured GCP location. From the field of computer vision, Lowe (2004) invented the Scale-Invariant Feature Transform (SIFT) to identify the unique points on two images that could be matched. Then, Snavely, Seitz, and Szeliski (2008) developed the SfM algorithm to derive point clouds where the images overlapped. When SIFT and SfM were incorporated into commercially available photogrammetric software, these algorithms became the preferred method for creating accurate orthomosaics from UAS imagery (Turner, Lucieer, and Watson 2012; Turner, Lucieer, and Wallace 2014; Harwin and Lucieer 2012; Westoby et al. 2012; Mathews and Jensen 2013).

One of the important intermediate products created during the orthomosaicing process is a digital surface elevation model. An important insight was that the difference between digital surface and actual ground elevation models is crop height and that the heights are relatively accurate because of the small ground sample distances (Bendig, Bolten, and Bareth 2013; Bendig et al. 2014; Bendig et al. 2015; Aasen et al. 2015; Torres-Sánchez, López-Granados, and Peña 2015; Brocks, Bendig, and Bareth 2016). As discussed above, crop height is an independent measure of crop growth (Section 1.1). The expression of a cultivar's genotype and environment interactions ($G \times E$) is the plant phenotype, and SfM photogrammetry is used with a suite of spectral measurements to document phenotype in the field (White et al. 2012; Sankaran et al. 2015). The high utility of automated concurrent measurements of plant growth and spectral reflectances was also incorporated into proximal sensors for high-throughput plant phenotyping (Andrade-Sanchez et al. 2014; Zaman-Allah et al. 2015).

3. Niches of UAS remote sensing for precision agriculture

Frequently in trade journals, white papers, and sales presentations on UAS in precision agriculture, we find confusion about the different types of remote sensing, different types of UAS, and the different types of precision agriculture. To clarify the situation, we suggest that there are three niches of UAS remote-sensing applications based on objectives and costs: scouting for problems, monitoring to prevent yield losses, and planning crop management operations. Using nutrient management as an example, 'scouting' checks to see whether a specific area has a nutrient deficiency, 'monitoring' systematically searches for areas that may need more nutrients, and 'planning' determines the economically optimal fertilization rates for variable rate application.

3.1. *'Scouting' for problems*

The first niche employs UAS for scouting by farmers or crop consultants (Table 2). Real-time video feeds are used to search fields for actual problems. When problems are encountered, the location may be recorded for ground verification. Scouting is not designed to be comprehensive or statistically valid; so, the steps required for producing high-quality data products from the UAS are not required (Table 2). Most likely, the UAS would be flown high above a field looking for problem areas, and then, the UAS would descend for closer inspection.

Frequently, the flights are planned to check areas in the field where problems were found in previous years. One problem in agricultural fields that occur annually is low-lying areas of the field become flooded from spring rains. As the result of flooding, seedlings may be killed or applied nitrogen may be lost. It is important to replant or re-fertilize these areas, because if a drought occurs later in the summer, these low-lying areas may have much higher yields compared to the rest of the field.

The economic and environmental benefits of scouting by UAS are marginal when compared to crop scouting on the ground only. On one hand, more area is effectively covered by a scout with a UAS. On the other hand, insect pests, weeds, and diseases may be missed completely, creating false impressions that there are no problems.

3.2. *'Monitoring' to prevent yield losses*

Monitoring with UAS provides early warning that will aid management because less area may require treatment and further yield losses are prevented. For monitoring to be

Table 2. Three niches of UAS remote sensing for precision agriculture.

Characteristic	Scouting	Monitoring	Planning
Sensors	Camera (visible, CIR, thermal)	Multispectral	Multispectral, hyperspectral
Sensor calibration	Not required	Up-looking sensor	Rigorous
Area covered	Specific locations	Whole field	Whole field
Output	GNSS tagged photographs	GIS map of field	Decision support model
Spatial accuracy	Low	Medium	High
Orthomosaicing required	No	Depends on data product	Yes
Timing	Immediate	About 1–2 days	About 3 days to 3 months
Cost	Low	Medium	High
Economic benefits	Marginal	Depends on action taken	Economically optimum rates
Environmental benefits	Marginal	Depends on action taken	Most reduction of agro-chemicals
Applications	Check locations in fields that may have problems	Yield potential, occurrence of weeds, pests, and diseases	Variable rate application

profitable for farmers in most cases, the cost of UAS data acquisition and analysis must be low.

From our observations of UAS operations by several commercial and non-profit governmental organizations, the output delivered to the farmer was a high-quality colour-coded NDVI image. The image is orthorectified using photogrammetric SfM algorithms requiring numerous flight-lines of the UAS over the same area. Usually, calibration is performed to insure that any changes in NDVI from one date to another are due to changes of the crop and not from changes of solar illumination and atmospheric conditions. In total, the costs of this type of UAS monitoring are higher than necessary for monitoring.

A key principle of precision farming is that the variation within the field serves as the basis for crop management. Early studies in precision farming collected samples at different points in the field and then used a geostatistical analysis to obtain a continuous data layer. This same sampling paradigm may be applied to analysis of UAS data. Statistically, each image acquired by the UAS may be treated as a single point along a transect (Karl 2010; Karl, Duniway, and Schrader 2012). The location of the centre point on the ground may be calculated from an inertial motion unit and GNSS. The mean or some other statistical value is calculated from the whole image and then is used as a single point in a GIS data layer. The final output is a GIS map delivered to a farmer, not an orthomosaic image. Unmanned aircraft cover much more area with non-overlapping flight lines and the time and effort of orthorectification are avoided. Of course, line-point transects will not be appropriate if the desired crop information is calculated from SfM canopy heights.

There are several differences between monitoring and scouting (Table 2); principally, monitoring examines changes over time so sensors need to be calibrated. The GNSS location for monitoring needs to be more accurate, since there may be minimal checking of problems on the ground. Using a typical multispectral sensor (6 mm lens focal length) at 60 m above ground level, the field of view of one image is about 40 m by 30 m, or about the area of one Landsat 8 Operational Land Imager pixel. Because this image may represent one point along a transect, the spatial accuracy required is about the same as a medium-resolution satellite pixel (Table 2).

The economic and environmental benefits of monitoring depend on what was found, when it was found, and what needed to be done. If the problem was ubiquitous, then uniform applications may be made over the field for no net environmental benefits. However, if a problem was found early, then large yield losses could be prevented, leading to an economic benefit. Multispectral sensors are suggested as the appropriate sensor for monitoring, because red-edge channels are very sensitive for distinguishing areas of low foliar chlorophyll content.

3.3. *'Planning' crop management operations*

Sustainable crop management is the goal for precision agriculture, and data are required for determining management operations, i.e. the four Rs. Acquiring data for planning are probably the role most people envisage when they think of UAS remote sensing for precision agriculture. Planning is required to determine economically optimum rates of nutrient application, which has the most potential for increasing farmer profits and providing the most environmental benefits (Table 2). However, using UAS for planning has the highest costs for data acquisition and analysis (Table 2).

There are several time horizons for which planning is desirable. Quick turnaround from data acquisition to crop recommendations is required for many data products, although the amount and complexity of the data may require several days for analysis (Table 2). Alternatively, planning may be for the next growing season, allowing months for data acquisition and analysis.

Comparisons of UAS remote sensing, maps from yield monitors, and proximal sensors for planning nutrient prescriptions have not been done with any rigour over multiple years. One important point in favour of UAS is that the initial cost may be high for a single task, e.g. nutrient management, but the same UAS could be used for multiple tasks.

There is much more to precision agriculture than nutrient management, such as spraying for insects, diseases, or weeds. A reduction in the amount of pesticides applied is a direct environmental benefit and the cost savings help the farmers' income. On-the-go sensors are also being developed for patch spraying of herbicides (Peteinatos et al. 2014); so just as with nutrient management, alternative technologies create a ceiling on prices for UAS services. If UAS are adopted by farmers for detection of insects, diseases, and weeds, then the UAS will be available for other roles like nutrient management.

3.4. *Costs of UAS operations*

UAS are advertised as low cost based on the initial cost of the platform and sensor. Matese et al. (2015) compared data acquisition by UAS, manned aircraft, and satellites for two field sizes, 5 and 50 ha. Their estimates include time spent image processing by professionals at a rate of €50 per hour. They found that UAS was slightly less costly for the 5 ha field but had significantly greater costs for the 50 ha field (Matese et al. 2015). In the USA, services from UAS providers may cost from \$12 per hectare for raw image files to \$70 per hectare for an orthomosaiced NDVI image.

The costs for remote sensing from manned aircraft range from \$1.20 to \$3.70 per hectare. The costs for satellite data area are low per hectare but have high total cost because commercial providers require a minimum area for coverage. The long waiting time between satellite data acquisition and delivery has been reduced to a few days at most, because of automated computer processing and online data delivery. However, if the information provided by satellite and manned-aircraft imagery were important to the farmer, then these providers should have been seeing increased demand for their services.

Following Matese et al. (2015), the costs for scouting, monitoring, and planning are ranked low, medium, and high, respectively (Table 2), based on the amount of a professional's time that is required for data acquisition and processing. If few farmers use variable rate technologies, there may not be enough demand for planning services using UAS. Therefore, we suggest that the niche of monitoring should be the focus of UAS service providers.

4. Crop monitoring with UAS

Is there potential for savings by reducing agricultural inputs, to offset the costs of using UAS for monitoring? Moreover, is there potential for the savings with UAS to be greater than alternative technologies for precision agriculture? In Table 2, we listed that the costs and benefits of monitoring depend on specific actions taken as the result of UAS remote sensing. Thus, we examine some of the details supporting this assertion.

4.1. *In-season biomass and yield potential*

Making accurate predictions of in-season yield is doable. Based on the current market price for a crop, economics is a consideration for important management decisions. If the market price is low, there may not be sufficient revenue from an increase in yields to cover the costs of monitoring and treatment. Another situation may arise when predicted yields are higher than the original yield goals. The differences would indicate if sufficient amounts of fertilizers applied at the beginning of the growing season remain in the soil to avert nutrient deficiency. However, actual yields will depend on weather conditions after the predictions are made; so at best, in-season predicted yields will have associated probabilities of occurrence based on the weather. Complicating in-season yield predictions is that long-term weather predictions based on past data may have large errors due to climatic change caused by greenhouse gas emissions.

Currently, the most accurate crop models for predicting yields by remote sensing are based on the total absorbed photosynthetically active radiation by the canopy over the growing season multiplied by the radiation use efficiency (Kiniry et al. 1989; Sinclair and Muchow 1999; Doraiswamy et al. 2003; Doraiswamy et al. 2004; Hatfield 2014). The critical remote-sensing input is the seasonal progression of NDVI, or another spectral vegetation index, to estimate the fraction of incident photosynthetically active radiation that is absorbed by the foliage. These crop models lose accuracy with small ground sample distances because of large variation in NDVI for a single plant, from a mixture of leaves, bare soil, and shadow.

SfM photogrammetric point clouds can be used to determine plant height and estimate plant biomass. A significant problem is how to define plant height. For many plants, the apical meristem at top of the main stem is unambiguous. For maize plants, the upper most stalk node at the base of the male tassels marks the final height (Abendroth et al. 2011). But what is the height of a maize plant during earlier vegetative growth stages, during which the apical meristem is hidden within whorls of unexpanded leaves? Relating SfM crop height models directly to ground measurements requires a clear definition of height for a specific crop, and consensus within the agricultural sciences that this height is biologically important. Multiple studies have shown that the fusion of SfM height models with spectral vegetation indices provides complementary information for estimation of biomass (Geipel, Link, and Claupein 2014; Aasen et al. 2015; Bendig et al. 2015; Gevaert et al. 2015; Rischbeck et al. 2016; Matese, Di Gennaro, and Berton 2017; Yue et al. 2017). While we suspect that these methods may be too costly for crop monitoring, they are important for research on interactions between genotype, environment, and management ($G \times E \times M$) for yields to address crop yield gaps.

Remote sensing with NDVI or another spectral vegetation index may be the best method for monitoring crop biomass and potential yields. From the small ground sample distances of UAS data, some of the possible causes for lower NDVI over the season may be determined, such as poor seed germination and seedling establishment.

For some crops such as canola, flower density and duration are critical for estimating yield; so, UAS images acquired during flowering may better estimate yields compared to seasonal changes in NDVI (Sulik and Long 2015). The question is how farmers would use the in-season biomass and potential yield estimates for management. To offset this uncertainty for the farmer, the in-season field maps must be acquired and delivered at the lowest possible cost.

4.2. *Weeds, pests, and diseases*

Both in the environmental sciences and agricultural sciences, invasive and noxious weeds are major ecological and economic problems and were one of the first applications of UAS (Hardin et al. 2007; Rasmussen et al. 2013; Samiappan et al. 2017). Many of the early successes using hyperspectral remote sensing were later shown to be site specific, because landscape variables such as LAI were correlated or were inversely correlated with the occurrence of invasive weeds in rangelands. The small ground-sample distances available from UAS platforms enable human interpreters to visually detect weed occurrence, disease outbreaks, and insect infestations. Furthermore, ground-based proximal sensors are being developed for on-the-go weed sensing and herbicide treatment (Peteinatos et al. 2014).

There are three general problems with remote sensing of weeds, insects, and diseases. The first is the accuracy of identification, which is important for selecting the best treatment. The second is how to monitor a field when locations for outbreaks are spatially random. Lastly, the third problem is how to automate the process in order to analyse hundreds to thousands of images, each covering a small area.

With broad-spectrum herbicides, such as glyphosate, weed identification may not be important; identification is more important if other herbicides (e.g. 2,4-dichlorophenoxyacetic acid) are used. However, to make agriculture more sustainable, multiple strategies from integrated weed management may be used to control weeds (Harker and O'Donovan 2013), and implementation requires much more accurate weed identification. Spatial randomness in outbreak locations generally requires the whole field to be monitored; otherwise, weed infestations that are small and easily treated could be missed. Automation of image processing is essential to reduce costs of using UAS technology.

Most weeds are spectrally similar to crops, but the shapes and locations may be separated using rule-based classifications in OBIA (Peña et al. 2013, 2015; Borra-Serrano et al. 2015; Torres-Sánchez et al. 2015; Mesas-Carrascosa et al. 2015, 2017; López-Granados et al. 2016). Weeds tended to be clustered spatially, so image ground-sample distance had to be small (Peña et al. 2013, 2015; Borra-Serrano et al. 2015). Even though the net effect of patch spraying on weed biomass was negligible compared to uniform spraying, Castaldi et al. (2017) showed that less herbicides were used by patch spraying thereby lowering costs.

Compared to weeds and crops, there is much more spectral contrast between green leaves and leaves infected with various plant diseases (Sankaran et al. 2010; Mahlein et al. 2012, 2013; Zhang et al. 2012a, 2012b; Yuan et al. 2014). Hyperspectral remote sensing and fluorescence are both promising methods for application to UAS.

Integrated pest management (IPM) is a collection of control methods based on the ecological system of insects and their host plants, in order to reduce insect damage to

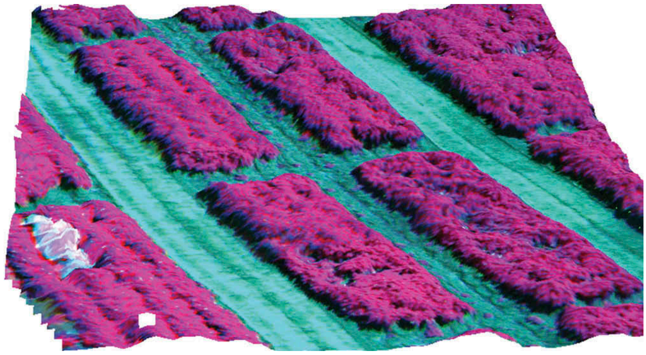

Figure 2. Three-dimensional oblique view created from structure-from-motion photogrammetric point clouds. The experiment was located at the Hermiston Agricultural Research and Extension Center, Hermiston OR (45.8198° N, 119.2841° W). Each plot of potato was 2.6 m wide (three rows) and 9.2 m long; the left side of the image points north. The canopy damage seen in the centre four plots is from Colorado potato beetle larvae (*Leptinotarsa decemlineata*). The day before, there was no visible damage (Hunt and Rondon 2017).

acceptable levels. Early detection and identification of insect pests allow for a greater range of options in IPM, and selection of the options which will provide the lowest cost: benefit ratio (Naranjo, Ellsworth, and Frisvold 2015). On-the-go proximal sensors are being developed for insect pest detection (Nansen 2016). Remote sensing with small ground sample distances seen as an important step for early detection (Yue et al. 2012; Nansen and Elliott 2016; Severtson et al. 2016).

Colorado potato beetles (*Leptinotarsa decemlineata*) are a widely distributed insect species that can rapidly defoliate potatoes and other members of the Solanaceae (e.g. tomatoes). Furthermore, Colorado potato beetles rapidly develop resistance to insecticides, leading to crop failure and spread of resistant populations. Early detection of damage will allow patch spraying or other strategies in IPM preventing exponential population increases over the summer.

Hunt and Rondon (2017) performed experiments to determine how early damage from Colorado potato beetles could be detected using UAS (Figure 2). The answer was on the same day when damage was first visually detected. There was no visible damage on 23 June 2014, and on the next day, damage was evident (Figure 2). Canopy height using SfM point clouds and OBIA feature extraction were effective for estimating the damage, whereas applying thresholds to spectral vegetation indices were not as effective. Estimating damage using canopy heights did not require training data for classification and therefore was more objective. On the other hand, much more effort was required to derive the SfM point clouds.

5. Summary and conclusions

Precision agriculture started out as a set of farmer practices to manage crop fertilization, by using geospatial technologies to reduce excess application, thereby saving money and preventing environmental degradation. UAS are expected to make ideal remote-sensing platforms for precision agriculture, because these platforms provide small ground sample distances, coverage on demand, and fast turnaround of information to the customer. Extensive surveys of farmers in 2010 and 2012 found that about 50% of farmers track yields spatially in a field with yield monitors, but only about 20% spread fertilizer using variable rate applicators. The required geospatial data for variable rate application is mostly met with yield maps, soil maps, and on-the-go sensors. Therefore, the demand for UAS remote sensing to manage fertilizer applications is less than originally proposed.

Whereas the total cost of remote sensing by manned aircraft is high, the marginal cost to fly one more field is small. For UAS remote sensing to be competitive with manned aircraft, research must focus on the advantages of using a UAS platform compared to the same sensor on-board a manned aircraft: small pixel ground sample distances, incident light sensors for atmospheric correction, and acquisition of photogrammetric SfM point clouds for crop height models. These advantages stem from the ability of UAS to fly at much lower altitudes.

We suggest that there are three niches of UAS in precision agriculture: (1) scouting for problems, (2) monitoring to prevent yield loss, and (3) planning crop management operations. Currently, many farmers or farm consultants use UAS for crop scouting; however, monitoring crops for pests, weeds, and diseases may become the most prevalent mode for UAS remote sensing. To make monitoring economically worthwhile for farmers, new methods of analysis are needed to bring down costs. SfM crop height models provide important new information on biomass, but model creation requires numerous overlapping images, which add to the cost of the flight and data analysis. If canopy height is not necessary, then non-overlapping line-point transects, where each image is one point on a transect, may provide the same information on a GIS map at lower cost.

Like all technologically driven enterprises, further advances in technology may render UAS remote-sensing obsolete for precision farming. This thought is disturbing because UAS technology is now available to give farmers the data products they have long been requesting from remote sensing.

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