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Drones: innovative technology for use in precision pest management

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Abstract

Arthropod pest outbreaks are unpredictable and not uniformly distributed within fields. Early outbreak detection and treatment application are inherent to effective pest management, allowing management decisions to be implemented before pests are well-established and crop losses accrue. Pest monitoring is time-consuming and may be hampered by lack of reliable or cost-effective sampling techniques. Thus, we argue that an important research challenge associated with enhanced sustainability of pest management in modern agriculture is developing and promoting improved crop monitoring procedures. Biotic stress, such as herbivory by arthropod pests, elicits physiological defense responses in plants, leading to changes in leaf reflectance. Advanced imaging technologies can detect such changes, and can therefore be used as non-invasive crop monitoring methods. Furthermore, novel methods of treatment precision application are required. Both sensing and actuation technologies can be mounted on equipment moving through fields (e.g. irrigation equipment), on (un)manned driving vehicles, and on small drones. In this review, we focus specifically on use of small unmanned aerial robots, or small drones, in agricultural systems. Acquired and processed canopy reflectance data obtained with sensing drones could potentially be transmitted as a digital map to guide a second type of drone, actuation drones, to deliver solutions to the identified pest hotspots, such as precision-releases of natural enemies and/or precision-sprays of pesticides. We emphasize how sustainable pest

management in 21st century agriculture will depend heavily on novel technologies, and how this trend will lead to a growing need for multi-disciplinary research collaborations between agronomists, ecologists, software programmers, and engineers.

Introduction

Arthropod pest outbreaks in field crops and orchards often show non-uniform spatial distributions. For some pests, such as cabbage aphids [*Brevicoryne brassicae* L. (Hemiptera: Aphididae)] in canola fields (*Brassica* spp.), and Asian citrus psyllids [*Diaphorina citri* Kuwayama (Hemiptera: Liviidae)] in citrus orchards (*Citrus* spp.) there is evidence of highest population densities along field edges (Sétamou and Bartels 2015, Severtson et al. 2015, Nguyen and Nansen 2018). For other pests, such as soybean aphids [*Aphis glycines* Matsumura (Hemiptera: Aphididae)] in soybean (*Glycine max* (L.) Merrill), and two-spotted spider mites [*Tetranychus urticae* Koch (Acari: Tetranychidae)] in cowpea (*Vigna unguiculata* (L.) Walp.), parts of fields that are exposed to abiotic stress, such as drought or nutrient deficiencies, tend to be more susceptible (Mattson and Haack 1987, Abdel-Galil et al. 2007, Walter and DiFonzo 2007, Amtmann et al. 2008, West and Nansen 2014). Thus, as pests are spatially aggregated, precision agriculture technologies can offer important opportunities for integrated pest management (IPM) (Lillesand et al. 2007).

Precision pest management is twofold: first, reflectance-based crop monitoring (using ground-based, airborne, or orbital remote sensing technologies) can be used to identify pest hotspots. Second, precision control systems, such as distributors of natural enemies and pesticide spray rigs, can provide localized solutions. Both technologies can be mounted on equipment moving through fields (such as irrigation equipment), on manned or unmanned vehicles driving around in fields, or on aerial drones.

In this review, we focus specifically on use of small drones in IPM. Small drones are here defined as remotely controlled, unmanned flying robots that weigh more than 250 g but less than 25 kg, including payload (FAA 2018a). These types of drones typically have flight-times of a few minutes to hours and limited ranges (Hardin and Jensen 2011). We will also briefly discuss the larger drones that are typically used for pesticide sprays. Discussion of smaller and larger drones is beyond the scope of this review, but see Watts et al. (2012), and Anderson and Gaston (2013) for more information. Drones used for detection of pest hotspots are here referred to as sensing drones, while drones used for precision distribution of solutions are referred to as actuation drones. Both types of drones could communicate to establish a closed-loop IPM solution (Figure 1). Importantly, use of drones in precision pest management could be cost-effective and reduce harm to the environment. Sensing drones could reduce the time required to scout for pests, while actuation drones could reduce the area where pesticide applications are necessary, and reduce the costs of dispensing natural enemies.

Reports of drones in agriculture started appearing around 1998, and increased dramatically in the last decade (Figure 2). According to the abstract of a licensed report, the worldwide drone market value is currently estimated about $6.8 billion and is anticipated to reach $36.9 billion by 2022 (WinterGreen Research 2016b). Another paid report predicts that drones will reach a value of $14.3 billion by 2028 (Teal Group, 2019). Agricultural small drones currently account for about $500 million, and their value is expected to reach $3.7 billion by 2022 (WinterGreen Research 2016a). A different paid report predicts similar values (ABI Research, 2018), while a freely available resource predicts the value of drone-based solutions for agriculture at $32 billion (PwC 2016). Recently, the United Nations published a report on the use of drones for agriculture, stressing its potential benefits for food security (Sylvester, 2018). A text message poll among ca. 900 growers based in the United States of America (USA) showed that around 30% use drone-based technology for farming practices (Farm Journal Pulse, 2019). Thus, although there is a big margin among predictions of future drone use, an increasing number of growers is expected to use and/or own a drone within the next decade.

There are various ways to classify drones (Watts et al. 2012). For our purpose, we currently distinguish two major types of small drones: rotary wing and fixed wing. Each of these has its own advantages and limitations (Hogan et al. 2017). Multi-rotor and single-rotor (helicopter) drones do not require specific structures for take-off and landing. Moreover, they can hover and perform agile maneuvering, making them suitable for applications (e.g., inspection near crops and orchards or pesticide applications) where precise maneuvering or the ability to maintain a visual of a target for an extended period of time is required. Especially multi-rotor drones tend to be easy to use, and relatively cheap to obtain. Fixed-wing systems are usually faster than rotor-based systems, and generally larger in size, allowing for higher payloads (Stark et al. 2013b, Dalamagkidis 2015). Both have been used for precision agriculture (Barbedo 2019). Since drone technology quickly improves, we will refrain from discussing drone types in further detail, but see Dalamagkidis (2015) and Stark et al. (2013b) for more information.

A number of reviews discuss the use of drones in precision agriculture, focusing on airborne remote sensing for various applications, such as predicting yield and characterizing soil properties (Hardin and Jensen 2011, Prabhakar et al. 2012, Zhang and Kovacs 2012, Mulla 2013, Gago et al. 2015, Nansen and Elliott 2016, Pádua et al. 2017, Hunt and Daughtry 2018, Aasen et al. 2018, Gonzalez et al. 2018, Barbedo 2019, Maes and Steppe 2019). In this review, we focus on precision management of arthropod pests, and describe the use of both sensing and actuation drones. First, we provide an update about airborne remote sensing-based detection of pest problems. Then, we evaluate the possibilities of actuation drones for precision distribution of pesticides and natural enemies. Also, we discuss the possibilities of sensing and actuation drones for novel functions in pest management. Lastly, we discuss challenges and opportunities in the adoption of drone technology in modern agriculture.

Sensing Drones to Monitor Crop Health

Traditional field scouting for pest infestations is often expensive and time consuming (Hodgson et al. 2004, Severtson et al. 2016b, Dara 2019). It may be practically challenging, such as when a large acreage is involved, when the arthropod pests are too small to see with the naked eye, or when they reside in the soil or in tall trees. In some cropping systems, effective scouting is hampered by lack of reliable pest sampling techniques. Hence, one of the main drivers for the implementation of drone-based remote sensing technologies into agriculture is the potential time saved by automatizing crop monitoring, making the technology cost-effective for growers (Carrière et al. 2006, Backoulou et al. 2011a, Dara 2019).

Compared to conventional platforms for remote sensing, such as ground-based, aerial (with manned aircraft) and orbital [with satellites such as Landsat (30 m spatial resolution), Sentinel 2 (10 m) or RapidEye (5 m) (Mulla 2013)], sensing drones present several advantages that make them attractive for use in precision agriculture. Sensing drones potentially allow for coverage of larger areas than ground-based, handheld devices. They can fly at lower altitudes than manned aircraft and orbital systems, increasing images' spatial resolution and reducing the number of mixed pixels (pixels representing reflectance of both plant and soil, discussed in more detail below). Also, they cost less to obtain and deploy than manned aircraft and satellites, and don't have long revisiting times like satellites, allowing for higher monitoring frequencies (Zhang and Kovacs 2012, Mulla 2013, Matese et al. 2015, Aasen and Bolten 2018, Barbedo 2019, Maes and Steppe 2019).

Remote Sensing in Precision Agriculture

Remote sensing is the detection of energy emitted or reflected by various objects, either in the form of acoustical energy or in the form of electromagnetic energy (including ultraviolet (UV) light, visible light, and infrared light) (Usha and Singh 2013). It is a non-invasive, relatively labor-extensive method that could be used to detect plant stress before changes are visible by eye. For crops, remote sensing equipment generally assesses the spectral range of visible light or photosynthetically active radiation (PAR, 400-700 nm) and near-infrared light (NIR, 700-1400 nm), with most studies referring to the 400-1000 nm range (Nansen 2016). Particular stressors, such as arthropod infestations, induce physiological plant responses, causing changes in the plants' ability to perform photosynthesis, which leads to changes in leaf reflectance in parts of this spectral range. For aerial remote sensing, a drone can be equipped with an RGB (red green blue) sensor, a multispectral sensor with between 3 and 12 broad spectral bands, or a hyperspectral sensor with hundreds of narrow spectral bands.

An RGB sensor is low-cost, but results in limited spectral information. A multispectral sensor results in more spectral information, but a hyperspectral sensor is generally much better at differentiating subtle differences in canopy reflectance than a multispectral sensor (Yang et al. 2009a). However, since hyperspectral sensors are generally larger, they would require mounting on drones adapted for heavier payloads. Also, they are generally more expensive, and data analysis requires more time and experience, limiting use for individual growers. A comprehensive review of the sensor types compatible with drones has been written by Aasen et al. (2018).

Remote Sensing and Arthropod Pests

Remote sensing technologies have been used in precision agriculture for the last few decades, with various applications, such as yield predictions and evaluation of crop phenology (Mulla 2013). Also, these techniques are being used to monitor different abiotic plant stressors, such as drought (Gago et al. 2015, Katsoulas et al. 2016, Zhao et al. 2017, Jorge et al. 2019) and nutritional deficiencies (Quemada et al. 2014), and biotic plant stressors, such as pathogens (Calderón et al. 2013, Mahlein et al. 2013, Zarco-Tejada et al. 2018), nematodes (Nutter et al. 2002), and weeds (Rasmussen et al. 2013, Peña et al. 2015). Likewise, remote sensing technologies have been successfully used to detect stress caused by various arthropod pests on a wide variety of field and orchard crops (Riley 1989, Nansen 2016, Nansen and Elliott 2016; Tables 1-4). A limited amount of studies concerning arthropod-induced stress detection used drone-based aerial remote sensing (Table 1), manned aircraft-based aerial remote sensing (Table 2), or orbital remote sensing (Table 3), while most studies used ground-based remote sensing (Table 4).

In these tables, optical sensors are grouped, in addition to the platform they are mounted on, into RGB, multispectral, and hyperspectral sensors. As stated above, generally, multispectral sensors have 3-12 broad spectral bands at selected wavelength ranges, whereas hyperspectral sensors have many (usually >20, but up to several hundreds) narrow, contiguous spectral bands, acquiring the spectrum within the selected spectral region with many measurement points.

However, there is no clear agreed on definition. Therefore, the tables include multispectral sensors acquiring more than 12 spectral bands. While grouping the sensors, we adhered to the authors' classifications (Tables 1-4).

Tables 1-4 focus on detection of arthropod pests; we did not address diseases caused by arthropod vectors (e.g. Garcia-Ruiz et al. 2013). Also, these tables only contain studies related to crops and orchards. We did not address forestry studies, as the body of literature on pest detection involves multi-species forests, adding an additional layer of complexity as opposed to crops and orchards in monoculture. More information about remote sensing in forestry settings can be found elsewhere (Dash et al. 2016, Pádua et al. 2017, Stone and Mohammed 2017, Dash et al. 2018).

It is important to note that with remote sensing, not the pests themselves are detected, but patterns of canopy reflectance that are indicative of arthropod-induced plant stress. Field observations to confirm the presence of specific stressors remain necessary, but field scouting can be more efficiently focused with the *a priori* knowledge from remote sensing.

Analysis of Reflectance Spectra

For the detection of plant stress using remote sensing, the spectral reflectance (the spectral signature or spectrum) of the vegetation is analyzed. Figure 3 shows a spectrum of healthy soybean leaves as recorded by a hyperspectral field spectrometer, together with the same spectrum resampled to the spectral resolution of a hyperspectral imaging spectrometer, and a multispectral sensor for drones. The figure shows the large loss of information between a hyperspectral sensor and a multispectral sensor. With higher spectral resolutions (i.e., more spectral bands), detailed spectral characteristics become visible and can be used to analyze vegetation spectra. This analysis can be done in various ways, e.g. by analyzing spectral reflectance features (e.g. absorption bands or reflectance peaks) that can be directly related to plant physiology, or indirectly by building vegetation indices (VIs). These two techniques are addressed below exemplarily. An overview of techniques to quantify vegetation biophysical variables using imaging spectroscopy is given in Verrelst et al. (2019).

Spectral Features and Vegetation Indices (VIs)

An important spectral feature light region is the red edge, i.e. the slope between the red and near infrared region of the spectrum, around 700 nm. This spectral region relates to the chlorophyll concentration (Horler et al. 1983, Delegido et al. 2011, Huang et al. 2015b) and the Leaf Area Index (LAI). The LAI is defined as the area of green leaves per unit of ground area (Delegido et al. 2013). The red edge position (REP), the point of maximum slope in the red edge region, is a valuable indicator of stress and senescence (Das et al. 2014, Verrelst et al. 2019), possibly because various stresses decrease leaf chlorophyll concentrations (Carter and Knapp 2001). For instance, an increased reflectance around 740 nm is associated with spider mite susceptibility in corn (*Zea mays* L.) (Nansen et al. 2013). Also, the overall reflection level of the spectrum might be characteristic.

It should be noted that a spectrum of an imaging spectrometer, such as those mounted on drones, always describes an area, not a point. This area, or pixel size, depends on the flight height of the drone and can range from less than 1 cm^2 to more than 10 cm^2. With larger pixels, the recorded spectrum consists of reflectance of both the plant and the soil (mixed pixels). This should be considered when analyzing the spectrum. Wherever possible, pixels that represent soil or other types of non-canopy area are excluded from data analysis.

Various vegetation indices (VIs) assist in interpreting remote sensing data (Roberts et al. 2011, Xue & Su 2017, Verrelst et al. 2019). These are mainly ratios between multiple spectral bands (Glenn et al. 2008). An often-used index is the Normalized Difference Vegetation Index (NDVI), which incorporates the ratio of NIR and visible red light. Compared to a healthy plant, an unhealthy plant will generally reflect more visible red(?) light and less NIR light. In farming, the NDVI can be used as a predictor of plant physiological status, as well as potential yield (Peñuelas and Filella 1998). NDVI has its limitations, for example when there is a lot of soil in the background. To solve that issue, other VIs have been developed, such as the Soil Adjusted Vegetation Index (SAVI) (Huete et al. 1988). Where these two indices are broad band indices (i.e., they can be calculated with multispectral data), hyperspectral data allows for narrow band VIs that can more precisely focus on a specific aspect. An example is the Modified Chlorophyll Absorption in Reflectance Index (MCARI), which is defined to be maximally sensitive to chlorophyll content (Daughtry et al. 2000). Xue and Su (2017) provide a review of over 100 VIs for vegetation analysis.

Classification Accuracy

Classification algorithms, which could be based on the red edge and/or VIs, can be developed to group plants based on spectral data by relating field observations to spectral measurements (e.g. “healthy” and “pest-infested” plants). The algorithms can be based on various statistical approaches (Lowe et al. 2017). Classification accuracy is high if data has high robustness or repeatability. Different remote sensing studies report different classification accuracies (Lowe et al. 2017). A recent study with drone-based remote sensing to detect susceptibility against green peach aphid [*Myzus persicae* Sulzer (Hemiptera: Aphididae)] in canola, using a multispectral sensor mounted on an octocopter, a drone with eight rotors, reported a classification accuracy of 69-100%. These values depended on experimental day, drone height above the canopy, and whether or not non-leaf pixels were removed. In this study, aphid infestations happened naturally, and aphids were counted on selected plants for ground verification of infestations (Severtson et al. 2016a). A study involving two-spotted spider mite-induced stress in cotton (*Gossypium* spp.), using a multispectral sensor mounted on a quadcopter, a drone with four rotors, reported a classification accuracy of 74-95%. These values depended on classification methods. Spider mite infestation levels were estimated based on plant damage (Huang et al. 2018). As it is hard to reach 100% accuracy, especially when data are obtained on different days, in most studies, there are certain numbers of false positives (plants are classified as infested while they are healthy) and/or false negatives (plants are classified as healthy while they are infested) (Congalton 1991, Lowe et al. 2017). Nevertheless, multiple robust classifications have been developed to detect pest problems in different agro-ecosystems, which provide good indicators for field scouting (Tables 1-4).

Drones, Remote Sensing, and Arthropod Pests

Everitt and co-authors (2003) provided an overview of the potential use of remote sensing data collected in a manned aircraft for pest management. The authors mapped four different pest-host systems (citrus orchards, cotton crops, forests, and rangelands), and concluded that aerial photography and videography could be used to detect arthropod infestations in both agricultural and natural environments (Everitt et al. 1994, Everitt et al. 1996). With the development of unmanned aircrafts, it has become more affordable and practically feasible to collect aerial remote sensing data. A recent study with drone-based remote sensing to detect crop pests includes stress induced by sugarcane aphid [*Melanaphis sacchari* Zehntner (Hemiptera: Aphididae)] in sorghum (*Sorghum bicolor* (L.) Moench), using a multispectral sensor mounted on a fixed-wing drone. Aphids were counted throughout the growing season for ground verification of infestations, and damage was assessed as coverage with sooty mold, a fungus not infesting the plant, but growing on the aphids' sugary honeydew secretions (Stanton et al. 2017). Colorado potato beetle [*Leptinotarsa decemlineata* Say (Coleoptera: Chrysomelidae)] damage in potato (*Solanum tuberosum* L.) has been assessed using a multispectral sensor mounted on a hexacopter, a drone with six rotors. Plants were infested with different numbers of beetles, and insects were counted and plant damage was visually assessed for ground verification of pest infestations (Hunt and Rondon 2017, Hunt et al. 2016). A study by F. Iost Filho, MSc, Dr. P. Yamamoto, and collaborators at the University of São Paulo, Brazil, is analyzing the effects of stress induced by several arthropod pests in soybean fields, including silverleaf whitefly [*Bemisia tabaci* Gennadius (Hemiptera: Aleyrodidae)], stink bugs (Hemiptera: Pentatomidae), and caterpillars (Lepidoptera: Noctuidae). The system is composed of a drone-based multispectral sensor and a ground-based hyperspectral sensor (Iost Filho 2019) (Table 1). Researchers at the University of Wisconsin, WI, USA are currently using a quadcopter equipped with a multispectral sensor to detect caterpillar damage in cranberry (*Vaccinium macrocarpon* Aiton) (Seely 2018). An ongoing study by Dr. E. de Lange, Dr. C. Nansen and collaborators at the University of California Davis, CA, USA involves detection of stress induced by two-spotted spider mite in strawberry (*Fragaria* × *ananassa* Duchesne), using an octocopter equipped with a hyperspectral sensor (Figure 4). Furthermore, aerial remote sensing can help distinguish between different non-crop plant species. If these plant species were differentially preferred as alternate hosts by important pests, remote sensing could contribute to vegetation management decisions (Sudbrink et al. 2015).

Barbedo (2019) compiled a list of drone-based remote sensing studies for various applications, including detection of pests, pathogens, drought, and nutrient deficiencies. Drones are increasingly used for remote sensing studies, and are particularly cost efficient for inspections of smaller fields (Matese et al. 2015). As technology improves and costs decrease, they may also become more competitive for use in larger fields. Ultimately, usefulness of drone-based remote sensing for detection of pest problems will depend on individual grower needs.

Distinguishing Multiple Stressors with Remote Sensing

Most of the above-mentioned studies are based on a system composed of one arthropod pest species and one specific crop. However, when multiple arthropod pests are present, more advanced methods of data calibration and analysis are necessary. Prabakhar and co-authors (2012) inferred that damage by different pests on the same host plant requires a combination of multiple spectral bands for accurate detection. Indeed, a greenhouse study in wheat (*Triticum aestivum* L.) showed that reflectance data could be used to differentiate between two different pests. Plants were experimentally infested with greenbugs [*Schizaphis graminum* Rondani (Hemiptera: Aphididae)] or Russian wheat aphids [*Diuraphis noxia* Kurdjumov (Hemiptera: Aphididae)], and insects were counted on a regular basis. The authors did mention that additional field studies would be needed, as other stresses could result in similar symptoms as aphid infestations (Yang et al. 2009b). A field study in wheat used reflectance data to differentiate between arthropod [wheat aphid, *Sitobion avenae* Fabricius (Hemiptera: Aphididae)] and pathogen (yellow rust and powdery mildew) infestations. Aphids occurred naturally in the field, and pathogens were inoculated; for all three stressors, damage levels were estimated. Overall classification accuracy was 76% (Yuan et al. 2014). Another field study in wheat used reflectance data to distinguish between arthropod infestations (Russian wheat aphid) and abiotic stresses (drought and agronomic conditions, possibly poor tillage, germination, or fertilization). The different stresses were verified onsite (Backoulou et al. 2011b).

However, laboratory and field studies on cotton plants exposed difficulties distinguishing two arthropod pests, cotton aphid [*Aphis gossypii* Glover (Hemiptera: Aphididae)] and two-spotted spider mite, based on spectral signatures. In these studies, plants were experimentally infested, and insects were counted, or their presence or absence was assessed, over time (Reisig and Godfrey 2007). It also proved difficult to separate nitrogen deficiencies and aphid infestations in cotton field studies. In these studies, aphids were naturally present, and plots were treated with pesticides to increase aphid populations, presumably by killing natural enemies. Aphids were counted throughout the experimental period. Different amounts of nitrogen were applied, which was verified with soil samples and analysis of plant nitrogen uptake (Reisig and Godfrey 2010).

An overview of the few studies on hyperspectral and multispectral sensors to distinguish various biotic and abiotic stressors can be found in Table 5. Spectral indices that accurately predict the presence of various arthropod pests, as well as distinguish arthropod-induced stress from other sources of stress, are required for a large number of crops in order to be widely used in precision agriculture (Mulla 2013).

Actuation Drones for Precision Application of Pesticides

While sensing drones could help detect pest hotspots, actuation drones could help control the pests at these hotspots. Pest hotspots could potentially be managed through variable rate application of pesticides. Aircrafts have been used for decades for pesticide sprays, but products are deposited over large areas, and a large amount is lost to drift (Pimentel 1995, Bird et al. 1996). This is a concern for neighboring terrestrial and aquatic ecosystems, as well as for human health (Damalas 2015). Major factors determining spray drift are droplet size (influenced by nozzle type and product formulation), weather conditions (e.g. wind speed and direction), and application method (e.g. spray height above the canopy) (Hofman and Solseng 2001, Heidary et al. 2014). Empirical and modeling studies showed that spray drift into non-target areas can be considerable (Woods et al. 2001, Sánchez-Bayo et al. 2002, Teske et al. 2002, Tsai et al. 2005, Heidary et al. 2014). Therefore, improved methods of pesticide application are highly needed (Lan et al. 2010), and there is potential for the use of drones in precision application of insecticides and miticides (Costa et al. 2012, Faiçal et al. 2014a, Faiçal et al. 2014b, Faiçal et al. 2016, Faiçal et al. 2017, Brown and Giles 2018). Some of the aspects that give drones a competitive edge over manned crop dusters are their relative ease of deployment, reduction in operator exposure to pesticides, and potential reduction of spray drift (Faiçal et al. 2014b).

Indeed, in Japan, where drones have been used in agriculture since the 1980s, drones are widely used to spray pesticides on rice, *Oryza sativa* L., crops. These drones are mostly heavier than 25 kg, but we discuss them here, as they are among the most widely used drones in pest management. Development of unmanned aerial vehicles for crop dusting started at the Japanese Agriculture, Forestry and Fishery Aviation Association, an external organization of the Japanese Ministry of Agriculture, Forestry and Fisheries. A prototype was completed in 1986 by Yamaha, a Japanese multinational corporation with a wide range of products and services, and the R-50 appeared on the market in 1987: the world's first practical-use unmanned helicopter for pesticide applications, with a payload of 20 kg (Miyahara 1993, Sato 2003, Yamaha 2014a, Xiongkui et al. 2017). A few successors have launched since, with greater payload capacities and simplicity of use (Yamaha 2014b, 2016). In Japan alone, as of March 2016, about 2,800 unmanned helicopters are registered for operation, spraying more than a third of the country's rice fields. The use of unmanned crop dusters has also spread to other crops, such as wheat, oats, and soybean, and the number of crops continues to expand (Yamaha 2016). Japanese unmanned crop dusters are also employed in South Korea (Xiongkui et al. 2017) and are currently being tested for spraying of pesticides in California vineyards (Bloss 2014, Giles and Billing 2015, Gillespie 2015). On a small but increasing scale, unmanned crop dusters are used in China, for crops such as rice, mango, and plantain (Zhou et al. 2013, Tang et al. 2016, Xiongkui et al. 2017, Lan and Cheng 2018, Yang et al. 2018, Zhang et al. 2019). Novel types of unmanned crop dusters and/or novel spray rigs fitting commercially available drones are currently being developed in China (Ru et al. 2011, Xue et al. 2016, Xiongkui et al. 2017), South Korea (Shim et al. 2009), the USA (Huang et al. 2009), Ukraine (Pederi and Cheporniuk 2015, Yun et al. 2017), and Spain (Martinez-Guanter et al. 2019), among other places.

Recently, smaller drone-based crop dusters appeared on the market, such as the DJI AGRAS MG-1S with a 10 kg payload (DJI 2019). A collaboration between Japan's Saga University, Saga Prefectural Government Department of Agriculture, Forestry, and Fisheries, and OPTiM Corporation resulted in AgriDrone, a small drone that can pinpoint pesticide application. Interestingly, AgriDrone is also equipped with an UV bug zapper, recognizing and killing over 50 varieties of nocturnal agricultural pests at nighttime (OPTiM 2016). However, no peer-reviewed literature on this system has appeared since its announcement.

Current research focuses on improved spray coverage, to enable large-scale adoption of drones for application of pesticides (Qin et al. 2016, Wang et al. 2019a, Wang et al. 2019b). In combination with precision monitoring, precision application of pesticides could reduce the overall number of sprays, contributing to reduced pesticide use and decreased development of resistance, as well as increased presence of natural enemies (Midgarden et al. 1997).

Actuation Drones for Precision Releases of Natural Enemies

Biological control is a potential sustainable alternative to pesticide use. It is the use of a population of one organism to decrease the population of another, unwanted, organism (Van Lenteren et al. 2018). Biological control organisms include, but are not limited to, parasitoids, predators, entomopathogenic nematodes, fungi, bacteria, and viruses. A large variety is commercially available. Drones may be a particularly useful tool for augmentative biological control, which relies on the large-scale release of natural enemies for immediate control of pests (Van Lenteren et al. 2018). They could distribute the natural enemies in the exact locations where they are needed, which may increase biocontrol agent efficacy and reduce distribution costs.

Some natural enemies, such as insect-killing fungi and nematodes, can conveniently be applied with conventional spray application equipment (Shah and Pell 2003, Shapiro-Ilan et al. 2012). Therefore, these biocontrol agents could potentially be applied by drones as described above for pesticides (Berner and Chojnacki 2017).

However, application of other natural enemies is often costly and time-consuming. For example, the predatory mite *Phytoseiulus persimilis* Athias-Henriot (Acari: Phytoseiidae), an important natural enemy of the worldwide pest two-spotted spider mite, is available in bottles mixed with the mineral substrate vermiculite, and the recommended way of dispersal is by sprinkling contents onto individual plants (e.g. Koppert 2017a, Biobest 2018). *P. persimilis* has such a high level of specialization that populations succumb when no prey is present (McMurtry and Croft 1997, Çakmak et al. 2006, Gerson and Weintraub 2007, Dara 2014). Various mechanical distribution systems have been developed to facilitate predator dispersal, such as the Mini-Airbug, a hand-held appliance with a fan (Koppert 2017b), as well as other devices (Giles et al. 1995, Casey and Parrella 2005, Opit et al. 2005), but adoption has not been widespread. Growers in Brazil are known to use dispensers attached to motorbikes (Parra 2014, Agronomic Nordeste 2015), but this could potentially damage the crop. Release of natural enemies by aircraft was proposed in the 1980s (Herren et al. 1987, Pickett et al. 1987), but small drones would offer myriad possibilities. Coverage of larger areas compared to manual distribution, reducing application costs per acre, potentially increases the use of natural enemies in favor of pesticide sprays. Development of drone-mounted dispensers has mainly focused on two types of natural enemies: predatory mites such as the above-mentioned *P. persimilis*, and parasitoid wasps such as the egg-parasitoid *Trichogramma* spp. (Hymenoptera: Trichogrammatidae).

To combat two-spotted spider mite, an important pest of a large number of crops worldwide, a California-based company is offering services to distribute predatory mites using drones, on crops such as strawberry (Parabug 2019). An Australia-based company also uses drones to distribute predatory mites on strawberry crops (Drone Agriculture 2018). At the University of Queensland in Australia, a drone-mounted device is being developed to distribute predatory mites in corn (Pearl 2015). At the University of California Davis, Dr. Z. Kong and Dr. C. Nansen, in collaboration with aerospace engineering students, have developed a platform for drone-based distribution of predatory mites, BugBot (Figure 5). They are currently testing the prototype and accompanying software, to optimize natural enemy releases. We propose that collaboration between growers, agricultural scientists, aerospace engineers, and software programmers is key in developing a product that is effective and user-friendly.

Trichogramma spp. parasitoids are important biocontrol agents of European corn borer [*Ostrinia nubilalis* Hübner (Lepidoptera: Crambidae)], a major pest of sweet corn in the USA and Europe (Smith 1996). Various companies and research institutes all over the world have started *Trichogramma* drone applications, including Austria, Germany, France, Italy, and Canada (e.g. Chaussé et al. 2017, Airborne Robotics 2018). Drone-released *Trichogramma* parasitoids are also deployed in China for control of pests in sugarcane (*Saccharum* spp.) (Li et al. 2013, Yang et al. 2018). In Brazil, drone applications of *Trichogramma* spp., as well as the parasitoid *Cotesia flavipes* Cameron (Hymenoptera: Braconidae), are employed to combat the sugarcane borer [*Diatraea saccharalis* Fabricius (Lepidoptera: Crambidae)] in sugarcane. *Trichogramma* spp. are also employed against various other lepidopteran pests in other crops (Parra 2014, Rangel 2016, Xfly Brasil 2017).

While we did not address pest management in forestry settings in this review, a recent report by Martel et al. (2018) deserves to be mentioned, as it is the first to compare drone release and ground release of natural enemies. The report evaluated the efficacy of *Trichogramma* spp. to combat spruce budworm [*Choristoneura fumiferana* Clemens (Lepidoptera: Tortricidae)], an important pest of fir and spruce trees in Canada and the USA. Drone releases, using *Trichogramma*-parasitized host eggs mixed with vermiculite, were compared to ground releases, using commercially available cards containing parasitized eggs of Mediterranean flour moth [*Ephestia kuehniella* Zeller (Lepidoptera: Pyralidae)]. Data were collected in two locations in Quebec, Canada. In one of these locations, drone release resulted in similar spruce budworm egg parasitism rates as ground release of natural enemies. Results for the other location were inconclusive, as egg parasitism rates were negligible. Drone releases were reportedly faster than ground releases of natural enemies. Although more studies are necessary, these preliminary results show the high potential of drone-based *Trichogramma* distribution in forests, especially on small scales, and in conditions under which insecticide applications are not appropriate (Martel et al. 2018). It is important to perform similar studies in field crops and orchards, to evaluate the efficacy of drone-released natural enemies.

Other types of natural enemies can be drone-applied as well, such as green lacewing, [*Chrysoperla* spp. (Neuroptera: Chrysopidae)] and minute pirate bug [*Orius insidiosus* Say (Hemiptera: Anthocoridae)] to control aphids and thrips, and mealybug destroyer [*Cryptolaemus montrouzieri* Mulsant (Coleoptera: Coccinellidae)] to control mealybugs (Parabug 2019). Researchers at the University of Southern Denmark, in collaboration with Aarhus University, are currently developing a dispensing mechanism for ladybirds and other important natural enemies of aphids (SDU 2018). EWH BioProduction, a producer of beneficial organisms (EWH BioProduction 2019), is also involved in this EcoDrone project, as well as Ecobotix, a company offering drone-based services, which is developing a separate solution for dispensing natural enemies (Ecobotix 2018). Drone-based dispensers could be adapted or newly developed for other types of beneficial arthropods as well.

Thus far, little to no peer-reviewed research exists on the efficacy of these operations. Therefore, this is a call for additional research. It is of utmost importance to verify that natural enemies distributed by drones are not damaged during transport and distribution and are still effective as biological control agents. Also, it is necessary to develop hardware and software mechanisms that can precisely distribute the natural enemies in different weather conditions, particularly considering that wind is a crucial factor for the distribution. Individual drone-mounted dispensers all use different technologies, which could be compared to optimize natural enemy distribution. This could pave the way for larger-scale operations of this promising resource.

Novel Uses for Drones in Precision Pest Management

Pest Outbreak Prevention

Sensing and actuation drones could potentially contribute to the prevention of pest outbreaks. Plants exposed to abiotic stresses, such as drought and nutrient deficiencies, are often more susceptible to biotic stressors. This holds true for a large variety of arthropod pests, such as spider mites (Garman and Kennedy 1949, Rodriguez and Neiswander 1949, Rodriguez 1951, Perring et al. 1986, Stiefel et al. 1992, Machado et al. 2000, Abdel-Galil et al. 2007, Chen et al. 2007, Nansen et al. 2013, Ximénez-Embún et al. 2017), aphids (Myers and Gratton 2006, Walter and Difonzo 2007, Lacoste et al. 2015), and lepidopteran larvae (Gutbrodt et al. 2011, Gutbrodt et al. 2012, Grinnan et al. 2013, Weldegergis et al. 2015). Due to this well-established association between abiotic stressors and risk of arthropod pest outbreaks, it may be argued that precision application of abiotic stress relief, such as application of water and fertilizer, represents a meaningful approach to reducing the risk of outbreaks by some arthropod pests (Nansen et al. 2013, West and Nansen 2014). Indeed, pest management focus could shift from being based mainly on responsive insecticide applications to a more preventative approach in which maintaining crop health is the main focus (Culliney and Pimentel 1986, Altieri and Nicholls 2003, Zehnder et al. 2007, Amtmann et al. 2008, West and Nansen 2014). Use of sensing and actuation drones could contribute to this shift, by assessing plant stress status, and preventative applications of water and fertilizers. To the best of our knowledge, drones have thus far not been deployed for precision irrigation purposes, and although drones are on the market that advertise the capacity to apply liquid or granular fertilizers, there is no peer-reviewed literature on their use. Many current spray tractors contain options for variable rate applications of nutrients, for an adequate response to deficiencies detected with remote sensing (Raun et al. 2002). However, there would be myriad opportunities for use of drones in this respect, due to their maneuverability and capacity to treat small areas.

Reducing Pest Populations: Sterile Insect Technique (SIT) and Mating Disruption

A potential new area for use of drones in pest management is the release of sterile insects. Codling moth [*Cydia pomonella* L. (Lepidoptera: Tortricidae)] is a major problem in apple orchards (*Malus domestica* Borkh.) (Judd and Gardiner 2005), and pilot programs to release sterile insects with drones have been successful in controlling codling moth populations in New Zealand, Canada, and the USA (DuPont 2018, M3 Consulting Group 2018, Seymour 2018, Timewell 2018). Furthermore, pilot programs for control of pink bollworm [*Pectinophora gossypiella* Saunders (Lepidoptera: Gelechiidae)] in cotton, and Mexican fruit fly [*Anastrepha ludens* Loew (Diptera: Tephritidae)] in citrus, with drone-released sterile insects proved effective for control of these pests in the USA (Rosenthal 2017). Similarly, false codling moth [*Thaumatotibia leucotreta* Meyrick (Lepidoptera: Tortricidae)] could successfully be controlled in citrus orchards in South Africa (FlyH2 Aerospace 2018, Greenfly 2018). The sterile insect technique (SIT) produces sterile or partially sterile insects through irradiation. After mating with wild insects, there is either no offspring, or the resulting offspring is sterile, resulting in reduced pest populations. SIT is environmentally friendly, species specific, and compatible with other management methods such as biological control, making it an important IPM tool (Simmons et al. 2010). Drone release of the sterile insects may be cheaper and faster than ground release, which occurs for instance by means of all-terrain vehicles (ATVs), or release by manned aircraft (Tan and Tan 2013). For sterile codling moth, drone-dispersal may also improve moth performance. Drones release the moths above the canopy whereas ATVs release them on the orchard floor. Codling moth prefer to mate in the upper one-third of the canopy, thus drone release may facilitate the moths reaching their preferred habitat, while minimizing biotic and abiotic mortality factors. Irradiated moths must be kept chilled during transportation prior to orchard dispersal to prevent damage and scale loss. An optimized delivery system from the rearing facility to the orchard may increase the sterile moths' effectiveness in mating with wild moths (DuPont 2018, Dr. E. Beers, personal communication). Therefore, drone releases may make SIT more widely available.

Drones could also be deployed to place mating disruptors such as SPLAT (specialized pheromone & lure application technology) in commercial fields (Greenfly 2018). SPLAT is an inert matrix which can be infused with pheromones and/or pesticides and is applied as dollops (ISCA 2019a, ISCA 2019b). Mating disruption relies on the release of pheromones, which interferes with mate finding (Miller and Gut 2015), while attract-and-kill involves an attractant and a killing agent (Gregg et al. 2018). A combination of these methods effectively control various pests in a number of cropping systems, including blueberry (*Vaccinium corymbosum* L.) and cranberry (Rodriguez-Saona et al. 2010, Steffan et al. 2017). Researchers from the University of Wisconsin are currently developing a drone release mechanism for SPLAT, to improve IPM practices in cranberry (Chasen and Steffan 2017, Seely 2018).

Pest Population Monitoring

Drones could also be used to track populations of mobile insects that can be equipped with transponders, such as locusts (Tahir and Brooker 2009). A recent paper by Stumph et al. (2019) described the use of drones equipped with a UV light source and a video camera to detect fluorescent-marked insects. Brown marmorated stink bugs [*Halyomorpha halys* Stål (Hemiptera: Pentatomidae)], 13-16 mm long, were coated in red fluorescent powder, and placed in a grass field. Drone data were obtained at night, and specific software was developed to visualize individual insects. This system provides a relatively fast alternative for manual, time-consuming, mark-release-recapture studies. Although insects still need to be coated initially, the method eliminates the need to physically recapture the insects. Also, it removes the need for destructive sampling, so that insects could potentially be sampled over a longer time period. Thus, use of this novel, drone-based system could improve efficiency and cost-effectiveness of mark-release-recapture studies of insect migration (Stumph et al. 2019).

Furthermore, drones could be used to collect pest specimens for monitoring (Shields and Testa 1999, Kim et al. 2018), or to survey for pests, such as Asian longhorned beetles [*Anoplophora glabripennis* Motschulsky (Coleoptera: Cerambycidae)], in tall trees, assisting tree climbers (Rosenthal, 2017). A recent review has even suggested the use of drones for collection of plant volatiles (Gonzalez et al. 2018). Indeed, plant volatiles induced in response to herbivory could indicate the presence of specific pests (Turlings and Erb 2018, De Lange et al. 2019), and drone-based volatile collections have been deployed for air quality measurements (Villa et al. 2016). Development of novel sensors and technology will undoubtedly open the door to various other uses of drones in agricultural pest management.

Technical and Cultural Challenges and Opportunities

Major challenges for the use of drones in precision agriculture are the costs of drones and associated sensors and material, limited flight time and payload, and continuously changing regulations. For a more comprehensive review of challenges and opportunities of drones in precision agriculture and environmental studies, two fields that share similar uses of drones, see Hardin and Jensen (2011), Zhang and Kovacs (2012), Whitehead and Hugenholtz (2014), and Whitehead et al. (2014). We here focus specifically on the technical challenges for use of drones in precision pest management, and highlight recent changes in regulations.

Costs

A major challenge for the use of drones in precision pest management is the initial steep costs of the material: the drone itself, the various sensors or application technologies, mounting equipment, and analysis software. Although costs are decreasing with improving technology, sums are still relatively high. In 2017, costs of a fixed-wing drone with hyperspectral sensor were estimated at €120,000 ($144,000), while costs of a multi-rotor drone with a multispectral sensor were estimated at €10,000 ($12,000) (Pádua et al. 2017). Therefore, various companies are offering drone-related services, such as renting out drones with remote sensing equipment (e.g. Blue Skies 2018) or offering predator dispersal services (e.g. Parabug 2019). Also, consulting companies offer remote sensing and data analysis services for a reasonable fee, even combined with other agriculture-related services, to provide one platform for efficient record keeping and planning (e.g. UAV-IQ 2018).

Data Collection, Analysis, and Interpretation

Concerning sensing drones, repeatability of remote sensing data is a recurring issue. Canopy reflectance varies depending on solar angle, cloud coverage, and various other factors. Therefore, it is difficult to compare data obtained on a specific day with data obtained the next day, even the next hour. Novel methods for calibration and processing of drone-based remote sensing data are continuously being developed (Singh and Nansen 2017, Aasen et al. 2018). Improved repeatability will render these data more useful for precision detection of pest problems.

Data analysis is also an important challenge. Each mission with a hyperspectral sensor typically results in multiple terabytes of data, which must be properly stored, processed with specific software, and analyzed by experts with years of experience. As a result, there is an important time lag between data collection and the visibility of results. Processing of multispectral data is currently much faster than processing of hyperspectral data, but the results are less precise in terms of detection of pest problems (Yang et al. 2009a). Ultimately, automation of data analysis will improve the usability of detailed hyperspectral datasets by growers directly, leading to a timelier detection and possible response to the discovery of pest hotspots. Also, automated data analysis will facilitate communication between sensing and actuation drones, so that an actuation drone can immediately be deployed to provide solutions. Or, a single drone could function simultaneously as sensor and actuator, and directly apply solutions where necessary (Figure 1).

Concerning actuation drones, peer-reviewed research has just started to emerge, with many challenges to be overcome. One major challenge is that, in order to develop an effective actuation drone system, knowledge and expertise from multiple fields must be integrated. First, knowledge from agricultural scientists will be needed to answer research questions such as where, when, and how much of the solutions (e.g. pesticides and natural enemies) should be applied in an agricultural field. Second, engineers and software developers will need to convert such knowledge into the design of hardware and software components for the effective and efficient distribution of the solutions. Another technical challenge is the automation of the distribution of solutions. Considering the complicated and varied field and weather conditions, preferentially, users shouldn't be asked to set up all the software parameters by themselves. Instead, the drone should be able to compute and implement the optimal distribution strategy automatically (potentially being given a digital map built by sensing drones).

Flight Time and Payload

Concerning both sensing and actuation drones, flight time and payload are among the most limiting factors for use of drones in agriculture. Although individual drones can have payloads of 24 kg and up (Yamaha 2016), it would be challenging, though not impossible to develop a drone that can both detect pest hotspots and apply solutions. Indeed, the above-mentioned AgriDrone can both detect pest hot spots and apply localized solutions (OPTiM 2016). However, to cover large areas, using a network of communicating drones, or swarm, may eventually be most efficient (Stark et al. 2013a, Faiçal et al. 2014a, Gonzalez-de-Santos et al. 2017). Ultimately, one or multiple sensing drones detecting pest hotspots will communicate with one or multiple actuation drones dispensing biological control organisms or agrochemicals exactly where needed; they can also autonomously fly back to their base stations to recharge, without further human intervention. Establishing drone swarms is an active research area in the drone community (Bertuccelli et al. 2009, Alejo et al. 2014, Ponda et al. 2015). However, how to translate these techniques into the pest management application domain is still an open question.

Adverse Weather Conditions and Other Environmental Factors

Adverse weather conditions could limit sensing and actuation drone activity. Most drones have an optimal operating temperature range. Strong wind could interfere with obtaining aerial remote sensing data, as well as with pesticide or biocontrol dispersal. Ideally, remote sensing measurements should be taken all under the same solar and sensor angle geometry, to avoid differences due to the effect that natural surfaces scatter radiation unequally into all directions (Weyermann et al. 2014). Data acquisition with a clear, cloudless sky, at solar noon reduces shadow influences as well as variations between measurements due to changing light intensity resulting from cloud cover (Souza et al. 2010). However, these conditions cannot be easily obtained in farms all over the world. Clouds and fog limit drone flights, and it is not recommended to fly a drone in rain or snow conditions, or during thunderstorms. Other environmental factors limiting drone activity are differences in elevation within fields or orchards, and presence of wildlife, such as birds (Park et al. 2012).

Rules and Regulations

In the USA, Federal Aviation Regulations (FARs) are in place for the commercial and research use of drones, prescribed by the FAA. Until 2016, a manned aircraft pilot license was necessary to fly a drone, which is costly to obtain and maintain. As of August 2016, a less stringent remote pilot license became available to operate small drones, which made commercial drone use much more readily available (FAA 2016). However, the regulations are regularly updated, which requires that pilots keep continuous track of current regulations.

A few basic rules in the USA include that the pilot in command must keep a visual line of sight (VLOS) on the drone at all times. Consequently, flying is only allowed at daylight hours.

Drones must fly at an altitude at or below 400 feet (122 m), at a speed at or below 100 mph (161 km/h). They are not allowed to fly over people that are not involved in the specific drone operation, and must always yield right of way to larger aircraft, including manned aircraft. Waivers from these regulations, for instance to fly at nighttime, can be requested through the FAA. Importantly, the pilot in command must perform a pre-flight check before each flight, to ascertain that the drone is in good condition for safe operation (FAA 2018b). In the USA, drones for both commercial and private use must be registered through the FAA. Regulations for operating and registering a drone may vary in different countries, so international collaborators must make sure to follow the proper rules (Cracknell 2017, Stöcker et al. 2017). In Brazil, where drones are regularly used in precision agriculture (Jorge et al. 2014, Parra 2014), the use of drones for civil and agricultural means was regulated as recently as May 2017 by the National Agency of Civil Aviation (ANAC) (Agência Nacional de Aviação Civil 2017). Ultimately, when drones become more mainstream, general rules may become more standardized.

Communication with Growers

Importantly, increased use of drones in commercial agricultural operations will not happen without adoption of the technology by growers, and they will only adopt technology that is proven to work, cost-effective, and compatible with established practices (Aubert et al. 2012, Pierpaoli et al. 2013). Extensive communication and collaboration between scientists, industry professionals, and commercial growers is needed to provide the best performing technology that tailors to growers' needs (Larson et al. 2008, Lindblom et al. 2017). Extension agents, dedicated to the translation of scientific research to practical applications, may facilitate these connections, through training and dialogue.

Conclusion

Drones are becoming increasingly adopted as part of precision agriculture and IPM. Drones with remote sensing equipment (sensors) are deployed to monitor crop health, map out variability in crop performance, and detect outbreaks of pests. They could serve as decision support tools, as early detection and response to suboptimal abiotic conditions may prevent large pest outbreaks. When outbreaks do occur, different drones (actuators) could be deployed to deliver swift solutions to identified pest hotspots. Automating pesticide applications and/or release of biological control organisms, through communication between sensing and actuation drones, is the future. This approach requires multi-disciplinary research in which engineers, ecologists, and agronomists are converging, with enormous commercial potential.

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Tables

Table 1. Studies on drone-based hyperspectral, multispectral, and RGB (red green blue) remote sensing to detect arthropod-induced stress in crops and orchards.

Table 2. Studies on aerial (manned aircraft) hyperspectral and multispectral remote sensing to detect arthropod-induced stress in crops and orchards.

Table 3. Studies on orbital hyperspectral and multispectral remote sensing to detect arthropod-induced stress in crops and orchards.

Table 4. Studies on ground-based hyperspectral and multispectral remote sensing to detect arthropod-induced stress in crops and orchards.

Table 5. Studies on hyperspectral and multispectral remote sensing to distinguish various biotic and abiotic stressors in crops.

Figures

Figure 1. (a) State-of-the-art open-loop remote sensing paradigm and (b) closed-loop integrated pest management (IPM) paradigm envisioned in this paper.

Figure 2. Number of articles published between 1998 and 2018 on the use of drones in agriculture. Shown is the number of publications for each year mentioning “drone”, “UAV” (Unmanned Aerial Vehicle), or “UAS” (Unmanned Aerial System) and “agriculture”. The words

“bee”, “honeybee”, and “hive” were explicitly excluded from the search, to avoid including publications on drones defined as male bees. Source: Web of Science.

Figure 3. Spectra of soybean leaves at different spectral resolutions. (a) As recorded by a handheld spectrometer with 1 nm spectral resolution (e.g. FieldSpec, ASD Inc., Boulder, CO). (b) Resampled to the spectral resolution of a hyperspectral imaging spectrometer (3-4 nm spectral resolution, e.g. OCI Imager, BaySpec, San Jose, CA). (c) Resampled to the spectral resolution of a multispectral sensor (4 spectral bands, e.g. Parrot Sequoia, Parrot, Paris, France).

Figure 4. Airborne remote sensing in California strawberry. Researchers from the University of California Davis obtain canopy reflectance data of arthropod-infested plants with a drone-mounted hyperspectral sensor in a commercial strawberry field.

Figure 5. Prototype of BugBot predatory mite dispenser. BugBot, developed by mechanical and aerospace engineering students at the University of California Davis, is a drone-mounted dispenser that can distribute predatory mites, important biological control agents of spider mites. In the picture, the BugBot dispenses vermiculite, the mineral substrate the predators can be obtained in.