

UC Davis

UC Davis Previously Published Works

Title

Drones: Innovative Technology for Use in Precision Pest Management.

Permalink

<https://escholarship.org/uc/item/2fd5h5c1>

Journal

Journal of economic entomology, 113(1)

ISSN

0022-0493

Authors

Iost Filho, Fernando H
Heldens, Wieke B
Kong, Zhaodan
et al.

Publication Date

2020-02-01

DOI

10.1093/jee/toz268

Peer reviewed

Drones: Innovative Technology for Use in Precision Pest Management

Fernando H. Iost Filho,^{1,✉} Wieke B. Heldens,² Zhaodan Kong,³ and Elvira S. de Lange^{4,✉}

¹Department of Entomology and Acarology, University of São Paulo, Piracicaba, São Paulo, Brazil, ²German Aerospace Center (DLR), Earth Observation Center, German Remote Sensing Data Center (DFD), Oberpfaffenhofen, D-82234 Wessling, Germany, ³Department of Mechanical and Aerospace Engineering, University of California Davis, 2094 Bainer Hall, Davis, CA 95616, ⁴Department of Entomology and Nematology, University of California Davis, 1 Shields Avenue, 367 Briggs Hall, Davis, CA 95616, and [✉]Corresponding author, e-mail: esdelange@ucdavis.edu

Subject Editor: Silvia Rondon

Received 4 February 2019; Editorial decision 10 September 2019

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 noninvasive 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.

Key words: biological control, integrated pest management, precision agriculture, remote sensing, unmanned aerial system

Arthropod pest outbreaks in field crops and orchards often show nonuniform 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 the 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 (Fig. 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 (Fig. 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 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 of 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

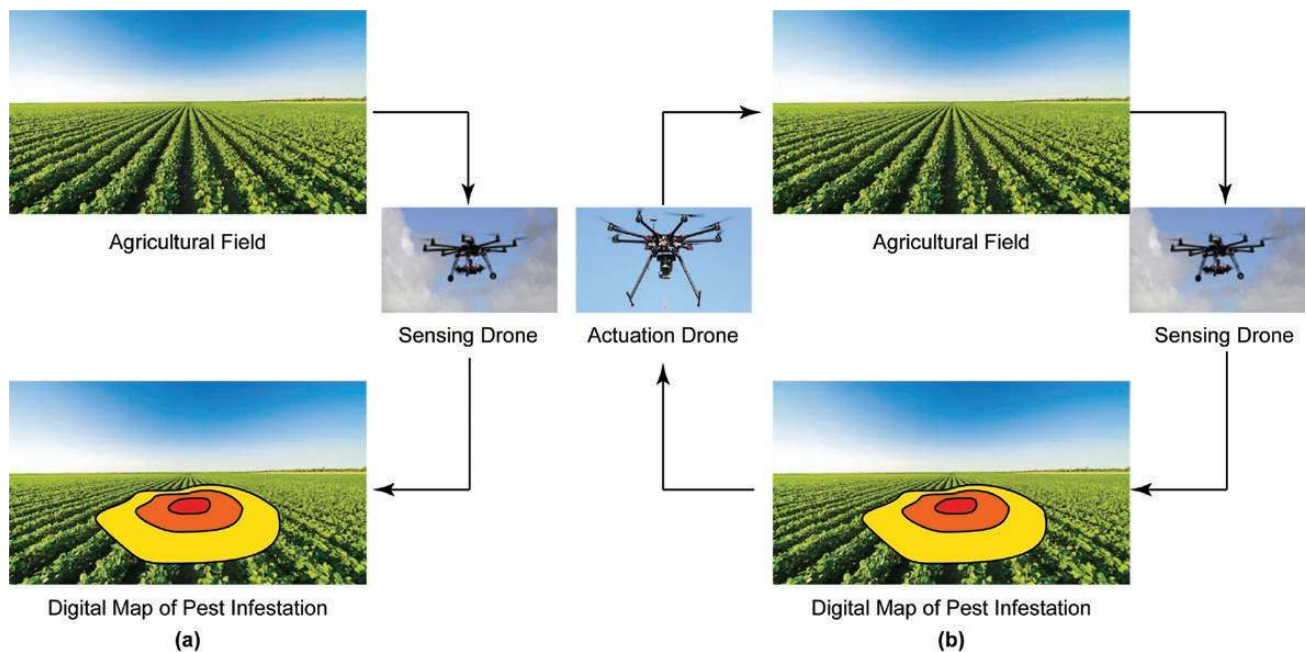


Fig. 1. (a) State-of-the-art open-loop remote sensing paradigm and (b) closed-loop IPM paradigm envisioned in this article. Sensing drones could be used for detection of pest hotspots, while actuation drones could be used for precision distribution of solutions. Adapted from Teske et al. (2019).

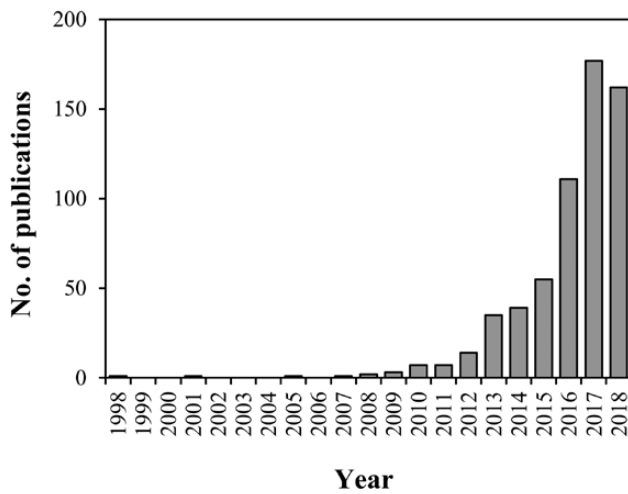


Fig. 2. Number of articles published between 1998 and 2018 on the use of drones in agriculture. Shown is the number of publications for each year mentioning 'drone', 'UAV' (Unmanned Aerial Vehicle), or 'UAS' (Unmanned Aerial System) and 'agriculture'. The words 'bee', 'honey bee', and 'hive' were explicitly excluded from the search, to avoid including publications on drones defined as male bees. Source: Web of Science.

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 do not 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, 700–1,400 nm), with most studies referring to the 400–1,000 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

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

Platform details	Type	Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
md4-1000, Microdrones	Four rotors	RGB	α ILCE-5100L with an E 20 mm F2.8 lens, Sony	3	Visual inspection of images	Grape	<i>Vitis vinifera</i> L.	Cotton jassid	<i>Jacobiasca lybica</i> Bergévin and Zanon	Hemiptera: Cicadellidae	Del-Campo-Sanchez et al. 2019
Aeryon Scout, Aeryon Labs Inc.	Four rotors	RGB + M	Photo3S, Aeryon Labs Inc. + ADC-Lite, Tetracam Inc.	3 + 3	Outbreak reported by grower	Wheat	<i>Triticum aestivum</i>	Fall armyworm	<i>Spodoptera frugiperda</i> Smith	Lepidoptera: Noctuidae	Zhang et al. 2014
S800 EVO, SZ DJI Technology Co.	Six rotors	RGB + M + H	5DsR, Canon Inc. + RedEdge, MicaSense Inc. + Nano-Hyperspec, Headwall Photonics Inc.	3 + 5 + 274	Ground traps and root digging, visual vigor assessments	Grape	<i>Vitis vinifera</i>	Grape phylloxera	<i>Daktulosphaira vitifoliae</i> Fitch	Hemiptera: Phylloxeridae	Vanegas et al. 2018a
S800 EVO, SZ DJI Technology Co. / Phantom3 Pro, SZ DJI Technology Co.	Six rotors / four rotors	RGB + M + H / RGB	5DsR, Canon Inc. + RedEdge, MicaSense Inc. + Nano-Hyperspec, Headwall Photonics Inc. / Phantom3 Pro associated camera ^b	3 + 5 + 274 / 3	Ground traps and root digging, visual vigor assessments	Grape	<i>Vitis vinifera</i>	Grape phylloxera	<i>Daktulosphaira vitifoliae</i>	Hemiptera: Phylloxeridae	Vanegas et al. 2018b
eBee, senseFly	Fixed wing	M	S110 NIR ^b , Canon	3	NA	Onion	<i>Allium cepa</i> L.	Thrips	NA	Thysanoptera: Thripidae	Nebiker et al. 2016
Cinestar-8 MK Heavy Lift, Freely Systems	Eight rotors	M	Mini-MCA6, Tetracam Inc.	6	Arthropod counts, soil and plant tissue nutrient analyses ^c	Canola	<i>Brassica</i> spp.	Green peach aphid	<i>Myzus persicae</i>	Hemiptera: Aphididae	Severtson et al. 2016a
Matrice 100, SZ DJI Technology Co.	Four rotors	M	ADC-Lite, Tetracam Inc.	3	Damage assessments	Cotton	<i>Gossypium hirsutum</i> L.	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Huang et al. 2018
Spreading Wings S800, SZ DJI Technology Co.	Six rotors	M	Mini-MCA6, Tetracam Inc.	6	Damage assessments	Potato	<i>Solanum tuberosum</i>	Colorado potato beetle	<i>Leptinotarsa decemlineata</i>	Coleoptera: Chrysomelidae	Hunt and Rondon 2017, Hunt et al. 2017
eBee, senseFly	Fixed wing	M	S110 NIR ^b , Canon	3	Arthropod counts	Sorghum	<i>Sorghum bicolor</i>	Sugarcane aphid	<i>Melanaphis sacchari</i>	Hemiptera: Aphididae	Stanton et al. 2017

^aRGB = red green blue, M = multispectral, H = hyperspectral.^bNIR = near infrared.^cRemote sensing was used to detect nutrient deficiencies, which were correlated to arthropod presence. NA = information not provided.

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

Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
M	K-17, Fairchild Camera and Instrument Corp. + Hasselblad camera	NA	Arthropod counts, sooty mold assessments ^b	Citrus	<i>Citrus</i> spp.	Citrus blackfly	<i>Aleurocanthus woglumi</i> Ashby	Hemiptera: Aleyrodidae	Hart et al. 1973
M	System composed of 3 video cameras	3	Visual inspections, sooty mold assessments ^b	Citrus	<i>Citrus</i> spp.	Citrus blackfly	<i>Aleurocanthus woglumi</i>	Hemiptera: Aleyrodidae	Everitt et al. 1994
M	K-17, Fairchild Camera and Instrument Corp.	NA	Arthropod counts, sooty mold assessments ^b	Citrus	<i>Citrus</i> spp.	Brown soft scale	<i>Coccus hesperidum</i> L.	Hemiptera: Coccidae	Hart and Meyers 1968
M	System composed of 3 video cameras	3	Visual inspections, sooty mold assessments ^b	Cotton	<i>Gossypium hirsutum</i>	Silverleaf whitefly	<i>Bemisia tabaci</i>	Hemiptera: Aleyrodidae	Everitt et al. 1996
M	MS2100, DuncanTech	3	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Beet armyworm	<i>Spodoptera exigua</i> Hübner	Lepidoptera: Noctuidae	Sudbrink et al. 2003
M	CRSP, NASA	3	Sweep net sampling, drop cloth sampling	Cotton	<i>Gossypium hirsutum</i>	Tarnished plant bug	<i>Lygus lineolaris</i> Palisot de Beauvois	Hemiptera: Miridae	Willers et al. 1999
M	RDACS, ITD ^c , Stennis Space Center	3	Sweep net sampling	Cotton	<i>Gossypium hirsutum</i>	Tarnished plant bug	<i>Lygus lineolaris</i>	Hemiptera: Miridae	Willers et al. 2005
M	MS3100, DuncanTech	3	Damage assessments	Sorghum	<i>Sorghum bicolor</i>	Sugarcane aphid	<i>Melanaphis sacchari</i>	Hemiptera: Aphididae	Elliott et al. 2015; Backoulou et al. 2018a, b
M	MS3100, DuncanTech	3	Visual inspections	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Backoulou et al. 2011a,b, 2013, 2016
M	SSTCRIS, SST Development Group Inc.	3	Proportion of infested plants	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Elliott et al. 2007
M	TerrAvion	2	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Hessian fly	<i>Mayetiola destructor</i> Say	Diptera: Cecidomyiidae	Bhattarai et al. 2019
M	MS3100, DuncanTech	3	Arthropod counts or visual inspection	Wheat	<i>Triticum aestivum</i>	Greenbug	<i>Schizaphis graminum</i>	Hemiptera: Aphididae	Elliott et al. 2009; Backoulou et al. 2015, 2016
M	CASI, Borstad Associates + EO Camera, NASA ARC ^d	4-8 ^e	Root digging	Grape	<i>Vitis vinifera</i>	Grape phylloxera	<i>Daktulosphaira vitifoliae</i>	Hemiptera: Phylloxeridae	Lobits et al. 1997
M + H	SAMRSS + AVNIR, Opto-Knowledge Systems	4 + 60	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Cotton aphid	<i>Aphis gossypii</i>	Hemiptera: Aphididae	Reisig and Godfrey 2006, 2010
M + H	SAMRSS + AVNIR, Opto-Knowledge Systems	4 + 60	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Spider mite	<i>Tetranychus</i> spp.	Acari: Tetranychidae	Reisig and Godfrey 2006
H	AVIRIS, NASA	224	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Strawberry spider mite	<i>Tetranychus turkestani</i> Ugarov and Nikolskii	Acari: Tetranychidae	Fitzgerald et al. 2004
H	AISA, Specim Spectral Imaging Ltd.	50	Visual inspection of images	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Mirik et al. 2014
H	RDACS-H4, ITD ^c , Stennis Space Center	120-240	Damage assessments	Corn	<i>Zea mays</i>	European corn borer	<i>Ostrinia nubilalis</i>	Lepidoptera: Crambidae	Carroll et al. 2008

^aM = multispectral, H = hyperspectral.^bA fungus not infesting the plant, but growing on the arthropod's sugary honeydew secretions.^cInstitute of Technology and Development.^dPrimary project sensors; five additional sensors were used with 3-8 spectral bands. NA = information not provided.

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

Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
M	QuickBird, DigitalGlobe	3	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Cotton aphid	<i>Aphis gossypii</i>	Hemiptera: Aphididae	Reisig and Godfrey 2006, 2010
M	QuickBird, DigitalGlobe	3	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Spider mite	<i>Tetranychus</i> spp.	Acari: Tetranychidae	Reisig and Godfrey 2006
M	Terra, MODIS, NASA	36	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Wheat stem sawfly	<i>Cephus cinctus</i> Norton	Hymenoptera: Cephidae	Lestina et al. 2016
M	Sentinel-2, S2A-L1C, ESA ^b	13	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Hessian fly	<i>Mayetiola destructor</i>	Diptera: Cecidomyiidae	Bhattarai et al. 2019
M	HJ-1A/B, CCD sensor, NDRCC/SEPA ^c ,	4	Arthropod counts, damage assessments	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Luo et al. 2014
M	Landsat-8, NASA	9	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Ma et al. 2019
M	Landsat-5 TM, NASA	7	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Aphid	NA	Hemiptera: Aphididae	Huang et al. 2011
M	RapidEye, Planet Labs	5	Arthropod counts	Corn	<i>Zea mays</i>	Stem borer	<i>Busseola</i> spp.	Lepidoptera: Noctuidae	Abdel-Rahman et al. 2017
M	HJ-1A/B, CCD sensor, NDRCC/SEPA ^c ,	4	Damage assessments	Corn	<i>Zea mays</i>	Oriental armyworm ^d	<i>Mythimna separata</i> Walker ^d	Lepidoptera: Noctuidae	Zhang et al. 2016

^aM = multispectral.

^bEuropean Space Agency.

^cNational Committee for Disaster Reduction and State Environmental Protection Administration of China.

^dThe arthropod species was originally misidentified as *Spodoptera frugiperda*; a correction was issued. NA = information not provided.

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 ground-based hyperspectral field spectrometer, together with the same spectrum resampled to the spectral resolution of a hyperspectral imaging spectrometer for drones, 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 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 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 stressors 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 one 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 cm² to more than 10 cm². With larger pixels, the recorded spectrum consists of reflectance of both

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

Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
M	12–1000 modular-multiband radiometer, Barnes Engineering Co.	3	Visual inspections, sooty mold assessments ^b	Cotton	<i>Gossypium hirsutum</i>	Silverleaf whitefly	<i>Bemisia tabaci</i>	Hemiptera: Aleyrodidae	Everitt et al. 1996
M	System composed of visible and NIR 'Varispec' liquid-crystal tunable-filters, Cambridge Research Instrumentation Inc. + Pluto digital camera, PixelVision Inc.	68	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Strawberry spider mite	<i>Tetranychus turkestanii</i>	Tetranychidae	Fitzgerald et al. 2004
M	Model 505 GreenSeeker optical sensor, Trimble Navigation	2	Controlled infestations or arthropod counts	Cotton	<i>Gossypium</i> spp.	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Martin et al. 2015, Martin and Latheef 2017, 2018
M	ADC, Tetracam Inc.	3	Controlled infestations	Cotton	<i>Gossypium hirsutum</i>	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Lan et al. 2013
M	Model 505 GreenSeeker optical sensor, Trimble Navigation	2	Controlled infestations	Pinto bean	<i>Phaseolus vulgaris</i> L.	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Martin and Latheef 2018
M	MSR 16 radiometer, CropScan Inc.	16	Visual inspections or controlled infestations	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Mirik et al. 2012
M	MSR 16R radiometer, CropScan Inc.	16	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Yang et al. 2009b
M	MSR 16R radiometer, CropScan Inc.	16	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Greenbug	<i>Schizaphis graminum</i>	Hemiptera: Aphididae	Yang et al. 2005, 2009b
M	GreenSeeker optical sensor, Trimble Navigation	2	Damage assessments	Corn	<i>Zea mays</i>	Banks grass mite + two-spotted spider mite	<i>Oligonychus pratensis</i> Banks + <i>Tetranychus urticae</i>	Acari: Tetranychidae	Martin and Latheef 2019
H	MS-720 spectroradiometer, EKO Instruments Co., Ltd.	213	Visual inspections	Pepper	<i>Capsicum annuum</i> L.	Chilli thrips	<i>Scirtothrips dorsalis</i> Hood	Thysanoptera: Thripidae	Mohite et al. 2018
H	FieldSpec Pro FR spectroradiometer, ASD	2,151	Damage assessments	Pepper	<i>Capsicum annuum</i>	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Herrmann et al. 2012, 2015, 2017
H	FieldSpec FR spectroradiometer, ASD	2,151	Arthropod counts	Strawberry	<i>Fragaria x ananassa</i>	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Fraulo et al. 2009
H	FieldSpec 4 Hi-Res spectroradiometer, ASD	2,151	Arthropod counts	Soybean	<i>Glycine max</i>	Soybean aphid	<i>Aphis glycines</i>	Hemiptera: Aphididae	Alves et al. 2015, 2019
H	FieldSpec 3, ASD	2,151	Damage assessments	Soybean	<i>Glycine max</i>	Silverleaf whitefly	<i>Bemisia tabaci</i>	Hemiptera: Aleyrodidae	Iost Filho 2019
H	FieldSpec Pro FR spectrometer, ASD	2,151	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Cotton aphid	<i>Aphis gossypii</i>	Hemiptera: Aphididae	Reisig and Godfrey 2006
H	FieldSpec Pro FR spectrometer, ASD + GER 1500 spectroradiometer, Spectra Vista Corp.	2,151 + 512	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Cotton aphid	<i>Aphis gossypii</i>	Hemiptera: Aphididae	Reisig and Godfrey 2007

Table 4. Continued

Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
H	FieldSpec 3 Hi-Res spectroradiometer, ASD	2,151	Damage assessments	Cotton	<i>Gossypium hirsutum</i>	Cotton aphid	<i>Aphis gossypii</i>	Hemiptera: Aphididae	Chen et al. 2018
H	FieldSpec 3 Hi-Res spectroradiometer, ASD	2,151	Damage assessments	Cotton	<i>Gossypium hirsutum</i>	Leafhopper	NA	Hemiptera: Cicadellidae	Prabhakar et al. 2011
H	FieldSpec spectroradiometer, ASD	2,151	Visual inspections	Cotton	<i>Gossypium hirsutum</i>	Whitefly	NA	Hemiptera: Aleyrodidae	Nigam et al. 2016
H	FieldSpec 3 Hi-Res spectroradiometer, ASD	2,151	Damage assessments, sooty mold assessments ^b	Cotton	<i>Gossypium hirsutum</i>	Solenopsis mealybug	<i>Phenacoccus solenopsis</i>	Hemiptera: Pseudococcidae	Prabhakar et al. 2013
H	GER 1500 spectroradiometer, Spectra Vista Corp.	512	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Beet armyworm	<i>Spodoptera exigua</i>	Lepidoptera: Noctuidae	Sudbrink et al. 2003
H	GER 1500 spectroradiometer, Spectra Vista Corp.	512	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Cabbage looper	<i>Trichoplusia ni</i>	Lepidoptera: Noctuidae	Sudbrink et al. 2003
H	FieldSpec Pro FR spectrometer, ASD + GER 1500 spectroradiometer, Spectra Vista Corp.	2,151 + 512	Arthropod counts or presence/absence assessments	Cotton	<i>Gossypium hirsutum</i>	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Reisig and Godfrey 2007
H	FieldSpec Pro FR spectrometer, ASD	2,151	Arthropod counts	Cotton	<i>Gossypium hirsutum</i>	Spider mite	<i>Tetranychus</i> spp.	Acari: Tetranychidae	Reisig and Godfrey 2006
H	SE590 spectroradiometer, Spectron Engineering, Inc.	252	Arthropod counts	Apple	<i>Malus domestica</i>	European red mite	<i>Panonychus ulmi</i>	Acari: Tetranychidae	Peñuelas et al. 1995
H	ImSpector V10E imaging spectrophotometer, Spectral Imaging Ltd.	512	Damage assessments	Rice	<i>Oryza sativa</i>	Striped stem borer	<i>Chilo suppressalis</i>	Lepidoptera: Crambidae	Fan et al. 2017
H	FieldSpec Full Range, ASD	2,151	Damage assessments, visual inspections or microscope analyses	Rice	<i>Oryza sativa</i>	Rice leaf folder	<i>Cnaphalocrocis medinalis</i>	Lepidoptera: Crambidae	Liu et al. 2012, 2018
H	FieldSpec Handheld spectroradiometer, ASD	512	Damage assessments	Rice	<i>Oryza sativa</i>	Rice leaf folder	<i>Cnaphalocrocis medinalis</i>	Lepidoptera: Crambidae	Huang et al. 2012a
H	GER 2600 spectroradiometer, Spectra Vista Corp.	640	Damage assessments	Rice	<i>Oryza sativa</i>	Rice leaf folder	<i>Cnaphalocrocis medinalis</i>	Lepidoptera: Crambidae	Yang et al. 2007
H	FieldSpec Handheld spectroradiometer, ASD	512	Arthropod counts or controlled infestations	Rice	<i>Oryza sativa</i>	Brown planthopper	<i>Nilaparvata lugens</i>	Hemiptera: Delphacidae	Huang et al. 2015a, Liu and Sun 2016, Tan et al. 2019
H	FieldSpec 3 Hi-Res spectroradiometer, ASD	2,151	Controlled infestations	Rice	<i>Oryza sativa</i>	Brown planthopper	<i>Nilaparvata lugens</i>	Hemiptera: Delphacidae	Prasannakumar et al. 2013, Zhou et al. 2010
H	GER 2600 spectroradiometer, Spectra Vista Corp.	640	Damage assessments	Rice	<i>Oryza sativa</i>	Brown planthopper	<i>Nilaparvata lugens</i>	Hemiptera: Delphacidae	Yang et al. 2007
H	FieldSpec Pro FR spectroradiometer, ASD	2,151	Damage assessments	Bean	<i>Phaseolus vulgaris</i>	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Herrmann et al. 2017

Table 4. Continued

Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
H	FieldSpec Pro spectroradiometer, ASD	2,151	Arthropod counts or damage assessments	Peach	<i>Prunus persica</i> (L.) Batsch	Spider mite	<i>Tetranychus</i> spp.	Acari: Tetranychidae	Zhang et al. 2008, Luedeling et al. 2009
H	FieldSpec 3 spectroradiometer, ASD	2,151	Arthropod counts or damage assessments	Sugarcane	<i>Saccharum</i> spp.	Sugarcane thrips	<i>Fulmekiola serrata</i> Kobus	Thysanoptera: Thripidae	Abdel-Rahman et al. 2009, 2010, 2013
H	Nexus FT-NIR spectrometer, Thermo Nicolet Corp.	531	Damage assessments	Tomato	<i>Solanum lycopersicum</i> L.	Leafminer	NA	NA	Xu et al. 2007
H	HR2000 spectroradiometer, Ocean Optics Inc.	62	Arthropod counts	Sorghum	<i>Sorghum bicolor</i>	Corn leaf aphid	<i>Rhopalosiphum maidis</i> Fitch	Hemiptera: Aphididae	Li et al. 2008
H	HR2000 spectroradiometer, Ocean Optics Inc.	62	Arthropod counts	Sorghum	<i>Sorghum bicolor</i>	Greenbug	<i>Schizaphis graminum</i>	Hemiptera: Aphididae	Li et al. 2008
H	Hyperspectral camera, Resonon	213	Controlled infestations and arthropod presence confirmations	Wheat	<i>Triticum aestivum</i>	Wheat stem sawfly	<i>Cephus cinctus</i>	Hymenoptera: Cephidae	Nansen et al. 2009
H	FieldSpec Handheld Spectroradiometer, ASD	512	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Sunn pest	<i>Eurygaster integriceps</i> Puton	Hemiptera: Scutelleridae	Gene et al. 2008
H	Personal Spectrometer II, ASD	512	Controlled infestations	Wheat	<i>Triticum aestivum</i>	Greenbug	<i>Schizaphis graminum</i>	Hemiptera: Aphididae	Riedell and Blackmer 1999
H	S2000 spectrometer, Ocean Optics Inc.	2,048	Arthropod counts or controlled infestations	Wheat	<i>Triticum aestivum</i>	Greenbug	<i>Schizaphis graminum</i>	Hemiptera: Aphididae	Mirik et al. 2006a, b
H	Pushbroom imaging spectrometer (PIS), Beijing Research Center for Information Technology in Agriculture and University of Science and Technology of China	1,024	Arthropod counts or damage assessments	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Zhao et al. 2012, Luo et al. 2013a
H	FieldSpec Pro spectroradiometer, ASD	2,151	Damage assessments	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Luo et al. 2011; Huang et al. 2012b, 2013, 2014
H	FieldSpec UV/VNIR spectroradiometer, ASD	2,151	Damage assessments or visual inspections	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Yuan et al. 2014, 2017; Zhang et al. 2017
H	FieldSpec FR spectroradiometer, ASD	2,151	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Luo et al. 2013b,c
H	FieldSpec spectroradiometer, ASD	2,151	Damage assessments	Wheat	<i>Triticum aestivum</i>	Wheat aphid	<i>Sitobion avenae</i>	Hemiptera: Aphididae	Huang et al. 2014, Shi et al. 2017

Table 4. Continued

Spectral resolution ^a	Sensor details	No. of spectral bands	Field observations	Plant common name	Plant species	Arthropod common name	Arthropod species	Order: Family	References
H	S2000 spectrometer, Ocean Optics Inc.	2,048	Arthropod counts	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Mirik et al. 2007
H	Personal Spectrometer II, ASD	512	Controlled infestations	Wheat	<i>Triticum aestivum</i>	Russian wheat aphid	<i>Diuraphis noxia</i>	Hemiptera: Aphididae	Riedell and Blackmer 1999
H	Pika II hyperspectral imaging camera, Resonon	240	Controlled infestations	Corn	<i>Zea mays</i>	Green belly stink bug	<i>Dichelops melacanthus</i>	Hemiptera: Pentatomidae	Do Prado Ribeiro et al. 2018
H	Pika II hyperspectral imaging camera, Resonon	160	Arthropod counts	Corn	<i>Zea mays</i>	Two-spotted spider mite	<i>Tetranychus urticae</i>	Acari: Tetranychidae	Nansen et al. 2010, Nansen 2012

^aM = multispectral, H = hyperspectral.

^bA fungus not infesting the plant, but growing on the arthropod's sugary honeydew secretions. NA = information not provided.

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 VIs assist in interpreting remote sensing data (Roberts et al. 2001, Xue and 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 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, e.g., 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 broadband indices (i.e., they can be calculated with multispectral data), hyperspectral data allows for narrowband 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 from the dataset. 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 et al. (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, 1996). With the development of unmanned

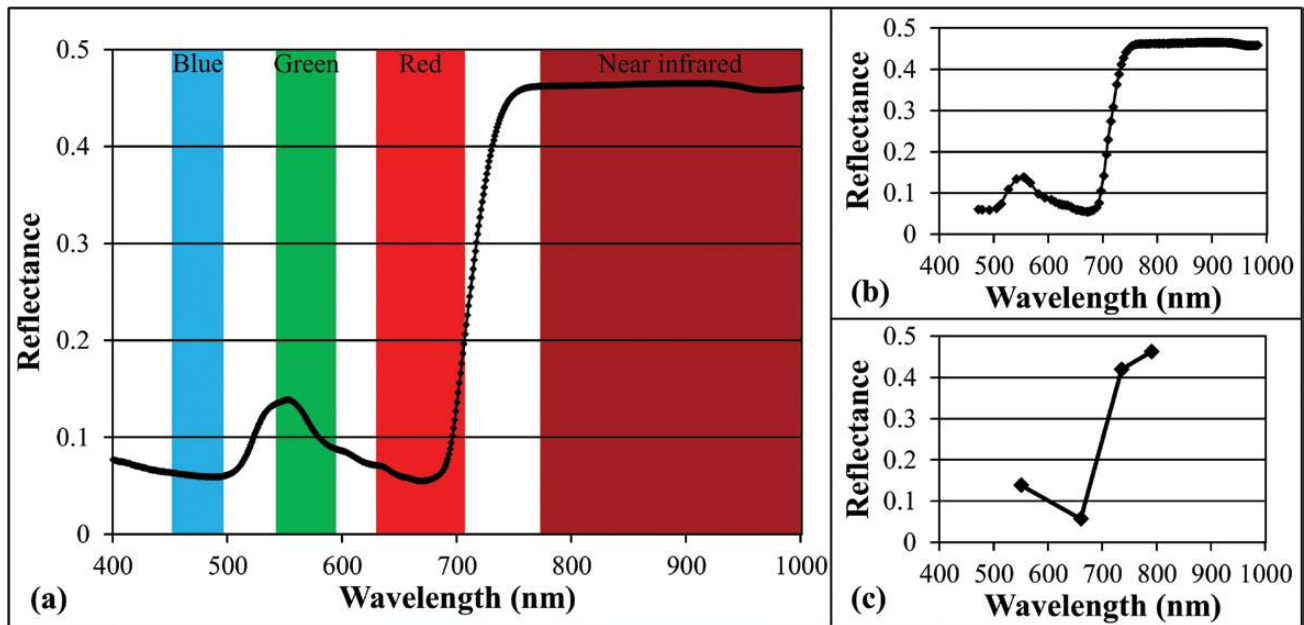


Fig. 3. Spectra of soybean leaves at different spectral resolutions. (a) As recorded by a handheld spectrometer with 1 nm spectral resolution (e.g., FieldSpec, ASD Inc., Boulder, CO). (b) Resampled to the spectral resolution of a hyperspectral imaging spectrometer (3–4 nm spectral resolution, e.g., OCI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

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 et al. 2016, Hunt and Rondon 2017) (Table 1). 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). Researchers at the University of Wisconsin, WI 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 involves detection of stress induced by two-spotted spider mite in strawberry (*Fragaria × ananassa* Duchesne), using an octocopter equipped with a hyperspectral sensor (Fig. 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. Prabhakar et al. (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 stressors 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, *Puccinia striiformis* Westend. f. sp. *tritici* Eriks and powdery mildew, *Blumeria graminis* (DC.) Speer) 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



Fig. 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.

(Russian wheat aphid) and abiotic stressors (drought and agronomic conditions, possibly poor tillage, germination, or fertilization). The different stressors 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, Al 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, Al 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,b, 2016, 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.. 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

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

Platform	Spectral resolution ^a	Sensor details	No. of spectral bands	Plant common name	Stress 1	Stress 2	Stress 3	Field observations 1	Field observations 2	Field observations 3	References
Ground-based	M	MSR 16R, CropScan Inc.	16	Wheat	Russian wheat aphid	Greenbug	-	Arthropod counts	Arthropod counts	Arthropod counts	Yang et al. 2009b
Ground-based	H	Pika II, Resonon	160	Corn	Two-spotted spider mite	Drought stress	-	Arthropod counts	Different irrigation levels	Arthropod counts	Nansen et al. 2010, Nansen 2012
Ground-based	H	FieldSpec Pro FR, ASD	2,151	Cotton	Cotton aphid	Spider mite	-	Arthropod counts	Arthropod counts	Arthropod counts	Reisig and Godfrey 2006
Ground-based	H	FieldSpec Pro FR, ASD + GER 1500, Spectra Vista Corp.	2,151 + 512	Cotton	Cotton aphid	Two-spotted spider mite	-	Arthropod counts	Arthropod counts or presence/absence assessments	Arthropod counts	Reisig and Godfrey 2007
Ground-based	H	FieldSpec Handheld, ASD	512	Rice	Brown planthopper	Nitrogen stress	-	Arthropod counts	Different fertilizer levels	Arthropod counts	Huang et al. 2015a
Ground-based	H	Personal Spectrometer II, ASD	512	Wheat	Russian wheat aphid	Greenbug	-	Controlled infestations	Controlled infestations	Controlled infestations	Riedell and Blackmer 1999
Ground-based	H	FieldSpec, FieldSpec Pro, or FieldSpec UV/VNIR, ASD	2,151	Wheat	Wheat aphid	Yellow rust	Powdery mildew	Damage assessments	Damage assessments	Damage assessments	Huang et al. 2014; Yuan et al. 2014, 2017, Shi et al. 2017, Zhang et al. 2017
Aerial – manned aircraft	M	MS3100, Duncan Tech	3	Wheat	Russian wheat aphid	Greenbug	-	Visual inspections	Visual inspections	Visual inspections	Backoulou et al. 2016
Aerial – manned aircraft	M	MS3100, DuncanTech	3	Wheat	Russian wheat aphid	Other factors ^b	-	Visual inspections	Visual inspections	Visual inspections	Backoulou et al. 2013
Aerial – manned aircraft	M	MS3100, DuncanTech	3	Wheat	Russian wheat aphid	Drought stress	Agronomic conditions ^c	Visual inspections	Visual inspections	Visual inspections	Backoulou et al. 2011a, b
Aerial – manned aircraft	M	MS3100, DuncanTech	3	Wheat	Greenbug	Drought stress	Agronomic conditions ^c	Visual inspections	Visual inspections	Visual inspections	Backoulou et al. 2015
Aerial – Manned aircraft	M + H	SAMRSS + AVNIR, Opto-Knowledge Systems	4 + 60	Cotton	Cotton aphid	Spider mite	-	Arthropod counts	Arthropod counts	Arthropod counts	Reisig and Godfrey 2006
Aerial – manned aircraft	M + H	SAMRSS + AVNIR, Opto-Knowledge Systems	4 + 60	Cotton	Cotton aphid	Nitrogen stress	-	Arthropod counts	Different fertilizer levels, soil samples, plant nutrient uptake analysis	Different fertilizer levels, soil samples, plant nutrient uptake analysis	Reisig and Godfrey 2010
Orbital	M	QuickBird, DigitalGlobe	3	Cotton	Cotton aphid	Spider mite	-	Arthropod counts	Arthropod counts	Arthropod counts	Reisig and Godfrey 2006
Orbital	M	QuickBird, DigitalGlobe	3	Cotton	Cotton aphid	Nitrogen stress	-	Arthropod counts	Different fertilizer levels, soil samples, plant nutrient uptake analysis	Different fertilizer levels, soil samples, plant nutrient uptake analysis	Reisig and Godfrey 2010
Orbital	M	Landsat-8, NASA	9	Wheat	Wheat aphid	Powdery mildew	-	Arthropod counts	Damage assessments	Damage assessments	Ma et al. 2019

^aM = multispectral, H = hyperspectral.

^bIncl. damage caused by drought or poor fertilization.

^cIncl. damage caused by poor fertilization, germination, or tillage. Only studies involving at least one arthropod pest are included in this table. Studies mentioned in this table are also included in Tables 2–4; plant and arthropod species names are mentioned there.

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 Chen 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 United States (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 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). *Phytoseiulus persimilis* has such a high level of specialization that populations

succumb when no prey is present (McMurtry and Croft 1997, Cakmak 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 handheld appliance with a fan (Koppert 2017b), as well as other devices (Giles et al. 1995, Casey and Parrella 2005, Opit et al. 2005). 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 (Teske et al. 2019) (Fig. 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 United States 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 United States. 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 [*Ephestbia 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



Fig. 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.

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 stressors, 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, 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 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 United States (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 United States (Rosenthal 2017). Similarly, false codling moth [*Thaumatotibia leucotreta* Meyrick (Lepidoptera: Tortricidae)] could successfully be controlled in citrus orchards in South Africa (FlyH2 Aerospace 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 (FlyH2 Aerospace 2018). SPLAT is an inert matrix which can be infused with pheromones and/or pesticides and is applied as dollops (ISCA 2019a, b). 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 (Miller 2015, 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.

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 the 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 2019) 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 (Bourgeon et al. 2016, 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 (Fig. 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 should not 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). (Fig. 1)

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 United States, 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 United States 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 United States, 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.

Acknowledgments

We thank April Teske and Kevin Goding for critical comments on an earlier version of this manuscript. Thanks to Eli Borrego for help creating Fig. 2. We thank the commercial growers who made their fields available for research activities. F.H.I.F. is supported by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) - Finance Code 001. Z.K. is supported by the California Department of Pesticide Regulation (project 18-PML-R004). E.S.d.L. is supported by Western Sustainable Agriculture Research and Education (project SW17-060, <http://www.westernsare.org/>). This study was also supported by the American Floral Endowment, the Gloeckner Foundation, and United States Department of Agriculture, Agricultural Research Service (USDA ARS) Floriculture and Nursery Research Initiative.

References Cited

- Aasen, H., and A. Bolten. 2018. Multi-temporal high-resolution imaging spectroscopy with hyperspectral 2D imagers – From theory to application. *Remote Sens. Environ.* 205: 374–389.
- Aasen, H., E. Honkavaara, A. Lucieer, and P. Zarco-Tejada. 2018. Quantitative remote sensing at ultra-high resolution with UAV spectroscopy: a review of sensor technology, measurement procedures, and data correction workflows. *Remote Sens.* 10: 1091.
- Abdel-Galil, F. A., M. A. M. Amro, and A. S. H. Abdel-Moniem. 2007. Effect of drought stress on the incidence of certain arthropod pests and predators inhabiting cowpea plantations. *Arch. Phytopathology Plant. Protect.* 40: 207–214.
- Abdel-Rahman, E. M., M. Van den Berg, M. J. Way, and F. B. Ahmed. 2009. Hand-held spectrometry for estimating thrips (*Fulmekiola serrata*) incidence in sugarcane, pp. 268–271. *In* IEEE International Geoscience and Remote Sensing Symposium, 12–17 July 2009, Cape Town, South Africa.
- Abdel-Rahman, E. M., F. B. Ahmed, M. van den Berg, and M. J. Way. 2010. Potential of spectroscopic data sets for sugarcane thrips (*Fulmekiola serrata* Kobus) damage detection. *Int. J. Remote Sens.* 31: 4199–4216.
- Abdel-Rahman, E. M., M. Way, F. Ahmed, R. Ismail, and E. Adam. 2013. Estimation of thrips (*Fulmekiola serrata* Kobus) density in sugarcane using leaf-level hyperspectral data. *S. Afr. J. Plant & Soil.* 30: 91–96.
- Abdel-Rahman, E. M., T. Landmann, R. Kyalo, G. Ong'amo, S. Mwalusepo, S. Sulieman, and B. Le Ru. 2017. Predicting stem borer density in maize using RapidEye data and generalized linear models. *Int. J. Appl. Earth Obs. Geoinf.* 57: 61–74.
- ABI Research. 2018. Drones in agriculture: undeniable value and plenty of growth, but not the explosion others predict. Available from <https://www.abiresearch.com/press/drones-agriculture-undeniable-value-and-plenty-gro/>
- Agência Nacional de Aviação Civil. 2017. Regas da ANAC para uso de drones entram em vigor. Available from http://www.anac.gov.br/noticias/2017/regas-da-anac-para-uso-de-drones-entram-em-vigor/release_drone.pdf
- Agronomic Nordeste. 2015. Trichobug (Trichogramma). Available from <http://agromicnordeste.com.br/produtos>
- Airborne Robotics. 2018. Agriculture & forestry. Available from <https://www.air6systems.com/portfolio/agriculture-forestry/>
- Alejo, D., J. Cobano, G. Heredia, and A. Ollero. 2014. Optimal reciprocal collision avoidance with mobile and static obstacles for multi-UAV systems, pp. 1259–1266. *In* IEEE International Conference on Unmanned Aircraft Systems (ICUAS), 27–30 May 2014, Orlando, FL.
- Al Heidary, M., J. P. Douzals, C. Sinfort, and A. Vallet. 2014. Influence of spray characteristics on potential spray drift of field crop sprayers: a literature review. *Crop Prot.* 63: 120–130.
- Altieri, M. A., and C. I. Nicholls. 2003. Soil fertility management and insect pests: harmonizing soil and plant health in agroecosystems. *Soil Tillage Res.* 72: 203–211.
- Alves, T. M., I. V. Macrae, and R. L. Koch. 2015. Soybean aphid (Hemiptera: Aphididae) affects soybean spectral reflectance. *J. Econ. Entomol.* 108: 2655–2664.
- Alves, T. M., R. D. Moon, I. V. MacRae, and R. L. Koch. 2019. Optimizing band selection for spectral detection of *Aphis glycines* Matsumura in soybean. *Pest Manag. Sci.* 75: 942–949.
- Amtmann, A., S. Troufflard, and P. Armengaud. 2008. The effect of potassium nutrition on pest and disease resistance in plants. *Physiol. Plant* 133: 682–691.
- Anderson, K., and K. J. Gaston. 2013. Lightweight unmanned aerial vehicles will revolutionize spatial ecology. *Front. Ecol. Environ.* 11: 138–146.
- Aubert, B. A., A. Schroeder, and J. Grimaudo. 2012. IT as enabler of sustainable farming: an empirical analysis of farmers' adoption decision of precision agriculture technology. *Decis. Support Syst.* 54: 510–520.
- Backoulou, G. F., N. C. Elliott, K. Giles, M. Phoofolo, and V. Catana. 2011a. Development of a method using multispectral imagery and spatial pattern metrics to quantify stress to wheat fields caused by *Diuraphis noxia*. *Comput. Electron. Agric.* 75: 64–70.
- Backoulou, G. F., N. C. Elliott, K. Giles, M. Phoofolo, V. Catana, M. Mirik, and J. Michels. 2011b. Spatially discriminating Russian wheat aphid induced plant stress from other wheat stressing factors. *Comput. Electron. Agric.* 78: 123–129.
- Backoulou, G. F., N. C. Elliott, K. L. Giles, and M. N. Rao. 2013. Differentiating stress to wheat fields induced by *Diuraphis noxia* from other stress causing factors. *Comput. Electron. Agric.* 90: 47–53.
- Backoulou, G. F., N. C. Elliott, K. L. Giles, and M. Mirik. 2015. Processed multispectral imagery differentiates wheat crop stress caused by greenbug from other causes. *Comput. Electron. Agric.* 115: 34–39.
- Backoulou, G. F., N. C. Elliott, and K. L. Giles. 2016. Using multispectral imagery to compare the spatial pattern of injury to wheat caused by Russian wheat aphid and greenbug. *Southwest. Entomol.* 41: 1–8.
- Backoulou, G., N. Elliott, K. Giles, T. Alves, M. Brewer, and M. Starek. 2018a. Using multispectral imagery to map spatially variable sugarcane aphid infestations in sorghum. *Southwest. Entomol.* 43: 37–44.
- Backoulou, G. F., N. C. Elliott, K. L. Giles, M. J. Brewer, and M. Starek. 2018b. Detecting change in a sorghum field infested by sugarcane aphid. *Southwest. Entomol.* 43: 823–832.
- Barbedo, J. G. A. 2019. A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. *Drones* 3: 40.
- Berner, B., and J. Chojnacki. 2017. Influence of the air stream produced by the drone on the sedimentation of the sprayed liquid that contains entomopathogenic nematodes. *J. Res. Appl. Agric. Eng.* 62: 26–29.
- Bertuccelli, L., H.-L. Choi, P. Cho, and J. How. 2009. Real-time multi-UAV task assignment in dynamic and uncertain environments, pp. 1–16. *In* AIAA Guidance, Navigation, and Control Conference, 10–13 August 2009, Chicago, IL.
- Bhattarai, G. P., R. B. Schmid, and B. P. McCornack. 2019. Remote sensing data to detect hessian fly infestation in commercial wheat fields. *Sci. Rep.* 9: 6109.
- Biobest. 2019. Drones bundled with cameras or sensors. Available from <https://www.blueskiesdronerental.com/product-category/rentals/drone-bundles/>
- Bird, S. L., D. M. Esterly, and S. G. Perry. 1996. Off-target deposition of pesticides from agricultural aerial spray applications. *J. Environ. Qual.* 25: 1095–1104.
- Bloss, R. 2014. Robot innovation brings to agriculture efficiency, safety, labor savings and accuracy by plowing, milking, harvesting, crop tending/picking and monitoring. *Ind. Rob.* 41: 493–499.

- Blue Skies. 2019. Drones bundled with cameras or sensors. Available from <https://www.blueskiesdrone.com/product-category/rentals/drone-bundles/>
- Bourgeon, M.-A., J.-N. Paoli, G. Jones, S. Villette, and C. Gée. 2016. Field radiometric calibration of a multispectral on-the-go sensor dedicated to the characterization of vineyard foliage. *Comput. Electron. Agric.* 123: 184–194.
- Brown, C. R., and D. K. Giles. 2018. Measurement of pesticide drift from unmanned aerial vehicle application to a vineyard. *Trans. ASABE* 61: 1539–1546.
- Cakmak, I., A. Janssen, and M. W. Sabelis. 2006. Intraguild interactions between the predatory mites *Neoseiulus californicus* and *Phytoseiulus persimilis*. *Exp. Appl. Acarol* 38: 33–46.
- Calderón, R., J. A. Navas-Cortés, C. Lucena, and P. J. Zarco-Tejada. 2013. High-resolution airborne hyperspectral and thermal imagery for early detection of *Verticillium* wilt of olive using fluorescence, temperature and narrow-band spectral indices. *Remote Sens. Environ.* 139: 231–245.
- Carrière, Y., P. C. Ellsworth, P. Dutilleul, C. Ellers-Kirk, V. Barkley, and L. Antilla. 2006. A GIS-based approach for areawide pest management: the scales of *Lygus hesperus* movements to cotton from alfalfa, weeds, and cotton. *Entomol. Exp. Appl.* 118: 203–210.
- Carroll, M. W., J. A. Glaser, R. L. Hellmich, T. E. Hunt, T. W. Sappington, D. Calvin, K. Copenhaver, and J. Fridgen. 2008. Use of spectral vegetation indices derived from airborne hyperspectral imagery for detection of European corn borer infestation in Iowa corn plots. *J. Econ. Entomol.* 101: 1614–1623.
- Carter, G. A., and A. K. Knapp. 2001. Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. *Am. J. Bot.* 88: 677–684.
- Casey, C. A., and M. P. Parrella. 2005. Evaluation of a mechanical dispenser and interplant bridges on the dispersal and efficacy of the predator, *Phytoseiulus persimilis* (Acari: Phytoseiidae) in greenhouse cut roses. *Biol. Control* 32: 130–136.
- Chasen, E., and S. Steffan. 2017. Update on mating disruption in cranberries: the story of SPLAT®. *Proceedings of the Wisconsin Cranberry School* 25: 23–25. Available from <https://fruit.wisc.edu/wp-content/uploads/sites/36/2017/03/2017-Cranberry-School-Proceedings-Final.pdf>
- Chaussé, S., L. Jochems-Tanguay, T. Boislard, D. Cormier, and J. Boisclair. 2017. Lâchers de trichogrammes par drones, une nouvelle approche pour lutter contre la pyralide du maïs dans le maïs sucré de transformation. *In Congrès Annuel de la Société d'Entomologie du Québec*, 23–24 November 2017, Longueuil, Canada. Available from https://www.irda.qc.ca/assets/documents/Publications/documents/simon_chausse_seq2017.pdf
- Chen, Y., G. P. Obit, V. M. Jonas, K. A. Williams, J. R. Nechols, and D. C. Margolies. 2007. Twospotted spider mite population level, distribution, and damage on ivy geranium in response to different nitrogen and phosphorus fertilization regimes. *J. Econ. Entomol.* 100: 1821–1830.
- Chen, T., R. Zeng, W. Guo, X. Hou, Y. Lan, and L. Zhang. 2018. Detection of stress in cotton (*Gossypium hirsutum* L.) caused by aphids using leaf level hyperspectral measurements. *Sensors* 18: 2798.
- Congalton, R. G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sens. Environ.* 37: 35–46.
- Costa, F. G., J. Ueyama, T. Braun, G. Pessin, F. S. Osório, and P. A. Vargas. 2012. The use of unmanned aerial vehicles and wireless sensor network in agricultural applications, pp. 5045–5048. *In IEEE International Geoscience and Remote Sensing Symposium*, 22–27 July 2012, Munich, Germany.
- Cracknell, A. P. 2017. UAVs: regulations and law enforcement. *Int. J. Remote Sens.* 38: 3054–3067.
- Culliney, T. W., and D. Pimentel. 1986. Ecological effects of organic agricultural practices on insect populations. *Agric. Ecosyst. Environ.* 15: 253–266.
- Dalamagkidis, K. 2015. Classification of UAVs, pp. 83–91. *In* K. P. Valavanis and G. J. Vachtsevanos (eds.), *Handbook of unmanned aerial vehicles*. Springer, Dordrecht, Netherlands.
- Damalas, C. A. 2015. Pesticide drift: seeking reliable environmental indicators of exposure assessment. *In* R. H. Armon and O. Hönninen (eds.), *Environmental indicators*. Springer, Dordrecht, Netherlands.
- Dara, S. K. 2014. Predatory mites for managing spider mites on strawberries. UC ANR eJournal of Entomology and Biologicals. Available from <https://ucanr.edu/blogs/blogcore/postdetail.cfm?postnum=14065>
- Dara, S. K. 2019. The new integrated pest management paradigm for the modern age. *J. Int. Pest Manag.* 10: 12.
- Das, P. K., K. K. Choudhary, B. Laxman, S. V. C. K. Rao, and M. V. R. Seshasai. 2014. A modified linear extrapolation approach towards red edge position detection and stress monitoring of wheat crop using hyperspectral data. *Int. J. Remote Sens.* 35: 1432–1449.
- Dash, J. P., D. Pont, R. Brownlie, A. Dunningham, M. Watt, and G. Pearse. 2016. Remote sensing for precision forestry. *NZ J. Forestry* 60: 15–24.
- Dash, J. P., G. D. Pearse, and M. S. Watt. 2018. UAV multispectral imagery can complement satellite data for monitoring forest health. *Remote Sens.* 10: 1216.
- Daughtry, C. S. T., C. L. Walthall, M. S. Kim, E. Brown de Colstoun, and J. E. McMurtrey III. 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. *Remote Sens. Environ.* 74: 229–239.
- De Lange, E. S., J. Salamanca, J. Polashock, and C. Rodriguez-Saona. 2019. Genotypic variation and phenotypic plasticity in gene expression and emissions of herbivore-induced volatiles, and their potential tritrophic implications, in cranberries. *J. Chem. Ecol.* 45: 298–312.
- Del-Campo-Sanchez, A., R. Ballesteros, D. Hernandez-Lopez, J. F. Ortega, and M. A. Moreno. 2019. Quantifying the effect of *Jacobiasca lybica* pest on vineyards with UAVs by combining geometric and computer vision techniques. *PLoS One* 14: e0215521.
- Delegido, J., J. Verrelst, L. Alonso, and J. Moreno. 2011. Evaluation of Sentinel-2 red-edge bands for empirical estimation of green LAI and chlorophyll content. *Sensors (Basel)* 11: 7063–7081.
- Delegido, J., J. Verrelst, C. M. Meza, J. P. Rivera, L. Alonso, and J. Moreno. 2013. A red-edge spectral index for remote sensing estimation of green LAI over agroecosystems. *Europ. J. Agronomy* 46: 42–52.
- DJI. 2019. AGRAS MG-1S. Available from <https://www.dji.com/mg-1s>
- Do Prado Ribeiro, L., A. L. S. Klock, J. A. W. Filho, M. A. Tramontin, M. A. Trapp, A. Mithöfer, and C. Nansen. 2018. Hyperspectral imaging to characterize plant-plant communication in response to insect herbivory. *Plant Methods* 14: 54.
- Drone Agriculture. 2018. Formerly aerobugs. Available from <https://www.droneagriculture.com.au/>
- DuPont, T. 2018. Adding to the codling moth IPM tool box. WSU Tree Fruit. Available from <http://treefruit.wsu.edu/article/adding-to-the-codling-moth-ipm-tool-box/>
- Ecobotix. 2018. Available from <https://www.ecobotix.com/>. In Danish.
- Elliott, N. C., M. Mirik, Z. Yang, T. Dvorak, M. Rao, J. Michels, T. Walker, V. Catana, M. Phoofolo, K. L. Giles, and T. Royer. 2007. Airborne multi-spectral remote sensing of Russian wheat aphid injury to wheat. *Southwest. Entomol.* 32: 213–219.
- Elliott, N., M. Mirik, Z. Yang, D. Jones, M. Phoofolo, V. Catana, K. Giles, and G. J. Michels. 2009. Airborne remote sensing to detect greenbug stress to wheat. *Southwest. Entomol.* 34: 205–211.
- Elliott, N. C., G. F. Backoulou, M. J. Brewer, and K. L. Giles. 2015. NDVI to detect sugarcane aphid injury to grain sorghum. *J. Econ. Entomol.* 108: 1452–1455.
- Everitt, J., D. Escobar, K. Summy, and M. Davis. 1994. Using airborne video, global positioning system, and geographical information system technologies for detecting and mapping citrus blackfly infestations. *Southwest. Entomol.* 19: 129–138.
- Everitt, J., D. Escobar, K. Summy, M. Alaniz, and M. Davis. 1996. Using spatial information technologies for detecting and mapping whitefly and harvester ant infestations in south Texas. *Southwest. Entomol.* 21: 421–432.
- Everitt, J. H., K. R. Summy, D. E. Escobar, and M. R. Davis. 2003. An overview of aircraft remote sensing in integrated pest management. *Subtrop. Plant Sci.* 55: 59–67.
- EWB BioProduction. 2019. Available from <https://bioproduction.dk/?lang=en>
- FAA. 2016. Press release - New FAA rules for small unmanned aircraft systems go into effect. Available from https://www.faa.gov/news/press_releases/news_story.cfm?newsId=20734

- FAA. 2018a. Unmanned Aircraft Systems frequently asked questions. Available from <https://www.faa.gov/uas/resources/faqs/>
- FAA. 2018b. Unmanned Aircraft Systems getting started. Available from https://www.faa.gov/uas/getting_started/
- Façal, B. S., F. G. Costa, G. Pessin, J. Ueyama, H. Freitas, A. Colombo, P. H. Fini, L. Villas, F. S. Osório, P. A. Vargas, and T. Braun. 2014a. The use of unmanned aerial vehicles and wireless sensor networks for spraying pesticides. *J. Syst. Architect.* 60: 393–404.
- Façal, B. S., G. Pessin, G. P. R. Filho, A. C. P. L. F. Carvalho, G. Furquim, and J. Ueyama. 2014b. Fine-tuning of UAV control rules for spraying pesticides on crop fields, pp. 527–533. *In IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*, Limassol, Cyprus.
- Façal, B. S., G. Pessin, G. P. R. Filho, A. C. P. L. F. Carvalho, P. H. Gomes, and J. Ueyama. 2016. Fine-tuning of UAV control rules for spraying pesticides on crop fields: an approach for dynamic environments. *Int. J. Artif. Intell. Tools* 25: 1660003.
- Façal, B. S., H. Freitas, P. H. Gomes, L. Y. Mano, G. Pessin, A. C. P. L. F. de Carvalho, B. Krishnamachari, and J. Ueyama. 2017. An adaptive approach for UAV-based pesticide spraying in dynamic environments. *Comput. Electron. Agric.* 138: 210–223.
- Fan, Y., T. Wang, Z. Qiu, J. Peng, C. Zhang, and Y. He. 2017. Fast detection of striped stem-borer (*Chilo suppressalis* Walker) infested rice seedling based on visible/near-infrared hyperspectral imaging system. *Sensors* 17: 2470.
- Farm Journal Pulse. 2019. Results: will you use a drone on your farm this year? Available from http://pulse.farmjournalmobile.com/index.php?campaign_id=476
- Fitzgerald, G. J., S. J. Maas, and W. R. Detar. 2004. Spider mite detection and canopy component mapping in cotton using hyperspectral imagery and spectral mixture analysis. *Precis. Agric.* 5: 275–289.
- FlyH2 Aerospace. 2018. Agriculture - greenfly aviation. Available from <https://flyh2.com/agriculture-greenfly-aviation/>
- Fraulo, A. B., M. Cohen, and O. E. Liburd. 2009. Visible/near infrared reflectance (VNIR) spectroscopy for detecting twospotted spider mite (Acari: Tetranychidae) damage in strawberries. *Environ. Entomol.* 38: 137–142.
- Gago, J., C. Douthe, R. Coopman, P. Gallego, M. Ribas-Carbo, J. Flexas, J. Escalona, and H. Medrano. 2015. UAVs challenge to assess water stress for sustainable agriculture. *Agric. Water Manag.* 153: 9–19.
- García-Ruiz, F., S. Sankaran, J. M. Maja, W. S. Lee, J. Rasmussen, and R. Ehsani. 2013. Comparison of two aerial imaging platforms for identification of Huanglongbing-infected citrus trees. *Comput. Electron. Agric.* 91: 106–115.
- Garman, P., and B. H. Kennedy. 1949. Effect of soil fertilization on the rate of reproduction of the two-spotted spider mite. *J. Econ. Entomol.* 42: 157–158.
- Genc, H., L. Genc, H. Turhan, S. Smith, and J. Nation. 2008. Vegetation indices as indicators of damage by the sunn pest (Hemiptera: Scutelleridae) to field grown wheat. *Afr. J. Biotechnol.* 7: 173–180.
- Gerson, U., and P. G. Weintraub. 2007. Mites for the control of pests in protected cultivation. *Pest Manag. Sci.* 63: 658–676.
- Giles, D. K., and R. C. Billing. 2015. Deployment and performance of a UAV for crop spraying. *Chem. Eng. Trans.* 44: 307–312.
- Giles, D. K., J. Gardner, and H. Studer. 1995. Mechanical release of predacious mites for biological pest control in strawberries. *Trans. Am. Soc. Agric. Eng.* 38: 1289–1296.
- Gillespie, A. 2015. Dispatches - FAA gives approval to pesticide-spraying drone. *Front. Ecol. Environ.* 13: 236–240.
- Glenn, E. P., A. R. Huete, P. L. Nagler, and S. G. Nelson. 2008. Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: what vegetation indices can and cannot tell us about the landscape. *Sensors (Basel)*. 8: 2136–2160.
- Gonzalez, F., A. Mcfadyen, and E. Ptuig. 2018. Advances in unmanned aerial systems and payload technologies for precision agriculture, pp. 133–155. *In G. Chen (ed.), Advances in agricultural machinery and technologies*. CRC Press, Boca Raton, FL.
- Gonzalez-de-Santos, P., A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoecker, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, et al. 2017. Fleets of robots for environmentally-safe pest control in agriculture. *Precis. Agric.* 18: 574–614.
- Gregg, P. C., A. P. Del Socorro, and P. J. Landolt. 2018. Advances in attract-and-kill for agricultural pests: beyond pheromones. *Annu. Rev. Entomol.* 63: 453–470.
- Grinnan, R., T. E. Carter, and M. T. J. Johnson. 2013. Effects of drought, temperature, herbivory, and genotype on plant-insect interactions in soybean (*Glycine max*). *Arthropod Plant Interact.* 7: 201–215.
- Gutbrodt, B., K. Mody, and S. Dorn. 2011. Drought changes plant chemistry and causes contrasting responses in lepidopteran herbivores. *Oikos* 120: 1732–1740.
- Gutbrodt, B., S. Dorn, S. B. Unsicker, and K. Mody. 2012. Species-specific responses of herbivores to within-plant and environmentally mediated between-plant variability in plant chemistry. *Chemoecology* 22: 101–111.
- Hardin, P. J., and R. R. Jensen. 2011. Small-scale unmanned aerial vehicles in environmental remote sensing: challenges and opportunities. *GISci. Remote Sens.* 48: 99–111.
- Hart, W. G., and V. I. Meyers. 1968. Infrared aerial color photography for detection of populations of brown soft scale in citrus groves. *J. Econ. Entomol.* 61: 617–624.
- Hart, W. G., S. J. Ingle, M. R. Davis, and C. Mangum. 1973. Aerial photography with infrared color film as a method of surveying for citrus blackfly. *J. Econ. Entomol.* 66: 190–194.
- Herren, H. R., T. J. Bird, and D. J. Nadel. 1987. Technology for automated aerial release of natural enemies of the cassava mealybug and cassava green mite. *Int. J. Trop. Insect Sci.* 8: 883–885.
- Herrmann, I., M. Berenstein, A. Sade, A. Karnieli, D. J. Bonfil, and P. G. Weintraub. 2012. Spectral monitoring of two-spotted spider mite damage to pepper leaves. *Remote Sens. Lett.* 3: 277–283.
- Herrmann, I., M. Berenstein, T. Paz-Kagan, A. Sade, and A. Karnieli. 2015. Early detection of two-spotted spider mite damage to pepper leaves by spectral means, pp. 661–666. *In European Conference on Precision Agriculture*, 12–16 July 2015, Volcani Center, Israel.
- Herrmann, I., M. Berenstein, T. Paz-Kagan, A. Sade, and A. Karnieli. 2017. Spectral assessment of two-spotted spider mite damage levels in the leaves of greenhouse-grown pepper and bean. *Biosyst. Eng.* 157: 72–85.
- Hodgson, E. W., E. C. Burkness, W. D. Hutchison, and D. W. Ragsdale. 2004. Enumerative and binomial sequential sampling plans for soybean aphid (Homoptera: Aphididae) in soybean. *J. Econ. Entomol.* 97: 2127–2136.
- Hofman, V., and E. Solseng. 2001. Reducing spray drift. AE-1210. North Dakota State University Extension Service, Fargo, ND. Available from <https://library.ndsu.edu/ir/bitstream/handle/10365/5111/ae1210.pdf?sequence=1>
- Hogan, S. D., M. Kelly, B. Stark, and Y. Chen. 2017. Unmanned aerial systems for agriculture and natural resources. *Calif. Agric.* 71: 5–14.
- Horler, D. N. H., M. Dockray, and J. Barber. 1983. The red edge of plant leaf reflectance. *Int. J. Remote Sens.* 4: 273–288.
- Huang, Y., W. C. Hoffmann, Y. Lan, W. Wu, and B. K. Fritz. 2009. Development of a spray system for an unmanned aerial vehicle platform. *Appl. Eng. Agric.* 25: 803–809.
- Huang, W., J. Luo, J. Zhao, J. Zhang, and Z. Ma. 2011. Predicting wheat aphid using 2-dimensional feature space based on multi-temporal Landsat TM, pp. 1830–1833. *In IEEE International Geoscience and Remote Sensing Symposium*, 24–29 July 2011, Vancouver, BC, Canada.
- Huang, J., H. Liao, Y. Zhu, J. Sun, Q. Sun, and X. Liu. 2012a. Hyperspectral detection of rice damaged by rice leaf folder (*Cnaphalocrocis medinalis*). *Comput. Electron. Agric.* 82: 100–107.
- Huang, W., J. Luo, J. Zhang, J. Zhao, C. Zhao, J. Wang, G. Yang, M. Huang, L. Huang, and S. Du. 2012b. Crop disease and pest monitoring by remote sensing. *In B. Escalante (ed.), Remote sensing – applications*. InTech, Rijeka, Croatia.
- Huang, W., J. Luo, Q. Gong, J. Zhao, and J. Zhang. 2013. Discriminating wheat aphid damage level using spectral correlation simulating analysis, pp. 3722–3725. *In IEEE International Geoscience and Remote Sensing Symposium*, 21–26 July 2013, Melbourne, VIC, Australia.
- Huang, W., Q. Guan, J. Luo, J. Zhang, J. Zhao, D. Liang, L. Huang, and D. Zhang. 2014. New optimized spectral indices for identifying and monitoring winter wheat diseases. *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.* 7: 2516–2524.

- Huang, J.-R., J.-Y. Sun, H.-J. Liao, and X.-D. Liu. 2015a. Detection of brown planthopper infestation based on SPAD and spectral data from rice under different rates of nitrogen fertilizer. *Precis. Agric.* 16: 148–163.
- Huang, J., C. Wei, Y. Zhang, G. A. Blackburn, X. Wang, C. Wei, and J. Wang. 2015b. Meta-analysis of the detection of plant pigment concentrations using hyperspectral remotely sensed data. *PLoS One* 10: e0137029.
- Huang, H., J. Deng, Y. Lan, A. Yang, X. Deng, L. Zhang, S. Wen, Y. Jiang, G. Suo, and P. Chen. 2018. A two-stage classification approach for the detection of spider mite-infested cotton using UAV multispectral imagery. *Remote Sens. Lett.* 9: 933–941.
- Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* 25: 295–309.
- Hunt, E. R., and C. S. T. Daughtry. 2018. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *Int. J. Remote Sens.* 39: 5345–5376.
- Hunt, J. E. R., and S. I. Rondon. 2017. Detection of potato beetle damage using remote sensing from small unmanned aircraft systems. *J. Appl. Remote Sens.* 11: 026013.
- Hunt, J. E. R., S. I. Rondon, P. B. Hamm, R. W. Turner, A. E. Bruce, and J. J. Brungardt. 2016. Insect detection and nitrogen management for irrigated potatoes using remote sensing from small unmanned aircraft systems, pp. 98660N. *In SPIE Commercial + Scientific Sensing and Imaging*, 17–21 April 2016, Baltimore, MD.
- Iost Filho, F. H. 2019. Remote sensing for monitoring whitefly, *Bemisia tabaci* biotype B (Hemiptera: Aleyrodidae) in soybean. Master's thesis. University of São Paulo, Piracicaba, São Paulo, Brazil (in Portuguese with English abstract).
- ISCA. 2019a. Mating disruption. Available from <https://www.iscotech.com/solutions/mating-disruption/>
- ISCA. 2019b. Attract & kill: the hybrid IPM solution. Available from <https://www.iscotech.com/solutions/attract-kill/>
- Jorge, L. A. C., Z. N. Brandão, and R. Y. Inamasu. 2014. Insights and recommendations of use of UAV platforms in precision agriculture in Brazil, pp. 18. *In SPIE Remote Sensing*, 22–25 September 2014, Amsterdam, Netherlands.
- Jorge, J., M. Vallbé, and J. A. Soler. 2019. Detection of irrigation inhomogeneities in an olive grove using the NDRE vegetation index obtained from UAV images. *Eur. J. Remote Sens.* 52: 169–177.
- Judd, G. J. R., and M. G. T. Gardiner. 2005. Towards eradication of codling moth in British Columbia by complimentary actions of mating disruption, tree banding and sterile insect technique: five-year study in organic orchards. *Crop Prot.* 24: 718–733.
- Katsoulas, N., A. Elvanidi, K. Ferentinos, T. Bartzanas, and C. Kittas. 2016. Calibration methodology of a hyperspectral imaging system for greenhouse plant water stress estimation. *Acta Hort.* 1142: 119–126.
- Kim, H. G., J.-S. Park, and D.-H. Lee. 2018. Potential of unmanned aerial sampling for monitoring insect populations in rice fields. *Fla. Entomol.* 101: 330–334.
- Koppert. 2017a. Spidex - *Phytoseiulus persimilis*. Available from <https://www.koppert.com/products/products-pests-diseases/spidex/>
- Koppert. 2017b. Mini-airbug. Available from <https://www.koppert.com/products/distribution-appliances/mini-airbug/>
- Lacoste, C., C. Nansen, S. Thompson, L. Moir-Barnetson, A. Mian, M. McNee, and K. C. Flower. 2015. Increased susceptibility to aphids of flowering wheat plants exposed to low temperatures. *Environ. Entomol.* 44: 610–618.
- Lan, Y., and S. Chen. 2018. Current status and trends of plant protection UAV and its spraying technology in China. *Int. J. Precis. Agric. Aviat.* 1: 1–9.
- Lan, Y., S. J. Thomson, Y. Huang, W. C. Hoffmann, and H. Zhang. 2010. Current status and future directions of precision aerial application for site-specific crop management in the USA. *Comput. Electron. Agric.* 74: 34–38.
- Lan, Y., H. Zhang, J. W. Hoffmann, and J. D. Lopez. 2013. Spectral response of spider mite infested cotton: mite density and miticide rate study. *Int. J. Agric. Biol. Eng.* 6: 48–52.
- Larson, J. A., R. K. Roberts, B. C. English, S. L. Larkin, M. C. Marra, S. W. Martin, K. W. Paxton, and J. M. Reeves. 2008. Factors affecting farmer adoption of remotely sensed imagery for precision management in cotton production. *Precis. Agric.* 9: 195–208.
- Lestina, J., M. Cook, S. Kumar, J. Morissette, P. J. Ode, and F. Peairs. 2016. MODIS imagery improves pest risk assessment: a case study of wheat stem sawfly (*Cephus cinctus*, Hymenoptera: Cephidae) in Colorado, USA. *Environ. Entomol.* 45: 1343–1351.
- Li, H., W. A. Payne, G. J. Michels, and C. M. Rush. 2008. Reducing plant abiotic and biotic stress: drought and attacks of greenbugs, corn leaf aphids and virus disease in dryland sorghum. *Environ. Exp. Bot.* 63: 305–316.
- Li, D., X. Yuan, B. Zhang, Y. Zhao, Z. Song, and C. Zuo. 2013. Report of using unmanned aerial vehicle to release *Trichogramma*. *Chin. J. Biol. Control* 29: 455–458 (in Chinese with English abstract).
- Lillesand, T. M., R. W. Kiefer, and J. W. Chipman. 2007. *Remote sensing and image interpretation*, pp. 736. Wiley, Hoboken, NJ.
- Lindblom, J., C. Lundström, M. Ljung, and A. Jonsson. 2017. Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. *Precis. Agric.* 18: 309–331.
- Liu, X.-D., and Q.-H. Sun. 2016. Early assessment of the yield loss in rice due to the brown planthopper using a hyperspectral remote sensing method. *Int. J. Pest Manag.* 62: 205–213.
- Liu, Z., J.-A. Cheng, W. Huang, C. Li, X. Xu, X. Ding, J. Shi, and B. Zhou. 2012. Hyperspectral discrimination and response characteristics of stressed rice leaves caused by rice leaf folder, pp. 528–537. *In* D. Li and Y. Chen (eds.), *Computer and computing technologies in agriculture V. CCTA 2011. IFIP advances in information and communication technology*, vol. 369. Springer, Berlin/Heidelberg, Germany.
- Liu, Z.-Y., J.-G. Qi, N.-N. Wang, Z.-R. Zhu, J. Luo, L.-J. Liu, J. Tang, and J.-A. Cheng. 2018. Hyperspectral discrimination of foliar biotic damages in rice using principal component analysis and probabilistic neural network. *Precision Agric.* 19: 973–991.
- Lobits, B., L. Johnson, C. Hlavka, R. Armstrong, and C. Bell. 1997. Grapevine remote sensing analysis of phylloxera early stress (GRAPES): remote sensing analysis summary. NASA Tech. Memo, Moffett Field, CA. 112218.
- Lowe, A., N. Harrison, and A. P. French. 2017. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. *Plant Methods.* 13: 80.
- Luedeling, E., A. Hale, M. Zhang, W. J. Bentley, and L. C. Dharmasri. 2009. Remote sensing of spider mite damage in California peach orchards. *Int. J. Appl. Earth Obs. Geoinf.* 11: 244–255.
- Luo, J., D. Wang, Y. Dong, W. Huang, and J. Wang. 2011. Developing an aphid damage hyperspectral index for detecting aphid (Hemiptera: Aphididae) damage levels in winter wheat, pp. 1744–1747. *In* IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2–29 July 2011, Vancouver, BC, Canada.
- Luo, J., W. Huang, Q. Guan, J. Zhao, and J. Zhang. 2013a. Hyperspectral image for discriminating aphid and aphid damage region of winter wheat leaf, pp. 3726–3729. *In* IEEE International Geoscience and Remote Sensing Symposium, 21–26 July 2013, Melbourne, VIC, Australia.
- Luo, J., W. Huang, L. Yuan, C. Zhao, S. Du, J. Zhang, and J. Zhao. 2013b. Evaluation of spectral indices and continuous wavelet analysis to quantify aphid infestation in wheat. *Precis. Agric.* 14: 151–161.
- Luo, J., W. Huang, J. Zhao, J. Zhang, C. Zhao, and R. Ma. 2013c. Detecting aphid density of winter wheat leaf using hyperspectral measurements. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* 6: 690–698.
- Luo, J., W. Huang, J. Zhao, J. Zhang, R. Ma, and M. Huang. 2014. Predicting the probability of wheat aphid occurrence using satellite remote sensing and meteorological data. *Optik* 125: 5660–5665.
- M3 Consulting Group. 2018. Codling moth sterile insect release. Available from <https://www.m3cg.us/sir/>
- Ma, H., W. Huang, Y. Jing, C. Yang, L. Han, Y. Dong, H. Ye, Y. Shi, Q. Zheng, L. Liu, and C. Ruan. 2019. Integrating growth and environmental parameters to discriminate powdery mildew and aphid of winter wheat using bi-temporal Landsat-8 imagery. *Remote Sens.* 11: 846.
- Machado, S., E. D. Bynum, T. L. Archer, R. J. Lascano, L. T. Wilson, J. Bordovsky, E. Segarra, K. Bronson, D. M. Nesmith, and W. Xu. 2000. Spatial and temporal variability of corn grain yield: site-specific relationships of biotic and abiotic factors. *Precis. Agric.* 2: 359–376.
- Maes, W. H., and K. Steppe. 2019. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends Plant Sci.* 24: 152–164.

- Mahlein, A. K., T. Rumpf, P. Welke, H. W. Dehne, L. Plümer, U. Steiner, and E. C. Oerke. 2013. Development of spectral indices for detecting and identifying plant diseases. *Remote Sens. Environ.* 128: 21–30.
- Martel, V., S. Trudeau, R. Johns, E. Owens, S. M. Smith, and G. Bovin. 2018. Testing the efficacy of *Trichogramma minutum* in the context of an ‘Early Intervention Strategy’ against the spruce budworm using different release methods. SERG-i Annual Reports. Quebec, Canada. pp. 276–283.
- Martin, D. E., and M. A. Latheef. 2017. Remote sensing evaluation of two-spotted spider mite damage on greenhouse cotton. *J. Vis. Exp.* 122: 54314.
- Martin, D. E., and M. A. Latheef. 2018. Active optical sensor assessment of spider mite damage on greenhouse beans and cotton. *Exp. Appl. Acarol* 74: 147–158.
- Martin, D. E., and M. A. Latheef. 2019. Aerial application methods control spider mites on corn in Kansas, USA. *Exp. Appl. Acarol* 77: 571–582.
- Martín, D. E., M. A. Latheef, and J. D. López. 2015. Evaluation of selected acaricides against twospotted spider mite (Acari: Tetranychidae) on greenhouse cotton using multispectral data. *Exp. Appl. Acarol* 66: 227–245.
- Martínez-Guanter, J., P. Agüera, J. Agüera, and M. Pérez-Ruiz. 2019. Spray and economics assessment of a UAV-based ultra-low-volume application in olive and citrus orchards. *Precision Agric.* doi:10.1007/s11119-019-09665-7
- Matase, A., P. Toscano, S. F. Di Gennaro, L. Genesio, F. P. Vaccari, J. Primmerio, C. Belli, A. Zaldei, R. Bianconi, and B. Gioli. 2015. Intercomparison of UAV, aircraft and satellite remote sensing platforms for precision viticulture. *Remote Sens.* 7: 2971–2990.
- Mattson, W. J., and R. A. Haack. 1987. The role of drought in outbreaks of plant-eating insects. *BioScience* 37: 110–118.
- McMurtry, J. A., and B. A. Croft. 1997. Life-styles of Phytoseiid mites and their roles in biological control. *Annu. Rev. Entomol.* 42: 291–321.
- Midgarden, D., S. J. Fleischer, R. Weisz, and Z. Smilowitz. 1997. Site-specific integrated pest management impact on development of Esfenvalerate resistance in Colorado potato beetle (Coleoptera: Chrysomelidae) and on densities of natural enemies. *J. Econ. Entomol.* 90: 855–867.
- Miller, N. 2015. CALS researchers deploy insect ‘birth control’ to protect cranberries. University of Wisconsin-Madison News. Available from <https://news.wisc.edu/cals-researchers-deploy-insect-birth-control-to-protect-cranberries/>
- Miller, J. R., and L. J. Gut. 2015. Mating disruption for the 21st century: matching technology with mechanism. *Environ. Entomol.* 44: 427–453.
- Mirik, M., G. J. Michels, Jr, S. Kassymzhanova-Mirik, N. C. Elliott, and R. Bowling. 2006a. Hyperspectral spectrometry as a means to differentiate uninfested and infested winter wheat by greenbug (Hemiptera: Aphididae). *J. Econ. Entomol.* 99: 1682–1690.
- Mirik, M., G. J. Michels, S. Kassymzhanova-Mirik, N. C. Elliott, V. Catana, D. B. Jones, and R. Bowling. 2006b. Using digital image analysis and spectral reflectance data to quantify damage by greenbug (Hemiptera: Aphididae) in winter wheat. *Comput. Electron. Agric.* 51: 86–98.
- Mirik, M., G. Michels, S. Kassymzhanova-Mirik, and N. Elliott. 2007. Reflectance characteristics of Russian wheat aphid (Hemiptera: Aphididae) stress and abundance in winter wheat. *Comput. Electron. Agric.* 57: 123–134.
- Mirik, M., R. Ansley, G. Michels, and N. Elliott. 2012. Spectral vegetation indices selected for quantifying Russian wheat aphid (*Diuraphis noxia*) feeding damage in wheat (*Triticum aestivum* L.). *Precis. Agric.* 13: 501–516.
- Mirik, M., R. J. Ansley, K. Steddom, C. M. Rush, G. J. Michels, F. Workneh, S. Cui, and N. C. Elliott. 2014. High spectral and spatial resolution hyperspectral imagery for quantifying Russian wheat aphid infestation in wheat using the constrained energy minimization classifier. *J. Appl. Remote Sens.* 8: 083661.
- Miyahara, M. 1993. Utilization of helicopter for agriculture in Japan. *Korean J. Weed Sci.* 13: 185–194.
- Mohite, J., A. Gauns, N. Twarakavi, and S. Pappula. 2018. Evaluating the capabilities of Sentinel-2 and Tetracam RGB+ 3 for multi-temporal detection of thrips on capsicum, pp. 106640U. *In* Autonomous air and ground sensing systems for agricultural optimization and phenotyping III, vol. 10664. SPIE Commercial + Scientific Sensing and Imaging, 15-19 April 2018, Orlando, FL.
- Mulla, D. J. 2013. Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. *Biosyst. Eng.* 114: 358–371.
- Myers, S. W., and C. Gratton. 2006. Influence of potassium fertility on soybean aphid, *Aphis glycines* Matsumura (Hemiptera: Aphididae), population dynamics at a field and regional scale. *Environ. Entomol.* 35: 219–227.
- Nansen, C. 2012. Use of variogram parameters in analysis of hyperspectral imaging data acquired from dual-stressed crop leaves. *Remote Sens.* 4: 180–193.
- Nansen, C. 2016. The potential and prospects of proximal remote sensing of arthropod pests. *Pest Manag. Sci.* 72: 653–659.
- Nansen, C., and N. Elliott. 2016. Remote sensing and reflectance profiling in entomology. *Annu. Rev. Entomol.* 61: 139–158.
- Nansen, C., T. Macedo, R. Swanson, and D. K. Weaver. 2009. Use of spatial structure analysis of hyperspectral data cubes for detection of insect-induced stress in wheat plants. *Int. J. Remote Sens.* 30: 2447–2464.
- Nansen, C., A. J. Sidumo, and S. Capareda. 2010. Variogram analysis of hyperspectral data to characterize the impact of biotic and abiotic stress of maize plants and to estimate biofuel potential. *Appl. Spectrosc.* 64: 627–636.
- Nansen, C., A. J. Sidumo, X. Martini, K. Stefanova, and J. D. Roberts. 2013. Reflectance-based assessment of spider mite “bio-response” to maize leaves and plant potassium content in different irrigation regimes. *Comput. Electron. Agric.* 97: 21–26.
- Nebiker, S., N. Lack, M. Abächerli, and S. Läderach. 2016. Light-weight multispectral UAV sensors and their capabilities for predicting grain yield and detecting plant diseases. *ISPRS Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* XLI-B1: 963–970.
- Nguyen, H. D. D., and C. Nansen. 2018. Edge-biased distributions of insects. *A review. Agron Sustain. Dev.* 38: 11.
- Nigam, R., R. Kot, S. S. Sandhu, B. K. Bhattacharya, R. S. Chandi, M. Singh, J. Singh, and K. Manjunath. 2016. Ground-based hyperspectral remote sensing to discriminate biotic stress in cotton crop, pp. 98800H. *In* SPIE Asia-Pacific Remote Sensing Symposium, 4–7 April 2016, New Delhi, India.
- Nutter, F. W., G. L. Tylka, J. Guan, A. J. Moreira, C. C. Maret, T. R. Rosburg, J. P. Basart, and C. S. Chong. 2002. Use of remote sensing to detect soybean cyst nematode-induced plant stress. *J. Nematol.* 34: 222–231.
- Opit, G. P., J. R. Nechols, D. C. Margolies, and K. A. Williams. 2005. Survival, horizontal distribution, and economics of releasing predatory mites (Acari: Phytoseiidae) using mechanical blowers. *Biol. Control* 33: 344–351.
- OPTiM. 2016. OPTiM’s AgriDrone undergoes the world’s first successful trials for insect extermination by drone. Available from <https://en.optim.co.jp/news-detail/11172>
- Pádua, L., J. Vanko, J. Hruška, T. Adão, J. J. Sousa, E. Peres, and R. Morais. 2017. UAS, sensors, and data processing in agroforestry: a review towards practical applications. *Int. J. Remote Sens.* 38: 2349–2391.
- Parabug. 2019. Parabug, biocontrol by drone. Available from <https://www.parabug.solutions/>
- Park, C. Y., B.-W. Jang, J. H. Kim, C.-G. Kim, S.-M. June 2012. Bird strike event monitoring in a composite UAV wing using high speed optical fiber sensing system. *Compos. Sci. Technol.* 72: 498–505.
- Parra, J. R. P. 2014. Biological control in Brazil: an overview. *Sci. Agric.* 71: 420–429.
- Pearl, E. 2015. Drone used to drop beneficial bugs on corn crop. The University of Queensland, Australia, News (UQ News). Available from <https://www.uq.edu.au/news/article/2015/04/drone-used-drop-beneficial-bugs-corn-crop>
- Pederi, Y. A., and H. S. Cheporniuk. 2015. Unmanned aerial vehicles and new technological methods of monitoring and crop protection in precision agriculture, pp. 298–301. *In* IEEE International Conference Actual Problems of Unmanned Aerial Vehicles Developments, 13–15 October 2015, Kiev, Ukraine.
- Peña, J. M., J. Torres-Sánchez, A. Serrano-Pérez, A. I. de Castro, and F. López-Granados. 2015. Quantifying efficacy and limits of unmanned aerial vehicle (UAV) technology for weed seedling detection as affected by sensor resolution. *Sensors* 15: 5609–5626.
- Peñuelas, J., and I. Filella. 1998. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. *Trends Plant Sci.* 3: 151–156.
- Peñuelas, J., I. Filella, P. Lloret, F. Munoz, and M. Vilajeliu. 1995. Reflectance assessment of mite effects on apple trees. *Int. J. Remote Sens.* 16: 2727–2733.

- Perring, T. M., T. O. Holtzer, J. L. Toole, and J. M. Norman. 1986. Relationships between corn-canopy microenvironments and banks grass mite (Acari: Tetranychidae) abundance. *Environ. Entomol.* 15: 79–83.
- Pickett, C. H., F. E. Gilstrap, R. K. Morrison, and L. F. Bouse. 1987. Release of predatory mites (Acari: Phytoseiidae) by aircraft for the biological control of spider mites (Acari: Tetranychidae) infesting corn. *J. Econ. Entomol.* 80: 906–910.
- Pierpaoli, E., G. Carli, E. Pignatti, and M. Canavari. 2013. Drivers of precision agriculture technologies adoption: a literature review. *Proc. Technol.* 8: 61–69.
- Pimentel, D. 1995. Amounts of pesticides reaching target pests: environmental impacts and ethics. *J. Agric. Environ. Ethics* 8: 17–29.
- Ponda, S. S., L. B. Johnson, A. Geramifard, and J. P. How. 2015. Cooperative mission planning for multi-UAV teams, pp. 1447–1490. *In* K. P. Valavanis and G. J. Vachtsevanos (eds.), *Handbook of unmanned aerial vehicles*. Springer, Dordrecht, Netherlands.
- Prabhakar, M., Y. Prasad, M. Thirupathi, G. Sreedevi, B. Dharajothi, and B. Venkateswarlu. 2011. Use of ground based hyperspectral remote sensing for detection of stress in cotton caused by leafhopper (Hemiptera: Cicadellidae). *Comput. Electron. Agric.* 79: 189–198.
- Prabhakar, M., Y. G. Prasad, and M. N. Rao. 2012. Remote sensing of biotic stress in crop plants and its applications for pest management, pp. 517–545. *In* B. Venkateswarlu, A. K. Shanker, C. Shanker and M. Maheswari (eds.), *Crop stress and its management: perspectives and strategies*. Springer, Dordrecht, Netherlands.
- Prabhakar, M., Y. G. Prasad, S. Vennila, M. Thirupathi, G. Sreedevi, G. R. Rao, and B. Venkateswarlu. 2013. Hyperspectral indices for assessing damage by the solenopsis mealybug (Hemiptera: Pseudococcidae) in cotton. *Comput. Electron. Agric.* 97: 61–70.
- Prasannakumar, N., S. Chander, R. Sahoo, and V. Gupta. 2013. Assessment of brown planthopper, (*Nilaparvata lugens*)[Stål], damage in rice using hyperspectral remote sensing. *Int. J. Pest Manag.* 59: 180–188.
- Prasannakumar, N., S. Chander, and R. Sahoo. 2014. Characterization of brown planthopper damage on rice crops through hyperspectral remote sensing under field conditions. *Phytoparasitica* 42: 387–395.
- PwC. 2016. Clarity from above. PwC global report on the commercial applications of drone technology. Available from <https://www.pwc.pl/pl/pdf/clarity-from-above-pwc.pdf>
- Qin, W.-C., B.-J. Qiu, X.-Y. Xue, C. Chen, Z.-F. Xu, and Q.-Q. Zhou. 2016. Droplet deposition and control effect of insecticides sprayed with an unmanned aerial vehicle against plant hoppers. *Crop Prot.* 85: 79–88.
- Quemada, M., J. Gabriel, and P. Zarco-Tejada. 2014. Airborne hyperspectral images and ground-level optical sensors as assessment tools for maize nitrogen fertilization. *Remote Sens.* 6: 2940–2962.
- Rangel, R. K. 2016. Development of an UAVS distribution tools for pest's biological control "Bug Bombs!", pp. 1–8. *In* IEEE Aerospace Conference, 5–12 March 2016, Big Sky, MT.
- Rasmussen, J., J. Nielsen, F. Garcia-Ruiz, S. Christensen, J. C. Streibig, and B. Lotz. 2013. Potential uses of small unmanned aircraft systems (UAS) in weed research. *Weed Res.* 53: 242–248.
- Raun, W. R., J. B. Solie, G. V. Johnson, M. L. Stone, R. W. Mullen, K. W. Freeman, W. E. Thomason, and E. V. Lukina. 2002. Improving nitrogen use efficiency in cereal grain production with optical sensing and variable rate application. *Agron. J.* 94: 815–820.
- Reisig, D., and L. Godfrey. 2006. Remote sensing for detection of cotton aphid- (Homoptera: Aphididae) and spider mite- (Acari: Tetranychidae) infested cotton in the San Joaquin Valley. *Environ. Entomol.* 35: 1635–1646.
- Reisig, D., and L. Godfrey. 2007. Spectral response of cotton aphid- (Homoptera: Aphididae) and spider mite- (Acari: Tetranychidae) infested cotton: controlled studies. *Environ. Entomol.* 36: 1466–1474.
- Reisig, D. D., and L. D. Godfrey. 2010. Remotely sensing arthropod and nutrient stressed plants: a case study with nitrogen and cotton aphid (Hemiptera: Aphididae). *Environ. Entomol.* 39: 1255–1263.
- Riedell, W. E., and T. M. Blackmer. 1999. Leaf reflectance spectra of cereal aphid-damaged wheat. *Crop Sci.* 39: 1835–1840.
- Riley, J. R. 1989. Remote sensing in entomology. *Ann. Rev. Entomol.* 43: 247–271.
- Roberts, D. A., K. L. Roth, and R. L. Perroy. 2001. Hyperspectral vegetation indices, pp. 309–327. *In* P. S. Thenkabail, J. G. Lyon, and A. Huete (eds.), *Hyperspectral remote sensing of vegetation*. CRC Press, Boca Raton, FL.
- Rodriguez, J. G. 1951. Mineral nutrition of the two-spotted spider mite, *Tetranychus bimaculatus* Harvey. *Ann. Entomol. Soc. Am.* 44: 511–526.
- Rodriguez, J. G., and R. B. Neiswander. 1949. The effect of soil soluble salts and cultural practices on mite populations on hothouse tomatoes. *J. Econ. Entomol.* 42: 56–59.
- Rodriguez-Saona, C., D. Polk, R. Holdcraft, D. Chinnsamy, and A. Mafr-Neto. 2010. SPLAT-OrB reveals competitive attraction as a mechanism of mating disruption in oriental beetle (Coleoptera: Scarabaeidae). *Environ. Entomol.* 39: 1980–1989.
- Rosenthal, G. 2017. PPQ explores the tantalizing promise of unmanned aircraft systems. USDA APHIS. Available from <https://www.aphis.usda.gov/aphis/ourfocus/planthealth/ppq-program-overview/plant-protection-today/articles/unmanned-aircraft-systems>
- Ru, Y., H. Zhou, Q. Fan, and X. Wu. 2011. Design and investigation of ultra-low volume centrifugal spraying system on aerial plant protection, no. 1110663. *In* ASABE Annual International Meeting, 7–10 August 2011, Louisville, KY.
- Sánchez-Bayo, F., S. Baskaran, and I. R. Kennedy. 2002. Ecological relative risk (EcoRR): another approach for risk assessment of pesticides in agriculture. *Agric. Ecosyst. Environ.* 91: 37–57.
- Sato, A. 2003. The RMAX helicopter UAV. Yamaha Moter Co., LTD., Shizuoka, Japan. Available from <https://pdfs.semanticscholar.org/5d80/faae7d1ffd27422df3ad6e3d08dc6bdb1920.pdf>
- SDU. 2018. EcoDrone. University of Southern Denmark (SDU). Available from https://www.sdu.dk/en/om_sdu/institutter_centre/sduascenter/researchprojects
- Seely, R. 2018. Drones, joysticks, and data-driven farming, pp. 16–21. *In* Grow. University of Wisconsin-Madison College of Agricultural and Life Sciences. Available from <https://grow.cals.wisc.edu/wp-content/uploads/sites/14/2018/06/Grow-Summer2018-web.pdf>
- Sétamou, M., and D. W. Bartels. 2015. Living on the edges: spatial niche occupation of Asian citrus psyllid, *Diaphorina citri* Kuwayama (Hemiptera: Liviidae), in citrus groves. *PLoS One* 10: e0131917.
- Svertson, D., K. Flower, and C. Nansen. 2015. Nonrandom distribution of cabbage aphids (Hemiptera: Aphididae) in dryland canola (Brassicales: Brassicaceae). *Environ. Entomol.* 44: 767–779.
- Svertson, D., N. Callow, K. Flower, A. Neuhaus, M. Olejnik, and C. Nansen. 2016a. Unmanned aerial vehicle canopy reflectance data detects potassium deficiency and green peach aphid susceptibility in canola. *Precis. Agric.* 17: 659–677.
- Svertson, D., K. Flower, and C. Nansen. 2016b. Spatially-optimized sequential sampling plan for cabbage aphids *Brevicoryne brassicae* L. (Hemiptera: Aphididae) in canola fields. *J. Econ. Entomol.* 109: 1929–1935.
- Seymour, R. 2018. Drones tested for moth drops in Okanagan orchards. Kelowna Daily Courier. Available from http://www.kelownadailycourier.ca/news/article_abc959f2-3376-11e8-8de7-efac785fe8d1.html
- Shah, P. A., and J. K. Pell. 2003. Entomopathogenic fungi as biological control agents. *Appl. Microbiol. Biotechnol.* 61: 413–423.
- Shapiro-Ilan, D. I., R. Han, and C. Dolinski. 2012. Entomopathogenic nematode production and application technology. *J. Nematol.* 44: 206–217.
- Shi, Y., W. Huang, J. Luo, L. Huang, and X. Zhou. 2017. Detection and discrimination of pests and diseases in winter wheat based on spectral indices and kernel discriminant analysis. *Comput. Electron. Agric.* 141: 171–180.
- Shields, E. J., and A. M. Testa. 1999. Fall migratory flight initiation of the potato leafhopper, *Empoasca fabae* (Homoptera: Cicadellidae): observations in the lower atmosphere using remote piloted vehicles. *Agric. For. Meteorol.* 97: 317–330.
- Shim, D. H., J.-S. Han, and H.-T. Yeo. 2009. A development of unmanned helicopters for industrial applications. *J. Intell. Robot. Syst.* 54: 407–421.
- Simmons, G. S., D. M. Suckling, J. E. Carpenter, M. F. Addison, V. A. Dyck, and M. J. B. Vreysen. 2010. Improved quality management to enhance the efficacy of the sterile insect technique for lepidopteran pests. *J. Appl. Entomol.* 134: 261–273.
- Singh, K., and C. Nansen. 2017. Advanced calibration to improve robustness of drone-acquired hyperspectral remote sensing data, pp. 1–6. *In* IEEE

- International Conference on Agro-Geoinformatics, 7–10 August 2017, Fairfax, VA.
- Smith, S. M. 1996. Biological control with Trichogramma: advances, successes, and potential of their use. *Annu. Rev. Entomol.* 41: 375–406.
- Souza, E. G., P. C. Scharf, and K. A. Sudduth. 2010. Sun position and cloud effects on reflectance and vegetation indices of corn. *Agron. J.* 102: 734–744.
- Stanton, C., M. J. Starek, N. Elliott, M. Brewer, M. M. Maeda, and T. Chu. 2017. Unmanned aircraft system-derived crop height and normalized difference vegetation index metrics for sorghum yield and aphid stress assessment. *J. Appl. Remote Sens.* 11: 026035.
- Stark, B., S. Rider, and Y. Chen. 2013a. Optimal pest management by networked unmanned cropdusters in precision agriculture: a cyber-physical system approach, pp. 296–302. *In* IFAC Proceedings. IFAC Workshop on Research, Education and Development of Unmanned Aerial Systems, 20–22 November 2013, Compiegne, France.
- Stark, B., B. Smith, and Y. Chen. 2013b. A guide for selecting small unmanned aerial systems for research-centric applications, pp. 38–45. *In* IFAC Proceedings. IFAC Workshop on Research, Education and Development of Unmanned Aerial Systems, 20–22 November 2013, Compiegne, France.
- Steffan, S. A., E. M. Chasen, A. E. Deutsch, and A. Mafram-Neto. 2017. Multi-species mating disruption in cranberries (Ericales: Ericaceae): early evidence using a flowable emulsion. *J. Insect Sci.* 17: 54.
- Stiefel, V. L., D. C. Margolies, and P. J. Bramel-Cox. 1992. Leaf temperature affects resistance to the banks grass mite (Acari: Tetranychidae) on drought-resistant grain sorghum. *J. Econ. Entomol.* 85: 2170–2184.
- Stöcker, C., R. Bennett, F. Nex, M. Gerke, and J. Zevenbergen. 2017. Review of the current state of UAV regulations. *Remote Sens.* 9: 459.
- Stone, C., and C. Mohammed. 2017. Application of remote sensing technologies for assessing planted forests damaged by insect pests and fungal pathogens: a review. *Curr. For. Rep.* 3: 75–92.
- Stumph, B., M. Hernandez Virto, H. Medeiros, A. Tabb, S. Wolford, K. Rice, and T. Leskey. 2019. Detecting invasive insects with unmanned aerial vehicles. *In* IEEE International Conference on Robotics and Automation (ICRA), 20–24 May 2019, Montreal, Canada.
- Sudbrink, D., F. Harris, J. Robbins, P. English, and J. Willers. 2003. Evaluation of remote sensing to identify variability in cotton plant growth and correlation with larval densities of beet armyworm and cabbage looper (Lepidoptera: Noctuidae). *Fla. Entomol.* 86: 290–294.
- Sudbrink, D. L., S. J. Thomson, R. S. Fletcher, F. A. Harris, P. J. English, and J. T. Robbins. 2015. Remote sensing of selected winter and spring host plants of tarnished plant bug (Heteroptera: Miridae) and herbicide use strategies as a management tactic. *Am. J. Plant Sci.* 6: 1313–1327.
- Sylvester, G. 2018. E-agriculture in action: drones for agriculture. Food and Agriculture Organization of the United Nations and International Telecommunication Union, Bangkok, Thailand. Available from <http://www.fao.org/3/i8494en/i8494en.pdf>
- Tahir, N., and G. Brooker. 2009. Feasibility of UAV based optical tracker for tracking Australian plague locust, pp. 1–10. *In* Australasian Conference on Robotics and Automation, 2–4 December 2009, Sydney, NSW, Australia.
- Tan, L. T., and K. H. Tan. 2013. Alternative air vehicles for sterile insect technique aerial release. *J. Appl. Entomol.* 137: 126–141.
- Tan, Y., J.-Y. Sun, B. Zhang, M. Chen, Y. Liu, and X.-D. Liu. 2019. Sensitivity of a ratio vegetation index derived from hyperspectral remote sensing to the brown planthopper stress on rice plants. *Sensors* 19: 375.
- Tang, Z., Y. Li, J. Zhao, and D. Hu. 2016. Research on trajectory planning algorithm of plant-protective UAV, pp. 110–113. *In* IEEE International Conference on Aircraft Utility Systems, 10–12 October 2016, Beijing, China.
- Teal Group. 2019. Teal Group predicts worldwide civil drone production will almost triple over the next decade. Available from <https://www.tealgroup.com/index.php/pages/press-releases/60-teal-group-predicts-worldwide-civil-drone-production-will-almost-triple-over-the-next-decade>
- Teske, M. E., S. L. Bird, D. M. Esterly, T. B. Curbishley, S. L. Ray, and S. G. Perry. 2002. AgDRIFT: a model for estimating near-field spray drift from aerial applications. *Environ. Toxicol. Chem.* 21: 659–671.
- Teske, A. L., G. Chen, C. Nansen, and Z. Kong. 2019. Optimised dispensing of predatory mites by multirotor UAVs in wind: a distribution pattern modelling approach for precision pest management. *Biosyst. Eng.* 187: 226–238.
- Timewell, E. 2018. Dropped in for fruitless sex. The New Zealand Institute for Plant and Food Research. Available from <https://www.plantandfood.co.nz/page/news/media-release/story/dropped-in-for-fruitless-sex/>
- Tsai, M.-Y., K. Elgethun, J. Ramaprasad, M. G. Yost, A. S. Felsot, V. R. Hebert, and R. A. Fenske. 2005. The Washington aerial spray drift study: modeling pesticide spray drift deposition from an aerial application. *Atmos. Environ.* 39: 6194–6203.
- Turlings, T. C. J., and M. Erb. 2018. Tritrophic interactions mediated by herbivore-induced plant volatiles: mechanisms, ecological relevance, and application potential. *Annu. Rev. Entomol.* 63: 433–452.
- UAV-IQ. 2018. An efficient approach to sustainable farming. Available from <http://www.uaviq.farm/en/home/>
- Usha, K., and B. Singh. 2013. Potential applications of remote sensing in horticulture - a review. *Sci. Hort.* 153: 71–83.
- Vanegas, F., D. Bratanov, K. Powell, J. Weiss, and F. Gonzalez. 2018a. A novel methodology for improving plant pest surveillance in vineyards and crops using UAV-based hyperspectral and spatial data. *Sensors* 18: 260.
- Vanegas, F., D. Bratanov, J. Weiss, K. Powell, and F. Gonzalez. 2018b. Multi and hyperspectral UAV remote sensing: grapevine phylloxera detection in vineyards, pp. 1–9. *In* IEEE Aerospace Conference, 3–10 March 2018, Big Sky, MT.
- Van Lenteren, J. C., K. Bolckmans, J. Köhl, W. J. Ravensberg, and A. Urbaneja. 2018. Biological control using invertebrates and microorganisms: plenty of new opportunities. *BioControl* 63: 39–59.
- Verrelst, J., Z. Malenovsky, C. Van der Tol, G. Camps-Valls, J.-P. Gastellu-Etchegorry, P. Lewis, P. North, and J. Moreno. 2019. Quantifying vegetation biophysical variables from imaging spectroscopy data: a review on retrieval methods. *Surv. Geophys.* 40: 589–629.
- Villa, T., F. Gonzalez, B. Miljevic, Z. Ristovski, and L. Morawska. 2016. An overview of small unmanned aerial vehicles for air quality measurements: present applications and future perspectives. *Sensors* 16: 1072.
- Walter, A. J., and C. D. Difonzo. 2007. Soil potassium deficiency affects soybean phloem nitrogen and soybean aphid populations. *Environ. Entomol.* 36: 2–33.
- Wang, G., Y. Lan, H. Qi, P. Chen, A. Hewitt, and Y. Han. 2019a. Field evaluation of an unmanned aerial vehicle (UAV) sprayer: effect of spray volume on deposition and the control of pests and disease in wheat. *Pest Manag. Sci.* 75: 1546–1555.
- Wang, G., Y. Lan, H. Yuan, H. Qi, P. Chen, F. Ouyang, and Y. Han. 2019b. Comparison of spray deposition, control efficacy on wheat aphids and working efficiency in the wheat field of the unmanned aerial vehicle with boom sprayer and two conventional knapsack sprayers. *Appl. Sci.* 9: 218.
- Watts, A. C., V. G. Ambrosia, and E. A. Hinkley. 2012. Unmanned aircraft systems in remote sensing and scientific research: classification and considerations of use. *Remote Sens.* 4: 1671.
- Weldegergis, B. T., F. Zhu, E. H. Poelman, and M. Dicke. 2015. Drought stress affects plant metabolites and herbivore preference but not host location by its parasitoids. *Oecologia* 177: 701–713.
- West, K., and C. Nansen. 2014. Smart-use of fertilizers to manage spider mites (Acari: Tetranychidae) and other arthropod pests. *Plant Sci. Today* 1: 161–164.
- Weyermann, J., A. Damm, M. Kneubühler, and M. E. Schaepman. 2014. Correction of reflectance anisotropy effects of vegetation on airborne spectroscopy data and derived products. *IEEE Trans. Geosci. Remote Sens.* 52: 616–627.
- Whitehead, K., and C. H. Hugenholtz. 2014. Remote sensing of the environment with small unmanned aircraft systems (UASs), part 1: a review of progress and challenges. *J. Unmanned Veh. Syst.* 2: 69–85.
- Whitehead, K., C. H. Hugenholtz, S. Myshak, O. Brown, A. LeClair, A. Tamminga, T. E. Barchyn, B. Moorman, and B. Eaton. 2014. Remote sensing of the environment with small unmanned aircraft systems (UASs), part 2: scientific and commercial applications. *J. Unmanned Veh. Syst.* 2: 86–102.
- Willers, J. L., M. R. Seal, and R. G. Luttrell. 1999. Remote sensing, line-intercept sampling for tarnished plant bugs (Heteroptera: Miridae) in mid-south cotton. *J. Cotton Sci.* 3: 160–170.
- Willers, J. L., J. N. Jenkins, W. L. Ladner, P. D. Gerard, D. L. Boykin, K. B. Hood, P. L. McKibben, S. A. Samson, and M. M. Bethel. 2005.

- Site-specific approaches to cotton insect control. Sampling and remote sensing analysis techniques. *Precis. Agric.* 6: 431–452.
- WinterGreen Research. 2016a. Agricultural drones market shares, strategies, and forecasts, worldwide, 2016 to 2022. WinterGreen Research, Inc. Lexington, MA.
- WinterGreen Research. 2016b. Drones market shares, strategies, and forecasts, worldwide, 2016 to 2022. WinterGreen Research, Inc. Lexington, MA.
- Woods, N., I. P. Craig, G. Dorr, and B. Young. 2001. Spray drift of pesticides arising from aerial application in cotton. *J. Environ. Qual.* 30: 697–701.
- Xfly Brasil. 2017. Lançador de Trichogramma Granel. Available from <https://www.xflybrasil.com/trichogramma>
- Ximénez-Embún, M. G., P. Castañera, and F. Ortego. 2017. Drought stress in tomato increases the performance of adapted and non-adapted strains of *Tetranychus urticae*. *J. Insect Physiol.* 96: 73–81.
- Xiongkui, H., J. Bonds, A. Herbst, and J. Langenakens. 2017. Recent development of unmanned aerial vehicle for plant protection in East Asia. *Int. J. Agric. Biol. Eng.* 10: 18–30.
- Xu, H., Y. Ying, X. Fu, and S. Zhu. 2007. Near-infrared spectroscopy in detecting leaf miner damage on tomato leaf. *Biosyst. Eng.* 96: 447–454.
- Xue, J., and B. Su. 2017. Significant remote sensing vegetation indices: a review of developments and applications. *J. Sensors* 1353691.
- Xue, X., Y. Lan, Z. Sun, C. Chang, and W. C. Hoffmann. 2016. Develop an unmanned aerial vehicle based automatic aerial spraying system. *Comput. Electron. Agric.* 128: 58–66.
- Yamaha. 2014a. Development of the R-50 industrial-use unmanned helicopters. Available from <https://global.yamaha-motor.com/about/history/stories/0028.html>
- Yamaha. 2014b. Industrial-use unmanned helicopters draw attention as solutions. Available from <https://global.yamaha-motor.com/about/history/stories/0044.html>
- Yamaha. 2016. Evolution from the RCASS - The original model that led to multipurpose capability. Available from <https://global.yamaha-motor.com/about/technology/electronic/010/>
- Yang, Z., M. N. Rao, N. C. Elliott, S. D. Kindler, and T. W. Popham. 2005. Using ground-based multispectral radiometry to detect stress in wheat caused by greenbug (Homoptera: Aphididae) infestation. *Comput. Electron. Agric.* 47: 121–135.
- Yang, C.-M., C.-H. Cheng, and R.-K. Chen. 2007. Changes in spectral characteristics of rice canopy infested with brown planthopper and leafhopper. *Crop Sci.* 47: 329–335.
- Yang, C., J. H. Everitt, J. M. Bradford, and D. Murden. 2009a. Comparison of airborne multispectral and hyperspectral imagery for estimating grain sorghum yield. *Trans. Am. Soc. Agric. Eng.* 52: 641–649.
- Yang, Z., M. N. Rao, N. C. Elliott, S. D. Kindler, and T. W. Popham. 2009b. Differentiating stress induced by greenbugs and Russian wheat aphids in wheat using remote sensing. *Comput. Electron. Agric.* 67: 64–70.
- Yang, S., X. Yang, and J. Mo. 2018. The application of unmanned aircraft systems to plant protection in China. *Precis. Agric.* 19: 278–292.
- Yuan, L., Y. Huang, R. W. Loraamm, C. Nie, J. Wang, and J. Zhang. 2014. Spectral analysis of winter wheat leaves for detection and differentiation of diseases and insects. *Field Crops Res.* 156: 199–207.
- Yuan, L., H. Zhang, Y. Zhang, C. Xing, and Z. Bao. 2017. Feasibility assessment of multi-spectral satellite sensors in monitoring and discriminating wheat diseases and insects. *Optik* 131: 598–608.
- Yun, G., M. Mazur, and Y. Pederii. 2017. Role of unmanned aerial vehicles in precision farming. *Proc. Natl. Aviat. Univ.* N1: 106–112.
- Zarco-Tejada, P. J., C. Camino, P. S. A. Beck, R. Calderon, A. Hornero, R. Hernández-Clemente, T. Kattenborn, M. Montes-Borrego, L. Susca, M. Morelli, et al. 2018. Previsual symptoms of *Xylella fastidiosa* infection revealed in spectral plant-trait alterations. *Nat. Plants* 4: 432–439.
- Zehnder, G., G. M. Gurr, S. Kühne, M. R. Wade, S. D. Wratten, and E. Wyss. 2007. Arthropod pest management in organic crops. *Annu. Rev. Entomol.* 52: 57–80.
- Zhang, C., and J. M. Kovacs. 2012. The application of small unmanned aerial systems for precision agriculture: a review. *Precis. Agric.* 13: 693–712.
- Zhang, M., A. Hale, and E. Luedeling. 2008. Feasibility of using remote sensing techniques to detect spider mite damage in stone fruit orchards, pp. 1323–1326. *In* IEEE International Geoscience and Remote Sensing Symposium, 7–11 July 2008, Boston, MA.
- Zhang, C., D. Walters, and J. M. Kovacs. 2014. Applications of low altitude remote sensing in agriculture upon farmers' requests—a case study in northeastern Ontario, Canada. *PLoS One* 9: e112894.
- Zhang, J., Y. Huang, L. Yuan, G. Yang, L. Chen, and C. Zhao. 2016. Using satellite multispectral imagery for damage mapping of armyworm (*Spodoptera frugiperda*) in maize at a regional scale. *Pest Manag. Sci.* 72: 335–348.
- Zhang, J., N. Wang, L. Yuan, F. Chen, and K. Wu. 2017. Discrimination of winter wheat disease and insect stresses using continuous wavelet features extracted from foliar spectral measurements. *Biosyst. Eng.* 162: 20–29.
- Zhang, X.-Q., Y.-J. Liang, Z.-Q. Qin, D.-W. Li, C.-Y. Wei, J.-J. Wei, Y.-R. Li, and X.-P. Song. 2019. Application of multi-rotor unmanned aerial vehicle application in management of stem borer (Lepidoptera) in sugarcane. *Sugar Tech.* 5: 847–852. doi:10.1007/s12355-018-0695-y
- Zhao, J., D. Zhang, J. Luo, D. Wang, and W. Huang. 2012. Identifying leaf-scale wheat aphids using the near-ground hyperspectral pushbroom imaging spectrometer, pp. 275–282. *In* International Conference on Computer and Computing Technologies in Agriculture, 29–31 October 2011, Beijing, China.
- Zhao, T., B. Stark, Y. Chen, A. L. Ray, and D. Doll. 2017. Challenges in water stress quantification using small unmanned aerial system (sUAS): lessons from a growing season of almond. *J. Intell. Robot. Syst.* 88: 721–735.
- Zhou, Z., Y. Zang, Z. Zhao, X. Luo, and X. Zhou. 2010. Canopy hyperspectral reflectance feature of rice caused by brown plant-hopper (*Nilaparvata lugens*) infestation, no. 1009569. *In* ASABE Annual International Meeting, 20–23 June 2010, Pittsburgh, PA.
- Zhou, Z., Y. Zang, X. Luo, Y. Lan, and X. Xue. 2013. Technology innovation development strategy on agricultural aviation industry for plant protection in China. *Trans. Chin. Soc. Agric. Eng.* 29: 1–10 (in Chinese with English abstract).