



## Review

## Low-altitude, high-resolution aerial imaging systems for row and field crop phenotyping: A review



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## ABSTRACT

Global plant genetics research efforts have focused on developing high yielding, stress tolerant, and disease resistant row and field crop varieties that are more efficient in their use of agronomic inputs (water, nutrients, pesticides, etc.). Until recently, a key bottleneck in such research was the lack of high-throughput sensing technologies for effective and rapid evaluation of expressed phenotypes under field conditions for holistic data-driven decision making and variety selection. This review focuses on technological aspects of integrating unmanned aerial vehicles with imaging systems to enhance field phenotyping capabilities. The state-of-the-art of unmanned aerial vehicle technology for various applications including crop emergence, vigor, and characterization of yield potential of row and field crops has been reviewed. The potential of using aerial imaging to evaluate resistance/susceptibility to biotic and abiotic stress for crop breeding and precision production management has been discussed along with future perspectives and developments.

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## 1. Introduction

Accelerated crop improvement techniques are needed to satisfy the global food production demands (Alston et al., 2009; Godfray et al., 2010), and counter the unprecedented abiotic and biotic stress conditions (Garrett et al., 2006; Mittler and Blumwald, 2010). In the last 20 years, advances in DNA sequencing and molecular technologies has significantly improved knowledge of plant genomes; however, current methods to phenotype crops remain slow, expensive, labor-intensive, and often destructive (Furbank and Tester, 2011; Walter et al., 2012; White et al., 2012; Cobb et al., 2013; Dhondt et al., 2013; Fiorani and Schurr, 2013; Araus and Cairns, 2014). Since 2010, rapid high-throughput crop phenotyping methods or 'phenomics' have been discussed as an approach that could significantly improve phenotyping efforts for plant breeding (Furbank and Tester, 2011; Walter et al., 2012; White et al., 2012; Cabrera-Bosquet et al., 2012; Dhondt et al., 2013; Fiorani and Schurr, 2013; Yang et al., 2013; Cobb et al., 2013; Araus and Cairns, 2014; Prashar and Jones, 2014; Deery et al., 2014). These techniques include the application of fluorescence sensing for estimating photosynthesis (Baker, 2008; Munns et al., 2010; Tuberosa, 2012), visible imaging for shoot biomass estimation (Berger et al., 2010; Goltzarian et al., 2011), visible-near infrared spectroscopy for identifying physiological changes induced by water and nutrient stresses (Peñuelas et al., 1994; van Maarschalkerweerd et al., 2013), and thermal imaging for detecting water stress (Jones et al., 2009). Field phenotyping is a critical component of crop improvement through genetics, as it is the ultimate expression of the relative effects of genetic factors, environmental factors, and their interaction on critical production traits such as yield potential and tolerance to abiotic/biotic stresses (White et al., 2012; Araus and Cairns, 2014). Factors such as soil characteristics, rainfall, temperature, and weather events along with the presence of disease, insect pests, and weeds greatly influence plant performance and affect the efficiency of selection across years. High-throughput phenotyping methods may be able to better account for these environmental variations than current practices, thereby increasing selection efficiency.

Both ground- and field-based platforms have been considered for field-based phenomics (White et al., 2012; Andrade-Sanchez et al., 2014; White and Conley, 2013; Araus and Cairns, 2014; Prashar and Jones, 2014; Deery et al., 2014). The ground-based sensing platforms have significant benefits, one of which is plot-level data captured with global positioning systems (GPS) enabled navigation and geospatial analysis. However, from a technology development point of view, there is no unique "fit for all" ground platform that can be used to phenotype diverse crops. The challenge has been developing cost-effective rapid field phenotyping platforms that can be adjusted in relation to row and plant spacing as well as to account for inconsistencies in plot sizes and plant height between different crops or different practices used by individual programs. There are other challenges that can limit the potential of ground-based platforms, which include (i) non-simultaneous measurement of different plots, which can take from minutes to hours, depending on the number of plots and plot size, (ii) compaction of soil, and (iii) vibrations resulting from uneven terrain surfaces. Some of these limitations can be addressed using high-resolution, low-altitude aerial platforms such as small unmanned aerial vehicles (UAVs). This review examines the potential of using low-altitude, high-resolution aerial imaging with UAVs for rapid phenotyping of crops in the field. Overview of UAVs and sensing systems, potential phenotypic traits that can be evaluated, and challenges needing further research and development to support genetics and other crop improvement programs are discussed. The paper is organized as follows: (1) overview of small UAVs, (2) integration of sensors with small UAVs, (3) application domain of

high-resolution aerial sensing in field phenomics, and (4) concluding remarks and future perspectives.

## 2. Overview of small unmanned aerial vehicles

Sensors such as thermal cameras, hyperspectral camera, multi-spectral camera, and Light Detection and Ranging (LIDAR) systems can be used for measuring crop growth and development (Zhang and Kovacs, 2012) as described in the following sub-section. However, the selection of small UAVs to carry these sensors and achieve desired temporal frequency and high spatial resolution are characteristics that need to be considered before using UAVs in phenomics research. Satellites are limited by frequency and spatial resolution. Similarly, ground-based sensing platforms pose difficulty in being transported from one location to another, may not be easy to generate surface maps in real time, and cannot measure plant parameters from several plots at a time. Such difficulties can be addressed by use of appropriate small UAVs to obtain data with desired temporal frequency and spatial resolution (Lelong et al., 2008; Araus and Cairns, 2014).

The vehicles with flying capacity without any person onboard to guide controls and decide direction or speed of the device are called unmanned aerial vehicles (Eisenbeiss, 2004). Availability of UAVs has rapidly increased in recent years and several types, ranging from multicopters and helicopters to fixed wing, are now available (Zhang and Kovacs, 2012; Araus and Cairns, 2014). Broadly, small UAVs can be classified into four types: parachutes, blimps, rotocopters, and fixed wing systems. Some of the factors influencing the selection of these small UAVs in phenomics are summarized in Table 1.

Selection of a specific UAV type is conditional on desired application and limitations. Parachutes can be flown easily under no-wind conditions, but cannot be operated under windy conditions. Moreover, they cannot hover in a single location although they have low speeds and relatively short flight time. Blimps are commonly used in commercial advertising; however they can also be used for aerial imaging. Although it is possible to obtain clear images of selected areas because of their hovering capabilities, blimps are slow to be moved from one location to another. In addition, blimps have larger surface area, which makes it difficult to be flown under windy conditions. The most widely used small UAV types are rotocopters and fixed wings. Rotocopters are copters that can fly at different altitudes driven by four to eight propellers. This platform has several advantages. They can hover at a given location, use GPS-based navigation, fly horizontally and vertically, and require very little space for take-off and landing. The major limitations for rotocopters are lower speed and flight time in comparison to fixed wing types.

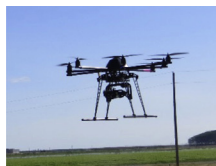
Fixed wing UAVs have longer flight time and faster travel speeds than multi-rotor UAV types. Nevertheless, they do not have hovering capability. The speed of this UAV type can result in image blurring, which can be addressed using imaging sensors with improved capabilities including high shutter speed. Research is ongoing to improve the battery technology that powers the multi-rotor and fixed wing UAVs to increase flight time. In regard to multi-rotors, a power tethered UAV (<http://www.hoverflytech.com/livesky/>) may also be a good option. Further advancements in flight time can derive from solar-powered platforms.

## 3. Sensor integration with small UAVs

A range of sensors can be integrated with the UAV platforms depending on payload lift capabilities. The sensors (Table 2) can be based on spectral interactions between object and the electromagnetic spectrum such as reflectance or emission in visible and infrared regions or time-of-flight of sound/light signals. The

**Table 1**  
Typical types of small unmanned aerial vehicles.<sup>a</sup>

Type	Payload <sup>b</sup> (kg)	Flight time <sup>b</sup> (min)	Benefits	Limitations	Examples <sup>a</sup>
Parachute	1.5	10–30	<ul style="list-style-type: none"> <li>• Simple operation</li> </ul>	<ul style="list-style-type: none"> <li>• Not operable in windy conditions.</li> <li>• Have limited payload</li> </ul>	HawkEye
Blimps	>3.0	~600	<ul style="list-style-type: none"> <li>• Simple operation</li> </ul>	<ul style="list-style-type: none"> <li>• Not operable in windy conditions</li> <li>• Have limited payload</li> </ul>	AB1100, Cameron Fabric Engineering
Rotocopter	0.8–8.0	8–120	<ul style="list-style-type: none"> <li>• Applicable with waypoint navigation</li> <li>• Hovering capabilities</li> <li>• Can hold range of sensors from thermal, multispectral to hyperspectral cameras</li> </ul>	<ul style="list-style-type: none"> <li>• Payload may limit battery usage and flight time</li> </ul>	DJI Inspire, Mikrocopter ARK OktoXL 6S12, Yamaha RMAX
Fixed wing	1.0–10	30–240	<ul style="list-style-type: none"> <li>• Applicable with waypoint navigation</li> <li>• Better flight time</li> <li>• Multiple sensors can be mounted</li> </ul>	<ul style="list-style-type: none"> <li>• Limited hovering capacity</li> <li>• Lower speeds are required for image stitching</li> </ul>	Landcaster Precision Hawk, senseFly eBee



Rotocopter



Fixed wing



Unmanned helicopter

<sup>a</sup> Provided is an overview of different UAV platform types and there may be many commercial companies developing similar types.

<sup>b</sup> Approximate values taken from manufacture provided specification.

**Table 2**  
Different types of sensors used in plant phenotype characterization.

Sensor type	Details	Applications	Limitations	References <sup>a</sup>
Fluorescence sensor	Passive sensing-visible and near infrared regions	Photosynthesis, chlorophyll, water stress	<ul style="list-style-type: none"> <li>• Not developed for UAV research yet</li> <li>• Can be subject to background noise</li> </ul>	Chappelle et al. (1984), Gamon et al. (1990), Flexas et al. (2000), Evain et al. (2004), Xing et al. (2006), Chaerle et al. (2007)
Digital camera (RGB)	Gray scale or color images (texture analysis)	Visible properties, outer defects, greenness, growth	<ul style="list-style-type: none"> <li>• Limited to visual spectral bands and properties</li> </ul>	Lu et al. (2011), Kipp et al. (2014), Klodt et al. (2015)
Multispectral camera/color-infrared camera	Few spectral bands for each pixel in visible-infrared region	Multiple plant responses to nutrient deficiency, water stress, diseases among others	<ul style="list-style-type: none"> <li>• Limited to few spectral bands</li> </ul>	Lenk et al. (2007), Moshou et al. (2005), Blasco et al. (2007), Svendsgaard et al. (2014), Zaman-Allah et al. (2015)
Hyperspectral camera	Continuous or discrete spectra for each pixel in visible-infrared region	Plant stress, produce quality, and safety control	<ul style="list-style-type: none"> <li>• Image processing is challenging</li> <li>• Sensors can be expensive</li> </ul>	Moshou et al. (2005), Delalieux et al. (2007), Gowen et al. (2007), Qin et al. (2009), Seiffert et al. (2010)
Thermal sensor/camera	Temperature of each pixel (for sensor with radiometric calibration) related to thermal infrared emissions	Stomatal conductance, plant responses to water stress and diseases	<ul style="list-style-type: none"> <li>• Environmental conditions affect the performance</li> <li>• Very small temperature differences are not detectable</li> <li>• High resolution cameras are heavier</li> </ul>	Chaerle and Van Der Straeten (2000), Leinonen and Jones (2004), Jones et al. (2009), Costa et al. (2013)
Spectrometer	Visible-near infrared spectra averaged over a given field-of-view	Detecting disease, stress and crop responses	<ul style="list-style-type: none"> <li>• Background such as soil may affect the data quality</li> <li>• Possibilities of spectral mixing</li> <li>• More applicable for ground-based systems</li> </ul>	Carter (1993), Belasque et al. (2008), Delwiche and Graybosch (2002), Naidu et al. (2009)
3D camera	Infrared laser based detection using time-of-flight information	Physical attributes such as plant height and canopy density	<ul style="list-style-type: none"> <li>• Lower accuracies</li> <li>• Field applications can be limiting</li> </ul>	Jin and Tang (2009), Chéné et al. (2012)
LIDAR (Light Detection and Ranging) sensor	Physical measures resulting from laser (600–1000 nm) time-of-flight	Accurate estimates of plant/tree height and volume	<ul style="list-style-type: none"> <li>• Sensitive to small variations in path length</li> </ul>	Donoghue et al. (2007), Koenig et al. (2015), Müller-Linow et al. (2015)
SONAR (Sound Navigation and Ranging) sensor	Sound propagation is used to detect objects based on time-of-flight	Mapping and quantification of the canopy volumes, digital control of application rates in sprayers or fertilizer spreader	<ul style="list-style-type: none"> <li>• Sensitivity limited by acoustic absorption, background noise, etc.</li> <li>• Lower sampling rate than laser-based sensing</li> </ul>	Tumbo et al. (2002)

<sup>a</sup> Representative studies that have used specified sensor for listed applications.

applications of time-of-flight based sensors are commonly used for evaluating physical/morphological plant characteristics such as plant growth, height, and canopy volume/vigor. These parameters are important in evaluating plant performances during breeding, and can be indicative of yield potential (Wei et al., 2010; Ilker et al., 2013; Alheit et al., 2014; Njogu et al., 2014). In regard to the spectroscopic and imaging techniques, a number of plant phenotypes such as disease susceptibility, susceptibility to drought stress, chlorophyll content, nutrient concentrations, growth rates, and yield potential can be evaluated (Zhang and Kovacs, 2012).

The plant trait can be related to wavelength of spectral radiation and amount of light energy emitted/absorbed, as sensed by the detector in the sensing module. Fluorescence, visible, near infrared, multi/hyperspectral, and thermal spectroscopic techniques work on these principles, although each have their unique characteristics. Such characteristics allow us to remotely sense key plant traits. However, one of the limitations, especially for visible to near-infrared-based sensing is that changes in ambient light conditions can influence the signal intensity (spectral reflectance values). Therefore, it is very important to correct for the ambient light conditions using reference calibration (e.g. Spectralon® Targets, Labsphere Inc., traceable to the National Institute of Standards and Technology, NIST) to compensate for the light variation from one day to another, and within a day at different time periods or due to cloud conditions. The changes in ambient light conditions can also be partly compensated using spectral ratios (such as vegetation indices) or a light sensor to estimate and correct for the incident light conditions. More information on some of these sensing techniques and data processing can be found in the literature (Lee et al., 2010; Sankaran et al., 2010; Zhang and Kovacs, 2012; Deery et al., 2014; Li et al., 2014).

#### 4. Applications of high-resolution aerial sensing in field phenomics

Small UAVs with suitable sensors for remote sensing of plant responses (to induced abiotic and biotic stress) and performance (yield) in field conditions have several benefits. The integrated system can provide (i) better access to the field, (ii) high-resolution data (1–2 cm depending on flying altitude), (iii) timely data collection (even under cloudy conditions), (iv) quick evaluations of the field growth conditions, (v) simultaneous image acquisition, (vi) self-automated flights for monitoring the plots at regular periods in a given growing season; and (vii) low operational costs (Hunt et al., 2008; Nebiker et al., 2008; Berni et al., 2009; Zhang and Kovacs, 2012; Perry et al., 2012; Araus and Cairns, 2014). For example, accessing field plots with high plant volume/biomass in the field or immediately after irrigation is challenging and can be time consuming. In this regard, using UAV provides higher operational flexibility.

There are several remote sensing applications in precision agriculture using small UAVs. Some of those include: weed detection (Herwitz et al., 2004; Göktoğan et al., 2010; Torres-Sánchez et al., 2013; Rasmussen et al., 2013), aerobiological sampling (Techy et al., 2008; Schmale et al., 2008; Gonzalez et al., 2011; Aylor et al., 2011), leaf area index estimation (Hunt et al., 2008), soil characterization (Sugiura et al., 2007; d'Oleire-Oltmanns et al., 2012), water status (Sullivan et al., 2007; Berni et al., 2009; Suárez et al., 2010; Zarco-Tejada et al., 2012; Gago et al., 2015), diseases (García-Ruiz et al., 2013; Sankaran et al., 2013; Calderón et al., 2013, 2014), pest management (Huang et al., 2009) and yield estimation (Irmak et al., 2000; Swain et al., 2010) among others. Some of these applications are discussed in Zhang and Kovacs (2012). Pertinent phenomic applications for UAVs are detailed below.

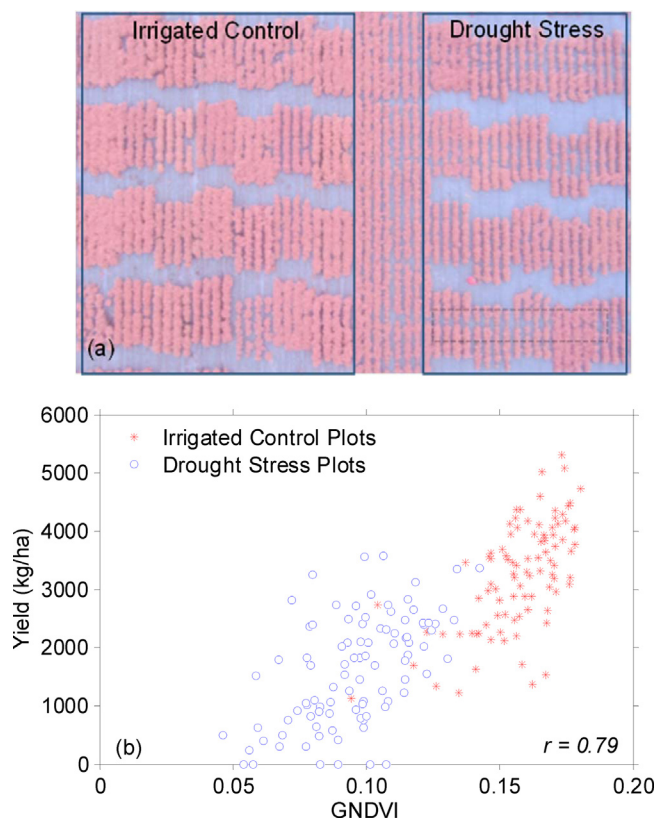
##### 4.1. Plant water stress

Water stress occurs when the plant-available water supply is lower than the water required by a plant species. Plant water stress can induce stomatal closure, which decreases photosynthesis and growth, and may exacerbate heat stress due to reduced transpirational cooling. Selection for water stress tolerance and increased water-use efficiency are core objectives in several breeding and agronomic research programs in the world, especially in the areas with frequent drought episodes.

Temperature can be an indicator of stomatal conductance and response of plants to water stress (Jackson et al., 1977, 1981; Idso, 1982). Although the use of temperature in precision agriculture application has been established (Sullivan et al., 2007; Suárez et al., 2010; Zarco-Tejada et al., 2012; Gonzalez-Dugo et al., 2013; Gago et al., 2015), more recently, researchers are utilizing temperature in leaves to determine the plant tolerance to water stress in breeding programs. Jones et al. (2009) and Chapman et al. (2014) demonstrated that plant temperature measurement under field conditions can be used effectively to select new varieties with water stress resistance traits. The authors emphasized the need for normalizing the imaging data to account for environmental variations in the readings. For phenotyping purposes, calibration may not be needed because the relative differences among genotypes are more important than the absolute data (Jones et al., 2009).

Thermal infrared data analysis requires elimination of background temperature (soil, trunks, dead leaves) from that attributable to leaves, especially when image pixels are bigger than that of the leaves (Giuliani and Flore, 1999; Jones et al., 2009; Jones and Sirault, 2014). Methods to achieve this objective include the use of sheet backgrounds that raise the temperature more than that of the leaves to allow easier background elimination (Giuliani and Flore, 1999; Jones et al., 2009), determining bare soil and complete canopy cover temperatures by a regression between temperature and percentage of leaves present in each image pixel (Jones et al., 2009), and masking the data over a known background temperature (Chapman et al., 2014). Nevertheless, it is necessary to compare visible and infrared images to know the coverage percent of the canopy (Jones et al., 2009).

Thermal infrared sensing in combination with UAVs facilitates scanning larger plot sizes, and may aid in selecting water stress tolerant genotypes with less time and resources than traditional methods (Jones et al., 2009; Chapman et al., 2014). In addition to thermal imaging, multispectral imaging can also aid in identifying water stress tolerant and susceptible genotypes. In Washington State University (WSU)-United States Department of Agriculture Agricultural Research Service (USDA-ARS) dry bean study, 20 most tolerant and 20 most susceptible recombinant inbred lines of dry bean were compared under terminal drought conditions (Trapp, 2015). The 40 lines (varieties) were planted in a randomized complete block design with two replications of non-stress and drought stress treatments. Aerial, high-resolution multispectral images were acquired at early mid-pod set (growth stage) and expected to have maximum growth vigor (Fig. 1a). Plot-to-plot comparison of the modified green normalized difference vegetation index (GNDVI, green as visible band) estimates with that of the yield data (plot-to-plot comparison), resulted in a strong correlation with correlation coefficient of 0.79 ( $p=0.01$ , Fig. 1b). The GNDVI is vegetation index similar to normalized difference vegetation index (NDVI), where green band is used instead of red bands as in NDVI. The GNDVI can be more sensitive to wide range of chlorophyll concentrations than NDVI (Gitelson and Merzlyak, 1998). In addition, there was a strong association in both non-stress and drought stress conditions, with both susceptible and tolerant dry bean varieties showing a significant



**Fig. 1.** UAV-based sensing of dry bean plant responses to water stress. (a) False color multiband image (NIR, G, B as RGB bands) of dry bean variety plots under irrigated control and drought stress treatments showing differences in crop canopy densities (note: compaction bands across the plots due to wheel tracks are more visible in drought stress plots, marked in dotted line box), and (b) plot-to-plot comparison of GNDVI ( $[\text{NIR} - \text{G}]/[\text{NIR} + \text{G}]$ ) estimated from image data with that of individual plot yield data. The correlation coefficient ( $r$ ) is inclusive of both treatments (control and drought).

correlation between NDVI and yield performance under both conditions ( $p = 0.01$ ).

The limited plant growth (biomass) due to water stress can typically be assessed using visible to near-infrared imaging. Importantly, periodic thermal and visible to near-infrared imaging throughout the crop growing season can provide vital qualitative and quantitative data that can be related to ground-truth measurements. These approaches will result in developing robust high-throughput non-contact sensing methods for evaluating plant traits and may eventually replace standard data collection methods.

#### 4.2. Plant nutrient deficiency and heat stress

UAV-based sensing systems are rapid and efficient techniques to evaluate growth, yield and adaptation to stress in plants (Cabrera-Bosquet et al., 2012). Genotypes of most crop species show quantitative variation for abiotic stress tolerances, and differences in nutrient- and water-use efficiencies. Although it is possible to detect differences in crop performance under different stress conditions (Fiorani and Schurr, 2013), more detailed research is needed to determine plant responses using real-time automated and non-destructive sensing technology. Research is needed to understand and modulate sensors that can detect and resolve specific abiotic stresses such as nutrient, salinity, and heat.

Nutrient deficiency can result in visual symptoms such as lower chlorophyll content, lower growth rate, tissue necrosis, and higher disease susceptibility (DeTurk, 1941). These factors can be evaluated using UAV-based sensing techniques with relative ease (Zhu

et al., 2009; Agüera et al., 2011; Kaivosoja et al., 2013; Cilia et al., 2014; Li et al., 2015). In a low nitrogen application study in maize (Zaman-Allah et al., 2015) with multispectral camera mounted in UAV, a good correlation between nitrogen stress index and grain yield with  $r$  of 0.40–0.79 was achieved ( $p \leq 0.05$ ) with multiple N treatments. The crop senescence index was also correlated with the NDVI values ( $r = 0.84$ ,  $p \leq 0.01$ ). The study indicated the potential of UAV-based sensing in field phenotyping, with well-developed data processing procedures and data management.

The evaluation of crop varieties resilient to salinity and heat stress can also be assessed efficiently using UAV-based sensing. In the case of salinity and heat stress, osmotic stress leads to stomatal closure, decreased stomatal conductance, increased leaf temperature (Bowman and Strain, 1988; Wang et al., 2003; Microbes, 2015), and decreased photosynthesis. These changes in photosynthetic rates and stomatal conductance can be detected by visible to near-infrared spectral reflectance (Stong, 2008). Thermal imaging can also be used to detect plant primary responses to salinity and water stress as the temperature increases due to stomatal closure (Leinonen and Jones, 2004; Jones et al., 2009; Costa et al., 2013).

Image acquisition systems mounted on small UAVs are widely used in crop mapping for stress detection, due to their ability to acquire images at high spatial, spectral, and temporal resolutions (Adams et al., 2000; Berni et al., 2009). Hairmansis et al. (2014) conducted an image-based study to detect salinity tolerance for two varieties of rice (IR64 and Fatmawati). They successfully used Red-Green-Blue (RGB) and fluorescence imaging, to sense tissue ion concentration, to differentiate between ionic and osmotic

stages of salinity stress and identify the genetic basis of salinity tolerance. Similarly, thermal images in combination with RGB imaging have been used to study canopy temperature changes in response to stomatal behavior and water deficit with data from *Vicia faba* L. and *Vitis vinifera* L. grown in greenhouse and field conditions (Leinonen and Jones, 2004). Effect of temperature was calculated assuming air temperature, active radiation, and relative humidity. Such crop sensing tools integrated with UAVs have potential for high-throughput crop phenotyping and management applications in horticulture and field crops. Deriving crop specific indicators (spectral signatures) for the above stressors to facilitate the development of specific, lightweight sensing modules to be integrated with UAVs remains a key challenge and opportunity.

#### 4.3. Plant biotic stress

The UAV-based disease management has three major applications: (i) assessing the pest/disease development and symptoms (Yue et al., 2012; Garcia-Ruiz et al., 2013; Sankaran et al., 2013), (ii) assessing and monitoring the pathogen in atmosphere (Gonzalez et al., 2011; Aylor et al., 2011), and (iii) precision spraying (Cao et al., 2013; Faiçal et al., 2014). Evaluating the susceptibility of different plant varieties to diseases caused by soil-borne fungal pathogens, nematodes, viruses, air-borne or vector-based fungal or bacterial infections is a promising application. Remote sensing technologies have been used for identifying and monitoring diseases (Nilsson,

1995; Kumar et al., 2012; Li et al., 2012; Usha and Singh, 2013). But, the application of UAV-based sensing for evaluating disease severity, and susceptibility of different varieties to diseases is relatively undeveloped.

A recent study on evaluating sugar beet varieties for *Cercospora* resistance indicated that simple vegetation indices such as normalized difference vegetation index (NDVI), leaf water index (LWI) and *Cercospora* Leaf Spot Index (CLSI) could be correlated with disease severity (Jansen et al., 2014). In WSU's ongoing study, 20 (Russets) and 30 (20 Russets + 10 Chip and Specialty) potato selections/lines were screened with two replications to identify varieties resistant and susceptible to viral (potato virus Y) and early die (Verticillium wilt) diseases, respectively. An aerial, high-resolution multispectral image was used to estimate the canopy vigor (leaf area) in terms of number of green pixels using GNDVI image, after thresholding. A correlation with  $r$  of about 0.58–0.80 (Fig. 2) was achieved when the estimated leaf area data of diseased plots at 40 days after planting were compared with the potato yield data. Similarly, susceptibility to pathogen infections in plants can be assessed effectively using UAV-based sensing without any bias or misinterpretations.

Several researchers have used UAV-based sensing for disease monitoring in tree fruit production (Calderón et al., 2013, 2014; Garcia-Ruiz et al., 2013). A multispectral imaging sensor with six different spectral bands (530, 610, 690, 740, 850 and 900 nm) was used to detect Huanglongbing (HLB) infected trees in a citrus orchard. High-resolution multispectral images (5.5 cm/pixel)

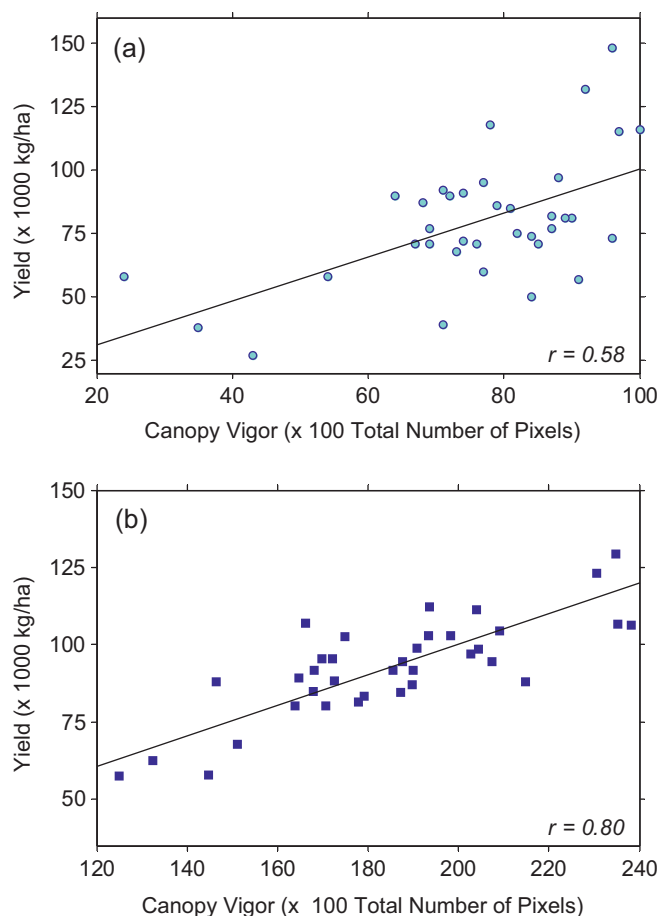
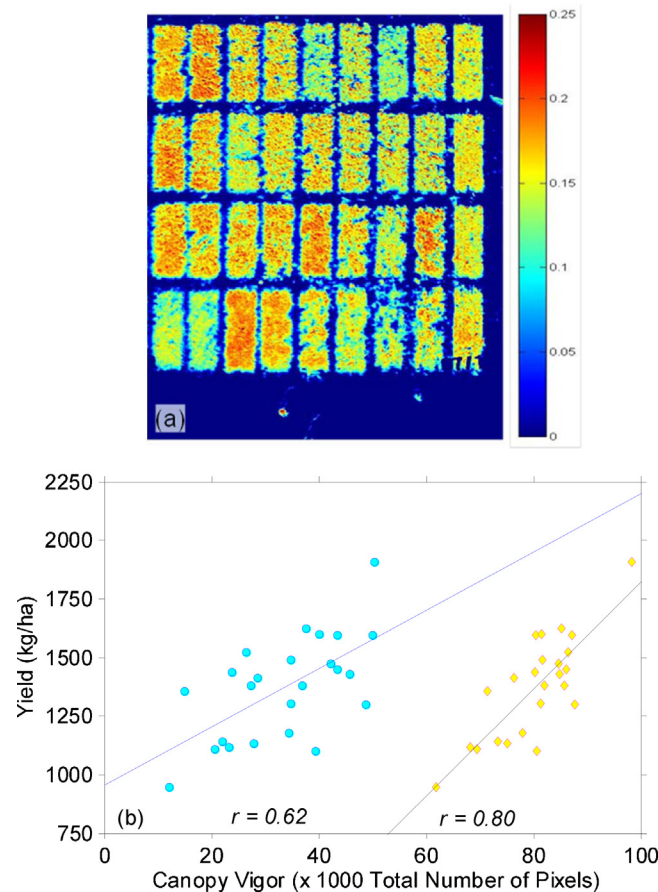


Fig. 2. Plot-by-plot comparison of UAV imaging-based canopy vigor at 40 days after planting and potato yield data in the field plots with (a) early die and (b) potato virus Y infections. The canopy vigor was estimated as total number of green pixels after thresholding using GNDVI image to remove background.



**Fig. 3.** (a) GNDVI pseudocolor image of chickpeas field plots imaged from 30 m altitude, and (b) relationship between image-based canopy vigor and yield at 31 days and 66 days after planting of 24 plots shown in (a). The four plots in the right represent border rows. The colors are assigned based on the GNDVI scale, for better visualization of image data. The canopy vigor was estimated as total number of green pixels after thresholding using GNDVI image to remove background.

with a suitable classification algorithm (support vector machine) could be used for identifying HLB-infected trees with up to 85% accuracy. Amongst the different spectral bands, 710 nm provided the most useful information. Similarly, *Verticillium* wilt in olive orchards was detected using high-resolution airborne hyperspectral and thermal imaging techniques (Calderón et al., 2013). Thermal data and Photochemical Reflectance Index (PRI) were significantly correlated with disease severity. Similar techniques can be applied to evaluate disease severity in breeding programs.

#### 4.4. Plant growth parameters

UAV-based sensing can also be used for evaluating plant growth parameters such as emergence (Sankaran et al., 2014), vigor, leaf area index (Hunt et al., 2010; Sugiura et al., 2005), and biomass. A recent study (Sankaran et al., 2014) evaluated emergence and spring stand after overwintering using GNDVI. Aerial multispectral images of field plots were acquired to estimate GNDVI. Correlation between ground-truth emergence and spring stand ratings data, and image-based data was 0.86 ( $p < 0.0001$ ). The technique was useful to identify winter wheat varieties that showed good emergence after planting combined with good winter hardiness, which are important traits in the U.S. Pacific Northwest wheat production regions.

In WSU-USDA-ARS chickpea trial, the chickpea plots were imaged at 31 days and 66 days after planting. The chickpeas were planted (randomized complete block design) at a density of 43 seeds  $m^{-2}$  in a 1.5 m  $\times$  6.1 m block ( $\approx 430,000$  seeds  $ha^{-1}$ ). As the remote sensing images were acquired in early growth stages, an altitude of 30 m was selected (Fig. 3a). A good correlation was established between canopy vigor (total number green pixels after thresholding with GNDVI image) and yield potential, especially for images acquired at 66 days after planting (Fig. 3b). Interestingly, the  $r$  between number of plants manually counted at 27 days after planting and the image-based leaf area (number of pixels) at 31 days after planting was 0.66; and  $r$  between manual plant count and the yield was 0.21. Similarly, GNDVI estimates extracted from a UAV-based multispectral camera were compared with leaf area index (LAI) from winter wheat field plots (Hunt et al., 2008, 2010). Variable nitrogen application treatments resulted in LAI differences. A good relationship between NDVI values and LAI was reported ( $R^2 = 0.85$ ). One of the limitations of using NDVI for estimating LAI could be that the NDVI saturates when canopies are greener (i.e. higher NDVIs).

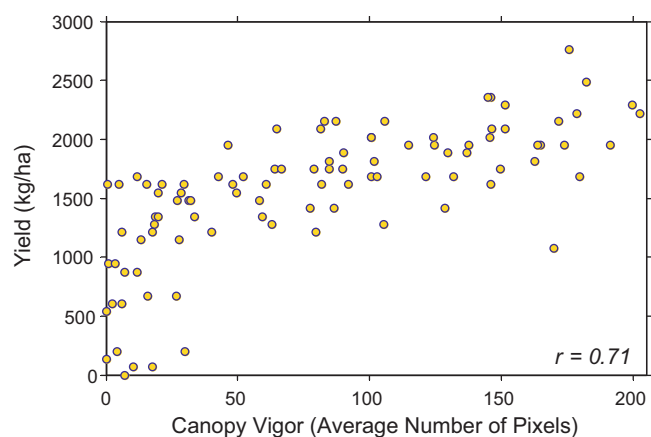
Another important trait that can be evaluated using UAV-based imaging is plant maturity (Trapp, 2015; Khot et al., 2014). For several crops such as chickpeas, dry beans, and potatoes, plant maturity (degree of foliar senescence) is an important characteristic for variety selection. Similarly, other growth parameters such as number of emerging plants to assess planting accuracy, efficacy

of germination-enhancing plant growth regulators, and genotypic differences can also be evaluated. Fig. 4 shows an example of emergence study in potatoes.

#### 4.5. Crop yield potential assessment

Most breeding efforts for row and field crops have focused on developing high yielding varieties that are resistant to disease, more efficient in their use of agronomic inputs, and can tolerate moderate levels of abiotic stressors. Plant flowering date (Marais, 1985; Guo et al., 2015), number of heads (seeds) per plant, and size, volume, and weight at seeds/plant at harvest (Huddleston, 1978; Giri and Schillinger, 2003) of selected genotypes and check varieties are common plant traits measured to establish yield potential of the new lines. Aerial platforms with adequately equipped portable multispectral sensors can critically aid in evaluating the yield potential of new lines and quantification of larger field plots, which has been the limitation of ground-based physical assessments. Recent studies have used aerial imaging-derived vegetative indices (as summarized in Table 3) to estimate the yield potential of row and field crops.

Although still evolving, periodic high resolution spectral imaging throughout the growing season will help in developing rapid yield estimation techniques as needed in crop phenotype characterization. In WSU's recent study (Khot et al., 2014), the periodic aerial images using multispectral sensor captured winter survival and spring stand of winter wheat breeding lines as part of ongoing wheat breeding efforts. The study successfully correlated the GNDVI image estimates of winter survival and spring stand to actual plot yield, with Pearson correlation coefficient in the ranges of 0.60–0.71 (Fig. 5). UAV-based multispectral imaging could not only be capable of estimating yield potential for breeding studies

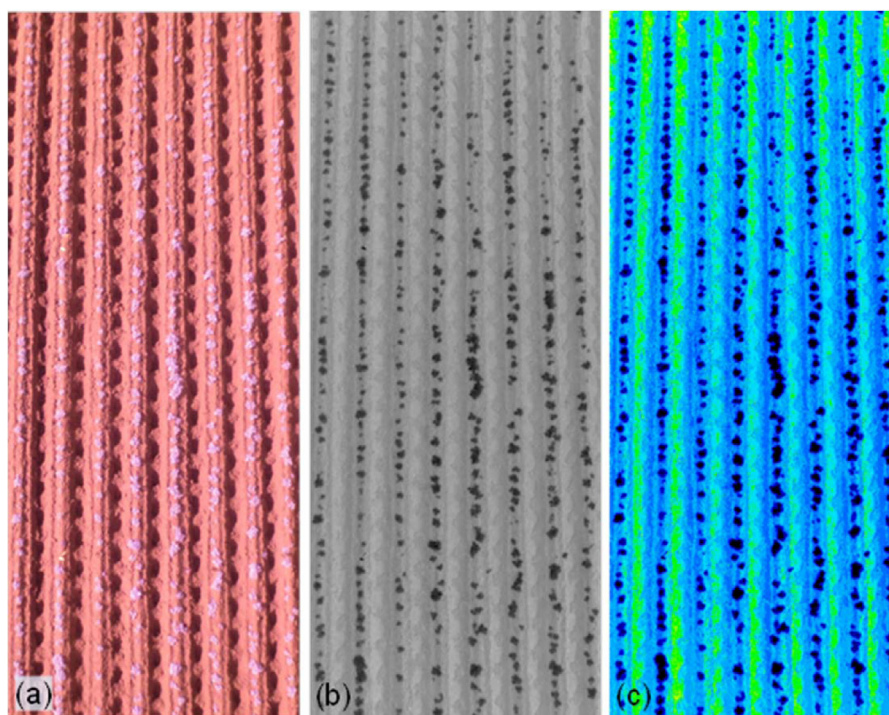


**Fig. 5.** Plot-to-plot correlation between the image-based canopy vigor representing spring stand and yield (kg/ha) in winter wheat variety field plots acquired from UAV-based multiband image from 100 m. The canopy vigor was estimated as average number of green pixels after thresholding to remove background.

but potentially can be used by growers for predicting yield and thus, market value of their crop.

#### 4.6. Other applications

UAV-based sensing technology can be applied to evaluate a number of other plant growth traits such as plant height, row width (plant vigor), canopy closure, etc. In addition, herbicide tolerance/injury, mineral deficiencies or toxicities (e.g. iron, boron, aluminum), and insect pest damage can also be evaluated. Moreover, the influence of other factors such as soil



**Fig. 4.** UAV imagery-based potato emergence 37 days after planting (images were acquired from 15 m altitude). (a) False color multiband image (R, G, NIR as RGB bands), (b) NDVI image in grayscale, and (c) pseudocolor image for better data visualization.



**Table 3**  
Examples of aerial (manned and unmanned) imaging based vegetative indices for yield estimation in row and field crops.

Crop	Sensing details	Yield $\approx f(VIs)$	References
Wheat (33 genotypes)	Platform: Cessna 172 (manned) Sensors: Canon F1 & Kodak 2236 Infrared filter (Wratten no. 12 gelatin filter) Resolution: 1: 6000 at 304 m altitude Imaging interval: 2 flights (weeks) June–July Analysis software: ERDAS	<i>Later growth stage:</i> NDVI $R^2$ : 0.11–0.47	Ball and Konzak (1993)
Cotton	Platform: – (manned) Sensors: Vis and NIR hyperspectral sensor (OKSI, Inc.) 430–1012 nm with 10-nm bandwidth Resolution: 1 m/pixel Imaging interval: 12 flights (15 days) June–October Analysis software: ENVI 3.6	<i>Early growth stage:</i> RDVI, MTVI, OSAVI <i>Later growth stage:</i> MCARI, TCARI $R$ : 0.09–0.61	Zarco-Tejada et al. (2005)
Wheat (17 genotypes)	Platform: Power glider (L'Avion Jaune) & Pixy (ABS-Aeroligt) Sensors: 3 channel Canon EOS350D and 4 channel Sony DSC-F828 with custom filters Resolution: 5 cm/pixel at 20–100 m Imaging interval: 6 flights February–June Analysis software: –	<i>Early and later growth stage:</i> LAI $\approx f$ (NDVI) RSE: 0.57	Lelong et al. (2008)
Rice	Platform: X-Cell Fury 91, Miniature Aircraft, Billings, MT Sensors: 3 channel Tetracam ADC Resolution: 0.71 m/pixel at 20 m Imaging interval: 65 days after planting Analysis software: Pixelwrench	<i>Mid growth stage:</i> NDVI $R^2$ : 0.76	Swain et al. (2010)
Potato	Platform: Piper Seneca Sensors: Kodak Megaplug 4.2i cameras customized for green, red, NIR bands Resolution: 1 m Imaging interval: 3 flights (monthly) July–August Analysis software: ERDAS	<i>Later growth stage:</i> SAVI, NDVI $R^2$ : 0.81	Sivarajan (2011)
Corn	Platform: customized E-Trainer 182 (Graupner GmbH) Sensors: Mono-lithic miniature spectrometer MMS1 (Carl Zeiss GmbH) 310–1100 nm (optimized to 360–900 nm) Resolution: 8–100 m altitude Imaging interval: 3 flight (monthly) August–October Analysis software: ArcGIS (ESRI). SigmaStat 3.5 (Dundas Software, Ltd.)	<i>Early and soft dough stages:</i> 740/730, 760/730 $R^2$ : 0.15–0.19	Link et al. (2013)
Wheat (112 genotypes)	Platform: – (manned) Sensors: 6 channel multispectral camera Resolution: 0.3 m/pixel at 300 m altitude Imaging interval: 6 flights (weekly) March–April Analysis software: –	<i>Later growth stage:</i> RDVI, TCARI, OSAVI, MCARI and GM1, NDVI $R$ : –0.70 to 0.73	Rodrigues et al. (2014)

RDVI, Randomized Difference Vegetation Index; MTVI, Modified Triangular Vegetation Index; OSAVI, Optimized Soil-Adjusted Vegetation Index; MCARI, Modified Chlorophyll Absorption Index; TCARI, Transformed Chlorophyll Absorption Index; NDVI, Normalized Difference Vegetative Index, GM1, Gitelson and Merzlyak; LAI, Leaf Area Index; RSE, Root Square Error; SAVI, Soil Adjusted Vegetation Index.

**Table 4**  
Summary of UAV-sensing based plant traits estimation in prior studies.

Phenotypic trait	Standard method	UAV-based sensing method	References
Plant height	Measuring scale	LIDAR system. Technology is in developmental scale, although UAV-based systems are available. Important to know the elevation of the terrain. 3D construction could be another possibility.	Merz and Chapman (2011), Zarco-Tejada et al. (2014)
Plant biomass Plant emergence	Visual rating; destructive sampling; Plant count	Visible-near infrared imaging to measure canopy coverage.	Chapman et al. (2014), Sankaran et al. (2014), Khot et al. (2014)
Plant senescence	Visual rating	Visible to near-infrared imaging to measure plant greenness.	Adamsen et al. (1999) <sup>a</sup> , Khot et al. (2014)
Plant flowering	Visual observation	Visible imaging to estimate number of flowers.	Thorp and Dierig (2011) <sup>a</sup> , Granados et al. (2013) <sup>a</sup> , Zarco-Tejada et al. (2012)
Water stress; stomatal conductance; Heat stress, salinity stress	Visual rating, soil moisture measurements, porometer	Visible, near and thermal infrared imaging to measure canopy temperature and water absorption bands. Plant growth can also be related to abiotic stress.	
Nutrition	Foliar and/or petiole nutrient analyses	Visible-near infrared imaging to estimate leaf nitrogen, and potentially other nutrients.	Jia et al. (2004) <sup>*</sup> , Lebourgeois et al. (2012)
Leaf area index	Destructive sampling, plant canopy analyzer	Visible-near infrared imaging to estimate plant biomass and coverage. May get saturated with LAI.	Hunt et al. (2010), Sugiura et al. (2005)
Disease susceptibility	Visual disease rating	Visible-near infrared imaging for assessing plant health/damage. Similar techniques can be applicable for toxicity studies.	Di Gennaro et al. (2012), Jansen et al. (2014)

<sup>a</sup> Non-UAV studies. The techniques can be integrated with low-altitude UAV-based sensing.

compaction (Fig. 1), field anomalies due to past production practices (e.g. saline and low nutrient zones), presence of weeds, and soil variability can also be easily assessed using aerial imaging. Table 4 summarizes some of the potential sensing methods for evaluating plant traits important for breeding lines and variety selection.

## 5. Concluding remarks and future perspective

The successful implementation of UAVs for field phenotyping depends on two major factors. The first factor is the characteristics of the UAV such as stability, safety, control, reliability, positioning, autonomy, sensor mount, and controller. The second important factor is the sensor characteristics such as specific spectral wavelengths, resolution, weight, calibration, and field of view. The UAV operation is often limited by sensor payload (size/weight), operating altitude (regulatory issues), and flight time (Ma et al., 2013; Deery et al., 2014). However, the above aspects of UAV technologies are rapidly improving. In addition, an alternative flight time solution could be using a powered tether to the UAV that would provide a continuous source of power, and also satisfy the regulatory requirements, especially in the United States. The U.S. Federal Aviation Administration (FAA) is currently developing rules and regulations to ensure privacy, safety, and security; while allowing UAV applications in agriculture. Another important aspect of UAV-based phenomics applications is the development of data-processing algorithms or tools to convert the sensory data into useful phenotypic data for variety selection and plant growth in general. Image blur and geometric distortion corrections (Xiang and Tian, 2011; Zhang and Kovacs, 2012), image stitching, georeferencing, and automated feature extraction capabilities need to be improved to utilize the full potential of UAV technologies in phenomics research.

In summary, UAV provides an opportunity for high-throughput phenotyping of crops, thus addressing a current 'bottleneck' in the selection of superior genotypes in breeding and variety development programs. UAV can significantly accelerate the selection of high-yielding crop varieties that are more efficient in their use of agronomic inputs and with significant resistance to biotic and abiotic stress. We predict that the use of UAV-based technology will grow exponentially in the next few years, resulting in the development of robust aerial sensing-based crop phenotyping methods available to the plant breeders and the research community at large.

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