



Review

A comprehensive review on recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping

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ABSTRACT

High-throughput phenotyping has been widely studied in plant science to monitor plant growth and analyze the influence of genotypes and environment on plant growth. To meet the demand of large-scale high-throughput phenotyping, unmanned aerial vehicles (UAVs) have been developed for near-ground remote sensing. UAVs based remote sensing has been used for high-throughput phenotyping of various traits of plants. This review focused on the applications of UAVs based remote sensing of different traits with different phenotyping sensors. In this review, the UAVs platforms and the phenotyping sensors were briefly introduced. The applications of UAVs to obtain and analyze plant phenotype traits were introduced and summarized by the traits in a more comprehensive way. A comparison of different phenotyping sensors was conducted. Furthermore, the challenges and future prospects of phenotype information acquisition and data analysis using UAVs as remote sensing platforms were also discussed. Since the current studies from various countries and researchers were fragmented to just explore the feasibility of UAVs based high-throughput phenotyping, this review aimed to provide the researchers and readers the current applications of UAVs for high-throughput phenotyping and how the studies were conducted, provide guidelines for future studies.

1. Introduction

In recent years, the rapid development of science and technology in agriculture and food helps to feed the rapidly increasing population (Pingali, 2012). With the growing population, the food supply is now becoming potentially challenging. Climate change, limited agricultural land, and unpredictable biotic and abiotic stresses are major challenges to maintaining and improving crop food production (Fu et al., 2020b). Breeding of high-yield, stress-resistant species is a possible way to improve food production (Lobos et al., 2017; Fu et al., 2020a). On the other hand, precision agriculture systems can maintain crop yield under different growth conditions (Fu et al., 2020c; Yost et al., 2017).

Plant phenotype can be used to evaluate various plant traits and phenotypic parameters, including growth, development, tolerance, yield, plant height, leaf area index, etc. (Asaari et al., 2019; Li et al., 2014; Li et al., 2020). By measuring and learning the phenotype traits, the predictive models can be established to evaluate plant growth characteristics. Traditional methods for obtaining field phenotypes include manual measurements and proximal sensors, which are

inefficient and difficult to be used in large-scale field operations. With the development of modern sensor technologies, non-invasive and high-throughput plant phenotyping techniques have been studied and developed rapidly (Prashar and Jones, 2014; Rebetzke et al., 2019; Shakoor et al., 2017; Yang et al., 2013). Many of these researches were in-door studies. Although some methods are for obtaining high-throughput phenotyping, their usage is limited by the difficulty of implementing large-scale field measurements. To overcome these limitations, reliable, automatic, multifunctional, and high-throughput phenotyping platforms should be developed (Yang et al., 2013).

UAVs can be applied to various missions due to the characteristics of easy to be operated and controlled remotely. Especially, UAVs can be used in fields where human beings are difficult to access. There are no significant differences in the basic architectures of UAVs used for different missions. UAVs based remote sensing are possible to obtain phenotype traits with the required time–frequency and spatial resolution at large scale field level (Yang et al., 2018). The UAV platform can provide high-temporal resolution and spatial resolution images for precision agriculture. And the images are important components for

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timely and non-destructive assessment of crop yields. A UAV equipped with one or more sensors, using communication technology and global navigation satellite system (GNSS) positioning technology, can rapidly acquire high-resolution images of the canopy of the field crop (Zaman et al., 2014; Zheng et al., 2020). UAVs with phenotyping sensors can obtain various phenotyping characteristics of crops, which can be used to monitor the crop planting area (Chen et al., 2016; Jin et al., 2017; Liu et al., 2017a,b; Senthilnath et al., 2016) and crop growth (Guerra-Hernández et al., 2017; Lukas et al., 2016), to evaluate the biological and physical characteristics of a crop (Schirrmann et al., 2016), to predict crop yield (Du and Noguchi, 2017; Geipel et al., 2014; Reza et al., 2019) and to detect stress level (Albetis et al., 2017; Gibson-Poole et al., 2017) (Zermas et al., 2015). UAVs-based phenotyping has become an essential method for quickly obtaining crop geometric features and agronomic traits (Näsi et al., 2018).

With the help of UAVs, researchers have made progress on large-scale field plant phenotype information capture and analysis. In this review, we comprehensively reviewed the application of UAVs equipped with different phenotyping sensors in field plants in recent years. Based on these applications, we summarized the current status of UAV based phenotyping in plants and compared performances of different phenotyping sensors. Moreover, the challenges and limitations of UAVs based on high-throughput phenotyping were discussed. Future trends of UAVs based on high-throughput plant phenotyping was also discussed.

1.1. Article search methods

The articles contained in this review were searched on the web of science and Google Scholar website. The searched keywords are UAV (abbreviations and full name) or drone with the plant (or a specific plant such as rice, wheat, etc.), phenotype (or a specific phenotype, such as plant height, biomass), phenotyping sensors (RGB cameras, multispectral/hyperspectral imaging sensors, thermal imaging sensors, etc.).

In addition to the search of keywords, we also paid attention to the cited references in the published literature. These papers also met the search scope. Consulted materials included peer-reviewed articles and meeting articles using UAVs for phenotypic research. For the current studies, some are hot issues and some are not. It should be noted that the uses of different phenotyping sensors are different, resulting in the different numbers of published articles for each phenotyping sensor. The searched articles are published between Jun 2003 and January 2021, in addition to a 1996 study on light detection and ranging (LIDAR). We have collected 236 papers as much as possible, but there might still be missing papers. We believe that the number of missing papers should be relatively small.

1.2. Related reviews

A few review articles have been published in the field of UAV based plant phenotyping from various aspects (Adao et al., 2017; Barbedo, 2019; Gautam and Pagay, 2020; Hassler and Baysal-Gurel, 2019; Huang et al., 2013; Jang et al., 2020; Kim et al., 2019; Maes and Steppe, 2019; Mukherjee et al., 2019; Poley and McDermid, 2020; Yang et al., 2017a,b,c). Among these reviews, our review has something in common with reviews (Maes and Steppe, 2019; Yang et al., 2017a,b,c), and our review is significantly different from the other presented reviews.

In the review of Maes and Steppe (2019), the application of unmanned aerial vehicle plant phenotyping is briefly introduced. A simple introduction of the applications is conducted. However, in our review, we introduced more applications and introduced more detailed information about the applications. More sensors and more application aspects were reviewed in our manuscript. And in the review of Yang et al. (2017a,b,c), detailed UAVs, sensors, applications and data processing methods are reviewed. Our review focuses on the applications of UAV remote sensing with various sensors. In all, as for applications, we introduce the applications in detail and more comprehensive. We wish

the reader to know how these researches were conducted, which were different from this review. How the authors of each study using UAV remote sensing for high-throughput phenotyping, and what are the main results that are the primary concern of our review. In our review, we do not introduce the UAVs and the sensors in detail. We summarize the use of different UAVs and sensors to present UAV remote sensing status for high-throughput phenotyping. In all, our review covers the applications of UAV remote sensing with various sensors for high-throughput phenotyping.

2. Overview of UAV systems for plant phenotyping

UAVs are unmanned aerial vehicles with power, radio control, or autonomous flight that can perform multiple missions. The UAV system includes an aircraft platform, sensors, and a flight control platform. Flight control systems and navigation systems are the key technologies to realize the autonomous flight of UAV and successfully complete the assigned task. UAVs flight attitude control and navigation are achieved through flight control, management, and navigation, and other functions, which are related to the acquisition efficiency of remote sensing information by UAV directly. UAVs are generally equipped with airborne avionics, a power system and an airframe. The UAV system used for phenotype analysis consists of a ground control station, UAV, communication systems and a logistics system (Fig. 1).

UAV equipped with one or more sensors can quickly and non-destructively obtain high-resolution phenotyping information of plants in the field using communications and GPS technology. Table 1 shows the information on UAVs and the flight parameters used in this review. Multi-rotor and fixed-wing UAVs are the two most used UAVs for plant phenotyping. Multi-rotor UAV has the advantages of low cost, hover ability, low take-off and landing requirements. The maximum limitations of multi-rotor UAVs are shorter flight times and lower flight loads (Pena et al., 2013). Compared with multi-rotor UAVs, fixed-wing UAVs have longer flight time, faster flight speed, large carrying capacity. However, fixed-wing UAVs cannot hover, which significantly limits their application (Herwitz et al., 2004; Link et al., 2013). Most fixed-wing UAVs have a significant flight time of 45 min due to their carrying capacity. Lithium polymer batteries (up to 6600 mAh capacity) had an average flight time of approximately 15 min (Bendig et al., 2013a,b). The fixed-wing UAV SenseFly eBee weighed approximately 700 g with payload and had a maximum operational flight time of approximately 45 min (Guerra-Hernandez et al., 2016). In the current study, the flight time of a multi-rotor UAV performing a flight is mostly around 15 min, and the less multi-rotor UAV system can reach 30 min. The advantage of a helicopter is that it can hover and fly at low altitude and low speed. Helicopters can carry large/heavy sensors. However, helicopter applications are limited by high vibration, noises, large maintenance workload, high cost, low speed, and short-range (Chapman et al., 2014; Sugiura et al., 2005; Swain et al., 2010). The flying wings have lightweight and low flight resistance advantages but have serious height errors in collecting images. Parachutes can fly easily in windless conditions but cannot be operated under strong wind conditions. A glider is lifted off by other means, such as towing the aircraft and then gains forward power against its gravity. They cannot hover in a single location, and they have low speeds and relatively short flight time (Sankaran et al., 2015). A blimp has hover ability, high payload, and vertical take-off and landing ability. However, due to their large size, blimps move slowly from one position to another, and their stability is poor in windy conditions, making it difficult to obtain accurate information (Liebisch et al., 2015).

2.1. Platform

UAV platforms used for phenotype analysis mainly include multi-rotor (Mesas-Carrascosa et al., 2014), fixed-wing (Quigley et al., 2005), helicopter (Wendel et al., 2006), flying wing (Lemko et al.,

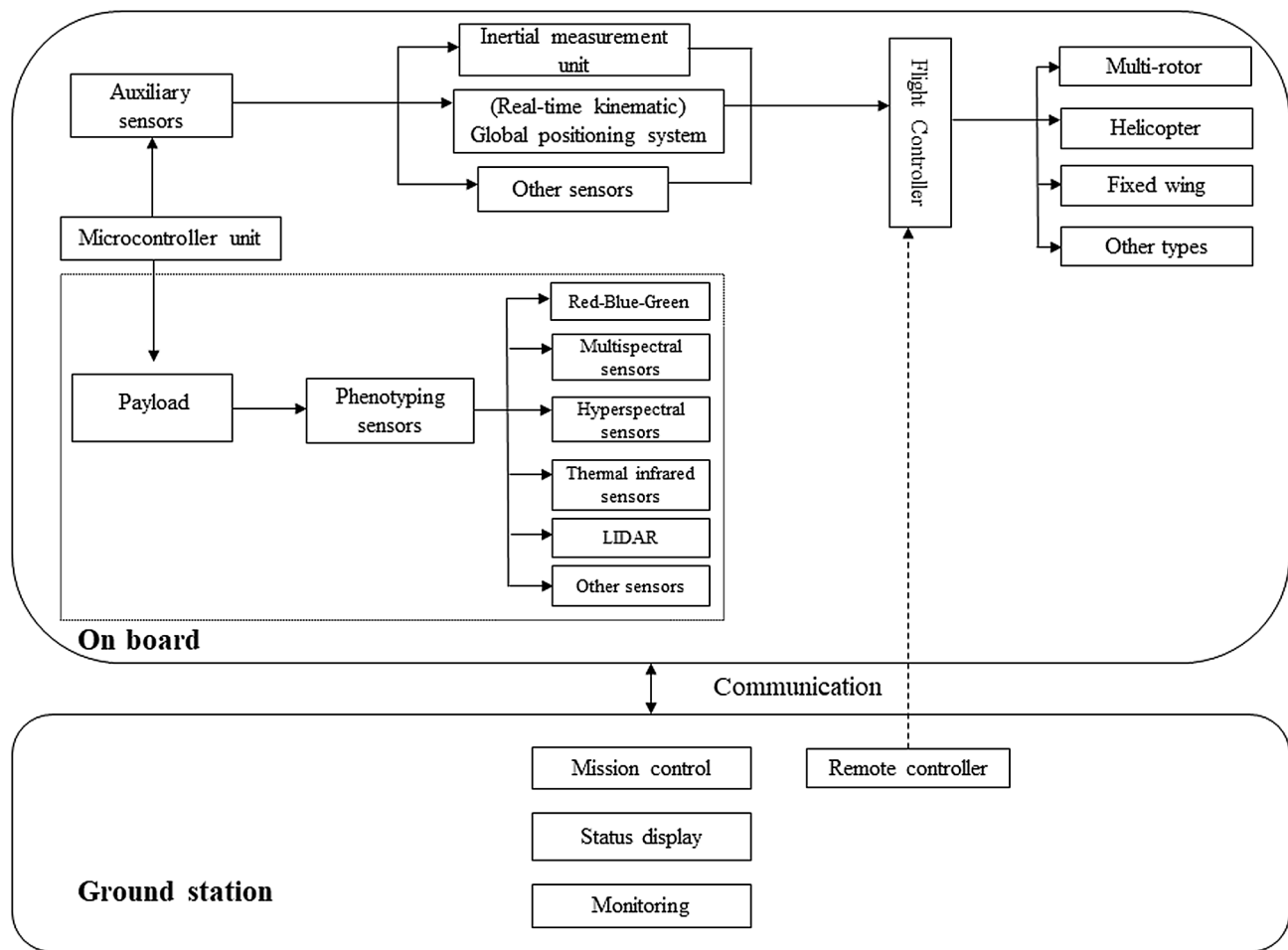


Fig. 1. General information of UAV systems.

2015), parachute (Smith and Pell, 2003), glider (Leonard et al., 2010) and blimp (Yamasaki and Goto, 2003). The sensor is the core for data acquisition of the UAV low-altitude remote sensing technology. Sensors can be divided into two main types, including auxiliary sensors and phenotyping sensors. Auxiliary sensors are used to ensure that UAVs can complete flight operations safely and efficiently. The UAV body's motion is perceived by an inertial measurement unit (IMU) (Jing et al., 2017), which keeps the camera in a balanced position. The barometric altimeter has the advantages of measuring height and has been used in UAVs' flight controller. Phenotyping sensors are used primarily to obtain crop phenotypic characteristics.

2.2. Phenotyping sensors

Phenotypic sensors are mainly used to obtain crop phenotypic characteristics. The phenotyping sensors installed on the UAV may include RGB, multispectral, hyperspectral, thermal infrared imaging camera, fluorescence sensor and LIDAR. RGB cameras are the most commonly deployed by UAV in crop phenotyping due to its high spatial resolution and relatively low cost (compared with other sensors). For example, above ground biomass (AGB) can be estimated from images collected from cameras mounted on UAVs. However, RGB cameras have only three spectral bands with less spectral information (Chee and Zhong, 2013). The multispectral sensor can collect the reflectance after atmospheric calibration, emittance, or backscattered energy from an object or area in multiple bands (Kerkech et al., 2020). The near-infrared spectral range is between 780 and 2526 nm. Hyperspectral cameras have a higher spectral resolution in the spectral region than multispectral cameras (Maes and Steppe, 2019). Therefore, the spectral

information obtained is large, but image processing is challenging, and the price is high compared with RGB and multispectral sensors.

RGB, multispectral and hyperspectral cameras can all acquire spectral information and spatial image information of the plants. Thermal infrared imaging (Sagan et al., 2019a,b) sensors use infrared detectors and an optical imaging lens to receive infrared radiation energy in the photosensitive element infrared detector. Thermal infrared imaging can produce time series or single-time-point analysis-based data. Thermal imaging cameras are highly targeted and sensitive to some environmental factors and can, therefore, be used to extract canopy temperatures. Light detection and ranging (LIDAR) (Wallace et al., 2012) is a physical measurement based on the time of flight of a laser beam. LIDAR has the advantages of high precision and is sensitive to small changes in measuring distance, while it is expensive compared with RGB and multispectral cameras. Fluorescence sensors (Barbagallo et al., 2003) are mainly used to monitor plant metabolic information and detect crop diseases.

2.3. The data collection and processing procedure

The UAV image analysis procedures usually include image acquisition, image preprocessing, image segmentation, image matching and correction, feature extraction, modeling (univariate and multivariate classification and regression analysis).

The type of camera and UAV platform must be selected according to requirements and budget before data collection. The flight plan needs to be arranged according to the camera's resolution and the maximum flight time of the UAV. The camera is mounted on the UAV, and the remote control device is used to control the UAV's flying distance, flying

Table 1
Statistics of UAV types and flight parameters mentioned in the paper.

Sensor type	UAV type	Flight time range	Flight payload	References	Comparison and summary
RGB	Fixed-wing UAV	15–50 min	0.69–1.5 kg	(De Souza et al., 2017; Guerra-Hernández et al., 2017; Han et al., 2018; Hu et al., 2018; Kachamba et al., 2016; Li et al., 2016a,b; Marino and Alvino, 2018; Selsam et al., 2017; Zarco-Tejada et al., 2014; Zhang et al., 2016)	Low cost, light weight, convenient operation; less visible light bands
	Multi-rotor UAV	5–50 min	0.23–1.25 kg	(Bendig et al., 2013a,b; Bendig et al., 2014; Li et al., 2016a,b; Madec et al., 2017; Nási et al., 2018; Peña et al., 2018; Watanabe et al., 2017)	
	Helicopter	20–50 min	5–10 kg	(Mathews and Jensen, 2013; Zhu et al., 2009)	
Multispectral sensor	Fixed-wing UAV	7–60 min	0.15–8 kg	(Ballester et al., 2018; Kang et al., 2018; Maresma et al., 2016; Nebiker et al., 2016; Shafian et al., 2018; Su and Chou, 2015)	Low cost, high work efficiency; low spectral resolution
	Multi-rotor UAV	30–60 min	1–5 kg	(Baluja et al., 2012; Borra-Serrano et al., 2015; Stroppiana et al., 2015; Sugiura et al., 2018)	
	Helicopter	30 min	5 kg	(De Biasio et al., 2013)	
Hyperspectral sensor	Fixed-wing UAV	10–50 min	3–5.8 kg	(Padua et al., 2018; Zarco-Tejada et al., 2012; Zarco-Tejada et al., 2013a,b,c)	More band information, high resolution; complex data processing
	Multi-rotor UAV	20–50 min	1.2–7 kg	(Liu et al., 2017a,b; Uto et al., 2013; Yue et al., 2018; Zheng et al., 2016)	
	Helicopter	/	/	/	
Infrared thermal sensor	Fixed-wing UAV	15–60 min	0.5–6 kg	(Gonzalez-Dugo et al., 2015; Gonzalez-Dugo et al., 2014; Lelong et al., 2008; Lukas et al., 2016)	Temperature quickly acquired; environment effect
	Multi-rotor UAV	20–50 min	1–5 kg	(Caruso et al., 2017; Gibson-Poole et al., 2017; Kefauver et al., 2017)	
	Helicopter	10–50 min	3–8 kg	(Berni et al., 2009)	
Lidar	Fixed-wing UAV	10–30 min	1 kg	(Li et al., 2016a,b)	High point density, high spatial resolution; high cost, narrow beam, large data processing
	Multi-rotor UAV	9–20 min	1 kg	(Madec et al., 2017; Sankey et al., 2018)	
	Helicopter	/	/	/	
Fluorescence sensor	Fixed-wing UAV	/	/	/	High resolution, rapid detection speed; high cost
	Multi-rotor UAV	15 min	1 kg	(Matese et al., 2013)	
	Helicopter	/	/	/	

speed, flying direction and other parameters. The collected data is stored in the camera's memory card, which can be taken out of the camera and connected to a computer for further processing.

The preprocessing of remote sensing images is mainly classified into two categories, sensor correction and geometric correction. Sensor calibration includes spectral radiation calibration, dark signal correction, distortion, vignetting, exposure time adjustment, etc. Radiation correction is the basic sensor calibration method, which could eliminate and mitigate radiation distortion. Geometric correction refers to the process of eliminating or correcting geometric errors in collecting remote sensing images.

3. Applications

In the application of plant phenotype detection, there are many kinds of UAVs. Besides, the UAVs' specific flight parameters are different, including flight payload, flight time, flight altitudes, and so on. Various UAVs have been developed with their advantages and limitations. So, there is no specific standard to select UAVs. Table 2 summarizes the studies of applying sensors to plant phenotyping. For distinct phenotypes, different types of sensors were chosen for collecting UAV images. Therefore, there were differences in the number of studies on various sensors. Besides, the current researches on phenotype are decentralized, and the studies lack systematization. Many types of plants were studied, such as barley, maize, rice, citrus orchard, grass, potato, sunflower, vineyard, etc.

3.1. Geometric related traits

Geometric characteristics are important phenotype information of

plants, indicating the growth status of the plants. Geometric features include plant height, leaf area index (LAI), lodging and plant density, etc. And the combination of geometric features and spectral features can more accurately evaluate plant phenotypic information.

3.1.1. Plant height

Plant height is one of the most critical parameters for the farmers to choose the suitable canopy management within the field. Plant height combined with other data can predict plants' growth, such as the lack of fertilizer, water shortage, lack of light, etc. And plant height can be used to indicate the lodging of yield and carbohydrate storage capacity, which can provide the basis for site-specific management (Holman et al., 2016; Lati et al., 2013). Since the manual method for plant height measurement is time-consuming and labor-intensive, various sensors have been used for rapid and accurate measurement of plant height.

Photogrammetric point clouds extracted from digital images have been used in plant height measurement with good performances (Khanna et al., 2015; Madec et al., 2017; Malambo et al., 2018; Rueda-Ayala et al., 2019). Point clouds could also be obtained directly from LIDAR (Ozdemir et al., 2021). The conventional data processing methods include gray extraction and feature extraction (Anthony et al., 2014). Images collected by high-resolution RGB cameras in some studies were generated into the digital surface model (DSM), crop surface model (CSM), and digital terrain model (DTM), which are used to extract the information of crop height (Guerra-Hernández et al., 2016; Han et al., 2018; Holman et al., 2016; Panagiotidis et al., 2017; Peña et al., 2018; Willkomm et al., 2016; Zarco-Tejada et al., 2014). Li et al. (2016b) collected stereo images relating to the structure from motion (SfM) by a UAV system to estimate maize canopy height and above-ground biomass. The results showed that the UAV-estimated maize

Table 2
Summary of studies applying sensors to plant phenotyping.

Sensor type	Research object	Research contents	Research locations	UAV	Type	Resolution	Flight altitude	Flight time	Results	Reference
RGB	Aspens	Canopy height	Huailai-Yanqing Basin, Beijing, China	Six-fixed-wing UAV	FW	GSD of 0.03 m and 0.02 m	100 m and 150 m	/	Matched ratio 66.94%	Li et al. (2016a,b)
	Sugarcane	Height	Euclides da Cunha Paulista, São Paulo State, Brazil	eBee Ag senseFly	FW	GSD of 106 mm pixel-1	200 m	50 min	Average error = 0.08 m, RMSE = 0.40 m	De Souza et al. (2017)
	Barley	Height	Campus Klein-Altendorf, Cologne, Germany	MK-Oktokopter	MR-8	4608 * 3464 px, GSD of 0.009 m	50 m	5–15 min	R ² = 0.92, standard error = 0.25 m	Bendig et al. (2014)
	Trees	Height	La Poveda experimental farm in Arganda del Rey, Madrid, Spain	MD4-1000	MR-4	12-megapixel	100 m	40–45 min	R ² = 0.599, RMSE = 0.21 cm	Peña et al. (2018)
	Grass ley	Height	NIBIO Særheim research station, Klepp Stasjon, Norway	DJI Mavic Pro	MR-4	1920 * 1080 px	30 m	/	R ² > 0.80	Rueda-Ayala et al. (2019)
	Olive tree	Height	Alameda del Obispo experimental farm, Córdoba, Spain and Todolivo S.L. cooperative in Pedro Abad, Córdoba, Spain	AP04	FW	4000 × 3000 px	300 m	45 min	Relative RMSE = 6%-20%	Díaz-Varela et al. (2015)
	Wheat	Height	Gréoux les Bains, France	/	MR-6	6000 * 4000 px	GSD of 1 cm	20 min	R ² > 0.97	Madec et al. (2017)
	Sorghum	Height	Tokyo University, Tokyo, Japan	USM-S1	MR-4	24 million px	40 m	10 min	r = 0.842	Watanabe et al. (2017)
	Sorghum	Height	Brazos Bottom research farm, TX, USA	Tuffwing Mapper	FW	6000 * 4000 px	120 m	40 min	R ² > 0.80	Han et al. (2018)
	Sorghum	Height	Hermitage, Queensland, Australia	Skywalker Technology Co X8	FW	5472 * 3648 px	20 m	50 min	R ² = 0.63, RMSE = 0.07 m	Hu et al. (2018)
	Grass swards	Biomass	LUKE research farm, Jokioinen, Finland	Gryphon dynamics quadcopter	MR	7360 * 4910 px	30 m and 50 m	25 min	PCC = 0.98, RMSEs = 0.34 t/ha	Viljanen et al. (2018)
	Miombo woodlands	Biomass	Muyobe community forest reserve, Mzimba, Malawi	SenseFly eBee	FW	16.1 megapixels	325 m	Average = 20 min	Mean value of biomass = 38.99 Mg/ha-1; RMSE = 46.7%	Kachamba et al. (2016)
	Sorghum	Biomass	Agronomy Center for Research and Education of Purdue University, Indiana, USA	DJI S1000+	MR	7360 * 4912 px	55 m	/	Multiple dates resulted better prediction	Zhang et al. (2017)
	Onion	Biomass	Tarazona de La Mancha, Albacete, Spain	Md4-200	MR-4	12 MP	44 m	/	R ² = 0.76 (canopy volume-dry leaf biomass); R ² = 0.95 (canopy volume-dry bulb biomass)	Ballesteros et al. (2018)
	Spartina	Biomass	Sansha Bay, Fujian, China	Microdornes MD4-1000	MR-4	0.10 m resolution	120 m	/	R ² = 0.898, RMSE = 0.415	Zhou et al. (2018)
	Wheat	LAI	Auzeville of French National Agronomical Research Institute station, Toulouse, France	“Pixy” motorized parachute and a powered glider	FW	8 gigapixels	/	/	R ² = 0.82, RSE = 19 (NDVI)	Lelong et al. (2008)
	Rice	Chlorophyll content	latitude 3 35'N and longitude 101 05' E	Swinglet CAM	Glider plane	16 megapixels	/	/	r = 0.78(crown index)	Saberioon and Gholizadeh (2016)
	Rice	Land surface water index	Heilongjiang, Jilin, and Liaoning province, China	eBee, senseFly	FW	spatial resolution of 1.5 cm	500 m	/	84% of the variation of paddy rice	Liu et al. (2018b)
	Grapevine	Frost stress	Chateau Zhihui Yuanshi vineyards, Ningxia, China	DJI Phantom 2 Vision	MR-4	4384 × 3288 px	80 m	15 min	16.8% of plants impacted	Su et al. (2016)
	Potato	Disease stress	west of Perth, Scotland	Custom built Vulcan	MR-8	/	35 m	14 min	Total accuracy = 91%, Kappa coefficient = 0.75	Gibson-Poole et al. (2017)
	Wheat	Weed	Oxfordshire, Bedfordshire, Norfolk, Lincoln and Yorkshire	DJI Phantom 2	MR-4	GSD of 3.2 cm/pixel	100 m	11 min	Accuracy = 87%	Lambert et al. (2018)

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Table 2 (continued)

Sensor type	Research object	Research contents	Research locations	UAV	Type	Resolution	Flight altitude	Flight time	Results	Reference
MS	Sunflower field	Weed mapping	farms, United Kingdom Monclova farm, Seville province, Spain	MD4-1000	MR-4	12 megapixels	30 m, 60 m and 100 m	5–12 min	WdA = 95%	Borra-Serrano et al. (2015)
	Sunflower field	Weed classification	La Monclova in La Luisiana, Seville, southern Spain	Md4-1000	MR-4	12 megapixels	30 m, 60 m, 100 m	45 min	Significant spectral difference	Torres-Sanchez et al. (2013)
	Rice	Yield	National Engineering and Technology Center for Information Agriculture, Jiangsu, China	MK-Oktokopter	MR-8	/	50 m	8–25 min	$R^2 = 0.73$ (yield-VARI)	Zhou et al. (2017)
	Vineyard	Disease detection	Gaillac Appellation d'Origine Contrôlée area, France	Long range DT-18	/	960 * 1280 px	120 m	/	Level of misclassification was at worst 12%	Albetis et al. (2017)
	Sunflower field	Weed mapping	Alameda del Obispo, Córdoba, Spain	Md4-1000	MR-4	1.3-megapixel	40 m, 60 m, 80 m, and 100 m	/	WdA = 91%	Pena et al. (2015)
	Vineyard	Stem water potential	Talca, Maule Region, Chile	Mikrokopter Okto XL	MR-8	/	60 m	/	$R^2 = 0.56$ – 0.87 , RMSE = 0.12	Poblete et al. (2017)
	Vineyard	Stem water potential	Yunnan, China	DJI Co.Ltd	MR	Spatial resolution of 4 cm	30 m	/	$R^2 = 0.83$, slope = 1, $p < 0.001$	Romero et al. (2018)
	Reservoir	Trophic state	Kinmen, China	SenseFly eBee	FW	12 million pixels	286 m and 250 m	50 min	$R^2 = 1.0$, averages of chlorophyll-a, total phosphorous, and secchi disk were 179.7 $\mu\text{g}\cdot\text{L}^{-1}$, 108.4 $\mu\text{g}\cdot\text{L}^{-1}$ and 1.4 m	Su and Chou (2015)
	Canola	Green peach aphid	a field near Williams, Australia	Cinestar-8 MK Heavy Lift	MR-8	1280 * 1024 px	15 m and 120 m	/	99% infected (K-deficiency)	Severtson et al. (2016)
	Vineyard	Grapevine leaf strip disease (GLSD)	Chianti Classico Domain, Tuscany, Italy	Mikrokopter OktoXL	MR-8	3.2-megapixel	150 m	/	High correlation between NDVI and GLSD symptoms	Di Gennaro et al. (2016)
	Maize	Yield	IRTA Research Station in Gimenezells, Lleida, Spain	Atmos-6	FW	14 megapixels	180 m	/	$R^2 = 0.92$, RMSE = $0.87 \text{ mg}\cdot\text{ha}^{-1}$ (WDRVI)	Maresma et al. (2016)
	Maize	Grain yield	North-east of Harare, Zimbabwe	Mikrokopter oktoxl 6 s12	MR-8	12 * 1.3 megapixels	30 m	/	Grain yield was significantly greater under CA conditions ($p < 0.0001$), by almost 20% relative to the CP.	Gracia-Romero et al. (2018)
	Sunflower crop	Yield, biomass, nitrogen content	Agricultural Research Centre of Cordoba, southern Spain	Microdrones MD4-200	MR-4	1200 * 1024 pixels	75 m	/	99% confidence level (NDVI)	Vega et al. (2015)
	Sorghum	Yield	TexasA&MAgriLife Research Farm near College Station, TX, USA	/	FW	1.2-megapixel	120 m	20–25 min	$R^2 = 0.58$ (NDVI- f_c)	Shafian et al. (2018)
	Cabbage	Yield	Heaje-myeon	eBee by senseFly	FW	1.2-megapixel	50 m	50 min	$R^2 = 0.697$, RMSE = 1170 g/plant, relative error = 67.1%	Kang et al. (2018)

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Table 2 (continued)

Sensor type	Research object	Research contents	Research locations	UAV	Type	Resolution	Flight altitude	Flight time	Results	Reference
		N concentration	National Engineering and Technology Center for Information Agriculture, Jiangsu province, China	Mikrokopter OktoXL		1.3 megapixel			$R^2 = 0.48-0.65$ (PRI), $R^2 = 0.39-0.68$ (BNI)	Zheng et al. (2018)
	Sunflower and cotton	Weed	Córdoba and Sevilla provinces, Southern Spain	MD4-1000	MR	24 megapixels	30 m and 60 m	/	$R^2 > 0.6$, WdA > 80%	de Castro et al. (2018)
	Forest	Physiological stress	Kinleith Forest in New Zealand's Central North Island	Aeronavics SkyJib	coaxial quad-copter	/	90 m	15 min	Weighted kappa = 0.694	Dash et al. (2017)
	Forest	Forest health	Kinleith Forest in New Zealand's Central North Island	Aeronavics	MR-4	/	90 m	15 min	$R^2 = 0.84$, RMSE = 15.04 (UAV and Satellite imagery)	Dash et al. (2018)
	Maize	Vis, reflectance and SPAD	Zhuozhou, Hebei Province, China	EM6-800	MR-6	1280 * 1024 px	50 m	40 min	Accuracy of reflectance: M > S	Deng et al. (2018)
	Maize, sunflower and wheat	Classification	Institute for Sustainable Agriculture, Córdoba, Spain	Md4-1000	MR-4	1.3-megapixel	30 m	/	Error = 0–10%	Torres-Sanchez et al. (2015)
	Vineyard	Classification	Navarra, Spain	Md4-1000	MR-4	1280 * 1024 px	250 m	/	Vegetation and weed distinguish effectively	Rey et al. (2013)

¹FW represents fixed-wing UAV and MR represents multi-rotor UAV; MR-4, MR-6 and MR-8 represent 4-rotor, 6-rotor and 8-rotor UAV, respectively. fc represents fractional vegetation coverage; ²BNI represents blue nitrogen index; ³WDRVI represents wide dynamic range vegetation index.

parameters were comparable to the field measurements with a mean error of 0.11 m for canopy height. Chu et al. (2016) explored the potential of UAS-based visible-band images to assess cotton growth. Applying an empirical model that converted the cotton plant height to canopy cover, the estimated canopy cover showed a strong correlation (coefficient of determination, $R^2 = 0.990$) with the observed canopy cover. The R^2 was from 0.42 to over 0.97, which showed that RGB cameras had the potential to measure crop height.

The LIDAR system consists of four parts: a laser scanning system, a global positioning system, an inertial measurement system, and a monitoring control system. And the laser scanning system is an important component of the LIDAR system consisting of a laser scanner and a ranging unit. There are a few applications of crop phenotyping using LIDAR (Ota et al., 2015). The LIDAR has been used to estimate plant height and biomass due to high point density, high spatial resolution, lighter weight, and good performance in low-altitude detection. Nilsson (1996) investigated estimating tree height and stand volume with an airborne LIDAR system. The average height estimated by the LIDAR was 2.1–3.7 m lower than the average ground tree height. Madec et al. (2017) compared the accuracy of UAV-based RGB images and ground LIDAR to estimate the wheat height. The plant height derived from LIDAR showed very high consistency with a strong correlation ($R^2 \approx 0.98$) and good performance (RMSE = 8.4 cm). Wang et al. (2017) investigated the ability of a UAV discrete LIDAR for modeling both the canopy height and fractional cover in grassland. The results showed that the LIDAR-derived mean canopy height was the most reasonable predictor of AGB ($R^2 = 0.340$, RMSE = 81.98 g/m², and a relative error of 14.1%). Li et al. (2016a,b) compared the performances of canopy height models (CHMs) derived from airborne laser scanning (ALS) data and UAV stereo images in the extraction of individual tree height and crown size. The results showed that the digital elevation models (DEM) generated from UAV stereo images, together with the ALS-derived DEM, could achieve better performance than ALS data alone. The point clouds acquired by UAV based LIDAR need to be processed into CHM and DEM to estimate plant height and biomass. Since the platform is extremely susceptible to environmental factors such as wind, the process of acquiring point clouds by LIDAR is also sensitive (Lefsky et al., 2002). Besides, the processing of LIDAR data is large, which greatly affects the application of LIDAR technology. There are also studies using a depth

camera, such as Kinect to obtain point clouds (Newcombe et al., 2011). The studies paid attention to the three-dimensional modeling of human faces or buildings (Khoshelham and Elberink, 2012). The acquired point clouds need to be accurately registered to ensure the accuracy of the result (Yue et al., 2014)

3.1.2. Biomass

Plant biomass is the amount of accumulated plant matter per unit area, which is also an important indicator of crop growth (Liu et al., 2019). Biomass plays a very important role in the formation of ecosystem institutions and functions, which is a concentrated expression of ecosystem functional indicators and energy harvesting capacity. Biomass can be detected by parameters such as chlorophyll content, leaf area index, plant height, vegetation index and plant dry weight. Biomass estimation is used to assess the impact of crop health, nutrient availability and is the most crucial crop parameter indicating yield for crop yield prediction (Bendig et al., 2015). Brocks and Bareth (2018) generated CSM from RGB images to estimate the biomass of wheat. The R^2 between 0.55 and 0.79 and root mean square errors (RMSE) between 97 and 234 g/m² were achieved. Ota et al. (2015) investigated the capabilities of a crop height model (CHM) derived from aerial photographs by LIDAR using the SfM approach to estimate above-ground biomass (AGB) in a tropical forest. In conclusion, AGB can be determined from CHM derived from aerial photographs using the SfM approach. Kachamba et al. (2016) evaluated the application of 3D data obtained from UAV-based RGB imagery to estimate biomass of tropical woodland. The model built using unsupervised ground filtering with a grid search approach had the smallest RMSE of 46.7% and a mean biomass value of 38.99 mg·ha⁻¹. Vegetation indices (VIs) developed from reflectance spectral values have been widely used to estimate biomass. For example, the EVI (Shafian et al., 2018), which is sensitive to soil background changes, can also be used for crop biomass monitoring. Zheng et al. (2019) improved the estimation accuracy of rice above ground biomass (AGB) by combining normalized difference texture indices and VI of UAV-based multispectral imagery, and the multivariate model produced the highest estimation accuracy ($R^2 = 0.78$ and RMSE = 1.84 t/ha). To improve the accuracy of biomass estimation, plant height index combined with plant height has been used to estimate crop biomass. Viljanen et al. (2018) developed a novel machine learning technique to estimate

canopy height and biomass of grass swards by utilizing a multispectral photogrammetric camera and the highest Pearson correlation coefficient (PCC) and RMSE were 0.98 and 0.34 t/ha (12.70%), respectively. Bendig et al. (2014) estimated the biomass of barley using CSMs derived from UAV-based RGB imaging. High correlation coefficients were found between plant height predicted from CSMs and fresh biomass ($R^2 = 0.81$) and dry biomass ($R^2 = 0.82$). Hyperspectral cameras also can be used to obtain spectral information. Yue et al. (2017) estimated AGB based on hyperspectral images obtained from a UAV. The crop height and hyperspectral reflectance of winter wheat canopies were calculated from hyperspectral images. The estimation accuracy of models using crop height and spectral parameters separately was low, and the prediction accuracy increased when crop height and spectral parameters were combined. Näsi et al. (2018) estimated biomass using the UAV and aircraft-based hyperspectral images, RGB images, and photogrammetric 3D features. The best results were obtained when integrating hyperspectral and 3D features in the biomass estimation. In dry matter yield estimation of barley, the PCC and the RMSE% were at best 0.95% and 33.2%, respectively. In the grass dry matter yield estimation, the best results were 0.79% and 1.9%, respectively.

3.1.3. Leaf area index

LAI reflects the nutritional status of the crop population, and it is closely related to crop yield. Vegetation indices can be built after processing the spectral reflectance data acquired by UAV-based spectrometers, and statistical methods are used to estimate LAI. Mathews and Jensen (2013) visualized and quantified vineyard canopy LAI using UAV based RGB images. The R^2 of 0.567 was found between the estimated and ground measured parameter. Van Iersel et al. (2018) evaluated the performance of multi-temporal high-spatial-resolution imagery equipped on a UAV to record the dynamics in floodplain vegetation height. The vegetation height could be determined from the normalized DSMs in leaf-on conditions via the linear regression method (RMSE = 0.17–0.33 m). Roosjen et al. (2018) improved the estimation accuracy of LAI of a potato crop using multi-angle spectral data to illustrate the potential of UAV-based multispectral images. Prosail model combined the prospect leaf model (Jacquemoud and Baret, 1990) and the sail canopy bidirectional reflectance model (Wu et al., 2020). Resulted showed that it was possible to simultaneously estimate both leaf and canopy parameters such as LAI and leaf chlorophyll content (LCC).

3.1.4. Plant density

Plant density is a critical agronomical trait used to manage crops and estimate yield. The most commonly used method for plant density quantification is based on visual counting from ground level, which is tedious and time-consuming. Jin et al. (2017) developed a method for estimating wheat plant density at the emergence stage based on high-resolution RGB imagery taken from UAV. This method achieved an RMSE and relative RMSE of 34.05 plants/m² and 14.31% with a bias of 9.01 plants/m². Liu et al. (2017b) developed a machine vision-based method with recursive feature elimination and Hough transform to automate the density survey of wheat at early stages. Results demonstrated that the density was accurately estimated with an average relative error of 12%. Burkart et al. (2018) detected distinct phenological events during barley development by UAV-based RGB images. The measured green ratio vegetation index (GRVI) values ranged from −0.10 (bare soil) to 0.20 (fully developed crop) and showed a clear drop at the time of ear pushing and ripening.

The current researches indicated that UAV remote sensing systems could monitor crop geometric traits, biomass, and other applications. Plant height is a major research area of geometric characteristics (22 articles in the references). Compared with hyperspectral and thermal infrared imaging sensors, RGB cameras and multispectral cameras were more used to study geometric features (30 articles in the references). Images obtained from the sensors could be processed to generate CSM, CHM, DSM, etc., which could estimate geometric features such as height

and biomass. The estimation method of the LAI can be divided into optical models and statistical models. The optical model needs to estimate LAI through inversion, and different functions in the inversion process will affect the accuracy of the LAI inversion result. In addition, the model inversion is time-consuming, which is not conducive to remote sensing image processing in a large area. The statistical model refers to the regression model that uses the VI to estimate LAI with higher accuracy. Besides, many VIs have been proposed for the study of plant phenotypes. For example, the normalized difference vegetation index (NDVI) was used to estimate LAI (Lelong et al., 2008) and the GNDVI was used to estimate AGB (Lukas et al., 2016). Various VIs can be selected according to different research objectives. Even if the geometric features of LIDAR estimation had high accuracy, the use of LIDAR was limited due to its high price and the complexity of point cloud processing. In all, the UAV remote sensing system has an extensive practical prospect for the application in the geometric and phenologies traits analysis. Further research should focus on developing data processing and related software to improve image processing efficiency.

3.2. Physiological parameter

The monitoring of plant physiological parameters, such as chlorophyll content, crown temperature and plant vigor, etc., is essential to understand crop growth, canopy reflectance changes, and growing season nitrogen and pesticide requirements. The biophysical parameters of the plant may further provide important information about the specific infection status of the fungal disease or stress status to make field-specific decisions for plant protection to achieve yield expectations (Newe et al., 2003).

The current researches on plant physiological parameters mainly focused on chlorophyll content and plant canopy temperature. As for physiological parameters detection, spectral features were the most used features. Therefore, multispectral cameras and hyperspectral cameras were more used for physiological parameter monitoring compared with RGB cameras and LIDAR. The linear regression model based on vegetation index can be used to estimate the leaf chlorophyll content. Some nonlinear regression methods such as principal component analysis, exponential model (Lelong et al., 2008), clustering algorithm (Giannini et al., 2018), etc., were also used to correlate spectral information with physiological parameters. The current researches proved the feasibility of crop physiological parameters detection by UAV remote sensing systems. In practical applications, factors such as the natural environment and soil background may also affect the physiological characteristics of crops. How to reduce the influence of external factors is the difficulty of research.

3.2.1. Chlorophyll

Chlorophyll is the main pigment for photosynthesis in plants and is affected by light, temperature, hydrogen ion concentration and oxygen. Leaf chlorophyll content also reflects the nutrient status of crops. Saberioon and Gholizadeh (2016) developed and tested new VI to determine the status of nitrogen and chlorophyll content in rice leaf by analyzing and considering all visible bands. The results indicated that the proposed index (principal component analysis index) at the canopy (correlation coefficient, $r = 0.78$) scale could monitor nitrogen in rice plants at different growth stages. The commonly used features in multispectral image processing mainly include color features, spectral indices, texture features, etc. A multispectral camera can capture the spectral and reflection characteristics of plants (Tahir et al., 2018). The reflectivity of plants under visible light is affected by the contents of chlorophyll and carotene in leaves, which can be estimated by various vegetation indices. Hunt et al. (2018) used NDVI and green normalized differential vegetation index (GNDVI) to estimate the potatoes' chlorophyll. Tewes and Schellberg (2018) estimated radiation use efficiency (RUE) of maize by UAV-based multispectral imagery, and the difference between RUE_{total} and RUE_{green} was minimal, which was possibly due to

the prolonged canopy greenness induced by the stay-green trait of the cultivar grown. Hyperspectral imaging has become a common method to obtain crop physiological traits, such as crop moisture content, leaf nitrogen content, chlorophyll content, and other physical and chemical parameters, to promote crop yield prediction. Uto et al. (2013) estimated the chlorophyll densities of rice using a UAV system equipped with a hyperspectral sensor covering a spectral range of 340–763 nm. The results demonstrated that chlorophyll densities could be estimated with high accuracy, even under unstable illumination conditions. Zarco-Tejada et al. (2013a,b,c) estimated leaf carotenoid content in vineyards using high-resolution hyperspectral imagery acquired from a UAV. It demonstrated that estimating leaf carotenoid content in vineyards using hyperspectral imagery was feasible, with prediction errors below $1 \mu\text{g}/\text{cm}^2$ (9.7% relative error). Hyperspectral images can also be used to calculate net photosynthesis. Zarco-Tejada et al. (2013a,b,c) assessed the relationships between chlorophyll fluorescence measures and net photosynthesis acquired at the grape leaves and canopy levels. At the hyperspectral image level, the relationships between net photosynthesis and steady-state chlorophyll fluorescence for 2010 ($R^2 = 0.54$, $P < 0.01$) and 2011 ($R^2 = 0.41$, $P < 0.01$) were significant. Domingues Franceschini et al. (2017) compared ground-based and UAV-based spectrometers in the context of organic potato cultivation. Accurate estimates were obtained for leaf chlorophyll (RMSE = $6.07 \mu\text{g}\cdot\text{cm}^{-2}$), LAI (RMSE = $0.67 \text{ m}^2\cdot\text{m}^{-2}$), canopy chlorophyll (RMSE = $0.24 \text{ g}\cdot\text{m}^{-2}$) and ground cover (RMSE = 5.5%) using UAV-based data acquisitions, which were slightly better than those derived from ground-based measurements (RMSE = $7.25 \mu\text{g}\cdot\text{cm}^{-2}$, $0.85 \text{ m}^2\cdot\text{m}^{-2}$, $0.28 \text{ g}\cdot\text{m}^{-2}$ and 6.8%, respectively). Zhu et al. (2020) estimated leaf chlorophyll content of maize and wheat via optimal UAV hyperspectral data at multi-scales. A Cubert S185 hyperspectral camera onboard a DJI M600 Pro was used to conduct six flight missions over a long term experimental field. Multi-variable linear regression, random forest, backpropagation neural network, and support vector machine (SVM) were used for modeling. Results showed that all four algorithms maintained an acceptable accuracy with respect to LCC estimation.

3.2.2. Crown temperature

The conventional method to measure the canopy temperature of crops is to use a hand-held infrared thermometer, which is difficult to conduct on the canopy temperature of crops under different experimental conditions at the same time. Sagan et al. (2019a,b) tested and evaluated three thermal cameras for their potential for vegetation stress detection, forest monitoring and plant phenotyping. The results demonstrated that all three UAV thermal cameras provided useful temperature data for precision agriculture and plant phenotyping.

3.3. Stress detection

During plant growth, various stresses may be suffered due to environmental factors. Stress factors, including water deficit (Mateo and Di Gennaro, 2018), temperature, nutrient stress, weed stress, pests, and disease stress (Kerkech et al., 2020; Mahendra Bhandari, 2020), have significant adverse effects on plant growth and could reduce plant yield ultimately. Studying the response of plants to different stress conditions is essential for plant cultivation and breeding.

Plants may be infected with various diseases and insect pests during their growth. Gibson-Poole et al. (2017) identified the onset of blackleg disease within potatoes using a modified camera collecting near-infrared images and an RGB camera. Disease and nutrition deficiency prevent plant growth (Albetis et al., 2017; Su and Chou, 2015). Severtson et al. (2016) used multispectral images acquired from a UAV platform to detect potassium deficiency and green peach aphid susceptibility in canola. UAV multispectral imagery with 65 mm spatial resolution showed higher classification accuracy (72–100%) than benchtop hyperspectral imagery acquired from field plants in laboratory conditions (78–88%). Di Gennaro et al. (2016) illustrated that the

multispectral images with high resolution obtained by UAV could discriminate grapevine leaf stripe disease before visual detection. Albetis et al. (2017) evaluated the feasibility of discriminating the *Flavescence dorée* symptoms from healthy vine vegetation in red and white vine cultivars using UAV multispectral imagery, and the worst misclassification level was 12%. Hyperspectral imaging can be used to detect pest and disease stress of crops in stress monitoring. Näsi et al. (2015) used UAV-based photogrammetry and hyperspectral imaging to map bark beetle damage to trees. The best classification accuracy was 76% (with Cohen's kappa of 0.60) when using three color classes (healthy, infested, dead). For two-color types (healthy and dead), the best classification accuracy was 90% (with Cohen's kappa of 0.80).

UAVs offer a good way to map the weeds and to allow for site-specific weed management (SSWM). There are two different approaches to detect weeds with UAVs. Spectral discrimination departs from detectable changes between the spectra of weeds and crop plants and has a long history in non-UAV remote sensing (PEZ-GRANADOS and Lopez-Granados, 2011). And the other method to detect the weed is the OBIA classification method. Perez-Ortiz et al. (2015) compared pixel-based and object-based analysis approaches for weed mapping using RGB imagery from UAV in the sunflower field. It could be concluded that an OBIA method was more suitable than the pixel-based approach for weed detection. Hough transform, machine learning paradigms (unsupervised, semi-supervised, and supervised techniques) and SVM were used to identify the weeds in sunflower crops (Perez-Ortiz et al., 2015). The weed in the sunflower field was identified using OBIA with RGB and multispectral images acquired by a four-rotor UAV. The weed classification accuracy could reach up to 95% (Borra-Serrano et al., 2015). Random forest (RF), OBIA, and multiple linear regression (MLR) were used to estimate the weed in wheat fields simultaneously. The accuracy of the weed classification reached 87% (Lambert et al., 2018). Pena et al. (2015) investigated the efficacy and limitations of remote images collected with a UAV for early detection of weed seedlings. Up to 91% accuracy was attained with the images captured by the multispectral camera. Gasparovic et al. (2020) tested four independent classification algorithms for the creation of weed maps, combining automatic and manual methods, as well as object-based and pixel-based classification approaches. UAV data were collected using a low-cost RGB camera. Of the four classification algorithms tested, the automatic object-based classification method achieved the highest classification accuracy, resulting in an overall accuracy of 87.1%.

Water plays an essential role in plant growth. Timely and accurate detection of plant water status is vital to ensure the normal growth of the plant. Poblete et al. (2017) predicted the spatial variability of vine water status using multispectral information obtained from a UAV. The R^2 obtained between artificial neural networks (ANN) outputs and ground-truth measurements of stem water potential was between 0.56 and 0.87. Romero et al. (2018) confirmed that multispectral sensors and machine learning modeling strategies could be an efficient and affordable option to assess vine water status, showing high correlation values between stem water potential and real stem water potential ($R^2 = 0.83$; slope = 1; $p \leq 0.001$). Zarco-Tejada et al. (2013a,b,c) demonstrated that a normalized photochemical reflectance index was highly related ($R^2 = 0.75$; $p < 0.001$) to the thermal indicator of water stress (crop water stress index, CWSI). The normalized photochemical reflectance index isolated the physiological changes better against a changing background of altered pigments and structure, tracking the stomatal aperture's daily dynamics more precisely. Hyperspectral imaging can be used to detect the water stress of crops in stress monitoring. Loggenberg et al. (2018) presented a remote sensing-machine learning framework for water stress modeling in vineyards using hyperspectral imaging. The results showed that RF and extreme gradient boosting (XGBoost) ensemble learners could both effectively analyze the hyperspectral data. Thermal infrared imaging sensors that can receive infrared radiation energy have been widely used to detect crop water stress (Gonzalez-Dugo et al., 2015) (Thorpe et al., 2018). CWSI was used in many studies to assess crop water

status (Gonzalez-Dugo et al., 2013). Matese et al. (2018) estimated water stress in grapevines from the UAV thermal imaging sensor. Indicators of crop water status (CWSI and linear thermal index) were calculated from UAV thermal images and ground infrared thermal images and then related to physiological measurements. The results showed that the differences in CWSI values between moderate and severe water deficit treatments were statistically significant in almost all cases (sites and varieties). Quebrajo et al. (2018) evaluated the water status of sugar beet plants using images captured by a UAV thermal imaging camera. The fresh root mass and sugar content tended to decrease when higher water stress levels were detected in the crop, with R^2 of 0.28 and 0.94 for fresh root mass and sugar content, respectively. Hoffmann et al. (2016) drew crop water stress maps of barley for an entire growing season from UAV visible and thermal imagery. CWSI, normalized green ratio difference index, land surface temperature, and water deficit index (WDI) were used in this study. Gonzalez-Dugo et al. (2014) demonstrated that CWSI was a valuable method to assess the water status in citrus orchards using high-resolution UAV thermal imagery. A close relationship was observed between CWSI and stem water potential (R^2 ranging between 0.59 and 0.66; $p < 0.001$), demonstrating that it was a suitable indicator of water status. Ludovisi et al. (2017) assessed the effects of two water treatments (well-watered and moderate drought) on a population of 4603 trees by conducting low-elevation (25 m) flights with an aerial drone to capture 7836 thermal infrared (TIR) images. The results showed the potential of UAV-based thermal imaging for field phenomics of poplar and other tree species. In addition to the errors caused by fuzzy images and image processing (Gomez-Candon et al., 2016; Ribeiro-Gomes et al., 2016), the monitoring of plant drought may also be misled by the plant itself, for example, the difference of maize canopy structure to water deficit (Berni et al., 2009), and the weak response of some mature crops with weak transpiration to water deficiency index (Hoffmann et al., 2016). Moreover, soil background, soil type, soil water movement (Katsigiannis et al., 2016), instrument calibration, and signal to noise ratio will also cause errors in water detection (Zarco-Tejada et al., 2012). It is necessary to eliminate the influence of soil and other background temperatures as much as possible.

In addition to disease stress, weed stress, and water stress, there are also studies focusing on plants' other stress. Su et al. (2016) detected the frost stress in vineyards using a UAV system equipped with a visible high definition RGB camera. A three-dimensional (3D) reconstruction was conducted from the RGB images collected from grapevines and the SfM technique to obtain the DSM applied on a per-plant basis. According to the halftone technique, the DSM was then expressed as greyscale images to finally extract the information of affected and missing grapevines using computer vision algorithms based on canopy cover measurement and classification. The results showed that the percentage of affected and missing grapevines were 9.5% and 7.3%, and the abiotic stress that affected the experimental vineyard (frost) impacted a total of 16.8% of plants. Dash et al. (2018) tested the sensitivity of multispectral imagery collected from time-series UAV and satellite imagery to detect herbicide-induced stress.

Fluorescence can reflect the information on plant metabolism emitted from the chlorophyll complex when plants are irradiated with ultraviolet rays (Kaye and Pittman, 2020). Fluorescence sensors are mainly used for leaf disease detection at an early stage. Chlorophyll fluorescence imaging combined with thermography has been used to monitor early changes in a plant's physiological status upon pathogen attack (Chaerle et al., 2004). Chlorophyll fluorescence imaging also revealed pre-symptomatic high-intensity spots for the plant-fungus system as sugar beet-*Cercospora beticola*. Fluorescence imaging technology is also used in crop metabolism and photosynthesis research (Keller et al., 2020). Perturbations of leaf metabolism and growth in *Arabidopsis* seedlings were detected using a rapid, noninvasive technique involving imaging of chlorophyll fluorescence parameters (Barbagallo et al., 2003). Herbicide-induced perturbations in metabolism

were identified from the changes in the images of fluorescence parameters considerably before any visual effects on seedling growth were observed. In early disease detection, changes in fluorescence parameters are usually earlier than the appearance of any other visible symptoms, making it useful in many disease detection studies (Jedrowski and Bruggemann, 2015; Massacci et al., 2008; Raji et al., 2015). Sugar beet lines differed in their susceptibility to *Cercospora beticola* infection and were screened using chlorophyll fluorescence imaging (Chaerle et al., 2007). Results showed that differences in fluorescence intensity were measured between susceptible and resistant plants. Citrus plants experiencing bacterial infection underlying citrus greening were distinguished using fluorescence spectroscopy (Wetterich et al., 2017). Fluorescence sensors combined with UAVs are rarely used for crop phenotypes. Matese et al. (2013) detected spatial variability of anthocyanin content in grape in situ using a fluorescence-based sensor. Although fluorescence imaging technology is developing, its application has also been limited. The limitations mainly include the shortage of field lighting conditions and environmental disturbances such as wind, making fluorescence imaging only for laboratory research (Pauli et al., 2016). In addition, fluorescence imaging technology is used primarily in early disease detection of crops since fluorescence is not sensitive to changes in crop moisture (Jansen et al., 2009).

Common types of plant stress include plant diseases and insect pests, water, weeds, and stresses caused by the natural environment. As for stress detection, spectral differences might be easier to obtain than image features, especially for those foreign materials with great similarity. Multispectral cameras, hyperspectral cameras, and thermal infrared cameras were more widely used to monitor crop stress. The processing methods of remote sensing images and the universality of classification models are the main problems in applying UAV remote sensing images in crop monitoring. For the fluorescence sensor, it was almost only used for stress detection based on its special imaging modality. Simultaneously, the application of the fluorescence sensor in other aspects of crop phenotype was limited due to the characteristics of being extremely susceptible to environmental influences. For future stress detection, it is vital to reduce the influence of soil background and other factors on the detection.

3.4. Yield estimation

Crop yield is closely related to the development and differentiation of organs and the distribution and accumulation of photosynthetic products, which is the core focus of crop science research. Crop yield can be estimated by plant height and biomass, which has been described before. There are also direct methods for estimating crop yield (Marques Ramos et al., 2020). Du and Noguchi (2017) validated the feasibility of utilizing multi-temporal color images acquired from a UAV based camera system to monitor wheat growth and map within-field spatial variations of wheat yield. The results showed that wheat yield correlated with four accumulative color vegetation indices, the R^2 and RMSE were 0.94 and 0.02, respectively. Yield in grain crops is one of the most important issues related to national food security and people's living standards (Wang et al., 2014). Zhou et al. (2017) found that the R^2 between yield and the visible atmospherically resistant index was 0.73.

The accuracy of crop yield estimation could be improved by using a UAV based multispectral remote sensing system. VIs derived from multispectral cameras were used to predict crop yields. Maresma et al. (2016) used different multispectral vegetation indices and crop height to predict grain yield, and linear regression analysis was performed between the image and in-field height, resulting in an R^2 of 0.82 and RMSE = 0.15 m ($p < 0.001$). Vega et al. (2015) found that the linear regression between NDVI and grain yield, aerial biomass, and nitrogen content in the biomass were significant at the 99% confidence level, except during very early growth stages. Hassan et al. (2019) used UAV's multispectral imagery to assess the VIs traits at various wheat growth stages. Significant correlations ranging from $R^2 = 0.38$ to 0.90 was observed between

NDVI detected from UAV and Greenseeker. Imaging hyperspectral technology can obtain more spectral bands and precise spectral information, which is expected to improve monitoring accuracy further. Wang et al. (2019a,b) proposed a rice yield estimation method using parcel-level relative spectral variables derived from UAV-Based hyperspectral imagery. The results showed that the relative normalized difference vegetation index (RNDVI_[880,712]) at the booting stage had the best correlation with rice yield with an R^2 -value of 0.75 for the single-growth-stage model. Kanning et al. (2018) used high-resolution hyperspectral imagery for LAI and chlorophyll estimations of wheat yield prediction. The predicted LAI and chlorophyll were used to calibrate the MLR model to estimate grain yield.

The current researches had achieved good results in crop yield estimation. Models with multiple vegetation indices can be used to predict crop yields. Besides, the combination of plant physiological parameters and vegetation indices had been used to predict yield. The physiological and phenotypic parameters for establishing yield prediction include LAI, chlorophyll content, biomass, and VIs. The accuracy of crop yield prediction could be improved by increasing the number of modeling parameters. However, the accuracy of yield prediction would be affected due to crop water stress and other factors. Therefore, it is worth studying to establish crop yield prediction models to improve yield prediction accuracy.

3.5. Nutrition status monitoring

Plants need to absorb nutrients during the growth stages. In addition to nutrients from the soil, nutrients can also be obtained through artificial fertilization. Nitrogen (N) fertilizer is the most widely used fertilizer in the world. The appropriate amount of nitrogen fertilizer plays an important role in improving crop yield and quality of agricultural products. Caturegli et al. (2016) estimated the variability of nitrogen status of turfgrasses of the RGB data and multispectral acquisition sources. Results showed that UAV imagery could adequately assess the N status of turfgrasses and their spatial variability. Giannini et al. (2018) monitored the wetlands' nutritional status, including N content and phosphorus. As for N uptake, reeds contributed 90%, and bayberry contributed 10%. As for absorbed phosphorus, reeds contributed 83%, and bayberry contributed 17%. Zermas et al. (2015) described a methodology for detecting and characterizing nitrogen deficiencies in cornfields. An accuracy of 79.2% was detected for different nitrogen stress. Nitrogen and grain protein content indicate the nutritional status of the crop. Geipel et al. (2016) presented a prototype multispectral camera system for aerial estimation of nitrogen content and grain protein content in winter wheat. The acquired multispectral images were processed to NDVI and red-edge inflection point (REIP) orthoimages for analysis with simple linear regression models. The best results for N content was estimated with the REIP ($R^2 = 0.58\text{--}0.89$, RMSE = 7.6%–11.7%). Zheng et al. (2018) estimated the nitrogen concentration of rice using UAV-based multispectral imagery. The R^2 between the photochemical reflectance index and the blue nitrogen index with nitrogen was 0.48–0.65 and 0.39–0.68.

Current research has confirmed the feasibility of estimating nitrogen levels in canopy or leaves based on UAV sensors for crop nutritional status monitoring. As UAV images were obtained in the experimental fields, the treatment range's nitrogen content was large. Differences in nutritional status might also be the result of spatial variability in water content or soil conditions. Also, most studies used empirical regression models to correlate observed signals with nutritional status. However, crop types and crop stages growth might have different requirements for the model. In all, the versatility of the model is the key to studying.

3.6. Classification

The UAV-based remote sensing system is also applied to image classification, including species classification, damage area

classification (Song et al., 2020; Tetila et al., 2020) and ground vehicle classification, etc. Mafanya et al. (2017) evaluated pixel and object-based image classification techniques for mapping plant invasions using RGB images based UAV. The classification accuracy of two classifiers Bhattacharya and Maxver were compared. The results showed that the Bhattacharya and Maxver classifiers estimated the spatial extent with an average detection accuracy of 86.1% and 65.2%, respectively. At the same time, some researchers focus on identifying damaged areas. Kuzelka and Surovy (2018) proposed a method for delineating the damaged wheat area via the automatic segmentation of the crop field. The range of wheat damage was estimated with an accuracy of 99.5% and 99.3% using field global navigation satellite system (GNSS) measurements and classification of an *ortho*-mosaic generated from UAV-based RGB imagery, respectively. Yang et al. (2017a,b,c) proposed a comprehensive and efficient classification technique for rice lodging classification using UAV-based RGB imagery. In addition to spectral information, the DSM and texture information of the images was obtained through image-based modeling and texture analysis. A decision tree classification model incorporating single feature probability (SFP) values yielded optimal results, with an accuracy of 96.17% and a Kappa value of 0.941, compared with a maximum likelihood classification model (90.76%). Gibson-Poole et al. (2017) identified the onset of blackleg disease within potatoes using a modified camera collecting near-infrared images and an RGB camera. An automated classification routine has been constructed using pixel and object-based image analysis (OBIA) methods, which have shown a total accuracy of 87% and a kappa coefficient of 0.61. Zhou et al. (2020) collected imagery data of 116 soybean genotypes using a UAV imaging system consisting of an RGB camera, an infrared thermal camera, and a multispectral camera. Image features were extracted, namely NDVI, green-based NDVI, temperature, color hue, color saturation, canopy size and plant height for quantifying canopy wilting trait under drought stress. Results showed that all image features significantly ($p\text{-value} < 0.01$) correlated with soybean yield under drought. A SVM was developed to classify the two wilting traits using the images features and achieved an average classification accuracy of 0.8 with the highest one of 0.9.

Multispectral cameras have been used to classify different land types and vegetations. (De Biasio et al., 2010) successfully classified different land types by using multispectral imaging. Rey et al. (2013) distinguished plant and weed effectively using multispectral imagery acquired from a UAV to access the spatial variability of a tempranillo vineyard.

Hyperspectral imaging sensors can also be used to identify seed quality (Feng et al., 2019a,b,c), seed variety (Zhao et al., 2018), and crop disease (Feng et al., 2019a,b,c; Kong et al., 2018). Hyperspectral sensors have also been used for species classification because of their high-resolution images. Cao et al. (2018) used object-based classification to classify mangroves through hyperspectral images and DSMs based hyperspectral images from UAVs. Several classification methods were used, and the highest classification accuracy obtained by SVM was 82.39%. Sandino et al. (2018) proposed a framework to detect and segment deteriorations by fungal pathogens in forests. The system achieved detection rates of 97.24% for healthy trees and 94.72% for affected trees.

Classification mainly includes image classification and feature classification. Crops might suffer from wild animals and natural disasters during their natural growth. UAV remote sensing images can also distinguish crop species, crops, and backgrounds, etc. The purpose of the distinction was to carry out precision field management of crops to increase yield. Many algorithms were used for classification problems, including OBIA, pixel-based image analysis, SVM, PCA, ANN, and deep learning (Gao et al., 2020). Therefore, UAV remote sensing system has a very large practical prospect for the application in classification.

3.7. Summary of applications

Sensors are the cores of the UAV low-altitude remote sensing. And

they are all important for obtaining plant phenotypes based on UAV low-altitude remote sensing. Because of its low price, the RGB cameras are more used to study geometric features such as plant height and LAI. In the height estimation, the RGB camera has more spatial resolution than the spectral camera (Lelong et al., 2008; Madec et al., 2017; Maresma et al., 2016). However, multispectral cameras perform better than RGB cameras in estimating LAI (Mathews and Jensen, 2013; Roosjen et al., 2018; Shi et al., 2016). LIDAR has also achieved good results in estimating geometric parameters like height and biomass (Sankey et al., 2018; Wang et al., 2017). For physiological traits, multispectral cameras can obtain more band information than RGB cameras, so the overall accuracy is higher than RGB cameras in studying physiological parameters, yield estimation and, but the price is also higher (Geipel et al., 2016; Schirrmann et al., 2016; Zhang et al., 2016). Hyperspectral cameras performed better than other sensors in estimating crop physiological parameters (Liu et al., 2017a,b; Yue et al., 2018). Multispectral and hyperspectral cameras are all multiband cameras containing the image and spectral information, while near-infrared thermal camera extracts feature from acquired images. For nutrition status detection, RGB cameras and multispectral cameras can both adequately assess the N status of turfgrasses and its spatial variability within a species (Caturegli et al., 2016; Kefauver et al., 2017). Hyperspectral cameras can obtain crop moisture, leaf nitrogen concentration, chlorophyll content, LAI, and other physical and chemical parameters using both spectral and image information. When a UAV carries a camera in the air to perform a flight mission, it will cause serious accidents such as plane crashes due to environmental factors or human errors. As a result, hyperspectral cameras are more expensive in crash situations than RGB cameras and multispectral cameras. In reality, hyperspectral cameras are not widely used in remote sensing platforms of UAVs. Hyperspectral cameras still have great potential in studying crop phenotypes.

The UAV image analysis procedures usually include image acquisition, image preprocessing, image segmentation, image matching and correction, feature extraction, modeling (univariate and multivariate classification and regression analysis). The preprocessing of remote sensing images is mainly classified into two categories, sensor correction and geometric correction. Image classification strategies for crop phenotypes can be divided into image classification and feature classification. Images classification can be used for leaf color monitoring, crop identification, region classification and so on (Geipel et al., 2014). OBIA is mainly devoted to dividing remote sensing imagery into meaningful objects by assessing their characteristics. The OBIA methods have been widely used in SSWM and classification problems in the field. Apart from object-based analysis, the pixel-based analysis was also an applicable method for weed classification and crop quality determination. Features extracted from images, such as spectral features, can be classified.

Remote sensing feature classification methods can be divided into supervised and unsupervised classification. Supervised classification methods include maximum likelihood discrimination, neural network classification, and minimum distance classification. Unsupervised classification methods include dynamic clustering, hierarchical clustering, fuzzy clustering and splitting (Belgiu and Drăguț, 2014). The commonly used classifiers include RF, SVM, logistic regression classifier and other algorithm classifiers. Data statistics methods include MLR, stepwise linear regression (SLR), SVM, PCC, and partial least squares regression (PLSR), etc. The absorbance and reflectance characteristics differ between spectral bands in the crop leaves. The VIs are widely used in many studies to analyze the growth of vegetation and measure the surface vegetation simply and effectively. Different types of sensors use different VIs to analyze vegetation growth. The vegetation index can be used to estimate chlorophyll content and leaf nitrogen content (Nigon et al., 2015; Samseemoung et al., 2012).

Simultaneous acquisition of crop phenotypes by multiple sensors provides higher spatial and temporal resolution. Many studies have also combined two or more sensors mounted on the UAVs to improve plant phenotype estimation accuracy. RGB cameras on UAVs combined with

multispectral cameras have been used to evaluate the potential of UAVs in monitoring agricultural information (Di Gennaro et al. (2018)). Near-infrared thermal imaging can detect thermal radiation on crop surfaces and has been used to detect stress and physiological parameters simultaneously combined with multi-spectral imaging (Ballester et al. (2018); Baluja et al. (2012); Berni et al. (2009)). Hyperspectral cameras and infrared thermal sensors have been used to detect stress and plant physiological status (Zarco-Tejada et al. (2012); Gonzalez-Dugo et al. (2015)). In comparison, Sankey et al. (2018) demonstrated UAV-based LIDAR and hyperspectral imagery applications along with a fusion method for individual plant species identification. The fusion approach of two different data sources provided 84–89% overall accuracy (Kappa values of 0.80–0.86) in target species classification at the canopy scale, comprised of the hyperspectral image classification alone produced 72–76% overall accuracies.

4. Challenges and future perspectives

4.1. Challenges

Unlike ground-based phenotyping, UAV-based phenotyping faces a severe problem, which is the safety of the UAV and the sensors. The prices of UAVs vary in a wide range, and no doubt that the more expensive, the better the UAVs are. The carried sensors, such as multispectral and hyperspectral sensors, are relatively expensive. Indeed, it is common to see the crash of the UAVs by improper operations or some other reason. The economic loss would be large in a UAV crash. Thus, the primary requirement of UAV is high reliability. To improve UAV's safety and reduce the potential risk of crash, low-cost, high-reliability UAV systems were more favored in near ground large area plant phenotyping.

The current researches on phenotype are decentralized, and the studies lack systematism. Phenotyping sensors are crucial in UAV based plant phenotyping. Stability is an important attribute to platforms that should be considered for the convenience of phenotypic analysis. At present, the sensors used to estimate the height and biomass of crops are mainly RGB and multispectral sensors. However, the use of hyperspectral research is currently a minority. Hyperspectral imaging has become a cutting-edge/emerging method to obtain crop characters such as water content, leaf nitrogen concentration, chlorophyll content, leaf area index, and other physiology and biochemistry parameters. LIDAR was more used for plant height and biomass estimation. The application of LIDAR in the phenotypic analysis is limited by its high cost, a large amount of data processing, and a narrow beam. The limitations of thermal infrared cameras are mainly the interference of soil signals, ambient air, and canopy temperature on their imaging. In general, the cost of the sensors varied. As for the same kind of sensors, different types of sensors also have different characteristics. The collected data information highly depends on these sensors and affects the final phenotyping results. As mentioned above, the possibility of a UAV crash makes the selection and use of the phenotyping sensors quite cautious.

Analysis of the data generated from different sensors and different acquisition conditions is challenging. Various data analysis procedures can be selected and conducted, and new data analysis strategies can also be proposed. Machine learning methods, vegetation indices, and data transformation are the most used data analysis strategies in the reviewed articles. Since the data collected by the UAV remote sensing system are mainly images, the image analysis procedures generally include image collection, segmentation and classification. Multi-functional platforms for obtaining large amounts of images and data make high capacity computing and data storage essential for phenotype platforms. Analyzing and managing these data also pose other informatics challenges. A single image has the potential to contain a large number of measurements or phenotype descriptions, and these factors add further complexity to the subsequent data analysis. The efficiency and accuracy of data processing can be improved from data acquisition. Such as, some

influencing factors can be eliminated by experimental design. Different camera corrections and other processing are required as different types of sensors have different spectral bands. To ensure the feasibility of phenotyping through UAV remote sensing, phenotyping is usually verified by obtaining ground truth data. Many studies tried to improve the accuracy of the results by increasing the number of ground control points. However, the study (Gindraux et al., 2017) found that there are certain thresholds for ground control points. Besides, when using VIs to analyze the phenotype, it is necessary to consider the impact of the ground and shadow, which will have a certain impact on the vegetation index maps. More works are needed to improve data analysis performances for revealing as much phenotype information and improve the precision and accuracy of phenotyping performances.

Environmental factors during the flight of UAVs also affect the phenotyping analysis, including noise, solar condition, wind (Feng et al., 2019a,b,c) and soil factors, etc. When estimating crop height, biomass, yield, leaf area index, physiological parameters and stress response, some environmental factors will affect the estimated results. Due to a large amount of interference during the experiment and the influence of the data on the measured data, a more accurate model can hardly be obtained (Lelong et al., 2008). Light quality changes caused small changes in NDVI and GNDVI (Hunt et al., 2018). Soil variability may have an impact on crop performance, and the use of CWSI as a crop water stress index for UAV based water stress detection required further experimentation. Due to the changes in the environmental climate, crop lodging was restricted to estimate wheat biomass and height (Bendig et al., 2014). Soil nutrients affect the biomass and LAI values of pasture, and the more nutrients there are, the greater the value is (Fan et al., 2018). Soil adjusted vegetation index should consider soil background (Marino and Alvino, 2018). Due to the different weather conditions of different vineyards on the day of the UAV flight, these environmental conditions have a related impact on canopy temperature and plant stress status, such as the effects of photosynthesis from the drought on the grapes, the effects of radiation, wind speed and temperature on the temperature of the leaves, etc. Slopes caused by different terrains of different vineyards, such as altitude, may be key factors in soil moisture dynamics.

There are various challenges when collecting images using the UAV remote sensing system. Since the collection of crop data by UAV has experienced different growth stages of crops, time-domain factors have a greater impact on crop parameter measurements. For example, when estimating biomass in the time domain, the relationship between dry biomass and plant height can only be emphasized because fresh biomass changes greatly with time (Brooks and Bareth, 2018). High time resolution and unprecedented observation frequency of the UAV eliminate adverse optical effects, resulting in the discovery of significant phenological events. The OBIA methods are useful in weed management in the winter season, but they may not be useful in crops that do not see rows (Lambert et al., 2018).

The images collected by the UAV need to be processed to extract the required information. Due to the different flight altitudes of the UAVs, the same aerial survey area's image resolution is also different. These changes lead to changes in image features, which affect the accuracy of the lodging recognition and classification accuracy of weed. And the influence of the texture feature changes is more significant. Therefore, when combining color features and temperature features to identify rice lodging, the results are less affected by UAVs' flight altitude (Liu et al., 2018a,b). Because of the UAV's pitch and roll during flight, using higher image resolution cameras makes capturing images more reliable (Bendig et al., 2013a,b). It is necessary to minimize the influence of various factors on the images during the actual flight process.

Accurate measurement of ground data is another factor influencing the classification performances. Although UAV-based remote sensing can acquire data at a lower altitude, it is impossible to measure every single plant's phenotyping trait. The commonly used procedure is to select samples from the selected region of interest and obtain the

average traits of the region of interest as reference values for analysis. Thus, it is essential to measure the phenotyping traits accurately. A scientific sampling of the plants for ground measurement is indispensable.

It is necessary to regulate the flight of various UAVs to ensure their flight safety. Different countries have different regulations for UAV airspace management. These regulations are mainly related to UAV flight practitioners, flight plans, flight areas, flight permissions, etc. Before performing flight missions, pilots must provide a flight plan to the aviation management department to obtain permission. Different airspace types have different requirements for pilot qualifications. Some countries or regions have put forward UAV traffic management systems, such as unmanned aircraft systems traffic management (UTM) in the US (Aweiss et al., 2019). The United States defined six types of airspace (Vincent et al., 2006). Aircraft flying in various airspaces are subject to corresponding air traffic management to varying degrees and fly by different flight rules. It stipulates the flight weight, flight altitude, and flight speed of civil UAVs (Quan et al., 2020). In Japan, the government agency bans flights of UAVs weighing 200 g or more in crowded residential areas, at height 150 m or more above the ground, and near airports (Xu et al., 2020). The German Aviation Management Law stipulates that all aircraft weighing >5 kg must have a license to fly. It also regulates privacy, such as photography and shooting. In China, any flight activity must be approved by the Civil Aviation Administration, and flights that have not been registered and approved are called "black flights". Institutions and individuals using UAVs must abide by flight activity management rules to ensure flight safety (Clarke and Moses, 2014). With the development of UAVs, the corresponding regulations are also being improved, which will also have a certain impact on the wide application of UAVs in field phenotype analysis.

4.2. Future aspects

These mentioned studies illustrated that UAV-based remote sensing was effective for plant phenotyping. There were great challenges to push these researches into a real application. In future studies, more works were needed to strengthen UAV-based remote sensing for plant phenotyping.

First, low cost and high-performance UAVs should be introduced in future studies. High-performance UAVs with high flight stability, high flight precision, long flight duration, and heavy load are needed for the long term and large field plant phenotyping. And the UAVs bring much convenience of low altitude remote sensing, and sometimes the crash of UAVs causes damages to the equipped phenotyping sensors. Thus, low cost and high-performance phenotyping sensors are also needed. The protection of these phenotyping sensors is needed, resulting in the optimal design of the payload. Researchers prefer high-performance sensors. Sensor fusion can improve the accuracy of UAVs to obtain phenotypes. Besides, the simultaneous acquisition and analysis of the same crop phenotypes by multiple sensors can evaluate crop traits more comprehensively and accurately. On the other hand, the acquired data quality is important, and these data depend on the sensors.

Second, UAV systems can obtain remote sensing images of crops, and the basic research ideas for images are similar. Different crop phenotypic characteristics can be extracted from the image, such as crop height, LAI, biomass, yield, diseases, lodging, etc. For example, crop yield can be estimated by a variety of methods, including plant height, biomass, vegetation index, plant physiological parameters, and LAI. Establishing a multi-parameter prediction model for crop yield to improve the accuracy of prediction can be used as a future research direction. Phenotyping related remote sensing data analysis methods need further improvement to find more traits. Phenotypic information can provide support for precision crop growth management. The acquisition and analysis of crop phenotype are efficient methods to determine the growth status of plants. And the phenotyping results indicate the direction for the realization of precision agriculture in many aspects, such

as fertilization, spraying and irrigation. However, most studies focused on crop varieties such as corn, wheat, rice, sugar beets, grapes, and citrus. It is necessary to study the changes of crop phenotypic characteristics in different crop varieties and different growth stages. The worthy research direction in the future lies in combining big data, computer vision, and other technologies to apply phenotypic analysis to every field. Furthermore, at present, UAV based phenotyping mainly aims to obtain phenotyping traits. The studies of the relationship between genotype, phenotype, and environment lack. In future studies, the connection between phenotype traits and gene should deepen, for example, quantitative trait locus and genome-wide association study which exploring the gene and the phenotype traits (Borevitz and Chory, 2004; Volkan Pehlivanoglu et al., 2007; Wang et al., 2019b; Xu et al., 2012; Yang et al., 2012).

Third, strategies and methods to reduce the influence of environmental factors should be proposed. For low altitude remote sensing, the ecological factors influence acquired data, and environmental factors should be reduced.

Fourth, cooperation from different researchers, institutes, countries, and regions should be strengthened. The various UAVs and phenotyping sensors make it difficult to extend the methods and models for general use. It would be better to cooperate to solve the common problems in plant phenotyping using UAV-based remote sensing and propose the conventional methods and models which are suitable for plant phenotyping in different geographical locations, especially for a certain kind of plant.

5. Conclusion

In this paper, we reviewed the recent applications of unmanned aerial vehicle remote sensing with various sensors for high-throughput plant phenotyping. According to different phenotype types, the applications of the UAV remote sensing system in phenotype analysis were summarized. UAVs have been increasingly used in field phenotyping analysis, and the results obtained mostly have a good correlation with the ground reference results. As the main phenotypic platform, multi-rotor UAV has been widely used in the phenotypic analysis in recent years. The sensors equipped with the UAV include RGB, multi-spectral sensors, hyperspectral sensors, infrared thermal imaging sensors, LIDAR, and fluorescence sensors. Different sensors have their advantages, disadvantages, and main characteristics. UAV remote sensing platform can be used to obtain plant phenotypes information, such as plant height, LAI, biomass, yield, weed detection, physiological parameters and various stresses. The phenotyping data is processed to extract features. Then the statistical analysis method is used to analyze the relationship between different features or the relationship between the remote sensing data and the ground reference index. How to reduce various influencing factors such as environmental factors, time-domain factors, image problems, and other aerial images errors is the focus of future research directions. Also, how to optimize the UAV flight hour cost, battery standby time, and speed to improve the production efficiency of the UAV is a problem that needs to be solved.

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CRediT authorship contribution statement

Lei Feng: Conceptualization, Investigation, Project administration, Validation. **Shuangshuang Chen:** Data curation, Funding acquisition, Investigation, Writing - original draft, Writing - review & editing. **Chu Zhang:** Investigation, Methodology. **Yanchao Zhang:** Methodology, Resources. **Yong He:** Conceptualization, Project administration,

Supervision, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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