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REVIEW

Drone-based imaging sensors, techniques, and applications in plant phenotyping for crop breeding: A comprehensive review

Boubacar Gano[1] | **Sourav Bhadra**[2,3] | **Justin M. Vilbig**[2,3] | **Nurzaman Ahmed**[1] | **Vasit Sagan**[2,3] | **Nadia Shakoor**[1]

[1]Donald Danforth Plant Science Center, St. Louis, Missouri, USA

[2]Geospatial Institute, Saint Louis University, St. Louis, Missouri, USA

[3]Department of Earth and Atmospheric Sciences, Saint Louis University, St. Louis, Missouri, USA

Correspondence
Nadia Shakoor, Donald Danforth Plant Science Center, 975 N. Warson Rd., St. Louis, MO 63132, USA.
Email: nshakoor@danforthcenter.org

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Abstract

Over the last decade, the use of unmanned aerial vehicles (UAVs) for plant phenotyping and field crop monitoring has significantly evolved and expanded. These technologies have been particularly valuable for monitoring crop growth and health and for managing abiotic and biotic stresses such as drought, fertilization deficiencies, disease, and bioaggressors. This paper provides a comprehensive review of the progress in UAV-based plant phenotyping, with a focus on the current use and application of drone technology to gain information on plant growth, development, adaptation, and yield. We reviewed over 200 research articles and discuss the best tools and methodologies for different research purposes, the challenges that need to be overcome, and the major research gaps that remain. First, the review offers a critical focus on elucidating the distinct characteristics of UAV platforms, highlighting the diverse sensor technologies employed and shedding light on the nuances of UAV data acquisition and processing methodologies. Second, it presents a comprehensive analysis of the multiple applications of UAVs in field phenotyping, underscoring the transformative potential of integrating machine learning techniques for plant analysis. Third, it delves into the realm of machine learning applications for plant phenotyping, emphasizing its role in enhancing data analysis and interpretation. Furthermore, the paper extensively examines the open issues and research challenges within the domain, addressing the complexities and limitations faced during data acquisition, processing, and interpretation. Finally, it outlines the future trends and emerging technologies in the field of UAV-based plant phenotyping, paving the way for innovative advancements and methodologies.

1 | INTRODUCTION

Increasing crop production to meet the food, fuel, and clothing needs of a growing populace is a global challenge for the 21st century (Yu et al., 2016). The United Nations Department of Economic and Social Affairs states that the world's population will steadily grow upward of 9 billion by 2050 (Gerland et al., 2014), threatening global supplies of food, energy, and water. An environmentally sustainable approach to meet these essential needs is through the development and dissemination of high-performing crop varieties to farmers (Tester & Langridge, 2010). It is, therefore, essential to implement innovative breeding programs to efficiently increase food crop production and allay food insecurity that is projected to increase worldwide in the coming decades (Ray et al., 2015).

Modern-day biotech has significantly impacted the progress and efficiency of crop breeding by increasing availability and access to genetic data and markers in breeding programs. We can now quickly and affordably sequence the genomes of many plants (Thomson, 2014). However, the value of genetic data in breeding programs depends on the quality of plant phenotype data collected across multiple and diverse environments. New advancements in phenotyping technologies are essential to ensure genetic gain and enhance crops to meet future needs. To improve high-throughput phenotyping for crop breeding, unmanned aerial vehicles (UAVs) are promising instruments that allow for increasingly high-quality field data acquisition (Floreano & Wood, 2015; Sankaran, Khot, Espinoza, et al., 2015; Yang & Zhai, 2022).

Precision phenotyping, with the help of UAV imaging, allows breeders to obtain information on plant growth and development status. One of the targeted traits in image-based precision phenotyping is the assessment of plant number or density. It is generally measured using RGB cameras and has been used to estimate field emergence and to develop accurate predictions of final yield parameters. Lin et al. (2021) did a comparison study between MobileNets and CenterNet (Duan et al., 2019), models of object detection (OD) for cotton stand counts using unmanned aerial system (UAS) imaging.

Temperature is an essential variable of the environment that has a significant impact on plant physiology traits like leaf transpiration, photosynthesis, and water potential (Pignon et al., 2021). Thermal remote sensing is a promising phenotyping methodology for measuring surface temperature of plant canopies (Khanal et al., 2017), and thermal sensors have gained popularity in recent years due to improvements in sensor technology and a decrease in costs. A number of studies have successfully shown the efficiency of thermal sensors to measure canopy temperatures and monitor drought stress (Anderson et al., 2013; Brewer et al., 2022; Khanal et al., 2017).

UAVs fitted with multispectral (MS) cameras can be used to monitor spatial and temporal variations of vegetation indices (VIs). VIs are spectral reflectance computations that help to measure the vegetation presence and status through photosynthetic response to incident light (Steven et al., 2015). For instance, for healthy plants, the reflectance is high in the infrared band and low in the red band due to chlorophyll absorption of red light. This can fluctuate in a stressed or unhealthy plant that may have reduced chlorophyll pigment (Khan et al., 2018). Several studies have validated the accuracy of VIs derived from aerially captured MS or hyperspectral imagery to quantify crop health, moisture, and nutrient content (Cuaran & Leon, 2021; Goswami et al., 2021; Shi et al., 2016; Tahir et al., 2018). MS sensor-derived VIs are also increasingly used to estimate leaf area index, biomass, and chlorophyll content (Gano et al., 2021; Li et al., 2018; Potgieter et al., 2017; Shafian et al., 2018). Yu et al. (2016) used high-resolution MS image data collected from a UAV-based high-throughput platform over the course of a complete soybean growth season to improve estimates of yield.

Core Ideas

- It is crucial to assess drone sensors for resolution, speed, and phenotyping suitability.
- Exploring machine learning algorithms in drone image processing enables automated trait prediction and disease detection.
- Drones enhance crop breeding, accelerating cycles and improving efficiency by identifying desirable traits.
- Addressing data processing challenges while anticipating future tech directions and standardization is needed.

Amid the challenges posed by field plot heterogeneity and dynamic environmental conditions in crop production systems, Light Detection and Ranging (LiDAR) technologies offer high-resolution three-dimensional (3D) images of crop plants while being less susceptible to the optical saturation issues often observed in dense vegetation (Maimaitijiang, Sagan, Erkbol, et al., 2020). In a similar vein, Radio Detection and Ranging (radar) technology provides an alternative to optical sensors, harnessing a higher frequency band and wider bandwidth to significantly enhance resolution capabilities (Jiao et al., 2021; Lee et al., 2021).

The aim of this review is to provide up-to-date insight into the application of drone-based remote sensing for phenotyping agronomic and physiological plant traits. We explore the current use, limitations, and opportunities of UAS in crop monitoring and precision agriculture, including camera and sensor restrictions, data processing challenges, and current aviation regulations. We propose key questions—Which UAV and sensor package best suits a precision phenotyping goal? What has successfully been done in previous studies? Which methods and tools were used? What were the challenges?—and provide background information to consider when choosing a UAV-based sensor platform for crop phenotyping.

The remainder of this review is structured as follows: Section 2 describes the method used to identify relevant papers for this review. Sections 3 and 4 explore the technology and sensor systems integral to UAVs. Section 5 delves into the methodology of data collection and processing, while Section 6 showcases real-world uses of UAVs in agriculture. Section 7 examines advanced data analysis techniques.

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Section 8 identifies current gaps and challenges in the field. Section 9 indicates the most interesting technologies for future research, culminating in Section 10, which summarizes key findings and outlines future directions for the use of UAVs in advancing plant phenotyping and agriculture.

2 | LITERATURE REVIEW METHODOLOGY

We conducted a comprehensive literature review using a set of key search terms to systematically explore scholarly databases, namely, Scopus, Web of Science, and Google Scholar, with the aim of identifying pertinent literature within peer-reviewed English language academic journals. Our focus was on literature that delved into UAV-based plant phenotyping applications. The search was conducted by scrutinizing article titles, abstracts, and keywords using specific search strings, which included the terms "UAV," "sensors," "plant," "phenotyping," and "machine learning" to extract relevant publications. 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 conference articles using UAVs for phenotyping research. The searched articles are published between 1973 and 2023. We have collected 289 papers, as many as possible, but there might still be missing papers. We believe that the number of articles should cover all pertinent information related to UAV for phenotyping. However, some papers were rejected due to reasons including too many articles from a single journal source and older publications.

3 | UAV PLATFORMS

UAV or drone-based platforms are a technology that can be used to obtain quantitative plant information for tens or even hundreds of lines in a crop field using noninvasive imaging techniques and protocols (Furbank & Tester, 2011; Ghanem et al., 2015). Fully integrated remote sensing platforms consist of an unmanned aircraft fitted with multiple sensors and use communication and Global Navigation Satellite System (GNSS) tools to acquire crop canopy images from the field.

UAV classifications are globally based on their wing design, which impacts their autonomy, size, and weight (De Rango et al., 2019). There are three major types of UAVs—fixed-wing, rotary-wing, and hybrids, also known as Vertical Takeoff and Landing (VTOL) drones (Figure 1). UAV characteristics (Table 1) within these three categories vary in their aerodynamic features and have a significant impact on flight time, altitude, speed, cost, resolution, and so forth (Custers, 2016; Feng et al., 2021; García et al., 2020).

TABLE 1 The pros and cons of main unmanned aerial vehicle (UAV) platforms.

UAV platforms	Pros	Cons
Rotary wings	High maneuverability	Low flight endurance
	Low cost	Low speed
	Excellent stability	Lower altitude
	Excellent hovering	Higher maintenance requirements
	Easy takeoff and landing	Energy consumer
	Less piloting skills	Weather sensitive
	No runaway	
	Good cameras protection	
Fixed wings	Long distance	High cost
	Less energy	Skilled pilot
	High endurance	Require runaway
	Faster speed	Less cameras protection
	High altitude	Unable to hover
	Heavier load	
Hybrids	High speed	Expensive
	High endurance	Hard transition between vertical to horizontal flight
	Good stability	Less controllable
	Good hovering	
	Vertical takeoff and landing	
	No runaway	
	No piloting skills	
	Heavy load	
	Good camera protection	

3.1 | Rotary wings

Rotary-wing drones include single-rotor and multirotor systems (Figure 1A). They operate like helicopters with vertical flight capability, which facilitates takeoff, landing, improved maneuverability, and reduced aerial velocity. They are convenient for plant monitoring of average-sized breeding plots, even if their flight endurance and speed are relatively low compared to other drone types. Multirotor drones usually hold eight or fewer rotors; they have excellent stability and hovering, which allows easy remote piloting compared to single-rotor drones; and they are often the drone of choice for researchers in crop phenotyping (Cuaran & Leon, 2021). However, this type of drone has greater mechanical and electronic complexity, which results in higher maintenance requirements and decreased operational time as they

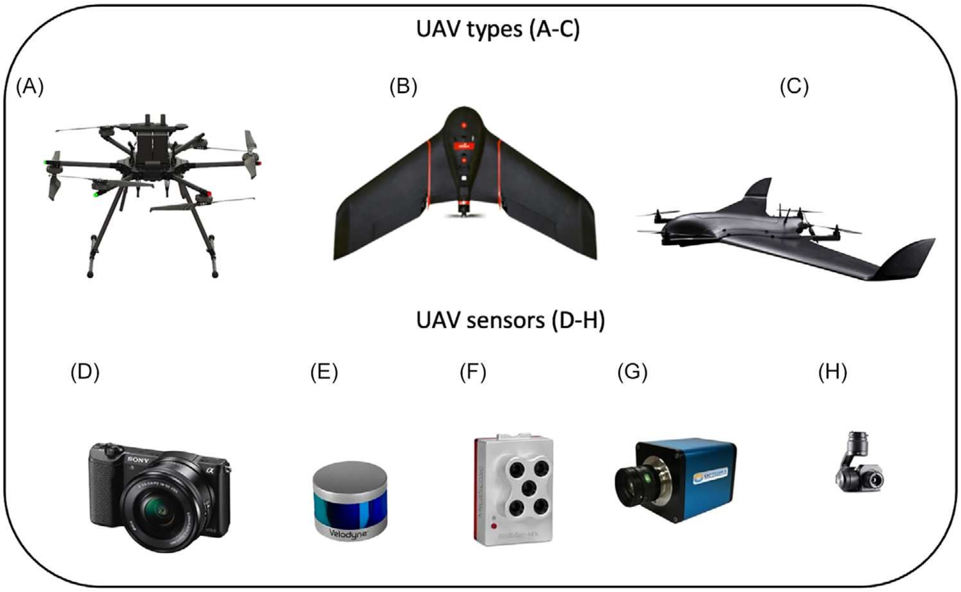

FIGURE 1 The main unmanned aerial vehicle (UAV) and sensor types used in precision phenotyping: (A) rotary wings (Inspired flight IF1200A); (B) fixed-wing (senseFly eBee SQ); (C) hybrid, VTOL fixed-wing (DeltaQuad Evo); (D) RGB camera (Sony); (E) Puck LITE LiDAR sensor (Velodyne); (F) multispectral camera (Micasense); (G) VIS-NIR hyperspectral camera (Optosky); and (H) DJI Zenmuse XT V2 640 thermal camera (DJI).

use greater energy to sustain lift and are more subject to damage under extreme weather conditions (e.g., winds, thunderstorms, tornadoes, lightning, hail, etc.).

3.2 | Fixed wings

A fixed-wing UAV can fly long distances using less energy due to their stabilized and level wings (Figure 1B). These drones are more adapted for surveying large areas compared to rotary-wing drones (Figure 1A). They have the greatest UAV endurance, and some can stay in flight for up to 24 h. For these reasons, they are generally used for long missions, such as large-area surveying and chemical spreading. Fixed-wing drones have faster speeds, fly at higher altitudes, and carry heavier loads than rotary-wing drones. This generally allows for a larger quantity of data collected from one flight. Some of the limitations of fixed-wing drones are high costs and the requirements for training and/or hiring highly skilled operators. They also require a physical runway for launching, which may be challenging to create in a research or crop field environment (Panagiotou et al., 2020).

3.3 | Hybrids

The third category of drone types is hybrid systems (fixed/rotary-wing) (Figure 1C). These drones capture the advantages of fixed and rotary wings; they achieve high speeds and are stable with long flight endurance and, due to the presence of rotors, allow vertical takeoffs and landings (VTOL) like a helicopter (Maddikunta et al., 2021). VTOL drones do not require runways; they feature wings like an airplane, which allow them to fly over a larger area more efficiently. Some VTOL hybrid drones, like WingtraOne, are able to carry heavier payloads than fixed wing and offer better camera protection during landing.

4 | UAV SENSORS

UAV systems are ideal for outdoor plant phenotyping because they can support high-resolution image data collection for large areas of field plots. Most manual field trait data collection methods are very labor and time intensive, and the requirement for high-throughput alternatives is crucial. UAV systems introduce an attractive opportunity to reduce the time, effort, and cost necessary to collect field phenotypes and data. However, the choice of which system and what sensors to use depends on the research question, target species, and phenotypes of interest. This section reviews common sensors deployed on UAVs and their utility for plant phenotyping.

4.1 | RGB

RGB, or true-color imagery, collects electromagnetic radiation in the red, green, and blue wavelengths and captures snapshots at both nadir and off-nadir angles. Such sensors are popular for phenotyping as they require minimal specialized data collection methods and processing knowledge and are commercially available at low costs (Sweet et al., 2022). It is possible to work directly with RGB digital numbers for trait discernment, though it is advisable to apply radiometric corrections and obtain reflectance values in outdoor environments (Svensgaard et al., 2021). A common approach is to collect RGB imagery for a field at a nadir depression angle, then, through photogrammetric structure-from-motion (SfM) algorithms, create an orthomosaic for the full study area. RGB data can capture phenotypic details such as growth rate (Shu et al., 2022), plant height (Lu et al., 2021; Volpato et al., 2021), canopy and vegetation cover models (Raman et al., 2022), disease detection (Kerkech et al., 2018; Schirrmann et al., 2021; Sugiura et al., 2016; Tang, Wang, et al., 2023), crop senescence (Buchaillot et al., 2019), and biomass and yield estimates (Castro et al., 2020; Johansen et al., 2020). Though limited by spectral resolution (Sweet et al., 2022), RGB data are able to provide key structural data, and some VIs of value for phenotyping, such as Excess Green-Red (Meyer & Neto, 2008), Green-Red Vegetation Index, Normalized Difference Index (Pérez et al., 2000), and Normalized Green-Red Difference Index (Hunt et al., 2005).

4.2 | Multispectral

MS sensors operate in a similar manner to RGB sensors but provide wider spectral resolution. There is no set number of bands that distinguish a sensor as MS, but if a sensor has between four and 15 bands, it may be considered MS; beyond this range, it is generally classified as hyperspectral. The primary benefit of additional spectral bands is the enhanced ability to derive information about a target's material and chemical composition (Santini et al., 2019). Due to the increased spectral sensitivity, MS sensors benefit from the use of downwelling light sensors (DLS) to manage changes in solar angle and ambient light that may occur during flight. Calibrated reflectance panels (CRPs) can also be used to radiometrically calibrate each spectral band (Ramírez et al., 2023). The improved spectral resolution, particularly in the near-infrared (NIR) range, allows for the generation of several spectral VIs related to crop vigor (Sankaran, Khot, & Carter, 2015), morphology and density (Wilke et al., 2021; Xu et al., 2019), and biochemical composition like chlorophyll content (Santini et al., 2019). Analysis of MS data from UAV systems has been shown to be successful in determining water content (Yang et al., 2020), disease detection (Garcia-Ruiz et al., 2013), yield prediction (Maimaitijiang, Sagan, Sidike, et al., 2020), biomass (Tang et al., 2021), and nutrient uptake (Ostos-Garrido et al., 2019; Zaman-Allah et al., 2015).

4.3 | Hyperspectral

Hyperspectral spectroscopy and snapshot hyperspectral cameras commonly used for drones further increase the spectral resolution of data, often capturing hundreds of bands in a contiguous fashion from visible (VIS) to NIR to short-wave infrared (SWIR) ranges (Hagen & Kudenov, 2013). Unlike most RGB and MS imagers, which carry out snapshot captures, most hyperspectral imagers work as pushbroom scanners that capture data cubes along a scan line. These data cubes, often called hypercubes, contain three dimensions, including one spectral and two spatial dimensions (Liu, Bruning, et al., 2020). Such narrow spectral bands increase sensitivity to noise, requiring careful field collection of CRPs to account for illumination variations and allow for radiance and reflectance conversions (Moghimi et al., 2020). Hypercubes collected by aerial platforms require both geometric and radiometric corrections to return standardized data products in the form of orthorectified reflectance imagery. As hypercubes tend to be big data with many superfluous elements, it can be difficult to extract meaningful information from them. Researchers are thus benefiting from advanced predictive modeling techniques created with machine and deep learning algorithms (Zhu et al., 2020). With proper handling, hyperspectral data have been particularly successful at differentiating the material composition of targets (Behmann et al., 2018). Areas of hyperspectral spectroscopy success in plant phenotyping include the extraction of both structural and physiological plant information (Li et al., 2020; Sarić et al., 2022), crop disease pathology (Nguyen et al., 2021), the development of new spectral indices that are extremely sensitive to specific material components of a target (Shu et al., 2021), and plant stress and health (Costa et al., 2022).

4.4 | Thermal

Between the spectral wavelengths of 3 and 14 μm lies the thermal imaging range of infrared radiation, with maximum atmospheric transmission occurring between 3–5 and 7–14 μm. For plant phenotyping, thermal imaging or thermography is particularly useful for understanding leaf surface temperature, which relates to stomatal conductance and the rate of evaporation or transpiration (Li et al., 2014). Changes in leaf temperature have also been shown to indicate a plant's physiological status in response to environmental stressors. This is significant for phenotyping, as water stress will trigger stomatal closure to reduce leaf transpiration, and this induces a decrease in plant growth and production. These thermal measurements can be associated with plant performance and, thus, yield (Tattaris et al., 2016). Thermography, however, is sensitive to factors like sensor characteristics, ambient meteorological conditions, and environmentally emitted sources of thermal radiation, therefore requiring careful field design and reference panel calibration (Gómez-Candón et al., 2016). Several investigations into thermography on vegetal surfaces have indicated that the values may not be suitable for multitemporal analysis. This limitation arises from the technology's high sensitivity to various environmental factors (Gómez-Candón et al., 2016; Hou et al., 2019). Analysis of water and drought stress with thermography is valuable not only for agricultural phenotyping but also for climate change research and vegetation analysis in noncrop and tree species (Lapidot et al., 2019; Ludovisi et al., 2017).

4.5 | Light Detection and Ranging

Unlike the abovementioned passive sensors, LiDAR actively emits infrared laser pulses (primarily 800–1000 nm), measuring the return speed and intensity to determine target height and material properties (Koenig et al., 2015). LiDAR data are documented in full waveform datasets that record the detailed 3D geometric shape of targets and can be classified by the pulse return intensity to reveal crop canopy layers and ground measurements (Zhang, Chen, et al., 2003; Zhu et al., 2021). These data are analyzed to assess crop growth and development phenotypes throughout a growing season (Sankaran, Khot, Espinoza, et al., 2015; Zhang & Kovacs, 2012), including height and above-ground biomass. These crop phenotypes are often used for modeling key yield traits (Jin et al., 2021; Madec et al., 2017; Xie & Yang, 2020). For example, plant height can be indicative of overall plant health and is often predictive of final yield (Wang et al., 2018). LiDAR height data are also useful for assessing plant lodging and stability and related phenotypic traits governing yield potential (Hassan et al., 2019; Yang et al., 2017).

4.6 | Radio Detection and Ranging

Radar is another active remote sensing system, operating in a similar fashion as LiDAR but in the microwave spectrum (0.3–300 GHz). Radar echo returns, called backscattered signals, are measured in amplitude and phase, and relate to the physical (geometry, roughness) and electrical (permittivity) properties of a target (Moreira et al., 2013). For plant phenotyping, radar represents a new frontier that has not yet been explored extensively. Most radar applications in phenotyping come from satellites (Zhang et al., 2020), piloted aircraft, and Ground Penetrating Radar (GPR) (Lombardi et al., 2021). Recent advances in both radar instrumentation and UAV design have created new opportunities to pair the technologies, but these tools remain in early commercial application stages (Fasano et al., 2017; Schartel et al., 2018; Wellig et al., 2018; Xing et al., 2009). Depending on the specific frequency and polarization used, radar data present potential phenotyping applications for measurements of soil moisture, root characteristics, and plant architecture (Araus & Kefauver, 2018; Pauli et al., 2016). More research is required, however, to realize the full potential of UAV-mounted radar for robust plant phenotyping.

5 | UAV DATA ACQUISITION AND PROCESSING

5.1 | Data acquisition

UAV flight planning is a critical task to ensure good-quality image acquisition. A UAV flight plan is the defined information that indicates the GNSS coordinates of the waypoints, drone altitude, speed, direction, camera activation frequency, among others. Novel technologies for UAV-based vegetation monitoring require continuously refined research on the optimization of the UAV flight and sensor configuration and data processing (Jiang et al., 2020). Drone flight parameters and performance can have a significant impact on image data quality and viability. Jiang et al. (2020) found that flight parameters such as the drone altitude and time of flight had a significant impact on normalized difference vegetation index (NDVI) calculations at different paddy rice growth stages. This study highlighted the importance of optimizing and standardizing the operating parameters of UAVs for in-field phenotyping and data collection. However, flight parameters to be set up depend also on UAV category, sensor onboard, and case of use. For instance, flight altitude above ground level determines the pixel resolution in the recorded images, flight duration, and covered surface. It is primary essential to define the orthomosaic spatial resolution requirement (depending on the case study) to achieve the ideal pixel size to be recorded by the sensor settings (Mesas-Carrascosa et al., 2016). To optimize imaging resolution for discerning features, a minimum of four pixels per unit is needed, aiding in efficient sensor selection and flight altitude determination for optimal ground sample distance (GSD). Data collections are usually done with many sensors (RGB, MS, etc.) at the same time because some sensors need other sensors to provide information for data processing. For example, some MS or hyperspectral images are challenging to delimit plot boundaries and we need this information to be obtained from RGB images.

5.2 | Data processing

5.2.1 | Photogrammetry

The steps for image processing begin after elaboration of fly mission and taking photos. The acquired overlapping

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and high-quality georeferenced images undergo different processing steps including radiometric calibration (MS), camera alignment, use of ground control points (GCPs), dense point cloud, digital elevation model (DEM), and orthomosaic generation. The most common software algorithms used in processing images are SfM algorithms that have been extended and allow processing RGB, MS, and thermal imagery, but may require optimization (Hoffmann et al., 2016; Pech et al., 2013). In some cases, reduced information in images complicates the identification of the common features, and SfM is unable to align camera photos. In many studies, GCPs positioned at fixed points in the field and surveyed with a real-time kinematic system (RTK) are needed for optimal georeferencing (Gano et al., 2021). These can be helpful in carrying out geometric image correction to reduce distortion (Boesch, 2017). Next, the image preprocessing step includes the reduction of blurry images and transformation into a file format with the same dynamic scale. Effective co-registration is fundamental in image processing, facilitating the optimization of alignment. The process involves aligning multiple images to a common coordinate system, ensuring accurate comparison and analysis. Tips for successful co-registration include careful selection of a reference image with distinct features, ensuring sufficient overlap between images, using GCPs for accurate alignment, and employing appropriate transformation models. While co-registration plays a major role in enhancing the reliability of images analyses, improvement of this framework is necessary to accommodate evolving technologies, increase accuracy, and overcome the challenges related to variations in sensor characteristics and environmental conditions. Image alignment (orthorectification), calibration, and correction considering atmospheric conditions are needed for building high-quality orthomosaics (Khanal et al., 2017). Then, VIs are extracted using both the orthomosaic and the plot's shapefile. These steps can be performed using QGIS, ArcGIS, and Pix4D software, Raster and FIELDimageR packages, and so forth (Kassim et al., 2022; Saravia et al., 2022). The background soil, which can affect canopy reflectance, is generally removed to reduce interference and improve data quality (Kassim et al., 2022). From dense point clouds, the digital terrain and surface models are generated to derive canopy traits, including height (Bendig et al., 2013). RGB image-based plant height retrieval of key crop phenotypes is most commonly used because of its high flexibility, recent advances in resolution, and low cost of RGB cameras (Remondino & El-Hakim, 2006; Remondino et al., 2014). Despite numerous existing software, photogrammetry still needs improvement to tackle common challenges regarding unpleasant defect like stripey 3D model, discrepancies in mesh texture or orthophoto, and noisy dense point cloud. Integrating photogrammetry seamlessly with other technologies, such as LiDAR, can be challenging. Establishing standardized workflows and data formats for interoperability remains an ongoing effort.

5.2.2 | Hyperspectral

Hyperspectral image preprocessing steps include the removal of drone motion effects and the flat terrain adjustments of surface reflectance spectra. This is processed using specific software such as ENVI image processing and analysis software (NV5 Geospatial Solutions). Hyperspectral data cubes are commonly collected using pushbroom style cameras that collect spectroscopic data along track, keeping a narrow aperture open while the camera moves along the target. These data cubes represent multiband strips that can be georectified and combined with other georectified data cubes from the same collection to recreate a larger scene (Fang et al., 2019). After all data cubes are combined together, high-ground-resolution images close to 1 cm or less are obtained. The whole hyperspectral images are geocoded into WGS84 coordinate system using ground control points that increase correspondence between the location of ground points and the pixel positions (Fang et al., 2019). The band range should be selected to get the best combination of spectral bands for computing the average canopy spectral reflectance of each plot. Another important preprocessing step is the reflectance calibration using spectrally known reflectance target to normalize the data cube, overcome the light source influence, and enable comparable measurements for time series within the same measurement setup, under different illumination conditions (Paulus & Mahlein, 2020; Sarić et al., 2022). Nevertheless, hyperspectral data processing confronts numerous challenges, encompassing the delicate balance between bandwidth and spatial resolution, the overwhelming data volume, its intricacy dictated by the laws of physics, and commercialization issues. To address these limitations, the industry is exploring sophisticated approaches such as leveraging cloud computing, onboard data processing, and implementing artificial intelligence to effectively handle the substantial influx of data.

5.2.3 | Light Detection and Ranging

The use of LiDAR has significantly evolved in recent years and represents an additional and valuable tool for UAV-based plant phenotyping (Hoffmeister et al., 2016). With the capacity of the LiDAR laser beam to penetrate crop vegetation, LiDAR mapping techniques allow the acquisition of high-quality crop surface models that correspond to canopy height, in addition to providing information about background surface altitude or digital terrain model (DTM) (Madec et al., 2017). LiDAR preprocessing involves creation of a Smoothed

Best Estimate Trajectory (SBET) file in software such as POSPac, if using Applanix equipment, from trajectory data from the onboard IMU-GNSS to build an automated flight line and carry out a LiDARsnap process that compares the geometric characteristics of overlapped flight lines to adjust and correct alignment factors and offsets from several flights (Maimaitijiang, Sagan, Erkbol, et al., 2020). LiDAR data can be postprocessed using cloud-based LiDAR postprocessing platform applications such as the LiDARMill. Point clouds generated from LiDAR sensors are processed for the extraction of key crop traits like plant height and biomass, and there are a number of studies reporting LiDAR scan accuracy equivalent to photogrammetry techniques (Deery et al., 2014; Virlet et al., 2017). While LiDAR stands as a formidable tool, processing LiDAR data comes with inherent challenges and limitations. A prevalent issue is data noise, where various factors such as atmospheric conditions, sensor noise, and reflections off nonterrain objects can introduce errors into the data, posing difficulties in accurately modeling the terrain and other features. Additionally, occlusions present another challenge, as LiDAR systems may struggle to penetrate dense foliage, hampering accurate terrain and feature modeling in these areas. Future research should identify the most effective angular resolution, laser beam footprint, scan window, and other techniques for acquiring high-resolution images from LiDAR data. Subsequent investigations could concentrate on designing a cost-effective LiDAR-based system that streamlines data acquisition, employs efficient data analysis methods for accurate information extraction, and ensures user-friendly operation.

5.2.4 | Synthetic aperture radar

The prime function of radar sensors is to collect information about the environment surrounding the drone, and a popular radar technology, commonly used in aircrafts, is synthetic aperture radar (SAR) (Moreira et al., 2013). SAR is an active microwave radar sensor used to process echo obtained from different locations to generate imagery. They are sensitive to operating parameters including frequency, polarization, and incidence angle, and these factors impact the ability of their transmitted microwaves to penetrate into plant vegetation (McNairn & Shang, 2016).

SAR interferometry is often used for remote sensing, and its primary application is to compare many radar images collected at different locations and times. SAR image pixels contain accurate information about object range and allow the detection and measurement of small length variations with centimetric accuracy (Moreira et al., 2013). The Sentinel Application Platform (SNAP) method is generally used to preprocess SAR sensor data using a boxcar filter, reducing speckle noise and increasing the number of looks. SAR channels are created in a slant range, and terrain correction is carried out by the Range Doppler algorithm (Jiao et al., 2021). Thus, SAR parameters (radar VIs and others) can be extracted and used for crop identification, classification, and monitoring. However, challenges in radar-based crop phenotyping may persist in improving resolution and managing costs, while future trends include advancements in radar technologies, increased integration with other sensing methods, and the growing influence of machine learning (ML) for data analysis and interpretation. The industry may also see efforts in miniaturization for wider accessibility and a focus on global collaboration and standardization.

6 | APPLICATION IN FIELD PHENOTYPING

UAV-based field phenotyping has become a common method to estimate crop phenotypes due to the platform's capacity to capture and/or directly measure field traits with one or more sensors. Figure 2 shows a schematic overview of how to extract spatial information from plants throughout a growing season, highlighting the different sensors that can be used for target phenotypes at a specific growth stage. However, the integration/fusion of these sensor modalities is key to extract the highly entangled traits.

A survey was conducted in Google Scholar and Dimension AI (app.dimension.ai) to identify the number of publications (articles, books, chapter, proceeding, preprint, etc.) related to each UAV application including canopy height; stand count; growth, biomass, and yield prediction; crop physiology; leaf nitrogen content (LNC); soil properties; and pest disease and management. Figure 3 shows that the number of publications has increased year after year for each application, with LNC recording the highest number of related publications, while pest disease and management recorded the lowest number of publications.

6.1 | Canopy height estimation

Red, green, blue (RGB) sensors are commonly used to monitor crop height dynamics. These sensors allow the creation of DEMs through a photogrammetric SfM process. There are two types of DEMs used to derive crop height—DTM, which provides information about the altitude of the earth surface obtained from a flight shortly after sowing or bare soil patches at late growth stage, and the digital surface model (DSM), which represents the altitude of the vegetation surface that is first encountered by the UAV system. Therefore, crop height calculation is obtained by deriving DTM from DSM (De Souza et al., 2017; Gano et al., 2021; Hu et al., 2018).

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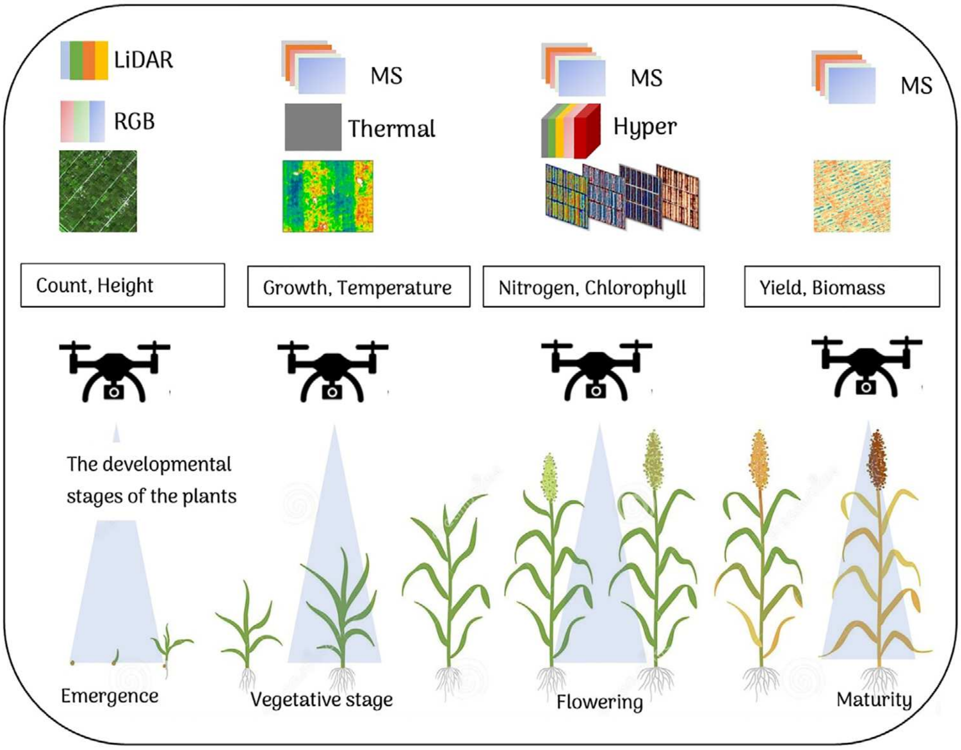

FIGURE 2 Schematic overview of the different ways to extract spectral information from plants throughout a growing season, highlighting the different sensors that can be used for target phenotypes at specific growth stages (e.g., emergence, vegetative stage, flowering, and maturity). RGB, red-green-blue; Hyper, hyperspectral; MS, multispectral.

Due to the variation in the structure of the plant canopies, the highest point in the point cloud is not usually the best way to extract crop height. Therefore, the phenotyping platform is split in grid cells of certain size, and the average plant height is derived by including a certain number of top-of-canopy points. RGB sensors are flexible, cheap, and easy to use, and they do not require a high-skill calibration setup, unlike MS, thermal, and hyperspectral sensors. For these reasons, they are appropriate sensors for measuring canopy height. A number of research studies have developed and assessed methods for rapidly measuring plant height and growth using multitemporal UAV datasets to create DSMs (Han et al., 2018; Hassan et al., 2019).

After comparing UAV SfM-modeled crop heights to ground truth field measurements measured by a ruler, some UAV-derived surface models achieve high accuracy with a root mean squared error (RMSE) of 0.03 m (Murcia et al., 2021) and 0.05 m (Hassan et al., 2019) in wheat (*Triticum aestivum*) and 0.01 m in sorghum (*Sorghum bicolor*) (Han et al., 2018). We may also point out that the type of crop can affect the accuracy in crop height estimate. While plant height estimation works well in sugar beet ($R^2 = 0.7$, RMSE = 7.4 cm) and winter wheat ($R^2 = 0.78$, RMSE = 3.4 cm), in potato (*Solanum tuberosum*), it proved to be less reliable ($R^2 = 0.5$, RMSE = 12 cm) due to the complexity of its canopy structure (Murcia et al., 2021). The UAV-based orthoimage quality can degrade due to the effect of motion blur, especially when a high-speed drone is used. During image acquisition, camera movement in a windy environment increases image motion blur, posing a significant challenge to automating data analysis of drone images (Sieberth et al., 2014). Several computer processing steps, including co-registration, orthoimage, and point cloud generation, are complicated by image motion blur (Boracchi, 2009). Another potential obstacle is obtaining enough tie point correspondence for good image matching, essential for generating usable 3D models with PhotoScan or Pix4D mapper software. Tie-point matching is difficult to carry out in a flat terrain due to the uniformity of pixels (Boracchi, 2009). Ultimately, plant height is a key agronomic trait for which measurement accuracy is particularly important as it is highly correlated to plant health, growth, yield, and adaptation to environmental stresses.

6.2 | Stand count

Crop yield in a given field can be calculated by multiplying the number of established plants by individual plant yield. Thus, a key approach for estimating potential yield is through plant counting (Shahid et al., 2024). The assessment of the number of plants, that is, digital counting of individual plants, has been carried out in a number of studies using RGB sensors with convolutional neural network (CNN) models to detect plants at early developmental stages (Lu et al., 2024; Xu et al.,

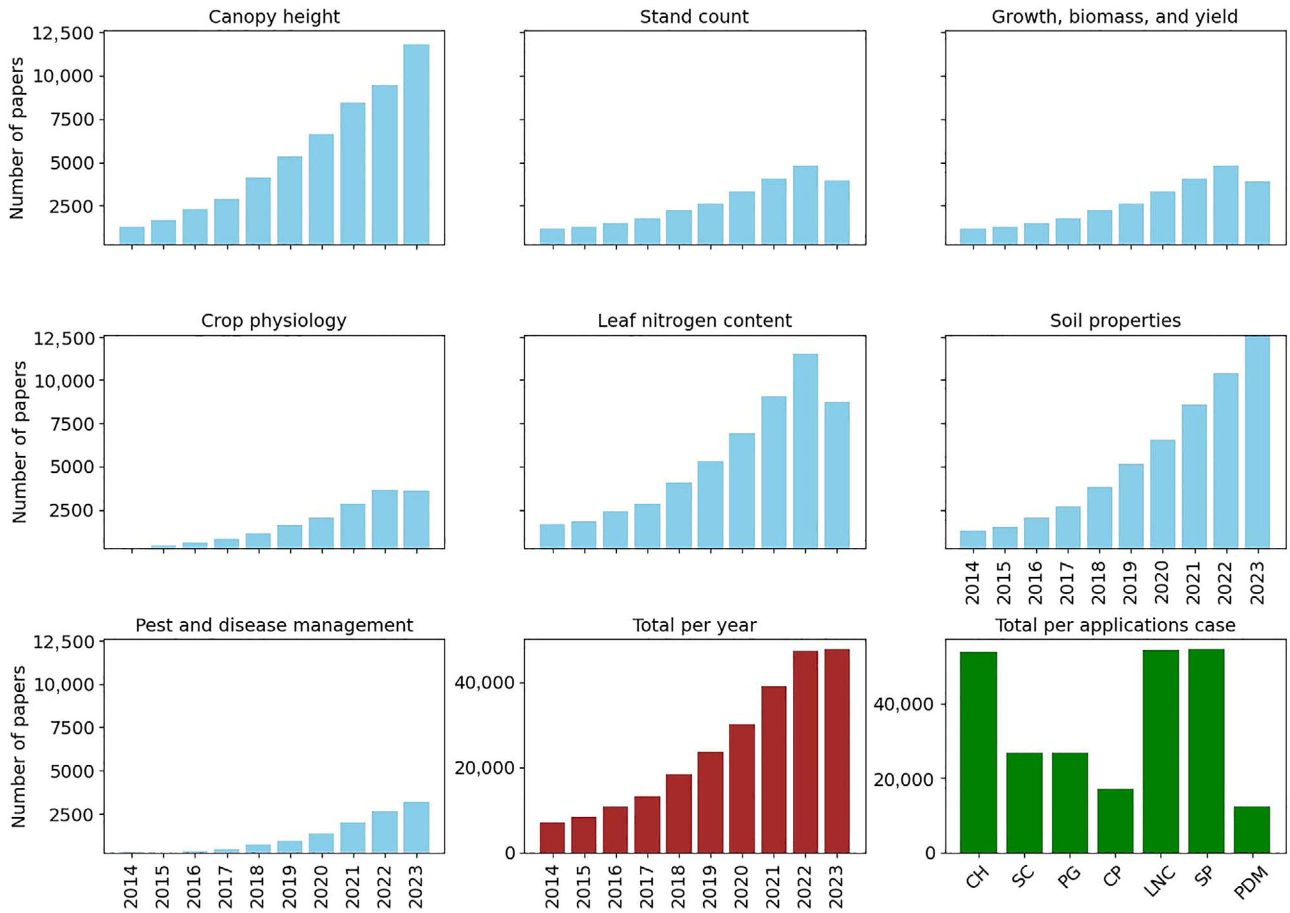

FIGURE 3 Number of publications per year for the main unmanned aerial vehicle (UAV) phenotyping applications in the last decade. CH, canopy height; SC, stand count; PG, plant growth; CP, crop physiology; LNC, leaf nitrogen content; SP, soil properties; PDM, pest disease management.

2018). These CNN models were successful despite the presence of weeds and blurry images. Similarly, Guo et al. (2018) demonstrated the potential of UAV image analysis for detecting and quantifying sorghum panicles, with a precision of 0.87 and an R^2 of 0.84 between the UAV-based and manual counting methods. Error was primarily attributed to variability in plant morphology and field design; panicles from plants in one plot would grow into adjacent plots and were counted in the total panicle counts of neighboring plots. In all of these studies, the final field emergence estimates of plants and the number of heads were able to be rapidly assessed and allowed for more accurate assessments of the final yield parameters. The main challenges encountered are related to ML models that rely heavily on costly labeled training image datasets.

6.3 | Plants growth, biomass, and yield prediction

Breeding efforts for crop improvement are primarily geared toward the development of high-performance varieties that respond well to agronomic inputs, are tolerant to environment stressors, and are resistant to pests and disease. The development of high-performing varieties often involves the study of growth traits that are related to production capacity. UAV-based sensing is appropriate for assessing these plant growth and yield traits, including vigor, leaf area index (Gano et al., 2021; Shafian et al., 2018), and biomass (Anchal et al., 2021; Zhang et al., 2017). VIs based on spectral reflectance values exported from MS sensors have been used to develop prediction models of growth traits in sorghum, including leaf area index (LAI) and biomass (Gano et al., 2021). Calculated with spectral reflectance, VIs (Table 2) have widely been implemented to evaluate crop growth traits (Li et al., 2018; Potgieter et al., 2017; Yang et al., 2020; Zhang & Zhou, 2019). Xue and Su (2017) reviewed the utilization of 100 key VIs, showing that some VIs captured robust information for growth traits, biomass, and yield prediction. VI-based yield prediction models are challenging for a complete growing season, as complex yield traits are highly affected by many variables including environment, genotype, and crop management practices (Rotili et al., 2020). Interactions between these

TABLE 2 Commonly used vegetation indices for plant traits.

Index	Formula	Traits associated
Normalized difference vegetation index (NDVI)	(NIR − R) / (NIR + R)	LAI, AGB, GY, CC
Normalized difference red edge (NDRE)	(NIR − RE) / (NIR + RE)	LAI, AGB, GY, CC
Red edge soil-adjusted vegetation index (RESAVI)	1.5 × [(NIR − RE) / (NIR + RE + 0.5)]	LAI, AGB, GY, CC
Difference vegetation index (DVI)	NIR − R	LAI, AGB, GY, CC, Ns
Soil-adjusted vegetation index (SAVI)	(1 + L) (NIR − R) / (NIR + R + L); L = 0.5	LAI, AGB, GY, CC
Red edge ratio vegetation index (RERVI)	NIR / RE	Chl., PhiPSII, AGB, Ns
Red edge difference vegetation index (REDVI)	NIR − RE	LAI, AGB, GY, CC, Ns
Ratio vegetation index (RVI)	NIR / R	LAI, AGB, GY, CC
Red edge wide dynamic range vegetation index (REWDRVI)	(a × NIR − RE) / (a × NIR + RE); a = 0.12	LAI, AGB, GY, CC, Ns
Transformed chlorophyll absorption reflectance index (TCARI)	3[(R700 − R670) − 0.2 (R700 − R550) (R700 / R670)]	Pn, Chl., Tr, C
Optimized soil-adjusted vegetation index (OSAVI)	(NIR − R) / (NIR + R + 0.16)	Pn, Chl., Tr, C
Reflection in red edge (RRE)	(NIR + R) / 2	LAI, AGB, GY, CC, Ns
Photochemical reflectance index	(R531 − R570) / (R531 + R570)	Pn, Chl., Tr, C, PhiPSII
Red edge chlorophyll index (CI_{RE})	NIR/RE − 1	Chl., PhiPSII
Canopy chlorophyll content index (CCCI)	(NDRE − NDREmin) / (NDREmax − NDREmin)	Chl., PhiPSII
Health-index (HI)	(R739 − R402) / (R739 + R402) − 0.5R403	PM, YR, A

Abbreviations: A, aphids; AGB, above ground biomass; C, stomatal conductance; CC, canopy cover; Chl., chlorophyll content; GY, grain yield; LAI, leaf area index; NIR, near-infrared; Ns, nitrogen status; PhiPSII, PSII photochemistry efficiency; PM, powdery mildew; Pn, photosynthesis rate; Tr, transpiration rate; YR, yellow rust.

variables, in addition to variation between VIs and crop traits that present at different phenology stages, contribute to relatively high levels of uncertainty in the data-driven yield prediction model generated by UAV-collected data (Zhou et al., 2017). For example, the link between NDVI and grain yield is so indirect and unstable and impacted by the harvest index (HI), specific leaf area (SLA), leaf angle, and soil background optical properties. Nevertheless, rice yield has been accurately estimated from spectral images acquired from an unmanned helicopter (Swain et al., 2010). In this study, NDVI was highly correlated with yield. Ultimately, data from these and related studies indicate that MS sensors on board aerial platforms can greatly facilitate phenotype quantification in field plots and estimation of crop yield potential.

6.4 | Crop physiology

The assessment of crop physiological traits, such as photosynthesis, chlorophyll fluorescence, leaf temperature, stomatal conductance, leaf transpiration, and so forth, is important for understanding and optimizing crop growth and canopy reflectance properties (Feng et al., 2021). Plant leaf reflectance in the VIS light range is influenced by concentrations of chlorophyll, carotene, and lutein, while reflectance in the NIR bands is linked to cell structure. Physiology research implementing UAV-based phenotyping is primarily focused on chlorophyll concentration and crop temperature. MS and hyperspectral cameras are commonly used for monitoring physiological parameters based on vegetation index-derived regression models to estimate traits. Studies have demonstrated the ability of photochemical reflectance index (PRI) normalized by NDVI and red-edge chlorophyll ratio to accurately reflect field measurements of stomatal conductance (Zarco-Tejada et al., 2013). Hunt et al. (2018) estimated chlorophyll content in potatoes through UAV-derived NDVI and green normalized differential vegetation index (GNDVI). Zhu et al. (2020) used UAV-collected hyperspectral images to estimate maize (*Zea mays*) and wheat leaf chlorophyll concentration. The evolution of narrow-band imagery has diminished the sensitivity to structural effects, particularly when using chlorophyll indices like the chlorophyll absorption in reflectance index (CARI), optimized soil adjusted vegetation index (OSAVI), and associated indices (TCARI and MCARI) (Haboudane et al., 2002). However, additional progress is needed to elucidate the dynamic variation of PRI pixels that accurately reflect different concentrations of pigments (e.g., xanthophyll, chlorophyll, anthocyanins, and carotenoids) (Zarco-Tejada et al., 2013). UAV-based thermal imagery is primarily used to monitor water stress due to its ability to measure canopy surface temperature reflecting plant transpiration and water status (Poblete et al., 2018; Santesteban et al., 2017; Zarco-Tejada et al., 2012). Crop water stress index (CWSI) obtained with thermal imaging systems has also demonstrated high correlations with leaf temperature. However, a major concern about thermal imaging remains the camera calibration and the need to correct temperature calculated by the camera's software, which makes the processing very challenging. Future progress on a range of challenges and opportunities is expected, including the advent of various software package.

6.5 | Leaf nitrogen content

Leaf nitrogen measured from a canopy can accurately indicate the current nutritional state of the crop, facilitating improved nitrogen fertilization management (Fitzgerald et al., 2010). While conventional methods for measuring leaf nitrogen are laborious and usually require field measurements and lab testing, UAV-based sensor systems offer nondestructive alternative methods for in-field crop nitrogen assessment. ML methods have been shown to be effective in predicting LNC using VIs and spectral imagery from UAV-based systems (Liu et al., 2017). UAV system and ML methods have been used to assess canopy accumulation and determine nitrogen levels at various phenology stages, and in 2017, LNC was calculated with a UAV-mounted hyperspectral system in wheat (Liu et al., 2017). Nitrogen-use efficiency has also been measured using UAV-mounted, RGB, MS, and thermal sensing systems (Kefauver et al., 2017). However, it is crucial to acknowledge the indirect nature of these quantifications. The models rely on correlations between spectral features and LNC, but factors such as environmental conditions, plant health, and genetic variations can influence these relationships. Thus, predictions may be affected by external variables, highlighting the need for caution in interpreting results and considering potential limitations in the robustness of predictions across diverse conditions.

Abiotic stressors such as nutrition deficiencies can drastically drop crop yield and quality. These stresses induce variations in the physiology, morphology, and also reflectance of the plant that can be potentially surveyed using sensors onboard a UAV (Ollinger, 2011). Therefore, UAV-mounted sensors (RGB and MS) are suited for monitoring abiotic stress (e.g., nitrogen deficiency). Such work, however, requires the ability to detect fine changes that may occur in leaf pigments. Improving nitrogen fertilization efficiency through the application of precision nitrogen is key to avoiding its overuse and limiting its cost and environmental impact (Bushong et al., 2018). Overall, UAV-based VIs assessing crop nitrogen status have been shown to be as reliable as ground truth measurements carried out with laboratory and in-field instruments.

6.6 | Soil properties

Soil variability contributes a significant proportion of the total environmental variability impacting crop growth and development in a field setting. Clay content, soil organic matter (SOM), and soil organic carbon (SOC) are key soil traits associated with crop growth and yield potential impacting nutrient uptake and water retention (Zhang et al., 2021). Several remote sensing studies have attempted to monitor SOC, SOM, and electrical conductivity, which are highly related to clay content, for a better understanding of soil types and quality in the field (Chen et al., 2021). Zhang et al. (2021) explored the potential of a UAV spectral imagery for assessing SOC levels in bare cropland. In recent years, UAV-based remote sensing has been used to estimate SOM or detect soil properties, and help manage salinity effect (Ma et al., 2020; Wang et al., 2020) that negatively affects the SOC content (Gong et al., 2021; Wong et al., 2010), and plant nutrient uptake (potassium, phosphorus, etc.) is affected by sodium competition (Hurtado et al., 2019). Surveying soil reflectance is another option to study soil features, and this method is often based on hyperspectral remote sensing for soil attribute monitoring.

Soil properties and crop growth and health are deeply interconnected, and most of earth's land surfaces are covered by vegetation. For these reasons, the majority of soil studies with UAV remote sensing systems examine the interaction between plant reflectance and soil for indirectly mapping soil traits (Chi et al., 2018). Generally, these studies often focus on developing prediction models between soil properties and UAV-derived VIs. The UAV-derived indices can be used as proxies for local soil properties and inform irrigation rate management practices; they can also aid in the identification and management of crop stress. In precision phenotyping, quick assessments of comprehensive soil properties, including proxies and indicators for soil fertility, are critical for agronomic management. However, drone-based soil monitoring presents unique challenges, contributing to potential errors in assessing soil properties. Several factors make this task difficult, including changes in surface roughness, wetness, limited penetration depth, soil moisture influence, and resolution and scale issues.

6.7 | Pest and disease management

Precision phenotyping of disease prevalence and severity and effects on crop output quality and yield is critical for production agriculture and breeding. Plant disease mitigation is also a significant topic of both basic and applied plant research (Mahlein, 2016). Plant pathogens affecting crop health have been found to decrease global production by approximately 40% (Oerke, 2006). Conventional methods globally used to diagnose and detect crop diseases include visual scoring with a manual rating and/or a ranking system, morphology study using a microscope to identify pathogens, and several molecular diagnostic technologies (Bock et al., 2010).

Ye et al. (2020) developed a novel method based on UAV-based MS sensing to map Fusarium wilt in bananas. In this study, the binary logistic regression (BLR) model was applied to derive the spectral relationship between eight VIs and Fusarium wilt infestation. Their investigations found that the green chlorophyll index (CI_{green}), red-edge chlorophyll index (CI_{RE}), NDVI, and normalized difference red edge (NDRE) indices allowed them to distinguish disease presence and distribution in trees. The CI_{RE} index exhibited a significant correlation, attesting to the role of the red-edge spectral band in the discrimination of infested plants (Ye et al., 2020). Diseases that have been identified through UAV-based sensing methods include rust infection (Huang et al., 2014), Fusarium head blight (Mahlein et al., 2019), and powdery mildew (Mahlein et al., 2019; Yuan et al., 2016; Zhao et al., 2018) in wheat, bacterial leaf blight in rice (*Oryza sativa*) (Ahsan et al., 2021; Liu, Shi, et al., 2020; Ullah et al., 2020), gray leaf spot in maize (Dhau et al., 2018), and late blight infection in tomato (*Solanum lycopersicum*) (Jones et al., 2010; Zhang, Qin, et al., 2003).

Detecting plant disease in advance is critical for agricultural sustainability and global food security, and the innovative advance of drone and computer vision such as deep learning algorithms to identify disease at the early stage has been reviewed by Bouguettaya et al. (2021). Early disease detection allows for timely intervention, reducing crop loss and ensuring a stable food supply. UAVs play a pivotal role in advancing early disease detection through their ability to provide real-time and large-scale crop monitoring (Arjoune et al., 2022). When plants are infected, there is often significant changes that occur in their biophysical and biochemical pool (e.g., pigments, leaf water content, and internal structures); these changes are subsequently reflected in the spectral properties of the infected plant (Zheng et al., 2018). However, in the field, plants encounter numerous pathogens, and many of these manifest similar symptoms. The accurate identification of plant diseases represents a fundamental, yet intricate, challenge and a great limitation of UAV-based disease detection. This drives scientists to program software capable of visually assessing every plant for disease detection, but challenges persist in achieving programming accuracy due to issues like background noise, adverse field conditions, sensor limitations, variations in symptoms, and discrepancies in training validation.

7 | ML FOR PLANT PHENOTYPING

ML algorithms are a critical addition to newly developed high-throughput phenotyping methods with UAV-based sensing (Angel & McCabe, 2022). Incorporation of novel ML algorithms in different phenotype extraction methods has accelerated the practices of precision agriculture (Gašparović et al., 2020; Niu et al., 2020) and crop breeding (Castro et al., 2020; Selvaraj et al., 2020) significantly in recent years. By leveraging ML models in conjunction with UAV-based sensing, researchers have been able to make significant strides in automating data analysis and interpretation, thereby facilitating informed decision-making and resource allocation in precision agriculture and crop breeding (Matese et al., 2023). The integration of ML has enabled the extraction of valuable insights from complex datasets derived from UAV imagery, leading to improved predictive modeling and enhanced crop management strategies. The purpose of an ML model is to learn a mapping function for a target variable (or phenotype) from a given series of UAV images. The learning of the function can be done in three ways—supervised, unsupervised, and semi- or self-supervised. In the plant phenotyping domain, fully supervised ML has gained more traction over the other two (Nagasubramanian et al., 2022; Tsaftaris et al., 2016). In supervised ML, a predictive model is trained by using ground truth data for a given phenotype. For example, if plant height is the target variable, then both UAV data and corresponding sample plant height values are manually collected as ground truth for the model. Alternatively, unsupervised models aim to find underlying patterns within the UAV-derived dataset and classify the dataset into different clusters or ranges for inference, which is often used for classification within crop phenotyping (Al-Shakarji et al., 2018). More recently, the semisupervised or self-supervised learning mechanism has gained popularity within the plant phenotyping community as these methods rely on little to no ground truth data while training (Güldenring & Nalpantidis, 2021; Yan & Wang, 2022; Zapata et al., 2020). Here, we describe in more detail the general methodologies involved in supervised ML, which is currently the more established ML approach for plant phenotyping.

A typical workflow of supervised ML for plant phenotyping tasks is illustrated in Figure 4. The workflow can be divided into data collection (including both UAV and ground truth), data splitting, feature engineering, ML training (either classical ML or deep learning), and evaluation.

7.1 | Feature engineering

Feature engineering is a task that selects, manipulates, and turns raw data into features required for supervised learning. It is one of the most important steps of remote-sensing-based ML. UAV sensors produce a multitude of information, including RGB, MS, and hyperspectral data, point clouds, radio intensities, and so on. Spectral reflectance can be extracted from well-calibrated MS and hyperspectral sensors and defines VIs (Yousfi et al., 2022). The reflective spectral signature can provide information associated with the biological state and biochemical composition of plant leaves

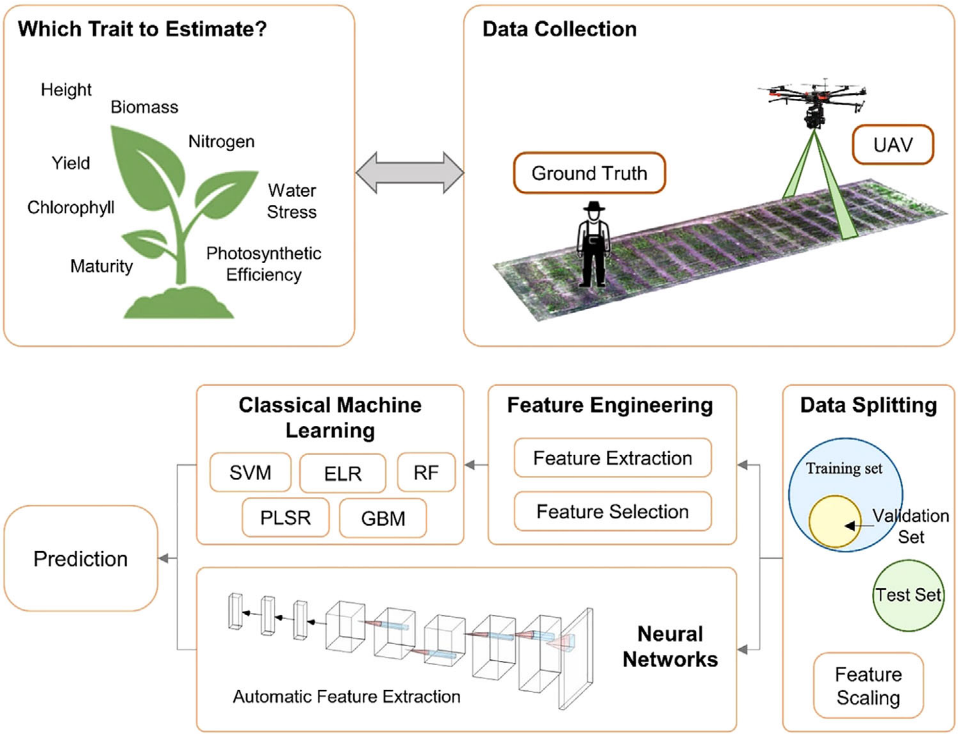

FIGURE 4 Typical workflow of a machine learning training pipeline for plant phenotyping. The workflow includes trait or phenotype selection, data collection, data splitting, feature engineering, model training, and prediction. PLSR, partial least squares regression; SVM, support vector machine; ELR, extreme learning machine; GBM, gradient boosting machine; RF, random forest.

and canopy (Boyd & Danson, 2005). In a typical vegetation reflectance spectrum, the VIS spectral region (400–700 nm) is dominated by leaf pigment absorption (e.g., chlorophylls, carotenoids, and xanthophylls), absorption by water is moderate in the SWIR region (1300–2100 nm), and absorption by plant leaves is low in the NIR region (700–1300 nm). Unique characteristics of different plants are captured within the reflective spectra, and VIs can be calculated to highlight certain plant traits (Ollinger, 2011). Therefore, when a certain ML model is being trained for plant phenotyping, instead of feeding direct reflectance data from different wavelengths, it is a common practice to use the VIs as the independent variables (Di Gennaro et al., 2018; Koh et al., 2022; Wang et al., 2021; Xu et al., 2019).

There has been a significant amount of VI development for different types of plant phenotype correlations. Typically, VI is calculated as the ratio of two wavelength bands in order to contrast two features (the absorbing and nonabsorbing) (Huete, 2012). However, the use of multiple wavelength bands and VIs has proven to be even more effective in signifying certain traits (Anderson et al., 2011; Zarco-Tejada et al., 2003). Table 2 shows a list of commonly used VIs for specific plant traits.

While VIs can identify certain spectral characteristics of plants, structural characteristics are also important for understanding the physical properties of a plant canopy. Phenotyping from only VIs is hampered by the asymptotic saturation of optical sensors in the dense vegetation of late plant development stages (Greaves et al., 2015; Rischbeck et al., 2016). Structure features often are calculated from the crop height model (CHM) generated by either high-resolution UAV RGB cameras or LiDAR point clouds. Usually, the plot-level descriptive statistics of CHM (e.g., mean, median, mode, entropy, coefficient of variation, and different percentiles of height) are used as structural features. Fusing structural information with VIs has improved estimation accuracy for different plant phenotypes, including crop biomass (Li et al., 2015; Maimaitijiang et al., 2019), LAI (Maimaitijiang et al., 2017), and yield (Bendig et al., 2015). In addition to structure features, texture features are also found to be highly effective in distinguishing the spatial heterogeneity in the canopy (Mutanga & Skidmore, 2004). Texture information captures the spatial difference in pixel intensities in a given image, which highlights the structural and geometric features of plant vegetation (De Grandi et al., 2009). Usually, texture features are obtained by calculating gray-level co-occurrence matrix or GLCM and then determining different texture statistics, such as mean, variance, contrast, homogeneity, heterogeneity, entropy, second moment, and correlation, from the plot-level data. More information about texture features can be found in Nichol and Sarker (2011).

Feature selection is another important component of feature engineering. Since there can be hundreds or even thousands of features from UAV-based sensors, it is often difficult for the ML model to learn from such a multitude of features. This is often known as the "curse of dimensionality," where the number of independent features is more than the training sample (Salimi et al., 2018). Where hyperspectral sensors are concerned, principal component analysis (PCA) or linear discriminant analysis (LDA) can be used to reduce the number of independent features into a few key components (Fang et al., 2019). Additionally, Pearson's correlation coefficient (Fang et al., 2019; Pooja et al., 2020), partial least squares (PLS) regression-based variance importance in the projection (Maimaitijiang et al., 2017; Peerbhay et al., 2014), and random forest (RF)-based mean decrease impurity score (Behnamian et al., 2017; Packalén et al., 2012; Pedergnana et al., 2013) are also often used to select the most important features. Therefore, the use of appropriate feature selection before training is a good practice in ML-based plant phenotyping.

7.2 | Classical ML algorithms

Classical ML algorithms have experienced a resurgence in the realm of UAV-based plant phenotyping, owing to their robust performance and versatile applications. The basis of these algorithms was highly concentrated on advanced statistics and probabilistic reasoning. In supervised learning, the commonly used classical ML algorithms such as support vector machine (SVM), RF, PLS, extreme learning machine (ELR), and Gaussian processes (GP) play a pivotal role in overcoming various challenges associated with nonlinear regression, time-series forecasting, and data classification. SVM is a highly used ML algorithm in the plant phenotyping community. It has the capacity to overcome forecasting issues in nonlinear regressions and time series (Thissen et al., 2003). SVM reduces the generalization error and avoids model overfitting (Tay & Cao, 2001). RF uses decision-tree frameworks for either classification or regression with noncorrelated and independent training data, thus relieving the artifacts of bias and sensitivity (Genuer et al., 2017; Shi & Horvath, 2006). PLS is another popular ML algorithm used mostly in regression problems, and it works well with hyperspectral data, as there exist hundreds of independent features in a spectrum. These classical ML algorithms, versatile in their application, can be seamlessly integrated into various regression and classification problems, with the prerequisite of comprehensive feature engineering and rigorous testing to ensure accurate and reliable inferences.

7.3 | Deep neural networks

Deep neural networks or deep learning is a part of the broader ML paradigm. In general, deep neural networks can be divided into three different types in the context of plant phenotyping—artificial neural networks (ANNs), CNNs, and recurrent neural networks (RNNs). Although there are other types of neural networks for different purposes, these three types are the most common networks used in plant phenotyping applications.

The ANN is the simplest form of neural network. Here, several neurons try to learn weights and biases from ground truth data to map a nonlinear function from the input variables and predict a certain output trait. Simple ANN uses a backpropagation algorithm to optimize the complex nonlinear models and requires several iterations to complete the training (Pang et al., 2020). Features extracted from UAV imagery are generally used as the input for the ANN (Chew et al., 2020). When a phenotyping problem involves plot-level statistical information as the input, ANN has been shown to accurately estimate the phenotype (Maimaitijiang, Sagan, Erkbol, et al., 2020; Zhang et al., 2019). ANN, however, cannot utilize images directly into the network, which led to the development of the CNN.

CNNs have revolutionized computer vision tasks as they use convolution and pooling layers to contemplate the inherent spatial characteristics of images for inference (Kattenborn et al., 2021; Maggiori et al., 2016). Instead of having neurons, it has kernels where the weights and biases are trained. CNNs learn spatial patterns and can be directly used with UAV imagery without the requirement of feature engineering (Pang et al., 2020). Many studies have utilized direct imagery-based CNNs in predicting different phenotypes and achieved significant improvement over traditional ML algorithms and/or ANNs (Tang, Qiu, et al., 2023; Tang, Zhou, et al., 2023; Wu et al., 2022, 2023). The phenotyping use case, however, drives the type of CNN that can be used. For example, custom-made CNN architectures involving multiple building blocks often are used for simple regression or classification problems. OD algorithms (e.g., YOLO and Faster-RCNN), however, are often used in tassel detection (Liu, Shi, et al., 2020), disease identification (Karthik et al., 2020), and segmentation of different leaf traits (Kolhar & Jagtap, 2021; Xu et al., 2018).

RNN is another type of deep neural network that leverages sequential data to learn certain patterns. In crop phenotyping, the different growth stages of plants provide interesting data collection and analysis opportunities through multitemporal UAV observations. Many studies have implemented RNN units such as long short-term memory (LSTM) (Shen et al., 2022; Zhou et al., 2021) and gated recurrent unit (GRU) (Mahlein, 2016) in understanding the temporal aspect of plant growth. Additionally, the use of both RNN units with CNN has proven to be highly efficient in structuring spatial, spectral, and temporal characteristics from UAV-based data.

While deep neural networks consistently exhibit enhanced accuracy and efficiency compared to classical ML algorithms, their performance heavily relies on the availability of extensive ground truth training datasets (Atanbori et al., 2020). Various tools have emerged to aid in generating training datasets for deep neural network applications in plant phenotyping. Researchers have developed Ladder and ROOSTER, software solutions offering intuitive graphical interfaces to streamline labeling, training, and deployment of OD models, with Ladder focusing on simplifying labeling and ROOSTER integrating labeling and prediction for enhanced efficiency in human labeling and machine vision system development (Tang & Zhang, 2023; Tang, Hu, et al., 2023). Despite potential constraints such as logistical, personnel, financial, and technological limitations, concerted efforts by global crop breeders and scientific communities to gather comprehensive phenotypic and environmental datasets have the potential to accelerate the progress of deep learning training. In this context, the accessibility of open-source and standardized datasets in plant phenotyping could significantly alleviate the challenges inherent in crop breeding and precision agriculture.

8 | OPEN ISSUES AND RESEARCH CHALLENGES

8.1 | Suitable UAV platform for phenotyping applications

When selecting a drone, one should first examine the application in order to select between a fixed or rotary wing type. The wing category has a significant effect on drone endurance and maneuverability. For example, a fixed-wing UAV is relatively easy to pilot, but it is not able to hover as well as a rotary-wing drone (Cuaran & Leon, 2021). The fixed-wing UAVs are also subject to controlled landings that may damage the drone and its cameras. Another essential characteristic to consider is endurance due to a wide range of flight times across drone types. While some UAVs can sustain flight for a few dozen minutes, others can fly for several hours depending on the aerodynamic efficiency and performance (Panagiotou et al., 2020). A drone's endurance may be influenced by wing category (fixed-wing drones support higher flight duration) and climate conditions. Moreover, it is recommended to consider the drone's payload capacity as they are built to support certain weights (for carrying tools, cameras, sensors, etc.). They are also often able to be modified to carry other objects, documents, or even liquid to be sprayed (AUAV, 2022).

If one's goal is to obtain a small UAV and camera, collecting phenotype data for short periods, a multi-rotor setup should be the best solution. Multi-rotors are also easy to fly, cost little, and provide appropriate control and framing for aerial imagery (Maddikunta et al., 2021). Disadvantages include decreased durability and speed and the requirements for significant energy to move against gravity. Single-rotor drones have one rotor and a tail rotor that guides the drone's heading; they are generally gas powered and allow for longer flight times. Fixed wings help the drones lift and move in a forward direction, but they do not stay up against gravity. Drawbacks of fixed wings include their bigger GSD, which has negative impact for acquiring comprehensive UAV imagery (Yang et al., 2017). The hybrid type is a UAV that has the advantages of a fixed wing and can hover like a rotary system (AUAV, 2022).

8.2 | Efficient UAV sensors for phenotyping applications

Electro-optic sensors are commonly used for plant phenotyping applications; however, their performance is strongly impacted by weather conditions (e.g., cloudy environments) (Chand et al., 2017). Table 3 provides an overview of different UAV sensors and applications that are suitable and highly suited for crop phenomics. MS sensors are very appropriate for UAV-based plant phenotyping as they provide spatially high-resolution images and reflectance values in the NIR range (Smith et al., 2015). These sensors can be very effective tools for scientists through the use and interpretation of MS bands for phenotyping crop health traits and plant growth. Analyses of MS data collected from UAVs are currently among the few methods available for the early detection of crop diseases and pests, weeds, and the estimation of plant biomass (Maddikunta et al., 2021). RGB cameras globally have higher spatial resolution than other sensors, including MS sensors; however, in agricultural fields, MS sensors have greater benefits than RGB in terms of information quantity and quality and their capacity to survey plant physiological status (Shu et al., 2022).

Hyperspectral cameras are heavy and large, and they require integration with several other devices in UAV setups, such as a frame grabber, battery, and a data storage device. These features and requirements for support equipment have traditionally made hyperspectral systems challenging to use in agricultural settings (Matese et al., 2023). However, the technology needed for miniaturizing hyperspectral sensors is advancing and will enhance integration into UAV-based field phenotyping platforms and increase their applications in agriculture (Adamopoulos & Rinaudo, 2020). Thermal sensors allow measurements of canopy temperature and crop water stress indices (Boesch, 2017). They can convert into an image the detected electromagnetic energy released by an object in the infrared range. However, some factors such as variation in environmental conditions and the possibility of having different targets that emit or reflect thermal infrared radiation can decrease the accuracy of thermal infrared camera

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TABLE 3 Overview of unmanned aerial vehicle (UAV) sensor applications in plant phenotyping.

Applications	RGB	Lidar	Multispectral	Hyperspectral	Thermal	Radar
Plant/stand count	HS	HS	S	–	–	–
Height	HS	HS	S	–	–	–
Biomass	S	S	HS	–	–	S
Yield	S	S	HS	–	–	S
Crop physiology	S	S	HS	HS	HS	–
Leaf nitrogen content	S	S	HS	HS	S	–
Soil properties	S	S	HS	HS	–	HS
Pest and disease management	HS	S	HS	HS	HS	–

Abbreviations: HS, highly suited; S, suited.

measurements; these systems also require periodic calibration (Pech et al., 2013).

Unlike electro-optic sensors, radar and LiDAR sensors are less sensitive to unfavorable environmental conditions. LiDAR sensors operate by illuminating a targeted object and analyzing the reflected light. They cover wide landscapes providing accurate digital terrain and surface models (Adamopoulos & Rinaudo, 2020). However, the larger size and weight of LiDAR systems can be problematic with certain UAV payload restrictions (Balestrieri et al., 2021). As UAVs fly at low altitudes, obstacles such as birds, buildings, trees, and so forth can also represent a critical challenge. Some sensors such as radar can detect obstructions in the local environment by continuously emitting electromagnetic waves (Chand et al., 2017). LiDAR has a short detection range compared to radar; however, it has the advantage of providing higher accuracy and detail (Chand et al., 2017).

8.3 | Challenges on ML-based phenotyping

Plant phenotype data can be expensive and time consuming to collect, and there may be limited availability of high-quality data. This can make it challenging to train accurate ML models. Despite the development of advanced software and tools to generate training datasets for ML (Tang & Zhang, 2023; Tang, Hu, et al., 2023), they still have several limitations including lack of accuracy, subjectivity and bias, difficulty in generating and validating complex data, limited domain coverage, and adaptability to model changes. There is a need for more open-access datasets and standardized data collection protocols to facilitate ML research on plant phenotypes.

The quality of the plant phenotype data used to train ML models is critical for accurate predictions. However, the quality of the data can be affected by various factors such as environmental conditions, measurement error, and human bias. It is essential to develop more reliable and accurate data collection methods to ensure high-quality data for ML (Gano et al., 2023). For plant phenotype analysis, it can be challenging to determine which features are most informative for predicting the traits of interest. Future research should focus on developing more advanced feature selection methods and tools to improve the accuracy of the models.

Moreover, ML models are often considered "black boxes" because it can be difficult to interpret how they make predictions. This is particularly problematic for plant phenotype research, where understanding the underlying biology of the plant is critical. There is a need for more transparent and interpretable ML models that can be easily understood by plant biologists. There is a requirement for more generalized ML models that can be applied to a wide range of plant phenotype datasets and species. Finally, as ML models are increasingly used in plant phenotype research, ethical considerations such as data privacy and bias need to be addressed. It is imperative for more ethical guidelines and standards to ensure that ML is used in a responsible and fair manner.

8.4 | Complexities in data processing

Developing "plug and play" analytical solutions for UAV-based phenotyping is crucial for enabling breeders and researchers to easily extract relevant information from the captured imagery. These solutions should be user-friendly, with intuitive interfaces and automated workflows that can handle diverse data types and formats. They should also provide accurate and reliable trait extraction algorithms that can account for variability in environmental conditions, crop types, and growth stages (Yang & Zhai, 2022). Many image processing steps are time consuming, and coding for automatic and repetitive tasks is a critical requirement. For example, manually drawing polygons on image mosaics for adjacent plot delimitation is a time-consuming activity that requires collaboration between the computer scientists carrying out the image analysis and the field agronomists that designed the experiment. Therefore, it is important to enhance communication and develop a "shared vocabulary" between both parties (Shi et al., 2016).

Research groups and companies around the world are also rapidly developing software to automate the critical steps necessary for successful UAV-based plant phenotyping, including identification of individual plots, radiometric calibration, and high-speed image processing. The analysis of hyperspectral and LiDAR images remains computationally challenging, and there is a growing demand for the development of high-speed software to improve efficiency and accuracy in the data processing pipeline for these systems. Additionally, there is a need for more efficient data management systems that can effectively store, organize, and analyze the large volumes of data collected by UAVs.

8.5 | Regulatory issues and additional challenges

The regulatory requirements in the United States and globally pose a significant obstacle for the use of UAVs in agronomic research and crop production. A less restrictive regulatory environment will be necessary for the full realization of this technology's potential (Shi et al., 2016). In the United States, current Federal Aviation Administration (FAA) rules request a certificate of authorization or Part 107 remote pilot permit for legally holding flight missions over field trials (Shi et al., 2016). FAA legislation also requests registration of UAV operators, in addition to pilot training. Globally, UAV flights should cohere with local and national regulations.

Additional challenges limiting the global adoption of UAVs in plant phenotyping include significant data loss due to lighting and environmental effects, airspace restriction, UAV battery and payload constraints, UAV-related safety concerns, and birds and other wildlife (Olson & Anderson, 2021; Tsouros et al., 2019). With further advancements in sensor technology and ML algorithms, UAV-based phenotyping is likely to become an essential tool for crop breeding programs in the future. The highlighted research issues and challenges will enable researchers to identify the problem domain quickly.

9 | FUTURE TRENDS AND EMERGING TECHNOLOGIES

As the field of UAV-based plant phenotyping continues to evolve, several key trends and emerging technologies are expected to shape the future of agricultural research and crop production. This section aims to provide insights into the most promising technologies and research directions that researchers can consider for future investigations and resource allocation.

9.1 | Anticipated trends

The future of UAV-based plant phenotyping is expected to witness innovative remote sensing technologies, a heightened integration of advanced ML algorithms for improved data analysis and prediction of complex plant phenotypes. Moreover, there will be a continued focus on the development of standardized protocols and open-access datasets to foster collaborative research and data sharing in the field.

9.2 | Promising technologies for future research

In the coming years, advancements in hyperspectral imaging techniques are anticipated to enhance crop health assessment and disease detection. Further exploration of LiDAR technology will enable high-resolution 3D mapping of crop vegetation and more accurate biomass estimation. Additionally, the integration of unmanned ground vehicles (UGVs) and UAVs will facilitate synergistic data collection and analysis in precision agriculture. The implementation of onboard and real-time data transmission and processing using edge computing capabilities, along with the integration with decision support systems, is also in development and will allow breeders to receive instant feedback on crop traits. Additionally, the development of modular UAV system that can be customized based on specific crop types, environmental conditions, or research objectives is underway. While increasing flight duration became a primary concern, some companies (such as Harris Aerial) are already working on integrating power generator (electric or solar) into the UAV platform.

9.3 | Practical guidance for researchers

To effectively contribute to the field of UAV-based plant phenotyping, researchers should prioritize the implementation of standardized data collection protocols and robust validation methods (Shu et al., 2022). Encouraging collaboration and data sharing within the research community will be instrumental in the development of open-access datasets and the advancement of UAV-based plant phenotyping. Furthermore, investments in interdisciplinary research collaborations and user-friendly software tools for streamlined data processing and analysis will be critical in enabling efficient decision-making for crop management and breeding programs.

10 | CONCLUSIONS

With rapid advancements in sensor technology and ML algorithms, UAV-based phenotyping is poised to become a crucial tool for crop breeding programs in the future. The primary objectives of this review were to explore and describe the current frameworks and applications of UAVs in agriculture, specifically in plant phenotyping for faster and improved data acquisition in crop breeding. Among the various drone-based platforms, the multi-rotor UAV is the most commonly utilized platform, providing a compelling alternative to the traditionally employed time-consuming and labor-intensive ground truth methods for in-field crop phenotyping. With customized approaches for acquisition, processing, and analysis of data collected from UAV-mounted RGB, MS, hyperspectral, thermal, and/or LiDAR sensors, recent studies have successfully achieved accurate and robust high-throughput phenotyping of biophysical, physiological, and biochemical plant traits.

However, a significant challenge in utilizing UAVs and sensors for crop phenotyping is the requirement for validation data, which may not always be feasible to obtain. Another limitation is the reduced or nonsignificant correlations when complex crop phenotypes are not directly related to canopy spectral information. Despite these challenges, the large volume of data generated from UAV systems can be harnessed for new ML approaches to extract and predict plant phenotypes. Selecting suitable ML approaches and adhering to best practices are crucial for obtaining high-quality phenotype data necessary for measuring and enhancing genetic gain.

From a perspective standpoint, the integration of physically based radiative transfer models and process-based crop models into phenotyping studies marks a noteworthy stride in the realm of remote sensing applications for agriculture. This shift away from conventional reliance on classical methods, particularly those focused on VIs, introduces fresh opportunities for a more intricate and process-driven comprehension of plant traits. Nevertheless, a thorough examination of these alternative approaches unveils a landscape rich in both advantages and challenges.

AUTHOR CONTRIBUTIONS

Boubacar Gano: Investigation; writing—original draft; writing—review and editing. **Sourav Bhadra**: Investigation; writing—original draft; writing—review and editing. **Justin Vilbig**: Investigation; writing—original draft; writing—review and editing. **Nurzaman Ahmed**: Investigation; writing—original draft; writing—review and editing. **Vasit Sagan**: Writing—review and editing. **Nadia Shakoor**: Writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ORCID

Boubacar Gano https://orcid.org/0000-0002-1395-2436
Nadia Shakoor https://orcid.org/0000-0002-2035-7117

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