

REVIEW

UAV image acquisition and processing for high-throughput phenotyping in agricultural research and breeding programs

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Abstract

We are in a race against time to combat climate change and increase food production by 70% to feed the ever-growing world population, which is expected to double by 2050. Agricultural research plays a vital role in improving crops and livestock through breeding programs and good agricultural practices, enabling sustainable agriculture and food systems. While advanced molecular breeding technologies have been widely adopted, phenotyping as an essential aspect of agricultural research and breeding programs has seen little development in most African institutions and remains a traditional method. However, the concept of high-throughput phenotyping (HTP) has been gaining momentum, particularly in the context of unmanned aerial vehicle (UAV)-based phenotyping. Although research into UAV-based phenotyping is still limited, this paper aimed to provide a comprehensive overview and understanding of the use of UAV platforms and image analytics for HTP in agricultural research and to identify the key challenges and opportunities in this area. The paper discusses field phenotyping concepts, UAV classification and specifications, use cases of UAV-based phenotyping, UAV imaging systems for phenotyping, and image processing and analytics methods. However, more research is required to optimize UAVs' performance for image data acquisition, as limited studies have focused on the effect of UAVs' operational parameters on data acquisition.

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1 | INTRODUCTION

The escalating challenges posed by a growing global population and climate uncertainties have created an urgent demand for a 70% increase in food production by 2050 (Aslan et al., 2022). In response, Industry 4.0, an integration of transformative technologies such as the Internet of Things (IoT), robotics, artificial intelligence (AI), unmanned aerial vehicles (UAVs), cloud computing, blockchain, and others, emerges as a potential solution to address these pressing agricultural challenges (Bongomin, Gilibrays Ocen, et al., 2020; Bongomin, Mwasiagi, et al., 2020). The ongoing fusion of Industry 4.0 with agriculture is known as Agriculture 4.0 (Alam & Habib, 2021; Aslan et al., 2022; Liu et al., 2021), presenting an opportunity to propel industrial agriculture into the next generation through enhancement of agricultural research and breeding programs to achieve sustainable agriculture (Radoglou-Grammatikis et al., 2020).

Within the broader framework of sustainable agriculture, various concepts like Agriculture 5.0 (Ragazou et al., 2022; Saiz-Rubio & Rovira-Más, 2020), Agriculture 4.0 (Bongomin, Yemane, et al., 2020; Mammarella et al., 2022), precision agriculture (PA) (Daponte et al., 2019; Michels et al., 2020), smart farming (Virk et al., 2020), circular agriculture (Helgason et al., 2021), conservation agriculture (FAO, 2022), and climate-smart agriculture (FAO, 2019; Kalele, 2021) have been developed to optimize productivity, reduce labor time, and manage agricultural inputs effectively. PA, in particular, has gained global adoption and is instrumental in breeding programs, offering a powerful toolset for developing high-yielding, resilient, and resource-efficient crop varieties tailored to diverse field environments (Daponte et al., 2019; Duan et al., 2021). The integration of PA with Agriculture 4.0 technologies holds promise for more efficient data collection and analysis (Javaid et al., 2022; Trivelli et al., 2019), while principles of smart farming can be harmoniously applied within a circular agriculture framework to optimize resource use and minimize waste (Bach & Mauser, 2018). The convergence of these concepts creates a comprehensive and effective agricultural system, illustrating the interconnected nature of modern agricultural practices.

As the agricultural landscape advances, the adoption of high-throughput phenotyping (HTP) and precision phenotyping emerges as critical concepts in plant breeding and biotechnology research (Chapu et al., 2022; Nyonje et al., 2021; Sagan et al., 2019; Wang, Qiu, et al., 2020). These approaches differ in their focus, with precision phenotyping emphasizing detailed and accurate measurement of specific traits, while HTP emphasizes quick and efficient data collection from a large number of samples (Nyonje et al., 2021; Sagan et al., 2019). HTP, driven by advancements in remote sensing technologies, provides researchers with accurate and nondestructive ways to analyze large-scale phenotypic data,

Core Ideas

- Unmanned aerial vehicle (UAV) classification and their phenotyping applications are investigated for a comprehensive understanding.
- The key parameters of UAV image acquisition, and their effect on the UAV performance and phenotypic data quality, are examined.
- The strengths and weaknesses of diverse UAV imaging sensors for varied applications are evaluated.
- A general approach for UAV image processing and analytics in phenotypic studies is defined.
- Traditional and high-throughput phenotyping are contrasted, paving the way for future UAV applications.

overcoming bottlenecks in genomics and phenomics studies (Hall et al., 2022; James et al., 2022; Jangra et al., 2021; Kim et al., 2021; Xiao et al., 2022).

The adoption of UAVs, known by various names such as drones, unmanned aerial systems (Quamar et al., 2023), uncrewed aerial vehicles (Irujo et al., 2023), small unoccupied aerial systems (Pugh et al., 2021), remotely piloted aerial systems, unoccupied aerial vehicles (Shi et al., 2016; Sweet et al., 2022), miniature pilotless aircraft, and flying mini robots (Hafeez et al., 2023), in agriculture has marked a transformative shift, offering cost-effective and flexible solutions with diverse applications (Feng et al., 2021; Guo, Carroll, et al., 2021; Ludwig et al., 2020; Yue & Feng, 2021). Equipped with various imaging systems, including red–green–blue (RGB) sensors, multispectral sensors, or hyperspectral sensors, UAVs play a pivotal role in HTP tasks, aiding in activities such as biomass and yield estimation (Agapiou, 2020; Barbedo, 2019; Cheng & Matsuoka, 2021; Lee, Lin, et al., 2022; Librán-Embid et al., 2020; Manfreda et al., 2018; Ogawa et al., 2021; Otto et al., 2018; Paulus & Mahlein, 2020; Xie et al., 2021; Yue & Feng, 2021).

However, alongside their advantages, UAVs also present challenges to widespread adoption. Factors such as limited flight time and varying regulatory frameworks across countries have been identified as obstacles impacting the broader integration of UAV technology (Frankelius et al., 2019; Jiang et al., 2021; Xu et al., 2020). Additionally, the processing and analysis of the substantial amount of plant or field images generated by these UAV-based sensors present their own set of challenges, necessitating a skill set in data analytics (Sagan et al., 2022; Wang, Duan, et al., 2021). Various preprocessing tasks, including radiometric calibration of hyperspectral or multispectral images, are deemed essential

for ensuring accurate analysis due to the inherent variations in imaging conditions (Guo et al., 2019; Xu et al., 2019). As the field advances, machine learning (ML) and deep learning algorithms, particularly convolutional neural networks (CNNs), have emerged as powerful tools for image processing, classification, and prediction based on these vast datasets (Bouguettaya et al., 2022; Lin & Guo, 2020; Prat, 2019; Quiñones et al., 2021; Rahaman et al., 2019; Selvaraj et al., 2020).

The intersection of advancements in image processing, big data analytics, ML, and deep learning allows for HTP at unprecedented levels, revolutionizing the monitoring of crop growth, seedling condition evaluation, yield prediction, and cultivation management (Chang et al., 2021; Li et al., 2021). However, despite these advantages, the widespread adoption of HTP is hindered by barriers such as the need for technical expertise, high implementation costs, and government regulations (Kim, 2020). Effective collaboration across interdisciplinary fields is deemed crucial for the development and widespread adoption of HTP technology. This interdisciplinary nature requires expertise ranging from engineering and manufacturing of sensors to computer science, data analysis, and plant biology (Campbell et al., 2018). Creating platforms for collaboration is essential to foster the development, implementation, and diffusion of HTP technology on a global scale.

In the realm of agricultural technology, the integration of high-throughput genotyping and phenotyping with genome-wide markers accelerates the discovery of novel alleles for breeding crops that are more efficient in nitrogen use and more resilient to climate uncertainties and diseases (Banerjee et al., 2020; Lamo et al., 2021; Rodene et al., 2022; Sweet et al., 2022). This holistic approach in agricultural research, blending advanced molecular breeding technologies with cutting-edge phenotyping methods, is pivotal for enhancing crop and livestock outcomes while contributing to sustainable food systems.

HTP has gained momentum, especially with the advent of UAVs and image analytics in agriculture. This review paper distinguishes itself by offering a comprehensive overview that goes beyond existing reviews. It encompasses overview of phenotyping concepts, UAV platforms, imaging sensors, image acquisition parameters, image processing, UAV use cases in phenotyping, and challenges and future research direction (Table 1). The objective of this paper is to provide a comprehensive understanding of the use of UAV platforms and image analytics for HTP in agricultural research. It aims to identify key challenges and future research in this area. The paper presents several important contributions, including a detailed classification of UAVs, a discussion of key parameters for UAV image acquisition, an overview of UAV applications in phenotyping, and insights into sensors and image processing techniques for phenotyping.

As agriculture stands at the crossroads of technological innovation and the urgent need for sustainable practices, the integration of Agriculture 4.0 concepts, PA, climate-smart agriculture, and HTP becomes pivotal. These approaches collectively contribute to meeting the growing demand for food production, adapting to climate uncertainties, and fostering sustainable agricultural practices on a global scale. The synthesis of cutting-edge technologies, interdisciplinary collaboration, and innovative research methodologies forms the foundation for a transformative future in agriculture.

2 | FIELD PHENOTYPING

Phenotyping is the process of measuring and analyzing observable traits or phenotypes of plants or organisms to understand their characteristics, performance, and genetic makeup (genotype) (Bian et al., 2022). It serves the crucial purpose of identifying and selecting crop genotypes that exhibit productivity and adaptability across diverse environments (Prasanna et al., 2013). Essentially, it involves assessing how plants respond to various environmental factors, generating valuable data that inform strategic breeding decisions in selecting and advancing breeding lines, especially concerning traits like yield, stress tolerance, disease resistance, and agronomic features (Morisse et al., 2022; Wang et al., 2018). Phenotyping is the critical step in breeding programs where the goal is to develop new and improved varieties with desirable traits.

To optimize the breeding pipeline, where selecting the most suitable varieties is paramount, achieving robust phenotyping is essential. The challenge lies in striking a balance between accuracy, speed, and cost-effectiveness in the phenotyping process. Leveraging remote sensing technologies, such as engineered phenotyping, becomes instrumental in enhancing data collection for making informed choices based on phenotypic characteristics (Kim, 2020).

In practice, field phenotyping not only reveals how crops respond to their environment but also allows breeders to discern the most promising varieties. The integration of remote sensing technologies, constituting engineered phenotyping approaches, contributes to the collection of comprehensive and high-quality data, enabling breeders to make well-informed decisions throughout the breeding pipeline. This streamlined approach ensures that the selected varieties meet the criteria of productivity, adaptability, and resilience, addressing the complexities of modern agricultural challenges (Cudjoe et al., 2023).

2.1 | Traditional field phenotyping

Traditional field phenotyping refers to the manual or semiautomated observation and measurement of plant traits in the

TABLE 1 Comprehensive overview of high-throughput phenotyping (HTP) in agriculture, encompassing overview of phenotyping, unmanned aerial vehicle (UAV) platforms, UAV image acquisition, UAV use cases in phenotyping, UAV imaging sensors, image processing, and challenges and future research: a comparison with the previous reviews.

Study	Overview of phenotyping	Overview of UAV platforms	Image acquisition parameters	UAV uses cases in phenotyping	UAV imaging sensors	Image processing	Challenges and future research
Sun, Wang, Wang et al., 2021	✗	✓	✗	✓	✗	✓	✓
Mohsan et al., 2023	✗	✓	✗	✓	✗	✗	✓
Bian et al., 2022	✓	✗	✗	✓	✓	✗	✓
Nduku et al., 2023	✗	✗	✗	✓	✓	✓	✗
Khuzaimah et al., 2022	✗	✓	✗	✓	✓	✗	✓
Ma et al., 2022	✓	✗	✗	✓	✓	✗	✓
Xie & Yang, 2020	✗	✓	✗	✓	✓	✗	✗
Feng et al., 2021	✗	✓	✗	✓	✓	✓	✓
Jang et al., 2020	✗	✓	✗	✗	✓	✓	✗
Zheng, Abd-Elrahman, et al., 2021	✗	✓	✗	✓	✓	✓	✓
Olson & Anderson, 2021	✗	✓	✗	✓	✓	✓	✓
Sweet et al., 2022	✗	✗	✗	✓	✓	✓	✓
Amarasingam et al., 2022	✗	✓	✗	✓	✓	✓	✓
Gill et al., 2022	✓	✓	✗	✓	✗	✓	✓
This review	✓	✓	✓	✓	✓	✓	✓

natural field environment. This approach has been a standard practice in plant breeding for many years and is still a common practice in many developing countries. Although it may be time consuming and labor intensive, it remains a valuable method for assessing a wide range of traits. However, this method is low throughput, and it may be impractical for selecting complex traits like improved yield potential or adaptation to abiotic stresses (Feldmann & Tabb, 2022). Additionally, trait and tool choices add complexity, varying with the target environment (Volpato et al., 2021).

Contrastingly, there is a global shift to modern HTP, offering enhanced accuracy and speed for crop genotype selection (Kim, 2020; Prasanna et al., 2013). Despite breeding advancements, progress in phenotyping lags in many developing countries due to reliance on traditional and manual methods (Chapu et al., 2022; Prasanna et al., 2013; Walter et al., 2019; Xiao et al., 2022).

In this low-throughput approach (Figure 1), researchers manually scout fields, assessing traits like plant height, leaf color, leaf area index (LAI), chlorophyll content, and biomass (Johansen, Morton, et al., 2020; Kim, 2020; Krishna, 2018; Yang et al., 2017). To overcome these limitations, UAV-based remote sensing becomes a transformative solution, offering quick and high-quality results, thanks to cost-effective, lightweight sensors and UAVs (Krishna, 2018).

2.2 | High-throughput phenotyping

HTP is an advanced approach to phenotyping that involves the rapid and automated collection of large-scale phenotypic data at various levels, from the molecular to the field level and over extended periods (Lane & Murray, 2021). Remote sensing technologies such as UAVs, satellites, and manned aircraft enhance throughput by rapidly capturing phenotypic data, enabling efficient measurement of numerous plants at different levels and reasonable costs (Rejeb et al., 2022; Tao et al., 2022).

This concept gained popularity in plant science and breeding, serving to monitor plant growth and assess the interplay of genotypes and the environment (Krishna, 2018). Integrated with genome-wide association studies (GWAS) or quantitative trait loci (QTL) (Xiao et al., 2022), HTP aids in bridging the gap between the genome and phenome in plant breeding, as illustrated in Figure 2 (Adak et al., 2023; Jung et al., 2021; Karunathilake et al., 2023; Yan et al., 2023). UAV-based remote sensing, particularly useful for large-scale HTP, offers near-ground capabilities, facilitating fast, precise, and cost-effective phenotyping in breeding programs (Chen et al., 2021; Feng et al., 2021; Rallo et al., 2020). Equipped with various sensors (such as RGB, multispectral, and hyperspectral), these UAVs capture multisource phenotypic data, enabling



FIGURE 1 Traditional phenotyping practices in rice fields. (a) Plant height measurement. (b) Tiller number counting. (c) Panicle length measurement. (d) Sample collection for grain weight measurement.

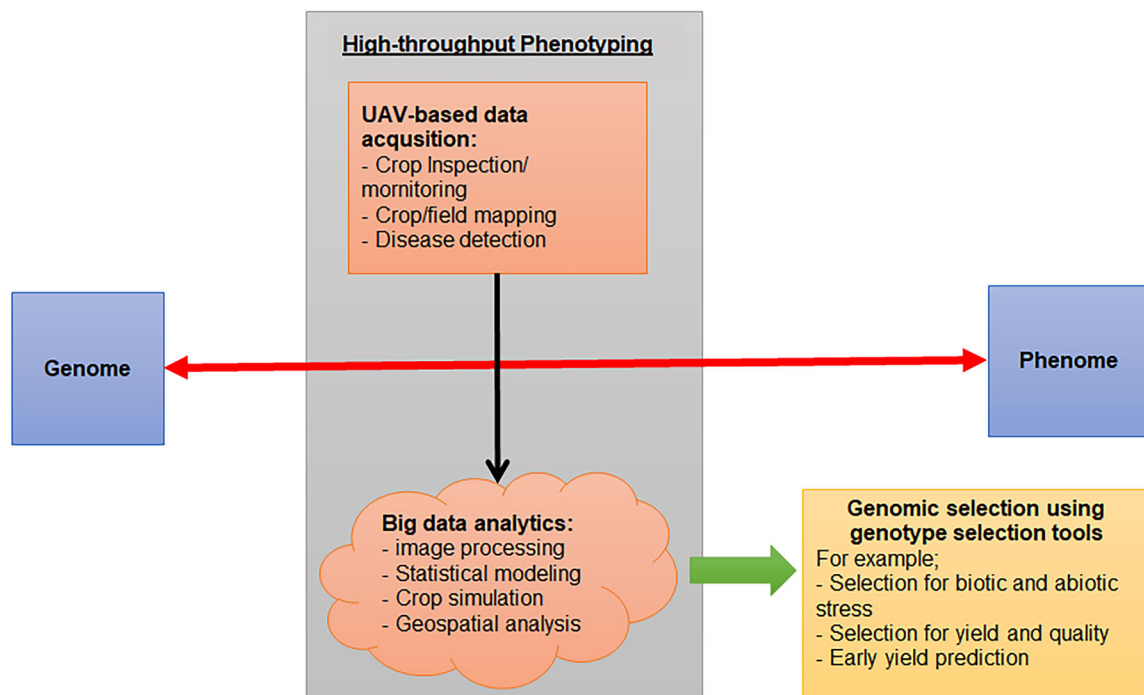


FIGURE 2 High-throughput phenotyping (HTP) in conjunction with genetic mapping; bridging the genome–phenome gap in plant breeding.

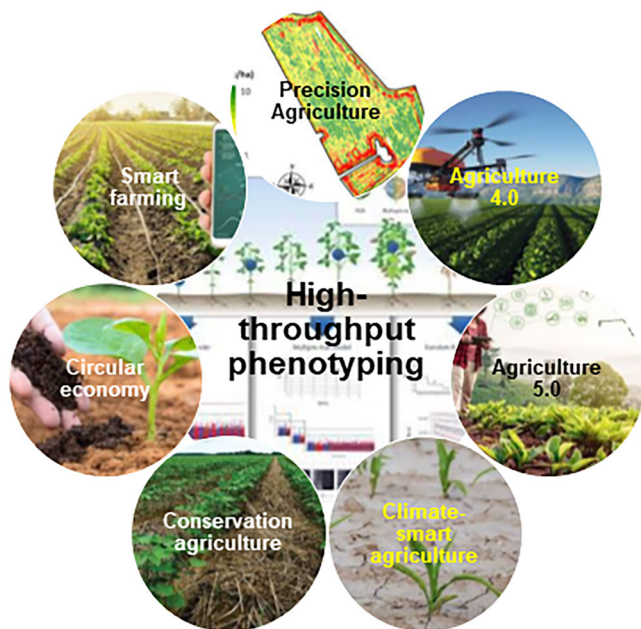


FIGURE 3 Interconnected concepts in modern agriculture; high-throughput phenotyping (HTP) and its integration with Agriculture 5.0, Agriculture 4.0, precision agriculture, smart farming, climate-smart agriculture, circular agriculture, and conservation agriculture.

the generation of three-dimensional (3D) crop images and extraction of parameters such as plant height, width, leaf dimensions, area, and inclination angle for comprehensive plant biology and genomics analysis (Guo et al., 2018).

HTP is a pivotal tool in modern agriculture, synergizing with various concepts such as Agriculture 5.0, Agriculture 4.0, PA, smart farming, climate-smart agriculture, circular agriculture, and conservation agriculture (Figure 3). HTP offers individual plant trait data for precision agricultural decisions, such as variable-rate fertilizer application and targeted pest control (de Alcântara et al., 2023; Qiao et al., 2022; Sheikh et al., 2023). It identifies crops with stress tolerance, vital for climate-smart agriculture (Danzi et al., 2019; Roitsch et al., 2022). In smart farming, HTP optimizes resource use and enhances crop health (Kamat et al., 2023; Panwar et al., 2022), playing a critical role in Agriculture 4.0 and additionally in Agriculture 5.0, where the focus is AI analysis of large datasets (Fan et al., 2021, 2023; Sarkar et al., 2023). In circular agriculture, HTP characterizes diverse plant traits at scale, supporting practices like breeding resilient crops and optimizing resource management (Kim et al., 2022; Zhang, Wang, et al., 2023). Moreover, HTP contributes to conservation agriculture by assessing cover crop impact, optimizing nitrogen application, identifying drought-tolerant genotypes, and managing weeds and pests (Deery et al., 2014; Gracia-Romero et al., 2020). The comparison in Table 2 illustrates the distinct focuses, key technologies, and roles of vari-

ous agricultural concepts, emphasizing their contributions to sustainable agriculture amid climate change.

The term high-throughput phenotyping platform (HTPP) denotes platforms designed for the rapid development, implementation, and diffusion of HTP, with variations depending on the country or institution. HTPPs, utilizing nondestructive and noninvasive tools such as UAVs, robotics, and automated data processing, contribute to precise trait measurements and reliable phenotype estimates (Prasanna et al., 2013). These platforms are instrumental in modeling to forecast genotypic performance across diverse environmental conditions. The outcomes of such modeling may include predictions related to factors such as crop yield, stress tolerance, disease resistance, and other essential agronomic traits. This information is valuable for making informed decisions in crop breeding, selection, and cultivation strategies (Yassue et al., 2022). Several global research institutions, including the Australian Plant Phenomics Facility (APPF), PhenoArch platform at INRAE Montpellier, and the FIP (Field Phenotyping) platform at ETH Zürich, have established HTPPs (Pérez-Valencia et al., 2022).

3 | UAV PLATFORMS AND SYSTEMS

UAVs are reshaping remote sensing by addressing limitations of traditional platforms like satellites, aircraft, and ground-based platforms. They provide high-resolution, flexible, cost-effective, real-time data collection, transforming fields such as environmental monitoring, agriculture, disaster management, infrastructure inspection, and archaeological research. Valued by researchers and professionals for their versatility, UAVs offer breakthroughs in remote sensing, with ongoing technological advancements promising innovative applications (Mohsan et al., 2023; Quamar et al., 2023; Shah et al., 2023).

3.1 | UAV classification

UAVs exhibit diverse types and designs, broadly classified based on altitude (Saad et al., 2020), operation type (UCAA, 2020), application (Tal & Altschuld, 2021), wing type (Krishna, 2020), GPS correction method (Kim et al., 2023), and size (Suab & Avtar, 2020). This classification complexity, as depicted in Figure 4, challenges buyers and users in making informed decisions. The broad spectrum of agricultural UAV further complicates this process, requiring a careful assessment of specific agricultural needs, considering factors like farm size, terrain, crop type, and desired functionalities and applications (Figure 5).

Wing type classification commonly encompasses fixed wing, rotary wing, and hybrid wing (Krishna, 2020).

TABLE 2 Comparing high-throughput phenotyping with related concepts in agriculture.

Concept	Focus	Key technology	Role in breeding programs	Contribution to sustainable agriculture
High-throughput phenotyping	Rapid and accurate measurement of plant traits	Sensors, robotics and automation, UAVs, data analytics, AI	Direct: Provides data for identifying desirable traits and developing new crop varieties with improved yields, resistance to diseases and pests, and tolerance to environmental stresses	Reduces need for pesticide and herbicide use by identifying resistant varieties.
Agriculture 5.0	AI-driven automation and optimization	AI, big data, robotics	Indirect: Provides tools for analyzing breeding data and automating breeding processes in the context of climate change	Optimizes resource use, minimizes waste, increases production efficiency, and reduces need for human labor and associated environmental impact
Agriculture 4.0	Digital technology for improved management	IoT, UAVs, big data, blockchain,	Indirect: Provides data for characterizing plant traits and informing breeding decisions, including those related to climate resilience	Improves farm management, reduces environmental impact, and increases data-driven decision-making
Precision agriculture	Spatial and temporal variability management	GPS, GIS, remote sensing, variable-rate technology	Direct: Enables targeted breeding approaches based on specific field conditions, including those influenced by climate change	Promotes efficient resource use, minimizes environmental impact through targeted application of inputs, and contributes to soil health and crop resilience
Smart farming	Data-driven decision-making and automation	Sensors, robots, data analytics, IoT	Varies: Can support some aspects of breeding program management and data analysis in the context of climate change	Can support various aspects of sustainable agriculture by optimizing resource use, reducing waste, and improving farm management
Circular agriculture	Resource efficiency and waste reduction	Range of technologies, for example, digital and regenerative agriculture	Indirect: Can influence breeding goals related to resource-efficient crop varieties and climate-resilient farming systems	Minimizes environmental impact by closing resource loops, reducing waste, and promoting resource reuse
Conservation agriculture	Soil health and sustainability	Minimal tillage, cover crops, crop rotation	Indirect: Can influence breeding goals related to soil health, resilience, and carbon sequestration	Improves soil health and fertility, increases soil carbon sequestration, and promotes long-term agricultural sustainability
Climate-smart agriculture	Climate change adaptation and mitigation	Efficient irrigation, drought-resistant crops	Direct: Drives specific breeding goals for developing climate-resilient and low-emission crop varieties	Enhances farm resilience to climate change and reduces greenhouse gas emissions

Abbreviations: AI, artificial intelligence; GIS, geographic information system; GPS, global positioning system; IoT, Internet of Things; UAV, unmanned aerial vehicle.

Fixed-wing UAVs use static wings for lift through forward airspeed, while rotary-wing UAVs employ multiple rotors for lift without forward airspeed. The fixed-wing UAVs are commonly used for high-resolution aerial mapping, surveying, and surveillance. On the other hand, rotary-wing UAVs are commonly used in photography, cinematography, and close-range inspections. Hybrid-wing UAVs combine both features, utilizing rotors for takeoff and landing and fixed wings for efficient forward flight. It is suitable for tasks requiring both

long-endurance flights and the ability to operate in confined spaces. The advantages and limitations of each UAV type are summarized in Table 3. The wing-based classification plays a pivotal role in selecting the most suitable UAV for specific applications, considering factors like endurance, maneuverability, and the nature of the mission at hand.

UAVs are also categorized by operating altitudes into low and high classifications. Low-altitude UAVs, operating below 500 feet, excel in precision tasks like agriculture and

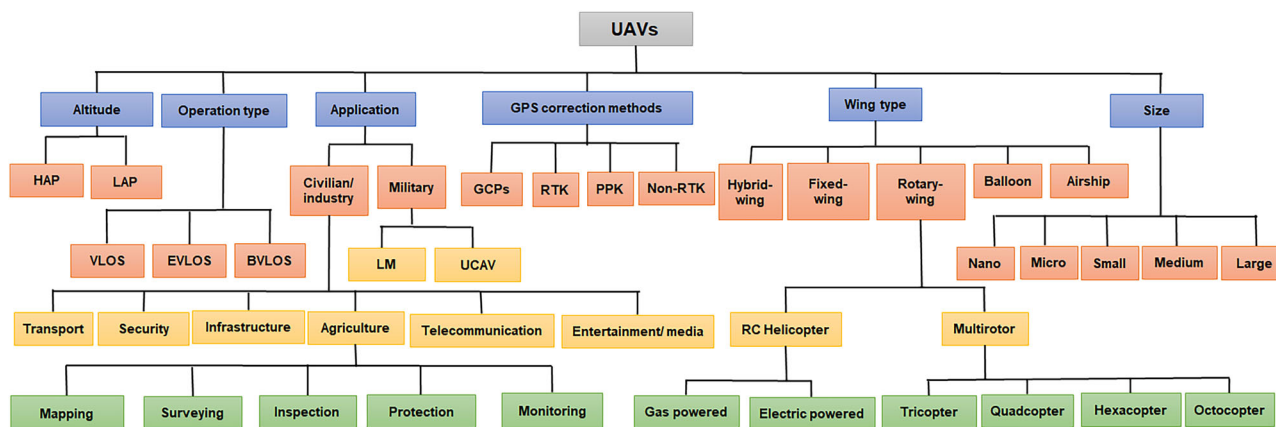


FIGURE 4 Detailed classification of unmanned aerial vehicles (UAVs). HAP, high-altitude platform; LAP, low-altitude platform; VLOS, visual line of sight; EVLOS, extended visual line of sight; BVLOS, beyond visual line of sight; RC, remote control; LM, loitering munitions (suicide drone or kamikaze drone); UCAV, unmanned combat aerial vehicle; GCPs, ground control points; RTK, real-time kinematics; PPK, postprocessing kinematics.

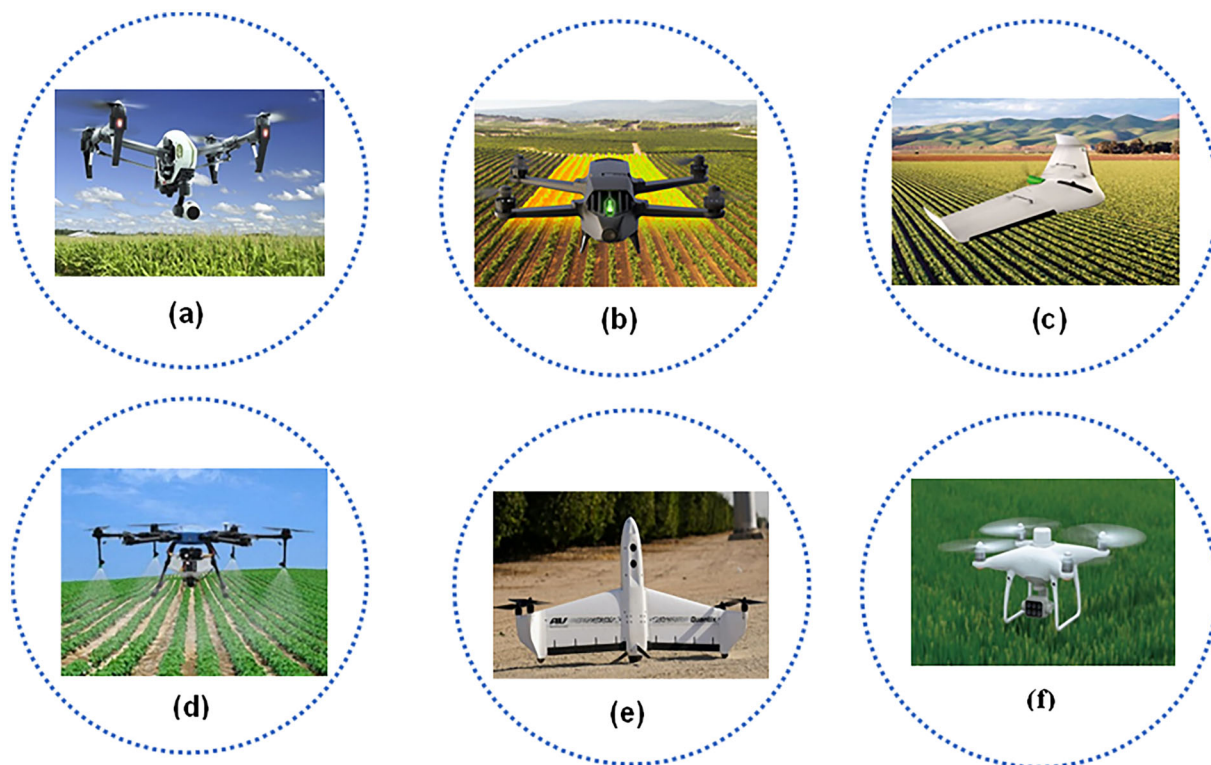


FIGURE 5 Examples of commercial agricultural unmanned aerial vehicles and their applications. (a) Quadcopter UAVLance for mapping and surveying in agriculture. (b) Quadcopter Parrot Blueglass, for crop scouting. (c) Hybrid-wing Delair UX11 Ag drone, for large-scale surveying in agriculture and forestry. (d) Multirotor UAV, for crop yield assessment. (e) Hybrid-wing QuanticMapper Aerovironment, for mapping. (f) Quadcopter DJI Phantom 4-multispectral, for crop inspection and monitoring.

inspections, offering close-range data collection. Conversely, high-altitude UAVs, flying above 500 feet, are designed for wide-area surveillance, playing crucial roles in military and environmental applications (Saad et al., 2020). This altitude-

based classification aids in mission selection, considering regulatory compliance and the scale of observation needed.

The size classification influences UAV applications and capabilities. Nano UAVs (up to 250 g) are small and used for

TABLE 3 Advantages and limitations of wing-based unmanned aerial vehicle (UAV) classification platforms.

UAV platform	Advantages	Limitations
Fixed-wing	• Longer flight times compared to other UAV types • Cover larger areas in a single flight • Stable in flight • Accurate navigation • Higher payload capacities compared to other types	• Less maneuverable compared to other UAV types • Needs large open area for takeoff and landing
Rotary-wing (multirotor)	• More maneuverable compared to fixed-wing • Fly at lower altitudes and capture higher-resolution images • Hover in place and capture detailed images	• Shorter flight times compared to other types • Less stable in flight compared to other types • Lower payload capacities compared to other types
Hybrid-wing	• Longer flight time compared to rotary-wing • Offers versatile payload capacity compared to rotary-wing • Greater flexibility compared to other types	• Higher cost than other types • More complex UAV platform • Poses additional safety concern due to combustible fuel source

close-range tasks. Micro UAVs (250 g to 2 kg) are for basic photography. Mini UAVs (2–25 kg) include consumer drones with advanced features. Small UAVs (25–150 kg) are used professionally. Medium UAVs (150–600 kg) are for surveillance. Large UAVs (600–1500 kg) are robust and used in military or cargo transport. Very large UAVs (1,500 kg and above) are massive and employed for heavy-cargo transport and military operations (Suab & Avtar, 2020). Size classifications often impact regulatory requirements. Application-based classification differentiates civilian/industry UAVs from military counterparts. Military UAVs, engineered for surveillance and combat (Boyle, 2020; Kreps, 2018), contrast with civilian UAVs designed for specific functions in different industry sectors including agriculture, transportations, security, media, infrastructure, and many others (Krishna, 2020; Suab & Avtar, 2020; Tal & Altschuld, 2021). Agricultural UAVs focus on precision farming, security UAVs monitor critical areas, media UAVs capture aerial visuals, transportation UAVs transport and deliver goods, and infrastructure inspection UAVs examine critical structures. This classification highlights the versatile contributions of UAVs across diverse industries and applications.

Operation type-based classification includes visual line of sight (VLOS), extended visual line of sight (EVLOS), and beyond visual line of sight (BVLOS) (Davies et al., 2018; Stöcker et al., 2017). VLOS pertains to UAV operations where the pilot maintains continuous, unaided visual contact with the UAV throughout the flight. EVLOS involves UAVs being flown beyond the visual range of the pilot but within the extended visual range of one or more trained observers. BVLOS represents a more advanced operational mode where the UAV is flown out of the visual range of both the pilot and observers (Davies et al., 2018). BVLOS operations can potentially offer advantages over VLOS or EVLOS operations, including the ability to collect more data, cost-effectiveness, and increased safety, depending on the specific use case (van der Sluijs et al., 2023).

Lastly, UAVs can also be classified based on the global positioning system (GPS) correction methods. These include ground control points (GCPs) or traditional method, real-time kinematic (RTK), postprocessed kinematic (PPK) or postmission precise point positioning (PPP) (Kim et al., 2023), and non-RTK (Pugh et al., 2021). GCPs represent a traditional and widely employed method for correcting GPS data in UAV surveys (Oliveira et al., 2023). RTK systems provide real-time corrections, enhancing safety and accuracy (Gilliot et al., 2022; Kim et al., 2023). Non-RTK UAVs may fall under either GCPs or PPK methods. Unlike RTK, PPK does not rely on real-time radio connections during the flight, offering flexibility in operation (Eker et al., 2021; Tomaščík et al., 2019). Combining correction methods, such as GCPs and PPK, has the potential to enhance overall accuracy in UAV surveys (Cho & Lee, 2023). However, it is crucial to acknowledge that the number and distribution of GCPs continue to significantly influence the overall accuracy, even when utilizing PPK methods (Martínez-Carricondo et al., 2023).

3.2 | UAV guidance and control systems

UAV guidance and control systems are the technological backbone that empowers UAVs to navigate, stabilize, and execute mission objectives with precision. Central to these systems are autopilot functionalities, managing flight dynamics and enabling both manual and autonomous modes. Inertial measurement units (IMUs) play a pivotal role in stabilizing UAVs by measuring accelerations and angular rates. GPS receivers provide accurate location data, facilitating autonomous navigation and waypoint following. Barometric altimeters ensure precise altitude control, while magnetometers contribute to orientation accuracy. Control surfaces and actuators govern the UAV's maneuvers, allowing for controlled pitch, roll, and yaw movements. Communication systems enable real-time data exchange between the UAV

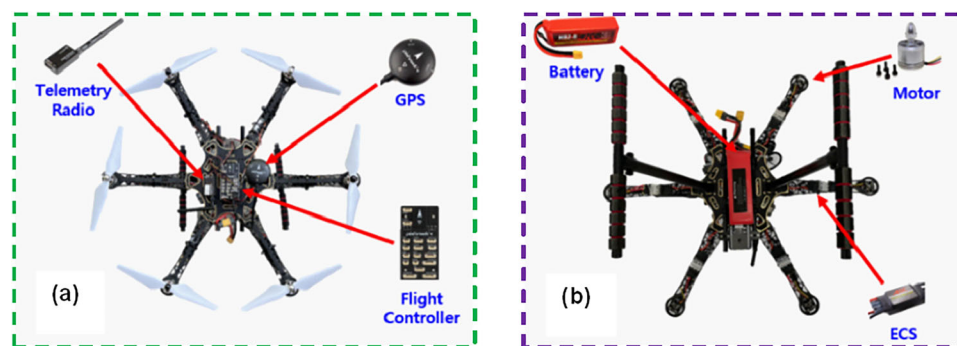


FIGURE 6 Components of multirotor (Quadcopter) unmanned aerial vehicle platform: (a) upper view and (b) bottom view. GPS, global positioning system; ECS, electronic control system.

and ground control, ensuring seamless command input and telemetry systems (Feng et al., 2021; Oluwaseun & Ehiagwina, 2022). The GPS, telemetry radio, and flight controller are normally located on the top part of UAV, as depicted in Figure 6 (Lee, Shin, et al., 2022). The ground control station (GCS) serves as a central hub, collecting flight-related data and facilitating communication with the UAV control system. Sensors, both ground based and onboard, contribute to data collection (Saad et al., 2020). Some UAVs incorporate collision avoidance systems, utilizing sensors to detect obstacles and enhance operational safety. These integrated systems collectively contribute to the UAV's ability to operate autonomously or under human supervision across a diverse array of applications, from PA to surveillance and beyond.

3.3 | UAV imaging sensors

UAV imaging sensors are crucial components that enable UAVs to capture valuable data for diverse applications. These sensors come in various types, including light detection and ranging (LiDAR) sensors, thermal sensors, visible light (RGB) sensors, multispectral sensors, and hyperspectral sensors, as shown in Figure 7, each designed to gather specific information. RGB sensors are commonly used to capture visible light images, suitable for general imaging purposes. Multispectral and hyperspectral sensors extend the spectrum, aiding applications like agriculture by providing data beyond human vision. Thermal infrared detects infrared radiation, facilitating tasks such as search and rescue or inspections. LiDAR sensors use laser beams to measure distances, creating precise 3D maps of terrain. These sensors, often accompanied by GPS receivers and IMUs for accurate positioning and stabilization, contribute to the versatility of UAVs across industries such as agriculture, environmental monitoring, and infrastructure inspection. As technology advances, integration with various imaging sensors continues to enhance the capabilities of UAV systems. Table 4 outlines the strengths

and weaknesses of commonly used UAV imaging sensors. Understanding these trade-offs is essential for selecting the most suitable UAV imaging sensor based on the specific requirements of the application.

3.3.1 | LiDAR image sensor

LiDAR technology employs lasers to calculate the time taken for emitted light to reflect back from an object to the sensor, generating precise LiDAR images or data. Integrated with RGB images, LiDAR provides topography data without image overlap (IOL), enhancing topographical mapping efficiency (van der Merwe et al., 2020). Therefore, it proves valuable for measuring canopy height (Suab & Avtar, 2020). While LiDAR sensors demonstrate high accuracy in estimating forest growing stock volume, the presence of inconsistencies in acquisition dates during field surveys introduces a potential source of inaccuracies. Variations in survey timing may impact the reliability of the estimates, emphasizing the need for careful consideration of temporal factors in order to ensure accurate and consistent results (Lin et al., 2022).

3.3.2 | RGB image sensor

RGB images, produced by visible light sensors like charge-coupled device (CCD) and complementary metal-oxide semiconductor (CMOS), are widely employed in phenotyping due to their cost-effectiveness, higher spatial resolution (SR), and ease of use compared to multispectral and hyperspectral sensors (Gonzalez et al., 2018; Sanches et al., 2018). Lightweight and adaptable to various weather conditions, they are suitable for calculating vegetation indices (VIs), generating digital elevation models, orthomosaics, and vegetation height maps (Barbosa, Ferraz, Dos Santos, et al., 2021; Esposito et al., 2021; Maes & Steppe, 2018). However, limitations arise when analyzing vegetation parameters requiring spectral information beyond the visible spectrum.

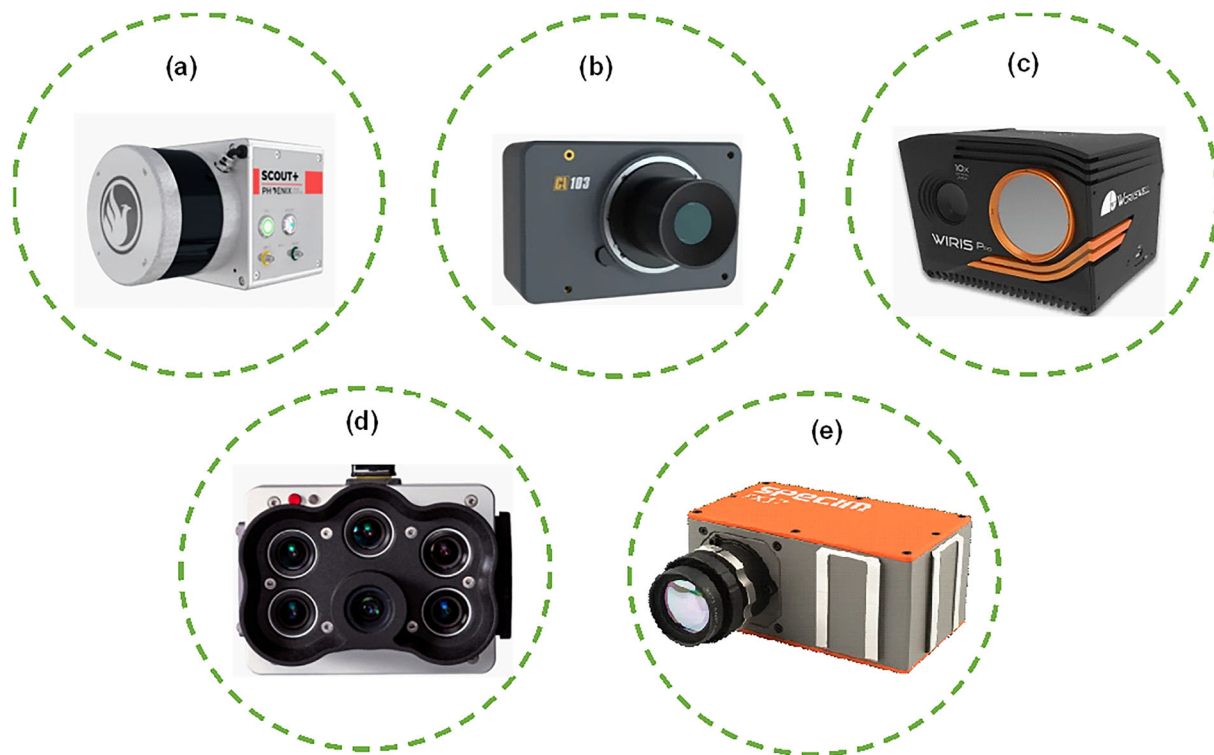


FIGURE 7 Unmanned aerial vehicle imaging sensors. (a) Light detection and ranging (LiDAR). (b) Red, green, and blue (RGB). (c) Thermal infrared. (d) Multispectral sensor. (e) Hyperspectral sensor.

To address this, RGB sensors are often combined with other sensors (Tsouros et al., 2019). Alternatively, modified RGB sensors, like near-infrared (NIR)-RGB, replace the NIR filter, providing NIR sensitivity without the high cost of multispectral sensors (Maes & Steppe, 2018). RGB images may require periodic calibration for accurate color metrics, introducing complexity and an additional step in their utilization. This need for calibration, while essential, can impact the consistency and reliability of color data if not performed regularly.

3.3.3 | Thermal image sensor

Thermal images, captured by infrared sensors and optical lenses, visualize object temperatures without relying on visible properties (Syeda & Alam, 2021). Beneficial for monitoring surface temperature and detecting drought stress, these images display warmer objects as yellow and cooler ones as blue (Tsouros et al., 2019). Despite their utility in applications like irrigation management and canopy temperature extraction (Guilherme et al., 2020; Hunt & Daughtry, 2018; Maes & Steppe, 2018; Tsouros et al., 2019), thermal sensors have limited applications that focused on monitoring or inspecting other crop characteristics (Raeva et al., 2019; Tsouros et al., 2019).

3.3.4 | Multispectral image sensor

Multispectral images, captured by sensors with four to six bands, offer richer data than traditional RGB images (Gonzalez et al., 2018; Raeva et al., 2019; Suab & Avtar, 2020; Syeda & Alam, 2021). Combining spectral and spatial data, these images are valuable for classification, mapping, prediction, and detection in crop phenotyping and remote sensing (Maes & Steppe, 2018). Commonly used for calculating normalized difference vegetation indices (NDVIs) to estimate biomass and identify stressed areas in crops, they require preprocessing, increasing computational time and cost (Nhamo et al., 2020). Additionally, multispectral sensors are more expensive than RGB sensors.

To enhance multispectral imagery resolution, pan-sharpening merges high SR from panchromatic images with multispectral richness for detailed analysis (Zhang, Zhang, et al., 2023). Various fusion strategies, including component substitution and spatial-spectral decomposition, are employed, with multiscale and multi-depth CNN presenting an innovative approach integrating deep neural networks (Yuan et al., 2018). Other fusion methods, such as method-based and deep CNN strategies, contribute unique perspectives (Aburaed et al., 2023; Deng et al., 2019; Yuhendra et al., 2012). Balancing spatial quality and spectral fidelity is challenging, with innovations like the alternating

TABLE 4 Advantages and limitations of unmanned aerial vehicle (UAV) imaging sensors.

Sensors	Advantages	Limitations
LiDAR	- Provides detailed 3D information on plant architecture and development, including plant height and canopy density - Accurately estimates plant biomass and yield - Useful for terrain mapping and vegetation structure analysis	- Requires specialized equipment and expertise to acquire and process LiDAR images - Limited ability to capture detailed information on individual plant structures - Can be heavier and more expensive compared to other sensors
RGB	- Provides high-spatial-resolution images with detailed information on plant color, size, and shape - Accurately estimates plant biomass and yield - Can capture senescence in response to stress - Lightweight and cost-effective	- Cannot capture important plant traits such as stress responses or physiological activity - Affected by variable lighting conditions and shadows - Inability to capture high-spectral-resolution images
Thermal	- Provides information on plant temperature and stress responses, which can be valuable for studying plant responses to environmental stressors such as drought or disease - Detect early signs of plant stress before visible symptoms appear	- Affected by variable environmental conditions such as wind or humidity - Limited to temperature-related information and lacks detailed visual data - Usually higher in cost compared to RGB or multispectral cameras
Multispectral	- Provides information on plant traits related to physiology, stress responses, and growth dynamics, including vegetation indices such as NDVI - Detects early signs of plant stress before visible symptoms appear - Provides more detailed information on plant traits compared to RGB sensors	- Affected by variable environmental conditions such as cloud cover, humidity, and temperature - Requires specialized equipment and expertise to acquire and process multispectral images - Limited ability to capture high-resolution images due to technical constraints in terms of spatial resolution - Limited spectral resolution compared hyperspectral sensors
Hyperspectral	- Provides detailed spectral information on plant tissues, which can be used to study plant physiology and stress responses - Detects early signs of plant stress before visible symptoms appear	- Requires specialized equipment and expertise to acquire and process hyperspectral images - Limited ability to capture high-resolution images due to technical constraints in terms of spatial resolution - Requires sophisticated data analysis techniques due to the complexity of hyperspectral data - Costlier than RGB and multispectral sensors; demands significant data storage and processing resources

Abbreviations: 3D, three-dimensional; LiDAR, light detection and ranging; NDVI, normalized difference vegetation index; RGB, red, green, and blue.

reverse filtering network and neighbor embedding-inspired methods effectively enhancing SR (Yan et al., 2022; Zhang et al., 2019), while addressing disparities in the fusion process (Gao et al., 2022).

3.3.5 | Hyperspectral image sensor

Hyperspectral images, captured by sensors with higher spectral but lower SR than multispectral images, enable more accurate estimation of phenotyping parameters like vegetation properties, leaf water content, and nutrient content (Gonzalez et al., 2018). Unlike multispectral images, hyperspectral images capture a broad light spectrum using hundreds or thousands of narrow bandwidths (Maes & Steppe, 2018; Syeda & Alam, 2021). However, their complex preprocessing requirements result in higher computation time and costs. Notably,

hyperspectral sensors are the most expensive option among all imaging sensors (Gonzalez et al., 2018). Additionally, hyperspectral images, with their extensive spectral bands capturing detailed information, require larger storage capacities compared to traditional RGB images. Efficient data management becomes crucial due to the increased volume of data in hyperspectral imagery.

4 | UAV IMAGE ACQUISITION PARAMETERS

Agricultural UAVs are specifically designed for farming applications, presenting a significant stride in field phenotyping through remote sensing (Seifert et al., 2019). Despite its promise, this technique poses challenges, necessitating thorough investigation of parameters for optimal UAV

performance. The diverse applications of UAVs in phenotyping are vast and continue to expand, indicating a burgeoning field of research. As demand for efficient breeding, precise cultivation, and sustainable agriculture rises, UAVs are poised for rapid growth, marking the early stages of a transformative era in agriculture. UAV image acquisition for phenotyping involves parameters grouped into four crucial categories: quality, flight, image, and efficiency (Frey et al., 2018; Mugnai et al., 2022; Seifert et al., 2019). Quality parameters focus on attaining precision and detail in the acquired images, encompassing sensor attributes such as resolution, exposure time (shutter speed), acquisition rate, focal length, and camera angle. Flight parameters consider the movement and positioning of the UAV during image acquisition, including altitude, IOL, and speed. Image parameters specifically relate to the characteristics of individual images, encompassing ground sample distance (GSD) and image per area. Efficiency parameters address time-related aspects in both the flight and image processing stages, namely, flight time, time of day (TOD), and processing time. Understanding and optimizing these parameters are essential for effective UAV-based phenotyping, ensuring the acquisition of high-quality data for subsequent analysis and interpretation. Table 5 provides a concise overview of key UAV image acquisition parameters crucial for precise phenotyping data, including GSD, TOD, IOL, flight altitude (FA), flight speed (FS), and SR.

4.1 | Ground sample distance

GSD is a vital parameter in UAV imagery, denoting the physical size of one pixel in an image relative to the ground, indicating the level of detail and sharpness in the captured data on the field. It depends on factors like FA, sensor pixel size, camera focal length, resolution, and subject distance. Lower GSD offers increased accuracy, detail, and data, achievable through lower altitudes or higher camera focal length and resolution (Mugnai et al., 2022). Conversely, higher GSD yields less accurate and less detailed images, stemming from greater altitude (Gonzalez et al., 2018). For instance, Zhou, Zhou, et al. (2020) classified soybean leaf wilting with UAV imagery at different GSDs (7.7, 4.7, and 20.4 mm/pixel for RGB, multispectral, and thermal images, respectively). However, the impact of varying GSD on UAV performance remains understudied, highlighting the need for further research in this critical area to determine optimal values for diverse UAV applications, including phenotyping.

4.2 | Time of day

TOD refers to a designated timeframe for conducting aerial imaging, considering factors such as lighting conditions, sun

angle, and shadows that influence the quality of acquired images (Rodrigues et al., 2022). While limited research focuses on TOD effects, commonly cited hours range from 9:00 a.m. to 2:00 p.m., 10:00 a.m. to 3:00 p.m., or 11:00 a.m. to 2:00 p.m., coinciding with optimal sunlight conditions (Gonc et al., 2022; Lee et al., 2020; Mao et al., 2021). TOD impacts data quality under different weather or lighting conditions, with studies like Allred et al. (2021) noting the effectiveness of late morning to late afternoon for mapping subsurface drainage systems. Rodrigues et al. (2022) analyzed TOD's effect on spectral bands and VIs, establishing 12:00 p.m. as the most reliable TOD for field flights and cultivar modeling. The choice of TOD for UAV-based image acquisition depends on sensors types, with thermal, multi-spectral, and hyperspectral sensors recommended within ± 2 h from 12:00 p.m. (Kefauver et al., 2019). Investigating optimal TOD for specific sensor types remains a valuable avenue for future research.

4.3 | Image overlap

IOL is a degree of redundancy between consecutive images captured during a flight mission, categorized into forward and side overlap (Lopes Bento et al., 2022). Forward overlap is managed by adjusting image capture rates, while side overlap is linked to the drone's flight path. Configured as a percentage before processing, various studies explored scenarios like 80% forward and 60% side overlap, revealing effects on processing time and spatial accuracy (Barbosa, Ferraz, Dos Santos, et al., 2021; Elhadary et al., 2022; Gonzalez et al., 2018; Torres-Sánchez et al., 2018). High overlaps increase processing time due to redundancy, while increased overlap improves spatial and geometric accuracy (Elhadary et al., 2022; Torres-Sánchez et al., 2018). Goodbody et al. (2021) found that decreasing IOL reduces canopy height accuracy, emphasizing the critical role of overlap in drone-based phenotyping.

4.4 | Flight speed

FS is the velocity at which the UAV moves while acquiring images, and it is intricately connected to the shutter speed or exposure time during the operation (Shi et al., 2021; Wang, Xu, et al., 2021). Shutter speed, a fundamental camera setting, dictates how long the camera's shutter stays open during the image capture process. Researchers explored FSs ranging from 1 to 8 m/s, assessing their impact on both UAV performance and the effectiveness of plant monitoring (Ahmad et al., 2020; Lee, Shin, et al., 2022; Shi et al., 2021). It is worth noting that some studies found the maximum speed to be 5 or 3 m/s for efficient UAV image acquisition. FS, managed by

TABLE 5 Overview of the critical unmanned aerial vehicle (UAV) image acquisition parameters used in the selected phenotyping studies.

Plant traits	GSD	TOD	IOL (FL/SL%)	FA (m)	FS (m/s)	SR	References
Aboveground biomass of maize	n.d.	11:00 a.m. to 2:00 p.m.	80/60	100	n.d.	5 cm/pixel	Zhang, Xia, et al., 2021
Winter wheat aboveground biomass	n.d.	11:00 a.m. to 2:00 p.m.	80/60	50	8	n.d.	Yue et al., 2021
Foliage disease severity	n.d.	n.d.	85/80	25	n.d.	n.d.	Bhandari et al., 2020
Wheat grain yield	n.d.	10:00 a.m. to 2:00 p.m.	80/85	20	1	n.d.	Shafiee et al., 2021
Rice grain yield	n.d.	10:00 a.m. to 2:00 p.m.	n.d.	200	n.d.	0.13 m/pixel	Wang, Yi, et al., 2021
Yield prediction	n.d.	n.d.	60/75	25	2.5	n.d.	Wan et al., 2020
Identifying tasseling date	n.d.	n.d.	85/80	50	5	n.d.	Guo, Fu, et al., 2021
Plant height estimation	n.d.	n.d.	50/55	120	7	n.d.	Yang, Yang, Ye, et al., 2021
Photosynthetic parameters in crops	n.d.	11:00 a.m. to 2:00 p.m.	n.d.	100	n.d.	n.d.	Zhang, Su, et al., 2020
Plant height, canopy coverage, and leaf nitrogen concentration	n.d.	12:00 p.m. to 2:00 p.m.	n.d.	30	n.d.	2.6 cm/pixel	Lu et al., 2021
Maize streak virus and grain yield	n.d.	10:00 a.m. to 2:00 p.m.	75/75	42.5	n.d.	n.d.	Chivasa & Mutanga, 2021
Biomass and grain yields	n.d.	9:30 a.m. to 3:00 p.m.	80/80	40	n.d.	n.d.	Das et al., 2021a
Maize crop tassels	n.d.	11:00 a.m.	80/80	10	1	n.d.	Kumar et al., 2021
Maize and soybean heights	n.d.	n.d.	70/70	150	n.d.	n.d.	Luo et al., 2021
Plant count and plantation-row detection	1.55 cm	n.d.	80/60	80	n.d.	n.d.	Oscos, dos Santos de Arruda, et al., 2021
Early corn stand density	n.d.	n.d.	75/75	10	2	n.d.	Vong et al., 2021
Cereal plant density	n.d.	n.d.	80/60	10	n.d.	0.2–0.69 cm/pixel	Wilke et al., 2021
Crop water stress	4.7 cm, 2.7 mm	n.d.	85/85	70, 10	n.d.	n.d.	Niu et al., 2021
Rice nitrogen nutrition index	n.d.	11:00 a.m. to 1:00 p.m.	80/60	100	8	n.d.	Qiu et al., 2021
Crop coefficient	n.d.	11:00 a.m. to 1:00 p.m.	85/85	70	n.d.	5 cm/pixel	Shao et al., 2021
Crop height	n.d.	n.d.	80/70	50	n.d.	n.d.	Tian et al., 2021
Maize water stress	4.7 cm	11:00 a.m. to 1:00 p.m.	n.d.	70	7	n.d.	Zhang, Han, et al., 2021
Rice plant height	n.d.	n.d.	70/90	20	n.d.	n.d.	Kawamura et al., 2020
Wheat grain yield and protein content	0.06 m	12:00 p.m. to 2:00 p.m.	n.d.	65	5	n.d.	Zhou, Kono, et al., 2021
Wheat and maize canopy nitrogen weight	n.d.	n.d.	80/80	40	n.d.	n.d.	Lee et al., 2020

Abbreviations: FA, flight altitude; FL, forward overlap; FS, flight speed; GSD, ground sample distance; IOL, image overlap; n.d., no data; SL, side overlap; SR, spatial resolution; TOD, time of day.

the UAV's control system or calculated from flight time, is a dual-edged factor influenced by proximity to plants and wind effects at lower altitudes (Ahmad et al., 2020; Ito et al., 2021; Shi et al., 2021). It significantly interacts with image quality, especially with mechanical shutters, minimizing rolling shutter artifacts for clear images (Simon et al., 2022). Optimal FS and shutter selection are critical, with considerations for mechanical and electronic shutters, each presenting unique advantages and challenges (Nex et al., 2022). The rolling shutter effect, capturing images line by line, requires correction methods for precise mapping results, showcasing the complexity in optimizing UAV performance (Bruno & Forlani, 2023; Tekavec et al., 2019; Vautherin et al., 2016; Zhou, Daakir, et al., 2020). The nuanced exploration of the intricate relationship between FS, shutter speed, and their respective types influencing UAV performance during image acquisition is highlighted by Irujo et al. (2023).

4.5 | Flight altitude

FA, the vertical distance between the UAV and the ground, plays a pivotal role in UAV image acquisition, influencing SR, coverage, and image quality. Opting for higher altitudes provides broader coverage but lowers SR, while lower altitudes offer higher resolution at the expense of coverage. The choice depends on mission goals and study area characteristics (Anders et al., 2020). This balance is crucial for successful UAV image acquisition (Borra-Serrano et al., 2015). Altitudes vary based on vegetation and sensor types, impacting different crop groups (Bazrafkan et al., 2023). Examining the estimation of wheat aboveground biomass, Zhu et al. (2023) showed that increasing flight height from 30 to 120 m reduced estimation accuracy by 48% and 41% for the canopy spectral model (CSM) and textures, respectively.

Studies emphasize the significance of FA ranging from 1 to 120 m (Lou et al., 2018; Seifert et al., 2019; Shi et al., 2021). It directly affects GSD and details in UAV imagery (Seifert et al., 2019). Increased altitude enhances object detection accuracy even at lower IOL (Torres-Sánchez et al., 2018), but elevated altitudes may compromise the geometric accuracy of point clouds (Elhadary et al., 2022). Overall, finding the right balance is key for successful UAV image acquisition for various applications such as crop monitoring and field mapping.

4.6 | Spatial resolution

SR, also known as sensor resolution, refers to the level of detail or clarity in the individual pixels of an image and is a critical aspect of image quality and processing efficiency in UAV-based imaging. Despite its impact on accuracy, studies

on this parameter are limited, often treating it as a constant factor. One study, investigating the effect of resolution on image classification accuracy using three resolutions (5, 10, and 15 cm), found similar overall classification accuracy in grassland, attributing this to minor variations in object features at the tested resolutions (Lu & He, 2018). Another study exploring the impact of resolution on LAI using the PROSAIL model and six resolutions (1, 5, 10, 15, 25, and 50 cm) found consistent LAI inversion performance from 0.26 to 10 cm/pixel, with declining performance at 15 cm/pixel and beyond (Sun, Wang, Yang, et al., 2021). Despite these findings, there is a notable gap in research optimizing UAV performance, necessitating further investigation.

5 | UAV IMAGE PROCESSING AND ANALYTICS

UAV image processing and analytics constitute a crucial phase in harnessing the vast data captured by UAVs for insightful applications. This multifaceted process involves a series of sophisticated techniques and algorithms, which are explored in this section, considering methodologies introduced in prior studies (Kim, 2020; Lu & He, 2018; Wang, Silva, et al., 2020). The current study enhances Omari et al.'s (2020) methodology for a more comprehensive approach. The general image processing and analytics steps include preprocessing, segmentation, feature extraction, data analysis, and evaluation (optional step) in a five-step process illustrated in Figure 8. This comprehensive approach empowers UAVs to contribute significantly to fields like PA and HTP by transforming raw imagery into actionable knowledge, fostering informed and efficient decision-making processes.

5.1 | Preprocessing

The main goal of image preprocessing is to improve the separation between plant and nonplant structures in the color space by enhancing their topological representation (Henke et al., 2021). This study covers multiple preprocessing techniques, such as image quality assessment, photogrammetric processing (mosaicking and orthorectification), geometrical correction, radiometric calibration, and pixel resampling.

5.1.1 | Image quality evaluation

The initial step in the image preprocessing approach is often overlooked in previous studies: image quality evaluation. This evaluation, typically conducted through visual inspection, includes checking for oblique scenes, identifying

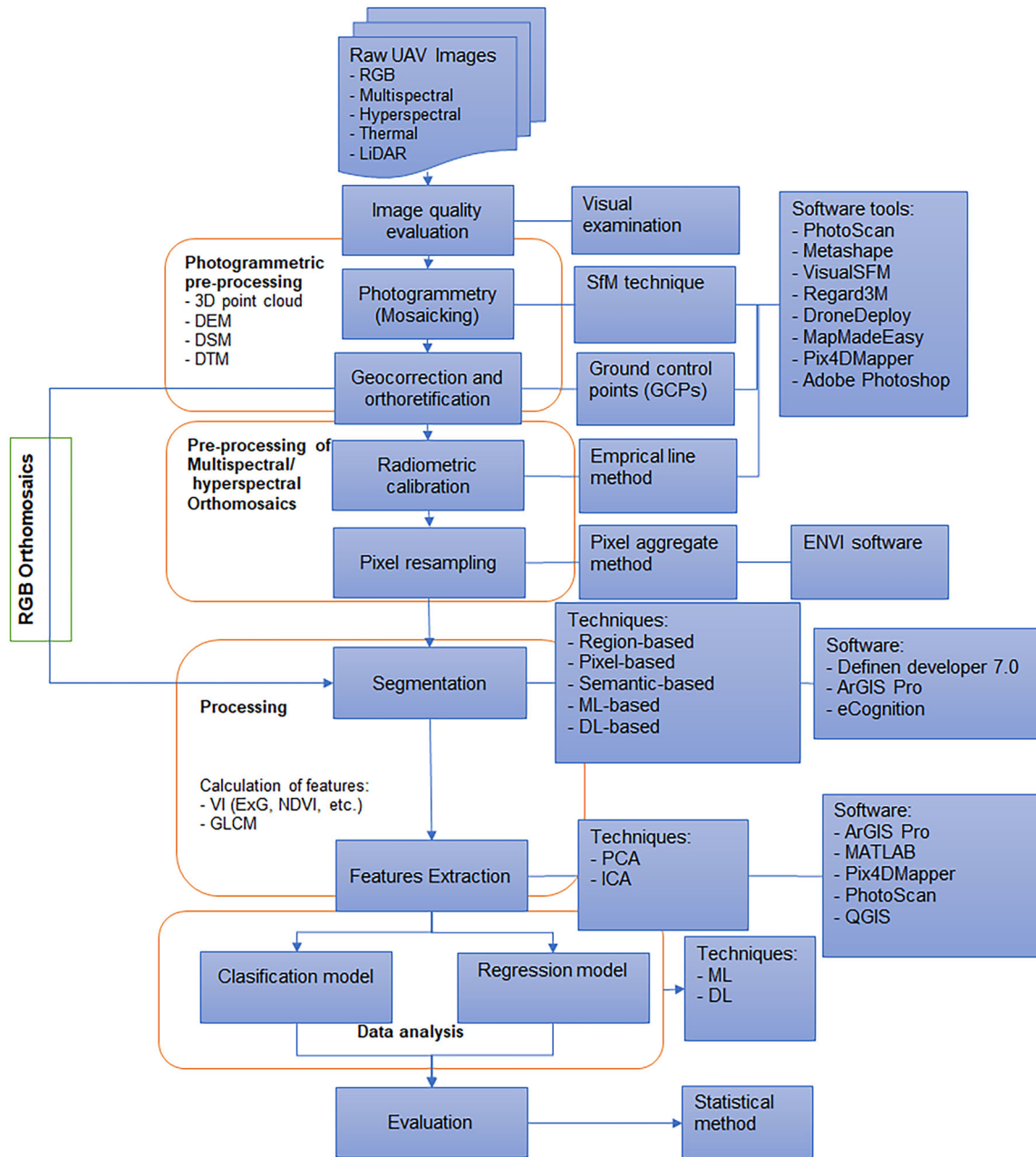


FIGURE 8 General approach to unmanned aerial vehicle (UAV) image processing and analytics. DEM, digital elevation model; DSM, digital surface model; DTM, digital terrain model; VI, vegetation index; ExG, excess greenness index; NDVI, normalized difference vegetation index; GLCM, gray-level co-occurrence matrix; ML, machine learning; DL, deep learning; PCA, principal component analysis; ICA, independent component analysis; SfM, structure from motion.

blurry images, and assessing radiometric distortion such as vignetting and signal-to-noise ratio. The removal of poor-quality images at this stage is crucial for ensuring more precise data analysis with the chosen method. Issues like oblique scenes and blurry images, often caused by wind gusts leading to drone image vibration, need elimination to enhance the accuracy of subsequent image processing steps. The impact of radiometric distortions induced by atmospheric effects is negligible at low drone altitudes (Lu & He, 2017).

5.1.2 | Photogrammetry (mosaicking and orthorectification)

The photogrammetric technique, employing the structure from motion (SfM) algorithm, creates high-resolution 3D models using overlapping two-dimensional images from different digital cameras and georeferencing information (Eltner & Sofia, 2020). This process yields Digital Surface Models (DSM), Digital Terrain Models (DTM), Digital Vegetation Models (DVM), Digital Elevation Models (DEM),

and orthophotos (Tompalski et al., 2021). These models provide insights into 3D crop characteristics, including height, canopy, and biomass density, benefiting applications using only RGB images (Tsouros et al., 2019). In phenotyping, the typical output is orthomosaics, formed through mosaicking or stitching techniques (Barbosa, Ferraz, Dos Santos, et al., 2021).

Various commercial software utilizing the SfM algorithm, such as Agisoft Metashape, VisualSFM, and Regard3D, have been widely used in phenotyping research, reducing computation time for image processing (Barbosa, Ferraz, Dos Santos, et al., 2021; Elkhachy, 2022; Goodbody et al., 2021; Ludwig et al., 2020; Tian et al., 2021). Cloud-based options like DroneDeploy and MapsMadeEasy generate orthomosaic images, DTM, 3D point cloud models, and NDVI data but lack support for aligning one-band cameras, limiting composite image layering. Other software packages like Pix4Dmapper are also employed in phenotyping research (Chang et al., 2021; Kim, 2020; Raeva et al., 2019).

5.1.3 | Geometrical correction

Geometrical correction aims to rectify distortions in orthomosaics, enhancing accuracy in subsequent processing steps. This correction establishes a relationship between image coordinates and geographic coordinate systems using sensor calibration data, GPS data, attitude data, and GCPs. SfM software or ArcGIS, with known GCPs, can be utilized for this purpose (Lu & He, 2017).

5.1.4 | Radiometric calibration

Radiometric calibration enhances the accuracy of VIs, like NDVI, in multispectral or hyperspectral orthomosaics. The commonly employed empirical line method, as recommended by Lu and He (2017, 2018), uses radiometric calibration panels to convert digital numbers to reflectance values. By comparing average digital numbers of reflectance panels in the orthomosaic with laboratory-measured reflectance values, empirical lines are established. These lines facilitate the conversion of pixel values in multispectral or hyperspectral orthomosaic images to reflectance values (Chang et al., 2021).

5.1.5 | Pixel resampling

Pixel resampling, the final step in image preprocessing, involves changing the size of digital images, typically done to prepare orthomosaics for subsequent processing like segmentation and feature extraction. ENVI by Visual Information Solutions Inc. is commonly known for pixel resampling, as reported in previous studies (Lu & He, 2018; Tian et al., 2021).

5.2 | Segmentation

Segmentation is a vital step in image processing, especially for geographic object-based analysis, directly influencing feature extraction and classification quality (Hossain & Chen, 2019). It entails dividing an image into homogeneous regions based on properties like color, texture, and size, employing techniques such as edge-based, region-based, pixel-based, and hybrid-based segmentation (Hossain & Chen, 2019). Deep learning-based segmentation, utilizing algorithms like CNN and PlantU-net (Li et al., 2021), is increasingly popular in UAV-based image processing (Osco, Marcato Jr., et al., 2021). Commercial software like Definiens Developer 7.0 (Lu & He, 2018), ArcGIS Pro v2.7, and eCognition (Abd-Elrahman et al., 2021) offer built-in segmentation algorithms, streamlining the process.

5.3 | Feature extraction

Following segmentation, the extraction of phenotypical features, such as plant height, width, and size, involves calculating values using pixel size in millimeters and specific functions (Wang, Qiu, et al., 2020). In this final image processing step, features are quantified and VIs are calculated. VIs combine operations or reflections of bands from RGB and/or spectral sensors to indicate vegetation vigor within a pixel. Effective with multispectral or hyperspectral data, VIs gained attention in plant phenotyping for monitoring various parameters by combining different spectral bands (Rodas et al., 2021; Tsouros et al., 2019).

VIs can be categorized based on multispectral/hyperspectral data or visible spectrum/RGB images. Examples include ratio vegetation index (RVI), NDVI, normalized difference red edge index (NDRE), and green normalized difference vegetation index (GNDVI) derived from multispectral/hyperspectral data (Holman et al., 2019). RGB-based VIs, like excess greenness index (ExG) and normalized difference index (NDI), are also common (Tsouros et al., 2019). Software such as ArcGIS, QGIS, or other GIS-based tools facilitate feature extraction and VI calculations (Tresch et al., 2019).

5.4 | Data analysis

Data analysis is the critical step, involving classification, regression, or a combination based on the application. Classification predicts discrete values for detection applications, while regression predicts continuous values for estimation applications (Reza Ghafarian Malamiri et al., 2021; Shu et al., 2021). Previous studies have employed various methods, including ML and deep learning algorithms for UAV image processing (Table 6). CNN is commonly used for

TABLE 6 Diverse methods employed in previous studies for unmanned aerial vehicle (UAV) image processing for phenotyping, incorporating machine learning, and deep learning algorithms.

Image type	Data analysis technique	Algorithms/models	Application	References
RGB images	Classification	Hybrid CNN model using TensorFlow 2.0 and Python	Rapid detection of infested maize plants with fall armyworms	Ishengoma et al., 2022
RGB images	Classification	CNN	Automatic detection of acacia longifolia invasive species	Gonc et al., 2022
RGB images	Classification	CNN	Individual tree detection and species classification of Amazonian palms	Ferreira et al., 2020
Multispectral and LiDAR images	Regression	SLAM	Fine-scale prediction of biomass and leaf nitrogen content	Shendryk et al., 2020
RGB images	Classification	OBIA	Genotype classification in olive breeding	Rallo et al., 2020
RGB images	Classification	<i>K</i> -means and MLR	Classify forest canopy vegetation	Jayathunga et al., 2020
RGB images	Classification	YOLOv2	Detecting and counting cattle	Shao et al., 2020
Hyperspectral images	Regression	Boruta algorithm-based linear regression model	Estimation accuracy of SPAD values for maize leaves	Shu et al., 2021
Multispectral images	Classification and regression	<i>K</i> -means clustering, Random Forest and Extreme Gradient Boosting	Winter wheat SPAD estimation	Yang, Yang, Cui, et al., 2021
RGB images	Regression	Linear, power, exponential, polynomial, and logarithmic regression	Estimation of aboveground volume and biomass of desert shrub communities	Mao et al., 2021
RGB images	Classification	Object-based random forest	Fine-scale detection of vegetation (riparian landscapes) in semiarid mountainous areas	Daryaei et al., 2020
RGB and multispectral images	Regression	Machine learning-based predictive modeling	Predicting yield and water-use efficiency in spinach	Awika et al., 2021
RGB images	Regression	SVM, GBR, RFR, PLSR, NEAT	Coffee yield prediction	Barbosa, Ferraz, Costa, et al., 2021

Abbreviations: CNN, convolutional neural network; GBR, gradient boosting regression; LiDAR, light detection and ranging; MLR, multinomial logistic regression; NEAT, neuroevolution of augmented topologies; OBIA, object-based image analysis; PLSR, partial least square regression; RFR, random forest regression; RGB, red, green, and blue; SLAM, simultaneous localization and mapping; SPAD, soil and plant analysis development; SVM, support vector machine.

classification in deep learning, while ML algorithms like linear regression, random forest, and support vector machine serve both classification and regression purposes (Guilherme et al., 2020; Xie et al., 2021). Additionally, other deep learning algorithms such as Plant-Unit, recurrent neural network (RNN), multilayer perceptrons (MLPs), and radial basis function networks (RBFNs) are utilized (Feng et al., 2021; Lu & He, 2018).

5.5 | Evaluation

The evaluation stage in most studies, while considered optional, is crucial for validating the method and ensuring result accuracy. Statistical analysis, particularly mean relative difference, is employed to compare field-measured values with OBIA-estimated values in field trials (Rallo et al., 2020). Additionally, statistical metrics, including overall accuracy,

producer's accuracy, user's accuracy, and the Kappa coefficient, derived from the confusion matrix, assess the accuracy of object-based classification in UAV orthophotos (Daryaei et al., 2020).

6 | UAV USE CASES IN PHENOTYPING

A meta-analysis of UAV applications in phenotyping, involving a comprehensive review of 114 peer-reviewed articles from 2018 to 2022, categorizes studies into seven groups: cereals, horticulture, forestry, legumes and oil crops, root crops, pasture and livestock, and other crops (Figure 9). Findings indicate a predominant focus on cereal crops, trailed by horticulture, forestry, legumes, and oil crops, with insights into the distribution of research emphasis among crop categories.

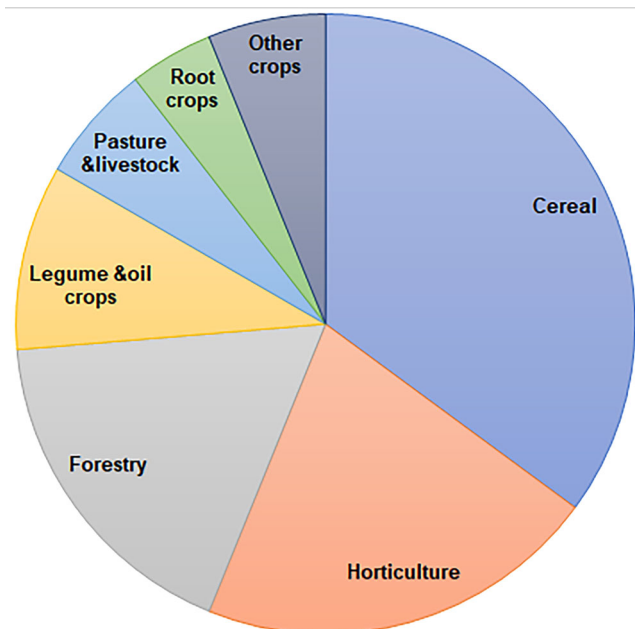


FIGURE 9 Quantitative distribution of unmanned aerial vehicle use cases in phenotyping, categorized by crops

UAV applications in cereal crop phenotyping, including maize, wheat (winter and spring), rice (low and upland), and barley, are outlined in Table 7. The summary covers application areas such as estimation, assessment, prediction, identification, and evaluation. Notably, yield estimation and prediction emerge as the primary focus, with significant attention directed toward crop count and row detection. The table details plant phenotypes, trait types, species, drone types, sensors, and analyses/models employed in these applications.

Table 8 outlines the application of UAVs in various categories: horticulture, forestry, legumes and oilseeds, root crops, pasture and livestock, and other crops. Horticulture includes fruits and vegetables, focusing primarily on yield estimation and prediction. Forestry emphasizes disease detection and assessment, followed by mapping. Legume and oilseed crops exhibit a predominant interest in yield prediction. Pasture crops emphasize aboveground biomass estimation and mapping, while livestock phenotyping centers on animal detection. Root crops, challenging for UAVs due to underground data capture difficulties, receive fewer studies. Among other crops, cotton is prominent, with a focus on yield estimation and prediction.

7 | CHALLENGES AND FUTURE RESEARCH DIRECTIONS

In the evolving landscape of agricultural monitoring, UAV-based HTP holds immense potential, yet it grapples with multifaceted challenges that necessitate innovative solutions

and strategic research directions. One of the primary challenges lies in the vulnerability of UAV-captured images to various factors, including atmospheric conditions, sensor calibration, and UAV stability. These factors collectively impact the reliability and accuracy of phenotyping data, crucial for informed decision-making in agriculture. Moreover, the sheer volume of data generated by drones, especially when equipped with advanced sensors capturing large datasets, presents significant challenges in terms of storage, processing, and efficient utilization.

The absence of standardized protocols emerges as a critical hurdle, hindering the seamless integration and comparison of results across diverse studies and platforms. Without a common framework, researchers face difficulties in replicating and validating findings, impeding progress and collaboration in the field. Additionally, the regulatory landscape governing the use of drones for research and commercial purposes varies across countries and regions. Negotiating these variations poses legal and logistical challenges for researchers and operators, contributing to the complexity of adopting drone technology in agriculture.

Financial constraints add another layer of difficulty, particularly for smaller research institutions or individual researchers. The cost associated with acquiring and maintaining drone technology, coupled with the expenses related to sophisticated data processing software, can be prohibitive. This financial barrier limits access to these transformative technologies, potentially excluding valuable contributors from participating in the advancement of agricultural monitoring.

The expertise required for effective drone-based phenotyping is a significant challenge. Operating drones and analyzing the vast amount of data they produce demand specialized skills that may act as a barrier to entry for researchers and operators lacking this expertise. Bridging this skill gap is crucial for ensuring the widespread adoption and successful implementation of drone-based technologies in agriculture.

Despite these challenges, the future of UAV-based HTP presents exciting research directions aimed at overcoming current limitations and maximizing the potential of this technology in agriculture. Researchers are exploring the development of advanced sensor technologies and algorithms to enhance the accuracy and precision of UAV-based platforms. This includes the detection and quantification of plant growth indicators, such as leaf chlorophyll content and plant height, using cutting-edge sensors and analytical techniques.

The integration of multiple sensors, including hyperspectral, thermal, and LiDAR, is a key area of exploration. This multisensor approach aims to provide a more comprehensive and accurate dataset for phenotyping, capturing nuanced information about crop health and growth. Such advancements hold the promise of transforming drone-based

TABLE 7 Unmanned aerial vehicle (UAV) use cases in cereal crop phenotyping.

S/N	Application areas	Plant phenotype	Plant traits types	Plant species	UAV platform	Sensor type	Plant traits analysis/model	References
1.	Estimation	Aboveground biomass, crop height	Physiological and morphological	Maize	Six-rotor DJI S1000	Hyperspectral	Stepwise regression, random forest, and XGBoost	Zhang, Xia, et al., 2021
		Plant height	Morphological	Rice	DJI Phantom 4	RGB	ANOVA	Kawamura et al., 2020
		Biomass, grain yield	Physiological and quantitative	Wheat	DJI S1000 UAV	RGB	AquaCrop model	Yue & Feng, 2021
		Aboveground biomass	Physiological	Wheat	Six-rotor DJI S1000	RGB and hyperspectral	Wavelet analysis techniques	Yue et al., 2021
		Grain yield	Quantitative	Rice	DJI M600 Pro	Hyperspectral	GLCM and image textural measures	Wang, Yi, et al., 2021
		Chlorophyll content	Physiological and biochemical	Wheat	Six-rotor	Hyperspectral	Cluster (<i>k</i> -means), random forests, and XGBoost	Yang, Yang, Ye, et al., 2021
		Crop transpiration	Physiological	Maize and soybean	DJI M600 Pro	Thermal	A three-temperature (3T) model	Hou et al., 2021
		Plant height	Morphological	Maize and soybean	Six-rotor UAV	LiDAR	Random forest	Luo et al., 2021
		Grain yield	Quantitative	Maize	DJI Phantom 3	RGB	Linear regression	Zhang, Zhou, et al., 2020
		Foliage disease severity	Physiological	Wheat	DJI Phantom 4 Pro	RGB	NDI, GI, and GLI	Bhandari et al., 2020
2.	Assessment	Canopy structure and chlorophyll content	Physiological and biochemical	Maize	Multirotor	Multispectral	Multiple linear, random forest, and ANN	Zhang, Han, et al., 2021
		Yield	Quantitative	Wheat	DJI Phantom 4 Pro	Multispectral	VI, SVR, and SFS hybrid, LASSO regressor with an internal feature selector	Shafiee et al., 2021
3.	Prediction	Yield	Quantitative	Maize	Sensefly eBee RTK fixed-wing	Multispectral	Random forest, Vegetation indices, NDVI, NDRE, and GNDVI	Paula et al., 2020
		Yield and canopy height	Quantitative and physiological	Rice	Octo-rotor	RGB and multispectral	Random forest, VI	Wan et al., 2020

(Continues)

TABLE 7 (Continued)

S/N	Application areas	Plant phenotype	Plant traits types	Plant species	UAV platform	Sensor type	Plant traits analysis/model	References
4.	Identification	Grain yield and biomass yield	Quantitative and physiological	Wheat	DJI Matrice 600 Pro Hexacopter	Thermal	CRT	Das et al., 2021a
		Yield	Quantitative	Maize	Delta fixed-wing eBee SQ	Multispectral	Multiple regression, decision trees, and linear regression	Chivasa & Mutanga, 2021
		Tasseling date	Quantitative	Maize	DJI Phantom 4 Pro V2.0	RGB	VI and GLCM	Guo, Fu, et al., 2021
		Tassels	Quantitative	Maize	DJI Inspire-1 Pro	Multispectral and RGB	K-means clustering with adaptive thresholding	Kumar et al., 2021
7.	Evaluation	Disease	Biotic stress	Vine	Scanopy Quadcopter	Multispectral and RGB	Deep learning network	Kerkech et al., 2020
		Leaf potassium concentration, crop water uptake, plant moisture content, and aboveground biomass	Physiological and biophysical	Wheat	DJI Matrice 600 Pro Hexacopter	Thermal	Agglomerative hierarchical clustering	Das et al., 2021b
		Nitrogen-use efficiency	Agronomic	Rice	DJI M100	Multispectral	Linear regression	Jiang et al., 2021

Abbreviations: ANN, artificial neural network; ANOVA, analysis of variance; CRT, classification and regression tree; GI, green index; GLCM, gray-level co-occurrence matrix; GLI, green leaf index; GNDVI, green normalized difference vegetation index; LiDAR, light detection and ranging; NDI, normalized difference index; RGB, red, green, and blue; SFS, sequential forward selection; SVR, support vector regression; VI, vegetation index; XGBoost, eXtreme Gradient Boosting.

TABLE 8 Unmanned aerial vehicle (UAV) use cases in horticulture, forestry, legume and oilseed, root crop, pasture, and other crops phenotyping.

Categories	Application(s)	Plant	Sensor(s)	UAV(s)	Reference
Horticulture	Disease detection	Vineyard	Multispectral and RGB	Scanopy Quadcopter	Kerkech et al., 2020
	Yield estimation and canopy water status assessment	Egg plant	Multispectral	Fixed-wing eBeeTM	Mwinuka et al., 2021
	Yield prediction	Coffee	RGB	DJI Phantom 3 Professional	Barbosa, Ferraz, Costa, et al., 2021
	Fruit size and yield estimation	Citrus	RGB	Quadcopter DJI Phantom 3 Professional	Apolo-Apolo et al., 2020
	Crop growth assessment	Chicory	RGB, multispectral, and thermal	DJI Phantom 4 Pro	Heidarian Dehkordi et al., 2020
	Maturity classification	Strawberry	RGB	DJI Phantom 4 Pro	Zhou, Lee, et al., 2021
	Monitoring yellow sigatoka	Banana	RGB	DJI Inspire-1	Calou et al., 2020
	Greening detection	Citrus	Multispectral	DJI Matrice 100	Lan et al., 2020
	Analysis of the canopy traits	Olive	RGB	Rotary-wing ZniR Sensing	Daniel et al., 2021
	Detecting powdery mildew disease	Squash	Hyperspectral	DJI Matrice 600 Pro Hexacopter	Abdulridha et al., 2020
	Detection and mapping of trees infected with citrus gummosis	Citrus	Hyperspectral	UAV-UX4 Model	Saito et al., 2021
	Estimation of crop energy balance	Vineyard	RGB and thermal	DJI M 600 Pro	Ortega-farias et al., 2021
	Plants counting and plantation-row detection	Citrus	RGB	Phantom 4 Advanced	Oscó, dos Santos de Arruda, et al., 2021
	Growing status observation	Oil palm trees	RGB	Fixed-wing Skywalker X8	Zheng, Fu, et al., 2021
Forestry	Prediction of yield and water-use efficiency	Spinach	Multispectral	Phantom 4 Multispectral	Awika et al., 2021
	Aboveground biomass estimation	<i>Robinia pseudoacacia</i>	RGB	Eight-rotor UAV	Lu et al., 2020
	Disease detection	Pine	Multispectral and RGB	DJI Phantom 4 Multispectral	Yu et al., 2021b
	Disease assessment	Pine	Hyperspectral and LiDAR	DJI Matrice 600	Yu et al., 2021a
	Disease detection	Pine	RGB	DJI Phantom 4PRO (version V2.0)	Hu et al., 2020, 2022
	Early diagnosis of pine wilt disease	Pine	RGB	DJI Phantom 4 RTK	Wu et al., 2021
	Canopy mapping	Macadamia	Multispectral	3DR Solo Quadcopter	Johansen, Duan, et al., 2020
	Canopy mapping	Boreal	RGB	DJI Phantom 3 4K Micro-quadcopter	Li et al., 2022
	Estimating LAI	Mangrove	Multispectral	Octa-rotor	Guo, Wang, et al., 2021
					(Continues)

TABLE 8 (Continued)

Categories	Application(s)	Plant	Sensor(s)	UAV(s)	Reference
Legume and oilseed	Automatic detection of invasion species	Acacia	RGB	DJI Phantom 3 Pro	Gonc et al., 2022
	Structured mixed deciduous canopies assessments	Mixed tree species	RGB	DJI S900 Hexacopter	Brühlhardt et al., 2020
	Fine scale plant community assessment	Coastal meadows	Multispectral	SenseFly ebee Fixed-wing	Villoslada et al., 2020
	Biomass characterization	Desert shrub	Multispectral	Parrot Disco-Pro Ag	Abdullah et al., 2021
	Canopy structure assessment	Mixed tree species	RGB	DJI Mavic Pro	Bourgoin et al., 2020
	Canopy structure characterization	Conifer	RGB	Trimble UX5	Jayathunga et al., 2020
	Tree height estimation	Mixed tree species	RGB	GerMAP G180	Adetokunbo et al., 2020
	Monitoring restored tropical forest diversity and structure	Mixed tree species	Hyperspectral, LiDAR, RGB, and thermal	DJI Matrice 600 Pro Hexacopter	Almeida et al., 2021
	Measuring tree height, growth, and phenology	Spruce	RGB	DJI Phantom 4-pro	Solvin et al., 2020
	Crop lodging identification	Sunflower	RGB and multispectral	DJI Matrice 600	Song et al., 2020
Root crop	LAI retrieval	Rapeseed	Multispectral	Matrice 600 Hexacopter	Sun, Wang, Yang, et al., 2021
	Seedpods maturity determination	Canola	Hyperspectral	DJI M600 Pro	Singh et al., 2021
	Crop height estimation	Rapeseed	RGB	DJI Phantom 4 RTK	Xie et al., 2021
	Yield estimation	Soybean	Multispectral and thermal	DJI S1000+ Octocopter	Maimaitijiang et al., 2020
	Pest detection, classification, and control	Soybean	Super-pixel RGB	DJI Phantom 4 Advanced	Brandoli et al., 2020
	Leaf wilting classification	Soybean	RGB and multispectral	DJI Matrice 600 Pro	Zhou, Zhou, et al., 2020
	Yield prediction	Soybean	Multispectral	Sensefly eBee RTK	da Silva et al., 2020
	Height estimation	Soybean	LiDAR	Six-rotor UAV	Luo et al., 2021
	Plant water status assessment	Soybean	Thermal	Tarot Iron Man 1000	Guilherme et al., 2020
	Biomass estimation and yield prediction	Potato	RGB and hyperspectral	DJI Phantom 4 Pro	Li et al., 2020
Late blight disease detection	Chlorophyll fluorescence study	Potato	Multispectral	DJI S1000 Octocopter	Wang, Suomalainen, et al., 2021
	Late blight disease detection	Potato	Multispectral	Tarot 680 Pro Hexacopter	Rodríguez et al., 2021
	Monitoring of growth indicators	Sugar beet	Multispectral	DJI Phantom 4A	Cao et al., 2020

(Continues)

TABLE 8 (Continued)

Categories	Application(s)	Plant	Sensor(s)	UAV(s)	Reference
Pasture and livestock	Biomass estimation	Grass	RGB	DJI Phantom 4	Sinde-González et al., 2021
	Mapping total aboveground biomass density	Savannah/grassland	LiDAR	DJI M600 Pro	da Costa et al., 2021
	Assessment of grass lodging	Grass	RGB	eBee senseFly	Tan et al., 2021
Other crops	Detection and counting	Sheep	RGB	DJI Phantom 3 Pro	Sarwar et al., 2021
	Detection and counting	Cattle	RGB	DJI Phantom 4	Shao et al., 2020
	Yield estimation	Sugarcane	RGB	DJI S1000 UAV	Yu et al., 2020
	Retrieval of plant water content	Cotton	Multispectral	Multirotor UAV M600	Chen et al., 2020
	Biomass and leaf nitrogen content estimation	Sugarcane	LiDAR and multispectral	DJI M600 Pro	Shendryk et al., 2020
	Yield prediction	Cotton	RGB and multispectral	DJI Phantom 4 RTK and Phantom 4 Multispectral	Xu et al., 2021
	Yield estimation	Cotton	RGB	DJI Matrice 600 Pro	Feng, Zhou, Vories, Sudduth, et al., 2020
	Crop water status variability detection	Cotton	Thermal	3DR Solo Quadcopter	Lacerda et al., 2022
	Evaluation of crop seedling emergence	Cotton	RGB	DJI Phantom 4 Advanced	Feng, Zhou, Vories, & Sudduth, 2020

Abbreviations: LAI, leaf area index; LiDAR, light detection and ranging; RGB, red, green, and blue.

phenotyping into a more sophisticated and reliable tool for agricultural monitoring.

AI and ML are playing a pivotal role in addressing the challenges associated with data processing. These technologies enable the automation of complex analyses, pattern recognition, and correlation identification within the vast datasets collected by UAV-based platforms. Implementing AI and ML algorithms enhances the efficiency and accuracy of phenotyping, unlocking new possibilities for extracting valuable insights from the data.

The integration of UAV-based platforms with other technologies, such as PA and unmanned ground vehicles (UGVs), is expanding the scope and impact of phenotyping. This holistic approach aims to provide a more comprehensive understanding of crop growth and health by combining UAV-captured data with information from other sources, such as weather data or soil moisture sensors. UGVs, when combined with UAVs, offer ground-level data and validation for the information gathered from aerial platforms, contributing to a more robust and reliable dataset.

To address the lack of standardization, researchers are actively working on developing protocols for UAV-based phenotyping. Standardized protocols would facilitate greater comparability and reproducibility of results across different studies and platforms. This concerted effort toward standardization is essential for establishing a cohesive framework that enables researchers to build upon each other's work and collectively advance the field.

Optimizing UAV parameters is another critical research direction. Identifying the optimal combination of parameters, including GSD, FA, speed, camera settings, and flight patterns, has the potential to significantly improve data quality, efficiency, and cost-effectiveness. Real-time monitoring of UAV parameters, coupled with the development of open-source software for sharing and comparing optimized parameters, promotes collaboration and standardization within the research community.

Expanding the applications of UAV platforms in phenotyping is a forward-looking research direction. Detection and monitoring of pests and diseases in crops using UAV technology represent a promising avenue for research. Developing new sensor technologies and analytical methods for detecting specific pests or diseases is key to enhancing the resilience and sustainability of agricultural practices.

Ultimately, while UAV-based HTP faces substantial challenges, ongoing and future research directions promise to overcome these obstacles and elevate the role of UAVs in agricultural monitoring. The integration of advanced sensor technologies, AI, and ML, coupled with the optimization of UAV parameters and the development of standardized protocols, is shaping the future of this transformative technology. By addressing the challenges head-on and charting a course toward innovation, researchers are paving the way for a more

precise, efficient, and widely applicable approach to agricultural monitoring. The collaborative efforts of the research community are instrumental in unlocking the full potential of UAV-based technologies and image processing technologies, contributing to sustainable and resilient agriculture in the years to come.

8 | CONCLUSIONS

The integration of UAV technology and image analytics in phenotyping has revolutionized the field of agriculture. With the ability to capture high-resolution images over large areas, UAVs have the potential to greatly increase the efficiency and accuracy of field phenotyping. The choice of UAV platform and its parameters, sensor type, and image processing techniques play important roles in obtaining reliable and accurate phenotyping data. ML and deep learning algorithms are rapidly advancing and have shown great potential in UAV-based phenotyping. However, there is a need for a standardized framework to aid in the decision-making process for selecting the appropriate methods and software for UAV-based phenotyping and image analytics. Overall, UAV-based phenotyping and image analytics hold great promise for advancing agricultural research and crop management practices.

AUTHOR CONTRIBUTIONS

Occident Bongomin: Conceptualization; data curation; methodology; visualization; writing—original draft; writing—review and editing. **Jimmy Lamo:** Resources; supervision. **Joshua Mugeziaubwa Guina:** Conceptualization; supervision. **Collins Okello:** Resources; supervision. **Gilbert Ocen:** Supervision; visualization; writing—review and editing. **Joshua Guina:** Conceptualization; supervision. **Morish Obura:** Resources; writing—review and editing. **Simon Alibu:** Methodology; supervision. **Cynthia Awuor Owino:** Resources; writing—review and editing. **Agnes Akwero:** Data curation; visualization. **Cynthia Owino:** Resources; writing—review and editing. **Agnes Akwero:** Data curation; visualization. **Samson Ojok:** Conceptualization; resources.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Research data underlying the findings of the study are included in the paper. The preprint version of this manuscript was deposited at SSRN server (<https://doi.org/10.2139/ssrn.4158755>) or <https://ssrn.com/abstract=4158755> (Bongomin et al., 2022).

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