REVIEW ARTICLE

Plant Phenotyping using Unmanned Aerial Vehicles (UAVs): A Comprehensive Review

Manisha Bhagyalaxmi[1], Simran Walia[1], Tatiana Minkina[2], Vishnu D. Rajput[2*], and Sudhakar Srivastava[1*]

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Abstract

Phenotyping plays an important role in agricultural research for determining the various traits of plants. To investigate the inheritance and expression patterns of the genome and discover how genomic and phenotypic information is related to boosting agricultural output, it is important to precisely and rapidly gather phenotypic information of plants or cells in various conditions. Manually measuring, processing, and analyzing the data of plant phenotypes such as yield, biomass, leaf color, size, plant height, chlorophyll, and density is a laborious and time-consuming procedure. To overcome such issues and precisely execute high-throughput phenotyping and analysis, unmanned aerial vehicles (UAVs) have been developed. This review focuses on the benefits of UAV-based remote sensing of various features utilizing different phenotyping sensors. The phenotyping sensors and UAV platforms are briefly introduced in this study. A more thorough introduction and summary of the uses of UAVs to collect and evaluate plant phenotypic characteristics is provided. Furthermore, the future prospects and the challenges of phenotype information through UAVs are also discussed. It aims to inform readers and researchers about the existing uses of UAVs for high-throughput phenotyping as well as the methodology used in the studies. The review proposes the applications of UAVs for advancements in agriculture to meet future needs.

Keywords: Plant Phenotyping; Remote Sensing; Unmanned Aerial vehicles (UAVs)

Highlights:

- High-throughput phenotyping is useful in plant characterization.
- UAVs are handy tools for precise phenotyping of a large number of plants.
- A variety of sensors can be used to phenotype plants.

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Introduction

Unmanned aerial vehicles (UAVs) are a topic of interest among scientists and commercial industries in the agricultural sector owing to their vast potential shortly (Guo *et al*., 2024). This newly developing technology can give the necessary throughput and precise description of traits in cropping systems and it is thus becoming widely accepted. Natural conditions are essential for the proper evaluation of crop productivity. Nowadays most field-based phenotyping systems use ground and aerial remote sensing approaches. For ground vehicles, the process of collection of data is very time-consuming when the number of samples is very large along with the number of plots in which the plants are planted. To overcome the problem additional vehicles and sensors can be used but it increases the cost.

For a quick and non-destructive estimate of crop attributes, the cable-suspended field phenotyping platform was created recently. There are benefits of safety, high accuracy, independence from soil conditions, and minimum tactile disturbance of plants for the cable-suspend field-based phenotyping platform. However, because it must be situated at certain locations, the cable-suspend field phenotyping platform's coverable area is very small, which restricts its use for large-scale phenotyping (Peng *et al*., 2025). The use of satellite imaging technologies in data collecting for a range of agricultural applications has grown significantly. However, it suffers from the high costs of satellite sensors, the lack of spatial resolution needed to identify desired qualities, particularly in the conditions of bad weather, and the interval time between one to visits the satellite is long.

Since its commercial introduction in the early 1980s, unmanned aerial vehicles (UAVs) have seen a sharp rise in utilization across several sectors. UAVs have been successfully used for a variety of purposes, including traffic surveillance, disaster management, agriculture and forest monitoring, and photogrammetry for 3D modeling. UAV imagery paired with machine learning models delivers more precise, quick, non-destructive data collection and automated analysis capabilities (Sun *et al*., 2024). Understanding plant growth and development helps crop managers and plant breeders enhance

[1]Institute of Environment & Sustainable Development, Banaras Hindu University, Varanasi, Uttar Pradesh 221011

[2]Academy of Biology and Biotechnology, Southern Federal University, 344090 Rostov-on-Don, Russia

***Corresponding author:** Sudhakar Srivastava, Institute of Environment & Sustainable Development, Banaras Hindu University, Varanasi, Uttar Pradesh, Email: sudhakar.iesd@bhu.ac.in

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crop productivity and precision agriculture while also examining how plants react to various management scenarios (Tunca *et al.,* 2023). In this timely review, the most recent technical developments for UAVs for estimating plant phenotypic characteristics at the field size are discussed.

Methodology

The articles reviewed in this paper were searched from ScienceDirect and Google Scholar. The keywords UAVs, unmanned aerial vehicles, and phenotyping and agriculture were used. A total of 697 articles from ScienceDirect and 8,320 from Google Scholar websites were generated for the period of 5 years from 2019 to 2023. So, a total of 9,017 articles were published from 2019 to 2023. Based on the analysis, UAVs and remote sensing technologies are developing very rapidly for crop phenotyping and monitoring purposes providing precise, safe, and minimum plant tactile interference. The key articles from the searched ones were used for presenting the topic in a clear, short, and concise manner presenting the technique and its advancements.

High throughput Phenotyping

The word *pheno* means observable or visible, and the word *typing* refers to categorization or measurement, thereby giving the meaning "measurement and categorization" of visible and observable traits of plants. Plant growth, development, and physiology are measured via phenotyping, which is the result of interaction between the genotypes of plants and the surrounding environment. Examples of these interactions include the photosynthetic mechanism and efficiency, growth and development rate, disease resistance, morphology, abiotic stress tolerance, yield and produce, etc. It is generally performed to identify important alleles and related genetic markers influencing variables associated with yield, biotic and abiotic stress tolerance, and other beneficial agronomic characteristics (Hickey *et al.,* 2019; Kim, 2020). Simple traits like plant height can be phenotyped in a fair period by people without specialized expertise. However, it takes a lot of time and requires the knowledge of experienced people to evaluate more complex features, particularly those connected to drought or, heat tolerance, or any other abiotic stress. Furthermore, it is often not feasible to phenotype a big collection of genotypes in a desired time frame. Additionally, traditional phenotyping has a high chance of measurement mistakes, which can be made worse by weariness and are subject to personal interpretation by each person, leading to no improvement in plants (Araus *et al.,* 2022).

The rapid development of phenomics with the integration of remote sensing and data science is making High Throughput Phenotyping (HTP) technology a trend as well as a need today. The automatic and non-invasive phenotyping system, having the capacity for automated data collection its processing, along with analysis and visualization, is called as High-throughput plant phenotyping. HTP is the solution to the labor and time-intensive problem of phenotyping and also provides accuracy and precision. The characteristics that can be phenotyped can be divided into morphological characteristics (stem diameter, leaf length, stalk length, width, canopy cover, etc.) and physiological characteristics (NDVI, Chlorophyll content, biomass, etc.). The drawback of morphological characters is that they only apply to the exterior phenotyping of plants, which is inadequate to precisely give insights about factors like water and nutrient content. All of the internal processes that occur in plants, such as photosynthesis, environmental stress, plant nutrition, etc., can be analyzed and understood by physiological phenotyping. For a plant's overall development and for the identification of genes to combat current environment and population concerns, it is essential to conduct HTP of multiple quantitative traits involving both physiological and morphological ones (Großkinsky *et al.,* 2015; Ma *et al.,* 2022).

A HTP system contains components that are interconnected and have several functions to measure the quantitative trait accurately. These components are platform, sensor, data and analysis (Figure 1). Platforms can be ground-based, aerial or satellite. Sensors are used for data acquisition (DAQ) and are associated with quality assurance (QA) or quality check (QC). Image processing and modeling help in the visualization and

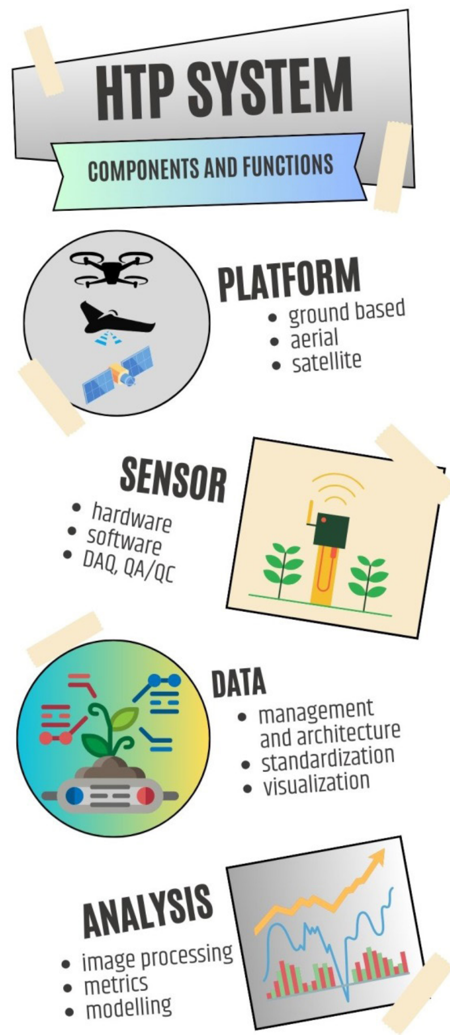

Fig. 1: A depiction of various components of HTP system that includes platform, sensors, data management and analysis

standardization of the collected data (Kim, 2020). Platforms for HTP combine a control terminal, data-gathering hardware, and data-processing software. They primarily use non-invasive imaging and spectroscopy methods to gather phenotypic data, and high-performance computational tools to quickly assess plant growth activities and physiological condition of the plant. HTP, as opposed to conventional phenotyping techniques, enables the dynamic monitoring of plants at various growth stages as well as the simultaneous data collection of many attributes in huge populations. In addition, the classification of traits based on spectra or images is more reliable than conventional techniques like visual scoring, which are prone to subjective interpretation. Furthermore, it enables model-based non-destructive estimates of biochemical parameters, minimizing the need for time-consuming procedures (Xiao *et al.,* 2022).

Unmanned Aircraft Systems (UAS)

Unmanned aircraft systems (UAS) have recently opened the door for the rapid development and better understanding of field high-throughput phenotyping for crops. It generally starts with an unmanned aerial vehicle (UAV) or drone that has a range of sensors and payloads intended to collect comprehensive data on plant properties (Figure 2). To collect information that can't be extracted from the human eye, such as infrared and ultraviolet data, which is essential for determining plant health and growth, these sensors frequently integrate multispectral or hyperspectral cameras. The UAS may also include GPS and navigational devices for accurate placement, enabling data georeferencing. Additionally, cutting-edge data processing and analysis software is a must since it makes it possible to extract useful data from the gathered aerial pictures (Ayankojo *et al.,* 2023; Delavarpour *et al.,* 2021).

Careful flight path planning using the ground control points (GCP), altitude, and timing of UAV missions is the first step in this process. At this stage, variables such as the outside temperature, the lighting, and the specific objectives, as per the parameter to be monitored, are taken into account. The choice of sensors is based on the objectives of the study, and they are configured and placed accordingly. The sensors collect data when the UAV is in flight as it follows the pre-planned flight path. To produce a complete dataset, the sensors gather pictures as well as other pertinent information, such as the GPS coordinates and altitude. The images obtained and sensor data are georeferenced using the GPS and GCP data that was gathered during the flight, guaranteeing that all information is precisely positioned inside the research area. To account for elements like atmospheric conditions, sensor noise, and geometric distortions, color, and spectral calibration, pre-processing may be necessary for the raw data from the sensors. This process makes sure the data is accurate and acceptable for analysis. Individual images are stacked together to form a single, complete dataset for multispectral or hyperspectral photography that covers the whole research region. To provide a more comprehensive knowledge of plant development and health, phenotypic data from UAV-based sensors can be combined with additional datasets such as ground-based measurements, meteorological data, and historical information. To simplify the modeling for plant phenotyping, algorithms (classification, regression, and cluster) are required after data collection (Figure 3). Researchers evaluate the retrieved phenotypic data using statistical and machine-learning approaches to find relationships, trends, and patterns that might guide decisions about agriculture, breeding, and research. (Ayankojo *et al.,* 2023; Guo *et al.,* 2021; Xie & Yang, 2020).

The advantages of unmanned aircraft systems (UAS) for plant phenotyping include their relatively low acquisition and deployment costs, simplicity and adaptability in control and operation, flexibility in reconfiguring sensor payloads to broaden sensing, and its ability to integrate easily into larger, interconnected phenotyping networks (Xie & Yang, 2020; G. Yang *et al.,* 2017).

Sensors used in UAVs

There are various sensors used in UAVs, which are described in the following section.

RGB digital Imaging

The RGB imaging technique is the most frequently used in UAVs. The sensor's benefits include inexpensive cost, convenient operation, lightweight, and straightforward data processing. Both bright and overcast situations can be used to gather data; however, exposure should be regulated according to the weather to prevent insufficient or excessive image exposure. Due to the robust hardware interaction with the UAS system, the RGB photos are geotagged with onboard GPS information. By doing this, geo-registration-related difficulties beyond the line are

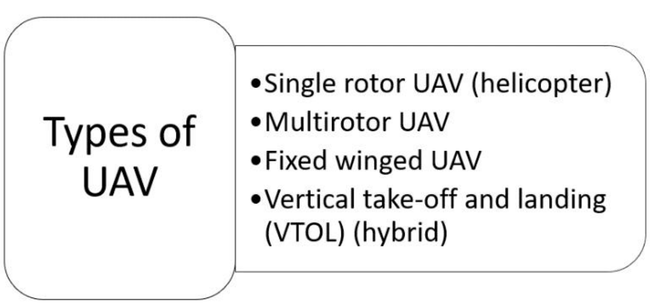

Fig. 2: Various types of UAVs in common practice and in developmental stages.

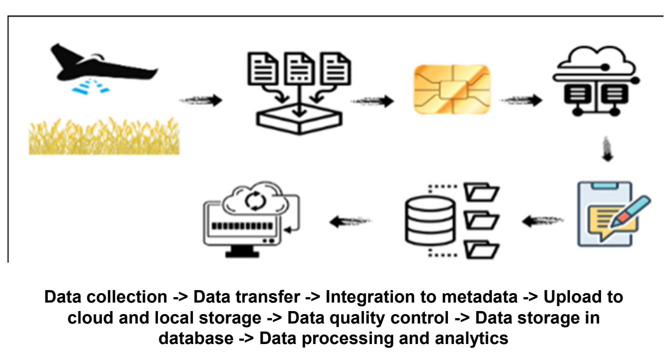

Fig. 3: A depictive workflow of collection, management and processing of data collected with the use of UAVs.

reduced(Guo *et al.,* 2021; G. Yang *et al.,* 2017). Unfortunately, the constraint of the less visible light bands prevents this approach from correctly analyzing crop phenotypic data for physiological parameters.

Multispectral Imaging

Multispectral cameras are those that can capture images of the electromagnetic spectrum at just a few wavebands (often between 3 and 10). Cameras that scan the red, green, and blue bands as well as the near-infrared and red edge bands, have been employed extensively in plant studies. This is due to the reflectance of chloroplast peaks in the near-infrared band (at about 850 m) and shifts at the red edge (at about 700 m) band. Thus, one may calculate other vegetation indicators by mixing these bands (Guo *et al.,* 2021; Jones & Vaughan, 2010; Seager *et al.,* 2005).

Hyperspectral Imaging

Hyperspectral cameras are those that can capture images across a wide range of electromagnetic spectrum wavebands that can reach up to 200 to 300. Both the single plant size and the field scale are the standard scales for using hyperspectral cameras. Because they cover a larger portion of the electromagnetic spectrum, HS cameras have several benefits over other imaging modalities. The biophysical and biochemical characteristics of crop species may be understood physiologically with the use of HS cameras, which can also identify biotic and abiotic stressors (Krause *et al.,* 2019; Nagasubramanian *et al.,* 2019).

Thermal Imaging

The infrared portion of an object's electromagnetic spectrum is measured using thermographic imaging. This is crucial from a physiological perspective because healthy plants, and particularly leaves, produce light in the infrared region of the spectrum. The infrared emission profile of the canopy can be indirectly linked to a number of biotic and abiotic stressors. This is due to the possibility that stressors (such as heat, drought, and biotic) might modify rate of photosynthesis and transpiration owing to variations in water uptake and gas and water exchanges, which would impact the canopy temperature and thus the thermal signature. Thus, thermal imaging may be used as a high-throughput technique to evaluate the plant's physiological state. However, the usage of thermal cameras on UAS has been very rare because of issues with hardware integration, camera cost, poor frame rate acquisition, and resolution compared to RGB imaging (Guo *et al.,* 2021; Xie & Yang, 2020).

LiDAR

LiDAR is a technique for surveying and imaging that uses laser light to measure a target's distance. It is used as a device that employs the photoelectric detecting technique and uses a laser as the transmitting light source. The advantages of LiDAR over traditional microwave radar are numerous and include a high point density and spatial resolution, a smaller and lighter body, and superior performance for low-altitude detection. LiDAR is comprised of a transmitter, receiver, tracking system, and information processing module. The pulse after emission interacts with the canopy and various components return different sections of it. The time difference between these portions gives information about the characteristics of the horizontal as well as vertical canopy structure (Wallace *et al.,* 2012; Yang *et al.,* 2017).

Microwaves

Remote sensing are based on optical, thermal infrared, and microwave sensors. Microwave remote sensing can easily penetrate clouds and fog and thus obtain properties of surface and soil very accurately (Dong *et al*., 2020). The information of soil moisture and surface qualities like roughness and relief can help in crop management. However, there are issues with microwaves as in the presence of vegetation on land, it is not able to penetrate and therefore, soil information from microwaves lacks accuracy in planted lands (Wu *et al*., 2024).

Data collection and processing

Before data collection, the type of camera and UAV platform must be chosen based on specifications and budget. The remote-control device is used to regulate the UAV's flying speed, flying direction, flying distance, and other characteristics. The memory card of the camera holds the gathered data, which may be removed and linked to a computer for additional processing. Pre-processing of the raw image data is necessary for image correction, format conversion using proprietary software for a particular sensor, ortho-mosaicking, secondary band registration, and, if required, radiometric calibration to transform pixel values from digital numbers to reflectance and brightness adjustment to reduce the cloud shadow effect (Shi *et al.,* 2016).

The pre-processing of remote sensing images is done by geometric and radiometric correction. Due to the UAV platform's height and speed, geometric correction is required to assign the correct elevation to the observed features. Owing to the air circumstances, sensor physical properties, the location of the sun, and measurement angle, the electromagnetic energy detected by the UAV deployed sensors might be different than the actual radiation spectrum of the target. Therefore, radiation correction is necessary to remove or correct the measurement error (Su *et al.,* 2019).

Applications of high-throughput phenotyping

Biomass measurement

Biomass has been measured by using RGB images in wheat, barley, pea, oat and other plants. In pea and oat, RGB images were obtained and the normalized green-red difference index (NGRDI) was calculated to monitor and estimate the phenology of the vegetation and above-ground biomass. Based on the results obtained, spatial variability maps have been created showing biomass, which helps farmers and researchers in the site-specific management of crops. The RGB camera on the UAV platform was also used to estimate the biomass of maize. A random forest (RF) model was used to predict results and generate spatial patterns of biomass. This was used to monitor the crop changes taking place in a field and find corresponding suitable strategies to use the change for benefit (Brocks & Bareth, 2018; Jannoura *et al.,* 2015; Li *et al.,* 2016; Schirrmann *et al.,* 2016; Xie & Yang, 2020). Using GRID software, alfalfa plot pictures were extracted to calculate the amount of vegetation based on the normalized difference vegetation index (NDVI) (Tang *et al.,* 2021).

Yield estimation

To estimate the rice yield, multispectral images using a radio-controlled unmanned helicopter were collected to calculate the NDVI. A spectroradiometer was used to obtain spectral reflectance at ground level, which exhibited a strong correlation for yield. UAV-based RGB sensor was used to estimate corn yield where different models were established using vegetation indices. In the case of maize, multispectral images were obtained using UAV to observe maize growth at different phosphorous fertilizations. The results obtained demonstrated a strong correlation between indices calculated and yield, along with a strong correlation with leaf phosphorous content. UAV-based multispectral images were obtained for sunflower plant to estimate its yield, nitrogen content and biomass (Geipel *et al.,* 2014; Gracia-Romero *et al.,* 2017; Vega *et al.,* 2015; Xie & Yang, 2020). Utilizing UAV data, the growth model *Gramineae* (GRAMI)-rice was effectively deployed to forecast rice yield. To accurately anticipate yields, however, much more study is required to determine the ideal sensor setup, flight schedule, and crop growth model adjustments (Liu *et al.,* 2018; Maes & Steppe, 2019).

Leaf area index (LAI), plant height, and canopy cover

The sorghum leaf area was estimated using multispectral images taken by the sensors installed on the UAV. NDVI and enhanced vegetation index (EVI) were calculated and showed high correlation with the leaf area index. Along with it, the normalized difference red edge index (NDRE) was calculated to monitor the senescence pattern, which showed a strong correlation with chlorophyll content, which can be used as a good indicator for photosynthetic capacity. LAI is also a crucial factor in the determination of canopy cover, which could also be predicted with the data (Potgieter *et al.,* 2017; Xie & Yang, 2020).

In the case of wheat, the booting and mid-grain fill periods of crop growth were assessed effectively with the help of UAVs. Using a computerized surface model it offered an efficient and quick way to measure the height of plants. To identify quantitative trait loci (QTL) linked to plant height, and improve comprehension of growth dynamics, this data was then incorporated into genetic studies and wheat breeding programs. This led to more effective wheat breeding for increased yield potential and lodging resistance (Hassan *et al.,* 2019). To estimate wheat height, RGB images taken from UAV platform were used to map the spatial variability of crop height. Olive tree height, along with its crown diameter, was estimated using UAV-based RGB sensors. Monitoring these traits helps find new cultivars for the breeding programs. In maize, to estimate the canopy cover and senescence, RGB images were taken from UAV-based sensors to understand and monitor crop response, facilitating the plant breeding techniques (Aasen *et al.,* 2015; Díaz-Varela *et al.,* 2015; Holman *et al.,* 2016; Madec *et al.,* 2017; Makanza *et al.,* 2018; Xie & Yang, 2020).

Nitrogen and Chlorophyll Content

In the cotton plant, multispectral images were taken with the help of UAV platforms to calculate various indices to understand the temporal and spatial variability of nitrogen content in the plant. Similarly, in the case of maize also, multispectral sensors placed on UAV were used to assess the spatial variability and low nitrogen tolerances. NDVI of turfgrass plant was calculated using images obtained from UAV-based multispectral sensors along with a handheld sensor and the correlation between the two was established. The results showed a strong correlation and demonstrated that the UAV method can be useful in diagnosing low nitrogen content in the plant. To assess nitrogen status in the rice canopy, RGB sensors placed on UAV were used and the nitrogen balance index (NBI) was calculated. Results gave a strong correlation between calculated and ground-based indices, proving UAV a potential tool to be used in the field. RGB, multispectral and thermal sensors placed on UAV were used to estimate chlorophyll content in soybeans, along with other biochemical and physical traits. Results showed that the fusion of data predicts best the condition and status of chlorophyll in plants. (Ballester *et al.,* 2017; Caturegli *et al.,* 2016; J. Li *et al.,* 2015; Maimaitijiang *et al.,* 2017; Xie & Yang, 2020; Zaman-Allah *et al.,* 2015). It was discovered that certain specific color bands were strongly related to the quantity of chlorophyll in potato leaves and canopies using the hyperspectral sensors on UAVs. The accuracy of estimating oat chlorophyll levels and soybean chlorophyll and nitrogen contents improved with the fusion of thermal data with these. This shows that hyperspectral data can offer more precise and in-depth insights about the health and nutrient levels of crops when paired with thermal data, which is beneficial for enhancing agricultural practices (Domingues Franceschini *et al.,* 2017; Elarab *et al.,* 2015; Liu *et al.,* 2017; Maes & Steppe, 2019; Maimaitijiang *et al.,* 2017).

Weed Detection

UAVs are an excellent way to precisely map weed infestations in fields since they are frequently not distributed uniformly and allow for targeted weed treatment. The technique, commonly known as spectral discrimination, makes use of distinctions in the colors of crops and weeds. If the weeds and crops have distinct color variations, even standard RGB cameras can be employed (Maes & Steppe, 2019; De Castro *et al.,* 2018; Tamouridou *et al.,* 2017).

Other biotic and abiotic stress

It was found that under drought circumstances, dry bean seed yield and biomass outputs were substantially connected with the canopy area and the green normalized difference vegetation index (GNDVI). Therefore, in the conditions of drought, GNDVI may be a reliable indication of both the yield as well as biomass of dry beans. This study also discovered that thermal imaging might be used to assess variations in stress-induced canopy temperature (Ayankojo *et al.,* 2023; Sankaran *et al.,* 2018). High-yielding accessions in salt-stressed tomatoes were identified using UAS-based RGB and multispectral data, while the link between water stress and the canopy temperature in the plant of soybean and sorghum was determined using thermal imaging (Johansen *et al.,* 2019; Sagan *et al.,* 2019). Crop disease monitoring, detection, and classification have all been accomplished with the use of remote sensor imaging, a few examples being maize streak virus disease, late blight disease in potatoes , etc. Contrary to multispectral and hyperspectral sensors, RGB sensors frequently exhibit inferior disease detection accuracy. In general, UAS technology offers a tremendous possibility for rapid disease categorization and identification of agricultural illnesses for breeding decision-making as well as early disease detection for prompt disease response (Ayankojo *et al.,* 2023).

Challenges and Future Perspectives

The UAVs face several challenges for plant phenotyping that need to be researched in the future to enhance the usage of UAVs in agriculture.

- *Cost:* The high cost of UAVs is a major constraint in their widespread usage, particularly in developing countries. Multispectral and hyperspectral sensors are relatively expensive as compared with the RGB cameras. Further, in case of accidental crashes of UAVs, high economic loss would occur. Thus, the cost and operational risks linked to UAVs need to be brought to an acceptable level.
- *Analysis of the data:* Since pictures make up the majority of the data gathered by the UAV remote sensing system, image analysis techniques need to be easy and user-friendly. Typically, image collection, segmentation, and classification require high-capacity computation and data storage for phenotypic platforms due to enormous volumes of pictures and data. The effectiveness and functionality of image processing, particularly the field software's capacity for quick processing, are insufficient in comparison to the fast growth of sensor and hardware platforms (Yang *et al.,* 2017).
- *Environmental factors:* Environmental elements, such as noise, sun condition, wind, and soil conditions, among others, have an impact on the phenotyping analysis when UAVs are in flight. Some environmental elements will have an impact on the findings when assessing crop height, yield, biomass, and other features. More precise models need to be developed in the future to counteract environmental factors effect (Lelong *et al.,* 2008).
- *Accurate measurement of ground data:* The classification results are also influenced by the accuracy of ground data measurement. Although data may be collected using UAV-based remote sensing at a lower height, not every plant's phenotyping attribute can be measured. Choosing samples from the chosen region of interest and using its average characteristics as the analysis's reference values is a frequent practice. Therefore, it is crucial to precisely quantify the phenotyping features. For ground measurement, a scientific sample of the plants is essential.

Conclusion

In high-throughput plant phenotyping, the use of UAVs has proved to be helpful and a wide range of uses in agriculture have been demonstrated, including benefits like effectiveness, affordability, adaptation to challenging field conditions, and high-resolution data collecting. For field-based phenotyping, sensors useful in digital or RGB imaging, multispectral imaging, hyperspectral imaging, thermal imaging, and LiDAR imaging techniques are frequently employed. Current research focuses on multi-sensor integration and improved data processing algorithms. Geometrical attributes, canopy spectral texture, physiological characteristics, stress responses, nutritional status of plants, and yield prediction are just a few of the crop phenotypic parameters that UAVs have the potential to gather. Validation across several crop kinds is still scarce, though. There are also difficulties, such as restrictions on UAVs, strict rules governing airspace, delays in data processing, and the requirement for models to predict complicated features under various environmental circumstances. Research trends should go in a direction that includes improving UAV performance, decreasing sensor prices, speeding up data processing, and improving crop phenotypic analysis via remote sensing. As UAV technology develops, sensor costs fall and regulatory frameworks become more flexible, and a wider range of UAV-based field phenotyping applications are anticipated to become possible.

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Author contribution

MB, SW and VDR prepared the draft of the MS. VDR reviewed the MS and finalized the draft. TM and SS supervised the work and finalized the MS for submission.

Declaration of Competing Interest

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

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