Review: Cost-Effective Unmanned Aerial Vehicle (UAV) Platform for Field Plant Breeding Application

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Abstract: Utilization of remote sensing is a new wave of modern agriculture that accelerates plant breeding and research, and the performance of farming practices and farm management. High-throughput phenotyping is a key advanced agricultural technology and has been rapidly adopted in plant research. However, technology adoption is not easy due to cost limitations in academia. This article reviews various commercial unmanned aerial vehicle (UAV) platforms as a high-throughput phenotyping technology for plant breeding. It compares known commercial UAV platforms that are cost-effective and manageable in field settings and demonstrates a general workflow for high-throughput phenotyping, including data analysis. The authors expect this article to create opportunities for academics to access new technologies and utilize the information for their research and breeding programs in more workable ways.

Keywords: high-throughput phenotyping; remote sensing; commercial unmanned aerial vehicle (UAV) platform

1. Introduction

Plant breeding research in the twenty-first century is a combination of genotyping, phenotyping, and computational data analytics [1]. Over the last two decades, genotyping technology has improved markedly in terms of cost, turnaround time from sample to data, and the change from assay-based to sequence-based technology. Innovation in computational data analytics has been exponential, along with advances such as algorithms for analyzing large data sets and cloud computing. Phenotyping has also advanced dramatically with emerging technologies, such as automation, sensing, imaging, robotics, and high-speed networks.

In the last twenty years, sensing technology has become one of the most promising high-throughput phenotyping technologies. It provides a non-destructive measurement of crop performance in both...
controlled and field environments. With various sensing technologies, the popularity of aerial platforms has substantially increased, especially for studies in field settings. Aerial platforms include satellites, manned aircrafts, and unmanned aerial vehicles (UAVs). Satellite and manned aircraft remote sensing platforms can monitor plant behaviors in large areas and measure various data concurrently, based on fine spectral data and wide wavelengths. However, their low spatial and temporal resolution and high equipment costs are critical bottlenecks [2]. In addition, their low payloads create limitations in sensor mounting and low battery capacity, resulting in short flight times [3]. Given the above limitations, the UAV is a valid technology and a suitable aerial platform for breeders with the advantages of high spatial resolution, derived from their low altitude for capturing images, and high temporal resolution, derived from their flexible image capturing capability, even in overcast sky conditions [4–8].

Phenotyping methods must balance accuracy, speed, and cost. This article reviews various methodologies and applications for phenotyping using commercial UAV platforms. It focuses on cost-effective equipment and end-to-end workflow to improve the accuracy and speed of utilizing collected datasets.

2. Overview of Cost-Effective Commercial UAV Platforms

UAV platforms are classified based on various specifications, such as speed, payload, mounted sensor, and maximum flight time, with a wide range of market prices. Thus, to obtain the maximum benefit, a UAV platform should be chosen by considering the target phenotypes, the workforce available to operate it, and the available budget. To balance the demands, assembling UAVs is one option for adapting commercial flight controllers, such as the Pixhawk, Naza, and Navio series [9]. However, they are labor-intensive to assemble, and handling the electronic components of a UAV platform is difficult for researchers who have limited knowledge of mechanics. Another option is purchasing commercially available industrial UAV platforms, which provide high payload and flight time and can mount various sensors and acquire images over a wide field; however, they are less economical and require professional skills to operate.

To overcome the limitations of both the hand-assembled and industrial options, the authors propose instead cost-effective commercial UAV platforms, which are significantly less expensive and easier to operate than industrial platforms. Cost-effective commercial UAV platforms (lower than USD 5000) are summarized in Table 1. Key features of the UAV platforms are flight time, spatial resolution, and sensors able to be mounted (mostly Red Green Blue sensors), acquiring visible spectral images with a 90° adjustable lens [10,11]. Mavic, Phantom, and Inspire are the commercial drone series from DJI (SZ DJI Technology Co., Ltd.) on which an RGB camera is mounted by default. Among the DJI series, the Inspire series has the highest specification and price, while Mavic has the lowest specification and price. The Parrot Drone series (ANAFI Work, ANAFI Thermal, and Bluegrass) is differentiated by the sensor mounted on the UAV. Yuneec drones have two series: Mantis (a quadcopter) and Typhoon (a hexacopter). Walkera supplies the Vitus with an RGB camera, the Vitus Starlight with illuminance correction, and the VOYAGER with RGB, thermal, and night vision as selectable options. The HolyStone drone series is the most cost-effective, although it also has relatively low specifications.
Table 1. Commercial unmanned aerial vehicle (UAV) platforms available in the market.

| Model                              | Price ($)  | Price (€)  | Flight Time (min) | Sensor (Spatial Resolution) | Application |
|------------------------------------|------------|------------|-------------------|----------------------------|-------------|
| DJI Mavic 2 pro                    | 1599.00    | 1499.00    | 29                | RGB camera (5472×3648)      | [12–14]     |
| DJI Mavic 2 zoom                   | 1349.00    | 1249.00    | 29                | RGB camera (4000×3000)      |             |
| DJI Mavic Air                       | 919.00     | 849.00     | 20                | RGB camera (4056×3040)      |             |
| DJI Mavic Pro Platinum             | 1149.00    | 999.00     | 30                | RGB camera (4000×3000)      |             |
| Phantom 4 Pro V2.0                 | 1599.00    | 1699.00    | 30                | RGB camera (5472×3648)      | [10,12,15–18]|
| Inspire 2                          | 3299.00    | 3399.00    | 23 – 27           | RGB camera (24Mega)         | [19–22]     |
| Parrot ANAFI Work                  | 999.00     | 999.00     | 25                | RGB camera (5344×4016)      |             |
| Parrot ANAFI Thermal               | 1900.00    | 1900.00    | 26                | RGB camera (5344×4016)      |             |
| Parrot Bluegrass Fields            | 4980.00    | 4510.59    | 25                | multispectral sensor (1260×960)  |             |
| Yuneec Mantis G                    | 699.99     | 699.00     | 33                | RGB camera (4160×2340)      | [23]        |
| Yuneec Mantis Q                    | 499.99     | 499.00     | 33                | RGB camera (4160×2340)      |             |
| Yuneec Typhoon H                   | 899.99     | 799.00     | 25                | RGB camera (4:3/12.Mega)    | [21,24]     |
| Yuneec Typhoon H520                | 1561.79 – 11,864.00 | 1382.93 – 10,505.00 | 25 | RGB camera (4:3/12 Mega)   |             |
| Walkera Vitus                       | 739.00     | 654.76     | 28                | RGB camera (4000×3000)      |             |
| Walkera VITUS Starlight            | 899.00     | 796.53     | 22                | RGB camera (1920×1080)      |             |
| Walkera VOYAGER 5                  | 17,999.00  | 15,947.37  | 20                | RGB camera (3840×2160)      |             |
| HolyStone HS720 GPS Drone with 2K Camera | 299.99   | 279.99     | 26                | RGB camera (2048×1152)      |             |
| HolyStone HS120D FPV Drone with GPS System | 159.99  | 139.99     | 16                | RGB camera (1920×1080)      |             |
| HolyStone HS100 FPV Drone with GPS  | 169.99     | 159.99     | 12–15             | RGB camera (1280×720)       |             |

Both prices are based on the price on 9 March 2020.

3. Proposed End-to-End Workflow of High Throughput Phenotyping Using Cost-Effective Commercial UAVs

Figure 1 shows a proposed end-to-end workflow of a remote sensing research methodology. It is based on determining relationships or constructing models of electromagnetic energy from a specific band and exploring actual target plant biophysical properties [25]. The first step is to identify the traits of the target plant species that will be observed by the remote sensor; second, determine the sensors to be mounted on the UAV platform that could be expected to demonstrate a high correlation between target traits and captured images. To improve prediction accuracy, we propose capturing images of the actual traits of the plant in the ground simultaneously with capturing aerial images using the UAV platform. They will be used to construct a proper model.
Figure 1. Workflow for high-throughput phenotyping using commercial unmanned aerial vehicle (UAV) platforms.

The processes proposed here are suitable for commercial UAV platforms in terms of operation easiness and work efficiency. The following Section 4, Section 5, Section 6, Section 7 demonstrates details of technical principle, method for acquiring data, image processing and applications.

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4. Considerations before Phenotyping Operation

Before starting operation, the hardware system mounted on the UAV platform should be calibrated for the safety of the vehicle and performance of the planned mission-based waypoints.
Inertial measurement unit (IMU) and global navigation satellite systems (GNSS) are critical for calibration. Most commercial UAV platform manufacturers provide a manageable calibration tool in a free remote-control application for manual control (Table 2). The flight should be planned to have overlapped aerial images with a regular, overlapped ratio and uniform spatial scale [26–28]. Images captured using an UAV platform can be processed to generate an orthoimage through image mosaicking techniques and a digital surface model (DSM) through photogrammetric techniques for extracting image variables. A ground control station (GCS) supporting flight planning software enables the collection of such images by fixing the travel route, time interval of image acquisition, and altitude of UAV flight with automated flying. A sensor perspective position-based autopilot mobile application, so-called waypoint navigation, has recently become available for use with commercial UAV platforms for capturing images for agriculture, construction, and environmental surveys. A list of commercial flight planning applications is given in Table 3, with advantages and disadvantages.

Table 2. Software for hardware calibration of commercial unmanned aerial vehicle (UAV) platforms.

| Manufacturer | Android _ Application | IOS _ Application |
|--------------|----------------------|-------------------|
| DJI          | DJI GO, DJI GO 4     | DJI GO, DJI GO 4  |
| Parrot       | FreeFlight 6, FreeFlight Pro | FreeFlight 6, FreeFlight Pro |
| Yuneec       | Yuneec Pilot, CGO3   | Yuneec Pilot, CGO |

Table 3. Software for flight mission planning of commercial unmanned aerial vehicle (UAV) platforms.

| Application   | Pros                                                                 | Cons                                                                 | Manufacturer          |
|---------------|----------------------------------------------------------------------|----------------------------------------------------------------------|-----------------------|
| DJI GS Pro    | - Free software that has a clean and intuitive interface.            | - Waypoints are limited in 99 maximums.                              | DJI [29]              |
|               | - Allows automated 3D Map Area systems.                              | - Only compatible with DJI drones and the iPad.                      |                       |
|               | - Seamlessly works with DJI products.                                |                                                                      |                       |
| DroneDeploy   | - User-friendly interface and option for drone mapping.              | - Relatively fewer robust solutions are provided than other programs.| DroneDeploy [30]     |
|               | - Provides numerous applications by allowing 3rd parties to interface with the collected aerial imagery and generate specific datasets. |                                                                      |                       |
| LITCHI        | - Simple to use and missions can be created on a regular PC and android phone, unlike DJI GS Pro. | - Lack of DJI warranty support.                                      | VC Technology [31]   |
|               |                                                                      |                                                                      |                       |
| Pix4D Capture | - Allows you to create flight plans for capturing image data with easy flight planning, automated pre-flight check, and real-time monitoring. | - Unable to plan flight missions that require multi-battery.          | Pix4D [32]            |
|               | - Produces georeferenced maps and models in Pix4D desktop or cloud software easily. | - Unable to set accurate velocity and interval of capturing time in android. |                       |
|               | - User can define the size of a mission to map areas of all sizes.   |                                                                      |                       |
|               | - Automated data uploading is available.                             |                                                                      |                       |
|               |                                                                      |                                                                      |                       |
| Propeller AeroPoints | - Efficient data coordination by streamlined data collection and management system. | - Interface is aimed at experienced users.                          | Propeller Aerobotics [33] |
|               | - Highly durable in extreme environmental conditions, ground control point (GCP) is provided. |                                                                      |                       |
|               |                                                                      |                                                                      |                       |
| Maps Made Easy | - Provided for the free package.                                    | - Multi-battery flight issues.                                       | Drones Made Easy [34] |
|               | - Easy to use, up to 7500 images can be processed.                  | - Less straightened interface than other software.                   |                       |

5. Sensors Mounted on UAVs

Sensors can be grouped into active and passive sensing systems. An active sensor system uses energy from an electrical source for measurements transmitted by the sensor, while a passive sensor is a device which does not use energy from an electrical source. Both systems can be used in a field environment for phenotyping, such as assessing biomass [35] and the nitrogen status of maize [36].
Sensor selection should be based on the target traits and the purpose of the study. Here, sensor types used in the remote sensing method are grouped in the following manner: visible and reflective infrared, thermal infrared, and microwave types [37]. Visible and reflective infrared types include RGB digital cameras and spectral cameras to obtain reflectance data from the plant [38]. Thermal infrared types, also called thermal sensors, detect the wavelength of thermal radiation emitted from the plant, depending on its temperature [39]. A light detection and ranging (LIDAR) sensor, which is representative of microwave types, measures the distance to one point of a target plant by illuminating the plant and analyzing the reflected light. LIDAR sensors construct a three-dimensional structure with the distances to several parts of the plant [40]. LIDAR sensors are based on a Time of Flight (ToF) method requiring pulse modulation for emitting light with a rotating, relatively heavy sensor [41]. Thus, LIDAR sensors are not suitable for mounting on a commercial UAV platform, and we do not recommend them.

Commercial UAV platforms are less expensive and relatively easy to operate, but their major limitation is the low payload, both the number and weight of sensors mounted on the UAV. Since the highest payload of a commercial UAV platform is 450 g, only sensors below 450 g are described in each of the following sections. Cutting-edge technology, known as non-orthogonal multiple access (NOMA), is now available for UAV operation with 5G networks [42]. Detailed information on RGB digital cameras, spectral sensors, and thermal sensors is given below.

5.1. RGB Digital Cameras

The low-cost RGB digital camera is widely used in remote sensing techniques, providing a high spatial resolution of radiation values in the red (~600 nm), green (~550 nm), and blue (~450 nm) spectral bands. Most commercial UAV platforms provide RGB sensors with differing spatial resolution determining the image quality (Table 1). Visible images, such as plant coverage, plant height, and color indices, can be extracted by processing the aerial image from an RGB camera [43].

Plant coverage is defined as the area of plant extracted from the total field image. Plant coverage is the proportion of the total field image that is solely occupied by plants [44]. It is highly correlated with indicators of biophysical status, such as biomass, plant vigor, leaf area index, and yield [43,45–47]. To acquire accurate plant coverage information in an orthoimage, plant pixels must be segmented from non-plant, background pixels [48]. The segmentation method is based on applying a color index, thresholding, or a learning method [49]. Discriminating plant from non-plant can be done by using Hue histogram conversion from the RGB image [50,51]. A red, green, blue image can be converted to hue–saturation–vibrancy space or grayscale, a color index for precise plant analysis. Additionally, an optimal threshold value can be applied to the converted image to segment plant from background [52–54]. Therefore, segmenting vine canopy and minimizing shadow effect can be successfully processed with those applications of RGB camera and Hue histogram conversion [55–58]. Classification learning methods, such as K-means, artificial neural networks (ANN), random forest (RForest), and spectral indices (SI), have been applied to analyzing vines and trees, with ANN and SI methods delivering high accuracy.

Plant height is the vertical distance between a ground reference and the upper boundary of the plants [59]. It is a meaningful indicator for estimating plant health, growth rate, biomass, and yield [60,61]. As mentioned above, regularly overlapped two-dimensional images captured at a steady altitude are required for elevation data. Each image with its GPS location is captured along the planned path from an RGB digital camera mounted on the UAV platform. Images are captured to generate a DSM with photogrammetric techniques based on a structure from motion (SfM) algorithm. The plant height can be calculated by subtracting a digital terrain model (DTM), which represents the field with no plants, from the DSM, which includes the plants [59,62,63]. However, the estimated plant height can show a low correlation with the actual plant height due to the spatial resolution of RGB sensors and the spiky form of the target plants [17,64]. Photogrammetric techniques based on an SfM algorithm are highly dependent on the image resolution and the overlapping proportions between acquired aerial
images [8]. Thus, having a higher resolution camera or setting a lower altitude and slow and stable flight speed for the UAV platform should be seriously considered [65]. It is also important to calibrate the height using the actual height of plants or some structure for estimating plant height to minimize this low correlation issue [66].

Color indices are acquired through algebraic calculation with reflectance values from the R (red), G (green), and B (blue) bands, respectively. While color indices can be used to segment plants from overall image as mentioned above, the main value of color indices is in facilitating the prediction or estimation of biophysical properties of target plants, such as biomass, leaf area index, and yield [67–69]. RGB digital cameras have advantages in their high resolution and low price, but the sensors also have limitations in overlapping the red, green, and blue wavelength spectra (Table 5).

5.2. Spectral Sensors

Green plants have the highest rate of reflectance in near-infrared (NIR) wavelengths (700–1300 nm) and have a relatively low reflection at wavelengths beyond 1300 nm [70]. Their reflectance varies significantly due to biotic and abiotic stresses that cause physical or physiological disorders in the plant [71–73]. Therefore, high-throughput phenotyping technology applies spectral sensors that can detect various wavelengths, not only in the visible spectrum (400–700 nm), such as RGB digital cameras, but also in the invisible, NIR spectrum (700–1300 nm). Spectral sensors acquire a spectral signature from radiance energy in each pixel by collecting the radiance reflected, emitted, and transmitted from the target plant. Spectral data is then processed and analyzed to estimate target traits [38,64,74].

Spectral sensors are divided into multispectral and hyperspectral sensors [75]. The criteria for distinguishing them are the number of spectrum bands and the width of each spectrum band. A multispectral sensor generally detects five to twelve spectral bands in each pixel. A hyperspectral sensor can acquire imagery data with hundreds or thousands of spectrum bands in each pixel through narrow widths (5–10 nm) in the visible–infrared region [76]. However, we do not recommend hyperspectral sensors because they need integrating with more devices than multispectral sensors to operate properly in UAV platforms [77]: these other devices include battery, frame grabber, data storage device, and GPS inertia navigation system (INS). Being heavier and larger, a hyperspectral sensor results in a heavy and large UAV with the extra devices for the sensor application. Moreover, in practice a multispectral sensor can produce image data suitable for vegetation indices, even though hyperspectral sensors produce more precise image data. Therefore, the multispectral sensor is a suitable tool for a cost-effective UAV platform due to its efficiency.

Vegetation indices (VIs) are algebraically calculated by combining radiation values that are transformed from the radiation value at each band of a multispectral sensor to highlight a specific characteristic of the target plant. Its value can be used in designing a model for estimating biophysical and biochemical traits, such as health status, chlorophyll contents, water stress, vegetation vigor, and canopy biomass [78], with better performance than an individual spectral channel [79]. Examples of VIs using multispectral images are listed in Table 4, and each index has its own advantages and disadvantages. The Normalized Difference Vegetation Index (NDVI) is a well-known VI which has values ranging from −1.0 to 1.0, negative values represent water, values −0.1 to 0.1 correspond to soil, and positive values indicate target plants due to their greenness [16,22,27]. However, the NDVI is limited by errors due to atmospheric influence and soil reflectance [80]. The Green Normalized Difference Vegetation Index (GNDVI) is calculated in the same way as the NDVI, but the radiation value of the green band is substituted by that of the red band, so it relates more to chlorophyll concentration than the NDVI. The Soil Adjusted Vegetation Index (SAVI) is calculated similarly to the NDVI but has a constant (L) for correction of soil reflectance, meaning the coverage of target plants [77]. The Transformed Chlorophyll Absorption in Reflectance Index (TCARI)/Optimized Soil-Adjusted Vegetation Index (OSAVI) are typically used in predicting water stress [81,82]. Equations and features of VIs using multispectral cameras are presented in Table 5.
Table 4. Multispectral sensors for commercial unmanned aerial vehicle (UAV) platforms.

| Model               | Weight (g) | Spectral Band Name (Center Wavelength)                                                                 | Spatial Resolution | Frame Rate                                      |
|---------------------|------------|--------------------------------------------------------------------------------------------------------|--------------------|-------------------------------------------------|
| MAIA WV             | 420        | PURPLE (422.5 nm), BLUE (487.5 nm), GREEN (550 nm), ORANGE (602.5 nm), RED (660 nm), RED EDGE (725 nm), NIR1 (785 nm), NIR2 (887.5 nm), RGB camera | 1280×960           | 3 fps with 10 bits and 12 bits (6 fps with 8 bits) |
| MAIA S2             | 420        | VIOLET (443 nm), BLUE (490 nm), GREEN (560 nm), RED (665 nm), RED EDGE1 (705 nm), RED EDGE2 (740 nm), NIR1 (783 nm), NIR2 (842 nm), NIR3 (865 nm) | 1280×960           | 3 fps with 10 bits and 12 bits (6 fps with 8 bits) |
| MAIA M2             | 70         | Select two bands among the following bands: VIOLET (422.5 nm), NVIOLET (443 nm), BLUE (487.5 nm), SBLUE (490 nm), GREEN (550 nm), NGREEN (560 nm), YELLOW (602.5 nm), RED (665 nm), NRED (665 nm), H RED EDGE (705 nm), RED EDGE (725 nm), L RED EDGE (740 nm), H NNIR (783 nm), H NIR (785 nm), WNIR (842 nm), L NNIR (865 nm), L NIR (887.5 nm), RGB camera | 1280×960           | 3 fps with 10 bits and 12 bits (6 fps with 8 bits) |
| Parrot Sequoia +    | 72         | GREEN (550 nm), RED (660 nm), RED EDGE (735 nm), Near infrared (790 nm), RGB camera                   | 1280×960           | 1 fps 10 bits                                    |
| MicaSense Rededge-MX| 231.9      | BLUE (475 nm), GREEN (560 nm), RED (668 nm), RED EDGE (717 nm), NIR (840 nm), RGB camera               | 1280×960           | 1 fps, 12 bits                                   |
| MicaSense ALTUM     | 357        | BLUE (475 nm), GREEN (560 nm), RED (668 nm), RED EDGE (717 nm), NIR (840 nm)                         | 2064×1544          | 1 fps, 12 bits                                   |
| Sentera Double 4k Sensor | 80       | BLUE (446 nm), GREEN (548 nm), RED (650 nm), RED EDGE (720 nm), NIR (840 nm)                         | 1080×720           | 30 fps                                           |
| Sentera AGX710      | 270        | BLUE (446 nm), GREEN (548 nm), RED (650 nm), RED EDGE (720 nm), NIR (840 nm)                         | 1080×720           | 30 fps                                           |
| Sentera High Precision Single Sensor | 30 | For Normalized Difference Vegetation Index (NDVI); RED (625 nm), NIR (850 nm) (For Normalized Difference Red Edge Index (NDREI); RED EDGE (720 nm), NIR (840 nm) | 1248×950           | 7 fps                                             |
| Sentera Quad Sensor | 170        | RED (655 nm), RED EDGE (725 nm), NIR (800 nm), (RGB camera                                          | 1248×950           | 7 fps, 12 bits                                   |

fps = frames per second.
Table 5. Examples of vegetation indices (VIs) which can be extracted using multispectral sensors.

| Index                                           | Sensors                          | Formula                                                                 | Features                                      | Reference |
|------------------------------------------------|----------------------------------|-------------------------------------------------------------------------|-----------------------------------------------|-----------|
| Excess Green (ExG)                             | RGB                              | $2g - r - b$                                                             | Vegetation classification                      | [83]      |
| Excess Red (ExR)                               | RGB                              | $1.4r - g$                                                              | Vegetation classification                      | [84]      |
| Photochemical Reflectance Index (PRI)          | RGB                              | $\frac{(R_{670} - R_{700})}{(R_{670} + R_{700})}$                       | Plant stress measure                          | [75]      |
| Modified Green Red Vegetation Index (MGRVI)    | RGB                              | $\frac{(R_{660})^2 - (R_{700})^2}{(R_{660})^2 + (R_{700})^2}$          | Crop and plant height prediction              | [85]      |
| Normalized Difference Vegetation Index (NDVI)  | RGB and Infrared                 | $\frac{NIR - RED}{NIR + RED}$                                           | Crop health status measurement                | [83]      |
| Green Normalized Difference Vegetation Index   | RGB and Infrared                 | $\frac{NIR - Green}{NIR + Green} + 1$)                                 | Crop health status measurement related to     | [86]      |
| (GNDVI)                                        |                                  |                                                                         | chlorophyll concentration                      |           |
| Soil Adjusted Vegetation Index (SAVI)          | RGB and Infrared                 | $\frac{NIR - Green}{NIR + Green}$                                       | Soil influences on canopy spectra are         | [87]      |
| Modified Soil Adjusted Vegetation Index (MSAVI)| RGB and Infrared                 | $0.5 \times [2R_{660} + 1 - \sqrt{2(2R_{660} - 2R_{735})^2 - 8(3R_{660} - R_{700})}]$ | Developed for the more reliable and simple    | [88]      |
|                                              |                                  |                                                                         | calculation of a soil brightness correction    |           |
| Transformations Chlorophyll Absorption in      | RGB and Infrared                 | $\frac{3\times [2R_{660} - 2R_{735} - 8(3R_{660} - R_{735})]}{(1 + 4L)^2}$ | Chlorophyll content, water status prediction,  | [89]      |
| Reflectance Index/Optimized Soil Adjusted      |                                  |                                                                         | and plant stress identification               |           |
| Vegetation Index (TCARI(OSAVI))                |                                  |                                                                         |                                               |           |
| Ratios Vegetation Index (RVI)                  | RGB and Infrared                 | $\frac{RED}{NIR}$                                                      | High-density vegetation coverage and biomass   | [90]      |
| Difference Vegetation Index (DVI)              | RGB and Infrared                 | $\frac{NIR - RED}{NIR + RED}$                                           | Developed for the vegetation monitoring by     | [91]      |
|                                              |                                  |                                                                         | distinguishing the soil and the vegetation,   |           |
|                                              |                                  |                                                                         | but do not include the effects of atmosphere  |           |
|                                              |                                  |                                                                         | or shadow                                     |           |
| Perpendicular Vegetation Index (PVI)           | RGB and Infrared                 | $\sqrt{(R_{660} - R_{NIR})^2 - (R_{660} - R_{RED})^2}$                  | Leaf area index estimation, vegetation        | [91]      |
|                                              |                                  |                                                                         | identification, and classification            |           |
| Atmospheric Resistant Vegetation Index (ARVI)  | RGB and Infrared                 | $\frac{NIR - RED}{NIR + RED}$                                           | Vegetation status measurement with the        | [92]      |
|                                              |                                  |                                                                         | elimination of the atmospheric effect         |           |
| Normalized Difference Red Edge Index (NDREI)   | RGB and Infrared                 | $\frac{R_{660} - R_{670}}{R_{670}}$                                     | Estimation of green leaf area during          | [93]      |
|                                              |                                  |                                                                         | senescence.                                  |           |
| Enhanced Normalized Difference Vegetation      | RGB and Infrared                 | $\frac{(R_{660} - R_{735}) - 2R_{660}}{(R_{660} - R_{735}) + 2R_{660}}$ | Produces better discrimination within the      | [94]      |
| Index (ENDVI)                                  |                                  |                                                                         | index than the NDVI by using green channel    |           |
|                                              |                                  |                                                                         | additionally                                  |           |
| Renormalized Difference Vegetation Index       | RGB and Infrared                 | $\frac{R_{660} - R_{735}}{(R_{660} - R_{735})}$                         | Crop health status measurement with           | [95]      |
| (RDVI)                                        |                                  |                                                                         | insensitivity to the effects of soil and sun  |           |
|                                              |                                  |                                                                         |                                               |           |
| Green Chlorophyll Index (CLG)                  | RGB and Infrared                 | $\frac{RED}{NIR} - 1$                                                  | Chlorophyll content estimation                | [96]      |
| Chlorophyll Vegetation Index (CVI)             | RGB and Infrared                 | $\frac{RED}{NIR}$                                                      | Chlorophyll content estimation                | [97]      |

$R_s$ = reflectance in corresponding spectrum, NIR = near infrared (770–895 nm); Green = green (510–580 nm); RED = red (630–690 nm); Blue = blue (450–510 nm); RB = [RED – Blue]; $R_{soil}$ = soil reflectance, $R_{veg}$ = vegetation reflectivity.
A multispectral sensor can collect radiation data from spectral bands with almost no overlapping [26,69]. Further, it can include data of near-infrared wavelength. Hence, it can result in more accurate and precise data for VIs compared to color indices using an RGB digital camera. Although a multispectral sensor has the disadvantages of higher price and lower spatial resolution than an RGB digital camera, it has great advantages, such as the ability to detect the invisible physiological status of the plant, which can be highly correlated with target traits. The multispectral sensors listed in Table 4 for commercial UAV platforms are relatively less expensive than others on the market.

5.3. Thermal Sensors

Plant surface temperature is an important parameter directly related to the physiological response to various environmental stresses [45]. All bodies emit electromagnetic energy in the infrared (IR) wavelength range depending on temperature according to the principle of black body radiation. A thermal sensor detects this invisible energy (with wavelengths from 3–14 µm), then converts it to visible images showing the temperature of the target [69]. A thermal sensor is prone to errors owing to fluctuating environmental conditions in the air and other objects emitting or reflecting thermal infrared radiation. Thus, periodical calibration for thermal sensors is crucial for collecting accurate data. The calibration of thermal sensors can be conducted in the laboratory with a black body or other reference targets of known accurate temperature [44].

One example of thermal sensor application is using an index such as the Crop Water Stress Index (CWSI) to predict water stress of target plants subjected to environmental effects [44,98,99]. The CWSI is calculated with wet and dry reference temperatures, which are the lower and upper bounds for plant surface temperature. Specifically, the wet temperature means that the stomata are opened in a fully transpiring state; the dry temperature means that the stomata are closed and not transpiring, which is the water-stressed state. Methods for computing CWSI are addressed in many studies [80,100]. Several additional thermal indices are listed in Table 7.

A thermal sensor is one of the best options for collecting plant surface temperature data, but its spatial resolution is lower than an RGB digital camera. The low resolution of the thermal sensor makes it difficult to extract surface temperature data of a targeted plant from the background of the whole image. However, this problem can be resolved by including RGB or other spectral sensors in the imaging process. Spectral image data concurrently obtained with the thermal data enables the segmentation of plant pixels. The original thermal image with plant and non-plant together is overlaid with the image of the plant extracted from the background; the plant pixels can then be extracted from the thermal image [101]. Therefore, weight and resolution should be considered when selecting more than one sensor for mounting on the UAV, and applicable thermal sensors are summarized in Table 6.

Other issues that might occur during the above process include gaining unwanted detector and offset non-uniformity in registered temperature data. These can be solved, as suggested in Mesas-Carrascosa et al. [102].

| Model          | Weight (g) | Spectral Range (µm) | Spatial Resolution | Operating Temperature Range (ºC) |
|---------------|------------|---------------------|--------------------|----------------------------------|
| FLIR Vue Pro R | 92–113     | 7.5–13.5            | 336×256            | −20 ~ 50                         |
| FLIR Vue Pro   | 92–113     | 7.5–13.5            | 336×256            | −20 ~ 50                         |
| FLIR Duo Pro R | 325        | 7.5–13.5            | 336×256            | −20 ~ 50                         |
| DJI Zenmuse XT | 270        | 7.5–13.5            | 640×512 336×256    | −40 ~ 550                        |
| Yuneec CGOET   | 275        | 8–14                | 1920×1080          | −10 ~ 40                         |
| Yuneec E10T    | 370        | 8–14                | 320×256 640×512    | −10 ~ 40                         |
Table 7. Examples of thermal indices which can be applied with thermal sensors.

| Index                     | Formula                        | Feature                                              | Reference |
|---------------------------|--------------------------------|------------------------------------------------------|-----------|
| Crop water stress index   | $\frac{T_{canopy} - T_{wet}}{T_{dry} - T_{wet}}$ | Value ranges from 0 to 1 which the values close to 1 are related to high levels of stress | [103]     |
| Jones index (IG)          | $\frac{T_{canopy} - T_{wet}}{T_{canopy} - T_{dry}}$ | Positive correlation with the stomatal conductance   | [100, 104]|
| Jones index (I3)          | $\frac{T_{canopy} - T_{wet}}{T_{dry} - T_{canopy}}$ | Positively correlation with the stomatal resistance  |           |

6. Pre-Processing of Acquired Images

Remote sensing using aerial platforms is highly affected by environmental conditions, including incoming light, atmospheric conditions, and climatic factors [105]. Extracting valid data from image variables in aerial images using satellite platforms requires radiometric and geometric calibration. There are several approaches to minimizing atmospheric influences using atmospheric models such as MODTRAN, ACRON, and FLAASH [23]. By contrast, commercial UAV platforms do not need such calibration because they obtain data from lower altitudes with higher resolution [75]. For atmospheric correction, however, illumination correction should be carried out.

The sensor digital number (DN) depends on the amount of light in each given moment that cannot provide the same spectral data due to different light conditions at each time. The DN should be converted to another referencing radiation value using empirical line calibration based on reference radiation data from a brightness calibration tarp or spectralon panel [106]. In addition, in the case of a thermal sensor, accurate plant surface temperature collection should be calculated as an absolute temperature based on empirical line calibration, as discussed above [107].

Before extracting aerial images, a georeferencing process using ground control points (GCPs) is required in site-specific image processing to take into consideration the influence of the unstable flight of the UAV platform [8]. The GCPs should be installed on the experimental field for the identification of captured images with visible markers to increase the accuracy of GPS data. In a photogrammetric procedure based on the SfM algorithm, the process of converting captured images to accurate geometric data is conducted prior to the orthomosaic image production [38]. To reduce the number of GCPs for correcting the errors of spatial data, an automatic georeferencing method could be used based on navigation data and camera lens distortion [21, 108, 109]. Nonetheless, image sensors with GPS and INS mounted on a UAV platform can collect appropriate data for the photogrammetric process.

7. Image Processing Software

Using post-processing software, aerial images from UAV platforms are converted to extract image variables. Photogrammetry and mapping software can generate orthoimages and DSM. The image variables mentioned above can be extracted from the generated orthoimage and DSM using geographic information system (GIS) software. A program to extract image variables can also be easily constructed using library modules from commercial programming languages such as Python, C++, and MATLAB. Extracted image variables are used for determining relationships or constructing models with linear or non-linear methods, using actual traits simultaneously acquired with captured aerial images. Table 8 includes examples of phenotyping traits using commercial UAVs and various sensors and suggested methods. In addition, commercial photogrammetry and mapping software, and GIS software are listed in Table 9, with advantages and disadvantages.
Table 8. Examples of options for obtaining physiological and morphological traits by UAVs and multispectral sensors.

| Traits                     | Recommended UAVs | Sensors          | Image Processing Methods                                             | Reference |
|-----------------------------|------------------|------------------|-----------------------------------------------------------------------|-----------|
| Plant height                | All              | RGB              | DSM – DTM, MGRVI                                                      | [67]      |
| Vegetation coverage         | All              | RGB, ExG, ExR    | NDVI, RVI, DVI, PVI, ARVI, ENDVI, RDVI                              | [52,83,84,110] |
| Biomass                     | UAVs with enough payloads for the multispectral sensor | Multispectral | ExG, ExR, MGRVI                                                      | [85]      |
| Plant stress                | Multispectral    | NDVI, ARVI, ENDVI| PRI, NDVI, TCARI/OSAVI, ENDVI, NDREI                                | [75,83,89,93,94,112,113] |
| Chlorophyll content         | Parrot ANAFI Thermal Yuneec H520 | Multispectral | TCARI/OSAVI, NDREI, PVI, CLG, CVI                                  | [91,114] |
| Water status                | Parrot ANAFI Thermal Yuneec H520 | Multispectral | PRI, NDVI, TCARI/OSAVI, CWSI, IG, I3                                | [112,115] |
| Canopy temperature          | Parrot ANAFI Thermal Yuneec H520 | Thermal         | -                                                                    | [116]     |
| Transpiration rate          | Parrot ANAFI Thermal Yuneec H520 | Thermal         | -                                                                    |           |
Table 9. Photogrammetry and mapping software and geographic information system (GIS) software for unmanned aerial vehicle (UAV) platforms.

| Type                      | Software                     | Pros                                                                 | Cons                                                                 | Manufacturer             |
|---------------------------|------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|--------------------------|
| Photogrammetry and Mapping software | Agisoft Photocam Pro (Metashape) | - Wide range of 3D modeling tools, including thermal, NIR, RGB, and advanced multi-spectral images.  
- Capable of creating digital surface models and point clouds and accurate measurements.  
- Wide range of supported camera.  
- Allows georeferenced (digital surface model DSM, (digital terrain model) DTM, and orthomage export options.  
- Provides a 4D Modeling process. | - Relatively complicated interface than other software.  
- One software package for one computer. | Agisoft [117] |
|                           | Maps Made Easy              | - Provided for the free package.  
- Easy to use, up to 7500 images can be processed. | - Multi-battery flight issue.  
- Less straightened interface than other software. | Drones Made Easy [34] |
|                           | Pix4D Mapper                | - Provides automated processes, such as world map image deployment, photo camera calibration, orthomage generation, and DSM generation.  
- Allows users to process image data in wide platforms, both online and offline. | - Topographic maps are created only manual process. | Pix4D [118] |
|                           | SimActive Correlator 3D     | - Provides accurate, survey-grade maps.  
- The fastest processing speeds of any mapping software currently available. | - PC based software. | SimActive [119] |
| GIS Software              | ArcGIS                      | - Standard geospatial analysis software which is fairly easy to use.  
- Provides robust spatial analysis and the data advanced statistical tools. Effective to handle a large amount of vector data.  
- Lots of tutorials are available online and offline.  
- Compatible with the open-source programming language Python. | - High-price for its license: $1500, $7000, or $12,000 per user.  
- Interface is not user-friendly. | Esri [120] |
|                           | QGIS                        | - Has the edge for consuming data  
- No license. open-source, thus, does not limit which tools can be used | - Slow processing time | QGIS Development Team [121] |
|                           | ENVI                        | - Simplified user-friendly interfaces. | - No tools for 3D imagery, geocoding and spatial analysis | Harris Geospatial Solutions [122] |
|                           | ERDAS Imagine               | - Wide array of tools for geospatial analysis, such as map composition, image enhancement, image classification, raster geographic information system (GIS) modeling, and stereo analysis, are available.  
- Provides light detection and ranging (LiDAR) tools, DSM data sets, spectral image data tools, radar tools, and spatial model editing. | - Unable to perform hierarchical object-based image analysis (OBIA). | Hexagon Geospatial [123] |
8. Conclusions

Efficient, high-throughput phenotyping methods can be implemented only when data accuracy, process speed, and cost are well balanced within the permitted limits. It is clear that limitations of the technology exist, such as low payload and a narrow area for image collection. However, we have demonstrated that the utilization of cost-effective commercial UAV platforms for phenotyping and methodologies for high-throughput phenotyping accelerate plant breeding cycles. Introducing suitable selection criteria and combining devices properly selected for the UAV platform promise efficient pathways within the limits of current technologies. Low-priced commercial UAVs, which provide safe flight and flight mission planning software, and free image processing software, such as QGIS, are recommended for users who seek RGB image data of crops with low budgets and unskilled flight control techniques. Users who want additional spectral data or data under specific environmental conditions will have a fuller choice, depending on the purpose. For instance, Parrot Bluegrass Field for NIR image data acquisition, Walkera VOYAGER for thermal data and night vision, and hexacopters, such as Yuneec Typhoon, for specific environments, are typical choices. There are multiple options for obtaining various physiological and morphological traits with cost-effective sensors and UAVs.

Cost-effectiveness and the ease of operation of a commercial UAV platform is a huge advantage compared to handcrafted or industrial drones. A commercial UAV platform will be a very good option for users who lack engineering knowledge and want high-throughput phenotyping with a tight budget. We are pleased to introduce such platforms to readers who are interested in cost-effective research on their target traits.

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