Applications of Drones and Image Analytics in Field Phenotyping: A Potential Breakthrough in Uganda's Agricultural Research

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Abstract

We are in the race against time to find new solutions amidst the threat of climate change, to increase food production by 70% to feed the ever-growing world population which is expected to double by 2050. Agricultural research plays astonishing roles in crop and livestock improvement through breeding programs and good agronomic practices to enable sustainable agriculture and food systems. The advanced molecular breeding or modern breeding technologies in genotyping have been well-embraced by most research institutions worldwide. However, phenotyping which plays great role in agricultural research and breeding programs has achieved little development or still a traditional method in most institutions across African countries. Noteworthy, the advancement of phenotyping has been gaining momentum and attracted a number of researchers in the recent past, this led to the coining of high-throughput phenotyping concept. Nevertheless, the comprehensive understanding of this concept remains limited in most research institutions in developing countries, especially Uganda. Therefore, the present review aimed to provide a summary of drone-based high throughput phenotyping used across different crops. The electronic literature search was conducted from non-academic and academic databases. The literature sources in the form of peer-reviewed journal articles, books, book sections, conference papers, thesis and dissertations, policy papers, organisation or company manuals, working papers, and reports were considered. In this review, the concepts of field phenotyping are discussed, drone classification and specifications are elaborated, the use cases of the drone-based high-throughput phenotyping are presented, drone imaging systems for phenotyping are discussed, and high-throughput image analytics method is explained. In this paper, it was found that cereals have been the most studied crop for drone-based phenotyping application in academic literature. However, root crops were the list studied, hence, extensive research is needed for drone-based phenotyping adoption in root crops. Moreover, limited studies have been focused on the effect of drones' operation parameters. Therefore, research focusing on the optimization of the drones' performance is required.

Keywords: Crop phenotyping, Plant phenotyping, UAV, Agricultural drone, Remote sensing, High-throughput phenotyping, Precision phenotyping, Precision Agriculture, Image processing, Field phenotyping, High-throughput phenotyping platform, Image processing, Image analysis, Machine learning, Deep learning

1. Introduction

Modern agriculture and food production systems have been threatened by climate uncertainty, amidst the exponentially growing demand of agricultural goods with the increasing world population growth, which raises questions to find new solutions to increase the food production by 70% by 2050 [1]. This can be addressed by continuous development and adoption of digital technologies (industry 4.0) [2]–[4], which are beyond information and communication technologies (ICT) concept in Agriculture and food systems [1], [5]. In addition, the advancement in agricultural research and breeding through utilization of remote sensing technologies (such as sensors, drones (UAVs), Internet of thing, cloud computing, etc.) and advanced image processing and big data analytics is inevitable to achieve sustainable agriculture [6].

Several concepts such as Agriculture 5.0 [7], [8], Agriculture 4.0 [9], [10], precision agriculture (PA) [11], [12], smart farming, circular agriculture [13], and conservation agriculture [14], have been develop to gear up the achievement of sustainable agriculture and food systems with increased productivity, reduced labor time, effective and efficient management of agricultural inputs. Out of the introduced concepts, precision agriculture emerged the most adopted among researchers and practitioners worldwide. PA is the science of improving crop yields and assisting management decisions using high technology sensor and analysis tools [15]. In other words, PA refers to the use of spatial and temporal information of crops in order to perform site-specific management [16]. It involves monitoring of crops through the use of remote sensing technologies for timely and accurate estimation of yield and farm profitability. Hence, It contributes to competitive agricultural industry with high quality standards as well as plays great role in breeding program [12], [17].

The concept of precision agriculture is similar to the concept of precision phenotyping [18], and/or high throughput phenotyping (HTP) [19]. However, precision phenotyping and HTP are the recently developed technologies that are being adopted in plant breeding and biotechnology or plant science research [20], [21]. The HTP methods and platforms are developing at rapid pace in the recent year and are already helping to bridge the genotype–phenotype gap or dress the bottlenecks of genomic and phenomics studies [22]–[24]. One of the great advantage of HTP is that, it provides researchers with a non-destructive and non-invasive method yet accurate in analyzing large-scale phenotypic data [23]. Moreover, it helps in unraveling the genetic basis of complex traits associated with plant growth and development and targeted traits [24], [25]. The HTP programs or platforms have been implemented in research institutions across the world, especially in the developed countries. One of the main drivers of HTP implementation is the need to improve the quality and increase the speed of phenotyping to fasten the plant breeding process. In addition, recent developments in affordable remote sensing technologies including sensors, and drones which enable automatic, high resolution, and non-destructive survey of agriculture fields (rapid and precise field phenotyping). Hence, provide the key basis for advancing plant breeding [26]. However, the barrier to HTP adoption in agricultural research institutions in most developing countries are the high investment cost and lack of expertise with basic engineering background on sensors, image processing, data management, and cloud-running architecture [27].

Remote sensing plays a vital role in crop evaluation and soil health conditions which are the concept of HTP and precision phenotyping, besides precision agriculture and smart farming [28], [29]. The main strength of remote sensing is that it indicates the problems at the right time and helps to resolve the problem wisely [30]. Moreover, it is often integrated with artificial intelligence to be used as tools to improve the resilience of agriculture production systems [31]. Planting crop management operation such as nutrient management can be considered as the most important environmental and economic benefit of remote sensing [29]. The remote sensing platform include drone, Satellite, ground based (robot, sensors), and manned aircraft. Among these, drone has proved to be most recently and widely adopted remote sensing platform for both precision agriculture and HTP.

Drones also known as Unmanned aerial vehicles (UAVs) or Unmanned aerial systems (UASs) [32], are an emerging technology with significant market potential, especially in research and management [33], [34]. They are cost-effective, flexible and offer a wide range of applications than other remote sensing platform [35]–[37]. UAVs are becoming a valuable tool to collect data in a variety of contexts [38]. They are popular tools for high-throughput phenotyping of crops in the field when mounted with imaging systems such as RGB, multispectral or hyperspectral cameras [39]–[42].

Small-scale plant production drones (also known as spraying drones) are being used widely in modern agriculture management (including aerial spraying) due to their high efficiency and flexibility, low labour or water requirement, low drift and non-destructive to crop and soils, which substantially increase agricultural productivity and sustainability [43], [44]. The spraying drones provide precision in fertilizer application like in the variable rate fertilizer application as well as appropriate pesticides spraying [45]. Drone is unmatched platform for determining the dynamic phenotypic traits of crops in the fields in a rapid and cost-effective manner, which can be used for crop biomass and yield estimation [35], [46]. More, they have considerable potential to radically improve environmental monitoring [47]. Despite the extensive benefits of drones, there are number of factors limiting its widely adoption. One of the main drawbacks of drone imaging technologies is the limited time window for large-area data collection. Besides, it also suffers from one main technical and design limitation that is low flight time (15 mins to 1 hour) [48]. The global law or regulation by the civil aviation authority greatly influence the diffusion of drones across, especially in Uganda [49]. Hence, the dissemination of drone concepts differs among countries, both in terms of time and magnitude [50].

The big data of plant or field images generated from the sensors or camera present huge challenge as it require pre-processing, processing as well as analysis which demands data analytics skills [51], [52]. For instance, the pre-processing such like radiometric calibration of hyperspectral or multispectral images need to be performed, because the imaging condition is different for every single image [53], [54]. Nevertheless, power tools or software (Pix4D and Agisoft Metashape) and techniques have emerged in the recent past, which are capable of performing image processing tasks and achieve incredible results. The commonly used techniques are machine learning and deep learning algorithms [55]. For example, Convolutional Neural Network (CNN) is the deep learning algorithm that has emerged as a powerful tool for image processing tasks [56], [57]. On the other hand, the machine learning algorithms including Linear Discriminant Analysis (LDA), Random Forest (RF), Support Vector Machine with linear (SVM-l) and radial basis (SVM-r) kernel are being used for classification/prediction based on the images [58]–[60].

Agricultural research plays astonishing roles in crop and livestock improvement through breeding programs and good agronomic practices to enable sustainable agriculture and food systems. The advanced molecular breeding or modern breeding technologies are well-adopted by most research institutions worldwide. However, phenotyping which plays great in agricultural research has achieved little development by institutions across developing countries [61]. Combining high-throughput genotyping and phenotyping with the advancements in the use of genome-wide markers (GWMs) will continue to expedite the discovery of novel alleles for breeding crop varieties with higher nitrogen use efficiency [62],

[63]. With the increasing uncertainty in climate, developing the resilient crops of the future or disease resistance crops through breeding programmes becomes inevitable [64], [65]. Noteworthy, the advancement of phenotyping has been gaining momentum and attracted a number of researchers in the recent past which led to the coining of high-throughput phenotyping concept. Nevertheless, the comprehensive understanding of this concept remains limited in most research institutions in developing countries, especially Uganda. Therefore, the present review aimed to provide a summary of drone-based phenotyping used across different crops. As the introduction of drones and image analytics in Agriculture egressed as multidisciplinary fields of study, the present paper is intended to reach large audience from both academic and non-academic communities.

The outstanding contributions of this paper are tri-fold: (i) identify the most studied crop for drone-based phenotyping application, (ii) develop an in-depth drone classification, and (iii) develop a compact and detailed methodology for drone-based high-throughput image analytics. This paper is structured as the following: section 2 presents the methodology for literature searches, followed by section 3 which highlights the agricultural research institutions in Uganda. Then, section 4 elaborates on field phenotyping by giving details on the current phenotyping practice in Uganda, discussing the concept of high-throughput phenotyping and precision phenotyping. While, section 5 provides the overview of drones with details on its classifications, communication and control systems, and drone regulation policy in Uganda. This is followed by section 6 which describes the agricultural drone for phenotyping with the focus on discussing the main drone parameters and showcasing the use of drones for phenotyping in different crops. Next, section 7 explains the different drone-based phenotyping images including LiDAR, RGB, thermal, multispectral, and hyperspectral images. Then, section 8 elaborates the drone-based phenotyping image analytics approach giving discussion on each step: image pre-processing, segmentation, feature extraction and data analysis. The last section is the conclusion which highlight the important observations and presents areas for extensive research.

2. Methodology

In this paper, comprehensive literature search was conducted from the electronic databases including Science Direct, Google scholar, Taylor & Francis, Springer, and Wiley. The published literature in the form of Journal articles, conference papers, books, book sections or chapters, white paper, working papers, thesis, dissertations, policy papers, organization or company manuals, and reports were considered. The search terms: “Drones and agriculture”, “Drones and plant breeding”, “UAV and Agriculture”, “UAV and plant breeding”, “Agricultural drones”, “Drones and images processing”, “UAV and image analysis”, “UAV and image process” were used. More general search was conducted using google search engine with following search terms: “Agricultural research and Uganda”, “MAAIF and agricultural research”, “Uganda University and agricultural research”, “Agricultural research institute and Uganda”, “National Agricultural research organisation and Uganda”, “Agricultural drones in Uganda”, “Drones regulation in Uganda”, and “Drones law in Uganda, “(crop or plant or field) and phenotyping”, “high-throughput phenotyping”, “high throughput phenotyping platform”, “ (drone or phenotyping) and image”, and “(drone image or phenotyping image) and (processing or analysis)”.

3. Agricultural research institutions in Uganda

The agricultural research in Uganda is conducted by both government, private sector, development partners, and CGIAR centers. The government sector in research consists mainly of National agricultural research organisation (NARO) and public universities. Currently, there are 9 public universities in Uganda. However, the most active university with agricultural research institute is Makerere university. The institution is called Makerere University Agricultural Research Institute Kabanyolo (MUARIK), which was established in 1953. While the private universities fall under the private sector. The other private sector which are involved in agricultural research are non-governmental organisation (NGO) and private companies (such as seed companies, food processing companies, etc.). Some of the examples of the NGOs (both national and international) and/or development agencies conducting agricultural research in Uganda include IITA (one of the CGIAR centers), GIZ, Rikolto and JICA.

Above all, the one that does extensive agricultural research in Uganda is NARO. It was launched in 1992 as a semi-autonomous institution consolidating Ugandan research in crops, livestock, fisheries and forestry. Nonetheless, the institution was re-structured in 2005 as an umbrella organization for all institutions that conduct agricultural research in Uganda using public fund [66]. It oversees all the national agricultural research activities in Uganda with current strategic plan, themed as “market-oriented research spurring agro-industrialization”. NARO is an agency of Ministry of Agriculture, Animal industry and Fisheries (MAAIF), and thus, is mandated to conduct research in all aspects of agriculture including livestock, fisheries, forestry, crops, agro-machinery, natural resources and socio-economics. It is composed of governing council, a secretariat and 16 public agricultural research institutes which spread all over the country as shown in **Figure 1**. Among the 16 research institutes, 9 are semi-autonomous Zonal Agricultural Research Institutes (ZARDIs). While, the remaining 7 are constituent institutes or National agricultural research institutes (NARIs) as shown in **Table 1.**

Table 1. National agricultural research institutes in Uganda [66], [67]

S/N	NARI and ZARDI	Function	Year of launch	Agroecological zone	Location
1.	National Crops Resources Research Institute (NaCRRI)	It conducts research on cereals, root crops, legumes, horticultural crops and oil palm.	2005	Lake Victoria crescent	27 km from Kampala on Gayaza-Zirobwe road, Namulonge
2.	National Forestry Resources Research Institute (NaFORRI)	It undertakes research in all aspects of forestry	2011	Lake Victoria crescent	12 km on Mukono – Kayunga Road, Kifu
3.	National Fisheries Resources Research Institute (NaFIRRI)	It conducts research in Capture fisheries as well as in aquaculture		Lake Victoria crescent	Oboja Road in Jinja Town
4.	National Coffee Resources, Research Institute (NaCORI)	It conducts and manage basic and applied research in all fields pertaining to coffee and cocoa	2014	Lake Victoria crescent	Mpoma, Mukono
5.	National Agricultural Research Laboratories (NaRL)	It conducts research on food biosciences & agribusiness, biosystems, agricultural engineering, soils, environment, agro meteorology, biodiversity, biotechnology and bananas.	2005	Lake Victoria crescent	13km north of Kampala city, along the Kampala-Gulu highway, Kawanda
6.	National Livestock Resources Research Institute (NaLIRRI)	It provides livestock research services	2005	Eastern Highlands	Nakasasa, Tororo and Namulonge Kampala

7.	National Semi-Arid Resources Research Institute (NaSARRI)	It undertakes research in crops production for semi-arid production systems in the areas of seed research and production management, together with range management	2005	Northern farming system	21 Km South of Soroti Town, Serere District.

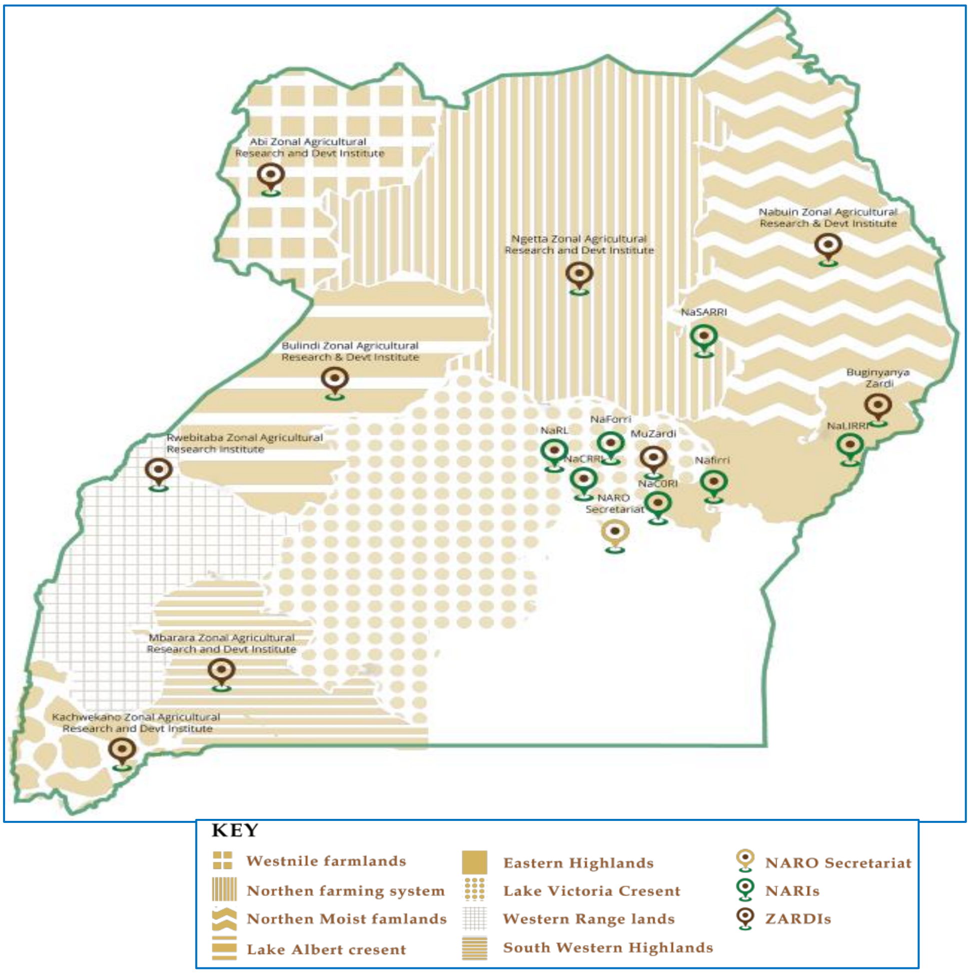


Figure 1. National agricultural research organisation institutes and agroecological zones. Source: https://naro.go.ug/about-naro/ . License; it is licensed under art free

4. Field Phenotyping

Field phenotyping also known as plant phenotyping or crop phenotyping deals with selection/breeding of crop genotypes for crop productivity [61]. It aims to capture plant response to the environment, and generates data that can be used to inform breeding and selection requirements [68], [69]. It involves measurement of plant's physiological and metabolic responses developed from the interaction of genotypes with the environment to identify key genes/alleles and associated molecular markers conditioning such as yield, abiotic stress tolerance, disease tolerance, and agronomic traits. In most cases, the plant breeding and biotechnology promote the development of new cultivars for sustainable agriculture. Thus, to enhance the selection process, robust phenotyping is critical because it is a crucial tool to determine line selection at every stage of the years-long breeding pipeline [27]. Improvements in phenotyping methods are highly desired and must address the balance of accuracy, speed, and cost. The engineered phenotyping (which involves the use of remote sensing) can increase what the breeders can see and offer better phenotype-based choices [27].

Field phenotyping is generally associated with high time consumption and labor-intensive exercise, though it maintains a high degree of pragmatism on the traits to choose and the way to assess them, especially when done with traditional method [70]. This is very common, when the targets for breeding involve complex quantitative trait, for example, improving yield potential, enhancing adaptation to abiotic stresses, etc. In contrast, the secondary trait is easier and less expensive than measuring yield itself. Additionally, the phenotyping strategy, which includes experimental design, traits (e.g., plant height) and tools, also depend on the target environment for selection [71]. Thus, increases the complexity of field phenotyping [61]. The traditional approach of field phenotyping or conventional phenotyping is common in developing countries. On other end, the engineered, improved, modern, precision, or high-throughput phenotyping is the recent approach being widely adopted by most research institutions in different countries [27], [61].

4.1 Current status of field phenotyping in Uganda.

The Uganda’s breeding research for crop improvement has increased significantly in the recent past. This is due to high adoption of modern breeding technology called the molecular breeding. Marker-assisted selection (MAS), marker-assisted backcrossing (MABC), marker-assisted recurrent selection (MARS) and genome-wide selection (GWS) are currently the most used molecular breeding schemes among the different research institutions in the country. Moreover, the open access to the complete genome sequences of the important food crops (such as rice, maize, wheat, etc.) are providing researchers access to unparalleled genomic information for improving these crops. In general, the use of molecular techniques within breeding pipelines has been successfully and widely adopted within Uganda’s agricultural research institutions, both private and public sectors. Despites the incredible advances in modern breading methodologies, advances in phenotyping have been much slower or rely solely on the traditional method. The conventional, traditional or low-throughput phenotyping mostly rely on manual measurement or visual assessment which has several disadvantages such as largely laborious, expensive, inaccurate, and time-consuming [21], [25], [61], [72].

Traditional field phenotyping basically encompasses breeders or research assistants walking through the trial fields and scoring plots based on how they look, taste, smell, and feel [27]. Moreover, it involves manual crop scouting and measuring a series of crop characteristics related to growth and yield traits such as plant height, leaf color, leaf area index (LAI), chlorophyll content, and above ground biomass [73]–[75]. The examples of manual rice plant phenotyping are depicted in **Figure 2.** In such scenarios, drone-based remote sensing is highly useful. Whereby, the drones can fly above the crop canopy rapidly and acquire sharp digital imagery of crop phenotype [73]. Thanks to the development of low cost, light wight and small-size sensors and drones.

Improving phenotyping platform using drones will provide the foundation for further success of conventional breeding, and for implementation of molecular and transgenic breeding for complex quantitative traits. Noteworthy, the level of advancement in phenotyping platforms will partly determine the amount of information used from molecular breeding into crop improvement programs. Hence, there is an urgent need to boost the throughput, precision and scale of phenotyping to meet the demands of molecular biologists and breeders in research institutions [61].

(a) (b)

(c) (d)

Figure 2. Manual or Traditional phenotyping of rice plant. (a) plant height measurement, (b) tiller number counting, (c) panicle length measurement, (d) sample collection for grain weight measurement. Source: author's own pictures

4.2 High-throughput field phenotyping

High-throughput phenotyping (HTP) is quite critical to phenomics and is characterized as a technology that demands huge amount of phenotypic data to be collected at molecular level (such as via ionomics), inflorescence imaging level, plant level, row level, plot level, field level, and/or over significant periods of time [76]. The remote sensing technologies such as drone, satellite, and manned aircraft are capable to collect phenotypic data at plant to field levels very rapidly, hence, increasing the throughput [77], [78]. This means that more plants can be measured than ever before to unmatched levels at reasonable cost [76].

In the main, the concept of HTP has recently gained interest in plant science and breeding to monitor plant growth and analyze the influence of genotypes and environment on plant growth [73], as depicted in **Figure 3**. The ability of drone for near-ground remote sensing, makes it more suitable for large-scale HTP than other remote sensing technologies. Therefore, drone based remote sensing is becoming unprecedented tool for implementing fast, precise and low-cost phenotyping strategies within crop breeding programs in the recent year [79]–[81]. These drones are often mounted with sensors or cameras (such as RGB cameras, multispectral cameras, hyperspectral cameras, etc.) in order to collect field or crop images [82]. These images contain the required phenotypic data which can then be processed and analyzed [79]. As compared with traditional crop phenotyping techniques, three dimension (3D) of crop can be generated from multi-source phenotypic data in the whole crop growing period and extract plant height, plant width, leaf length, leaf width, leaf area, leaf inclination angle and other parameters for plant biology and genomics analysis [83].

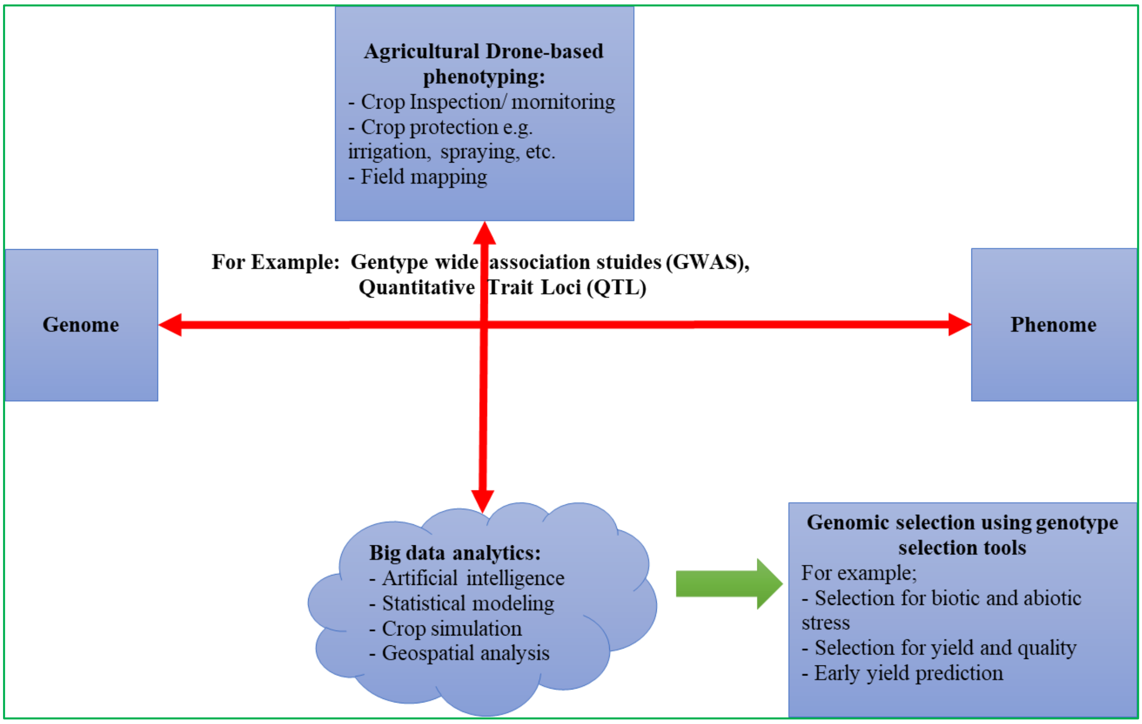


Figure 3. The concept for bridging genome-phenome gap using an agricultural drone-based high-throughput phenotyping system [31]

The advancement of image processing and big data technologies including machine learning and deep leaning has reached unprecedented level. These technologies are enabling high-throughput acquisition and analysis of phenotypes for crop populations, which is incredible for crop growth monitoring, evaluation of seedling condition, cultivation management, yield prediction, and many more [84], [85].

Even with the enormous benefits of HTP in breeding programs and research farms, its wide adoption has been limited by so many factors such as need for technical skills from diverse fields of specialty, high investigation cost, and government regulatory constraints on the use of some technologies like drones. Further, a series of components and steps must be considered for HTP system design which includes sensors, platforms, analytics, and data management, thus, demands for extremely focused teamwork [27].

So far, collaboration has been considered paramount for high-throughput phenotyping technologies development and adoption or diffusion in different countries. Additionally, it involves creation of platforms because HTP is an interdisciplinary area of research with expertise from the actual engineering and manufacturing of the sensors and platforms, to the design and implementation of images analysis schemes by computer scientists, data aggregation, visualization, statistical analysis, and modeling, as well as deep knowledge of plant biology, genetics and biochemistry needed to interpret the meaning of all these data [86]. This platform known with general name across literature as high-throughput phenotyping platform (HTPP). However, the name differs from country to country or institution to institution.

The HTPP is useful for obtaining detailed measurements of plant characteristics that collectively provide reliable estimates of trait phenotypes. It is also being utilized in modelling (especially taking into account 'hidden variables') for predicting genotypic performance in different climate scenarios (under controlled experimental conditions) [87]. In general, the platform operations are based on three key criteria, namely; data recording/scoring, speed of data collection, and automation (either partially or fully). As discussed under HTP, the platform depends mostly on non-destructive, non-invasive and remote sensing phenotyping tools like drone, together with robotics and automatic data gathering, image processing and analysis algorithms [61]. The curiosity to contemplate the concept and benefits of HTP in breeding programs and farm research has led to the establishment HTPPs by the research institutions worldwide. One of the examples of these platforms is called Australian Plant Phenomics Facility (APPF), located at the University of Adelaide, Australia. The other examples includes PhenoArch platform (INRAE Montpellier) and the FIP (Field Phenotyping) platform (ETH Zürich) [88].

4.3 Precision field phenotyping

The phenotyping environment is very much crucial in the quality of phenotypic data generated through experiments as well as the efficiency of breeding. In most cases, highly variable field sites produce highly variable data which masks the important genetic variation for key traits and reducing repeatability, notwithstanding the precision and cost of a specific phenotyping protocol [61]. This variation in a population is caused by both genetic (known as signal) and environmental factors (known as noise). The variability of the experimental sites affects the accuracy of broad sense heritability estimation. Hence, without an increase in the signal-to-noise ratio within experimental sites, the breeding process cannot be properly optimized, and the power of genomics cannot be fully exploited [61]. The above variability can be minimized by removing the highly variable sites prior to the initiation of expensive phenotyping efforts, or to development of management strategies and experimental designs to reduce variability [61]. This is only possible with greater knowledge of inherent soil variability. In most present breeding practices, the importance of site uniformity and the measures to understand and deal with soil heterogeneity for field phenotyping have often been overlooked. Yet, non-uniform experimental fields could have significant reduction of genetic gains.

The concept of precision agriculture involves quantification of soil spatial variability and crop characteristics to optimize the amount and timing of field applications of inputs like seed, fertilizer, and irrigation [89]. However, soil variability analysis is rarely practice within the breeding programs to improve phenotyping precision. The use of low-cost drones, sensors and data analysis techniques or software is currently increasing for mapping variability within field sites based on soil sampling, soil sensors and measurements of plant growth as surrogates of variability. As a result, a number of research institutions are practicing precision phenotyping within the HTPP.

5. Overview of Drones

5.1 Definition and classification of Drones

Drones are known with various names such as unmanned aerial vehicles (UAVs), unmanned aerial systems or unoccupied aerial systems (UASs) [64], [89], and remotely piloted aerial system (RPAS). It has been referred to as the flying robot. Simply put, drones are UAVs with power, radio control, or autonomous flight that can perform multiple missions [79]. The design and structure of drone are quite simple, however, there are so many types of drones in the market today which contributes to the decision-making challenge to the buyers or the users. In this paper, a broader classification of drone has been developed based on five terms or features: altitude [90], operation type [91], application [92], wing type [93], and size [94] as shown in **Figure 4**. The examples of different types agricultural drones and their applications are depicted in **Figure 5.**

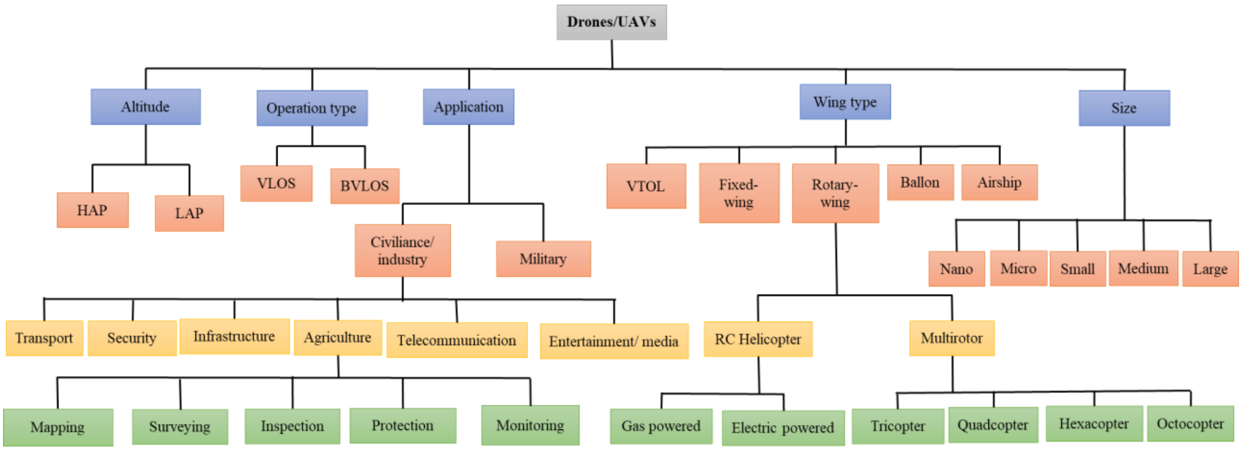


Figure 4. Detailed classification of drones. HAP- High altitude platform, LAP- low altitude platform, VLOS- visible line of sight, BVLOS- beyond visible line of sight, RC- remote control, VTOL- vertical takeoff and landing. Source: author's own illustration

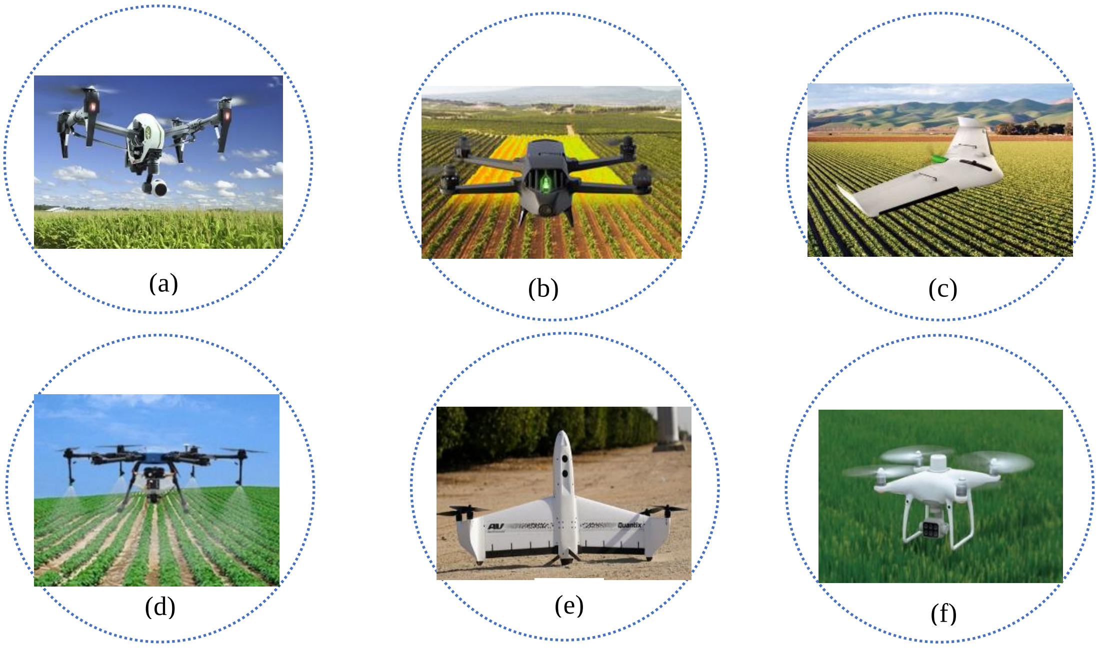


Figure 5. Commercial agricultural drones and applications.
(a)-UAVLance, for mapping and surveying in agriculture. (b)- Parrot Blueglass; for crop scouting (c)- Delair UX11 Ag drone, for large scale surveying in Agriculture & Forestry. (d)- NLA610 Agricultural Plant Protection Drone, 10L Agriculture Spraying drone for Farm. (e)- QuanticMapper Aerovironment (f)- DJI Phantom 4-multispectral, for crop inspection and monitoring. Source: author's own modification based on licensed free art.

The main classification of drone is based on the aerodynamic features or wing types. These include fixed wing, rotary-wing and hybrid [93]. While the other classification can be based on the in-built functions such as spraying, mapping, and crop monitoring. In this paper, fixed-wing, rotary-wing and hybrid drones have been briefly discussed. The fixed-wing agricultural drone possesses a predefined airfoil of static and fixed wings that enable lift based on forward airspeed. The control of this type of drone is accomplished through elevators, ailerons and rudder that are attached to the wings. While for case of rotary-wing drones. the airflow is composed of several rotors that generate the appropriate power necessary for lifting. In contrast to the fixed-wing drones, this type does not need a forward airspeed for lifting. Therefore, the control of this type of drone is based on the torque and thrust of the rotors. Rotary-wing drone are further classified based on the number of the rotors such as helicopter (one or two rotors), tricopter (3 rotors), quadcopter (4 rotors), hexacopter (6 rotors) and octocopters (8 rotors), and so on. The recent drone design has about 12 rotors. Each type of the drone presents the good and the bad. On one end, a rotary wing drones have better and easier control and are able to carry a heavier payload compared to the fixed-wing one. On the other end, a fixed-wing drones have efficient and simpler architecture facilitating the maintenance and has longer endurance and larger coverage. With these regards, the third type of drone i.e., the hybrid also known as vertical takeoff and landing (VTOL) is designed to overcome the limitations and harness the benefits of the previous two drone types. The hybrid drone combines both the fixed wing and the rotary-wing. This drone has a gigantic advantage over the previous ones as it possesses rotors for taking off and landing, but also has fixed-wings for covering large areas.

A closer look on military and agricultural drones, it is important to note that military drones are design for surveillance and war or combat purposes [95], [96]. While, agricultural drones are designed to handle agricultural tasks such as crop protection, field mapping, crop monitoring, spraying, and many others [93], [94]. The comparison between military drones and agricultural drones' specifications is well detailed in **Table 3.**

Table 3. Different between agricultural drones and military drones [73]

S/N	Drone specifications	Military Drones	Agricultural drones
1.	Weight	Super heavy drones (2 tonnes), heavy weight drones (200 – 2000kgs), and medium-weight drones (50-200kgs)	Light weight drones (5-50kgs), microdrones (< 5kgs)
2.	Endurance and flight range	Long endurance drones (flight time of 24 hours or more, cover distance of 1500-20,000 km), medium endurance drones (fight time of 5-24 hours, cover distance of 100-1500 km), low endurance drone (flight of one hour, cover distance of 100 km).	Very short endurance (Fight time range from 15 mins to 1 hour, cover distance of 50 km)
3.	Maximum altitude	High-altitude drones (height above ground: above 10,000 m)	Medium altitude drones (height above ground: 1000-10,000 m) Low altitude drones (height above ground: 10-1000 m)
4.	Wing load	High wing loading (over 100 kg.m^{-2}) Medium wing loading (50-100 kg.m^{-2})	Low wing loading (< 50 kg.m^{-2}) Few copter drones with medium wing loading (50-100 kg.m^{-2})
5.	Engine type	turbofans, two- stroke piston engines, turboprop, push and pull and electric with propeller	Small flat-winged and multi-rotor drones are energized mostly by electric batteries. Larger copter drones (uses petrol or diesel engines)
6.	Power source	Most them are powered using internal combustion engines dependent on petrol	Most of them uses pre-charged electric batteries

5.2 Communication and control systems in drones

The communication and control systems in drones are so advanced [90]. These include but not limited to ground control station (GCS), drone control and navigation systems, and sensors for data acquisition. The GCS is a computer that either communicates with the drone control system or controls and monitors the drone directly. It monitors the flight related information such as flight altitude, flight speed, and so on [97]. With this system, the user can receive data relevant to the drone flight and the data recorded by the sensors that support the flight. These are ground-based sensors or drone in-built sensors. Moreover, the ground control system contains the software for the processing of data acquired by the drone and the extraction of the information necessary by the system operator for the crop monitoring. On the other end, drone control and navigation systems are used to control the drone flight. This system is either remote control or a built-in computer (usually with a built in GPS). It includes the flight control system and/or the autopilot system, which control the operation of the drone.

The flight control and navigation systems (e.g. flight altitude, flight speed, etc.) are the main technologies of drone to achieve the autonomous flight [79], [98]. The drone control and navigation systems receive and process data from the autopilot or flight control system for the proper operation of the drone. These systems usually contain sensors to monitor the flight properties, such as sensors for measuring distance from ground, air force, and so on. In the main, these systems have the ability to process information from sensors to correct any problems that may arise, and to communicate in real time by sending and receiving the necessary information. Sensors for data acquisition are cameras intended to collect the information needed. The main types of camera used in agricultural drone include thermal, infrared, RGB, Multispectral and hyperspectral cameras [28].

5.3 Drone regulatory framework in Uganda

In many countries, the operation of drones for both commercial and research or academic purpose requires registration and/or certification, and needs to be carried out under regulated conditions. However, some rules apply only to a particular type of drones. While some have to do with all drones or other aircraft operating under certain weather conditions or flight types [16]. In this line, the application domains of drones are not only limited by their types but they are also constrained by potential regulations that are being imposed by various governmental agencies. For instance, drones are accompanied by several restrictions and concerns such as privacy, public safety, security, collision avoidance, and data. In order to contain these concerns, a lot of efforts have egressed to provide rules and regulations to control the use and operation of drones while taking into account their types and capabilities. All in all, there are five key criteria often considered for regulatory purposes on drones as shown in **Table 4** [90].

Table 4. Key criteria considered for drone regulatory framework [90].

S/N	Criteria	Description
1	Applicability	This involves specifying the scope (considering type, weight, and role of drone) within which certain regulatory rules will be applied
2	Operational limitations	These include restrictions on the locations where drones can fly or operate.
3	Administrative procedures	These include precise, legal processes that must be put in place in order to deploy and use a drone
4	Technical requirements	These include constraints on the communications, control, and mechanical capabilities of drones.
5	Ethical constraints	The ethical considerations can include ways to protect the privacy of generated data and the way in which a drone can be used in commercial and military scenarios

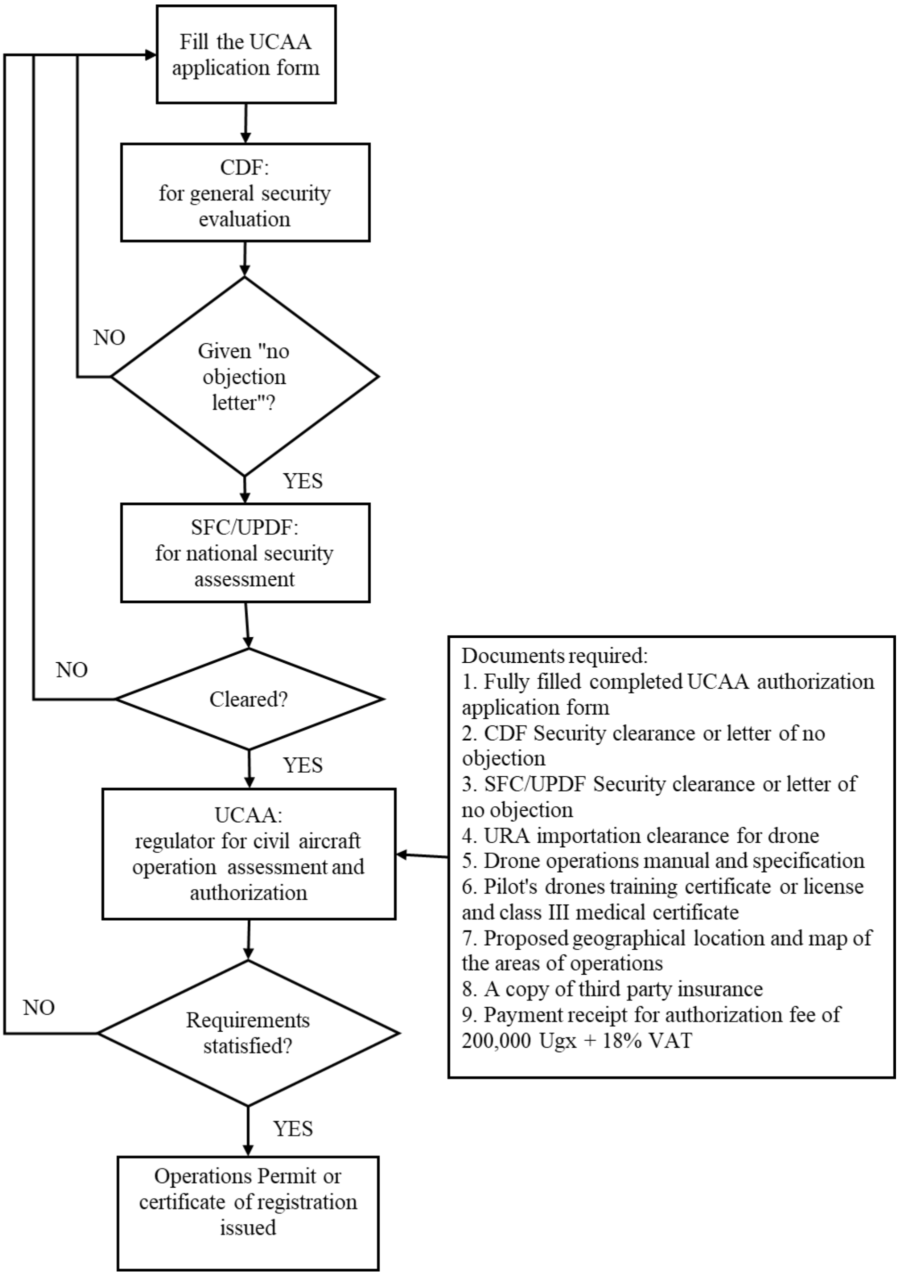
The drone regulations vary between different countries and types of geographical areas (e.g., urban or rural) [99]. In Uganda, regulations for drone operations are issued by the Uganda Civil Aviation Authority (UCAA). While in the united stated, the regulation is issued by the Federal

Aviation Authority (FAA) and National Aeronautics and Space Administration (NASA). The UCAA regulations apply to any person who imports, exports, tests, owns, operates, procures, assembles, manufactures or maintains a drone registered in Uganda, wherever they may be, and any other similar aircraft operating in Uganda [91]. For the case of Uganda, the regulatory framework governed everything to do with drone which is not the case with other countries. Especially, the countries which design and manufacturer their own drones. **Table 5** presents the comparison of the drone operation regulations among countries: US, China, Australia, South Africa and Uganda.

The drones' acquisition and certification in Uganda is such a complex and daunting process that very few individuals can afford to have a registered drone. The UCAA authorization process for registration or operation of drones is depicted in **Figure 6**. Besides the UCAA Authorization, the Uganda communication commission (UCC) presents regulatory and technical requirements guidelines to facilitate operations of drones in Uganda. This implies that the use of drones whether for recreational, commercial, research or else must also comply with the UCC's requirements for the respective radio frequency spectrum usage to avert any potential risk of harmful interference to other duly licensed radio communications systems [100]. In a nutshell, the drone regulation in Uganda does not favor agricultural drones especially when they are used for spraying. This is because spraying drone has higher take-off weight depending on the tank capacity such as 5 liters, 10 liters, 20 liters, 30 liters, and 40 liters. Therefore, the rule governing this kind of drones' application needs to be adopted in the drone regulation framework in Uganda. For instance, China considered agricultural drones in different ways from other types of drones. It allows maximum payload weight of 5,700 kg for agricultural drones and must fly at the altitude of 15 m above the surface [101].

Table 5. Comparison of regulation of drone operations in Uganda with other countries

Country	Maximum altitude (m)	Minimum distance to people, building (m)	Minimum distance to airport or aerodrome (km)	Maximum payload or drone weight (kg)	VLOS required	References
USA	120	N/A	8	25	Yes	[102]
China	120	N/A	N/A	150	Yes	[101]
Australia	120	30	5.5	150	Yes	[90]
South Africa	46	50	10	7	Yes	[90]
Uganda	120	50	10	25	Yes	[91]



Documents required:
1. Fully filled completed UCAA authorization application form
2. CDF Security clearance or letter of no objection
3. SFC/UPDF Security clearance or letter of no objection
4. URA importation clearance for drone
5. Drone operations manual and specification
6. Pilot's drones training certificate or license and class III medical certificate
7. Proposed geographical location and map of the areas of operations
8. A copy of third party insurance
9. Payment receipt for authorization fee of 200,000 Ugx + 18% VAT

Figure 6. UCAA authorization process for registration or operation of Drone [91]. CDF- office of the chief defense forces (ministry of defense), SFC- Special forces command, UPDF- Uganda people defense forces, UCAA- Uganda civil aviation authority, URA- Uganda revenue authority, VAT- value added tax

6. Agricultural drones in phenotyping

6.1 Key parameters of agricultural drone performance

Agricultural drones are different from the other types because of its applications which are designed or dedicated for agriculture operations (on either livestock, crops, forestry, or both). Remote sensing with agricultural drones is one the most breakthrough techniques in field phenotyping. However, there are numbers of parameters that have to be considered. As the result, this technique has endless challenges of parameters investigation and/or finding the optimum parameter settings of drone performance for the different applications [103]. Moreover, the applications of drones are so numerous and many other applications are still to be discovered or investigated by researchers. With these regards, the research on the remote sensing with drones is just at the dawn, and is expected to rise exponentially due to the growing demand of precise cultivation or precision agriculture as a sustainable food system for the ever-increasing global population.

The parameters of agricultural drones can be classified under five broad parameters namely; quality parameters (include detail and precision) , sensor parameters (consist of sensor resolution, exposure time, image acquisition rate, focal length and camera angle), flight parameters (include altitude, image overlap, and flight speed), image parameters (ground sample distance and image per area) and efficiency (flight time and image processing time) [103]–[105]. In this paper, some of the commonly studied parameters of agricultural drones are discussed. These include ground sample distance (GSD), time of day (TOD), image overlap, flight speed or cruise speed, flight height, maximum payload capacity and spatial resolution.

6.1.1 Ground sample distance (GSD)

GSD represents the size of the pixel on the field and thus, it is one of the important agricultural drone parameters for field-based phenotyping. The GSD is the distance between the center of two adjacent pixels measured on the ground and is a function of the flight altitude, size of the sensor's pixel, camera's focal length, resolution and distance from the subject. GSD which is measure centimeter per pixel is also known as lower ground resolution. This implies than a lower value of GSD is considered as more accurate than the higher value [104]. In this line, higher level of accurate of GSD can be achieved by flying drone at low altitude, or increasing the camera focal length and camera resolution. While high GSD provides less detailed images, less accurate, less data, and requires higher altitude [16]. Therefore, the optimum value for GSD is necessary to be determined of the different agricultural drones' applications.

6.1.2 Time of day

Time of day (TOD) also known as Time in day (TID) is the most frequently used parameters. It is the external, environmental or weather factor that can affect the performance of drones. However, not much research has been studied under the different factor setting. The most cited hours range between 9 am to 2 pm [106], 10 am to 3 pm [107], or 11am to 2 pm [108]. These are the time (hours) that the sun is well shining and the clouds are quite clear or blue skies. This parameter is important in studying the quality of data collected under different weather conditions or lighting conditions. Interestingly, one of the studies investigated agricultural drone's performances under two levels of lighting which were controlled for by the choice of day for flights. These levels of lighting include uniformly clear and uniformly cloudy (diffuse) [109]. On one end, a recent study by Allred et al. [110] assessed the impact of TID on mapping agricultural subsurface drainage systems. The study revealed that late morning through late afternoon are the best times for locating drainage pipes with drones' thermal infrared sensor. Moreover, in certain cases, exceptional drainage pattern recognition can be achieved at sunrise/sunset.

6.1.3 Image overlap

Image overlap is the one of the most studied flight parameters amongst researchers. The influence of overlap is normally divided in two parts: the forward overlap and side overlap. The forward overlap is also known as end-lap or along-track overlap. It can be managed by varying the number of images per second. On the other hand, side overlap is also called as side-lap, lateral overlap or across-track overlap. It is considered as a key variable in planning the flight path of the drone. The image overlap is measured in percentage and is normally configured prior to photogrammetric processing. Several scenarios of the forward overlap and side overlap have been studied in literature. For instance, 80% forward and 60% side overlap between images has been studied by Gonzalez et al. [16]. While Goodbody et al. [111] profoundly investigated forward and side overlap under five scenarios: 80/80, 80/60, 80/40, 60/60, 60/40.

6.1.4 Flight speed

The flight speed (FS) or cruise speed (CS) is among the most commonly studied flight parameters and has obvious influences on the agricultural drone performance [112], [113]. The flight speed is normally automatically determine by the flight control system but it can also be calculated from the fight time between the start point and goal point [114]. The influence of flight speed has been studied at different levels ranging from 1 m/s to 8 m/s [113], [115]. However, in some studies, the maximum flight speed is set 5 or 3 m/s [82]. The flight speed can have effect on the drone performance as well as the plant. Flying drone at very low altitude closer to the plant can have the wind-induced effect [113]. The increasing flight speed can negatively influence the performance of drone during spraying operation [115].

6.1.5 Flight height

The flight height as known as altitude above the ground or plant surface is a very important flight parameter with significant influence on agricultural drone performance. The influence of flight height has also been investigated at several value ranging from 1 to 120 m [43], [103], [113]. Flight height has effects on all drone application including spraying, crop monitoring and field mapping. This is because altitude directly impacts achievable GSD as well as the details that can be detected from the imagery [103].

6.1.6 Maximum payload capacity

Payload capacity is essential parameter when using drone for spraying. Payload of a drone refers the total of weight of components attached to drone’s body. In other word, it is the amount of weight it can transport. Payload is considered separately from the drone's weight and includes anything not included in the drone's weight. Hence, there are two kinds of payloads that can be integrated into a drone depending on their size and weight. These include sensors payload and other payloads (such as spraying tanks with chemical or irrigation water, pump and nozzle) [6], [98]. Payload capacity has significant effect on the revolution per minute (RPM) of the agricultural drone’s rotors [116]. Effect of payload variation on agricultural performance been studied at different ranging from 10, 8, 6, 4, and 2 kg.

6.1.7 Spatial resolution

Spatial resolution or sensor resolution is one of the commonly studied sensors’ parameters that have influence on the image quality and image processing efficiency. The ultrahigh spatial resolution drone images are effective for biomass classification, especially in heterogeneous ecosystems such as grasslands and wetlands. Despites the significant effects of spatial resolution on the accuracy of image processing, very few studies have taken interest to study its effect. In most cases, it considered as constant factors. One of the few studies investigated the overall accuracy of classification for images with three spatial resolutions: 5, 10, and 15 cm [117]. The different spatial resolutions can be acquired by two methods: either by varying the flight height or resampling imagery having ultrahigh spatial resolution to the imagery with coarser resolution. Therefore, further study is encouraged to compare imagery obtained from the two method [117].

To this end, it is worthy to note that the effect of parameters on the drones' performances have not been fully addressed by the previous studies. In addition, very few studies focus on the optimization of agricultural drone's performance.

6.2 Use cases of drones for phenotyping

This section contains the meta-analysis and showcases of the several applications of agricultural drones used in phenotyping. The literature under the drone applications in agriculture were thoroughly reviewed and analyzed to identify the plant or crop which has received the highest application of drones. In the analysis, 123 peer-reviewed journal articles published between the years 2018 to 2022 were considered. Then, the articles were grouped based on plant or crops research categories including cereal crops, horticulture, forestry, legumes and oil crops, root crops, pasture and livestock, other crops, and non-crop applications. From the **Figure 7**, it can be observed that cereal was the most studied crops among analyzed journal articles followed by the horticulture, forestry, legume & oil crops, and so on. Root crops emerged as the least studied crops and this clearly show the need for extensive research on the drone's assisted phenotyping in root crops.

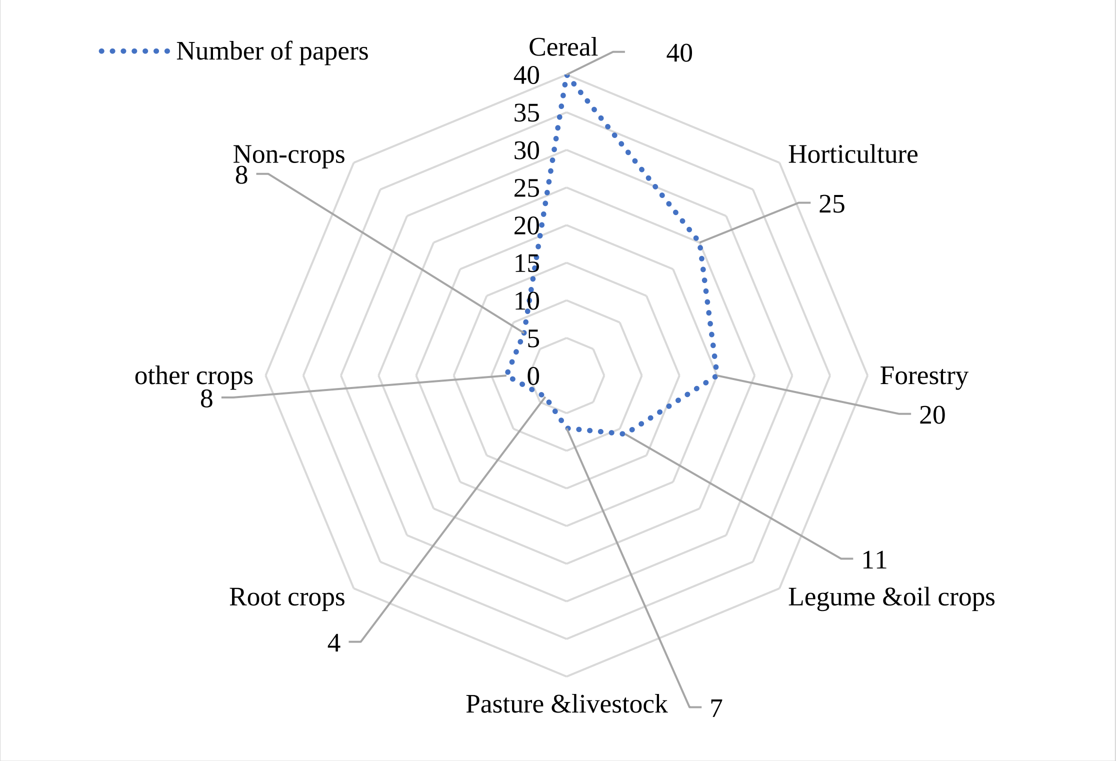


Figure 7. Categories of areas of applications for Agricultural drone-base remote sensing

6.2.1 Cereals phenotyping

The cereal crop considered include; maize, wheat (winter and spring), rice (low and upland), and barley. The showcases of cereal crop phenotyping using drones are summarized in **Table 6** based on the application, crop type, image type, and drone type and parameters. Yield estimation and prediction is the most studied application of drone in cereal crops followed by the crop count and row detection.

Table 6. A summary of literature on drones' applications in cereal phenotyping

S/N	Application	Crop	Image type	Drone type/ flight parameters	References
1.	Above-biomass estimation	Maize	Hyperspectral images	Six-rotor DJI S1000 UAV HAG: 100m; SR: 5cm; SOL: 60%; FOL: 80%; TID: 11 am to 2pm	[118]
		wheat	Digital and hyperspectral images	Six-rotor DJI S1000 UAV HAG: 50m; CS: 8m/s SOL and FOL: 80%; MFT: 30mins; TID: 11 am to 2pm	[119]
2.	Disease detection/ assessment (wheat foliage disease)	Winter wheat	RGB images	DJI Phantom 4 Pro HAG: 25m; SOL: 80%; FOL: 85%	[120]
3.	Yield estimation/ prediction	Spring wheat	Multispectral images	DJI Phantom 4 Pro MPC: 250g; HAG: 20m TID: 10am to 2pm; SOL: 85%; FOL: 80% CS: 1m/s	[121]
		Rice	Hyperspectral images	DJI M600 Pro UAV MFR: 5km; MFT: 16mins; MPC: 6kg; TID: 10am to 2pm; HAG: 200m; SR: 0.13m	[122]
		Rice	RGB and multispectral images	Octo-rotor UAV platform HAG: 25m; CS: 2.5m/s; LOL: 75%; FOL: 60%	[123]
		Maize	multispectral orthoimages	Sensefly eBee RTK fixed-wing	[124]
		Rice	Multispectral images	UAV (S1000, SZ DJI Technology, Co., Ltd., China) TID: 10am to 2pm	[17]
4.	Identification the tasseling date	Summer maize	RGB images	DJI Phantom 4 Pro V2.0 FOL: 85%; SOL: 80%; CS: 5m/s; HAG: 50m	[125]
5.	Soil plant analysis development (SPAD) values estimation's	Winter wheat	hyperspectral images	six-rotor UAV (Da Jiang Company, Shenzhen, China) HAG: 120m; CS: 7m/s; COL: 50%; SOL: 55%	[126]
6.	Pest detection, classification and control (fall armyworms)	Maize	Digital images	Phantom 4 Pro v2 HAG: 6m FOV: 84°	[127]
7.	Monitoring daily variation of leaf layer photosynthesis	Rice	Multispectral images	six-rotor UAV (M 600 Pro) MPC: 5.5kg; MFS: 65km/h; SFT: 10-25mins; HAG: 100m; TID: 11 am to 2pm	[128]
8.	Estimate leaf nitrogen concentration (Combining plant height, canopy coverage and vegetation index)	summer maize	RGB images	six-rotor UAV (M600) MFT: 40mins; MTW: 15.1kg; MFS: 18m/s; HAG: 30m; TID: 12pm to 2pm	[129]
9.	Prediction and selection accuracy in maize varieties under artificial MSV inoculation	Maize	Multispectral images	Delta fixed wing eBee SQ UAV TID: 10 am to 2pm FOL & SOL: 75%; HAG: 42.5m;	[130]

10.	Evaluate and rank physiological performance of wheat genotypes	Wheat	Thermal images	DJI Matrice 600 Pro hexacopter TID: (9:30; 12:00; 15:00 hrs)	[131]
11.	Evaluation of water status of wheat genotypes to aid prediction of yield	Wheat	Thermal images	DJI Matrice 600 Pro hexacopter drone TID: (9:30; 12:00; 15:00 hrs) SOL & FOL: 80%; HAG: 40m;	[132]
12.	Identification of maize; leaves infected by fall armyworms	Maize	Digital images	Quad-copter drone Phantom 4 pro v2 HAG: 5m; FOV: 84°	[133]
13.	Efficient Maize Tassel-Detection	Maize	Multispectral and RGB images	DJI Inspire-1 Pro UAV FOL & LOL: 80%; TID: 11am; HAG: 10m; CS: 4km/h;	[134]
14.	Height estimation	Maize	LiDAR images	six- rotor UAV HAG: 150 m; SOL: 70%	[135]
15.	Count plants and detect plantation-rows	Maize	RGB images	Phantom 4 Advanced (ADV) UAV FOL: 80%; LOL: 60% GSD: 1.55cm; HAG: 80m	[136]
		Maize	Digital and RGB images	DJI Matrice 600 Pro UAV {HAG: 30m; SR: 10mm} DJI Inspire -1 UAV {HAG: 45m; SR: 25mm}	[137]
		Maize	RGB images	Phantom 4 Advanced UAV FOV: 84° ; SOL % FOL: 75%; CS: 2m/s; HAG: 10m;	[138]
16.	Estimation of crop transpiration and its scale effect	Corn (maize)	Thermal infrared images	DJI M600 Pro SR: 10 cm; MFT: 30mins; HAG: 80m	[139]
17.	Assessment of plant density	wheat	Multispectral and RGB images	Falcon 8 octocopter HAG: 10m; SR: 0.2cm-0.69 cm; MFT: 10-20 mins SOL: 60%; FOL: 80%	[140]
18.	Estimating fractional vegetation cover	Maize	Multispectral and RGB images	DJI Phantom 4 Pro GSD: 47mm & 2.7mm; HAG: 70m &10m; FOL & SOL: 85%	[141]
19.	Estimation of nitrogen nutrition index	Rice	RGB images	Phantom 4 Professional UAV HAG: 100m; CS: 8m/s; SOL: 60%; FOL: 80%; TID: 11am to 1pm	[142]
20.	Diagnosis of water stress	winter-wheat	Multispectral images	UAV DJ M600 HAG: 15m; SR: 0.008m;	[143]
21.	Mapping maize crop coefficient Kc	Maize	Multispectral images	Six-rotor UAV MPC: 2kg; MFT: 18mins; HAG: 70m; TID: 11am to 1pm; SR: 5cm; FOL & SOL: 85%	[144]
22.	Assessment of root and stem lodging	Maize	UAV images	-	[145]
		Rice	RGB and multispectral images	DJI Phantom 3 Advanced FOV: 94°; FOL: 80%; LOL:70% HAG: 50m	[146]
23.	Estimation of maize yield and effects of variable-	Maize	RGB images	DJI Phantom 3 HAG: 100m; SOL & FOL: 75%	[147]

	rate nitrogen application				
24.	Intra-Field Canopy Nitrogen Retrieval	Wheat	Multispectral images	DJI Matrice 100 quadcopter HAG: 40m; SOL & FOL: 80%; MFT: 30-45mins	[106]
		Corn	Multispectral images	DJI Matrice 100 quadcopter HAG: 40m; SOL & FOL: 80%; MFT: 30-45mins	[106]
25.	within-field variability in grain yield and protein content	winter wheat	Multispectral images	UAV (Solo, 3DR, USA) TID: 12pm to 2pm; HAG: 65m; CS: 5m/s; GSD: 0.06m	[148]
26.	Field phenotyping of plant height	upland rice	RGB images	DJI Phantom 4 SOL: 70%; FOL: 90%; HAG: 20m; FOV 80°; MFT: 12mins	[149]
27	Identification and quantification of potassium (K+) deficiency	Maize	Multispectral and hyperspectral images	Octocopter UAV, model Tarot Iron Man 1000 HAG: 400m; SR: 16cm	[150]
28.	Mapping winter-wheat biomass and grain yield	Winter wheat	RGB images	DJI S1000 UAV	[35]
29	Evaluation of rice nitrogen use efficiency	Rice	Multispectral images	DJI M100 UAV TID: 6am to 6pm; MFT: 15mins	[48]
30	Evaluating the sensitivity of water stressed maize chlorophyll and structure	Maize	Multispectral images	multi-rotor UAV multispectral TID: 11am to 1pm GSD: 4.7cm; HAG: 70m; CS: 7m/s	[151]
31	Assessment of plant density	Barley	Multispectral and RGB images	Falcon 8 octocopter	[140]

6.2.2 Horticulture phenotyping

In this study, the plants considered under horticulture include fruits and vegetables. The fruit categories consist of vineyard, coffee, citrus, strawberry, banana, oat, olive tree, oil palm tree, pecan nuts, and longan fruits. On the other hand, vegetable categories include eggplant, chicory, tomato, Squash, and spinach. The examples of done based phenotyping in horticulture is shown in **Table 7.** Similar to cereal, yield estimation and prediction is the most studied application of drone in horticulture.

Table 7. A summary of literature on drones' applications in horticulture phenotyping

S/N	Application	Crop	Image type	Drone type	References
1.	Disease detection/assessment	Vineyard	Multispectral and RGB images	Scanopy Quadcopter drone	[152]
2.	Yield estimation/prediction	Egg plant	Multispectral images	Fixed wings UAV eBeeTM drone	[153]
		Coffee	RGB images	DJI Phantom 3 professional	[154]
		Citrus	RGB images	quadcopter DJI Phantom 3 Professional	[155]
3.	Crop growth assessment	Chicory	RGB, multispectral and thermal images	A DJI Phantom 4 Pro	[156]

4.	canopy water status assessment	Eggplant	Multispectral images	Fixed wings UAV eBeeTM drone	[153]
5.	Phenotyping	Tomato	RGB images	UAV FV8 (Atyges, Malaga, Spain)	[157]
6.	Maturity Classification	Strawberry	RGB images	DJI Phantom 4 Pro	[158]
7.	Information collection on the vegetative state of the crop, soil and plant moisture, and biomass density maps	Vineyard	RGB and multispectral images	UAV Hexacopter dji S900	[159]
8.	Monitoring yellow sigatoka	Banana	RGB images	DJI Inspire-1 UAV	[160]
9.	Greening detection	Citrus	Multispectral images	DJI Matrice 100 UAV	[161]
10.	weed mapping	Oat	RGB images	UAV senseFly eBee Plus RTK	[162]
11.	Estimating fruit size	Citrus	RGB images	quadcopter DJI Phantom 3 Professional	[155]
12.	genotype selection	Olive	RGB images	MD4-1000	[80]
13.	analysis of the canopy traits	Olive	RGB images	a rotatory- wing UAV ZniR Sensing	[163]
14.	Detecting powdery mildew disease	Squash	Hyperspectral images	DJI Matrice 600 Pro, Hexacopter	[164]
15.	Computer vision-based citrus tree detection	Citrus	Multispectral images	DJI V8 octocopter	[165]
16.	Detection and mapping of trees infected with citrus gummosis	Citrus	Hyperspectral	UAV- UX4 model	[166]
17.	estimate vineyard energy balance	Vineyard	RGB and Thermal images	DJI M 600 Pro	[167]
18.	count plants and detect plantation-rows	Citrus	RGB images	Phantom 4 Advanced	[136]
19.	Growing status observation for oil palm trees	Oil palm trees	RGB images	Fixed-wing Skywalker X8	[168]
20.	Estimating crop evapotranspiration	Pecan nuts	Thermal images	-	[169]
21.	Fast detection and location of fruits	longan fruits	RGB images	-	[170]
22.	Automatic Detection of Oil Palm Tree	Oil palm tree	RGB images	-	[171]
23.	Prediction of yield and water-use efficiency	Spinach	Multispectral images	Phantom 4 Multispectral	[172]

6.2.3 Forestry phenotyping

In this study, the application of drone phenotyping in both wild tree species and domestic tree species are considered. In some cases, the tree species or group name were not identified and have been considered as mixed forest. The identified tree species or group name include pine, robina pseudoacacia, invasive shrub, macadamia, mangrove, desert shrub, acacia, Coastal meadows, spruce, conifer, boreal, and mixed forest. The use cases of agricultural drones for phenotyping in forestry is summarized in **Table 8.** In forestry, disease detection and assessment emerged to be the most studied application of drones followed by mapping.

Table 8. A summary of previous studies on drones' applications in forestry

S/N	Application	Tree species	Image type	Drone type	References
1.	Above-biomass estimation	Robinia pseudoacacia	RGB images	Eight- rotor UAV	[173]
2.	Disease detection/assessment	Pine	Multispectral and RGB images	DJI Phantom 4 multispectral	[174]
		Pine	Hyperspectral images and LiDAR data	DJI Matrice 600	[175]
		Pine	RGB images	DJI phantom 4PRO UAV (version V2.0)	[176]
		Pine	RGB images	DJI phantom 4PRO UAV (version V2.0)	[177]
3.	Mapping	Invasive shrub	RGB images	-	[178]
		Macadamia	Multispectral images	3DR Solo quadcopter.	[179]
4.	Estimating leaf area index	Mangrove	Multispectral images	Octa-rotor	[180]
5.	Automatic detection of invasion species	Acaccia	RGB images	DJI Phantom 3 Pro	[107]
6.	structured mixed deciduous canopies assessments	Forest (mixed species)	RGB images	DJI S900 hexacopter	[181]
7.	Fine scale plant community assessment	Coastal meadows	Multispectral images	SenseFly Ebee fixed wing UAV	[182]
8.	Characterizing biomass and developing biological indicators for the selection of suitable revegetation sites	desert shrub	Multispectral images	fixed-wing UAV (Parrot Disco-Pro Ag)	[183]
9.	assess changes in forest structure from long-term degradation	Forest (mixed tree species)	RGB images	DJI mavic pro UAV	[184]
10.	Characterizing reflectance anisotropy of background soil in open-canopy plantations	Forest (mixed tree species)	Multiangular and multispectral images	-	[185]
11.	Forest tree height estimation	Forest (mixed tree species)	RGB images	GerMAP G180 Drone	[186]
12.	Monitoring restored tropical forest diversity and structure	Forest (mixed tree species)	Hyperspectral, lidar, RGB, and thermal images	DJI Matrice 600 Pro hexacopter	[187]
13.	Early diagnosis of pine wilt disease	Pine	RGD images	DJI Phantom 4 RTK UAV	[188]
14.	Measuring tree height, growth, and Phenology	Spruce	RGB images	DJI Phantom 4-pro	[189]
15.	Ultrahigh-resolution boreal forest canopy mapping	Boreal	RGB images	DJI Phantom 3 4 K micro-quadcopter	[190]
16.	characterization of forest canopy structure in uneven-aged mixed conifer–broadleaf forests	Mixed conifer	RGB images	Trimble UX5	[191]

6.2.4 Legume and oil crops phenotyping

The legume and oil crops considered in this study include sunflower, rapeseed, canola, and soybean. The examples of application of drones in legume and oil crops phenotyping is shown in **Table 9**.

Table 9. summary of literature on agricultural drones' applications in legume and oil crops

S/N	Application	Crop	Drone image	Drone type	Reference
1.	Identifying crop lodging	Sunflower	RGB Digital and Multispectral images	DJI Matrice 600 drone (DJI-Innovations,	[192]
2.	Retrieval of rapeseed leaf area index	Rapeseed	Multispectral images	Matrice 600 hexacopter	[193]
3.	Seedpods Maturity	Canola	Hyperspectral Images	DJI M600 Pro	[194]
4.	Crop height estimation	Rapeseed	RGB images	DJI Phantom 4 RTK	[46]
5.	Yield estimation/prediction	Soybean	Multispectral and thermal images	DJI S1000+ Octocopter	[195]
6.	Pest detection, classification and control	Soybean	Super-pixel RGB digital images	DJI Phantom 4 Advanced	[196]
7.	Estimating relative maturity	Soybean	RGB images	-	[197]
8.	Classification of soybean leaf wilting due drought stress	Soybean	Digital images, RGB and multispectral images	DJI Matrice 600 Pro	[198]
9.	Grain yield prediction	Soybean	Multispectral images	Sensefly eBee RTK fixed-wing unmanned	[199]
10.	Height estimation	Soybean	LiDAR images	six- rotor UAV	[135]
11.	assessment of water status of soybean plants	Soybean	Thermal images	Tarot Iron Man 1000	[200]

6.2.5 Pasture and livestock phenotyping

The pasture crops include grasses, ryegrass while the livestock include cattle and sheep. The above-biomass estimation and mapping is the key application of agricultural drone in pasture phenotyping. On the other end, detection of animal is the most studied application of drone in livestock phenotyping. The showcases of the applications of drone in pasture and livestock phenotyping is summarized in **Table 10**.

Table 10. Application of agricultural drones in pasture and livestock phenotyping

S/N	Application	Pasture and livestock type	Image type	Drone type	Reference
1.	Above-biomass estimation	Grass	RGB images	DJI Phantom 4	[201]
2.	Quantification of grassland five structural and functional traits	Grass (meadow steppe)	Lidar images	-	[202]
3.	Biomass retrieval	Ryegrass	Multispectral images	-	[203]
4.	Mapping total aboveground biomass density	Savana/grassland	Lidar images	DJI M600 Pro	[204]
6.	Assessment of grass lodging	Grass	RGB images	eBee senseFly	[205]
7.	Detection and counting	Sheep	RGB images	DJI Phantom 3 Pro	[206]

		Cattle	RGB images	DJI Phantom 4	[207]

6.2.6 Root crops phenotyping

Root crop has received the least number of studies on the application of drones' phenotyping. Only one root crop (potato) was studied by drone phenotyping among the reviewed literature. The examples of application of agricultural drones in root crop phenotyping is presented in **Table 11**.

Table 11. A summary of literature on the application agricultural drones in root crops

S/N	Application	Crop	Image type	Drone type	References
1.	Above-biomass estimation	Potato	RGB and hyperspectral images	DJI Phantom 4 Pro	[208]
2.	Yield estimation/ prediction	Potato	RGB and hyperspectral images	DJI Phantom 4 Pro	[208]
3.	Sun-induced chlorophyll fluorescence (SIF) study	potato	Multispectral images	DJI S1000 octocopter	[209]
4.	Late blight	Potato	Multispectral images	Tarot 680 Pro hexacopter	[210]

6.2.7 Other crops phenotyping

In this paper, the crops considered under the other crop category consist of sugarcane, cotton, and sugar beet. Cotton crop was the most studied among the crops in this category. With yield estimation and prediction as the most studied application of drones in other crop phenotyping. The examples of application of agricultural drones in these crops are summarized in **Table 12**.

Table 12. Summary of studies on the applications of drones in cotton, sugarcane and sugar beet

S/N	Application	Crop type	UAV images	Drone type	References
1.	sugarcane yield estimation	Sugarcane	Digital images and RGB images	DJI S1000 UAV	[211]
2.	Retrieval of cotton plant water content	Cotton	Multispectral images	Multi-rotor UAV M600	[212]
3.	Fine-scale prediction of biomass and leaf nitrogen content	Sugarcane	UAV LiDAR data and multispectral images	DJI M600 Pro	[213]
4.	Monitoring of sugar beet growth indicators	Sugar beet	Multispectral images	DJI Phantom 4A	[214]
5.	Yield estimation/prediction	Cotton	Digital, RGB and Multispectral images	DJI Phantom 4 RTK and Phantom 4 Multispectral	[215]
		Cotton	RGB images	DJI Matrice 600 Pro	[216]
6.	Detect crop water status variability	Cotton	thermal images	3DR Solo quadcopter	[217]
7.	Evaluation of cotton emergence	Cotton	RGB images	DJI Phantom 4 Advanced	[218]

6.2.8 Precision (non-crops) phenotyping

Agricultural drones have numerous applications. They have also been used in soil, water, irrigation systems analysis which is known as precision phenotyping or non-crop phenotyping. The examples of the other applications of agricultural drones are summarized in **Table 13**.

Table 13. Summary of literature on precision or non-crop phenotyping

S/N	Application	Camera / manufacturer/ country	Drone type	Manufacturer/ country	References
1.	Estimating the spatial distribution of soil total arsenic content	Hyperspectral camera Nano-Hyperspec (Headwall Photonics Inc., Bolton, MA, USA)	DJI M600 Pro	DJI, Shenzhen, Guangdong, China	[219]
2.	Soil sampling	RGB camera	DJI Phantom 4 Pro	DJI, Shenzhen, Guangdong, China	[220]
3.	Mapping of tillage direction and contour farming	Parrot Sequoia multispectral sensor (Parrot SA, Paris, France); 1″ CMOS camera (DJI Ltd., Shenzhen, China)	Parrot Bluegrass quadcopter; DJI Phantom 4 Pro	(Parrot SA, Paris, France) DJI, Shenzhen, Guangdong, China	[221]
4.	Pairing soil sampling	RGB camera; a Parrot Sequoia multispectral camera	SkyRanger R60; DJI Inspire-1	FLIR Systems, USA DJI, Shenzhen, Guangdong, China	[222]
5.	mapping agricultural subsurface drainage systems	SenseFly SA S. O.D.A. camera; SenseFly SA thermoMap radiometric thermal infrared (TIR) camera	eBee Plus RTK/ PPK fixed-wing	A senseFly SA (Cheseaux-sur-Lausanne, Switzerland)	[110]
6.	Mapping vegetation-induced obstruction in agricultural ditches	RGB camera 1-inch CMOS Sensor	DJI Phantom 4 Pro	DJI, Shenzhen, Guangdong, China	[223]
7.	classifying Karst wetland vegetation communities	24 million pixels' cameras	Phantom 4 Pro V2.0	DJI, Shenzhen, Guangdong, China	[224]
8.	Effect of spring irrigation on soil salinity monitoring	Micro- MCA multispectral sensor (Tetracam Corporation, USA)	Matrice 600 six-rotor UAV	DJI, Shenzhen, Guangdong, China	[225]

7. Phenotyping images

Phenotyping or drone images are generated by different imaging systems (sensors or cameras) which are often mounted on the drone platforms. The commonly used imaging systems are LiDAR, thermal infrared sensors, RGB or visible light sensors, Multispectral sensors, and hyperspectral sensors, which have been discussed in this section [226]. The other imaging systems which are not commonly used in phenotyping include but not limited to the following; fluorescence sensors, quantum efficiency of photosynthesis II sensors [86].

7.1 LiDAR images

Light detection and ranging (lidar) images or data are produced by the LiDAR sensor. The LiDAR is a Portmanteau of light and radar which uses a laser to emit light and then measures the time for that light to reflect off an object and return to the sensor. The LiDAR images can be used to describe a surface in a cloud point. In some cases, it can be integrated with other images especially the RGB images. One of the outstanding strengths of LiDAR images is that it provides topography data without the image overlap, hence increasing topographical mapping efficiency [227]. It regarded as the most data for accurate forest-growing stock volume estimation. However, LiDAR images suffer from the inconsistent acquisition dates with field survey which eventually result in poor forest-growing stock volume estimation accuracy [228]. Nonetheless, the LiDAR images can also be used in canopy height measurement [94].

7.2 RGB Images

RGB images are produced by RGB sensors or visible light sensors. The common RGB sensors used in the digital camera are the charge-coupled device (CCD) and complementary metal-oxide semiconductor (CMOS). They are the well-known active-pixel sensors. The RGB images are the most frequently used data for phenotyping. This is because the RGB sensors less expensive compared to the other types including multispectral and hyperspectral sensors [229] [16]. Moreover, RGB sensors can acquire higher resolution images than the counterpart. Further, RGB sensors are light weight, and easy to use and operate. Additionally, the RGB images requires simple processing. Interestingly, the RGB images can be taken in different weather conditions (cloudy and sunny days). However, it should be at specific time frame to avoid excessive or inadequate exposure of the images. The RGB images can be useful in calculating a range of vegetation indices [230], as well as in creation of high-resolution digital elevation models (DEMs), georeferenced orthomosaics and vegetation height maps [231] [232]. The RGB sensors have got some limitations. One of the outstanding drawbacks is that they are inadequate for analyzing a lot of the vegetation parameters that require spectral information in the non-visible spectrum. Therefore, they are commonly used in combination with to other types of sensors to overcome the limitation [28]. On the other end, modified RGB sensors can be used to avoid meeting the higher cost of acquiring multispectral sensors. The modified RGB sensors are the sensors in which the near-infrared filter has been substituted with a red filter, making the former red band sensitive to the near-infrared spectrum (NIR) or red edge resulting into a hybrid (e.g., NIR-RGB) sensor [232].

7.3 Thermal images

Thermal images are acquired by using thermal sensors or cameras. The thermal sensors use infrared sensors and optical lens to acquire infrared energy [226], which is useful in capturing information about the temperature of the objects and generate images displaying them without basing on their visible properties. Thermal images are useful in monitoring of surface temperatures to prevent crop damage and detect drought stress [28]. They usually display warmer objects as yellow and cooler objects as blue, hence, it can be used to create thermal maps for temperature analysis [233]. The thermal images are used for very specific applications. For instance, they are used in irrigation management (i.e., calculate the actual amount of water for irrigation) [28], [29]. In addition, they can be used for canopy temperature extraction [232]. The thermal sensors are not frequently used in agricultural drone-based remote sensing for phenotyping application that focus on monitoring or inspecting other characteristics of the crops [28].

7.4 Multispectral images

The multispectral images are produced by multispectral sensors. The multispectral sensors also known as red-edge sensors are similar to modified RGB sensors which are able to provide images with more massive data than the traditional RGB images [16]. The multispectral sensors are made of 4–6 bands of around 10–50 nm bandwidth in blue, green, red, red-edge, and NIR regions of the electromagnetic spectrum [94], [226], [233]. The multispectral images combine both spectral and spatial data which are useful in classification, mapping, forecasting, prediction, and detection purposes [232]. Therefore, they have numerous applications in crop phenotyping and other remote sensing application. For examples, multispectral images can be used in the assessment of groundwater use in irrigated agriculture [234]. They are generally used to calculate normalized difference vegetation indices (NDVIs) which are used in biomass estimation and identification of highly stressed areas in the crop fields [94]. However, one of the drawbacks of multispectral images is that they require pre-processing (i.e., the radiometric calibration, atmospheric correction, geometric correction, image fusion and image enhancement) which increases the computational time and cost [231]. In addition, the cost of multispectral sensors is higher than that RGB sensors.

7.5 Hyperspectral images

The hyperspectral images are produced with the help of hyperspectral sensors. The hyperspectral images have higher spectral resolution compared to the multispectral images, but have lower spatial resolution. Therefore, they enable more accurate estimations of various phenotyping parameters, such as vegetarian properties or leaf water content, nutrient content, and so on [16]. The critical distinctive feature of hyperspectral image from the multispectral image lies in the fact that it often captures more bands (hundreds or thousands), but in a narrower bandwidth [232]. The hyperspectral sensors focus on assessing a broad light spectrum rather than identifying red, green and blue colors to each pixel [226]. The hyperspectral images also a number of disadvantages. Similar to multispectral images, the hyperspectral images also need to undergo through complex pre-processing methods in order to extract useful information from the spectral images, hence, higher computation time and cost. The cost of buying hyperspectral sensors is the highest among all the phenotyping or agricultural drone sensors.

8. Phenotyping image analytics

This section discusses the different approaches involved in image analytics. Several image analytics methodologies have been produced in the previous studies [27], [117], [235]. Nevertheless, for case this study, we have developed more complete methodology by modifying the one proposed by Omari et al. [236]. The general image analytic approaches include; image processing, segmentation, feature extraction and classification. The adopted image analytics methodology involves 5 steps approaches with regression step as the optional last step is depicted **Figure 8**.

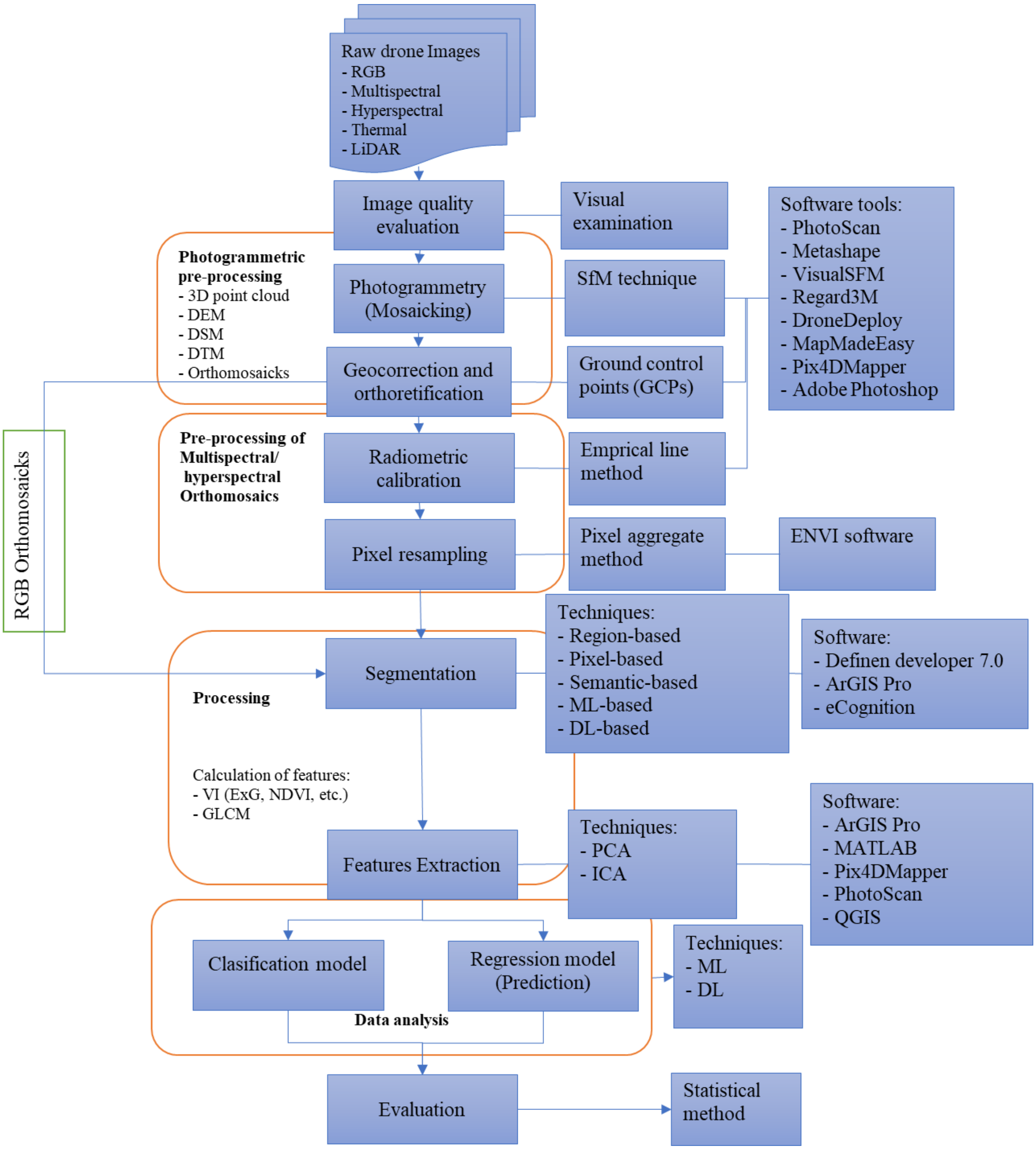


Figure 8. General approach to High-throughput phenotyping image analytics. DEM- digital elevation model, DSM-digital surface model, DTM- digital terrain model, MF, VI- vegetation indices, ExG- Excess greenness index, NDRE- normalized difference red edge index, GLCM- Gray level co-occurrence matrix, ML- Machine learning, DL- Deep learning, PCA- Principal component analysis, ICA- independent component analysis. Source: author's own illustration

8.1 Pre-processing

The main purpose of image pre-processing is to make representation of fore-and background image structures in color spaces topologically more suitable for improving the separability of plant and not plant image [237]. In this paper, the following pre-processing steps were discussed; image quality evaluation, photogrammetric processing (mosaicking and orthorectification), geometrical correction, radiometric calibration and pixel resampling.

8.1.1 Image quality evaluation

Image quality evaluation is the first step of image pre-processing approach; however, only few studies have included in their methods. Image quality evaluation is commonly performed through a visual examination of the image quality such as oblique scene in image and blurry image. It also involves an evaluation of image radiometric distortion, namely, vignetting effect and signal to noise ratio (SNR). Screening the poor quality at the beginning is essential to increasing more accurate data analysis depending on the method used. Therefore, image quality evaluation needs to be conducted before further processing. Moreover, oblique scenes and blurry images mostly caused by wind gusts, results into vibration of the drone images. Images with such problems have to be removed in order to increase chances of achieving accurate results in the subsequence image processing steps. The radiometric distortion caused by atmospheric effects are negligible if the drone is operated at low altitudes [238].

8.1.2 Photogrammetry (mosaicking and orthorectification)

Photogrammetric technique employs the Structure from Motion (SfM) algorithm generates hyper-scale three-dimensional (3D) landform models using overlapping 2D images acquired from different digital cameras and geo-referencing information [239]. Thus, in most cases, it is necessary to collect many overlapping images to construct 3D point cloud model which is used to generate Digital surface model (DSM), Digital terrain model (DTM), Digital vegetation model (DVM), Digital Elevation Model (DEM) of the crops and/or create orthophotos (also referred to as orthomosaics) [240]. The 3D models and the orthophotos contain information about the 3D characteristics of the crops based on the structure of the vegetation such as the vegetation height, the canopy, the biomass density, etc. Therefore, they can be very useful for some applications that can exploit only RGB images [28]. However, for other applications image types, further processing is required. In phenotyping, the suitable end product of photogrammetry should arrive at orthomosaics. Hence, this process is also known as mosaicking or stitching [230].

There are number of software developed based on the SfM algorithm which are commercially available. The use of software reduces the computation time to be spent during photogrammetry. Hence, most of the preview studies used at least a software to complete the pre-processing of the phenotyping images. Three commonly used software include Agisoft Metashape (also known as Photoscan) [36] [111] [146], VisualSFM, and Regard3D [241] [230]. The cloud-based software including DroneDepoly (DroneDeploy, San Francisco, CA, USA) and MapsMadeEasy (Maps Made Easy, Bend, OR, USA) require tile images uploaded to their website and complete stitching on their cloud server, providing orthomosaic images, DTM, 3D point cloud model, and NDVI data. However, the major drawbacks of cloud-based packages are that they do not support 1-band cameras' alignment with each other, as the result, stitched images cannot be layered into a composite image. Nonetheless, the other software packages like Pix4Dmapper (Pix4D, Lausanne, Switzerland) and PhotoScan (Agisoft, St. Petersburg, Russia) have been used [27], [85], [233].

8.1.3 Geometrical correction

The geometrical correction is normally performed on the orthomosaics to avoid geometric distortion form the distorted images with might cause low accuracy in the subsequence processing. Geometrical correction is accomplished by establishing the relationship between the image coordinate and geographic coordinate systems using calibration data of the sensor, measured data of position (GPS) and attitude, and ground control points (GCPs). In most cases, the geometrical correction can be done using the SfM software such as the ones mention before. It can also be performed with ArcGIS (ESRI Inc., Redlands, CA, United States) software using a known GCPs [238].

8.1.4 Radiometric calibration

Radiometric calibration is often conducted for multispectral/ hyperspectral orthomosaics to calculate more accurate vegetation index such as NDVI. The most common method used for radiometric calibration is the empirical line method [117], [238]. In this method, the radiometric calibration panels are used to convert the digital number in the multispectral/hyperspectral orthomosaic image to the reflectance value. The average digital number of each reflectance panel in the orthomosaic can be compared with the actual reflectance values measured in the laboratory to generate empirical line. The entire pixel value of the multispectral orthomosaic image was converted to reflectance by the empirical line [85].

8.1.5 Pixel resampling

The pixel resampling is the final step of image pre-processing. It is referred to as a process of geometrically transforming digital images. Pixel resampling is often conducted to prepare orthomosaics for further processing, namely, segmentation and feature extraction. There are limited data on the software used for pixel resampling. However, the well-known software for pixel resampling is ENVI (Visual Information Solutions Inc., Boulder, Colorado, USA) [146] [117].

8.2 Segmentation

Image segmentation is most critical and important step of image processing especially for case the of object-based image analysis (OBIA) or GEograhic Object-based image analysis (GEOBIA). This is because the final feature extraction and classification is highly dependent on the quality of image segmentation [242]. In general, segmentation refers to a method of dividing an image into homogenous regions (known as land covers) such as building, trees, water bodies, and grasslands which are represented as image object in GEOBIA [242]. It partitions an image into a set of disjointed regions that are different according to specific properties such as texture, color, shape, size and gray level. Several techniques of segmentation have been used in the previous studies. These include edge-based segmentation, region-based segmentation, pixel-based segmentation, hybrid-based segmentation [242], semantic segmentation, machine learning-based segmentation [5], and deep learning-based segmentation [243], clustering-based segmentation. Deep learning-based segmentation is the most used technique for drone based-image processing in recent years [243]. The commonly used deep learning algorithms for segmentation problem include convolutional neural network (CNN), deep neural network, and PlantU-net [84]. A number of software are commercially available with in-built algorithms for performing segmentation based on the selected or chosen technique. The examples of these software include Definiens Developer 7.0 (Definiens AG, Munich, Germany) [117], ArcGIS Pro v2.7, and eCognition [244]

8.3 Feature extraction

Based on the segmented images, the phenotypical features of plants can be extracted. With the known information of the pixel size in millimeters, plant height, width, and size can be calculated using the functions [20]. This is the last step in image processing where quantification of features or vegetation indices (VIs) calculation is conducted. The VIs use combinations of different arithmetic operations or reflection of several bands acquired from RGB and/ or spectral sensor. In other words, they are mathematical transformation of the absorption and scattering in different bands of the electromagnetic spectrum. They are used in a way designed to produce a simple vale that indicated the amount of vigor of vegetation within a pixel. With this, it is possible to estimate and evaluate the health status of the foliage, just from the measurement of radiation that plants absorb or reflect [245]. The VI is known to be the most effective when multispectral or hyperspectral information is used. The VIs have gained more attention in plant phenotyping for monitoring various parameters, by using different combination of spectral bands [28]. The VIs can be categorized into two which include; VIs based on multispectral or hyperspectral data and VIs based on information from the visible spectrum or RGB images [28]. For instance, the commonly used VIs derived from the multispectral/hyperspectral information are ratio vegetation index (RVI), normalized difference vegetation index (NDVI), normalized difference red edge index (NDRE), green normalized difference vegetation index (GNDVI) [246]. While the mostly used RGB-based VIs include Excess greenness index (ExG) and normalized difference index (NDI) [28]. The following software can be used for feature extraction; ArcGIS, QGIS, or other GIS-based software [247].

8.4 Data analysis

The final step of phenotyping image analytics is the data analysis. Here, there are two options or approaches of data analysis depending on the application, that is, either classification or regression, or even the combination of the two. They all proceed after the feature extraction step, and thefore, their use depend on the intended application. The classification method involves prediction of discrete values, and thus mainly used for detection application [248]. While regression helps to predict continuous values and are generally used for prediction, or estimation application [46], [200]. More so, regression method involves prediction model development [249]. In each approach, several methods or algorithms have been used in the previous studies and the examples are given in **Table 14.** The use of machine learning and deep learning algorithms for drone-based phenotyping have attracted large number of research in the recent years, with deep learning as the most commonly applied technique for classification. Among the several deep learning algorithms that have been developed, CNN ranked the most highly adopted algorithms for classification in drone-based phenotyping. The other deep learning algorithms such as Plant-Unet, RNN, MLPs, Radial Basis Function Networks (RBFNs), etc., are also being used. One the other end, machine learning algorithms have been widely used for both classification and prediction (regression). For examples, linear regression, random forest and support vector machine (SVM) algorithms have been used in drone-based phenotyping image analytics [79], [117].

Table 1. Examples of agricultural drones and flight parameters used in previous studies

S/N	Drone name/ type	Sensor type and image type	Drone flight parameters	Image analysis technique, algorithms, and application	References
1.	Phantom 4 Pro v2, Quadcopter	Standard built- in camera with a resolution of 5472 × 3078 pixels; RGB images	HAG: 6m FOV: 86°	Classification; Hybrid CNN model using TensorFlow 2.0 and the Python programming language; for a quicker detection of infested maize plants with fall armyworms	[127]
2.	Phantom 3 Pro, Quadcopter	Pixel camera auto-focus; RGB images	HAG: 25m TID: 10am to 3pm	Classification; Convolutional Neural Networks (CNN); For automatic detection of Acacia longifolia invasive species	[107]
3.	Phantom 4 Professional, Quadcopter;	RGB camera of 20-megapixel resolution and a 24 mm autofocus lens; RGB images	HAC: 120 m CS: 13m/s Endlap: 86% Sidelap: 86.36% TID: 10am to 12am GSD: 4cm	Classification: CNN (deep learning); for individual tree detection and species classification of Amazonian palms	[250]

4.	DJI M600 Pro, Six-rotor	Micasense RedEdge and Emesent Hovermap; multispectral and LiDAR images	FOV: 47.2º HAG: 30 m SR: 2cm/pixel Frame rate: 0.5 Hz	Regression; Simultaneous Localization and Mapping (SLAM) algorithm; Fine-scale prediction of biomass and leaf nitrogen content	[213]
5.	MD4-1000 (microdrones GmbH, Siegen, Germany), Quadcopter	Sony ILCE-6000 model with 23.5 × 15.6 mm APS-C CMOS sensor; RGB images	HAG: 50m FOL: 93% SOL: 60% SR: 1 cm/pixel	Classification: OBIA algorithm; for genotype classification in olive breeding	[80]
6.	Trimble UX5 (Trimble Navigation, Sunnyvale, CA, USA), Small fixed-wing	Sony NEX-5 16.1-megapixel RGB camera (Sony, Tokyo, Japan); RGB images	HAG: 600m CS: 140km/h	Classification: k-means clustering and multinomial logistic regression algorithms; to classify forest canopy vegetation	[191]
7.	DJI Phantom 4, Quadcopter	4000 x 3000 pixels camera; RGB images	MFT: 28mins TW: 1380g HAG: 50m SOL and FOL: 80%	Classification; YOLOv2 algorithm: for detecting and counting cattle	[207]
8.	DJI M600 (DJI, Shenzhen, China), Six-rotor	an Ultra-High-Definition (UHD) 185 hyperspectral sensor (Cubert GmbH, Ulm, Germany); hyperspectral images	LOL: 80% FOL: 85% HAG: 60m CS: 6 m/s TID: 12:00 am	Regression: Boruta algorithm based linear regression model; for estimation accuracy of SPAD values for maize leaves	[249]
9.	DJI Matrice 600, Six-rotor UAV	a Micro- MCA multispectral sensor (manufactured by Tetracam Corporation, USA)	HAG: 120 m CS: 7 m/s COL: 50% SOL: 55%	K-means clustering algorithm; Regression algorithms: Random Forest and Extreme Gradient Boosting; For winter wheat SPAD estimation	[225]
10.	Phantom 4 Pro, Quadcopter	Standard camera, the visible-light camera; RGB images	TID: 11 am to 2 pm FOL: 90% SOL: 75% HAG: 10 m FOV: 45º CS: 2-3 m/s MFT: 30 mins SI: 2 s	Regression models: linear, power, exponential, polynomial, and logarithmic regression; for estimation above-ground volume and biomass of desert shrub communities	[108]
11.	DJI Phantom 4 Pro (DJI, Shenzhen, China),	20 Megapixel RGB camera; RGB images	HAG: 100 m FOL: 80% SOL: 60% TID: 10am to 2pm	Classification: object-based random forest; for fine-scale detection of vegetation in semi-arid mountainous areas with focus on riparian landscapes	[251]
12.	Phantom 4 Multispectral, Quadcopter	RGB sensor for visible light imaging and five monochrome sensors for multispectral imaging	SOL and FOL: 75% TID: 11 am to 1 pm HAG: 20m	Regression method: machine learning based predictive modelling; for predicting or determining yield and water-use efficiency in spinach	[172]

13.	DJI Phantom 3 professional, Quadcopter	Digital RGB camera Sony brand, model EX- MOR 1/2.3'', with a resolution of 4000 ×3000 pixels	HAG: 30m FOL and LOL: 80% CS: 3m/s	Regression methods: SVM, GBR, RFR, PLSR, NEAT; for coffee yield prediction	[154]

HAG- Height above ground or flight altitude; FOL- forward overlap; LOL- lateral overlap; SOL-side overlap; CS- cruise speed or flight speed, SI- shooting interval; TID- time in a day; MFT- maximum flight time; TW- takeoff weight; SR- Spatial resolution, GBR- gradient boosting regression, RFR- random forest regression, PLSR- partial least square regression, NEAT- neuroevolution of augmenting topologies

8.5 Evaluation

The evaluation step in drone-based phenotyping image analytics has been considered as an optional final step. However, this is an important step that helps to validate the drone-phenotyping method used to achieve the results. Evaluation or validation step is used to estimate the drone accuracy. In evaluation step, statistical analysis becomes a very important method. For instance, the mean relative difference can be used to compare field-measured values per genotype and OBIA-estimated values per the genotype for field trials [80]. In addition, statistical analysis can also be used to assess the accuracy of the object-based classifications of the drone orthophotos. For the case of classification performance evaluation, several conventional statistical metrics derived from the confusion matrix have been used including overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and Kappa coefficient [251].

9. Conclusion

The present review has successfully presented a comprehensive summary of drones and image analytics in phenotyping. Manual phenotyping or visual assessment is very tedious and inaccurate method; therefore, the research institutions need to advance to high throughput phenotyping using the drone platform. There are so many categories of drones developed in the recent years, agricultural drones are the category derived based on the application. The choice of drone to use for a particular application is very critical. In this paper, detailed classification of drones was presented and elaborated. A number of drone parameters have the potential to influence the results of field phenotyping. Several parameters of agricultural drones exist, however, only several key parameters including GSD, TOD, image overlap, flight speed or cruise speed, flight height, maximum payload capacity and spatial resolution were discussed in this paper. It was revealed that very limited studies on agricultural drone applications have been focused towards investigating the effects of these parameters on the drones' performance. The application of drones and image analytics in field phenotyping have attracted a number of research in the recent past with cereals being the most studied crop. The rapid development of light weight sensors or camera is incredibly increasing drones' deployment in field phenotyping. The RGB sensor is currently the most commonly used, however, hyperspectral and multispectral are being adopted rapidly despite their higher cost. Image processing and analysis are fundamental for the drone-based phenotyping. Photogrammetric and orthorectification are the most studied pre-processing approach for the drones' images. While the radiometric calibration pre-processing is only applied to multi-spectral and hyperspectral images. The machine learning and deep learning techniques are the artificial intelligence techniques that are advancing and being adopted in phenotyping. They have been applied in image processing (segmentation and feature extraction) and data analysis (classification and regression models). So many algorithms and software have been developed and adopted in drone-based field phenotyping in the recent years. However, there is need to develop a framework to aid the decision making in choosing the methods or software for drone-based phenotyping image analytics.

Competing interest statement

The authors have no competing interests to declare

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