IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 7 April 2024, accepted 10 May 2024, date of publication 15 May 2024, date of current version 22 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3401018

SURVEY

Unmanned Aerial Vehicle for Precision Agriculture: A Review

FRANCESCO TOSCANO[1], **COSTANZA FIORENTINO**[1], **NICOLA CAPECE**[2], **UGO ERRA**[2], **DANILO TRAVASCIA**[1], **ANTONIO SCOPA**[1], **MARIOS DROSOS**[1], **AND PAOLA D'ANTONIO**[1]

[1]School of Agricultural, Forest, Food, and Environmental Science, University of Basilicata, 85100 Potenza, Italy
[2]Department of Mathematics, Computer Science, and Economics, University of Basilicata, 85100 Potenza, Italy

Corresponding author: Francesco Toscano (francesco.toscano@unibas.it)

ABSTRACT Digital Precision Agriculture (DPA) is a comprehensive approach to agronomic management that utilizes advanced technologies, such as sensor data analysis and automation, to optimize crop productivity, enhance farm income, and minimize environmental impacts. DPA encompasses various agricultural domains, including pest control, pest management, fertilization, irrigation management, sowing, transplanting, crop health monitoring, yield forecasting, harvesting, and post-harvest stages. Among the enabling technologies for DPA, Unmanned Aerial Vehicles (UAVs) have gained significant attention and market growth. The advancements in control systems, robotics, electronics, and artificial intelligence have led to the development of sophisticated agricultural drones. UAVs offer advantages such as versatility, quick and accurate remote sensing capabilities, and high-quality imaging at affordable prices. Furthermore, the miniaturization of sensors and advancements in nanotechnology enable UAVs to perform multiple operations simultaneously without compromising flight autonomy. However, various variables, including aircraft mass, payload capacity, size, battery characteristics, flight autonomy, cost, and environmental conditions, impact the performance and applicability of UAV systems in agriculture. The economic considerations involve the purchase of drones, equipment, and the expertise of trained pilots for flight management and data processing. Payload capacity, flight range, and financial factors influence agriculture's choice and implementation of UAVs. The research and patent trends show the growing interest in UAVs for agricultural applications. This paper provides a general review of UAV types, construction architectures, and their diverse applications in agriculture until 2022.

INDEX TERMS Imaging techniques, remote sensing, smart farming.

I. INTRODUCTION

DPA represents a set of strategic agronomic management methods for agroecosystems based on innovative technologies that acquire, analyze, and interpolate data from the latest generation of sensors. The aim is to implement automated management information systems to carry out agronomic interventions weighted according to real crop needs and the chemical, physical, and biological characteristics of the soil. This optimization seeks to increase crop productivity, boost farm income, and minimize environmental impacts. It is a broad field covering diverse agricultural contexts such as insect and pest control [1], pest management [2], fertilization [3], irrigation management [4], sowing [5], crop health mapping and monitoring [6], yield forecasting, harvesting and post-harvest stages [7]. UAVs are among the leading enabling technologies for DPA and are widely researched and discussed topics and the subjects of research [8]. They are characterized by a significantly growing market trend [9], [10]. Consumer attention has also increased, as observed by monitoring the trends in offers and sales of major online retailers [11], [12]. Figure 1 displays the strongly increasing market trend of commercial UAVs in different sectors in North America.

The associate editor coordinating the review of this manuscript and approving it for publication was Jon Atli Benediktsson.

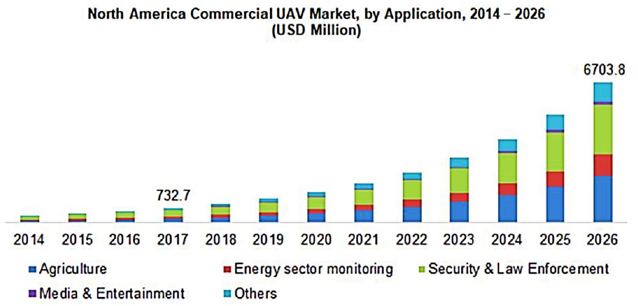


FIGURE 1. North america commercial UAV market [13].

The progress in control systems, robotics, electronics, and artificial intelligence has spurred significant advancements in drone technology. Reference [14]. This progress has led to the development of highly sophisticated and capable drones with enhanced design and functionality. Notably, agricultural drones were acknowledged as pioneering technology by the Massachusetts Institute of Technology in 2014, positioning them among the top ten breakthrough technologies [15]. Several studies [16], [17], [18] have concluded that UAVs are one of the most successful technologies in precision agriculture, where they are now widely used and deployed [19]. Being, particularly versatile instruments and capable of carrying out remote sensing operations quickly and accurately, even in unfavorable weather conditions (such as in the presence of fog), UAVs offer spatial and temporal resolutions that other systems, such as satellite systems, do not guarantee [20]. UAVs can obtain high-quality images at low prices, whereas satellites and aircraft require high altitudes, cloud penetration, and other capabilities for clear photography [21]. Furthermore, thanks to advancements in nanotechnology [22], [23] and sensor miniaturization [24] used in Precision Agriculture (PA), it is now possible to mount multiple instruments on board UAVs, enabling them to perform multiple operations simultaneously [25], [26], without compromising flight autonomy. However, there are considerable variables that affect the performance and applicability of these systems: aircraft mass, payload capacity, size, battery characteristics, flight autonomy under different conditions, purchase cost, environmental conditions, configurations, *etc.* From an economic point of view, the use of UAVs systems in agriculture requires investment linked to the purchase of the drone, the equipment to be mounted on it (laser scanner, thermal, multispectral, or hyperspectral cameras), and the professionalism of a trained pilot, both for flight management and for the subsequent phases of processing the acquired data. In the case, on the other hand, of UAVs for crop treatments, again from an economic point of view, the main cost items are related to the purchase of the suitable drone, the purchase of the product to be administered, and finally, the professionalism of a trained pilot. The payload capacity, flight range, and financial factors are the three essential parameters that influence the choice and implementation of unmanned aerial vehicles in agriculture [17]. Moreover, in recent years, these systems have seen increasing interest from researchers around the world. Table 1 below shows an analysis we carried out on Scopus data to identify the trend of interest from the world of scientific research concerning applications of UAVs in agriculture. A study was conducted to quantify the dynamics of the number of indexed scientific contributions and patents realized. From the analysis of the data in Table 1, it is clear that the trend of interest is highly positive and assumes, as shown in Figure 2, a strongly increasing trend starting in 2014 when it takes on exponential characteristics. The analysis also reveals that a significant percentage of articles (>70%) address the topic of drones in agriculture, even if not the primary focus. This demonstrates the coordinated nature of this dynamic with various other subsectors of agriculture, such as environmental sustainability, IoT, AI, *etc.* It is challenging to provide up-to-date, comprehensive, and exhaustive information on all technologies related to UAVs, such as various types of imaging cameras, distribution systems, flight systems, new prototypes, market novelties, *etc.* This paper aims to provide a comprehensive review of the primary types of UAVs used in the agricultural sector up to 2022, accomplished through a systematic analysis of pertinent scientific contributions in the literature. In the present landscape of production, agricultural enterprises are increasingly pursuing more effective solutions to increase the effectiveness of their production processes.

After a thorough examination of UAV platform architectures used in PA, extensive exploration has been conducted into various contributions concerning their agricultural applications. These applications encompass soil monitoring, vegetation assessment, weed and pest detection, insect monitoring, precision treatments, and beyond. The aim is to provide a comprehensive overview of UAV innovations and applications within the agricultural domain, drawing upon the most recent scientific research available.

II. ARCHITECTURE

The classification of drone platforms for civil, scientific, and military uses, based on characteristics such as size, flight endurance, and capabilities, was conducted by [27]. They categorized them as Micro or Miniature Air Vehicles (MAVs), Nano Air Vehicles (NAVs), Vertical Take-Off & Landing (VTOL), Low Altitude, Short-Endurance (LASE), LASE Close, Low Altitude, Long Endurance (LALE), Medium Altitude, Long Endurance (MALE), and High Altitude, Long Endurance (HALE). UAVs can be electric or fuel-powered; the former in addition to being more prevalent in agricultural applications, is also more interesting concerning the issue of pollutant emissions. In this paper, we will focus our attention precisely on this construction solution.

A. PLATFORMS

For the purposes of this paper, UAV construction types can be simplified and essentially traced back to two distinct platforms: fixed-wing and rotary-wing (Figure 3).

TABLE 1. Scopus data analysis.

YEAR	PATENT SCOPUS (reporting unmanned&aerial& vehicle in the title)	SCOPUS ARTICLE (reporting unmanned&aerial& agriculture in the text)	SCOPUS ARTICLE (reporting unmanned&aerial& agriculture in the title)
2022	13391	4621	1422
2021	12509	3902	1508
2020	11068	2890	1380
2019	8614	2207	1382
2018	6260	1414	1154
2017	4459	957	900
2016	2578	619	669
2015	1693	423	508
2014	1227	231	416
2013	948	156	375
2012	910	102	318
2011	650	70	254
2010	676	52	221
2009	496	37	201
2008	402	28	166
2007	354	20	140
2006	244	11	123
2005	243	12	140
2004	137	9	84
2003	119	3	46

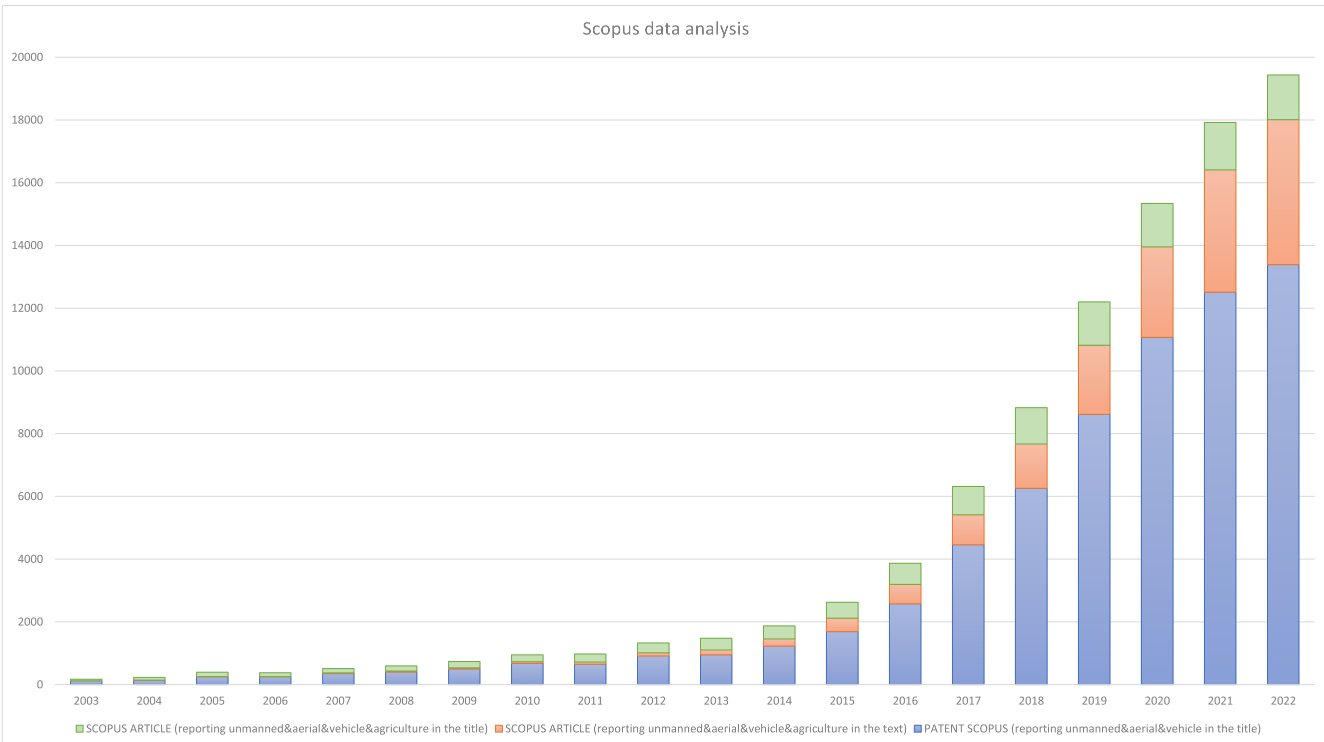


FIGURE 2. Scopus data analysis bar chart.

Fixed-wing UAVs are characterized by the presence of stationary airfoil-shaped wings that generate lift, enabling the craft to take off from the ground [28]. These drones have a greater flying capacity, relying on aerodynamic lift, and can cover large areas in a single flight, making them suitable for large-scale one-off operations [29]. However, they require skilled pilots, proper training, and suitable take-off and landing areas. Rotor-wing UAVs can be differentiated based on weight and the number of rotors. Generally, they are more affordable and easier to handle [30], suitable for daily operations on small to medium scales. They are further classified into helicopters and multicopters. Helicopter UAVs feature a single set of blades connected to a central shaft, which rotates at a specific speed to generate lift for take-off. Additionally, a counter-rotor is located at the tail to control yaw. Multicopter UAVs, on the other hand, have multiple sets of rotors where blades are attached and rotated to achieve lift for take-off. The same set of blades is used for controlling movement in terms of yaw, roll, and pitch. Unlike single-rotor systems, multi-rotor vehicles have greater "thrust capabilities", as single-rotor designs have obvious limitations related to structural mechanics, rotor sizing, and the resulting achievable peak angular speed. Today, many configurations are available, including customizable ones, starting with 2 and even up to more than 8 rotors.

Helicopters and multicopters have the advantage of flying in any direction, both horizontally and vertically, and hovering in a fixed position [31], resulting in stable flight conditions, including low speed and stationary flight if needed, which appear to be recommendable when precision data sensing or precision product delivery is expected by the flying systems [17]. Their rotary-wing configurations gain a particular relevance due to their hovering, vertical take-off, and landing capabilities [32]. Regarding the issue of flight autonomy, the technical data sheets analyzed and the various scientific contributions on the subject [33], [34], [35], [36] agree that fixed-wing systems provide greater autonomy than rotary-wing systems. This is determined both by the fact that rotary-wing systems have higher masses and lower aerodynamic profiles than fixed-wing models. Among rotary-wing systems, helicopters also exhibit higher flight autonomies than multicopters. Certain manufacturers, such as Yamaha and DJI, have designed customized UAVs to meet agricultural needs. Yamaha's remotely piloted helicopters have been utilized in agricultural operations since 1991. While these helicopters are not directly available for purchase, the manufacturer offers comprehensive services, including maintenance and qualified pilot provision. Conversely, DJI has developed specialized drone models tailored for crop protection, integrating advanced sensors like multispectral sensors, high-precision Real-Time Kinematic (RTK) Global Positioning System (GPS), and high-resolution cameras. Another notable solution is the Parrot Bluegrass Fields, which provides a comprehensive drone system for crop analysis, consisting of a drone, multispectral sensor, and dedicated processing software [37]. Figure 3 below schematizes the most important platform types and characteristics of UAVs.

The most prominent platform types and characteristics of the professional drones most commonly used in DPA are shown in 2 below.

UAVs can also be categorized based on their flight altitude, distinguishing between low-altitude platforms ($< 3,000$ m a.s.l.), medium-altitude platforms ($3,000 \div 9,000$ m a.s.l.), and high-altitude platforms ($> 9,000$ m a.s.l.).In general, high-altitude platforms are characterized by greater mass and flight autonomy. Drones are used to transport various types of instrumentation, including GPS, infrared cameras, batteries, and sensors. These drones are often equipped with

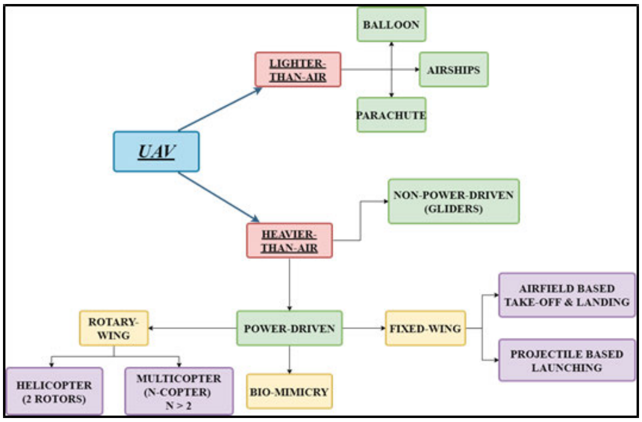


FIGURE 3. The most important platform types and features of UAVs.

high-energy lithium batteries, which allow a flight time of approximately $20 - 40$ minutes. However, the limited battery capacity poses a challenge for the range and endurance of UAVs. Increasing the size of the battery is not a feasible solution, as it would increase the weight of the drone, which is another critical concern. Several research studies have focused on UAV battery charging but still require further investigation by the scientific community [38], [39].

B. HARDWARE

There is a wide variety of UAVs on the market, and depending on the applications they can perform, they will be equipped with different hardware. Hardware denotes the set of immutable physical components of a system, such as power supplies, circuits, and memory units. In the case of UAVs used in DPA, we can find elements such as chambers of various types [21], Brushless Direct Current [40], Electronic Speed Controller [41], Global Position System [42], Wireless Sensor Network [43], Altimeter [44], Accelerometer [45], Gyroscopes [46], Magnetometer [47] and, obviously, battery. Both sensors and computer platforms are indispensable to ensure the proper functioning of UAVs. Typically, sensors are installed on integrated computing platforms such as Arduino, Raspberry Pi, Orange Pi, Odroid, and Nvidia Jetson. Control platforms such as Pixhawk, Ardupilot, Multiwii, and Naza are also connected to the computing platforms. However, in some cases, certain sensors like GPS receivers and IMUs can be directly installed or connected to the control platforms [21]. Figure 4 below schematizes the basic infrastructure of UAVs used in DPA. Recently, several commercial drones have integrated RTK technology, which represents a significant leap in enhancing the accuracy of positional data. The RTK system in drones comprises two main components: a mobile station (or rover) situated on the drone and a stationary base station with a known position. The base station plays a pivotal role in this setup; it continually measures satellite signals and calculates correction data based on its established location. This correction data, which compensates for errors due to atmospheric disturbances, satellite and receiver discrepancies,

TABLE 2. Platform types and salient features of professional drones used in Digital Precision Agriculture (DPA).

Platform types	Mass (kg)	Estimated battery life (min)	Capability						
			Speed	Level Flight	Endurance	Range	Simplicity	VTOL	Hover
Fixed-wing	$\sim 5 \div 23$ kg	$60 \div 90$	High	Good	Good	Good	Good	Bad	Bad
Helicopter	$\sim 5 \div 35$ kg	Highly variable	Low	Bad	Medium	Bad	Bad	Good	Good
Multicopter	$\sim 0.25 \div 20$ kg	$10 \div 20$	Low	Bad	Bad	Bad	Good	Good	Good

and orbital inaccuracies, is then transmitted to the mobile station in real-time. Consequently, the drone adjusts its positional calculations, achieving a remarkable centimetre-level accuracy. This heightened precision has noteworthy implications, especially in applications like mapping and surveying. For instance, imagery captured by the drone can be tagged with highly precise geospatial data, drastically reducing or eliminating the need for Ground Control Points (GCPs). Beyond mapping, the stable flight facilitated by RTK proves invaluable, particularly in low-altitude flights or areas with potential GPS interferences. One domain reaping substantial benefits from RTK drones is precision agriculture. Here, farmers acquire accurate field maps that are instrumental in optimizing irrigation, monitoring crop health, and applying farm inputs. Interestingly, while RTK provides instantaneous corrections, there's also an option for Post-Processed Kinematic (PPK), where corrections are integrated during the data processing phase post-flight. When combined with other drone systems, such as multispectral sensors or high-resolution cameras, RTK's precise positioning yields comprehensive and detailed data sets tailored for specialized applications. However, to ensure optimal RTK performance, it's imperative to maintain a clear line of sight between the drone and the base station and understand conditions that might affect GPS signal quality. When the use of a base station is impractical due to several restrictions, another approach to enhance the accuracy of positional data based on RTK is through the Networked Transport of RTCM via Internet Protocol (NTRIP). NTRIP streams this differential Global Navigation Satellite System (GNSS) data over the internet. Instead of a dedicated base station, NTRIP uses a network of reference stations to provide corrections. Drones with RTK and cellular connectivity can access real-time corrections via NTRIP without a nearby base station (in some nations, there are free NTRIP servers based on open source and open data stuff). This is especially useful in large-scale operations or challenging terrains, offering flexible and precise mapping solutions over vast areas.

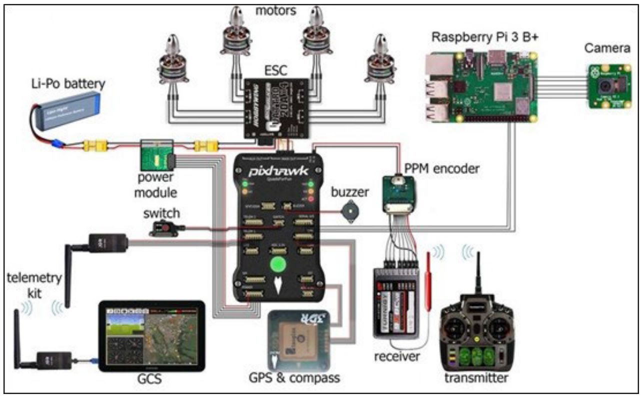


FIGURE 4. Accurate landing of unmanned aerial vehicles using ground pattern recognition [48].

C. SOFTWARE

The use of UAVs in Drone-Assisted Precision Agriculture (DPA) is closely tied to the development of dedicated software capable of processing, even in real-time, the valuable information captured by onboard sensors. The essence of UAVs in this context is often linked with image analysis, necessitating the correction and processing of photos captured during overflight activities. The sector is so significant that [49] estimates its market value at around USD 32 billion. It plays a crucial role in collecting and processing essential UAV data, which enhances the overall system's effectiveness. Unlike its hardware components, UAV software comprises a comprehensive set of specialized programs, methods, and operations that perform specific functions. The proper functioning of UAVs relies on the unique interplay of hardware and software components. The most commonly used software for data processing includes Geographic Information System (GIS) programs like QGIS and ArcGIS, and Python, Matlab, Pix4D, and R [50]. Beyond dedicated software available on the market today, drones can be programmed with new features using their manufacturers' Software Development Kit (SDK). The SDK offers developers a powerful toolkit to craft custom applications, extending the drone's native capabilities. With this SDK, developers can tailor flight paths, design unique maneuvers, and automate data capture. For instance, they can programmatically fine-tune camera settings to execute advanced photography routines such as time-lapses or panoramas. Integration capabilities are broad, from syncing drone data to cloud platforms to embedding control components in third-party applications. Furthermore, the SDK facilitates granular control of additional payloads or sensors mounted on drones, ensuring diverse data acquisition needs are met. Some commercial drones have a USB port that enables a custom payload that can communicate on the ground. Developers can also implement advanced safety and

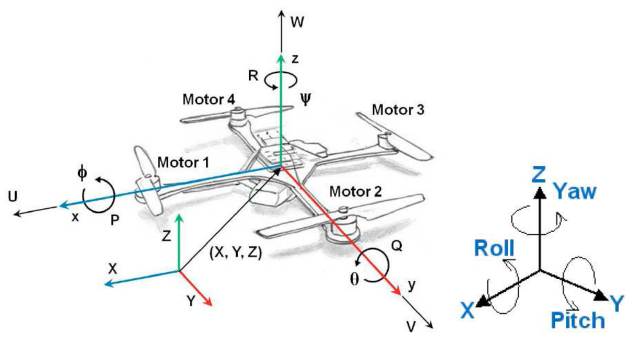


FIGURE 5. Schematization of UAV flight control system [51].

geofencing rules, which are crucial for adhering to regulatory standards or ensuring drone operations within designated areas. Moreover, they can harness telemetry data to analyze intricate details like flight patterns and drone health. Even more intriguing is the potential to control multiple drones simultaneously, enabling synchronized operations for tasks like swarm displays.

III. FLIGHT CONTROL SYSTEMS

UAVs have six degrees of freedom, enabling movement in three spatial directions: x, y, and z, with corresponding linear velocities U, V, and W. Furthermore, they can rotate around three axes - roll (ϕ), pitch (θ), and yaw (ψ), with corresponding angular velocities P, Q, and R (refer to Figure 5).

Previous research has extensively focused on controlling this intricate nonlinear system, as exemplified by the works of [52] and [53]. UAVs are controlled by an embedded computer known as the Flight Control System (FCS) or flight controller, which consists of control software loaded into a suitable microcontroller, as discussed by [54] and [55]. According to [56], the flight control system comprises two main components: a reference generator (outer loop) that records the desired position and flight altitude to generate command signals, and an on-board control system (inner loop) that utilizes these commands as output to regulate motor speed, as investigated by [57]. These components operate within a cascade control structure, where the inner loop operates at a higher speed than the outer loop, typically during ground operations. The reference generator calculates control signals based on the drone's position and orientation along the z-axis, while the positioning measurement system determines the drone's position and speed. Various control strategies and approaches exist to regulate the reference generator's operation, ranging from basic heuristic techniques to advanced dynamic models. Examples include Fuzzy logic, Linear Quadratic Controller (LQG), Sliding Mode Control (SC), Proportional Integral Derivative (PID) control, and Neural Network (NN) methods. The fundamental assumption underlying the model derivation is that the aircraft's dynamics can be described through rigid body motion. Thus, the dynamic model of the aircraft can be derived by incorporating inertial and body reference systems, as explained by [19]. The inertial reference systems include an Inertial Measurement Unit (IMU) and a navigation computer, as detailed by [58]. The IMU typically includes three orthogonal rate-gyroscopes, three orthogonal accelerometers, and, in some cases, a 3-axis magnetometer to respectively measure angular velocity, linear acceleration, and orientation, as described by [59]. Additionally, an inertial reference system is often integrated with a GPS receiver to provide the drone's position information The PID controller functions as a closed-loop system wherein a sensor measures the process variable and provides feedback to the control system. The discrepancy between the process variable and the desired setpoint is utilized by the PID controller to regulate the motor speed accordingly. Consequently, the reference generator aims to acquire position coordinates, determining the desired attitude, directional speed, and thrust of the drone, which serve as references for the onboard control system. However, classical PID controllers have limitations when operating in harsh and unpredictable environments, such as wind disturbances affecting trajectory tracking by impairing the performance of the attitude controller. This issue has prompted researchers to develop model-based nonlinear controllers, including Nonlinear Model Predictive Control (NMPC), which has gained popularity as a control algorithm in numerous recent research papers. To address this challenge, some studies have focused on leveraging learning algorithms such as the Gaussian process or Neural Networks, to actively estimate the robot's dynamic parameters and update the prediction model in real-time [60]. An interesting approach proposed by [61] involves an intelligent flight control system built using neural networks to learn the dynamics of quadcopters. This method enables real-time adaptation to external disturbances and unmodeled dynamics. Consequently, these models can be further refined by integrating increasingly sophisticated algorithms, as recommended by [19]. Similarly, the on-board control system consists of two components: the attitude controller and the rate controller. These components enable the estimation of the drone's attitude and angular velocities, which are subsequently utilized by the on-board control loop. It is worth noting that such a control architecture is considered "closed", meaning that modifications to the control gains or the control loop are not feasible. These limitations become particularly crucial when designing flight control systems for precision agriculture scenarios, where the aircraft must maintain its position effectively despite severe weather conditions. Due to these considerations, it is imperative to pay close attention to ensure the safety of operators during UAV flights. Therefore, scientific research plays a pivotal role in implementing novel solutions and innovations that prioritize enhanced safety and flight control within this specific field.

IV. USE IN PRECISE AGRICULTURE

UAVs have witnessed significant advancements in the last two decades in technology and various applications.

In particular, in agriculture, remote sensing by drones has proven to be the most efficient way to monitor crops, soil, weeds, and pathogens through spatial imaging techniques. Below, we delve into the primary applications of UAVs in precision agriculture.

A. SOIL MONITORING

Soil is a matrix of organic and inorganic materials that serves as the substrate for the growth of field crops. The study of its characteristics is crucial for the preparation of any management strategy. Soil monitoring encompasses various techniques, classified into three primary categories:

- Soil sampling and laboratory study;
- Use of proximate sensors;
- Use of remote sensors.

Soil sampling represents a destructive, costly, and time-consuming method of analysis [62] and is often unsuitable for investigating dynamic phenomena, such as those affecting agricultural soils across three-dimensional space and time. Presently, it mainly serves to corroborate results obtained through proximal and remote sensing methods [63]. Proximity sensors for the study of soil properties have seen significant technological and commercial development over recent decades; however, they exhibit several limitations in monitoring large areas [64] and also require constant maintenance or replacement, obliging operators to enter the field even when unnecessary [65]. The most widely used remote sensors for monitoring soil properties are satellites [66] and drones, the latter of which are becoming increasingly popular on the market as they offer great advantages in terms of both data quality and flexibility of use (spatial and temporal). However, not all soil properties can be effectively examined using these instruments. A review of scientific literature highlights the parameters most commonly investigated:

1) Soil moisture;
2) Soil salinity;
3) Gas detection;
4) Organic matter.

1) SOIL MOISTURE

Soil moisture content (SMC) is a critical physical parameter that impact not only soil aggregate structure but also influences nutrient availability, hydrological processes, and soil degradation [67], [68], [69], [70]. Advancements in hyperspectral technology in remote sensing have facilitated the acquisition of SMC information over larger areas and with improved efficiency compared to conventional thermo-gravimetric methods [71], [72]. Reference [73] proposed a UAV radar system for monitoring soil moisture, while [74] demonstrated a significant correlation between soil moisture and the brightness of UAV visible images. They successfully estimated surface soil moisture by combining the brightness of UAV visible images with vegetation coverage. Commonly investigated indices for soil moisture estimation include Superficial Soil Moisture (SSM) and Soil Water Index (SWI). Remote sensing techniques offer various domains for soil moisture estimation, with visible and thermal infrared sensing providing excellent spatial resolution and microwave sensing being less affected by adverse weather conditions [75]. Hyperspectral technology integrates the benefits of spectroscopy and digital imaging [76]. Leveraging drones introduces new possibilities in terms of spatial and temporal resolution, enhancing outcomes obtained through other remote sensing methods. Furthermore, [77] successfully combined hyperspectral imagery and machine learning algorithms, achieving a high level of accuracy ($R2 = 0.907$) in estimating SMC.

2) SOIL SALINITY

Soil salinization poses a significant environmental threat, contributing to soil degradation, loss of arable land, and ecological deterioration. While multispectral and hyperspectral satellite remote sensing are commonly used for monitoring salinized soils, they suffer from limitations like reduced spatial and temporal resolution. In contrast, the use of hyperspectral sensors mounted on UAVs show promising potential for estimating and mapping soil salinity. However, the full potential of this technology in this area remains largely unexplored; indeed, standardized operational methodologies for these surveys are not yet available [78]. Currently, the main scientific references are based on the use and reworking of vegetation indices of crops in the soil [79] or, alternatively, on estimates based on canopy temperature [80], [81]. All methodologies used report high levels of correlation; however, strong operational limitations in terms of repeatability and accuracy in other study areas are noted. Reference [82] investigated the impact of saline reclaimed waters and deficit irrigation on Citrus physiology assessed by UAV remote sensing, suggesting that statistical analyses of field and remote sensing data, derived from multispectral imagery using a UAV, confirm the feasibility of applications to assess physiological and structural properties of Citrus under water and salt stress. Combining field geophysical prospecting techniques with remotely acquired measurements emerges as the most efficient solution to address these limitations [83]. Finally, among the new research frontiers in the field, we highlight the work produced by [84], who proposed a methodology to estimate soil salinity through the combined analysis of hyperspectral and multispectral images acquired from UAVs, obtaining very significant and accurate results.

3) GAS DETECTION

Measuring gases in soils intended for agricultural crops can be a very effective solution for both defining the right management strategies and monitoring the impacts of agronomic activities. A 2019 study [85], explored the combination of miniaturized sensors mounted on UAVs to understand the potential related to ethylene surveying in an apple orchard, obtaining interesting results on the intensity of gas dispersion in response to wind action determined by the drone's rotors . This severely limits the system's capacity for gas monitoring. More encouraging results were obtained by [86], who accurately described the design and flight tests of a UAV equipped with an on-board camera and CO2 sensor, demonstrating the infrastructure's ability to analyze air quality through a real-time processing system and offering important perspectives for applications in emissions from agricultural biomass combustion and detection of chemical and biological agents in agriculture. However, it is currently emphasized that there is a lack of standardized, effective, and accurate methodologies in this area, which is certainly one of the most interesting to investigate in the future.

4) SOIL ORGANIC MATTER DETECTION

Soil Organic Carbon (SOC) is certainly one of the most crucial indicators of soil fertility [87]. Estimating it can be accomplished through various methods and technologies. The emergence of UAVs equipped with high-resolution, both spatially and spectrally cameras has facilitated the rapid advancement of remote sensing methodologies. Drone-based surveys can overcome the limitations imposed by weather conditions and resolution, which are often encountered in satellite surveys [88]. Reference [89] investigated the utilization of UAV imagery of bare soil combined with auxiliary datasets to map the distribution of SOC in an erosion-affected agricultural field, achieving reliability indices close to 0.85. However, there exist numerous research approaches in this domain, including those employing predictive systems and neural networks capable not only of estimating the content of SOC in the soil but also of forecasting its temporal changes [90], [91], [92].

B. CROP MONITORING

In this work, more than 30 articles were analyzed concerning the use of drones for monitoring crops in agriculture and the study of different vegetation indices. It was found that the most frequently monitored crops through remote sensing are cereals. The main applications related to crop monitoring include defining the health and vigor status of the crop and the use of remote sensing for crop phenotyping, i.e., the evaluation of the physical characteristics of a crop based on environmental variations to select plants or seeds with favorable genotypes and phenotypes. The type of UAV most commonly used in these fields is the multirotor equipped with RGB and multispectral sensors. The characterization of agricultural crops necessitates evaluating and measuring their observable physical traits, which define the phenotypes of a species across multiple generations and growth stages [93], [94]. However, the traditional approach to phenotyping, based on direct observation in the field, is extremely time and resource-consuming [95]. Consequently, the adoption of drones for non-invasive phenotyping is gaining popularity due to their capacity to capture high-resolution images with both temporal and spatial precision. These images allow the acquisition of various models representing the phenotypic characteristics of crops [96]. The authors agree that phenotyping is a widely used process to select plants or seeds with a ''favorable phenotype'', capable of conferring advantageous properties to cultivars such as higher productivity, better response to fertilizers [94], and better resistance to pests and diseases [97]. Crop monitoring via UAVs typically employs imaging techniques aimed at defining vegetation indices, quantitative indicators enabling the monitoring of crop conditions, as well as other entities, such as soil, weeds, pests, *etc.*- providing information on growth, biomass content, vigor, health status, and water content in plant tissue, *etc.* Data from red or infrared bands can provide important information regarding biomass content, canopy structure, and leaf area index [98]. Reference [99] suggest that the analysis of visible bands can be useful for assessing pigment concentration in leaves and nitrogen content. Another index that can be measured using infrared radiation is canopy temperature, which can provide an indication of the transpiration rate of plants and their performance under low water stress conditions [100]. Reference [101] carried out an extensive collection of sensor data, vegetation indices, and remote sensing applications, all of which are currently available on an open-access website. However, acquiring images for vegetation index extraction can be challenging due to the requirement for stable lighting conditions [102], while the time of day and camera angle during image acquisition can also influence these indices [103]. It's worth noting that the reflectance of plants may vary depending on their growth stage. Table 3 below summarizes the main vegetation indices used in agro-forestry sciences in the literature and their formulas for estimating their value concerning data from different spectral bands.

The use of drones and remote sensing in agricultural crop monitoring holds significant potential, yet the technical and logistical constraints concerning image acquisition and interpretation of vegetation indices need thorough consideration.

C. WEED MONITORING

According to several authors [132], [133], [134], weeds are the main cause of yield loss in agricultural production, covering about one-third (approximately $\sim$ 34%) of the total. These are followed by animal pest infestations (approximately $\sim$ 18% loss) and plant pathogens (approximately $\sim$ 16% loss). Wild species, especially weeds, are characterized by different mechanisms of environmental adaptation (remarkable physiological, phenotypic, morphological, and anatomical plasticity) and great competitive abilities (seed heteromorphism, intraspecific variability, allelopathy) that result in higher tolerance to environmental stresses compared to cultivated species [133], [135], [136], [137]. Many studies have investigated crop-weed interactions; in particular, it has been found that these dynamics have not remained unchanged over the centuries but have evolved in tune with the progress of management strategies adopted by agricultural

TABLE 3. Vegetation index formulas.

Sequence	Spectral Index abbreviation	Index Formula	Main Reference
1	NDVI	$\frac{NIR-R}{NIR+R}$	[104]
2	RVI	$\frac{R}{NIR}$	[105]
3	VIN	$\frac{NIR}{R}$	[105]
4	NDI	$\frac{NIR-MIR}{NIR+MIR}$	[106]
5	TVI	$\sqrt{NDVI}+0.5$	[107]
6	DVI	$NIR-R$	[108]
7	PVI	$\frac{NIR-10.489R-6.604}{\sqrt{(1+10.489^2)}}$	[109]
8	EVI	$2.5\cdot\frac{NIR-R}{NIR+6R-7.5B+1}$	[110]
9	GNDVI	$\frac{NIR-G}{NIR+G}$	[111]
10	RDVI	$\frac{NIR-R}{\sqrt{NIR+R}}$	[112]
11	SAVI	$\frac{NIR-R}{NIR+R+L}(1+L)$	[113]
12	OSAVI	$(1+0.16)\left(\frac{R800nm-R670nm}{R800nm+R670nm+0.16}\right)$	[114]
13	NLI	$\frac{NIR^2-R}{NIR^2+R}$	[115]
14	NDGI	$\frac{G-R}{G+R}$	[116]
15	RI	$\frac{R-G}{R+G}$	[117]
16	MGRVI	$\frac{G^2-R^2}{G^2+R^2}$	[118]
17	GBNDVI	$\frac{NIR-(G+B)}{NIR+G+B}$	[119]
18	GBNDVI	$\frac{NIR-(G+R)}{NIR+G+R}$	[119]
19	BNDVI	$\frac{NIR-B}{NIR+B}$	[120]
20	MSAVI	$\frac{2NIR+1-\sqrt{(2NIR+1)^2-(8NIR-R)}}{2}$	[121]
21	RBNDVI	$\frac{NIR-(R+B)}{NIR+R+B}$	[119]
22	Pan NDVI	$\frac{NIR-(G+R+B)}{NIR+R+B}$	[119]
23	GRVI	$\frac{NIR}{G}$	[122]
24	RRI1	$\frac{NIR}{Rededge}$	[123]
25	VARI	$\frac{G-R}{G+R-B}$	[124]
26	NGRDI	$\frac{G-R}{G+R}$	[125]
27	NRI	$\frac{R1510nm-R660nm}{R1510nm+R660nm}$	[126]
28	RGBVI	$\frac{G^2-(B\cdot R)}{G^2+(B\cdot R)}$	[127]
29	GLI	$\frac{2G-(R+B)}{2G+R+B}$	[128]
30	RENDVI	$\frac{NIR-R\_edge}{NIR+R\_edge}$	[129]
31	TCARI	$3\cdot\left[(R700nm-R670nm)-0.2\cdot(R700nm-R550nm)\cdot\left(\frac{R700nm}{R670nm}\right)\right]$	[130]
32	MTVI	$1.2\cdot[1.2\cdot(R800nm-R550nm)-2.5\cdot(R670nm-R550nm)]$	[131]
33	MTVI2	$1.5\frac{[1.2\cdot(R800nm-R550nm)-2.5\cdot(R670nm-R550nm)]}{\sqrt{(R2800nm+1)^2-\left(R6800nm-5\cdot\sqrt{R670nm}\right)-0.5}}$	[131]
*R = *Red*; G = *Green*; B = *Blue*; NIR = *Near Infrared*;			

producers [138]. Conventional modes of chemical and mechanical pest control show several limitations, both in terms of operational efficiency and economic-environmental sustainability [139], [140], [141]. From this assumption, we note the need to opt for site-specific management systems based on the strategic use of new technologies, and drones in particular (see Figure 7).

Early diagnosis is crucial for preventing and limiting pest development [142]. Recent years have seen the development of systems combining drone image acquisition or field spectro-radiometers with machine learning methodologies [143], aimed at managing weed removal activities with robots [144] for automated weed control. In this contex, a primary role is being played today by research based on the use of artificial neural networks to implement new techniques for localized weed management through selective application of herbicides using eco-friendly methods [145]. The key aspect of implementing automated weed control systems lies in employing detection techniques and technologies characterized by high reliability to achieve accurate differentiation between weeds and crop species. Various machine learning algorithms, such as Convolutional Neural Networks Convolutional Neural Networks (CNN), Artificial Neural Network (ANN), and Support Vector Machines Support Vector Machines (SVM), are effectively applied in this domain. Hyperspectral imaging appears to be a highly promising solution, demonstrating a great capability in real-time differentiation between crops and weeds [143].

As per the findings of [2], the combination of Integrated Weed Management and Unmanned Aerial Vehicles UAVs offers a promising opportunity for targeted Weed Management 6. This innovative approach not only proves to be a remarkably effective technique but also holds significant environmental advantages. Pest control methods utilizing new technologies, particularly through UAVs, are notably efficient, especially regarding the potential for employing site-specific methodologies promptly. Regarding the application of UAVs in pest management, a primary concern lies in the diverse technologies and modes of image acquisition necessary to obtain the identification, characterization, and geographic location of pests in a field. A review of the pertinent literature shows that the main types of sensors used are:

1) RGB (Red, Green, Blue) or VIS (Visible) cameras;
2) Multispectral cameras also capable of capturing NIR (Near Infrared) and LWIR (Longwave Infrared);
3) Hyperspectral cameras also capable of capturing over different spectral ranges, generally between 400 and $1700\mu m$ with bands from 2 to 14 μm.

While RGB cameras are cost-effective and don't require special radiometric calibration, they have notable limitations in discriminating and characterizing different weed types. On some crops, RGB imaging techniques still exhibit excellent potential and high levels of accuracy [146], but they are limited in their use to supervised learning mechanisms in which training datasets must be manually compiled, and results can be particularly affected by temporal variability due to physiological or environmental changes [147]. Solutions involving multispectral and hyperspectral sensors prove to be more efficient and versatile across in different contexts. They offer flexibility and adaptability to the spatiotemporal variability inherent in agroecosystems and the associated pests [148]. Hyperspectral data analysis allows not only the accurate determination of the exact classification [149], [150], [151] and mapping [152] of weeds in the field but also the identification of their peculiar characteristics of fundamental importance, such as resistance or sensitivity to chemical agents like glyphosate [153], [154].

D. INSECT AND PATHOGEN MONITORING

Insects that harm crops are notorious for causing widespread devastation and significant decreases in global food grain yields. The Food and Agriculture Organization (FAO) has projected that losses of more than 37% are expected due to pests and diseases. Agri-food product losses because of animal pathogens and pests can be considerable, about 34% according to [132], and must be prevented or at least controlled with appropriate management strategies. Recent developments in multispectral imaging technology, acquired by UAVs, have opened up new perspectives for agricultural crop monitoring and management, even for small-scale agricultural enterprises. Reference [155] tested the possibility of identifying pests in rice fields through machine learning systems capable of analyzing data acquired from thermal and multispectral cameras. Reference [156] used an RTK drone-stabilized imaging system based on multispectral image processing to realize the monitoring of diseases and insect infestations on banana plantations. According to [157], UAV technologies are considered one of the most efficient solutions for pest surveillance, monitoring, and management. The identification of diseases caused by pathogens, as stated by several authors [158], [159], [160], now appears to be a well-established practice based on advanced hyperspectral imaging techniques ($380 - 1020nm$). Specifically, the use of hyperspectral imaging can reduce the number of samples required for analysis and enable multiple repetitions, resulting in more efficient work. Furthermore, hyperspectral imaging is an objective method that differs from visual assessment and can be integrated into automated systems, leading to a significant reduction in workload (as demonstrated in studies conducted by [161], [162], and [163]). This leads to reduced economic and ecological costs in agricultural production. It has been shown that during pathogen infestations, the plant's photosynthetic apparatus undergoes changes that can be detected through wavelength analysis ranging from 500 to $680nm$. Pathogens also have a significant influence on near-infrared wavelengths, extending from 700 to $1000nm$. Specifically, necrotrophic pathogens cause necrosis of plant cells and alterations in water content, which is manifested through increased reflectance in specific water absorption bands in the shortwave infrared at 1400 and $1930nm$.

E. UAV TREATMENTS

Although UAVs in agriculture have historically been used for monitoring agro-environmental parameters, they have

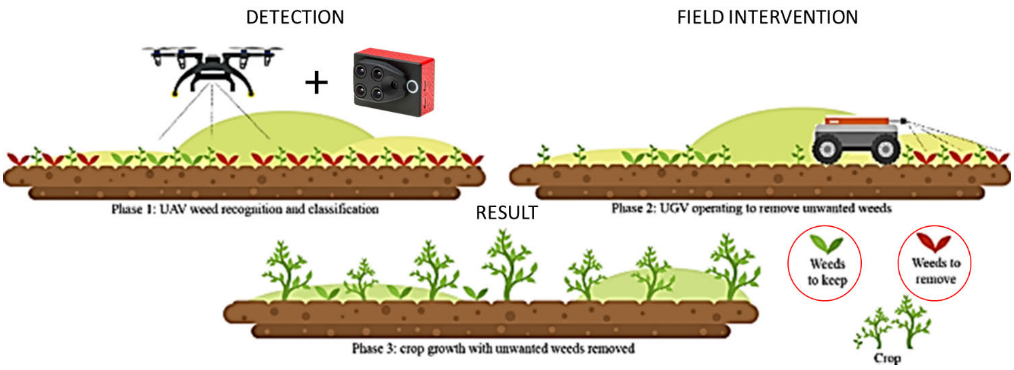


FIGURE 6. Example of weed management with UAVs system [2].

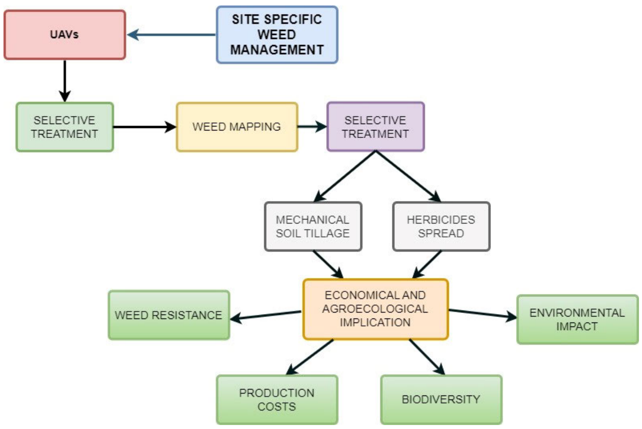


FIGURE 7. Site-specific weed management by UAVs system.

recently begun to see new applications and operational perspectives. Today, there are significant opportunities for active field management as well. For instance, DJI Agras T30, T20, and T10 are agricultural drones used for aerial and crop spraying. Equipped with D-RTK technology, these drones can achieve centimeter-level horizontal accuracy when enabled. Moreover, the T30 boasts a maximum load capacity of $40kg$ and a spraying flow of 7.2 L/min, while the T20 features a $20L$ tank and a radar module ensuring ± 0.1 m vertical accuracy. In contrast, the T10 has an $8L$ tank and a nominal takeoff weight of 24.8 kg. All these models facilitate efficient, data-driven active field management. Among the most popular ways of use in carrying out crop operations are irrigation, fertilization, phytosanitary treatments, and integrated pest management.

While there are also promising prospects for artificial pollination interventions, these will not be addressed in this paper.

1) FERTIGATION

The literature search conducted yielded limited scientifically valid content pertaining to the topic under consideration. When considering field irrigation, especially for low- to middle-income crops, the utilization of UAVs is deemed unsuitable. The substantial water volumes required, along with limitations related to flight time and flyable areas, make periodic interventions with drones currently impractical. Moreover, the high demand for operational repeatability, including multiple interventions within a single day for certain crops, exacerbates the inconvenience. Nevertheless, there are notable ongoing and completed studies, such as the one conducted by [164], which focused on designing efficient trajectories for precision irrigation using drones. One of the primary challenges in these applications is ensuring a uniform distribution of products across the entire area, without the capability to address heterogeneous demands based on crop and soil conditions. The authors attempted to mitigate this issue by adjusting flight paths and proposing a hypothetical spatially variable distribution function, denoted as $P(t)$, which resulted in up to 45% savings in distributed liquid. However, the authors themselves acknowledged significant limitations of the model, with percentage errors exceeding 50% in certain instances. Reference [165] also developed a model for optimizing energy and water consumption in crop irrigation using UAVs, highlighting an important trade-off between water and energy savings. However, no information regarding the efficiency of the model was provided.

2) DEFENSE AND PEST CONTROL

In conventional agriculture, the primary equipment used for pesticide spraying on crops includes handheld compressed-air sprayers and battery-powered shoulder-mounted sprayers. However, the utilization of such sprayers can lead to severe environmental and human health consequences, with approximately one million cases of pesticide-related side effects during manual spraying reported by the World Health Organization. To address these negative impacts and overcome labor shortages, adopting of mechanized spraying techniques becomes imperative. Agricultural aerial spraying, whether operated by humans or autonomously, often represents the fastest and most cost-effective approach to ensure efficient pesticide application on crops and promptly respond to pest outbreaks, thereby minimizing environmental and human health risks [166]. Over time, human-operated aerial platforms have supplemented manual and vehicle-mounted sprayers. UAVs offer significant advantages compared to the aforementioned methods. Their size and technological capabilities eliminate the need for a pilot, allowing them to operate at low altitudes, perform precise site-specific management, and easily adapt to soil topography. Notably, there are distinctions between chemical spraying from UAVs and conventional applications, including drift dynamics and vertical flow symmetry [167]. As a result, numerous drone models have been developed in recent years for plant protection treatments. The drone spraying system typically comprises a tank and a nozzle. Unlike fertilizer distribution, pesticide spraying typically requires the use of a pressure pump [168]. For obvious reasons, missions involving UAVs for pesticide distribution are considered more hazardous compared to remote sensing tasks. The market offers a wide variety of UAVs today, with load capacities ranging from 5 to over 30 liters. In one study, [169] developed a fumigation prototype for the M600 Pro drone, which was compared with the DJI Agras T30 A. In another study, [170] described the spraying process and assessed the effectiveness and primary operational characteristics of the DJI AGRAS T16, T20, and T30 models with plant protection products. Furthermore, [171] conducted experiments involving a remote weed mapping system combined with autonomous spraying using UAVs, achieving significant results in terms of herbicide product savings but also encountering important inaccuracies in terms of percentage coverage of the target area. Ultimately, we emphasize the importance of having centimeter-level satellite RTK correction, which serves as an additional driver for these systems.

F. PARAMETERS FOR THE UAVs

Considering the dynamics discussed earlier, selecting the most suitable drone for a farm's specific requirements necessitates a thorough assessment of several crucial parameters.

1) LOAD CAPACITY AND FLIGHT DURATION [172], [173], [174]

The drone's payload capacity is crucial as it dictates the number of sensors or instruments it can accommodate. Evaluating whether the drone can support data collection devices like multispectral or thermal cameras, and if its flight duration is adequate to cover the entire monitoring area without frequent battery replacements, is essential.

2) ACCURACY AND RESOLUTION OF SENSORS [175]

The precision and resolution of the sensors attached to the drone significantly impact the data quality. Choosing a drone with sensors capable of detecting subtle changes in field conditions is crucial for precise monitoring of crops, soil moisture levels, and the presence of pests or diseases.

3) EASE OF USE AND USER INTERFACE [176]

A user-friendly and intuitive interface is essential to ensure efficient drone operation by agricultural personnel, minimizing the need for extensive training. Additionally, having accessible data processing software for image analysis and map generation further enhances usability.

4) RESISTANCE TO ENVIRONMENTAL CONDITIONS [177]

Environmental conditions within a farm can vary significantly over time, necessitating a drone capable of operating in various situations, including windy conditions, light rain, and extreme temperatures. Weather resistance is crucial for ensuring flight safety and the continuity of monitoring operations.

5) SCALABILITY AND INTEROPERABILITY [178]

The capacity to expand or upgrade the drone system in the future is a crucial factor to consider, particularly for expanding farms. Moreover, the drone's compatibility with other agricultural management systems, such as crop planning software or automatic irrigation systems, can enhance the overall efficiency of agricultural operations.

6) TYPE OF ANALYSIS TO BE PERFORMED [179]

The selection of a drone should take into account the specific analysis required. Various types of cameras, such as thermal, multispectral, hyperspectral, infrared, *etc.*, can be integrated into UAV survey systems. Depending on the management objectives, it is essential to determine the type of analysis needed and, consequently, the sensors to be incorporated into the system.

7) TYPE OF CROPS TO MONITOR [180]

Monitoring requirements can differ based on the crop types cultivated on the farm, which may include annual or perennial herbaceous crops, shrub crops, or tree crops. Selecting instrumentation capable of detecting essential physiological and soil parameters is crucial and should be aligned with the specific crop types found on the farm.

8) TYPE OF TREATMENT TO BE ADMINISTERED [181]

Furthermore, as discussed, certain drones can also be utilized for applying phytoparasitic treatments or fertigation. Evaluating the compatibility of the chosen drone with the applications outlined in the farm management plan is essential.

9) ECONOMIC EVALUATION OF INVESTMENT AND OPERATOR TRAINING [182]

It's crucial to evaluate the investment needed for acquiring the drone and its accessories, along with the expenses for operator training. An accurate assessment of the economic advantages of drone usage, such as time and resource savings, is crucial for ensuring a favorable return on investment. Ultimately, choosing the most appropriate drone (and accompanying sensors) for a farm entails a comprehensive evaluation of various technical, operational, and economic factors. Understanding the farm's specific requirements alongside the technical features of drones available in the market is essential for enhancing crop monitoring effectiveness and optimizing overall resource management.

V. CONCLUSION

This study examines the primary models and applications of UAVs currently available in the market and used in research within the broad field of DPA. Significant advancements have been made in the past two decades, leading to the development of crucial models for monitoring essential agro-environmental parameters and the creation of autonomous Decision Support Systems (DSS). Presently, main limitations are associated with flight autonomy and the limited number of operations that can be performed. Leading manufacturers of UAVs, such as DJI, Parrot, Precisionhawk, AGEagle, and Trimble Navigation, are actively addressing emerging needs in the field. However, the combination of high spatial and temporal resolution capabilities, the ability to operate in adverse conditions, and the repeatability of operations contribute to the overall positive impact of UAV utilization. Exciting prospects for further development are linked to emerging technologies such as artificial intelligence, machine learning systems, and next-generation radio systems. The study reveals that implementing these technologies significantly enhances the operational potential of UAVs. The challenge lies in maximizing the potential of complex systems where the integration of different technologies (UAVs, robots, artificial intelligence, big data, internet of things, intelligent sensing, *etc.*) operates effectively in a symbiotic manner.

ABBREVIATIONS

The following abbreviations are used in this manuscript:

CNN	Convolutional Neural Networks
DPA	Digital Precision Agriculture
UAV	Unmanned Aerial Vehicles
PA	Precision Agriculture
MAVs	Micro or Miniature Air Vehicles
NAVs	Nano Air Vehicles
VTOL	Vertical Take-Off & Landing
LALE	Low Altitude, Long Endurance
MALE	Medium Altitude, Long Endurance
HALE	High Altitude, Long Endurance
LASE	Low Altitude, Short-Endurance
RTK	Real-Time Kinematic
GCPs	Ground Control Points
GIS	Geographic Information System
PPK	Post-Processed Kinematic
SDK	Software Development Kit
NTRIP	Networked Transport of RTCM via Internet Protocol
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
FCS	Flight Control System
LQG	Linear Quadratic Controller
SC	Sliding Mode Control
PID	Proportional Integral Derivative
NN	Neural Network
IMU	Inertial Measurement Unit
NMPC	Nonlinear Model Predictive Control
SMC	Soil moisture content
SSM	Superficial Soil Moisture
SWI	Soil Water Index
ANN	Artificial Neural Network
SVM	Support Vector Machines
FAO	Food and Agriculture Organization
DSS	Decision Support Systems
SOC	Soil Organic Carbon

REFERENCES

[1] K. S. Subramanian, S. Pazhanivelan, G. Srinivasan, R. Santhi, and N. Sathiah, "Drones in insect pest management," *Frontiers Agronomy*, vol. 3, Dec. 2021, Art. no. 640885.

[2] M. Esposito, M. Crimaldi, V. Cirillo, F. Sarghini, and A. Maggio, "Drone and sensor technology for sustainable weed management: A review," *Chem. Biol. Technol. Agricult.*, vol. 8, no. 1, pp. 1–11, Mar. 2021.

[3] E. V. Truflyak, M. Y. D. Mones, and I. S. Truflyak, "Comparative experiment on the use of unmanned and ground-based technologies of fertilizer and crop protection products on winter barley," in *Proc. E3S Web Conf.*, vol. 398, 2023, p. 1024.

[4] J. Gago, C. Douthe, R. E. Coopman, P. P. Gallego, M. Ribas-Carbo, J. Flexas, J. Escalona, and H. Medrano, "UAVs challenge to assess water stress for sustainable agriculture," *Agricult. Water Manage.*, vol. 153, pp. 9–19, May 2015.

[5] Z. Wu, M. Li, X. Lei, Z. Wu, C. Jiang, L. Zhou, R. Ma, and Y. Chen, "Simulation and parameter optimisation of a centrifugal Rice seeding spreader for a UAV," *Biosystems Eng.*, vol. 192, pp. 275–293, Apr. 2020.

[6] B. Berner and J. Chojnacki, "Use of drones in crop protection," Dept. Mach. Exploitation Manag. Prod. Process., ULS, Lublin, Poland, Tech. Rep., 2017, doi: 10.24326/fmpmsa.2017.9.

[7] S. A. Shvorov, N. A. Pasichnyk, S. D. Kuznichenko, I. V. Tolok, S. V. Lienkov, and L. A. Komarova, "Using UAV during planned harvesting by unmanned combines," in *Proc. IEEE 5th Int. Conf. Actual Problems Unmanned Aerial Vehicles Develop. (APUAVD)*, Oct. 2019, pp. 252–257.

[8] A. Rejeb, A. Abdollahi, K. Rejeb, and H. Treiblmaier, "Drones in agriculture: A review and bibliometric analysis," *Comput. Electron. Agricult.*, vol. 198, Jul. 2022, Art. no. 107017.

[9] M. Mazur, A. Wisniewski, and J. McMillan, "Clarity from above: PWC global report on the commercial applications of drone technology," in *Warsaw: Drone Powered Solutions, PriceWater House Coopers*. PriceWaterhouseCoopers, 2016.

[10] L. Brief, "Growth opportunity in global UAV market," Las Colinas, Irving, TX, USA, Tech. Rep., 2011.

[11] W. Yoo, E. Yu, and J. Jung, "Drone delivery: Factors affecting the public's attitude and intention to adopt," *Telematics Informat.*, vol. 35, no. 6, pp. 1687–1700, Sep. 2018.

[12] G. Macrina, L. Di Puglia Pugliese, F. Guerriero, and G. Laporte, "Drone-aided routing: A literature review," *Transp. Res. C, Emerg. Technol.*, vol. 120, Nov. 2020, Art. no. 102762.

[13] *Commercial UAV (Unmanned Aerial Vehicle) Market Share, Size, Trends & Industry Analysis Report by Type (Rotary Blade UAV, Fixed Wing UAV); by End-Use (Agriculture, Energy & Public Utilities, Construction, Media & Entertainment, Government)); by Region; Segment Forecast, 2021–2028*, Polaris Market Res., New York, NY, USA, 2021.

[14] J. Karimi and S. H. Pourtakdoust, "Optimal maneuver-based motion planning over terrain and threats using a dynamic hybrid PSO algorithm," *Aerosp. Sci. Technol.*, vol. 26, no. 1, pp. 60–71, Apr. 2013.

[15] C. Anderson, "Agricultural drones," *Technol. Rev.*, vol. 117, no. 3, pp. 58–60, 2014.

[16] K. R. Krishna, *Agricultural Drones: A Peaceful Pursuit*. Boca Raton, FL, USA: CRC Press, 2018.

[17] F. Marinello, A. Pezzuolo, A. Chiumenti, and L. Sartori, "Technical analysis of unmanned aerial vehicles (drones) for agricultural applications," *Eng. Rural Develop.*, vol. 15, no. 2, pp. 870–875, 2016.

[18] F. Veroustraete, "The rise of the drones in agriculture," *EC Agricult.*, vol. 2, no. 2, pp. 325–327, 2015.

[19] P. Daponte, L. De Vito, L. Glielmo, L. Iannelli, D. Liuzza, F. Picariello, and G. Silano, "A review on the use of drones for precision agriculture," *IOP Conf. Ser., Earth Environ. Sci.*, vol. 275, no. 1, May 2019, Art. no. 012022.

[20] S. Manfreda et al., "On the use of unmanned aerial systems for environmental monitoring," *Remote Sens.*, vol. 10, no. 4, pp. 1–12, 2018.

[21] J. Kim, S. Kim, C. Ju, and H. I. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," *IEEE Access*, vol. 7, pp. 105100–105115, 2019.

[22] J. S. Duhan, R. Kumar, N. Kumar, P. Kaur, K. Nehra, and S. Duhan, "Nanotechnology: The new perspective in precision agriculture," *Biotechnol. Rep.*, vol. 15, pp. 11–23, Sep. 2017.

[23] R. Prasad, A. Bhattacharyya, and Q. D. Nguyen, "Nanotechnology in sustainable agriculture: Recent developments, challenges, and perspectives," *Frontiers Microbiol.*, vol. 8, p. 1014, Jun. 2017.

[24] F. Marinello, A. Pezzuolo, F. Gasparini, J. Arvidsson, and L. Sartori, "Application of the Kinect sensor for dynamic soil surface characterization," *Precis. Agricult.*, vol. 16, no. 6, pp. 601–612, Dec. 2015.

[25] P. Katsigiannis, L. Misopolinos, V. Liakopoulos, T. K. Alexandridis, and G. Zalidis, "An autonomous multi-sensor UAV system for reduced-input precision agriculture applications," in *Proc. 24th Medit.Conf. Control Autom. (MED)*, Jun. 2016, pp. 60–64.

[26] A. Lambertini, E. Mandanici, M. A. Tini, and L. Vittuari, "Technical challenges for multi-temporal and multi-sensor image processing surveyed by UAV for mapping and monitoring in precision agriculture," *Remote Sens.*, vol. 14, no. 19, p. 4954, Oct. 2022.

[27] A. C. Watts, V. G. Ambrosia, and E. A. Hinkley, "Unmanned aircraft systems in remote sensing and scientific research: Classification and considerations of use," *Remote Sens.*, vol. 4, no. 6, pp. 1671–1692, Jun. 2012.

[28] H. Gu, X. Lyu, Z. Li, S. Shen, and F. Zhang, "Development and experimental verification of a hybrid vertical take-off and landing (VTOL) unmanned aerial vehicle(UAV)," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2017, pp. 160–169.

[29] X. Li and L. Yang, "Design and implementation of UAV intelligent aerial photography system," in *Proc. 4th Int. Conf. Intell. Hum.-Mach. Syst. Cybern.*, vol. 2, Aug. 2012, pp. 200–203.

[30] K. Schauwecker, N. R. Ke, S. A. Scherer, and A. Zell, "Markerless visual control of a quad-rotor micro aerial vehicle by means of on-board stereo processing," in *Autonomous Mobile Systems 2012*, P. Levi, O. Zweigle, K. Häußermann, and B. Eckstein, Eds. Berlin, Germany: Springer, 2012, pp. 11–20.

[31] H. Zhu, H. Nie, L. Zhang, X. Wei, and M. Zhang, "Design and assessment of octocopter drones with improved aerodynamic efficiency and performance," *Aerosp. Sci. Technol.*, vol. 106, May 2020, Art. no. 106206.

[32] G. Avanzini, E. L. de Angelis, and F. Giulietti, "Optimal performance and sizing of a battery-powered aircraft," *Aerosp. Sci. Technol.*, vol. 59, pp. 132–144, Dec. 2016.

[33] D. Floreano and R. J. Wood, "Science, technology and the future of small autonomous drones," *Nature*, vol. 521, no. 7553, pp. 460–466, May 2015.

[34] A. Troudi, S.-A. Addouche, S. Dellagi, and A. Mhamedi, "Sizing of the drone delivery fleet considering energy autonomy," *Sustainability*, vol. 10, no. 9, p. 3344, Sep. 2018.

[35] L. Corral, I. Fronza, N. E. Ioini, and A. Ibershimi, "Towards optimization of energy consumption of drones with software-based flight analysis," Knowl. Syst. Inst. Graduate School, Skokie, IL, USA, Tech. Rep., 2016.

[36] T. Lee, S. Mckeever, and J. Courtney, "Flying free: A research overview of deep learning in drone navigation autonomy," *Drones*, vol. 5, no. 2, p. 52, Jun. 2021.

[37] J. del Cerro, C. Cruz Ulloa, A. Barrientos, and J. de León Rivas, "Unmanned aerial vehicles in agriculture: A survey," *Agronomy*, vol. 11, no. 2, p. 203, Jan. 2021.

[38] B. Lee, S. Kwon, P. Park, and K. Kim, "Active power management system for an unmanned aerial vehicle powered by solar cells, a fuel cell, and batteries," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 50, no. 4, pp. 3167–3177, Oct. 2014.

[39] M. Lu, M. Bagheri, A. P. James, and T. Phung, "Wireless charging techniques for UAVs: A review, reconceptualization, and extension," *IEEE Access*, vol. 6, pp. 29865–29884, 2018.

[40] D. van Niekerk, M. Case, and D. V. Nicolae, "Brushless direct current motor efficiency characterization," in *Proc. Int. Aegean Conf. Electr. Mach. Power Electron. (ACEMP), Int. Conf. Optim. Electr. Electron. Equip. (OPTIM) Int. Symp. Adv. Electromech. Motion Syst. (ELECTROMOTION)*, Sep. 2015, pp. 226–231.

[41] A. Gong and D. Verstraete, "Experimental testing of electronic speed controllers for UAVs," in *Proc. 53rd AIAA/SAE/ASEE Joint Propuls. Conf.*, Jul. 2017, p. 4955.

[42] A. Cesetti, E. Frontoni, A. Mancini, A. Ascani, P. Zingaretti, and S. Longhi, "A visual global positioning system for unmanned aerial vehicles used in photogrammetric applications," *J. Intell. Robotic Syst.*, vol. 61, nos. 1–4, pp. 157–168, Jan. 2011.

[43] C. Zhan, Y. Zeng, and R. Zhang, "Energy-efficient data collection in UAV enabled wireless sensor network," *IEEE Wireless Commun. Lett.*, vol. 7, no. 3, pp. 328–331, Jun. 2018.

[44] A. Cho, Y.-S. Kang, B.-J. Park, C.-S. Yoo, and S.-O. Koo, "Altitude integration of radar altimeter and GPS/INS for automatic takeoff and landing of a UAV," in *Proc. 11th Int. Conf. Control, Autom. Syst.*, Oct. 2011, pp. 1429–1432.

[45] W. Youn, H. Choi, A. Cho, S. Kim, and M. B. Rhudy, "Accelerometer fault-tolerant model-aided state estimation for high-altitude long-endurance UAV," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 10, pp. 8539–8553, Oct. 2020.

[46] I. A. Faisal, T. W. Purboyo, and A. S. R. Ansori, "A review of accelerometer sensor and gyroscope sensor in IMU sensors on motion capture," *J. Eng. Appl. Sci.*, vol. 15, no. 3, pp. 826–829, Nov. 2019.

[47] C. A. Walter, A. Braun, and G. Fotopoulos, "Impact of three-dimensional attitude variations of an unmanned aerial vehicle magnetometry system on magnetic data quality," *Geophys. Prospecting*, vol. 67, no. 2, pp. 465–479, Feb. 2019.

[48] J. Wubben, F. Fabra, C. T. Calafate, T. Krzeszowski, J. M. Marquez-Barja, J.-C. Cano, and P. Manzoni, "Accurate landing of unmanned aerial vehicles using ground pattern recognition," *Electronics*, vol. 8, no. 12, p. 1532, Dec. 2019.

[49] H. Shakhatreh, A. H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N. S. Othman, A. Khreishah, and M. Guizani, "Unmanned aerial vehicles (UAVs): A survey on civil applications and key research challenges," *IEEE Access*, vol. 7, pp. 48572–48634, 2019.

[50] M. F. F. Rahman, S. Fan, Y. Zhang, and L. Chen, "A comparative study on application of unmanned aerial vehicle systems in agriculture," *Agriculture*, vol. 11, no. 1, p. 22, Jan. 2021.

[51] D. A. Tesch, D. Eckhard, and W. C. Guarienti, "Pitch and roll control of a quadcopter using cascade iterative feedback tuning," *IFAC-PapersOnLine*, vol. 49, no. 30, pp. 30–35, 2016.

[52] S. Bouabdallah, A. Noth, and R. Siegwart, "PID vs LQ control techniques applied to an indoor micro quadrotor," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Mar. 2004, pp. 2451–2456.

[53] T. Madani and A. Benallegue, "Control of a quadrotor mini-helicopter via full state backstepping technique," in *Proc. 45th IEEE Conf. Decis. Control*, Dec. 2006, pp. 1515–1520.

[54] E. Ebeid, M. Skriver, K. H. Terkildsen, K. Jensen, and U. P. Schultz, "A survey of open-source UAV flight controllers and flight simulators," *Microprocessors Microsyst.*, vol. 61, pp. 11–20, Sep. 2018.

[55] L. Zhou, J. Zhang, H. She, and H. Jin, "Quadrotor UAV flight control via a novel saturation integral backstepping controller," *Automatika*, vol. 60, no. 2, pp. 193–206, Apr. 2019.

[56] G. Silano, E. Aucone, and L. Iannelli, "CrazyS: A software-in-the-loop platform for the crazyflie 2.0 nano-quadcopter," in *Proc. 26th Medit. Conf. Control Autom. (MED)*, Jun. 2018, pp. 1–6.

[57] S. Bouabdallah, P. Murrieri, and R. Siegwart, "Towards autonomous indoor micro VTOL," *Auto. Robots*, vol. 18, no. 2, pp. 171–183, Mar. 2005.

[58] X. Cai, H. Hsu, H. Chai, L. Ding, and Y. Wang, "Multi-antenna GNSS and INS integrated position and attitude determination without base station for land vehicles," *J. Navigat.*, vol. 72, no. 2, pp. 342–358, Mar. 2019.

[59] G. Kumar, A. Patil, R. Patil, S. Park, and Y. Chai, "A LiDAR and IMU integrated indoor navigation system for UAVs and its application in real-time pipeline classification," *Sensors*, vol. 17, no. 6, p. 1268, Jun. 2017.

[60] G. Cao, E. M. Lai, and F. Alam, "Gaussian process model predictive control of unmanned quadrotors," in *Proc. 2nd Int. Conf. Control, Autom. Robot. (ICCAR)*, Apr. 2016, pp. 200–206.

[61] T. Dierks and S. Jagannathan, "Output feedback control of a quadrotor UAV using neural networks," *IEEE Trans. Neural Netw.*, vol. 21, no. 1, pp. 50–66, Jan. 2010.

[62] L. Guo-Shun, J. Hou-Long, L. Shu-Duan, W. Xin-Zhong, S. Hong-Zhi, Y. Yong-Feng, Y. Xia-Meng, H. Hong-Chao, L. Qing-Hua, and G. Jian-Guo, "Comparison of Kriging interpolation precision with different soil sampling intervals for precision agriculture," *Soil Sci.*, vol. 175, no. 8, pp. 405–415, 2010.

[63] Y. Ge, J. A. Thomasson, and R. Sui, "Remote sensing of soil properties in precision agriculture: A review," *Frontiers Earth Sci.*, vol. 5, pp. 229–238, Jun. 2011.

[64] T. Angelopoulou, A. Balafoutis, G. Zalidis, and D. Bochtis, "From laboratory to proximal sensing spectroscopy for soil organic carbon estimation—A review," *Sustainability*, vol. 12, no. 2, p. 443, Jan. 2020.

[65] M. R. Carter and E. G. Gregorich, *Soil Sampling and Methods of Analysis*. Boca Raton, FL, USA: CRC Press, 2007.

[66] C. Fiorentino, P. D'Antonio, F. Toscano, A. Donvito, and F. Modugno, "New technique for monitoring high nature value farmland (HNVF) in Basilicata," *Sustainability*, vol. 15, no. 10, p. 8377, May 2023.

[67] M. Amani, B. Salehi, S. Mahdavi, A. Masjedi, and S. Dehnavi, "Temperature-vegetation-soil moisture dryness index (TVMDI)," *Remote Sens. Environ.*, vol. 197, pp. 1–14, Aug. 2017.

[68] M. Sadeghi, E. Babaeian, M. Tuller, and S. B. Jones, "The optical trapezoid model: A novel approach to remote sensing of soil moisture applied to Sentinel-2 and Landsat-8 observations," *Remote Sens. Environ.*, vol. 198, pp. 52–68, Sep. 2017.

[69] Y. Wang, J. Yang, Y. Chen, A. Wang, and P. De Maeyer, "The spatiotemporal response of soil moisture to precipitation and temperature changes in an arid region, China," *Remote Sens.*, vol. 10, no. 3, p. 468, Mar. 2018.

[70] M. A. E. AbdelRahman, M. R. Metwalli, M. Gao, F. Toscano, C. Fiorentino, A. Scopa, and P. D'Antonio, "Determining the extent of soil degradation processes using trend analyses at a regional multispectral scale," *Land*, vol. 12, no. 4, p. 855, Apr. 2023.

[71] S. V. Kumar, P. A. Dirmeyer, C. D. Peters-Lidard, R. Bindlish, and J. Bolten, "Information theoretic evaluation of satellite soil moisture retrievals," *Remote Sens. Environ.*, vol. 204, pp. 392–400, Jan. 2018.

[72] S. Park, D. Ryu, S. Fuentes, H. Chung, E. Hernández-Montes, and M. O'Connell, "Adaptive estimation of crop water stress in nectarine and peach orchards using high-resolution imagery from an unmanned aerial vehicle (UAV)," *Remote Sens.*, vol. 9, no. 8, p. 828, Aug. 2017.

[73] K. S. Lyalin, A. A. Biryuk, A. Y. Sheremet, V. K. Tsvetkov, and D. V. Prikhodko, "UAV synthetic aperture radar system for control of vegetation and soil moisture," in *Proc. IEEE Conf. Russian Young Researchers Electr. Electron. Eng. (EIConRus)*, Jan. 2018, pp. 1673–1675.

[74] F. Lu, Y. Sun, and F. Hou, "Using UAV visible images to estimate the soil moisture of steppe," *Water*, vol. 12, no. 9, p. 2334, Aug. 2020.

[75] D. Zhang and G. Zhou, "Estimation of soil moisture from optical and thermal remote sensing: A review," *Sensors*, vol. 16, no. 8, p. 1308, Aug. 2016.

[76] E. Ben-Dor, S. Chabrillat, J. A. M. Demattê, G. R. Taylor, J. Hill, M. L. Whiting, and S. Sommer, "Using imaging spectroscopy to study soil properties," *Remote Sens. Environ.*, vol. 113, pp. S38–S55, Sep. 2009.

[77] X. Ge, J. Wang, J. Ding, X. Cao, Z. Zhang, J. Liu, and X. Li, "Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring," *PeerJ*, vol. 7, p. e6926, May 2019.

[78] K. Ivushkin, H. Bartholomeus, A. K. Bregt, A. Pulatov, M. H. D. Franceschini, H. Kramer, E. N. van Loo, V. Jaramillo Roman, and R. Finkers, "UAV based soil salinity assessment of cropland," *Geoderma*, vol. 338, pp. 502–512, Mar. 2019.

[79] M. Rahmati and N. Hamzehpour, "Quantitative remote sensing of soil electrical conductivity using ETM+ and ground measured data," *Int. J. Remote Sens.*, vol. 38, no. 1, pp. 123–140, Jan. 2017.

[80] K. Ivushkin, H. Bartholomeus, A. K. Bregt, and A. Pulatov, "Satellite thermography for soil salinity assessment of cropped areas in Uzbekistan," *Land Degradation Develop.*, vol. 28, no. 3, pp. 870–877, Apr. 2017.

[81] K. Ivushkin, H. Bartholomeus, A. K. Bregt, A. Pulatov, E. N. Bui, and J. Wilford, "Soil salinity assessment through satellite thermography for different irrigated and rainfed crops," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 68, pp. 230–237, Jun. 2018.

[82] C. Romero-Trigueros, P. A. Nortes, J. J. Alarcón, J. E. Hunink, M. Parra, S. Contreras, P. Droogers, and E. Nicolás, "Effects of saline reclaimed waters and deficit irrigation on citrus physiology assessed by UAV remote sensing," *Agricult. Water Manage.*, vol. 183, pp. 60–69, Mar. 2017.

[83] D. L. Corwin and E. Scudiero, "Review of soil salinity assessment for agriculture across multiple scales using proximal and/or remote sensors," *Adv. Agronomy*, vol. 158, pp. 1–130, Jan. 2019.

[84] J. Hu, J. Peng, Y. Zhou, D. Xu, R. Zhao, Q. Jiang, T. Fu, F. Wang, and Z. Shi, "Quantitative estimation of soil salinity using UAV-borne hyperspectral and satellite multispectral images," *Remote Sens.*, vol. 11, no. 7, p. 736, Mar. 2019.

[85] J. Valente, R. Almeida, and L. Kooistra, "A comprehensive study of the potential application of flying ethylene-sensitive sensors for ripeness detection in apple orchards," *Sensors*, vol. 19, no. 2, p. 372, Jan. 2019.

[86] T. Kersnovski, F. Gonzalez, and K. Morton, "A UAV system for autonomous target detection and gas sensing," in *Proc. IEEE Aerosp. Conf.*, Mar. 2017, pp. 1–12.

[87] M. Ajami, A. Heidari, F. Khormali, M. Gorji, and S. Ayoubi, "Environmental factors controlling soil organic carbon storage in loess soils of a subhumid region, northern Iran," *Geoderma*, vol. 281, pp. 1–10, Nov. 2016.

[88] M. Nocita, A. Stevens, C. Noon, and B. van Wesemael, "Prediction of soil organic carbon for different levels of soil moisture using vis-NIR spectroscopy," *Geoderma*, vol. 199, pp. 37–42, May 2013.

[89] J. K. M. Biney, J. HouŠka, J. Volánek, D. K. Abebrese, and J. Cervenka, "Examining the influence of bare soil UAV imagery combined with auxiliary datasets to estimate and map soil organic carbon distribution in an erosion-prone agricultural field," *Sci. Total Environ.*, vol. 870, Apr. 2023, Art. no. 161973.

[90] M. Ding, X. Li, and Z. Jin, "Digital mapping of soil organic carbon using UAV images and soil properties in a thermo-erosion gully on the Tibetan Plateau," *Remote Sens.*, vol. 15, no. 6, p. 1628, Mar. 2023.

[91] J. Heil, C. Jörges, and B. Stumpe, "Fine-scale mapping of soil organic matter in agricultural soils using UAVs and machine learning," *Remote Sens.*, vol. 14, no. 14, p. 3349, Jul. 2022.

[92] L. Guo, P. Fu, T. Shi, Y. Chen, H. Zhang, R. Meng, and S. Wang, "Mapping field-scale soil organic carbon with unmanned aircraft system-acquired time series multispectral images," *Soil Tillage Res.*, vol. 196, Feb. 2020, Art. no. 104477.

[93] M. Tattaris, M. P. Reynolds, and S. C. Chapman, "A direct comparison of remote sensing approaches for high-throughput phenotyping in plant breeding," *Frontiers Plant Sci.*, vol. 7, pp. 1–10, Aug. 2016.

[94] F. Holman, A. Riche, A. Michalski, M. Castle, M. Wooster, and M. Hawkesford, "High throughput field phenotyping of wheat plant height and growth rate in field plot trials using UAV based remote sensing," *Remote Sens.*, vol. 8, no. 12, p. 1031, Dec. 2016.

[95] A. Haghighattalab, L. González Pérez, S. Mondal, D. Singh, D. Schinstock, J. Rutkoski, I. Ortiz-Monasterio, R. P. Singh, D. Goodin, and J. Poland, "Application of unmanned aerial systems for high throughput phenotyping of large wheat breeding nurseries," *Plant Methods*, vol. 12, no. 1, pp. 1–15, Dec. 2016.

[96] Y. Shi et al., "Unmanned aerial vehicles for high-throughput phenotyping and agronomic research," *PLoS ONE*, vol. 11, no. 7, pp. 1–26, 2016.

[97] S. Chapman, T. Merz, A. Chan, P. Jackway, S. Hrabar, M. Dreccer, E. Holland, B. Zheng, T. Ling, and J. Jimenez-Berni, "Pheno-copter: A low-altitude, autonomous remote-sensing robotic helicopter for high-throughput field-based phenotyping," *Agronomy*, vol. 4, no. 2, pp. 279–301, Jun. 2014.

[98] H. Aasen, A. Burkart, A. Bolten, and G. Bareth, "Generating 3D hyperspectral information with lightweight UAV snapshot cameras for vegetation monitoring: From camera calibration to quality assurance," *ISPRS J. Photogramm. Remote Sens.*, vol. 108, pp. 245–259, Oct. 2015.

[99] C. Lelong, P. Burger, G. Jubelin, B. Roux, S. Labbé, and F. Baret, "Assessment of unmanned aerial vehicles imagery for quantitative monitoring of wheat crop in small plots," *Sensors*, vol. 8, no. 5, pp. 3557–3585, May 2008.
[100] J. A. J. Berni, P. J. Zarco-Tejada, L. Suarez, and E. Fereres, "Thermal and narrowband multispectral remote sensing for vegetation monitoring from an unmanned aerial vehicle," *IEEE Trans. Geosci. Remote Sens.*, vol. 47, no. 3, pp. 722–738, Mar. 2009.
[101] V. Henrich, E. Götze, A. Jung, C. Sandow, D. Thürkow, and C. Gläßer, "Development of an online indices database: Motivation, concept and implementation," in *Proc. 6th EARSeL Imag. Spectrosc. Sig Workshop Innov. Tool Sci. Commercial Environ. Appl.*, 2009, pp. 16–18.
[102] F. A. Vega, F. C. Ramírez, M. P. Saiz, and F. O. Rosúa, "Multi-temporal imaging using an unmanned aerial vehicle for monitoring a sunflower crop," *Biosyst. Eng.*, vol. 132, pp. 19–27, Apr. 2015.
[103] J. Rasmussen, G. Ntakos, J. Nielsen, J. Svensgaard, R. N. Poulsen, and S. Christensen, "Are vegetation indices derived from consumer-grade cameras mounted on UAVs sufficiently reliable for assessing experimental plots?" *Eur. J. Agronomy*, vol. 74, pp. 75–92, Mar. 2016.
[104] J. W. Rouse, R. H. Haas, D. W. Deering, J. A. Schell, and J. C. Harlan, "Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation. [Great plains corridor]," Remote Sensing Center, Texas A&M Univ., Tech. Rep. 36103 CR, 1973.
[105] R. Person, "Remote mapping of standing crop biomass for estimation of the productivity of the short-grass Prairie, Pawnee National Grasslands, Colorado," Tech. Rep., 1972.
[106] H. McNairn and R. Protz, "Mapping corn residue cover on agricultural fields in Oxford county, ontario, using thematic mapper," *Can. J. Remote SNonstandardens.*, vol. 19, no. 2, pp. 152–159, Apr. 1993.
[107] J. W. Rouse Jr., R. H. Haas, D. W. Deering, J. A. Schell, and J. C. Harlan, "Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation," Texas A&M Univ., College Station, TX, USA, Tech. Rep. NASA-CR-139243, 1974.
[108] J. Clevers, "The application of a vegetation index in correcting the infrared reflectance for soil background," in *Proc. Symp. Rem. Sens. Res. Dev. Envir. Manage.*, Enschede, The Netherlands, 1986, pp. 221–226.
[109] R. D. Jackson, P. J. Printer, J. Paul, R. J. Reginato, J. Robert, and S. B. Idso, "Hand-held radiometry. Agricultural reviews and manuals ARM-W-19. Okland, CA," Dept. U.S. Dept. Agricult., Sci. Educ. Admin., Phoenix, AZ, USA, Tech. Rep. ARM-W-19, 1980.
[110] A. Huete, C. Justice, and W. Van Leeuwen, "MODIS vegetation index (MOD13)," *Algorithm Theor. Basis Document*, vol. 3, no. 213, pp. 295–309, 1999.
[111] A. A. Gitelson, Y. J. Kaufman, and M. N. Merzlyak, "Use of a green channel in remote sensing of global vegetation from EOS-MODIS," *Remote Sens. Environ.*, vol. 58, no. 3, pp. 289–298, Dec. 1996.
[112] N. H. Broge and E. Leblanc, "Comparing prediction power and stability of broadband and hyperspectral vegetation indices for estimation of green leaf area index and canopy chlorophyll density," *Remote Sens. Environ.*, vol. 76, no. 2, pp. 156–172, May 2001.
[113] A. R. Huete, "A soil-adjusted vegetation index (SAVI)," *Remote Sens. Environ.*, vol. 25, no. 3, pp. 295–309, Aug. 1988.
[114] G. Rondeaux, M. Steven, and F. Baret, "Optimization of soil-adjusted vegetation indices," *Remote Sens. Environ.*, vol. 55, no. 2, pp. 95–107, Feb. 1996.
[115] N. S. Goel and W. Qin, "Influences of canopy architecture on relationships between various vegetation indices and LAI and FPAR: A computer simulation," *Remote Sens. Rev.*, vol. 10, no. 4, pp. 309–347, Oct. 1994.
[116] M.-F. Courel, P. C. Chamard, M. C. Guenegou, J. Lerhun, J. Levasseur, and M. Togola, "Utilisation des bandes spectrales du vert et du Rouge pour une meilleure évaluation des formations végétales actives," in *Proc. Congrès AUPELF-UREF*, 1991, pp. 203–209.
[117] R. Escadafal and A. Huete, "Etude des propriétés spectrales des sols arides appliquée à l'amélioration des indices de végétation obtenus par télédétection," *Comp. Rendus l'Académie Sci., Série 2, Mécanique, Physique, Chimie, Sci. de l'Univers, Sciences Terre*, vol. 312, no. 11, pp. 1385–1391, 1991.
[118] M. Willkomm, A. Bolten, and G. Bareth, "Non-destructive monitoring of rice by hyperspectral in-field spectrometry and uav-based remote sensing: Case study of field-grown rice in north Rhine-Westphalia, Germany," *Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol. 41, pp. 1071–1077, Jun. 2016.
[119] F.-M. Wang, J.-F. Huang, Y.-L. Tang, and X.-Z. Wang, "New vegetation index and its application in estimating leaf area index of rice," *Rice Sci.*, vol. 14, no. 3, pp. 195–203, Sep. 2007.
[120] C. Yang, J. H. Everitt, J. M. Bradford, and D. Murden, "Airborne hyperspectral imagery and yield monitor data for mapping cotton yield variability," *Precis. Agricult.*, vol. 5, no. 5, pp. 445–461, Oct. 2004.
[121] J. Qi, A. Chehbouni, A. R. Huete, Y. H. Kerr, and S. Sorooshian, "A modified soil adjusted vegetation index," *Remote Sens. Environ.*, vol. 48, no. 2, pp. 119–126, May 1994.
[122] A. A. Gitelson, Y. J. Kaufman, R. Stark, and D. Rundquist, "Novel algorithms for remote estimation of vegetation fraction," *Remote Sens. Environ.*, vol. 80, no. 1, pp. 76–87, Apr. 2002.
[123] A. Ehammer, S. Fritsch, C. Conrad, J. Lamers, and S. Dech, "Statistical derivation of fPAR and LAI for irrigated cotton and rice in arid Uzbekistan by combining multi-temporal RapidEye data and ground measurements," *Proc. SPIE*, vol. 7824, pp. 66–75, Jul. 2010.
[124] A. A. Gitelson, M. N. Merzlyak, Y. Zur, R. Stark, and U. Gritz, "Non-destructive and remote sensing techniques for estimation of vegetation status," Univ. Nebraska Lincoln, Lincoln, NE, USA, Tech. Rep., 2001. [Online]. Available: https://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1275&context=natrespapers
[125] P. J. Zarco-Tejada, J. R. Miller, T. L. Noland, G. H. Mohammed, and P. H. Sampson, "Scaling-up and model inversion methods with narrowband optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data," *IEEE Trans. Geosci. Remote Sens.*, vol. 39, no. 7, pp. 1491–1507, Jul. 2001.
[126] I. Herrmann, A. Karnieli, D. J. Bonfil, Y. Cohen, and V. Alchanatis, "SWIR-based spectral indices for assessing nitrogen content in potato fields," *Int. J. Remote Sens.*, vol. 31, no. 19, pp. 5127–5143, Oct. 2010.
[127] J. Bendig, K. Yu, H. Aasen, A. Bolten, S. Bennertz, J. Broscheit, M. L. Gnyp, and G. Bareth, "Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 39, pp. 79–87, Jul. 2015.
[128] N. Gobron, B. Pinty, M. M. Verstraete, and J.-L. Widlowski, "Advanced vegetation indices optimized for up-coming sensors: Design, performance, and applications," *IEEE Trans. Geosci. Remote Sens.*, vol. 38, no. 6, pp. 2489–2505, Nov. 2000.
[129] A. Gitelson and M. N. Merzlyak, "Quantitative estimation of chlorophyll—A using reflectance spectra: Experiments with autumn chestnut and Maple leaves," *J. Photochem. Photobiol. B, Biol.*, vol. 22, no. 3, pp. 247–252, Mar. 1994.
[130] D. Haboudane, J. R. Miller, N. Tremblay, P. J. Zarco-Tejada, and L. Dextraze, "Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture," *Remote Sens. Environ.*, vol. 81, nos. 2–3, pp. 416–426, Aug. 2002.
[131] D. Haboudane, "Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture," *Remote Sens. Environ.*, vol. 90, no. 3, pp. 337–352, Apr. 2004.
[132] E.-C. Oerke, "Crop losses to pests," *J. Agricult. Sci.*, vol. 144, no. 1, pp. 31–43, Feb. 2006.
[133] Y. Gharde, P. K. Singh, R. P. Dubey, and P. K. Gupta, "Assessment of yield and economic losses in agriculture due to weeds in India," *Crop Protection*, vol. 107, pp. 12–18, May 2018.
[134] S. Korav, A. K. Dhaka, R. Singh, N. Premaradhya, and G. C. Reddy, "A study on crop weed competition in field crops," *J. Pharmacognosy Phytochem.*, vol. 7, no. 4, pp. 3235–3240, 2018.
[135] G. Adeux, E. Vieren, S. Carlesi, P. Bàrberi, N. Munier-Jolain, and S. Cordeau, "Mitigating crop yield losses through weed diversity," *Nature Sustainability*, vol. 2, no. 11, pp. 1018–1026, Nov. 2019.
[136] V. Cirillo, R. Masin, A. Maggio, and G. Zanin, "Crop-weed interactions in saline environments," *Eur. J. Agronomy*, vol. 99, pp. 51–61, Sep. 2018.
[137] P. Neve et al., "Reviewing research priorities in weed ecology, evolution and management: A horizon scan," *Weed Res.*, vol. 58, no. 4, pp. 250–258, Aug. 2018.
[138] L. Guo, J. Qiu, L.-F. Li, B. Lu, K. Olsen, and L. Fan, "Genomic clues for crop–weed interactions and evolution," *Trends Plant Sci.*, vol. 23, no. 12, pp. 1102–1115, Dec. 2018.
[139] S. O. Duke and I. Heap, "Evolution of weed resistance to herbicides: What have we learned after 70 years," in *Biology, Physiology and Molecular Biology of Weeds*. Boca Raton, FL, USA: CRC Press, 2017, pp. 63–86.

[140] H. L. Hicks, D. Comont, S. R. Coutts, L. Crook, R. Hull, K. Norris, P. Neve, D. Z. Childs, and R. P. Freckleton, ''The factors driving evolved herbicide resistance at a national scale,'' *Nature Ecology Evol.*, vol. 2, no. 3, pp. 529–536, Feb. 2018.
[141] A. Muola, B. Fuchs, M. Laihonen, K. Rainio, L. Heikkonen, S. Ruuskanen, K. Saikkonen, and M. Helander, ''Risk in the circular food economy: Glyphosate-based herbicide residues in manure fertilizers decrease crop yield,'' *Sci. Total Environ.*, vol. 750, Jan. 2021, Art. no. 141422.
[142] S. Nebiker, N. Lack, M. Abächerli, and S. Läderach, ''Light-weight multispectral uav sensors and their capabilities for predicting grain yield and detecting plant diseases,'' *Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol. 41, pp. 963–970, Jun. 2016.
[143] W.-H. Su, ''Advanced machine learning in point spectroscopy, RGB- and hyperspectral-imaging for automatic discriminations of crops and weeds: A review,'' *Smart Cities*, vol. 3, no. 3, pp. 767–792, Aug. 2020.
[144] B. Liu and R. Bruch, ''Weed detection for selective spraying: A review,'' *Current Robot. Rep.*, vol. 1, no. 1, pp. 19–26, Mar. 2020.
[145] M. Dadashzadeh, Y. Abbaspour-Gilandeh, T. Mesri-Gundoshmian, S. Sabzi, J. L. Hernández-Hernández, M. Hernández-Hernández, and J. I. Arribas, ''Weed classification for site-specific weed management using an automated stereo computer-vision machine-learning system in Rice fields,'' *Plants*, vol. 9, no. 5, p. 559, Apr. 2020.
[146] N. Islam, M. M. Rashid, S. Wibowo, S. Wasimi, A. Morshed, C. Xu, and S. Moore, ''Machine learning based approach for weed detection in chilli field using RGB images,'' in *Proc. Int. Conf. Natural Comput., Fuzzy Syst. Knowl. Discovery*. Cham, Switzerland: Springer, 2020, pp. 1097–1105.
[147] A. Wendel and J. Underwood, ''Self-supervised weed detection in vegetable crops using ground based hyperspectral imaging,'' in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2016, pp. 5128–5135.
[148] N. Sulaiman, N. N. Che'Ya, M. H. M. Roslim, A. S. Juraimi, N. M. Noor, and W. F. F. Ilahi, ''The application of hyperspectral remote sensing imagery (HRSI) for weed detection analysis in Rice fields: A review,'' *Appl. Sci.*, vol. 12, no. 5, p. 2570, Mar. 2022.
[149] R. Casa, S. Pascucci, S. Pignatti, A. Palombo, U. Nanni, A. Harfouche, L. Laura, M. Di Rocco, and P. Fantozzi, ''UAV-based hyperspectral imaging for weed discrimination in maize,'' in *Precision Agriculture'19*. Wageningen, The Netherlands: Academic, 2019, pp. 24–35.
[150] B. Lu and Y. He, ''Species classification using unmanned aerial vehicle (UAV)-acquired high spatial resolution imagery in a heterogeneous grassland,'' *ISPRS J. Photogramm. Remote Sens.*, vol. 128, pp. 73–85, Jun. 2017.
[151] P. K. Goel, S. O. Prasher, J. A. Landry, R. M. Patel, and A. A. Viau, ''Hyperspectral image classification to detect weed infestations and nitrogen status in corn,'' *Trans. ASAE*, vol. 46, no. 2, p. 539, 2003.
[152] P. K. Kingra, D. Majumder, and S. P. Singh, ''Application of remote sensing and gis in agriculture and natural resource management under changing climatic conditions,'' *Agricult. Res. J.*, vol. 53, no. 3, p. 295, 2016.
[153] K. N. Reddy, Y. Huang, M. A. Lee, V. K. Nandula, R. S. Fletcher, S. J. Thomson, and F. Zhao, ''Glyphosate-resistant and glyphosate-susceptible Palmer amaranth (*Amaranthus palmeri* S. Wats.): hyperspectral reflectance properties of plants and potential for classification,'' *Pest Manage. Sci.*, vol. 70, no. 12, pp. 1910–1917, Dec. 2014.
[154] B. Scherrer, J. Sheppard, P. Jha, and J. A. Shaw, ''Hyperspectral imaging and neural networks to classify herbicide-resistant weeds,'' *J. Appl. Remote Sens.*, vol. 13, no. 4, p. 1, Nov. 2019.
[155] V. Agnihotri, ''Machine learning based pest identification in paddy plants,'' in *Proc. 3rd Int. Conf. Electron., Commun. Aerosp. Technol. (ICECA)*, Jun. 2019, pp. 246–250.
[156] S. Choosumrong, R. Hataitara, K. Sujipuli, M. Weerawatanakorn, A. Preechaharn, D. Premjet, S. Laywisadkul, V. Raghavan, and G. Panumonwatee, ''Bananas diseases and insect infestations monitoring using multi-spectral camera RTK UAV images,'' *Spatial Inf. Res.*, vol. 31, no. 4, pp. 371–380, Aug. 2023.
[157] N. V. Maslekar, K. P. Kulkarni, and A. K. Chakravarthy, ''Application of unmanned aerial vehicles (UAVs) for pest surveillance, monitoring and management,'' in *Innovative Pest Management Approaches for the 21st Century*, 2020, pp. 27–45.
[158] J. Abdulridha, Y. Ampatzidis, S. C. Kakarla, and P. Roberts, ''Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques,'' *Precis. Agricult.*, vol. 21, no. 5, pp. 955–978, Oct. 2020.
[159] S. Thomas, M. T. Kuska, D. Bohnenkamp, A. Brugger, E. Alisaac, M. Wahabzada, J. Behmann, and A.-K. Mahlein, ''Benefits of hyperspectral imaging for plant disease detection and plant protection: A technical perspective,'' *J. Plant Diseases Protection*, vol. 125, no. 1, pp. 5–20, Feb. 2018.
[160] A.-K. Mahlein, M. T. Kuska, J. Behmann, G. Polder, and A. Walter, ''Hyperspectral sensors and imaging technologies in phytopathology: State of the art,'' *Annu. Rev. Phytopathology*, vol. 56, no. 1, pp. 535–558, Aug. 2018.
[161] A. Walter, F. Liebisch, and A. Hund, ''Plant phenotyping: From bean weighing to image analysis,'' *Plant Methods*, vol. 11, no. 1, p. 14, 2015.
[162] A.-K. Mahlein, ''Plant disease detection by imaging sensors—Parallels and specific demands for precision agriculture and plant phenotyping,'' *Plant Disease*, vol. 100, no. 2, pp. 241–251, Feb. 2016.
[163] N. Virlet, K. Sabermanesh, P. Sadeghi-Tehran, and M. J. Hawkesford, ''Field scanalyzer: An automated robotic field phenotyping platform for detailed crop monitoring,'' *Funct. Plant Biol.*, vol. 44, no. 1, p. 143, 2017.
[164] C. Albornoz and L. F. Giraldo, ''Trajectory design for efficient crop irrigation with a UAV,'' in *Proc. IEEE 3rd Colombian Conf. Autom. Control (CCAC)*, Oct. 2017, pp. 1–6.
[165] C. D. López and L. F. Giraldo, ''Optimization of energy and water consumption on crop irrigation using UAVs via path design,'' in *Proc. IEEE 4th Colombian Conf. Autom. Control (CCAC)*, Oct. 2019, pp. 1–5.
[166] Y. Lan, C. Shengde, and B. K. Fritz, ''Current status and future trends of precision agricultural aviation technologies,'' *Int. J. Agricult. Biol. Eng.*, vol. 10, no. 3, pp. 1–17, 2017.
[167] H. Chen, Y. Lan, B. K. Fritz, W. C. Hoffmann, and S. Liu, ''Review of agricultural spraying technologies for plant protection using unmanned aerial vehicle (UAV),'' *Int. J. Agricult. Biol. Eng.*, vol. 14, no. 1, pp. 38–49, 2021.
[168] D. Yallappa, M. Veerangouda, D. Maski, V. Palled, and M. Bheemanna, ''Development and evaluation of drone mounted sprayer for pesticide applications to crops,'' in *Proc. IEEE Global Humanitarian Technol. Conf. (GHTC)*, Oct. 2017, pp. 1–7.
[169] A. A. B. Argudo, K. D. M. Rivera, D. R. Ñ. Estrella, and M. D. T. Farinango, ''Análisis y comparación de un sistema de fumigación para un dron matrice 600 pro vs el dron fumigador dji agras t30 a,'' *Revista Científica Arbitrada Multidisciplinaria PENTACIENCIAS*, vol. 5, no. 1, pp. 539–556, 2023.
[170] O. Kholodyuk and O. Tokarchuk, ''The efficiency of using agras drones for spraying, their design, technical and technological features,'' *Eng., Energy, Transp. AIC*, vol. 2, no. 117, pp. 63–74, Aug. 2022.
[171] J. E. Hunter, T. W. Gannon, R. J. Richardson, F. H. Yelverton, and R. G. Leon, ''Integration of remote-weed mapping and an autonomous spraying unmanned aerial vehicle for site-specific weed management,'' *Pest Manage. Sci.*, vol. 76, no. 4, pp. 1386–1392, Apr. 2020.
[172] A. Thibbotuwawa, P. Nielsen, B. Zbigniew, and G. Bocewicz, ''Energy consumption in unmanned aerial vehicles: A review of energy consumption models and their relation to the UAV routing,'' in *Proc. 39th Int. Conf. Inf. Syst. Archit. Technol.* Cham, Switzerland: Springer, 2018, pp. 173–184.
[173] J. Li, B. Long, H. Wu, X. Hu, X. Wei, Z. Zhang, L. Chai, J. Xie, and H. Mei, ''Rapid evaluation model of endurance performance and its application for agricultural UAVs,'' *Drones*, vol. 6, no. 8, p. 186, Jul. 2022.
[174] N. Delavarpour, C. Koparan, J. Nowatzki, S. Bajwa, and X. Sun, ''A technical study on UAV characteristics for precision agriculture applications and associated practical challenges,'' *Remote Sens.*, vol. 13, no. 6, p. 1204, Mar. 2021.
[175] D. C. Tsouros, S. Bibi, and P. G. Sarigiannidis, ''A review on UAV-based applications for precision agriculture,'' *Information*, vol. 10, no. 11, p. 349, Nov. 2019.
[176] S. C. Hassler and F. Baysal-Gurel, ''Unmanned aircraft system (UAS) technology and applications in agriculture,'' *Agronomy*, vol. 9, no. 10, p. 618, Oct. 2019.
[177] P. Velusamy, S. Rajendran, R. K. Mahendran, S. Naseer, M. Shafiq, and J.-G. Choi, ''Unmanned aerial vehicles (UAV) in precision agriculture: Applications and challenges,'' *Energies*, vol. 15, no. 1, p. 217, Dec. 2021.
[178] A. D. Boursianis, M. S. Papadopoulou, P. Diamantoulakis, A. Liopa-Tsakalidi, P. Barouchas, G. Salahas, G. Karagiannidis, S. Wan, and S. K. Goudos, ''Internet of Things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review,'' *Internet Things*, vol. 18, May 2022, Art. no. 100187.

[179] D. C. Tsouros, A. Triantafyllou, S. Bibi, and P. G. Sarigannidis, "Data acquisition and analysis methods in UAV- based applications for precision agriculture," in *Proc. 15th Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, May 2019, pp. 377–384.

[180] J. Cuaran and J. Leon, "Crop monitoring using unmanned aerial vehicles: A review," *Agricult. Rev.*, vol. 42, no. 2, pp. 121–132, Mar. 2021.

[181] D. Rakesh, N. Akshay Kumar, M. Sivaguru, K. V. R. Keerthivaasan, B. Rohini Janaki, and R. Raffik, "Role of UAVs in innovating agriculture with future applications: A review," in *Proc. Int. Conf. Advancement Electr., Electron., Commun., Comput. Autom. (ICAECA)*, Oct. 2021, pp. 1–6.

[182] L. Loures, A. Chamizo, P. Ferreira, A. Loures, R. Castanho, and T. Panagopoulos, "Assessing the effectiveness of precision agriculture management systems in Mediterranean small farms," *Sustainability*, vol. 12, no. 9, p. 3765, May 2020.

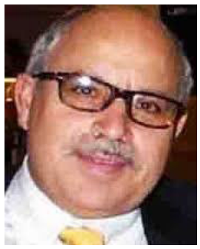
FRANCESCO TOSCANO received the M.Sc. degree (cum laude) in forestry and environmental sciences from the University of Basilicata, with an academic mention. His M.Sc. thesis entitled "Innovative systems for the sustainable management of agroforestry and environmental heritage: the Bari-Matera 5G Project." In the past, he was the University Tutor and also lectured with various technical high schools in disciplinary sectors related to agricultural techniques, and was an Internal Member with the VI State Examination Commission 2021, Higher Education Institute 'Consoli Pinto,' Castellana Grotte (BA). He is currently a Research Fellow of agricultural mechanics with the University of Basilicata. He has several scientific publications to his credit and has been a speaker at national and international conferences and congresses.

COSTANZA FIORENTINO received the degree in physics and the master's degree in remote sensing from the University of Bari, Italy, and the Ph.D. degree in crop systems from the University of Basilicata, Potenza, Italy. She is currently a Researcher (RTDB) with the School of Agricultural Forestry and Environmental Sciences (SAFE), University of Basilicata. Previously, she was a Researcher with CREA, National Italian Council for Research in Agriculture. She is the author of several publications and participations in national and international conferences as well as having received two awards as best paper. She has participated in national and international projects. Her research interests include the application of proximal and remote sensing in agriculture, precision agriculture technology and innovation, sensor networks, UAVs, automatic guides, and precision agricultural machinery and equipment.

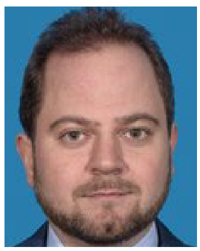
NICOLA CAPECE is currently a Postdoctoral Researcher with the University of Basilicata, Italy. Additionally, he is an Adjunct Professor of software engineering, virtual archeology lab, and operating systems courses. He has authored numerous papers published in international journals and conferences. He is involved in several research projects concerning XR and HCI for cultural heritage storytelling, virtual dressing rooms, virtual reality 3D modeling, and hand gesture recognition systems. His research interests include real-time and offline rendering, deep learning, computer graphics, eXtended reality (XR), and human–computer interaction (HCI).

UGO ERRA is currently an Associate Professor with the Department of Mathematics, Computer Science, and Economics, University of Basilicata, Potenza, Italy, where he founded the eXtended Reality and Artificial Intelligence Laboratory, where he supervised four Ph.D. students. He was the principal investigator in several research projects concerning XR and HCI for cultural heritage storytelling, virtual dressing rooms, virtual reality 3D modeling, and hand gesture recognition systems. His research interests include computer graphics, information visualization, and artificial intelligence. He served at more than 20 international conferences as a program committee member and more than ten journals as a referee.

DANILO TRAVASCIA received the M.Sc. degree (cum laude) in forestry and environmental science from the University of Basilicata, with an academic mention. His M.Sc. thesis project focused on both the study of protected areas and their sustainable management, with a focus on the Pantano Forest of Policoro. He is currently pursuing the Ph.D. degree in Pollino National Park, with a focus on the analysis and study of old-growth forests. His research interests include the study and assessment of areas with high environmental value, and in particular forests as a key resource for fighting climate change, biodiversity loss, and promoting sustainable development.



ANTONIO SCOPA has been an Associate Professor of agricultural chemistry with the University of Basilicata, Italy, since 2002. His research interests include soil chemistry, remediation, biotic and abiotic stress effects on soil and plants, pesticide chemistry, and xenobiotic fate. He collaborates with international institutions, serves as an associate editor and is a reviewer for 30 journals.



MARIOS DROSOS received the Ph.D. degree from the University of Ioannina, Greece. He is currently an Associate Professor with the University of Basilicata, Italy. Previously, he held positions with the University of Patras, Greece, and Nanjing Agricultural University, China. His research on humic substances has resulted in 75 articles and numerous citations. He is actively involved in the International Humic Substances Society and serves as an editor for reputable journals.

PAOLA D'ANTONIO received the degree (Hons.) in agricultural sciences, and the Ph.D. degree in rural engineering, in 1995. She has been teaching uninterruptedly, since 2005, as a Lecturer of agricultural mechanics with the University of Basilicata. She is the President of degree course in landscape, environment, and urban greening, and the university pro-rector and the coordinator of the 1st level master's degree in precision agriculture. She has several scientific articles to her credit and participates as a speaker at various national and international conferences.

Open Access funding provided by 'Università degli Studi della Basilicata' within the CRUI CARE Agreement