Volume 1, 2025, Pages 89-99 *Journal of Smart and Sustainable Farming*
| Regular Article | Open Access

Applications of Unmanned Aerial Vehicles within the Field of Precision Agriculture

Sungsoo Song
Wonkwang Health Science College, Iksan-si, Jeonbuk State, South Korea.
sungsoo586@hotmail.com

Article Info
Journal of Smart and Sustainable Farming
https://www.ansispublications.com/journals/jssf/jssf.html

Received 30 March 2025
Revised from 02 May 2025
Accepted 29 May 2025
Available online 15 June 2025
Published by Ansis Publications.

https://doi.org/10. 64026/JSSF/2025009

Corresponding author(s):
Sungsoo Song, Wonkwang Health Science College, Iksan-si, Jeonbuk State, South Korea.
Email: sungsoo586@hotmail.com

Abstract – The development and widespread use of unmanned aerial vehicles (UAVs), typically identified as drones, in the last decade have enabled the acquisition of data with exceptional spatial, spectral, and temporal resolution. The use of UAVs in precision agriculture (PA) has emerged as a significant catalyst for economic growth. PA, often known as precision farming, is an agricultural approach characterized by the execution of management activities with utmost accuracy on the basis of both temporal timing and spatial position. The use of technology in PA is often seen in the automation of agricultural operations, which serves to improve diagnostics, decision-making, and overall performance. The origins of conceptual research on PA and its first practical applications may be traced back to the late 1980s. Researchers in the area of PA are now engaged in efforts to develop a Decision Support System (DSS) for comprehensive farm control, with the primary objective of boosting input use for profit maximization and waste reduction. This article provides a comprehensive analysis and assessment of the many applications of UAVs in the field of agriculture. There are three major categories of UAVs applications: a) multi-UAV applications, b) spraying applications, and c) monitoring applications.

Keywords – Unmanned Aerial Vehicles, Global Positioning System, Precision Agriculture, Decision Support System.

I. INTRODUCTION

Various types of unmanned aerial vehicles (UAVs) have been industrialized and are currently in different stages of development. These include fixed-wing aircraft, helicopters, multi-copters, motor parachutes and gliders, UAVs capable of vertical takeoff and landing, UAVs assembled from prefabricated components, and commercially available UAVs. Each entity has a distinct arrangement of binary digits, consisting of ones and zeros, which have been programmed to fulfill a specific objective. The design and manufacturing markets for fixed-wing drones have been saturated due to the widespread adoption of larger fixed-wing aircraft with few modifications and enhancements, notwithstanding the inherent simplicity of these drones. The velocity in the advancing direction induces the production of lift by the stationary wings. The magnitude of the aerodynamic force known as lift is contingent upon the velocity and angle of attack of the airstream passing over the stationary wings.

According to Acosta and Hassanalian [1], drones equipped with fixed wings need a reduced thrust-to-load ratio and an increased initial velocity in order to achieve lift-off. When doing a comparison of drones with identical payload capacities, it is seen that fixed-wing aircraft use less power and exhibit lower thrust loading in comparison to their multirotor counterparts. The adjustment of aircraft orientation may be achieved by the use of certain control surfaces, namely the rudder, elevators, and ailerons, which are responsible for controlling roll, pitch and yaw, respectively. **Fig. 1** illustrates the applied load on a fixed-wing aircraft, whereas **Fig. 2** examines the diminished longitudinal dynamics of the fixed-wing UAV. The primary factors that are given the most consideration in this analysis is the aircraft's mass (mg), the lift generated by the main wing (L(a)), and the control input exerted by the tail elevator (u).

Drones equipped with fixed wings lack the ability to maintain a stationary position or sustain a low velocity. Hence, the ratio of lift to drag generated by a wing is referred to as the lift-to-drag ratio. The Fixed-wing drone is more appropriate for larger lift-to-drag ratios and higher Reynolds numbers. Fixed-wing drones become more difficult to detect within the range where the ratio of length to diameter (L/D) is less than or equal to 10, since both the Reynolds number and efficiency experience a significant decline in this region. Drones equipped with flapping wings get their design inspiration from a diverse array of insects, spanning from little hummingbirds to colossal dragonflies. The lightweight and flexible nature of bug and bird feathers provides valuable inspiration for enhancing the aerodynamic properties of wings.

The proliferation of precision agriculture has been facilitated by the use of user-friendly unmanned and cost-effective aerial vehicles. UAVs used in the agricultural sector have the capability to capture several images of a given field simultaneously, afterwards using photogrammetric methodologies to seamlessly merge these images into orthophotos. In the processing and analysis of vegetative indices, the use of multispectral imagery is common practice. This is due to the fact that multispectral images provide a greater number of traits per pixel compared to the traditional blue, green, and red values. These additional values include near red-edge and infrared spectral values. The user did not provide any text to rewrite. These drones have the capability to capture aerial imagery and give additional geospatial enabling software to perform map algebra, elevation operations and generate highly detailed topographic maps. To enhance agricultural inputs such as fertilizer, chemicals like herbicides, water and regulators growth through variable applications, it is possible to use topographic maps to establish a correlation between crop health and topography.

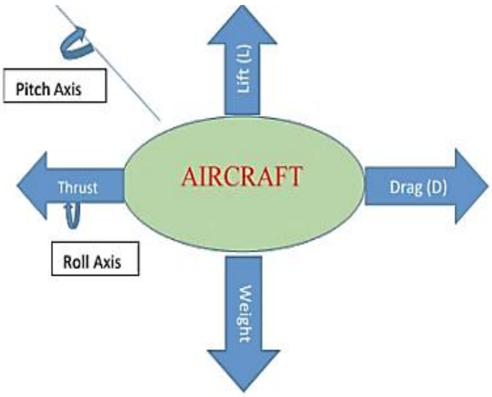

Fig 1. Fixed Wing UAV Aerodynamics

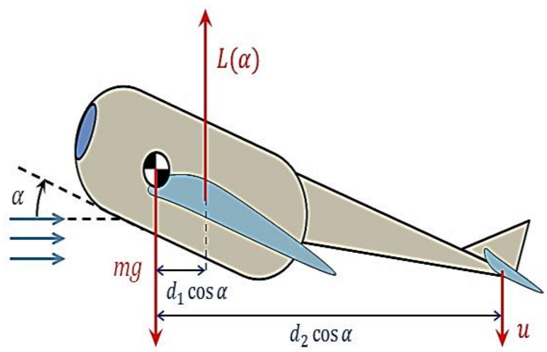

Fig 2. Longitudinal Model of a Fixed-Wing UAV

This article provides an analysis and assessment of the potential applications of UAVs in the field of agriculture. Specifically, most of, these applications may be classified into 3 distinct categories: a) applications for surveillance and monitoring purposes; b) applications for aerial spraying activities; or c) applications that include the coordinated deployment of many unmanned aerial vehicles. The following section outlines the organizational framework of this scholarly article: Section II focusses on UAV-based monitoring applications; Section III reviews UAV-based spraying systems; while Section IV discusses multi-UAV applications. Lastly, Section V presents final remarks regarding the research on the application of UAVs in precision agriculture.

II. UAV-BASED MONITORING APPLICATIONS

The objective of this section is to conduct research and analysis on the utilization of UAVs for monitoring crop. These UAVs capture image data, which is processed subsequently to extract relevant data and indicators of vegetation. This enables the identification of regions within a crop that are affected by various diseases and pests. UAV sensors have the capability to gather temporal, spatial, and spectral data. The selection of an appropriate sensor and corresponding data is contingent upon the specific use case. For example, thermal data may be used to assess the water status of a plant, while spectral data can aid in identifying possible illnesses. The evaluated papers use a range of sensors like, hyperspectral cameras, multispectral, and thermal. Every paragraph of the text focuses on a distinct situation.

Radoglou-Grammatikis, Sarigiannidis, Lagkas, and Moscholios [2] provide a study including UAV flights with the objective of identifying prospective drainage pipes. To efficiently extract moisture from the soil, farmers often undertake the task of repairing damaged drainage systems or constructing new ones. Furthermore, the drainage processes have the potential to produce phosphate (PO_4) and nitrate ($N0_3$), hence posing potential environmental hazards. Consequently, possessing knowledge of the precise locations of these drain lines is of utmost importance. Regrettably, such information is often absent in several regions, including several states within the United States such as Indiana, Minnesota, Illinois, and Ohio. In this research, the investigators perform UAV flights to examine the efficacy of Near Infrared (NIR), Thermal Infrared (TIR) and Visible (VIS) imaging in detecting pipes of drainage in desert areas. The Ohio farmland used for the missions is equipped with established drainage systems, a well-recognized aspect. The agricultural landscape was populated with corn and soybeans, which included the crops and residues from the preceding year's cultivation period. Siamabele [3] begin his study by implementing the requisite apparatus to ascertain the aridity index by the collection of data pertaining to precipitation, temperature, and moisture levels.

Additionally, the Bucket Tipping Rain Collector manufactured by Technologies that are spectrum, Inc., was used to meticulously quantify the rate of rainfall. The SMEC 300 Temperature sensors or soil moisture, manufactured by Technologies of Spectrum, Inc., are used to assess the moisture and temperature levels of the soil. The estimated water content was around 16%, but the temperature exceeded 33 degrees Celsius, resulting in a rate of rainfall below 5mm. The flying flights were conducted using the sensefly fixed-wing drone, equipped with 2 cameras: the sensefly SA thermomap and Parrot SA Sequoia. The first device emits both visible and near-infrared wavelengths, while the subsequent device only emits infrared wavelengths. In order to undertake a detailed analysis of the photographs, we used the sense Fly SA application eMotion3 to mainly eliminate any occurrences of overlap. The experimental results indicate that thermal infrared (TIR) imaging has the potential to accurately choose lines that drain in desert conditions.

In their study, Szczepanski and Purushothaman [4] who attended the UAV designed system for the purpose of monitoring agricultural output and conditions. More precisely, an UAV is used, which is outfitted with a LiDAR (Light Detection and Ranging) sensor, to conduct an analysis of textual material pertaining to winter wheat fields. LiDAR employs a sensor to detect the reflected pulses and utilizes pulsed laser light to spotlight a specific object of interest, hence ascertaining its distance. An analysis of a text was done on the data by LiDAR sensor in order to determine the total soil surface and plant volume for particular pixels of crops. The scholars employed DIT Matrice 100 UAVs manufactured by DJI Enterprise, together with a crop field located at University of Aarhus in Flakkebjerg. Two distinct aerial tactics were subjected to experimentation and afterwards evaluated for comparison. The first observer exhibited meticulous scrutiny of the perimeters of the agricultural plots, but the subsequent observer conducted a more comprehensive examination of the individual rows inside. The second method exhibited enhanced spatial resolution, but resulting in significant energy use.

Primicerio et al. [5] present and use VIPtero as an UAV application for the purpose of monitoring and evaluating vineyard crops in their publication. Specifically, the methodology used by the researchers involves the examination of aerial photographs acquired by UAVs and the subsequent generation of vitality maps based on the NDVI (Normalized Difference Vegetation Index). The UAV used in this study is a six-rotor Mikrokopter Hexa-II (HI Systems), designed to operate autonomously over a pre-defined flight path. Furthermore, the device has Global Positioning System (GPS) functionalities, a magnetic compass, and integrated flight control boards. The writers made enhancements to Hexa-II and subsequently developed the VIPtero platform. The Eagle Tree first-person view platform was introduced, consisting of Flight CTR, Navigation control board, and a GPS receiver. These components facilitate the operator ability to both transmit and receive commands pertaining to the unmanned aerial vehicles' (UAV) flight path and operational condition. The document reflectance of the canopy and primary purpose of VIPtero is to assess.

The energy maps are generated using the photographs obtained by VIPtero, which undergo a multi-stage processing pipeline. To go into the topic more comprehensively, it is fundamental to note that a digital elevation model (DEM) is used to examine and ortho-rectify the photographs. Once georeferenced, the data undergoes a specific analytical process that converts individual pixels into spectral radiance, which is then transformed into reflectance. The software then distinguishes the soil pixels from the canopy pixels by using the calculated NDVI. The strength maps are subsequently generated. To assess the efficiency of recommended methodology, the researchers performed field study in an authentic Monteboro vineyard. The accuracy was assessed using a comparison of the NDVI values obtained from the VIPtero system and a spectroradiometer. A correlation coefficient of 0.98 has been observed between the two values. It is important to highlight that the mean power consumption of VIPtero's testing amounts to 350 Watts.

In the study conducted by Thibbotuwawa, Nielsen, Zbigniew, and Bocewicz [6], a methodology is presented for quantifying the energy consumption of a prototype UAV. The author takes into consideration several aspects such as altitude and weight to effectively measure the power use. The proposed deployment of the UAV prototype focused on the use of cassava crops, which are a commercially significant kind of agricultural crop in Thailand. Cassava is mostly used in commercial applications such as food production, alcohol manufacturing, sweetener production, and animal feed production. According to the author's assertion, fixed-wing UAVs have better performance characteristics in terms of endurance and range, making them the preferred choice for practical applications in the field. The following elements exhibit notable characteristics: The empty weight of the aircraft is recorded as 2 kilograms, with a wingspan of 2 meters. The payload weight is specified as 1 kilogram. The power source for the aircraft consists of a brushless motor with a 1300kv rating, coupled with a propeller measuring 10 inches in diameter and 5 inches in pitch.

The battery used is a LiPro battery with a voltage of 14.8 volts. In order to enhance the capability of autonomous flights, many components were included into the autopilot system of the UAV prototype, namely: a barometer, an accelerometer, a magnetometer, and a 3-axis angular velocity sensor. The experimentation was place inside a round rectangular area 400 multiply by 400 located in Thailand. This territory was divided into 8 predetermined waypoints, and the testing included the use of various payloads and altitude settings. The empirical evidence indicates that the power consumption for payloads weighing 0.4 kg, 0.2 kg and 0.6 kg is insignificant. The payload, however, exhibits a marginal increase of just 0.8 kg. In the event of a disruption leading to a decrease in altitude or velocity, the UAV will expend the highest amount of power in order to compensate for the deviation.

In this study, Gutiérrez, Fernández-Novales, Diago, Iñiguez, and Tardaguila [7] provide a method for assessing the fluctuations in water status inside a vineyard. This method utilizes thermal imaging analysis via the use of an UAV as described by Ward, Hensler, Alsalam, and Gonzalez [8]. The assessment of crop water stress included a comparison between manually obtained measurements of stem water potential and stomatal conductance at different sites, and the values of Crop Water Stress Index (CWSI) resulted retrieved from UAVs images. In this instance, the software was used inside an actual Spanish vineyard, which was partitioned into two distinct grid dimensions. The first grid, comprising of 92 spatial points, is used to delineate the agronomic attributes of the vineyard. The second object has a shape that closely resembles a rectangle and is equipped with a total of 14 stations dedicated to the monitoring of water. Each of the 92 SPs exhibits distinct characteristics such as yield value, vegetative development rate, grape composition at harvest, and berry carbon isotope ratio time. Nevertheless, the identification of each of the 14 water stress periods (WSPs) is achieved by the use of the measurements of weekly of stem potential of water.

Additionally, statistics pertaining to PCD and EC were made available. In this study, a multi-rotor UAV model, namely the MikrocopterOktoXL, was used. The UAV had a flying duration of 15 minutes and a maximum cargo capacity of 2 kilos. The aforementioned attributes are as follows: The bundled components consist of a flight controller, navigation controller, FLIR TAU II 320, universal camera, GPS module, digital compass, pressure sensor, and microSD thermal imaging sensor. By using the Mikrokopter Tools software, we conducted a computational analysis to determine an ideal trajectory for aerial navigation, aiming to achieve an 80% overlap between captured images and the flight path. The CWSI index was then computed, and a geographic analysis was conducted using the Edition 1.1.6 program of Agisoft Photoscan Professional and to ascertain the stem water potential values (WSP) and stomatal conductance for each water stress period (WSP). The practical results indicate that thermal data has the potential to effectively and substantially assess the status of water of a vineyard.

In their publication [9], Amarasingam, Ashan Salgadoe, Powell, Gonzalez, and Natarajan provide a detailed account of a hybrid application including an UGV and UAV for the purpose of crop monitoring and management. Jordan [10] implementation primarily focuses on leveraging the capabilities of UAVs. These capabilities include conducting periodic inspections, extracting various indices that provide information about the density, greenness, capturing multiple images them, and overall health of vegetation. In contrast, Unmanned Ground Vehicles (UGVs) were mostly used for the purpose of gathering data pertaining to the composition of the terrain, specifically focusing on factors such as acidity and pH levels. The operational functionality of the UAV is facilitated by a Beagle bone Black board, which operates on the open-source Debian operating system. The GY80 10DOF Inertial Measurement Unit (IMU), which comprises a magnetometer, accelerometer, barometer, and gyroscope, is furthermore provided.

The UAV is equipped with a Sequoia camera, which has the capability to record pictures throughout a broad spectrum of wavelengths, including near-infrared (NIR), visible (red), and near-ultraviolet (UV) regions. Both vehicles use Beagle bone Black boards, with the Unmanned Ground Vehicle (UGV) further equipped with a single-piece camera and LiDaR sensor. According to Meyer, Sendobry, Kohlbrecher, Klingauf, and von Stryk [11] the capabilities of UAVs were first simulated in Gazebo via the use of the Hector UAV package. By using the rviz software, a map of an unexplored region was successfully generated. After collecting the necessary data, Zhao, Huang, and Zhang [12] proceed to implement a homography technique using the RANSAC algorithm, the Lucas-Kanade approach, and the Harris corner detector. The final ortho-mosaic that yielded image of 3 indices of vegetation indices: Renormalized Difference Vegetation Index (RDVI), Enhanced Normalized Difference Vegetation Index (ENDVI) and Soil Adjusted Vegetation Index (SAVI).

In their publication, Anand et al. [13] present a multispectral imaging system designed to collect and analyze photographs of agricultural crops in Peru. The system utilizes UAV technology for data acquisition. The key innovation introduced by their image to implement system of acquisition, which is responsible for determining the optimal methods for storing and processing photographs captured by the cameras on the UAVs. The two threads responsible for storing the photographs play a role that is vital in the functioning of the image capture system. Specifically, these threads are executed sequentially and have the capability to temporarily store up to 30 images in local memory. The first thread is responsible for storing images in the local memory until it reaches the predetermined threshold, at which point it proceeds to transfer them to an SD card. Furthermore, a third thread has the responsibility of transmitting the occurrence of a photograph being captured to the two aforementioned threads.

Mahfoudhi, Qassim University Buraidah, Khodja, Mahroogi, Qassim University, and Islamic University of Madinah [14] used a Pixhawk flight controller, two-point Gray Chameleon monochromatic cameras, a PCDuino v2 single-board computer, and a Skywalker X8 UAV in order to assess their implementation. It is worth noting, however, that the use of six Blackfly cameras in conjunction with the Jetson TK1 board, which have GPU capabilities, results in enhanced performance. The trajectory of the flight was plotted using Mission Planner. A variety of crops in Peru were used for the experimental trials. The aforementioned items included sweet potatoes, grapes, asparagus, and sugar cane. On a weekly basis, pilots would go on their assigned missions. The calculation of the NDVI index is performed subsequent to the generation of an ortho-mosaic map derived from the acquired photographs. The use of NDVI indicators demonstrates the potential effectiveness of the whole system in assessing the status of crops.

UAVs are increasingly accessible in response to the growing need for efficient and immediate monitoring in orchard management. This is made possible by advancements in sensor miniaturization, as evidenced by studies conducted by Mohsan, Othman, Li, Alsharif, and Khan [15]. Fruit trees may be effectively monitored via the use of various data collection techniques, such as heat light detection and ranging (LiDAR), multi-spectral sensors and sensor systems. The process of choosing an UAV that can effectively accommodate these sensors and meet the essential criterion of spatial resolution and time frequency of orchard management is hindered by many complex factors. The relocation of a terrestrial platform to a different location might provide logistical challenges, while the process of doing real-time field mapping may pose difficulties. The use of a suitable UAV for the purpose of data collection, with the capability to acquire information at the required temporal frequency and geographical resolution, has been suggested as a potential option to circumvent these limitations.

The use of UAVs for monitoring purposes necessitates weather conditions that are comparatively less adverse in comparison to satellite-based remote sensing techniques. In the study conducted by Alvarez-Vanhard, Corpetti, and Houet [16], a comparison was made between UAVs and satellites for the purpose of monitoring overcast regions. The researchers determined that UAVs exhibited a data-acquisition probability ranging from 45% to 70%. Several advantages of UAVs have been recognized in the literature, such as their ability to efficiently gather data and capture geo-referenced photographs. UAVs have limitations in their efficacy due to variables such as the duration of battery life and the upper limit of achievable speed. UAVs have the potential to be effective in orchards of varying sizes, ranging from modest to considerable, because to their extended battery longevity. According to Burger and Wöllner [17], the operational tempo of human flying platforms is comparatively slower. Ensuring a harmonious balance between the velocity of flight and the quality of data is necessary in order to get data of superior quality.

Zhang, Valente, Kooistra, Guo, and Wang [18] introduced a paradigm for orchard management using UAVs in **Fig. 3**. This paradigm enables researchers to make comparisons across studies that have a similar or equivalent objective. Different management contexts necessitated the use of diverse data sources, as shown. The LiDAR sensor was used just for the estimation of geometric characteristics. Subsequently, state-of-the-art methodologies were used to extract or calculate decision indicators from the accumulated datasets. Under each sub-category of "orchard management," there are significant aspects of management that can be identified, one of which is thermal drift correction. This particular facet aims to enhance the accuracy of assessing water stress. The fundamental aim of diverse research remains consistent across different application scenarios.

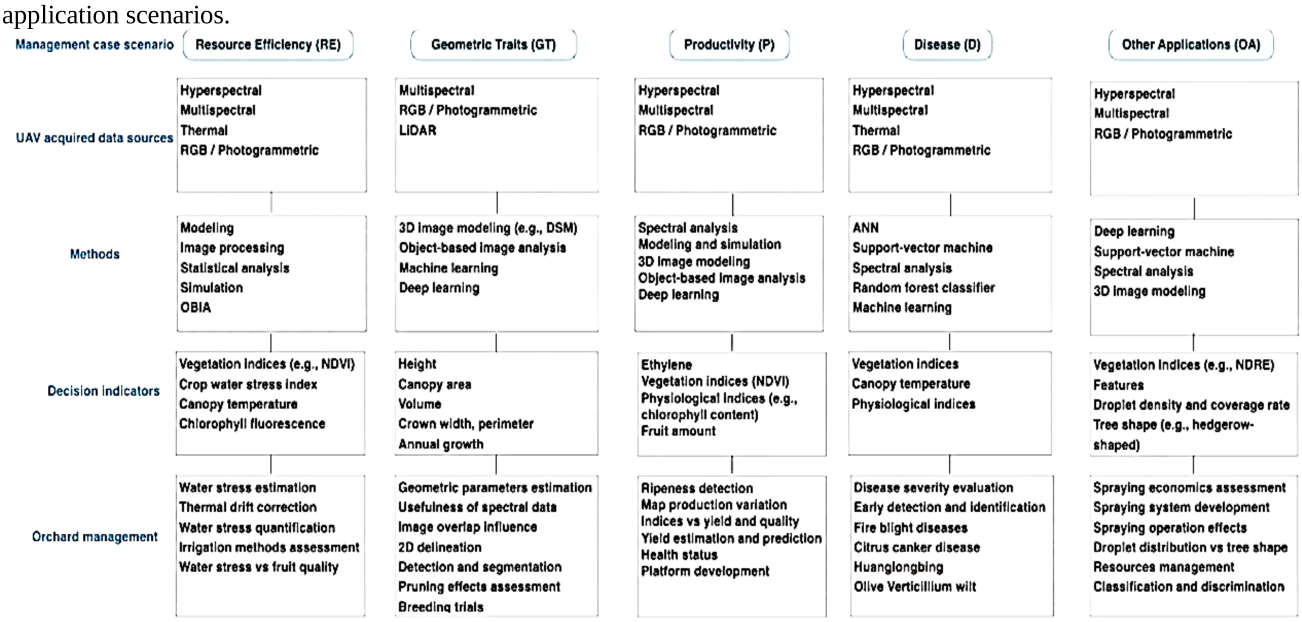

Fig 3. UAV-Based Data-Decision Architecture in Orchard Management

In a study conducted by Li, Jiang, Sun, Cai, and Wen [19], a UAV application was developed and assessed to determine the efficacy of 2 cameras in following the state of trees of citrus. The 2 cameras were compared based on 3 criteria: image resolution, accuracy, and classification. The term "classification accuracy" refers to the degree of precision in correctly identifying healthy trees as healthy and sick trees as diseased. The hexacopter UAV has the following specifications: a) A mass of 2 kilograms, b) A Lithium-Ion Polymer battery with a capacity of 6600 milliampere-hours, c) A set of six propellers, d) A configuration consisting of six brushless motors, e) A global positioning system, f) A compass, gyroscope, h) A radio transmitter, and i) An accelerometer. The XNiteCanon SX230 NDVI, developed by LDCLLC in Carlstadt, NJ, has the distinction of being the UAV integrated from first camera. This camera possesses the capability to acquire pictures throughout the green, blue, and near-infrared (NIR) spectrums. The second camera used in the study was manufactured by Tetracam Inc., Chatsworth, CA. This camera, similar to the first one, was equipped with spectral bands capturing green, red, and near-infrared (NIR) wavelengths.

The experiments were done in citrus plantations located in Florida, whereby some trees exhibited signs of robust health while others were afflicted with citrus greening or huanglongbing. A sequence of images was captured using three distinct heights, namely 90, 60, and 30 meters. The aforementioned attributes were derived from each individual photograph. A total of six datasets were generated, consisting of two cameras and three elevations. These datasets were prepared using three different methods: a) using the near-infrared, b) employing the GNDVI (Green Normalized Difference Vegetation Index) and c) including GNDVI derived information to a histogram. The process of reducing dimensionality was achieved by using Principal Component Analysis (PCA). In order to differentiate between the two categories of trees, a SVM model was ultimately used. SVM model was ultimately used. The training of SVM model was done using seventy five percent of the databases, while the remaining 25% were allocated for testing purposes. Furthermore, the software was implemented using the Matlab programming language and included the use of the radial basis function. Based on the analysis of the testing data, it can be concluded that the first camera exhibits higher performance in all aspects.

III. UAV-BASED SPRAYING SYSTEMS

In this section, we go into the investigation and examination of UAV systems that are especially designed for the purpose of conducting spraying operations. The majority of the literature examined pertains to software applications designed to administer precise amounts of fertilizers and pesticides. Agrochemical products are used to mitigate the adverse impacts of pests and diseases on agricultural crops. Nevertheless, the excessive utilization of these substances might give rise to a myriad of challenges for the human population, encompassing environmental disasters as well as various health ailments such as respiratory complications, neurological disorders, and cancer. The majority of the examined publications include instructions for the installation of a spraying apparatus and consider various aspects, such as weather conditions, that might potentially influence the efficacy of the spraying process. The following paragraphs focus on distinct illustrations.

The optimization of the spraying process in a UAV system is achieved by the use of an algorithm proposed by Yazdani, Yazdani, Yazdani, Omidvar, Gandomi, and Yao [20], which is oriented on the principles of Particle Swarm Optimization (PSO). Matzrafi [21] believe that the effectiveness of pesticides is notably influenced by weather patterns due to their tendency to result in the unintended dispersion of substantial amounts of these chemicals. The proposed methodology was formulated and evaluated for a particular use case that integrates the capabilities of WSN with UAV. The sensor nodes of the Wireless Sensor Network (WSN) are strategically positioned inside the designated mission area, facilitating the acquisition of meteorological data such as wind speed and direction. This data set is then transferred to the UAVs. Subsequently, the UAV acquires the aforementioned data and employs the algorithm developed by Liu, Dai, Wang, Imran, Wang, and Shoaib [22] to make accurate assessments about the UAV's position and velocity. In more elaboration, the suggested methodology is dependent on Particle Swarm Optimization (PSO) to identify a sub-optimal solution for a variable referred to as route Changing Factor. This variable governs the trajectory of the UAV throughout its flight. It is important to acknowledge that this methodology must not exceed the computational time required for the actual spraying process. The proposed methodology has been executed by using the Mixim framework and the OMNeT++ software. The experimental findings show that the recommended approach demonstrates an approximate accuracy of 86% when used for pesticide application.

Pathak et al. [23] presents a discussion of the inappropriate use of pesticides. Numerous studies have put forth various terrestrial or aerial spraying systems as potential solutions for effectively regulating pesticide quantities. However, these systems have been found to overlook crucial factors such as weather conditions, including fluctuations in wind speed and direction. Consequently, this oversight may result in adverse consequences such as economic setbacks, environmental harm, and untreated regions. Benmad, Driouch, and Kardouchi [24] suggest an integrated cooperative spraying system that combines UAVs with Wireless Sensor Networks (WSNs) for the purpose of monitoring weather conditions and adapting the spraying strategy appropriately. The system, AdEn, consists of 2 primary components: collAct and the OPTIC module. The software program known as CollAct operates on the computer of an UAV and weather conditions monitoring responsible. It does this by sharing data with a wireless sensor network (WSN) consisting of several sensors distributed over a wide geographic area. CollAct establishes sensor communication nodes of subarea geolocation information being transmitted.

Upon receipt of a CollAct message, the sensor nodes will thereafter transmit the prevailing weather conditions. Subsequently, CollAct conveys the average value of the meteorological state to OPTIC module. The OPTIC software suite is used on the ground station for operational purposes. The system collects meteorological data and employs 4 algorithms of metaheuristic to identify the optimum course of action for the UAV by dynamically modifying the route Changing Factor. The algorithms of heuristic that have been examined and assessed by researchers include Genetic Algorithm (GA), Simulated Annealing (SA), Next Ascent Hill Climbing (NAHC), and Particle Swarm Optimization (PSO). Subsequently, CollAct is provided with the revised value and commits to modifying the behavior of the UAV in accordance with it. The results of the testing have verified that system proposed has the ability to effectively oversee the process of spraying pesticide by UAVs, with the most optimal decisions being made by the genetic algorithm (GA) metaheuristic.

In their publication [25], Ahmad, Khaliq, Qiu, Sultan, and Ma introduce a specialized spraying system using UAVs for the purpose of spraying fruits on trees. The system proposed demonstrated strong performance in a comparable competition finally achieving the top position. The main purpose of this system is to provide a mean that operates without human intervention, enabling the precise spraying of predetermined sites. The researchers utilized UAV + DJI equipped with various components. These components included: a) the spraying device, b) an extended magnetometer, c) a point Grey BFS-U3 camera, d) a GPS receiver, e) an HMC5883 magnetometer, f) an MS5611 barometer, and g) a PixHawk controller. In contrast, station on the ground is outfitted with a robust computer system, with a 5G communication interface, a 128-gigabyte solid-state drive, an Intel Core i5-6260, and 8 gigabytes of random-access memory.

The contribution of this work is from accompanies of software UAVs. This platform has three key components: a navigation system that relies on an Extended Kalman Filter (EKF), a control system, and a vision system. The researchers give out a dual-subsample rotation technique of vector based on EFK to predict position, altitude, and speed of the UAV. The control system operation is supported by many types of P and controllers of PID, such as Angular velocity controller, Attitude controller, Velocity controller, and Position controller. The system of vision encompasses three fundamental functions, namely target identification, preprocessing, and target localization. To ascertain and determine the whereabouts of a certain objective, information is consolidated via the use of a preprocessing methodology. The target area is accurately determined by the use of a machine learning classification approach known as K-Nearest Neighbor (KNN). The localization technique is thereafter tasked with enhancing the precision of the aforementioned method.

The present location of the UAV is ascertained by the use of an onboard high-precision Global Positioning System (GPS), which transmits real-time data to the controller. This data is then compared to the coordinates of the designated region on the UAV's operational route map. The successful matching of UAV position data yields the most current location prescription value. The spraying procedure is conducted subsequent to the transmission of the data about the amount of spray to the variable spray controller. Indu, Baghel, Bhardwaj, and Ibrahim [26] provide a detailed explanation of the computational aspects involved in the spraying process for optimal plant care applications. When formulating a strategy for a spraying operation, it is crucial to consider several elements, including but not limited to wind speed and direction, effectiveness of the spraying system itself, drone flying speed, fluid dynamics, and operating altitude. The variables of the sprayer system, namely gallons per acre (GPA), miles per hour (MPH), GPM, W, OPM, NFR, benchmark and computed in creation of this variable rate, which is a precise platform based on UAVs.

Nevertheless, it is important to consider the limitations and restrictions that govern the methods and approaches used in every given situation. The performance of individuals will be negatively impacted by the influences of the field environment, leading to a decrease in accuracy. The system conducted a comprehensive study by considering environmental factors and performing computations. Nevertheless, the manipulation of meteorological conditions by artificial means is not now feasible. **Fig. 4** is an illustrative instance of a UAV application that exhibits superior performance and using variable-rate techniques. This application is designed to effectively address the issues of insect infestation and plant diseases by tailoring the treatment based on the specific geographical coordinates. There exists a significant probability that, despite the high efficacy of the spray, the therapy may fail to satisfy the designated criteria, necessitating an appropriate quantity of the spray. The system's failure to include accurate measurements of wind speed and direction is often identified as the primary cause.

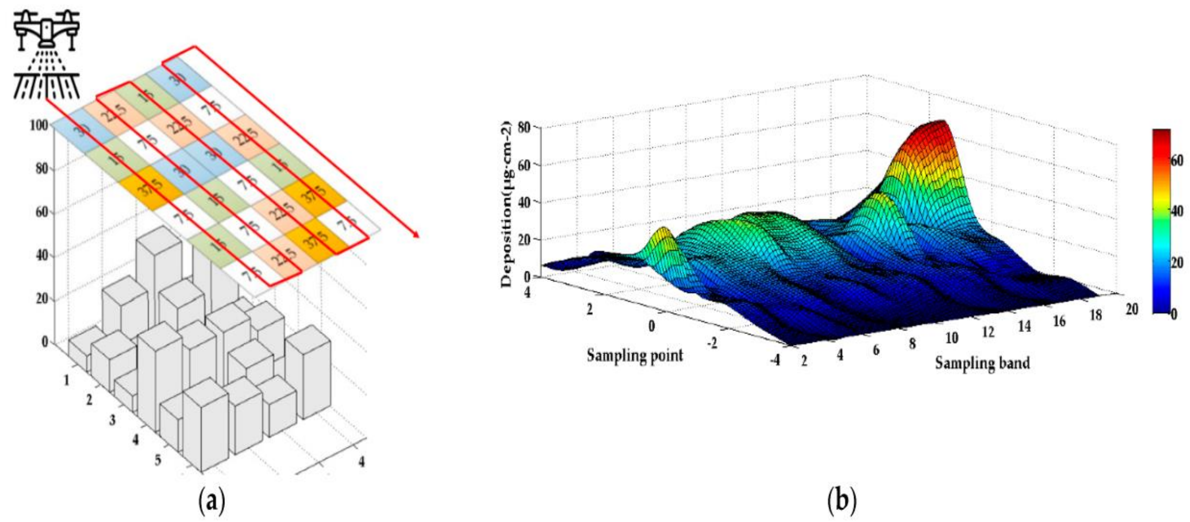

Fig 4. Comparison of Reference Dataset (A) With Spray Execution Data (B) To Determine Whether Mistakes are Caused by Drifting

IV. MULTI-UAV APPLICATIONS

Here, we go into the domain of multi-UAV applications, often known for using several UAVs to carry out precision agriculture (PA) operations. Currently, the predominant focus of published studies pertains to the utilization of a solitary UAV for the purpose of conducting monitoring procedures. However, because to its constrained power resources, namely its restricted battery capacity, an individual UAV may not be able to complete the monitoring method independently in some situations, such as when dealing with large-scale crops. Nevertheless, this challenge may be effectively addressed via the use of a multi-UAV application. This application achieves this objective by partitioning the given territory into a number of smaller regions equivalent to the total count of UAVs. It is noteworthy to mention that there is a scarcity of published research that specifically examine the applications of multiple UAVs. The following paragraphs center on distinct illustrations.

In their publication, Bayerlein, Theile, Caccamo, and Gesbert [27] provide an innovative approach to UAV path planning in the multi-UAV scenario. The present study examines a hypothetical situation whereby a substantial fleet of UAVs is deployed for the purpose of pesticide application on two major agricultural fields located inside China's Shaanxi Province. According to the writers, it is said that a solitary UAV is incapable of traversing the whole of such region during a singular flight. Consequently, the researchers examine the feasibility of using a multi-UAV system, whereby each UAV has responsibility for surveillance of a distinct segment of the structure. The quadcopter UAV used in this investigation is outfitted with a spraying system that has a capacity of 15 liters. The "Merak" kind of UAV is characterized by the following attributes: The longest duration of flight is limited to a period of 30 minutes. The highest attainable height is restricted to 4000 meters. The maximum weight that can be maintained is 30 kilograms. The average velocity during flight is recorded to be 6 meters per second. Vukićević, Ratli, Rivenq, and Zrikem [28] use a technique known as Variable Neighborhood in their study. This literature text is meant to optimize the flight routes of UAVs while simultaneously minimizing the overall flight duration. This is achieved via the utilization of a method called Descend improved Genetic-PSO.

To address persistent optimization challenges, the well-established Particle Swarm Optimization (PSO) method was used. Nevertheless, this poses many computational challenges in relation to issues of combinatorial optimization. The researchers use a Genetic-PSO method enhanced with a Variable Neighborhood Descent (VND) technique. This algorithm changes the position of particles by using a discrete Particle Swarm Optimization (PSO) approach, while also integrating genetic operators. Furthermore, it employs the Variable Neighborhood Descent (VND) approach to achieve faster convergence. In summary, their methodology is to minimize the make-span in order to optimize the flying paths of UAVs. Tao et al. [29] conducted a comparative analysis between their technique and an alternative approach that aims to limit the distance traveled by flights, as a component of the evaluation methodology. The objective of both tactics was to reduce the duration of trip. The testing results indicated that the approach used by Albreiki, Zaki, and Alashwal [30] exhibited superior performance compared to the strategy mentioned in the reference.

In their study, Ogunsina and DeLaurentis [31] propose a decentralized system for flight scheduling and optimization, aimed at using several UAVs for surveillance purposes in agricultural settings. Several 3DR IRIS unmanned aerial vehicles (3DR) are outfitted with a Raspberry Pi Foundation board circuit and establish a connection to a World Knowledge Base server. After configuring the system's parameters, the economical field is partitioned into predefined squares according to the capabilities of UAVs. Each square is assigned a distinct timestamp to denote its unsupervised time period. Subsequently, every UAV undertakes the task of monitoring a certain quantity of squares, determined by two factors: a) the squares that can be observed without prolonged intervals, and b) the pathways that provide the greatest challenges in terms of number of turns and distance. The Key Performance Indicator (KPI) is a comprehensive metric used to evaluate the performance of UAVs, considering the aspects discussed above. The measure is worked out by adding the scores of last indicators. Consequently, the final performance of each UAV is assessed by aggregating its specific key performance indicators (KPIs). In the context of optimization, UAVs have got the capability to converse with one another and engage in square trading in order to efficiently accomplish their flying missions. Yan, Li, Panadero, Yang, Yang, and Lao [32] took into account many factors in their evaluation, including a) the duration needed for forecasting, b) the overall KPI, and c) the duration needed for scheduling and rescheduling. The trials demonstrate that an increase in the number of UAVs leads to a reduction in the time needed for monitoring and scheduling. It is important to highlight that Wanzer [33] conducted many simulations using the General Designers Stand tool in order to validate these results.

In their study, Skorobogatov, Barrado, and Salamí [34] conduct a comparative analysis between the utilization of a solitary UAV and the utilization of many UAVs. Additionally, they examine the remote-control state vs autonomous control state, with a particular focus on the activities related to remote sensing (RS) in the agricultural sector, which serves as a unifying element. The act of remote control involves the system operator via a teleoperation device, whereas autonomous control pertains to the independent operation of an UAV during its flight duration, achieved by first recognizing certain distinctive characteristics. Given the aforementioned circumstances, Kangunde, Jamisola Jr, and Theophilus [35] conducted experiments to examine four distinct scenarios: a) a singular UAV system with remote control, b) a system comprising multiple UAVs operating under remote control, c) a system comprising multiple UAVs operating autonomously, and d) a singular UAV system with autonomous control. Apart from that, we used six distinct criteria to assess the efficacy of our endeavors, namely: a) total length, b) duration of flight, c) time required for setup, d) precision of landing, e) consumption of battery, and f) ratio of coverage. The time required to do the work, including both travel and preparation.

The flying time is obtained by differentiating time setup from the overall duration. Therefore, the term "setup time" is known as the duration allocated for preparatory activities prior to initiating takeoff. This statistic quantifies the degree of deviation between the actual landing location of the UAV or UAVs and the intended destination. The coverage ratio is an indicator of the effectiveness of the RS procedures. The researchers used a set of three quadcopters, namely three 3DR SOLO UAVs, in order to carry out their experiments and facilitate their comparisons. The results of the tests indicate that the numerous UAVs system exhibits a longer setup time, although demonstrates much superior performance in all aspects. When comparing autonomy with remote control, it is seen that the latter offers advantages in terms of time efficiency, both during the initial setup phase and throughout operation. Nevertheless, it has been shown that the use of a remote control leads to a reduction in the length of flight and a corresponding escalation in power consumption. Furthermore, it has been observed that the use of remote control demonstrates superior outcomes in relation to the landing accuracy metric when compared to autonomous control. However, no discernible difference has been found in terms of the coverage ratio statistic.

In their study, Ju et al. propose usage of a distributed control method in the form of a swarm control method for the remote management of a fleet of agricultural UAVs. The concept of swarming has been adopted from the field of biology, where it is seen in a wide range of creatures, ranging from bacteria to very intricate mammals. Flocks of avian creatures, groups of aquatic organisms, and communities of ants collectively display swarming behavior via the formation of Multi-Agent Systems (MASs) to achieve various objectives such as predator deterrence, food acquisition, and energy-efficient migration. In recent decades, there has been a growing use of the biological swarm system by Cheung, Xu, Ding, and Shen [36]. Zhu, Xie, Han, Meng, and Teo provided a comprehensive overview of the latest developments in the regulation and augmentation of swarm systems. Furthermore, the matter of control cooperative for the system of swarming was examined in the study referenced as [37].

Awasthi, Balusamy, and Porkodi [38] created a prototype system that utilizes a swarm of UAVs. This system incorporates synchronized flight plans and allows for disruptive events in the event of reconfiguration. A brand control formation strategy using consensus that is smoothly distributed control is presented in [39] for multi-UAV systems. Xia, Du, Jiang, Wang, Ren, and Li [40] proposed a target that is cooperative for tracking solution for UAVs by multi-agent reinforcement, using end-to-end learning system. This system incorporates intelligent flight choice algorithms to enhance the cooperative tracking capabilities of the UAVs. The obstacle avoidance strategy described by Li, Yang, and Wang [41] utilizes shared obstacle information in the process of flocking. Notwithstanding these advancements, the conventional cooperative control of LS-MASs (large-scale multi-agent systems) continues to confront the typical challenge of "Curse of Dimensionality" and the problem of communications dependability.

To mitigate these issues, a hybrid game-theoretic method is used to construct the optimum swarming issue for massive multi-agent systems. The phenomenon of swarming, as seen in **Fig. 5**, is examined within the framework of proven mixed game theory. The LS-MAS is configured as a multi-segment massive-scale leader-follower method by the subdivision of the initial large-scale agent system into smaller subgroups. Each subgroup consists of a leader and a significant follower's number. The target of each subset is to demonstrate the optimal form of swarming distributed in terms of efficiency. To attain the required swarming behavior, a combined game theory approach was formulated by incorporating two key components. Firstly, a game of cooperative was utilized to make sure the swarming collective behavior in some of the leaders belonging to multiple groups. This involved each group producing a leader cooperating with leaders from other groups to maintain the final swarming behavior across multiple groups, while also avoiding collisions between groups. Secondly, a Stackelberg game was employed to establish a connection between the leader and its respective followers. In this context, the leader introduced a set of coupling functions to establish a connection with the followers. The communication complexity problem and phenomenon known as the "Curse of Dimensionality" associated with an analogue cooperative game are factors that have an impact on the MFG transaction. In the context of the Mean Field Game (MFG) framework, the individual state information of a significant population of agents is substituted by a probability density function (PDF), also known as a mass function. The mass function, when aligned with the state space dimensions, effectively decreases the cost function and so alleviates the correlation between increasing computer complexity and the number of agents.

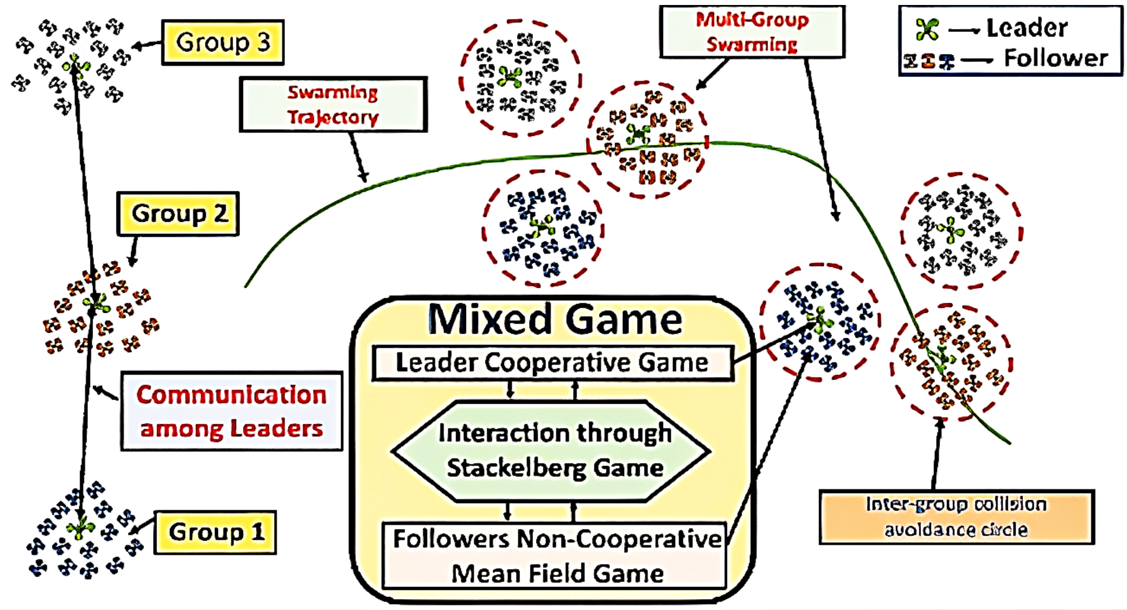

Fig 5. An Example of Leader-Follower Multi-Group Swarming in a Mixed Game

The implementation of this system comprises two distinct control levels, namely a teleoperation layer and a specialised layer for unmanned aerial vehicles. The main role of the first layer is to interpret the haptic signals sent by the operator of the system. The speed of the UAVs may be regulated by the system operator, who can also get valuable feedback from the haptic device through the teleoperation layer. Nevertheless, the control layer of UAVs is influenced by three characteristics that determine its functionalities. Several aspects contribute to the effectiveness of UAVs, including their speed, the desired formation, and their collision prevention capabilities. The determination of UAV velocities is mostly governed by the teleoperation layer. The attainment of the necessary configuration is accomplished by taking into consideration the distance between UAVs. In conclusion, UAVs use collision avoidance mechanisms to mitigate potential risks by using algorithms to determine and maintain safe distances from obstacles. The Gazebo simulator, the Robot Operating System (ROS) and Open Dynamic Engine (ODE) tool are used by Mengacci, Zambella, Grioli, Caporale, Catalano, and Bicchi [42] to construct a simulated environment for evaluating their system on the Novint Falcon haptic device (Haptics House). As part of the system evaluation, a number of UAVs will be deployed to traverse a predetermined trajectory. The efficacy of the proposed system has been shown via experimental validation.

V. CONCLUSION

The relevance and scope of information and communication technology (ICT) services have seen significant and rapid growth. The contemporary concept of a "digital society" is underpinned by advanced technologies like the growth of broadband infrastructure, the deployment of IoT applications, and the extensive use of big data analytics. The current momentum presents promising prospects for enhancing and refining agricultural processes via the adoption and use of these technologies as precision agriculture solutions. The significance of precision agriculture (PA) is increasingly recognized as we endeavor to address the challenges faced by the agricultural sector. These challenges include the diminishing availability of arable land, escalating demands for clean water resources, and the profound impacts of climate crisis. Usage unmanned aerial vehicles in agricultural practices offers significant advantages. These include enhancing the effectiveness of pesticides and fertilizers, facilitating early identification of possible pests and diseases, and optimizing the spraying procedure.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare that they have no conflicts of interest regarding the publication of this paper.

Funding
No funding was received for conducting this research.

Competing Interests
The authors declare no competing interests.

References

[1]. G. Acosta and M. Hassanalian, "Power minimization of fixed-wing drones for Venus exploration in various altitudes," Acta Astronaut., vol. 180, pp. 1–15, 2021.
[2]. P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, and I. Moscholios, "A compilation of UAV applications for precision agriculture," Comput. Netw., vol. 172, no. 107148, p. 107148, 2020.
[3]. B. Siamabele, "The significance of soybean production in the face of changing climates in Africa," Cogent Food Agric., vol. 7, no. 1, 2021.
[4]. C. J. Szczepanski and R. Purushothaman, "Sensors for UAVs dedicated to agriculture: current scenarios and challenges," Aircr. Eng. Aerosp. Technol., vol. 94, no. 1, pp. 31–44, 2022.
[5]. J. Primicerio et al., "A flexible unmanned aerial vehicle for precision agriculture," Precis. Agric., vol. 13, no. 4, pp. 517–523, 2012.
[6]. 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 Advances in Intelligent Systems and Computing, Cham: Springer International Publishing, 2019, pp. 173–184.
[7]. S. Gutiérrez, J. Fernández-Novales, M.-P. Diago, R. Iñiguez, and J. Tardaguila, "Assessing and mapping vineyard water status using a ground mobile thermal imaging platform," Irrig. Sci., vol. 39, no. 4, pp. 457–468, 2021.
[8]. S. Ward, J. Hensler, B. Alsalam, and L. F. Gonzalez, "Autonomous UAVs wildlife detection using thermal imaging, predictive navigation and computer vision," in 2016 IEEE Aerospace Conference, 2016.
[9]. N. Amarasingam, A. S. Ashan Salgadoe, K. Powell, L. F. Gonzalez, and S. Natarajan, "A review of UAV platforms, sensors, and applications for monitoring of sugarcane crops," Remote Sens. Appl. Soc. Environ., vol. 26, no. 100712, p. 100712, 2022.
[10]. J. Jordan, "The future of unmanned combat aerial vehicles: An analysis using the Three Horizons framework," Futures, vol. 134, no. 102848, p. 102848, 2021.
[11]. J. Meyer, A. Sendobry, S. Kohlbrecher, U. Klingauf, and O. von Stryk, "Comprehensive simulation of quadrotor UAVs using ROS and gazebo," in Simulation, Modeling, and Programming for Autonomous Robots, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 400–411.
[12]. Y. Zhao, X. Huang, and Z. Zhang, "Deep Lucas-Kanade Homography for Multimodal Image Alignment," in 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2021.
[13]. V. Anand et al., "Single shot multispectral multidimensional imaging using chaotic waves," Sci. Rep., vol. 10, no. 1, p. 13902, 2020.
[14]. S. Mahfoudhi, Qassim University Buraidah, M. Khodja, F. Mahroogi, Qassim University, and Islamic University of Madinah, "A second-order sliding mode controller tuning employing particle swarm optimization," Int. J. Intell. Eng. Syst., vol. 13, no. 3, pp. 212–221, 2020.
[15]. S. A. H. Mohsan, N. Q. H. Othman, Y. Li, M. H. Alsharif, and M. A. Khan, "Unmanned aerial vehicles (UAVs): practical aspects, applications, open challenges, security issues, and future trends," Intell. Serv. Robot., vol. 16, no. 1, pp. 109–137, 2023.
[16]. E. Alvarez-Vanhard, T. Corpetti, and T. Houet, "UAV & satellite synergies for optical remote sensing applications: A literature review," Science of Remote Sensing, vol. 3, no. 100019, p. 100019, 2021.
[17]. B. Burger and C. Wöllner, "The challenge of being slow: Effects of tempo, laterality, and experience on dance movement consistency," J. Mot. Behav., pp. 1–14, 2021.
[18]. C. Zhang, J. Valente, L. Kooistra, L. Guo, and W. Wang, "Orchard management with small unmanned aerial vehicles: a survey of sensing and analysis approaches," Precis. Agric., vol. 22, no. 6, pp. 2007–2052, 2021.
[19]. B. Li, Y. Jiang, J. Sun, L. Cai, and C.-Y. Wen, "Development and testing of a two-UAV communication relay system," Sensors (Basel), vol. 16, no. 10, p. 1696, 2016.
[20]. D. Yazdani, D. Yazdani, D. Yazdani, M. N. Omidvar, A. H. Gandomi, and X. Yao, "A species-based particle swarm optimization with adaptive population size and deactivation of species for dynamic optimization problems," ACM Trans. Evol. Learn. Optim., 2023.
[21]. M. Matzrafi, "Climate change exacerbates pest damage through reduced pesticide efficacy," Pest Manag. Sci., vol. 75, no. 1, pp. 9–13, 2019.
[22]. Y. Liu, H.-N. Dai, H. Wang, M. Imran, X. Wang, and M. Shoaib, "UAV-enabled data acquisition scheme with directional wireless energy transfer for Internet of Things," Comput. Commun., vol. 155, pp. 184–196, 2020.
[23]. V. M. Pathak et al., "Current status of pesticide effects on environment, human health and it's eco-friendly management as bioremediation: A comprehensive review," Front. Microbiol., vol. 13, 2022.
[24]. I. Benmad, E. Driouch, and M. Kardouchi, "Trajectory Planning for Data Collection in Multi-UAV Assisted WSNs," in 2022 IEEE 95th Vehicular Technology Conference: (VTC2022-Spring), 2022.
[25]. F. Ahmad, A. Khaliq, B. Qiu, M. Sultan, and J. Ma, "Advancements of spraying technology in agriculture," in Technology in Agriculture, IntechOpen, 2021.
[26]. Indu, A. S. Baghel, A. Bhardwaj, and W. Ibrahim, "Optimization of pesticides spray on crops in agriculture using machine learning," Comput. Intell. Neurosci., vol. 2022, pp. 1–10, 2022.
[27]. H. Bayerlein, M. Theile, M. Caccamo, and D. Gesbert, "Multi-UAV path planning for wireless data harvesting with deep reinforcement learning," IEEE Open J. Commun. Soc., vol. 2, pp. 1171–1187, 2021.
[28]. M. Vukićević, M. Ratli, A. Rivenq, and M. Zrikem, "Covering delivery problem with electric vehicle and parcel lockers: Variable neighborhood search approach," Comput. Oper. Res., vol. 157, no. 106263, p. 106263, 2023.
[29]. Y. Tao et al., "A comparative analysis of trajectory similarity measures," GIsci Remote Sens., vol. 58, no. 5, pp. 643–669, 2021.
[30]. B. Albreiki, N. Zaki, and H. Alashwal, "A systematic literature review of student' performance prediction using Machine Learning techniques," Educ. Sci. (Basel), vol. 11, no. 9, p. 552, 2021.

[31]. K. Ogunsina and D. DeLaurentis, "Enabling integration and interaction for decentralized artificial intelligence in airline disruption management," arXiv [cs.AI], 2021.
[32]. Z. Yan, Z. Li, E. Panadero, M. Yang, L. Yang, and H. Lao, "A systematic review on factors influencing teachers' intentions and implementations regarding formative assessment," Assess. Educ., vol. 28, no. 3, pp. 228–260, 2021.
[33]. D. L. Wanzer, "What is evaluation?: Perspectives of how evaluation differs (or not) from research," Am. J. Eval., vol. 42, no. 1, pp. 28–46, 2021.
[34]. G. Skorobogatov, C. Barrado, and E. Salamí, "Multiple UAV systems: A survey," Unmanned Syst., vol. 08, no. 02, pp. 149–169, 2020.
[35]. V. Kangunde, R. S. Jamisola Jr, and E. K. Theophilus, "A review on drones controlled in real-time," Int. J. Dyn. Contr., vol. 9, no. 4, pp. 1832–1846, 2021.
[36]. N. J. Cheung, Z.-K. Xu, X.-M. Ding, and H.-B. Shen, "Modeling nonlinear dynamic biological systems with human-readable fuzzy rules optimized by convergent heterogeneous particle swarm," Eur. J. Oper. Res., vol. 247, no. 2, pp. 349–358, 2015.
[37]. B. Zhu, L. Xie, D. Han, X. Meng, and R. Teo, "A survey on recent progress in control of swarm systems," Sci. China Inf. Sci., vol. 60, no. 7, 2017.
[38]. S. Awasthi, B. Balusamy, and V. Porkodi, "Artificial intelligence supervised swarm UAVs for reconnaissance," in Data Science and Analytics, Singapore: Springer Singapore, 2020, pp. 375–388.
[39]. W. Ren, "Consensus based formation control strategies for multi-vehicle systems," in 2006 American Control Conference, 2006.
[40]. Z. Xia, J. Du, C. Jiang, J. Wang, Y. Ren, and G. Li, "Multi-UAV cooperative target tracking based on swarm intelligence," in ICC 2021 - IEEE International Conference on Communications, 2021.
[41]. X. Li, Y. Yang, and J. Wang, "Active vehicle obstacle avoidance based on integrated horizontal and vertical control strategy," Automatika, vol. 61, no. 3, pp. 448–460, 2020.
[42]. R. Mengacci, G. Zambella, G. Grioli, D. Caporale, M. G. Catalano, and A. Bicchi, "An open-source ROS-Gazebo toolbox for simulating robots with compliant actuators," Front. Robot. AI, vol. 8, 2021.