June 2025 Vo4. Issue No. 01
e-ISSN: 2663-7073
DOI: https://doi.org/10.58921/ijaims.v4i1

Enhancing Agricultural Efficiency with Uav-Aided Smart Irrigation Systems

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Received: 1-02-2025; Accepted: 20-05-2025; Published: 1-7-2025

Abstract

Agriculture faces a critical obstacle: the limited availability of timely, precise data needed for effective decision-making and farm operations. To maximize production, minimize expenses, and increase yields, farmers need immediate access to actionable information. Technology-driven crop management approaches, known as precision agriculture, present transformative opportunities for agricultural stakeholders. Among these technological advances, unmanned aerial vehicles (UAVs) have emerged as innovative instruments that deliver multiple advantages. When outfitted with sophisticated sensors, these aerial platforms can acquire high-resolution imagery, track biological and environmental stress factors, identify pest infestations and plant diseases, and support targeted spraying and pollination activities. UAV applications extend to monitoring livestock, tracking natural resources, and various other functions. Through UAV deployment, farmers obtain vital field and environmental data at significantly lower costs compared to conventional approaches. The substantial data volumes produced by UAVs enable analytical processes that yield practical recommendations, resulting in heightened agricultural output, minimized resource waste, and improved environmental stewardship. This study examines the contemporary application of UAVs in farming contexts, intelligent irrigation technologies, and opportunities for their combined implementation to advance agricultural efficiency and ecological sustainability.

Keywords: Unmanned Aerial Vehicle; Precision Agriculture; Sensor; Smart irrigation, Real-time.

1. INTRODUCTION

Advanced technologies, particularly Unmanned Aerial Vehicles and precision irrigation infrastructure, are driving substantial changes across the agricultural sector.

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These emerging tools have the potential to fundamentally alter farmers' approaches to resource allocation and operational planning, generating improvements in both efficiency and output [1]. Recent years have witnessed growing interest in deploying Unmanned Aerial Vehicles for precision farming applications. UAVs provide an economical and adaptable remote sensing solution, allowing farmers to gather detailed crop and field condition data more frequently and across broader areas than conventional techniques permit [2-3]. Through the deployment of these airborne systems, farmers can make better-informed choices regarding input applications, including water, fertilizers, and pesticides, leading to decreased waste and reduced environmental harm [4-5]. Furthermore, agricultural UAVs provide functionality extending well beyond simple visual field assessment. These platforms can carry diverse sensor arrays to compile extensive datasets encompassing nitrogen content, chlorophyll concentration, biomass measurements, and moisture levels. Machine Learning (ML), a subset of artificial intelligence, proves essential for enhancing soil and crop surveillance, forecasting analysis, and irrigation timing. Training these computational models requires data gathered through soil mapping techniques, imaging devices, sensor arrays, and wireless communication systems.

Advances in wireless sensor networks and data transmission capabilities have generated substantial interest in Internet of Things (IoT) applications for agricultural data gathering and automated irrigation control. UAVs are transforming precision agriculture through real-time data assessment and flexible irrigation management. Nevertheless, widespread implementation of UAV-driven precision agriculture encounters specific obstacles, notably regarding workflow standardization and the synthesis of data collection with image processing procedures [6]. To overcome these barriers, researchers have investigated novel methods for effectively combining UAV-based remote sensing with intelligent irrigation infrastructure [3]. These frameworks utilize real-time data acquisition and evaluation to deliver accurate and responsive irrigation approaches customized to the distinct requirements of specific crop areas [7]. The paper proceeds as follows: Section II examines intelligent irrigation systems in agricultural settings, Section III contrasts traditional irrigation approaches with smart irrigation systems, Section IV explores the components and operational mechanisms of smart irrigation systems, Section V addresses the integration of UAV-supported smart irrigation, Section VI analyzes both advantages and obstacles associated with UAV-assisted smart irrigation systems, and Section VII provides concluding remarks.

2. SMART IRRIGATION SYSTEMS IN AGRICULTURE

In agriculture, the safe and sustainable provision of quality and quantity of crop production is essential for food security and to ensure the success of the agricultural system. Irrigation is one of the solutions to increase agricultural productivity, especially in arid and semi-arid regions of the world. Traditional irrigation methods include flooded, automated, and manual irrigation, among others [8]. However, these methods are becoming less cost-effective and accessible than they once were. The increased use of water and energy for crop production is placing greater agricultural demands on surface and underground sources. Therefore, agricultural irrigation is essential to meet future nutritional needs and to support large populations with higher living standards. Smart irrigation systems are being rapidly developed due to their potential to transform and replace traditional irrigation methodologies [9]. These systems can reduce some of the conventional irrigation limitations and may result in increased crop productivity. Smart irrigation is an optimized irrigation system that reduces cost, chemical use, and water loss [10]. Such optimization may lead to a significant cost reduction for agricultural activities and therefore increase productivity affordability. A typical smart irrigation system comprises some or all of the following components: sensors, cyber-physical systems, a microcontroller, and/or a programmable logic controller, wireless network, cloud computing, fog computing, edge computing, data analytics, controllers, decision support systems, mobile apps, etc. [11]. These systems provide continuous and real-time data required for decision-making; based on the data, controllers initiate and stop the irrigation of the crop. In this way, farmers never need to be present to manage irrigation since the system operates automatically based on the optimization algorithms. This is especially advantageous when a farmer resides far from the land, resides in another county or country, has to attend to other work commitments, or goes through the planting season.

2.1. TRADITIONAL IRRIGATION METHODS VS. SMART IRRIGATION SYSTEMS

Traditional methods of irrigation suffer from some inherent disadvantages, such as inefficiencies, water wastage, reduced effectiveness, and supply quantity mismatch at high costs. In poor agricultural countries, the surface irrigation system remains a technique for cultivation in irrigated agriculture. Though efforts have been made at distributing water properly, there is still scope for improvement [12]. The traditional method of irrigation is mostly through flood irrigation, where about 30–40% of water can be saved. Artificial replenishing methods require more accurate mathematical modeling. The traditional methods are designed to satisfy old water and agricultural needs. Pressures were less wide open in earlier days, and permits were not needed for underground bore wells. The surface method of agriculture was developed by scientists during the late 19th century, and this has continued till now. The method mostly used is manual scheduling of irrigation. Irrigation scheduling is a scientific concept that provides moisture for plant growth. Smart irrigation is an essential application for any country to increase efficiency, save water, and enhance its contribution to the people and the country. Drip irrigation has emerged as the most suitable and acceptable method for irrigation. It requires 30–50% less water compared to flood irrigation. The basic principle of drip irrigation is the frequent application of water at slow rates required for immediate and optimum use by the crop [13]. Smart irrigation systems may be an efficient way to sustain agricultural needs for future generations. For an agricultural-based society, irrigation is an important way of providing water to crops. Sufficient water provision will ensure not only a sufficient amount of food for the table but also sustain economic activity for many societies. These systems have been introduced to increase irrigation application efficiency and sustain economic activities. With this system, human labor requirements can also be reduced, and several additional economic activities can then be pursued. The most common spatial irrigation technology is drip irrigation. Solar photovoltaic (PV) systems offer a sustainable and cost-effective solution for powering agricultural water pumping and irrigation, reducing reliance on fossil fuels and grid electricity. While these systems align with global sustainability goals, their adoption faces challenges such as high initial costs, data management issues, and scalability limitations, especially for small-scale farmers. The study confirms that integrating solar PV technology can enhance resource efficiency, boost agricultural productivity, and minimize environmental impact [14].

Fig. 1. Automation irrigation demonstration in Hart, MI, USA. [15]

2.2. COMPONENTS AND WORKING PRINCIPLES OF SMART IRRIGATION SYSTEMS

Smart irrigation systems are next-generation precision agriculture solutions, engineered to further optimize agriculture through real-time decision-making. The system consists of three main components, which are integrated together to make up an efficient irrigation management controller [16]. The smart irrigation system kicks off immediately when the soil moisture sensor detects a high moisture value, automatically commanding the nodes to close the solenoid valves to stop watering the farm. As a result, the smart irrigation system saves water and energy to irrigate crops. Thus, it guarantees that all the crops are treated with the required amount of water through a monitored irrigation schedule. By encompassing all these stages, the smart irrigation systems are used to optimize the yield production of different kinds of plants, crops, and trees, regardless of the geographical area or the season. The operation of modern smart irrigation systems is entirely based on the use of different sensors and software to process collected environmental data. The soil moisture sensor measures the volume of water in the soil and sends the signal to the controller. Based on the weather conditions like relative humidity, temperature, leaf wetness, soil texture, soil temperature, and other factors affecting soil moisture, an advanced smart irrigation controller system then generates the necessary irrigation strategies. Each component of the smart irrigation system operates according to well-defined principles. The components are often different from system to system and support many additional functions. Following is the working principle of the typical smart irrigation system components.

Components of Smart Irrigation Systems: 1) Sensors collect essential information like soil moisture, soil temperature, salinity, and other parameters that can vary according to the sensor type and the research aim. 2) Data collectors receive and organize data coming from the sensors. Collected data can be stored on-site and off-site [17]. This stage allows avoiding loss of data in case of transmission problems but introduces the risk of handling large amounts of data. 3) Data analytics processes collected data. Through the analysis of the collected information, the system can generate an irrigation schedule. In some applications, sensors and data collectors send data to external data analysis platforms based on subscription fees, databases, and software through internet communication. The data analysis is realized by employing the appropriate model that converts the sensory data into a strategy for scheduling irrigation.

In setting up a smart irrigation system, several factors must be put into consideration. Factors such as: 1. crop type, 2. type of irrigation, 3. farm size, 4. soil topography, 5. size and site of the farm office, 6. volume, number and site of the water tanks, 7. type of soil, soil homogeneity and water holding capacity, 8. type and number of sensors required, 9. sensor placement, 10. sensor node and gateway design or purchase of already-made nodes, 11. choice of actuator and actuator placement, 12. choice of communication technology [18].

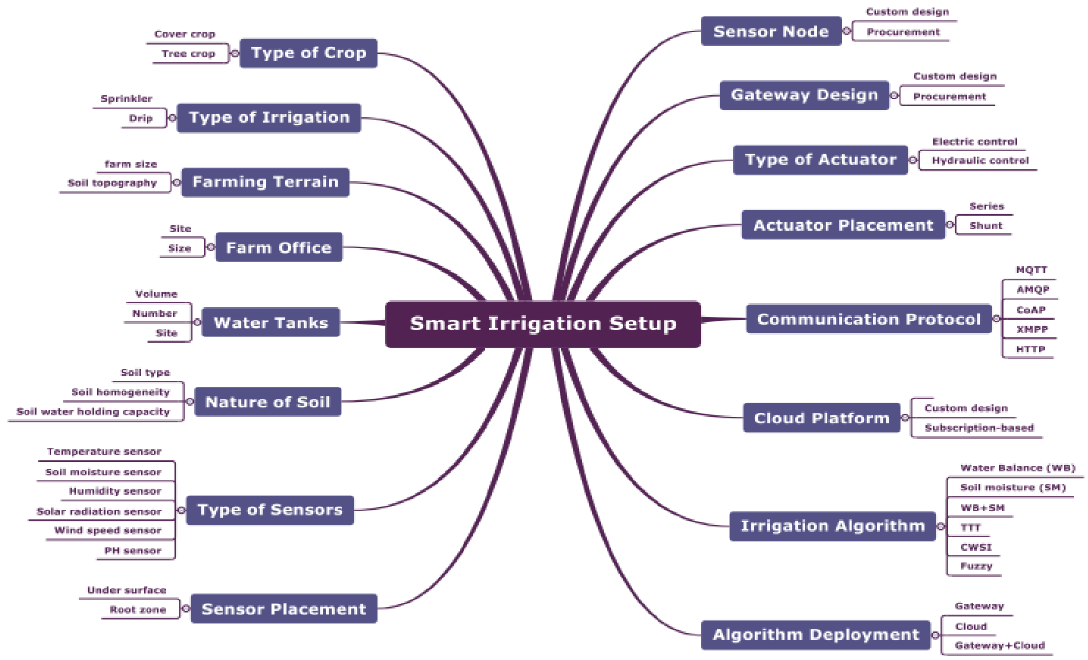

Fig. 2. Points of Consideration in Setting up a Smart Irrigation System [18]

2.3. INTEGRATION OF UAVS IN SMART IRRIGATION SYSTEMS

Smart irrigation systems are simple systems that use field data inputs, such as soil moisture sensor readings and weather forecasts, and apply a little intelligence typically based on rule-based expert systems to inform the irrigation system control with a decision parameter such as when to start or stop irrigating or when and how long to irrigate [19]. Because these systems have the intelligence to make real-time and continuous adjustments to water applications, they are considered to be "intelligent" or "smart." The relationships between UAV photogrammetry and GIS-based interpolated predictions and values gathered from the field are contingent upon the accuracy and resolution of the available data. There are also a number of challenges in using UAVs and smart irrigation in their current form, such as the interoperability of the technologies and the investment costs, including the use of GPS overhead irrigation or in-ground irrigation control. There is also a need for effective training and continuing support for farmers, especially during practice change processes when adopting new technologies such as UAVs and smart irrigation. The integration of UAV-based and sensor-based smart irrigation may be seen as a practical and sustainable application, where the benefits can be directly quantified when water, particularly in the case of fixed sprinkler irrigation, and other resources are being wasted by over irrigation.

UAVs capture spatially detailed vegetation conditions precisely at the point of interest in the field. Moreover, real-time data from UAVs can be used for decision support for adjusting the GPS-based travel speed of drip irrigation equipment and actuators to open or close valves in order to apply variable rates in real time and inform the in-ground or overhead irrigation timing control systems. Hence, when integrating UAV technology with GIS and GPS, we can fully optimize scheduling irrigation in a way that has the potential to improve both yield and the quality of the produce while optimizing water use [19].A typical UAV used in agriculture is depicted in Figure 3.

Fig. 3. Unmanned aerial vehicle platform used in smart farming [20]

3. THE APPLICATION OF UAV TECHNOLOGY IN SMART AGRICULTURE

One of the most significant emerging technologies in smart farming is remote sensing [21]. The incorporation of miniature MEMS sensors into UAVs has significantly increased the attractiveness of drones in agriculture. In 2014, the Massachusetts Institute of Technology (MIT) referred to agricultural UAVs as a green technology in the context of smart farming [22]. Over the past few years, UAVs have proven to be vital in agricultural crop management, and it is anticipated that as UAV technology continues to evolve, its use in smart agriculture will grow further [23]. A systematic review of UAVs' role in smart farming, emphasizing its critical significance and dynamic contribution to precision agriculture are discussed as follows.

UAVs have been utilized in agriculture to tackle various challenges in farm production. In [24], the authors proposed a new method for capturing crops images using UAVs. Their model introduced a technique for aligning 3D point clouds of the field, enabling the reconstruction of 3D crop models to track growth parameters at the plant level. A similar approach was used in [25] to assess the height of maize and sorghum plants in the field. Another innovative method for measuring sorghum crop height through UAVs and 3D model reconstruction was explored in [26], where the authors reported an

RMSE of 0.33 m when comparing average sorghum height data with hand-sampled field measurements. A different issue was tackled by the researchers in [27], who employed UAVs and 3D models to extract the leaf area index (LAI) of soybean plants. The accuracy of the measured LAI was comparable to that of a handheld device ($R^2 = 0.92$) and showed strong correlation with destructive LAI measurements ($R^2 = 0.89$). In [69], the authors mounted a multispectral camera on a multi-rotor UAV to simultaneously capture multispectral imagery and Soil-Plant Analysis Development (SPAD) values for maize, demonstrating that UAV-based multispectral remote sensing is valuable for precision agriculture. Another study in [28] used a UAV equipped with an RGB digital camera to extract vegetation indices based on visible light reflectance to assess crop biomass. A platform for managing farmland crop data gathered by UAVs was presented in [29]. The integration of multi-UAV systems in smart farming holds the potential to revolutionize cultivation practices. Despite the ongoing technological challenges, there has been a noticeable rise in the adoption of multi-UAV systems in agriculture. In [30], the authors developed a multi-UAV system for agricultural use based on a distributed swarm algorithm. They assessed the system's performance and compared the results with those from a single-UAV system, finding that the multi-UAV system outperformed the single-UAV configuration. In [31], an autonomous system using multiple UAVs was introduced for precision agriculture. Furthermore, in [32], the authors combined Particle Swarm Optimization (PSO) with Genetic Algorithms (GA) to tackle the multi-objective optimization problem of mission planning for multi-UAV systems. Their proposed precision farming system employed multiple agents (UAVs) working together to complete complex agricultural tasks while optimizing the use of limited resources. Lastly, the combination of UAVs and unmanned ground vehicles (UGVs) was explored in various agricultural settings in [33]. Smart sensors have also been integrated into precision agriculture through the use of UAVs. In [34], researchers designed a smart flying sensor using UAV technology to measure the volume of grain within a trailer during forage harvesting. A combination of different sensors, including a gas sensor, RGB-D sensor, Adafruit AMG8833 IR thermal camera, and a Raspberry Pi 3B, was utilized in [35] to enhance agricultural drone functionality. This setup was tested during the plowing process, and data analysis was performed using a supervised learning model based on Support Vector Machines (SVM). In [35], a feasibility study explored the use of a safe tiltrotor within specific smart farming applications, employing Remotely Piloted Aircraft Systems (RPAS). Additionally, [36] introduced a novel approach for real-time data processing in smart agriculture. The researchers developed a hyper-spectral UAV platform equipped with advanced processing capabilities, enabling onboard analysis of various vegetation indices. This system was successfully tested in a vineyard field.

Weed detection and management represent one of the most critical and practical uses of UAV technology in smart farming. In [37], a method was developed to integrate low-resolution multispectral images with high-resolution RGB images for identifying weeds in rice fields. By employing three different Neural Networks (NNs), the researchers found that the network delivering the best weed detection performance achieved an M/MGT1 index of 80-108% and an MP2 value of 70-85%. Similarly, in [38], a system was proposed to detect vegetation, extract features, and classify data using the Random Forest (RF) technique to estimate the distribution of crops and weeds in sugar beet fields. Experimental results showed that the system could differentiate between crops and weeds accurately. In [39], the authors utilized a similar machine learning approach as in [40] but applied it to UAV images of sunflower and cotton fields, developing an automated object-based image analysis algorithm. Researchers in [41,42] focused on sugar beet fields to tackle the issue of selective weed treatment in autonomous crop management. They implemented semantic weed classification using multispectral imagery captured by a micro aerial vehicle (MAV), achieving a weed detection F1-score3 of 0.8. Additionally, a new classification system leveraging Convolutional Neural Networks (CNN) was introduced in [43,44] to detect weeds in vegetable fields such as spinach, beet, and bean. By incorporating deep learning and line detection techniques, the system achieved precision rates of 69% for beans, 81% for spinach, and 93% for beets. Lastly, [45-47] presented an innovative weed detection method using RGB images captured by a cost-effective UAV system.

UAV technology has been utilized in smart farming to assess agricultural crops by extracting various vegetation indices. In [48], single-state and multi-temporal vegetation indices (VIs) were employed to forecast grain yield using multi-spectral and digital images captured by UAVs. In [49], UAV-acquired imagery with a multi-spectral sensor was used to analyze the relationship between reflectance and vegetation indices. UAV technology has been applied to estimate key parameters in agronomic wheat crops, including vegetation indices such as NDVI, SVI, GAI, and high-resolution imagery. These methods have been used to predict grain yield [50], monitor wheat breeding in large trials [51], track development stages of winter wheat [52], detect yellow rust disease stress in winter wheat [53], support decision-making for wheat and rapeseed crops [54], and assess plant density in wheat crops [55].

UAV technology has also been applied in smart farming across various agricultural crops for yield management. In [56], UAV-based smart agriculture solutions were employed to address several challenges in palm oil plantations, including disease detection, yield forecasting, pest monitoring, and virtual plantation creation. In [57], a wireless sensor network (WSN) was integrated with a smart UAV platform to conduct real-time measurements affecting grape yield and quality, with the goal of optimizing production efficiency in a cost-effective manner. A novel approach for assisting farmers with automated tools and strategies for analyzing fertilization methods in barley was introduced in [58] In this study, UAVs were used to capture aerial RGB images to estimate nitrogen fertilization and barley yield. A deep convolutional neural network (CNN) was developed to automatically extract critical features from the images, achieving an accuracy of 83% in nitrogen fertilization estimation and showing a strong correlation with low RMSE for yield predictions. Additionally, a deep convolutional neural network was developed for crop yield prediction in [59].

Field-level phenotyping is widely recognized as a significant challenge in enhancing the efficiency of breeding programs. Recent advancements in IoT and UAV technologies are expected to address this challenge in the context of precision farming and phenotyping. For example, researchers in [60] explored the use of UAVs combined with image processing as a method for high-throughput phenotyping, conducting experiments with four different maize varieties. A similar study in [61] focused on evaluating the potential of multi-spectral UAV imagery as a phenotyping tool. In [62], a high-throughput phenotyping framework using unmanned aerial systems (UAS) was proposed for selecting cotton genotypes. The team in [63] assessed UAS-based phenotyping techniques, such as measuring chlorophyll content, nitrogen levels, and leaf area index (LAI) of soybeans, using a fusion of multi-sensor data (including high-resolution RGB, multispectral, and thermal imagery) and advanced machine learning models like Partial Least Squares Regression (PLSR), Support Vector Regression (SVR), and Extreme Learning Machine-based Regression (ELR).

Additionally, in [64], researchers developed a dual-camera UAV platform for high-throughput phenotyping in large soybean breeding fields, applying Random Forest machine learning to analyze crop geometric characteristics, achieving 93% accuracy in classifying soybean maturity. UAV technology has been applied to address more intricate challenges in smart farming. In [65], researchers proposed that UAVs could be used to estimate flower counts, nectar volume, and habitat suitability for honeybees. Since flowers are part of a delicate ecosystem that is difficult to analyze, the authors developed a methodology for assessing flowers in tree plantations, successfully estimating 5.3 million flowers within a one-hectare area. Irrigation management, another complex aspect of smart agriculture, was explored in [66], where UAV-mounted thermal cameras were used to assess soil conditions around sugar beet plants in relation to water usage. The role of pesticides in farming, essential for both crop productivity and environmental impact, was addressed in [67], where researchers developed an algorithm to adjust UAV flight paths during chemical spraying, reducing pesticide and fertilizer waste. Building on this, [68] expanded the algorithm by incorporating meta-heuristics, including Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing, and Hill Climbing, to enhance route adaptation for UAVs. Finally, in [69], a novel solution for bird invasions in rice fields was presented, using a UAV-based system that scares away birds by emitting various distress or predator calls. In [70] a comprehensive framework for designing and integrating solar photovoltaic (PV) energy systems to power water pumping solutions in precision agriculture was presented. The challenges and opportunities associated with sustainable water pumping in agricultural contexts and propose a novel approach that leverages solar energy to address these challenges.

4. BENEFITS AND CHALLENGES OF UAV-AIDED SMART IRRIGATION SYSTEMS

This subsection provides a brief examination of both the advantages and obstacles related to UAV-based smart irrigation systems.

The advantages include:

I. Enhanced Efficiency and Output: Agricultural drones substantially improve operational efficiency and farm productivity. These devices rapidly assess large agricultural zones, detecting problems and facilitating swift responses. This optimized methodology conserves both time and resources, enabling farmers to concentrate on essential activities. Through refined crop surveillance and administration, drones markedly enhance productivity, resulting in greater harvests and diminished losses [71].

II. Evidence-Based Decision Processes: Drones provide farmers with valuable intelligence by gathering critical information about soil characteristics, plant vitality, and meteorological conditions. This intelligence supports evidence-based decision processes, helping farmers make well-informed determinations regarding water application, nutrient management, and pest mitigation. Utilizing drone capabilities, farmers can optimize resource distribution, reduce waste generation, and advance environmentally responsible methods [72].

III. Economic Viability: Drones represent an economically viable approach to farm management, lowering workforce expenses while improving precision. These systems reduce requirements for manual field examinations, conserving both time and materials. Furthermore, drones refine input distribution, decreasing waste and ecological consequences. Farmers implementing drone systems experience notable financial savings and enhanced profit margins [71].

IV. Advanced Crop Oversight: Drones revolutionize crop oversight through detailed imaging and immediate data interpretation. Farmers can detect initial indicators of plant stress, pathological conditions, or pest presence, implementing focused interventions to avoid crop deterioration. Drones additionally facilitate optimal strategies for seeding, water distribution, and harvest operations, producing improved yields and fewer losses [73].

V. Ecological Advantages: Drones encourage environmentally sustainable farming methods, diminishing the ecological impact of agricultural activities. They refine water consumption, reduce chemical usage, and enable targeted farming techniques. Farmers adopting drone systems contribute to ecological preservation, protecting natural assets for subsequent generations. Moreover, drones assist in tracking and reducing climate change impacts, promoting environmentally conscious agriculture [74].

While UAVs provide numerous advantages, their successful deployment presents various concerns requiring consideration. Specifically, several critical challenges demanding immediate attention are outlined in this subsection.

i. Security and Privacy Issues: A principal challenge in agricultural UAV deployment involves ensuring adequate security measures. Safeguarding information against cyber intrusions and preserving privacy throughout UAV activities remains essential. Multiple cyber vulnerabilities can compromise UAVs during operations, including Wi-Fi-related threats such as unauthorized monitoring, denial of service (DoS) incidents, and data manipulation, which can substantially interrupt operations. Multiple research efforts, including [75-77], have documented these attack varieties. Regarding privacy, concerns encompass unauthorized imaging of properties adjacent to farming zones and matters involving surveillance activities. Resolving these problems demands considerable resources. Blockchain frameworks have been suggested as viable solutions for strengthening security [78]. Concerning privacy matters, implementing comprehensive regulatory standards appears to offer a feasible strategy, although supplementary solutions warrant exploration.
ii. UAV Technology Integration: Technology effectiveness depends substantially on user acceptance. Implementing sophisticated systems like UAVs requires particular expertise and comprehension. Farmers possessing limited or absent technical abilities face considerable difficulties in UAV operation. Furthermore, new technology integration depends heavily on user preparedness and enthusiasm for adoption. Requirements for specialized operational knowledge may discourage farmers with restricted experience, consequently affecting their inclination to integrate this technology into agricultural workflows [75].
iii. Substantial Investment Requirements: Initial acquisition expenses for UAVs, encompassing necessary elements like sensing equipment and computational programs, can be substantial. Farmers operating with constrained financial resources may find costs exceeding anticipated benefits. Furthermore, damage to UAV systems or components could generate significant expenditures for restoration or replacement [75].
iv. Limited Flight Duration: UAVs typically possess restricted battery capacity, with operational periods ranging from minutes to approximately one hour. This limitation constrains their ability to monitor expansive agricultural regions during individual flights. Additionally, operational range is confined to specific distances, requiring frequent recharging or battery replacement, potentially diminishing effectiveness across extensive farming operations.

5. CONCLUSION

Incorporating Unmanned Aerial Vehicles (UAVs) into smart irrigation frameworks represents a transformative development for agriculture, providing multiple advantages including improved accuracy, diminished waste generation, and enhanced environmental sustainability. However, this technology introduces obstacles concerning investment requirements, operational complexity, and regulatory adherence. Successful deployment of UAV-supported smart irrigation frameworks requires farmers and stakeholders to commit resources toward education, technological infrastructure, and regulatory compliance. Notwithstanding these obstacles, UAV integration possesses the capacity to reshape agricultural practices, rendering them more efficient, environmentally sustainable, and productive.

ACKNOWLEDGEMENT
This research is sponsored by TETFUND under the National Research Fund NRF2020/SETI/11.

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