ADVANCING PRECISION AGRICULTURE WITH UAV'S: INNOVATIONS IN FERTILIZATION
/
PROGRESUL AGRICULTURII DE PRECIZIE CU UAV-URI: INOVAȚII ÎN FERTILIZARE

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DOI: https://doi.org/10.35633/inmateh-74-89

Keywords: *drone, precision, agriculture, crop, plating, health, UAV*

ABSTRACT
Unmanned Aerial Vehicles (UAVs) are revolutionizing precision agriculture, particularly in the domain of fertilization. Equipped with advanced sensors, mapping tools, and variable-rate application systems, drones enable farmers to precisely distribute fertilizers based on field variability. This targeted approach reduces waste, minimizes environmental impact, and optimizes crop yield. The integration of technologies such as multispectral imaging and AI-driven decision-making systems further enhances efficiency by allowing real-time assessment of soil and crop conditions. Despite their numerous advantages, challenges such as high costs, regulatory limitations, and technical scalability remain key barriers to widespread adoption. This article explores the innovations UAVs bring to precision fertilization, their benefits, and the obstacles hindering their broader application in agriculture.

REZUMAT
Vehiculele Aeriene Fără Pilot (UAV-uri) revoluționează agricultura de precizie, în special în domeniul fertilizării. Echipate cu senzori avansați, instrumente de cartografiere și sisteme de aplicare cu rată variabilă, dronele permit fermierilor să distribuie fertilizanții cu precizie, în funcție de variabilitatea terenului. Această abordare țintită reduce risipa, minimizează impactul asupra mediului și optimizează randamentul culturilor. Integrarea tehnologiilor precum imagistica multispectrală și sistemele de luare a deciziilor bazate pe inteligență artificială îmbunătățește eficiența prin evaluarea în timp real a condițiilor solului și ale culturilor. În ciuda numeroaselor avantaje, provocările precum costurile ridicate, limitările reglementărilor și scalabilitatea tehnică rămân bariere semnificative în calea adoptării pe scară largă. Acest articol explorează inovațiile aduse de UAV-uri în fertilizarea de precizie, beneficiile acestora și obstacolele care împiedică aplicarea lor extinsă în agricultură.

INTRODUCTION
The rapid growth of global agriculture demands innovative solutions to improve productivity, optimize resource usage and reduce environmental impacts. Traditional agricultural practices, especially in fertilization, often face challenges such as overuse of fertilizers, uneven application, labor shortages, and inefficiency in large-scale farming operations. To address these issues, smart agriculture, driven by advanced technologies, is emerging as a transformative approach to modern farming (*Subeesh et. al., 2021)*.

Drones, also known as Unmanned Aerial Vehicles (UAVs), have become a pivotal tool in smart agriculture due to their versatility, cost-effectiveness, and ability to perform precision-based tasks (*Zhou et. al., 2024)*. When integrated with technologies such as Global Positioning Systems (GPS), remote sensing, and artificial intelligence (AI), drones can revolutionize fertilization practices. They enable precise delivery of fertilizers, monitor crop health, and reduce waste, thereby enhancing yields and promoting sustainable farming (*Zhou et. al., 2023)*.

This review explores the role of drones in fertilization within smart agriculture systems. It discusses the technologies involved, benefits, challenges, and future trends. The integration of drone technology for fertilization not only ensures efficient use of agricultural inputs but also contributes to reducing environmental degradation and improving food security.

The global demand for food is steadily increasing due to population growth, which necessitates more efficient and sustainable agricultural practices (*Gokool et. al., 2024)*. Smart agriculture, driven by advancements in technology, aims to optimize farming processes (*Van Klompenburg et. al., 2020)* by integrating tools such as sensors, data analytics, and unmanned aerial vehicles (UAVs), commonly known as drones. Drones have emerged as a versatile solution for precision farming, offering applications in crop monitoring, irrigation management, and fertilization (*Singh et. al., 2024)*.

Smart agriculture, or precision agriculture, uses advanced technologies like sensors, GPS, drones, and AI to optimize farming practices. By collecting real-time data on factors such as soil moisture, crop health, and weather, farmers can make more informed decisions about irrigation, fertilization, pest control, and harvesting (*Eckert et. al., 2024)*.

This approach enhances farm efficiency, reduces waste, and minimizes environmental impact by applying resources like water and fertilizers precisely where needed. It also supports sustainability by lowering resource use while maintaining or increasing crop yields (*Tanaka et. al., 2024)*. Automation and robotics further improve productivity and reduce labor costs. Also, technologies like remote sensing, enhanced by cloud-based server-side processing of high-resolution satellite imagery, and Big Data analytics platforms such as Google Earth Engine (GEE), along with uncrewed aerial vehicles (UAVs), have significantly improved the ecological monitoring of natural habitats (*Tripathi et. al., 2024)*.

According to the International Society of Precision Agriculture (ISPA), precision agriculture is an approach to agricultural management that utilizes technology and agricultural data to enhance the quality, sustainability, and productivity of farming (*Zualkernan et. al., 2023)*.

Bhat et. al., 2021, talks about achieving sustainable agricultural production, mentioning that the agriculture sector must adopt advanced technologies such as blockchain, IoT, and (AI *Shadrin et. al., 2019)*. With the progression of 6th generation (6G) communication (*Sitharthan et. al. 2023)*, new demands are emerging for integrated sensing and communication (ISAC) (*Htun et. al. 2024)*. Sensing improves communication accuracy by detecting nearby objects and delivering real-time feedback on relevant environmental information (*Li et. al., 2024)*.

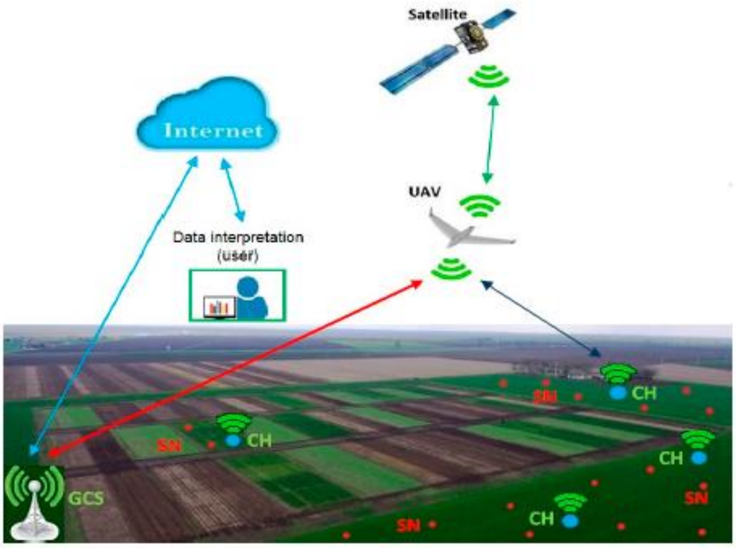


Fig. 1 - Concept of the integrated UAV
(Popescu et. al., 2020)

As global food demand rises and resources like water and arable land become scarcer, there is an urgent need for efficient, sustainable agricultural practices (*Sharma et. al., 2020)*. Smart agriculture, or precision farming, uses technologies like sensors, GPS, drones, and AI to optimize crop management (*Andreasen et. al., 2022)*. This approach helps farmers use resources more efficiently, reduce waste, and minimize environmental impact (*Yang et. al., 2024)*. By providing real-time data on soil conditions and crop health, smart agriculture enables precise irrigation, fertilization, and pest control, improving yields and sustainability (*Kumar et. al. 2023)*. In the face of resource limitations and environmental challenges, smart agriculture is key to meeting food demand while protecting the planet (*Chiu et. al., 2024)*.

Ali et. al., 2008, discusses the importance of water productivity, emphasizing its critical role in sustainable agricultural practices. By addressing factors such as soil quality, crop type, irrigation techniques, and climate conditions, the paper identifies opportunities to enhance water efficiency (*Yang et. al., 2020)*. The importance of improving water productivity lies in its potential to increase food production, conserve water resources, and ensure agricultural sustainability in the face of growing global water scarcity and demand (*Chen et. al., 2023)*.

To improve agricultural productivity and food management, there is an urgent need for precision agriculture monitoring on a larger scale (*Murugan et. al., 2017)*.

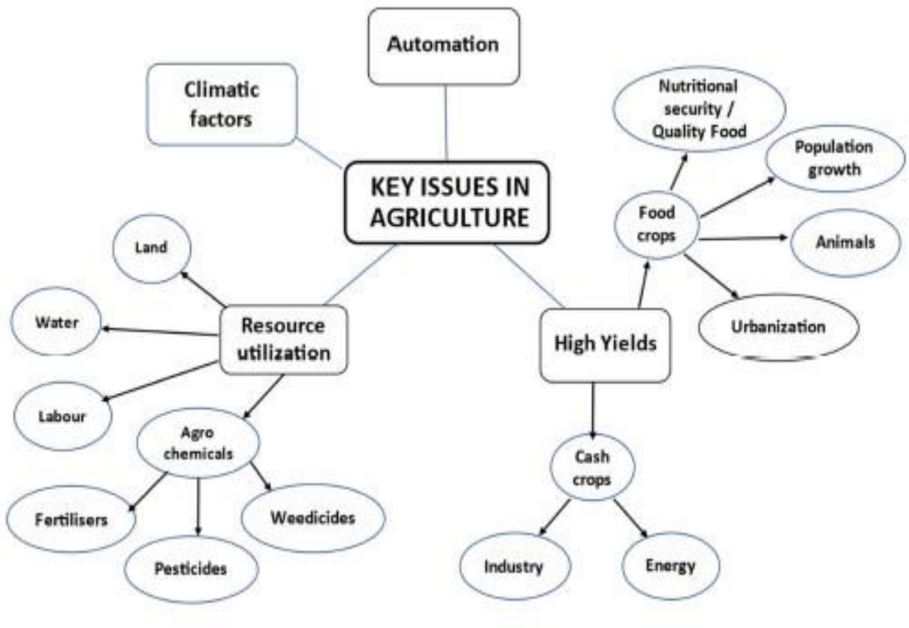


Fig. 2 - Key issues in Agriculture
(*Dhanaraju et. al., 2022*)

In the agricultural context, *Canicattì et. al., 2024*, says that vegetables play a vital role as protective foods, offering essential nutrients to the human diet. They are rich in vitamins, fibers, minerals, and nutraceuticals, contributing significantly to overall health and well-being.

Gokool et. al., 2023, talks about precision agricultural practices supported by unmanned aerial vehicles. UAVs have gained significant traction in the agricultural sector and hold great potential for applications on smallholder farms (*Albetis et. al., 2019)*.

Drones, or Unmanned Aerial Vehicles (UAVs), are transforming precision agriculture by providing farmers with innovative tools for field management (*Caballero et. al., 2024)*. Equipped with advanced sensors and cameras, drones capture real-time aerial data, allowing farmers to monitor crop health, detect pests, and assess irrigation needs (*Rejeb et. al., 2022)*.

Drones also enable precise application of fertilizers, pesticides, and herbicides, reducing waste and environmental impact (*Yacoob et. al. 2024)*. By targeting specific areas (*Dou et. al., 2023)*, they help optimize resource use, improve yields, and lower costs. UAV systems represent, in most cases, the most efficient option to reach the inaccessible portions of the objects, providing a complete coverage of the infrastructure to be monitored (*Massimo et. al., 2024).*

Dronova et. al., 2021, talks about the fact that UAVs have become valuable tools in the global remote sensing community, functioning as small, flying robots capable of accessing hazardous or remote areas *(Lee et. al., 2024)*. They capture high-resolution imagery and support environmental monitoring and research (*Couturier et. al., 2021),* spanning broad applications like agricultural management to specialized fields such as marine mammal behavioral ecology. UAVs are particularly advantageous for environmental monitoring (*Shahi et. al., 2022), (Shahi et. al., 2023)* as they overcome constraints in complex, dynamic, and limited-access environments that have traditionally been difficult to survey (*Ming et. al., 2024)*. Additionally, UAVs reduce the time and labor required for ground-based surveying and sampling, allowing for more focused managerial activities, such as restoration assessments, that might otherwise be neglected (*Pereira et. al., 2024)*.

UAVs provide high operational efficiency, excellent adaptability to various terrains, and safe applications (*Nahiyoon et. al., 2024)*.

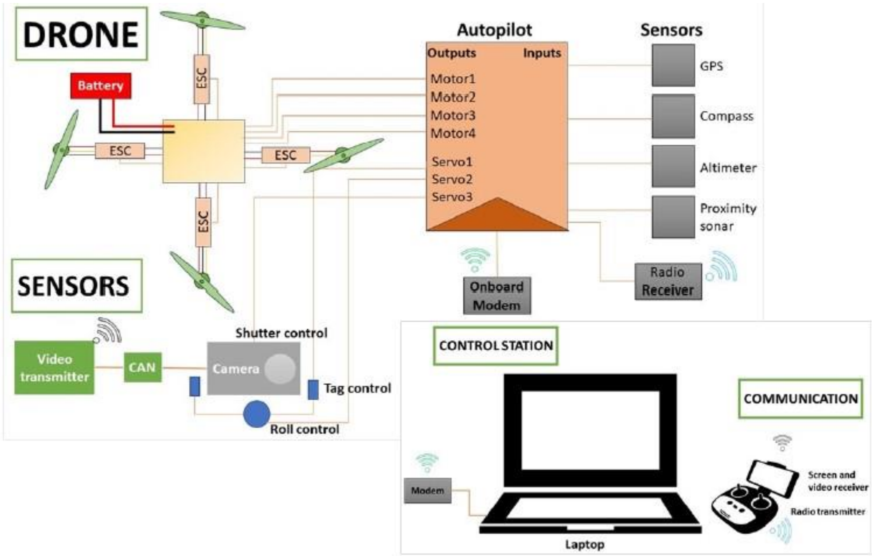


Fig. 3 - Block diagram of a drone system
(*Guebsi et. al., 2024*)

UAVs are already established across various fields (*Khan et. al., 2021)*, and their market is projected to grow to $200 billion in the coming years. Yamaha introduced its first UAV model, the Yamaha RMAX, designed for crop monitoring and pest control; however, production was discontinued in 2007 (*Castro et. al., 2023).* They developed a spray system integrated into a UAV platform, resulting in an autonomous spraying system used for pest management and vector control. Additionally, a Pulse Width Modulation (PWM) controller was implemented for UAV precision agriculture sprayers, enabling the UAV to be remotely controlled or operated autonomously through preprogrammed flight plans (*Buters et. al., 2019)*.

Fertilization plays a fundamental role in enhancing crop productivity and maintaining soil fertility (*Yuan et. al., 2024)*. However, traditional fertilization methods often lead to inefficiencies, including excessive fertilizer use, environmental pollution, and increased costs. Precision fertilization, enabled by drone technology, aims to address these issues by delivering the right amount of nutrients to crops in a targeted manner (*Niu et. al., 2024)*.

Currently, there is excessive use of fertilizer and inadequate uniformity in the fertilizer distribution in corn fertilizer planters (*Wang et. al., 2022)*.

Fertilization is essential for boosting crop yields by providing key nutrients like nitrogen, phosphorus, and potassium. These nutrients support plant growth, resulting in higher productivity and better-quality crops (*Hasan et. al., 2020)*.

However, improper fertilization can harm soil health (*Scherrer et. al., 2019)*. Overuse can lead to nutrient imbalances, soil degradation, and environmental issues like water pollution. Balanced and precise fertilization, based on soil testing, helps avoid these problems while maintaining soil fertility (*Kannan et. al., 2024)*.

Chebrolu et. al., 2018, talks about the automated crop monitoring being a crucial component of precision farming, enabling farmers to make informed decisions about when, where, and how much fertilizer or pesticide to apply *(Pu et. al., 2015)*. It also enhances yield estimation, contributing to improved efficiency and productivity in agricultural practices.

Esposito et. al., 2021, talks about precision agriculture utilizing technologies that integrate sensors, information systems, and data-driven management practices to enhance crop productivity while minimizing environmental impact. Nowadays, precision agriculture has diverse applications across various agricultural contexts, including pest control, fertilization, irrigation, sowing, and harvesting.

The knowledge of plant nutrient requirements and the use of inorganic fertilizer allow an increase in crop production (*Farias et. al., 2020)*.

However, as drones began to be utilized in crop management (*Valente et. al., 2013)*, challenges emerged regarding the standardization of operational parameters, such as height, speed, nozzle type, angle, flow rate, and spray width, as well as issues related to application drift and the type of agrochemicals used (*Martínez-García et. al., 2023)*. To address these challenges, advanced precision technologies have been incorporated into drones for crop spraying, enhancing efficiency across multiple areas *(García-Munguía et. al., 2024)*.

Drones equipped with advanced technologies, such as GPS, multispectral cameras, and variable-rate application systems, enable precision fertilization by delivering nutrients directly to targeted areas (*Huang et. al., 2024)*. This approach not only enhances fertilization accuracy but also reduces input costs and minimizes the environmental footprint, making it an attractive solution for modern agriculture (*Carreño et. al., 2024)*.

a) b)

Fig. 4 - DJI Multispectral drones

(*Panday et. al., 2020)*

(a) DJI P4 senseFly eBee SQ (https://www.dji.com/global/support/product/p4-multispectral), (b) fixed-wing drone (https://www.senseflу.com/solutions/drones/)

a) b)

Fig. 5 - DJI M600 Pro

(*Panday et. al., 2020)*

Khanal et. al., 2017, states that precision agriculture (PA) leverages advanced tools and technologies to detect variability in soil and crops within fields, aiming to enhance farming practices and optimize the use of agronomic inputs. Traditionally, optical remote sensing (RS), which uses visible light and infrared regions of the electromagnetic spectrum, has been a key component of PA for monitoring crops and soil conditions (*Huang et. al. 2024)*. The use of agricultural drones not only helps reduce production costs but also boosts crop yields by minimizing losses during cultivation (*Zhichkin et. al., 2023)*.

This review aims to assess the application of drones in smart agriculture for fertilization, focusing on the technologies and methods utilized in drone-based fertilization, the efficiency and precision of these systems compared to traditional approaches, the environmental and economic benefits they offer, as well as the challenges and opportunities for future advancements.

MATERIALS AND METHODS

After full-text analysis, 80 studies were included in this review based on their relevance to drone-based fertilization in agriculture.

From the selected studies, data on drone type and sensor technologies, fertilization methods, operational efficiency, and case study results were extracted. Findings were organized into categories such as technological advancements, application accuracy, and environmental impacts. A qualitative synthesis of the findings was performed, focusing on recurring trends, technological improvements, and challenges in drone-based fertilization. Quantitative data, such as coverage efficiency and cost savings, were extracted for comparative analysis.

Data on drone types and sensor technologies

The DJI Phantom 4 Multispectral is a specialized drone designed for precision agriculture and environmental monitoring. It combines DJI's reliable drone technology with a multispectral imaging system to provide accurate data on crop health, soil condition, and vegetation analysis.

Fig. 6 - DJI Phantom 4 Multispectral
(Dong et. al., 2024)

DJI A3 System is a high-performance flight controller designed for professional drones, particularly in industrial applications, aerial photography, and custom drone builds. It provides advanced flight control, stability, and customization options for multirotor platforms

Fig. 7 - 6-rotor drone and spreading device controlled by DJI A3 system
(Han et. al., 2024)

The DJI Phantom 4 Pro is widely preferred in agriculture due to its compact design, affordability, and advanced features that make it ideal for various farming tasks.

Although the DJI Inspire 1 is less commonly used in routine agricultural operations compared to the Phantom 4 Pro, it remains valuable for specialized applications that require more advanced capabilities.

Fig. 8 - DJI Drones *(Messina et. al., 2020)*
(a) DJI Phantom 4 pro (b) DJI Inspire 1

Tabel 1

Features DJI Phantom 4 pro and DJI Inspire 1

Feature	**DJI Phantom 4 Pro**	**DJI Inspire 1**
Camera	20 MP, 1-inch sensor, 4K at 60 fps	4K camera with Zenmuse X3 or X5 gimbal (interchangeable lenses)
Flight Time	30 minutes	18-20 minutes
Speed	45 mph (72 km/h)	50 mph (80 km/h)
Flight Range	OcuSync (up to 4.3 miles or 7 km)	Lightbridge (up to 1.2 miles or 2 km)
Obstacle Avoidance	5 sensors (front, rear, downward)	Front and downward sensors only
Dual Control	No	Yes, dual operator control (pilot + camera operator)
Intelligent Flight Modes	ActiveTrack, TapFly, Return-to-Home	Follow Me, Waypoints, Point of Interest
Camera Control	Fixed camera	Interchangeable lenses with high control over the camera
Best For	General crop monitoring, field mapping, surveying, precision agriculture	Advanced inspections, professional-grade mapping, specialized tasks

Fig. 9 - Fixed-wing Drones
(Radoglou-Grammatikis et. al., 2020)

a) Fixed-wing UAVs b) Rotary-wing UAVs

Tabel 2

Key differences between fixed-wing UAVs and rotary-wing UAVs

Aspect	**Fixed-wing UAVs**	**Rotary-wing UAVs**
Lift Mechanism	Lift generated by fixed wings during forward flight	Lift generated by rotating blades/rotors
Takeoff & Landing	Requires a runway or launch method (except VTOL models)	Vertical takeoff and landing (VTOL)
Flight Duration	Longer flight times due to higher efficiency	Shorter flight times due to energy-intensive hover
Speed	Faster, suitable for long-distance travel	Slower, more maneuverable
Maneuverability	Less maneuverable, limited to forward flight	Highly maneuverable, can hover and move in any direction
Applications	Long-range surveying, mapping, agriculture	Aerial photography, inspections, search and rescue

Sensor technologies

UAVs rely on advanced sensors to capture important data for various applications. Four key types of sensors used by UAVs include thermal, RGB, multispectral, and hyperspectral sensors.

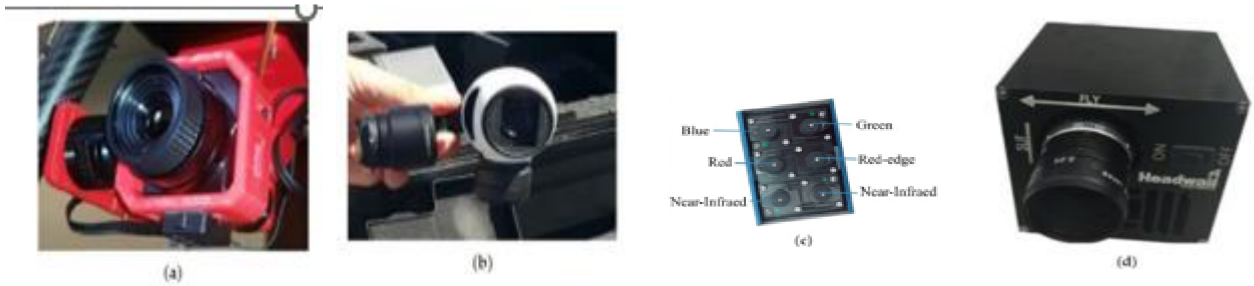


Fig. 10 - Examples of sensors used by UAVs
(*Tsouros et. al., 2019)*
(a) thermal sensor, (b) RGB sensor, (c) multispectral sensors (d) hyperspectral sensor

Seeding methods

Fig. 11 - Seed metering device for aero sowing of forest pelleted seeds
(Lysych et. al., 2021)

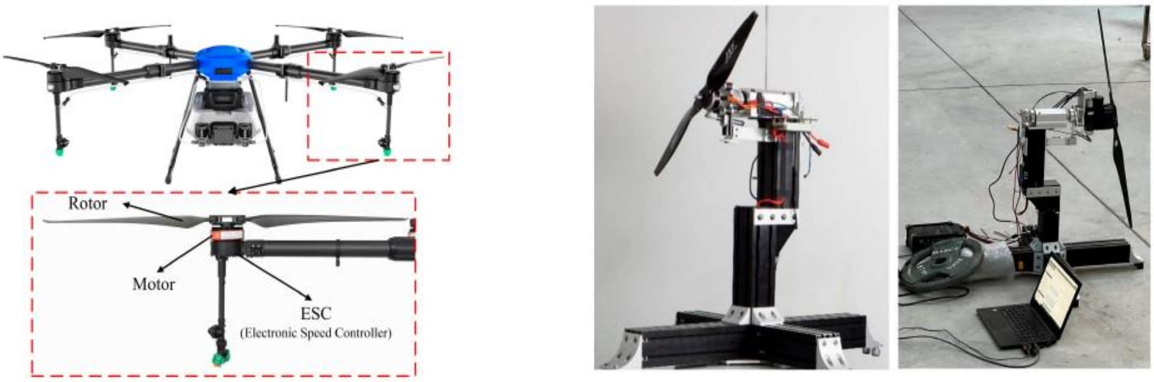
In this paper, *Lysych et. al., 2021,* studied the design and simulation of a precision seed metering device tailored for aero sowing forest pelleted seeds. The system is developed to address the challenges of reforestation in difficult-to-access areas by leveraging drone technology. The seed metering device integrates advanced components, including a rotary seed metering mechanism, precise release systems, and simulation models to ensure uniform seed distribution. The design focuses on achieving optimal sowing accuracy, minimizing seed waste, and adapting to diverse terrain conditions. Results from simulations validate the system's efficiency, highlighting its potential for sustainable reforestation and ecological restoration efforts. This system uses balls with seed and fertilizer to help the seed develop.

Fig. 12 - Spraying system reservoir developed
(*Barcelos et. al., 2024)*

Case Study Results

Han et. al., 2024, studied the development of a rotor speed prediction model for multi-rotor unmanned aerial spraying systems (UASS) which enhances the efficiency and effectiveness of agricultural spraying. By predicting rotor speed based on real-time flight speed and payload, the system ensures stable flight and optimal spraying conditions. The study highlights the importance of matching rotor speed with the UASS load to optimize power consumption, performance, and reliability.

It also emphasizes the impact of rotor speed on the downwash field, which affects droplet deposition and spray effectiveness. Using a neural network for the prediction model demonstrates the potential of machine learning in precision agriculture, enabling real-time monitoring, adjustments, and improved operational efficiency, ultimately reducing waste and increasing crop yields.



a) b)

Fig. 13 – Rotor speed prediction model for multi-rotor unmanned aerial spraying systems

(*Han et. al., 2024)*

a) TopXGun F16 b) UAV power system test platform

The rotor speed prediction model, developed using a neural network with real-time flight speed and payload as inputs, showed strong accuracy with correlation coefficients (R^2) of 0.728, 0.719, and 0.726 for training, validation, and test sets, respectively. A quadratic relationship between rotor speed and thrust was established, with a fitting parameter (R^2 > 0.999), indicating excellent alignment with test data. Under full-load conditions, the single-axis load capacity reached 50% of its maximum, increasing by over 75.83% compared to the no-load state, significantly affecting rotor speed and system performance. The model accurately predicted rotor speed, aligning well with theoretical calculations and test results. This study provides a reliable foundation for optimizing UASS performance and efficiency during continuous operation.

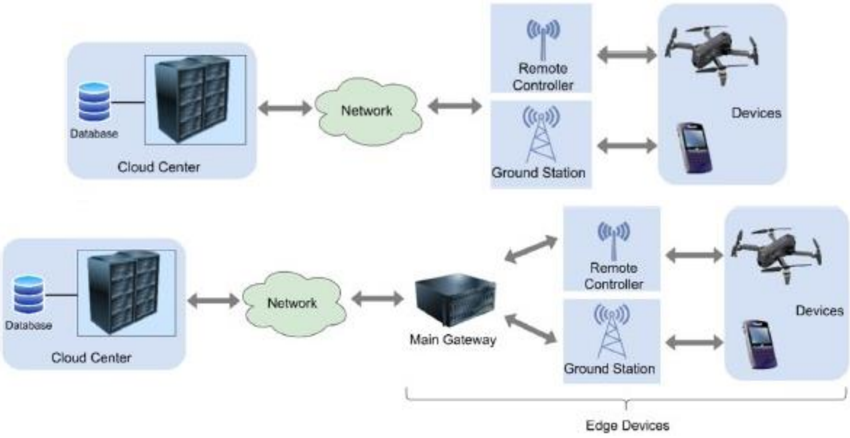
Jibon et. al., 2023, demonstrates that the use of an autonomous UAV greatly reduces the time and labor required for seed planting and fertilizer distribution. By operating without constant human intervention, the UAV ensures precise application, optimizing resource use and improving crop yields while minimizing waste. Equipped with ArUco markers and a computer vision-based control system, the UAV can navigate autonomously, enhancing its range and effectiveness. Automation of these processes reduces overall costs, making farming more economical, especially for small-scale farmers. Additionally, precise seed and fertilizer application reduces environmental impact, supporting sustainable farming practices. The UAV system is scalable and adaptable to different crops and field conditions, making it suitable for both small and large-scale agricultural operations.

a) b)

Fig. 14 – System hardware architecture and autonomous flight plan

(*Han et. al., 2023)*

Liu et. al., 2021, study highlights the use of small fixed-wing and rotor-wing UAVs in precision agriculture, equipped with sensors to capture high-resolution images for monitoring crop health, detecting pests, and optimizing field practices. Deep learning (DL) techniques like CNNs and RNNs enable tasks such as crop classification, weed detection, and growth monitoring. The study emphasizes edge intelligence, combining AI with edge computing for real-time data processing on UAVs and IoT devices, reducing latency and bandwidth issues. Techniques like parameter pruning and quantization optimize DL models for resource-limited edge devices. It also provides UAV-based remote sensing datasets for validating DL methods and suggests future research on advanced DL models, multi-source data integration, and improved edge intelligence to enhance precision agriculture scalability and performance.



a)
b)

Fig. 15 - The use of small fixed-wing and rotor-wing UAVs in precision agriculture
(*Liu et. al., 2021)*
a) Cloud computing paradigm b) Edge computing paradigm for UAVs RS

Studies on precision agriculture highlight the benefits of integrating advanced technologies like GPS, remote sensing, and wireless sensors for real-time monitoring and data collection, enabling informed decisions on fertilization and irrigation (*Lu et al., 2022).* These technologies, along with variable rate technology (VRT), help optimize resource use, improve crop health, and reduce costs. Similarly, UAV-captured multispectral images can effectively estimate nitrogen concentration, uptake, and the nitrogen nutrition index (NNI) in grass seed crops, with NDRE and CIRE indices showing the best performance for predicting nitrogen status *(Wang et al., 2019).*

Research by *Xu C. et al., 2017,* found that increasing planting density boosted grain yield by 7% and improved nitrogen use efficiency by enhancing nitrogen remobilization, while reducing N2O emissions and greenhouse gas intensity by 61.5% and 46.2%, respectively. Additionally, *Xue X. et al., 2024,* identified that sampling point height significantly affected droplet deposition rate, with UAV flight height and particle size having minimal impact. They used machine learning methods to predict droplet deposition and drift, with ELM showing the best prediction accuracy. The study also employed grid atomization technology to optimize droplet size, reducing drift and improving deposition for more effective spraying.

Fig. 16 - Spraying operations of the plant protection drone (*Yu et. al., 2023)*
a) XAG V40; b) DJI T30 six-rotor electric; c) Knapsack Electric Sprayer

Yu et. al., 2023, found that increasing spray volume from 60 L/ha to 120 L/ha significantly improved droplet density, coverage, and uniformity in the citrus canopy. The XAG V40 drone achieved 18.7–41.7 droplets/cm² with an 87.8% increase in coverage, while the DJI T30 reached 146.0–205.3 droplets/cm², with better penetration, particularly in the lower and middle canopy layers.

Droplet distribution uniformity improved, with the coefficient of variation decreasing by 22.0% for the XAG V40 and 26.8% for the DJI T30. In contrast, the knapsack electric sprayer (2400 L/ha) showed higher droplet density in the lower canopy but less uniform coverage (40.3%–42.4%).

RESULTS

A qualitative synthesis of the findings was performed, focusing on recurring trends, technological improvements, and challenges in drone-based. Quantitative data, such as coverage efficiency and cost savings, were extracted for comparative analysis.

This graph displays the qualitative analysis results for using drones in smart agriculture for fertilization. Each factor is rated on a scale from 1 to 5, with **efficiency, environmental impact, precision, and resource optimization** achieving the highest scores. Cost savings and scalability also show strong performance, highlighting the overall benefits of drones in precision fertilization.

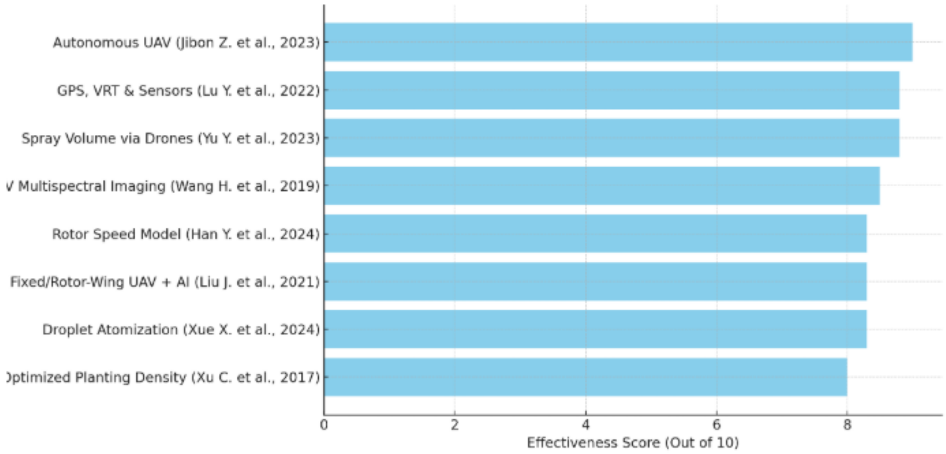


Fig. 17 - Comparative analysis for the case studies

The next table provides a comprehensive comparison of 8 UAVs used for liquid fertilizers application based on essential features such as payload capacity, spray efficiency, power source, battery life, spraying system, navigation, obstacle avoidance, durability, ease of use, and cost.

Tabel 3

Comprehensive comparison of 8 UAVs used for liquid fertilizers

Feature	DJI Agras T30	XAG P100 Pro	TTA M6E	Yamaha Fazer R	Hylio AG-122	EAVision EAV-10	Walkera VITUS AG 18	Agribotix Hornet
Payload Capacity	30L	40L	16L	20L	20L	10L	18L	10L
Spray Efficiency	40 ha/day	16 acres/hour	Moderate	High	Moderate	Low	Low	Moderate
Power Source	Electric	Electric	Electric	Gas	Electric	Electric	Electric	Electric
Battery Life	~25 min	~20 min	~20 min	1-2 hours (gas tank)	~22 min	~25 min	~15-20 min	~25 min
Spraying System	High-precision, variable-rate spraying	Smart modular system	Smart flow control	Customizable nozzles	Autonomous sprayer	Target-specific sprayer	Targeted sprayer	Multi-purpose system
Navigation System	RTK GPS + AI mapping	RTK GPS + Wind Resistance	RTK GPS	Standard GPS	Fully autonomous GPS	Binocular vision + GPS	GPS	GPS
Obstacle Avoidance	Advanced (AI sensors)	Moderate	Basic	None	Moderate	Terrain sensing	Basic	Basic
Durability	Rugged and durable	Rugged and modular	Medium	High (gas-powered)	Medium	Designed for slopes	Compact	Medium
Ease of Use	User-friendly	Modular and flexible	Simple interface	More complex to operate	Very user-friendly	Plug-and-play design	Easy to operate	Easy to configure

Feature	DJI Agras T30	XAG P100 Pro	TTA M6E	Yamaha Fazer R	Hylio AG-122	EAVision EAV-10	Walkera VITUS AG 18	Agribotix Hornet
Cost approx.	High	High	Medium	High	Medium-high	Medium	Low	Medium

Observations:

Agricultural drones vary in payload, efficiency, durability, ease of use, specialization, and precision, catering to different farming needs. High-payload models like the XAG P100 Pro and DJI Agras T30 excel in large-scale operations, while specialized options such as the EAVision EAV-10 and Walkera VITUS AG 1 handle unique terrains, gas-powered drones like the Yamaha Fazer R ensure endurance, user-friendly models like Hylio AG-122 suit small farmers, GPS + RTK-equipped drones like Hylio AG-130 offer precision, and ground-based alternatives like the XAG R150 serve specific terrains, all optimizing fertilizer application, reducing waste, and enhancing efficiency.

Tabel 4

Versatility of drones in spreading solid fertilizers

Feature	DJI Agras T30	DJI Agras T40	XAG P100	XAG R150	Kisan Drone	Hylio AG-130	HSE Endurance	Yamaha RMAX	Krishna Drone	Drone AG Spreader
Payload Capacity (Kg)	30	40	60	60	10	25	20	28	15	10
Flight Time (Minutes)	20-25	25-30	30	Ground-based	15-20	25	30	90	15	20
Application Width (m)	7-9	10	10-12	Ground-based	5-8	8	7-8	6	5	6-8
Navigation System	GPS + RTK	GPS + RTK	GPS + RTK	GPS	GPS	GPS + RTK	GPS + RTK	GPS	GPS + Manual	GPS
Battery Type	Lithium-ion	Lithium-ion	Lithium-ion	Lithium-ion	Lithium-ion	Lithium-polymer	Lithium-ion	Combustion	Lithium-ion	Lithium-ion
Cost (USD)	~18,000	~20,000	~25,000	~30,000	~12,000	~18,000	~20,000	~80,000	~10,000	~15,000

CONCLUSIONS

The use of drones in smart agriculture for fertilization represents a significant advancement in agricultural technology, revolutionizing how farmers approach resource management. Drones equipped with advanced sensors and precision tools allow for the accurate application of fertilizers, ensuring that the right amount of nutrients is delivered to crops at the right time and place. This precision not only leads to higher crop yields but also helps reduce the overuse of fertilizers, minimizing environmental damage such as nutrient runoff and soil degradation.

This paper considers that the integration of drones in fertilization is a game-changer for modern agriculture, offering unparalleled precision and efficiency. The ability to monitor crop health and soil conditions in real time allows for targeted fertilizer application, reducing waste and maximizing productivity. From our perspective, this data-driven approach not only optimizes resource allocation but also improves farm profitability, making it a valuable tool for farmers of all scales.

Drones provide a **practical and scalable solution** for both small and large farming operations. Their autonomous capabilities **reduce labor costs and enhance efficiency**, while their adaptability to different crops and terrains makes them a versatile asset in agriculture. In our experience analyzing agricultural innovations, drones stand out as one of the most effective ways to **modernize and streamline fertilization practices**.

Furthermore, drone technology is seen as a **key contributor to sustainable agriculture**. By minimizing over-fertilization and reducing the environmental footprint of traditional methods, drones promote more **eco-friendly and responsible farming**. As technology continues to advance, drones will become even more essential in shaping the future of **efficient, sustainable, and environmentally conscious agriculture**.

ACKNOWLEDEMENT

This work was supported by a grant of the Romanian Ministry of Education and Research, through the project "Intelligent technology for high precision application of plant protection products, fertilizers and for seeding in hard-to-reach areas" – PN 23 04 01 01– Ctr. 9N/01.01.2023.

REFERNCES

[1] Albetis, J., Jacquin, A., Goulard, M., Poilvé, H., Rousseau, J., Clenet, H., Dedieu, G., & Duthoit, S. (2019). On the Potentiality of UAV Multispectral Imagery to Detect Flavescence dorée and Grapevine Trunk Diseases. *Remote Sensing*, 11(1), 23. https://doi.org/10.3390/rs11010023

[2] Ali M.H., Talukder M.S.U., (2008). Increasing water productivity in crop production—A synthesis. *Agricultural Water Management*, Volume 95, Issue 11, pp. 1201-1213, ISSN 0378-3774, https://doi.org/10.1016/j.agwat.2008.06.008

[3] Andreasen C., Scholle K., Saberi M., (2022). Laser Weeding with Small Autonomous Vehicles: Friends or Foes. *Frontiers in Agronomy, 4*., DOI: 10.3389/fagro.2022.841086

[4] Barcelos, C. O., Fagundes-Júnior, L. A., Mendes, A. L. C., Gandolfo, D. C., & Brandão, A. S. (2024). Integration of Payload Sensors to Enhance UAV-Based Spraying. *Drones*, 8(9), 490. https://doi.org/10.3390/drones8090490

[5] Bhat S.A., Huang N., (2021) Big Data and AI Revolution in Precision Agriculture: Survey and Challenges. *IEEE Access*, vol. 9, pp. 110209-110222, 2021, doi: 10.1109/ACCESS.2021.3102227

[6] Buters, T., Belton, D., & Cross, A., (2019). Seed and Seedling Detection Using Unmanned Aerial Vehicles and Automated Image Classification in the Monitoring of Ecological Recovery. *Drones*, 3(3), 53. https://doi.org/10.3390/drones3030053

[7] Caballero-Martin, D., Lopez-Guede, J. M., Estevez, J., & Graña, M. (2024). Artificial intelligence applied to drone control: a state of the art. *Drones*, 8(7), 296. https://doi.org/10.3390/drones8070296

[8] Canicattì M., Vallone M., (2024). Drones in vegetable crops: A systematic literature review. *Smart Agricultural Technology*, Volume 7, 100396, https://doi.org/10.1016/j.atech.2024.100396

[9] Carreño Ruiz, M., Bloise, N., Guglieri, G., & D'Ambrosio, D. (2024). Toward Virtual Testing of Unmanned Aerial Spraying Systems Operating in Vineyards. *Drones*, 8(3), 98. https://doi.org/10.3390/drones8030098

[10] Castro, G. G. R. d., Berger, G. S., Cantieri, A., Teixeira, M., Lima, J., Pereira, A. I., & Pinto, M. F. (2023). Adaptive Path Planning for Fusing Rapidly Exploring Random Trees and Deep Reinforcement Learning in an Agriculture Dynamic Environment UAVs., *Agriculture*, *13*(2), 354. https://doi.org/10.3390/agriculture13020354

[11] Chebrolu N., Läbe T., Stachniss C., (2018). Robust Long-Term Registration of UAV Images of Crop Fields for Precision Agriculture. *IEEE Robotics and Automation Letters*, pp. (99):1-1, DOI: 10.1109/LRA.2018.2849603

[12] Chen B., Huang G., Lu X., Gu S., Wen W., Wang G., Chang W., Guo X., Zhao C., (2023) Prediction of vertical distribution of SPAD values within maize canopy based on unmanned aerial vehicles multispectral imagery. *Front Plant Sci. 2023*; 14:1253536. doi: 10.3389/fpls.2023.1253536. PMID: 38192698; PMCID: PMC10773710.

[13] Chiu, M. S., & Wang, J. (2024). Evaluation of Machine Learning Regression Techniques for Estimating Winter Wheat Biomass Using Biophysical, Biochemical, and UAV Multispectral Data. *Drones*, 8(7), 287. https://doi.org/10.3390/drones8070287

[14] Couturier A., Akhloufi M.A., (2021). A review on absolute visual localization for UAV. *Robotics and Autonomous Systems.* Vol.135, 103666, ISSN 0921-8890, https://doi.org/10.1016/j.robot.2020.103666.

[15] Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. *Agriculture*, 12(10), 1745. https://doi.org/10.3390/agriculture12101745

[16] Dong, P., Wang, M., Li, K., Qiao, H., Zhao, Y., Bacao, F., Shi, L., Guo, W., & Si, H. (2024). Research on the Identification of Wheat Fusarium Head Blight Based on Multispectral Remote Sensing from UAVs. *Drones,* 8(9), 445. https://doi.org/10.3390/drones8090445

[17] Dou, W., Zhu, L., Wang, Y., & Wang, S. (2023). Research on Key Technology of Ship Re-Identification Based on the USV-UAV Collaboration. *Drones*, 7(9), 590. https://doi.org/10.3390/drones7090590

[18] Dronova I., Chippie K., Zack D., Maggi K., (2021). A Review of Unoccupied Aerial Vehicle Use in Wetland Applications: Emerging Opportunities in Approach, Technology, and Data, *Drones,* 5, no.2: 45. https://doi.org/10.3390/drones5020045

[19] Eckert, C., Hernandez-Jaramillo, D. C., Medcraft, C., Harrison, D. P., & Kelaher, B. P. (2024). Drone-Based Measurement of the Size Distribution and Concentration of Marine Aerosols above the Great Barrier Reef. *Drones*, 8(7), 292. https://doi.org/10.3390/drones8070292

[20] Esposito M., Crimaldi M., Cirillo V., Sarghini F., Maggio A., (2021). Drone and sensor technology for sustainable weed management: a review. *Chem. Biol. Technol. Agric*. 8, 18, https://doi.org/10.1186/s40538-021-00217-8

[21] Farias G.D., Dubeux Jr. J.C., Savian J.V., Duarte L.P., Martins A.P., Tiecher T., Alves L., Carvalho P.C., Bremm C., (2020). Integrated crop-livestock system with system fertilization approach improves food production and resource-use efficiency in agricultural lands. *Agronomy for Sustainable Development*, 40(39), DOI: 10.1007/s13593-020-00643-2

[22] García-Munguía A., Guerra-Ávila P., Islas-Ojeda E., Flores-Sánchez J., Vázquez-Martínez O., García-Munguía A., García-Munguía O., (2024). A Review of Drone Technology and Operation Processes in Agricultural Crop Spray. *Drones*. 8. 674. DOI: 10.3390/drones8110674

[23] Gokool, S., Mahomed, M., Clulow, A., Sibanda, M., Kunz, R., Naiken, V., & Mabhaudhi, T. (2024). Exploring the Potential of Remote Sensing to Facilitate Integrated Weed Management in Smallholder Farms: A Scoping Review. *Drones*, 8(3), 81. https://doi.org/10.3390/drones8030081

[24] Gokool, S., Mahomed, M., Kunz, R., Clulow, A., Sibanda, M., Naiken, V., Chetty, K., & Mabhaudhi, T. (2023). Crop Monitoring in Smallholder Farms Using Unmanned Aerial Vehicles to Facilitate Precision Agriculture Practices: A Scoping Review and Bibliometric Analysis. *Sustainability*, 15(4), 3557. https://doi.org/10.3390/su15043557

[25] Guebsi, R., Mami, S., & Chokmani, K. (2024). Drones in Precision Agriculture: A Comprehensive Review of Applications, Technologies, and Challenges. *Drones*, 8(11), 686. https://doi.org/10.3390/drones8110686

[26] Han, J., Zhang, T., Liu, L., Wang, G., Song, C., & Lan, Y. (2024). Impact of Variable Device Structural Changes on Particle Deposition Distribution in Multi-Rotor UAV. *Drones*, 8(10), 583. https://doi.org/10.3390/drones8100583

[27] Han, Y., Chen, P., Xie, X., Cui, Z., Wu, J., Lan, Y., & Zhan, Y. (2024). Rotor Speed Prediction Model of Multi-Rotor Unmanned Aerial Spraying System and Its Matching with the Overall Load. *Drones*, 8(6), 246. https://doi.org/10.3390/drones8060246

[28] Hasan, R. I., Yusuf, S. M., & Alzubaidi, L. (2020). Review of the State of the Art of Deep Learning for Plant Diseases: A Broad Analysis and Discussion. *Plants*, 9(10), 1302. https://doi.org/10.3390/plants9101302

[29] Htun, N. M., Owari, T., Tsuyuki, S., & Hiroshima, T. (2024). Detecting Canopy Gaps in Uneven-Aged Mixed Forests through the Combined Use of Unmanned Aerial Vehicle Imagery and Deep Learning. *Drones*, 8(9), 484. https://doi.org/10.3390/drones8090484

[30] Huang, J., He, W., Yang, D., Lin, J., Ou, Y., Jiang, R., & Zhou, Z., (2024). Quantity Monitor Based on Differential Weighing Sensors for Storage Tank of Agricultural UAV. *Drones*, 8(3), 92. https://doi.org/10.3390/drones8030092

[31] Huang X., Li Y., Ma H., Huang P., Zheng J., Song K., (2024) Fuel cells for multirotor unmanned aerial vehicles: A comparative study of energy storage and performance analysis, *Journal of Power Sources*, 613(6):234860, DOI: 10.1016/j.jpowsour.2024.234860

[32] Jibon Z., Adnan M., Nora N., Akash M., Ahammed F., (2023) Development of an Autonomous UAV for Seed and Fertilizer Distribution in Precision Agriculture, *Conference: 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, DOI: 10.1109/ICCCNT56998.2023.10308182

[33] Kannan, N., Martin, D., Srinivasan, R., & Zhang, W. (2024). Adjuvants for Drone-Based Aerial Chemical Applications to Mitigate Off-Target Drift. *Drones*, 8(11), 667. https://doi.org/10.3390/drones8110667

[34] Khan S., Tufail M., Khan M.T., Khan Z.A., Iqbal J., Wasim A., (2021). Real-time recognition of spraying area for UAV sprayers using a deep learning approach. *PLoS One. 2021*;16(4):e0249436. doi: 10.1371/journal.pone.0249436. PMID: 33793634; PMCID: PMC8016340.

[35] Khanal S., Fulton J., Shearer S., (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. *Computers and Electronics in Agriculture*, Vol.139, pp. 22-32, https://doi.org/10.1016/j.compag.2017.05.001 .

[36] Kumar, C., Mubvumba, P., Huang, Y., Dhillon, J., & Reddy, K. (2023). Multi-Stage Corn Yield Prediction Using High-Resolution UAV Multispectral Data and Machine Learning Models. *Agronomy*, 13(5), 1277. https://doi.org/10.3390/agronomy13051277

[37] Lee, D-H., Seong, B-G., Baek, S-Y., Lee, C-G., Kang, Y-H., Han, X., & Yu, S-H. (2024). Coverage Estimation of Droplets Sprayed on Water-Sensitive Papers Based on Domain-Adaptive Segmentation. *Drones*, 8(11), 670. https://doi.org/10.3390/drones8110670

[38] Li X., Liu Y., Zhang X., Huang J., Bian J., (2024). Characteristics Analysis and Modeling of Integrated Sensing and Communication Channel for Unmanned Aerial Vehicle Communications. *Drones, 8*(10):538 DOI: 10.3390/drones8100538

[39] Liu, J., Xiang, J., Jin, Y., Liu, R., Yan, J., & Wang, L. (2021). Boost Precision Agriculture with Unmanned Aerial Vehicle Remote Sensing and Edge Intelligence: A Survey. *Remote Sensing*, 13(21), 4387. https://doi.org/10.3390/rs13214387

[40] Lu, Y., Liu, M., Li, C., Liu, X., Cao, C., Li, X., & Kan, Z. (2022). Precision Fertilization and Irrigation: Progress and Applications. *AgriEngineering*, 4(3), 626-655. https://doi.org/10.3390/agriengineering4030041

[41] Lysych, M., Bukhtoyarov, L., & Druchinin, D. (2021). Design and Research Sowing Devices for Aerial Sowing of Forest Seeds with UAVs. *Inventions*, 6(4), 83. https://doi.org/10.3390/inventions6040083

[42] Martínez García, M., Ramos Cabral, S., Pérez Zúñiga, R., & Martínez Rodríguez, L.C.G. (2023). Automatic Equipment to Increase Sustainability in Agricultural Fertilization. *Agriculture*, 13(2), 490. https://doi.org/10.3390/agriculture13020490

[43] Massimo F. and Monego M., (2024). A Drone-Based Structure from Motion Survey, Topographic Data, and Terrestrial Laser Scanning Acquisitions for the Floodgate Gaps Deformation Monitoring of the Modulo Sperimentale Elettromeccanico System (Venice, Italy)" *Drones 8*, no. 10: 598. https://doi.org/10.3390/drones8100598

[44] Messina, G., & Modica, G. (2020). Applications of UAV Thermal Imagery in Precision Agriculture: State of the Art and Future Research Outlook. *Remote Sensing*, 12(9), 1491. https://doi.org/10.3390/rs12091491

[45] Ming, R., Wu, T., Zhou, Z., Luo, H., & Hassan, S. G. (2024). Research and Design of an Active Light Source System for UAVs Based on Light Intensity Matching Model. *Drones*, 8(11), 683. https://doi.org/10.3390/drones8110683

[46] Murugan D., Garg A., Singh D., (2017)., Development of an Adaptive Approach for Precision Agriculture Monitoring with Drone and Satellite Data, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, pp. (99):1-7, DOI: 10.1109/JSTARS.2017.2746185

[47] Nahiyoon, S. A., Ren, Z., Wei, P., Li, X., Li, X., Xu, J., Yan, X., & Yuan, H. (2024). Recent Development Trends in Plant Protection UAVs: A Journey from Conventional Practices to Cutting-Edge Technologies—A Comprehensive Review. *Drones*, 8(9), 457. https://doi.org/10.3390/drones8090457

[48] Niu, Y., Xu, L., Zhang, Y., Xu, L., Zhu, Q., Wang, A., Huang, S., & Zhang, L. (2024). Enhancing the Performance of Unmanned Aerial Vehicle-Based Estimation of Rape Chlorophyll Content by Reducing the Impact of Crop Coverage. *Drones*, 8(10), 578. https://doi.org/10.3390/drones8100578

[49] Panday, U. S., Pratihast, A. K., Aryal, J., & Kayastha, R. B., (2020). A Review on Drone-Based Data Solutions for Cereal Crops. *Drones*, *4*(3), 41. https://doi.org/10.3390/drones4030041

[50] Pereira, A., Warwick, S., Moutinho, A., & Suleman, A. (2024). Infrared and Visible Camera Integration for Detection and Tracking of Small UAVs: Systematic Evaluation. *Drones*, 8(11), 650. https://doi.org/10.3390/drones8110650

[51] Popescu, D., Stoican, F., Stamatescu, G., Ichim, L., & Dragana, C. (2020). Advanced UAV–WSN System for Intelligent Monitoring in Precision Agriculture. *Sensors*, 20(3), 817. https://doi.org/10.3390/s20030817

[52] Pu Q., Ananthanarayanan G., Bodik P., Kandula S., Akella A., Bahl P., Stoica I., (2015). Low Latency Geo-Distributed Data Analytics, ACM SIGCOMM Computer Communication Review, *Medium*, 45(5):421-434, DOI: 10.1145/2829988.2787505

[53] Radoglou-Grammatikis P., Sarigiannidis P., Thomas Lagkas T., Moscholios I., (2020) A compilation of UAV applications for precision agriculture, *Computer Networks*, Vol. 172, 107148, ISSN 1389-1286 https://doi.org/10.1016/j.comnet.2020.107148.

[54] Rejeb A., Abdollahi A., Rejeb K., Treiblmaier H., (2022). Drones in agriculture: A review and bibliometric analysis, *Computers and Electronics in Agriculture*, Volume 198,107017, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2022.107017

[55] Scherrer B., Sheppard J., Jha P., Shaw J., (2019). Hyperspectral imaging and neural networks to classify herbicide resistant weeds, *Journal of Applied Remote Sensing*, 13(04):1, DOI: 10.1117/1.JRS.13.044516

[56] Shadrin D., Menshchikov A., Somov A., Bornemann G., Hauslage J., Fedorov M. (2019). Enabling Precision Agriculture Through Embedded Sensing With Artificial Intelligence, *IEEE Transactions on Instrumentation and Measurement*, pp(99):1-1, DOI: 10.1109/TIM.2019.2947125

[57] Shahi, T. B., Dahal, S., Sitaula, C., Neupane, A., & Guo, W. (2023). Deep Learning-Based Weed Detection Using UAV Images: A Comparative Study. *Drones*, 7(10), 624. https://doi.org/10.3390/drones7100624

[58] Shahi T.B., Xu C-Y., Neupane A., Guo W., (2022). Machine learning methods for precision agriculture with UAV imagery: a review, *Electronic Research Archive*, 30(12): 4277-4317, DOI: 10.3934/era.2022218

[59] Sharma A. Jain A., Gupta P., (2020). Chowdary, Machine Learning Applications for Precision Agriculture: A Comprehensive Review, *IEEE Access*, pp. (99):1-1, DOI: 10.1109/ACCESS.2020.3048415

[60] Singh N., Gupta D., Joshi M., Yadav K., Nayak S., Kumar M., Nayak S., Kumar M., Nayak K., Gulaiya S., Rajpoot A.S., (2024), Application of Drones Technology in Agriculture: A Modern Approach, *Journal of Scientific Research and Reports*, Volume 30, Issue 7, pp. 142-152, 2024; Article no.JSRR.118020ISSN: 2320-0227

[61] Sitharthan R., Rajesh M., Vimal S., Saravana Kumar E., Yuvaraj S., Abhishek K., Jacob R. I., Vengatesan K., (2023). A novel autonomous irrigation system for smart agriculture using AI and 6G

enabled IoT network, *Microprocessors and Microsystems*, Volume 101,104905, ISSN 0141-9331, https://doi.org/10.1016/j.micpro.2023.104905

[62] Subeesh A., Mehta C.R., (2021) Automation and digitization of agriculture using artificial intelligence and internet of things, *Artificial Intelligence in Agriculture*, Volume 5, pp. 278-291, ISSN 2589-7217, https://doi.org/10.1016/j.aiia.2021.11.004.

[63] Tanaka, T. S. T., Wang, S., Jørgensen, J. R., Gentili, M., Vidal, A. Z., Mortensen, A. K., Acharya, B. S., Beck, B. D., & Gislum, R. (2024). Review of Crop Phenotyping in Field Plot Experiments Using UAV-Mounted Sensors and Algorithms. *Drones*, 8(6), 212. https://doi.org/10.3390/drones8060212

[64] Tripathi R.N., Ramachandran A., Tripathi V., Badola R., Hussain S.A., (2024). Optimizing Riparian Habitat Conservation: A Spatial Approach Using Aerial and Space Technologies, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, pp. (99):1-20, DOI: 10.1109/JSTARS.2024.3454453

[65] Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A Review on UAV-Based Applications for Precision Agriculture. *Information*, 10(11), 349. https://doi.org/10.3390/info10110349

[66] Valente J., Del Cerro J., Barrientos A., Sanz D., (2013). Aerial coverage optimization in precision agriculture management: A musical harmony inspired approach, *Computers and Electronics in Agriculture*, Volume 99, Pp. 153-159, ISSN 0168-1699, https://doi.org/10.1016/j.compag.2013.09.008.

[67] Van Klompenburg T., Kassahun A., Catal C., (2020) Crop yield prediction using machine learning: A systematic literature review, *Computers and Electronics in Agriculture*, Volume 177, 105709, https://doi.org/10.1016/j.compag.2020.105709

[68] Wang B., Wang Y., Wang H., Mao H., Zhou L., (2022). Research on accurate perception and control system of fertilization amount for corn fertilization planter, *Frontiers in Plant Science*, Vol. 13, DOI=10.3389/fpls.2022.1074945

[69] Wang H., Mortensen A., Mao P., Boelt B., Gislum R., (2019) Estimating the nitrogen nutrition index in grass seed crops using a UAV-mounted multispectral camera, *International Journal of Remote Sensing*, 40:7, 2467-2482, DOI:10.1080/01431161.2019.1569783

[70] Xu C., Huang S., Tian B., Ren J., Meng Q., Wang P., (2017). Manipulating Planting Density and Nitrogen Fertilizer Application to Improve Yield and Reduce Environmental Impact in Chinese Maize Production, *Front Plant Sci. 2017 Jul 12* 8:1234. doi: 10.3389/fpls.2017.01234. PMID: 28747925; PMCID: PMC5506086.

[71] Xue X., Tian Y., Yang Z., Li Z., Lyu S., Song S., Sun D., (2024). Research on a UAV spray system combined with grid atomized droplets, *Frontiers in Plant Science*, vol. 14, DOI:10.3389/fpls.2023.1286332

[72] Yacoob, A., Gokool, S., Clulow, A., Mahomed, M., & Mabhaudhi, T. (2024). Leveraging Unmanned Aerial Vehicle Technologies to Facilitate Precision Water Management in Smallholder Farms: A Scoping Review and Bibliometric Analysis. *Drones*, 8(9), 476. https://doi.org/10.3390/drones8090476

[73] Yang M., Hassan M.A., Xu K., Zheng C., Rasheed A., Zhang Y., Jin X., Xia X., Xiao Y., He Z., (2020) Assessment of Water and Nitrogen Use Efficiencies Through UAV-Based Multispectral Phenotyping in Winter Wheat, *Frontiers in Plant and Science, 11*, DOI: 10.3389/fpls.2020.00927

[74] Yang, S., Yuan, J., Chen, Z., Zhang, H., & Cui, X. (2024). Advances in Surveying Topographically Complex Ecosystems with UAVs: Manta Ray Foraging Algorithms. *Drones*, *8*(11), 631. https://doi.org/10.3390/drones8110631

[75] Yu Y., Yubin L., Guobin W., Mujahid H., Huizheng W., Xiaoqing Y., Changfeng S., Baoju W., Cancan S., (2023). Evaluation of the deposition and distribution of spray droplets in citrus orchards by plant protection drones, *Frontiers in Plant Science*, 14, DOI: 10.3389/fpls.2023.1303669

[76] Yuan, J., Zhang, Y., Zheng, Z., Yao, W., Wang, W., & Guo, L. (2024). Grain Crop Yield Prediction Using Machine Learning Based on UAV Remote Sensing: A Systematic Literature Review. *Drones,* 8(10), 559. https://doi.org/10.3390/drones8100559

[77] Zhichkin K., Nosov V., Zhichkina L., Anichkina O., Borodina I., Beketov A., (2023). Efficiency of using drones in agricultural production, *E3S Web of Conferences*, 381(2), DOI: 10.1051/e3sconf/202338101048

[78] Zhou X., Minfeng X., Binbin H., Jinfei W., Yang S., Jiali S., Chunhua L., Min X., and Xiliang Ni., (2023). A Ground Point Fitting Method for Winter Wheat Height Estimation Using UAV-Based SfM Point Cloud Data. *Drones 7*, no. 7: 406. https://doi.org/10.3390/drones7070406

[79] Zhou, X., Shi, G., & Zhang, J. (2024). Improved Grey Wolf Algorithm: A Method for UAV Path Planning. *Drones,* 8(11), 675. https://doi.org/10.3390/drones8110675

[80] Zualkernan, I., Abuhani, D. A., Hussain, M. H., Khan, J., & ElMohandes, M. (2023). Machine Learning for Precision Agriculture Using Imagery from Unmanned Aerial Vehicles (UAVs): A Survey. *Drones*, 7(6), 382. https://doi.org/10.3390/drones7060382

[81] https://www.dji.com/global/support/product/p4-multispectral

[82] https://www.sensefly.com/solutions/drones/

[83] https://www.sensefly.com/solutions/drones/

[84] https://www.dji.com/global/support/product/mavic-2